Fault Detection Method in the Startup Operation of Nuclear Power Plants

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1. Introduction

Nuclear power plants operate an online monitoring system that detects anomalies early by analyzing real-time signal data complexly for stable plant operation in the normal operation [1]. However, there is a limit to securing fault detection performance when using the signal prediction technique in the normal operation since the signal pattern is irregular and the correlation between the signals is weakened in the startup operation from the planned preventive maintenance to reaching the normal operation. In this regard, various prediction techniques are being studied [2], but it is difficult to use only statistics-based prediction techniques universally for the entire operation of nuclear power plants.

As nuclear power plants repeatedly perform planned preventive maintenance at regular intervals, it is possible to periodically secure signal patterns in the startup operation. Therefore, this paper proposes a fault detection method suitable for the startup operation using an approximate nearest neighbor search technique based on the similar vector search by learning the data patterns of the past startup operation and describes its effect.

2. Methods and Results

The fault detection system used in the normal operation of nuclear power plants uses the Auto-Associative Kernel Regression (AAKR) technique, which sets strong correlation signals as a group and learns data patterns of the past normal operation to predict normal status [3]. The period of the startup operation is shorter than the normal operation, but this period is of considerable importance as the section where the power of the plant reaches 100% after the planned preventive maintenance. In this section, the change of patterns in the signal group is diverse and the correlation between signals is also weakened. In case of the approximate nearest neighbor search technique, a tree index model is built by learning the data patterns of the past startup operation section, and the past value most similar to the current value is searched for as the predicted value. The predicted value is complemented to determine the symptom of anomalies through the approximate nearest neighbor search technique that determines whether there is a defect by comparing the residual with the actual value. In this method, it is possible to secure prediction accuracy by reflecting the effect of signal change due to long-term operation of systems and equipment by learning data patterns of the most recent startup operation.

2.1 Building an experimental model

Approximate Neatest Neighbors Oh Yeah (ANNOY) is an approximate nearest neighbor search technique that uses random projection. This technique constructs a tree index model by finding hyperplanes in the vector space based on the number of tree nodes set by the operator [4]. Using this tree index model, the tree node to which a newly input signal vector belongs is identified, and the most similar vector within that area is used to generate a predicted value [5].

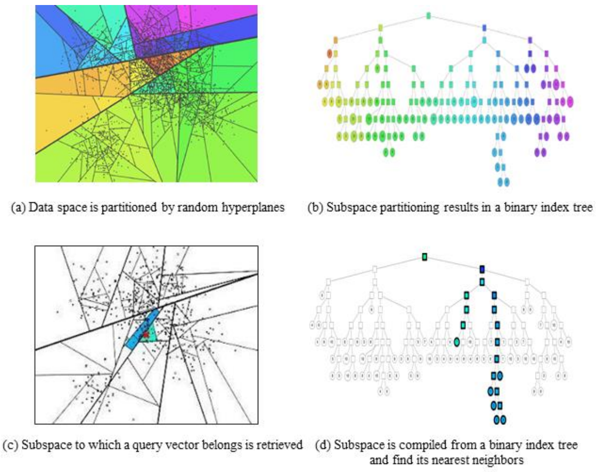


Fig. 1. Process of ANNOY algorithm

The subjects of the experiment were selected as the most representative signal groups exhibiting increasing trend, decreasing trend, and different physical units in the startup operation. The prediction accuracy was compared by applying the AAKR and ANNOY technique for each signal group. Since most of the signal group of the nuclear power plant fault detection system consists of less than 10 signals, it is suitable to apply the ANNOY technique.

2.2 Experimental procedure

The learning model for each signal group was trained with a total of 13,501 time-series data for the $n\text{-}1^{th}$ startup operation. For the experimental data, a total of 4,490 time-series data of the n^{th} startup operation were used. As the prediction accuracy becomes inaccurate when vectors with high similarity are located on the border of the hyperplane, 10 adjacent vectors are searched for priorities and then corrected with the average value. The detailed experimental information is presented in Table 1.

Table 1. Experimental dataset and parameters

Dataset	Train set	13,501 raw data
	Test set	4,490 raw data
AAKR	Kernel bandwidth	0.7
ANNOY	Number of Tree nodes	100
	Number of Nearest neighbors	10

The accuracy of prediction was determined by using the Euclidean distance in the same way as the existing fault detection system in the normal operation, and the Mean Square Error (MSE) obtained by squaring the residual, which is the difference between the actual value and the predicted value, was used:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\widehat{Y_i} - Y_i)^2 \quad (1)$$

2.3 Experimental results

The increasing trend signal group consists of a total three pressure signals, and the ANNOY showed that the MSE was 29.6 times more accurate on average compared to the AAKR. The decreasing trend signal group also consists of a total of three pressure signals, and the ANNOY was more than 218 times accurate on average. A signal group with different physical unit group consists of one current signal and three temperature signals, and the ANNOY showed that the current signal was 15 times and the temperature signal was 5.9 times more accurate on average. The MSE comparison results for each signal of the model groups are described in Table 2.

Table 2. MSE of residuals for each group

Group	Signal (Unit)	AAKR	ANNOY
Increasing Trend Group	Pressure 1 (kg/cm^2)	1.494	0.049
	Pressure 2 (kg/cm^2)	1.481	0.049
	Pressure 3 (kg/cm^2)	1.426	0.051
Decreasing Trend Group	Pressure 1 (kg/cm^2)	0.245	0.001
	Pressure 2 (kg/cm^2)	0.263	0.001
	Pressure 3 (kg/cm^2)	0.292	0.002
Different Physical Unit Group	Current (A)	0.046	0.003
	Temperature 1 (Degree C)	0.043	0.007
	Temperature 2 (Degree C)	0.043	0.007
	Temperature 3 (Degree C)	0.048	0.009

The time-series graph results for the actual and predicted values of the representative signals for each model group are shown in Fig. 2~4.

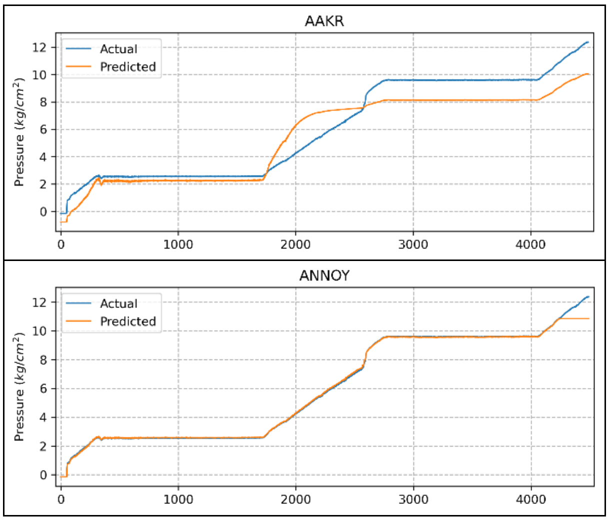


Fig. 2. Pressure 1 signal results of the increasing trend group

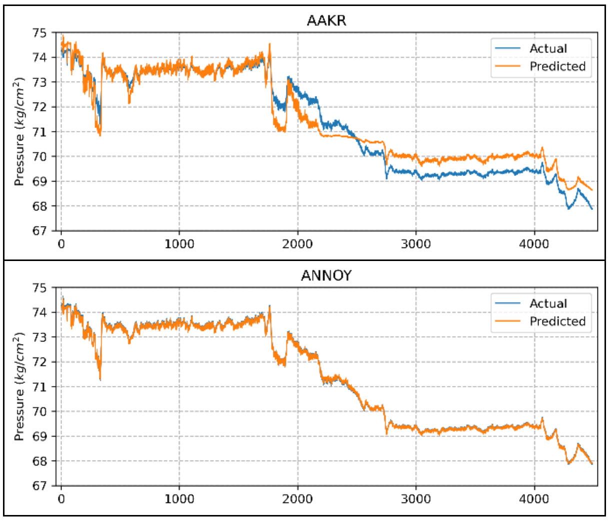
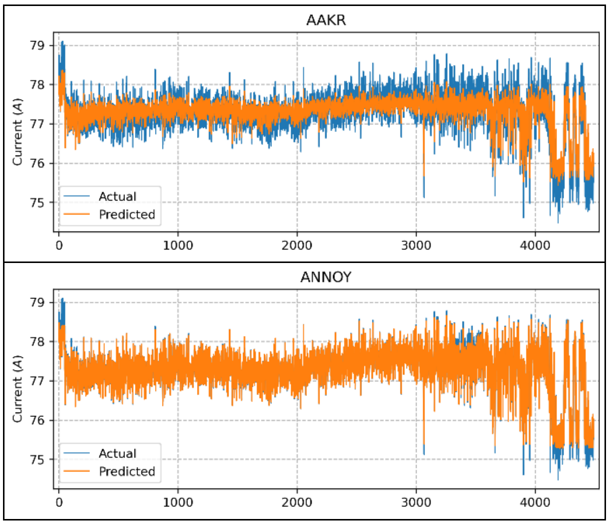


Fig. 3. Pressure 1 signal results of the decreasing trend group



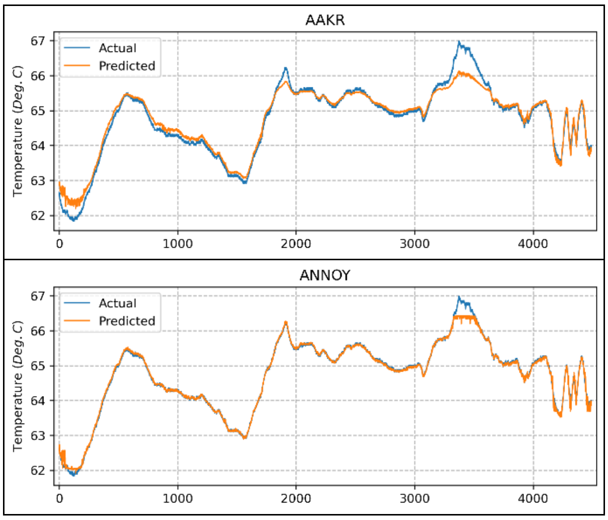


Fig. 4. Current signal & Temperature 1 signal results of the different physical unit group

As shown in the graphs, the AANOY has a smaller residual than the AAKR and follows the actual value well. It means that the AANOY enables early warning by detecting residuals at a faster time when an anomaly occurs.

3. Conclusions

As the signal patterns in the startup operation of nuclear power plants have a wide range of variation and weak correlation, prediction errors may occur above the allowable level when using existing statistics-based prediction techniques. Therefore, a suitable fault detection method for the startup operation is proposed which can reduce the prediction error by learning historical data patterns to create an index tree model and using an approximate nearest neighbor search technique. As a result of the experiment by selecting signal groups with the increasing trend, the decreasing trend, the different physical units representing the startup operation, it was shown that the prediction accuracy was high in all groups. It is possible to detect residual changes at a faster time in the event of anomalies during the actual startup operation, so that the warning is notified early to safely reach the normal output operation.

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