International Journal of Modern Physics C
Vol. 16, No. 7 (2005) 1043–1050

EXTRACTION OF ILLUMINATED SOLAR CELL AND SCHOTTKY DIODE PARAMETERS USING A GENETIC ALGORITHM

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Received 27 September 2004
Revised 7 January 2005

Details concerning the implementation of a versatile genetic algorithm are presented. Solar cell and Schottky diode model parameters are extracted based on the fitness of experimental data to theoretical curves simulated in the framework of certain physical processes and the use of this genetic algorithm. The method is shown to be a reliable alternative to conventional numerical techniques in fitting experimental data to model calculations and the subsequent determination of model related parameters. It is demonstrated, through two examples in particular, that some of the drawbacks associated with the conventional methods can be circumvented if a genetic algorithm is used instead. For instance, a good initial guess is not a critical requirement for convergence and an initial broad range for each of the fitting parameters is enough to achieve reasonably good fits.

Keywords: Characterization methods; genetic algorithm; solar cell parameters; Schottky diodes.

1. Introduction

Genetic algorithms (GAs), successfully applied in various fields of engineering in particular, are based on the two Darwinian concepts of "survival of the fittest" and "natural genetics"[1] currently described more often as "evolution". The ultimate goal of the GA algorithm is to find the fittest solutions that optimize a given fitness or cost function starting from a randomly generated population of solutions. Although GAs are mainly applied to, and known to be most efficient in, problems with a global minimum or maximum where least square and other conventional numerical techniques get easily trapped in local extrema,[2] the technique is proving to be very attractive and advantageous in other situations such as the fitting tasks exemplified here.

In the present paper, the details of a genetic algorithm and its implementation are presented. The basic advantages and performance of the GA technique are then illustrated through two numerical examples leading to the extraction of parameters in the cases of illuminated solar cells and Schottky diodes. The parameters of usual interest, in these cases, are the series resistance, ideality factor, saturation current, the shunt conductance and photocurrent. Most of the methods proposed in literature concentrate mainly on the series resistance since it is by far the most important of the above parameters. The determination of all the five parameters, however, is essential for better designs of solar cells and a more accurate estimation of their performance. Nonlinear least square and other calculus-based techniques give usually satisfactory results but their shortcomings include the requirement of an explicit form of derivatives of the optimized functions and their tendency to get trapped in local extrema. Furthermore, the rapid convergence of these methods depends largely on the initial guesses for solutions.[3,4] It is often a requirement to have the initial guesses as close as possible to the solutions, otherwise convergence difficulties might arise. This somehow requires prior knowledge and good anticipation of what the model parameters should be before a refinement of these is achieved through numerical procedures. This is a constraint that is, to some extent, circumvented in the present method based on a genetic algorithm and which does not particularly necessitate "good" initialization for the fitting parameters of the function to be optimized. Required only is a very broad range for each of the parameters to be specified as an initial input. The model parameters of interest are then extracted based on the fitness of experimental data to theoretical curves simulated in the framework of certain physical processes and the GA with, we believe, a very good accuracy.

2. Genetic Algorithm and Procedure

As a first step in developing the GA, the physical parameters of the problem are coded using a binary string representation. By analogy to the Darwinian theory of evolution of species, each binary is called a gene and the set of genes constitute a chromosome. A fitness function is evaluated for each of the chromosomes and only some of these are selected according to their fitness to experimental data (this is the *selection* part of the process). The selected chromosomes (parents generation) are then subjected to crossover and mutation, both performed with a certain probability, to generate a new population of chromosomes (children generation). In the crossover process, two parents are interchanged at a random gene point to produce two offspring (this is known as single-point crossover). The mutation operation consists of randomly changing the values of randomly selected genes from the offspring. The new generation is in turn subjected to the fitness test to select new parents that will subsequently undergo crossover and mutation to produce the next

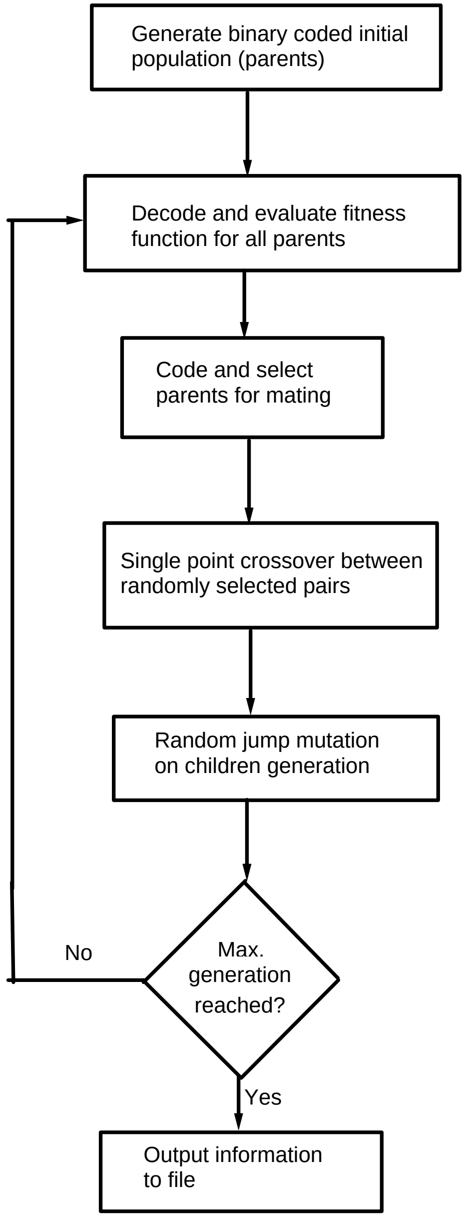

Fig. 1. Basic flowchart of the genetic algorithm.

generation of chromosomes (this is the *evolution* part of the process). The selection and evolution procedures are repeated until either the best fitness level does not change for several generations or the, initially set, maximum number of generations is attained.

The basic flowchart of the genetic algorithm developed here is shown in Fig. 1. In the FORTRAN code implemented on a personal computer, an initial random sample of individuals with different parameters to be optimized is generated. The tournament selection scheme with a shuffling technique is then called for choosing random pairs for mating. Other routines included in the code consist of binary coding/decoding for the individuals, jump mutation at a chosen rate (between 0 and 1), and the option for single-point or uniform crossover with a pre-selected probability. The code is normally set for a maximum population size of up to 800, the number of chromosomes (binary bits) can be varied between 16 and 128 and a maximum of eight parameters can be optimized at the same time. For flexibility, the fitness function was included as a separate subroutine and will, ultimately, allow the code to run with alternative fitness functions.

3. Numerical Examples

To demonstrate the application of the genetic algorithm to the fitting of the measured data, two examples related to solar cells under illumination and Schottky diodes are given here. In both cases, the model parameters of interest are determined based on the fitness of I–V measurements to theoretical equations. The current–voltage relation of a solar cell under illumination and normal conditions of operation is given by[5]:

$$I = I_{ph} - I_S \cdot (e^{q(V+Rs \cdot I)/nkT} - 1) - G_{sh}(V + IR_s)\,. \tag{1}$$

The parameters that need usually to be determined in this case are the photocurrent (I_{ph}), the shunt or parallel conductance (G_{sh}), the saturation current (I_s), the ideality factor (n) and, most importantly, the series resistance (R_s). The other constants are the temperature (T), the Boltzmann constant (k) and the electron charge (q). The measured I–V data, for this first example, was obtained from a 57 mm diameter commercial silicon solar cell (RTC France).[3]

In the GA fitting process in this case, an initial population size of 100 chromosomes was chosen with each chromosome consisting of five randomly generated numbers representing the five parameters to be extracted. A generation size of 200 was found to be more than enough to assure convergence to a satisfactory solution with a high fitness value. A larger generation size (up to 800) has also been used but it only rendered the calculations longer with no noticeable refinement in the best solution. The tournament technique[1] was adopted to select the fittest parents that will take part in mating. The single point crossover was performed with a probability of 0.5 followed by a mutation operation where genes of a given chromosome are randomly changed if they meet the mutation rate (probability) chosen to be 0.02. For both examples considered here, a fitness function based on the root mean square error between measured and calculated currents was used. This is given by:

$$F = -\sqrt{\sum_{i=1}^{N_{\exp}} \left(\frac{I_{i,\text{meas}} - I_{i,\text{cal}}}{I_{i,\text{meas}}}\right)^2}\,, \tag{2}$$

where N_{exp} is the number of experimental points, $I_{i,meas}$ and $I_{i,cal}$ are respectively the measured and calculated current values.

The best fitness parameters are shown in Table 1 along with the initial ranges specified for each parameter. For the sake of comparison, the table includes also the values of parameters obtained using a Newton-least-square method.[3]

The most remarkable feature in using the GA method lies in its convergence to reasonably good solutions despite the wide ranges specified for the parameters at the start of the calculation procedure. For a satisfactory convergence to an accurate solution, the Newton method required very good "guesses" as an initial input. The GA method in this respect is advantageous especially in situations where it is difficult to anticipate on an initial guess for the desired solution. Once the five parameters are satisfactorily determined, these are re-injected in Eq. (1). The voltage is then varied in small steps and for each voltage the nonlinear equation is numerically solved, for the current, to yield the calculated (I–V) curve that best fits the measured data. Figure 2 shows the measured data and the best fit obtained using

Table 1. Optimal solar cell parameters obtained using the GA and Newton methods.

Parameter	GA method	Initial specified ranges	Least square (Newton) method
R_s (Ω)	0.0454	[0.01, 0.6]	0.0364
G_{sh} (Ω^{-1})	0.0297	[0.01, 0.5]	0.0202
n	1.5	[1, 2]	1.5039
I_s (μA)	0.325	[0, 1]	0.4039
I_{ph} (A)	0.762	[2, 10]	0.7609

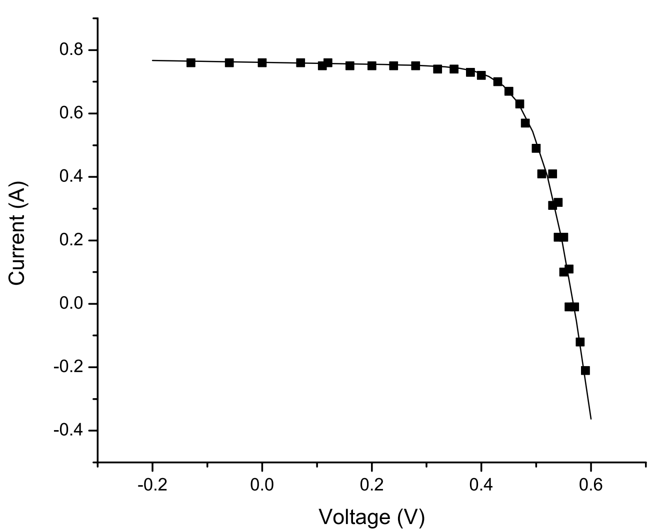

Fig. 2. Experimental data and the fitted curve for the solar cell I–V characteristic.

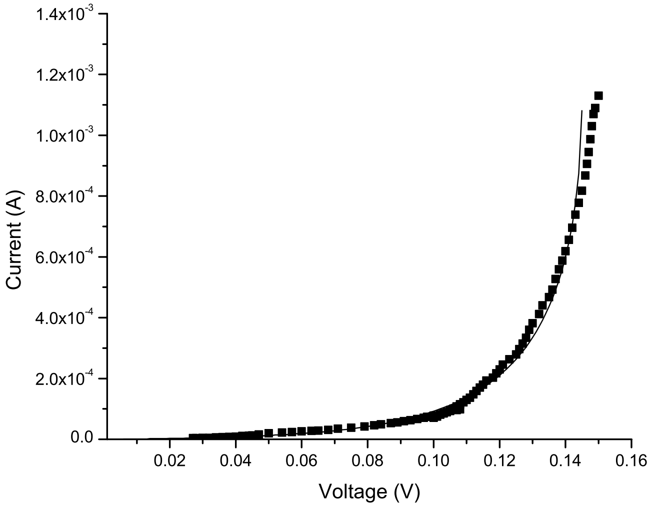

Fig. 3. Experimental data and the fitted curve for the Schottky diode I–V characteristic.

the parameters given in Table 1. For the second example, the measured I–V data is from Al–GaAs Schottky diodes designed originally for detection experiments with surface plasmon excitations.[6] They consisted of a 2.5 μm thick silicon-doped n-type GaAs layer with a nominal doping level of 3×10^{16} cm^{-3} grown on a (100) n^+ silicon-doped GaAs substrate of thickness 650 μm and doping level 1×10^{18} cm^{-3}. The ohmic contact consisted of a multiplayer of Ni–AuGe–Ni–Au evaporated on the back and annealed at 420°C. The Al top electrode in the large area devices (each measuring 10×11 mm^2) is 40 nm thick. Conventional methods were used[6] to extract some of the diode parameters considering only the low voltage region. For the sake of comparison, the same voltage range was considered, here, in the GA calculations. A typical current–voltage characteristic is shown in Fig. 3 along with the best-fitted curve obtained from the usual I–V relationship, derived assuming that thermionic emission is the dominant conduction mechanism:

$$I = A \cdot A^* T^2 e^{-q\phi_b/kT}\left(e^{q(V+Rs\cdot I)/nkT} - 1\right). \tag{3}$$

The undefined parameters in the above equation are the device active area (A), the modified Richardson's constant (A^*) and the barrier height (ϕ_b). Following the same procedure as in the solar cell example, four parameters (R_s, ϕ_b, n and A^*) were fitted with the best fitting values given in Table 2.

The values obtained from the usual semi-logarithmic plots and linear fits are also given in the table for comparison. The values are overall comparable but the Richardson's constant derived following the GA method is much closer to the theoretical value for GaAs, which is 8×10^4 A/m^{2}K. Less than 50 generations, for a population size of 50, were needed to attain the best fitness level in this case. There are a few points to be highlighted with respect to the GA runs in these examples.

Table 2. Optimal Schottky diode parameters obtained using the GA and a conventional method.

Parameter	GA method	Initial specified ranges	Conventional method[6]
R_s (Ω)	24	[5, 30]	—
n	1.09	[1, 1.5]	1.06
A^* (A/m^{2}K)	9.0×10^4	[8×10^3, 1×10^5]	8.55×10^3
ϕ_b (eV)	0.669	[0.6, 0.8]	0.68

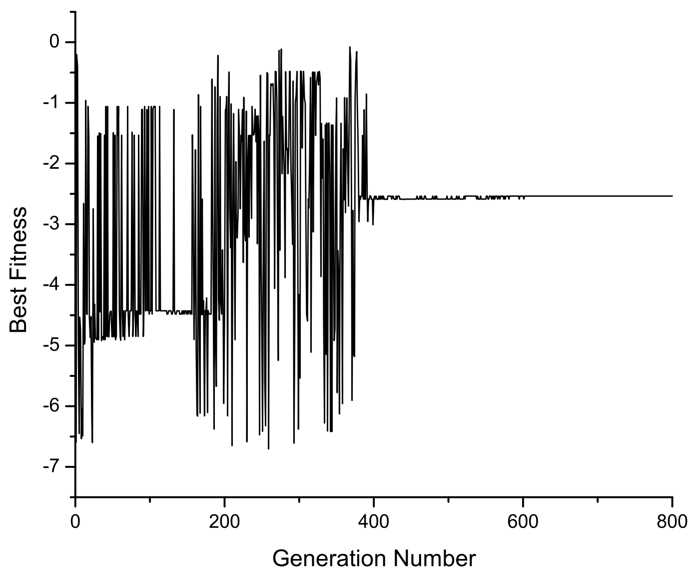

Fig. 4. Fitness level as a function of generation number for a population size of 50. Best fit achieved at generation 368.

First, the maximum number of generations needed to achieve convergence depends, obviously, on the initial ranges specified for the different fitted parameters. Convergence with good fitness was achieved in any case but the smaller the range over which the parameter was allowed to vary the faster the convergence was reached. The maximum number of generations also depended on the number of parameters to be fitted. Moreover, it was found that the convergence to the solution was more sensitive to the population size in one generation than to the number of generations itself. The larger the population size, the less was the number of generations needed to achieve a satisfactory fitness level and which remained unchanged for several subsequent generations. This is illustrated in Fig. 4, showing the best fitness as a function of generation number. A population size of 100 was, generally, found to be adequate for achieving a satisfactory fitness after slightly over 200 generations. Reducing the population size to 50 would require over 400 generations to achieve the best fitness. Figure 5 shows the best fitness versus the generation number in the

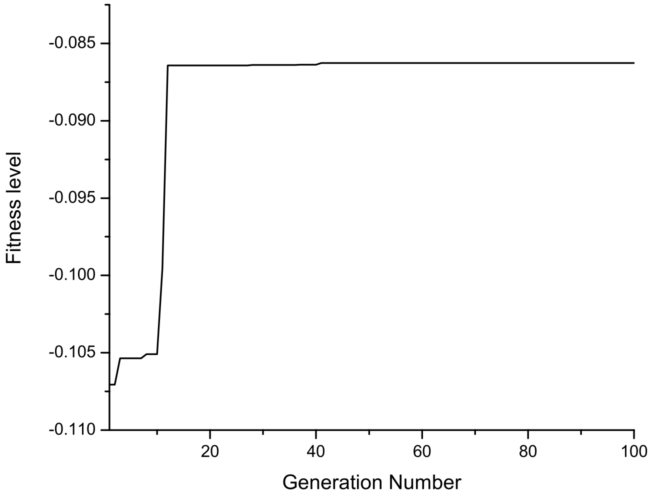

Fig. 5. Fitness level as a function of generation number for a population size of 100.

case of two fitting parameters (R_s and n) instead of five. The convergence, here, is attained in less than 20 generations for a population size of 100.

4. Conclusion

The details of a general and flexible genetic algorithm and its implementation on a personal computer were presented. It was shown, through two illustrative examples, that the GA could be efficiently used to fit experimental data to theoretical curves leading to a reasonably accurate determination of useful model parameters. The obtained fits to measured I–V data of both a solar cell under illumination and a Schottky diode were very satisfactory compared to results from the conventional Newton least square method. The advantages of using the GA method combine easy and fast convergence in addition to a remarkable higher degree of freedom in specifying the initial ranges of parameters to be fitted.

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