An Empirical Assessment of Steam Generator Tube Wear Rate

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1. Introduction

Wear of heat exchange tubes is a widespread degradation mechanism of most nuclear steam generators. Excessive wear may become a serious threat to the structural and leakage integrity of the steam generator tubes. Many plants keep the 40%-depth repair criteria, so that any tubes with wear damage the depth of which exceeds the criteria shall be repaired.

The growth rate of wear depth is an important parameter when assessing the integrity of steam generator tubes. The wear depth growth rate is assessed using empirical statistics from plant inspection database. The plant wear depth measurement database has been established by in-service non-destructive examination. The consequence of inspection error in the measurement of wear depth will be discussed by Monte Carlo simulation.

2. Methods and Results

2.1 Plant Wear Rate Database

The wear of tubes against the anti-vibration bar is a steady active degradation mechanism of Westinghouse model F steam generators. All the in-service eddy current inspection databases from 14 model F steam generators under operation in Korea are merged into a single database.

The wear rate is defined, for each wear, as below,

$$WR_j = \frac{(WD_j - WD_{j-1})}{(EFPY_j - EFPY_{j-1})} \qquad (1)$$

, where WR_j is wear rate during the j^{th} cycle, $EFPY_j$ is the cumulated effective full power year and WD_j is the depth of wear at the end of the jth cycle. The wear depth is denoted as % of tube thickness, and wear rate as %-depth/EFPY.

The wear rate distribution is shown in figure 1. It should be noted that the wear rate is fastest during the first cycle and diminished as the operation cycles are repeated. The wear depth growth rate database shown in figure 1 was built by calculation of extensive wear rate database. The wear rate during the i^{th} cycle was calculated only when the wear depths data are recorded both at the end of $(i-1)^{th}$ and i^{th} cycle. It is found that all the wear indications whose depths exceed 20% have been recorded in the inspection report, while the recording criteria have not been consistent for smaller indications.

A careful examination of wear rate database from each steam generator did not find any steam generator specific peculiar trend.

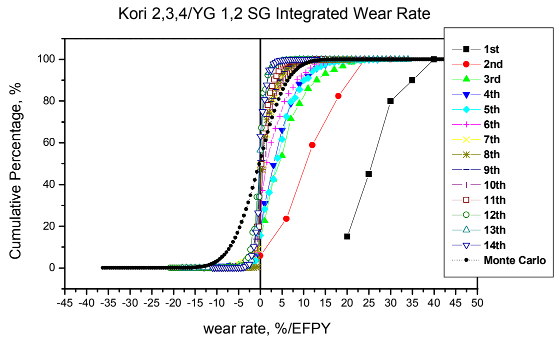

Figure 1 Cumulative Distribution of Wear Depth Growth Rate

2.2 Inspection Measurement Error

The wear depth are measured by the general purpose Bobbin coil eddy current inspection each outage. The quantitative precision of the eddy current depth measurement is good for the volumetric flaws like wear when compared to cracks. There are still some errors. The minus growth rates shown in figure 1 are surely caused by the inspection uncertainties.

An experimental program was implemented to measure depth of a set of artificial wear scars by eddy current inspection[1]. Figure 2 shows the result of the experimental program. The depth measured by inspection is plotted versus the real depth of each wear. The following statistical correlation is proposed.

$$WD_{ECT} = WD_{actual} \times 0.996 + 1.227 + \varepsilon \qquad (2)$$

The correlation coefficient is 0.992. ε is error between the measured ECT depth and the predicted ECT depth from the correlation using the actual depth. The standard deviation is calculated to be 2.893 assuming a normal distribution. It is believed that the normal distribution is a good assumption when there are more than 30 data points [2].

2.3 Monte Carlo Calculation of Inspection Error

The regression of equation (2) is written as,

$$y = ax + b + \varepsilon \qquad (3)$$

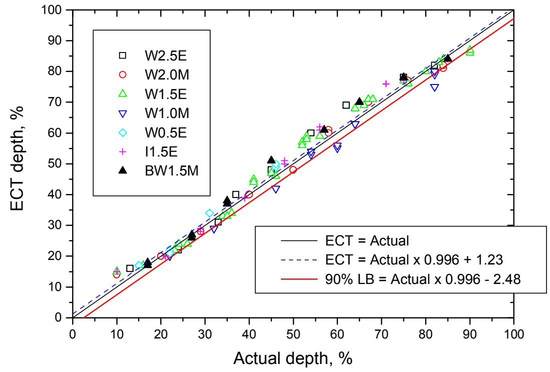

Figure 2 ECT Measured Depth vs. Actual Depth

For a given set of (x_i, y_i), $\hat{y}_i$ is an estimation of y_i calculated by (3). The standard deviation of the set ($\hat{y}_i$,y_i) is calculated as $\sigma\sqrt{1+\frac{1}{n}+\frac{(x-\bar{x})^2}{SS_{xx}}}$

Where σ is the standard deviation, n is number of data points, $\bar{x}$ is the average valued of x_i, and $SS_{xx}=\sum_{i=1}^{n}(x_i-\bar{x})^2$ in the regression of equation (2) [2].

A Monte Carlo calculation is performed in order to simulate the influence of inspection wear depth measurement error. For a given actual wear, the predicted wear depth measured by inspection is calculated by random number generation using equation (3). The wear depth growth rate distribution was simulated by the Monte Carlo simulation, as shown in figure 1.

2.4 Discussion

It is clearly seen from figure 1 that the wear depth growth rate is fastest during the first operation cycle, and decreases with the operation year. It is believed that small misfits within manufacturing tolerance limit causes the initial fast wear rate for a few tubes. Those tubes are repaired during the early outages. The wear may continue to grow fast after repair.

The wear depth growth rate is reduced to the practically insignificant level after sixth to seventh cycles where the wear rate calculated from the plant in-service inspection measurement database is slower than the Monte Carlo calculation. When we apply the 40% wall thickness repair criteria strictly, we repair some tubes and don't repair others depending on inspection measurement error among tubes whose actual wear depth approaches 40%.

It is concluded that periodic in-service inspection is good enough to guarantee the structural integrity of tubes against anti-vibration bar wear. A careful inspection of 100% tubes is an important element against excessive wear damage at the end of first operation cycle.

3. Conclusions

The wear depth growth rate of tubes against anti-vibration bar is assessed using empirical statistics for 14 Westinghouse model F steam generators. The wear rate is fastest for a few selected tubes during the first operation cycle, and then decreases with operation years. The wear depth growth rate is practically insignificant level after sixth or seventh cycles.

REFERENCES

[1] Hansub Chung and Hongduk Kim, unpublished report (2001)
[2] R. L. Scheaffer and J. T. McClave, Probability and Statistics for Engineers, PWES-KENT Publishing Company 1990