Application of the Genetic Algorithm to Compact MOSFET Model Development and Parameter Extraction

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ABSTRACT

The Genetic Algorithm is investigated as a parameter extraction tool for a compact MOSFET model. In addition it is shown that application of the Genetic Algorithm can be used in compact model development in order to reduce the ambiguity associated with selection of the model parameter set. The new approach is illustrated by including Coulomb scattering in the effective mobility model of a MOSFET and is verified by comparison with experimental data at different temperatures.

Keywords: Genetic Algorithm, MOSFET model

1 INTRODUCTION

Compact MOSFET models intended for use in circuit simulators are subject to several, often contradictory, requirements. In order to achieve a high degree of accuracy, a compact model should include most of the relevant device physics without sacrificing the computational efficiency. It has been witnessed that the surface-potential-based approach can increase the physical content of the compact model. However, the total number of model parameters is still high, especially if a global fit for different geometries is required. This necessitates an elaborate extraction process which is not easily formalized. Gradient-based optimization techniques, in particular the Levenberg-Marquardt(LM) method, were found to be useful but somewhat limited in their scope. The main difficulty is that the error profile has numerous local minima which can trap the convergence process. This phenomenon has been recently illustrated in [1] and prevents automation of the parameter extraction process. Similarly, the error surface of the type shown in Fig. 1 is not conducive to successful application of classical gradient-based methods. In this work, the feasibility of using the Genetic Algorithm (GA) for compact MOSFET model parameter extraction is investigated. To achieve unambiguous results we concentrate primarily on the effective mobility model development and parameter extraction. Consequently, this investigation is restricted to wide long-channel MOSFETs described by combining a new form of a charge-sheet model [2] with an elaborate effective mobility model presented below.

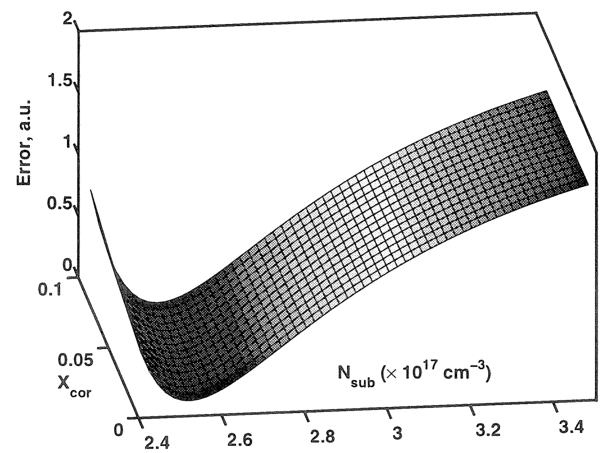

Figure 1: Error surface for T_{ox}=3.93nm, V_{fb}=-0.93V, $\mu_0 = 568\text{cm}^2/\text{Vs}$, μ_1=1.14m/V and C_s=0.7

2 MOSFET MODEL

The current-voltage characteristics of long-channel devices can be accurately described using a combination of the charge-sheet model with an elaborate description of the low-field mobility. In fact, the analysis of long-channel devices is the best way to extract the low-field mobility. In this work, we use a recent version of the charge-sheet model based on a symmetric linearization of the bulk and inversion charges [2]. This assures that when the GA is applied to a complete surface-potential-based model [3], this work will automatically be incorporated as a proper long-channel limit of the general result. In particular, the low-field effective mobility model discussed below is used without any change in the complete model [3].

The drain current is given by

$$I_d = \mu_{eff}(W/L)C_{ox}(q_{im} + \alpha_m\phi_t)(\phi_{sd} - \phi_{ss}) \qquad (1)$$

where μ_{eff} is the effective channel mobility, W and L denote the channel length and width respectively, C_{ox} is the oxide capacities per unit channel area, q_{im} is the normalized inversion charge at the potential midpoint [2, 3], ϕ_t is the thermal voltage, ϕ_{sd} and ϕ_{ss} are the values of the surface potential at the source and drain ends of the channel respectively. In (1) the linearization parameter

$$\alpha_m = 1 + (\gamma/4)(\phi_{ss} + \phi_{sd} - 2\phi_t)^{-1/2} \tag{2}$$

where γ is a body factor, is different from the standard practice [4] in order to preserve node symmetry with respect to source-drain interchange. The vertical field dependence of the effective mobility used in this work is given by

$$\mu_{eff} = \frac{\mu_0(1 + X_{cor}V_{sb})/(1 + 0.2X_{cor}V_{sb})}{1 + (\mu_1 E_{eff})^\theta + C_s[q_{bm}/(q_{im} + q_{bm})]^2} \tag{3}$$

Here q_{bm} and E_{eff} are the bulk charge density and the effective vertical field at the potential midpoint [2], C_s, μ_0, μ_1, θ and X_{cor} are model parameters. Parameter C_s is used to introduce Coulomb scattering essential for heavily doped devices and low temperature. Indeed, Coulomb scattering which is essential under such circumstance cannot be modelled in terms of the effective field concept. A physically motivated semiempirical model of Coulomb scattering incorporated in (3) is that of Ref. [5]. It describes the screening of the scattering centers by the inversion charge and is well-behaved in all regions of MOSFET operation.

3 THE GENETIC ALGORITHM

Gradient-based methods may converge outside the physical range and produce far-from-optimal solutions due to the presence of multiple minima of the error function. They are also sensitive to the choice of initial parameter values and convergence is easily degraded by numerical noise in evaluating derivatives. One alternative is to use genetic algorithms which are broadly applicable, efficient search algorithms based on the mechanics of natural genetics. The GA has the capability of speculating on new points in the search space with expected improved performance by exploiting historical information making it very robust in finding near-optimal results in irregular error surfaces [6].

The flow-chart of the GA used in this work [7] is illustrated in Fig. 2. The initial population of chromosomes is generated randomly. For a small number of parameters (8), a population of 100 is sufficient. Each chromosome represents a candidate for the parameter set. The parameters are coded as strings of zeros and ones. The parameter range is defined for each parameter individually and is summarized in Table 1. A 10 bit binary-coded gene represents the value of each of the parameters. This value is then mapped linearly in the parameter range to yield the actual value of the parameter. This mapping uses minimum and maximum values of each parameter shown in Table 1. In the next step each parameter set is sent to the model and the fitness value is calculated according to the objective function.

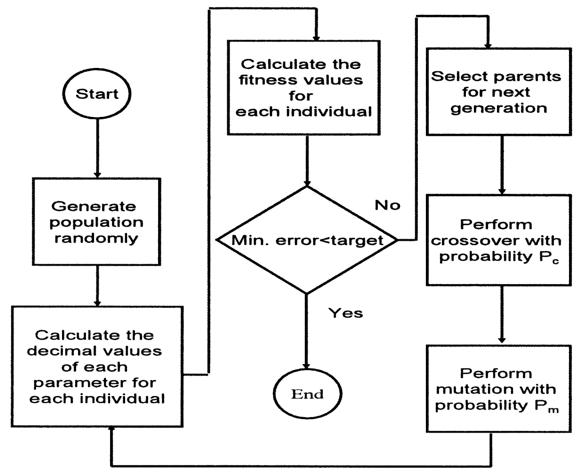

Figure 2: Flow-chart of GA

The measured data is comprised of a series of $I_d(V_d)$ (drain current vs. drain voltage with different back biases) and $I_d(V_g)$ (drain current vs. gate voltage with different drain biases) characteristics. To meet the needs of analog circuit designers, the model must accurately predict current derivatives as well as the drain current. Therefore, the transconductance $G_m(V_g) = \partial I_d/\partial V_g$, and drain conductance $G_d(V_d) = \partial I_d/\partial V_d$ are included in the fitness evaluation. Consequently, the overall objective is to minimize the error function

$$g = \sum_{V_{gs}}\sum_{V_{sb}} g_1 + \sum_{V_{gs}}\sum_{V_{sb}} g_2 + \sum_{V_{sb}}\sum_{V_{ds}} g_3 + \sum_{V_{sb}}\sum_{V_{ds}} g_4 \tag{4}$$

where g_1, g_2, g_3 and g_4 are defined as

$$g_1 = \sum_{V_{ds}} \left[(I_{d,lab} - I_{d,model}) \Big/ \sum_{V_{ds}} I_{d,lab}\right]^2 \tag{5}$$

$$g_2 = \sum_{V_{ds}} \left[(G_{d,lab} - G_{d,model}) \Big/ \sum_{V_{ds}} G_{d,lab}\right]^2 \tag{6}$$

$$g_3 = \sum_{V_{gs}} \left[(\log I_{d,lab} - \log I_{d,model}) \Big/ \sum_{V_{gs}} \log I_{d,lab}\right]^2 \tag{7}$$

subscript "lab" indicates test data, and

$$g_4 = \sum_{V_{gs}} \left[(G_{m,lab} - G_{m,model}) \Big/ \sum_{V_{gs}} G_{m,lab}\right]^2 \tag{8}$$

Depending on applications difference, the fit of a particular MOSFET characteristics can be emphasized by assigning weighting factors to the components of g.

After the initial evaluation of the error function (4), basic operations of the GA, i.e. reproduction, crossover and mutation, are performed on the population. The roulette wheel selection combined with elitist model is employed for reproduction and single position crossover and mutation operations are performed. Table 1 shows the parameter ranges and the optimal values that the GA was able to achieve to maximize the objective function taken in the form "$const - g$". Comparison of the measured and simulated data for two values of the ambient temperature is shown in Fig. 3. An excellent fit was achieved without human interruption or intentional initial value setting. In agreement with MOSFET physics the effect of Coulomb scattering is relatively small at room temperature: the error is reduced by 38% when $C_s \neq 0$ is allowed. However the inclusion of the Coulomb scattering term (C_s) allows one to obtain an excellent fit in the -55 to 25^0C range. More specifically, by applying the GA for $T = -55^0C$ one obtains an error of $1.49e-3$ with $C_s = 0.624$ (optimal value at this temperature) and of $6.80e-3$ when $C_s = 0$ but the other five parameters are optimized (T_{ox} and N_{sub} were fixed at their optimal values for $T = 298K$). This unambiguously shows both the need for the Coulomb scattering term if the reduced temperature operation is important. This example also illustrates the value of the GA not only in parameter extraction but also in compact model development.

The results of applying the Levenberg-Marquardt algorithm are shown in Table 2 for two different initial setting of the parameters. There are several problems: the algorithm converges to the values of some parameters (most importantly T_{ox}) outside of the physical range. Furthermore, the results are strongly dependent on the initial parameter setting. Finally, an attempt to enforce the same parameter ranges as in Table 1 results in non-convergence depending on the initial parameter setting. This indicates that the LM method is best used for fine-tunning of parameters within a narrow range obtained manually or by using the GA.

4 CONCLUSIONS

Genetic Algorithms are search algorithms that are able to locate near-optimal solutions after having sampled only small portions of the search space. There are no convergence problems regardless of the parameter range but narrowing the range using physical considerations reduces the extraction time. In addition to insensitivity to the numerical noise, one of the most attractive features of GA is the ease with which physics based parameter ranges are enforced without encountering the convergence problems associated with gradient-based methods. In the process of model development GA allows one to quantitatively assess the need for including new device physics. The combination of GA and gradient-based methods to further reduce the extraction time has been found useful.

Table 1: Example of GA application for $T = 298K$

Name	Unit	min	max	optimal	
				$C_s \neq 0$	$C_s = 0$
T_{ox}	nm	3.9	4.1	3.928	3.949
N_{sub}	$10^{17} cm^{-3}$	2.0	5.0	2.554	2.875
V_{fb}	V	-1.1	-0.9	-0.929	-0.947
μ_0	cm^2/Vs	300	800	566.9	428.1
μ_1	m/V	0.0	3.0	1.143	0.863
θ	none	0.0	3.0	1.658	2.585
X_{cor}	V^{-1}	0.01	0.10	0.0597	0.044
C_s	none	0.0	3.0	0.5734	0.0
Error	a.u.	27.76	1.90	9.35e-4	1.29e-3

Table 2: Example of LM application for $T = 298K$

	LM1		LM2	
	Initial	Final	Initial	Final
T_{ox}	4.0	3.61	3.9	4.53
N_{sub}	3.0	3.017	2.0	1.877
V_{fb}	-1.0	-0.9415	-1.0	-0.9091
μ_0	600.0	597.6	400	788.6
μ_1	1.0	1.2317	1.0	1.6756
θ	2.0	1.4948	1.0	1.40
X_{cor}	0.04	0.0402	0.04	0.0403
C_s	1.0	0.8789	2.0	0.934
Error	0.26	1.49e-3	2.895	1.58e-3

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REFERENCES

[1] J. Watts, C. Bittner, D. Heaberlin and J. Hoffmann, ICMSM, 176, (1999)

[2] T.L. Chen and G. Gildenblat, Electronics Letters, **37**, 791, (2001)

[3] T.L. Chen and G. Gildenblat, ICMSM, 657-661, (2002)

[4] N. Arora, "MOSFET Models for VLSI Circuit Simulations", Springer-Verlag, NY, (1993)

[5] C.L. Huang and N.D. Arora, Solid State Electronics, **37**, 97, (1994)

[6] C.L. Karr, D.A. Stanley and B.J. Scheiner, Dept. of the Interior, Bureau of Mines, Washington, D.C., (1991)

[7] D.E. Goldberg, "Genetic algorithms in search, optimization, and machine learning", Addison-Wesley, MA, (1989)

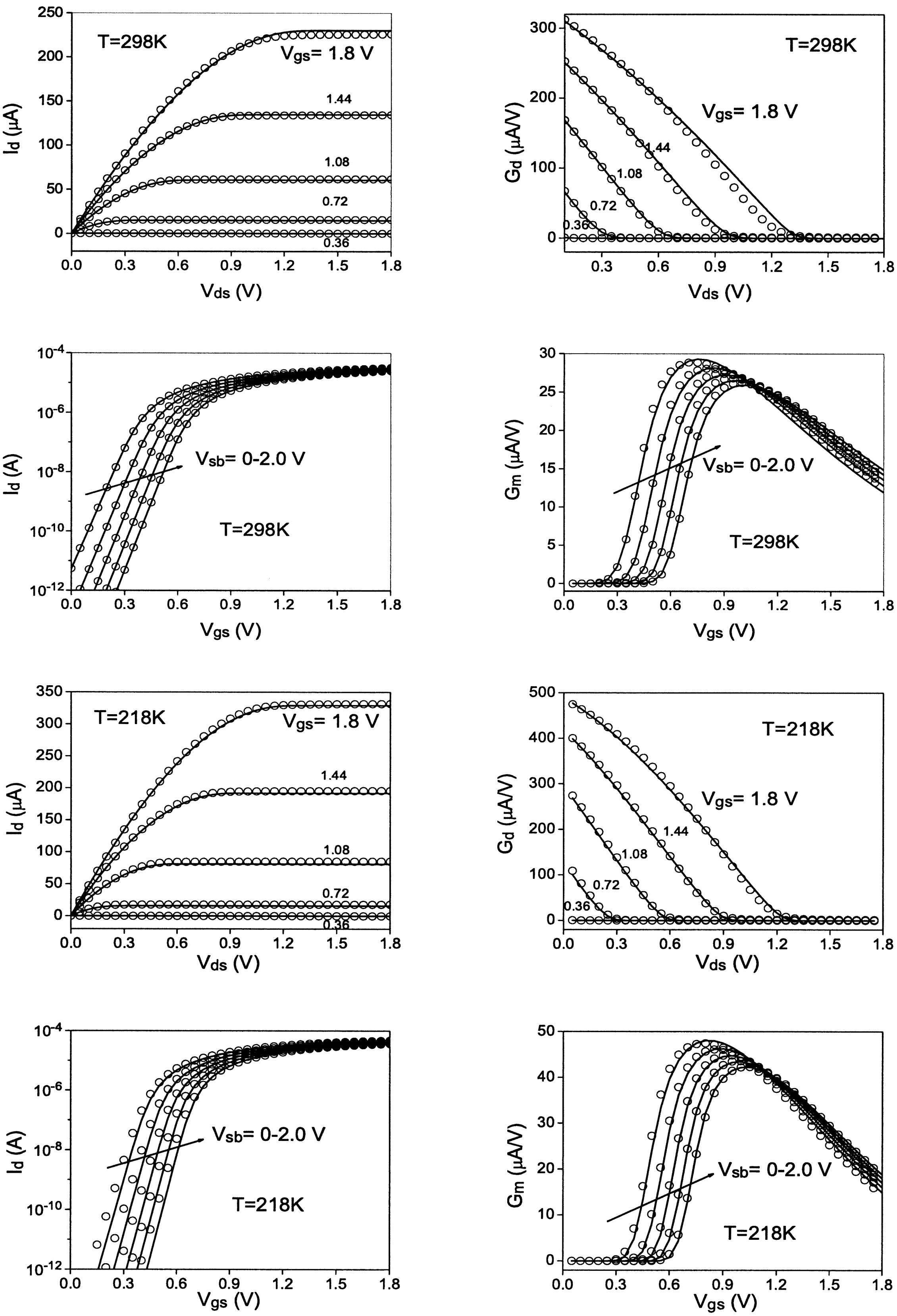

Figure 3: Comparisons of the model (solid lines) with test data (circles) for a 10/10 μm MOSFET