Risk Based Reliability Demonstration Test Planning for Decision Making Under Uncertainty

Martin Dazer[a], Alexander Grundler[a], Philipp Mell[a], Achim Benz[a] and Marco Arndt[a]
[a]Institute of Machine Components, University of Stuttgart, Stuttgart, Germany,
dazer@ima.uni-stuttgart.de

Abstract: Reliability assurance by empirical data collected from lifetime tests is always subject to uncertainty and thus to a risk of making wrong decisions. The type-I statistical error is quantified and minimized over the generally known confidence interval to ensure that the reliability of the population in field operation is valid. The type-II statistical error quantifies the risk of a failed reliability test and thus the risk of the product developer. A failed test generally means further iteration loops in the verification process and should be avoided accordingly. However, in the context of reliability demonstration, the type-II error is often neglected and consequently it is not known how high the probability of successful reliability demonstration is with the chosen test strategy. In this paper, a method is presented that allows a calculation of the type-II error based on prior knowledge, which is called probability of test success (P_{ts}). P_{ts} enables the objective comparison of available test strategies for scenarios with a wide variety of boundary conditions such as accelerated testing, system and component testing or different reliability targets. In the end, the test strategy and the required number of specimens can be determined, which has the lowest remaining risk under the available budget.

1. INTRODUCTION

In reliability engineering and especially in reliability demonstration, life tests are still used because failure mechanisms of new technologies cannot be fully understood and thus cannot be described physically. I.e. there is always the problem that the limited information from the sample must be transferred to the population [1]. This lack of information in the sample poses a challenge to engineers because there is always uncertainty in decision making [2]. It is not possible to simply use a point estimator, because the information only corresponds to a certain confidence level, most of the times to 50 %. Especially for reliability demonstration, this confidence is much too low to send thousands of potentially safety-critical products into field operation. In order to safeguard against the worst case, interval estimators are used consequently, which have a confidence interval as their result [1]. From a statistical point of view, this concerns the type-I error. For the calculation of the confidence interval, many different approaches are known as state of the art. Thus, approximative solutions like the Fisher confidence interval or numerical-simulative methods like bootstrapping exist to estimate the confidence interval [4]. The risk of misestimation can thus be reduced to a defined and acceptable level and prevent from disastrous field failure behavior. With this, the customer risk can be limited.

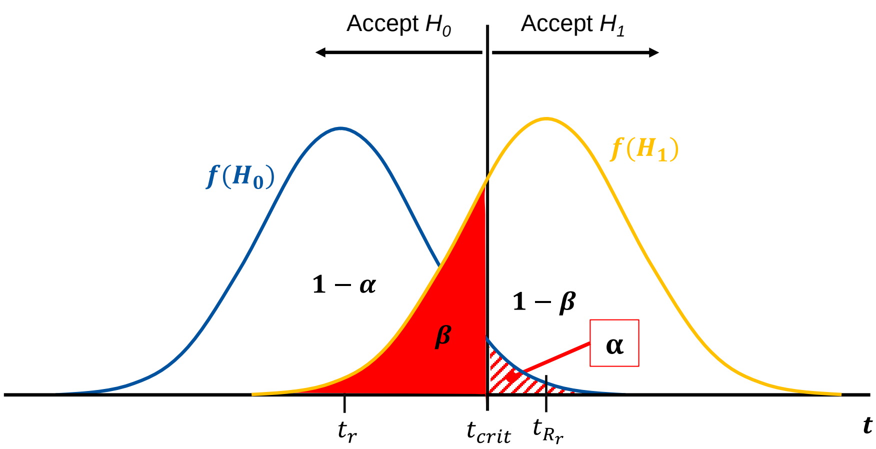
From a statistical point of view, we know that in addition to the type-I error, there is also the type-II error [3]. The uncertainty of the tested sample also affects directly the life test itself, which means that wrong decisions are made due to uncertainty in testing. Imagine that a test strategy with only 3 specimens is chosen to demonstrate a very high reliability target. It is obvious that the probability of this test being able to achieve the desired target will be very small even without doing any mathematical calculation.

In contrast to the type-I error, procedures and calculation approaches for the type-II error are almost completely missing in reliability demonstration. Although, it is established practice e.g., in the area of Design of Experiments (DOE). Few calculation approaches for the type-II error exist, which are also by no means able to deal with different boundary conditions. Beside the approaches of DOE like e.g., from Montgomery, some few approaches by Meeker exist, but only for zero failure testing [3,4]. However, calculating the type-II error is almost inevitable to determine a suitable test strategy for the corresponding reliability target. In addition to many available test strategies that differ greatly in their essence, the risk of a failed test must also be calculable in order to keep it to a minimum. Without considering the uncertainty of the sample for decision making, a failing test would almost exclusively lead to classifying the tested product as inadequate. This is due to the uncertainty allowing the possibility for the test to fail, although the product meets the reliability requirement in reality. Such a failed decision results in unnecessary additional development stages and increased time to market [5]. Furthermore, it can motivate unnecessary oversizing of products and therefore increase the carbon footprint as well as the product development cost.

2. PROBABILITY OF TEST SUCCESS FOR DECISION MAKING UNDER UNCERTAINTY

From the considerations described, it can be deduced that life tests are statistical tests with non-normally distributed data. The planning and the results of the tests can therefore be treated and evaluated as hypothesis tests [6]. From the reliability demonstration point of view, the test is "only" performed to collect data that shows the product meeting the reliability target. From the classical hypothesis testing point of view, it should be shown that the product is as least as good than the requirement or the null hypothesis. Plotted on the life scale, the dependencies are shown in Fig. 1. The blue line shows the distribution of lifetimes under validity of the null hypothesis H_0 with the required lifetime t_r, the yellow line shows the distribution under validity of the alternative hypothesis H_1 of the test results t_{R_r}.

Figure 1: Life tests for reliability demonstration from a hypothesis testing point of view



The null (H_0) and alternative hypotheses (H_1) can be expressed in terms of the corresponding life values. The null hypothesis represents the developmental starting point, where the developers do not know whether the product will achieve the required service life t_r or not. Accordingly, the worst case has to be assumed, saying that the service life actually achieved t_{R_r} falls short of the required service life t_r. The null hypothesis is then written as:

$$H_0 \colon t_{R_\mathrm{r}} < t_\mathrm{r} \tag{1}$$

The life tests are performed in order to be able to reject the null hypothesis with the help of the empirical life data. At the same time, the alternative hypothesis is accepted, which consequently confirms that the product meets or exceeds the required service life:

$$H_1 \colon t_{R_\mathrm{r}} \geq t_\mathrm{r} \tag{2}$$

Confidence results from the complement of the significance level α to:

$$C = 1 - \alpha \tag{3}$$

and has been generally known under this term.

Since the hypotheses in the context of the reliability demonstration can always be written in the same way, the statistical power of such a reliability demonstration test was defined as the Probability of Test Success P_ts [2, 6] for better comprehensibility and in analogy to the confidence C. P_ts can be written as:

$$P_\mathrm{ts} = 1 - \beta \tag{4}$$

According to Dazer et al. [2, 7], P_{ts} is the probability with which a reliability test is able to demonstrate the required service life of a product with given reliability and confidence. Therefore, it is linked to the remaining risk of the manufacturer or producer. With this consideration, the planning of reliability tests corresponds consistently to the hypothesis testing idea thought. Both the risk for the type-I error (field risk) and that for the type-II error (test risk) can be quantified. Both risks can be used accordingly in the context of development activities. Similar to the context of DOE, the confidence interval is used for field assurance while the P_{ts} serves as a basis for effort planning and selection of the best test strategy. As an objective measure of risk, it can be used to compare different testing strategies such as end-of-life testing, zero failure testing, etc., including the required sample size.

2.1. Risk based end-of-life test planning

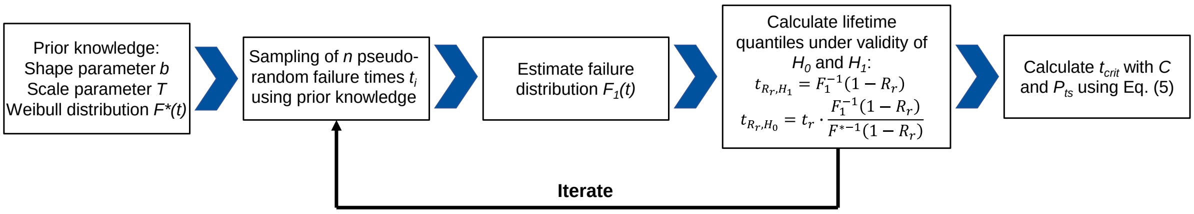
The P_{ts} can be calculated for a given sample size as the integral of the distribution function of the alternative hypothesis H_1 [8].

$$P_{\mathrm{ts}} = \int_{t_{\mathrm{crit}}}^{+\infty} f_{H_1} \, \mathrm{d}t_{R_{\mathrm{r}}} \tag{5}$$

In Eq. 5. t_{crit} is the lifetime quantile linked to the selected confidence level. However, the distribution of the alternative hypothesis is required for the calculation, which makes the planning of End-of-Life (EoL) tests more complex than for the zero failure tests, see section 2.3. This is due to the scattering failure times, which means that the test time also scatters and thus the costs incurred must be statistically evaluated in the planning process. Since the exact same failure times never occur, a slightly different test result is always obtained - even if the test is performed with exactly the same conditions and sample size. Due to the scattering failures, the confidence interval also scatters. Therefore, no exact sample size can be determined for which the requirement can be demonstrated with 100 % confidence [8].

For the reasons mentioned above, prior knowledge about the expected failure behavior is required for test planning to give an estimation about the test result. Predecessor products, simulations or expert estimates can be used for this purpose. To calculate the P_{ts} for a given test configuration of an EoL test, the test is simulated multiple times using a Monte-Carlo-Simulation. With a parametric or also non-parametric bootstrap approach, the distribution functions of the null and alternative hypothesis are determined. Fig. 2 shows the procedure for the calculation with Parametric Bootstrap, i.e. the prior knowledge is available as distribution function (in this case Weibull distribution). When the prior knowledge is coming directly out of a sample than non-parametric bootstrap should be applied.

Figure 2: Parametric Bootstrap Approach for the Calculation of P_{ts} of an EoL Tests [8]



The procedure starts with prior knowledge. Prior knowledge is always linked to the alternative hypothesis H_1. If it were already apparent that the reliability requirement cannot be met by prior knowledge, a life test would be obsolete. From the prior knowledge, which in this case is available as a Weibull distribution $F^*(t)$, n pseudo-random failure times are generated. The sample size corresponds to that of the test to be planned. From these pseudo-random numbers, which then represent simulative failure times, the failure distribution $F_1(t)$ is determined. From this, the lifetime quantile corresponding to the required reliability t_{R_{r},H_1} can be calculated in the next step under the validity of the alternative hypothesis. Since the estimated failure distribution $F_1(t)$ contains the uncertainty of the sample, a Monte Carlo iteration is performed until the remaining numerical error is small enough. Finally, a calculated lifetime quantile is available from each iteration, describing the distribution of the test result (alternative hypothesis). The lifetime quantiles of the null hypothesis H_0 are calculated using the location of the alternative hypothesis and the lifetime requirement t_r. Since the lifetime requirement is connoted with the null hypothesis, the random numbers already generated can be shifted [6, 8]. Since only the location of the lifetime quantiles should be changed, they are shifted by the ratio of lifetime requirement t_r and estimated lifetime from the prior knowledge $t^* = F^{*-1}(1-R_r)$, so that the following applies:

$$F_0^{-1}(0{,}5) \mathrel{\widehat{=}} t_r \tag{6}$$

Because the real reliability is obviously unknown we assume that the information from prior knowledge is a good estimate, stating that:

$$t_r(1-R_r) \cong t^*(1-R_r) \tag{7}$$

The ratio of lifetime requirement and assumed attainable lifetime from prior knowledge can also be referred to as design safety margin, since it relates requirement and real attainable service life (assuming correct prior knowledge) [2]. The design safety margin can be expressed and calculated as the following:

$$S = 1 - \frac{t_r(1-R_r)}{t_{real}(1-R_r)} \tag{8}$$

with $t_{real}(1-R_r)$ being the real but unknown lifetime of the product for required reliability R_r.

Even if the Monte Carlo simulation means a high computational effort, it has the advantage that all test configurations can be simulated and there are almost no restrictions. Different censored tests can be easily represented in an analogous way to the EoL test. Special test rig conditions or other infrastructural restrictions can also be represented with the Monte-Carlo-Simulation of the test. Resulting duration and cost of the test can be supplemented by the required specimens and the running times.

2.2 Risk based accelerated end-of-life test planning

A test with equivalent field load is not possible for all products. This applies in particular to products with very long service lives for which it is not possible to accelerate sufficiently in time. In these cases, acceleration by using an increase of load is necessary. The test load is therefore deliberately increased in order to provoke failures more quickly. With the help of the determined lifetime model, it is possible to extrapolate the demonstrated lifetime to field load, which can be used for reliability demonstration as well. The method of P_{ts} has also been extended for accelerated reliability demonstration tests. In essence, the calculation of P_{ts} is based on the approach in Fig. 2, but the lifetime model of the particular failure mechanism must be taken into account [9].

Many lifetime models such as Wöhler and Arrhenius can be described as straight lines by logarithmic transformation. While the shape parameter must still be estimated as a variance measure, the scale parameter is now dependent on the load and can thus be expressed as a function of the lifetime model. For the log-linear case, the following applies:

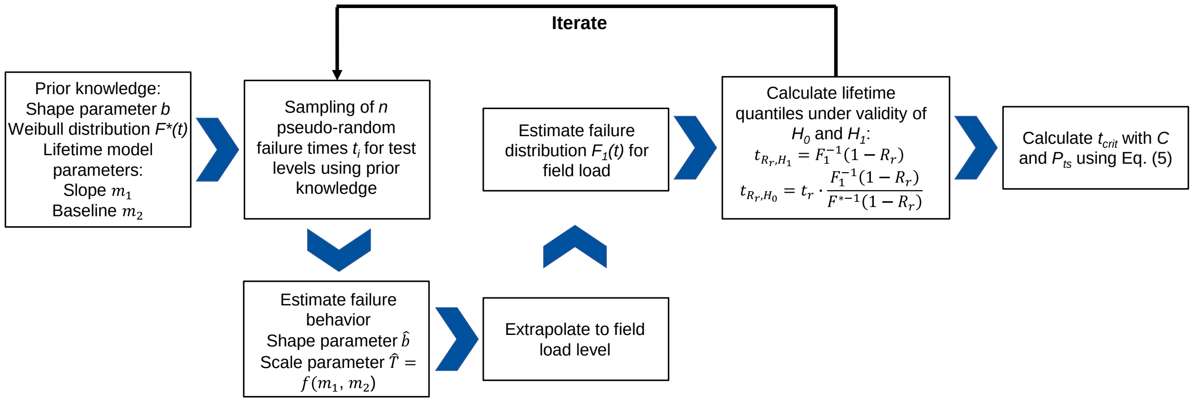
$$\ln(T) = \ln(m_2) - \ln(B) \cdot m_1 \tag{9}$$

In Eq. 9, m_2 is the baseline, m_1 is the slope parameter, and *B* is the acceleration variable. The likelihood function for Weibull distributed failure times with shape parameter *b* just needs to be extended for the estimation for all load levels of the acceleration variable *B*.

$$\ln L = \sum_{i=1}^{n} \ln\left(\frac{b}{m_2 \cdot B^{-m_1}} \cdot \left(\frac{t_i}{m_2 \cdot B^{-m_1}}\right)^{b-1} \cdot e^{-\left(\frac{t_i}{m_2 \cdot B^{-m_1}}\right)^b}\right) \tag{10}$$

The test planning procedure is shown in Fig. 3. It starts once again with the prior knowledge, this time extended by the lifetime model. Pseudo-random failure times are then generated for the specified increased test levels. From these, the parameters of the lifetime model and the shape parameter are determined from the likelihood function, see Eq. 10. The estimated lifetime model is then extrapolated to field load level. Thus, the model can be used to determine the field-level failure distribution $F_1(t)$ corresponding to the alternative hypothesis. Since the sampling error needs be considered as well, iteration must also be performed in a Monte-Carlo-Simulation. The remaining procedure is identical to the test planning on field load level. Due to the large number of parameters, the question quickly arises of how to select them for optimal test planning. Especially the location of the test levels and the allocation of the specimens to them have a significant influence on the P_{ts}. Herzig examined accelerated test planning in great detail in his work in a parameter study and gives general recommendations for application [9, 10, 11].

Figure 3: Parametric Bootstrap Approach for the Calculation of P_{ts} of an accelerated EoL Tests



2.2 Risk based zero failure testing

The Success Run Test is the best-known representative of the zero failure test procedures and is used very frequently in practice. It is a test with predefined running times to provide reliability demonstration, i.e. to verify that the product or system has a certain minimum reliability. It is common that no failure is expected during test run, therefore it is called Success Run Test. The Success Run Test could therefore also be seen as a special case of a right-censored test, where all test items are censored, i.e. all specimen are still intact at end of the test time.

In contrast to EoL test strategies, the Success Run Test cannot be used to make statements about failure behavior. Since the test should have only few or no failures, no life data analysis can be performed and thus no lifetime distribution can be determined. For this reason, the Success Run Test is also limited to reliability demonstration, because it is used exclusively to verify a minimum level of reliability and can thus only confirm reliability requirements. This may sound like a minor limitation, but in fact it has quite far-reaching constraints, because no statement can be made about the actual location (scale) of the service life with Success Run Testing.

Reliability demonstration is based on the binomial distribution with binary classification. Confidence is calculated as:

$$C = 1 - \sum_{i=0}^{f} \binom{n_{SR}}{i} \cdot \left(R_r(t_r)\right)^{n_{SR}-i} \cdot \left(1 - R_r(t_r)\right)^{i} \tag{11}$$

Success Run is only able to estimate reliability, lifetime cannot be determined. Therefore, the hypotheses for calculating P_{ts} cannot be defined on the lifetime scale. Thus, reliability is used for defining the hypotheses [8]:

$$H_0 : R(t_r) < R_r(t_r) \tag{12}$$
$$H_1 : R(t_r) \geq R_r(t_r) \tag{13}$$

The binomial distribution can also be used to calculate the P_{ts}. However, instead of using the requirements, the estimated failure probability or reliability at test time of the products is used coming from prior knowledge. Thus, one calculates the total probability that all test items survive the test according to their probability of survival at test time coming from prior knowledge $R^*(t_r)$. The P_{ts} is given by [5]:

$$P_{ts} = \sum_{i=0}^{f} \binom{n_{SR}}{i} \cdot \left(R^*(t_r)\right)^{n_{SR}-i} \cdot \left(1 - R^*(t_r)\right)^{i} \tag{14}$$

n_{SR} being the necessary sample size for reliability demonstration using the Success Run Test. If planning is done without tolerating failures, Eq. (14) reduces to:

$$P_{ts} = \left(R^*(t_r)\right)^{n_{SR}} \tag{15}$$

The reliability of the required service life can be calculated from prior knowledge. If this is available as a Weibull distribution, the result is:

$$R^*(t_r) \approx e^{-\left(\frac{t_r}{T^*}\right)^{b^*}} \tag{16}$$

with T^* and b^* being scale and shape parameter of the prior information Weibull distribution.

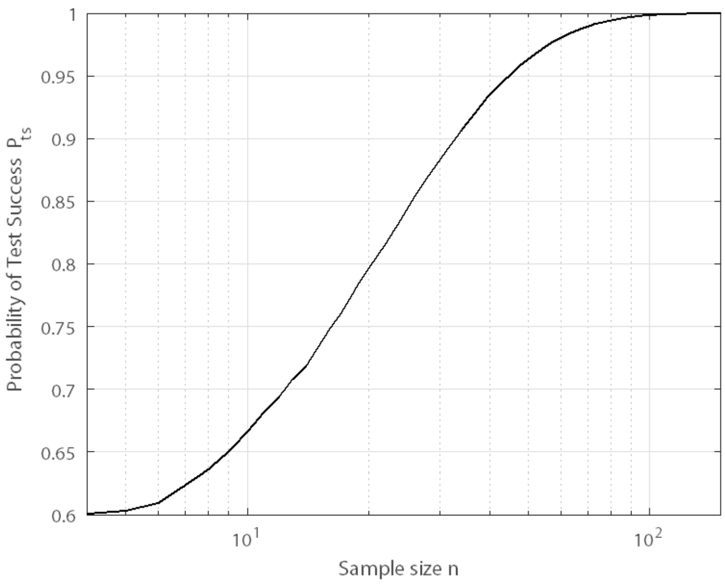
3. CASE STUDIES FOR RISK-BASED DEMONSTRATION TEST PLANNING USING P_{ts}

The scope of the study of optimal test planning is very large due to the large number of influencing factors. For example, reliability objectives (R, C, t_r), prior knowledge, design safety margin and many other parameters can change. For this reason, Mell trained neural networks for universal application of risk-based test planning [12]. In the following, the possible applications of risk-based test planning are illustrated using specific scenarios.

3.1 End-of-life test planning

In an investigation, the necessary sample size is usually needed at first, with which it is possible to demonstrate the reliability target with sufficient probability.
Reliability demonstration is to be carried out for a gearwheel. The reliability requirement for tooth fracture is R = 90 %, C = 90 % with $t_r = 2$ million revolutions. An EoL test should be used for demonstration purpose. The failure behavior can be estimated by early prototype testing with $b = 3$ and $T = 6{,}060{,}606$ revolutions and thus serves as prior knowledge for test planning. Since the prototype does not represent the final production status and the production has been adjusted, the prototype tests cannot be used to demonstrate reliability. However, this prior knowledge is very useful for planning the reliability demonstration test. For an EoL test, the Bootstrap approach from Fig. 2 is used to obtain the curve of the P_{ts} as a function of the sample size, shown in Fig. 4.

Figure 4: Probability of Test Success for different sample sizes of an EOL test



With this result, the necessary sample size can now be determined for the individual accepted risk of a failed test. In this context, a failed test means that reliability demonstration for the requirements cannot be provided. However, it should be noted, that a failure of the EoL test can be corrected very easily by performing a few additional tests. To achieve a P_{ts} of 80%, at least 21 specimens are required.

For comparison, if a Success Run test were planned, 22 specimens would be needed for demonstration, see Eq. 11, but the P_{ts} would be only 45.4% and would not be suitable in this case. Realizing that the Success Run is unsuitable here is only possible using the concept of P_{ts}. However, it remains to be verified that the 21 specimens of the EoL test can be run to failure by the available budget. For this purpose, the simulated failure times can be used for estimation. For example, if it is concluded that the test budget would be used more than 50% of the time, a censoring time could be introduced if necessary to limit the run times of the specimen and thus reduce the run time costs. However, this could change the required number of specimens for a consistently high P_{ts}.

3.2 Accelerated test planning

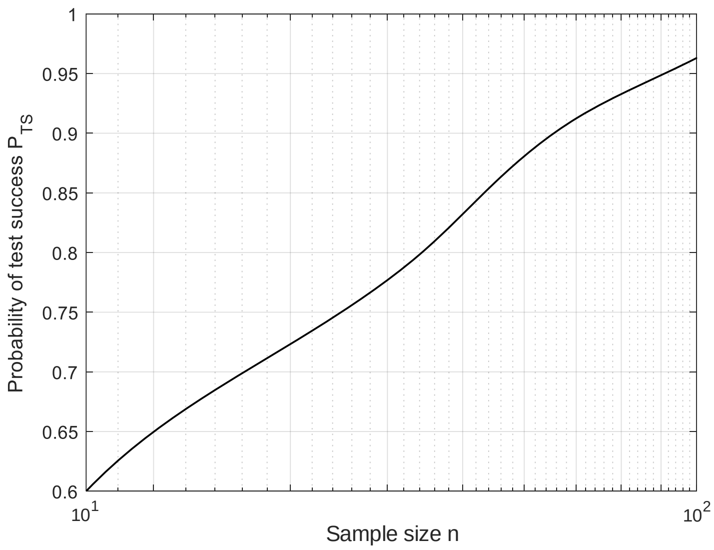
For the example shown above, in addition to the EoL test with field load, an accelerated test can also be used for the reliability demonstration. For this, the P_{ts} is calculated using the procedure in Fig. 3. The reliability target remains the same and a Wöhler exponent of $k = 5$ was assumed. The field load level and the test load levels are given in normalized notation to:

$B_{Field} = 1$
$B_{Test,1} = 1{,}2$
$B_{Test,2} = 4$

The normalization basis is the field level with $B_{Field} = 1$. The low load level is tested with 1.2 times the field load. The high load level at 4 times the field load. According to Herzig's recommendations, 60% of the specimen are tested at the high load level, because this corresponds to the most economic test, which at the same time gives statistically very good results [11]. For a test sample size of 21, this results in a P_{ts} of about 65 %, see Fig. 5. This contrasts with the 80 % of the pure EoL test. This effect is mathematically justifiable and arises from extrapolation to the field level, which introduces additional uncertainty and thus reduces the P_{ts}. In the pure EoL test, no extrapolation is necessary due to the field load level. For this reason, an EoL test will always achieve the highest P_{ts} under comparable boundary conditions.

Nevertheless, it must always be considered for decision making process that the strong acceleration can reduce the testing effort. Due to the significantly shorter test time, more specimen can be tested than within the EoL test. Accelerated tests are therefore particularly suitable for tests with cost-intensive test durations.

Figure 5: Probability of Test Success for different sample sizes of an accelerated EoL test



3.3 Failure free test planning

Reliability demonstration for a switching relay with a Success Run Test is to be provided. The requirements are as follows:

$t_r = 30{,}000\ cycles$
$R_r = 90\ \%$
$C = 90\ \%$

Using the binomial distribution, the required number of samples is $n = 22$. Since this is only a small product update, the failure distribution can be estimated from the field data of the predecessor product, which is:

$b^* \approx 3$
$T^* \approx 96{,}000\ cycles$

The design safety margin in this example is also about $S \approx 30\ \%$ as it is in the previous examples. According to Eq. 16, the survival probability per test specimen is as follows:

$$R^*(t_r) \approx e^{-\left(\frac{t_r}{T^*}\right)^{b^*}} = e^{-\left(\frac{30{,}000}{96{,}000}\right)^3} \approx 97\ \% \tag{17}$$

Eq. 15 can now be used to calculate the P_{ts}:

$$P_{ts} = \left(R^*(t_r)\right)^{n_{SR}} = (0{,}97)^{22} \approx 51\ \% \tag{18}$$

If this test was carried out in exactly this configuration, there would only be a chance of success of just over 40%. In addition, it should be considered for decision making, that a failure in the Success Run cannot be easily corrected. Either significantly more specimens would have to be tested without further failure or even more failures would have to be generated in order to perform an EoL life data analysis. Both variants are associated with considerable additional effort in the event of a failed test.

3.4. Comparison of different test strategies regarding P_{ts}

As it can be seen from the case studies, it is possible to calculate the remaining risk of a failed test utilizing P_{ts} for all common test strategies. This remaining risk should always be the basis for decision making. It became apparent that zero failure test strategies have considerable disadvantages from a statistical point of view. With comparable design safety margin, one will always achieve lower probabilities of test success. Grundler, Herzig and Dazer already carried out very extensive parameter studies on this topic [2, 5, 6, 7, 9, 10, 11]. Furthermore, a failing zero failure test entails further disadvantages, since it cannot be improved simply by a few additional specimens.

If economic aspects such as test costs and time are added, the performance of zero failure tests improves slightly. With high design safety margins, high probabilities of test success can be achieved at very low cost, since the specimen all have to be tested only up to the required test time. As soon as the design safety margin decreases, the accelerated EoL tests are to be preferred in particular.

4. CONCLUSION

Reliability test planning and reliability demonstration always take place under uncertainty. Due to the scattering lifetime (aleatory uncertainty) and the lack of information (epistemic uncertainty), decisions can only ever be made with a probability and therefore also with a remaining risk. For this reason, it is even more astonishing that the consideration of type-II error in reliability test planning has still not become well established. The P_{ts} gives a tool with which the entrepreneurial risk of a failed reliability test can be evaluated. Furthermore, all known reliability test strategies can be evaluated with this objective statistical metric. This gives the possibility to identify the best possible test strategy for the individual use case just before decision making.

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