Transactions of the Korean Nuclear Society Autumn Meeting
Pyeongchang, Korea, October 30-31, 2014

Validation uncertainty of MATRA code for subchannel void distributions

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1. Introduction

Subchannel analysis technology has been developed during past several decades, and still widely used in the design calculations for PWR cores. MATRA is a KAERI in-house subchannel code which adopted a homogeneous mixture model for two-phase flow, and some empirical models for considering the phasic slip and subcooled boiling effects. It includes an equal volume exchange with void drift two-phase mixing model. To extend code capability to the whole core subchannel analysis, pre-conditioned Krylov matrix solvers such as BiCGSTAB and GMRES are implemented in MATRA code as well as parallel computing algorithms using MPI and OPENMP. It is coded by fortran 90, and has some user friendly features such as graphic user interface. MATRA code was approved by Korean regulation body for design calculation of integral-type PWR named SMART.

The major role subchannel code is to evaluate core thermal margin through the hot channel analysis and uncertainty evaluation for CHF predictions. In addition, it is potentially used for the best estimation of core thermal hydraulic field by incorporating into multi-physics and/or multi-scale code systems. A preliminary study has been conducted to evaluate the performance of multi-physics two-way coupling between a KAERI in-house subchannel code MATRA and neutronics codes as well as fuel performance code[1] as shown in Fig. 1.

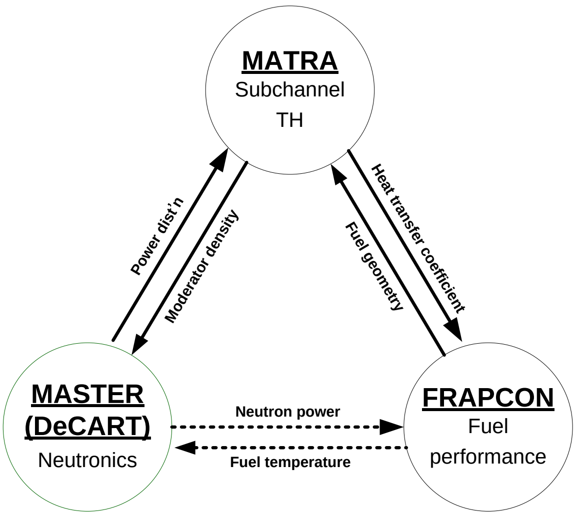

Fig.1. Multi-physics code coupling with MATRA code

In this study we examined a validation process for the subchannel code MATRA specifically in the prediction of subchannel void distributions. The primary objective of validation is to estimate a range within which the simulation modeling error lies. The experimental data for subchannel void distributions at steady state and transient conditions was provided on the framework of OECD/NEA UAM benchmark program[2]. The validation uncertainty of MATRA code was evaluated for a specific experimental condition by comparing the simulation result and experimental data. A validation process should be preceded by code and solution verification. However, quantification of verification uncertainty was not addressed in this study.

2. Methods and Results

2.1 Uncertainty analysis methodologies

In order to examine a validation procedure of MATRA code, an accuracy analysis was conducted for a steady-state void distribution problem on the basis of a typical standard issued by ASME at 2009[3]. The final goal of this standard is to evaluate the uncertainty range of the model error from the comparison error and the validation uncertainty. The comparison error (E) is defined as the difference between a simulation result (S) and a measured data (D). It contains all of the errors in the simulation and experimental results. The simulation error account for the model error(δ_{model}), numerical error(δ_{num}), and input error(δ_{input}). Thus the model error can be estimated from the comparison error and standard uncertainties (δ_{num}, δ_{input}, and δ_D) which are the estimates of errors. The validation uncertainty (u_{val}) is defined as an estimate of standard deviation of the combined errors (δ_{num}, δ_{input}, and δ_D). If those errors are statistically independent, then

$$u_{val} = \sqrt{u_{num}^2 + u_{input}^2 + u_D^2}$$

From the comparison error and the validation uncertainty, we can estimate the uncertainty range of the model error as

$$E - u_{\mathrm{val}} \le \delta_{\mathrm{model}} \le E + u_{\mathrm{val}}$$

Two traditional approaches, sensitivity coefficient approach and Monte-Carlo approach, are used for the analysis of uncertainty propagated from the input parameters. In the sensitivity coefficient approach as shown in Fig. 2, the local sensitivity coefficient is calculated around the nominal condition. The simulation uncertainty due to the input parameter (input uncertainty, u_{input}) is calculated by combining the sensitivity coefficient and the coefficient of variation for each input parameter.

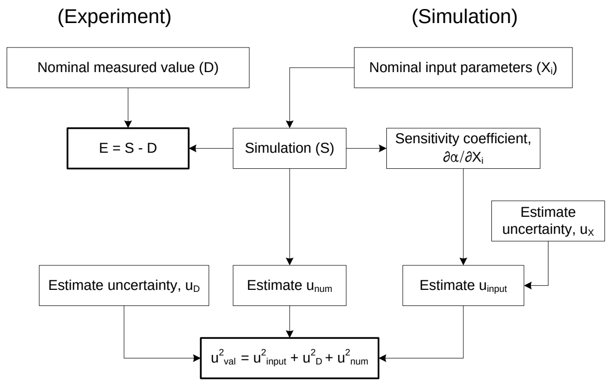

Fig.2. Uncertainty analysis by sensitivity coefficient approach

In the Monte-Carlo approach as shown in Fig. 3, the input uncertainty to the simulation result was evaluated by a simple random sampling for each input parameter. It is compared with the random sampled experimental data that results in a distribution of the comparison error after a number of sampling. Combined uncertainty of input parameter and experimental data can be evaluated from the variance of a distribution of comparison error.

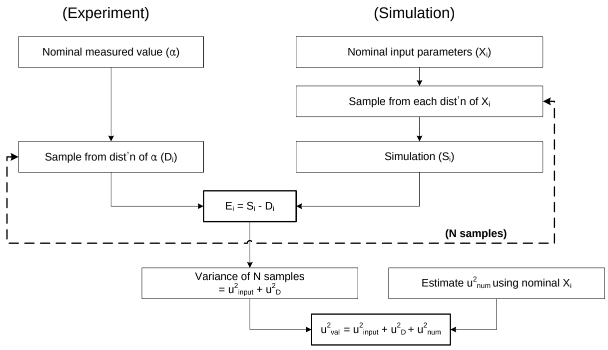

Fig.3. Uncertainty analysis by Monte-Carlo approach

2.2 Analysis of steady-state void distribution benchmark

2.2.1 Uncertainty parameters

A steady-state subchannel void distribution benchmark problem was selected for the uncertainty analysis. The test condition and measured data was obtained from the PSBT run 6.1122 as described in table 1. The subchannel void fraction was measured by a gamma-ray beam CT scanner, and void fraction averaged for the central four subchannels (as shown in Fig. 4) is provided at three different axial levels. The axial measuring location is near the upstream of mixing vaned grid.

Table 1: Important parameters for UAM benchmark

Parameter	Value
Test condition (Run 6.1122):	
Pressure, MPa	16.4
Mass flux, kg/m^{2}s	4214
Inlet temperature, ^{o}C	306.7
Bundle power, kW	3376
Measured data (central 4-ch.):	
Z=2216 mm	0.0000
Z=2669 mm	0.0699
Z=3177 mm	0.2394
Void measurement uncertainty	4% (1σ)

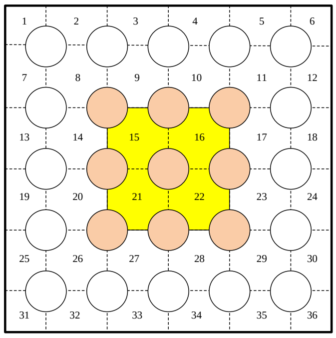

Fig.4. Cross-section of PSBT 5x5 test bundle

In Monte-Carlo approach, the power distribution uncertainty was accounted for by re-normalizing the power distribution after a random sampling of power at every calculation node. Rod displacement uncertainty was considered by changing the rod position in diagonal direction. Positive variation means movement toward the corner of the test bundle. Uncertainty parameters employed in this study are listed in table 2. The probability distribution functions for all parameters are normal except the inlet temperature which has a flat distribution.

Table 2: Uncertainty parameters

Parameter	Nominal	1-σ
Boundary conditions:		
System pressure, MPa	16.4	0.33%
Inlet temperature, ^{o}C	306.7	1.0
Inlet mass flux, kg/m^{2}s	4214	0.5%
Heat flux, kW/m^2	1237	0.33%
Power distribution	Non-uni	1.0%
Geometry:, mm		
Rod diameter (corner)	9.5	0.007
Rod displacement	0.0	0.15
Modeling:		
Bundle friction factor	0.184Re$^{-0.2}$	10%
Grid loss factor	1.0/ 0.7/ 0.4	10%
TDC	0.04	21%
Subcooled void	Levy	10%
Bulk void	Mod. Armand	10%
2-phase friction multiplier	Armand	10%

2.2.2 Sensitivity coefficient approach

The sensitivity coefficient (S_i) is defined as the ratio between the percent change of void fraction to the percent change of input parameter. The magnitude of sensitivity coefficient for each uncertainty parameter is compared in Fig. 5. The coefficient of pressure has negative sign because an increase of pressure results in a decrease of void fraction. The maximum sensitivity was appeared for the inlet temperature variation. Actually, the importance of a parameter to the overall uncertainty is not the same with the magnitude of the sensitivity coefficient as shown in Fig. 6. The contribution of a parameter to the overall uncertainty is defined as the importance factor (IF) which is calculated by combining the coefficient of variation and the sensitivity coefficient. For predicting subchannel void distribution, major contribution to the overall uncertainty was due to a subcooled void model, bulk void model, and turbulent mixing parameter. In the sensitivity coefficient approach, the input uncertainty is expressed as

$$u_{input} = \sqrt{\sum_k \left(S_k \frac{\sigma_k}{\mu_k} \right)}$$

For the PSBT run 6.1122 problem, u_{input} without considering the power distribution uncertainty was calculated by 2.5%, 3.2%, and 3.2% at Z=2216, 2669, and 3177 mm, respectively.

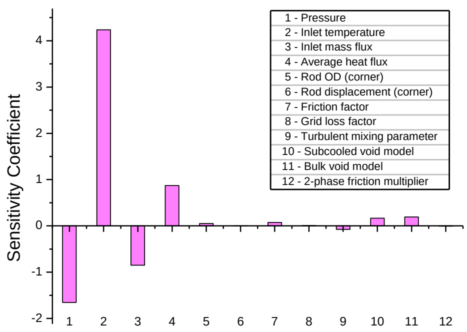

Fig.5. Comparison of sensitivity coefficients for subchannel void distribution

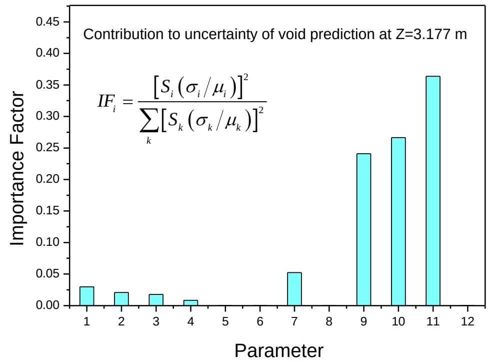

Fig.6. Comparison of importance factors

2.2.3 Monte-Carlo approach

Nonlinear effects on the propagation of input parameter uncertainties were evaluated by employing a direct Monte-Carlo approach. Fig. 7. shows a propagation of input parameter uncertainties at each axial level from a direct simulation with 2000 simple random sampling. In Monte-Carlo simulation, the void uncertainty revealed a maximum near the center of axial level where the local heat flux reveals maximum due to a cosine shaped axial power profile. This trend was not observed by the local sensitivity approach which cannot account for the nonlinear effects on the void calculation accompanied with the axial power shape. Due to the Monte-Carlo approach without considering the power distribution uncertainty, u_{input} was calculated by 4.1%, 3.8%, and 2.8% at Z=2216, 2669, and 3177 mm, respectively. The power distribution uncertainty revealed a minor effect on u_{input} by increasing about 0.1% at Z=2216 mm.

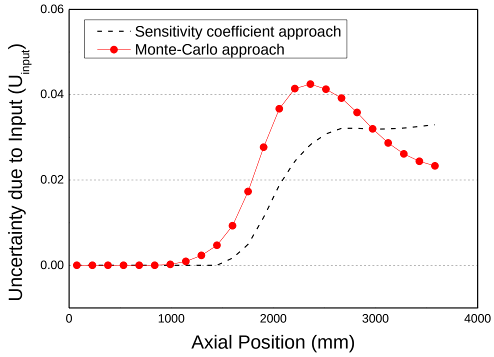

Fig.7. Propagation of input parameter uncertainties at each axial level

2.2.4 Evaluation of validation uncertainty

Ignoring the code numerical error, the validation uncertainty (u_{val}) can be evaluated by combining the experimental data uncertainty (u_D) and the input uncertainty (u_{input}). In the Monte-Carlo approach, a void fraction was calculated from a set of random sampled input parameters. Independently, we have a random sampled experimental data. From these two values, a distribution of comparison error was obtained for randomly sampled 2000 cases. It is illustrated in Fig. 8 at the lower elevation level (Z=2216 mm). From Kolmogorov-Smirnov test, the parent distribution of the comparison error was regarded as a normal distribution with a 5 % significance level. As the result, the validation uncertainty with the power distribution uncertainty was calculated by 5.0%, 4.9%, and 4.0% at at Z=2216, 2669, and 3177 mm, respectively.

In the sensitivity coefficient approach, if we do not consider the numerical solution uncertainty, u_{val} is calculated by a root sum square of the experimental data uncertainty and the input uncertainty. That is,

$$u_{val} = \sqrt{u_D^2 + u_{input}^2}$$

As the result, the validation uncertainty without the power distribution uncertainty was calculated by 4.7%, 5.1%, and 5.1% at at Z=2216, 2669, and 3177 mm, respectively.

The magnitude of u_{val} for the two different approaches were compared in Fig. 9. In the Monte-carlo approach, the validation uncertainty decreases as the elevation increases.

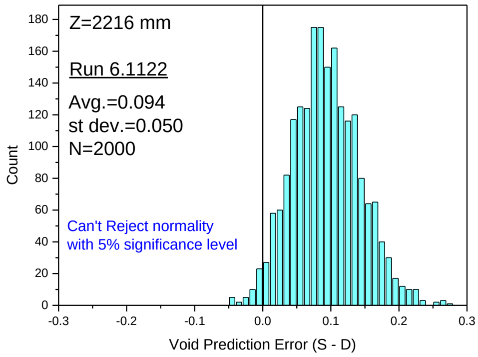

Fig.8. Distribution of validation comparison error

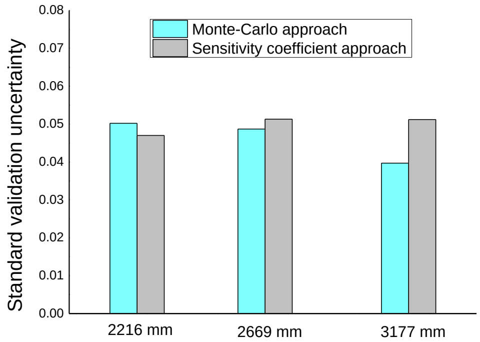

Fig.9. Comparison of validation uncertainties

2.3 Analysis of transient void benchmark

The input uncertainty for a transient void distribution was evaluated by employing a Monte-Carlo approach for a power increase transient in PSBT 5x5 test bundle. Fig. 10 shows transient history plot for the selected transient. Transient calculations were performed for 2000 random sampled initial conditions. The average and standard deviation of predicted voids at each calculation time step is plotted in Fig. 11 in comparison with the experimental data at Z=2669 mm. As the result of analysis, it was found that the MATRA code tends to under-predict the void fraction as the axial elevation increases. It was also found that the input uncertainty decreases with increased axial level at the voiding region where the void fraction is approximately greater than 10%.

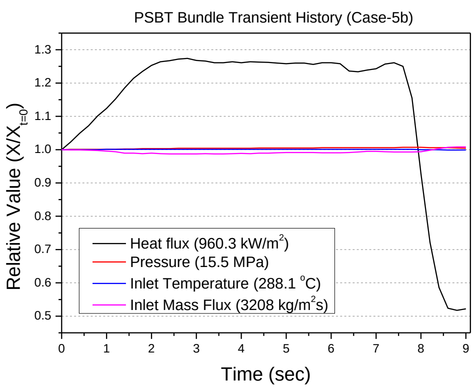

Fig.10. Transient history plot

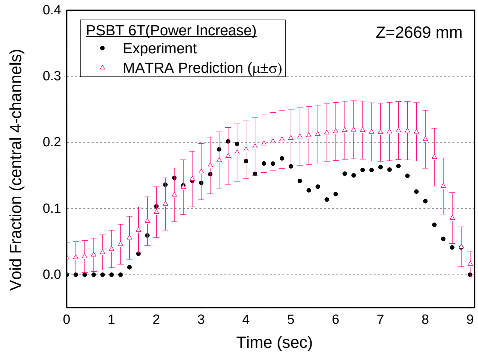

Fig. 11. Comparison with experimental data during transient

3. Conclusions

The validation uncertainty of the MATRA code for predicting subchannel void distribution was evaluated for a single data point of void fraction measurement at a 5x5 PWR test bundle on the framework of OECD UAM benchmark program. The validation standard uncertainties were evaluated as 4.2%, 3.9%, and 2.8% with the Monte-Carlo approach at the axial levels of 2216 mm, 2669 mm, and 3177 mm, respectively. The sensitivity coefficient approach revealed similar results of uncertainties but did not account for the nonlinear effects on the uncertainty propagation. A preliminary analysis for the input uncertainty of transient void distribution was evaluated by employing a Monte-Carlo approach.

ACKNOWLEGEMENTS

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIP) (No. 2012M2A8A4026261)

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