A Bayesian Probabilistic Approach to Improved Health Management of Steam Generator Tubes

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ABSTRACT

Steam generator tube integrity is critical for the safety and operability of pressurized water reactors. Any degradation and rupture of tubes can have catastrophic consequences, e.g., release of radioactivity into the atmosphere. Given the risk significance of steam generator tube ruptures, it is necessary to periodically inspect the tubes using nondestructive evaluation methods to detect and characterize unknown existing defects. To make accurate estimates of defect size and density, it is essential that detection uncertainty and measurement errors associated with nondestructive evaluation methods are characterized properly and accounted for in the evaluation. In this paper we propose a Bayesian approach that updates prior knowledge of defect size and density with nondestructive evaluation data, accounting for detection uncertainty and measurement errors. An example application of the proposed approach is then demonstrated for estimating defect size and density in steam generator tubes using eddy current evaluation data. The proposed Bayesian probabilistic approach helps improve health management of steam generator tubes, thereby enhancing the overall safety and operability of pressurized water reactors.

1. INTRODUCTION

Pressurized water reactors (PWR) use heat produced from nuclear fission in the reactor core to generate electricity. In the process of generating electricity, steam generators (SG) play an important role by keeping the reactor core at a safe temperature and acting as the primary barrier between radioactive and non-radioactive sides of a nuclear power plant. Since SG tubes play such an important role, any degradation and rupture in the tubes can be catastrophic (Chatterjee & Modarres, 2011). According to the US Nuclear Regulatory Commission (2010), there have been 10 steam generator tube rupture (SGTR) occurrences in the US between 1975 and 2000. One such incident occurred in the North Anna power station in 1987 when the plant reached its 100% capacity (US Nuclear Regulatory Commission, 1988). The cause of tube rupture was found to be fatigue, caused by combination of alternating stresses resulting from flow-induced tube vibration and flaws resulting from denting of tubes at support plates.

Given the risk significance of SGTRs, it is absolutely necessary to periodically inspect the tubes using nondestructive evaluation methods in order to detect and quantify the severity of unknown existing defects.[1] All nondestructive evaluation methods have detection uncertainty and measurement errors associated with them that are a result of test equipment complexity, defect attributes, as well as human error. These uncertainties and errors need to be characterized properly and accounted for while estimating the size and density of defects.

A defect of a given size might be detected only a certain percentage of the time (out of total attempts during nondestructive testing) depending on factors such as, noise level, test probe sensitivity, test equipment repeatability and human error. Hence, a defect has an associated probability of detection, which can be defined as the probability the inspection will detect the defect of true size, a, and is denoted by POD(a) (Kurtz, Heasler, & Anderson, 1992). The data from which POD curves are generated can be categorized into two types: qualitative data, i.e., hit/miss; and quantitative data, i.e., signal response amplitude ($\hat{a}\ vs.\ a$), where $\hat{a}$ is signal response. The hit/miss data type is based on a binary process, i.e., whether a defect is detected or not detected. The POD for this data type is calculated as the ratio of the number of successful detection over the total number of inspections performed for a particular defect size, and is called the averaged POD. Hit/miss data are obtained from test equipments such as Sonic IR, and are very subjective in nature depending on operator experience (Li & Meeker, 2008), which induces uncertainty in the values of the POD. A logistic function is

[1] In this paper defect may indicate a crack, flaw, pit, or any other degradation in a structural component. Size may refer to either through-wall depth or surface length of a defect, unless specified. Density refers to number of defects observed per unit volume.

found to best-fit hit/miss data for modeling POD (Jenson, Mahaut, Calmon & Poidevin, 2010).

The other type of POD data is more continuous in nature and is a measure of the amplitude of signal response recorded by the nondestructive test equipment, e.g., ultrasonic or eddy current. In the signal response data-based POD estimation method, the most important parameters are the inspection threshold (noise level) and the decision threshold. The inspection threshold is chosen to account for the noise indications by test equipment, and responses above this threshold are considered for detection/non-detection decisions. Decision threshold is often based on previous field inspections and knowledge of the noise distribution, laboratory experience, and operator experience. The POD curve for signal response data type is modeled using a cumulative log-normal distribution function (Department of Defense, 1999; Jenson, et al., 2010), by determining the cumulative probability of responses (defect signals) greater than the decision threshold. The selection of decision threshold also determines the probability of false call (or false positive).[2] Hence, there is lot of uncertainty associated with the values chosen for inspection and decision threshold, which lead to uncertainties in the values of the POD. In some cases, the signal response data is also converted into hit/miss data (Jenson et al., 2010) by using the decision threshold and averaged POD values are estimated, which are then fitted into a logistic function.

The precision and accuracy of nondestructive test equipment, and also the techniques used to analyze and process the test results can contribute to measurement errors. For example, large volume of sensor data (such as ultrasound or digital images) are filtered, smoothed, reduced, and censored into another form by subjectively accounting for only certain features of the data. Also, often measurement models are used to convert the form of a measured or observed data into the corresponding value of the reality of interest (i.e., defect size). Uncertainties associated with data processing, model selection and human error can contribute to measurement errors. Measurement error is defined as the difference between the measured and the true value of a defect size. There are two components of measurement error: systematic (bias) error and random (stochastic) error (Jaech, 1964; Hofmann, 2005). Systematic error or bias is a consistent and permanent deflection in the same direction from the true value (Hofmann, 2005). Systematic error (bias) may indicate overestimation (positive bias) or underestimation (negative bias). In most nondestructive measurements, small defects are oversized and large defects are undersized (Kurtz et al., 1992; Wang & Meeker, 2005). Random error arises due to the scattering or random variation in measured values (measurement uncertainty).

[2] A nondestructive test equipment response interpreted as having detected a flaw but associated with no known flaw at the inspection location (Department of Defense, 1999).

In the past, there have been efforts to model defect severity in structural components considering nondestructive evaluation uncertainties. Celeux, Persoz, Wandji, and Perrot (1999) describe a method to model defects in PWR vessels considering the POD and random error in measurements. Yuan, Mao, and Pandey (2009) followed the idea of Celeux et al. (1999), to propose a probabilistic model for pitting corrosion in SG tubes considering the POD and random error of the eddy current measurements. However, both Celeux et al. (1999) and Yuan et al. (2009) did not consider the effect of systematic error or bias in measured defect sizes. Also, the POD has not been adjusted for measurement errors in their models. Further, they did not consider uncertainties in the values of the POD, which can affect the defect severity estimates considerably.

This paper addresses some of the shortcomings of existing literature and develops a Bayesian probabilistic approach for modeling defect severity (size and density) in structural components considering the detection uncertainty (i.e., POD and associated uncertainty) and measurement errors (and associated uncertainty) associated with nondestructive evaluation methods. The paper then presents example application of the proposed approach for estimating defect severity in SG tubes using eddy current evaluation data.

2. PROPOSED BAYESIAN APPROACH

The proposed Bayesian approach updates prior knowledge of defect size and density with nondestructive evaluation data, considering the POD, measurement errors (systematic and random), and associated uncertainties, to infer the posterior distributions of defect size and density. The combined effect of POD, measurement errors, and associated uncertainties on measured defect sizes is captured by a likelihood function. In this section, models for measurement errors and POD function will be first defined; then the defect severity models will be presented, followed by the likelihood functions and Bayesian inference equations.

The analysis of measurement error is based on assessing the deviation of the measured defect size from the actual or true defect size, as shown in Eq. (1):

$$E_m = a^* - a \tag{1}$$

where, E_m is the measurement error, a^* is measured and a is the true defect size. Generally a linear regression relationship of the form shown in Eq. (2) is used to model measurement error (Kurtz et al., 1992; Jaech, 1964).

$$a^* = ma + c + \varepsilon(0, \sigma_a) \tag{2}$$

where, m and c are regression coefficients obtained through a regression analysis of a^* $vs.a$, and ε is the random error in measurement (scattering of the data), which is assumed to follow a normal distribution with mean zero and standard deviation σ_a (function of defect size). The regression coefficients (m & c) are jointly measure of systematic error or bias in measurements. Distributions of bias parameters represent epistemic uncertainty in the chosen measurement error model. From Eqs. (1) and (2), the measurement error can be expressed as:

$$E_m = \overbrace{(m-1)a + c}^{Bias} + \overbrace{\varepsilon(0, \sigma_a)}^{Random\ error} \tag{3}$$

Measurement error can then be expressed as a function of measured defect size using Eqs. (1) and (3) as:

$$E_m = \overbrace{\left(\frac{m-1}{m}\right)a^* + \frac{c}{m}}^{Bias} + \overbrace{\frac{\varepsilon(0, \sigma_a)}{m}}^{Random\ error} \tag{4}$$

The probability density function (PDF) of the measurement error can then be defined using a normal distribution with mean as the bias, B_a, standard deviation as that of random error, $\frac{\sigma_a}{m}$, and measurement error as random variable.

$$g(E_m) = N\left(B_a, \frac{\sigma_a}{m}\right) \tag{5}$$

Assume that true defect size, a, is treated as random variable with the PDF, $f(a|\psi)$, where ψ is the vector of the PDF parameters. Defect size PDF considering measurement error can then be expressed as shown in Eq. (6).

$$f(a|\psi) = \int_{E_m} f\big((a^* - E_m)\big|\psi\big)\, g(E_m) dE_m \tag{6}$$

All the defects in a structure are not detected during nondestructive testing. The detection of a defect depends on its size and is represented by the POD curve. The POD of a defect of size, a, can be represented by a function as shown in Eq. (7):

$$POD(a|\theta, \sigma_{POD}) = h(a, \theta, a_{th}) + \varepsilon_{POD}(0, \sigma_{POD}) \tag{7}$$

where, $h(a, \theta, a_{th})$ is the POD function, a_{th} is the detection threshold, θ is vector of parameters of the POD function, and ε_{POD} is the random error, which represents uncertainty in the POD data and is assumed to follow a normal distribution with mean zero and standard deviation σ_{POD} (function of true defect size). The POD function is selected based on the type of data, e.g., hit/miss or signal response as discussed in Section 1. Joint distribution of the parameters of the POD function, $k(\theta)$, represents the epistemic uncertainty associated with the choice of the POD function.

The marginal POD independent of random variables, θ and σ_{POD}, can be expressed as shown in Eq. (8), where, $m(\sigma_{POD})$ represents the PDF of random variable, σ_{POD}.

$$POD(a) = \int_{\sigma_{POD}} \int_{\theta} POD(a|\theta, \sigma_{POD}) k(\theta) m(\sigma_{POD}) d\theta d\sigma_{POD} \tag{8}$$

The likelihood function for detecting defect of true size, a, given that the defect is detected ($D = 1$), can then be expressed as shown in Eq. (9) (Celeux et al., 1999):

$$L(a|D = 1) = \frac{f(a|\psi) \times POD(a)}{P_d(\psi)} \tag{9}$$

where, $P_d(\psi)$ is the marginal POD that is a function of defect size distribution parameters only (independent of defect size), and can be expressed as:

$$P_d(\psi) = \Pr(D = 1) = \int_0^\infty POD(a) f(a|\psi) da \tag{10}$$

During nondestructive measurements true defect sizes are unknown, while the only known quantities are the measured defect sizes and number of detections. The likelihood function of true defect sizes corresponding to measurements consisting of n_e^* exact defect sizes (using Eq. 9) considering measurement errors can be represented as:

$$L(a_{exact}|\psi) = \frac{1}{[P_d(\psi)]^{n_e^*}} \prod_{i=1}^{n_e^*} \int_{E_m} POD(a_i^* - E_m) f\big((a_i^* - E_m)|\psi\big) g(E_m) dE_m \tag{11}$$

Nondestructive measurements are in most cases interval or left censored, in which case the likelihood function of true defect sizes corresponding to measurements consisting of $n_{int,j}^*$ defects within the j_{th} interval (or in a left censored interval) (Cook, Duckworth, Kaiser, Meeker & Stephenson, 2003), can be expressed as shown in Eq. (12).

$$L_j(a_{int}|\psi) = \left[\frac{1}{P_d(\psi)} \int_{a_{j-1}^*}^{a_j^*} \int_{E_m} POD(a^* - E_m) f\big((a^* - E_m)|\psi\big) g(E_m) dE_m\, da^*\right]^{n_{int,j}^*} \tag{12}$$

Therefore, the likelihood function of true defect sizes corresponding to total measurements consisting of m defect size intervals each with certain number of defects ($n_{int,j}^*$ in j_{th} interval), and n_e^* exact defect sizes can then be expressed as shown in Eq. (13).

$$L(a|\psi) = \prod_{j=1}^{m} \left[\frac{1}{P_d(\psi)} \int_{a_{j-1}^*}^{a_j^*} \int_{E_m} POD(a^* - E_m) f\big((a^* - E_m)|\psi\big) g(E_m) dE_m\, da^*\right]^{n_{int,j}^*}$$

$$\times \frac{1}{[P_d(\psi)]^{n_e^*}} \prod_{i=1}^{n_e^*} \int_{E_m} POD(a_i^* - E_m) f\big((a_i^* - E_m)|\psi\big) g(E_m) dE_m \tag{13}$$

The posterior defect size distribution parameters can then be estimated using Bayesian inference as:

$$\pi_1(\psi|Data) = \frac{L(Data|\psi)\pi_0(\psi)}{\int_\psi L(Data|\psi)\pi_0(\psi)d\psi} \tag{14}$$

where, $\pi_1(\psi|Data)$ is posterior distribution of defect size parameters and $\pi_0(\psi)$ is prior distribution of the parameters. The posterior defect size parameters obtained from Bayesian inference can then be used to estimate the corresponding marginal POD values (Eq. 10).

The likelihood of observing n^* $(= n_e^* + \sum_{j=1}^{m} n_{int,j}^*)$ number of defects given n actual number of defects can be expressed by a binomial function (detection process is binary, i.e., either detection or no detection), as shown by Eq. (15):

$$L(n^*|n) = \binom{n}{n^*}[P_d(\psi)]^{n^*}[1 - P_d(\psi)]^{n-n^*} \tag{15}$$

where, $P_d(\psi)$ is the marginal POD value corresponding to posterior defect size parameters. In Eq. (15), the actual number of defects, n, is unknown whereas n^* and $P_d(\psi)$ are known. The actual number of defects can be estimated using Bayesian inference as shown in Eq. (16):

$$\pi_1(n|n^*) = \frac{L(n^*|n)\pi_0(n)}{\sum_n L(n^*|n)\pi_0(n)} \tag{16}$$

where, $\pi_1(n|n^*)$ is posterior distribution of actual number of defects given the observation, n^*, and $\pi_0(n)$ is the prior distribution of number of defects. The prior distribution of number of defects can be estimated from a Poisson function, which gives the likelihood of observing n total number of defects in a volume V, given prior defect density ρ as shown in Eq. (17). Here Poisson distribution is used because defects are assumed to occur with the same average intensity and independent of each other.

$$\pi_0(n) = e^{-\rho V}\frac{(\rho V)^n}{n!} \tag{17}$$

The posterior distribution of actual number of defects (Eq. 16) can then be used to obtain the posterior defect density. The standard conjugate prior employed for Poisson distribution likelihood (Eq. 17) is a two-parameter gamma distribution (Simonen, Doctor, Schuster, & Heasler, 2003), in which case the posterior has the same functional form as the gamma distribution. Assume that prior distribution of defect density is:

$$\pi_0(\rho) = gamma(\rho|\alpha_1, \alpha_2) \tag{18}$$

where, α_1 and α_2 are parameters of gamma distribution. Then the posterior distribution of defect density can be expressed as shown in Eq. (19).

$$\pi_1(\rho) = gamma(\rho|V + \alpha_1, n + \alpha_2) \tag{19}$$

A MATLAB routine was developed to implement this entire Bayesian approach for estimating defect severity in structural components. The proposed Bayesian approach considers systematic (bias) and random error in nondestructive measurements; suitably adjusts measurement errors in POD; considers uncertainty in POD values; incorporates prior knowledge of defect size and density; provides a framework for updating probability distributions of defect model parameters when new data become available; and is applicable to exact, interval, and censored measurements.

3. APPLICATION OF PROPOSED BAYESIAN APPROACH TO EDDY CURRENT DATA

An example application of the proposed Bayesian approach is presented in this section for estimating flaw severity in SG tubes using eddy current measurements of flaw sizes (through-wall depth). In this section, we first model POD and measurement error for eddy current evaluation using available data from literature, and then use the proposed Bayesian approach to estimate the posterior distributions of flaw size and density.

The eddy current measurement error is assessed in this paper by a Bayesian regression approach (Azarkhail & Modarres, 2007) in light of available data from literature (Kurtz, Clark, Bradley, Bowen, Doctor, Ferris & Simonen, 1990). The regression result is illustrated by Figure 1 with the 50% regression line representing the bias corresponding to mean values of the parameters m and c of Eq. (3). The 95% uncertainty bounds of Figure 1 corresponds to the random error with a constant standard deviation, σ. The parameters m, c and σ obtained through Bayesian regression were then used in Eq. (5) to estimate the PDF of measurement error as a function of measured flaw size.

In order to derive the POD model, it was assumed in this paper that eddy current signal response data were converted into equivalent hit/miss. The POD curve can then be expressed by a logistic function of the form as shown in Eq. (20) (Yuan et al., 2009):

$$POD(a|\beta_1, \beta_2, a_{th}) = \begin{cases} 1 - \frac{1+e^{-\beta_1\beta_2}}{1+e^{\beta_1(a-\beta_2-a_{th})}} + \varepsilon_{POD}(0, \sigma_{POD}) & for\ a > a_{th} \\ 0 & otherwise \end{cases} \tag{20}$$

where, a is flaw size, a_{th} is threshold size for detection, β_1 and β_2 are logistic function parameters, and ε_{POD} is the random error, which is assumed to follow a normal distribution with mean zero and standard deviation σ_{POD}. A flaw of size less than detection threshold will not be detected. Distributions of the POD model parameters β_1, β_2, and σ_{POD} were estimated using Bayesian regression approach in light of POD data available from literature (Kurtz et al., 1992). Figure 2 illustrates a sample logistic function curve and associated uncertainties fitted on POD data through Bayesian regression, with $a_{th} = 0$.

Flaws in nuclear reactor vessel and piping are in most cases best fitted with an exponential distribution, with smaller size flaws having higher probability density and larger size flaws having lower probability density. Here we define the PDF of random variable a, i.e., true flaw size in SG tubes, assuming exponential distribution as:

$$f(a|\lambda) = \lambda e^{-\lambda a} \quad (21)$$

where, λ is flaw size intensity. Flaw size distribution considering measurement errors can then be expressed as shown in Eq. (22).

$$f(a|\lambda) = \int_{E_m} \lambda e^{-\lambda(a^* - E_m)} g(E_m) dE_m \quad (22)$$

Eddy current measurements for SG tubes (Dvorsek & Cizelj, 1993) used in our paper to demonstrate the application of the proposed Bayesian approach, were left and interval censored. The likelihood function of true flaw sizes corresponding to eddy current measurements was defined using Eq. (13), with measurement error limits set as -1 and 1 (to cover the extremes of bias and random error). The Bayesian posterior inference of the flaw size intensity was carried out using the MATLAB routine (Section 2). Prior distribution for flaw size intensity was generated using available data from literature (Liao & Guentay, 2009). Figure 3 illustrates the posterior and prior flaw size intensity distributions. Flaw size intensity values were sampled from the posterior distribution (Figure 3), and the corresponding marginal POD values, $P_d(\psi)$, were estimated (Eq. 10).

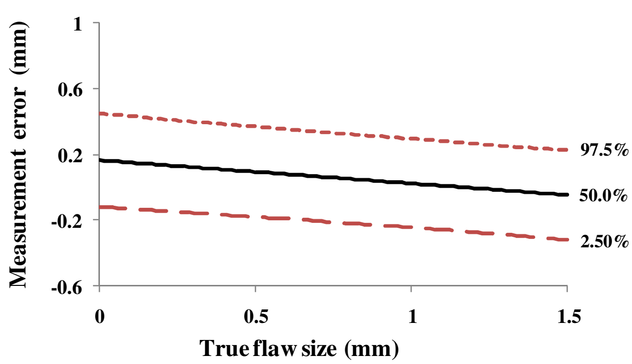

Figure 1. Measurement error and uncertainty bounds (95%)

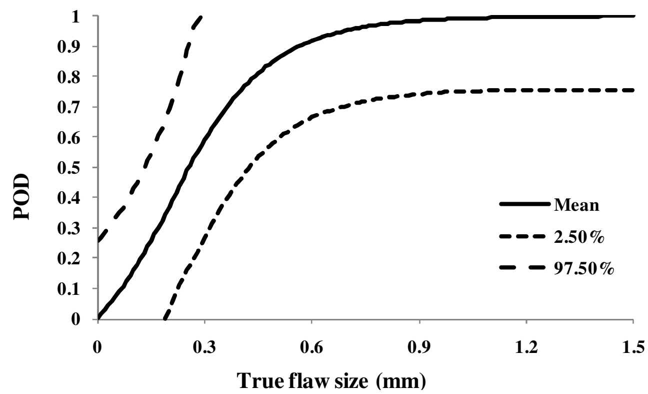

Figure 2. POD curve and uncertainty bounds (95%)

The likelihood function of observed number of flaws was then defined using Eq. (15), and the Bayesian posterior inference of the actual number of flaws (Eq. 16) computed. The prior flaw density distribution used to obtain prior information on number of flaws (Eq. 17) was obtained from the available data in the literature (Liao & Guentay, 2009). Figure 4 illustrates the distribution of actual number of flaws for mean, 2.5% and 97.5% values of posterior flaw size intensity. Posterior distribution of flaw density was then estimated using Eq. (19) for a given volume corresponding to the tube-support plate 9. Figure 5 presents a box and whisker plot showing the distribution of actual number of flaws at tube support plate 9 for different flaw size intervals.

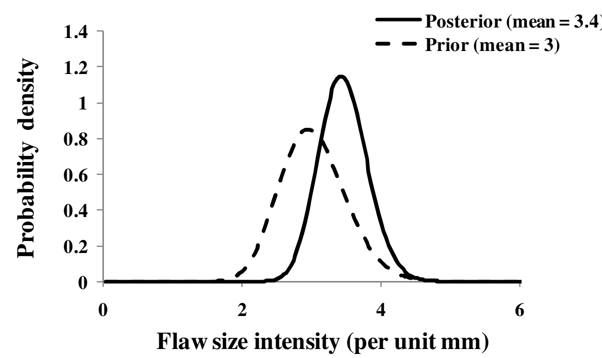

Figure 3. Posterior and prior flaw size intensity

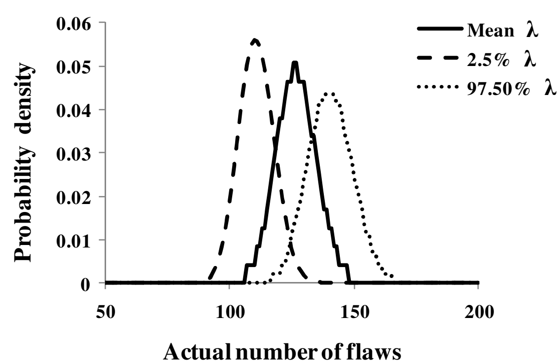

Figure 4. Distributions of actual number of flaws

A comparison between the eddy current measurements and mean of estimated actual number of flaws is presented in Table 1 for different flaw size intervals. It is evident from Table 1 that nondestructive evaluation methods cannot detect and measure all the defects existing in a structure due to associated detection uncertainty and measurement errors. In Table 1, the mean number of flaws estimated using the proposed Bayesian approach (column 3) after considering all uncertainties and prior information, is substantially higher than eddy current measurements (column 2), especially for very small sizes.

As illustrated by the example application, it is critical to consider detection uncertainty and measurement errors associated with nondestructive evaluation methods, in order to estimate the actual defect size and density distributions in critical structures. This is important because the defect size and density distributions estimated during in-service inspections can help in making appropriate and timely replacement/repair decisions, thereby preventing unanticipated failures.

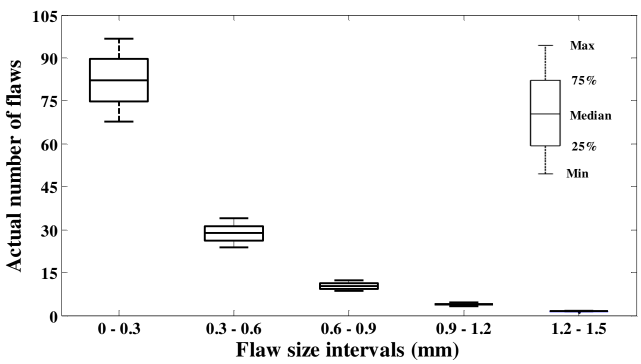

Figure 5. Box and whisker plot of actual number of flaws by size intervals at support plate 9

Flaw size intervals (mm)	Measured # of flaws from eddy current inspection (support plate 9)	Mean actual # of flaws using our Bayesian approach (accounting for all uncertainties)
a < 0.3	40	81
0.3 ≤ a < 0.6	3	29
0.6 ≤ a < 0.9	3	11
0.9 ≤ a < 1.2	6	4
1.2 ≤ a < 1.5	8	1

Table 1. Measured vs. actual number of flaws

4. CONCLUSIONS

It is imperative to assess the health condition of SG tubes periodically during their operating life in order to prevent the occurrence of SGTR failures. Estimating defect size and density in SG tubes require appropriate methods to account for all uncertainties associated with nondestructive evaluation methods. This paper presents a Bayesian approach for estimating defect size and density in structural components considering detection uncertainty and measurement errors. The proposed Bayesian approach updates prior knowledge of defect size and density with nondestructive evaluation data, considering the POD, measurement errors, and associated uncertainties, to give the posterior distributions of defect size and density. The proposed approach considers both systematic and random error in nondestructive measurements, suitably adjusts measurement errors in POD, considers uncertainties in POD values, and captures the combined effect of POD and measurement errors (including associated uncertainties) on measured defect sizes by a likelihood function. The approach is applicable to exact, interval, and censored measurements; and also provides a framework for updating defect model parameter distribution as and when new information becomes available. An application of this proposed approach is demonstrated for estimating defect size and density in SG tubes using eddy current nondestructive evaluation data. This developed Bayesian probabilistic approach not only fills a critical gap in health management and prognosis of SG tubes, but can also help improve reliability of safety-critical structures in a broad range of application areas, including medical, avionics, and nuclear.

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