RELIABILITY ANALYSIS FOR INSPECTIONS OF CANDU COMPONENTS AND SYSTEMS

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Abstract

Condition assessment of complex systems requires more than inspection data for the individual elements of the system. At the component level, knowledge of the probability of detection (POD) and sizing accuracy for defects is needed to properly interpret results. At the system level, probabilistic and deterministic methods guide safety assessments and life management strategies. The field of reliability analysis provides a framework for quantitative application of inspection results to both levels.

Quantitative knowledge of inspection reliability can reduce the requirement to use conservative values for every quantity. A sound analysis of inspection reliability can produce a more targeted inspection scope, leading to fewer but more effective inspections and, consequently, lower radiation dose. Restart cases can be based on correct detection probability distributions rather than worst-case scenarios, and inspection intervals and expected life estimates can be optimized based on measured sizing uncertainties.

This paper illustrates applications of inspection reliability analysis to optimize the inspect-repair-operate cycle for major CANDU® primary heat transport elements, such as steam generator tubing, feeder piping, and fuel channels.

1. INTRODUCTION

Utilities perform inspections to assess the components and systems of their generating stations for regulatory, safety, and economic reasons. However, the inspection data for the individual elements of a complex system are not of themselves sufficient input for condition assessment of the system. At the component level, knowledge of the probability of detection (POD) and measurement accuracy is needed for repair/replace decisions. At the system level, this knowledge serves as input to probabilistic and deterministic methods that guide safety assessments and life management strategies. The field of reliability analysis provides a framework for quantitative application of inspection results to both levels. This paper examines four topics in inspection reliability analysis with the goal of optimizing the inspect-repair-operate cycle.

- Analysis of inspection reliability can produce a more targeted inspection scope, leading to less extensive, but more effective, inspection and, consequently, to lower cost and lower radiation

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dose to personnel. Recent interest in Risk-Informed Inspection is motivated by this goal and highlights the need to quantify detection probabilities.

- Restart cases based on quantitatively determined distributions of measurement accuracy may be less restrictive than those based on worst-case scenarios. However, determining measurement accuracy can be difficult: laboratory tests are not always representative of in-reactor work, and the in-reactor conditions measured may be changed by the verification process of removing or accessing the object of interest.
- Overall accuracy is not the only information needed about sizing. A more detailed knowledge of error propagation through the analysis process can further reduce the requirement to use overly conservative values, *e.g.*, in finding the rate of change for a degradation mode that determines plugging criteria for tubing.
- Inspection intervals and expected life estimates can be optimized based on measured detection and sizing uncertainties.

These points are illustrated with examples from major CANDU primary heat transport elements, such as steam generator tubing, feeder piping, and fuel channels.

2. RELIABILITY ANALYSIS AND RISK-INFORMED INSPECTION

Many national regulatory bodies, among them the Canadian Nuclear Safety Commission, are assessing the potential benefits from replacing predetermined inspection strategies by Risk-Informed In-Service Inspection, or RI-ISI. A consensus document [1] by the European Commission characterizes the role of “risk” in the process as guiding the decisions on locations to be inspected, based on identification of anticipated degradation mechanisms and how likely these are to lead to various failure modes. The final recommendation of the consensus document was that, “The influence of different assumptions about probability-of-detection curves and independent versus dependent inspections on calculated failure rates and the link to inspection system qualification should be studied.” In other words, detection probabilities and the confidence levels associated with them must be known and validated; their values must then be combined with the component and system failure risks if the calculated probabilistic safety assessments are to be meaningful.

POD plays an important role in determining the “delta-risk”, *i.e.*, the increase or decrease in risk incurred by adopting an alternative inspection strategy. Periodic inspections, to confirm that no new generic degradation mode has appeared in a set of N components over the past operating period, may employ a variety of sampling philosophies, ranging from that prescribed by CSA N285.4 [2], which defines the minimum sample size as $F(n) = 1 + 2.22\ log_{10}(n)$, to the EPRI recommendations [3] of 20% for steam generator inspections. The fractions of the components to be inspected are very different in the two cases, but the objective for both is the capability to detect the onset of a degradation mechanism, with “onset” defined as being present in a certain number of the components. The sample size should provide assurance to a given confidence level that at least one of the affected components will be sampled. The probability, p, of selecting x out of m degraded components, when n out of a system of N components are tested, is the classical problem of sampling without replacement:

$$p(x) = \frac{\left[\frac{m!}{x!(m-x)!}\right]\left[\frac{(N-m)!}{(n-x)!(N-m-(n-x))!}\right]}{\left[\frac{N!}{n!(N-n)!}\right]}. \tag{1}$$

The assumption implicit in this approach is that, when an affected component is sampled, the degradation will always be detected. Then, only the probability of not selecting any degraded components, *p(0)*, needs to be considered. However, if the POD is not unity, the possibility of selecting one or more degraded components, but not finding the degradation, must be considered. The total probability of detecting at least one degraded unit is then

$$p(\text{detecting onset}) = 1 - \sum_{x=0}^{m} p(x)(1-POD)^{x}\ . \tag{2}$$

Thus, if the detection probability for relevant degradations is less than 1 (for example, if it is required to be 0.80 at 90% confidence, as is often the case), the sample size should be increased accordingly.

A fictitious example for inspections of two very different systems of components is illustrated schematically in Figure 1. "Risk", taken as proportional to the extent of degradation, *m/N*, that would lead to a detection 90% of the time, is plotted as a function of the fraction, *n/N*, of components inspected. Inspection A is the calculation for a large number of components with a high POD, achieving an early risk reduction for a small inspection effort and little additional gain for further effort. Inspection B is the calculation for a small set of components with a low POD, showing that further effort continues to reduce a more significant risk up to the 100% inspection level. Optimization of inspection strategies with a quantitative knowledge of their effectiveness would suggest a limited, but not zero, scope of Inspection A in favor of a full scope for Inspection B.

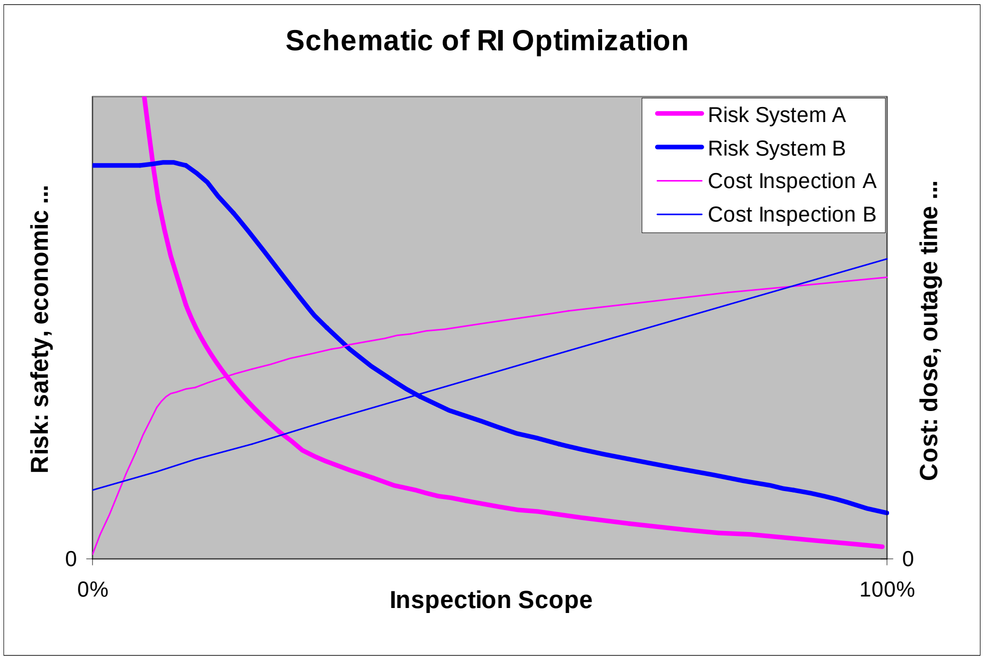

Figure 1: Illustration of risk (left-hand ordinate) and cost (right-hand ordinate) for two different inspection activities. Inspection A addresses a system with a large number of components with a high POD; Inspection B has a low POD and addresses a system with a small number of components. Cost curves are arbitrary illustrations. If Inspection A reduces the associated risk to a negligible level with a modest effort, further resources are better diverted to Inspection B, where significant gains can be made from the full inspection scope.

3. ASSESSMENT OF MEASUREMENT ERROR

Assessment of uncertainties may help avoid use of conservative worst-case scenarios, but measurement error encountered in-reactor is often difficult to quantify because there may be no way to ascertain the “true” value corresponding to the measured value. Laboratory measurements do provide access to “truth”, but often give an optimistic assessment of uncertainties because they lack many of the uncontrolled variables encountered the field.

Measurement of the clearance between pressure tubes (PT) and calandria tubes (CT), provides an example of difficult-to-quantify error. An eddy current technique provides an estimate of PT-CT gap, used to ensure the two components do not come in contact over the next operating period. Measured gap values are then combined with the predicted reduction in gap obtained from deformation codes. Near the end of a fuel channel’s service life, an overly conservative gap error estimate could lead to a need for remedial action, such as spacer relocation, selective defuelling or channel replacement, costing dose, time, and money, or resulting in degraded performance.

A more accurate gap measurement technique is obviously of value for reducing conservatism to extend service life, but even for existing techniques, simply quantifying the measurement error distribution may enable a probabilistic assessment showing negligible likelihood of contact. However, restricting qualification to laboratory tests may not be appropriate. Table 1 shows measurement errors for old and for improved technologies [4], obtained from the available historical and laboratory data; in both cases, the errors determined for laboratory work are quite small. For these measurements, quantities controlled in the laboratory but not in reactor can include temperature variations, lift-off variations, or resistivity variations; electrical noise and other unknown background contributions may also be different in reactor.

Table 1
Error Analysis for Conventional and Improved Measurements of PT-CT Gap in mm
(Comparing Laboratory and In-Reactor Results

Location	Probes	Analysis	Sample Mean	Sample std Deviation	Root-mean Square Diff.
Field	Conventional	Old	0.32	0.96	1.00
Lab	Conventional	Old	-0.22	0.31	0.38
Field	Improved	New	0.58	0.29	0.65
Lab	Improved	New	0.05	0.20	0.21

For each channel, four points in the field data, where the gap is defined by the known thickness of a detected spacer, provide a reference value. While this is useful for comparison, it does not provide reference value in the critical range of about 2 mm gap. The tabulated “Field” values do, however, indicate that the errors measured in laboratory work do not directly apply to in-reactor measurements.

Figure 2a shows the difference between the measured gap in the region of the spacer and the thickness of the spacer itself. The width of a normal distribution fitted through the data is more than twice the standard deviation of the corresponding laboratory measurement. A major technique improvement, namely the use of a surface-riding probe, gives a more tightly grouped set of in-reactor gap values (see Figure 2b), but since the laboratory data collected with this technique are better still, laboratory measurements again do not realistically represent the errors encountered in channel.

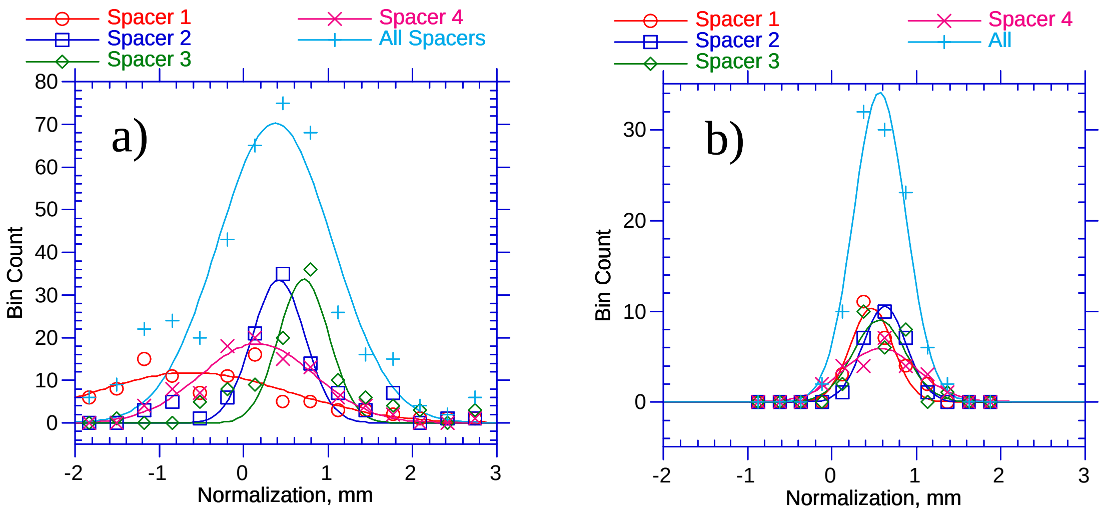

Figure 2: Difference between measured PT-CT gap and nominal spacer thickness at spacer locations. a) Conventional probe and old analysis software. b) Improved probe and new software. In both cases an approximately normal error distribution is observed [4].

The laboratory error assessment does show that measurement error decreases with decreasing gap, and the field data provides a reference point at 5 mm gap. Perhaps the optimum error assessment would utilize the trend of the lab measurements, benchmarked by the fixed points of field data.

4. ERROR PROPAGATION IN FLAW GROWTH ESTIMATES

When inspection of steam generator tubing provides evidence of fretting wear, a decision must be taken as to whether the tube should be plugged to remove it from the primary heat transport circuit. Plugging costs dose, time, and money, and degrades future performance of the steam generator. The depth limit for wear scars, at which tubes are plugged, is chosen so the degradation will not progress beyond the maximum tolerable flaw size before the end of the next operating period. The maximum acceptable depth, minus the depth increase over the next operating interval, combined with the depth measurement uncertainty, generally determines the plugging limit.

Measurement uncertainty, therefore, contributes to a more restrictive plugging limit. Further, the projected depth increase over the next period, determined by comparing successive measurements for this and similar wear locations, contributes additional uncertainty. Even for small projected depth increases, uncertainty can make the worst-case future depth so large, that quite shallow wear marks exceed the plugging limit. Clearly, reducing and quantifying overall measurement error improves the uncertainty of both the present size estimate and the future growth estimate.

Further, distinguishing correlated measurement errors from uncorrelated errors allows for a less conservative error propagation in the growth estimates. Current work for the CANDU Owners Group is examining sources of error associated with ET steam generator tube inspection and is developing a sensitivity model for flaw growth estimation. Figure 3 shows a pair of successive measurements, for which errors can be correlated or uncorrelated.

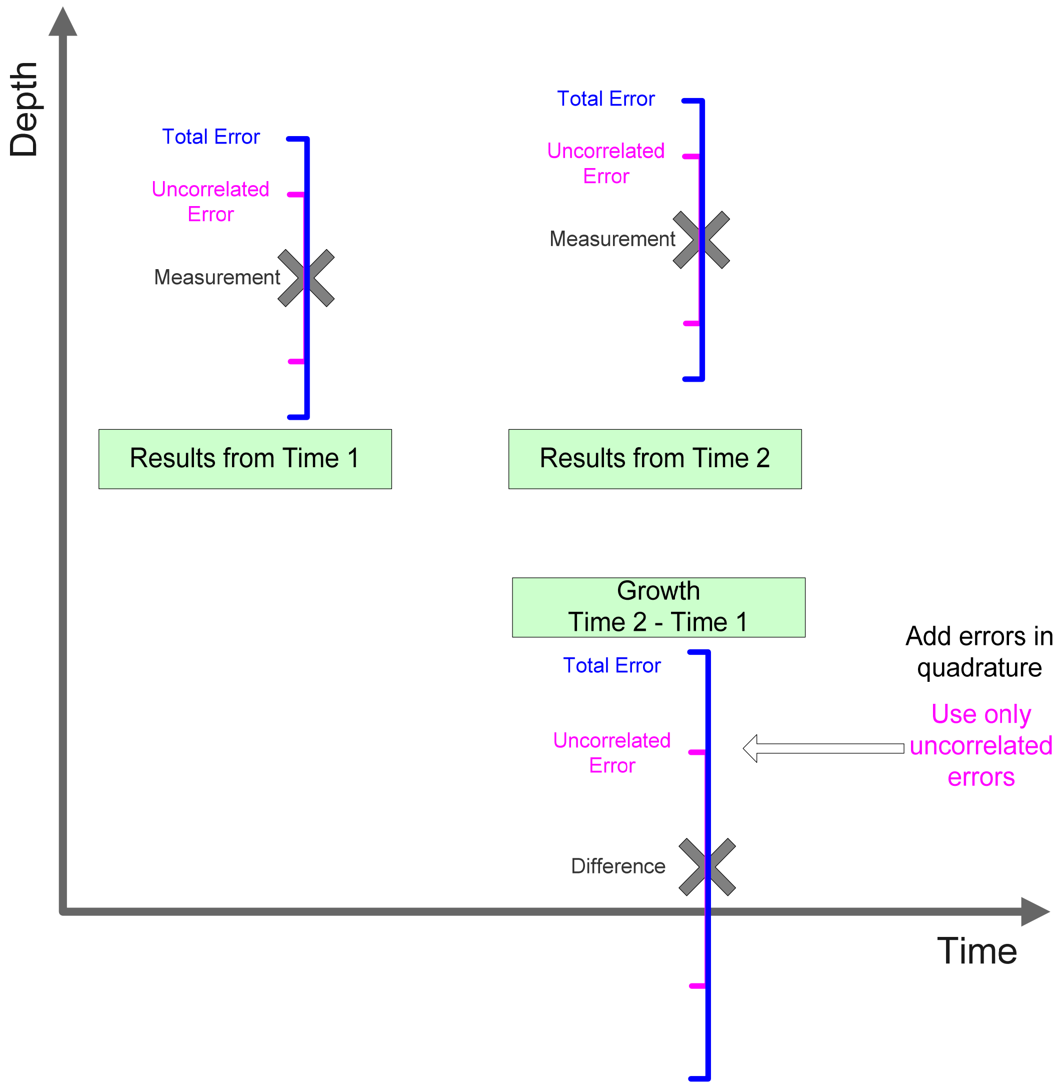

Figure 3: Schematic representation of error propagation in flaw growth assessment. Only the uncorrelated uncertainties are included in the relative growth assessment, but the total uncertainty of the Time 2 measurement is combined with the growth assessment when projecting to future worst-case depth.

Systematic offsets caused, for example, by a consistent calibration bias or by a constant background signal component are correlated and will contribute to the total error, but not to the measured difference between two successive measurements. An EPRI case study applying risk-informed steam generator inspection to fretting wear by anti-vibration bars [3] addresses operator and technique contributions to growth uncertainty but does not address the gains to be made by detailed error propagation. Figure 3 illustrates the removal of unnecessary conservativism by proper error propagation in growth estimates: only the uncorrelated error in the growth value needs to be included in the future depth projection.

A sensitivity analysis for the various error contributions may be performed by setting up the covariance matrix and partial derivatives for the entire processing chain. This permits use of the correct analytical expression of error effects, which may not be constant or linear in flaw size.

5. EVOLUTION OF FLAW POPULATIONS

Reliability analysis can predict the evolution of flaw populations over the life of a system subject to inspection and maintenance programs. The example of Section 2 shows how scope can be optimized by quantitative analysis. Bickel and Douglas [5] have given examples of how such calculations can give a condition assessment for a system of feeders by inverting the selection probabilities using Bayes' theorem and have also built a Monte Carlo model to assess the effects of various growth and inspection scenarios. Blain, Lefebvre, and Billy [6] have shown that stochastic degradation models require proper treatment of NDE errors to avoid overly pessimistic maintenance decisions. Such assessments of system condition and system rate of change are of value, since they can help determine inspection intervals, and expected life estimates. The critical ingredients of any flaw population model are shown in Figure 4.

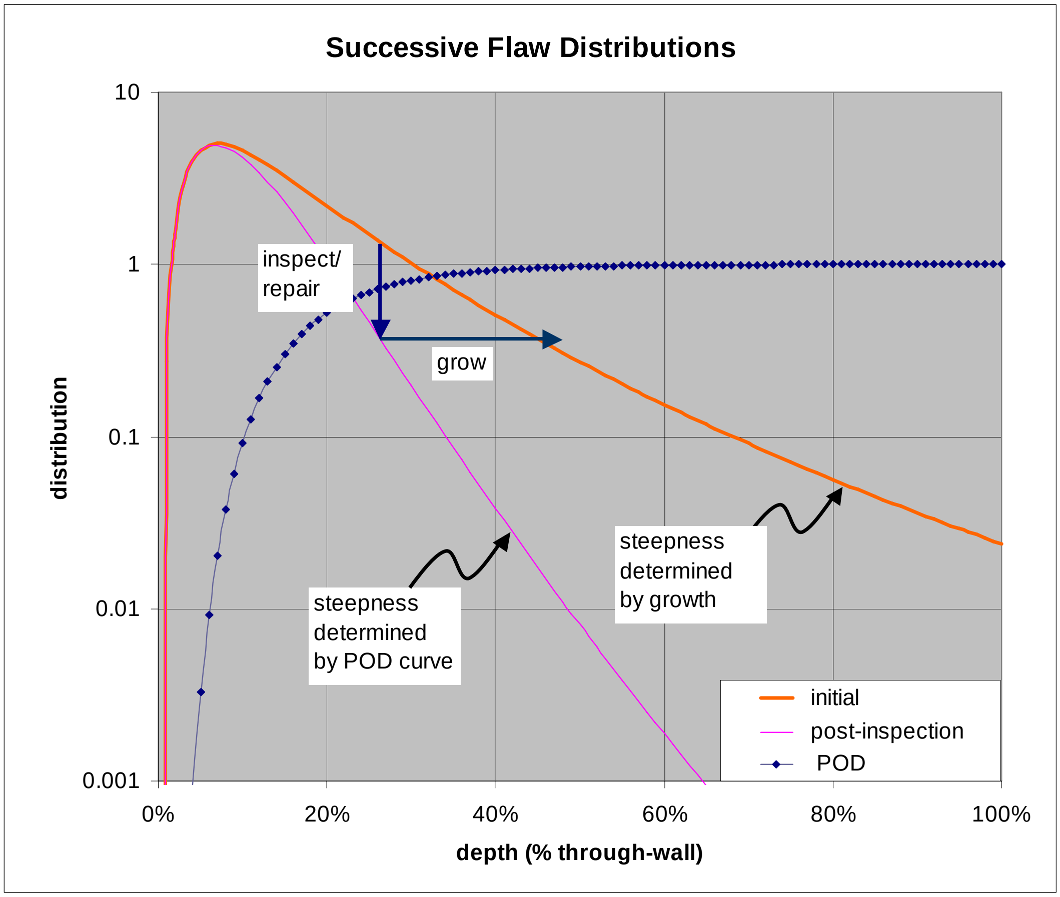

Figure 4: Flaw population and the effect of applying detection probability and growth to the distribution.

In the simplest picture, a flaw distribution is determined by initiation and growth rate distributions. The inspection parameters determine the post-inspection flaw distribution. In the region of low POD (the left side of the figure), the distribution is not changed by the inspect/repair process, but the large-depth part of the distribution is governed by POD and scope. The growth rate distribution for the remaining flaw population and initiation and growth rate for new flaws determine the population at the end of the subsequent operating period.

Systems of identical components subject to regular inspection and maintenance would benefit from a condition assessment and prediction framework. Further work on the evolution of flaw populations should be based on reliability analysis and NDE performance parameters.

6. CONCLUSIONS

This paper has illustrated applications of reliability analysis to optimize the inspect-repair-operate cycle for major CANDU primary heat transport components.

- Recent interest in Risk-Informed Inspection is motivated by the desire for a more targeted inspection scope and POD values are a necessary component of RI-ISI.
- Knowing quantitatively the distribution of measurement uncertainties is important, but laboratory tests are not always representative of in-reactor work, and the in-reactor conditions measured may be changed by the verification process of removing or accessing the object of interest.
- Detailed knowledge of error propagation through the analysis process can improve rate-of-change estimates for a degradation mode, such as one determining plugging criteria for tubing.
- Inspection intervals and expected life estimates can be optimized based on measured uncertainties of detection and sizing.

7. REFERENCES

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