Statistical Compact Modeling of Variations in Nano MOSFETs

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Introduction

In the sub-45nm CMOS technology regime, the impact of device variations on circuit functionality becomes critial. The two main approaches for simulating the impact of variation in a design are (i) worst- and best-case corner method, and (ii) Monte Carlo (MC) SPICE simulation [1]. The corner approach usually gives overly pessimistic or optimistic performance prediction due to insufficient attention to the correlations between variations and to electrical test (ET) variation data. The second method provides more accurate prediction but is computationally expensive and impractical for very large circuits. In addtion, the second method also suffers from insufficient attention to correlation [2] and ET variation data. ET based statistical modeling was proposed to improve the accuracy of the corner method [3] but was not fully developed.

In this paper, a novel methodology for generating Performance Aware (Corner/Distribution) Models (PAM) is presented. More accurate and application-specific (for speed, power, gain, etc) model cards can be easily generated at any distribution levels (such as +2σ, -1σ). The methodology also improves the accuracy of Monte Carlo simulation by reconciling the physical and ET variances.

Methodology

Fig. 1 shows the proposed flow for performance aware modeling of device variation. The inputs to the BSIM variation modeling process are the nominal model card, the ET variations (V_{th}, I_{on}, I_{off}, R_{out}, etc) and the process variations (L_g, T_{ox}, W, etc.). The nominal BSIM card already includes the layout-dependent variation (strain, well proximity effect, etc.). To demonstrate the methodology, pseudo ET distribution data are generated using 32nm technology node PTM [4] (Fig. 2). The assumed $3\sigma L_g$ and $3\sigma T_{ox}$ are 10% and 5%, respectively.

The electrical variation inputs are first reconciled with the process variations and decomposed into components due to various physical causes. For example, the total V_{th} variance is decomposed into four causes in the present example: (i) L_g variation, (ii) T_{ox} variation, (iii) random dopant fluctuation (RDF), and (iv) unknown causes. The first two causes are modeled with BSIM4 equations and the nominal model card which contains the nominal model parameters. σV_{th} due to RDF is modeled with percolation theory (atomistic simulation) [5]. The unknown cause category is used to reconcile the ET σV_{th} data with the variations attributable to the other causes. Hierarchical rules govern how to reconcile cases when a negative component due to other causes is indicated. The same process is applied to other ET data (I_{on}, I_{off}, $G_m R_{out}$, etc.). Table 1 shows examples of σV_{th} and σI_{on} separated into various component contributions by this procedure.

The reconciled variations (σL_g, σT_{ox}, $\sigma V_{th,RDF}$, $\sigma V_{th,unknown}$, $\sigma_{mobility}$) are used to generate one thousand model cards. For easier visualization the cards are numbered according to the ascending sequence of I_{on} that each predicts (Fig. 3). The stars indicate the median, ±σ and ±2σ PAM cards based on the I_{on}'s these card generate. As expected, another set of PAM cards based on I_{off} (Fig. 4) are close but not identical to those based on I_{on}. We propose to select the median, ±σ and ±2σ PAM cards based on multiple electrical PERFORMANCE metrics (hence the name Performance Aware Models) such as I_{on}, I_{eff}, I_{off}, $G_m R_{out}$, and the speed of circuit fabrics. For example, based on the small sample of cards shown in Table 2, one may select #845 instead of #840 (based on I_{on} alone) as the +1σ card. One can add other electrical performance in Table 2, of course. One may choose to select a separate set of PAM cards for applications that are particularly sensitive to voltage gain. Therefore, PAM can be application specific.

Result and Discussion

After so selecting the 5 PAM cards, Fig. 5 shows the PAM prediction of 55-stage RO speed (stars) with the 1000 Monte Carlo simulations (circles). In Fig. 6 the same PAM cards give good prediction (stars) relative to 1000 MC simulations (circles) of the speed of a 4-bit adder, which was not considered in the PAM generation process.

PAM is easy to use as the traditional corner models but is more rational and accurate. The accuracy improvement arises from two fronts: i) deliberate inclusion of more electrical variation data such as I_{on}, I_{eff}, I_{off}, R_{out}, speed of circuit fabrics and ii) a methodology to reconcile the many physical, electrical, and RDF variations.

A scrubbed set of variances that are part of the PAM cards defines the technology for SPICE MC simulations. If the variation inputs are separated between global and local variations [6], the PAM cards will support MC simulations for global variation only, local variation only, and total variation. These three types of MC simulations are performed for RO delay. In Fig. 7, the local variations contribute little to the delay variation because the local variations of individual devices in a long logic chain tend to average themselves out. This type of circuits is served well by the PAM corner model. On the other hand, Fig. 8 shows the MC result of local-variation only effect on the static noise margin (SNM) of SRAM cell using the same variation model employed in Fig. 7. In the SRAM case, the same local variations produce very large SNM variations. New variation mechanisms such as MC flicker noise will be modeled and added to the BSIM device variation model.

Summary

We present a methodology to generate performance-aware corner models--PAM. Accuracy is improved by emphasizing electrical variation data and reconciling the process and electrical variation data. PAM supports corner (±σ and ±2σ) simulation and MC simulation. Furthermore, PAM supports application-specific corner cards, for example, for gain sensitive applications.

Acknowledgment

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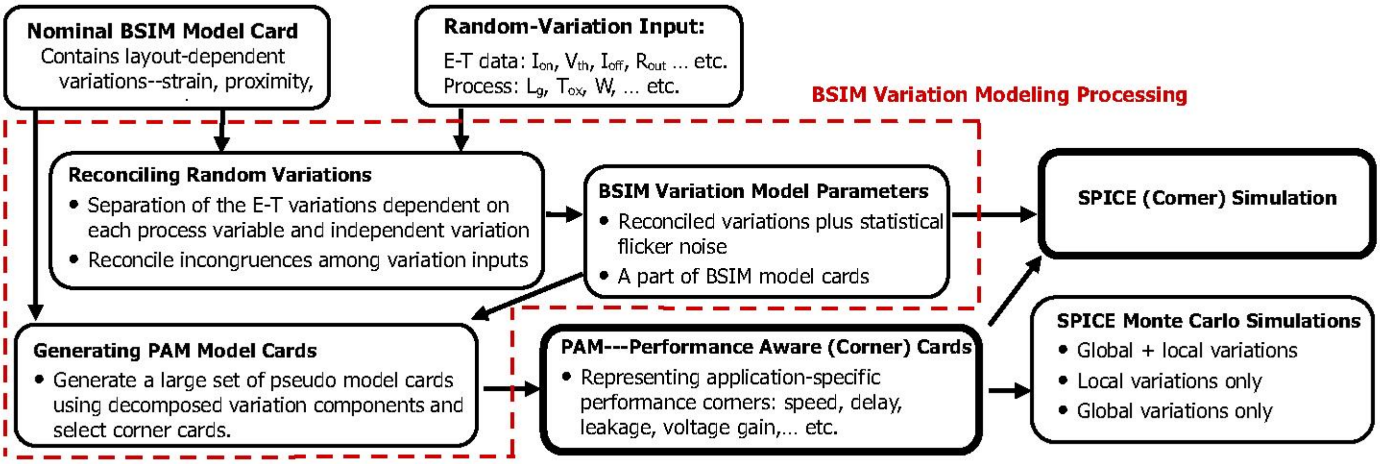

Fig. 1: Proposed flow chart for statistical compact modeling of variations

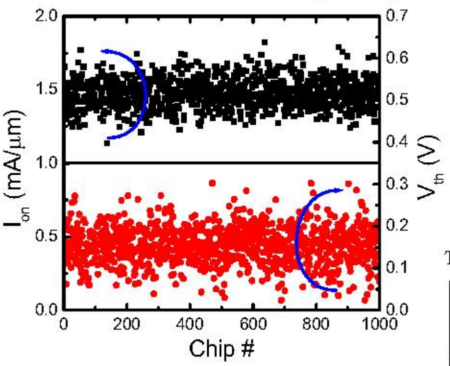

Fig. 2: V_{th} and I_{on} variations in the 32nm technology node are generated to represent ET data for illustration. Sigma/mean is 28% for V_{th} and 6.5% for I_{on}.

Table 1: Separation of V_{th} and I_{on} variations into various causes.

ET σV_{th}	43.7mV	**ET σI_{on}**	96.7 (µA/µm)
$\sigma V_{th,\,Lg}$	29.6mV	**$\sigma I_{on,\,Lg}$**	69.2 (µA/µm)
$\sigma V_{th,\,Tox}$	1.4mV	**$\sigma I_{on,\,Tox}$**	6.2 (µA/µm)
$\sigma V_{th,\,RDF}$	30mV	**$\sigma I_{on,\,RDF}$**	63.5 (µA/µm)
$\sigma V_{th,\,unknown}$	11.5mV	**$\sigma I_{on,\,mobility}$**	22.2 (µA/µm)

Table 2: Based on the I_{on}, I_{eff}, I_{off}, G_m*R_{out} and RO speed, the application-specific +1σ card (#845) is selected.

Card #	I_{on} (A/µm)	I_{eff} (A/µm)	I_{off} (A/µm)	G_m*R_{out}	RO Speed
+1σ target	**1.58E-3**	**9.02E-4**	**9.59E-7**	**3.63 (-1σ)**	**238.7GHz**
835	-0.2%	-0.4%	0%	0.12%	-3.4%
840	0%	-0.13%	-21.6%	-2.2%	-5.3%
844	0.14%	0.19%	-6.5%	-0.26%	10.3%
845	0.15%	0.57%	6.8%	2.2%	1.7%

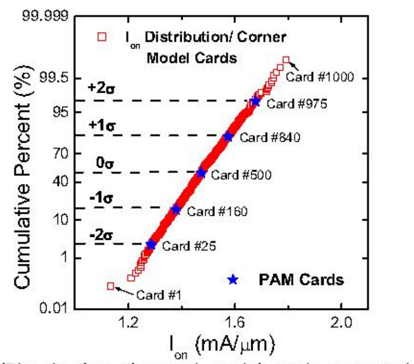

Fig. 3: One thousand model cards generated with reconciled variation components. The cards are numbered according to ascending sequence of I_{on} that each predicts.

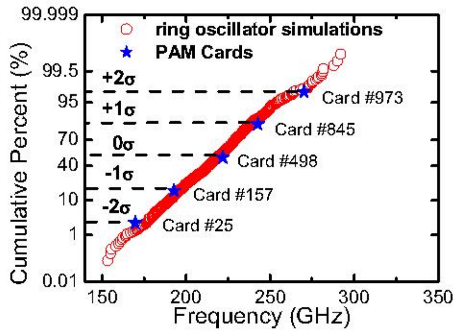

Fig. 5: The speed distribution of 55-stage ring-oscillator (1000 simulations). The improved corner model cards can predict the speed very well.

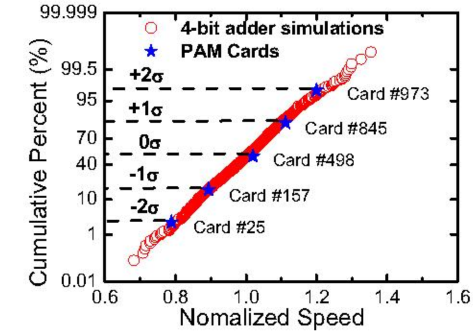

Fig. 6: The speed distribution of 4-bit adder (1000 simulations). The improvedP cards can predict the speed of larger scale circuit very well.

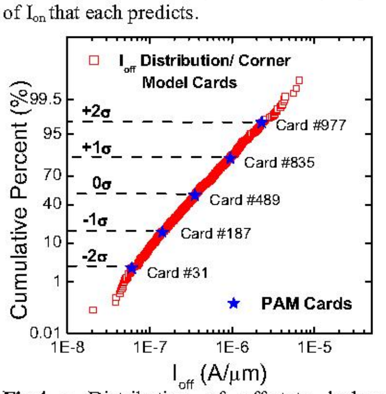

Fig.4 : Distribution of off-state leakage current (I_{off}). The represented cards number between +2σ and -2σ are identified.

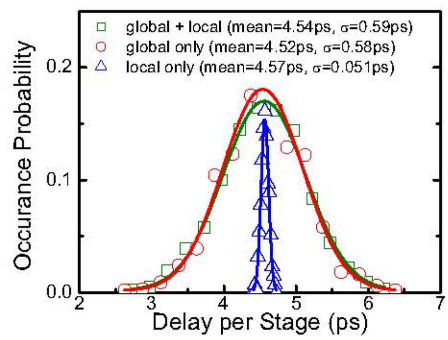

Fig. 7: The Monte Carlo simulation of delay distribution of 55-stage RO (1000 simulations). The separation of global and local model card is needed for improving the accuracy of Monte Carlo simulation.

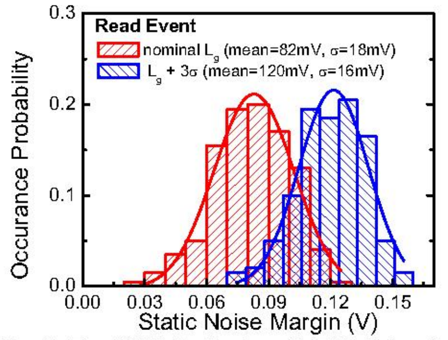

Fig. 8: The SNM distribution of 6T-SRAM under different global variation conditions. The sigma of SNM is only affected by the local variation while the mean of SNM is affected by the global variation.