Dealing with Uncertainty in Systems Engineering

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Topics Today

• Uncertainty in Systems Engineering
• Using Probability in SE to Model Uncertainty
• Using Statistics in SE to Reduce Uncertainty
• Four JSC Examples Using the Methods Discussed
Uncertainty in Systems Engineering
Without Uncertainty, There would be No SE

- Clearly, If
  - We *Fully Understand* the *Problem*, AND
  - We *Fully Understand* the *Solution*, AND
  - The *Solution* is *Feasible* within *all* the *System Constraints*, THEN:
    - We Just Build it and Solve the Problem
    - *We don’t need Systems Engineering!*

- Never Been There, Never Done That – *Have You?*
But, What is Uncertainty? Let’s Get Philosophical!

• First, What do Engineers, Specifically Systems Engineers, Really Do?
  • In Decomposition and Definition: Model Abstractions of a System to Solve the Abstractions of the Problem
  • In Integration and Verification: Model Observed Data taken from the System that was Actually Built, and use Data to Verify that the System should Solve the Problem

• Uncertainty is Epistemological, not Ontological
  • We Want to Determine What is Knowable
  • We can Never Truly Know Reality
What Can Be Uncertain in SE?

- **Unknown Future Event**
  - Will Definitely Occur, Outcome Uncertain  
    e.g., Shuttle Mission to Repair Hubble  
  - Occurrence Uncertain, Outcome Uncertain  
    e.g., Debris Conjunction (collision?) on Orbit with ISS

- **Unknown Existing State**, not directly Observable
  - Measurement Uncertainties  
    e.g., Shuttle Position as determined from Radar Data with Noise  
  - Precision Limitations in Data  
    e.g., Round-off and Truncation

- **Known and Knowable Item**, but Unknown to Us
  - e.g., The Millionth Digit of $\pi$;  
    Which Canal is Longer, Suez or Panama?  
    Can we believe a GFE Item’s Spec’s?
More Things in SE Uncertain

- **Deterministic Event or State**
  - Uncertain States of Nature, Initial Conditions, Parameters  
    e.g., Flip of a Coin
  - Outcome Uncertain, Uncertain Model  
    e.g., Atmospheric Density at ISS Orbit

- **Physical Randomness in Nature**
  - Heisenberg Uncertainty Principle
  - Quantum Mechanics
  - Radioactive Decay
  - Statistical Mechanics
Where Exactly does Uncertainty Appear in SE?

• Much **Bigger Role for Systems Engineers** than Most Realize, e.g.,
  • Requirements
  • Functional Analysis and Decomposition, Allocation, and Architecture Synthesis
  • Systems Design
  • Integration of Engineering Specialties
  • Quality Assurance, Verification
  • Integration, both System Builds and Interfaces
  • Risk Management, Probabilistic Risk Assessment

• In **Decisions for All of the Above and More**
Where Exactly does Uncertainty Appear in SE?

It’s Everywhere!!!
The Real Challenges
Uncertainty Presents to SE

• SE Usually Deals with *New* Systems – *NEW* ≡ Uncertain
  • Constellation
  • Future Combat Systems
  • Generation II GPS
• SE Usually Deals with *Stringent* Performance and Specialty Requirements – *Uncertainty is Not Well Tolerated*
  • High Required Levels of Performance, e.g., Accuracies
  • Safety
  • Reliability

In SE, We Usually Have *Very Little Event or Other Data,* We Usually Have *Speculative Heuristics,* and are faced with *Very Low Probability Events with Severe Consequences*
How SE Must Respond

• We Must Always *Model* Uncertainty Well
• We Must Always *Reduce* Uncertainty as Much as We Can *Afford*
• We Must Always Make *Good* Decisions *despite* Uncertainty

**Good Decision Making** by the SE
**Under Conditions of Uncertainty**
Makes
**Good Systems Engineering**
Using Probability in SE to Model Uncertainty
Refresher: All of Probability Theory on One Slide

- **The Axioms**: (A, B ≡ A AND B; A|B ≡ A given B; ~A ≡ NOT A)
  - 0 ≤ P(A|H) ≤ 1; Values of Probability
  - P(A|A,H) = 1; Maximum Value if True
  - P(A|H) + P(~A|H) = 1; Mutual Exclusivity and Exhaustiveness
  - P(A,B|H) = P(B|H)*P(A|B,H) = P(A|H)*P(B|A,H); Conditional Law
- **OR Operation**: P(A OR B|H) = P(A|H) + P(B|H) - P(A,B|H)
- **Mutually Exclusivity**: If B and C are Mutually Exclusive
  - AND Operation: P(B,C|H) = 0
  - OR Operation: P(B OR C|H) = P(B|H) + P(C|H)
- **Independence**: If A and B are Independent
  - P(A,B|H) = P(A|H)P(B|H)
  - P(A OR B|H) = P(A|H) + P(B|H) - P(A|H)P(B|H)
- **Marginalization**: For Propositions A, B, and C
  \[ P(B | H) = \int_{all A} \int_{all C} P(A, B, C | H) dA dC \]

Probability is Actually Quite Easy!
In SE, We Model Stuff: How to Model Uncertainty?

- As in every other engineering discipline and scientific endeavor, **we always model uncertainty as randomness**
  - Randomness is a *metaphor*
  - This is very *reasonable*

- Why?
  - *Probability theory* and *probability models* developed specifically to deal with *randomness*
  - *More importantly*, probability theory and models based on *axioms of rational and coherent behavior*

This is *very good* for systems engineering!
Some Uses of Probability in SE

- Probabilistic Requirements
- Performance Allocation in Functional Analysis and Decomposition
- Integration Planning and Execution
- Verification Planning
Probabilistic Requirements

- Many Performance Requirements are *Normally* Stated Probabilistically, but not so Obviously
  - The “illities”, by definition, e.g.
    - Reliability – Probability of Survival during Mission
    - Availability – Probability of Readiness for Mission
    - Maintainability – Probability can be Repaired in Time
    - Safety – Probability of No Injury or Death
    - Logistics – Probability Part is There for Repair
  - Quality Assurance Requirements – Verification
  - Some Performance Requirements – Inherently
- By Probabilistically, we mean *in terms of a Probability of Achieving the Performance*
- Many Requirements that should be Stated Probabilistically are *NOT*
Probabilistic Requirement Example

- Original International Space Station Microgravity Mission Requirement
  
  *The ISS Program shall provide 180 days of microgravity per year in periods of no less than 30 days.*
  
  - Known Random Events can Make Mission Impossible
    - Debris Avoidance Maneuvers
    - Unscheduled Maintenance Requiring Use of Attitude Jets
  
  - Corrected Requirement:
    
    *The ISS Program shall provide a 70% probability of achieving 180 days of microgravity per year in periods of no less than 30 days.*
Proper Verification Planning

- Verification Requirements and Planning Establish the **Maximum Acceptable Risk** that the Delivered System will **NOT** Perform as Required with Successful Verification
- Example: Reliability Requirement and Test for a Vehicle
  - **Performance Requirement:** *The vehicle shall have 95% reliability at 100,000 miles.*
  - **Verification Requirement:** *Vehicle reliability shall be verified by Test. The test shall demonstrate 90% assurance that the vehicle will have 95% reliability at 100,000 miles.*
  - **Maximum Acceptable Risk:** 10%; we have 90% **Assurance** (or Probability) that Design achieved 95% Reliability at 100,000 miles *with a Successful Test*
  - **The Test:** Drive two vehicles 107,000 miles
  - **Success Criterion:** Neither fails by 107,000 miles (the data)
- INCOSE IS2004 Paper – Contact me if you want it
Using Statistics in SE to Reduce Uncertainty
Use of Statistics in SE

• Statistics is the Process to Reduce Uncertainty – Quantitatively
• Statistical Recipes that we Learned in Stats 101 – Do NOT Work Well for SE
  • Overconservative – SE’s cannot afford
  • Require Many Data – SE rarely Gets a lot of data
  • Require Many Assumptions (usually hidden) – SE’s all Know the Danger of Using Assumptions
  • Can Only Use Actual Event Data – SE’s have Other Data
    • Censored Data – Event has not happened yet
    • Expert Opinion
    • Surrogate or Analog Data
• SE’s Must Use All Available Data and Information
  • To Reduce Uncertainty as Much as Possible
  • To Make Good Decisions
SE Decision Making

• Systems Engineers Make Decisions with Uncertainty in *Every* Facet of the Project Lifecycle, e.g.,
  • Verification and QA – Obvious
  • Acceptable Risk in Probabilistic Requirements
  • Allocation of Performance and Risk
  • Design and Other Decisions
  • Risk Management

• *Good Decision Making* Makes *Good SE*
Suppose …

- You could Make an SE Decision *without Making any Dangerous or Questionable Assumptions*?
- You could *Fuse* together every scrap of data and information about the Decision, *including non-event data and heuristics*, to *Reduce* your Uncertainty the Very Most Possible?
- You could be *Sure About the Risk* of each Alternative Producing the Desired Outcome of Every Important SE Decision?

*Would that Help with those Important SE Decisions?*
The Premise

- All Decisions are *Always* Based on Risk Assessments
  - SE Decisions select an Alternative (or Action) to Produce a *Desired Outcome*
  - The Decision Maker selects an Alternative based on *only* one thing:
    - *How Sure they can be, considering the available data, information, and their best judgment, that the Alternative will Produce the Desired Outcome*
  - A *Risk Assessment* (statistical processing of the data) tells the Decision Maker the Level of Assurance (*How sure they can be, based on the Data and Information*) for the Risk of an Alternative *NOT* producing the Desired Outcome
- *Better Risk Assessments Produce Better Project Decisions*

*If you know your Risk for each Alternative, Decisions are Smart and Easy*
Risk Assessments

• **Qualitative** Risk Assessments
  • Decision Maker *Mentally* Integrates and Fuses a variety of Data and Personal Judgments to produce a *Qualitative Measure of Assurance* the Alternative will produce the Desired Outcome
  • Usually requires *Many Assumptions*
  • For Many SE Decisions, Sufficient
• A **Quantitative** Risk Assessment is a Computational Statistical Inference
  • *Mathematically* Integrates and *Fuses All* Data, Information, and Judgments, producing a *Probability Distribution* for the *Risk* of the Alternative Producing the Desired Outcome
  • A *Numerical Value* for Assurance of Risk Can be Computed from the Risk Probability Distribution
  • *Important* SE Decisions *Need* Quantitative Risk Assessments

**Using the Same Data, Quantitative Risk Assessments Always Produce Better Decisions**
Problems with Quantitative Risk Assessments

- **Difficult** to Perform
- Time *Consuming* and *Expensive*
- Mathematically *Intense*
- Usually *Forced by the Math* to Ignore or Overlook Important and Relevant Data or Information (e.g., Heuristics and Censored Data)
- Inability to Find Suitable Math Models forces the Use of *Assumptions*
- Statisticians Usually *do not Know Enough about the Problem Space* to provide a Usable Result
- Sometimes, *Impossible* to Obtain a Usable Result
Now, The Good News

• You do **NOT** Have to Be a PhD Statistician and Computer Programming Guru to Do a Quantitative Risk Assessment
• *New* Numerical Methods Make Quantitative Risk Assessments *Quick, Easy, and Inexpensive*
  • With just a *little* Programming, you can solve Important Decisions Right at Your Desk in Just a Few Hours
  • Knowing about these Methods, you can *Direct* a Quantitative Risk Assessment by Support Staff doing a little Programming in Just a Few Hours

**You can Make Much Better SE Decisions, Now!**
The Foundation: Bayes’ Law

- The **Basis** for all of Decision Theory and Analysis
- Bayes Published in 1763
- Laplace Rediscovered and Republished in 1812
- Jeffreys Rediscovered and Republished again in 1939
- Analytical Derivation from Axiom 4
  - Now consider only the **Rightmost** Equality
  - \( P(A|B,H) = P(B|A,H)^*P(A|H)/P(B|H) \)
- **That’s it!**
Interpretation of Bayes’ Law

• **Bayes’ Law**: \( P(B|A,H) = P(A|B,H) \cdot P(B|H)/P(A|H) \)
  - If \( B \) is a Proposition, and \( A \) is Data, we get \( P(\text{Prop}|\text{Data},H) = P(\text{Data}|\text{Prop},H) \cdot P(\text{Prop}|H)/P(\text{Data}|H) \)
  - Now, \( P(\text{Data}|H) \) is just a *Constant Marginal* Probability, and *unimportant*, so we can ignore it and say \( P(\text{Prop}|\text{Data},H) \propto P(\text{Data}|\text{Prop},H) \cdot P(\text{Prop}|H) \)

• **The Interpretation**
  - \( P(\text{Prop}|H) \) is called the *Prior* - the Marginal Probability (Uncertainty) on the Proposition *before* getting the Data
  - \( P(\text{Data}|\text{Prop},H) \) is called the *Likelihood* - the Probability of Getting the Data Given the Proposition
  - \( P(\text{Prop}|\text{Data},H) \) is called the *Posterior* - the Probability (Uncertainty) on the Proposition *after* the Probability of Getting the Data Given the Proposition is Compounded with the *Prior*

• **Works for Probability Density Functions Also!**
• **Can Fuse Any and All Data Types in the Likelihood!**
Now, How to Avoid Dangerous Assumptions

- Almost All of Our SE or Engineering Assumptions are about Our Models for Uncertainty
- Cannot Completely Avoid Assumptions, However
  - You Can Avoid *Overconservative* Assumptions that can Compound into Overconservative Risks
  - You Can Avoid *Questionable* Assumptions that Managers Always Second Guess
- The Key: Use *Purely Objective* Uncertainty Models (*Non-informative* or *Reference* Models) Instead of Assumptions
  - To Model Uncertainty when you Are *Ignorant* about the Uncertainty, Usually as the Prior Model
  - Provides *Realistic* Worst Case Scenarios without Applying Any Risk Aversion or Tolerance
  - Derivable Using Three Independent Methods
  - Very *Simple* Functions, Generally Inverses and the Constant 1
  - Bernardo and Smith, Excellent Reference

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Problems with Bayesian Statistics

- Ever Wonder *Why* You were not Taught Bayesian Statistics in Engineering?
- For Real World Problems, When You *Fuse* All the Data and Information, and Use *Objective* Models, Bayesian Stats:
  - Almost Always Produce *Unrecognizable Uncertainty Models* that are *Multivariate with all Variables Correlated*
  - Usually Produce *Analytically Intractable Solutions* – Impossible to Integrate to Compute Probabilities
  - Are Usually *Impossible to Solve Numerically* using *Ordinary Monte Carlo Methods* – Impossible to Sample Unrecognized Correlated Multivariate Models

Up Until the mid-1990’s, Bayesian Statistics were *Impractical* and Usually *Impossible* to Use to Reduce Uncertainty in *Real World SE Problems*
The Solution

• Markov Chain Monte Carlo (MCMC)
  • A Numerical Method Developed in Europe in 1990’s mainly for Risk and Decisions in Biostatistics and Biomedical Research
  • Uses a Markov Chain to Sample an Uncertainty Model, Including very Complex (correlated, multi-dimensional) and Analytically Intractable Probability Models (like we actually get in the Real World of SE)
  • Ordinary Monte Carlo Calculations Then Can be Used on Samples to Approximate Complex Probability Integrals
  • Simple Algorithm (Metropolis-Hastings)

• Recently Applied to SE Problems
  • INCOSE IS02 Paper (Maintenance Interval)
  • INCOSE IS04 Paper (Optimal Cost Verification)
The Metropolis-Hastings MCMC Algorithm

• To Start, formulate the Posterior density model \( pd(\Theta|\text{data}) \), and select a proposal step size \( d\Theta \)
• Select any legal value for the first Sample: \( \Theta_1 = \Theta_1 \)
• Repeat this Loop to get new samples
  • Propose a new sample: \( \Theta_{i+1} = \Theta_i + \Delta\Theta \), where \( \Delta\Theta \sim U(-d\Theta,d\Theta) \), a Uniform Model Sample
  • Calculate the ratio of Posterior densities:
    \( \alpha = \frac{pd(\Theta_{i+1}|\text{data})}{pd(\Theta_i|\text{data})} \)
  • Obtain a sample \( u \) from a Uniform Model: \( u \sim U(0,1) \)
  • If \( u < \alpha \), then accept the proposed sample as \( \Theta_{i+1} \), else, set the new sample to the previous one: \( \Theta_{i+1} = \Theta_i \)
• Markov Chain is Tuned Manually Using Proposal Step Size \( d\Theta \)
But Sometimes, MCMC Needs Outrageous Assumptions

- For Many Real World SE Decisions, Posteriors Using non-Event Data and/or Objective Models will **NOT** produce a Stable Markov Chain
- Metropolis-Hastings Algorithm will not Work
- Solution: Use *Pseudo-Ignorance* Models
  - Truncate Your Prior Models
  - Limit Range of Scale and Shape Parameters in Models to Some **Outrageous** Value (say, to 10 times larger than realistic)
  - Stabilizes the Markov Chain, Produces Good Sampling and Integration Values
Four Relevant JSC Examples

- **Space Shuttle Cargo Transfer Bag Test (MCMC)**
  - Shows Quantitative Risk Assessment for a *Single Censored Datum* using *Pseudo-ignorance* Models
  - Parameterized by Acceptable Risk
- **Drift of ISS O₂ Sensor for EVA (MCMC)**
  - Lots of Observed Data
  - *Pure Objective* Models Used
- **RSR Locker Loose Screw Probabilistic Risk Assessment**
  - Few Observed Data, *Lots of Censored Data*, Uses *Pure Objective* Models, *Actual Analytical Solution*
  - Parameterized by Failure Modes
- **Human Spaceflight Bone Fracture Risk (MCMC)**
  - *Lots of Censored Data ONLY*, no Actual Breaks, *Pseudo-ignorance* Models
  - Parameterized by Mission Duration
- **Contact Me for Details on these Examples and Others!**
Cargo Transfer Bag Test

- Cargo Transfer Bags (CTB) to be Carried on Shuttle to Space Station
- Required Zipper Cycle Life – 2,000 Cycles
- If CTB Zipper Fails During Launch or Descent, Loose Object could Penetrate the Hull (Rare Event with Extreme Consequences)
- Performed a Single Test
  - One CTB Only
  - 8,000 Successful Zipper Cycles – One Censored Datum Only!

**THE Relevant Question**

*How Sure can we be from the Test Result that the True Risk of CTB Zipper failure by 2,000 Cycles is below some Acceptable Level?*
Synopsis for the CTB Test

- Test Datum: Only One Censored Datum
  Successful 8K Cycles without a Failure on One CTB Zipper
- Assumptions (Outrageous):
  - Zipper Cycling Cannot Improve Reliability of the CTB Zipper
  - At Least 62.4% of CTB failures will occur before 30,000 Cycles
- No Stated Maximum Acceptable Risk – So Parameterize

<table>
<thead>
<tr>
<th>Maximum Acceptable Risk of CTB Zipper Failure by 2K Cycles (R_{2K})</th>
<th>Assurance Provided by Test Result P(True R_{2K} &lt; R_{2K})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>P(True R_{2K} &lt; 1%) = 75%</td>
</tr>
<tr>
<td>5%</td>
<td>P(True R_{2K} &lt; 5%) = 88%</td>
</tr>
<tr>
<td>10%</td>
<td>P(True R_{2K} &lt; 10%) = 94%</td>
</tr>
<tr>
<td>20%</td>
<td>P(True R_{2K} &lt; 20%) = 98%</td>
</tr>
</tbody>
</table>
ISS O₂ Sensor Drift

• Problem: Space Station Oxygen Sensor Measurement Accuracy is Observed to drift with Time
  • If the Measured O₂ is in Error by more than ±6mmHG within 270 days since Calibration, it could *Kill* an Astronaut
  • High Error: Severe Brain Damage; Low Error: The Bends
• Proposed Solution Alternatives:
  • Test for Drift rates and Compensate for Drift; *OR*,
  • Redesign O₂ Sensor and Ship Up to ISS, No EVA’s Until Then
• Relevant Questions:
  • What is the *Existing* Risk of Sensor Accuracy Drift Beyond Acceptable Limits?
  • What is the Risk *After* the Proposed Drift Compensation?
  • How *Sure* can we Be about These Risk Values?
O$_2$ Sensor Test Data

Drift of the CSA-O2s During Long Life Evaluation
(Data is pressure corrected)

Accuracy (mmHg) vs. Days Since Calibration

- Linear (1039)
- Linear (1037)
- Linear (1031)
- Linear (1026)
- Linear (1014)
- Linear (1037)

270 Days
Drift Corrected O₂ Sensor Test Data

The Decision is Still Unclear!

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Before and After Drift Correction Risk Results

Linear Scale

Logarithmic Scale

JSC Band-aid Chart Guide:

- 5th Percentile Risk
- 95th Percentile Risk
- Color Density = Risk Density
- Most Likely Risk
O₂ Sensor PRA Summary

- Without Drift Compensation: Risk of Exceeding Accuracy Limits at 270 Days is 36% - 46% (with 90% Certainty)
- With Drift Compensation:
  - 95% Sure: Risk within 270 days is < 1.5%
  - 90% Sure: Risk is between 0.55% - 1.5%
- Achieved Stable Markov Chain – No Outrageous Assumptions Needed
RSR Loose Screw PRA

- **Problem:** Screws holding locker door in place in Shuttle Bay are too short
  - If door loses integrity, or falls off, something could penetrate the Shuttle Hull during launch or descent
  - What is the risk of having a loose screw, that could then lead to a risk of losing a door

- **Decision:**
  - Replace and retighten all screws, **OR**
  - Delay flight
Risk of Panel Door Loss

- Complex Risk Question
  - Loss of any Latch or Hinge Plate on Door will cause Loss of Door Integrity
  - Loss of a Latch or Hinge Plate requires Loss of One or More Screws
  - How many lost screws, in what patterns for Latch or Hinge Plate will Cause Loss of Door?
  - The Answer Defines Failure Modes

- Potential Failure Modes
  - Any One to Six Screws Lost in a Latch or Hinge Plate Causes Door Integrity Loss - Conservative
  - Specific Pattern of One to Six Screws Lost in a Latch or Hinge Plate Causes Door Integrity Loss – Realistic Engineering, and Less Conservative
The Probability Equations for Risk of Panel Door Loss

- The Complete Probability Equations are usually Neglected, Usually a Mistake
- The Probability Statements for this Risk
  - \( P(\text{loss of any door}) = 1 - (1 - P(\text{loss of single panel door}))^{(# \text{ of single panel doors})} \times (1 - P(\text{loss of double panel door}))^{(# \text{ of double panel doors})} \times (1 - P(\text{loss of triple panel door}))^{(# \text{ of triple panel doors})} \)
  - \( P(\text{loss of door}) = P(\text{loss of any Latch OR loss of any Hinge Plate on the door}) = 1 - (1 - P(\text{loss of latch}))^{(# \text{ of latches and hinge plates on door})} \)
  - \( P(\text{loss of latch}) = P(\text{loss of Hinge Plate}) = P(M \text{ screws lost of Pattern of 6}) - \text{the failure mode} \)
  - \( = \sum_{j=0}^{6} [P(M \text{ Lost} | j \text{ Loose})P(j \text{ Loose}) + P(M \text{ Lost} | 6 - j \text{Tight})P(6 - j \text{Tight})] \)
Predicted Risk of RSR Panel Door Failure

- The Data: 8 of 273 Screws were Observed to be Loose, no Screws Actually Lost
- Consider All Conservative Failure Modes (1 to 6 screws may be needed to Retain Each Latch and Each Hinge Plate)
- A Worst Case – Specific Screw Patterns will Reduce Risks
- Table of Predicted Risks for Failure due to Lost Screws

| Failure Mode Definition (# Lost Screws in Pattern of 6) | P(Loss Single Door|Data) | P(Loss Double Door|Data) | P(Loss Triple Door|Data) | P(Loss Any Door|Data) |
|--------------------------------------------------------|-----------------|-----------------|-----------------|----------------|
| 1 or more                                              | 1.91%           | 3.78%           | 5.62%           | 29.34%         |
| 2 or more                                              | 2.35e-2%        | 4.69e-2%        | 7.04e-2%        | 0.422%         |
| 3 or more                                              | 2.57e-4%        | 5.14e-4%        | 7.71e-4         | 4.63e-3%       |
| 4 or more                                              | 2.23e-6%        | 4.47e-6%        | 6.70e-6%        | 4.02e-5%       |
| 5 or more                                              | 1.34e-8%        | 2.68e-8%        | 4.02e-8%        | 2.41e-7%       |
| 6                                                      | 4.11e-11%       | 8.23e-11%       | 1.23e-10%       | 7.41e-10%      |
Human Spaceflight
Bone Fracture Risk

- Space and Life Sciences Directorate Needed **Quantification of Risk of Bone Fracture** during Long Duration Missions to Mars, and For Extended Stays on ISS
- Mission Duration can Vary in Length
- Never any Broken Bones during Any Flight, Ever
- Risk Assessment **Believed Impossible**
Human Spaceflight Bone Fracture Data

- No Bone Fractures Reported for any Human Spaceflight Mission
- 977 µG Exposures
  - No Significance to Index # or Order of Data
  - All Crewmembers Included
  - 294 Flights
  - Includes all Russian flights
  - Includes all U.S. flights
  - 1 Chinese Flight
  - 3 Spaceship One flights
  - All ISS Missions as of May 2005
- 56 MIR missions
- Source is Astronautix.com
Spaceflight Bone Fracture Risk

- Logarithmic Scale, Truncated on Right for Some Detail
- 5th, 50th, and 95th Quantile Contours
- Bandaids Superimposed on Contours
Synopsis

- Uncertainty is *Prevalent* Throughout Systems Engineering
- By Properly Using Probability and Statistics, Uncertainty can *Now* be Handled *Very Effectively* by an SE
- New Methods (*MCMC*, *Reference Models*, and *Pseudo-Ignorance Priors*) are Available to SE’s to Allow Good Statistics
  - Better Reduction of Risk and Uncertainty
  - Better SE Decisions
  - *Better SE!*
Naked Proselytization

- SE Courses Available at Stevens Institute of Technology via the Web
  - SYS601: *Probability and Statistics for Systems Engineers* – Spring Semesters
  - SYS660: *Decision and Risk Analysis for Complex Systems* – Fall and Summer Semesters
  - [http://webcampus.stevens.edu/](http://webcampus.stevens.edu/)
- Upcoming Two Day Tutorial: ILTAM, Herzeliya, Israel in November 2007
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