A Novel Approach to the Statistical Generation of Non-normal Distributed PSP Compact Model Parameters using a Nonlinear Power Method

U. Kovac, D. Dideban , B. Cheng, N. Moezi, G. Roy, and A. Asenov
Dept. Electronics & Electrical Engineering, University of Glasgow,
Glasgow, G12 8LT, UK
e-mail address : kovac@elec.gla.ac.uk

***Abstract*— Statistical variability (SV) is one of the fundamental limiting factors for future nano- CMOS scaling and integration of. Variability aware design is essential to achieve reasonable yield and reliability in the manufacture of circuit and systems. To develop effective variability aware design technologies it is essential to have a reliable and accurate statistical compact modeling strategy. In this study a nonlinear power method (NPM) based statistical compact modeling strategy is presented. The results indicate that statistical compact model parameters generated by a NPM approach are significantly better at capturing the tails and non-normal shape of statistical parameter distributions when compared with principal component analysis (PCA).**

I INTRODUCTION

Statistical variability (SV) in the characteristics of contemporary MOSFETs, introduced by Random Discrete Dopants (RDD), Line Edge Roughness (LER) and Poly Gate Granularity (PGG) / Metal Gate Granularity (MGG), presents an increased challenge to CMOS scaling and integration [1]. At the 45nm technology generation, the magnitude of variation introduced by SV can be comparable to the global process variation. In the 32nm technology generation and beyond SV will become the major source of variation. This ever-increasing SV calls for a change in digital circuit design practices to create variability aware design technology, the prerequisite for which is reliable statistical compact models (SCM). In previous publications by the authors an improvement to the accuracy of SCM parameter generation has been shown with the inclusion of principle component analysis (PCA) [2]. A naive approach to SCM parameter generation assumes each parameter is statistically independent while with the introduction of PCA correlations between parameters are maintained. However, as shown in [2], directly extracted SCM parameters do not always follow a normal distribution typically assumed by the PCA approach. This limits the PCA capability to accurately reproduce the shape and the tails of the distributions of SCM parameters. The development of suitable statistical tools that can capture and maintain higher order moments of distributions in the statistical parameter generation process are urgently needed. In this paper we present a novel nonlinear statistical compact model parameter generation approach that can accurately reproduce the shapes and tails of non-normally distributed directly extracted SCM parameters, and compare its accuracy with previously used PCA method.

II STATISTICAL COMPACT MODEL SIMULATION METHODOLOGY

A 35nm physical gate length n-MOSFET with performance matching 45nm technology node devices reported by Intel [3] and TSMC [4] was used as a test-bed device in this study. The proper prediction of SV relies upon large scale statistical 3D device simulation which create large statistical samples of target current voltage characteristics for the statistical compact model extraction. Due to the number of simulations required a computationally economical drift diffusion (DD) simulation approach is strongly favored for this task [5]. The Glasgow 3D 'atomistic' drift diffusion (DD) simulator was employed to simulate statistical ensemble of 1000 microscopically different square transistors subject to the impact of combined RDD, LER, and PGG SV sources. RDD distributions are generated based on the continuous doping profile by placing dopant atoms on silicon lattice sites with the probability determined by the local ratio between dopant and silicon atom concentrations [6]. LER is generated through a 1-D Fourier synthesis using a power spectrum corresponding to a Gaussian autocorrelation function [7]. The generation of PGG uses a SEM template grain image from which a random section representing the gate region of the simulated device is selected. Along the grain boundaries, the gate potential in the poly-silicon is modified so the Fermi level remains pinned at a certain position in the silicon bandgap [8]. The simulated I_D-V_G characteristics of the statistical ensemble are presented in Fig.1. An inset illustrates the potential profile of one of the simulated transistors under the influence of combined RDD, LER and PGG SV sources. QQ plots of the threshold voltage (V_{th}) and on current (I_{on}) distributions in the tail regions are presented in Fig. 2. The tails of both V_{th} and I_{on} distributions deviate from a normal distribution, and consequently a normal distribution based SCM approaches may distort the occurrence of rare events in statistical circuit simulation and reduce the accuracy of the corresponding estimation of yield.

978-1-4244-7700-5/10/$26.00 ©2010 IEEE

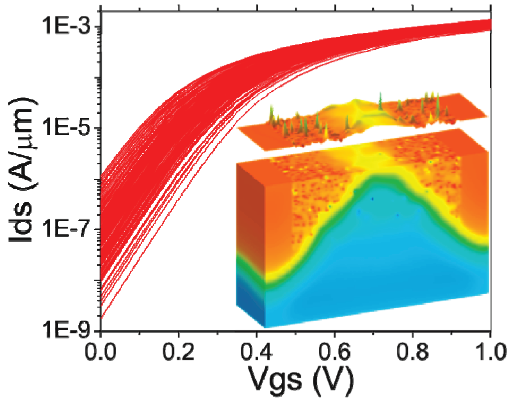


Fig.1 The I_D-V_G curves obtained from DD simulation under influence of SV at high drain bias. Inset: Typical potential profile in a 35nm nMOSFET with combined sources of SV.

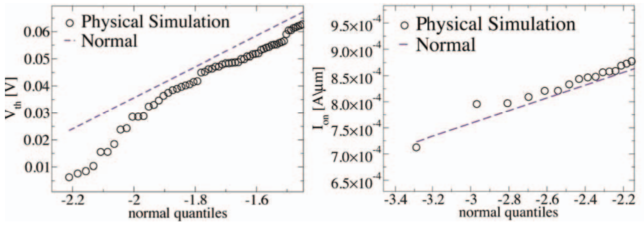


Fig.2 QQ plots of the tails of the distributions of the key device electrical parameters. The dashed line represents a normal distribution.

In order to benchmark the proposed SCM parameter generation strategies, a two-stage direct SCM parameter extraction procedure [2] is first applied without any assumption of device electrical performance parameter distributions. As a result within the accuracy of the compact model fitting, this approach will be the most accurate representation of the current voltage characteristics obtained from the physical 3D simulations or from measurements. The new industry standard compact model, PSP, is employed in this study and 7 PSP parameters [2] were selected to capture the impact of SV on device characteristics. NSUBO is the basic substrate doping parameter, and is chosen to capture a threshold voltage variation; both CFL and ALPL parameters can account for short channel effects variations; UO and CSO mobility parameters are capable of capturing transport variation introduced by SV; CTO represents interface state effects, and CTO in combination with NSUBO, can be used to mimic the effects of variation on subthreshold behavior; RSW1 is a source/drain series resistance parameter, and is selected to capture the influence of SV at S/D region.

The mean RMS error of the direct extraction SCM approach is 2%. The strong correlation between electrical and key statistical PSP parameters is illustrated in Fig. 3, which indicates that the physical meaning of the SCM parameters is preserved during the direct statistical parameter extraction. Fig. 4 shows the distribution of typical extracted PSP SCM parameters, which clearly demonstrates that they do not follow a normal distribution.

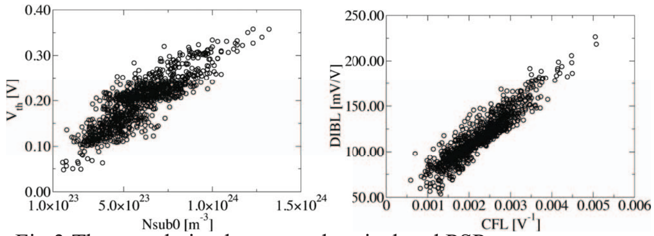


Fig.3 The correlation between electrical and PSP parameters.

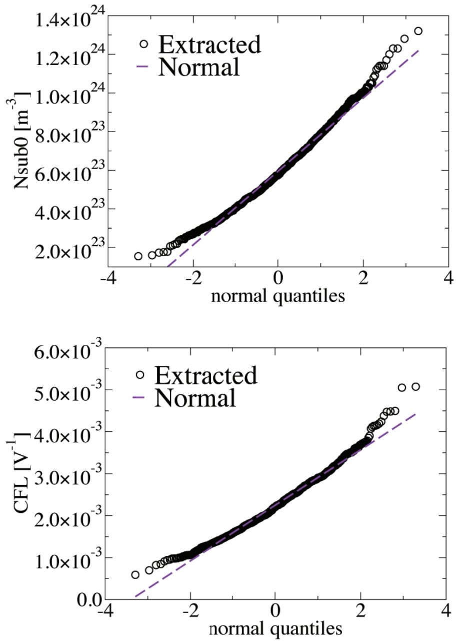


Fig.4: QQ plots of PSP parameters under the influence of combined sources of SV. The dashed line represents normal distribution. Directly extracted PSP parameters are non-normally distributed.

III NPM APPROACH

In order to accurately reproduce the non-normal behavior of SCM parameter distributions, a statistical Nonlinear Power Method (NPM) [9] is employed to capture the higher moments of the distribution. The NPM approach is based on a moment-matching technique, and an accurate approximation to the distribution can be quickly obtained with modern computational resources even when the calculation involves a large number of moments. The number of moments that are required in a NPM approach depended on the degree of irregularity of the target distribution function. In this study the first four moments of PSP parameters distributions are used. The NPM approach is as follows, if we let Y_i denote the standard non-normal random variable with zero mean and unit variance representing the chosen normalized *ith* direct extracted PSP parameter which needs to be reconstructed with the non-normal distribution property preserved. NPM generates the non-normal random variable Y_i using the third order polynomial transformation of the standard normal random variable Z_i~N(0,1) as

$$Y_i = c_{0i} + c_{1i}Z_i + c_{2i}Z_i^2 + c_{3i}Z_i^3 \, , \qquad (1)$$

where c_{ki} for k=0,1,..,3 are unknown constants. This allows to control the degree of skew and kurtosis. Therefore, we derive the expressions for the first four moments of Y_i in order to determine the constants c_{ki}. This requires knowing the even central moments of Z_i up to the 12th order. The odd central moments of Z_i are equal to zero. Substituting the values of central moments of Z_i into the moment formulas of Y_i leads to an algebraic system of nonlinear equations as follows

$$E[Y_i] = c_{0i} + c_{2i} = 0 \tag{2}$$

$$VAR[Y_i] = c_{1i}^2 + 6c_{1i}c_{3i} + 2c_{2i}^2 + 15c_{3i}^2 = 1 \tag{3}$$

$$\gamma_{1i} = 2c_{3i}\left(c_{1i}^2 + 24c_{1i}c_{3i} + 105c_{2i}^2 + 2\right) \tag{4}$$

$$\begin{aligned}\gamma_{2i} = 24\ & c_{1i}c_{3i} + c_{2i}^2\left(1 + c_{1i}^2 + 28c_{1i}c_{3i}\right) + \\ & + 24c_{3i}^2\left(12 + 48c_{1i}c_{3i} + 141c_{2i}^2 + 225c_{3i}^2\right)\end{aligned} \tag{5}$$

where $E[Y_i]$ is a mean value, $VAR[Y_i]$ is a variance, γ_{1i} is a skewness and γ_{2i} is a kurtosis. This system of equations (2-5) is simultaneously solved to provide the constants c_{ki}. To maintain the correlations between directly extracted PSP SCM parameters it is necessary to calculate intermediate correlations matrix between Y_i variables following the procedure described in [10]. The element of intermediate correlations matrix can be computed using the following expression

$$\begin{aligned}\rho_{Y_iY_j} = c_{0i}&\left(c_{0j} + c_{2j} + c_{1i}c_{1j}\rho_{Z_iZ_j} + 3c_{3i}c_{1j}\rho_{Z_iZ_j} + \right. \\ & + 3c_{1i}c_{3j}\rho_{Z_iZ_j} + 9c_{3i}c_{3j}\rho_{Z_iZ_j} + 6c_{3i}c_{3j}\rho_{Z_iZ_j}^3 + \\ & + c_{2i}\ c_{0j} + c_{2j} + 2c_{2j}\rho_{Z_iZ_j}^2\end{aligned} \tag{6}$$

where ρ_{YiYj} is the desired correlation between two chosen PSP parameters Y_i and Y_j and ρ_{ZiZj} is called the intermediate level correlation coefficient between two standard normal random variables Z_i and Z_j. The total of (N-1)xN/2 polynomial equations need to be solved in order to obtain a complete intermediate correlations matrix. In this case, setting N=7 indicates roots of 21 cubic polynomials need to be calculated. Finally, the multivariate non-normal distribution of the random variable Y_i will be generated using a combination of Singular Value Decomposition of the intermediate correlations matrix and the NPM approach. As a result, four moments of the distributions of SCM parameters and the correlations between these SCM parameters will be preserved after this procedure.

IV RESULTS AND DISCUSSION

By applying the NPM approach, statistical PSP parameters have been generated based on the directly extracted results. Fig.5 demonstrates that the correlations between statistical parameters have been well preserved, similar to the PCA approach. Meanwhile, by maintaining the corresponding higher moments through the NPM approach, the nonlinear shape of SCM parameter distributions are well preserved as opposed to the PCA approach which results in normally distributed SCM parameters that only preserves the mean value and variance of each individual parameter. This is demonstrated in Fig. 6, which compares distributions of the PCA and NPM generated typical SCM parameters with their original distributions taken from direct extraction.

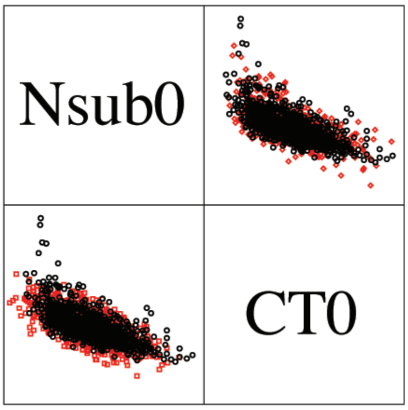


Fig.5: The correlation between two mapped PSP parameters Nsub0 and CT0. Bottom-left: Comparison between extracted (black-circle) and PCA red-square) generated SCM parameters; Top-right: Comparison between extracted and NPM (red-diamond) generated SCM parameters.

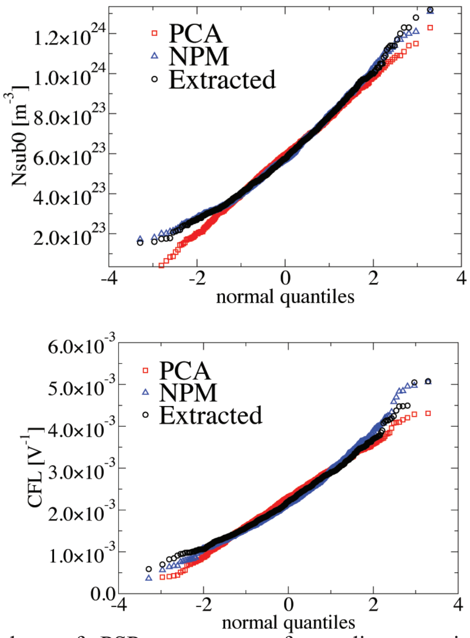


Fig.6: QQ plots of PSP parameters from direct statistical parameter extraction compared with PCA and NPM generated SCM parameters It is clearly seen that NPM approach successfully preserves the shapes and tails of directly extracted SCM parameters distributions.

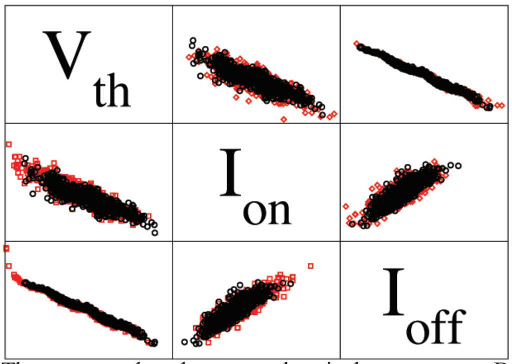


Fig.7: The scatter plots between electrical parameters. Bottom-left: Comparison between results from direct SCM and PCA; Top-right: Comparison between results from direct SCM and NPM approach.

Although both the NPM and PCA approaches are capable of maintaining the correlation among SCM parameters and the correlation between key MOSFET figures-of-merit, as illustrated in Fig. 7 only then NPM approach is able to preserve the shapes and tails of V_{th} and I_{on} as demonstrated in Fig.8.

Furthermore, based on the accurate directly extracted SCM approach, the impact of both NPM and PCA approaches on the accuracy of delay simulation are investigated in detail. The delay is calculated for an inverter designed with minimum size transistors of *W/L* equal to 35nm/35nm for NMOSFET and *W/L* of 70nm/35nm and at a supply voltage of 1V. Monte Carlo SPICE simulations were carried out for 1000 inverter samples for each SCM method, and the results of Monte Carlo circuit simulation are presented in Fig. 9. The delay distribution based on the NPM approach shows very close agreement with the distribution obtained using the directly extracted SCM parameters, while the PCA method produces a significant error in the lower tail of the delay distribution.

CONCLUSIONS

The previously employed PCA approach to the generation of SCM parameters is limited by its assumption of normally distributed parameters. Through its use of higher order moments the proposed NPM approach not only maintains the correlations between generated SCM parameters, but also accurately captures the tails and nonlinear shape of their distributions. The results presented in this paper can provide a guideline for reliable SCM characterization that is still a research hotspot. Although the direct parameter extraction approach gives the best accuracy, NPM is a step toward the development of a general statistical compact modeling approach.

REFERENCES

[1] A. Cathignol, B. Cheng, D. Chanemougame, A.R. Brown, K. Rochereau, G. Ghibaudo and A. Asenov, “Quantitative evaluation of statistical variability sources in a 45nm technological node LP nMOSFET,” *IEEE Electron Device letter*, vol. 29, pp. 609-611,2008

[2] B. Cheng, D.Dideban, N.Moezi, C.Millar, G.Roy, X.Wang, S.Roy, A. Asenov, "Statistical Variability Compact Modeling Strategies for BSIM4 and PSP", IEEE Design and Test of Computers, vol. 27, iss. **2**,pp.26-35, Mar./Apr. 2010.

[3] Mistry, K., et al.,"A 45nm Logic Technology with High-k+Metal Gate Transistors, Strained Silicon, 9 Cu Interconnect Layers, 193nm Dry Patterning, and 100% Pb-free Packaging," In IEDM Digest of Technical Papers, pages 247–250, 2007.

[4] Kuan-Lun Cheng, et al., "A highly scaled, high performance 45 nm bulk logic CMOS technology with 0.242 µm2 SRAM cell," In IEDM Digest of Technical Papers, pages 243–246, 2007.

[5] C. Millar, D. Reid, G. Roy, S. Roy, and A. Asenov, "Accurate Statistical Description of Random Dopant Induced Threshold Voltage Variability," IEEE Electron Device Letters, vol. 29, iss. 8, pp. 946–948, Aug. 2008.

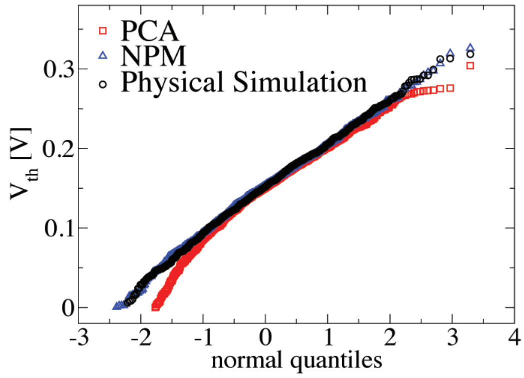
[6] Frank D.J., Taur Y., Ieong M., Wong H., “Monte Carlo modeling of threshold variation due to dopant fluctuations,” In: VLSI symp tech dig; pp. 169–170.1999.

[7] A. Asenov, S. Kaya and A. R. Brown, “Intrinsic Parameter Fluctuations in Decananometre MOSFETs Introduced by Gate Line Edge Roughness,” IEEE Trans. Electron Dev., vol. 50 p. 1254-1260, 2003.

[8] A.R. Brown, G. Roy, A. Asenov, “Poly-Si gate related variability in decananometre MOSFETs with conventional architecture,” IEEE Trans. Electron Devices, vol. 54, pp. 3056-3063, 2007.

[9] A. Fleishman, “A Method for Simulating Non-normal Distributions” , Psychometrika 43,pp.521-532,1978

[10] T.C. Headrick, S.S. Sawilowsky, “Simulating Correlated Non-normal Distributions: Extending the Fleishman Power Method”, Psychometrika 64,pp. 25-35,1999.



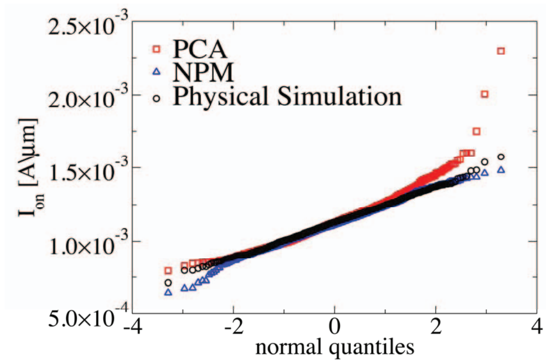


Fig.8 QQ plots of the directly extracted key device electrical parameters **c**ompared with key electrical parameters extracted from PCA and NPM generated SCM parameters .

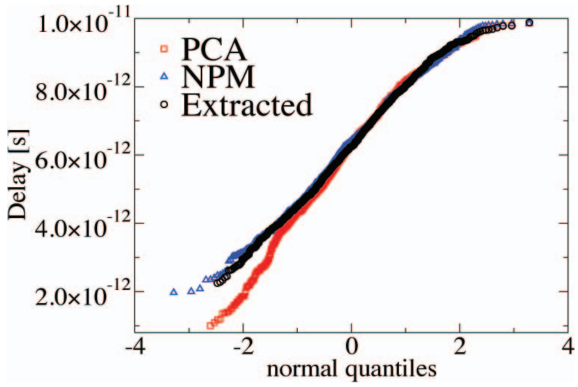


Fig.9: QQ plots of the time delay of inverter simulations using directly extracted, PCA and NPM generated SCM parameters.