Chapter 19

Other Topics in Accelerated Life Testing

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Based on Meeker, Escobar, and Pascual (2021): *Statistical Methods for Reliability Data, Second Edition*, John Wiley & Sons Inc.

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Chapter 19
Other Topics in Accelerated Life Testing

Topics discussed in this chapter are:

- An ALT with interval-censored data.
- Using Bayesian methods to rescue an ALT
- An ALT with two accelerating variables.
- A multifactor ALT with a single accelerating variable.
- Pitfalls of accelerated testing.

Chapter 19

Other Topics in Accelerated Life Testing

Segment 1

An ALT with Interval-Censored Data

New-Technology IC Device ALT Data Analysis

Analysis of Interval-Censored ALT Data on a New-Technology IC Device

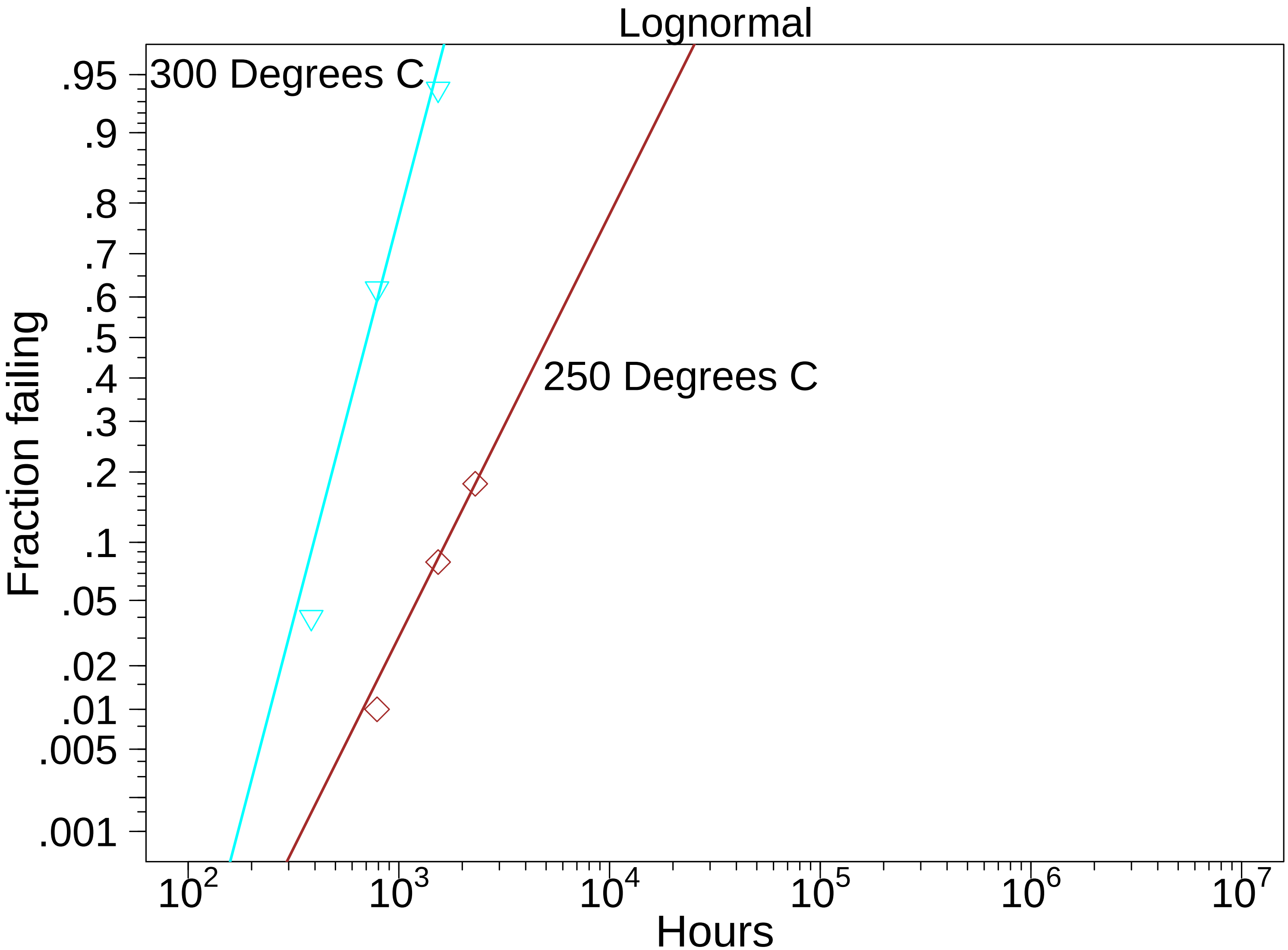
- Tests were run at 150, 175, 200, 250, and 300°C.
- Developers were interested in B01 life at 100°C.
- Failures had been found only at the two higher temperatures.
- After early failures at 250 and 300°C, there was some concern that no failures would be observed at 175°C before decision time.
- Thus the 200°C test was started later than the others.

New-Technology IC Device ALT Data

Hours Lower	Hours Upper	Status	Number of Devices	Temperature °C
1536	—	Right Censored	50	150
1536	—	Right Censored	50	175
96	—	Right Censored	50	200
384	788	Failed	1	250
788	1536	Failed	3	250
1536	2304	Failed	5	250
2304	—	Right Censored	41	250
192	384	Failed	4	300
384	788	Failed	27	300
788	1536	Failed	16	300
1536	—	Right Censored	3	300

Lognormal Multiple Probability Plot
New-Technology Integrated Circuit Device ALT
ML Fits Different Shape Parameters σ_i

$$\widehat{\Pr}[T(\textbf{Temp}_i) \leq t] = \Phi_{\textbf{norm}}\left[\frac{\log(t)-\widehat{\mu}_i}{\widehat{\sigma}_i}\right], \; i = 250, 300$$



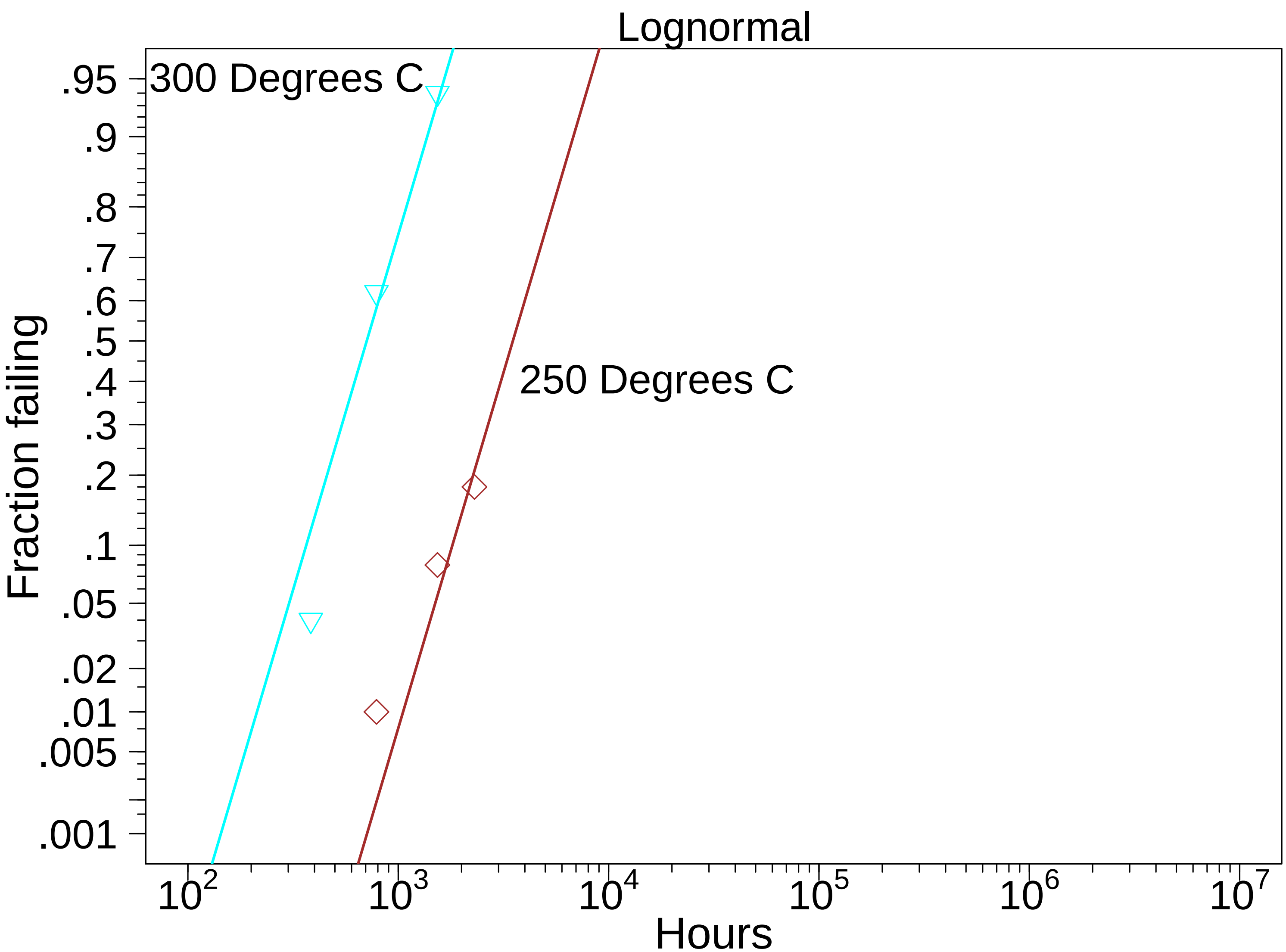
Individual Lognormal ML Estimation Results for the New-Technology IC Device

Temp °C	Parameter	ML Estimate	Standard Error	95% Approximate Confidence Intervals Lower	Upper
250	$t_{0.01}$	674.4	249.0	327.1	1390.4
	σ	0.87	0.26	0.48	1.57
300	$t_{0.01}$	244.6	35.9	183.5	326.1
	σ	0 .46	0.05	0.36	0.58

The confidence intervals are based on the Wald method.

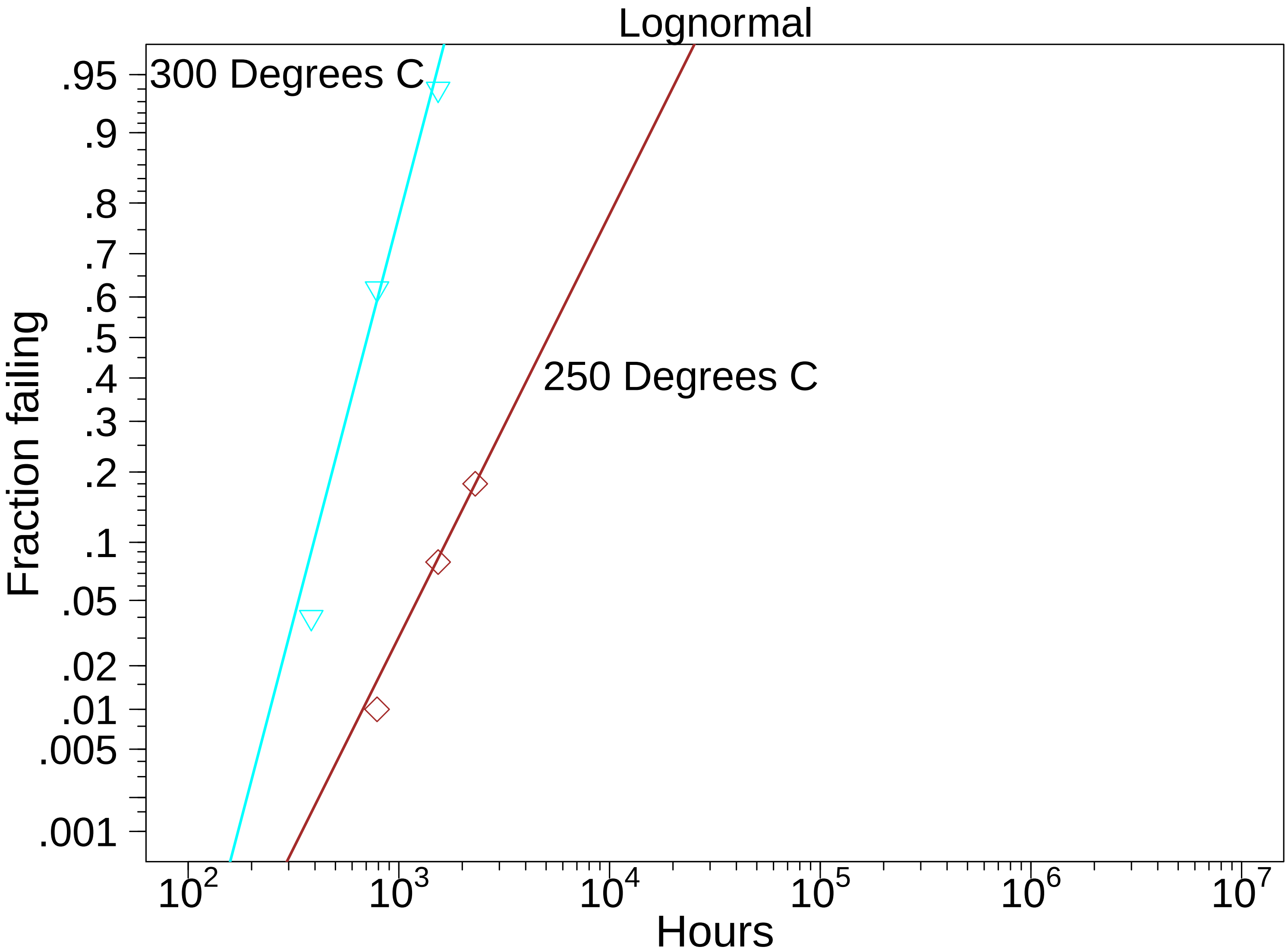
Lognormal Multiple Probability Plot
New-Technology Integrated Circuit Device ALT
ML Fits Equal Shape Parameter σ

$$\widehat{\Pr}[T(\mathbf{Temp}_i) \le t] = \Phi_{\mathbf{norm}}\left[\frac{\log(t)-\widehat{\mu}_i}{\widehat{\sigma}}\right], \; i = 250, 300$$



Lognormal Multiple Probability Plot
New-Technology Integrated Circuit Device ALT
ML Fits Different Shape Parameters σ_i

$$\widehat{\Pr}[T(\textbf{Temp}_i) \le t] = \Phi_{\textbf{norm}}\left[\frac{\log(t) - \widehat{\mu}_i}{\widehat{\sigma}_i}\right], \ i = 250, 300$$



Individual Lognormal ML Estimation Results for the New-Technology IC Device with Equal Shape σ

Temp °C	Parameter	ML Estimate	Standard Error	95% Approximate Confidence Interval Lower	Upper
250	$t_{0.1}$	1054.4	132.6	824.1	1349.0
300	$t_{0.1}$	213.0	33.0	157.2	288.7
	σ	0.52	0.057	0.42	0.64

The confidence intervals are based on the Wald method.

Likelihood for Lognormal Distribution Simple Regression Model with Interval-Censored Data

The likelihood for independent observations grouped into K bins is

$$L(\beta_0, \beta_1, \sigma) = \prod_{k=1}^{K} [\Phi_{\text{norm}}(z_{uk}) - \Phi_{\text{norm}}(z_{\ell k})]^{\omega_k \delta_k} [1 - \Phi_{\text{norm}}(z_{\ell k})]^{\omega_k (1-\delta_k)}$$

where $\text{data}_k = (x_k, t_{\ell k}, t_{uk}, \delta_k, \omega_k)$, $\mu(x_k) = \beta_0 + \beta_1 x_k$,
$x_k = 11604.52/(°\text{C}_k + 273.15)$,

$$z_{\ell k} = \frac{\log(t_{\ell k}) - \mu_k}{\sigma}, \quad z_{uk} = \frac{\log(t_{uk}) - \mu_k}{\sigma},$$

ω_k is the number of observations in bin k,

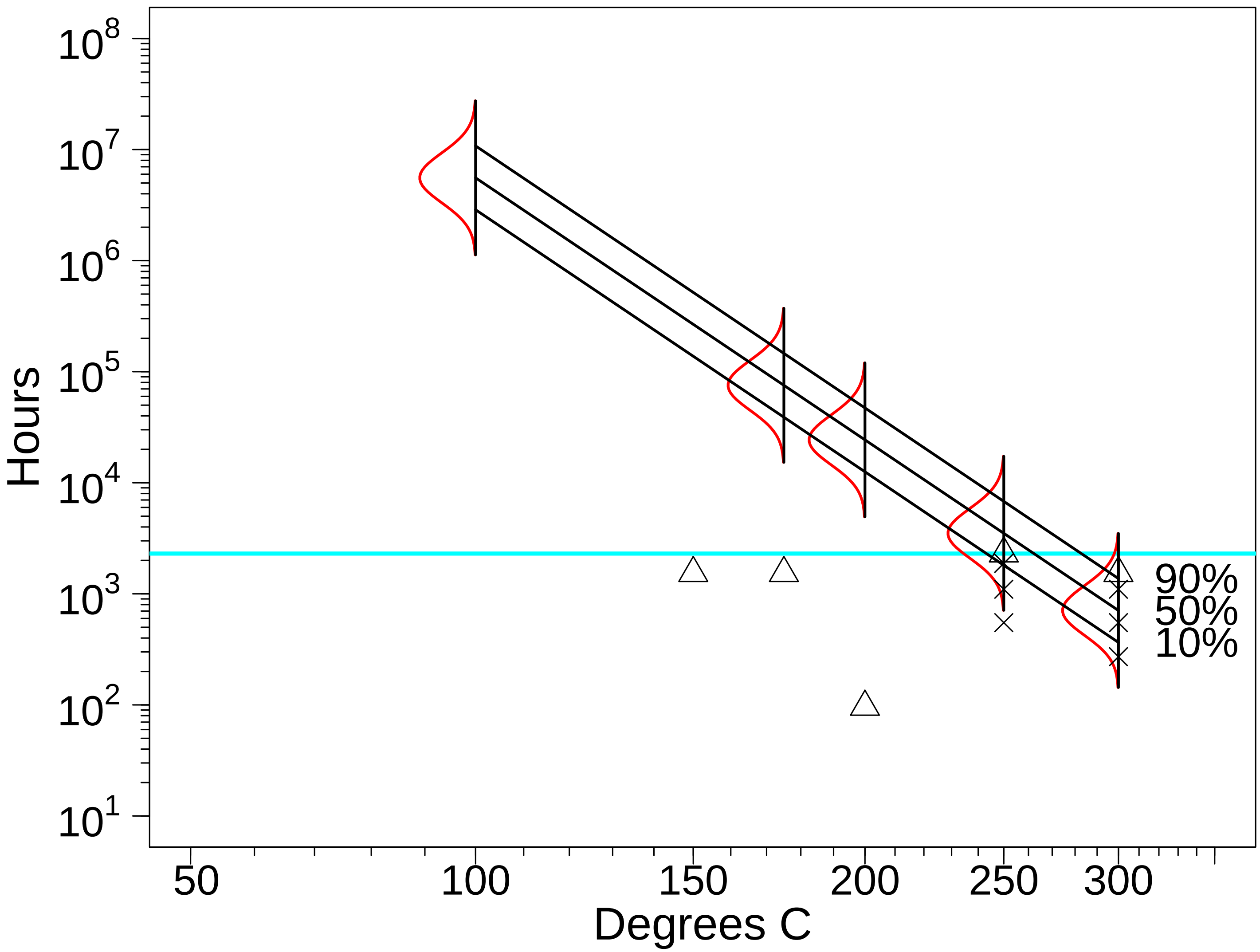
$$\delta_k = \begin{cases} 1 & \text{interval-censored observation} \\ 0 & \text{right-censored observation,} \end{cases}$$

and $\Phi_{\text{norm}}(z)$ is the standardized normal cdf.

The parameters are $\boldsymbol{\theta} = (\beta_0, \beta_1, \sigma)$.

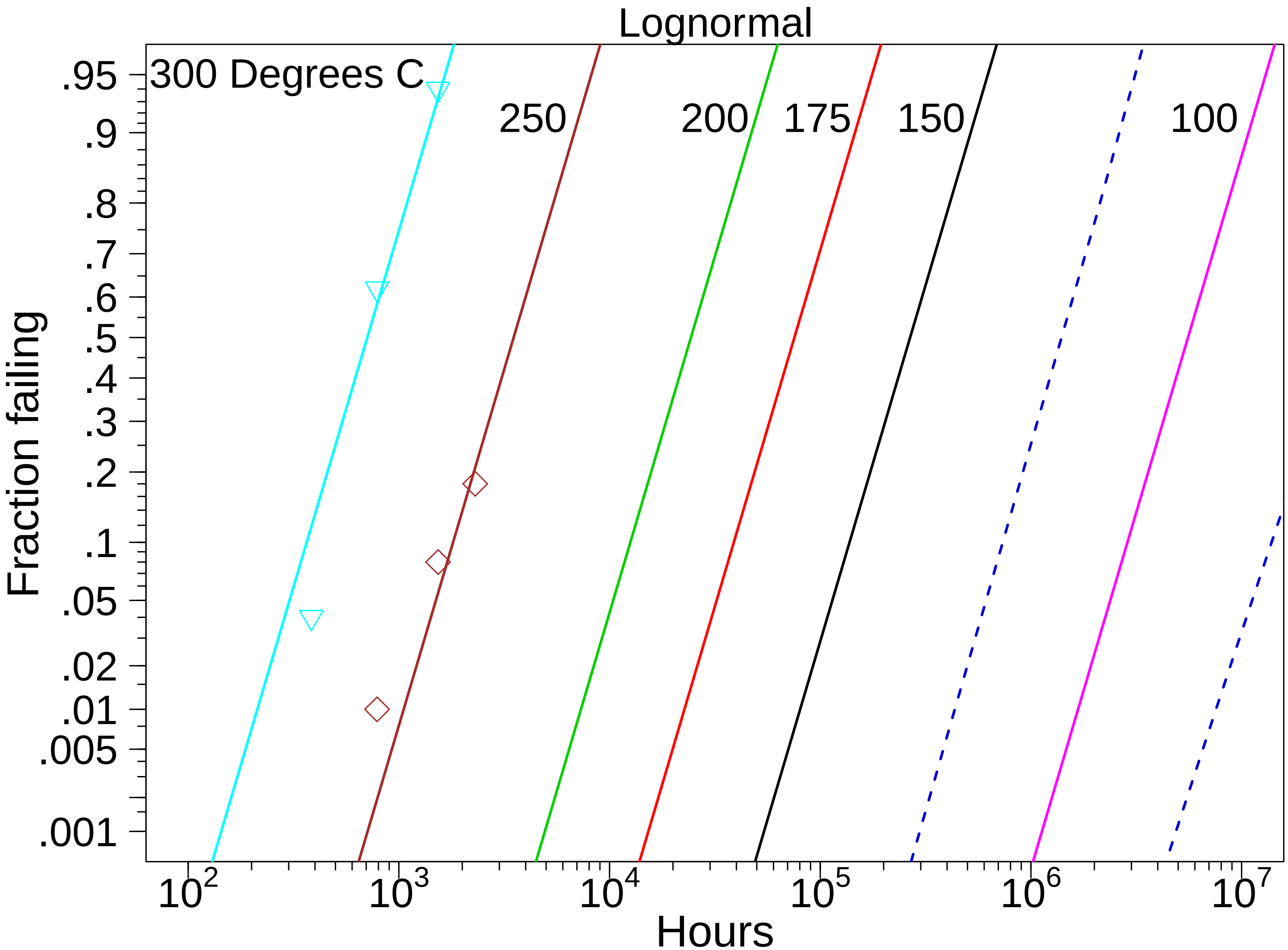
Arrhenius Plot Showing ALT Data and the Arrhenius-Lognormal Model ML Estimation Results for the New-Technology IC Device

$$\log[\widehat{t}_p(x)] = \widehat{\mu}(x) + \Phi^{-1}_{\textbf{norm}}(p)\widehat{\sigma}, \ \widehat{\mu}(x) = \widehat{\beta}_0 + \widehat{\beta}_1 x$$



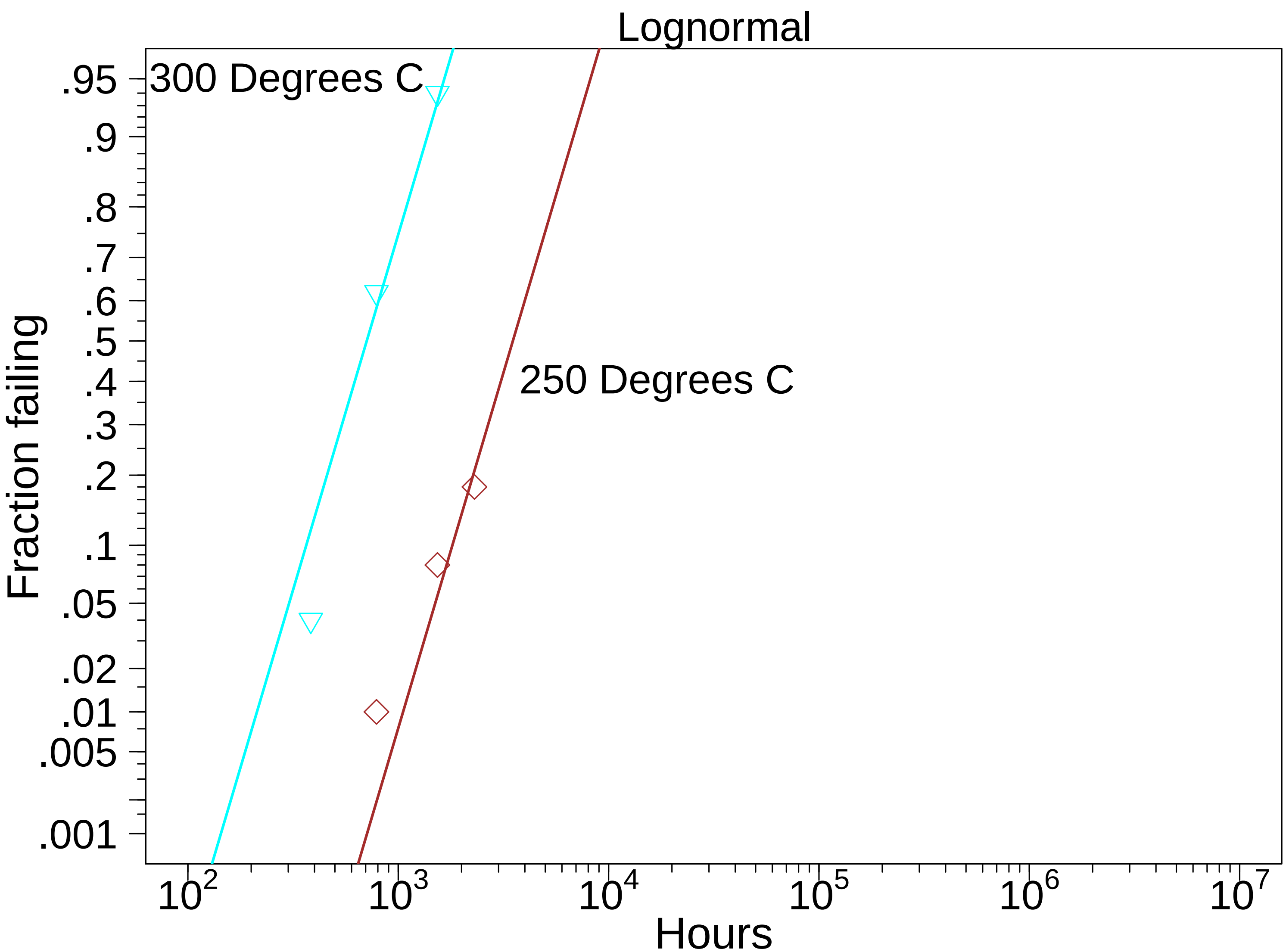
Lognormal Probability Plot Showing the Arrhenius-Lognormal Model ML Estimation Results for the New-Technology IC Device

$$\widehat{\Pr}[T(\textbf{Temp}) \le t] = \Phi_{\textbf{norm}}\left[\frac{\log(t) - \widehat{\mu}(x)}{\widehat{\sigma}}\right], \; \widehat{\mu}(x) = \widehat{\beta}_0 + \widehat{\beta}_1 x$$



Lognormal Multiple Probability Plot
New-Technology Integrated Circuit Device ALT
ML Fits Equal Shape Parameter σ

$$\widehat{\Pr}[T(\mathbf{Temp}_i) \le t] = \Phi_{\mathbf{norm}}\left[\frac{\log(t) - \widehat{\mu}_i}{\widehat{\sigma}}\right], \; i = 250, 300$$



Arrhenius-Lognormal Model ML Estimation Results for the New-Technology IC Device

Parameter	ML Estimate	Standard Error	95% Approximate Confidence Intervals Lower	Upper
β_0	-10.2	1.5	-13.2	-7.2
β_1	0.83	0.07	0.68	0.97
σ	0.52	0.06	0.42	0.64

New-Technology IC Device
Lognormal Model-Fitting Summary

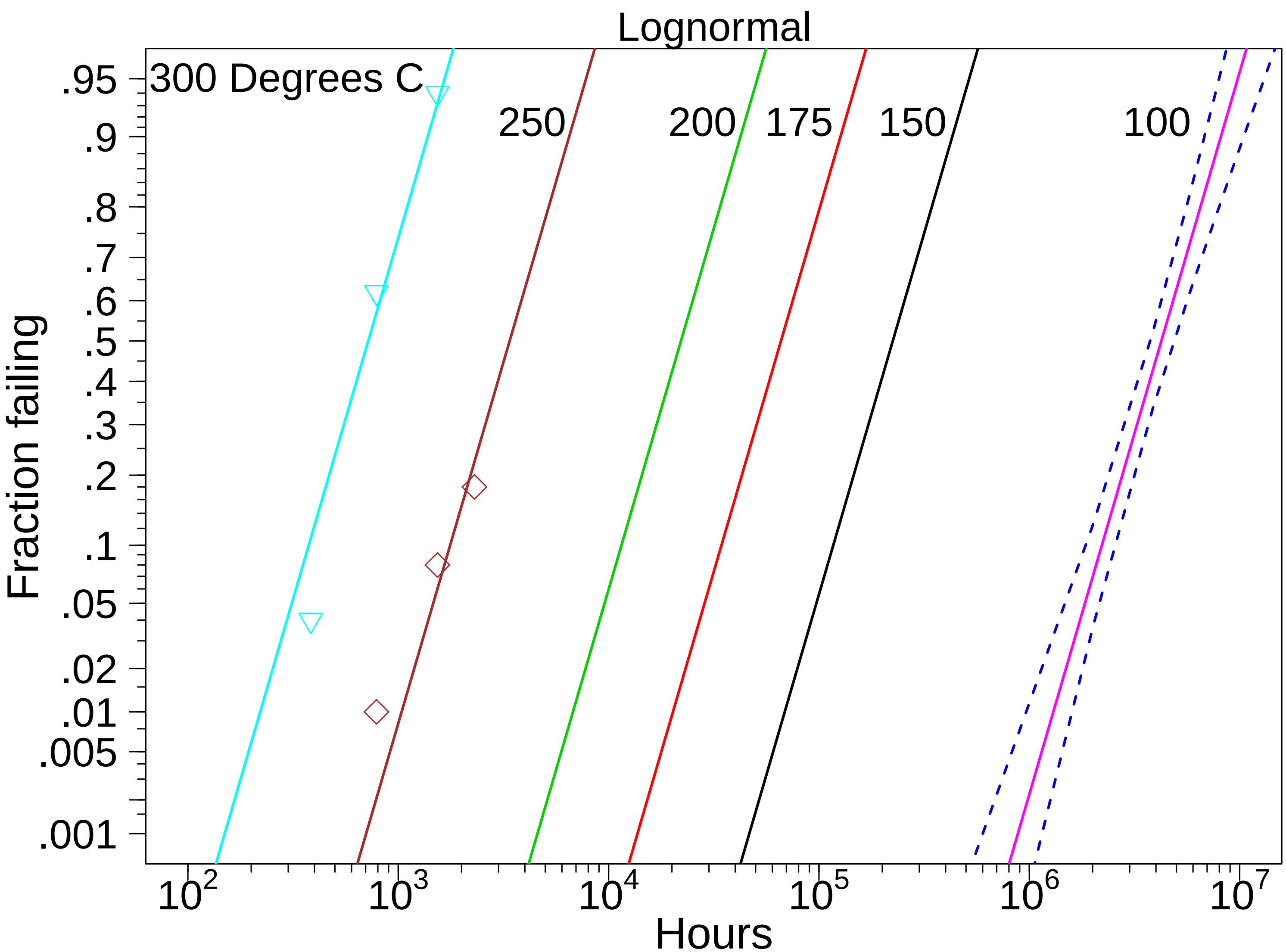
Model	$-2\mathcal{L}(\boldsymbol{\theta})$	AIC	# Param
SepDists	172.0	180.0	4
EqualSig	176.7	182.7	3/6
RegrModel	176.7	182.7	3
Pooled	366.8	370.8	2

Likelihood-Ratio Tests

Comparison	LR Statistic	dof	p-value
SepDists vs EqualSig	4.72	1	0.028
EqualSig vs RegrModel	0.0	3	1.0
RegrModel vs Pooled	190.1	1	< 0.001

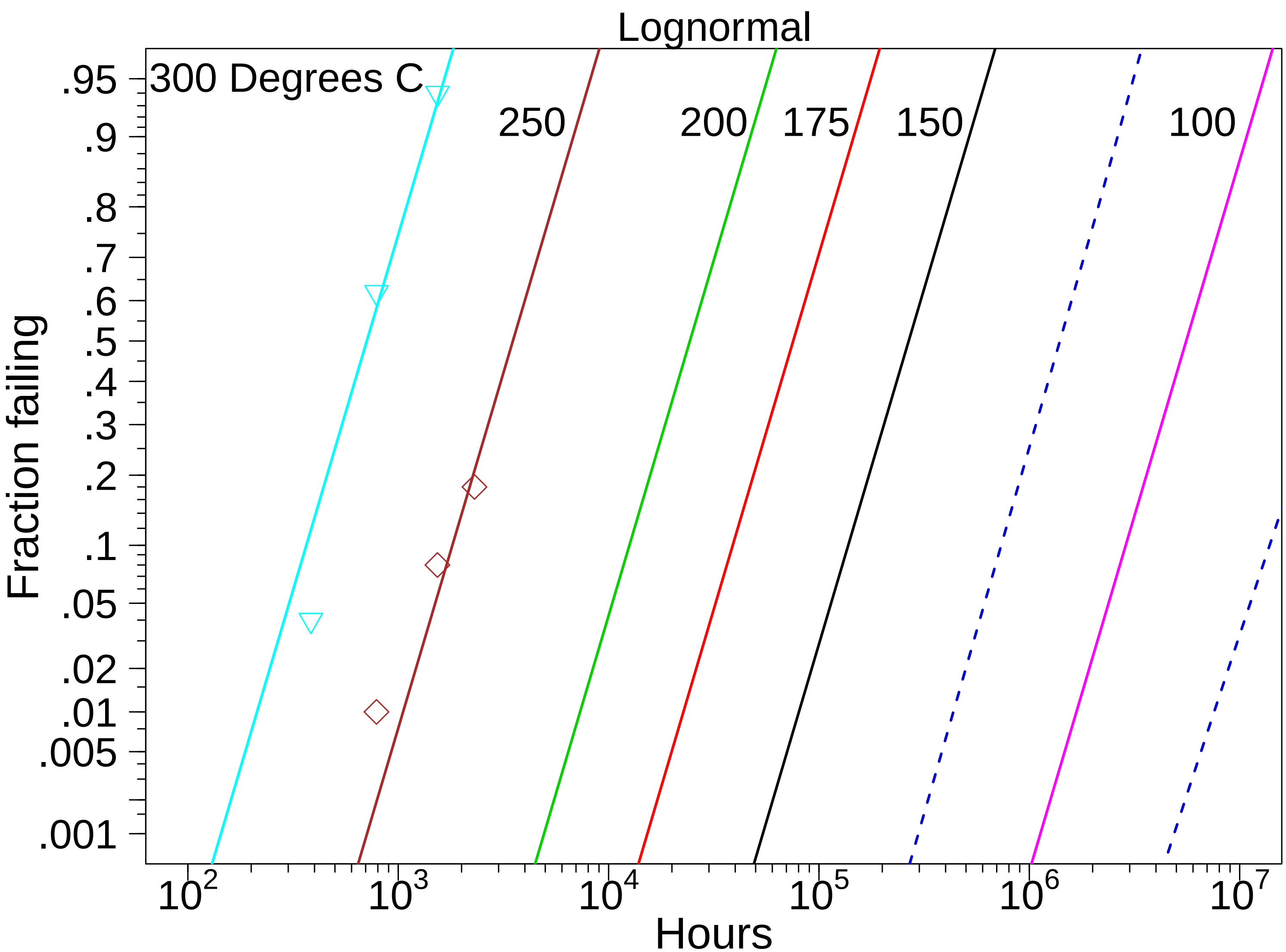
Lognormal Probability Plot Showing the Arrhenius-Lognormal Model ML Estimation Results for the New-Technology IC Device with Given $E_a = 0.80$

$$\widehat{\Pr}[T(\textbf{Temp}) \le t] = \Phi_{\textbf{norm}}\left[\frac{\log(t) - \widehat{\mu}(x)}{\widehat{\sigma}}\right], \ \widehat{\mu}(x) = \widehat{\beta}_0 + 0.80x$$



Lognormal Probability Plot Showing the Arrhenius-Lognormal Model ML Estimation Results for the New-Technology IC Device

$$\widehat{\Pr}[T(\textbf{Temp}) \le t] = \Phi_{\textbf{norm}}\left[\frac{\log(t) - \widehat{\mu}(x)}{\widehat{\sigma}}\right], \ \widehat{\mu}(x) = \widehat{\beta}_0 + \widehat{\beta}_1 x$$



Chapter 19

Other Topics in Accelerated Life Testing

Segment 2

Bayesian Analysis for the New-Technology IC Device ALT

New-Technology IC Device ALT
Problem and Rescue

- Failures at 300°C were caused by a different failure mode and had to be dropped (or right-censored).

- With failures at only 250°C, there is no information in the data about β_1, the effective activation energy.

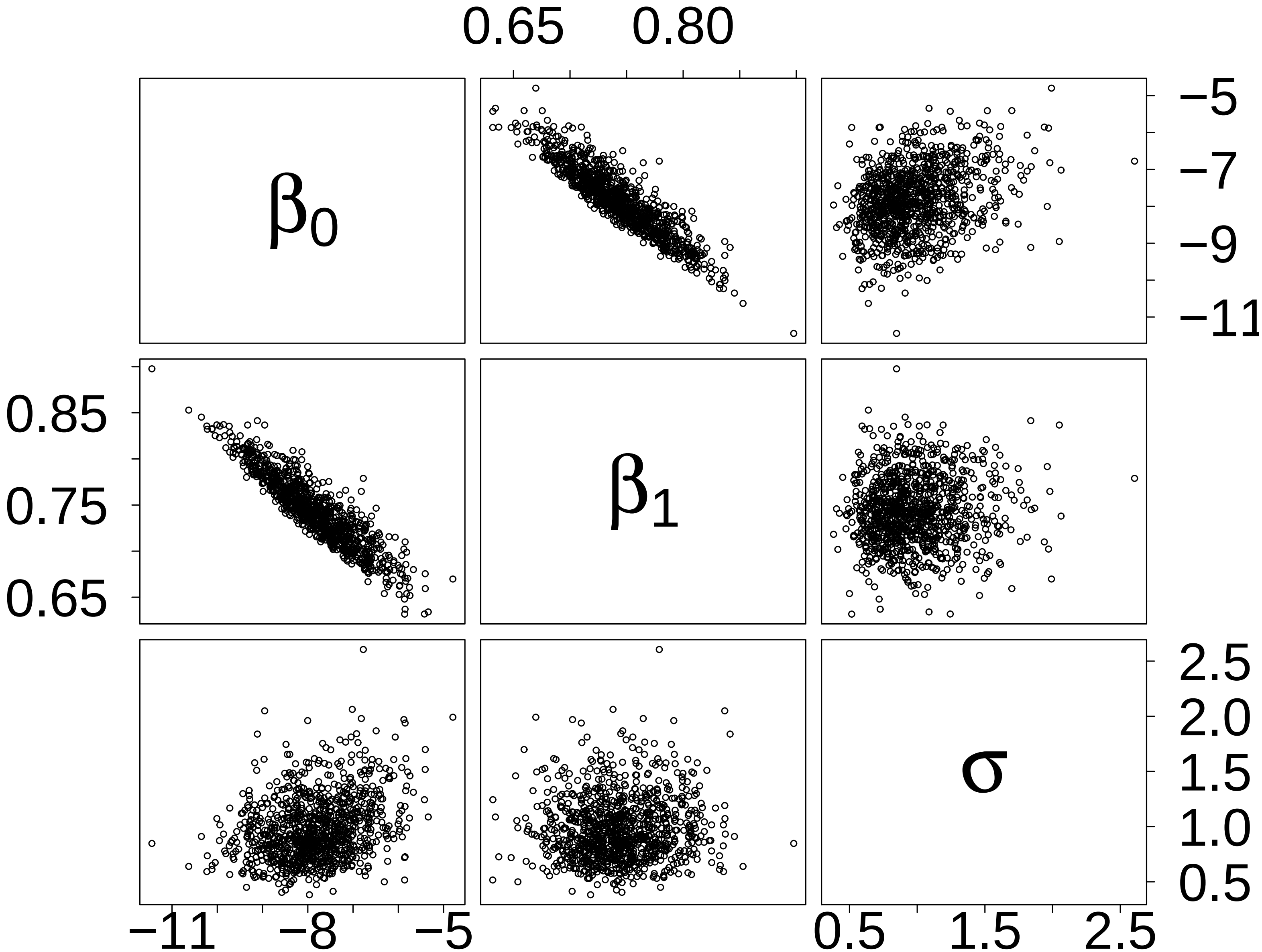
- Previous experience with the same failure mode suggested a prior distribution for β_1.

- Bayesian estimation could be used to estimate the failure-time distribution at 100°C.

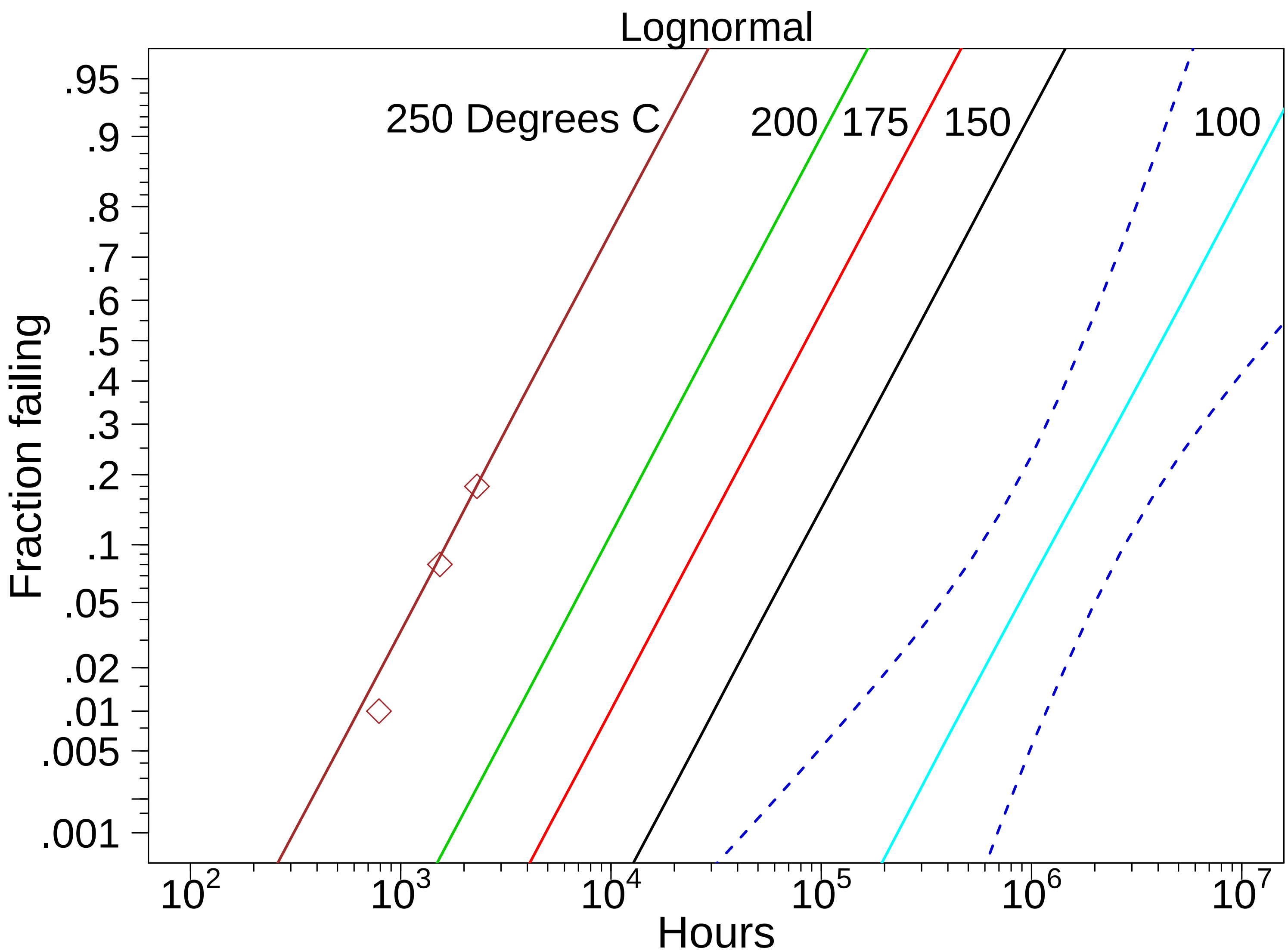
New-Technology IC Device Prior Distributions

Parameter	Prior Distributions
$t_{0.1}(250)$	<LNORM>$(100, 10000)$
β_1	<LNORM>$(0.65, 0.85)$
σ	<LNORM>$(0.05, 5.0)$

Pairs Plot of the Joint Posterior Distribution Draws for the New-Technology IC Device



Lognormal Probability Plot Showing the Arrhenius-Lognormal Model Bayesian Estimation Results for the New-Technology IC Device



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Other Topics in Accelerated Life Testing

Segment 3

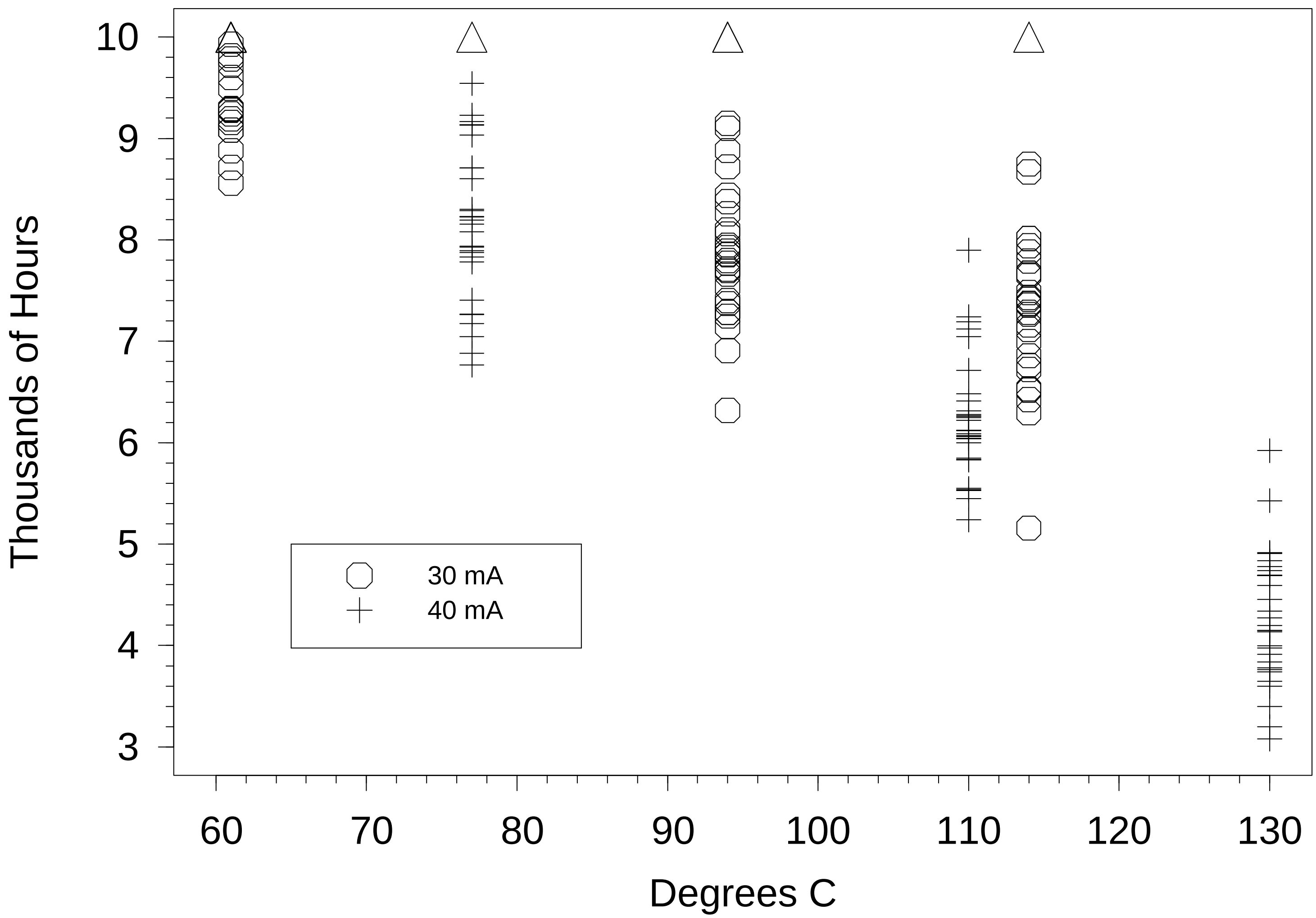
An ALT with Two Accelerating Variables

Increasing Temperature and Current to Estimate an LED Failure-Time Distribution

Temperature/Current ALT for LEDs

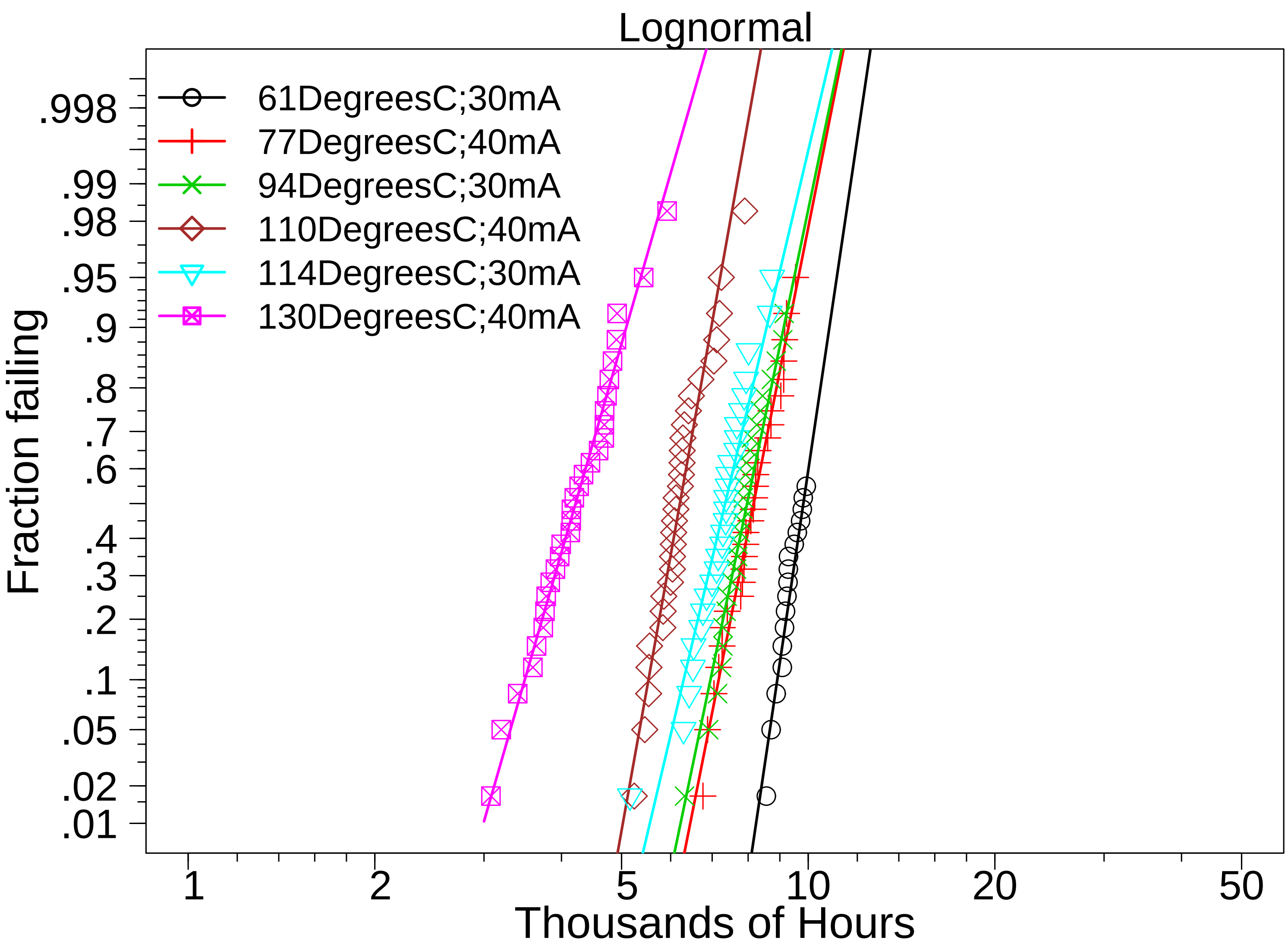
- ALT light emitting diode (LED) with two accelerating variables.
- Purpose of the test was to evaluate an LED for suitability for use in an LED flashlight.
- Actual response was percent drop in light output.
- An LED fails when light output decreases to 60% of the initial light output.
- There were no failures during the accelerated test.
- Degradation data mapped into pseudo failure times by fitting a straight line to the degradation path and extrapolating to the failure level.
- Non-rectangular design due to ambient versus junction temperature.

Scatter Plot of the LED ALT Data Showing Hours to Failure Versus Temperature with Current Indicated by Different Symbols



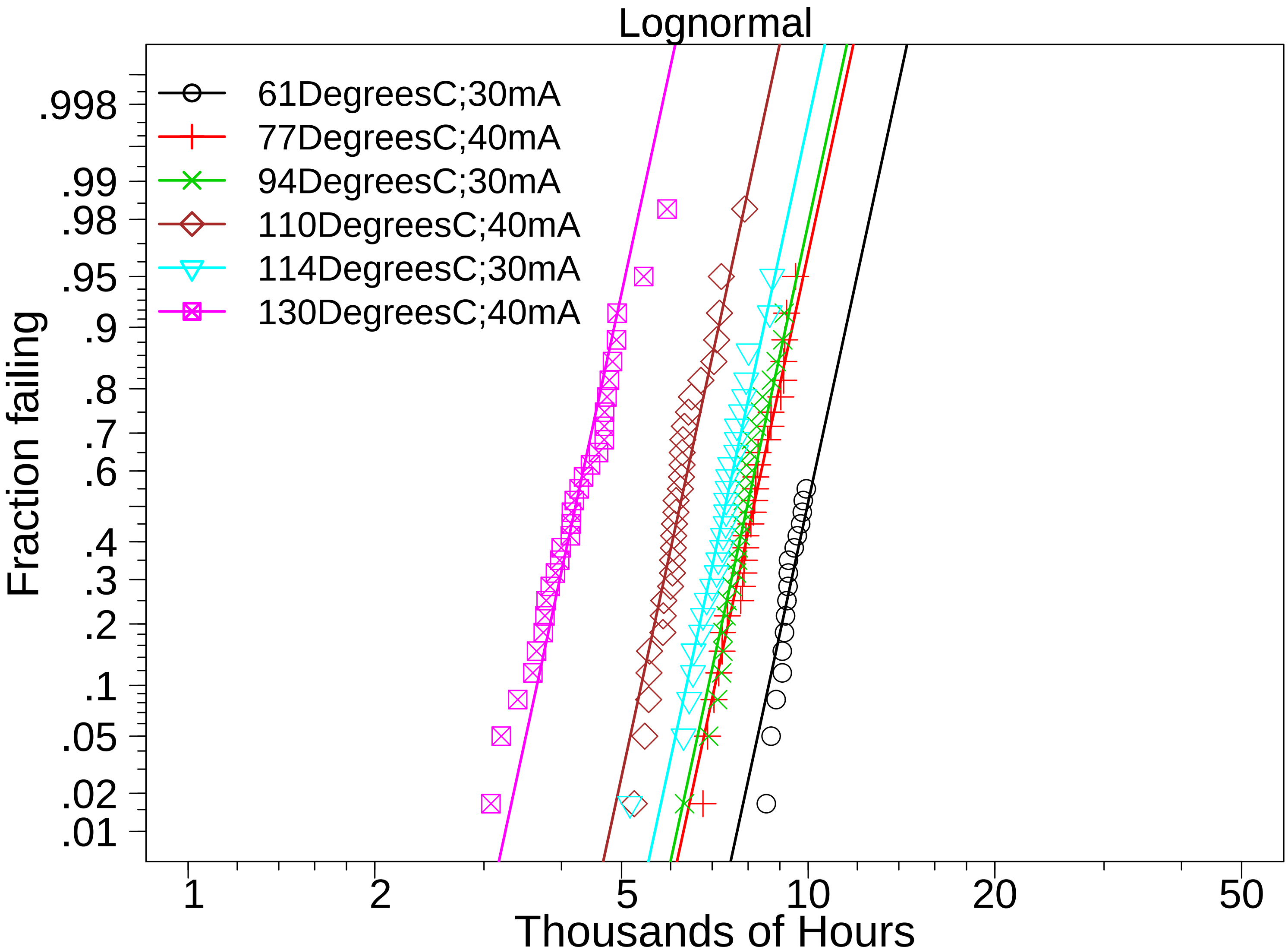
Lognormal Multiple Probability Plot
LED ALT Data
Different Shape Parameters

$$\widehat{\Pr}\left[T(\mathbf{Temp}_i, \mathtt{Current}_j) \le t\right] = \Phi_{\mathbf{norm}}\left[\frac{\log(t) - \widehat{\mu}_{i,j}}{\widehat{\sigma}_{i,j}}\right]$$



Lognormal Multiple Probability Plot
LED ALT Data ML Estimates
Equal Shape Parameter

$$\widehat{\Pr}\left[T(\mathbf{Temp}_i, \texttt{Current}_j) \le t\right] = \Phi_{\mathbf{norm}}\left[\frac{\log(t) - \widehat{\mu}_{i,j}}{\widehat{\sigma}}\right]$$



LED ALT
Lognormal/Arrhenius/Inverse-Power Relationship Models

Model 1: $\mu(\boldsymbol{x}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2$

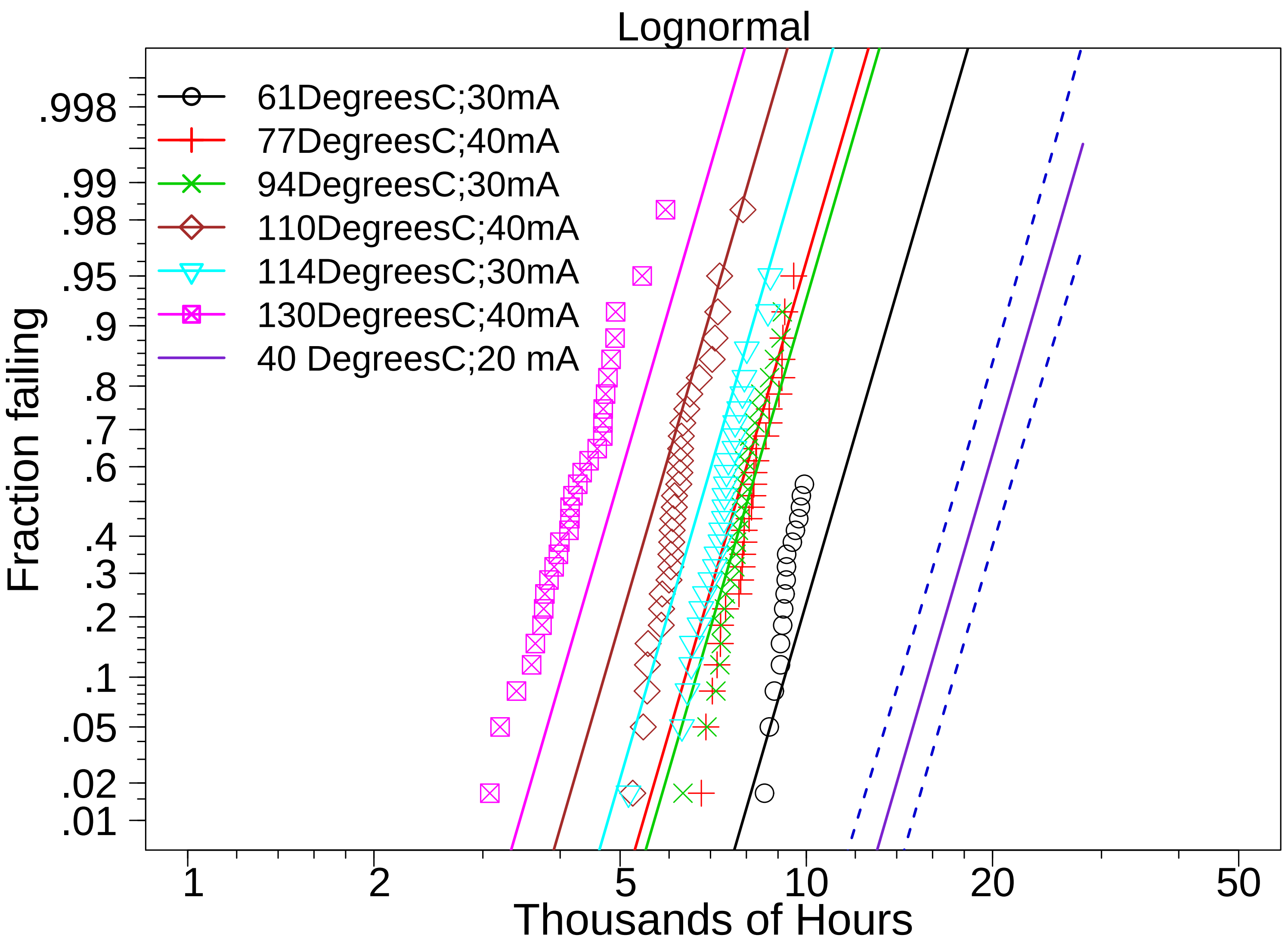
Model 2: $\mu(\boldsymbol{x}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$

where

- $x_1 = 11604.52/(\text{Temp}\,^\circ\text{C} + 273.15)$,
- $x_2 = \log(\texttt{Current})$,
- $\beta_2 = E_a$ and,
- σ is constant.

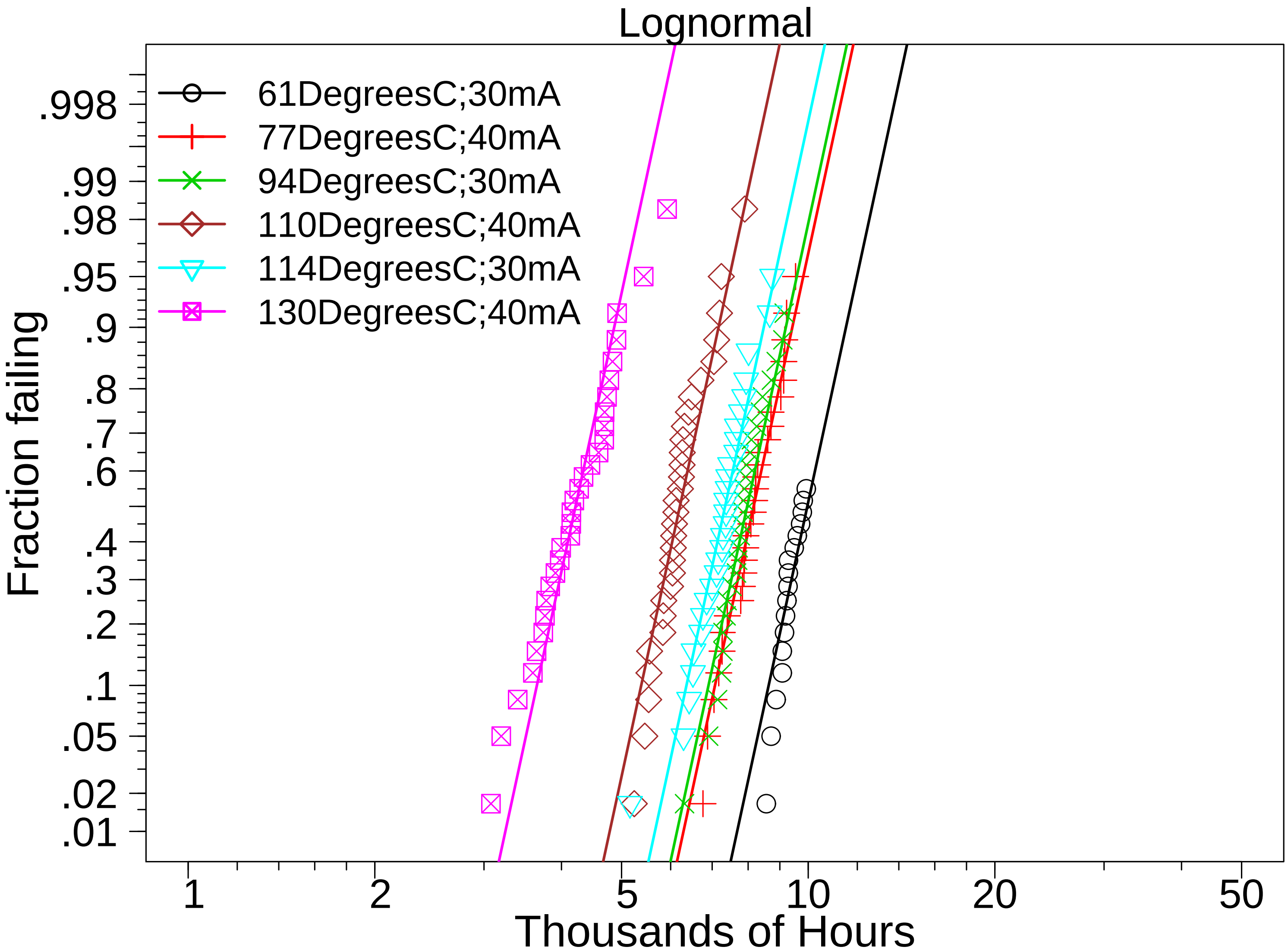
Lognormal Multiple Probability Plot of the LED ALT Data Arrhenius-Inverse-Power Relationship Lognormal Model (with no Interaction)

$$\widehat{\Pr}[T(\mathbf{Temp}, \texttt{Current}) \le t] = \Phi_{\mathbf{norm}}\left[\frac{\log(t) - (\widehat{\beta}_0 + \widehat{\beta}_1 x_1 + \widehat{\beta}_2 x_2)}{\widehat{\sigma}}\right]$$



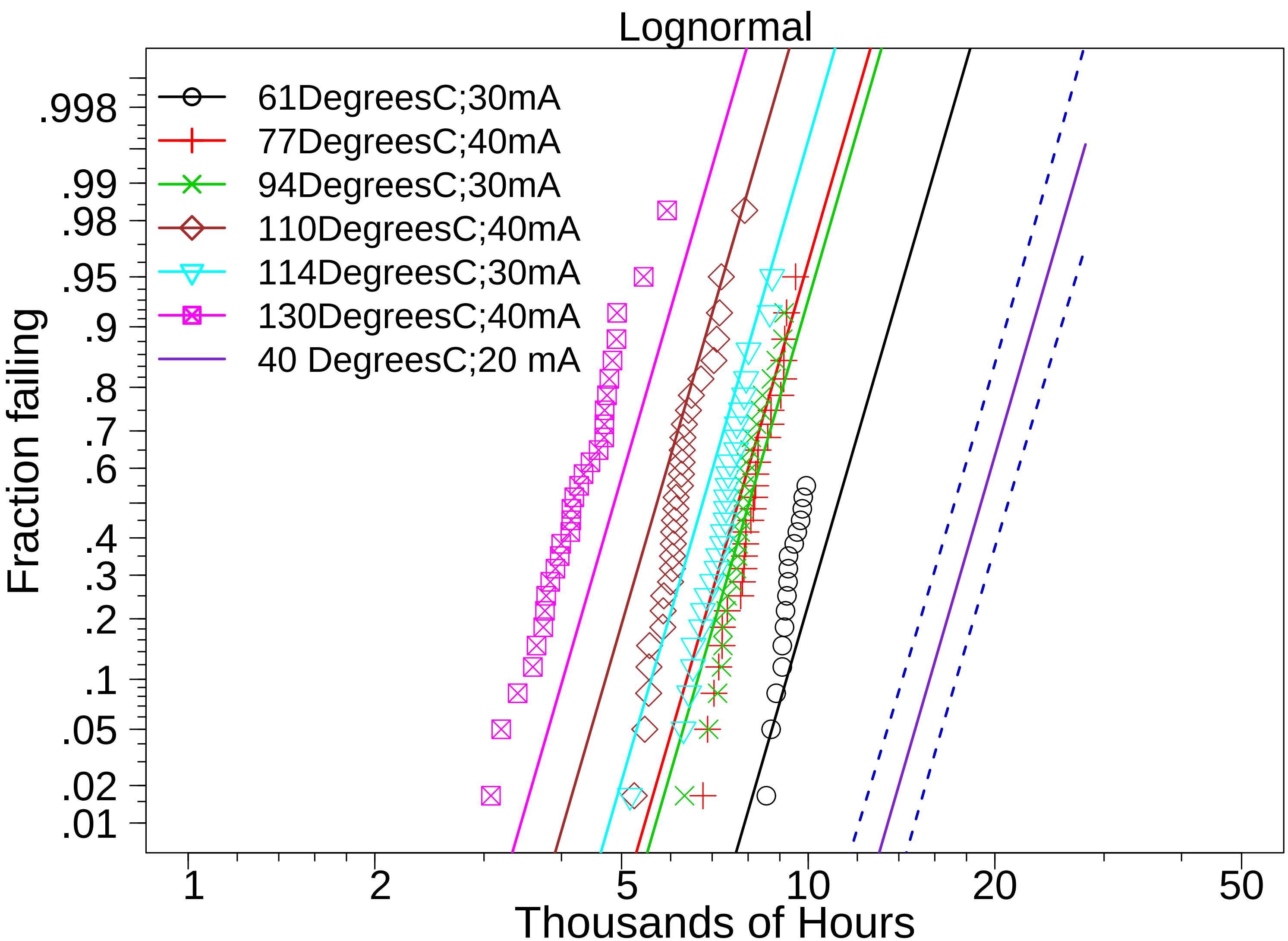
Lognormal Multiple Probability Plot
LED ALT Data ML Estimates
Equal Shape Parameter

$$\widehat{\Pr}\left[T(\mathbf{Temp}_i, \mathtt{Current}_j) \leq t\right] = \Phi_{\mathbf{norm}}\left[\frac{\log(t) - \widehat{\mu}_{i,j}}{\widehat{\sigma}}\right]$$



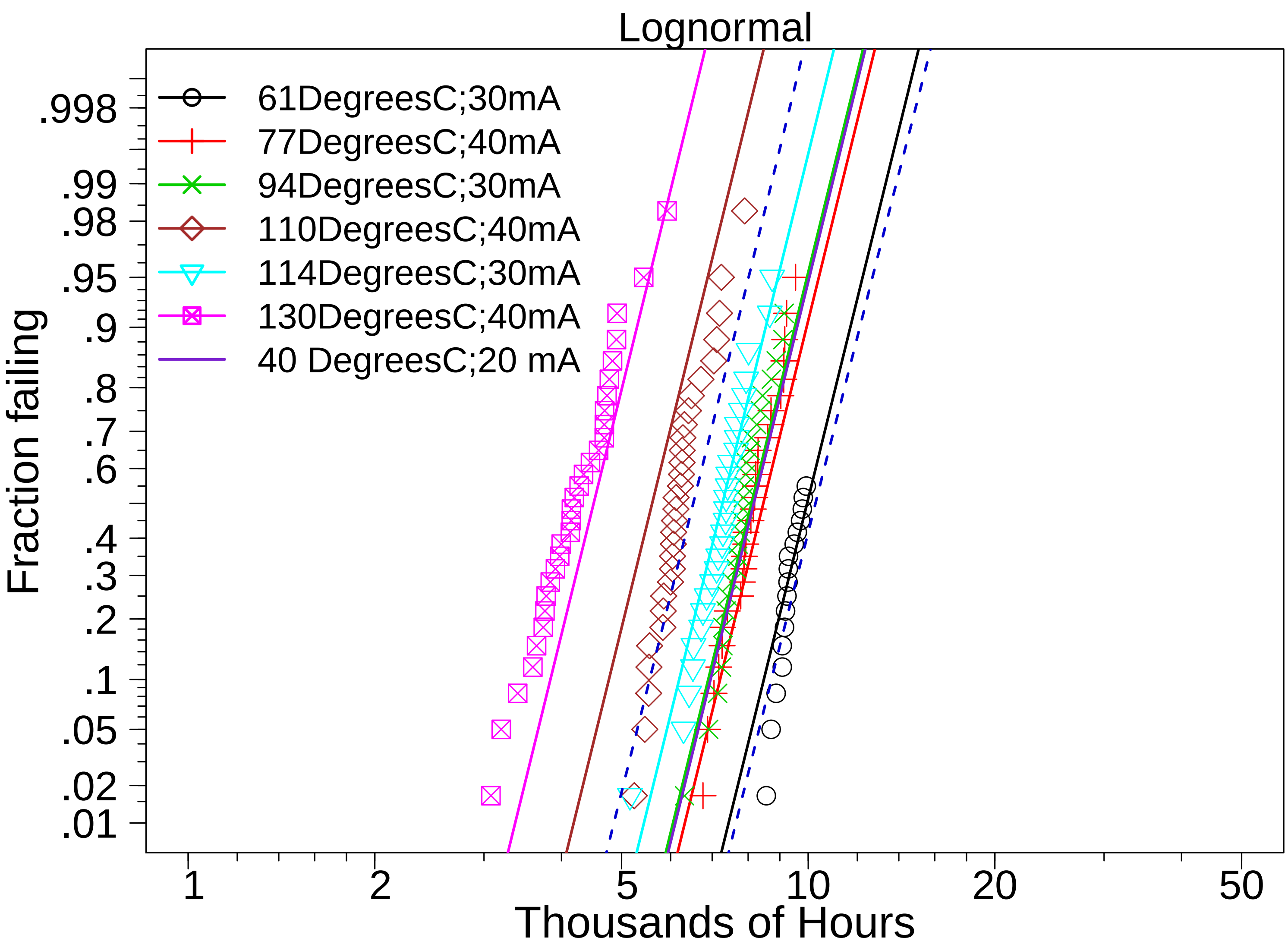
Lognormal Multiple Probability Plot of the LED ALT Data Arrhenius-Inverse-Power Relationship Lognormal Model (with no Interaction)

$$\widehat{\Pr}[T(\textbf{Temp}, \texttt{Current}) \leq t] = \Phi_{\textbf{norm}}\left[\frac{\log(t) - (\widehat{\beta}_0 + \widehat{\beta}_1 x_1 + \widehat{\beta}_2 x_2)}{\widehat{\sigma}}\right]$$



Lognormal Multiple Probability Plot of the LED ALT Data Arrhenius-Inverse-Power Relationship Lognormal Model (with Interaction)

$$\widehat{\Pr}[T(\textbf{Temp}, \texttt{Current}) \le t] = \Phi_{\textbf{norm}}\left[\frac{\log(t) - (\widehat{\beta}_0 + \widehat{\beta}_1 x_1 + \widehat{\beta}_2 x_2 + \widehat{\beta}_3 x_1 x_2)}{\widehat{\sigma}}\right]$$



LED Lognormal Regression Model-Fitting Summary Using the Bad Data

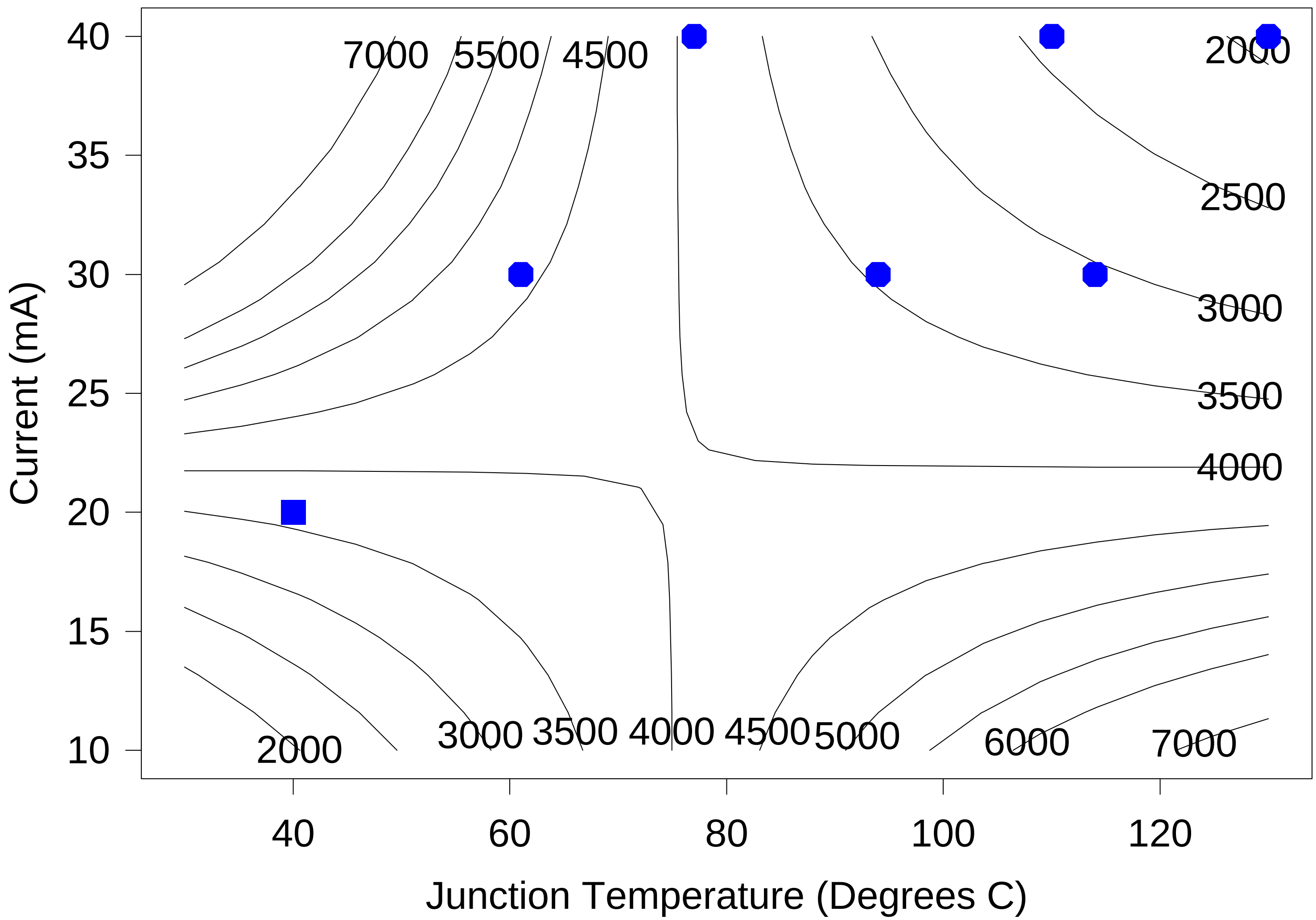
Model	$-2\mathcal{L}(\boldsymbol{\theta})$	AIC	# Param
SepDists	389.9	413.9	12
EqualSig	402.0	416.0	7
Additive RegrModel	485.9	493.9	4
Interaction RegrModel	437.7	447.7	5
Pooled	737.7	741.7	2

Likelihood-Ratio Tests

Comparison	LR statistic	dof	p-value
SepDists vs EqualSig	12.1	5	0.034
EqualSig vs Additive RegrModel	83.9	3	< 0.001
EqualSig vs Interaction RegrModel	35.7	2	< 0.001
Additive RegrModel vs Pooled	251.8	2	< 0.001

LED ALT 0.10 Quantile Estimates (with Interaction)

$$\widehat{\Pr}[T(\textbf{Temp}, \texttt{Current}) \leq t] = \Phi_{\textbf{norm}}\left[\frac{\log(t) - (\widehat{\beta}_0 + \widehat{\beta}_1 x_1 + \widehat{\beta}_2 x_2)}{\widehat{\sigma}}\right]$$



Chapter 19

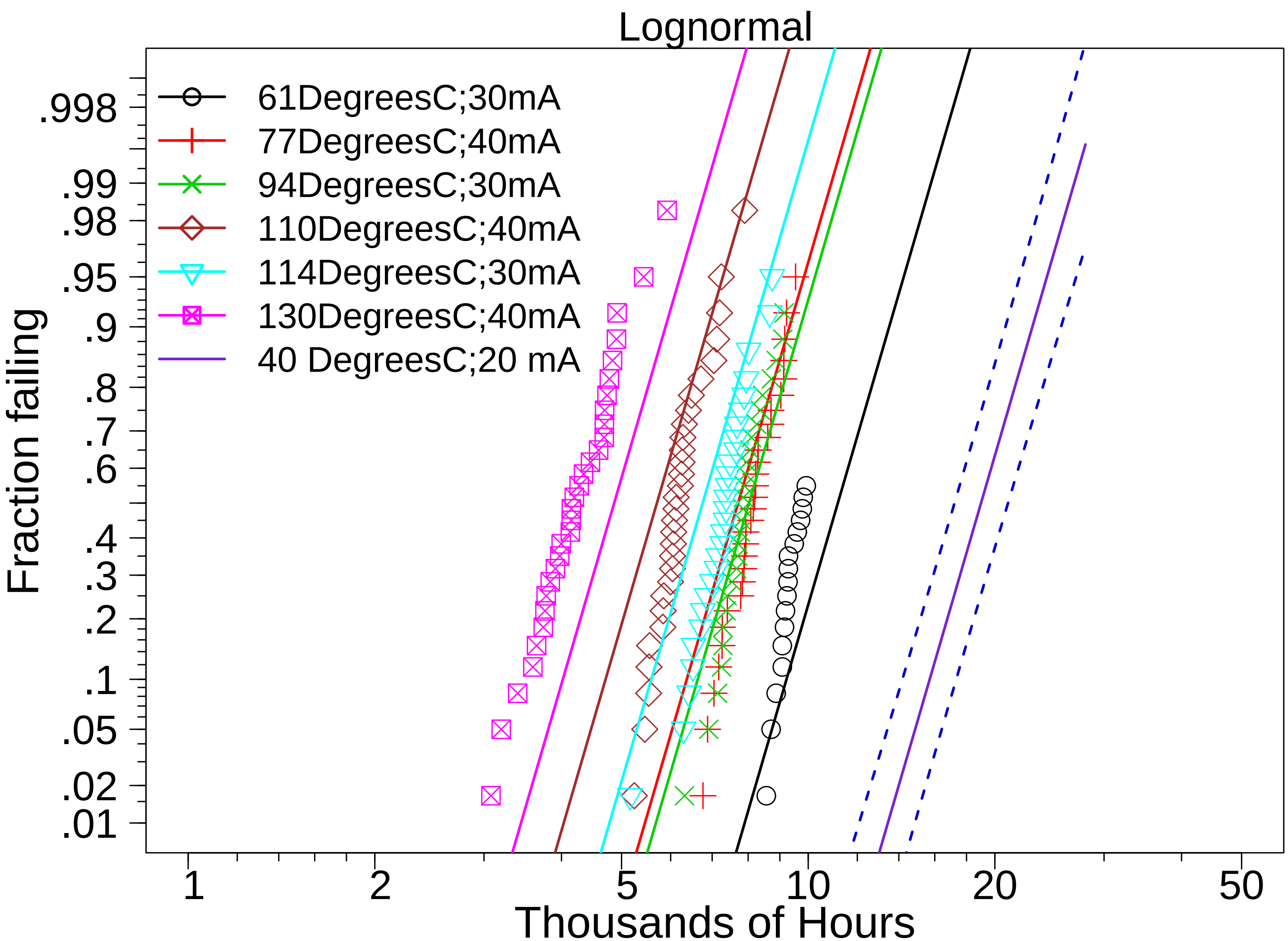
Other Topics in Accelerated Life Testing

Segment 4

Fixing the LED ALT Analysis

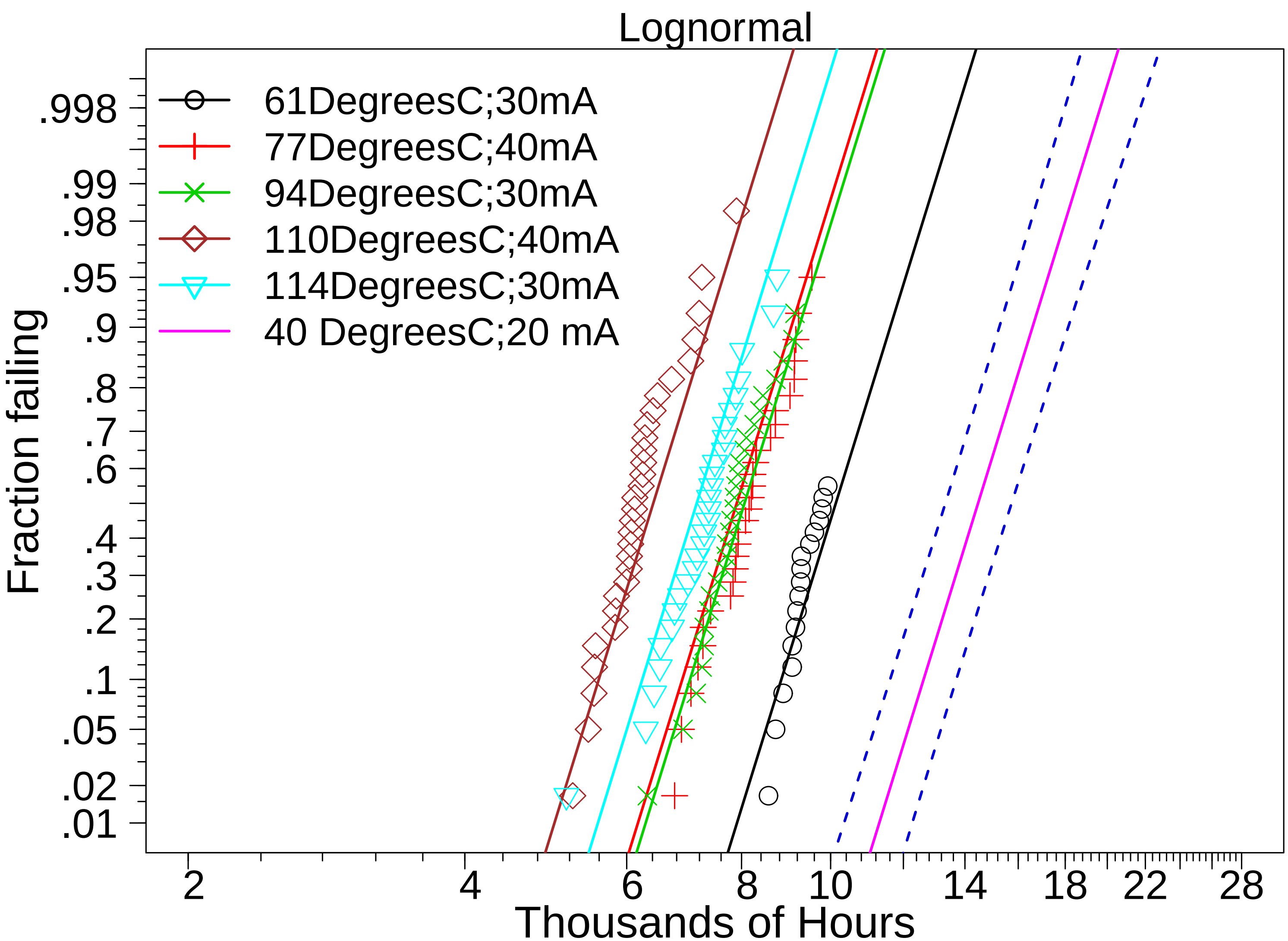
Lognormal Multiple Probability Plot of the LED ALT Data Arrhenius-Inverse-Power Relationship Lognormal Model (with no Interaction)

$$\widehat{\Pr}[T(\mathbf{Temp}, \texttt{Current}) \le t] = \Phi_{\mathbf{norm}}\left[\frac{\log(t)-(\widehat{\beta}_0+\widehat{\beta}_1 x_1+\widehat{\beta}_2 x_2)}{\widehat{\sigma}}\right]$$



Lognormal Multiple Probability Plot of the Good LED ALT Data Arrhenius-Inverse-Power Relationship Lognormal Model (with no Interaction)

$$\widehat{\Pr}[T(\textbf{Temp}, \texttt{Current}) \le t] = \Phi_{\textbf{norm}}\left[\frac{\log(t) - (\widehat{\beta}_0 + \widehat{\beta}_1 x_1 + \widehat{\beta}_2 x_2)}{\widehat{\sigma}}\right]$$



LED Lognormal Regression Model-Fitting Summary Using the Good Data

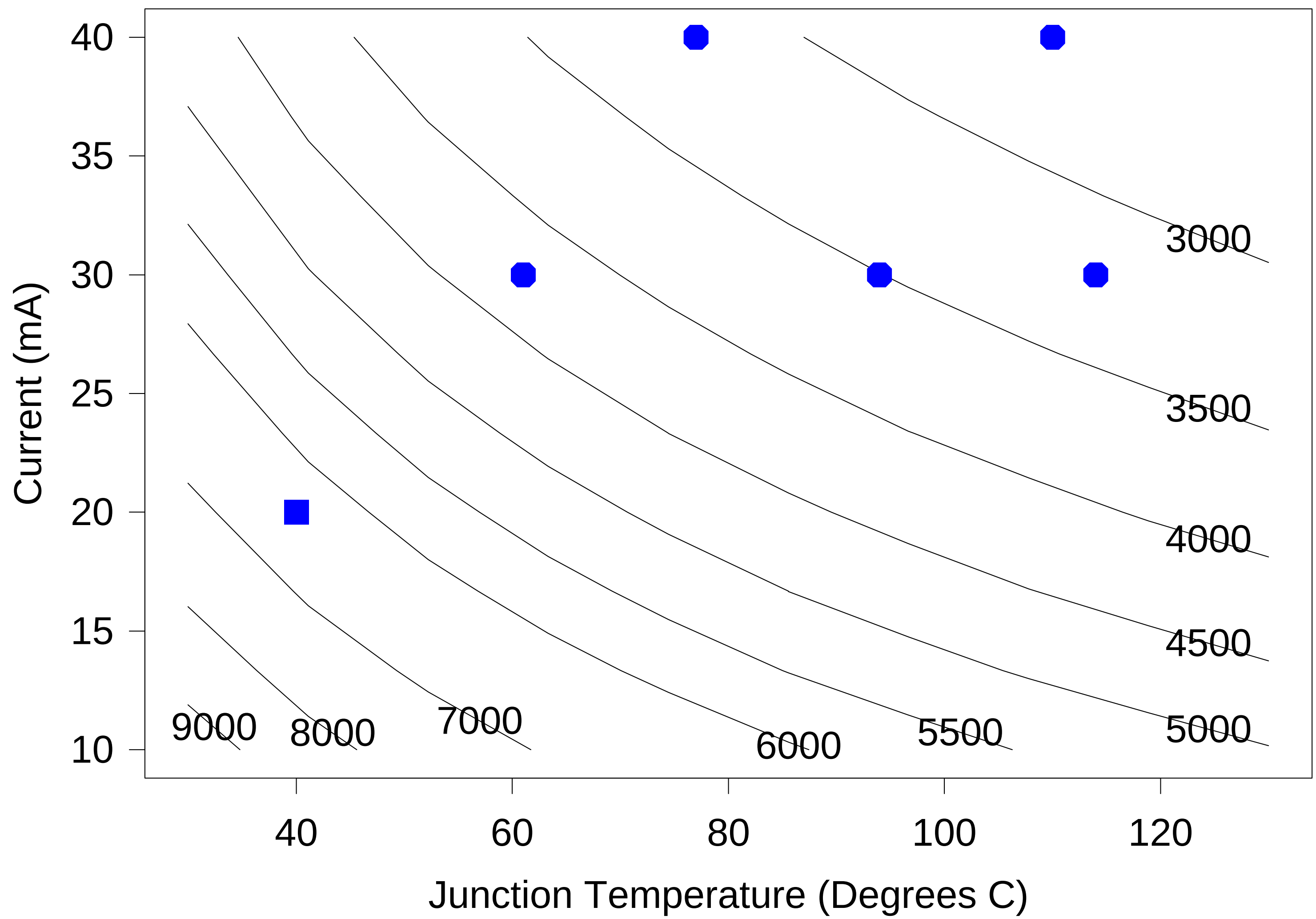
Model	$-2\mathcal{L}(\boldsymbol{\theta})$	AIC	# Param
SepDists	333.5	353.5	10
EqualSig	338.1	350.1	6
RegrModel	347.0	355.0	4
Pooled	510.3	514.3	2

Likelihood-Ratio Tests

Comparison	LR statistic	dof	p-value
SepDists vs EqualSig	4.62	4	0.33
EqualSig vs RegrModel	8.94	2	0.011
RegrModel vs Pooled	163.2	2	$<$ 0.001

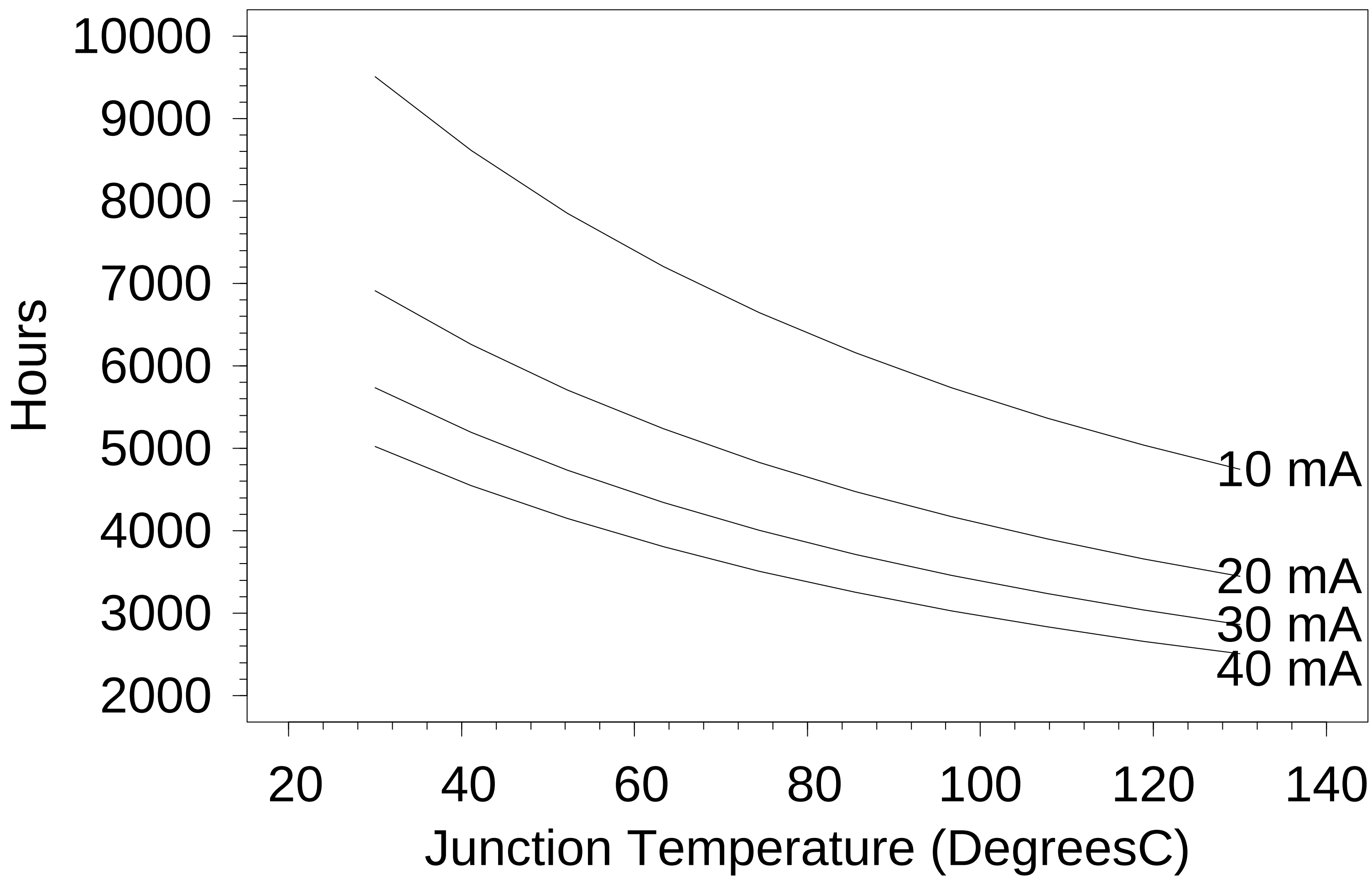
LED ALT 0.10 Quantile Estimates Based on Good Data

$$\widehat{\Pr}[T(\mathbf{Temp}, \texttt{Current}) \le t] = \Phi_{\mathbf{norm}}\left[\frac{\log(t) - (\widehat{\beta}_0 + \widehat{\beta}_1 x_1 + \widehat{\beta}_2 x_2)}{\widehat{\sigma}}\right]$$



LED ALT 0.10 Quantile Estimates Versus Temperature at Different Current Levels Based on Good Data

$$\widehat{\Pr}[T(\textbf{Temp}, \texttt{Current}) \le t] = \Phi_{\textbf{norm}}\left[\frac{\log(t) - (\widehat{\beta}_0 + \widehat{\beta}_1 x_1 + \widehat{\beta}_2 x_2)}{\widehat{\sigma}}\right]$$



Chapter 19

Other Topics in Accelerated Life Testing

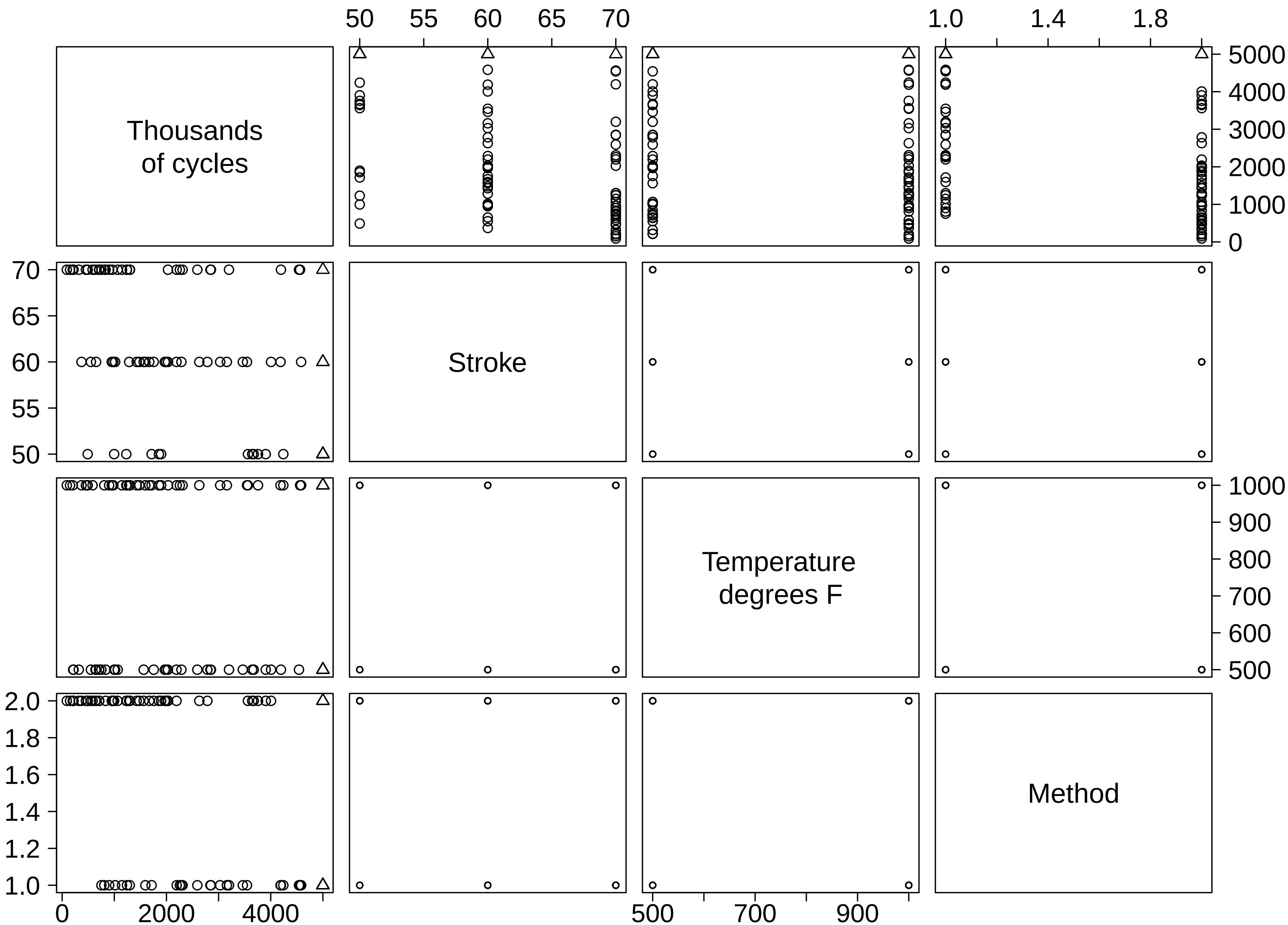
Segment 5

A Multi-Factor ALT with One Accelerating Variable

An Experiment to Estimate the Fatigue Life of a New Spring

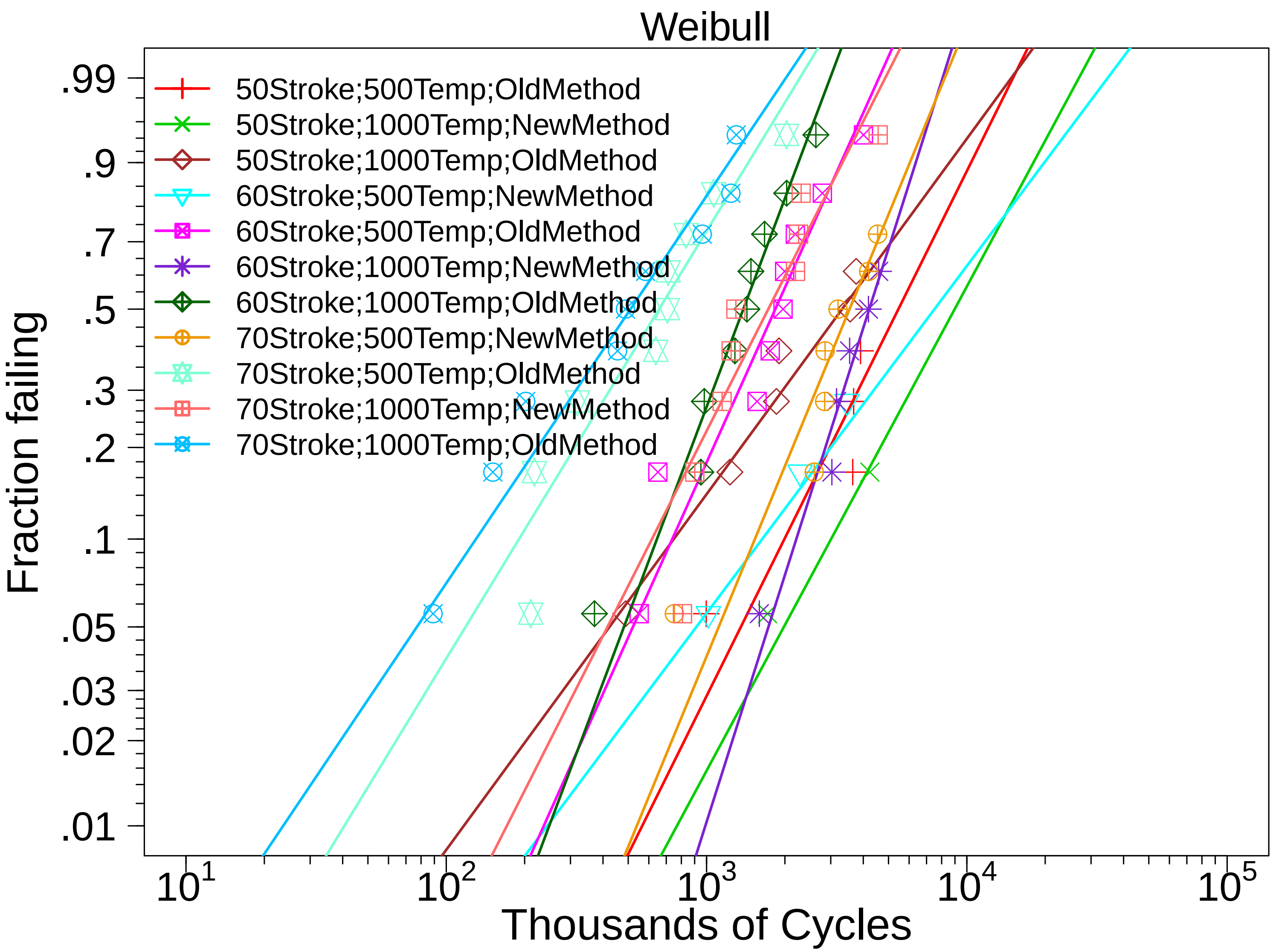
- Large factorial accelerated test experiment. Three factors, 12 combinations of levels, and 9 reps at each combination.
- All 108 springs tested until failure or to a maximum of 500,000 thousand cycles
- Goals:
  - ▶ Compare New and Old processing methods.
  - ▶ Determine if B10 life (the 0.10 quantile) is at least 500,000 thousand cycles at 30 mils stroke.
- Data from Meeker, Escobar, and Zayac (2003).

New Spring Accelerated Test Data Pairs Plot



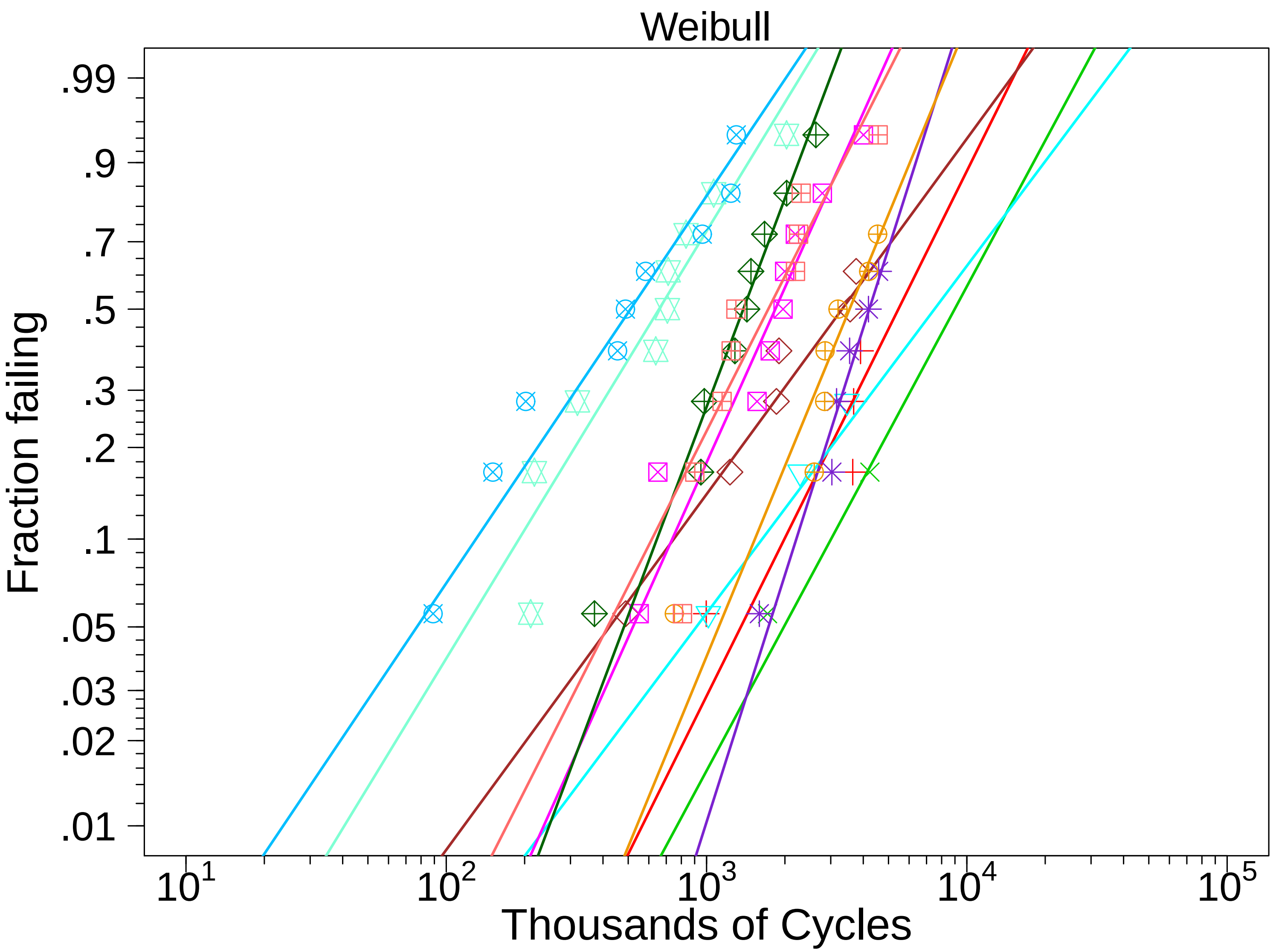
Weibull Multiple Probability Plot New Spring Data
Individual Weibull ML Fit at Each Combination
Different Shape Parameters

$$\widehat{\Pr}[T(\boldsymbol{x}_i) \le t] = \Phi_{\text{sev}}\left[\frac{\log(t) - \widehat{\mu}_i}{\widehat{\sigma}_i}\right], \ i = 1, \ldots, 11$$



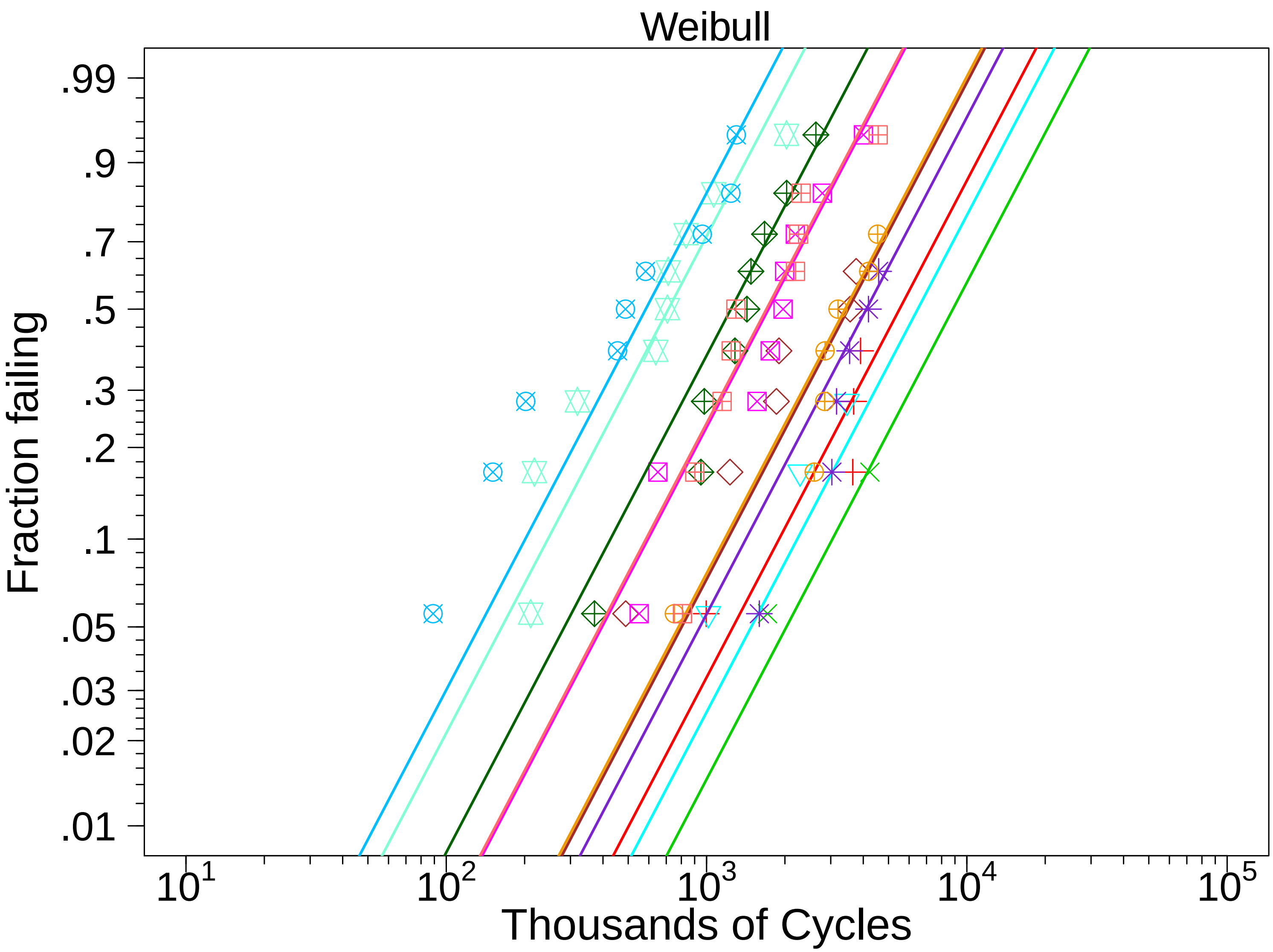
Weibull Multiple Probability Plot New Spring Data
Individual Weibull ML Fit at Each Combination
Different Shape Parameters

$$\widehat{\Pr}[T(\boldsymbol{x}_i) \le t] = \Phi_{\textbf{sev}}\left[\frac{\log(t) - \widehat{\mu}_i}{\widehat{\sigma}_i}\right], \ i = 1, \ldots, 11$$



Weibull Multiple Probability Plot New Spring Data
Individual Weibull ML Fit at Each Combination
Equal Shape Parameter

$$\widehat{\Pr}[T(\boldsymbol{x}_i) \le t] = \Phi_{\textbf{sev}}\left[\frac{\log(t)-\widehat{\mu}_i}{\widehat{\sigma}}\right], \; i = 1, \ldots, 11$$



New Spring Failure-Time Regression Model

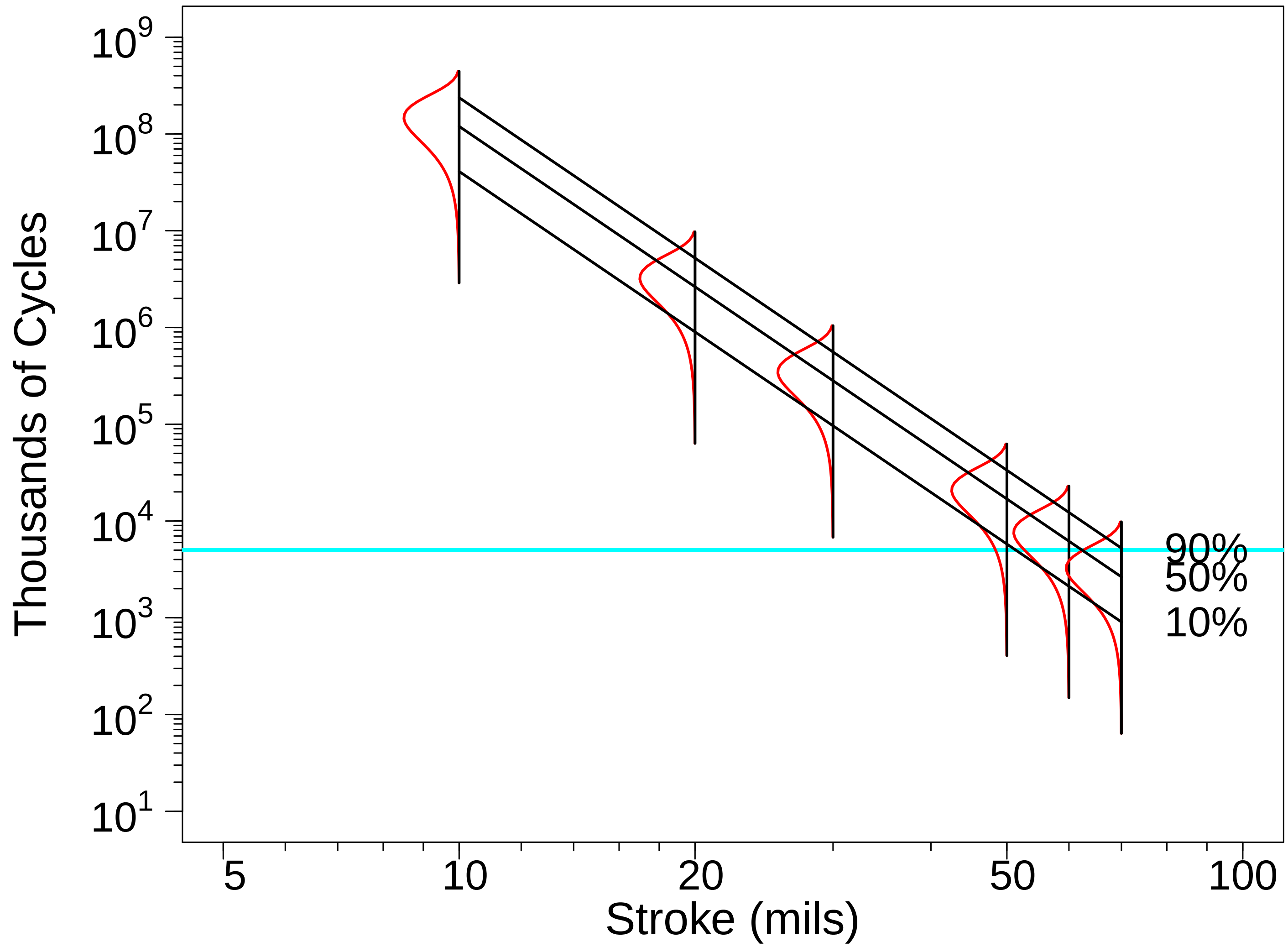
$$\boldsymbol{x} = (\text{Stroke}, \text{Temp}, \text{Method})$$

$$\text{Log(Life)} = \beta_0 + \beta_1 \log(\text{Stroke}) + \beta_2 \text{Temp} + \beta_3 \text{Method}$$

where

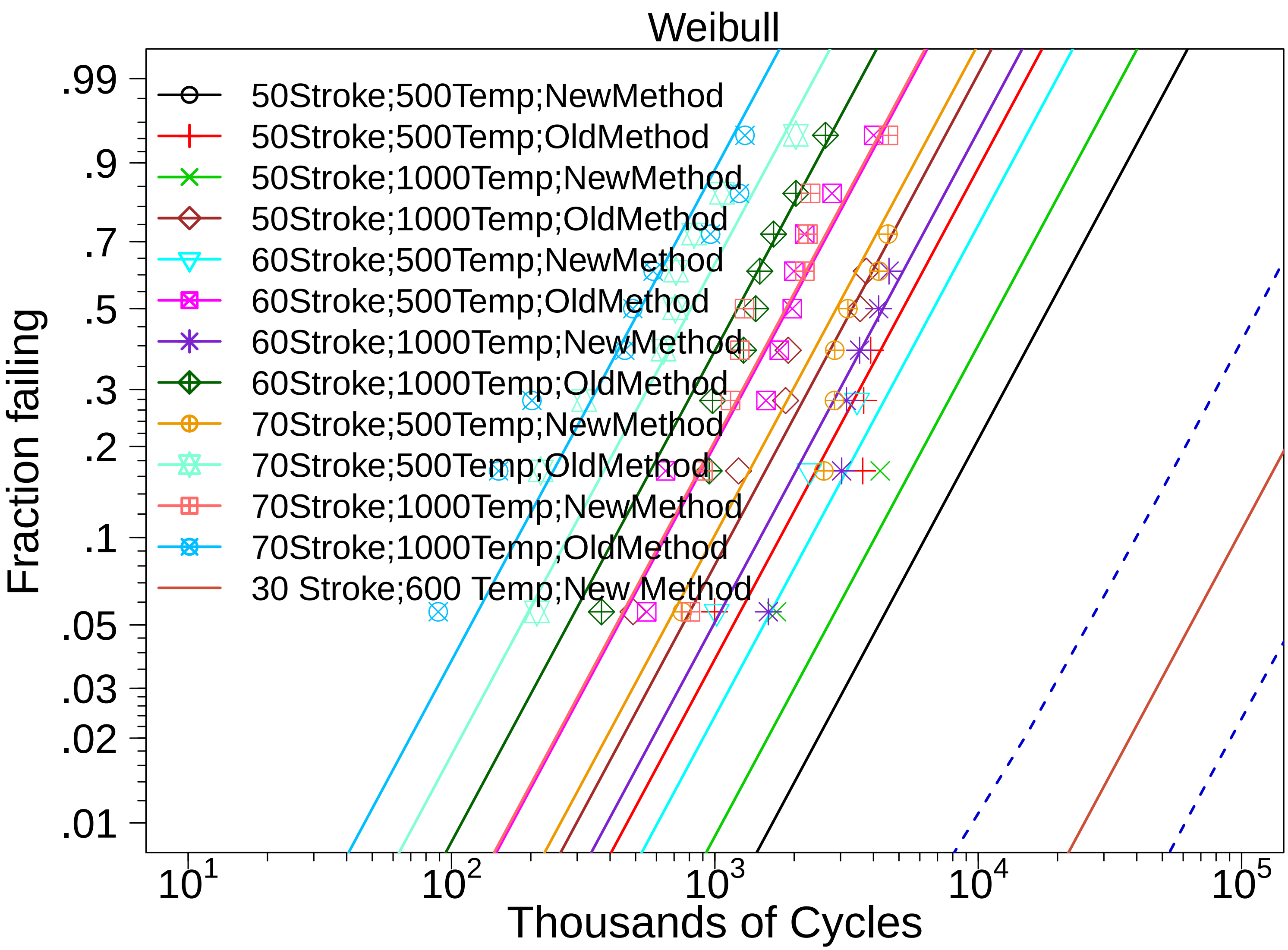
$$\text{Method} = \begin{cases} 1 & \text{Old} \\ 0 & \text{New} \end{cases}$$

New Spring Conditional Model Plot
Conditional on Temperature 600°F
and the New Method



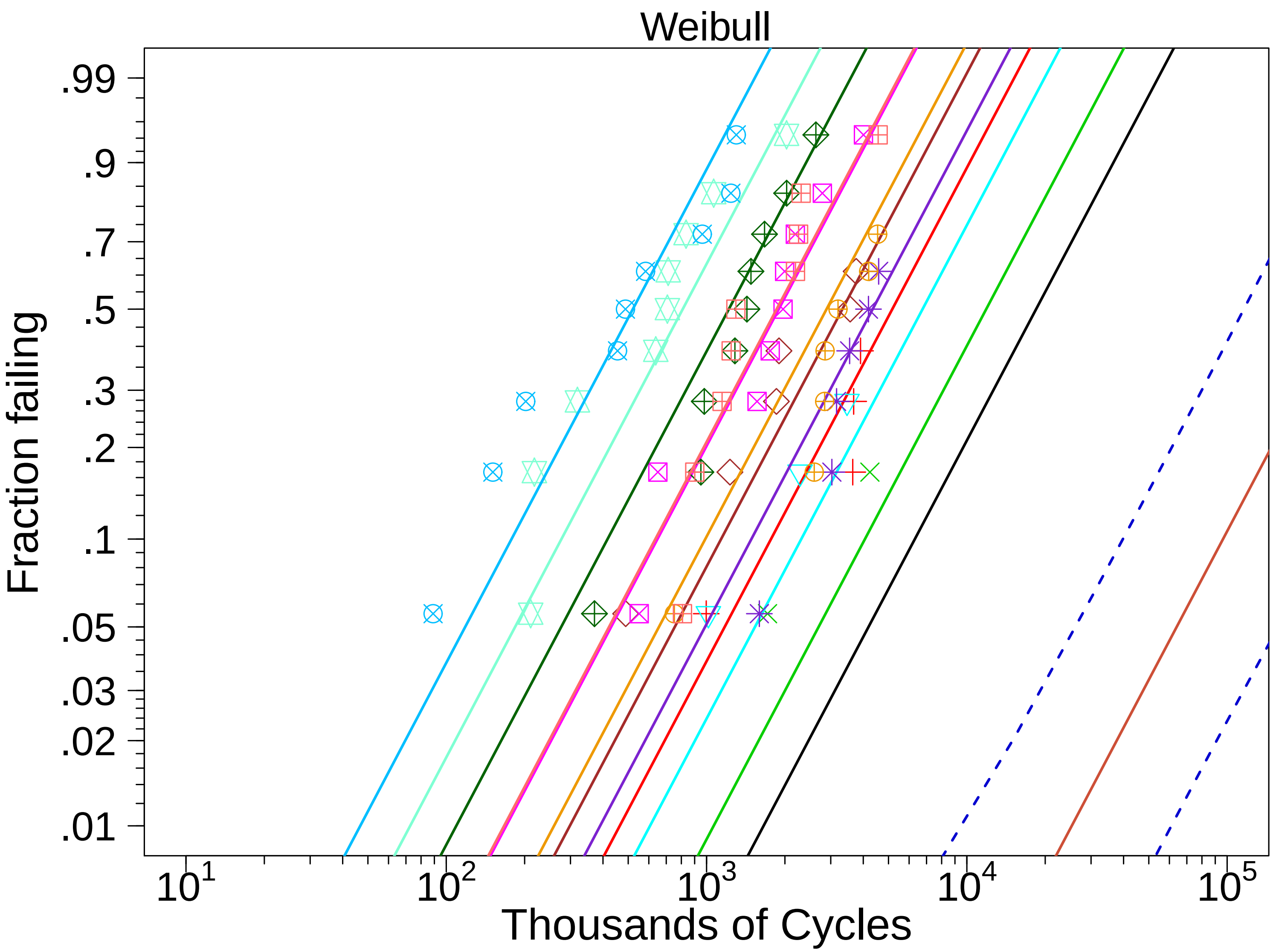
Weibull Multiple Probability Plot New Spring Data
Weibull Regression Model
Equal Shape Parameter

$$\widehat{\Pr}[T(\boldsymbol{x}_i) \le t] = \Phi_{\mathbf{sev}}\left[\frac{\log(t) - \widehat{\mu}(\boldsymbol{x}_i)}{\widehat{\sigma}}\right], \;\; \widehat{\mu}(x) = \widehat{\beta}_0 + \widehat{\boldsymbol{\beta}}' \boldsymbol{x}$$



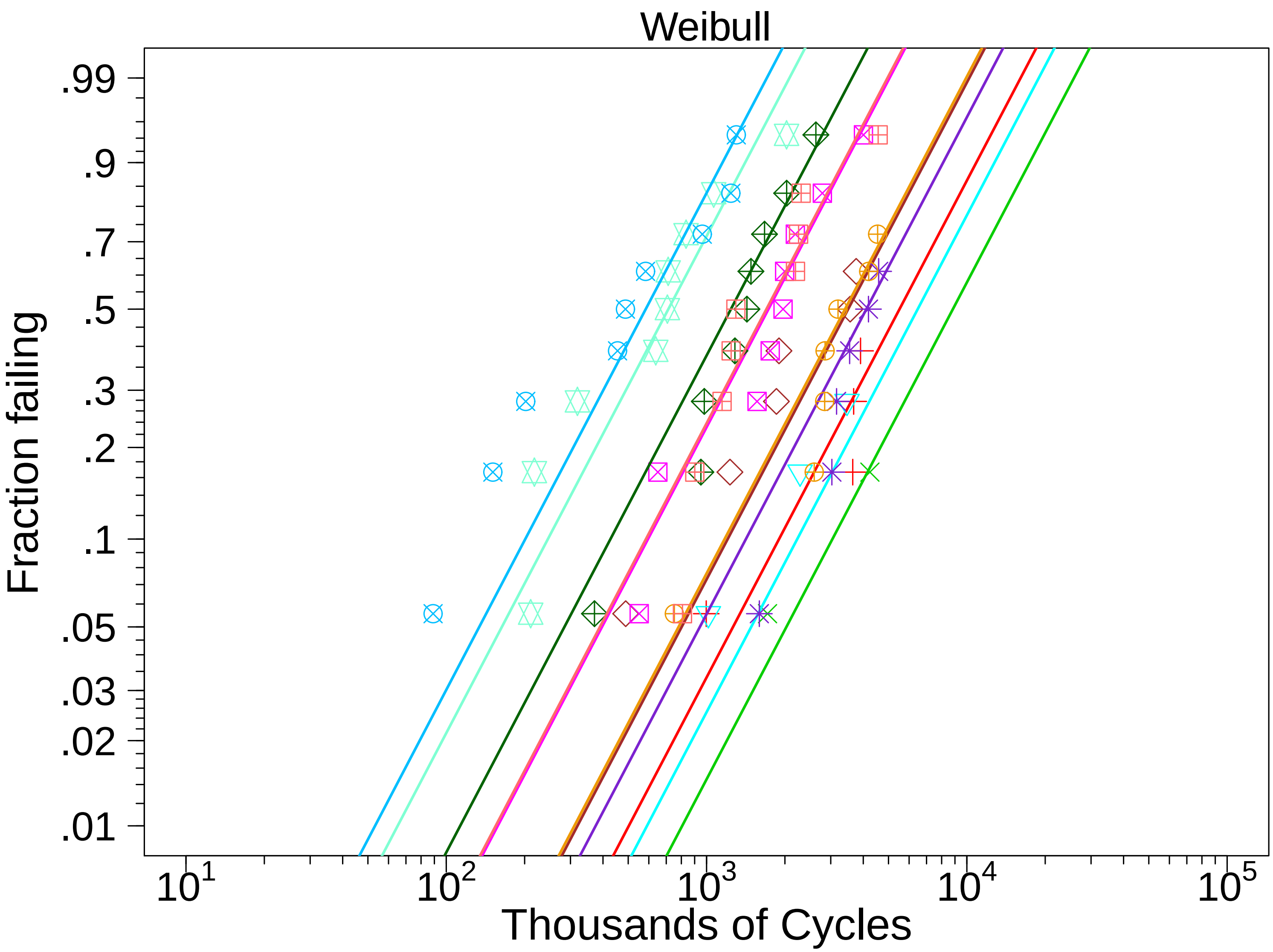
Weibull Multiple Probability Plot New Spring Data
Weibull Regression Model
Equal Shape Parameter

$$\widehat{\Pr}[T(\boldsymbol{x}_i) \le t] = \Phi_{\textbf{sev}}\left[\frac{\log(t) - \widehat{\mu}(\boldsymbol{x}_i)}{\widehat{\sigma}}\right], \;\; \widehat{\mu}(x) = \widehat{\beta}_0 + \widehat{\boldsymbol{\beta}}'\boldsymbol{x}$$



Weibull Multiple Probability Plot New Spring Data Individual Weibull ML Fit at Each Combination Equal Shape Parameter

$$\widehat{\Pr}[T(\boldsymbol{x}_i) \le t] = \Phi_{\textbf{sev}}\left[\frac{\log(t)-\widehat{\mu}_i}{\widehat{\sigma}}\right],\ i = 1, \ldots, 11$$



New Spring Data
Weibull Model-Fitting Summary

Model	$-2\mathcal{L}(\boldsymbol{\theta})$	AIC	# Param
SepDists	1242	1286	22
EqualSig	1252	1276	12/13
RegrModel	1256	1266	5
Pooled	1362	1366	2

Likelihood-Ratio Tests

Comparison	LR Statistic	dof	p-value
SepDists vs EqualSig	10.13	10	0.43
EqualSig vs RegrModel	4.19	8	0.84
RegrModel vs Pooled	106.0	3	< 0.001

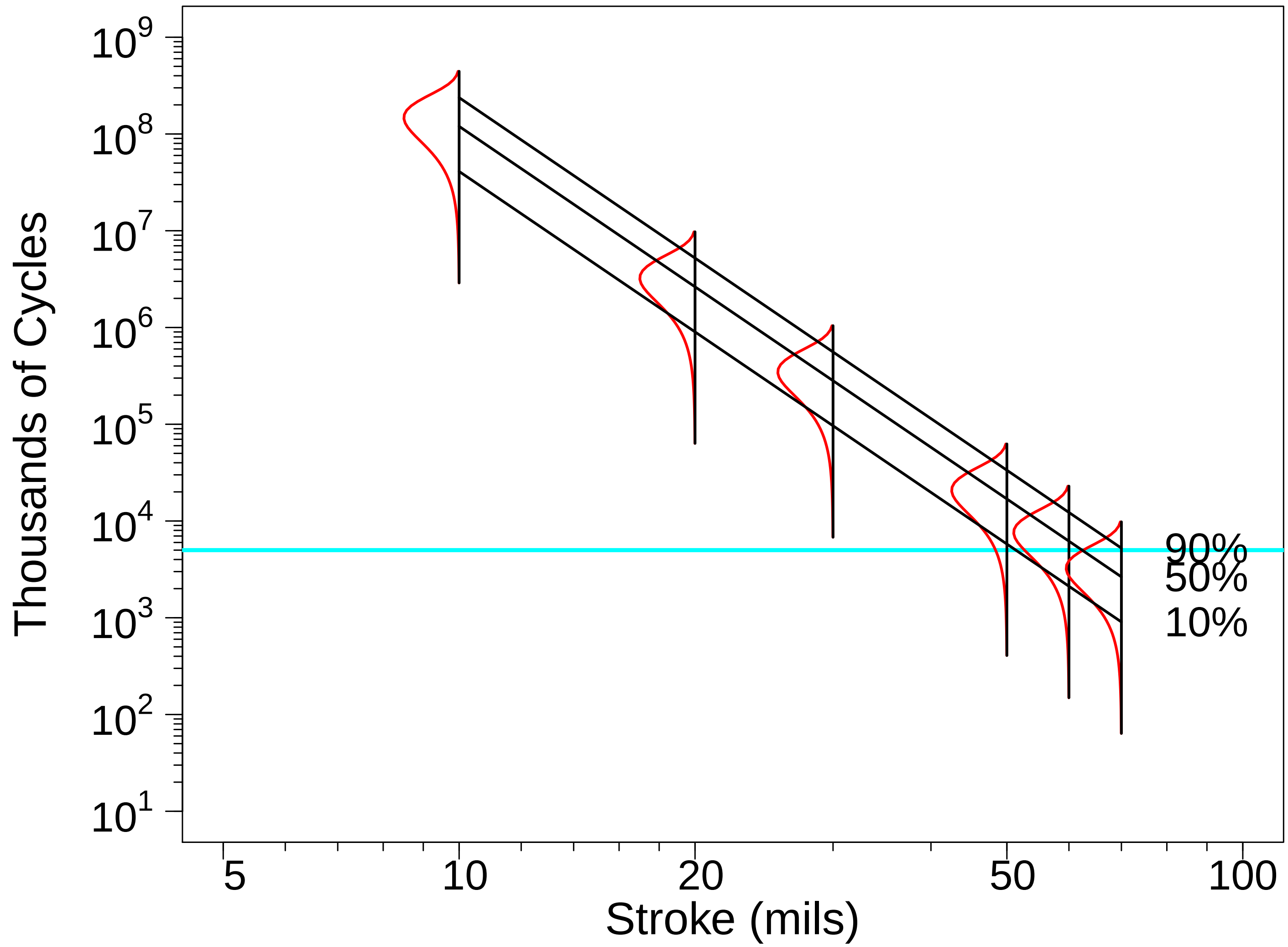
Chapter 19

Other Topics in Accelerated Life Testing

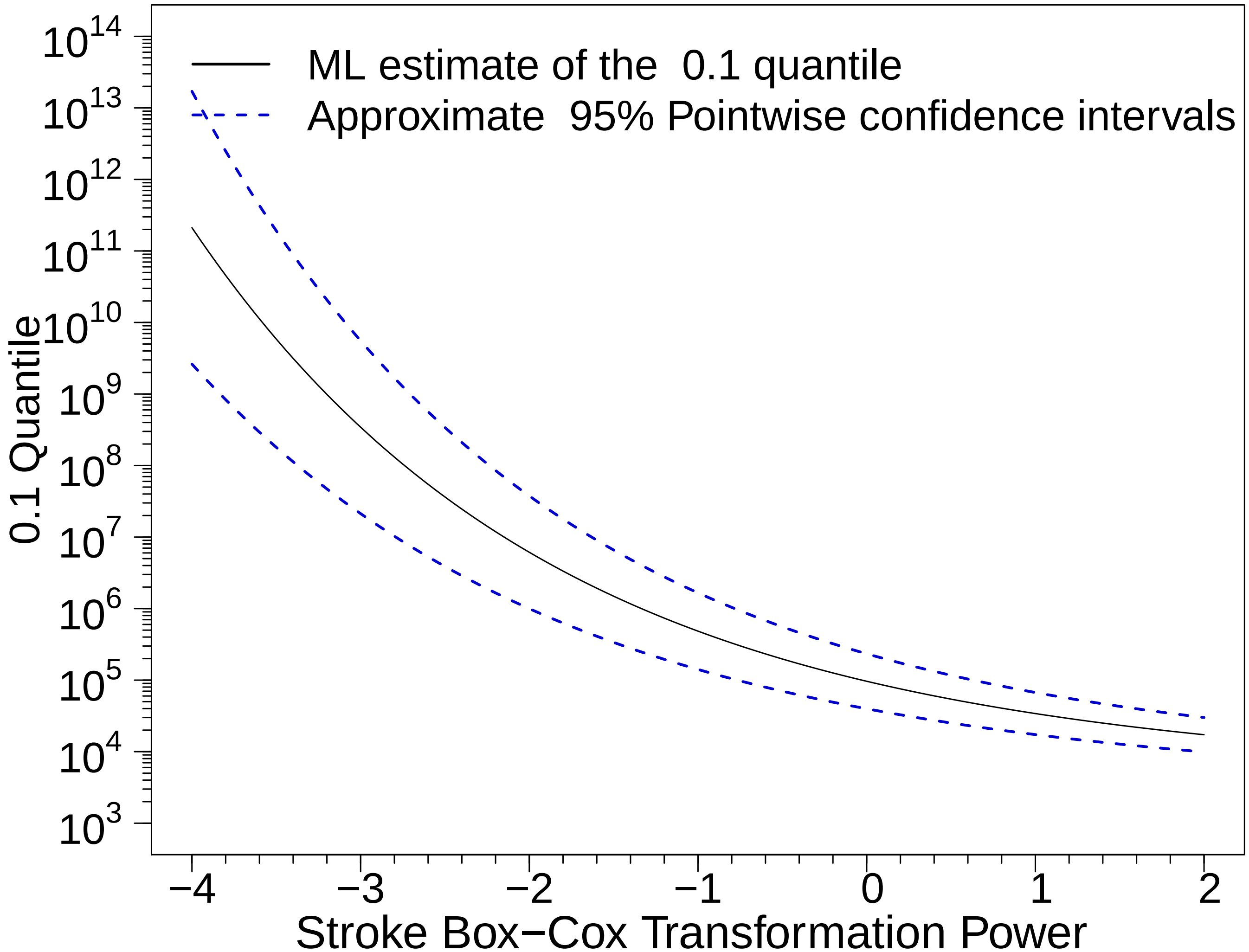
Segment 6

Model Sensitivity Analysis

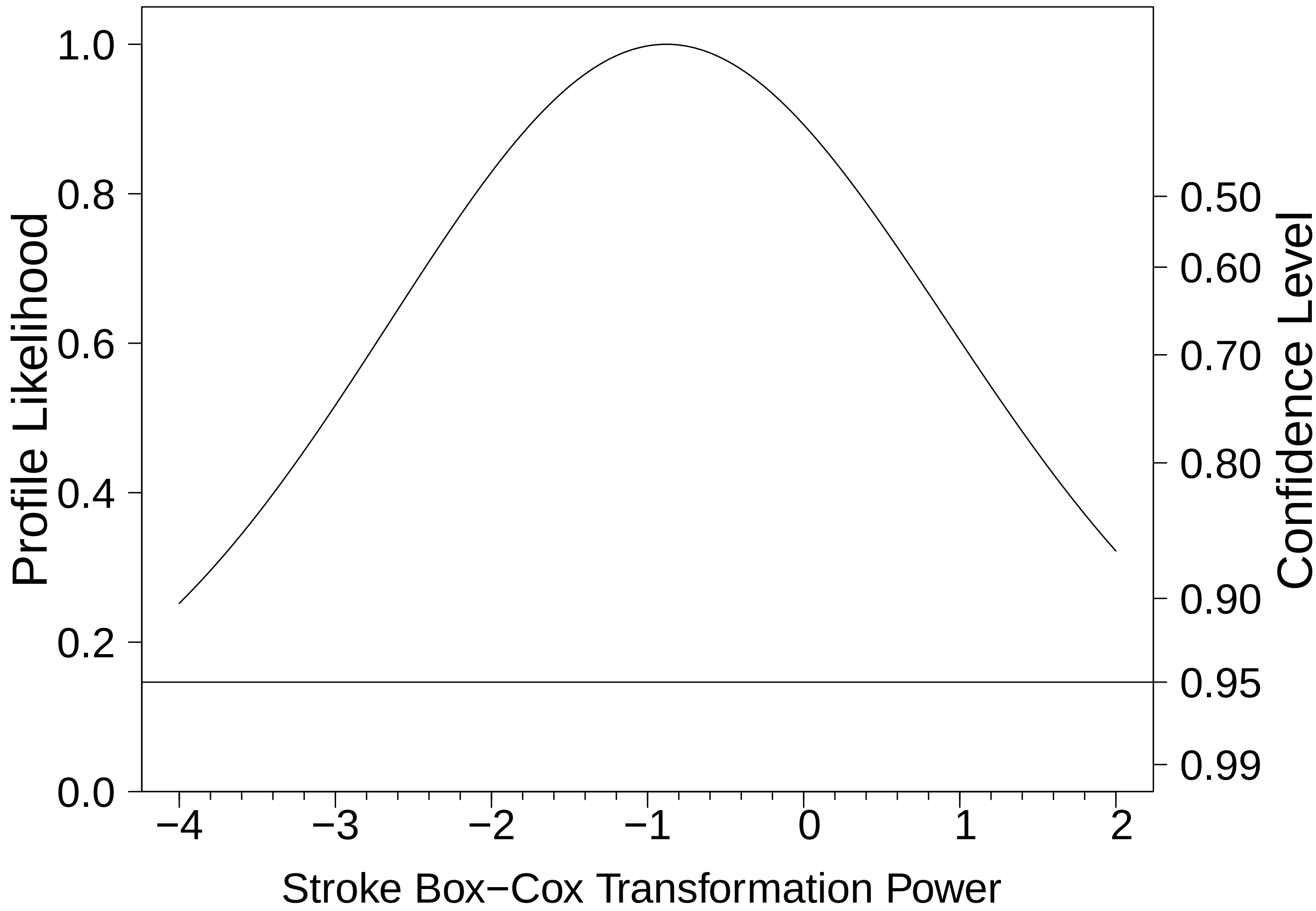
New Spring Conditional Model Plot
Conditional on Temperature 600°F
and the New Method



New Spring Box-Cox Sensitivity Analysis
B10 at 30 mils and 600 Degrees F



New Spring Box-Cox Sensitivity Analysis Profile



Chapter 19

Other Topics in Accelerated Life Testing

Segment 7

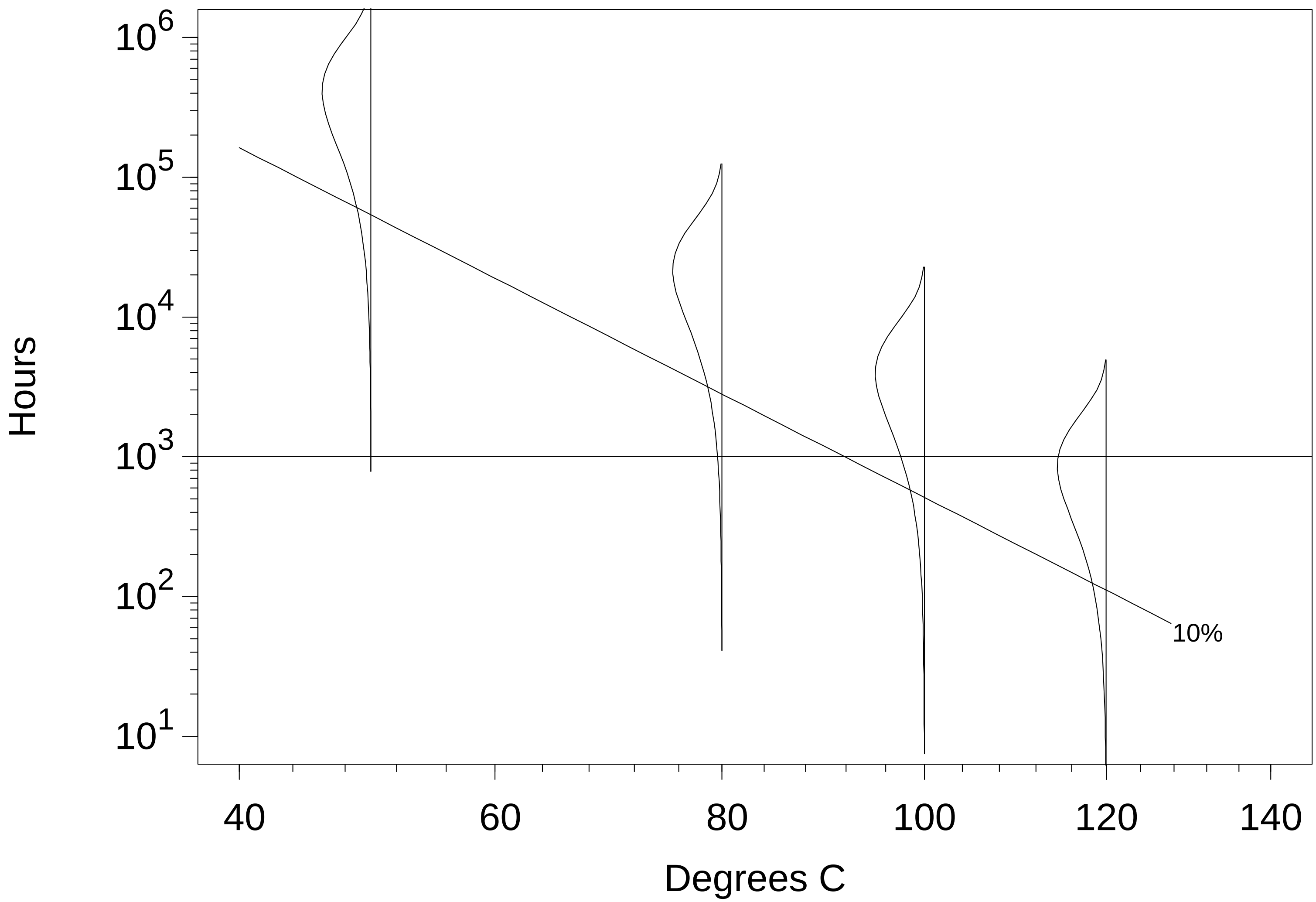
Pitfalls of Accelerated Testing

Pitfalls of Accelerated Testing

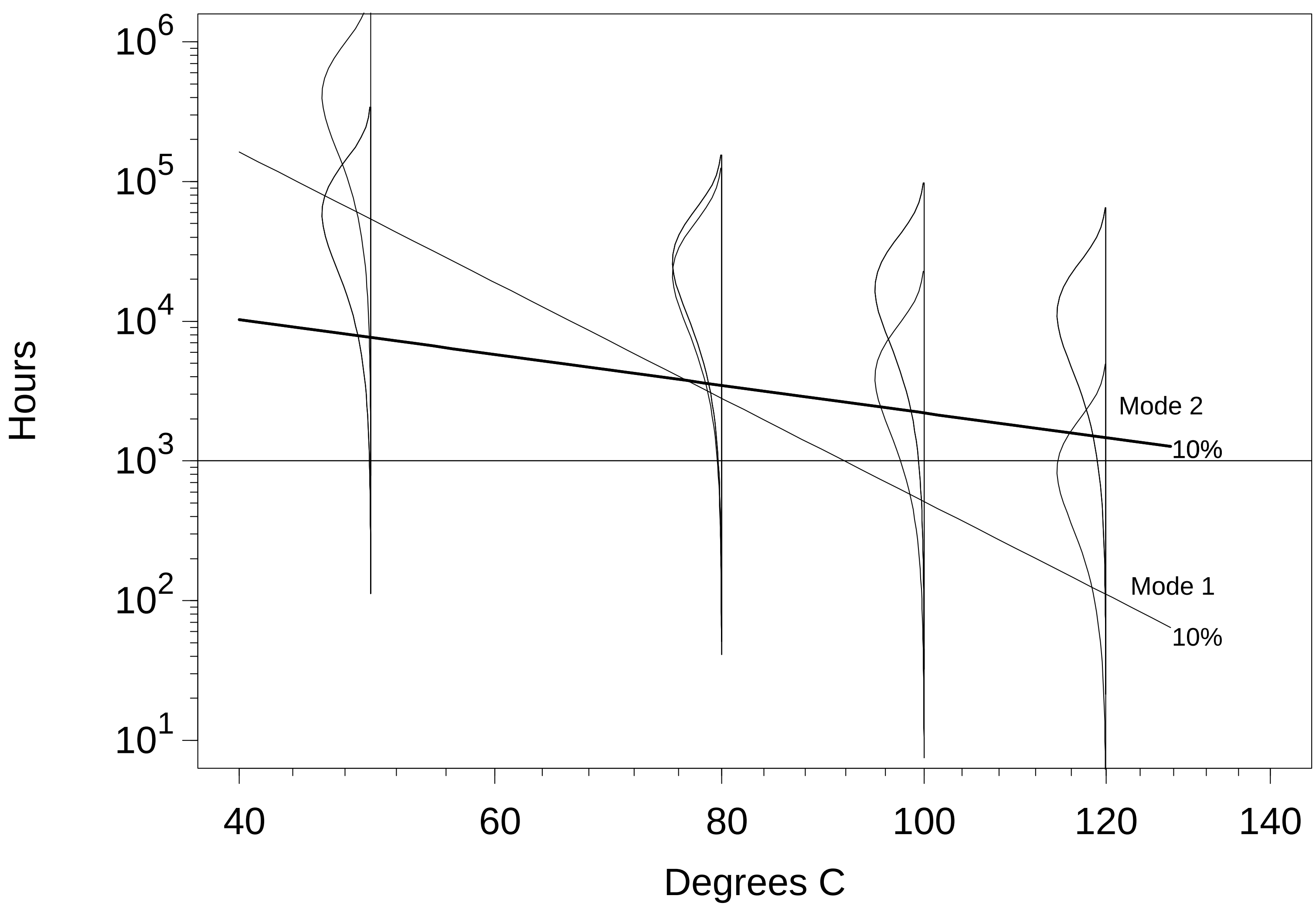
- Pitfalls arise in
  - Accelerated test planning,
  - Accelerated test execution, and
  - Accelerated test interpretation.

- Several papers have been written describing accelerated-test pitfalls. These include Meeker and Escobar (1998) and Meeker, Sarakakis, and Gerokostopoulos (2013).

Temperature-Accelerated Life Test for an IC Device



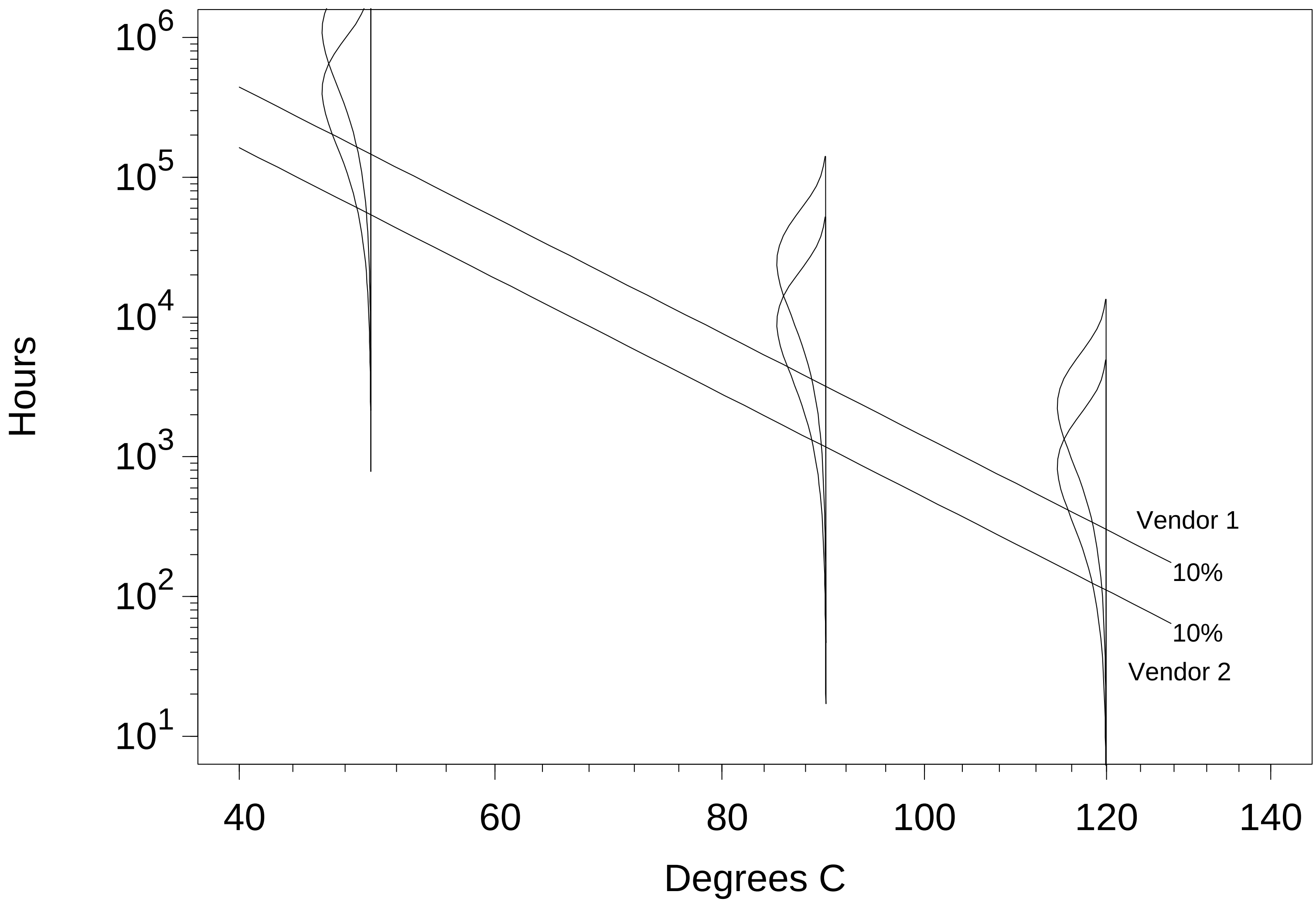
Unmasked Failure Mode with Lower Activation Energy for an IC Device



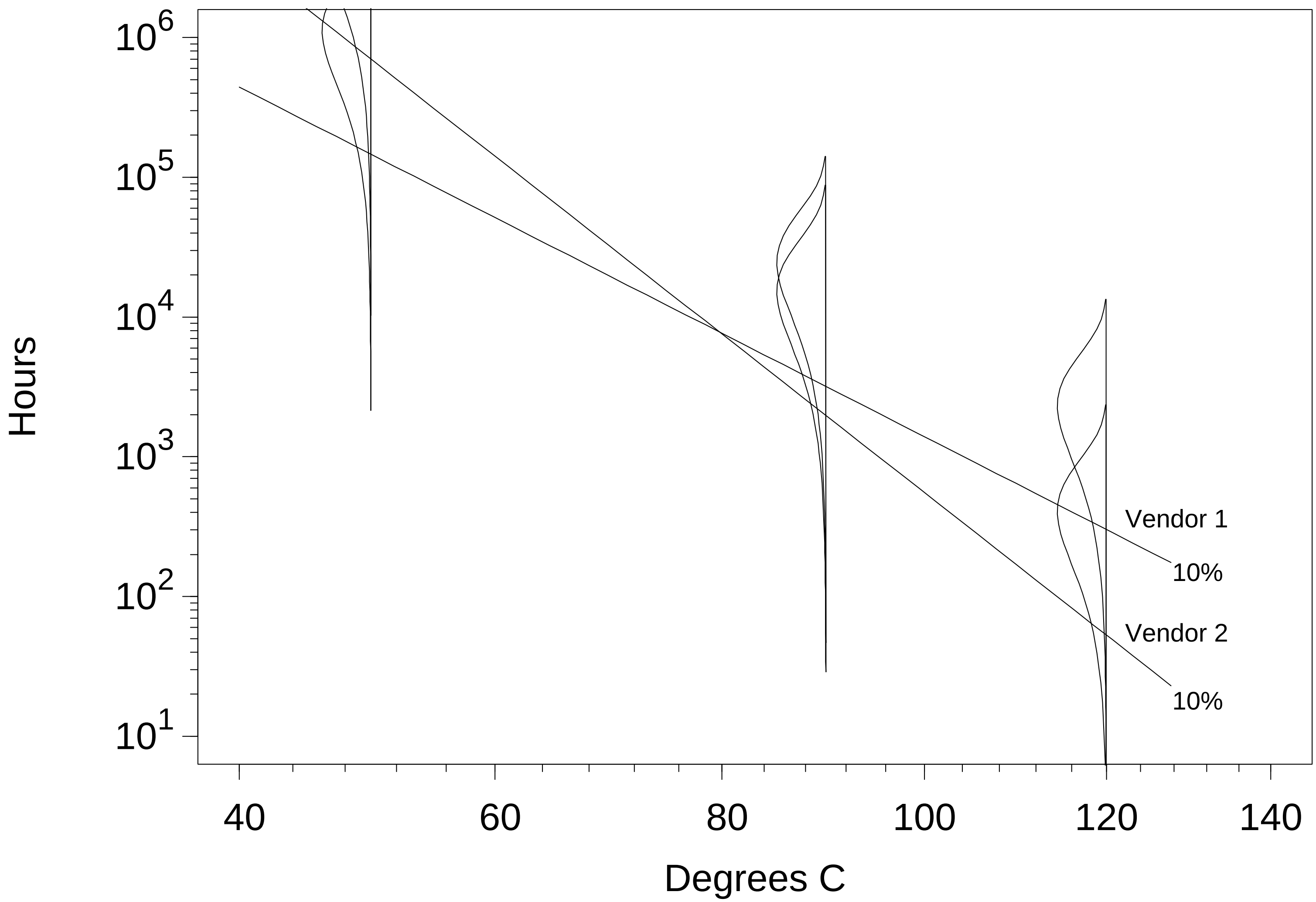
Pitfall 4: Masked Failure Mode

- Accelerated test may focus on one known failure mode, masking another!
- Masked failure modes may be the first one to show up in the field.
- Masked failure modes could dominate in the field.
- Suggestions:
  - ▶ Know (anticipate) different failure modes.
  - ▶ Limit acceleration and test at levels of accelerating variables such that each failure mode will be observed at two or more levels of the accelerating variable.
  - ▶ Identify failure modes of all failures.
  - ▶ Analyze failure modes separately.

Comparison of Two Products
Simple Comparison



Comparison of Two Products
Questionable Comparison



Pitfall 5: Faulty Comparison

- It is sometimes claimed that Accelerated Testing is not useful for predicting reliability, but is useful for comparing alternatives.
- Comparisons can, however, also be misleading.
- Beware of comparing products that have different kinds of failures.
- Suggestions:
  - ▶ Know (anticipate) different failure modes.
  - ▶ Identify failure modes of all failures.
  - ▶ Analyze failure modes separately.
  - ▶ Understand the physical reason for any differences.

Pitfall 6: Acceleration Factors Can Cause Deceleration!

- Increased temperature in an **accelerated** circuit-pack reliability audit resulted in fewer failures than in the field because of lower humidity in the **accelerated** test.
- Higher than usual use rate of a mechanical device in an accelerated test inhibited a corrosion mechanism that eventually caused serious field problems.
- Automobile air conditioners failed due to a material **drying out** degradation, lack of use in winter (not seen in continuous accelerated testing).
- Inkjet pens fail from infrequent use.
- **Suggestion**: Understand failure mechanisms and how they are affected by experimental variables.

Pitfall 7: Untested Design/Production Changes

- Lead-acid battery cell designed for 40 years of service.
- New epoxy seal to inhibit **creep** of electrolyte up the positive post.
- Accelerated life test described in published article **demonstrated** 40 year life under normal operating conditions.
- 200,000 units in service after 2 years of manufacturing.
- First failure after 2 years of service; third and fourth failures followed shortly thereafter.
- Improper epoxy cure combined with charge/discharge cycles hastened failure.
- Most of the population had to be replaced with a re-designed cell.

References

Meeker, W. Q. and L. A. Escobar (1998). Pitfalls of accelerated testing. *IEEE Transactions on Reliability 47*, 114–118. []

Meeker, W. Q., L. A. Escobar, and F. G. Pascual (2021). *Statistical Methods for Reliability Data* (Second Edition). Wiley. [1]

Meeker, W. Q., L. A. Escobar, and S. Zayac (2003). Use of sensitivity analysis to assess the effect of model uncertainty in analyzing accelerated life test data. In W. R. Blischke and D. N. P. Murthy (Editors), *Case Studies in Reliability and Maintenance*, Chapter 12, 269–292. Wiley. Available from: https://lib.dr.iastate.edu/stat_las_preprints/26/. []

Meeker, W. Q., G. Sarakakis, and A. Gerokostopoulos (2013). More pitfalls of accelerated tests. *Journal of Quality Technology 45*, 213–222. []