A systematic approach to RTN parameter fitting based on the Maximum Current Fluctuation

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***Abstract*— This paper addresses the automated parameter extraction of Random Telegraph Noise (RTN) models in nanoscale field-effect transistors. Unlike conventional approaches based on complex extraction of current levels and timing of trapping/de-trapping events from individual defects in current traces, the proposed approach performs a simple processing of current traces. A smart optimization problem formulation allows to get distribution functions of the amplitude of the current shifts and of the number of active defects vs. time.**

Keywords—RTN, time dependent variability, modeling characterization

I. Introduction

Random Telegraph Noise (RTN) has become a subject of increasing concern in deeply-scaled CMOS technologies [1], due to its role as a source of time-dependent transistor variability and the resulting impact on circuit performances [2], [3]. At device level, RTN is observed as discrete jumps of the drain current, which are caused by threshold voltage shifts that are associated to sudden and stochastic charge trapping/de-trapping events in/from device defects [4]. The stochastic parameters that characterize the RTN phenomenon are the number of defects in the transistor, the amplitude of the current shifts (or, analogously, the amplitude of the threshold voltage shifts) associated to each of these defects, and their time constants, which may depend on the bias and temperature conditions. These time constants are the capture time (τ_c), i.e., the average time that an empty defect takes to capture a charge carrier, and the emission time (τ_e), i.e., the average time that an occupied defect takes to emit the charge carrier. It is therefore crucial to characterize this phenomenon and extract information about the statistical distributions of its main parameters.

The extraction of the number of RTN defects traditionally relies on the detailed analysis of individual current traces containing RTN [5]-[7]. This analysis either detects the number of transitions with a distinct amplitude, each of which would correspond to a different defect, or the total number of current levels. From this value, the number of defects can be easily calculated. However, these conventional approaches are convoluted and error-prone, being even unable to correctly extract the number of defects if the trace is very complex (i.e., with a large number of distinct transitions, often with similar amplitudes), or if some of the defects produce current shifts with an amplitude below the noise level.

To overcome the limitations of these approaches, the Maximum Current Fluctuation (MCF) metric has been introduced [8]. The MCF can be related to the number of active defects, i.e., the defects that have experienced at least one trapping/de-trapping event in a given time interval, and the current shift amplitude of each of those defects. An advantage of this metric is that it is extremely easy to compute and is not subject to the limitations of conventional approaches. Moreover, this approach is able to accurately account for small-amplitude defects.

However, no systematic procedure has been reported yet to determine the distribution parameters of the current shift amplitudes and the temporal evolution of the number of active defects. In this paper, a global optimization procedure is proposed to address their systematic determination. Several alternatives are discussed to arrive at a final approach with optimal efficiency and effectiveness. The MCF approach is described in Section II. The optimization strategy to extract parameter models is introduced in Section III and experimental results are shown in Section IV.

II. The MCF Approach to RTN Parameter Fitting

A. Maximum current fluctuation

To introduce the MCF concept Fig. 1a shows the current trace measured in a PMOS device of W/L=80nm/60nm, fabricated in a 65-nm CMOS technology [9]. The current trace was obtained when biasing with $|V_{GS}| = 1.2\text{V}$ and $|V_{DS}| = 0.1\text{V}$ using the experimental setup in [10]. In such a trace, the trapping and de-trapping event of several RTN defects can be observed.

We define the MCF at any time instant t' of a measurement window as the difference between the cumulative maximum current, i.e. the maximum current within the time interval $0 \leq t \leq t'$, and the cumulative minimum current, i.e. the minimum current within the time interval $0 \leq t \leq t'$:

$$MCF(t') = \max_{\forall t \in [0,t']} I(t) - \min_{\forall t \in [0,t']} I(t) \qquad (1)$$

The number of defects, their time constants and associated amplitude shifts are all stochastic variables. Then, it becomes obvious that each device will show a different MCF trace. Fig. 1b shows the evolution of MCF as a function of time for 20 PMOS transistors.

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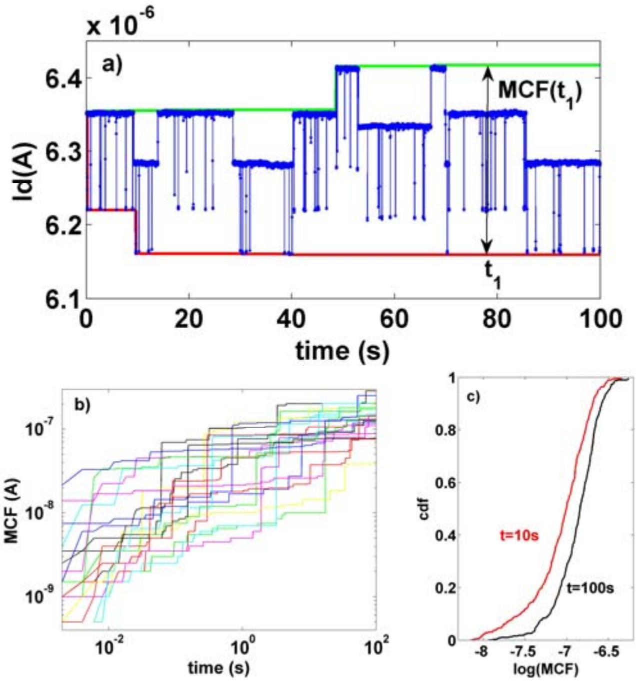

Fig. 1. a) Experimental RTN trace and current bounds from which the MCF is computed. The arrow indicates MCF at t=78s. b) MCF(t) obtained from 20 RTN traces. c) The cumulative distribution functions (cdf) of the MCFs for t=10s and t=100s for a set of 400 transistors.

B. Relationship to defect parameter distributions

The MCF at any time instant t' can be approximated by the additive contribution of current shift amplitudes of all defects and the background noise:

$$MCF(t') = MCF_{RTN}(t') + MCF_{noise}(t') = \sum_{i=1}^{N(t')} \Delta I_i + MCF_{noise}(t') \quad (2)$$

where MCF_{RTN} represents the MCF component induced by RTN and MCF_{noise} corresponds to the MCF component induced by the background noise. $N(t')$ represents the number of active defects at time t', i.e., the number of defects that have captured or emitted a charge since the beginning of the measurement window up to time t'. ΔI_i represents the current shift amplitude associated to the trapping/de-trapping event of the i-th defect. $MCF_{noise}(t')$ accounts for the contribution of the background noise to the MCF.

The number of defects in a transistor has usually been modeled as a Poisson distribution [11]. The probability of detecting N defects in a certain transistor is given by

$$\mathrm{P}(N) = \frac{\langle N\rangle^N e^{-\langle N\rangle}}{N!} \quad (3)$$

where $\langle N\rangle$ is the mean number of active defects per device during a given time window.

A two-lognormal has been proposed for the current shifts ΔI [8]:

$$f(\Delta I) = \frac{K}{\Delta I\sqrt{2\pi}\sigma_l} e^{-\frac{(\log(\Delta I)-\mu_l)^2}{2\sigma_l{}^2}} + \frac{(1-K)}{\Delta I\sqrt{2\pi}\sigma_u} e^{-\frac{(\log(\Delta I)-\mu_u)^2}{2\sigma_u{}^2}} \quad (4)$$

where μ_l, μ_u, σ_l and σ_u are the mean and standard deviation of the lower and upper lognormals and K accounts for the relative amplitude of both distributions.

The background noise can be properly approximated by a normal distribution:

$$f(I_{noise}) = \frac{1}{\sqrt{2\pi}\sigma_{NOISE}} e^{-\frac{(I_{noise})^2}{2\sigma_{NOISE}{}^2}} \quad (5)$$

and its contribution to the MCF can be formulated as

$$MCF_{noise}(t') = \max_{\forall t\in[0,t']} I_{noise}(t) - \min_{\forall t\in[0,t']} I_{noise}(t) \quad (6)$$

In summary, the current amplitude shift distribution is characterized by five parameters (K, μ_l, μ_u, σ_l and σ_u), the Poisson distribution of the number of defects is characterized by just one parameter (the mean number of defects $\langle N\rangle$) and the background noise is characterized by its standard deviation σ_I. Then, in total, there are seven fitting parameters.

The goal is to find the parameter values governing the statistical distributions of the RTN defects that match the experimental MCF cumulative distribution functions (cdf), like those shown in Fig. 1c. The fundamental idea is to compare the experimental MCF values to MCF values generated assuming certain parameters for the distributions corresponding to the RTN activity and the background noise.

C. Generation of MCF values

The procedure to generate the term of the MCF associated to RTN defects, MCF_{RTN}, is illustrated in Fig 2. First, a Poisson distribution with mean value $\langle N\rangle$ is sampled. The resulting sampled value N corresponds to the number of active defects in that device during the time window, i.e., till t'. Fig. 2a shows an example in which according to the Poisson distribution a device with four defects has been assumed. Then, a current shift amplitude ΔI_i is assigned to each one of these defects by sampling a two lognormal distribution such as the one described in (4) and illustrated in Fig. 2b. Then, the sum of the amplitudes of the N defects yields the RTN-induced component of the MCF for that device. In the example represented in Fig. 2b, this would be:

$$MCF_{RTN} = \sum_{i=1}^{4} \Delta I_i \quad (7)$$

To generate the component of the MCF associated to the

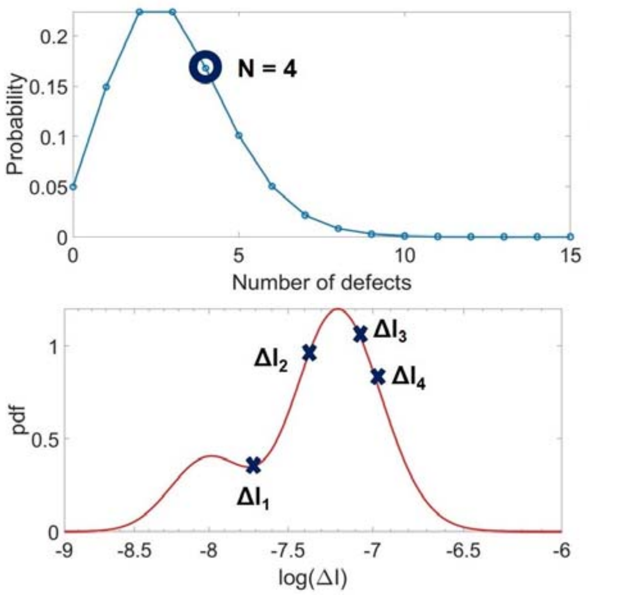

Fig. 2. Examples of (a) Poisson distribution for certain mean number of defects $\langle N \rangle$; (b) Four samples of the current shift amplitude distribution for a given set of K, μ_l, μ_u, σ_l and σ_u values.

background noise, MCF_{noise}, a Gaussian background noise with zero mean is assumed, which is a very good approximation to the one observed in the experiments. For the sake of illustration, one can consider a current trace consisting of *npoints* points of measured background noise. This means that both the mean current level and the RTN transitions have been removed so that the trace consists only of the background noise. Then, each of these points would correspond to a sample of the Gaussian noise distribution, and the MCF noise component up to a given time instant t would be the difference between the maximum value and the minimum value of those samples. These maximum and minimum values are time dependent, since longer measurement windows translate into higher values of *npoints*, and therefore a larger number of samples of the Gaussian distribution, which may lead to a larger noise-induced MCF. During the parameter fitting process, different time instants will be considered and it must be analyzed how the values that the maximum and minimum current can take depend on *npoints*. Additionally, notice that even if the background noise of two different devices follows the same statistical distribution, their associated noise-induced MCF at any given instant may actually be different, since the points of the noise traces are stochastic samples of that distribution.

III. Optimization Problem Formulation for RTN Parameter Fitting

The fundamental idea towards an automated optimization-based parameter fitting is to compare the experimental cumulative distribution functions of the MCF values to those generated according to the procedure presented in the Section II. The cdfs are compared at 1,000 points of the MCF axis (see Fig. 1c), and the absolute differences are added. Then, the sum of those differences is the fitness function to minimize. The distribution parameters that lead to the minimization of such a fitness function are retrieved through an optimization procedure. The optimization method used has been Particle Swarm Optimization (PSO) [12], which makes use of a population of candidate solutions, called particles, which move across a search space along a number of iterations. PSO is an efficient global optimization algorithm that does not require any initial estimate of parameter values for proper convergence.

However, it must be taken into account that the MCF is a function of time, and for each time instant, a cdf like those in Fig. 1c can be obtained. It can be reasonably assumed that (i) the standard deviation of background noise is the same for any time instant, and (ii) the distribution of current shift amplitudes is the same independently of the time instant in which the MCF is considered, but $\langle N \rangle$ is a time-dependent variable, since the number of active defects is a monotonic non-decreasing function of time. Let us assume that matching the experimental and simulated cdfs is considered at M different time instants. The alternatives to formulate an optimization problem that potentially can get the desired parameters are the following.

A first direct approach would be to formulate M optimization problems consisting in the minimization of the difference of the M cdfs. The search space for each these M optimization problems is formed by the seven fitting parameters discussed in Section II. A major obstacle is that all seven parameters but one ($\langle N \rangle$) should be the same for the M optimization problems. There is not a simple solution to this problem beyond a semi-empirical iterative procedure among the M optimization problems.

A second approach is to formulate a single optimization problem, involving the fitting parameters of the current shift amplitudes and the background noise, and an optimization variable corresponding to the mean number of defects for each of the M time instants. Hence, the total number of optimization variables is $M + 6$. This avoids the problems of the previous approach but a major problems arises: the search space grows exponentially with the number of time instants, M. Such a high dimensional search space makes the optimization process much more difficult and prone to stuck at local optima.

To overcome the problems above, we have considered a third approach. Since it has been observed that the evolution of $\langle N \rangle$ agrees well with the cdf of a lognormal function of time [8], the parameters that characterize such a distribution are used as optimization variables. The expression for the lognormal cumulative distribution function of $\langle N \rangle$ along time is:

$$\langle N \rangle(\mathrm{t}) = \frac{N_0}{2}\left[1 + erf\left(\frac{\log(t) - \mu_N}{\sigma_N\sqrt{2}}\right)\right] \quad (8)$$

where erf is the error function and $N_{0,}$ σ_N, and μ_N its fitting parameters. Notice that, with this formulation, the total number of optimization variables amounts to nine, independently of the number of time instants at which the cdf is calculated.

IV. Experimental Results

To obtain the experimental data, three groups of 400 PMOS devices have been measured for 100s at $|V_{DS}| = 0.1V$ and different gate biases $|V_{GS}| = 0.6V$, $0.9V$ and $1.2V$. Then, the cumulative distribution functions of their MCF values have been evaluated at M =22 time instants. On the other hand, MCF values at those same 22 time instants have been generated through the procedure discussed above for each iteration of the optimization procedure, while the differences between the experimental and the generated cdfs have been minimized.

Fig. 3 displays the experimental and generated cumulative distribution functions at 3 out of the 22 time instants for the three different bias conditions. The parameters found by PSO with 50 particles and 200 iterations for the three considered gate voltages are displayed in Table I. Fig. 4 shows how the number of active defects increases with the gate bias.

V. Conclusions

A systematic optimization-based methodology based on Maximum Current Fluctuation has been developed to extract some of the main parameters that characterize RTN, in particular, those related to the amplitude associated to the RTN defects, and the number of active RTN defects and its evolution with time. The same methodology can be applied in case different distribution functions are proposed for the number of defects or amplitude shift distribution. The main advantages of this methodology are that it does not require any complex processing, and that it is able to account for defects with a small associated amplitude.

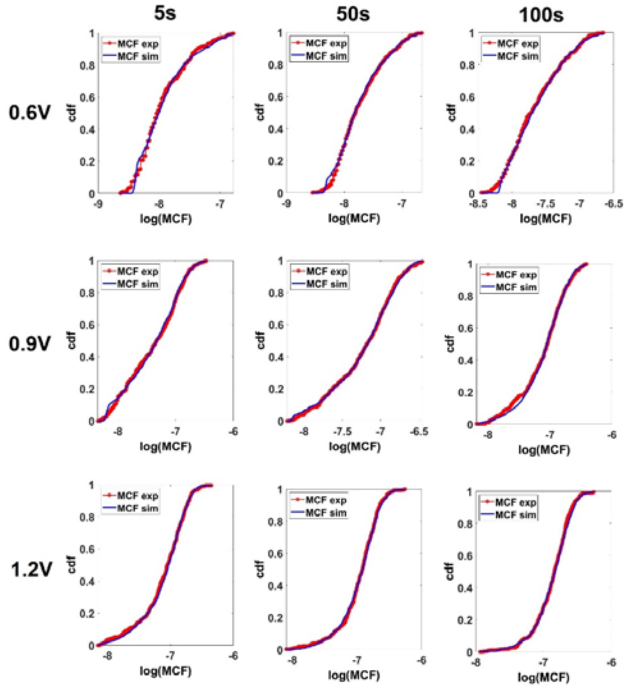

Fig. 3. Experimental and simulated cdfs for three different gate voltages and three time instants out of the 22 used for the parameter extraction.

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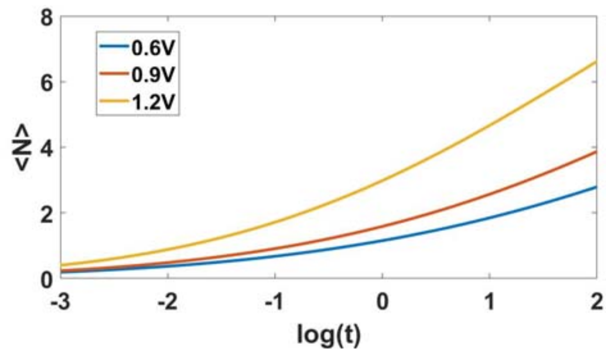

Fig. 4. Temporal evolution of the mean number of active defects.

TABLE I. Parameters Extracted for the δI Distribution of RTN Defects and the Time Evolution of <N>

$\lvert V_{gs}\rvert$	K	μ_l	σ_l	μ_u	σ_u	N_0	μ_N	σ_N	σ_{NOISE}
0.6V	0.915	-8.485	0.426	-7.240	0.250	14.67	5.26	3.72	0.6nA
0.8V	0.793	-8.076	0.448	-7.216	0.221	14.93	4.15	3.33	0.9nA
1.2V	0.755	-8.147	0.494	-7.325	0.150	13.60	2.09	2.70	1.1nA