Transactions of the Korean Nuclear Society Autumn Meeting
Changwon, Korea, October 24-25, 2024

Signal Verification and Restoration Using LSTM-VAE in Nuclear Power Plants

Ji Woo Hong, Ji Hun Park, 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 failure types, signal verification, signal restoration, nuclear power plants

1. Introduction

Nuclear power plants (NPPs) are a significant source of stable electricity generation, and thus ensuring the safety of these facilities is important. Ensuring safety is particularly important in emergency and severe accident situations, where the likelihood of radioactive material release increases. Such situations can expose sensors within the NPPs to extreme conditions, including radiation, high temperatures, and high pressures. When sensors are exposed to these conditions, sensor performance can be compromised, resulting in reduced reliability. Therefore, it is essential to implement procedures for signal verification and restoration to ensure the reliability of sensors in emergency and severe accident situations.

In this study, the long short-term memory-variational autoencoder (LSTM-VAE) is used to detect signal failures through signal verification and to restore anomalous signals to the original healthy data. The restored data are used for the initial event identification, where the explainable boosting machine (EBM) is used to diagnose the scenario. Following scenario diagnosis, a second restoration is performed using scenario-specific signal restoration models to refine the signal restoration. By dividing the signal restoration process into two steps, the approach aims to achieve more accurate restoration. The data used to train and test these models were collected through the compact nuclear simulator (CNS).

The objective of this approach is to effectively detect and restore signal failures in NPPs during emergency situations, providing accurate data. It is expected to improve response capabilities in emergency situations and contribute to ensuring the safety of NPPs.

2. Methods

In this study, two models, LSTM-VAE and EBM, were used to effectively detect and restore signal failures that can occur during emergency situations in NPPs. The LSTM-VAE model was used to detect and restore signal failures, while the EBM model was used to identify the initial events.

2.1 LSTM-VAE

The LSTM-VAE is a deep-learning model commonly used for the reconstruction, generation, and anomaly detection of time-series data [1]. The LSTM-VAE combines the LSTM method with the VAE method to effectively train complex patterns in time-series data.

The VAE method encodes the input data in latent space and then decodes it to reconstruct data similar to the original. Meanwhile, the LSTM method captures the long-term dependencies in the time-series data, preserving the temporal characteristics of the data. The LSTM-VAE can detect anomalies based on reconstruction errors after learning normal data patterns. The data are considered anomalous if the reconstruction error exceeds a threshold. The structure of the LSTM-VAE is shown in Fig. 1.

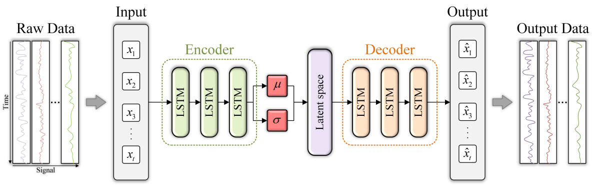


Fig. 1. Structure of the LSTM-VAE.

2.2 EBM

The EBM is an interpretable machine learning model that uses boosting algorithms to analyze data patterns and make predictions [2]. The EBM is developed to maintain the robust performance of traditional boosting models while reducing complexity and improving the interpretability of the results.

In the EBM, the contribution of each feature is evaluated step by step. After each iteration, residuals are calculated, representing the differences between the predicted and actual values. These residuals are used to refine the model by focusing on the errors made in the previous step, allowing the model to gradually improve its predictions. This iterative process continues until the model reaches final state. The EBM is particularly strong in interpreting complex data relationships because each feature effect is calculated independently, and the model is iteratively adjusted based on the residuals. The structure of the EBM is shown in Fig. 2.

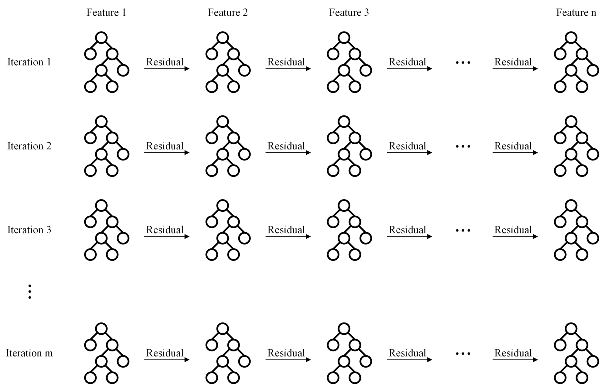


Fig. 2. The EBM training iterations for feature residuals.

3. Data

The data used in this study are based on emergency situation collected through the CNS, a simulator designed based on the Westinghouse 993MWe 3-loop pressurized water reactor. In this study, two scenarios were considered: loss of coolant accidents (LOCA) and excess steam demand event (ESDE). The CNS consists of a total of 2,222 signals, from which 15 signals were selected through scenario analysis.

3.1 Data pre-processing

The selected signals were normalized to values between 0 and 1 using the min-max scaling technique. This normalization process adjusts the scale of signals with different units and ranges to make the data consistent, improving model performance.

3.2 Data configuration

There are three categories of signal failures observed in NPPs: bias, drift, and stuck. The bias refers to the addition of a constant value to the original data, resulting in a consistent increase or decrease in the data values. The drift refers to the original data changing over time with a constant slope, resulting in a pattern of gradual increase or decrease in the data values. The stuck refers to a situation where the data values suddenly become fixed at a constant value at a particular time and do not change.

To evaluate the performance of the signal failure detection and restoration process, signal failure data were generated by injecting signal failures into the collected data. The anomalies for all three types were injected starting at 500 seconds. Specifically, the bias was injected by increasing the original data values by 20% starting at 500 seconds. The drift was injected by adding a linear function with a slope of 1% over time starting at 500 seconds. Starting at 500 seconds, the stuck was injected by fixing the data value at 0. The signal failure datasets were used to evaluate the performance of the signal failure detection and restoration algorithms. A list of the data used in this study is shown in Fig. 3.

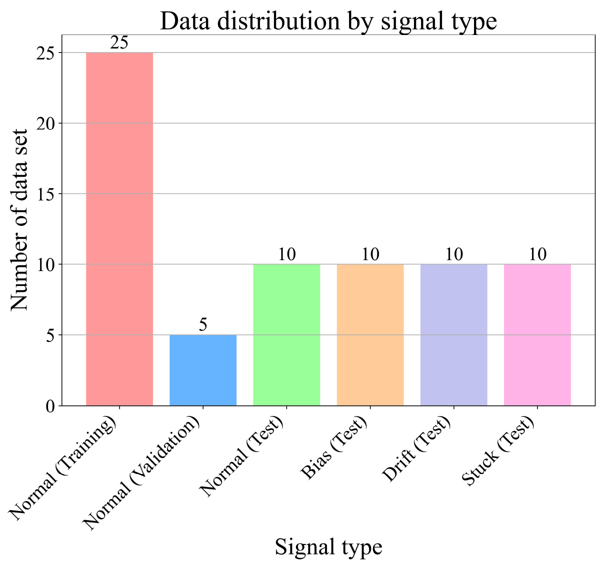


Fig. 3. Data distribution summary.

4. Result

The overall procedure of the study is shown in Fig. 4 and consists of the following steps: data pre-processing, signal verification, signal restoration, and initial event identification. In particular, the signal restoration process is conducted in two stages. In the first restoration step, the signals are restored using the trained model without distinguishing between scenarios. In the second step, the restoration focuses on individual scenarios to produce more accurate data.

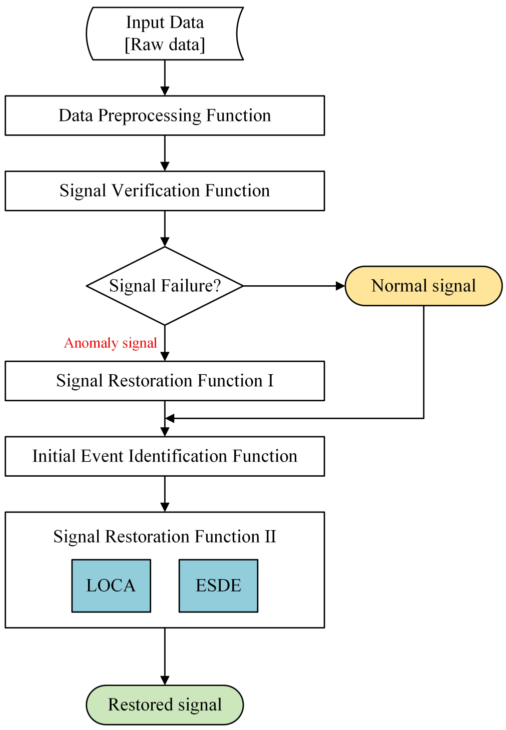


Fig. 4. Schematic of the signal verification and restoration algorithm.

4.1 Signal verification

In this study, the LSTM-VAE model was used to detect signal failures that may occur in emergency situations. The LSTM-VAE model was trained on normal data, which allowed it to learn the normal patterns of the signals. Signal failures are detected based on the reconstruction error between the original and reconstructed signals. As shown in Fig. 5, the signal is classified as an anomaly if the reconstruction error exceeds a threshold. In this study, the threshold was set using the 3-sigma criterion, which reflects a 99.7% confidence interval. As a result, the signal failure detection achieved an accuracy of 95.2%.

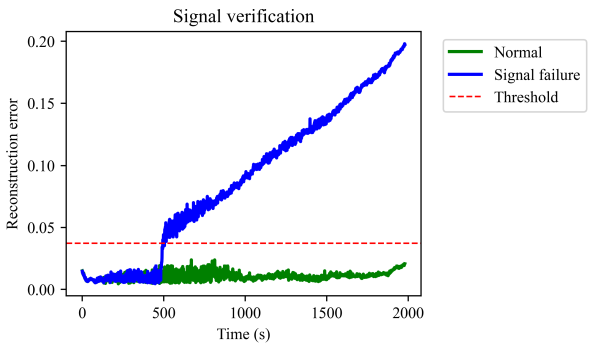
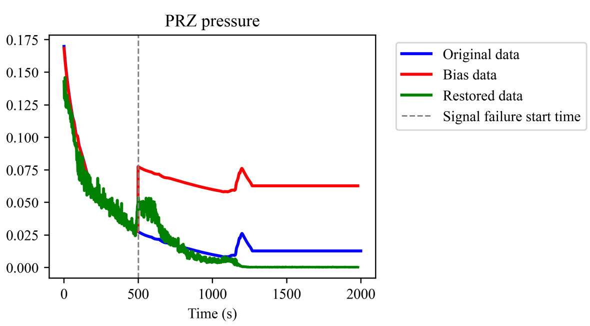


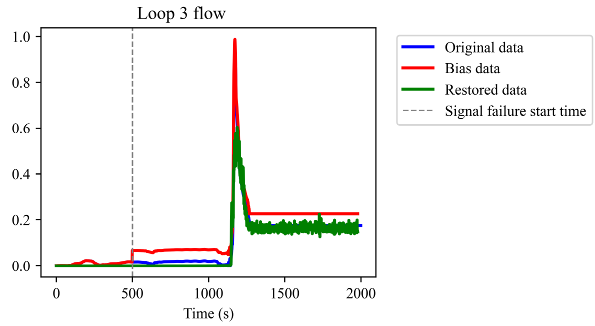
Fig. 5. Detection of signal failure (i.e., drift) through reconstruction error.

4.2 Signal restoration I: Standard model

The data identified as failures by the signal failure detection process were subjected to the initial stage of reconstruction using the LSTM-VAE model. The LSTM-VAE model reconstructs the input data to approximate the original signal. The reconstructed signal is shown in Fig. 6, where the blue line represents the normal data with no signal failures, the red line represents the signal failure data, and the green line represents the data reconstructed by the LSTM-VAE model.



(a) LOCA scenario data.



(b) ESDE scenario data.

Fig. 6. Example of signal restoration I results.

4.3 Initial event identification

Following the initial signal reconstruction, the reconstructed data were input into the EBM model to identify the initial events. The EBM model was used to distinguish between the LOCA and ESDE scenarios. This process identified the emergency scenario based on the reconstructed data following the detection of signal failures. The results of scenario identification are shown in Fig. 7.

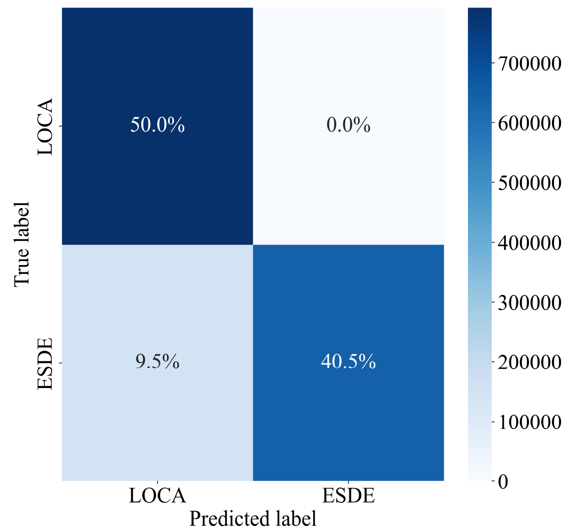
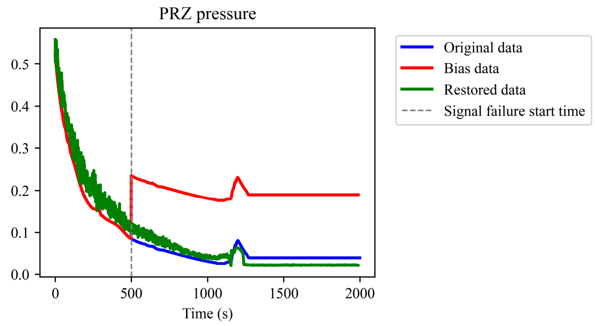


Fig. 7. Confusion Matrix for initial event identification result.

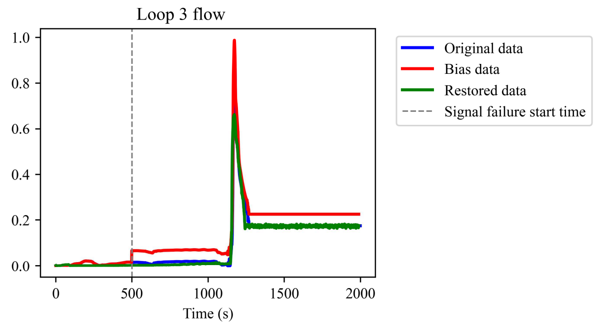
4.4 Signal restoration II: Scenario-specific models

Following the initial scenario identification, a second signal reconstruction was performed using reconstruction models that were specific to each scenario. These scenario-specific models were designed to improve the ability to capture the characteristics of each scenario, compared to the initial reconstruction model. This approach allowed for a more accurate reconstruction of signal characteristics. The results of the second reconstruction are shown in Fig. 8. As shown in Table I, the mean squared error (MSE) decreased compared to the initial reconstruction. The initial signal reconstruction was performed using a general reconstruction model, while the subsequent reconstruction models were adapted to each specific scenario.

This approach provides a more accurate reflection of the signal characteristics, allowing a reconstruction that is close to the original signal. The reduction of the MSE in the secondary reconstruction indicates that the reconstruction model considering the characteristics of each scenario is more effective in signal reconstruction. Additionally, this approach provides more precise data for accurate identification and response to emergency situations. Therefore, a secondary signal reconstruction performed after scenario identification can provide more precise data. This restoration process is important for providing precise data during emergency situations in NPPs.



(a) LOCA scenario data.



(b) ESDE scenario data.

Fig. 8. Example of signal restoration II results.

Table I: Comparison of the MSE results for signal restoration I and II in the types of signal failure

Scenario	Signal failure type	MSE	
		Signal restoration I	Signal restoration II
LOCA	Bias	0.0648	0.0603
	Drift	0.1038	0.0856
	Stuck	0.4204	0.1114
ESDE	Bias	0.2611	0.0376
	Drift	0.3253	0.0905
	Stuck	0.3898	0.1081

4. Conclusion

In this study, an algorithm for signal verification, restoration, and initial event identification was developed that can be used in the NPPs emergency situations. The LSTM-VAE was used for signal verification and restoration, while the EBM was used to implement initial event identification. The algorithm was trained and tested using data collected from the CNS, and signal failure data were generated by artificially injecting signal failures for testing purposes.

The experimental results showed that the signal verification process detected signal failures with an accuracy of 95.2%. The initial scenario identification achieved 90% performance after signal restoration using the standard model. In addition, the scenario-specific restoration model provided even more accurate signal restoration. Differences between the two restoration processes were observed, confirming that scenario-specific restoration provided more precise data. This suggests that scenario-specific restoration model can better capture the detailed characteristics of the signals.

In conclusion, the proposed algorithm can contribute to decision making in emergency situations. In particular, the scenario-specific restoration following scenario identification is expected to improve response capabilities by providing more precise data. However, the results of this studies indicate that further performance improvements are needed. Future study should focus on optimizing the hyperparameters to develop the more robust model and exploring specialized restoration models for different types of signal failures, as well as models capable of handling complex signal failures.

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. H. Park, H. S. Jo, and M. G. Na, System and Component Anomaly Detection Using LSTM-VAE, 2021 5th International Conference on System Reliability and Safety (ICSRS), p. 131-137, 2021.

[2] H. J. Lee, J. H. Park, J. W. Hong, and M. G. Na, Enhancing the Reliability of Abnormal State Diagnosis in Nuclear Power Plants Using Explainable Boosting Machine, Proc. of KNS Spring Mtg, Jeju, Korea, May 18-19, 2023.