Method for Detection and Confirmation of Multiple Failure Modes with Numerous Survivor Data

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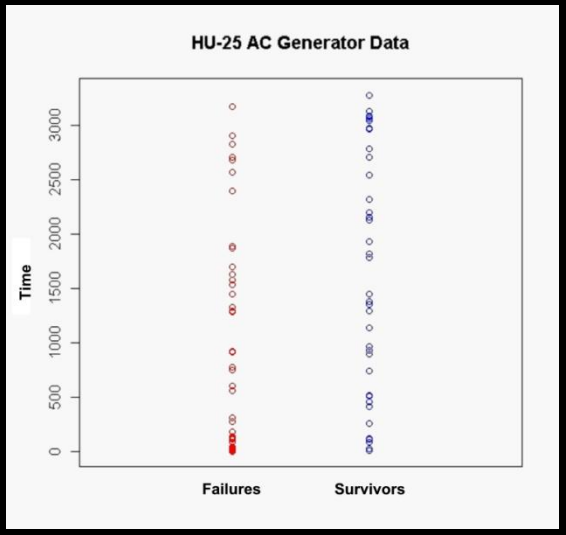
Introduction

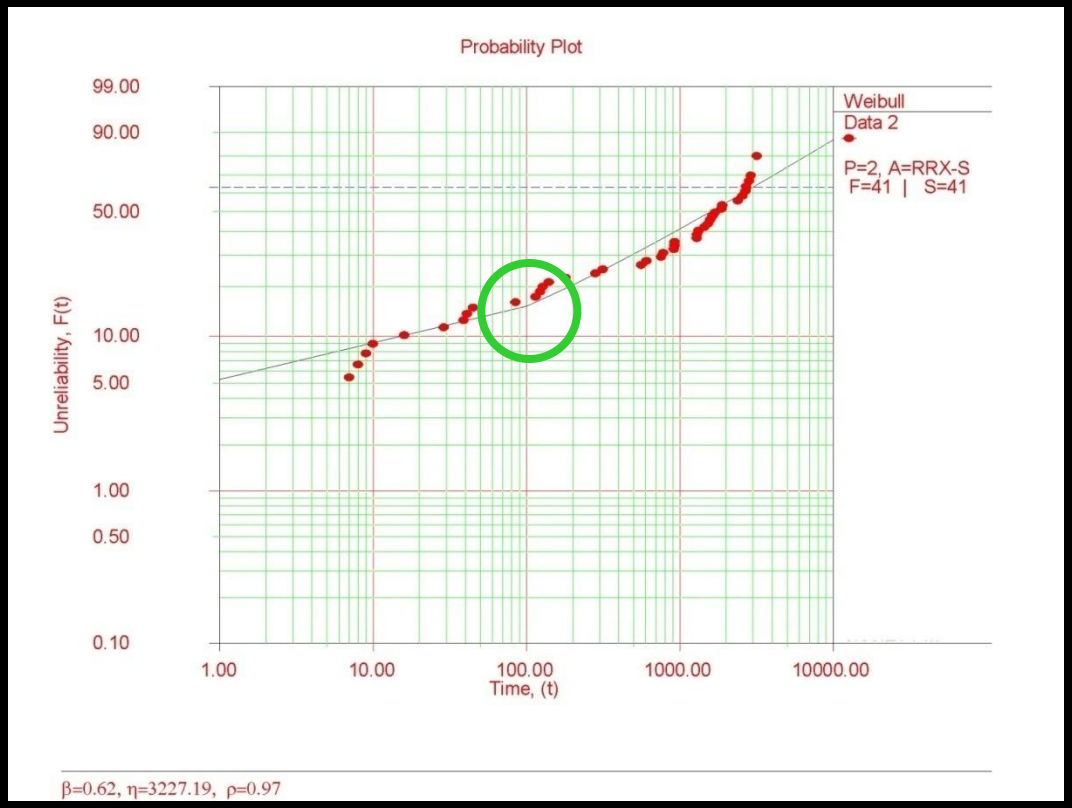
- **Sometimes,**
  Aerospace Systems Fail for More than One Reason
- **Sometimes Easy to See in Data, Sometimes Not**
- **When it Fails, In Which Mode is it Failing?**
- **Identification of Failure Modes Needed to Find and Fix the Problems, or to Improve Preventative Maintenance**
- **US Coast Guard HU-25 Aircraft Had such a Problem with its AC Generator**
- **Commercial Reliability Analysis Software Did not Help Much**
- **Another Approach was Needed**

The USCG HU-25 Falcon

- **The AC Generator was Failing, *Often***
  - **45 Failures**
  - **41 Survivors**
- **The Solution**
  - **Perform Reliability Analysis with a Commercially Available SW Tool**
  - **Investigate the Failure Mode; then Fix the Problem or Modify PM Procedure**



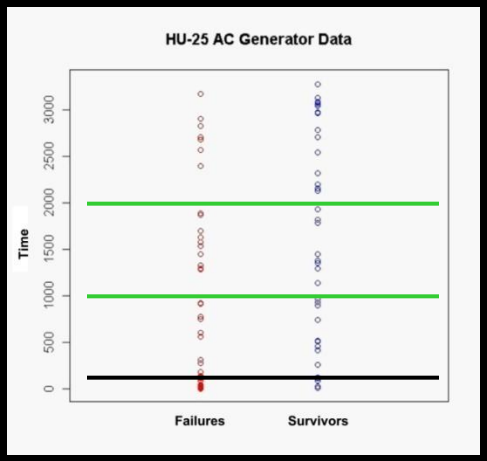
The COTS Reliability Analysis Results



- ***Bent*** **Regression Line Suggests Multiple Failure Modes**
- **Now What?**
  - **Segregate Data and Reprocess Separately**
  - **How Do you Segregate Survivor Data?**

Segregation/Reprocess COTS Results

- Reference Single Batch Mean Estimates
  - η : 3227.19
  - β : 0.62
- Segregation: t ≤ 1,000 Hours
  - η : 547.25
  - β : 0.72
- Segregation: 1,000 < t ≤ 2,000 Hours
  - η : 1730.55
  - β : 4.67
- Segregation: t > 2,000 Hours
  - η : 3156.37
  - β : 11.05



Not Particularly Conclusive, or Insightful, or Satisfying

An Alternate Solution

- **Model the Data with Two Failure Modes**

$$pd(t_f \mid \gamma, \eta_a, \beta_a, \eta_b, \beta_b)$$

$$= \gamma * Weib_a\left(t_f \mid \eta_a, \beta_a\right) + (1-\gamma) * Weib_b\left(t_f \mid \eta_b, \beta_b\right)$$

- **No Classical Method Exists to Estimate Joint Model for γ, η_a, β_a, η_b, and β_b**
- **Use Conditional Approach**
  - **Avoid Unnecessary Questionable Assumptions**
  - **No Data Segregation Necessary**
  - **Must Use Markov Chain Monte Carlo (MCMC) Numerical Methods**
- **But will This Conditional Approach Work?**
  - **Will it Detect *Phantom* Failure Modes?**
  - **Will it Work with Survivor Data?** ***Yes!***

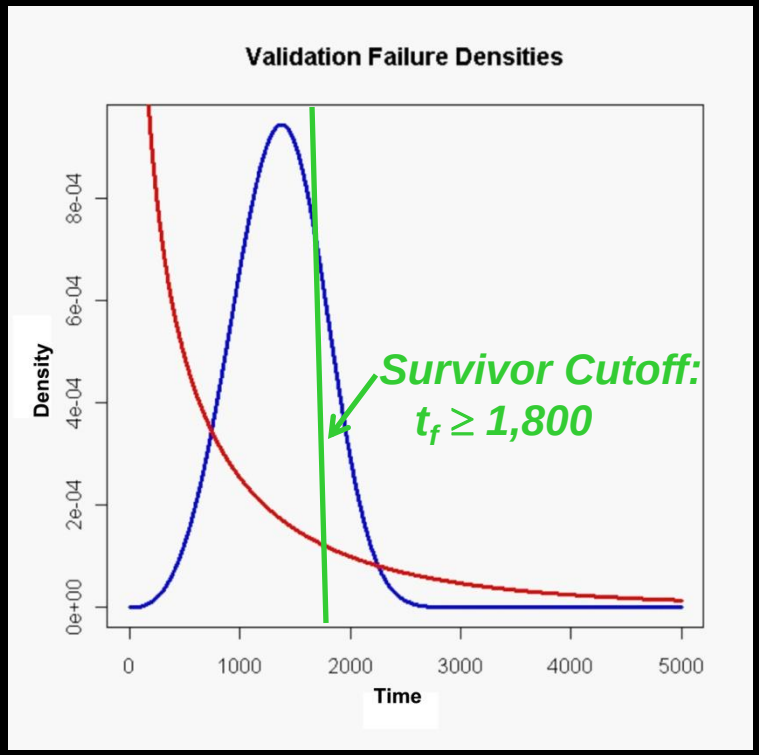
Validate the Method

- **Create Dummy Data for Reference Multimode Models, and Test**

Parameter	Value
η_a	800
β_a	0.7
η_b	1500
β_b	3.7

Survivors for t_f > 1,800

10,000 Samples for Each Set:
γ = 0.01, 0.25, 0.5, 0.75, and 0.99



Validation Results

- **Markov Chain Initial Conditions for all Tests**
  γ = 0.5, $\eta_a = \eta_b$ = 1,192, $\beta_a = \beta_b$ = 1.5
- **First, for Data Sets with γ = 0.01 and 0.99, Markov Chains Never Stabilized *No Phantom Modes Detected!***

MCMC Marginal Sample Stats for $\gamma = 0.25$

	Minimum	Maximum	Mean (True)	σ
γ	0.066	0.423	0.223 (0.25)	0.066
η_a	118.6	1864.4	777.5 (800)	351.2
β_a	0.573	1.156	0.789 (0.7)	0.077
η_b	1387.3	1593.4	1500.9 (1500)	28.9
β_b	2.822	4.892	3.638 (3.7)	0.295

10,000 Joint MCMC Samples Post Burn-in

More Validation Test Results

	Minimum	Maximum	Mean (True)	σ
γ	0.267	0.720	0.528 (0.5)	0.090
η_a	182.7	1223.7	747.1 (800)	218.6
β_a	0.579	0.922	0.707 (0.7)	0.043
η_b	1360.4	1657.8	1507.4 (1500)	52.3
β_b	2.359	5.632	3.893 (3.7)	0.599

MCMC Marginal Sample Stats for $\gamma = 0.5$

MCMC Marginal Sample Stats for $\gamma = 0.75$

	Minimum	Maximum	Mean (True)	σ
γ	0.458	0.775	0.609 (0.75)	0.050
η_a	216.7	800.0	391.9 (800)	64.1
β_a	0.650	0.902	0.757 (0.7)	0.034
η_b	1333.7	1562.0	1454.9 (1500)	32.5
β_b	2.68	6.72	4.01 (3.7)	0.524

HU-25 Data Results

- **Same Markov Chain Initial Conditions for HU-25 Data**
  γ = 0.5, $\eta_a = \eta_b$ = 1,192, $\beta_a = \beta_b$ = 1.5

	Minimum	Maximum	Mean	σ
γ	0.026	0.869	0.412	0.148
η_a	0.7	3497.7	1106.1	987.0
β_a	0.033	0.574	0.284	0.068
η_b	1547.2	4496.2	3052.0	491.4
β_b	0.439	5.919	2.099	0.909

- **Two Failure Modes Detected – Infant Mortality, Early Wearout – Markov Chains Stabilized Nicely**
- **Results not as Crazy as with Segregation and Reprocessing with COTS**

Method Comparisons

- **Recall, With COTS Segregation Sets**
  - **$0.62 < \beta < 11.05$**
  - **$547.25 < \eta < 3227.19$**
- **With Conditional Approach**
  - **No Arbitrary Segregation of Survivors**
  - **Markov Chains Stabilized Nicely, *No Phantom Modes***
  - **About 40/60% Split on Modes *$Weib_a$* and *$Weib_b$***
  - **$\beta_a \cong 0.3$; $\beta_b \cong 2$**
  - **$\eta_a \cong 1{,}100$; $\eta_b \cong 3{,}000$**
- **Recall, Validation Tests with $0.25 < \gamma < 0.75$ Well Behaved for Similar Infant Mortality and Early Wearout Combination of Failure Modes**

Summary and Conclusions

- **Many More Details and Plots in Paper #1497 (11.0801)**
- **Conditional Approach Using Mixture Model Validated**
  - **If only one Failure Mode in Data, Markov Chain will not Stabilize – Method will *NOT* Detect *Phantom Failure Modes*, Will Detect Multiple Modes**
  - **No *Arbitrary* Segregation of Survivor Data**
- **Method is Indicated When Failure Data Appears Clustered, or COTS Reliability SW Shows a *Bent* Regression Line**
- **Method can be Expanded for More than Two Failure Modes**
- **May Lead to Improved Failure Mode Investigations and PM Programs**

If you have Data and a Similar Problem, Call Me!

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