



Reliability, QMU, Systematic Error & Model Acceptance Criteria

With a Little Discussion on Parameterization of Joint Models

**Presented at USNCCM
July 2009**

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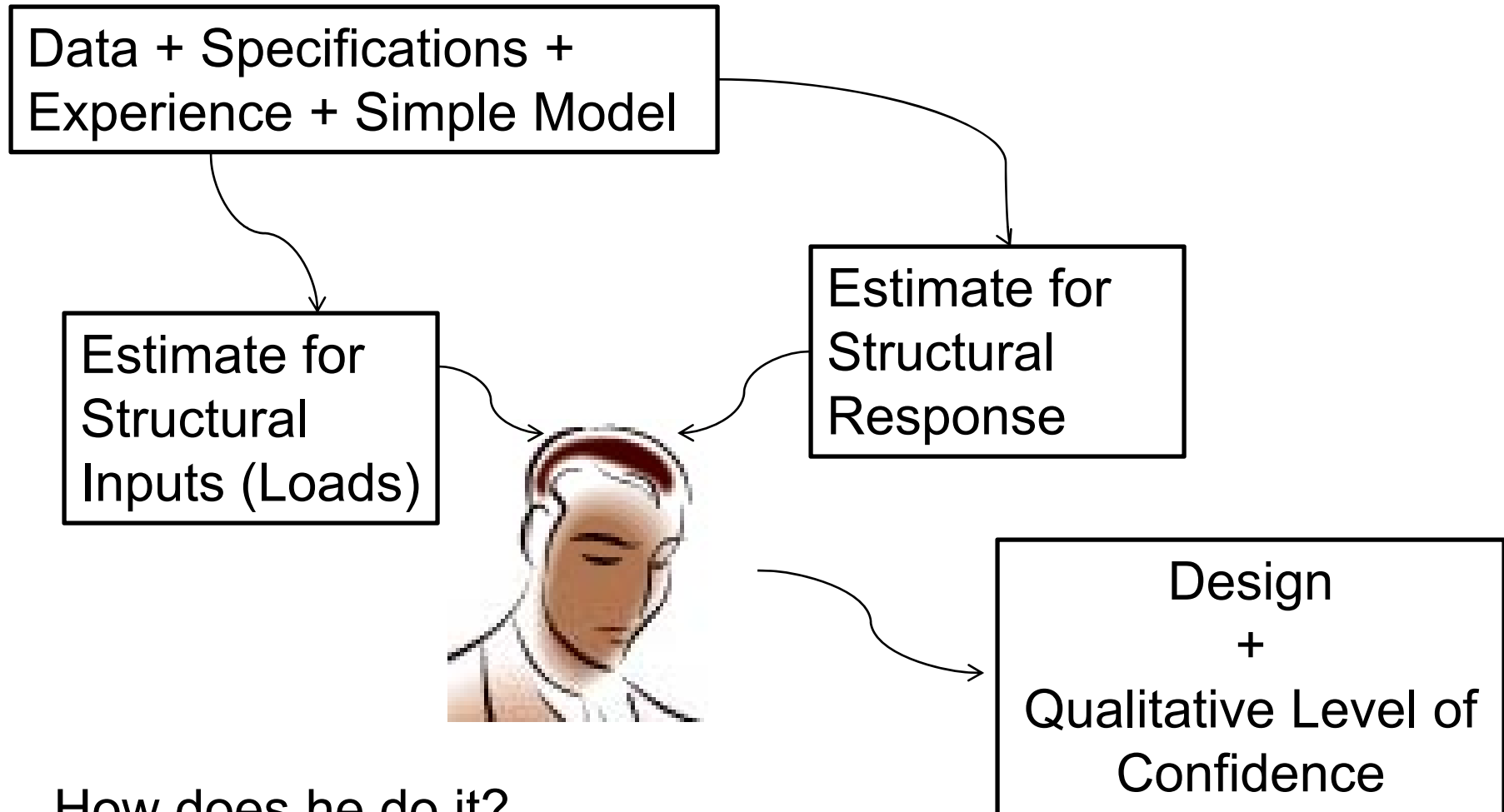


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A Design Engineer



How does he do it?

What is the source of confidence?

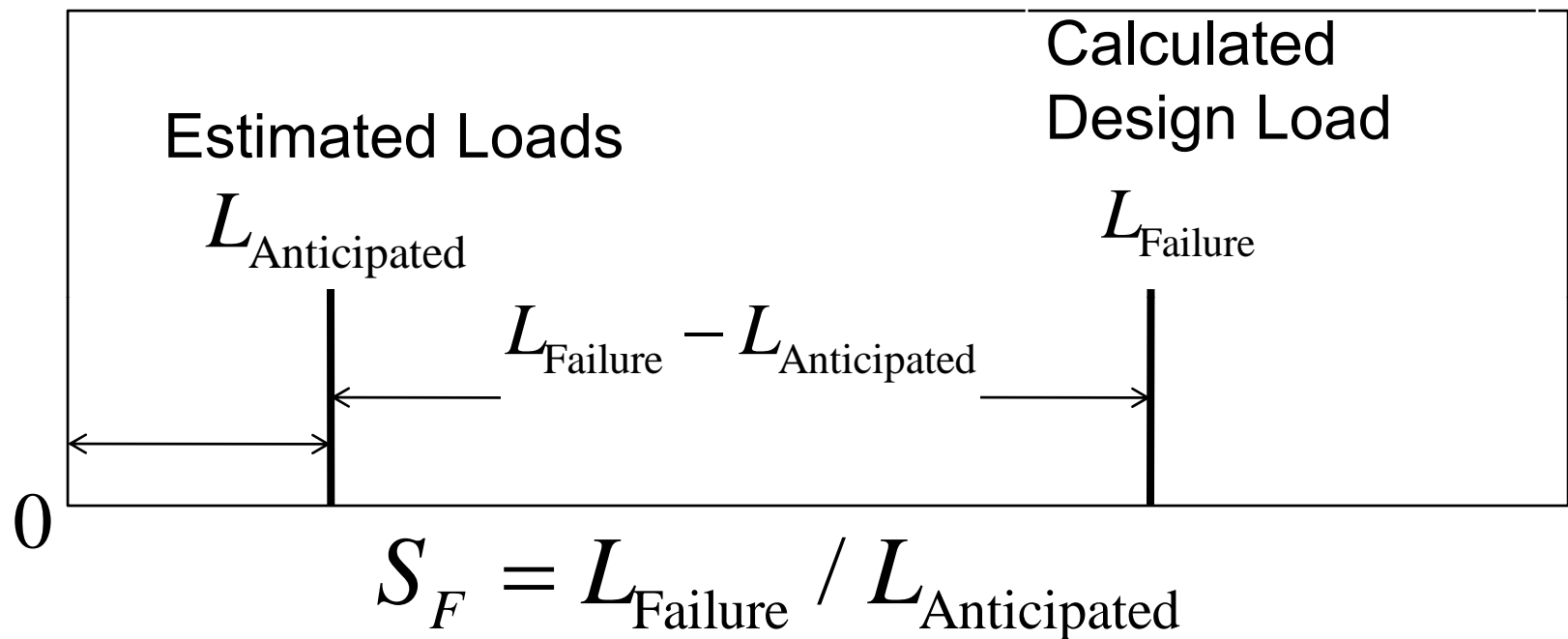


Question: How does the design engineer deal with the many sources of uncertainty?

- **Much data must be guessed at.**
- **Requirements are almost always provided in approximate form. (Think of Shock Response Spectra)**
- **All models are incomplete. The analyst strives to account for the most dominant elements of a problem.**
- **Nothing is ever exactly as specified.**



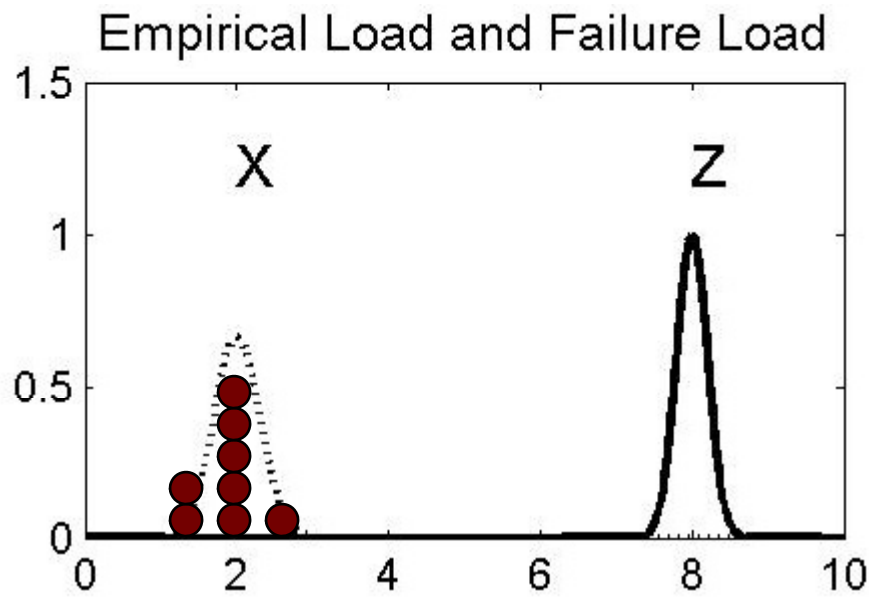
Design Engineer's Answer: Factors of Safety



$$\text{Margin} = S_F - 1$$



Reliability



X: loads expected on structure from past measurement

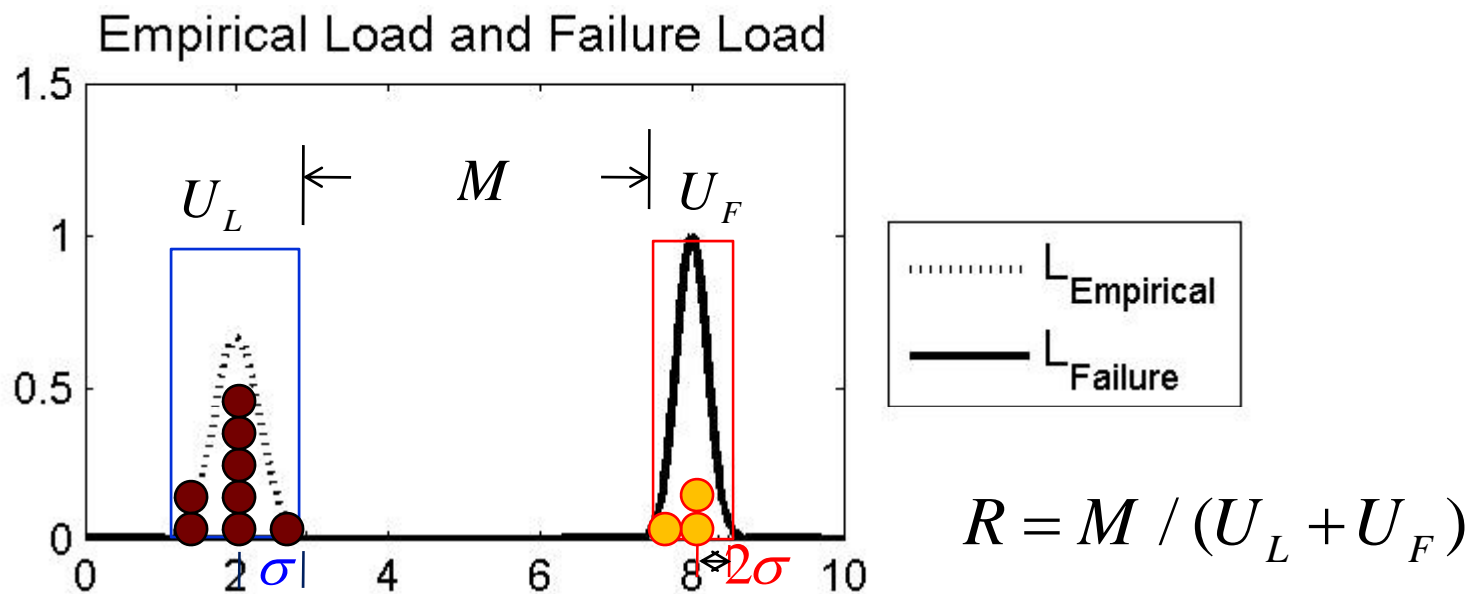
Z: loads structure is anticipated to survive.

- $$P_F = \int_0^{\infty} f_Z(z) \int_z^{\infty} f_X(x) dz dx$$

- There is almost no information about the tails of the distributions.



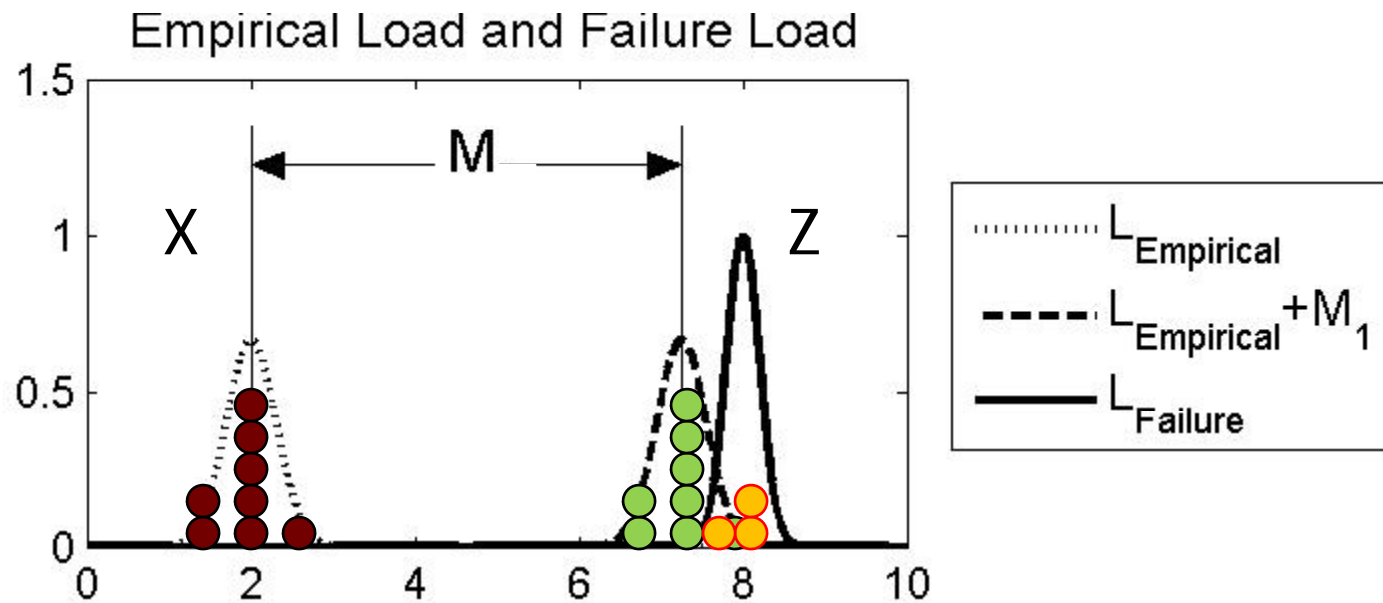
Quantification of Margins and Uncertainty



- Captures some of the uncertainty.
- Captures the margin features of factor of safety.
- May require more information on the tails than is available
- Little guidance to validation.



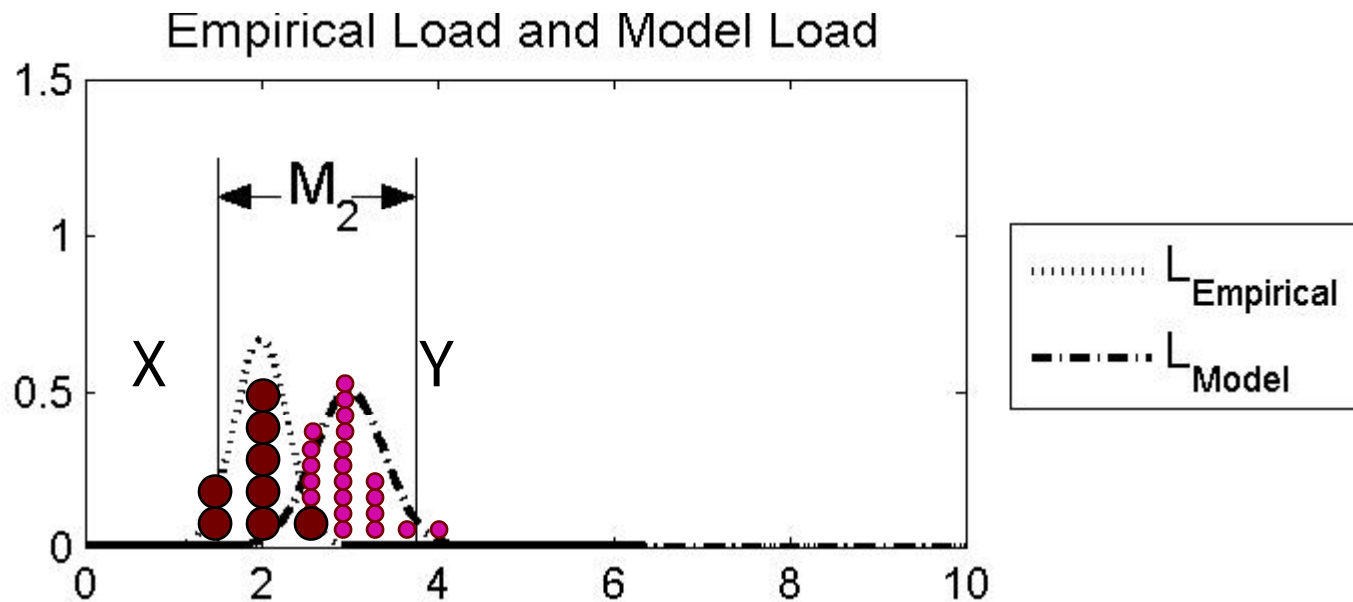
Another Approach to QMU



- Can make statements like $P(Z < X + M) < \beta$
- Employs what distribution data there is
- Makes very little use of the tails of the distributions
- Includes some of the sense of *factor of safety*



Another Approach to QMU: Connection to Validation

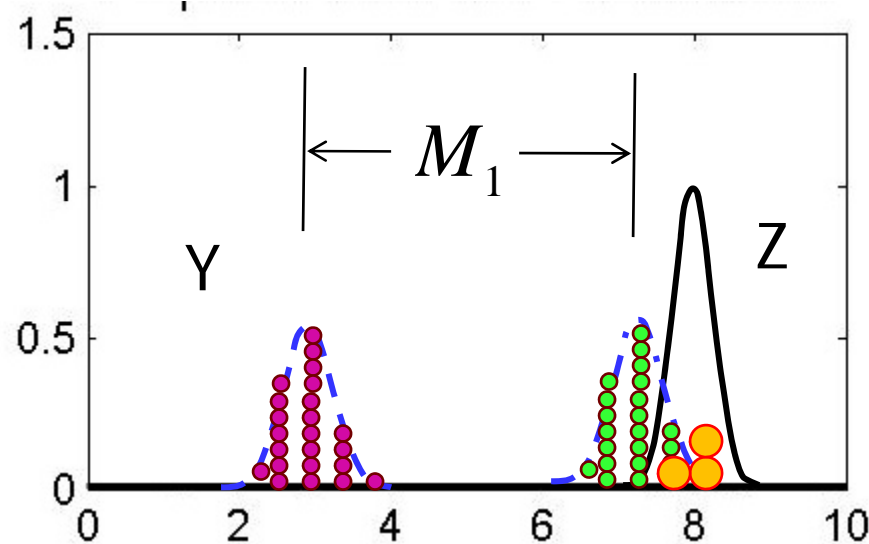


- Note: All models have systematic error
- One may talk about the distance from model to experiment

$$P(X > Y - M_2) < \beta_2$$



Another Approach to QMU: Interpreting Model Predictions



$$P(Z < Y + M_1) < \beta_1$$

- Including *Margin* and *Probability*
- Without reference to tails



Another Approach to QMU: Combination of Inequalities

Margin Predicted by Model

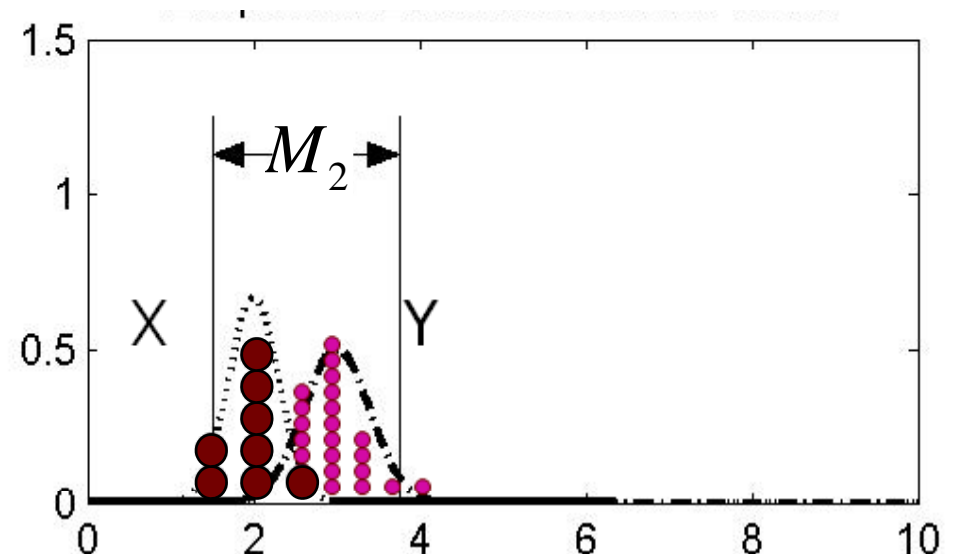
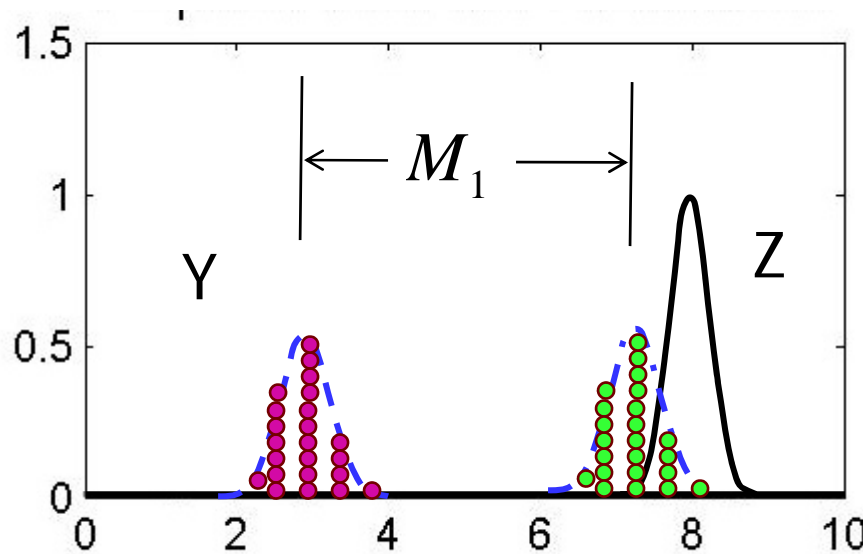
$$P(Z < Y + M_1) < \beta_1$$

Statement of Model Accuracy

$$P(X > Y - M_2) < \beta_2$$

Deduce

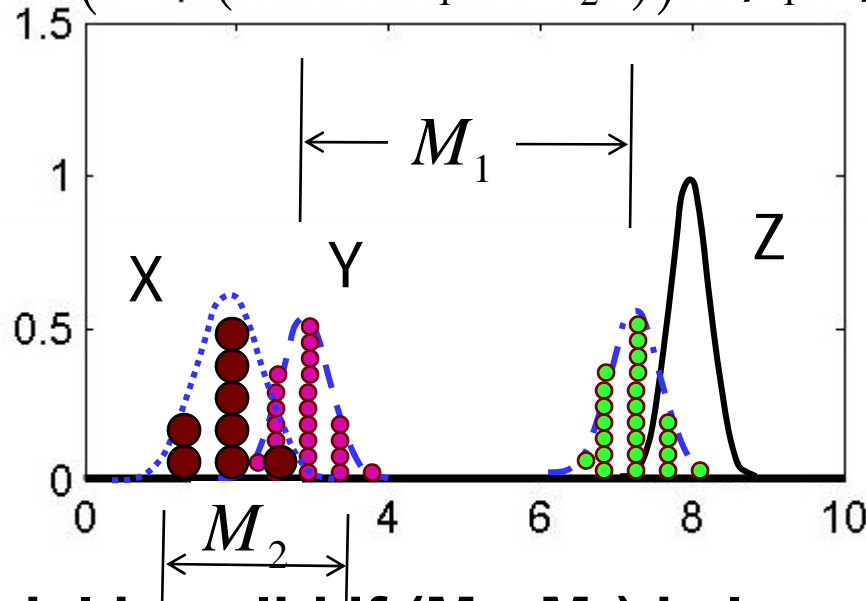
$$P\left(Z < \left(X + (M_1 + M_2)\right)\right) < \beta_1 + \beta_2$$





When is a Model Valid for Design/Certification of a System?

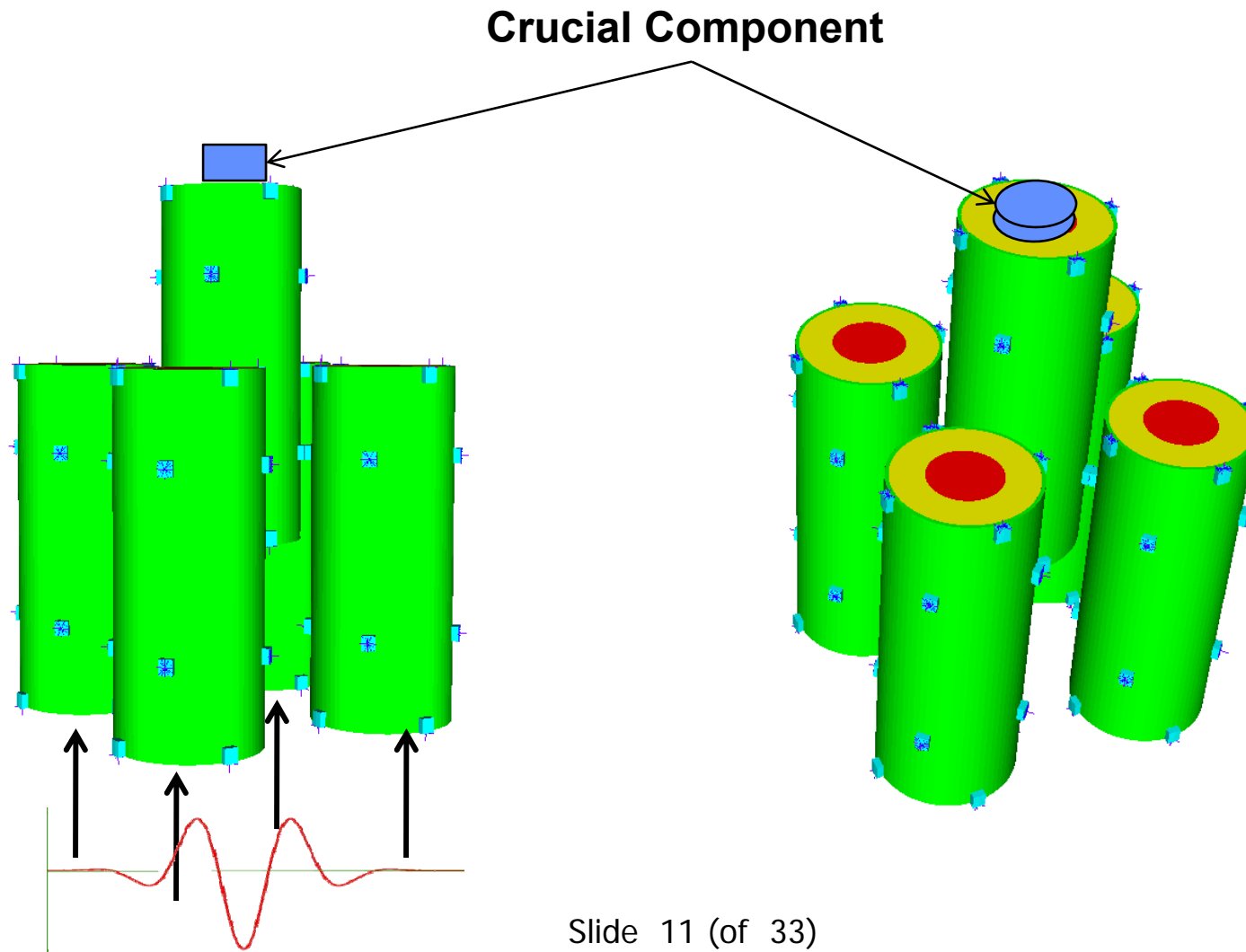
$$P(Z \leq (X + (M_1 + M_2))) < \beta_1 + \beta_2$$



- The model is valid if $(M_1 + M_2)$ is large enough and $\beta_1 + \beta_2$ is small enough to satisfy the designer.
- This definition can be implemented without much knowledge of tails of distribution.



An Artificial Example Problem: Blast Loads on a Jointed Structure





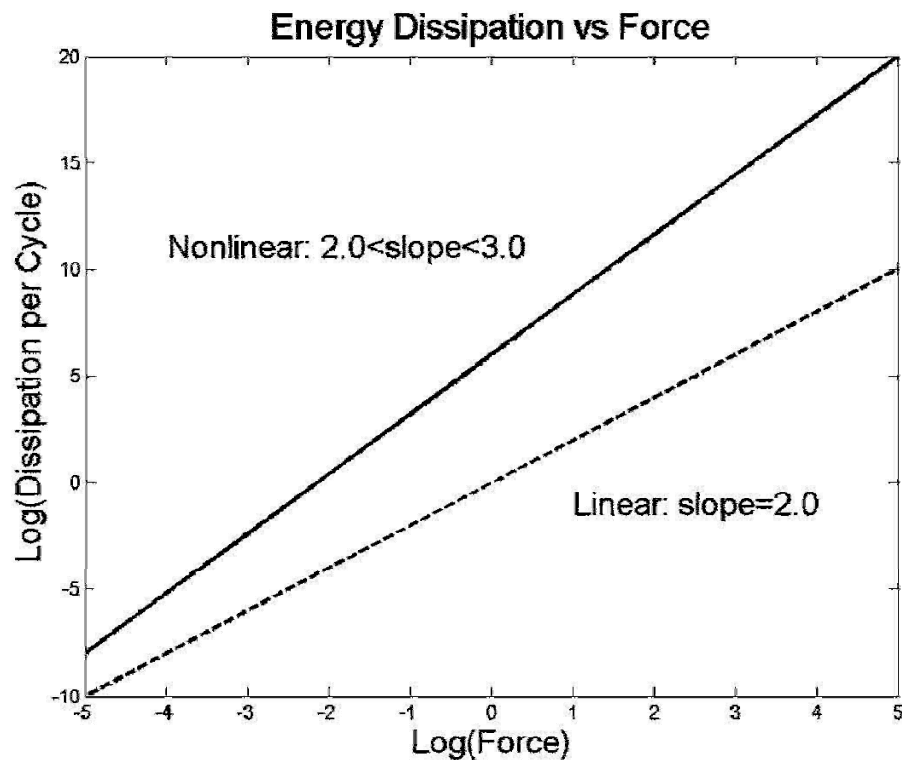
Note Intrinsic Nonlinearity and Variability in Joints (Bolted, Compression, Threaded, ...)

- 1. Bolted Joint Nonlinearities and Models**
- 2. Bolted Joint Variability**
- 3. Limitations of Testing and Parameterization**
- 4. Limitations of Fine-Mesh Finite Element Modeling and Parameterization**
- 5. Integration of Experimental and FMFE Properties**
- 6. Integration into Structural Modeling**



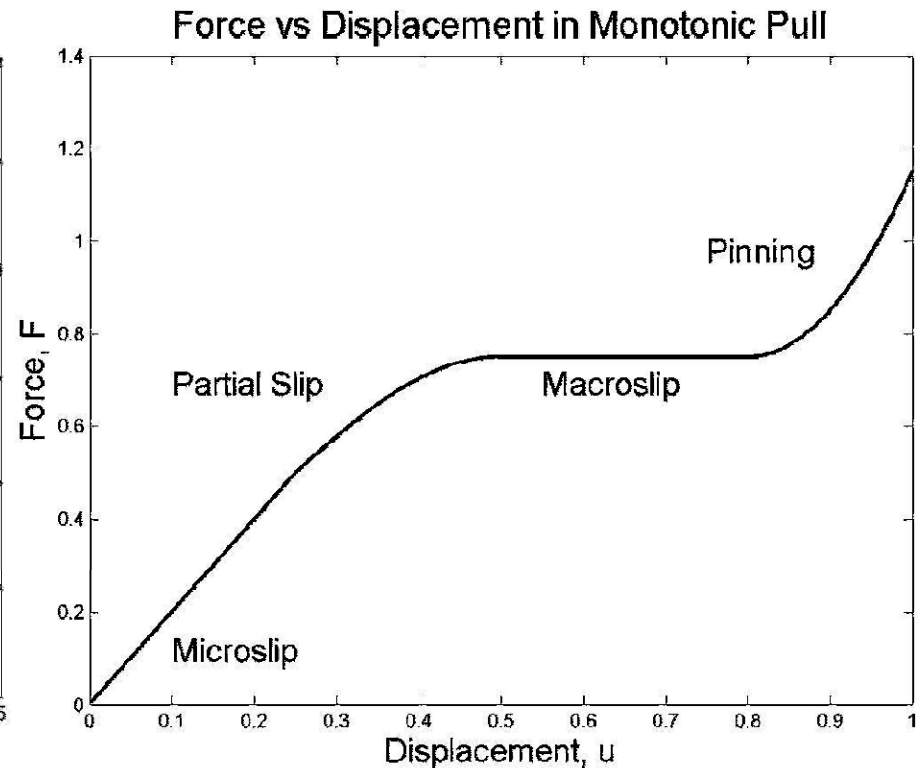
Empirical Nonlinearity of Joints

Base Excitation or Free Vibration



**Nonlinearities even at
Small Displacement**

Monotonic Pull

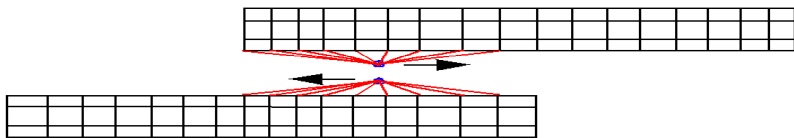


Large Displacement

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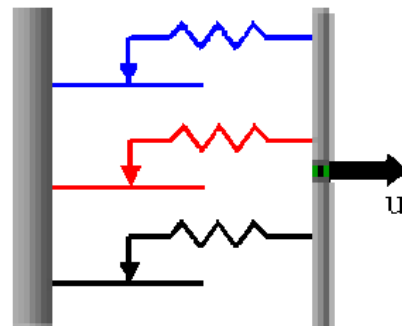
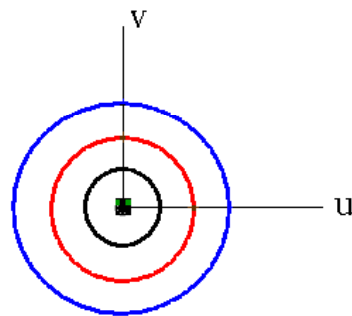
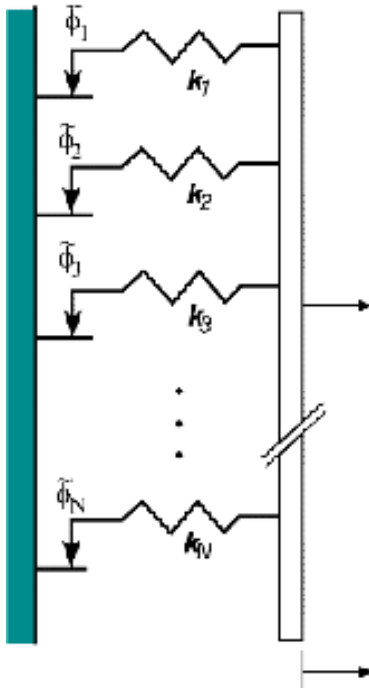
The Whole-Joint Approximation and Iwan Models for Shear Joints



Whole-Joint approximation for interface

$$f(t) = \int_0^\infty \rho(\phi) [u(t) - x(t, \phi)] d\phi$$

$$\dot{x}(t, \phi) = \begin{cases} \dot{u} & \text{if } |u - x(t, \phi)| = \phi \text{ and } \dot{u}(u - x(t, \phi)) > 0 \\ 0 & \text{otherwise} \end{cases}$$

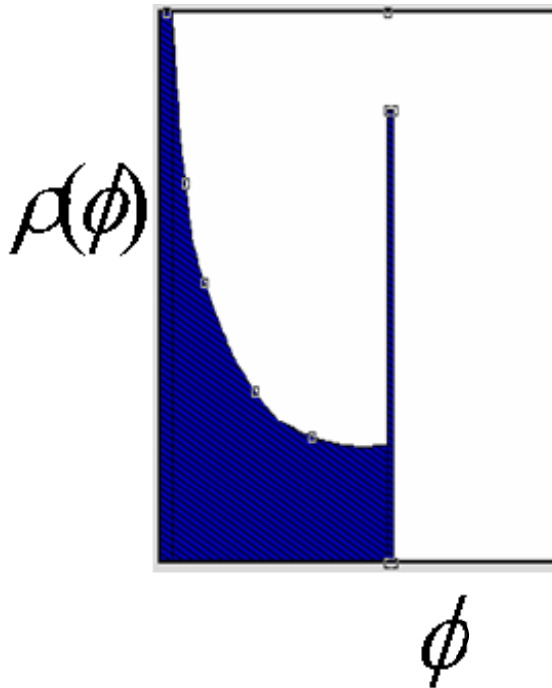


The joint properties are characterized by $\rho(\phi)$



A Four-Parameter Iwan Distribution

$$\rho(\phi) = R\phi^\chi (H(\phi) - H(\phi - \phi_{\max})) + S\delta(\phi - \phi_{\max})$$

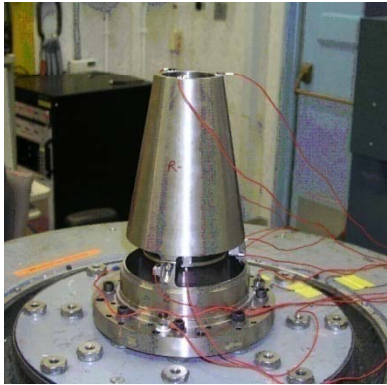


- Nearly linear behavior at low amplitude.
- Power-law energy dissipation
- Physically reasonable
- Tractable

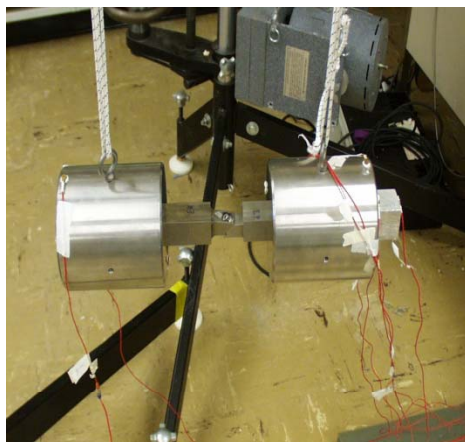
Parameters map into F_S, K_T, χ, β

- Macro-slip force
- Low-load stiffness
- Dissipation slope at small load
- Tangent stiffness at inception of macro-slip

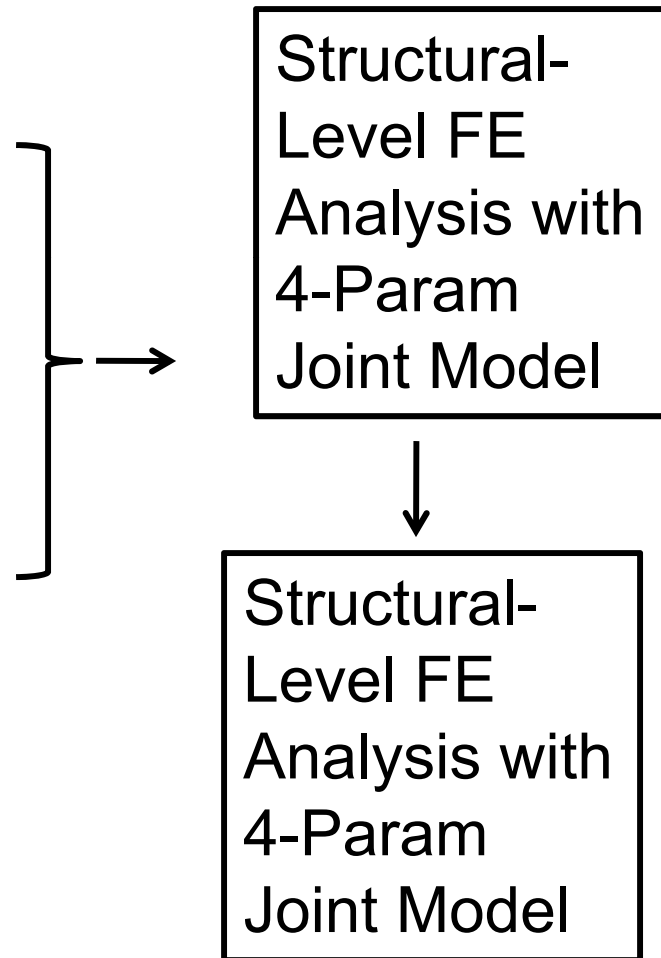
Calibration of Individual Joints to Predict Dynamics of 3-Legged Structure



Simple
Jointed
Structure



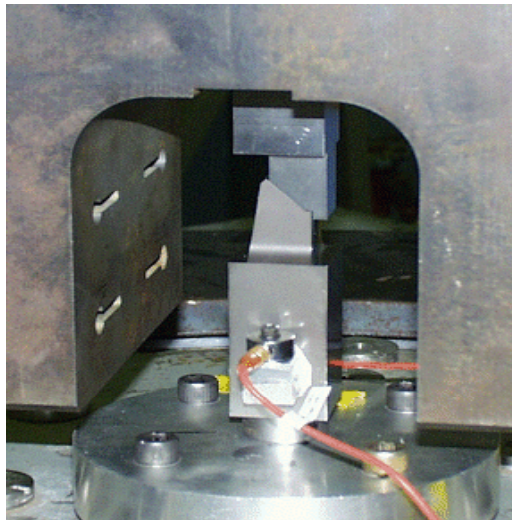
Calibration



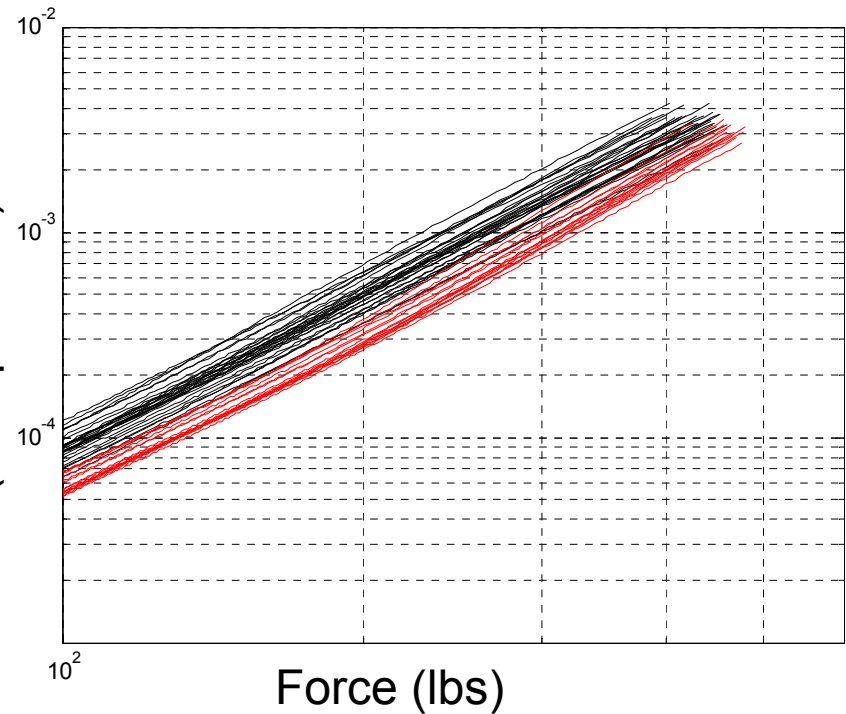


Variability of Joint Response and Scarcity of Data

Three “tops” and three “bottoms” yield nine unique
conformal joint assemblies



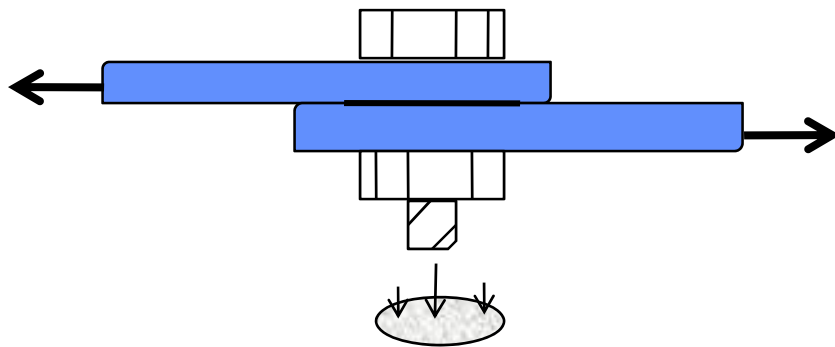
Energy Dissipation per Cycle
(inch-pounds)





Testing and Limitations

- **Scarcity**: Capturing variability requires many more specimens than are practically available.
- **Specificity**: Testing capabilities are not available for all loading combinations.

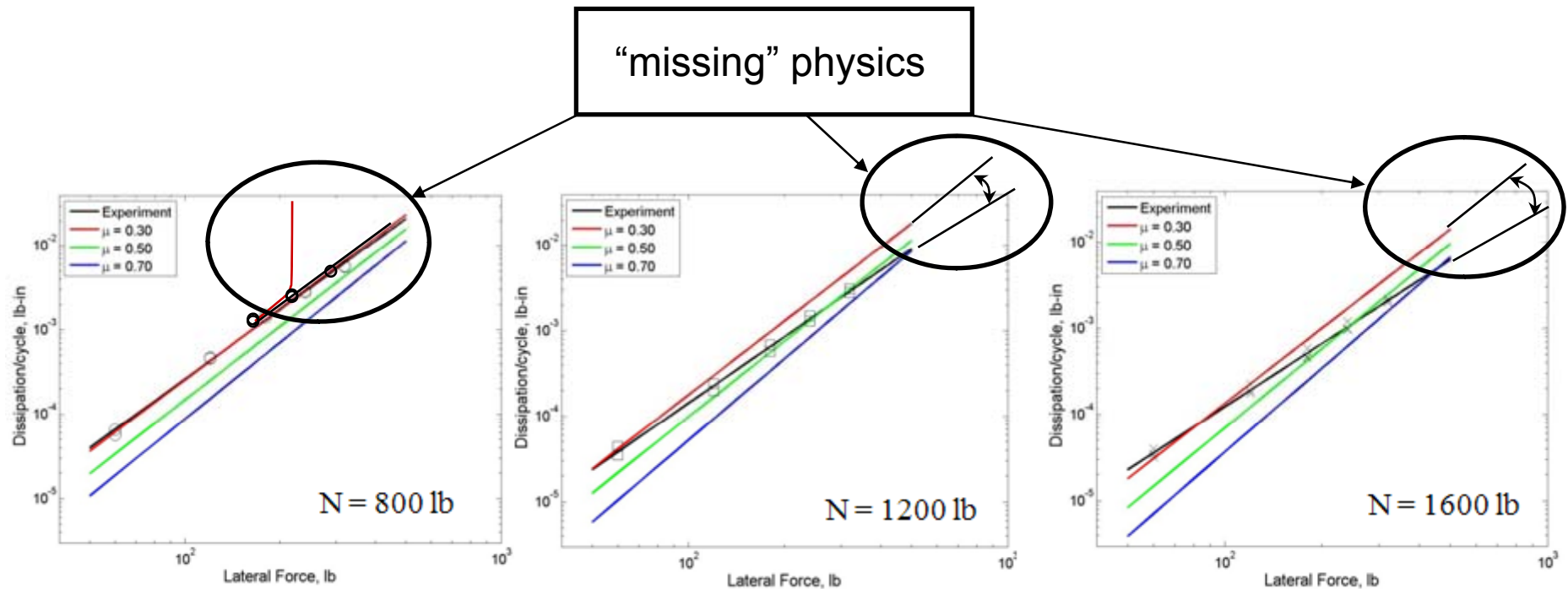


Individual Joint Experiments were Designed to Achieve Flush Connection.

- **Practicality**: Developing a test program for every joint configuration is also not practical.



Fine Mesh Finite Element Modeling (FMFE)



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FMFE modeling of joints using Coulomb friction yields similar, but different results than are seen in the laboratory.

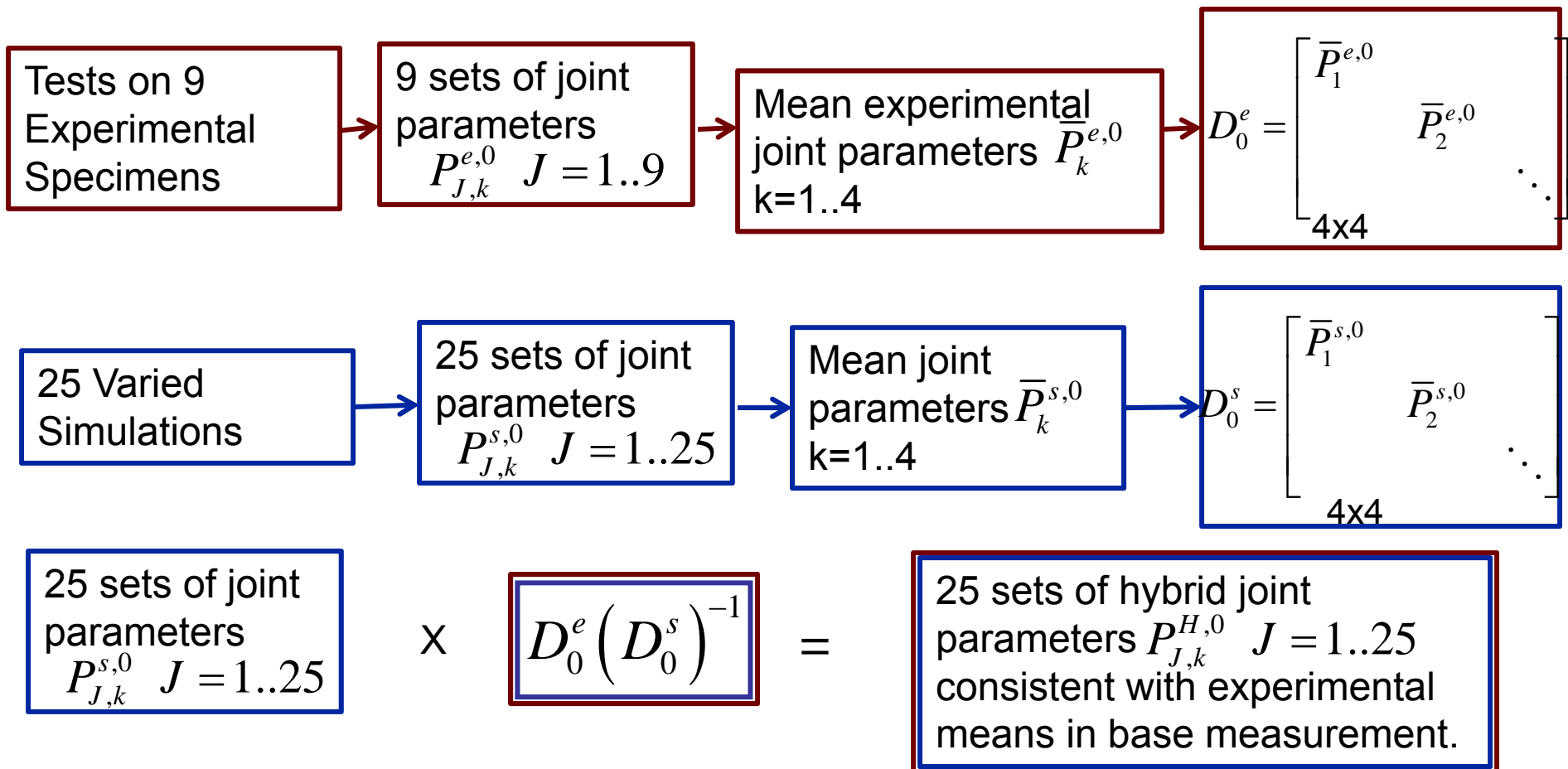
- Not all data can be fit by the same coefficient of friction
- FMFE predicts macro-slip where it is not observed.



How to Use FMFE to Leverage Laboratory Data

- 1. Extract basic parameter information from sparse laboratory data of a base experiment**
- 2. Considering FMFE results on the same experiments, create filter to make simulation results consistent with laboratory values.**
- 3.**
- 4.**

Reconciling Joint Parameters from FMFE with Scarce Experimental Data in Base Experiment





Generating Joint Parameters for Structural Dynamics Simulations

Recall from Base Experiment

25 sets of joint parameters
 $P_{J,k}^{s,0} \quad J = 1..25$

x

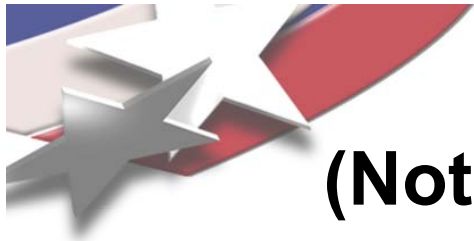
$$D_0^e \left(D_0^s \right)^{-1}$$

=

25 sets of hybrid joint parameters $P_{J,k}^{H,0} \quad J = 1..25$ consistent with experimental means in base measurement.

Principal Component Analysis (log normal)

Pool of 2000_~ joint parameters $\tilde{P}_{J,k}$ having experimental means of base experiment and reproducing correlations from simulations



Notionally

(Note, Actual Distribution is of 4-Vectors)

Scaling adjusts the results of the many FMFE analysis to be statistically consistent with the sparse experimental data.



Sparse
Experimental
Data of Base
Experiment

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FMFE
Simulations
of Base
Experiment

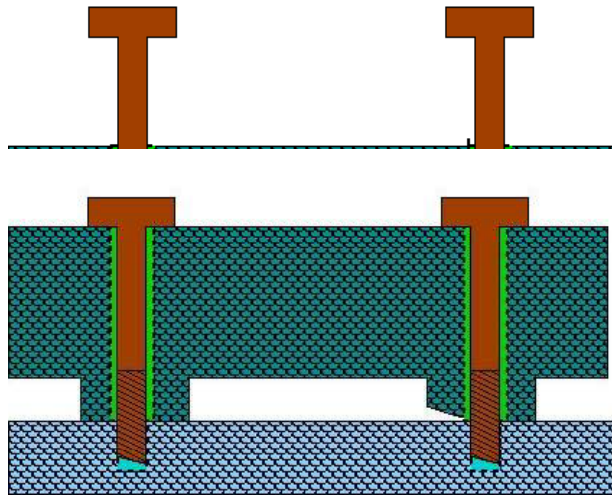


How to Use FMFE to Leverage Laboratory Data

1. Extract basic parameter information from sparse laboratory data of a base experiment
2. Considering FMFE results on the same experiments, create filter to make simulation results consistent with laboratory values.
3. **Use FMFE simulation to provide results for other boundary conditions and correct with filter of Step 2.**
4. **Do the above in a manner that yields useful estimates of parameter uncertainty.**



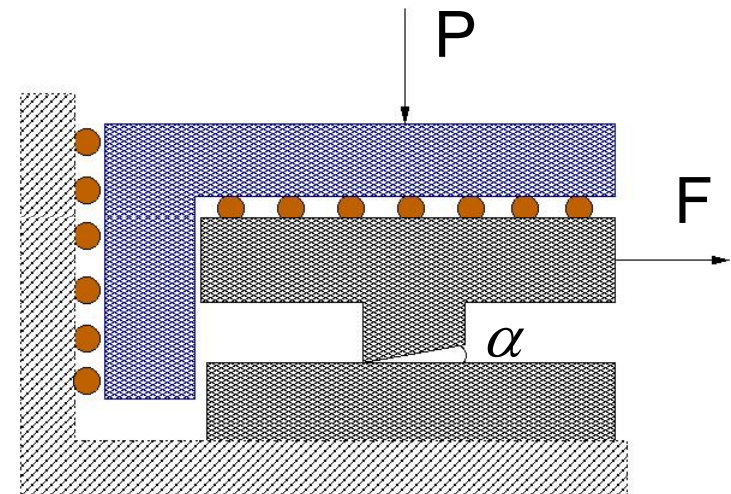
Joints in Statically Indeterminate Structures



In general, statically indeterminate structures will have non-flush interfaces.



200 lb Force are required to align the bolt holes



$$-0.1^\circ < \alpha < 0.1^\circ$$

Experiment of interface with angular off-set.

- Laboratory experiments unavailable so far.
- FMFE experiments are performed in straight-forward manner.



Use of Joint Parameters from FMFE Conditions other than Base Experiment

Recall from Base Experiment

25 sets of joint
parameters
 $P_{J,k}^{s,0}$ $J = 1..25$

\times

$$D_0^e \left(D_0^s \right)^{-1}$$

$=$

25 sets of hybrid joint
parameters $P_{J,k}^{H,0}$ $J = 1..25$
consistent with experimental
means in base measurement.

For Simulations of other Boundary Conditions

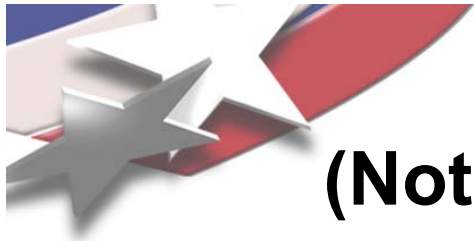
M sets of joint
parameters $P_{J,k}^H$
over variety of
conditions (preload,
surface topography,
misalignment,...)

\times

$$D_0^e \left(D_0^s \right)^{-1}$$

Principal Component
Analysis (log normal)

Pool of MANY joint
parameters $\tilde{P}_{J,k}$
reflecting anticipated
variability in preload,
surface topography,
misalignment, ...

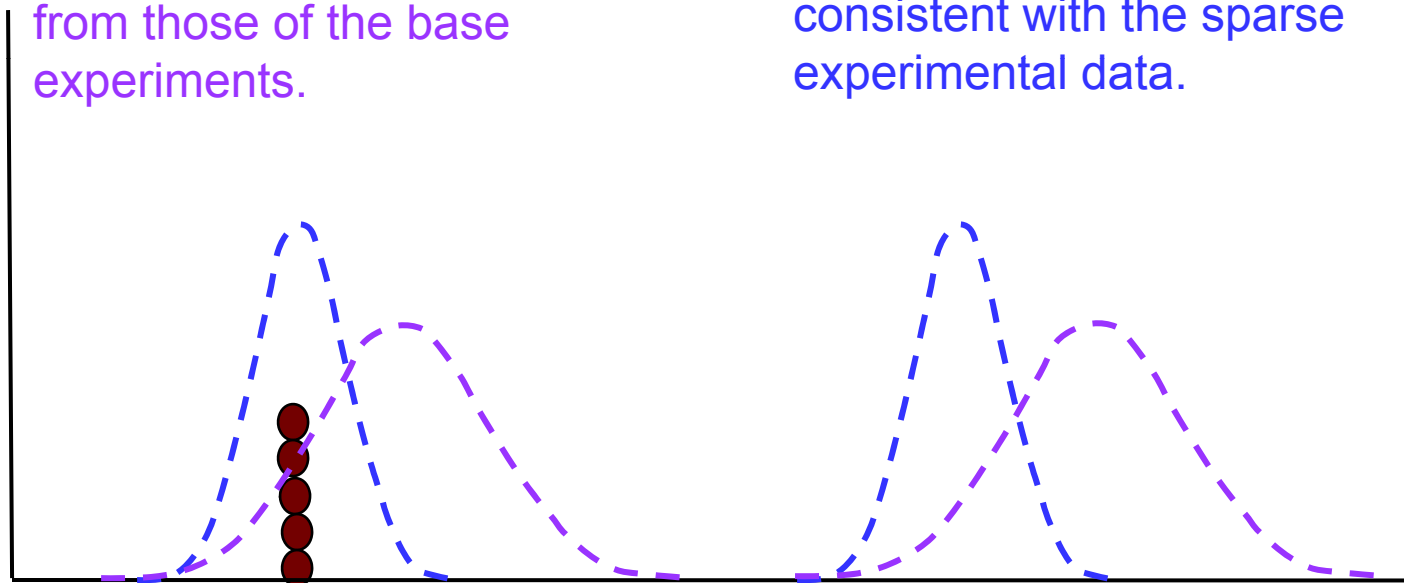


Notionally

(Note, Actual Distribution is of 4-Vectors)

Scaling adjusts the results of the many more FMFE analysis, though the statistics are different from those of the base experiments.

Scaling adjusts the results of the many FMFE analysis of the **Base Experiment** to be statistically consistent with the sparse experimental data.



Sparse
Experimental
Data of **Base**
Experiment

FMFE Simulations
of **Base**
Experiment

FMFE Simulations
over Distribution
of α

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Where are We Now?

- **Sparse amount of laboratory joint data for a base experiment (flush interface)**
- **Constitutive model that reproduces joint behavior for the configurations of calibration**
- **MP Fine-Mesh Finite Element simulations provide many sets of joint parameters, though the simulations do not quite jibe with base laboratory experiments.**
- **Scaling process to adjust mean properties of FMFE results for base experiments**
- **Extension of scaling process for other experiments**



Structural Modeling and Margins

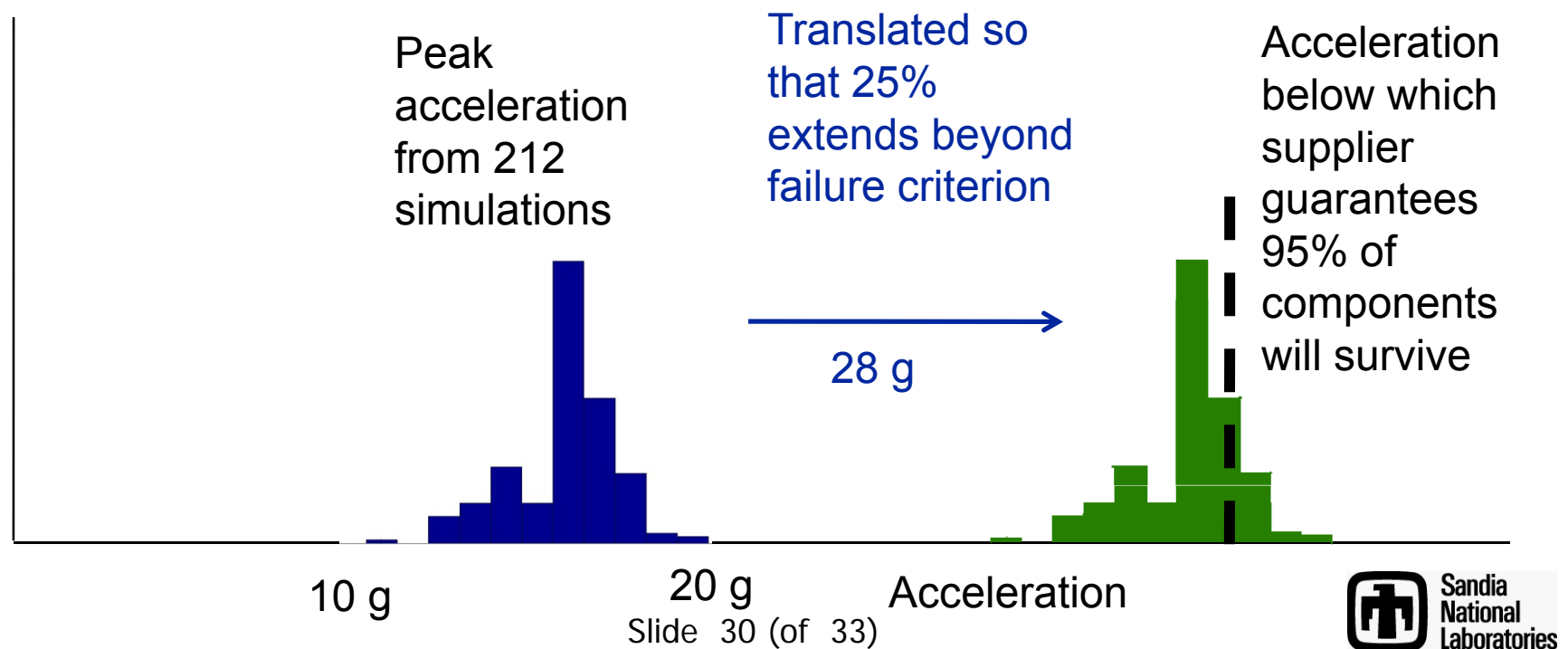
- **Many finite element dynamics simulations**
 - **Employing joint parameters selected from distribution devised as discussed above (capturing distributions of preload, surface properties, misalignment)**
 - **Predicting accelerations of key components**
- **Some failure criterion, perhaps also expressed as a probability distribution.**



Simulations and Confidence

Statements of Confidence

1. Under the environment anticipated, the components would have to be accelerated 28g more than expected for even 28% to fail.
2. Under the environment anticipated, there is a 2.4 factor of safety that no more than 28% of components will fail.





Summary

- Have presented an mathematical approach to quantification of uncertainty retaining valuable features of traditional design engineering:
 - Makes almost no use of knowledge of tails of distributions
 - Retains the “Factor of Safety” notion of design engineering
 - Makes practical definition of model adequacy
- Typically, the designer/analyst must scrounge for data, attempting to reconcile and leverage data from disparate
- Demonstration of how even when there is a lot of uncertainty in model parameters, *useful* statements can be made.



R&A

Submittal Details	
Document Info	
Title : Reliability, QMU, Systematic Error & Model Acceptance Criteria	
Document Number : 5273594	SAND Number : 2009-4242 C
Review Type : Electronic	Status : Approved
Sandia Contact : SEGALMAN,DANIEL J.	Submittal Type : Conference Paper
Requestor : SEGALMAN,DANIEL J.	Submit Date : 07/08/2009
Comments : This is the presentation associated with abstract having SAND number 2009-1174 A	
Peer Reviewed? : N	
Author(s)	
PAEZ,THOMAS L.	SEGALMAN,DANIEL J.
Event (Conference/Journal/Book) Info	
Name : US National Congress on Computational Mechanics	
City : Columbus	State : OH Country : USA
Start Date : 07/16/2009	End Date : 07/19/2009
Partnership Info	
Partnership Involved : No	
Partner Approval :	Agreement Number :
Patent Info	
Scientific or Technical in Content : No	
Technical Advance : No	TA Form Filed : No
SD Number :	
Classification and Sensitivity Info	
Title : Unclassified-Unlimited	Abstract : Document : Unclassified-Unlimited
Additional Limited Release Info : None.	
DUSA : None.	