Operational Anomaly Detection Methodology using MARS-KS Nuclear Safety Transient Simulation Database

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1. Introduction

Accident prevention and mitigation of operating nuclear power plants depend on automatic control of the central control panel and actions of operators who were trained through operational manuals and real-time simulator. Nuclear power plant operators can cause human errors due to heavy workloads. In order to prevent the operator's workloads and enhance safety of the plant, the need for improvement of man machine interface system (MMIS) for the central control panel to support operators using artificial intelligence technology has been globally initiated [1]. Accordingly, research and development are underway on predicting device failures due to deterioration of facilities of the operating nuclear power plants [2-3]. Abnormal signals generated by cable contamination and aging of sensors [4], and operational anomaly diagnosis using artificial intelligence models [5] are also globally studied. For the accident diagnosis models, it is confirmed that a high prediction accuracy is hard to be obtained if the input data, even the normal ones, were not trained with these models. Therefore, this study aims to improve the reliability and accuracy of the operational anomaly diagnosis model by developing an anomaly detection model using the long short term memory-autoencoder (LSTM-AE) which determines whether the data is trained or untrained in the operational anomaly diagnosis model before the operational anomaly diagnosis model discriminates the input data.

2. Anomaly Detection Methods

In this study, machine learning models are tested for the operational anomaly detection of the reference APR1400 nuclear power plant using MARS-KS nuclear safety transient simulation database. These models include long short term memory (LSTM), autoencoder (AE). LSTM-AE combines the LSTM model useful for time series with autoencoder model using dimensionality reduction. As shown in Fig. 1, the dimension of the data is reduced and expanded as it passes through the encoder, repeat vector, and decoder of the LSTM-AE model. Reconstruction error occurs through this process, and this error can be reduced through training. Accordingly, the gap between the reconstruction error of the trained and untrained data exists. Through the threshold of reconstruction error, the trained data and the untrained data are discriminated.

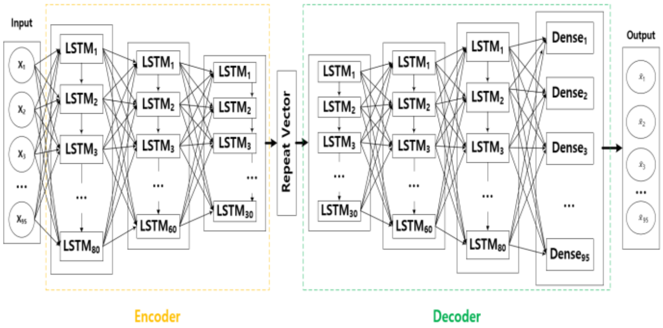


Fig. 1. Structure of LSTM-AE model

2.1 LSTM

LSTM is a type of recurrent neural network (RNN). As shown in the Fig. 2, it is composed of 6 parameters and 3 gates, and it is used to predict future data by appropriately considering past and present data [6].

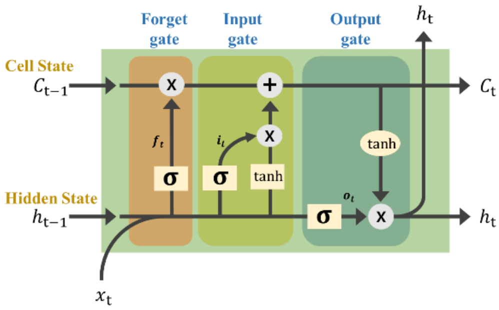


Fig. 2. Structure of LSTM layer

The functions in Fig. 2 are computed as follows;

$$x_t \text{ : current input} \quad (1)$$
$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \quad (2)$$
$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (3)$$
$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (4)$$
$$C_t = f_tC_{t-1} + i_t\tanh(W_{xg}x_t + W_{hg}h_{t-1} + b_c) \quad (5)$$
$$h_t = o_t tanh(C_t) \quad (6)$$

where, t is the time step, W is the weighting factor, and b is the bias. x and h are the input and hidden state. σ is the sigmoid function as defined in Eq. (7).

$$\sigma(x) = \frac{1}{1+e^x} \quad (7)$$

The LSTM layer in Fig. 2 is like a conveyor belt and information is added or removed according to the structure of each gate. The input data learns the information to be added or discarded through training.

The forget gate (f_t) determines how much the past information is learned and discarded, and the input gate (i_t) determines how much the current information is added. Number 0 means to delete all information, and number 1 means to save all information. Accordingly, the forget gate result and the input gate result are updated in the cell gate (C_{t-1}) and sent to the next cell gate (C_t). Also, the output gate (o_t) determines the output value to be output at the current stage and affects the value of the hidden state (h_t) of the next step.

2.2 Autoencoder

Autoencoder aims to generate the same data as the input data after transforming the data through dimensionality reduction and expansion of the input data. An autoencoder consists of an encoder, a repeat vector, and a decoder. Data is compressed by reducing the dimension of the data in the encoder. The compressed information is sent to the repeat vector as a 2D array through the output of the encoder, and the repeat vector replicates the vector as much as the time step, transforms it into a 3D array, and sends it to the decoder as an input. At this time, the decoder reconstructs the data through dimension expansion. The reconstructed data through dimensionality reduction and expansion causes a reconstruction error, and this error is used to the operational anomaly diagnosis model.

2.3 Threshold

The LSTM-AE model inherently includes a reconstruction error due to dimensionality reduction and expansion. The threshold for this reconstruction error is used to differentiate between the trained and untrained data. First, to get the threshold value, compute the reconstruction error for each time step using the mean absolute error (MAE) of the trained data as follows;

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{Y}_i - Y_i\right| \tag{8}$$

Where,
Y_i : original data
$\hat{Y}_i$: reconstruction data
n = reconstruction data number

Second, in order to set the threshold including the trained data, the upper control limit (UCL) is set as the threshold using the method proposed by Shewhart's method [8].

$$\mathrm{UCL} = \mu + 3\sigma \tag{9}$$

The μ and σ refer to the mean value and standard deviation of MAE. UCL value means the top 99.73% of the entire data. This value is used as threshold of anomaly detection.

3. MARS-KS Transient Database

3.1 Data Set

In order to build a deep learning anomaly detection model, learning process through database construction as well as model construction is required. For database construction, APR1400 was selected as a reference nuclear power plant, and the MARS-KS best estimate safety analysis regulatory code [9] was used for database construction. Fig. 3 shows the MARS-KS nodalization of the APR1400 including the reactor primary system, secondary system, and safety injection system. Starting from a normal steady state with the best estimate input of the APR1400 [10], transient analyses were performed and the changes of major parametric variables over time were calculated.

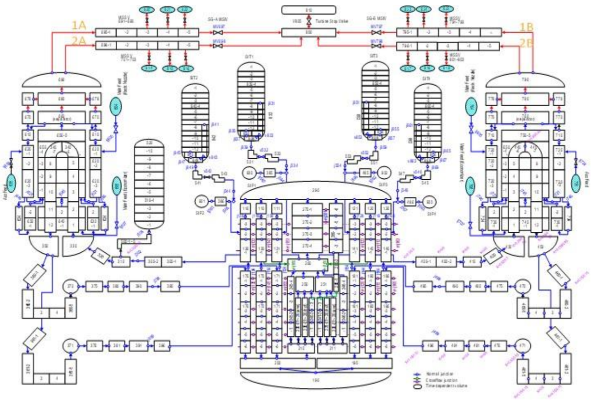


Fig. 3. APR1400 MARS-KS Nodalization

Based on the APR1400 final safety analysis report (FSAR), the input and output variables of the MARS-KS analysis were comprehensively considered, and the important variables according to the type and location of the detector signal and the important safety variables of the APR1400 reference plant were selected. A total of 95 variables were set as important variables. They include 23 variables for pressure and temperature, 38 variables for mass flow, 4 variables for water level, and 1 variable for reactor thermal power [10].

The trained cases were selected as Normal, inadvertent opening steam generator atmospheric dump valve (IOSGADV), main steam line break (MSLB), and 10% sudden power increase at 90% power which is a performance related design basis event (PRDBE). The untrained case was selected as large break loss of coolant accident (LBLOCA). A total of 21 event cases with 374,827 datasets (i.e., 95 parameter values at each time step) are used for training and validation testing as shown in Table I.

Table I: Event cases for anomaly detection

Accident case	No	Used
Normal	2	Training, Validation, and Test
IOSGADV	4	
MSLB	12	
PRDBE	2	
LBLOCA	1	Untrained Test
Total	21	

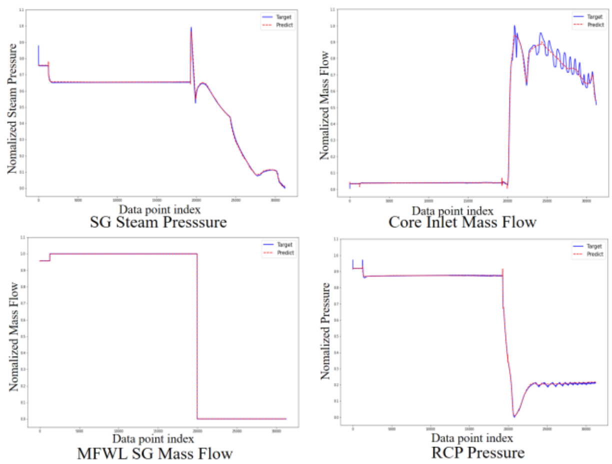
3.2 Pre-processing of input data

Deep learning algorithms compare the variables in the data and find patterns of the data. However, if there is a difference between the variable and the value of the variable, the relatively small value of the variable has a weak effect on the deep learning algorithm to find the pattern. In addition, normalization is necessary because the units (temperature, pressure, flow rate, etc.) are different for each variable. The function used for the nomalization is MinMaxScaler. The MinMaxScaler function is a function that normalizes all data to have a value between 0 and 1, and the normalization formula is as follows;

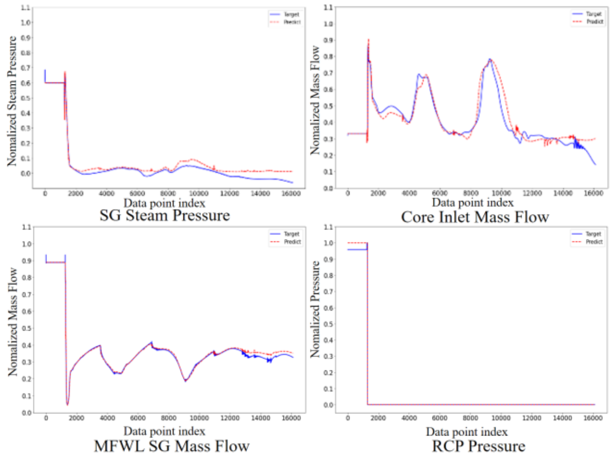
$$x_{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{12}$$

4. Result of Anomaly Detection

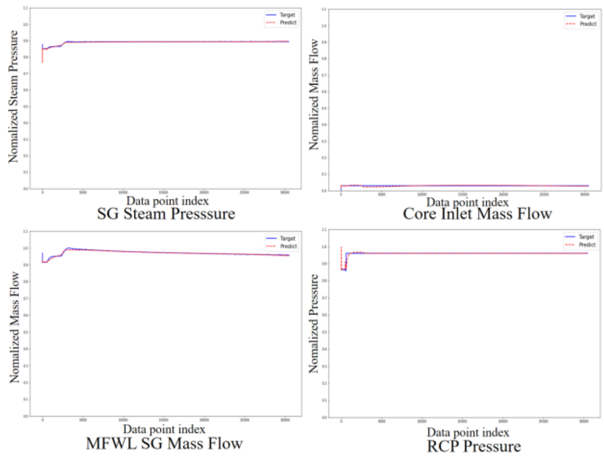
Figures 4 and 5 show the comparison between the original and reconstructed data of the trained and untrained data through the LSTM-AE model. In the case of the trained data in Fig. 4, the reconstructed data (red color) follows the original data (blue color) well, whereas, in the case of the untrained data in Fig. 5, the reconstructed data does not follow the original data trend.



(a) IOSGADV



(b) MSLB



(c) PRDBE

Fig. 4. Compare original and reconstructed data of trained case

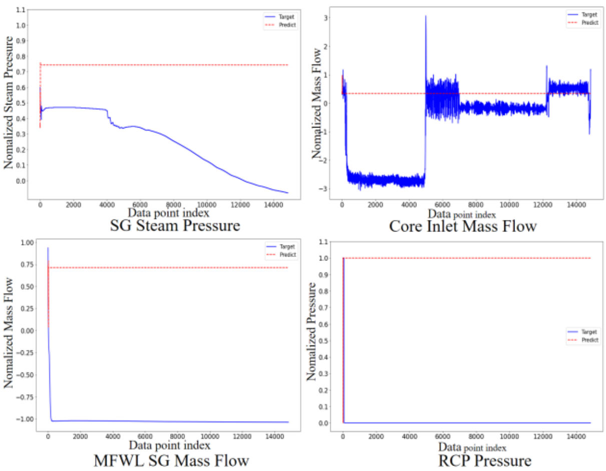
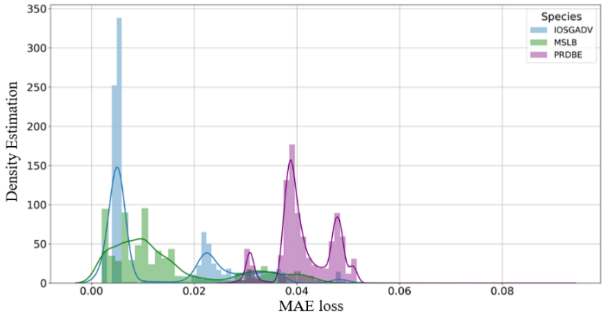
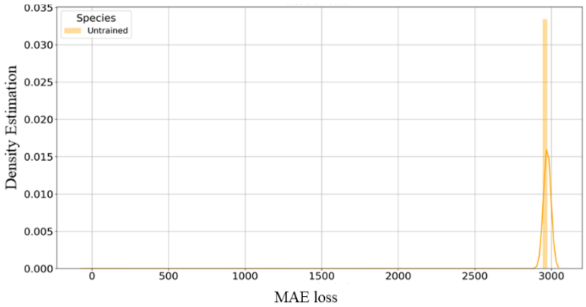


Fig. 5. Compare original and reconstructed data of untrained case

Figure 6 shows the distribution of the MAE loss as a function of reconstruction error between the original data and the reconstructed data. Figure 6(a) is the MAE loss distribution for learned events (IOSGADV, MSLB, PRDBE) and Figure 6(b) is the MAE loss distribution for unlearned events (LBLOCA). While the MAE loss for the trained data is less than 0.08, most of the untrained data shows a MAE loss of around 2900.



(a) Test of trained type



(b) Test of untrained type

Fig. 6. Distribution of MAE loss of LSTM-AE

The threshold was set by calculating the UCL value using the MAE loss of the trained and untrained data. The distribution of trained and untrained data according to threshold settings is shown in Fig. 7. Data above the threshold are classified as untrained data, and data below the threshold are classified as trained data. It is clearly shown in Fig. 7 that the untrained LOCA data is well above the threshold.

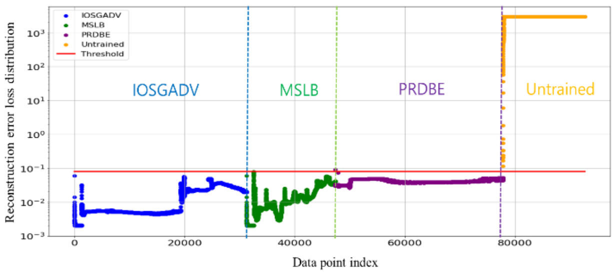


Fig. 7. Data threshold configuration according to MAE loss

5. Conclusions

In this paper, operational anomaly detection model was developed using LSTM-AE model and APR1400 MARS-KS transient simulation database. It was confirmed that the deep learning anomaly detection model can improve the accuracy and reliability of the operational anomaly diagnosis model using trained data. In future study, the improvement for accuracy of the operational anomaly diagnosis model through the operational anomaly detection model will be quantitatively identified.

ACKNOWLEDGMENTS

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