Data Assimilation-Based Enhancement of ATWS Analysis

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1. Introduction

Anticipated Transients Without Scram (ATWS) are serious reactor events where the system fails to shut down properly, posing significant safety risks due to potential radioactive release. Many existing reactors lack robust ATWS mitigation systems, making this a critical concern, especially in older plants with higher core damage frequencies. Accurate thermal-hydraulic analysis of both primary and secondary systems is essential to ensure safety during such events, as these analyses rely on factors like coolant pressure, reactivity feedback, and heat removal. The L9-3 experiment [1,2], simulating an ATWS scenario, has been widely used to validate simulation codes like RELAP5, though discrepancies between model predictions and experimental data highlight the need for improved modeling. This study applies Data Assimilation (DA) techniques to enhance the predictive accuracy of the MARS-KS code [3] using experimental data and machine learning to identify key sources of uncertainty in ATWS simulations.

2. Methods and Results

In this section the ATWS test, MARS-KS model, and data assimilation preparation are described.

2.1 L9-3 test description

Experiment L9-3 (see Figure 1), conducted at the Loss of Fluid Test (LOFT) facility [1,2], simulated a loss-of-feedwater ATWS to evaluate reactor shutdown methods, validate computational codes, and test the applicability of point kinetics models using neutron flux and thermal-hydraulic data. It also provided critical data on secondary-side dryout in the steam generator and on high-pressure flow behavior through the Pressurizer Power-Operated Relief Valve (PORV) and the Safety Relief Valve (SRV), both key components in pressure control. Flow rate measurements showed large discrepancies from expected values; for example, the PORV was expected to pass 0.66 kg/s of steam at 16.2 MPa but actually discharged 0.80 kg/s of steam and 2.44 kg/s of liquid at 16 MPa, indicating high uncertainty in valve behavior. The experiment began with main feedwater pump shutdown, followed by manual closure of the steam valve, and activation of the PORV and SRV at their respective setpoints, with the SRV capping system pressure at a peak of 17.4 MPa. At 600 seconds, recovery actions were initiated including activation of the high-pressure injection system, startup of auxiliary feedwater, and opening of the PORV, while control rods remained fully withdrawn to simulate a scram failure.

2.2 MARS-KS model

This study used the MARS-KS 1.4 code, developed by the Korea Atomic Energy Research Institute and the Korea Institute of Nuclear Safety, to simulate the Anticipated Transient Without Scram (ATWS) L9-3 experiment, utilizing its ability to model liquid, vapor, and droplet phases in multidimensional space. The Loss of Fluid Test (LOFT) facility was modeled with detailed nodalization, including 134 hydrodynamic volumes and 148 heat structures, with accurate representations of the reactor vessel, primary coolant system (PCS), pressurizer, and steam generator (SG). The reactor kinetics model included both moderator density and Doppler temperature feedback, and decay heat was simulated using the American Nuclear Society 1979 (ANS-79) model with scram behavior also considered. Components such as the pressurizer and SG were modeled with trip logic and friction models, simulating flow through the pressurizer PORV, SRV, and the main steam control valve (MSCV). The simulation results closely matched experimental data and successfully reproduced key transient events such as feedwater pump trip, valve activations, and the continuous operation of the primary coolant pumps.

2.3 Data assimilation preparation

This study selected eighteen physical models commonly used in the MARS code for uncertainty quantification, including two critical flow models specifically for the PORV and SRV, due to high uncertainties in mass flow rate predictions. These models involved uncertainty multipliers for key phenomena such as two-phase wall friction, interfacial drag and heat transfer, entrainment behavior, droplet Weber number, and empirical correlation adjustments. A 30 percent uncertainty range was applied to all models, based on prior evaluation results from reference studies [4]. To assess predictive accuracy, six system responses were compared to experimental data using the absolute relative difference (ARD) method and its scaling factors, as implemented in the STARU [5] uncertainty analysis framework. Special emphasis was placed on reactor coolant system pressure, as it directly affects the timing of PORV and SRV activation, and its weight was increased in the data assimilation process to improve model alignment with experimental behavior.

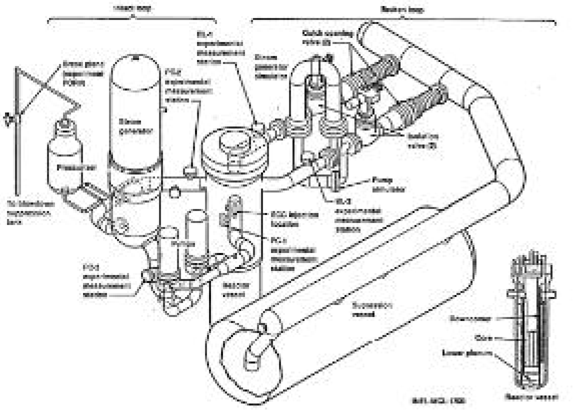

Fig. 1. The ATWS L9-3 test [1].

2.4 Uncertainty quantification results

The reactor coolant system pressure was found to strongly depend on when the calculated pressure exceeded the SRV and PORV setpoints, which are affected by their flow areas and pressure values (see Figure 2). Due to large uncertainties in these flow areas and the critical flow model, the Henry–Fauske model was adopted as a key component in the uncertainty quantification analysis. The results showed that data assimilation improved the predictive accuracy by about 55%, demonstrating better agreement with experiments and enhanced simulation fidelity for later machine learning use.

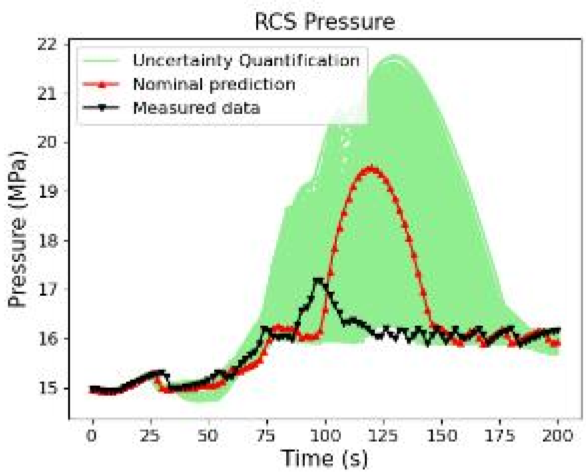

Fig. 2. RCS pressure. There are over 10,000 green lines, each of them indicates single calculation corresponding to a specific scenario of parameter's values.

2.5 The calibrated candidate

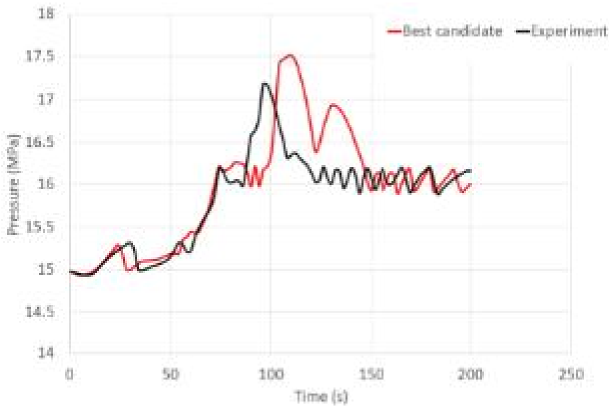

Fig. 3. The best candidate of the uncertainty quantification results for RCS pressure prediction.

Figures 3 and 4 present the best candidate response for RCS pressure prediction and their corresponding multipliers, which yield the minimum uncertainty compared with the experimental data. Comparison of the predicted system pressure from the best candidate (red line) with the experimental data (black line). The model captures the general pressure trend well, including the initial rise and post-peak behavior. However, it slightly overpredicts the pressure peak and shows a delayed response of approximately 17 seconds compared to the experiment. This discrepancy may be attributed to an underestimation of the interfacial drag, critical flow model for PORV and SRV, suggesting that the model's current setting is too low. A broader adjustment range, possibly more than 30 percent, may be necessary to improve the predictions.

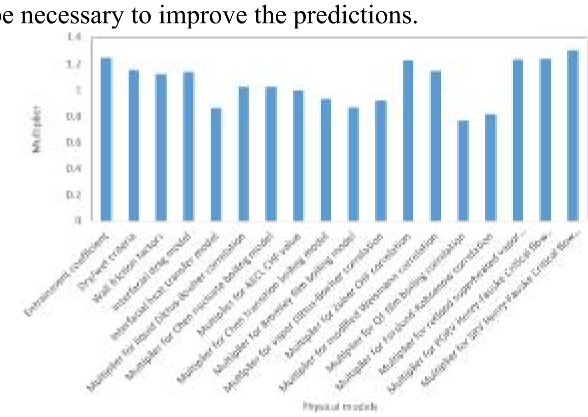

Fig. 4. The multipliers of the best candidate

3. Conclusions

A simulation model for the LOFT L9-3 test was adopted using the MARS-KS code. Although the nominal results generally matched the experiment, noticeable errors appeared in the RCS pressure prediction. Data assimilation was applied to tune 18 physical models within the uncertainty quantification framework, resulting in about a 55% improvement in predictive accuracy over the baseline. Some overprediction of the pressure peak and delayed response remained, likely due to limits in the interfacial drag and critical flow models.

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