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Development of an Artificial Intelligence-Based Vibration Monitoring System for Centrifugal Pump Anomaly Detection

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1. Introduction

Nuclear power plants require high-level safety management. The pumps play a critical role by moving coolant or cooling water in a nuclear power plant, and any abnormal operation of the pumps can impact the safety and reliability of the entire system. Therefore, the necessary of condition monitoring of the pump integrity has been continually emphasized in relation to the safe operation of nuclear power plants [1-3]. The vibration monitoring systems for pumps in nuclear power plant are installed and operated using sensors such as accelerometers, acoustic emission (AE) sensors, and temperature sensors [4].

However, the conventional vibration monitoring systems operate by triggering alarms based on predefined vibration tolerance thresholds. Detailed anomaly diagnosis still heavily relies on expert judgment.

As one of the ways to address these issues, research on the development of monitoring and diagnosis technologies using artificial intelligence (AI) models has recently been actively conducted [5,6]. The introduction of artificial intelligence can be a solution to improve the reliability and automation in the monitoring field, but research on several considerations such as data collection and labeling, feature parameters and model selection, preventing overfitting still needed. These considerations are interrelated.

Data collection is the first problem faced in applying artificial intelligence in the nuclear power plant field, where amount of abnormal data is very small and it is difficult to obtain field data. The lack of data causes the possibility of overfitting of AI model. An overfitting model is applicable only to a limited subject, and that are difficult to apply to actual fields. Preventing the overfitting, research about feature parameter for condition monitoring and model development for diagnosis are needed.

In this research, a pump test bed was used to obtain data. The abnormal state was simulated on the pump test bed, and the normal data and abnormal data was acquired by measuring the vibration signal and some sensor signals generated at each state. To build an AI model for fault diagnosis using the acquired data, recurrent neural networks (RNNs) or variational autoencoders (VAEs) are considered. In addition, studies were conducted to utilize feature parameters as well as time series data to reduce domain dependence and prevent model overfitting.

As a result of this research, one of the functional elements of the pump vibration monitoring system using artificial intelligence was developed.

2. Experiments and Results

In this section experiments for securing data and artificial intelligence models for diagnosis of anomalies were explained.

2.1. Data acquisition

By employing a pump test bed system as shown in Fig. 1, normal state signals and abnormal signals resulting from pump misalignment have been acquired. Through experimentation, both types of faults, Angular misalignment and parallel misalignment, were implemented across four distinct severity levels for each. Additionally, data pertaining to scenarios where these two faults occur simultaneously have also been obtained.

Fig. 1. Pump test bed for acquiring vibration data according to shaft misalignment

Table I: Misalignment Defect

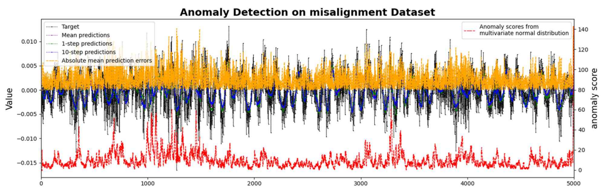
	Angular (mm)	Parallel (mm)
Defect1	0.13	0.17
Defect2	0.35	0.35
Defect3	0.55	0.55
Defect4	0.85	0.85

2.2. Anomaly Detection

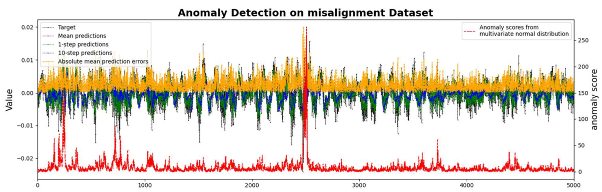
Prior to applying artificial intelligence, parameters generally used for diagnosing rotating machinery such as statistical parameters and time-frequency features were analyzed. Through this process, it was confirmed whether the acquired data included the shaft misalignment abnormal state characteristics of the pump, and it was confirmed how the characteristic parameters commonly used for diagnosing pump abnormalities differ according to the defect stage.

For anomaly detection, Recurrent Neural Network (RNN) was used in this research. RNN can identify and predict time series patterns by using this sequential information and can consider the temporal dependence of data. Therefore, RNN can be appropriately used for diagnosing rotating machinery that utilizes periodicity data. However, RNNs do not handle long-term dependencies well. Therefore, in order to overcome these disadvantages, researchers use variant models of RNNs such as LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit). In this study, these models were also applied to examine the appropriateness of diagnosing rotating machines using RNN models.

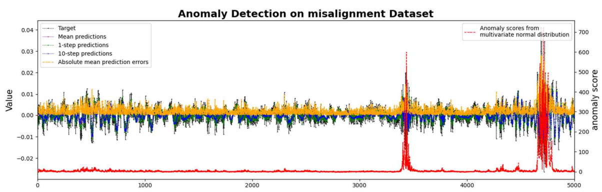
The model was trained using only the normal data among the acquired data, and anomaly scores were calculated by the difference between the data predicted by the train model and the abnormal to diagnose the abnormal state.



(a) Normal State



(b) Abnormal State - Angular



(c) Abnormal State - Parallel

Fig. 2. Result of pump abnormality diagnosis using artificial intelligence model

Fig. 2 shows a graph of the abnormality detection results using vibration signals. The red line represents the anomaly score, and the anomaly score of normal data were analyzed and the standard value was set to 100. If the anomaly score was above the standard, an abnormality was detected. The accuracy of diagnosis for experimental data is approximately 90%.

3. Conclusions

Research was conducted to develop a technology for diagnosing abnormalities using vibration signals and artificial intelligence for pump condition monitoring.

Vibration signals due to shaft misalignment were obtained using a pump test bed, and an anomaly diagnosis model using time-series data was constructed using an RNN, and pump misalignment diagnosis performance of the built model was confirmed using anomaly data.

Result of this study can be used as a one of technology for vibration monitoring system of rotating machinery in nuclear power plants.

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