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PROBABILITY OF DETECTION ESTIMATIONS FOR DISSIMILAR METAL WELDS

Ryan M. Meyer[1], Aimee E. Holmes,
Pacific Northwest National Laboratory (PNNL)
Richland, WA USA

Bruce Lin
United States Nuclear Regulatory Commission (NRC)
Washington, D.C.

ABSTRACT

Estimations of probability of detection (POD) for examinations performed in the nuclear power industry are derived from empirical studies performed in laboratory-like environments on test blocks that simulate relevant component geometries in the field. The data generated by these studies provide technical bases to inform regulatory decision making. However, due to the physical size of many components, the resources required to manufacture test blocks and to perform a study can be extensive. As a result, sample sizes are often determined by feasibility and confidence bounds for resulting POD estimates can be large. Further, because the data are collected under well-controlled laboratory conditions, it is possible that these studies provide non-conservative estimations of POD relative to examinations performed in the field. Model-Assisted POD (MAPOD) concepts can potentially enhance existing POD estimations without requiring additional empirical testing. This work provides an overview of MAPOD in the context of nuclear power applications and presents existing POD estimations for dissimilar weld components that have been obtained by empirical testing. Finally, discussion is provided regarding how MAPOD concepts may enhance the existing POD estimates for reducing uncertainty or to more accurately reflect field POD.

Keywords: probability of detection, dissimilar metal welds, nuclear power, nondestructive examination

1. INTRODUCTION

Estimations of probability of detection (POD) for examinations performed in the nuclear power industry are derived from empirical studies performed in laboratory-like environments on test blocks that simulate relevant component geometries in the field. The data generated by these studies provide technical bases to inform regulatory decision making. However, due to the physical size of many components, the resources required to manufacture test blocks and to perform a study can be extensive. As a result, sample sizes are often constrained by feasibility and confidence bounds for resulting POD estimates can be large. Further, the techniques for simulating flaws in physical test blocks are usually only able to provide an approximate representation of the complex geometries and morphologies of actual field defects. The responses from simulated flaws may not accurately represent the response from field flaws contributing additional uncertainty to relevancy of results obtained from simulated flaws. Finally, because the data are collected under well-controlled laboratory conditions, it is possible that these studies provide non-conservative estimations of POD relative to examinations performed in the field. Model-Assisted POD (MAPOD) concepts can potentially enhance existing POD estimations without requiring additional empirical testing.

The most extensive source of empirical data from which estimates of POD can be obtained come from the data accumulated as part of the industry's Performance Demonstration Initiative (PDI). A description of the analysis performed to develop POD estimates from the industry PDI database is provided in report MRP-262 Rev. 3 [1], which provides these estimates for several component types. In addition to the PDI data, empirical POD data has been generated for dissimilar metal weld (DMW) components as part of the U.S. Nuclear Regulatory Commission (NRC)-supported round robin studies—Program for Inspection of Nickel Alloy Components [PINC; 2] and Program to Assess the Reliability of Emerging Nondestructive Techniques [PARENT; 3].

Section 2 of this paper provides some background on the empirical POD data collected in PINC and PARENT studies while Section 3 provides an overview of MAPOD concepts. "Virtual flaw" tools are introduced and briefly described Section 4 and this is followed, in Section 5, by a discussion of future efforts under the Program for Investigation Of NDE by International Collaboration (PIONIC), which is a follow-on to PINC and PARENT.

[1] Contact author: Ryan.Meyer@pnnl.gov

2. BACKGROUND

POD curves resulting from binary nondestructive evaluation (NDE) responses can be represented mathematically by a logistic function [4],

$$\mathrm{POD}(a) = \frac{1}{1+\exp(-\beta_1 - \beta_2 a)} = \frac{\exp(\beta_1 + \beta_2 a)}{1+\exp(\beta_1 + \beta_2 a)}. \tag{1}$$

This model includes two parameters, β_1, and β_2, to be determined from curve fitting with empirical data. This model has been used to curve fit binary NDE data to estimate POD for NDE performance studies involving nuclear power plant components [5]. In this equation, the parameters β_1 and β_2 are determined using maximum likelihood estimation (MLE) [6]. In the analysis of data from PINC and PARENT, the flaw size, a, is represented by the flaw depth x (normalized as a fraction of component through-wall [TW] thickness).

2.1 False Call Probability

In the PINC and the PARENT round-robin studies, the model represented by Eq. (1) is applied over a range of x that includes 0 TW using data collected from false calls to define POD at 0 TW. The formula for converting false call rate (# of false calls per length of examined material) to false call probability (FCP) is described in NUREG reports documenting the results from the PINC [2] and PARENT studies [3]. A false call is defined as a call that does not intersect with a flawed grading unit. These false calls were used to estimate a false call rate, λ_{fc} (false calls per meter),

$$\lambda_{fc} = \frac{\text{\#False Calls}}{\text{Length of Material Inspected}} \tag{2}$$

Using this rate and the assumption that false calls are randomly (i.e., Poisson) distributed, the probability that a call would intersect a blank grading unit of length L_{gu} can be calculated. If the average length of a false call is L_{fc}, the probability of a false call intersecting the grading unit is,

$$\begin{aligned} \mathrm{FCP} &= \Pr(\text{Grading Unit Intersection}) \\ &= 1 - \exp\left(-\lambda_{fc}\left(L_{gu} + L_{fc}\right)\right) \end{aligned} \tag{3}$$

2.2 Uncertainty in Probability of Detection

The uncertainties in model parameters, β_1, and β_2, are represented by a covariance matrix from which the standard deviations in the model parameters, σ_{β_1} and σ_{β_2}, and the covariance in the model parameters, $\rho_{\beta_1\beta_2}$, can be estimated. In practice, this uncertainty is often expressed in terms of 95% confidence intervals, which are included on plots of the calculated POD. A wide confidence interval indicates that performance was variable and that there is less confidence in the POD for a given flaw depth. This may be due to inconsistency in detections or to a small number of data points, or both.

2.3 Empirical POD Results from PINC and PARENT

Empirical data collected in the PINC and PARENT programs were analyzed using the method described in previous sections. Data was collected from test blocks classified as "small-bore" dissimilar metal welds (SBDMW) and "large-bore" dissimilar metal welds (LBDMW), which are distinguished by their dimensions as summarized in Table 1. In addition, inspections are distinguished according to if the inspection was performed by accessing the inner diameter (ID) or outer diameter (OD) surface of test blocks. Some results from PINC and PARENT are presented in Figure 1 for circumferential flaws. It appears that POD for OD access is consistent for SBDMW and LBDMW test blocks in PARENT and that POD for ID access is consistent between PINC and PARENT.

TABLE 1. SUMMARY OF TEST BLOCK DIMENSIONS FOR PINC AND PARENT.

	PINC	PARENT	
	SBDMW	SBDMW	LBDMW
Outer Diameter (mm)	386–390	289 and 815	852–895
Wall Thickness (mm)	42–46	35 and 39.5	68–78
Access	OD and ID	OD	OD and ID

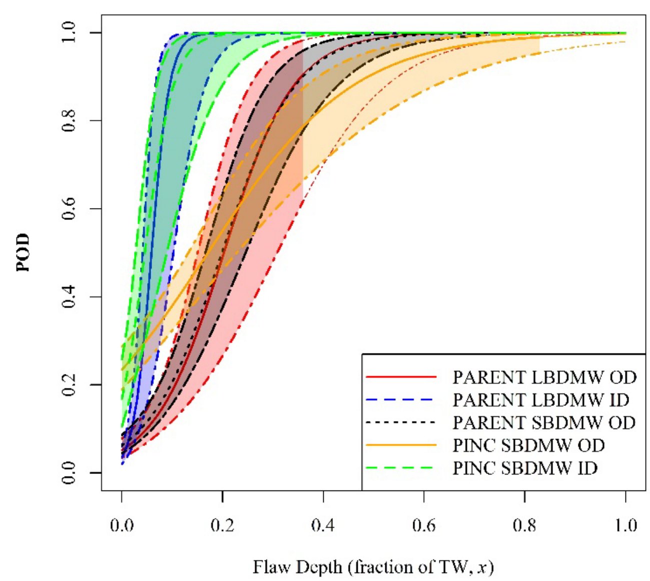

FIGURE 1. POD CURVES FOR CIRCUMFERENTIAL FLAWS FROM PINC [2] AND PARENT [3]

3. OVERVIEW OF MAPOD

A literature review of MAPOD was previously conducted to assess approaches that may be useful for improving estimates of field POD for nuclear power applications [7]. Methods vary significantly and include approaches that leverage existing empirical POD data sets to derive POD estimates for similar examination scenarios. The existing empirical baseline POD data may be augmented with additional data obtained through laboratory testing or physics-based computer modeling and simulation. Alternatively, MAPOD may be used to derive POD curves from scratch. In this approach, factors that control the variability of an examination are systematically identified. The variability contributed by factors that are represented by well understood physical phenomena can be investigated with physics-based computer modeling and simulation while the variability contributed by other factors must be determined empirically [8].

The literature review cites several studies that demonstrated MAPOD and categorized them based on employing Bayes theorem versus other techniques. A summary of the demonstrations that utilized binary NDE response data is provided in Table 2. All the studies in Table 2 employed Bayes Theorem for augmenting data except for Bode, Newcomer and Fitchett [9]. In Leemans and Forsyth [10], a limited set of field data is utilized to update prior assumptions of the POD curve. The study showed that the influence of the field data depended on the uncertainty in prior assumptions. If the uncertainty was large, the new data significantly influence the POD estimate. If the uncertainty was small, the new data would not have a large influence. In the nuclear power industry, field data regarding missed detections is not readily available so approaches that minimize the requirement for field data will be more feasible to implement.

TABLE 2. SUMMARY OF POD DEMONSTRATIONS USING BINARY NDE RESPONSE DATA.

Augmenting Technique	NDE Method	Description	Reference
Other	Ultrasonic Testing	Airplane lap joint specimen sets with multiple site fatigue damage	[9]
Bayes Theorem	Visual testing	Determination of field POD based on limited field data	[10]
Bayes Theorem	Eddy current testing	POD determination using computer models to generate additional infor-mation to supple-ment limited data from experiment.	[11]

The review highlights some challenges with applying MAPOD to nuclear power beyond availability of pertinent field data. Human factors are significantly influential in nuclear power inspection processes, and robust methods for modeling human factors and quantifying their influence on variability in NDE performance have not been developed for nuclear power applications. In addition, much of the literature assumes a single response parameter (i.e., amplitude) for determination of POD. In ultrasonic testing, practitioners may apply more complex methods for discrimination. For example, flaw detection may depend on the spatial pattern of amplitude in an NDE response image or might consider how a response signal feature varies with probe position or incident angle.

4. VIRTUAL FLAW TOOLS

Recent developments include the creation of “virtual flaw” tools, which enable the creation of a large sample of realistic flaw responses for POD estimations and NDE qualification applications. These tools are based on the digital manipulation of a small number of recorded physical flaw responses to create a much larger sample of flaw responses. Copies of the flaw responses can be manipulated to create variation in the flaw sample population. The process also requires the creation of a blank “canvas” file, which contains the background response for the target material. The digitally manipulated flaw responses can be pasted into the canvas at the desired locations. A more thorough description of this type of approach developed for ultrasonic testing data is provided in Virkunnen et al. [12]. Application of the tool for NDE qualification is considered in [12] and [13] while application to POD estimation is discussed in Koskinen et al. [14].

5. FUTURE WORK UNDER PIONIC

The efforts of PINC and PARENT continue under the Program for Investigation Of NDE by International Collaboration (PIONIC). An objective of PIONIC is the improvement of POD estimations obtained in PINC and PARENT with respect to reducing uncertainty and attempting to obtain a better understanding of field POD. The data collected under PINC and PARENT provide useful sources of baseline data that can be updated with MAPOD concepts and virtual flaw tools. Conversely, the data from PINC and PARENT provide opportunities to validate virtual flaw tools with empirical data sets.

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