

# Introduction to the Real-Space Model Validation Approach and Its Advantages vs. the ASME VV10 and VV20 Validation Approaches\*

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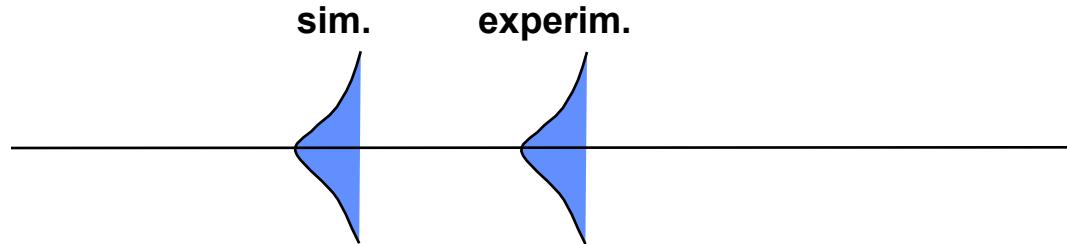


# The Significance of Aleatory vs. Epistemic uncertainty in model validation



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These PDFs line up perfectly. Is the model prediction perfect or likely biased?



- **Answer: it depends pivotally on the nature of the uncertainty represented by the PDFs**
  - Perfect model if the PDFs represent populations of results from a stochastic system tested multiple times w/ no other uncertainty in the tests (aleatory uncertainty only)
  - Model likely has error if the PDFs represent only epistemic uncertainty (lack of knowledge) regarding the deterministic value of a response



# Treatment of Aleatory and Epistemic Uncertainties in Model Validation



- Real Space approach can be viewed as an extended hybrid of other well-established validation frameworks:
  - **ASME V&V20 2009 Standard for V&V in CFD and Heat Transfer**
    - Subtractive-difference metric is geared for validation of models of effectively deterministic systems (i.e., no “traveling” uncertainties intrinsic to the model)
    - Full treatment of epistemic lack-of-knowledge type uncertainties in model discretization solution error and modeled experimental ICs/BCs and measured experimental inputs and outputs
    - 2-parameter probabilistic uncertainty treatment based on mean and stdev.
  - **ASME V&V10.1 2012 Supplement for V&V in Computational Solid Mech.**
    - built for validation of models of stochastic systems with significant aleatory variability
    - uses Ferson/Oberkampf “Area” validation metric for mis-match of sim. & exper. CDFs
    - can be extended to treatment of aleatory and epistemic uncertainties (e.g., with a segregated “Probability box” uncertainty representation per Ferson & Oberkampf)
    - ignores some important types of experimental epistemic uncertainty that ASME VV20 and Real Space include
  - **Real Space: no restrictions, + significant extensions**



# Concept of “Traveling” and “Non-Traveling” Uncertainties

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**Traveling Uncertainties** are intrinsic to the model being validated

They come with the model as a consequence of model-form error and/or lack of knowledge about values of parameters in the model.

They are consistent between the validation conditions and model applications beyond the validation activity.

**Non-Traveling uncertainties** are particular to the validation activity

They are outside the traveling model of extrapolation interest

- e.g., experimental measurement uncertainties and model discretization related solution uncertainty in the validation activity

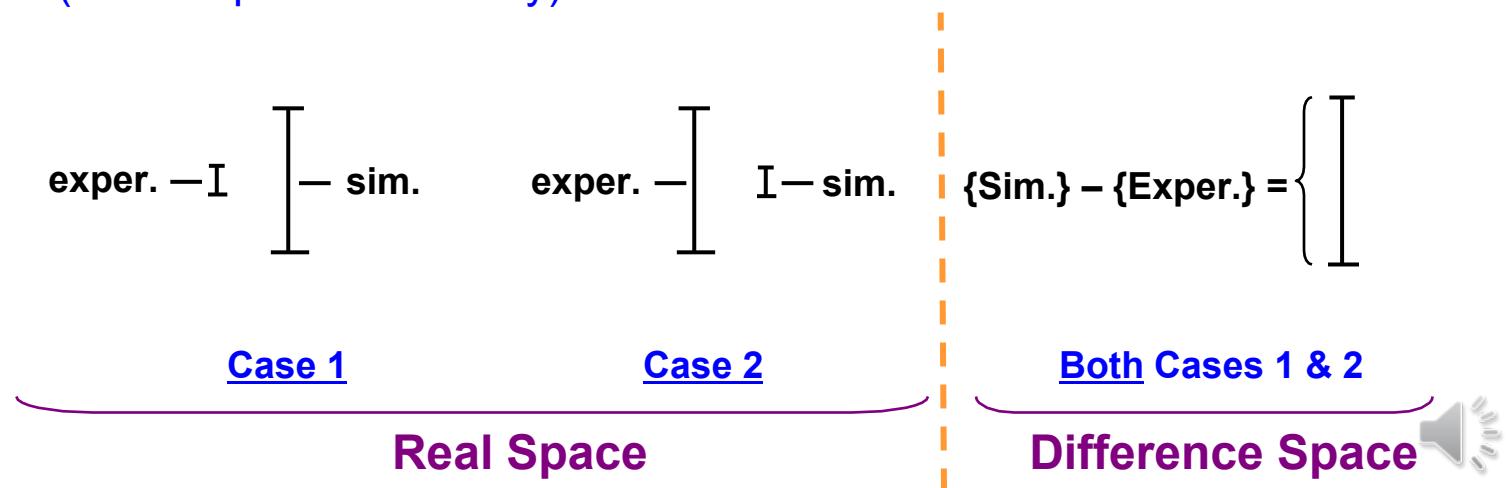


# Real Space vs. Subtractive-Difference Transform Representation of Model Discrepancy



- Subtractive difference is a popular way of comparing data against model predictions for model validation assessments (but best used for only non-traveling epistemic uncertainties)
- The subtractive difference transform yields a less definitive validation result vs. staying in real space – see example below
- Subtractive Difference has non-unique mapping from real space to transform space, as do other (perhaps all?) validation metric discrepancy transforms
- Subtractive Difference non-uniqueness is not a problem if constrained to Non-Traveling epistemic uncertainties, but is a problem for Traveling epistemic uncertainties (to be explained verbally)

Example  
with Traveling  
Epistemic  
uncertainties in  
the model and  
differing risk  
connotations  
with its use



# ASME VV10 Applicability to One Experiment with Epistemic Uncertainty Only



- Depending on the details, ASME VV10 does in some cases properly account for traveling and non-traveling epistemic uncertainties in the model
- But does not show how to handle complex experimental uncertainty:
  - random and systematic components of error and correlated errors in measurements of inputs and outputs
- ASME VV20 has demonstrated complex experimental uncertainty with probabilistic non-traveling uncertainties
- Real Space has demonstrated complex experimental uncertainty with probabilistic and/or interval traveling and/or non-traveling uncertainties

# Model Builder's Risk vs. Model User's Risk with respect to systematic uncertainty in experiment conditions



- Where place burden of proof?
  - Optimistic stance: Assume model is unbiased if don't have positive proof that it is biased (outside expr. uncer.)
    - Oberkampf & Roy: "*When the simulation is a P-Box due to insufficient information provided by the validation experiment, the model is given more leeway in comparing with the experiment, as is appropriate.*"
    - “Free lunch”— the more experimental uncertainty, the more model-bias leeway allowed
    - eliminates Model Bldr.'s risk but increases Model User risk
  - Conservative: Treat model as potentially biased up to magnitude allowed by resolution uncertainty in expers.
    - Real Space – reduces Model User's risk but increases Model Builder's risk
    - ASME V&V20 – similar



## **Now Consider Multiple Replicate Tests with Stochastically Varying Systems**

- For validation of models with traveling aleatory uncertainty that represents the stochastic variability in the systems
- random/aleatory variation of the systems from test-to-test
- test-to-test random/aleatory variation of measurement errors on inputs and/or outputs (“random” uncertainties)
- test-to-test effectively constant errors in measurements of inputs and/or outputs (“systematic” uncertainties)

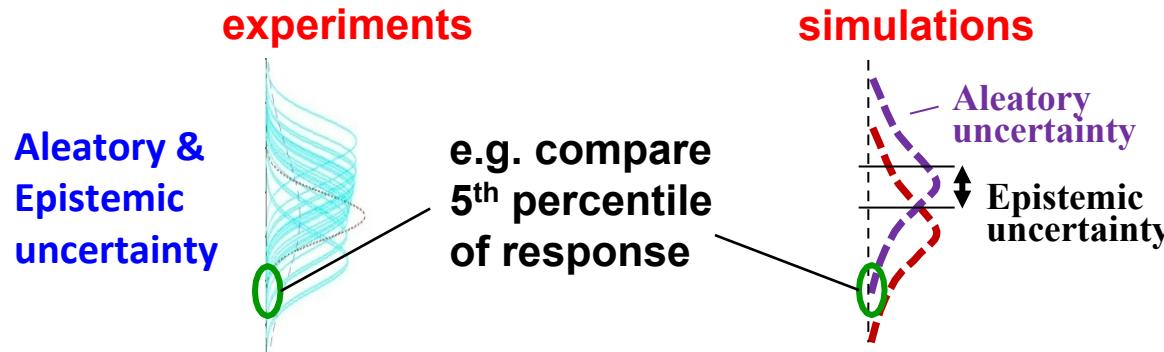


# Real Space comparison for Stochastic Experimental and Simulation Results



(at same input conditions, shown side-by-side for comparison)

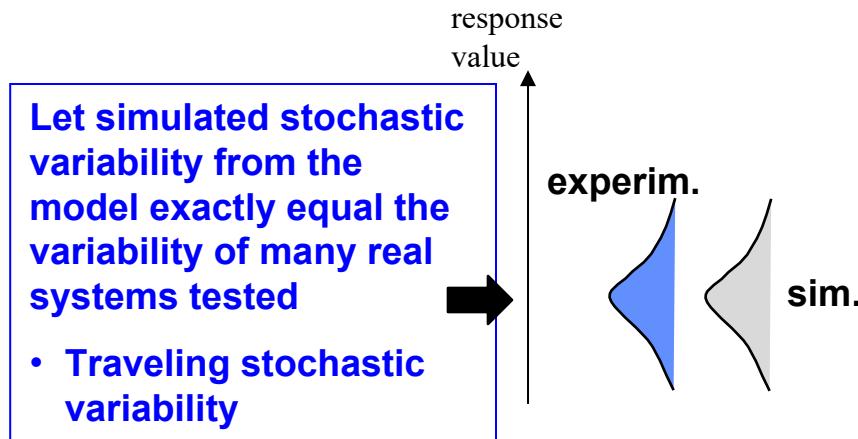
- Compare statistical measures of response, not whole CDFs
- Use sparse-sample UQ methods to bound experim. and sim. statistics



- Intuitive visual indication of how accurate the model is, on several fronts:
  - Means of the predicted and experimental populations
  - Variances
  - Percentiles
  - Range of response %, e.g. the “central” 95% between 2.5 and 97.5 percentiles

(These last two account for combined uncertainty in mean, variance, and possible higher moments of stochastic response and are found to be the most useful in practice)
- Percentile comparisons are particularly useful for validation of models to be used for analysis of performance and safety margins

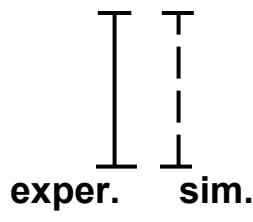
# VV20 Subtractive-Difference Metric prevents proper handling of Modeled Variability among a Population of Stochastic Systems in Replicate Experiments



- Conditions: no measurement errors in the experiments; and large # of tests
- Observed response variability is due to unit-to-unit stochastic variability of the tested systems, and not due to testing variability

## Real Space approach

- ✓ works; no model error indicated



## ASME VV20 Subtractive Diff. Metric

- non-zero uncertainty results--attributed as possible model bias

$$\{\text{Diff}\} = \{\text{Sim}\} - \{\text{Exper}\}$$

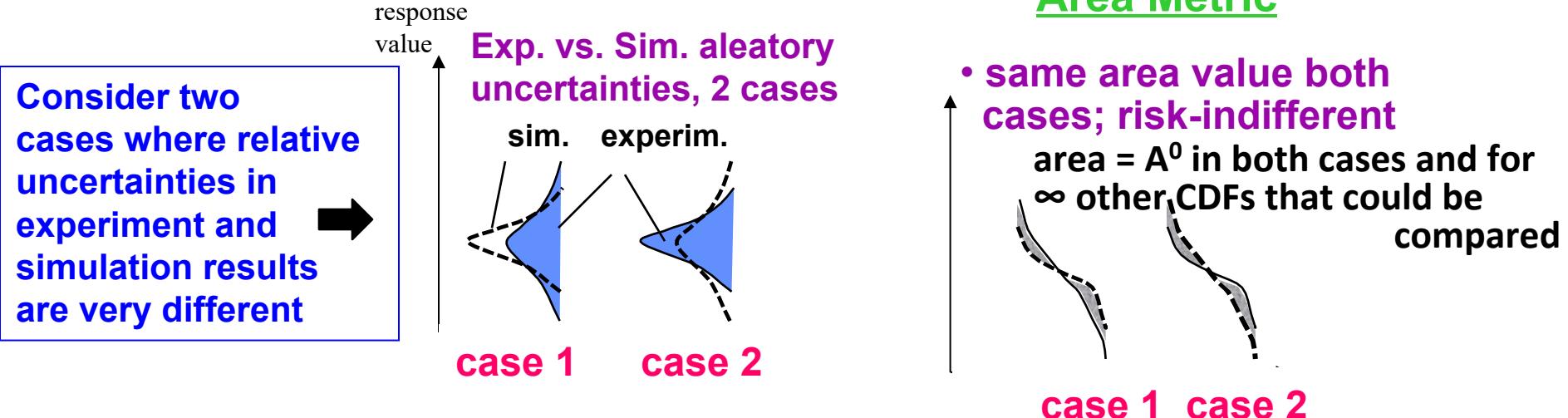
## VV10 Area Metric

- ✓ works; no model error indicated
- zero area between exper. and sim. CDFs

Uncertainty should be zero for exact match between experim. and sim. results



# Non-Uniqueness of Area Metric of CDF Mismatch



- non-uniqueness of Area Metric can hide prediction risk and undermine metric use for extrapolation (next slide)

## Real Space method

- like-percentiles of CDFs are compared
- Unique and more granular quantification of how CDFs differ
- reveals different prediction risks in these two cases

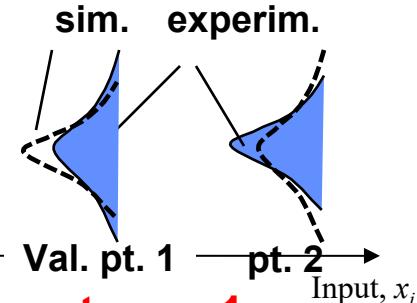


# Area Metric Non-Uniqueness can also obscure the Trend of Model Error

## Real Space method

response value

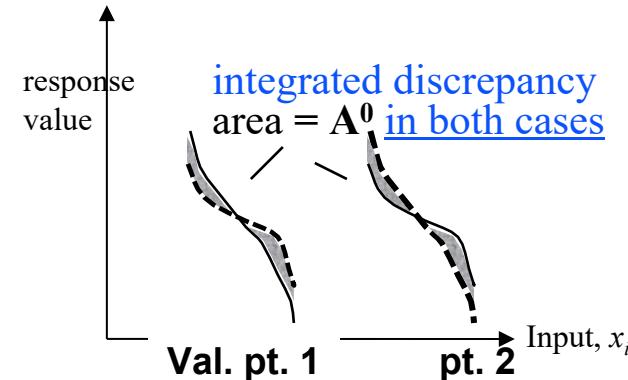
- reveals differing sim. & exper. trends



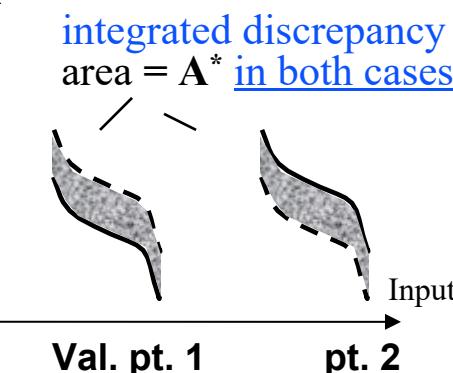
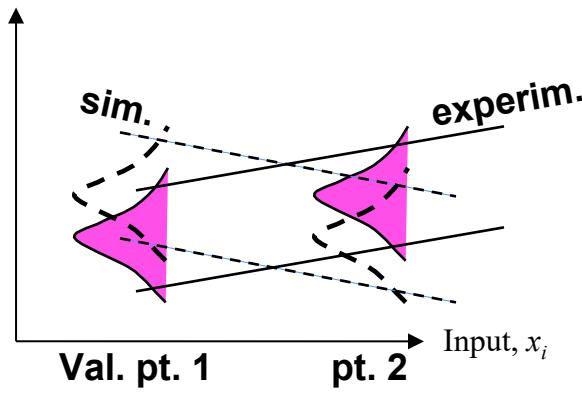
circumstance 1

## Area Metric

- same areas for diff. model trend errors



circumstance 2

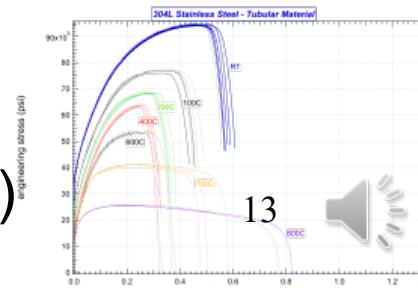


# Other Differentiating Features of the Real Space methodology

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- **Explicitly accounts for epistemic uncertainty arising from small sample sizes (limited numbers of replicate tests) in experimental characterization of mtl., systems**
  - a dominant or significant uncertainty in many cases
- **The RS framework has demonstrated protocols for treatment of the following representations of uncertainty, individually and in combination:**
  - Interval
  - Distributional (probability density functions)
  - Discrete (non-parametric)
    - e.g. different turbulence model forms and discrete stress-strain curves (functional data)

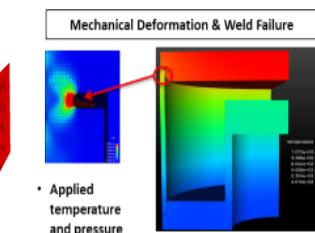
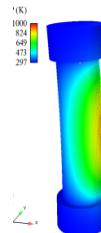
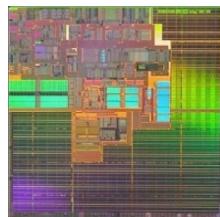
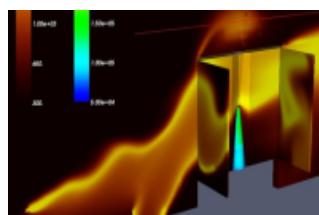
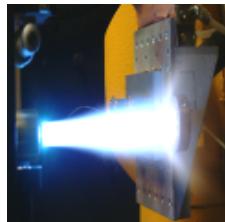


# Support for Prediction Bias Correction and Extrapolation

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- **ASME VV10**
  - A possible extension exists per Roy & Oberkampf, but only when the experimental and simulation PDFs don't overlap significantly.
    - Then the Area metric has a physical connotation of the difference between the means of the distributions, so a mean correction can be applied to the simulation PDF (but not percentile-by-percentile like the Real Space method allows).
- **ASME VV20**
  - no established connectivity to bias-correction or extrapolation
- **Real Space**
  - Prediction bias correction for a selected percentile of response and Predictor-Corrector extrapolation of the correction, with extrapolation UQ scaled to extrapolation distance



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- **The Real Space validation methodology is versatile and practical, geared for:**

- expensive computational models (minimal # of simulations)
- stochastic phenomena and models
- multiple replicate experiments with random and systematic uncertainties on experimental inputs and outputs
- few replicates (sparse data)
- rollup of various types, sources, and representations of uncertainty
  - aleatory and epistemic
  - traveling, non-traveling
  - probabilistic, interval, and discrete variables and functions

- **Real Space Validation results are:**

- relatively straightforward to interpret for model adequacy and bias corr.
- especially relevant for assessing models to be used for the analysis of performance and safety margins

