Identification of Abnormal Situations using Long Short-Term Memory

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1. Introduction

Diagnosis tasks in Nuclear Power Plants (NPPs) are known as one of difficult tasks to operators. Monitoring and diagnosis of the state of NPPs are typically performed by operators who consider process variables based on operating procedures [1]. Most of the NPPs have a lot of alarms about systems and components. When an alarm occurs, the operator should diagnose the state and perform recovery actions in accordance with the operating procedure.

However, when complex situations occur, it is difficult for operators to make a diagnosis with rapidly changing parameters in a limited time. Therefore, how to help the operator diagnose and identify abnormal operating procedures accurately is an important issue [2].

In order to help operators to make decisions in an abnormal situation, several algorithm have been suggested based on artificial intelligence (AI) techniques such as expert system, Fuzzy logic, Hidden Markov Model (HMM), Artificial Neural Networks (ANNs) [1,4,5]. ANNs are considered one of the most relevant means since they can handle pattern recognition as well as nonlinear problems.

This study suggests a diagnosis algorithm for abnormal situations. An algorithm based on the Long Short-Term Memory (LSTM) network was developed. Then, this study gathered the data for training and testing from a Compact Nuclear Simulators (CNS) that are based on a Westinghouse three-loop, 930-MWe pressurized water reactor. Finally, the algorithm has been trained and tested.

2. Method

2.1. LSTM

We propose LSTM for sequence learning to deal with the recurrent neural networks (RNNs) for the vanishing gradient problem. LSTM is a neural network architecture based on the RNN for processing long temporal sequences of data.

Each LSTM cell uses the input gate, forgetting gate, and output gate to adjust its output while maintaining the cell state. The information in the cell state does not change, and information can be added or deleted through each gate. In addition, the operation of each gate consists of an addition operation added to the cell state, thus it can avoid the vanish gradient problem.

The input gate determines the capacity of the input value. The forgetting gate determines how much of the previous cell state is forgotten, and the output gate determines how much to output. Equation (1), indicated by g, represents the input node and has a tanh activation function denoted by ø; Equations (2) to (4) represent the gate indicated by i,f, and o, respectively; σ represents a relu function.

$$g_l^{(t)} = ø(W_g \cdot [h_{t-1}, x_t + b_l^g) \quad (1)$$

$$i_l^{(t)} = \sigma(W_i \cdot [h_{t-1}, x_t + b_l^i) \quad (2)$$

$$f_l^{(t)} = \sigma(W_f \cdot [h_{t-1}, x_t + b_l^f) \quad (3)$$

$$o_l^{(t)} = \sigma(W_o \cdot [h_{t-1}, x_t + b_l^o) \quad (4)$$

2.2. Softmax

Softmax function is used for the post-processing of LSTM output. The softmax function is an activation function commonly used in the output layer of the deep learning model; it aims to classify more than three classes. The softmax is a function that exponentially increases the importance through an exponential function; it also increases the deviation between the values and then normalizes. It normalizes the input value to the output value between zero and one via the following Equation (5), and the sum of the output values is always one.

$$S(y_i) = e^{y_i} / \sum_{k=1}^{K} e^k (\text{for } i = 1, \dots, K) \quad (5)$$

3. Diagnosis algorithm of abnormal situations

This study suggests a diagnosis algorithm for abnormal situations based on the LSTM network and Softmax function. Fig. 1 shows an architecture of the algorithm. This algorithm uses the multilabel classification model of LSTM in the core. In addition, pre- and post-processing methods of data are also suggested.

3.1. Pre-processing of input data

The number of input data for training is 164. Each input does not have the same unit and scale (e.g., a normal state of Pressurizer pressure: 158kg/cm^2, alarm state: on or off). Variables with higher values will essentially have more impact on the results. However, this does not necessarily mean that this is more important as a predictor. This problem detects local minima. The min-max normalization can help prevent local minima. It performs a linear transformation on the raw data, and to use Equation (6). The min-max scaling data ranges from 0 to 1.

$$X_{norm} = (X - X_{\min})/(X_{max} - X_{min}) \tag{6}$$

3.2 LSTM network model

As shown in Fig. 1, a model for accident diagnosis is designed for multilabel classification because diagnoses may not be mutually exclusive. To predict an accident, the trend of such a sequence of variables is needed as inputs. Thus, a many-to-one structure is applied to design the model. According to the specific number of NPP input data sequences, the model can diagnose the plant state by recognizing the pattern (i.e., the NPP trend).

3.3. Post-processing of output data

As a post-processing for the output of the network, the softmax function is used to determine the ranking of abnormal situation probability. The softmax function assigns a probability to the result of LSTM network.

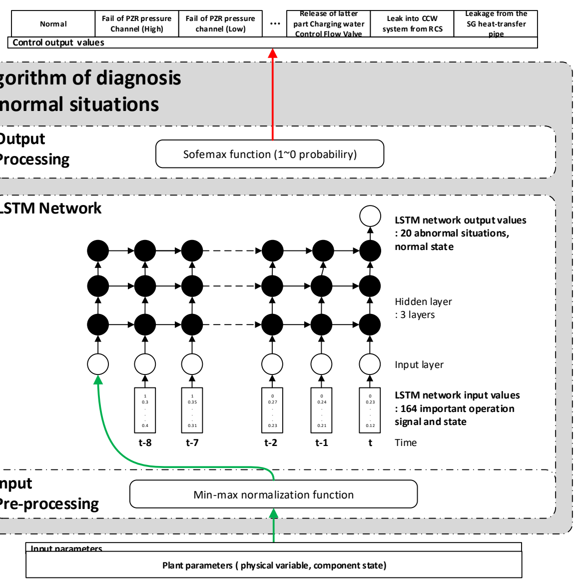

Fig. 1. Overview of the process of abnormal situation diagnosis.

4. Experiment

The data for the training and test were collected for three types of abnormal situations: instrumentation and control (I&C) failure (1-6 scenarios, as shown in Table I), equipment failure (7-16 scenarios, as shown in Table I), and leakage (16-20 scenarios, as shown in Table I). The total of 20 abnormal situations and 568 scenarios (453 for training and 115 for testing) are collected from the CNS.

Table I: Scenarios

No.	Scenarios of measuring instrument error	Number of Scenarios
1	Failure of Pressurizer pressure channel (High)	18
2	Failure of Pressurizer pressure channel (Low)	27
3	Failure of Pressurizer water level channel (High)	6
4	Failure of pressurizer water level channel (Low)	15
5	Failure of steam generator water level channel (Low)	40
6	Failure of steam generator water level channel (High)	42
7	Control rod drop	48
8	Continuous insertion of control rod	8
9	Continuous withdrawal of control rod	8
10	Opening of pressurizer PORV	52
11	Failure of pressurizer safety valve	51
12	Open of pressurizer spray valve	50
13	Stopping of charging pump	1
14	Stopping of 2 main feedwater pumps	3
15	Main steam line isolation	3
16	Rupture at the inlet of the regenerative heat exchanger	50
17	Leakage from chemical volume and control system (CVCS) to Component Coolant Water (CCW)	50
18	Leakage at the outlet of charging control flow valve	30
19	Leakage into the CCW system from Reactor Coolant System (RCS)	30
20	Leakage from steam generator tube	36
	Total	568

4.1. Training

We conducted the training using a total of 20 abnormal situations of 453 scenarios with 203,964 data sets including 164 CNS parameter values in each time step. After 15 epoch of training, loss values of training data and test data are 0.0026 and 0.0076, respectively, as shown in Fig.2. The accuracies defined by an equation (7) of training data and test data are 0.9992 and 0.9986. Fig. 3 shows the trend of accuracy with the epoch.

In this training, a desktop computer with the following hardware configurations is used: NVIDIA GeForce GTX 1080 8GB GPU, Intel 4.00 GHz CPU, Samsung 850 PRO 512 GB MZ-7KE512B SSD, and 24 GB memory. Python 3.7.3 is used for coding languages. The Python libraries developed to model the algorithm for machine and deep learning (e.g., Keras and Pandas) were used.

$$\text{Accuracy} = \frac{correctly\ predicted\ data}{total\ testing\ data} \tag{7}$$

4.2. Validation

After 15 epoch of training, the accuracy of prediction for 115 scenarios becomes 0.9986, as shown in Fig. 3. Figs. 4 and 5 shows the results of the suggested algorithm for the leakage into CCW system from RCS and the opening of pressurizer PORV, respectively. The results indicate that the suggested algorithm can diagnose the abnormal situations fast and accurately.

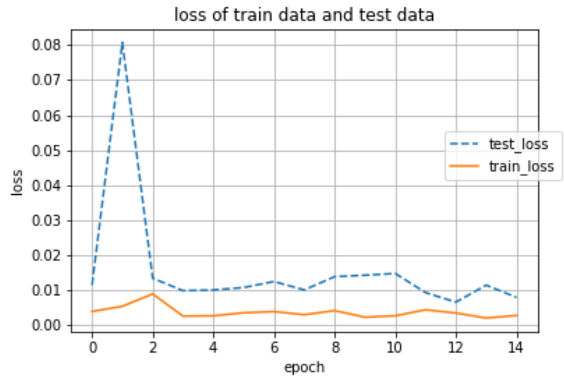

Fig. 2. Value of train and test data loss

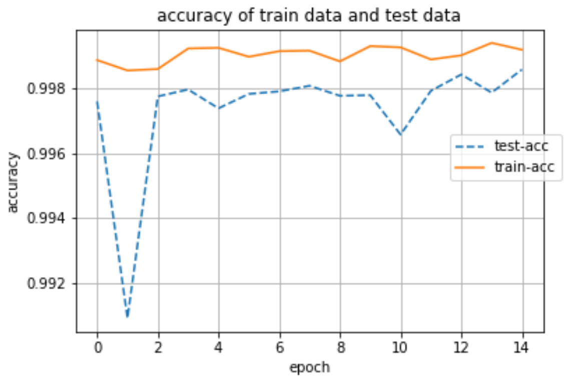

Fig. 3. Accuracy of prediction train data and test data

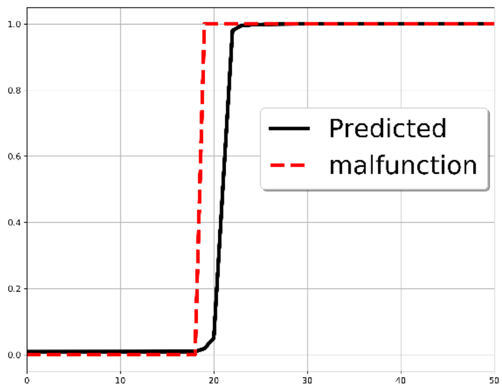

Fig. 4. The result for the leakage into CCW system from RCS

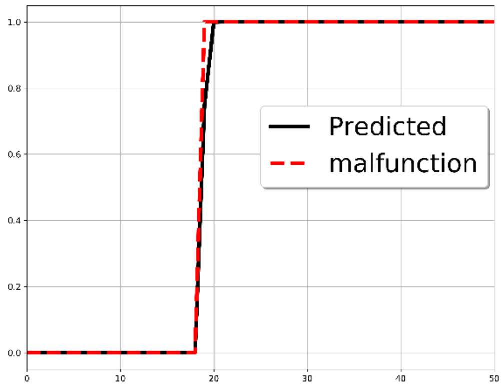

Fig. 5. The result for the opening of pressurizer PORV

5. Conclusion

This study proposed an algorithm to diagnose abnormal situations by using AI techniques. An algorithm using the LSTM and softmax has been suggested and trained with the data collected from the CNS. The results also indicated that the algorithm could diagnose abnormal situations fast and accurately.

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