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The parameter extraction of the thermally annealed Schottky barrier diode using the modified artificial bee colony

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Abstract In this paper, a new method based on the modified artificial bee colony (MABC) algorithm to determine the main characteristic parameters of the Schottky barrier diode such as barrier height, ideality factor and series resistance. For this model, the Ni/*n*-GaAs/In Schottky barrier diode was produced and annealed at different temperature in a laboratory. The performance of the modified ABC method was compared to that of the basic artificial bee colony (ABC), particle swarm optimization (PSO), differential evolution (DE), genetic algorithm (GA) and simulated annealing (SA). From the results, it is concluded that the modified ABC algorithm is more flexible and effective for the parameter determination than the other algorithms.

Keywords Artificial bee colony algorithm · Modified artificial bee colony algorithm · Particle swarm optimization · Schottky barrier diode · Parameter determination

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1 Introduction

The Schottky barrier diode (SBD) is actually one of the oldest and most used semiconductor devices in electronics. It is a metal-semiconductor (MS) contact diode with low forward voltage drop, fast response and low resistance. Schottky barrier diodes are an essential part of a large number of compound semiconductor electronic devices, including microwave diodes, solar cells and photo detectors [1, 2]. The device characterization of the semiconductor devices plays an important role in researching and designing areas of semiconductor electronics circuits. The performance of the SBD depends on the main electrical parameters such as the ideality factor, barrier height and series resistance. Therefore, the understanding and determining of these parameters that give useful information about the nature of the SBD are important for the device application [3, 4]. However, the performance of the SBDs is determined by interface between the metal and semiconductor surface. For this reason, the thermal annealing of the SBDs is most commonly used process to create good quality and stable Schottky diodes [5]. Because of this, the thermal annealing behavior of the SBDs has attracted much attention for scientific as well as technological developments [6, 7].

Recently, some authors have proposed several different methods to determine the parameters of the SBDs [8–25], such as Norde [10], Li [20] and Ferhat-Hamida [9]. Swarm intelligence and evolutionary algorithm based electronic device parameter determination approaches have attracted significant attention, too. For example, a technique based on the artificial bee colony algorithm has been recently proposed to improve the accuracy of the small-signal model of MESFET [26], and Wang and Ye have used differential evolution (DE) for parameter determination of Schottky barrier diode model [27]. The basic artificial bee colony algorithm has been used by Karaboga et al. for the parameter extraction for the SBD [28].

However, the swarm intelligence based and evolutionary algorithms that were employed in this paper have been used not only to determine the parameters of the electronic devices, but also to solve different problems in many research areas such as automation, design, image processing, etc. [29–33]. For instance, artificial bee colony algorithm has been applied to compute threshold selection for image segmentation [29]. The other well-known swarm intelligence based algorithm is particle swarm optimization and it is proposed for the efficient design of the armored vehicle [30]. In addition to swarm intelligence based algorithms, the evolutionary algorithms such as genetic algorithm, differential evolution and simulated annealing have been used to design the test pattern generator, to propose a hybrid model and to optimize the fuzzy ant-miner, respectively [31–33].

The artificial bee colony algorithm is a new optimization algorithm based on the intelligent foraging behavior of honey bee swarm. In 2005, the artificial bee colony (ABC) algorithm was proposed by Karaboga for numerical optimization problems [34]. In addition, Basturk and Karaboga compared the performance of ABC with that of some other well-known population-based optimization algorithms [35, 36] and they stated that ABC is simple to implement and also quite robust. Moreover, the modified versions of the ABC (MABC) algorithm are introduced by Karaboga and Akay for constrained optimization problems [37]. ABC has been applied to solve various problems from different areas since 2005 [38–41].

The work described in [28] presents a limited analysis of the parameter determination method based on basic ABC for the Ni/n-GaAS/In Schottky barrier diode which had been grown and annealed at only 300 degrees C. In the present work, it is aimed to describe a modified ABC (MABC) algorithm to solve the considered problem and to analyze its performance in detail by comparing the well-known optimization algorithms such as particle swarm optimization (PSO), differential evolution (DE), genetic algorithm (GA), simulated annealing (SA) and basic ABC. The modified artificial bee colony, differential evolution (DE), genetic algorithm (GA) and simulated annealing (SA) are used for parameter determination with synthetic I–V data and ABC, PSO and MABC are applied to determine the parameters with experimental I–V data, where Ni/n-GaAs/In Schottky diode was annealed at two different temperatures, 200 degrees C and 400 degrees C. The rest of paper is organized as follows. After the problem and experimental data preparation are defined in Sect. 2 and Sect. 3, respectively, the basic artificial bee colony (ABC) and modified artificial bee colony (MABC) algorithm are described in Sect. 4. In Sect. 5, the MABC approach is compared to the ABC, particle swarm optimization (PSO), differential evolution (DE) [27], genetic algorithm (GA) [27] and simulated annealing (SA) [27] for the synthetic I–V data and secondly, the modified ABC and the basic ABC and particle swarm optimization approaches are compared using the experimental I–V data for the different annealing temperatures since these algorithms are swarm based and finally conclusions are presented.

2 Definition of the problem

2.1 The description of the SBD model

For the ideal SBD, it is assumed that the forward bias current of the device is due to the thermionic emission current and can be expressed as [7],

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

where

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

is the saturation current. In the above equations, the symbols of V, I, A, A^*, q, T, k are the bias voltage, diode current, diode area, Richardson constant, electron charge, absolute temperature and Boltzmann constant, respectively. The ideality factor (n), Schottky barrier height (Φ_{SB}) and series resistance (R_s) are the characteristic parameters of the SBDs.

2.2 Fitness function

In this paper, it is considered that the SBD denoted by Eq. (1) can be formulated as

$$J(I, V, P) = I - I_0\left[\exp\left(\frac{q(V - IR_S)}{nkT}\right) - 1\right] \tag{3}$$

where $P = [\Phi_{SB}, n, R_s]$ are the main characteristic parameters of the SBD model. The fitness function can be expressed by [27]

$$\varepsilon = \sqrt{\frac{1}{N}\sum_{i=1}^{N} J(I_i, V_i, P)^2} \tag{4}$$

where I_i and V_i are the experimental data pair in I–V characteristics, respectively. N and P are the number of data and the model parameters.

Here, the aim is to reduce the value of the fitness function ε in a short time and to make it approach minimum as much as possible. So, when the fitness function moves closer to zero, the accuracy of the SBD parameters will increase.

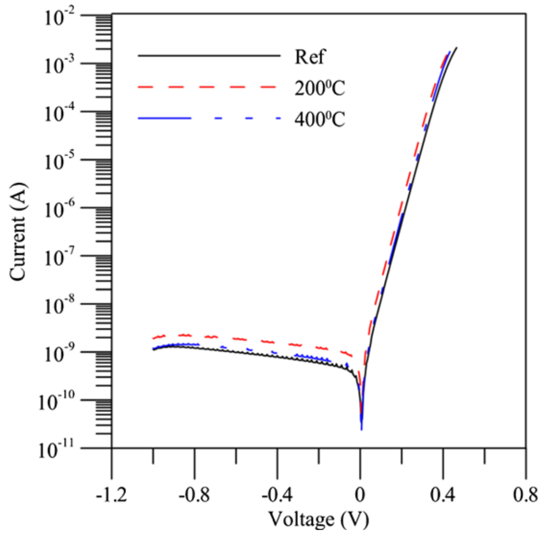


Fig. 1 Forward and reverse bias I–V characteristics of the annealed Ni/n-GaAs/In SBD

3 Experimental data preparation

The used n-type GaAs wafer (Si doped) was (100) oriented, with free carrier concentration of $7.3 \times 10^{15}\ \text{cm}^{-3}$ and 300–400 μm width at room temperature. The back side ohmic contact was made on the semiconductor sample in order to form an oxide layer interface. It was kept in the laboratory during the time of 3 days. These samples are taken back to the vacuum environment and the Schottky contacts were formed on the front face of the pieces as dots with diameter of about 1.5 mm by evaporation of Ni. So, we have obtained Ni/n-GaAs/In Schottky diode with native oxide interface layer. Then the current-voltage (I–V) characteristic of Ni/n-GaAs/In Schottky diode was measured using a Keithley 487 Picoammeter/Voltage source at room temperature in darkness. The diode was annealed at temperature 200 degrees C and 400 degrees C for 1 min in N_2 atmosphere. After each annealing step, the current-voltage measurements of Schottky diodes were repeated [42]. The characteristics of Schottky diodes have been plotted. Figure 1 shows the I–V characteristics of the annealed Ni/n-GaAs/In SBD for forward and reverse bias. Normally, Schottky barrier diode can be made of metal-semiconductor or metal-insulator-semiconductor (MIS) junction. According to MS or MIS structure, the diode specification such as current-voltage characteristic or diode parameters might change. The study presented in [28], proposed examination of MS junction. In this study, the metal-insulator-semiconductor structure of the Schottky barrier diode has been examined. The experimental data preparation section has focused on the MIS Schottky diode. In addition to this, the constructive effect of thermal annealing process on the SBD is studied with different annealing temperature.

4 The modified artificial bee colony (MABC) algorithm

The artificial bee colony algorithm is a new swarm intelligence algorithm based on the foraging behavior of a bee colony. In the ABC algorithm, the foraging honey bees are grouped into three categories; employed bees, onlookers and scout bees. The employed bees exploit their food sources and interact with onlooker bees. Onlooker bees wait in the hive and decide which food source to exploit. Scout bees carry out random searches for new food sources around the hive. The number of the employed bees or the onlooker bees is equal to the number of solutions. The position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source is related to the fitness of the solution [43]. The employed bees interact about the food sources with onlookers by dancing in the dance area inside the hive. The nature of the dance that is called waggle dance is proportional to the nectar amount of the food source. Onlooker bees watch the dance and choose a food source according to the probability which is proportional to the profitability of that food source. Thus, rich food sources draw more attention from onlooker bees as compared to other food sources. When a food source is exploited fully by its employed bee associated with it then, the food source is abandoned and becomes scout. Scout bees can be visualized as performing the job of exploration, whereas employed and onlooker bees can be visualized as performing the job of exploitation.

In this work, the modified artificial bee colony algorithm has been applied to compare with the other competitor algorithms for the parameter determination of the SBD. The modified ABC algorithm described as in literature was used for the optimization purpose [37, 40]. In the basic ABC, only one parameter is changed to produce a neighbor solution from the present one. In the modified ABC, all parameters are changed to generate a neighbor solution as explained. Hence, the convergence speed of the algorithm is improved. The basic and modified ABC algorithms have three main control parameters: Limit, population size and cycle number. The Pseudo-code of the modified ABC algorithm is given below:

Step 1: Initialize the population of solutions $x_{ij}, i = 1, \ldots, SN$, $j = 1, \ldots, D$ (SN: number of solutions in the colony), (D: the number of optimization parameters)
Step 2: Evaluate the population
Step 3: cycle = 1
Step 4: repeat
Step 5: Produce a new solution v_{ij} for each employed bee using $v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj})$ and evaluate it. Here, $j \in (1, 2, \ldots, D)$ and $k \in (1, \ldots, SN)$ $(k \neq i)$, is a randomly chosen index. ϕ_{ij} is random number in the range $[-1, 1]$.
Step 6: Apply the greedy selection process for the employed bees

Table 1 Parameter settings for ABC, MABC, PSO, DE, GA and SA algorithms

ABC, MABC		PSO		DE [27]		GA [27]		SA [27]	
Colony size	24	Swarm size	24	Population size	24	Population size	24	T_0	5000
Limit	36	Inertia weight (w)	0.9–0.4	CR	0.3	P_c	0.8	C_F	0.95
Cycle	500	C_1, C_2	1.494	F	0.8	P_m	0.2	L	100
		$V_{\max}$	0.5, 0.5, 25						

Table 2 The produced by ABC, MABC, PSO, DE, GA and SA methods by using synthetic I–V data

	Original values	ABC	MABC	PSO	DE method [27]	GA method [27]	SA method [27]
Φ_{SB} (eV)	0.68	0.6750	0.6800	0.6800	0.6802	0.6753	0.6274
n	1.12	1.1407	1.1200	1.1200	1.1199	1.1416	1.3239
R_S (Ω)	3.3	3.2972	3.3000	3.3000	3.3001	3.2891	3.1845
$\varepsilon_{\min}$	–	1.7878×10^{-4}	1.4334×10^{-9}	1.4334×10^{-9}	3.2995×10^{-9}	6.2834×10^{-5}	6.9412×10^{-4}
Time (s)	–	10.5230	9.0980	87.88	26.53	33.74	51.564

Table 3 Relative errors obtained by ABC, MABC, PSO, DE, GA and SA methods by using synthetic I–V data

Parameters	Relative errors (%)					
	ABC	MABC	PSO	DE method [27]	GA method [27]	SA method [27]
Φ_{SB} (eV)	0.735	0.000	0.000	0.029	0.700	7.7231
n	1.848	0.000	0.000	0.009	1.929	18.2054
R_S (Ω)	0.084	0.000	0.000	0.003	0.330	3.5

Step 7: Calculate the probability values p_i for the solutions x_i by $p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n}$
Step 8: Produce the new solutions υ_i for the onlookers from the solutions x_i selected depending on p_i and evaluate them
Step 9: Apply the greedy selection process for the onlookers
Step 10: Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution x_i by $x_i^j = x_{\min}^j + \text{rand}[0,1](x_{\max}^j - x_{\min}^j)$
Step 11: Memorize the best solution achieved so far
Step 12: cycle = cycle + 1
Step 13: until cycle = Maximum Cycle Number

5 Results and discussion

5.1 Parameter determination with synthetic I–V data

At the first step, the synthetic I–V data were used to confirm the feasibility and accuracy of the modified ABC method in the parameter determination for the SBD model. With this goal, the synthetic I–V data were generated according to the parameters $\Phi_{SB} = 0.68$ eV, $n = 1.2$ and $R_s = 3.3$ Ω at 297 K as reported in the literature [11]. Then, the modified ABC method was applied to extract the SBD parameters. Finally, the extracted parameters were checked against the original and obtained values by the basic ABC, MABC, PSO, DE, GA and SA.

The control parameter setting of the competitor algorithms are given in Table 1. The control parameter values of the competitor algorithms have a significant effect on their performance. In this work the values suggested in the literature were employed for the both of ABC [43].

In this simulation study, each algorithm of the basic ABC, MABC and PSO was run 30 times with different random seed. The search ranges were set as follows $\Phi_{SB} \in [0.1, 1]$, $n \in [1, 2]$ and $R_S \in [0, 50]$. A PC with the following features was used in the simulation study: Intel Pentium Core 2 Duo T7500 2.2 GHz CPU, 2048 MB RAM and a Windows Vista OS.

The values in the Tables 2 and 3 are important in terms of the comparison for the competitor algorithms. As can be seen in Table 2, the extracted parameters Φ_{SB}, n, R_s by the modified ABC and PSO algorithms are the same as the values of the original parameters in literature [11]. However, the minimum fitness value $\varepsilon_{\min}$ found by MABC and PSO methods are much less than the values found by the other methods. The MABC method gives the results immediately because its running time is very short when compared with the basic ABC, PSO, DE, GA and SA methods. In addition, Table 3 shows that the relative errors of the MABC and PSO models are almost zero and smaller than that of other methods.

Table 4 shows mean values and standard deviations of the final results after 30 runs by ABC, MABC and PSO.

Table 4 Mean value and standard deviations of the final results after 30 runs by ABC, MABC and PSO

	Original values	ABC		MABC		PSO	
		Mean value	Standard deviations	Mean value	Standard deviations	Mean value	Standard deviations
Φ_{SB} (eV)	0.68	0.6704	0.0340	0.6800	5.0124e-011	0.6800	3.8107e-007
n	1.12	1.1857	0.1738	1.1200	2.3158e-010	1.1200	1.7330e-006
R_S (Ω)	3.3	3.2780	0.0868	3.3000	2.3158e-010	3.3000	9.5567e-007
$\varepsilon_{\min}$	–	8.4584e-004	3.9285e-004	1.4334e-009	8.8105e-016	3.9590e-009	4.7824e-009

(a)

(b)

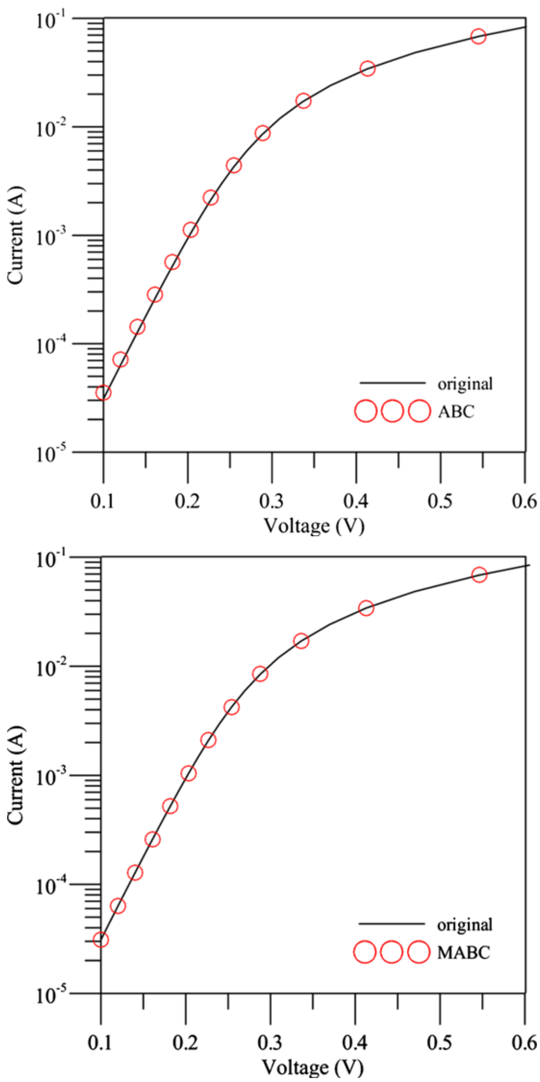


Fig. 2 (**a**) I–V characteristics of the SBD obtained from synthetic and fitted data using ABC. (**b**) I–V characteristics of the SBD obtained from synthetic and fitted data using MABC. (**c**) I–V characteristics of the SBD obtained from synthetic and fitted data using PSO

Although mean values of the MABC and PSO methods are very close, standard deviations of PSO are larger than ABC. The performance of the basic ABC is not enough good compared with that of the others. This case shows that the MABC algorithm is more robust than basic ABC and PSO.

(c)

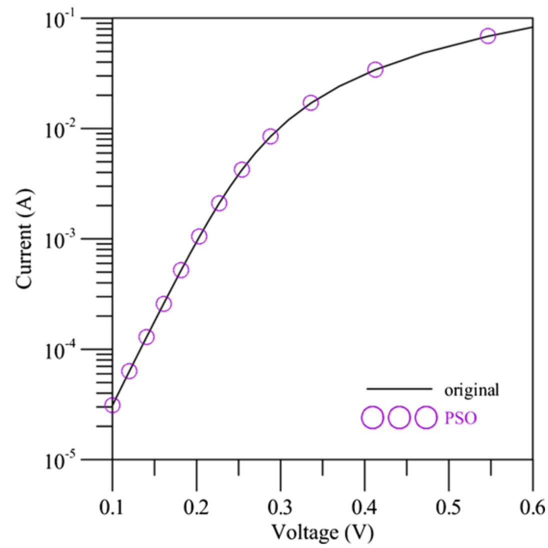


Fig. 2 (*Continued*)

Figures 2(a), 2(b) and 2(c) show comparisons between the synthetic I–V data of the SBD and the I–V characteristics obtained by ABC, MABC and PSO. Figures 2(b) and 2(c) show that MABC and PSO methods are feasible for the parameter determination and the I–V characteristics obtained the MABC and PSO methods are similar with the synthetic data in all regions.

Figure 3 shows the convergence characteristics of ABC, MABC and PSO models for the synthetic I–V data. At the beginning, the PSO converges rapidly, but then its convergence speed decreases. In contrast to this situation, the convergence speed of MABC increases significantly and MABC evaluates the parameters of the SBD before the PSO. The convergence performance of ABC is good during the first iterations, but the solutions of the ABC are worse than that of the other algorithms.

The results show that the running time, the value of fitness function, the convergence speed and the accuracy of the parameters determined by the MABC model are better than ABC, PSO, DE, GA and SA. Also MABC is more robust than ABC and PSO. As a result, MABC is an effective, robust and fast approach for the parameter determination of the SBD.

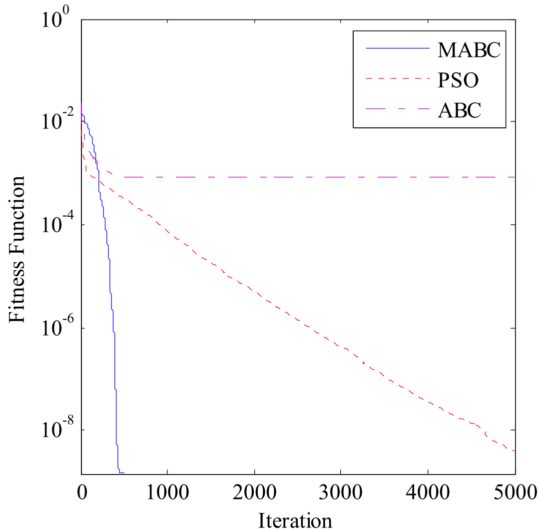


Fig. 3 Convergence characteristics of ABC, MABC and PSO

5.2 Parameter determination with experimental I–V data

At the second step, the experimental I–V characteristics of the Ni/n-GaAS/In Schottky Barrier diode have been used for the parameter determination of the SBD. The Ni/n-GaAs/In SBD was prepared as in Sect. 3. Then, this diode was annealed at 200 degrees C and 400 degrees C. The I–V characteristics of the annealed SBD are shown in Fig. 1.

The goal of this section is to prove how MABC is applied successfully to the real world problem as in the simulation Sect. 5.1. With this aim, ABC, MABC and PSO are used for comparison because MABC and PSO algorithms are more effective and robust than the above mentioned methods. The control parameters of ABC, MABC and PSO and search ranges are the same as in the previous section and each of ABC, MABC and PSO algorithms is run 30 times.

Performance indicator parameters of the SBD model for the as-deposited and annealed at 200 degrees C, 400 degrees C diode are tabulated in Tables 5, 6 and 7, respectively. In Table 5, the best values of the MABC and PSO are $\Phi_{SB} = 0.7927$ eV, $n = 1.0920$, $R_S = 16.9657\ \Omega$ and $\varepsilon_{\min} = 1.4205\text{e-}007$. The running time of MABC is about ten times shorter than PSO. The mean and standard deviation values of MABC are better than PSO. The mean values and standard deviations of ABC are larger than MABC and PSO, but its running time is shorter than PSO. The best values of ABC are $\Phi_{SB} = 0.7949$ eV, $n = 1.0840$, $R_S = 18.0356\ \Omega$ and $\varepsilon_{\min} = 2.8812\text{e-}007$, respectively.

In Table 6, the best values of the barrier height, ideality factor, series resistance and fitness function are obtained as $\Phi_{SB} = 0.7704$ eV, $n = 1.0880$, $R_S = 15.0338\ \Omega$ and $\varepsilon_{\min} = 2.9036\text{e-}007$ by MABC and PSO, respectively. However, the values of ABC are $\Phi_{SB} = 0.7726$ eV, $n = 1.0811$, $R_S = 15.0671\ \Omega$ and $\varepsilon_{\min} = 8.6145\text{e-}007$. The running times of ABC, MABC and PSO are 17.6030, 15.6 and 154.231, respectively. The mean values of MABC and PSO are same, but the standard deviation values of PSO are larger than MABC. The mean values and standard deviations of ABC are larger than MABC and PSO.

Table 5 Results obtained by ABC, MABC and PSO methods with experimental I–V data for the as-deposited Ni/n-GaAs/In SBD

	ABC			MABC			PSO		
	Mean value	Standard deviations	Best value	Mean value	Standard deviations	Best value	Mean value	Standard deviations	Best value
Φ_{SB} (eV)	0.7818	0.0257	0.7949	0.7927	1.3254e-008	0.7927	0.7927	7.0590e-007	0.7927
n	1.1390	0.0939	1.0840	1.0920	4.5334e-008	1.0920	1.0920	2.4573e-006	1.0920
R_S (Ω)	12.6348	8.0873	18.0356	16.9657	3.8900e-006	16.9657	16.9657	2.2604e-004	16.9657
$\varepsilon_{\min}$	2.0174e-006	9.7137e-007	2.8812e-007	1.4205e-007	1.6252e-017	1.4205e-007	2.3550e-007	5.1182e-007	1.4205e-007
Time (s)	–	–	17.3510	–	–	15.7900	–	–	160.075

Table 6 Results obtained by ABC, MABC and PSO methods with experimental I–V data for the annealed Ni/n-GaAs/In SBD at 200 °C

	ABC			MABC			PSO		
	Mean value	Standard deviations	Best value	Mean value	Standard deviations	Best value	Mean value	Standard deviations	Best value
Φ_{SB} (eV)	0.7546	0.0275	0.7726	0.7704	1.3726e-008	0.7704	0.7704	9.4066e-007	0.7704
n	1.1563	0.1067	1.0811	1.0880	4.8255e-008	1.0880	1.0880	3.3191e-006	1.0880
R_S (Ω)	11.9557	5.3387	15.0671	15.0338	2.3925e-006	15.0338	15.0338	1.5532e-004	15.0338
$\varepsilon_{\min}$	5.7204e-006	2.2364e-006	8.6145e-007	2.9036e-007	1.5161e-017	2.9036e-007	2.9036e-007	9.9963e-014	2.9036e-007
Time (s)	–	–	17.6030	–	–	15.6000	–	–	154.231

Table 7 Results obtained by ABC, MABC and PSO methods with experimental I–V data for the annealed Ni/n-GaAs/In SBD at 400 °C

	ABC			MABC			PSO		
	Mean value	Standard deviations	Best value	Mean value	Standard deviations	Best value	Mean value	Standard deviations	Best value
Φ_{SB} (eV)	0.7841	0.0248	0.7928	0.7947	2.0925e-008	0.7947	0.7947	2.5674e-006	0.7947
n	1.0929	0.0874	1.0562	1.0502	6.7007e-008	1.0502	1.0502	8.2713e-006	1.0502
R_S (Ω)	9.3838	5.2060	11.9221	12.2326	3.9052e-006	12.2326	12.2325	4.9990e-004	12.2326
$\varepsilon_{\min}$	3.7240e-006	1.9677e-006	2.7546e-007	8.3199e-008	9.8475e-017	8.3199e-008	8.3200e-008	1.1152e-012	8.3199e-008
Time (s)	–	–	17.2690	–	–	15.5610	–	–	146.402

In Table 7, the best values of the Φ_{SB}, n, R_S and $\varepsilon_{\min}$ are 0.7947, 1.0502, 12.2326 and 8.3199e-008 by MABC and PSO, respectively. The running time of PSO is larger than MABC and ABC. The mean and standard deviation values of PSO are larger than MABC. The best values of the barrier height, ideality factor, series resistance and minimum fitness function are obtained $\Phi_{SB} = 0.7928$ eV, $n = 1.0562$, $R_S = 11.9221$ Ω and $\varepsilon_{\min} = 2.7546\text{e-}007$ by the ABC. The running time of ABC, MABC and PSO are 17.2690, 15.5610 and 146.402, respectively.

Figures 4(a), 4(b) and 4(c) show the convergence characteristic of ABC, MABC and PSO for the as-deposited and annealed sample at different temperature of the SBD. In all figures, the convergence speed of PSO is faster than MABC within the beginning iterations, but then the convergence speed of MABC increases while PSO gets slow.

Figures 5(a), 5(b) and 5(c) show comparisons between the forward bias experimental I–V data of the SBD and the I–V characteristics obtained by MABC for different annealing temperatures. In Fig. 5(a), 5(b) and 5(c), the experimental I–V characteristics and fitting curves obtained by MABC are almost congruent. In conclusion, the MABC method is suitable in both simulation and experimental applications.

As Figs. 5(a), 5(b) and 5(c) are compared, an excellent fitting curve can be seen in Fig. 5(c). This situation can be explained as follows. From Tables 5, 6 and 7, the ideality factor n are obtained as 1.0920, 1.0880, 1.0502 and the series resistances R_s are determined as 16.9657, 15.0338, and 12.2326, respectively. As can be seen from these parameters, the effects such as unwanted impurity and native oxide layer between metal-semiconductor interfaces that causes the series resistance in the diode are eliminated depending of the annealing temperature, and the series resistance of the SBD is significantly decreased. At the same time, the ideality factor of the SBD approaches one. So, the annealed SBD at 400 degrees C is similar to the ideal SBD.

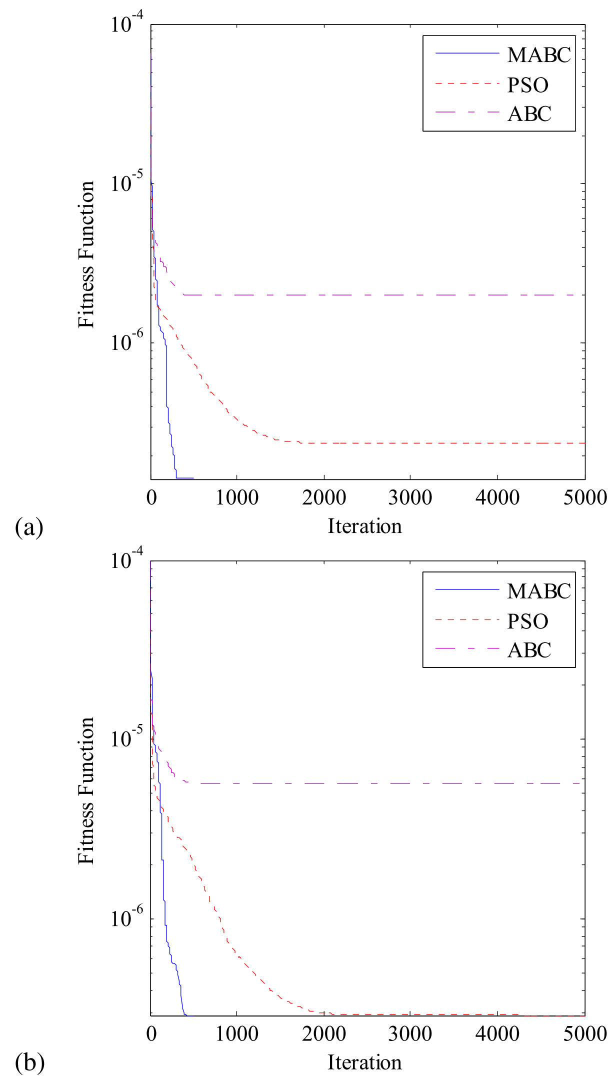
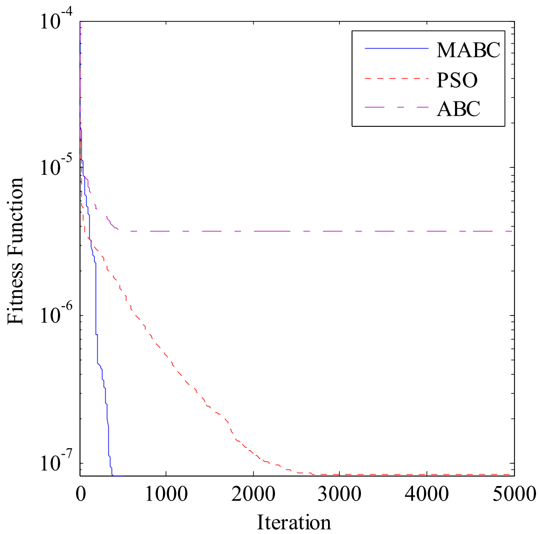
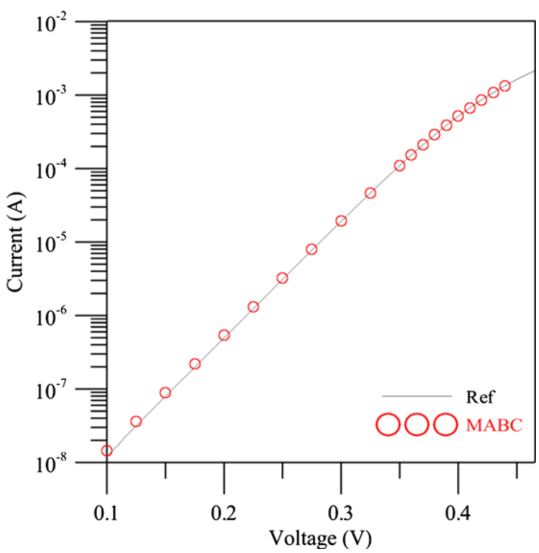


Fig. 4 (**a**) Convergence characteristics of ABC, MABC and PSO methods with experimental I–V data for the as-deposited Ni/n-GaAs/In SBD. (**b**) Convergence characteristics of ABC, MABC and PSO methods with experimental I–V data for the annealed Ni/n-GaAs/In SBD at 200 °C. (**c**) Convergence characteristics of ABC, MABC and PSO methods with experimental I–V data for the annealed Ni/n-GaAs/In SBD at 400 °C



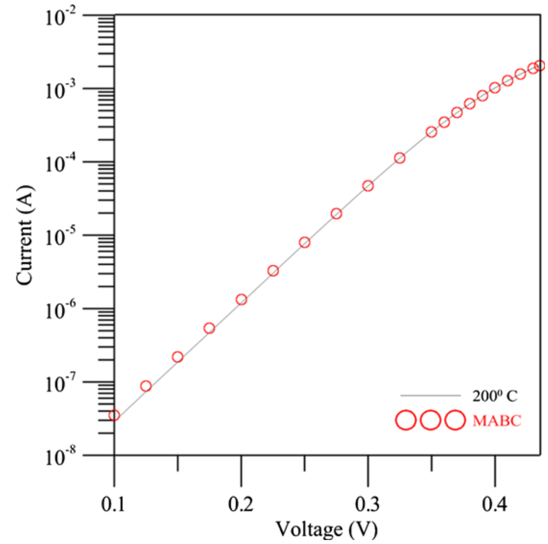
(c)

Fig. 4 (*Continued*)

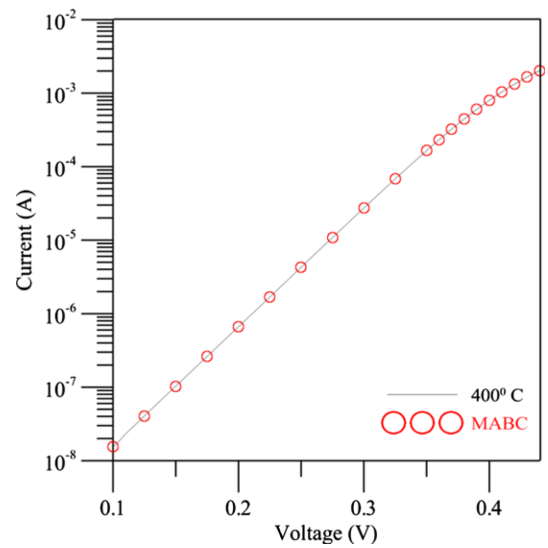


(a)

Fig. 5 (**a**) I–V characteristics of the SBD obtained from experimental I–V data for the as-deposited Ni/n-GaAs/In SBD and fitted data by using MABC. (**b**) I–V characteristics of the SBD obtained from experimental I–V data for the annealed Ni/n-GaAs/In SBD at 200 °C and fitted data by using MABC. (**c**) I–V characteristics of the SBD obtained from experimental I–V data for the annealed Ni/n-GaAs/In SBD at 400 °C and fitted data by using MABC



(b)



(c)

Fig. 5 (*Continued*)

6 Conclusion

In this paper, the modified artificial bee colony algorithm, which is a robust optimization algorithm, is used to determine the parameters of the SBD model from synthetic and experimental I–V data. First, the performance of MABC is compared to that of ABC, PSO, DE, GA and SA on parameter determination of the SBD for synthetic I–V data. Secondly, MABC method is applied with the experimental I–V data at different annealing temperatures and compared with ABC and PSO. From all results, it can be concluded that MABC model has a superior performance to the other considered methods. The results show that the parameters such as ideality factor, barrier height, series resistance, running time and the fitness function value obtained by MABC are better than the other algorithms. From this study, it can also be concluded that the MABC can be applied to determine the other parameters of the SBD such as parallel conductance and it is suitable for other parameter extraction problems in electronics.

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