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A new estimation approach for determining the I–V characteristics of solar cells

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Abstract

A new application of pattern search optimization technique for estimating the parameters of solar cell and PV module is introduced in this article. The estimated parameters are the generated photocurrent, saturation current, series resistance, shunt resistance, and ideality factor. A new objective function formulation is introduced to guide the estimation technique toward the model parameters. The proposed approach is tested and validated using different test cases, e. g. solar cell and PV module, to show its potential. Outcomes of the developed approach are compared with those of different parameter estimation techniques to measure its accuracy. Comparison results are in favor of pattern search algorithm in all cases.

Keywords: Photovoltaic; Solar cell; Parameter estimation; Pattern search

1. Introduction

Rising oil prices, global warming, threat of terrorist attacks on oil industry, tense political environments in oil producing countries, and severe weather conditions have compelled many nations to look for alternative sources to reduce reliance on fossil based fuels. Solar energy is one of the most promising renewable sources that is currently being used worldwide to contribute for meeting rising demands of electric power. Solar cells were first used to provide electrical power for space vehicles and satellite communication systems in the late 1950s as they require no maintenance over long periods (Jha, 2010). 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 (Renewables, 2010).

PV systems comprise of different parts centered around a solar panel that typically has arrays of interconnected solar cells. Different models were developed to describe the non-linear characteristics of the current–voltage (I–V) curve of a solar cell (Xiao et al., 2006; Chegaar et al., 2003; Ye et al., 2009). A lumped parameter equivalent circuit model is commonly used to simulate the solar cell 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 main parameters that describe solar cell models behavior are the generated photocurrent, saturation current, series resistance, shunt resistance, and ideality factor. Periodical and accurate estimation of these parameters is always required to provide precise modeling and accurate performance evaluation of a given solar system.

Various deterministic and heuristic estimation techniques have been developed to approximate different parameters of solar cell models. Ref. (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 set back of this approach is its dependency on the initial values used in the proposed iterative technique.

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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. An analytical solution technique, uses 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 model 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 model 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. A 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 reference (Ye et al., 2009) 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 cell models.

Recently, pattern search (PS), a multivariate nonlinear global optimizer capable of solving different classes of optimization problems, has been receiving a considerable attention. Unlike deterministic methods, PS is a non-gradient method which gives the PS the flexibility to deal with objective functions that are not necessarily continuous, convex or differentiable, Key attractive features of this optimization algorithm are concept simplicity, ease of implementation, and computational efficiency. Kolda et al. (2003) presents a comprehensive coverage of PS developments.

This paper proposes an efficient PS technique for estimating the solar cell parameters as it introduces a new objective function to this estimation problem. The goal is to minimize the error associated with the estimated parameters. Section 2 discusses solar cell modeling and its equivalent circuit. Mathematical formulation of the estimation problem is presented in Section 3. A description of the proposed approach is provided in Section 4. Section 5 presents testing and simulation results. The paper is then concluded in Section 6.

2. Solar cell modeling

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: the terminal current, I_{ph}: the cell-generated photocurrent, I_{D1}, I_{D2}: the first and second diode currents, I_{sh}: 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 Eq. (5).

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

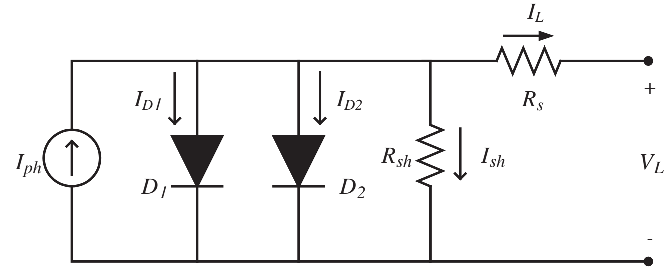

Fig. 1. Equivalent circuit of a double diode model.

The seven parameters to be estimated that fully describe the I–V characteristics are R_s, R_{sh}, I_{ph}, I_{SD1}, I_{SD1}, n_1, andn_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

This model 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 shaded. 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 Eq. (7).

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

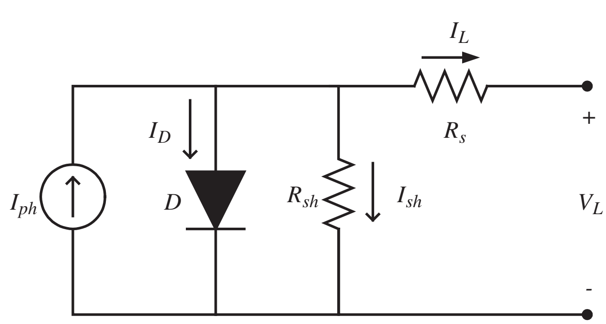

Fig. 2. Equivalent circuit of a single diode model.

3. Problem formulation

Eqs. (5)–(7) are implicit nonlinear transcendental functions that involve the overall output current produced by the solar cell and PV module 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 I_L. Numerical methods, curve fitting techniques, and different optimization methods are often utilized to solve such functions. In this paper the estimation problem is formulated as a nonlinear optimization one. The PS optimization technique is employed to estimate the parameters by minimizing a pre-selected objective function.

3.1. Objective function

In this work, a new objective function is proposed to minimize the summation of the individual absolute errors (IAE). In order to form the objective function, the I–V relationships given in any of Eqs. (5)–(7) is rewritten in the following homogeneous equations:

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

The new objective function that sums IAEs for any given set of measurements is defined as:

$$f = \sum_{i=1}^{N} |f(V_{Li}, I_{Li}, R_s, R_{sh}, \ldots)| \tag{8}$$

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

During the PS 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. Therefore the smaller the objective function, the better the solution obtained.

4. Pattern search algorithm

PS is a subclass of direct search optimization method that was originally introduced by Box in 1957 and later by Hook and Jeeves in 1961. In fact, Hooke and Jeeves are often accredited as the first to name such heuristic method by its current term "Direct Search" (Hooke and Jeeves, 1961). Not until the end of the last century that PS gained popularity and interest, as a heuristic optimization tool, among researchers working on optimization problems. Such method gained its popularity because it is quite flexible, straightforward to implement and simple, yet effective optimization technique that can easily be applied to various categories of optimization problems. In the past two decades, PS has started competing with traditional optimization tools in terms of their efficiency and convergence characteristics (Torczon, 1991, 1997). PS as a zero-order method only needs objective function evaluations towards its search for optimality. Sometimes, It is used as an alternative solution method to traditional optimization techniques when the objective function derivative is not available or has a stochastic nature (Kolda et al., 2003). The salient features of PS optimization method are: It is a non-gradient method that does not construct approximations of the objective function, it is insensitive to choosing the starting initial point, and it utilizes its own past search history in determining the forthcoming new search direction (Lewisa et al., 2000). The solar cell parameter estimation problem is mathematically formulated as a multidimensional nonlinear optimization problem and is expressed as follows

$$\min_{\mathbf{x}\in\mathbf{R}^n} f(\mathbf{x}) \tag{9}$$

where $\mathbf{x}$ is the vector of n independent variables and f: $\mathbf{R}^n \to \mathbf{R}$ is a real valued objective function. The utilized optimization solution method starts from an arbitrary initial point, called Base Point (BP) $\mathbf{x}_{BP}^{(k-1)}$where $k \in \mathbf{N}^+$ and serves as the iteration index. It searches for optimality in a sequential technique and has two routines at each iteration: exploratory search and pattern move routines.

4.1. Exploratory search routine

The exploratory search routine explore the local proximity of the BP in multiple directions for an improved objective function value. The exploratory search routine starts by spanning $2n$ coordinate directions and generate a mesh of $2n$ points, i.e. $\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_{2n}]$ and such mesh is centered at the current BP. The mesh itself is constructed along $2n$ independent positive and negative unit length coordinate vectors that belong to a finite set of $\mathbf{D}$ vectors and $\mathbf{D}$ is defined as $\mathbf{D} = \{\mathbf{D}^{+} \wedge \mathbf{D}^{-}\}$ where

$$\mathbf{D}^+ = \{+u_i | i = 1, 2, \ldots, n\} \tag{10}$$

$$\mathbf{D}^+ = \{+u_i | i = 1, 2, \ldots, n\} \tag{11}$$

where u_i is the ith unit coordinate vector. The resultant $\mathbf{D}$ can be rewritten in a vector form as follows:

$$\mathbf{D} = [\pm u_1, \pm u_2, \pm u_3, \ldots, \pm u_n] = [d_1, d_2, \ldots, d_{2n}] \tag{12}$$

As an illustration, consider an objective function of three variables, i.e. $n = 3$, the n independent positive unit length coordinate vectors forming PS exploratory search mesh are $\mathbf{D}^+ = \{[1, 0, 0], [0, 1, 0], [0, 0, 1]\}$ while the negative coordinate vectors are $\mathbf{D}^- = \{[-1, 0, 0], [0, -1, 0], [0, 0, -1]\}$. Graphical illustration of the exploratory search mesh formation is shown in Fig. 3. In a subsequent step during the exploratory search routine, the unit coordinate vectors are multiplied by a mesh size factor control parameter, Δ, where $\Delta \in \mathbf{R}^+$ and added to the best previously seen BP to generate the mesh points as demonstrated in Eq. (13). Accordingly, those newly obtained mesh points serve as the next trial points at the current iteration.

$$\mathbf{s}_i^{(k)} = \mathbf{x}_{BP}^{(k-1)} + \Delta d_i \tag{13}$$

Next, the objective function is evaluated at all the mesh points, and the point $\mathbf{s}^*$ that yields the greatest decrease in the objective function, i.e. $f(\mathbf{s}^*)^{(k)}$, is chosen to be compared with that of the initial BP, $\mathbf{x}_{BP}^{(k-1)}$, as illustrated in Eqs. (14) and (15).

$$f(\mathbf{s}^*)^{(k)} = \min\left\{f(\mathbf{s}_1^{(k)}), f(\mathbf{s}_2^{(k)}), \ldots, f(\mathbf{s}_{2n}^{(k)})\right\} \tag{14}$$

$$\mathbf{x}_{BP}^{(k)} = \begin{cases} \mathbf{s}^* & \text{if} \quad f(\mathbf{s}^*)^{(k)} < f\left(\mathbf{x}_{BP}^{(k-1)}\right) \\ \mathbf{x}_{BP}^{(k-1)} & \text{if} \quad f(\mathbf{s}^*)^{(k)} \geqslant f\left(\mathbf{x}_{BP}^{(k-1)}\right) \end{cases} \tag{15}$$

The exploratory search routine is deemed successful, if at least one of the mesh points' objective function value improved, and consequently the point that yielded the lowest value is considered as the new BP, $\mathbf{x}_{BP}^{(k)}$. Such new BP is now chosen to be the candidate for starting the second routine, i.e. pattern move routine. On the contrary, if there is no improvement, the obtained BP, $\mathbf{x}_{BP}^{(k)}$, is abandoned and the next exploratory search starts with the old BP, $\mathbf{x}_{BP}^{(k-1)}$, though with a smaller mesh size factor.

For an unsuccessful exploratory search routine, PS decreases the current mesh size factor, Δ, through multiplying it by a reduction factor, i.e. $\frac{1}{\tau}$, where $\tau \in \mathbf{N}^+ \setminus \{1\}$. A τ value of one is exempted from the positive integer number set, simply because it would lead to the mesh size factor of the previous failed exploratory move. Such mesh size factor adjustment is performed until a termination criterion is met.

4.2. Pattern move routine

The pattern move routine accelerates the search by moving the newly obtained optimal point BP, $\mathbf{x}_{BP}^{(k)}$, to a new improved position in the same direction. That is, pattern move routine shifts each variable in the new BP, $\mathbf{x}_{BP}^{(k)}$, linearly by an amount equivalent to the distance between the older BP, $\mathbf{x}_{BP}^{(k-1)}$ and the newer PB, $\mathbf{x}_{BP}^{(k)}$, as illustrated in Eq. (16). The resultant BP, $\mathbf{x}_{BP}^{(k)^+}$, becomes the newest temporary BP at which the objective function is to be evaluated as well. It can be seen from Eq. (16) that the newest temporary BP is determined based on the last two BPs that is the search history has been utilized in the second routine. If such a pattern move resulted in a lower objective function value, then the BP is successfully updated and accepted as the new BP, $\mathbf{x}_{BP}^{(k)^+}$, for the upcoming exploratory move in a subsequent iteration. However, if the objective function value did not improve with the new $\mathbf{x}_{BP}^{(k)^+}$, the pattern move routine is deemed unsuccessful

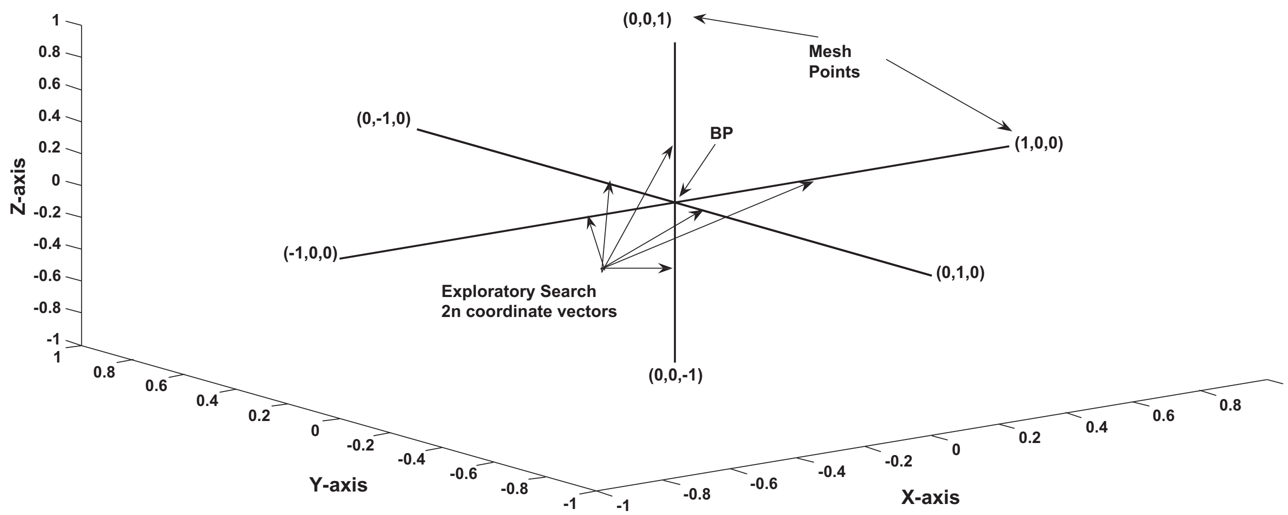

Fig. 3. Mesh formation during the exploratory search routine.

Table 1
Estimated parameters for the solar cell model using different methods.[a]

Case	Item	PS	Easwarakhanthan et al. (1986)	Bouzidi et al. (2007)	GA
Solar cell	I_{ph}	0.7617	0.7608	0.7607	0.7619
	I_{SD} (μA)	0.9980	0.3223	0.3267	0.8087
	R_s (Ω)	0.0313	0.0364	0.0364	0.0299
	G_{sh} (S)	0.0156	0.0186	0.0166	0.0236
	n	1.6000	1.4837	1.4816	1.5751

[a] G_{sh} (S) is the conductance of the shunt resistance.

and $\mathbf{x}_{BP}^{(k)}$ is the one that would start the new exploratory search routine in the next iterate.

$$\mathbf{x}_{BP}^{(k)^+} = \mathbf{x}_{BP}^{(k)} + \left[\mathbf{x}_{BP}^{(k)} - \mathbf{x}_{BP}^{(k-1)}\right] \tag{16}$$

5. Testing and simulation results

The proposed algorithm was implemented in Matlab® computing environment. Practical I–V data for solar cell and PV module are used to validate its potential. The experimental data were obtained using an automated measuring system with a CBM 8096 microcomputer and data acquisition card as reported in Easwarakhanthan et al. (1986). To provide a comprehensive evaluation of the proposed PS algorithm in estimating the solar cell parameters, both solar cell and PV module models are considered using the single diode model.

5.1. Case study 1: solar cell model

The validity of the proposed estimation method is tested in this section for the solar cell model case. The objective function as illustrated in Eq. (8) is to be minimized in order to reach an optimal set of parameters that reflects the solar cell characteristics. Thus, a value of zero for the objective function would yield an optimal solution. Table 1 shows the extracted parameters from experimental data of a silicon solar cell. Voltage and current measurements were taken using a 57 mm diameter commercial (R.T.C France) silicon solar cell under 1 sun (1000 W/m^2) at 33 °C. The obtained results are compared with different sets of results

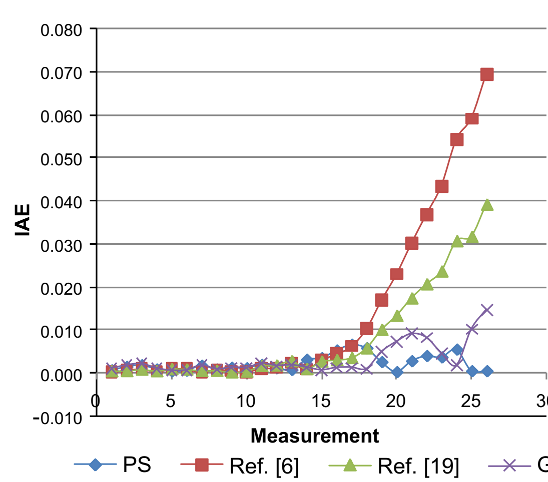

Fig. 4. IAE profiles for different estimation techniques (solar cell case).

Table 2
Curve fitting of the estimated solar cell parameters.

Measurement	V_a (V)	I_a (A)	IAE based on PS	IAE based on Easwarakhanthan et al. (1986)	IAE based on Bouzidi et al. (2007)	IAE based on GA
1	−0.2057	0.7640	0.000537	0.000109	0.000347	0.000936
2	−0.1291	0.7620	0.001343	0.000686	0.000383	0.001666
3	−0.0588	0.7605	0.001747	0.000879	0.000717	0.001999
4	0.0057	0.7605	0.000739	0.000321	0.000355	0.000927
5	0.0646	0.7600	0.000314	0.000919	0.000835	0.000445
6	0.1185	0.7590	0.000453	0.000931	0.000739	0.000533
7	0.1678	0.7570	0.001622	0.000120	0.000410	0.001662
8	0.2132	0.7570	0.000737	0.000826	0.000448	0.000755
9	0.2545	0.7555	0.001151	0.000369	0.000085	0.001178
10	0.2924	0.7540	0.001032	0.000261	0.000251	0.001127
11	0.3269	0.7505	0.001817	0.001044	0.001581	0.002074
12	0.3585	0.7465	0.001005	0.001182	0.001688	0.001571
13	0.3873	0.7385	0.000628	0.002309	0.002682	0.001707
14	0.4137	0.7280	0.003040	0.000775	0.000843	0.001185
15	0.4373	0.7065	0.003405	0.003065	0.002581	0.000530
16	0.4590	0.6755	0.005220	0.004330	0.002930	0.001094
17	0.4784	0.6320	0.006581	0.006168	0.003427	0.001150
18	0.4960	0.5730	0.005747	0.010241	0.005676	0.000829
19	0.5119	0.4990	0.002477	0.016846	0.009993	0.004796
20	0.5265	0.4130	0.000112	0.022874	0.013259	0.007163
21	0.5398	0.3165	0.002691	0.030060	0.017316	0.009007
22	0.5521	0.2120	0.003910	0.036806	0.020599	0.008115
23	0.5633	0.1035	0.003590	0.043444	0.023594	0.004458
24	0.5736	−0.0100	0.005423	0.054194	0.030641	0.001648
25	0.5833	−0.1230	0.000334	0.059145	0.031672	0.010085
26	0.5900	−0.2100	0.000339	0.069445	0.039175	0.014679
Total IAE			0.055993	0.367349	0.212223	0.081320

Table 3
Parameters extraction for the PV module model.

Case	Item	PS	Easwarakhanthan et al. (1986)	Bouzidi et al. (2007)	GA
PV module	I_{ph}	1.0313	1.0318	1.0339	1.0441
	I_{SD} (μA)	3.1756	3.2875	3.0760	3.4360
	R_s (Ω)	1.2053	1.2057	1.2030	1.1968
	G_{sh} (S)	0.0014	0.0018	0.0018	0.0018
	n	48.2889	48.4500	48.1862	48.5862

reported from references (Easwarakhanthan et al., 1986; Bouzidi et al., 2007) and results obtained using GA. These three methods represent different estimation methodologies used in parameter estimation, namely Newton based techniques, static estimation methods, and population based algorithms respectively. Table 1 shows that most of the parameters extracted using the proposed method, are very close to those reported in the other two references. A curve fitting is performed next to evaluate the goodness of fit of the obtained solution as shown in Table 2.

The parameters extracted using the PS method are substituted in Eq. (6) in its homogeneous form to evaluate the fitness. A similar procedure is done with the results obtained from references (Easwarakhanthan et al., 1986; Bouzidi et al., 2007). The optimal value is to be zero for each of the 26 equations. It is noteworthy that the IAE associated with most measurements is lower in case of PS results. Also, the sum of IAEs is 0.055993, which is much lower than those obtained using other methods. Fig. 4 shows the pattern of IAE for all four different methods. It is obvious that the parameters extracted using PS generated the best IAE profile. It can be seen from this figure that other competing methods have diverged above measurement 15 or so.

5.2. Case study 2: PV module model

In this section, the PV module model is used to characterize a set of I–V data. The 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

Table 4
Curve fitting for the PV module model.

Measurement	V_a (V)	I_a (A)	IAE based on PS	IAE based on Easwarakhanthan et al. (1986)	IAE based on Bouzidi et al. (2007)	IAE based on GA
1	0.1248	1.0315	0.002135	0.002197	7.74758E−05	0.010193793
2	1.8093	1.0300	0.003030	0.003783	0.001645391	0.008698485
3	3.3511	1.0260	0.001267	0.002651	0.000495255	0.009911526
4	4.7622	1.0220	0.000558	0.001406	0.000771843	0.011228492
5	6.0538	1.0180	0.002262	0.000236	0.001971045	0.012457628
6	7.2364	1.0155	0.001986	0.001009	0.001243466	0.011728394
7	8.3189	1.0140	0.000419	0.003879	0.001553998	0.008880327
8	9.3097	1.0100	0.002528	0.006421	0.003985862	0.006327239
9	10.2163	1.0035	0.006023	0.010319	0.007721693	0.00237697
10	11.0449	0.9880	0.006603	0.011258	0.008442889	0.001333667
11	11.8018	0.9630	0.006499	0.011449	0.008368167	0.000977468
12	12.4929	0.9255	0.005437	0.010586	0.007217233	0.001607955
13	13.1231	0.8725	0.002350	0.007565	0.003931467	0.004322128
14	13.6983	0.8075	0.002308	0.007422	0.003598334	0.004074905
15	14.2221	0.7265	0.000119	0.004707	0.000824159	0.006303696
16	14.6995	0.6345	0.001255	0.003093	0.000681443	0.007322338
17	15.1346	0.5345	0.000617	0.003074	0.000404116	0.00662565
18	15.5311	0.4275	0.001154	0.001730	0.001261056	0.007121865
19	15.8929	0.3185	0.000390	0.002341	1.36166E−05	0.005535372
20	16.2229	0.2085	0.001615	0.002547	0.001034466	0.00423231
21	16.5241	0.1010	0.005205	0.005052	0.004482183	0.000525321
22	16.7987	−0.0080	0.000561	0.000669	0.000225555	0.004951548
23	17.0499	−0.1110	0.000051	0.002283	0.000751118	0.0052044
24	17.2793	−0.2090	0.000244	0.003185	0.000524973	0.004701146
25	17.4885	−0.3030	0.002267	0.006750	0.002956545	0.006836252
Total IAE			0.056883	0.115612	0.064183	0.153479

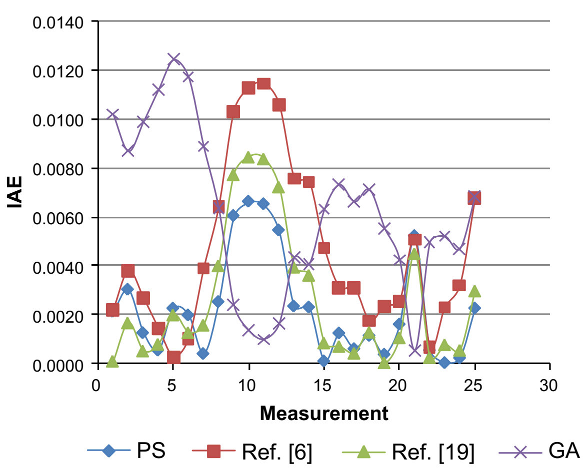

Fig. 5. IAE profiles for different estimation techniques (PV module case).

region. From estimation point of view, this will lead to bad estimation results. In similar manner to the solar cell model case, the parameters are estimated using the proposed PS technique. Estimated parameters along with curve fitting values are given in Tables 3 and 4 respectively. The summation of IAEs equals 0.056883. The maximum absolute error recorded in this case was 0.006603. Fig. 5 shows the IAE profiles for different estimation methods. Again, parameters estimated using PS generated the best IAE profile. Reductions in the IAE as well as the sum of IAEs are quite noticeable when PS results are compared to other competing methods.

6. Conclusion

This paper addresses the problem of solar cell parameters identification using PS algorithm. Different models, namely solar cell and PV module, are used to validate the performance of the proposed approach in tackling this estimation problem. A new objective function is proposed to guide the PS algorithm to the optimal estimated parameter values. The solution framework is implemented and tested using actual recorded data. Results obtained using PS algorithm, especially when compared to other competing methods, are quite promising and deserve serious attention. It sheds light on the PS 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 future work, impact of different operating conditions such as shading on solar cell modeling and parameters estimation will be investigated.

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