Advancing the MISO Strategy: Hybrid Architectures for Thermal-Hydraulic Forecasting in Severe Accidents

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1. Introduction

The progression of severe accidents in nuclear power plants is highly nonlinear and characterized by complex interactions among thermal-hydraulic (TH) phenomena. During such events, accurate and timely prediction of plant behavior is essential for supporting operator decision-making and implementing effective mitigation strategies. Traditional system codes such as the Modular Accident Analysis Program (MAAP) provide detailed simulations of accident progression; however, the required computational resource makes such sophisticated code to be impractical for real-time applications. To address this challenge, data-driven surrogate models based on machine learning have been investigated as alternatives for predicting severe accident progression with less resource and quicker results. In particular, a recent study applied a rolling-window forecasting scheme to improve multi-step prediction performance, demonstrating significant reduction in prediction error compared to single-step approaches [1].

Among various modeling strategies, the Multi-Input Single-Output (MISO) approach [2] has recently been proposed as a promising framework. In this strategy, each TH variable is predicted by an independent model trained on the same set of inputs, thereby avoiding the error propagation and divergence issues that often occur in Multi-Input Multi-Output (MIMO) formulations. Prior studies have demonstrated that the MISO framework enhances prediction accuracy, particularly in capturing the peak values and long-term dynamics of accident scenarios. Nevertheless, most existing MISO implementations rely on a single neural network architecture across all variables, which may not fully exploit the distinct temporal and dynamic characteristics inherent to different TH signals.

The present study advances the MISO methodology by developing a Hybrid MISO approach, in which different neural architectures are selectively applied to individual variable with respect to the characteristics. Specifically, convolutional neural networks (CNNs) are employed for variables dominated by short-term fluctuations, whereas long short-term memory networks (LSTMs) are adopted for variables exhibiting strong temporal dependencies. The proposed framework is trained and tested on datasets generated from MAAP simulations of a Total Loss of Feedwater (TLOFW) initiating event in the APR1400 nuclear power plant, with severe accident mitigation actions randomly applied within 1–24 hours after the onset of accident. The model performance is evaluated using conventional error metrics (MAE, RMSE) as well as dynamic time warping (DTW) distance, with the latter serving as a key indicator of trajectory-level accuracy. By combining the strengths of CNN and LSTM architectures within the MISO framework, this work demonstrates improved predictive fidelity for severe accident progression.

2. Methods

2.1 Accident Scenario and data generation

Table 1. Target SAMG Mitigation

#	SAMG mitigation
1	Reactor cooling system depressurization
2	Steam Generator external injection
3	Reactor cooling system external injection
4-1	Containment Spray pump activation
4-2	Emergency Containment Spray Backup System

The initiating event of the accident scenario was defined as a Total Loss of Feedwater (TLOFW). Following this condition, it was assumed that all engineered safety systems of the APR1400 were unavailable once the nuclear power plant enters severe accident conditions. Consequently, the mitigation strategies listed in Table 1 were considered as the only available countermeasures during severe accident. Strategies 1 (reactor cooling system depressurization), 2 (steam generator external injection), 3 (reactor cooling system external injection), and 4 (containment spray systems) were modeled as an independent variable. For the containment spray options (4-1 and 4-2), however, a dependency was imposed such that either one could be activated or neither, but both could not be simultaneously applied.

Each mitigation strategy was allowed to be initiated at a random time between 1 and 24 hours after the onset of the severe accident. In addition, the possibility that a strategy would not be activated at all was also incorporated into the sampling design. To ensure comprehensive coverage of the input space while minimizing redundancy, a maximin sampling technique was employed, resulting in the generation of 10,000 distinct accident scenarios.

2.2 Training Condition

A total of 10,000 accident scenarios were generated, each including the seven-target thermal-hydraulic variables listed in Table 2. These variables, such as primary system pressure, hot and cold leg temperatures, and containment pressure, represent critical information that can be monitored in the main control room and are therefore essential indicators for tracking the progression of a severe accident.

Table 2. Target Thermal-hydraulic Variable

#	Target thermal-hydraulic variable
1	Primary system pressure (PPS)
2	Cold leg temperature (Cold leg T)
3	Hot leg temperature (Hot leg T)
4	Steam generator pressure (SG P)
5	Steam generator water level (SG WL)
6	Containment Pressure (CTMT P)
7	Cavity water level (CWL)

The dataset was partitioned into 7,000 cases for training and 3,000 cases for testing. Model training was performed exclusively on the training set, and 5% of the training cases were randomly extracted to construct a validation set. The mean absolute error (MAE) of the validation set was continuously monitored, and an early stopping criterion was applied such that if no improvement in validation MAE was observed for 10 consecutive epochs, the training process was terminated.

2.3 Model Performance Evaluation

The performance of the surrogate models was evaluated using mean absolute error (MAE) and root mean square error (RMSE), which served as baseline indicators of point-wise prediction accuracy. These metrics are effective in quantifying deviations at each time step but are limited in reflecting temporal misalignments that often arise in sequential forecasting.

Since the model predicts future thermal-hydraulic variables in a recursive manner, where previously predicted values are reused as inputs for subsequent steps, temporal consistency of the trajectory is of particular importance. To address this, the dynamic time warping (DTW) distance was employed as the key evaluation metric. Unlike MAE and RMSE, DTW measures the similarity between entire time series by optimally aligning two sequences through warping. The DTW distance between sequences $\mathrm{X} = (\mathrm{x}_1, \mathrm{x}_2, .., \mathrm{x}_N)$ and $\mathrm{Y} = (\mathrm{y}_1, \mathrm{y}_2, \ldots, \mathrm{y}_\mathrm{M})$ is formally defined as:

$$\mathrm{DTW}(\mathrm{X}, \mathrm{Y}) = D(N, M)$$

where the cumulative distance matrix $\mathrm{D}(\mathrm{i}, \mathrm{j})$ is compute recursively as

$$\mathrm{D}(\mathrm{i}, \mathrm{j}) = d(x_i, y_j) + \min\{D(i-1, j), D(i, j-1), D(i-1, j-1)\}$$
$$* \, \mathrm{d}(\mathrm{x_i}, \mathrm{y_j}) = \|x_i - y_j\|$$

2.4 Model Architecture

This study adopts a Multi-Input Single-Output (MISO) strategy, in which each thermal-hydraulic variable is predicted by an independent model trained on the same set of inputs. The input vector consists of 12 features (seven plant state variables and five mitigation measures), while the output is a single normalized variable.

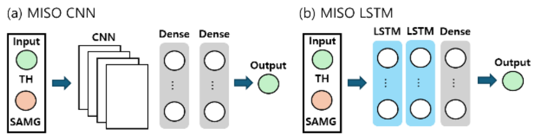

Figure 1 Overview of the Multi-Input Single-Output (MISO) Framework with Two Implementations: (a) MISO CNN and (b) MISO LSTM.

Two architectures were designed. The MISO CNN (Figure 1. a) uses a one-dimensional convolution (12→400, kernel size 3) to capture local temporal dependencies, followed by fully connected layers (400→400→1) with ReLU activations and a final sigmoid output. The MISO LSTM (Figure 1. b) employs two stacked LSTM layers (12→400→400) to represent sequential correlations, after which the last hidden state is mapped to a single output through a fully connected layer and sigmoid activation.

By training each output variable with its own dedicated model, the MISO framework avoids error propagation across variables and allows the architecture to specialize in variable-specific dynamics.

3. Results & Discussions

Table 3 reports the MAE and RMSE for the MISO-CNN and MISO-LSTM models, while Table 4 presents the corresponding DTW distances. For each thermal-hydraulic variable, the architecture yielding the lower MAE/RMSE was highlighted in bold, and the Hybrid model was constructed by adopting that architecture. As a result, variables such as PPS and SG P were represented by CNN models, whereas variables with stronger temporal correlations such as cold leg and hot leg temperatures were represented by LSTM models.

Table 3 Prediction Performance of the MISO-CNN and MISO-LSTM Models for each Target Thermal-hydraulic variable

	MISO CNN		MISO LSTM	
	MAE	RMSE	MAE	RMSE
PPS	**2.5.E-03**	**4.1.E-03**	4.2.E-03	6.1.E-03
Cold leg T	4.9.E-02	7.0.E-02	**4.1.E-02**	**6.1.E-02**
Hot leg T	1.8.E-01	2.3.E-01	**9.3.E-02**	**1.3.E-01**
SG P	**5.3.E-02**	**1.3.E-01**	9.2.E-02	2.0.E-01
SG WL	**5.4.E-02**	**1.2.E-01**	7.2.E-02	1.4.E-01
CTMT P	**6.0.E-02**	**1.0.E-01**	1.1.E-01	1.6.E-01
CWL	1.1.E-02	1.8.E-02	**6.1.E-03**	**1.0.E-02**

Table 4 Dynamic Time Warping (DTW) Distances of the MISO-CNN, MISO-LSTM, and Hybrid Models.

	Dynamic Time Wrapping Distance		
	MISO CNN	MISO LSTM	Hybrid
PPS	0.1869	0.2245	0.1403
Cold leg T	2.2860	1.7953	1.6711
Hot leg T	15.3558	4.4814	3.9768
SG P	2.7061	3.9652	2.6930
SG WL	2.8416	3.8104	2.8247
CTMT P	4.6974	6.0578	4.1765
CWL	0.6399	0.4632	0.8095
Average	4.1020	2.9711	2.3274

Compared to the single-architecture approach, the Hybrid model consistently reduced DTW distances across most variables. The average DTW distance decreased from 4.1020 for CNN and 2.9711 for LSTM to 2.3274 for the Hybrid approach. These results confirm that selecting the more suitable architecture for each variable within the MISO framework improves the fidelity of accident progression prediction.

4. Conclusions & Future Work

This study examined the use of deep learning–based surrogate models for predicting thermal-hydraulic variables during severe accidents with the MISO (Multi-Input Single-Output) framework. Although the MISO strategy has already been proposed in prior studies, this work extends the approach by developing a Hybrid MISO framework that leverages variable-dependent architectures to better capture diverse temporal and dynamic features. By adopting CNNs for variables with more localized dynamics and LSTMs for variables with stronger temporal correlations, the Hybrid model consistently achieved lower DTW distances compared to single-architecture baselines. These results demonstrate that combining multiple architectures within the MISO framework enhances the overall fidelity of accident progression prediction.

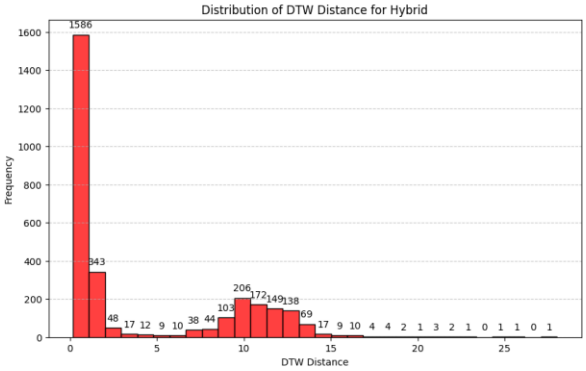

Figure 2 Distribution of Dynamic Time Warping (DTW) Distances for Containment Pressure (CTMT P) with the Hybrid Model.

Despite the improvement achieved by the Hybrid MISO model, certain variables, most notably the containment pressure (CTMT P), still exhibited relatively large DTW values. Figure 2 shows the DTW distance distribution for CTMT P, where the right-skewed pattern indicates difficulty in capturing long-term dynamic responses. Future work will aim to shift this distribution toward lower DTW values by exploring advanced sequence modeling techniques, physics-informed constraints, or hybrid architectures that further integrate domain knowledge into the prediction process.

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