Risk-Informed Prediction of Feeder End of Life

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Abstract

The operating life of feeder piping is negatively impacted by flow accelerated corrosion (FAC). In this study, an assessment of a large set of inspection data reveals that FAC in feeders is a relatively stationary process, with variability only at the local scale. Given the added uncertainty from inspection coverage, a new method for estimating the thinning rate and feeder EOL is developed using a probabilistic approach. The results of the study illustrate the benefits of the methodology in supporting risk-informed decision making at the station by quantifying the present and incremental risk in the feeder system over time.

1. Introduction

One of the major forms of degradation affecting the operating life of the CANDU feeder system is wall thinning by flow accelerated corrosion (FAC) [1]. The wall loss is most significant in the tight-radius bends near the outlet feeder Grayloc weld, due to the highly disturbed flow in this region.

Because of safety concerns associated with feeder wall thinning, a specified lower limit of wall thickness must be established for each feeder to ensure adequate safety and fitness-for-service prior to the next scheduled inspection. In this context, feeder end-of-life (EOL) implies exceeding (i.e., being below) the limiting wall thickness criteria. Clearly, being below the regulatory limit does not result in feeder structural failure and subsequent forced outage, however, repair/replacement or other intervention must take place in order to maintain the specified level of safety. The critical minimum thicknesses are estimated based on a design pressure consistent with Section III of the ASME Boiler and Pressure Vessel Code [2]. Typically, the maximum allowable wall loss is equal to 40 % of the initial wall thickness.

Predicting the timing of feeder EOL is important for both continued fitness-for-service and feeder life cycle management (LCM). Determining the remaining life of feeders is challenging, however, due to the uncertainties involved, including the lack of initial wall thickness measurements, errors associated with the inspection probes, and variability in chemistry and other operational parameters affecting the wall thinning process.

The current approach to feeder management utilizes the measured (point) values of minimum wall thickness and the industry developed QV model [3] to estimate the wall thinning rates. The worst case rate is then typically used to predict (deterministically) the time to reach the limiting wall thickness, and hence, the appropriate time (i.e., outage) for feeder replacement. While these methods are useful for fitness-for-service applications in the short term (i.e., in the next outage interval), they may lead to conservative predictions in the long term.

The objective of this paper is to present a methodology that allows the feeder EOL predictions to be performed in a risk-informed setting. The methodology is based on the analysis of a large dataset, consisting of 1582 separate wall thickness scans from 519 unique feeders at seven different operating nuclear reactors. The proposed method is based on a probabilistic approach that accounts for the underlying uncertainties in a consistent manner. The objective is to compute the probability that the feeder wall thickness is below the regulatory limit at any time in the future. This directly supports risk-informed decision making at the station by quantifying not only the risk associated with the feeder system at any time, but also the residual or incremental risk associated with any delay in the replacement of specific feeders.

2. Feeder wall thickness characterization

The wall thickness of feeder pipes is measured using ultrasonic NDE tools. The probes consist of varying number of ultrasonic (UT) transducers, typically arranged within an array or bracelet. Figure 1 illustrates a typical result from the ultrasonic scan of a 2 inch diameter outlet feeder left cheek region using a 14-probe bracelet. The 14-point array probe covers approximately 140 degrees of the 2 inch feeder pipe circumferentially, and is advanced axially along the length of the pipe.

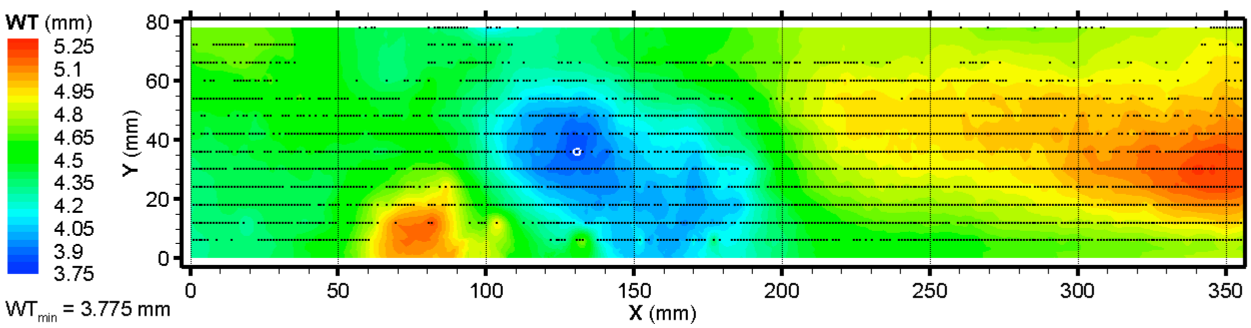

Figure 1 Contoured wall thickness of a 2 inch outlet feeder 14-probe left cheek scan.

The y-axis in Figure 1 represents the circumferential direction around the diameter of the pipe which contains the 14 regularly spaced (i.e., 6 mm apart) ultrasonic transducers. The x-axis corresponds to the axial direction, with x = 0 mm located near the Grayloc hub. The black dots represent the probe measurements, spaced approximately 1 mm apart in the axial direction, while the small white circle shows the location of the measured minimum thickness for the scan. As shown in Figure 1, the wall thickness ranges from approximately 3.75 mm to 5.25 mm, with the probe reporting a minimum thickness equal to 3.775 mm.

The interpolated wall thickness profile in Figure 1 was generated using a Kriging algorithm as implemented in Tecplot [4]. The surface fitting was performed over a uniform 1 mm by 1 mm grid. Kriging is a robust statistical method used extensively in geostatistics for the modelling of sparse spatial data [5]. As opposed to other interpolation algorithms, such as inverse distance weighting that rely on deterministic attributes, kriging analyzes the spatial correlation structure statistically over the entire domain.

The pattern of wall thickness loss due to FAC is clearly evident as the blue area in Figure 1. The thicker red areas reflect the non-uniform wall thickness profile due to the fabrication process, i.e., bending. Based on the assessment of the 1582 separate scans in the large dataset from the industry, the pattern of wall loss (in terms of shape and location) is directly related to the feeder geometry. This means that feeders with the same geometry will generally experience FAC related wall loss at the same locations (due to similar flow conditions), regardless of the reactor unit. The actual depth, however, is highly variable as a result of specific local and global operating conditions (i.e., chemistry, temperature, etc.).

2.1 Inspection uncertainties

The key sources of uncertainty associated with NDE inspection data include

- Probability of detection (POD)
- Sizing error
- Contact error, and
- Coverage error.

The concept of POD is generally associated with flaw detection, where the main purpose is to confirm or discover the presence of a certain type (and size) of defect, e.g., a crack. Therefore, POD is not directly applicable in the present context of general wall thickness measurement.

The classic concept of sizing error or pure measurement error (i.e., bias plus random noise) appears to have a negligible impact on the results in this study. Although it is difficult to discern the presence (or absence) of bias using solely the in-service measurements, the presence of random noise is not evident in the wall thickness scans analyzed in this study (e.g., many adjacent probe values are exactly the same). This means that the individual values reported by the probe transducers are likely to be highly accurate and subject to minimal error.

The main limitation with using ultrasonic probes for feeder inspection, besides challenges with accessibility (both physical and radiation dose), is the probe coverage issue. Ultrasonic probes are highly dependent on the specimen geometry and surface conditions, resulting in the probes losing full contact in certain conditions. This effect is illustrated in Figure 1 by the missing data along the length of the scan for some of the transducers (in particular, the transducers on the ends of the bracelet, i.e., near y = 0 mm and y = 78 mm are yielding few, if any measurements along the length of the scan). While the overall coverage or contact is quite good for the specific scan in Figure 1, the average probe contact error is in the order of 40 to 50 % among all the scans in the large dataset, meaning that on average, 40 to 50 % of the possible values in each scan are missing.

The other significant issue, particularly for long-term prediction, is the probe coverage error due to the fixed spacing of the probes on the bracelet. Here “coverage error” refers to the inability to measure the wall thickness between the 6 mm spaced transducers. This effect is readily apparent on overlapping and replicate scans (not shown here) that report a slightly different (point) value for the minimum wall thickness in the same area of pipe.

Clearly, the impact of the probe coverage error depends on the underlying FAC process. If the loss of wall thickness across the pipe is very gradual, as is the case with generalized thinning, the error in the value of the minimum wall thickness within the space of 6 mm is expected to be small. However, if the thinning is more localized, the error may be more significant (and can further be compounded by the probe contact error). Regardless of the magnitude of the error, it is evident that the observed minimum wall thickness is always greater than or equal to the “actual” minimum wall thickness (i.e., because of negligible sizing error, the minimum value reported by the probe can never be less than the “actual” minimum thickness in the pipe).

Based on the analysis of the large dataset, the coverage error is generally in the order of 30 to 50 μm, depending on the nature of the FAC process (i.e., general vs. localized). Clearly, this small effect has a negligible impact on short term prediction, however, it should be properly accounted for when estimating the feeder EOL. In practice, the probe contact and coverage errors can be reduced by replicate scans or by scanning each of the bend sections (i.e., Extrados, Intrados, Left Cheek, and Right Cheek) separately. The overlap between the sectional scans increases the likelihood of the thinned area to be scanned twice (i.e., the thinned area must be located near the edge of the scan).

3. Thinning rate estimation

Unlike the FAC analysis of other nuclear piping, which are typically more readily accessible and allow for precise measurements at fixed locations [6], the fundamental challenge with feeder wall thickness inspection is the lack of fixed location referencing. During each inspection, the UT bracelet is mounted somewhere near the Grayloc hub and advanced manually in the general axial direction of a particular pipe section (e.g., Extrados region). Because of the manual nature of the inspection process and the loss of wall thickness over time due to FAC, it is impossible to match any two points precisely between inspection outages.

Estimating the thinning rate using the minimum wall thickness (point) value from each inspection outage appears intuitive, however, there is no guarantee that the two values correspond to exactly the same location in the pipe. Because of the probe contact and coverage errors, the method of using point values may also lead to unexpected results (e.g., negative thinning rates) in some cases. It is expected that the impact is likely to be small for generalized thinning (i.e., where a larger area of the pipe shares the same, or nearly the same wall thickness), and can further be reduced by the overlapping scans.

To circumvent these issues and uncertainties, we develop a more robust methodology for estimating the wall thinning rate and predicting the feeder EOL. The method utilizes a sample based approach that accounts for uncertainties in the underlying FAC process, while at the same time minimizing the impact of the probe coverage issue.

3.1 Methodology

Figure 2 shows a close-up of the wall thickness profiles for the previous and most recent outage for the feeder presented earlier in Figure 1. The operating time between the two outages is approximately 1.1 effective full power years (EFPY). As shown in Figure 2, the overall shape of the wall thickness loss appears not to be changing significantly over time, indicating that the FAC process is relatively uniform or stationary over time for this feeder.

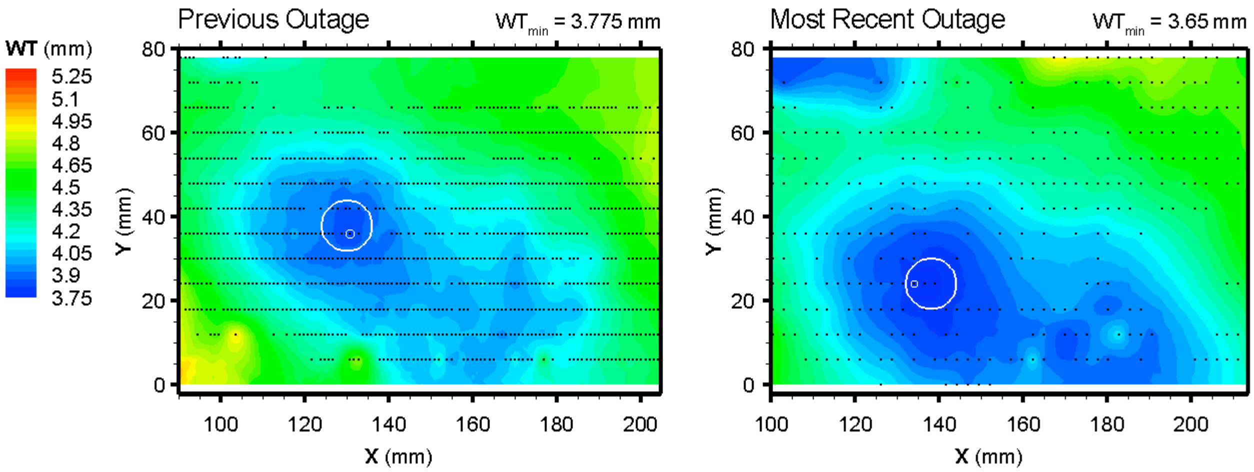

Figure 2 Contoured wall thickness of a 2 inch outlet feeder 14-probe left cheek scan from the previous and most recent outage. The larger white circle indicates a 12 mm diameter circular area having the lowest average wall thickness within the scan.

Due to the inherent variability in the FAC process, there are small changes in wall thickness at the local scale, as evidenced by the shifting of the minimum wall thickness location (i.e., the small white dot) in Figure 2 over time. This demonstrates that while the wall thickness profiles may be "lined-up" visually, it is impossible to find a fixed reference for each point in the pipe.

To overcome the uncertainty and difficulty associated with the point value approach, consider all the points in the "vicinity" of the minimum thickness location as a sample. As an example, consider a small, e.g., 12 mm diameter circular patch or spot area as shown by the larger white circles in Figure 2. The location of each spot area was determined using an optimization algorithm that minimizes the average wall thickness inside each spot. Because of the symmetric pattern of wall thickness loss around the minimum point, the spot area typically contains the observed (point) value of minimum thickness.

From Figure 2, it appears, at least visually, that the two circular patches represent reasonably the same area of the pipe. This determination is easier to make in terms of the larger patch, as opposed to using the single point-value approach. The patches also correspond to the areas with the lowest average wall thickness, and therefore should theoretically represent the same area, assuming the FAC process is reasonably stationary over time.

Assuming a linear model for the FAC process, the thinning rate can then be estimated in terms of the average wall thickness in each patch as

$$R = \frac{WT_1 - WT_2}{\Delta t} \tag{1}$$

where R is the thinning rate, WT_1 and WT_2 are the average wall thicknesses for each patch in the previous and most recent outage, respectively, and Δt is the outage interval. Because each patch corresponds to the lowest average wall thickness, the patch average represents the average "minimum" wall thickness for the scan. Using the concept of averages here implies that any point inside the small circular patch is assumed to have an equal likelihood of becoming the actual minimum point in the future. This assumption seems reasonable, as shown by the shifting of the minimum point inside the patch area in Figure 2.

3.2 Uncertainty in estimation

As shown in Figure 2, the resolution of the scan for the most recent outage is less than in the previous outage, with values recorded approximately every 2.6 mm (rather than 1 mm) in the axial direction. Hence, because of the probe resolution and contact errors, there are only three actual observations inside the 12 mm circular patch for the most recent outage.

To overcome the issues with probe contact and coverage, the analysis should be conducted using the interpolated surface rather than the observed point values. Using surface interpolation methods, particularly kriging, allows the missing data due to contact error and the lack of coverage between the individual transducers to be replaced with regionally (and statistically, in case of kriging) consistent estimates. That is, the trends (local or regional) in the change in wall thickness between the measurement points are used to predict values in the unobserved locations (a uniform 1 mm by 1 mm grid in this case). This approach minimizes both the contact and coverage errors and therefore reduces the overall uncertainty in the estimated thinning rates. Naturally, a large number of missing data near the actual location of minimum thickness would obviously have a negative impact on the results.

Figure 3 shows the impact of the circular patch size on the estimated thinning rates. A total of 24 feeders with repeat measurements were considered in the analysis.

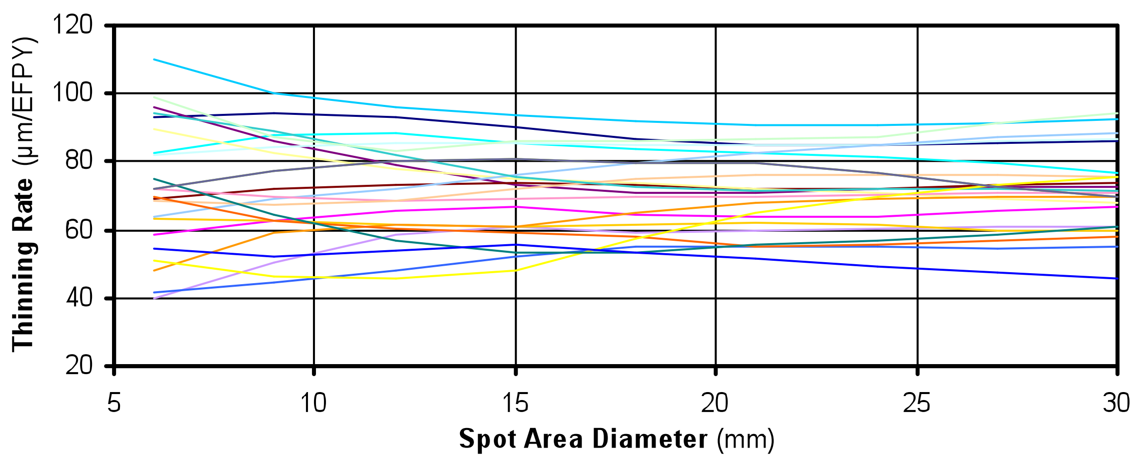

Figure 3 Impact of patch size on the estimated thinning rates.

Each of the 24 feeders is represented by a different coloured line in Figure 3. Only a small number of the total of 519 total feeders from the different reactors had good quality measurements of the same pipe section from different outages. Furthermore, the thinned areas need to be located near the middle of the scan (in the circumferential direction) to accommodate the larger patch sizes used in the analysis.

As shown in Figure 3, there is higher variability for smaller patch sizes, however, the thinning rates seem fairly constant for patch sizes greater than 12 mm. This is to be expected because of the underlying resolution of the inspection probes and the local scale variability in the FAC process. In other words, there is higher uncertainty and variability in the estimates at the smaller scale, which again highlights the uncertainty associated with the minimum point-value approach.

Figure 4 shows the comparison of the estimated thinning rates using the circular patch method versus the minimum point-value approach. As shown in Figure 4, the thinning rates estimated using the point value approach are generally higher, particularly for feeders with higher thinning rates, resulting in shorter EOL predictions and hence earlier replacement times.

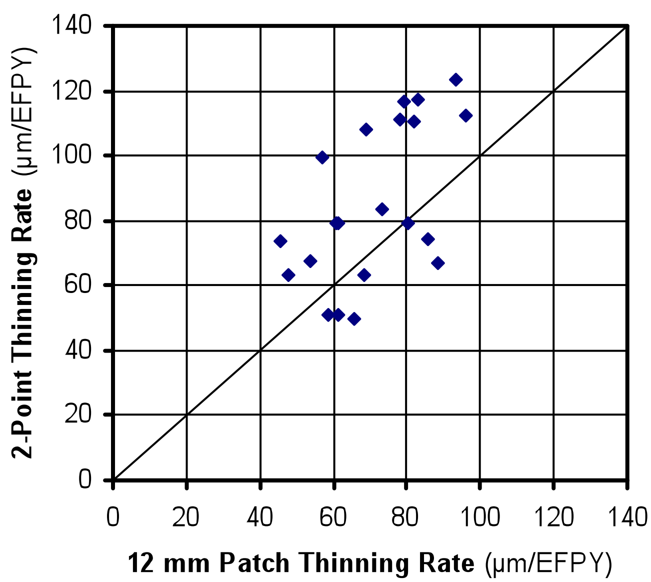

Figure 4 Impact of patch size on the estimated thinning rates.

4. Probabilistic prediction of feeder EOL

The linear random rate model is commonly used for modelling time-dependent deterioration processes. In the random rate model, the wall thickness at any time is estimated as

$$WT(t) = WT(0) - R \cdot t \tag{2}$$

where WT is the wall thickness and R is the random thinning rate. Because the thinning rate is a random variable, the variance or standard deviation of the wall thickness increases as a function of time.

In the methodology developed in the previous section, the average "minimum" wall thickness was estimated by the average wall thickness in the circular patch. The variability of the wall thickness within the patch is described by the standard deviation. As opposed to a purely statistical measure, however, the standard deviation in this case represents the underlying morphology of the FAC "flaw" or thinned area. For example, a deeper thinned area would have a higher standard deviation than a shallower one for the same patch size. Therefore, in the case of FAC, the standard deviation of wall thickness is connected with the physical manifestation of the underlying degradation process.

Figure 5 shows the difference in the circular patch standard deviation between the previous and most recent outages in terms of patch size. Again, only the 24 feeders with repeat measurements were used in the analysis. As shown in Figure 5, the difference in standard deviation is relatively insensitive to the patch size, which again demonstrates that the FAC in feeders appears to be stationary process. The overall difference in standard deviation is quite small, generally between +/- 20 μm. In this case, positive values indicate that the standard deviation in the patch is greater in the first outage than the second one, meaning that the thinned area is getting slightly shallower over time. Negative difference indicates the opposite effect, meaning that the thinned area is deepening with time.

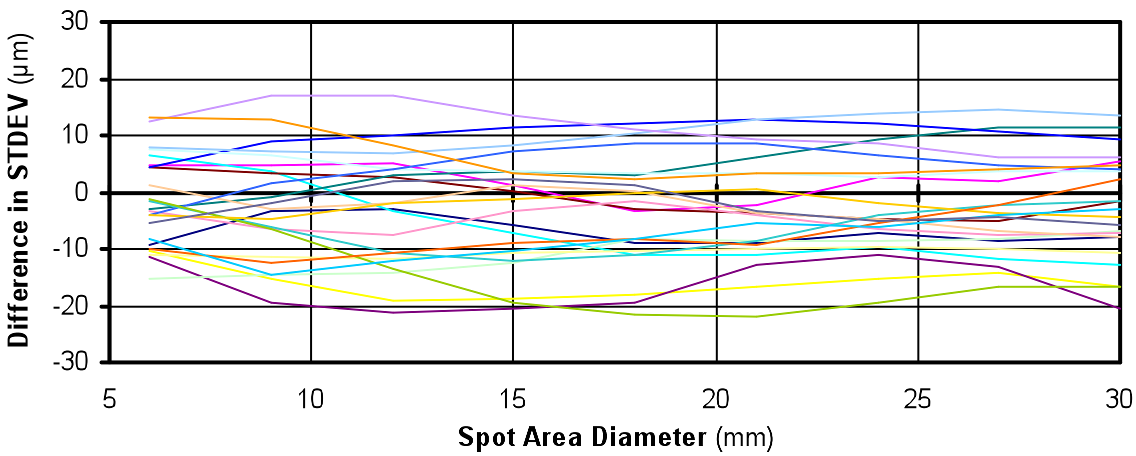

Figure 5 Difference in spot area standard deviation between outages vs. spot area size.

It is possible that the small differences observed in Figure 5 may be due to missing data near the minimum points. Less data will generally make the interpolated surface "coarser" resulting in a higher standard deviation. Observations of a small number of feeders with three consecutive outages in the large dataset seem to support this argument, as there is no clear trend evident in the standard deviations over time (results not shown here).

Theoretically, it is plausible that the standard deviation of wall thickness may either increase (i.e., thinning is becoming more focused and deeper) or decrease (i.e., thinning is becoming more generalized and shallow) over time as a result of FAC. For feeder wall thinning, however, the results of this study indicate that the process is relatively stationary, implying that the thinning rate and the standard deviation of wall thickness remain reasonably constant over time.

Therefore, it follows that the classic random rate model is not applicable in this particular problem. Although the standard deviation of wall thickness does not grow as a function of time and the thinning rate has limited uncertainty or randomness associated with it, the linear model in Eq. (2) can still be used to predict the average "minimum" wall thickness over time.

4.1 EOL prediction

For risk assessment, we need to estimate the "actual" minimum wall thickness and then compare it to the required minimum wall thickness for each feeder. Based on the assessment of the large dataset, the wall thickness inside the circular patch can be fitted well using the Normal distribution (R^2 on Normal probability paper is greater than 0.97 for nearly all cases). The "actual" minimum wall thickness over time can therefore be described by the Normal distribution, with average predicted using Eq. (2) and a constant standard deviation derived from the circular patch (e.g., either from the most recent outage, or as and average between the two outages). Again, the key assumptions here are that

1. FAC is a stationary process, hence the standard deviation does not change over time
2. Any point within the circular patch has an equal likelihood of becoming the actual minimum point in the future.

While the thinning rate may be estimated reasonable well with any patch size greater than 12 mm (see Figure 3), the average and standard deviation of each patch are directly dependent on the patch size. It is therefore important to determine the appropriate patch size to be used for the prediction of EOL.

Clearly, the issue of the appropriate patch size is related to the "area of influence" of the FAC process. A larger patch implies higher local scale variability in the wall thinning, whereas a smaller patch means that the thinning is more uniform and hence less uncertain. In the case of generalized thinning, the standard deviation of the patch is small to begin with, making the analysis less sensitive to the patch size. The impact may be larger for more localized thinning, however, the patch size should then naturally also be smaller.

Figure 6 shows the EOL prediction for the 2 inch outlet feeder shown earlier in Figure 1 and Figure 2. The plot in Figure 6 shows the probability that the estimated (actual) minimum wall thickness is less than the required wall thickness over time for several patch sizes. The required wall thickness for the feeder is equal to 3.1 mm.

As shown by Figure 6, there is a high probability that this feeder will reach EOL between 7 and 8 years from the last outage. The probabilities are lower for larger patch sizes because the "average" wall thickness of larger patches is higher. For comparison, the estimated EOL for this feeder using the point-value method (i.e., based on the minimum point values only) is 4.9 years. This is mostly due to a higher thinning rate predicted by the point-value approach.

It is evident that Figure 6 can readily be used to estimate the risk associated with delaying the replacement of this feeder, for example, from 4.9 years to 7 years from the latest outage. Similar analysis can be performed for other feeders with repeat wall thickness measurements.

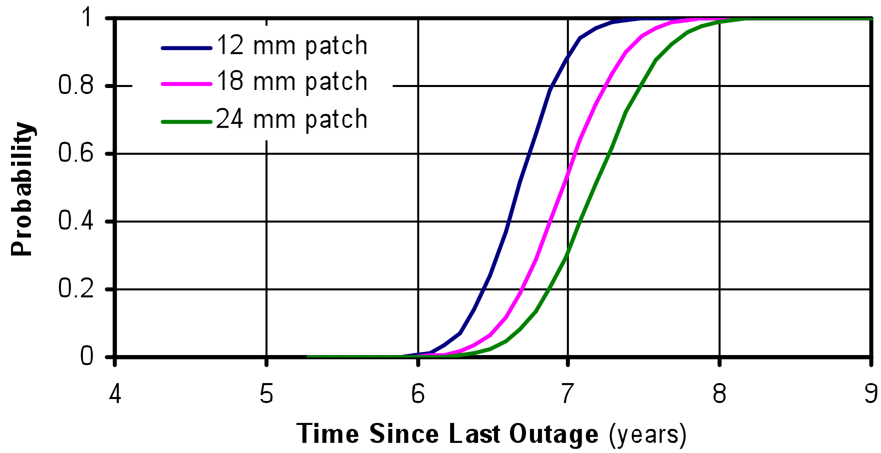

Figure 6 Probability of EOL over time vs. patch size for the 2 inch feeder.

4.2 Multiple inspection data

The preceding approach can be adopted for the analysis of feeders with multiple inspection data. Rather than Eq. (1) and Eq. (2), the thinning rate and EOL can be predicted using linear regression of the "average" patch estimates, with the slope of the regression line corresponding to the thinning rate. Assuming that the FAC process is relatively stationary, the regression error should be small. Any variability in the regression may be due to missing data near the point of minimum thickness inside each patch, or different operating conditions (e.g., pressure, temperature, flow rates, etc.) between the outages.

Similar to before, the uncertainty in the "actual" minimum wall thickness is reflected by the standard deviation, which can be estimated, for example, as the average of the multiple patches. The uncertainty from the linear regression line (i.e., the standard error) can further be added to the estimate to reflect the additional sources of error in the analysis.

5. Summary

Wall thinning by flow accelerated corrosion (FAC) is a severe form of degradation affecting the operational lifetime of the feeder system. Based on the assessment of a large inspection dataset from the nuclear industry (with 1582 separate wall thickness scans of 519 unique feeders at seven different nuclear reactors), it was observed that the FAC process in feeders is a relatively stationary process, with small variability only at the local scale. In addition to the inspection coverage issue, however, this local variability adds uncertainty to feeder end-of-life (EOL) prediction using the current minimum point-value approach.

To minimize the uncertainty in prediction, a new method for estimating the thinning rate and feeder EOL was developed in this paper using a probabilistic approach. The method focuses on a small circular area in the vicinity of the minimum point, rather than only the minimum point itself. Because the FAC process is relatively stationary over time, the analysis is insensitive to the patch size, and therefore provides a highly robust way to estimate the feeder thinning rates. The only significant uncertainty is due to the probe coverage and contact error, which is minimized by the sample based approach and the surface interpolation and fitting scheme (i.e., kriging).

The study showed how the method can be used to compute the probability that the feeder wall thickness is below the specified regulatory limit at any time in the future, and hence the risk associated with the feeder system over time. The model can further be used to estimate the residual or incremental risk associated with the delay of replacement of specific feeders.

In summary, the developed methodology can readily be applied to any feeders with repeat inspection data to support risk-informed decision making and feeder life cycle management (LCM).

6. Acknowledgements

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7. References

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