Modern Code Validation: How Do We Do It?

William L. Oberkampf
W. L. Oberkampf Consulting
wloconsulting@gmail.com
Austin, Texas

Nuclear Energy Knowledge and Validation Center Workshop Georgia Institute of Technology Atlanta, Georgia January 15 – 16, 2015

Outline

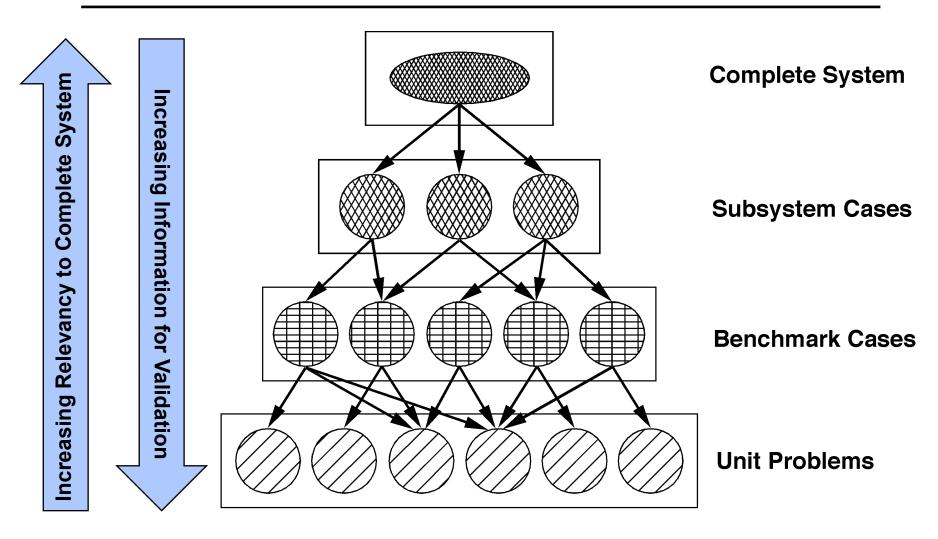
- Traditional experiments vs. validation experiments
 - Validation hierarchy
 - Existing validation databases
- Characteristics of a validation experiment
- Nondeterministic simulation of experiments
 - Experimental uncertainties
 - Model form uncertainty
- Suggestions for the path forward

Traditional Experiments vs. Validation Experiments

Goals of traditional experiments:

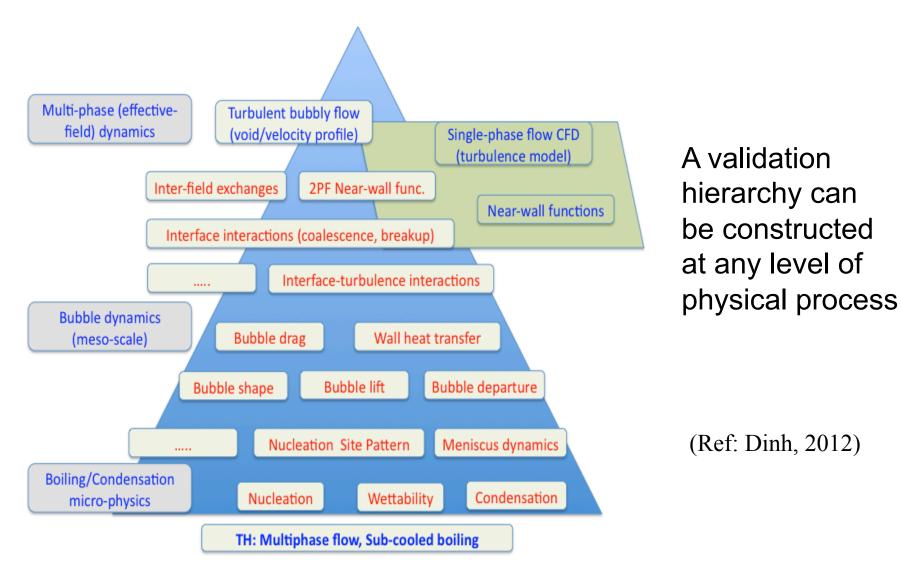
- 1. Improve the fundamental understanding of the physics:
 - Ex: performance of new fuels; departure from nucleate boiling
- 2. Determine parameters in existing mathematical models:
 - Ex: model calibration experiment for bubbly flows; model calibration experiment for crack propagation in fuels
- 3. Assess subsystem or complete system performance:
 - Ex: loss of coolant experiment; plant safety performance during various subsystem failure and excitation scenarios
- Goal of a model validation experiment:
 - An experiment that is designed and executed to quantitatively estimate a mathematical model's ability to simulate a well characterized experiment.
- The customer of a model validation experiment is usually a model developer or computational analyst.

Validation Experiment Hierarchy



(Ref: AIAA Guide, 1998)

Validation Hierarchy for Sub-cooled Boiling



Examples of Validation Databases Related to Nuclear Power

- Organization for Economic Co-operation and Development/ Nuclear Energy Agency (OECD/NEA), International Fuel Performance Experiments (IFPE) Database
- OECD/NEA Shielding Integral Benchmark Archive and Database (SINBAD)
- OECD/NEA International Reactor Physics Benchmark Experiment Evaluation (IRPhE) Project
- OECD/NEA Expert Group on Multi-Physics Experimental Data, Benchmark, and Validation (EGMPEBV), newly formed
- Generation IV Materials Handbook database
- Loss-of-Fluid Test (LOFT) database at INL
- Proprietary or classified databases, e.g., Westinghouse Advanced Loop Testing, Bettis Atomic Power Laboratory, Knolls Atomic Power Laboratory, etc.

Six Characteristics of a Validation Experiment

- 1. A validation experiment should be jointly designed and executed by experimentalists and computationalists:
 - Close working relationship from inception to documentation
 - Elimination of the typical competition between each
 - Complete candor concerning strengths and weaknesses
- 2. A validation experiment should be designed to capture the relevant physics, all initial and boundary conditions, and all auxiliary data needed for a simulation:
 - Computational simulation input data should be measured in the experiment and key modeling assumptions understood
 - Characteristics and imperfections of the experimental facility should be measured and included in the simulation

(Ref: Aeschliman and Oberkampf, 1998)

Characteristics of a Validation Experiment (continued)

- 3. A validation experiment should use any possible synergisms between experiment and computational approaches:
 - Offset strengths and weaknesses of computation and experiment
 - Use simulations of the "empty" facility to better understand the operation of the facility
 - Use experimental data from the "empty" facility to calibrate certain model parameters
- 4. Independence between computational and experimental results should be maintained where possible:
 - The flavor of a blind comparison should be maintained if possible
 - All input data needed for the simulation should be measured and provided
 - Once system response measurements are available to the analyst, calibration usually occurs

Characteristics of a Validation Experiment (continued)

- 5. A hierarchy of experimental measurements should be made which presents an increasing range of computational difficulty:
 - Qualitative data (e.g., visualization) and quantitative data
 - Functionals, local variables, derivatives of local variables
 - Computational solution data should be processed in a manner similar to the experimental measurement data
- 6. Carefully employ experimental uncertainty analysis procedures to delineate and quantify random and correlated bias errors:
 - Experimentalist should provide uncertainty estimates on system response data and input quantities needed by the code
 - Use traditional or statistical design of experiments methods to estimate random and correlated bias errors in measurements
 - If possible, conduct experiments using different diagnostic techniques or different experimental facilities

What is the Goal of a Model Validation Experiment?

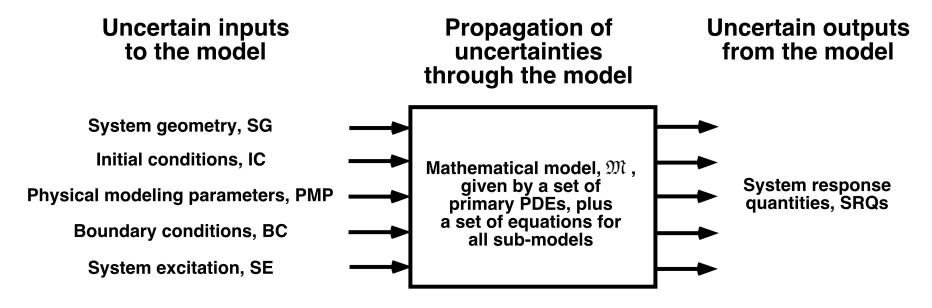
- Estimation of the model form uncertainty for the specific conditions and physics of the experiment
- What makes this difficult?
 - Measurement of all important model input data
 - Estimation of response variability and measurement uncertainty
- Measured input data characterizes:
 - System geometry
 - Initial conditions
 - System physical parameters
 - Boundary conditions
 - System excitation
- As a result, the experimentalist must:
 - Measure and document model input and system response data
 - Estimate and document experimental uncertainty on both model input data and system response data

Nondeterministic Simulation of Experiments

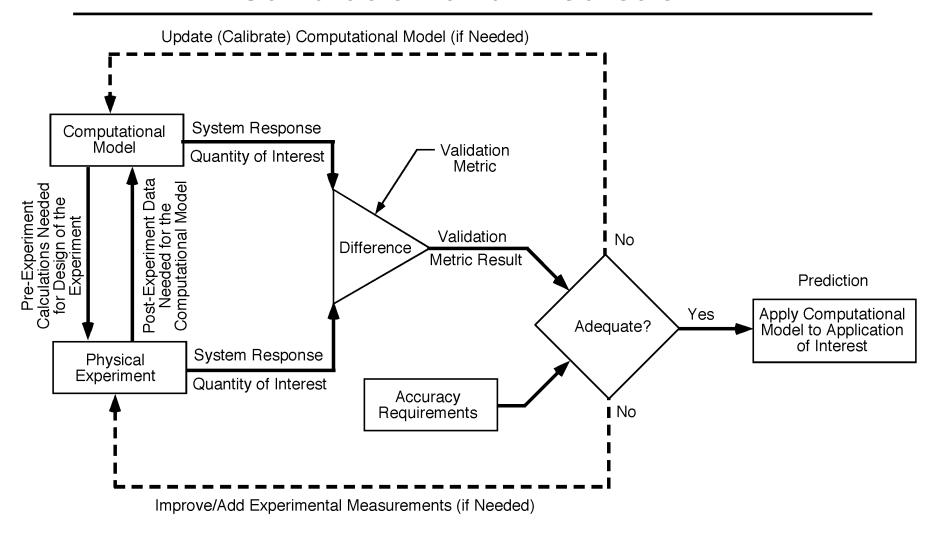
 Computational simulation can be viewed as a mapping of input data to output data using the mathematical model

$$\mathfrak{M}(SG,IC,PMP,BC,SE) \rightarrow SRQ$$

• Because of missing data or variability of input data from the experiment, we must conduct non-deterministic simulations



Model Accuracy Assessment, Calibration and Prediction

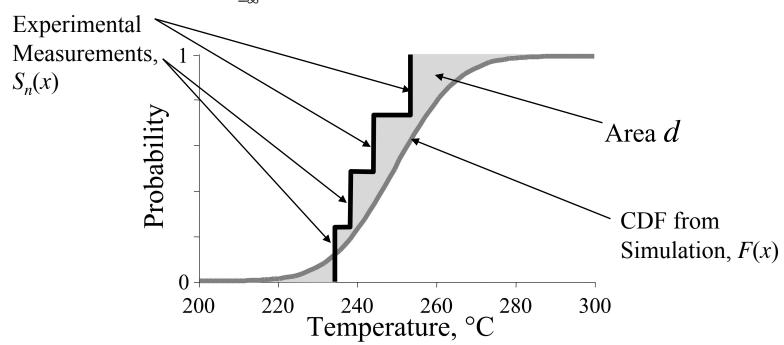


(from Oberkampf and Barone, 2006)

Example of a Validation Metric: Area Metric

 The validation metric is defined to be the area between the CDF from the simulation and the empirical distribution function (EDF) from the experiment

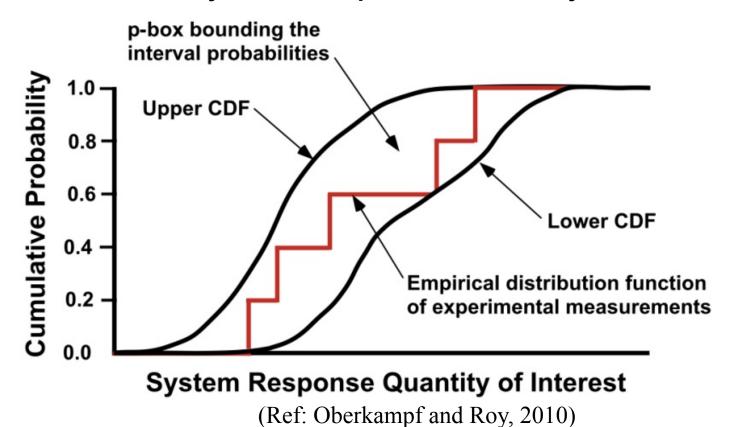
$$d(F,S_n) = \int_{-\infty}^{\infty} |F(x) - S_n(x)| dx \qquad \text{(Minkowski L}_1 \text{ metric)}$$



(Ref: Ferson et al, 2008)

What is the Impact of Missing Input Data from the Experiment?

- Unmeasured or undocumented input data leads to <u>either</u>:
 - Calibration or tuning of parameters in the model
 - Increased uncertainty in the predicted output. This does <u>not</u> allow us to critically assess the predictive accuracy of the model.



Suggestions for the Path Forward

- Evaluation of existing experimental databases for completeness and documentation of:
 - Input data needed for simulation
 - Estimation of experimental uncertainty on both input and output data
 - Existence of multiple experimental realizations or different facilities
- Which perspective is more constructive for planning new validation experiments?

Physical processes in need of improved modeling versus Applications areas in need of improved understanding

- Whichever perspective is used, conduct simulations of planned experiments to determine the most important <u>input data</u> to be measured, i.e., conduct sensitivity analyses
- Improve the understanding of recommended characteristics of validation experiments among experimentalists and analysts

References

- Aeschliman, D. P. and W. L. Oberkampf (1998). "Experimental Methodology for Computational Fluid Dynamics Code Validation." *AIAA Journal.* 36(5), 733-741.
- AIAA (1998), "Guide for the Verification and Validation of Computational Fluid Dynamics Simulations," American Institute of Aeronautics and Astronautics, AIAA-G-077-1998.
- ASME (2006), "Guide for Verification and Validation in Computational Solid Mechanics,"
 American Society of Mechanical Engineers, ASME V&V 10-2006.
- ASME (2012), "An Illustration of the Concepts of Verification and Validation Computational Solid Mechanics," American Society of Mechanical Engineers, ASME V&V 10.1-2012.
- Dinh, N. (2012). "CIPS Validation Data Plan." Idaho National Laboratory, INL/ EXT-12-25347, Idaho Falls, ID.
- Ferson, S., W. L. Oberkampf, and L. Ginzburg (2008), "Model Validation and Predictive Capability for the Thermal Challenge Problem," *Computer Methods in Applied Mechanics and Engineering*, Vol. 197, pp. 2408-2430.
- Ferson, S. and W. L. Oberkampf (2009), "Validation of Imprecise Probability Models," *International Journal of Reliability and Safety*, Vol. 3, No. 1-3, pp. 3-22.
- Hills, R. G. (2006), "Model Validation: Model Parameter and Measurement Uncertainty," Journal of Heat Transfer, Vol. 128, No. 4, pp. 339-351.
- Oberkampf, W. L. and T. G. Trucano (2002), "Verification and Validation in Computational Fluid Dynamics," *Progress in Aerospace Sciences*, Vol. 38, No. 3, pp. 209-272.

References (continued)

- Oberkampf, W. L., T. G. Trucano, and C. Hirsch (2004), "Verification, Validation, and Predictive Capability," *Applied Mechanics Reviews*, Vol. 57, No. 5, pp. 345-384.
- Oberkampf, W. L. and M. F. Barone (2006), "Measures of Agreement Between Computation and Experiment: Validation Metrics," *Journal of Computational Physics*, Vol. 217, No. 1, pp. 5-36.
- Oberkampf, W. L. and T. G. Trucano (2008), "Verification and Validation Benchmarks," *Nuclear Engineering and Design*, Vol. 238, No. 3, 716-743.
- Oberkampf, W.L. and C. J. Roy (2010), <u>Verification and Validation in Scientific Computing</u>, Cambridge University Press, Cambridge, UK.
- Oberkampf, W. L. and B. L. Smith (2014). "Assessment Criteria for Computational Fluid Dynamics Validation Benchmark Experiments." AIAA Science and Technology Forum and Exposition, AIAA Paper 2014-0205, National Harbor, MD.
- Roache, P. J. (2009), <u>Fundamentals of Verification and Validation</u>, Hermosa Publishers, Socorro, NM.
- Roy, C. J. and W. L. Oberkampf (2011). "A Comprehensive Framework for Verification, Validation, and Uncertainty Quantification in Scientific Computing." *Computer Methods in Applied Mechanics and Engineering.* 200(25-28), 2131-2144.
- Trucano, T. G., M. Pilch and W. L. Oberkampf. (2002). "General Concepts for Experimental Validation of ASCI Code Applications." Sandia National Laboratories, SAND2002-0341, Albuquerque, NM.