Exploring Reliability

William Q. Meeker
Iowa State University

Reliability

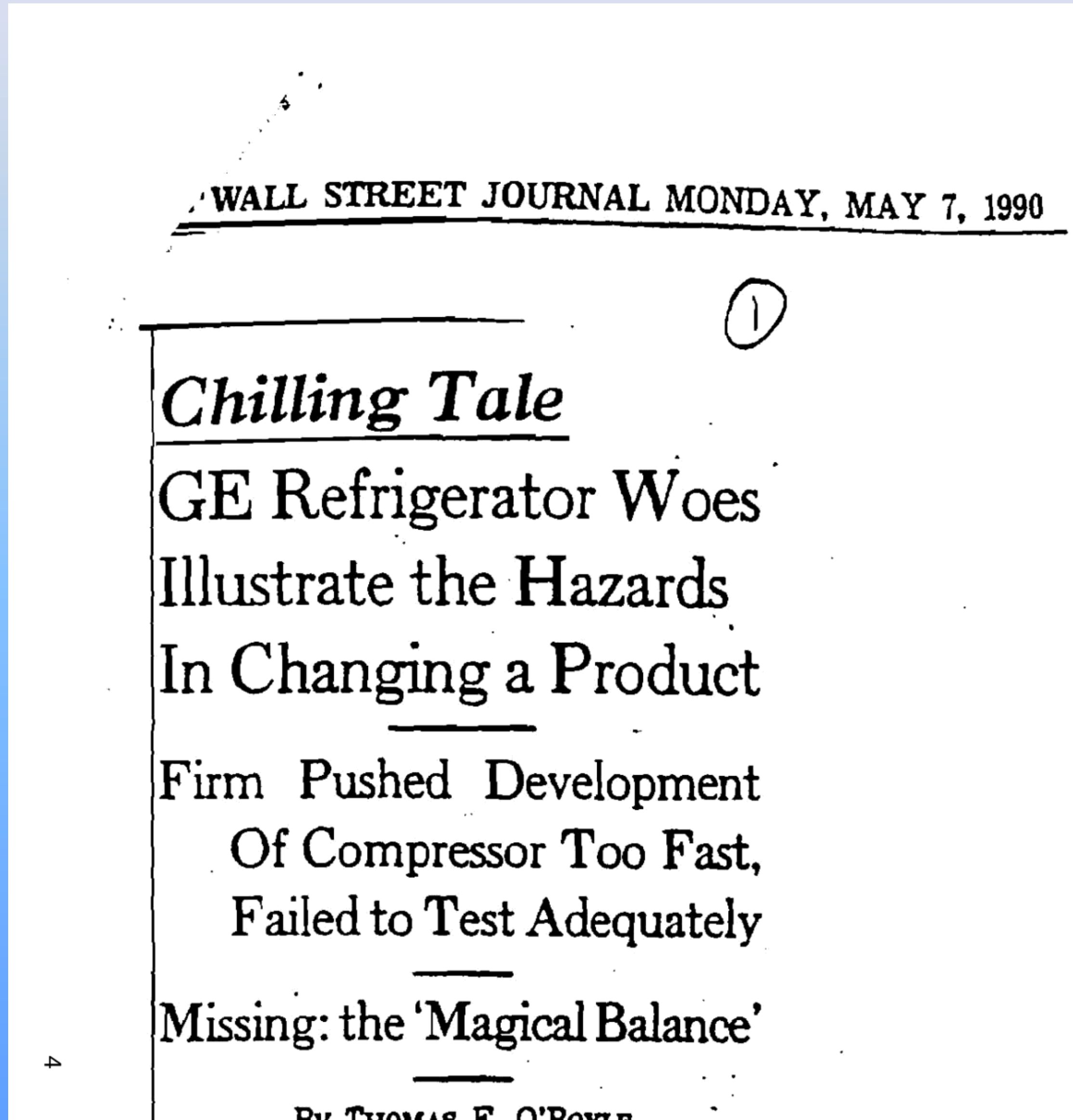
- ***Probability*** that a system, vehicle, machine, device, and so on, will perform its intended function under ***encountered*** operating conditions, for a specified period of time (Meeker and Escobar 1998)
- Quality over time (Condra 1993)
- A highly quantitative engineering discipline, often requiring complicated statistical and probabilistic analyses
- Today's customers expect high reliability

Examples of Reliability Disasters

- These are the kind of things all companies want to avoid
- Some Well Known Classic Examples:
  - Challenger and Columbia Space Shuttle failures
  - United Airlines 232 (aka Sioux City accident)
  - Automobile clear-coat failures (early 1990's)
  - Ford Explorer/Firestone tires
  - Desktop computer electrolytic capacitors
  - GE refrigerator compressor
  - Sony laptop battery design defect

Chilling Tale

This is the kind of thing we are trying to avoid



WALL STREET JOURNAL MONDAY, MAY 7, 1990

Chilling Tale

GE Refrigerator Woes Illustrate the Hazards In Changing a Product

Firm Pushed Development Of Compressor Too Fast, Failed to Test Adequately

Missing: the 'Magical Balance'

Sony Battery Problem

Probability Plots
Life Distribution

William Q. Meeker
Iowa State University

Probability Plots

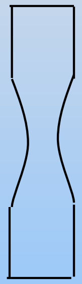
- Probability plots are the most widely used reliability data analysis tool
- Plot a “nonparametric” estimate on a distribution-specific scale
- Assess whether the nonparametric estimate is approximately linear

Purposes of Probability Plots

- Assess the adequacy of a particular distributional model (e.g. Weibull versus lognormal)
- Detect multiple failure modes or mixture of different populations
- Display the results of a parametric maximum likelihood fit along with the data

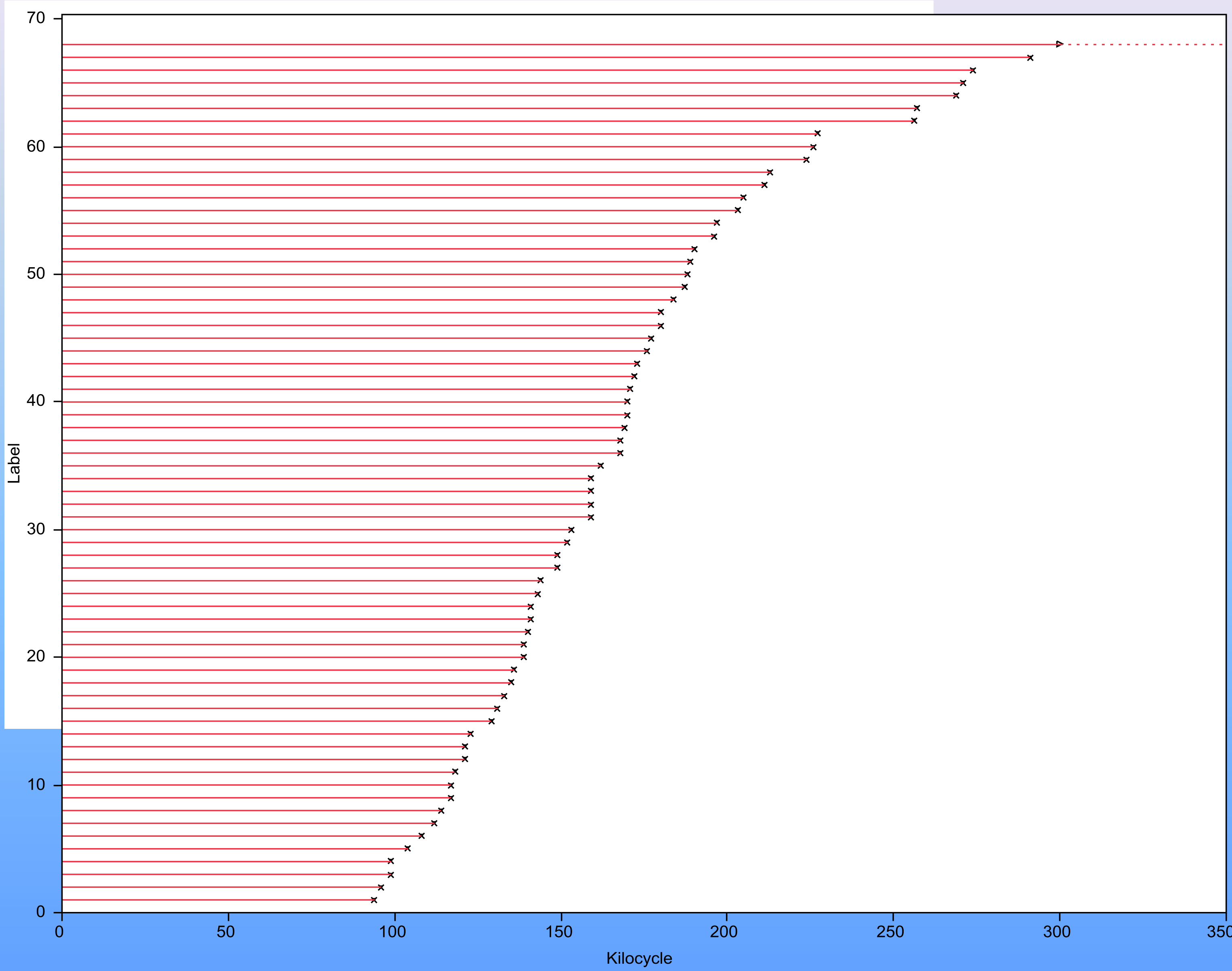
Example
Alloy T7987 Fatigue Data

- Data from Meeker and Escobar (1998)
- Dogbone shaped specimens

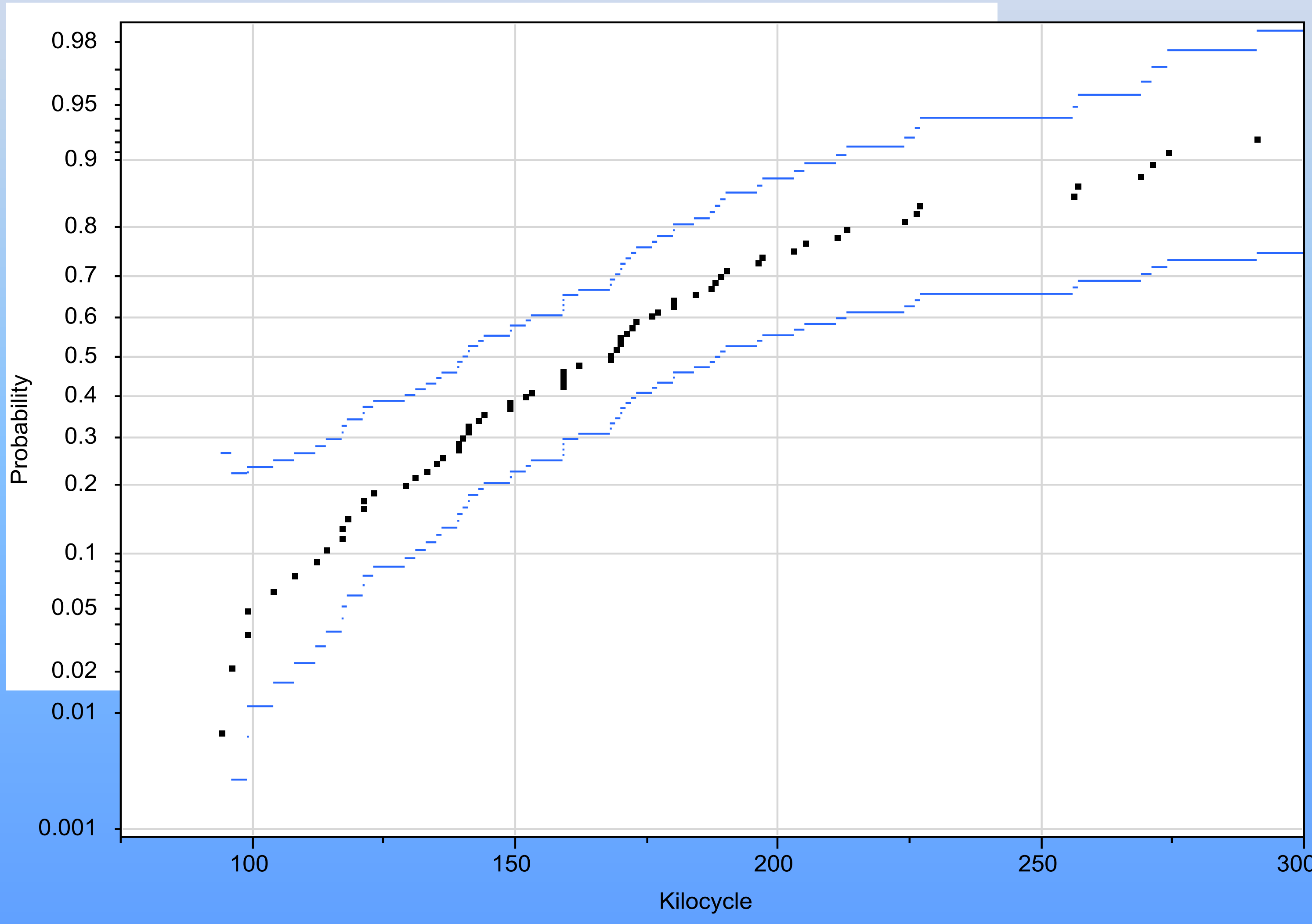


- Test run until 300 thousand cycles
  - 67 failures
  - 5 right-censored observations
- Need to estimate cycles-to-failure distribution
- Primary interest in the lower tail of the distribution

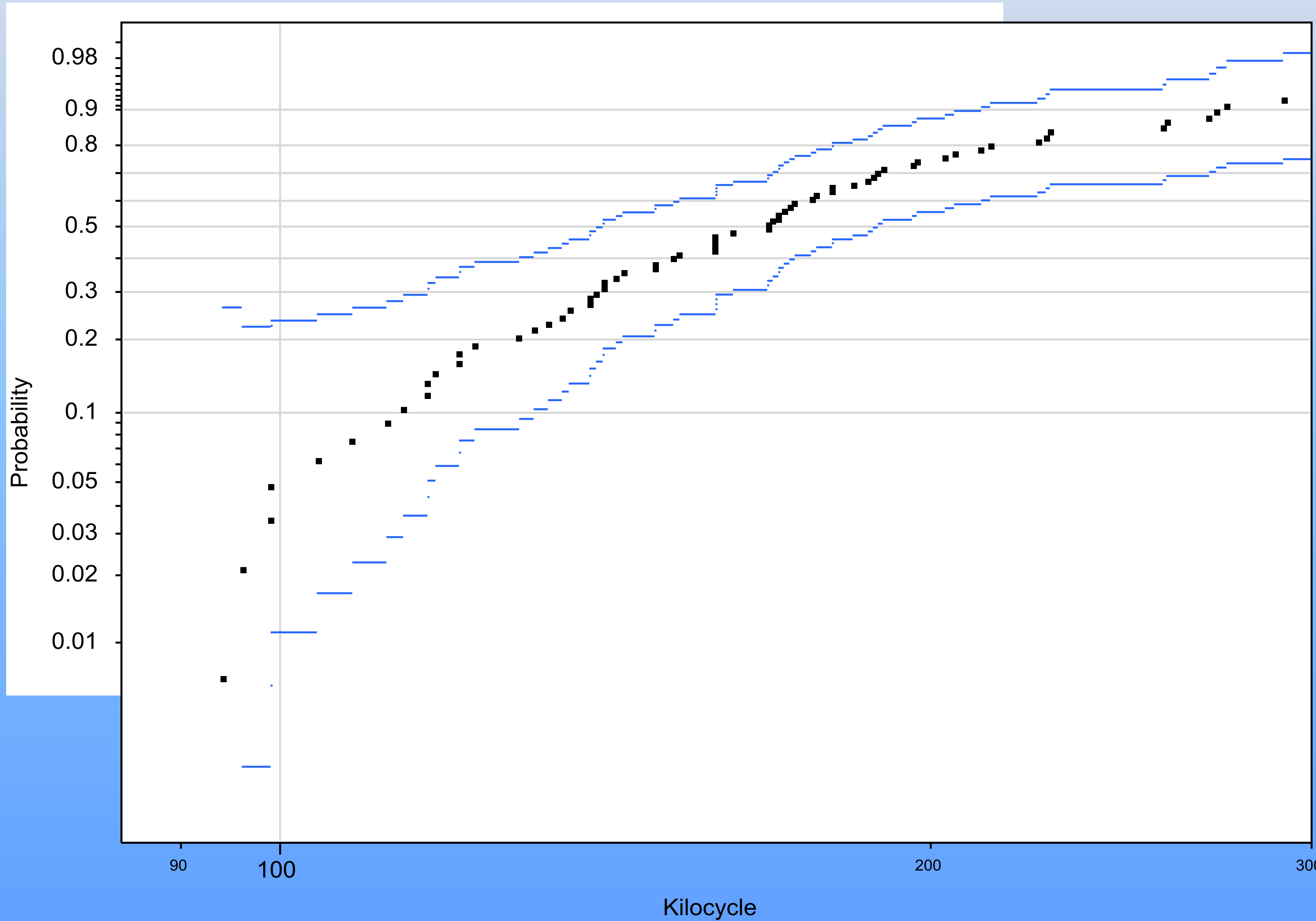
Alloy Fatigue Data Event Plot



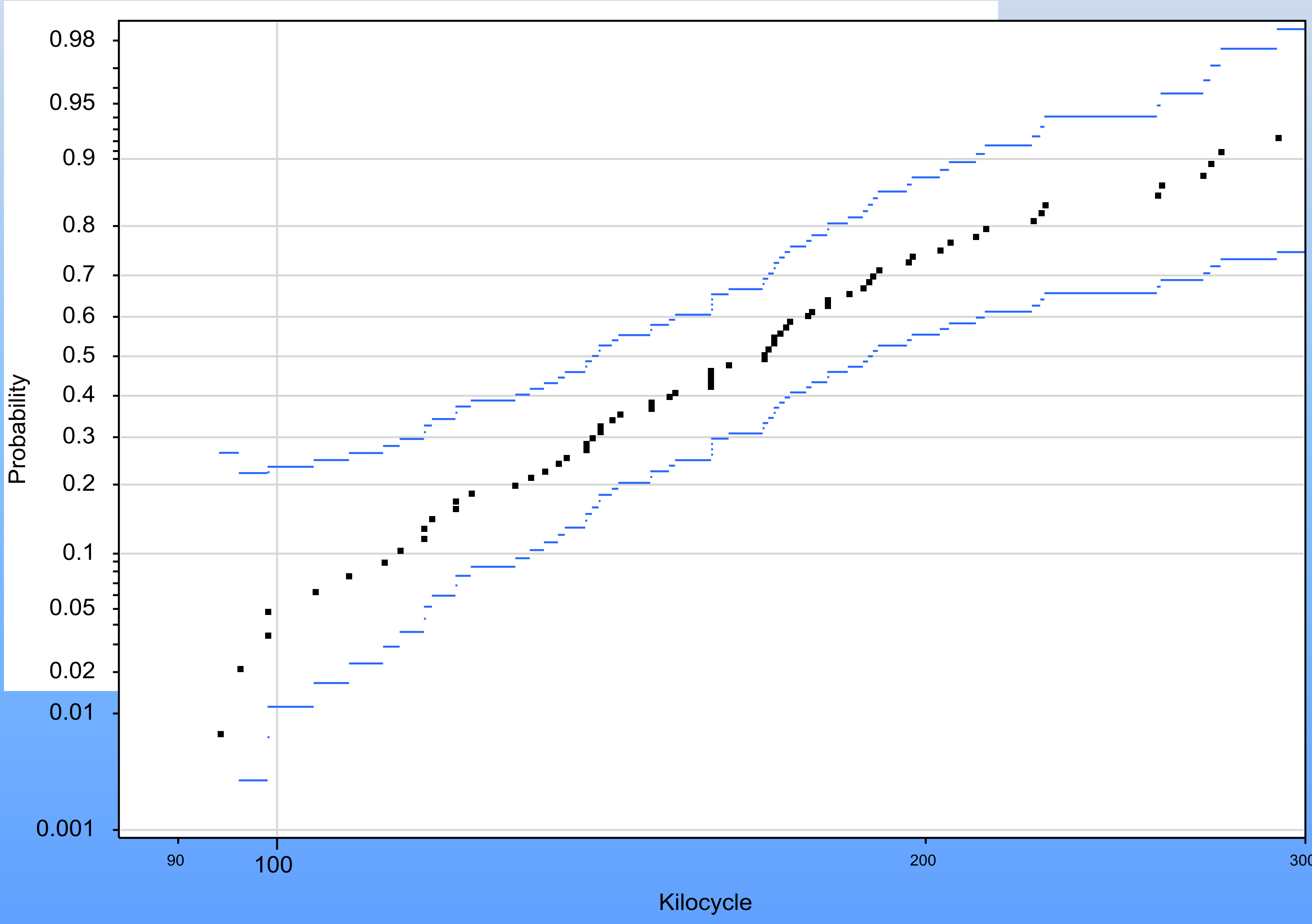
Alloy Fatigue Data
Normal Distribution with Nonparametric Pointwise 95% Simultaneous Confidence Bands



Alloy Fatigue Data
Weibull Distribution with Nonparametric Pointwise 95% Simultaneous Confidence Bands



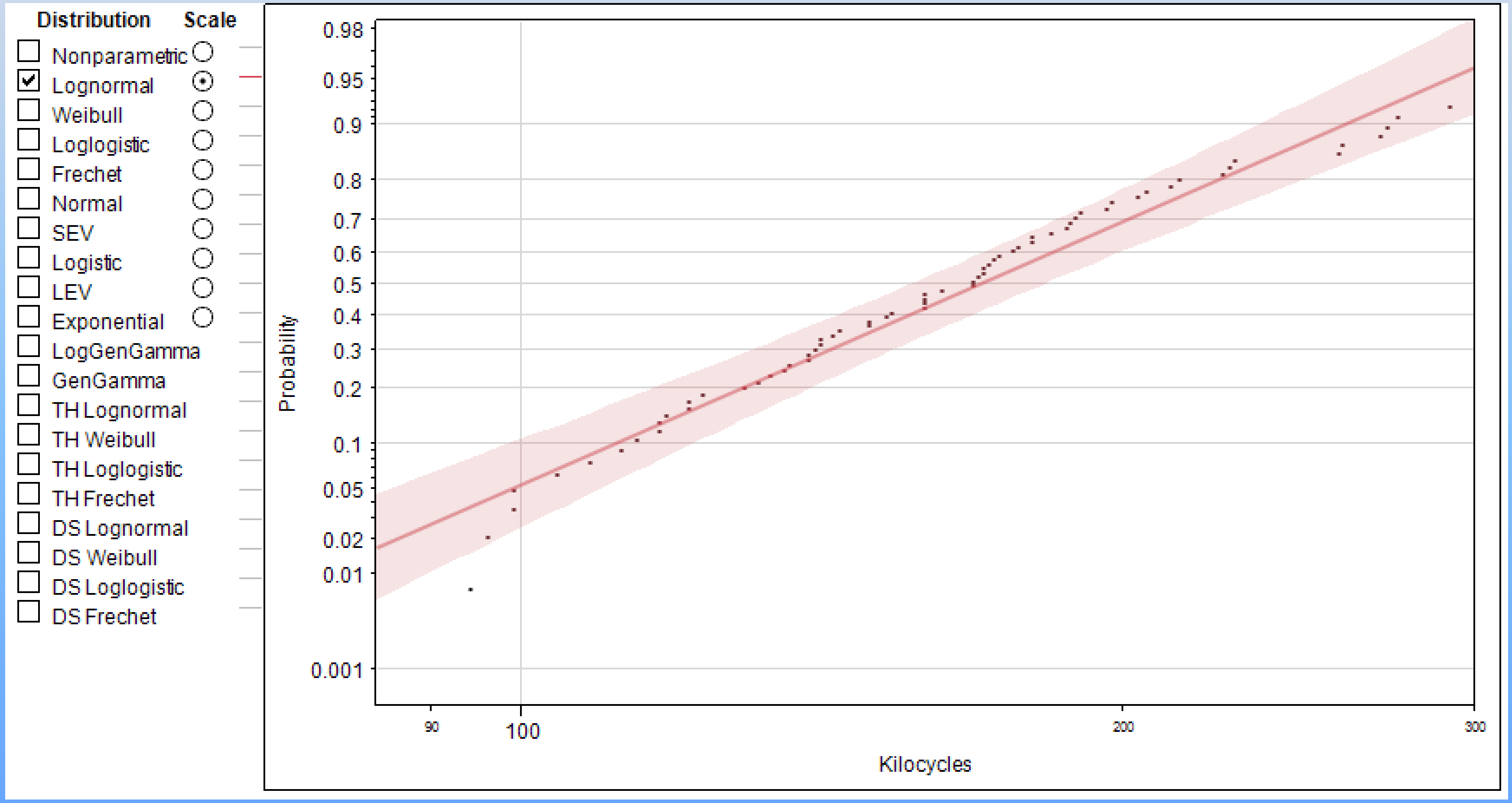
Alloy Fatigue Data
Lognormal Distribution with Nonparametric Pointwise 95% Simultaneous Confidence Bands



Fitting a Distribution

- Drawing a line through the points on an XX probability plot is equivalent to fitting an XX distribution
- Fitting a distribution allows extrapolation
- We use maximum likelihood (ML) to fit a line because ML
  - Is versatile
  - Has good statistical properties
  - Allows assessment of statistical uncertainty

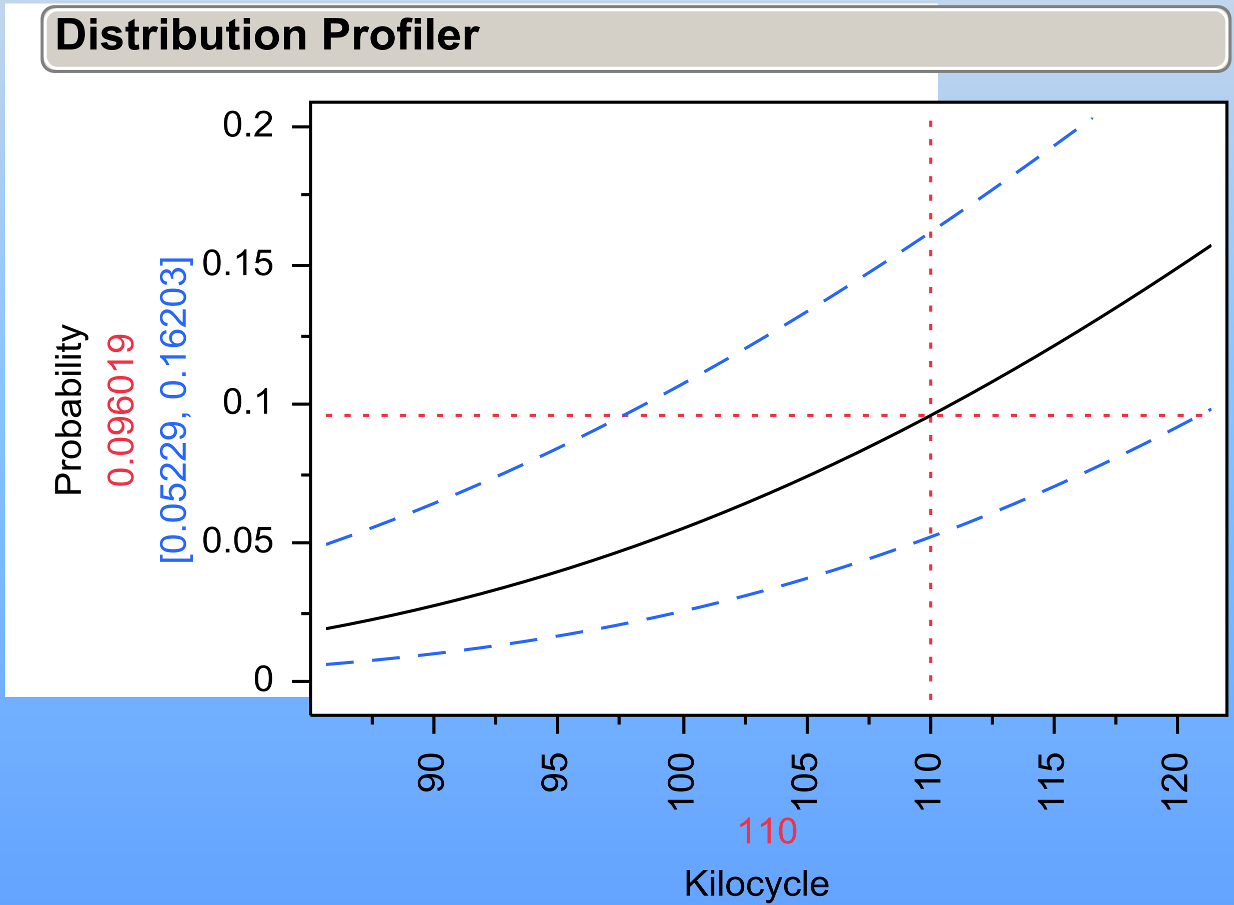
Alloy Fatigue Data
Lognormal Probability Plot with Lognormal ML Estimate and Pointwise 95% Confidence Intervals



Alloy Fatigue Data
Lognormal Probability Plot - Interactive Distribution Profiler

Estimate of the fraction failing @ 110 Kilocycles

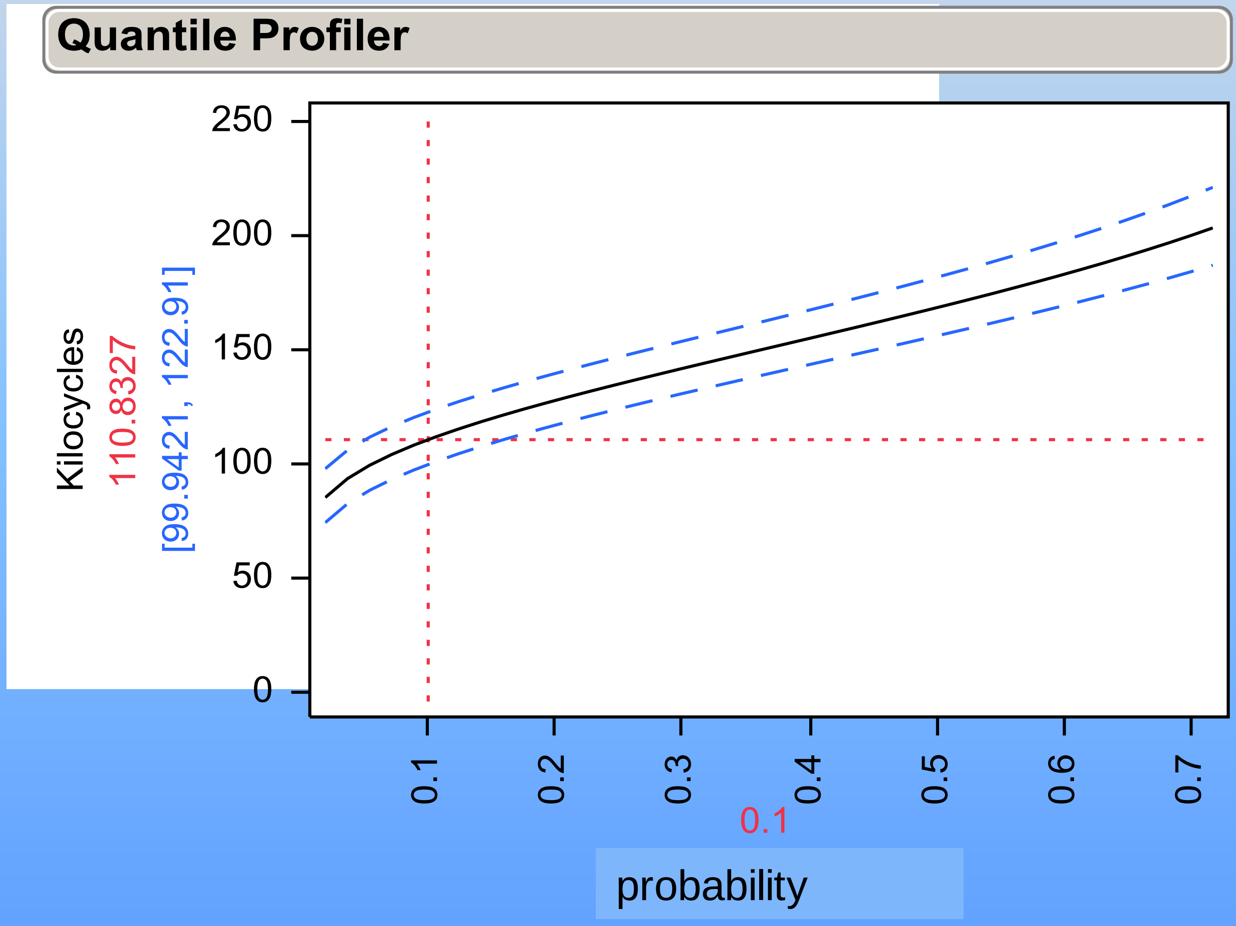
0.0960



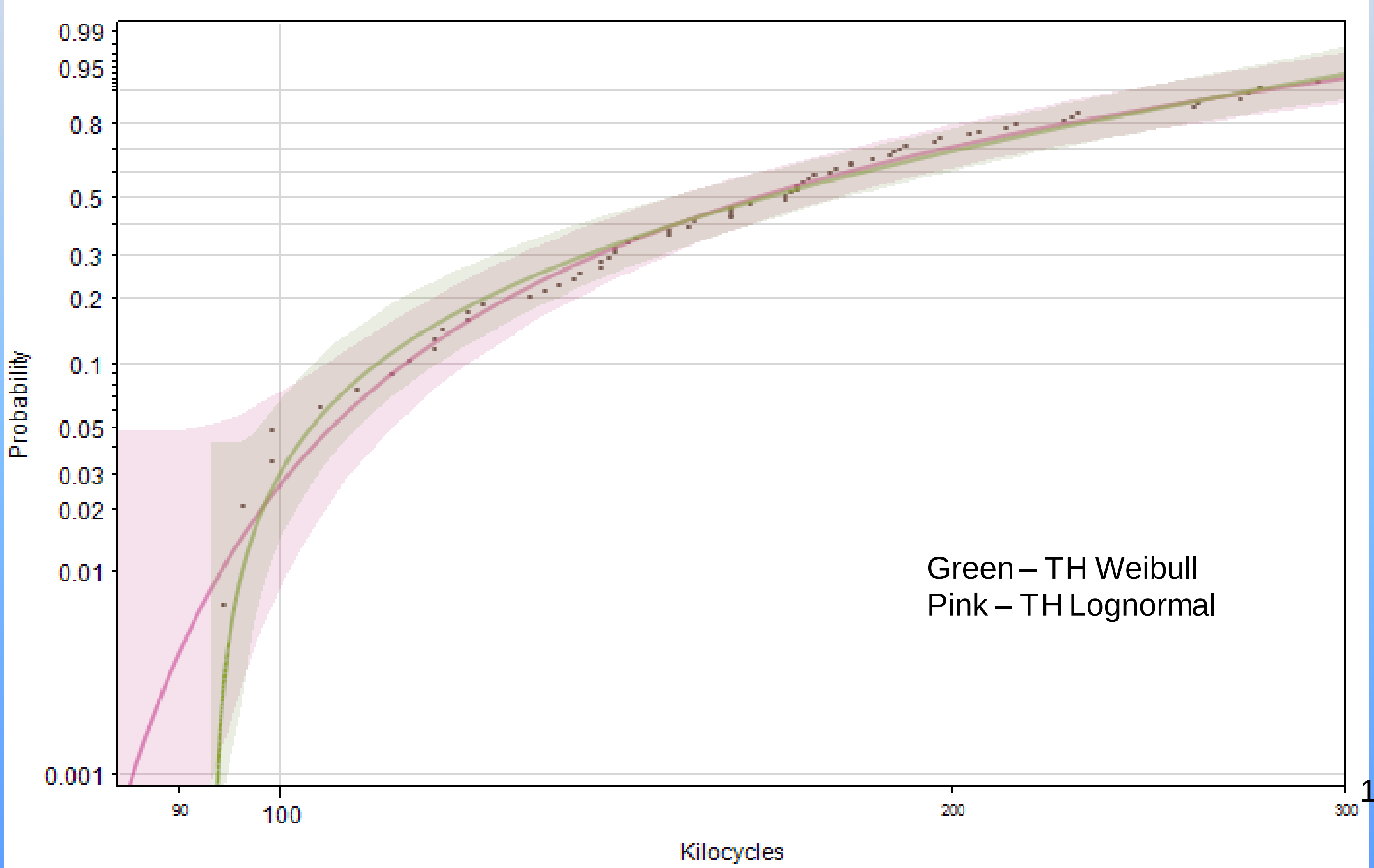
Alloy Fatigue Data
Lognormal Probability Plot - Interactive Quantile Profiler

Estimate of the time at which 10% Fail

110.8 Kilocycles



Alloy Fatigue Data
Weibull Probability Plot with Threshold Distributions and Pointwise 95% Confidence Intervals



Lessons Learned

- Probability plots provide the analyst with much useful information
- Fitting a three-parameter Weibull or Lognormal distribution might provide a better fit
- In some cases the use of a three-parameter distribution can be justified because it is known that there is an initial period where the probability of a failure is 0
- Fitting a three-parameter distribution can lead to anti-conservative inferences

Reliability Demonstration Test Planning

William Q. Meeker
Iowa State University

Reliability Demonstration Tests

- Frequently used to demonstrate that a system, subsystem, or component has the required reliability
- Purpose is different than estimation
- Most implementations require an assumption that the Weibull shape parameter is known

Basic Ideas: Minimum Sample Size Test

- Want to demonstrate reliability $\Pr(T > t_d)$ is at least ______.   (e.g., 0.90, 0.99, or 0.999).
- Test few units for a relatively long time (e.g., number of hours, cycles, or operations).
- Pass the test only if there are 0 failures.
- **Required:** Specification of the Weibull shape parameter.
- **Drawback:** The probability of passing the test will be small unless your reliability is ***much*** larger than the level to be demonstrated

Minimum Sample Size Test
Sample Size Formula

$$n = \frac{1}{k^{\beta}} \times \frac{\log(\alpha)}{\log(R)}$$

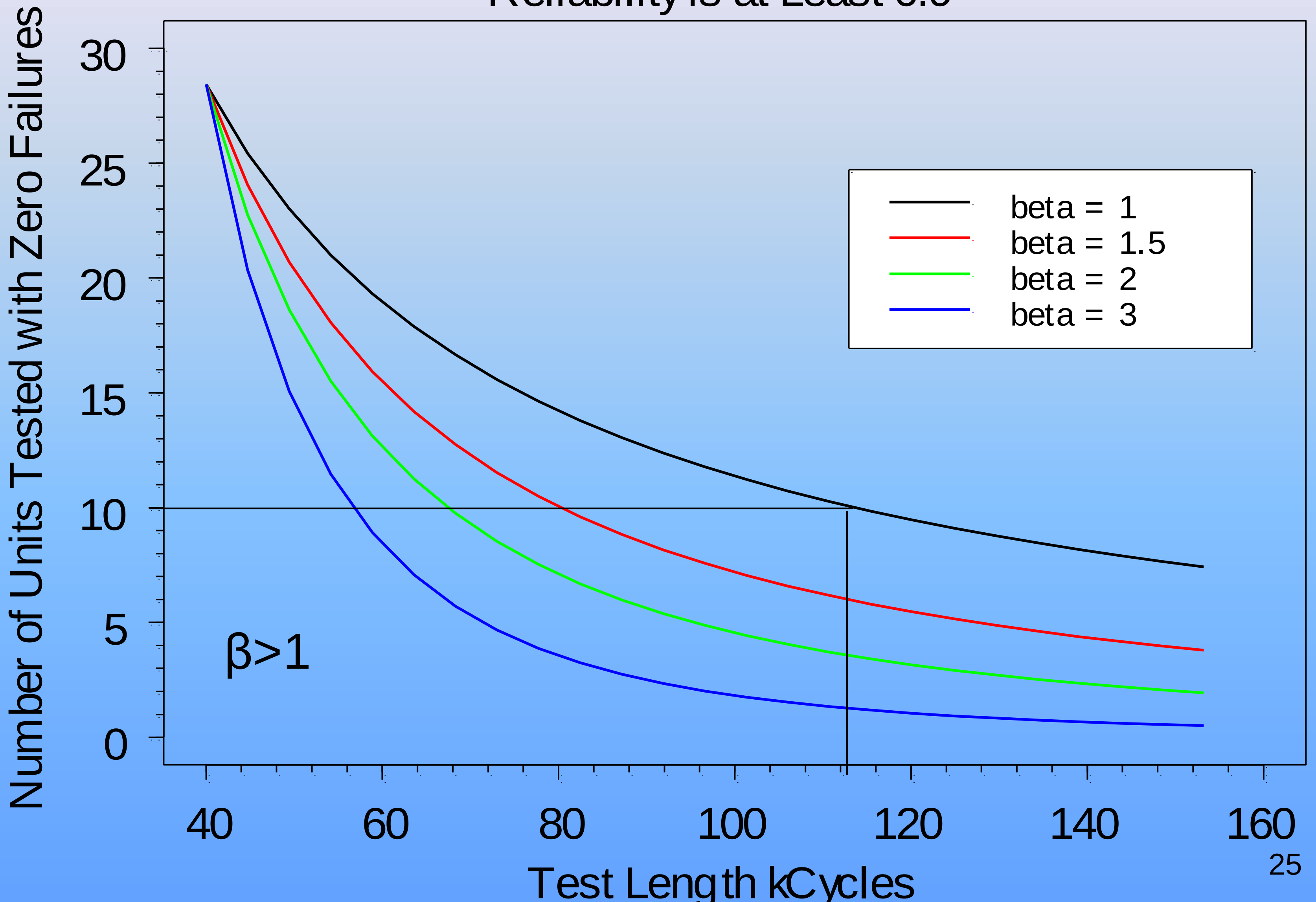
.

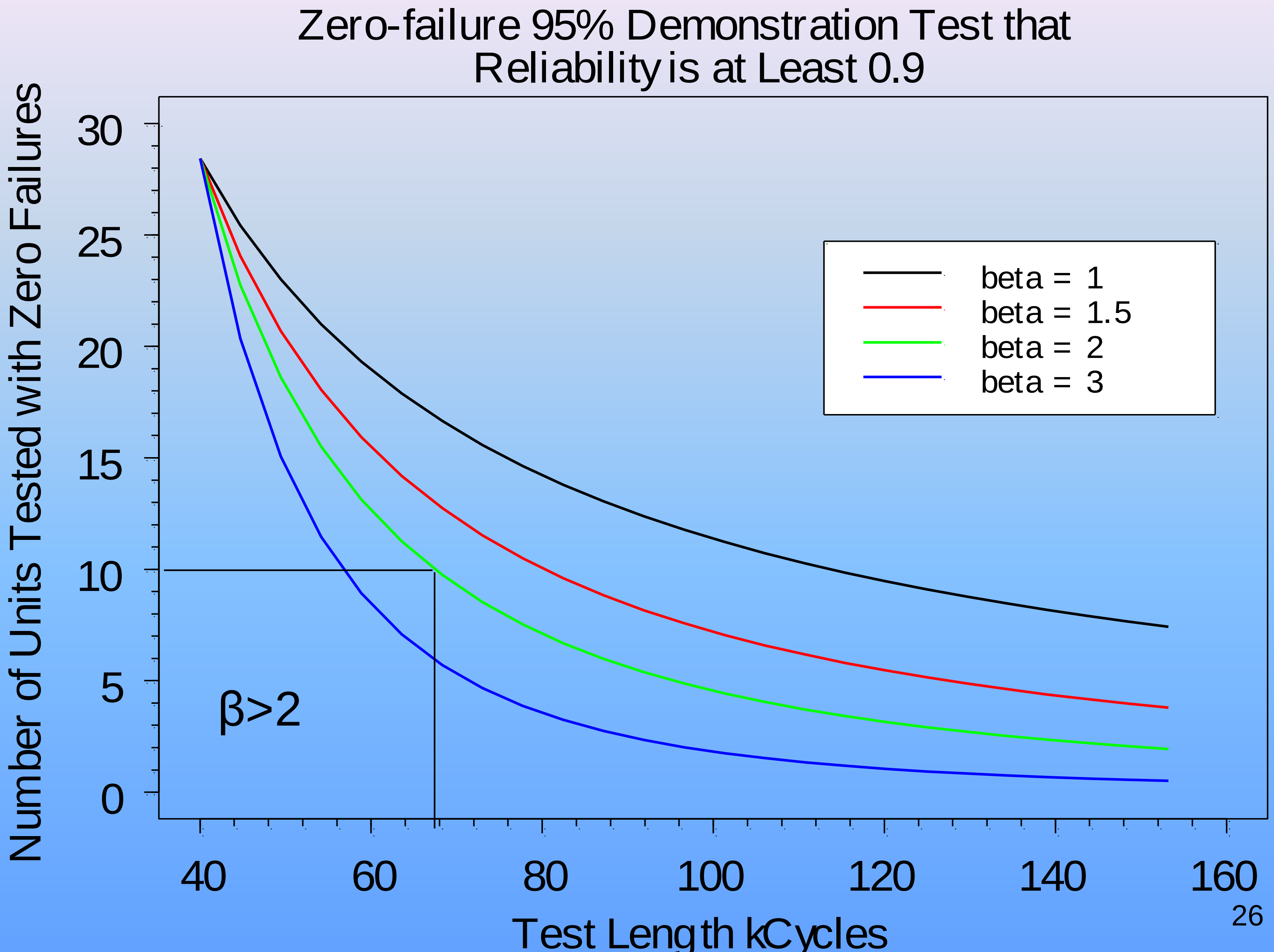
- $(1-\alpha)$ is the confidence level ($\alpha = 0.05$ for 95% confidence)
- R is the reliability to be demonstrated.
- β is the Weibull shape parameter
- Need to run test k times the length of time to be verified

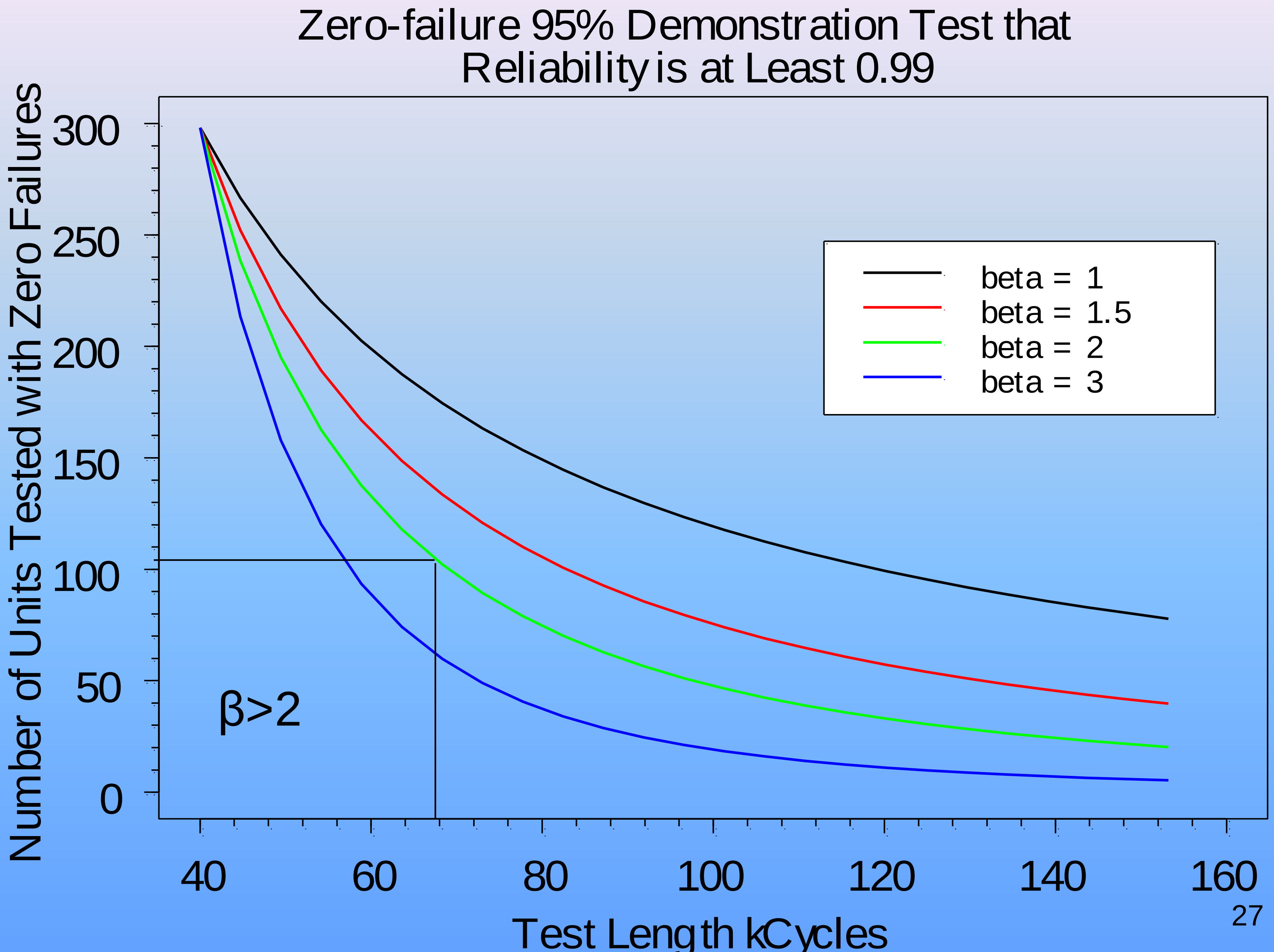
Metal Spring Reliability Demonstration

- Need to demonstrate, with 95% confidence, that a new lower-cost metal spring has 0.90 reliability at 40 thousand cycles of use
- A minimum sample size test is desired.
- Results needed quickly

Zero-failure 95% Demonstration Test that Reliability is at Least 0.9

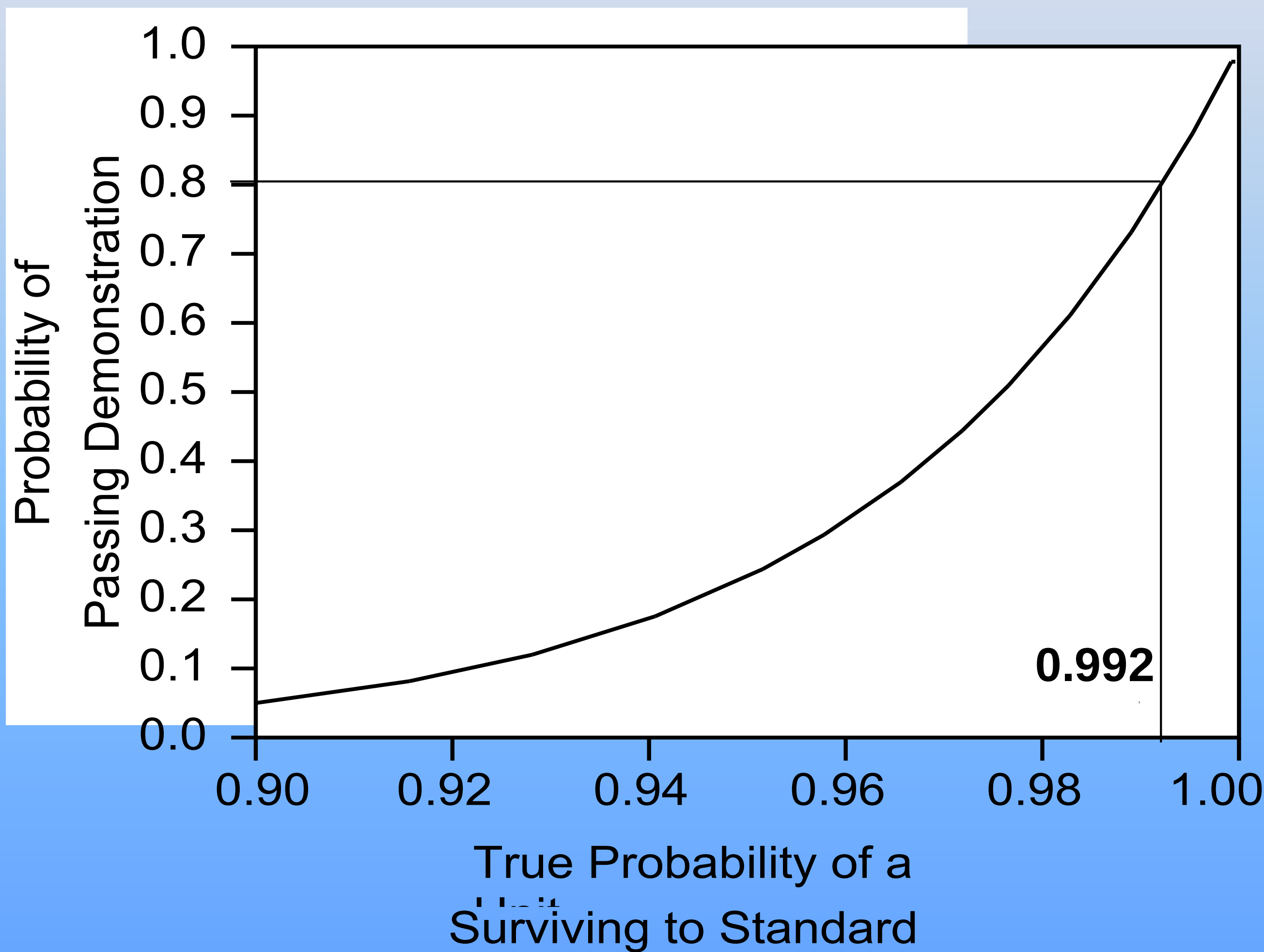



Zero-failure 95% Demonstration Test that
Reliability is at Least 0.9
Number of Units Tested with Zero Failures
30
25
20
15
10
5
0
40
60
80
100
120
140
160
Test Length kCycles
beta = 1
beta = 1.5
beta = 2
beta = 3
β>2



Zero-failure 95% Demonstration Test that
Reliability is at Least 0.99
Number of Units Tested with Zero Failures
300
250
200
150
100
50
0
40
60
80
100
120
140
160
Test Length kCycles
beta = 1
beta = 1.5
beta = 2
beta = 3
β>2

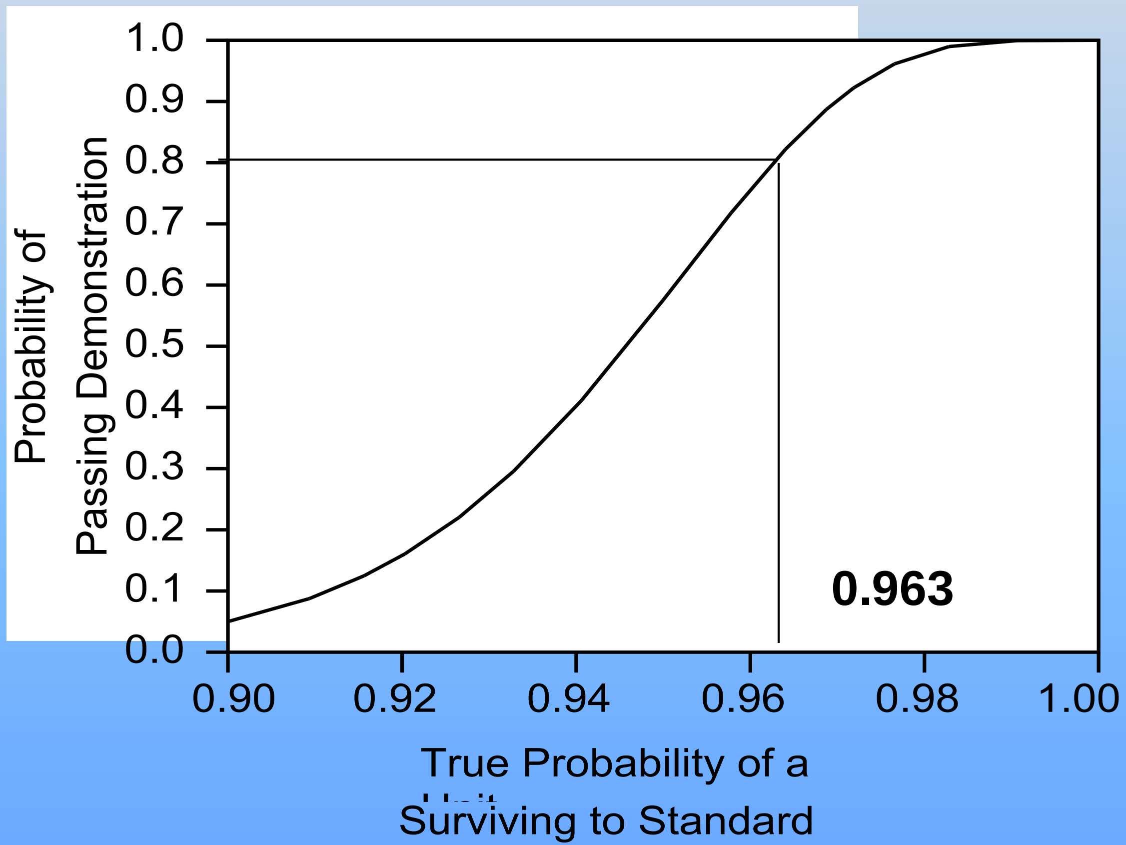
Probability of Successful Demonstration
0-failure Test to Demonstrate
0.90 Reliability with 95% Confidence



Allowing More Failures

- Will improve the probability of successful demonstration
- Will require a larger sample size <u>or</u> a longer test
- For the metal spring demonstration, allowing 5 failures out of 10 tested units will require 152 kCycles, but will have almost 0.80 probability of being successful if the actual reliability is 0.963

Probability of Successful Demonstration 5-failure Test to Demonstrate 0.90 Reliability with 95% Confidence



Other Extensions of the Demonstration Testing Method

- Other distributions such as lognormal
- Can develop similar tests that require estimation of both Weibull parameters, but sample size requirements go up dramatically

Lessons Learned

- Demonstration tests may not require a large sample size
- Require assumed distribution shape parameter is known (e.g., assuming $\beta = 1$ is conservative if failure modes is known to be due to wearout)
- Minimum sample-size (0-failure) tests generally have a small probability of successful demonstration unless the true reliability is much better than that to be demonstrated

Multiple Failure Modes
Competing Causes of Failure

William Q. Meeker
Iowa State University

Multiple Failure Modes

- If information is available on causes of failure, it is possible to do separate analysis on each failure mode
- Failure from one failure mode causes censoring for the other failure modes
- Assumption of independence needed to estimate marginal distributions

When is Multiple Failure Mode Analysis Important?

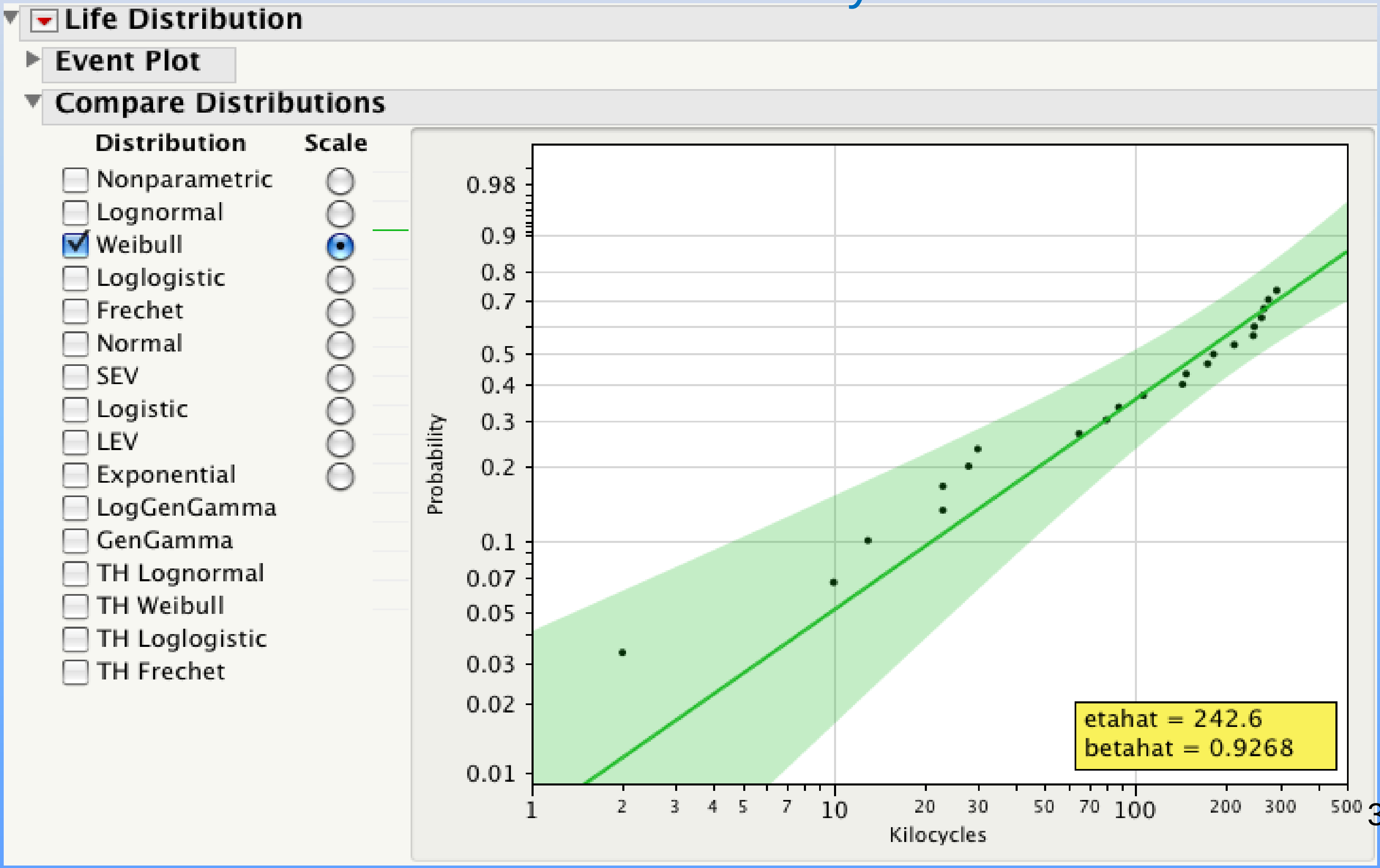
- Failure modes behave differently
- Warranty prediction and failure modes have different costs
- Predictions needed for the number of replacement parts to stock
- Engineers need to improve reliability

Device-G Field-Tracking Data

- Data from Meeker and Escobar (1998)
- Design life of 300 thousand cycles
- Units were failing in the field more rapidly than had been expected
- Needs: information on how to improve reliability and an estimate of device MTTF
- Two failure modes: surge and wear

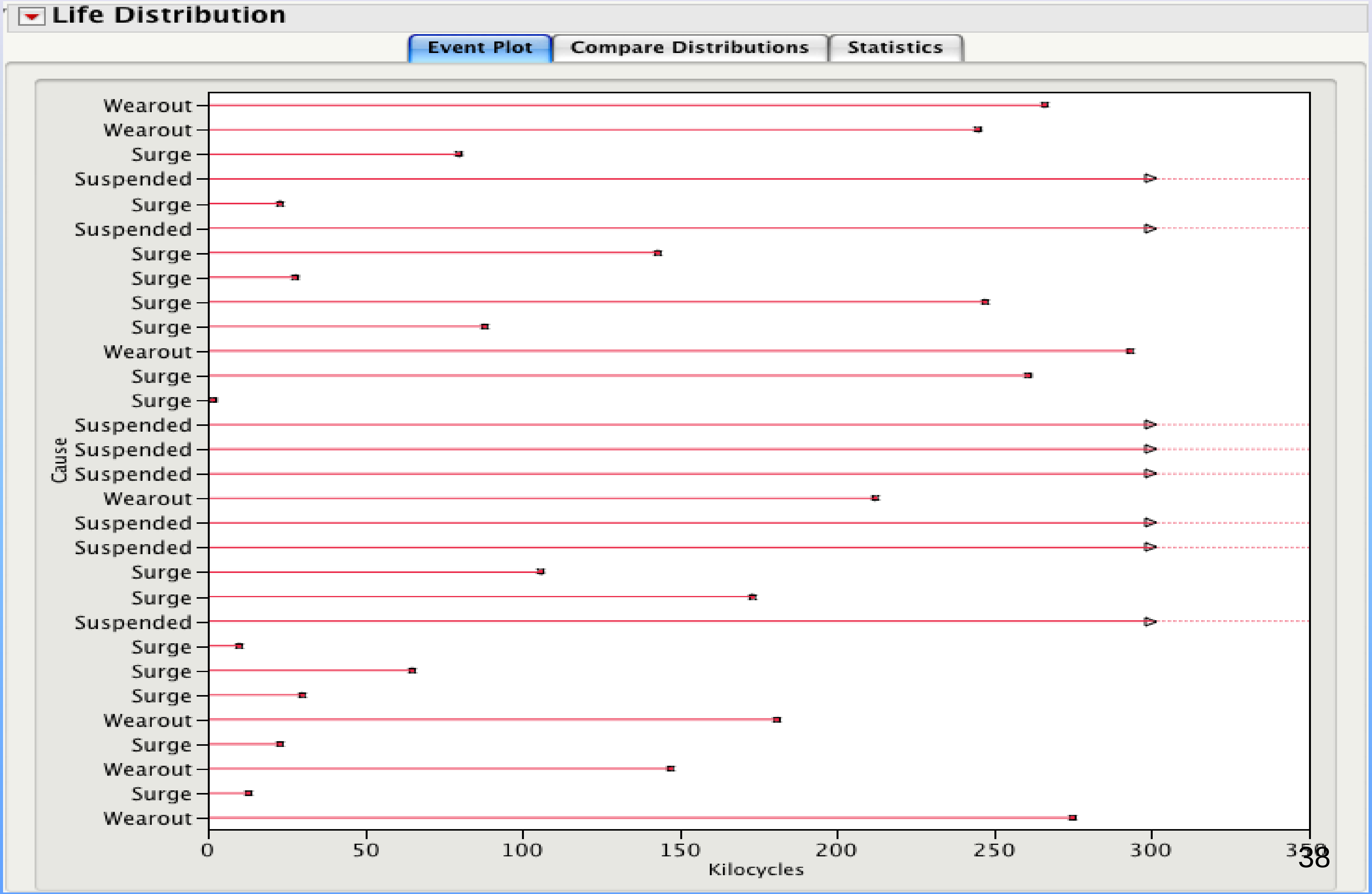
Device-G Field Data Weibull Probability Plot with Weibull ML Estimate and Pointwise 95% Confidence Intervals

Weibull Probability Plot



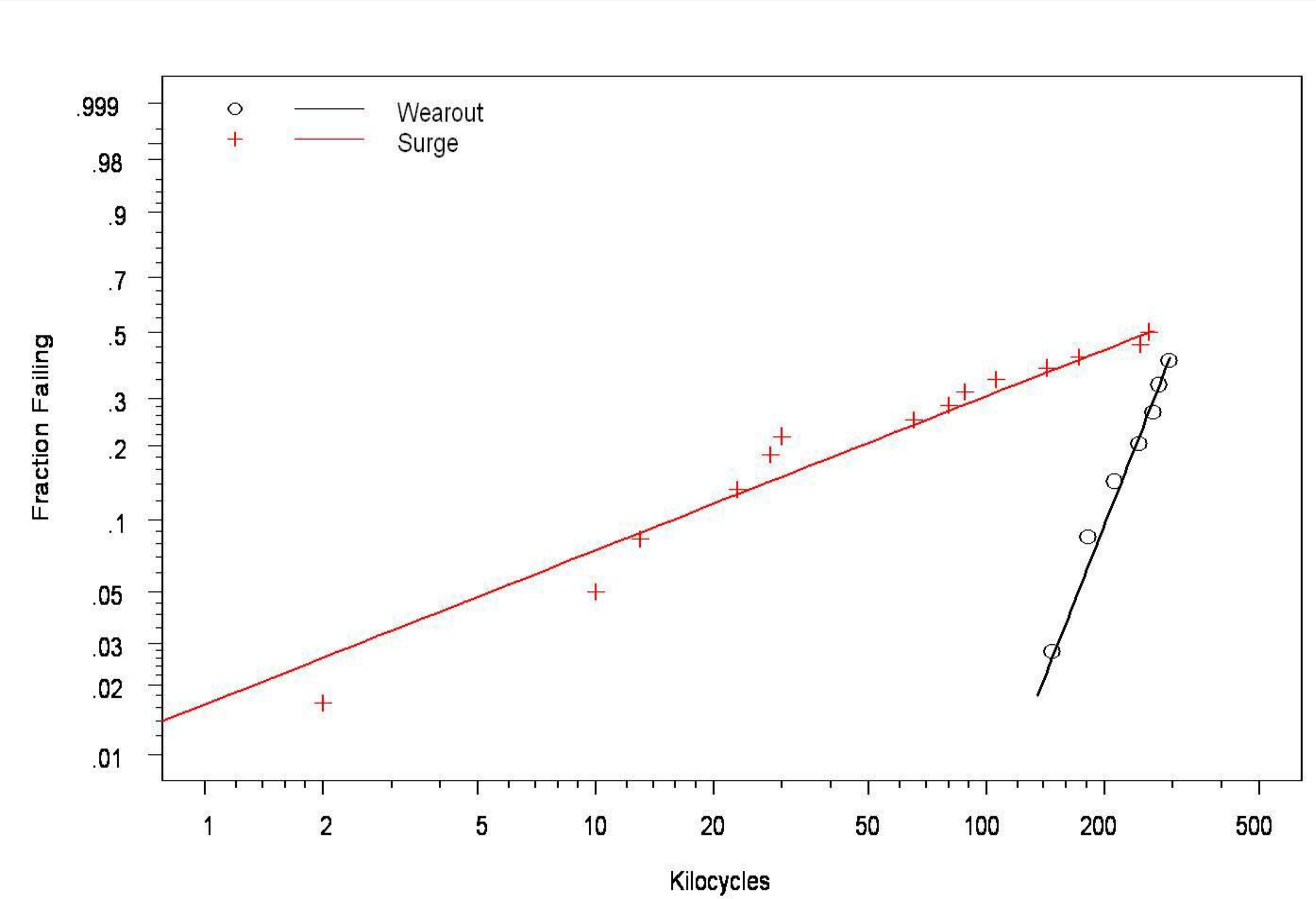
Device-G Field Data

Event Plot



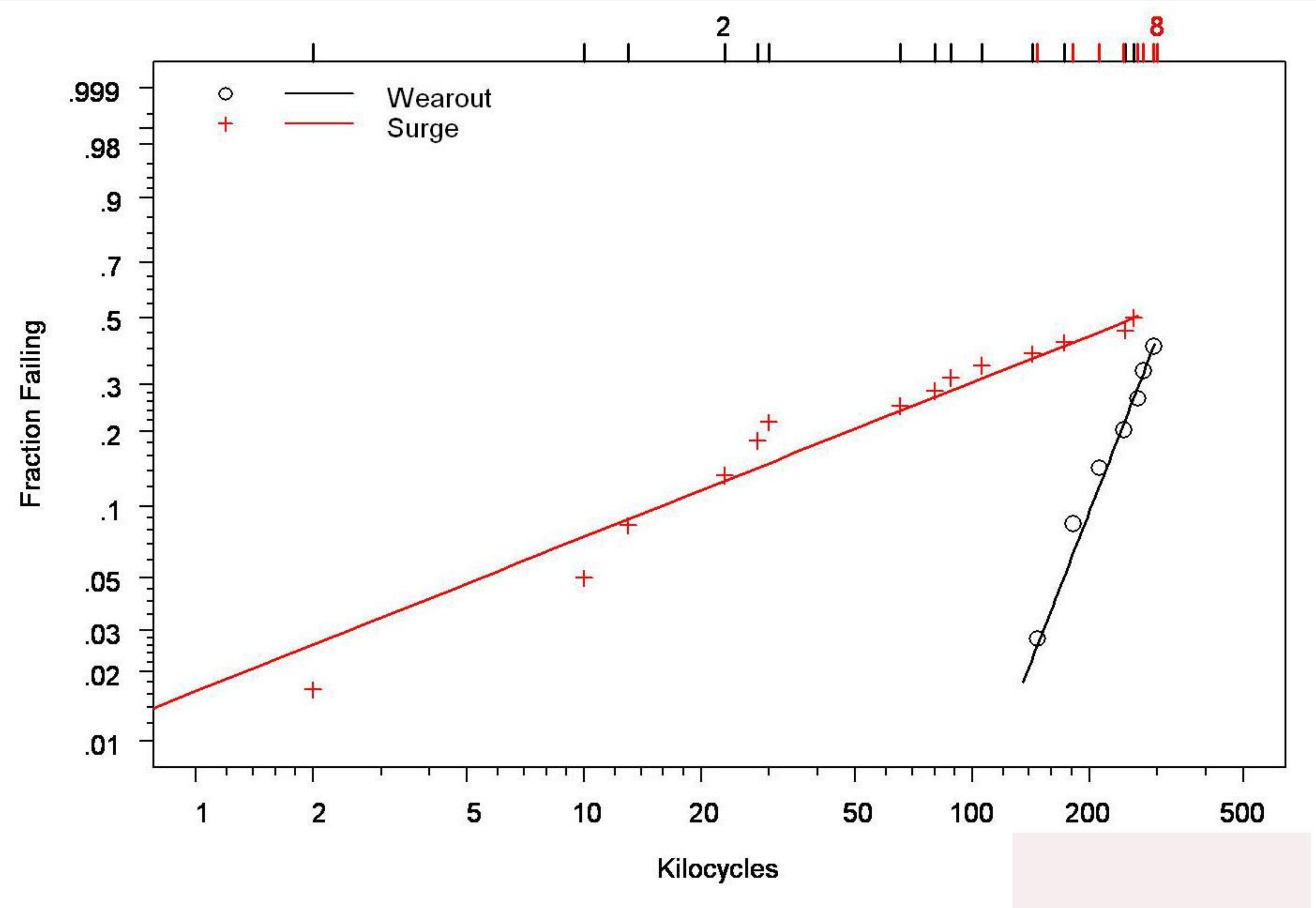
Individual Device-G Field Data Failure Mode Weibull MLEs

Weibull Probability Plot



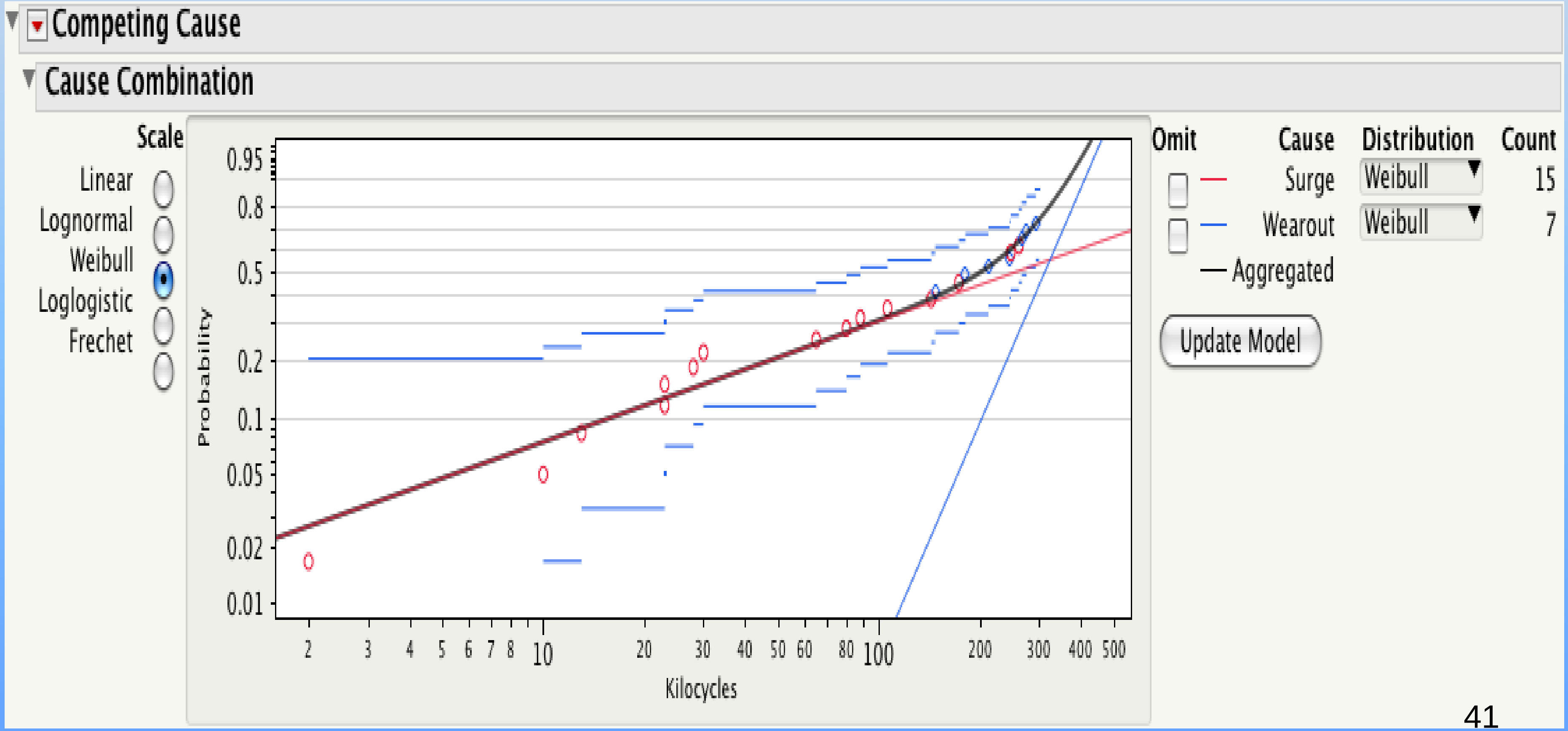
Individual Device-G Field Data Failure Mode Weibull MLEs

Weibull Probability Plot

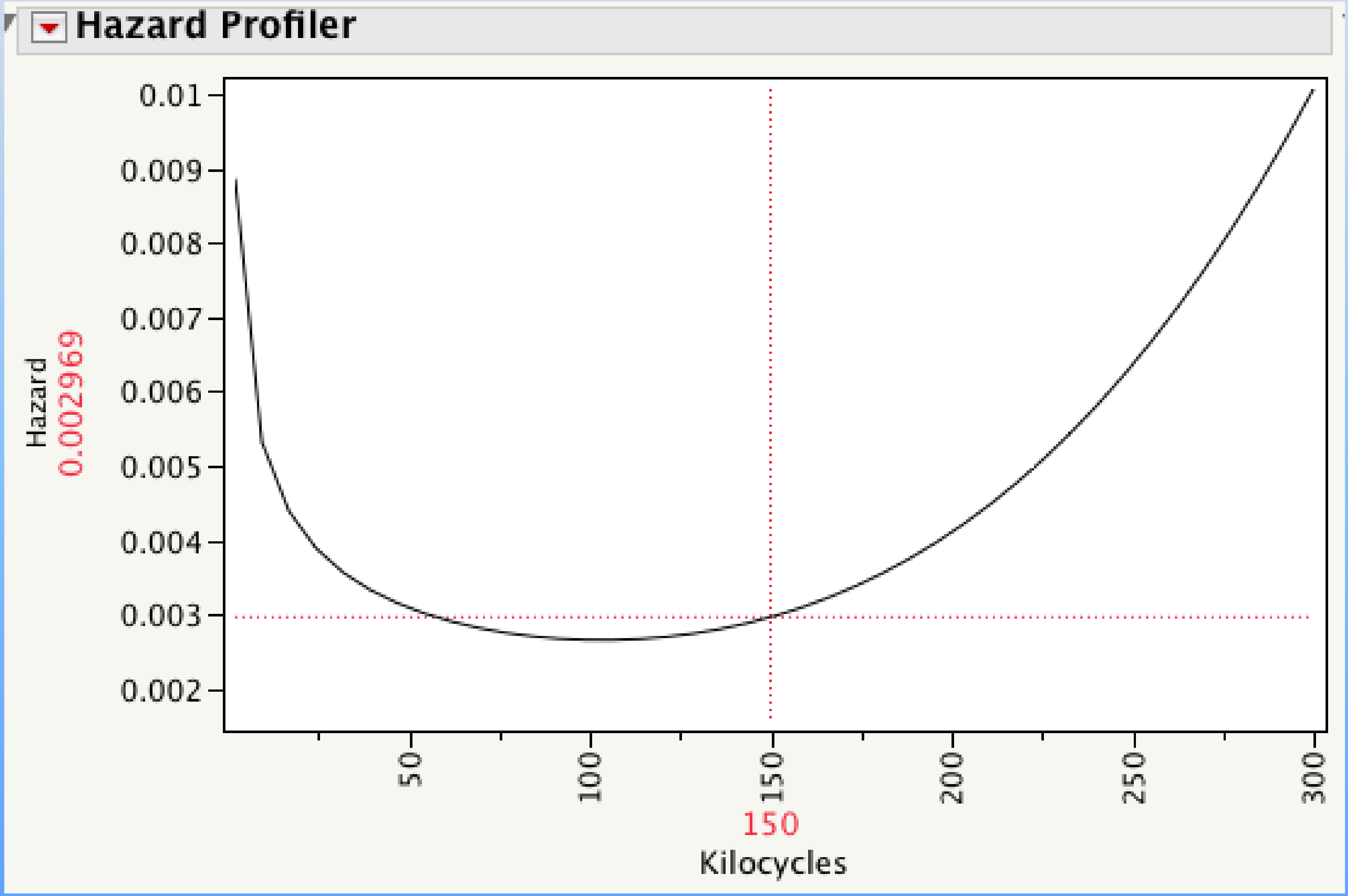


Series System Combined Failure Mode ML Estimates and Pointwise Approximate 95% Confidence Intervals Device-G Field Data

Weibull Probability Plot



Estimate of the Device-G Hazard Function

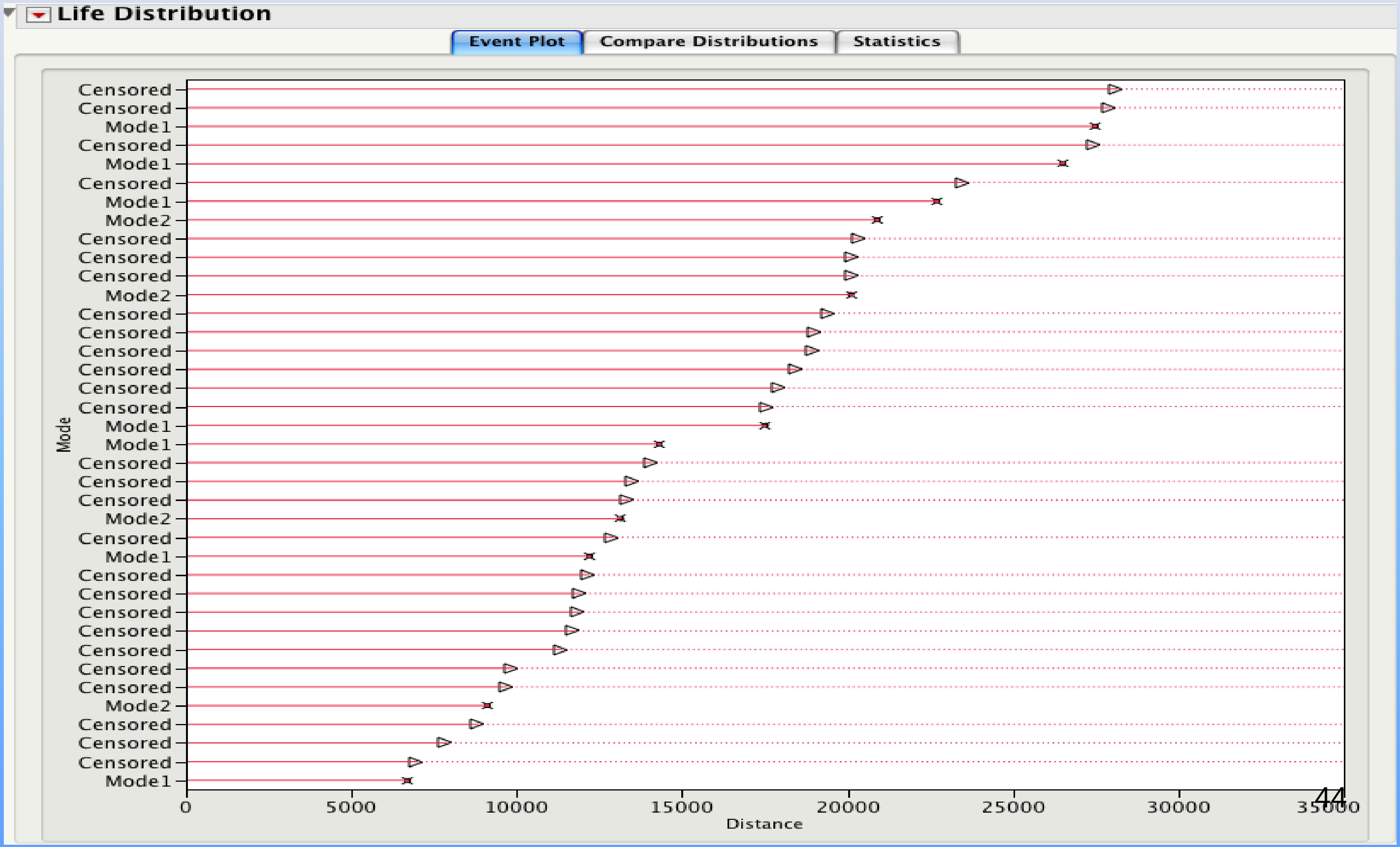


Shock Absorber Field Data

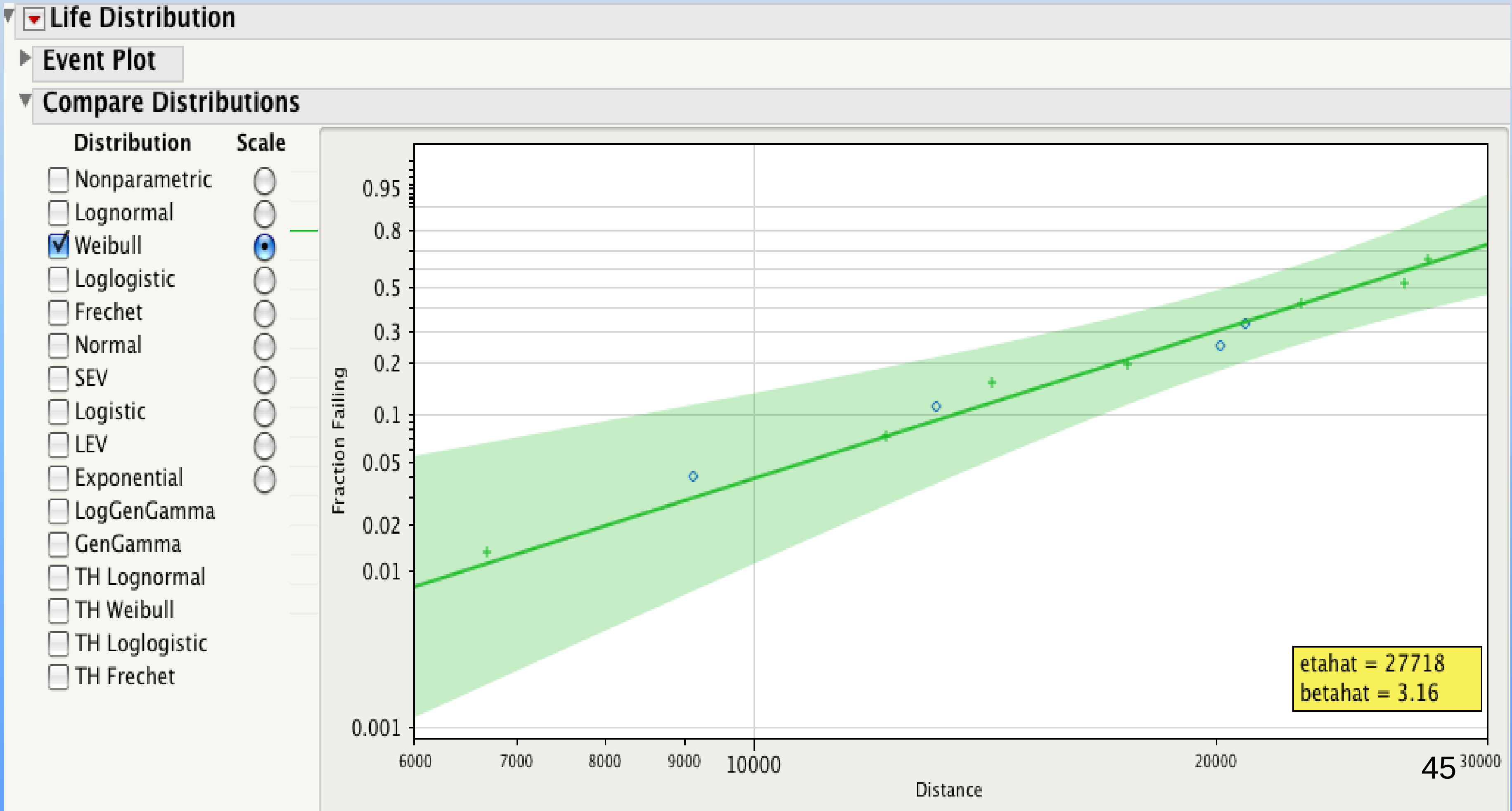
- Data from O’Connor (1985)
- Two failure modes (identified as Mode 1 and Mode 2)
- Need to estimate the failure-time distribution for the shock absorbers

Shock Absorber Data (Both Failure Modes)

Event Plot

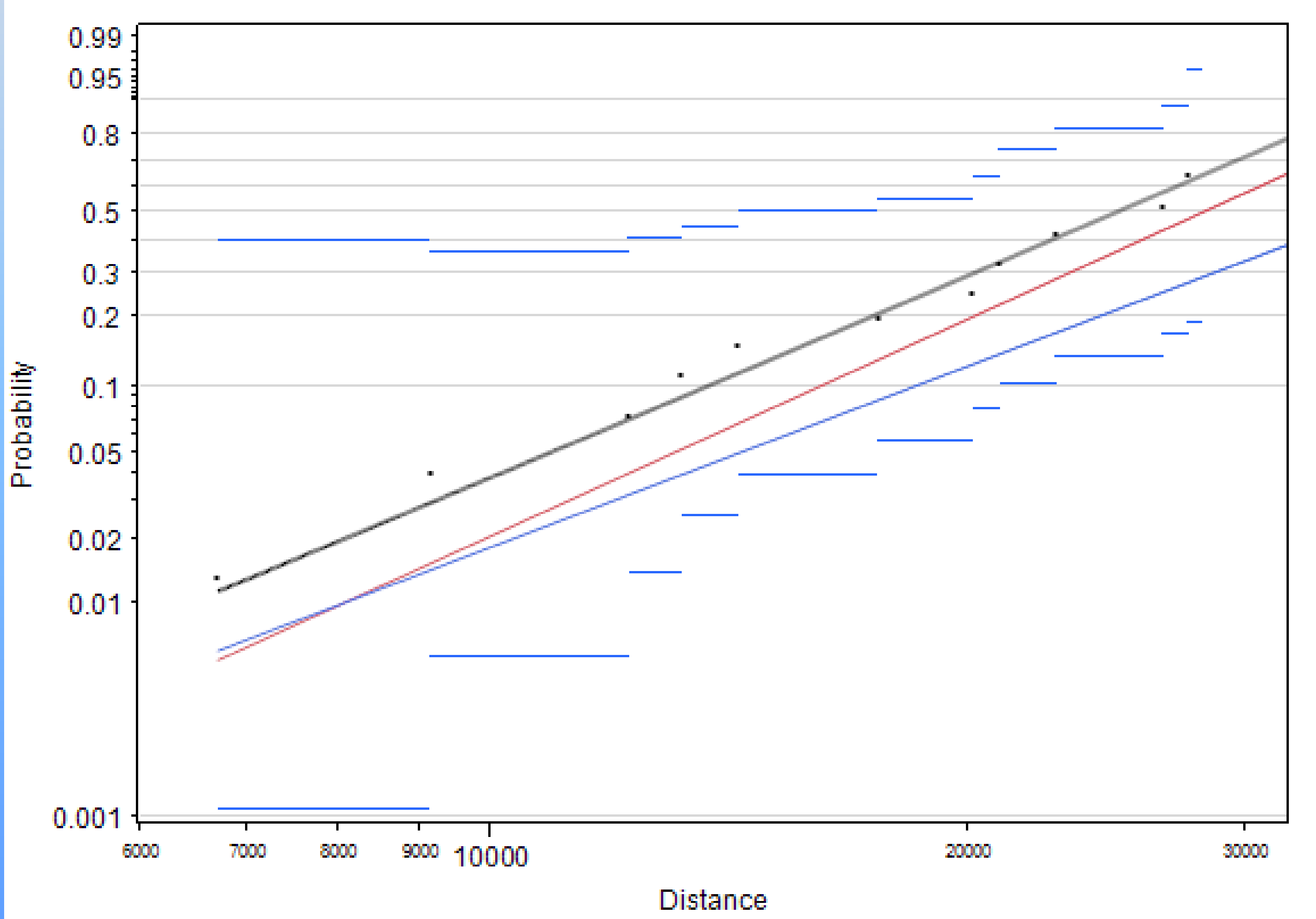


Shock Absorber Data Weibull Probability Plot with Weibull ML Estimate and Pointwise 95% Confidence Intervals

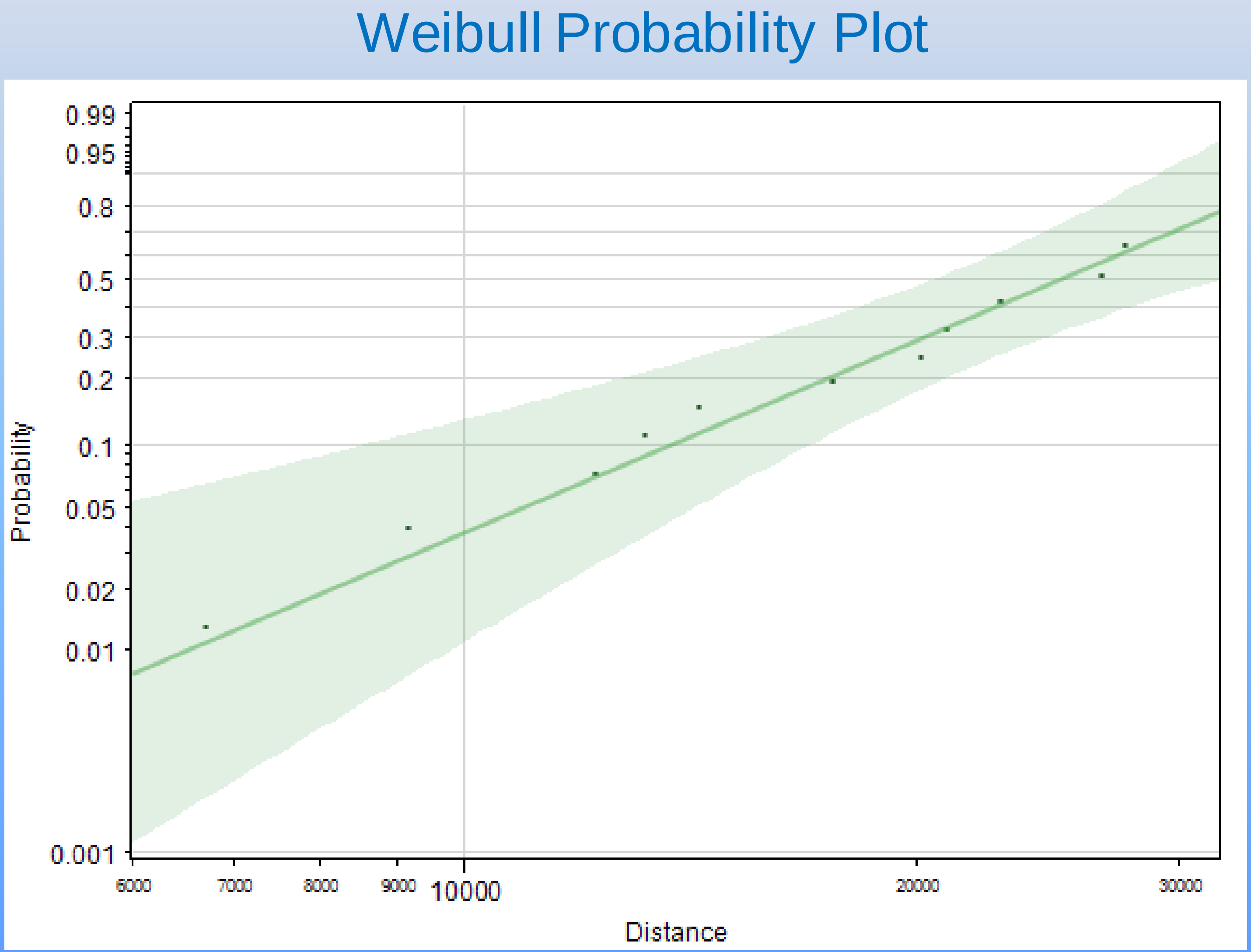


Shock Absorber Data (Failure Modes Analysis) Series System Combined Failure Mode ML Estimates and Pointwise Approximate 95% Confidence Intervals

Weibull Probability Plot



Shock Absorber Data (Ignore Failure Modes) Weibull Probability Plot with Weibull ML Estimates and Pointwise Approximate 95% Confidence Intervals



Lessons Learned

- If there is more than one failure mode, it is important to separate and analyze failure modes separately when
  - Shape parameters are very different
  - There is need to assess the impact of eliminating a failure mode

Accelerated Testing

- Test units at high levels of temperature, voltage, stress, or other “accelerating variable” to get reliability information quickly
- Use a physically-motivated model to extrapolate to use conditions

Motivation for Accelerated Testing

Today's manufacturers need to develop newer, higher technology products in record time while improving productivity, reliability, and quality.

- Rapid product development
- Changing technologies/new materials
- More complicated products with more components
- Higher customer expectations for better reliability

Levels of Accelerated Testing

- Materials
- Components
- Subsystem
- Full system

Usually testing at higher levels of integration will result in less acceleration.

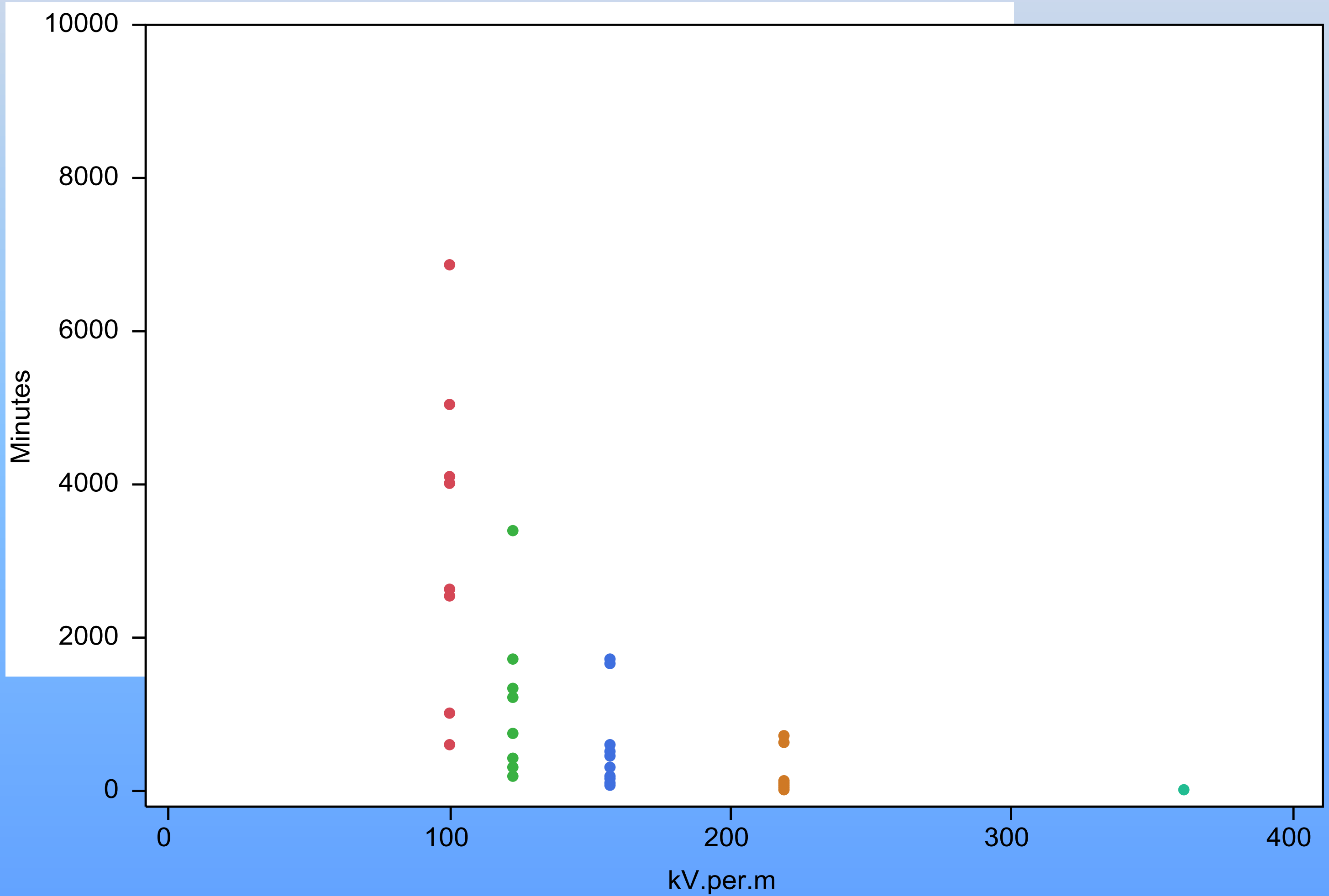
Most accelerated tests are run at lower levels of a product.

Voltage-Accelerated Life Test of a Mylar-Polyurethane Laminated Direct Current High Voltage Insulating Structure

- Data from Kalkanis and Rosso (1989)
- Time to dielectric breakdown of units tested at 100.3, 122.4,157.1, 219.0, and 361.4 kV/mm
- Needed to evaluate the reliability of the insulating structure and to estimate the life distribution at system design voltages (e.g. 50 kV/mm)

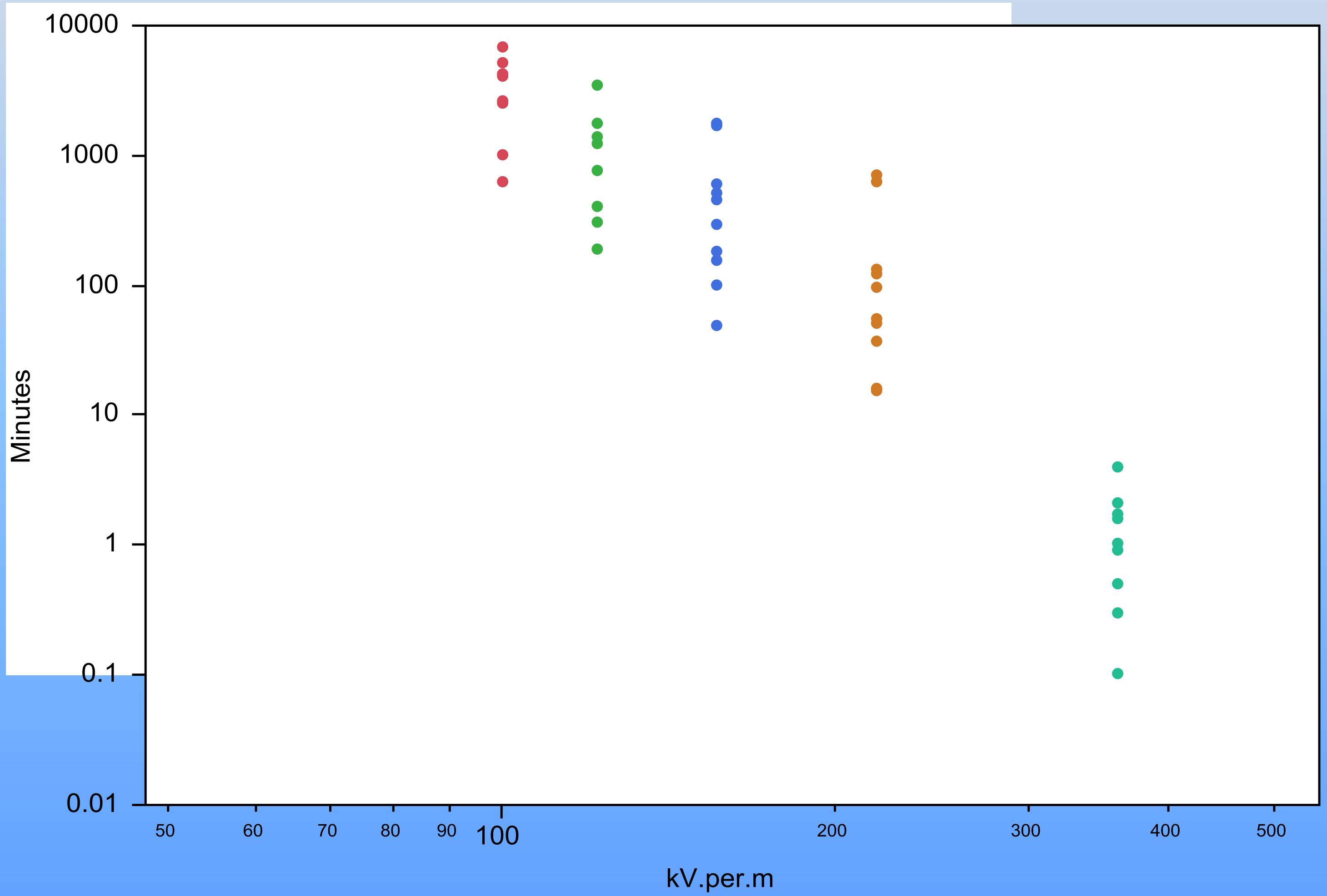
Mylar-Polyurethane Laminated Direct Current High Voltage Insulating Structure

Cross Plot on Linear-Linear Axes



Mylar-Polyurethane Laminated Direct Current High Voltage Insulating Structure

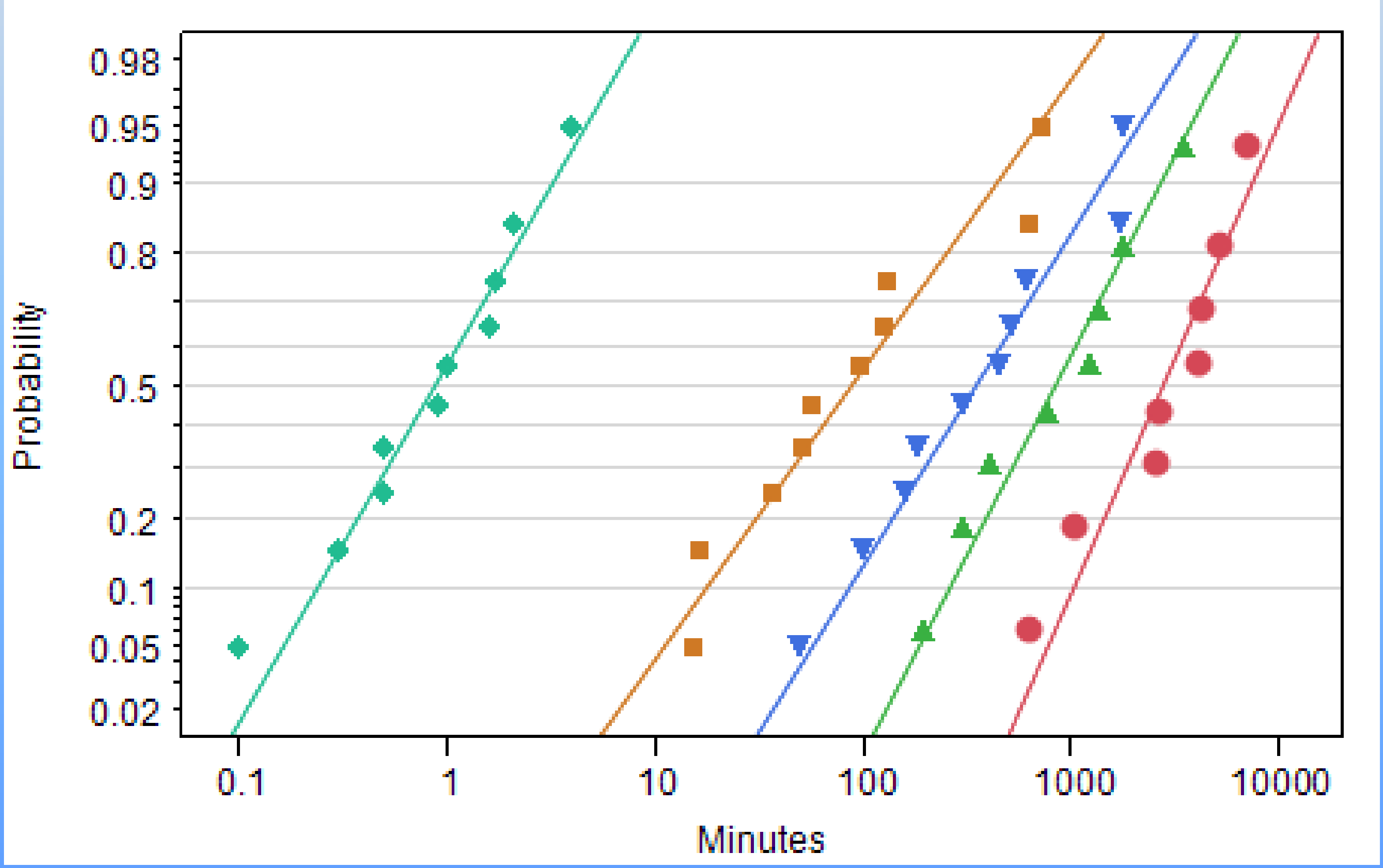
Cross Plot on Log-Log Axes



Mylar Polyurethane Insulating Structure

Data Analysis at Individual Conditions

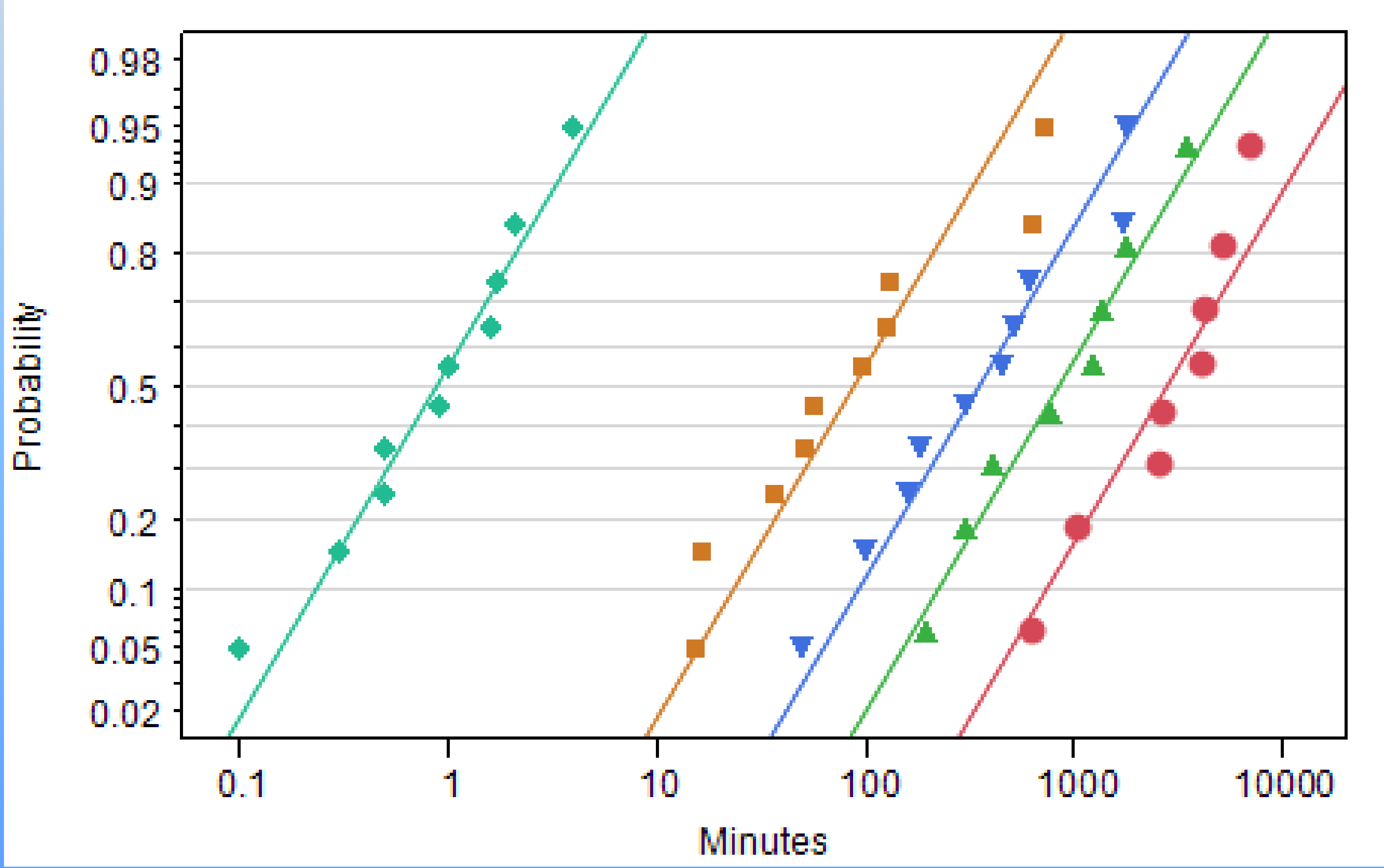
With Individual Lognormal Distribution ML Estimates
Lognormal Probability Plot



Mylar Polyurethane Insulating Structure Data

Constant Slope (Shape Parameter) Constraint

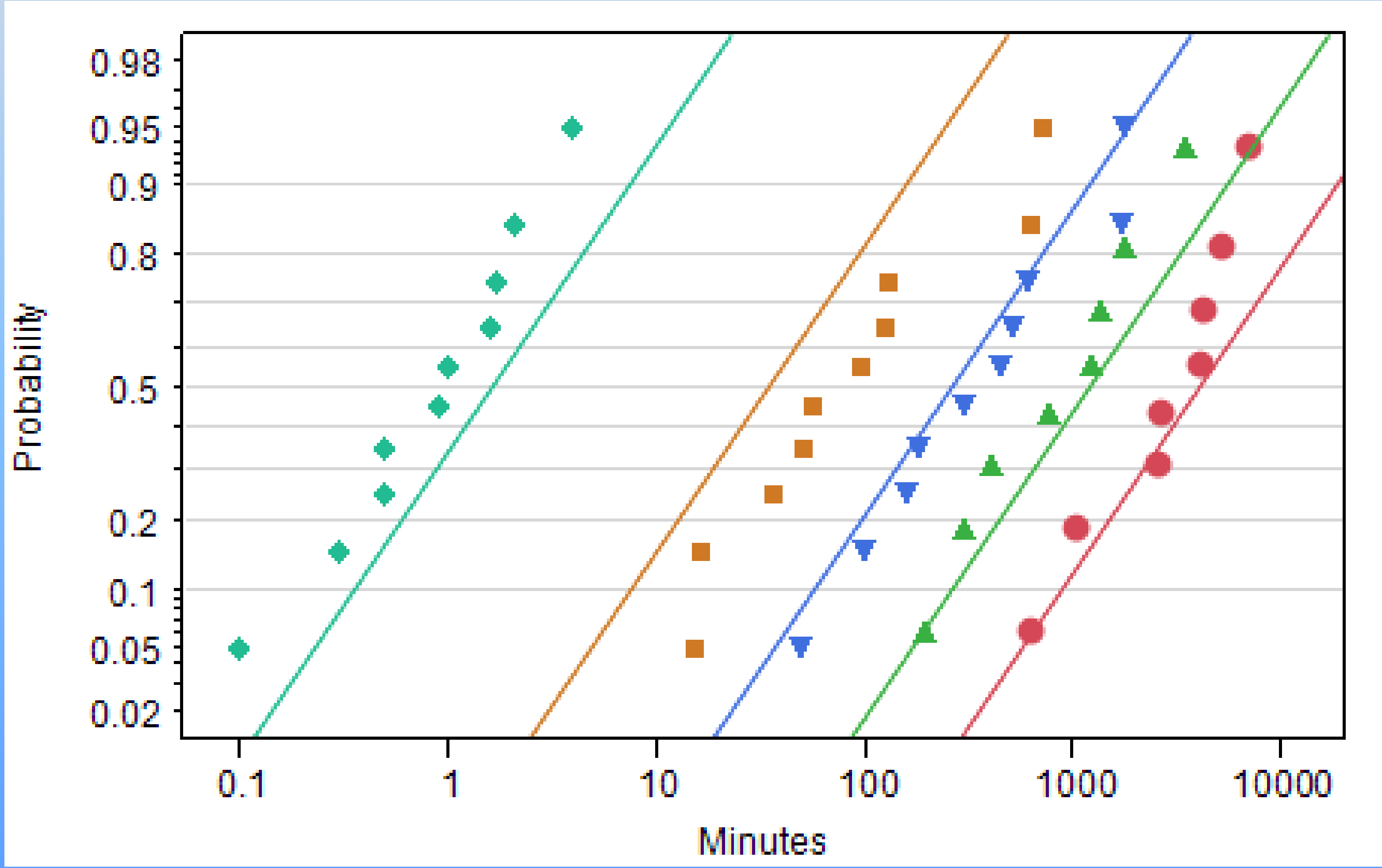
Lognormal Probability Plot



Mylar Polyurethane Insulating Structure Data

Inverse Power Regression Model - All Data

Lognormal Probability Plot



The Inverse Power Law/Lognormal Model for Insulation Lifetimes

- $\text{Life} = CV^{\beta_1}$
- The probability of failure as a function of time is

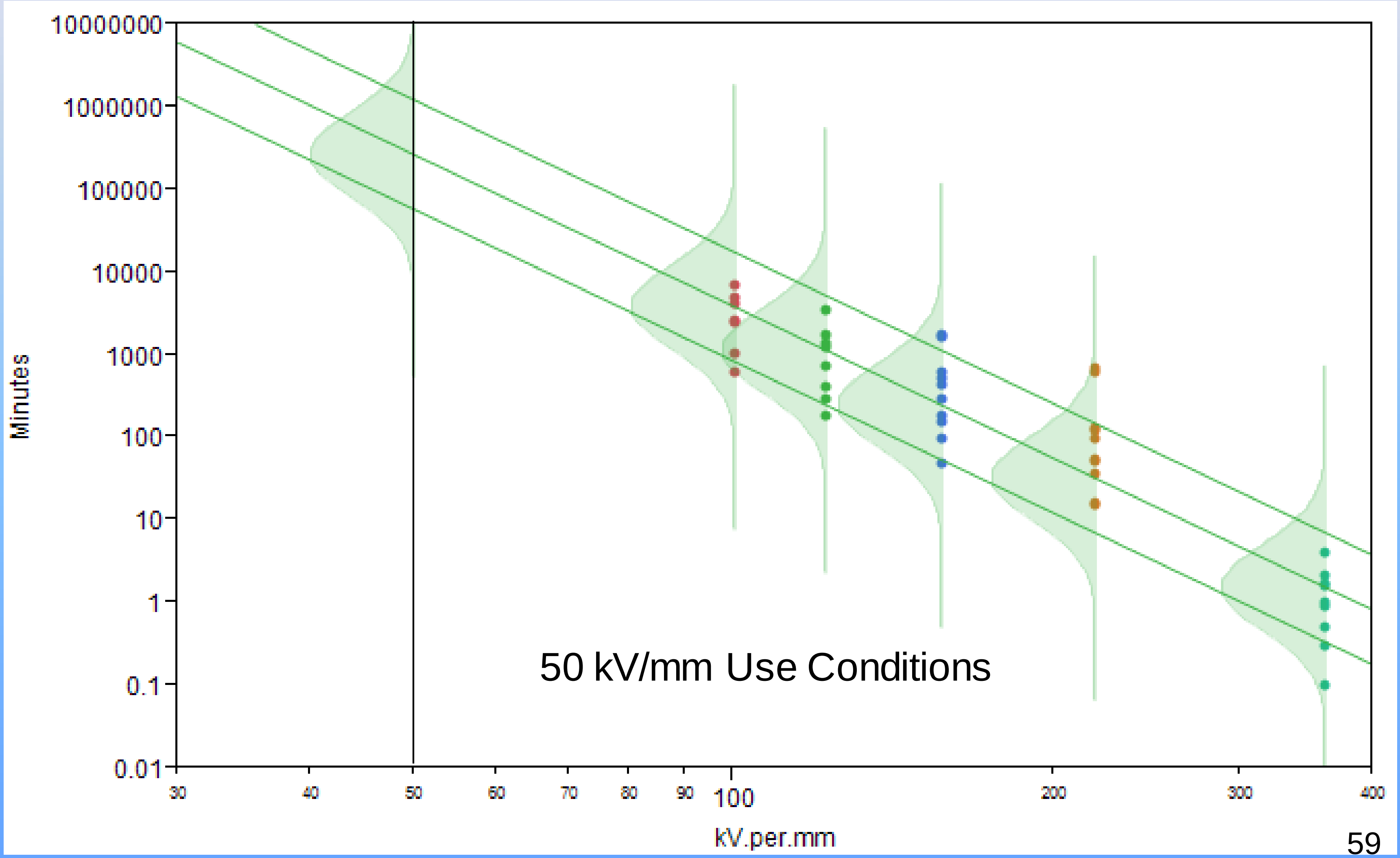
$$\Pr[T(\text{temp}) \le t] = \Phi_{\text{NOR}}\left[\frac{\log(\text{t})\text{-}\mu(x)}{\sigma}\right]$$

$$\mu(x) = \beta_0 + \beta_1 x$$

- x = log(Voltage Stress)
- β_1 is negative because life is shorter at higher levels of voltage stress
- σ is assumed not to depend on voltage stress
- Similar relationships used for pressure and cycling rate

Mylar Polyurethane Insulating Structure Data

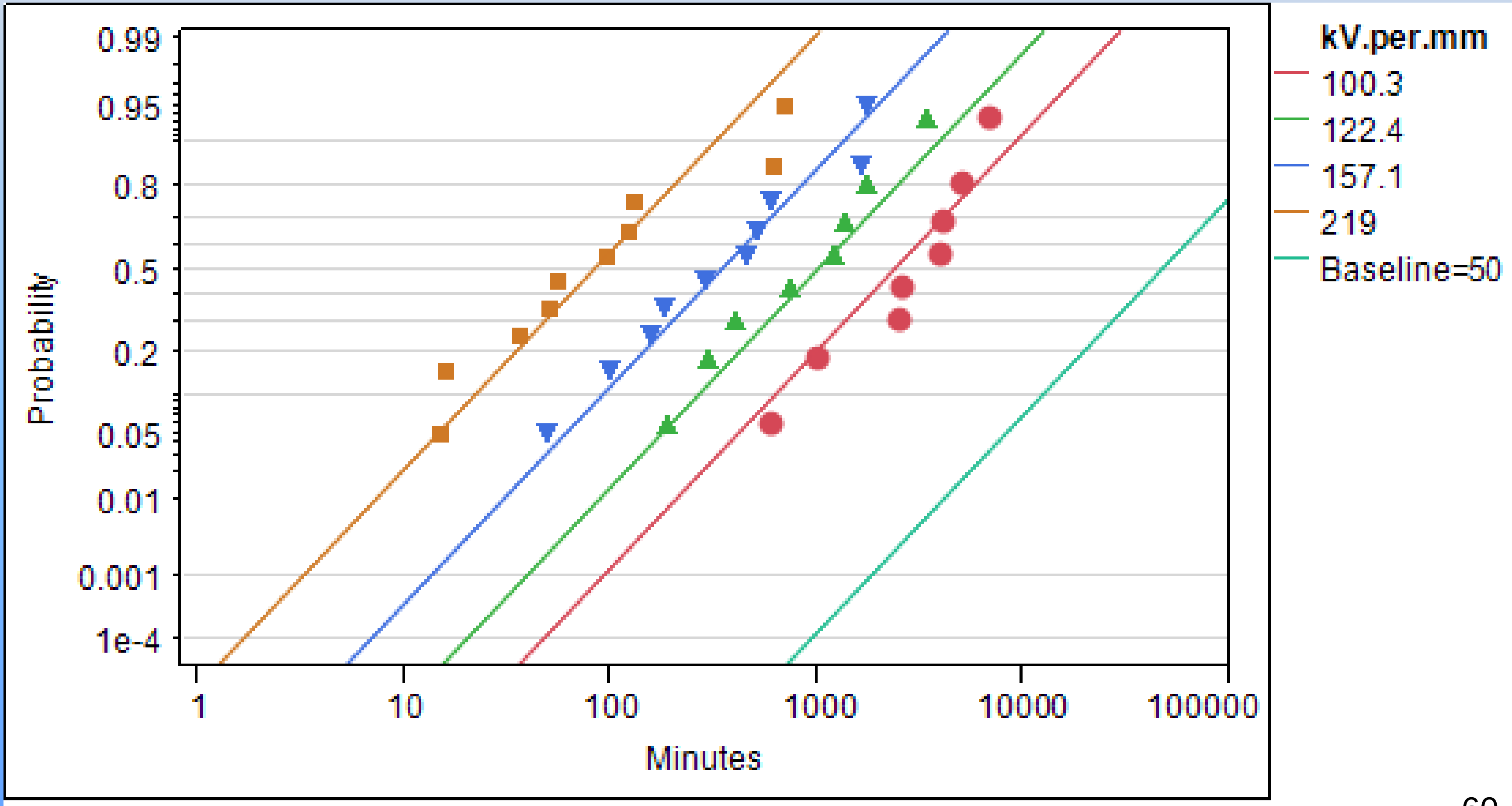
Inverse Power Regression Model - All Data



Mylar Polyurethane Insulating Structure Data

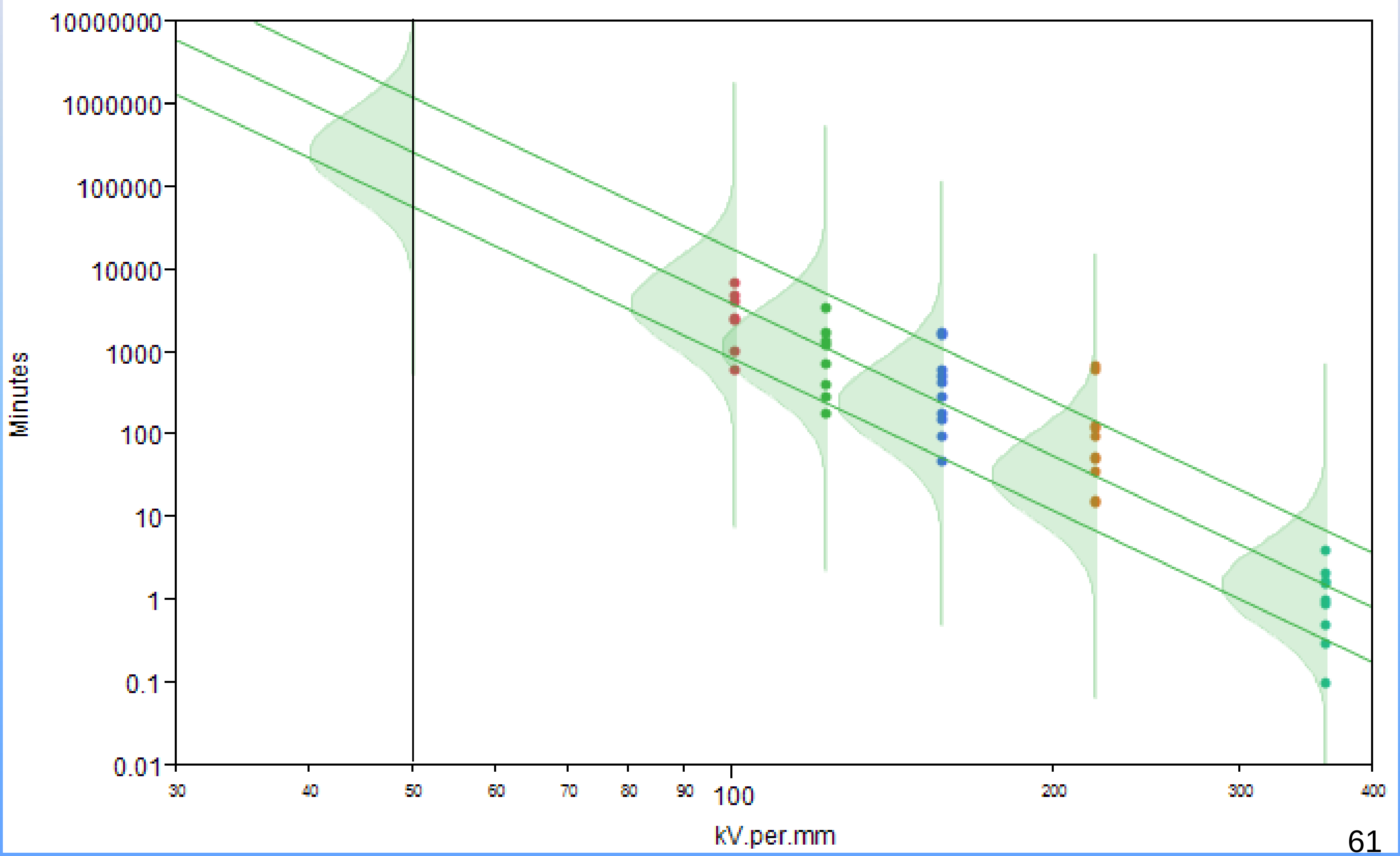
Inverse Power Regression Model - Good Data

Lognormal Probability Plot



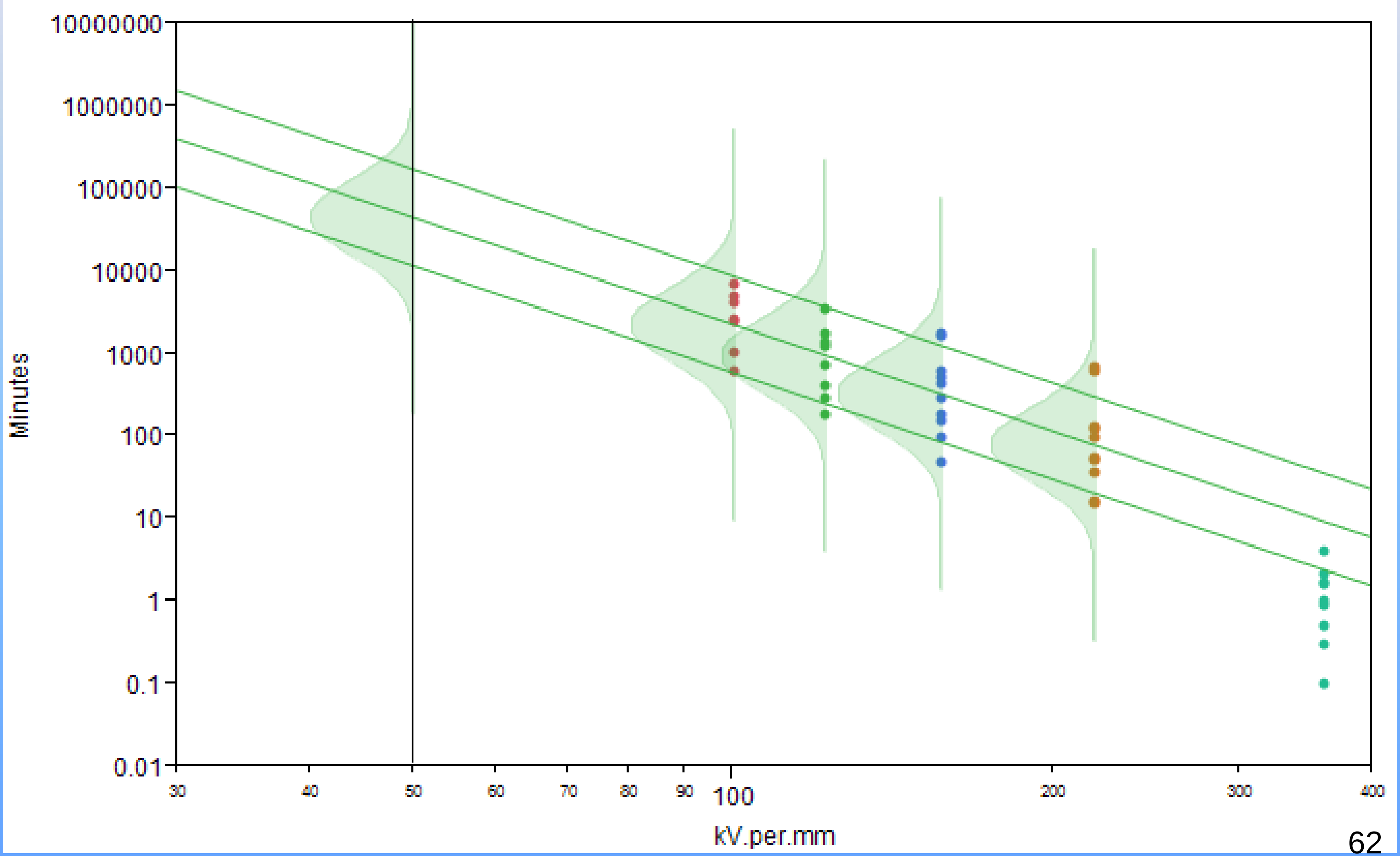
Mylar Polyurethane Insulating Structure Data

Inverse Power Regression Model - All Data



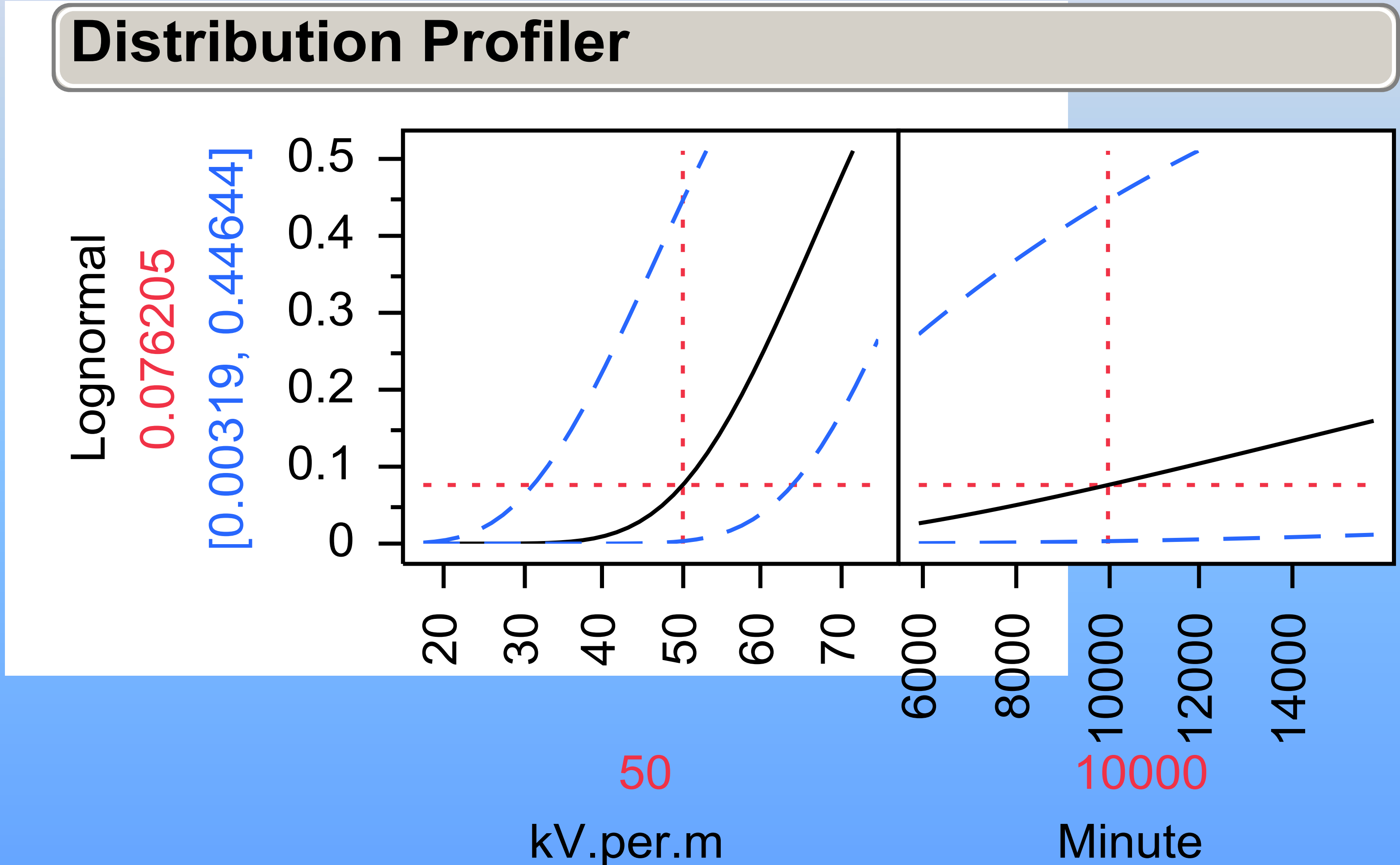
Mylar Polyurethane Insulating Structure Data

Inverse Power Regression Model - Good Data



Mylar Polyurethane Insulating Structure Data

Inverse Power Regression Model - Profiler



Lessons Learned

- Transformation of data can simplify modeling
- The inverse power relationship implies that log life is linear in log Voltage Stress - useful for modeling dielectric life
- Testing at a voltage stress that is too high can cause new failure modes
- New failure modes at the higher levels of stress, if unrecognized, leads to incorrectly optimistic conclusions
- Structure on a data plot can hide important information

Degradation Analysis

Resistor Accelerated Test

William Q. Meeker
Iowa State University

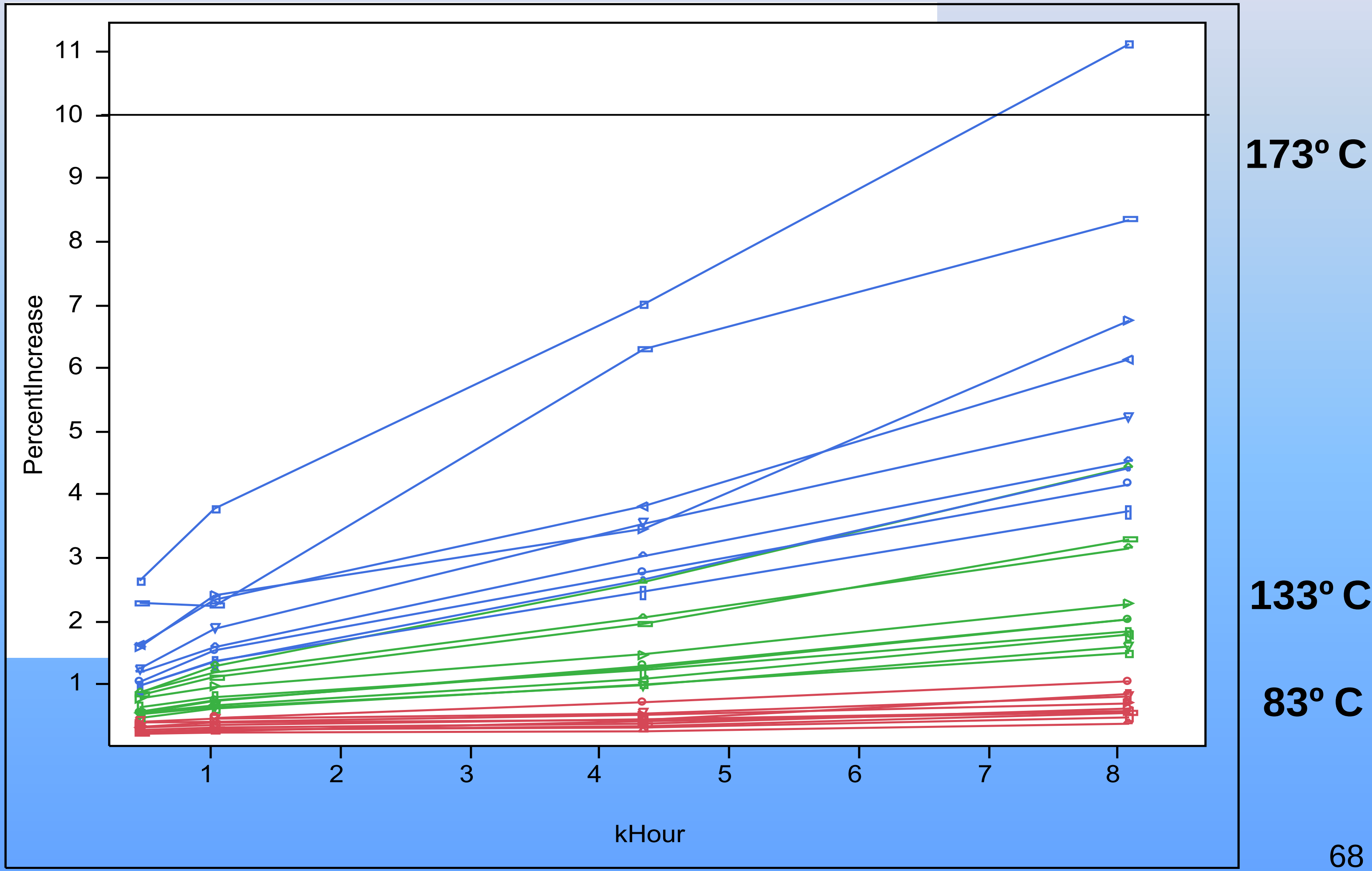
Repeated Measures Degradation Data

- Units measured multiple times during a study, perhaps at accelerated conditions
- Many applications
  - Reliability of electronic devices such as lasers, LEDs, and power amplifiers
  - Pharmaceutical stability testing
  - Physical and chemical deterioration of paints and coatings and other organic materials

Carbon-Film Resistor Accelerated Test

- Failure defined by a 10% increase in resistance
- Need to estimate the failure-time distribution at 50ºC
- Limited time for testing
- No significant degradation expected at 50ºC
- Accelerated repeated measures tests run at higher-than-usual levels of temperature

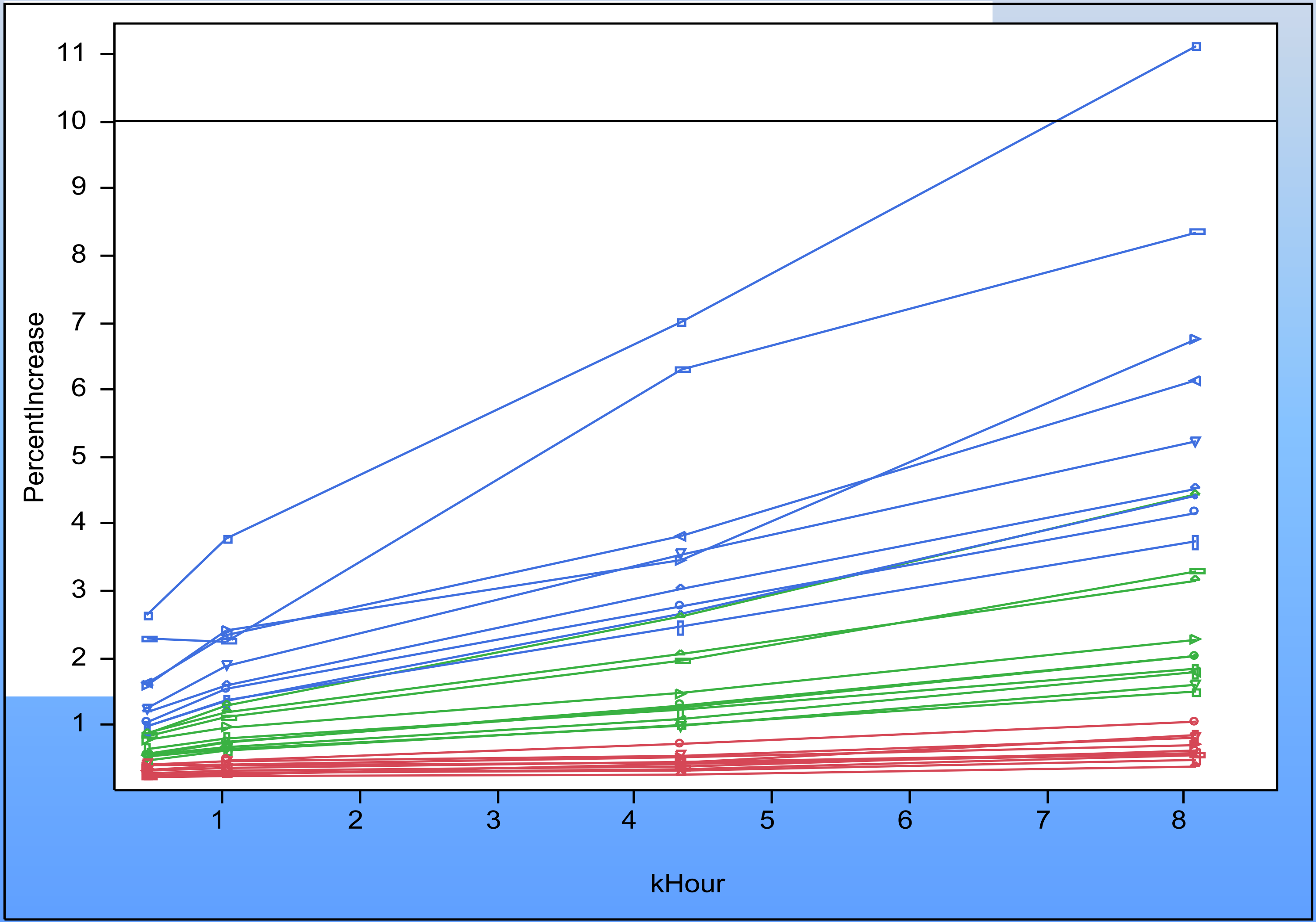
Carbon-Film Resistor Accelerated Test Data



Repeated Measures Degradation Models

- Mixed effects model allowing parameters to vary from one unit to another
- Stochastic process models, perhaps with mixed effects
- Simple linear regression for each sample path
- Transformation of the response and/or time may be needed to linearize the sample paths

Carbon-Film Resistor Accelerated Test Data



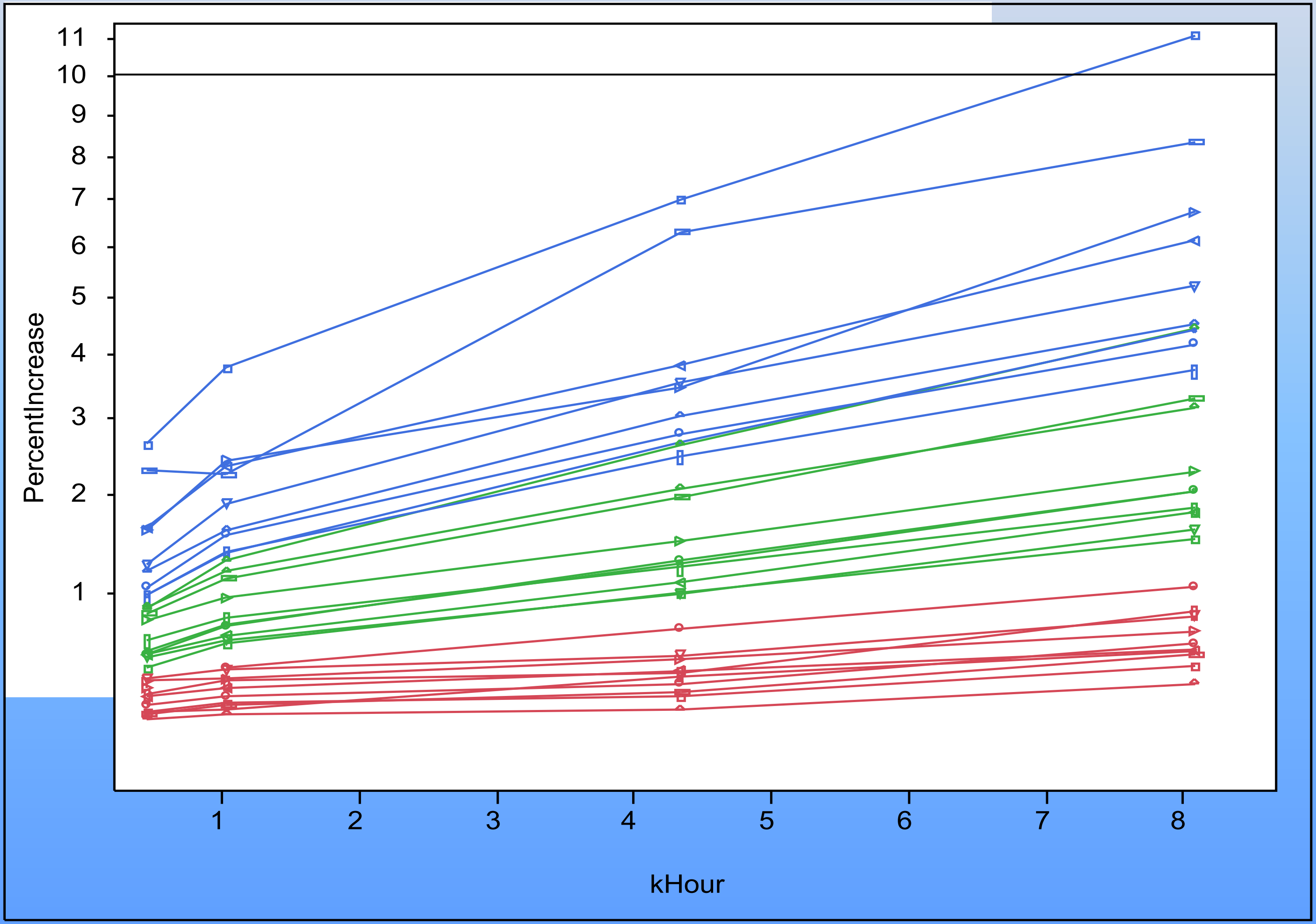
173º C

133º C

83º C

Carbon-Film Resistor Accelerated Test Data

square root-linear plot



173º C

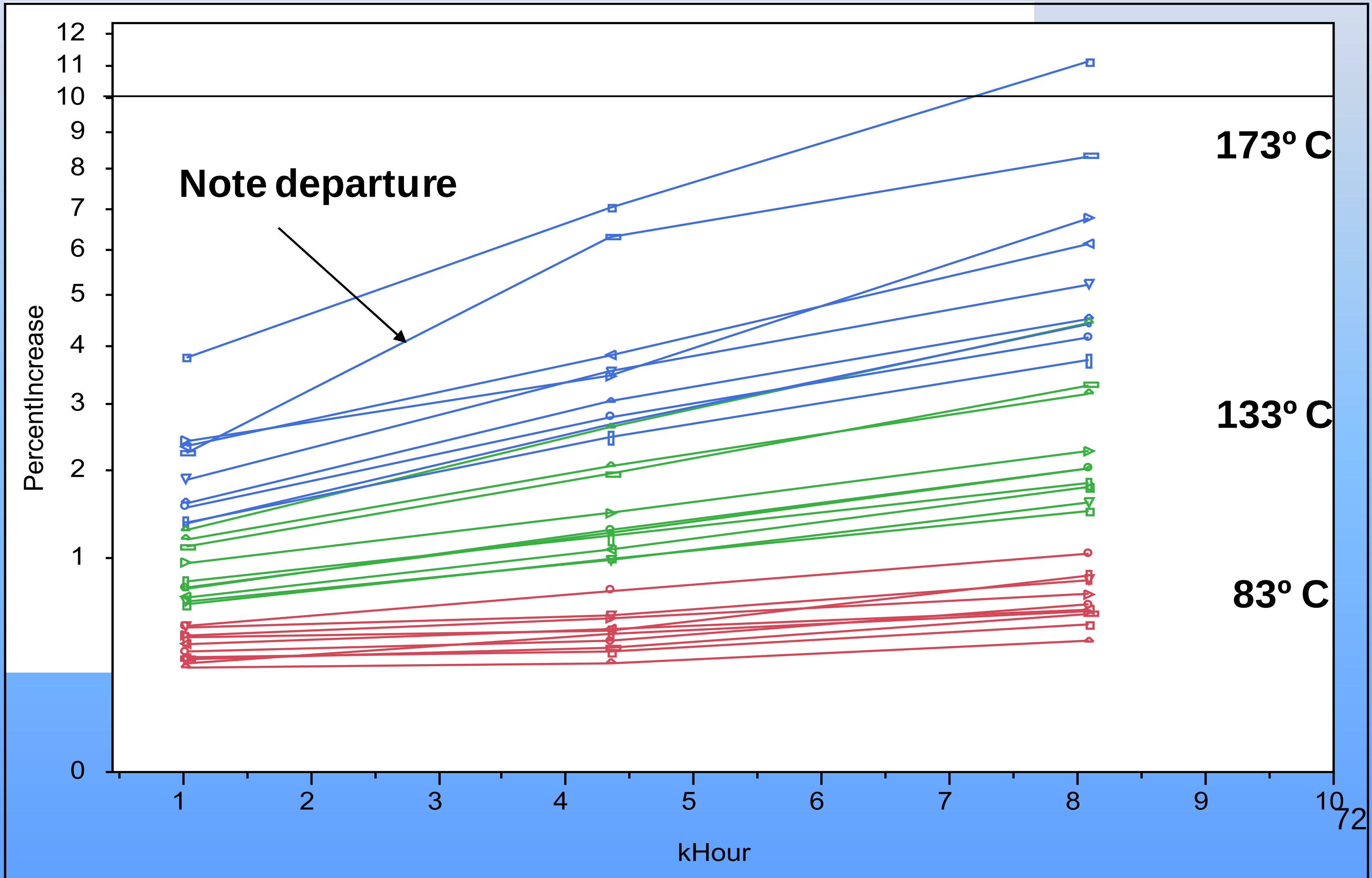
133º C

83º C

Carbon-Film Resistor Accelerated Test Data

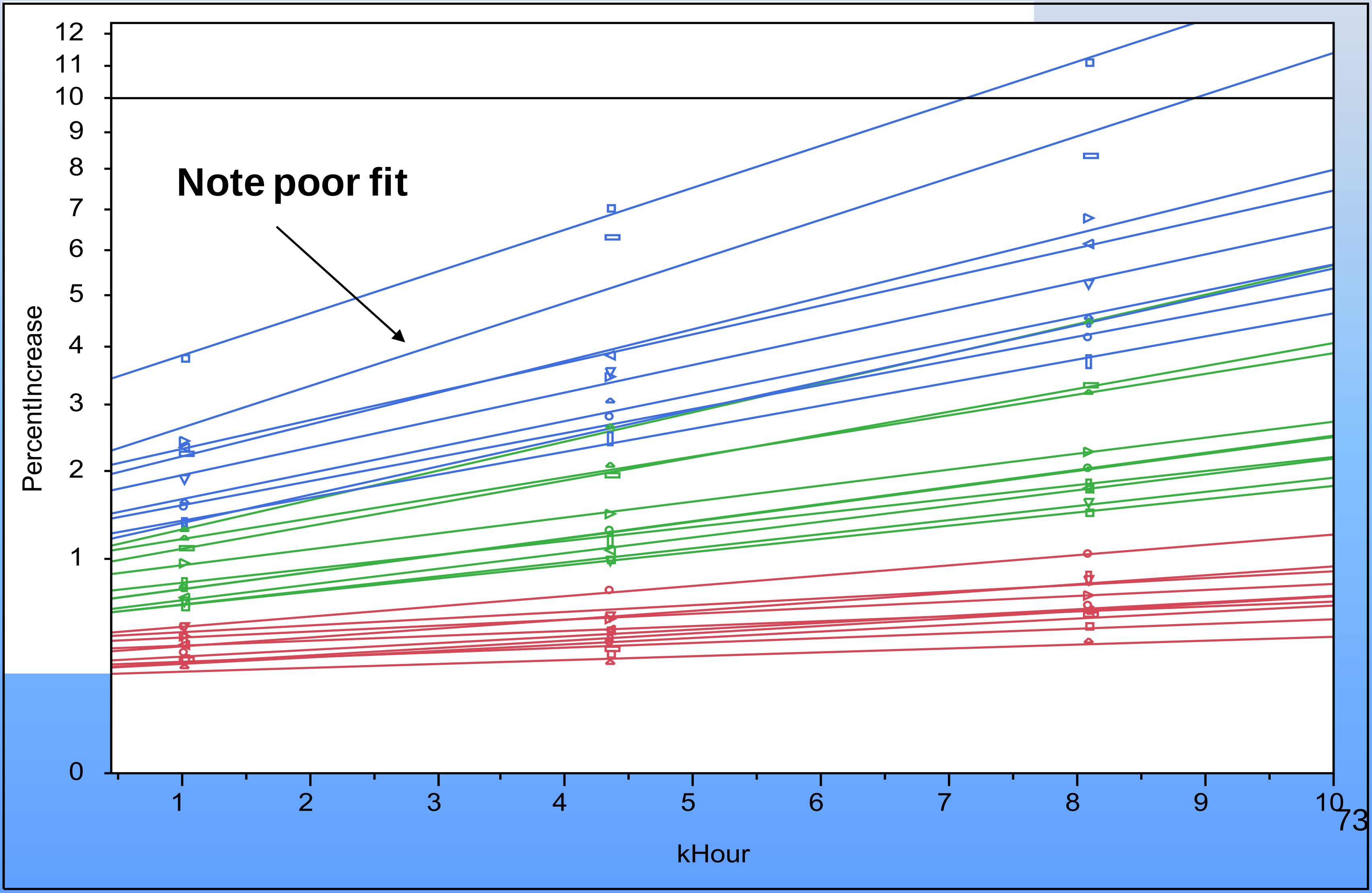
square root-linear plot

first observation deleted to avoid bias



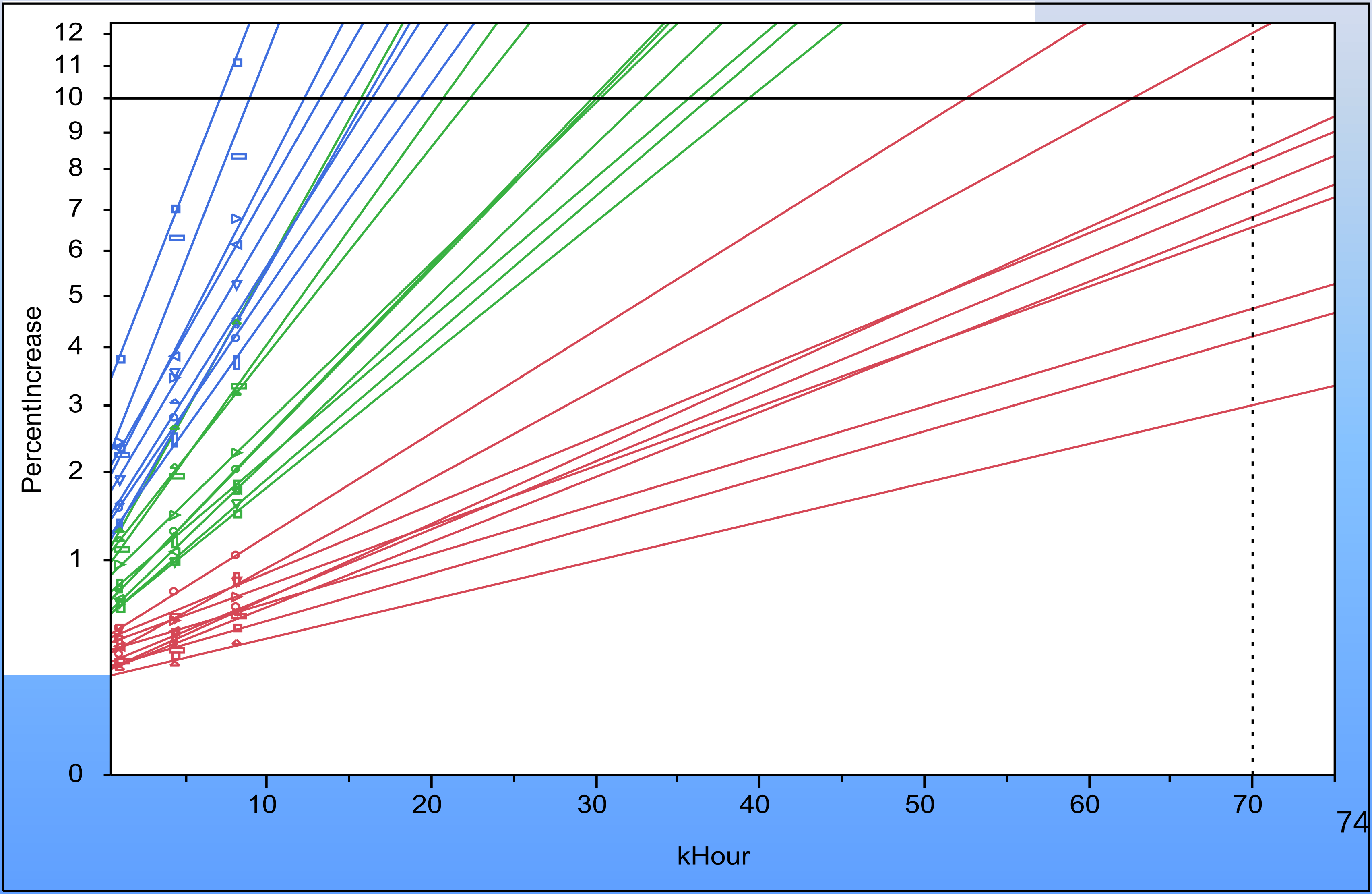
Carbon-Film Resistor Accelerated Test Data

square root-linear plot with fitted lines



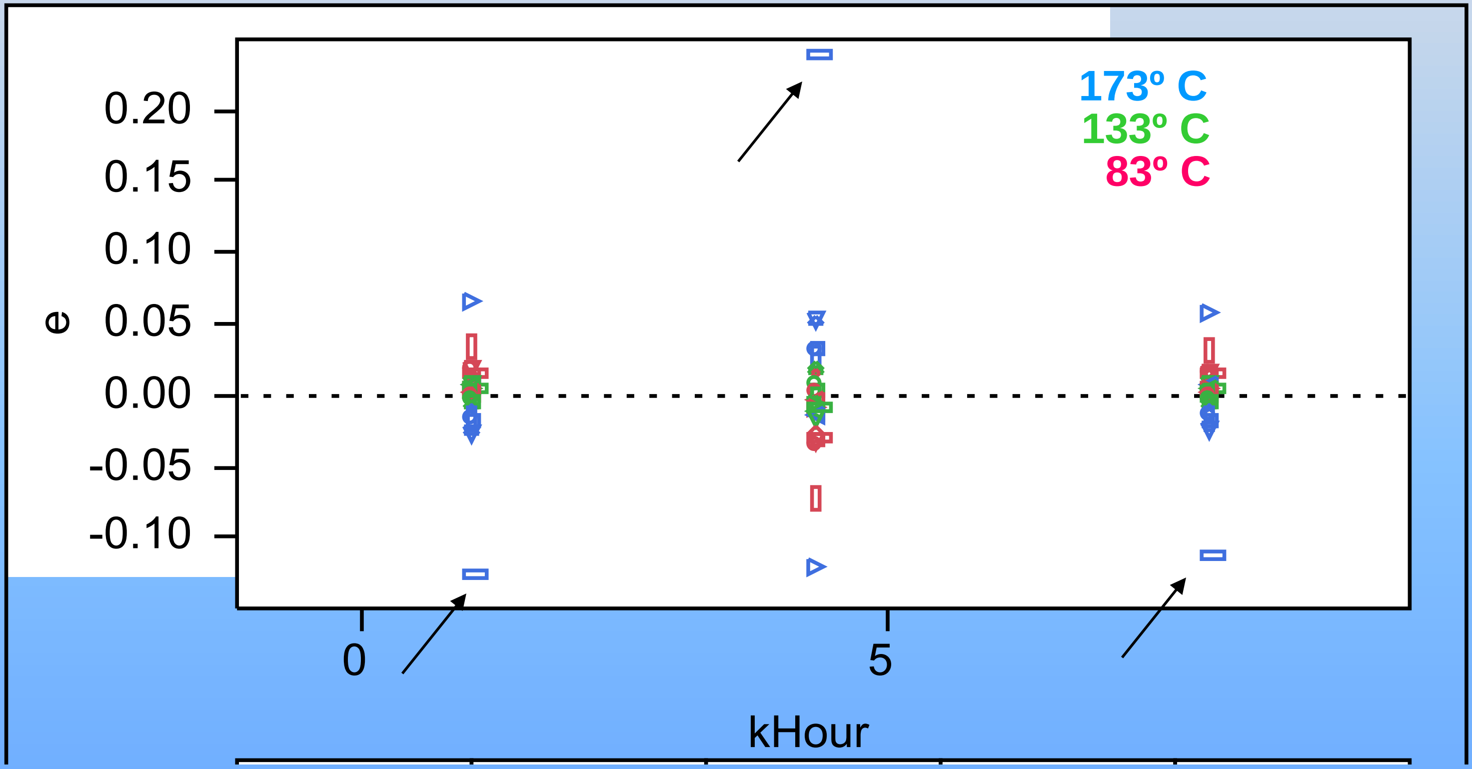
Carbon-Film Resistor Accelerated Test Data

square root-linear plot with fitted lines, extrapolated to failures



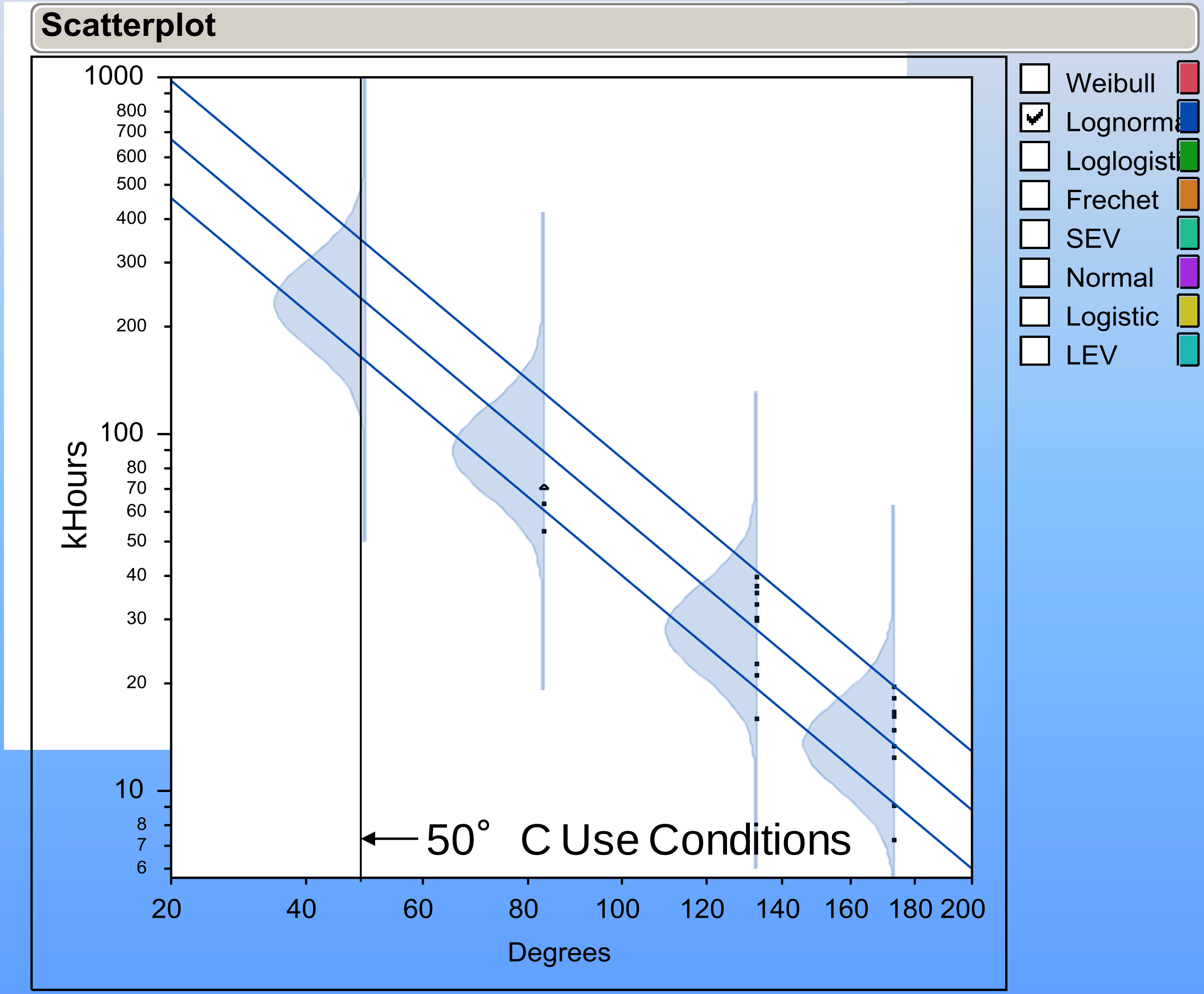
Carbon-Film Resistor Accelerated Test Data

regression residuals



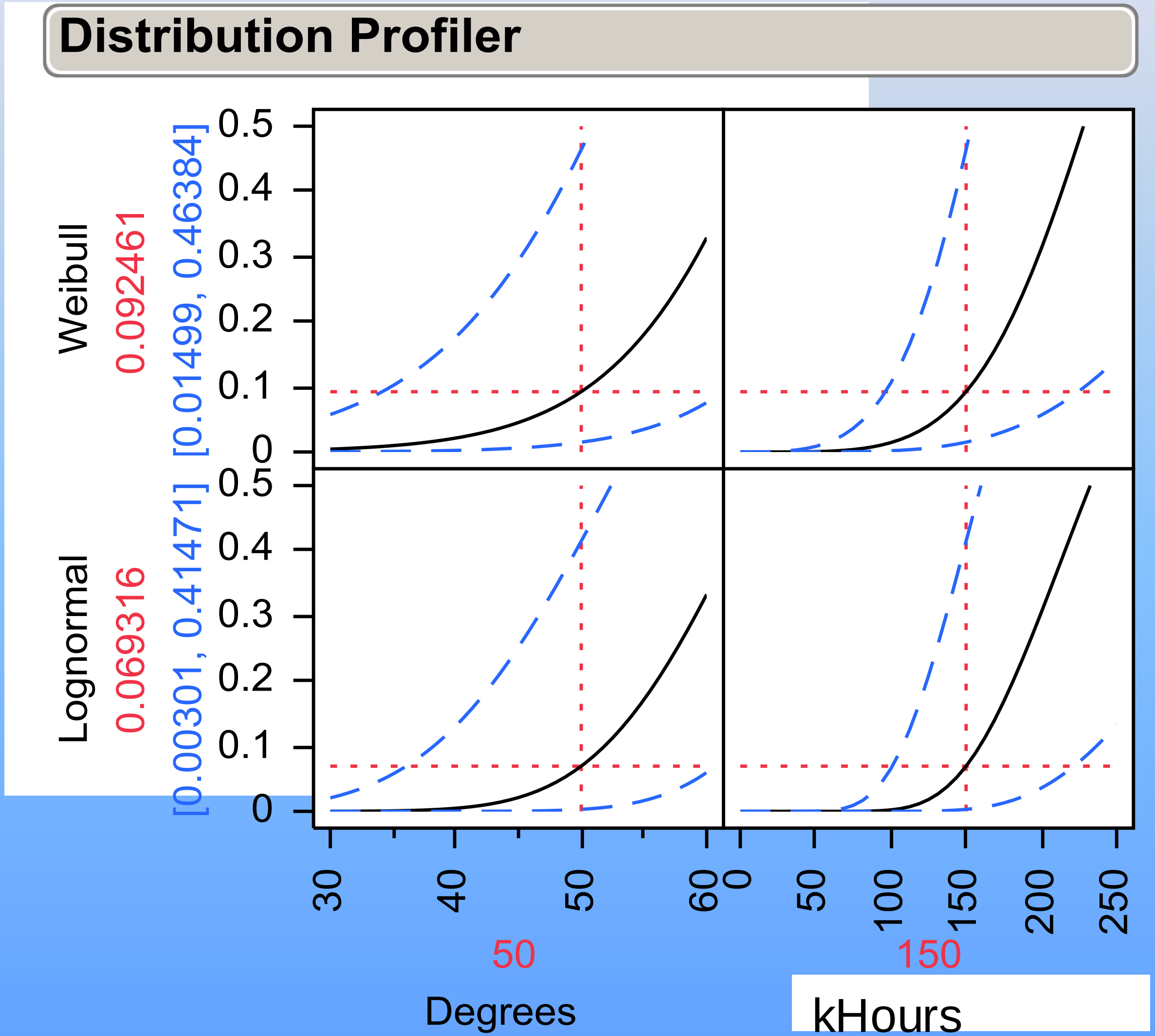
Carbon-Film Resistor Accelerated Test Data

Fit Life by X Arrhenius Model Plot



Carbon-Film Resistor Accelerated Test Data

Comparison of Weibull and Lognormal Distributions



Lessons Learned

- Early part of degradation path may be complicated, but can be ignored
- Repeated measures degradation data can provide much more information than failure-time data
- Reliability information possible with few or no failures

The End