

Industrial Perspective of V&V in Engineering Decisions

John A. Cafeo

General Motors Research & Development

john.cafeo@gm.com

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PRESENTATION OUTLINE

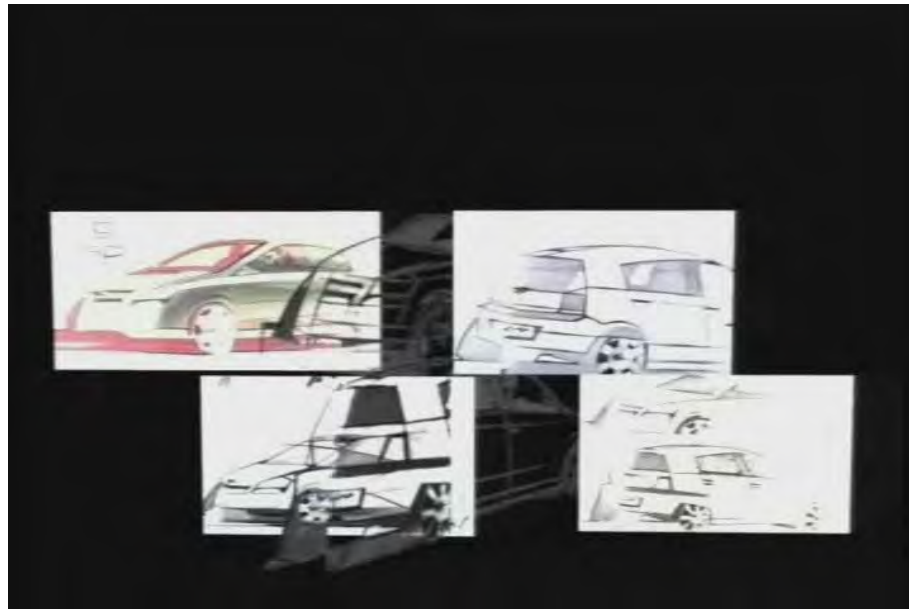
- I. Vehicle Development & Math-based Computer Models**
- II. Decisions in Product Development
- III. Model Verification and Validation
- IV. Steps for Validation
- V. An Example
- VI. The Message

With Math...

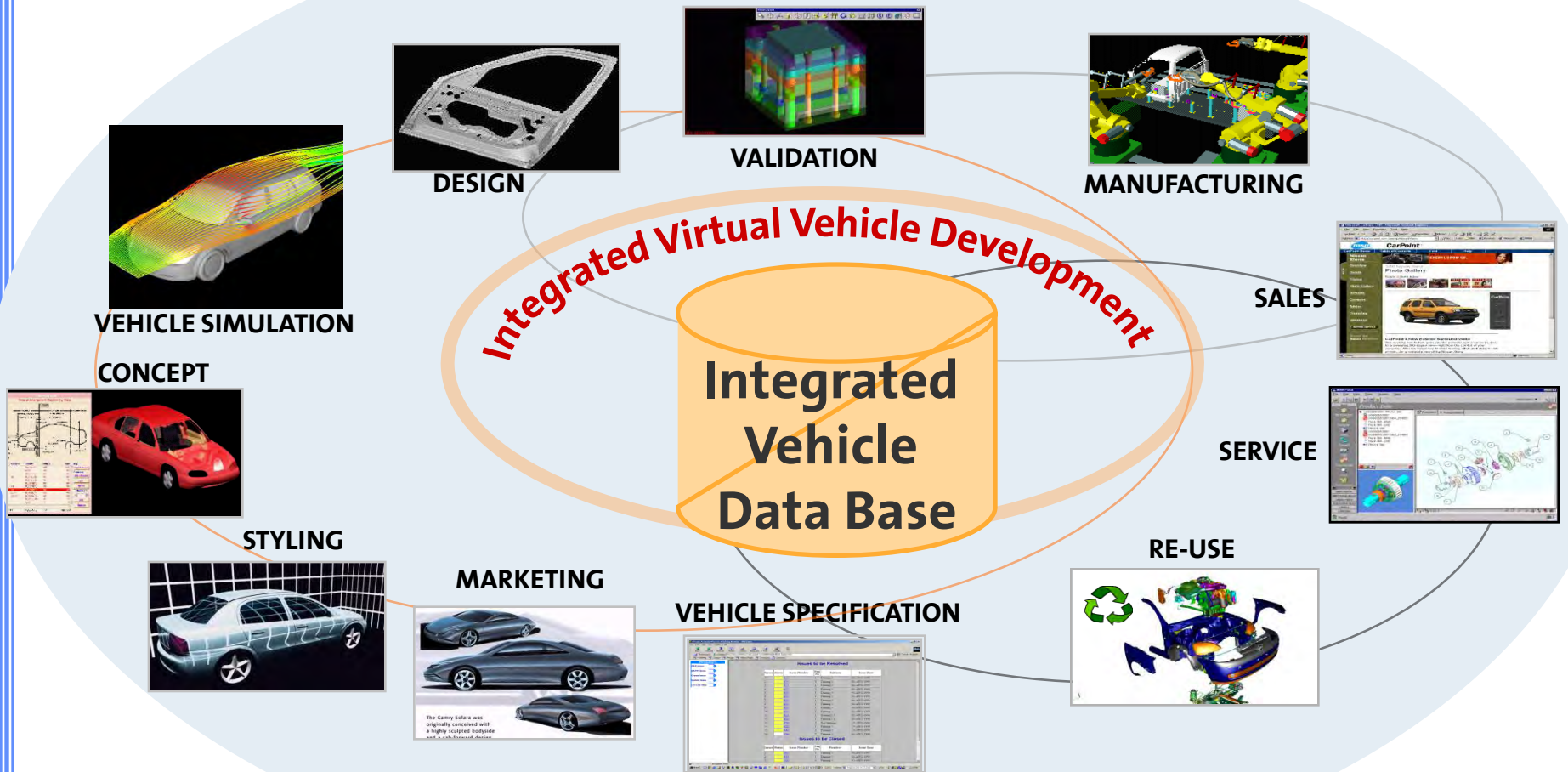
$$M\ddot{x} + C\dot{x} + Kx = P_m \sin \omega t$$

Why Models in Engineering?

1. **Quality Improvement** – explore more designs, eliminate early physical model uncertainty, explore variation effects.
2. **Time Constraints/Demand** – shorten time from Concept to Showroom
3. **Capital Reduction** – minimal physical costs for iteration, hardware reduction



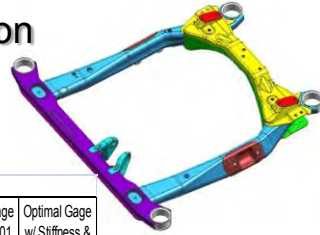
Models in Product Development



Models used to assess many types of performance in the complete vehicle life cycle

Optimization Technique in Automotive Chassis Design

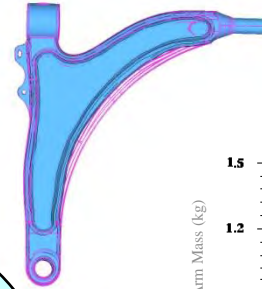
Engine Cradle Gauge Optimization



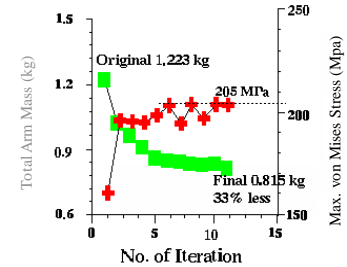
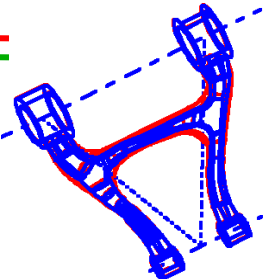
Control Arm Shape Optimization

Morph

Geometry based Design Parameterization

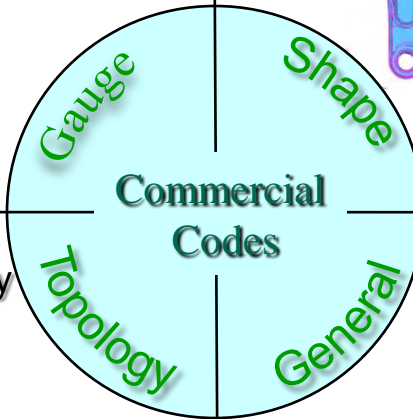


Original Shape
Final Shape



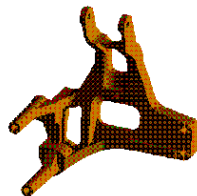
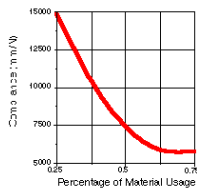
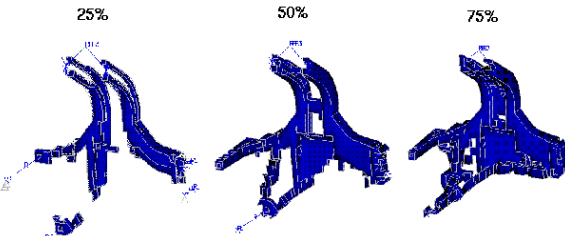
Front Cradle Gauge Optimization Summary

Design Gage ID	Design Variable Label	Part Mass (kg)	Lower Limit (mm)	Current I/VER Design (mm)	Upper Limit (mm)	Optimal Gage w/ Stiffness Target Only (mm)	Optimal Gage w/ GO Schedule Target Only (mm)	Optimal Gage w/ GMN9801 Schedule Target Only (mm)	Optimal Gage w/ Stiffness & GO Schedule Target (mm)
1	FVMEB Up	1.87 (7.6%)	2.0	2.0	2.8	2.0	2.0	2.0	2.0
2	FVMEB Lwr	2.06 (8.3%)	2.0	2.0	2.8	2.0	2.1	2.1	2.1
3	RVMEB Up	2.79 (11.3%)	2.0	3.0	3.3	3.2	3.0	2.7	3.0
4	RVMEB Lwr	2.69 (10.9%)	2.0	3.3	3.3	3.3	3.0	2.7	3.0
5	Rail	10.56 (42.7%)	2.0	2.8	3.0	2.7	2.8	2.6	2.8
6	Frt. Torq. Mnt	0.45 (1.8%)	2.0	2.3	2.8	2.0	2.3	2.1	2.3
7	LCA Frt. Plate	1.12 (4.5%)	2.0	3.5	4.0	4.0	4.0	4.0	4.0
8	LCA Rr. Bot	0.27 (1.1%)	2.0	2.0	2.8	2.0	2.0	2.0	2.0
9	Stab/Bart Brkt	0.55 (2.2%)	2.0	3.5	4.0	2.0	2.3	2.2	2.3
Total Mass		24.71		24.71		24.27	24.42	23.00	24.42
ΔMass (Opt-Current) (kg)						-0.44	-0.29	-1.71	-0.29



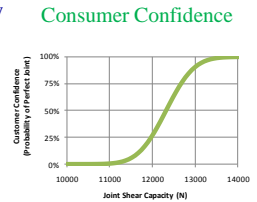
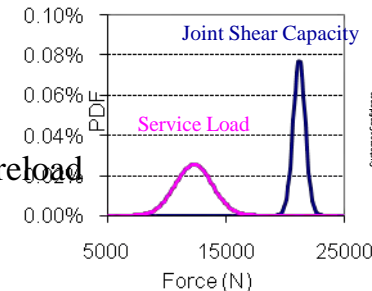
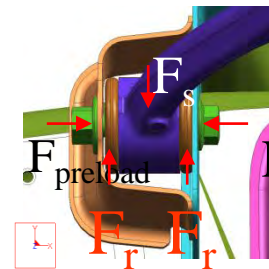
Powertrain Mount Bracket Topology Study

Material Growth Simulation



- Multi-discipline Design Optimization (MDO)
- Design of Experiment (DOE)
- Design Response Surface (DRS)
- Stochastic Design Optimization (SDO)
- Design for Six Sigma (DFSS)

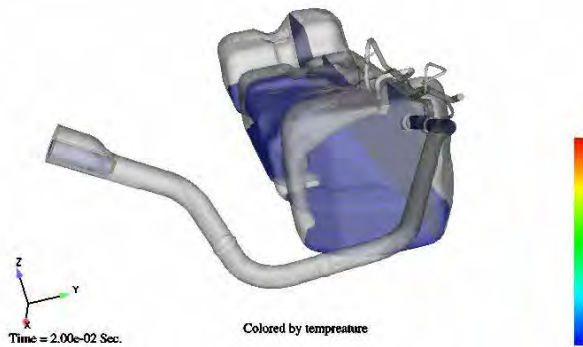
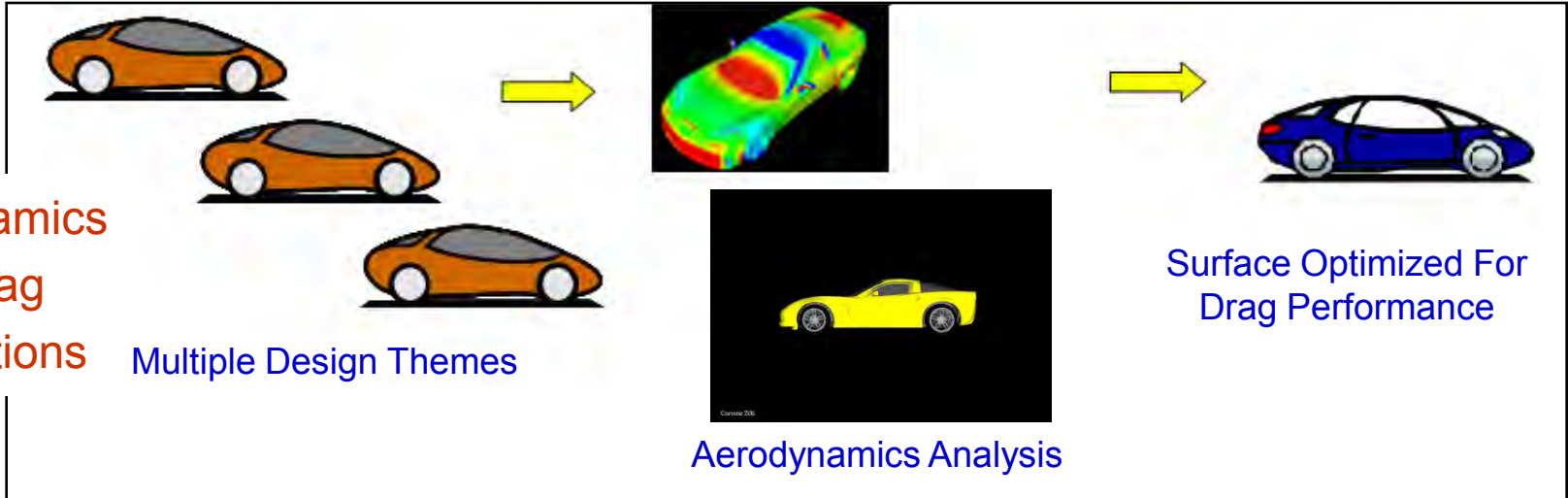
Customer Detection of Joint Slip



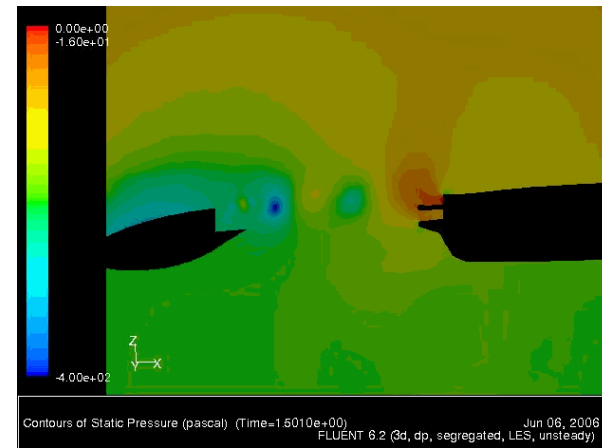
Computational Fluid Dynamics (CFD) for Performance Assessments

Aerodynamics
for Drag
Calculations

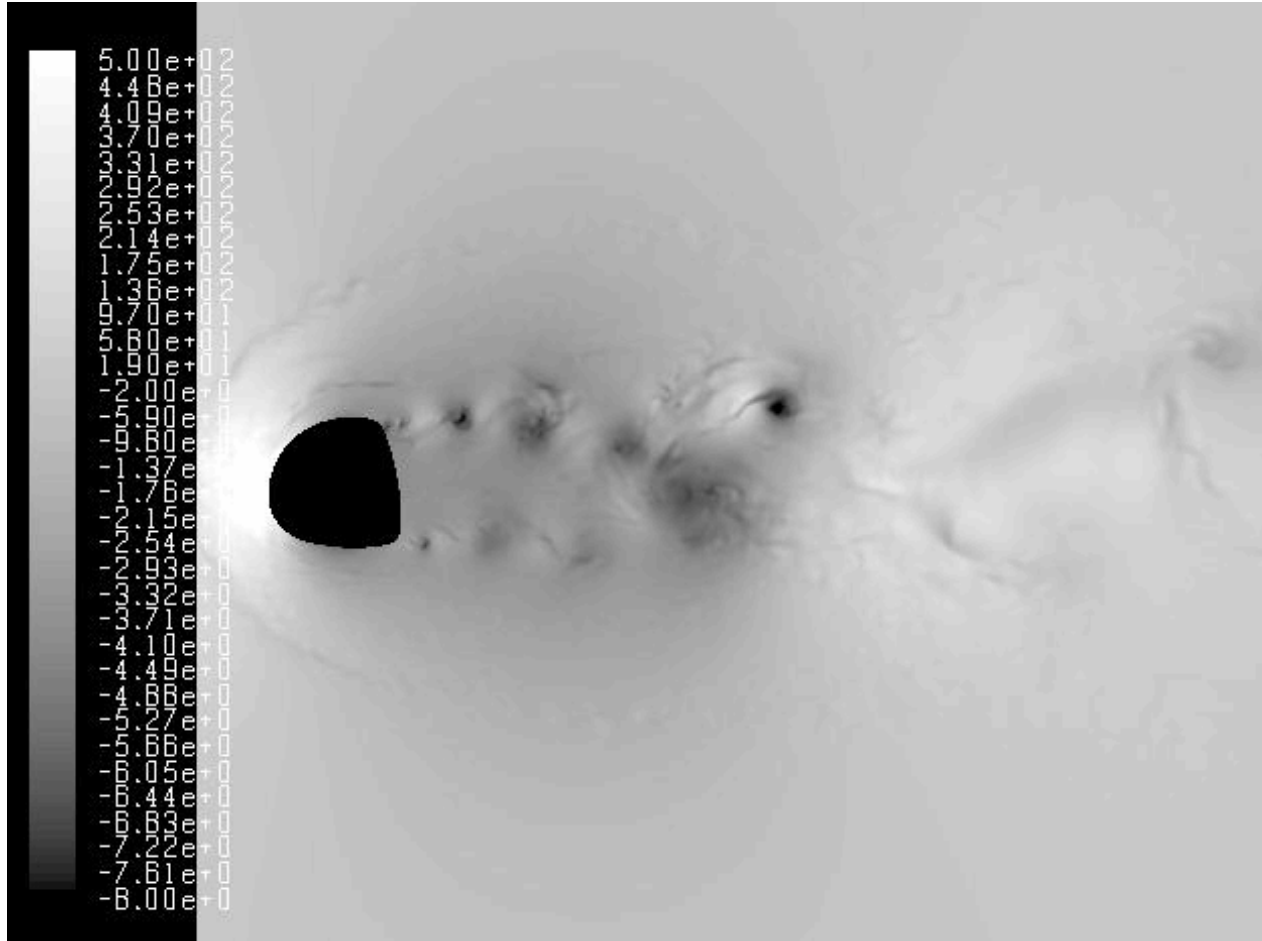
Multiple Design Themes



Fuel Fill & Fuel Slosh

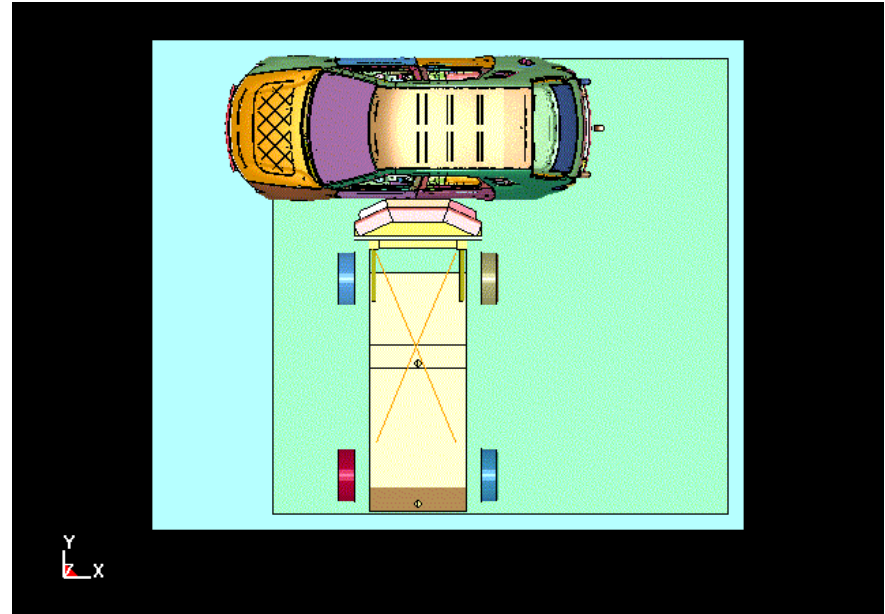
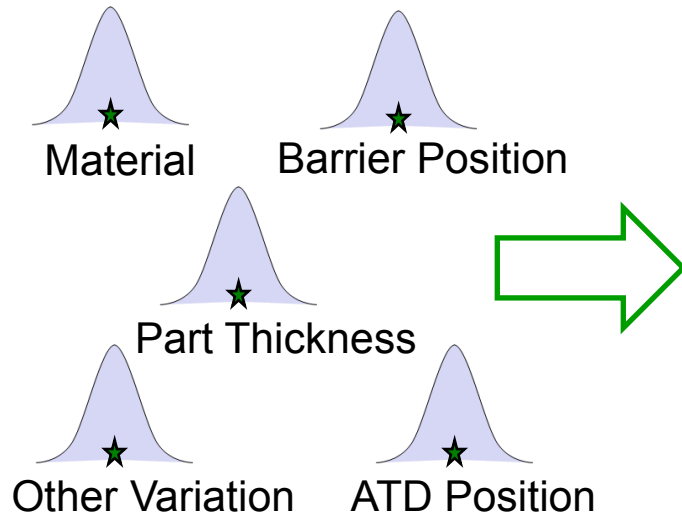


Sunroof Helmholtz
Resonator Effect

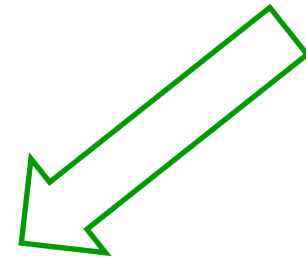
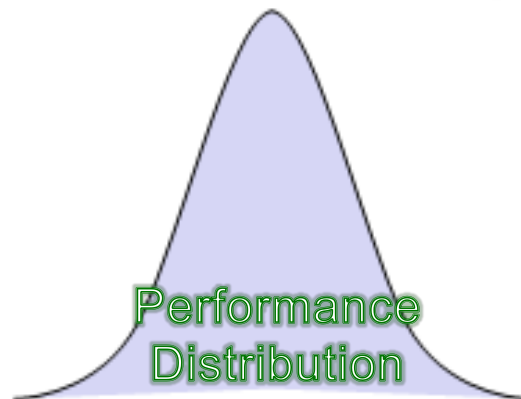


High Resolution Outside Rear View Mirror Flow modeling

Stochastic Design Study



Maximum Target



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MOTIVATION – WHY Verification & Validation?



Decision makers want to know:

- Can we use this model to ***predict*** frontal barrier impacts?
- What is the ***error*** between the model and tests?
- How much ***confidence*** do we have in the model predictions?
- Can we use this model to ***predict*** offset frontal barrier impacts?

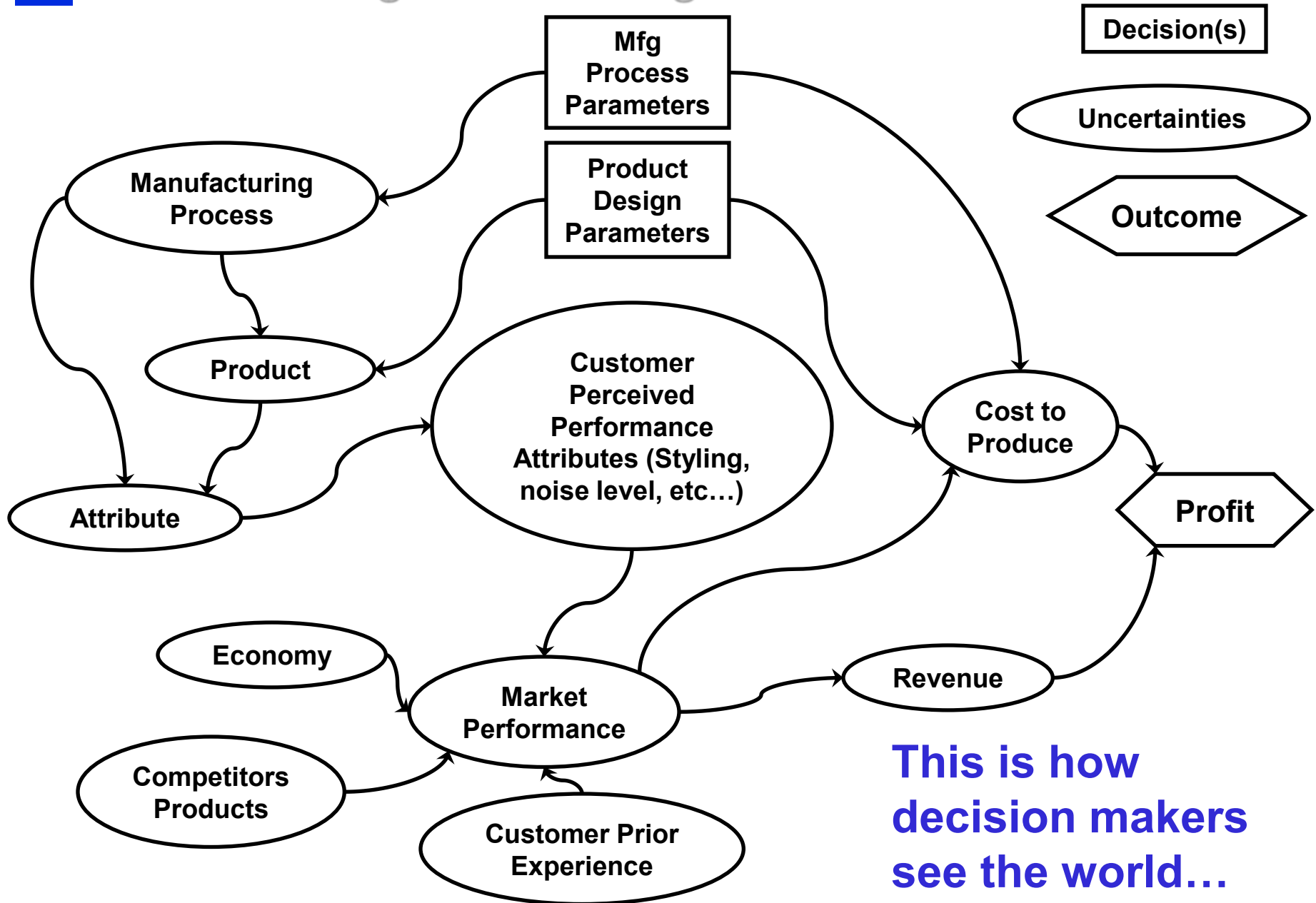
V&V can *help* answer these questions.

Decision Definition

“A decision is an irrevocable allocation of resources, in the sense that it would take additional resources, perhaps prohibitive in amount, to change the allocation.” *[Matheson and Howard]*

“A good decision is based on the information, values and preferences of a decision-maker. A good outcome is one that is favorably regarded by a decision-maker. It is possible to have good decisions produce either good or bad outcomes. Most persons follow logical decision procedures because they believe that these procedures, speaking loosely, produce the best chance of obtaining good outcomes.”

Decision Diagram for Design Alternatives



Product Development can be Viewed as a Temporal Set of Decisions

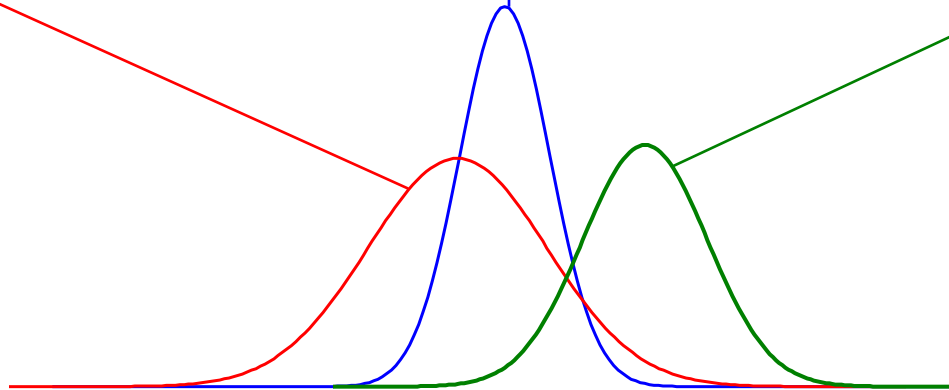
- Product development process is a set of decisions...
 - inevitably made under uncertainty (**lack of knowledge, inherent variation**) and risk (**probability and consequence of failure**)
 - analysts' (**including engineers**) role is to develop alternatives and predict outcomes
 - *Analyses should be performed when the results are relevant to the decision at hand and the value of the results exceeds the cost of obtaining them*
 - *Analysis results should include assessment of confidence (**validation**)*
 - product program leaders assess uncertainties and choose alternatives (**make decisions**) that they hope will lead to desired outcomes.

The Situation – Reality, Measurements, Simulations

- Quantity of Interest: Fuel Economy e.g. Mid-Size SUV Segment (y^R)
- Metric: Actual Population of Vehicles Produced for 2004 [REALITY]
- Status: Unknowable

- Quantity of Interest: Fuel Economy e.g. Mid-Size SUV Segment (y^F)
- Metric: Estimate from field test of production vehicles [MEASURE]
- Status: Observable with uncertainty

- Quantity of Interest: Fuel Economy e.g. Mid-Size SUV Segment (y^M)
- Metric: Estimate from mathematical model [CALCULATE]
- Status: Observable with uncertainty



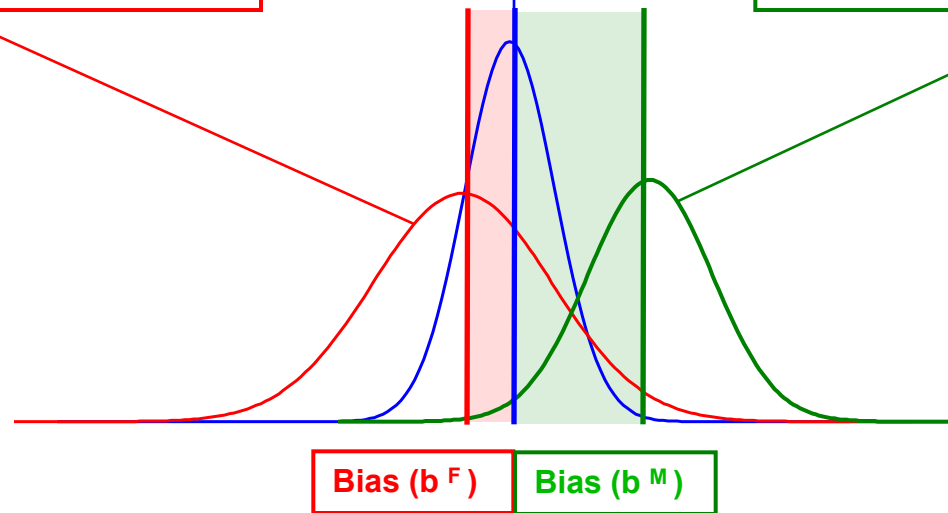
Reality is unknowable but observable either by measurement or calculation

Bias – What we would like to know

- Quantity of Interest: Fuel Economy
e.g. Mid-Size SUV Segment (y^R)
- Metric: Actual Population of Vehicles
Produced for 2004 [REALITY]
- Status: Unknowable

- Quantity of Interest: Fuel Economy
e.g. Mid-Size SUV Segment (y^F)
- Metric: Estimate from field test of
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- Quantity of Interest: Fuel Economy
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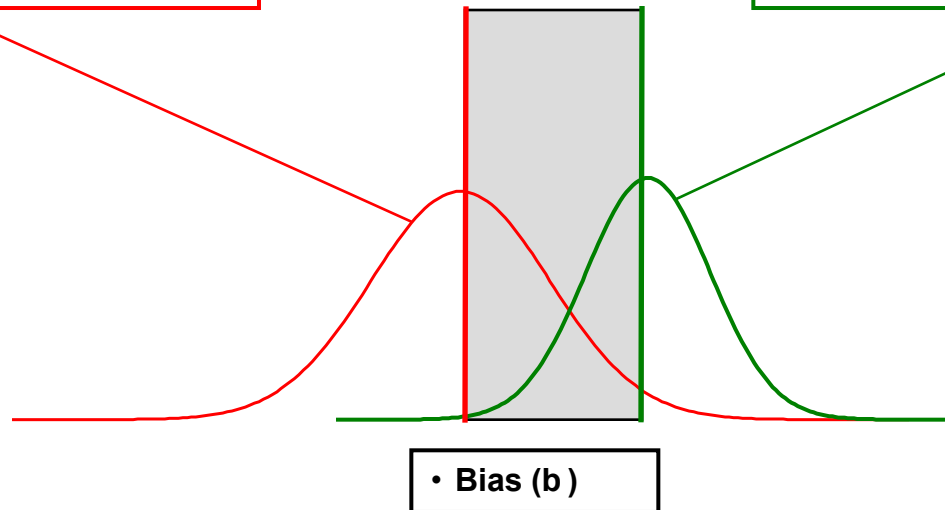


We would like to know the difference (bias, error) between the different types of observations (measure, calculate) and reality.

Bias – What we can know

- Quantity of Interest: Fuel Economy e.g. Mid-Size SUV Segment (y^F)
- Metric: Estimate from field test of production vehicles [MEASURE]
- Status: Observable with uncertainty

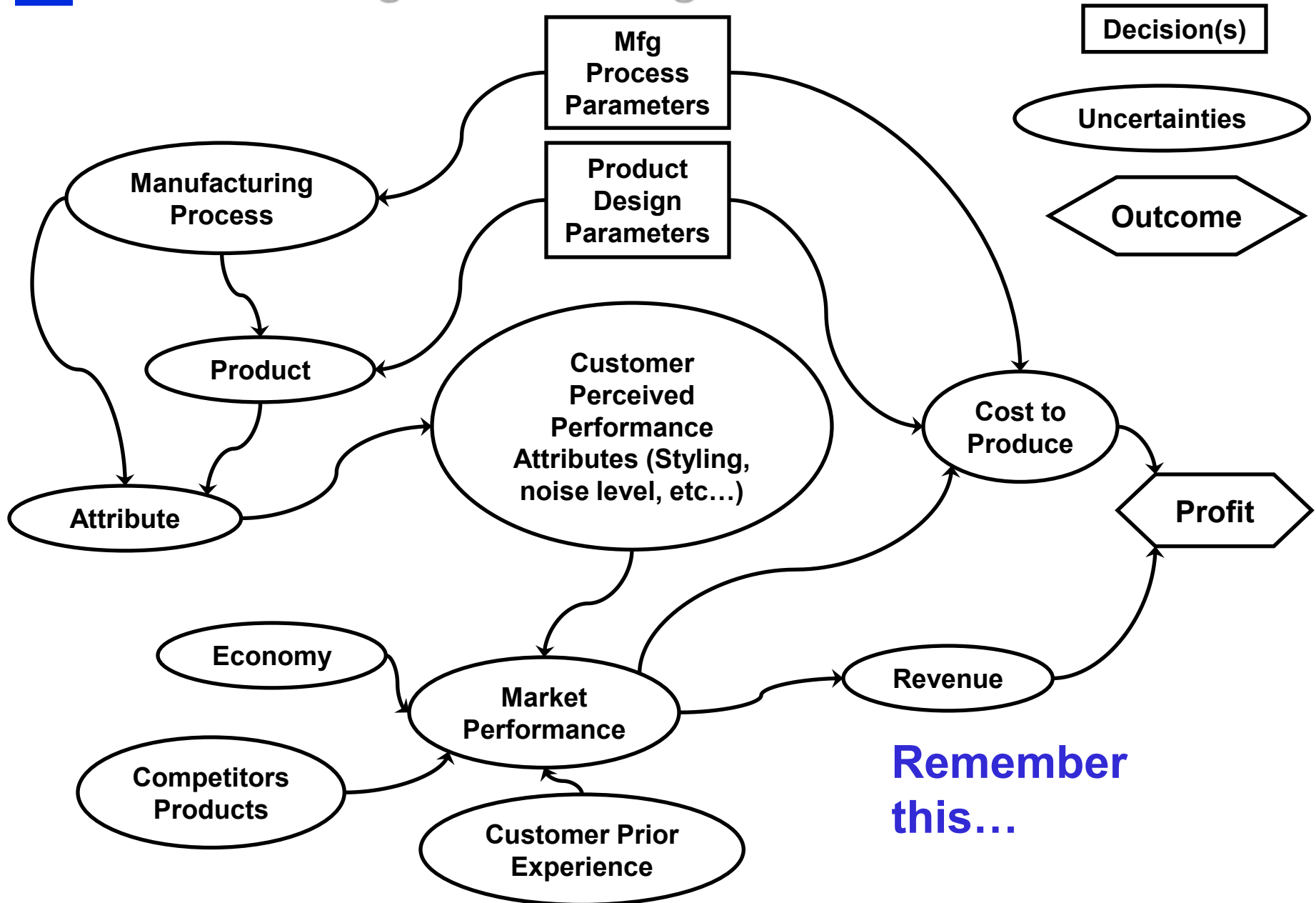
- Quantity of Interest: Fuel Economy e.g. Mid-Size SUV Segment (y^M)
- Metric: Estimate from mathematical model [CALCULATE]
- Status: Observable with uncertainty



However, we can only estimate the difference (bias, error) between the two different types of observations: 1. measure, 2. calculate.

One of these then must be the reference quantity. Because we speak of model V&V, we are choosing our test results as our referent.

Decision Diagram for Design Alternatives



Evidence the decision maker uses.

REALITY (Unknowable)

- Basis: Actual population of products
- Uncertainties: Mfg Variation

PHYSICS BASED CALCULATION

- Basis: Mathematical physics model
- Uncertainties: Parametric, model form, use conditions, etc...
- Credibility Assessment: Math model verification and validation
- Neg. Issues: Detailed design not known, can be slow to construct, etc...
- Pos. Issues: Flexible, accurate, etc...

EXPERT OPINION

- Basis: Experience
- Uncertainties: level of optimism, range and applicability of experience, differing opinions, etc...
- Credibility: Reputation
- Neg. Issues: Accuracy suspect, etc...
- Pos. Issues: Fast, do not need detailed representation

STATISTICAL MODELING

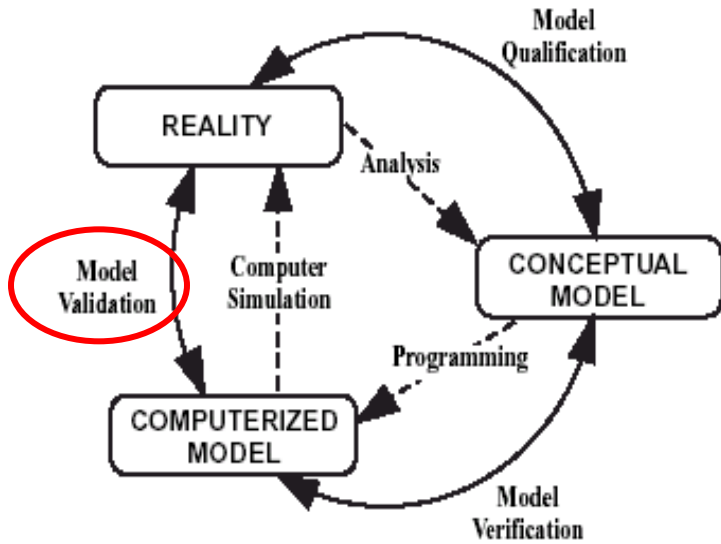
- Basis: Statistical model built from past evidence (test data, observations of market, etc...)
- Uncertainties: Applicability of past data, sampling, etc...
- Credibility: Use has led to favorable outcomes on past decisions
- Neg. Issues: Not flexible. Must have relevant factors
- Pos. Issues: Fast. Do not need detailed physical representation

Because the decision maker is human, they must actually understand and believe in the verification and validation process.

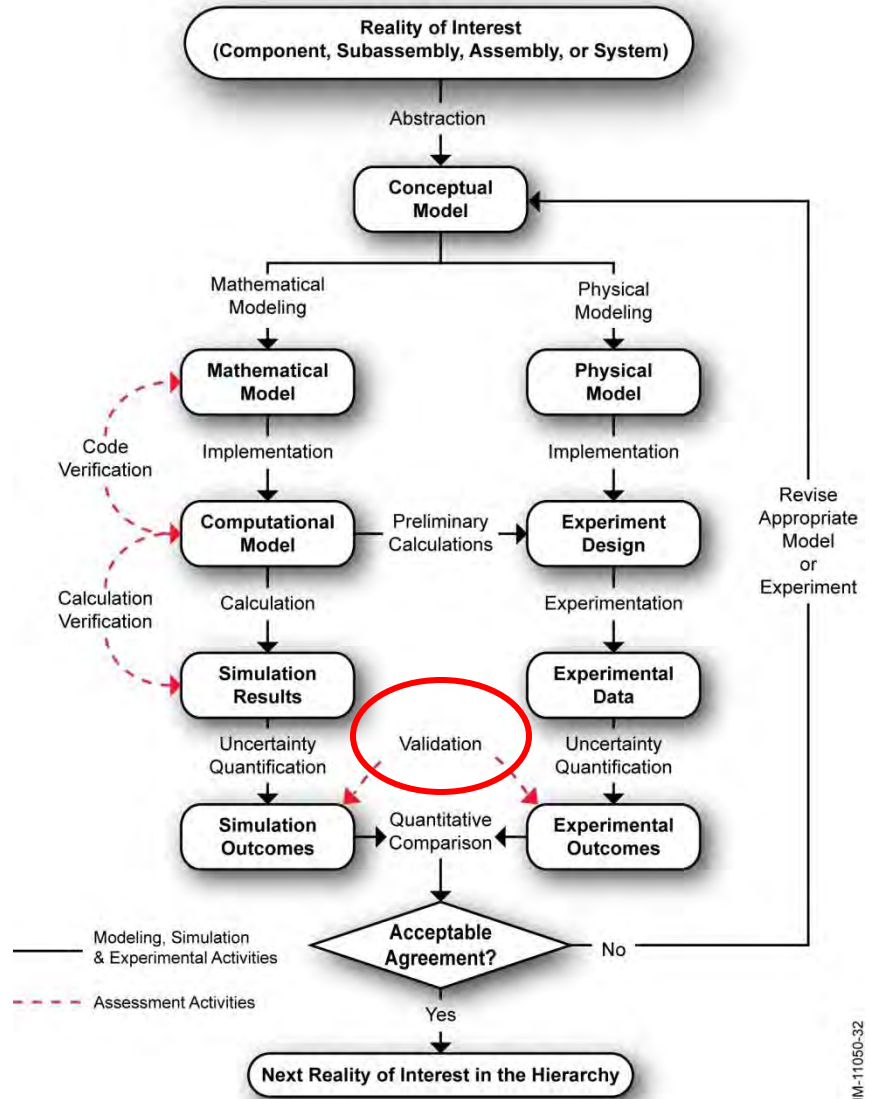
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Background

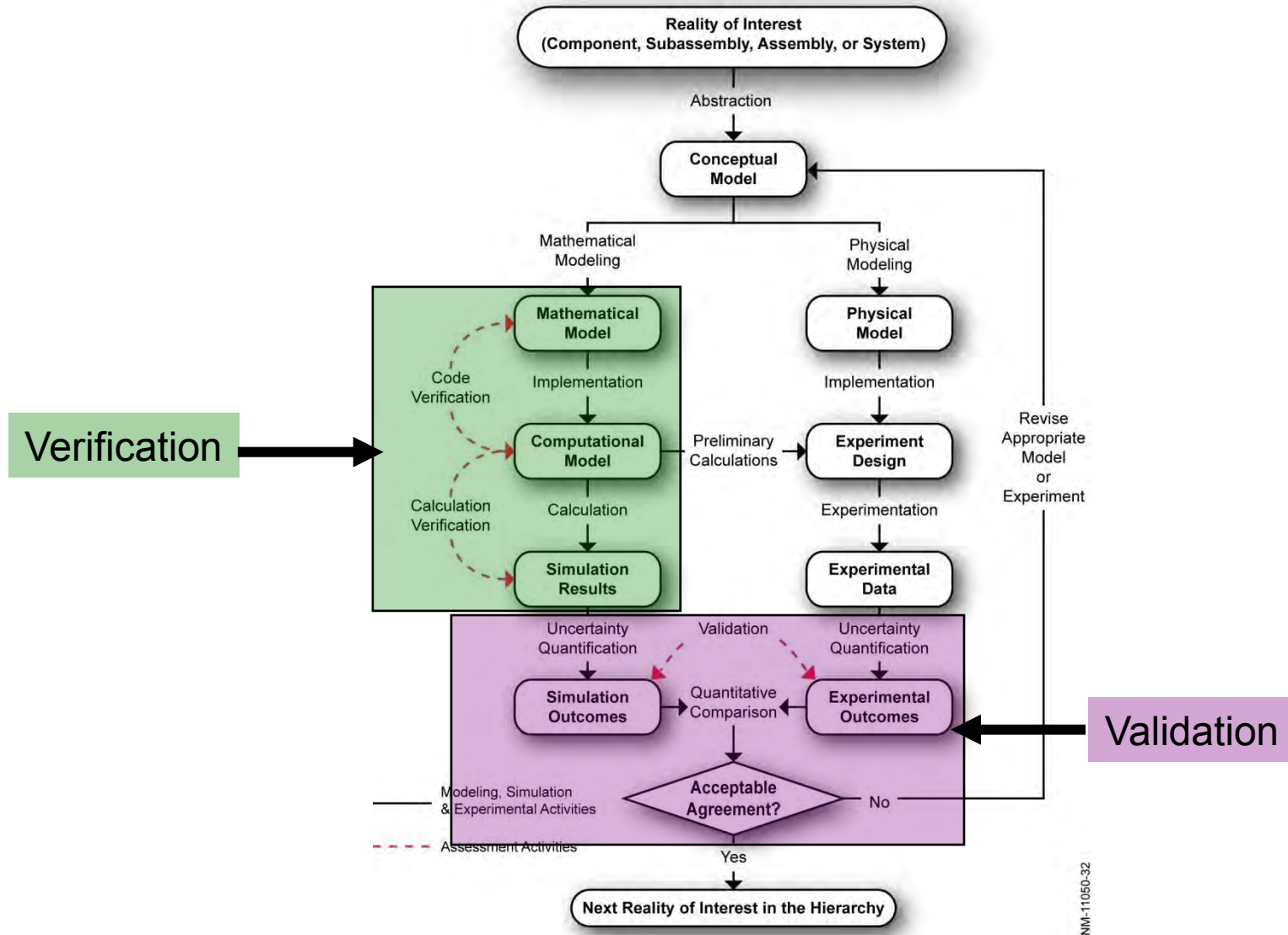


Phases of modeling & simulation (AIAA Guide – G-077-1998)



ASME Committee on V&V in Computational Solid Mechanics, PTC 60 Guide – ASME V&V 10-2006

Verification & Validation Process



Put most simply, verification is the domain of mathematics and validation is the domain of physics.

Verification

The process of determining that a computational model accurately represents the underlying mathematical model and its solution.

Code Verification – establish confidence, through the collection of evidence, that the mathematical model and solution algorithms are working correctly.

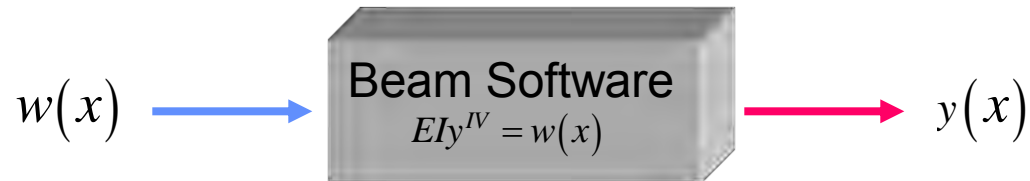
- Code Solution = Analytical Solution?
- **Developers** & Users

Calculation Verification - establish confidence, through the collection of evidence, that the discrete solution of the mathematical model is accurate.

- Discretization Error?
- Developers & **Users**

Code Verification

One formal method for Code Verification is the **Method of Manufactured Solutions**:



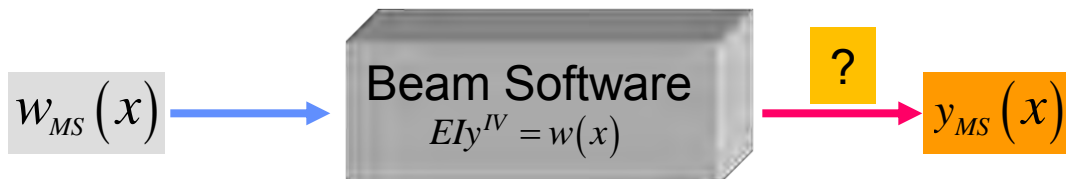
Manufacture (assume) a solution:

$$y_{MS}(x) = A \sin \frac{\alpha x}{L} + B \exp\left(\frac{x}{L}\right) + C$$

A, α, B, C constants determined from boundary conditions

Apply Differential Operator to solution:

$$EIy_{MS}^{IV} = w_{MS}(x) = EI \left\{ A \left(\frac{\alpha}{L} \right)^4 \sin \frac{\alpha x}{L} + \frac{B}{L^4} \exp\left(\frac{x}{L}\right) \right\}$$

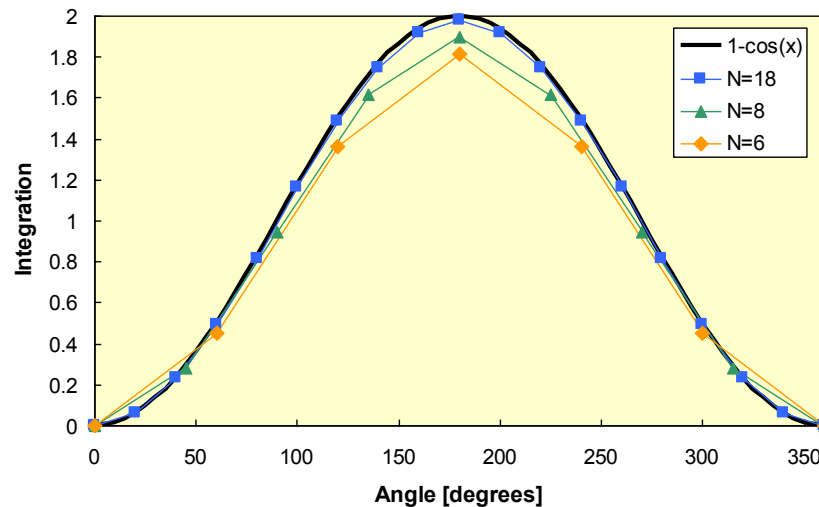


Calculation Verification

Calculation Verification – Every numerical solution contains discretization error.

$y'(x) = \sin x \Rightarrow$ Integrate using Trapezoidal Rule

$$y(x) = \int_0^\theta \sin x dx = 1 - \cos \theta \approx \frac{\theta}{2N} \sum_{i=0}^N [\sin(x_i) + \sin(x_i + \Delta x)] \text{ with } \Delta x = \frac{\theta}{N}$$



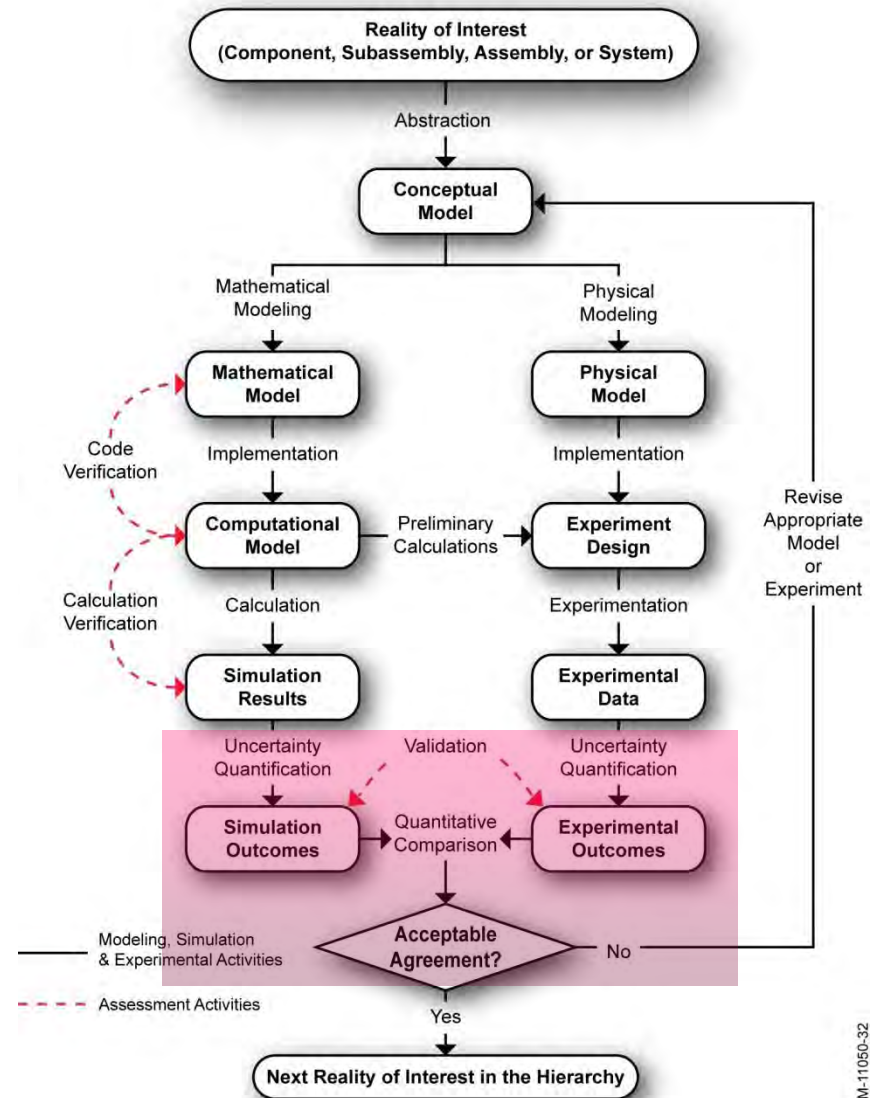
How do we quantify the discretization error when we do not know the analytical solution? One method available is the *Grid Convergence Index* (GCI) – an estimate of the percentage that the computed value is away from the **asymptotic** numerical value . [See: Roache, P. J., 1994, “Perspective: A Method for Uniform Reporting of Grid Refinement Studies,” *Journal of Fluids Engineering*, 116(3), pp. 405-413.]

Validation

The *validation process* has the goal of assessing the predictive capability of the model by comparing the predictive results of the model with validation experiments.

Three key elements of Validation:

1. Precision Testing
2. Uncertainty Quantification
3. Comparative Metrics



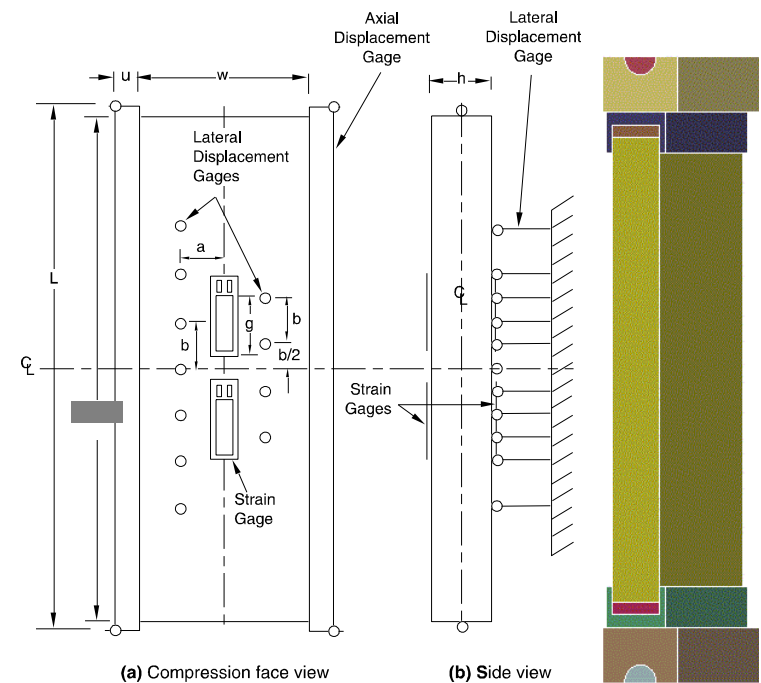
Validation

The goal of a **validation experiment** is to be a physical realization of an initial boundary value problem, since an initial boundary value problem is what the computational model was developed to solve.

Redundancy of the Data – repeat experiments to establish experimental variation.

Supporting Measurements - not only are measurements of the important system response quantities of interest recorded, but other supporting measurements are recorded. An example would be to record the curvature of a beam to support a strain gauge measurement.

Uncertainty Quantification - errors are usually classified as being either random error (precision) or systematic error (bias).

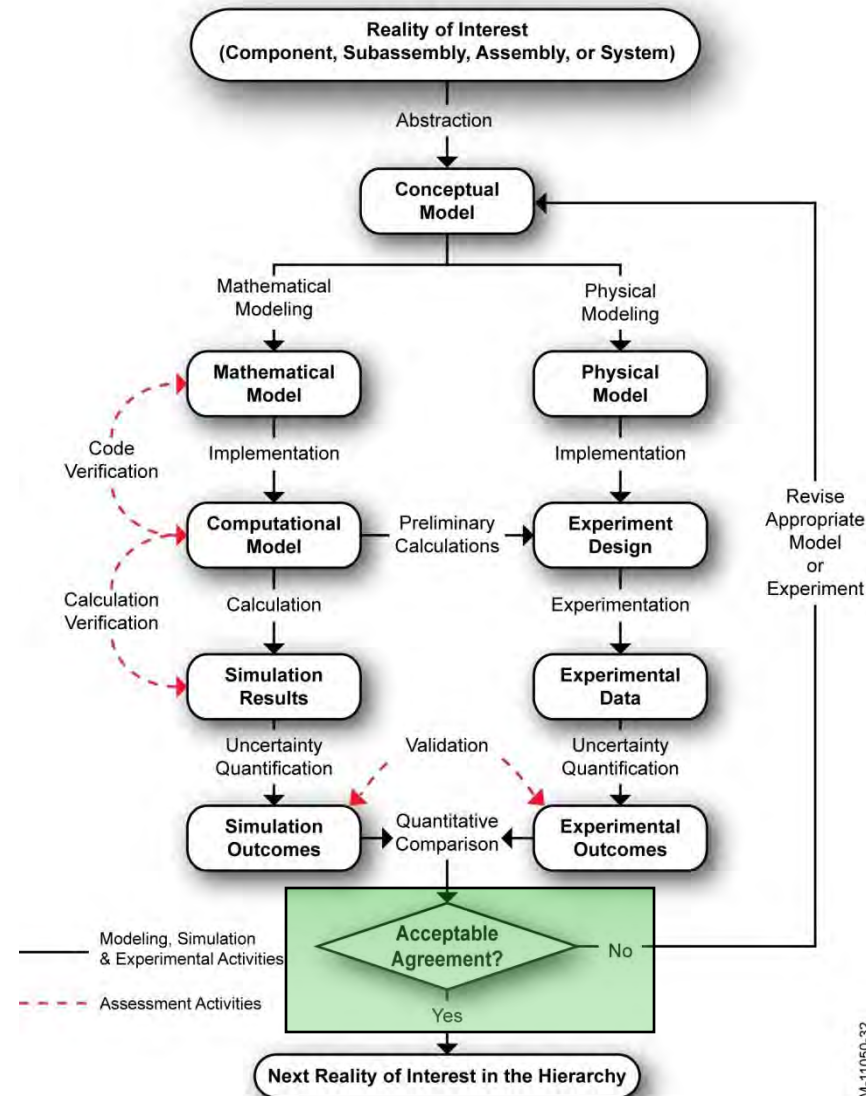


What is a validated model?

If the model passes the comparison tests in the **V&V Plan**, then it can be used to make the desired predictions with confidence.

When it is said that the **model is validated** for the intended use, it is not just the **Computational** model, which likely will have to change for the predictions of interest, but the **Mathematical** and **Conceptual** models upon which the Computation model was built that have been validated.

It is through the **Validation** of the **Conceptual** model that confidence is gained that the correct physics (mechanic) were included in the model development.



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Six-Step Process

1. Specify an input/uncertainty map

Identify and quantify the important parameters and inputs to the model that are believed to be potentially significant contributors to [error and uncertainty](#) in model predictions. Assess their impact. During the validation process this map is revisited, revised and updated.

2. Determine evaluation criteria

Specification of what physical quantities or system response measures are being chosen for validation purposes.

3. Design of validation experiments

This includes both designed computer and designed field or laboratory experiments. Explore range-of-use and range-of-uncertainty. DOE deals with controllable and uncontrollable factors.

4. Data collection and generate model outcomes

Approximate fast running surrogate models are usually key for enabling the analyses carried out in Step 5.

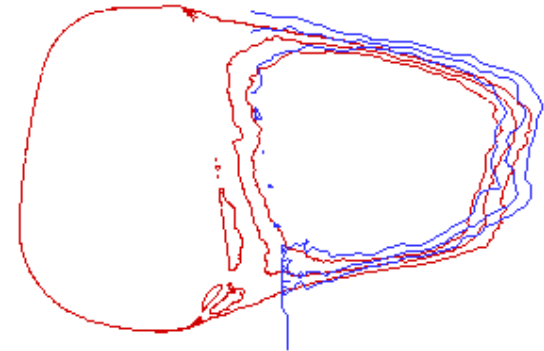
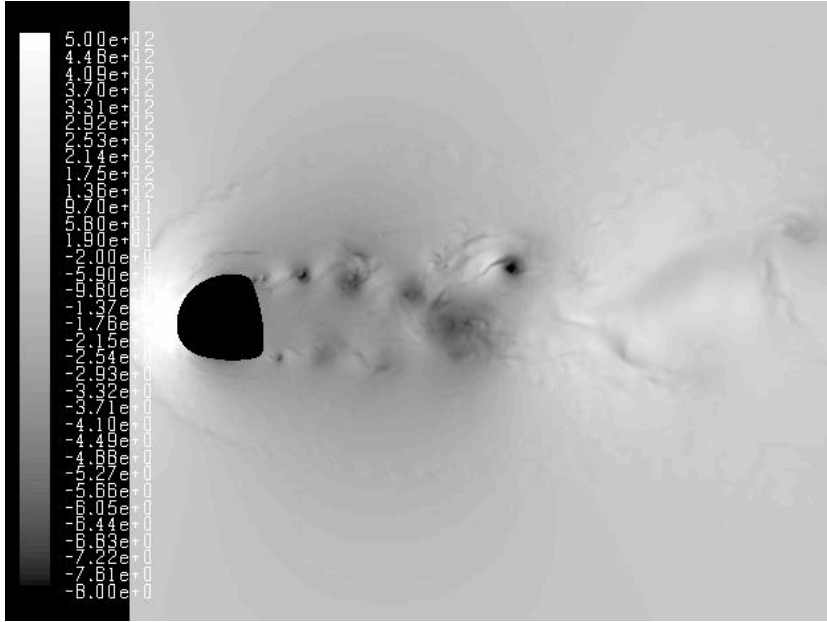
5. Compare computer model output with field output

Calculate bias, variance and (potentially) model tuning/calibrating parameters. Simple (algebra with normal dist) to complex (Bayesian) techniques can be used.

6. Feedback information into current validation exercise and feed-forward information in future validation activities

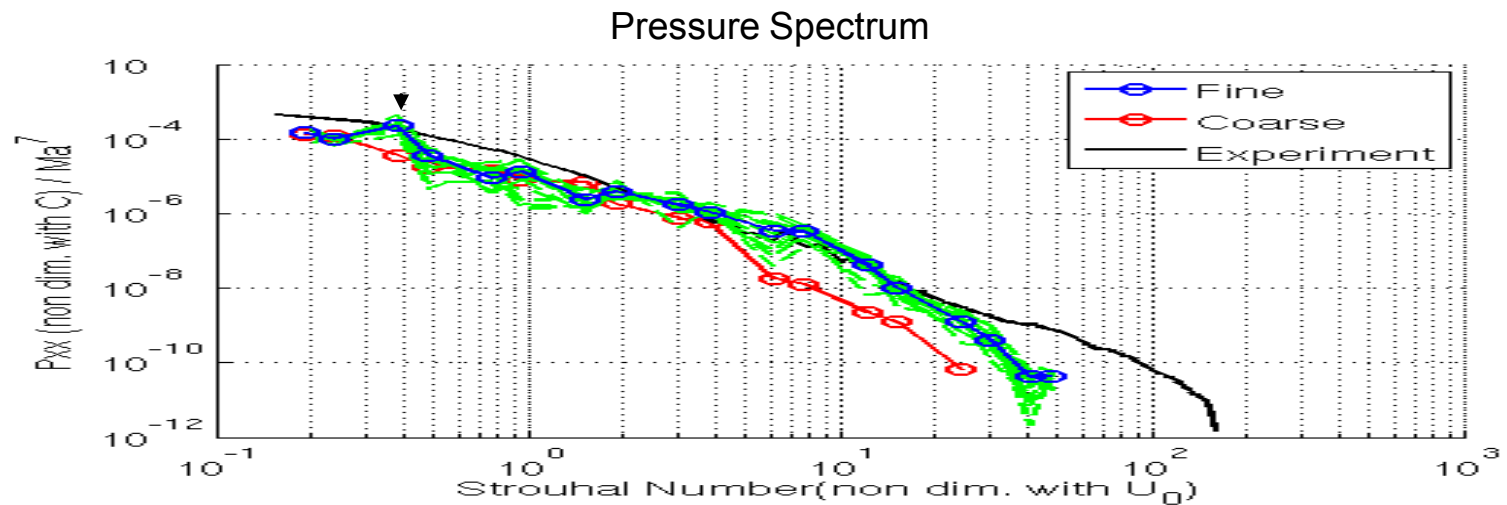
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LES Experiment(PIV)
Recirculation Area

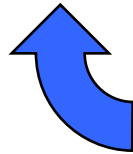
High Resolution Outside Rear View Mirror Flow Modeling for Noise



Multi-body Dynamics (MBD) Math Model



Replacement of Road Load Data
Acquisition with Analytical Loads



Simulation:

- Multi Body Dynamics models of vehicles built in math
- Digital road profiles are used as loads
- Response calculated at spindles, suspension-body interfaces

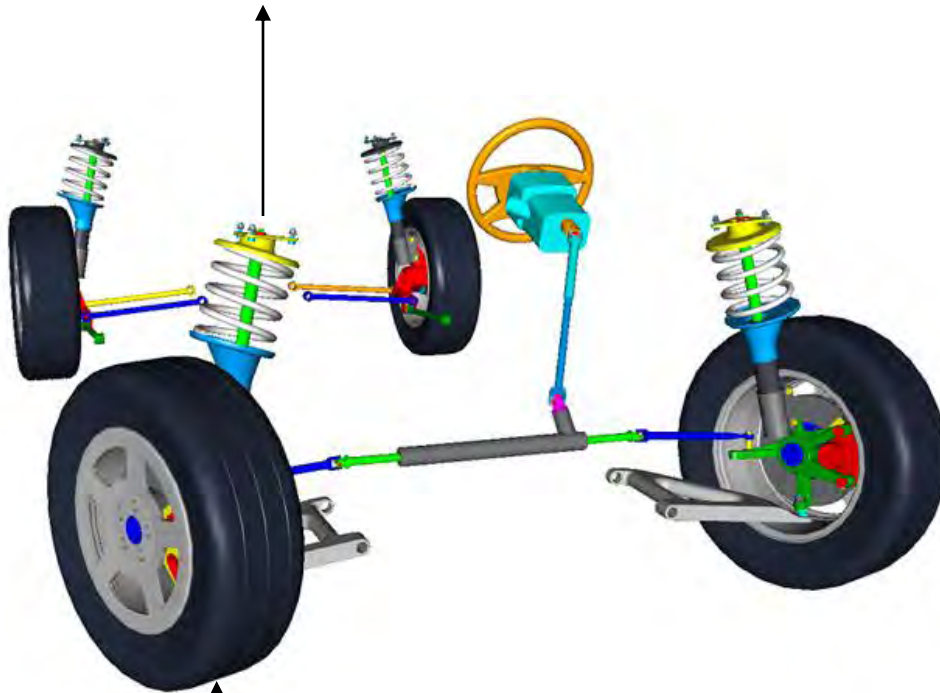
Typical

measurements:

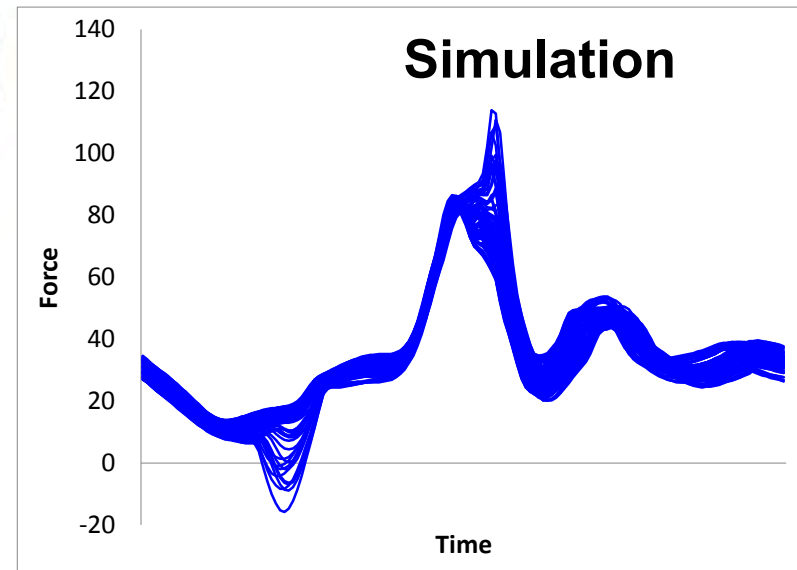
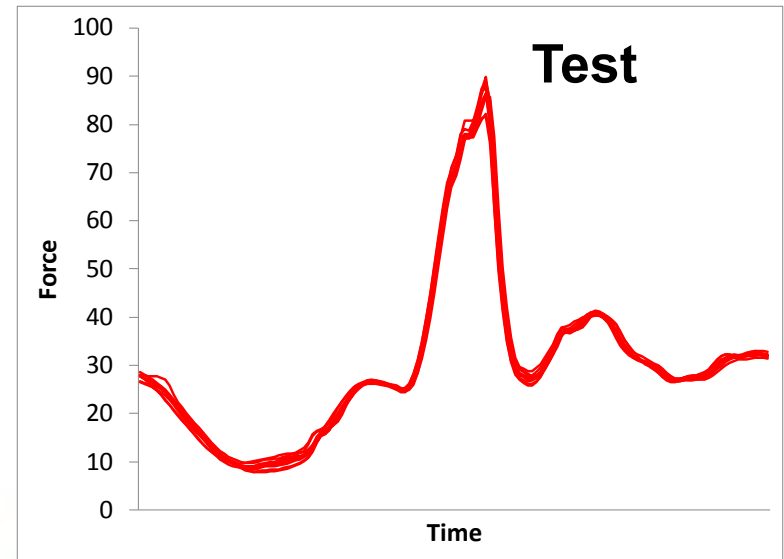
- force
- moment
- acceleration
- displacement

Road Load Prediction – Pot Hole Event

Load (FORCE) response
at the shock-to-body
interface



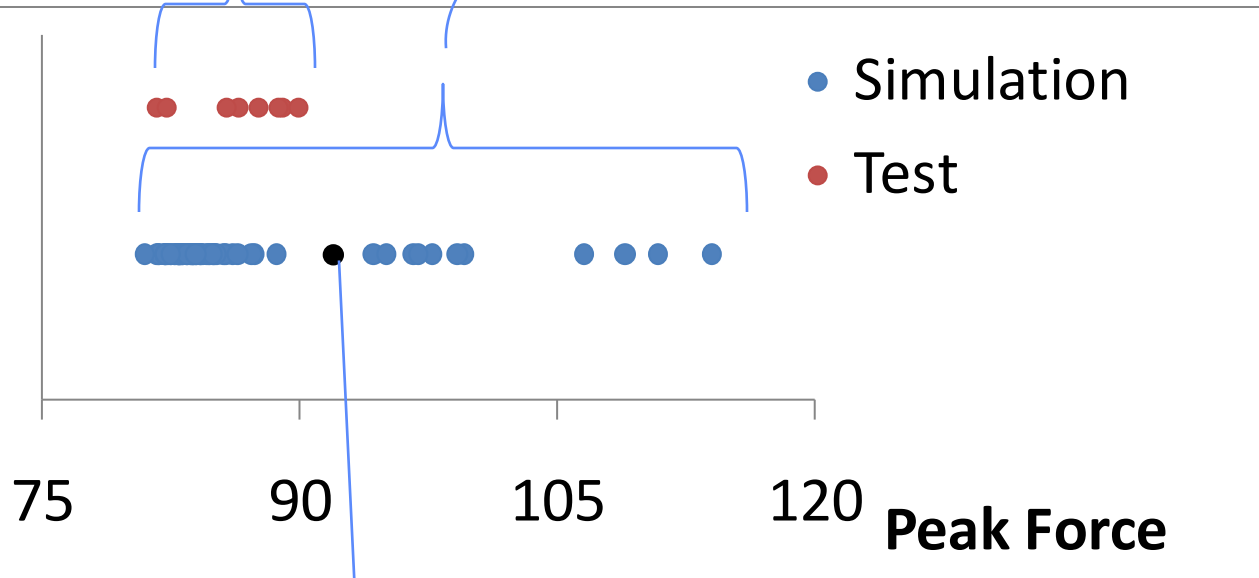
Pothole event road input
at the tire



Road Load Prediction – Pot Hole Event

Variability due to repeatability

Variability due to parameter uncertainty



Simulation

Nominal = 92.1
Average = 86.7
Std. dev = 7.47
Samples = 65

Test

Average = 86.4
Std. dev = 3.08
Samples = 9

Nominal
Simulation

- *Do simulation and test come from same population?*
- *What is the bias between simulation & test?*
- *Statistical comparison of results*

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Messages

- The value of simulation results often exceeds the cost of obtaining them.
- Rigorous V&V can establish credibility in math models. Credibility is essential for use.
- Uncertainty Quantification as a language of V&V and so this means that statisticians and engineers will need to team up and work together to accomplish V&V.
- Effective communication of validation results to the decision makers is key. The decision makers must understand and buy-in to the V&V process.
- Decision making is done by humans – not computers!

Acknowledgements

- **ASME PTC 60 Overview presentation put together by Len Schwer**
- **ASME PTC 60 committee members**
- **Ramesh Rebba (GM) for his contributions to the methods used at GM and providing information for this talk**
- **Mary Fortier (GM) for championing model V&V within GM**