Assessing Crack Detection Capability

Statistical Models in Practice

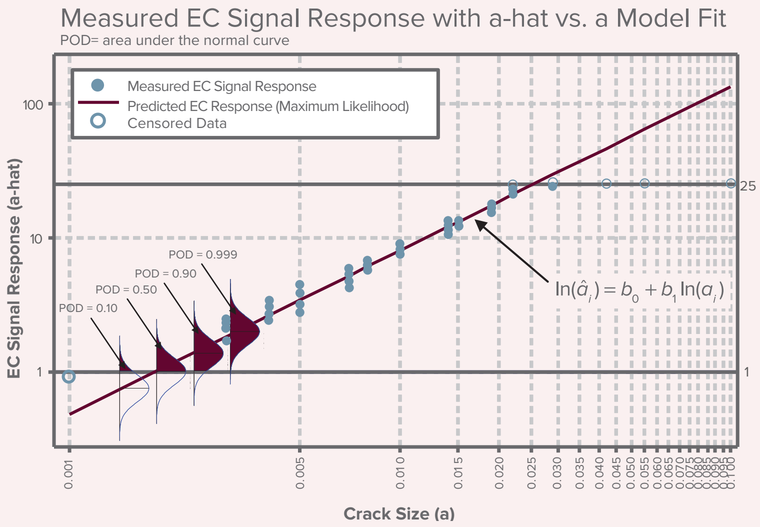
By Jennifer Brown

Q What statistical procedure is used to determine the typical crack size that can be detected with a given probability?

A Cracks and crack propagation are a concern in the aerospace industry. If a surface or near-surface crack is present in metallic hardware, it has the potential to grow to a critical length, which could impact structural integrity. Hence methods for detecting cracks are a critical part of flight quality assurance programs for commercial, military and rocket engine hardware. Various nondestructive testing methods are used to detect cracks in metallic hardware. Two examples are eddy current inspection, which uses the principle of electromagnetism to detect surface or near-surface cracks, and fluorescent penetrant inspection, which uses fluorescent dye and visual inspection under black light to detect surface cracks only.

Crack size is one factor that affects detection capability. Larger surface cracks, for example, tend to produce a larger EC signal response and will emit a brighter fluorescence than smaller surface cracks. Hence, as crack size increases, the probability of detection tends to increase. Given NDT data generated through a controlled experiment, a generalized linear model is commonly used in the aerospace industry to determine the typical size crack than can be detected with a given probability under standard NDT system operation.

Figure 1 — POD is the area under the normal curve.



In essence, a GLM is a generalization of the classic linear regression model that can accommodate a non-normal error structure. For example, the theoretical form of a GLM with a single predictor variable is:

$$g(y_1) = \beta_0 + \beta_1 \cdot x_1 + \varepsilon_1$$

where y is the response variable, x is the predictor variable, g is the function that links the response variable with the predictor variable, β_0 and β_1 are the model coefficients, and ε_i is the error term that follows one of the distributions in the exponential family (e.g., normal, binomial, Poisson). The appropriate link function and assumed distribution of the error term are dependent on the nature of the response variable. For example, when the response variable is continuous with a normal error structure and the identity link function $g(y) = y$ is used, the result is the classic simple linear regression model with predictive form:

$$\hat{y} = b_0 + b_1 \cdot x$$

where $\hat{y}$ is the average response for a given value of the predictor variable x, and b_0 and b_1 are the estimated model coefficients.

Data generated by an EC inspection system is continuous. When an EC probe scans over a surface crack or near surface crack, the EC testing instrument processes the signal and displays it as a measurable quantity. The measured EC signal response for cracks of the same size will vary due to other physical characteristics of the crack, such as depth and the inherent variability in the EC inspection process. This variation is assumed to be normally distributed on a log scale. Hence, one common model fit to EC data is the simple linear regression model:

$$\ln(\hat{a}) = b_0 + b_1 \cdot \ln(a)$$

where $\hat{a}$ is the measured EC signal response and a is the known crack size.[2] Normal probability theory is used to determine the POD for a given crack size. In general, probability is represented by the area under the normal curve. Hence, POD equates to the area under the normal curve above the smallest value of the measured signal response that can be considered a find. For example, if a measured signal response above 1 is considered a find, then POD equates to the area under the normal curve beyond one as illustrated in Figure 1.[2] POD can be calculated for each crack size and plotted to establish what is commonly referred to as a POD curve as illustrated in Figure 2.[2] The resulting "POD curve" is used to estimate the typical crack size that can be detected with a given probability.

Data generated by an FP inspection system is binary. That is, the crack was either found or missed during the visual inspection. One possible link function for binary data which is often used with FP inspection data[1] is the logit link function:

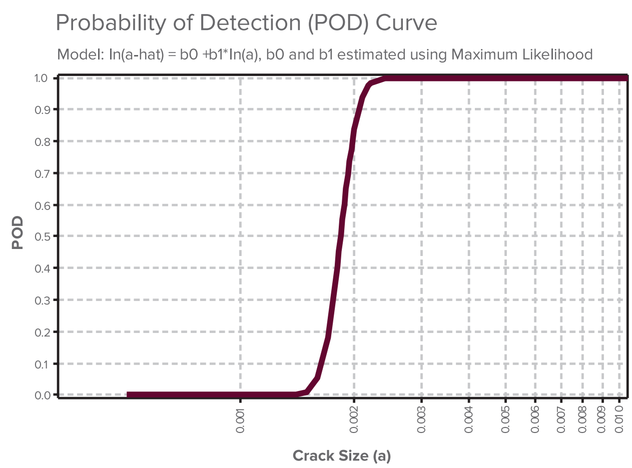


Figure 2 — Resulting POD Curve

"Given NDT data generated through a controlled experiment, a generalized linear model is commonly used in the aerospace industry to determine the typical size crack than can be detected with a given probability under standard NDT system operation."

$$g(y) = \ln\left(\frac{p}{1-p}\right)$$

When the logit link is used, the model is known as a logistic regression model. One possible predictive model fit to FP inspection data is:

$$\ln\left(\frac{p}{1-p}\right) = b_0 + b_1 \cdot \ln(a)$$

where p = POD. Note that the model can be expressed in terms of POD. That is:

$$POD = \frac{\exp\left(b_0 + b_1 \cdot \ln(a)\right)}{1 + \exp\left(b_0 + b_1 \cdot \ln(a)\right)}$$

Hence, the logistic regression model is the POD curve itself (and will look similar to Figure 2), whereas the simple linear model is the first step to generating the POD curve.

In general, each GLM has its own underlying assumptions, one of which deals with the distribution of the error term. As discussed earlier, the simple linear regression model assumes the error term is normally distributed. The logistic regression model assumes the error term follows a binomial distribution. If any of the underlying assumptions do not hold, then the predictive model is not valid and can be entirely misleading. Hence, a basic understanding of the model assumptions is required. Two ASTM standards are available as a resource. The next revision of E2586, Practice for Calculating and Using Basic Statistics, will include simple linear regression. ASTM E2862, Practice for Probability of Detection Analysis for Hit/Miss Data, discusses GLMs for binary data as applied to POD. The book by McCullagh and Nelder, *Generalized Linear Models*, is useful as a reference for anyone who may be interested in learning more about GLMs.[3]

REFERENCES

1. Herberich, J., "Applying MIL-HDBK-1823 for POD Demonstration on a Fluorescent Penetrant System," Materials Evaluation, Vol. 67, No. 3, p. 293.
2. Herberich-Brown, J., "Probability of Detection Analysis for Eddy Current Inspection Systems," Proceedings of the 2009 ASNT Fall Conference and Quality Testing Show, Columbus, Ohio, Oct. 19-23, 2009.
3. McCullagh, P., and Nelder, J.A., Generalized Linear Models, 2nd ed., Chapman and Hall/CRC, Boca Raton, Fla., 1989.

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