

Development of a Flow-Aware CNN-AE Surrogate Model for OPR1000 Total Loss of Feed-Water Accident Analysis

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1. Introduction

Thermal-hydraulic system codes such as MARS-KS are widely used for nuclear power plant accident analysis[1]. However, repeated calculations under various accident conditions require considerable time and computational cost. With recent advances in deep learning techniques and computing capabilities, deep-learning-based surrogate models have been actively investigated to rapidly predict the results of system code calculations[2]. However, intermittent flow variables that remain zero for most of the transient and become active only during specific intervals can be difficult to model using conventional continuous-value regression because of their zero-heavy response characteristics [3,4]. In particular, for safety injection tank (SIT), high-pressure safety injection (HPSI), pilot-operated relief valve (PORV), and pressurizer safety valve (PSV) flows, prediction errors may occur in actuation timing and peak magnitude, together with residual flow during inactive periods. Therefore, this study developed a CNN-AE-based flow-aware surrogate model using MARS-KS simulation results for a pressurized water reactor total loss of feedwater (TLOFW) accident to simultaneously predict the time-dependent responses of major thermal-hydraulic variables and the actuation characteristics of intermittent flow variables.

2. Methods and Results

2.1 MARS-KS TLOFW Dataset

The OPR1000 TLOFW accident was selected as the target scenario for surrogate model development [5]. The scenario includes operator actions for manual RCP trip and PORV opening following the loss of main and auxiliary feedwater. Loss of secondary-side heat removal causes the RCS pressure to increase, leading to repeated PSV actuation and intermittent discharge flow. Subsequent PORV opening depressurizes the RCS and enables HPSI and SIT injection.

About 2,000 accident conditions were generated by applying Latin Hypercube Sampling (LHS) to six input variables, and each case was simulated using MARS-KS [6]. Transient responses were recorded over 0–

6000s at 1-s intervals, yielding 6001 time steps. The six inputs were core power, decay heat, number of available HPSI pumps, manual RCP trip delay, manual PORV opening delay, and number of available PORVs.

The 9 physical outputs were pressurizer pressure, pressurizer level, core collapsed water level, secondary-side inventory, peak cladding temperature (PCT), and HPSI, PORV, PSV, and SIT flows. Variable-specific normalization was applied to the physical outputs, and 4 additional binary channels were generated to represent the on/off states of the 4 flow variables. The dataset was divided into training, validation, and test sets at ratios of 0.70, 0.15, and 0.15, respectively.

2.2 Flow-Aware CNN-AE Architecture

A three-layer one-dimensional convolutional neural network (1D-CNN)-based autoencoder (AE) was employed to model the multivariate TLOFW transient responses [7, 8]. The model treats the 0–6000s thermal-hydraulic responses as a transient pattern, compresses their temporal features into a low-dimensional latent space through the encoder, and reconstructs the full time-domain responses through the decoder. Batch normalization and LeakyReLU activation were applied to each convolutional layer [9, 10].

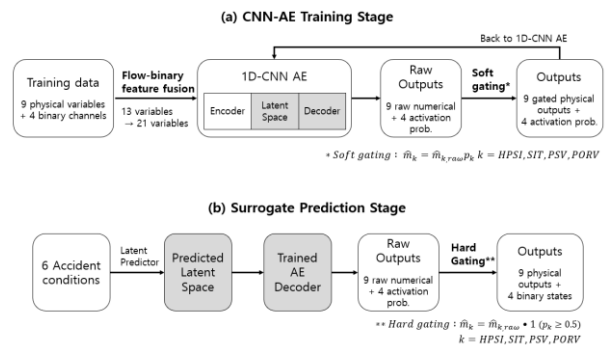


Fig. 1. Schematic of the proposed flow-aware CNN-AE surrogate model with flow-binary feature fusion and gating: (a) CNN-AE Training Stage, (b) Surrogate Prediction Stage

Because the HPSI, PORV, PSV, and SIT flows remain zero for most of the transient and become active only during limited periods, conventional continuous-

value regression may produce residual flow during inactive periods or errors in actuation timing and peak magnitude. To address this issue, an on/off binary activation channel was generated for each flow variable, producing 13 input channels consisting of 9 physical variables and 4 binary variables.

Flow-binary feature fusion was applied to jointly represent each flow variable and its corresponding activation state. Each flow-binary pair was transformed into 4 features through a dense embedding layer and combined with the five non-flow thermal-hydraulic variables, resulting in 21 internal feature channels for the CNN-AE encoder. This representation allows the model to learn both flow magnitude and activation characteristics within the transient response.

The decoder reconstructs 9 raw numerical responses and 4 binary activation probabilities. During CNN-AE training, soft gating was applied by multiplying each raw flow prediction by its corresponding activation probability, maintaining differentiability while suppressing residual flow during inactive periods. The resulting AE output consists of 9 gated numerical channels and 4 activation-probability channels.

To predict accident responses directly from the six input conditions defined in Section 2.1, a separate latent predictor was trained using the latent representations generated by the trained CNN-AE encoder as target values. The predicted latent representation was then fed into the trained decoder to reconstruct the complete 0–6000s response. For final surrogate prediction, the decoder-generated activation probabilities were converted into binary on/off states, and hard gating was applied to the raw flow predictions. This removes residual flow during inactive periods while preserving the predicted flow magnitude during active periods. Thus, the proposed surrogate predicts long-duration TLOFW responses through the learned CNN-AE latent representation rather than directly mapping the six accident conditions to the full time-series outputs.

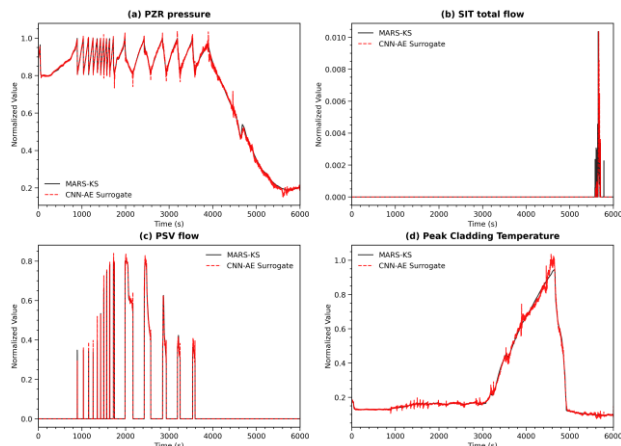


Fig. 2. Comparison of MARS-KS and surrogate model predictions for a representative case: (a) pressurizer pressure, (b) SIT flow, (c) PSV flow, and (d) PCT.

2.3 Prediction Results

The predictive performance of the proposed flow-aware CNN-AE surrogate model was evaluated by comparing its predictions with MARS-KS results for the test set. Fig. 2 presents the pressurizer pressure, peak cladding temperature (PCT), SIT flow, and PSV flow for a representative case with active SIT and PSV flows. These variables were selected to represent the major pressure, safety-related temperature, and intermittent flow responses of the TLOFW transient.

For the representative case, the proposed model reproduced the overall pressurizer pressure and PCT responses in reasonable agreement with MARS-KS. Major transient features, including the pressure increase and subsequent depressurization as well as the gradual PCT variation and the timing of its maximum value, were adequately captured. The model also reproduced the on/off characteristics and major actuation timings of the SIT and PSV flows. In particular, the repeated PSV actuation associated with changes in RCS pressure was captured, indicating that the model reproduced the overall temporal correlation between the pressure response and PSV actuation.

Fig. 3 further compares the flow and activation-state predictions for representative SIT and PSV cases. The PSV flow and its repeated activation states were closely reproduced, whereas the SIT prediction captured the major activation interval but showed larger discrepancies in short-duration flow peaks and rapid state transitions. These observations are consistent with the quantitative results in Table I.

Quantitative performance over the entire test set is summarized in Table I using normalized root mean square error (NRMSE), on/off F1 score, first-onset mean absolute error (MAE), and peak-flow error. Numbers in parentheses indicate the number of actuating cases among 302 test cases. The mean NRMSE of the non-flow variables was 1.32%. HPSI, PORV, and PSV flows achieved on/off F1 scores above 99.6% and first-onset MAEs of 1 s or less, indicating accurate prediction of their activation states and initial actuation timings. Their peak-flow errors were also limited to approximately 9–12%.

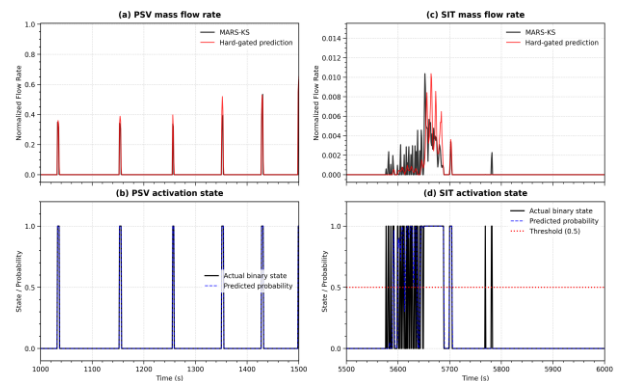


Fig. 3. Prediction of SIT and PSV flow characteristics using the flow-aware surrogate model: (a) PSV flow, (b) PSV

activation state, (c) SIT flow, and (d) SIT activation state

Table I. Prediction performance of the flow-aware CNN-AE on the test set

Variables	NRMSE (%)	On/off F1 (%)	First Onset MAE (s)	Peak Error(%)
Non-flow variables	1.32	N/A	N/A	N/A
HPSI flow (202/302)	1.45	99.98	1	10.7
PORV flow (299/302)	1.35	99.69	0.1	11.73
PSV flow (302/302)	0.75	99.69	0	8.76
SIT flow (166/302)	1.05	94.63	24	68.83

SIT flow was relatively more difficult to predict, with an on/off F1 score of 93.17%, a first-onset MAE of 24 s, and a peak-flow error of 68.83%. Some SIT cases exhibited underprediction or overprediction of sharp flow peaks, which may be attributable to the short SIT actuation duration relative to the entire transient and the sensitivity of its peak-flow profile to the accident input conditions.

Overall, the results demonstrate that the proposed flow-aware CNN-AE can reproduce both continuously varying thermal-hydraulic responses and intermittent flow activation behavior during TLOFW transients, while further improvement is required for short-duration sharp flow peaks such as SIT injection.

3. Conclusions

In this study, a flow-aware CNN-AE surrogate model was developed using MARS-KS simulation data for the OPR1000 TLOFW accident to simultaneously predict major thermal-hydraulic variables and intermittent flow actuation characteristics. The proposed model was based on a three-layer 1D-CNN autoencoder designed to compress and reconstruct long-duration transient responses, and flow-binary feature fusion and the proposed gating framework were incorporated to represent the intermittent actuation characteristics of the HPSI, PORV, PSV, and SIT flows.

For the representative test case, the proposed model reproduced the major time-dependent responses of pressurizer pressure and PCT in reasonable agreement with the MARS-KS results and generally captured the on/off characteristics and major actuation timings of the SIT and PSV flows. Quantitative evaluation over the entire test set showed high accuracy in reproducing the activation states and actuation timings of the intermittent flow variables, while relatively larger errors remained in the peak magnitude of SIT flow. These results indicate that the proposed flow-aware framework is particularly effective for representing intermittent flow activation behavior, while further

improvement is required for sharp short-duration flow peaks.

Future work will apply the flow-binary feature fusion and the proposed gating framework to RNN based models to compare their predictive performance and assess the general applicability of the proposed methodology. The framework will also be extended to other accident scenarios, including loss-of-coolant accidents (LOCA).

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