Relationships between ASME VV 10 & 20, AIAA CFD, and Real Space Model Validation Frameworks*

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Context

• Point out high-level **structural** similarities and differences between the validation frameworks

• Point out some low-level procedural approaches and details that lead to substantial quantitative differences even if similar high-level intent or paradigm for a given element or step in the methods

• Audience familiarity with the VV10 and VV20 validation approaches is assumed.
The Significance of Aleatory vs. Epistemic uncertainty in model validation

Is this 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 uncer. 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 frameworks

– **ASME V&V20 Standard for V&V in CFD and Heat Transfer**
  - emphasis on **epistemic** uncertainty and **deterministic** systems
  - scalar QOIs, **S – D subtractive metric**, probabilistic uncer.
  - some applicability to stochastic systems: **Eca et al. 2020 V&V Symp.**

– **ASME V&V10 for Solid Mech., AIAA CFD (2016 Lee et al. AIAA pap.)**
  - emphasis on **aleatory** uncertainty and **stochastic** systems
  - scalar QOIs, **Area metric** difference measure for aleatory CDFs
  - probabilistic aleatory and interval epistemic uncertainties

– **Real Space**
  - fully spans both **epistemic** and **aleatory** uncertainties, **deterministic** or **stochastic** systems
  - scalar QOIs, **no metric** (“real space” comparisons)
  - interval and/or probabilistic uncertainties of deterministic or statistical QOIs + **traveling models & uncertainties** + **sparse-data treatment**
The following updates a talk from 5 years ago

The Real-Space Model Validation Approach as a Unifying? Extended Hybrid of the ASME VV10 and VV20 Approaches‡

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‡Sandia National Laboratories document SAND2015-3752C (unlimited release)

Structural Equivalence between ASME VV20 and Real-Space for **special case**:  

- 1 validation test (epistemic uncertainty only, no test-to-test aleatory variation of errors or associated uncertainty)  
- Probabilistic uncertainty descriptions  
- No “traveling” uncertainties (defined later)  

(next 3 slides)
Equivalence between ASME VV20 and Real-Space for 1 test and epistemic non-traveling uncertainties

- Start with uncertainty in measurement of output quantity

Prediction bias error (nominal) indicated in Real Space

Prediction bias error (nominal) indicated in Difference Space

Data/experimental result, D (nominal measured)

Uncertainty of measured result

Uncertainty of prediction bias (S – D), VV20

Boundary Condition parameter

Sim. result, S
Equivalence between ASME VV20 and Real-Space for 1 test and epistemic non-traveling uncertainties

- Uncertainty in measured input but no uncertainty in measured output

Real Space choice
Equivalence between ASME VV20 and Real-Space for 1 test and epistemic non-traveling uncertainties

- Uncertainty in measured experimental input and output

Real Space choice
Concept of “Traveling” and “Non-Traveling” Uncertainties

**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.
Handling **Traveling** Epistemic Uncertainty in Model

**Non-Equivalence** between ASME VV20 and Real-Space

- Model-intrinsic traveling uncertainty and uncertainty in measured experimental output

Real Space interpretation:
Model prediction encompasses reality if within the experimental uncertainty, go forward with the model and traveling uncertainty

Indicated uncertainty of prediction bias by \( (S - D) \), VV20 is larger than the already large-enough traveling uncertainty in the model
ASME VV10 and AIAA CFD approaches (One Experiment)

- Depending on the details, *ASME VV10 and AIAA CFD do in some cases properly account for traveling epistemic uncertainties in the model*

- But do 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 uncertainties

- Real Space has demonstrated complex experimental uncertainty with probabilistic and/or interval uncertainties
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; associated “random” uncertainties
- Test-to-test systematic (constant) errors in measurements of inputs and/or outputs; associated “systematic” uncertainties
Treatment of Experimental Uncertainties in Multiple Replicate Tests

- ASME VV10 and AIAA CFD approaches
  - have not shown how to treat complex experimental uncertainties on the output data samples and input conditions

- ASME VV20
  - treatment of complex experimental uncertainties is applied for probabilistic uncertainties

- Real Space
  - treatment of complex experimental uncertainties is applied for probabilistic and/or interval uncertainties
  - Normalization to subtract-out variability in output data samples due to test-to-test differences of experimental inputs is also part of the RS method (my talk earlier today) – avoids exaggeration of response variability and yields better IID basis for statistics
Sparse Experimental Sample Data:

Treatment of associated Epistemic Uncertainty in CDFs or Statistics

- Epistemic uncertainty is huge for realistically sparse sample data in most physical engineering situations:
  - **Example**
  - A 95% coverage interval estimated from a Normal fit to 8 samples drawn from a Normal distribution has an empirical confidence of about 26% for capturing the true central 95%, 32 samples → 28% confidence

- **ASME VV10 and AIAA CFD approaches**
  - no demonstrated adequate treatment

- **ASME VV20**
  - no demonstrated adequate treatment

- **Real Space**
  - substantial theoretical and empirical basis for statistical treatments
Real Space comparison for Stochastic Experimental and Simulation Results

- Compare **decision-intuitive** statistical measures of response, not CDFs

- Intuitive visual indication of how accurate the model is, on several fronts:
  - **Means** of the predicted and experimental populations
  - Variances
  - Percentiles
  - Range of response %age, 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**, e.g. QMU.
ASME VV20 validation approach for Stochastic Experimental and Simulation Results

• **Today’s talk** by Eca et al. indicated a **subtractive difference metric** and uncertainty applied to predicted and experimental 1-parameter statistics of response:
  - **Means** of the predicted and experimental populations
  - **Variances**
  - **Percentiles**
  - **Not 2-parameter statistical quantities** like prediction intervals, central 95% range of response, etc.

• The $u_{\text{val}} = [(u_{\text{input}})^2 + (u_D)^2 + (u_{\text{num}})^2]^{1/2}$ formulation for uncertainty of the bias between the experimental and predicted statistics may not give reliable results given the nature of estimation uncertainties (e.g. one-sided bounds for percentiles) when sparse data are involved
ASME VV10 and AIAA CDF validation approach for Stochastic Experimental and Simulation Results

- Area metric gives a measure of disagreement of experimental and simulated CDFs

- Somewhat difficult to interpret what it means for two CDFs to be different by x.y in any metric, including the Area metric

- Non-uniqueness: any number of CDF mismatches can yield the same metric value x.y

- The two CDFs being compared will in general both be uncertain, so represented by Probability Boxes; the metric value becomes an uncertain quantity. How best handle?

- Interpretability may hamper decision making regarding model adequacy and correction of prediction bias and extrapolation of the correction to new predictions
Support for Prediction Bias Correction and Extrapolation

- ASME VV10 and AIAA CFD approaches
  - Bias correction exhibited for Area metric can only be exact for at most a single percentile of the CDF and will not be accurate for other percentiles; this carries over to extrapolation

- 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 uncertainty scaled to extrapolation distance (V&V Symposium talk last year)
Closing Remarks

- Model validation is complex -- philosophically, conceptually, and procedurally

- Many different conceptions, approaches, and frameworks exist and the area is still rapidly evolving

- There are significant structural and procedural similarities and differences between the reviewed model validation frameworks

- It may be beneficial to more deeply analyze and test the various frameworks and develop a hybrid framework with the best features of each approach