A Bayesian Method for Estimating Potential Impact of Increase in STI on Component Failure Rates

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Abstract: In the U.S., the Nuclear Energy Institute (NEI) guidance document NEI 04-10 describes methods to extend the time interval between inspections of surveillance test intervals (STIs) for risk-informed applications. One example of this is the surveillance frequency control program (SFCP). The methodology includes a step to account for a periodic reassessment of the overall program impact. Here, data collection and statistical analysis are required to remove modeling conservatism. Because of the scarcity of failure events for some components, the availability of failure data to perform statistical analysis may be limited (insufficient evidence). This lack of data could limit the implementation of this step under the SFCP to conservative assumptions. To this end, this paper presents a technical basis to establish a Bayesian framework to assess the periodic failure rate re-assessment under the SFCP that could form the basis for a practical approach to be utilized under NEI 04-10. Bayesian updating, past plant-specific test/inspection, operational records, and failure mode assessment are considered in a general framework for how a relevant technical basis can be derived for further use. Actual plant data information from a U.S. nuclear power plant utilizing the SFCP was leveraged to support the development of a mathematical framework. It is expected that this framework can be used for further piloting by considering practical implications of its use with a PRA model currently being used for SFCP, as well as broader industry data utilization to further calibrate its inputs. At this time, this effort represents an initial formal investigation into a basis for future practical use, in an area that was not previously explored with mathematical rigor.

1. INTRODUCTION

Inspection and surveillance procedures are essential to ensure the safety and optimal operation of any system. Performing inspections periodically at nuclear power plants (NPPs) comes at the cost of labor, system operation interruption, among other undesired costs. Ideally, NPP operators aim to reduce the number of inspections while maintaining safety standards. However, extending the time interval between inspections could potentially lead to an increase in the component's failure rate due to unseen or in-progress failure mechanisms.

In the U.S., programs such as the surveillance frequency control program (SFCP) include guidance on addressing the potential impact of a component's failure rate due to unseen and/or in-progress failure mechanisms when extending the time interval between inspections of surveillance test intervals (STIs) for risk-informed applications. The STI extension methods described in the Nuclear Energy Institute (NEI) guidance for SFPC (NEI 04-10) provides details in terms of addressing the overall impact of the SFCP on the NPP's risk profile by modelling STI-modified components in a probabilistic risk assessment (PRA) model [1].

For many U.S. NPPs, the selection and prioritization of specific target STI extensions in accordance with NEI 04-10 is documented in surveillance test risk-informed documented evaluation (STRIDE) packages. The scope of these STRIDE packages includes PRA case studies (among other things such as deterministic assessment evaluations and, where required, instrument drift evaluation). More specifically, STRIDEs include the results of assessment of the changes in plant risk associated with

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proposed changes in STIs for specified surveillance tests. The evaluation covers the potential changes in predicted baseline core damage frequency (CDF) and large early release frequency (LERF) that could result from the proposed STI changes. Furthermore, its goal is to determine whether the proposed STI changes explicitly or implicitly impact the calculation of plant risk by evaluating the functional impact of the proposed STI changes on the PRA model logic and data elements.

The guidance in NEI 04-10 includes a step (Step 19) to account for a periodic reassessment of the overall program impact. Part of the periodic reassessment also includes evaluating the SFCP with updates in the PRA model (see Figure 3 of NEI 04-10). One possible outcome of this periodic assessment is the exclusion (removal) of the component's failure rate increase from the PRA model. This is the desired outcome of SFCP program managers in order to remove the burden of carrying an increased risk from the conservative assessment of STI-modified components once sufficient time and/or operating experience has been accumulated to justify exclusion of that component from the PRA model.

Within Step 19, NEI 04-10 provides two options for performing a periodic reassessment of STI-modified components into the base PRA model. The first option is to use the original conservative data assumptions that were utilized in performing the initial STI assessment. The second option is to utilize data collection and statistical analysis to show that the reliability of the component affected by the STI change has not been impacted (or has improved) from the revised STI frequency value. This second option has the potential to support the exclusion of components from the PRA model.

However, there are currently limitations preventing implementing of this second statistical option:

- The statistical method is not explicitly defined in NEI 04-10, and
- Data are sparse (insufficient evidence), particularly on a plant-specific basis.

These challenges could limit the implementation of Step 19 to conservative assumptions under the first option. For example, the STRIDEs reviewed within the scope of this study adjust the constant failure rate of the affected component using a factor proportional (1:1) to the increase in STI, which is conservative and consistent with option 1 of NEI 04-10 Step 19.

Since the failure rates of components of interest are typically very small, sufficient data for traditional statistical analysis for reliability estimation may take several years to accumulate. In this paper, we investigate and recommend an approach to analyze the possible impacts of change in failure rate rates due to changes in STI without requiring such long duration data collection.

The remainder of this paper is structured as follows. Section 2 describes the proposed Bayesian methodology to assess the impact of STI changes in the component's failure rate. Section 3 describes data collection and analysis. Section 4 provides a sensibility analysis on the failure rate for different STIs. Finally, conclusions are presented in Section 5.

2. METHODOLOGY

This section presents a methodology to infer the change in a component's failure rate based on limited failure data, expert knowledge, and varying STIs. An adjustment value is also presented to correct the prior knowledge, which allows for the evaluation of the methodology in the context of different component and failure mode types.

2.1. Framework

The base framework for the proposed approach is to leverage past performance data in creating a database of extended STI conditions. That evidence can then be used in standard statistical analysis (such as Bayesian) to estimate the expected failure rate associated with the extended STI.

When considering a component for STI extension, it is necessary to assess the corresponding impact (increase) in its hazard rate λ_θ, where θ is a set of parameters that define the probability density function (PDF) for a given failure distribution (e.g., Exponential or Weibull). Let this new inspection interval be (t_s, t_e). Assume that, to date, *N* intervals have been observed (that is, $(t_s, t_e)_i$ with $i = 1, 2, \dots, N$) and that the number of failures observed at each inspection interval is k_i. The likelihood of observing k_i failures in $(t_s, t_e)_i$ can then be expressed by the following Poisson distribution:

$$P(E_i|\theta) = \frac{[\lambda_\theta (t_e - t_s)_i]^{k_i}}{k_i!} e^{-\lambda_\theta (t_e - t_s)_i} \tag{1}$$

where the instantaneous hazard rate λ_θ is assumed to be constant in $(t_s, t_e)_i$ and is evaluated in the interval's mid-point.

Assume that the engineering judgement on the impact of a change in the inspection interval on the hazard rate λ_θ is elicited (or obtained through "data mapping" described in Section 2.3) as the adjustment factor c with an uncertainty distribution given by $P(c)$ (the expert's uncertainty over c). Then, the impact on the hazard rate λ_θ is assessed by modifying the observed numbers of failures k_i as follows:

$$k_i' = c \cdot k_i \tag{2}$$

where k_i' is the (new) expected number of failures in the modified inspection interval $(t_s, t_e)_i$, with $i = 1, 2, \dots, N$.

Now, the likelihood function for the *i-th* modified inspection interval $E_i = (t_s, t_e)_i$ in terms of the adjustment factor c and the hazard rate's parameters θ is given by:

$$P(E_i|\theta) = \int_c P(E_i, c|\theta) \cdot P(c) dc \tag{3}$$

Therefore, for a given number of failures k_i' in an interval $(t_s, t_e)_i$, the term $P(E_i, c|\theta)$ is given by the probability density function, f_θ of the corresponding time to failure probability model. Important information from the censored data can also be extracted, considering the reliability function $R_\theta = R(t, \theta)$ in the likelihood function. Thus,

$$P(E|\theta) = \left(\prod_i \int_c P(E_i, c|\theta) \cdot P(c)\, dc\right) \cdot \prod_j R(E_j|\theta) \tag{4}$$

$$P(E|\theta) = \prod_i \left(\int_c \left(f_\theta(t_s^i, t_e^i)\right)^{k_i'} \cdot P(c)\, dc\right) \cdot \prod_j R_\theta(t_s^j, t_e^j) \tag{5}$$

The loglikelihood is then given by:

$$\Lambda(E, \theta) = \sum_i \log\left(\int_c \left(f_\theta(t_s^i, t_e^i)\right)^{k_i'} \cdot P(c)\ dc\right) + \sum_j \log\left(R_\theta(t_s^j, t_e^j)\right) \tag{6}$$

Thus,

$$\Lambda(E, \theta) = \sum_i \log\left(\sum_c \left(f_\theta(t_s^i, t_e^i)\right)^{k_i'} \cdot P(c)\right) + \sum_j \log\left(R_\theta(t_s^j, t_e^j)\right) \tag{7}$$

Regardless of the chosen alternative, the posterior distribution of the component's hazard rate is as follows:

$$\pi(\theta|E) = \frac{\Lambda(E, \theta) \cdot \pi_o(\theta)}{\int_i \Lambda(E, \theta) \cdot \pi_o(\theta)\, d\theta} \tag{8}$$

where, $\pi_o(\theta)$ is the prior distribution over the hazard rate's set of parameters.

An estimate of the component's hazard rate can be obtained by averaging over all possible values of θ, which results in:

$$\overline{\lambda_\theta}(t) = \int_\theta \lambda(t|\theta) \cdot \pi(\theta|E) \cdot d\theta \quad (9)$$

2.2. The Cases of the Weibull and Exponential Distributions

For the case of a Weibull Distribution, the hazard rate λ_θ and the PDF f_θ are replaced in the previous equations as follows:

Hazard rate:

$$\lambda(t) = \frac{\beta}{\alpha} t^{\beta-1} \quad (10)$$

Probability density function:

$$f(t) = \frac{\beta}{\alpha^\beta} t^{\beta-1} e^{-\left(\frac{t}{\alpha}\right)^\beta} \quad (11)$$

where α and β are the scale and shape parameters, respectively.

A similar and simpler case would consider an Exponential distribution (i.e., constant hazard rate) with

$$\lambda(t) = \lambda \quad (12)$$

and probability density function:

$$f(t) = \lambda e^{-\lambda t} \quad (13)$$

Once the PDF is selected, one can use Markov Chain Monte Carlo (MCMC) simulation through Metropolis Hastings [2], [3] to sample from Equation 8 and obtain the posterior distribution of the hazard rate parameters based on the evidence presented in the inspection data.

2.3. Assessment of the Adjustment Factor

As discussed in the previous sections, the adjustment factor *c* can be assessed based on engineering knowledge and through the interpretation of the available plant specific and industry reliability data. One approach is to review past inspection results and for each inspection period assess the inspection/test outcome (Failure, Success, Degraded State), and also assess whether the outcome would have been different if the inspection interwall was longer.

For this sample study, data were obtained from the RADS - PRA Data Calculations webapp [4] for three sample plants. Table 1 includes those events considered and illustrates the process of data re-interpretation and engineering judgement. Failure data were collected from 1998 until 2020. In this sample study, the number of failures is increased from 3 to 4.7, meaning the c factor in Equation 2 is $c = 4.7/3 = 1.56$.

Note that data interpretation via adjustment factor *c* is based on the probability of observing a given event. For example, for the second event in Table 1, the analyst has assigned a probability of 70% of observing a failure when considering the increased inspection interval even though no failure was observed. In practice, this assessment would be based on engineering knowledge and observed physical evidence of degradation such as noise and elevated vibration in the original plant record. This approach is similar to the data mapping method used in development of database for common cause failure probability assessment [5], [6].

Table 1: Expert knowledge evaluation for failure events.

Event Terminated in Failure?	Failure Cause	Would it Fail if Inspection Time is Increased?	Would it Fail if Inspection Time is Increased?
1.0 (Yes)	Internal to component; piece-part	1.0 (Yes)	1.0 (Yes)
0.0 (No)	Observed higher than normal vibration after start *	0.7 (Yes)	0.7 (Yes)
1.0 (Yes)	Internal to component; piece-part	1.0 (Yes)	1.0 (Yes)
0.0 (No)	Pumped at low flow rate *	0.5 (Yes)	0.5 (Yes)
1.0 (Yes)	Inadequate maintenance	1.0 (Yes)	1.0 (Yes)
0.0 (No)	Pumped at low flow rate *	0.5(Yes)	0.5(Yes)
3.0			**4.7**

* Degradation was assumed for illustrative purposes

3. DATA COLLECTION AND IMPLEMENTATION

The methodology presented in Section 2 is tested using the data from Table 1. The Turbine-driven pump (TDP) component in the auxiliary feedwater (AFW) system is analyzed for plants which reported failure detection during inspection procedures. The “failure to start” failure mode is considered. These plants share a common characteristic – each had only one failure detected during inspection in a period of over 20 years.

The following assumptions were made:

- It is assumed that the system follows a Renewal Process. That is, after a failure is detected during inspection, the component is set back “as-good-as-new” condition for the failure mode under study.
- To analyze and combine data from different plants simultaneously, the populations are considered to be homogeneous (that is, they follow the same failure distribution).
- Failures are considered only if detected during inspection. Therefore, the starting time ($t = 0$) for the reliability function is reset from the last detection of a failure.
- It is assumed that the failure event occurs at the end of the interval ($t = t_e$).
- If a failure is detected during inspection, then it is assumed that the provided date corresponds to an inspection and, therefore, dates for the inspection intervals can approximately be defined based on the reported failure date.
- Consistent with common practice in PRA, the Exponential distribution will be considered for the failure distribution function.

Thus, for an exponential distribution, Equation 7 becomes:

$$\Lambda(E, \lambda) = \sum_i \log\left(\sum_j (\lambda\, exp(-\lambda t))^{k_{i,j}} \cdot P_j\right) - \sum_z \lambda t_z \qquad (17)$$

Considering that the expert knowledge adjustment value does not have any uncertainty, then:

$$\Lambda(E,\lambda) = \sum_i \log\left((\lambda\, exp(-\lambda t_i))^{k'_i}\right) - \sum_z \lambda t_z \quad (18)$$

$$\Lambda(E,\lambda) = \sum_i k'_i(\log(\lambda) - \lambda t_i) - \sum_z \lambda t_z \quad (19)$$

Note that, even though failure on demand events are used in this illustrative example, the approach holds as the failure on demand at a given point in time can be obtained as a function of the component's exposure and the corresponding failure rate during standby periods:

$$Q(at\ the\ end\ of\ inspection\ interval\ T) = 1 - \exp\,(\lambda T)$$

MCMC simulation is performed to estimate the λ (hazard rate) parameter for the Exponential distribution. The prior distribution $\pi_0(\lambda)$ in this calculation is taken to be a Uniform distribution between $\lambda_1 = 10^{-4}$ and $\lambda_2 = 10^{-2}$. This can be substituted with other forms of prior distribution such as lognormal distribution. Using the data from Table 1, the posterior distribution is estimated considering an inspection interval of three months (i.e., $t_e - t_s = 3\, months$). Figure 1 illustrates the accepted and rejected samples from the Metropolis Hastings method when applying Bayesian inference. The distribution of values converges after only a few iterations.

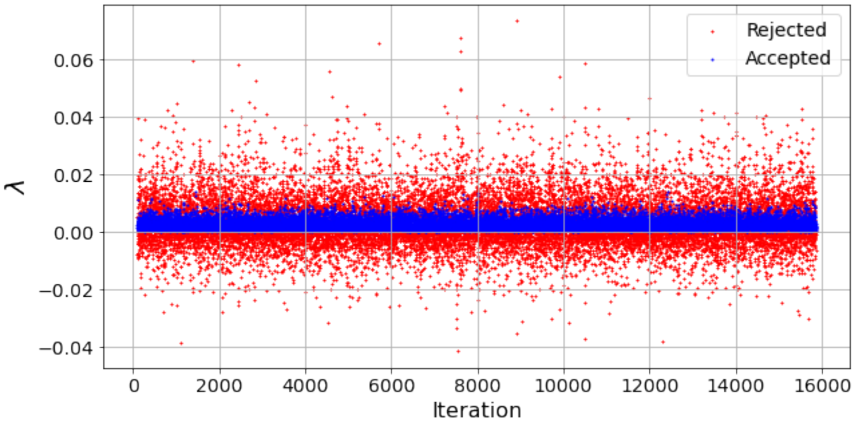

Figure 1: Accepted and rejected samples Bayesian inference process for a uniform prior distribution.

Figure 2 presents the histogram for the posterior λ values after the last iteration. For an inspection interval of 3 months, the estimated hazard rate of the Exponential distribution average is $2 \cdot 10^{-3}$.

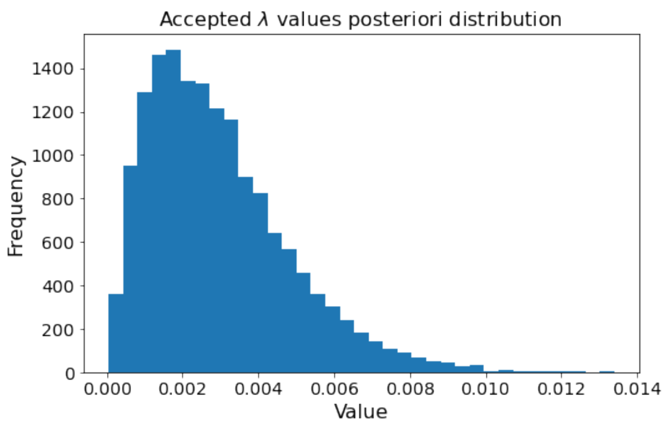

Figure 2: Hazard rate parameter distribution histogram for a uniform prior distribution.

As stated earlier, a different distribution for the prior $\pi_0(\lambda)$ can be considered. As a first approximation, the frequentist approach can be used to estimate the mean value of λ. In this case, $\hat{\lambda} \sim \frac{1}{20} = 0.05$ 1/yr.

Then, considering a Lognormal distribution with $\mu = \hat{\lambda}$ and $\sigma = 0.2 \cdot \hat{\lambda}$, the Bayesian inference results in an average hazard rate of $\bar{\lambda} = 7 \cdot 10^{-3}$, as shown in Figures 3 and 4.

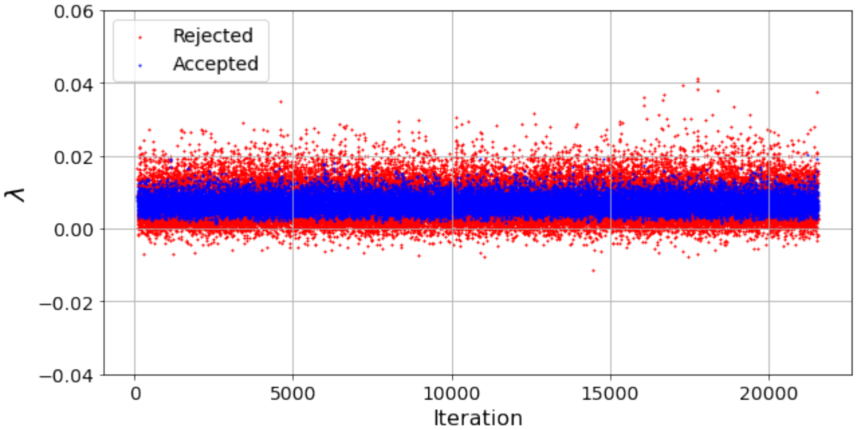

Figure 3: Accepted and rejected samples Bayesian inference process for a lognormal prior distribution.

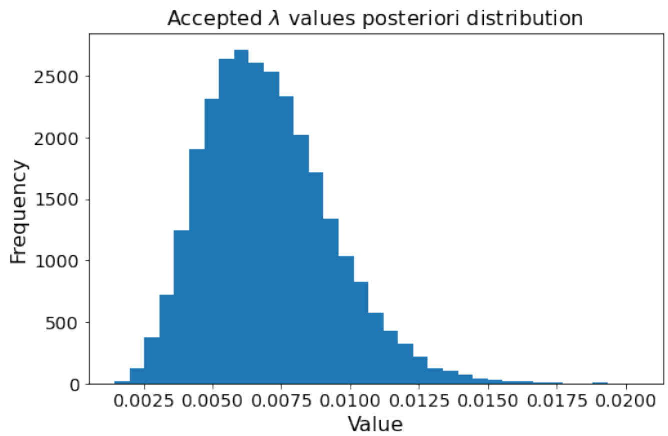

Figure 4: Hazard rate parameter distribution histogram for a lognormal prior distribution.

4. IMPACT OF CHANGE IN INSPECTION INTERVAL

With the capability to obtain a hazard rate parameter for any given time interval between inspections, the hazard rate λ changes for different time intervals can then be analyzed. This is shown in Figure 5, where the average λ is estimated for 3-, 6-, 9-, and 12-month inspection intervals for different values of c. As expected, for higher c values, the increasing hazard rate curve shift upwards. Additionally, the increase of the hazard rate accelerates with respect to the inspection intervals (that is, curves with higher slopes) for higher c values. A nearly linear increase is observed for the hazard rate with respect to the inspection interval, regardless of the c value.

The calculated increase in failure rate as a function of increase in inspection intervals is the result of two factors:

1. Predicted change in the number of failures based on engineering analysis of observed failures and detected degradations (through event mapping), resulting in c values greater than 1.
2. The effect of reducing the number of inspections, thus reducing the opportunity of renewal (corrective and preventive actions) provided by each inspection/test episode. This is reflected in Equation 4 through the form and number of survival terms (reliability function, R, for inspections/tests resulting in success).

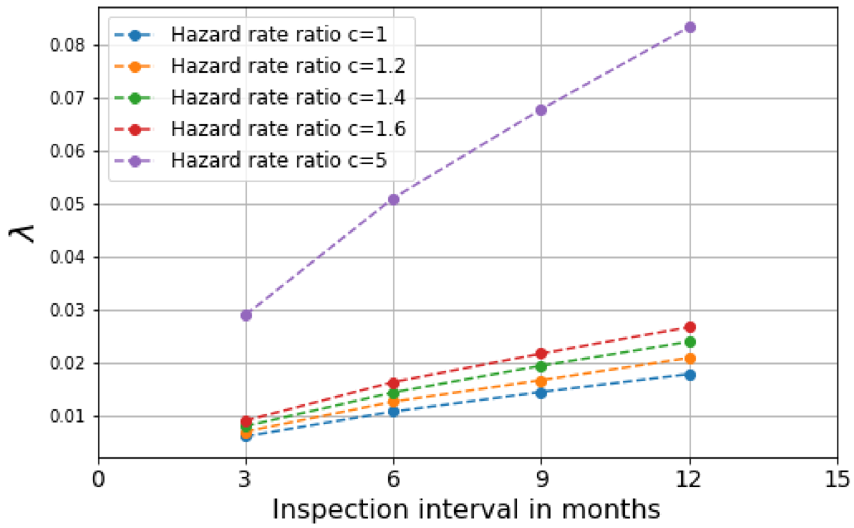

Figure 5: Sensitivity analysis on inspection interval effect on the hazard rate. Values are normalized with respect to 3 months interval.

5. CONCLUSIONS

5.1. Summary of Proposed Procedure

As described in the Framework section, the base framework for the proposed approach is to leverage past performance data in creating a database of extended STI conditions. That evidence can then be used in standard statistical analysis (such as the Bayesian approach proposed in this) to estimate the expected failure rate associated with the extended STI. The steps for applying the proposed procedure are:

1. Data Source: For the component under consideration for STI extension, use past plant-specific test/inspection and operational records. The input information should include: (a) current surveillance time interval length; (b) results of such surveillance in the past in terms of any observed failures, performance degradations, anomalies, root cause analysis and corrective action, if any, and (c) similar information for actual component demands. This provides the raw data and basis for engineering analysis of events in Step 2 ("event mapping"). Ideally, several years of such plant-specific records would be used for this analysis to have a stronger statistical basis in Step 3. Crucially, this methodology allows the use of similar data from other plants to augment plant specific data if needed (if insufficient evidence does not exist within the operating history at the specific NPP).
2. Event Mapping: For each inspection/test or failure event, assess whether the condition could become worse or better under the proposed extended inspection interval. This means a subjective assignment of a weight or probability like the examples given in Table 1. Specific guidelines need to be developed to ensure consistent and defensible numerical assessment. Such guidelines may be inspired by those developed for creating plant- specific databases of common cause failures in references [1]and [2].
3. Failure Rate Estimation: The number (i=1, 2, …, n) and lengths of the extended inspection intervals in the data base, and the corresponding projected "failure events" k_i' for the extended intervals assessed in Step 2 are the basic input to the Bayesian estimation procedure outlined in Section 2 (using Equation 19 for the case of constant failure rate). The procedure requires

numerical solutions using MCMC or similar methods. This results in an estimated uncertainty distribution of the new failure rate for the extended inspection interval (see Figure 4).

5.2. Concluding Remarks

1. As noted above, **specific guidelines need to be developed for Step 2 (event mapping)** to ensure consistent and defensible numerical assessment. Such guidelines may be inspired by those developed for creating plant- specific databases of common cause failures in references [1] and [2].

2. In practice, the ratio of assessed number of failures, k_i', over observed number of failures, k_i , 1=1,2,…*n*, (where *n*= number of inspection intervals in the database) is not expected to be much larger than 1. Based on limited number of simulations to test the methodology with hypothetical data in this paper, it appears that **the most important contributor to change (increase) in the failure rate for extended surveillance intervals is the decrease in the number of inspections and not increase in the increase in k values** (see Section 2.5). The change in the failure rate under the stated assumptions in the proposed procedure seems to be nearly linear with respect to change in the inspection interval (see Figure 5). Therefore, a practical approximate method could be based on the linear model, thus bypassing the proposed data mapping and estimation procedure. That is

$$\lambda_{post} = \left(\frac{T_{post}}{T_{prior}}\right)\lambda_{prior}$$

However, more exercises with a larger data set need to be conducted to confirm this.

This result, if substantiated by further exploration, would validate one of the current common practices of adjusting the constant failure rate of the affected component using a factor proportional to the increase in STI.

3. It may be possible to show a different relationship when **considering the number of tests** rather than the test interval, irrespective of the increased STI. This may be explored further.

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