Extraction of Photovoltaic Characteristics Using Simulated Annealing

M. R. AlRashidi, K. M. El-Naggar, and M. F. AlHajri

***Abstract*—**This paper presents Simulated Annealing based approach for optimal extraction of Photovoltaic characteristics. Key factors such as generated photocurrent, saturation currents, series resistance, shunt resistance, and ideality factors govern the current-voltage characteristics of Photovoltaic panels. The objective of this paper is to estimate these model parameters using simulated annealing by formulating the estimation problem as a non-linear optimization problem. Real measured data is used to test and validate the reliability of accurately estimating various parameters of photovoltaic panel parameters using the proposed approach.

***Keywords*—**Simulated Annealing, Photovoltaic Panel, Optimization, Parameter Extraction.

I. Introduction

SOLAR energy is becoming more popular as alternative means of generating electricity in various parts of the world. Several reasons are promoting serious involvement of environmental friendly energy sources in electricity production in many countries. Some of these reasons are: environmental concerns due to greenhouse effect, possible depletion and price increase of conventional energy primary resource. Solar energy is one of the most promising emission free resources that is currently being used worldwide to contribute to meeting rising demands of electric power. Solar photovoltaic (PV) is the fastest growing power-generation technology in the world with an annual average increase of 60% between 2004-2009 [1]. PV is an environmental friendly distributed generation unit that has the capability of directly converting solar energy to direct current.

Solar systems convert sun radiation into direct current through a solar panel that typically has arrays of interconnected solar cells. A non-linear current-voltage (I-V) characteristics exist in solar cell's behavior. Various representations have been proposed to describe the current-voltage relationship (I-V) in solar cells [2-4]. 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 [5].

Various algorithms have been applied to determine model parameters of solar cells. Reference [6] proposed a modified non-linear least error squares estimation approach based on Newton's method to determine solar cell parameters. However, this approach suffers from its high dependency on the initial values used in the proposed iterative technique. Another analytical solution technique called "Co-content function" which is based on Lambert function has been proposed in reference [7] to estimate the solar cell parameters. Genetic Algorithm (GA) based algorithm is introduced to extract solar cell parameters in reference [8]. Negative aspect of reported results are the relatively high percentage of errors associated with the extracted parameters. Reference [5] proposed Pattern Search (PS) technique for extracting the solar cell parameters. This paper proposes a simulated annealing (SA) based approach as an alternative method to extract key parameters of PV module.

II. Solar Cell Modeling

Providing a mathematical model that accurately describes the electrical behavior of solar cell is quite crucial. Many equivalent circuit models have been developed and proposed to describe the PV's behavior. It is quite often single diode model is used in modeling PV panel. Diffusion and recombination currents are often combined together under the introduction of a non-physical diode ideality factor to represent the single diode model. This is the most commonly used model and it has been used successfully to fit experimental data. The single diode model equivalent circuit is shown in Fig. 1.

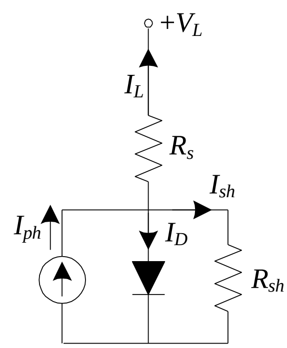

Fig. 1 Equivalent circuit of a single diode model.

In this model, load current (I_L) is computed using the following equation:

M. R. AlRashidi is with the electrical engineering Department, College of Technological Studies, (PAAET), Kuwait, (Phone:965-22314312; email: malrash2002@yahoo.com).

K. M. El-Naggar is with the electrical engineering Department, College of Technological Studies, (PAAET), Kuwait, (Phone:965-22314312; email: knaggar60@hotmail.com).

M. F. AlHajri is is with the electrical engineering Department, College of Technological Studies, (PAAET), Kuwait, (Phone:965-22314312; email: mfalhajri@yahoo.com).

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

In this case, the parameters to be estimated are:
R_s, R_{sh}, I_{ph}, I_{SD}, and n.

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.2, 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. (2).

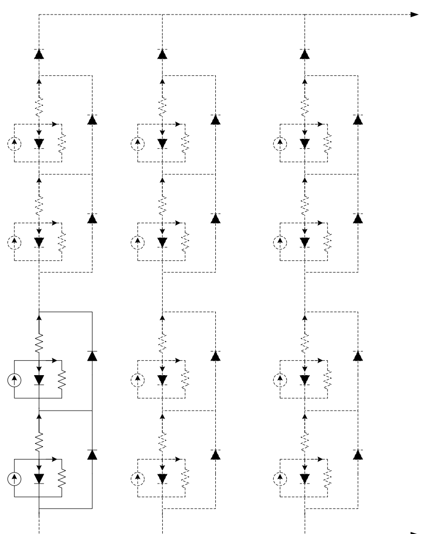

Fig. 2 Equivalent circuit model of a PV module

$$I_L = I_{ph}N_p - I_{SD}N_p\left[\exp\left(\frac{q\left(\frac{V_L}{N_s} + I_L\frac{R_s}{N_p}\right)}{nkT}\right) - 1\right] - \left[\frac{\frac{V_L N_p}{N_s} + I_L R_s}{R_{sh}}\right] \quad (2)$$

SA optimization technique is employed in this paper to estimate the parameters by minimizing the total error. In order to form the objective function, the I-V relationships given in is rewritten in the following form:

$$f(V_L, I_L, I_{ph}, I_{SD1}, I_{SD2}, R_s, R_{sh}, n_1, n_2) = 0$$

The new objective function that sums the individual absolute errors (IAEs) for any given set of measurements is defined as:

$$f = \sum_{i=1}^{N}\left|f\left(V_{Li}, I_{Li}, R_s, R_{sh}, \ldots\right)\right| \quad (3)$$

Where, N is the number of data points, I_{Li} and V_{Li} are i^{th} measured current and voltage pair values, respectively.

III. Simulated Annealing

SA algorithm involves two major steps: transition mechanism between states and cooling schedule with the objective being finding the state of minimum energy. Forming a perfect crystal is simply done by carefully controlling temperature in the cooling (or annealing) process. In SA, a new generation of possible solutions is randomly generated at each iteration. A probability distribution with a scale proportional to the temperature governs the distance of the new solution candidate from existing one. Just like in the case of most heuristic techniques, an objective function is used to guide the optimization process and temperature parameter decreases based on a cooling schedule as it converges to the best estimation [1].

SA technique was proposed independently by Kirkpatrick et al. in 1983 [9] and by Cerny in 1985 [10]. They have discovered that alternative physical states of the matter resemble the solution space of an optimization problem and the objective function corresponds to the free energy of the material. Forming a perfect crystal corresponds to finding optimal solution whereas a defected crystal corresponds to finding a local solution. This model generates a sequence of solid states and assumes that the probability for a physical system to have a certain energy level E 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 S_i with energy level E_i and the next state S_j with energy E_j, if the difference between the two energy levels is less than or equal to zero, the new state S_j is accepted. Otherwise, if the difference is greater than zero, the new state is accepted with probability

$$P(E,T) = e^{\left(\frac{E_i - E_j}{k_B * T}\right)} \quad (4)$$

IV. Simulation Results

Reported I-V data of solar cell are employed to validate SA performance in estimating PV model parameters [6]. Solar cell data is used to extract its parameters using the PV module. The extracted parameters for the PV module are shown in Table I. Curve fitting procedure is done and the IAE for each measurement is calculated and presented in Table 2. This is done based on the extracted parameters and the I-V data set is reconstructed. Small values of IAEs clearly indicate that SA succeeded in accurately estimating PV main characteristics.

TABLE I
PARAMETERS EXTRACTION FOR THE PV MODULE

Case	Parameter	SA
PV Module	*Iph*	1.0331
	ISD (μA)	3.6642
	Rs (Ω)	1.1989
	Gsh (S)	0.0012
	n	48.8211
	RMSE	0.0027

V. CONCLUSION

PV key parameters are estimated using SA. The proposed approach is implemented and tested using actual measured data. Results obtained using SA algorithm are quite promising and deserve serious attention. It highlights the strong potential of SA as a valuable new method for parameters estimation and system identification due to its simplicity and ease of use.

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TABLE II
IAES BASED ON THE EXTRACTED PARAMETERS FOR PV MODULE

Measurment	Va (V)	Ia (A)	IAE based on SA
1	0.1248	1.0315	0.00006
2	1.8093	1.0300	0.00064
3	3.3511	1.0260	0.00141
4	4.7622	1.0220	0.00349
5	6.0538	1.0180	0.00541
6	7.2364	1.0155	0.00529
7	8.3189	1.0140	0.00296
8	9.3097	1.0100	0.00083
9	10.2163	1.0035	0.00282
10	11.0449	0.9880	0.00370
11	11.8018	0.9630	0.00403
12	12.4929	0.9255	0.00350
13	13.1231	0.8725	0.00100
14	13.6983	0.8075	0.00152
15	14.2221	0.7265	0.00044
16	14.6995	0.6345	0.00122
17	15.1346	0.5345	0.00036
18	15.5311	0.4275	0.00080
19	15.8929	0.3185	0.00074
20	16.2229	0.2085	0.00189
21	16.5241	0.1010	0.00534
22	16.7987	-0.0080	0.00059
23	17.0499	-0.1110	0.00006
24	17.2793	-0.2090	0.00000
25	17.4885	-0.3030	0.00262
Total IAE			0.05071

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