Transactions of the Korean Nuclear Society Autumn Meeting
Gyeongju, Korea, October 26-27, 2023

Anomaly Detection of Six CSFs during LOCA in Nuclear Power Plants

Sang Hyun Lee [a], Ji Woo Hong [a], Man Gyun Na [a*]
Department of Nuclear Engineering, Chosun Univ., 309 Pilmun-daero, Dong-gu, Gwangju, Korea 61452
[*]*Corresponding author: magyna@chosun.ac.kr*

***Keywords**: nuclear power plant, critical safety function, anomaly detection, unsupervised learning

1. Introduction

For the operation of nuclear power plants (NPPs), operators should play a critical role of restoring to normal conditions when an abnormal event occurs. Operators use procedures to respond appropriately. However, in emergency situations, operators often experience high levels of work stress that can disturb the operator's ability to control rapidly changing variables or perform tasks requiring swift actions. If this work stress leads to human error, it can result in undesirable situations within NPPs.

To mitigate this work stress, a lot of researches are being conducted to develop various operator support systems. For example, in the case of a single diagnosable accident, an appropriate emergency operating procedure (EOP) can effectively maintain the integrity of the critical safety functions (CSF) of the NPPs. However, when dealing with complex and undiagnosable accidents, relying on EOPs becomes challenging for maintaining CSF integrity. In addition, existing diagnostic researches are often based on a single event diagnosis.

In this study, we propose to use unsupervised learning to detect CSF malfunction in a single accident [1]. Unsupervised learning does not require labeling and is a popular method for anomaly detection. Scenarios for the loss of coolant accident (LOCA) and steam generator tube rupture (SGTR) events were obtained using a compact nuclear simulator (CNS). Anomaly detection can be carried out on each of the CSF during LOCA and SGTR accidents to identify the CSF that are at the highest risk.

It is expected that operators will be able to mitigate human errors during a complex undiagnosable accident situation with the use of the identification method of high anomaly CSF explained in this paper.

2. Methods

2.1 Long Short-Term Memory

The structure of the long short-term memory (LSTM) includes four separate feature cell and gates [2]. These cell state and gates approach effectively addresses the long-term dependency challenge present in conventional recurrent neural networks. It also overcomes the limitation of these networks in remembering information distant from the output. The following delineates the functionality of each of the four feature cell and gates:

1) The cell state carries information like a conveyor belt.

2) The forgetting gate is the step that determines how much of the previous input is retained when passing information.

3) The input gate is calculated using a sigmoid function and a tanh function. This determines how much to update and generates new candidate values to add to the cell state.

4) The output gate is responsible for updating the cell state because it has determined the information from the forgetting and input gates.

Each gate is shown in Eqs. (1-3). And, Fig.1 shows the structure of the LSTM.

$$F_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

$$I_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{3}$$

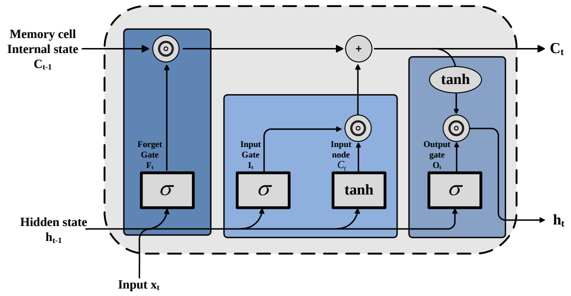

Fig. 1. Structure of the LSTM.

2.2 Variational Autoencoder

Variational autoencoder (VAE) is a technique that utilizes a concept with autoencoder. It reconstructs the input data by learning an encoder [3]. The difference between the reconstructed data and the input data indicates reconstruction error (RE). VAE differs from the autoencoder in that its structure is similar to that of AE but it generates a pair of outputs (the mean and standard deviation) from the encoder part (refer to Fig. 2). The mean and standard deviation of the input data contribute to the creation of a gaussian distribution. The VAE learns a probability distribution for the input data. The RE is shown in Eq. (4) and expressed as the square errors. Where X is the input and X' is the output. Fig. 2 shows the structure of the VAE.

$$RE(AE) = \|X - X'\|^2 \tag{4}$$

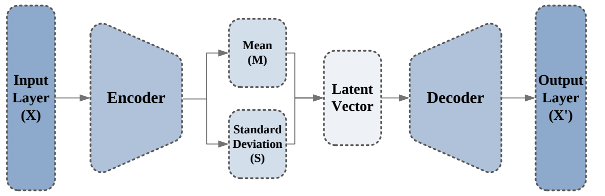

Fig. 2. Structure of the VAE.

3. Data Processing

The data were collected on the basis of the CNS that was designed by reference to a 3-loop Westinghouse-type NPP and developed by the Korea Atomic Energy Research Institute. Normal data were collected and used as training data. Because an artificial intelligence model is trained on normal data, it tries to reconstruct the input data with a normal distribution. Using this characteristics, when anomaly data are input as test data, the RE becomes higher and anomaly detection is possible. And, test data were collected for LOCA and SGTR scenarios. For the anomaly detection of 6 CSFs, variables corresponding to the CSF were extracted from the CNS [4]. Table I shows the number of variables used in artificial intelligence training and testing.

The normal data were used for training by adding noise to the data to increase the amount of data. Because training in deep learning, the amount of training data has an impact on the performance. In addition, CNS is limited in acquiring various normal states. Each test scenario has a different break size and includes data collected up to 10 minutes after the reactor trip. Table II shows the number of scenarios collected.

The details of each of the 6 CSFs are as follows.

1) Reactivity control: This function is a function that directly controls the heat generated in the reactor core and determines how much thermal energy must be removed from the core and the reactor coolant system (RCS). Failure of reactivity control can affect the integrity of the RCS.

2) RCS inventory control: This function is the ability to control the mass or volume of coolant and is critical in the event of a LOCA. Inventory loss can also occur in other incident scenarios.

3) RCS pressure control: This function maintains the RCS pressure boundary conditions and keeps the coolant in a normal state. The designed high pressure must be maintained to keep the coolant hot and prevent the hot coolant from boiling.

4) RCS heat removal: This function transfers heat through the RCS and is controlled by a secondary heat removal system by releasing steam or injecting feed water into the SG.

5) Core heat removal: This function controls the heat transfer from the core to the coolant to remove heat generated in the reactor core.

6) Containment pressure and temperature control: This function prevents radioactivity from escaping from the containment by controlling containment pressure and temperature.

Table I: Number of variables in the CSF

CSF	Number of variables
Reactivity control	12
RCS inventory control	14
RCS Pressure control	14
RCS heat removal	13
Core heat removal	5
Containment heat removal	5

Table II: The number of scenarios collected.

Scenarios	Number of scenarios
Normal	1 (noising)
LOCA	10
SGTR	10

4. Experiment

Anomaly detection was performed using the LSTM-VAE method. The training was performed with normal state only and then the trained model was tested with single event scenario, LOCA, and SGTR. Fig. 3 shows the results of the anomaly detection model for the six CSFs. The test data used in the figure is a LOCA scenario, and the blue line in the graph shows the output of the training, with the 3-sigma value widely used in the general industry as the threshold. If it is exceeded, an anomaly is detected as a red dot. The vertical black line is the reactor trip time in the test data, which is 178 seconds for a reactor trip in this specific test scenario. Finally, the green line is the maximum RE for the test data. The higher the RE, the higher the anomaly for the CSF. Thus, the result suggests that the CSF with the highest RE is the primary one that contributed to the event. In the figure, among the 6 CSFs, the RCS inventory is the largest with 0.6698 which seems to be the highest anomaly and the most important CSF in the LOCA scenario. The NPPs design control document also identifies the RCS inventory as the most important CSF in the LOCA scenario, confirming the effective performance of this study [5].

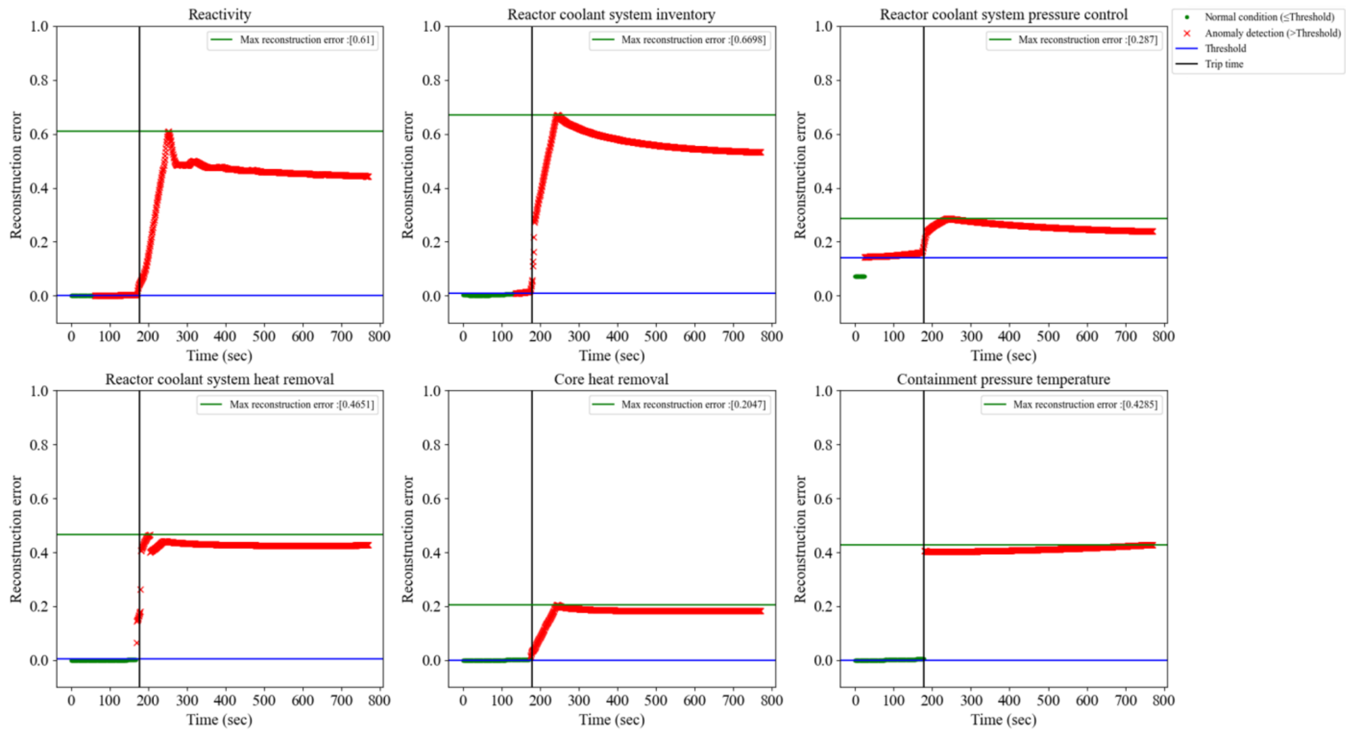

Fig. 3. Anomaly detection of 6 CSF in a LOCA situation.

5. Conclusion

In this study, we conducted basic research to detect abnormalities in six CSFs using the LSTM-VAE method. The results showed that anomaly detection was successful in single event scenario for LOCA or SGTR event. In addition, among the six CSFs, the CSF with the highest anomaly was shown to be consistent with the NPPs design control document.

In the future, our plans encompass not only anomaly detection within complex events but also predicting the contributions and errors of variables in accordance with the trends observed in NPPs.

ACKNOWLEDGMENTS

This work was supported by the National Research Foundation of Korea (NRF) (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).

REFERENCES

[1] S. W. Oh, H. S. Jo, H. J. Lee, and M. G. Na, Anomalies Detection by Unsupervised Learning Using Explainable Artificial Intelligence in Nuclear Power Plants, Transactions of the Korean Nuclear Society Spring Meeting, May.19-20, 2022, Jeju, Korea.

[2] Hochreiter. S, and Schmidhuber. J, Long short-term memory. Neural computation, Vol. 9, No. 8, pp. 1735-1780, 1997.

[3] D. P. Kingma, S. Mohamed, D. J. Rezende and M. Welling, Semisupervised learning with deep generative models, In Advances in neural information processing systems, pp. 3581-3589, 2014.

[4] D. I. Lee, P. H. Seong, and J. H. Kim, Autonomous operation algorithm for safety systems of nuclear power plants by using long-short term memory and function-based hierarchical framework, Annals of Nuclear Energy, Vol. 119, pp, 289-299, 2018.

[5] APR1400, Design Control Document Tier 2. Chapter 19, Probabilistic Risk Assessment and Severe Accident evaluation, Korea Electric Power Corporation and Korea Hydro and Nuclear Power Co., Ltd., Naju-si, South Korea, 2014.