

A FinFET LER V_T variability estimation scheme with $300\times$ efficiency improvement

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Abstract—In this paper, we have proposed a computationally efficient method to evaluate threshold voltage (V_T) variability due to Line Edge Roughness (LER) in sub-20nm node FinFETs. For channel lengths less than 15 nm, the variability in threshold voltage may be estimated to a great accuracy (error $< 10\%$) with a decrease in computation time of over $300\times$. The method thus proposed provides a fast and accurate way of estimating σV_T from LER specifications of a fin patterning technology.

Keywords—FinFETs, Variability, Line Edge Roughness, Threshold Voltage

I. INTRODUCTION

Line Edge Roughness (LER) is a major contributor to the threshold voltage (V_T) variability in advanced FinFETs in sub-20nm node [1]. Two technology developments focus on addressing the above concern:

1) Improvement of LER by various technologies used for fin patterning, such as self-aligned dual patterning (SADP), extreme ultra-violet (EUV) and nano-imprint lithography (NIL) [2], which requires LER evaluation based on CD-SEM analysis, so that the LER specification may then be translated to V_T variability using computationally intensive TCAD simulations.

2) Novel device design that reduces V_T variability due to LER [3-6], and hence, requires estimation of V_T variability due to LER.

Thus, technology validation based on V_T variability (σV_T) specifications requires intensive computation to obtain V_T distributions from statistical simulations of a large number of samples (≥ 200 [7]) by TCAD. A simple extraction of V_T variability that does not require stochastic TCAD simulation is attractive for rapid evaluation of patterning technology based on device V_T variability specs. In this paper, we propose and verify a hypothesis, that, for a FinFET, V_T is strongly correlated to minimum fin width (W_{\min}). Based on this, we formulate a method of estimating σV_T , which is described as follows:

1) In first step, sensitivity of V_T of FinFET with fin width is evaluated using TCAD. We refer to this analysis as sensitivity check (SC) in the discussion to follow. This is the

only TCAD simulation step in the proposed scheme.

2) In the second step, a distribution of minimum fin width (W_{\min}) is generated from experiment (CD-SEM analysis of a patterning technology) or from LER model (using computer-generated LER lines with given LER specifications).

3) In the third and last step, σV_T is evaluated as an RMS of V_T at W_{\min} (referred to as $V_T(W_{\min})$) from SC, weighted by the W_{\min} distribution. The estimated σV_T matches the one obtained from conventional computationally intensive statistical TCAD analysis of FinFET LER variability very closely.

II. CONVENTIONAL STATISTICAL ANALYSIS (SA)

To simulate statistical LER based variability for FinFETs, random lines with an exponential autocorrelation function with $3\Delta = 2$ nm [1] and variable correlation length Λ [8] were generated (Fig. 1(a)). The exponential autocorrelation function (ACF) is a property of the solution of Langevin Equation, which was used to generate the random lines. High frequency components of exponential ACF generated sharp corners, and hence, are unrealistic. They were removed by passing each line through a low-pass filter. The resultant ACF is approximately Gaussian (Fig. 1(b)). An ensemble of 200 such devices was simulated for LER V_T distribution (Fig. 1 (c)) [7].

A calibrated density-gradient quantum correction model for Si was used to evaluate quantum confinement (QC) due to LER. High QC (shown as higher density gradient potential correction) is observed in the narrower regions of the fin (Fig. 2 (a)) compared to a uniform correction in uniform fin, which represents SC (Fig. 2 (b)). Maximum barrier is shown to be at W_{\min} and barrier increases for more uniform fin i.e. increased Λ/L_G (Fig. 2 (c)). Thus, V_T is expected to be strongly correlated to W_{\min} , which is demonstrated in the next section.

III. CORRELATION OF SA TO SENSITIVITY CHECK (SC)

The sensitivity check curve, i.e. $V_T(W)$ for W (fin width) of uniform fins, is compared with SA results of 200 samples (V_T as a function of W_{\min}) for various Λ/L_G of 0.5, 2, 5 in Fig. 3 (a-c). The plots show excellent correlation of SA to SC with improvement at higher Λ/L_G . Inset shows that, for $\Lambda/L_G=0.5$, the fin has significant undulation (high spatial frequency), while, for $\Lambda/L_G \geq 2$, the fin looks fairly uniform (closer to SC

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case), consequently producing better correlation at higher Λ/L_G .

The percentage RMS error of SC vs. SA decreases strongly to less than 8% for $\Lambda/L_G \geq 2$. This is the regime of interest based on literature, as typical Λ of 20-50 nm [8], and $L_G = 10-15$ nm and below, is equivalent to $\Lambda/L_G \geq 2$. This excellent correlation also demonstrates that V_T is a function of W_{\min} , which is the basis of the V_T variability estimation scheme proposed next.

IV. PROPOSED SC BASED σV_T ESTIMATION METHODOLOGY

A comparison of the methodology based on conventional SA and proposed SC is shown in Fig. 4. The proposed SC based method is as follows – experimental (from CDSEM analysis) or computer-generated LER based lines are used to compute W_{\min} , W_{avg} and W_{\max} distributions, which are Gaussian with same σ (Fig.5 (a)). μ of W_{\min} and W_{\max} are symmetrically shifted about W_{avg} . Thus, we can obtain W_{\min} distribution i.e. Gaussian distribution with characteristic μW_{\min} and σW_{\min} . As we expected, μW_{\min} and μW_{\max} converge to μW_{avg} at high Λ/L_G (almost uniform fin), while they deviate symmetrically from μW_{avg} as Λ/L_G reduces (inset of Fig.5 (b)). σW_{\min} remains fixed ($\sim \sqrt{2} \Delta$).

Finally, σV_T is estimated as an RMS of the $\Delta V_T (=V_T(W) - \mu V_T)$ from SC weighted by the W_{\min} distribution (Fig.5 (c)), where μV_T is V_T at $W = \mu W_{\min}$ in SC. If the W_{\min} distribution lies in the linear $V_T(W)$ regime, $\sigma V_T = m \cdot \sigma W_{\min}$ is a further simplification (where m is the slope of V_T versus W).

V. BENCHMARKING OF SC CF. SA

Fig. 6(a) shows a comparison of σV_T for SC vs. SA at various Λ/L_G . An excellent match is observed at $\Lambda/L_G \geq 2$, which is consistent with SC to SA correlation in Fig. 3(d). The % RMS error (normalized against V_T) shows exponential reduction of error at higher Λ/L_G , with error <8% at $\Lambda/L_G \geq 2$, and with error <1% at $\Lambda/L_G \geq 3$, which is the relevant Λ/L_G regime for technology evaluation.

Time required for SC analysis is nearly 4 minutes on a parallel cluster of 16 core Intel Xeon™ Processor E5620 (where, each core has 2.4 GHz frequency and total memory is 31.3 GiB). However, total time required for 200 statistical simulations on the same cluster is nearly 24 hours, considering the need of simulating complex geometries. Thus, the method proposed herein improves the computation time by a factor of over 300 at the cost of introducing only >8% error in σV_T estimation (Fig. 6(c)).

VI. CONCLUSIONS

In this work, we have proposed a simplified method of estimation of V_T variability due to LER for a FinFET device for channel length 15 nm or below. The method is a very fast way of predicting V_T variability for a LER specification with a fairly high accuracy (less than 10% error) in comparison to traditional computationally intensive statistical TCAD

analysis. Such a method can be used for quick and accurate evaluation of V_T variability from experimental LER data.

ACKNOWLEDGMENT

Research grant from Department of Science and Technology, India is gratefully acknowledged.

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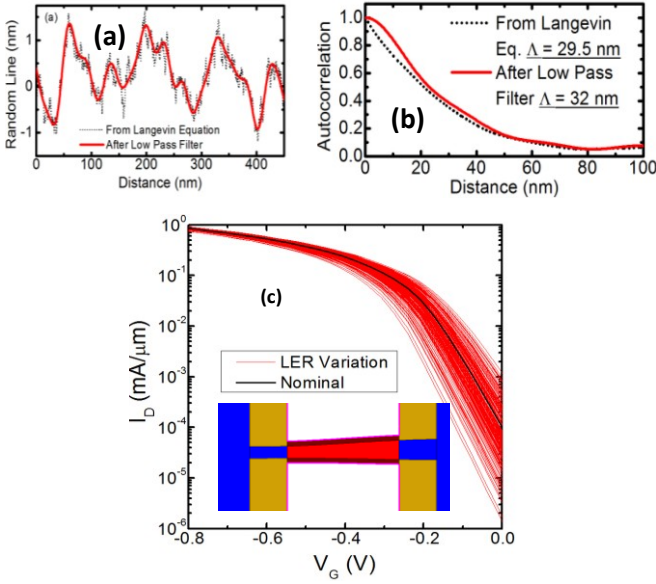


Fig.1. Statistical Analysis (SA) method for LER (a) Random Line generated using Langevin Equation with given correlation length Λ and specified 3Δ to simulate LER and GER variability before and after passing through Low Pass Filter (used to remove high frequency components). (b) Autocorrelation of random lines obtained for the two. (c) I_D - V_G of 200 random FinFET structures simulated with this methodology. Inset shows generated FinFET with LER.

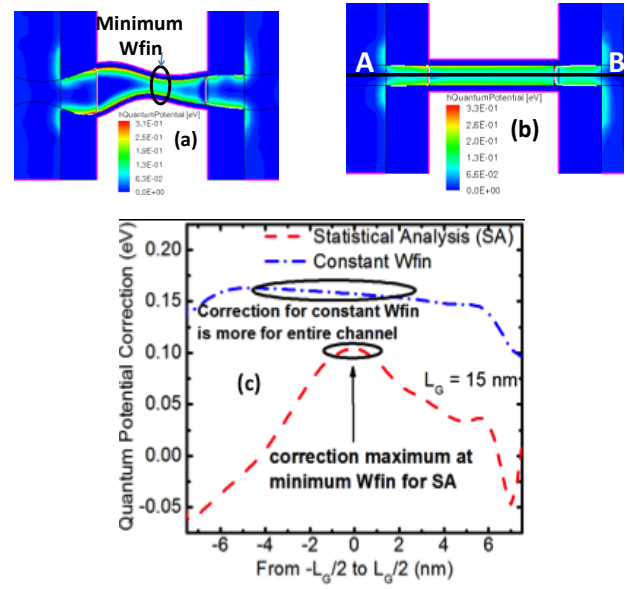


Fig.2. Quantum Potential correction in density gradient quantum confinement model depicting maximum barrier due to quantum confinement (QC) (a) in FinFET with LER during SA, where maximum barrier is defined by minimum W_{fin} (W_{min}); (b) in a constant W_{fin} FinFET during sensitivity check (SC). (c) Cut from A to B shows that (i) W_{min} produces the highest QC to define the V_T in statistical analysis (SA), (ii) QC for constant W_{fin} is slightly stronger, resulting in a small increase in barrier height.

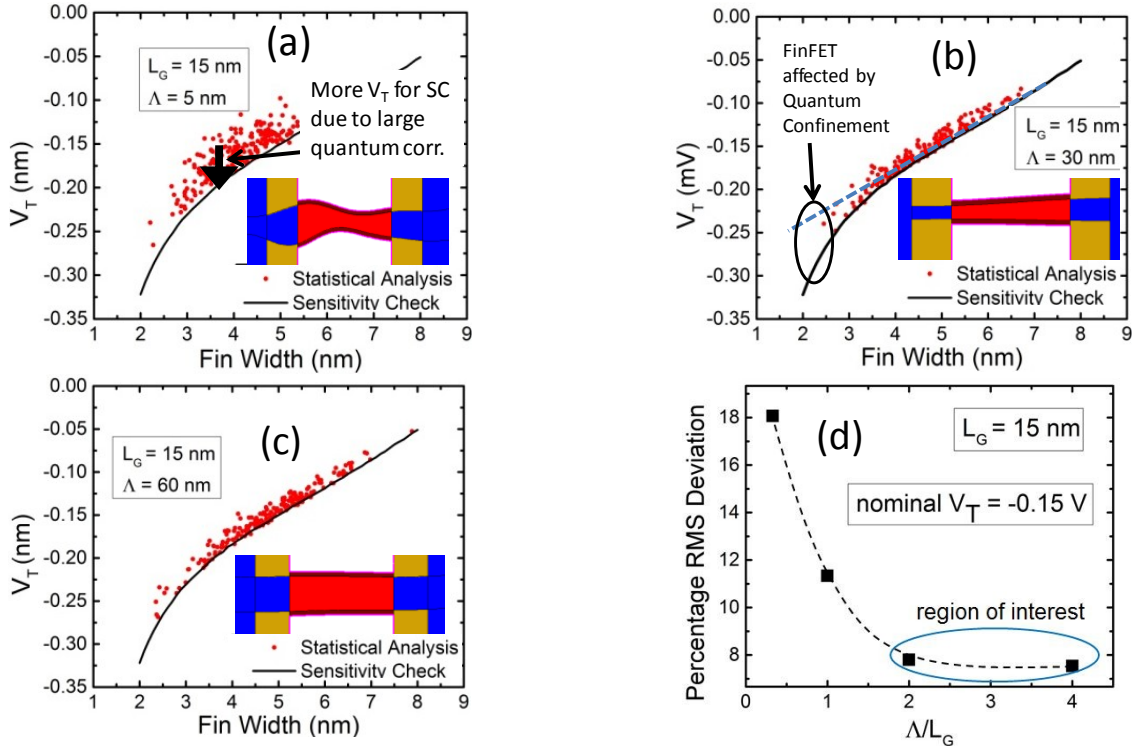


Fig.3. V_T vs. uniform W_{fin} based SC compared to V_T variation vs. W_{min} SA for various Λ (a) 5 nm (b) 20 nm (c) 60 nm for typical $3\Delta=2\text{nm}$ [1], $W_{fin} = 5$ nm at $L_G = 15\text{nm}$. Inset of (a), (b) and (c) shows cartoon of sample FinFET generated which indicates that increase in Λ produces a more uniform fin. Consequently, (d) shows a strong correlation between SC and SA indicated by the strongly reducing RMS error ($\leq 8\%$) with increasing Λ/L_G (≥ 2). For typical Λ of 20-50 nm [8], and $L_G = 10$ -15 nm and below, $\Lambda/L_G \geq 2$. The high correlation between SC and SA in the relevant regime ($\Lambda/L_G \geq 2$) motivates the proposed simplification in Fig. 4.

Statistical Analysis (SA) Sensitivity Check (SC) Scheme

If $\Lambda/L_G < 2$	If $\Lambda/L_G > 2$	
Langevin Eqn based LER	Run SC ($V_T(W)$) in TCAD $n=10$ samples	
Generate $n=200$ device samples for TCAD	If SC is linear	If SC is non-linear
	$\sigma V_T = m \cdot \sigma W$	Obtain W_{min} Dist.
Run $n=200$ TCAD simulations	σV_T is RMS $\Delta V_T(W)$ weighted by W_{min} dist.	
Analyze V_T dist. for σV_T	Where $m = \text{slope of SC}$ $\sigma_W = \sqrt{2} \Delta$	

Fig.4: Statistical Analysis (SA) shows conventional estimation of σV_T where Langevin Equation is solved first to generate random lines with LER (shown in Fig. 1) followed by TCAD simulation of statistically large ($n=200$) samples with complex geometry. For $\Lambda/L_G > 2$, SC scheme is proposed based on low RMS error cf. SA. Computational requirement is decreased as the procedure reduces to (i) TCAD for SC i.e. $V_T(W)$ for $n=10$ samples with uniform geometry and (ii) using W_{min} distribution to obtain σV_T as a RMS of $V_T(W)$ weighted by W_{min} distribution. Further simplification is possible if the SC graph is linear.

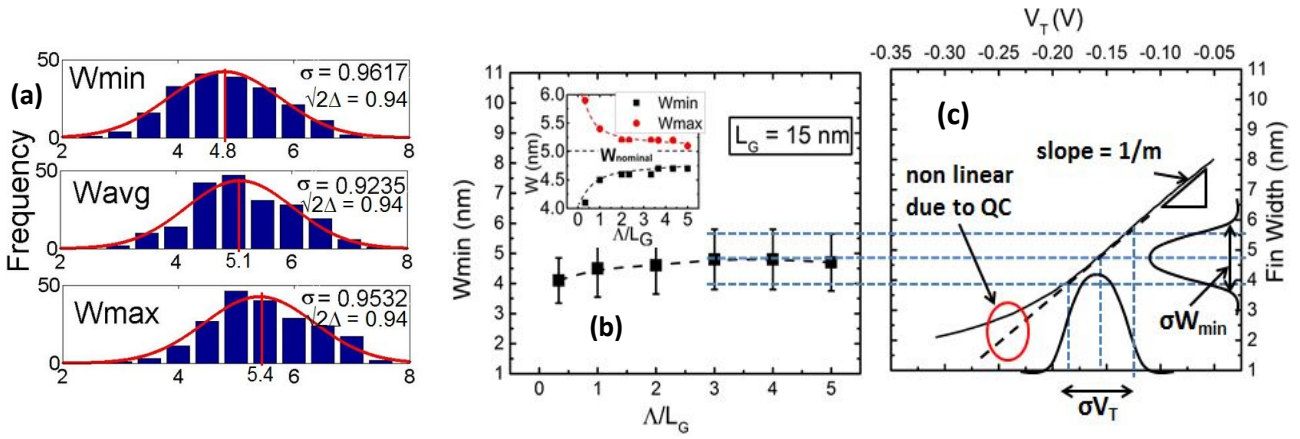


Fig.5: (a) Frequency distribution of W_{max} , W_{avg} , W_{min} for $(\Lambda/L_G)=2$ showing same σ (on fig) about shifted mean for W_{max} and W_{min} cf. W_{avg} . (b) $\mu W_{min} \pm \sigma W_{min}$ with (Λ/L_G) shows that μW_{min} decreases with decrease in (Λ/L_G) while σW_{min} remains constant ($\sim \sqrt{2} \Delta$). (c) SC curve with extraction methodology of σV_T from RMS of V_T weighted by the W_{min} distribution with characteristic μW_{min} and σW_{min} from (a).

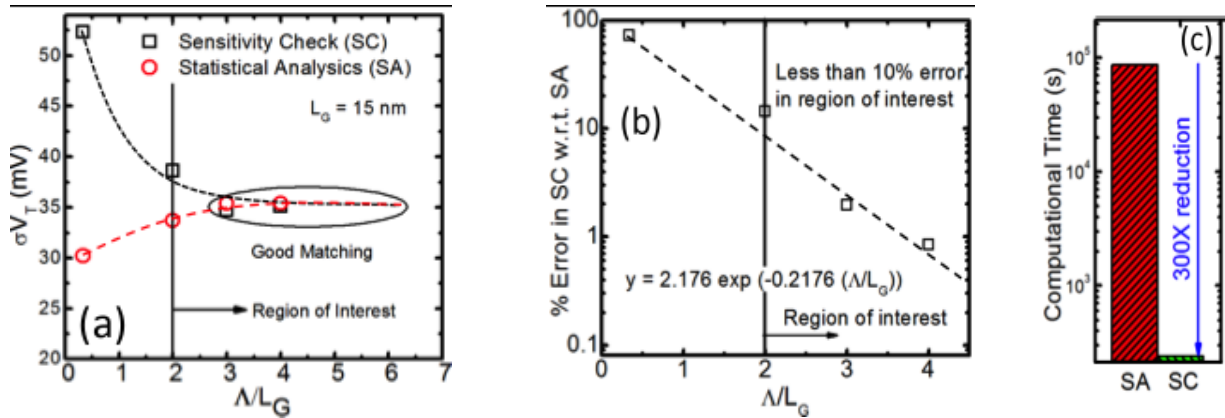


Fig.6: (a) σV_T obtained for SA and SC with (Λ/L_G) . SC matches SA in region of interest i.e. $\Lambda/L_G \geq 2$, (b) % error in σV_T estimation w.r.t. SA is around 10% at $\Lambda/L_G=2$ and falls off exponentially, (c) $>300\times$ reduction in computation time achieved by presented SC scheme over SA.