Technology Introduction

Condition monitoring for hydraulic equipment

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1 Introduction

In recent years, there has been a rising demand in the hydraulic equipment market for improving maintenance efficiency through deterioration and failure prediction. More than half of all hydraulic equipment problems are caused by contaminated and/or deteriorated hydraulic fluid (Fig. 1). Although such fluid should be replaced with proper oil before equipment failure occurs, fluid contamination and deterioration management is said to involve many challenges. Against this backdrop, KYB launched an oil condition diagnosis initiative, prioritizing the resolution of the hydraulic equipment maintenance challenges through fluid sensing.

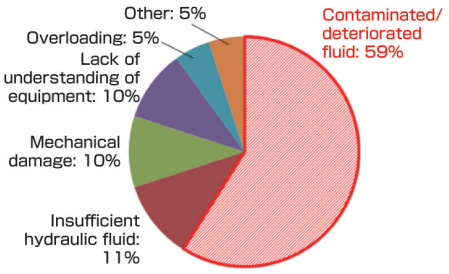

Fig. 1[1] Causes of hydraulic equipment problems

Two popular types of conventional hydraulic equipment maintenance are proactive maintenance and time-based maintenance (TBM). Proactive maintenance involves loss due to equipment downtime because maintenance actions occur after a failure. TBM poses the issue that the fluid must be changed even if it can still be used, incurring unnecessary cost.

KYB has promoted the independent development of an oil condition sensor and the development of an oil condition diagnosis system using IoT technology (described later) to achieve condition-based monitoring (CBM) through real-time monitoring using sensing technology. Additionally, to further optimize total maintenance, KYB is developing and implementing AI that can be applied to the system (Fig. 2).

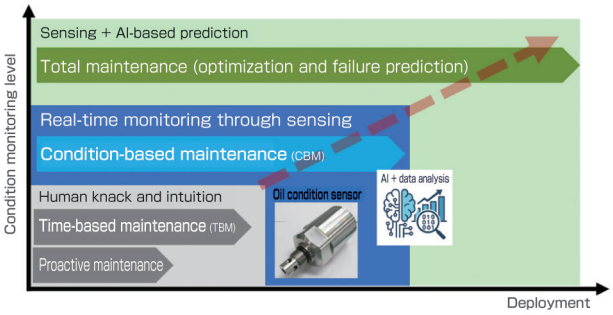

Fig. 2 KYB's goal of hydraulic equipment maintenance

This paper reports on our research regarding the data analysis and classification algorithms using AI technology planned for implementation in KYB's newly established oil condition diagnosis system.

2 Oil Condition Diagnosis System

The oil condition diagnosis system (Fig. 3) has been developed by Hydraulic Components Operations and is released in April 2026. The system uses collection terminals to compile data from on-site oil condition sensors and transfers it to the cloud for analysis and classification. The classification algorithm introduced in this paper is implemented in the trend diagnosis service shown in Fig. 3.

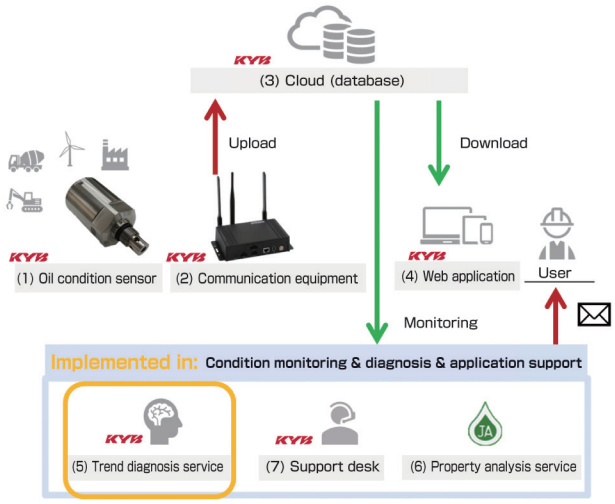

Fig. 3 Oil condition diagnosis system

3 Purpose

The purpose is to build data analysis and classification algorithms for the commercialization of KYB's proprietary condition monitoring system.

4 Targets

The target values for anomaly detection and property estimation accuracies are shown in Table 1. Two target values were set for oil anomaly detection accuracy: the F1 value[Note 1)] and the recall rate[Note 2)]. The F1 value was selected as the algorithm for detecting oil anomalies and was set to 0.7 or higher, which is generally considered good in the AI field. The recall rate was selected as a metric to minimize anomaly detection failures because overlooking an anomaly can result in equipment failure or other issues that cause downtime and significant loss. This metric was set to a target value of 0.9 or higher. Oil property estimation, on the other hand, involves grasping the overview of the occurring anomaly, locating components requiring maintenance, and proposing necessary maintenance actions. A target correlation coefficient with property analysis by an analysis institution that is inherently required was set to 0.8 or higher (generally considered a strong correlation).

Table 1 Target values

Item	Target value
Anomaly detection accuracy	Recall rate: 0.9 or higher F1 value: 0.7 or higher
Property estimation accuracy	Correlation coefficient between true values and estimated values: 0.8 or higher

Note 1) An indicator representing how accurately and comprehensively a classification model can detect something as a single numerical value.

Note 2) An indicator showing the percentage of items that the model correctly classified.

5 Oil Anomaly Detection[2),3)]

We trained and evaluated the classification algorithm using internal and external field data that we collected under historic themes and from HC Operations. Table 2 shows a list of data sources.

Table 3 shows the measurement data items of the internally developed oil condition sensor. Fig. 4 plots oil measurement data from the KYB Sagami Plant as an example of data and anomaly labeling. Sensor readings (relative permittivity and conductivity) vary due to oil deterioration, contamination, and temperature variations. Portions where sensor readings substantially fluctuate due to external factors are defined as abnormal, while the rest are defined as normal.

Table 2 List of data sources

Source location	Data collected from
(1) Company A	Waste plastic presses (2 locations: tank feed and return)
(2) Company B	Test vehicle of construction machinery (1 location: tank return)
(3) KYB Sagami Plant	Assembly line offline filter (2 locations: before and after the filter)

Table 3 Oil condition sensor measurement data items

Item	Description
Oil temperature	Temperature of hydraulic/lubricating oil
Relative permittivity	A measure of a material's ability to store electrical energy in an electric field
Conductivity	An electrical measure of a material's ability to conduct electrical charges in an electric field

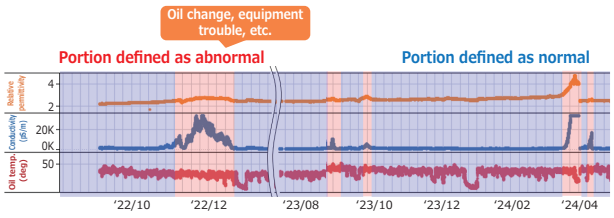

Fig. 4 Oil measurement data (KYB Sagami Plant)

In reality, it is difficult to implement supervised

learning sufficiently covering anomaly classes because field measurements provide data that is rarely labeled as anomalous and involve a variety of operating conditions. Therefore, for the purposes of this research, we selected the unsupervised (or semi-unsupervised) approach to train the model with normal data distribution, thereby detecting outlier behavior (Fig. 5).

Basic statistics, including maximum, minimum, mean, standard deviation, median, mode, range, variance, skewness, and kurtosis, were extracted as features for each fixed window width. These features were subjected to scaling and outlier removal. Temperature was incorporated as a feature to ensure that the model could properly learn temperature dependence.

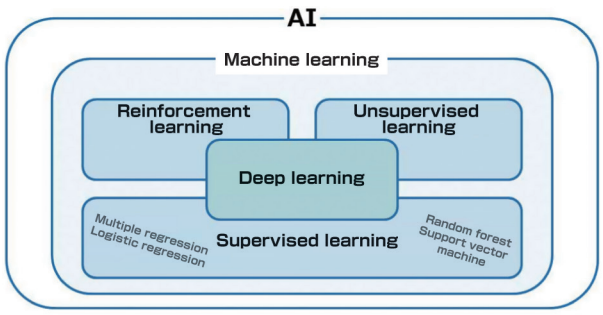

Fig. 5 AI model selection

We adopted the One-Class SVM (OCSVM)[Note 3] as a classification method. OCSVM learns the normal range using normal data only and can identify outlier behaviors as anomalies. Thus, OCSVM excels at identifying various anomalies in the absence of labels (Fig. 6). Compared with the autoencoder (Fig. 7) and the threshold method, OCSVM offered the best balance of training stability, operational load, and classification accuracy.

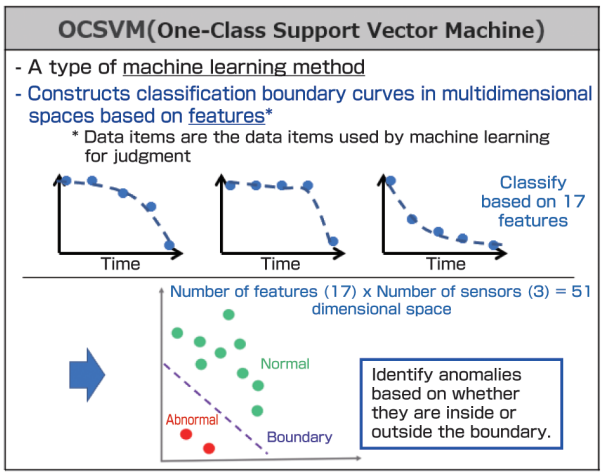

Fig. 6 OCSVM overview

Note 3) One-Class Support Vector Machine.

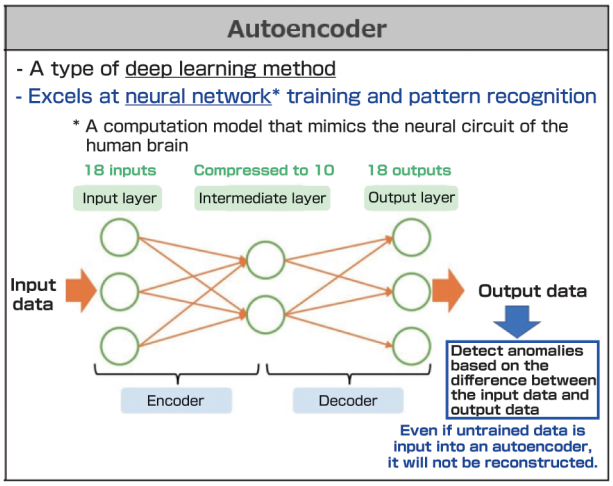

Fig. 7 Autoencoder overview

We defined a training period to teach the model to recognize normal boundaries and evaluated its performance using known anomaly periods as labels. We used recall rate and the F1 score as evaluation indices. The target recall rate was set to 0.9 or higher and the target F1 score to 0.7 or higher. Table 4 shows these indices.

Table 4 Definition of evaluation indices (recall rate, precision, and F1 score)

Index	Definition	Remarks
Recall rate	The percentage of anomaly data that has been correctly classified	Suppressing false negatives
Precision	The percentage of data classified as an anomaly that was actually abnormal	Suppressing false positives
F1 score	The harmonic mean of precision and recall rate	Balanced evaluation index

We trained the OCSVM model with the data collected from three locations shown in Table 2 and evaluated its precision. As a result, the model achieved the targets for all three locations.

The results demonstrated that the model could detect anomalies other than regular behaviors, such as oil changes, cleaning, progressing contamination, and equipment trouble. The model was proven to be effective when applied to the assumed oil condition diagnosis system shown in Fig. 8.

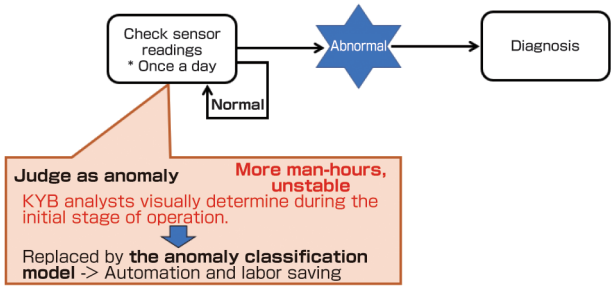

Fig. 8 Operation on the oil condition diagnosis system

6 Estimation of Oil Deterioration[4)]

We tried to estimate oil deterioration based on measurement data from oil condition sensors. Table 5 shows the oil properties. In this research, we focused on total acid value and water content.

Table 5 Oil properties

Property	Description
Total acid value	The amount of acid components of oil. A measure of the degree of oxidative deterioration.
Water content	Water content of oil.
Contamination	The number of solid contaminants in oil (ISO: the number of particles of 4, 6, and 14μm or larger)
Metallic elements	The amount of metallic elements in oil. An indicator of additives or worn metallic components. (Target elements: Fe, Pb, Cu, Cr, Al, Ni, Ag, Sn, Si, B, Na, P, Zn, Ca, Ba, Mg, Mo)

A preliminary study identified the possibility of distinguishing between abnormal and normal conditions based on temperature characteristics derived from time-series oil variations (i.e., changes in conductivity and relative permittivity with respect to oil temperature). Fig. 9 plots abnormal and normal data, with oil temperature plotted on the horizontal axis and conductivity plotted on the vertical axis.

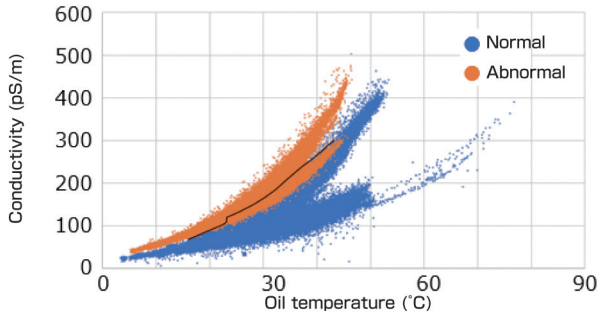

Fig. 9 Plotted abnormal and normal data

Next, we investigated whether it was possible to estimate the total acid value and water content using the temperature coefficients of conductivity and corrected relative permittivity. When verifying biodegradable oils, we found a strong correlation between total acid value and the temperature coefficient of conductivity. We also found that water content could be estimated using the temperature coefficient of the corrected relative permittivity (Table 6). Using this analytical approach, we calculated the estimated property values for biodegradable oils and determined the correlation coefficients with respect to the property analysis results provided by the relevant analytical institutions. As a result, we confirmed that the correlation coefficients were 0.8 or higher.

Table 6 Relationship between temperature coefficient and total acid value/water content

Item	Metric	Findings
Total acid value	Temperature characteristics of conductivity	Strong correlation (found for biodegradable oils)
Water content	Temperature characteristics of corrected relative permittivity	Estimatable (requiring testing with more types of oils)

7 Conclusions

This report introduced the anomaly classification algorithms scheduled to be implemented in KYB's oil condition diagnosis system.

The OCSVM used in these algorithms has provided sufficient accuracy for anomaly classification, achieving a target recall rate of 0.9 and a target F1 score of 0.7. We development a mathematical model to estimate total acid value and water content from oil sensor data, achieving a correlation coefficient of 0.8 or higher between the estimated and true property values.

Moving forward, we will standardize the procedures for constructing the classification model and verify the property estimation method with more types of oils. This will enable the algorithms to be applied to a broader range of applications. Additionally, to facilitate future implementation, we will research general-purpose anomaly classification algorithms that can be used from the initial implementation stage independently of oil and equipment types.

8 In Closing

Through this project, we have successfully achieved valuable findings and results that enhance the value of the oil condition diagnosis system. I would like to express my deepest gratitude to everyone in the relevant departments who provided tremendous support and cooperation in carrying out this project.

References

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4) Internal Report: Estimation of Total Acid Value and Water Content (Temperature Coefficient).

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Joined the company in 2016.
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