

POD Tutorial Part III

Advanced Data Analysis Methods for POD

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Overview

Advanced Topics in Empirical POD

- Principles of designing a POD study
- POD from field finds
- Bivariate response regression for inspections with dual rejection criteria
- Dealing with errors in sizing

Designing the Study

- Acquisition/fabrication of the experimental units, e.g., specimen(s).
 - Type of flaws
 - Number of flaws
 - Position and orientation of flaws in specimen(s)
- Design of the inspection plan
 - Which sources of variability need to be captured (e.g., setup, operators, locations)?
 - How many scans?
- A poorly designed experiment will limit the information that you will obtain from the experiment

Examples of Experimental Specimens

- Block of titanium with flat-bottom holes
- Block of titanium with synthetic hard alpha cylinders
- Wedding cake specimen with flat bottom holes
- Billet with seeded synthetic hard alpha inclusions
- Billet with WC spheres seeded at various depths
- Forging with flat-bottom holes at different depths
- Plates with fatigue cracks
- Real parts, taken from service, with cracks

How Many Flaws Needed to Estimate POD?

- Depends on
 - Number of type of factors in the study.
 - Variability in the inspection process. More data is needed if there is more variability.
 - Precision with which POD must be estimated. More data required for more precision (tighter confidence bounds).
 - Budget

How Many Inspections are Required?

- Depends on:
 - Factors that vary in the actual inspection (operators, systems, locations). If you want to assess POD when there are multiple operators in use, need to use multiple operators in the experiment, if they are different.
 - Amount of variability caused by the inspection factors.
 - Budget

Note: Multiple inspections of the same unit may complicate modeling and analysis because of **multiple sources of variability** (simple models assume only one common source of variability).

Simple, General Idea, for Planning an Experiment

- Need “Planning Information” giving the model for data that you expect to see
- Simulate the experiment in the computer
- Analyze the data
 - Any surprises?
 - How is the precision?
- Repeat the simulation many times
- Plot the results in a meaningful way
- How reliably can you reproduce the “truth?”

POD Studies

Based on Field-Find Data

- Data needs
- Data sources
- Dealing with misses using the truncated regression model

Key References

- Burkel, R. H., Sturges, D. J., Tucker, W. T., and Gilmore, R. S.(1996), “Probability of Detection for Applied Ultrasonic Inspection,” *Review of Progress in Quantitative NDE*, Vol. 15
- *The Use of In-Service Inspection Data in the Performance Measurement of Non-Destructive Inspections* NATO Research and Technology Organisation (RTO) Technical Report TR-AVT-051 (www.rta.nato.int)
- R. B. Thompson, W.Q. Meeker, M. Keller, J. Umbach, C.P. Chiou, Y. Wang, R. Burkel, W. Hassan, K. Smith, T. Patton, and L. Brasche, *Update of Default Probability of Detection Curves for the Ultrasonic Detection of Hard-Alpha Inclusions in Titanium Alloy Billets*, report in preparation for the FAA William J. Hughes Technical Center, Atlantic City, NJ

Concerns with Estimating POD from Field Inspection Data

- Adequate flaw characterization information may not be available
- Misses, if they are ignored (naïve estimation), can cause serious anti-conservative estimation bias

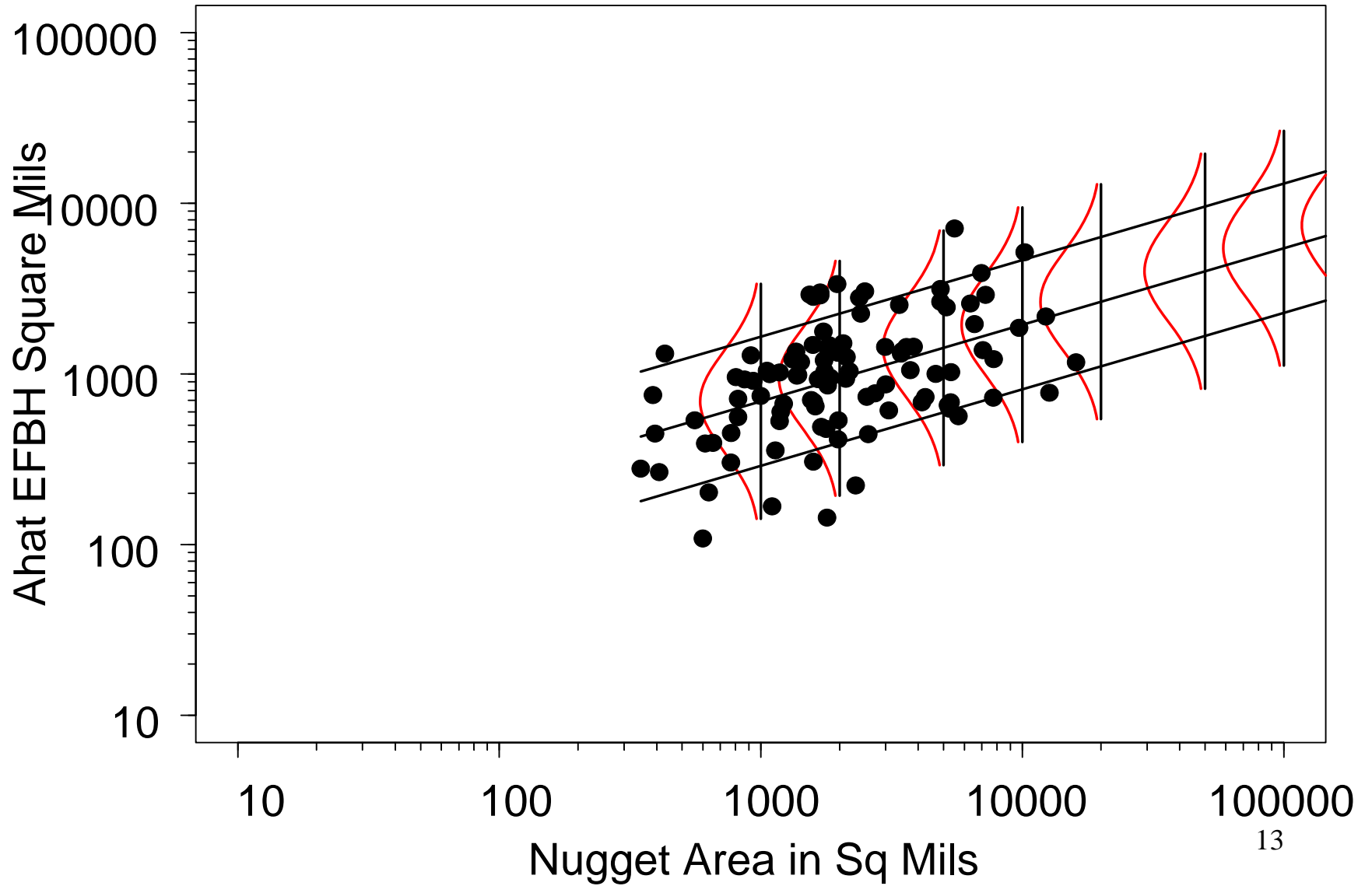
Use of Truncation to Adjust for Misses in Field Inspection Data

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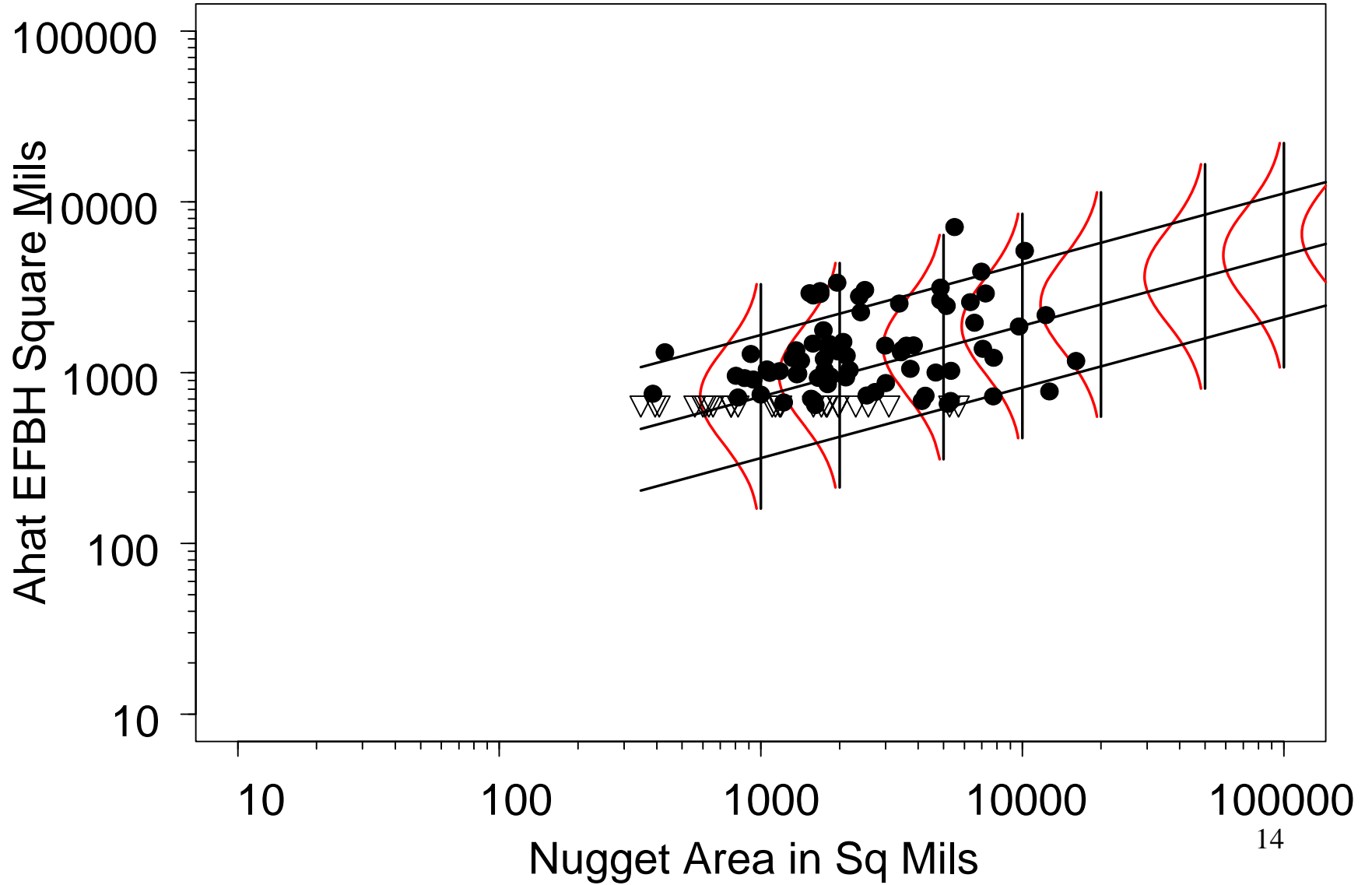
Examples of Field-Find Data Sets

- DPD data field finds from conventional inspection used to find default POD curves in Phase I of the ETC
- JETQC data field finds for conventional and Multizone billet and forging inspection
- Contaminated Billet Study (CBS) in Phase II of ETC conventional and Multizone billet inspections

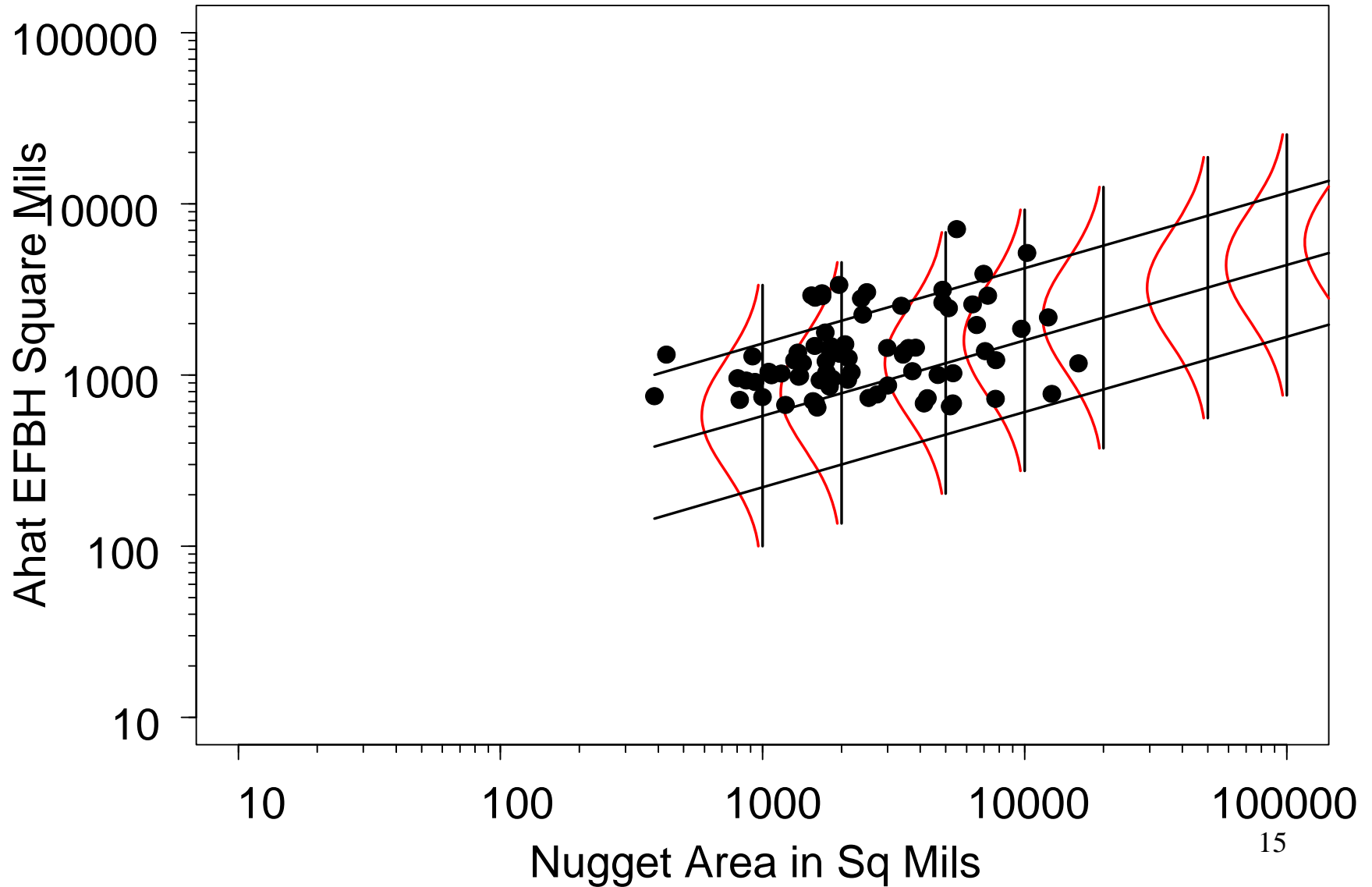
Regression Analysis with Complete Data (No Misses)



Regression Analysis with Left-Censored Data (Known Misses)

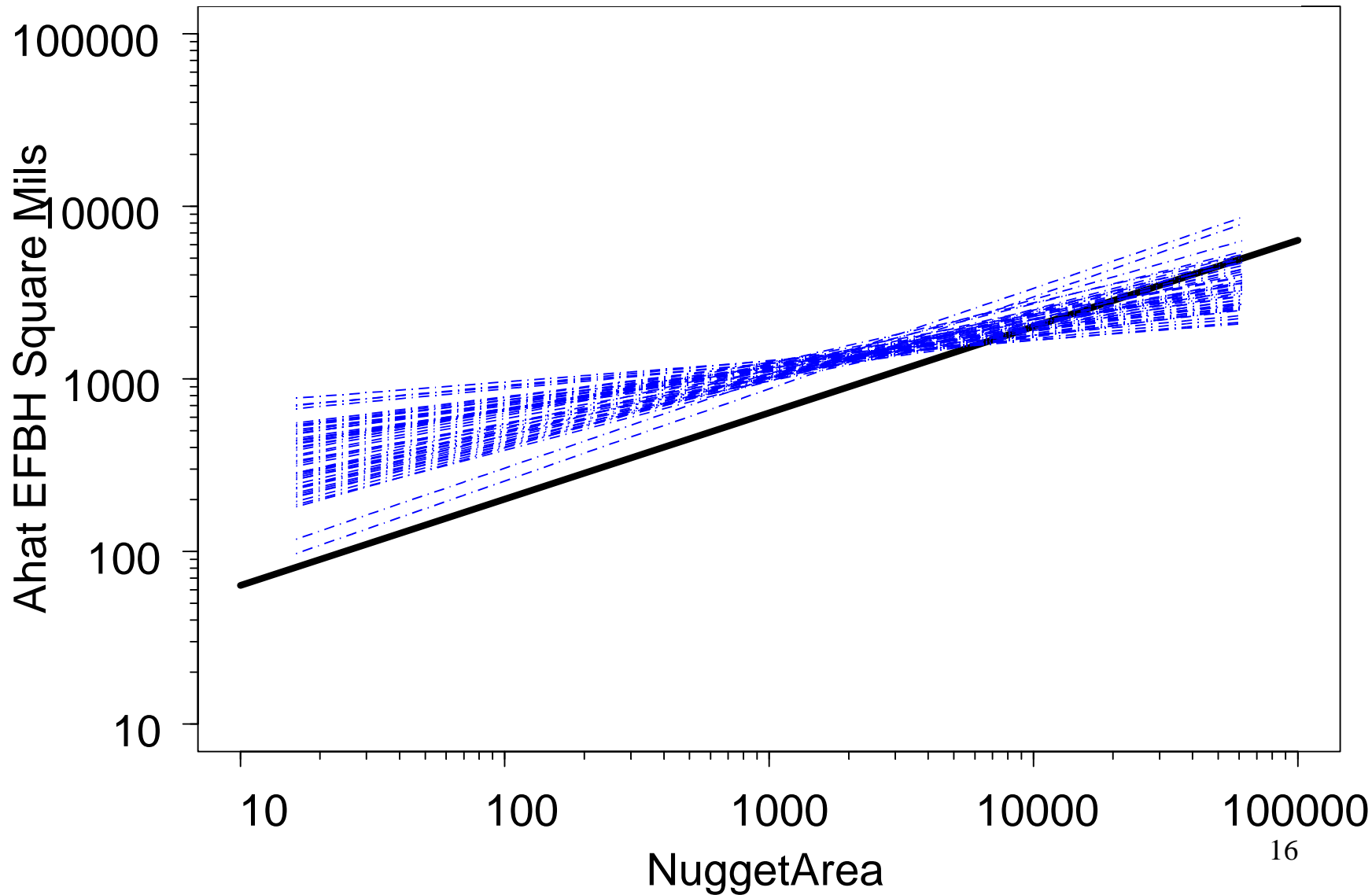


Regression Analysis fitting Left-Truncated Distributions (Unknown Misses)



Regression Results for 50 Simulations

Unknown Misses Naïve Estimation

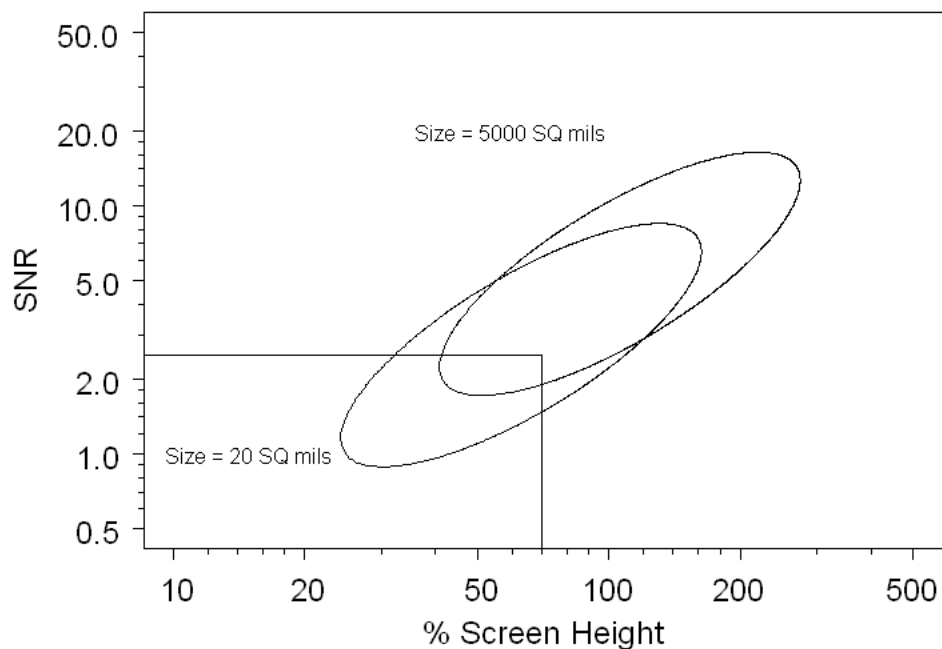


Assessment of POD with a Dual Rejection Criterion

- In Multizone billet inspection, detection depends on both amplitude and signal-to-noise ratio
- In some conventional inspections, detection depends on information from both normal angle probe-alignment inspections.

Contours Indicating the Joint Flaw Signal Distribution for a Multizone Inspection

Bivariate Model CBSMZ95



Bivariate Regression Model for the CBS Multizone Inspection Data

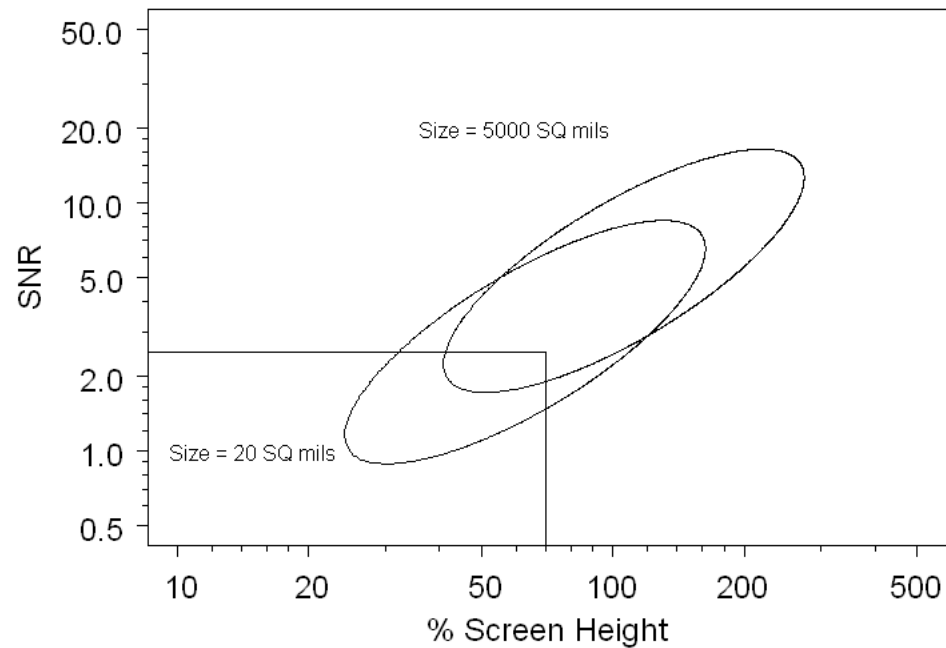
- To fully capture the bivariate regression model would require a three-dimensional display.
- The previous slide shows contours of the distribution for two different sizes for the “CBS 61” data.
- Those portions of the distribution falling outside the lower, left hand box correspond to rejects. Hence POD is the volume of the distribution (normalized to unity total volume) outside of this region
- As expected from practical experience, the SNR criteria rejects more flaws than the amplitude criteria

Key References

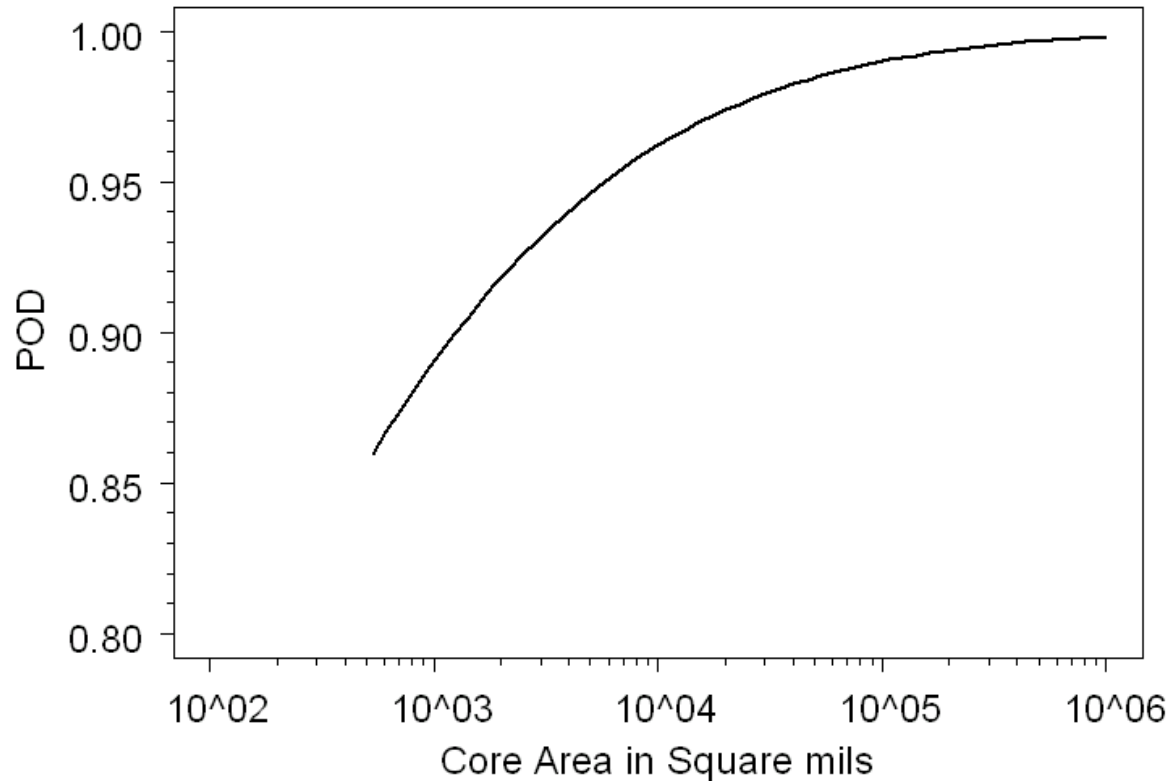
- Y. Wang and W. Q. Meeker (2006), “A Bivariate Regression Model for Assessment of Multizone Ultrasonic POD,” *Review of Progress in Quantitative NDE*, Vol. 21.
- R. B. Thompson, W.Q. Meeker, M. Keller, J. Umbach, C.P. Chiou, Y. Wang, R. Burkel, W. Hassan, K. Smith, T. Patton, and L. Brasche, *Update of Default Probability of Detection Curves for the Ultrasonic Detection of Hard-Alpha Inclusions in Titanium Alloy Billets*, report in preparation for the FAA William J. Hughes Technical Center, Atlantic City, NJ

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Bivariate Model CBSMZ95

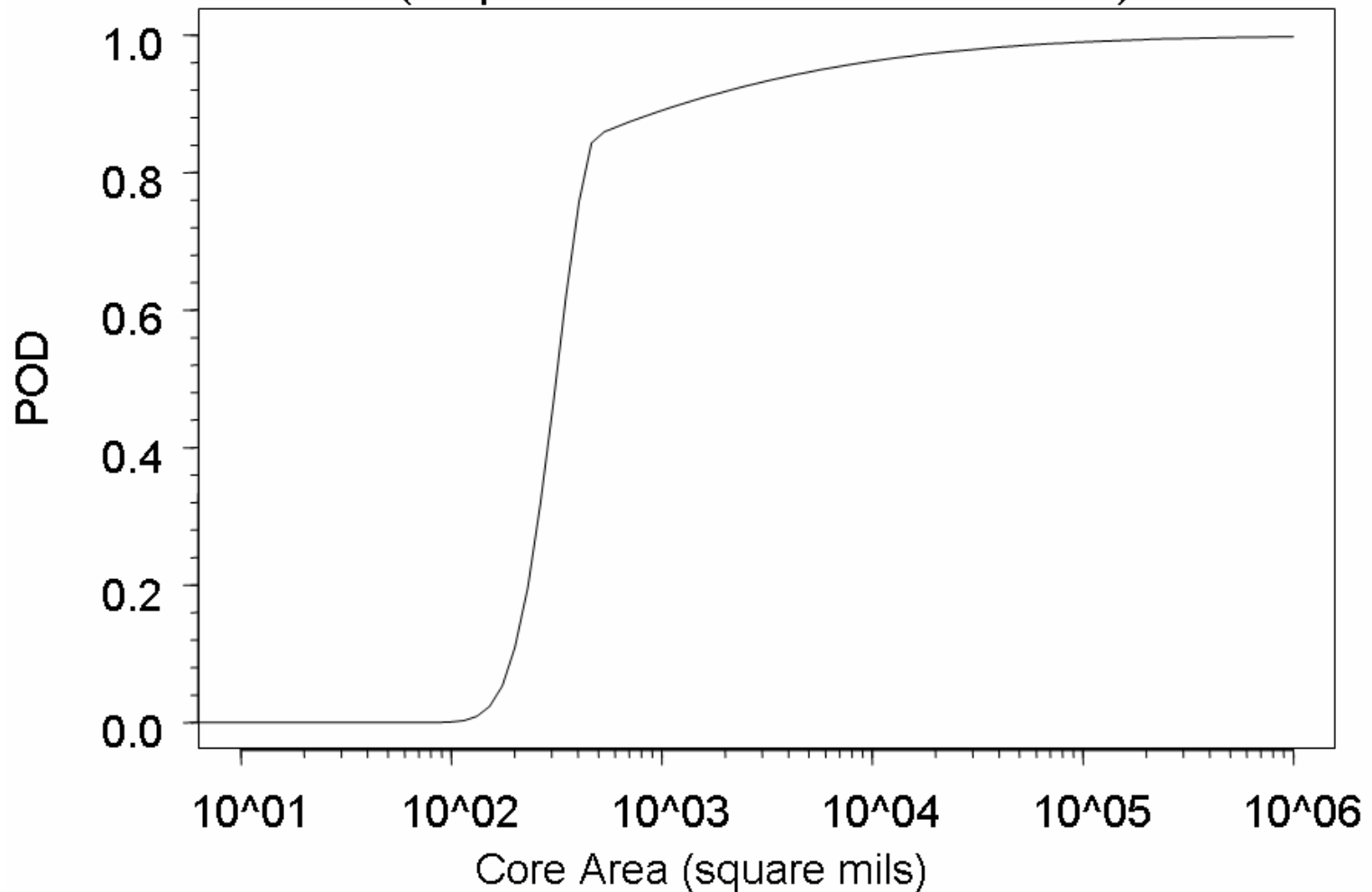


POD Curve from the CBS Multizone Data for Flaws Greater than 300 Square Mils



Complete POD Curve from the CBS Multizone Data

Multizone Normal Incidence POD Estimate
(Amplitude + S/N Detection Criterion)



Dealing with Errors in Flaw Sizing

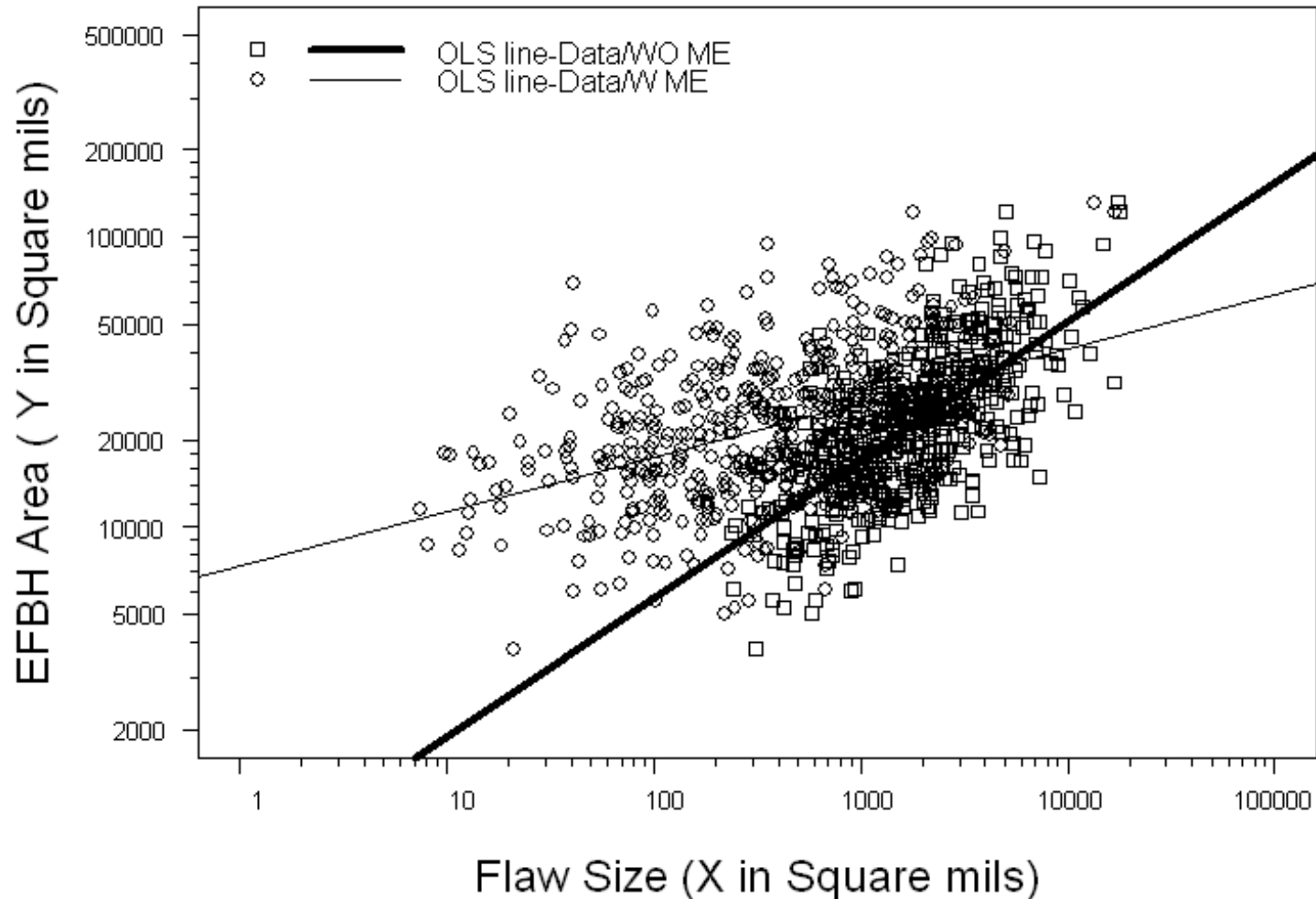
- A standard assumption in regression analysis is that the X variables are known and have no measurement error
- If the assumption is not met, there will be downward bias in the estimates of the slope, even if the measurement error is “unbiased.”
- In NDE applications, the measurement error is not unbiased, in some cases.

Key References

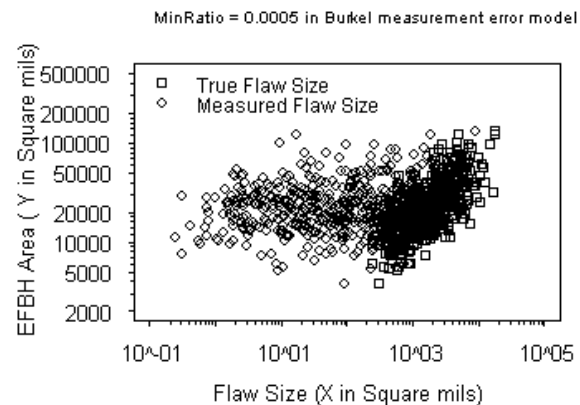
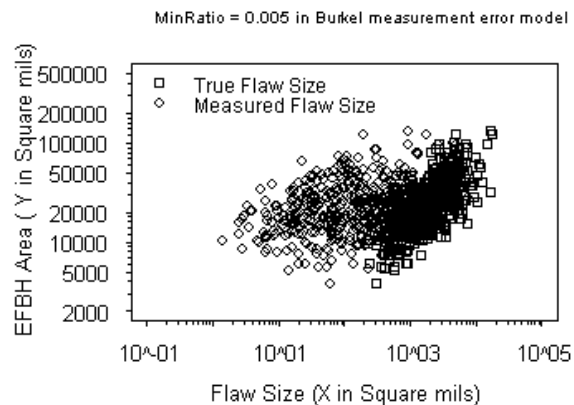
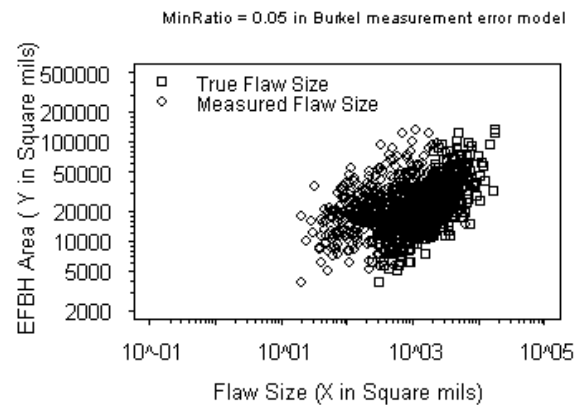
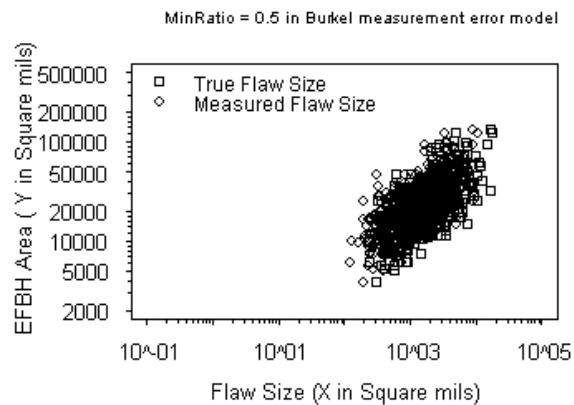
- Y. Wang and W. Q. Meeker (2006), “A Statistical Model to Adjust for Flaw-Size Bias in the Computation of Probability of Detection,” *Review of Progress in Quantitative NDE*, Vol. 21.
- W. A. Fuller (1987) “Measurement Error Models,” *New York: Wiley*.
- R. J. Carroll, D. Ruppert, and L. A. Stefanski (1995) *Measurement Error in Nonlinear Models*, London; New York, Chapman Hall.
- MIL-HDBK-1823 (1999), *Non-Destructive Evaluation System Reliability Assessment* (but they did not get it quite right, in my opinion)

Simulated Data With and Without Measurement

Burkel measurement error model



Simulated Data with Different Sizes of the MinRatio (δ_1)



Comparison of Burkel Model Estimates and Naïve (OLS) Estimates with Different δ_1

