

On the distribution of the FET threshold voltage shifts due to individual charged gate oxide defects

B. Kaczer^{1,*}, S. M. Amoroso², R. Hussin³, A. Asenov^{2,3}, J. Franco¹, P. Weckx¹, Ph. J. Roussel¹, G. Rzepa⁴,
T. Grasser⁴, and N. Horiguchi¹

¹imec, Leuven, Belgium, ²Synopsys, Glasgow, UK, ³Glasgow University, Glasgow, UK, ⁴TU Wien, Vienna, Austria

*ben.kaczer@imec.be

Abstract— The factors contributing to the FET threshold voltage shift Δv_{th} caused by charging of an individual trap, such as during Random Telegraph Noise (RTN), are discussed by analyzing device-calibrated simulation data. The Δv_{th} distribution is observed to be a convolution of i) the position of the trap along the channel, randomized by ii) the random dopant distribution (RDD) responsible for percolative transport in the FET channel. In our TCAD simulation data the RDD component is observed to be roughly log-normally distributed. “Meta-simulations” varying this log-normal component are able to qualitatively reproduce a range of observed Δv_{th} distribution shapes. In longer devices and/or in devices with high channel doping (or otherwise highly randomized channel potentials), the Δv_{th} distribution tends toward log-normal. In the other, more relevant cases, the exponential Δv_{th} distribution appears to be an acceptable approximation.

Keywords—Reliability, Trap impact, Variability, Distributions

I. INTRODUCTION

The device-to-device distribution of the *total* threshold voltage shifts ΔV_{th} due to Random Telegraph Noise (RTN) and Bias Temperature Instability (BTI) in deeply scaled devices seems acceptably described by the so-called Defect-centric or Exponential-Poisson (EP) statistic [1-3]. This statistic assumes a Poisson-distributed number of charged traps in the gate oxide of each device, while the threshold voltage shift Δv_{th} caused by an *individual* trap in a device (and denoted here by a small v_{th}) is assumed to be *exponentially* distributed, with its Cumulative Distribution Function (CDF) described by

$$1 - \exp\left(-\frac{\Delta v_{th}}{\eta}\right), \quad (1)$$

where η is a physical quantity—the mean Δv_{th} per charged trap.

The factors contributing to Δv_{th} and its distribution are discussed here by analyzing device-calibrated TCAD simulation data. We observe that the contribution of individual charged defects to Δv_{th} is a convolution of i) the position of the trap along the channel, randomized by ii) the random dopant distribution (RDD) responsible for percolative transport in the FET channel. In our simulation data we observe the RDD component roughly *log-normally* distributed. We then perform “meta-simulations” in which we vary this log-normal component, and are able to *qualitatively* reproduce a range of observed Δv_{th} distribution shapes. In longer devices and/or in devices with high channel doping (or otherwise highly randomized channel potentials), the Δv_{th} distribution tends toward log-normal. In the other, more relevant, cases of shorter channels and less-randomized channel potentials, the exponential Δv_{th} distribution appears to be an acceptable approximation.

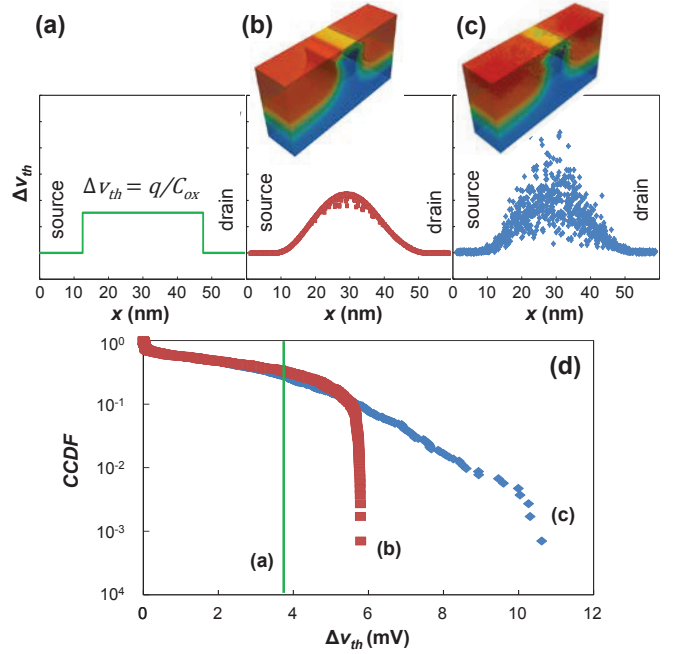


Fig. 1: (a) In the most trivial charge-sheet approximation, all charged traps contribute q/C_{ox} to Δv_{th} . With realistic doping profiles, namely (b) continuous (CONT) doping, traps close to the S/D junctions contribute less, while with (c) discrete doping (RDD), the impact of each trap is further randomized. (d) Δv_{th} from the top three cases sorted into a Complementary CDF (CCDF) plot. RDD (case c) adds approx. an exp. tail to the CONT distribution (case b).

II. SIMULATION METHODOLOGY

We performed three-dimensional (3-D) numerical simulations of a 70nm bulk n-channel MOSFET featuring a 2.2 nm SiON gate oxide. Source and drain doping has a Gaussian vertical profile with a junction depth and peak doping calibrated to match Scanning Spreading Resistance Microscopy (SSRM) measurements [4]. Substrate and HALO doping profiles have been optimized to match the electrical characteristics, including statistical variability [4]. Simulations were carried out by means of the drift-diffusion module of the atomistic simulator GARAND [5], activating density-gradient quantum corrections to correctly reproduce the electrostatic effect of dopants and quantum confinement in the channel. The statistical Δv_{th} distribution was calculated by means of a Monte Carlo (MC) procedure [5], where a large number (1000) of transistors having a different atomistic configuration of substrate doping and a different position of a single charged trap over the channel area and at the Si/SiO₂ interface were simulated. From each simulation, Δv_{th} was

obtained as the change of the gate voltage allowing the same current to be collected at the drain contact for the unoccupied (neutral) and the occupied (negatively charged) gate oxide trap. A read current of 160 W/L nA has been used for Δv_{th} evaluation.

III. RESULTS AND DISCUSSION

Fig. 1 classifies the distributions of Δv_{th} under progressively more complex assumptions. Specifically, it shows that already assuming a realistic *continuous* (CONT) doping (Fig. 1b) results in a distribution of Δv_{th} 's, as charged gate oxide traps closer to the FET junctions contribute less [6]. The introduction of RDD further randomizes the impact (Fig. 1c), resulting in an approximately exponential CDF (Fig. 1d). Note in Fig. 1d that the top portion of the RDD distribution follows the CONT distribution.

The two contributions to the RDD Δv_{th} distribution are deconvoluted in Fig. 2. It is apparent that Δv_{th} is controlled by i) the position of the trap along the channel, randomized by ii) the random dopant distribution (RDD). This latter contribution appears from Fig. 2b to be approx. log-normal, with the parameter $\sigma_{perc} = \sim 0.35$ ($\mu = 0$), hence

$$F = \frac{1}{2} + \frac{1}{2} \operatorname{erf}\left(\frac{\ln r}{\sqrt{2}\sigma_{perc}}\right), \quad (2)$$

where

$$r = \frac{\Delta v_{th,RDD}}{\Delta v_{th,CONT}}. \quad (3)$$

We note that the log-normal distribution is invoked in some percolation studies [7], as well as describing the distribution of the number of steps in the game of “Chutes and Ladders” (MC simulation: $\mu = 3.49$, $\sigma = 0.59$) [8].

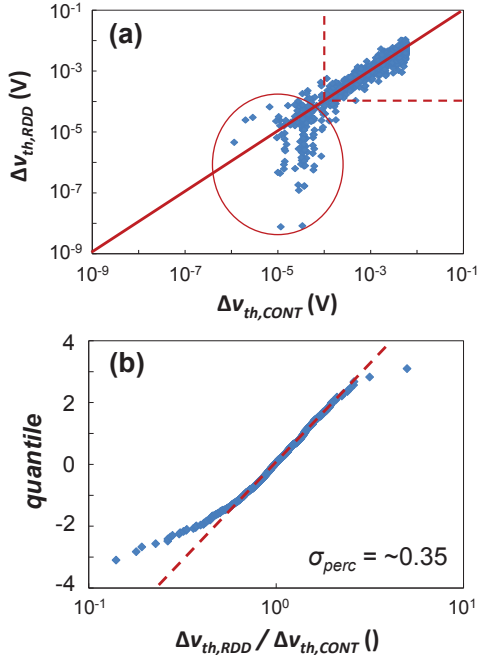


Fig. 2: (a) The randomization of Δv_{th} added by RDD on top of the CONT case (cf. Fig. 1) is analyzed by plotting the two quantities vs. each other. Data below ~ 0.1 mV (ellipse) are below the resolution limit of the simulation and the v_{th} extraction procedure and only add noise to further analysis. Consequently, only data above the dashed lines are used further. (b) The ratio of $\Delta v_{th,RDD} / \Delta v_{th,CONT}$ constitutes the added impact of RDD and the bulk of the distribution can be acceptably described with a log-normal with parameter σ_{perc} (Eq. 2). The deviating low- r tail (approximately Weibull-shaped) does not affect the full Δv_{th} distribution.

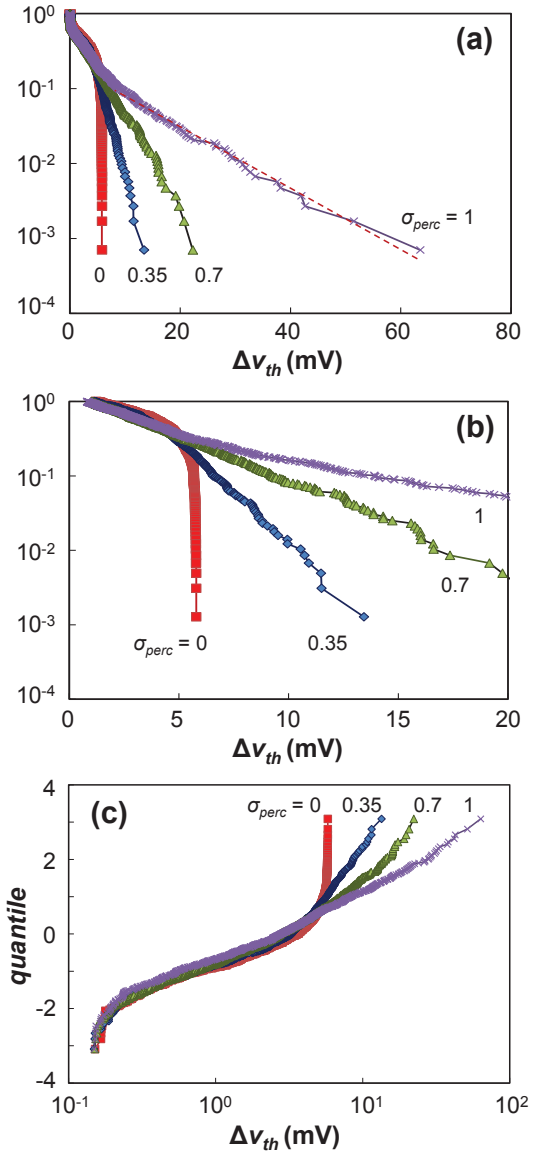


Fig. 3: (a) The result of a 1000-sample meta-simulation assuming a convolution of CONT Δv_{th} impact (Fig. 1b) and different amounts of RDD impact, represented by varying σ_{perc} (note: $\sigma_{perc} = 0$ means no additional RDD impact). The dashed line illustrates exponential fitting of the CCDF tail with $\eta = 10.2$ mV. (b) The same data as in (a), truncated at ~ 1 mV to emulate measurement resolution. (c) The same data as in (a), truncated at 0.15 mV, in a quantile/log-normal plot.

We now perform a limited, 1000-sample meta-simulation in which the RDD contribution is varied through the parameter σ_{perc} (Fig. 3a). A range of σ_{perc} 's can describe a range of Δv_{th} distributions, from the original CONT distribution (i.e., no additional RDD: $\sigma_{perc} = 0$, cf. Fig. 1b) to a distribution with a strong low-percentile tail ($\sigma_{perc} = 1$). We note that the tails of all thus-generated distributions, which control the shape of the total device-to-device Δv_{th} EP distribution [1,2], still appear exponential-like (i.e., approx. straight lines in the Complementary CDF Δv_{th} plot, cf. Fig. 3a). The parameter η (cf. Eq. 1) extracted by fitting these tails in Fig. 3a appears to scale with σ_{perc}^2 , namely $\eta \cong 0.01 \sigma_{perc}^2$ (V).

The behavior in Fig. 3a is observed in real-world RTN and Time-Dependent Defect Spectroscopy (TDDS) measurements [9]. The application of back bias changes the contribution of dopants and results in a variation of the low-percentile tail emulated by varying σ_{perc} (Fig. 4) [10].

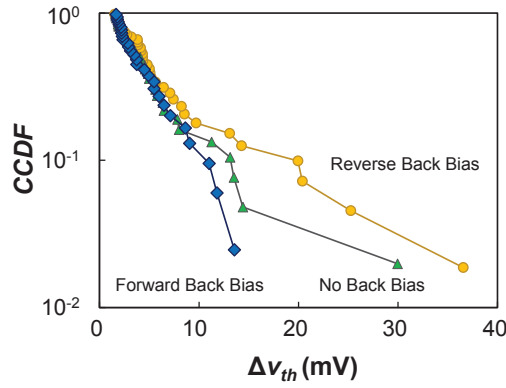


Fig. 4: Impact of back-bias on the ΔV_{th} distribution resembles varying σ_{perc} in Fig. 3a. Note that ΔV_{th} measurement values below ~ 1.5 mV cannot be resolved by the experiment [10].

Fig. 4 also illustrates the fact that real-life RTN and TDDS measurements have finite voltage-step resolution. The experimental distributions are therefore truncated at the ΔV_{th} resolution threshold. This is illustrated for our meta-simulated data in Fig. 3b. The advantage of *assuming* an exponential distribution then is that the fraction of unmeasured ΔV_{th} can be easily calculated and factored into the fit [11].

We note that the *single-trap* ΔV_{th} (i.e., the RTN) distribution has been claimed to be log-normally distributed [12, 13]. (N.b.: this is unrelated to attempts to describe the *total* ΔV_{th} distribution as log-normal). This is not entirely surprising—e.g., our meta-simulated distributions in Fig. 3a, replotted in a log-normal plot (Fig. 3c), resemble closely the distributions reported in Ref. 12.

The log-normal nature of the percolative conduction can become more pronounced in longer devices (i.e., when the impact of the FET junctions can be neglected) and/or in devices with high channel doping (or otherwise highly randomized channel potentials). Fig. 5 shows an extended meta-simulation with 10^5 samples per distribution. The RDD contribution is again varied through the parameter σ_{perc} (cf. Fig. 3a). For $\sigma_{perc} > 0.35$, the ΔV_{th} distributions visibly deviate from exponential and tend toward log-normal behavior at progressively higher percentiles. Note, however, that a deviation from an exponential behavior of the ΔV_{th} distribution at a certain percentile will influence only much higher percentiles of the *total* ΔV_{th} distribution [14]. Fig. 5 shows that for short devices (i.e., with appreciable impact of the CONT distribution) with low channel doping (i.e., low σ_{perc}), the exponential distribution, controlled by the single, physically-based parameter η , appears to be an acceptable approximation of the ΔV_{th} distribution.

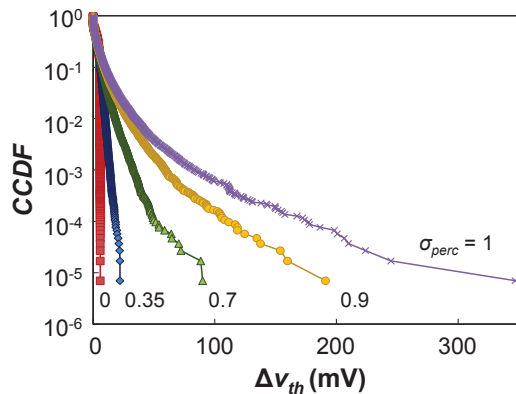


Fig. 5: 10^5 -sample “meta-simulation” assuming a convolution of CONT ΔV_{th} impact (Fig. 1b) and different amounts of percolative conduction (Eq. 2, cf. Fig. 3a). The ΔV_{th} distributions visibly deviate from exponential (a straight line in the CCDF plot) for higher σ_{perc} values.

IV. CONCLUSIONS

We have discussed the factors contributing to the distribution ΔV_{th} due to individual charged gate oxide traps. We have observed that ΔV_{th} is a convolution of i) the position of the trap along the channel, randomized by ii) the random dopant distribution, the latter being approx. log-normally distributed *in our simulations*, likely reflecting the underlying percolative nature of channel transport. Further “meta-simulations” showed that varying this log-normal component can reproduce a range of ΔV_{th} distributions observed in our measurements and in the literature. In longer devices (i.e., when the impact of the FET junctions can be neglected) and/or in devices with high channel doping (or otherwise highly randomized channel potentials), the ΔV_{th} distribution may tend toward log-normal. In the other cases, more relevant to modern VLSI technologies, the exponential distribution, controlled by the single, physically-based parameter η , appears to be an acceptable approximation of the ΔV_{th} distribution.

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