The Sushi Sensor and Machine Learning for Achieving Condition-based Maintenance (CBM)

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The trend in plant equipment maintenance has shifted from the conventional breakdown maintenance (BDM), in which devices are repaired and parts are replaced only after a failure occurs, to time-based maintenance (TBM), in which inspection, repair, and replacement are performed at regular intervals. However, TBM has the risk of over-maintenance, which increases maintenance costs and even the failure rate. Instead, condition-based maintenance (CBM), which detects the conditions of plant instruments, predicts their deterioration, and performs preventive maintenance, is increasingly attracting attention. However, this method is not yet used in practice because Industrial Internet of Things (IIoT) technology that can be easily implemented in plants is not yet available. In addition, data analysis for CBM is limited to simple methods such as threshold assessment. This paper describes the feasibility of CBM in plants. We believe it is achieved with Yokogawa's Sushi Sensor, which can easily monitor the vibration and surface temperature of equipment, and data analysis based on the latest machine learning technology.

INTRODUCTION

The trend in plant equipment maintenance has shifted from the conventional breakdown maintenance (BDM), in which devices are repaired and parts are replaced only after a failure occurs, to time-based maintenance (TBM), in which inspection, repair, and replacement are performed at regular intervals. Because BDM does not prevent equipment failures, the equipment is used until an abnormality occurs. Thus, BDM carries the risk of impairing plant safety and causing an unexpected suspension of production. In contrast, TBM avoids such risks by performing equipment maintenance at regular intervals regardless of whether the equipment is malfunctioning or not. However, TBM carries the different risk of over-maintenance, which increases maintenance costs and even the failure rate. Condition-based maintenance (CBM) is increasingly attracting attention, because it can solve the problems of BDM and TBM by monitoring the conditions of plant instruments, predicting their deterioration, and performing preventive maintenance. However, this method is not yet used in practice because monitoring equipment conditions is expensive and because the technologies are not yet mature enough to assess the state of equipment deterioration and detect indications of failure based on acquired data.

To monitor equipment conditions quantitatively, Yokogawa has developed Sushi Sensor, which can easily monitor the vibration and surface temperature of equipment. Recent developments in machine learning technology also help analyze equipment conditions based on acquired data.

This paper demonstrates the feasibility of sensing or predicting the state of equipment deterioration using the latest machine learning technology, by analyzing virtual data that simulate those from Sushi Sensors. The paper also discusses the practical feasibility of using CBM.

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OUTLINE OF JUDGING TECHNOLOGY BASED ON MACHINE LEARNING

The procedure for analyzing data using machine learning and the types of machine learning are described below.

Two Phases of Machine Learning

A method or program with which a computer learns patterns of given data and autonomously finds rules among the patterns is called machine learning. In general, data analysis based on machine learning consists of the learning phase and the judging phase.

- Learning phase

  In the learning phase, multidimensional data–some are relevant and others are irrelevant–collected by various sensors are input to the learner of a computer. After learning autonomously, the computer outputs the results in the form of models. These models include rules extracted from the data. There are various learners depending on machine learning algorithms, and each learner creates different models (Figure 1).

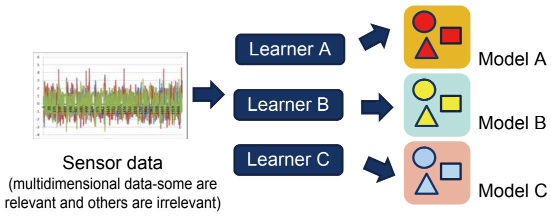

Figure 1 Structure of learning phase

- Judging phase

  Based on a model in the learning phase, a judging tool is created. In the judging phase, online data from various sensors are input to the tool, which compares these data with the model, and judges and outputs whether they are normal or abnormal (Figure 2).

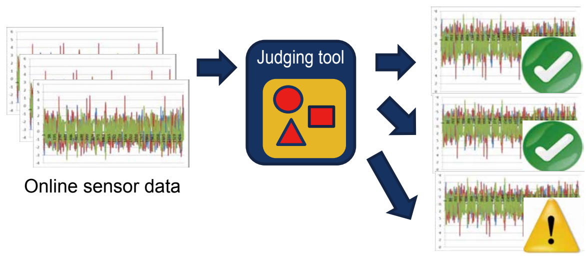

Figure 2 Structure of judging phase

In general, it takes a long time to create a model in the learning phase whereas the judgement in the judging phase requires only a short time. In the plant data analyses that Yokogawa performed using machine learning, the learning phase typically took about 20 hours, whereas the judging phase took no longer than 100 msec. Online data judgement is completed very quickly, so it is highly feasible to judge equipment conditions in actual plants with machine learning judging tools in real time.

Types of Machine Learning and Their Application to Actual Plants

In general, machine learning is classified into three types: supervised learning, unsupervised learning, and reinforcement learning(1). This paper describes supervised learning and unsupervised learning.

- Supervised learning

  Sensor data and answers to the data (criteria for normality and abnormality: teaching labels) are input to the learner during the learning phase.

- Unsupervised learning

  Sensor data without answers (teaching labels) are input to the learner during the learning phase. This method is used when answers to data are not clearly defined.

In the early stages of data analysis in actual plants, it is difficult to obtain data on deteriorated or failed equipment (teaching labels). This paper focuses on data analysis using unsupervised learning, which can be easily used to judge equipment conditions in actual plants. The paper also discusses the effectiveness of supervised learning. See Reference (2) for the details of supervised learning.

DATA ANALYSIS USING UNSUPERVISED LEARNING

This chapter discusses whether data analysis with unsupervised machine learning can judge equipment conditions that deviate from the normal state.

Contents of Sushi Sensor Data

Focusing on specific parameters, a simple threshold assessment on sensor data judges whether equipment conditions are normal or abnormal. Since there are a wide variety of causes of actual equipment abnormalities, judgements are often made by comparing correlations among multiple sensor data with those in the normal state.

Abnormal equipment vibration can be detected by monitoring changes in the correlation among data from multiple vibration sensors mounted on the equipment. Figure 3 shows an example. Vibration sensors A and B measure the vibration of two pipes, and vibration sensor C measures the vibration at the pipe joint. The values of sensors A and B have a linear (positive or negative) correlation with that of sensor C in the normal state, but the correlation breaks down in the abnormal state. For example, when cavitation occurs in the piping, this disturbance breaks the correlation.

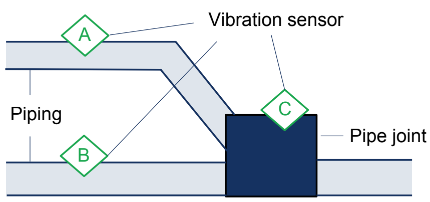

Figure 3 Example of monitoring equipment conditions with vibration sensors

In this paper, the feasibility of applying machine learning to judging such a correlation among sensors was examined by using virtual data that simulate the data from Sushi Sensors. The details of the virtual data are as follows.

- The number of data from each Sushi Sensor is 1000.
- The data from Sushi Sensors A, B, and C mounted on equipment are intended to be governed by a rule. Data in accordance with the rule are considered normal.
  The rule is defined as 3X + 4Y = Z, where 3X, 4Y, and Z are data from Sushi Sensors A, B, and C, respectively. A random number ($0 \leq n < 1$) is assigned to X and Y at each data point.
- The 100 sets of data (at data points No. 801 to No. 900) are made to deviate from the rule. Specifically, disturbance vibration γ is added to the rule ($3X + 4Y + \gamma = Z$). γ is a random number with a normal distribution (average value: 0, standard deviation: 0.5). These data including disturbance vibration are abnormal (deviating from the normal state).

Limits of Data Analysis by Humans

Figure 4 shows graphs of the data from each Sushi Sensor, which were generated under the above conditions. Figure 5 shows superimposed Sushi Sensor data at each data point. In these graphs, the vertical axis shows the value of sensor data and the horizontal axis represents data points from 0 to 1000. In Figure 5, the area in the red box indicates the data deviating from the rule.

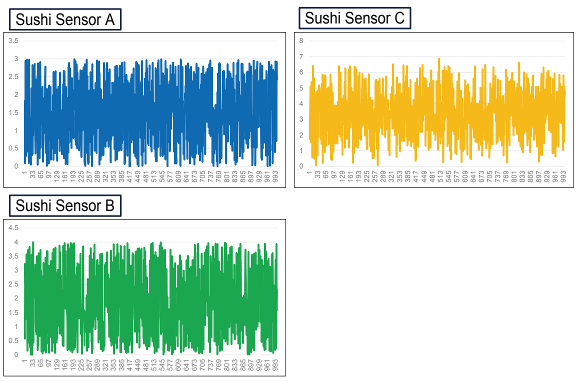

Figure 4 Virtual Sushi Sensor data

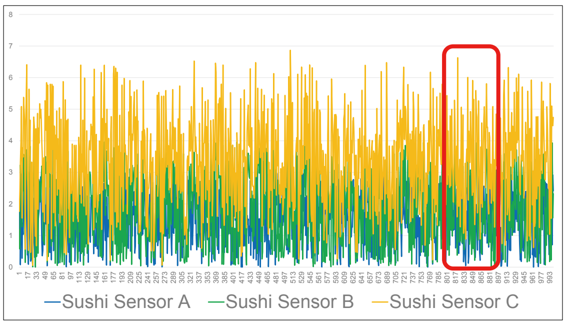

Figure 5 Superimposed virtual Sushi Sensor data at each data point

It is clear from Figure 5 that it is extremely difficult for humans or a simple threshold value assessment to identify the data deviating from rules.

Figure 6 shows a 3D scatter diagram of the data in Figure 5. In Figure 6, blue points are data of Sushi Sensors A, B, and C in accordance with rules (all data except those at points No. 801 to 900), and the red points are those deviating from rules (data points No. 801 to 900).

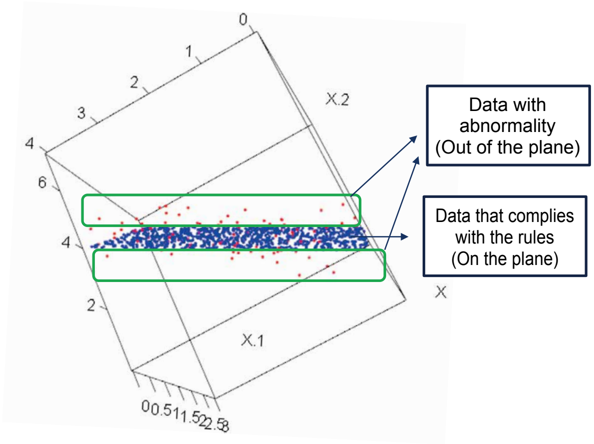

Figure 6 3D scatter diagram of virtual Sushi Sensor data

The data that comply with the rule lie on a plane, because these data are generated under the rule that the sum of data from Sushi Sensors A and B is the data value of Sushi Sensor C. In contrast, the abnormal data are scattered out of the plane because these data deviate from the rule.

If any rule governing sensor data is known, it is possible for human workers to analyze the data based on the rule and identify abnormal data. In most cases, however, it is not easy to identify the underlying rule of sensor data, and rules in actual plants are not as simple as in this case. Furthermore, even if any rule is found, data analysis may take a great deal of time. Although this case assumes only three sensors, it is difficult to identify which sensors are critical for judging equipment conditions in actual plants. Therefore, it is necessary to handle data from many sensors around the equipment for analysis, making it impossible for humans to analyze data in actual plants.

In contrast, machine learning can analyze data with several dozen to several hundred dimensions, autonomously identify underlying rules, and judge equipment conditions.

Unsupervised Learning, Data Analysis, and Results

After unsupervised learning was performed, the virtual Sushi Sensor data described above were analyzed. This process and the results are described below.

Only the data from Sushi Sensors A, B, and C were input to the learner. Unsupervised learning requires only sensor data even in the case of actual plants. Since a computer autonomously learns and judges the input data, there is no need for human analysis or teaching labels.

In the learning phase, data No. 1 to 700 from Sushi

Sensors A, B, and C were input to the learner for unsupervised learning to create a learning model. With this amount of data, the process can be completed within a few seconds.

A judging tool was created based on this model. In the judging phase, all 1000 data from Sushi Sensors A, B, and C were input to the judging tool, and the judgement results were obtained.

Figure 7 shows the results. The vertical axis shows the degree of normality or abnormality. Higher positions indicate a higher possibility of abnormality. The horizontal axis corresponds to data points No. 1 to 1000. The data in the red box clearly show abnormality.

As shown in Figure 7, data deviating from the rule are clearly identified although some noise is included. These results suggest the high feasibility of using machine learning for judging normality, which is a difficult task for human monitoring or threshold assessment.

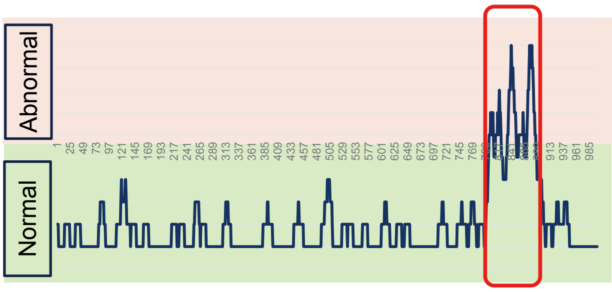

Figure 7 Judgement results obtained by unsupervised learning

Supervised Learning for Practical Use of CBM

As described above, unsupervised learning was able to clearly identify the abnormal state. When judging equipment deterioration and failure in actual plants, however, abnormal states are not necessarily related to equipment abnormalities or equipment failures.

Although unsupervised learning is useful in the early stage of data analysis in which teaching labels are not easily obtained, supervised learning seems to be more useful for the practical use of CBM than unsupervised learning. By inputting the normal/abnormal conditions of actual equipment as the teaching labels and creating models and judging tools, supervised learning enables the highly accurate judgement of equipment conditions for equipment maintenance.

Therefore, it is helpful for the practical use of CBM to first apply unsupervised learning to the early stage of analysis and then gradually switch to supervised learning.

CONCLUSION

This paper explained that machine learning technology is applicable to actual plants, and presented an example in which unsupervised learning successfully identified normality/abnormality that could not be easily identified by human analysis. The paper also noted that teaching labels could improve the feasibility of identifying equipment failures and abnormalities for equipment maintenance.

In the conventional TBM, maintenance is conducted at regular intervals, which are determined based on the empirical knowledge of human workers and past events. In the analysis method using machine learning, a computer autonomously finds underlying rules and judges the input data based on the rules. The input data are only sensor data in the case of unsupervised learning. In the case of supervised learning, answers defining normality or abnormality (teaching labels) are also input.

With recent developments in the Industrial Internet of Things (IIoT), many sensors including Sushi Sensors are mounted on plant equipment for easy acquisition of quantitative data. By analyzing such sensor data using machine learning, equipment deterioration or failure can be detected with high accuracy. These two technologies–sensor technology including Sushi Sensors and data analysis technology using machine learning–will enable the practical use of CBM.

REFERENCES

(1) Yutaka Matsuo, "Will Artificial Intelligence Surpass Human Beings?" KADOKAWA, 2015
(2) Hiroaki Kanokogi and Go Takami, "Machine Learning Applied to Sensor Data Analysis: Part 2," Yokogawa Technical Report English Edition, Vol. 60, No. 1, 2017, pp. 35-38

* Sushi Sensor is to be released outside Japan soon. For details, please visit Yokogawa's website.