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Performance Analysis of Bi-LSTM Models for Severe Accident Prediction with Limited Time-Series Data in Nuclear Power Plant

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1. Introduction

In the event of a severe accident at a nuclear power plant, which could lead to reactor core meltdown beyond the design basis accidents, mitigation strategies must be implemented to minimize the radioactive material release. These mitigation strategies follow the Severe Accident Management Guideline (SAMG). In SAMG, instead of following a predefined procedure, one of the available mitigation strategies is selected based on the symptom-based approach, depending on the specific accident conditions [1]. However, during an accident, selecting a mitigation strategy can lead to human error due to the high-stress environment. Therefore, having an accident management support tool (AMST) that can assist in this decision-making process would greatly contribute to the effective mitigation of the accident [2].

One of the essential functions that an AMST must have is the ability to accurately predict the progression of an accident, minimizing uncertainties as much as possible. Suppose the AMST can accurately forecast the outcome of severe accidents based on the application of different mitigation strategies, it will enable operators to identify which strategy is the most effective.

To develop a AMST prediction model, deep learning methods can be employed. According to the Universal Approximation Theorem, these methods are capable of approximating nonlinear data, making them suitable for modeling complex accident scenarios [3]. Lee et al. developed a severe accident prediction model using deep learning methods, demonstrating strong predictive performance [4].

Building upon this research, the goal is to evaluate whether the deep learning model can accurately predict accident progression in time intervals that were not included in the training data. While the previous study trained the model using the entire 72-hour dataset, this research aims to train the model with only the first 24 hours of data and assess its ability to predict the progression of the accident beyond that time. In real accident scenarios, there is no guarantee that an accident will be mitigated within 72 hours, as seen in the Fukushima accident, which lasted over a week. Therefore, if the model demonstrates strong predictive performance in untrained periods, it would greatly enhance its practical applicability in real situations.

2. Methods

2.1 Generation of Accident Scenario Dataset

The dataset used in this study is fundamentally based on the dataset from previous research [4]. This dataset was calculated using the severe accident analysis code MAAP 5.03 [5] and was based on the OPR1000 nuclear power plant. A total of 10,679 accident scenarios were generated, and in these scenarios, the random failure of seven components and the application of mitigation strategies occurred within the 72-hour period. The list of components that can fail under these scenarios is shown in Table I, which includes components selected based on their likelihood of failure in the event of a TLOCCW. The list of mitigation strategies includes SAMG 1, 2, and 3, which are selected for their applicability to the primary system.

While the previous study extracted data with 1-hour interval and trained the model on the entire 72-hour dataset, this study intends to train the model using only the first 24 hours of data. Therefore, the data was extracted at more frequent 15-minute intervals. Additionally, to improve the generalization performance of the model, 3,679 scenarios were selected by excluding data with similar accident progressions.

Table I Components those can be failed during TLOCCW accident scenario

Component Name
RCP seal LOCA
HPSI
LPSI
CHP
CSS
MDAFW
HX

2.2 Bi-LSTM model

The methodology used in this study is the Bidirectional LSTM (Bi-LSTM) model. This model was chosen because it demonstrated the best performance in the previous research.

A Bi-LSTM model is an extension of the traditional LSTM network, designed to capture temporal dependencies in sequence data. While a standard LSTM processes data in one direction (from past to future), the Bi-LSTM processes the input data in both forward and backward directions. This enables the model to have a more comprehensive understanding of the sequence by considering both past and future context.

LSTM networks are well-known for their ability to handle long-term dependencies due to their internal memory mechanism, which helps in retaining important information over extended time intervals while mitigating the vanishing gradient problem. As shown in Fig. 1, in a Bi-LSTM model, two separate LSTM layers are used: one processes the sequence in the original time order (forward pass), and the other processes the sequence in reverse order (backward pass). The outputs from both directions are then combined, allowing the model to leverage information from the entire sequence at each time step.

This bidirectional approach makes the Bi-LSTM model particularly effective for tasks where the context from both past and future data points is important for making accurate predictions, which is highly useful in time-series forecasting or sequence prediction.

The input and output structure of the Bi-LSTM model used in this study is illustrated in Fig. 2. The model uses data from past three time steps to predict the thermal-hydraulic variables for the next time step. In this process, the input consists of thermal-hydraulic variables along with the status of component failures and the application of mitigation strategies, represented as binary values of 0 or 1.

The thermal-hydraulic variables used for prediction are limited to those that can be measured in the Main Control Room (MCR), ensuring that the model relies on information that would be available during an actual accident.

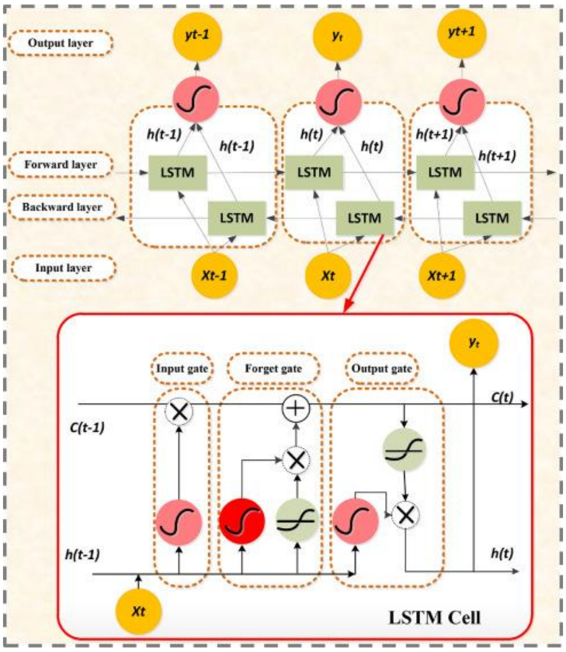

Fig. 1 Architecture of LSTM cell and Bi-LSTM [6]

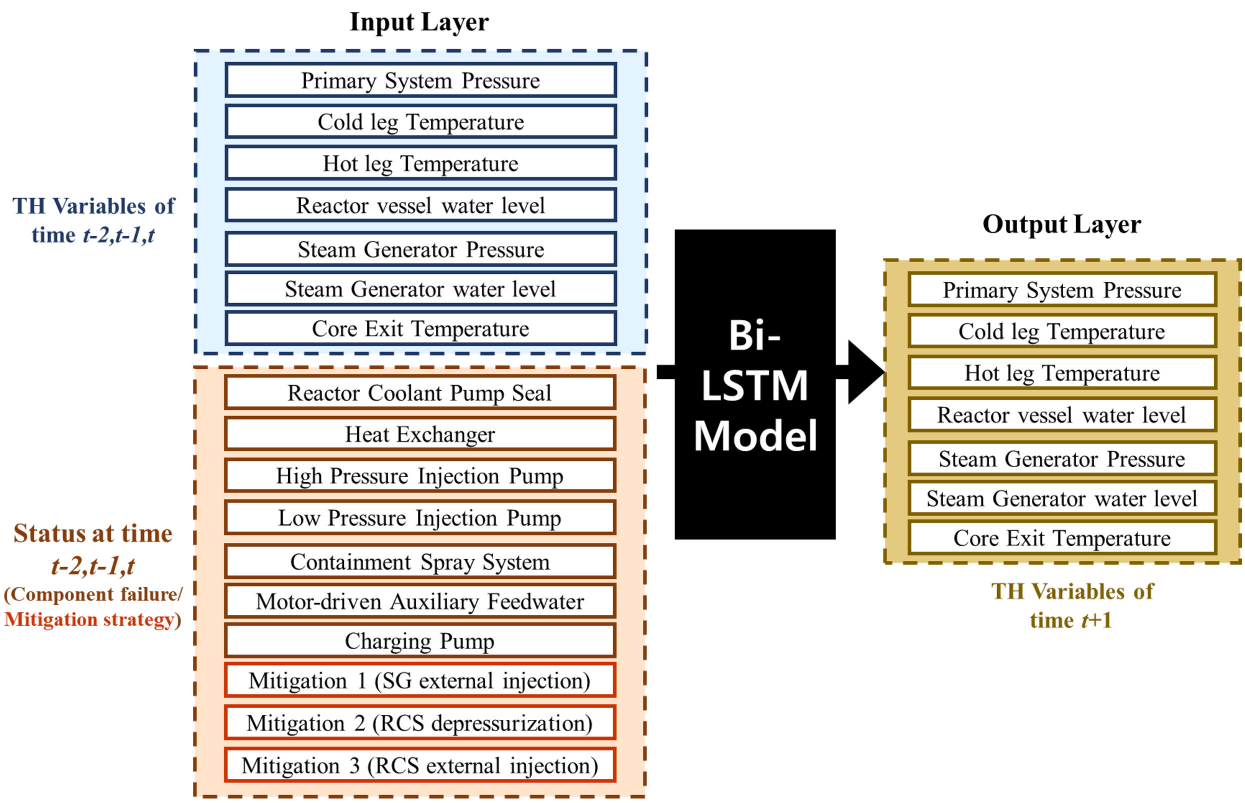

Fig. 2 Input and output structure of Bi-LSTM model

2.3 Performance Metrics

The performance metrics used in this study are the same as those employed in the previous research [4]. To evaluate the regression performance of the model—specifically, how well it predicts the next time step when the actual values are used as input—Mean Absolute Error (MAE) was used.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \qquad (1)$$

Additionally, the full scenario prediction performance of the model, where predicted values are fed back as input for subsequent predictions, was assessed by measuring the similarity between the predicted data and the actual MAAP data using Dynamic Time Warping (DTW) distance, a common method for measuring similarity in time-series data. For both MAE and DTW distance, lower values indicate better performance. In this study, dynamic time warping distance was calculated using DTAIDistance tool of python [7].

3. Results and Discussion

To compare the performance of the Bi-LSTM model trained on 24-hour data, a second model was developed using the full 72-hour dataset at 15-minute intervals, referred to as the 72-hour Bi-LSTM model. Both models were trained using the same dataset, divided in a 7:2:1 ratio for training, validation, and test sets. However, the 24-hour model was trained using only one-third of the time-series data (24 hours), while the 72-hour model used the full dataset. All input variables were normalized to values between 0 and 1. The hyperparameters of the Bi-LSTM models are summarized in Table II.

Table II Hyperparameter of Bi-LSTM model

	Number of LSTM cell	Number of layers	Epoch	Loss	Optimizer
Hyper-parameter	32	2	500 with early stopping	MSE	Adam

Using the above hyperparameter settings, both the 24-hour and 72-hour models were trained, and their predictive performance on the test set was compared using MAE, as shown in Table III. The 24-hour model showed a slightly lower MAE value compared to the 72-hour model, likely due to the higher dependency between data points when using a shorter time series. Additionally, when the 24-hour model was tested on the test set of 72-hour model, the MAE value was around 0.023, which is approximately four times higher than the original MAE, indicating a significant drop in performance when predicting beyond the trained time range.

Table III Test set MAE of Bi-LSTM model

	24-hour model	72-hour model	24-hour model with 72-hour test set
Test set MAE	0.0049	0.0062	0.0229

Next, the full scenario prediction was conducted for both the 24-hour model and the 72-hour model. The predictions were compared with the 72-hour MAAP data, and the DTW distance was calculated. As shown in Table IV, the DTW distance for the 24-hour model was approximately 1.3 times larger than that of the 72-hour model. This confirms the expected outcome that the predictive performance of the 24-hour model is inferior to that of the model trained on the full 72-hour dataset.

Table IV DTW distance between full scenario prediction results and 72-hour MAAP data

	24-hour model	72-hour model
DTW distance	3.785	2.930

In Fig. 3, the distribution of the full scenario prediction results of 24-hour model and the MAAP data for the primary system pressure is shown. This figure represents the mean and 1-sigma distribution for the test set. From the graph, it can be observed that up to around 24 hours, the mean values are nearly identical, but beyond that point, the model predicts nearly constant values, making it difficult to accurately predict the actual values.

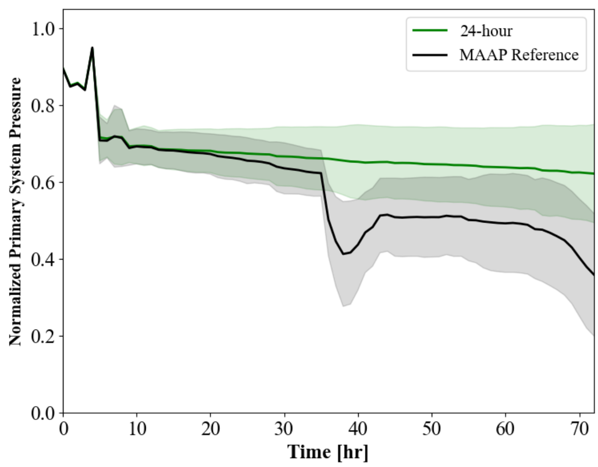

Fig. 3 Comparison between primary system pressure of full scenario prediction results of 24-hour model and MAAP data (Solid line : mean, envelop : std)

4. Summary and Further Works

In this study, Bi-LSTM model was developed to predict severe accident progression in a nuclear power plant. Building on the previous research, which used 72-hour datasets for training, this study aimed to evaluate the ability of model to predict beyond trained time intervals by focusing on the first 24 hours of data.

Two models were developed for comparison: one trained on the full 72-hour dataset and another on the first 24 hours. The results showed that the 24-hour model had a slightly lower MAE compared to the 72-hour model when predicting the test set, which can be attributed to the stronger dependency between data points in the shorter time series. However, when the 24-hour model was tested on the 72-hour test set, its MAE increased significantly, approximately four times higher than its original value, indicating a drop in predictive accuracy when applied to longer, untrained time ranges.

Additionally, when evaluating the full scenario prediction performance, the 24-hour model showed very accurate predictions for the first 24 hours but predicted nearly constant values beyond that point, leading to discrepancies with the actual data. This is likely an unavoidable result due to the limited training data. However, it is possible that there are models capable of better predictions even with restricted training data, and with optimized hyperparameters, improved results could be achieved.

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