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Solar cell parameter extraction using genetic algorithms

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Abstract
In this paper, a technique based on genetic algorithms is proposed for improving the accuracy of solar cell parameters extracted using conventional techniques. The approach is based on formulating the parameter extraction as a search and optimization problem. Current–voltage data used were generated by simulating a two-diode solar cell model of specified parameters. The genetic algorithm search range that simulates the error in the extracted parameters was varied from ±5 to ±100% of the specified parameter values. Results obtained show that for a simulated error of ±5% in the solar cell model values, the deviation of the extracted parameters varied from 0.1 to 1% of the specified values. Even with a simulated error of as high as ±100%, the resulting deviation only varied from 2 to 36%. The performance of this technique is also shown to surpass the quasi-Newton method, a calculus-based search and optimization algorithm.

Keywords: genetic algorithms, parameter extraction, photovoltaics, solar cell

1. Introduction

Accurate extraction and optimization of solar cells and solar panel parameters are very important in improving the device quality during fabrication and in device modelling and simulation [1–3]. The series resistance for instance, has a significant effect on both the fill factor and the conversion efficiency [3, 4]. Solar cell and panel circuit parameters are conventionally extracted from either the load I–V data measured under illumination or in the dark. Several methods for solar cell parameter extraction using the I–V characteristics have been proposed [1–11]. The direct approaches are based on the use of the I–V curve features such as the axis intercepts and the gradients at selected points to determine some of the cell parameters. The accuracy of these techniques is therefore limited by the accuracy of the measured data, the errors introduced by numerical differentiation and the simplified formulae used for parameter extraction. The other approaches for parameter extraction rely on the use of fitting algorithms to determine the solar cell parameters. Their accuracy depends on the applied fitting algorithm, the user defined error function and the starting values of the parameters to be fitted [1].

In this context, we propose a novel technique based on genetic algorithms for improving the accuracy of solar cell parameters extracted using direct techniques. The underlying concept is to formulate the solar cell parameter extraction as a search and optimization problem for a two-diode model. The application of this technique in practice would entail using one of the existing techniques to determine approximate starting values for these parameters. The proposed genetic algorithm method may then be used to refine these values.

2. Two-diode model of a solar cell

With reference to figure 1, the current–voltage relation of a two-diode model for a silicon solar cell may be expressed as [12]

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

where I_{ph} is the cell-generated photocurrent,

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

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

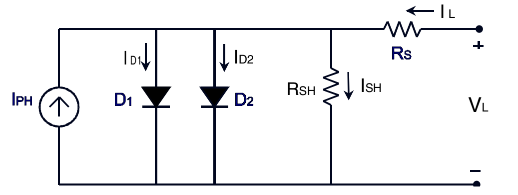


Figure 1. Solar cell two-diode equivalent circuit model.

and

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

In the equations above, R_s and R_{sh} are the series and shunt resistances respectively, I_{SD1} and I_{SD2} are the diffusion and saturation currents respectively, 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 temperature in kelvin.

From the above equations, it is seen that the solar cell parameter extraction problem reduces to determination of the seven parameters (R_s, R_{sh}, I_{ph}, I_{SD1}, I_{SD2}, n_1 and n_2) from the I–V characteristics. In this paper, this process is formulated, using genetic algorithms, as a search and optimization procedure as discussed below.

3. Genetic algorithms

Genetic algorithms (GAs) are a subclass of what are known as evolutionary algorithms [13]. These are computational models that mimic *natural evolution* in their design and implementation; i.e. they are based on survival of the fittest. GAs differ from conventional search techniques in that they operate on a coded parameter set of the solution, are global in their search, make use of a cost function that does not involve derivatives and finally employ pseudo-probabilistic rules and not deterministic ones. Genetic algorithms have been used in recent years in solving optimization problems in science and engineering applications [14, 15]. Implementation of GAs involves making the following preliminary decisions.

(1) *Solution encoding*. This involves coding a possible solution (individual) as a string of variables using some alphabet, e.g. binary $\{0, 1\}$. Individuals are likened to *chromosomes* and variables to *genes*. A chromosome (solution) is composed of several genes (variables).
(2) *Evaluation function*. This determines the fitness score attached to each chromosome (solution). The higher this score, the greater is the chance of an individual (solution) being selected for reproduction.
(3) *Initial population generation*. Generation of the initial population (set of possible solutions) can be random or from known approximate solution(s).
(4) *Selection criterion*. Methods of selecting individuals for reproduction are numerous and include roulette wheel sampling, stochastic universal sampling, tournament selection, elitism, sigma scaling, rank selection etc.
(5) *Recombination/reproduction*. This is achieved through two genetic operators, namely *crossover* and *mutation*. A number of variations of crossover are in use such as single-point, multi-point or uniform crossover. In single-point crossover where binary encoding is used, a *locus* (bit location) is randomly chosen. Bits after that locus are exchanged between two chromosomes to create two offspring (new solutions). Mutation on the other hand involves randomly flipping some of the bits in a string (chromosome). A very small probability is usually attached to occurrence of mutation at each bit location (e.g. 0.001). This operation is performed to ensure that new areas of the solution are explored.
(6) *Termination criteria*. The algorithm can be terminated if the maximum number of generations (iterations) is achieved, or convergence of the solution is attained (i.e. all solutions yield the same fitness value or differ by less than a specified tolerance).

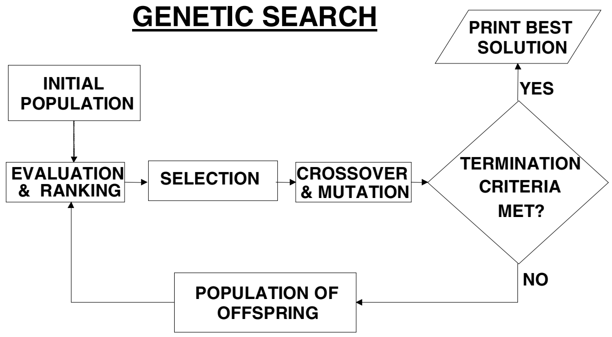


Figure 2. GA flowchart.

Based on the decisions made above, the search algorithm can be invoked. Figure 2 illustrates a typical GA flowchart.

3.1. GA implementation for solar cell parameter extraction

A Matlab implementation of a GA [16] is used to extract the parameters of a solar cell under illumination. Implementation of the GA for solar cell parameter extraction was based on the following.

- Solution encoding: floating point representation.
- Parameter precision: 10^{-6}.
- Evaluation function: based on equation (1), expressed as

$$\begin{aligned} &f(I_{ph}, I_{SD1}, I_{SD2}, R_s, R_{sh}, n_1, n_2) \\ &\quad = -I_L - I_{ph} + I_{D1} + I_{D2} + I_{sh} \end{aligned} \tag{5}$$

where all the variables are as defined before. (The GA program used [16] was developed for maximization of a multivariable function. Thus, $-f^2(\ldots)$ was used as the cost function and the optimal solution is attained when $f^2(\ldots) = 0$.)
- Initial population generation: randomly generated and of size ten.
- Selection criterion: roulette wheel.
- Crossover: simple crossover with two calls per generation.
- Mutation: boundary mutation with four calls per generation.
- Maximum number of generations: 25.

A set of values for the I–V characteristics serves as the input data for the GA. The parameters that are extracted by optimization are I_{ph}, I_{SD1}, I_{SD2}, R_{sh}, R_s, n_1 and n_2. Theoretically, the cost function should be zero for any I–V

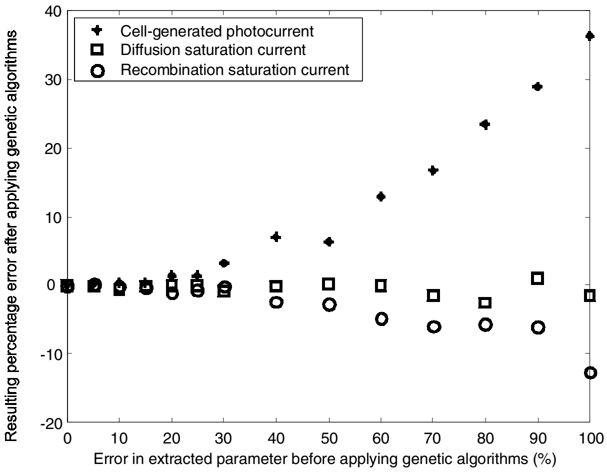


Figure 3. Relative error in the extracted diffusion current I_{SD1}, saturation current I_{SD2} and cell-generated photocurrent I_{ph}, before and after applying genetic algorithms.

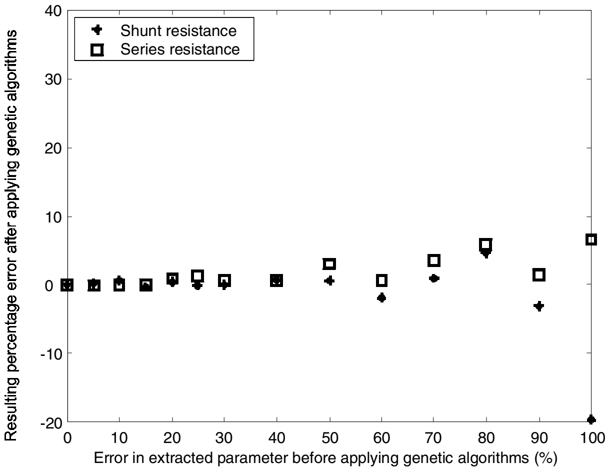


Figure 4. Relative error in the extracted series resistance R_s and shunt resistance R_{sh}, before and after applying genetic algorithms.

pair when the exact value has been determined for each and every parameter. Before invoking the genetic algorithms, a search range has to be set for the solar cell parameters. Each range was centred on the specified value of the parameter and varied by ± 5 to $\pm 100\%$. The deviation between the extracted and the specified values of the parameters is then computed for each range. This is done because existing extraction techniques have different degrees of accuracies in determining solar cell parameters. A discussion of the results obtained using GA and a comparison with results of the quasi-Newton (QN) method [17], a calculus-based search and optimization technique, follow.

4. Results

The set of I–V data for the solar cell model shown in figure 1 has been obtained using the SPICE software program. The parameters used for the SPICE model are $I_{ph} = 2.19$ A, $I_{SD1} = 2.4$ nA, $I_{SD2} = 55$ μA, $R_{sh} = 200$ Ω, $R_s = 25$ mΩ, $n_1 = 0.9$ and $n_2 = 1.9$. The simulations have been carried out for a temperature of 328 K. The GA routine implemented using

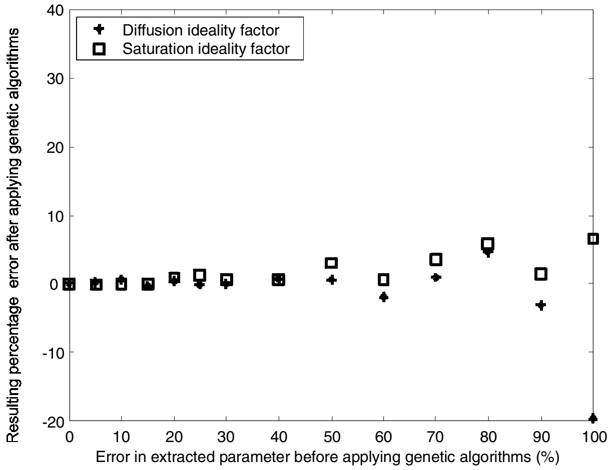


Figure 5. Relative error in the extracted diffusion diode ideality factor n_1 and recombination diode ideality factor n_2, before and after applying genetic algorithms.

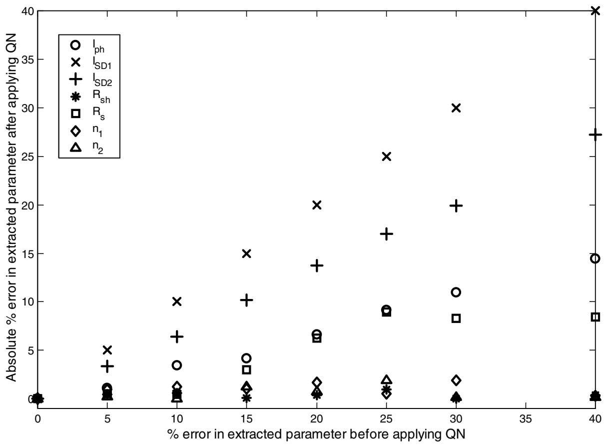
Matlab is run for a set of search ranges of the parameter values used in the model. Expressed as percentages, the search ranges are varied from ± 5 to $\pm 100\%$ of the model values. The relative errors obtained with respect to the model values are averaged for ten different runs of the GA algorithm. The outcome of the simulations is shown in figures 3–5. With reference to these figures, one can see that the worst-case error is about 35% for n_1 and I_{ph} when the search range is $\pm 100\%$ for each of the specified values. However, for some other parameters the error can be as low as 2%, for I_{SD1}, and about 7%, for the series resistance R_s.

The same set of I–V data of the GA algorithm was also processed using the E04JYF NAG Fortran Library Routine [18]. This routine is a QN algorithm for finding a minimum of a multivariable function subject to fixed upper and lower bounds on its independent variables. The results obtained for a search range of up to 40% of the specified solar cell parameters are shown in figure 6(a). It is seen that the error in the extracted parameters varies from 0 to 40% when using the QN algorithm. However, with the GA, the variation is only up to 15% as shown in figure 6(b) for the same search range.

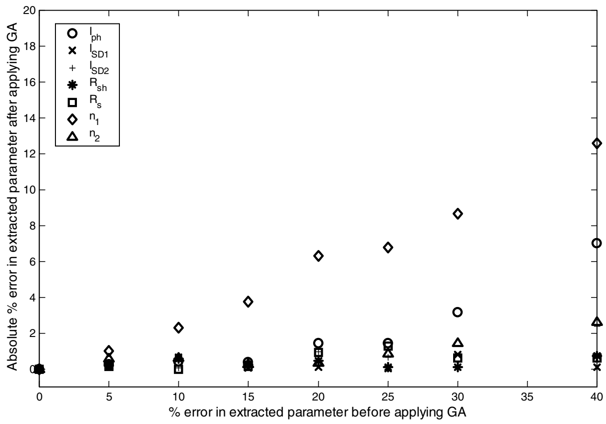
These results show that the use of genetic algorithms for solar cell parameter extraction significantly decreases the error in the extracted values and hence improves the accuracy of the determined parameters.

5. Conclusions

A technique for improving the accuracy of the extracted values of solar cell parameters using genetic algorithms has been implemented. It is based on formulating the parameter extraction problem as a search and optimization one. Since determination of the search range is of importance in applying this technique, one of the known extraction methods is to be used to determine approximate values for the solar cell parameters. The present method is then used to improve the accuracy of the extracted values. The error in a parameter such as series resistance, whose value has been determined initially to within $\pm 100\%$, can be reduced to less than $\pm 7\%$ with the proposed technique. The results obtained, when compared



(a)



(b)

Figure 6. Absolute percentage error in the solar cell extracted parameters before and after applying (a) QN and (b) GA.

with the QN method, indicate the viability of using genetic algorithms in reducing significantly the error in the extracted parameters for solar cells.

References

[1] Gottschalg R, Rommel M, Infield D G and Kearney M J 1999 The influence of the measurement environment on the accuracy of the extraction of physical parameters of solar cells *Meas. Sci. Technol.* **10** 796–804

[2] Ortiz-Conde A, Ma Y, Thomson J, Santos E, Liou J J, Garcia F J, Lei M, Finol J and Layman P 2000 Parameter extraction using lateral and vertical optimisation *Proc. 22nd Int. Conf. on Microelectronics, MIEL 2000 (Nis, 2000)* vol 1, pp 165–8

[3] Martil I and Diaz G G 1992 Determination of the dark and illuminated characteristic parameters of a solar cell for I–V characteristics *Eur. J. Phys.* **13** 193–7

[4] Kaminski A, Marchand J J, Fave A and Laugier A 1997 New method of parameters extraction from dark I–V curve *Proc. 26th PVSC (Anaheim, CA, 1997)* pp 203–5

[5] Phang J and Chan D 1986 A comparative study of extraction methods for solar cells I–V characteristics *Solar Cells* **18** 1–12

[6] Araujo F, Sanchez E and Marti M 1982 Determination of the two-exponential solar cell equation parameters from empirical data *Solar Cells* **5** 199–204

[7] Lee J I, Brini J and Dimitriadis C A 1998 Simple parameter extraction method for non-ideal Schottky barrier diodes *Electron. Lett.* **34** 1268–9

[8] Ouennoughi Z and Cheggar M 1999 A simpler method for extracting solar cell parameters using the conductance method *Solid-State Electron.* **43** 1985–8

[9] Werner J H 1988 Schottky barrier and pn-junction I–V plots, small signal evaluation *Appl. Phys.* A **47** 291–300

[10] Lyakas M, Zaharia R and Eizenberg M 1995 Analysis of non-ideal Schottky and pn junction diodes, extraction of parameters from I–V plots *J. Appl. Phys.* **78** 5481–9

[11] Aubray V and Meyer F 1994 Schottky diodes with high series resistance: limitations of forward I–V methods *J. Appl. Phys.* **76** 7973–84

[12] Wolf M, Noel G T and Stirn R J 1997 Investigation of double exponential in the current–voltage characteristics of silicon solar cells *IEEE Trans. Electron. Devices* **24** 419–28

[13] Davis L 1991 *Handbook of Genetic Algorithms* (New York: Van Nostrand Reinhold)

[14] Man K F, Tang K S and Kwong S 1996 Genetic algorithms: concepts and applications *IEEE Trans. Industrial Electron.* **43** 519–34

[15] Jervase J A and Bourdoucen H 2000 Design of resonant-cavity-enhanced photodetectors using genetic algorithms *IEEE J. Quantum Electron.* **36** 325–32

[16] Houck C, Joines J and Kay M 1995 *A Genetic Algorithm for Function Optimisation: a Matlab Implementation* NCSU-IE TR 95-09

[17] Press W H, Teukolsky S A, Vetterling W T and Flannery B P 1987 *Numerical Recipes* (Cambridge: Cambridge University Press)

[18] NAG 1999 *NAG Fortran Library Manual* mark 19