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MOSFET Spice parameter extraction by modified genetic algorithm

Muhammed Emin Başak[1], Ayten Kuntman[2], Hulusi Hakan Kuntman[3]

[1,2]Istanbul University, Faculty of Engineering, Department of Electrical & Electronics Engineering, Avcılar, Istanbul, Turkey
[3]Istanbul Technical University, Faculty of Electrical &Electronics Engineering, Maslak, Istanbul, Turkey

Abstract: This paper presents a modified genetic algorithm to extract MOSFET BSIM3V3 model parameters. There are several techniques for solving nonlinear optimization problems. Model equations are all non-linear functions and these functions are difficult to be employed in order to extract parameters using deterministic methods.

In this study, modified genetic algorithm is applied to extraction of MOSFET BSIM3V3 model parameters. The results of experimental studies of both 0.35µm fabricated by C35 process and 0.7µm test transistors fabricated by TUBITAK Laboratories have been used for parameter extraction. Threshold voltage and mobility related to model parameters have been found for BSIM3V3. I-V characteristics have been obtained by using both genetic and modified genetic algorithm and then the results were compared with the measurement data. The simulation results show that the modified genetic algorithm implemented for parameter extraction is much more effective and accurate compared to the genetic algorithm.

Keywords: MOSFET, parameter extraction, genetic algorithm, modified genetic algorithm

Določitev Spice parameterov MOSFET s pomočjo spremenjenega generičnega algoritma

Izvleček: Članek predstavlja spremenjen generičen algoritem za določitev modelnih parametrov MOSFET BSIM3V3. Obstajajo številni algoritmi reševanja nelinearnih optimizacijskih problemov. Vse enačbe so nelinearne, kar otežuje določitev parametrov sz determisnističnimi metodami.

Ta določitev parametrov so bili uporabljeni eksperimentalni rezultati tranzistorjev TUBILAK Laboratories v 0.35 µm in 0.70 µm tehologiji. Pragovna napetost in mobilnost je bila določena za BSIM3V3. Za generičen in spremenjen generičen algoritem so bile določene I-U karakteristike. Rezultati kažejo, da so parametri pridobjeni s spremenjenim modelom precej boljši od parametrov pridobljenih z generičnim modelom

Ključne besede: MOSFET, določitev parametrov, keneričen algoritem, spremenjen generičen algoritem

* Corresponding Author's e-mail: mebasak@istanbul.edu.tr

1 Introduction

The BSIM models derived for MOS transistors use a very large number of parameters. These parameters are extracted for particular operating conditions. Finding a set of parameters is an optimization problem and hence genetic algorithms are good candidates for this task. Optimum parameter extraction exhibits great significance in modern technology [1-2]. Because of the local optimum in the solution space with traditional methods of parameter extraction, this type of extraction processes can produce results far from optimal solutions [3]. In this study, the abilities of genetic algorithm such as easiness, suitability for simple operation, effectiveness, and converging to global optimum are reflected to extraction of MOSFET model parameters. Generally, model parameters are extracted by using commercial software such as ICCAP, UTMOST, BSIMPro [1-3]; since model equations are all non-linear functions, the combination of least squares and Newton Raphson iteration is often adopted. Other nonlinear fitting methods require simplification of the model equations and complex computation such as gradient and inverse Hessian matrix [1-3]. There are also analytical methods [4-5] to extract only a few parameters so that they are not practical for extraction of a complex model such a BSIM3V3. Although SaPOSM [1] and Fast Diffusion [6] methods are global optimization methods, the extraction process in these methods is slow and difficult because they use derivatives in the calculation. Genetic algorithm (GA) method doesn't need complex computation. Consequently, this method is more practical than conventional and analytical methods. One of the other known simple models, called α-power model [7], ignores the channel–length modulation effect and is also unable to predict an accurate value for the drain current in the saturation region. The n-th power model [8] considers the channel–length modulation but the accuracy of this method may not be satisfactory for some applications. A computational intelligence technique is used to extract and simulate the stationary and high-frequency properties of bipolar junction transistors in [9]. Genetic algorithm and simulated annealing are performed in determining the model parameters in [10, 11], but only nine parameters are used for the accuracy and the error prediction is found as 1.3% in these methods. The performance of the particle swarm optimizations (PSO) is better than the genetic algorithm in terms of accuracy and consistency shown in [12]. However, the root mean square (RMS) error between measurement data and model results is within 3-7% for various characteristics in PSO method. PSO and GA have been used to extract parameters for NMOS device in [13]. The calculated average errors have been found as 4.84% and 7.15% for PSO and GA, respectively. In a recent work, an application of differential evolution to extract 16 small signal model parameters of GaAs MESFET (metal extended semiconductor field effect transistor) has been presented [14]. The MOS 9 Model is optimized using the simplified model instead of direct optimization by using GA in [15]. In essence, most of the research on GA has been done on electrical parameter extraction [15-21].

Before the actual fabrication of a designed circuit, the circuit performance should be predicted and evaluated. A better modeling is needed to predict and evaluate the behavior of the circuit. These models, designed mathematically, get the great benefit of improving and predicting the real time behaviour of the transistors. In this context, there are several works performed to realize accurate MOS transistor modeling [22-27].

Genetic Algorithm is an intelligence optimization algorithm that simulates the evolution of natural biology [28-29]. It originates from a population that represents a gather of probable results. GA is well suited for finding near optimal results in irregular parameter spaces. A population is composed of a certain quantity of individuals. These individuals are obtained by gene coding. After the generation of the initial population, the solution becomes more adequate with the population evolution according to the principle of natural selection. In every generation, individuals are selected according to their fitness. A new population that represents the new gather of new solutions is produced through crossover and mutation by using genetic operators [30]. The latter population is more suitable than former population. The most excellent individual of the last population is output as the approximately most suitable solution. Z. Michalewicz and et al. [31] proposed a modification of GA which uses the floating point representation and some specialized operators. In addition to applying the enhancements of GA, we proposed some extra contributions in MGA. In our study, the main structure of the flowchart, the order of the operators, ending condition, and using the method of the crossover and mutation operators are the main differences between GA and MGA. The aim of this paper is to show how the genetic algorithm can be modified and used.

In this study, Spice BSIM3V3 MOS model parameters have been extracted and optimized with both genetic algorithm and modified genetic algorithm, separately. Both threshold voltage and mobility related model parameters have been found for BSIM3V3.3. I-V characteristics have been extracted by using both genetic algorithm and modified genetic algorithm. I-V characteristics of extracting parameters data results have been compared with measurement results. The simulation results show that a modified genetic algorithm extracts accurately and effectively all 26 model parameters of the MOSFET. This study not only extracts the BSIM3V3.3 MOSFET model parameters, but also enhances the genetic algorithm. Although the work has been performed using old technology, the proposed extraction strategy has been verified for the current technology devices. In this work, Section 2 gives an overview of genetic algorithm and modifications of the standard GA design. Section 3 describes basic points, including the necessary steps on parameter extraction using GA and MGA. Section 4 reflects the results and discussion, including the evaluation of measurements and the model parameters obtained, finally followed by Section 5 to conclude the work.

2 The genetic algorithm

The genetic algorithm is an inspiration from the genetic process of nature. It offers acceptable solutions for hard problems in reasonable computation times. GA tries to optimize the solution set for a number of iterations and picks up the most optimized solution available to a problem at the end. Initial population creation, fitness evaluation, selection, crossover, and mutation are the five basic functions of the algorithm.

Creation of the initial population is the first step of the genetic algorithm. A population is a set of individuals used as parameters. Each individual has its own genetic content, called chromosomes. In the initial population creation process, chromosomes are produced randomly in order to assume diversity in the initial population. In our program, each chromosome is coded as floating point numbers in order to generate the solution vector. The lower and upper bound of the parameters representing the solution of the problem are given in Table 1. The population size is chosen as 500 in this study. After creating the initial population of parameters, the fitness value of parameters is evaluated. The fitness function which is used in both GA and MGA is presented in Equation 1.

$$f = \sqrt{\sum \left(\frac{I_{d,lab} - I_{d,model}}{I_{d,lab}} \right)^2} \tag{1}$$

where f is the fitness function, $I_{d,lab}$ and $I_{d,model}$ corresponds to the measured and extracted values of I_{ds} of the MOSFET, respectively.

If all chromosomes in fitness function are becoming nearly same, the program is terminated. Otherwise, either two parameters are randomly picked from the mating pool generated by the selection operator as the potential parents or they may be copied into the next generation directly. In each case, they have the ability to carry their superior properties to the next generation. The exchange of genetic material occurs between the parameters with a probability of β. New chromosomes (p_{new}) are obtained by using the following equation.

$$p_{new} = \beta p_{mn} + (1-\beta) p_{dn} \tag{2}$$

Here, β is the random number on the interval [0, 1]; p_{mn} is the n-th variable in the mother chromosome and p_{dn} is the n-th variable in the father chromosome. Crossover plays a primary role with the reproduction operator in GA. After reproduction emphasizes the highly fit strings, crossover recombines these selected strings to produce better individuals. After crossover, some randomly selected members are mutated according to some parameters in order to produce different genes that are not existed in the population.

The number of mutations (M_{num}) is determined in Equation 3 by multiplying the number of chromosomes (N_{chr}) chosen as 26, the number of genes (N_{gen}) chosen as 500, and mutation rate (Mrate) chosen as 0,02. New mutated chromosomes (p_{newmut}) are obtained by using Equation 4.

$$M_{num} = N_{chr} \cdot N_{gen} \cdot M_{rate} \tag{3}$$

$$p_{new_{mut}} = p_n + \sigma \mathrm{N}_n(0,1) \tag{4}$$

Where σ is a standard deviation of the normal distribution and $\sim N_n(0,1)$ is a random number whose average and deviation are zero and one, respectively. The iterations continue for a predefined number of times, called generation, to reveal the most optimal solution. Classical genetic algorithm main program flowchart is given in Figure 1. In our program, number of generations are chosen as 100.

Table 1: The upper and lower bound of MOSFET BSIM3V3 model parameters extracted by both GA and MGA

No	Parameters	Lower Bound	Upper Bound
1	VTHO	1×10^{-2}	1
2	K1	1×10^{-10}	1
3	K2	-1×10^{-10}	1×10^{-10}
4	U0	1	1×10^{5}
5	UA	-1×10^{-20}	1×10^{-20}
6	UB	1×10^{-20}	1
7	UC	1×10^{-20}	1
8	NLX	1×10^{-10}	1
9	DVT0	-100	100
10	DVT1	-100	100
11	DVT2	-1×10^{-10}	1×10^{-10}
12	RDSW	1	1×10^{5}
13	PRWG	1×10^{-20}	1
14	PRWB	-1×10^{-20}	1
15	WR	1	2
16	W0	1×10^{-20}	1
17	K3	-10	10
18	K3B	-10	10
19	A0	-10	10
20	AGS	-1	1
21	B0	1×10^{-20}	1
22	B1	1×10^{-20}	1
23	KETA	1×10^{-20}	1
24	DVT0W	1×10^{-20}	1
25	DVT1W	1	1×10^{10}
26	DVT2W	-1×10^{-20}	1

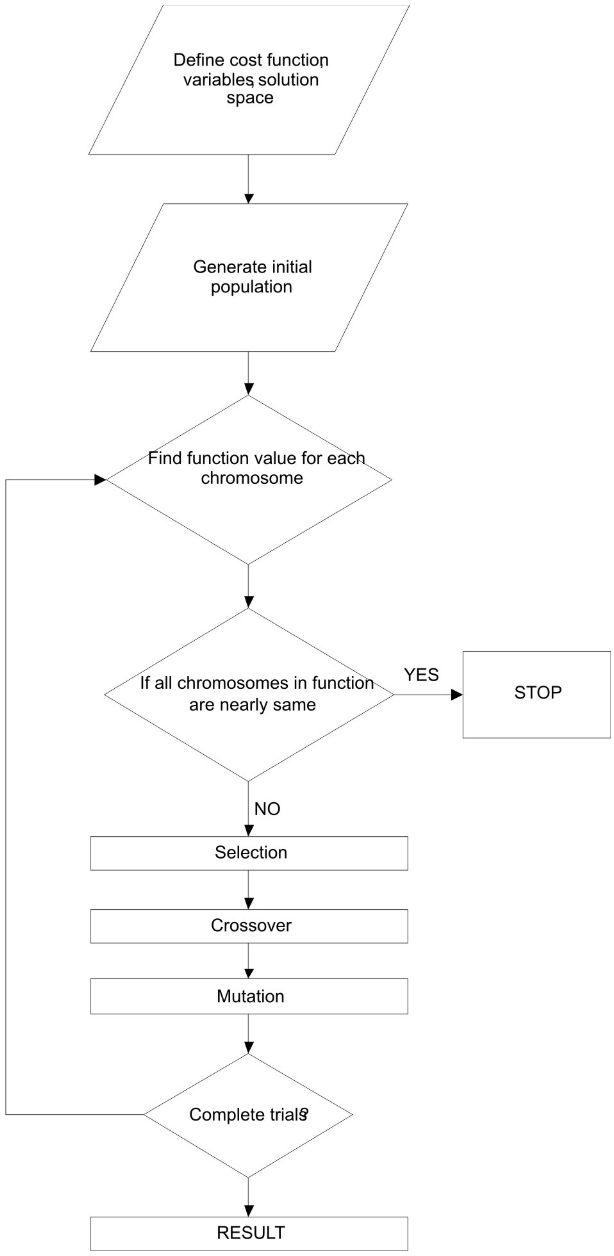

Figure 1: Main program flowchart of genetic algorithm

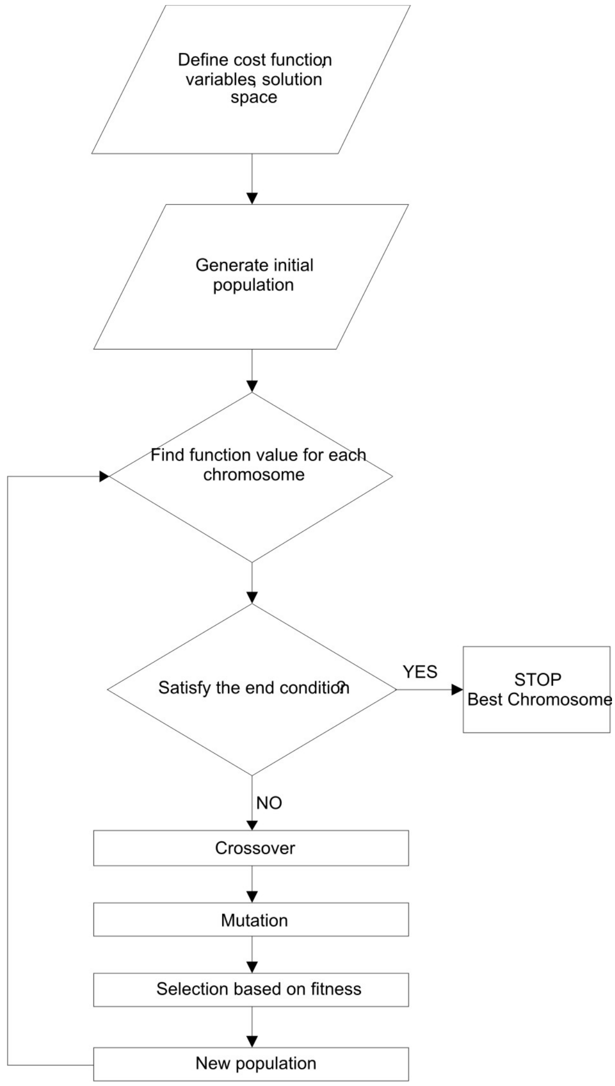

Figure 2: Main program flowchart of modified genetic algorithm

2.1 A modified genetic algorithm

Creation of the initial population is the first step of the modified genetic algorithm same as genetic algorithm. A population is a set of individuals used as parameters. Each individual has its own genetic content, called chromosomes. The modified genetic algorithm uses the floating point representation, where lower and upper bound for the parameters are used as the same as genetic algorithm. The population size is also chosen as same as genetic algorithm.

The main differences between GA and MGA are listed below.

1. The main flowchart of MGA shown in Figure 2 is different from the standard GA shown in Figure 1.
2. Using a selection operator is one of the main differences between the GA and MGA. Selection operator is used after the crossover and mutation operators are applied to all the population in the GA. Unlikely, the selection operator is used after the each individual of the population is applied to mutation and crossover operator in the MGA.
3. Crossover and mutation operators simultaneously apply to all populations in GA, but chromosomes are taken one by one and new parameter is obtained by randomly selected another three or five chromosomes in MGA. The suitability of existing chromosomes is compared with the suitability of the new chromosomes and then whichever is better is transferred into the next population.

4. The condition that terminates the GA is satisfied when either the values of all chromosomes are nearly same in the function or determined trials are completed. However, the end condition of MGA is satisfied either in the minimum value of the fitness function or when determined trial number is completed.

3 Parameter extraction

Measurement of I-V characteristics of MOSFET was carried out using a parametric analyzer and wafer prober. After performing measurements using a wafer probe and parametric analyzer, the results of the I-V measurement were applied to GA and MGA. MOSFET model parameters determined by using five different steps applied to both genetic algorithm and modified genetic algorithm. These steps are defined below and summarized in Table 2. GA and the MGA program were written in MATLAB file. The operating temperature was settled at 294K.

Different combinations of GA and MGA parameters were used to find the best fitness chromosome. The default generation count was taken as 100. If the result of the first run after 100 generations was not satisfactory and had an error greater than 10%, then a second run with a different random seed number was executed. Moreover, both of the algorithms were applied to the population during the simulation as the number of parameters was chosen as 500.

Before extracting model parameters, some process parameters are required to be known. These process parameters are the gate oxide thickness (Tox), doping concentration in the channel (Nch), the temperature at which the data are taken (T), mask level channel length (Ldrawn), mask level channel width (Wdrawn) and junction depth (Xj). The values of the process parameters are shown in Table 3.

Table 2: MOSFET model parameters extraction steps

Step	Parameters	Dimensions of Transistors	Measurement
Step 1	VTH0, K1, K2, µ0, UA, UB, UC	Wide channel width and long channel length transistors	I_d vs V_{gs} data at V_{ds} equals low voltage with different V_{bs} values
Step 2	K3, W0, K3B	Narrow channel width and long channel length transistors	I_d vs V_{gs} data at V_{ds} equals low voltage with different V_{bs} values
Step 3	RDSW, DVT0, DVT1, DVT2, NLX, WR, PRWG, PRWB	Wide channel width and short channel length transistors	I_{ds}-V_{gs} at V_{ds}=0.05V, V_{bs} is Parameter
Step 4	A0, AGS, B0, B1, KETA	Short channel length and narrow channel width transistors	I_d - V_{ds} curves obtained from different values of V_{gs} and V_{ds} with the condition of zero.
Step 5	DVT0W, DVT1W, DVT2W	Short channel length and narrow channel width transistors	I_d – V_{gs} curves obtained from different values of V_{bs} and V_{ds} equals low voltage

Table 3: Some process parameters are used in extraction

Process Parameters	Value
Tox	7.575×10^{-9} m
Nch	2.611×10^{17} 1/cm3
T	294 K
Ldrawn	0.45 µm
Wdrawn	0.538 µm
Xj	3.0×10^{-7} m

One large sized device and two sets of small-sized devices are required to extract the transistor parameters. Geometric features of transistors used in the extraction of parameters are shown in Figure 3. Equations of the extracted parameters are taken from BSIM3V3.3 User's Manual [2] for the extraction process.

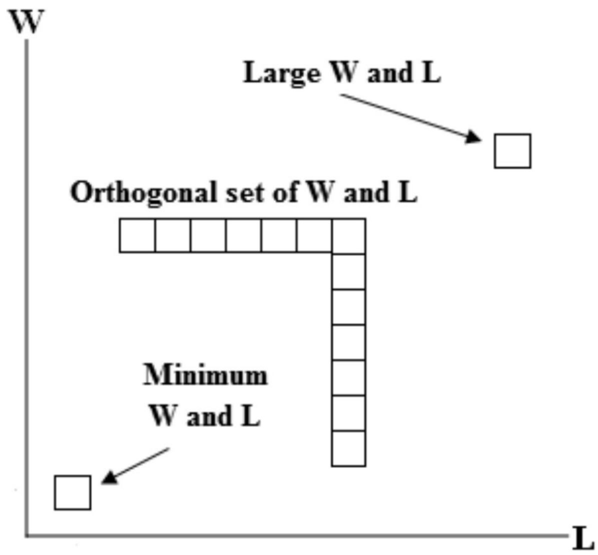

Figure 3: Geometric features of transistors used in the extraction of parameters

The first step is applied to the wide and long transistor and the target parameters are **VTH0, K1, K2, µ0, UA, UB,** and **UC.** It requires I_d - V_{gs} curves at low voltage of V_{ds} with different V_{bs} values [2-3].

$$V_{th} = V_{TH0} + K_1\left(\sqrt{\phi_s - V_{bs}} - \sqrt{\phi_s}\right) - K_2 V_{bs} \tag{5}$$

$$\mu_{eff} = \frac{\mu_0}{1 + \left(U_a + U_c V_{bs}\right)\left(\frac{V_{gst} + 2V_{th}}{Tox}\right) + U_b\left(\frac{V_{gst} + 2V_{th}}{Tox}\right)^2} \tag{6}$$

The second step is applied to the narrow W and long L transistor and the target parameters are **K3, W0** and **K3B.** It requires I_d - V_{gs} curves at low voltage of V_{ds} with different V_{bs} values [2-3].

$$\begin{aligned} V_{th} &= V_{TH0} + K_1\left(\sqrt{\phi_s - V_{bseff}} - \sqrt{\phi_s}\right) - K_2 V_{bseff} \\ &+ K_1\left(\sqrt{1 + \frac{N_{LX}}{L_{eff}}} - 1\right)\sqrt{\phi_s} + \left(K_3 + K_{3B} V_{bseff}\right)\frac{T_{OX}}{W_{eff}^{'} + W_0}\phi_s \\ &- D_{VT0}\left(\exp\left(-D_{VT1}\frac{L_{eff}}{2l_t}\right) + 2\exp\left(-D_{VT1}\frac{L_{eff}}{l_t}\right)\right)\left(V_{bi} - \phi_s\right) \\ &- \left(\exp\left(-D_{SUB}\frac{L_{eff}}{2l_{to}}\right) + 2\exp\left(-D_{SUB}\frac{L_{eff}}{l_{to}}\right)\right)\left(E_{TA0} + E_{TAB} V_{bseff}\right) V_{ds} \end{aligned} \tag{7}$$

The third step is applied to the wide W and short L device and the target parameters are **RDSW, DVT0, DVT1, DVT2, NLX, WR, PRWG,** and **PRWB** [2-3].

$$\begin{aligned} V_{th} &= V_{TH0} + K_1\left(\sqrt{\phi_s - V_{bseff}} - \sqrt{\phi_s}\right) - K_2 V_{bseff} \\ &+ K_1\left(\sqrt{1 + \frac{N_{LX}}{L_{eff}}} - 1\right)\sqrt{\phi_s} + \left(K_3 + K_{3B} V_{bseff}\right)\frac{T_{OX}}{W_{eff}^{'} + W_0}\phi_s \\ &- D_{VT0}\left(\exp\left(-D_{VT1}\frac{L_{eff}}{2l_t}\right) + 2\exp\left(-D_{VT1}\frac{L_{eff}}{l_t}\right)\right)\left(V_{bi} - \phi_s\right) \\ &- \left(\exp\left(-D_{SUB}\frac{L_{eff}}{2l_{to}}\right) + 2\exp\left(-D_{SUB}\frac{L_{eff}}{l_{to}}\right)\right)\left(E_{TA0} + E_{TAB} V_{bseff}\right) V_{ds} \end{aligned} \tag{8}$$

$$R_{ds} = \frac{R_{DSW}\left(1 + P_{RWG} V_{gsteff} + P_{RWB}\left(\sqrt{\phi_s - V_{bseff}} - \sqrt{\phi_s}\right)\right)}{\left(10^6 W_{eff}^{'}\right)^{W_r}} \tag{9}$$

The fourth step is applied to only small sized device (short channel and narrow width). In this step, the large sized transistor with the fixed channel width and short-channel length was used for extraction of **A0** and **AGS** parameters. Also fixed channel length with a large channel width of transistors and other small sized transistors were used for determining **B0, B1,** and **KETA** parameters. I_d - V_{ds} curves were obtained from different values of V_{gs} and V_{bs} with the condition of zero [2-3].

$$\begin{aligned} A_{bulk} &= \left(1 + \frac{K_{1ox}}{2\sqrt{\phi_s - V_{bseff}}}\left(\frac{A_0 L_{eff}}{L_{eff} + 2\sqrt{X_J X_{dep}}}\left(1 - A_{gs} V_{gsteff}\left(\frac{L_{eff}}{L_{eff} + 2\sqrt{X_J X_{dep}}}\right)^2\right) + \frac{B_0}{W_{eff}^{'} + B_1}\right)\right) \cdot \\ &\cdot \frac{1}{1 + Keta V_{bseff}} \end{aligned} \tag{10}$$

The fifth step is applied to small sized transistors. **DVT0W, DVT1W,** and **DVT2W** parameters were determined by using a small-sized transistor with the short channel length and narrow channel width. I_d – V_{gs} curves were obtained from different values of V_{bs} [2-3].

$$\begin{aligned} V_{th} &= V_{TH0} + K_1\left(\sqrt{\phi_s - V_{bseff}} - \sqrt{\phi_s}\right) - K_2 V_{bseff} \\ &+ K_1\left(\sqrt{1 + \frac{N_{LX}}{L_{eff}}} - 1\right)\sqrt{\phi_s} + \left(K_3 + K_{3B} V_{bseff}\right)\frac{T_{OX}}{W_{eff}^{'} + W_0}\phi_s \\ &- D_{VT0}\left(\exp\left(-D_{VT1}\frac{L_{eff}}{2l_t}\right) + 2\exp\left(-D_{VT1}\frac{L_{eff}}{l_t}\right)\right)\left(V_{bi} - \phi_s\right) \\ &- \left(\exp\left(-D_{SUB}\frac{L_{eff}}{2l_{to}}\right) + 2\exp\left(-D_{SUB}\frac{L_{eff}}{l_{to}}\right)\right)\left(E_{TA0} + E_{TAB} V_{bseff}\right) V_{ds} \\ &- D_{VT0W}\left(\exp\left(-D_{VT1W}\frac{W_{eff}^{'} L_{eff}}{2l_{tw}}\right) + 2\exp\left(-D_{VT1W}\frac{W_{eff}^{'} L_{eff}}{l_{tw}}\right)\right)\left(V_{bi} - \phi_s\right) \end{aligned} \tag{11}$$

GA and the MGA program were written in MATLAB file. The main program flowcharts of a genetic algorithm and modified genetic algorithm are given in Figure 2 and Figure 3, respectively.

4 Results and discussion

The values of MOSFET BSIM3V3 model parameters extracted by GA and MGA for 0.7µm test transistors fabricated by TUBITAK Laboratories are shown in Table 4. The results of the fitted drain current using BSIM3V3 model with different bias gate are shown in Figure 4 - 5. In these figures, solid lines, squared lines, and dashed lines represent the I – V data measured, parameters extracted by using GA, and parameters extracted by using MGA, respectively. Model generated data with extracted values of parameters has shown excellent agreement with measurement data for all types of characteristics.

Table 4: GA and MGA extracted MOSFET BSIM3V3 model parameters for 0.7 µm test transistors fabricated by TUBITAK

Parameters	Extracted by GA	Extracted by MGA
VTHO	6.518×10^{-1}	6.438×10^{-01}
K1	7.935×10^{-01}	7.7351×10^{-01}
K2	-7.3912×10^{-02}	-8.4912×10^{-02}
U0	$4.491\times10^{+02}$	$4.511\times10^{+02}$
UA	$-3.1652\cdot10^{-10}$	$-3.055\cdot10^{-11}$
UB	2.565×10^{-18}	2.7711×10^{-18}
UC	2.3660×10^{-11}	3.1660×10^{-14}
NLX	4.23×10^{-7}	4.1617×10^{-7}
DVT0	3.05	3.013
DVT1	3.59	3.292
DVT2	-7.3916×10^{-2}	-7.5516×10^{-2}

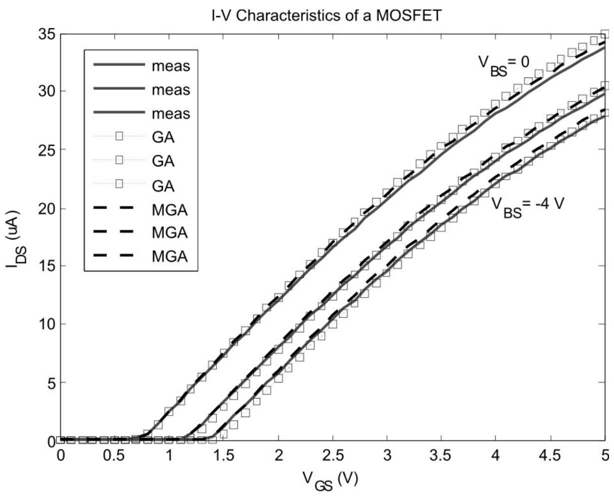

Figure 4: The results of the fitted drain currents where V_{BS} varies from 0 to -4.0 V with the step of 2 V. (The dimensions of transistor are W = 27 µm and L = 27 µm.)

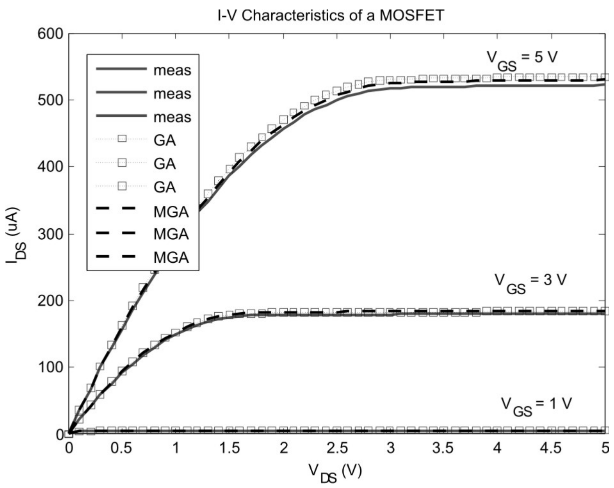

Figure 5: The results of the fitted drain currents where V_{GS} varies from 1 to 5.0 V with the step of 2 V and bulk bias V_{BS} is 0 V. (The dimensions of transistor are W = 27 µm and L = 27 µm.)

The values of MOSFET BSIM3V3 model parameters extracted by GA and MGA for 0.35µm test transistors fabricated by C35 process are shown in Table 5. The result of the fitted drain current using BSIM3V3 model with different bias gate is shown in Figure 6 - 10. In these figures, solid lines, dotted lines, and dashed lines represent the I – V data measured, parameters extracted by using GA, and parameters extracted by using MGA, respectively. Model generated data with extracted values of parameters has shown excellent agreement with measurement data for all types of characteristics.

Table 5: GA and MGA extracted MOSFET BSIM3V3 model parameters for 0.35 µm transistors fabricated by C35 process

No	Parameters	Extracted by GA	Extracted by MGA
1	VTHO	4.999×10^{-1}	5.013×10^{-01}
2	K1	4.96296×10^{-01}	5.0302×10^{-01}
3	K2	3.3385×10^{-02}	3.41×10^{-02}
4	U0	$4.788\times10^{+02}$	$4.7905\times10^{+02}$
5	UA	4.605×10^{-12}	4.396×10^{-12}
6	UB	2.039×10^{-18}	2.112×10^{-18}
7	UC	7.785×10^{-20}	2.914×10^{-17}
8	NLX	2.048×10^{-7}	1.856×10^{-7}
9	DVT0	4.9101×10^{1}	4.9513×10^{1}
10	DVT1	1.04	1.091
11	DVT2	-8.975×10^{-3}	-8.416×10^{-2}
12	RDSW	3.603×10^{2}	3.317×10^{2}
13	PRWG	7.433×10^{-19}	1.901×10^{-17}
14	PRWB	-2.016×10^{-1}	-2.518×10^{-1}
15	WR	1.0091	1.0012
16	W0	3.173×10^{-7}	2.731×10^{-7}
17	K3	-1.536	-1.151
18	K3B	-4.409×10^{-1}	-0.4361
19	A0	2.164	2.704
20	AGS	1.848×10^{-1}	2.598×10^{-1}
21	B0	7.0391×10^{-9}	5.359×10^{-9}
22	B1	1.98×10^{-18}	9.194×10^{-17}
23	KETA	4.102×10^{-2}	2.420×10^{-2}
24	DVT0W	1.129×10^{-10}	9.919×10^{-11}
25	DVT1W	5.981×10^{4}	6.1702×10^{4}
26	DVT2W	-2.332×10^{-2}	-2.0141×10^{-3}

Root Mean Squared (RMS) percentage errors of 0.35µm transistors fabricated by C35 process for both GA and

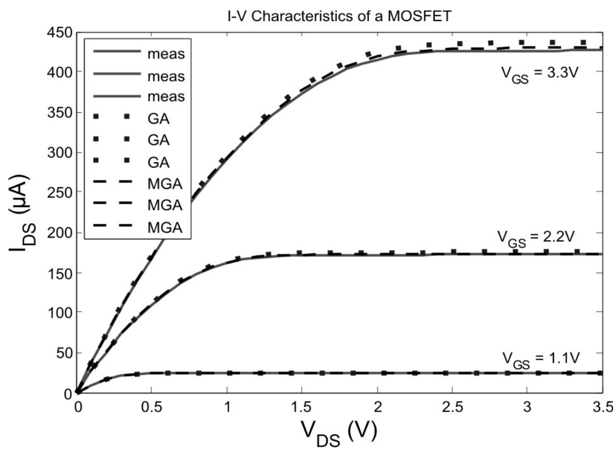

Figure 6: The results of the fitted drain currents where V_{GS} varies from 1.1 to 3.3 V with the step of 1.1 V and bulk bias V_{BS} is 0 V. (The dimensions of transistors are W = 10 µm and L = 10 µm).

MGA were calculated. The results showed that MGA implemented parameter extraction is more successful than GA implemented parameter extraction. The RMS error between measurement data and extracted data was shown in Table 6. It was observed that this error occurs between 0.75% and 2% for various characteristics of 0.35µm device. MGA results agree very well with the measurements.

Table 6: Root Mean Squared (RMS) percentage errors of 0.35 µm transistors fabricated by C35 process

Root Mean Squared Percentage Error (%) for GA				Root Mean Squared Percentage Error (%) for MGA	
Id-Vds			Id-Vgs	Id-Vds	Id-Vgs
W=10µm L=10µm	Vds=0.05V	2.44	2.09	1.19	1.61
	Vds=3.3V	1.11	1.67	0.75	1.13
W=10µm L=0.35µm	Vds=0.05V	1.09	1.66	0.76	0.81
	Vds=3.3V	2.45	2.03	1.11	1.23
W=0.35µm L=10µm	Vds=0.05V	2.25	2.11	1.08	1.06
	Vds=3.3V	2.71	2.50	1.21	1.04
W=0.35µm L=0.35µm	Vds=0.05V	3.01	3.58	1.93	1.63
	Vds=3.3V	2.62	2.29	0.99	1.28

5 Conclusion

In this research, based on a global optimization algorithm, modified genetic algorithm is employed to specify the MOSFET model parameter values. For this extraction experiment, the industrial Standard BSIM3V3.3 SPICE model is adopted. The results show that this technique reduces the engineering effort required to

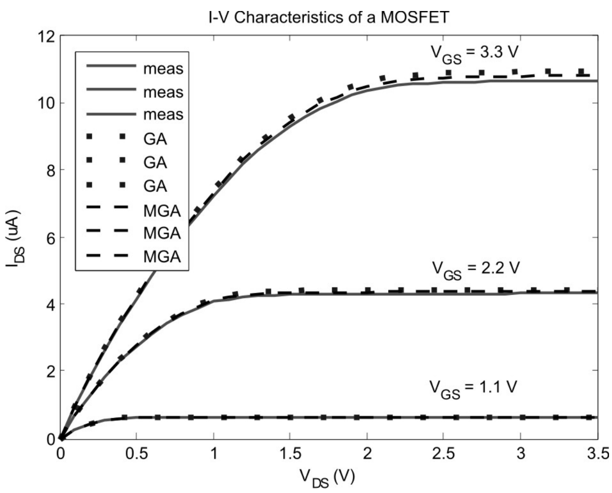

Figure 7: The results of the fitted drain currents where V_{GS} varies from 1.1 to 3.3 V with the step of 1.1 V and bulk bias V_{BS} is 0 V. (The dimensions of transistors are W = 0.35 µm and L = 10 µm).

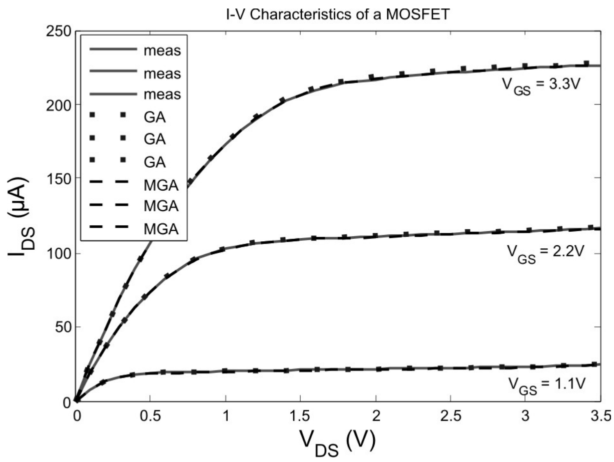

Figure 8: The results of the fitted drain currents where V_{GS} varies from 1.1 to 3.3 V with the step of 1.1 V and bulk bias V_{BS} is 0 V. (The dimensions of transistors are W = 0.35 µm and L = 0.35 µm).

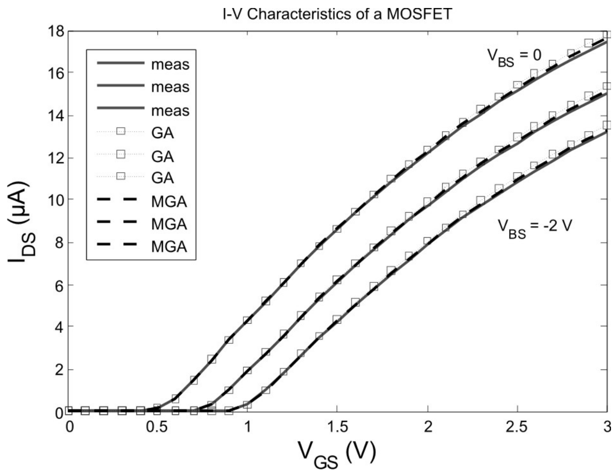

Figure 9: The results of the fitted drain currents where V_{BS} varies from 0 to -2.0 V with the step of 1 V. (The dimensions of transistors are W = 10 µm and L = 10 µm.)

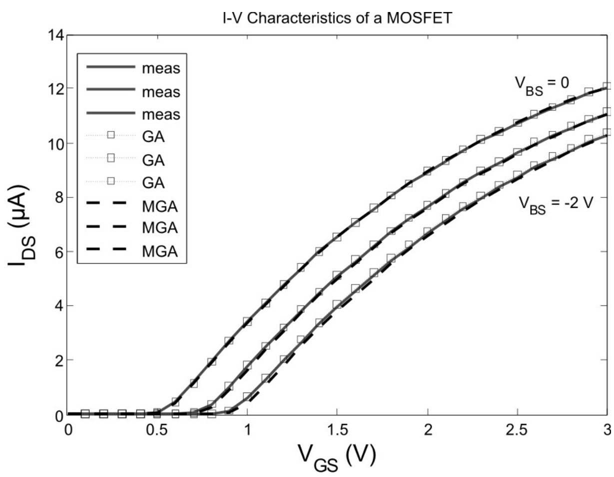

Figure 10: The results of the fitted drain currents where V_{BS} varies from 0 to -2.0 V with the step of 1 V. (The dimensions of transistors are W = 0.35 µm and L = 0.35 µm.)

produce a model while improving overall model quality. The modified genetic algorithm is empirically shown as a robust, general purpose optimizer, and suitable for optimizing multimodal and high dimensional objective functions. Furthermore, MGA is used as powerful genetic operators to concurrently guide its research throughout the solution space by considering a set of parameter at a time. The parameters are extracted step-by-step depending upon the characteristics where they play a major role.

We have used a genetic algorithm and modified genetic algorithm to extract parameters for NMOS device. MGA is deemed highly effective in order to solve the non-linear and the transient problems. The results of the extracted parameters and measurement curves are obtained close to each other due to the fact that the same determined parameters of the mathematical models are used in the both algorithms. Values obtained in determining working conditions for especially small sized transistor parameters are found to be in high accuracy. This can be considered as the success of this work because small-sized problems on behalf of the designer is crucial for troubleshooting. This study not only extracts the BSIM3V3.3 MOSFET model parameters, but also enhances the genetic algorithm. It was observed that MGA exhibits much better performance compared to GA in terms of accuracy and consistency. The simulations showed that MGA accurately extracts all 26 model parameters of MOSFET in an effective way.

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