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Development of Continuous Pipe Leakage Diagnosis System for Secondary Systems of Operating Nuclear Power Plants

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1. Introduction

Secondary systems in operating Nuclear Power Plants (NPPs) play an important role in generating electricity by converting thermal energy from the primary system to mechanical energy using components such as turbines, condensers, pumps, and pipes. As mechanical components degrade with time, even small, undetected defects can lead to unexpected downtime, jeopardizing both economy and safety. To mitigate these risks, the development of a reliable fault diagnosis system has become essential [1].

In general, the fault diagnosis system involves monitoring with sensors. Collected signals are subjected to signal processing techniques such as denoising and filtering to extract meaningful features. Then, the trained AI model determines the presence of defects using the processed data. However, the current system still requires a certain degree of manual operation, implying that human error is inevitable. Furthermore, AI models tend to perform well in experimental settings, but require adjustments when installed in different NPPs due to variations in environmental and operational conditions.

To address these challenges, this paper proposes the development of a continuous pipe leakage diagnosis system for the secondary systems of operating NPPs, adapting cloud-native and MLOps.

2. Continuous Diagnosis System

The proposed system allows continuous diagnosis and flexible AI model adjustment by integrating cloud computing and MLOps. The cloud-native solution automates application management, hardware scaling, and failure controls. However, the conventional cloud pipelines alone do not suffice for AI systems, as they lack the capabilities of model version control and performance monitoring. MLOps complements these shortages by managing the full lifecycle of AI, including model training, hyperparameter tuning, and deployment. Integration of cloud computing and MLOps significantly reduce human error and increase the system reliability and scalability.

2.1 Cloud-Native Solution

Cloud-based systems dynamically allocate hardware resources and automate software tasks such as initiating and managing applications through programmable infrastructure. Additionally, cloud-native solutions offer auto-scaling capabilities, which adjust the number of running applications to the demands by the system without requiring human intervention [2]. In the event of a system failure, the proposed system can also re-initiate the corresponding task and facilitate real-time, continuous fault diagnosis. The proposed fault diagnosis system aims to minimize human intervention as much as possible by integrating cloud-native solutions.

2.2 Optimizing AI model

The AI model training is an important step in the development process. The performance of the model depends heavily on the balance between external and internal parameters. Especially for NPPs, fine tuning AI models is essential, for each NPPs have their unique environmental and operational conditions. MLOps assist this section by adjusting internal parameters such as biases and weights of a pre-trained model to improve its performance on a decision-making task. Hyperparameter tuning, which includes optimizing the learning rate, number of epochs, and optimizers can further improve the accuracy of the model performance.

3. System Implementation

The proposed pipe leakage diagnosis system begins with data collection from wireless sensors. The sensor transmits ultrasonic acoustic signals, which are processed using Fast Fourier Transform (FFT) technique. The processed data is then sent to the trained deep learning model for decision-making.

3.1 Ultrasonic Acoustic Signal Processing

According to the Nyquist theorem, the sampling rate should be twice the highest frequency of the signal. Since the highest frequency of the signal was 100kHz, a sampling rate of 256kHz was selected for accurate representation. Each FFT takes about 4ms to process, and the graph on the display server represents the average frequency spectrum of 10 FFT results. In the absence of delay, it would be updated approximately every 40ms.

3.2 System Integration

After FFT processed signals undergo AI-model-based diagnosis, the real-time sensor data and their respective leakage probabilities are displayed on the implemented Graphical User Interface (GUI). In addition, every material has their characteristic frequency regions which are used to determine the presence of the leakage. For this experiment, the frequency spectrum data is represented in the range of 20kHz to 100kHz, Fig. 1. The pipe leakage is determined by looking at the leakage probability of the specific sensor on the graph.

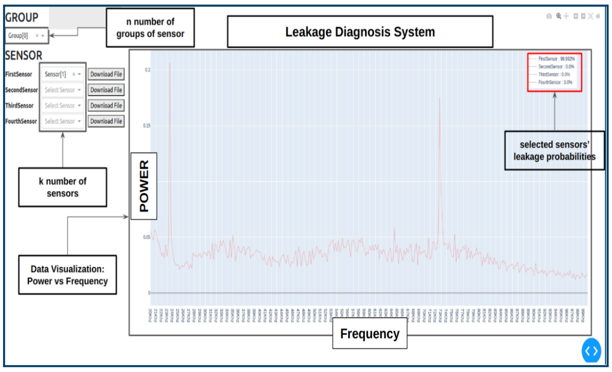

Fig. 1. Display server draws a real-time graph of sensor data with failure probabilities on the top right corner.

To prevent hardware overuse, the proposed system is divided into individual servers based on their unique functions: signal collection, processing, and display. These servers communicate through wireless network protocols such as Transmission Control Protocol (TCP) and Representational State Transfer (REST). Then, the pipe leakage diagnosis servers are integrated to the cloud-native solution. The status of each server application is easily managed through terminal commands. The auto-scaling and failure control functionalities of the cloud-native solution was confirmed by intentionally stopping one random server while the system was running. The GUI was not interrupted during this process, thus ensuring reliability to the proposed system.

For AI model optimization, hyperparameter tuning was studied using as a preliminary study. The goal was to find the optimal external parameters, such as learning rate, batch size, and optimizer, for training. Experiment was conducted by simulating the training of a 6-layered convolutional neural network (CNN) for 30 times. The best simulation result was found when 1.48e-3 learning rate, 11 epochs and the Adam optimizer were set with the highest accuracy of 97.92%.

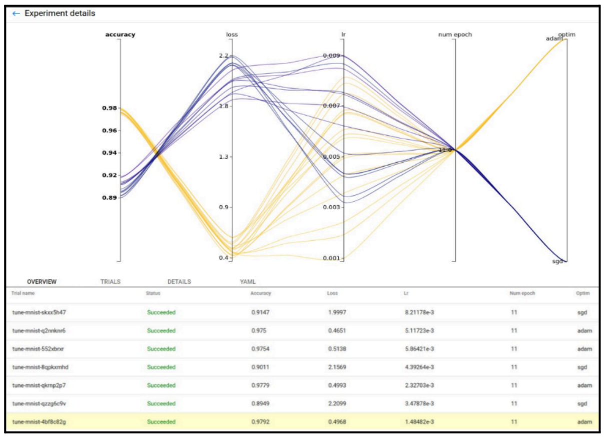

Fig. 2. Experimental result of hyperparameter tuning testing.

Currently, more research is being conducted for the development of environment-adaptive AI models. Once its performance is verified, it will be integrated into the implemented diagnosis system.

4. Conclusions

In summary, a wireless sensor-based pipe leakage diagnosis system has been implemented to monitor secondary systems in operating NPPs. Auto-scaling and autonomous system-wide management capability of the cloud-native solution allow the proposed system to run continuously and minimize human error. MLOps integration can improve the system performance consistency by providing flexibility to adapt to various NPPs. As a result, the implemented system significantly reduces unplanned plant downtime and provides an effective diagnostic strategy. Future research focuses on developing a mechanism to automate the optimization of AI models for fault diagnosis in an air-gapped condition.

REFERENCES

[1] Korea Institute of S&T Evaluation and Planning (KISTEP), KISTEP Report, 11-1721000-000597-01, 2011.
[2] G. Kulkarni, P. Khatawkar, and J. Gambhir, Cloud Computing-Platform as Service, International Journal of Engineering and Advanced Technology (IJEAT), Vol-1, Issue-2, 2011.

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