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ROBUST DECISION-MAKING
Applied to Model Selection

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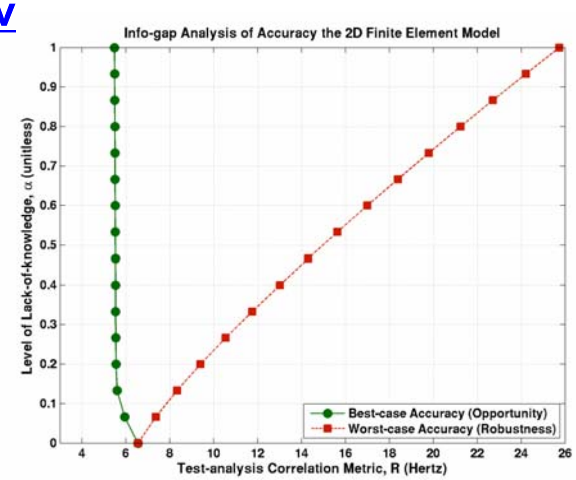

Abstract

ROBUST DECISION-MAKING APPLIED TO MODEL SELECTION

The scientific and engineering communities are relying more and more on numerical models to simulate ever-increasingly complex phenomena. Selecting a model, from among a family of models that meets the simulation requirements, presents a challenge to modern-day analysts. To address this concern, a framework is adopted anchored in info-gap decision theory. The framework proposes to select models by examining the trade-offs between prediction accuracy and sensitivity to epistemic uncertainty. The framework is demonstrated on two structural engineering applications by asking the following question: *Which model, of several numerical models, approximates the behavior of a structure when parameters that define each of those models are unknown?* One observation is that models that are nominally more accurate are not necessarily more robust, and their accuracy can deteriorate greatly depending upon the assumptions made. It is posited that, as reliance on numerical models increases, establishing robustness will become as important as demonstrating accuracy.

(Approved for unlimited, public release on August xx, 2012, LA-UR-12-xxxx.)

Acknowledgments

- Professor Yakov Ben-Haim, Technion
- Dr. Christopher Stull, Los Alamos National Laboratory
- Kendra Van Buren, Clemson University

Outline

- Opening comments on “culture change”
- Framework for establishing robustness
- Application to Earthquake engineering
- Application to the CX-100 wind turbine blade
- Concluding remarks

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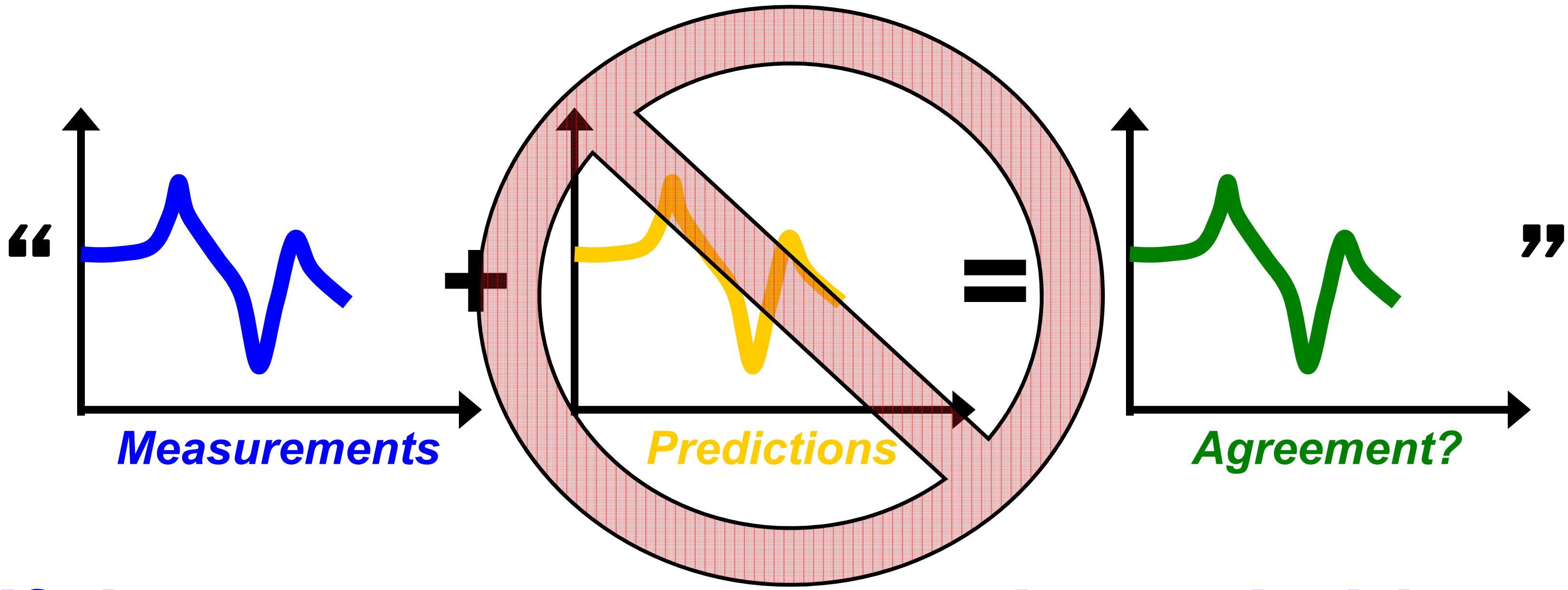
Despite nearly two decades of tremendous ASC achievements, "culture" remains a significant hurdle at National Laboratories.

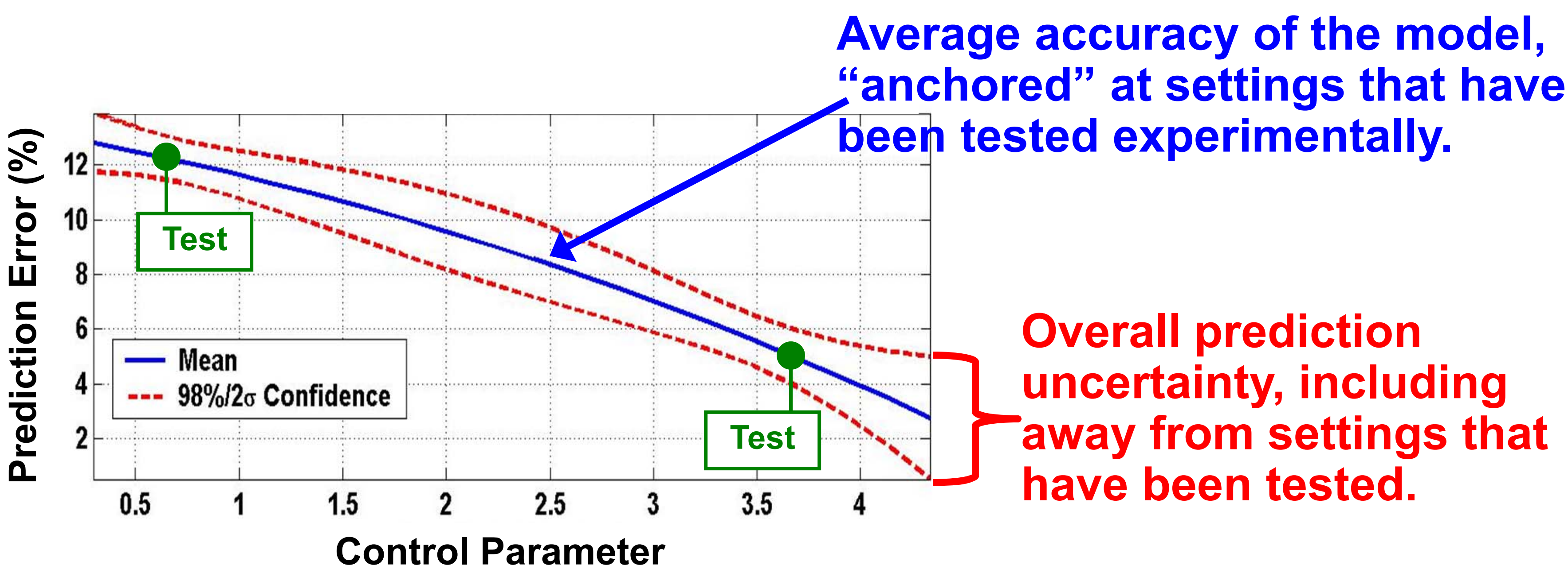
- A computational model is still considered "good-quality" if its predictions match the physical measurements.
- These predictions are, in fact, only "post-dictions."
- It renders "validation" synonymous to calibration.
- Calibration requires to execute physical experiments.
- Calibrated models are well-known to exhibit little-to-no forecasting "power" away from tested configurations.

The quote below exemplifies this state-of-the-practice; it is from one of the most well-respected designers at Los Alamos.



“If the measurements are shown in blue and predictions are shown in yellow, then all that I want to see is green.”

My contention is that "predictability" is the quantification of prediction *accuracy* and *uncertainty*, including away from settings that have been tested experimentally.(#)



(#) Caveat: As long as the "extrapolation" of predictions away from settings that have been tested, is justified physically.

Mature technology is available to analyze *aleatoric* sources of uncertainty … but progress has been slow when dealing with issues that do not fit this "mold."

- What if a source of uncertainty cannot be described as random variability of one of the code parameters?
- What about types of uncertainty that are due to our *ignorance*, such as an assumption or discretization?
- How are different types of uncertainty aggregated?
- How to establish the forecasting "power" of a model that may have been (partly) calibrated?
- … And numerical uncertainty, due to truncation effects, is still largely ignored. (But that's another story.)

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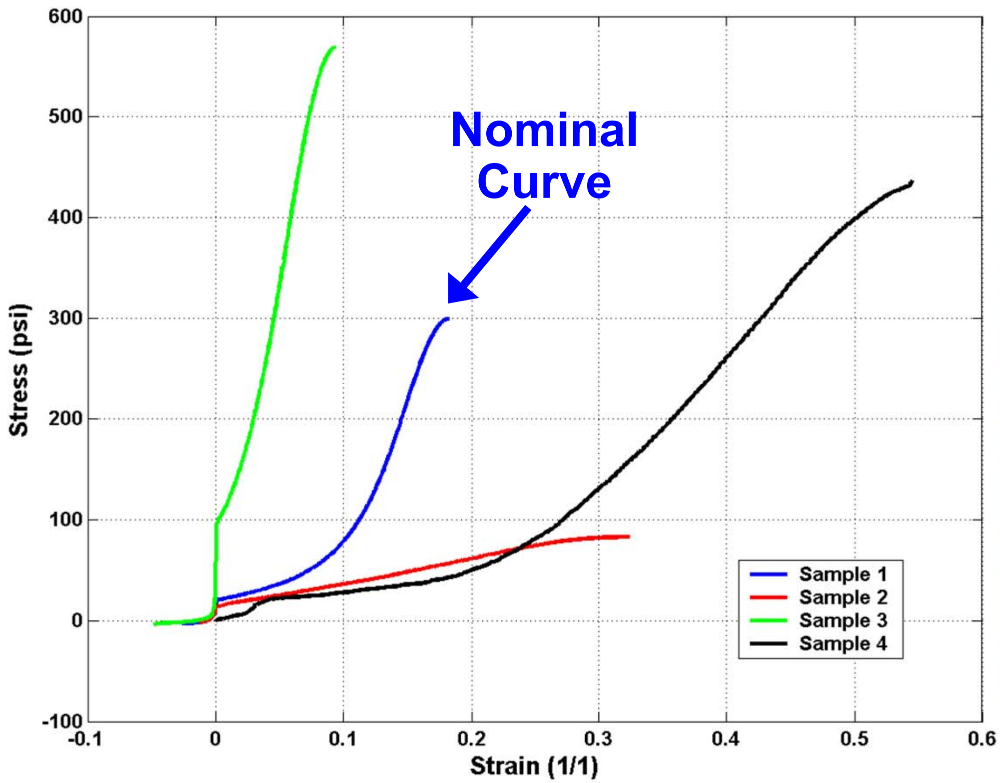
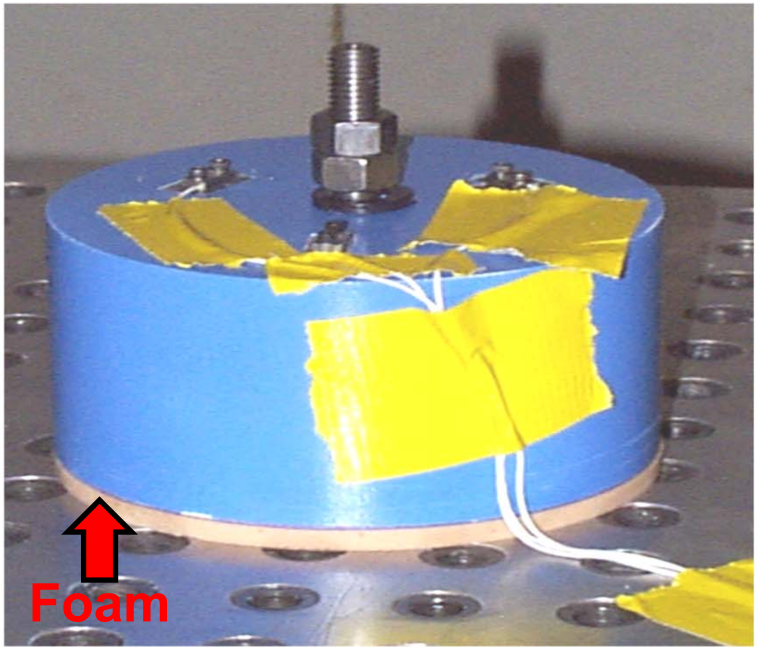
My contention is that this lack-of-progress results from our tendency to often treat *ignorance* and *variability* interchangeably.

- **Changes in predictions, due to (random) experimental variability, can be explored through statistical sampling.**
- **The role of an assumption, such as the level of mesh resolution or choice of a particular model structure, is to mitigate an existing lack-of-knowledge (or ignorance).**
- **It makes no sense to "sample" these assumptions!**
- **Instead, one should demonstrate that the predictions are as insensitive as possible (or *"robust"*) to these choices.**

"Lack-of-knowledge ≠ Randomness"

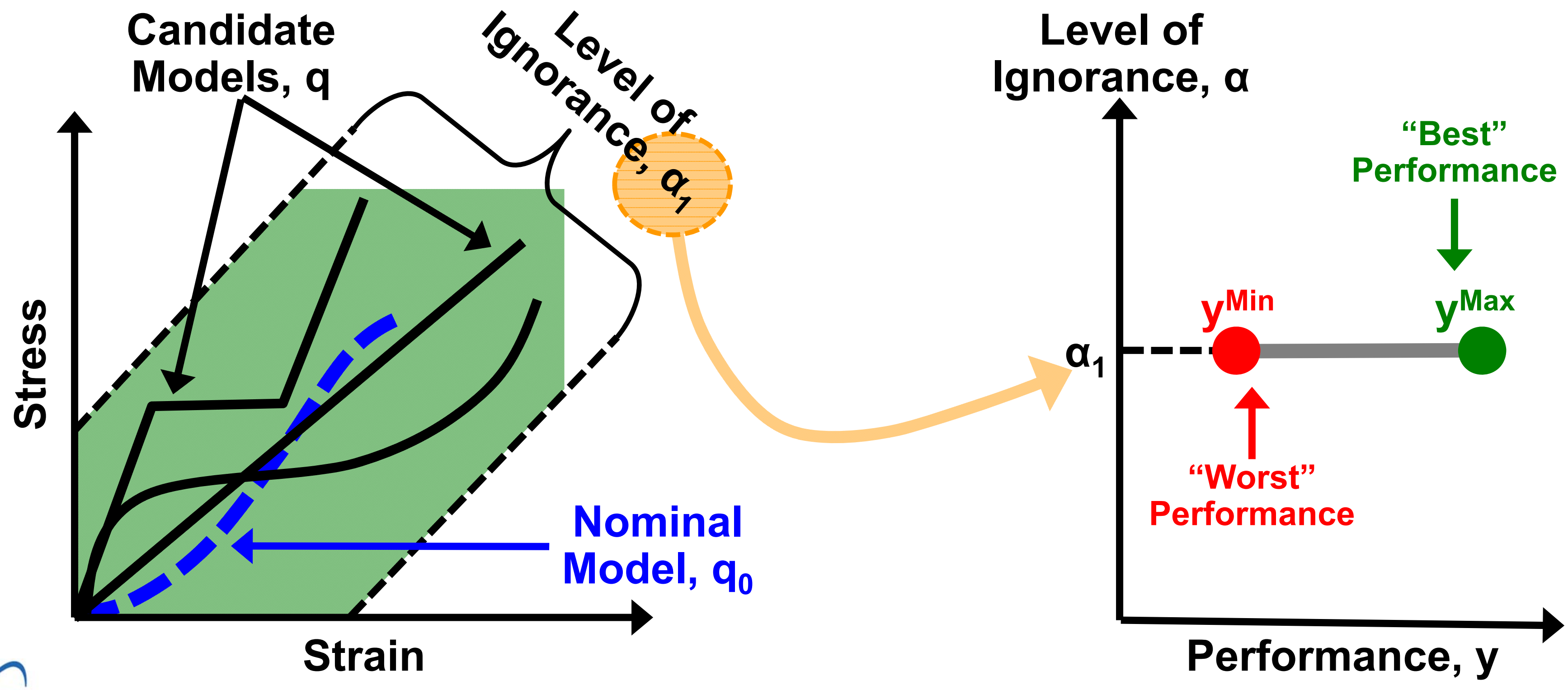
Consider, for example, a foam material … Can predictions, that may be sensitive to how the material is modeled, be trusted?



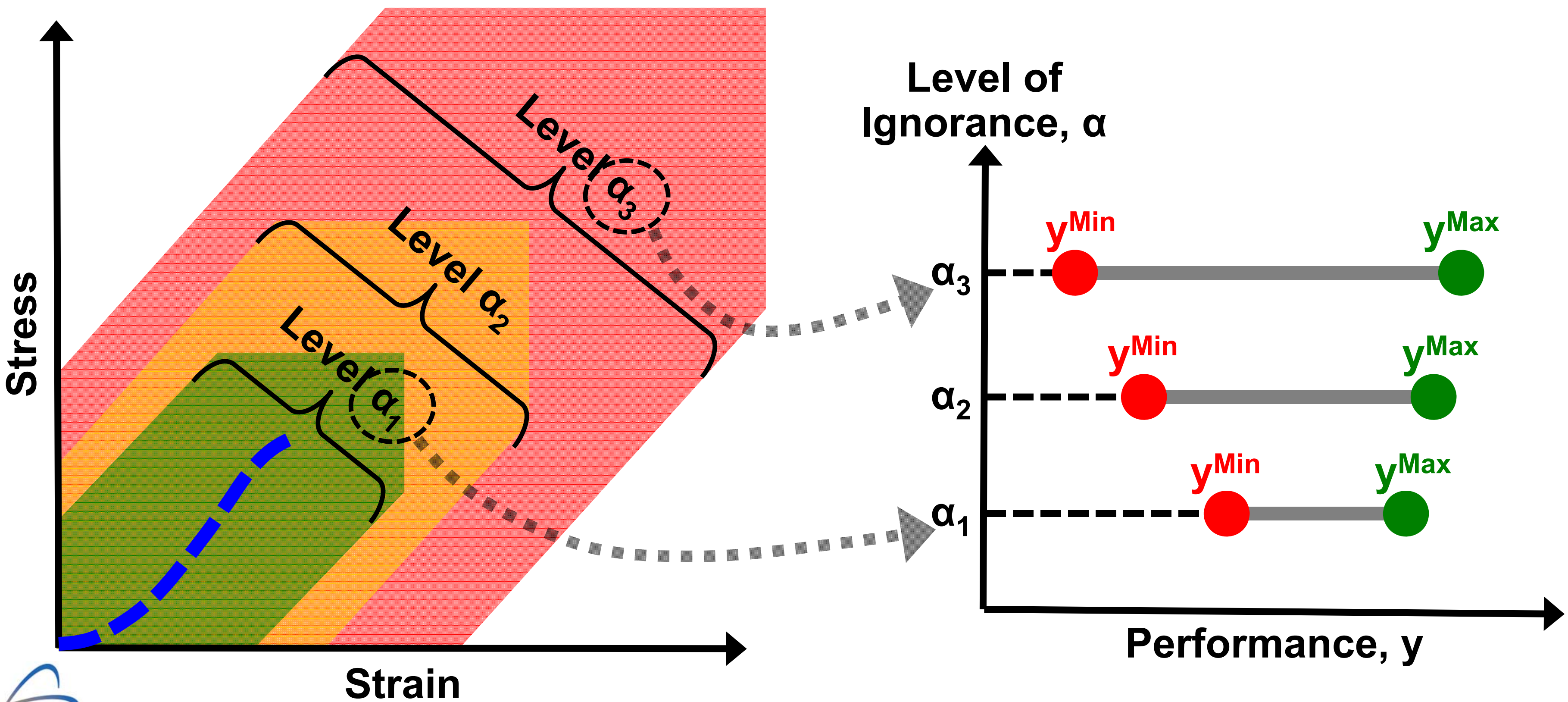


Reference: LA-UR-04-4650.

The influence on predictions exercised by a *family* of candidate material models is explored, up to a given level of ignorance.



Robustness is quantified by exploring the effect on code predictions of progressively increasing the level of ignorance.



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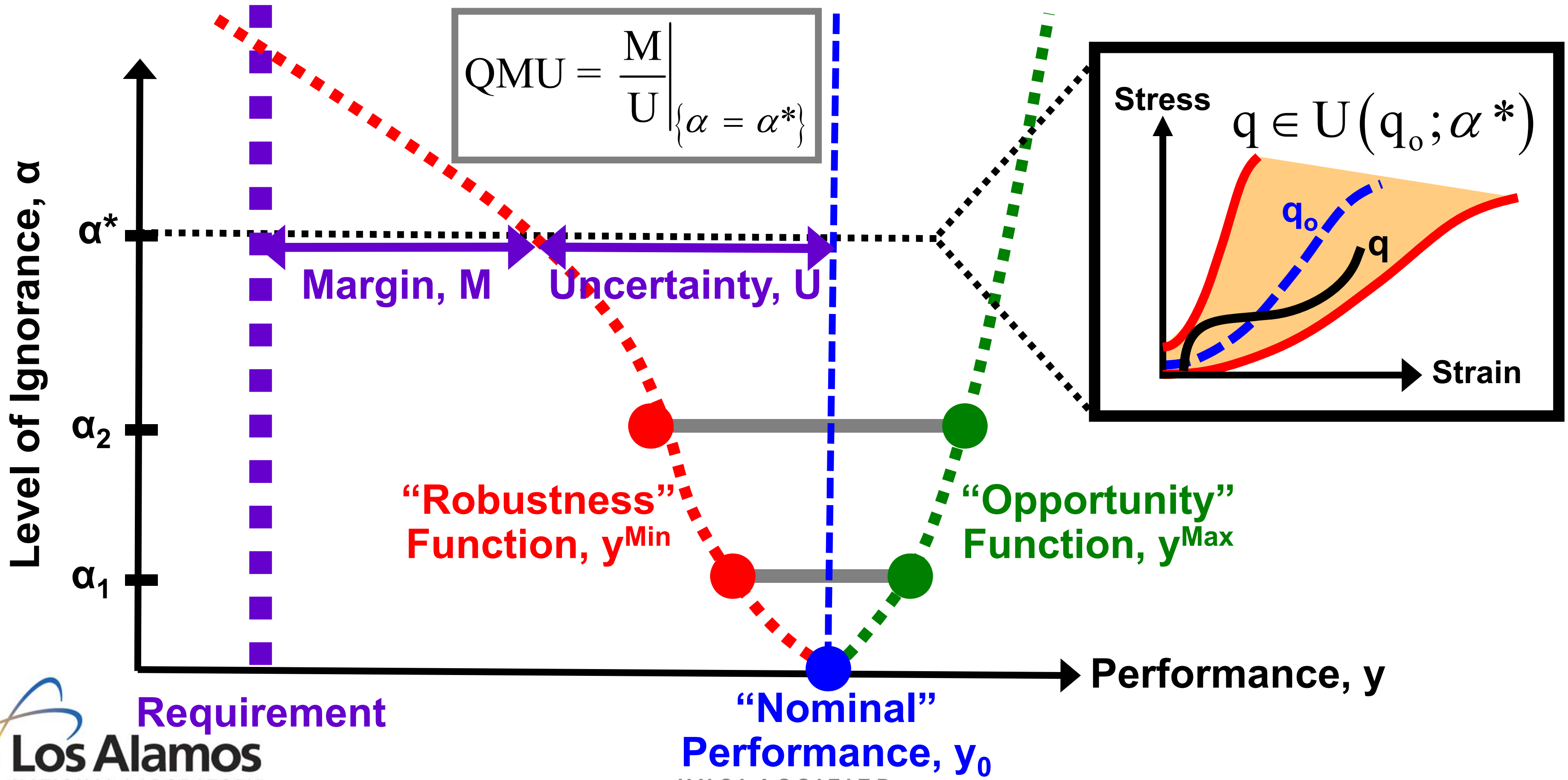
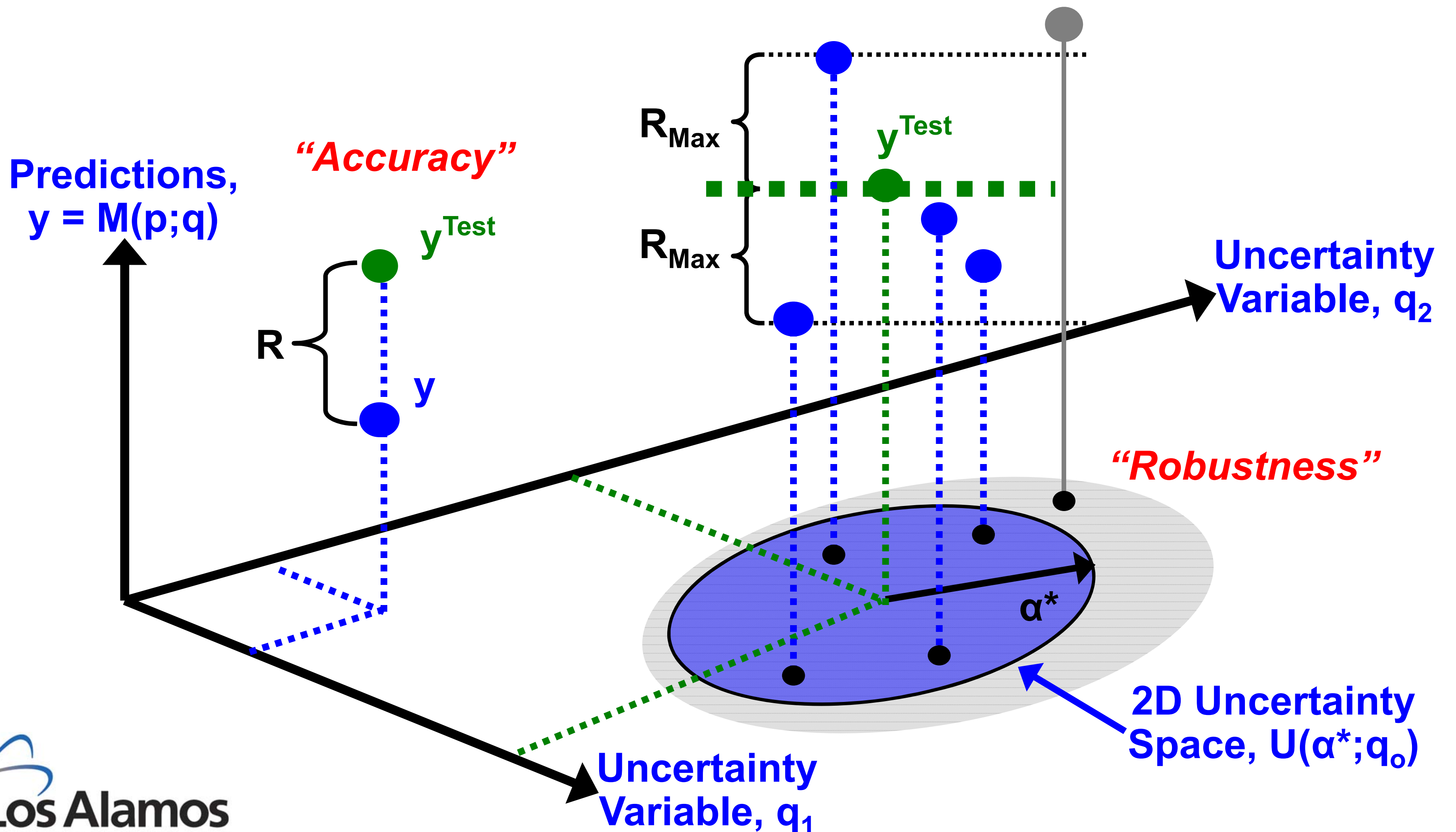
This framework *integrates* decision-making seamlessly, irrespective of the type of uncertainty considered in the analysis.



For model selection, "performance" is simply defined as the prediction accuracy.



For any family of models, there always is a *trade-off* between prediction accuracy and robustness to ignorance. (It is a theorem!)

- **Accuracy R is quantified using a fidelity-to-data metric.**
- **Robustness α* is the maximum level of ignorance α for which all models of a family $U(\alpha;q_o)$ meet the accuracy requirement R_{Max}.**

$$R = \left\| y^{Test} - y(p;q) \right\|$$

Yakov Ben-Haim, Technion, Israel

$$\alpha^* = \underset{\alpha \geq 0}{\mathrm{Argmax}} \left\{ R \leq R_{Max} \text{ for all } y \in U(\alpha; q_o) \right\}$$

- **The accuracy R_{Max} and robustness α* of a family of models are antagonistic!**

$$\text{"}\frac{\partial\, \text{Robustness}}{\partial\, \text{Accuracy}} \leq 0\text{"}$$

Reference: Ben-Haim, Y., Hemez, F.M., *Royal Society Proceedings A*, Sep 2011. LA-UR-11-0497.

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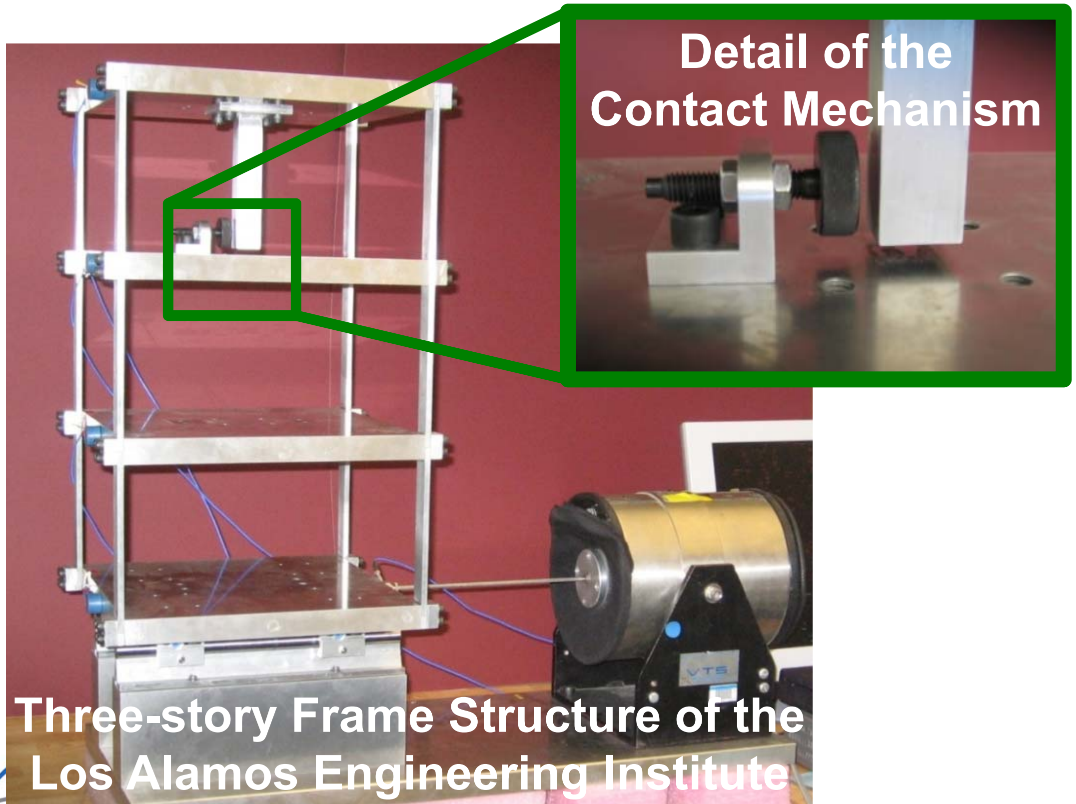
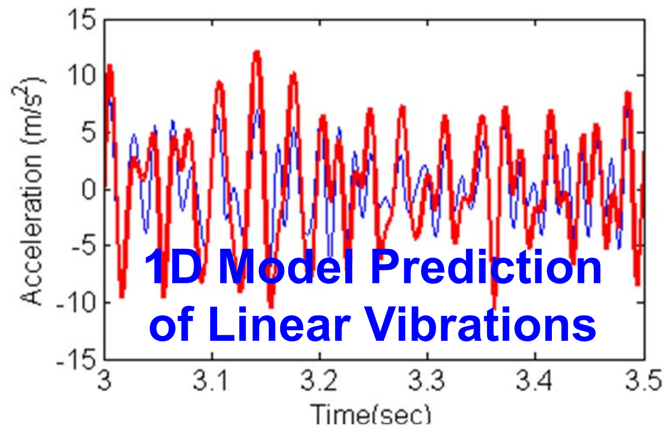
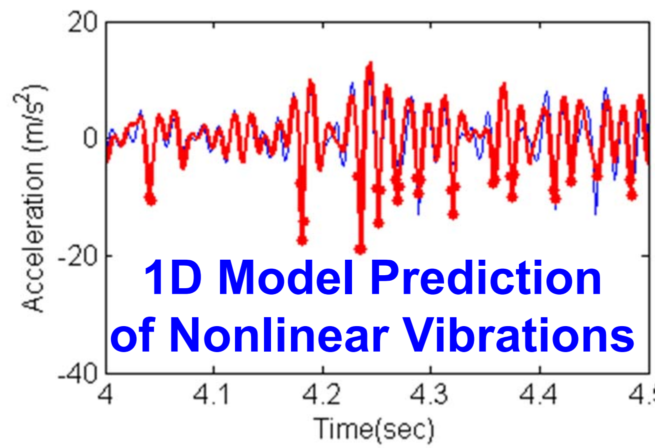
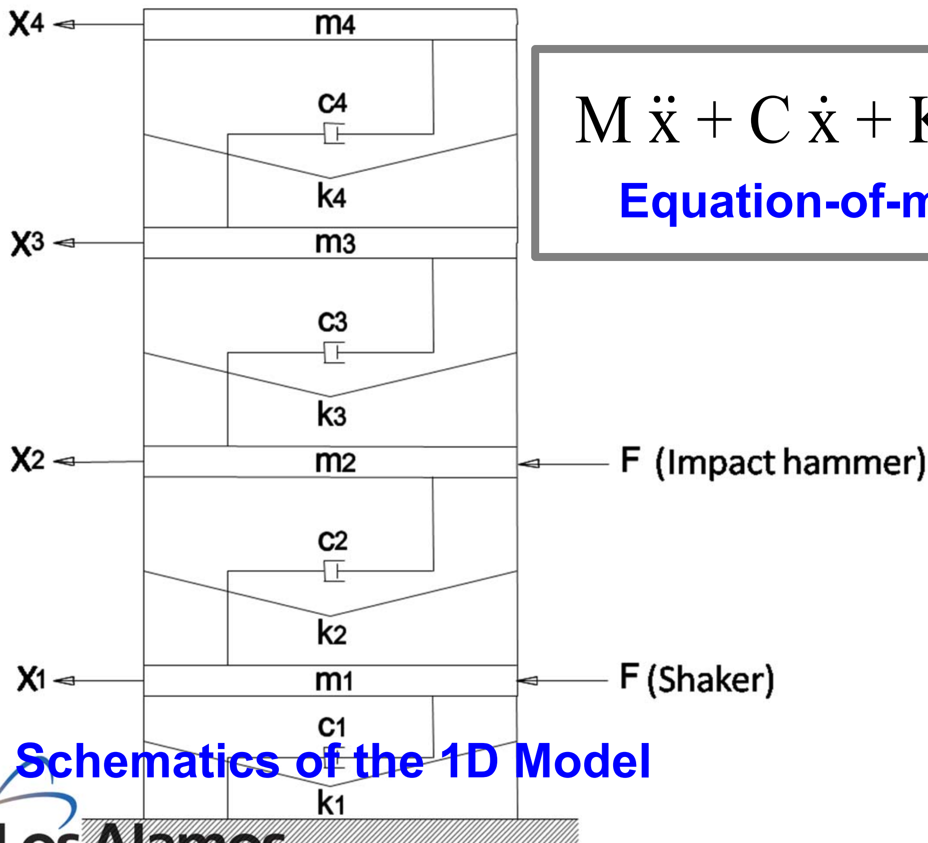
This application selects a computational model to simulate the vibration response of a scaled, three-story frame structure.







The 1D model simulates bending vibration with a calibrated assembly of masses, spring stiffness and damping coefficients.



Schematics of the 1D Model

$$M\ddot{x} + C\dot{x} + Kx = F$$

Equation-of-motion

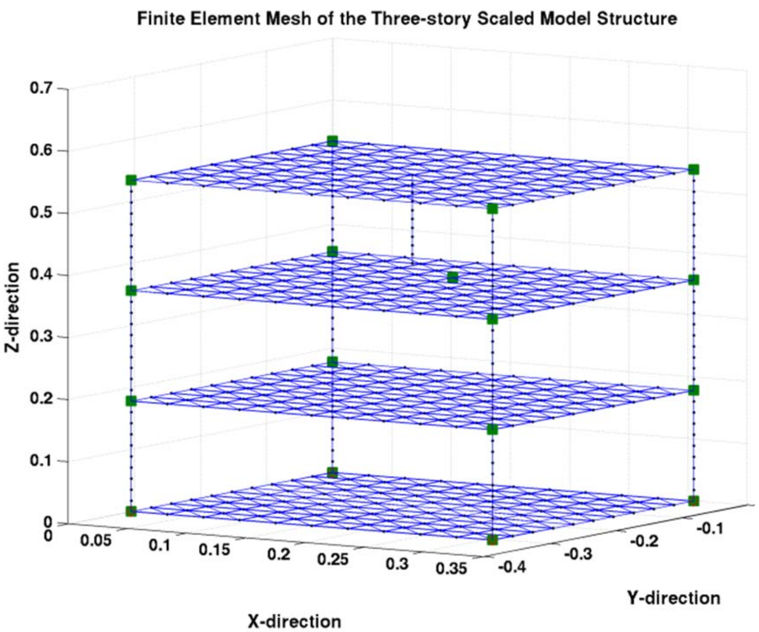
$$M = \begin{bmatrix} m_1 & 0 & 0 & 0 \\ 0 & m_2 & 0 & 0 \\ 0 & 0 & m_3 & 0 \\ 0 & 0 & 0 & m_4 \end{bmatrix}$$

$$K = \begin{bmatrix} k_1+k_2 & -k_2 & 0 & 0 \\ -k_2 & k_2+k_3 & -k_3 & 0 \\ 0 & -k_3 & k_3+k_4 & -k_4 \\ 0 & 0 & -k_4 & k_4 \end{bmatrix}$$

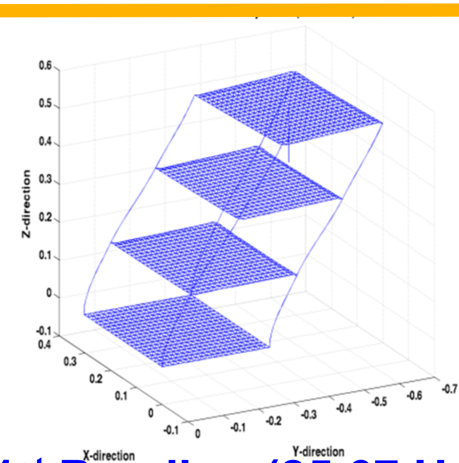
$$C = \begin{bmatrix} 2\zeta_1\omega_1 m_1 & 0 & 0 & 0 \\ 0 & 2\zeta_2\omega_2 m_2 & 0 & 0 \\ 0 & 0 & 2\zeta_3\omega_3 m_3 & 0 \\ 0 & 0 & 0 & 2\zeta_4\omega_4 m_4 \end{bmatrix}$$

Mass, Stiffness, Viscous Damping

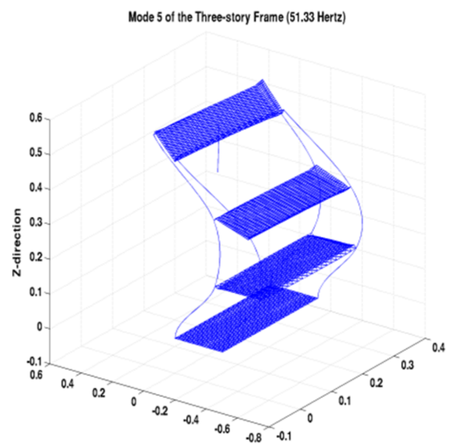
The 2D model represents the frame using (linear) beam and shell finite elements.

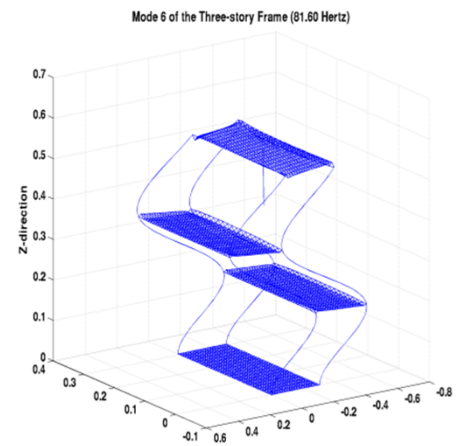


2D Finite Element Model (with 12,048 Elements)



1st Bending (25.67 Hz)

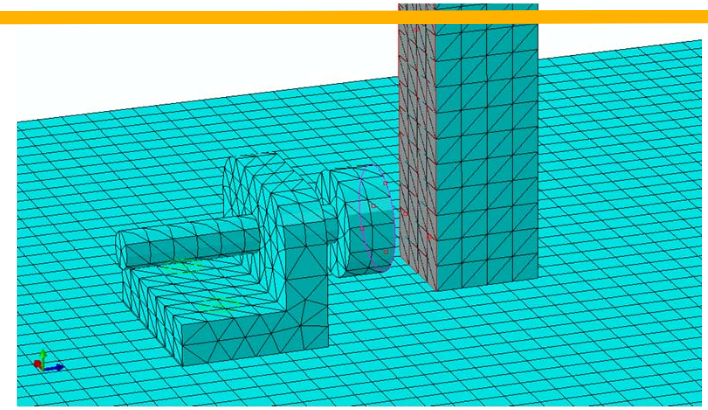




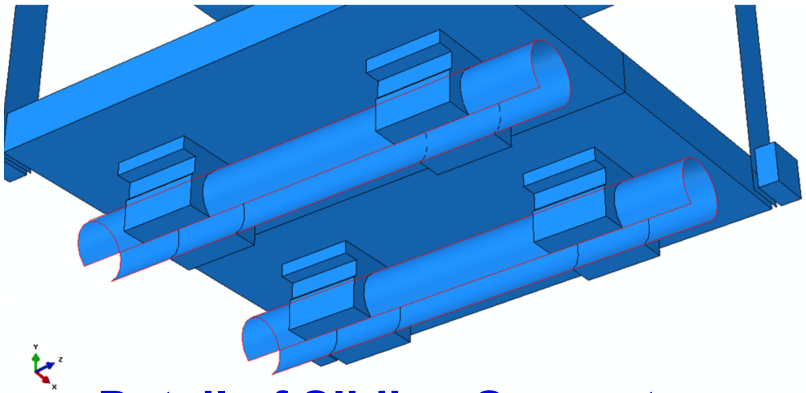
2nd Bending (51.33 Hz) **3rd Bending (81.60 Hz)**

The 3D model implements Abaqus (6.10-1) quadratic tetrahedral continuum elements, contact/friction surfaces, and a few shells.

3D Finite Element Discretization

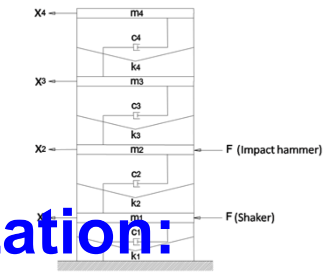


Detail of the Contact Mechanism



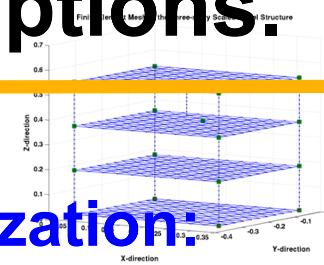
Detail of Sliding Supports

The problem is to select an accurate model given that each candidate simulation relies on different sets of (arbitrary) assumptions.



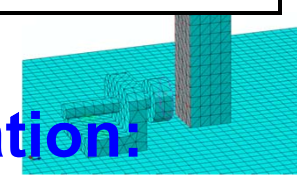
- **1D Parameterization:**

Unknown	Definition
1	Spring bending stiffness
2	Base stiffness
3	Mass of floor plate
4	Mass of column
5	Mass of 3rd-floor column
6	Mass of contact backstop
7	Mass of connection bolt



- **2D Parameterization:**

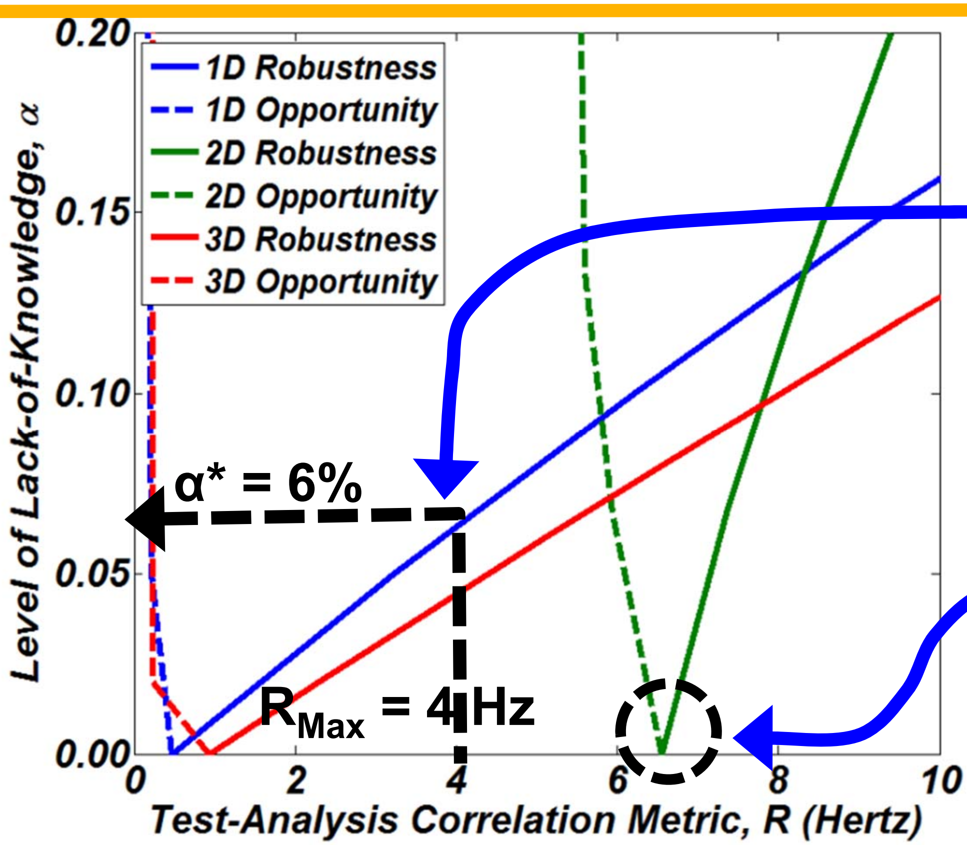
Unknown	Definition
1	Elastic modulus of floors
2	Mass density of floors
3	Elastic modulus of columns



- **3D Parameterization:**

Unknown	Definition
1	Aluminum elastic modulus
2	Aluminum mass density
3	Bolt "radius of influence"

The 1D model provides better trade-offs between robustness and accuracy than the 3D model, at any level of ignorance.

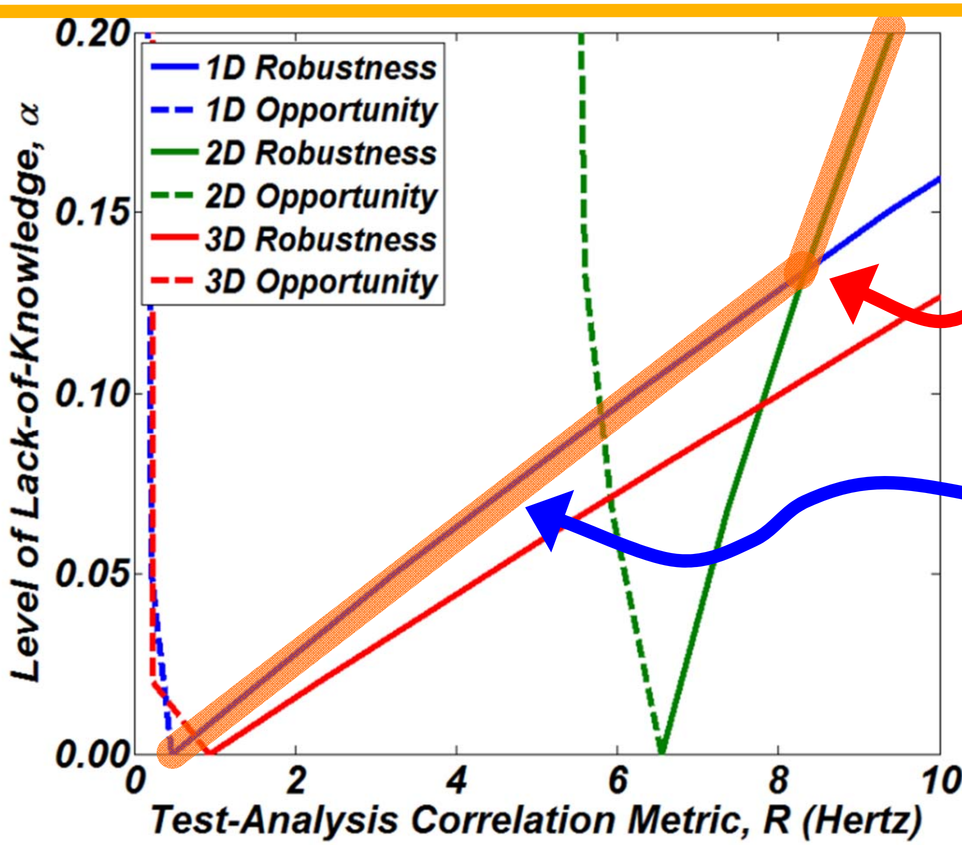


"An accuracy of 4 Hertz is guaranteed for the 1D model if one can limit the uncertainty to ± 6%."

A calibrated model has *no* robustness.

Credit: Christopher Stull, LANL (AET-6). LA-UR-12-0379.

If the uncertainty exceeds ± 13%, or a prediction error worse than 8 Hertz can be tolerated, then the 2D model is the best.



Preference Reversal !!

"The 1D model is better as long as the prediction accuracy needs to be better than 8 Hertz."

Credit: Christopher Stull, LANL (AET-6). LA-UR-12-0379.

Outline

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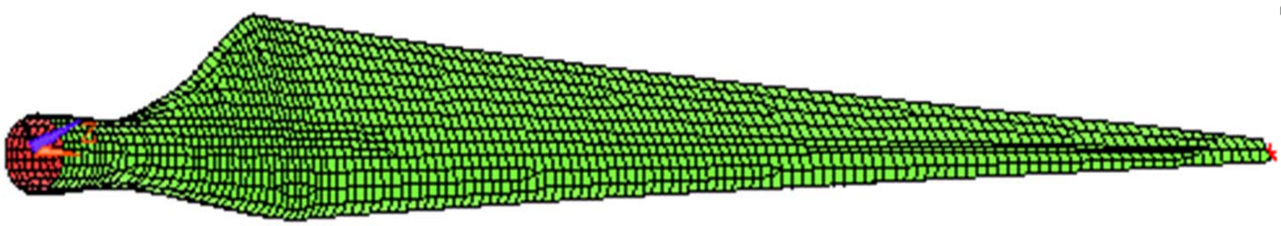
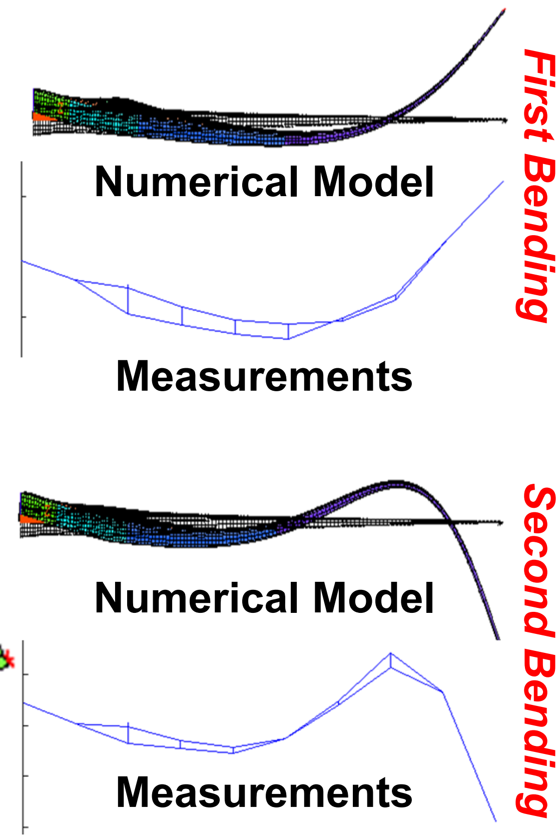
This application selects a computational model to simulate the bending deformation of Sandia's CX-100 wind turbine blade.

Sandia's 9-meter CX-100 Composite Blade

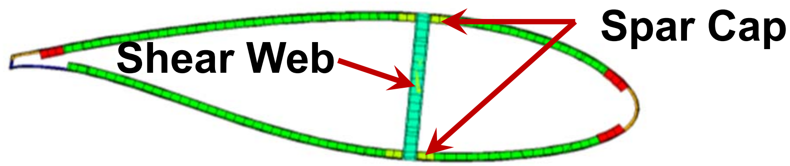


ANSYS Finite Element Model
(SHELL-281 Elements, 8-cm Mesh Size)



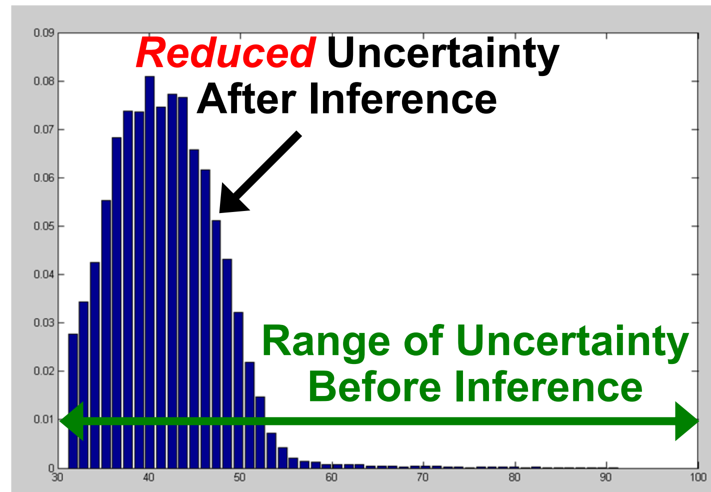
Test-analysis Correlation

The six sections of the model, determined from the material makeup, are assigned isotropic, smeared material properties.

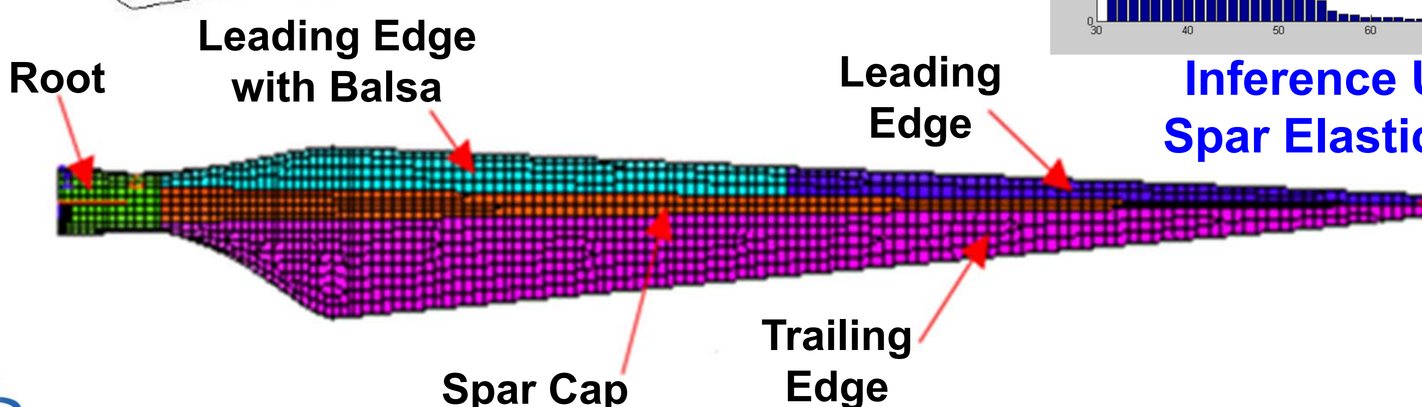


Blade Cross-section

Spar Cap Geometry

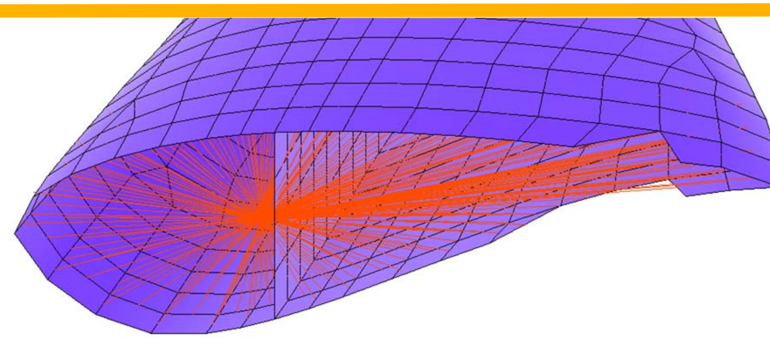


Inference UQ of the Spar Elastic Modulus

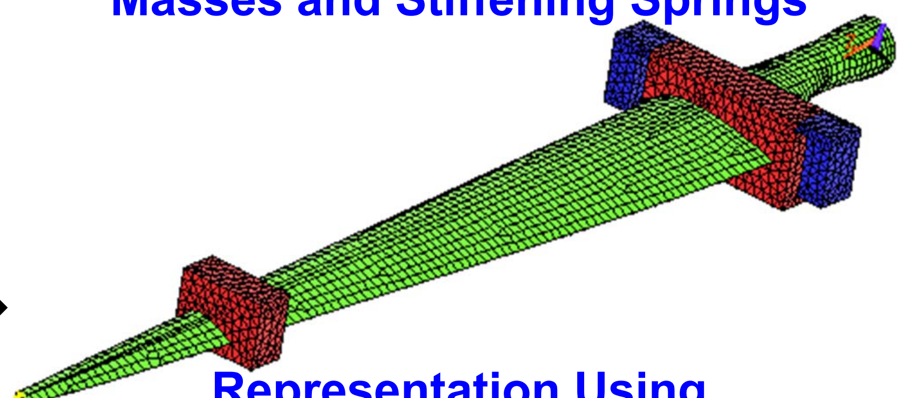


Definition of Six Regions of the Model

Two competing models are developed to simulate the vibration in a configuration of the blade that has *not* been calibrated.



Representation Using Point Masses and Stiffening Springs



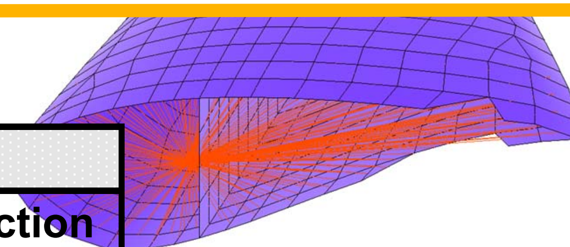
Representation Using High-fidelity Solid Elements

Credit: National Renewable Energy Laboratory and Stuart Taylor, LANL (INST-OFF).

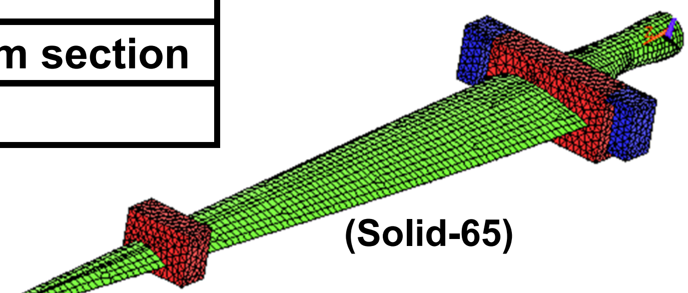
Each modeling strategy relies on different sets of (arbitrary) assumptions that affect the prediction accuracy in various ways.

- **Point-mass Parameterization:**

Unknown	Description
(1; 2)	(Translation; rotation) springs at 1.60-m section
3	Point mass at 1.60-m section
(4; 5)	(Translation; rotation) springs at 6.75-m section
6	Point mass at 6.75-m section



(Mass-21, Combin-14)

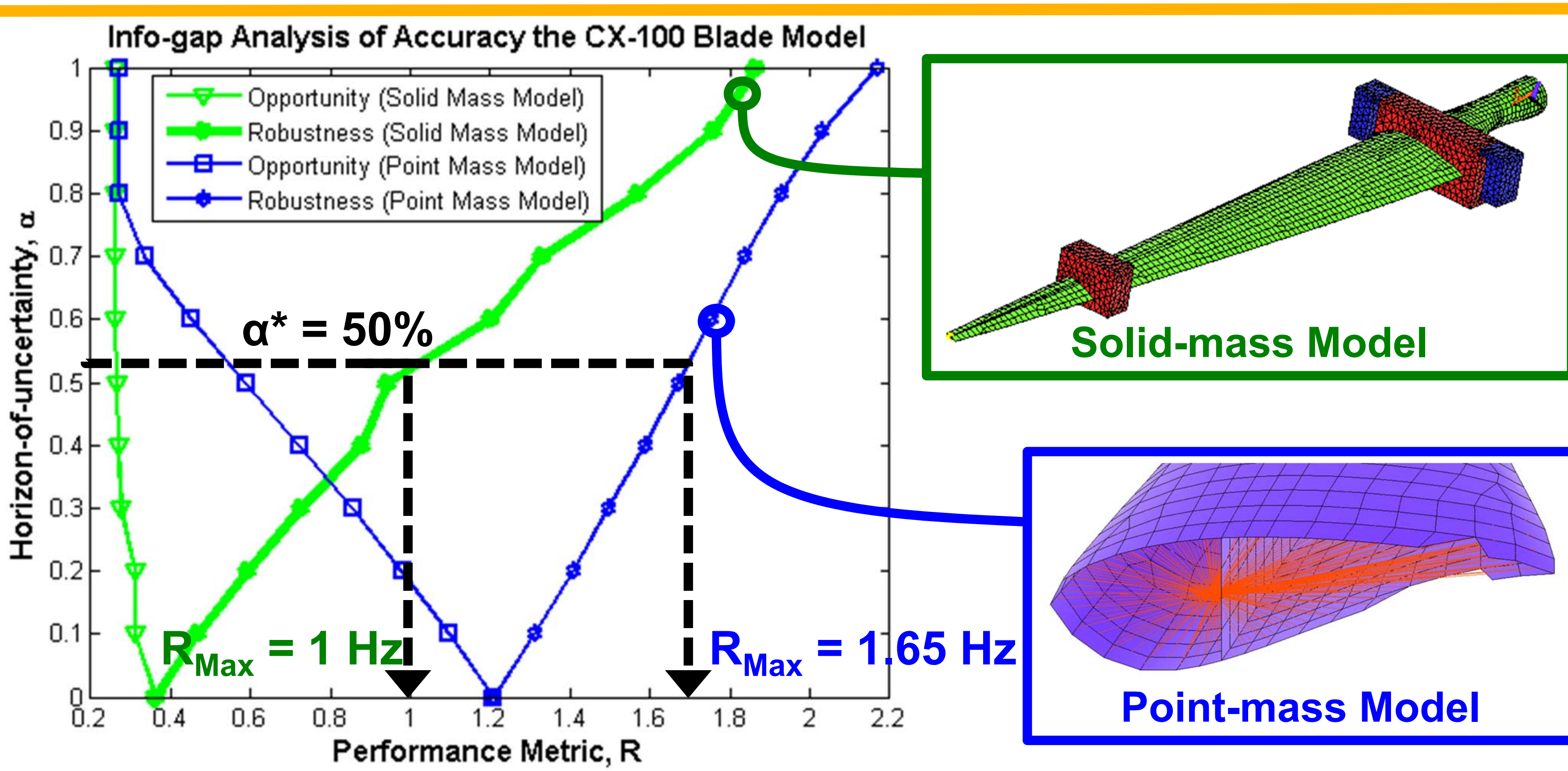


(Solid-65)

- **Solid-mass Parameterization:**

Unknown	Description
(1; 2)	(Elastic modulus; density) of 1.60-m section
(3; 4)	Center-of-gravity (X; Y) coordinates of 1.60-m offset mass
5	Density of 1.60-m offset mass
(6; 7)	(Elastic modulus; density) of 6.75-m section

The solid-mass model (*green line*) is more accurate *and* more robust to ignorance than the point-mass model (*blue line*).



Credit: Kendra Van Buren, Clemson University. LA-UR-12-7103.

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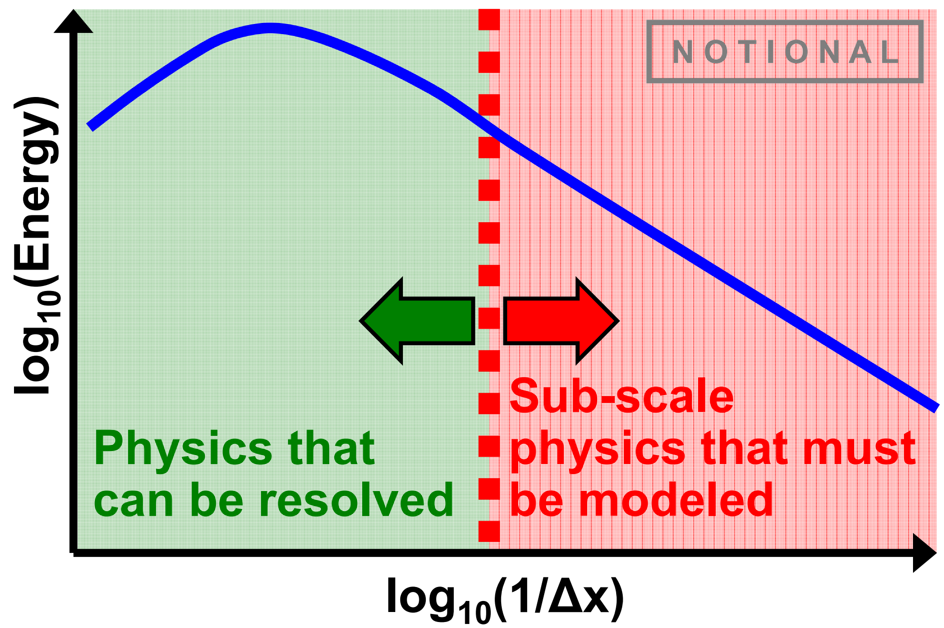
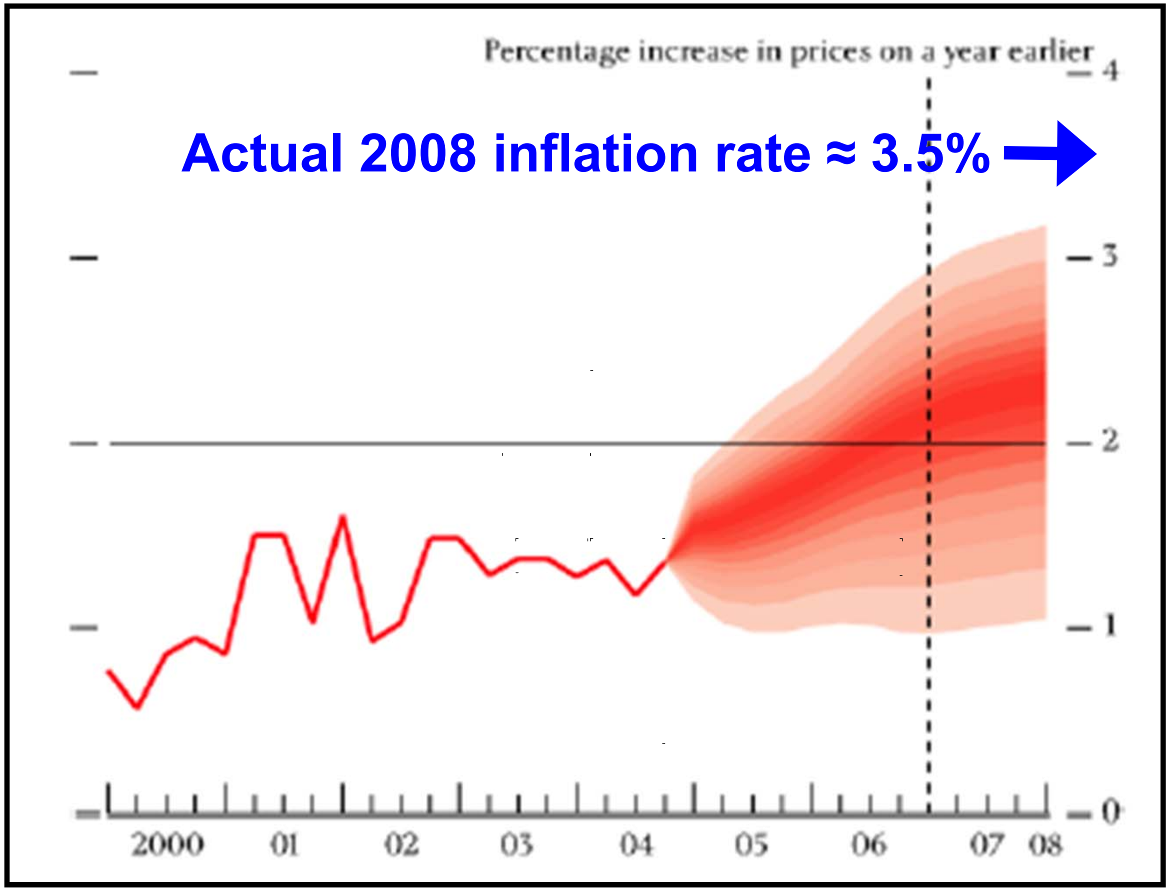
Concluding Remarks

- In the activity of modeling, robustness to ignorance *deteriorates* as the fidelity-to-data *improves*.
- Relying, therefore, on calibration only to select models is a dangerous proposition!
- Robust decision-making offers a framework to integrate uncertainty, and study these trade-offs.



- Models, especially those implemented to simulate the sub-scale physics that cannot be resolved explicitly, should be selected by exploiting these trade-offs.

"Doubt is not a pleasant condition, but certainty is absurd." – Voltaire



Credit: Bank of England.