# 1 Introduction

Just as mechanical constructs have lifetime and reliability limits, electronic components in general, and semiconductor devices in particular, can fail when reaching their technical limits as well. This can lead to a malfunctioning or complete failure of the superior system, may it be a consumer product, a leading-edge industrial application, or a safety-critical system in cars and airplanes. In order to test the coverage of customer's requirements by the reliability limits of the device, reliability qualification is performed.

The current situation in reliability qualification and testing of semiconductor devices is challenging, because already well-established qualification test-plans are confronted with novel and more demanding lifetime requirements than ever before. Especially in the automotive sector, with its mega-trends of driver assistance systems, autonomous driving, electric mobility and car connectivity on their way into the market, new lifetime and failure rate requirements appear that are new to the automotive supply chain. Thus, qualification plans that have fixed test conditions and test times cannot withstand the current evolution. In conclusion, to satisfy the needs for adequate reliability qualification, new approaches are necessary and inevitable for assuring failure free products in the future.

> “*If an automotive* [*original equipment manufacturer (OEM)*] *goes to their tier 1 or 2 and asked for a system with a failures in time (FIT) rate of 1 per billion hours of operation, and you take an existing 100 million gate chip and place the same requirement on that supplier – we don't even really know what that means. How do I take a 100 million gate chip and determine that is has a FIT of 1 per billion hours of operation? When I first found out how this is being done today, I tried to turn off all of the electronics in my car. If that was how they determined that it was safe, then I was better off without the electronics.*”
>
> — Apurva Kalia, vice president of Research & Development in the System and Verification group of Cadence. [Bai18]

A step has to be made towards mission profile aware reliability and robustness validation, which is a thorough evaluation of all reliability aspects of the technology and product as well as the specific requirements imposed on it. This includes an advanced understanding and modeling of the real environmental and functional stresses on the product, a concept of time-saving and more elaborated testing, suitable reliability theory and models, and of course empirical validation of all the aforementioned.

**Chapter 2** provides the necessary foundations in the areas of statistical description of failure behavior and reliability predictions based on accelerated testing in order to enable the assessment of the reliability investigations and statements appropriately. The introduced concepts are clearly illustrated and pitfalls in the implementation are pointed out.

**Chapter 3** elaborates the presented methods on the basis of the failure mechanism of time-dependent dielectric breakdown. The current state of research on the failure physics and the methods used to investigate the reliability behavior of this mechanism are presented in detail. They are illustrated comprehensively on the basis of in-house measurements and in comparison with qualification data from a semiconductor manufacturer.

**Chapter 4** outlines the reasons for the importance of processing and evaluating mission profile based reliability requirements for the automotive industry and the fact that fundamental aspects have not yet been fully described and empirically verified. First using well-known cumulative damage models, the failure behavior of semiconductor components under alternating step-stresses is analyzed and essential differences are identified. The gained insights are then used to develop a method to transform mission profile stresses into effective stress conditions. This is demonstrated and proven by cyclical stress measurements for the stressors voltage and temperature, which were conducted for the first time. Furthermore, findings are made about the applicability of cumulative damage models that have not previously been reported in this context. Finally, the coupling of stressors in multi-dimensional mission profiles is examined in detail and the consequences of consideration and neglect of these interdependencies are clearly illustrated using a real-world example.

**Chapter 5** highlights the specific challenges that can be addressed using more sophisticated reliability testing methods. In particular, voltage ramp-stress testing can provide significant benefits for wafer level reliability in technology development and production. The individual stress transformation characteristics of the four voltage acceleration models used for dielectric breakdown are analyzed comprehensively and the implications for the scale and shape parameters of the ramped failure distribution are elaborated. Finally, the capabilities of ramp-stress measurements for model verification and parameter fitting are presented and compared to the standard methods currently used in reliability qualification.

**Chapter 6** concisely summarizes the results and contributions of this work. Potential fields for further research and new as-yet unsolved issues are identified and outlined.

# 2 Theory of Reliability Testing

To characterize a given component in terms of reliability prediction, an understanding of statistical distributions and reliability methodology is necessary. Hence, this chapter will give an introduction into the theory of reliability testing. Especially, the statistical methods and distributions used in this work will be described in detail.

For a greater insight into the topic of reliability, the works of A. Strong [Str09] and J. McPherson [McP19] are recommended as supplementary literature. As an excursion into statistical methods, the respective handbook of the American National Institute of Standards and Technology (NIST) [NIS13] is endorsed.

## 2.1 Statistical Description of Failures

To begin with, fundamental terms, definitions, and concepts are introduced to facilitate the understanding of the following chapters.

### 2.1.1 Basic Concepts of Failure Statistics

When expressing failure behavior in a mathematical way, the first encountered term is the failure function $F(t)$. It simply describes the probability that a device will fail at or before time $t$. It is expressed as cumulated failed percentage of a given population and is generally a continuously increasing function. Contrarily, the survival or reliability function $R(t)$ states the probability that a device has not failed and thus is still working until time $t$. Failure and survival are considered to be complementary by nature:

$$F(t) = 1 - R(t) \tag{2.1}$$

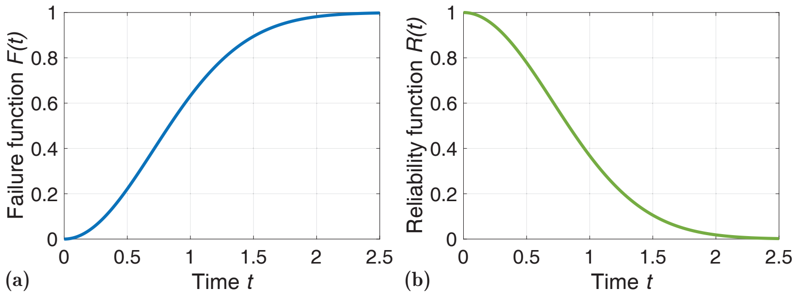



**Figure 2.1:** Complementary behavior of **(a)** the failure function and **(b)** reliability function for the same population.

Both functions are illustrated in Fig. 2.1 and exhibit function values ranging from 0 to 1 and vice versa, until the entire population has failed. [Str09]

Due to its cumulative behavior, the failure function $F(t)$ is also called cumulative distribution function (CDF). When explicitly talking about the empirically obtained failure function, the terms empirical CDF or empirical distribution function (EDF) are often used. As depicted in Fig. 2.2a, the EDF exhibits steps-like behavior due to the discrete nature of measured data. The CDF, whether derived theoretically or fitted from data, is usually displayed as a continuous function.

When failures are not described in a cumulative way but rather as failures in each period of time, the derived progression is called probablity density function (PDF) $f(t)$. It is the derivative of the CDF $F(t)$ and can be for example displayed as a histogram for empirical data:

$$f(t) = \frac{\mathrm{d}F(t)}{\mathrm{d}t} \qquad \text{or} \qquad F(t) = \int_0^t f(x)\,\mathrm{d}x \tag{2.2}$$

The PDF is usually the most encountered function when dealing with probability distributions in mathematical analysis because of its convenient properties as density function of the distribution (see Fig. 2.2b). [Str09]

Another important concept in statistics is that of the instantaneous failure rate (FR) or hazard function $h(t)$. It states the probability of the surviving specimens at time $t$ to fail within the next time frame. It is expressed as the PDF $f(t)$ divided by the remaining survivors, which is given by the reliability function $R(t)$:

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{R(t)} \tag{2.3}$$

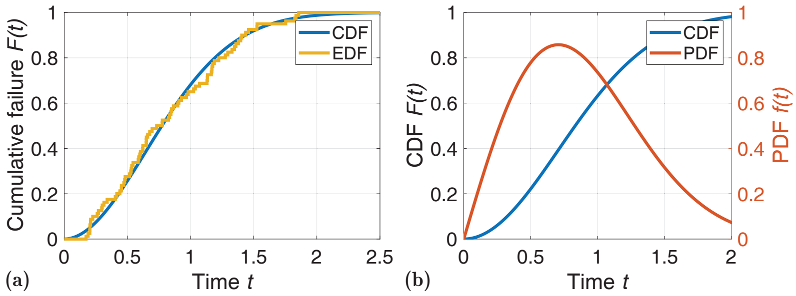



**Figure 2.2: (a)** CDF of a Weibull distribution and EDF of randomly generated data, often depicted as a stairstep graph. **(b)** CDF and its derivation PDF.

It is often used for describing the reliability behavior in certain time spans of a system's course of life or when fail probability of the current state and the immediate future is discussed. The most prominent application of the hazard function, the so-called *bathtub curve*, is described in the following section 2.1.2. [Str09]

For certain time frames, the average failure rate (AFR) $\langle h(t) \rangle$ can be an interesting figure of merit when comparing products from different suppliers for fails during equal time intervals, like the first year or the required lifetime of the component or system. The AFR is defined as the total number of fails within a given interval of time. In the reliability community, AFR represents a rate and is usually given in units of failures in time (FIT), which is fails per billion device hours ($^{10^{-9}}/_{\mathrm{h}}$):

$$\langle h(t) \rangle = \frac{\int_0^t h(x)\,\mathrm{d}x}{\int_0^t \mathrm{d}x} = \frac{1}{t}\int_0^t \frac{f(x)}{1-F(x)}\,\mathrm{d}x = \frac{1}{t}\ln\left[\frac{1}{1-F(t)}\right] \tag{2.4}$$

Along with the AFR, there is also a reciprocal expression of this rate called mean time between failures (MTBF) ($\mathrm{MTBF} = {}^{1}/_{\langle h(t) \rangle}$), which acts as a very important parameter for reliability statements as well.

The last concept in this introductory section will be that of the acceleration factor (AF). The dimensionless quantity AF is defined as the ratio between two failure times, often named time-to-failure (TTF), which are corresponding failure times of the same or different distributions:

$$\mathrm{AF} = \frac{\mathrm{TTF}_{\mathrm{nop}}}{\mathrm{TTF}_{\mathrm{acc}}} \tag{2.5}$$

In manner of speaking, the corresponding stress level of $\mathrm{TTF}_{\mathrm{acc}}$ is said to be AF-times more accelerated than the stress level under normal operating conditions of

$TTF_{nop}$ (if $AF > 1$). In case of $AF < 1$, the relation of these stress levels would be referred to as deceleration — or the fraction would simply be inverted in order to conform to the prior statement. The application of AF is universal and can be used for reliability requirements, measurements, and extrapolations alike. Hence, there is no consistent definition covering all individual cases.

### 2.1.2 The Bathtub Curve

The most used image for visualizing the reliability behavior of any system or device is probably the so-called *bathtub curve* for reliability. It depicts the relation of instant failure rate $h(t)$ to lifetime and consists of three different segments. These are shown in Fig. 2.3a–c as falling, constant, and rising regime, which give it, because of the bathtub-like appearance, its descriptive name. Regardless of whether semiconductor devices, living beings, or structural components are being described by this curve, generally speaking, these main characteristics apply to all statistical failure mechanisms.

The first segment on the left is the *early fails* or *infant mortality* region, named early failure rate (EFR). It is caused by production and manufacturing related (gross) defects that results in early fails of the devices even under normal operating conditions. The failure rate, which is often given units of FIT, is characterized by

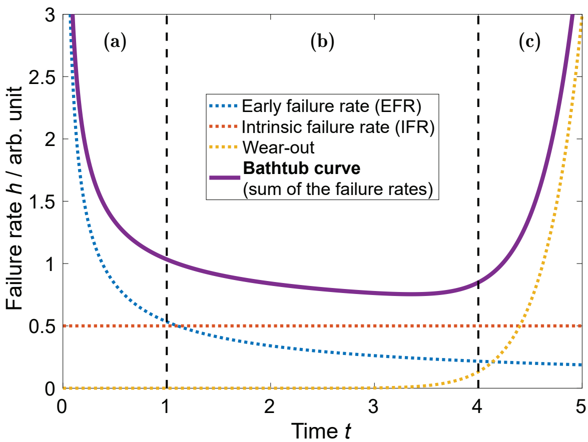



**Figure 2.3:** The *bathtub curve* has three distinctive regions (from left to right): **(a)** Infant mortality region with strongly decreasing EFR, **(b)** operating life with an overall low IFR, and **(c)** end-of-life when the wear-out failure rate increases until all specimens have failed.

a considerably high starting value and a following rapid decrease usually within the warranty period of the product.

In order to minimize the impact early fails have on customer satisfaction, one method for the manufacturer is to screen out such material and production defects by a so-called *burn-in* stress, where weak devices will fail under short and highly accelerated stress conditions. However, the burn-in conditions have to be precisely adjusted to not cause unnecessary degradation and premature aging of the remaining specimens. The other approach, more suitable for high-value products, is a specially tailored guarantee time to absorb the consequences of early fails after shipment to the customer. [Str09]

After the failure rate drop of the initial EFR regime, a stable and preferably low intrinsic failure rate (IFR) bottom segment of the bathtub curve emerges — this is considered the *operating life*. This area presents the maximal capabilities of the production and failures are due to intrinsic weaknesses, such as very small defects in the material [McP19]. While the characteristic of the IFR region is described as having a constant failure rate in general, the failure rate is usually slightly decreasing over the span of the operating life [Str09].

For obvious reasons, the operating life regime with the lowest failure rate should be extended as long as possible before the upcoming *wear-out* regime with a sharp increasing failure rate sets in. Even the best devices will start to fail at some point due to wear-out effects. This is not correlated to any manufacturing or preexisting material defects but rather the utmost achievable reliability of the used materials and design-rules under the experienced use conditions [McP19]. This region defines the *end-of-life* of the product as eventually all devices will fail. Therefore, the manufacturer strives to determine the onset of the wear-out accurately to ensure that the reliability requirements of the customer are met with a high degree of certainty.

In conclusion, understanding and subsequently controlling all three segments of the bathtub curve during product development is key to good product reliability.

### 2.1.3 Failure Distributions

When using the bathtub curve for reliability modeling, the curve's three regimes, i.e. *early fails*, *operating life*, and *wear-out*, feature different failure characteristics and can therefore be described by separate failure distributions. One distribution which is capable of modeling all regions of the bathtub curve is the renowned Weibull distribution.

### Weibull Distribution

In 1951, Waloddi Weibull published a distribution function with wide applicability and illustrated his claim with several examples. This included fitting data from yield strength and fatigue life of steel, fiber strength of cotton, and size distributions of fly ash, beans, and humans. Weibull was aware that this function is not always valid, but hoped for it to be of good service in some cases. [Wei51]

The Weibull distribution in its two-parametric form with scale parameter $\alpha$ and shape parameter $\beta$ is valid for times $t$ and parameters $\alpha$, $\beta$ all $> 0$ and given by the following formulas:

$$\text{PDF}: \qquad f(t) = \left(\frac{\beta}{\alpha}\right) \cdot \left(\frac{t}{\alpha}\right)^{\beta-1} \cdot \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right] \tag{2.6a}$$

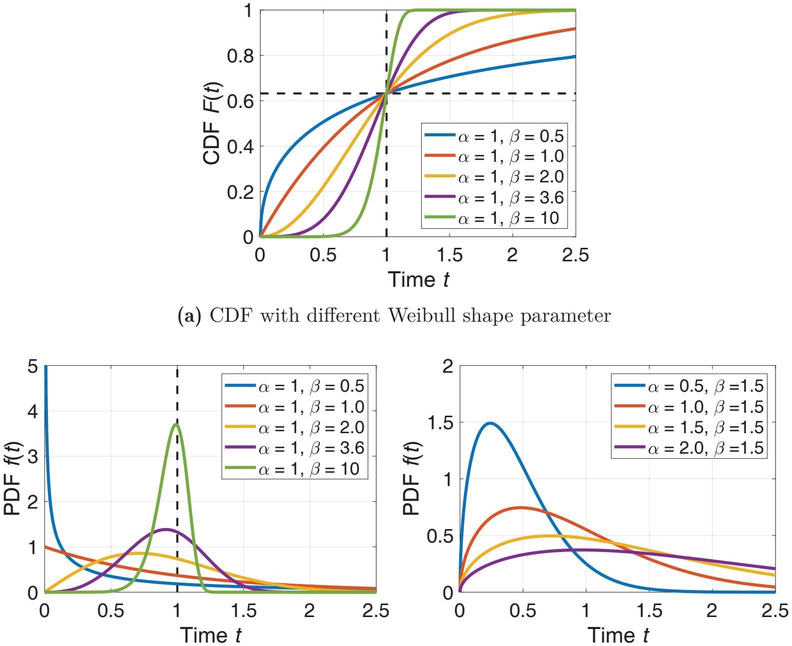
$$\text{CDF}: \qquad F(t) = \int_0^t f(x)\,\mathrm{d}x = 1 - \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right] \tag{2.6b}$$

$$\text{FR}: \qquad h(t) = \frac{f(t)}{1-F(t)} = \left(\frac{\beta}{\alpha}\right) \cdot \left(\frac{t}{\alpha}\right)^{\beta-1} \tag{2.6c}$$

$$\text{AFR}: \qquad \langle h(t)\rangle = \frac{1}{t}\ln\left[\frac{1}{1-F(t)}\right] = \left(\frac{1}{\alpha}\right) \cdot \left(\frac{t}{\alpha}\right)^{\beta-1} \tag{2.6d}$$

The scale parameter $\alpha$ is the pivot point of the distribution, as can be seen in Fig. 2.4a, and corresponds to the moment in time when $F(\alpha) = 1 - \exp\left[-\left({}^{\alpha}/_{\alpha}\right)^{\beta}\right] = 1 - \mathrm{e}^{-1} = 0.63212056\ldots$ and thus approximately 63 % of the specimens have failed by that time. The scale parameter $\alpha$ is therefore also known as $t_{\mathbf{63}}$. Due to the fact that $t_{\mathbf{63}}$ is independent of the shape parameter $\beta$, it is called the *characteristic life* of the Weibull distribution and also determines the spread of the distribution as depicted in Fig. 2.4c. Since $\alpha$ is a Weibull distribution specific parameter, it is usually used in the context of reliability and distribution modeling, whereas the denotation $t_{\mathbf{63}}$ is generally used to describe experimental data which are considered to be Weibull distributed. [Str09, Nel82]

Depending on the shape parameter $\beta$, the Weibull distribution can change its characteristics and can match or closely resemble other distributions, as can be seen in Fig. 2.4b. For the case that $\beta = 1$, the Weibull distribution reduces to a simple exponential distribution, for $\beta = 2$ it equates to the Rayleigh distribution, and for larger values $\beta \gtrsim 10$ it approaches the smallest extreme value distribution. In the mid-range of $\beta \approx 3.6$ the Weibull distribution can resemble the normal distribution with the largest deviation at about 8 % cumulated fails [Nel82]. Hence the Weibull shape parameter $\beta$ has the ability to produce left and right skewed distributions, which makes it quite convenient for fitting different reliability data of unknown nature as well as the different sections of the bathtub curve. As a rough guideline,




**(a)** CDF with different Weibull shape parameter

**(b)** PDF with varying shape parameter

**(c)** PDF with varying scale parameter

**Figure 2.4:** Different varying scale and shape parameters of the Weibull distribution. Vertical dashed lines indicate fixed $t_{63}$ lifetimes.

values of $\beta \leq 0.8$ suggest extrinsic failure mechanisms which most likely cause early fails and $\beta \geq 2.4$ typically indicates intrinsic wear-out mechanisms [JED16].

Primarily, the application and original purpose of the Weibull distribution is to model *weakest-link* type failure mechanisms and problems. That is the probability that a system made of many components, which are subject to the same failure distribution, fails due to the failure of a single part or segments — like a chain fails due to the failure of one of its chain links. Examples for Weibull distributed events are static or dynamic strengths, electrical insulation breakdowns in dielectrics, and even the death of living systems. The weakest-link model also applies to the reliability of assembled systems which will fail if a single component fails and thus can be described by the Weibull distribution. [Wei51, McP19, Str09, Nel82]

### Lognormal Distribution

The second important reliability distribution is the lognormal or logarithmic normal distribution. As the name indicates, it is derived from and in close relation to the normal distribution. If $Y$ is a normal distributed random variable, then $Z = \mathrm{e}^Y$ is lognormal distributed with the scale or median parameter $\mu$, and the shape parameter $\sigma$ [Str09]. The parameter $\mu$ is also called *log mean* and is therefore the mean of the logarithm of time $t$. The mean of lifetime, when 50 % of the population have failed, which is usually denoted as $t_{\mathbf{50}}$, is hence related to $\mu$ as $\mu = \ln(t_{\mathbf{50}})$ (see Fig. 2.5a). Analogously, the shape parameter $\sigma$ is called *log standard deviation* and is therefore the standard deviation of the logarithm of time $t$, which can be approximated by $\sigma \approx \ln(t_{\mathbf{50}}) - \ln(t_{\mathbf{16}})$. This of course implies that, unlike time $t$, the parameters $\mu$ and $\sigma$ are not times but instead dimensionless numbers [Nel82]. Note that the formulas and descriptions of the lognormal distribution in this work use the natural logarithm ln( ) whereas other authors may use the common logarithm log( ).

The distribution functions of the lognormal distributions are defined with positive $t$ and $\sigma$ [McP19, Bro12]:

$$\text{PDF}: \qquad f(t) = \frac{1}{\sigma t\sqrt{2\pi}} \cdot \exp\left[-\left(\frac{\ln(t)-\mu}{\sigma\sqrt{2}}\right)^2\right] \tag{2.7a}$$

$$\text{CDF}: \qquad F(t) = \Phi\left(\frac{\ln(t)-\mu}{\sigma}\right) \tag{2.7b}$$

with the standard normal distribution $\Phi$:

$$\Phi(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{t} \exp\left(-\frac{x^2}{2}\right) \mathrm{d}x \tag{2.8}$$

With this, the CDF of the lognormal distribution in Eq. (2.7b) can further be expressed as:

$$F(t) = \int_0^t f(x)\,\mathrm{d}x = \frac{1}{2} \cdot \operatorname{erfc}\left(\frac{\mu - \ln(t)}{\sigma\sqrt{2}}\right), \qquad \text{for } t \leq t_{\mathbf{50}} \tag{2.9a}$$

$$F(t) = \int_0^t f(x)\,\mathrm{d}x = 1 - \frac{1}{2} \cdot \operatorname{erfc}\left(\frac{\ln(t) - \mu}{\sigma\sqrt{2}}\right), \qquad \text{for } t \geq t_{\mathbf{50}} \tag{2.9b}$$

where erfc( ) is the error function complement erfc( ) = 1 − erf( ) and the error function is given as:

$$\operatorname{erf}(t) = \frac{2}{\sqrt{\pi}} \int_0^t \exp\left(-x^2\right) \mathrm{d}x \tag{2.10}$$