Enhanced Six Sigma with Uncertainty Quantification

Mark Andrews – SmartUQ, Madison WI

SMARTUQ

ASQ
The Global Voice of Quality

ASQ World Conference – Session T05 – May 1, 2017

Learning Objectives

- In this session you will:

    - Learn basic concepts of Uncertainty Quantification.

    - Understand how quantifying uncertainties in numerical simulations enhances Six Sigma methods.

Examples of Uncertainties in Everyday Life

- Stock Market.

- Reliability of automobiles and household appliances.

- Weather Forecasts: Hurricanes, Tornados, and Floods.

http://uqufiqubuja.prv.pl/national-hurricane-data-center.php

https://commons.wikimedia.org/wiki/File:02L_2007_Five-day_cone.gif

Uncertainties in Systems Engineering

Space Shuttle Catastrophes, 1986 and 2003:
Unforeseen variations of system conditions led to the *Challenger* and *Columbia* space shuttle accidents.
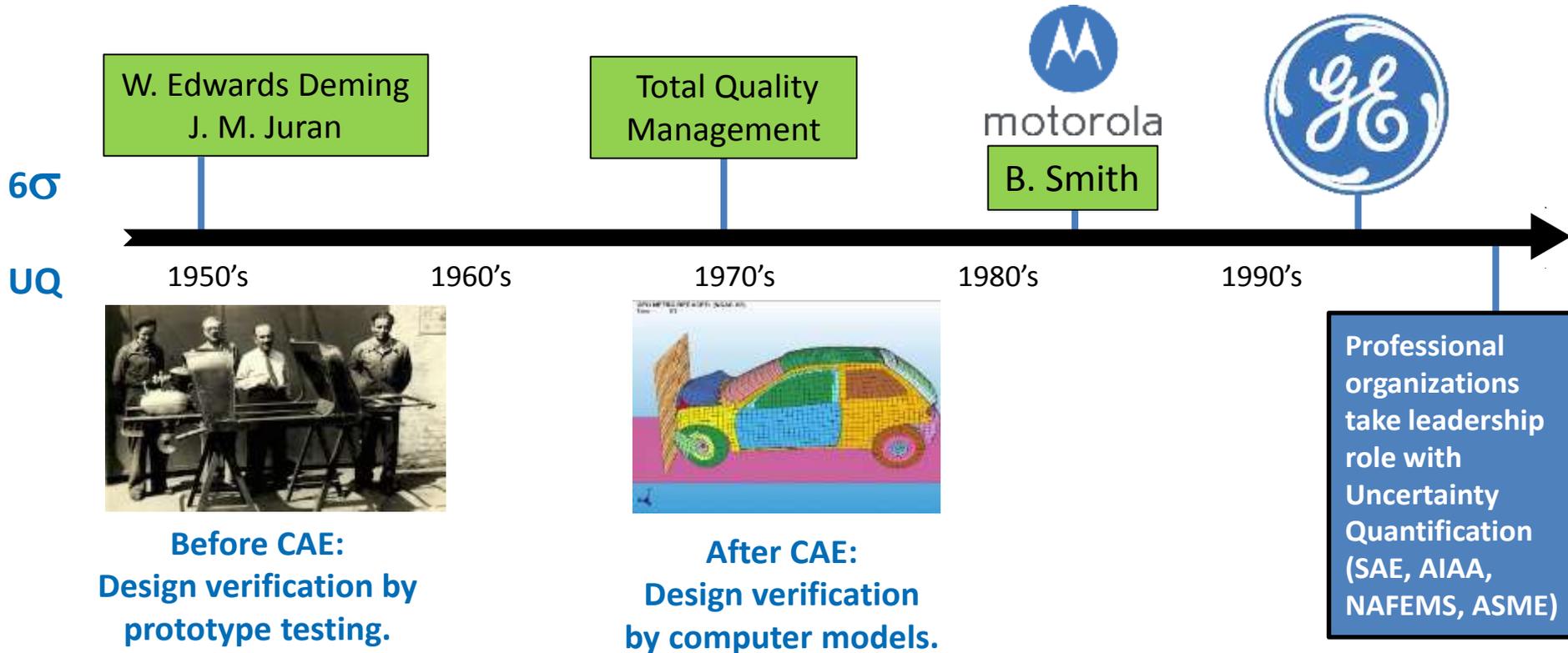

http://www.nasa.gov/mission_pages/shuttle/flyout/GlennShuttle.html

https://commons.wikimedia.org/wiki/Commons:Featured_picture_candidates/Log/August_2012

Brief Historical Timeline

6σ

W. Edwards Deming J. M. Juran		Total Quality Management			B. Smith	

UQ

1950's	1960's	1970's	1980's	1990's

Before CAE:
Design verification by prototype testing.

After CAE:
Design verification by computer models.

Professional organizations take leadership role with Uncertainty Quantification (SAE, AIAA, NAFEMS, ASME)

Computer Aided Engineering (CAE) imposes new rules:
  have I built the <u>model right</u>? . . . (model verification).
  have I built the <u>right model</u>? . . .   (model validation).
  have I accounted for real-life uncertainties?

https://commons.wikimedia.org/wiki/File:Motorola_logo.svg
https://commons.wikimedia.org/wiki/File:General_Electric_logo.svg
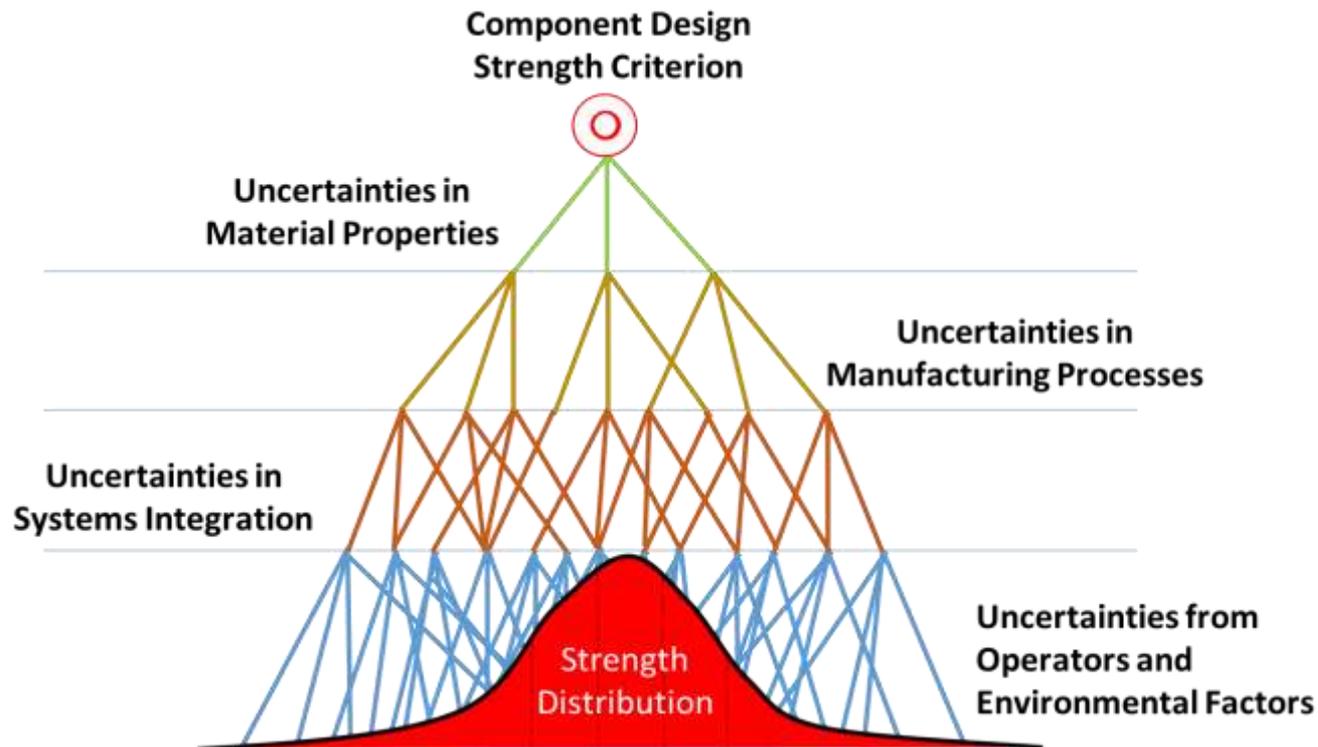https://jalopnik.com/5563048/the-weirdly-awesome-microcars-of-hungary

Challenges to the Six Sigma Process

- Ensuring that the *quality* and *quantity* of data collected is sufficient for making decisions.

- Designing a new process or product when there is no baseline data to collect.

- Analyzing complex processes can be time consuming when using traditional statistical methods.

- Justifying the high cost of physical test.

- Quantifying the improvements in a process using a small number of physical tests.

- Conducting physical DOE tests in an environment where it is impractical.

# What is Uncertainty Quantification (UQ)?

Formulation of a statistical model to characterize imperfect and/or unknown information in engineering simulation and physical testing for predictions and decision making[1].

Component Design Strength Criterion

Uncertainties in Material Properties

Uncertainties in Manufacturing Processes

Uncertainties in Systems Integration

Uncertainties from Operators and Environmental Factors

Strength Distribution

UQ are innovative analytical methods for studying complex systems under uncertainties.

[1] NAFEMS Stochastics Working Group and ASME V&V 10 Definition

Uncertainty Quantification and Calibration Process Flow

Direct Sampling Approach
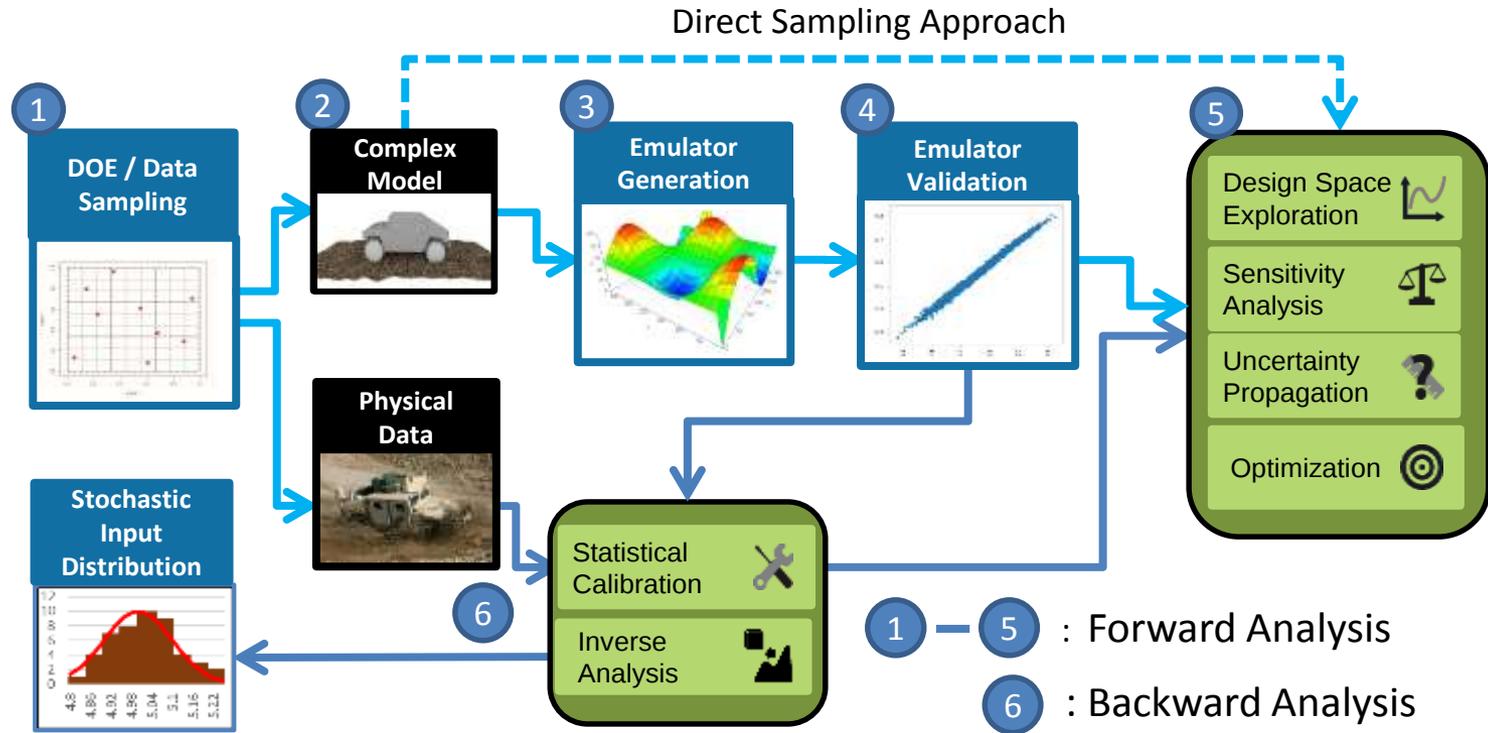
Emulators are statistical models built to mimic the physics-based simulation. They are also known as Surrogate or Metamodels.
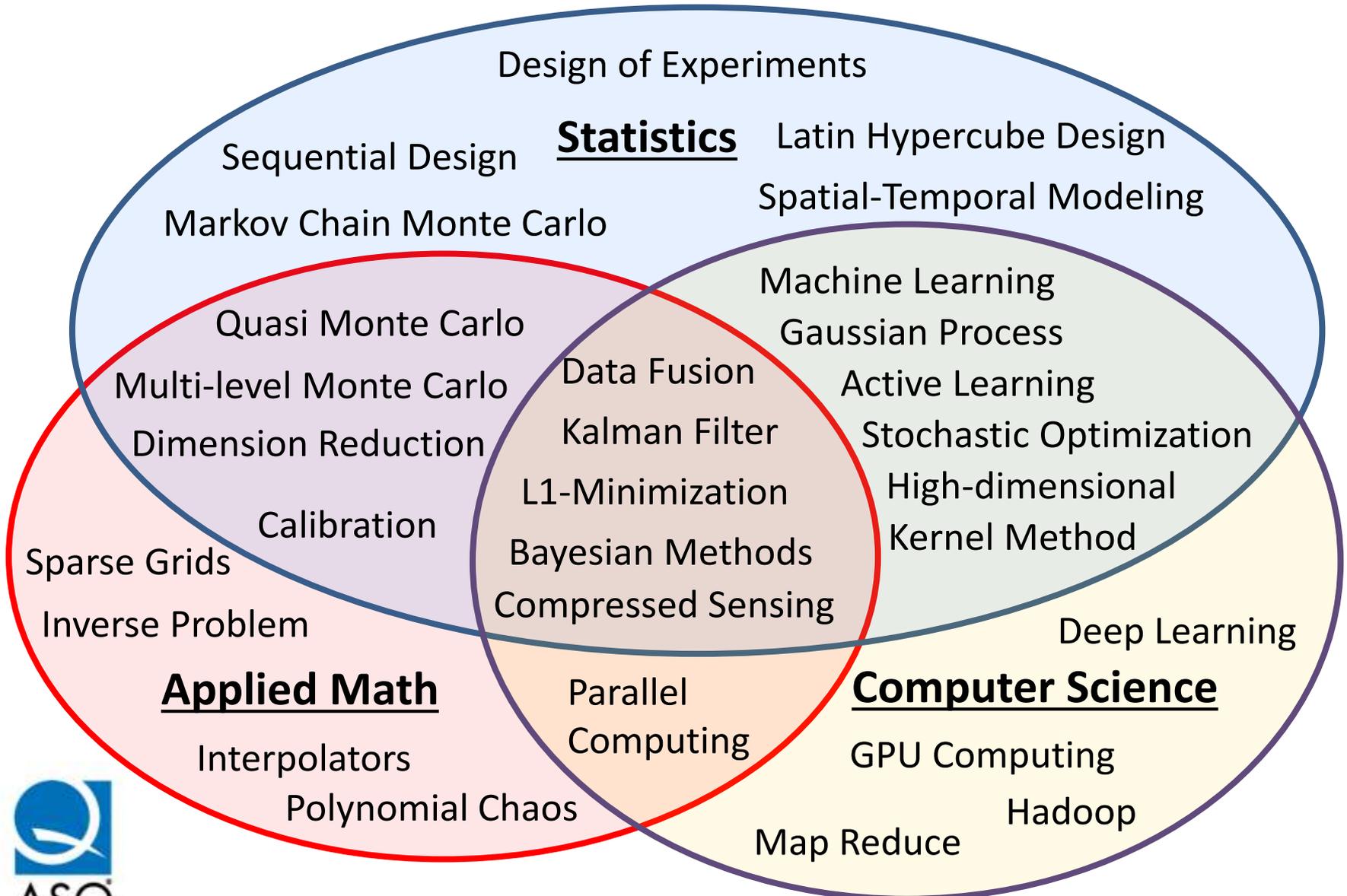
Inverse Analysis is used for determining the underlying distribution for a model input that has limited data or is poorly characterized and noisy.

8

How do Six Sigma Statistical Techniques Compare to UQ?

- The Six Sigma process utilizes traditional statistical methods

    - Measurement system analysis

    - Design of Experiments

    - General linear regression models

    - Statistical tests: Hypothesis, F-test, etc.

    - Probability distributions: Normal, t, Chi-squared, Poisson, etc.

    - ANOVA

- UQ is a multi-disciplinary field that merges statistics, applied mathematics, and computer science methods to handle more complicated, high dimension, nonlinear systems

Elements of the Multi-Disciplinary Field of UQ

Design of Experiments

Statistics

Sequential Design

Latin Hypercube Design

Spatial-Temporal Modeling

Markov Chain Monte Carlo

Quasi Monte Carlo

Machine Learning

Gaussian Process

Multi-level Monte Carlo

Data Fusion

Active Learning

Dimension Reduction

Kalman Filter

Stochastic Optimization

L1-Minimization

High-dimensional

Calibration

Kernel Method

Bayesian Methods

Sparse Grids

Compressed Sensing

Inverse Problem

Deep Learning

Applied Math

Parallel Computing

Computer Science

Interpolators

GPU Computing

Polynomial Chaos

Hadoop

Map Reduce

ASQ

UQ Analytics for Complex Systems, Process Simulations and Physical Data

Sensitivity analysis quantifies the variation in the outputs of a process simulation model with respect to changes in process simulation inputs.

Which process inputs are Critical to Quality?

Are there interactions among process inputs?

Statistical Calibration accounts for uncertainty in all aspects of the process simulation model, including uncertainty in the fitted calibration parameters.

Understand the magnitude of the uncertainty in the process model.
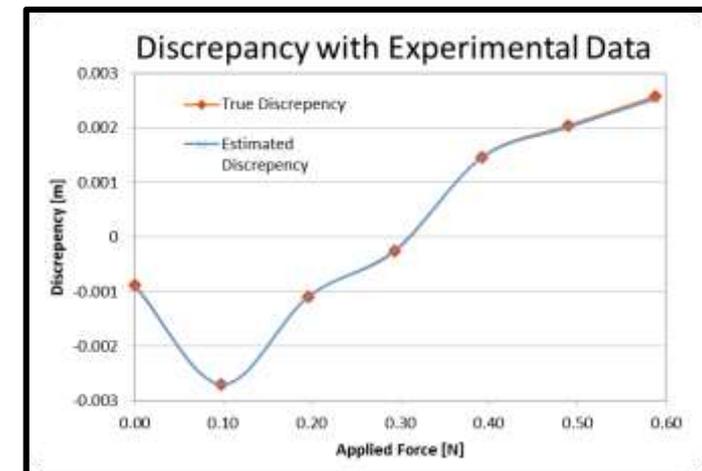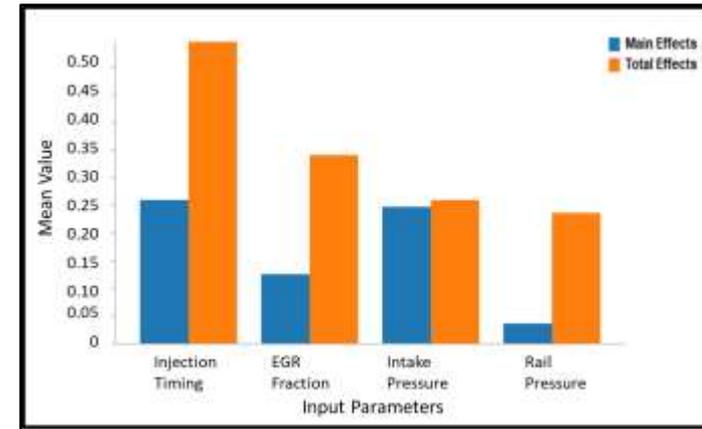
UQ Analytics for Complex Systems, Process Simulations and Physical Data

Propagation of uncertainty calculates the effects of the uncertainty in the process inputs on the process outputs.

How robust are my solutions for reducing variations in manufacturing?

Inverse analysis characterizes the unknown stochastic parameters of a process using a model of the system and corresponding noisy physical data.

How to reduce process variation when I have noisy or missing input data?
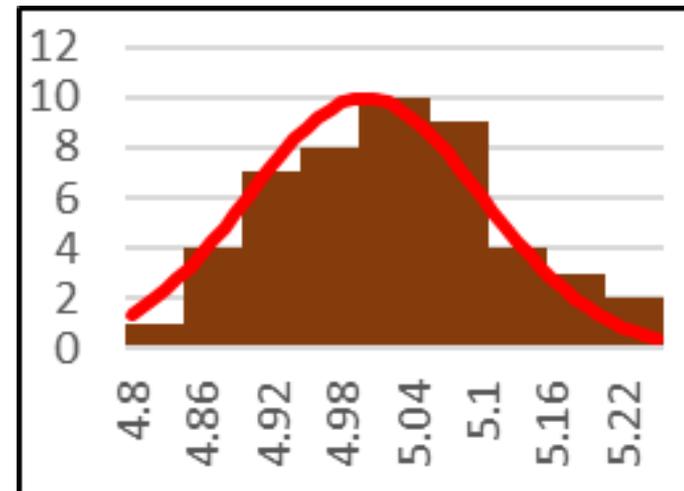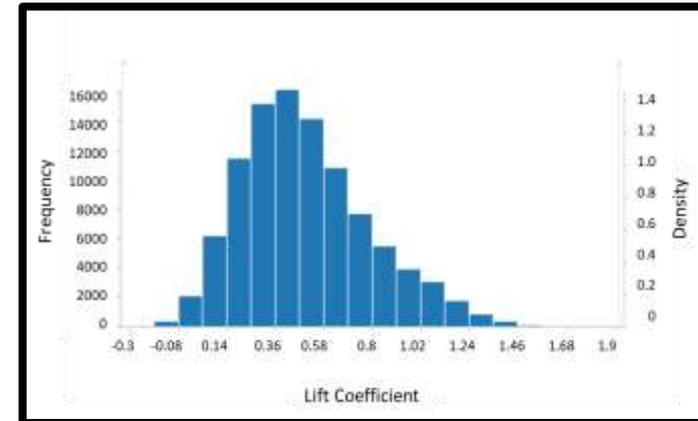
Industrial ROI: UQ Enables a *One-Time Process* for Product Development

- **Reduce Costs Driven by Variability**
  - Prevent unnecessary design iterations.
  - Shorter development times; fewer tests & prototypes.
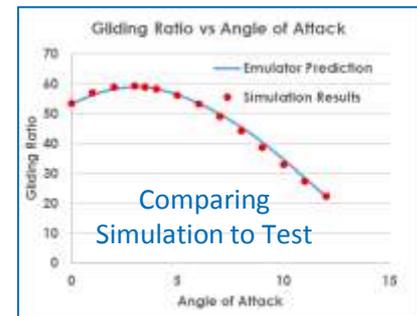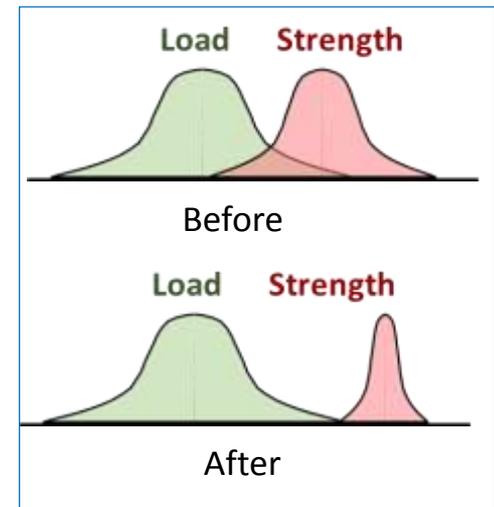- **Maximize Product Reliability and Durability**
  - Reducing part-to-part variability; increasing product life.
  - Fixing problems in design is cheaper than in the field.
- **Ensure Simulation Results are Credible and Realistic**
  - Critical for model validation and what-if scenarios.
  - Essential for understanding risks for decision making.
- **Government Oversight (FAA, DoD, FDA)**
  - Guidance documents for Model Verification, Validation and Uncertainty Quantification available.

Design › Build › Test

Load   Strength

Before

Load   Strength

After

Gliding Ratio vs Angle of Attack

Comparing Simulation to Test

How UQ Can Enhance Six Sigma

1.0 Define Opportunities

↓

2.0 Measure Performance

↓

3.0 Analyze Opportunity

↓

4.0 Improve Performance

↓

5.0 Control Performance

- Increases in computational power and numerical simulation accuracy has made simulations an efficient method for analyzing complex engineering systems.

- UQ methods essentially put 'error bars' on simulations, making the results trustworthy and credible.

- Simulations that use UQ methods have many advantages:

  – providing accurate analytics on a process or system when physical testing is impractical.

  – identifying parameters that govern the variations in manufacturing.

  – efficiently exploring the design space in less time and at a lower cost than testing methods.

  – generating baseline data for a new product of process.

Uncertainty Quantification Applications

Three case studies will be presented to illustrate the following UQ benefits to Six Sigma:

- Refinement of quality criteria

- Robust risk estimation

- Identification of key drivers of manufacturing variability

- More informed when making critical decisions, yielding more favorable outcomes.

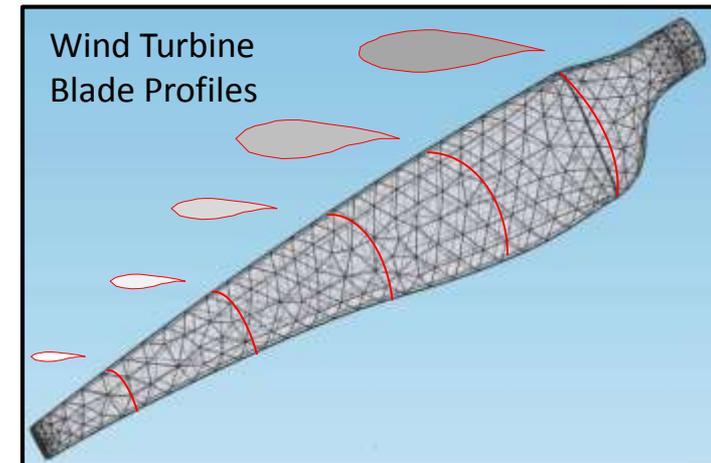# UQ Case Study: Refining Quality Criteria for Manufacturing

Challenges in Using Simulations to Refine Manufacturing Quality Criteria

- **How to determine acceptable tolerances for parts with complex surfaces?**

  - Each blade must meet aerodynamic, structural, vibrational, impact, and durability criteria.

  - Simple dimensional criteria may not relate to performance.

- **Cost to meet performance can be significant:**

  - Safety is important for wind turbine blade performance while scrap and rework are expensive.

- **Physics simulations can predict blade performance metrics:**

  - However, high fidelity simulations can be too computationally demanding to use for each manufactured part.

Complex surface of wind turbine blade

Wind Turbine Blade Profiles

From https://www.ecn.nl/news/newsletter-en/2009/december-2009/aerodynamics-wind-turbines/

Source: pixabay.com

Building a Relationship Between Physical Measurements and Performance

1. Build the System Emulator

- 3D scans are made to measure the critical dimensions of the complex wind turbine blade surface.

- The critical dimensions are used as input into the high fidelity numerical simulations.

- The responses from the high fidelity numerical simulations are performance metrics of the wind blade.

- The inputs and responses from the high fidelity simulations are used to train the emulator.

2. **Predict performance**

- Measurements are made of wind turbine blades during manufacturing.

- These measurements are used as inputs to the trained emulator.

- Responses from the emulator predict the performance of the blade based on measurements.

Use Emulators to Predict Performance

1. **Build system emulators**

   – Train and validate emulators on a limited set of accurate physics-based simulations.
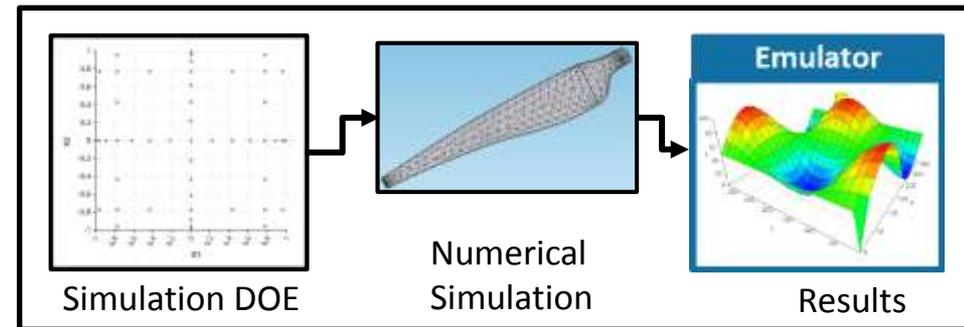
2. **Predict performance**

   – Detailed dimensions are measured during manufacturing and used as inputs to predict performance.

   – Predictions are compared to acceptance criteria.

- **Acceptance criteria is based on actual performance prediction!**

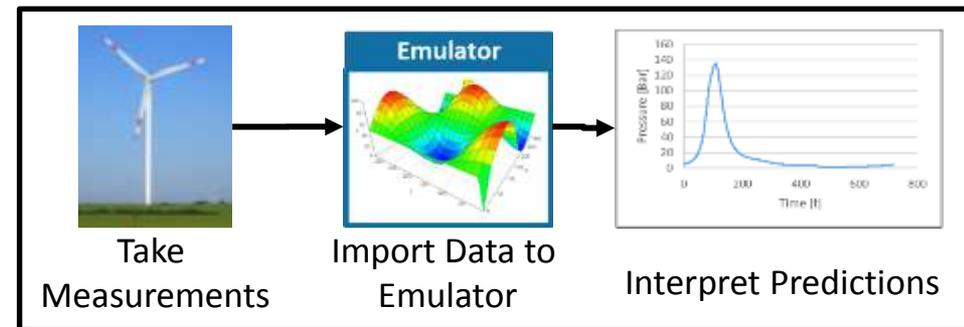   – Emulation can be used to incorporate dimension measurement uncertainties into performance predictions.

1: Create an Emulator using Simulation Results.

Simulation DOE   Numerical Simulation   Results

https://3ohkdk3zdzcq1dul50oqjvvf-wpengine.netdna-ssl.com/wp-content/uploads/2016/01/G1-the-FEA-mesh.jpg

2: Predefined Emulator Predicts Component Responses.

Take Measurements   Import Data to Emulator   Interpret Predictions

Wiki Commons: Windkraftkonverter (WKK) / Windrad-Bild / (Windräder)

Example: Segmented Emulation w/Airfoil Surface Coordinates as Inputs

- **Original data sets:**

  - **Input:** Two-dimensional cross section coordinates for 209 Eppler airfoils.

  - **Output:** Max *Coefficient of Lift (Cl)* and *Coefficient of Drag (Cd)* for each airfoil.

- **Curve representation:**

  - For each airfoil, a curve is built from the 2D coordinates; true shape for analysis.

- **Segmented Emulation:**

  - Build emulator using the curves as inputs and the ratio of Cl and Cd as the output.
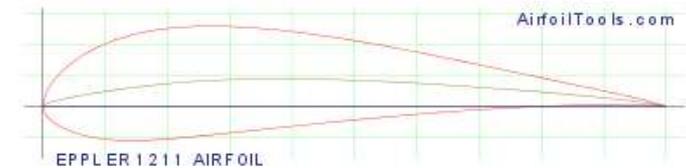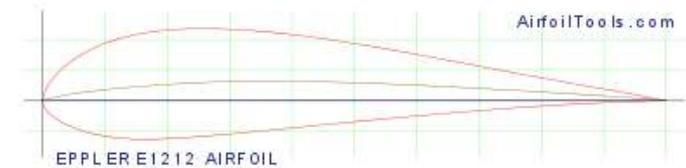
(e1200-il) EPPLER 1200 AIRFOIL

AirfoilTools.com
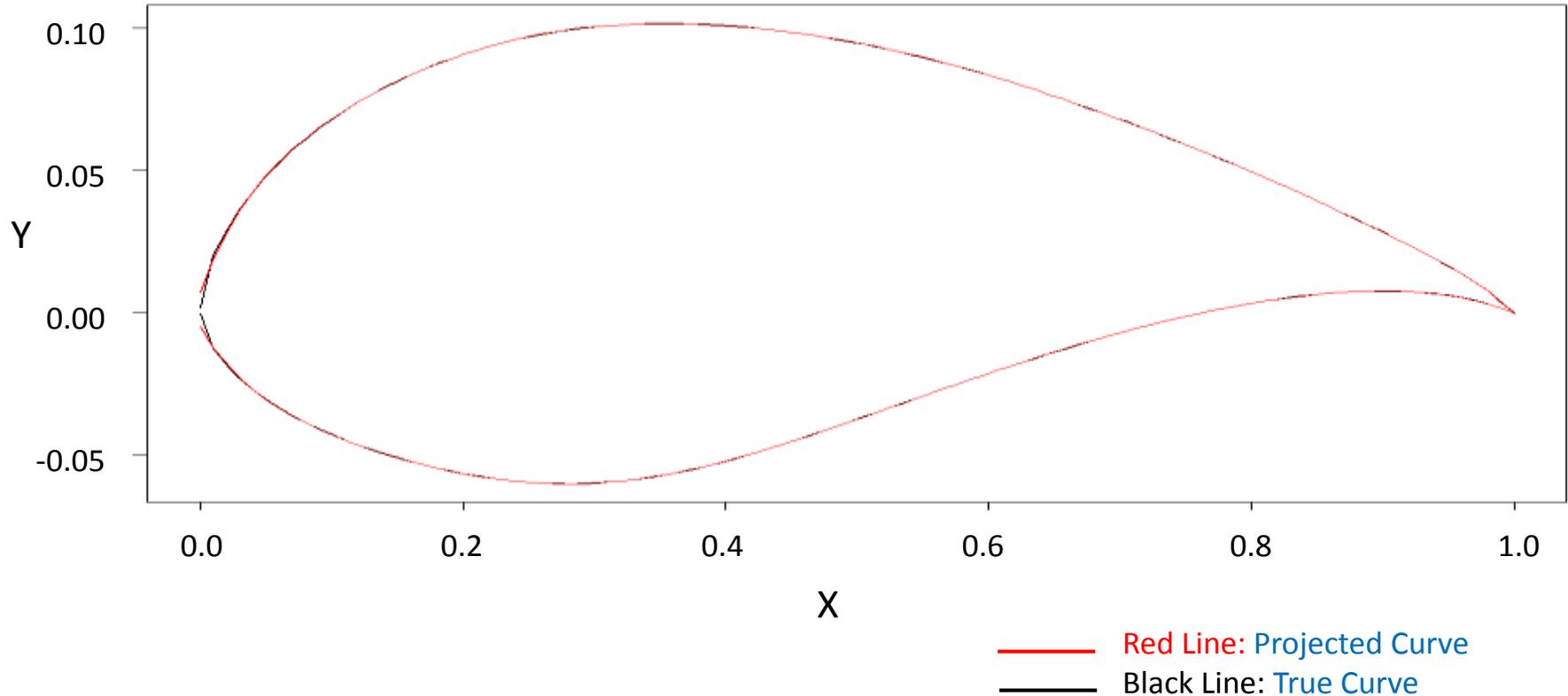
EPPLER 1200 AIRFOIL
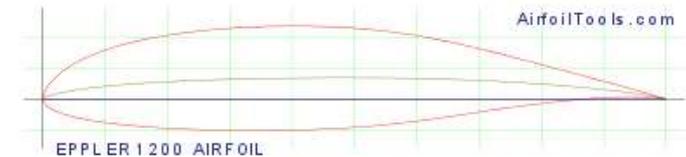
(e1210-il) EPPLER 1210 AIRFOIL

AirfoilTools.com

EPPLER 1210 AIRFOIL
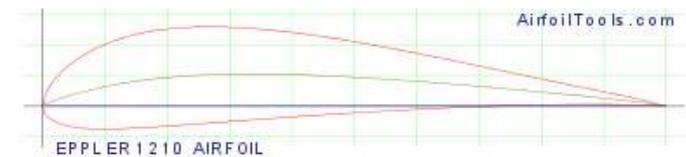
(e1211-il) EPPLER 1211 AIRFOIL

AirfoilTools.com

EPPLER 1211 AIRFOIL

(e1212-il) EPPLER E1212 AIRFOIL

AirfoilTools.com

EPPLER E1212 AIRFOIL

from http://www.airfoiltools.com

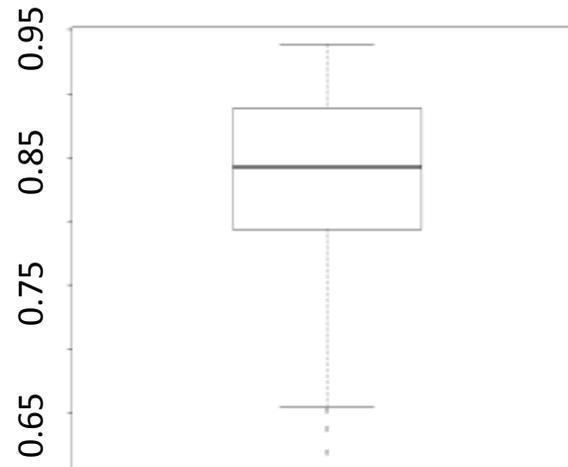# Comparing True and Fitted Profile Projections

Red Line: Projected Curve
Black Line: True Curve

Comparing True and Emulated Cl/Cd Responses
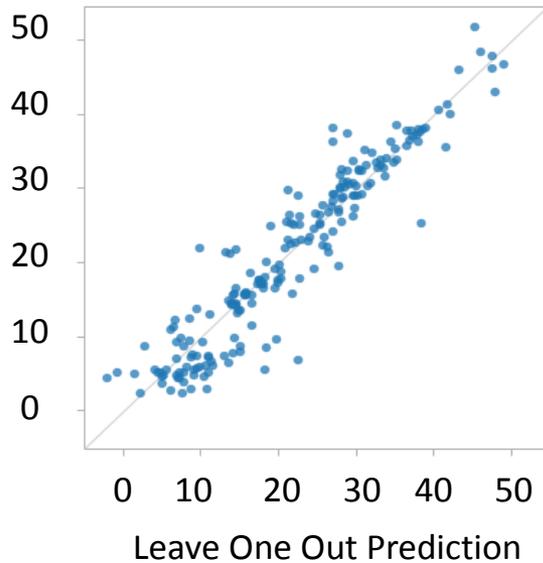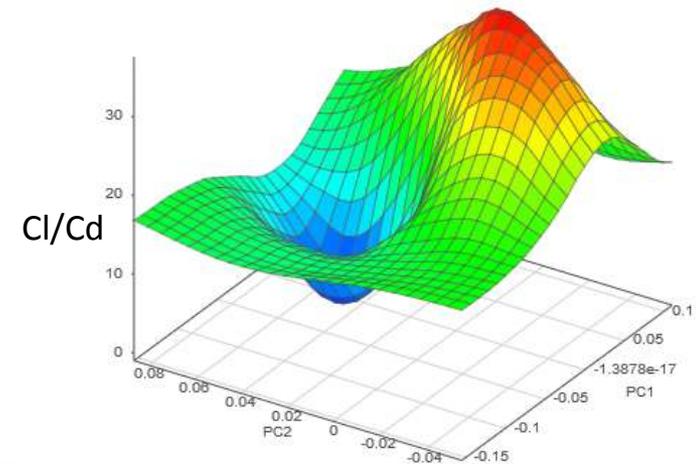

Actual (x axis) vs predicted (y axis) Cl/Cd for the training data.

Accuracy Testing:

- Use 180 airfoils as training set and 19 as test set.

- Replicate 100 times with different samples.

- Avg. R-squares value = 0.85

Response surface showing Cl/Cd with respect to the two most important curve parameters. **The surface can predict manufacturing variation about a design point.**

Summary: Using Simulations to Refine Manufacturing Quality Criteria

- **Part performance** (such as fatigue life or efficiency) are often dependent on geometry in complex ways.

- **Emulators** trained from physics-based simulations can be used to make functional relationships between the complex wind turbine geometry and its performance.

- **Predictions** of the wind turbine performance are made during manufacturing using the emulator and geometric inputs.

- **Emulator improvements** can be made by continued monitoring of parts throughout their useful life and using this data as input.

UQ Case Study: Redesign of Bracket Fatigue Model

- Robust risk estimation

- Identify key drivers of manufacturing variability

- Leveraging the strengths of simulation with test data

- Being more informed when making critical decisions, yielding more favorable outcomes
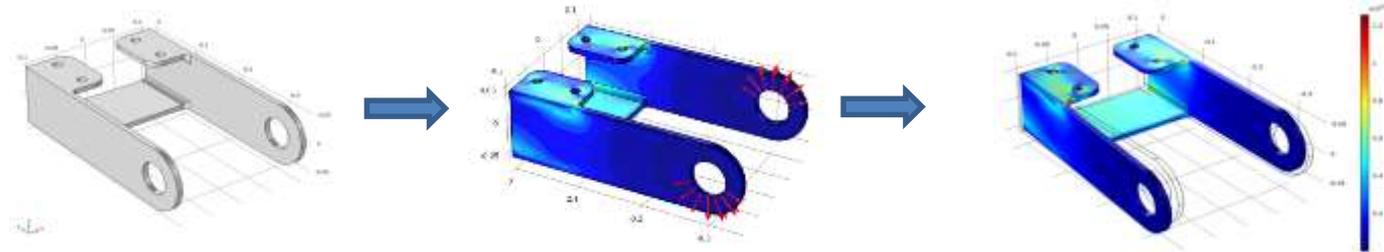
Background: Bracket Redesign for Light-Weighting

Original Bracket Fatigue Criteria:
Life > 450,000 cycles
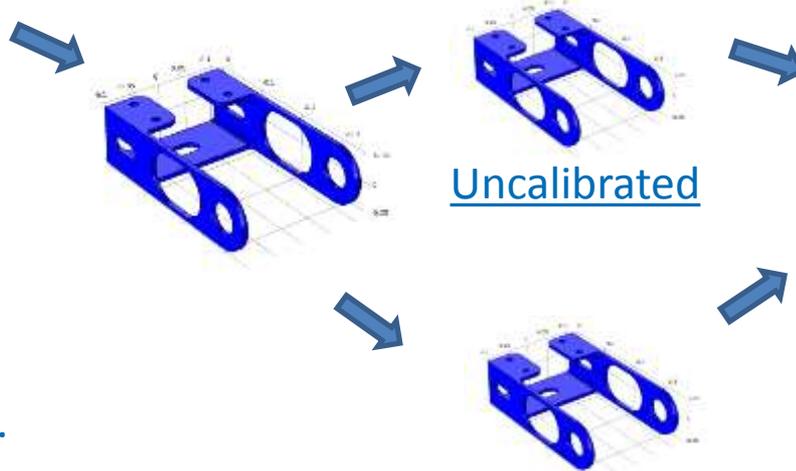Deflection < 2.5 mm

Optimized Bracket for Light-Weighting
1. Reduce mass by at least 15%.
2. Reduce life no more than 10%.
3. Increase deflection no greater than 10%.
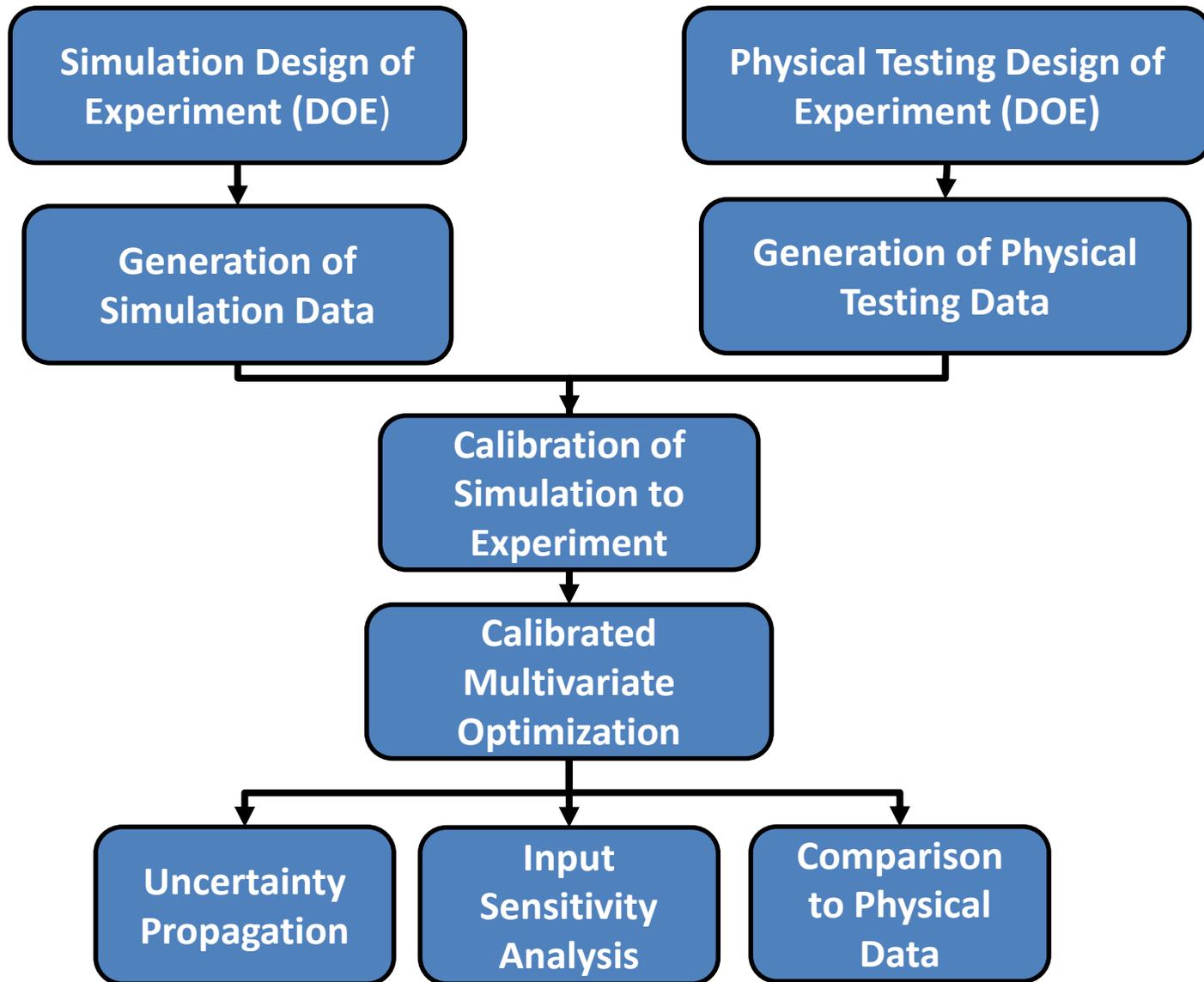
Uncalibrated

Statistical Calibration

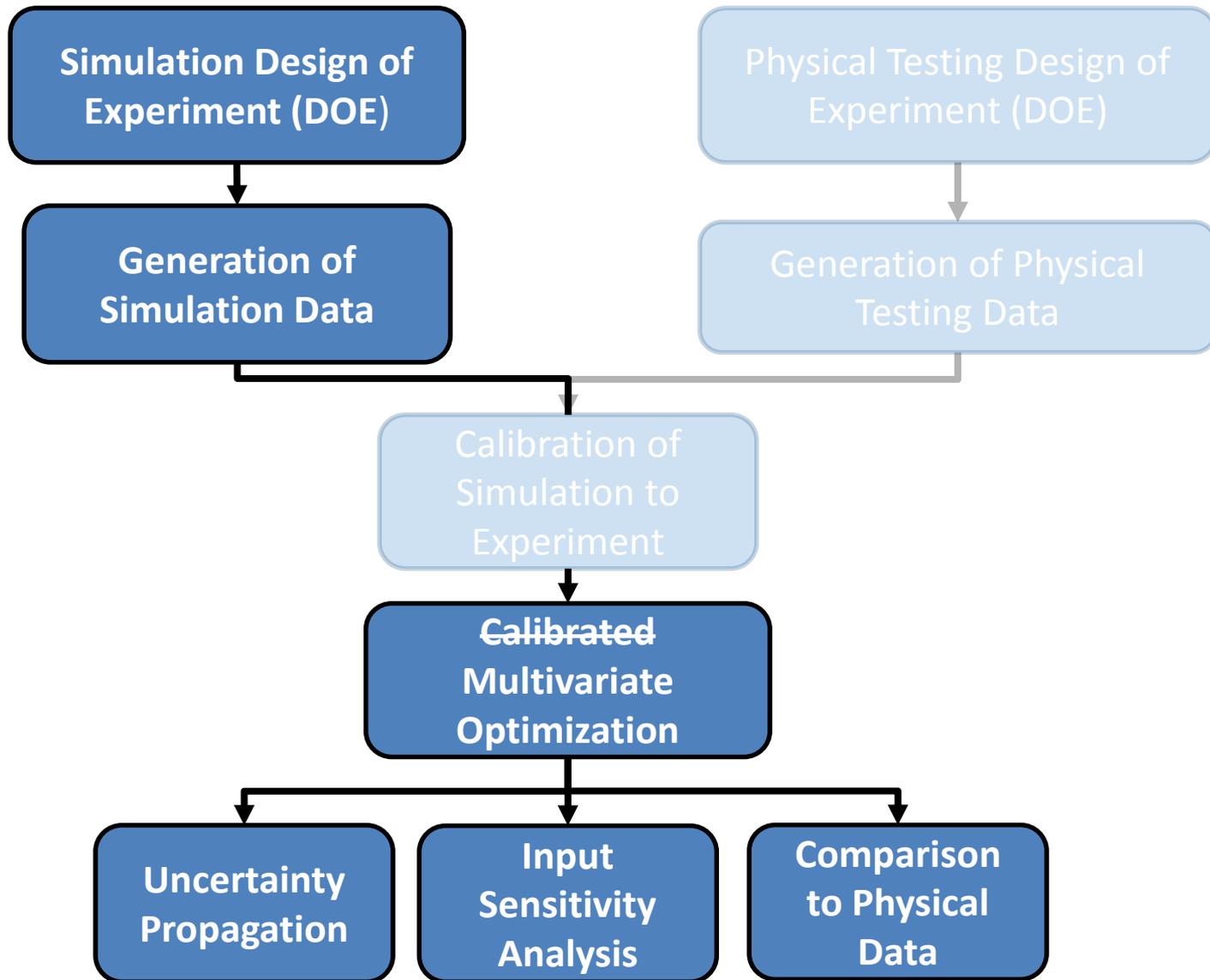**Compare Results from the Uncalibrated and Calibrated Models as Follows:**

1. Optimization Results
2. Physical Data
3. Sensitivity Analysis
4. Uncertainty Propagation
5. Meeting Project Goals

Calibrated Emulator Process Flow Chart

```
┌─────────────────────────┐       ┌─────────────────────────┐
│  Simulation Design of   │       │ Physical Testing Design of│
│   Experiment (DOE)      │       │   Experiment (DOE)       │
└───────────┬─────────────┘       └───────────┬─────────────┘
            ↓                                   ↓
┌─────────────────────────┐       ┌─────────────────────────┐
│    Generation of        │       │  Generation of Physical │
│   Simulation Data       │       │     Testing Data        │
└───────────┬─────────────┘       └───────────┬─────────────┘
            └──────────────┬────────────────────┘
                           ↓
              ┌─────────────────────────┐
              │     Calibration of      │
              │    Simulation to        │
              │      Experiment         │
              └───────────┬─────────────┘
                          ↓
              ┌─────────────────────────┐
              │      Calibrated         │
              │     Multivariate        │
              │     Optimization        │
              └───────────┬─────────────┘
        ┌─────────────────┼─────────────────┐
        ↓                 ↓                 ↓
┌──────────────┐  ┌──────────────┐  ┌──────────────┐
│  Uncertainty │  │    Input     │  │  Comparison  │
│  Propagation │  │  Sensitivity │  │ to Physical  │
│              │  │   Analysis   │  │     Data     │
└──────────────┘  └──────────────┘  └──────────────┘
```

Uncalibrated Emulator Process Flow Chart

Flow chart:

- **Simulation Design of Experiment (DOE)** → **Generation of Simulation Data**
- Physical Testing Design of Experiment (DOE) → Generation of Physical Testing Data
- Both feed into → Calibration of Simulation to Experiment
- → ~~Calibrated~~ **Multivariate Optimization**
- → **Uncertainty Propagation**, **Input Sensitivity Analysis**, **Comparison to Physical Data**

Simulation Results Summary

Optimization: (each scenario found a different optimum)

- Uncalibrated Emulator
- Statistically Calibrated Emulator

Comparing Emulation to Physical Data:

- Average Percent Error
- Standard Deviation

Sensitivity Analysis:

- Uncalibrated Emulator
- Calibrated Emulator

Uncertainty Propagation: (assumed 10% variation from manufacturing)

- Uncalibrated Emulator about the Uncalibrated Emulator Optimum
- Calibrated Emulator about Calibrated Emulator Optimum

Results for Uncalibrated and Calibrated Emulation: Optimization

	Original Design	Uncalibrated Optimized Design	%	Calibrated Optimized Design	%
Mass (kg)	6.03	4.76	-21	4.79	-21
Fatigue Life (N)	460,000	450,555	-2.2	414,217	-8.3
Displacement (mm)	2.28	2.50	+9.7	2.50	+9.7

- Both Calibrated and Uncalibrated emulators met the optimization goals of mass reduction, fatigue life and displacement.

- However,

  – Are the optima from the calibrated emulator more accurate and robust than the uncalibrated emulator?

  – Are key design parameters significantly affected by calibration?

  – Will variations in manufacturing influence key design requirements?

Comparing Accuracy of Uncalibrated and Calibrated Emulators to Physical Data

Average Percent Error [%]			
Response Name	Uncalibrated Emulator	Calibrated Emulator	Average Percent Error Difference
Displacement	0.0639	0.0046	0.0593
Mass	0.0493	0.0261	0.0231
Fatigue	24.095	1.959	22.136
Standard Deviation			
Response Name	Uncalibrated Emulator	Calibrated Emulator	Standard Deviation % Difference
Displacement [m]	1.773E-06	2.663E-07	84.98 %
Mass [kg]	0.00253	0.00171	32.15 %
Fatigue [Cycles]	20,356	5,973	70.65 %

The calibrated emulator has a smaller average percent error and standard deviation than the uncalibrated emulator for all simulation responses.

Sensitivity Analysis for Fatigue Life Uncalibrated and Calibrated Emulators

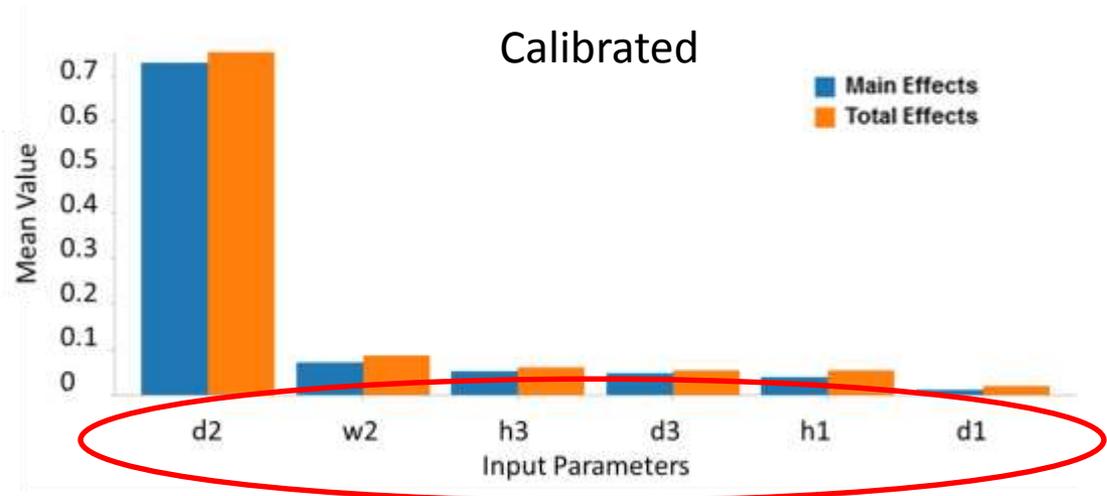- The d2 slot dimension governs the fatigue cycles to failure response for both emulators.
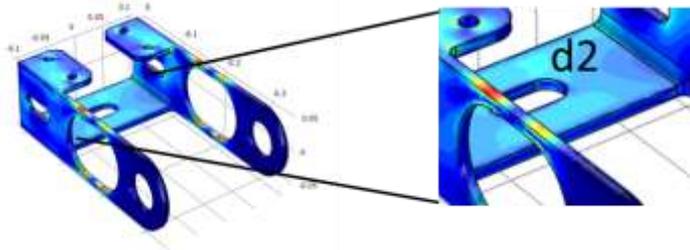
- The parameter sensitivity rankings were found to be equivalent for both emulators.

Uncalibrated

Calibrated

31
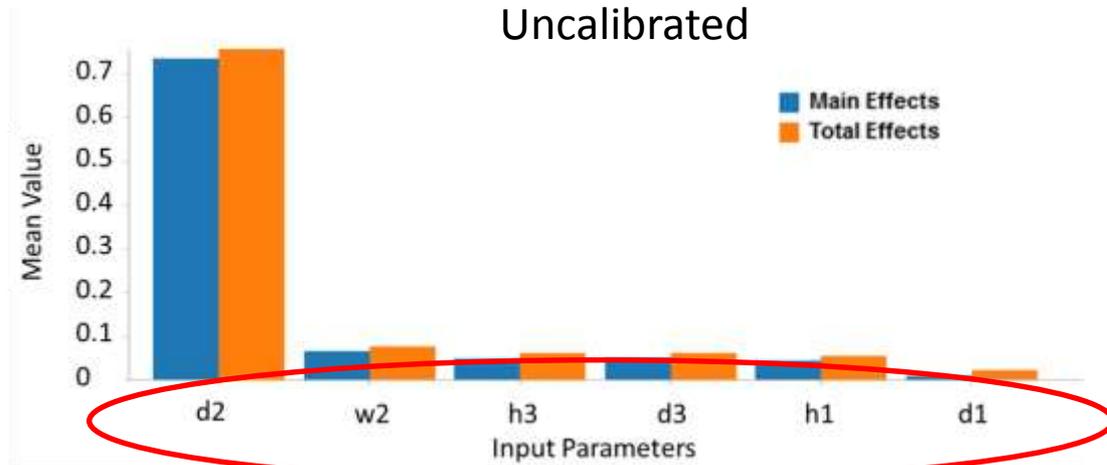
Interpreting the Sensitivity Analysis Results

- **The d2 slot parameter has greatest influence on fatigue cycles:**

  – Turn this 'knob' to improve the fatigue cycle response.

- **If the parameter sensitivities rankings were different:**

  – Implies the original physics may not be correct.

- **Since the parameter rankings were equivalent:**

  – No evidence to suggest the use of this model is incorrect.

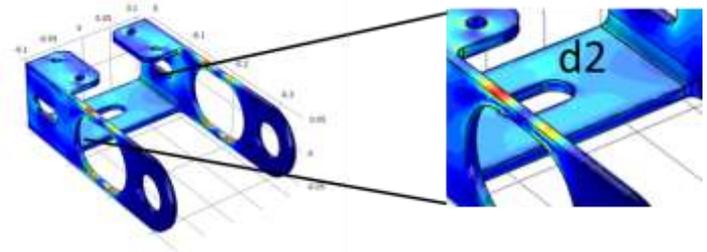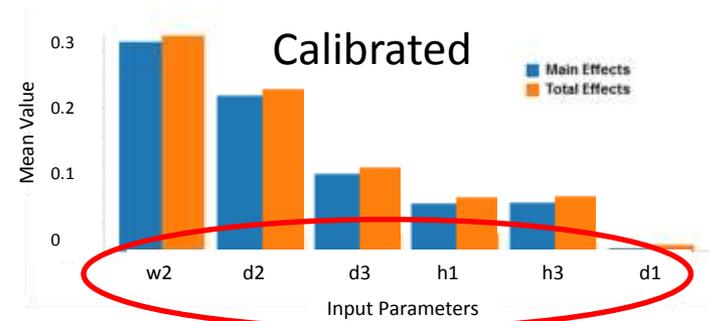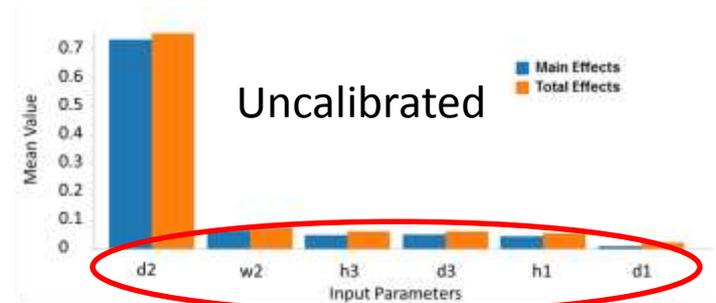   – The equivalent input sensitivity rankings supports model validation.

Illustration for when parameter sensitivities *rankings are different*
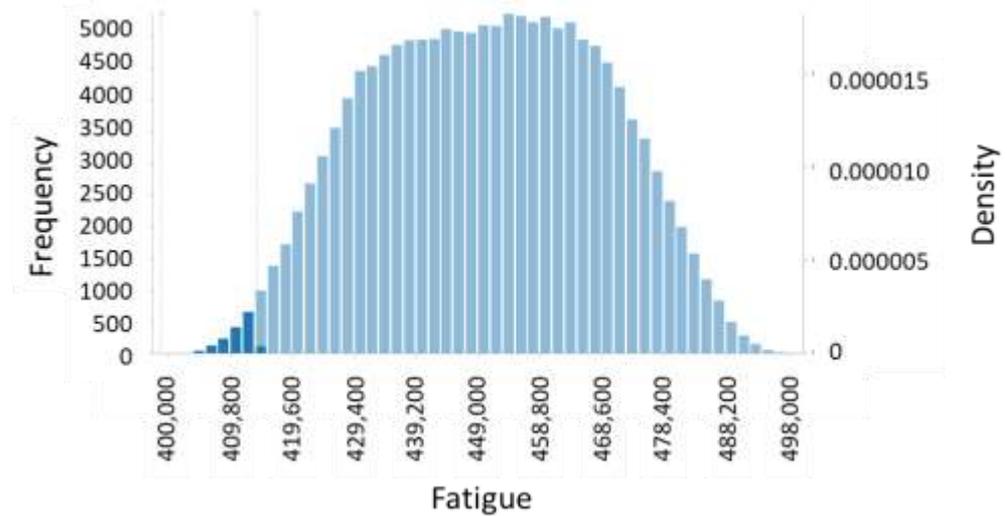
Uncertainty Propagation with Uncalibrated Emulator

Uncalibrated Emulator about
Uncalibrated Emulator Optimum

Lower Bound [N Cycles]	Upper Bound [N Cycles]	Percent Difference
398,775	414,000	1.10%

Output	Mean	Standard Deviation
Displace (mm)	2.51	0.036
Stress (MPa)	127.0	0.0076
Mass (kg)	4.753	0.095
Fatigue (cycles)	450,555	18,167

Only 1% chance of not meeting the minimum 414,000 cycles Fatigue Cycles Criterion.
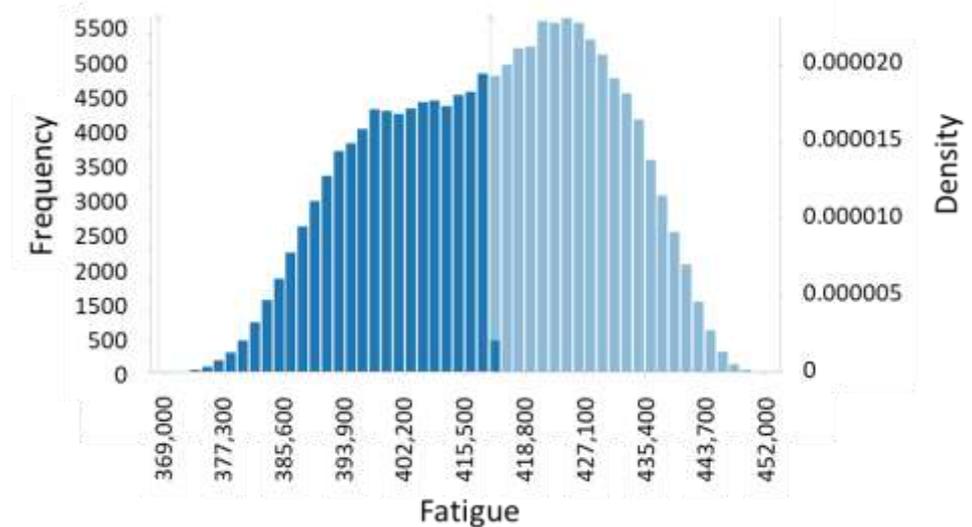
Uncertainty Propagation with Calibrated Emulator and Calibrated Optimum

Calibrated Emulator about Calibrated Emulator Optimum

Lower Bound [N Cycles]	Upper Bound [N Cycles]	Percent Difference
367,960	414,000	47.2%

| Output	Mean	Standard Deviation
Displace (mm)	2.49	0.03
Stress (MPa)	124.0	0.0079
Mass (kg)	4.735	0.099
Fatigue (cycles)	414,217	15,738

There is a 47% chance of not meeting the minimum 414,000 cycles Fatigue Cycles Criterion.

Interpreting the Uncertainty Propagation Results

When compared to the physical data, the Calibrated Emulator had reduced uncertainty over the Uncalibrated Emulator.

- If you *did not calibrate* the model:

  – *Would likely proceed forward with this optimal bracket design.*

- If you *calibrated* the model:

  – *Would not proceed forward with this optimal bracket design.*
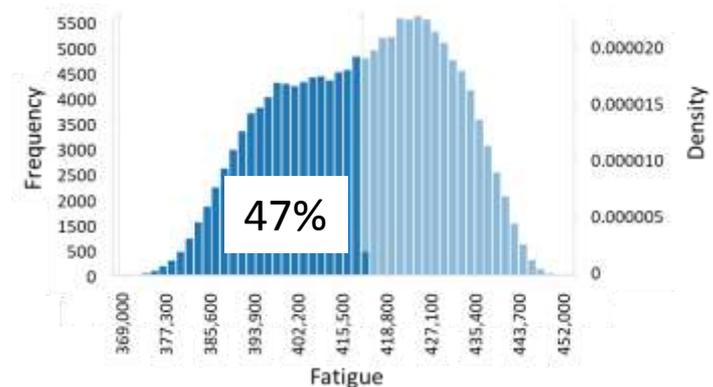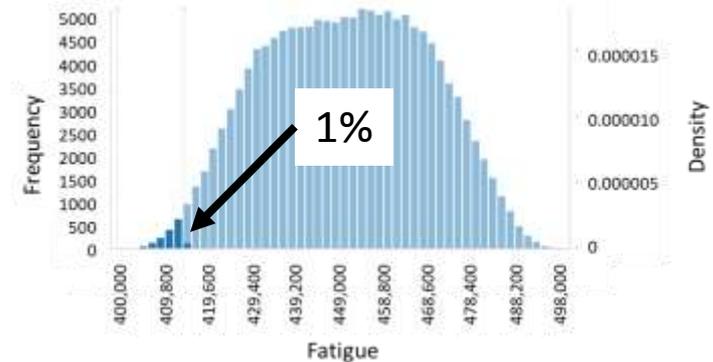
Summary for Bracket Fatigue Case Study

- **Propagating uncertainties** through the calibrated model assessed the impact of manufacturing variations to performance metrics. Risk = (uncertainty with consequence).

- **Sensitivity analysis** was used to identify key drivers in manufacturing variability.

- **Statistical Calibration** of the model to physical data made the simulation results more realistic and reduced the risk of poor decision making.

Using Inverse Analysis for Reducing Variations in Manufacturing

Inverse Problems are 'Backward Analysis'

- Inverse problems describe the *model inputs* based on the *model outputs*.

- Inverse problems are often nonlinear, ill-posed and may not have a unique solution.

- Statistical inverse analysis methods find the most likely input distributions which yield the observed outputs.
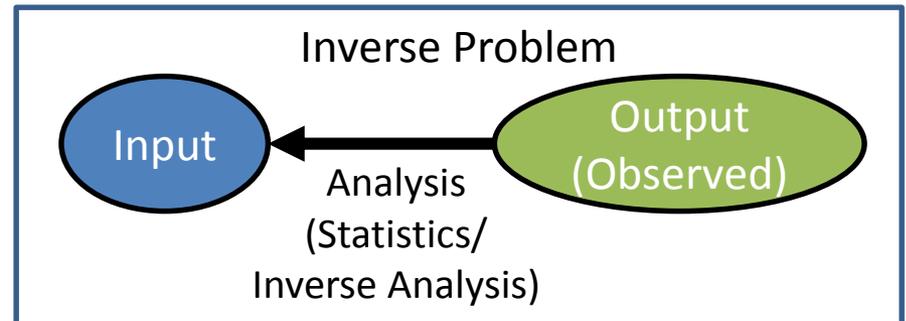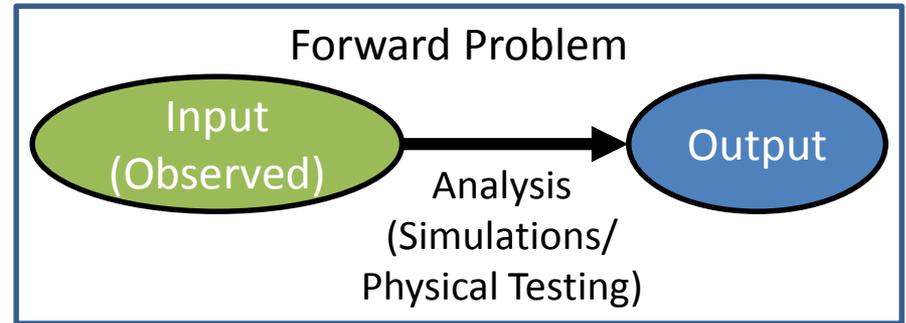
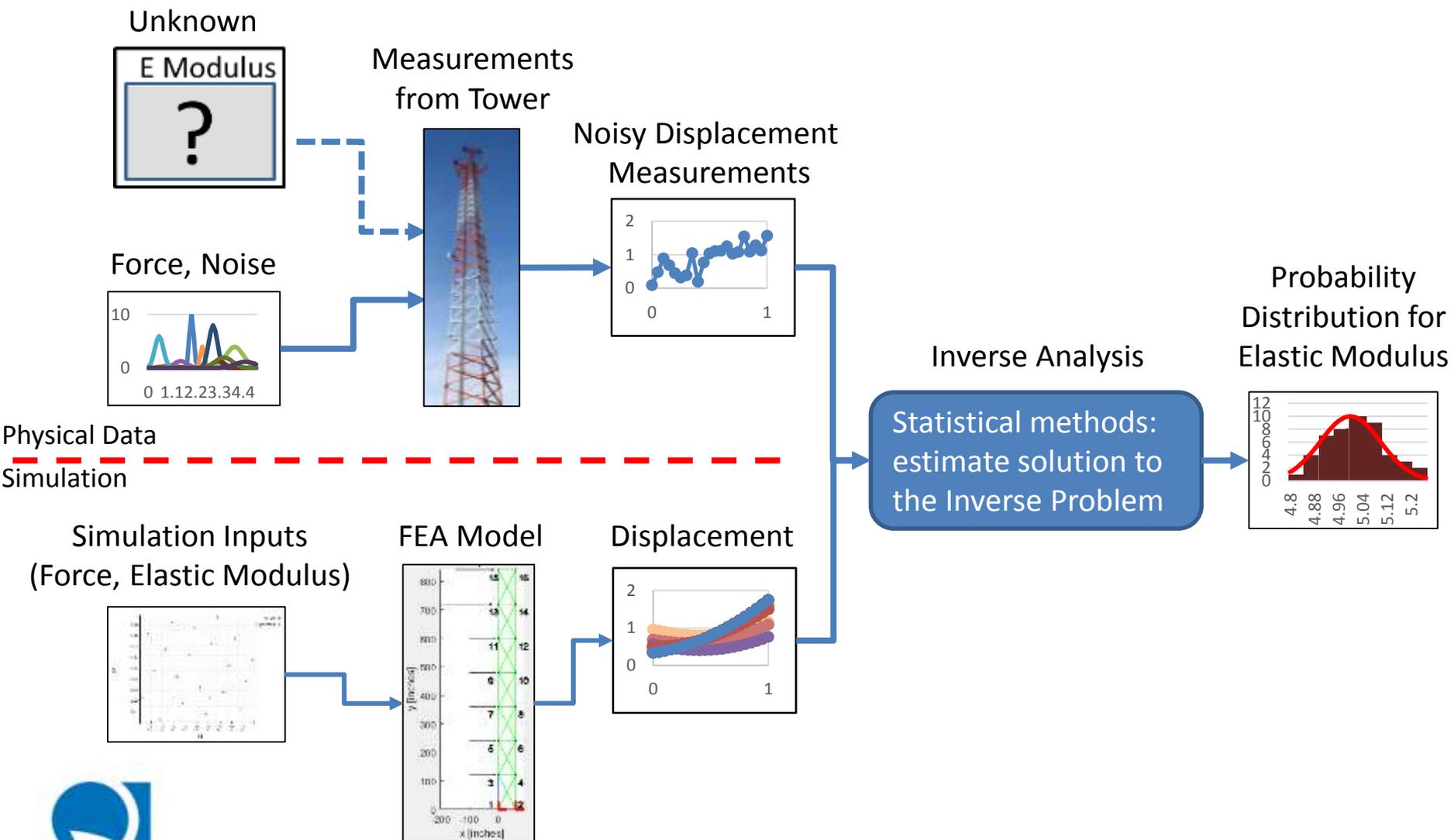 – Observed output data may be physical testing data or simulation results.

Forward Problem

Input (Observed) → Output

Analysis (Simulations/ Physical Testing)

Inverse Problem

Input ← Output (Observed)

Analysis (Statistics/ Inverse Analysis)

Example of Inverse Analysis Problem

- What is the Elastic Modulus of the truss-based cell phone tower?
- Observed tower displacement of inter-tower microwave transmission:
  - 10 noisy 'physical' load observations.
  - Measurement error estimated at ~5%.
- FEA model used to calculate displacement & stress in truss-based cell phone tower:
  - 20 simulations data points.
- Use inverse analysis to estimate underlying distribution of the unknown Elastic Modulus of the truss system in the presence of noisy data.

Statistical Framework for Inverse Problem

Unknown

E Modulus
?

Measurements from Tower

Force, Noise
10
0
0 1.12.23.34.4

Noisy Displacement Measurements
2
1
0
0   1

Physical Data
Simulation

Simulation Inputs
(Force, Elastic Modulus)

FEA Model

Displacement
2
1
0
0   1

Inverse Analysis

Statistical methods: estimate solution to the Inverse Problem

Probability Distribution for Elastic Modulus
12
10
8
6
4
2
0
4.8 4.88 4.96 5.04 5.12 5.2

ASQ

Inverse Analysis Problem Results

- Inverse analysis estimates the Elastic Modulus at 29.2 ksi which is very close to the true value of 29.0 ksi.

Young's Modulus	Mean [KSI]	Std. Dev. [KSI]
Estimate	29.2	1.44
True	29.0	1.45
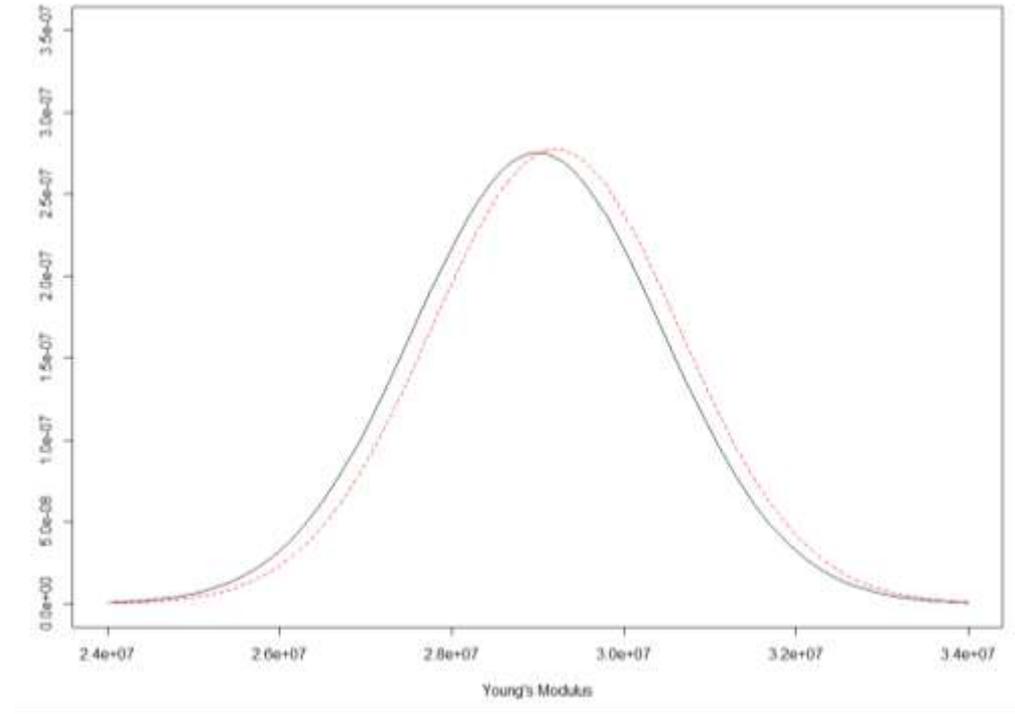
Elastic modulus probability distributions. Solid black line is actual and dashed red line is estimated.
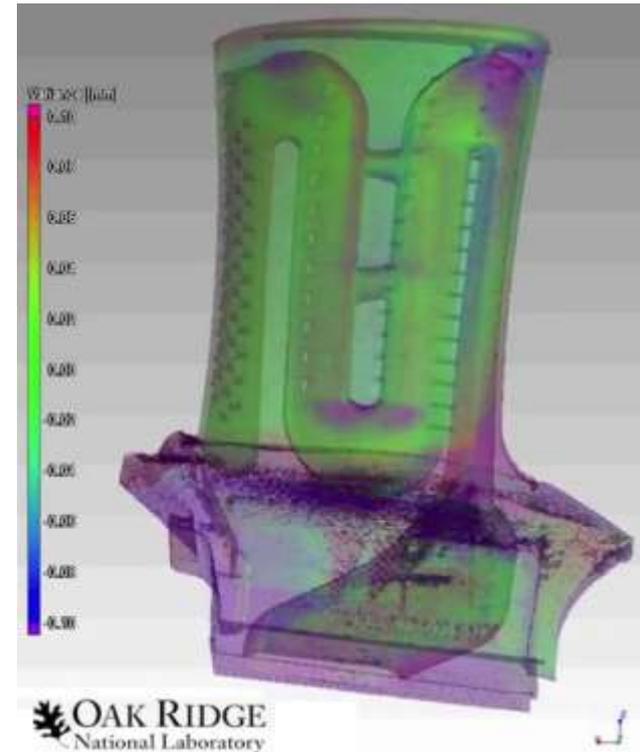
Applying Inverse Analysis In Manufacturing

- Manufactured parts have complex relationships between parameters and performance.

  - Some parameters may be difficult to measure.

  - Difficult to connect observed performance metrics to parameters.

- Inverse analysis can identify which parameter controls the observed performance metric.

  - Used to set parameter tolerances to meet a specified performance goal
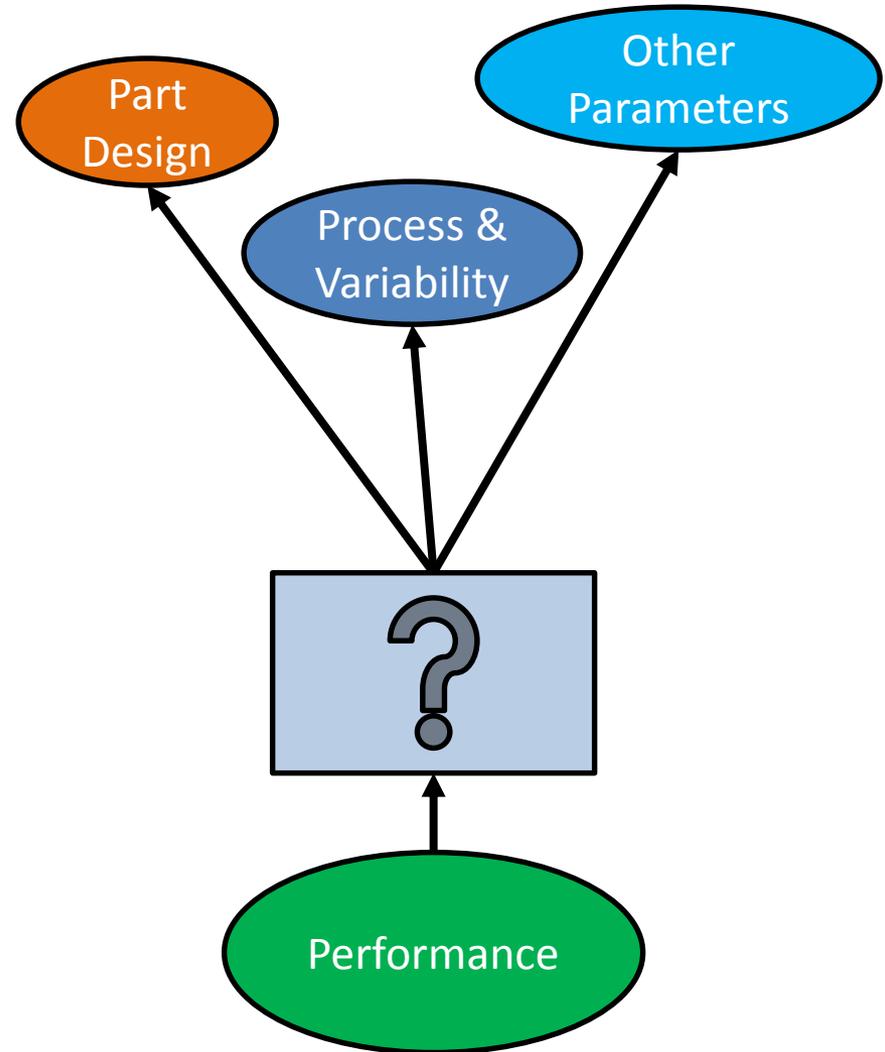
Potential Application: Tolerance Specification for Turbine Blade Performance

- Turbine blade performance is a complex function of many parameters:

  – Some parameters are difficult to measure, e.g., internal turbine Cooling Channel Geometries (CCGs).

- Goal: find the parameter tolerance bounds which lead to goal performance:

  – Internal turbine Cooling Channel parameters are typically not measured.

  – Sensitivity analysis can determine which parameters are important, but does not determine which parameters are varying to cause an observed response.
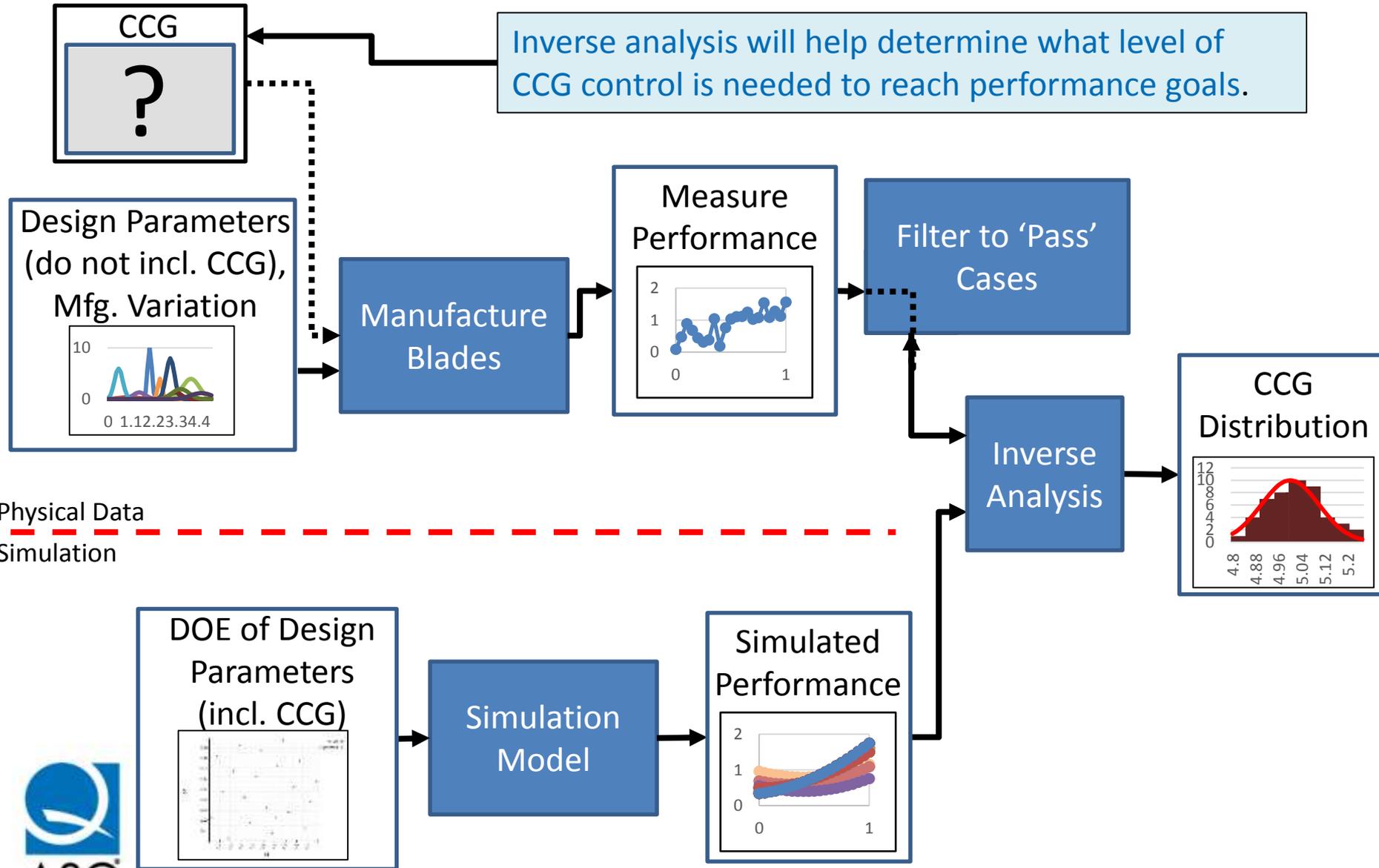
  – How does inverse analysis help?

Hot side turbine blade
Image is from Oak Ridge National Lab and is for demonstration purposes only.

Inverse Process Map for Manufacturing

CCG

?

Inverse analysis will help determine what level of CCG control is needed to reach performance goals.

Design Parameters (do not incl. CCG), Mfg. Variation

Manufacture Blades

Measure Performance

Filter to 'Pass' Cases

CCG Distribution

Inverse Analysis

Physical Data

Simulation

DOE of Design Parameters (incl. CCG)

Simulation Model

Simulated Performance

Summary: Inverse Analysis for Manufacturing

- Inverse analysis provides a way to estimate the underlying distribution of an unknown stochastic parameter in the presence of noise.

- The parameter tolerance bounds for meeting performance metrics can be determined from the inverse analysis.

- Inverse analysis can also identify measurable parameters that best detect *out-of-conformance* conditions.

- Characterizing difficult to measure physical parameters using inverse analysis may change the decision you make for reducing manufacturing variations.

Presentation Take-Aways
Enhancing Six Sigma with UQ

- Using simulations with UQ early in the Six Sigma process will identify ways to reduce uncertainties and risks before implementing solutions.

- Leveraging UQ with simulation and the Six Sigma process creates a holistic view of the performance improvement.

- Using emulation, the uncertainty in meeting manufactured part tolerances can be expressed in terms of performance.

- UQ predictive analytics can forecast how likely will the project goals be met given manufacturing variations.

- Calibrating the model to physical data improved simulation realism and reduced the risk of making poor decisions.

Questions?

Mark Andrews – Phone: (309) 258-2309 – Email: mark.andrews@smartuq.com