Prediction of Random Dopant Induced Threshold Voltage Fluctuations in NanoCMOS Transistors

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***Abstract*—The detailed analysis of a ground-breaking sample of 100,000 n-Channel MOSFETs, simulated with the Glasgow 3D device simulator, has allowed the distribution of random discrete dopant induced threshold voltage fluctuations to be constructed based on underlying physical processes. The construction may also be statistically enhanced, allowing a significant reduction in the computational effort necessary to accurately model random discrete dopant induced variability.**

I. Introduction

Statistical device variability, introduced by the discreteness of charge and matter, is of significant importance for the design of future generation CMOS devices [3]. The main source of threshold voltage, V_T, variability in current bulk MOSFETs is from random discrete dopants (RDD). 3D simulations of device variability are presently carried out using relatively small statistical samples of approx 200 devices [4], [9]. However, for practical giga-transistor SRAM design, devices in the far tails of the statistical distributions of device parameters, 6σ and more away from the mean, are becoming important. Simulations based on statistical sample sets which are restricted in size cannot accurately predict the shape and the tails of the distribution, leading to excessively pessimistic design margins at the circuit and system level [6]. Due to the significant computational cost of 3D device simulation, it would be useful to find ways to accurately construct device parameter distributions based on relatively small statistical samples. In order to achieve this goal, we first carry out a very large number of device simulations in order to understand the physical processes that govern statistical device behaviour. This physical insight can guide the construction of distributions based on restricted sample sizes of devices with physically enhanced statistical accuracy.

In this paper we present, for the first time, a methodology which can be used to construct the full distribution (including distant tails) of the threshold voltage based on an in-depth physical understanding of the processes which govern threshold voltage variability. We develop and validate our approach based on the simulation of a very large statistical ensemble of 100,000 macroscopically identical 35 nm bulk MOSFETs with microscopically different random dopant distributions.

II. Simulation Methodology

The simulations are carried out with the Glasgow 3D 'atomistic' drift/diffusion (DD) simulator [9]. The DD approach accurately models transistor characteristics in the sub-threshold regime, making it well suited for the study of V_T fluctuations. The simulator also includes Density Gradient quantum corrections which accurately capture quantum confinement effects and are essential for preventing artificial charge trapping in the sharply resolved Coulomb potential of discrete impurities.

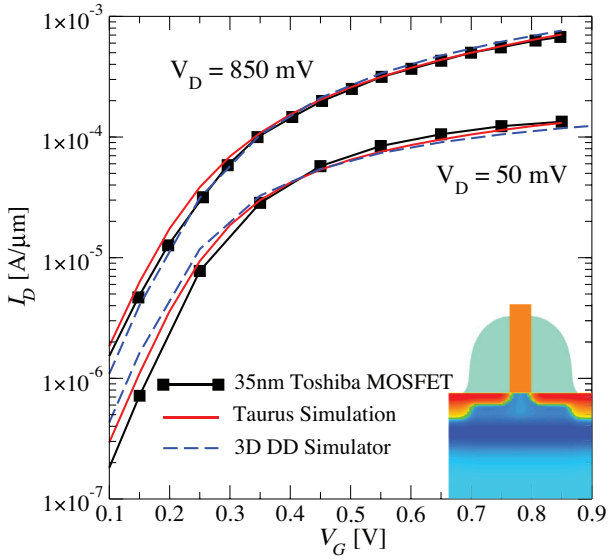

Figure 1. $I_D V_G$ characteristics of the 35nm Toshiba device as produced by the Glasgow simulator at a low drain voltage of 50 mV and a high drain voltage of 850 mV, calibrated against results obtained from both TCAD process simulation and experiment. The continuous doping profile is shown inset.

The large computational resources required for this study were facilitated by Grid simulation technologies under development at the University of Glasgow in the framework of the NanoCMOS project [10].

In order to perform simulations of the entire statistical ensemble, approximately 15 CPU years on a 2.4 GHz AMD Opteron system were required and significant technical challenges had to be overcome. The primary resource used was ScotGrid [2], a compute facility at the University of Glasgow. Primary job submission is performed via the Globus software toolkit which is currently limited to single job submission and monitoring. In order to overcome this limitation, large scale job submission was achieved using Ganga [1] software, where the maximum number of concurrent jobs per user is limited to 1,000. Since our simulator itself can create and simulate a sta-

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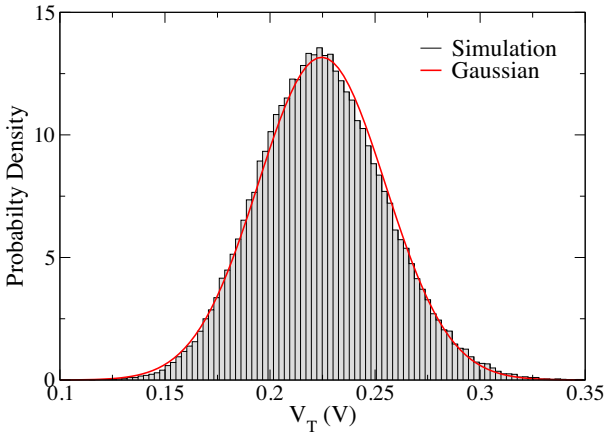

Figure 2. The distribution of simulated V_T data compared to a Gaussian distribution with the data mean and standard deviation.

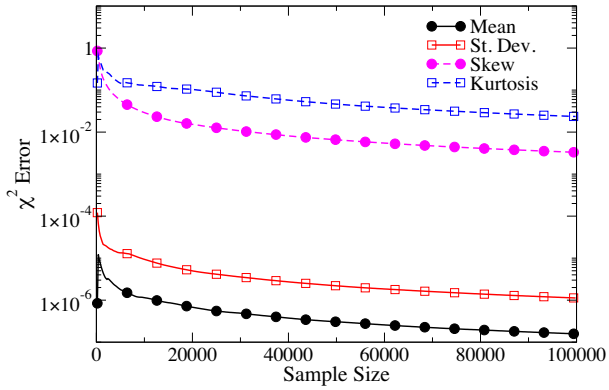

Figure 3. χ^2 error of the first four moments of the simulated distribution as a function of sample size. It is assumed that the final value is an accurate representation of the population value.

tistical sample of devices in a single job this proved sufficient. An additional technical hurdle was the tracking of failed and/or numerically unstable simulations, since in order to preserve the statistical integrity of the calculations it is essential to ensure that duplicate devices are not included in the sample. Finally, the ability to manage extremely large, distributed data sets was required, and a data management system based on a PostgreSQL database backend was developed with good scalability in the range of 100,000's of jobs. The database also facilitated better job status monitoring over Ganga/Globus and allowed complex data mining searches to be performed on the data via SQL and providing direct interface to statistical tools such as 'R'.

The device under investigation is a 35 nm gate length n-Channel MOSFET, published by Toshiba [5]. The transistor has a junction depth of 20 nm and equivalent oxide thickness of 0.88 nm. The simulator was calibrated to experimental device characteristics published by Toshiba using device structural data obtained from commercial TCAD process simulation. The I_DV_G characteristics and doping profile of the continuously doped device are shown in Figure 1. Random dopants were generated in each device of the statistical sample from the initial continuous doping distribution based on the probability for a dopant atom to occupy any silicon lattice site [8].

III. Results and Discussion

The experimental distribution of random dopant induced variations in the threshold voltage for the whole statistical sample of 100,000 devices is shown in Figure 2, with additional information on the moments of the distribution as a function of sample size in Figure 3. Visual inspection and the non-zero third and forth moments of the distribution reveal that the distribution is non-Gaussian with a mean of $\mu = 225.9\,mV$, a standard deviation of $\sigma = 30.3\,mV$, a skew of 0.1597 and kurtosis of 0.0486. Results showing similar asymmetry in experimentally measured V_T distributions have recently been reported [7] giving a strong degree of confidence in the simulation method. This asymmetry can be attributed to the Poisson distribution that governs the number of dopants in the gate depletion region determining V_T. Traditionally, V_T distributions of bulk MOSFETs have been described using Gaussian distributions, however this leads to systematic over or under estimation of the population in the tails of the distribution [6], which has significant implications for the design margins of very large circuits like SRAMs which are sensitive to local statistical variability.

The physics determining device behaviour indicates that dopants in certain regions of the device will have a greater impact on V_T fluctuations than in others. Therefore, we must determine the statistically significant region (SSR) which dominates the statistical behaviour of the device ensemble. In order to do this we calculate the correlation coefficient between V_T and dopant number in a series of 1 nm deep horizontal slabs bounded between the source and the drain which range from the oxide interface down through the device body. A similar procedure is repeated for 1 nm wide vertical slabs ranging through the channel from source to drain. These procedures are illustrated schematically in Figure 4. The correlation in the Y direction is approximately constant, and is therefore omitted from this analysis. The results lead to the assembly of a two dimensional map of the correlation between dopant position and V_T (Figure 5) which outlines the SSR of the transistor. The SSR is bounded by the metallurgical junctions of the source and the drain and extends down approximately 20nm from the interface.

For a fixed number of dopants within the SSR, it is possible to estimate the distribution of threshold voltage caused by the random *position* of dopants. Figure 6 illustrates the evolution of the V_T distribution as a function of the number of dopants in the SSR. It can be seen that both the mean and standard deviation of the threshold voltage distribution increase with the number of dopants in the SSR. A detailed examination of the moments of each of these distributions (each based on a fixed number of dopants) show that both the mean and standard deviation depend linearly on the number of dopants, N_D, as illustrated in Figure 7. For densely populated samples with a

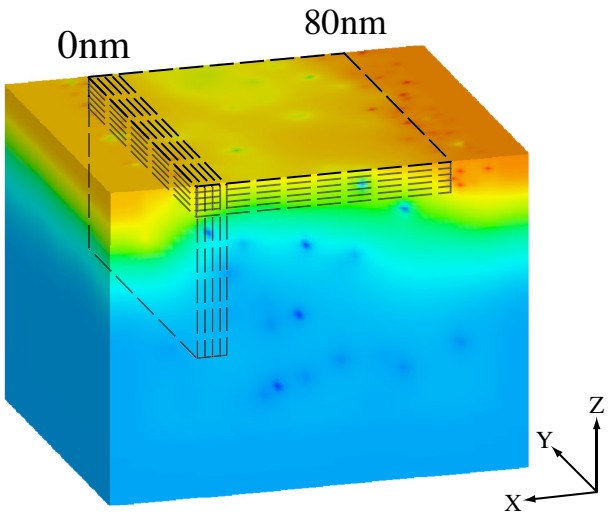

Figure 4. The device is divided into 1nm boxes in both the X and Z axes. The number of dopants in each box is used to calculate the correlation between position and threshold voltage. The extent of the SSR (Fig 5) is indicated.

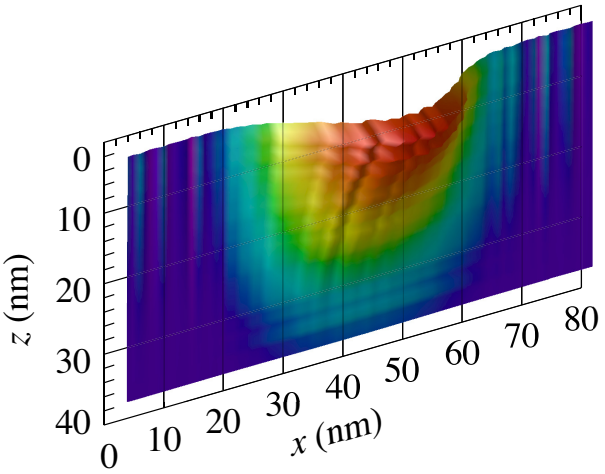

Figure 5. The two dimensional correlation of dopant position and V_T in the statistically significant region.

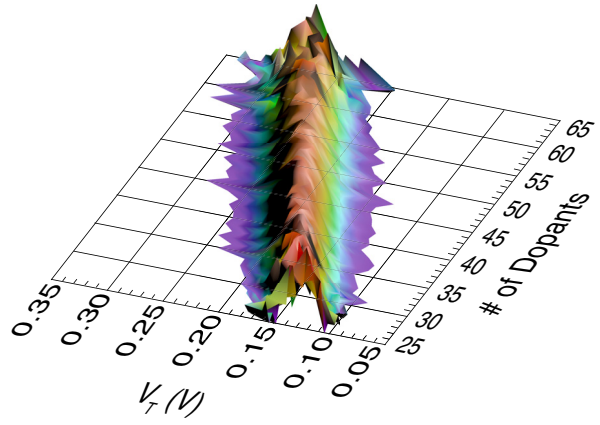

Figure 6. The distribution of V_T as a function of the number of dopants in the SSR. For a fixed value of N_D the distribution of V_T is determined by the position of the dopants. Note the increasing mean and standard deviation of V_T as a function of N_D.

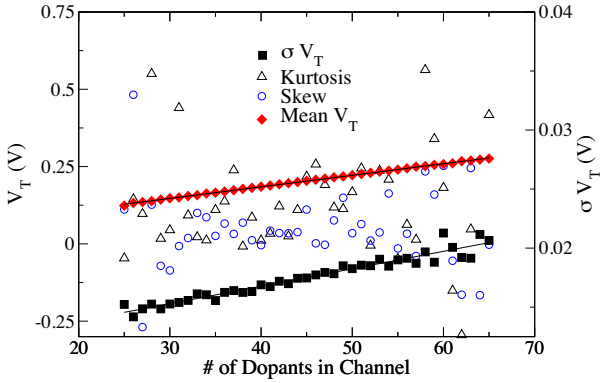

Figure 7. The dependence of the mean and standard deviation of V_T on the number of dopants in the SSR. The linear dependence allows the extrapolation of the positional dependence out to larger values of σ.

constant number of dopants in the SSR (around the mean value $N_D = 44$) the skew and kurtosis are negligibly small, which leads to the conclusion that the threshold voltage distributions due to random dopant positions for fixed N_D are Gaussian.

Given the positional dependence of V_T and the mean number of dopants in the SSR, an analytical distribution of V_T may be constructed through the discrete convolution (Equation 1) of a Poisson distribution ($f(i, \overline{N_D})$) with a mean value $\overline{N_D}$, which governs the number of dopants in the SSR, and the Gaussian distributions ($g(V_T, \mu_{N_D}, \sigma_{N_D})$) from the dopant positions, as illustrated in Figure 8. The constructed distribution is compared with that obtained from simulation in Figures 9 and 10, where the convolution has been calculated for the values of $25 < N_D < 65$ and it can be seen that it matches extremely well the extracted distribution obtained from the 100,000 simulations.

$$P(V_T) = \sum_{i=N_{Dmin}}^{N_{Dmax}} f(i, \overline{N_D}) \cdot g(V_T, \mu_i, \sigma_i) \qquad (1)$$

Since the mean and standard deviation of the positional distributions depends linearly on the number of dopants, it is possible to extrapolate the values of μ(i) and σ(i) in order to extend the distributions further into the tails and to obtain data equivalent to a statistical sample of 100,000s of devices from a significantly reduced sample. In this case, where the mean number of dopants in the SSR is 44, if we select the distributions for $n = 42$ and $n = 46$ and use only the data available at these points to calculate the mean and standard deviation of the Gaussian distributions for values of $1 < N_D < 200$, we obtain a distribution from equation 1 that very closely matches the available data. In fact, this extrapolated distribution better fits the simulation data than the convolution calculated with gaussian distributions extracted from simulation, which is borne out by the calculated χ^2 error values, 0.55 for the extrapolated distribution and 0.94 for the extracted. In fact, this reduction in the measured error indicates

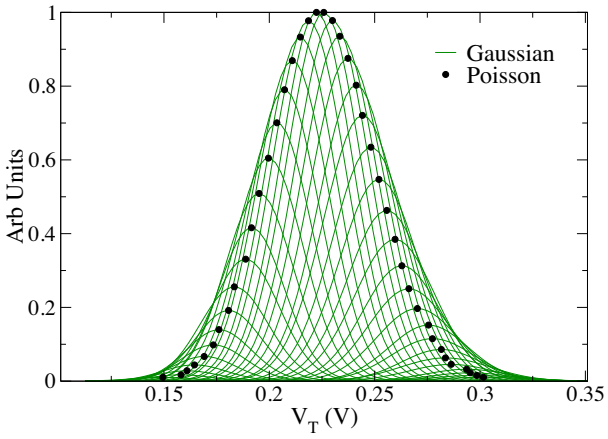

Figure 8. Graphical illustration of how the full distribution is built up from the convolution of a Poissonian and the positional Gaussians.

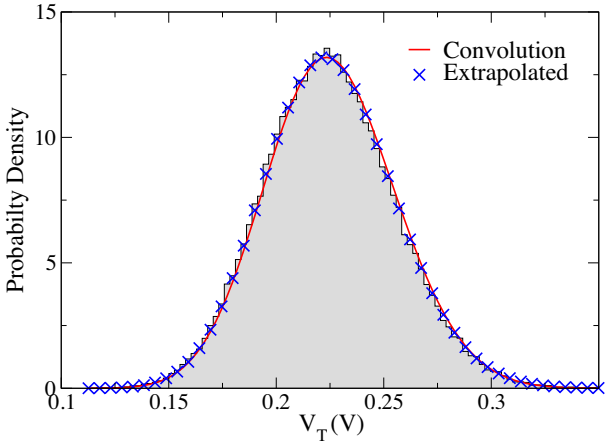

Figure 9. Comparison of calculated and extrapolated distributions with simulation data.

that the extrapolated distribution is a better representation of the real underlying V_T distribution than that from the extracted values. Since the linear extrapolation removes noise in the values of $\mu(\mathrm{i})$ and $\sigma(\mathrm{i})$, as seen in Figure 7, at small and large $\mathrm{N_D}$ and the measured error compared to the data is reduced, it is reasonable to assume that the extrapolation is providing an accurate description of the positional gaussian distributions.

The value of $\mathrm{N_D}$ can be calculated from the average doping concentration in the SSR. By using this value and the aforementioned extrapolation technique to provide input values to equation 1 it becomes possible to accurately predict the effect of random dopant distributions on bulks MOSFETs over a very wide range of threshold voltages from a significantly reduced simulation sample than is required by standard statistical extraction methods.

IV. Conclusions

By performing statistical simulation on an unprecedentedly large statistical sample we have demonstrated that, contrary to conventional assumptions, the distribution of RDD induced threshold voltage fluctuations is non-Gaussian. We have

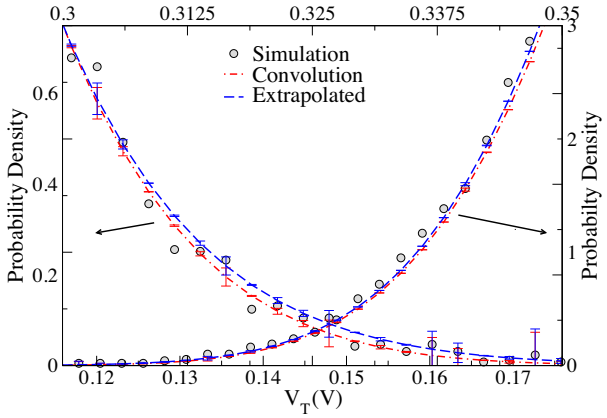

Figure 10. Tails of the convolved distribution. The convolution yields an excellent fit across the whole distribution.

also shown the effects of RDD at the distant tails of the threshold voltage distribution. After in-depth analysis, we have proposed a recipe for constructing the threshold voltage distribution based on underlying physical processes. A wide ranging threshold voltage distribution can be constructed from a reduced set of simulation results which can be used to extrapolate the effect of the random dopant positions on the V_T distribution. This extrapolated data can, in turn, be used to correctly and efficiently determine the probability distribution of V_T out to arbitrary values of σ. This may have significant impact on the evaluation of design margins in future SRAM and other giga-transistor circuits.

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