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Parameter determination of Schottky-barrier diode model using differential evolution

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ABSTRACT

In this article, a new method, based on the differential evolution (DE) of determining the Schottky-barrier height, ideality factor and series resistance of Schottky-barrier diode (SBD) model using forward current–voltage (*I–V*) characteristics, is discussed. For the DE method, initial guesses close to the solutions are not required. It can combat the parameter determination problem of the SBD model based on a very broad range specified for each parameter. The performance of the proposed DE method is compared with other commonly used model parameter determination technologies, including genetic algorithm (GA), simulated annealing algorithm (SA), Nelder–Mead simplex search method (SM) and least squares technique (LS). The comparative result indicates that the DE method can obtain optimum solutions more easily than others.

1. Introduction

The Schottky-barrier diode (SBD) is one of the most commonly used semiconductor devices, and it has advantages of low turn-on voltage and high response frequency. SBD can be used as rectifying and continuous-flow unit in high frequency rectifying, switching and holding circuit, yet reducing the power consumption and circuit noise, enhancing the circuit efficiency and operation frequency. Determining the fundamental SBD model parameters including Schottky-barrier height (SBH), ideality factor and series resistance, which must be taken into account in practical application, plays an important role in the designing and manufacturing process [1,2]. Several different methods that determine the parameters of the SBD have been proposed by some authors [3–10]. For example, Norde established an auxiliary model based on the thermionic emission theory so that the value of SBH could be obtained [5]; Sato and Yasumura used Norde's model at two different temperatures to determine the key parameters of the SBD [6]; Cibils and Buitrago presented an extension of Norde's forward current–voltage (*I–V*) plot to gain the parameters of SBD with high series resistance [9]. Meanwhile, using a junction diode as an example, a summary of methods for parameter determination is given in the literature [11,12]. However, the parameter determination methods mentioned above are based on the use of the *I–V* curve features. The accuracy of these techniques are therefor restricted by the measured *I–V* data, whose errors are introduced by the numerical differentiation and simplified formulae are used in parameter determination as well. On the other hand, most of these methods are step-by-step procedures that essentially rely on extracting each parameter from restricted regions of the *I–V* characteristics where the effect of other parameters is assumed to be negligible [13].

Recently, artificial intelligence based semiconductor devices parameter determination techniques have attracted much attention. For instance, techniques based on genetic algorithm (GA) and simulated annealing algorithm (SA) are proposed to improve the accuracy of the semiconductor parameter determination [14–18]. GA and SA can handle both discrete and continuous variables, nonlinear objective and constrain functions without requiring gradient information. Although GA and SA have been widely used to solve complex optimization problems, recent research has identified some deficiencies in their performance. To be more specified, low speed, premature convergence, and the degradation in efficiency when applying to highly epistatic fitness function, etc., come to researchers' focus [19,20].

As an alternative to GA and SA, differential evolution (DE) method is a recently invented high-performance evolutionary computation method [21]. As a stochastic optimization method, DE borrows the Nelder–Mead's method and uses the random generated initial population, differential mutation, probability crossover and greedy criterion based selection to find the minimum of objective function

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[22]. DE extracts the differential information, which is the distance and direction information from the current population of solutions, to guide its further search. The features of the DE such as simple structure, fast convergence speed and little information need about problems make it be suitable to solve some complex optimization problems.

In the present work, the DE method is proposed to determine the parameters of the SBD model through experimental *I–V* data. Some other usual parameter determination methods are also used to solve the same problem for comparison.

2. Parameter determination with DE

2.1. The description of SBD model

The forward bias *I–V* characteristics, according to thermionic emission of the SBD model with a series resistance, can be expressed as [6]

$$I = I_0\left[\exp\left(\frac{q(V-IR_s)}{nkT}\right)-1\right] \tag{1}$$

where

$$I_0 = AA^*T^2\exp\left(-\frac{q\Phi_{SB}}{kT}\right) \tag{2}$$

is the saturation current. I the diode current at bias V, q the electron charge, k the Boltzmann constant, T the absolute temperature, A the effective diode area, A^* the effective Richardson constant. R_s the series resistance, Φ_{SB} the SBH and n the ideality factor. R_s, Φ_{SB}, n are the unknown parameters and should be determined as accurately as possible. The typical *I–V* characteristics of the SBD model is shown in Fig. 1.

2.2. Parameter determination

SBD model parameters are determined with the following method: Given a set of experimental *I–V* data of the SBD, then we can apply the DE method to tune the parameters until the experimental data is in accord with the relation of Eq. (1).

As shown, Eq. (1) is a highly nonlinear equation which is not easy to solve by a direct analysis. The authors in the literature [23] transform the implicit equation, like Eq. (1), to an explicit solution in terms of the Lambert function. So fitting the explicit form of an equation, instead of its original implicit form, in general would lessen the procedure's computational burden. The proposed DE method does not require complex transformation for the original equation, only a simple fitness function formulation is essential.

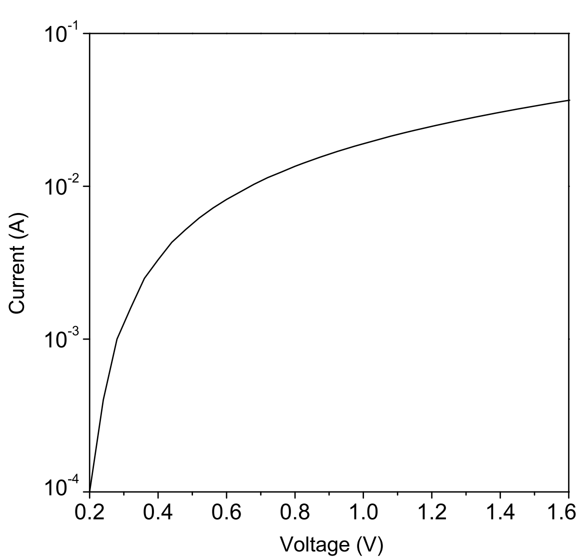

Fig. 1. The typical *I–V* characteristics of the SBD model ($\Phi_{SB} = 0.69$ eV, $n = 1.05$, $R_s = 36.18\ \Omega$).

In this work, we consider the SBD model indicated by Eq. (1) can be rewritten as

$$y(I,V,\theta) = I - I_0\left[\exp\left(\frac{q(V-IR_s)}{nkT}\right)-1\right] \tag{3}$$

where $\theta = [\Phi_{SB}, n, R_S]$ are unknown for practical system, to be determined as accurately as possible.

Since the DE method depends only on the fitness function to guide the search, it must be defined before DE is initialized. In this work, the fitness function can be given by

$$\varepsilon = \sqrt{\frac{1}{L}\sum_{j=1}^{L} y(I_j, V_j, \theta)^2} \tag{4}$$

where I_j and V_j are experimental data pair in *I–V* characteristics, respectively, L is the number of experimental data, and θ is the model parameters defined before.

Our objective is to make the value of fitness function ε be minimized, approaching zero as much as possible. And then, the parameters θ can be determined by using the proposed DE method, which only need to evaluate the fitness function to guide its search and does not require derivatives about its system.

2.3. DE method

DE is a newly emerging computation technique introduced first by Storn and Price (1995) as a heuristic optimization method, which has been successfully applied in solving the nonlinear and non differentiable continuous optimization problem [24]. DE starts with a random population and generates new offsprings by forming a trial vector of each parent individual (target vector) of the population. The population is developed by three operations: mutation, crossover and selection. Although the names of these operations are the same as in GA, the ways they are performed are essentially different. Firstly, mutation operator creates mutant vectors by adding the extracted distance and direction information from the current population members to another individual. The mutated vector is then mixed with the components of another predetermined vector, this operation is called crossover. If an generated offspring has a lower fitness value than a predetermined population member, it will replace this population member, and this operation is called selection. If the maximum number of iterations or any other predefined criterions are met, the repeated evolution process stops.

The contribution of this paper is to apply the proposed DE method to minimize the value of ε so that the actual parameters of the SBD model are accurately determined. Namely, the smaller the value of ε, the better the fitness of an individual. Therefore, the fitness function value should be zero as much as possible for any *I–V* pairs when the exact value has been determined for each parameter.

The whole procedure of DE is described as follows:

Step 1: Initialization. Set iteration number $N = 1$, and randomly generate NP individuals to form an initial population in the D-dimensional search space. The individuals here, are represented by D-dimensional vectors. The ith individual at iteration N can be expressed as $X_i^N, i = 1, 2, \ldots, NP$.

Step 2: Mutation. For each vector X_i^N, a mutant vector V_i^{N+1} is generated according to

$$V_i^{N+1} = X_{r_1}^N + F \times (X_{r_2}^N - X_{r_3}^N) \tag{5}$$

where $r_1, r_2, r_3 \in \{1, 2, \ldots, NP\}$ are chosen randomly and are different from the running index *i*. $F \in (0, 2]$ is a real and constant factor called scaling factor that controls the amplification of the differential vector $(X_{r_2}^N - X_{r_3}^N)$.

Step 3: Crossover. In order to increase the diversity of the population, the trial vector

$$U_i^{N+1} = [u_{i,1}^{N+1}, \ldots, u_{i,D}^{N+1}] \tag{6}$$

with

$$u_{i,j}^{N+1} = \begin{cases} v_{i,j}^{N+1}, & \text{if } (rand(j) \leqslant CR) \text{ or } j = randn(i) \quad \text{(a)} \\ x_{i,j}^N, & \text{otherwise} \quad \text{(b)} \end{cases} \tag{7}$$

is formed where $j = 1, 2, \cdots, D$. $rand(j)$ is the *j*th uniform random number distributed within the range [0,1], $randn(i) \in \{1, 2, \cdots, D\}$ is the random chosen index, which ensure that $u_{i,j}^{N+1}$ obtain at least one element from V_i^{N+1}. $CR \in [0, 1]$ is the crossover rate that control the diversity of the population.

Step 4: Selection. The selection in DE is deterministic and simple: for a minimum optimization problem, the trial vector V_i^{N+1} is compared with the target X_i^N by the greedy selection criterion

$$X_i^{N+1} = \begin{cases} U_i^{N+1}, & \text{if } \varepsilon(U_i^{N+1}) < \varepsilon(X_i^N) \quad \text{(a)} \\ X_i^N, & \text{otherwise} \quad \text{(b)} \end{cases} \tag{8}$$

where ε is the fitness function, X_i^N is the individual of the new population.

Step 5: Let $N = N + 1$

Step 6: Go to *Step* 2, and repeat until meet the stop criterion. The stop criterion can be that the maximum iteration number N_{max} is reached or the minimum fitness function ε_{min} condition is satisfied.

Step 7: Output the best solution X_{best} and its fitness value. The complete application of DE, as well as the method to do parameter determination of SBD model, is discussed in the following section.

3. Results and discussion

3.1. Parameter determination with synthetic I–V data

To verify the feasibility of the proposed DE method in the parameter determination for the SBD model, the synthetic *I–V* data have been first used. For the sake of comparison, the synthetic *I–V* data were calculated with parameters $\Phi_{SB} = 0.68$ eV, $n = 1.12$, $R_s = 3.3\ \Omega$ at 297 K as reported in the literature [6]. Then the proposed DE method was applied to determine the parameters of the SBD. At last, the determined parameters were compared with the original values in the literature [6]. Whether the DE method is applicable to parameter determination for the SBD model depends on the extent of determined parameters close to the original ones.

The related values assigned to the variables of the DE method were given by maximal iteration number $N_{max} = 5000$, population size *NP* = 24 (the reasonable choice for the population size *NP* is between $3 \times D$ and $8 \times D$, where *D* is the dimension of problem), scaling factor *F* = 0.8 and crossover rate *CR* = 0.3, which are the same as those recommended by the literature [25]. The search ranges were set as follows: $\Phi_{SB} \in [0.1, 1]$, $n \in [1, 2]$, $R_s \in [0, 50]$. Moreover, some other frequently used methods including intelligent methods: GA with the common variables setting for crossover rate $P_c = 0.8$ and mutation rate $P_m = 0.2$; SA with the initial temperature $T_0 = 5000$ K, iteration number *L* = 100 in every temperature value, cooling factor $C_F = 0.95$; as well as traditional methods: Nelder–Mead simplex search method (SM) and least squares technique (LS), were used for comparison. To perform fair comparison, the same computational effort is used in all methods. That is, the maximal iteration number and search ranges of the unknown parameters in the GA and SA are the same as those in DE. Moreover, population size in the GA is also the same as in DE. For SM and LS, they have the same maximal iteration number as DE.

Above methods have been implemented by MATLAB. The calculation was processed in a PC with the following features: Intel Pentium Core2 Duo E2140 1.6 G CPU, 1024 MB RAM and a Windows XP OS.

Fig. 2 shows comparisons between the synthetic *I–V* data of the SBD and the *I–V* characteristics derived by DE and GA. It seems that the DE and GA methods are both suitable for the parameter determination of the SBD model due to that the *I–V* characteristics obtained by the two methods are in good agreement with synthetic data over its whole range. As for Fig. 3, it illustrates the convergence characteristics of the DE and GA for this example. Although GA converges rapidly, there is still a difficulty in converging to the global optimal solution. In contrast, the DE method has much lower fitness value than the GA if the number of iteration times is large enough. So the DE can achieve better solutions than the GA.

Table 1 makes a detailed comparison and contrast of the DE, GA and SA methods for parameter determination with synthetic *I–V* data. All the statistics are compared in three items: difference between original and determined parameters, minimum fitness function values and running time. As can be seen, the obtained results using the DE are very close to the original parameters, while the relative errors between the determined and original by using GA and SA are much larger than those obtained by DE method for the same search ranges. Moreover, as shown in Table 1, it is observed that the minimum fitness value ε_{min} of DE method is far less than that of other methods. The elapsed time demonstrates that computational speed of using the DE is the fastest of all.

Table 2 indicates the parameter determination results obtained by two traditional methods with different initial values. The initial values for unknown parameter are chosen as the up, down and middle of the border of search ranges for DE. It can be seen that the performance of SM is much better than the LS, but not as good as DE. Furthermore, an obvious characteristic of the two methods is that they are sensitive to the initial values. We know that many iteration based methods need precise initial guesses. SM and LS are two of the most commonly used technologies in parameter determination and curve fitting. The performance of them is unstable at different initial values. Only when the initial values close to the global optimum, they can converge; if not, they are easy to drop into local optimum.

To sum up, these results show that the use of DE method for SBD parameter determination evidently decreases the errors in the determined values, and hence improves the accuracy of the determined parameters. It is concluded that the DE method is applicable to parameter determination for the SBD model and the DE is the most effective one of the GA, SA, SM and LS methods in this study.

3.2. Parameter determination with experimental I–V data

Secondly, to further validate the competence of the present parameter determination method, it is once more applied but now to a nickel silicide SBD sample with Pt-doped. Through 400 °C annealing, experimental *I–V* data of this SBD sample were measured

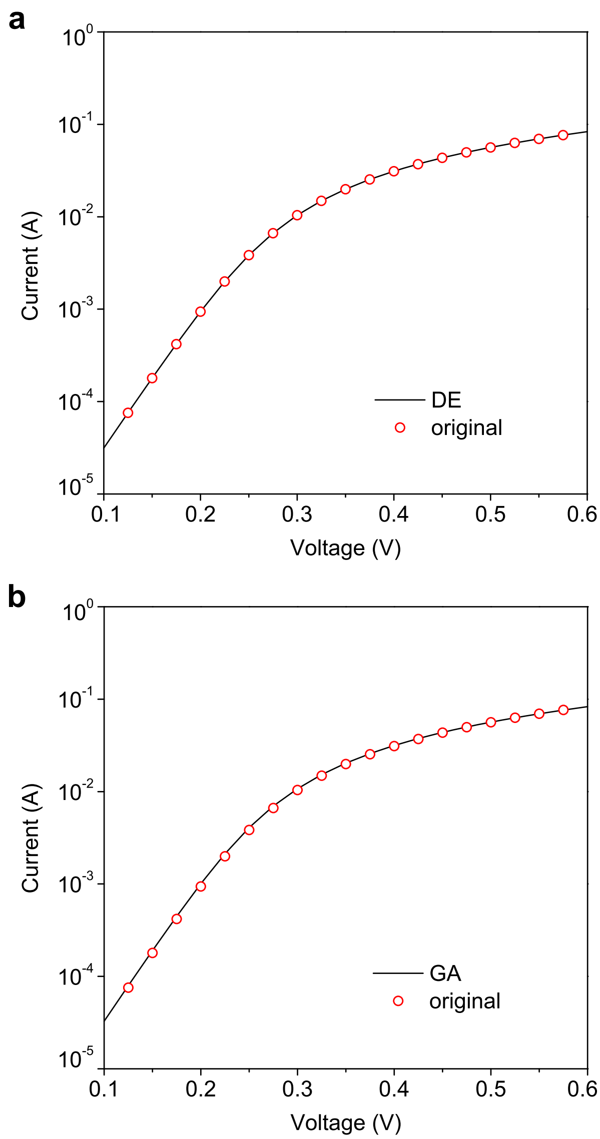

Fig. 2. *I–V* characteristics obtained from synthetic and from fitted by (a) DE and (b) GA methods.

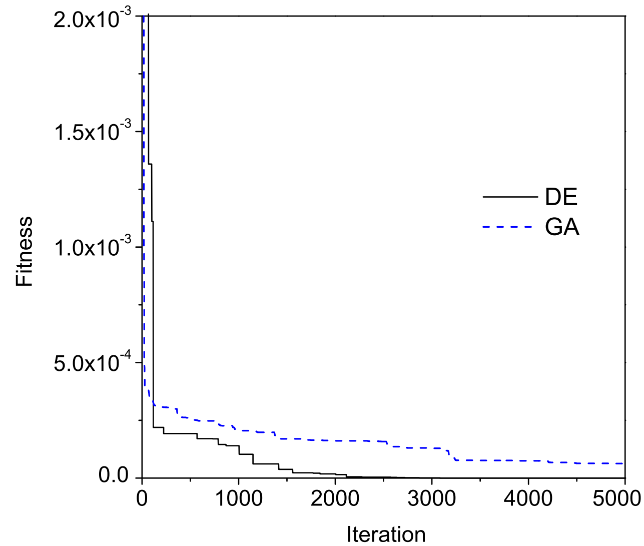

Fig. 3. Convergence characteristics of the fitness functions by different methods.

for parameter determination. The variable settings of the DE, GA, SA, SM and LS methods are given the same as in simulation part.

An excellent fitting curve obtained by DE can be seen in Fig. 4, in which the *I–V* characteristics nearly move towards the experimental data. On the other hand, Fig. 5 shows the convergence characteristics of the DE and GA methods. Obviously, the DE method also has a lower fitness value than the GA, when the maximum iteration number reaches.

In the case of experimental *I–V* data, we used the same variables setting, as in the simulation part, for the DE, GA and SA methods to make comparisons. The results of the parameter determination are summarized in Table 3. Due to using the experimental data, there is no way to know how good the results obtained are. For this reason, any advance in achieving a best value of the fitness function is very important as it leads to the improvement in the knowledge of the real values of the determined parameters. The minimum fitness function values ε_{min} of the DE, GA and SA are 3.6283×10^{-5}, 1.9738×10^{-4} and 1.3258×10^{-4}, respectively, which demonstrates that the results achieved by DE method outdo that achieved by the GA and SA methods; and then, compared with GA and SA, the execution time of the DE running to find the global optimum is the shortest, which shows that the DE method has a better computation efficiency than the GA and SA. Lastly, as illustrated in Table 3, it can be detected that the DE method does not chiefly require initial guesses as close as possible to the solution in the parameter determination of the SBD, while only demands a broad search range specified for each parameter.

In the meantime, Table 4 shows the instability of SM and LS with various initial values once again. It can be found that when initial values for Φ_{SB}, n and R_s are 0.5, 1.5 and 25, respectively, SM and LS have the best performance of other tries. From Table 3, it can be detected that 0.5, 1.5 and 25 are close to the parameters determined by DE method, which expresses that the importance of initial guess when using SM and LS methods. However, it is hard to give appropriate initial values in practical problems, like this SBD sample. Broad search ranges are usually much easier to set.

3.3. The influences of different control variable values

To investigate the effects of population size, scaling factor and crossover rate on the performance of DE, experiments were carried out on the above mentioned SBD sample.

Table 1
Results of parameter determination obtained by DE, GA and SA methods with synthetic *I–V* data.

	Original values	DE method	GA method	SA method	Relative errors (%)		
					DE method	GA method	SA method
Φ_{SB} (eV)	0.68	0.6802	0.6753	0.6274	0.029	0.700	7.7231
n	1.12	1.1199	1.1416	1.3239	0.009	1.929	18.2054
R_s (Ω)	3.3	3.3001	3.2891	3.1845	0.003	0.330	3.5
ε_{min}	–	3.2995×10^{-9}	6.2834×10^{-5}	6.9412×10^{-4}	–	–	–
Time (s)	–	26.53	33.74	51.564	–	–	–

Table 2
Results of parameter determination obtained by SM and LS methods with synthetic *I–V* data.

	Φ_{SB} (eV)	n	R_s (Ω)	ε_{min}	Time (s)
Initial values	0.1	1	0		
SM	0.6683	1.1087	3.3001	2.0185×10^{-6}	42.621
Relative errors (%)	1.7206	1.0089	0.0030	–	–
LS	0.5305	2.3695	2.7939	8.0255×10^{-4}	60.624
Relative errors (%)	21.9853	111.5625	15.3364	–	–
Initial values	1	2	50		
SM	1.8964	0.1974	3.5967	7.6000×10^{-3}	52.5801
Relative errors (%)	178.8824	82.375	8.9909	–	–
LS	4.8668	2.8871	58.0888	1.7420×10^{-1}	58.743
Relative errors (%)	615.7059	157.7768	1660.267	–	–
Initial values	0.5	1.5	25		
SM	0.6683	1.1087	3.3001	2.0185×10^{-6}	42.24
Relative errors (%)	1.7206	1.0089	0.0030	–	–
LS	2.8125	2.8373	29.2718	8.3000×10^{-3}	60.639
Relative errors (%)	313.6029	153.3304	787.0242	–	–

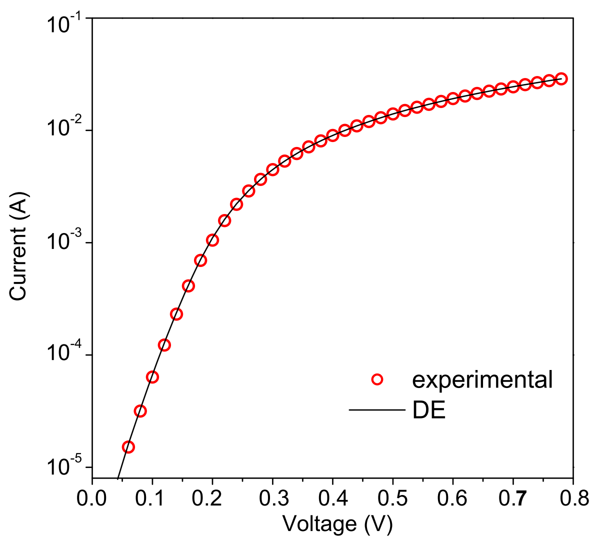

Fig. 4. *I–V* characteristics of the SBD sample obtained from experimental and from fitted using DE method.

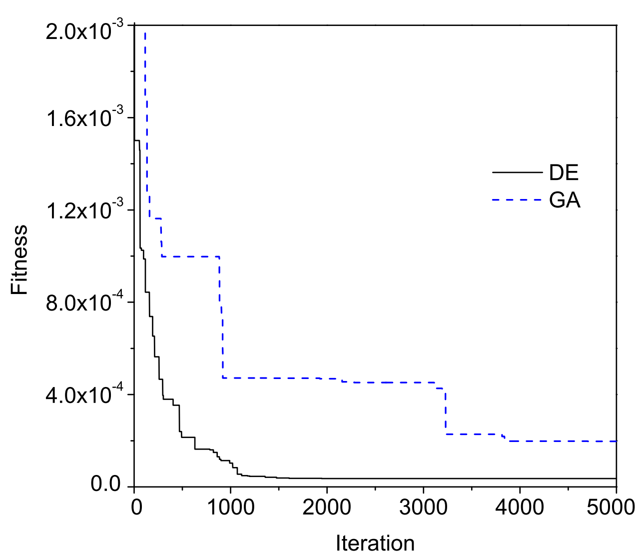

Fig. 5. Convergence characteristics of the fitness functions using DE and GA methods with experimental *I–V* data.

Table 3
Results of parameter determination obtained by DE, GA and SA methods with experimental *I–V* data.

	Search ranges	DE method	GA method	SA method
Φ_{SB} (eV)	[0.1,1]	0.6459	0.6469	0.6276
n	[1,2]	1.1338	1.1208	1.2474
R_s (Ω)	[0,50]	17.5027	17.6045	17.3185
ε_{min}	–	3.6283×10^{-5}	1.9738×10^{-4}	1.3258×10^{-4}
Time (s)	–	30.294	43.047	73.92

Table 4
Results of parameter determination obtained by SM and LS methods with experimental *I–V* data

	Φ_{SB} (eV)	n	R_s (Ω)	ε_{min}	Time (s)
Initial values	0.1	1	0		
SM	0.4733	7.1672	9.0929	1.8000×10^{-3}	45.8482
LS	0.4768	7.5856	7.0846	6.2162×10^{-4}	61.52
Initial values	1	2	50		
SM	0.5445	2.2719	15.7971	7.4806×10^{-4}	45.897
LS	10.861	0.345	49.8562	4.7000×10^{-3}	58.743
Initial values	0.5	1.5	25		
SM	0.5904	1.5608	16.8718	3.5354×10^{-4}	40.57
LS	0.6877	0.9411	17.7729	1.0121×10^{-4}	60.236

First of all, to observe the influences of different values of scaling factor F and crossover rate CR upon optimization quality of DE, population size NP was fixed to 24. Fig. 6 displays the results on the minimum fitness function value ε_{min}. Then, to investigate the influence of population size NP on the performance of DE, NP varied linearly from 5 to 100 with the fixed F and CR values, and the results are expressed in Fig. 7.

Fig. 6 directly exhibits the effect of the variation of scaling factor and crossover rate on the minimum fitness function value. When F and CR change from 0 to 0.2, the results are poor. Note that DE can not get a good solution when F at the range of 0–0.5. If F is chosen too small, it gets more difficult to escape from local optimum; the same situation experiences when $CR < 0.1$. DE gets best results when F at 0.6 to 1.0 and CR at 0.2 to 1.0, according to the deep color in the 3D drawing.

As shown in Fig. 7, the minimum fitness values obtained by the DE method are much lower than those obtained by the GA method in all population size cases. In this investigation, the minimum fitness values obtained by the DE method fluctuate only a little with various population size. By contrast, the situation is quite different

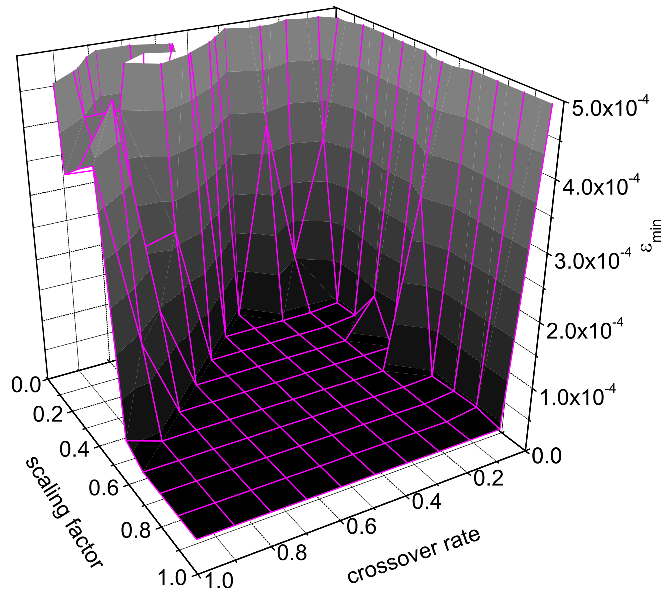

Fig. 6. The minimum fitness function values obtained by the DE method with different scaling factors and crossover rates.

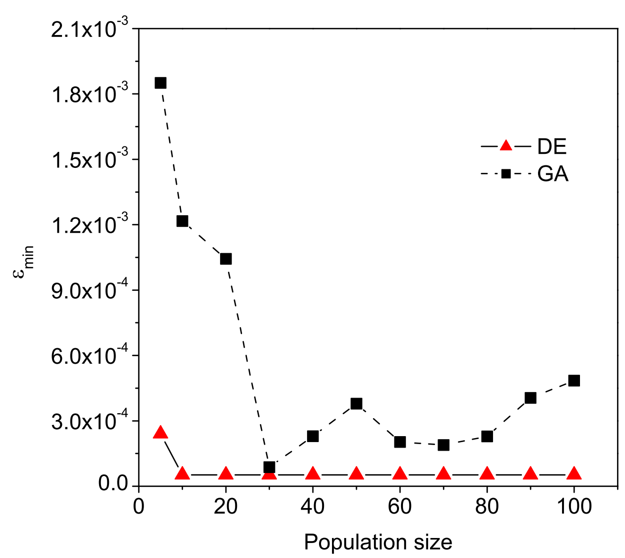

Fig. 7. The minimum fitness function values obtained by the DE and GA methods with different population size; for DE, $F = 0.3$, $CR = 0.8$; for GA, $P_c = 0.8$, $P_m = 0.2$.

when using GA method, which is sensible with the change of population size as shown in Fig. 7. As for the DE and GA methods, when population size is too small, the results are poor because the solution space will not be explored enough. As population size increasing, the results become better. But there is a threshold, beyond which the results will not be affected in a significant manner. Therefore, considering both the searching quality and computational effort, it is recommended to choose population size between 20 and 60. If more parameters need to be determined, larger population size is recommended.

4. Conclusions

This paper presents a new technique of parameter determination for the SBD model containing a series resistance using the DE method, and the results are compared with the other intelligent methods –GA and SA, as well as traditional methods – SM and LS. The feasibility of the proposed DE method has been validated by applying it to both synthetic and experimental *I–V* data. The execution time, shape of the fitted *I–V* characteristics, fitness function value and parameters precision obtained by using the DE method are shown to be better than those obtained by other methods. Furthermore, unlike the traditional methods (e.g. SM and LS), the DE method does not particularly necessitate initial guesses as close as possible to the solutions, while only require a broad range specified for each parameters. It is expected that the proposed method can be applied to many other parameter determination of semiconductor devices, which will be interested in our future work.

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