Improved Anomaly Detection in Air Conditioners Using IoT Technologies

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***Abstract*—The prediction of anomalies and the diagnosis of various machines using Internet of Things (IoT) technology is a topic of extensive research. In this study, IoT technology was utilized to develop a system for collecting data and diagnosing existing air conditioners, with a focus on anomaly detection. Building on our previous research, which explored strategies for deploying vibration sensors in various locations to optimize seasonal diagnosis models, this study introduces a method for improving anomaly detection accuracy. The method leverages air-conditioner-specific sensor data analyzed using the Mahalanobis-Taguchi (MT) method, which calculates the Mahalanobis distance for normal sensor values and vibration data. Discrepancies in sampling rates between vibration and air-conditioner-specific sensor data were addressed using the proposed analysis method.**

***Index Terms*—IoT, Anomaly detection, AI, Data mining**

I. Introduction

Machines installed in various facilities are critical components of infrastructure, and their anomalous behavior can significantly impact both the environment and business continuity. Consequently, anomaly prediction and diagnosis are crucial for preventing such issues. This study focused on employing Internet of Things (IoT) technology to implement a system for collecting data and diagnosing existing air conditioners, with a particular emphasis on anomaly detection. We discussed strategies for deploying vibration sensors in optimal locations within noisy environments, ensuring the precise tuning of seasonal diagnosis models, and the automated construction of anomaly detection models [1] [2].

We enhanced anomaly detection accuracy by incorporating air-conditioner-specific sensor data alongside vibration data. While the former represents device-specific information, similar data can be collected across various models and utilized by experienced technicians to diagnose abnormalities. Previous studies demonstrated the feasibility of detecting abnormalities in air conditioners year-round. However, instances of reduced detection accuracy were observed, particularly due to failures in indoor units. To address this, we showed that anomaly detection accuracy could be further improved by analyzing air-conditioner-specific sensor data using the Mahalanobis-Taguchi (MT) method [3]. Discrepancies in the sampling rates of vibration data and air-conditioner-specific sensor data were resolved using the proposed analysis method.

Hereafter, Section 2 presents relevant prior studies in this field. Section 3 provides details about the target air conditioner and IoT sensors, while Section 4 outlines our solution approach. Section 5 presents the experimental results, and Section 6 summarizes our findings.

II. Related work

Extensive research has been conducted on machine anomaly detection. For industrial applications, Kondo [4] developed a diagnostic system for vehicle equipment using octave band analysis and one-class classification for anomaly detection. Nomura et al. [5] evaluated the integrity of piping valves by detecting changes in vibration within a bubble body caused by fluid pressure fluctuations, employing a convolutional neural network [6] [7].

These studies, however, relied on the assumption of accurate data availability and overlooked the influence of climatic and seasonal conditions on the operational states of the machinery. Furthermore, these studies did not focus on the abnormalities specific to air conditioning.

The MT method has been widely applied to tasks such as diagnosing the deterioration of power distribution equipment [8] and evaluating stress from biological data [9]. However, these studies relied solely on the MT method without integrating it with other approaches. Building on our previous research, we proposed a method to enhance anomaly detection accuracy using air-conditioner-specific sensor data analyzed using the MT method alongside vibration data.

III. System configuration

Figure 1 illustrates the configuration of the air conditioner and sensor installation location. We focused on both indoor and outdoor air conditioning units. The compressor, serving as the primary power source, increases the refrigerant's temperature and pressure through compression. The expansion

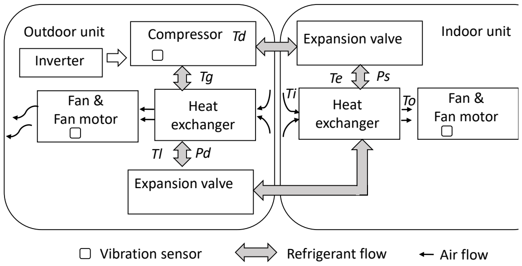
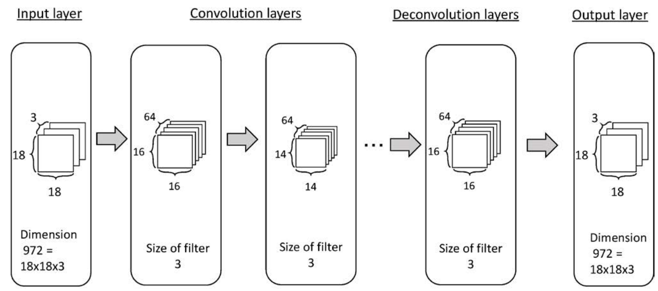


Fig. 1. Configuration of air conditioner and sensor installation

#	Data group	Related unit	Symbol	Measured amount(unit)	Description
1	Data group 1	Indoor unit	*Ti*	Celsius(°C)	Intake temperature
2			*To*	Celsius(°C)	Outlet temperature
3	Data group2	Outdoor unit/Indoor unit	*Pd*	MPa	Pressure(High Pressure side)
4			*Ps*	MPa	Pressure(Low Pressure side)
5			*Td*	Celsius(°C)	Compressor upside temperature
6			*Tl*	Celsius(°C)	Heat exchanger liquid side temperature
7			*Tg*	Celsius(°C)	Gas Pipe Temperature
8			*Te*	Celsius(°C)	Evaporation temperature

Sampling rate : Every minute

#	Sensor category	Measurements(unit)	Sampling freq
1	Vibration sensor	Acceleration(m/s²)(3axis)	50Hz



Convolution layer	Deconvolution layer	Each layer number of filters
7	7	[64,64,128,128,256,256,256]

Fig. 2. Configuration of Convolutional Autoencoder

valve, by forcing the refrigerant through a constricted opening, reduces its temperature and pressure while automatically regulating the flow rate and superheating process. Air circulation in both indoor and outdoor spaces is managed by the fan motor, and the heat exchanger facilitates heat transfer between the refrigerant and the surrounding air in both environments. The inverter, in conjunction with the temperature controller, regulates the compressor's operation to maintain the desired temperature.

Based on the prior experiment [1], three-axis vibration sensors were installed in outdoor and indoor fan motors to detect equipment failure at early stages. We also installed air-conditioner-specific sensors *Ti*, *To*, *Pd*, *Ps*, *Td*, *Tl*, *Tg*, and *Te* within the air conditioner. These sensors measured the air temperature, refrigerant temperature, and refrigerant pressure at each location, as shown in Figure 1. Similar sensors are widely used diagnostic tools in modern air conditioners.

IV. Anomaly detection method

A. Data collection condition

Table I lists the data collection conditions of the vibration sensors. Based on sensor specifications, the sampling rate of each vibration sensor was set to 50 Hz. Vibration data were collected using the same method employed in a previous study using an IoT-gateway (GW) [1].

Table II details the data collected by the air-conditioner-specific sensors. *Ti* and *To*(data group 1) are associated with the operation of the indoor unit; while *Pd*, *Ps*, *Td*, *Tl*, *Tg*, and *Te*(data group 2) are linked to the operation of both indoor and outdoor units. The sampling rate for all sensors was set to every minute, and the data were collected through a port dedicated to air conditioners.

B. Data analysis procedure

Our study employed a convolutional autoencoder (CAE) [10] to analyze vibration data. Autoencoders [11], which are neural networks designed to model normal operational conditions, were utilized, with the CAE specifically incorporating convolution and deconvolution layers for data processing (see Figure 2). The input to the CAE comprised 324-point power spectra, derived from fast Fourier transform (FFT) calculations on each three-axis vibration measurement. The size and number of filters were determined through preliminary experiments [1].

Given that the input data represent normal operational status, the difference between the input and output is relatively small. Anomalies are detected by comparing these differences against a specific threshold. The anomaly score E is defined as the mean square error from the predicted data x and observed data x' below:

$$E = \frac{\sum_{n=1}^{N}(\parallel x_n - x'_n \parallel)^2}{N}$$

where the dimension N of x and x' is 972.

Next, we outline an analysis procedure for air-conditioner-specific sensor data, which is expected to improve detection accuracy. The sensor data were collected at a sampling rate of 1 per minute, in accordance with device specifications. Due to the smaller volume of air-conditioner-specific data compared to vibration data (sampling rate of 20 ms), it was not feasible to directly apply the CAE. Instead, we employed the simpler MT method. The MT method utilizes the Mahalanobis distance, a measure that accounts for correlations between variables, enabling it to sensitively detect deviations from the normal data group. The procedure for the MT method is formulated as follows:

Step1: Prepare data D = $\{x_1, .., x_N\}$that are known to be normal and observed data D' = $\{x'_1, , , x'_{N'}\}$ to be evaluated. Both the variables are M-dimensional.

Step2: Calculate the sample mean

$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

and sample covariance matrix

$$\hat{\sum} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{\mu})(x_i - \hat{\mu})^\top$$

based on D.

Step3: Calculate the Mahalanobis distance (anomaly sc

$$d(x_i') = (x_i' - \hat{\mu})^\top \hat{\sum}^{-1} (x_i' - \hat{\mu})$$

to evaluate D'. If $d(x_i')$ is smaller than the threshold, the observed data are considered normal; otherwise, they are determined to be anomalous.

The MT method was used to evaluate the two input cases corresponding to data groups 1 and 2.

The final anomaly evaluation was determined by combining the results for the vibration and air-conditioner-specific sensor data as follows:

Step1: Determine whether anomalies are detected in vibration data analysis. If an anomaly is detected, the location of the corresponding sensor (outdoor or indoor) is considered abnormal. Otherwise, proceed to Step 2.

Step2: Determine whether anomalies are detected in the data group 1 analysis. If an anomaly is detected, it can be assumed to occur in an indoor unit; otherwise, proceed to Step 3.

Step3: Determine whether anomalies are detected in the data group 2 analysis. If an anomaly is detected, it can be assumed to occur in an indoor unit; otherwise, the air conditioner can be assumed to operate normally.

The results of the preliminary experiments indicated that abnormalities in the outdoor unit could be detected from vibration data alone, Steps 2 and 3 are required to detect abnormalities in the indoor unit.

V. EXPERIMENTAL RESULTS

A. Test items and condition

Table III presents an overview of the field test result. We collected data for normal and anomalous operational conditions for one day each in summer and winter. For the failure tests, the air volume was decreased by 50% and 80% as the inhalation port was closed step by step while maintaining a fixed temperature settings of 27 ° C and 20 ° C for summer and winter, respectively.

B. Failure test results

Figures 3 and 4 show the results of failure tests conducted on the indoor and outdoor units during the summer. The learning data were collected over a one-hour period during which the air conditioner operated normally on the day of the experiment. The threshold was set to the lowest level at

#	Test round	Test date	Testing scenario
1	1st failure test	8/21/2020	Air volume decrease caused by closing the intake port of the indoor and outdoor unit by 50% and 80%. (Cooling mode, temperature set to 27 °C)
2	2nd failure test	12/15/2020	Air volume decrease caused by closing the intake port of the indoor and outdoor unit by 50% and 80%. (Heating mode, temperature set to 20 °C)

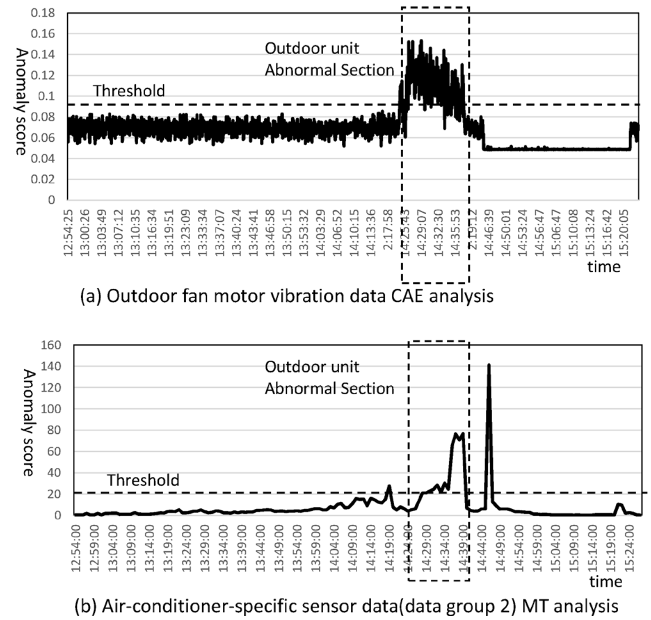


Fig. 3. Transition in CAE and MT anomaly score in outdoor failure test(1st failure test)

which normal and abnormal operations could be distinguished. In the outdoor unit failure test(Figure 3), both the vibration and air-conditioner-specific sensor data were used to detect anomalies; and the air-conditioner-specific sensor data yielded an abnormality score that corresponded to the proportion of inhalation port closures (50% and 80%). For the indoor unit(Figure 4), the trends observed were similar to those of the outdoor unit; however, the anomaly detection accuracy—measured by the difference in anomaly scores between normal and abnormal data—was lower in the vibration data compared to the outdoor units. Additionally, there were instances where abnormalities could not be detected using the air-conditioner-specific sensor data.

Figures 5 and 6 show the results of the failure tests on the indoor and outdoor units during winter, using the same method for determining the learning data and anomaly detection threshold as those used in the summer experiment. In the outdoor/indoor unit failure test(Figure 5), the vibration data successfully detected abnormalities. However, the air-conditioner-specific sensor data were unable to detect abnormalities where the degree of closure was 50% (during the first half of the abnormal section). In the indoor unit failure test(Figure 6), neither the vibration data nor the air-conditioner-specific sensor data (data group 1) could detect

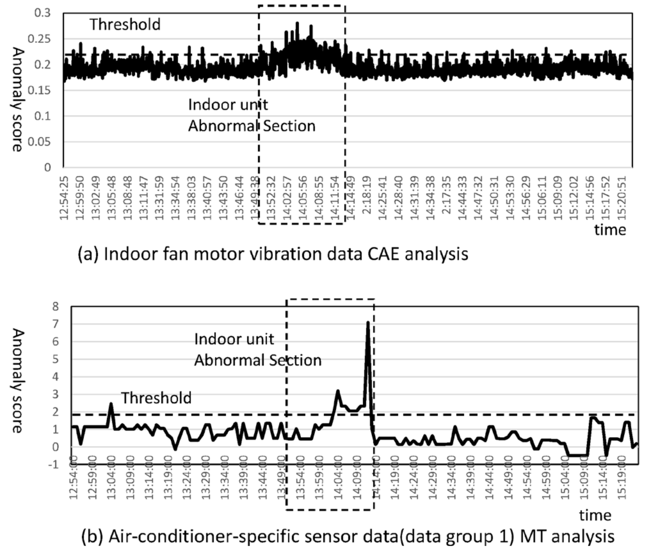


Fig. 4. Transition in CAE and MT anomaly score in indoor failure test(1st failure test)

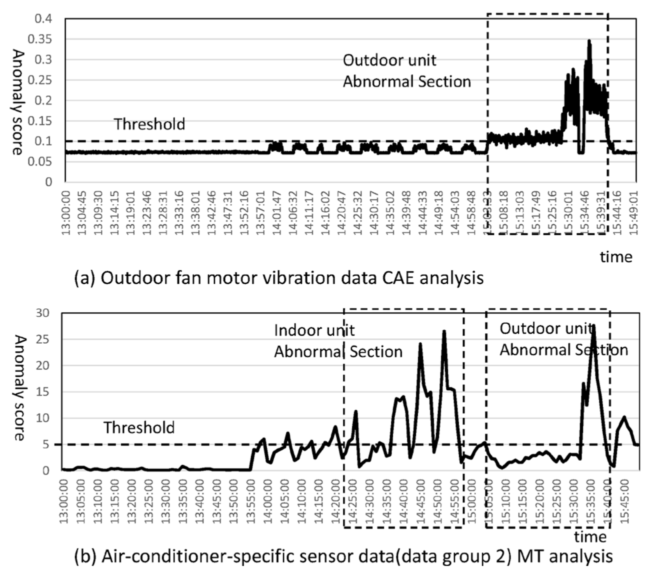


Fig. 5. Transition in CAE and MT anomaly score in outdoor/indoor failure test(2nd failure test)

abnormalities. However, as shown in Figure 5(b), the air conditioner-specific sensor data (data group 2) can be used to detect indoor unit failures under winter conditions.

C. Summary and suggestion

Table IV summarizes the results of the failure tests, showing that the procedure described in Section IV accurately detected failures in both the outdoor and indoor units. Furthermore, by using both vibration and air-conditioner-specific sensor data, the degree of abnormality can be determined from the anomaly score, thereby improving the reliability of anomaly detection.

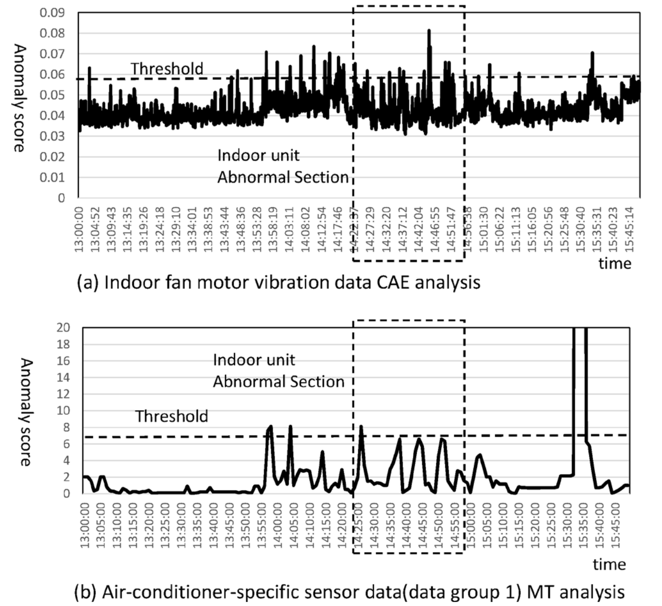


Fig. 6. Transition in CAE and MT anomaly score in indoor failure test(2nd

#	Test scenario	Failure location	Vibration data(Indoor fan motor)	Vibration data(Outdoor fan motor)	Air- conditioner-specific sensor data (data group 1)	Air-conditioner-specific sensor data (data group 2)
1	Failure test(1st:Cooling)	Indoor unit	Ob	Nob	Pob	Nob
2		Outdoor unit	Nob	Ob	Nob	Ob
3	Failure test(2nd:Heating)	Indoor unit	Nob	Nob	Nob	Ob
4		Outdoor unit	Ob	Ob	Nob	Pob

Ob:Observed Nob:Not observed Pob:Partially observed

VI. Conclusion

In this study, we developed a method for improving anomaly detection accuracy by analyzing air-conditioner-specific sensor data using the MT method, which calculates the Maharanobis distance for a normal sensor values along with vibration data. The features of the proposed method are summarized below.

- The anomaly detection procedure can identify failures in both outdoor and indoor units by combining the analysis of vibration and air-conditioner-specific sensor data.
- The difference in sampling rates between the data was addressed using the convolutional autoencoder(CAE) for vibration data and the MT method for air-conditioner-specific sensor data.
- By using both vibration and air-conditioner-specific data, the anomaly score can indicate the degree of abnormality, enhancing the reliability of anomaly detection.

The experimental findings presented in this paper confirm the effectiveness of the proposed method.

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