A Novel Virtual Age Reliability Model for Time-to-Failure Prediction

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ABSTRACT

Mean Time To Failure (MTTF) is widely accepted as the main reliability metric in industry. However, several works indicate that MTTF does not accurately capture the reliability characteristics of Integrated Circuits (ICs) and systems given their relatively short operating lifetime. To overcome the MTTF weakness, this paper proposes a novel virtual age based reliability model, which is able to predict the electronic systems Time-To-Failure (TTF). The aging and degrading factors that have an influence on the system's reliability are modeled as cumulative increments of the system’s virtual age, and the system's failure point is defined as a proper cut-off cumulative failure rate during its operating lifetime. Thus, system's TTF can be easily estimated based on its virtual age, which reflects the current and historical reliability status of the system. The proposed model is computationally recursive and provides real-time reliability status and prediction, which are critical requirements for enabling reliability-aware resource management and computing.

INTRODUCTION

Driven by the aggressive scaling of device feature size, the long-term or so called "lifetime" reliability, as determined by hard failures duo to wear-out and aging related hard errors, has become a major concern in today's high performance Integrated Circuits (ICs) designing and manufacturing [1], [5]. With billion-scale transistor counts, devices approaching physical feature size limits and nuclear plant comparable power density, archiving high-performance computing with a limited power budget while meeting the reliability requirements has become a very challenging task.

Major failure mechanisms, such as Time-Dependent Dielectric Breakdown (TDDB), Electro Migration (EM), Stress Migration (SM), Hot Carrier Injection (HCI), Negative Bias Temperature Instability (NBTI), and Thermal Cycling (TC) have been fairly well understood at device and circuit level, with widely accepted empirical reliability models [1]. Recently, attempts have been made to build reliability models, e.g., RAMP [2], at architectural level or system level by using the MTTF metric. However, the MTTF metric can only result in models that are reflecting the averaging characteristics of numerous populations. As indicated by P. Ramachandran et al. [8], MTTF doesn’t provide information on reliability characteristics during IC's relatively short operating lifetime. Thus a different informative metric should be introduced in order to capture the reliability of a system according with its service time.

In this paper we propose a new approach to estimate the reliability status and the Time To Failure (TTF) of an individual IC in real-time during its serving lifetime. The reliability estimation is based on the cumulative aging progress reflected by the IC’s virtual age. Out proposal encompass three main components: (i) on-line physical monitoring, (ii) conditional reliability estimation, and (iii) TTF forecasting.

The main contributions of the paper can be summarized as following:

- We propose a novel metric called “virtual age” to model the IC’s cumulative aging progress.
- We propose a novel reliability model based on virtual age, which can be used to estimate the IC reliability in real-time;
- We propose an approach to estimate the IC TTF based on historical information.

To our best knowledge, this paper presents the first attempt to quantify an IC real-life reliability status (TTF) by means of its virtual age.

BACKGROUND

A. Why MTTF is not good?

MTTF is widely accepted as reliability metric in industry, but as pointed out in [8] MTTF loses too much information in averaging, which makes it an inaccurate indication for lifetime reliability, especially for the early life reliability prediction.

To illustrate this problem, we can take the Weibull distribution as an example. The Weibull distribution's failure density function is:

$$f(t) = \frac{\beta}{t}\left(\frac{t}{\alpha}\right)^{\beta} \cdot e^{-\left(\frac{t}{\alpha}\right)^{\beta}}, \tag{1}$$

and its Cumulative Distribution Function (CDF) is:

$$F(t) = 1 - R(t) = \int_0^t f(t)dt = 1 - e^{-\left(\frac{t}{\alpha}\right)^{\beta}}, \tag{2}$$

where α is the scale parameter and β is the shape parameter. Weibull's MTTF is:

$$MTTF = \alpha\Gamma(1+\frac{1}{\beta}), \tag{3}$$

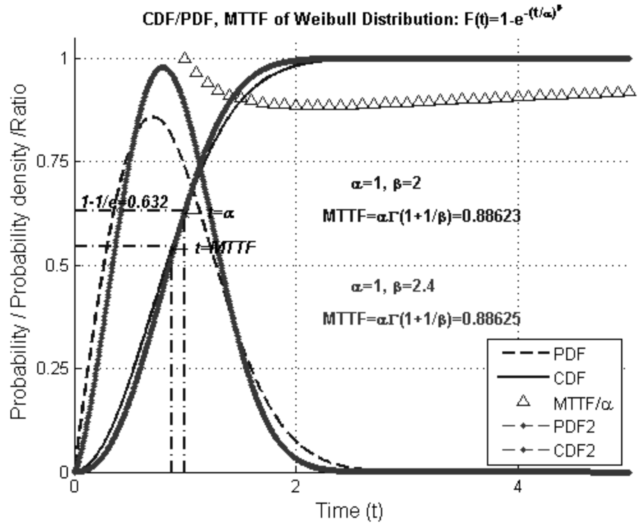
where $\Gamma(n)$ is the gamma-function.

α is also called the "characteristic parameter" because it indicates the lifetime reliability reduction from 100% to 1/e (36.8%), which is far more beyond the normal operational expectation (0.01%).

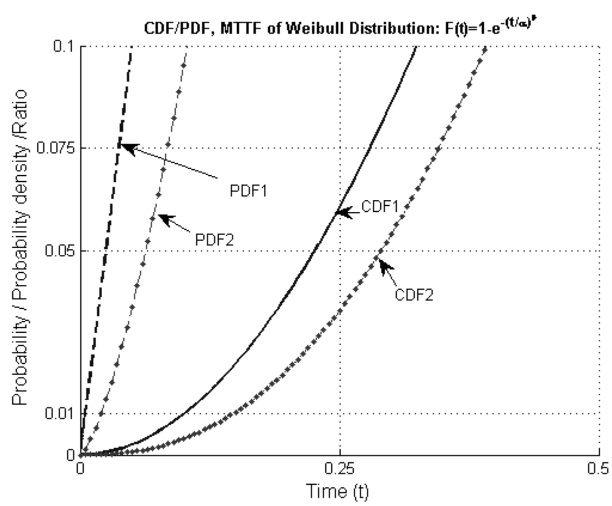
Table I – Acceleration Factors for Major Failure Mechanisms [1]

Failure	MTTF	AF_s	AF_T	E_{aa} (eV)
TDDB	$A_0 e^{\beta V} e^{E_{aa}/kT}$	$e^{\beta(\frac{1}{V_2}-\frac{1}{V1})}$	$e^{\frac{E_{aa}}{k}\left(\frac{1}{T_2}-\frac{1}{T_1}\right)}$	0.75
EM	$A_0 (J - J_{crit})^{-n} e^{E_{aa}/kT}$	$\left(\frac{J_2}{J_1}\right)^{-n}$		0.90
SM	$B(T_0 - T)^{-N} e^{E_{aa}/kT}$	$\left(\frac{T_0 - T_2}{T_0 - T_1}\right)^{-N}$		-0.15
HCI	$B I_{sub}^{-N} e^{E_{aa}/kT}$	$\left(\frac{I_{sub2}}{I_{sub1}}\right)^{-N}$		0.75
NBTI	$\sqrt[n]{V_T / A_0 e^{E_{aa}/kT} e^{\alpha V_G}}$	$\left(\frac{V_{G2}}{V_{G1}}\right)^{\frac{\alpha}{n}}$	$\sqrt[n]{e^{\frac{E_{aa}}{k}\left(\frac{1}{T_2}-\frac{1}{T_1}\right)}}$	-0.02

For a degrading system ($\beta \geq 1$), the relationship between MTTF and scale parameter α in Weibull Distribution is depicted in *Figure 1*.



(a)



(b)

Figure 1. Relationship between MTTF and Weibull Distribution's parameters: (a) Two different Weibull distribution having almost the same MTTF value; and (b) The difference between these two distributions at early-life time where failure rate is small.

One can clearly observe in the figure that MTTF doesn't capture the reliability characteristics very well, as it is just the estimation of average TTF and it is not time-dependent. To overcome the intrinsic weakness of MTTF, we propose to evaluate the device's "health condition" by its virtual age, which is estimated based on cumulative historical information as described in the next section.

B. Major Failure Mechanisms and Acceleration Factors

As most prior works on lifetime reliability have done, our efforts emphasize on intrinsic failure mechanisms experienced by ICs. Intrinsic failure mechanisms in ICs are caused by continuous stressing factors, including voltage, current density, electric field, temperature, humidity, mechanical stress and so on. Different stressing factors have different Acceleration Factor (AF) in an IC's typical working regime. Particularly, thermal stressing (temperature, AF_T) plays a common accelerating role among all the major failure mechanisms, which can be illustrated by Arrhenius Model $AF_T = \exp(E_{aa}/kT)$, E_{aa} is activation energy. Table I summarizes acceleration factors for major failure mechanisms on a 65nm CMOS technology IC (with gate length 30nm, supply voltage 1.0V, gate oxide thickness 2.0nm, and 11 Cu interconnect layers using ultra-low k dielectric k=2.25).

From Table I we can observe that failure mechanisms like TDDB, EM, and SM are highly sensitive to temperature, for they have high activation energy for Arrhenius Equation. However, HCI and NBTI are hardly affected by temperature (ignoring the recovery progress of NBTI), as both of them have negative thermal activation energy.

VIRTUAL AGE BASED RELIABILITY MODEL

A. Basic Concepts

The term "virtual age" was originally defined as the corresponding "equivalent" age of a repairable item when a repair is imperfect [7]. But a typical integrated circuit is a non-repairable system, thus we define our "virtual age" as the reliability status of items relative to a standard baseline.

Assume two similar items (ICs) working in two different environments: one is an identical continuous baseline environment where the temperature (or other concerned factors) is constant, and the other one is a stochastic severe environment (real working conditions).

Virtual age can be calculated by referring the severe environment's reliability to its equivalent in the baseline environment, as follows:

$$R_s(t) = R_b(t_s), \tag{4}$$

where $R_s(t)$ and $R_b(t)$ are the CDFs. The virtual age of severe environment referring to the baseline is:

$$t_s = V(t) = R_b^{-1}(R_s(t)). \tag{5}$$

On a discrete case, assuming that the system has a uniform CDF, then following equation can be stated at time t_i:

$$R_s(t_i) = R_b(t_{s,i}). \tag{6}$$

Then after a time interval Δt, we can obtain:

$$R_s(t_i + \Delta t) = R_b(t_{s,i+1}) = R_b(t_{s,i} + \Delta t_{s,i}), \tag{7}$$

where $\Delta t_i > 0$ is the cumulative aging factor during this time interval. Given that CDF is defined as $R(t) = \Pr[T > t]$, where T is the random variable, and assuming that a device survives at time t_x, then the probability it also survives after Δt follows the conditional probability:

$$\begin{aligned} R_x(\Delta t \mid t_x) &= \Pr[T > t_x + \Delta t \mid T > t_x] \\ &= \frac{\Pr[T > t_x + \Delta t]}{\Pr[T > t_x]} \\ &= \frac{R_x(t_x + \Delta t)}{R_x(t_x)} \end{aligned} \tag{8}$$

where R_x is the CDF in time [t_x, $t_x + \Delta t$). By substituting Equation (6) and (8) into Equation (7), we obtain:

$$\Delta t_{s,i} = R_b^{-1}(R_s(\Delta t_i)). \tag{9}$$

Equation (9) gives the iteration relationship of a severe system's virtual age, which is identical to the following equation:

$$\begin{aligned} V(t_n) &= t_0 + \sum_{i=0}^{n} R_b^{-1}(R_{s,i}(\Delta t_i)) \\ &= V(t_{n-1}) + R_b^{-1}(R_{s,n}(\Delta t_n)), \end{aligned} \tag{10}$$

where t_0 is the initial virtual age in case system's initial reliability is not 100%.

B. Virtual Age with Competing Failures

Generally speaking, multiple failure mechanisms are simultaneously active in an IC. These simultaneous failures can be modeled with a competing risk model, such that the system fails when a failure happens. In such a case the CDF of reliability can be expressed as:

$$R(t) = \prod_{i=1}^{n} R_i(t). \tag{11}$$

Then system's virtual age can be written as:

$$V(t_n) = V(t_{n-1}) + R_b^{-1}\Big(\prod_{j=1}^{m} R_{s,jn}(\Delta t_n)\Big). \tag{12}$$

TIME-TO-FAILURE ESTIMATION

A. TTF Based on Virtual Age

Generally, the end of an IC's operating lifetime can be defined as the time point when its failure rate accumulates to a certain value *n*:

$$D_n = TTF(n) = R^{-1}(1-n), or \int_0^{D_n} f(t)dt = n, \tag{13}$$

where *n* ranges from 0.001 to 0.05 depending on the IC reliability requirements. Thus, TTF as seen from the virtual age prospective can be expressed by:

$$TTF^n = D_n - VG = R_b^{-1}(1-n) - \sum_{0}^{n} \Delta t_{s,i}, \tag{14}$$

where $\Delta t_{s,i}$ is the virtual age increment in every time interval.

B. TTF Estimation

Given a time series of virtual age increments (an aging process), the TTF for real-life normal operation conditions can be obtained by reliability forecasting. To address the real-life operation time to failure, we create a time series data by comparing virtual age increment to the real time interval, which we call "time scale parameters" s_i:

$$s_i = \frac{\Delta t_{s,i}}{\Delta t}. \tag{15}$$

For real-life conditions, exponential smoothing is an option for on-line reliability modeling and short-term forecasting. The simplest exponential smoothing is given by the following equations:

$$\begin{aligned} L_0 &\equiv s_0; \\ L_n &\equiv \alpha s_{n-1} + (1-\alpha)L_{n-1}. \end{aligned} \tag{16}$$

However, simple exponential smoothing is not accurate enough when there is a trend in the data. Thus, double exponential smoothing, for the linear trend model has to be applied:

$$\begin{aligned} L_n &= \alpha s_n + (1-\alpha)(L_{n-1} + b_{n-1}); \\ b_n &= \beta(L_n - L_{n-1}) + (1-\beta)b_{n-1}, \end{aligned} \tag{17}$$

where { L_n } represents the smoothed value, { b_n } is the best estimate of the trend at time t_n ,α is the data smoothing factor, 0 < α < 1, β is the trend smoothing factor, 0 < β < 1.

Then an estimation of the time scale parameters at time t_{n+m} can be expressed as:

$$\hat{L}_{n+m} = L_t + mb_t \tag{18}$$

To begin the calculation, initial value can be estimated as:

$$b_1 = s_2 - s_1. \tag{19}$$

Applying the time series data described in Equations (15) to (18), we can estimate the "future scale parameter" $\hat{s}$, and then the TTF in real life operation conditions can be estimated as:

$$TTF = \frac{D_n - \sum_0^n \Delta t_{s,i}}{\frac{1}{l} \cdot \sum_{i=1}^{l} \hat{s}_{n+i}}, \tag{20}$$

which implies a mean degrading factor for future.

MODEL EVALUATION

To evaluate the model proposed, both stress accelerated testing data and normal operating data are required. We obtained accelerated testing data from the work in [3-6]. The related normal operating information was obtained by running simulation with the SESC simulator [9], and Monte-Carlo analysis was used to estimate the unknown parameters.

Figure 2 presents the simulated result for the stress and aging factors. One can easily observe that when compared with models using MTTF as reliability metric, the virtual age model captures the dynamic aging progress well, because virtual age accumulates according to the stress level dynamically. This characteristic makes the virtual age model suitable for lifetime reliability assessment and TTF prediction.

Figure 3 depicts the forecasted failure rate compared with the original accelerated test result. During an IC's normal servicing lifetime (failure rate less than 0.05), the predicted value is converging to the accelerated data gradually. When the number of failures inside IC circuits increases, the forecasted aging process trends to be more severe than what accelerated tests indicated. We note however that a pessimistic TTF prediction is preferable to an optimistic one for systems for which reliability is a main concern.

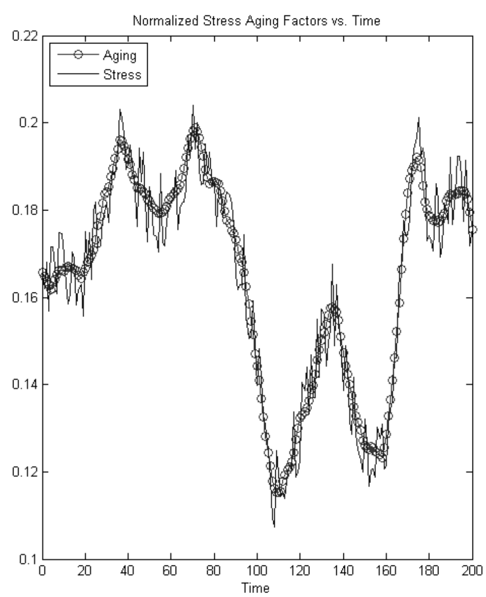


Figure 2. Normalized stress and calculated aging factors versus time. The results indicate that the proposed model captures the aging progress caused by stress well, especially when the stress trend changes smoothly.

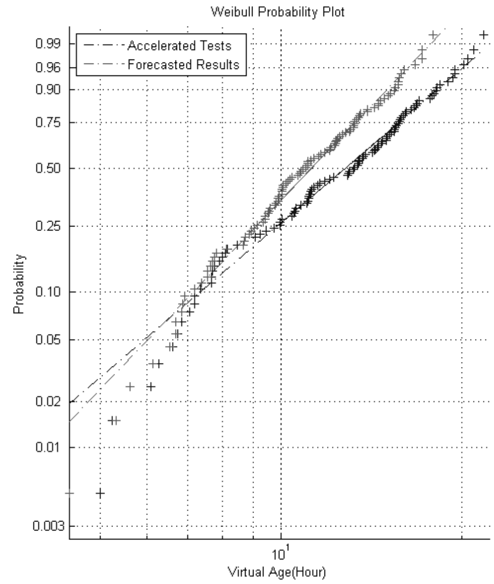


Figure 3. Forecasted failure rates compared to accelerated tests results.

CONCLUSIONS

Virtual age reliability model establishes a relationship between historical operating information and failure time of an individual IC. It provides the critical support for reliability-aware design and resource management. To improve the accuracy of prediction, more detailed reliability model like physics-of-failure based models should be introduced.

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