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SOI MOSFET Model Parameter Extraction via a Compound Genetic Algorithm

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Abstract: We improve the genetic algorithm by combining it with a simulated annealing algorithm. The improved algorithm is used to extract model parameters of SOI MOSFETs, which are fabricated with standard 1.2μm CMOS/SOI technology developed by the Institute of Microelectronics of the Chinese Academy of Sciences. The simulation results using this model are in excellent agreement with experimental results. The precision is improved noticeably compared to commercial software. This method requires neither a deeper understanding of SOI MOSFETs model nor more complex computations than conventional algorithms used by commercial software. Comprehensive verification shows that this model is applicable to a very large range of device sizes.

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1 Introduction

Silicon on insulator (SOI) technology[1] is a promising technology that may replace bulk silicon CMOS technology. It has great advantages over bulk silicon, such as high speed, low power consumption, and freedom of latch-up. SOI device modeling is the bridge that links VLSI design and manufacturing. Many SOI models have been proposed in recent years[2~5]. The BSIM SOI[6] model has become the industry standard because it is based on the physical mechanisms of SOI devices and it has passed the verification of the (CMC compact model council). But model parameter extraction for SOI MOSFETs is more difficult than for conventional bulk silicon MOSFETs because of more complex physical phenomena such as the floating body effect. The difficulty of extracting model parameters for SOI MOSFETs in the industry has influenced the application of integrated circuit design based on SOI technology.

Model parameters are usually extracted by commercial software[7] such as ICCAP, UTMOST, and BSIMPro. Because all of the model equations are non-linear, a combination of least square and Newton-Raphson iteration is often adopted. Besides these, other non-linear fitting methods may be adopted such as the Gauss-Newton and Marquardt methods. These methods require the simplification of model equations and complex computations such as the gradient and inverse Hessian matrix. Such commercial software is therefore often very expensive and does not effectively extract SOI MOSFET model parameters. Analytical methods are proposed in Refs. [8,9] that can extract a few given parameters, but they are not practical for the extraction of a full model card, especially for complex models such as BSIM3V3 and BSIM SOI. In 1999, Watts *et al*. at IBM proposed a method based on genetic algorithm[10] for which 51 parameters of BSIM3 can be extracted at one time using global optimization. Unfortunately, they present no model verification in their report. Evidently, a long time is needed to obtain the optimal solution from a variable space of 51 dimensions, particularly since these parameters must fit many device dimensions.

In this paper, a novel method for extracting SOI model parameters is proposed. It is based on the combination of a genetic algorithm (GA) and a simulated annealing algorithm (SA). It is more practical than conventional and analytical methods, and it can be easily applied to new technology and other device models such as bulk silicon MOSFETs, diodes, and BJTs.

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2 Compound genetic algorithm

Genetic algorithm[11] is an intelligence optimization algorithm that simulates natural biological evolution. It starts from a population of many individuals, each of which represents a possible solution. As a global optimization algorithm, genetic algorithm is applied in many fields, such as auto control and function optimization. It can find the region of probable solutions quickly because of its inherent parallel-computation mechanisms. However, it can easily yield premature solutions. Furthermore, it has poor mountain-climbing ability. After the region of the optimal solution is found, a genetic algorithm takes a long time to find the final solution. The simulated annealing algorithm[12], on the other hand, has strong mountain-climbing ability. Also, it can accept a worse solution according to the Metropolis principle, enabling it to escape the trap of local optimization. Thus it has the capability of global optimization. The disadvantage of SA is its low efficiency and high time consumption.

The compound genetic algorithm proposed in this paper has the advantages of both GA and SA. It is a combination of two different solution search mechanisms. It can perform global optimization through population evolution and local optimization through the mountain-climbing ability of SA.

3 SOI model parameter extraction

3.1 Local optimization

The extraction of parameters is based on local optimization. Its flow is presented in Fig. 1. Before the model parameter extraction of step 1, the initial parameter set P_0, which can be chosen according to the BSIM SOI user's manual, is produced. The parameter set P_1 are the parameters targeted for extraction in step 1. The values of the other parameters of the model card take their default values. P_1 is produced after step 1 is finished through the compound GA. Measurement data set 1 and model equations are used. P_2 is the set of parameters targeted for extraction in step 2. In this step, P_1 is fixed at the values extracted in step 1. Measurement data set 2 and model equations are used. These steps are repeated until all the model parameters have been extracted. In each step, a parameter set P_i is extracted, and it cannot be modified in following steps. The index "i" is the index of the optimization step.

The key point in model parameter extraction is the definition of the strategy in each step. Table 1 shows some local optimization steps used in this paper, which are defined based on a physical understanding of the BSIM SOI model and local optimization.

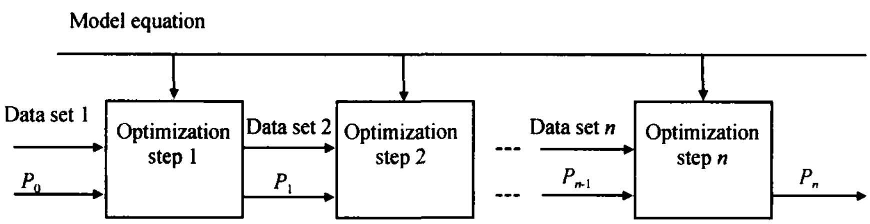

Fig. 1　Model parameter extraction strategy

Table 1　Some local optimization steps in BSIM SOI model parameter extraction

Parameters to be extracted and target data set	Devices and measurement data set
V_{th0}, U_0, U_a, U_b; Target data: I_d-V_g curve at different V_{bs}	Devices with large W and L; I_d-V_g curves (V_{ds} = 0.05V, V_{bs} = 0V)
K_1, K_2, U_c; Target data: I_D-V_G curve at different V_{bs}	Devices with large W and L; I_d-V_g curves (V_{ds} = 0.05V, different V_{bs})
N factor, V_{off}; Target data: I_d-V_g curve at V_{bs} = 0	Devices with large W and L; I_d-V_g curves (V_{ds} = 0.05V)
V_{bsa}, K_{b1}, K_{b3}; Target data: I_d-V_g curve at different V_{bs}	Devices with large W and L; I_d-V_g curves (V_{ds} = 0.05V, different V_{bs})

3.2 Optimization strategy

A chart of the optimization module is presented in Fig. 2.

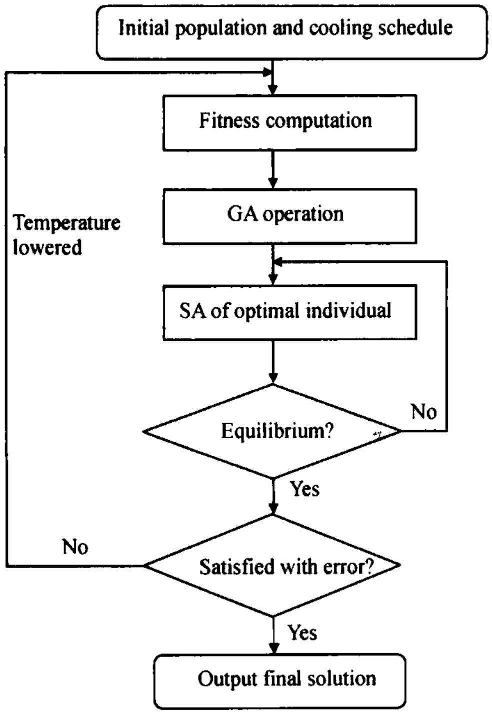

Fig. 2 Optimization procedure using compound GA

(1) An initial population is produced at random. A large enough number of individuals should be chosen to prevent a premature solution. In this work the number of individuals used is 50. Every individual represents a possible set of model parameters, and every parameter to be extracted is confined within a reasonable boundary defined in advance. Since the SA operation is sensitive to the cooling schedule, it must be defined carefully. The cooling schedule is comprised of four parameters: the initial temperature value t_0, the differential step dt that controls temperature decline, a stop criterion parameter s, and the Mapkob chain length l.

(2) The GA fitness of each individual is computed. The fitness is actually the negative value of the objective function. Thus, the smaller the value of the objective function, the bigger the fitness, and the more likely it is that the corresponding individual will be selected.

(3) Genetic operations such as selection, reproduction, crossover, and mutation are performed according to the fitness value of each individual. An individual with greater fitness is more likely to be selected and reproduced. Its genetic information is propagated to its offspring through the selection, reproduction, and crossover operations. Mutation is an important part of the GA operation that preserves the diversity of the population and prevents premature termination. The mutation operator is usually a very small number.

(4) Then the SA acts on the fittest individual of the new population after the genetic operations. In order to achieve quasi-equilibrium at every temperature, the Mapkob chain must be long, and the corresponding computation time will be long as well. Computation time of the SA is sacrificed to reduce model error of the GA. The SA can be turned on when the error of the optimal solution is less than a value defined in advance. During the SA operation, the new solution will be accepted according to the Metropolis rule:

$$P_t(i \Rightarrow j) = \begin{cases} 1, & f(j) \leq f(i) \\ \exp\dfrac{f(i) - f(j)}{t}, & \text{otherwise} \end{cases} \quad (1)$$

Here t is the current temperature, i represents the current solution, j represents the new solution, and P is the probability that the solution will transfer from the current solution to the new solution. Equation (1) shows that a worse solution than the optimal solution may be accepted according to a given probability, which allows the SA to escape the trap of locally optimal solutions. This is a key difference between SA and the local searching algorithm.

(5) Whether quasi-equilibrium is achieved at each temperature depends on the criterion that no new solution has been produced in consecutive Mapkob chains of length l. The number of Mapkob chains is defined by s. If this criterion is met, the algorithm advances to the next step. If not, it returns to the former step. In this work, l is long enough that s can be taken as unity.

(6) Whether the optimal solution meets the error requirement is determined in this step. If the solution meets the error requirement, it is output as the final solution; If it does not meet the error requirement, the current SA temperature is lowered and we return to step (2). The solution obtained from the SA operation is treated as a member of the GA population.

Binary coding is often used during the GA operation. An individual is composed of a string of binary numbers. When using binary coding, the GA operation is simple, and crossover and mutation are easily performed. However, complexity of computation and low efficiency arise because the conversion between binary and point numbers is often performed. The conversion is performed according to the equation

$$X = a + \frac{b - a}{2^n - 1}\sum_{k=1}^{n}(x^{(k)} \times 2^{k-1}) \quad (2)$$

where a is the lower limit of the variable, b is the upper limit of the variable, and $x^{(k)}$ is the k-th binary code of the binary string. The equation illustrates that the variable value is not consecutive. The difference between two adjacent variables is in the length of their binary strings. If the binary string is too short, the solution will be very inaccurate. If the binary string is too long, the efficiency of the computation will suffer.

We adopt floating-point coding in the procedure of mapping from phenotype to genotype to ensure the solution precision and efficiency. The floating-point code directly corresponds to the variable. This approach has great advantages such as computation simplicity and high efficiency because it needs not convert between different codings.

Before beginning the model parameter extraction, the following process parameters must be defined as shown in Table 2. These parameters are fixed at their measured values during model parameter extraction.

Table 2 Process parameters required for SOI MOSFET model parameters extraction

Parameter	Physical meaning	Value
T_{ox}	Thickness of gate oxide	19nm
T_{si}	Thickness of silicon film	340nm
T_{box}	Thickness of buried oxide	400nm
N_{ch}	Doping concentration in channel	$4.5 \times 10^{16} cm^{-3}$
N_{sub}	Doping concentration in substrate	$8 \times 10^{14} cm^{-3}$
T_{nom}	Norm measurement temperature	10 ℃
L_{drawn}	Designated channel length	20～1.2μm
W_{drawn}	Designated channel width	20～1.2μm
X_j	Junction depth	310nm

3.3 Requisite measurement data

In terms of required device geometry, there are two methods of model parameter extraction: single device extraction and group device extraction. Single device extraction is the extraction of all model parameters with only one type of device geometry. In early days, when silicon technology was not as mature as it is now, device models had fewer parameters, and device geometry had little effect on device models. This type of model is called a point model. It is no longer practical because it cannot extract parameters related to short the channel effect and narrow channel effect. Today, group device extraction is often used in model parameter extraction. Usually devices whose model parameters are to be extracted are divided into three types, as shown in Fig. 3: devices with wide channel width and long channel length; devices with wide channel width and varying channel lengths; and devices with long channel length and varying channel widths.

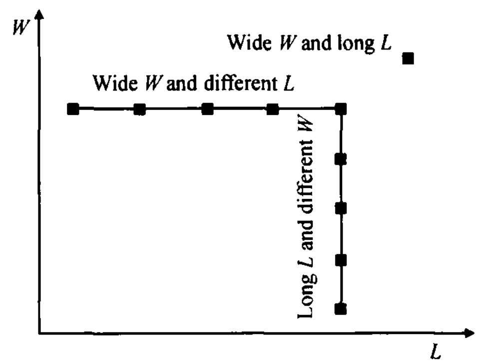

Fig. 3 Requisite devices for parameter extraction

The devices used to extract model parameters are shown in Table 3.

Table 3 Devices used to extract model parameters

Device	W/L (μm/μm)			
Wide W, Long L	20/20			
Wide W, Different L	20/10	20/5	20/2	20/1.2
Different W, Long L	10/20	5/20	2/20	1.2/20

These devices are all fabricated with standard 1.2μm CMOS/SOI technology at the Institute of Microelectronics of the Chinese Academy of Sciences. SMART-CUT wafers are used during the device fabrication. The thickness of the silicon film is 340nm, and that of the (BOX buried oxide) is 400nm. The substrate is p-type. The thickness of the gate oxide is 19nm. Body contact technology is adopted in all devices. Devices with wide channel width and long channel length are used to extract parameters that have weak relations to device geometry. Devices with wide channel width and varying channel lengths are used to extract parameters that are related to the short channel effect.

Devices with long channel length and varying channel widths are used to extract parameters that are related to the narrow channel effect. Four groups of measurements are performed on each device with a DC parameter analyzer HP4155:

(a) I_{ds}-V_{gs} (small V_{ds}, different V_{bs})

(b) I_{ds}-V_{gs} ($V_{ds} = V_{dd}$, different V_{bs})

(c) I_{ds}-V_{ds} (different V_{gs}, $V_{bs} = 0$)

(d) I_{ds}-V_{ds} (different V_{gs}, high V_{bs})

3.4 Objective function

The objective function is one of the most important factors in the success of model parameter extraction. Jiang *et al*[13]. have proposed a BSIM parameter extraction method based on the (S3 search space smoothing) theory. The objective function is defined as

$$Q(P) = \sum [(I_k - f_k(V_k, P))^2]^{\alpha} \quad (3)$$

This objective function can be used only for the fitting of one piece of the device's characteristic curve. For example, the saturation current when the gate voltage is 5V may be ten times higher than the saturation current when the gate voltage is 1V. Using the above function may result in a better fitting of the saturation current when the gate voltage is 5V and a worse fitting of the saturation current when the gate voltage is 1V. The above objective function is not adequate for optimization using different device geometries. This may achieve a good fit between measured data and simulated data for single device geometry, but it cannot accomplish a good tradeoff between different operation regions and between different device geometries. An ideal model should cover a large enough operation region and device geometry region.

The objective function adopted in this paper is[14]

$$F = (f_n^{meas} - f_n^{sim})^2 \quad (4)$$

$$F = \sum_{devices} \sum_{curves} \sum_{n=0}^{N} \left(\frac{f_n^{meas} - f_n^{sim}}{f_n^{meas}} \right)^2 \quad (5)$$

where "meas" means measured data, "sim" means simulated data, "devices" means devices with different channel width and channel length that are used to extract model parameters, "curves" means different curves of measured data, and n means the scanning points of each curve. When only one curve is needed to extract some given parameters, objective function (4) should be used. When the given parameters are to be extracted using many curves of different devices, objective function (5) should be used.

For example, when V_{th0}, U_a, U_b, and U_c are extracted, only the measured I_d-V_g data with $V_{bs} = 0$ for a wide W and long L device are needed. This is because these parameters have weak relations with channel width, channel length, and body effect. Therefore, objective function (4) should be used. If objective function (5) is used to extract these parameters, the extracted value of V_{th0} will be less than a reasonable value. This is because the value of the objective function at low V_{gs} plays an important role.

4 Results and verification

The SOI MOSFET model parameters of 1.2μm SOI technology have been extracted using compound the GA proposed above. Figure 4 shows schematics of the optimization process of the compound GA when extracting the width offset parameter WINT and the back bias effect parameters DWG and DWB. The SOI nMOSFETs with narrow channels and varying channel lengths are used. The

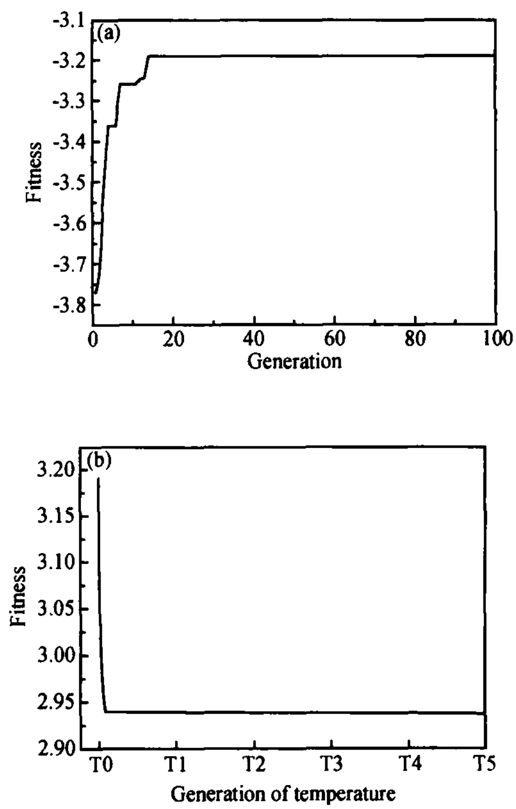

Fig. 4 (a) Optimization process of GA; (b) Optimization process of compound GA population has 50 individuals, which is just enough in this paper. Figure 4(a) illustrates the optimization process using the GA. The fitness of the best individual reaches equilibrium by only the 15th generation. The population is premature if only the GA is used during model parameter extraction. Figure 4(b) illustrates a fast optimization process of the compound GA. The fitness reaches equilibrium in one step of annealing, and the value of the fitness decreases by 8%. This improvement is due to the powerful local optimization ability of the compound GA. The sign of the fitness in Fig. 4(b) is opposite to that of the fitness of the GA in Fig. 4(a). The GA is an optimization algorithm that searches for the maximum value, so its fitness is the negative value of the objective function. The SA is an optimization algorithm that searches for the minimal value, so its fitness is the positive value of the objective function.

Figures 5 and 6 show the output and transfer characteristics of short channel and narrow channel devices, respectively. The measured data are represented by the solid line, the simulated data with model parameters extracted in this paper are marked by solid circles, and the simulated data[15] with model parameters extracted by the commercial software UTMOST (developed by Silvaco) are marked with hollow circles.

The simulated data shown in Fig. 5 are in excellent agreement with measured data. The kink effect is fitted very well. The model from UTMOST cannot simulate the kink effect at all, which will hinder VLSI design based on SOI technology. The ratio between the device channel width and length is an important factor that affects the occurrence of the kink effect. If the ratio is bigger, the kink effect is more evident. Thus in Fig. 6(a), there is no evident kink effect. The simulation results in this paper agree with measured data very well, but the results from UTMOST deviate far from measured data, which can also be seen in Fig. 6(b).

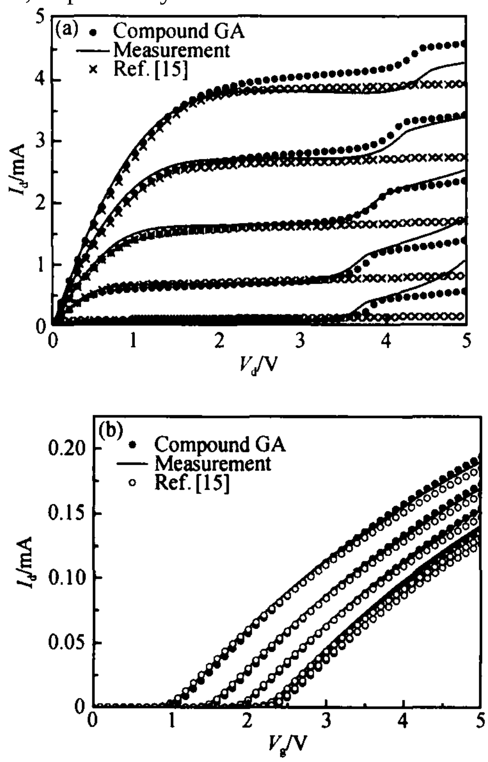

Fig. 5　(a) Output characteristics of SOI nMOSFET with $W/L = 20/1.2$　The solid line represents measured data. The solid circles represent the simulation results in this paper, and the hollow circles represent the results from Ref. [15]; (b) Transfer characteristics of SOI nMOSFET

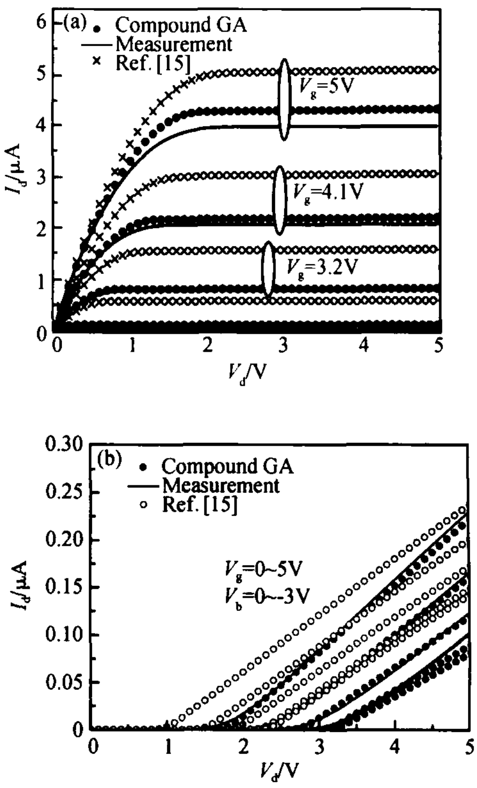

Fig. 6　(a) Output characteristics of SOI nMOSFET with $W/L = 1.2/20$　The solid line represents measured. The solid circles represent the simulation results in this paper, and the hollow circles represent the results from Ref. [15]; (b) Transfer characteristics of SOI nMOSFET

The accuracy of model parameters can be evaluated with the equation

$$\text{Error} = \left[\sum_{n=1}^{N}\left(\frac{D_{meas} - D_{sim}}{D_{meas}}\right)^{2}\right]^{1/2} \tag{6}$$

This equation can be used to evaluate the error between simulated and measured data for every segment of the curve. Equation (6) resembles Equation (5) except for the square root computation, and is just adequate to evaluate the precision of model parameters. Table 4 gives detailed comparisons between the compound GA and UTMOST for Figs. 5 and 6.

Table 4 Error comparison between compound GA and UTMOST

	$W/L = 20/1.2$, output characteristics, V_d:0～5V, V_g:1.4～5V				
Compound GA	1.4625	0.59079	0.28914	0.2409	0.43118
Ref. [15]	3.1711	1.6228	0.99247	0.56171	0.25769
	$W/L = 20/1.2$, transfer characteristics, V_g:0～5V, V_b:0～-3V				
Compound GA	1.9654	1.8718	1.4882	1.1555	2.1753
Ref. [15]	3.1913	4.1209	7.042	6.2033	1.2032
	$W/L = 1.2/20$, output characteristics, V_d:0～5V, V_g:1.4～5V				
Compound GA	7.0172	0.96152	0.2231	0.37777	0.51844
Ref. [15]	958.04	22.594	6.5359	3.0153	1.6869
	$W/L = 1.2/20$, transfer characteristics, V_g:0～5V, V_b:0～-3V				
Compound GA	2.2593	1.8024	1.8517	1.8294	2.1142
Ref. [15]	185.21	100.38	268.49	182.69	180.54

Least square and Newton-Raphson iteration are often used by commercial parameter extraction software. Such methods require complex processes such as model equation simplification and complex computations such as gradients and Hessian matrices, which are very difficult to carry out and inevitably introduce errors. Compared with commercial software, the model obtained using the method in this paper is more precise.

Comprehensive verification is performed with devices of different geometries. The results show that the model parameters extracted in this paper cover a large device geometry region that $1.2\mu m \leq W \leq 20\mu m$ and $1.2\mu m \leq L \leq 20\mu m$.

5 Conclusion

We have proposed an improved genetic algorithm and a novel SOI model parameter extraction method based on the genetic algorithm. The method requires neither complex computations such as the simplification of model equations and inverse Hessian matrices nor a profound understanding of SOI model equations.

Comprehensive verification has been performed using many device geometries. The simulation results obtained using model parameters extracted in this paper are in excellent agreement with measured data. The kink effect of SOI MOSFETs is fitted better than with commercial software. The precision is improved noticeably compared with commercial parameter extraction software. The method in this paper can also be conveniently used in parameter extraction for other devices, such as bulk silicon MOSFETs, diodes, and BJTs.

References

[1] Colinge J P. Silicon-on-insulator technology: materials to VLSI. Boston: Kluwer Academic Publishers, 1991

[2] Chen S S, Kuo J B. An analytical cad kink effect model of partially-depleted SOI nMOS devices operating in strong inversion. Solid-State Electron, 1997, 41(3): 447

[3] Hammad M Y, Schroder D K. Analytical modeling of the partially-depleted SOI MOSFET. IEEE Trans Electron Devices, 2001, 48(2): 252

[4] Lee M S L, Tenbroek B M, Redman-White W, et al. A physically based compact model of partially depleted SOI MOSFETs for analog circuit simulation. IEEE J Solid-States Circuits, 2001, 36(1): 110

[5] Banna S R, Chan P C H, Chan M, et al. A physically based compact device model for fully depleted and nearly depleted SOI MOSFET. IEEE Trans Electron Devices, 1996, 43(11): 1914

[6] BSIM Group. BSIMSOI 3.1 MOSFET model user's manual. University of California, Berkeley, 2003

[7] Cheng Yuhua, Hu Chenming. MOSFET modeling & BSIM3 user's guide. Kluwer Academic Publisher, 1999

[8] Garcia Sanchez F J, Ortiz-Conde A, Cerdeira A, et al. A method to extract mobility degradation and total series resistance of fully-depleted SOI MOSFETs. IEEE Trans Electron Devices, 2002, 49(1): 82

[9] Lou C L, Chim W K, Chan D S H, et al. A novel single-device DC method for extraction of the effective mobility and source-drain resistance of fresh and hot-carrier degraded drain-engineered MOSFETs. IEEE Trans Electron Devices, 1998, 45(6): 1317

[10] Watts J, Bittner C, Heaberlin D, et al. Extraction of compact model parameter for ULSI MOSFETs using a genetic algorithm. Technical Proceedings of the 1999 International Coference on Modeling and Simulation of Microsystems, 1999: 176

[11] Liu Yong, Kang Lishan, Chen Yuping. Non-numeric-parallel algorithm: second part-genetic algorithm. Scientific Publish-

er ,1995

[12] Kang Lishan , Xie Yun , You Shiyong , et al. Non-numeric-parallel algorithm: second part-simulated annealing algorithm. Scientific Publisher ,1994

[13] Jiang Min , Yang Bin , Zhang Liang , et al. MOSFET parameters extraction in VDSM ULSI CAD with a parallel-programming strategy. ASICON ,2001 :673

[14] Li Ruizhen , Han Zhengsheng. Model parameters extraction of a BSIM SOI model based on the genetic algorithm. Chinese Journal of Semiconductors ,2005 ,26(8) :1676

[15] Li Qinghua. Model parameters extraction for 1. 2μm CMOS/SOI. Master Thesis , GSCAS ,2003

基于混合遗传算法的 SOI MOSFET 模型参数提取

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摘要：通过将遗传算法和模拟退火算法相结合得到了改进的遗传算法，这种改进的遗传算法可用于提取 SOI MOSFET 模型参数. 用这种方法提取了基于中国科学院微电子研究所开发的标准的 1. 2μm CMOS/ SOI 工艺的 SOI MOSFET 模型参数，用此模型模拟的数据与测试数据吻合很好，与商业软件相比精度得到了明显的提高. 这种方法与商业软件使用的传统的方法相比，不需要对 SOI MOSFET 模型有非常深入的了解，也不需要复杂的计算. 更深入的验证表明，该模型适用的器件尺寸范围很广.

关键词：SOI；参数提取；遗传算法；模拟退火算法

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