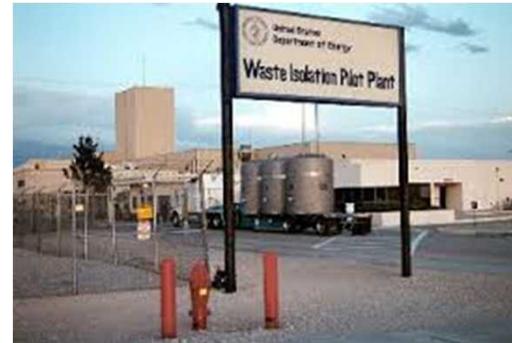


*Exceptional service in the national interest*



## When the Safety and Security of the Free World are at Stake and Other High Consequence Applications of Risk Assessment

**Martin Pilch, PhD, PMP**  
Thermal Sciences and Engineering, Mgr 1514  
Sandia National Laboratories

Palisade Risk Conference  
New Orleans, LA  
November 19-20 2014



Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

# My first exposure to Palisade software was circa 1997

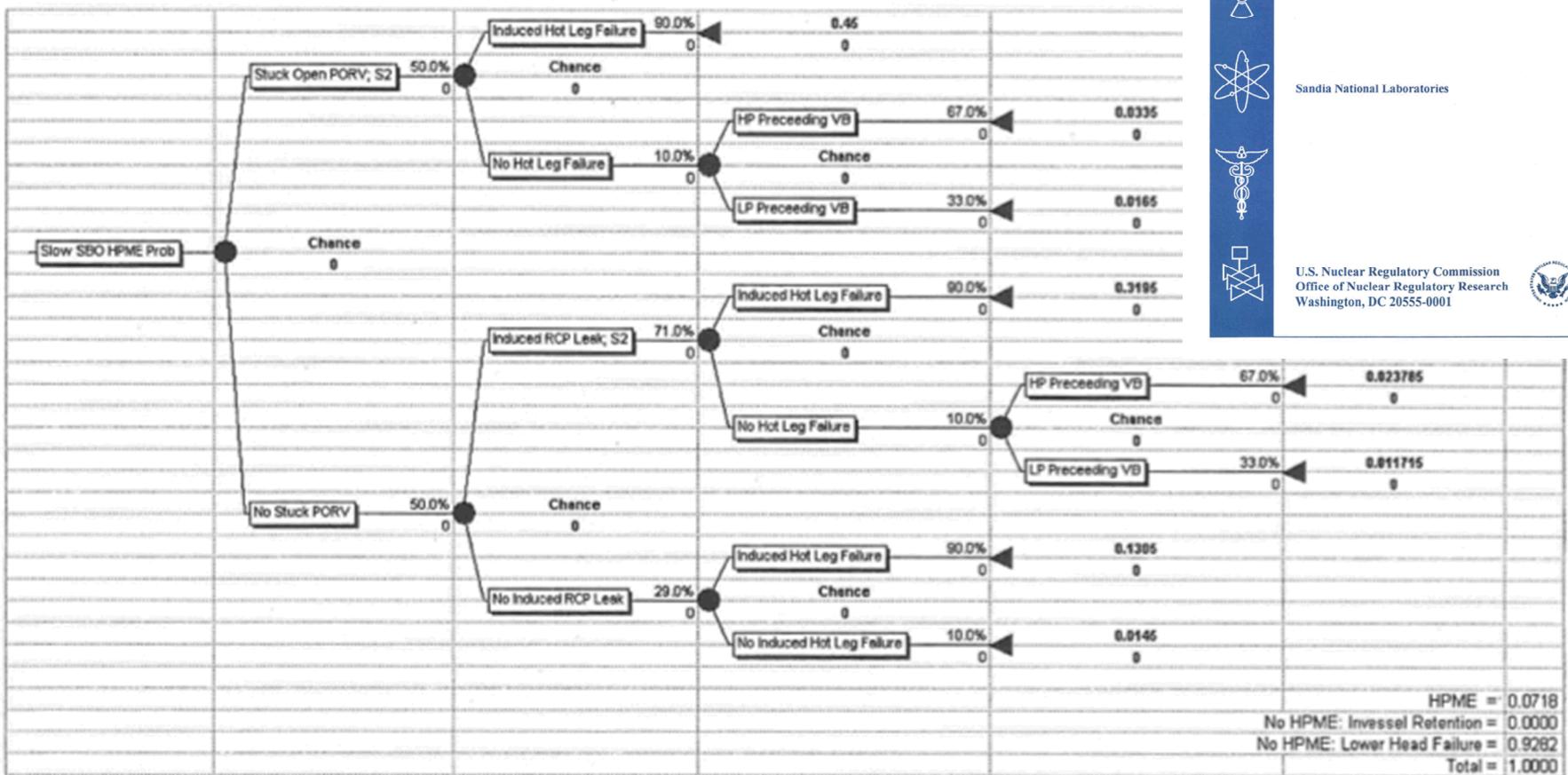
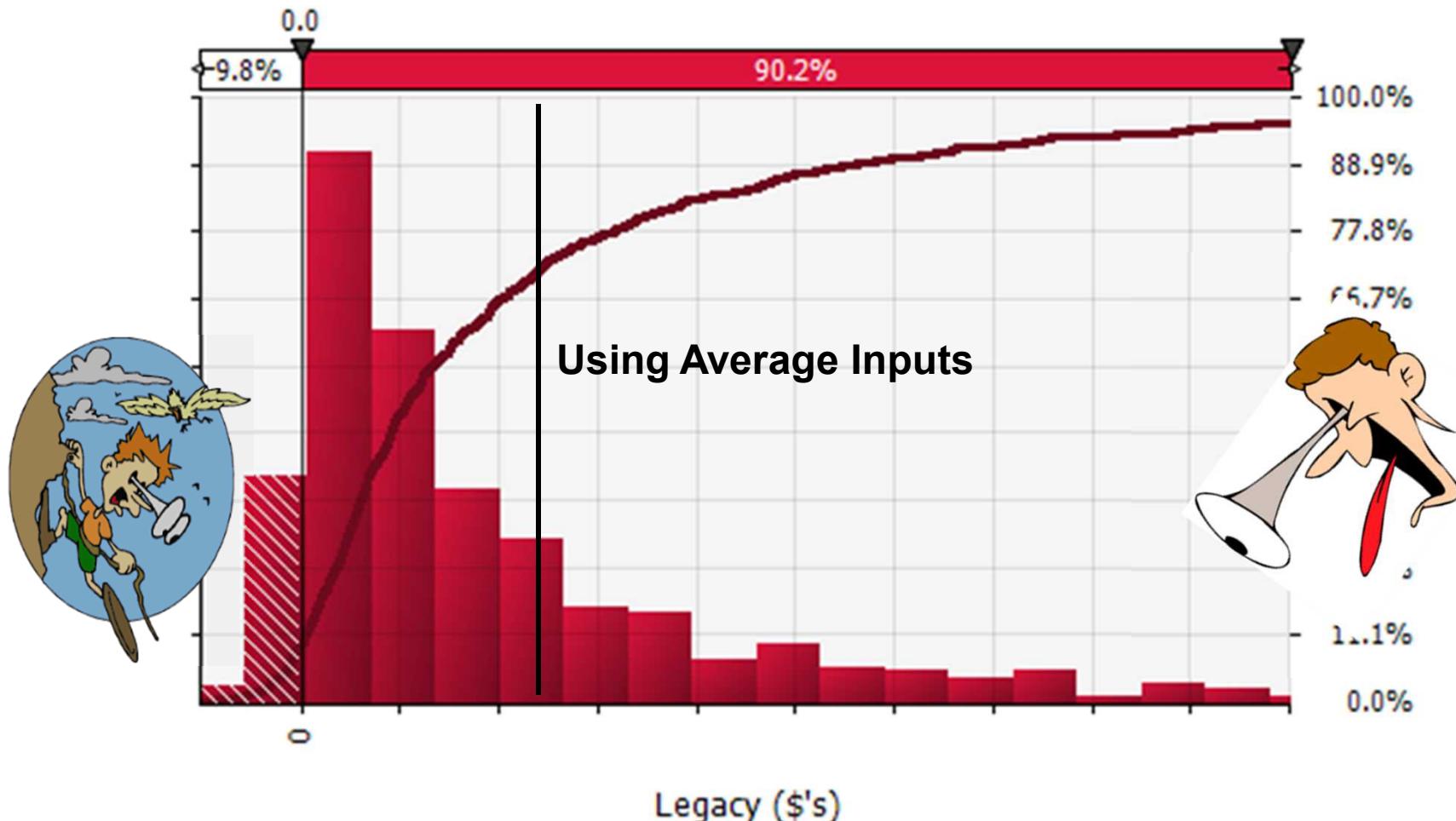


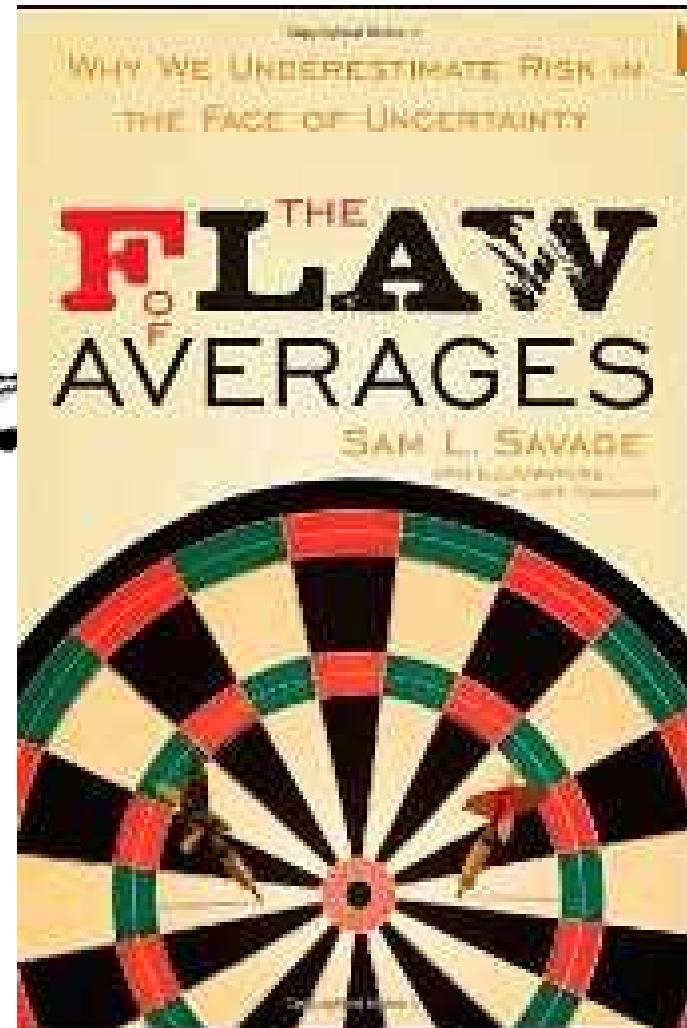
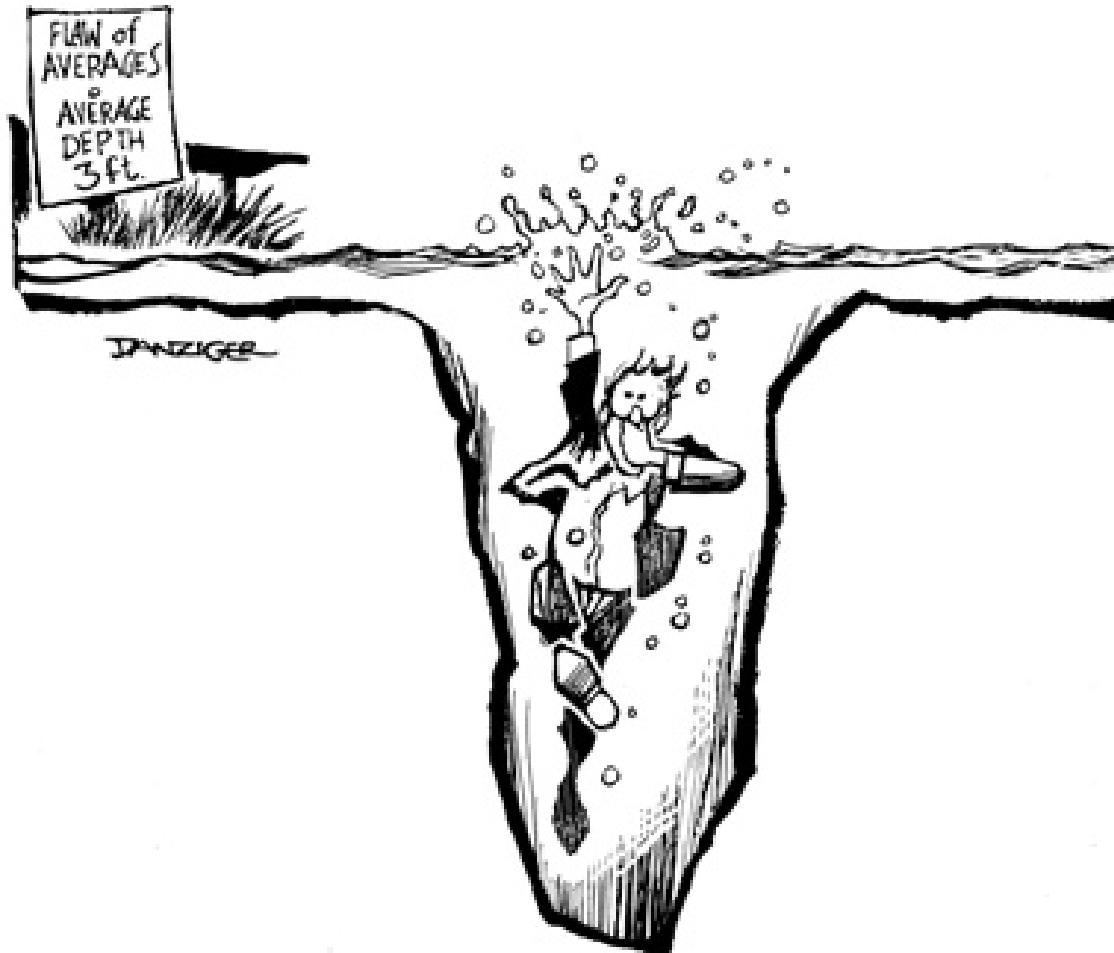
Figure 4.1 HPME probability for slow station blackouts in Sequoyah

# I currently use @Risk for my personal retirement planning

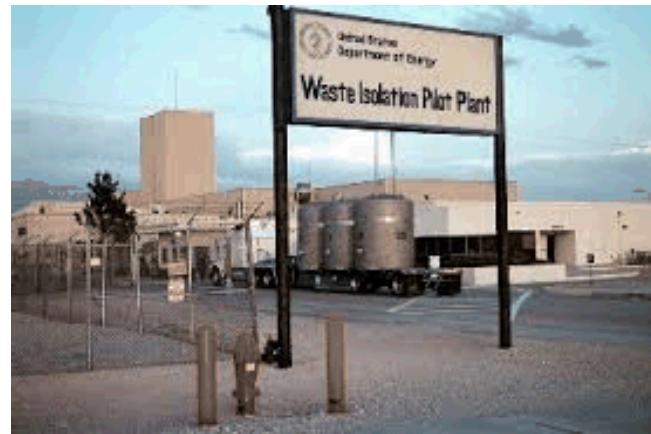
Assessments performed with my personal computer, on my personal time, with my own personally purchased software



**“An estimate based on the assumption  
that average conditions will occur  
will almost always be wrong”**

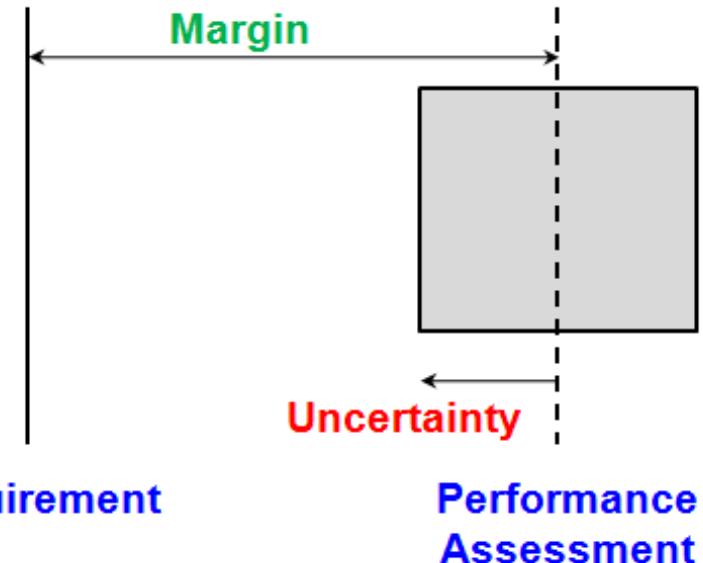


# SNL has a rich history of risk assessment for high consequence applications



**Best practice is to separate aleatory and epistemic uncertainties**

# The National Academy of Sciences has weighed in with an opinion



$$QMU = \text{Margin} / \text{Uncertainty}$$

EVALUATION OF QUANTIFICATION OF MARGINS AND UNCERTAINTIES METHODOLOGY  
FOR ASSESSING AND CERTIFYING THE RELIABILITY OF THE NUCLEAR STOCKPILE,  
National Research Council of the National Academy of Sciences, 2008

1. Take a system perspective
2. Separate aleatory and epistemic uncertainties

# Uncertainty has a dual personality

Jon C. Helton, *Conceptual and Computational Basis  
for the Quantification of Margins and Uncertainty*, SAND2009-3055

- **Aleatory uncertainty:** (perceived) randomness in the occurrence of future events (**frequency interpretation**)
- **Epistemic uncertainty:** Lack of knowledge wrt appropriate value to use for a quantity that has a fixed value in the context of a specific analysis (**confidence or belief interpretation**) – Associate “Probability” or “Subjective Probability” with Epistemic Uncertainty



# Does the distinction between aleatory and epistemic uncertainty matter?

Pure Aleatory

Frequency of failure is 2%

100% confident that 2% of us will not get home safely

Attribute of the system, therefore not reducible



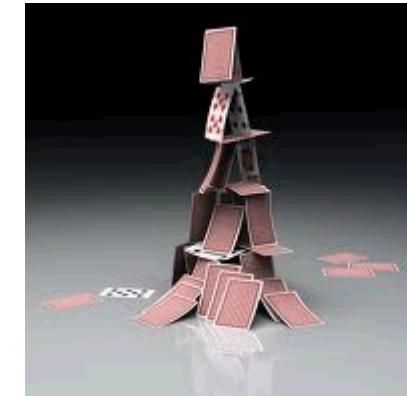
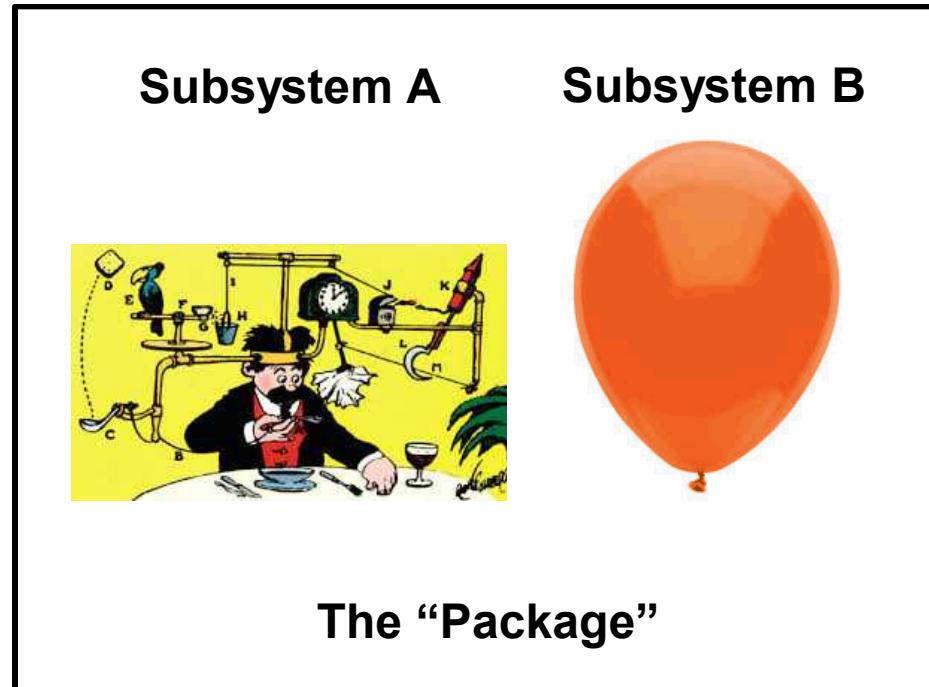
Pure Epistemic

Probability of failure is 2%

2% belief that none of us will get home safely

Attribute of the assessor, therefore reducible

# A contrived case study with features and methodologies representative of real applications



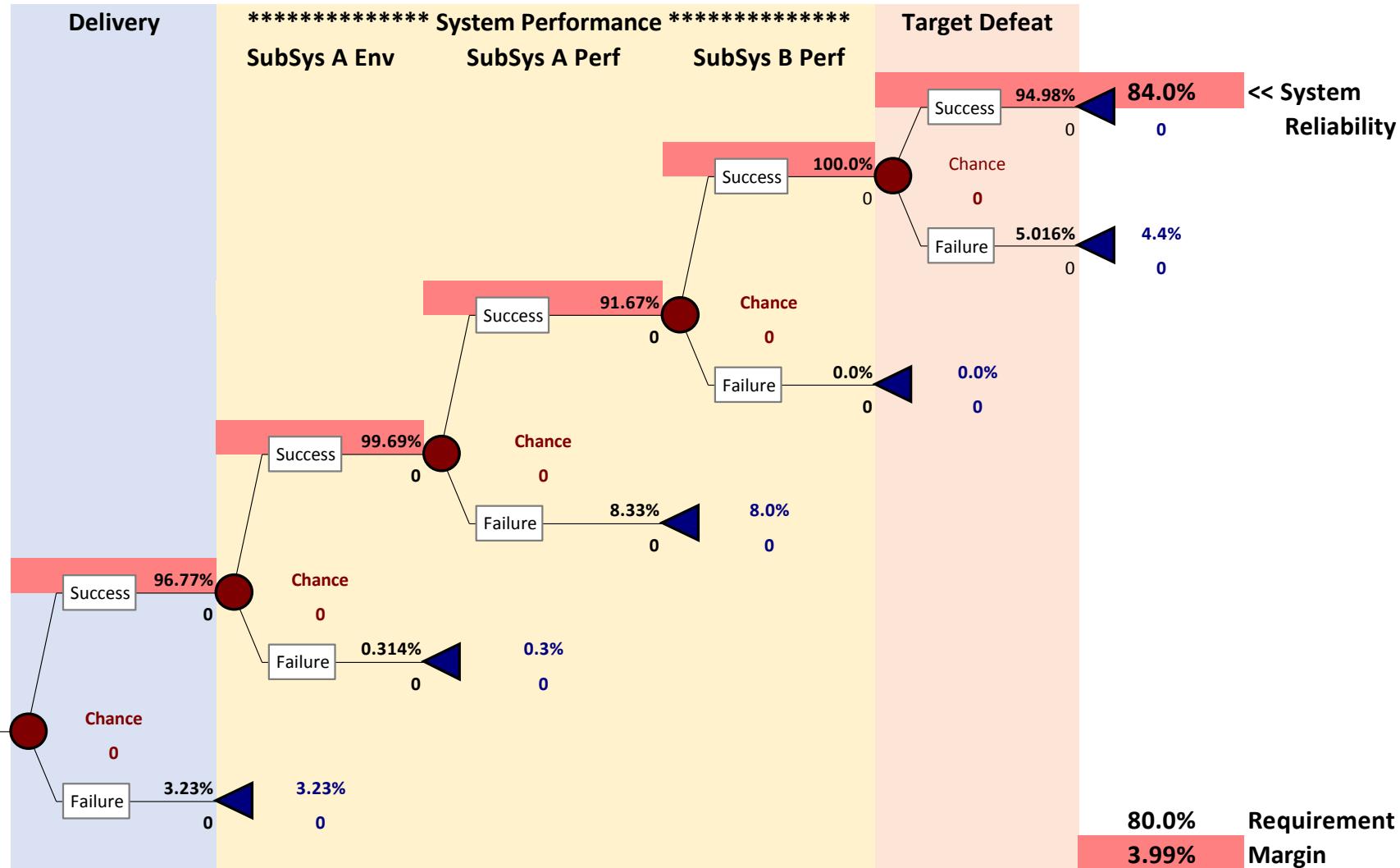
Delivery

Survivability and Performance

Target Defeat

**Requirement:**  
Overall end-to-end reliability > 80%

# System reliability is a frequency statement

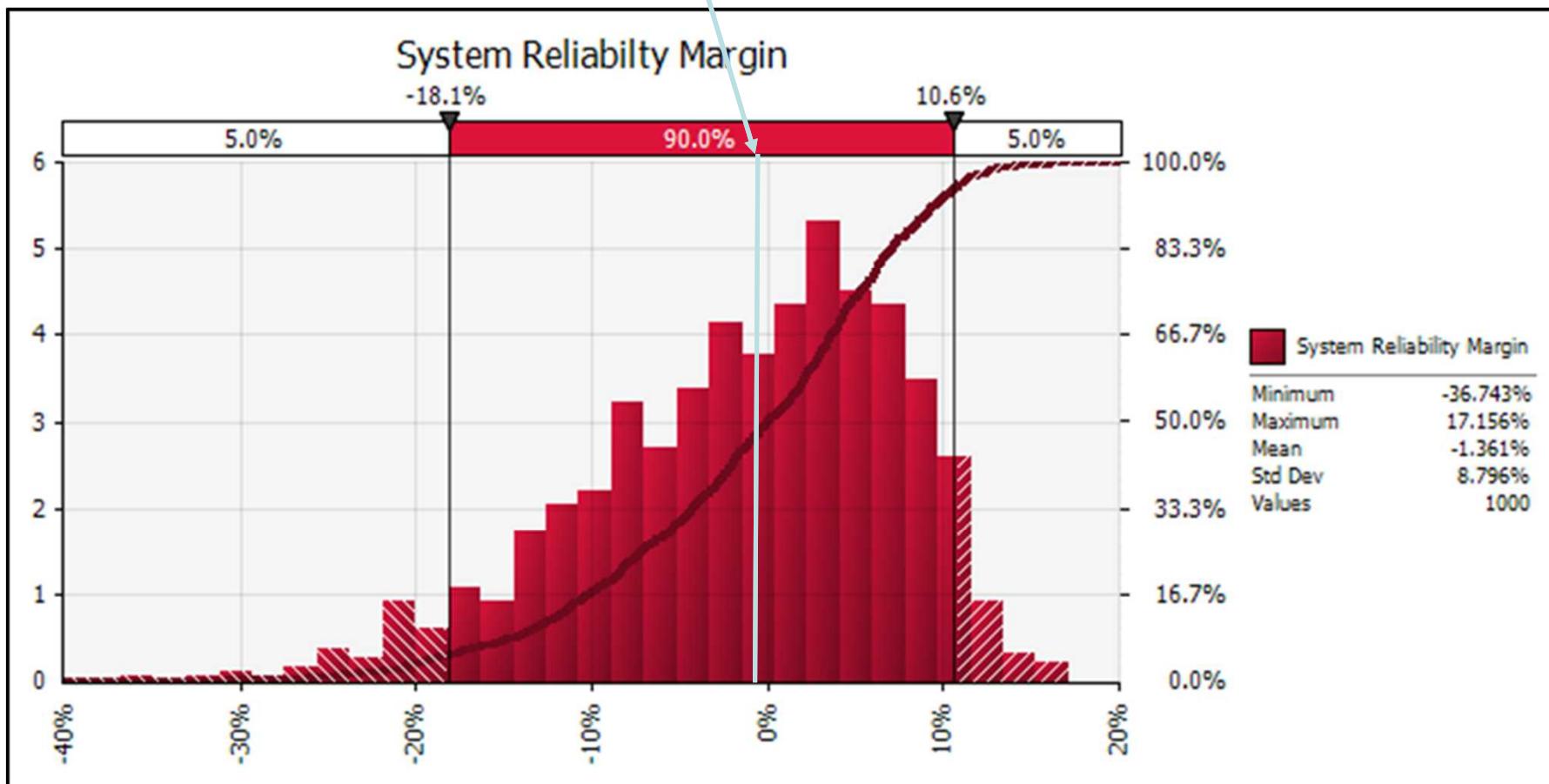


# Presentation of the sausage

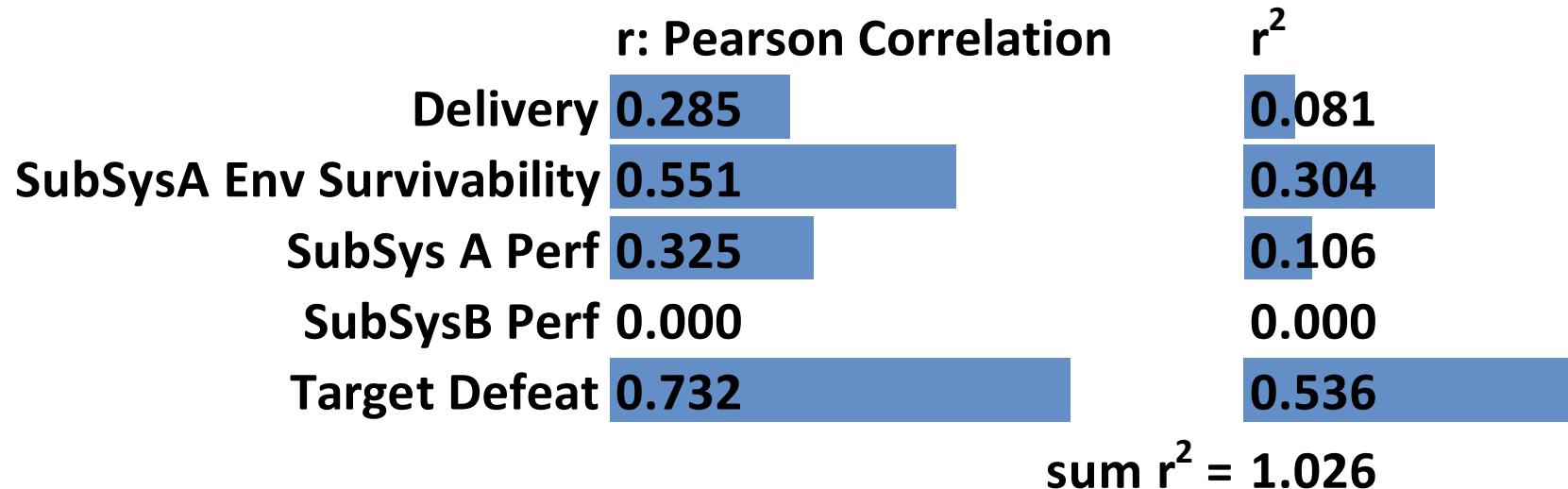


# Uncertainty in our assessment of reliability

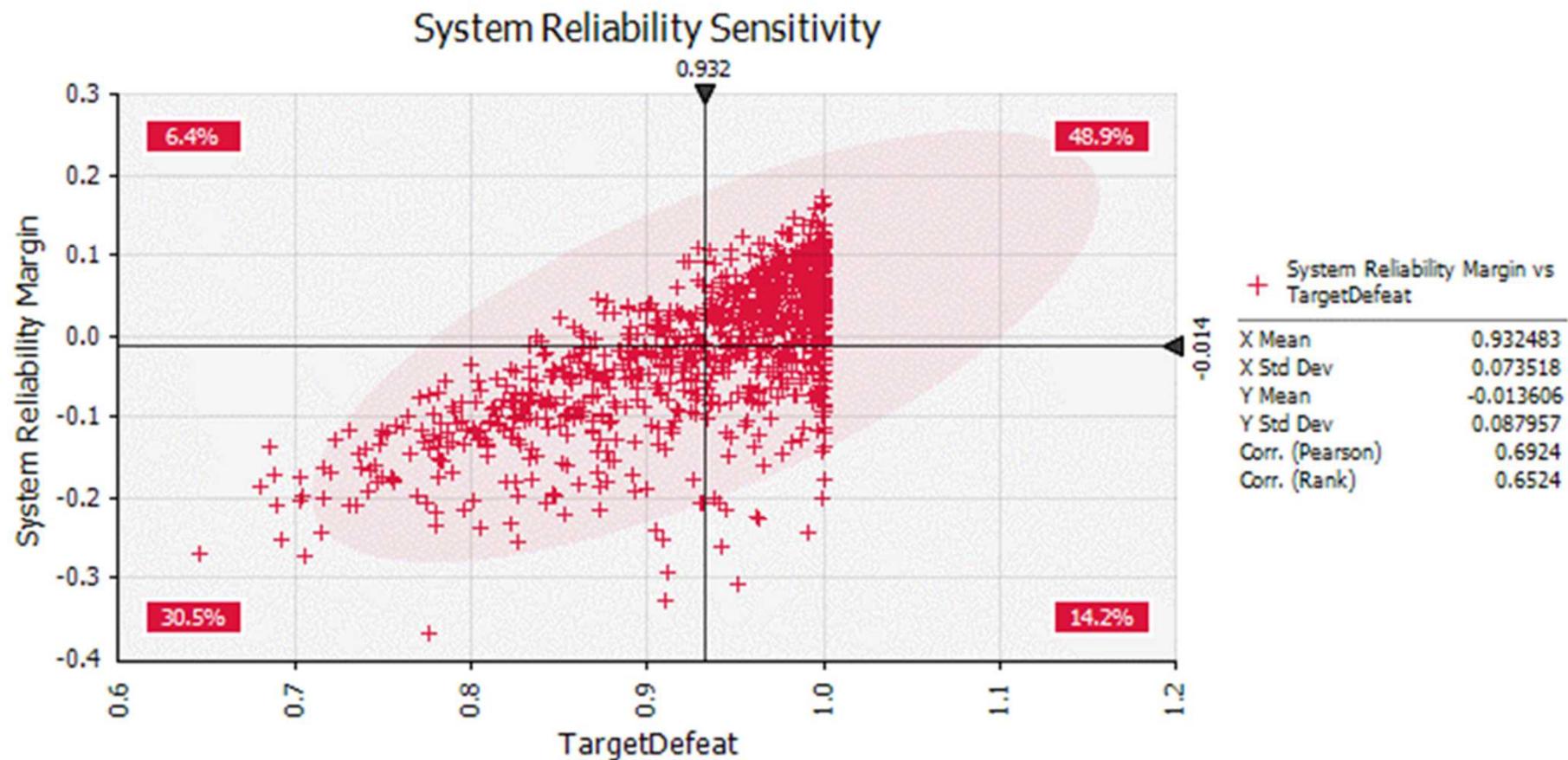
Based on mean branch  
reliabilities: -1.4%



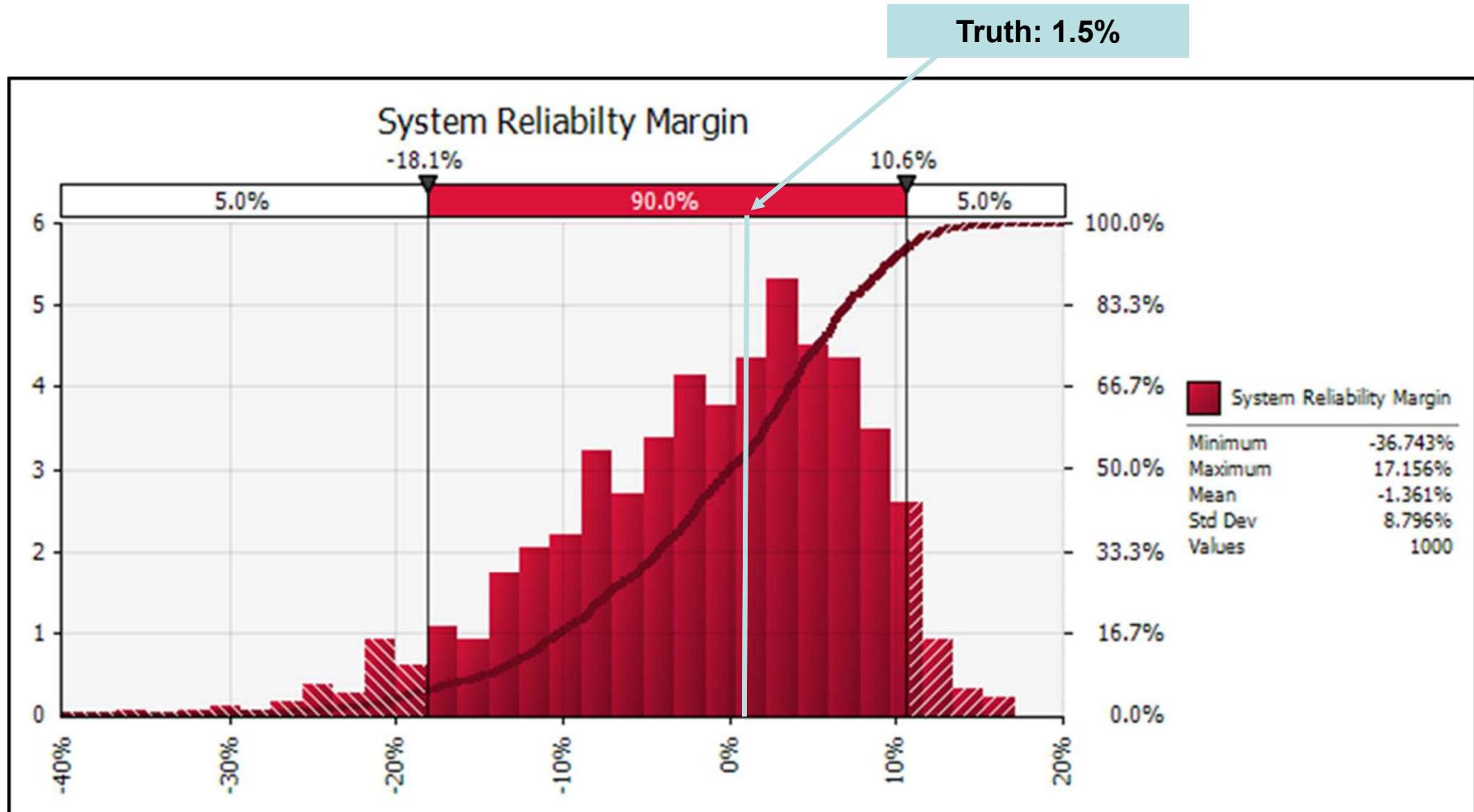
# Sensitivity analysis tells you what branch unc. contribute most to system unc.



# Spend resources (\$'s, time) to reduce uncertainty only if it can change decisions



# We know the truth for this demonstration



# Spend some time on the reliability tab in the spreadsheet

- Turn your Mac into a PC
  - “Parallels” to run Windows OS and Excel
  - Launch blank Excel file, load Palisade products, open application file
- PrecisionTree settings to work with @Risk
  - Ribbon: Settings – Model Settings - @Risk – Select: Expected Value of Model
- @Risk settings
  - Ribbon: Settings – General – Select: Multiple CPU Support = Disabled
  - Ribbon: Settings – Sampling – Select: Sampling Type = Monte Carlo
  - Ribbon: Help – Select: Color @Risk Functions
- Reliability model
  - Success branches linked to calculations in other tabs
  - Failure = 1= Success
  - Demonstrate dynamic updating of model

# Our customers care about presentation AND how the sausage is made



Technical peer review is an integral part of doing business

# *Delivery as an example of binary success/failure types of data*



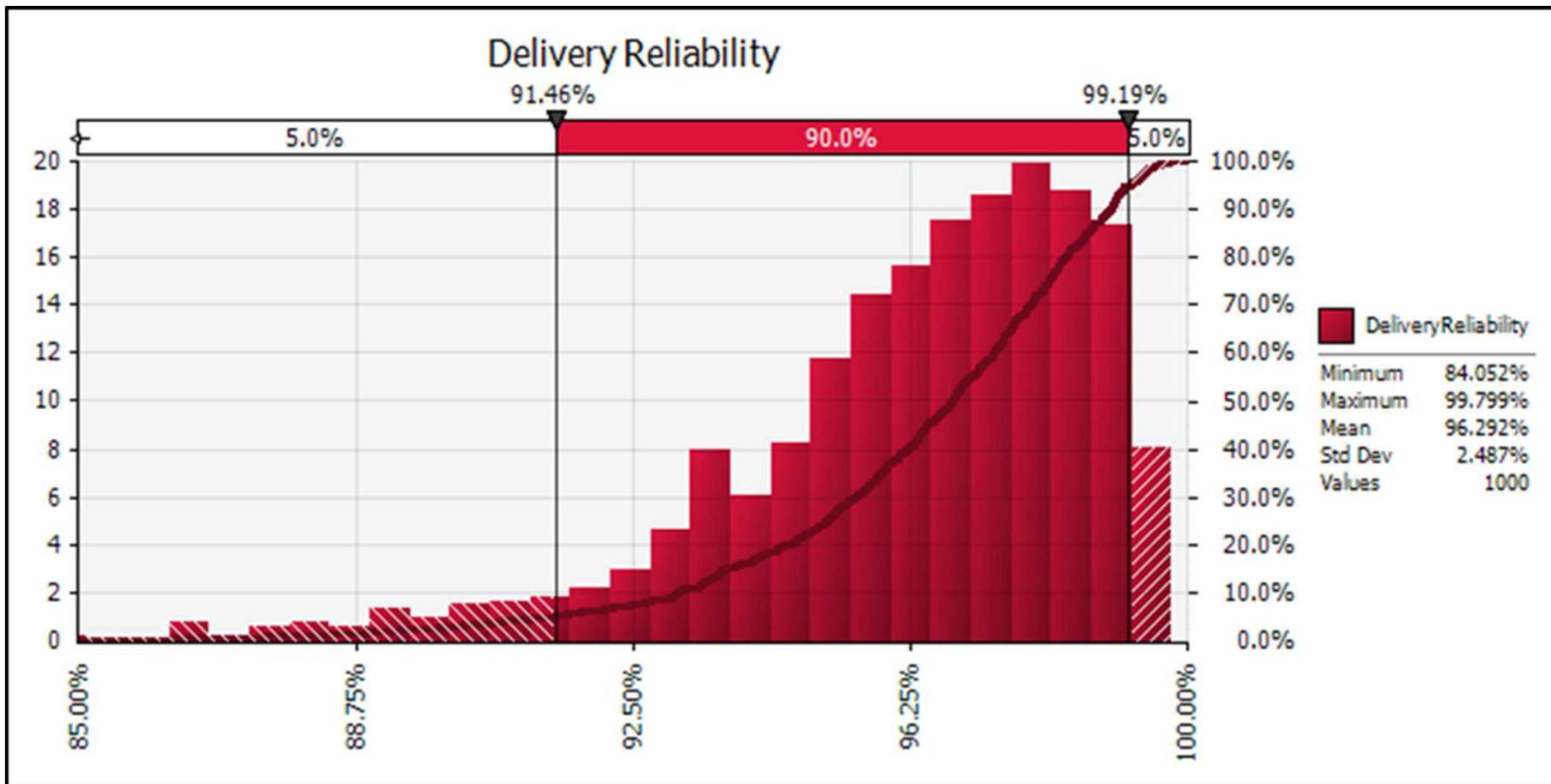
**Success**



**Failure**

# Estimated launch reliability is uncertain

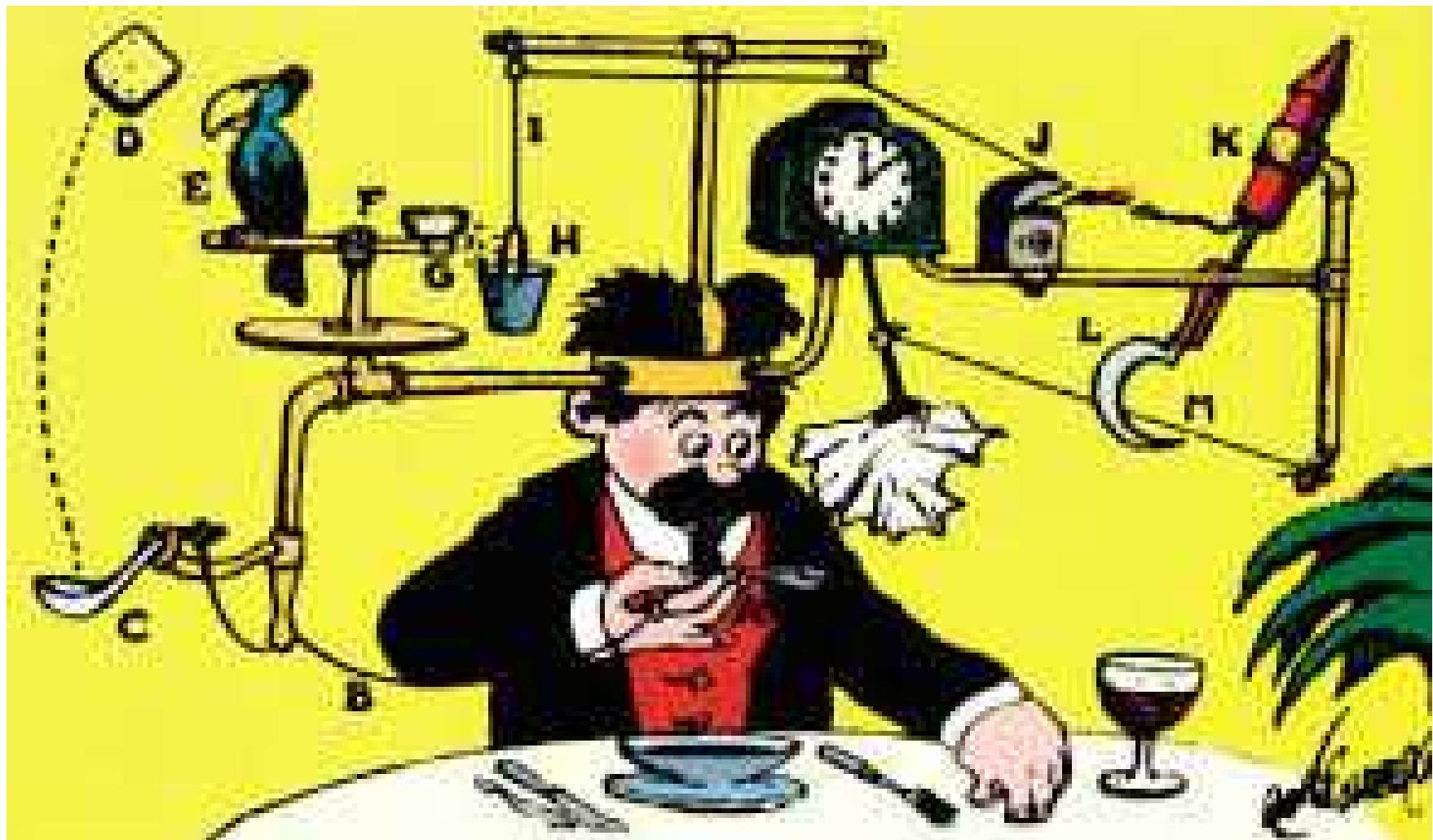
NLaunches	Launch Successes	Observed Reliability							
50	49	0.98	92.1%	<= RiskBeta(Successes+1, NLaunches-Successes+1)					



# Spend some time on the delivery tab in the spreadsheet

- Introduce the truth model hidden to the far right
- Dynamic demonstration of different possible data sets and resulting success/failure histories
- Assessment based on one specific data set
- Pre-ran 1000 iterations
  - Ribbon: Simulation – Select: Iterations=1000
  - Ribbon: Results – Browse Results
- Updating of embedded graphs and simulation results
  - Ribbon: Insert Function – Miscellaneous – RiskResultsGraph
  - Ribbon: Insert Function – Simulation Results - RiskMean

# *Subsystem A makes the system go boom*



# Subsystem A has to survive extreme environments and perform!



Vibration



Thermal

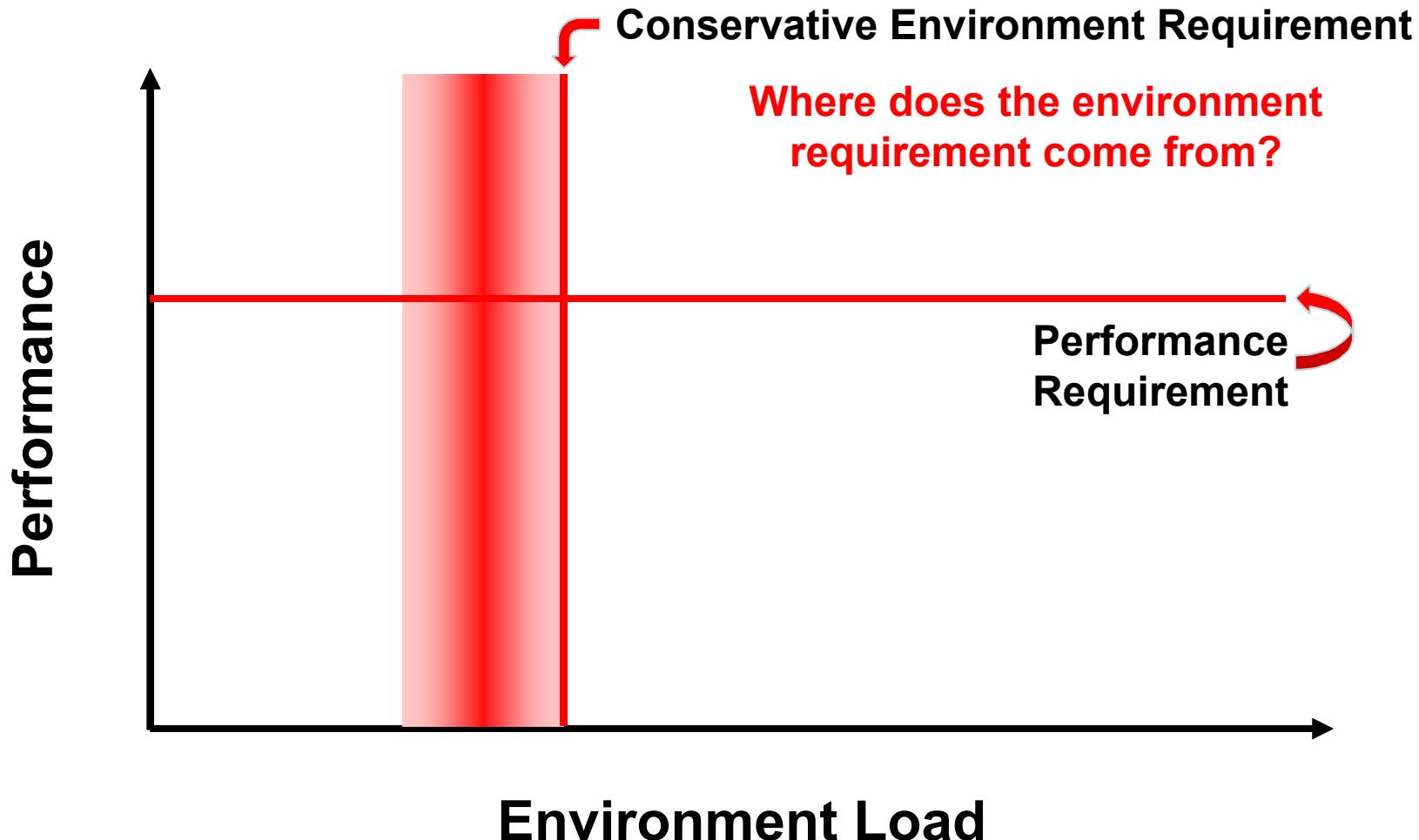


Radiation



Shock

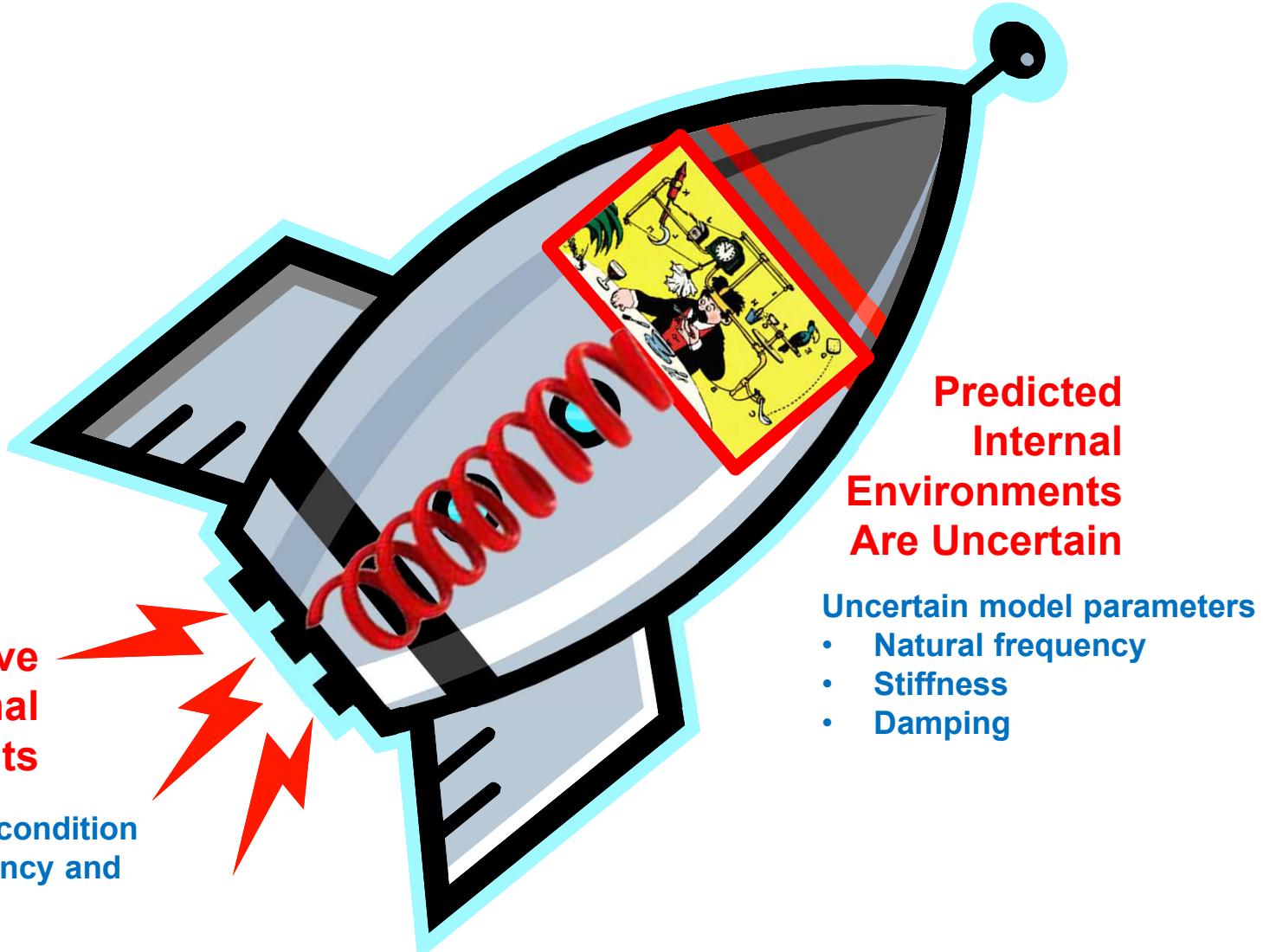
# There are both performance requirements and survivability requirements for SubSys A



# Big computer codes are used to translate external environments to internal environments



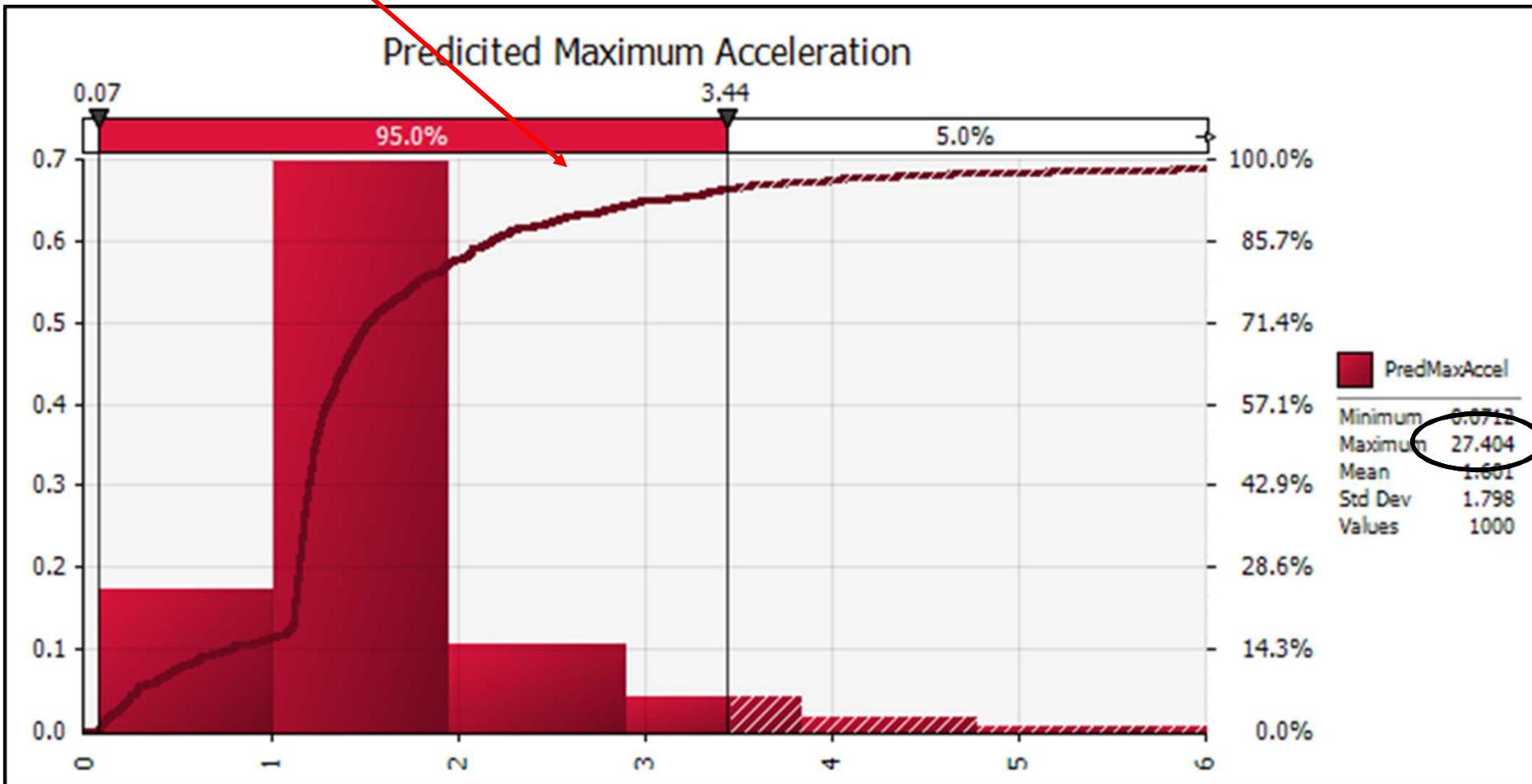
Vibration Environments



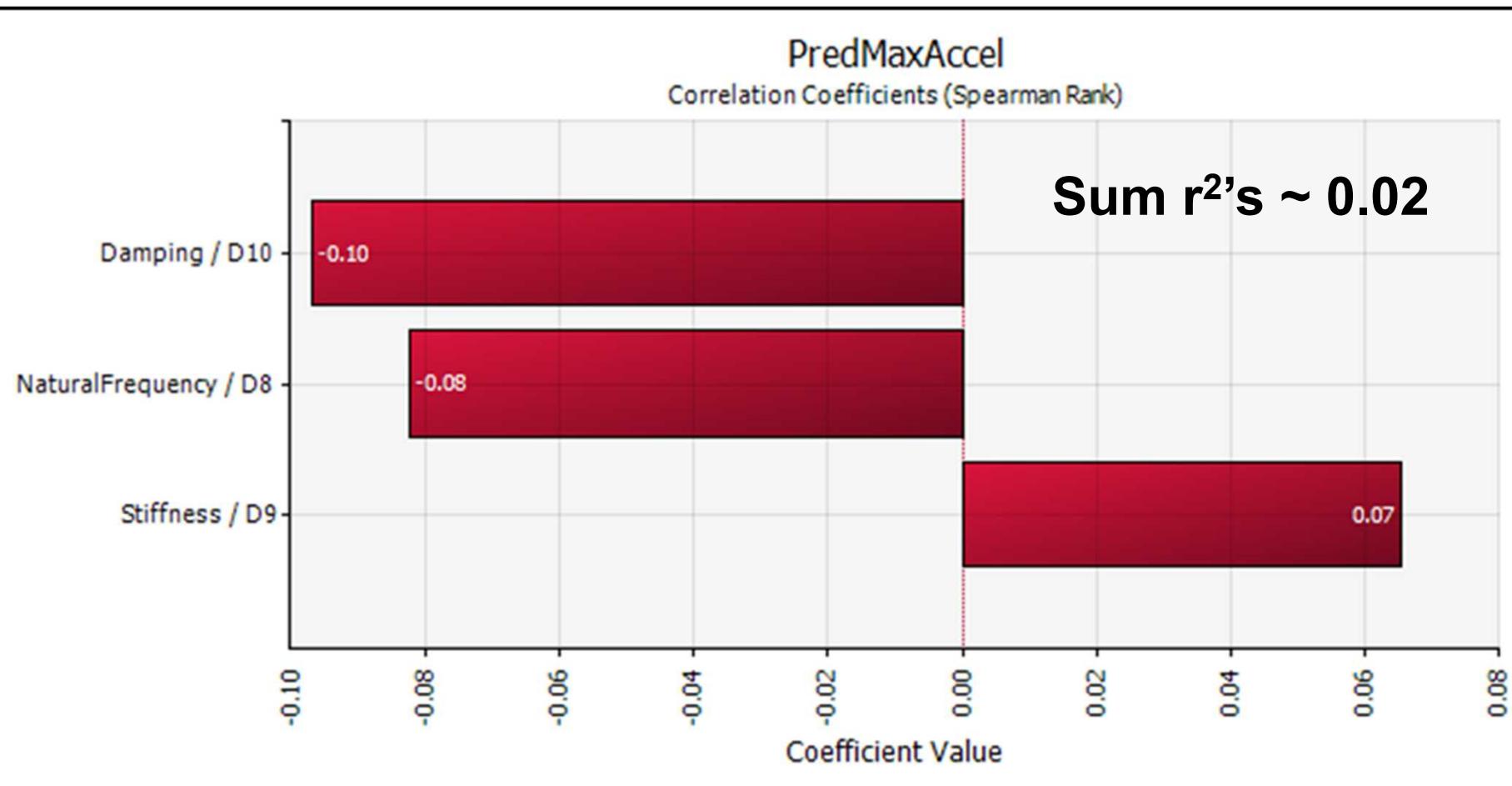
Known boundary condition  
• Forcing frequency and magnitude

# 95% confidence limit used as SubSys A environment requirement

Distribution is bi-modal

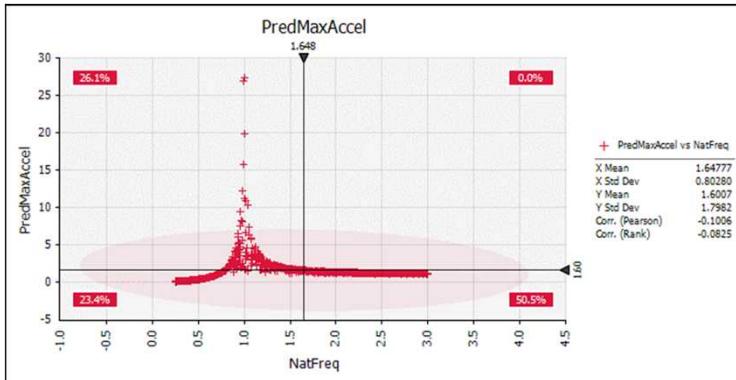


# What can you say about contributors to uncertainty?

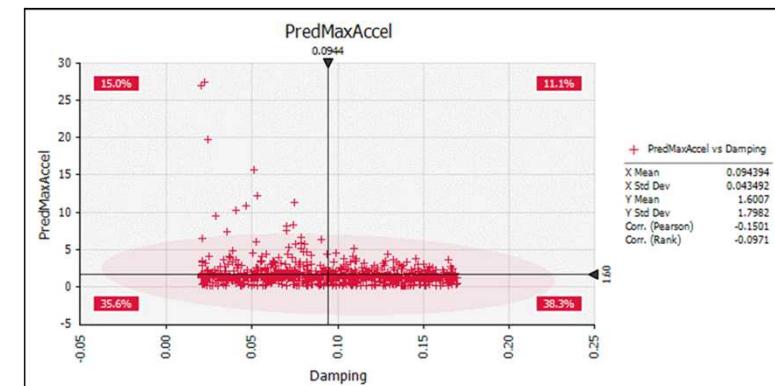
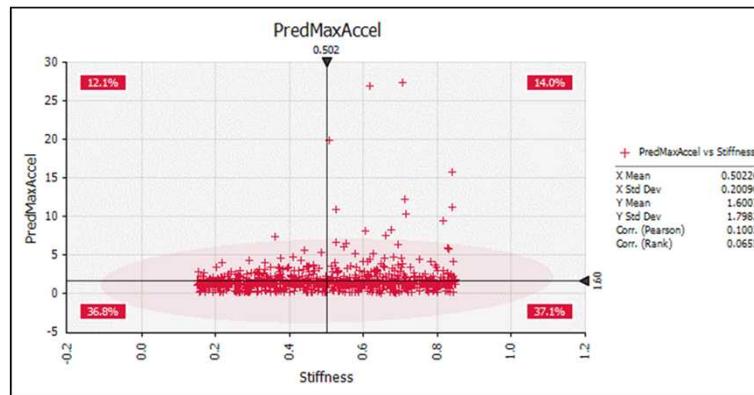


Answer: Nothing is important! How can that be?

# Always examine the scatter plots



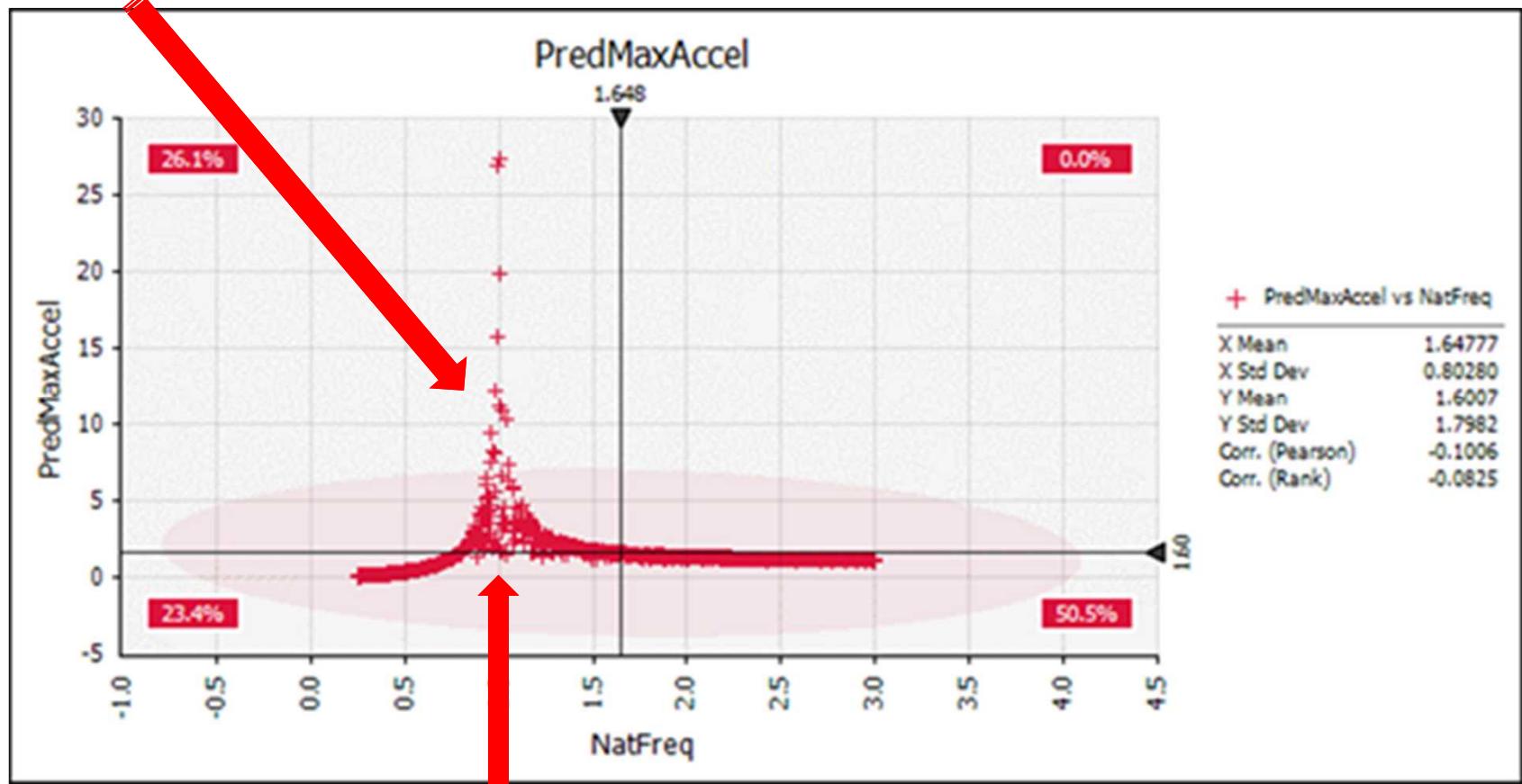
Uncertainties in natural frequency dominate



# Peel the onion, understand *what the* results are really telling you

Highly non-linear non-monotonic dependence on natural frequency

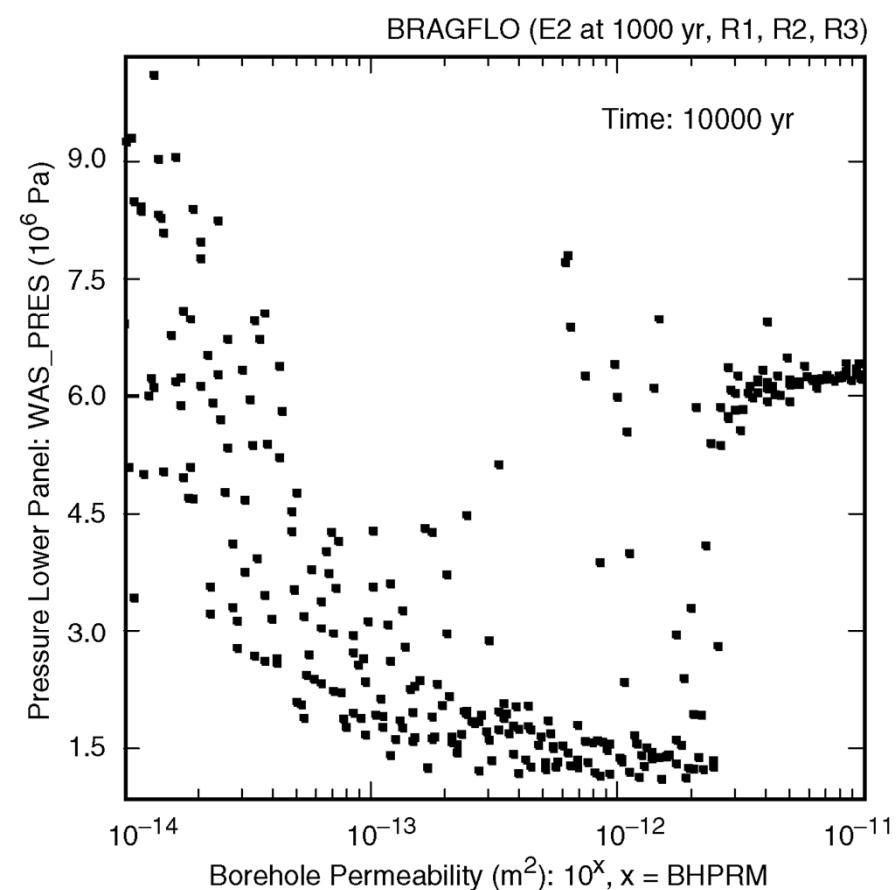
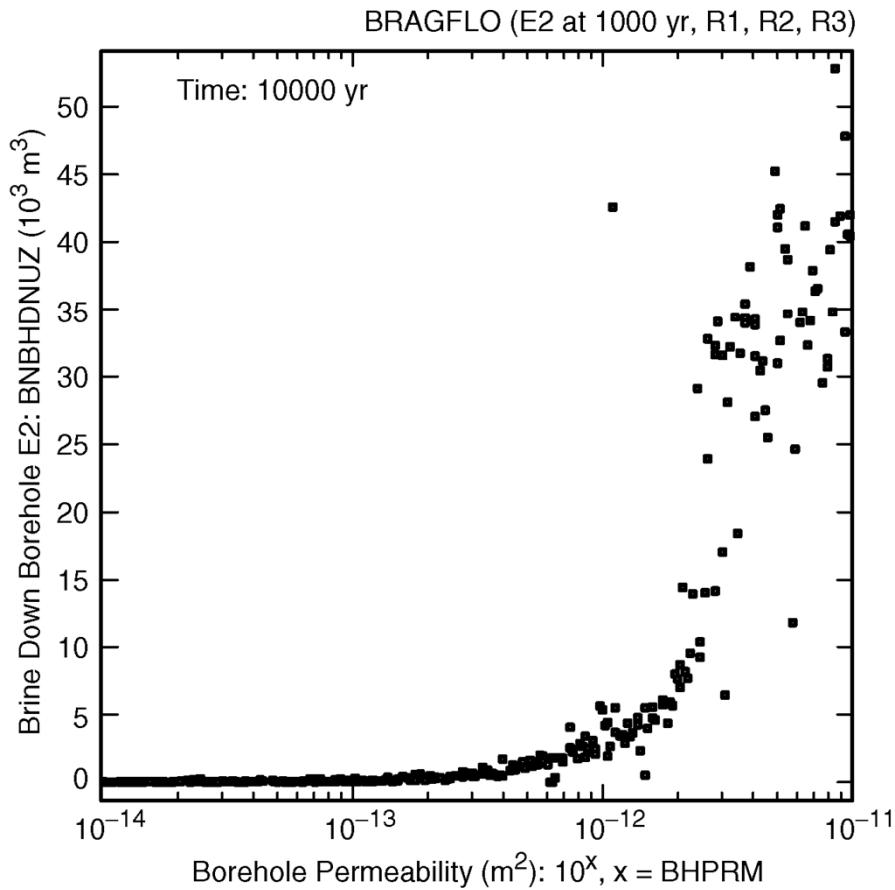
- Correlation coefficients are measures of linear association (*bad assumption*)



Resonance behavior

- Extreme response does not occur at the extremes of the input

# Assumptions of linearity could miss-characterize important features



TRI-6342-5371-0

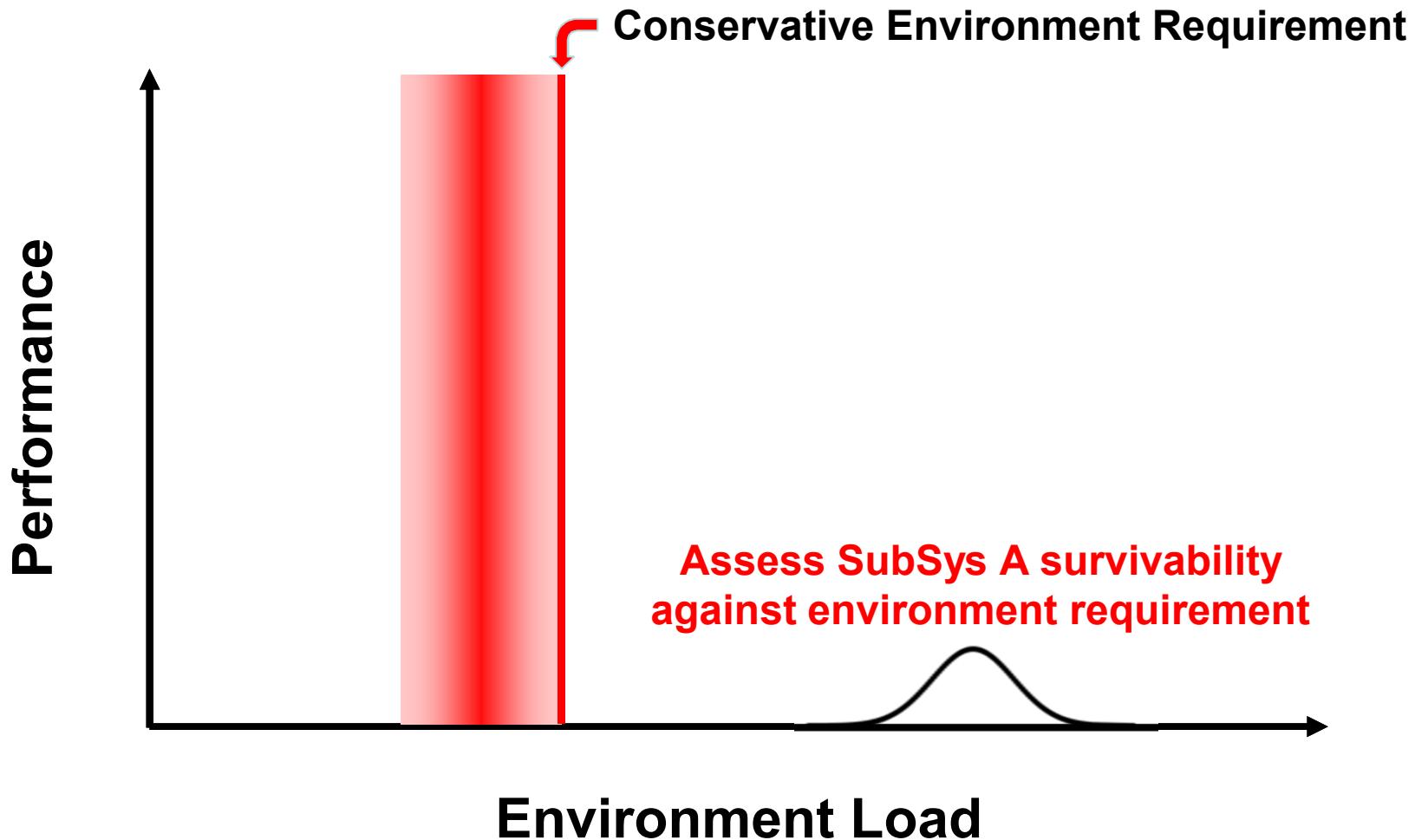
TRI-6342-5372-0

Sensitivity study form WIPP performance assessment

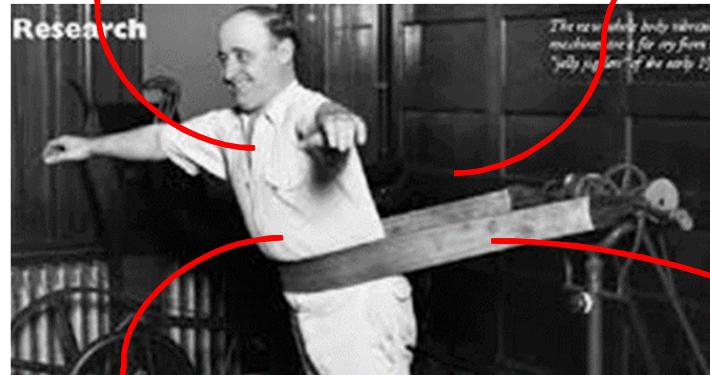
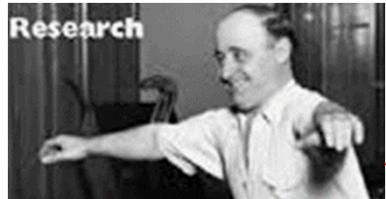
# Spend some time on the environment requirement tab in the spreadsheet

- Demonstrate dynamic environment load calculation
  - VBA Function Procedure as replacement for really big computer code

# There are survivability requirements on SubSys A

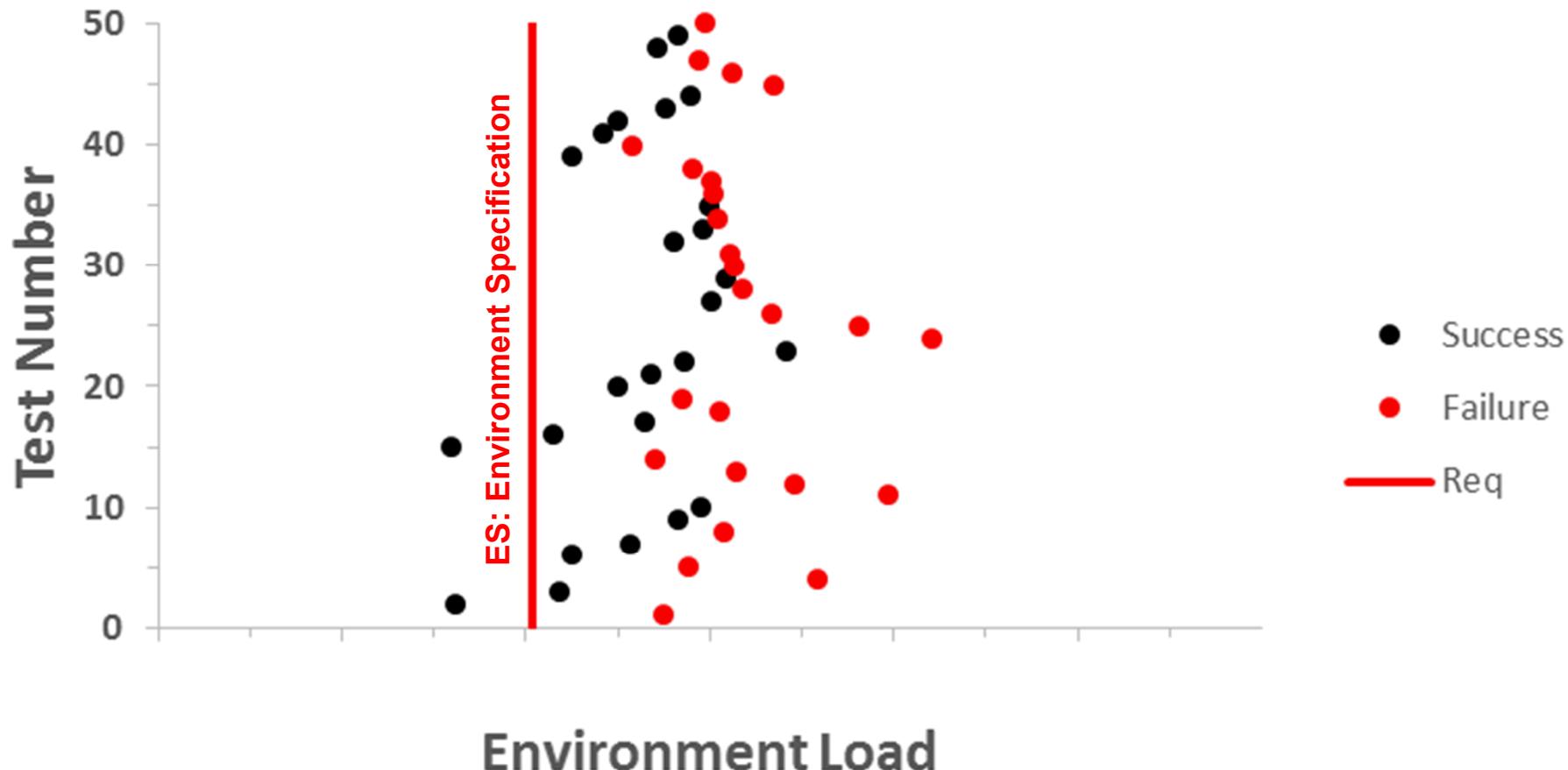


# How hard do you have to shake it before it fails catastrophically?

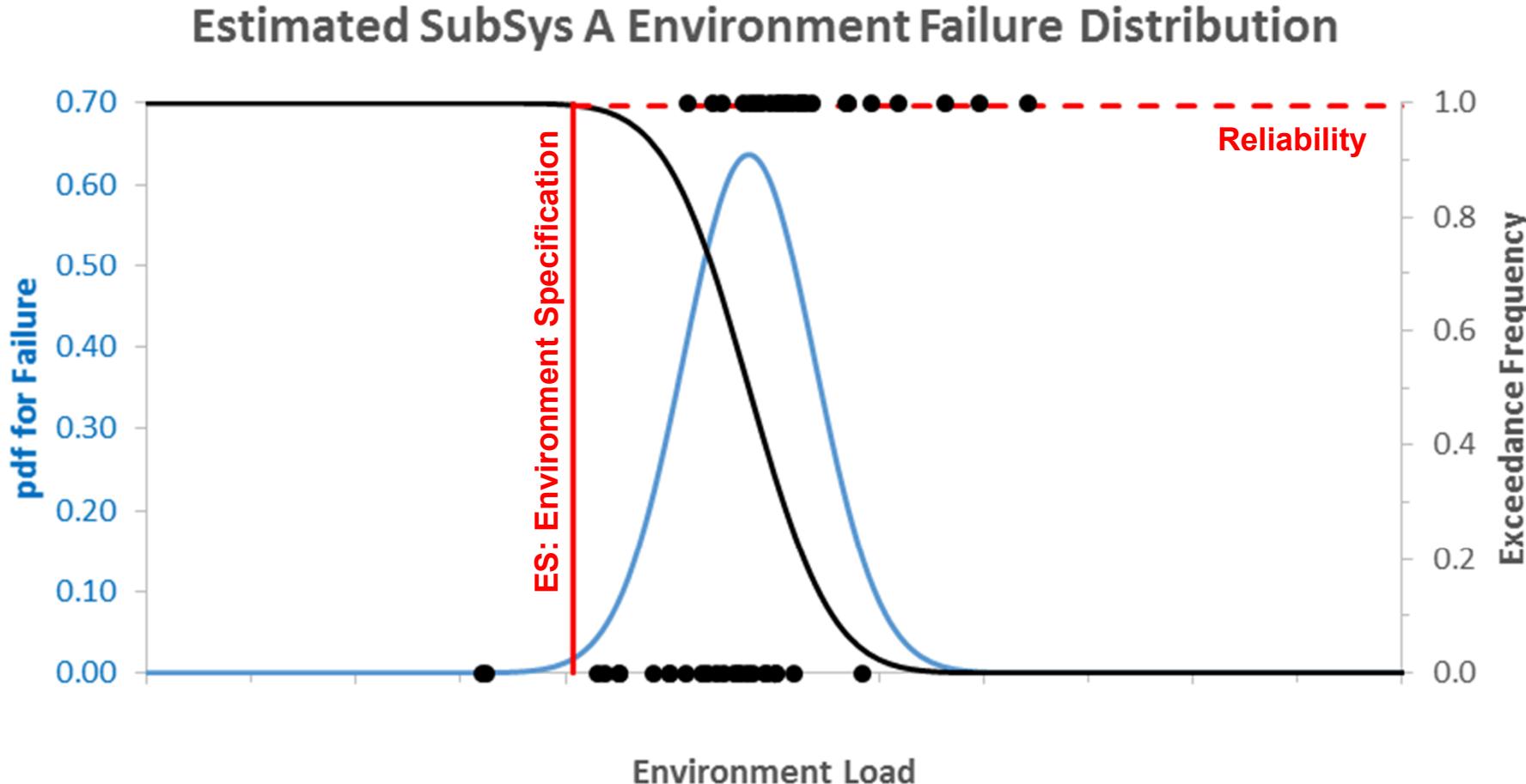


One shot tests

# We look for a survivability transition by doing over-tests with different loads on different units

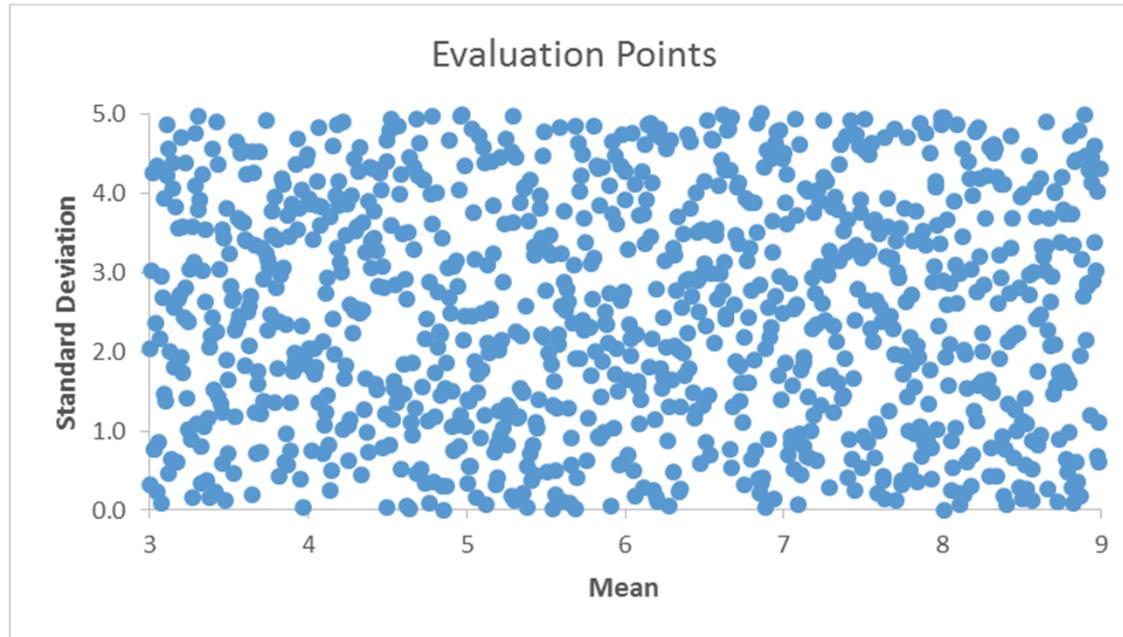


# We want to transform success/failure data into a failure distribution as a function of load



# Assume a normal (frequency) distribution with uncertain mean and standard deviation, $\text{Norm}(\mu, \sigma)$

- Select evaluation points for  $\mu, \sigma$  by casting a wide net



Mean = RiskUniform(3,9)  
 Std = RiskUniform(0,5)

- Use Bayes Theorem to calculate probability that any  $\mu, \sigma$  pair could have produced the observed data

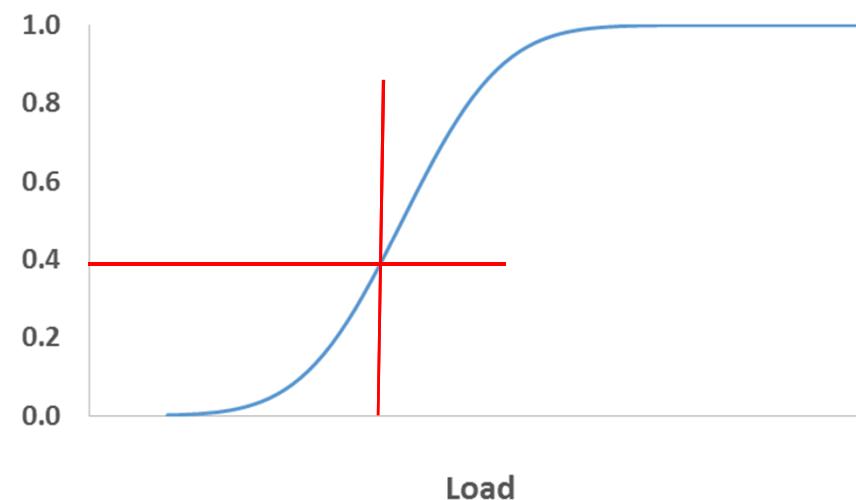
# Distribution parameters are calibrated using Bayes Theorem

- Posterior  $(\mu, \sigma) \sim \text{Likelihood(Data: } \mu, \sigma) * \text{Prior}(\mu) * \text{Prior}(\sigma)$
- Un-informed priors for  $\mu, \sigma$ 
  - $\text{Prior}(\mu) \sim 1$  any value is equally likely
  - $\text{Prior}(\sigma) \sim 1/\sigma$  invariant to translation
- Likelihood(Data:  $\mu, \sigma$ )

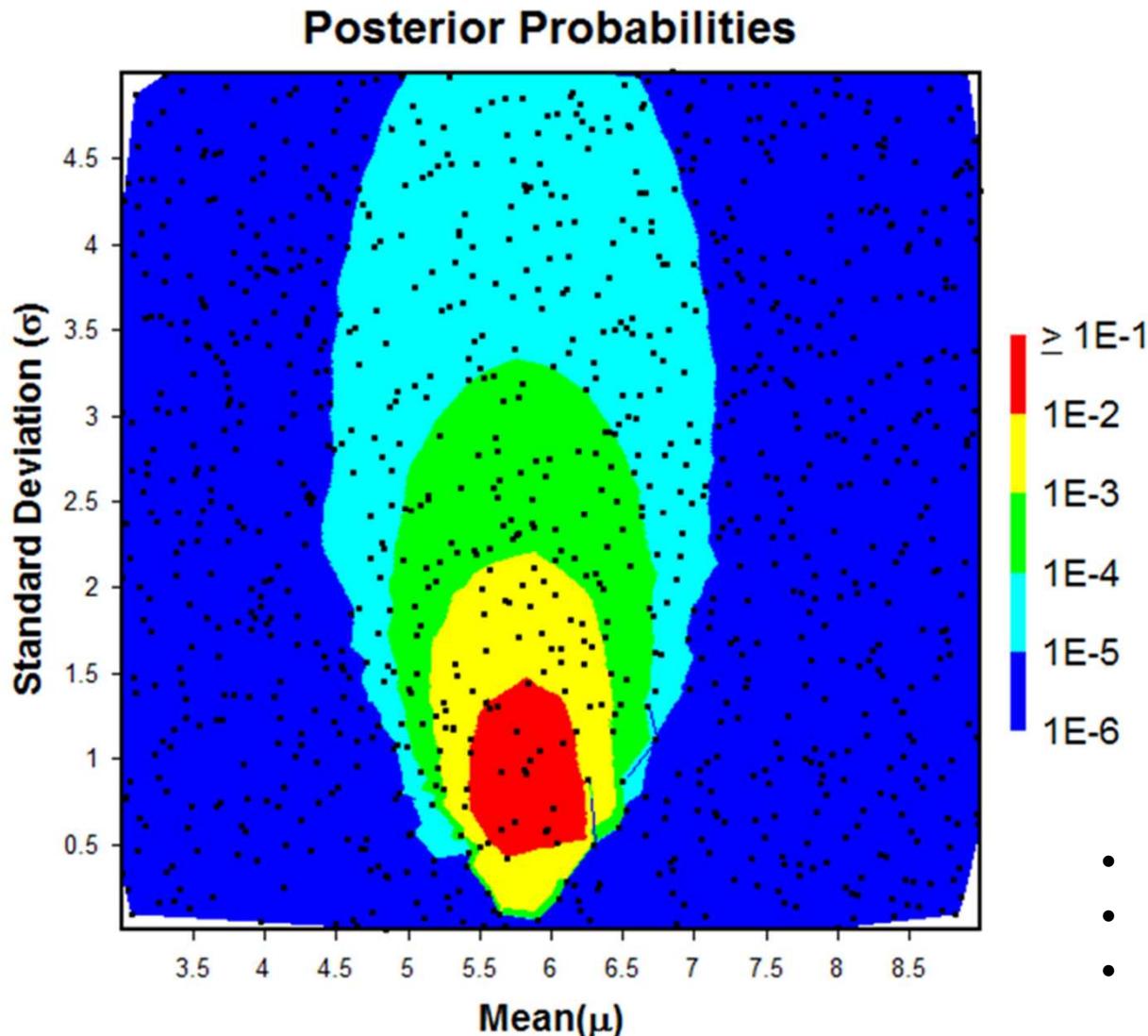
$$\text{Likelihood(Data: } \mu, \sigma) = \sum_{i=1}^{N\text{Data}} \left\{ \begin{array}{l} \text{Index} * \text{CumNorm}(\mu, \sigma) \\ + (1 - \text{Index}) * (1 - \text{CumNorm}(\mu, \sigma)) \end{array} \right\}$$

Likelihood of Success:  
Index = 0

Likelihood of Failure:  
Index = 1

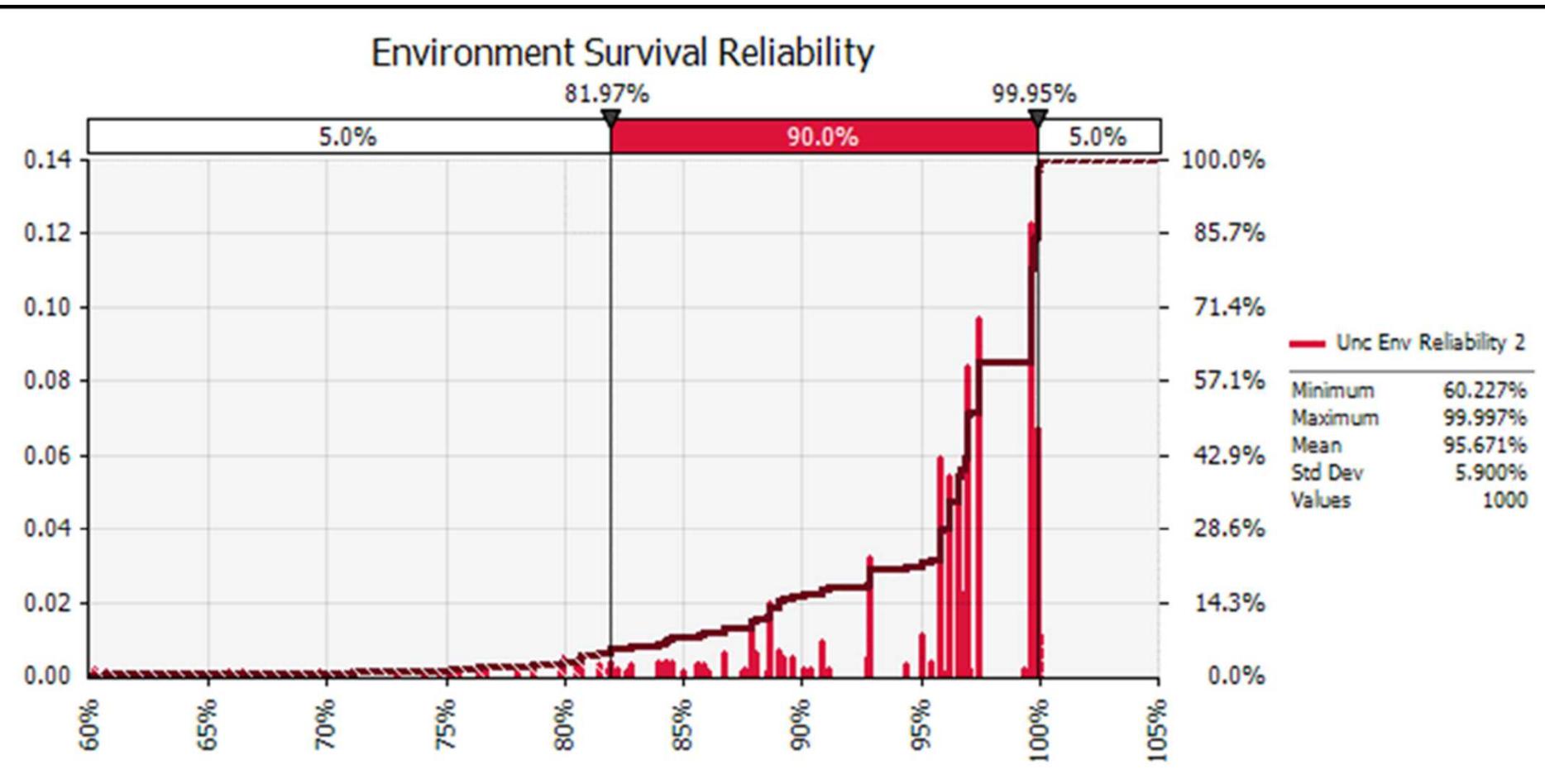


# Sample from the posterior probabilities



- `EvalPoint = RiskDiscrete`
- $\mu = \text{vlookup}$
- $\sigma = \text{vlookup}$

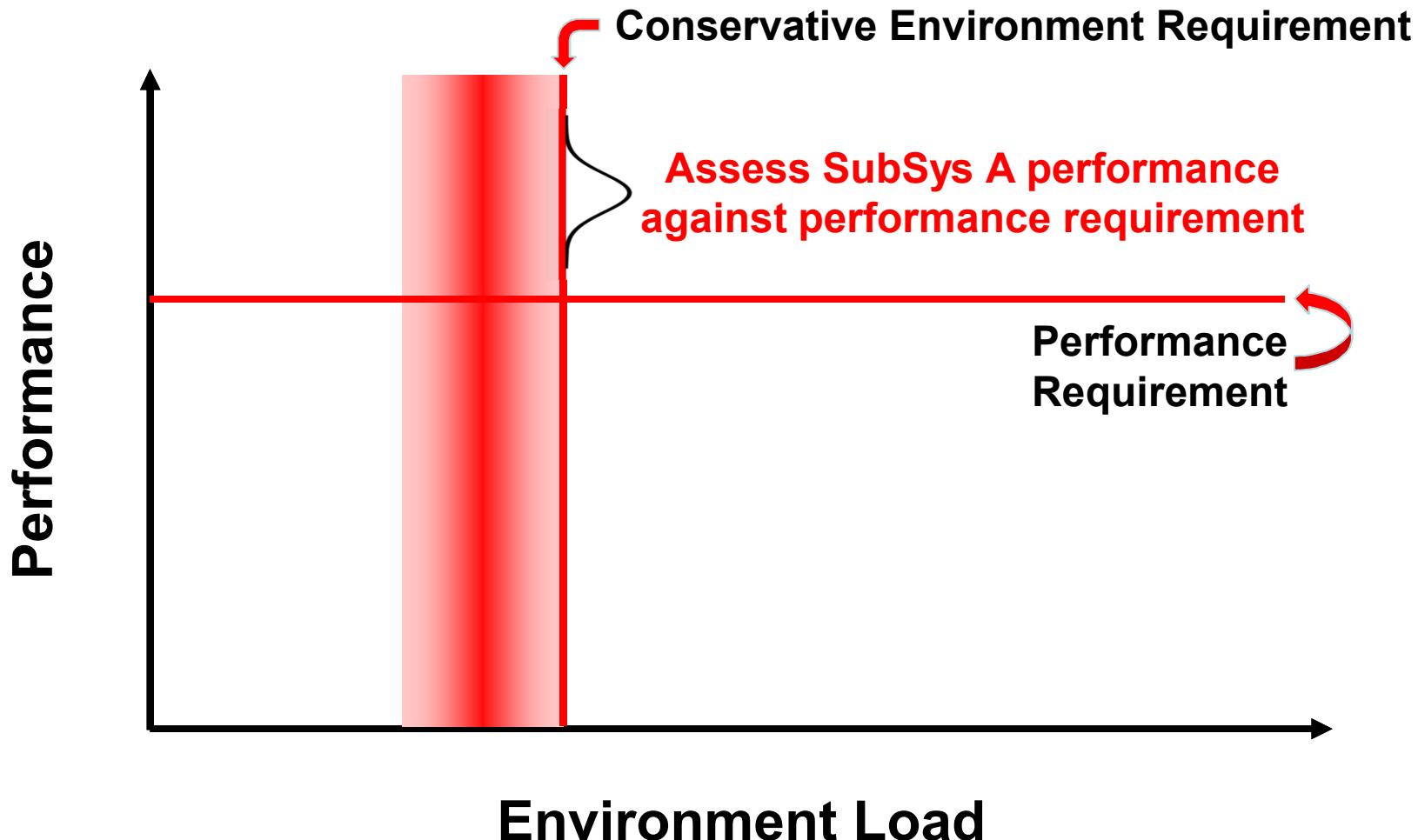
# Estimated environment survivability is uncertain



# Spend some time on the SubSys A env. survivability tab in the spreadsheet

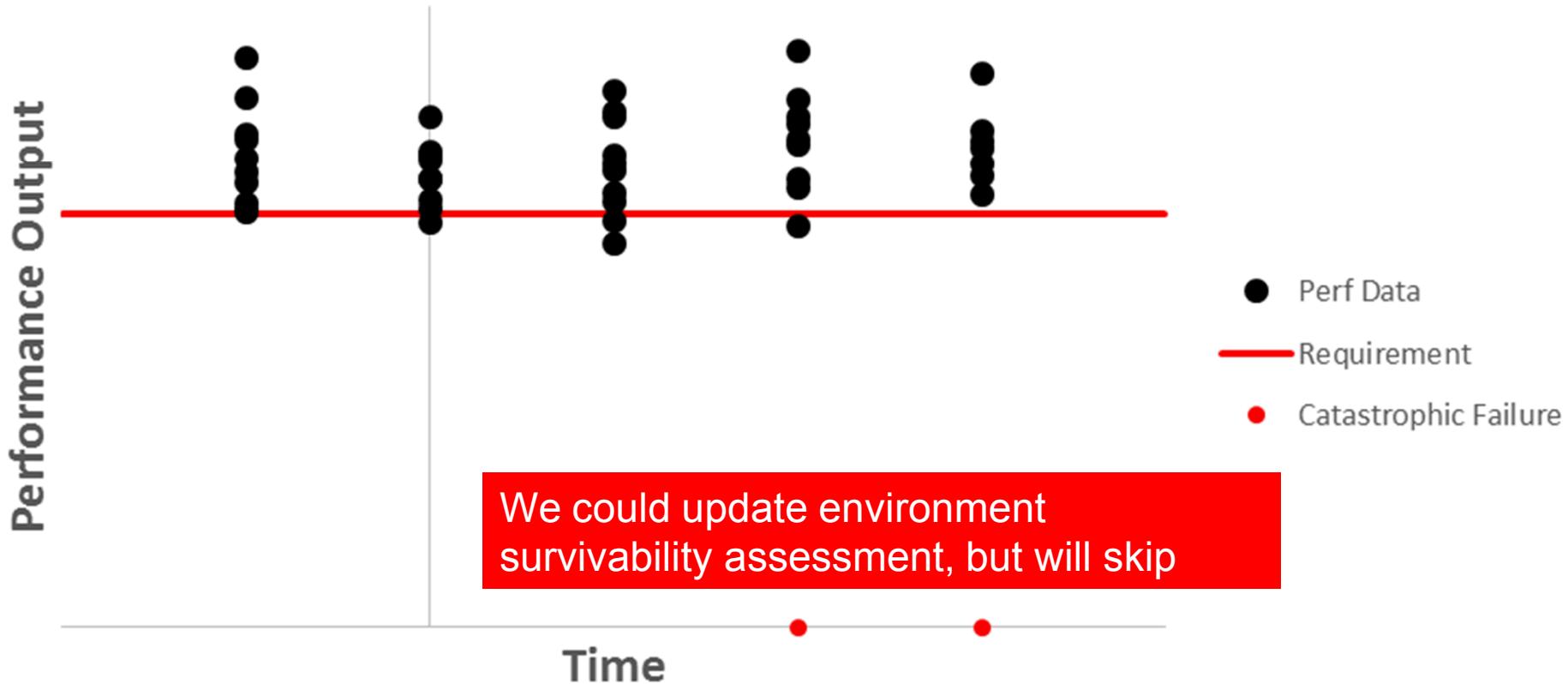
- Demonstrate dynamic data sets using Langley algorithm
- Walk through Bayesian updating
  - $\mu, \sigma$  evaluation points
  - $\mu, \sigma$  priors
  - Evaluation of likelihood function
  - Posterior and normalized posterior
- Demonstrate sampling of posterior
  - RiskDiscret and VLOOKUP
- Demonstrate dynamic failure load distribution

# There are performance requirements on SubSys A

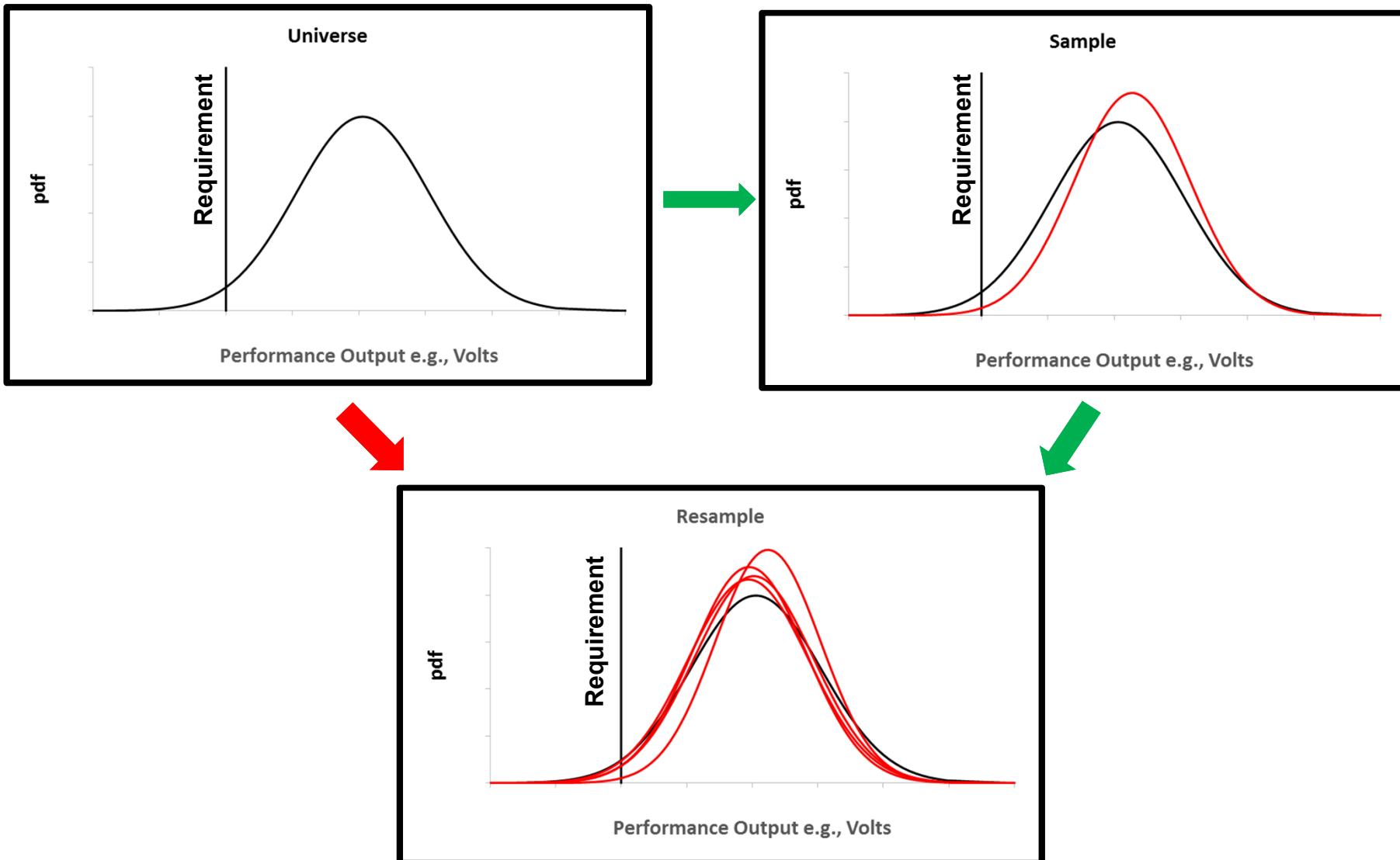


# We have performance data taken on *SubSys A*

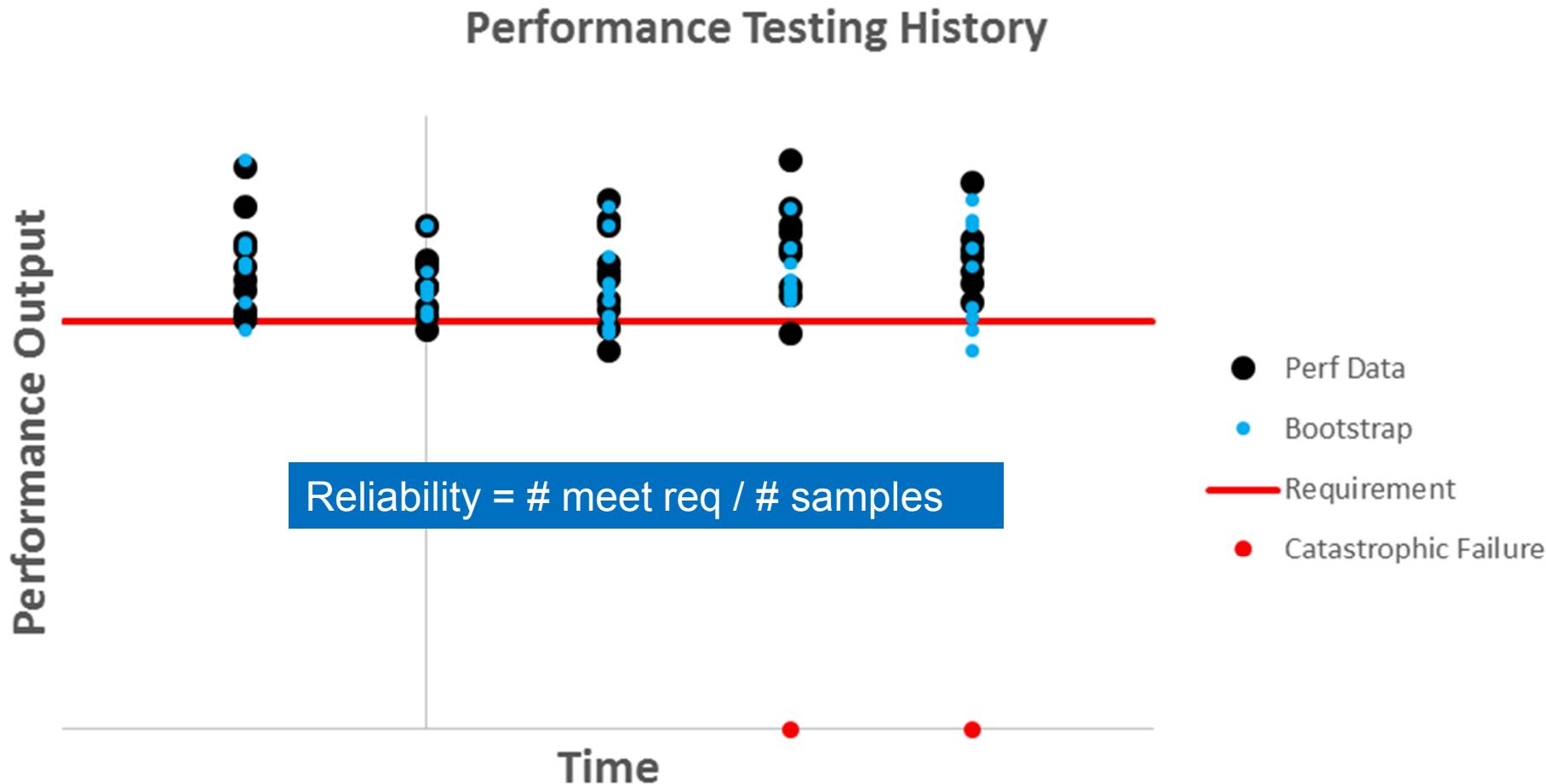
## Performance Testing History



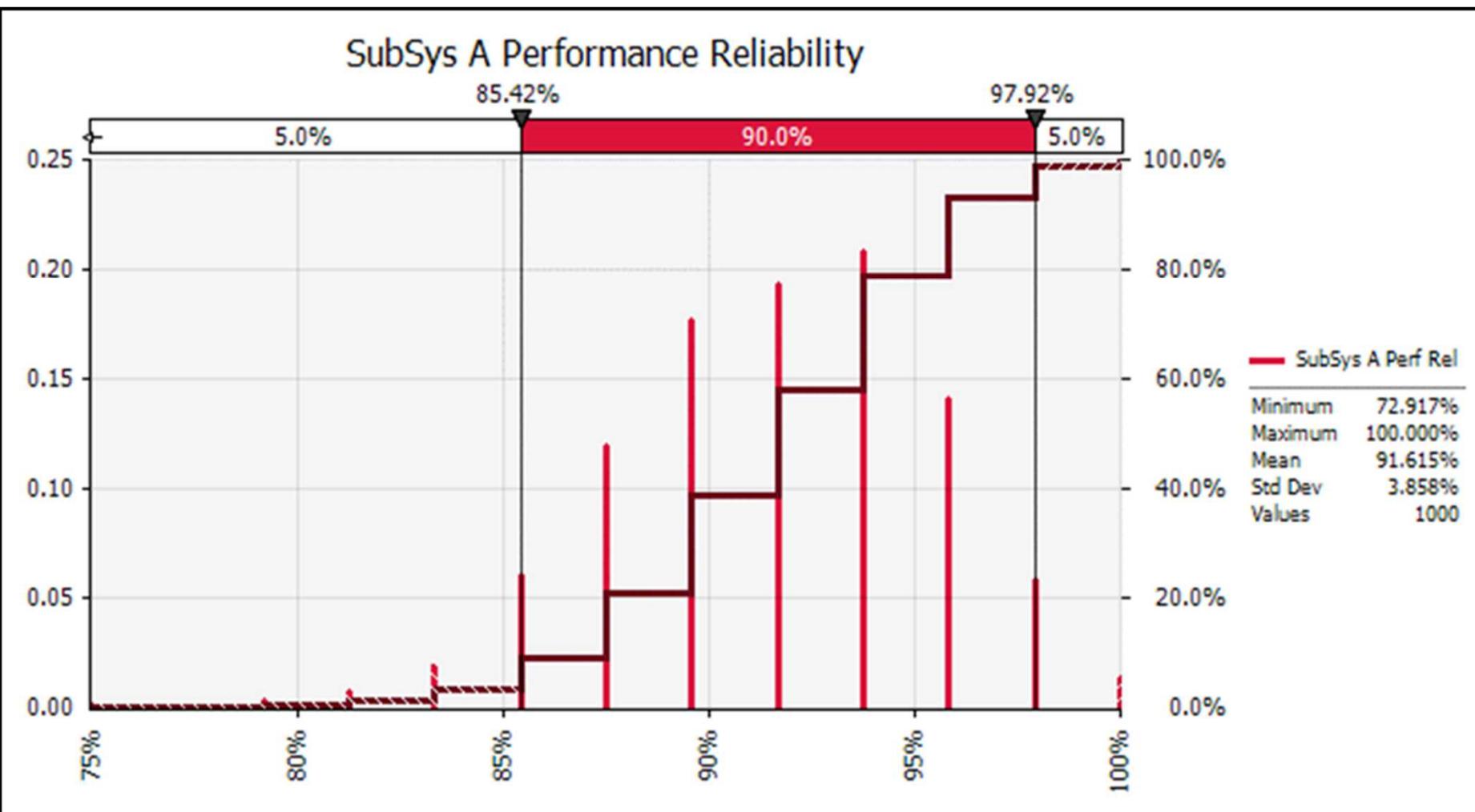
# How do you estimate the uncertainty in any statistic from any distribution? – Bootstrap!



# Bootstrap samples used to estimate SubSys A reliability



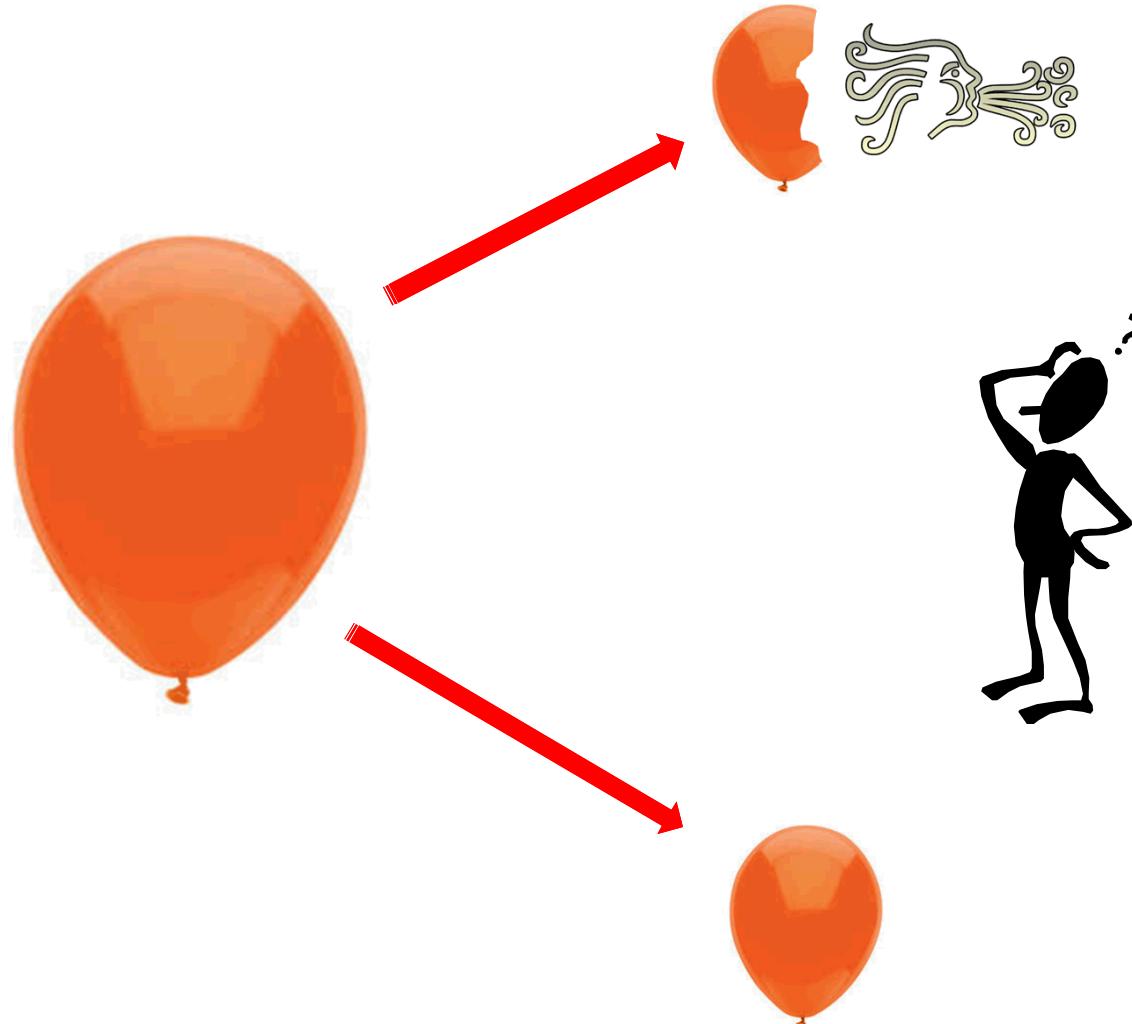
# Estimated performance reliability for *SubSys A* is uncertain



# Spend some time on the SubSys A performance tab in the spreadsheet

- Demonstrate dynamic bootstrapping
- Demonstrate dynamic reliability based on bootstrap samples
- We have skipped updating of environment survivability

# *SubSys B either performs all of the time or none of the time; but we are uncertain about which*

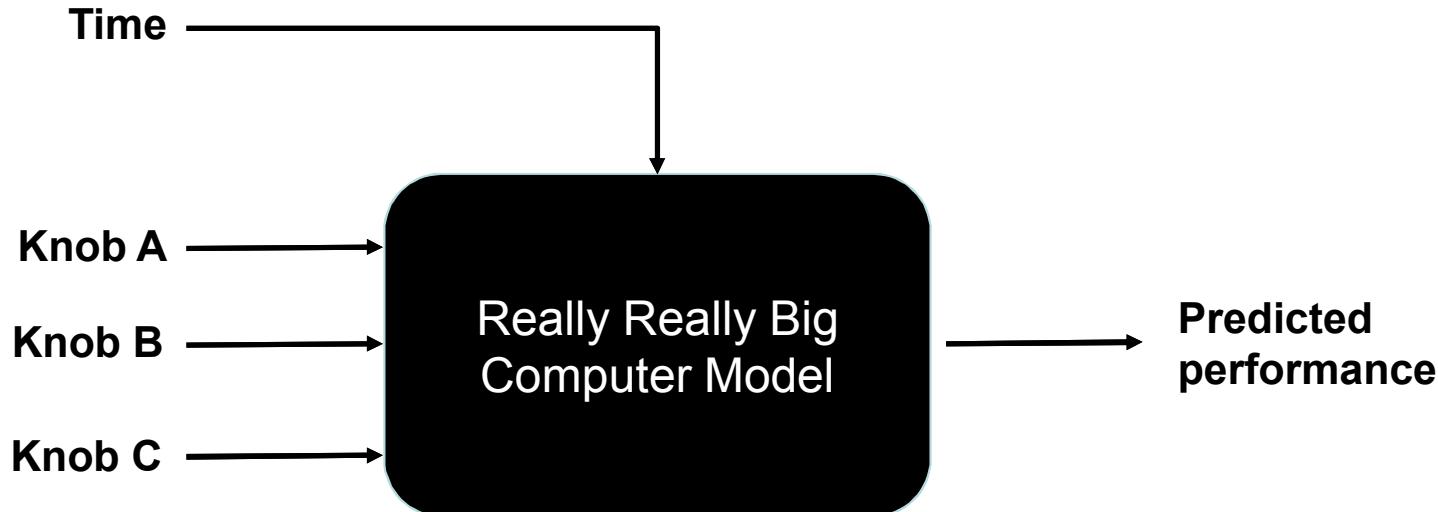


**Either it Goes Boom!  
Reliability = 1.0**

**Epistemic  
Uncertainty**

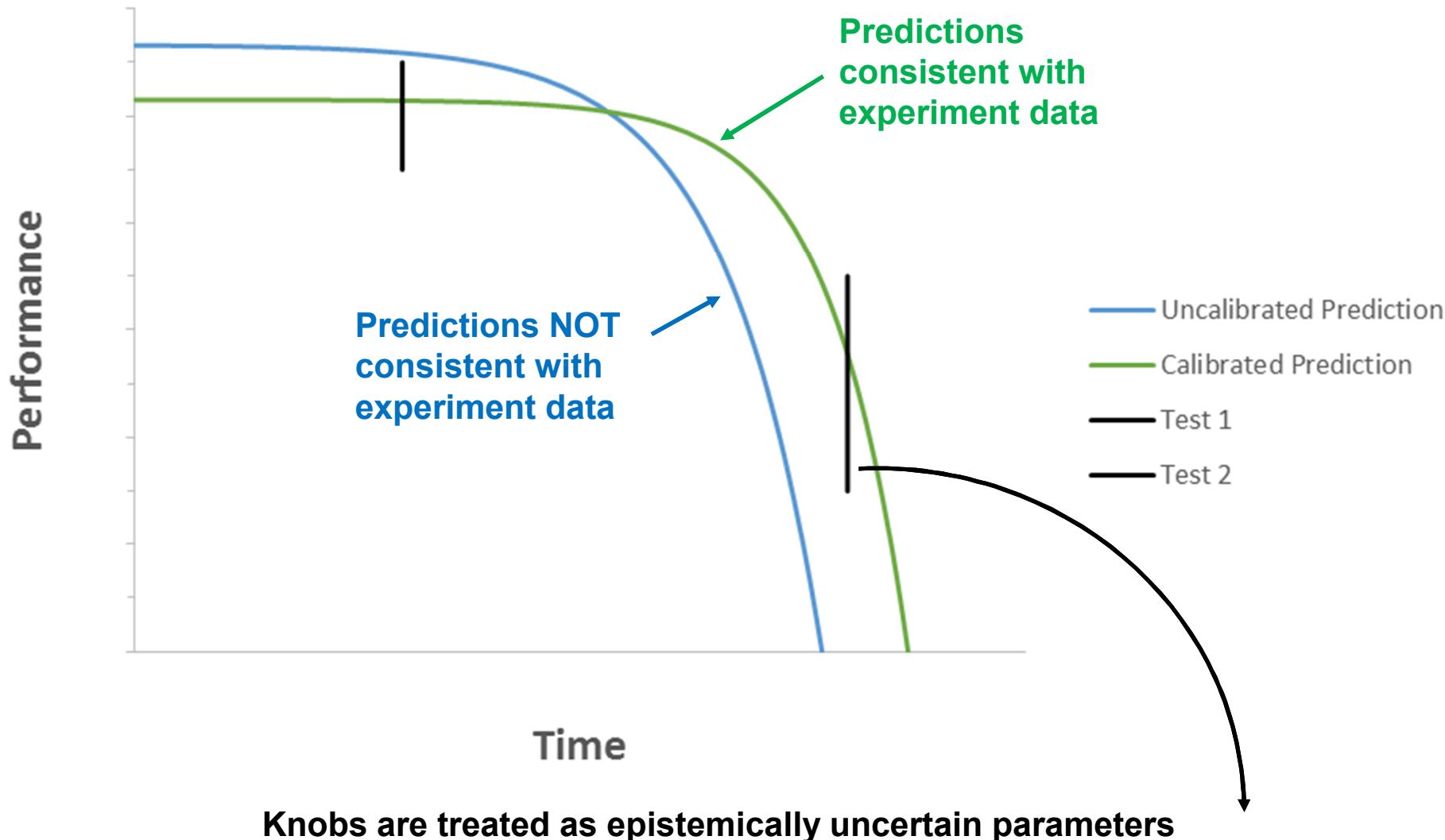
**Or it's A Dud!  
Reliability = 0.0**

# Really really big computer models are used to predict SubSys B performance



Knobs are surrogates for missing or unknown physics; consequently, they are treated as epistemic uncertainties

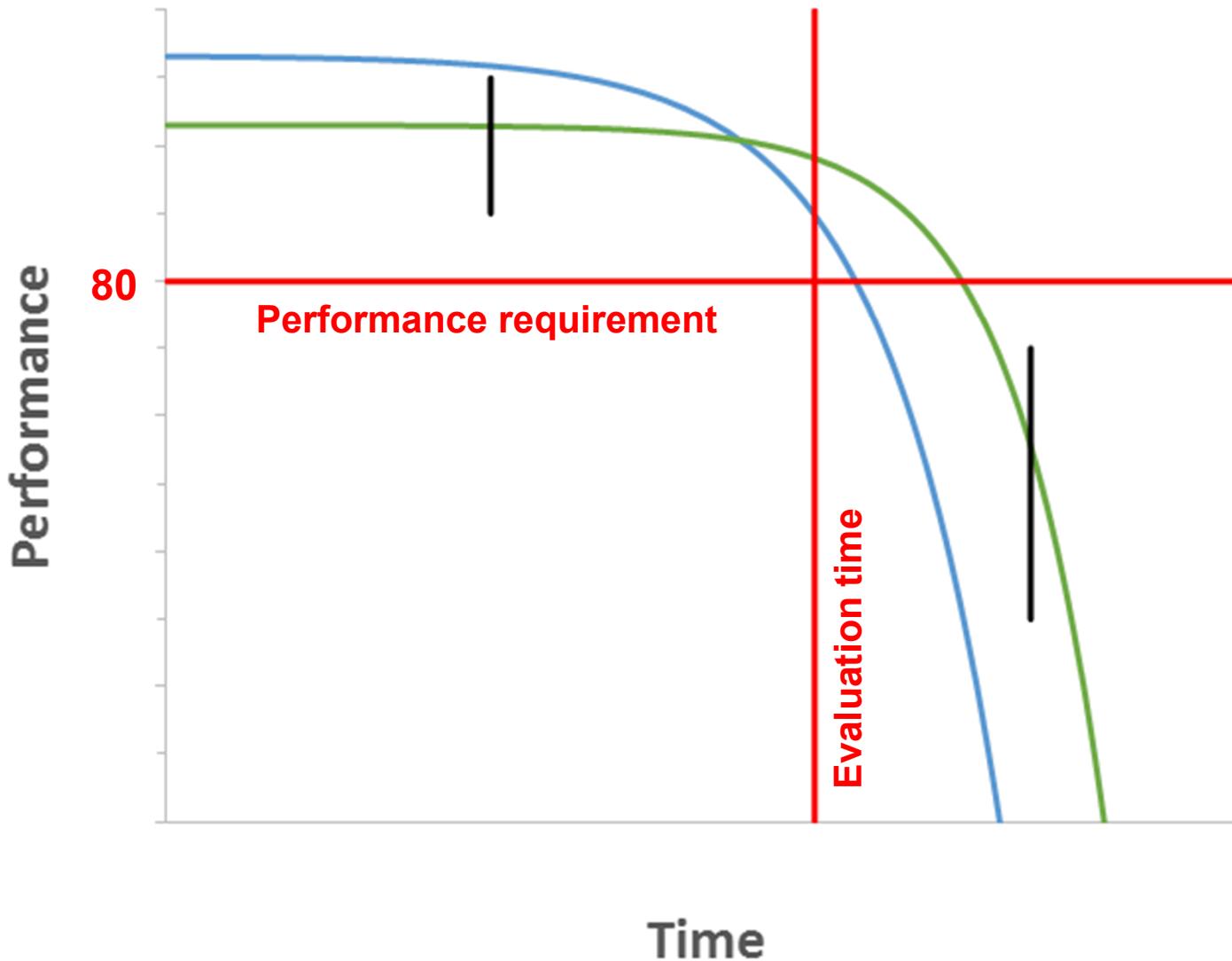
# Knobs are calibrated so that predictions are consistent with limited experiment data



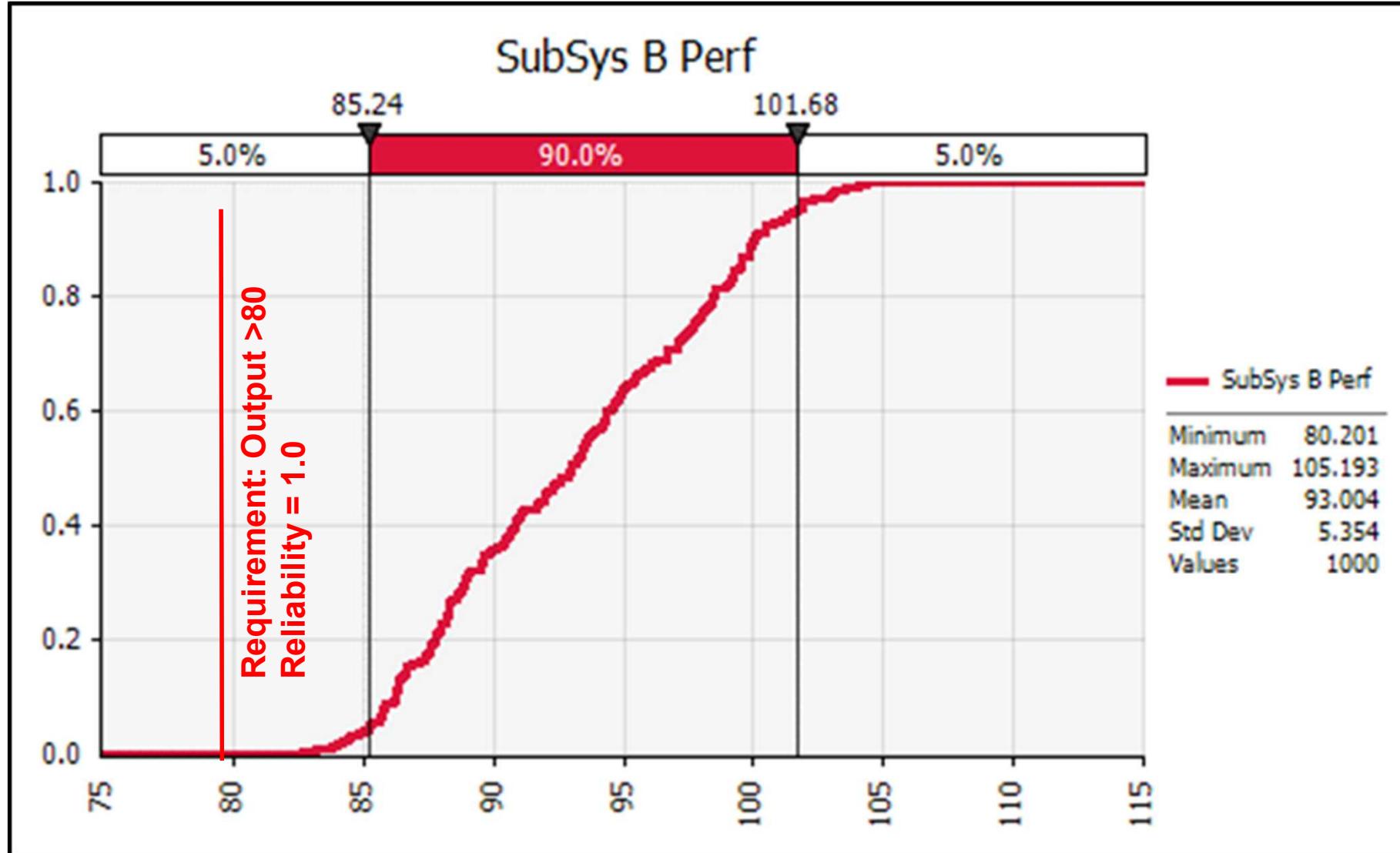
# Computer model parameters (knobs) are calibrated using Bayes Theorem

- Posterior (Knobs:Data)  $\sim$  Likelihood(Data: Knobs) \* Prior(Knobs)
- Un-informed priors for the Knobs
  - Prior(Knobs)  $\sim$  1 any value is equally likely for wide range of possibilities
- Likelihood(Data: Knobs)
  - = 1 if prediction passes though error bar of both data points
  - = 0 otherwise

# *SubSys B has performance requirements*



# SubSys B has uncertain performance



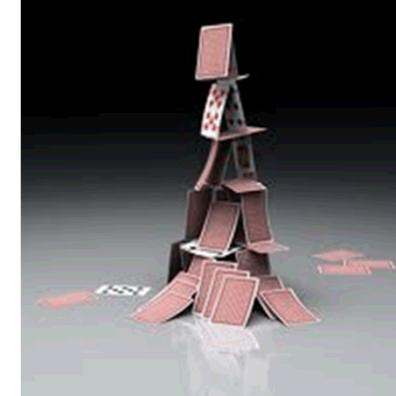
# Spend some time on the SubSys B performance tab in the spreadsheet

- Demonstrate un-calibrated and calibrated performance curves

# It's all about target defeat

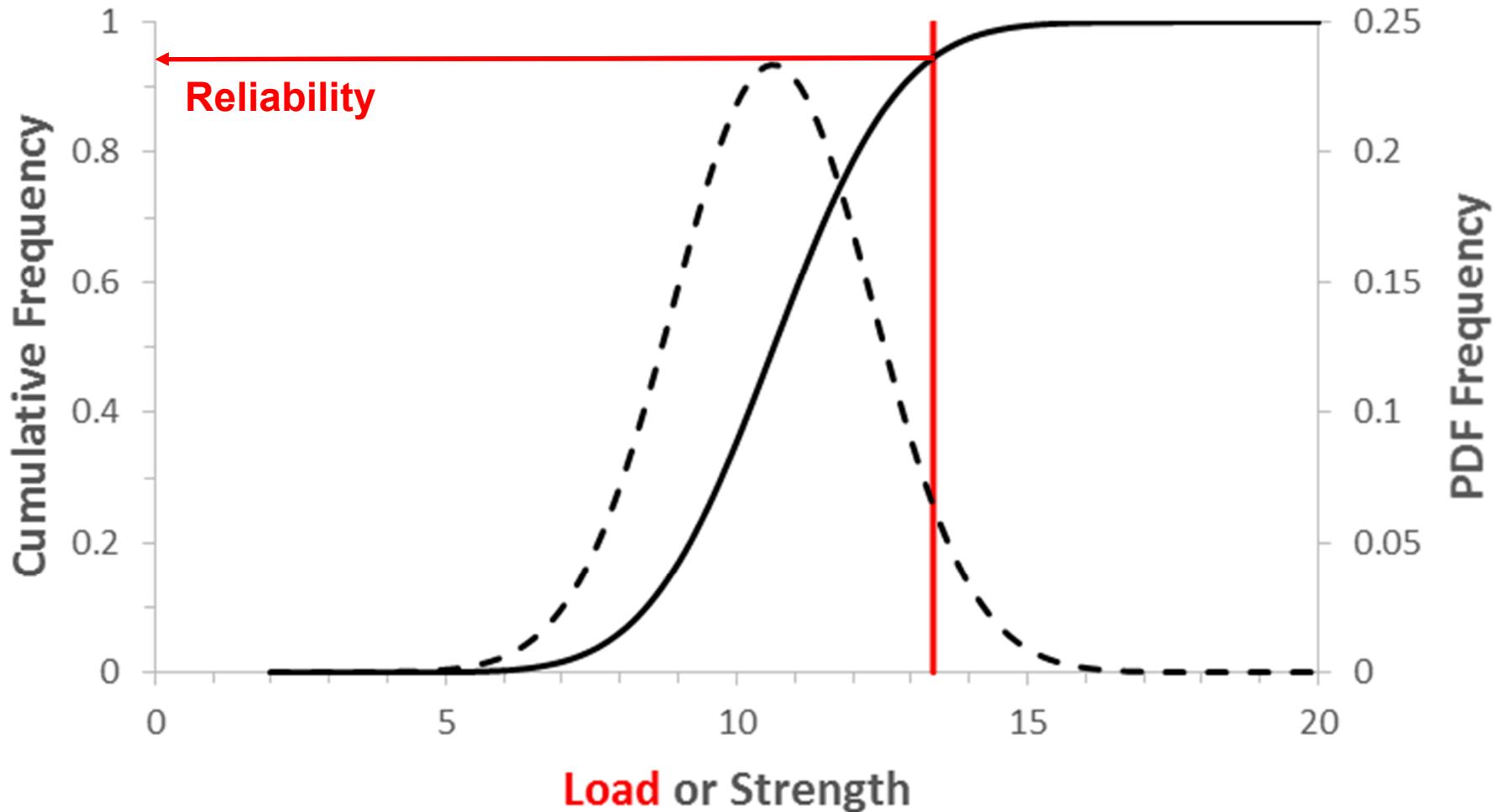


**Load has attributes of epistemic uncertainty only**

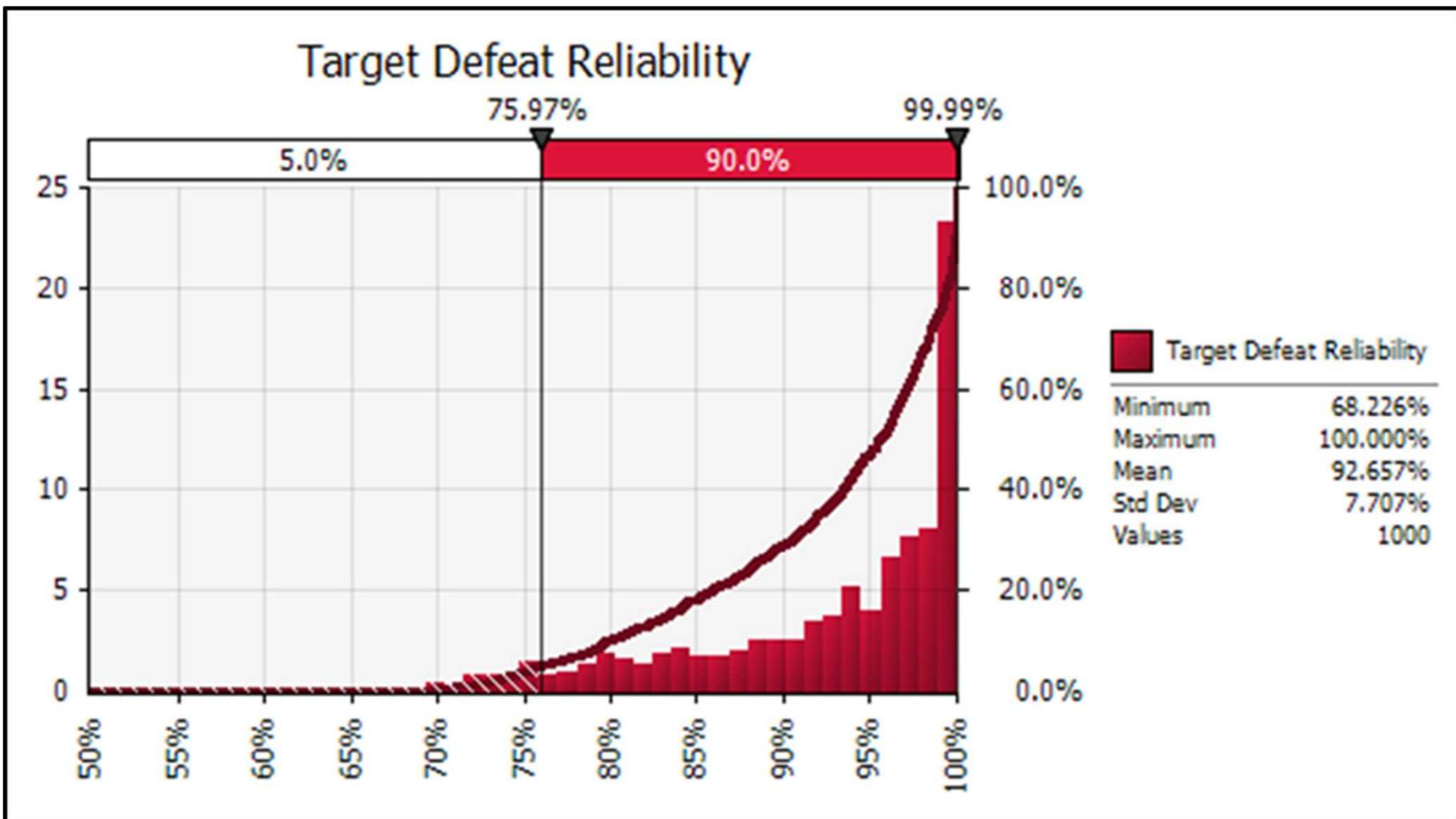


**Strength has attributes of aleatory uncertainty and epistemic uncertainty**

# Different Target Defeat reliabilities for different load strength curves



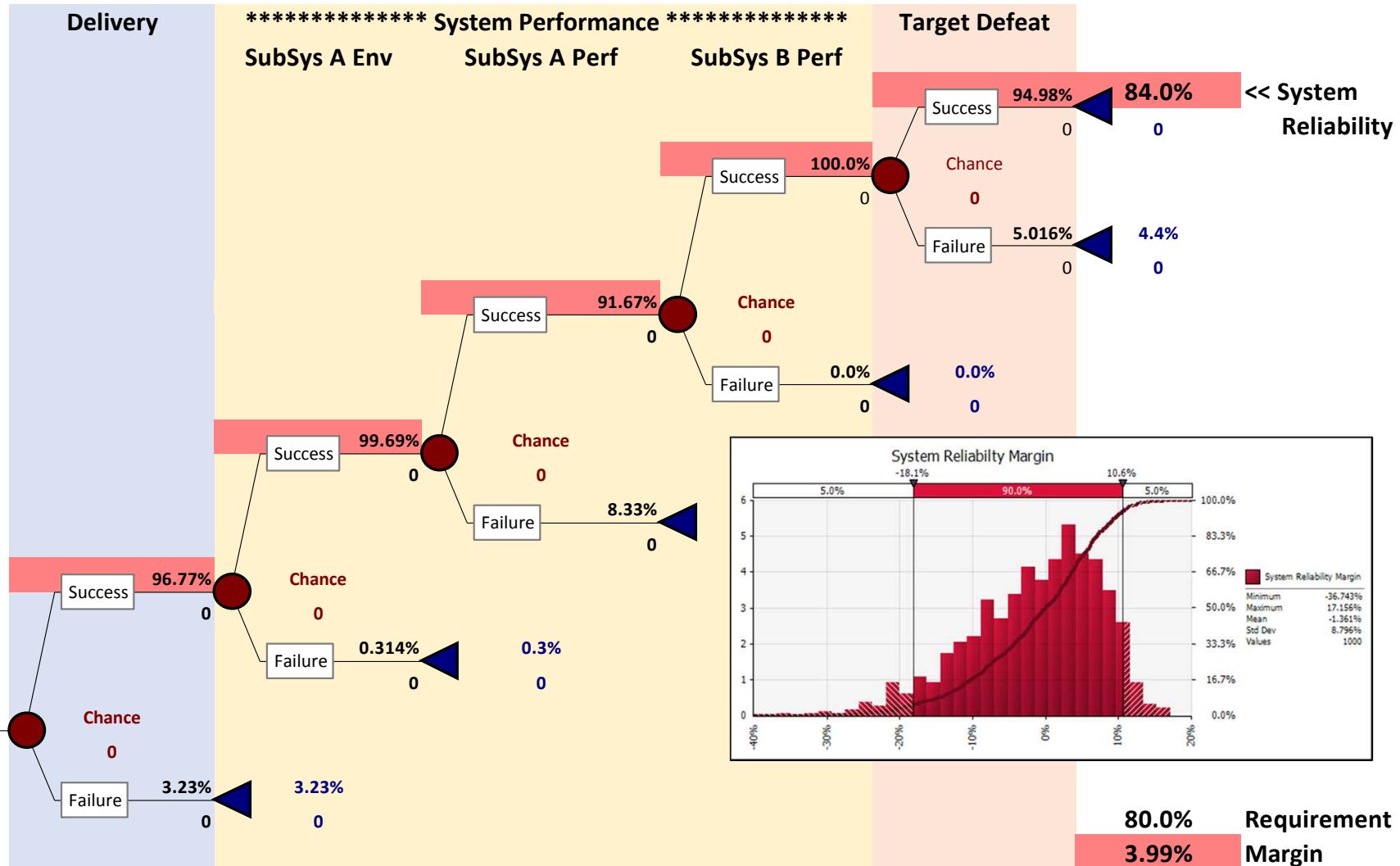
# Target Defeat reliability is uncertain



# Spend some time on the Target Defeat tab in the spreadsheet

- Demonstrate dynamic load strength curves and reliability

# We've used probabilistic methods to propagate both aleatory and epistemic uncertainty



# Your life, or that of a loved one, hangs in the balance of a risk assessment



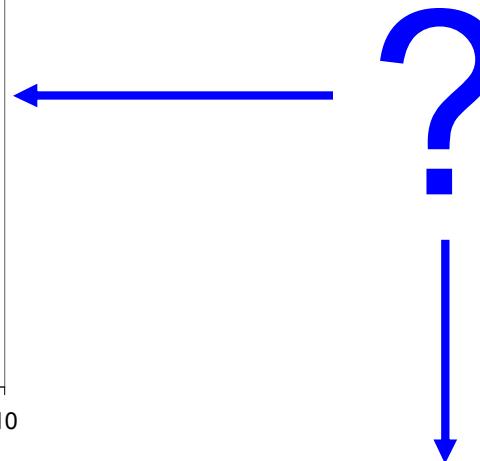
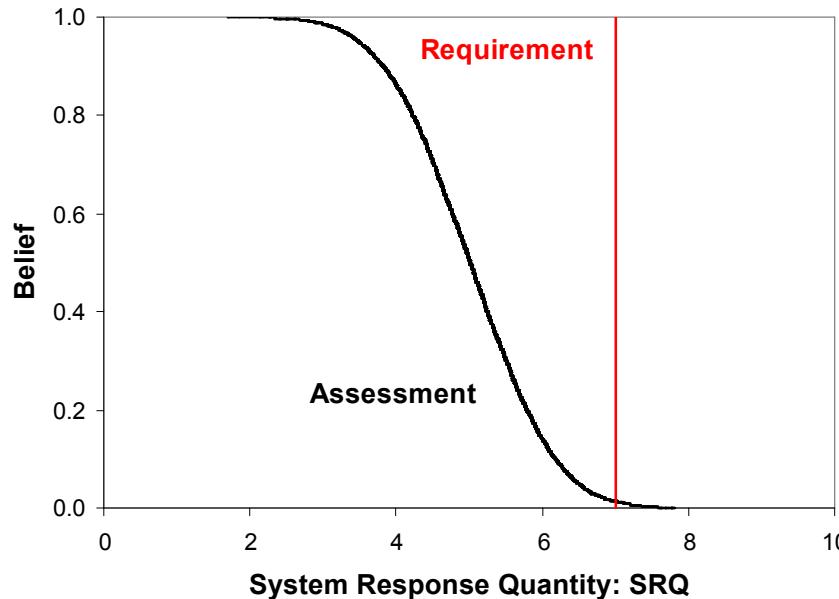
$$SRQ = \sum_{i=1}^{10} X_i \quad X_i = [0,1] \quad \text{Requirement : } SRQ \leq 7$$

**Dominated by epistemic uncertainties**

# You have to pick a framework for representing and propagating epistemic uncertainties

$$SRQ = \sum_{i=1}^{10} X_i \quad X_i = [0,1]$$

Requirement:  $SRQ \leq 7$



**Belief(SRQ > 7) = 0.014**

**SRQ = [0,10]**

Probabilistic framework

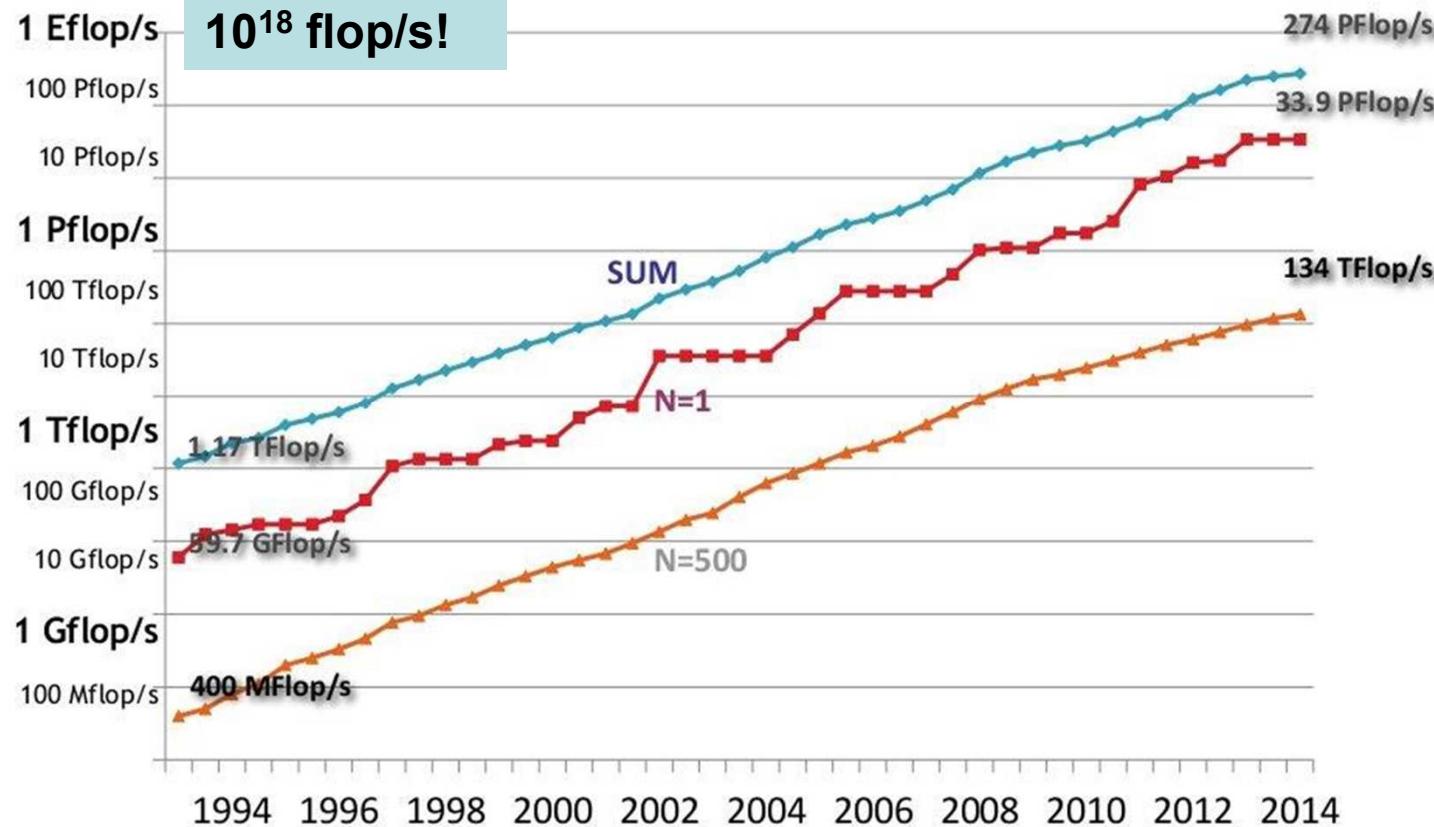
- Bayesian methods
- SOA for risk assessment community

Non-probabilistic framework

- Interval analysis
- Dempster/Shaffer (evidence) theory
- P-Boxs

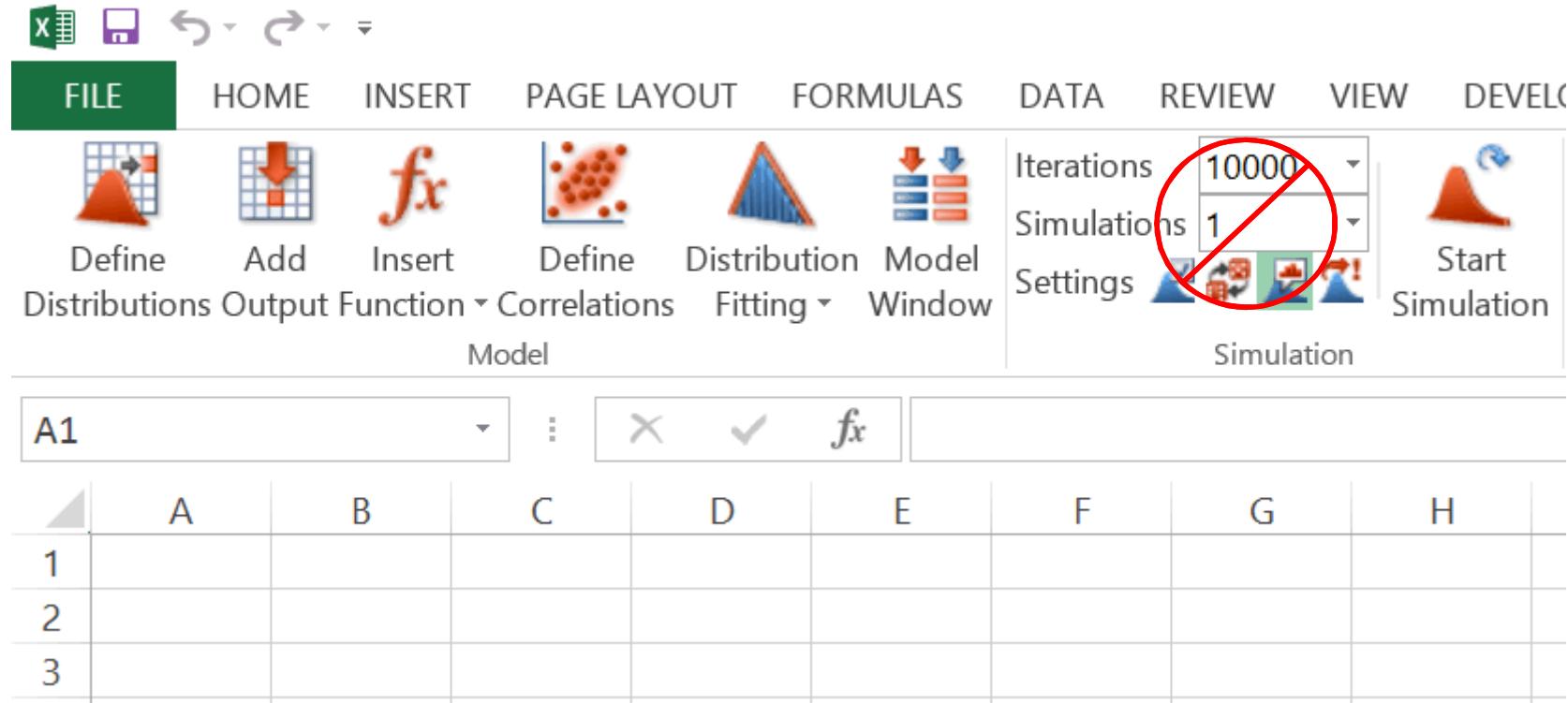
# The world of high performance computing has changed a lot in my lifetime

HPC (~ 1 flop/s)  
1620 - 1950



Is todays engineering 18 orders of magnitude better?

# Even with all this CPU, this is still not an option for our most challenging applications



Use computer model to train surrogate models i.e., NeuralTools

# Credibility of comp. predictions is assessed in terms of six attributes and associated best practices

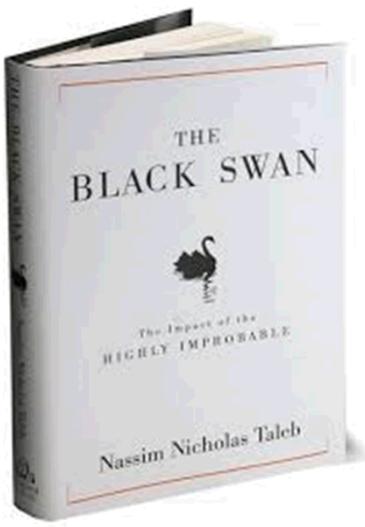
What *evidence* do we demand to assert credible computer predictions?

1. Representation or geometric fidelity
2. Physics and material model fidelity
3. Code verification
4. Solution verification
5. Validation
6. Uncertainty quantification

## Best Practices:

1. Calibrate SMEs
2. Look broadly for uncertainties
3. Separate aleatory and epistemic uncertainties
4. Perform sensitivity analyses
5. Reduce uncertainties only if decisions could change
6. Avoid strong assumptions
7. Ensure that uncertainty propagation errors do not pollute results
8. Document evidence/rational for uncertain inputs
9. Perform technical peer review

# A common criticism of risk assessment relates to the prevalence of *Black Swans*\*



Metaphor for events characterized by surprise and high consequence that seem obvious only in retrospect

\* Unknown/Unknowns



**Surprise???**

**High  
Consequence???**

**I'm Not Feeling It!**

# Now I feel it!



**Surprise!**

**High Consequence!**

# How do you deal with “The Bird”?



Be Proactive: Begin With  
Unkn/Unkns in Mind



Analysis Paralysis:  
Extreme Risk  
Aversion



Ignore It: What I  
Don't Know Can't  
Hurt Me

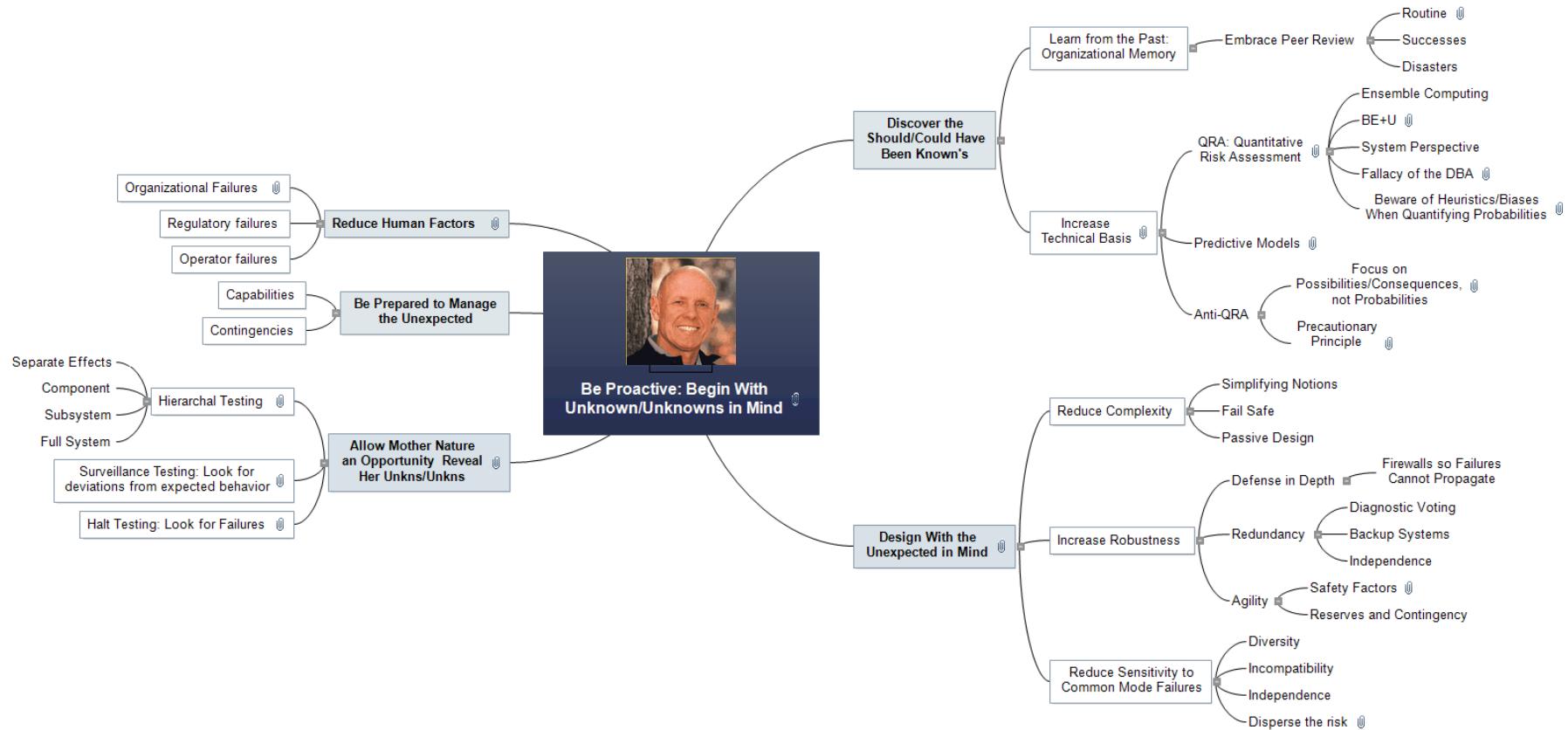


Unknown/Unknowns =  
Surprise + High Consequence



Hubris: Nothing  
Can Go Wrong

# Be proactive, begin with “The Bird” in mind



I'd like to hear your thoughts on this

# You laughed when you first heard it because you didn't understand



**Now you do!**

## **Known/Knowns**

- **Fixed value**
- **Aleatory uncertainty if there is variability**
- **Not reducible**

## **Known/Unknowns**

- **Epistemic uncertainty**
- **Reducible**

## **Unknown/Unknowns**

- **Black swans**
- **Discovery**

