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An approach to statistical analysis of gate oxide breakdown mechanisms

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Abstract

A credible statistical algorithm is required to determine the parameters of the bimodal Weibull mixture distribution exhibited by the gate oxide breakdown phenomenon, consisting of extrinsic early-life defect-induced failures and intrinsic wear-out failure mechanisms. We use a global maximization algorithm called simulated annealing (SA) in conjunction with the expectation–maximization (EM) algorithm to maximize the log-likelihood function of multi-censored gate oxide failure data. The results show that the proposed statistical algorithm provides a good fit to the stochastic nature of the test failure data. The Akaike information criterion (AIC) is used to verify the number of failure mechanisms in the given set of data and the Bayes' posterior probability theory is utilized to determine the probability of each failure data belonging to different failure mechanisms.

1. Introduction

Gate oxide failure study is increasingly important as we downscale devices further and advance towards the 45 and 32 nm technologies with a gate oxide thickness (t_{ox}) of 1 nm and below. The physics that governs gate oxide failures has been well established, and it is found that gate oxide failures are generally caused by two failure mechanisms [1]. One of them is the *extrinsic* early life breakdown due to large size defects induced by low-quality processing. The other mechanism is the *intrinsic* wear-out failure mechanism where percolation paths are gradually formed, which eventually short the gate to the substrate.

However, as gate oxide thickness undergoes further downscaling resulting in an increased electric field, it may be possible for new failure mechanisms to occur. In such cases, the number of components in the multi-modal distribution describing the time-dependent dielectric breakdown (TDDB) data may be greater than the two failure mechanisms currently observed since every failure mechanism has its own characteristic distribution and its associated parameters. The Akaike information criterion (AIC) [2,3] will be used in this study to determine the number of failure mechanisms in a given set of TDDB data.

The presence of two or more failure mechanisms implies that the TDDB data consists of a mixture of statistical distributions. In order to be able to analyze such mixture distributions, the expectation–maximization (EM) algorithm [4,5] has been conventionally used. However, given the drawbacks of the EM algorithm in its ability to perform only local optimization, it is necessary to use other algorithms in conjunction with it so that the globally optimal values of the distribution parameters for the various failure mechanisms are obtained. In this study, we make use of a global optimization algorithm, known as simulated annealing (SA) [6,7] in conjunction with the EM algorithm for this purpose.

Most reliability tests are time-terminated where the accelerated tests on a sample of test units are stopped after some time $t = \tau$. When analyzing such time-terminated test data, it is necessary to consider the unfailed test units in addition to the failed test units. In this case, the unfailed test units are interpreted as *censored data* at time $t = \tau$.

Additionally, some test units may be purposely withdrawn during the TDDB test for other reasons even before they fail. The time of withdrawal of these units from the test must also be considered as *censored data*. It is therefore

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necessary to have a statistical algorithm that is capable of analyzing mixture distribution data which is *multi-censored* in nature. The EM and SA algorithms are in fact capable of such a data analysis. It is essential to consider censored data during failure data analysis because ignorance of censored data can lead to a large under-estimation of the device reliability, especially when extrapolated to normal use conditions.

Considering the time and expenses incurred in extensive failure analysis (FA), the proposed statistical algorithm is capable of determining the probability of each failure data belonging to the different failure mechanisms using the Bayes' posterior probability [5] theory. The use of this technique enables us to selectively identify a small number of failed units from the entire test sample on which FA needs to be performed. The failure analysis on these selected units will be sufficient to uncover the physical nature of breakdown for all the possible failure mechanisms in the given test.

The novelty of this work lies in using the EM and SA algorithms together for the first time for analyzing multi-censored mixture distribution TDDB data. Furthermore, the Akaike information criterion (AIC) is used to determine the number of failure mechanisms in a given set of failure data and the Bayes' posterior probability theory is applied to determine the probability of each failure unit belonging to the different failure mechanisms. The main motivation behind this work is to illustrate the applicability and usefulness of statistics in the semiconductor industry for precise data analysis.

Since the formation of percolation breakdown paths in the TDDB process is catastrophic in nature, the Weibull distribution is the best description of the statistical nature of gate oxide failures [8]. Therefore, in this work, we apply the mixture distribution theory to the Weibull statistics.

2. Experimental details

TDDB time-terminated tests were conducted on 51 MOS capacitors with an oxide thickness $t_{ox} = 11$ nm with the accelerated E-field stress set to 10.4 MV/cm. A total of 44 failures were observed and the remaining 7 devices correspond to censored data removed from the test for various reasons. The set of failure data obtained is tabulated in Table 1. Note that the test was time-terminated at $\tau = 207.5$ s, when 3 out of the 51 units had not yet failed. The censored times for the 7 devices are 0.15, 2.5, 19.03, 120.21, 207.5, 207.5 and 207.5 s.

Table 1
TDDB failure data for the accelerated test at E-field stress of 10.4 MV/cm

5.847×10^{-10}	5.543×10^{-9}	2.999×10^{-8}	5.138×10^{-8}
4.628×10^{-7}	5.631×10^{-7}	5.301×10^{-5}	8.097×10^{-5}
2.246×10^{-4}	8.172×10^{-4}	2.09×10^{-3}	0.112
0.142	3.217	6.515	8.599
19.205	21.347	72.218	131.85
145.08	145.98	146.67	154.37
157.17	159.13	159.75	164.04
168.56	169.78	171.77	172.89
173.75	174.30	176.38	180.43
182.26	186.43	186.44	186.69
186.69	187.29	206.07	207.5

3. Akaike information criterion (AIC)

Although past research studies reveals that TDDB failures always exhibit two failure mechanisms, it may be possible for other new failure mechanisms to exist in today's 65 nm and below technologies. Therefore, a robust statistical technique is needed to determine the possible number of failure mechanisms in a given set of data. For this purpose, we make use of the Akaike information criterion (AIC) [2,3], which was derived based on the χ^2-statistic.

This AIC is a measure of the goodness of fit of a proposed statistical mixture model. It is used to determine the optimal number of mixture components that fit a given set of failure data. The expression for AIC is given in (1) where L is the maximum likelihood estimation (MLE) of the fitted mixture model and m is the number of degrees of freedom (d.o.f) in a k-failure modes mixture distribution, The relationship between m and k is given by $m = 3k - 1$. The term $2m$ in (1) is the *penalty factor* which prevents too many mixture components to be redundantly added to fit the data more accurately. The number of components k, for which the AIC is the lowest, is found to be the best estimated number of failure mechanisms in the test data.

$$\text{AIC} = -2\log[L(k)] + 2 \cdot m \tag{1}$$

Table 2 lists the MLE values for different assumed number of mixture components for the given failure data set in Table 1 using the expectation and maximization (EM) algorithm results. From Table 2, it can be noticed that a two-component mixture model ($k = 2$) is the best fit to the set of TDDB test failure data in Table 1 because it has the lowest AIC criterion value. The optimal number of components that fit a given set of failure data is precisely indicative of the number of failure mechanisms in that data set. Therefore, since $k = 2$, there are two failure mechanisms in the data set in Table 1.

4. Simulated annealing (SA)

4.1. Theory of simulated annealing

The simulated annealing (SA) algorithm, as its name suggests, is a technique adopted from the thermodynamic

Table 2
AIC value for different number of mixture components (k)

k	m	MLE	Penalty ($2m$)	AIC
1	2	−906.73	+4	1817.47
2	5	60.54	+10	−111.08
3	8	63.43	+16	−111.85
4	11	63.89	+22	−105.79