Source Data Impacts on Epistemic Uncertainty for Launch Vehicle Fault Tree Models

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ABSTRACT

Launch vehicle systems are designed and developed using both heritage and new hardware. Design modifications to the heritage hardware to fit new functional system requirements can impact the applicability of heritage reliability data. Risk estimates for newly designed systems must be developed from generic data sources such as commercially available reliability databases using reliability prediction methodologies, such as those addressed in MIL-HDBK-217F. Failure estimates must be converted from the generic environment to the specific operating environment of the system in which it is used. In addition, some qualification of applicability for the data source to the current system should be made. Characterizing data applicability under these circumstances is crucial to developing model estimations that support confident decisions on design changes and trade studies. This paper will demonstrate a data-source applicability classification method for suggesting epistemic component uncertainty to a target vehicle based on the source and operating environment of the originating data. The source applicability is determined using heuristic guidelines while translation of operating environments is accomplished by applying statistical methods to MIL-HDK-217F tables.

The paper will provide one example for assigning environmental factors uncertainty when translating between operating environments for the microelectronic part-type components. The heuristic guidelines will be followed by uncertainty-importance routines to assess the need for more applicable data to reduce model uncertainty.

INTRODUCTION

Today's space launch vehicles are typically evolved from a combination of both heritage hardware and new technology. This developmental approach is often driven by cost, schedule, and reliability considerations. The Probabilistic Risk Assessment (PRA) team is developing PRA models for use in risk-informed decision making. PRA is a methodology for quantifying the risk of high-consequence events such as loss of crew and loss of mission. The process involves developing fault-tree logic models based on the current design and then quantifying the basic events in the model. Basic events in the model represent failure events, which can be functional (critical component failures), phenomenological (structural, fire/explosion, etc.), or human caused. This paper focuses on developing estimates for functional failure of components. Component failure rates are derived from a wide variety of data sources such as demonstrated reliability data for heritage hardware, reliability predictions developed by the prime contractors, and component failure databases, such as RIAC EPRD/NPRD, and NUCLARR. An important consideration in PRA modeling is an explicit treatment of uncertainty. Reliability prediction methodologies typically do not address uncertainty. Therefore, when using prediction data sources, methods need to be developed for consistently characterizing the uncertainty of component reliability predictions. Uncertainties in a PRA can be aleatory (random variation) or epistemic (lack of knowledge). Often epistemic uncertainties are the dominant contributors. Therefore, characterizing epistemic uncertainty is crucial to risk-informed decision making to support design trade studies and flight readiness decisions.

The team developed a two-part approach for quantifying epistemic uncertainty of component basic events in the PRA model. The first part reviews the data sources used in the component reliability prediction, evaluates the applicability of the data sources used in the prime contractor's estimate, and assesses the uncertainty based on a heuristic approach. The second part of the approach accounts for epistemic uncertainty associated with translating failure rate estimates from the data-source environment to the launch vehicle's operating environment.

By reducing the fault tree logic to cutsets through Boolean logic reduction, basic event uncertainties are propagated

to the top event using Monte Carlo simulation methods. It then becomes important to identify those basic events that are important contributors to the uncertainty of the top event. Once identified, additional effort can focus on ways to reduce their uncertainty, such as by identifying additional data sources, reviewing and analyzing test data, and recommending additional testing. Therefore, the two step process is followed with a process to identify basic-event contributions to the uncertainty of the top event in the logic model through the use of uncertainty-importance routines.

BACKGROUND ON UNCERTAINTY

Failure rates of components cannot be measured directly, and components used in space applications are highly reliable. Hence, system-specific failure data is rare. Consequently, estimates developed from generic sources must be used extensively, but are uncertain due to lack of knowledge and applicability. Typically in PRA applications, components are proof tested for flight and qualified for operation within their service life. Under these constraints, the exponential failure model is used, which has a constant hazard function equal to the mean failure rate (λ). The exponential distribution is a single parameter (λ) model. The uncertainty of the failure-rate parameter is represented as a Lognormal probability density function (p.d.f.). Unique to the Lognormal distribution is a measure of dispersion called the Error Factor (EF). The EF is defined in terms of the 5th, 50th (median), and 95th percentiles of the probability distribution. Specifically, the EF is equal to the 95th divided by the 50th (median). The Lognormal failure rate uncertainty p.d.f. is illustrated in Figure 1.
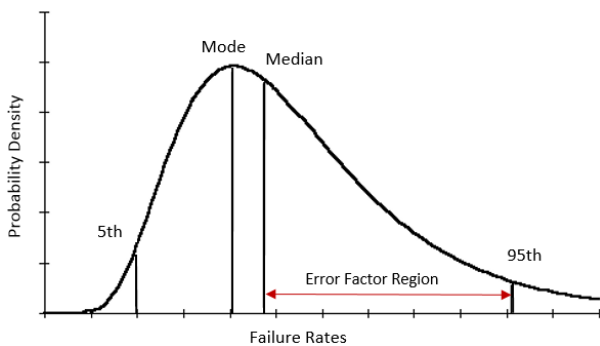

Figure1. Lognormal Probability Density Function (PDF)

As noted above, uncertainty has two sources typically inherent in every system, aleatory and epistemic. Aleatory uncertainty is due to random variation, which is an inherent characteristic of the system and as such cannot

be reduced except through physical changes to the system, such as quality improvement. Epistemic uncertainty can be reduced through acquisition of additional knowledge, such as better data sources, additional testing, flight experience, etc. Epistemic uncertainties stem from the modeling context, such as component reliability data (failure rates), model assumptions, and model completeness (e.g., missing scope or scenarios). This paper focuses on epistemic uncertainty associated with component reliability data. This context was selected based on the fact that model completeness and model assumptions are specific to their launch vehicle design whereas component reliability is more general to any launch vehicle design and is extensible to other systems as well.

1. APPROACH TO ASSESS PARAMETER EPISTEMIC UNCERTAINTY

The approach described below aims to consistently assess epistemic uncertainty across launch vehicle subsystems (e.g., booster, core stage, upper stage, engine, thrust vector control, avionics) by providing heuristic guidelines for assessing uncertainty based on the data-source applicability and operating environment. The discussion of this approach will be divided into two parts, Data-Source Applicability and Data-Source Operating Environment.

1.1 Source-Data Applicability

It is important to note that the guidelines in this part of the approach are tailored to new launch vehicle systems or subsystems that lack historical flight data. Failure rates in this case often come from generic sources, such as reliability databases, and are usually provided as point estimates (mean or median). This section uses the point estimate and the applicability guidelines to estimate the parameters of the Lognormal failure rate uncertainty distribution for use in basic events in the PRA logic model. Bayesian reliability requires a prior distribution to represent degree of belief about the value of a component failure rate before system specific data become available from testing or operations. Hence, the uncertainty distributions developed with this method are prior distributions that will be updated using Bayes theorem when system specific information becomes available through testing or flight experience.

This section describes the heuristic uncertainty classification method for assessing uncertainty due to data-source applicability. Applicability refers to the

relevance of the source-data, used in developing the point estimate of the component's failure rate, to the specific launch vehicle system being modeled. Table 1. *Data Source Applicability & Error Factor Assignment,* lists the typical reliability data sources for new components. It is used to assess data-source uncertainty and assign an error factor, which along with the provided mean or median, completely specifies the basic event distribution in the PRA fault tree model. Notice that the error factors increase from the most applicable source (Category A) to the least applicable source (Category E) as one would expect.

Table 1. Data Source Applicability & Error Factor Assignment

Note: This table is intended to be used for point estimates that lack distribution data. Do not use if the distribution is already known					
Source	Category	Source Descrption	Source Application	Source Application Error Factor	Adjusted Environment
Legacy Hardware	A	Other Launch Vehicle Data (Most Applicable)	Same component	3	Increases the Error Factor
			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	

Table 2 below provides an example of how to apply the guidelines based on Table 1. Consider a simple launch vehicle subsystem comprised of four components operating in the Airborne Uninhabited Fighter (AUF) environment. The failure rate and the assessed Error Factor for each component is listed in Table 2 based on Table 1 uncertainty guidelines.

Table 2. Example for Assigning Failure Rates EFs of a LV System

Component	Data Source	Mean (Point Estimtae)	Error Factor
1	Engineering Judgement (Documentent Process)	3.00E-06	10
2	MIL-KBK-217F Piece Part Method	6.01E-06	8
3	Aerospace Historical Data (Same Component)	1.00E-06	5
4	Engineering Judgement (Undocumentent Process)	3.50E-07	15

1.2 Environmental Factors & Uncertainty

Reliability data for a particular component operating in a specific environment, such as Missile Launch (ML) or AUF, may not be available from the desired operating environment to the extent necessary to develop an adequate prior distribution. MIL-HDBK-217F provides an environmental factor conversion method which allows for converting the failure rate from one environment to another. These conversion factors are presumably mean values based on data, but are also uncertain. 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 process followed begins with a derivation of the equation for the environmental conversion factor, identifies the variables in this equation, generates an uncertainty distribution for each variable, and finally propagates uncertainty to the resulting failure rate through the environmental equation. To implement this process, it was necessary to derive the equation for the environmental factor from the general failure rate, Equation [1], for microelectronics as given in MIL-HBK-217F:

$$\lambda_P = (C_1 \pi_T + C_2 \pi_E) \pi_Q \pi_L \qquad [1]$$

Where

λ_p is the component failure rate in million hours

C_1 is the circuit complexity

C_2 is the packaging complexity

π_E is the environmental factor

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

$$\pi_E = \frac{\left(\frac{\lambda_p}{\pi_Q}\right) - C_1 \pi_T}{C_2} \qquad [2]$$

The challenge with the 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. Information about the standard deviations of the variables was necessary in order to develop uncertainty distributions for each of the variables in the equation. The next subsections explain how this was accomplished.

1.2.1 Estimating C_1, C_2, π_Q, and π_T Uncertainty Distributions

A literature research was conducted using the references cited in the MIL-HDBK-217F but yielded no insight into

the standard deviations of the variables C_1, C_2, π_T and π_Q. This forced the team to make engineering assumptions about the distribution of the means to estimate uncertainty. There is no basis for assuming skewed distributions, and physical parameters tend towards Normality [Reference 3, Page 144], therefore, it was deemed appropriate to assumed normality.

The coefficient of variation (CV), which is defined as the ratio of the standard deviation to the mean and is often expressed as a percentage, was used to estimate a reasonable relationship between the mean and the standard deviation

$$\left(CV = \frac{\sigma}{\mu} \right)$$

A value of 20% was assumed. Standard deviation was then calculated by multiplying the assumed CV by the provided mean. Microcircuits Example 1, Section 5.13, Page 5-20 of the MIL-HBK-217F was used to illustrate the approach to generating uncertainty distributions for the variables in the equation for π_E. See Table 2 for distribution results.

Table 2. Uncertainty Distribution for C_1, C_2, π_Q, and π_T

Variable	Mean	SD(σ)
C1	2.00E-02	4.00E-03
C2	1.10E-02	2.20E-03
π_T	2.90E-01	5.80E-02
π_Q P.V.	80.00	16.00

1.2.2 Estimating The Environmental Factor (π_E) Failure Rate (λ_p) Uncertainty Distribution

Reference [3] *Revision of Environmental Factors for MIL-HDBK-217B for Microelectronics* provides revised data for estimation of the environmental factors for the microelectronics part type. The report summarizes the data analysis methodology in Section 5.0 and reports the data on Tables 5.5-1 and 5.5-2. The report used demonstrated failure rate data to determine λp for five environments with ample historical data, namely Ground Benign (GB), Space Flight (SF), Ground Fixed (GF), Ground Fixed Non-Operating (GF-Non), and Naval Submarine (NSB). The average of the constant failure rate and the adjusted failure rate was assumed in this analysis to be Normally distributed and the standard deviation was calculated based on this assumption. Equation [2] was then modeled to a statistical software scripted in R language called Programmable Uncertainty Parameter Propagation into Equation Software (PUPPIES) to use a

Monte Carlo routine to solve for the environmental factor using a random seed and 20000 simulations. The results of the Monte Carlo simulations for the five environments utilizing PUPPIES are depicted in Figure 2. The distribution results for the five environments do not appear to be normally distributed, since the median and mean are not identical. It is evident from the figure that the distributions are skewed and it was assumed that the data fit a Lognormal distribution.

GB environment was used in Reference [2] as the reference environment for π_E. Since the results shown in Figure 2 appear to fit lognormal distribution, the error factor (a measure of uncertainty for lognormal distribution) for the GB π_E equation was calculated to be 3.00 using the formula (95th/median).
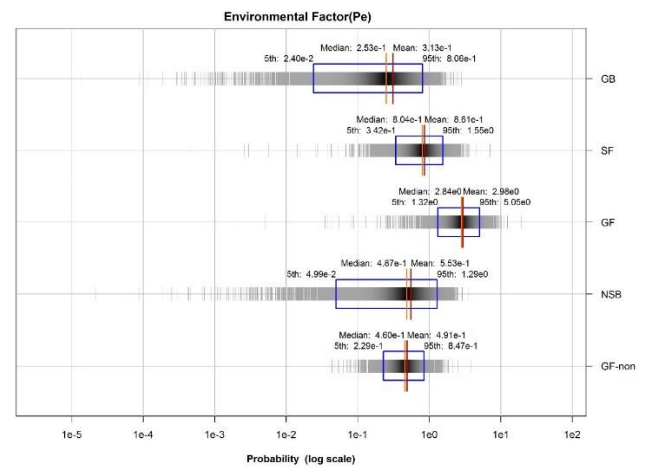

Figure 2. Environmental Factor Epistemic Uncertainty for Five Environments

2. Process to Reduce Uncertainty

The purpose of this section is to demonstrate the process the team used to reduce model's epistemic uncertainty by focusing on data-source applicability of the key contributors to the uncertainty. This process conforms to the flow chart in Figure 3.

The collected failure rate data for each component basic event of the model was compared to the different categories found in Table 1 and was assigned a Lognormal distribution by selecting the appropriate EF. After solving the models fault tree, an uncertainty analysis was conducted using Monte Carlo simulations. This step created an uncertainty distribution for the entire model (as opposed to the uncertainty distribution for a single basic event). In cases where the Monte Carlo analyses yielded a high model uncertainty, uncertainty-importance analyses routines were used to identify the basic events

that drive the uncertainty bounds. This step assessed the degree of need for more applicable data to reduce uncertainty by showing where additional resources need to be placed to the PRA model. Finally, the iterative loop should end when the model uncertainty results are satisfactory.
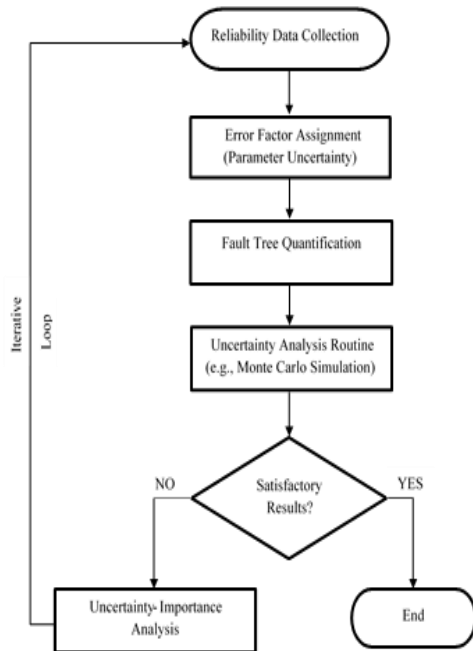

Figure3. Process Flow Chart for Reducing Epistemic Uncertainty

2.1   Case Study

The purpose of this section is to provide an example for applying the uncertainty-importance process shown in Figure 4. Consider the simple LV system example given in Section 1.1. Table 2 in the same section shows components failure rates. Assume the fault tree logic is implemented using a PRA software.

Applying Monte Carlo simulation to the fault tree yields a median estimate of 1.59E-07 and 95th percentile of 1.63E-06. A quantification of the model error factor (95th/median) equates to 10.25. This is considered a high model uncertainty. According to the flow chart in Figure 3, uncertainty-importance analyses identifies Component1 to be responsible for driving this high uncertainty. A more advanced data search is conducted and finds a failure rate from a historical aerospace data of 3.00E-06. Based on the new source applicability, this new failure rate is assigned an error factor of 5. Another trial of Monte Carlo simulation, with the same number of samples and seed, is simulated and the model error factor is now reduced to 5.15 (2.15E-06/4.23E-07). This is considered satisfactory uncertainty and the process of the flow chart ends here.

3.   Conclusion

Parameter epistemic uncertainty applied in PRA represents the lack of knowledge of the component failure rate used in the logic model. As evident in Figure 1, the wider the distribution the larger the uncertainty. The heuristic guidelines developed for use in launch vehicle design risks and discussed in this paper provide a standard approach for better traceability of the epistemic uncertainty associated with the environmental factors and parameter failure rate data source. Once parameter uncertainty is categorized the proposed process flow chart in Figure 3 can be followed to prioritize the need to collect additional parameter data in order to reduce uncertainty if needed.

The uncertainty about the environmental factor conversion, Equation2, was statistically estimated with an error factor of about 3. There were assumptions made about the variables uncertainty distributions due to the fact that very little data was provided about the mean values and nature of their distributions. Possible future work includes reaching out to the authors of MIL-HBK-217F to confirm the uncertainties about the variables mean estimates that were not supplied in the handbook. This part of the approach only assessed the microelectronics part type, and future work will assess other part types pertinent to launch vehicles control systems to ultimately develop an environmental conversion uncertainty matrix for use in PRA.

4. References

[1] MIL-HDBK-217F, Military Handbook, Reliability Prediction of Electronic Equipment, December 1991

[2] Ronald E. Walpole, Raymond H. Myers, Sharon L. Myers, & Keying Ye (2002). Probability & Statistics for Engineers & Scientists, Seventh Edition, New Jersey, Prentice Hall

[3] RADC-TR-80-299, AD A091837, Revision of Environmental Factors for MIL-HDBK-217B, Martin Marietta   Corporation, September 1980