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Abnormal State Diagnosis about Actual Sensor Data with Noise

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1. Introduction

If nuclear power plants (NPP) are out of normal condition, an operator can perform abnormal operating procedures (AOPs) to stabilize it. The operator must understand entry conditions for all AOPs in order to conduct the appropriate AOP, depending on the situation. However, types of AOP and abnormal events vary widely, making it difficult for the operator to conduct these tasks in a short time. For example, advanced power reactor 1400 (APR1400) has 82 AOPs. In addition, there are about 200 abnormalities [1].

There are many prior researches available to assist these operators in determining an abnormal state. Prior researches suggested an operator support system that uses an artificial neural network to diagnose states of an NPP [2]. In addition, convolutional neural networks can be used to diagnose NPPs for abnormalities [3]. These studies show excellent performance in diagnosing causes of an event and classifying abnormal states.

However, many prior studied models have the limitation because of using virtual data from simulators or system analytic codes. Actual sensor data, unlike simulator data, includes noise from mechanical components and may vary in size. In other words, the actual sensor data can be found to contain approximately 1 % to 5 % noise, unlike the simulator data, as shown in Figure.1 below.

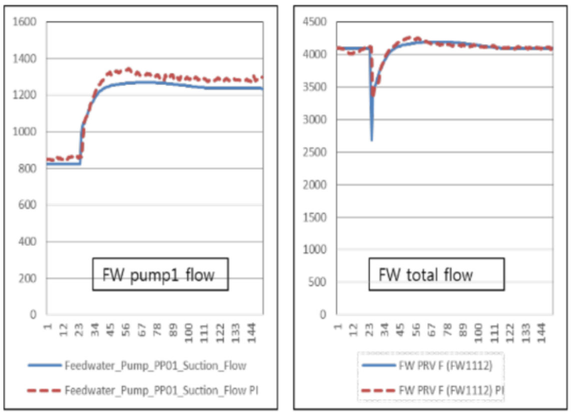

Fig. 1. Flow rate about actual sensor data and simulator data [3]

To take this into account, the experiment has been designed following methods: A Grate Recurrent Unit (GRU) algorithm is used to train the abnormal state diagnosis model with data generated by the NPP simulator. We used this model to identify the accuracy degradation as the noise increases. To overcome this, the first method was to preprocess test data using each smoothing filter. And secondly, we trained the model with the data that adds noise through data augmentation to training data. Two methods reduce the difference in diagnosis performance between the simulator data and the real plant data.

2. Methods

This section uses simulator data that was modified similar to real plant data. Additionally, it shows the stability about noise for real plant data in the base GRU model and identifies effects of how to reduce the difference between each data has on accuracy.

2.1 Accuracy for Data with Noise

Unlike the virtual data, the actual sensor data has about 1 % to 5 % noise. As adding 1 % to 5 % Gaussian noise to the simulator data randomly, it can create a test data set to replace a real plant data set. And using this modified data, it can identify the robust or the stability of the noise in the existing GRU model.

2.2 Smoothing Filters

The data preprocessing by using each smoothing filter make the virtual data similar to the actual data. It reduces misjudgment due to gaps between each data such as noise. This paper uses four filters as moving average filters, triangular moving average filters, Gaussian filters and Savitzky-Golay filters [4] to smooth the modified dataset which have 3 % to 5% Gaussian noise instead of actual data. At the all experiments, the window size of each filter is 9 spaces (9 seconds).

2.3 Data Augmentation

Learning models are difficult to make right judgments about untrained data sets. Thus, the previous method preprocessed untrained data similar to trained data by using filters. Conversely, complexity is arbitrarily added to test data to make it look similar to training data. It enhances the complexity of the simulator data set by adding 1 % to 3 % Gaussian noise [5].

Using test data set which have 0 % to 5 % noise, It tests models that are trained with augmented noisy data and original data. This modified model which is trained new augmented data sets can classify well without having to go through a pre-processing to reduce noise.

2.4 Total Experimental Algorithm

The 3KEYMASTER NPP simulator, manufactured by Western Corporation Service, injects abnormal event malfunction to generate data [6]. In this paper, there are three abnormal event malfunction which are about condenser, pilot operated safety relief valve and reactor coolant pumps. It trains for the GRU model with 200 data sets with 944 variables per each event. All data in this paper is used for training after reducing dimensions with Principal Component Analysis (PCA) [7].

In addition, it is difficult to produce as much abnormal state data as required for model training and validation from the actual NPP. Thus, it uses modified data that adds 1 % to 5 % noise to the already generated simulator data to resemble the actual data. The total experimental algorithm for data generation, model training and model validation is shown in the following figure. 2.

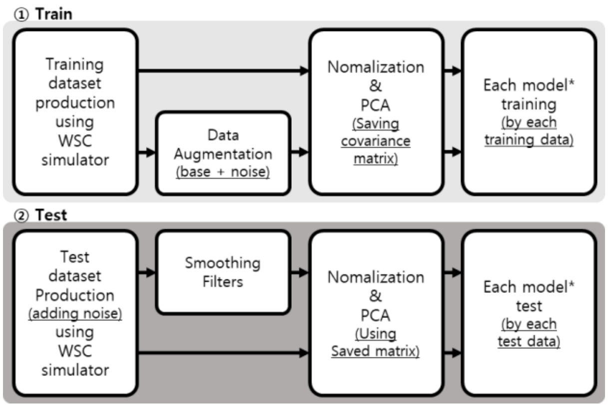

Fig. 2. Total experimental algorithm

3. Results

3.1 Base GRU Model Accuracy with Noise

As the noise increases as shown in Figure.3 below, the accuracy of the GRU model decreases. If the noise is only 3%, the accuracy of the model is reduced to 50%. Noise can be seen to have a significant impact on the stable judgment of the GRU model.

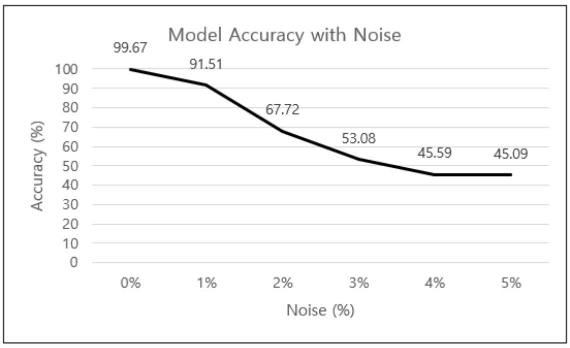

Fig. 3. Base model accuracy with noise

3.2 Model Accuracy with Each Method

According to Table. I below, untrained noisy data preprocessing by smoothing filters can be seen to enhance the stability of the model. The stability of the model is increased by up to 12.42 % and an average of 8.58 % by noise filtering.

Table I: Accuracy about Smoothing Filter Preprocessed Test Set

Smoothing Filter	3% noise	4% noise	5% noise	Avg(x'-x)
Base (x)	53.08	45.59	45.09	
Moving avg.	68.55	57.9	54.58	12.42
Triangle avg	64.56	55.57	53.24	9.87
Gaussian	60.90	53.24	51.08	7.15
Savitzky-Golay	58.07	49.75	50.58	4.88

Table. II and Figure. 4 below are the results of accuracy for models that have been trained together with data sets augmented by noise.

Table II: Modified Model Accuracy by Training Data Augmentation

Data Aug.	0% noise	1% noise	2% noise	3% noise	4% noise	5% noise
Base	99.67	91.51	67.72	53.08	45.59	45.09
1%	99.83	99.67	96.34	80.53	68.22	65.39
2%	99.83	99.83	99.67	99.17	92.85	87.18
3%	99.83	98.67	95.84	99.50	97.50	90.18

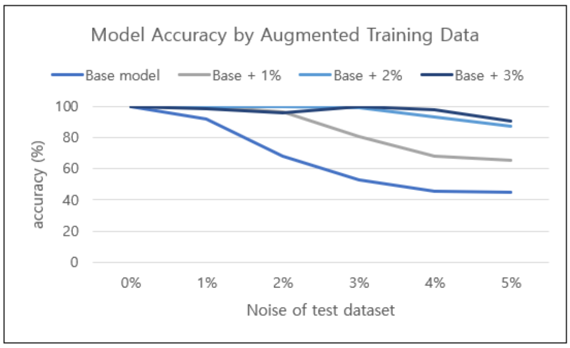

Fig. 4. Model accuracy by augmented training data

This method increases accuracy from 45% to 90% of 5% noise test data, even though only 3% of the noise is present in the training data set. In other words, even though untrained datasets had 3% higher noise than the training datasets, they maintained 90% correct diagnosis when tested. However, the higher noise is included in the training data set, the less accurate the test data for the lower noise is.

4. Conclusions

This paper considered the difference between the actual sensor data and the simulator data in the GRU model for diagnosing abnormal states. As the noise size of virtual data, similar to the actual sensor data, increases, the accuracy of the model decreases. However, virtual data preprocessed by smoothing filters made the model diagnose them easily. In addition, when the data set considering Gaussian noise was trained together, the model can modify to have high stability for noise. However, training with augmented data set which have greater difference between virtual and real data, it can make the model have lower stability for small noisy data. In the future work, it is necessary to find appropriate preprocessing methods and data augmentation degree through a sensitivity study to create a model optimized for actual data.

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