Application of Machine Learning Technology to Trend Monitoring with Sushi Sensor

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To achieve condition-based maintenance (CBM), Yokogawa has developed Sushi Sensor, which can easily collect data on the status of equipment and facilities. With the previous application, however, it was necessary to manually set alarm thresholds to each Sushi Sensor for monitoring the trend, and extensive know-how and considerable manpower and time were needed when this device was installed in large numbers. To simplify this task and improve efficiency, we introduced machine learning technology.

This paper explains how to use such machine learning to improve the efficiency of a trend monitoring system to detect anomalies, and describes the verification test of a newly developed application.

INTRODUCTION

Trend monitoring technology monitors the condition of equipment, detects signs of mechanical wear and deterioration, and helps avoid equipment breakdowns. The approach of monitoring trends and maintaining equipment depending on its condition is called condition-based maintenance (CBM). To achieve CBM, Yokogawa has developed the Sushi Sensor, a sensor for the Industrial Internet of Things (IIoT), which can continuously monitor the condition of equipment [(1)(2)(3)(5)(6)]. The XS770A, one of the Sushi Sensors, is a compact battery-powered wireless sensor with built-in vibration and temperature sensors. The XS770A can measure the vibration velocity and acceleration as well as the surface temperature of equipment. Figure 1 shows an external view of the XS770A.

The Sushi Sensor can be installed in places where wiring is difficult, thus reducing installation costs, and trends can be monitored by installing a large number of Sushi Sensor throughout the plant. However, setting thresholds to each sensor requires extensive know-how, manpower, and time.

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This paper proposes a method for solving this problem by using machine learning and describes its application and a demonstration for verifying the effectiveness of the method.

Figure 1 XS770A Sushi Sensor

TREND MONITORING USING MACHINE LEARNING

This section describes a problem in trend monitoring using the Sushi Sensor, its solution with machine learning, and an application created to verify it.

Problem in Trend Monitoring

In trend monitoring, a threshold for sensor data is usually set as a standard for judging unusual conditions of equipment,

and an alert is issued when the data deviate from the threshold. The XS770A was installed in plant pumps to clarify what problem occurs in this setting.

One Sushi Sensor was mounted on each of the two pumps. Figure 2 shows a one-month trend graph of the velocity and acceleration of vibration and the surface temperature. The vertical axis is the sensor data and the horizontal axis is the time. Even if the same parameters are measured, the distribution of the sensor data differs greatly by pump. The variance of the sensor data also varies depending on the pumps and target parameters.

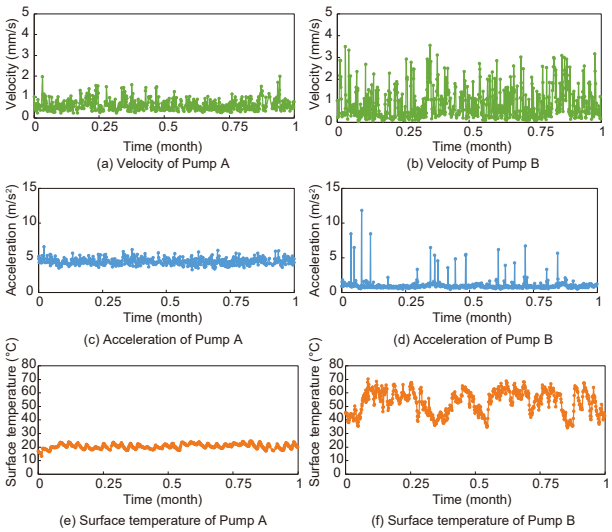

Figure 2 Data measured by the Sushi Sensor on two pumps

As in this case, the range of velocity of multiple pumps is not uniform and can vary greatly even under normal conditions depending on the pump specifications, individual differences, operating conditions, the sensor location, and other factors. Therefore, it is not possible to automatically determine thresholds for velocity, acceleration, and temperature for each pump based on simple indicators; the task requires operators' expertise and know-how.

In addition, as more than 100 Sushi Sensors are usually installed in a single project, setting thresholds to individual sensors requires much manpower and time.

The problem is to streamline the setting of thresholds, which requires extensive know-how, manpower, and time.

Solution with Machine Learning

To solve the problem regarding threshold setting, we created a method in which unsupervised machine learning is used to discriminate unusual states of equipment. This method consists of a learning phase and a judgment phase. See reference [4] for details.

- Learning phase
  On the assumption that the pump is operating normally at the start of monitoring, the unsupervised learner creates and stores models for each pump to be monitored. The input is the sensor data obtained during the period just after the sensor is mounted.
- Judgment phase
  The learning data used by the model-based classifier are multiple sensor data measured at the same time, such as velocity, acceleration, and temperature, during a period when the equipment is assumed to operate normally. When the model is properly created, the classifier outputs a judgment value that clearly shows the operating state of the equipment. Positive values mean normal operations while negative values imply abnormal conditions.

Figure 3 illustrates how to calculate judgment values. The upper graph shows typical characteristics of the velocity, acceleration, and temperature data measured by the Sushi Sensor during one month before a pump fails. The lower graph shows judgment values calculated based on these data. Note that the learning data were obtained from the earlier normal period.

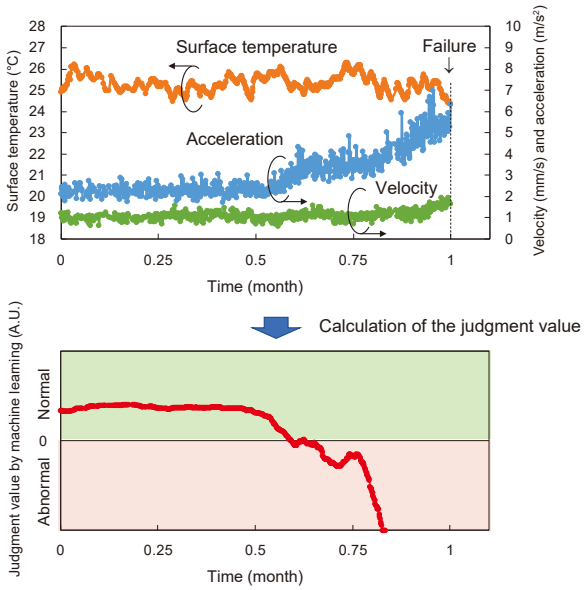

Figure 3 Judgment value derived by the classifier

It is clear from the sensor data that the acceleration value increased sharply in the latter half of the period, and then the failure occurred. The trend of the judgment value changed from positive to negative well before the failure. Thus, the method is considered to have successfully captured a sign of the failure.

Note that normal and abnormal operations can be divided at judgment value "0." With this simple standard, trend monitoring can be performed far more easily than by existing trend monitoring methods that use different threshold values for each pump and physical quantity to be measured.

Also note that this method detects unusual conditions based on the data input during the learning period and that detected unusual conditions do not necessarily mean that an abnormality or failure will occur; the equipment or operating conditions may have changed. Unsupervised learning alone does not always classify these events. However, easily detecting unusual states is still noteworthy. At least,

unsupervised learning is useful for applications that need to detect subtle signs of failure or abnormality from large numbers of sensors, and then alert operators.

In unsupervised learning, models can be created only by determining the range of the learning data. This process is applicable to a large number of sensors. Unsupervised learning can derive a judgment value that can detect signs of abnormalities efficiently without needing to set individual thresholds to each sensor. This means that unsupervised learning can solve the problem described earlier.

Application for Verification

To verify the efficiency of trend monitoring by machine learning, we built a system application in the cloud, which remotely monitors dozens of pumps via the web (Figure 4).

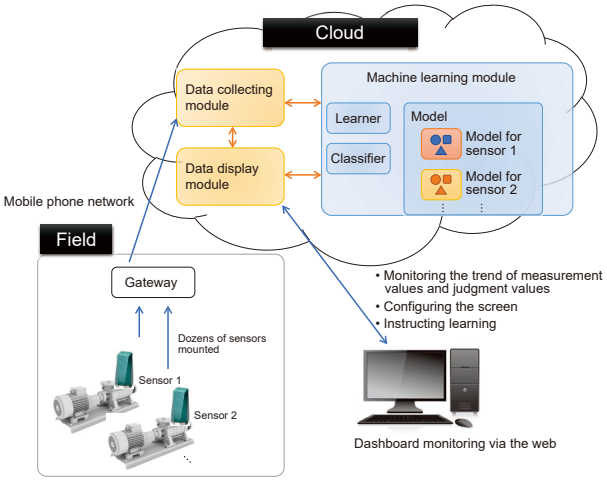

Figure 4 System configuration of the application

The role of each module in the system is as follows.

- Gateway
  Collects data from Sushi Sensors mounted on the pumps and sends them to the data collecting module in the cloud via a mobile phone network.
- Data collecting module
  Receives the data from Sushi Sensors via the Gateway and records them as time-series data. Bundles the data measured at the same time by a sensor for which a model has been created, uses the machine learning module to calculate judgment values, and records them as time-series data. The recorded data can be read out by other modules.
- Data display module
  Provides a dashboard that enables the data to be monitored via the web. Access to the data is controlled with the general user privilege and the editor privilege.
  The general user privilege allows users to monitor the trend of sensor data and judgment values.
  The editor privilege allows users to use the screen configuration function to allocate visualization components, such as graphs and tables, for monitoring. Users with this privilege can also select the target sensor and its normal data period on the dashboard and instruct the learner to perform learning. This instruction is sent from the display module to the machine learning module.
- Machine learning module
  - Learner
    Uses the sensor data in the specified period as inputs, creates a model through unsupervised learning, and saves it with the sensor ID.
  - Classifier
    Uses the model corresponding to the specified sensor ID and calculates a judgment value based on a set of sensor data.

FIELD TEST

We performed a field test in which the trend monitoring application that uses machine learning technology described above was applied to an actual plant. This section describes the details and problems identified in the process.

Introduction and Operation

The field test was carried out in two stages. In the introductory stage, normal data were collected and a model was created, and in the operational stage, trend monitoring was performed using the model.

- Introductory stage
  After Sushi Sensors were mounted, data were collected for three weeks. We applied machine learning to the data and created a model for each sensor. Judgment values were automatically calculated. The sensor data and judgment values were displayed in time series on the dashboard.
- Operational stage
  Monitoring operators checked the judgment values of the pumps on the dashboard. If any value was worsening, they reported it to field workers, who then checked whether the trend was a sign of abnormality in equipment or was due to other causes such as changes in operating conditions. This stage was continued for several months.

Results

The following effects were confirmed in the field test.

- Easy setup and re-setup
  There was no need to check information on individual pumps and sensor data to determine thresholds. Simply by implementing machine learning, it was possible to create a model for each pump, calculate judgment values, and start trend monitoring.
  When it was necessary to update a model due to sensor replacement or pump maintenance, a new one was easily created through re-learning from the dashboard. The new model immediately started to detect unusual conditions.
- Efficiency of trend monitoring
  There was no need to monitor the trend of the three sensor data (velocity, acceleration, and temperature) for each pump separately. The judgment value determined based on them well represented the state of the pump, making it much easier to understand the trend.

Root-cause investigation also became efficient. The judgment value helped operators to easily identify those pumps with deteriorating values among the multiple pumps and to concentrate on sensor data that affected the judgment value.

Identified Problem and its Countermeasure

During the test, the following problem was identified and countermeasures were taken.

- Problem: seasonal changes in the ambient temperature
  Changes, especially rises, in the surface temperature were monitored because they were an excellent indicator of heat generation in the pump.
  However, it was found that, over a long period, seasonal changes in the ambient temperature also affected the surface temperature. By default, the machine learning classifier looked at this change as an unusual condition and output a judgment value indicating deterioration, which might mislead operators.
- Countermeasure: using differential temperature values
  As a countermeasure, we added the ambient temperature sensor and calculated the difference from the surface temperature to eliminate the disturbance. Figure 5 shows a typical trend of these values. For approximately one month, sensors monitored the surface temperature and the ambient temperature.
  There is no increase in the surface temperature, but the ambient temperature decreased over the period and the differential value increased. Therefore, it is reasonable to conclude that more heat was generated in the pump. A detailed investigation of operating conditions revealed an increase in the load on the pump and thus more heat generation.

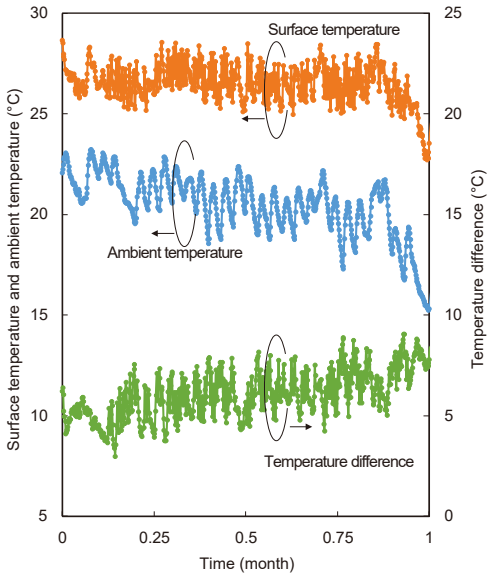

Figure 5 Excluding the effect of ambient temperature

According to these results, we switched the measurement value from the surface temperature to the differential temperature. This parameter was input to the machine learning classifier used for trend monitoring, along with velocity and acceleration values.

This countermeasure eliminated the influence of the ambient temperature and enabled the system to focus on temperature changes caused by the pump heat. This made trend monitoring more precise.

CONCLUSION

The Sushi Sensor is a useful tool to monitor the operational trend of equipment. This paper introduced a method of using unsupervised machine learning to improve the efficiency of monitoring and described its application and field test.

By leveraging the findings in this test, we will continue research on machine learning and applications to improve systems for equipment maintenance.

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