Improving the Restoration of Stuck Signals Using LSTM in Nuclear Power Plants

Ji Woo Hong, Min Seon Kim, Man Gyun Na*
Department of Nuclear Engr., Chosun Univ., 10, Chosundae 1-gil, Dong-gu, Gwangju, 61452
**Corresponding author: magyna@chosun.ac.kr*

Keywords: signal restoration, artificial intelligence, nuclear power plants

1. Introduction

Signals in nuclear power plants (NPPs) are important for monitoring system status, ensuring operational stability, and maintaining safety. A failure in these signals can lead to misinterpretation, delayed decision-making, and severe accidents. In addition, these signals serve as inputs to artificial intelligence (AI)-based operator support systems, where anomalies can disrupt the responses of AI models and lead to incorrect actions. Therefore, the accurate restoration of signal failures is essential to maintain system integrity and ensure safe operation. It also enhances the reliability of decision support systems by preventing AI-induced errors.

2. Background

Previous studies have used a long short-term memory-variational autoencoder (LSTM-VAE) based restoration model that reconstructs the corrupted signal using an encoder-decoder structure [1]. The LSTM-VAE model learns the distribution of normal signals and reconstructs the anomalous signal to restore its original shape. While this model performed well for certain types of signal failures, it struggled to restore stuck failures, where the signal remains at a constant value. The LSTM-VAE model is less effective for signals with minimal temporal variation, such as stuck failures, because it relies on temporal variation for reconstruction. For signals with minimal inherent temporal variation, partial restoration was achievable. However, in the NPPs, most signals exhibit complex, nonlinear patterns; therefore, reconstruction alone is insufficient for satisfactory restoration performance. An iterative reconstruction approach was applied to improve restoration performance, but stuck signals remained difficult to restore, even after multiple iterations. Moreover, low performance of signal restoration negatively impacted the subsequent scenario diagnosis, which can reduce the overall system reliability.

In this study, a prediction-based restoration model using LSTM instead of reconstruction is proposed to address these problems. The approach predicts the target variable with anomalies using information from the remaining variables. This approach allows the model to learn normal time-series patterns more effectively by excluding signal failure input. Therefore, this study aims to enhance signal integrity and ensure stable operation in the NPPs by improving restoration performance.

3. Methods

In this study, we developed the signal restoration model using the LSTM method. The NPPs data consist of multivariate time-series data, in which capturing the temporal patterns is essential for accurate signal restoration. LSTM is a machine learning algorithm optimized for processing time-series data [2]. It was designed to address the vanishing gradient problem in traditional recurrent neural networks (RNNs). Unlike RNNs, which suffer from long-term dependency problems and loss of information in long sequences, LSTM preserves past information through cell states and gate mechanisms. Because of these properties, LSTM is well suited to learn the nonlinear variations in the NPPs data and can be effectively applied to signal restoration. The structural differences between the RNN and the LSTM are shown in Fig. 1.

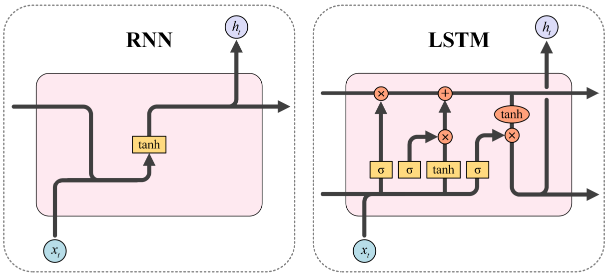


Fig. 1. Comparison of RNN and LSTM architecture.

4. Data

In this study, we collected signal data using the compact nuclear simulator (CNS). Four emergency scenarios were selected to evaluate signal restoration under different conditions, and various malfunctions were injected to generate diverse datasets. Signals were collected for 1,800 seconds and divided into training, validation, and test sets. The distribution of each dataset is summarized in Table I.

Table I: Distribution of scenarios and datasets

No.	Scenario	No. of train/val/test
1	LOCA	18/2/5
2	ESDE	18/2/5
3	FWLB	15/2/4
4	MSLB	16/2/4

We analyzed the variables to be monitored by operators in the CNS and selected a total of 28 variables. This study focuses on signal restoration, particularly in cases involving single signal failures. Table II lists 28 selected variables that are referenced in the results section.

Table II: Example variables from the selected dataset

No.	Variables description
0	Pressurizer pressure
1	Pressurizer delta level
2	Pressurizer level
3	Pressurizer uncompensated level
4	Pressurizer temperature
5	Charging line outlet temperature
6	Containment pressure
7	Steam generator #1 pressure
⋮	
15	Hot-leg #1 temperature
16	Hot-leg #2 temperature
17	Hot-leg #3 temperature
18	Loop #1 average temperature
19	Loop #2 average temperature
20	Loop #3 average temperature
21	Cold-leg #1 temperature
22	Cold-leg #2 temperature
23	Cold-leg #3 temperature
24	H2 concentration
25	Cold-leg #1 safety injection flow
26	Cold-leg #2 safety injection flow
27	Cold-leg #3 safety injection flow

5. Results

In this study, a prediction-based signal restoration model was developed using the LSTM method. The model used the remaining 27 variables to predict the target variable, excluding the target variable. This ensures that signal failures are not directly input into the AI model. By preventing direct input of signal failures, the model learns normal time-series patterns more effectively, improving the reliability of restoration.

A set of 28 restoration models was developed, each responsible for restoring a specific target variable. The performance evaluation is divided into two approaches: Numerical performance evaluation and similarity evaluation.

5.1 Numerical performance evaluation

The numerical error metrics are used to evaluate the predictive accuracy of the model. Specifically, they measure the difference between the restored and actual values, providing an objective assessment of restoration performance.

The performance evaluation was conducted using mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and R-square (R^2) metrics. MAE measures the mean absolute error between the predicted value and the actual values, with lower values indicating better performance. MSE is the mean square error between the predicted and the actual values, and RMSE is the square root of the MSE. R^2 is a metric that indicates how well the model predicts, with values closer to 1 representing better predictive performance. These metrics are calculated by Eqs. (1)-(4).

$$(1)\ MAE = \frac{1}{n}\sum \left| y_{true} - y_{pred} \right|$$

$$(2)\ MSE = \frac{1}{n}\sum \left(y_{true} - y_{pred} \right)^2$$

$$(3)\ RMSE = \sqrt{\frac{1}{n}\sum \left(y_{true} - y_{pred} \right)^2}$$

$$(4)\ R^2 = 1 - \frac{\sum \left(y_{true} - y_{pred} \right)^2}{\sum \left(y_{true} - \bar{y}_{true} \right)^2}$$

Table IV summarizes the top five best performing models and the bottom five worst performing models. Table III provides a comparison of training performance based on the test performance criteria. Most models showed high performance, although some variables showed relatively lower restoration performance. Nevertheless, the overall results confirm stable restoration performance.

Table III: Restoration model performance on train data

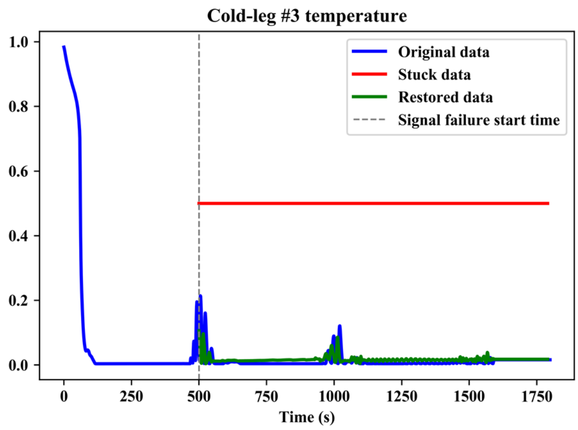
Variable number	Performance metrics			
	MAE	MSE	RMSE	R^2
23	0.0077	0.0001	0.0089	0.9655
20	0.0075	0.0001	0.0089	0.9590
26	0.0094	0.0002	0.0124	0.9634
4	0.0189	0.0008	0.0247	0.9183
21	0.0166	0.0005	0.0191	0.9636
⋮				
7	0.0569	0.0088	0.0712	0.9458
1	0.0312	0.0034	0.0524	0.9542
22	0.0730	0.0067	0.0750	0.9018
15	0.0607	0.0079	0.0643	0.9586
3	0.0134	0.0004	0.0182	0.9695

Table IV: Restoration model performance on test data

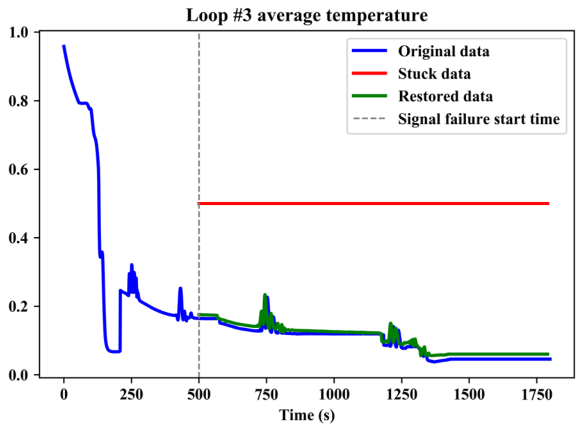
Variable number	Performance metrics			
	MAE	MSE	RMSE	R^2
23	0.0079	0.0001	0.0089	0.9640
20	0.0077	0.0001	0.0089	0.9584
26	0.0096	0.0002	0.0124	0.9634
4	0.0133	0.0004	0.0181	0.9709
21	0.0164	0.0004	0.0188	0.9631

⋮				
7	0.0573	0.0091	0.0711	0.9463
1	0.0432	0.0051	0.0683	0.8933
22	0.0726	0.0066	0.0744	0.9017
15	0.0621	0.0083	0.0653	0.8570
3	0.1104	0.0155	0.1225	0.8895

The signal restoration performance for selected variables is shown in Fig. 2. The blue line represents the original signal, while the red line indicates the stuck failure where the signal remains constant. The green line is the restored signal using the proposed model. The results demonstrate that restored signal closely follows the original data.



(a) Cold-leg #3 temperature
(best-performing variable, No. 23)



(b) Loop #3 average temperature
(second best-performing variable, No. 20)

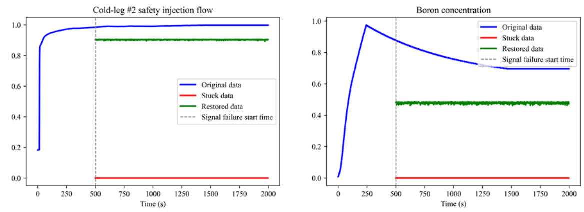
Fig. 2. Signal restoration results.

5.2. Similarity evaluation

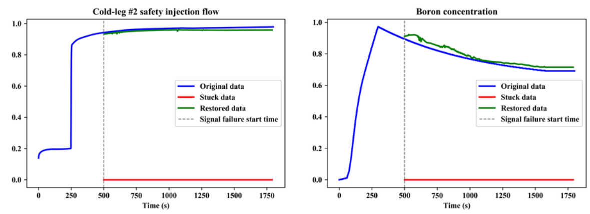
The similarity metric evaluates how closely the restored signal follows the pattern of the original signal. The cosine similarity was calculated to evaluate the similarity between the restored signal and the original signal. Cosine similarity is a measure of similarity based on the cosine angle between two vectors. The closer this value is to 1, the higher the similarity. The average cosine similarity of the 28 models was 0.98379, ranging from 1 to 0.82012. The cosine similarity results for stuck signal failures in previous studies are shown in Table V. While previous studies exhibited lower restoration performance, with an average similarity of 0.65-0.75, the proposed model maintained higher similarity, demonstrating improved restoration performance. The restoration performance of the proposed model compared to previous studies is shown in Fig. 3. The results demonstrate that the proposed model achieves higher similarity to the original signal, confirming its effectiveness in restoring stuck failures.

Table V: Cosine similarity of restored signals for different levels of stuck failure

	Level of signal failure	Cosine similarity
Stuck	1	0.73
	0.5	0.75
	0	0.65



(a) Previous study results [1]



(b) Proposed model results

Fig. 3. Comparison of signal restoration performance.

These results indicate that the proposed restoration model provides the more stable and accurate restoration by excluding signal failures and using only normal variables. In particular, the proposed model outperforms previous approaches in handling stuck failures, ensuring more reliable restoration.

6. Conclusions

In this study, a prediction-based restoration model was developed to improve the restoration performance of stuck failures, which had limited performance in previous studies. Existing reconstruction-based methods have failed to effectively restore stuck signals, leading to the proposed approach using LSTM for prediction-based restoration. The proposed model predicts the target variable using the remaining variables and replaces the signal failure with the predicted value. This approach prevented the direct input of signal failures into the model, allowing it to learn normal time-series patterns, and thereby improving the reliability of restoration.

The results confirm that the proposed method achieves more stable and accurate restoration compared to the existing models. In particular, the reliability of the signal failure identification and restoration system is improved by addressing the stuck problem identified in previous studies.

However, some variables exhibited relatively lower restoration performance. This suggests differences in restoration difficulty between variables. Future studies are required to develop a more robust restoration model. In addition, the proposed model was developed on accurately identifying the anomalous variable during the signal failure detection phase. Misidentification of the signal failure can lead to reduced restoration performance. Therefore, integrating a signal failure detection model with the restoration process is essential to improve reliability.

Acknowledgment

This work was supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government (MOTIE) (No. 20224B10100130, Development of operational state simulator for operating nuclear power plant and commercialization technology for artificial intelligence decision-making support system to prevent human error in accident operation) and the National Research Council of Science & Technology (NST) grant by the Korea government (MSIT) (No. GTL24031-000).

REFERENCES

[1] J. W. Hong, M. S. Kim, and M. G. Na, Development of Signal Identification and Restoration Algorithms for Signal Error Types in Nuclear Power Plants, ISOFIC 2024, Jeju, Korea, Dec. 3-6, 2024.

[2] S. Hochreiter and J. Schmidhuber, Long Short-Term Memory, Neural Computation, Vol.9, pp.1735-1780, 1997.