Transactions of the Korean Nuclear Society Spring Meeting
Jeju, Korea, May 17-18, 2018

Accident Diagnosis Algorithm during the Startup Operation using LSTM

Jaemin Yang, Jonghyun Kim *
Department of Nuclear Engineering, Chosun University, 309 Pilmun-daero, Dong-gu, Gwangju, 501-709, Republic of Korea
**Corresponding author: jonghyun.kim@chosun.ac.kr*

1. Introduction

Diagnosis of the accident or transient at Nuclear Power Plants (NPPs) are known to be complex tasks for operators. An urgent situation may give pressure to the operators. Even under such situation, an operator must carry out diagnostic activity and make judgements based on the procedures. Therefore, this kind of difficulty can cause human error that can deteriorate the safety and integrity of the plant. Moreover, according to NPP operational experiences (e.g., Diablo Canyon in 1987, Wolf Creek in 1994 [1]), the risk of NPPs during Low Power and Shutdown (LPSD) operation cannot be negligible compared with the risk during the full power operation.

The diagnostic activities in case of full power operation, initial condition before accident or anomaly is steady state. That is, anomaly or abnormal condition can be detected more easily than LPSD operation. In addition, the application of procedures are relatively well prepared in NPPs. Depending on the anomaly or accident, the procedures such as Abnormal Operating Procedures (AOPs), Emergency Operating Procedures (EOPs) or Functional Recovery Procedures (FRPs) are applied in order.

However, accident diagnosis in LPSD operation has different features that can disrupt the accident diagnosis, because it has several operation modes by the plant states (e.g., reactivity condition, power level, average reactor coolant temperature). Due to those different features of operation modes, even if there are procedures for the specific situations, it is possible that operators may not recognize the accident in time. Also, the availability of components and systems are different so that they cannot be operable when it is necessary to respond. In addition, during this period, there are a lot of maintenance activities that can cause a decrease of safety due to the weakening of the defense in depth concept and lack or risk management [2].

In that sense, this study aims at develop an algorithm for the diagnosis of NPP accidents considering the features of startup operation by using improved Recurrent Neural Networks (RNNs), i.e., Long Short Term Memory (LSTM) which is are kinds of the Artificial Neural Networks (ANNs). Training of network is performed with compact nuclear simulator (CNS), which is based on a Westinghouse three-loop, 930MWe pressurized water reactor (PWR). Then, the algorithm is tested to demonstrate its applicability.

2. Long Short Term Memory

A variety of diagnostic algorithms and operator supporting systems have been proposed to reduce the burden of operators and help diagnose or detect accidents in NPPs. These approaches are generally based on artificial intelligence techniques (e.g., ANNs, fuzzy logic, Hidden Markov model (HMM), and Support Vector Machine (SVM)). The accident diagnosis can be classified as pattern recognition problem, and ANNs have shown good performance. Among them, RNN, which is a kind of ANN, can cope with the dynamic emergent situation simultaneously. However, there are a couple of issues from backpropagation of long temporal sequences such as blowing-up and vanishing gradient problems. To cope with these issues, LSTM, which is based on RNN architecture, has been developed.

2.1 Recurrent Neural Network

Even though there are numerous ANNs, this study chooses RNN to model the accident diagnosis algorithm because of good performance to analyze sequential data (i.e., time-series data). One of the main assumption of RNN is that input and output are not independent from each other. In other words, it uses data which has sequential information as input. Therefore, it can have memory to reflect the feature of data.

However, in case of original RNN, it tracks past values and goes back in time (i.e., back propagation). Too much back propagation by the long time causes both blowing up and vanishing gradients problems. In case of blowing-up, it can cause the oscillation of weights, while vanishing gradients can lead weights to be almost zero so that they cannot reflect the feature of datasets exactly [3].

2.2 LSTM

To improve RNN due to these problems, LSTM is introduced for long sequence learning. It is based on RNN architecture, thus, sequential data can also be dealt. Despite being based on the same network architecture, structural differences of LSTM cell unit with RNN cell unit can overcome these problems. Each LSTM cell adjusts the output value using the input gate, the forgetting gate, and the output gate while maintaining the cell state. The input gate determines capacity of the input value. The forgetting gate determines how much to forget the degree of previous cell state, and the output gate determines how much to output. The following Equations (1) to (4) stand for each gate denoted by ‘i', ‘o’ and ‘f’ respectively. ‘g’ means the input node and has a tanh activation function denoted by ϕ. Also, σ stands for a sigmoid function.

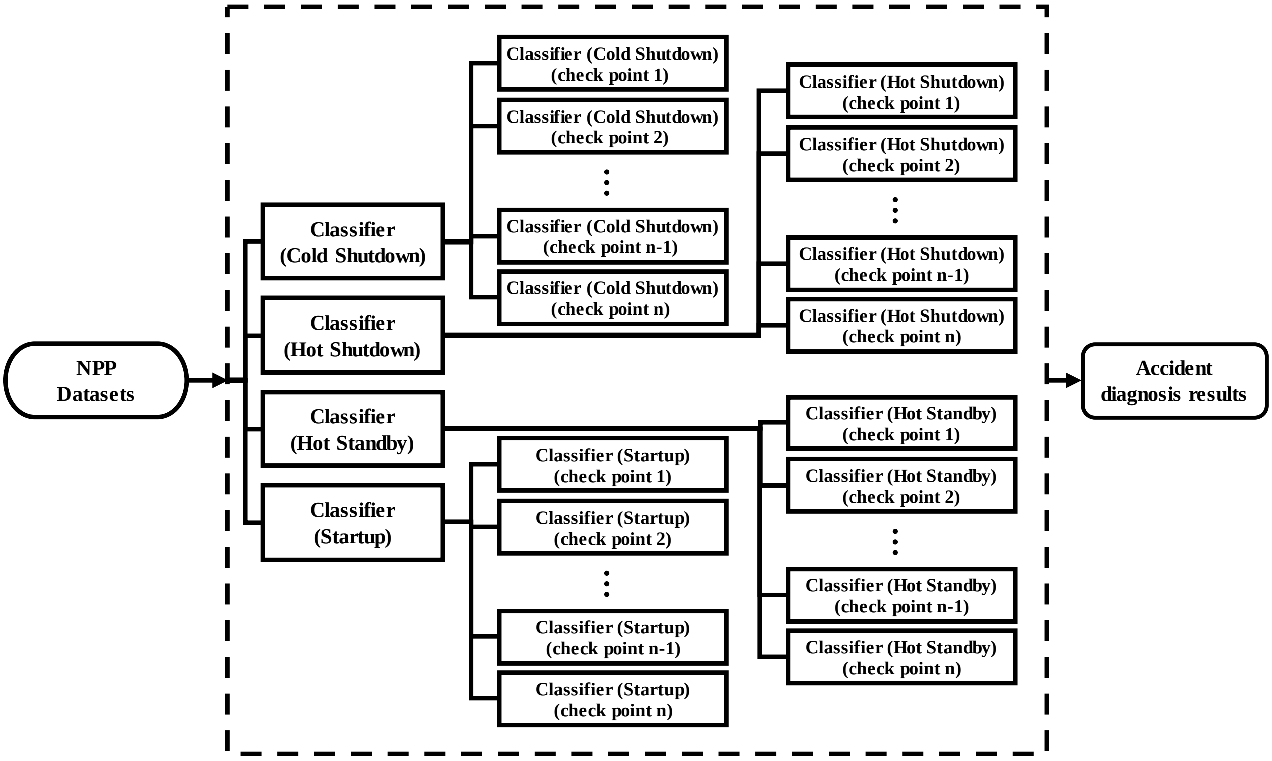

Fig. 1.Overview of accident diagnosis algorithm during startup operation

$$g_l^{(t)} = \phi(W_l^{gx} h_{l-1}^{(t)} + W_l^{gh} h_l^{(t-1)} + b_l^g) \qquad (1)$$
$$i_l^{(t)} = \phi(W_l^{ix} h_{l-1}^{(t)} + W_l^{ih} h_l^{(t-1)} + b_l^i) \qquad (2)$$
$$f_l^{(t)} = \phi(W_l^{fx} h_{l-1}^{(t)} + W_l^{fh} h_l^{(t-1)} + b_l^f) \qquad (3)$$
$$o_l^{(t)} = \phi(W_l^{ox} h_{l-1}^{(t)} + W_l^{oh} h_l^{(t-1)} + b_l^o) \qquad (4)$$

These equations give the update for a layer of memory cells $h_l^{(t)}$ where $h_{l-1}^{(t)}$ stands for the previous layer at the same sequence step and $h_l^{(t-1)}$ stands for the same layer at the previous sequence step.

Because the disadvantages of RNNs are improved by changing the structure of cell unit, it is applicable for long sequential data, such as natural language processing, video classification on frame level, automatic speech recognition, and so on [4].

3. Accident Diagnosis Algorithm

3.1 Overview of Accident Diagnosis Algorithm

The accident diagnosis algorithm should be built considering the dynamic characteristics of startup operation. In case of startup operation, there are several modes which have different initial conditions, dynamic plant states and available components. Moreover, it has the long process, thus the checkpoints should be made by the mode considering the important steps which can affect the component availability or can affect the safety. The Fig. 1 shows an overview of accident diagnosis algorithm during startup operation. Not only one classifier for each mode, but also the several classifiers should be made by the critical steps that can change the availability of components and systems. Therefore, this suggested algorithm can deal with the situation considering startup operation characteristics.

3.2 LSTM Network Model for Accident Diagnosis

The accident diagnosis algorithm is implemented using LSTM in this study. The accident diagnosis can be regarded as multi-label classification. Thus, this study applies a many-to-one structure to design the model. Fig. 2 shows a structure of LSTM model for multi-label classification. The model consists of three LSTM layers and one output layer. Their batch sizes are 64 and 8, respectively. Also, the softmax function is performed at output layer for multi-label classification to set the ranking of diagnosis results.

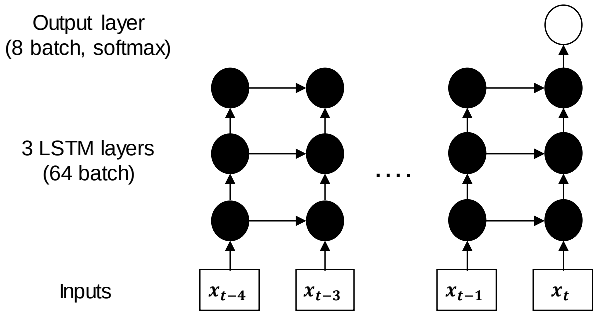

Fig. 2. Structure of LSTM model for multi-label classification

3.3 Pre-processing & Post-processing

Pre-processing of the input data is performed to be used in input layer. Because normalization can help not only to reduce the learning speed but also to prevent getting stuck in local minima (i.e., not global minima among the several minimum points) that can aggravate the performance of algorithm. In order to normalize the data, the min-max scaling method is applied via the following equation (5). It scales the data from zero to one considering minimum and maximum of the collected data [5].

$$X_{\mathrm{norm}} = (X - X_{min})/(X_{max} - X_{min}) \qquad (5)$$

In case of post-processing, it is performed at output layer, which uses softmax function for activation function. The softmax function is commonly used for multi-label classification of the deep learning model to classify several classes (i.e., more than three classes). It normalizes the output value within zero to one via the following equation (6). Despite the normalization, the magnitude relation among output values does not change [6].

$$S(y_i) = e^{y_i}/\sum e^{y_i} \qquad (6)$$

3.4 Training of the LSTM Network

The network is trained and implemented using the CNS developed by the Korea Atomic Energy Research Institute (KAERI), which implements the Westinghouse three loop, 930MWe PWR. The coding of algorithm was implemented with Python 3.6.3. A total of 51 parameters were selected based on procedures and by importance for control of NPP operation. Up to date, 65 scenarios (i.e., 11,571 seconds of data including 51 plant variable values in each time step) were used for training. Table I shows the scenarios used for training (2% power).

Table I: Scenarios used for training (2% power)

Initiating Events	Number
Loss of Coolant accident (LOCA)	32
Main Steam Line Break (MSLB) inside containment	12
Main Steam Line Break (MSLB) outside containment	12
Steam Generator Tube Rupture (SGTR)	9
Total	65

4. Results

4.1 Training Result

The trained network is validated with 17 scenarios (i.e., 3,395 seconds of data including 51 plant variable values in each time step). Table II shows the scenarios used for test (2% power). As a result of validation, Fig. 3 and Fig. 4 shows the validation results on the basis of accuracy and loss metrics. Thus, the accuracy is almost 0.94 with 20 epochs of training, and the loss is almost 0.13. Also, the validation accuracy and loss are almost converged to trained algorithm accuracy and loss, it means the algorithm is trained well without overfitting or underfitting.

Table II: Scenarios used for test (2% power)

Initiating Events	Number
Loss of Coolant accident (LOCA)	8
Main Steam Line Break (MSLB) inside containment	3
Main Steam Line Break (MSLB) outside containment	3
Steam Generator Tube Rupture (SGTR)	3
Total	17

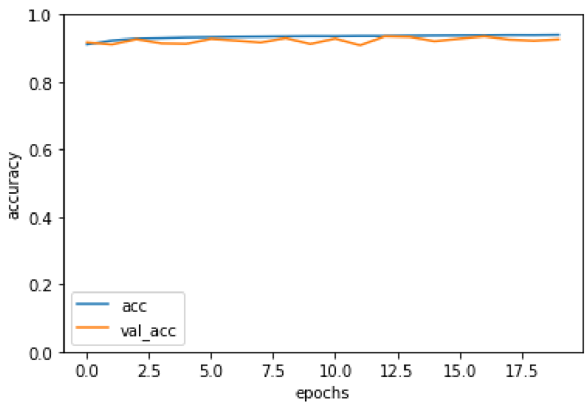

Fig. 3. Validation result of trained algorithm with accuracy

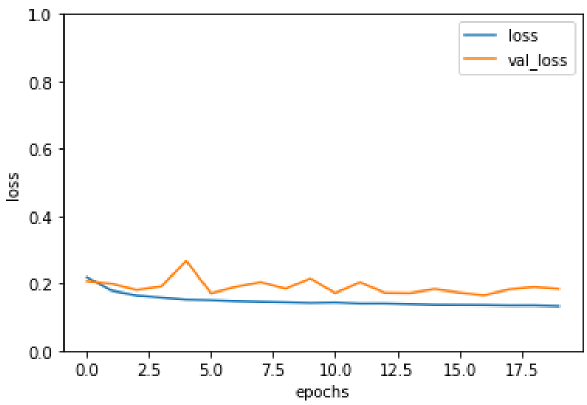

Fig. 4. Validation result of trained algorithm with loss

4.2 Diagnosis Results

The designed accident diagnosis algorithm has been tested with two test scenarios (i.e., SGTR and LOCA) in the startup operation at 2% power. The malfunction is injected at 10 seconds. The solid line means the actual value of test data. The dotted line means the diagnosis result of algorithm. The X-axis and Y-axis represent the time and diagnosed result, respectively. In addition, each line represents the accident or normal state of NPP.

Fig. 5 shows the diagnosis result for SGTR with size of 10 cm^2 in loop 1. The results show that the accident is diagnosed right after the injection of malfunction. Also, the Fig. 6 shows the diagnosis result for LOCA with size of 40 cm^2 in loop2 cold-leg. After approximately 20 seconds, its diagnoses constantly converge to almost 1.

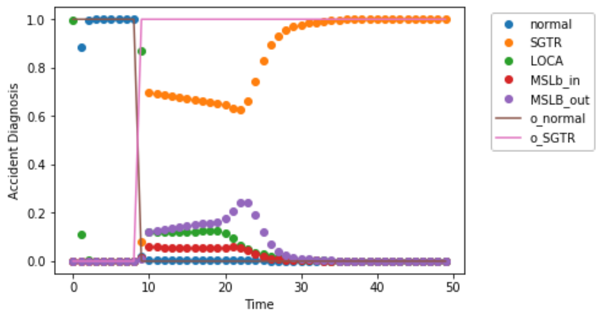

Fig. 5. 10cm^2 SGTR in loop1

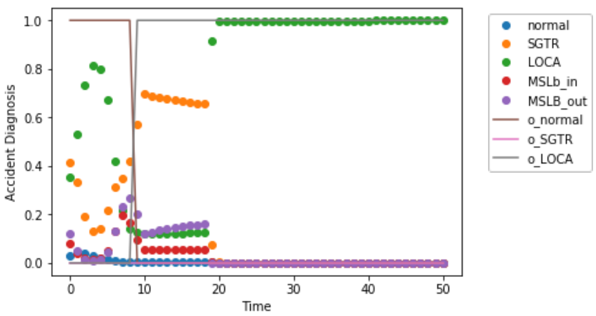

Fig. 6. 40cm^2 LOCA in loop 2 cold-leg

5. Conclusion

In case of accident diagnosis algorithm, if unknown events or untrained events are given, it cannot classify accidents by itself. Though untrained events can be overcome by gathering more data, to cope with unknown events, it needs specific standards (e.g., probability standards).

Also, this study only shows the implementation of suggested accident diagnosis algorithm for startup mode. There is still room for improvement to implement other modes considering availability of components or systems. In addition, the trained algorithm can be improved by hyperparameter tuning.

This study suggests an algorithm for accident diagnosis during startup operation to unload operator's task in abnormal or emergent situation for safety. As a result of accident diagnosis, it is expected that the safety of NPP during startup operation can be improved by application of algorithm for diagnosis of accidents.

REFERENCES

[1] Park, Jin Hee, et al. Event data collection and database development during plant shutdown and low power operations at domestic and foreign reactors. No. KAERI/TR--2471/2003. Korea Atomic Energy Research Institute, 2003.

[2] Jang, Seung Cheol, et al. Development of Risk Assessment Technology for Low Power, Shutdown and Digital I and C System. No. KAERI/RR--2794/2006. Korea Atomic Energy Research Institute, 2007.

[3] Hochreiter, Sepp, and Jurgen Schmidhuber. "Bridging long time lags by weight guessing and "Long Short-Term Memory"." Spatiotemporal models in biological and artificial systems 37, 65-72, 1996.

[4] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8, 1735-1780, 1997.

[5] Jain, Y.K, Bhandare, S.K, Min max normalization based data perturbation method for privacy protection. International Journal of Computer & Communication Technology 2 45-50, 2011.

[6] Lei, Yaguo, et al. An intelligent fault diagnosis method using unsupervised feature learning towards mechanical big data. IEEE Transactions on Industrial Electronics 63.5 3137-3147, 2016.