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Evaluation of Multi-Input Single-Output ANN Models for Thermal-Hydraulic Predictions in Nuclear Severe Accidents: Branched vs. Non-Branched Structures

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1. Introduction

In the event of a severe nuclear power plant accident, the ability to rapidly predict the progression of events and formulate an effective response is crucial for mitigation. Severe accidents exhibit complex, highly nonlinear behaviors, making accurate predictions inherently challenging. These complexities can lead to unforeseen interactions and cascading failures, as demonstrated by historical incidents such as the Three Mile Island and Fukushima accidents. The unpredictable nature of such events necessitates advanced predictive methodologies to enhance situational awareness and decision-making.

To address these challenges, artificial neural networks (ANNs) have been widely explored for predicting thermal-hydraulic variables in nuclear reactors. Previous studies have shown that adaptive radial basis function (RBF) neural networks offer superior fitting capabilities and forecasting accuracy compared to conventional methods, achieving a maximum error of just 0.5% under steady-state conditions [1]. Additionally, deep learning models such as long short-term memory (LSTM) networks have been utilized for predicting key nuclear power plant parameters, demonstrating strong potential in capturing complex dynamic behaviors [2].

Further research utilizing MAAP-generated data has investigated the prediction of thermodynamic variables during severe accident scenarios using ANNs incorporating convolutional neural networks (CNNs), LSTMs, and hybrid architectures. In one study, LOCCW-based incident data were used to predict key thermal-hydraulic variables essential for Severe Accident Management Guidelines (SAMG) mitigation strategies. The results indicated a high recursive predictive capability, achieving a Mean Absolute Error (MAE) of approximately 0.05 in predicting hydrothermal variables [3]. In a subsequent study, predictive performance was further improved by transitioning from a conventional multi-input, multi-output (MIMO) model to a multi-input, single-output (MISO) model [4]. This methodological shift resulted in a reduction of the Root Mean Square Error (RMSE) by up to 20.65% compared to the traditional MIMO model, highlighting the effectiveness of the MISO architecture in enhancing prediction accuracy for severe accident scenarios.

In this study, further improvements in predictive performance are pursued by refining the architecture of the artificial neural network (ANN). In the previous study, an ANN model composed of two stacked Long Short-Term Memory (LSTM) layers and a dense layer was used. In the current study, a branched path is introduced within the ANN, and its effect on performance is compared to the previous architecture. A comparative analysis is conducted under identical training conditions, with the structural configuration being the only variable, while the same dataset from the previous study is used. Hyperparameters, such as the number of nodes per layer and the learning rate, are inherited from prior work without additional optimization. By isolating the impact of the branched path, this study aims to provide deeper insights into the effect of architectural changes on the prediction of thermal-hydraulic behavior in severe nuclear accident scenarios.

2. Methods

2.1 Accident Scenario and data generation

Table 1. Target Component Failure and SAMG Mitigation

#	Component failure
1	Reactor coolant pump (RCP) seal LOCA
2	Letdown heat exchanger (HX)
3	High-pressure injection (HPI) pump
4	Low-pressure injection (LPI) pump
5	Containment spray system (CSS) pump
6	Motor-driven auxiliary feedwater (MDAFW) pump
7	Charging pump (CHP)
#	**SAMG mitigation**
1	Steam generator external injection
2	Reactor cooling system depressurization
3	Reactor cooling system external injection

The data utilized in this study consists of LOCCW-based accident scenarios from the OPR1000 reactor. The failure times for components susceptible to malfunction during the LOCCW accident process were randomized, as summarized in Table 1. Additionally, Severe Accident Management Guidelines (SAMG) mitigation actions 1, 2, and 3, which can be executed in any sequence, were set to activate upon meeting the predefined mitigation conditions. To introduce variability, mitigation actions were also triggered at randomized times, even when the activation conditions were satisfied. Through this process, approximately 11,000 accident scenario datasets were generated, with each scenario simulating a 72-hour period from the initial event, specifically the Reactor Coolant Pump (RCP) trip.

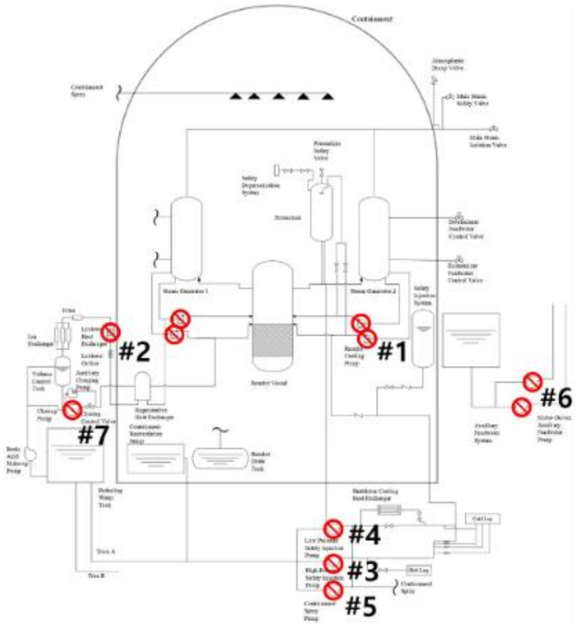

Figure 1. Detailed Location of Component Failure on OPR1000 Safety System

2.2 Training Condition

Excluding certain scenarios from the 11,000 randomly generated accident cases that failed to complete the 72-hour simulation due to errors in the MAAP code, a total of 109 scenarios, accounting for approximately 1% of the 10,917 successfully simulated cases, were isolated from the dataset and designated as the validation set for final model evaluation. These scenarios were entirely excluded from the training process and were later utilized to assess the general regression capability of the trained model.

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	Reactor vessel water level (RV WL)
5	Steam generator pressure (SG P)
6	Steam generator water level (SG WL)
7	Max CET

For the remaining dataset, thermal-hydraulic information at time t+1 was predicted using thermal-hydraulic data from $t-2$, $t-1$, and t, along with instrumentation and SAMG-related information at t, following the established methodology [3-4]. The specific thermal-hydraulic variables predicted in this study are listed in Table 2, which includes key parameters available in the Main Control Room (MCR) of a nuclear power plant and essential for implementing SAMG mitigation measures.

To mitigate the risk of overfitting during the training process, 5% of the training data was randomly extracted and designated as a test set, which was excluded from model training and reserved for evaluating training performance. Unlike the previously separated 1% validation set, which was isolated based on total data set, the test set was randomly selected across different time points within all scenarios.

During model training, an early stopping criterion was applied, where training was terminated if the mean absolute error (MAE) on the test set did not improve for 10 consecutive epochs. The model weights corresponding to the lowest test set MAE recorded during training were retained. This approach ensured that data points excluded from training were utilized to regulate the training process, preventing overfitting while optimizing the computational time required for training. The proportion of the test set and the termination criteria based on the number of epochs can be further optimized in future studies to enhance model performance.

2.3 Model Performance Evaluation

The performance of the model was evaluated based on the 72-hour Euclidean distance of the predicted accident scenario rather than using mean absolute error (MAE) or root mean square error (RMSE), which are typically employed to assess model learning or general regression capability. MAE and RMSE were not calculated for individual data points, as the model utilizes a rolling-window prediction methodology, where each prediction is based on the previously predicted values and subsequently used to forecast the next time step.

The evaluation was conducted by comparing the full dataset of accident scenarios included in the validation set with the accident scenarios predicted by the model. In this process, only the initial accident conditions, the failure time of a specific component, and the activation time of SAMG mitigation measures were provided as input to the model. This approach ensures that the model's long-term predictive performance is assessed in a manner that reflects real-world accident progression and mitigation response dynamics.

$y_{MAAP,i,t}$: $Thermal\ hydrualic\ variable$ "i" $at\ time\ t\ in\ validation\ set$

$y_{pred,i,t}$: $Predicted\ Thermal\ hydrualic\ variable$ "i" $at\ time\ t\ in\ model$

$$Euclidean\ distance_i = \Sigma_{t=1}^{72} \left\| y_{MAAP,i,t} - y_{pred,i,t} \right\|$$

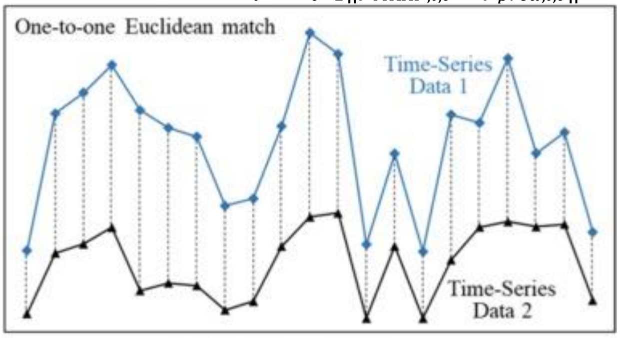

Figure 2. Euclidean distance

The evaluation method used the formula described above, along with Figure 2, and summed the Euclidean distances to evaluate the performance of the model for a single scenario. The Euclidean distance was calculated by treating both the MAAP data in the validation set and the predicted accident scenario data as independent time series. This approach allowed for a direct comparison between the observed (MAAP calculated) and predicted thermal-hydraulic variables, facilitating the assessment of model performance in simulating the progression of the accident scenario.

2.4 Model Architecture

In this study, the effect of introducing branched hidden layers in a Multi-Input Single-Output (MISO) Long Short-Term Memory (LSTM) model is analyzed. The MISO LSTM architecture, which demonstrated high predictive performance in the previous study [4], serves as the baseline for this analysis.

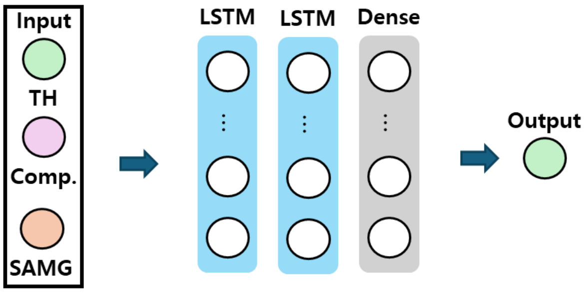

Figure 3. Diagram of Non-branched Model

The structure of the existing MISO LSTM model is illustrated in Figure 3. The model receives input in the form of a tensor with dimensions (3,17), consisting of seven thermal-hydraulic variables at time steps $t-2$, $t-1$, and t, along with ten component failure states and SAMG mitigation action information at time steps $t-2$, $t-1$, and t. The model processes this input using a dual-layer LSTM structure followed by a dense layer, producing an output tensor of dimensions (1,1), which corresponds to the predicted values of the thermal-hydraulic variables at time t+1.

To predict all seven thermal-hydraulic variables, seven independent models of the same structure are trained separately, with each model dedicated to predicting a single thermal-hydraulic variable. This approach ensures that each variable is individually optimized, potentially enhancing predictive accuracy compared to a single multi-output model.

Figure 4 illustrates the structure of the branched model. Unlike the traditional model, which utilizes a tensor of dimensions (3,17) that includes SAMG mitigation information as input, the branched model processes an input tensor of dimensions (3,14), where SAMG mitigation measures are instead used to determine the computational path within the network.

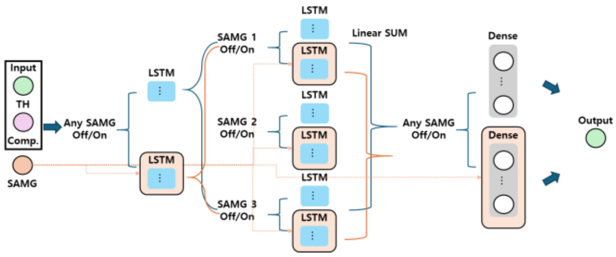

Figure 4 Diagram of Branched Model

The output structure remains the same as the original model, producing a tensor of dimensions (1,1) after passing through a dual-layer LSTM structure followed by a dense layer. However, the branched model introduces structural modifications in the LSTM layers. In the initial LSTM layer, two independent LSTM networks operate in parallel. If any of the SAMG mitigation measures (1, 2, or 3) are activated, the input is processed through the lower LSTM path, as shown in Figure 3. Otherwise, the input follows the upper LSTM path.

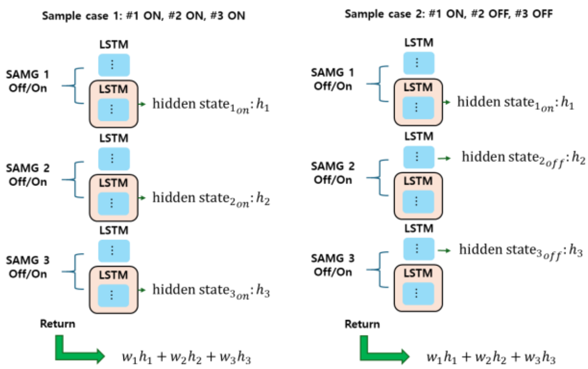

Figure 5. Return of Second LSTM Layer

As shown in Figure 5, the second LSTM layer consists of six independent LSTM networks, organized into three pairs, with each pair corresponding to one of the SAMG mitigation measures (1, 2, or 3). In the sample case presented in Figure 5, depending on whether SAMG mitigation is enabled or disabled, one pair of LSTM networks produces the hidden state from the relevant network. A total of three hidden states are generated based on SAMG mitigation strategies 1, 2, and 3, and the linear sum of these hidden states is calculated, with fixed weight values w_1 ,w_2, and w_3. This summed output is then used as input to the final dense layer.

The final dense layer consists of two independent sub-layers, with the output being determined based on the activation status of SAMG mitigation measures. This architecture allows the model to dynamically adjust its processing pathway depending on the mitigation strategy applied, potentially improving predictive accuracy in scenarios where different accident management measures influence thermal-hydraulic behavior.

3. Results & Discussions

Table 3 MAE and RMSE of Variables from MISO LSTM and MISO LSTM Branched Model

	MISO LSTM		MISO LSTM Branched	
	MAE	RMSE	MAE	RMSE
PPS	1.32.E-02	4.15.E-02	1.11.E-02	2.39.E-02
Cold leg T	9.09.E-02	1.34.E-01	5.17.E-02	7.52.E-02
Hot leg T	5.21.E-02	7.89.E-02	4.14.E-02	5.88.E-02
RV WL	8.19.E-02	1.37.E-01	5.98.E-02	1.02.E-01
SG P	9.91.E-02	1.38.E-01	6.81.E-02	1.05.E-01
SG WL	1.02.E-01	1.28.E-01	1.69.E-02	2.89.E-02
MAX CET	5.60.E-02	9.95.E-02	4.32.E-02	8.19.E-02

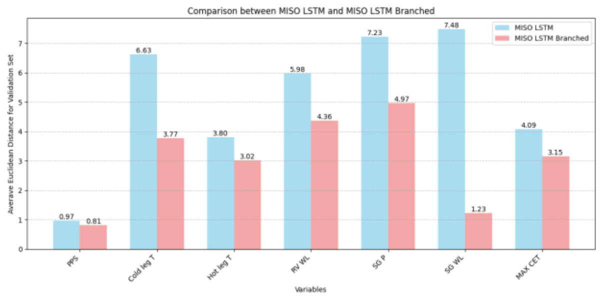

Figure 6. Average Euclidean Distance for Thermal-hydraulic Variable

Figure 6 presents the performance metrics for both the non-branched and branched models. It is evident that, for all thermal-hydraulic variables, the branching architecture generally improves model performance. Variables such as primary system pressure, which are also accurately predicted by the non-branched model, show a slight reduction in Euclidean distance. However, variables like steam generator water level exhibit a significant reduction in error, with the Euclidean distance decreasing by approximately a factor of six when branching is applied. This indicates that the cumulative error in predicting a single 72-hour accident scenario is reduced by a factor of six.

While the overall trend suggests that branching improves prediction accuracy, high error accumulation is still observed for certain variables, particularly steam generator pressure. This points to the need for further refinement of the prediction model to enhance its accuracy for these specific variables.

Figure 7 shows the steam generator pressure for the scenarios in the validation set where the branched MISO LSTM model exhibits the lowest prediction performance. The Euclidean distance for steam generator pressure in this scenario is 19.64, which is significantly higher than the average value of 4.97, indicating very poor forecast performance. While the calculation using MAAP (black line) shows a steady decrease in steam generator pressure, the forecast from the branched MISO LSTM model fails to follow this trend. This discrepancy can be attributed to the ineffective communication of information regarding the operating components (dashed lines) early in the scenario.

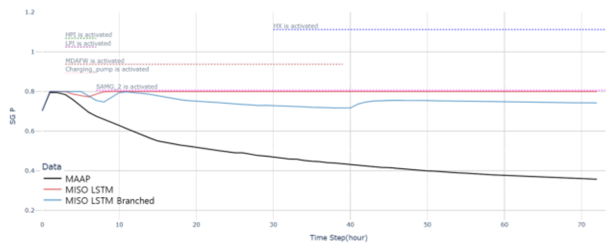

Figure 7. Steam Generator Pressure Trends in Scenarios with Poor Predictive Performance

4. Conclusions & Future Work

This study evaluates the performance of Multi-Input Single-Output (MISO) LSTM models with branched and non-branched architectures for predicting thermal-hydraulic variables during severe nuclear power plant accidents. The results show that branching generally improves model performance for predicting most thermal-hydraulic variables. In particular, variables such as steam generator water level exhibit a substantial reduction in error, highlighting the benefits of the branched structure. However, certain variables, such as steam generator pressure, still experience high error accumulation, pointing to areas where model refinement is needed.

Future work will address the issue of component failure information not being effectively communicated to the model, particularly at the beginning of the scenario. This issue contributed to poor predictive performance for some variables, such as steam generator pressure, in the branched MISO LSTM model. Improving the communication of operational component states and incorporating more precise failure data will be essential to enhancing the model's forecasting accuracy. Additionally, further optimization of model architecture will be explored to improve the generalization capability and reduce the prediction errors for critical variables in severe accident scenarios.

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