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Optimal extraction of solar cell parameters using pattern search

M.F. AlHajri, K.M. El-Naggar, M.R. AlRashidi*, A.K. Al-Othman

Electrical Engineering Department, Collage of Technological Studies (PAAET), P.O. Box 42325-70654, Shuwaikh, Kuwait

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ABSTRACT

This paper presents an application of pattern search optimization technique for extracting the parameters of different solar cell models. These models are single diode, double diode, and photovoltaic module. The solar cell parameters estimation is viewed and formulated as a multivariate non-linear optimization problem. The proposed 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. Comparison among different parameter estimation techniques is presented to show the effectiveness of the developed approach. Moreover, error and statistical analyses are carried out to measure the accuracy of the estimated parameters and model suitability.

1. Introduction

Recently, serious involvement of renewable energy sources in producing electricity is being sought by many nations due to various reasons. Among these are possible depletion and price increase of fossil based fuels, global warming, air pollution, strict environmental laws, and rapid advances being made with regard to renewable energy technologies. 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 [1]. Unlike other noisy distributed generation units such as wind turbines, PV is capable of directly converting solar energy to electricity in quite environment without polluting the atmosphere.

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 [2–4]. 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 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.

Several estimation techniques have been reported to approximate different parameters of solar cells. Ref. [5] 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 Ref. [6] 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 Ref. [7]. Similar analytical solution methods are presented in Refs. [8–10]. 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 Ref. [11]. Shortcomings of reported results are the relatively high percentage of errors associated with the extracted parameters and

* Corresponding author. Tel.: +965 22314312; fax: +965 481 6568.
E-mail addresses: mr.alrashidi@paaet.edu.kw, malrash@hotmail.com (M.R. AlRashidi).

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the binary conversion pertaining to GA implementation. Particle swarm optimization (PSO) is introduced in Ref. [4] 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. In more recent work, Refs. [12,13] present further investigations of PSO potential in extracting solar cell parameters. In PSO, improper tuning of many key parameters, such as acceleration constants (C_1 and C_2) that keep balance between the particle's individual and social behavior and the inertia weight that balances between exploration and exploitation of particles, may lead the search process to get trapped in local solution rather than global one. PS has less parameters, as seen in Section 3, when compared to PSO which simplify the tuning process.

Lately, Pattern Search (PS), a global optimizer capable of solving a wide range of optimization problems, has been receiving a significant attention. Unlike many conventional optimization techniques, it does not require the gradient information to guide its search process nor does it impose certain characteristics on the objective function such as convexity or continuity. Key attractive features of this optimization algorithm are concept simplicity, ease of implementation, and computational efficiency. Ref. [14] presents a comprehensive coverage of PS developments.

This paper proposes a robust and efficient PS technique for extracting the solar cell parameters. The goal is to minimize the error associated with the estimated parameters. Section 2 discusses the solar cell modeling and mathematical formulation of the estimation problem. A description of the proposed approach is provided in Section 3. Section 4 presents testing and simulation results. The paper is then concluded in Section 5.

2. Solar cell modeling and problem formulation

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 [15]. 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.

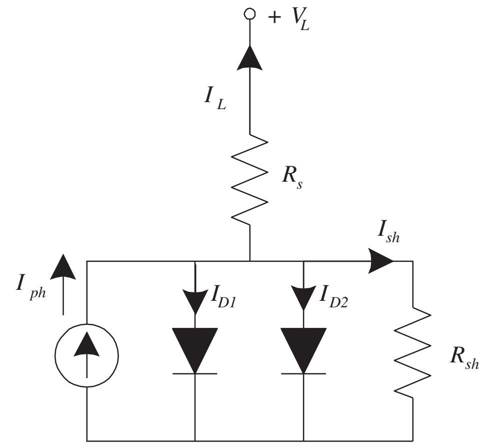

Fig. 1. Equivalent circuit of a double diode model.

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).

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

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:

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

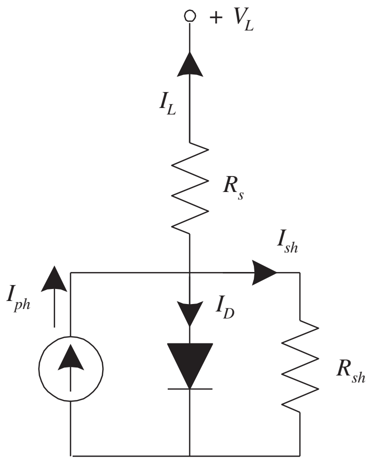

Fig. 2. Equivalent circuit of a single diode model.

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 Eq. (7).

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

2.4. Problem formulation

It is noted that Eqs. (5)–(7) are implicit non-linear 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 (both deterministic and heuristic) are often utilized to solve such functions. In this paper the estimation problem is formulated as a non-linear optimization one. The PS 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, an absolute error 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) are rewritten in the following homogeneous equations:

$$f_i\left(V_L, I_L, I_{ph}, I_{SD1}, I_{SD2}, R_s, R_{sh}, n_1, n_2\right) = 0 \quad \text{for the double diode model}$$

$$f_i\left(V_L, I_L, I_{ph}, I_{SD}, R_s, R_{sh}, n\right) = 0 \quad \text{for the single diode model}$$

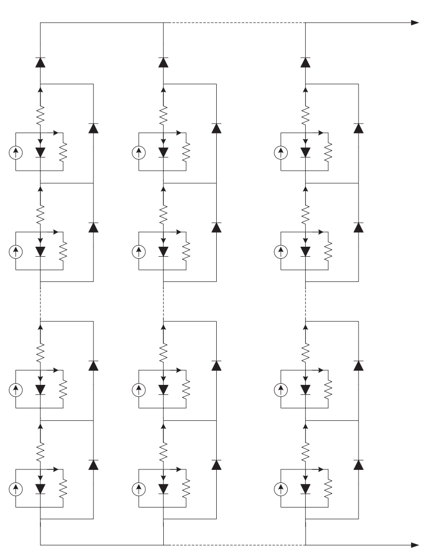

Fig. 3. Equivalent circuit model of a PV module.

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

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

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

Eq. (8) represents the objective function that was used in this study to guide the proposed approach in extracting different model parameters. Unlike the error square formulation presented in previous studies, it is formulated in absolute error form. Thus, a different objective is presented as an alternative one to find the optimal sets of solar cell parameters.

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. Moreover the smaller the objective function, the better the solution obtained.

3. Pattern search

Multivariate non-linear optimization problems deal with minimizing (or maximizing, depending on the goal) a non-linear objective function in a given domain. Such mathematical programming problems are usually solved via deterministic and/or heuristic optimization solution methods. Direct Search method of Hooke and Jeeves is the heuristic technique used in this paper to solve for the solar cell parameter estimation problem 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: $\mathbf{R}^n \rightarrow \mathbf{R}$ is a real valued objective function.

Hooke and Jeeves are accredited as the first to name such heuristic method by its current term "Direct Search", and introduced PS as one of the Direct Search subclass methods in 1961 that only needs objective function values toward its search for optimality [16]. Recently PS has competed with traditional optimization tools in terms of their efficiency and convergence characteristics [17,18]. It is quite flexible, straightforward to implement and a simple, yet effective optimization technique that can easily be applied to various categories of optimization problems. Sometimes, PS is used as an alternative solution method to traditional optimization techniques when the objective function derivative is not available or has a stochastic nature [14]. The salient features of PS optimization method are: it is a zero-order 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 [19].

PS is a derivative-free algorithm that starts from any arbitrary initial point, called Base Point (BP) $\mathbf{x}_{\mathrm{BP}}^{(k-1)}$ where k serves as the iteration index. It searches for optimality in a sequential technique in which each step is comprised of two types of moves, exploratory and pattern moves. In the exploratory move, the search direction 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 in a compact form as $\mathbf{D} = \{\pm u_i | i = 1, 2, \ldots, n\} = \{d_i\}_{i=1}^{2n}$ or in a vector form as:

$$\mathbf{D} = [u_1, u_2, \ldots, u_n, -u_1, -u_2, \ldots, -u_n] = [d_1, d_2, \ldots, d_{2n}] \tag{10}$$

where u_i is the ith unit coordinate vector. In a subsequent step during the exploratory move, the unit coordinate vectors are multiplied by a step size 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. (11). Accordingly, those newly obtained mesh points serve as the next trial points at the current iteration.

$$\mathbf{s}_i^{(k)} = \mathbf{x}_{\mathrm{BP}}^{(k-1)} + \Delta d_i \tag{11}$$

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, $\mathbf{x}_{\mathrm{BP}}^{(k-1)}$, as illustrated in Eqs. (12) and (13).

$$F\left(\mathbf{s}^*\right)^{(k)} = \min\{F(\mathbf{s}_1^{(k)}), F(\mathbf{s}_2^{(k)}), \ldots, F(\mathbf{s}_{2n}^{(k)})\} \tag{12}$$

$$\mathbf{x}_{\mathrm{BP}}^{(k)} = \begin{cases} \mathbf{s}^* & \text{if} \quad F(\mathbf{s}^*)^{(k)} < F\left(\mathbf{x}_{\mathrm{BP}}^{(k-1)}\right) \\ \mathbf{x}_{BP}^{(k-1)} & \text{if} \quad F(\mathbf{s}^*)^{(k)} \geq F\left(\mathbf{x}_{\mathrm{BP}}^{(k-1)}\right) \end{cases} \tag{13}$$

The exploratory move is deemed successful, if at least one of the mesh points objective function value improved, and the point that yielded the lowest value is considered as the new BP, $\mathbf{x}_{\mathrm{BP}}^{(k)}$. Such new BP is now chosen to be the candidate for starting the second type of move, i.e. pattern move. On the contrary, if there is no improvement, the obtained BP, $\mathbf{x}_{\mathrm{BP}}^{(k)}$, is discarded and the next exploratory search starts with the old BP, $\mathbf{x}_{\mathrm{BP}}^{(k-1)}$, though with a smaller step size. It can be seen that the exploratory move iteratively replaces the 'old' coordinate search direction vertices with better ones.

For an unsuccessful exploratory move, PS decreases the current step size, Δ, through multiplying it by a reduction factor, i.e. $1/\tau$, where $\tau \in \mathbf{N}^+\backslash\{1\}$. A τ value of one is exempted from the positive integer number set, simply because it would lead to the step size of the previous failed exploratory move. Such step size adjustment is performed until it reaches a predefined tolerance of δ.

The pattern move shifts the new BP, $\mathbf{x}_{\mathrm{BP}}^{(k)}$, linearly according to Eq. (14), and the resultant BP, $\mathbf{x}_{\mathrm{BP}}^{(k)^+}$, becomes the newest temporary BP at which the objective function is to be evaluated as well. It can be seen from Eq. (14) that the newest temporary BP is determined based on the last two BPs; that is the search history has been utilized in the second type of move. If such a pattern move resulted in a lower objective function value, then the BP is successfully updated and accepted as the new BP, $\mathbf{x}_{\mathrm{BP}}^{(k)^+}$, for the upcoming exploratory move in a subsequent iteration. However, if the objective function value did not improve with the new $\mathbf{x}_{\mathrm{BP}}^{(k)^+}$, the pattern move is deemed unsuccessful and $\mathbf{x}_{\mathrm{BP}}^{(k)}$ is the one that would start the new exploratory move in the next iterate.

$$\mathbf{x}_{\mathrm{BP}}^{(k)^+} = \mathbf{x}_{\mathrm{BP}}^{(k)} + \left[\mathbf{x}_{\mathrm{BP}}^{(k)} - \mathbf{x}_{\mathrm{BP}}^{(k-1)}\right] \tag{14}$$

The flowchart in Fig. 4 illustrates the PS algorithm.

4. Testing and simulation results

To provide a thorough evaluation of the proposed PS algorithm in estimating the solar cell parameters, both single and double diode models are considered. Moreover, for the single diode model, two sets of I–V data are used to estimate model parameters of commercial solar cells and solar module.

4.1. Case study 1: single diode model

The validity of the proposed estimation method is tested in this section for the single diode model case. Practical measured I–V data of a solar cell and solar module are considered for testing. Data of 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 Ref. [5].

The objective function as illustrated in (8) is to be minimized in order to reach an optimal set of parameters that reflect 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 and PV module at 33 °C and 45 °C, respectively. The obtained results are compared with two different sets of results obtained from Refs. [5,20]. Table 1 shows that, in both cases, 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 Tables 2 and 3 for the solar cell and PV module, respectively.

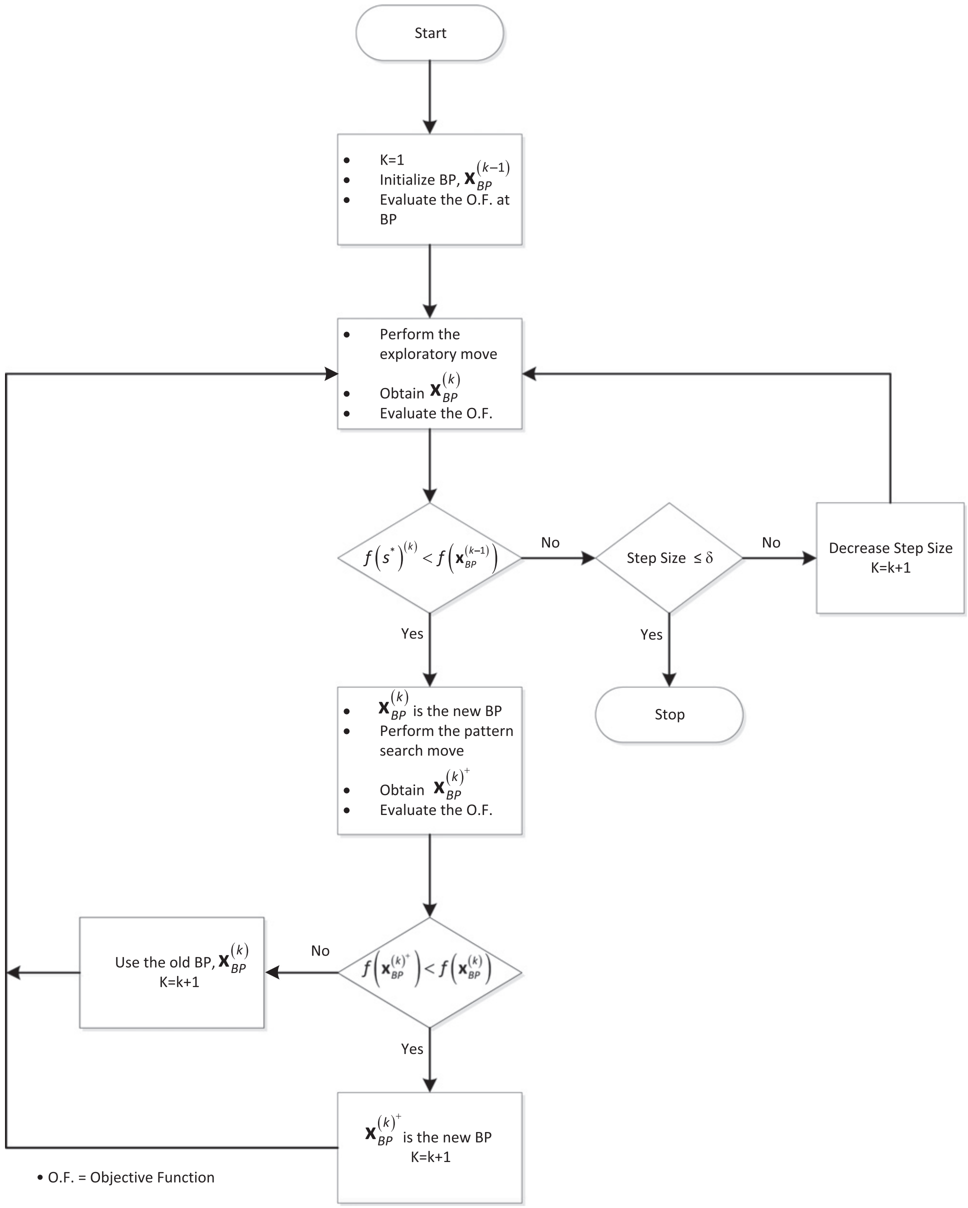

Fig. 4. Flowchart of PS algorithm.

Table 1
Comparison of parameters extraction for the single diode model.

Case	Item	PS estimation	Ref. [5]	Ref. [20]
Solar cell	I_{ph}	0.7617	0.7608	0.7607
	I_{SD} (μA)	0.9980	0.3223	0.3267
	R_s (Ω)	0.0313	0.0364	0.0364
	G_{sh} (S)	0.0156	0.0186	0.0166
	n	1.6000	1.4837	1.4816
	RMSE	0.2863	0.6251	0.3161
PV module	I_{ph}	1.0313	1.0318	1.0339
	I_{SD} (μA)	3.1756	3.2875	3.0760
	R_s (Ω)	1.2053	1.2057	1.2030
	G_{sh} (S)	0.0014	0.0018	0.0018
	n	48.2889	48.4500	48.1862
	RMSE	0.0118	0.7805	0.6130

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 Refs. [5,20]. 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. In Table 3, fitting results obtained for the module case are reported. Reductions in the IAE as well as the sum of IAEs are quite noticeable when PS results are compared to references' results.

4.1.1. *Error analysis*

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

Table 2
Curve fitting of the estimated solar cell parameters.

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

The RMSE, MBE and MAE are given by:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(e_i)^2} \tag{15}$$

$$\text{MBE} = \frac{1}{N}\sum_{i=1}^{N}e_i \tag{16}$$

Table 3
Curve fitting of the estimated PV module parameters.

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

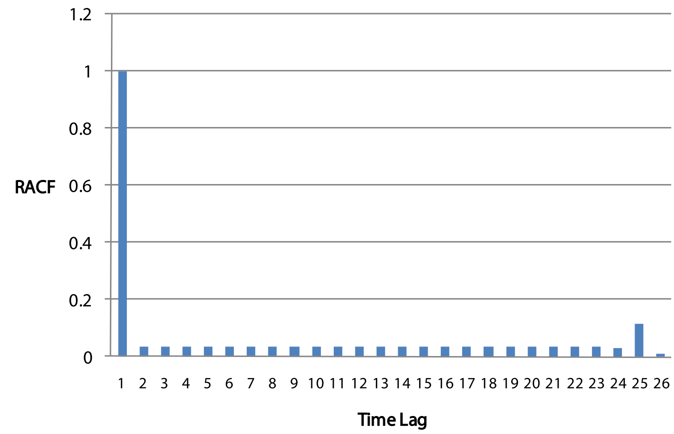

Fig. 5. Results of the whiteness test for the solar cell case.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|e_i| \tag{17}$$

where

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

4.1.2. *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:

$$\text{RACF}_k = \frac{\sum_{t=k+1}^{N}\varepsilon_t\varepsilon_{t-k}}{\sum_{t=1}^{N}\varepsilon_t^2} \tag{18}$$

where,

k: is the time lag which is an integer value denoting how many time steps separate one value from another.

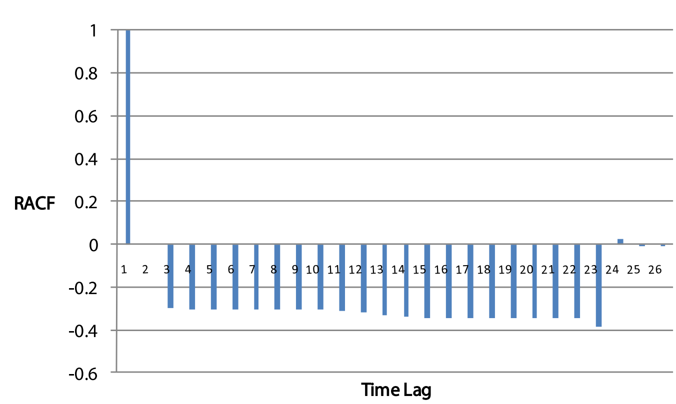

Fig. 6. Results of the whiteness test for the PV module case.

Table 4
Parameters extraction for the double diode model.

Parameter	PS estimation
I_{ph}	0.7602
I_{SD1} (μA)	0.9889
R_s (Ω)	0.0320
G_{sh} (S)	0.0123
n_1	1.6000
I_{SD2} (μA)	0.0001
n_2	1.1920

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

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.

The computed values of the statistical factors show high accuracy in both cases. It has been found that RMSE, MBE, and MAE values are respectively 0.2863, −0.0529, and 0.07795 for the solar cell case. The corresponding values for the PV module are 0.1180, 0.0011, and 0.0054.

When compared to references' values, RMSE computed from PS results is much lower than the corresponding reference' values as shown in Table 1. In addition, the proposed method reduces the overall estimation error (in an absolute sense) at a very low standard deviation. Whiteness test results shown in Figs. 5 and 6 confirm the higher quality of results obtained.

4.2. Case study 2: double diode model

In this section, the double diode model is used to characterize a set of I–V data of a solar cell. In this case, two more unknowns are added to the problem (I_{SD2}, n_2). Therefore, the overall unknowns parameters become seven rather than five. These unknowns are given in the double diode model described by Eq. (5). In similar manner to the single diode model case, the parameters are estimated using the proposed PS technique. Estimated parameters along with curve fitting values are given in Tables 4 and 5 respectively. The summation of IAEs equals 0.050585. Compared with IAE = 0.055993 which was obtained using the single diode model, no significant improvement in the accuracy has been achieved. The maximum absolute error recorded in this case was 0.0075294. This indicates that the single diode model reasonably describes the model characteristics. However, it is important to emphasize that the goal of this work is to estimate model parameters rather than validating model accuracy.

Table 5
Curve fitting for the double diode model.

Measurement	V_a (V)	I_a (A)	IAE based on PS
1	−0.2057	0.764	0.0015815
2	−0.1291	0.762	0.0005264
3	−0.0588	0.7605	0.000106
4	0.0057	0.7605	0.0006918
5	0.0646	0.76	0.0009248
6	0.1185	0.759	0.0006106
7	0.1678	0.757	0.0007182
8	0.2132	0.757	1.963E-05
9	0.2545	0.7555	0.0005262
10	0.2924	0.754	0.0005259
11	0.3269	0.7505	0.0014101
12	0.3585	0.7465	0.0006727
13	0.3873	0.7385	0.0003336
14	0.4137	0.728	0.0033565
15	0.4373	0.7065	0.0038234
16	0.459	0.6755	0.0058478
17	0.4784	0.632	0.0075294
18	0.496	0.573	0.0071042
19	0.5119	0.499	0.0042714
20	0.5265	0.413	0.0023209
21	0.5398	0.3165	0.0001889
22	0.5521	0.212	0.0012975
23	0.5633	0.1035	0.0011202
24	0.5736	−0.01	0.0034277
25	0.5833	−0.123	0.0015812
26	0.59	−0.21	6.878E-05
Total IAE			0.0505855

5. Conclusion

The problem of solar cell parameters identification is addressed in this paper using PS algorithm. Different models, namely single diode, double diode, and photovoltaic module, are used to validate the performance of the proposed approach in tackling this estimation problem. An alternative 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 over-simplifying 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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