Development of operating history prediction model using deep learning

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1. Introduction

After the Fukushima Daiichi accident occurred in 2011, it allows us to rethink how we are able to strengthen the operational safety of NPPs. Among lessons learned from the Fukushima Daiichi accident, a lack of information is drawn as one of the key issues [1, 2]. 'a lack of information' denotes the situation in which human operators who have to draw a decision cannot access necessary information due to several reasons such as the failure of indicators or the limitation of dispatching field operators to a local area with a high radiation level. To overcome a lack of information, in this paper, a dedicated tool, namely DeBRIEF (Deep-learning Based Reliable Information Estimator for Functionality), is proposed. The DeBRIEF is able to solve a lack of information by predicting operating history based on the behavior of process parameters from the past.

2. Methods

This section described the concept of DeBRIEF in an aspect of deep learning techniques. In addition, a detailed model configuration is described.

2.1 The concept of DeBRIEF

The DeBRIEF is a deep learning model that is able to predict operating histories (e.g., pump action and time, human action and time) by using the behavior of process variables from past to present. Figure 1 expresses the concept of DeBRIEF. In Figure 1, the left graph shows the behavior of process variables in the nuclear power plants (NPPs) and the right graph shows the results of the DeBRIEF, which is predict operating histories.

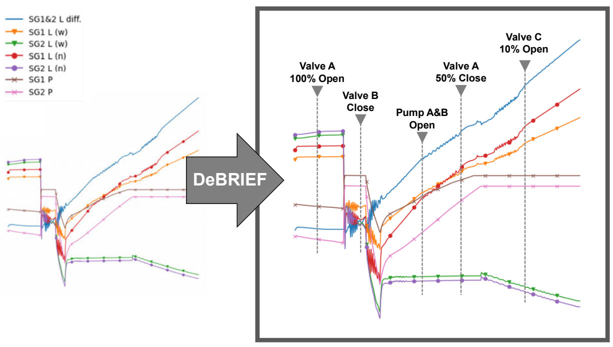


Fig. 1. The concept of DeBRIEF

In the only view of deep learning techniques, the DeBRIEF is a multi-label classification model. In general, multi-class classification has been well used for accident diagnosis or others diagnosis [3, 4]. Fig. 2 shows differences between the multi-class and the multi-label. For the multi-class, a sample has only one class, on the contrary, the multi-label has one or may class for a sample. In summary, the multi-class is mutually exclusive, and the multi-label is a non-exclusive.

Multi-class

	C_1	C_2	C_3	C_4
Sample 1	0	1	0	0
Sample 2	0	0	1	0
Sample 3	1	0	0	0

Multi-label

	C_1	C_2	C_3	C_4
Sample 1	0	1	1	0
Sample 2	1	0	1	0
Sample 3	1	0	0	1

Fig. 2. Comparing the multi class and multi label

2.2 The configuration of DeBRIEF

The DeBRIEF is developed by referring to a resnet structure and modified using a 1-dimensional convolution (1D conv.). The reason why uses the 1D conv. is because a problem considered in this paper is the time-series.

The characteristic of the resnet is a residual connection, and one residual connection is called a residual block [5]. By adapting the residual connection, it avoids a gradient vanishing problem. Generally, the resnet consists of the residual block that is serially connected to deeper. The conventional residual block is illustrated in Fig. 3.

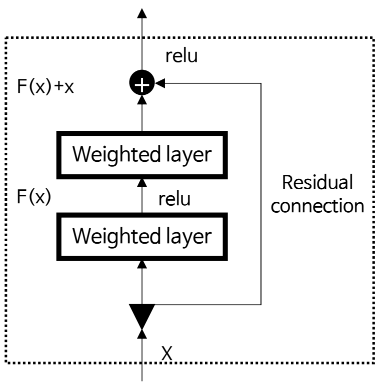
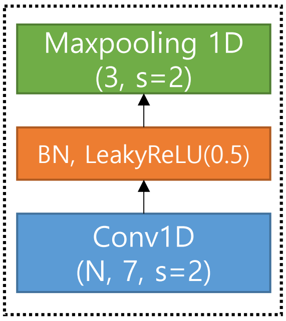


Fig. 3. Residual connection in the conventional resnet

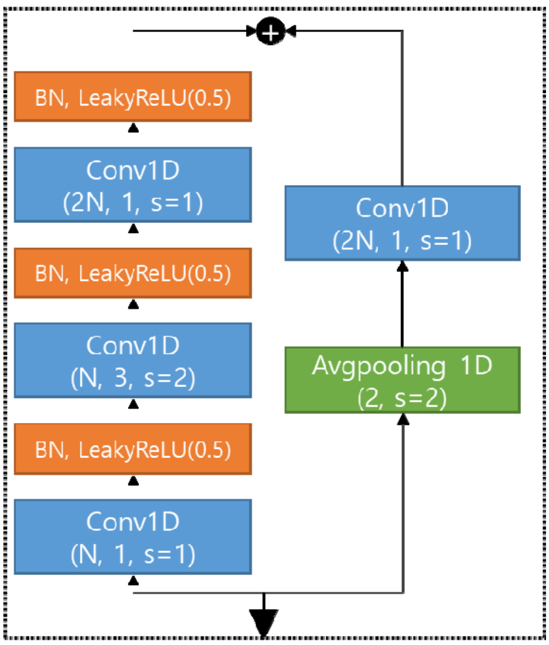
In this paper, the conventional residual block is modified referring Ref. 6. Fig. 4 and Fig 5 show the pre-block and modified residual block. In the Fig. 4 and Fig 5, BN is an abbreviation of Batch normalization. In addition, Conv1D (N, 7, s=2) means the number of filter is N, kernel size is 7, and strides is 2. Similarly, Maxpooling 1D (3, s=2) means kernel size is 3 and strides is 2.



[Pre-block]

Fig. 4. Designed pre-block

In the Fig. 5, the residual connection is changed by adding the average pooling layer and 1D conv layer. The conventional residual block has a bottleneck problem. To avoid bottleneck problem, a small kernel size is applied.



[Residual block]

Fig. 5. Modified residual

The developed model structure is illustrated in Fig. 6. To handle the multi-label problem, the developed model is divided into the parent model and the child model. The parent model transfers the weight to the child model.

The parent model consists of the pre-block and residual block (N is 64, 128, and 256). The child model is connected as many as the number of variables that need to be predicted. Table 1 summarized hyperparameter.

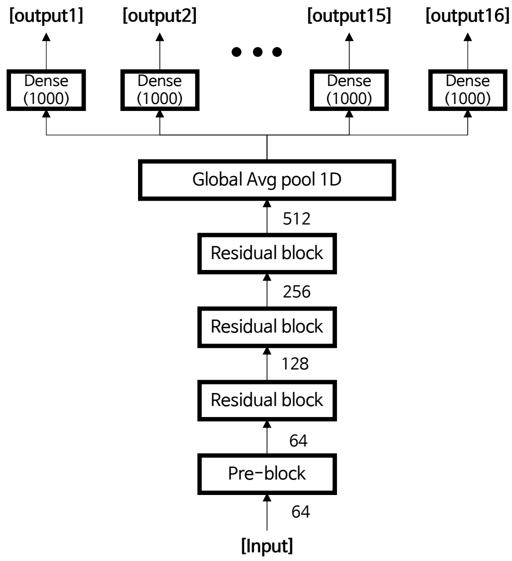


Fig. 5. The structure of developed model

Table 1. Hyperparameter in developed model

Parameter	Value
Activation function	LeakyRelu(0.5)
Optimizer (epsilon)	NAdam (0.1)
Learning rate	0.0001
Cost function	Categorical_crossentropy
Epoch	300
Batch size	32

3. Results and conclusions

To generate training and test data for the model, accident scenarios that various conditions that can be considered in the SPTA (standard post trip action) for SGTR (steam generator tube rupture) and MSLB (main steam line break). The reference NPP (nuclear power plant) for generating data is OPR-1000 (optimized power reactor-1000), and a MARS (multi-dimensional analysis of reactor safety) was used for the simulation of plausible accident scenarios. The initial condition of SGTR and MSLB is described in Table 2. Table 3 and 4 describe the process parameter (model input) and control variables (model output). The control variables are role of operating histories in this paper.

Table 2. Initial condition of SGTR and MSLB

Event	Location	Size (Area; A)	Calculation time / Sampling rate
SGTR	Lower side at tube	A, 2A, 4A	1 hour / 1 sec
MSLB	In containment	A, 2A	

Table 3. List of process parameter

Process parameter
Time
Reactor Power
SG1&2 level difference
RCP1 on/off
RCP2 on/off
RCP3 on/off
RCP4 on/off
SG1 level (wide)
SG2 level (wide)
SG1 level (narrow)
SG2 level (narrow)
FW flow (to SG1)
FW flow (to SG2)
AFW flow (to SG1)
AFW flow (to SG2)
PZR pressure
PZR level
RCS subcooling margin (RCS)
SG1 pressure
SG2 pressure

Table 4. List of control variables

Control variables	Size	Time
PZR Level control	0, 50, 100	0, 1.77, 3.1, 5.425, 9.3
PZR heater control	0, 50, 100	0, 2.06, 3.6, 6.3, 10.3
SIAS Activation	0, 1	0, 2.06, 3.6, 6.3, 10.3
RCP stop	0, 1	0, 2.06, 3.6, 6.3, 10.3
Open TBV	0, 5, 10, 25, 50, 75, 100	0, 2.629, 4.6, 8.05, 13.8
Open ADV	0, 5, 10, 25, 50, 75, 100	0, 2.629, 4.6, 8.05, 13.8

Table 5. Model accuracy

Control variables	Accuracy	
	Action	Time
PZR Level control	33 %	74 %
PZR heater control	64 %	34 %
SIAS activation	100 %	100 %
RCP stop	90 %	91 %
TBV open	97 %	98 %
ADV open	99 %	92 %

Table 5 shows the model accuracy for each control variable. The total average accuracy is 81%. Among the control variables, the accuracy of PZR level control and PZR heater control was calculated to be low. Because SGTR and MSLB accidents were already assumed when generating the dataset, it is judged that the influence of variables related to PZR is insignificant.

In this study, deep learning model that classifies the past operating history based on the behavior of the NPPs. The developed model can help decision-making in case of an accident, and what-if analysis is expected to be possible using the DeBATE (Deep learning based accident trend estimator) jointly developed.

The developed model was calculated to have a total average accuracy of 81%. Therefore, more accurate performance improvement is needed in further studies. There are three main method to improve the performance of the model. First, the developed model is composed of three residual blocks, so the model's performance can be increased by accumulating more deeply. Second, the model can be modified to reflect better the correlation between variables (influence between channels from a deep learning perspective). Finally, we can perform model ensembles.

In addition, more accurate and precise performance metrics are needed. If possible, it determines how accurate the performance of the developed model is through comparison with expert reasoning. If XAI technology develops in the future and it combines suggested method, it can be more helpful in decision making.

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