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PARAMETER ESTIMATION OF SCHOTTKY-BARRIER DIODE MODEL BY PARTICLE SWARM OPTIMIZATION

KAIER WANG and MEIYING YE*

Department of Physics, Zhejiang Normal University, Jinhua
Zhejiang Province, 321004, People's Republic of China
**ymy@zjnu.cn*

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This paper presents particle swarm optimization (PSO) method to solve the parameter estimation problem of the Schottky-barrier diode model. Based on the synthetic and experimental data, we have demonstrated that the proposed method has high parameter estimation accuracy. Besides, the initial guesses for the model parameter values are not required in the PSO method. Also, the performance of the PSO method is compared with that of the genetic algorithm (GA) method. The results indicate that the PSO method outperforms the binary-coded and real-coded GA methods in terms of estimation accuracy and computation efficiency.

Keywords: Schottky-barrier diode; particle swarm optimization; parameter estimation; genetic algorithm; device modeling.

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1. Introduction

Parameter estimation for the Schottky-barrier diode model is an important issue during the designing and manufacturing process. Schottky-barrier height (SBH), ideality factor, series resistance and effective Richardson constant are the parameters that mainly define the static behavior of the device. Over the last few years, several alternative methods had been proposed to estimate these Schottky-barrier diode parameters.[1–6] To illustrate, Norde established an auxiliary model based on the thermionic emission theory so that the value of SBH could be obtained;[1] Sato and Yasumura used Norde's model at two different temperatures to determine the key parameters of the Schottky-barrier diode;[2] Clibils and Buitrago presented an extension of Norde's forward $I-V$ plot to gain the parameters of Schottky-barrier diodes with high series resistance.[5] However, the parameter estimation methods mentioned above are based on the use of the $I-V$ curve features. The accuracy of

*Corresponding author.

these techniques is therefore restricted by the measured $I-V$ data, whose errors are introduced by the numerical differentiation and simplified formulae in parameter estimation.

Optimization techniques based on artificial intelligence are the effective methods in semiconductor devices modeling. For example, genetic algorithm (GA), an evolutionary computation technique, is proposed to improve the accuracy of the semiconductor parameter estimation.[7–10] GA mimics the mechanics of natural genetics, which essence is survival of the fittest.[11,12] GA has been successful in applying to solve complex optimization problems, since it can handle both discrete and continuous variables, nonlinear objective and constrain functions without requiring gradient information.[13] It is important to maintain the diversity of the population in the GA in order to identify most, if not all, of the local optimum solutions in a non-convex optimization problem.[14] But GA has the deficiencies such as low speed, premature convergence, and the degradation in efficiency when applying to highly epistatic fitness function, etc., which come to researchers' focus.[15] Consequently, it is important to develop new effective approaches for modeling problems of complex nonlinear systems.

Particle swarm optimization (PSO) is a newly arisen optimization technique. This method is introduced first by Kennedy and Eberthart (1995)[16] as a sociologically inspired population based on evolutional technology. PSO simulates simplified social models, such as birds flocking or fish schooling to a promising position to achieve precise objectives in a multi-dimensional space. PSO uses a population of candidate solutions, called particles, with their positions initialized randomly from the search space. Meanwhile, each particle is assigned a randomized velocity. These particles fly across the hyperspace and record the best positions that they have ever encountered. Members of a swarm communicate desirable positions to one another and adjust their own velocities and positions accordingly. So the knowledge of good solutions is retained by all particles, i.e., PSO has memory, whereas in GA, previous knowledge of the problem is destroyed once the population changes. Hence, PSO has higher speed of convergence than GA. Due to the simple concept, easy implementation and quick convergence, nowadays PSO has emerged as an attractive optimization tool and been successfully applied in a variety of different fields.[17–22]

In this paper, parameter estimation for the Schottky-barrier diode model is formulated as a multi-dimensional optimization problem, and the PSO method is implemented to solve the problem. The results are compared with those obtained by GA. In Sec. 2, a brief description of the Schottky-barrier diode mode is first provided, then a terse review and an implementation for PSO are presented. In order to examine the feasibility of parameter estimation for the Schottky-barrier diode model by PSO, a simulation is shown in Sec. 3. Furthermore, the proposed method to accurately estimate the characteristic parameters of the Schottky-barrier diode model is developed. Finally, in Sec. 4, we end the paper with some conclusions and future work.

2. Parameter Estimation with PSO

2.1. *Schottky-barrier diode model*

The forward bias $I - V$ characteristics, according to thermionic emission of the Schottky-barrier diode model with a series resistance, can be expressed as[2]

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

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. A typical $I - V$ characteristic cure of the Schottky-barrier diode model is shown in Fig. 1.

2.2. *Parameter estimation*

The Schottky-barrier diode model parameters are estimated within the following method: Given a set of experimental $I - V$ data of the Schottky-barrier diode, then we can apply the PSO method to tune the parameters until the experimental data is in accord with the relation of the Eq. (1).

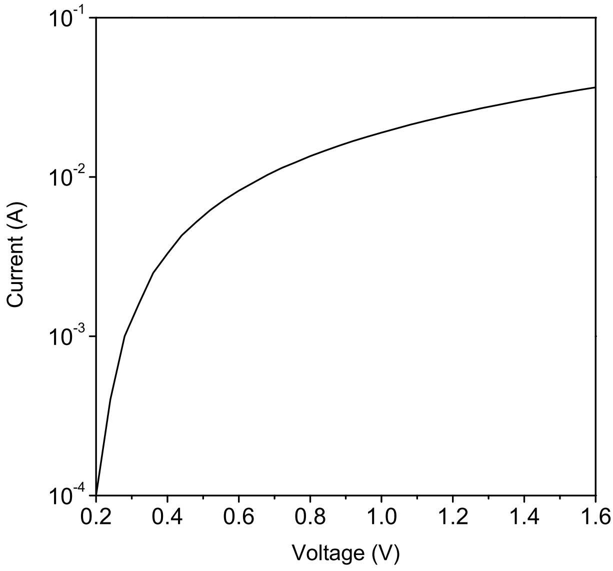


Fig. 1. Typical $I - V$ characteristic curve of a Schottky-barrier diode model.

Equation (1) is a highly nonlinear equation which is not easy to solve by a direct analysis. In this work, we consider the Schottky-barrier diode model indicated by the Eq. (1) can be rewritten as

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

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

Since the PSO method depends only on the fitness function to guide the search, it must be defined before the PSO is initialized. Therefore, the problem of parameter estimation can be formulated as minimizing the root-mean-square error (RMSE), which is taken as a fitness function and given by

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

where I_j and V_j are experimental current-voltage data respectively, L is the number of the experimental data, and θ is the model parameters defined before.

Our objective is to minimize the value of e in Eq. (4), approaching zero as much as possible. And then, the parameters θ can be determined based on using the proposed PSO method, which only need to evaluate the fitness value to guide its search and does not require derivatives about its system.

2.3. *PSO algorithm*

PSO is an evolutionary computation technique mimicking the behavior of flying birds and their means of information exchange. PSO differs from traditional optimization algorithms in that a population of potential solutions is used in the search. The guidance of search is direct fitness information, instead of function derivatives or related knowledge. This method is robust, adapted to handle nonlinear, non-convex design spaces with discontinuities. The advantages with respect to other common methods make PSO be an ideal choice to be used in optimization tasks.[17–25]

Let us consider a swarm that consists of N particles, which fly through the d-dimensional search space R^d with a velocity v_i (there i indicates a particle's index in the swarm). To search for the optimal solution, each particle changes its velocity according to its own previous best solution $pbest_i$ and the previous best solution *gbest* of the entire swarm. The velocity updates are estimated as a linear combination of position and velocity vectors according to the following equations:

$$v_i^{t+1} = \omega^t \times v_i^t + c_1 \times \text{rand1}_i^t \times (pbest_i^t - x_i^t) + c_2 \times \text{rand2}_i^t \times (gbest^t - x_i^t) \quad (5)$$

$$x_i^{t+1} = x_i^t + \Delta\tau \times v_i^{t+1} \quad (6)$$

where each particle's position x_i (corresponding to a set of Schottky-barrier diode parameter values) represents a possible solution point in the problem search space. $\Delta\tau = 1$; c_1 and c_2 are acceleration factors, usually about $c_1 = c_2 = 2.1$; rand1_i and rand2_i are random numbers in the range [0, 1]. Velocity values must be within a range defined by two variables $v_{\min}$ and $v_{\max}$ to avoid too rapid movement of particles in the search space. In PSO, the inertia weight ω plays a considered important role, since the balance between the global and local exploration abilities is mainly controlled by the inertia weight. ω is commonly taken as a decreasing linear function in iteration times t by varying the value as following:

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min})\frac{t}{t_{\max}} \quad (7)$$

where $\omega_{\max}$ and $\omega_{\min}$ are the initial and final weight respectively; and $t_{\max}$ is the maximum iteration times. In the literature,[26] Shi and Eberhart had observed that the optimal solution can be improved by linearly varying inertia weight value from 0.9 at the beginning of the search to 0.4 at the end for most problems.

The contribution of this paper is to apply the PSO algorithm to minimize the value of fitness function e so that the actual parameters of the Schottky-barrier diode model are accurately estimated. The smaller the value of e, the better the fitness of an individual. Therefore, the fitness function value should be zero as much as possible for any $I - V$ data pairs when the exact value has been estimated for each parameter.

The whole procedure of the PSO algorithm is described as follows:

Step 1: Initialize the individual velocity and position.

Step 2: Evaluate the fitness values of all particles.

Step 3: For each particle, compare its current fitness value with the fitness of its $pbest_i$, if the current value is better, then update $pbest_i$ and its fitness value with the current position and fitness value.

Step 4: Determine the best particle of the current population with the best fitness value. Update *gbest* and its fitness value with the position and fitness value of the current best particle, if its fitness value is better than that of *gbest*.

Step 5: Update the velocity and position for each particle according to Eqs. (5) and (6).

Step 6: If a stopping criterion is met (the maximum iteration times $t_{\max}$ is reached or the fitness condition is satisfied), then output *gbest* and its fitness value; otherwise go to *Step* 2.

In the following section, we will apply the PSO algorithm to estimate the parameters of the Schottky-barrier diode model.

3. Results and Discussion

3.1. *Parameter estimation with synthetic data*

This section provides a simulation example in order to verify the feasibility of the proposed PSO method to the parameter estimation for the Schottky-barrier diode model.

From the literature,[2] the original value of the Schottky-barrier diode parameters in Eqs. (1) and (2) are fixed at $\Phi_{SB} = 0.68$ eV, $n = 1.12$, $R_s = 3.3\Omega$, $A = 3.14 \times 10^{-6}$ m^2, $A^* = 120$ A cm^{-2} K^{-2}, $T = 297$ K. Our simulation process can be described as following: firstly, get the synthetic $I - V$ data calculated with parameters mentioned above; then the proposed PSO method is applied to determine the parameters of the Schottky-barrier diode; lastly, the estimated parameters are compared with the original values.[2] Whether the PSO method is applicable to parameter estimation for the Schottky-barrier diode model depends on the extent of estimated parameters close to the original ones.

In PSO, the maximal iteration times t is set to 5000, population size N is set to 40, acceleration factors $c_1 = c_2 = 2.1$, inertia weight ω decreases linearly from 0.9 to 0.4. These control variables are the same as those recommended by other papers[26–28] and the values do not depend on the problems. For more information on control variables selection, we refer reader to the literature,[29–31] including the guidance and selection strategy of control variables. The searching range for each parameter is set as follows: $\Phi_{SB} \in [0.1, 1]$, $n \in [1, 2]$, $R_s \in [0, 50]$, $A^* \in [1, 200]$.

Moreover, in order to compare the performance of GA with PSO method, a MATLAB implementation of GA (this GA method was carried out by the function *ga* available in the Genetic Method and Direct Search toolbox of the MATLAB software) is used to estimate the parameters of Schottky-barrier diode model. Implementation of the GA for this case was based on the following.

► Type of coding: considering the convergence of the GA depends on the type of coding and nature of genetic operators,[13,32,33] real-coded and binary-coded represent respectively.

► Selection: *Roulette* function.

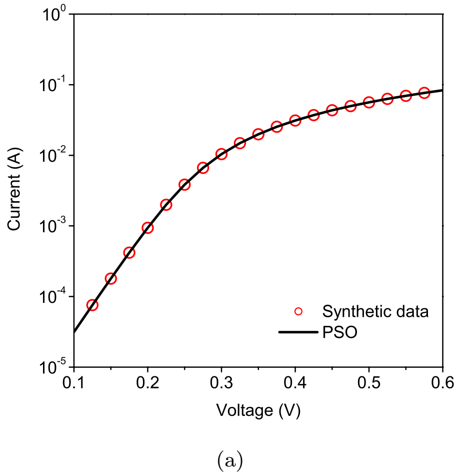
► Crossover: *Heuristic* function with the crossover rate 0.8.

► Mutation: *Uniform* function with the mutation rate 0.2.

► Reproduction: the elite strategy with the elite count 1 was used, where the best individual of each iteration was copied into the succeeding iteration in order to speed convergence.

To perform fair comparison, the same computational effort is used in both the PSO and GA methods. That is, the maximal iteration times, population size and searching ranges of the unknown parameters in the GA are the same as those in the PSO. For GA, the procedure of parameter estimation was done 10 times and then the best performance was selected.

Figure 2 shows the simulation results by making comparisons between the synthetic $I-V$ data of the Schottky-barrier diode and the $I-V$ characteristic curves derived by PSO and GA. Clearly, $I-V$ characteristic curves obtained by PSO and real-coded GA are in good agreement with synthetic data, whereas binary-coded GA experiences difficulty in curve fitting. As for the Fig. 3, it illustrates the convergence characteristics of the PSO and GA for this simulation example. Although both GA coding types converge drastically, there is still a difficulty in converging



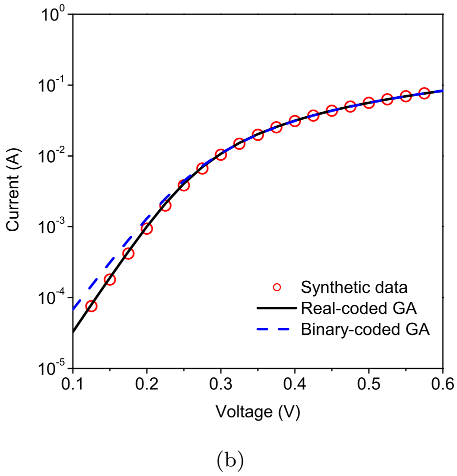


Fig. 2. The synthetic $I-V$ data and the characteristic curves fitted by (a) PSO and (b) GA methods.

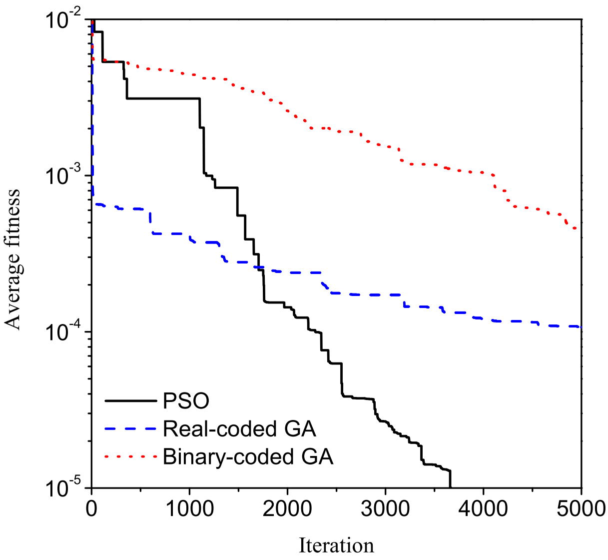


Fig. 3. Convergence characteristics of the PSO and GA methods.

Table 1. Results of parameter estimation with synthetic $I - V$ data.

	Original values	PSO method	Relative errors	GA methods			
				Real-coded	Relative errors	Binary-coded	Relative errors
Φ_{SB}(eV)	0.68	0.6801	0.01%	0.6882	1.20%	0.6493	4.51%
n	1.12	1.1196	0.04%	1.0844	3.18%	1.2751	13.85%
R_s(Ω)	3.3	3.3002	0.01%	3.3185	0.56%	3.2257	2.25%
A^*(A cm^{-2} K^{-2})	120	120.76	0.63%	126.53	5.44%	128.64	7.20%
$e_{\min}$	—	1.1472×10^{-6}	—	1.0697×10^{-4}	—	4.2721×10^{-4}	—
Time(s)	—	13.67	—	36.16	—	32.96	—

to the global optimal solution. In contrast, the PSO method has much lower fitness value than the GA if the number of iteration times is large enough. So the PSO can achieve better solutions than the GA.

Table 1 makes a detailed comparison and contrast of the PSO and GA methods for parameter estimation of this simulation example. All the statistics are compared in three items, difference between original and estimated parameters, minimum fitness values, and running time. From Table 1, we can see that the estimated results using the PSO are nearly the same as the original parameters, while the relative errors between the original parameters and the parameters estimated by GA methods are larger for the same search ranges. The elapsed time demonstrates that computational speed of PSO is much faster than the GA methods. As for the different GA coding types, binary-coded GA searches more rapidly than the real-coded GA, but the greater fitness value expresses the difference between synthetic data and fitted ones is evident too, which is proved in Fig. 2(b). Moreover, although the characteristic cure obtained by the real-coded GA appears in good agreement with synthetic data in Fig. 2(b), the relative errors obtained by the real-coded GA are much larger than those obtained by the PSO as shown in Table 1.

To sum up, the values of estimated parameters obtained by the PSO method are closer to the original ones than those obtained by the GA methods. It is concluded that the PSO method is applicable to parameter estimation for the Schottky-barrier diode model and the PSO is more effective than the GA methods in this optimization problem.

3.2. *Parameter estimation with experimental data*

In this section, to further validate the competence of the present parameter estimation method, it is once more applied but now to a nickel silicide Schottky-barrier diode sample with Pt-doped (effect diode area $A = 1 \times 10^{-6}$ m^{-2}). Through 400°C annealing, experimental $I - V$ data of this Schottky-barrier diode sample were measured for parameter estimation. The related values assigned to the variables of the PSO and GA are the same as in previous experiment.

From Fig. 4, it provides a high quality agreement between the experimental data and fitting curve using PSO method. Figure 5 shows the convergence characteristics

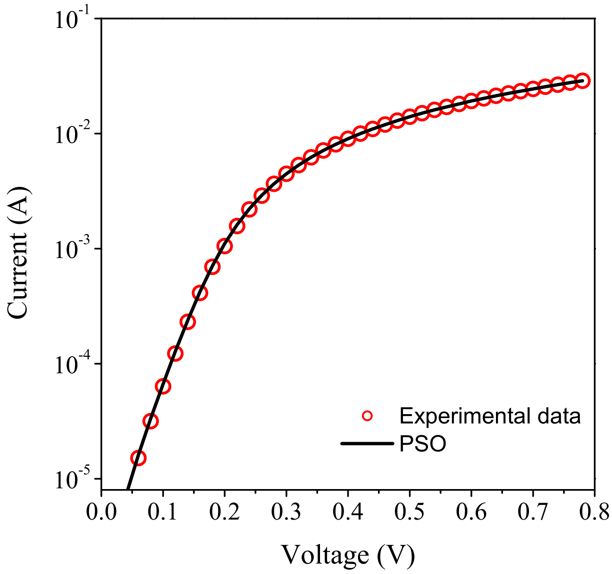


Fig. 4. The experimental $I-V$ data of the Schottky-barrier diode and the characteristic curve fitted by PSO method.

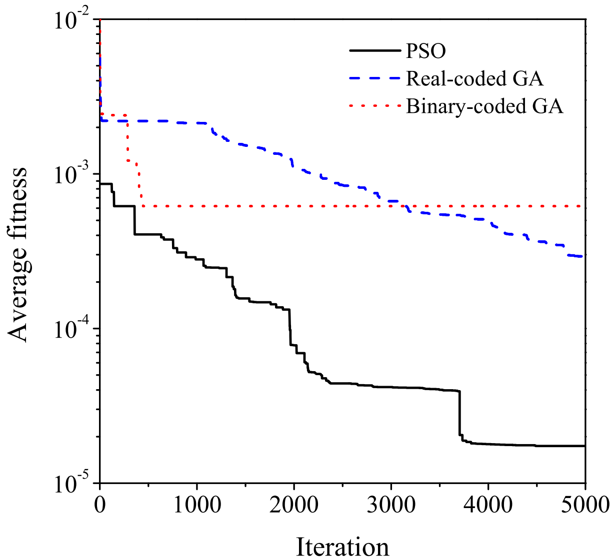


Fig. 5. Convergence characteristics of the PSO and GA methods with experimental $I-V$ data.

of the PSO and GA methods. Obviously, the PSO method also has a lower fitness values than the GA methods, when the maximum iteration times reaches.

In the case of experimental $I-V$ data, we use the same variables setting of population size, maximal iteration times and search ranges of the PSO and GA methods

Table 2. Results of parameter estimation with experimental $I-V$ data.

	Search ranges	PSO method	GA method	
			Real-coded	Binary-coded
Φ_{SB}(eV)	[0.1, 1]	0.6454	0.6052	0.5735
n	[1, 2]	1.1335	1.4173	1.9458
$R_s(\Omega)$	[0, 50]	17.5030	17.0881	16.053
A^*(A cm^{-2} K^{-2})	[1, 200]	100.9160	109.1264	108.3028
$e_{\min}$	—	1.7311×10^{-5}	2.4456×10^{-4}	6.2749×10^{-4}
Time(s)	—	45.916	66.64	58.36

to make comparisons. The results of the parameter estimation are summarized in Table 2. 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 improvement in the knowledge of the real values of the estimated parameters. The minimum fitness function values $e_{\min}$ of the PSO, real-coded and binary-coded GA are 1.7311×10^{-5}, 2.4456×10^{-4} and 6.2749×10^{-4} respectively, which indicates the optimum searching quality of the PSO method is the highest; and then, compared with the GA, the execution time of the PSO running is shorter, which shows that the PSO method has a better computation efficiency.

Consequently, as we can see from Tables 1 and 2, it can be observed that the PSO and GA methods do not particularly call for initial guesses as close as possible to the solution in the parameter estimation of the Schottky-barrier diode, while only require a broad search range specified for each parameter. But according to the fitting curves and minimum fitness values, the performance of PSO is outdo that of GA in both simulation and experimental cases. The reasons why the PSO method has a better search efficiency and quality than the GA may be as follows: Firstly, PSO does not have genetic operation such as crossover and mutation, particles in PSO update themselves with the internal velocity. Thus, from comparison with evolutional generation, solutions of PSO show stronger randomness and easier calculation than the GA. Secondly, PSO has memory, which is important to the algorithm. That is, the knowledge of good solutions is retrained by all particles, which makes PSO find the final solution in a short time. Although similar operator called elite strategy is also possible in GA, the performance of PSO is much better than the GA due to that each individual (particle) in PSO can obtain information directly from the historical experience of individuals and entire swarm. Lastly, the information sharing mechanism is significantly different between PSO and GA. In GA, chromosomes share information with each other, so the whole population move like one group towards an optimal area; while in PSO, the flow of information is unidirectional, in other words, the information transforms from *gbest* to other particles, which is a one-way information sharing mechanism. The evolution only looks for the best solution. As a result, compared with GA, all the particles tend to converge to the best solution quickly.

3.3. *The influences of population size and acceleration factors*

To investigate the effects of population size and acceleration factors on the performance of the PSO, experiments were carried out on the above mentioned experimental data of the Schottky-barrier diode. Figures 6 and 7 illustrate the effect of population size and acceleration factors on the minimum fitness value.

As shown in Fig. 6, when population size is too small, the results are poor because the solution space will not be explored enough. As population size increases, the results become better. Moreover, the minimum fitness $e_{\min}$ fluctuates only a little with different population sizes after it is large enough. 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 a population size between 40 and 60. If more parameters are needed to be estimated, a larger population size is recommended.

Acceleration factors c_1 and c_2 are used to control the relative influence between memory form self-referent and neighbors. That is, acceleration factors represent random acceleration weight of evaluation to *pbest* and *gbest* by particles. Small acceleration factors may make particles oscillate in an area far away from the object region; large acceleration factors enable particles to fly to objective rapidly, but in a high probability, particles will fly away. Figure 7 gives the description as mentioned above. So, the appropriate acceleration factors can speed up computational

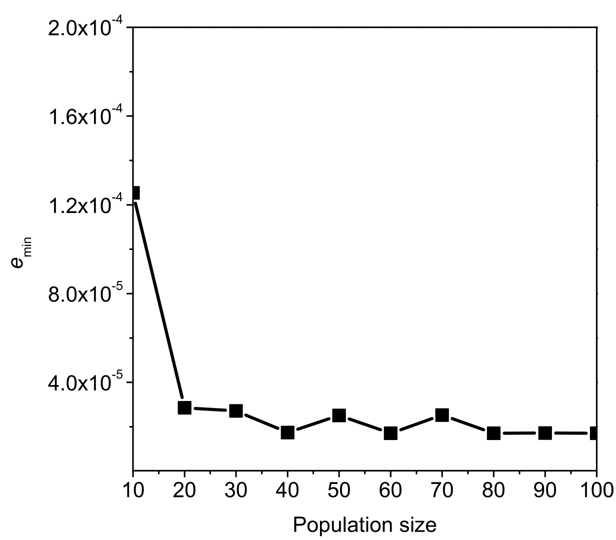


Fig. 6. The minimum fitness values obtained by the PSO method with different population sizes, $c_1 = c_2 = 2.1$.

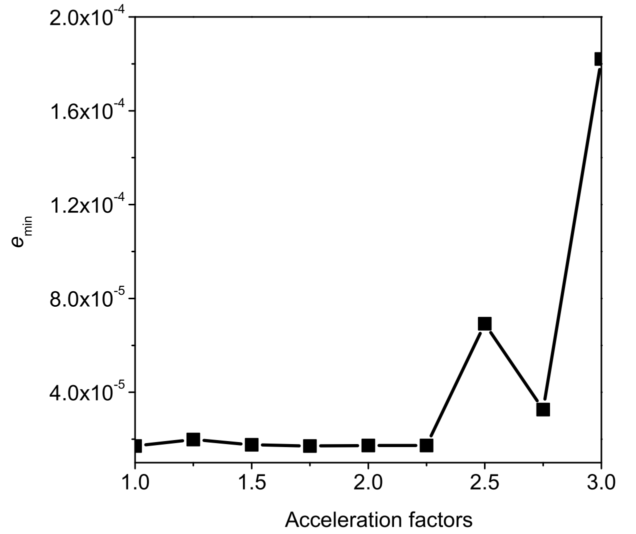


Fig. 7. The minimum fitness values obtained by the PSO method with different acceleration factors, $N = 40$, $c_1 = c_2$.

efficiency and avoid to lapse into local minimum. According to Fig. 7, it is reasonable to choose the values of c_1 and c_2 less than 2.5.

4. Conclusions

This paper presents a method for solving the parameter estimation problem of the Schottky-barrier diode model using particle swarm optimization (PSO). The parameters, including Schottky-barrier height, ideality factor, Richardson constant and series resistance, can be accurately determined by the proposed method with synthetic and experimental data. Compared with the binary-coded and real-coded GA methods, the proposed PSO method has the superior performance according to estimation accuracy and computation efficiency. In addition, the PSO method does not particularly necessitate initial guesses as close as possible to the solutions, while only requiring a broad range specified for each parameter. It is expected that the proposed method can be applied to many other parameter estimation of semiconductor devices, which will be interested for our future work.

Acknowledgments

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