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Application of genetic algorithms for the extraction of electrical parameters of multicrystalline silicon

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Abstract
The application of the genetic algorithms (GAs) concept in measurements science deals with a fitting procedure used for the numerical prediction of physical parameters from an experimental data curve. In this work, GAs were applied for the extraction of electrical parameters of multicrystalline silicon solar cells. The experimental technique used is the light-beam-induced-current (LBIC). From LBIC measurements, we deduced the values of the diffusion length L and the grain boundary recombination velocity V_r of the minority carriers of the multicrystalline silicon wafers using the fitting procedure. The nonlinear fitting procedure is based on the minimization of the standard deviation of the theoretical LBIC profile from the experimental one. However, this criterion is not convex, and using traditional deterministic optimization algorithms leads to local minima solutions. To overcome this problem, the nonlinear least-square minimization technique was computed with the GAs strategy, increasing the probability of obtaining the best minimum value of the cost function in very reasonable time. The results of the proposed algorithm are presented and compared with the Levenberg–Marquardt algorithm and the Gauss–Newton method. The GAs-based numerical technique was found to be a promising and a powerful technique for numerical evaluation of the electrical parameters of silicon solar cells.

Keywords: genetic algorithms, optimization, LBIC, silicon solar cell, electrical characterization

1. Introduction

The light-beam-induced-current (LBIC) is a powerful technique for the local electrical characterization of multicrystalline silicon (mc-Si) wafers [1–3]. From the short circuit current measurements (LBIC), we can estimate the minority carrier diffusion length L and the recombination velocity V_r at the grain boundaries [1–6]. The latter parameters (L, V_r) can be deduced by fitting the theoretical LBIC profile to the experimental one. In general, L and V_r were taken as two numerical parameters in the fitting procedure [3, 4]. Generally, the nonlinear numerical simulation is based on the least-square procedure [7], which gives good results if the numerical fitting is a single parameter problem (L or V_r). However, when the number of numerical parameters becomes greater than or equal to 2, the function that describes the standard deviation of the theoretical LBIC profile from the experimental one can present many local minima in the parameter space [8]. This behaviour may lead to different values of L and V_r that correspond to a theoretical LBIC profile fitting very well the experimental LBIC curve.

In this paper we present a study on a numerical treatment of an experimental LBIC profile. The numerical procedure

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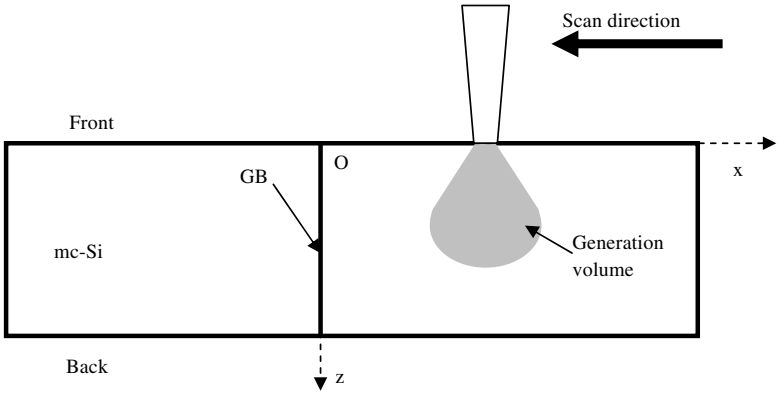

(*b*)

Figure 1. (*a*) Photograph of the LBIC setup. (*b*) Basic scheme adopted in the LBIC theory. (This figure is in colour only in the electronic version)

is based on a nonlinear least-square method, and performed by a genetic algorithms approach [9]. The performances of GAs are compared with those of the Levenberg-Marquardt algorithm and the Gauss–Newton method in terms of relative efficiency.

2. Experiments

The LBI-current was measured on a multicrystalline silicon (mc-Si) solar cell around a grain boundary. A He–Ne laser source was used as an excitation source. The laser beam was focused on a small disc having a diameter of around 15 μm; this was done by employing a CCD camera that ensures a good beam focus [10]. The multicrystalline silicon wafer is a p-type boron-doped material having a resistivity of 0.5–2.0 Ω cm. The n^+–p junction was achieved by diffusing phosphorus at a temperature of about 925 °C for 20 min. The back and the front metallic contacts are in Al and Ag, respectively. The sole LBIC experimental values that were considered are those measured 10 μm beyond the grain boundary (GB) (the GB is situated at the plane $x = 0$) in order to ensure that all the focused laser beam is in the right region of the GB; in fact such a condition is considered in the theory to solve the diffusion equation and then to get the theoretical LBIC expression [1, 3].

Figure 1(*a*) shows a photograph of the LBIC setup. Figure 1(*b*) depicts the scheme adopted in the LBIC theory. The focused laser beam scans the front surface of the solar cell around a grain boundary (GB).

3. Theory and simulations

We used the normalized LBIC expression $I(x_0)$ developed by Donolato [1] and other works [3, 4], which is given by

$$I(x_0) = \int_{-\infty}^{+\infty} \mathrm{d}x \int_0^{+\infty} Q(x,z)h(x-x_0,z)\,\mathrm{d}z \qquad (1)$$

where h and Q are given by

$$h(x-x_0,z) = \int_{-\infty}^{+\infty} g(x-x_0,y,z)\,\mathrm{d}y \qquad (2)$$

$$Q(x,z) = \frac{2}{\pi}\int_0^{+\infty} \frac{k}{\mu^2}\left[1 - \frac{s}{2\mu+s}\,\mathrm{e}^{-\mu|x|}\right]\sin(kz)\,\mathrm{d}k. \qquad (3)$$

The generation volume function $\boldsymbol{g}$ given from Marek analysis [5, 6] is

$$g(x, y, z) = \frac{\alpha\, e^{-\alpha z}}{2\pi\sigma^2} \exp\left(-\frac{(x - x_0)^2}{2\sigma^2} - \frac{(y - y_0)^2}{2\sigma^2}\right) \quad (4)$$

$$\sigma = \sqrt{\sigma_0^2 + \beta^2 z^2} \quad (5)$$

$$\mu^2 = k^2 + \frac{1}{L^2} \quad (6)$$

$$s = \frac{V_r}{D} \quad (7)$$

α is the light absorption coefficient, x_0 and y_0 are the laser beam spot coordinates in the (x, y) plane, D is the diffusion constant, σ_0 and σ are respectively the diameter of the laser beam spot at the front surface of the cell, and at a depth z, β is a constant describing light divergence in bulk silicon [3, 5, 6].

The nonlinear fitting procedure is based on the minimization of the standard deviation χ of the theoretical normalized LBIC profile from the experimental one, given by equation (8):

$$\chi^2 = \sum_{i=1}^{m} [I_{exp}(x_{0i}) - I(x_{0i}; L, V_r)]^2. \quad (8)$$

In the numerical treatment of the LBIC measurements, we performed a fitting procedure based on the genetic algorithms (GAs).

The GAs constitute a class of research strategies carrying out a balanced and reasonable compromise between exploration and exploitation. In fact, the GAs method uses a random choice-like tool to guide a highly intelligent exploration in the space of the coded parameters.

The GAs are algorithms of exploration based on the mechanisms of natural selection and genetics. They use at the same time the principles of the survival of the best-adapted structures, and the random pseudo-exchanges of information to form an algorithm of exploration which has some of the biological exploration characteristics.

In principle, the GAs are iterative and the goal is to optimize a preset function called the criterion or the cost function (χ). To carry out this objective, the algorithm works in parallel on a whole set of points representing the potential solutions of the problem, forming a unit called population. Each constituting point is called a chromosome ((L, V_r) in our case).

A chromosome is a solution representation of a given problem. The chromosome (L, V_r) consists of a group of elements (parameters) called genes. The goal is then to seek the best combination of these elements, which gives the minimum error (χ). At each iteration or generation, a new population is created by using parts of the best elements of the preceding generation, as well as innovating parts on the occasion. Although using chance, the genetic algorithms are not purely random. They effectively exploit previously obtained information to speculate on the position of new points to explore, with the hope that the new individuals will tend towards the best minimum value of the χ function.

To apply the GAs, we define a matrix corresponding to the initial population (IPOP) of the chromosomes (L, V_r). It is given by equation (9) [9]:

$$\text{IPOP} = (\text{hi} - \text{lo}) * \text{random}\{N_{ipop}, N_{par}\} + \text{lo} \quad (9)$$

where N_{ipop} is the initial number of the population; N_{par} is the number of parameters ($N_{par} = 2$ in our case); lo and hi are respectively the lowest and the highest values of parameters L and V_r.

Very common operators used in GAs are selection, reproduction and mutation [9], which are described as follows:

(1) *Selection.* This procedure is applied to select chromosomes that participate in the reproduction process to give birth to the next generation. Only the best chromosomes are retained for the next generation of the algorithm, while the bad ones are discarded. There are several methods for this process, including the elitist model, the ranking model, the roulette wheel procedure, etc.

(2) *Reproduction/pairing.* This procedure takes two selected chromosomes from a current generation (parents) and crosses them to obtain two individuals for the new generation (offspring). There are several types of crossing, but the simplest methods choose one or more points in the chromosome to mark as crossover points. Then the parameters between these points are merely swapped between the two parents.

(3) *Mutation.* Consists of introducing changes in some genes of a chromosome of the population. This procedure is performed by GAs to explore new solutions. Random mutations alter a small percentage of the population (mutation rate) except for the best chromosomes. A mutation rate between 1% and 20% often works well. If the mutation rate is above 20%, too many good parameters can be mutated, and then the algorithm stalls.

In figure 2, we give the flow chart of the GAs. In the first generation (figure 2) we started with 14 400 chromosomes as the initial population. After evaluating the cost function for each chromosome, we apply a selection in IPOP (select mate): only a family of good chromosomes that corresponds to good values of the cost was kept for the pairing (reproduce) and the others (bad) were killed. To ensure that the parameter space is suitably explored, a mutation of 4% in the chromosomes was operated (mutate). At the end of the algorithm, the convergence was tested. If the result (last value of χ) does not give satisfaction compared to a predefined error, all steps below are repeated in the second generation and so on.

In figure 3, we plot the mean and the minimum values of the χ function with respect to the generation number. We can see that beyond the fourth generation, the standard deviation becomes stable in a relative good minimum (approximately 2.75% in the seventh generation).

Due to the fact that, during the simulations, the GAs found the value $\chi = 2.75\%$ since the first generation and intelligently kept it for all followed generations, we did not observe any variations in the curve describing the minimum cost in figure 3.

4. Performance comparison

To show the superiority of the GAs approach compared with deterministic search methods, the GAs technique has been compared to two other numerical methods for the treatments of an experimental normalized LBIC profile. All

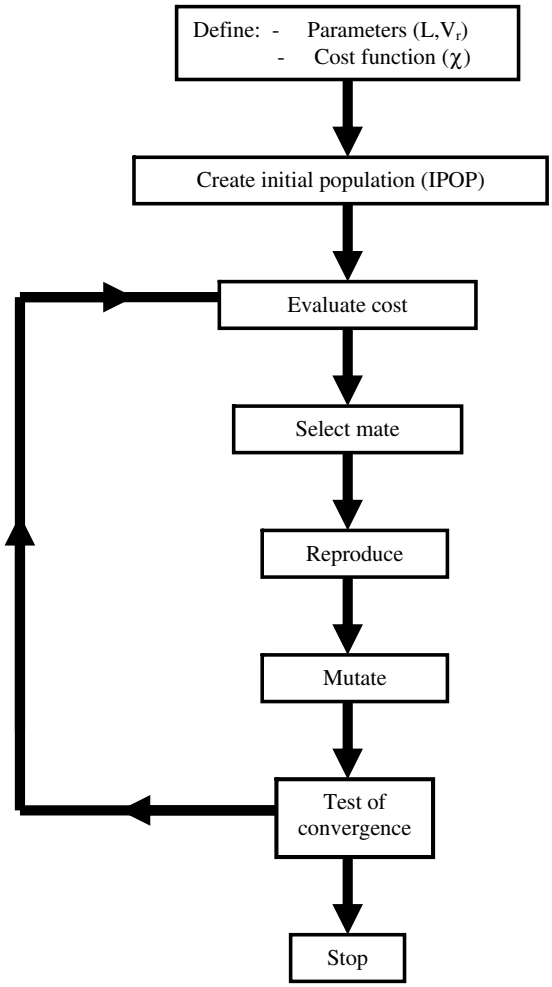

Figure 2. Flow chart of the genetic algorithms.

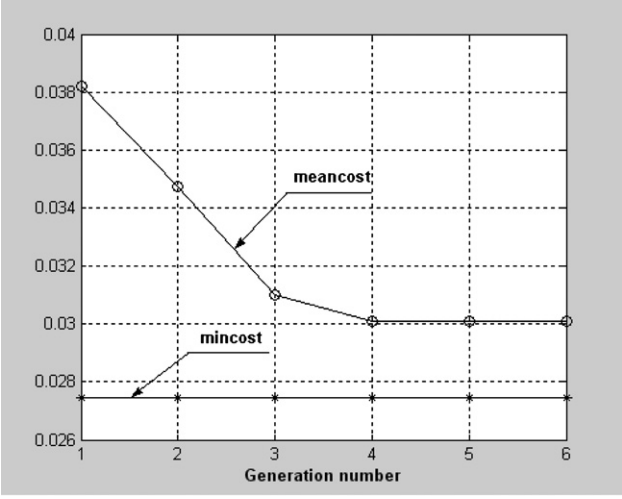

Figure 3. Plots of the mean and the minimum values of the standard deviation χ with respect to the generation number.

of these numerical procedures are based on a nonlinear least-square method. The first one was done with a FORTRAN compiler and used the Levenberg–Marquardt algorithm [3, 4]. The second was achieved with the optimization toolbox of MATLAB software using the Gauss–Newton method.

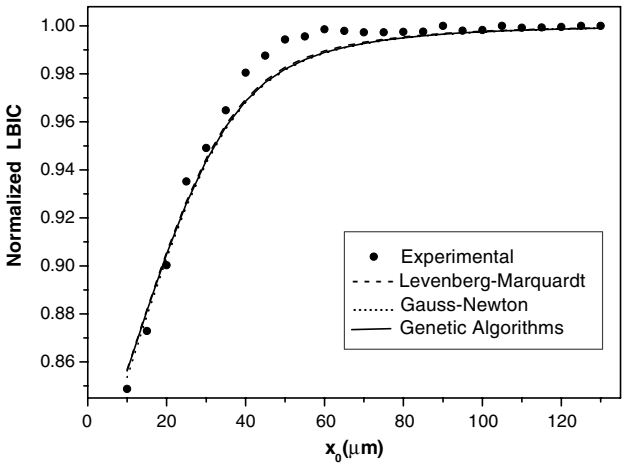

Figure 4. Adjustments of the theoretical normalized LBIC profiles $I(x_0)$ to the experimental one (I_{exp}) using the Levenberg–Marquardt, the Gauss–Newton and the GAs methods.

Table 1. Numerical values of the diffusion length L, the GB recombination velocity V_r and the standard deviation χ obtained from the fitting procedures with the Levenberg–Marquardt, the Gauss–Newton and the genetic algorithms.

	Levenberg–Marquardt algorithm	Gauss–Newton algorithm	Genetic algorithms
L (μm)	49.2	52.7	51.8
V_r (10^6 cm s^{-1})	2.6	3.3	2.1
χ (%)	3.00	2.80	2.75

In figure 4, we give the adjustment results of the theoretical normalized LBIC profiles ($I(x_0)$) to the experimental ones (I_{exp}). The results of the three different algorithms for the minimization of the standard deviation of the theoretical normalized LBIC profile from the experimental one are shown in table 1.

One can note (figure 4) a weak difference between the three algorithms; i.e., the three fitting procedures seem to give the same apparent result.

The weak difference in the χ value (table 1) between the GAs and the Levenberg–Marquardt (first case) is at least 0.25%, and only 0.05% in the case of the Gauss–Newton algorithm (second case). Surprisingly, this apparently weak variation of the cost function χ represents in fact a relatively large variation of the parameter values. Indeed, in our case, the value of the recombination velocity (V_r) shows significant changes, by a rate of 21.3% for the first case and 44.4% for the second case.

The recombination velocity value obtained by the Levenberg–Marquadt method appears to be closer to the one obtained by the GAs, although this method shows the highest standard deviation of all algorithms ($\chi = 3.00\%$). This is due to the fact that we have to consider the value of the standard deviation as a critical choice among the three algorithms. Hence, when the recombination velocity seems to have the same value in the Levenberg–Marquadt and the GAs algorithms, the diffusion length is modified by a rate of 5.15%, which is approximately three times its change (1.72%) when we compare the Gauss–Newton and GAs methods. This is

proof that we have to take care when we use a nonlinear fitting procedure with a parameter number greater than or equal to 2.

In this electrical parameters extraction problem, an optimal solution can be guaranteed and quickly found with calculus based methods if the optimization criterion is convex. For such a case, the traditional optimization approaches outperform the GAs in terms of speed of convergence. However, in this LBIC optimization problem, the standard deviation criterion is not monotonic. As a result we are forced to use the GAs which belongs to heuristic solutions that represent a trade-off between solution quality and time. The GAs have a stochastic search procedure in nature; they usually outperform gradient-based techniques in getting close to the global minima and hence avoid being trapped in local ones. In the past years, GAs have found wide acceptance in many areas of science and engineering [11]. The LBIC technique is no exception.

The GAs are designed to search for a global minimum; however they cannot guarantee that the obtained solution is the best, and how to prevent this difficulty remains an important challenge, stressed by the fact that in this solar cell parameters evaluation problem there is no way to know how good are the results obtained. For this reason, any advance in achieving a best value of the cost function is very important as it leads to improvement in the knowledge of the real values of the extracted parameters. The comparison results of GAs with deterministic methods given in table 1 shows that the GAs approach provides an efficient way to generate good quality solutions.

5. Conclusion

In this work, we used the light-beam-induced-current technique for the local electrical characterization of multicrystalline silicon solar cells. In order to evaluate the bulk diffusion length L and the grain boundary recombination velocity V_r of the minority carriers from normalized LBIC measurements, we used the nonlinear numerical fitting procedure. This practice is based on the minimization of the standard deviation χ of the theoretical normalized LBIC profile from the experimental one by considering L and V_r as the simulation parameters. To reach this goal, we proposed to use the GAs approach. Results obtained from other numerical examples such as the Levenberg–Marquardt algorithm and the Gauss–Newton method showed the superiority of the GAs in terms of relative efficiency. The GAs seem to be a promising and a powerful tool for numerical evaluation of the electrical parameters from experimental LBIC profiles. A better estimation of the electrical parameters L and V_r can be achieved by the improvement of the standard deviation χ. To improve the later, several ways can be investigated including the demystification of optimal choice of GAs parameters, and the use of a computer with higher performance. In fact, GAs written on parallel processing computers could give best solutions by either increasing the population size and/or allowing for long runs. Another powerful alternative may be provided by the hybrid algorithms which combines GAs with local search methods. These approaches can be investigated in the future. This GAs technique can also be easily applied to other physical and industrial systems.

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