Source Data Applicability Impacts On Epistemic Uncertainty For Launch Vehicle Fault Tree Models

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Objective

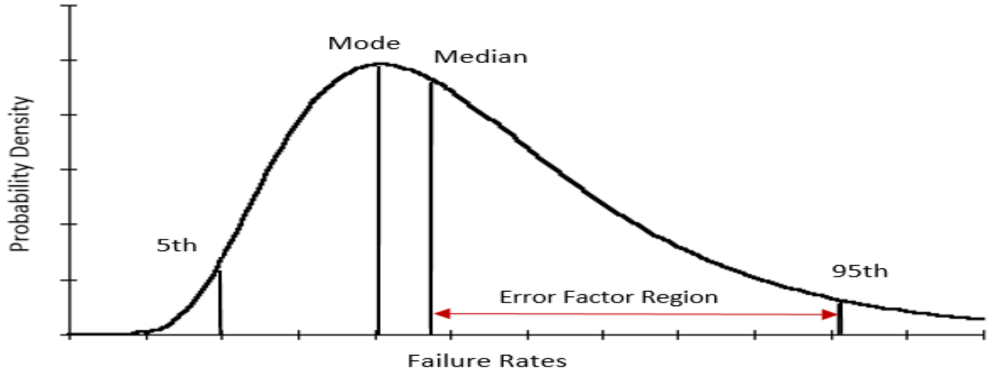
To support risk-informed decision making by understanding the sources of uncertainty, how to estimate it, and proposing methods for reducing it

- Design and Development of Complex Launch Vehicles
- Launch Readiness Decisions
- Scenario and System Trade Studies

- Identify Uncertainty sources
- Estimate parameter uncertainty bounds
    - Introduce heuristic and statistical guidelines for Launch Vehicles (LV) to apply a consistent method for estimating uncertainty across all LV elements
- Apply a standard method for uncertainty reduction

Uncertainty Definition

- A point estimate is a single parameter value that represents an entire population
  - Failure data are often provided in reliability databases as point estimates (mean or median)
- Failure rates (1/MTTF) are represented in traditional reliability as point estimates;
  - In Bayesian reliability they are considered random variables that are represented as probability distributions
- Parameter uncertainty is measured by the spread of the distribution, which can be expressed as the bounds (e.g. 5^{th} and 95^{th} percentiles) of the probability distribution
- Failure rates are often modeled by the lognormal distribution
  - Quantitatively, the error factor (EF) is a measure of the spread of uncertainty for the lognormal about the Median
  - EF = 95^{th}/Median



Lognormal Probability Density Function

Cont. Uncertainty

- Two types of uncertainty
  - Aleatory (random variability)
    - Inherent characteristic of the system, which cannot be reduced without improving the system
  - Epistemic (lack of knowledge or ignorance)
    - Can be reduced by increasing knowledge

- Epistemic uncertainty has many sources:
  - Completeness (missing scope/scenarios)
  - Parameter (component/subsystem)
  - Model (assumptions and development)

- This presentation focuses on epistemic uncertainty associated with the parameters of reliability models developed from available data sources

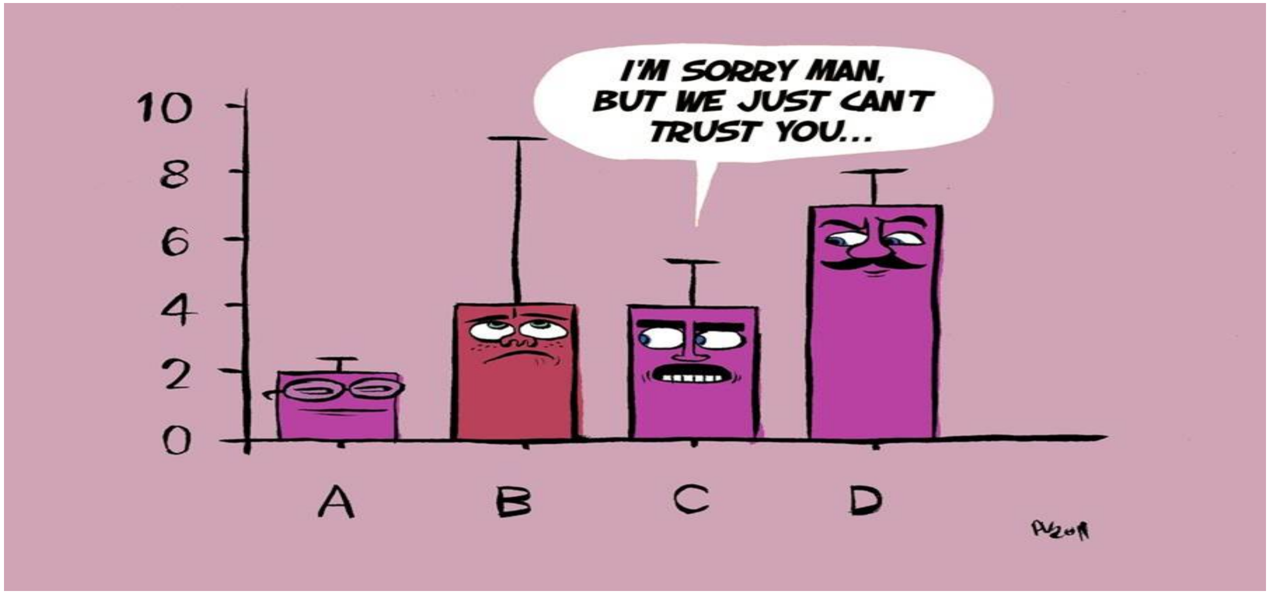
Parameter Data Sources and Applicability

- New Launch vehicles (LV) comprise heritage and new hardware
- Reliability models are often developed from data from multiple sources:
  - Component databases (NPRD, EPRD, NUCLARR, etc.)
  - Aerospace historical data
  - Other industry historical data
  - Piece part count method (MIL-HDBK-217F)
  - Engineering judgment
- These data sources reflect different levels of applicability to a specific LV

What is Data Applicability?

- Applicability is the degree of relevance of the source data to the LV model

- Data applicability may be a significant source of epistemic parameter uncertainty (lack of knowledge), as represented by the spread of the lognormal parameter distribution (i.e., the Error Factor)



An approach for quantifying data applicability

- Data source application
  - The purpose of this section of the approach is to use the applicability guidelines to apply concsistent uncertainty distribution for a mean value (point estimate) with unknown distribution information
  - Classify the applicability of the data source
  - For each data source, quantify its applicability to the system being modeled by using a set of heuristic (rule of thumb) guidelines
- Source Environment
  - The purpose of this section of the approach is to estimate the epistemic uncertainty associated with converting the failure rate from one environment to the other
  - Increase the parameter uncertainty due to environmental conversion

Data Source Application Classification

Note: This table is intended to be used for point estimates that lack distribution data. Use the distribution for uncertainty if it is known

Source	Category	Source Descrption	Source Application	Source Application Error Factor
Legacy Hardware	A	Other Launch Vehicle Data (Most Applicable)	Same component	3
			Like component	4
	B	Aerospace Data	Same component	5
			Like component	6
	C	Other Industry Data	Same component	6
			Like component	7
New Hardware	D	MIL-HDBK-217F Methods	Same component	8
			Like component	9
	E	Non-expert Engineering Judgment (Least Applicable)	Documented Process	10
			Undocumented Process	15

Example of Applying the Guidelines

Component	Applicability	Mean (Point Estimate)	EF
1	Engineering Judgment (Documented Process)	3.00E-06	10
2	Piece Part Method	6.01E-06	8
3	Aerospace Historical data for same component	1.00E-06	5
4	Engineering Judgment (Undocumented Process)	3.50E-07	15

Estimating Environmental Factors Uncertainty

- Reliability data for a particular component operating in a specific environment , such as Autonomous Uninhabited Fighter (AUF), may not be available for that environment, however, a failure rate for the same component may be available from another operating environment, such as Missile Launch (ML)

- MIl-HDBK-217F provides environmental tables for converting the provided failure rate point estimate from one environment to another, but does not estimate the uncertainty associated with this conversion.

- The purpose of this section of the approach is to estimate this source of epistemic uncertainty and propagate it to the failure rate prediction

- The calculations carried out to assess this uncertainty relied upon statistics, historical data and engineering judgment

Process to Estimate Environmental Factors Uncertainty

- Process Steps:
  - Derive the equation for the environmental conversion factor
  - Identify the variables in this equation,
  - Generate an uncertainty distribution for each variable, and ;
  - Propagate uncertainty to the resulting failure rate through the environmental equation using Monte Carlo simulation
- Using the microelectronic part-type example 1, Section 5.13, Paige 5-20 of the handbook, the environmental factor (π_E) conversion formula was first derived from the failure rate (λ_p) reference
  - $\lambda_P = (C_1\pi_T + C_2\pi_E)\pi_Q$
  - C_1 is the circuit complexity, C_2 is the packaging complexity
  - π_T is the component joint temperature factor, π_Q is the component quality factor
  - π_L is the learning factor (assumed 1 by the handbook)
- Solving for π_E , the equation becomes

$$\pi_E = \frac{\left(\frac{\lambda_P}{\pi_Q}\right) - C_1\pi_T}{C_2}$$

Cont. Process to Estimate Environmental Factors Uncertainty

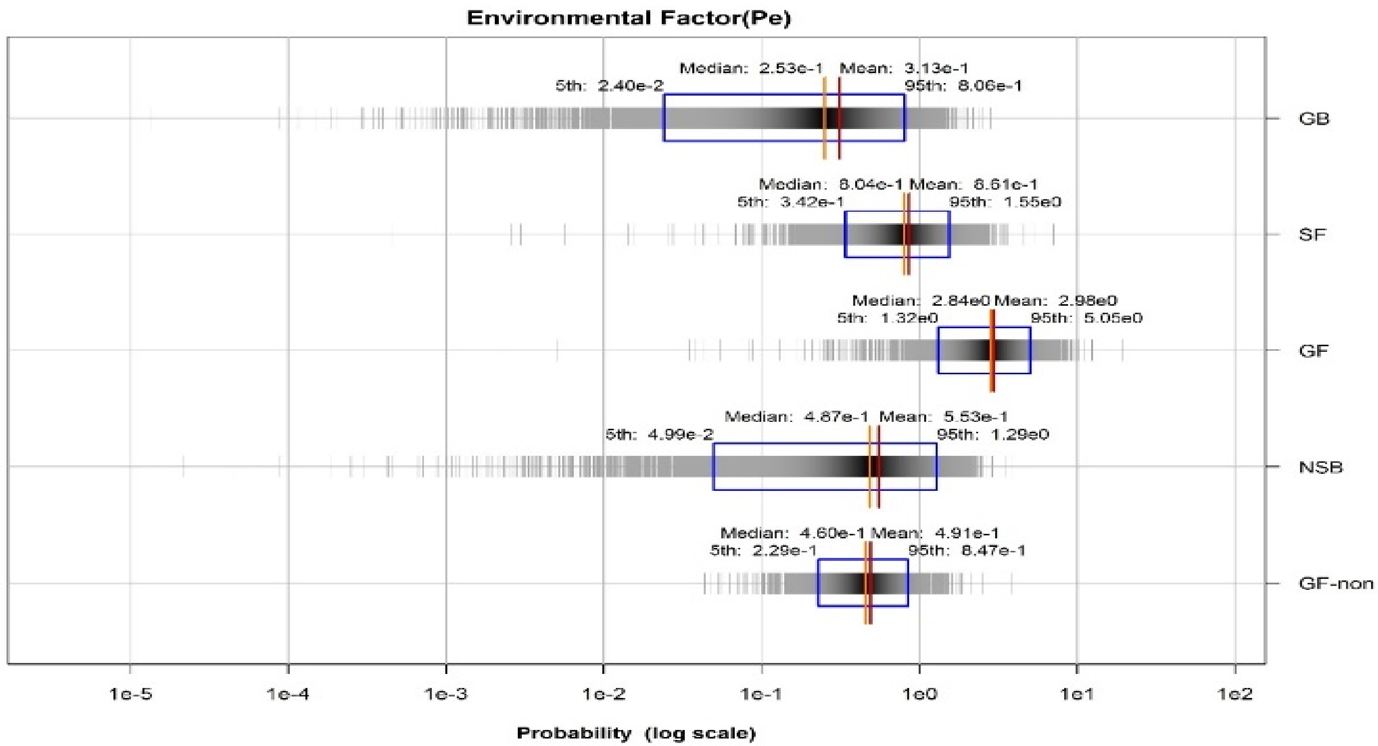
- Data availability obstacles
  - The challenge with MIL-HDBK-217F tables was that values for λ_p, C_1, C_2, π_Q, and π_T were provided as mean estimates only

- The handbook references yielded distribution information on λ_p
  - But no distribution information on C_1, C_2, π_Q, and π_T
- The following engineering assumptions were made based on engineering judgement
  - Normality was assumed for C_1, C_2, π_Q, and π_T distribution. Referenced the Probability & Statistics For Engineers & Scientists, Paige 144, 7th Edition by Walpole, Myers and Ye
    - "Physical measurements in areas such as meteorological experiments, rainfall studies, and measurements of manufactured parts are often more that adequately explained with a normal distribution"
  - The relationship between the mean and the standard deviation is expressed via coefficient of variance (CV)
  - CV = standard deviation / mean estimate
  - CV was assumed to be 20%

Cont. Process to Estimate Environmental Factors Uncertainty

- References in the MIL-HDBK-217F provided distribution information on the λ_p for the microelectronic part-type
- Data was found for 5 environments (GB, GF, SF, ML, NSB)
- Standard deviation was calculated for each environment
- The uncertainty propagation for $\pi_E = \frac{\left(\frac{\lambda p}{\pi_Q}\right) - C_1\pi_T}{C_2}$ was estimated using Monte Carlo (MC) simulations

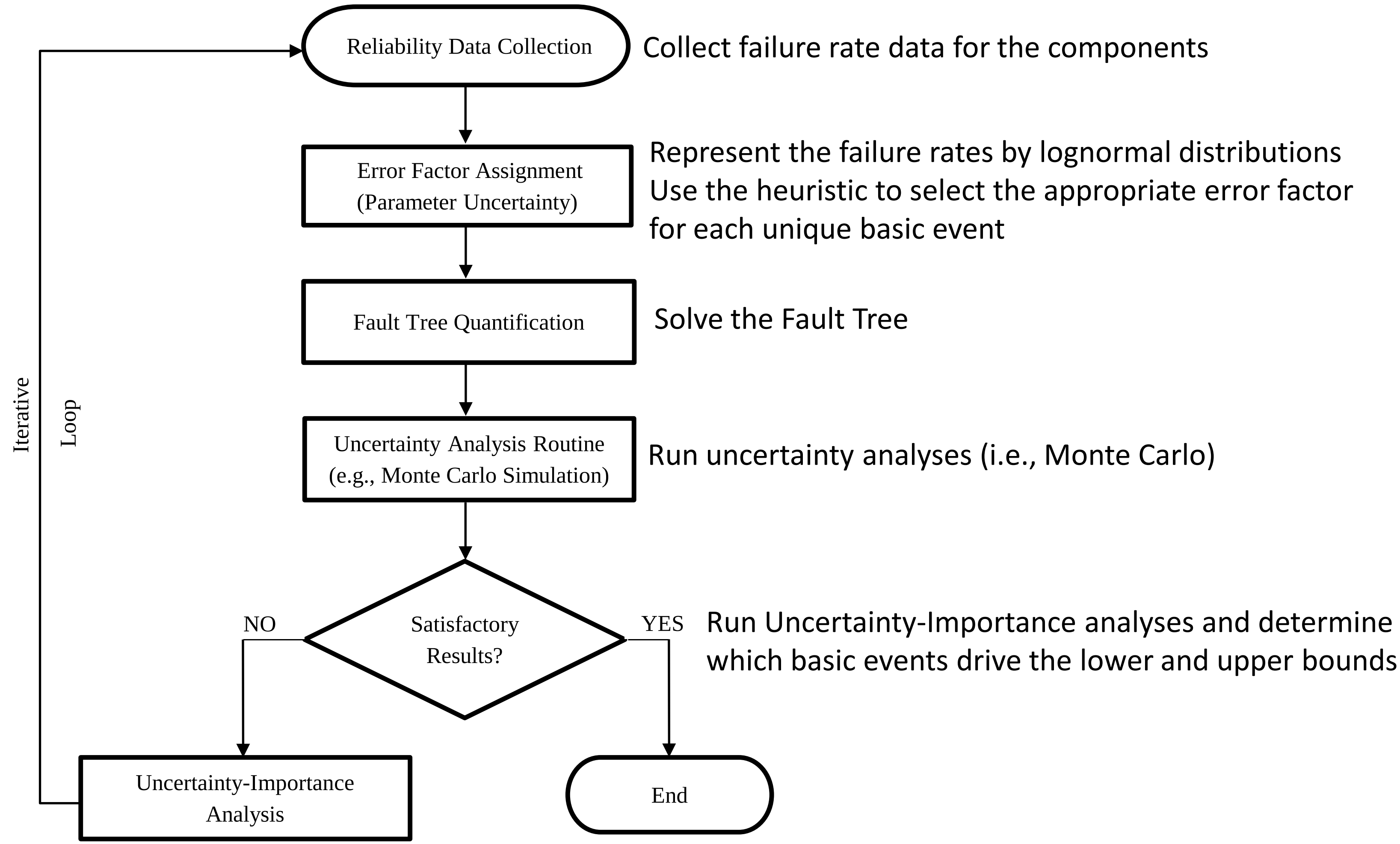
Cont. Process to Estimate Environmental Factors Uncertainty



- The MC samples in the figure fit the lognormal distribution
- The error factor (a measure of uncertainty for lognormal distribution) for the GB π_E equation was calculated to be 3 using the formula (EF= 95th/Median)
- GB was selected because the source used it as the reference environment

Process Flow Chart to Reduce Uncertainty

- This flow chart shows an iterative process using Uncertainty-Importance routines to prioritize components for additional data collection or testing to reduce uncertainty



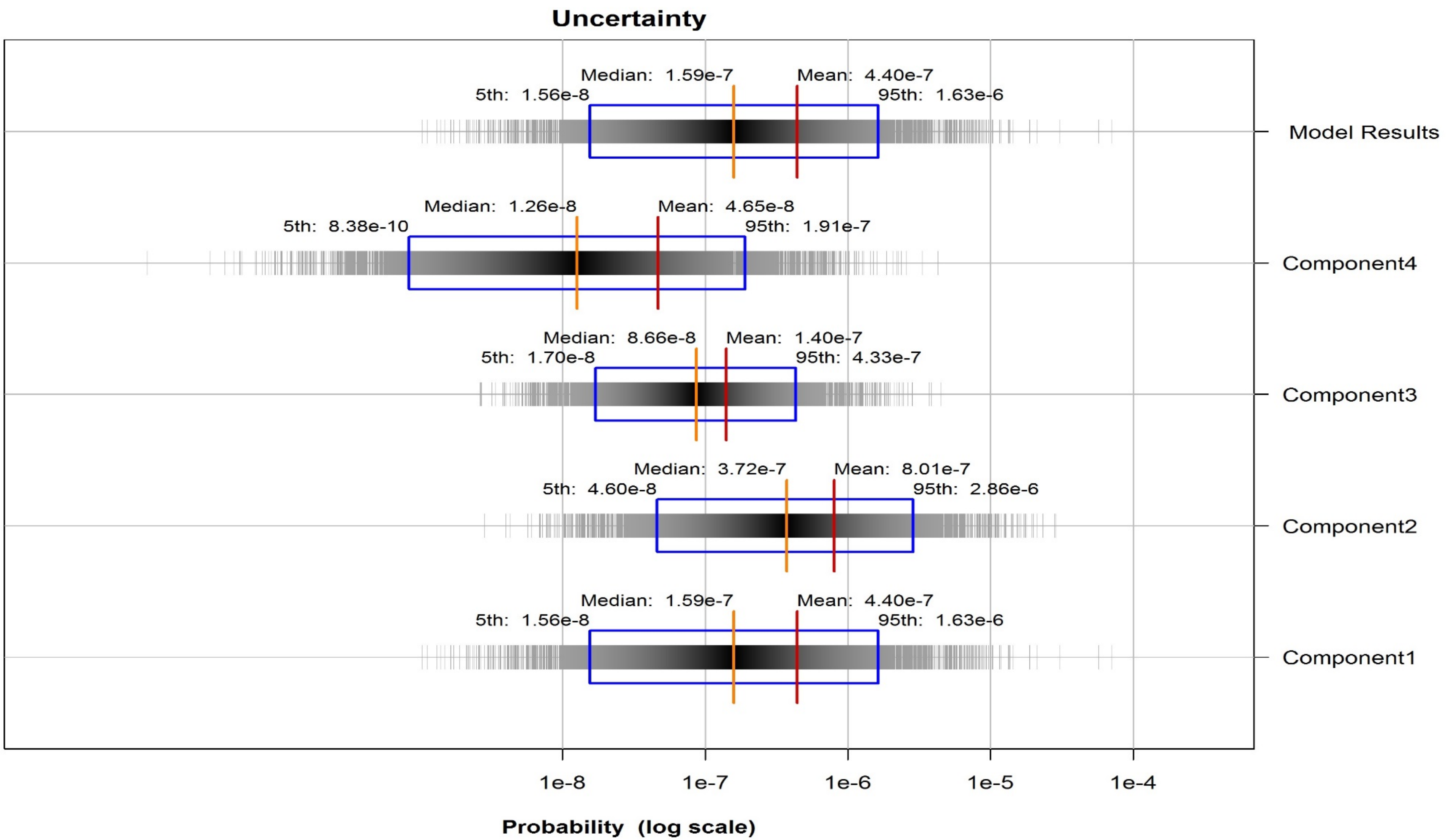
Case Study
Simple Fault Tree

- A simple model consists of 4 components 1, 2, 3 and 4 operating for a duration of 500 sec (0.14 hrs.)
- Component 1 is in series with components 2, 3, and 4
- Components 2, 3, and 4 are connected in a parallel configuration

- case_study OR Data Analysis
  - COMPONENT1 (4.170E-007) Source: Non-Expert Judgment (Documented Process). EF = 10
  - components_in_series AND
    - COMPONENT2 (8.354E-007) Source: Piece Part Count. EF = 8
    - COMPONENT3 (1.390E-007) Source: Aerospace Historical Data for same component. EF = 5
    - COMPONENT4 (4.865E-008) Source: Non-Expert Judgment (Undocumented Process). EF = 15

Note: Numbers shown on this slide are examples only and do not represent data from NASA systems

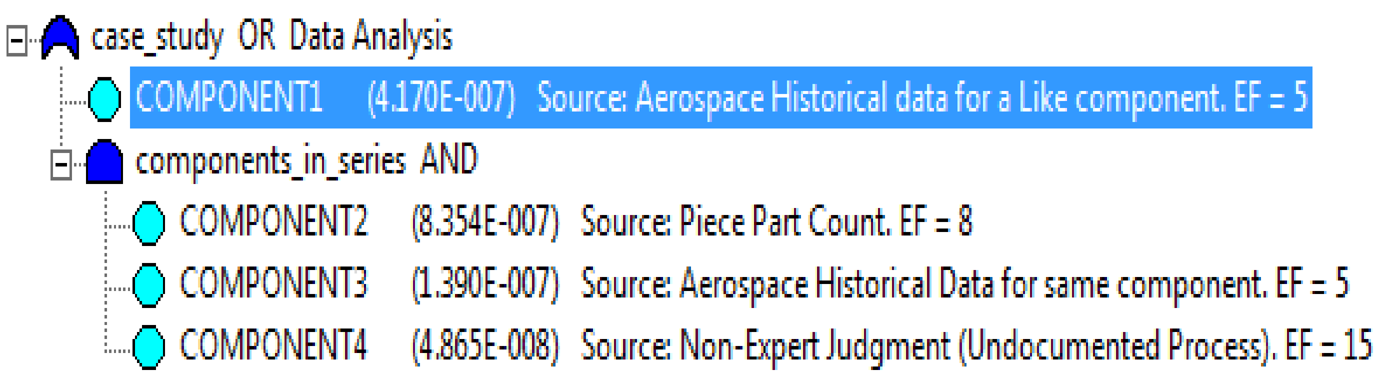
Case Study
Uncertainty Quantification Results
Run1



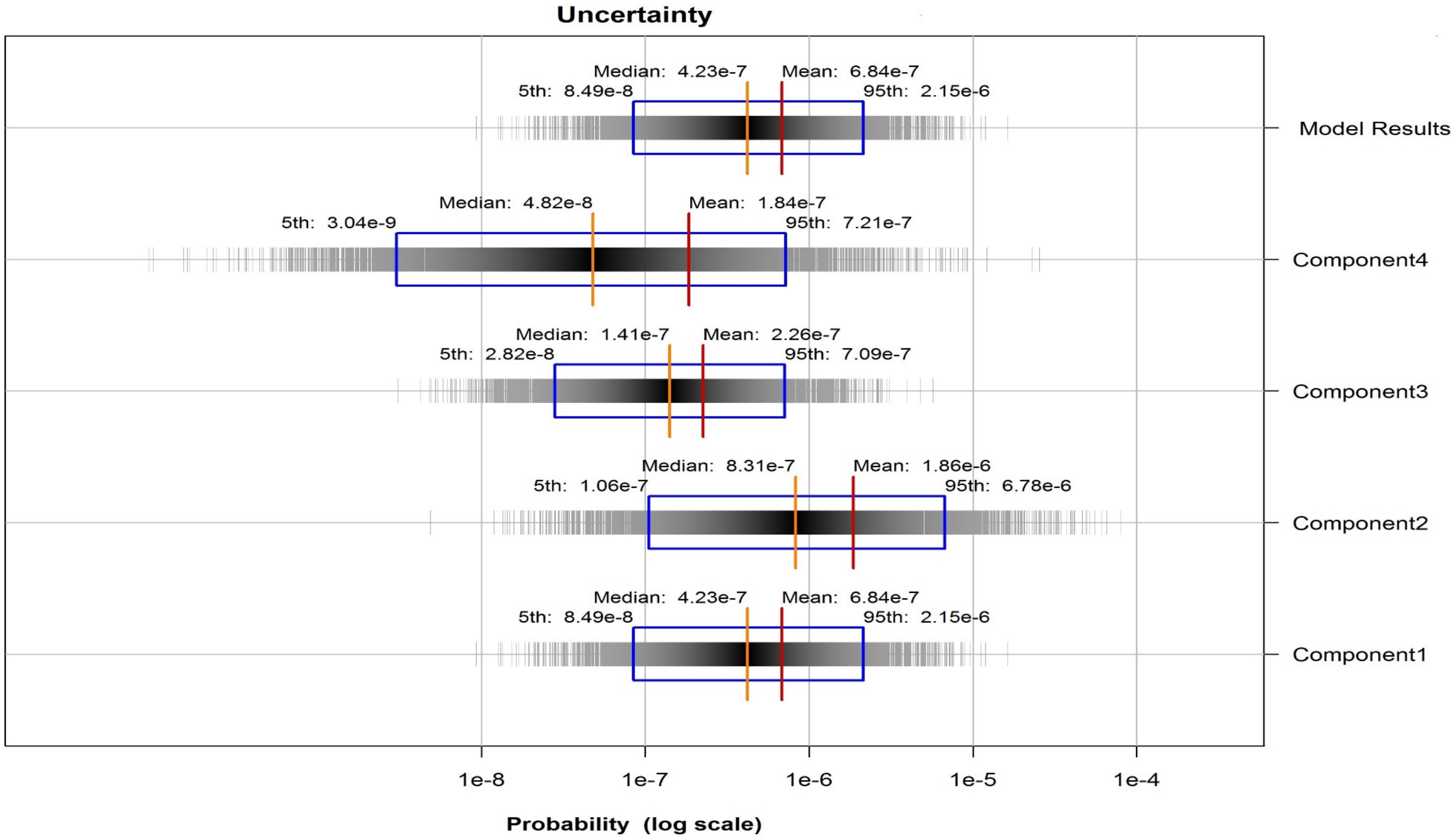
- Model Error Factor (EF) = 95^{th}/Median = 10.25

Case Study
Uncertainty-Importance Analysis

- The Uncertainty-importance routine identified component 1 as a major driver of the model uncertainty
- A data research to reduce uncertainty on Component 1 identified more applicable data
  - Found historical data for a like component from the aerospace industry



Case Study
Uncertainty Quantification Results
Run2



Model New EF = 95th/ Median = 5.08 vs. Old EF of 10.25

Conclusion

- Uncertainty represents the spread of the parameter estimate. How certain are we that the estimate is correct?
  - Useful for decision makers
  - Applicability is a source of uncertainty
- Highly applicable data improves the certainty of model estimates
  - Crucial step that increases the credibility of the component's failure rate estimate
- Translating between environments is an unknown source of epistemic parameter uncertainty
- The uncertainty about the environmental factor conversion formula was statistically estimated with an error factor of about 3
  - Aggregate with the source data applicability to achieve a complete estimate of epistemic uncertainty
- This assessment was made for the GB, GF, SF, ML, and NSB environment for microelectronic part-type
- Uncertainty-Importance routines can be a basis for data analysis efforts
  - By prioritizing the need to collect additional parameter data
- Future work will assess other part types and other environments

Questions?

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