

Dealing with Uncertainty in Systems Engineering

Jet Propulsion Laboratory

Systems Engineering Advancement Seminar

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Without Uncertainty, There would be No SE

- **Clearly, If**
 - ***We Fully Understand the Problem***
 - ***We Fully Understand the Solution***
 - ***The Solution is Feasible within all the System Constraints***
 - **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?

- **First, What do Engineers, Specifically Systems Engineers, Really Do?**
 - In Analysis and Design, *Model Abstractions of a System to Solve the Abstractions of the Problem*
 - In Integration and Test, *Model Uncertain Observed Data from the System that was Actually Built to Verify that it Actually has a good Chance to Solve the Problem*
- **Uncertainty is *Epistemological*, not *Ontological***
 - We Want to Determine What is Knowable
 - We can *Never Truly Know Reality*

Types of SE Uncertainty

- ***Unknown Future Event***
 - Will Definitely Occur, Outcome Uncertain
 - Occurrence Uncertain, Outcome Uncertain
- ***Unknown Existing State, not directly Observable***
 - Measurement Uncertainties
 - Precision Limitations
- ***Deterministic Event or State***
 - Uncertain States of Nature, Initial Conditions, Parameters
 - Outcome Uncertain
 - Uncertain Model
- ***Known and Knowable Item, but Unknown to Us***
- ***Physical Randomness in Nature***
 - Heisenberg Uncertainty Principle
 - Quantum Mechanics
 - Radioactive Decay
 - Statistical Mechanics

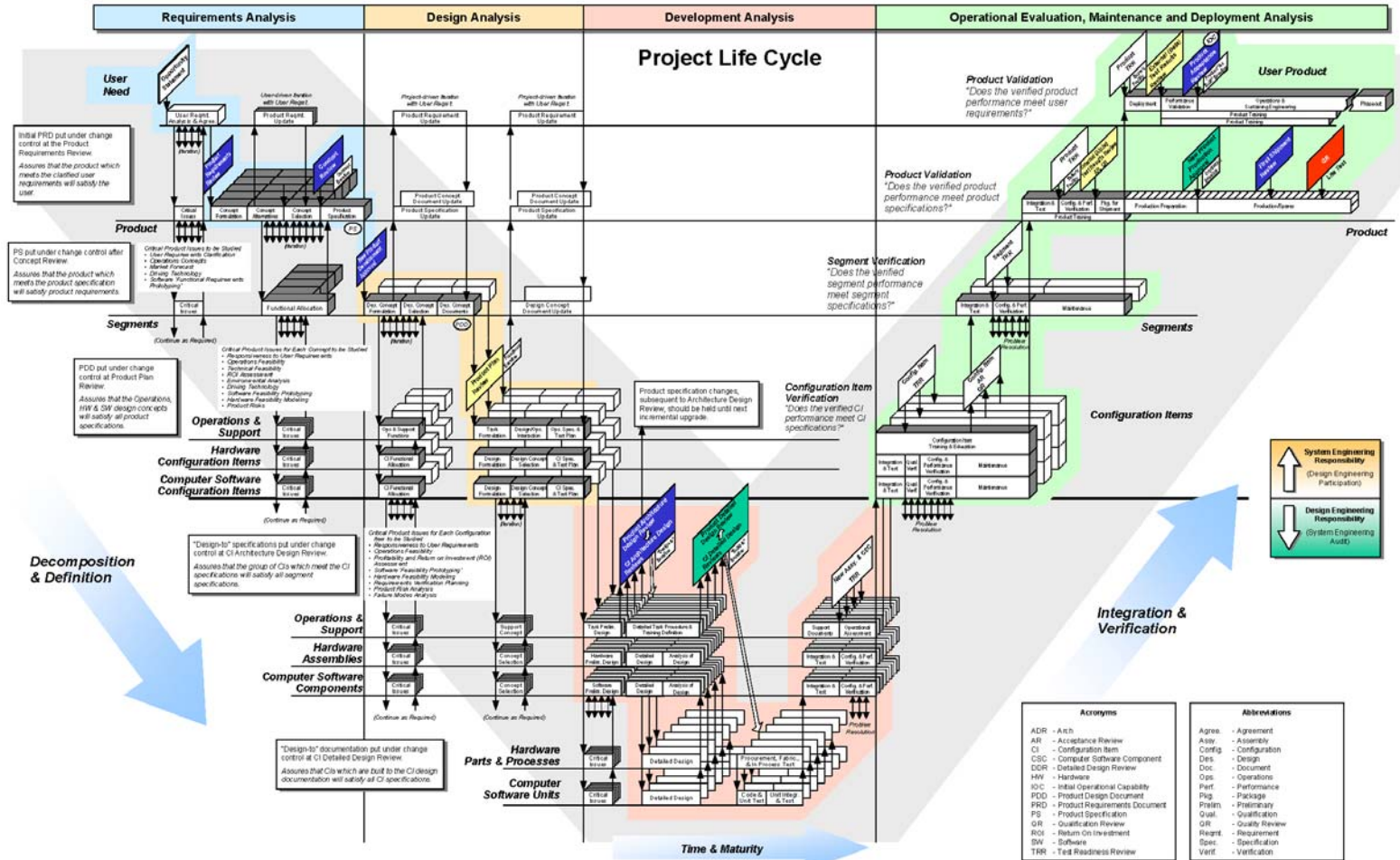
Modeling Uncertainty

- **We Always model Uncertainty as *Randomness Using Probability and Probability Models***
 - **Randomness is a *Metaphor* for Our Personal Uncertainty**
 - ***Very Reasonable***
- **Probability and Probability Models Based on *Axioms of Rational and Coherent Behavior***
- ***Very Good* for Systems Engineering!**

Where Uncertainty Appears in SE

- **Much *Bigger Role* for *Systems Engineers* than Most Realize**
 - Requirements
 - Functional Analysis and Decomposition (Allocation)
 - Design
 - Integration of Engineering Specialties
 - Quality Assurance
 - Integration and Test
 - Risk Management, PRA
 - *Decision Making*
- **Usually Perceived as *Very Difficult*, or else Glossed Over as *Very Simple***
- **A Primary Function of SE is to *Reduce* the Uncertainty (or *Risk*) about the System Satisfying the Need to some Acceptable Level**

The Project Life Cycle



Acronyms	Abbreviations
ADR - Arch	Agree - Agreement
AR - Acceptance Review	Assy - Assembly
CI - Configuration Item	Config - Configuration
CSC - Computer Software Component	Des - Design
DDR - Detailed Design Review	Doc - Document
HW - Hardware	Ops - Operations
IOC - Initial Operational Capability	Perf - Performance
PDD - Product Design Document	Plg - Package
PRD - Product Requirements Document	Prblm - Problem
PS - Product Specifications	Qual - Qualification
QR - Quality Review	Reqmt - Requirement
ROI - Return On Investment	Spec - Specification
SW - Software	Verif - Verification
TRR - Test Readiness Review	

SE Decision Making

- **Systems Engineers Make Decisions with Uncertainty in *Every* Facet of the Project Lifecycle**
 - **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 Assumptions?*
- You could *Fuse* together every scrap of data and information about the Decision to Reduce your Uncertainty?
- You could be *Sure About the Risk* of each Alternative Producing the Desired Outcome of the Decision?

Would that Help with those Important SE Decisions?

The Premise

- **SE 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* tells the Decision Maker the Level of Assurance (How sure they can be) for the Risk of an Alternative producing the Desired Outcome**
- ***Better Risk Assessments Produce Better Project Decisions***

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

Better 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
 - This *Mental Fusion* Usually requires *Many Assumptions*
 - For Many SE Decisions, Qualitative Risk Assessments are Sufficient
- ***A Quantitative Risk Assessment is a 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***
- ***Expensive***
- ***Sometimes, they Still Require Assumptions***
- ***Mathematically Intense***
- ***Statisticians Usually do not Know Enough about the Problem to provide a Usable Result***
- ***Usually Forced by the Math to Ignore or Overlook Important and Relevant Data or Information***
- ***Sometimes, Impossible to Obtain a Usable Result***

Now, The Good News

- You do ***NOT*** Have to Be a PhD Statistician 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!***

Using Probability to Deal with Uncertainty in SE

Probability Theory on Just One Slide

- The Axioms: $0 \leq P(A|H) \leq 1$; $P(A|A,H) = 1$;
 $P(A|H) + P(\sim A|H) = 1$;
 $P(A,B|H) = P(B|H)*P(A|B,H) = P(A|H)*P(B|A,H)$
- OR Operation: $P(A \text{ OR } B|H) = P(A|H) + P(B|H) - P(A,B|H)$
- Mutually Exclusivity:
 - For *Mutually Exclusive* Propositions B and C:
 $P(B,C|H) = 0$; $P(B \text{ OR } C|H) = P(B|H) + P(C|H)$
 - If $A_1, A_2, A_3, \dots, A_N$ comprise the set of *N Exhaustive, Mutually Exclusive* Outcomes for Proposition A, then

$$P(A_1 \text{ OR } A_2 \text{ OR } \dots \text{ OR } A_N | H) = \sum_{i=1}^N P(A_i | H) = 1$$
- Independence: If A and B are *Independent*
 - $P(A,B|H) = P(A|H)P(B|H)$
 - $P(A \text{ OR } B|H) = P(A|H) + P(B|H) - P(A|H)P(B|H)$
- Marginalization: For Propositions A, B, and C
 $P(B|H) = P(B, \text{ any } A, \text{ any } C|H)$
 $= P(B|\text{any } A, \text{ any } C, H)P(\text{any } A|\text{any } C, H)P(\text{any } C|H)$

Uses of Probability in SE

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

Probabilistic Requirements

- Many 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***

Example of a Probabilistic Requirement

- **Known, Common Scenarios Exist where Many Absolutely Stated Performance Requirements cannot be Satisfied**
- **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.

Verification

- **Verification Requirements Establish the *Minimum Acceptable Risk* that the Delivered System will not Perform as needed**
- **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.***
 - **Test: Drive two vehicles 107,000 miles**
 - **If none fail (the data), have 90% Assurance (or Probability) that Design achieved 95% Reliability at 100,000 miles**
 - **Accept 10% Risk in Design**
 - **(INCOSE IS2004 Paper – Contact me if you want it)**

Using Statistics in SE to Reduce Uncertainty

Reducing Uncertainty

- **We Reduce Uncertainty in SE by using *Observations* and *Data* from a System as it is being Developed and Built**
- **We Use *Statistics* to Process the Observations/Data to *Infer* a Reduced Uncertainty based on *Probability Models***
- **Properly Performed in SE, Statistics can Provide a High Level of *Assurance* that a System will Perform Properly**
- **Verification is the Process to use Statistics to Reduce Uncertainty or *Risk***
- ***Risk Assessments* are used to Reduce Uncertainty to Make SE Decisions**

Verification Method Considerations

- ***Inspection and Demonstration -
Insufficient and Inappropriate Methods for
Verifying Probabilistic Requirements***
- ***Analysis and Test***
 - ***Methods require Prior Uncertainty and Data***
 - ***In Integration Stages, Data may be Test
Results from Earlier Tests or Analyses***
 - ***QA Requirements for these Verification
Methods may be Quite Complex***

Use of Statistics in SE

- **Statistics is the Process used to Reduce Uncertainty *Quantitatively***
- **Classical Statistics *Does NOT Work Well* for SE**
 - ***Overconservative*** – SE cannot afford
 - **Requires *Many Data*** – SE rarely Gets a lot of data
 - **Can *Only Use Actual Event Data*** – SE's have Other Data
 - **Censored Data** – Event has not happened
 - **Expert Opinion**
 - **Surrogate or Analog Data**
- **SE's Need to Use *All Available Data* to Reduce Uncertainty as Much as Possible**
- **SE's Need to Use *Bayesian Statistics***

The Foundation: Bayes' Law

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

Interpretation of Bayes' Law

- **Bayes' Law:** $P(B|A,H) = P(A|B,H)P(B|H)/P(A|H)$
 - If B is a Proposition, and A is Data, we get
 $P(B|Data,H) = P(Data|B,H)P(B|H)/P(Data|H)$
 - Now, $P(Data|H)$ is just a *Constant Marginal Probability*, and *unimportant*, so we can ignore it and say
 $P(B|Data,H) \propto P(Data|B,H)P(B|H)$
- **The Interpretation**
 - $P(B|H)$ is called the *Prior* - the Marginal Probability (Uncertainty) on the Proposition *before* getting the Data
 - $P(Data|B,H)$ is called the *Likelihood* - the Probability of Getting the Data Given the Proposition
 - $P(B|Data,H)$ 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!**

Problems with Bayesian Statistics

- **Ever Wonder why You were not Taught Bayesian Statistics in Engineering?**
- **For Real World Problems**
 - **Bayesian Solutions are Usually *Analytically Intractable***
 - **Numerical Solutions are Usually Impossible using *Ordinary* Monte Carlo Methods**
- **Up Until the mid-1990's, Impractical and Usually Impossible to Use by SE or Engineering**

The Solution

- **Markov Chain Monte Carlo**
 - Developed in *Europe* in 1990's mainly for Risk and Decisions in Biostatistics and Bio-medical Research
 - More General Numerical Method than Ordinary Monte Carlo, but Produces Same Results
 - Works for Analytically Intractable Bayesian Statistics Solutions (like we get in the *Real World of SE*)
 - *Simple* Algorithm (M-H): Generates *Multivariate Correlated Random Samples* for use in Ordinary Monte Carlo Calculations (No Need to ignore Conditionality)
- **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 $pd(\Theta|data)$, and select a proposal step size $d\Theta$**
- **Start with any legal value: $\Theta_i = \Theta_1$**
- **Repeat Loop to get new samples**
 - **Propose a new sample: $\Theta_{i+1} = \Theta_i + \Delta\Theta$,
where $\Delta\Theta \sim U(-d\Theta, d\Theta)$**
 - **Calculate the ratio of Posterior densities:
 $\alpha = pd(\Theta_{i+1}|data) / pd(\Theta_i|data)$**
 - **Obtain a sample u from a uniform distribution: $u \sim U(0, 1)$**
 - **If $u < \alpha$, then accept the proposed sample as Θ_{i+1} ,
else set the new sample to the previous one: $\Theta_{i+1} = \Theta_i$**

How to Avoid Making Assumptions

- **Cannot Completely Avoid Assumptions**
 - Can Avoid *Overconservative* Assumptions
 - Can Avoid *Questionable* Assumptions
- **The Key: Use *Non-informative* or *Reference* Prior Models**
 - Model Uncertainty when you Are *Ignorant* about the Uncertainty
 - Provide *Realistic* Worst Case Scenarios
 - *Derivable* with the Same Solutions Using Three Independent Methods
 - Very Simple Functions, Generally Inverses and the Constant 1
 - Bernardo and Smith, Excellent Reference

Sometimes, MCMC Needs Outrageous Assumptions

- **For Many Real World SE Decisions, Posteriors Using non-Event Data will Not produce a *Stable* Markov Chain**
- **M-H Algorithm will not Work**
- **Solution: Use *Pseudo-Ignorance* Priors**
 - **Limit Range to Some *Outrageous* Value (10 times larger than realistic) for Scale and Shape Parameters**
 - **Effective Truncation of Inverses**
 - **Stabilizes the Markov Chain, Good Sampling**

Example: Space Shuttle 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**
- **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

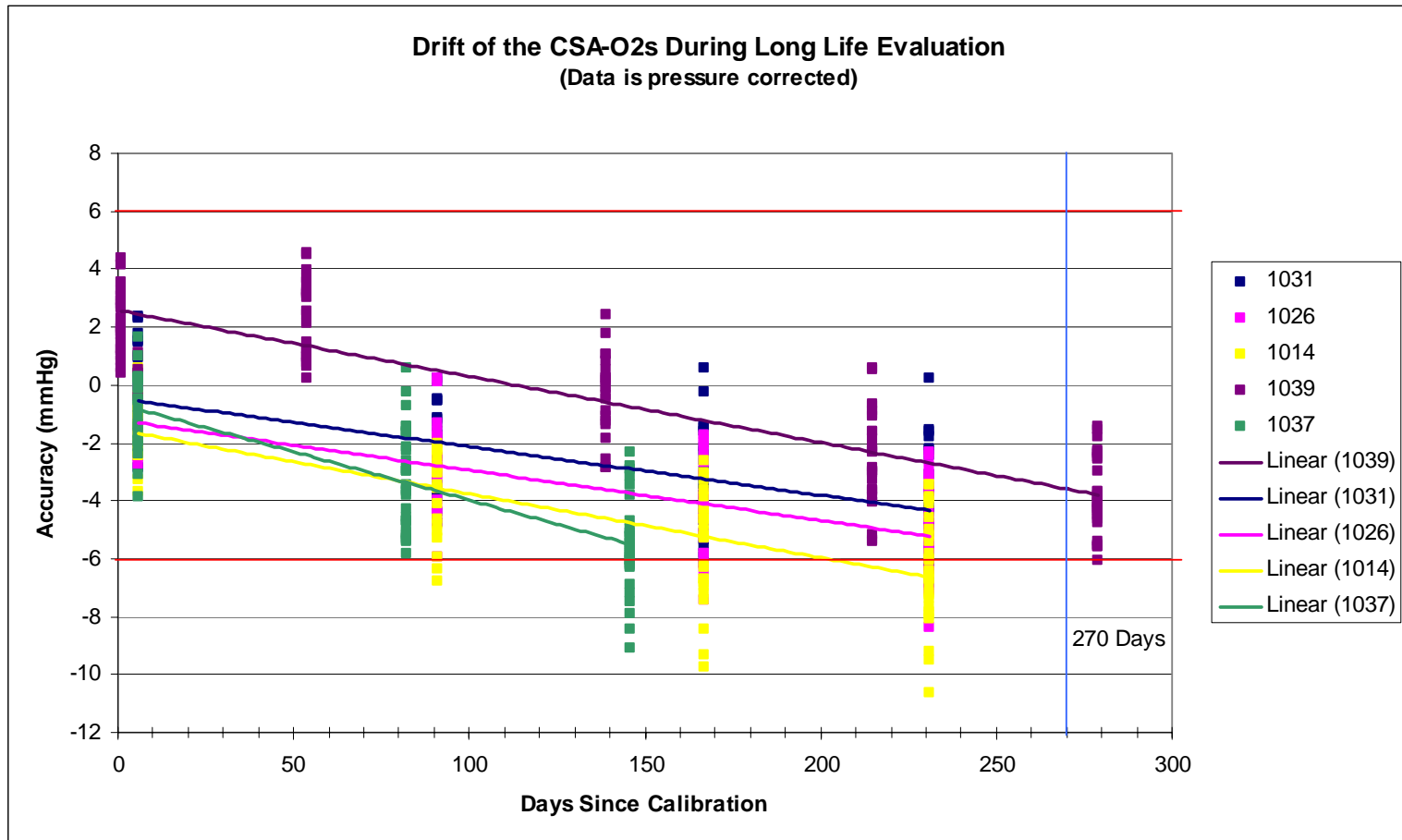
- **Test Datum:**
 Successful 8K Cycles without a Failure on One CTB Zipper
- **Assumptions (*outrageous*):**
 - Zipper Cycling Cannot Improve Reliability of the CTB Zipper
 - At Least 62.4% of CTB failures will occur before 30,000 Cycles
- **No Stated Minimum Acceptable Risk – So Parameterize**

Risk of CTB Zipper Failure by 2K Cycles (R_{2K})	Assurance Provided by Test Results $P(\text{True } R_{2K} < R_{2K})$
1%	75%
5%	88%
10%	94%
20%	98%

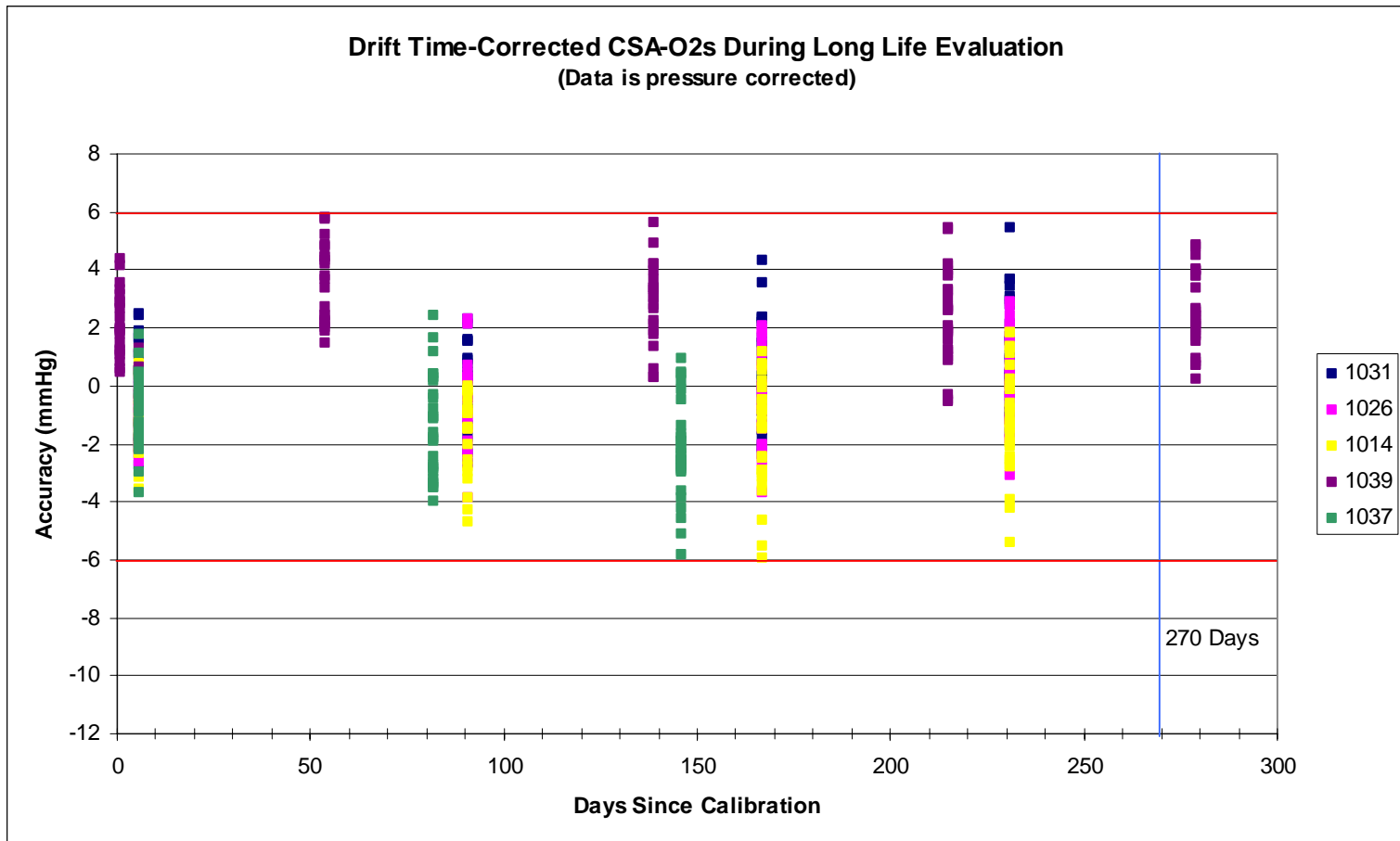
Example: ***ISS O₂ Sensor Drift***

- **Problem: Space Station Oxygen Sensor Measurement Accuracy is Observed to drift with Time**
 - If the Measured O₂ is in Error by more than ± 6 mmHG within 270 days since Calibration, it could *Kill* an Astronaut
 - Already Compensating for Pressure Variations in Measurement Accuracy (Successful)
- **Proposed Solution Options:**
 - Test for Drift rates and Compensate for Drift; *OR*,
 - Redesign O₂ Sensor and Ship Up to ISS
- **Questions:**
 - What is the *Existing* Risk of Sensor Accuracy Drift Beyond Acceptable Limits?
 - What is the Risk *After* the Proposed Drift Compensation?

O2 Sensor Test Data

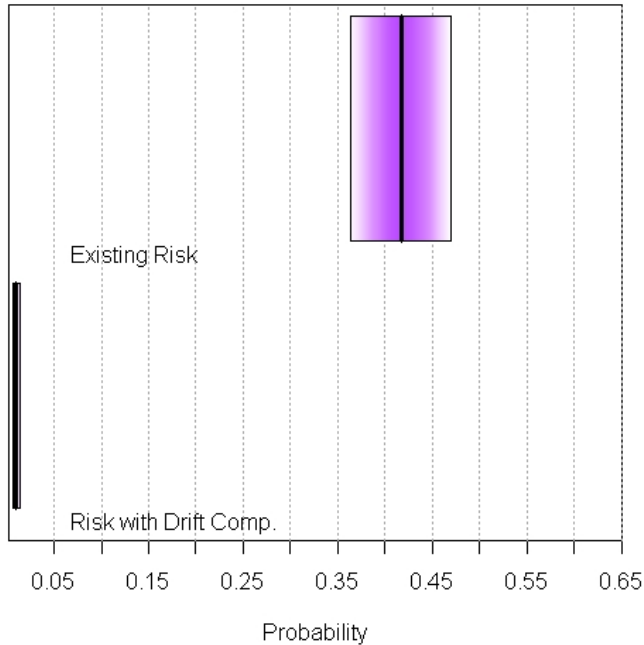


Drift Corrected O2 Sensor Data



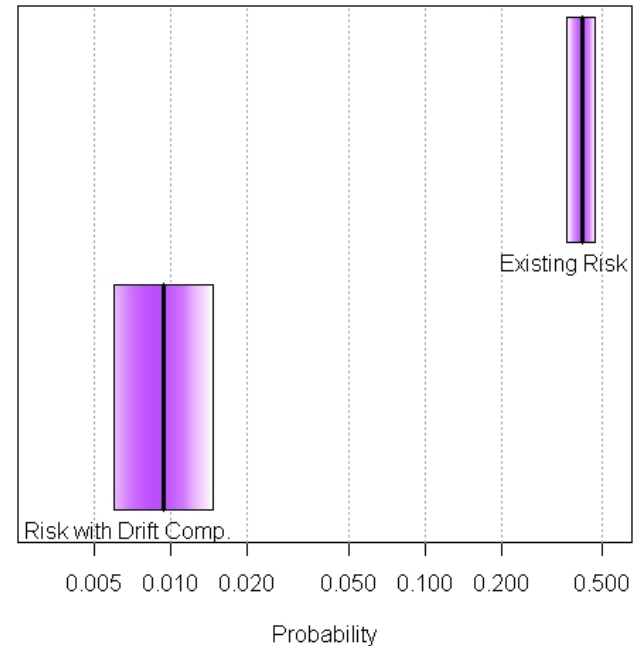
Before and After Drift Correction Risk Results

CSA O2 Sensor Accuracy Limit Risk at 270 Days



Linear Scale

CSA O2 Sensor Accuracy Limit Risk at 270 Days



Logarithmic Scale

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 of Exceeding Accuracy Limits at 270 Days is $< 1.5\%$**
- **Additional O2 Level Compensation could Reduce Risk Further**
- **Achieved Stable Markov Chain – *No Outrageous Assumptions Needed***

Example: 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(loss of any door)**
 = $1 - (1 - P(\text{loss of single panel door}))^{(\# \text{ of single panel doors})}$
 * $(1 - P(\text{loss of double panel door}))^{(\# \text{ of double panel doors})}$
 * $(1 - P(\text{loss of triple panel door}))^{(\# \text{ of triple panel doors})}$
 - **P(loss of door)**
 = **P(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(loss of latch) = P(loss of Hinge Plate)**
 = **P(M screws lost of Pattern of 6) – the failure mode**
 = $\sum_{j=0}^6 [P(\text{M Lost} \mid j \text{ Loose})P(j \text{ Loose}) + P(\text{M Lost} \mid 6 - j \text{ Tight})P(6 - j \text{ Tight})]$

Predicted Risk of RSR Panel Door Failure

- Consider All Conservative Failure Modes (1 to 6 screws may be needed to Retain Each Latch and Each Hinge Plate)
- Worst Case – Specific Screw Patterns will Reduce Risk
- 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%

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 Priors*, 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 (starting 5 September 2006)***
- **<http://webcampus.stevens.edu/>**
- **Full Day Tutorial at EUSEC 2006: *Dealing with Uncertainty in Systems Engineering***

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