Failure Rates from Data of Field Returns

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Abstract: To determine failure rates is a challenge, if there are only a few failures and typical failure rates are low. As an application example we are interested in failure rates of electrical automotive components for automated/autonomous driving. As method we focus here on the exploitation of field data. Our contribution classifies different approaches from statistics and shows how this can be applied to real-world production figures as available in industry.

Keywords: modelling uncertainties and stochastic systems, automotive vehicle electrical systems, autonomous driving, reliability, failure rates, confidence intervals, field data

1. APPROACHES TO FAILURE RATES

For applications like autonomous/automated driving a high reliability of the used components is required for functional safety. Therefore long survival times with a high statistical confidence should be known for the components before the design of the vehicle electrical system and its production. So-called *FIT rates*, i.e. failure rates in the order of 1 FIT, i.e. 1 failure in 1 billion ($=10^9$) hours of lifetime seem to be acceptable for the envisaged application. Since components are under certain stresses not only when in use and ageing happens all the time, failure rates are calculated w.r.t. hours of lifetime, not hours of operation.

Moreover, it is necessary to define a failure precisely by a so-called *failure criterion.* This might depend on the type of the component, e.g. the doubling of the Ohmic resistance for a welded splice. Furthermore, we could differentiate between failure modes like “open” or “short-circuit”.

There are three important approaches to determine failure rates: (i) exploitation of data from field returns (so-called field data), (ii) standardized handbooks with failure rates, and (iii) laboratory exposure tests. In approach (i) the field data, i.e. failures and survivals from components used in the field, is evaluated statistically. The number of legitimate failures (e.g. a wrong coloring of the component might not enhance its functionality) compared with the number of components and hours of lifetime allow to estimate a failure rate (not necessarily constant). This approach is also known as REX (return of experience). The handbooks in (ii) rely on expert opinions and previous records (including statistics and partially field data). There are several international standards for failure rates, FIDES (2022) being the most recent. For approach (iii) long term exposure tests are designed, that try to trigger each a specific physical failure mechanism. In order to observe failures in reasonable time and for a sufficient number of specimens, exposure tests that can speed-up time due to overstresses are crucial. is then analyzed statistically. Here the focus is on the approach (i) using field data to determine low failure rates, in particular in the case of zero or only a few observed failures.

2. PROBABILISTIC AND STATISTICAL MODELS

We examine a family of identical, independent, newly manufactured specimens over a given time period where it is possible to track the specimen for failures. As collective we consider the number of specimen N times the time period under consideration T (in h). We consider X as the random variable with values in $\mathbb{N}_0$, x denotes the observed realizations. A point estimate of the failure rate in our collective serving as a sample is

$$\hat{\Theta} = \frac{X}{n} = \frac{X}{N\,T} \quad (\mathrm{FIT} = \#\,\mathrm{failures}/(10^9\mathrm{h})). \tag{1}$$

However, a point estimate lacks a statement about the statistical confidence of the result. If, let's say we observe 0 failure among a sample of length $N = 1000$ or $N = 10^9$ (for the same T) should make a difference, but in both cases we estimate $\hat{\Theta} = 0\,\mathrm{FIT}$ for the failure rate.

We assume that a required confidence level ν, e.g. 90%, is prescribed (by rules or economically) for the application. If we consider a suitable confidence interval $[\underline{\Theta}, \bar{\Theta}]$ for the unknown parameter Θ for the confidence level ν, than the upper bound $\bar{\Theta}$ of the confidence interval may be considered as a conservative estimate for the failure rate λ_{total} that here incorporates all influences on the failure rate. However, the construction of a confidence interval depends on the underlying model, e.g. whether a non-parametric or parametric estimate is appropriate. We will discuss shortly the two models in the following.

2.1 Binomial Distribution as Model

We suppose that Θ is the probability that an event occurs among N components in a given time interval of length

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T. Let X denote the random variable of the sum of events E within $n = NT$ trials. Accordingly the probability for observing events per time is given by (1).

We follow Stange (1970, p. 436) for the construction of the corresponding (typically non-unique) confidence interval. If a required confidence level ν or vice versa the probability of error $\alpha_1 + \alpha_2 = 1 - \nu$ is given [1] , then there holds

$$\mathbb{P}\left(\underline{x} \leq X \leq \bar{x}\right) = \sum_{i=\underline{x}}^{\bar{x}} \binom{n}{i} \Theta^i (1-\Theta)^{n-i} = 1-\alpha_1-\alpha_2, \quad (2)$$

where $\underline{x}$ or $\bar{x}$ is the smallest / largest natural number greater / less than or equal to $n\Theta \mp q_{1/2}\sqrt{n\Theta(1-\Theta)}$, where $q_i = q_{1-\alpha_i}^{\mathcal{B}(\Theta,n)}$ is the quantile of the binomial distribution with parameters Θ and n w.r.t. $1 - \alpha_i$, $i = 1, 2$. The crucial estimate $\bar{\Theta}$ for $X = x$ is determined by

$$\sum_{i=0}^{x} \binom{n}{i} \bar{\Theta}^i (1 - \bar{\Theta})^{n-i} = \alpha_1. \quad (3)$$

In particular, in the case $x = 0$, that is important for the applications, (3) simplifies to $\bar{\Theta} = 1 - \sqrt[n]{\alpha}$,where we have naturally $\alpha_1 = \alpha$ and $\alpha_2 = 0$. Thus we have the confidence interval $[0, \bar{\Theta}]$ for zero failures.

If we have zero failures the question whether failed components are (instantaneously) replaced is obsolete. Moreover, for a few failures, i.e. $x \ll n$ the question of replacing components has no numerical influence on the results.

We see that the construction of a confidence interval as for the binomial distribution may yield technical challenges. By using Fisher's F-distribution this might be overcome. Further details yielding the so-called Pearson-Clopper values, see Stange (1970, p. 433 ff.), will be presented on site.

2.2 Maximum Likelihood

In addition, we have modelling challenges due to the *censoring* of the data. In statistics censored data means that random variables, as the survival times here might not be observed/measured over the whole time. If we cannot track each sample until a failure occurs, then this is a typical example for *right-censoring*, whereas if the starting time of the observation/measurement cannot be traced back yields a so-called *left-censoring*.

Considering a constant (random) failure rate, we illustrate here the case of the exponential distribution. For $X \geq 1$, the maximum likelihood estimate is in the uncensored case identical to (1), in the general case of censored data (no replacement of the component)

$$\hat{\Theta} = \frac{X}{\sum_{i=1}^{N} t_i} = \frac{X}{\sum_{i=1}^{X} t_i + (N - X)T}, \quad (4)$$

where t_i denotes the random survival time of component i, being T, if component i does not fail in the observed time period. W.l.o.g. the components with failures get the lowest indices. For the observed times with components in function, appearing in the denominator, we abbreviate $T_{obs} = \sum_{i=1}^{X} t_i + (N - X)T$. We obtain (Sundberg (2001)) the confidence interval

$$\mathbb{P}\left(\frac{q_{\alpha_1}^{\chi^2(2X)}}{T_{obs}(X)} \leq \hat{\Theta} \leq \bar{\Theta} := \frac{q_{1-\alpha_2}^{\chi^2(2X)}}{2T_{obs}(X)}\right) = 1 - \alpha_1 - \alpha_2, \quad (5)$$

[1] α_1 is the probability of an error above the sample mean plus a margin of error and α_2 is the probability of the error below.

where $q_{\tilde{\nu}}^{\chi^2(2X)}$ is the quantile of the χ^2-distribution with $2X$ degrees of freedom w.r.t. the confidence level $\tilde{\nu}$. We see that the results for the sample mean for the binomial as for the exponential distribution coincide, whereas the relevant estimate in (5) might be different already in the uncensored case.

3. DATA OF FIELD RETURNS AND OUTLOOK

On site we present data of field returns for welded automotive splice and follow approach (i). Moreover, we include here so-called dark figures for N and X, these percentages model that not all components in the collective may be tracked and that not all failures might be reported in the real world. Finally, we will discuss phenomena due to the size of the collective and to the split of components into smaller groups.

It turns out in this example that the binomial model and the maximum likelihood method yield the same estimates for the failure rate λ_{total}. Following approach (ii) we obtain a higher value for the failure rate. However, both values were undercut by laboratory long exposure tests following approach (iii) for this component (ZVEI-BI, 2021, Section 7.5). Note that the three approaches yield different FIT rates not only here and to be on the safe side, the worst (highest) FIT rate is used as prescribed in the FIDES. The reason for this is that a chain is only as strong as its weakest link. However, it is recommendable to use several approaches as pillars for the FIT rates.

Finally, we will discuss the stated results and close with an outlook. It should also be mentioned that we consider here only constant failure rates, modelling random errors. Systematic errors are assumed to be avoided by a strong quality management. This approach has been applied by the authors together with industrial partners for several electric components as splice, power and data cables, fuses, and mass connections in automotive cable harnesses, see, e.g., ZVEI-BI (2021); Kimmerle & Liess (2019).

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