How to Define the Adequate Reliability Requirement for a Power Electronic System?

Reliability is a key design factor for the vast majority of power electronic systems. Lifetimes of 20 years and more are often required for power applications, while low failure rates during the useful life of a system are implicitly presumed. **Uwe Scheuermann, Product Reliability Manager, SEMIKRON Elektronik, Nuremberg, Germany**

System designers thus request component manufacturers to supply a Mean-Time-To-Failure (MTTF) values for power electronic components in the early design phase, often even before specific operational conditions are defined. The following discussion illustrates that an MTTF value can only be specified on the basis of all relevant application parameters on the one hand and that such a single value is not sufficient to describe the reliability of a system on the other.

The bathtub curve

As an example for the following discussion, we will use the common graphical representation of system reliability: the 'bathtub curve' (Figure 1). Such a bathtub curve is found in every textbook on reliability, however usually not with scaled axes. The bathtub curve is describing the reliability of a hypothetical power electronic system, constructed as the sum of three statistical Weibull distributions. The parameters of the Weibull distributions are for this hypothetical system are selected according to field experience according to equation 1:

$$f(t)=\frac{b}{T}\cdot\left(\frac{t}{T}\right)^{b-1}\cdot\exp\left(-\left(\frac{t}{T}\right)^{b}\right) \quad (1)$$

The probability density function f(t) of a Weibull distribution is determined by two parameters: the scale factor T and the shape factor b. The survival probability R(t) and the failure rate λ(t) can then be calculated by:

$$R(t)=\exp\left(-\left(\frac{t}{T}\right)^{b}\right) \quad (2) \quad \text{and} \quad \lambda(t)=\frac{f(t)}{R(t)}=\frac{b}{T}\cdot\left(\frac{t}{T}\right)^{b-1} \quad (3)$$

The construction of the bathtub curve by parameterized statistical distributions thus allows the calculation of the survival rates for each contribution as well as for the sum of all failure rates.

Contributions to the total failure rate

For the early life failures, the Weibull shape factor is <1 which results in a decreasing failure rate over time. Early life failures are related to process and assembly errors,

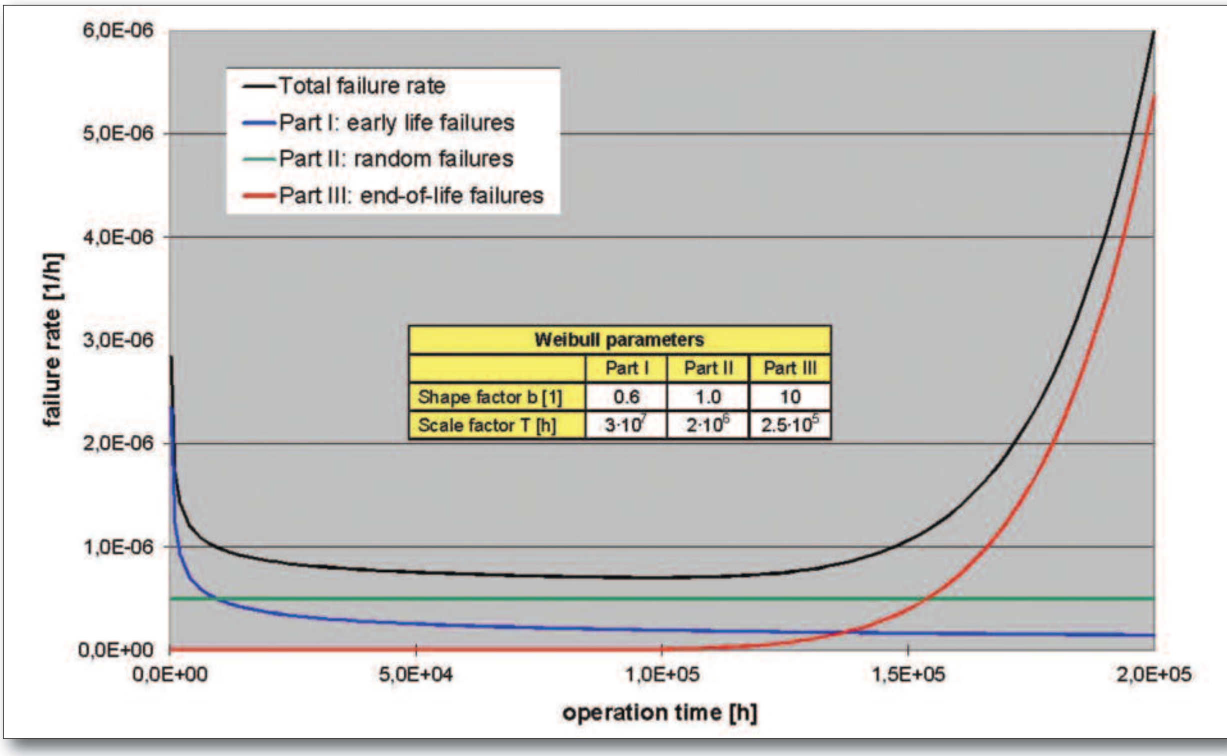

Figure 1: 'Bathtub curve' for a hypothetical power electronic system constructed as the sum of three Weibull distributions representing early life failures (blue), random failures (green) and end-of-life failures (red)

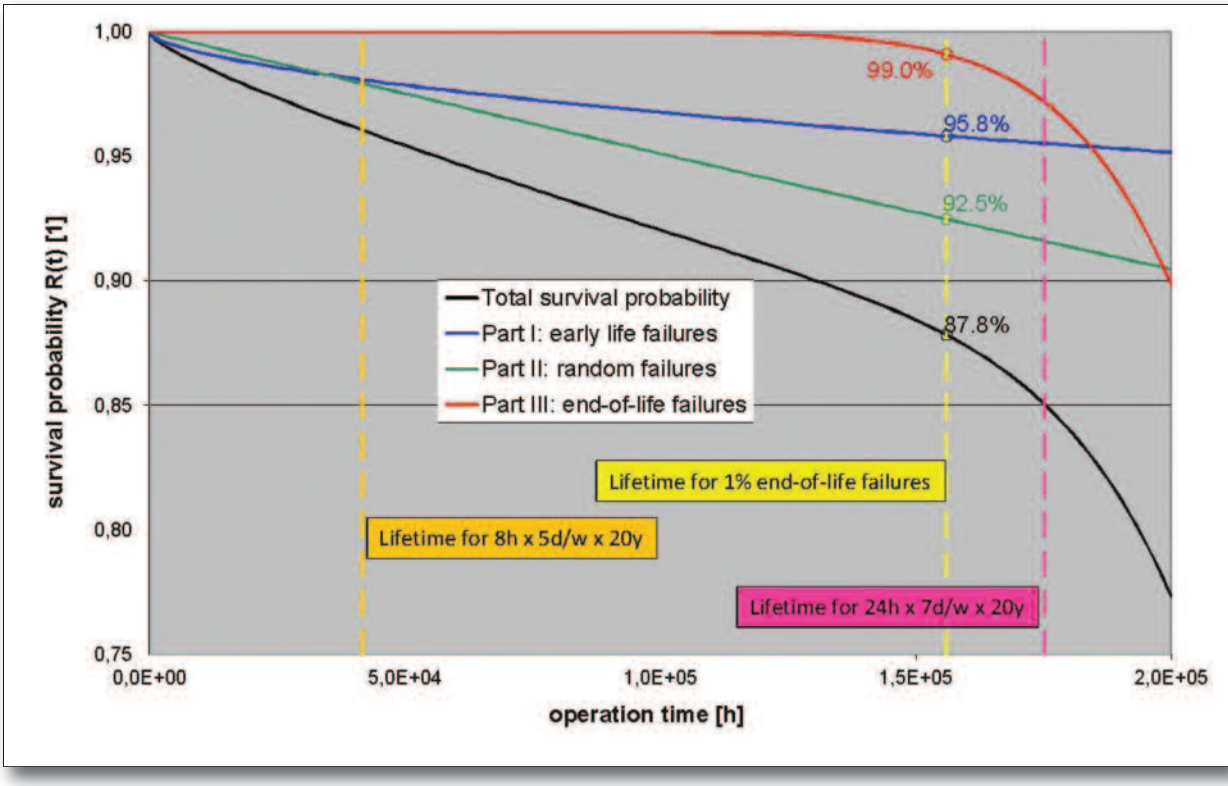

Figure 2: Total survival probability for the hypothetical system together with the contributions of the three Weibull distributions representing early life failures (blue), random failures (green) and end-of-life failures (red)

material defects and application related overstress, which result in a fatal destruction of the component. Since weak components are selected out of the population the failure rate associated to weakness of components decreases over time.

The second contribution represents random failures with a Weibull shape factor of 1. The root causes of these random failures are handling and maintenance errors and statistical physical failure causes. The cause of failure has its origin outside of the system and therefore generates a constant failure rate during the system lifetime.

The third contribution is describing end-of-life failures by a Weibull distribution with a shape factor >1. It comprises degradation, wear-out mechanisms and corrosion effects and thus increases towards the end of the useful life of the system. Since these aging mechanisms are generated by stress, the conditions of operation determine this failure rate.

On the commonly accepted assumption that these individual contributions are independent we can add up the failure rates and obtain the well-known bathtub curve shown in Figure 1.

The survival probability

Since we have constructed the bathtub curve for this hypothetical system by statistical distributions, we can now calculate the survival rate over time as shown in Figure 2. Using a common definition for the end of the useful life as the point in time when the end-of-life failures reach 1 % of the population, we find that for this hypothetical system the early life failures accumulate to 4.2 % and the random failures contribute with 7.5 %, thus resulting in a total survival rate of 87.8 % after an operational interval of 156,000h.

Figure 2 visualizes the impact of time of operation on the survival rate. If the application is operating 24 hours, 7 days a week for 20 years, a useful life of 175,000 hours is required which would result in a total survival probability of 85 %. If, however, the system is operating 8 hours, 5 days a week for 20 years, this would require only 41,000 hours with a survival probability of 94 % for the hypothetical system.

End-of-life failures

End-of-life failures result from the repetitive stress generated in a component by the application conditions. Considerable effort has been invested in the investigation of the physical failure modes and technology improvements to increase the component lifetime are continuously developed. Lifetime models, which are derived by extrapolation from highly accelerated laboratory tests, are used to estimate the useful lifetime of a system.

The strong focus on these end-of-life failures resulted in the proposal of health monitoring facilities, which will warn the user before a failure occurs by evaluating parameter shifts caused by degradation. However, even if such a facility would be able to detect all end-of-life failures before occurrence, no early life failures and no random failures would be detected. For our hypothetical system, less than 10 % of the total system failures would be detected by a health monitoring system, which would hardly be acceptable.

Random failures

Besides handling and maintenance errors, which can potentially be avoided by appropriate measures, the random failure rate includes statistical physical failure modes. A significant contribution to this group of failure modes is the 'single event burn-out' (SEB) caused by cosmic rays. The theoretical description of this effect, which was first identified in the early 1990s, is well understood today. A high energy particle that hits the silicon device in blocking mode can destroy the device without any precursor. Therefore, it is impossible to detect these SEB events by health monitoring. The DC-link voltage has a major impact on this failure rate. A state-of-the-art 1200 V IGBT exhibits a failure rate in the range of 1..10 FIT/cm^2 for a blocking voltage of 840 V at sea level and room temperature, it will rise by an order of magnitude for a blocking voltage of 900 V. The unit FIT is equivalent to 1 failure in 10^9 hours.

Especially for high power applications

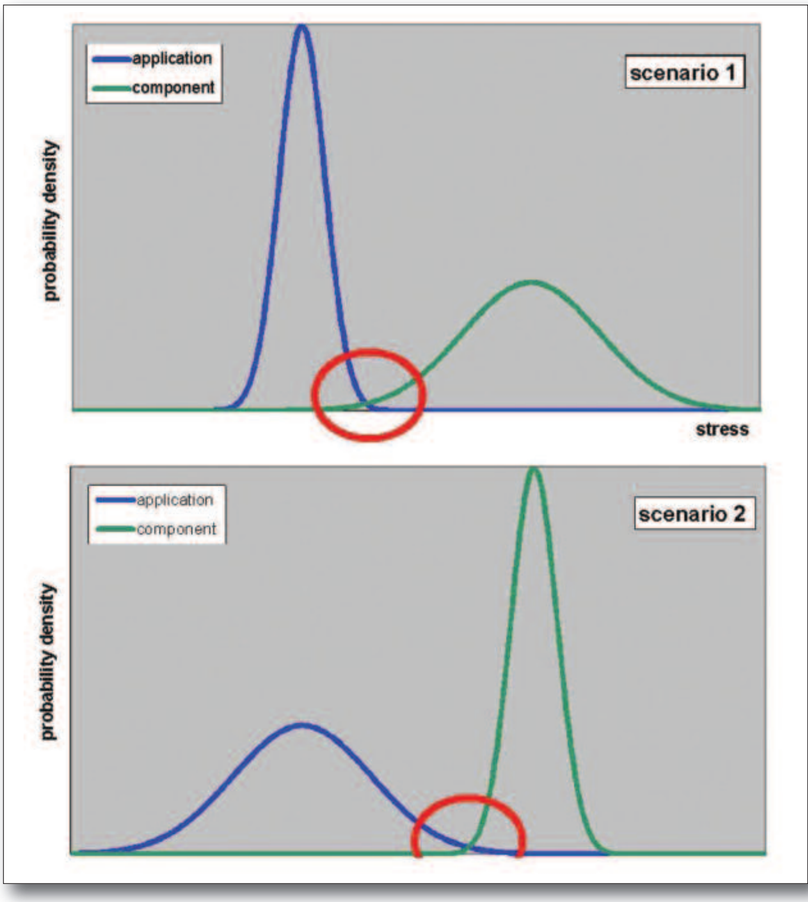

Figure 3: Comparison of application stress demand and component stress capability: Scenario 1 (top) shows a well-defined application and a component with a large variation of stress capability, while scenario 2 illustrates a well-defined component with a wide distribution of stress for individual instances of the application

containing 100 chips and more, the constant failure rate can easily reach values of 500 FIT or 0.5 ppm as in our hypothetical system. Since cosmic rays cannot be shielded by any practical means, the only way to reduce this failure rate is to reduce the DC-link voltage.

Early life failures

Early life failures are also a significant contribution to the total failure rate. While continuous improvement programs can reduce tolerances and process flaws, these failures cannot be completely eliminated. A burn-in test is necessary to further reduce this failure mode for high reliability applications. Such a test is stressing the component under worst case operational conditions for a limited time interval. Since the stress applied during burn-in testing is imperatively reducing the useful operational life of the component, its duration must be limited. The trade-of between lifetime reduction and reduction of the early life failures prevents the elimination of all early life failures.

The MTTF value

The MTTF value combines all the previously discussed failure modes into a single parameter that specifies the component reliability. It is by definition the expectation value for a component failure, reflecting both the component capability and the application stress demand. Therefore, it is not possible to determine a specific MTTF value for a component without taking into account the application conditions.

The detailed discussion of the different contributions to the failure rates shows, that this single value contains only limited information. It can be shown, that different bathtub curves with diverging failure contributions can result in the same MTTF value. Moreover, a bathtub curve with a smaller MTTF value can result in higher failure rates of the application. Therefore, the statement of a single MTTF value is not sufficient to characterize the reliability of a system.

Relation between application demand and component capability

So far, we have focused the discussion on the component stress capability in a system application. However, application related overstress is also contributing to the total failure rate. It can contribute to early life failures in case of a fatal stress condition - for example if the blocking voltage is exceeded - or it will affect the end-of-life failure rate if the impact is not fatal, for example by an increased temperature swing. Therefore, the relation between statistical distribution of stress capability of components and the statistical distribution of stress requirement by the individual application are fundamentally relevant.

This is illustrated in Figure 3 which shows the statistical distribution of component stress capability together with the statistical distribution of stress requirement by the application. Whenever a component with a low stress capability will be operating in an application with a high stress demand, indicated by the overlap of both distributions, an impact on the system reliability must be expected.

Often, scenario 1 is implicitly associated with such failures: The application conditions are clearly defined, but a fraction of the component population will not fulfill the requirement.

However, the same result must be expected when the component stress capability is statistically well defined, but the application stress demand shows a wide variation as depicted in scenario 2.

The knowledge of the statistical distribution of stress demand by an application is part of the core competence of the system designer. The better the knowledge about the stress demand, the higher the potential of designing systems with a well-defined reliability. If the distribution of stress demand is known, then the system designer can decide on the stress level that should be required over the useful operational life. A system designer can chose to fulfill the stress demand even for the highest demanding application, but this will possibly impact the commercial success of his product. Imagine a car manufacturer, which will design his car for a twenty years lifetime as a taxi. Of cause, all taxi drivers will be very happy with such a high reliability, but the other 95 % of the customers will have to pay for a reliability level they do not need. The decision of the reliability level is thus a genuine task of the system designer.

A well-defined reliability is of fundamental importance for a successful system design. It comprises much more than a simple statement of MTTF values; it is achievable only by close cooperation between the system designers and the component manufacturers. It must bring together the knowledge on stress demand by the applications and the stress capability of the components in a close relationship between system and component manufacturers. And it must finally be validated by field experience.