Abnormal State Detection Model Using Deep One-Class Classification in Nuclear Power Plant

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1. Introduction

Nuclear power plant (NPP) operators are trained to select appropriate operating procedures according to the situation and act. For instance, when an abnormal situation occurs, the appropriate abnormal procedure manual is selected and acted by synthesizing the situation such as indicators and alarms in the main control room.

However, it is difficult to diagnose a suitable abnormal condition. For advanced power reactor1400, a Korean nuclear power plant, thousands of indicators and 82 abnormal procedures which are made up of 224 sub-procedures cause confusion for well-trained operators. In addition, if proper measures are not taken within a limited time, operators feel burdened because an abnormal state can enter an emergency state that requires reactor shutdown [1]. In this respect, human errors may occur, and in the case of Korea, about 20% of the unexpected reactor trip of nuclear power plants is caused by human errors.

To reduce this human error, previous studies focused on diagnosing the type of abnormal state using an artificial intelligence model. The performance of artificial intelligence models depends on the quality and amount of data, and it is difficult to obtain a large amount of high-quality abnormal data of NPP. Therefore, research that detects an abnormal state only with normal state data should be preceded because it's hard to get all kinds of the abnormal state data.

In this study, a deep support vector data description (Deep SVDD) artificial intelligence model is introduced to determine whether the current state is normal or abnormal by using only information of a normal state [2]. Deep SVDD aims to find the smallest range surrounding normal data according to the feature space of trained normal data based on deep learning. As a result, the normal state and 15 abnormal states are tested to determine whether the state is normal or abnormal.

2. Methods

In this study, Deep SVDD is used as a model for training normal data to determine whether it is normal or abnormal state. As the test data, a normal state and 15 abnormal states are used. Deep SVDD uses the distance from the feature space as a test score and determines the normal and abnormal status according to the value of the score. Figure 1 is the overall algorithm for this study.

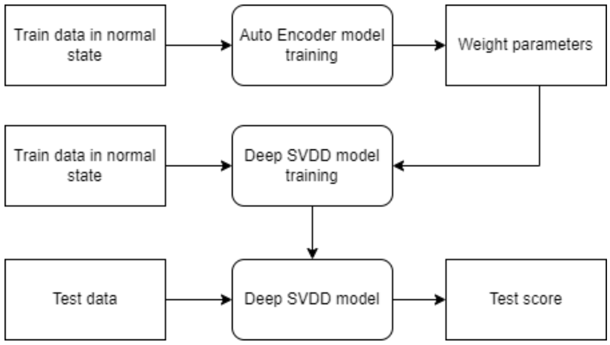

Fig. 1. Overall algorithm of Abnormality detection using Deep SVDD

2.1 Data Production

For data production, a 3KEYMASTER nuclear power plant simulator from western services corporation was used, and the plant model is 2-loop generic pressurized water reactor [3]. All data are generated in the middle of life state for 60 seconds, and the types are one normal state and 15 abnormal states, as shown in Table 1.

Table I: Test data description

Label	Description
Normal	Initial condition #2 MOL* 100%
SGTL*	Steam generator A tube leak
CHRG*	Charging line break upstream
LTDN*	Letdown line leak inside containment
CDS*	Loss of condenser vacuum
POSRV*	Pilot operated safety relief valve leak
CWS*	Circulating water tube leak in LP* condenser
MSIV*	Main steam isolation valve positioner failure
RCP*	CCW* service loop header leak to aux atm
MSS*	Steam generator A steam line 1A break inside containment
PZR*	Pressurizer spray valve positioner failure
CCW	CCW service loop header leak to aux atm
LFH*	Feedwater heater 4A tube break

HFH*	Feedwater header break
MFW*	MFWP recirculating valve positioner open failure
TCS*	High pressure turbine control valve positioner close failure

* MOL: middle of life; SGTL: steam generator tube leakage; CHRG: charging water system; LTDN: letdown water system; CDS: condensate system; POSRV: pilot operated safety relief valve; CWS: circulating water system; LP: low pressure; MSIV: main steam isolation valve; RCP: reactor coolant pump; CCW: component cooling water; MSS: main steam system; PZR: pressurizer; LFH: low pressure feedwater heater; HFH: high pressure feedwater heater; MFW: main feed water; TCS: turbine control system;

2.2 Data preprocessing

Data preprocessing is largely divided into two categories. It is parameter selection and normalization to be used for training and testing. The parameter selects the variable to be used based on the rate of change in the steady-state data among the 944 parameters used for the human machine interface. The selected parameters perform minmax normalization based on the normal state data.

$$X = \frac{x - x_{min}}{x_{max} - X_{min}} \ (1)$$

2.3 Descriptions of Deep SVDD

The existing support vector data description aims to find the smallest hypersphere that enclosing feature spaces using kernel function [4]. Deep SVDD is also looking for the smallest hypersphere surrounding the feature space. However, the difference is that deep learning-based data reprocessing is performed instead of kernel function []. Let $\phi(x_i; W)$ represents transformed data with data set $x_i \in X$, neural network ϕ and weight W. The objective function of Deep SVDD is defined as

$$\min_{R,W} R^2 + \frac{1}{\nu n}\sum_{i=1}^{n} \max\left\{0, \left|\left|\phi(x_i; W) - c\right|\right|^2 - R^2\right\} + \frac{\lambda}{2}\sum_{l=1}^{L}\left|\left|W^l\right|\right|_F^2 \ (2)$$

Where c is the center of the hypersphere, R is the radius of the hypersphere, and λ and ν balancing hyperparameter. The simplified objective function of Deep SVDD can be defined as follows by removing radius of hypersphere.

$$\min_{W} \frac{1}{n}\sum_{i=1}^{n}\left|\left|\phi(x_i; W) - c\right|\right|^2 + \frac{\lambda}{2}\sum_{l=1}^{L}\left|\left|W^l\right|\right|_F^2 \ (3)$$

The abnormal detection score of Deep SVDD is expressed as the distance between the test data and the center of hypersphere.

$$s(x) = \left|\left|\phi(x; W) - c\right|\right|^2 \ (4)$$

Learning goes through two main courses. First, the autoencoder using the bottleneck structure based on 2d convolutional natural network (CNN) extracts important features of the normal state data by minimizing reconstruction error and sets the weights for the center of hypersphere [[5], [6]].

Second, the weights through the autoencoder are applied to Deep SVDD using the same structure as the bottleneck part of the autoencoder, and the existing data is represented by utilizing the distance between hypersphere and normal state data as loss.

2.4 Structures of models

Basically, the Deep SVDD model exactly matches the bottle structure of Autoencoder, and the base model of Autoencoder is as follows.

-Number of 2d convolutional layer for encoder: 2
-Number of 2d convolutional layer for decoder: 3
-Activation function of each convolutional layer: leaky ReLU
-Optimizer : Adam (learning rate=0.001)

3. Results

As described in preprocessing, a total of four types of parameter sets were selected according to the rate of change in the normal state data, and the number of parameters was 142, 238, 332, and 468. Due to the model structure of Deep SVDD, 2d CNN should be implemented, so the data was converted into 2d according to the number of parameters, and the size of the insufficient data was added by zero padding. Due to the character of one-class classification, the farther the distance between the normal state data and the abnormal state data is, the better the test result is, so not only the accuracy but also the area under curve (AUC) is used.

Table II: Average AUCs in % with standard deviations per parameter numbers of 1 normal and 15 abnormal state data

Training data		Training result		
Param Num*	Data size	Norm Acc*	Abnorm Acc*	AUC*
142	12×12	100 ± 0	93.4 $\pm$ 0.02	93.6 $\pm$ 0.02
238	16×16	100 ± 0	96.4 $\pm$ 0.04	96.5 $\pm$ 0.04
332	19×19	100 ± 0	99.8 $\pm$ 0.01	99.8 $\pm$ 0.01

468	22×22	100 ± 0	99.9 ± 0.02	99.9 ± 0.02

* Param Num: parameter numbers; Norm Acc: normal state accuracy; Abnorm Acc: abnormal state accuracy; Total Acc: total state accuracy;

From the test results, it may be seen that the data in the normal state is accurately determined, and some of the data in the abnormal state is determined to be in the normal state. In addition, it may be seen that as the number of parameters increases, the accuracy of the abnormal state increases. Since the extracted general characteristics of the normal state data are insufficient to cover the main factors of the abnormal state, the accuracy is low when the number of parameters is small. For example, when RCP abnormality occurs, the accuracy of abnormal detection was relatively low. This is because there was little difference from the normal state data when the change rate of the RCP seal flow rate, which is a major variable, was low.

4. Conclusions

This study introduced an artificial intelligent model that accurately informs whether the current state is in a normal or abnormal state because of the difficulty of processing a large amount of high-quality abnormal state data according to the characteristics of nuclear power plants. Deep SVDD, a one-class classification model that built the model utilizing Autoencoder based on 2d CNN, was used. Normal state data were used as training data, and normal state data and 15 abnormal state data were used as test data. Through this study, it was shown by testing 15 abnormal states that it is possible to detect abnormal states by using only steady state data.

If an abnormal state detection model is applied to an actual power plant, it shows the possibility that operators can be notified of the transition to an abnormal state faster than an alarm or faster than before. Through this, operators' quick perception of abnormal conditions will be able to help reduce human errors that may occur due to many plant variables and complicated AOPs. Furthermore, if this model makes it possible to detect more abnormalities, the models for diagnosing the abnormalities studied above no longer need to include the normal condition in the diagnosis target and may show higher accuracy.

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