

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

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1. Introduction

The secondary system of an operating nuclear power plant (NPP) is responsible for generating electricity. Components such as turbines, condensers, and associated pipes and pumps work together to convert thermal energy of the primary system into mechanical energy. Undetected mechanical failure in any of these components can result in unexpected downtime, putting both economic losses and safety at risk. To mitigate these risks, recent research has focused on developing fault diagnosis systems [1].

A fault diagnosis system begins with collecting data using appropriate transducers and sensors. The captured signals are then processed using various signal techniques, including time-, frequency-, and time-frequency domain analyses. The processed data is subsequently fed into a trained artificial intelligence (AI) model for decision-making.

However, current diagnosis systems require a certain degree of human intervention, implying that human error is inevitable. Furthermore, the performance of AI models is often limited to experimental environments and requires modifications when used in different NPPs due to varying environmental factors and operating conditions. To address these challenges, this paper proposes the development of a continuous diagnosis system for the secondary systems of operating NPPs that is also capable of tuning AI models.

2. Continuous Diagnosis System

A comprehensive approach is required to enable continuous diagnosis and improve the adaptability of AI models to secondary systems in operating NPPs. This approach involves the integration of advanced technologies that not only automate the fault detection process but also enable the AI models to be continuously tuned to meet the unique operating conditions of different plants. By leveraging a cloud-native solution, the proposed system aims to provide a robust and adaptable diagnosis system that can significantly reduce the chance of human error and improve the overall reliability. The following sections

explain cloud-native infrastructure and the model optimization to achieve these goals.

2.1 Cloud Native Solution

The proposed fault diagnosis system aims to minimize human intervention by integrating cloud-native solutions. Cloud-based models allow dynamic provisioning of hardware resources and automate tasks such as initiating and managing applications through programmable infrastructure. Additionally, cloud-native solutions offer auto-scaling capabilities, allowing the number of applications to adjust to demands without human intervention [2]. In the event of system failure, the proposed system can also restart the affected application, facilitating real-time, continuous fault diagnosis of secondary systems in NPPs.

2.2 Optimizing AI model

Training an AI model is a critical step in the development process. The performance of the model highly depends on the balance of external and internal parameters. Especially in NPPs, fine-tuning the AI models is essential, because every NPPs have unique environments. This process involves adjusting internal parameters such as biases and weights of a pre-trained model to improve its performance on a specific task. Hyperparameter tuning, which includes optimizing the learning rate, number of epochs, and optimizers can further enhance the accuracy of the model.

3. System Implementation

The proposed fault diagnosis system begins with data collection from wireless sensors. The data collected for the experiment are noise signals to test pipe leakage. The transmitted signals are processed using Fast Fourier Transform (FFT) technique and then sent to a trained deep learning model for decision-making. The signals and diagnosis results are displayed in a Graphical User Interface (GUI), so that users can access real-time sensor data and the corresponding leakage probability.

To prevent hardware overuse, the proposed system is divided into individual servers based on unique features

(signal collection, processing, and displaying). These servers communicate using wireless network protocols such as Transmission Control Protocol (TCP) and Representational State Transfer (REST). Leakage diagnosis servers are integrated into the cloud-native solution, and the status of each server application is managed through terminal commands in cloud-native solution. To validate the performance of the implemented system, the display server was tested using wireless sensor data.

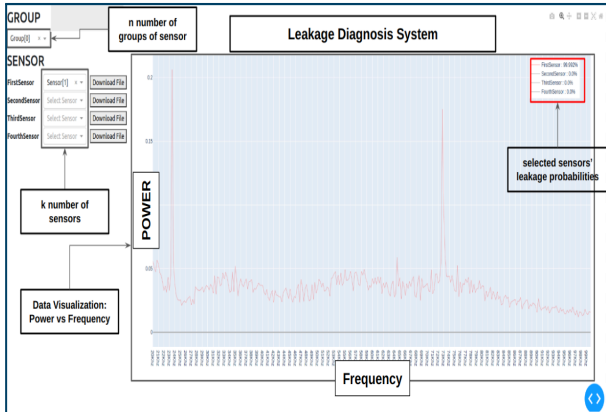


Fig. 1. Display server draws a real-time graph of sensor data with failure probabilities on the top right corner.

In the experiment, FFT takes the wireless sensor data (time-domain signal) and represents it in the frequency domain. This allows the analysis of the signal with respect to a specific frequency range. For every material, there is a characteristic frequency region that can be used to determine the presence of faults. For this experiment, the frequency spectrum data is displayed in the range of 20kHz to 100kHz, Fig. 1.

According to the Nyquist theorem, the sampling rate should be at least twice the highest frequency present in the signal. Since the highest frequency of the signal is 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. This means that in the absence of delay, it would be updated approximately every 40ms. This configuration allows for real-time, continuous monitoring and analysis. The presence of a pipe leakage can be easily determined by looking at the top right corner of the graph, which indicates the leakage probability of a specific sensor.

For model optimization, hyperparameter tuning was tested using the MNIST dataset as a preliminary study. The goal is to find the optimal settings for training by adjusting external parameters like the learning rate, batch size, and optimizer. A simple Convolutional Neural Network (CNN) architecture (5-layered) is employed for this task. Experimental result shows that the highest accuracy is achieved with a learning rate of $1.48e-3$, 11 epochs and the Adam optimizer, Fig. 2.

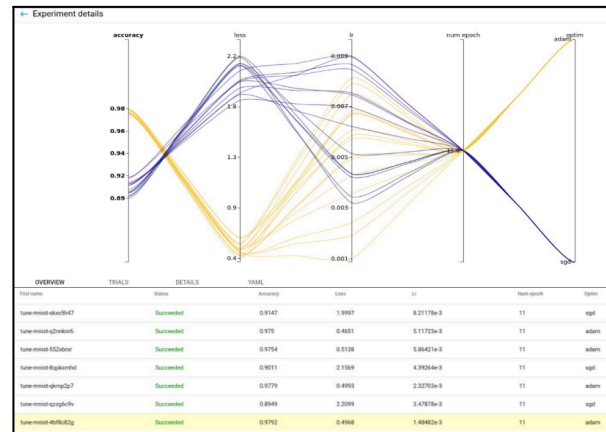


Fig. 2. Experimental result of hyperparameter tuning testing.

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

4. Conclusions

In summary, a cloud-native integrated, wireless sensor-based pipe leakage diagnosis system has been implemented for the secondary systems in operating NPPs. The proposed system enables continuous diagnosis with the ability to autonomously restart erroneous applications, thereby minimizing human errors. Consequently, the implemented system offers an effective diagnosis strategy that significantly reduces unplanned interruptions during operation and positively influences the efficiency and reliability of plant operations. Future work will focus on developing and integrating a strategy to automate the optimization of the diagnosis model, adding flexibility and further enhancing the reliability of the proposed diagnosis system.

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