EXTRACTION OF MOSFET BSIM3V3 THRESHOLD VOLTAGE AND MOBILITY EFFECT PARAMETERS WITH GENETIC ALGORITHM

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ABSTRACT

Extracting an optimal set of parameter values for a MOS device is a complex problem. Since the existence of local minima in the solution space, the traditional methods of parameter extraction rely on gradient techniques may not produce near optimal solutions. Genetic algorithms are well suited for finding near optimal solutions in irregular parameter spaces.

*In this study**, BSIM3V3 Model C35 process fabricated chips were used, *A genetic algorithm have been applied to the problem of device model parameter extraction and are able to be produced models of superior accuracy in much less time and with less reliance on human expertise. The threshold voltage related model parameters and mobility related model parameters were found for BSIM3V3. Extracted parameter values reproduce I-V characteristics.*

I. INTRODUCTION

To predict and evaluate the circuit performance of the VLSI systems before the actual fabrication of a designed circuit, device model for circuit simulation has to be accurate and robust.Traditional model-extraction methods are based on a combination of direct parameter extraction that uses mathematical simplification of the model equations, and optimization that uses the full, highly non-linear model equations [1]. Because of the complexity of the model and data, these methods allow optimization of only a few parameters at a time. Optimization also leads to local optima which do not result in a model that is accurate enough to be useful [2].

To realize accurate parameter extraction, we propose a genetic algorithm based parameter extraction method for threshold voltage related and mobility related model parameters.

II. BSIM3V3 MODELLING

BSIM3V3 model is based on deep understanding of submicrometer MOSFET and is a physical model including major short channel effects. BSIM3V3 has fewer parameters and every parameter has its own physical meaning. Because of the simple analytical nature of the model, BSIM3V3 can be used to explain how the various physical parameters will affect device performance [1-3].

BSIM3V3 model can be used to predict the scaling effects on the output characteristics of deep-submicrometer MOSFETs. It is applicable for both digital and analog circuit simulations. It also has a fast option for digital circuit simulation and an accurate option for analog circuit simulation. As all device currents and their first order derivatives are continuous, convergence of simulation has been improved and the number of iterations has been reduced. Furthermore, time consulting functions are excluded in BSIM3V3 in order to achieve computational efficiency.

The default set of parameters is highly usable for light doped drain devices. BSIM3V3 model is good for devices with a variety of transistor width and length down to 0,2 µm, and gate oxide thickness down to 5nm. Because of the physical nature of the model, the parameters extracted from an old process can be used to predict the device behaviours of future generation.

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BSIM3V3 model can be used easily to predict MOSFET performance and scaling effects before the device is fabricated. BSIM3V3 makes some simplifying assumptions which reduce the accuracy but help reveal the physics of the device operation and improve the calculation efficiency through a simple analytical expression for the drain current. Physical parameters extracted from the process can be used to characterize device fabrication and then simulate circuit performance.

The standard long channel threshold voltage equation had been modified not to take into account for the non-uniform doping effect and short channel effect [1-5]. In the model, the threshold was proposed as

$$V_{th} = V_{T0} + K_1\left(\sqrt{\Phi_s - V_{bs}} - \sqrt{\phi_s}\right) - K_2 V_{bs} \qquad (1)$$

V_{th} =Threshold voltage

V_{T0}= Threshold voltage under zero substrate bias

K1= Body bias sensitivity of V_{th}

K2= Body bias sensitivity of V_{th}

ϕ_s =Surface Potential

V_{bs} = Substrate to source voltage

Surface carrier mobility is very critical to the accuracy of modelling. The scattering mechanisms responsible for the surface mobility basically include phonons, coulumbic scattering sites and surface rougness. The unified formulation of mobility was emprically given by

$$\mu_{eff} = \frac{\mu_0}{1 + \left(E_{eff} / E_o\right)^v} \qquad (2)$$

By Taylor expansion and using mobMod = 1,

$$\mu_{eff} = \frac{\mu_0}{1 + \left(U_a + U_c V_{bs}\right)\left(\frac{V_{gst} + 2V_{th}}{Tox}\right) + U_b\left(\frac{V_{gst} + 2V_{th}}{Tox}\right)^2} \qquad (3)$$

μ_{eff} = Effective mobility

μ_0 =Mobility at tempereture=27°C

U_a =First order mobility degradation coefficient

U_b =Second order mobility degradation coefficient

U_c =Body bias sensitivity coefficient of mobility

V_{gs} =Gate voltage

V_{th} =Threshold voltage

V_{bs} =Substrate to source voltage

$V_{gst} = V_{gs} - V_{th}$

Tox = Gate oxide thickness

It should be pointed out that the above equation works for devices which had very small parasitic resistance. If the parasitic resistance was not negligible compared to the channel resistance, then the above equation should be modified accordingly.

III. GENETIC ALGORITHM

In its most general usage, Genetic Algorithm (GA), simply termed as GA, refers to a family of computational models inspired by evolution. These algorithms encode a potential solution to a specific problem on a simple chromosome-like data structure and apply recombination operators to these structures so as to preserve critical information.

The Genetic Algorithm utilizes a non-gradient-based random search and is used in the optimization of complex systems. The algorithm models the process of biological evolution and optimizes the parameters of problem. In the algorithm, each unknown parameter is called gene and each vector of these parameters is called a chromosome. The purpose of the genetic algorithm is to determine the elements of the unknown vector (chromosome) which maximizes or minimizes the defined fitness function. The algorithm starts with a population of (typically random) chromosomes. In each generation, new population of the chromosomes is enhanced in the fitness function by means of some operators such as crossover and mutation. The initial population is chosen randomly. The GA creates a new population of solutions from an existing, ranked population as follows. First, members of the population are selected as parents based on their fitness. In our GA we employ "roulette-wheel" selection, in which a member's chance of being selected as a parent is directly proportional to its fitness. The net effect of the selection operator is that the best members in the population are used to create new solutions, while the worst members are discarded. To paraphrase basic GA theory, the information needed to create the globally optimal solution to the problem is probably contained in the starting population [6 - 7].

Once created, the new population is sent to the evaluation routine where each member is decoded into parameter values, a simulation is run using those parameters, and the population member is assigned fitness. Once evaluation is complete, the population is ready for another iteration of the GA. The GA can monitor the best of generation fitness as the run proceeds, and stop once a certain quality of fit has been reached, or once successive generations show no progress toward better solutions. Both crossover and mutation will have created new parameter sets, some will be highly fit and some will be very unfit.

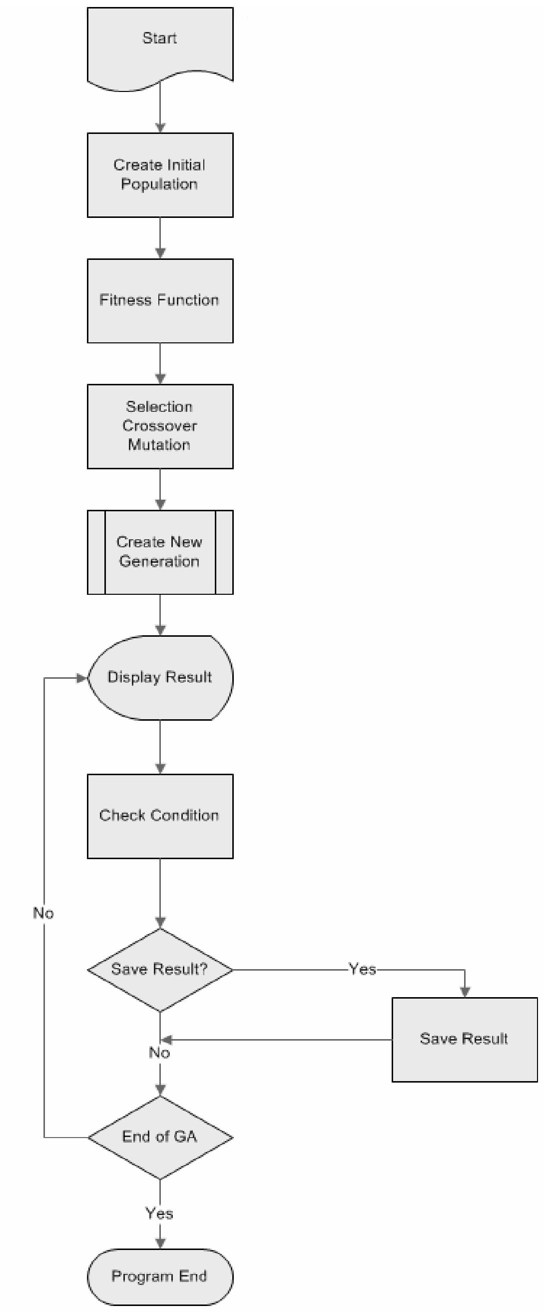

Figure 1:Main program flowchart of Genetic Algorithm

IV. GA PARAMETER EXTRACTON

The main program flowchart of Genetic Algorithm is shown in Figure 1. According to the flowchart firstly, an initial population is constructed by the random initialization technique. Each individual was represented by random numbers, called as chromosome. The user input parameters are number of generation, population size, crossover rate [0, 1], and mutation rate [0, 1]. After the construction of initial parameters, the fitness was evaluated. The fitness functions used in GA was f is shown below.

$$f = \min\left[\left|f_1 - V_{th}\right| + \left|f_2 - \mu_{eff}\right|\right] \quad (4)$$

$$f_1 = V_{Tideal} + K_1\left(\sqrt{\Phi_s - V_{bs}} - \sqrt{\phi_s}\right) - K_2 V_{bs} \quad (5)$$

$$f_2 = \frac{\mu_0}{1 + \left(U_a + U_c V_{bseff}\right)\left(\frac{V_{gst} + 2V_{th}}{Tox}\right) + U_b\left(\frac{V_{gst} + 2V_{th}}{Tox}\right)^2} \quad (6)$$

Before any model parameters can be extracted, some process parameters have to be provided as it is shown in the Figure 2. They are Gate oxide thickness (T_{ox}), Doping concentration in the channel (N_{ch}), Tempereture at which data is taken (T), Mask level channel length (L_{drawn}), Mask level channel width (W_{drawn}), and Junction depth (X_j). In this study we try to find threshold voltage related model parameters which are threshold voltage VTH0, and the body effect coefficients K_1 and K_2, and mobility related model parameters which are U_0, U_a, U_b, and U_c.The large sized device (W≥ 10µm, L≥ 10µm) is used to extract parameters which are independent of short/narrow channel effects and parasitic resistance. This large sized device measured Ids vs. Vgs @ Vds=0.05V with different Vbs [1].

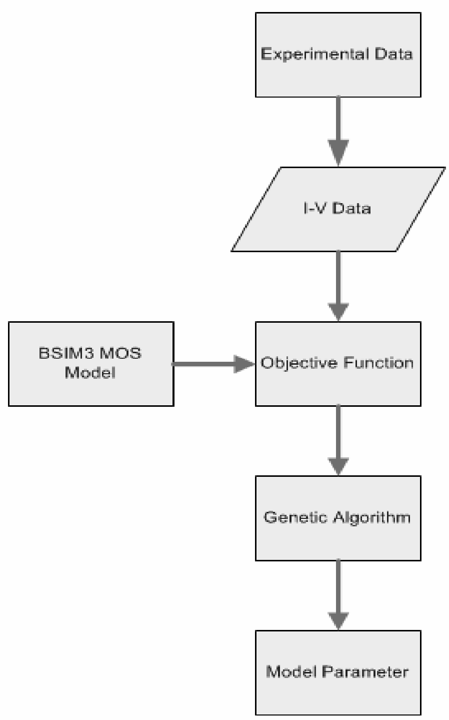

Figure 2: Flowchart of Parameter Extraction

$$s = \Sigma\left(\frac{I_{d,lab} - I_{d,\bmod el}}{I_{d,\bmod el}}\right)^2 \quad (7)$$

After the fitness function used the parameter extracted, we used the function s to optimize the extracted values to the measured values in the selection which is applied to the current population to create an intermediate population. Then mutation and crossover applied to the intermediate population to create the next population. The crossover is variation where some random number, β, is chosen on the interval [0, 1] and the offspring variable values [5]

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

β =random number on the interval [0, 1]

p_{mn} =nth variable in the mother chromosome

p_{dn} =nth variable in the father chromosome

After recombination, a mutation operator can be applied. Each member in the population can be mutated with some low probability m; typically the mutation rate is applied with less than 1% probability.

From the function optimization viewpoint, the mutation operator may be viewed as a combination of a random search method and a local search method. It ensures that the population maintains reasonable variability and also provides the means for making small changes to number. After the process selection, recombination and mutation are complete, the next population can be evaluated. Actually, GA is formed by the processes of selection, recombination, mutation and reproduction.

Table 1: Results of trial runs with different GA parameters

Test No	Population Size	Initial Mutation Rate	Crossover Rate	Min % Error obtained
1	100	0,002	0,9	3,0
2	100	0,005	0,9	1,9
3	100	0,007	0,9	1,98
4	100	0,01	0,9	2,5
5	100	0,005	0,7	1,8
6	100	0,005	0,7	2,9
7	100	0,005	0,5	1,7
8	100	0,005	0,5	1,4

The large sized device (W = 10µm, L = 10µm) is used to extract parameters which are threshold voltage related and mobility related parameters. Different combinations of Genetic Algorithm parameters were used to find the best fitness chromosome.We took the default generation count is 200. If the result of the first run after 200 generations was not satisfoctary and had an error greater than 2%, then second run with a different random seed number would be executed.

The results were recorded and shown in Table 1. As shown in Table 1 GA was improved by incresing initial mutation probability from 0,002 to 0,005 and 0,007; but degraded as mutation probability reached 0,01. Although increasing the mutation rate will maintain sufficient diversity of population for continuing improvement, too high the mutation rate will make the searching process resemble of a simple random search, and thus, the performance will be degraded. It was also found that eiher too small or too large a population would degrade the performance of GA. Too small population size would suffer from the sampling errors due to too small a searching area. On the other extreme, if the population size was too large, the system would spend most of time in function evaluation other than searching. It should be noted that the performance of GA mainly depends on the processes of selection and recombination.

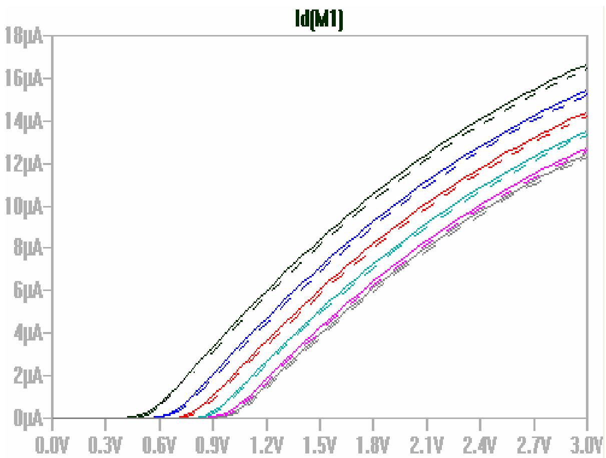

Figure 3: Measured Id-Vgs data (lines) for 10µ/10µ MOSFET BSIM3V3 model calculation (dots) fitted to them

Table 2 shows that the extracted and measured 10µ/10µ MOSFET BSIM3V3 model parameters.Figure 3 and Figure 4 show the result of the fitted Drain Current using BSIM3V3 model. The average rms error obtained using the BSIM3V3 model was about 1,4% after 200 generations. The extracted parameter were presented in Table 2.

Table 2:Meausered and Extracted Values of parameters

	Measured	Extracted
VTideal	4.979e-01	5.105e-01
K1	5.0296e-01	5.0756e-01
K2	3.3985e-02	3.033e-02
U0	4.758e+02	4.137e+02
Ua	4.705e-12	4.08870e-12
Ub	2.137e-18	2.0943e-18
Uc	1.000e-20	2.947e-18

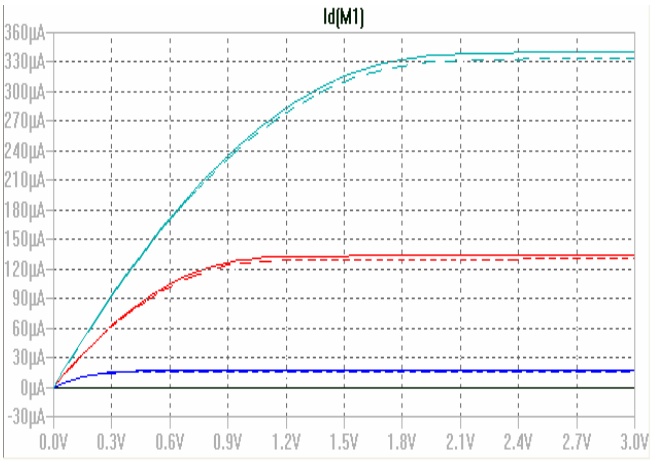

Figure 4: Measured Id -Vds data (lines) for 10µ/10µ MOSFET BSIM3V3 model calculations (dots) fitted to them.

V. CONCLUSION

In this research, based on a global optimization algorithm, Genetic Algorithm was employed to find model parameter values for MOSFET. Genetic Algorithm had been employed in researches on MOSFET model parameter extraction, this work is only applied to the long channel devices with constant channel length and width. This technique reduces the engineering effort required to produce a model while improving overall model quality. Genetic Algorithm had been shown empirically to be a robust, general purpose optimizer and suitable for optimizing multimodal, high dimensional objective functions. Furthermore, GA used powerful genetic operators to guide its research through out the solution space concurrently by considering a set of parameter at a time.

VI. REFERENCES

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