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Estimating uncertainty in reliability of electricity supply analyses considering component condition

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The reliability of the electric power transmission system depends on the reliability of its components. As components age, the technical condition degrades, and the probability of failure will increase. Consequently, to estimate the reliability of a transmission system it is valuable to include the effect of deteriorating components. Recent work has demonstrated how this can be done. However, condition dependent reliability models introduce new sources of uncertainty that needs to be accounted for and that may be especially important in a long time horizon. This work presents a novel approach to propagate the uncertainty in input parameters through the system reliability analysis. Monte Carlo simulation is used to create an ensemble to span the sample space of reliability of supply indices. The effect of each source of uncertainty may be seen separately, or the effect of several sources is seen jointly. The methodology is demonstrated using a failure model for high voltage power transformers in the transmission system. The example illustrates that the methodology can identify which sources of uncertainty have significant impact on the uncertainty of system reliability indices and to what degree system uncertainty is amplified or moderated by interactions between the sources of uncertainty. Moreover, it is shown that the uncertainty will not necessarily increase uniformly over time.

Keywords: Power system reliability, Security of supply, Monte Carlo simulation, Uncertainty analysis.

1 Introduction

To determine the reliability of supply, system operators carry out a power system reliability analysis (PSRA). Aging power transmission grids have higher rates of failure and is thus a major concern for the reliability of the power supply. To meet this concern, it is important that PSRAs account for component condition. Integration of component condition in system reliability has been the topic of several research articles, e.g., (Li 2002) which handled end of life failures for transformers or (J. H. Jürgensen, L. Nordström, and P. Hilber 2019) which handled condition dependent repairable failures. Recent work (Toftaker, Foros, and Sperstad 2023) has shown how one may account for both condition dependent failures and preventive replacement for transformers in PSRA and how this can be carried out over an extended time horizon of several years (Toftaker and Sperstad 2022).

Information about component condition apparently provides more accuracy and better ability to inform system operator decision making. However, the condition dependent failure models rely on several parameters, each with an associated uncertainty. The added complexity of the model thus makes it more important but also more challenging to assess the uncertainty of the results. The main aim of this paper is to develop a methodology to propagate the uncertainty in input parameters through the system reliability analysis and assess the consequent uncertainty in reliability of supply indices. Quantifying the uncertainty in reliability indices is useful for several reasons. First, it can inform decision makers of the level of confidence that can be put on the results. Second, it quantifies the value of reducing uncertainty in input parameters, and shows which parameters contribute more. Third, it can help assess the value of introducing new features to the model like condition dependent failure rates, as compared to simpler models. Finally, in the long-term analysis it shows how far into the future the model may be useful.

Different methods for uncertainty analysis for PSRA have been explored in the literature. According to (Aven and Zio 2011) uncertainty analysis for risk assessment can be placed in 5 categories: probabilistic analysis, probability bound analysis, imprecise probability, random sets and possibility theory. Which approach is most appropriate depends on the context of the analysis. Reliability analysis is often concerned with rare events and may be based on scarce empirical data, purely probabilistic approaches are often not sufficient, and this has given inspiration to the alternative approaches. For high impact events with low probability (HILP events), a hybrid probabilistic-possibilistic approach is used to assess the effect of uncertainty (Sperstad, Kjølle, and Norum 2021). For power system reliability analysis considering component condition, (Awadallah, Milanović, and Jarman 2016) used Second Order Probability and Dempster-Shafer Evidence Theory to evaluate how the uncertainty in end-of-life probability models influence the uncertainty in system reliability indices.

This paper builds on the work in (Toftaker, Foros, and Sperstad 2023) and (Toftaker and Sperstad 2022), which presented estimates for condition-dependent reliability indices but no estimate for their accuracy. A novel method to estimate the uncertainty in reliability indices is thus presented. Uncertainty in input parameters is represented as probability distributions and the uncertainty in reliability indices is represented by the distribution of the index marginalized over the input parameters, like a prior predictive distribution in Bayesian statistics (Gelman et al. 2013). The assessment of the distribution and thus the uncertainty is propagated through the PSRA by a Monte Carlo simulation. Furthermore, the analysis distinguishes between aleatory uncertainty which describes the random variability of the outcome and the epistemic uncertainty which describes the systematic uncertainty caused by lack of knowledge about the model and its parameter values (Aven et al. 2014).

The paper is structured as follows. Section 2 briefly introduces the theoretical background for PSRA and presents the proposed methodology to uncertainty analysis for PSRA. Section 3 describes the condition dependent component reliability model and details how the methodology can be applied to perform uncertainty analysis for that model. A case study is described in section 4, while section 5 discusses the results and considers implications and future work.

2 Power system reliability analysis

Reliability of supply is a measure of the long-term average ability of the power system to provide electric power to end users. The results of a reliability of supply analysis are the values of a set of reliability indices for a set of delivery points, or load points. The annual energy not supplied is an important example of such a reliability index.

In this paper we are concerned with analytical methods to evaluate reliability indices, and specifically, the methodology is illustrated using the OPAL framework (Kjølle and Gjerde 2012). OPAL is based on the analytical minimal cut set methodology (Kjølle and Gjerde 2012; Gjerde et al. 2016). Contributions to the reliability of supply indices are calculated for each operating state, each delivery point, and each contingency j that correspond to a minimal cut set for delivery point k and operating state i. For the expected annual energy not supplied ($EENS$), these contributions can be calculated as

$$EENS_{i,j,k} = \lambda'_{i,j} \cdot r_{i,j} \cdot P_{\mathrm{interr},i,j,k} \qquad (1)$$

where $\lambda'_{i,j}$ and $r_{i,j}$ denote equivalent failure rates and outage times for contingency j, and $P_{\mathrm{interr},i,j,k}$ denotes the power interrupted at delivery point k. For other details of the PSRA method we refer to (Toftaker and Sperstad 2022).

2.1 Uncertainty analysis for PSRA

This section presents a method to quantify the uncertainty in reliability indices that are outputs of analytical power system reliability analyses as presented in Section 2. For concreteness it is presented for the reliability index EENS, but the method is equally applicable to other reliability indices.

The expected energy not supplied is the expected value of the stochastic variable ENS, which in turn depends on the stochastic process $X(t)$ indicating whether the components of the system are in a functional state or a fault state at time t. The process $X(t)$ depends on several factors $Y_1, \dots, Y_k$, and let Y denote the vector of factors. The expected energy not supplied may be expressed as an expected value with respect to the distribution of Y, $f_Y(y)$, ie. $E(ENS) = E_Y(E(ENS|Y))$. To assess the uncertainty in E(ENS) that can be attributed to Y we follow a probabilistic framework (Aven and Zio 2011) and analyze the distribution of E(ENS|Y), analogous to a prior predictive distribution. The approach was chosen because it provides interpretability and that different sources of uncertainty are treated consistently. In addition, the prospect of integrating the approach in a Bayesian approach is appealing. The conditional expectation may be considered a function $g(y)$ and gives rise to the corresponding random variable $G = g(Y)$. If g is a bijective function, the percentiles g_p of G are given by the percentiles y_p of Y as $g_p = g(y_p)$. However, in the general case the percentiles are given by an integral over the set $A = \{y \in R: E(ENS|Y = y) < g_p\}$,

$$\begin{aligned} P\big(E(ENS|Y) < g_p\big) &= P(Y \in A) \\ &= \int_A f_Y(y)dy \\ &= \int_0^\infty I\big(g(y) < g_p\big) f_Y(y)dy \end{aligned} \tag{2}$$

The integral may best be evaluated by Monte Carlo simulation based on a sample $y_1, \dots, y_n$ where $y_i \sim f_Y(y)$.

3 Component reliability

This section gives a brief recap of the component reliability model introduced in (Toftaker, Foros, and Sperstad 2023) and (Toftaker and Sperstad 2022). The main purpose of the reliability model is to include technical condition of individual power system components in the system reliability analysis.

It is assumed that a component can fail due to mid-life failures or wear out failures and additionally that it may be replaced preventively to avoid failure. The time to mid-life failure T_{ml} follows an exponential distribution with rate λ_{ml}. The time until preventive replacement T_{pm} is for simplicity assumed to be exponentially distributed with rate λ_{pm}. Following (Toftaker, Foros, and Sperstad 2023), the time until wear-out failure T_w follows the probability distribution $F_{T_w}(s(t)|\mu, \sigma)$, where $s(t)$ is the apparent age of the component, μ is the expected value, and σ is the standard deviation. It is assumed that if the health index at calendar age t_0 is HI_0 and the corresponding apparent age s_0 is $\tau(HI_0)$. The relation τ between health index and apparent age may be obtained through statistical data as illustrated by (Foros and Istad 2020). To obtain apparent age as a function of calendar time it is further assumed that apparent age follows the function $s(t) = \tau(HI_0) + t$ where it is assumed that the present time is $t = 0$. If a wear-out failure occurs, the transformer is replaced and its apparent age restarts at 0. If a mid-life failure has occurred a minimal repair is sufficient, and the condition remains unchanged. For any failure the time spent in a failed state T_R is exponentially distributed with rate η. Following (Toftaker, Foros, and Sperstad 2023) we assume that that within a one-year analysis horizon the technical condition does not change significantly and that after the component is replaced, the probability of wear out failure is negligible. This means the functional state of the component is well described by a Markov model where the time to wear-out failure is exponentially distributed with rate

$$\lambda_w(s_0) = \frac{F_{T_w}(s_0 + 1) - F_{T_w}(s_0)}{1 - F_{T_w}(s_0)} \tag{3}$$

Let N_{t_1,t_2} denote the number of failures within the time-period t_1 to t_2. It can be derived that, with $\lambda_w = \lambda_w(s_0)$, the expected number of wear out failures within the next year, is given by

$$E(N_{0,1}) = \frac{\lambda_w}{\lambda_w + \lambda_{pm}}\left(1 - e^{-(\lambda_w+\lambda_{pm})}\right) \tag{4}$$

3.1 Extended time horizon

To extend the component reliability model to a longer time horizon than one year we adopt the recursive scheme introduced in (Toftaker and Sperstad 2022). The expected number of wear-out failures for component j in year t is given by the law of total expectation as

$$E(N_{t,t+1}) = \sum_{s=0}^{\infty} E(N_{t,t+1}|S_t = s)\, P(S_t = s) \tag{5}$$

where S_t is the apparent age of the component at the end of year t, and $E(N_{t,t+1}|S_t = s)$ is given by (*4*) with $\lambda_w = \lambda_w(s)$. Let $\omega_{w,t}$ denote the expected number of wear-out failures in year t. Let s_0 denote the present apparent age of a component such that $P(S_0 = s_0) = 1$. The recursive expression for the probability of having a certain apparent age at the beginning of year *t* is then

$$P(S_t = s) = \textstyle\sum_{s'=0}^{\infty} P(S_{t-1} = s')\, Q_{s',s}, \tag{6}$$

where $Q_{s',s} = P(S_{t+1} = s|S_t = s')$.

Finally, an overall time-dependent failure rate λ_t for the transformer, considering mid-life failures as well as wear-out failures, is derived from $\omega_{w,t}$ (Toftaker, Foros, and Sperstad 2023). This failure rate can then be used as input data to the analytical PSRA by setting the value λ_j in (1) to estimate annual reliability indices. In this way, each of the years of the analysis horizon can be evaluated independently by the power system reliability analysis.

3.2 Custom aging rate

Above it was assumed that the increase in apparent age is equal to the increase in calendar age. Here we generalize the approach to the situation where $s(t) = \tau(HI_0) + \xi t$, such that ξ is the aging rate. By replacing λ_{pm} by λ_{pm}/ξ, the methodology above serves to find the expected number of failures in the time scale of apparent age. This means (*5*) gives the expected number of wear out failures in a time period $t\xi$ to $(t + 1)\xi$. To find an approximation of the expected number of failures within a calendar year t to $t+1$ we integrate the piecewise constant function defined in (*5*). If we define $r_0 = \lfloor s(t) \rfloor$ and $r_1 = \lceil s(t+1) \rceil$ the integral reduces to the following sum $E(N_{t,t+1}) \approx \sum_{s=r_0}^{r_1-1} w_s E(N_{s,s+1})$ where $w_{r_0} = r_0 + 1 - t\xi$, $w_{r_1} = (t+1)\xi - r_1 + 1$, and $w_s = 1$ elsewhere.

3.3 Uncertainty in component reliability

The condition dependent reliability model contributes to uncertainty in energy not supplied. In the short term, within one year, uncertainty in input parameters μ and σ contribute to uncertainty in the distribution F_{T_w}. This combined with uncertainty in the rate of aging ξ contribute to uncertainty in $\lambda_w(s_0)$ as given by (2). The uncertainty in μ, σ and ξ represents *epistemic* uncertainty in the model.

In the long term, i.e., for year $t > 1$, there will be additional, *aleatory* uncertainty stemming from the variability within the period prior to t. Specifically, this contributes to uncertainty in the initial condition of the components at the start of year t.

The different contributions and how they are propagated through the reliability model is illustrated in Fig. 1.

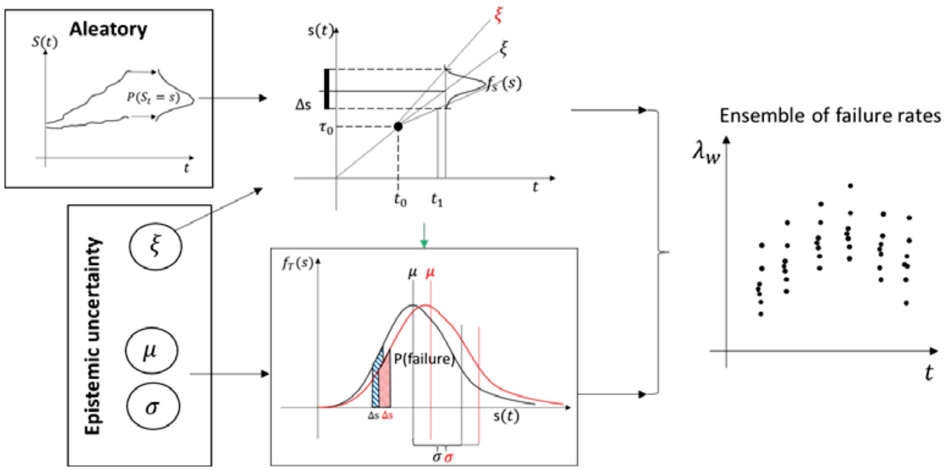

Fig. 1. Illustration of how uncertainty is propagated from input parameters to component failure rates.

3.4 Propagating epistemic uncertainty

To assess the joint uncertainty of the input parameters we need to sample from the joint distribution. According to Section 2.1, the uncertainty attributed to μ, σ, and ξ is summarized by the distribution $E(ENS|\mu, \sigma, \xi)$. This is analyzed by generating an ensemble $(\mu_1, \sigma_1, \xi_1), \ldots, (\mu_{n_e}, \sigma_{n_e}, \xi_{n_e})$ of size n_e. For each member (μ_i, σ_i, ξ_i) of this ensemble we calculate ω_{w,t_i} as described in 3.1. In case we seek to exclude the contribution of one parameter, e.g., σ, we assign the same value to each member of the ensemble, e.g., $(\mu_1, \sigma, \xi_1), \ldots, (\mu_{n_e}, \sigma, \xi_{n_e})$.

3.5 Propagating aleatory uncertainty

The recursive scheme allows for the quantification of aleatory uncertainty in the long-term analysis. To clarify, we quantify the uncertainty in ENS_t, that is due to the variability in the input to the reliability analysis at the start of year *t*. We quantify this, once again, following the definition given in Section 2.1 and use the results in Section 3.1, to analyze the distribution of $E(ENS|S_t)$. For this purpose, we sample the apparent age at year t, s_t, from the distribution $P(S_t = s)$, to obtain a set of n_a apparent ages $s_t^1, \ldots, s_t^{n_a}$. Each sampled initial age corresponds to a failure rate $\omega_{w,t}^i$. The failure frequencies $\omega_{w,t}^1, \ldots, \omega_{w,t}^{n_a}$ form an ensemble representing the probability distribution of $\omega_{w,t}$.

3.6 Joint epistemic and aleatory uncertainty

To assess the joint uncertainty due to epistemic and aleatory uncertainty we first generate an ensemble $(\mu_1, \sigma_1, \xi_1), \ldots, (\mu_{n_e}, \sigma_{n_e}, \xi_{n_e})$ as in Section 3.4. For each member (μ_i, σ_i, ξ_i) we then generate an ensemble $s_t^1, \ldots, s_t^{n_a}$ from $P(S_t = s|\mu_i, \sigma_i, \xi_i)$, obtained from (6), where the recursion is started with μ_i, σ_i, ξ_i as the input parameters. For each element in the joint ensemble, we calculate the failure frequency to obtain the ensemble $\omega_{w,t}^1, \ldots, \omega_{w,t}^N$ where $N = n_e n_a$.

4 Case studies

To illustrate the proposed methodology, we extend the case study that was presented in (Toftaker, Foros, and Sperstad 2023; Toftaker and Sperstad 2022). This case is based on the 25-bus electric power test system described in (Sperstad et al. 2020), and the system includes 8 transformers with failure rates based on the failure model from (Foros and Istad 2020). Where not otherwise stated, input parameters of the case study are identical to the ones used in (Toftaker and Sperstad 2022).

In this paper, we evaluate the reliability of the test system by estimating the expected energy not supplied for a 25-year period. This time horizon is chosen to be able to clearly see the trends in the results, since condition deterioration evolves over time scales of decades. Note that in a real power system, several other changes will also occur in the system over so large time scales, but in this paper, these are neglected to be able to isolate fundamental effects related to component condition. How these effects interact with effects due to load growth, system development measures, etc. will be a subject of further research.

As our aim in this paper is to evaluate how uncertainty propagates in the model, we assume some initial probability distributions for selected input parameters. How these probability distributions can be estimated from condition information is left for future work. For the rate of aging, we choose a log normal distribution with parameters $\mu_\xi = 1$ and $\sigma_\xi = 0.25$. The mean lifetime of transformers μ_w is assigned a normal distribution with mean 60 and standard deviation 5. The variance of the lifetime distribution is set to be $\sigma^2 = \sigma_0^2 + Z$ where Z is inverse gamma distributed with shape parameter $\alpha = 3$ and scale parameter $\beta = 250$. The parameter σ_0 is a location parameter and is assumed to be 18. The chosen distributions correspond to conjugate prior distributions (Gelman et al. 2013) for the Gaussian distribution.

4.1 Scenarios and sensitivity case

In addition to the base case described above (case 1), we define a sensitivity case (case 2). The sensitivity case is designed to investigate the importance of the specific choice of initial technical condition for the transformers in the test system. To this end, we take the transformer that has the worst technical condition in the system and assign it an apparent age of 30 years, representing half the expected lifetime.

For each of the cases we define 4 scenarios, as specified in Table *1*.

Table 1. Specification of the scenarios. A 1 means included, while 0 means not included.

Scen. no.	Aging rate	Distribution parameters	Aleatory uncertainty
1	0	1	0
2	1	1	0
3	0	0	1
4	1	1	1

The column *Aging rate* specifies whether uncertainty in aging rate is included, *Distribution parameters* specifies whether uncertainty in μ_w and σ_w is included, while *Aleatory* specifies whether the accumulated variability between years is included.

4.2 Results

The results of the case studies are presented in terms of the distribution $P(E(ENS|Y) < g_p)$ as defined in (2). In Fig. 2 to Fig. 5, the results are displayed in terms of 95 and 50 percent confidence intervals together with the median $E(ENS_t|Y)$ per year. Fig. 2. and Fig. 3. shows that the uncertainty due to input parameters slightly decreases as time passes. Fig. 4 shows that the aleatory uncertainty accumulates over time and at about ten years the aleatory uncertainty dominates the epistemic uncertainty. Fig. 5 suggests that when all sources of uncertainty are included, the uncertainty is stabilized by the end of the analysis horizon.

Each member of the ensemble corresponds to the path of EENS over the analysis horizon. and it is also informative to plot the individual paths. Fig. 6. shows the paths for case 1, scenario 2 which forms the basis for the plot in Fig. 3. As time passes the paths get closer. This is due to the oscillatory behavior of component reliability which stems from the convolutional integral that determines the time dependent failure probability (Rausand and Høyland 2004). The sensitivity analysis in case 2 shows similar results as case 1. Fig. 7 shows $E(ENS_t)$ for scenario 1, and we

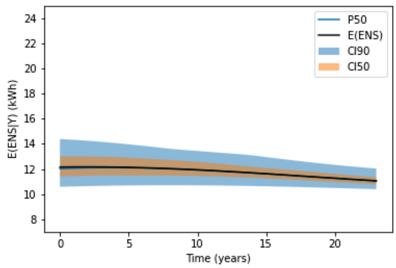

Fig. 2. Percentiles and mean of the distribution of E(ENS|Y) per year for case 1 scenario 1

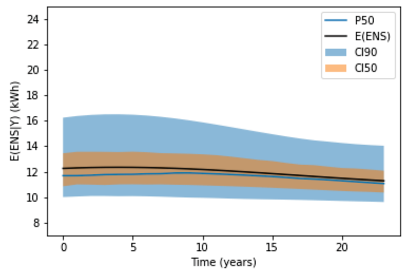

Fig. 3. Percentiles and mean of the distribution of E(ENS|Y) per year for case 1 scenario 2

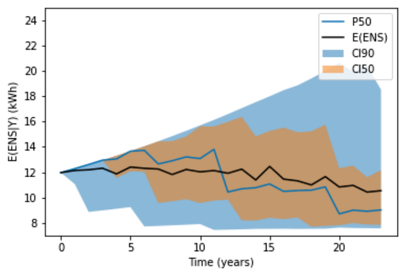

Fig. 4. Percentiles and mean of the distribution of E(ENS|Y) per year for case 1 scenario 3

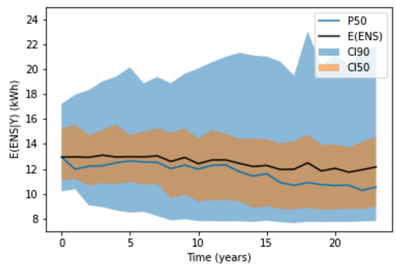

Fig. 5. Percentiles and mean of the distribution of E(ENS|Y) per year for case 1 scenario 4

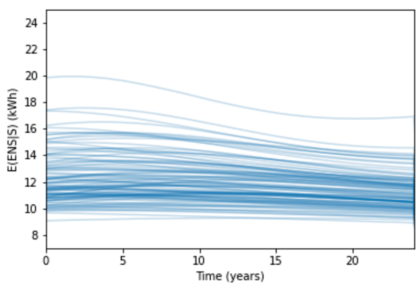

Fig. 6. E(ENS|Y) per year for case 1 scenario 2, with 100 paths shown.

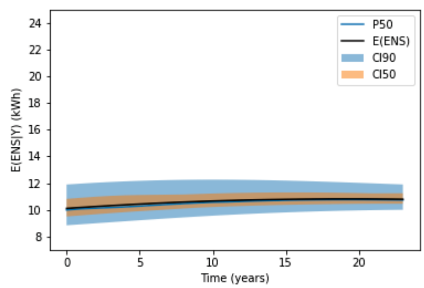

Fig. 7. Percentiles of the distribution of E(ENS|Y) per year for case 2 scenario 1.

observe the same behavior as for case 1 and the uncertainty decreases as time approaches 25 years.

5 Discussion

This work extends previous work to include condition dependent failure probability in power system reliability analyses by presenting a methodology to analyze uncertainty. Specifically, a methodology is proposed that quantifies how uncertainty in input parameters affects the uncertainty in reliability indices. The methodology is developed and illustrated on a model for condition dependent failure probabilities. The analysis covers both the short term (around one year) and how uncertainty develops over a longer time horizon.

The case studies have revealed that in the

short term, the uncertainty in estimated EENS is dominated by uncertainty in the parameters of f_{T_W}. For the long term, the random variability steadily increases, while the uncertainty contribution from input parameters decreases slightly. This might seem counter intuitive but is a consequence of the model reaching an equilibrium state and that the initial state of the transformer is forgotten as time passes. As a result, random variability will dominate the uncertainty at some point. These conclusions hold for a variety of initial conditions as indicated by the sensitivity case.

The presented methodology makes it possible to represent the probability distribution of reliability indices which may be useful in a decision-making context especially if the decision maker is risk averse or not only considering the expected value. It may also be valuable in deciding what information to gather. To further utilize the proposed methodology, a necessary next step is to quantify the uncertainty in input parameters, i.e., to estimate the probability distributions f_μ, f_σ, and f_ξ. In addition to applications in decision support for asset management, one may test the hypothesis that a more detailed model, like the one including component condition, gives a statistically significant different result than the simpler model using average failure rates.

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