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The Compatible Abnormality Diagnosis Model in the distinct Nuclear Power Plants

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1. Introduction

The nuclear power plants (NPPs) consist of huge number of safety and operating systems to generate electricity safely and efficiently with hundreds of indicators and tens of thousands of components. When the transition occurs into abnormal events, operators must find appropriate abnormal operating procedures (AOPs) and take actions within a limited time from the dynamic indicators to prevent entry into a reactor trip and to return to a normal condition. Since in the case of Korean advanced power reactor 1400, there are about 200 sub-procedures in the AOPs, operators are trained to cope with abnormal events using AOPs, while under huge number of dynamic indicators. The limited time and the dynamic change of numerous indicators in abnormal events get more burden to operators and are likely to cause human errors [1].

To solve these problems, recent studies have been conducted in the nuclear engineering fields to support operators of NPPs with artificial intelligence (AI) [2, 3]. However, most studies have not prepared proper measures to apply to actual power plants. Even for the same types of pressurized water reactors, the components of NPPs differ from the offset, magnitude of increase or decrease, and recovery time. Resisting the fluctuated and changed parameters will be challenging task for the common data-driven AI models.

To address these problems, this study introduces the compatible abnormality diagnosis model that can diagnose abnormal events where the original simulator data and intentionally modified data to depict real-world plants. Proposed model only trains the original data and then, the model will test the original and modified data together. The modified data is generated different from the original data with abnormality injection time for different recovery time and go across the modified filter for offset, magnitude of the change. To cope with data differences, we utilize robust preprocessing with plant-knowledge scaling and fuzzification filter to recognize how increase, decrease, or maintenance. We compared the simple feedforward neural network (FNN) and one-dimension convolutional neural network (CNN) with our methodology.

2. Data differences between NPPs simulators

In this section, the data differences are described by the 3KEYMASTER simulator of western services corporation and Barakah nuclear power plant simulator [4]. Two simulators are two-loop 1400MWe pressurized water reactor, but not exactly the same. The Fig. 1. shows data trends of the volume control tank level and condenser cooling water outlet temperature according to (a) and (b), respectively. From (a), the magnitudes of offset and increase are different and from (b), the recovery time and magnitude are also different between two simulators. In addition, figure (c) illustrates pressurizer level of 3KEYMASTER simulator with and without noise. In these data differences, some strategies distinct from the existing abnormality diagnosis models are needed.

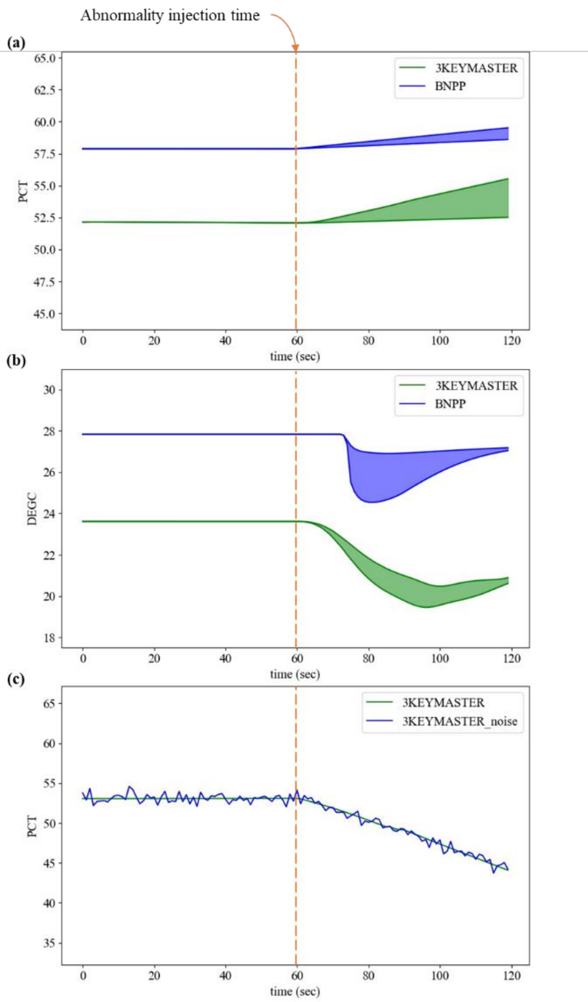

Fig. 1. Data difference between 3KEYMASTER and BNPP simulators.; (a): volume control tank level; (b): condenser cooling water outlet temperature; (c): pressurizer level.

3. Methodology

Fig. 2. illustrates the overall framework of the compatible abnormality diagnosis model. Since real NPP data is inaccessible and difficulties in the absences of common variables between simulators, we selected 3KEYMASTER simulator and tried to depict characteristics of real plants. In this study, we call the data that depict the characteristics of real plants as *modified data*. The points below briefly introduce the framework of the compatible abnormality diagnosis model.

- Data preprocessing: Raw data are preprocessed through feature selection, normalization, and data transformation. Feature selection is based on the knowledge of the symptoms of abnormal events or the representative plant parameter. The normalization range is knowledge-based and robust to cover a wide range of offsets and rates of change. Data transformation is performed by using data differences and fuzzification filter to get how much time-series variables have changed. In the case of modified data, there are additional steps in the data production stage and the preprocessing process.
- Compatible abnormality diagnosis models: The compatible abnormality diagnosis model is trained and tested through FNN and 1D-CNN. The proposed models train only original data and test original and modified data either.

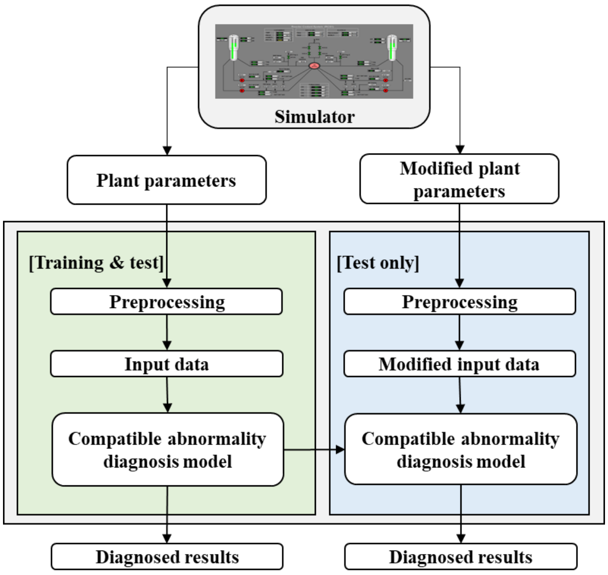

Fig. 2. The framework of Compatible abnormality diagnosis model.

3.1 Data preprocessing

Raw data is reformed in data preprocessing process through feature selection, normalization, fuzzification filters. In the feature selection process, we choose some variables of the simulator based on the knowledge of the abnormal events and general monitoring parameters. Normalization process performs minmax scaling with wider ranges than the minimum and maximum value of the train data to cover offset and high change-rate of modified data like below equation (1) where t is time, n is the order of the variable, and m is a regulator for margin to cover modified data.

$$\hat{x}_{t,n} = \frac{x_{t,n} - x_{\min\, of\ nth\ parameter} \times (1-m)}{x_{\max\, of\ nth\ parameter} \times (1+m) \; - x_{\min\, of\ nth\ parameter} \times (1-m)}$$

$$where\ 1 \le n \le N,\quad N\ is\ the\ number\ of\ the\ parameters\ and\ 0 < m < 1 \qquad (1)$$

Data transformation processes consist of two steps. The first step expresses the normalized data as the data differences by simple subtraction between before and after abnormality injection. The second step uses fuzzification filters. According to the number of membership functions of the fuzzification filters, data is augmented as the input data. Data transformation processes are illustrated as the Fig. 3. and 4.

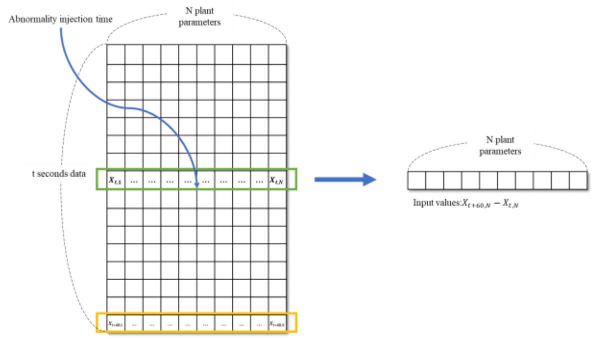

Fig. 3. Data transformation by data differences.

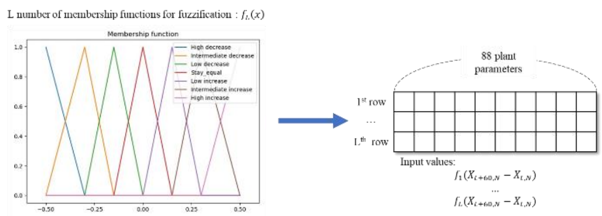

Fig. 4. Data transformation by fuzzification filters.

3.2 Compatible abnormality diagnosis models

The proposed model will be compared using two neural networks (FNN and CNN), and the training data is only preprocessed original data, and the test data is preprocessed original and modified data that depict real-plant data.

3.2.1. Feedforward neural network

The FNNs consist of a feedforward single- or multi-layer perceptron and are widely used in various fields such as classification, forecasting even in manufacturing industries [5]. In this study, FNNs are used as the classification model for abnormality diagnosis as an operator support system. FNNs have generally the input, hidden, and output layer. The input layer transfer data to hidden layers which calculate and update weights for feature extraction with activation functions. The output layer is formed with fully connected layer which is called FC-layer or dense layer and in classification problems the number of dense layers are the same as the number of classes or labels. Fig. 5. Shows the basic architecture of the FNNs.

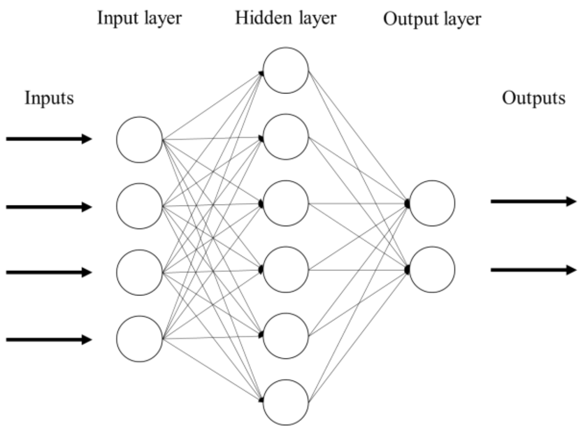

Fig. 5. The basic architecture of the FNNs

3.2.2. One-dimensional convolutional neural network

The CNNs show state-of-the-art results and facilitate the feature extraction between adjacent input parameters or image from the characteristics of convolutional calculations. Because of the CNNs are specially used in the pattern recognition fields of images or classification problems [6].

4. Experimental settings

4.1 Description of datasets

All datasets are produced from the 3KEYMASTER simulator which is a 2-loop 1400MWe generic pressurized water reactor. The shape of each dataset is 120 seconds and 88 plant parameters, and all abnormal malfunction is injected into 61 seconds. The number of the datasets are 50 for each ramp time datasets of each label. For instance, the number of datasets of ramp time 0 seconds is 550. The sorts of the datasets and description is shown as Table I.

Table I: Test data description

Label	Description
Normal	Initial condition #2 MOL* 100%
POSRV*	Pilot operated safety relief valve leak
SGTL*	Steam generator A tube leak
RCP*	RCP seal water injection valve positioner close failure
PZR*	Pressurizer spray valve positioner open failure
LTDN*	Letdown line leak inside containment
CHRG*	Charging line valve positioner close failure
TCS*	High pressure turbine control valve positioner close failure
LFH*	Feedwater heater 4A tube break
CDS*	Loss of condenser vacuum
MFW*	MFWP recirculating valve positioner open failure

* MOL: middle of life; POSRV: pilot operated safety relief valve; SGTL: steam generator tube leakage; RCP: reactor coolant pump; PZR: pressurizer; LTDN: letdown water system; CHRG: charging water system; TCS: turbine control system; LFH: low pressure feedwater heater; CDS: condensate system; MFW: main feed water.

Training datasets are generated with 10 seconds ramp time which is the time at which the malfunction injects linearly. Modified datasets are generated with 0-, 20-, and 30-seconds ramp time for diverse datasets of the different recovery time or magnitude of the peak values. After that, modified datasets are processed again through offset, change-rate, and noise. Fig. 6. depicts the processes of the modified datasets.

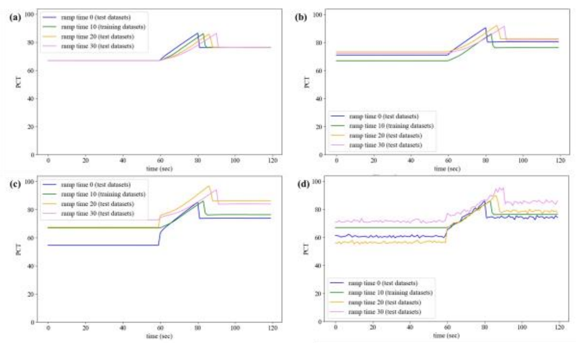

Fig. 6. The processes of the modified datasets; (a): ramp time 0, 10, 20, 30 seconds datasets; (b): the datasets with offset

Each dataset is preprocessed by normalization and data transformation. After normalization of equation (1), data is transformed through $f_L(X_{120,n} - X_{60,n})$ where

$f_L(x)$ is the L[th] membership function and $X_{120,n}$ is the time 120 seconds data of n[th] plant parameters and $0 \leq L \leq 7, and\ 1 \leq n \leq 88$.

4.2 Descriptions of models

We used FNNs and 1D-CNNs to test and compare the compatible abnormality diagnosis model. Below Table II and III show the architectures of the models.

Table II: The architecture of the FNNs

Characteristic	Description
Input size	(# of membership function of the fuzzification filter, 88)
# of dense layers	2
Activation function	ReLU, softmax
Loss function	Sparse categorical crossentropy
Optimizer	Adam
Epochs	1000

Table III: The architecture of the CNNs

Characteristic	Description
Input size	(# of membership function of the fuzzification filter, 88)
# of Conv1D layers	1
# of maxpooling1D	1
# of dense layer	1
Activation function	ReLU, softmax
Loss function	Sparse categorical crossentropy
Optimizer	Adam
Epochs	1000

5. Results

Training datasets are not modified but preprocessed ramp time 10 seconds data and test trained datasets and other ramp time datasets with modified as an alternative to real world plants datasets. The cases were divided into various types of applying proposed methods, modified degree, number of membership functions of the fuzzification filters, and type of models. The gaussian distribution facilitates to make up offset, change-rate, and noise.

Table IV: The results of no fuzzification filters

	Case 1	Case 2	Case 3	Case 4
Proposed methods	X	O	X	O
# of membership functions	X	X	X	X
Offset	N(0,0.05)	N(0,0.05)	N(0,0.1)	N(0,0.1)
Change-rate	N(0,0.05)	N(0,0.05)	N(0,0.1)	N(0,0.1)
Noise	N(0,0.005)	N(0,0.005)	N(0,0.01)	N(0,0.01)
NN model	FNN	FNN	FNN	FNN
Accuracy (%)	9.39	94.67	9.09	85.52

Table V: The results of FNNs

	Case 5	Case 6	Case 7	Case 8
Proposed methods	O	O	O	O
# of membership functions	3	7	3	7
Offset	N(0,0.05)	N(0,0.05)	N(0,0.1)	N(0,0.1)
Change-rate	N(0,0.05)	N(0,0.05)	N(0,0.1)	N(0,0.1)
Noise	N(0,0.005)	N(0,0.005)	N(0,0.01)	N(0,0.01)
NN model	FNN	FNN	FNN	FNN
Accuracy (%)	97.39	99.03	92.39	94.61

Table VI: The results of CNNs

	Case 9	Case 10	Case 11	Case 12
Proposed methods	O	O	O	O
# of membership functions	3	7	3	7
Offset	N(0,0.05)	N(0,0.05)	N(0,0.1)	N(0,0.1)
Change-rate	N(0,0.05)	N(0,0.05)	N(0,0.1)	N(0,0.1)
Noise	N(0,0.005)	N(0,0.005)	N(0,0.01)	N(0,0.01)
NN model	CNN	CNN	CNN	CNN
Accuracy (%)	96.91	98.61	83.21	92.3

Table IV shows the novelty of the proposed preprocesses at modified datasets similar to actual plant datasets and distinct accuracy. The results mean that in order to be less affected by the data level, information of how much increase and decrease is necessary as input values described in Fig. 3. Naturally, the more data is modified, the less accurate it is.

Table V and VI show the results in the point of view of the types of models, number of the membership functions of the fuzzification filters, and how much modified as real plant datasets. In all results, the accuracy of the FNNs with the simplest architecture was high. CNNs' classification performance is valuable, but since creating a robust model is the core of the compatible abnormality diagnosis model, the features that capture the characteristics of specific data played a role in hindering diagnosis process in modified data. In contrast, we have increased the compatibility by building a simple architecture model of FNNs. Rather than simply applying an increasing and decreasing amounts as inputs, we could further improve accuracy by using fuzzy filters to identify the increasing and decreasing tendency.

6. Conclusions

NPPs consist of complex systems for safety and efficient electricity production with hundreds of indicators and tens of thousands of components. Furthermore, to improve safety and operate NPPs, there are more than 200 sub-procedures of AOPs in Korean APR-1400. Nowadays, some studies have been done utilizing AI into NPPs as operator support systems. However, additional measures are needed to apply to actual power plants. We considered the characteristics of real plant variables as a steppingstone for the application to real power plants and modified actual power plant variables with simulator data in ramp time, offset, change-rate, and noise.

In addition, rather than focusing on absolute data values, a robust and compatible abnormality diagnosis model was developed by adopting the behavior or trend of the plant variables according to abnormal conditions as input values. Fuzzification was performed to maximize the exploration into plant variable behavior, and in the case 6 and case 8 using FNNs, the accuracy was 99.03 and 94.61%, respectively. CNNs are obviously an artificial intelligence that is good for feature extraction, but it has shown that overfitting to certain data rather results in lower performance for compatibility.

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REFERENCES

[1] Lee, S. J., and Seong, P. H, Development of an integrated decision support system to aid cognitive activities of operators, Nuclear Engineering and Technology, 39(6), 703, 2007.
[2] Shin, J. H., Bae, J., Kim, J. M., and Lee, S. J, An interpretable convolutional neural network for nuclear power plant abnormal events, Applied Soft Computing, 132, 109792, 2023
[3] Choi, J., and Lee, S. J, RNN-based integrated system for real-time sensor fault detection and fault-informed accident diagnosis in nuclear power plant accidents, Nuclear Engineering and Technology, 55(3), 814-826, 2023.
[4] Western Service Corporation, 3KEYMASTER Simulator, Western Service Corporation, Frederick, MD, USA, 2013.
[5] Svozil, D., Kvasnicka, V., and Pospichal, J, Introduction to multi-layer feed-forward neural networks, Chemometrics and intelligent laboratory systems, 39(1), 43-62, 1997.
[6] Shin, J. H., Bae, J., Kim, J. M., and Lee, S. J, An interpretable convolutional neural network for nuclear power plant abnormal events, Applied Soft Computing, 132, 109792, 2023.