Annals of Nuclear Energy 111 (2018) 499–508

Contents lists available at ScienceDirect

Annals of Nuclear Energy

journal homepage: www.elsevier.com/locate/anucene

Validation and uncertainty quantification for FEBA, FLECHT–SEASET, and PERICLES tests incorporating multi-scaling effects

Jaeseok Heo *, Kyung Doo Kim, Seung-Wook Lee

Korea Atomic Energy Research Institute, 1045 Daedeok-daero, Yuseong-gu, Daejeon 34057, South Korea

A R T I C L E I N F O

Article history:
Received 6 January 2017
Received in revised form 4 June 2017
Accepted 16 August 2017
Available online 25 September 2017

Keywords:
Model calibration
Uncertainty quantification
Bayes' theorem
Scaling

A B S T R A C T

This paper presents model parameter estimation conducted by data assimilation and associated uncertainty quantification for predictive engineering with specific application to reflood phenomena in PWR rod bundles. The uncertainties in the prediction of engineering systems are known to be originated from various non-input parameters, e.g., numerics, scaling effects, etc., as well as modeling parameters such as initial and boundary conditions, and physical models. Since the physical models are usually developed by small scale experiments and the experiments used for validation and uncertainty evaluation may not cover the real plant scale, the up-scaling capabilities of a best-estimate safety analysis code must be evaluated. The objective of this work is thus first of all, to refine the model parameters based on the Bayes' theorem and subsequently estimate the uncertainties on parameters/responses during reflood phase. To illustrate this, reflood experiment data were collected and utilized to complete model calibration for the thermal–hydraulic parameters. The second goal of this study is to suggest optimum parameter distributions for the simulation of the multiple reflood tests performed at different facilities with different scales and dimensions. Since existing experimental data and physical models/correlations were produced from several tests performed at the small scale with limited initial and boundary conditions, scaling considerations must be addressed when simulating larger scale tests for the uncertainty analysis. Blind calculations were carried out to observe whether the *a posteriori* parameter samples obtained via the model calibration against a basis test, i.e., a small scale test, which was performed by compensating the scaling distortions properly simulate scaled up tests. Simulations were performed using Safety and Performance Analysis Code (SPACE) developed by multiple research institutes in Republic of Korea to predict the thermal hydraulic system behaviors of nuclear power plants.

1. Introduction

For a number of years, many researchers have worked on the development of uncertainty quantification methodologies to estimate uncertainties on the model parameters and the responses of interest. The Code Scaling, Applicability, and Uncertainty (CSAU) evaluation method was developed to establish the requirements for quantifying code uncertainties in specific scenarios for Nuclear Power Plants (NPPs) (Boyack et al., 1989, 1990). The CSAU method provides not only guidelines for developing specific uncertainty methodologies but also the relevance of scaling issues when using system codes for licensing.

For the uncertainty quantification, CSAU proposes the Phenomena Identification and Ranking Table (PIRT) which has become a standard process accepted throughout the international nuclear community providing guidance of executing Best Estimate Plus Uncertainty (BEPU) applications. Since the uncertainty analysis performed with CSAU in 1980s, many new methodologies such as model calibration and parameter estimation have been proposed. In an inverse problem, unlike the forward problem, the uncertain parameters to a computational model are inferred from observations of the outputs of the model. Methodologies for the model calibration (also called data assimilation) have been developed based on Bayesian theorem by mathematics, statistics, and engineering community, and applied to complex engineering systems to estimate an optimum parameter distribution (Kennedy and O'Hagan, 2001; Oberkampf et al., 2004; Tarantola, 2005; Williams et al., 2006; Bui-Thanh et al., 2013; Petra et al., 2014; Cacuci and Ionescu-Bujor, 2010; Petruzzi and D'Auria, 2014; Kovtonyuk et al., 2016). Markov Chain Monte Carlo (MCMC) (Andrieu et al., 2003) simulations are primarily used for calculating numerical approximation of multi-dimensional distributions in

* Corresponding author.
E-mail addresses: jheo@kaeri.re.kr (J. Heo), kdkim@kaeri.re.kr (K.D. Kim), nuclist@kaeri.re.kr (S.-W. Lee).

https://doi.org/10.1016/j.anucene.2017.08.033
0306-4549/

Nomenclature

Acronyms:

BEPU	Best Estimate Plus Uncertainty
BEMUSE	Best-Estimate Methods – Uncertainty and Sensitivity Evaluation
CA	Cold Assembly
CSAU	Code Scaling, Applicability, and Uncertainty
DAKOTA	Design Analysis Kit for Optimization and Terascale Applications
DSS	Dynamic System Scaling
FEBA	Flooding Experiments with Blocked Arrays
FLECHT–SEASET	Full-Length Emergency Core Heat Transfer Separate Effects And System Effects Tests
FSA	Fractional Scaling Analysis
H2TS	Hierarchical Two Tiered Scaling
HA	Hot Assembly
ITF	Integral Test Facility
LOCA	Loss of Coolant Accident
MCMC	Markov Chain Monte Carlo
NPP	Nuclear Power Plant
PAPIRUS	PArallel computing Platform IntegRated for Uncertainty and Sensitivity analysis
PIRT	Phenomena Identification and Ranking Table
PREMIUM	Post-BEMUSE REflood Models Input Uncertainty Methods
PWR	Pressurized Water Reactor
QUESO	Quantification of Uncertainty for Estimation, Simulation and Optimization
SET	Separate Effect Test
SPACE	Safety and Performance Analysis Code
SOAR	State Of the Art Report
UMAE	Uncertainty Methodology based on Accuracy Extrapolation

Symbols:

$\mathbf{r}$	simulation response vector
$\mathbf{p}_0$	nominal values of the parameters
$\mathbf{p}$	parameter vector
$\mathbf{r}_m$	experiment data vector
$\mathbf{C}_m$	measurement error covariance matrix
$\mathbf{C}_p$	parameter covariance matrix
α	regularization parameter

Bayesian statistics and predictive engineering. In Bayesian statistics, the recent development of MCMC methods has been a key step in making it possible to compute multi-scale and multi-dimensional system that require integrations over hundreds of unknown parameters. Many software programs such as the Quantification of Uncertainty for Estimation, Simulation and Optimization (QUESO) (Estacio-Hiroms and Prudencio, 2012), Design Analysis Kit for Optimization and Terascale Applications (DAKOTA) (Adams et al., 2014), PArallel computing Platform IntegRated for Uncertainty and Sensitivity analysis (PAPIRUS) (Heo and Kim, 2015), etc. that perform statistical analysis for complex engineering problems also have been developed to support users. The application of this work can be broadened to the machine learning (Murphy, 2012) that gives computers the ability to learn without being explicitly programmed, where the methodology is mainly developed base on Bayesian theorem.

For the scaling analysis, CSAU method focuses on scaling up a particular process from a test facility to a full scale NPP, which primarily relies on the empirically determined relations that model the process. For the CSAU evaluation, test facility design and operation were considered to evaluate whether or not the facility as well as the initial and boundary conditions of a test are properly scaled so that the processes related to the scenario are not affected by scaling distortions. The test matrix was also considered to evaluate whether test parameters cover the range of interest to NPP applications. Since the scaling algorithms were introduced by CSAU, several methodologies were suggested by many institutes throughout the world. Scaling and uncertainty quantification methods for thermal hydraulic system codes were suggested by many experts through the W-GAMA project and well explained in the SOAR report (OECD NEA Report, 2017). Several scaling analysis including Uncertainty Methodology based on Accuracy Extrapolation (UMAE) (D'Auria et al., 1995), Hierarchical Two Tiered Scaling (H2TS) (Zuber et al., 1998), three level scaling approaches (Ishii et al., 1998), Fractional Scaling Analysis (FSA) (Zuber et al., 2007), and Dynamic System Scaling (DSS) (Reyes, 2015a,b) have been developed and applied in the design of new test facilities to evaluate the scaling distortion.

The goal of our study is to develop an advanced uncertainty quantification algorithm for best estimate simulation of multi-scale and multi-dimensional phenomena, and to apply these methods to the analysis of reflood phenomena for the nuclear reactor. Reliable prediction of complex physical systems requires first of all, sophisticated mathematical models of the physical phenomena involved. In addition a comprehensive treatment of the calibration and validation of the models, as well as the quantification of the uncertainties inherent in such models are required for the best estimate analysis. This paper introduces the application of data assimilation methodology to determine the uncertainty of the physical models based upon the statistical approach. Data assimilation suggests a mathematical methodology for the best estimate bias and the uncertainties of the physical models which optimize the system response following the calibration of model parameters and responses. The mathematical approaches include probabilistic methods of data assimilation to solve nonlinear problems with the *a posteriori* distribution of parameters derived based on Bayes' theorem. Safety and Performance Analysis Code (SPACE) (SPACE Code Manual, 2010) is used to predict reflood phenomena and subsequently to demonstrate the data assimilation method by determining the bias and the uncertainty bands. Multiple reflood tests performed at different facilities with different scales and dimensions were selected for this analysis and blind calculations were conducted to observe whether the calibrated parameter distributions obtained by compensating the scaling distortions properly simulate scaled up tests.

A similar analysis was performed for the Post-BEMUSE REflood Models Input Uncertainty Methods (PREMIUM) benchmark (OECD NEA Report, 2016a,b), where the parameter uncertainties were determined by 6 FEBA tests, and their uncertainties were propagated through the simulation of the 2-D reflood PERICLES to examine whether the PERICLES test data are enveloped by the uncertainty band resulting from the propagation. The participants obtained valuable results, but the quantified uncertainties showed a large variability and discrepancy among participants and sometimes the results were not satisfactory especially when simulating PERICLES for the blind calculation. To avoid the scaling distortion