STATISTICAL ANALYSIS OF PIT GROWTH IN CANDU STEAM GENERATOR TUBES

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ABSTRACT

During the outage of steam generators in a CANDU reactor unit, eddy current inspection detected volumetric indications (pitting) in the tubes at top-of-tubesheet region (TTS). The majority of the indications were found to be pre-existing pit-type defects based on a signal-to-signal analysis of previous inspection data. This investigation studies the pit growth by collecting individual pit size change from the data of two outages and calculating the growth rates and their confidence intervals.

The pits at the TTS are divided into separate populations according to their locations and statistical test of homogeneity. The mean growth rate, 95% upper bound growth rate, and their confidence intervals of each population are evaluated using the bootstrap resampling method. A method is also proposed to lower the 95% upper bound growth rate by adjusting for the effect of the eddy current measurement error.

1.0 BACKGROUND

Various forms of degradations on tubes can occur during the operation of CANDU steam generators (Fig. 1). At the U-bend supports, there may be fretting and stress corrosion cracking (SCC). At the tube support plates, fretting, denting, SCC and denting can exist. In the sludge pile at top-of-tubesheet (TTS), SCC, pitting and wastage are not uncommon.

The current investigation focuses on the growth rate of pitting at top-of-tubesheet. Pitting is localized corrosion over a relatively small region as a result of chemical attack. Growth of pits is promoted by local chemistry in sludge pile. Pit growth is sometimes limited to chemistry excursions - there may be little growth during normal operation. Figure 2 presents an example of the physical appearance of pitting on steam generator tubes.

During an outage of steam generators in a CANDU reactor unit, eddy current inspection detected volumetric indications (pitting) in the tubes at TTS region. The majority of the indications were found to be pre-existing pit-type defects based on a signal-to-signal analysis of previous inspection data. The proper evaluation of pit growth rate based on these data is important for the condition monitoring and operational assessment of the steam generator tubes.

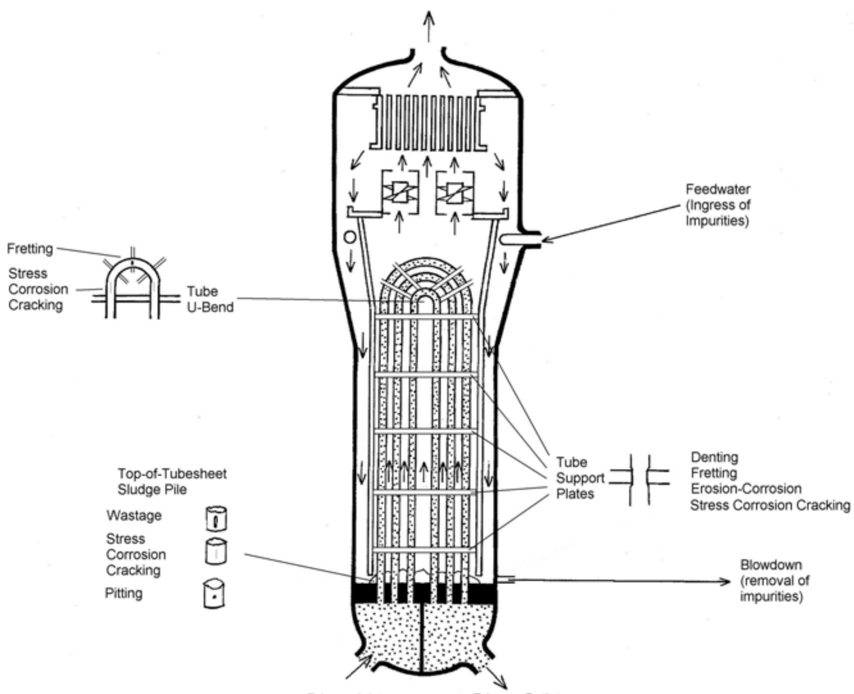

Figure 1 Various Forms of Degradations in a CANDU Steam Generater

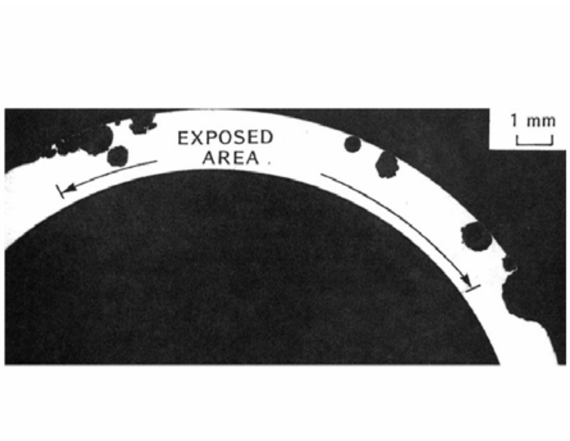

Figure 2 Physical Appearance of Pitting on Steam Generator Tubes

2.0 PIT INSPECTION DATA

Pits in the steam generator (SG) tubes were detected in the TTS region using eddy current inspection techniques. The signal-to-signal analysis of previous inspection data revealed that the majority of the pits are pre-existing. Table 1 presents a sample of the eddy current inspection data.

In the table, a set of row and column number corresponds to a tube in a steam generator. The depth values are the eddy current pit sizing for the previous and current outage in terms of fraction of tube wall thickness. The growth is the current depth minus previous depth for each pit. It is interesting to notice that some of the growth values are negative. This is due to the measurement error of the eddy current technique.

The purpose of this investigation is to study the pit growth by collecting individual pit size change from the data of two outages and calculate the growth rates and their confidence intervals. Please note that the data in this presentation are artificial but statistics resemble actually observed data.

Table 1 A Sample of Eddy Current Inspection Data

Row	Column	Depth Previous	Depth Current	Growth
13	55	0.32	0.38	0.06
28	72	0.22	0.18	-0.04
32	50	0.38	0.34	-0.04
43	49	0.20	0.13	-0.07
45	49	0.19	0.19	0.0
45	53	0.25	0.33	0.08
45	71	0.28	0.33	0.05
56	36	0.35	0.42	0.07
55	49	0.31	0.32	0.01

3.0 STATISTICAL ANALYSIS

3.1 Data Observation

The pits found at TTS are divided into two populations: pits in SG1 (110 pits) and pits in other SGs (22 pits). This division is due to the fact that SG1 has significantly more pits than other SGs.

Figure 3 shows the plots of cumulative probability curves of pit size for current outage and previous outage for SG1 and other SGs. For both SG1 and other SG1, the cumulative pit size curve for the current outage is generally on the right side of the curve for previous outage. This indicates an appreciable amount of growth for the pits.

Figure 4 presents histograms of individual pit growth from previous to current outage for SG1 and other SGs. The histogram for SG1 shows a spread of value at both positive and negative growth while the histogram for other SGs is more of a one-sided shape.

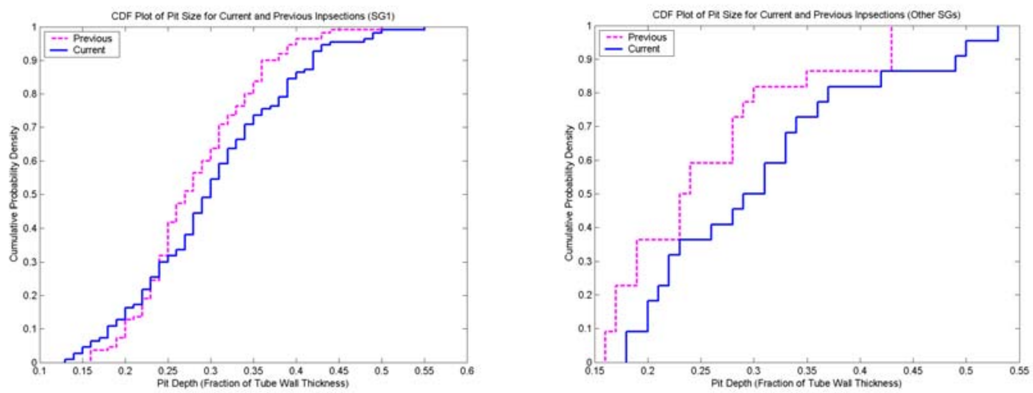

Figure 3 Cumulative Probability Distributions of Pit Size from Previous to Current Outage for SG1 and Other SGs

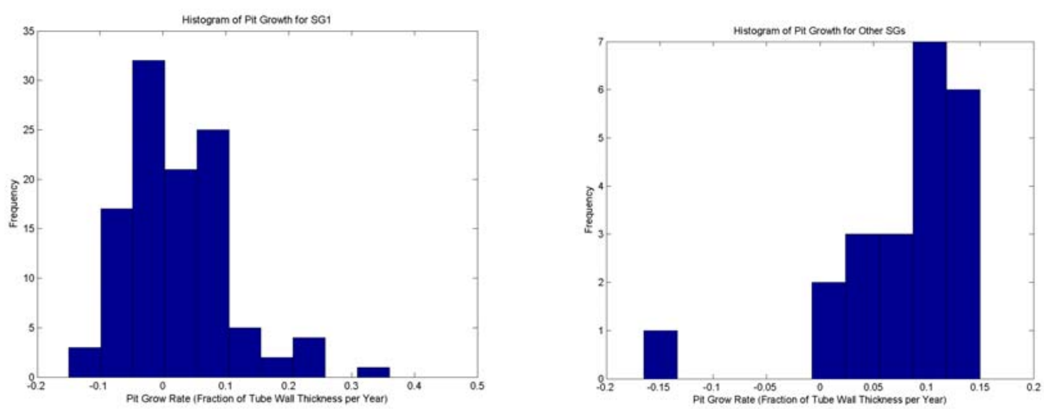

Figure 4 Histograms of Individual Pit Growth from Previous to Current Outage for SG1 and Other SGs

3.2 Kolmogorov-Smirnov Two-Sample Test

To investigate whether the two populations of pits can be combined, Kolmogorov-Smirnov test of homogeneity can be used. This test is used to determine if two samples differ significantly. It is non-parametric and distribution free, and it uses the maximum deviation between two cumulative probability curves.

Let $x_1, x_2, \ldots, x_n$ and $y_1, y_2, \ldots, y_m$ be two samples collected from two populations. The test of homogeneity is to test whether these two populations are the same. Let F_n and G_m be empirical cumulative distributions (defined in Section) of x_i and y_i respectively. The two-sample K-S statistics can be defined as

$$D_{n,m} = \max_x \left\{ \sqrt{\frac{nm}{n+m}} \left| F_n(x) - G_m(x) \right| \right\}$$

Generally, if $D_{n,m}$ is greater than 1.22 then it can be concluded that two populations do not have the same distribution with a 90% confidence.

Figure 5 presents the cumulative probability distribution curves for pit growth rate for SG1 and other SGs. The two curves seem to be very different from each other. The K-S statistics $D_{n,m}$ is 1.87, which indicates that it is not appropriate to combine the two populations. In the following sections, the investigation for pit growth rate focuses on SG1 not only because the it has more data but also because the 95% upper bound growth rate of SG1 bounds that of the other SGs (see Fig. 5).

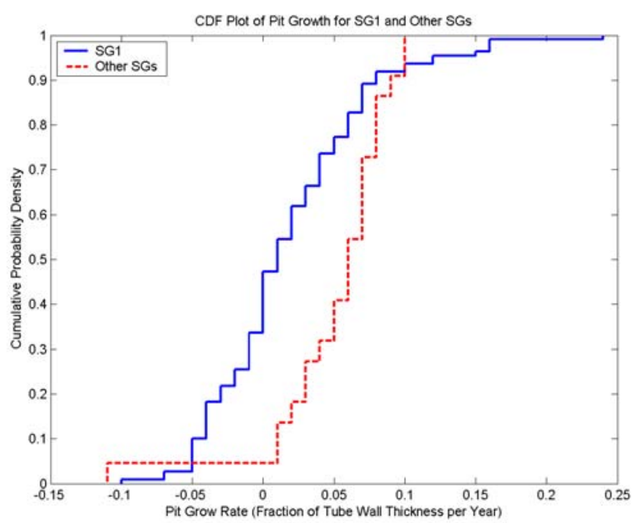

Figure 5 Cumulative Probability Curves for Pit Growth Rate for SG1 and Other SGs

3.3 Estimating Bounding Growth Rates using Bootstrap Resampling Method

The following are the statistics for the growth rate from the 110 pits in SG1:

Mean Growth Rate: 2.75% tw/yr

95% Upper Bound (UB) Growth Rate: 18.0 % tw/yr

For the condition monitoring and operational assessment, growth rates at certain confidence levels are desired, such as 95% UB growth rate at 95% confidence level.

Usually, to estimate the mean and 95% upper bound at certain confidence level, the normal distributions are usually used to approximate the sampling distributions and to calculate the confidence intervals. But if the underlying distribution is unknown, a more general and "distribution free" method called bootstrap resampling method can be used to estimate the confidence interval [1].

A common technique of bootstrap resampling method is as follows:

- Start with original sample of size N,

- Create a new sample:
  - Randomly choose 1 value from original sample and place in new sample,
  - Replace the value to the original sample,
  - Repeat until desired size of new sample is achieved (typically N).
  - Note: some values in the original sample may be drawn more than once and some not at all.

- Repeat bootstrap resampling many times (several 100 or 1000 times)
  - Generate a complete new sample each time,
  - Calculate mean (or 95% upper bound) each time.

- Calculate confidence bounds:
  - Derive the confidence interval around the mean (or 95% upper bound) from statistics of individual means (or 95% upper bound). For example, the mean value at 95% confidence is the 95^{th} percentile of the 1000 means from the 1000 bootstrap samples.

Table 2 gives the results of using bootstrap resampling method to calculate 50% and 95% confidence level for the mean and 95% UB pit growth rate. There are 10,000 bootstrap samples generated during the process.

Table 2 Bootstrap Results of Pit Growth Rate for SG1 Pits (10,000 samples)

	Mean Growth Rate	95% UB Growth Rate
50 % Confidence	2.76 % tw/yr	18.8 % tw/yr
95% Confidence	4.09 % tw/yr	24.0 % tw/yr

3.4 Adjusting Pit Growth Rate by Removing Measurement Error

It can be seen from Table 2 that 95% UB growth rate is very conservative for pits. The actual pit growth rates are lower. The reason lies in the fact that the observed growth rate contains the eddy current measurement error. A less conservative growth rate can be obtained if the measurement error can be wholly or partly removed from the observed growth rate.

1. Estimation of the Variance of Error for Growth

Since there is inherent measurement error in eddy current technique, the reported pit size is composed of the actual size and the measurement error as

$$x_t = y_t + e_t$$

where x_t is the eddy current reported size for the indications at times t, y_t is the actual size at time t and e_t is the measurement error. Then the growth rate can be expressed as (See also Fig. 6)

$$\begin{aligned} gr &= (y_{t2} - y_{t1}) / \Delta t + (e_{t2} - e_{t1}) / \Delta t \\ &= \tau / \Delta t + \varepsilon / \Delta t \\ &= \rho_{\Delta t} + \zeta_{\Delta t} \end{aligned}$$

where $\Delta t = t_2 - t_1$, ε is the error for growth, $\zeta_{\Delta t}$ is the error for growth rate and $\rho_{\Delta t}$ is the actual growth rate. If e_t is a random distribution with variance σ^2, ε has variance of $2\sigma^2$ and $\zeta_{\Delta t}$ has variance of $2\sigma^2 / \Delta t^2$. Although ε cannot be accurately evaluated from the observed growth, a lower bound estimate can be obtained by using the negative observed growth [2].

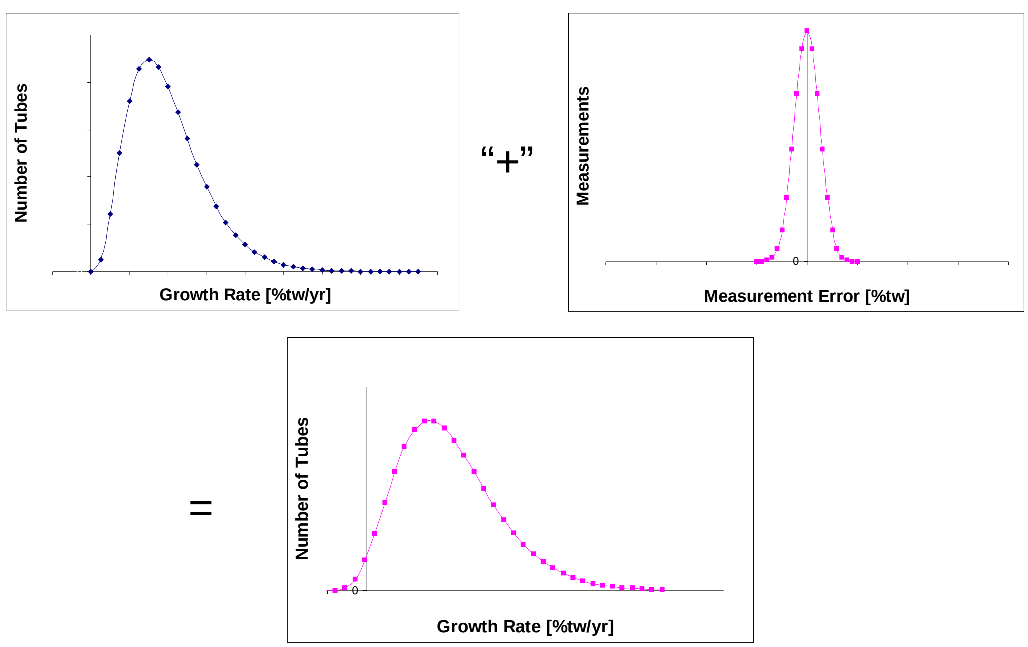

Figure 6 Actual Growth Rate, Measure Error and Observed Growth Rate

The observed growth is given as

$$g = \tau + \varepsilon$$

Since $\tau > 0$, it implies that $|\varepsilon| \geq |g|$ for negative observed growth. As a result, we have

$$\frac{1}{n_{g\leq 0}} \sum_{g\leq 0} \varepsilon^2 \geq \frac{1}{n_{g\leq 0}} \sum_{g\leq 0} g^2$$

Since the left term of the above equation is the variance of ε ($2\sigma^2$), the right term provides a lower bound estimate for the variance of error for growth Var (ε) [2].

2. Adjusting the Observed Growth for Measurement Error

Once the variance of growth error is estimated, the variance of the sample Var (g) can be reduced as

$$\text{Var}(\tau) = \text{Var}(g) - \text{Var}(\varepsilon)$$

The error distribution is assumed to be a normal distribution with zero mean. With the variance of error Var (ε) known, the normal distribution can be determined. The actual growth distribution is assumed to be a Gamma distribution given in probability density form as [3]

$$f(\tau;\sigma,\lambda) = \frac{1}{\sigma\Gamma(\lambda)}\left(\frac{\tau}{\sigma}\right)^{\lambda-1} \exp\left\{-\frac{\tau}{\sigma}\right\}$$

where τ is the variable, λ and σ are parameters and $\Gamma(\lambda)$ is the gamma function. To determine the Gamma parameters, we have

Mean of the Gamma distribution: $\sigma\lambda$ = mean of pit sample
Variance of the Gamma distribution: $\sigma^2\lambda$ = Var (τ)

Therefore the Gamma parameters are acquired, and this represents the upper bound estimation of the true growth with adjusted error effect. The benefit of this approach is that it provides a lower growth rate compared to the bootstrap one.

Table 3 lists the intermediate and final results of the error adjustment process for growth rate of the pit data from SG1. The 95% UB growth rate is reduced to 13.53 %tw/yr. Figure 7 gives the plot of cumulative probability curves for the pit growth rate of the pit data in SG1 before and after the error adjustment. The reduction of growth rate is obvious.

This adjustment process can be applied to the 1,000 bootstrap samples to obtain the reduced 95% UB growth rate at 50% and 95% confidence levels. Table 4 compares the results after the adjustment with the results before the adjustment. The reduction of growth rate is significant because the 95% UB growth rate at 95% confidence after adjustment is less than the 95% UB growth rate at 50% confidence before adjustment.

Table 3 Results for the Measurement Error Adjusted Growth Rate for Pits in SG1

Variance of observed negative growth Rate **Var(ε)**	37 $(\%tw/yr)^2$
Variance of all observed growth Rate **Var(g)**	69 $(\%tw/yr)^2$
Variance of upper bound true growth Rate **Var(τ)**	32 $(\%tw/yr)^2$
Lower bound standard deviation of error	9.43 %tw/yr
Gamma parameters of upper bound growth rate	$\lambda = 0.2377$ $\sigma = 0.1159$
95% UB growth rate for Gamma distribution	13.53 %tw/yr

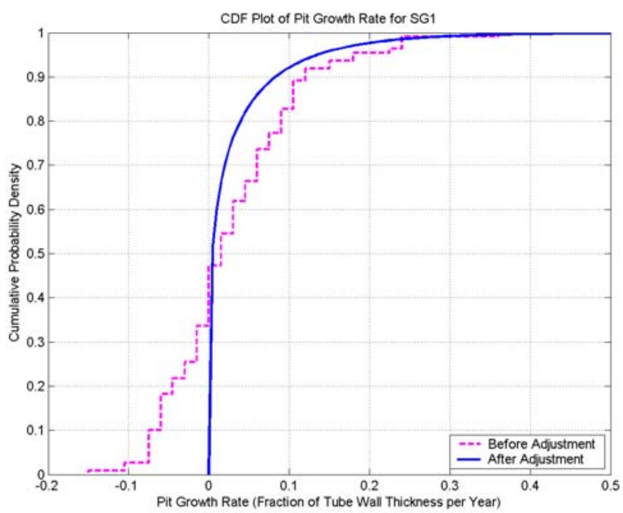

Figure 7 Cumulative Probability Curves of Growth Rate Before and After Adjustment

Table 4 95% Upper Bound Growth Rate of SG1

	50% Confidence	**95% Confidence**
Before Adjustment	18.8 %tw/yr	24.0 %tw/yr
After Adjustment	12.8 %tw/yr	17.7 %tw/yr

3. Comparison of Gamma Growth Model with Lognormal and Weibull Models

The growth model of the actual growth distribution in the above section is assumed to be Gamma probability distribution [3, 4]. Other probability distributions can also be assumed, such as the Lognormal and Weibull distributions. For the growth rate of 110 pits in SG1, the mean value is 2.75% tw/yr, and the reduced variance is 32 $(\%tw/yr)^2$.

With these two inputs, the parameters for the Lognormal and Weibull distributions can be evaluated. Figure 8 compares the cumulative distribution curves from all three models. It is obvious that the Gamma probability curve is more conservative at the tail of curve (above the 80% probability).

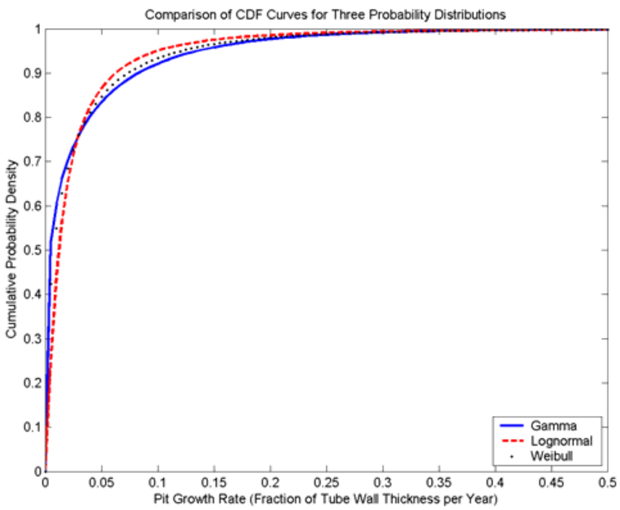

Figure 8 Comparison of Cumulative Curves for Three Probability Distributions

4.0 CONCLUSIONS

Pit growth is studied by collecting individual pit size changes from the inspection data from two outages. Bounding pit growth rate (confidence bounds) can be estimated using bootstrap resampling method. Bounding pit growth rate can be reduced by adjusting for the effect of NDE measurement error.

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