Experiences in Reliability Data Analysis

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Jointly work with William Q. Meeker from
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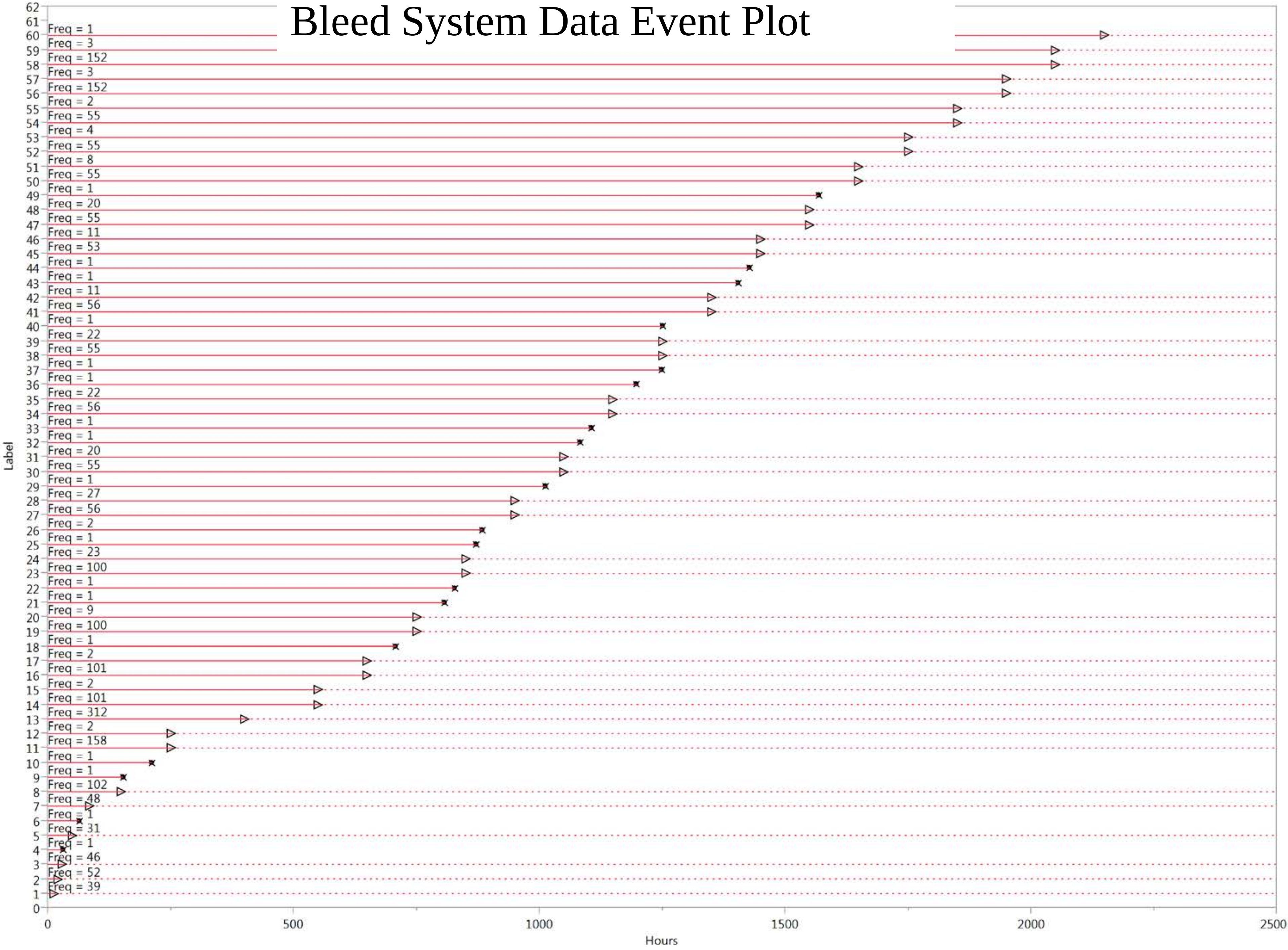
Overview

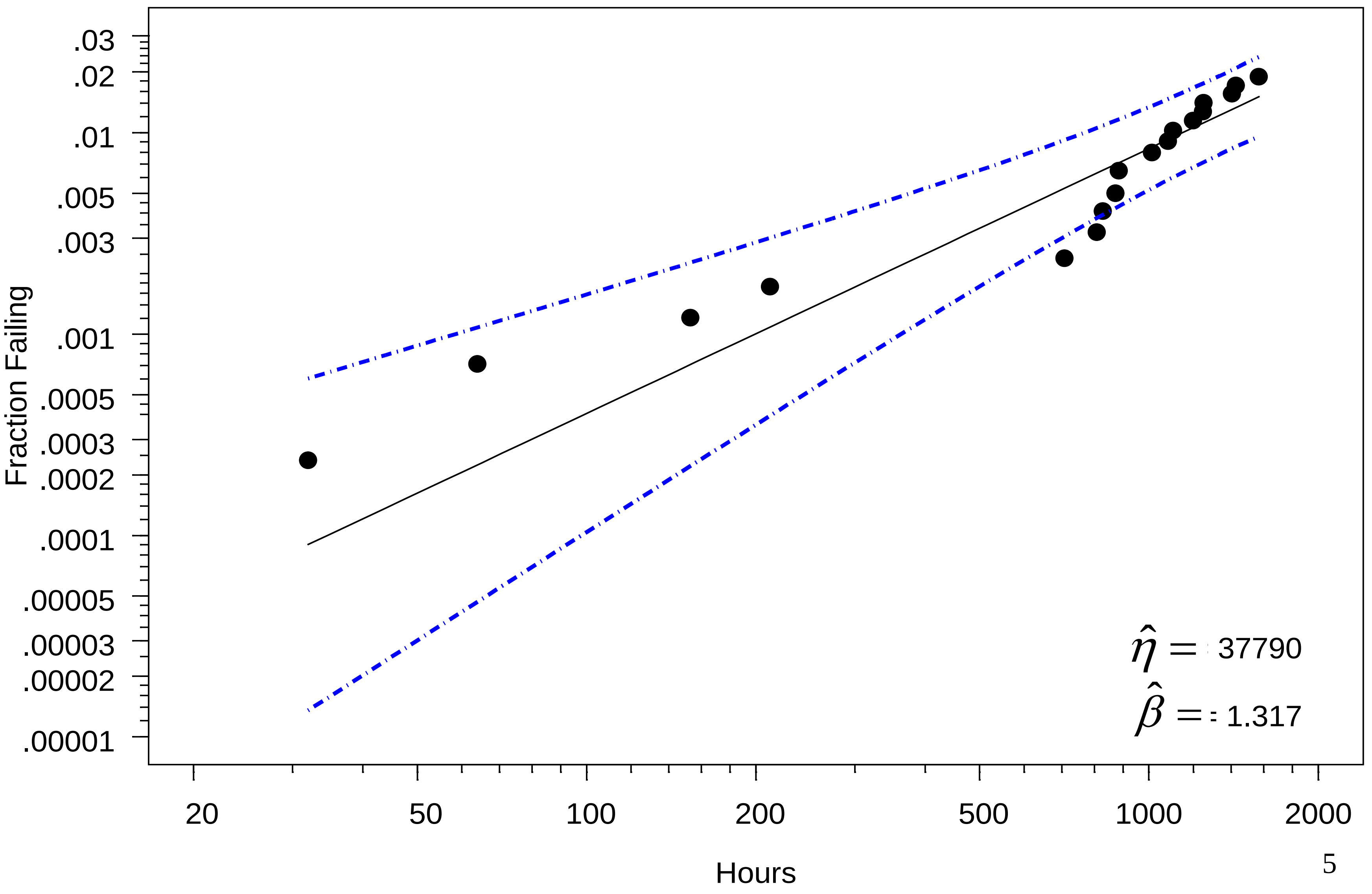
- Analysis of Field/Warranty Data
  - Solving a reliability problem with statistics: jet engine bleed system failure
  - Using assumptions sensitivity analysis t strengthen data: bearing cage field failure data
  - Correct analysis of data with multiple failure modes: Device-G field-tracking and Shock Absorber data
  - Other examples
- Accelerated Testing
  - Accelerated life tests (Insulating structure)
  - Accelerated repeated-measures degradation tests (LEDs)
  - Accelerated destructive degradation tests (adhesive bond)
  - Other examples

Jet Engine Bleed System Failure

- Data from the *Weibull Handbook (1984)*
- Field data from 2256 systems in the field; staggered entry--multiple censoring
- Unexpected failures
- What is going on??

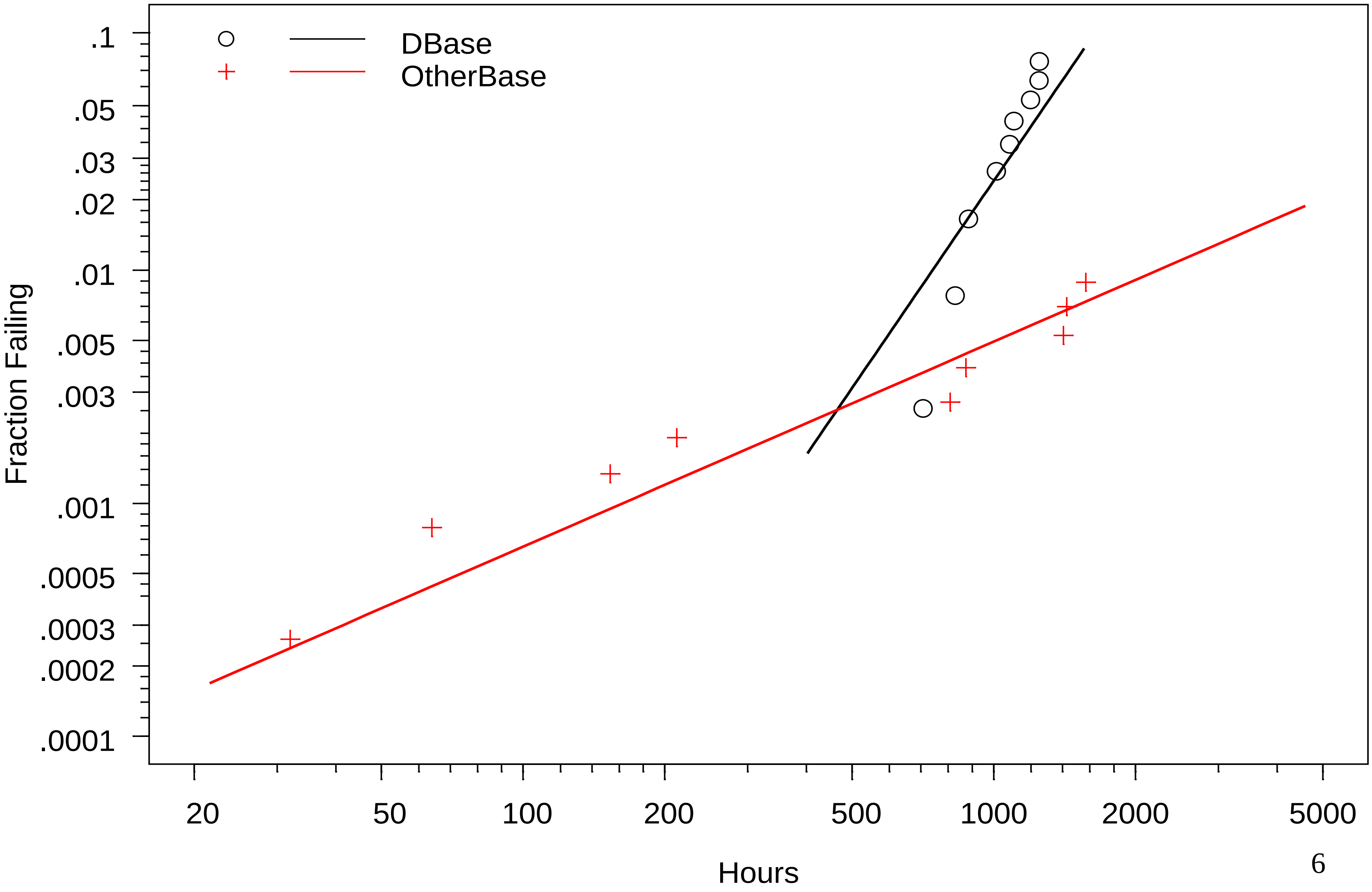
Bleed System Data Event Plot





Bleed System Failure Data
with Weibull ML Estimate and Pointwise 95% Confidence Intervals
Weibull Probability Plot

Bleed System Failure Data
With Individual Weibull Distribution ML Estimates
Weibull Probability Plot



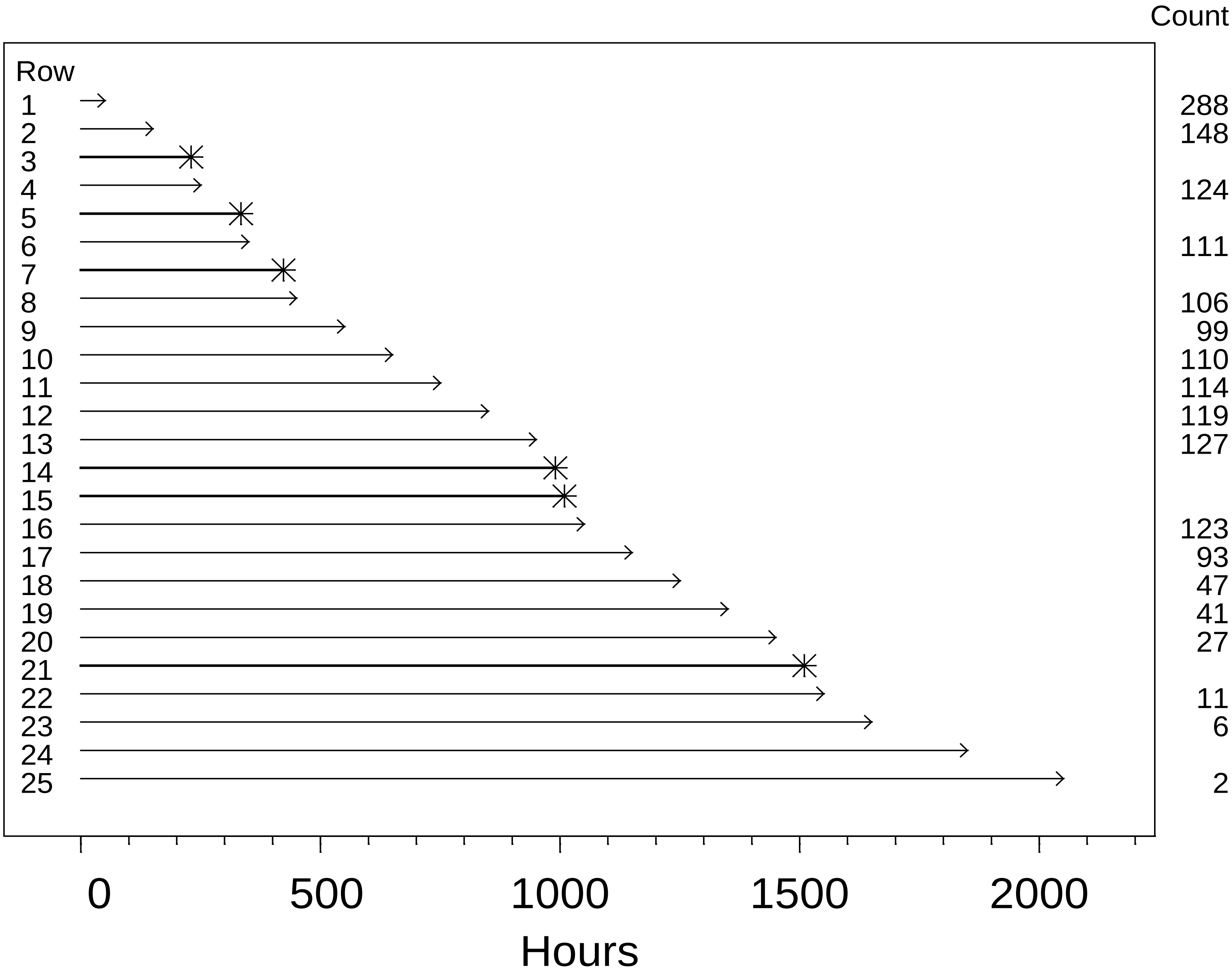
Lessons Learned

- A shift in the slope of a probability plot often indicates a different failure mode
- Look for explanatory variables to help better understand data sources

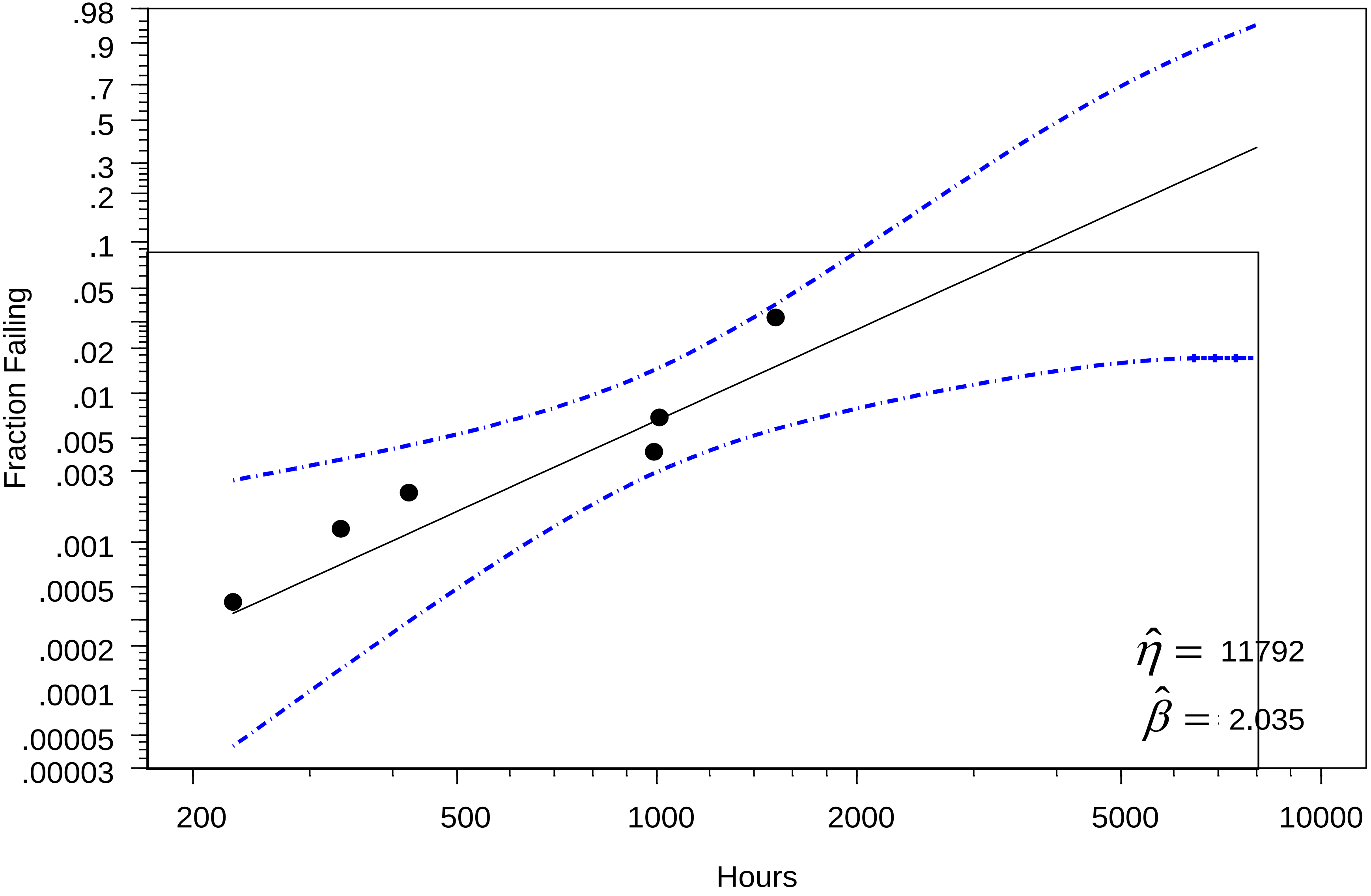
Bearing Cage Field Failure Data

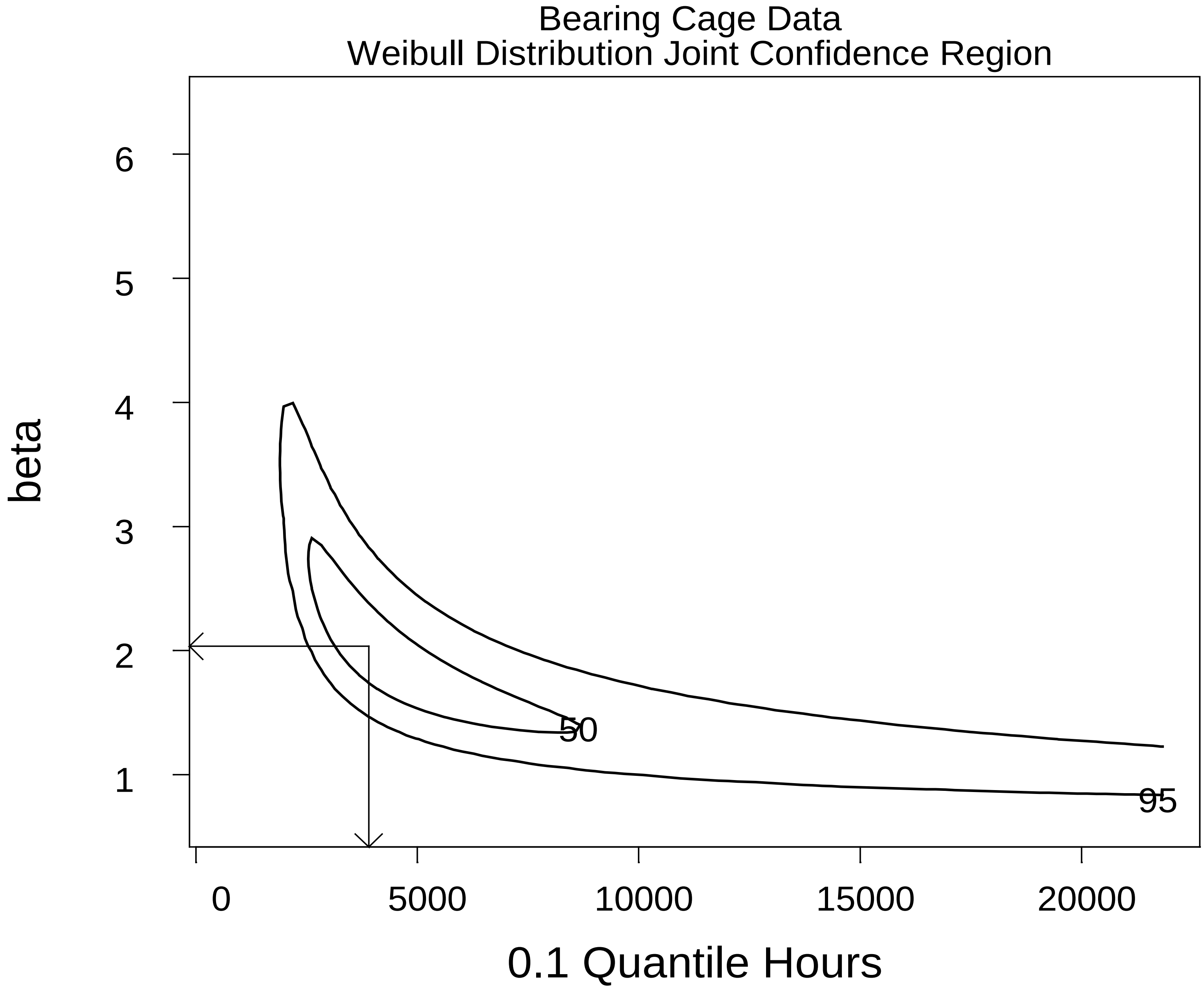
- Data from the *Weibull Handbook (1984)*
- 1703 units had been introduced into the field over time; oldest unit at 2220 hours of operation.
- 6 units had failed
- Design life specification was B10 = 8000 hours of operation
- Do we have a serious problem? Re-design needed?
- How many spares needed?

Bearing Cage Data

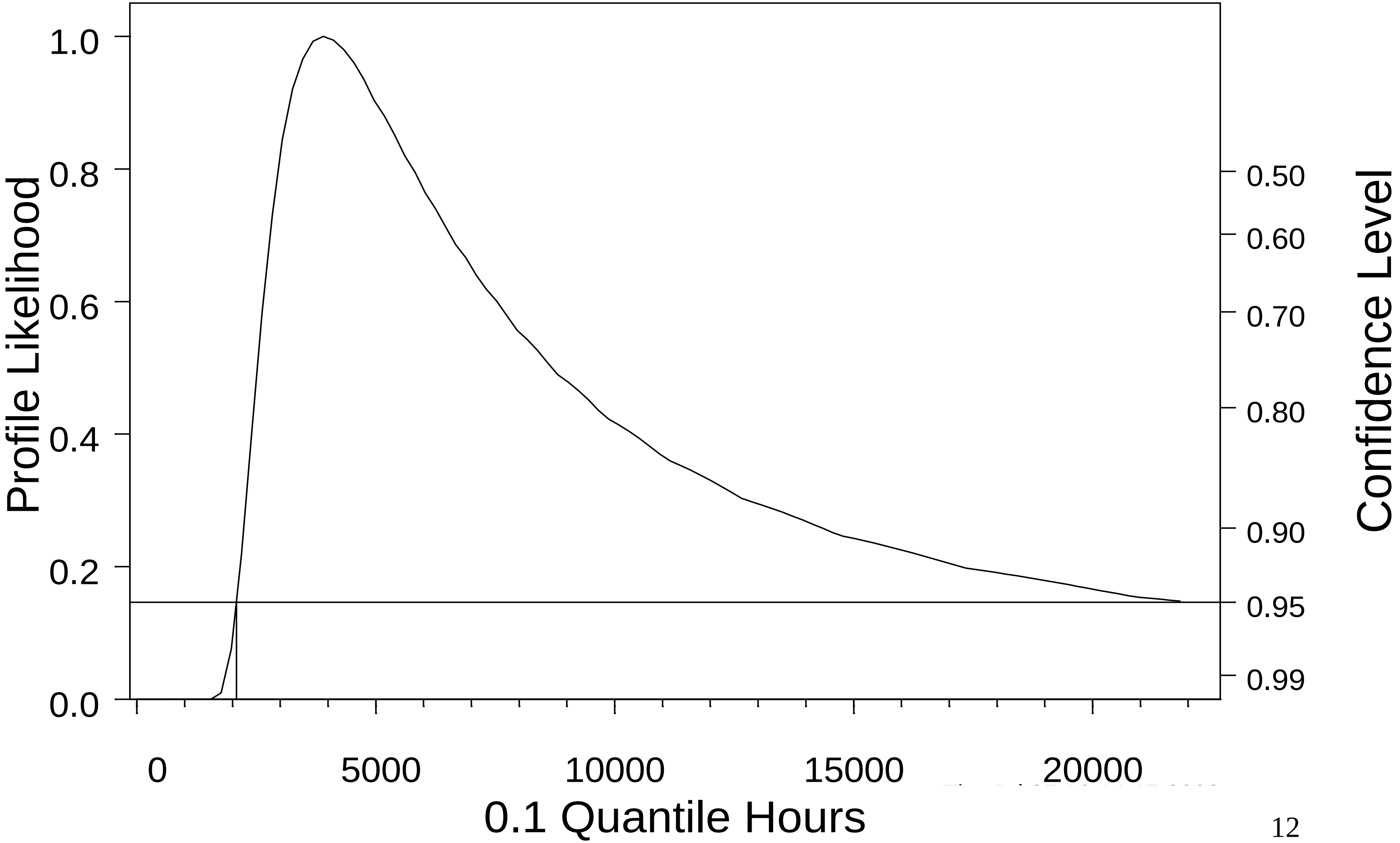


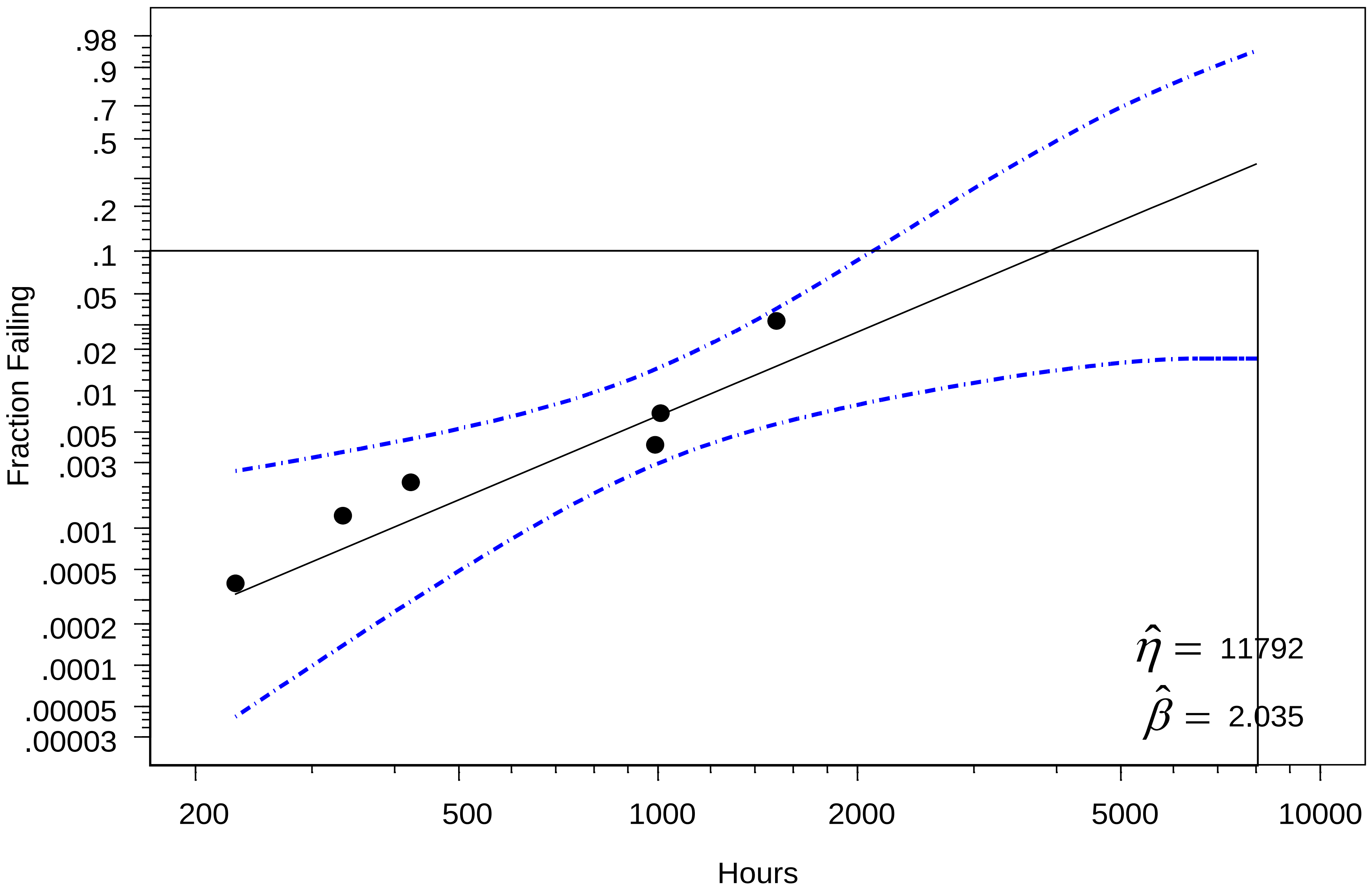
Bearing Cage Data
with Weibull ML Estimate and Pointwise 95% Confidence Intervals
Weibull Probability Plot




Bearing Cage Data
Weibull Distribution Joint Confidence Region
beta
6
5
4
3
2
1
0
5000
10000
15000
20000
0.1 Quantile Hours
50
95

Bearing Cage Data
Profile Likelihood and 95% Confidence Interval
for 0.1 Quantile Hours from the Weibull Distribution





Bearing Cage Failure Data
with Weibull ML Estimate and Pointwise 95% Confidence Intervals
Weibull Probability Plot

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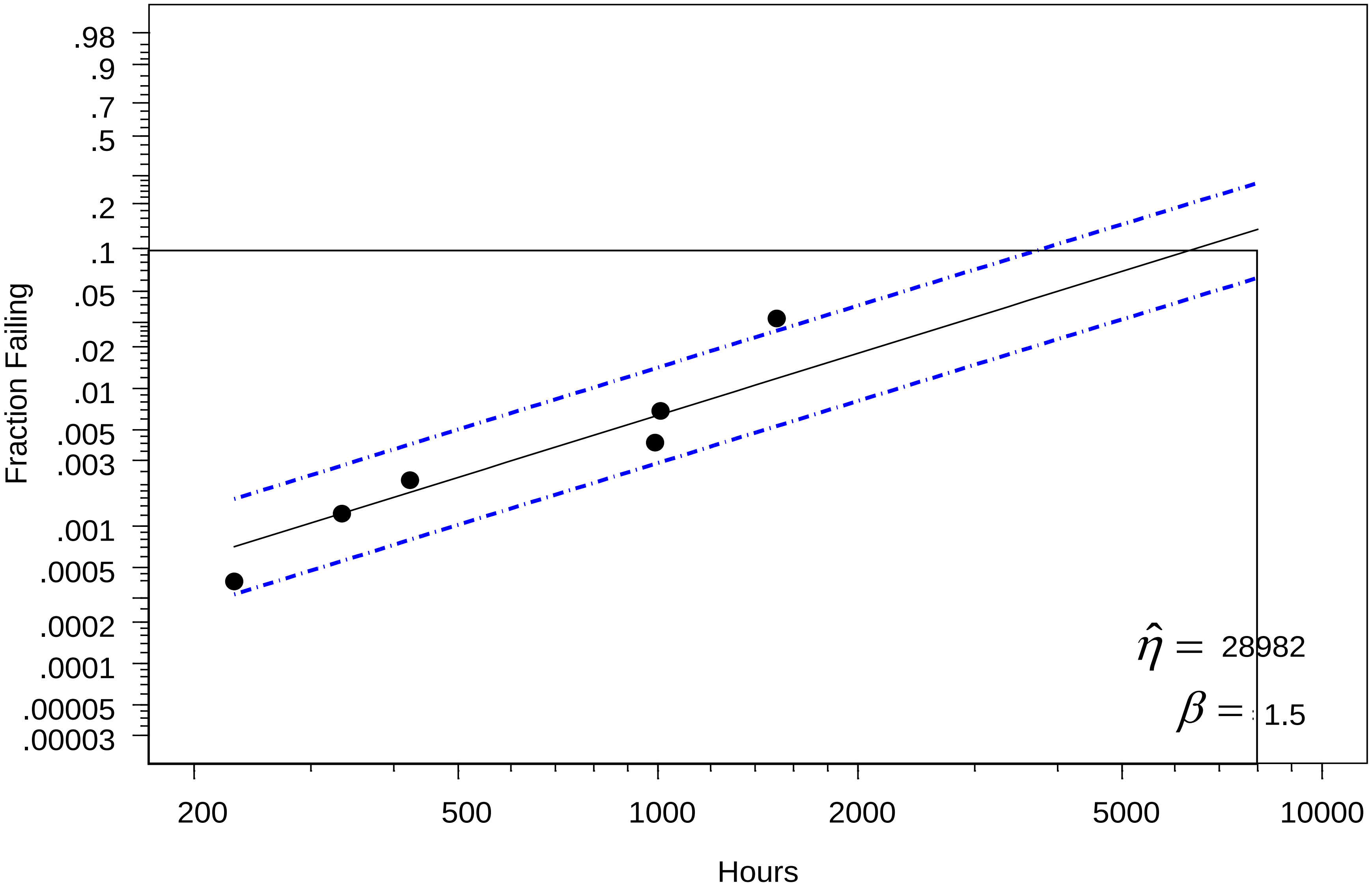

Bearing Cage Failure Data
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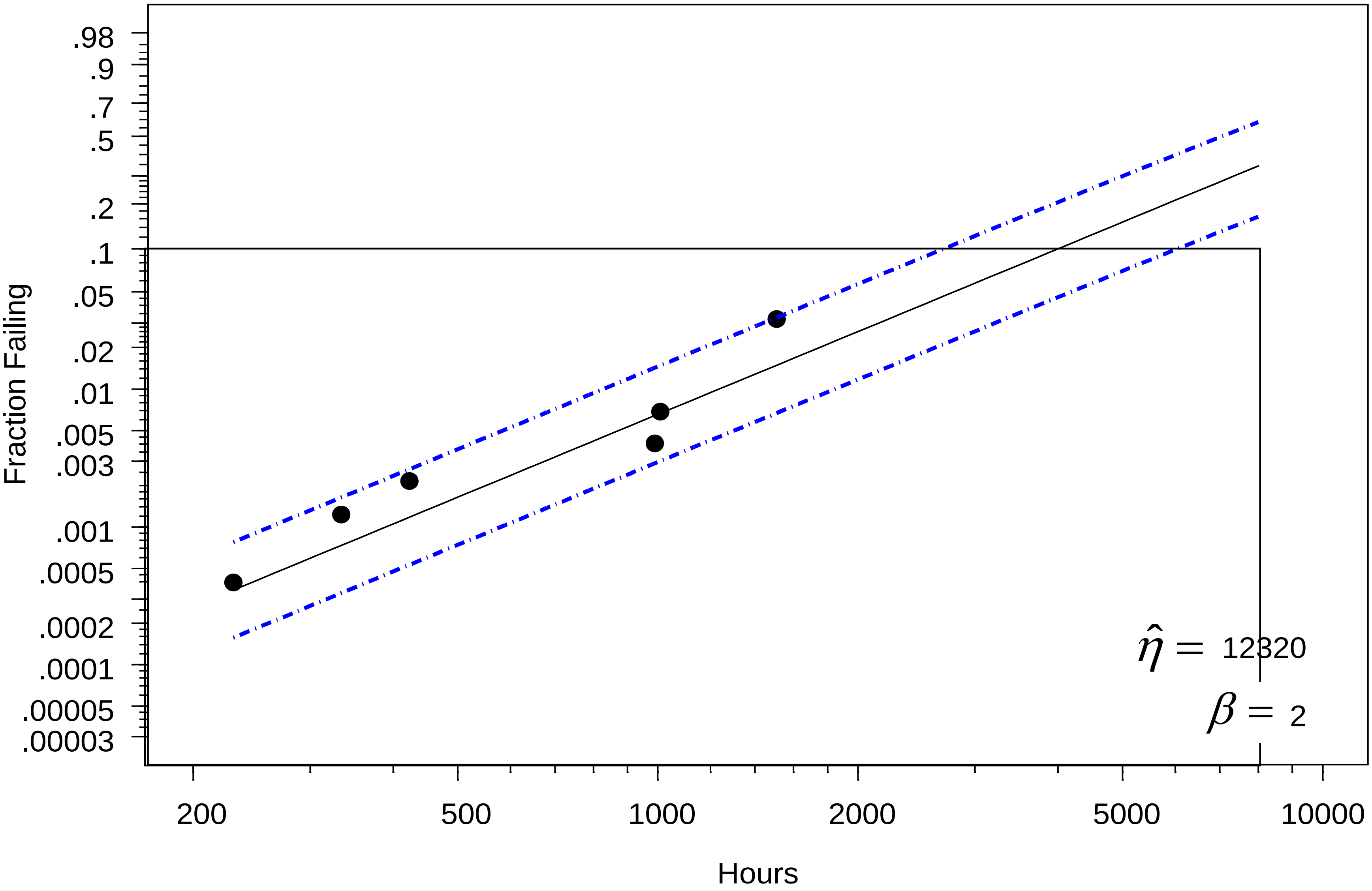
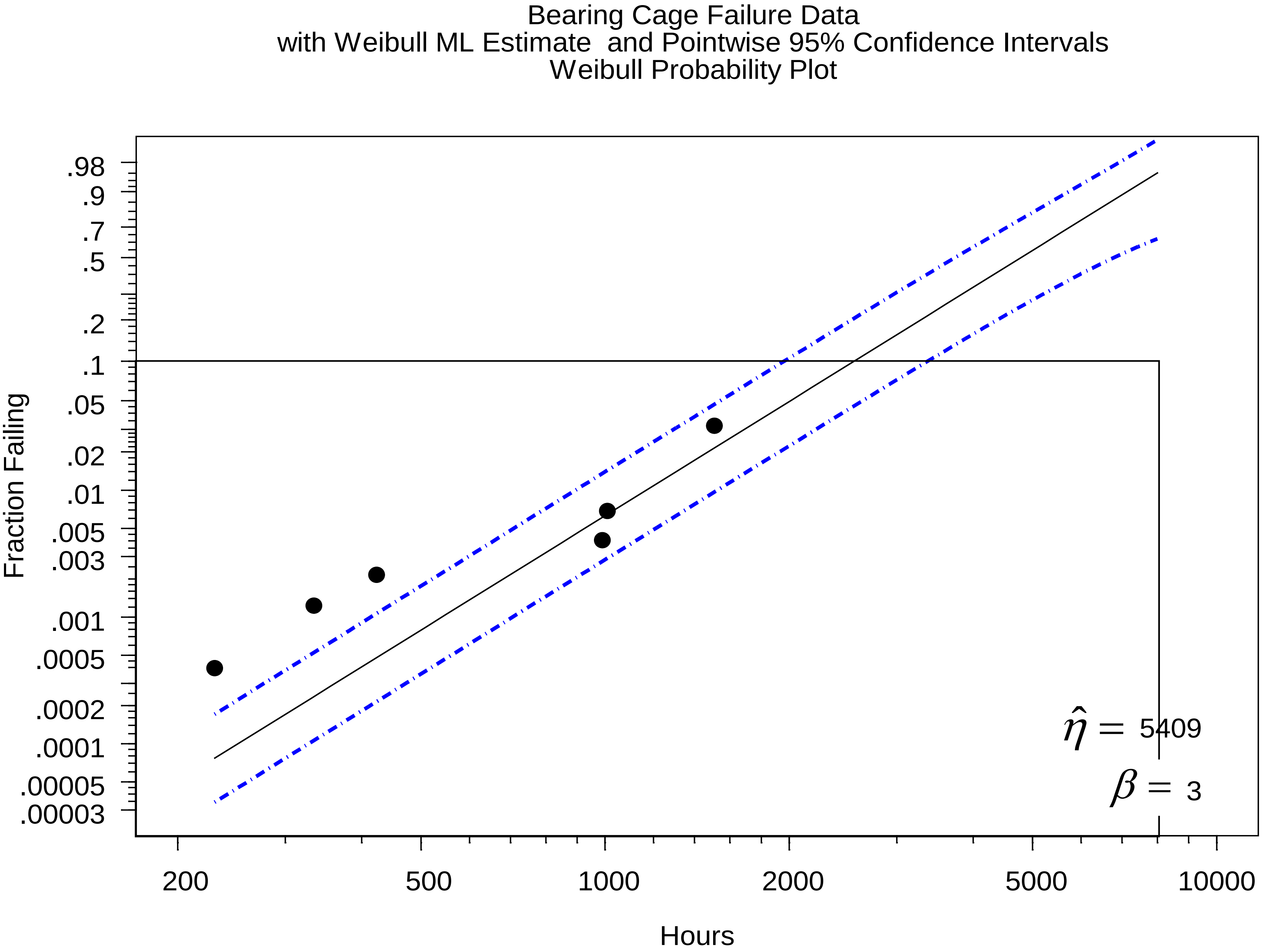
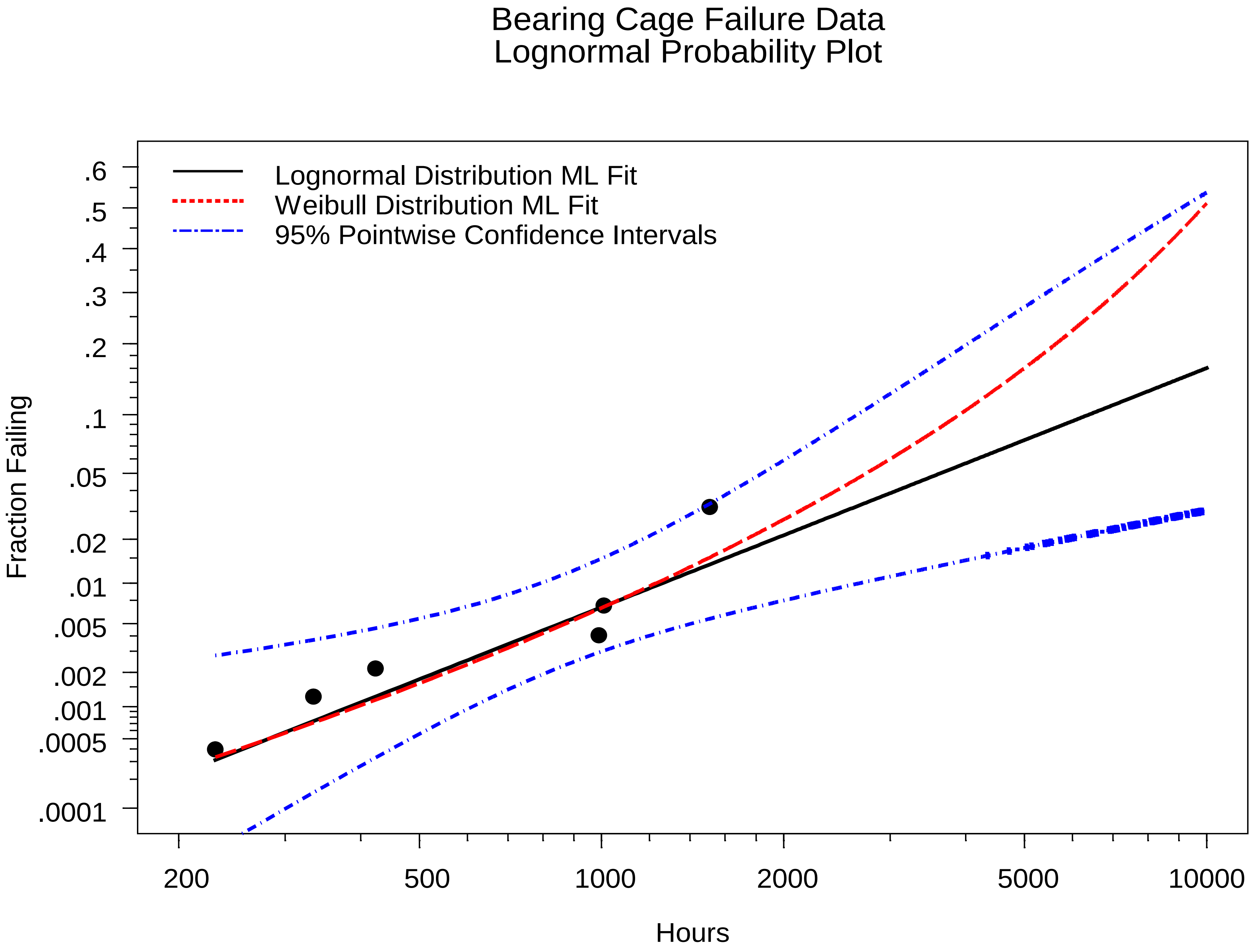
Weibull Probability Plot





Bearing Cage Failure Data
with Weibull ML Estimate and Pointwise 95% Confidence Intervals
Weibull Probability Plot


Bearing Cage Failure Data
Lognormal Probability Plot
Lognormal Distribution ML Fit
Weibull Distribution ML Fit
95% Pointwise Confidence Intervals
Fraction Failing
.6
.5
.4
.3
.2
.1
.05
.02
.01
.005
.002
.001
.0005
.0001
200
500
1000
2000
5000
10000
Hours

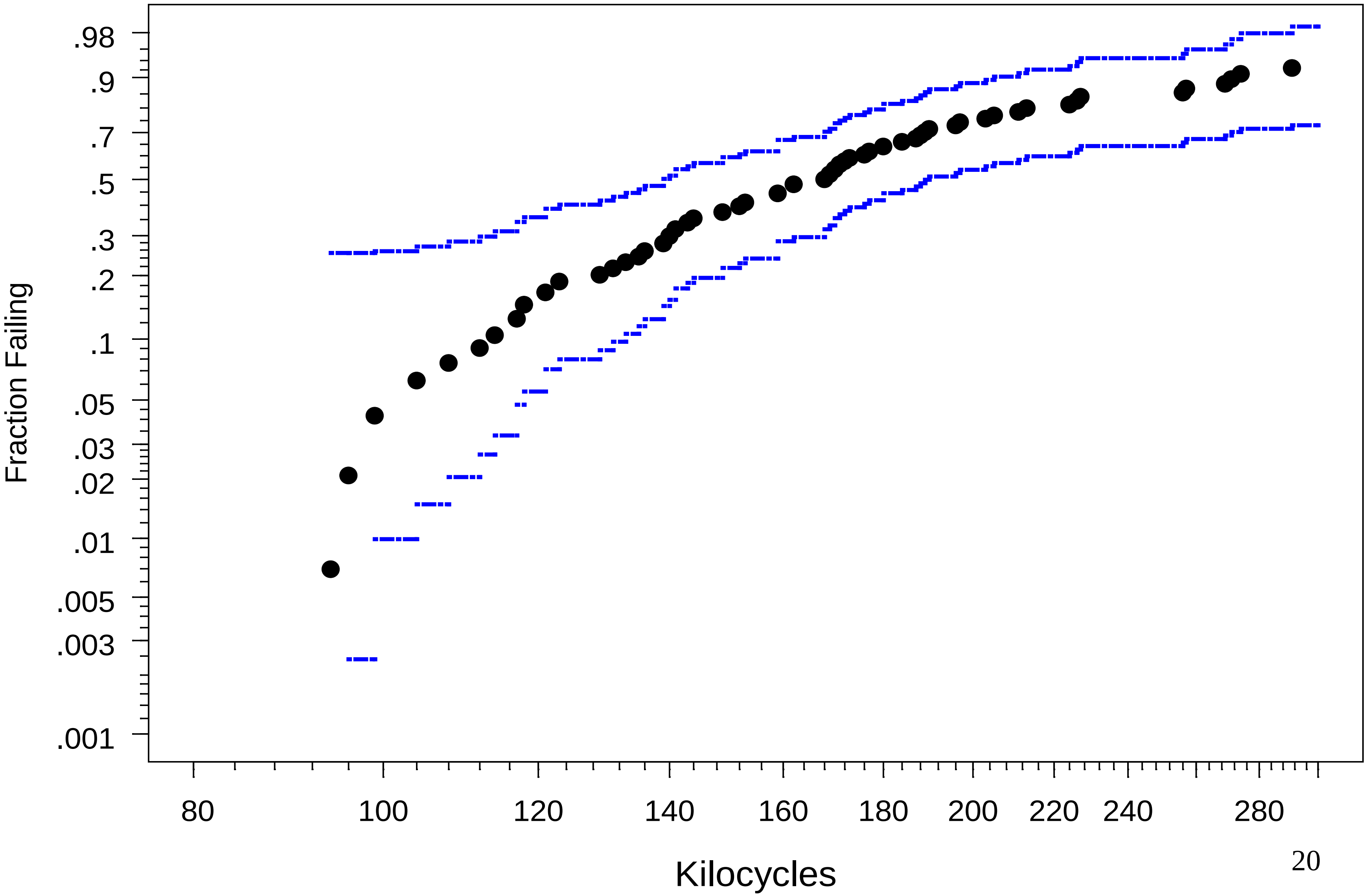
Lessons Learned

- When data are not sufficient to answer the question, it is important to seek external information (e.g., on the Weibull shape parameter) from past experience or engineering/physical/chemical knowledge about failure mechanisms
- Sensitivity analysis provides insight and assessment of uncertainty

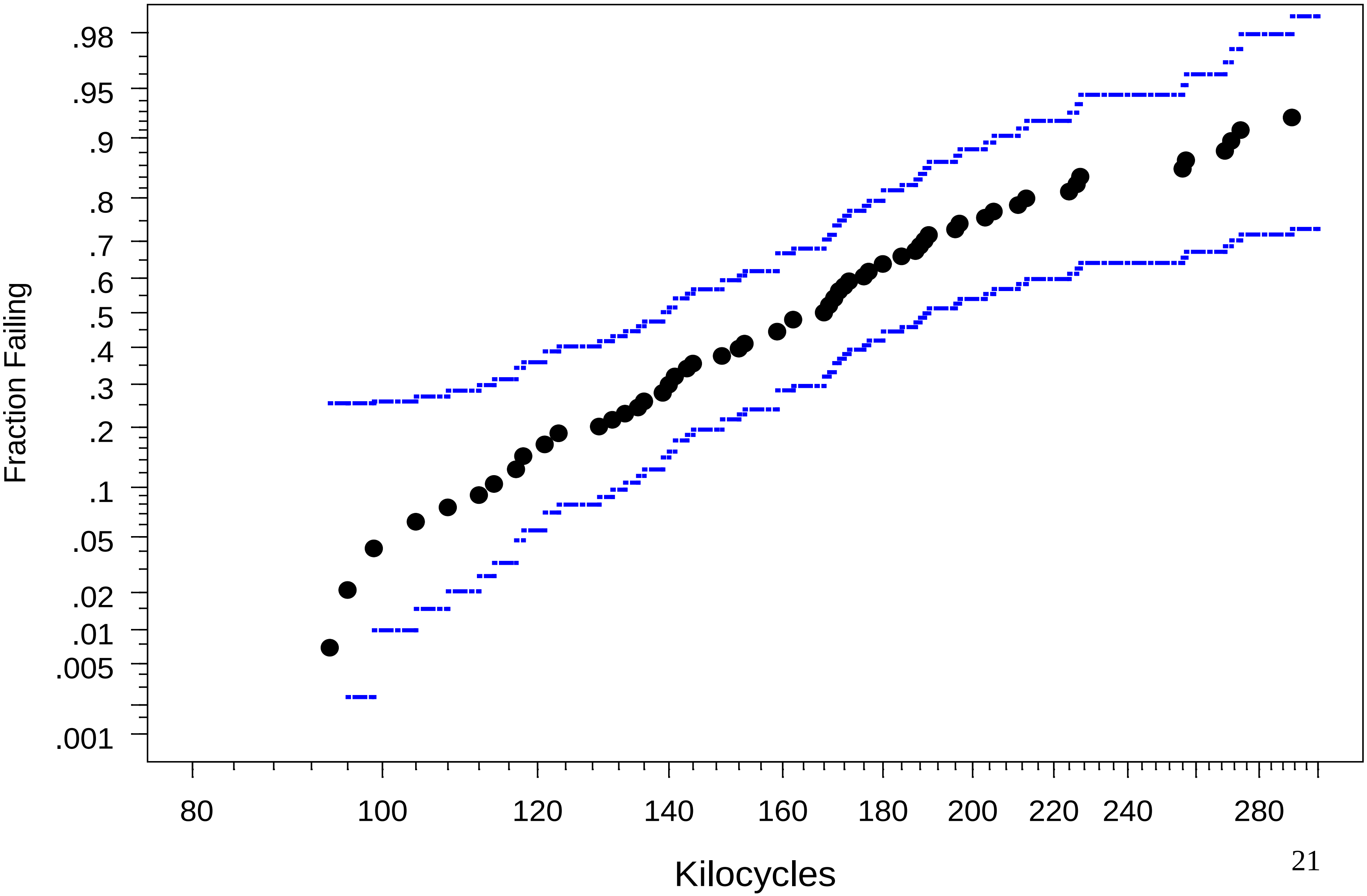
Alloy T7987 Fatigue Data

- 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.

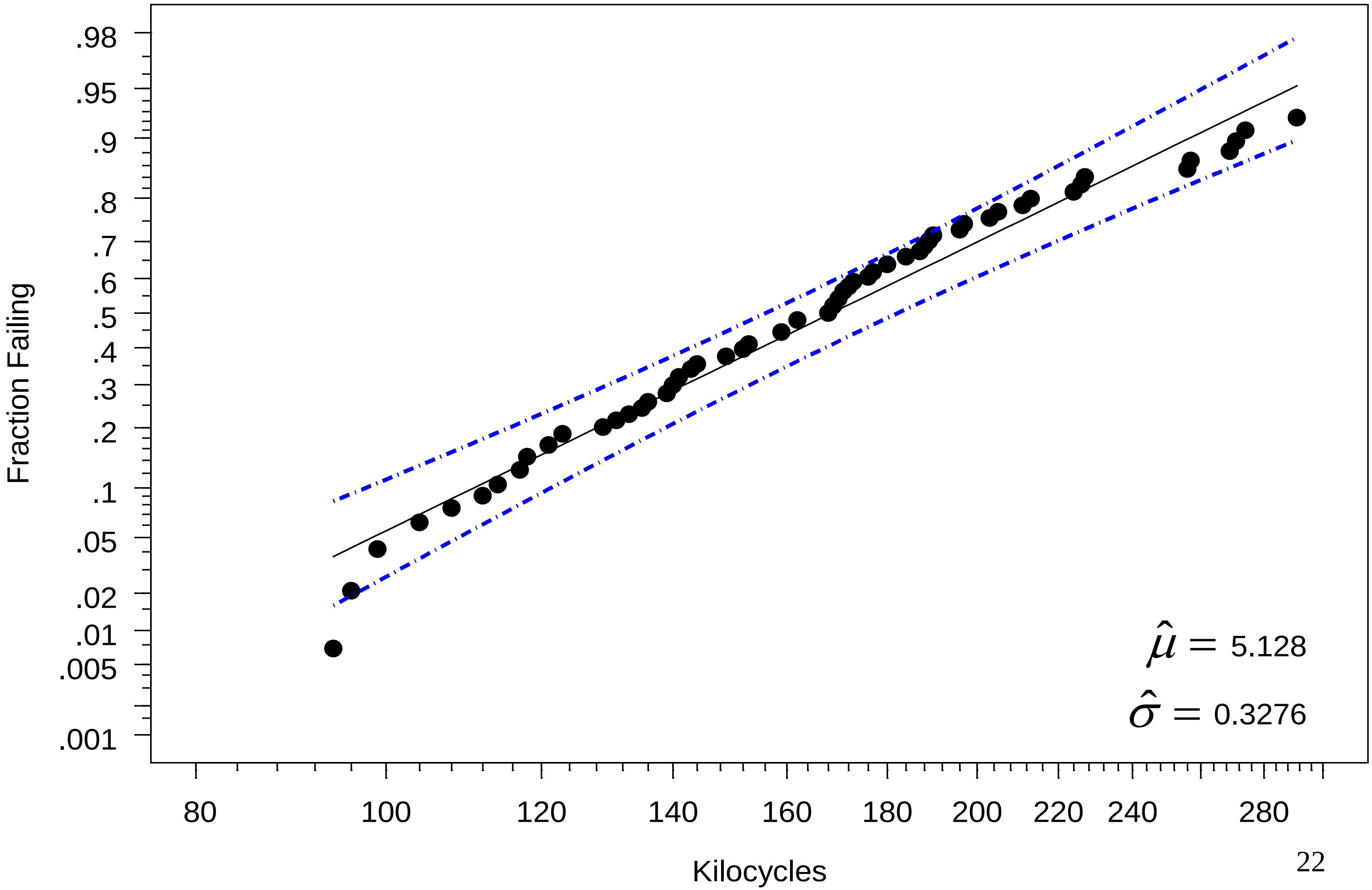
Alloy T7987 Fatigue Data
with Nonparametric Simultaneous 95% Confidence Bands
Weibull Probability Plot



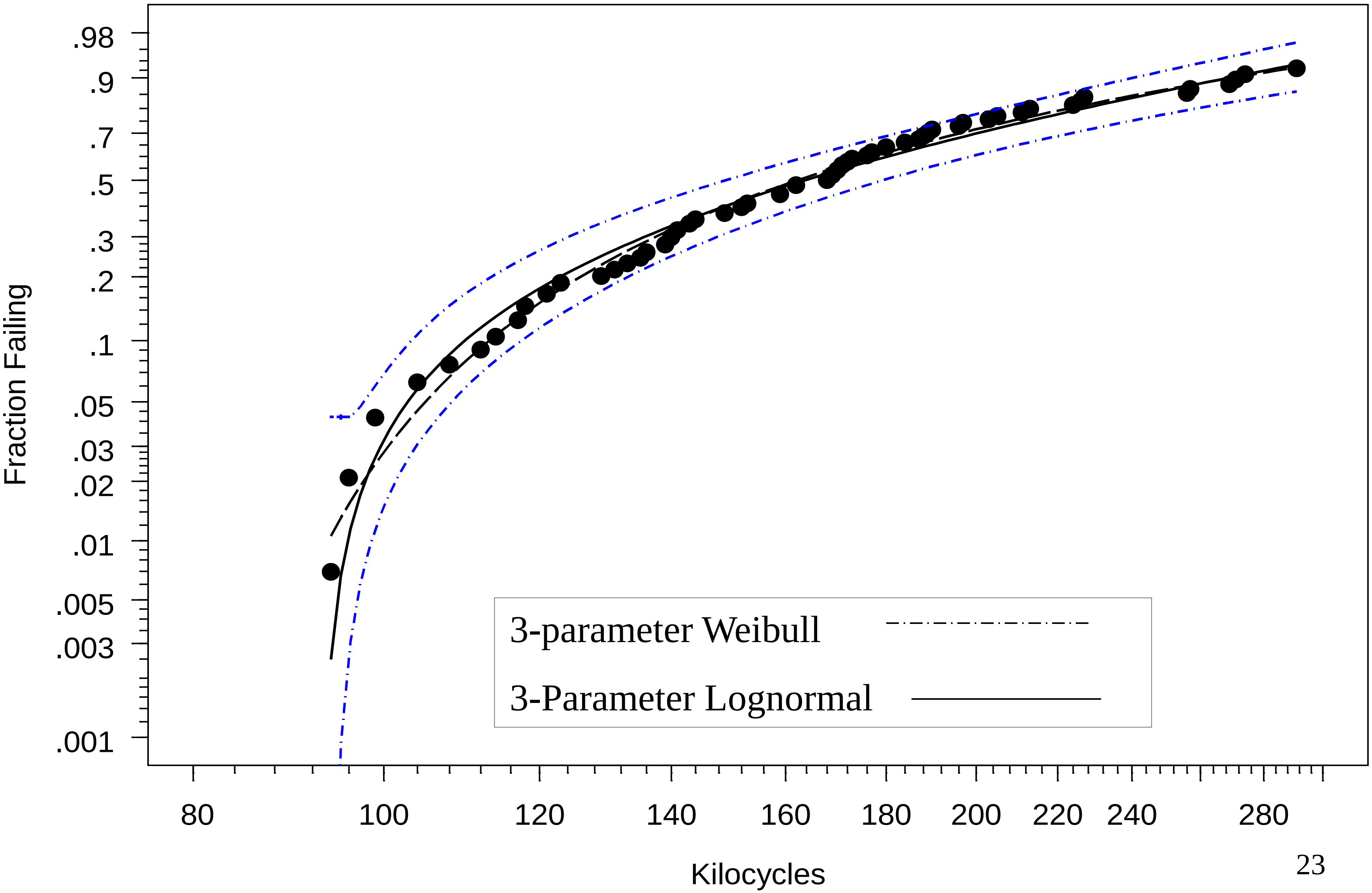
Alloy T7987 Fatigue Data
with Nonparametric Simultaneous 95% Confidence Bands
Lognormal Probability Plot



Alloy T7987 Fatigue Data
with Lognormal ML Estimate and Pointwise 95% Confidence Intervals
Lognormal Probability Plot



Alloy T7987 Fatigue Data
Weibull Probability Plot

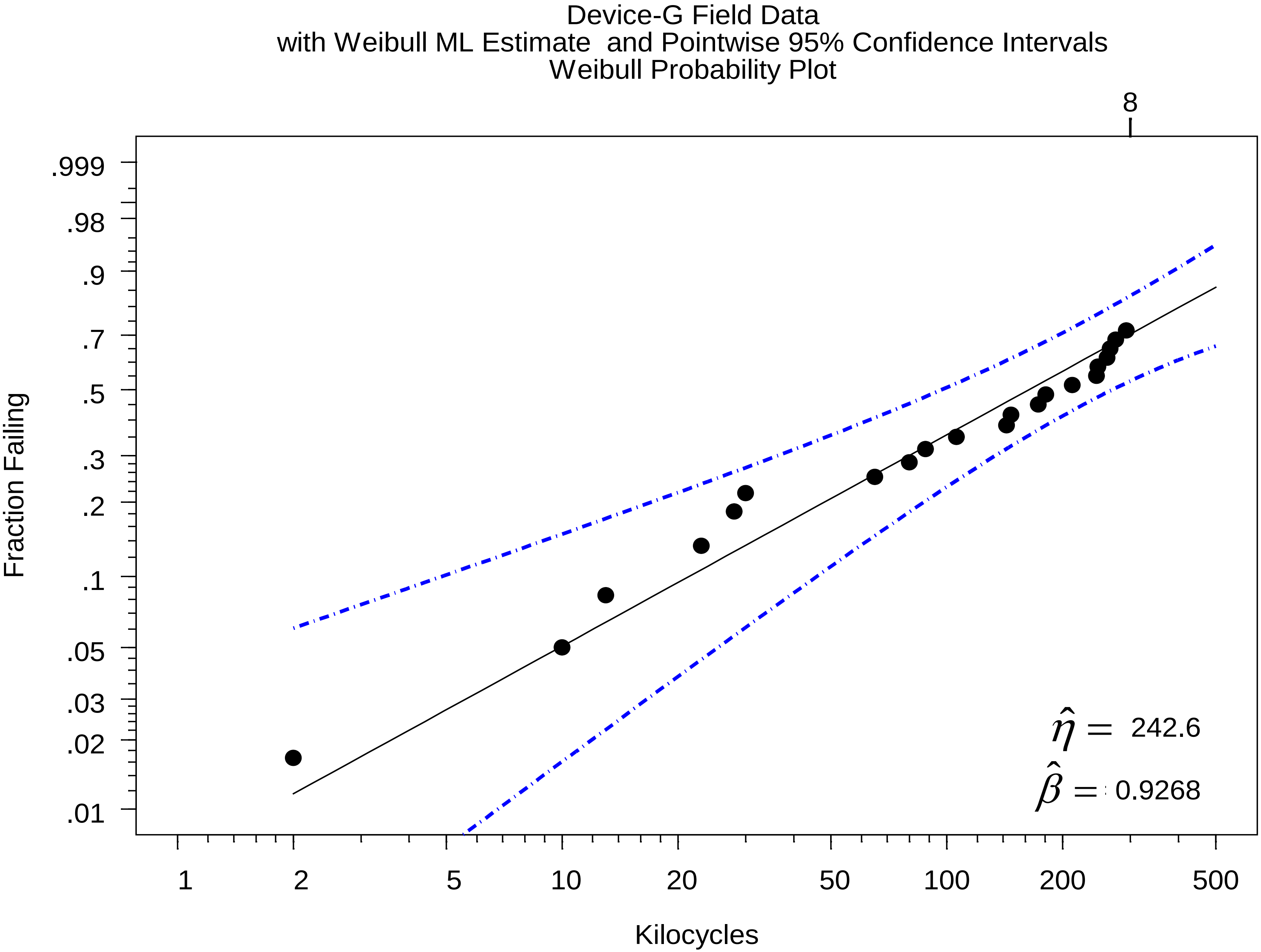


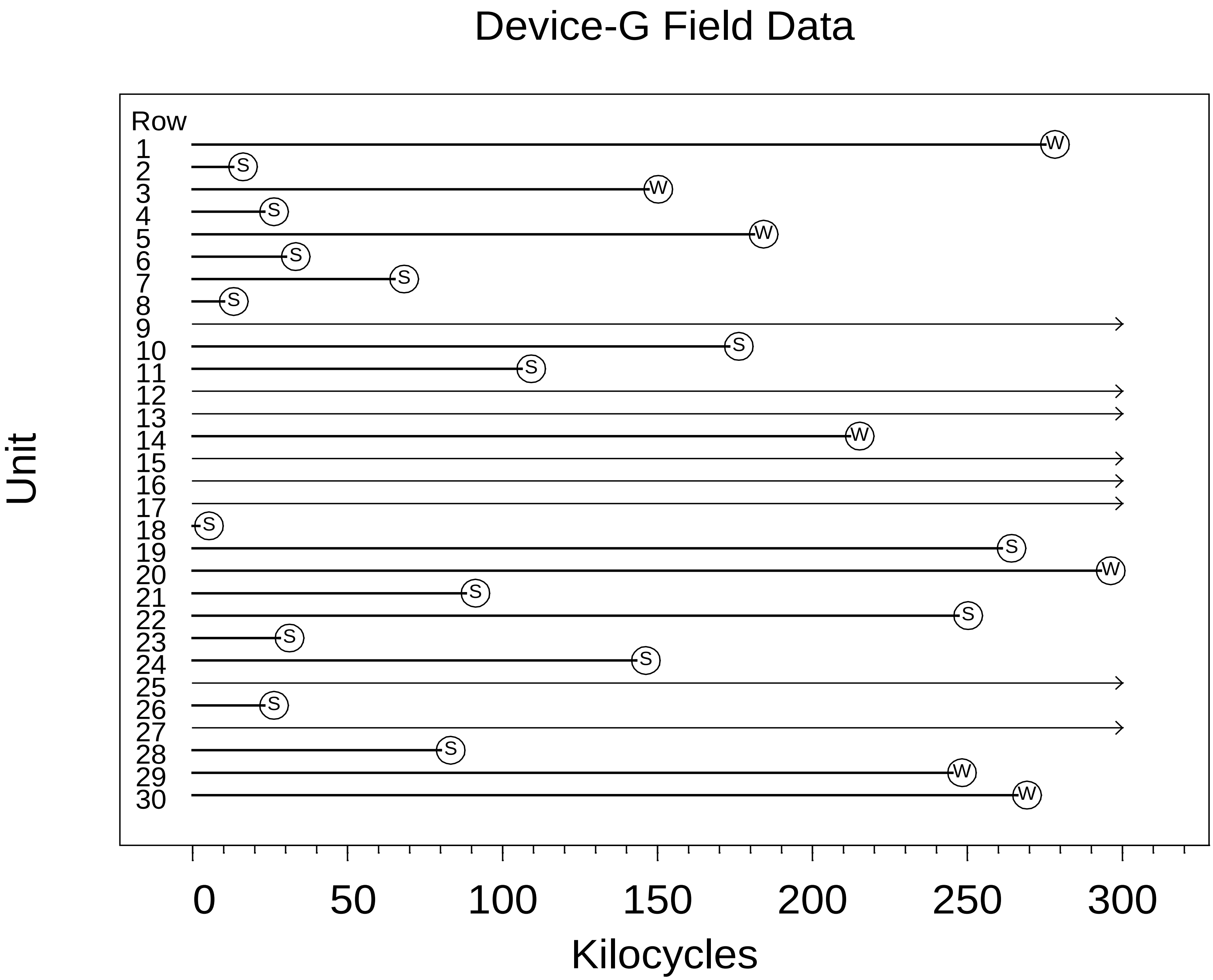
Lessons Learned

- 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

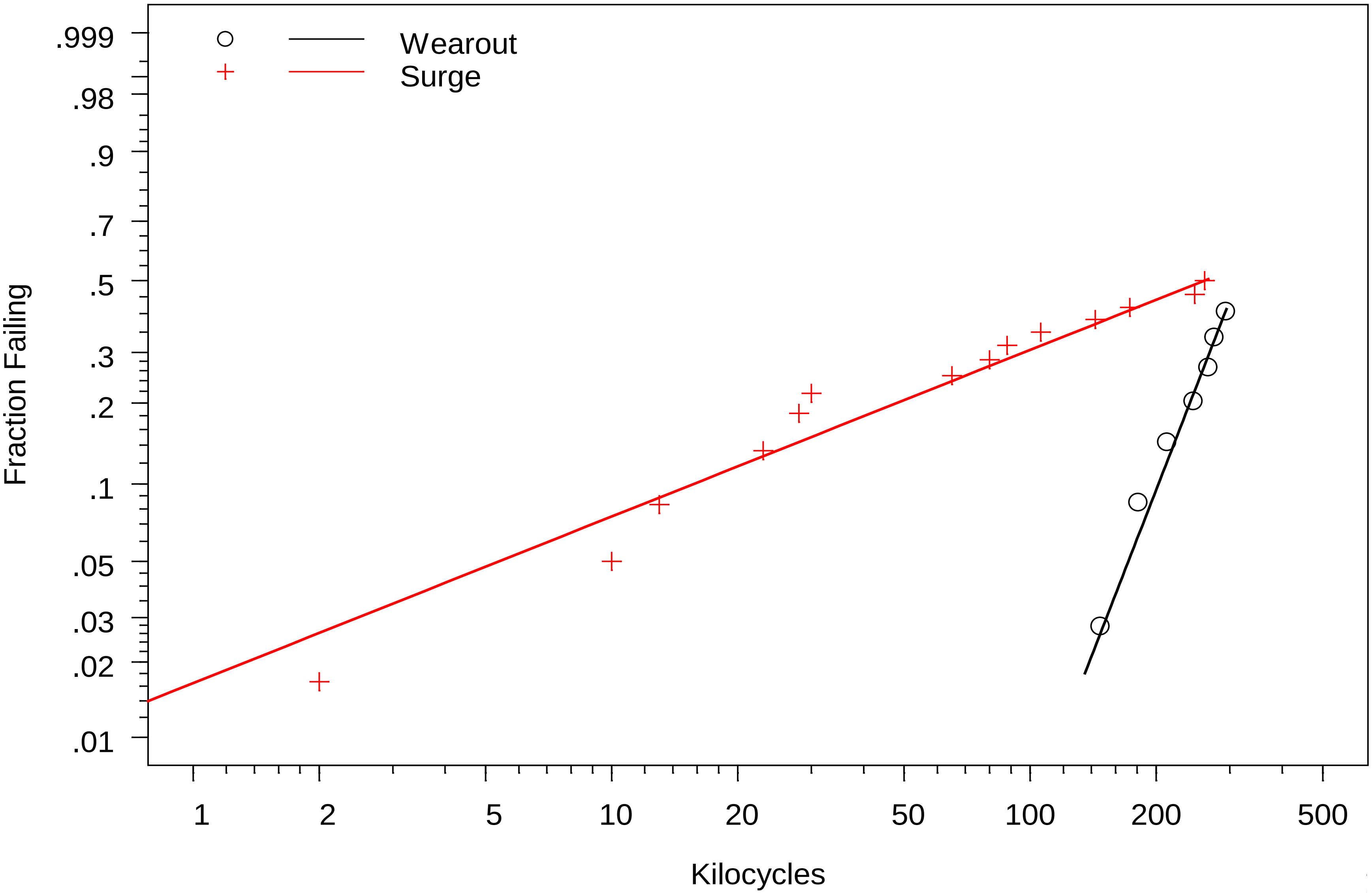
Device-G Field-Tracking Data

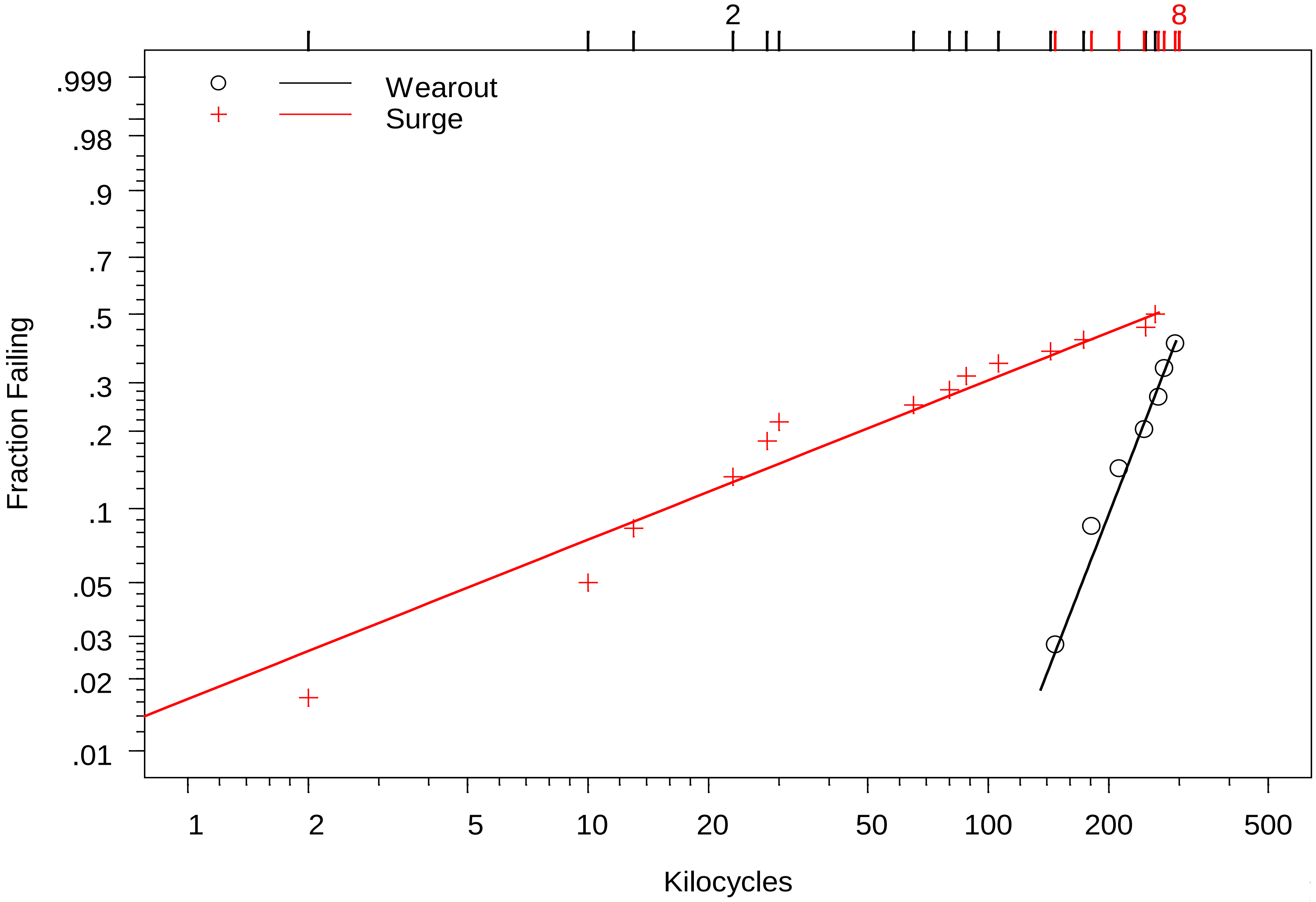
- Data from Meeker and Escobar (1998)
- Design life of 300 thousand cycles
- Units were failing in the field more rapidly than had been expected.
- Needs: information on how to improve reliability and an estimate of device MTTF.
- Two failure modes: surge and wear


Device-G Field Data
with Weibull ML Estimate and Pointwise 95% Confidence Intervals
Weibull Probability Plot
8
Fraction Failing
.999
.98
.9
.7
.5
.3
.2
.1
.05
.03
.02
.01
1
2
5
10
20
50
100
200
500
Kilocycles
$\hat{\eta} =$ 242.6
$\hat{\beta} =$ 0.9268

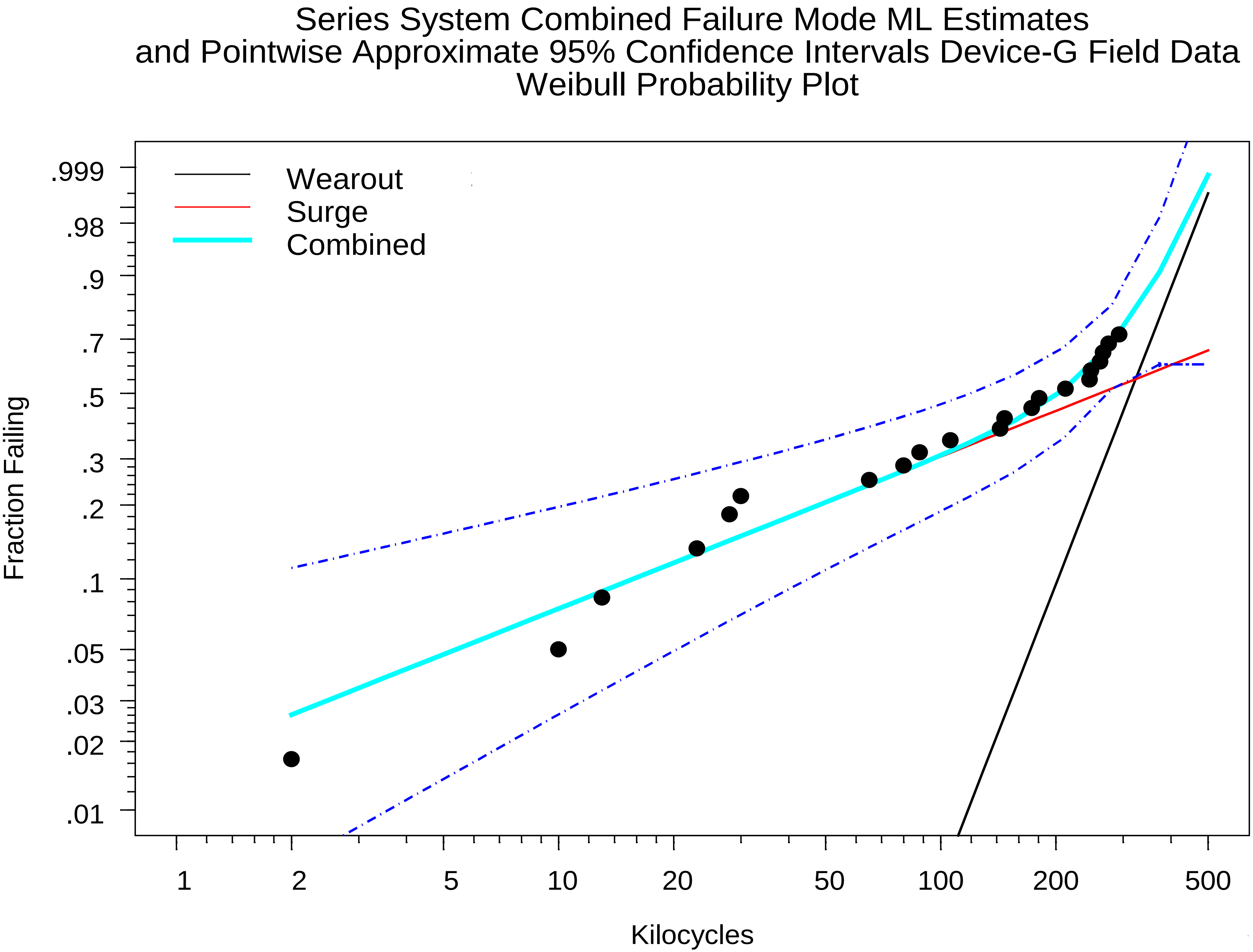

Device-G Field Data
Unit
Row
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
W
S
W
S
W
S
S
S
S
S
W
S
S
W
S
S
S
S
S
W
W
0
50
100
150
200
250
300
Kilocycles

Individual Device-G Field Data Failure Mode Weibull MLE's
Weibull Probability Plot





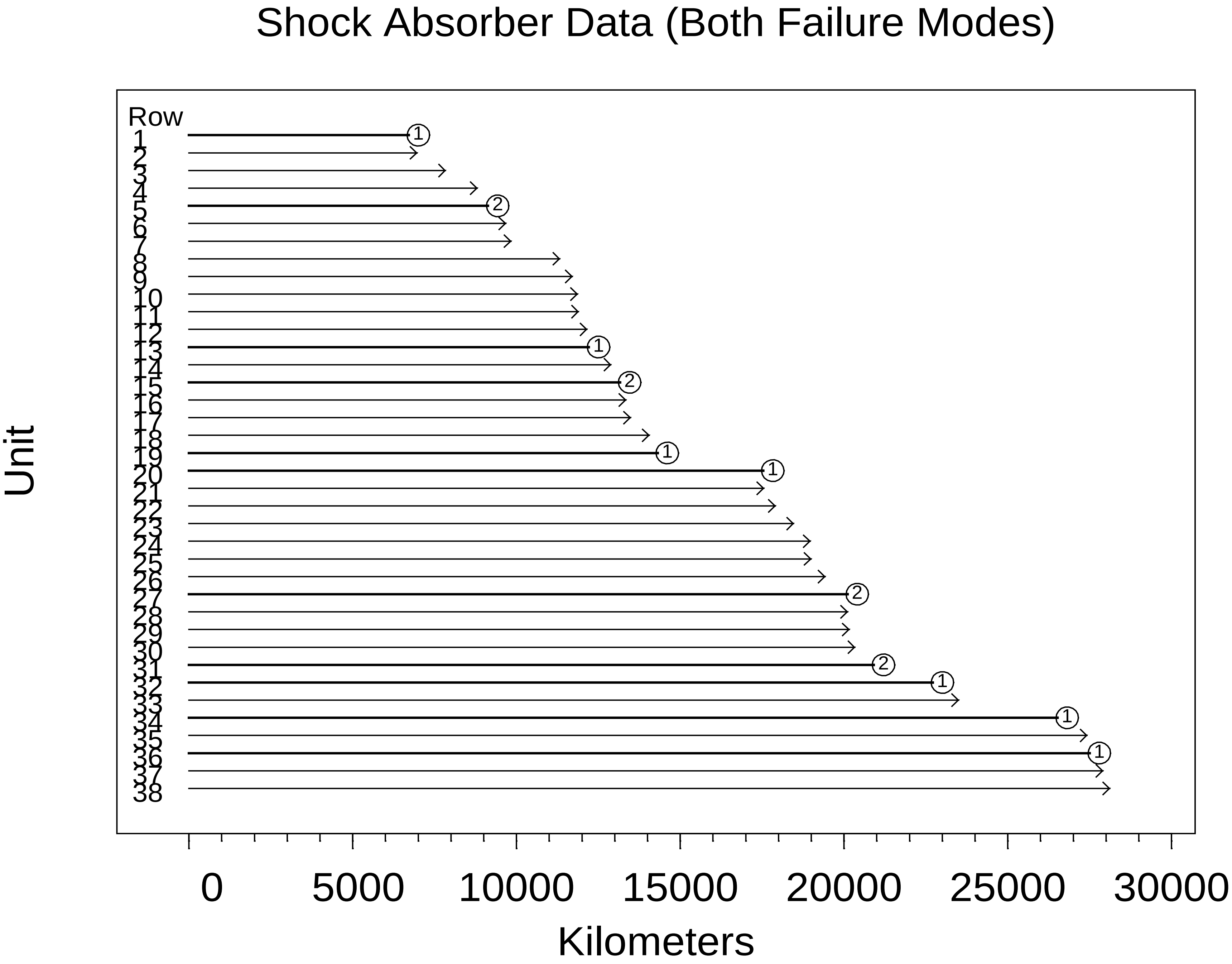
Individual Device-G Field Data Failure Mode Weibull MLE's
Weibull Probability Plot

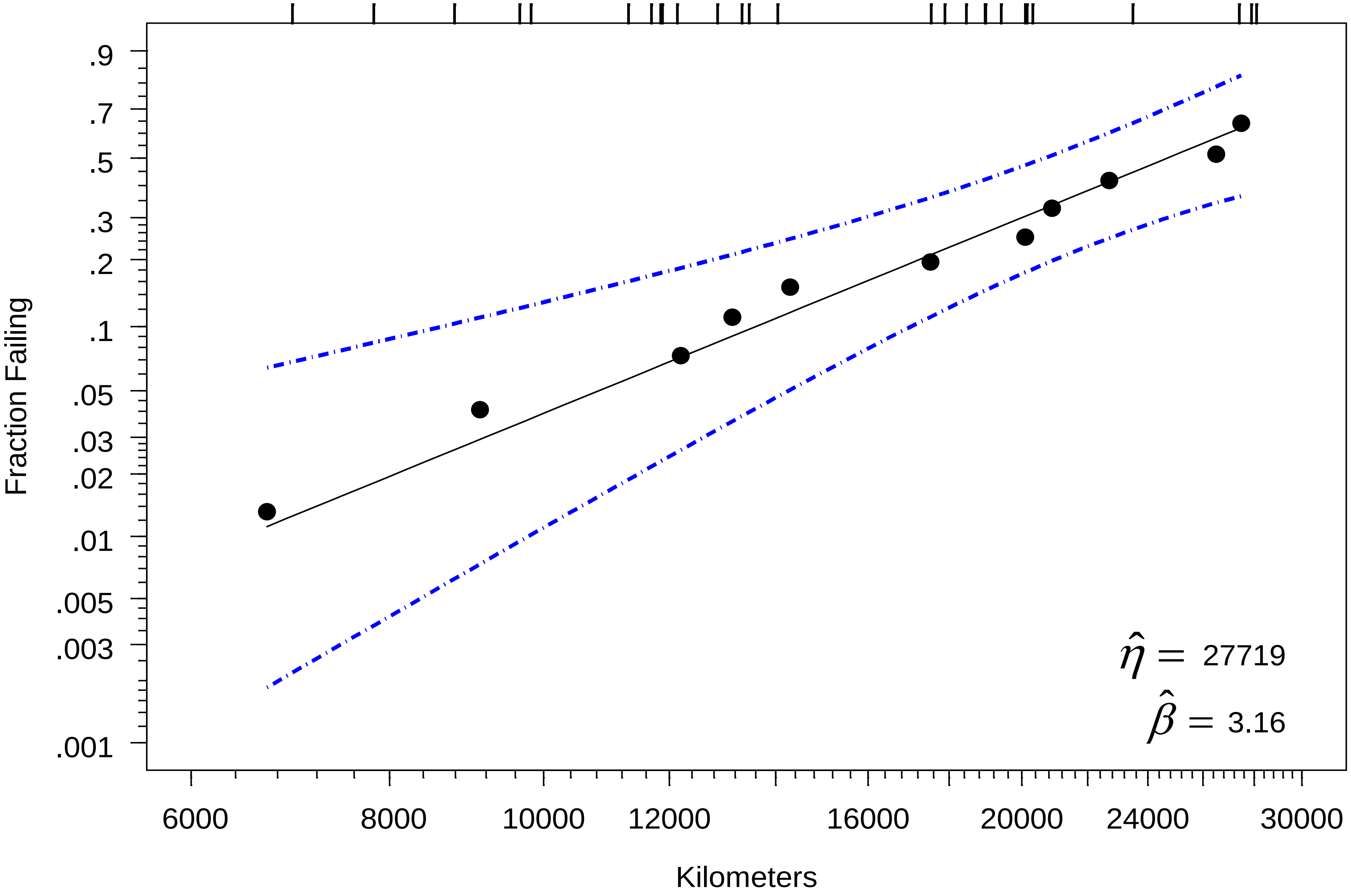


Series System Combined Failure Mode ML Estimates
and Pointwise Approximate 95% Confidence Intervals Device-G Field Data
Weibull Probability Plot

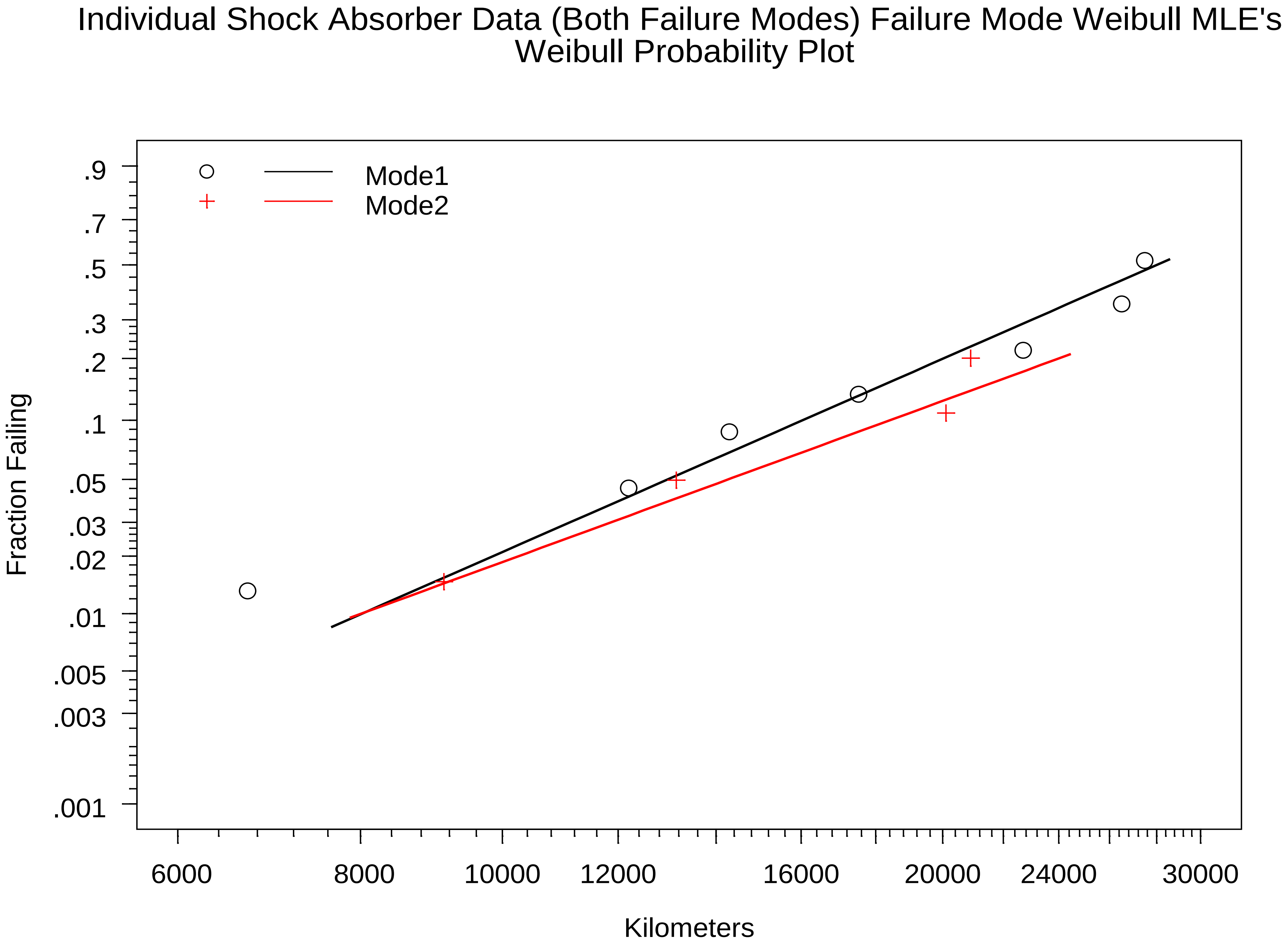
Shock Absorber Field Data

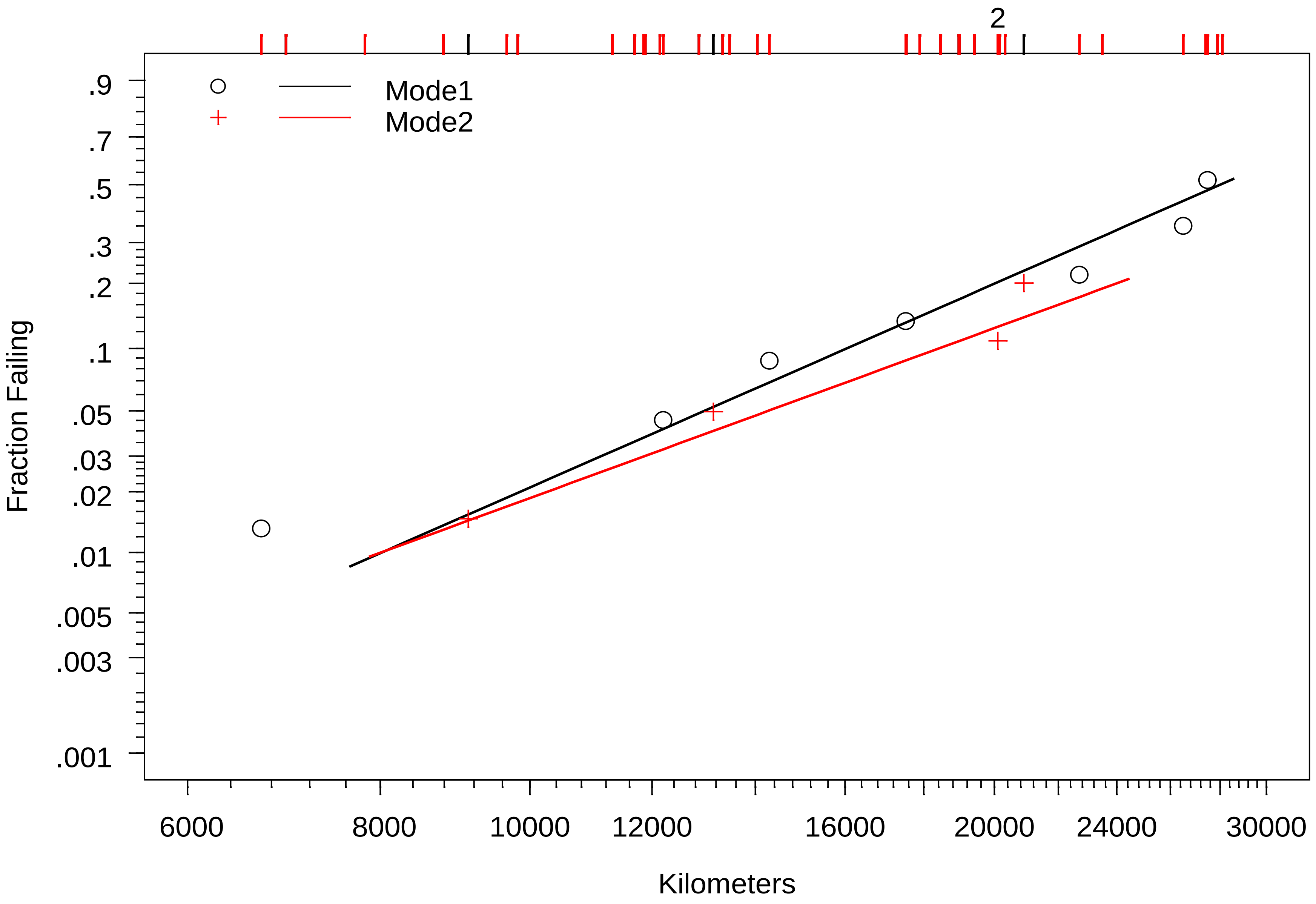
- Data from O’Connor (1985)
- Two failure modes (identified as Mode 1 and Mode 2)
- Need to estimate the failure-time distribution for the shock absorbers


Shock Absorber Data (Both Failure Modes)
Row
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
①
②
①
②
①
①
②
②
①
①
①
Unit
0
5000
10000
15000
20000
25000
30000
Kilometers



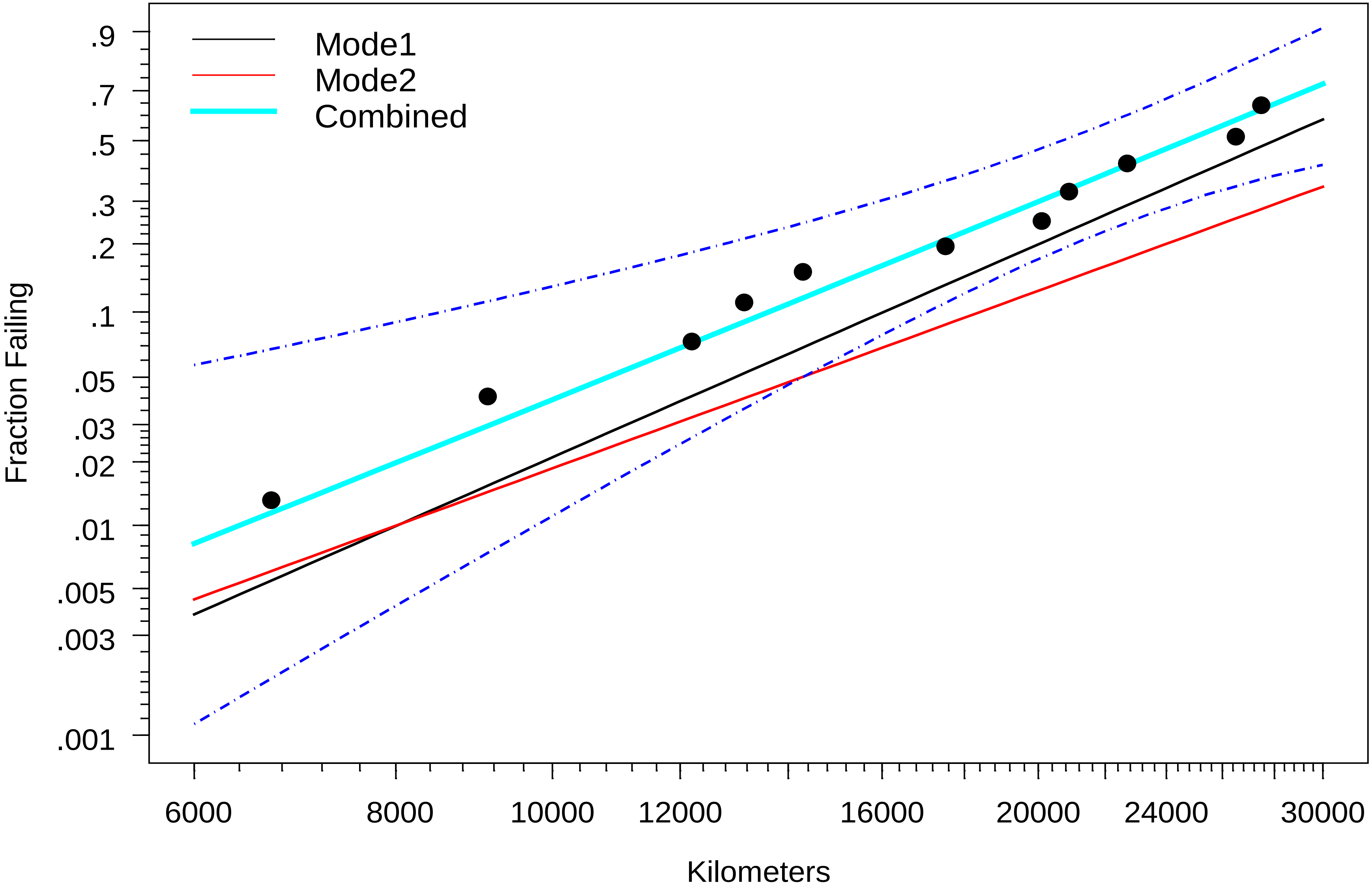
Shock Absorber Data (Both Failure Modes)
with Weibull ML Estimate and Pointwise 95% Confidence Intervals
Weibull Probability Plot

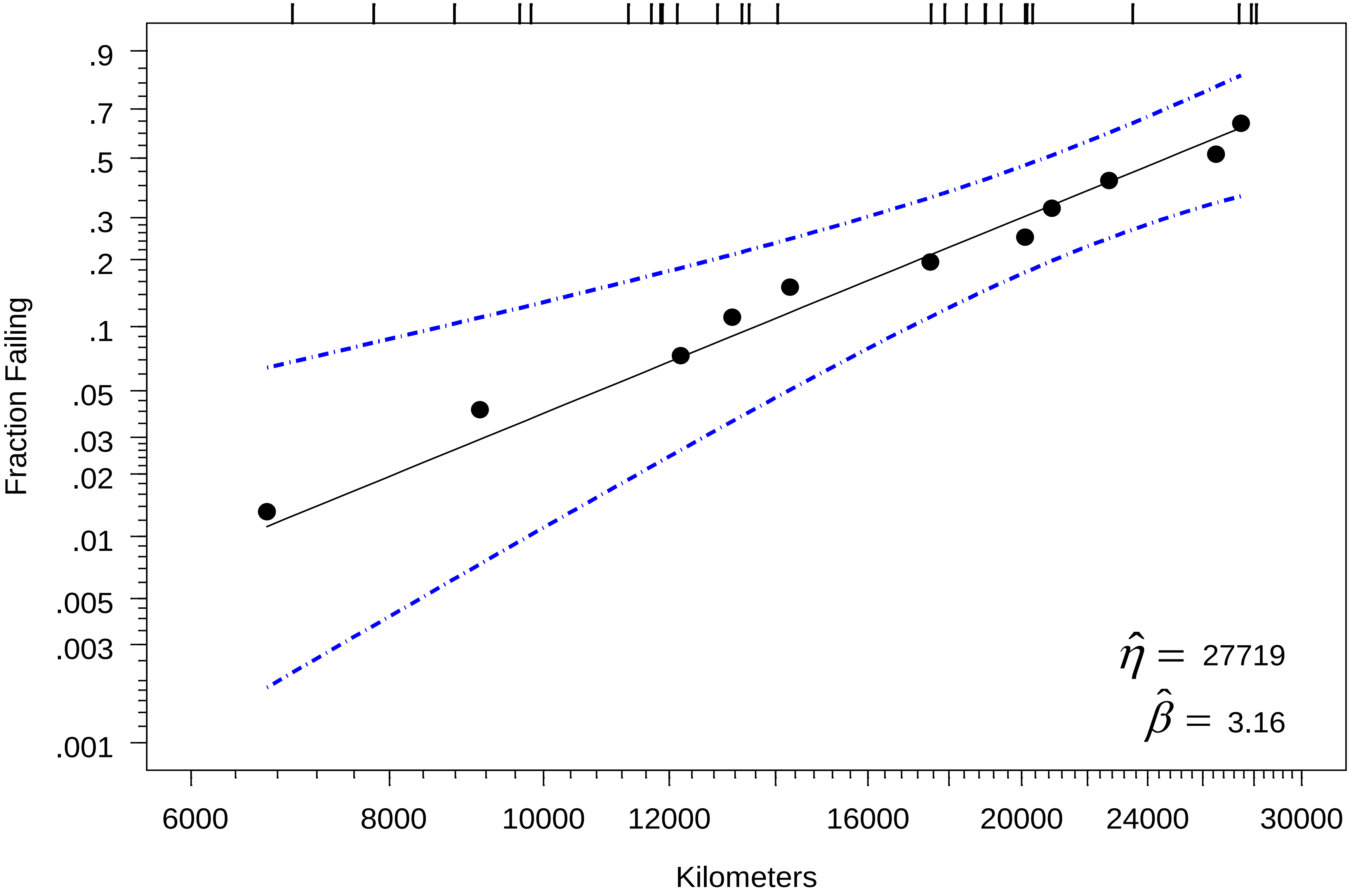

Individual Shock Absorber Data (Both Failure Modes) Failure Mode Weibull MLE's
Weibull Probability Plot
Mode1
Mode2
Fraction Failing
.9
.7
.5
.3
.2
.1
.05
.03
.02
.01
.005
.003
.001
6000
8000
10000
12000
16000
20000
24000
30000
Kilometers



Individual Shock Absorber Data (Both Failure Modes) Failure Mode Weibull MLE's
Weibull Probability Plot

Series System Combined Failure Mode ML Estimates
and Pointwise Approximate 95% Confidence Intervals Shock Absorber Data (Both Failure M
Weibull Probability Plot





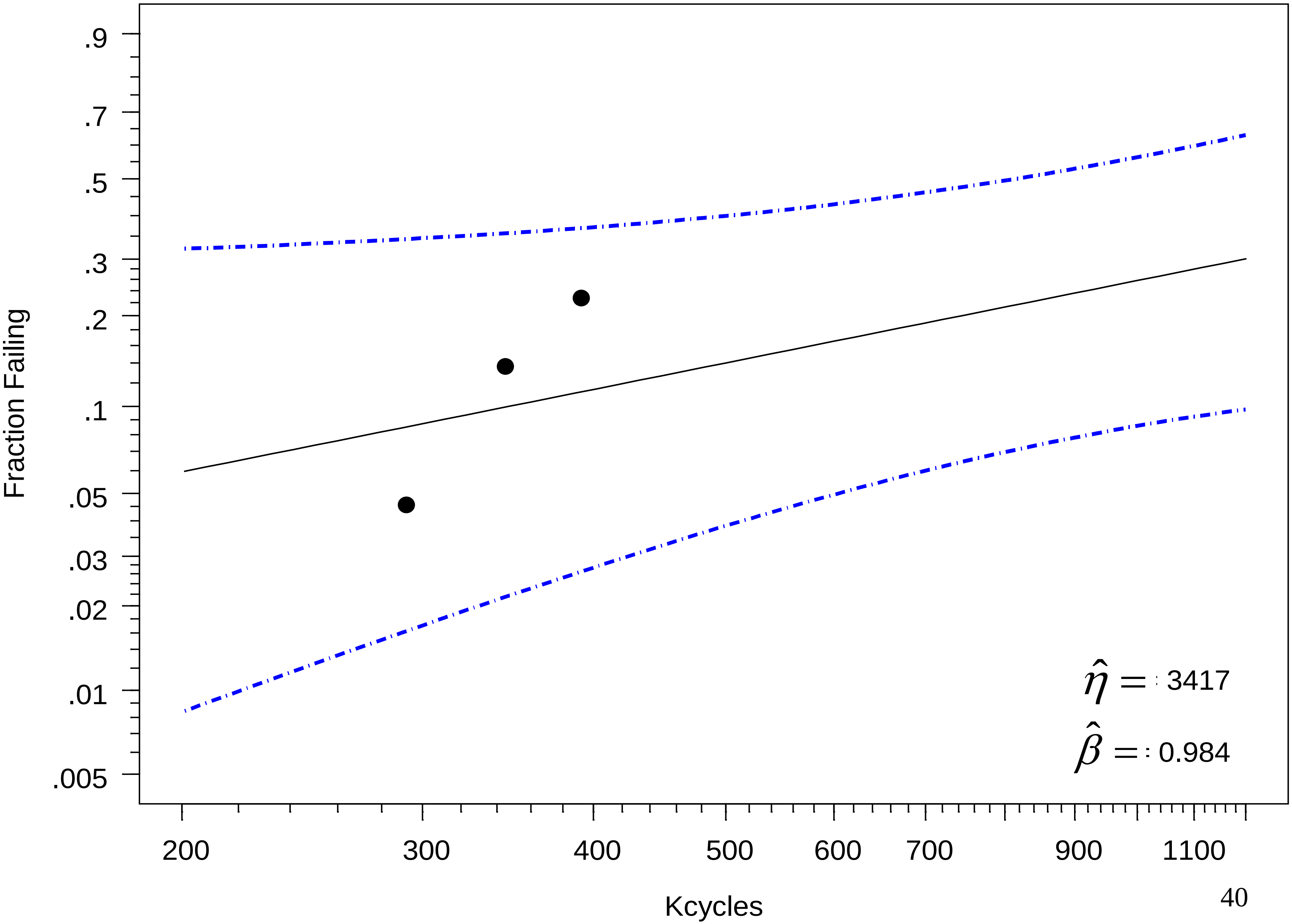
Shock Absorber Data (Both Failure Modes)
with Weibull ML Estimate and Pointwise 95% Confidence Intervals
Weibull Probability Plot

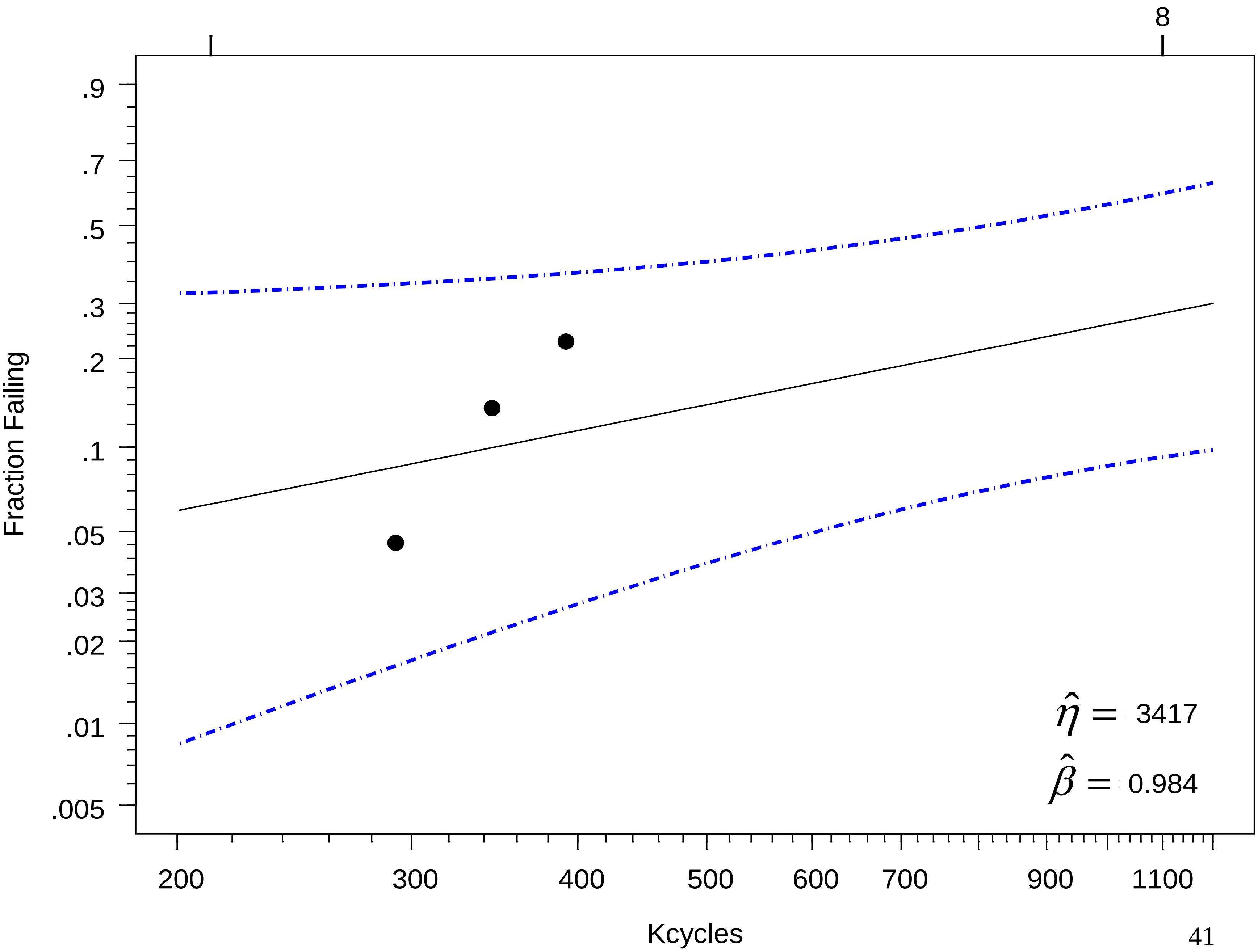
Lessons Learned

- 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

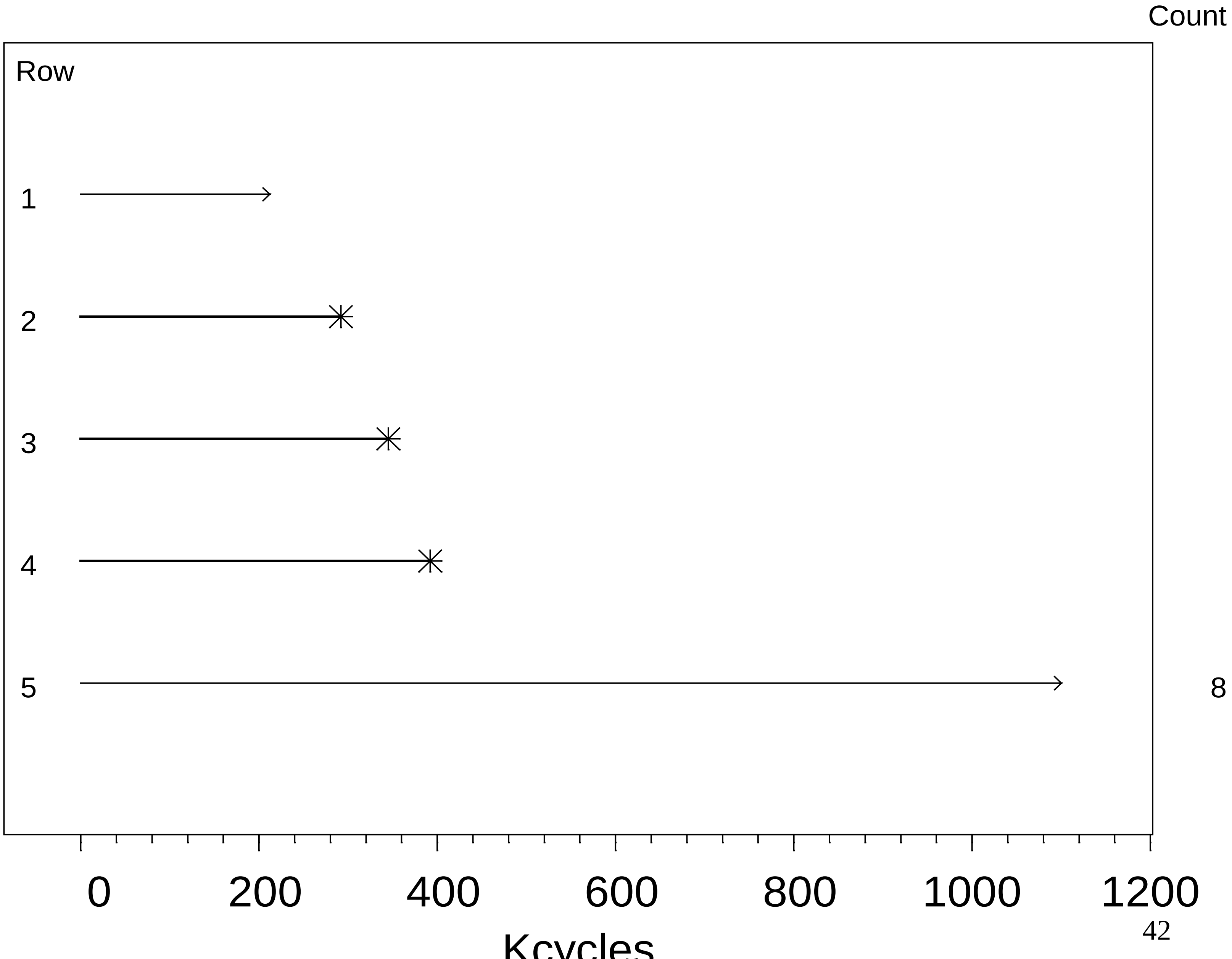
Bearing-A Bench Test Results

- Data from student in 1999 FTC short course
- Continuous-run test for a newly designed bearing
- Sample of 12 units put on test; one early removal; 3 failures.
- Test terminated at 1100 thousand cycles


.9
.7
.5
.3
.2
.1
.05
.03
.02
.01
.005
Fraction Failing
200
300
400
500
600
700
900
1100
Kcycles
$\hat{\eta} =$ 3417
$\hat{\beta} =$ 0.984


8
.9
.7
.5
.3
.2
.1
.05
.03
.02
.01
.005
Fraction Failing
200
300
400
500
600
700
900
1100
Kcycles
$\hat{\eta} =$ 3417
$\hat{\beta} =$ 0.984

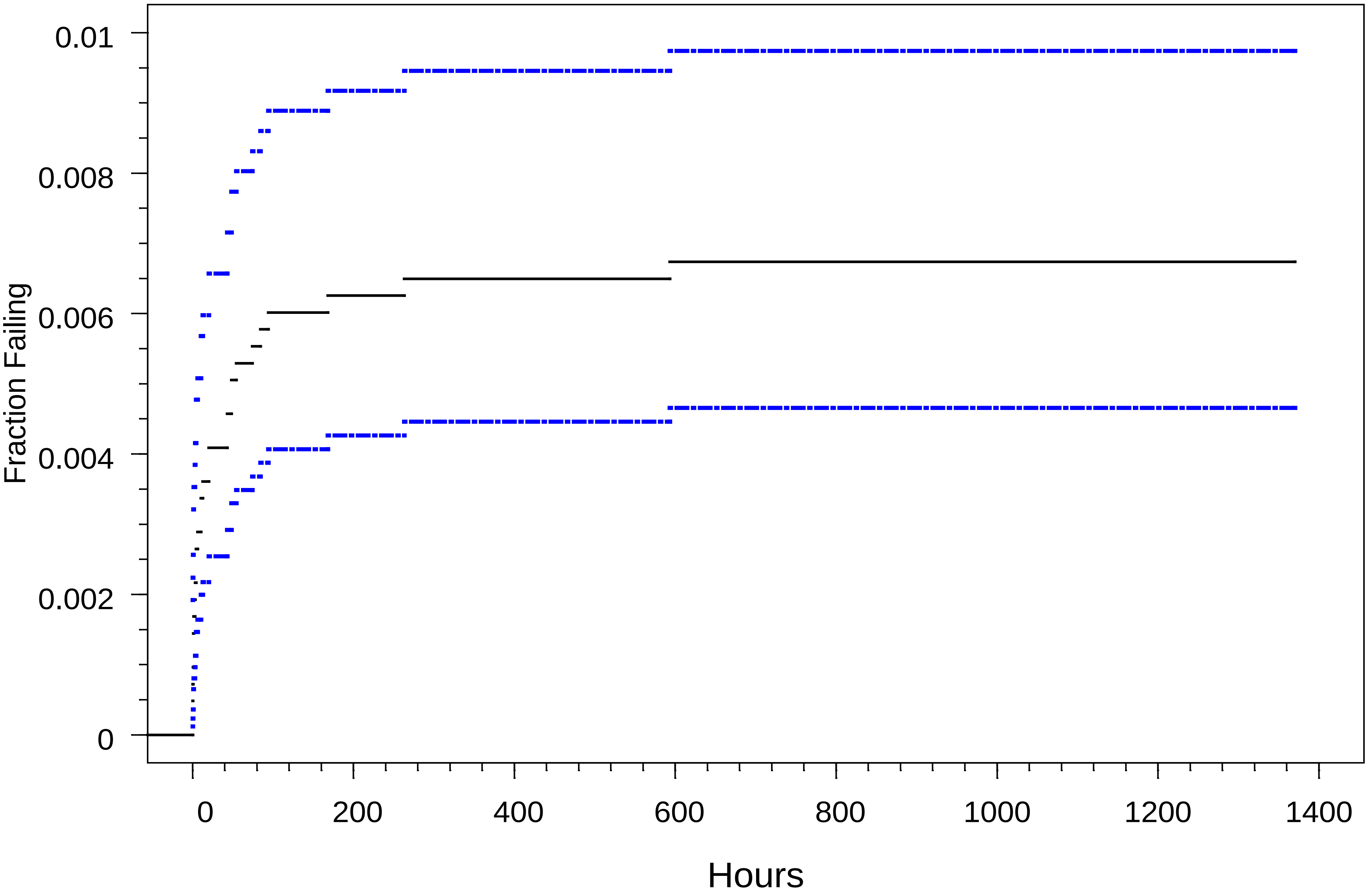
BearingA data

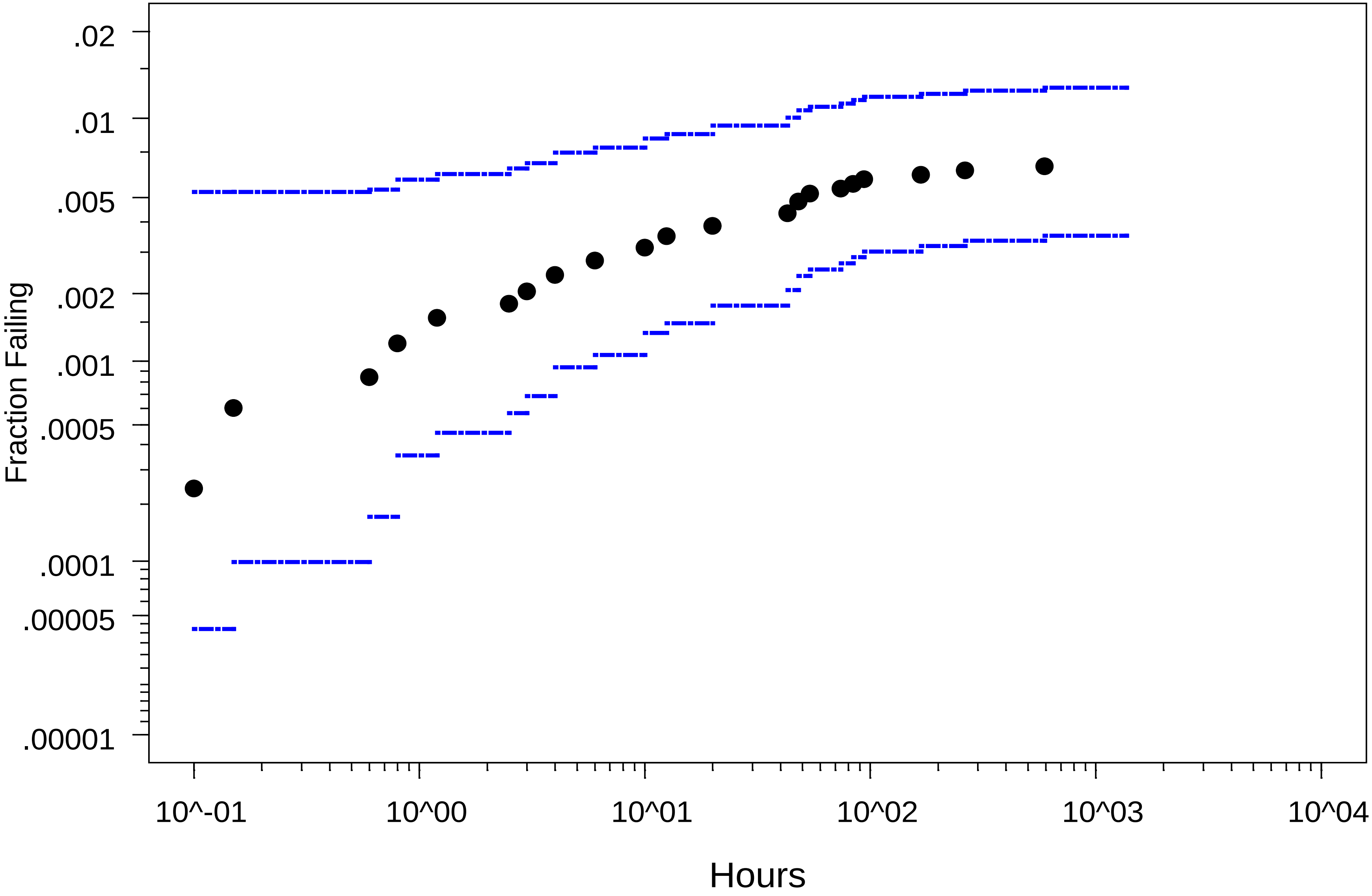


IC Device Accelerated Life Test

- Data from Meeker (1987)
- 4156 units tested for 1370 hours
- 28 failures; last failure at 593 hours
- Needed information: fraction failing at 20,000 hours

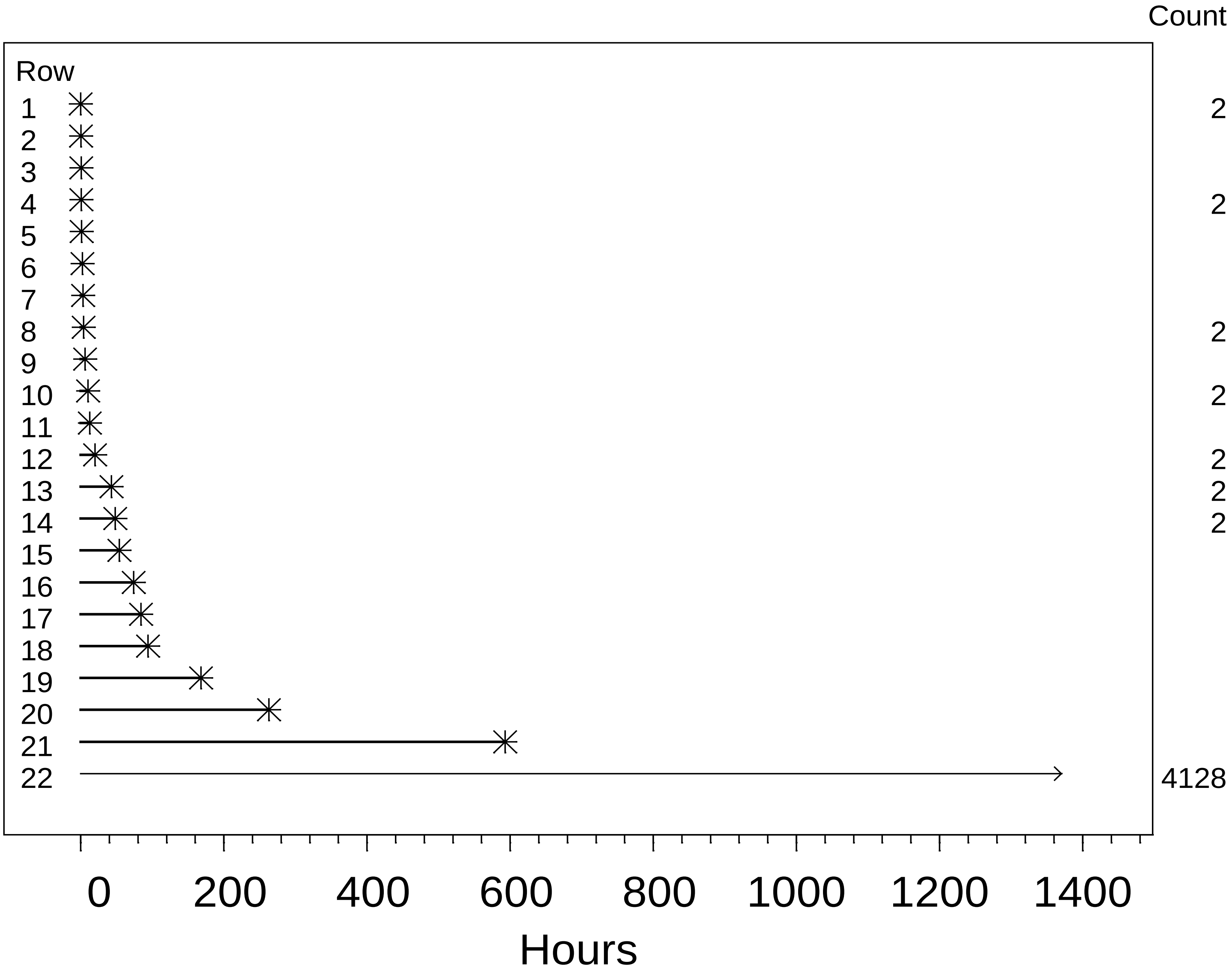
Integrated Circuit Failure Data After 1370 Hours
with Nonparametric Pointwise 95% Confidence Bands



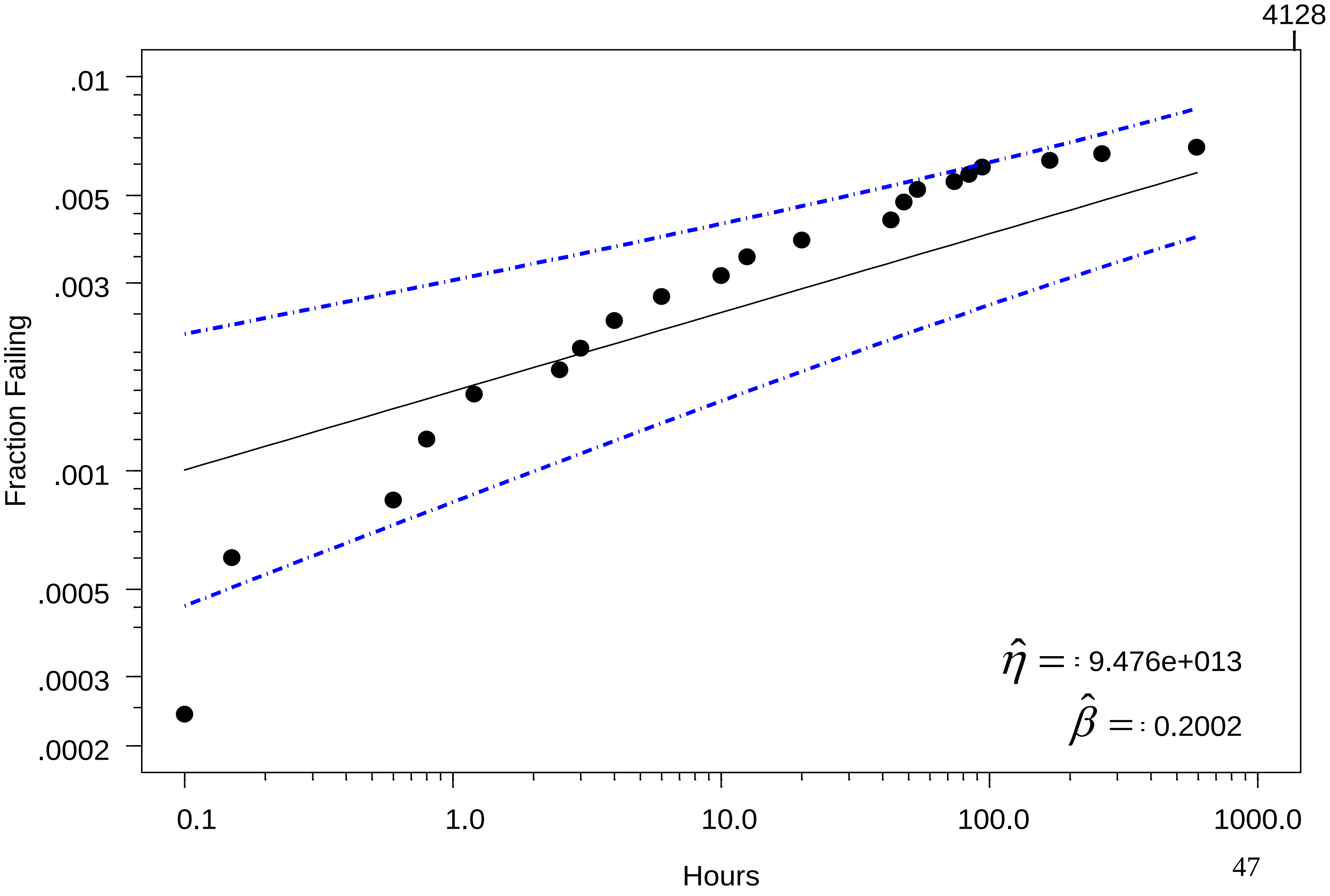


Integrated Circuit Failure Data After 1370 Hours
with Nonparametric Simultaneous 95% Confidence Bands
Lognormal Probability Plot

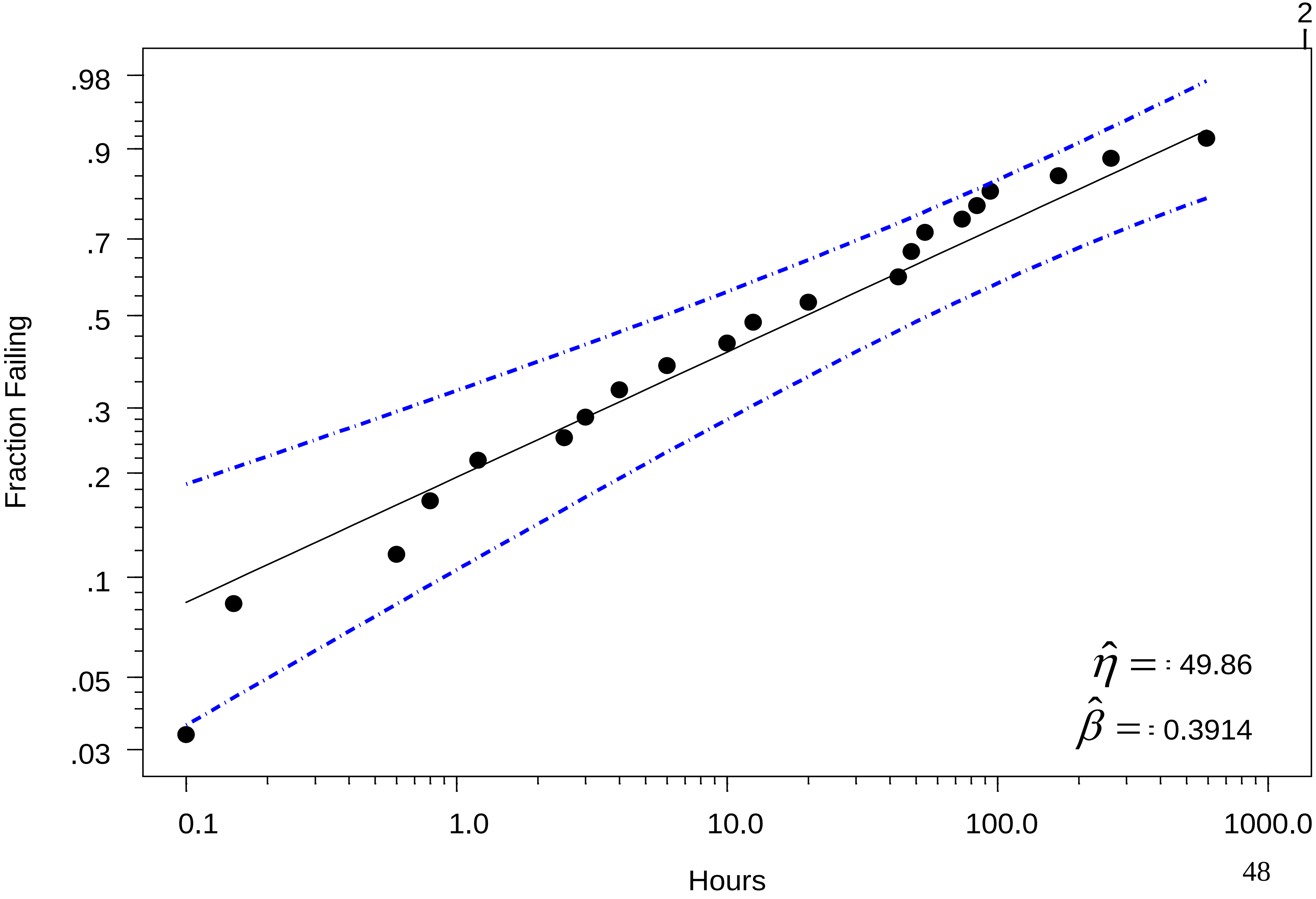
Integrated Circuit Failure Data After 1370 Hours

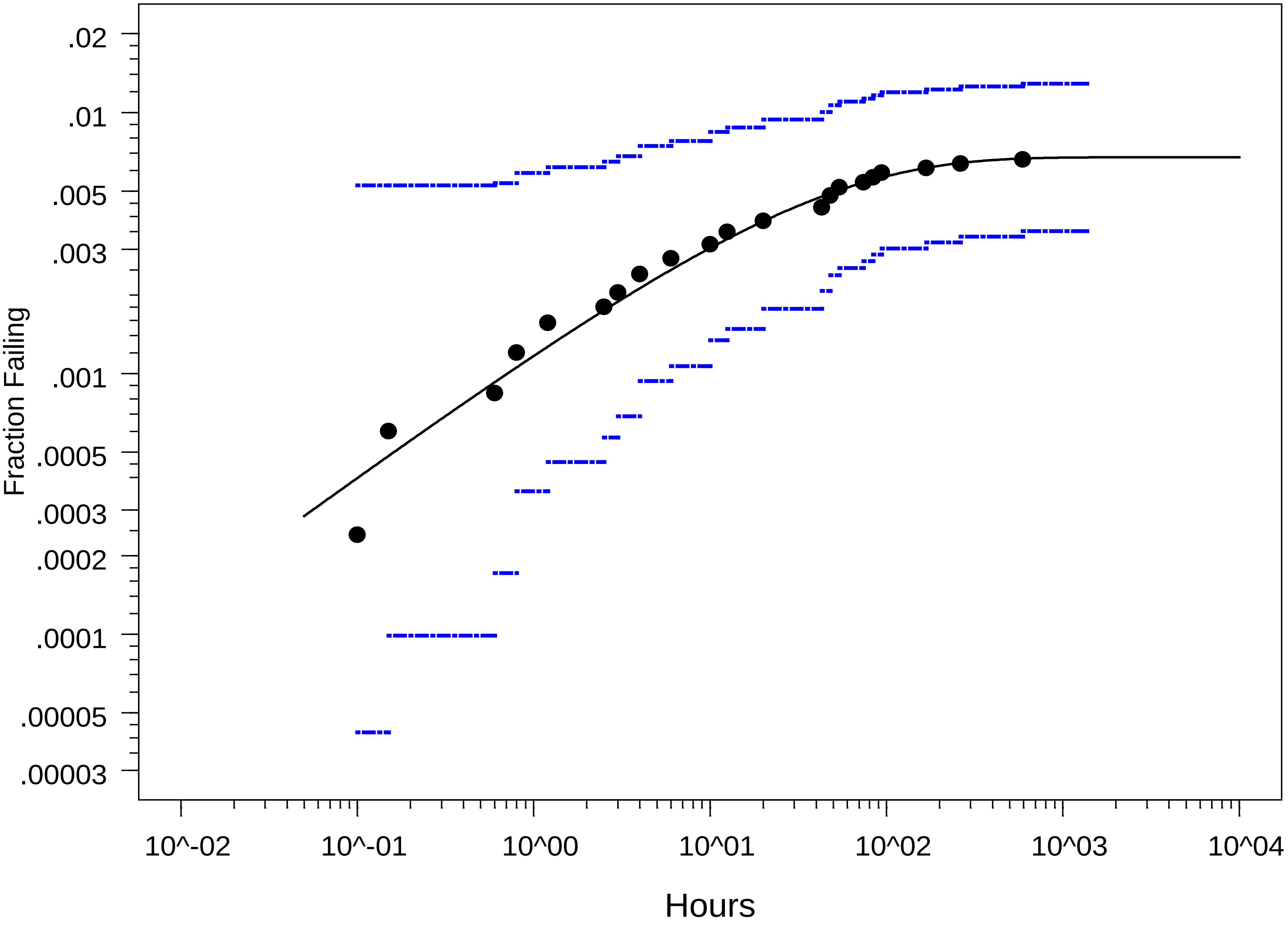


Integrated Circuit Failure Data After 1370 Hours with Weibull ML Estimate and Pointwise 95% Confidence Intervals Weibull Probability Plot



lfp1370Fix2 data
with Weibull ML Estimate and Pointwise 95% Confidence Intervals
Weibull Probability Plot




.02
.01
.005
.003
.001
.0005
.0003
.0002
.0001
.00005
.00003
Fraction Failing
10^-02
10^-01
10^00
10^01
10^02
10^03
10^04
Hours

Lessons Learned

- Leveling of a probability plot usually implies a “limited failure population.”
- If you do not wait long enough
  - You cannot decide if you have many units failing slowly or a small fraction failing early.
  - Conclusions will depend strongly on the assumed distribution model

Motivation for Accelerated Testing

Today manufactures 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

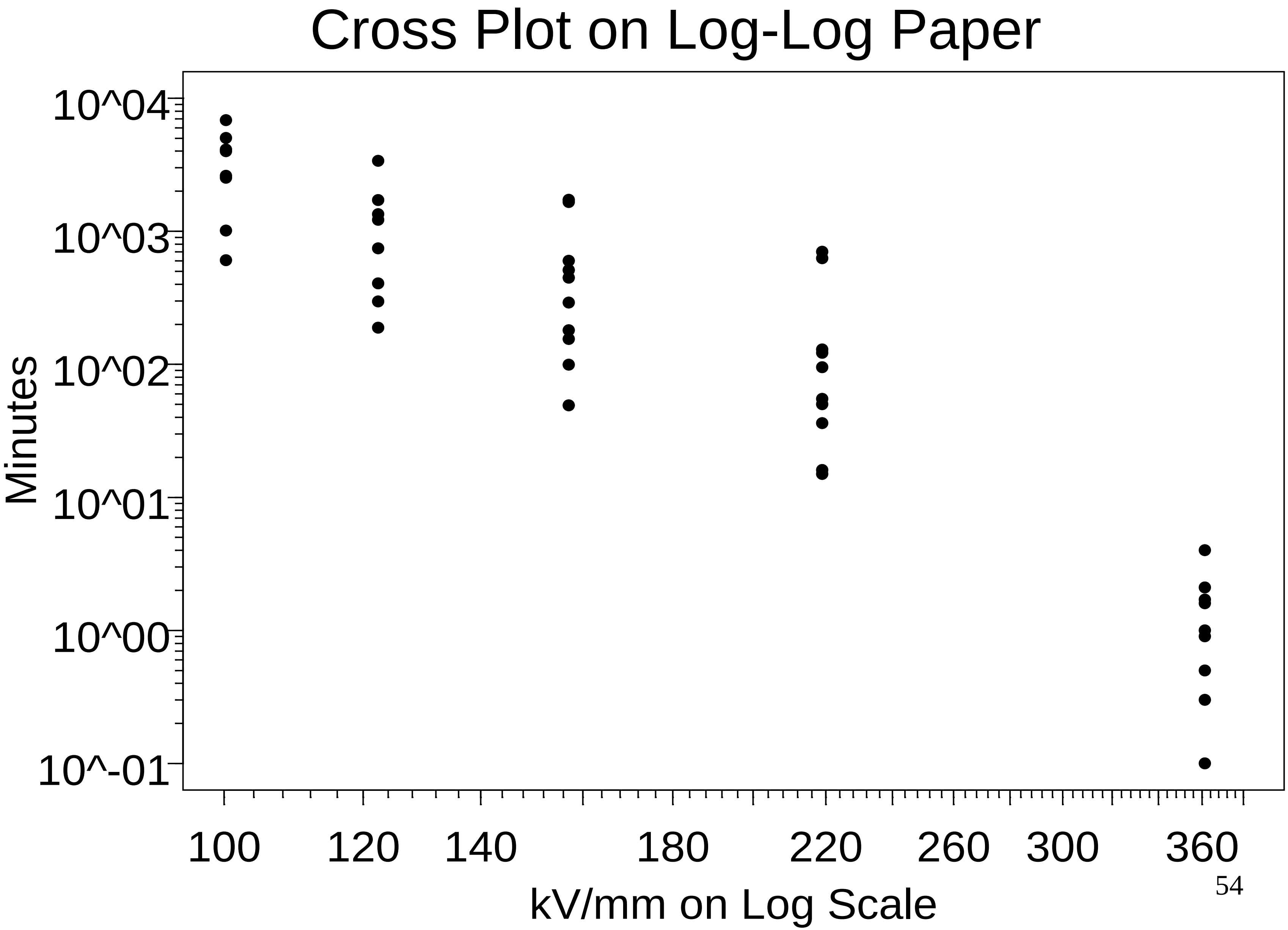
Usually testing at higher levels of integration will result in less acceleration

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).

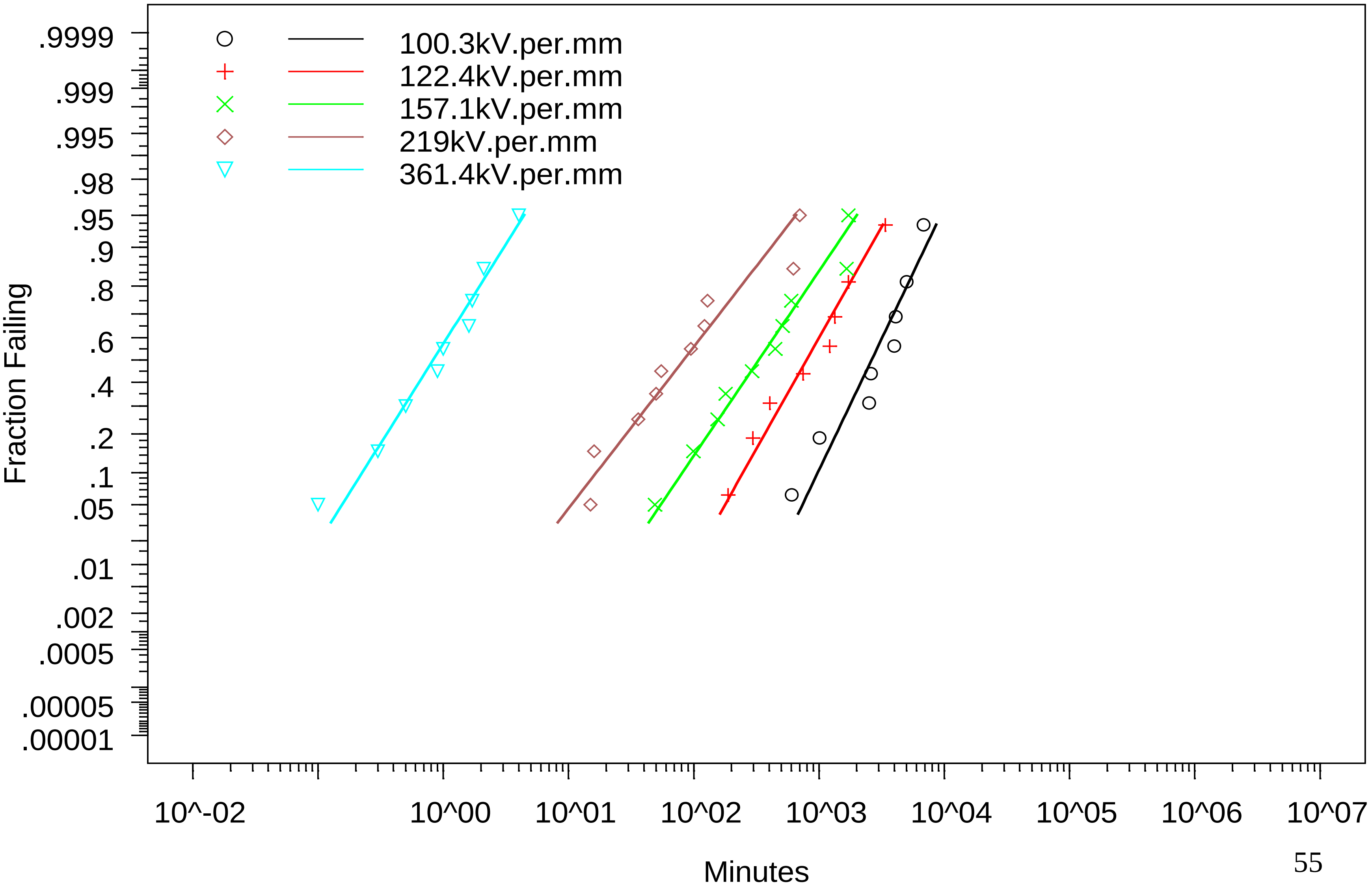
Mylar-Polyurethane Laminated Direct Current High Voltage Insulating Structure



Cross Plot on Log-Log Paper

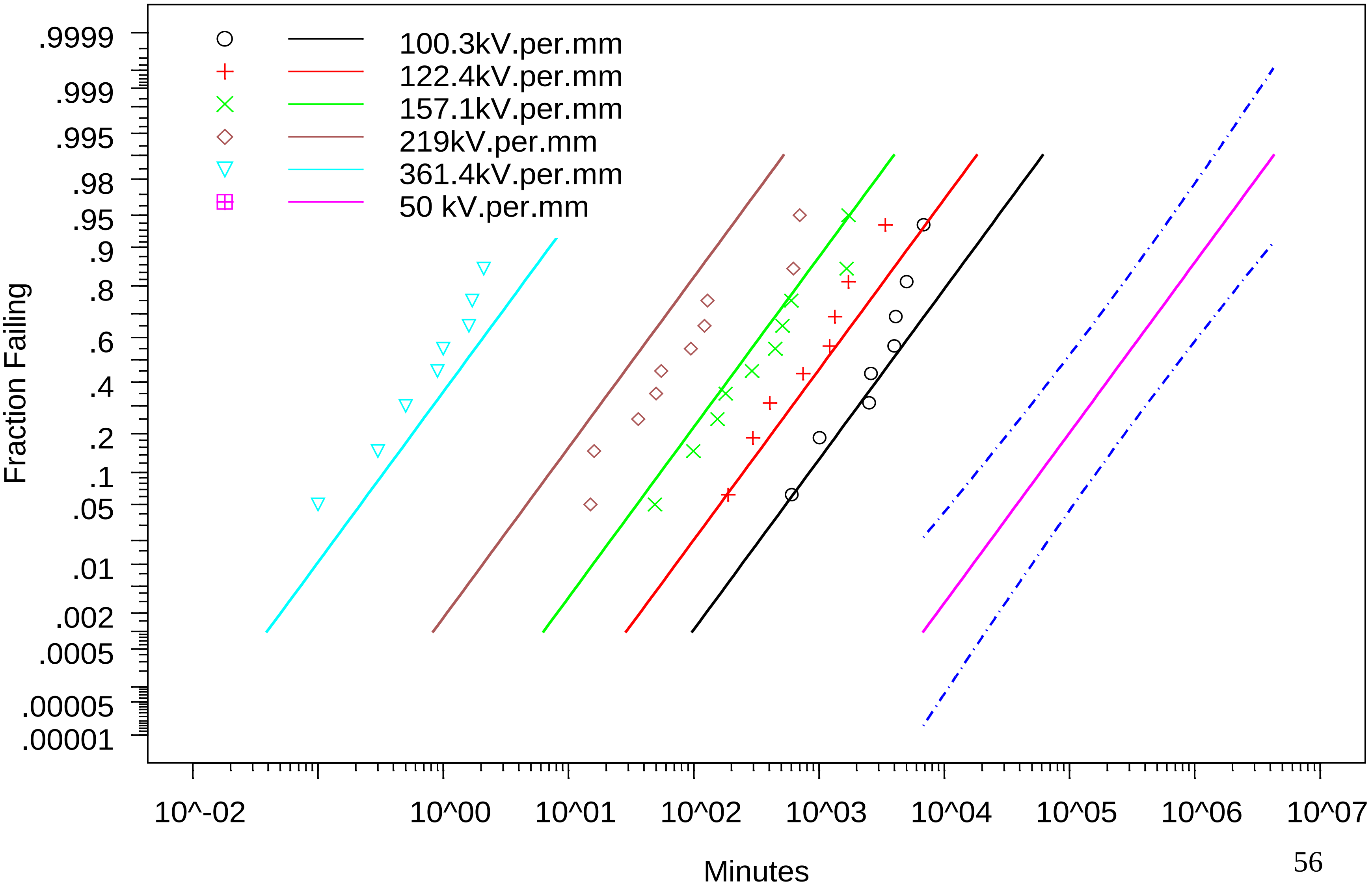
Mylar Polyurethane Insulating Structure

Data Analysis at Individual Conditions



Mylar Polyurethane Insulating Structure Data

Inverse Power Regression Model All Data



The Inverse Power Law/Lognormal Model for Insulation Lifetimes

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

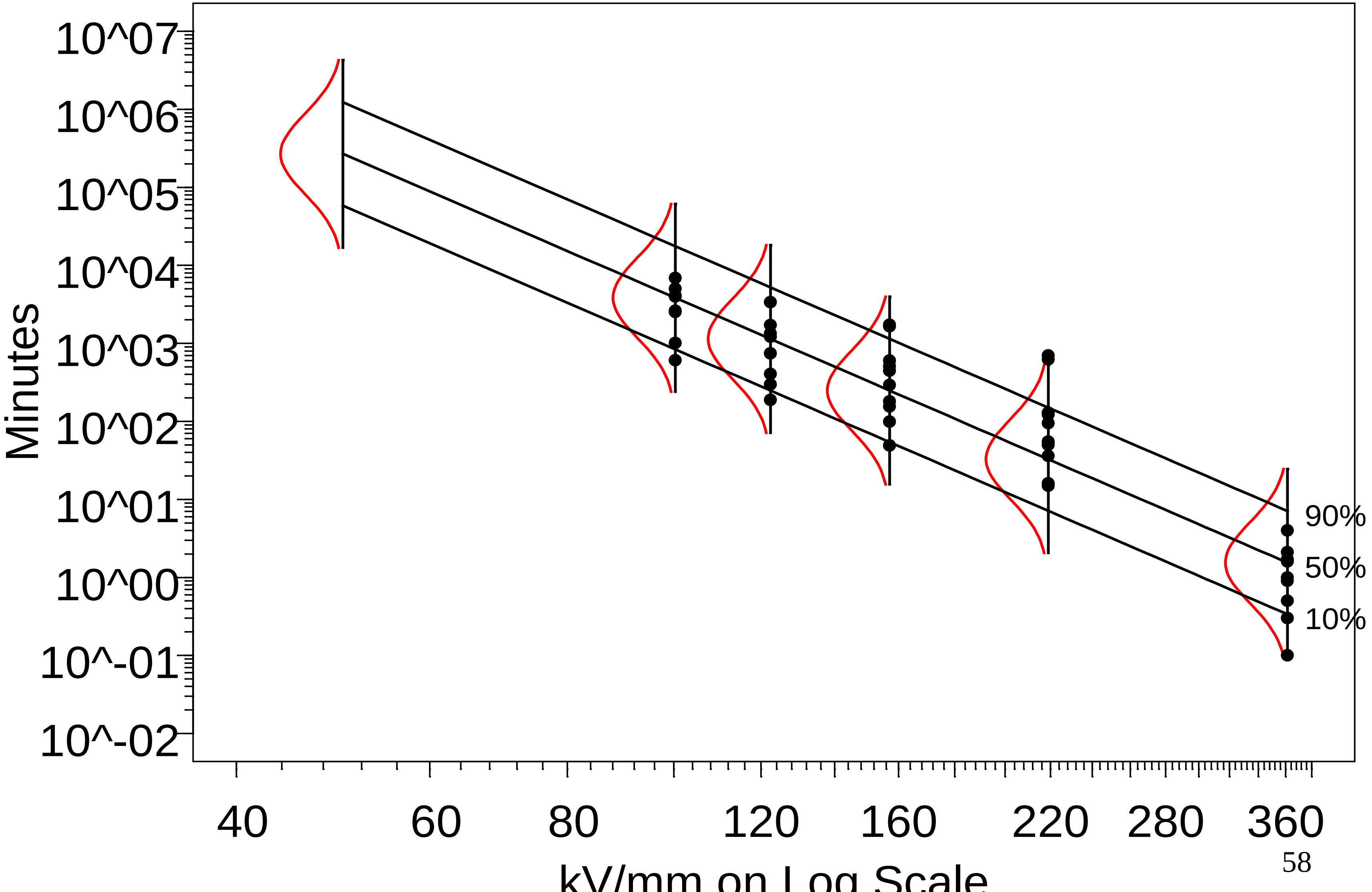
$$\Pr[T(\text{temp}) \le t] = \Phi_{\text{NOR}}\left[\frac{\log(\text{t})\text{-}\mu(x)}{\sigma}\right]$$

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

- 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

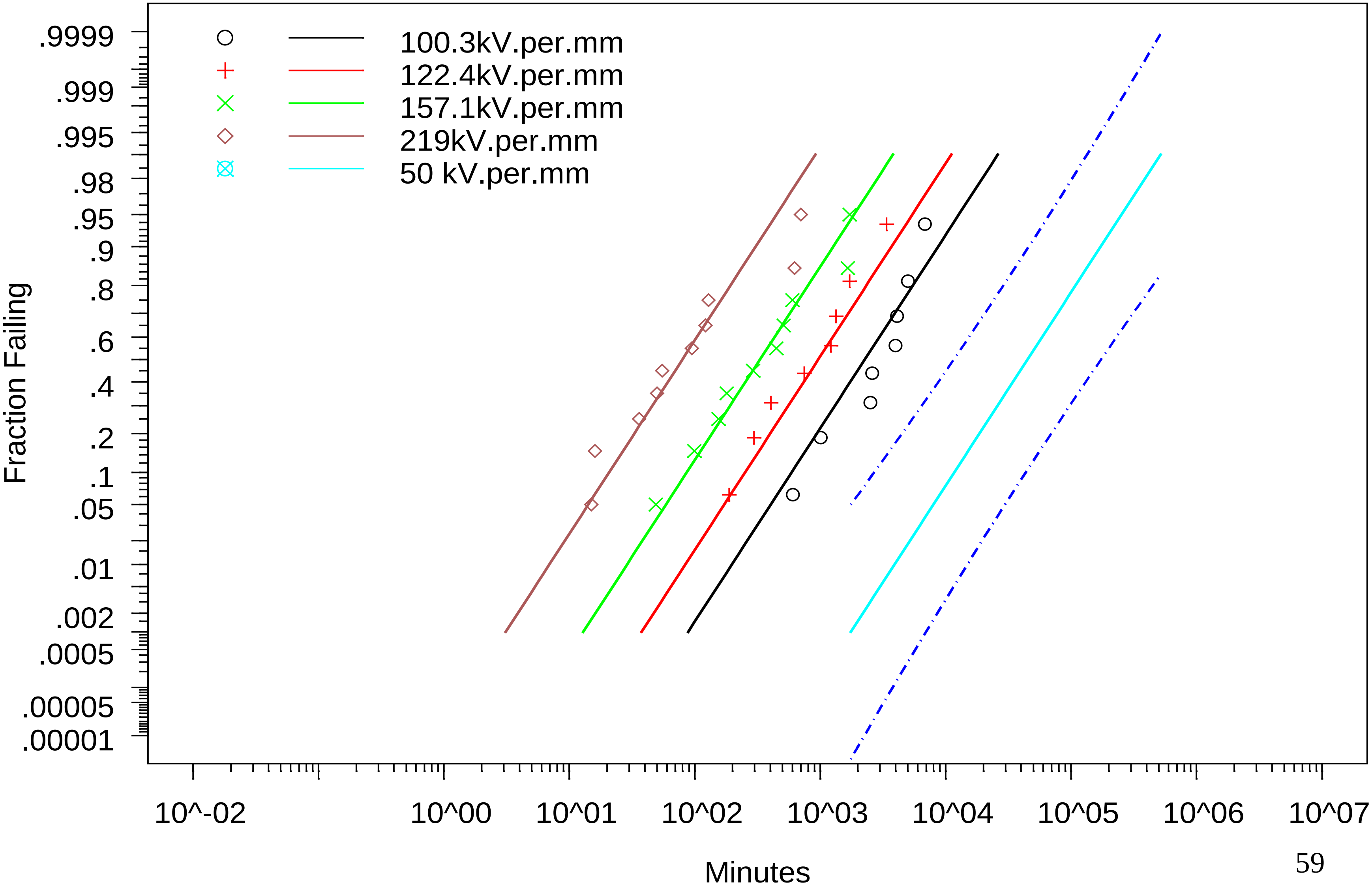
Mylar Polyurethane Insulating Structure Data

Inverse Power Regression Model All Data



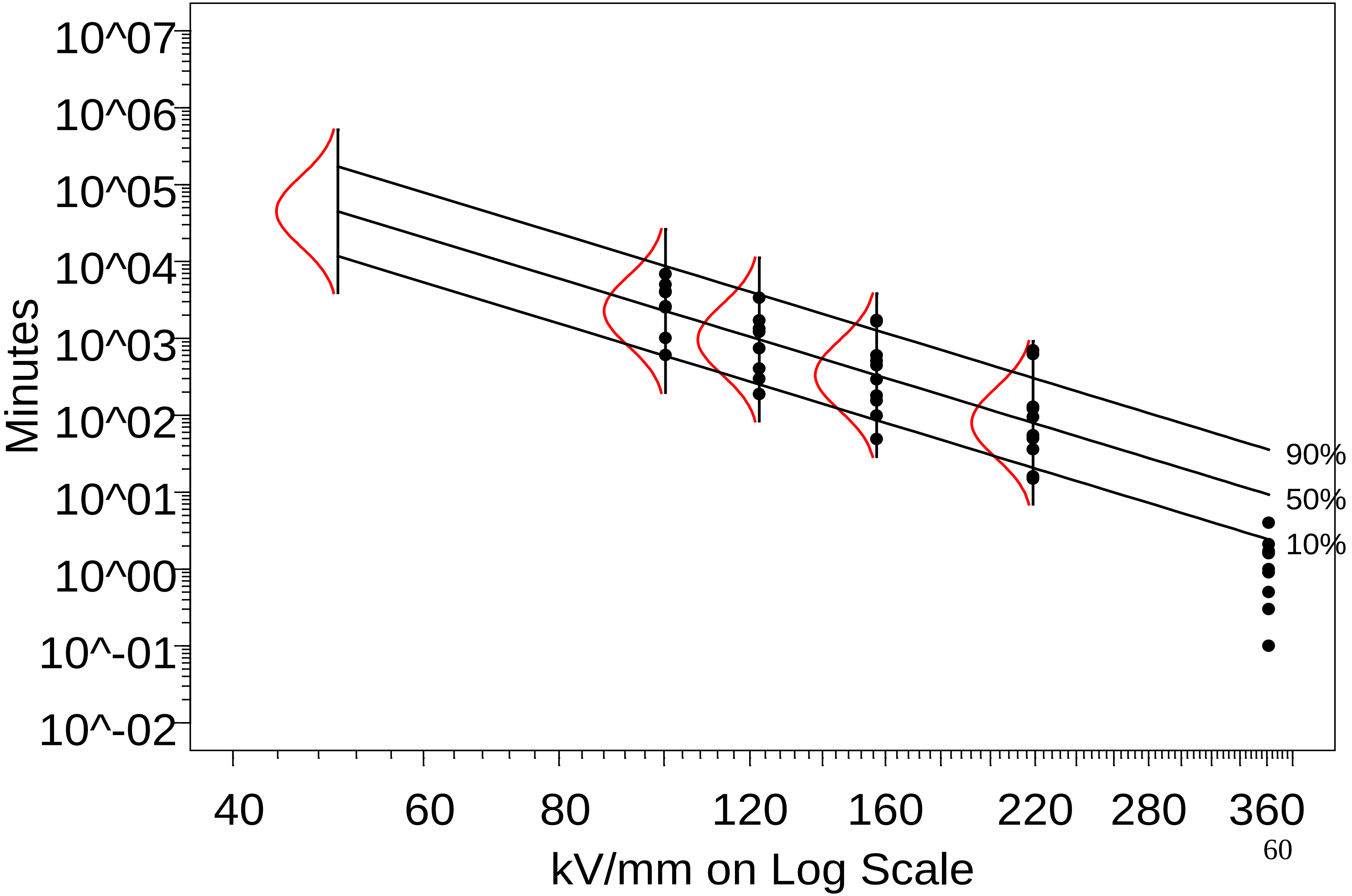
Mylar Polyurethane Insulating Structure Data

Inverse Power Regression Model Good Data



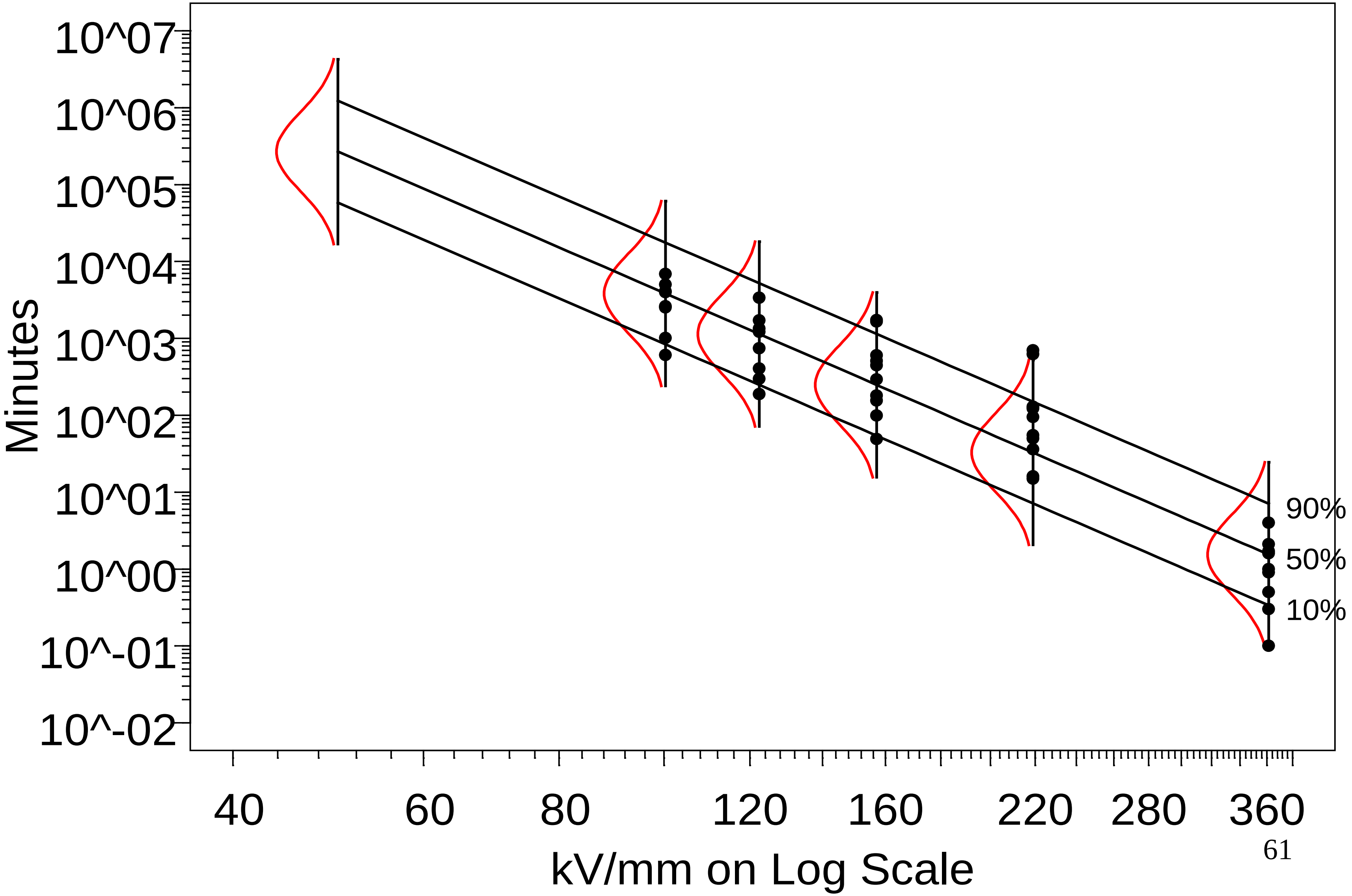
Mylar Polyurethane Insulating Structure Data

Inverse Power Regression Model Good Data



Mylar Polyurethane Insulating Structure Data

Inverse Power Regression Model All Data



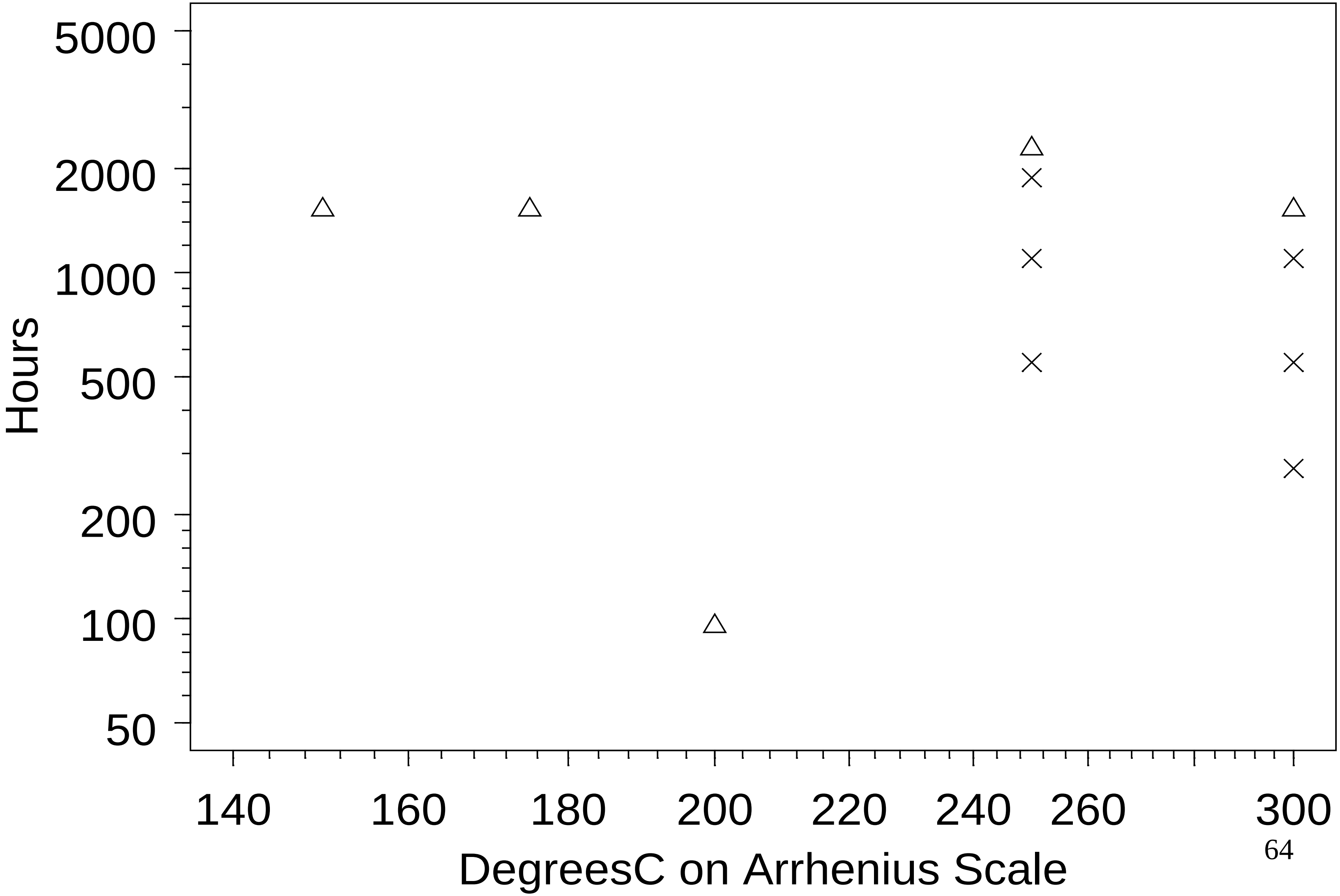
Lessons Learned

- Transformation of data can simplify modeling
- The inverse power relationship [log life is linear in log(Voltage Stress)] may be 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

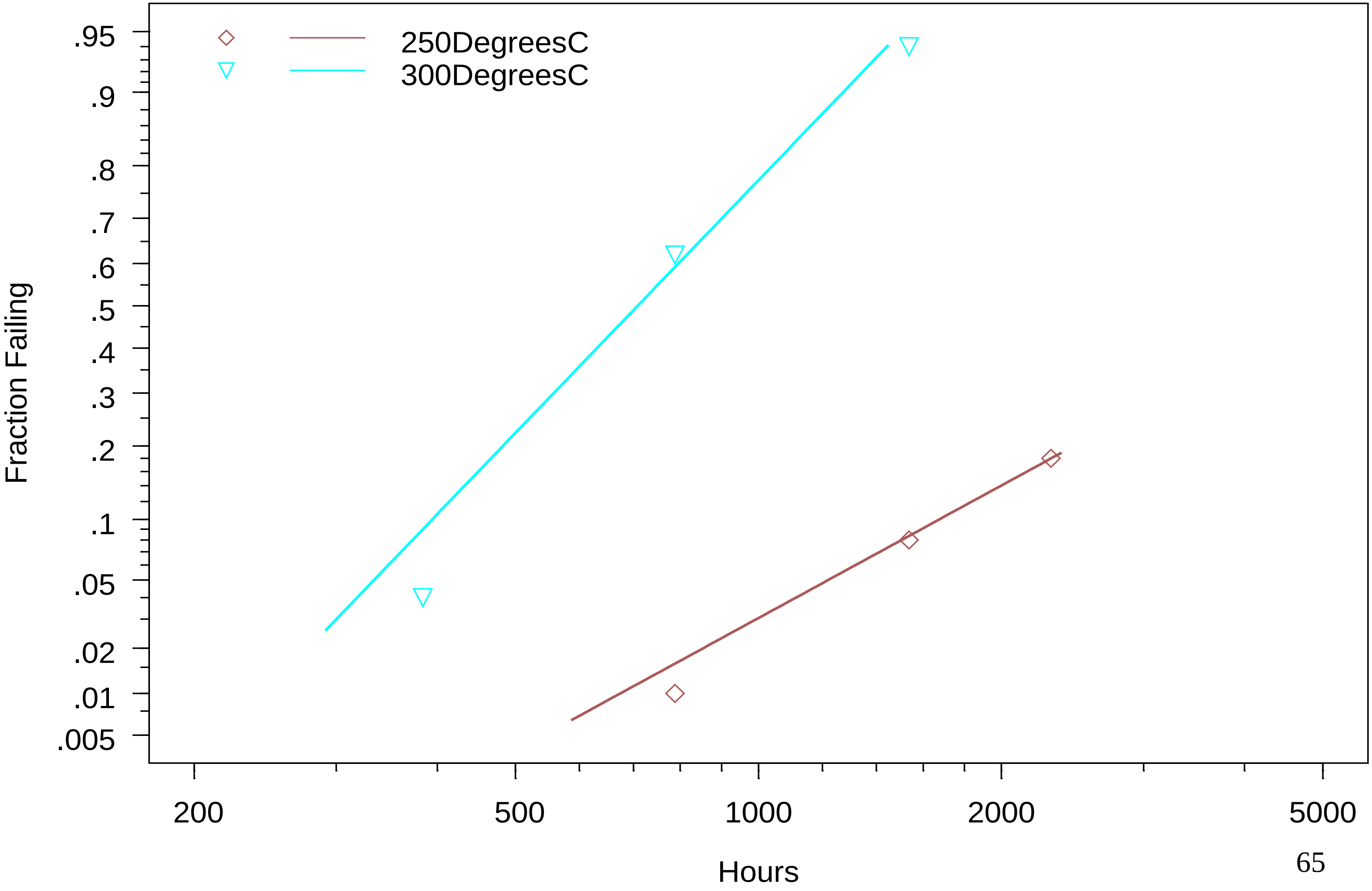
New Technology IC Device ALT

- Data from Meeker and Escobar (1998)
- 50 devices tested at each of 150, 175, 200, 250, and 300 degrees C
- Interval censoring (inspection of devices approximately every four days)
- Failures seen only at 250 and 300 degrees C
- Need to estimate the life distribution at 100 degrees C

New Technology Device ALT



New Technology Device ALT
With Individual Lognormal Distribution ML Estimates
Lognormal Probability Plot



The Arrhenius/Lognormal Model for Temperature Acceleration

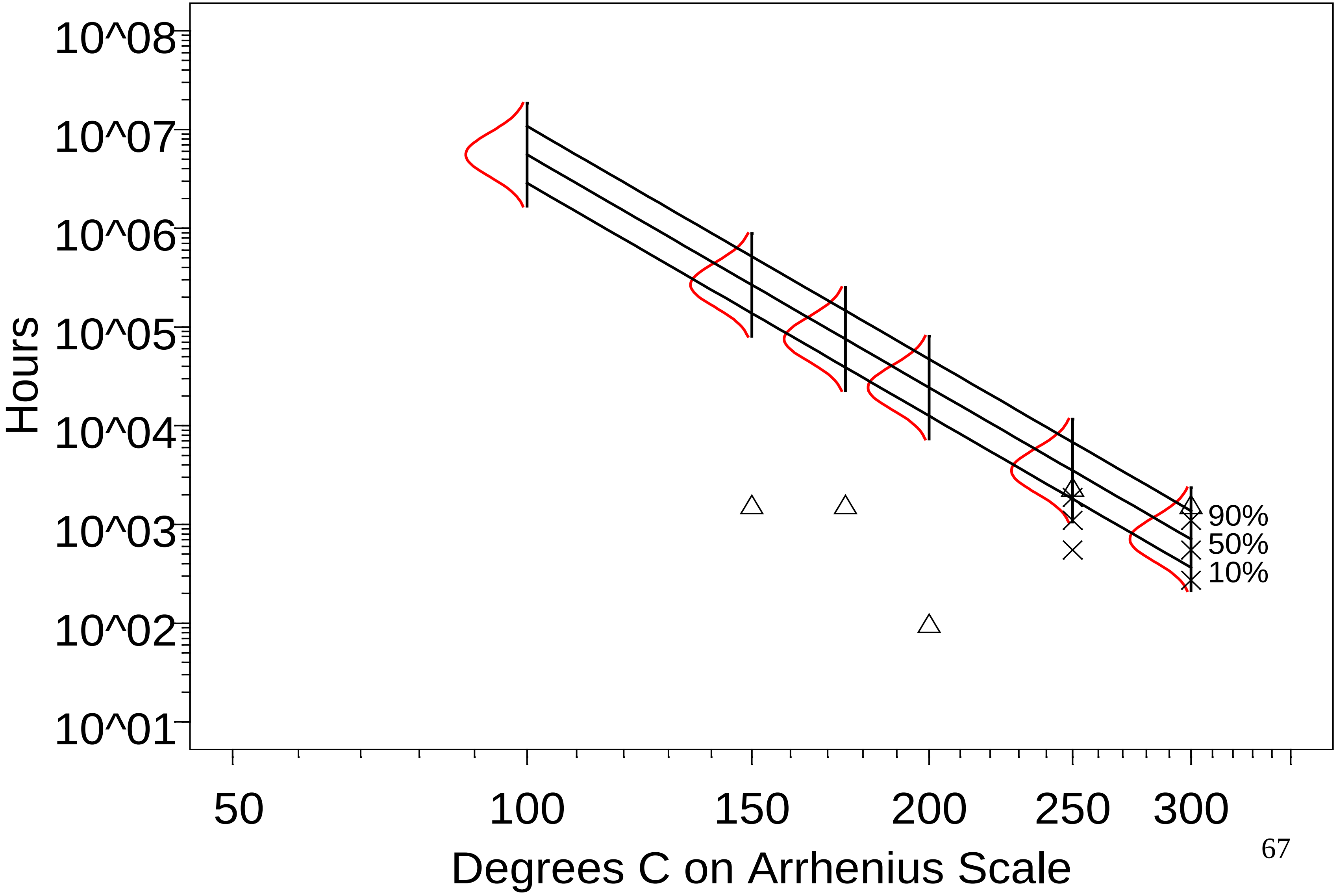
- Log life is inversely proportional to reciprocal Kelvin temperature
- The probability of failure as a function of time is

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

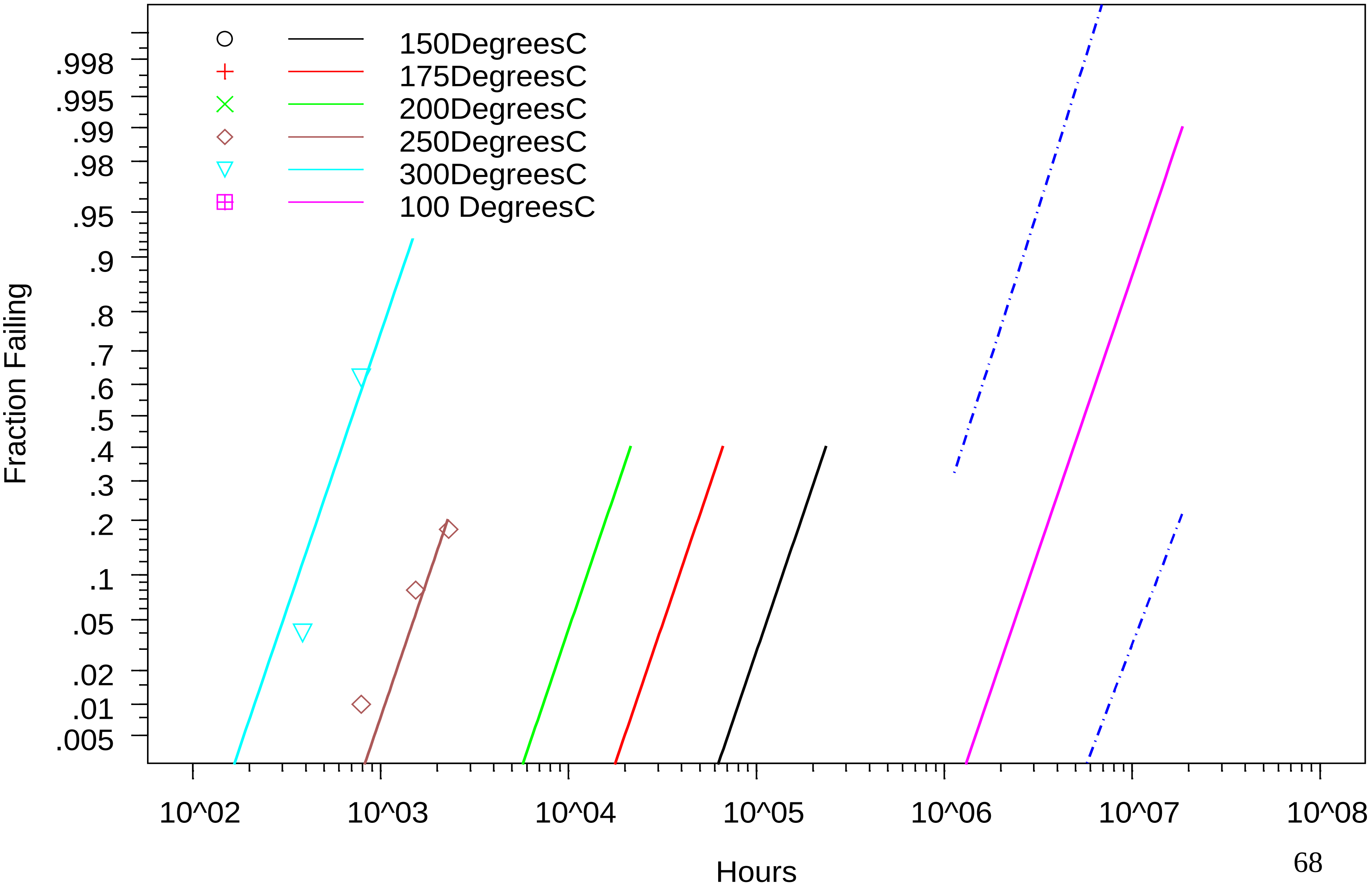
$$\mu(x) = \beta_0 + \beta_1 x$$

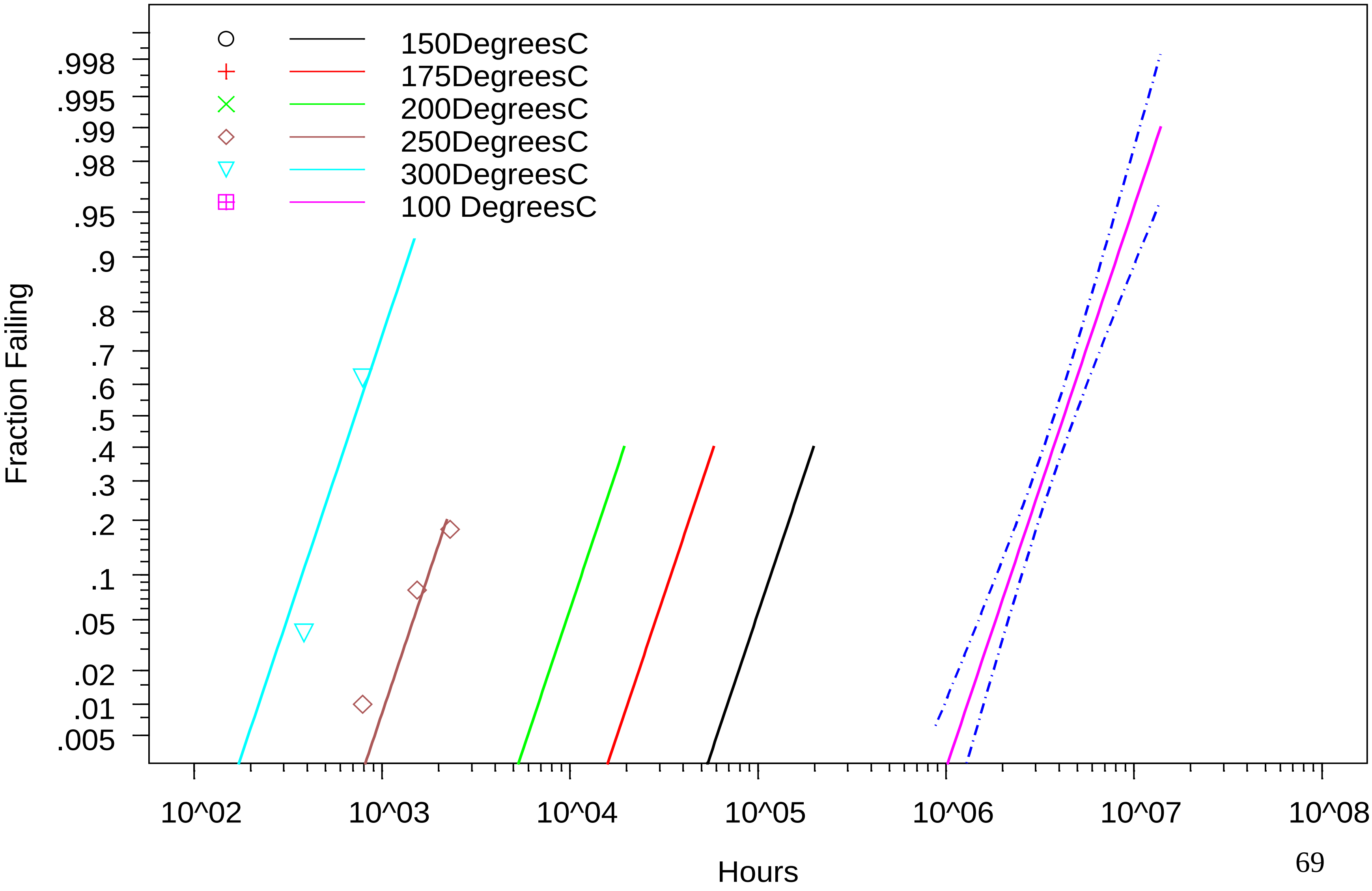
- x = 11605/(Degrees C + 273.15)
- β_1 is the “effective activation energy”
- σ does not to depend on temperature
- Widely used in the evaluation of electronic components

New Technology Device ALT
DegreesCArrhenius , Dist:Lognormal



New Technology Device ALT   Model MLE
DegreesCArrhenius, Dist:Lognormal
Lognormal Probability Plot





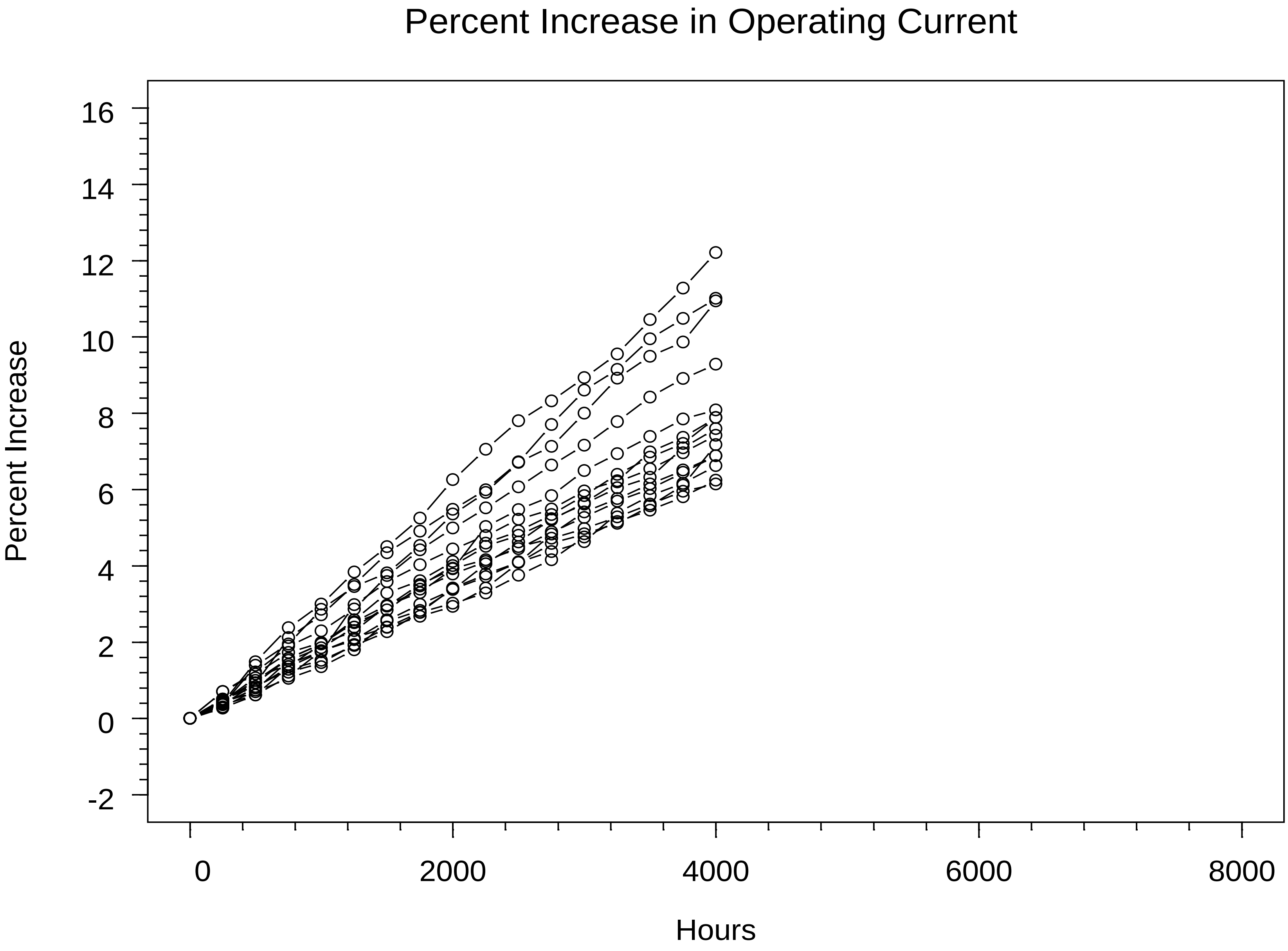
New Technology Device ALT Model MLE
DegreesCArrhenius, Dist:Lognormal
Lognormal Probability Plot

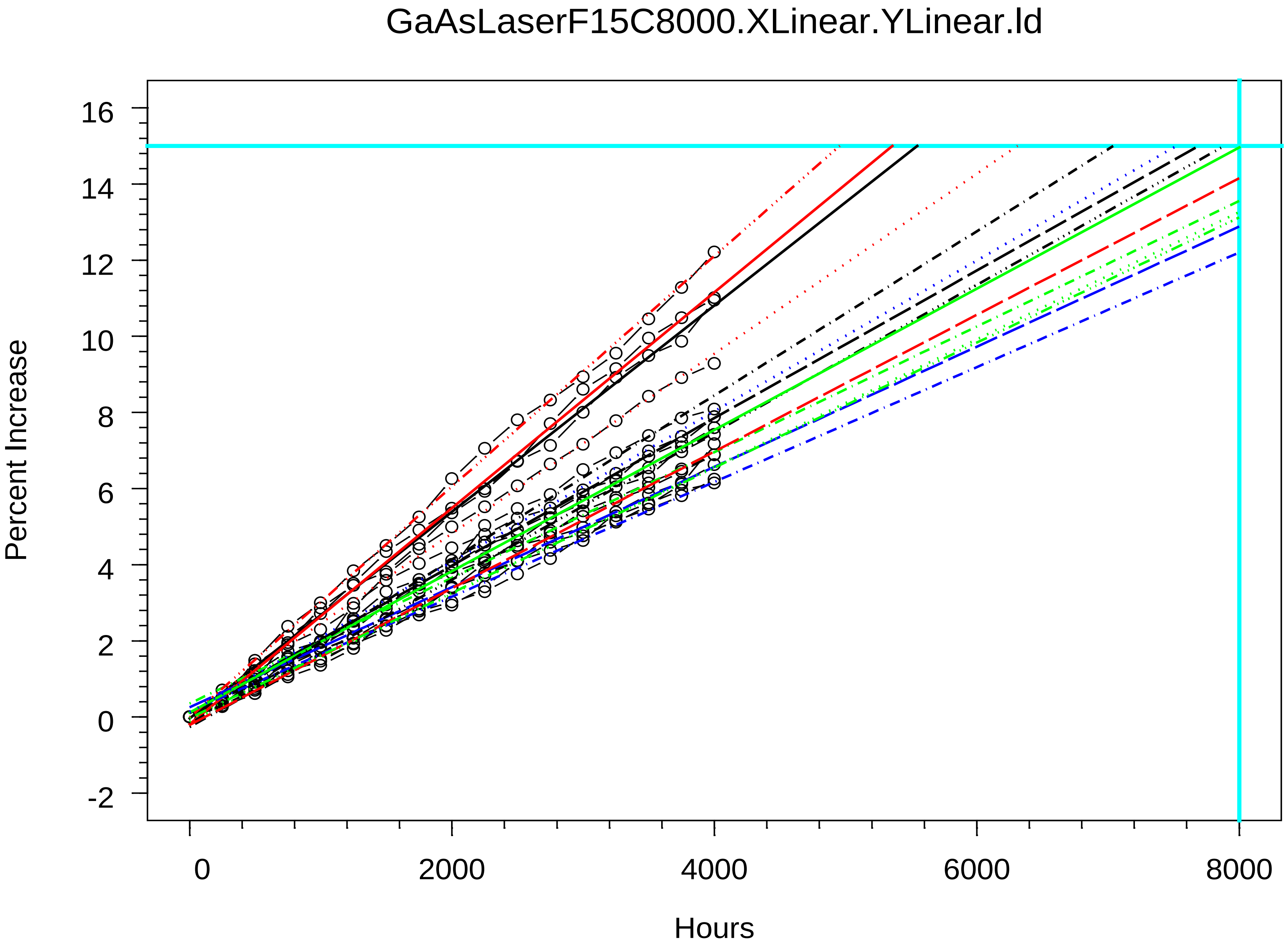
Lessons Learned

- Maximum likelihood can easily deal with interval-censored data
- A change in the distribution slope parameter implies that simple acceleration models are not appropriate
- Too much stress can cause new failure modes
- Statistical error is greatly amplified when extrapolating
- Engineering information is important in accelerated life testing

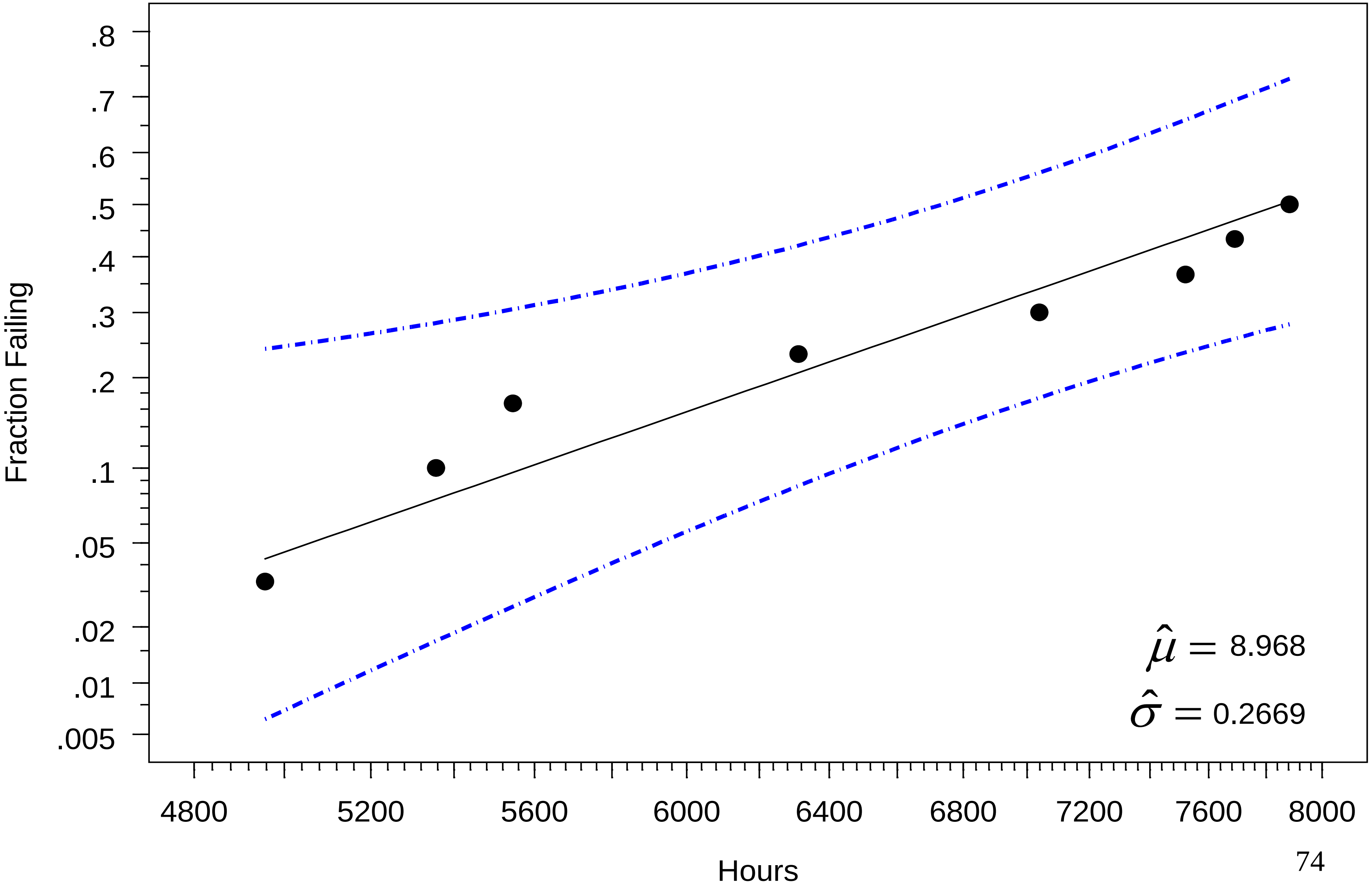
GaAs Laser Repeated Measures Degradation Data Analysis

- Lasers used in telecommunications applications
- Lasers tested at 80 degrees C to accelerate life
- Few failures expected even in the accelerated life test


Percent Increase in Operating Current
Percent Increase
16
14
12
10
8
6
4
2
0
-2
0
2000
4000
6000
8000
Hours


GaAsLaserF15C8000.XLinear.YLinear.ld
Percent Increase
Hours
16
14
12
10
8
6
4
2
0
-2
0
2000
4000
6000
8000

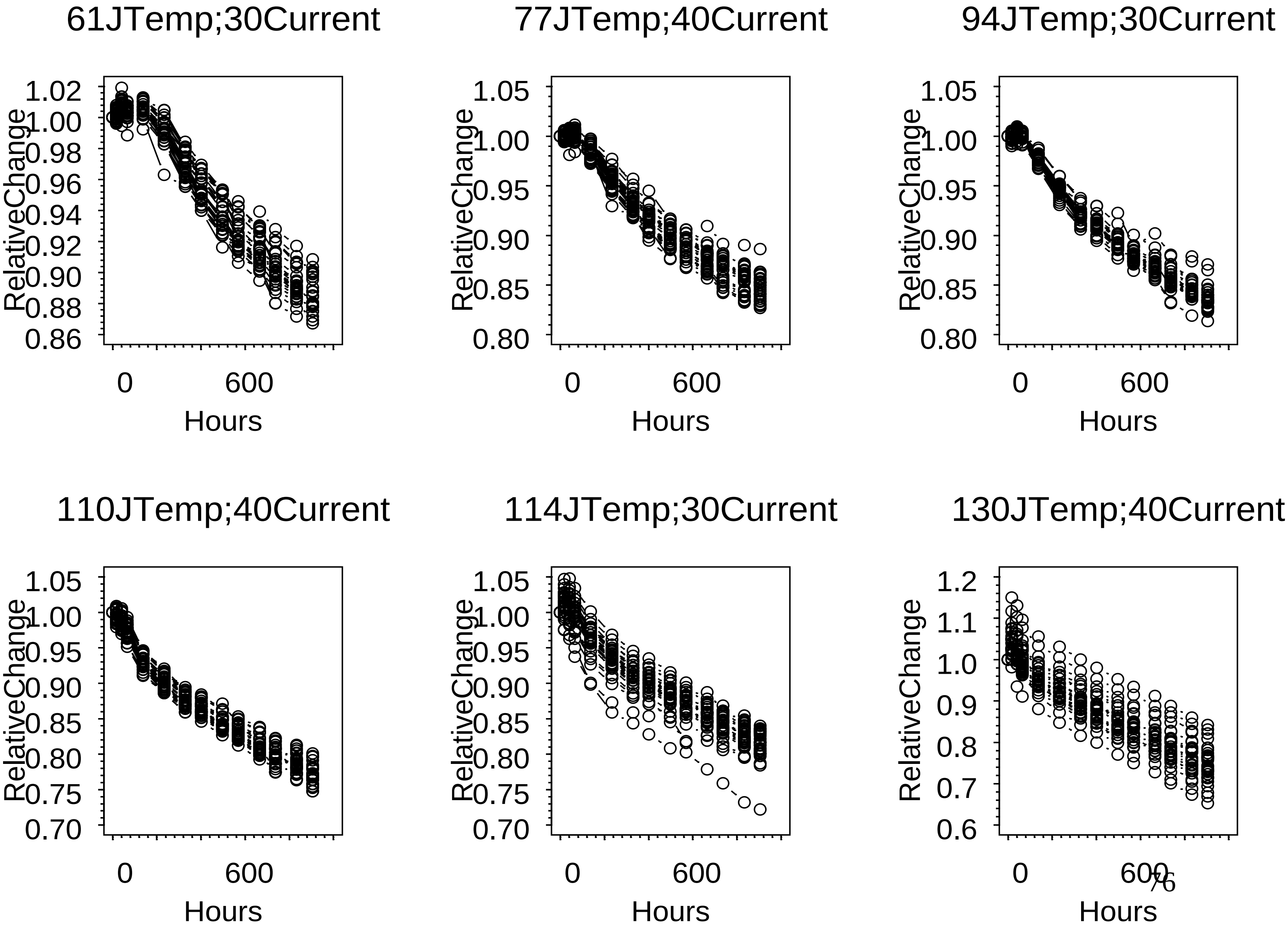
GaAsLaser.CurrentF15C8000.XLinear.YLinear.ld
with Lognormal ML Estimate and Pointwise 95% Confidence Intervals
Lognormal Probability Plot



Accelerated Repeated Measures Degradation Test of LEDs

- Tests run with 50 LEDs at each of six combinations of temperature and current (two accelerating variables)
- Measured light output on each unit periodically
- Data are messy

LED Relative Change in Light Output (Zero Start)
x axis: linear y axis: linear



61JTemp;30Current

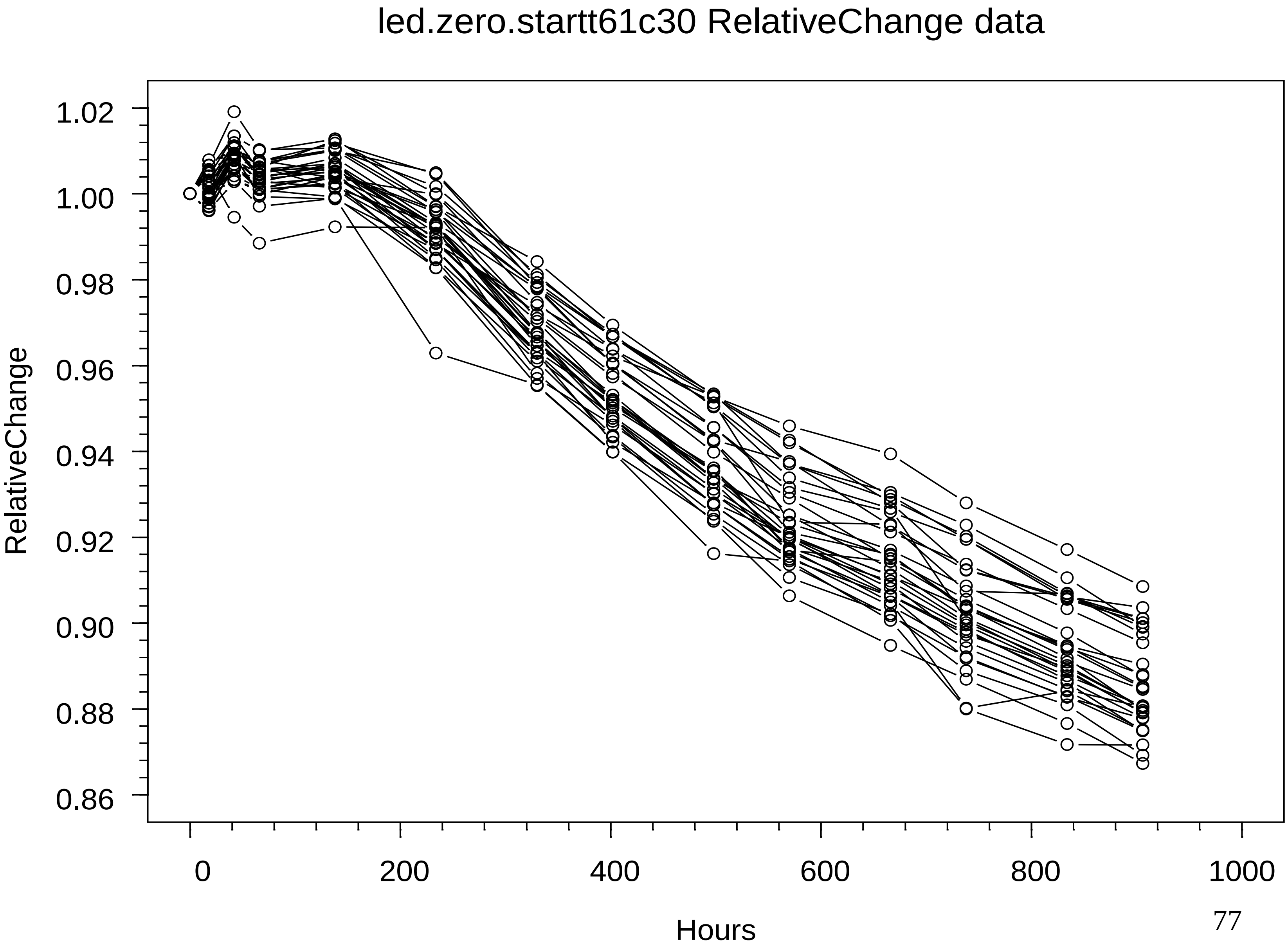
77JTemp;40Current

94JTemp;30Current

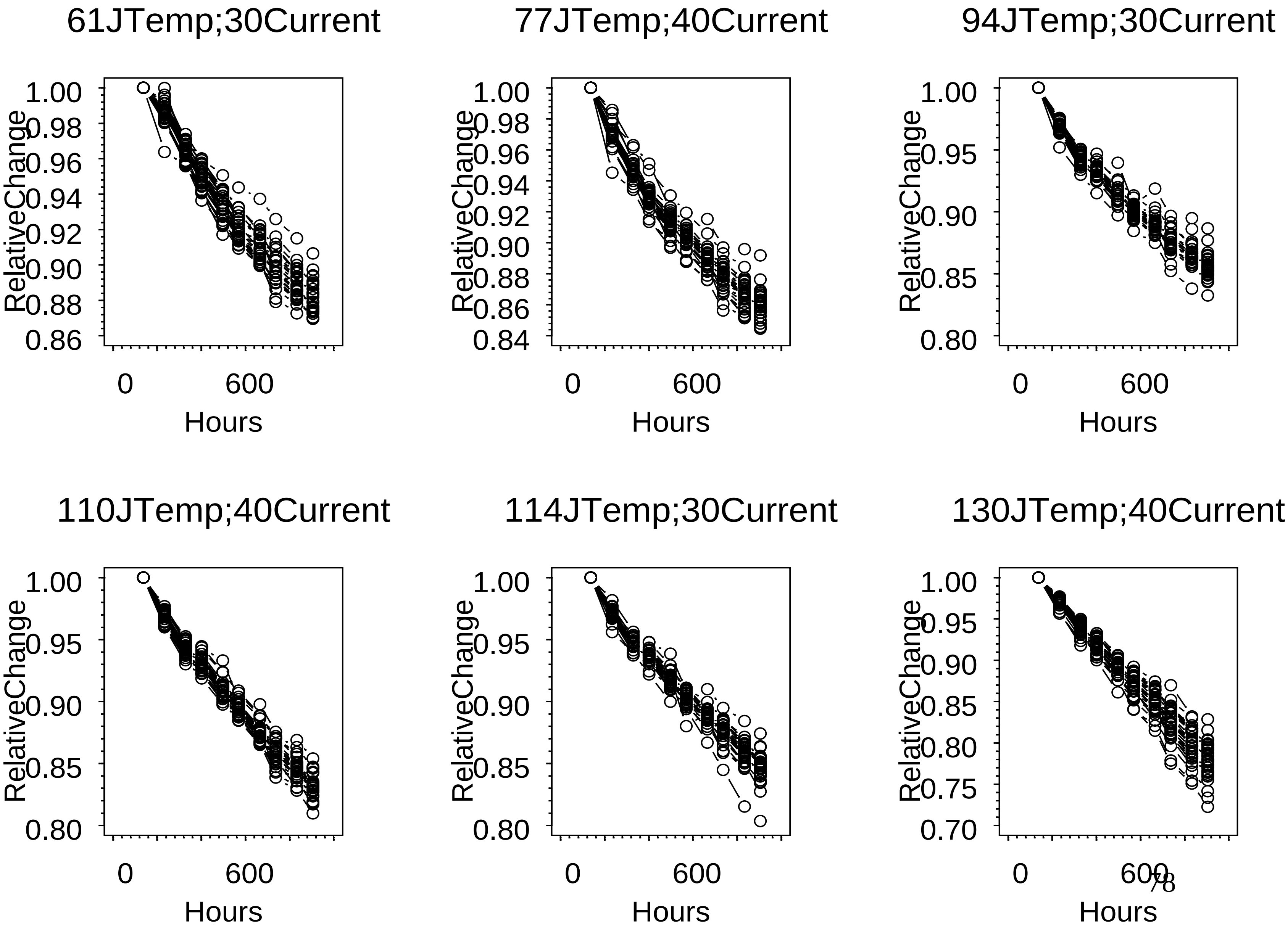
110JTemp;40Current

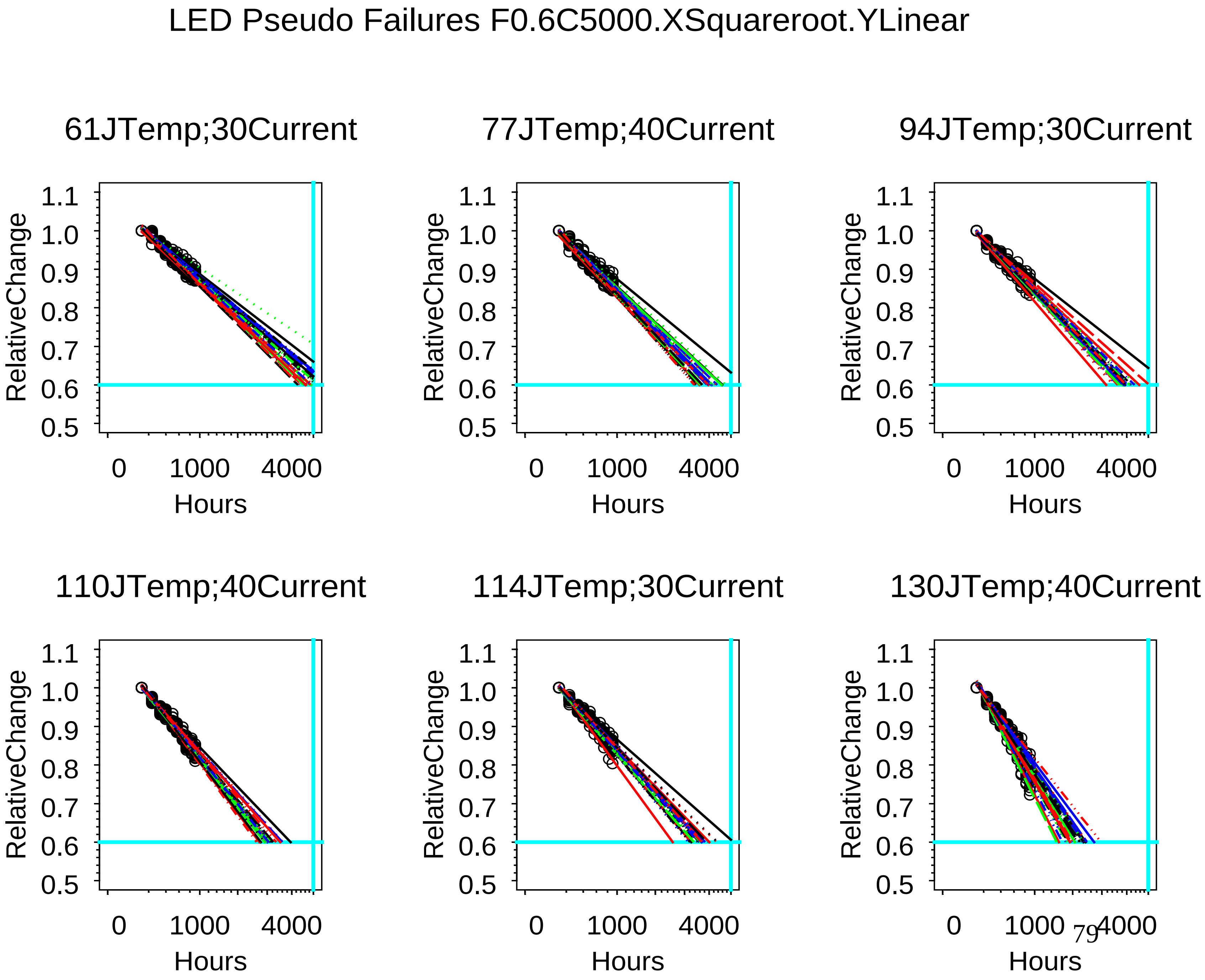
114JTemp;30Current

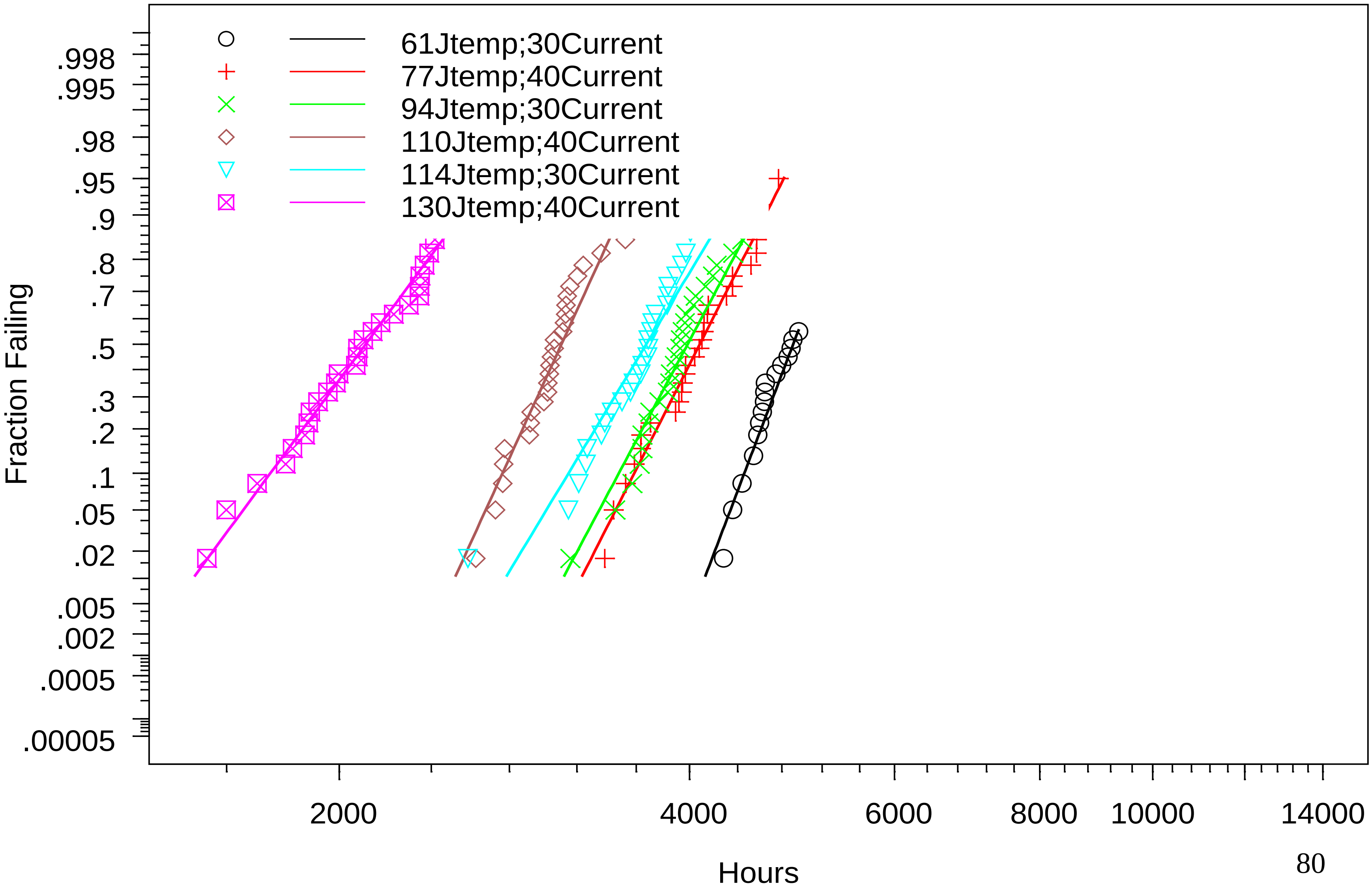
130JTemp;40Current


led.zero.startt61c30 RelativeChange data
RelativeChange
1.02
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
0
200
400
600
800
1000
Hours

Relative Change in Light Output from 138 Hours
x axis: linear   y axis: linear

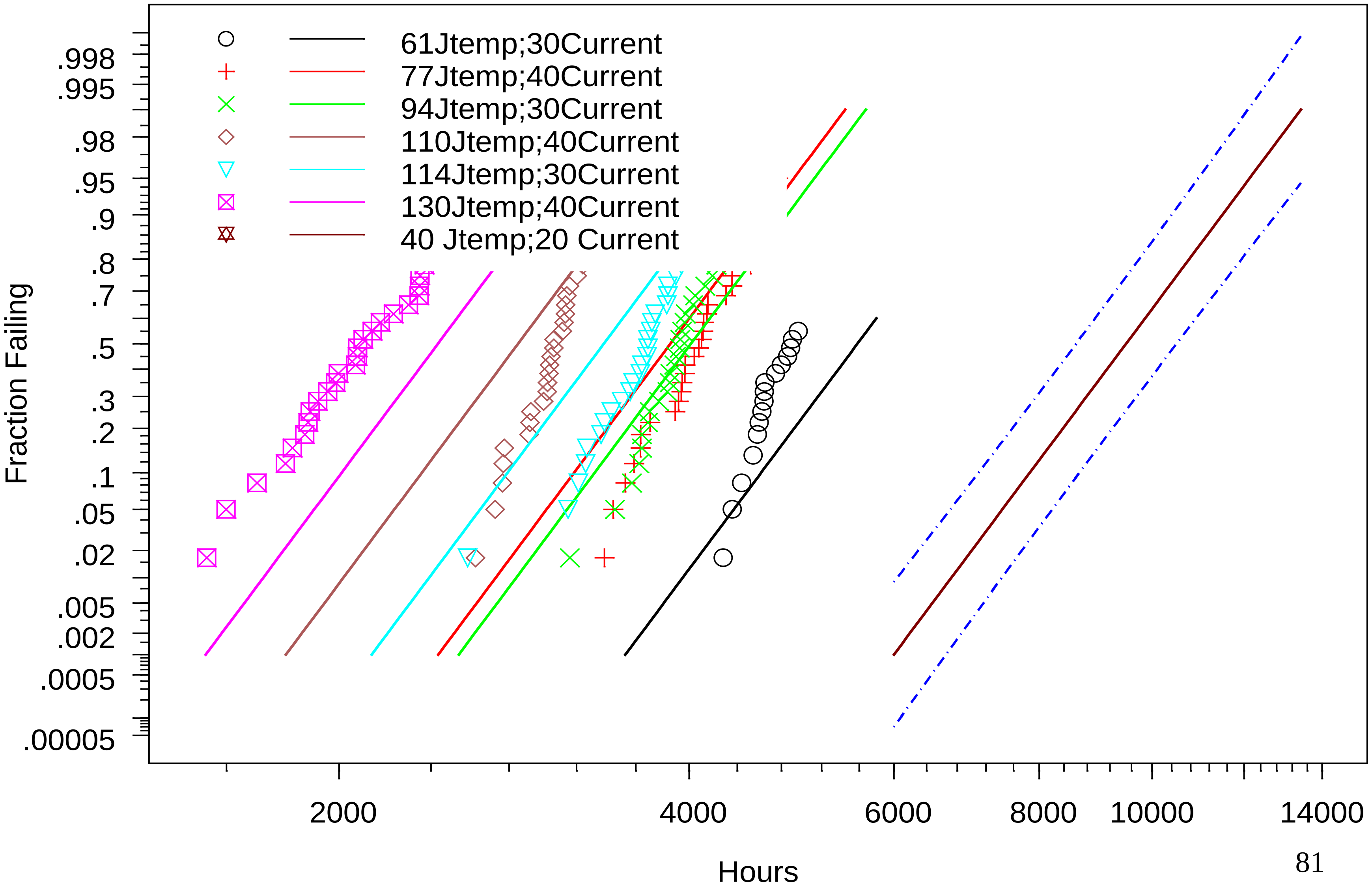



LED Pseudo Failures F0.6C5000.XSquareroot.YLinear
61JTemp;30Current
77JTemp;40Current
94JTemp;30Current
110JTemp;40Current
114JTemp;30Current
130JTemp;40Current
RelativeChange
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0
1000
4000
Hours

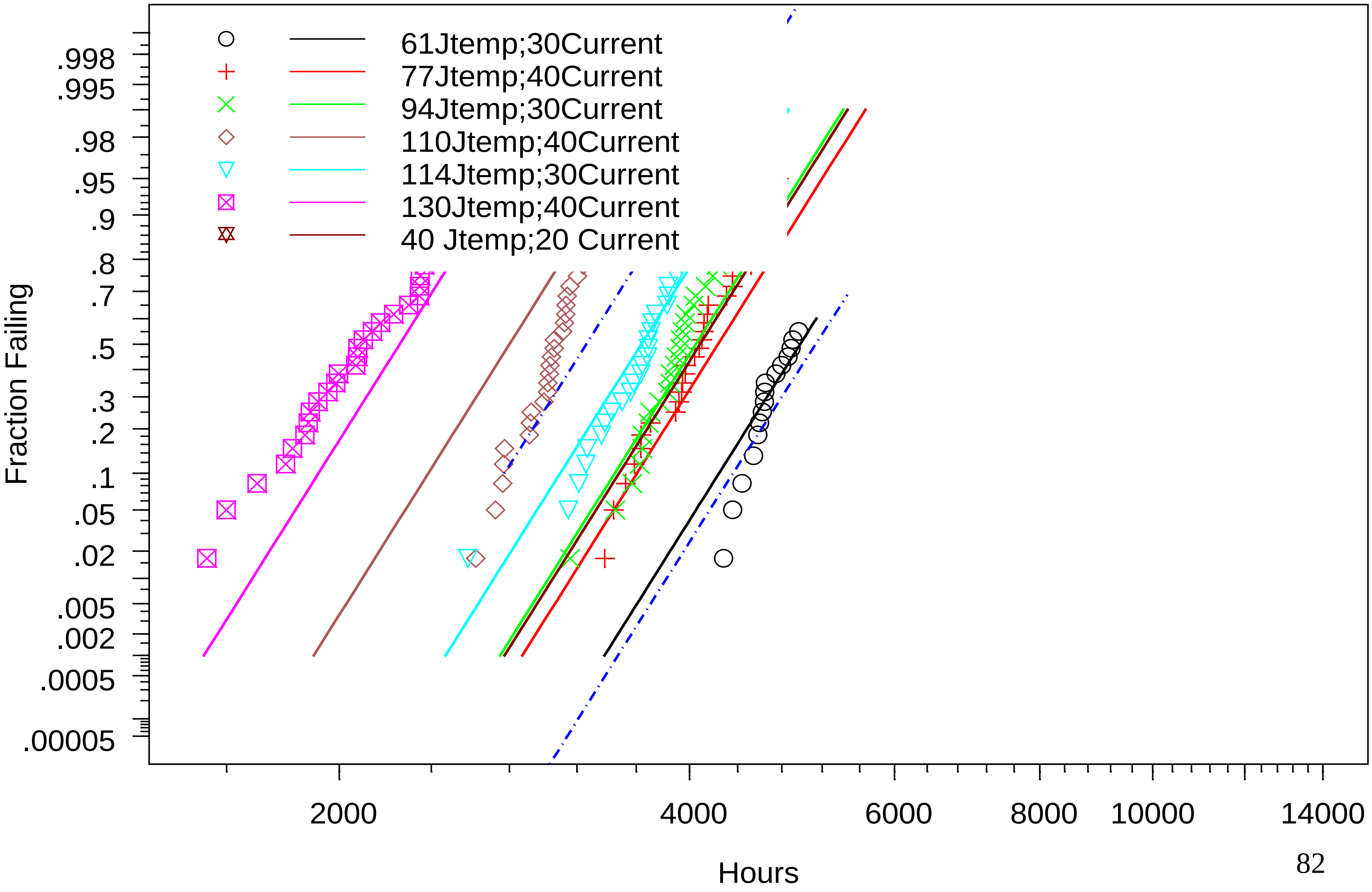


DeviceL Pseudo Failures F0.6C5000.XSquareroot.YLinear
With Individual Lognormal Distribution ML Estimates
Lognormal Probability Plot

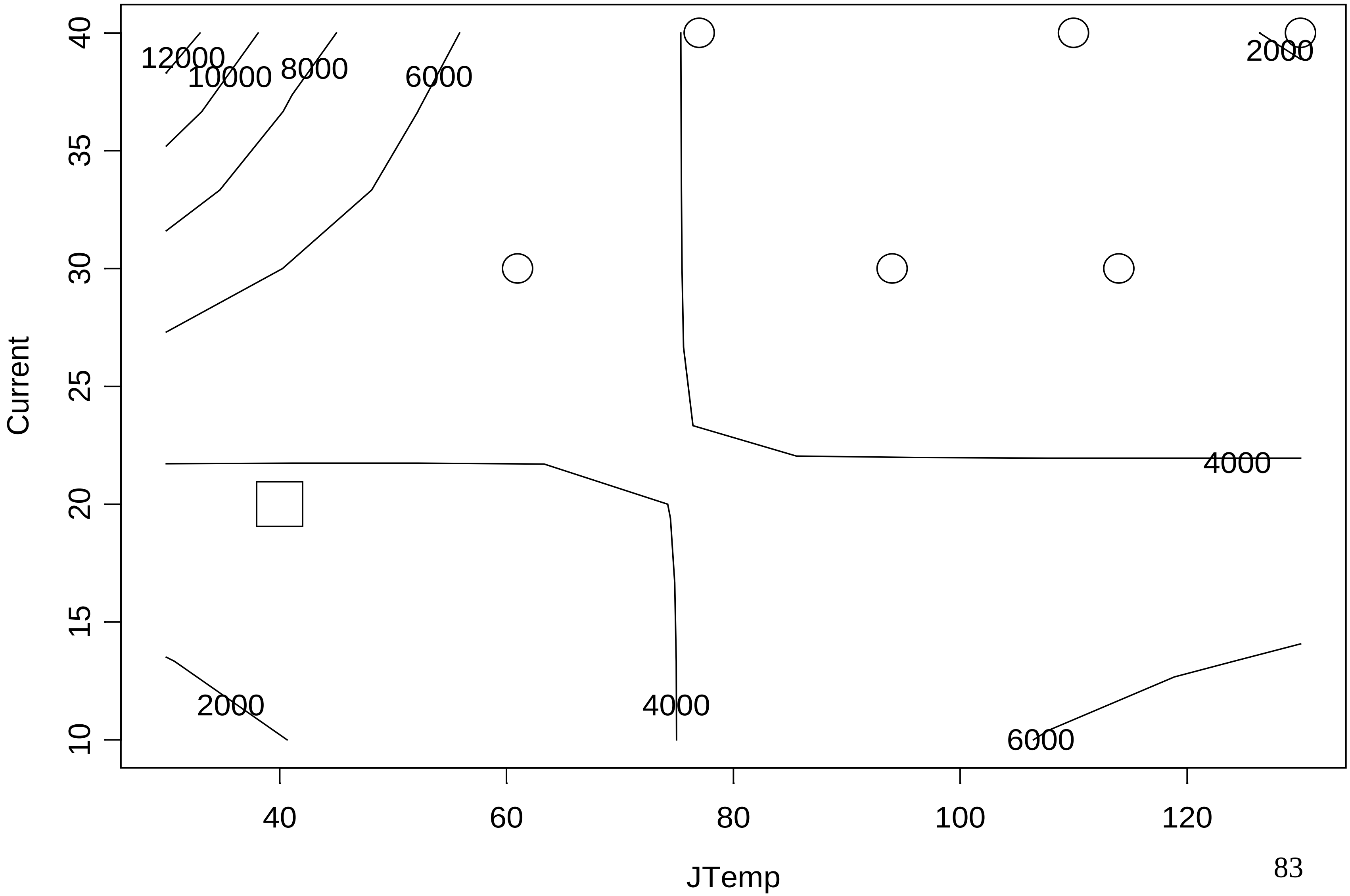
DeviceL Pseudo Failures F0.6C5000.XSquareroot.YLinear Model MLE
JtempArrhenius, CurrentLog, Dist:Lognormal
Lognormal Probability Plot



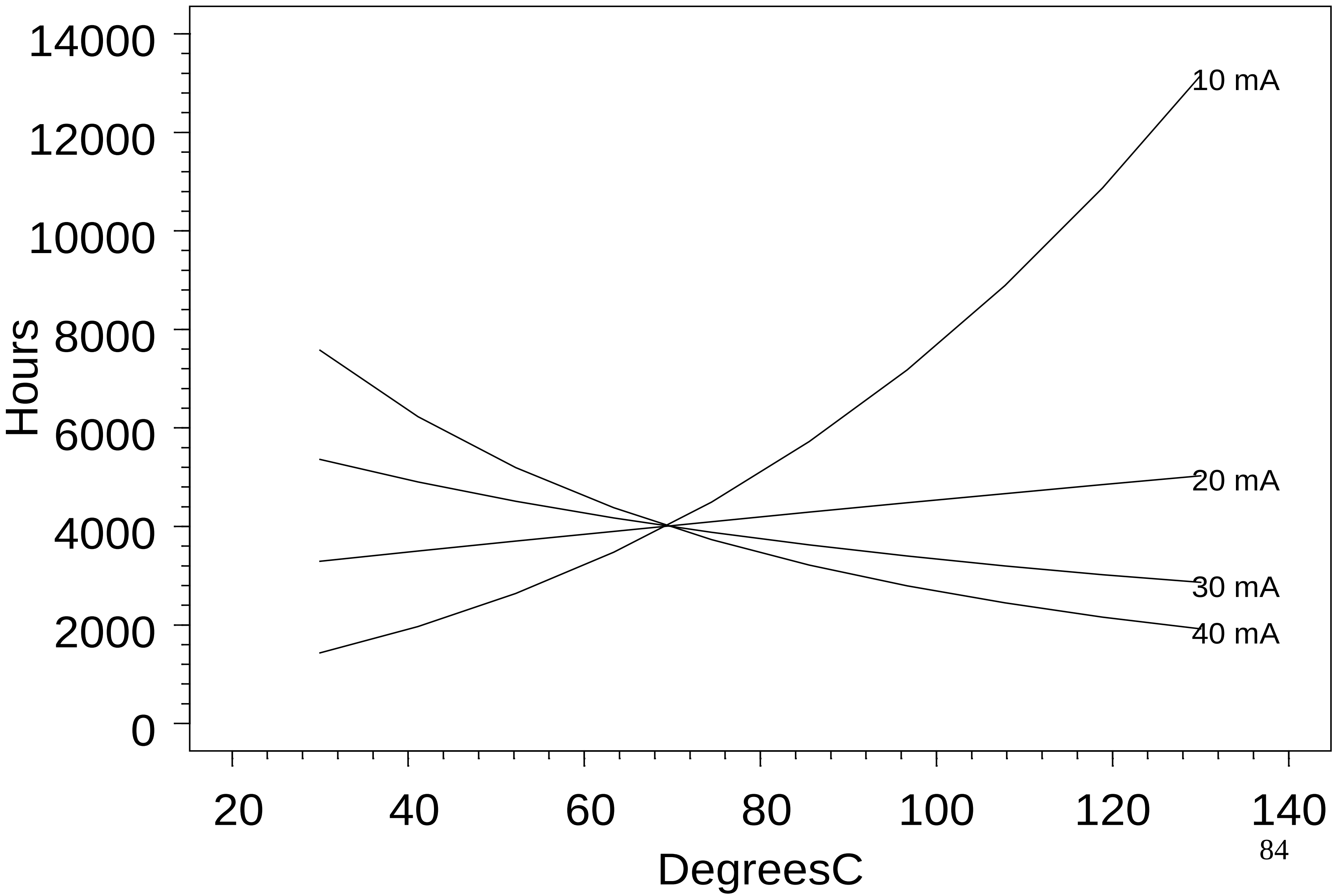
DeviceL Pseudo Failures F0.6C5000.XSquareroot.YLinear   Model MLE
JtempArrhenius, CurrentLog, Dist:Lognormal
Lognormal Probability Plot



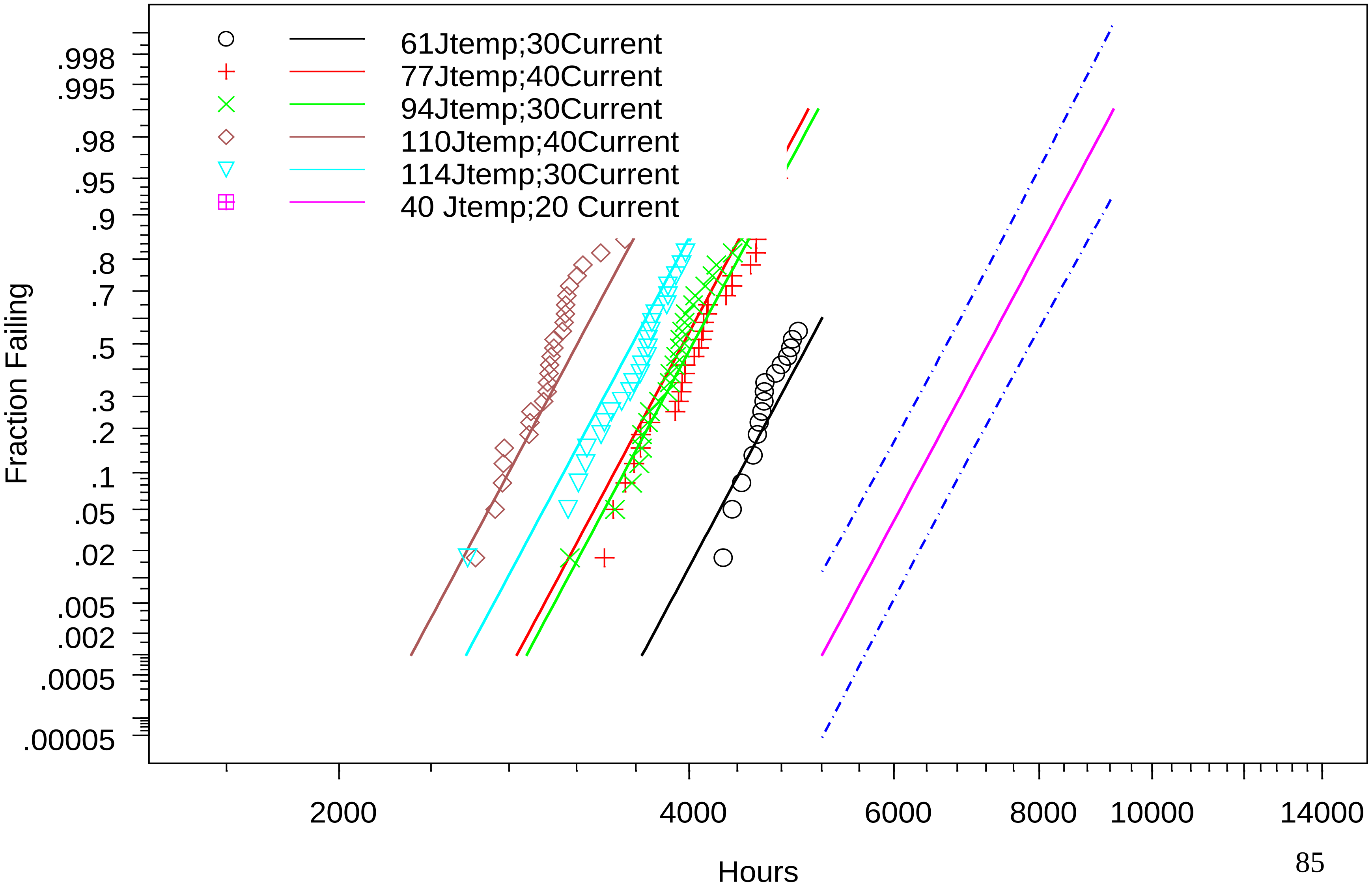
Response Surface Giving Lifetime as a Function of Current and Junction Temperature Showing the Nonsensical Saddle Point Shape



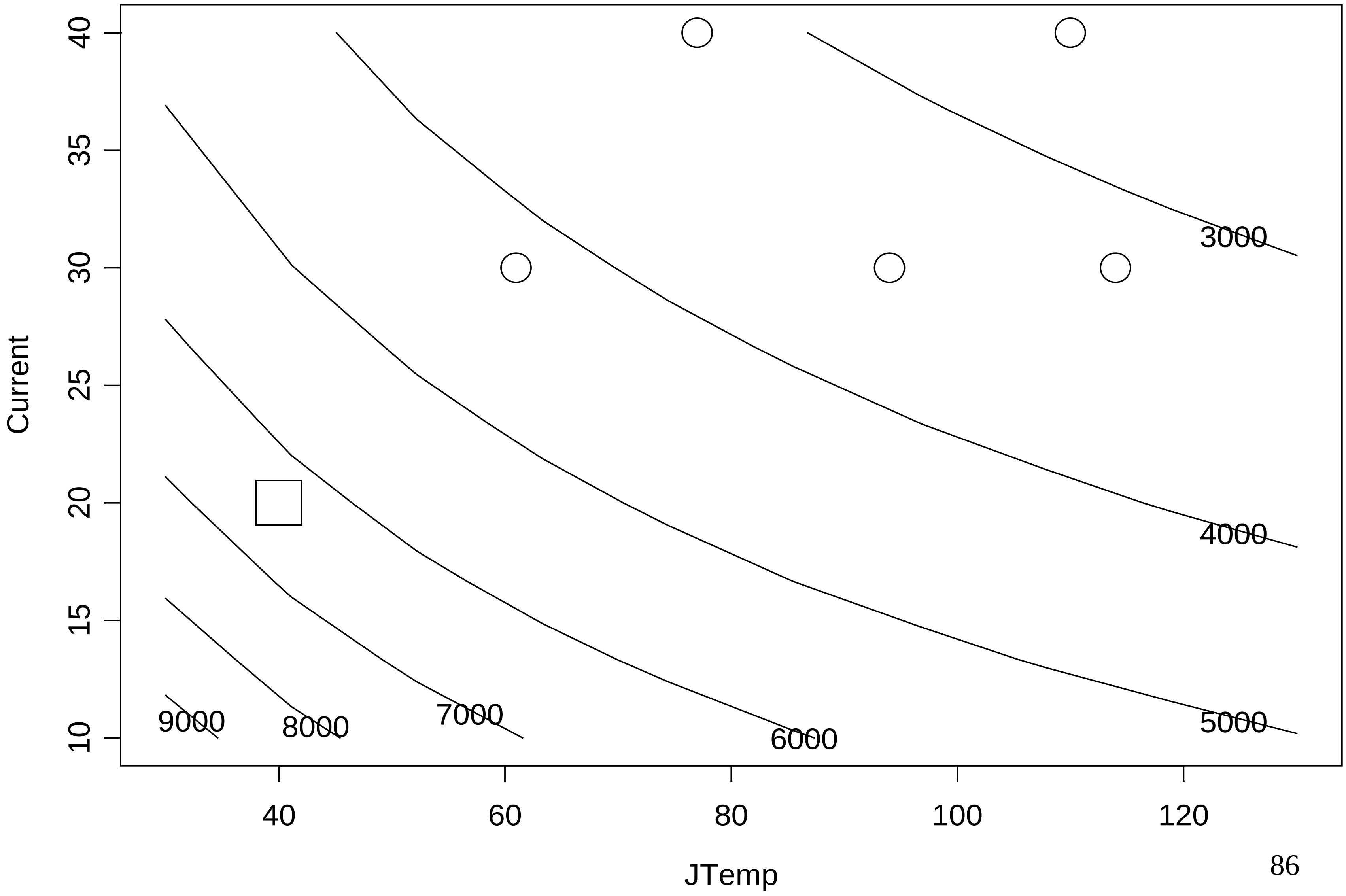
Lifetime as a Function of Current and Junction Temperature Showing the Nonsensical Relationships for Low Current Values



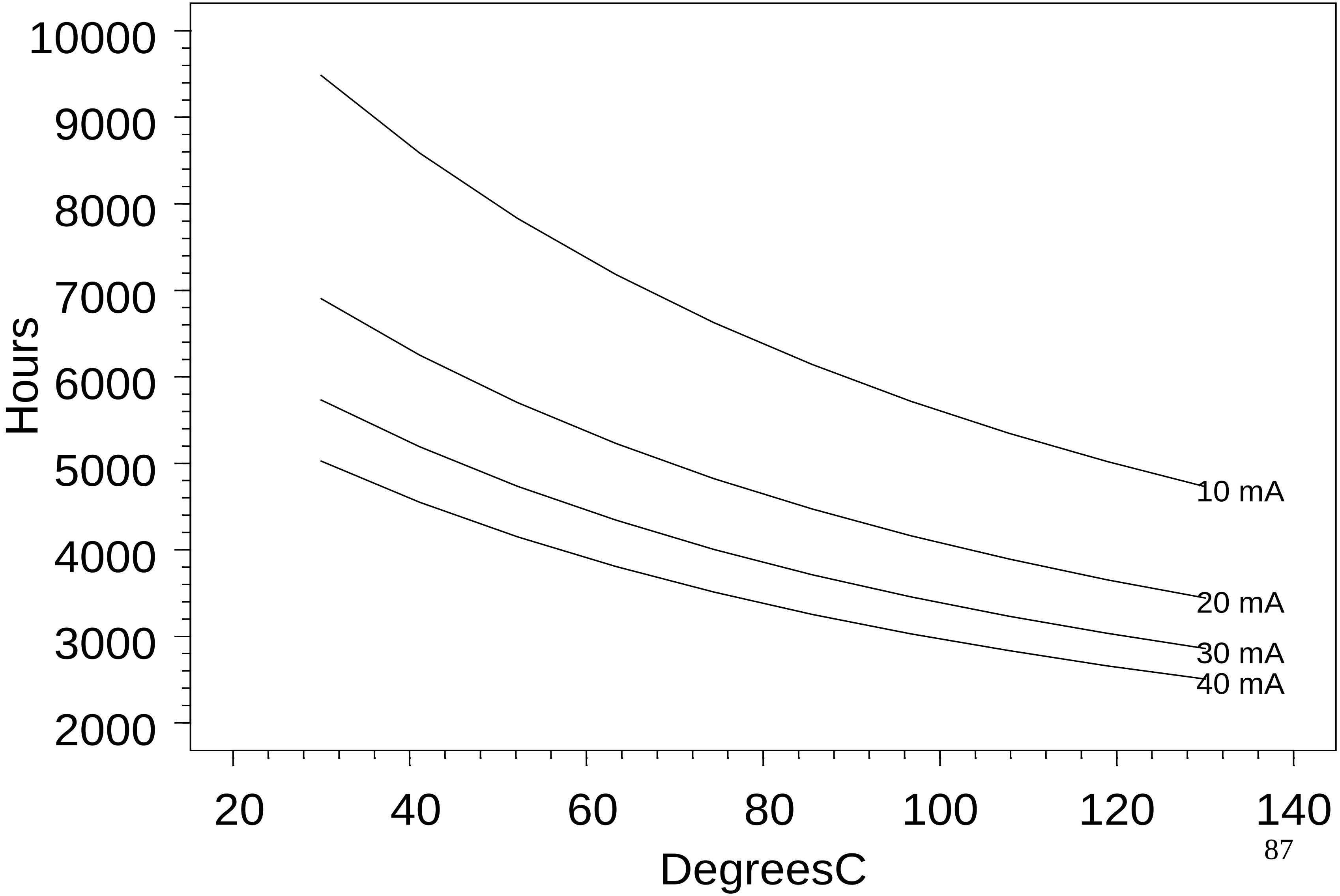
Fixed DeviceL Pseudo Failures F0.6C5000.XSquareroot.YLinear   Model MLE
JtempArrhenius, CurrentLog, Dist:Lognormal
Lognormal Probability Plot



Lifetime as a Function of Current and Junction Temperature After the Bad Data Was Removed



Lifetime as a Function of Current and Junction Temperature After the Bad Data Was Removed

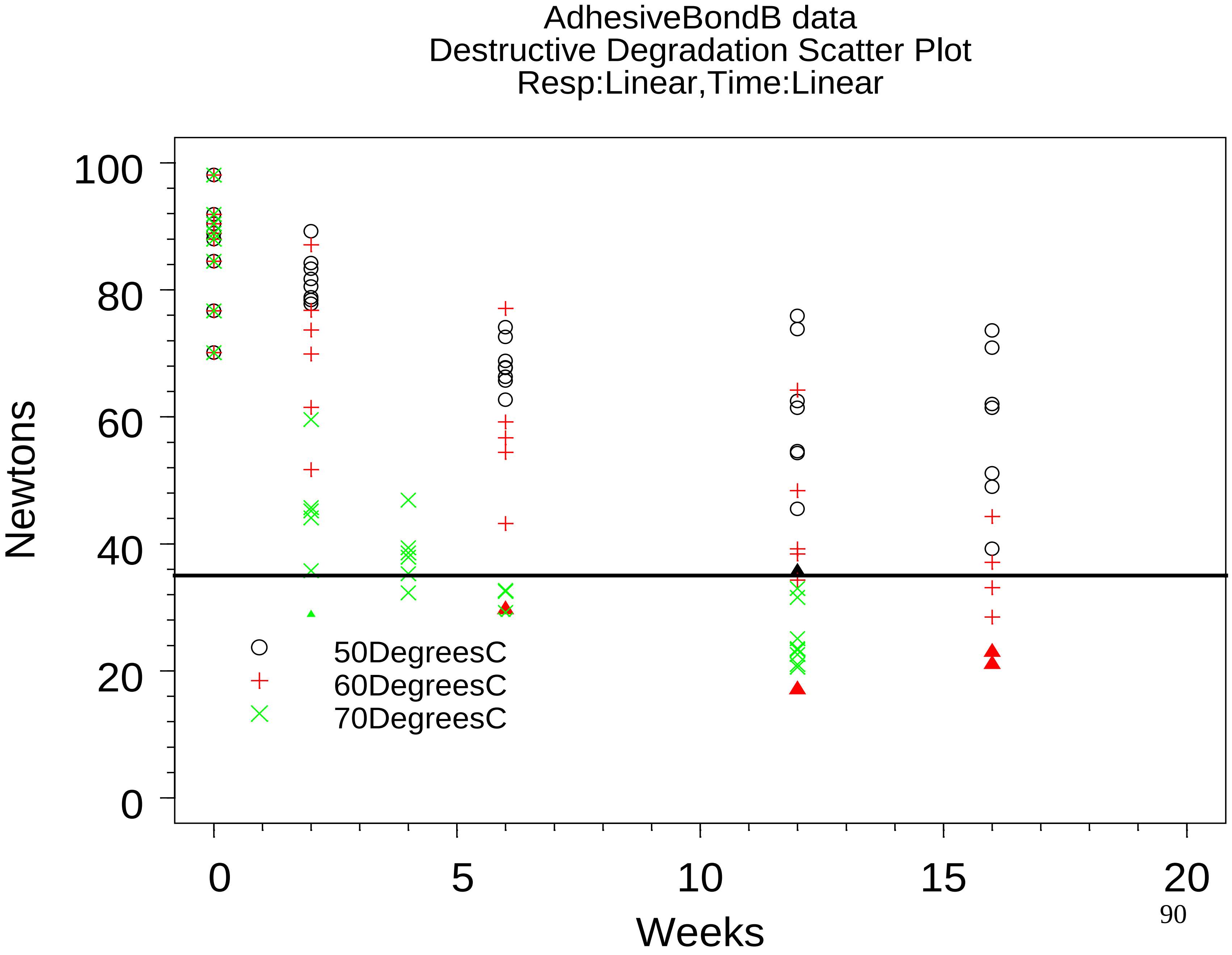


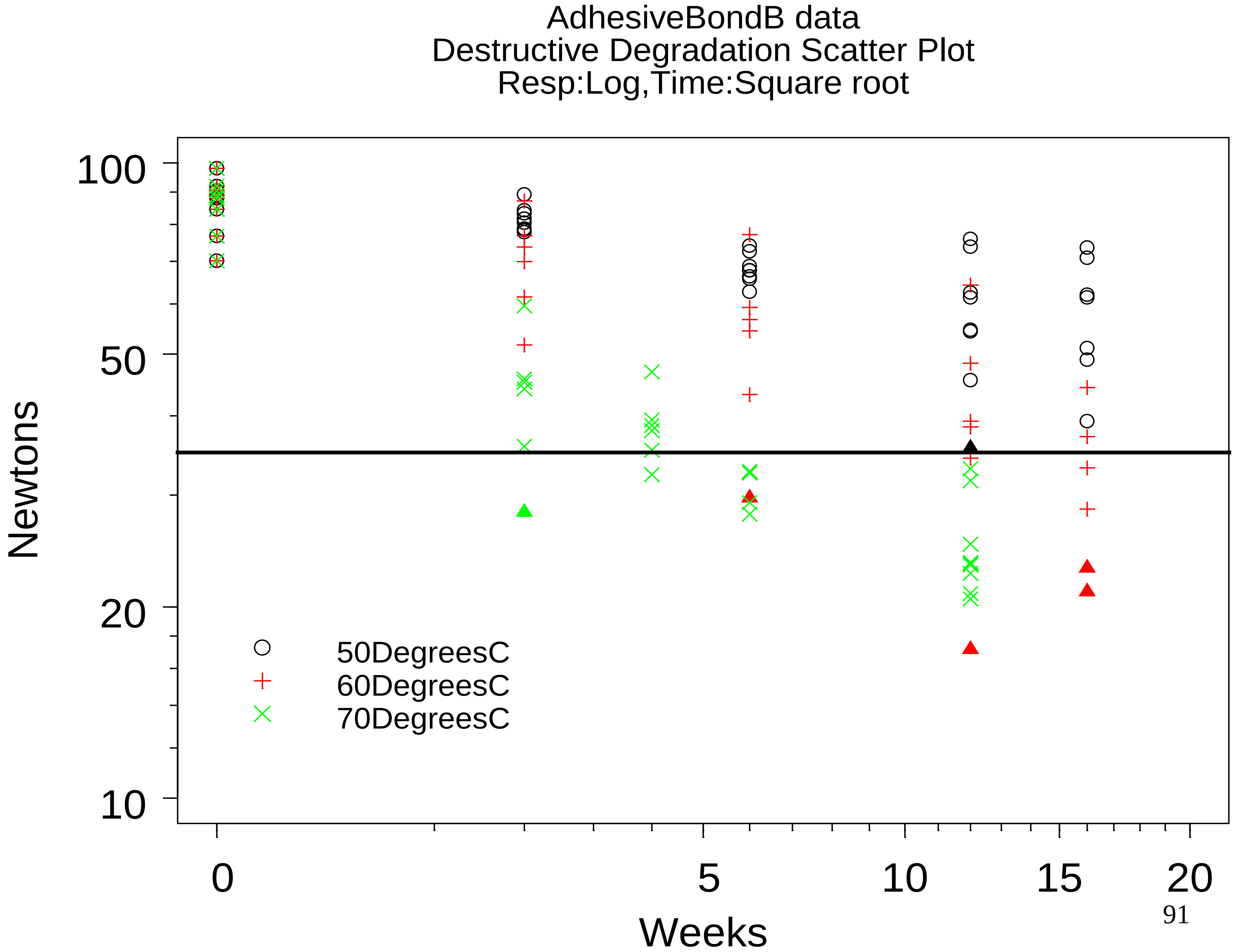
Lessons Learned

- Repeated measures degradation data can provide much more information than failure-time data
- Early part of degradation path may be complicated, but can be ignored.
- Testing at stress levels that are too high can cause new failure modes
- Modeling and extrapolation in two dimensions (two accelerating variables) can be more complicated and more risky

Accelerated Destructive Degradation Test to Evaluate the Lifetime of an Adhesive Bond

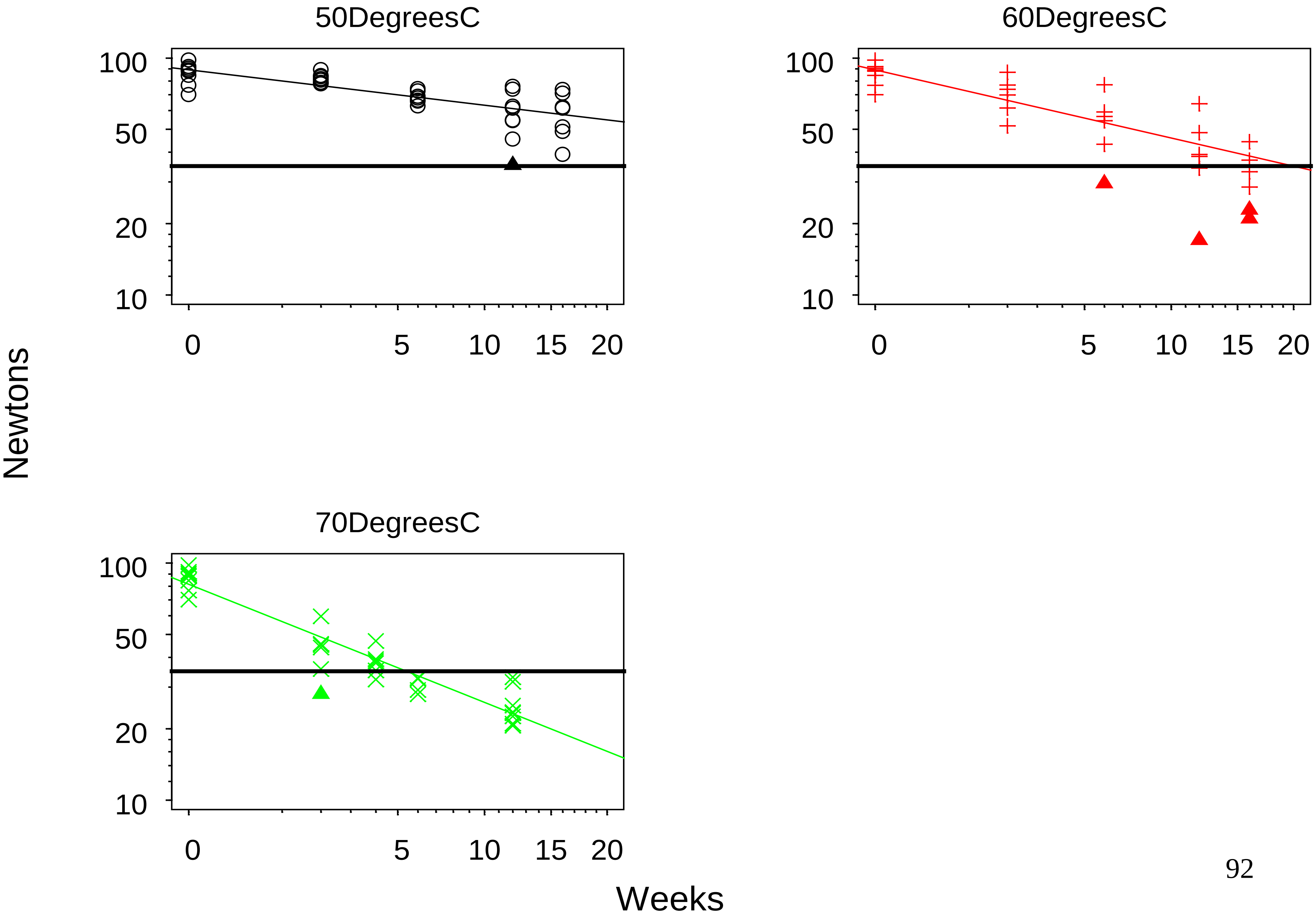
- Some baseline units tested without aging
- Samples of units placed into chambers operating at 50, 60, and 70 degrees C
- Some units removed at specific times and destructively evaluated for strength
- Units with adhesive strength below 35 Newtons are considered to be failures

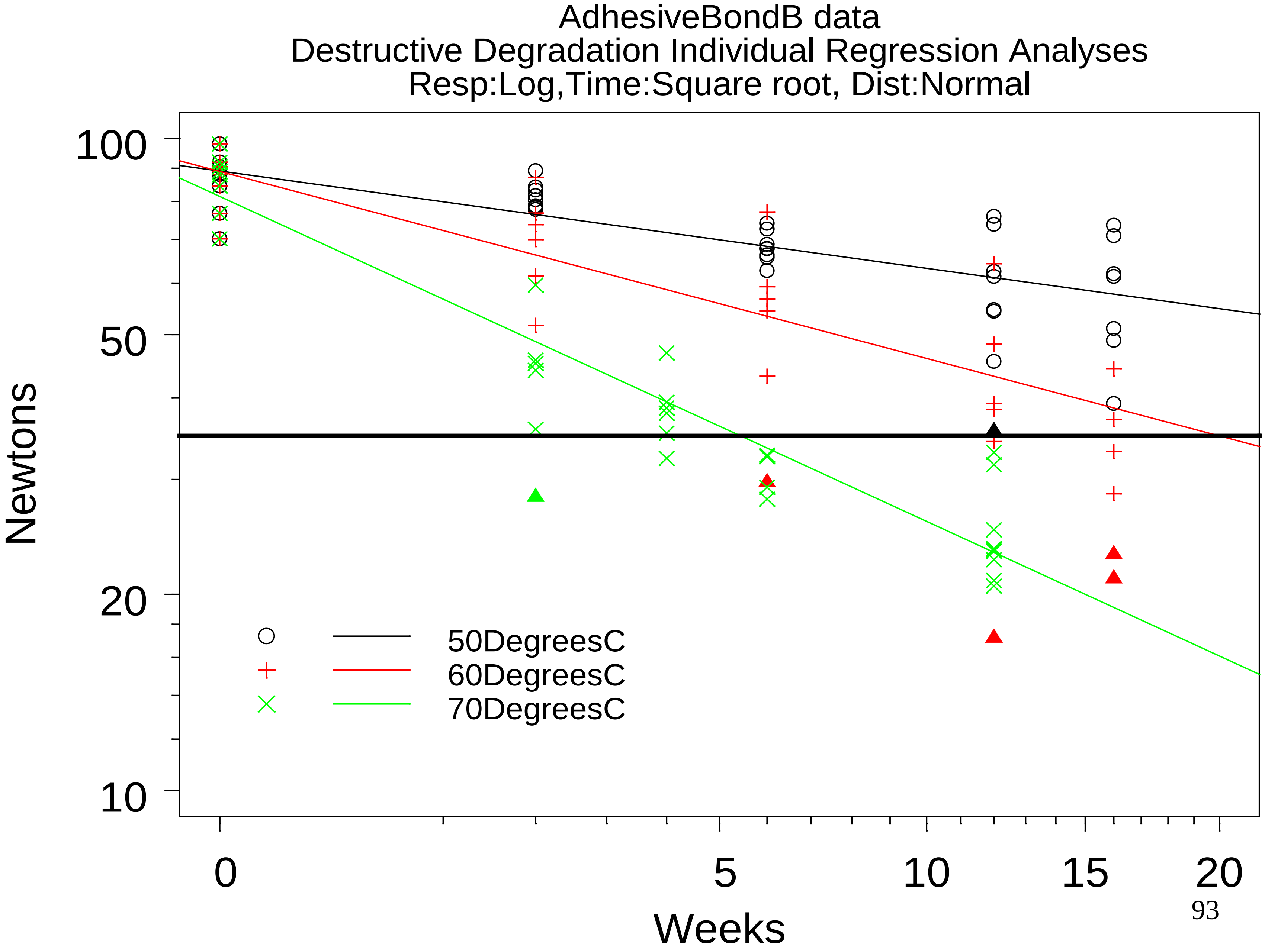

AdhesiveBondB data
Destructive Degradation Scatter Plot
Resp:Linear,Time:Linear
Newtons
100
80
60
40
20
0
Weeks
0
5
10
15
20
○ 50DegreesC
+ 60DegreesC
× 70DegreesC

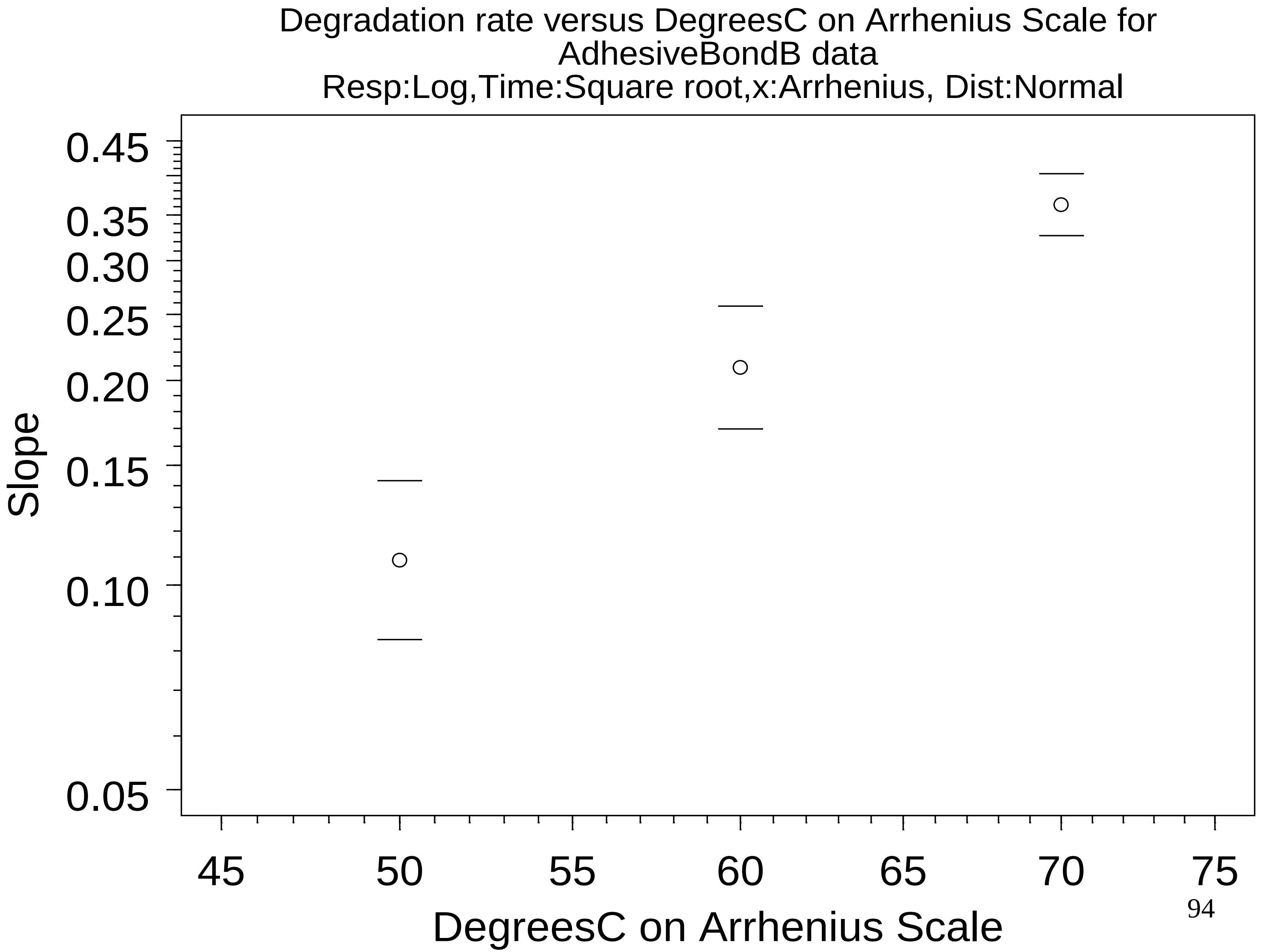


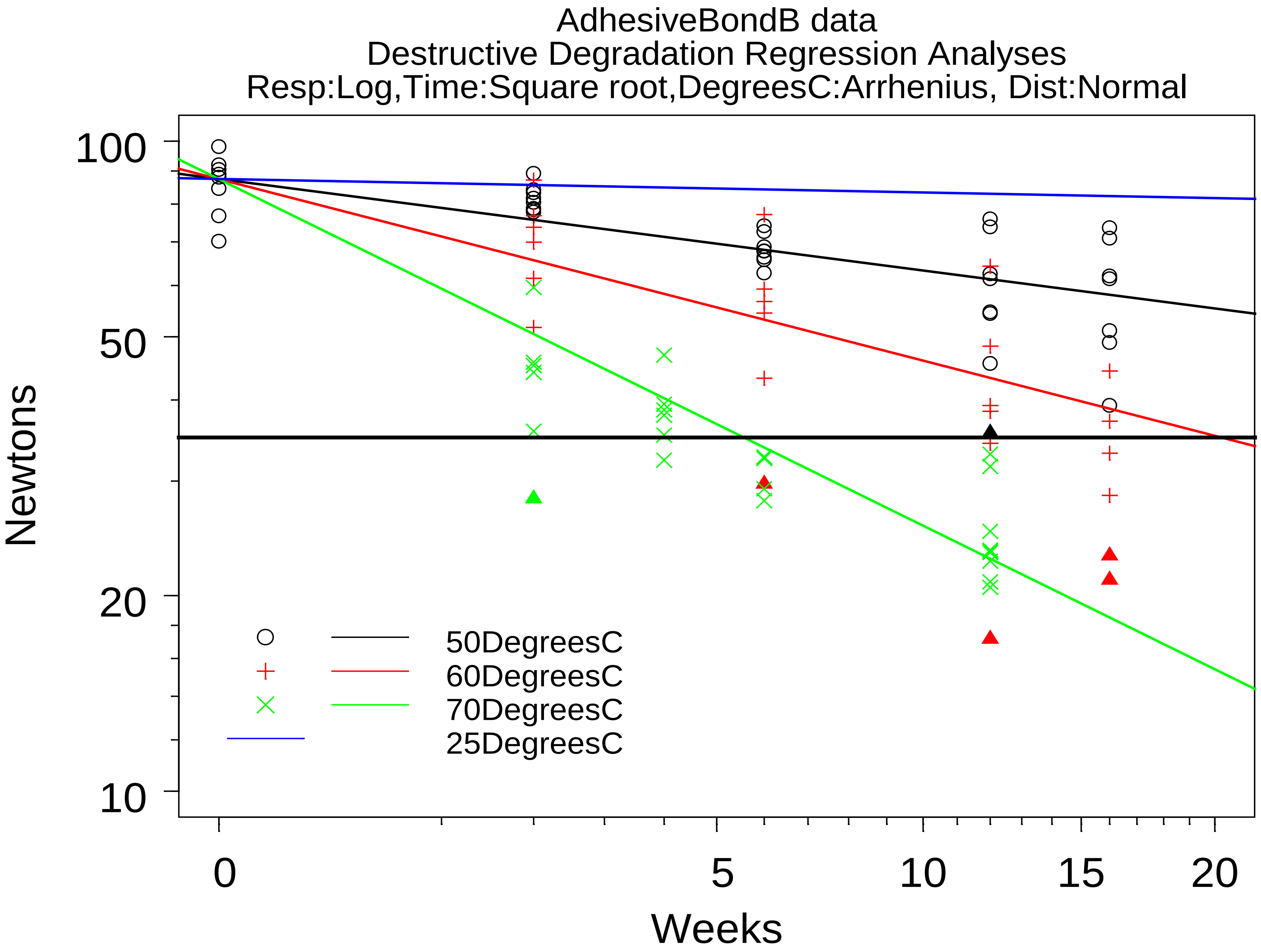
AdhesiveBondB data
Destructive Degradation Scatter Plot
Resp:Log,Time:Square root

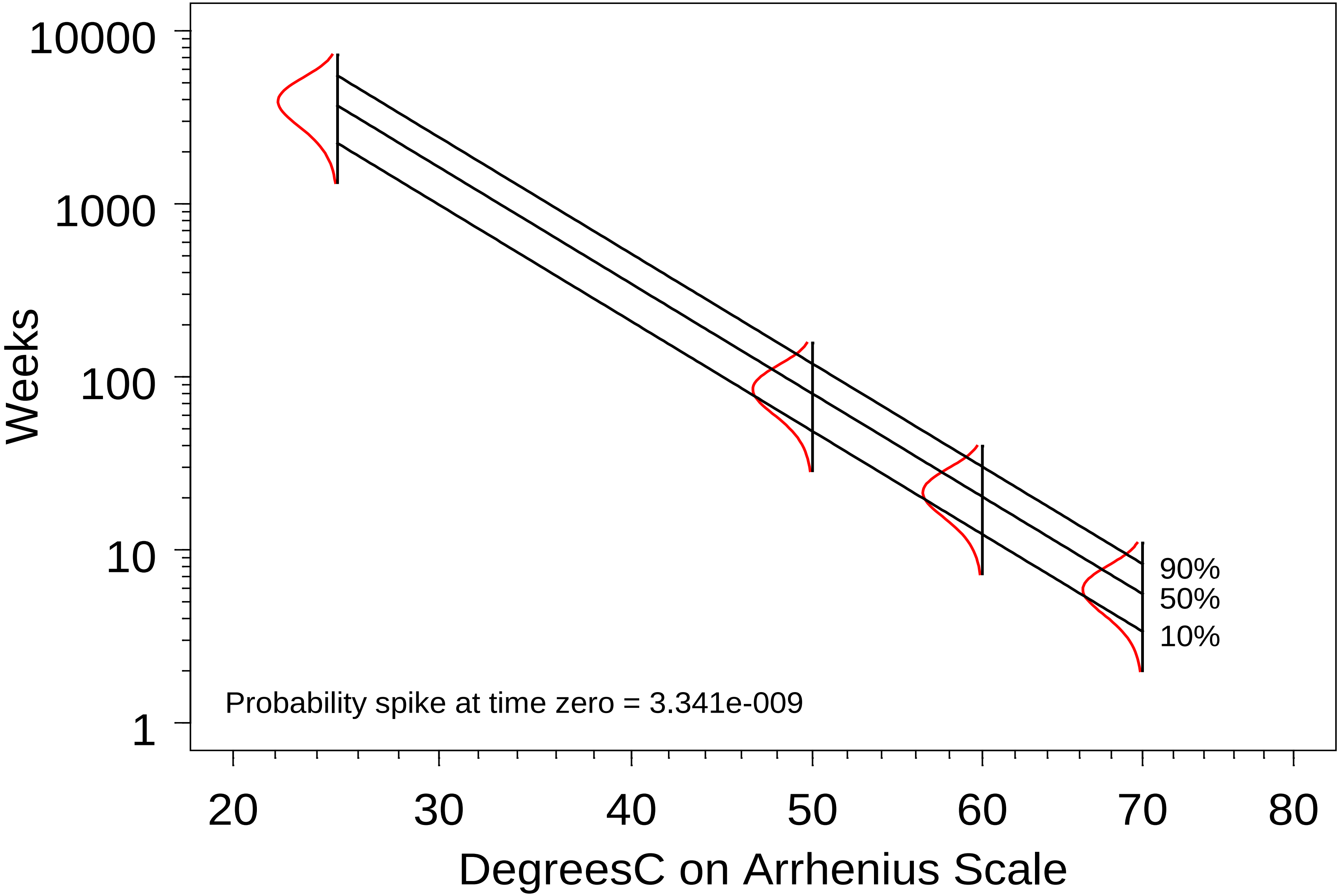
AdhesiveBondB data
Resp:Log,Time:Square root, Dist:Normal




AdhesiveBondB data
Destructive Degradation Individual Regression Analyses
Resp:Log,Time:Square root, Dist:Normal
100
50
20
10
Newtons
0
5
10
15
20
Weeks
○ 50DegreesC
+ 60DegreesC
× 70DegreesC


Degradation rate versus DegreesC on Arrhenius Scale for
AdhesiveBondB data
Resp:Log,Time:Square root,x:Arrhenius, Dist:Normal
Slope
0.45
0.35
0.30
0.25
0.20
0.15
0.10
0.05
45
50
55
60
65
70
75
DegreesC on Arrhenius Scale


AdhesiveBondB data
Destructive Degradation Regression Analyses
Resp:Log,Time:Square root,DegreesC:Arrhenius, Dist:Normal
100
50
20
10
Newtons
0
5
10
15
20
Weeks
50DegreesC
60DegreesC
70DegreesC
25DegreesC



Model plot for AdhesiveBondB data
Resp:Log,Time:Square root,DegreesC:Arrhenius, Dist:Normal
Failure-time distribution for degradation failure level of 35 Newtons

Lessons Learned

- Destructive degradation data are also useful, but more units need to be tested
- Transformations of variables can sometimes simplify model assumptions
- One needs to understand the reason for anomalous observations before acting on them

Concluding Remarks

- There are many kinds of reliability data: life, repeated measures degradation, destructive degradation, recurrence
- We often need to use available information outside of your data, but recognize uncertainty in that information.
- Divide and analyze (e.g., failure cause, stratification).
- Do not ignore model uncertainty, especially in extrapolation.
- There is no magic in accelerated testing or statistics
- Finding appropriate accelerating variables and a model adequate for extrapolation are critical concerns.
- Modern software can make the analysis easy, but answers may depend critically on assumptions that cannot be tested.

Some Important References

- Meeker, W. Q., and L. A. Escobar (1998). *Statistical Methods for Reliability Data*, New York, NY: Wiley.
- Nelson, W. (1982). *Applied Life Data Analysis*, New York, NY: Wiley.
- Nelson, W. (1990). *Accelerated Testing: Statistical Models, Test Plans, and Data Analyses*, New York, NY: Wiley.
- Nelson, Wayne B. (2003). *Recurrent Events Data Analysis for Product Repairs*, Disease Recurrences, and Other Applications, ASA-SIAM Series on Statistics and Applied Probability
- Tobias, P. A., and D. C. Trindade (2011). *Applied Reliability*, Third Edition, New York, NY: Van Nostrand Reinhold.