IoT for Industrial Furnace –Data Analysis Engineering for Detecting Signs of Anomalies–

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Since the operation of industrial equipment cannot be stopped, people in the industrial field have strongly wished for failure prediction from long ago, but practical application has been elusive. However, the recent evolution of information technology has greatly advanced the possibility of failure prediction becoming a reality. We have built a platform for data collection and analysis on the cloud, and developed a system for detecting signs of anomalies and diagnosing deterioration in carburizing furnaces as a first step. In this article, we introduce the system with a focus on data analysis examples.

Key Words*: IoT, anomaly prediction, data analysis, industrial furnace, carburizing furnace*

1. Introduction

Carburizing is often used as a surface hardening treatment for mechanical parts that require high endurance strength and abrasion resistance. In the carburizing process, carbon penetrates the steel surface in a high-temperature carbon atmosphere, followed by quenching to harden the surface. The interior of a carburizing furnace is a highly reactive carbon gas atmosphere, and the complex changes in temperature and airflow make it an extremely harsh environment for the mechanical parts inside the furnace. Continuous carburizing furnaces ("continuous furnaces" below), in particular, are operated continuously for extended periods of time once they are put into operation, and there is a great possibility of serious damage to the furnace and the treated products if anomalies in the furnace fail to be detected. Also, due to the large heat capacity of the furnace body, it can take up to a week to cool the furnace and restart it, which can seriously interfere with production planning. For this reason, operators have been calling for development of a technology to detect anomalies in the carburizing furnace at the safety stage before a serious failure occurs.

Meanwhile, the rapid evolution of IT infrastructures and data analysis environments in recent years has opened up new computing worlds one after another, which have come to be used in a wide range of fields as IoT (Internet of Things) technologies that connect digital cyberspace and real physical space. We took this challenge as an opportunity to research data mining technology and to develop a cloud computing-based data acquisition and analysis platform, and as a first step, we are now working on a demonstration test of the system using actual carburizing furnaces in operation and in-house experimental equipment for carburizing furnaces with the aim of providing an IoT system that only a heat treatment equipment manufacturer could provide. This article presents examples of our developments in detection of anomaly signs in heat treatment equipment and its data acquisition and analysis system.

2. From Anomaly Detection to Detection of Anomaly Signs

Conventional anomaly detection in the field of industrial equipment has been based on judgment of threshold values from the current value of sensor signals. Even though past experience has shown many times that this methodology does not work, the view that threshold values can be used still persists. Some say that the issue is that threshold values are fixed. However, threshold values are rules, and real-world diversity cannot be expressed using rules. AI (Artificial Intelligence) has become practical because we have abandoned the rule-based expression method and have acquired a probability-based expression method.

Even so, anomaly detection methods based on the statistical distribution of signals, such as the Hotelling's theory[1] and the Mahalanobis-Taguchi method[2] ("MT method" below) are based on the logic that a value that rarely appears is not normal (=abnormal) without reference to the characteristics of the physical quantity, and there is no concept of physical causality. To advance anomaly detection to the level of detection of anomaly signs, quantification of the deterioration process is desired, which requires a physical model.

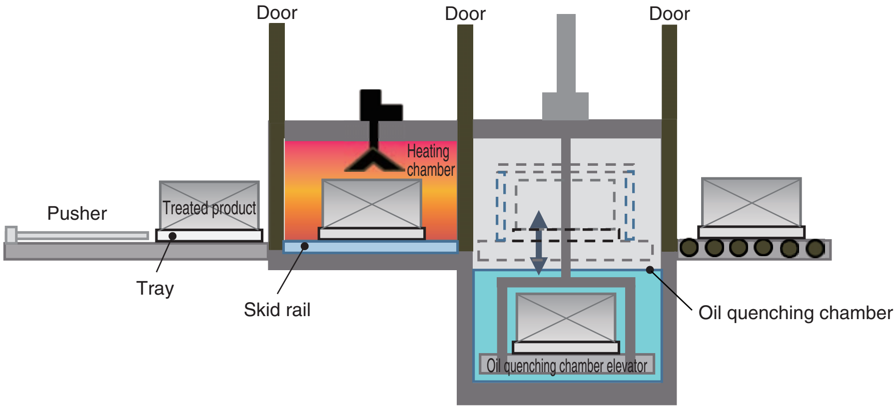

Fig. 1 Schematic diagram of batch type carburizing furnace

Sensor signals are not necessarily physical quantities that are effective in determining or predicting anomalies. A time axis can be added to the above principles to enable discussion of these signals by using their input-output relationships and correlations with other signals or by replacing them with other signals to give them physical meaning. In a feedback control system, a slight disturbance or change in the environment will not change the control result on the surface, but this is because the control output is moving so that the control result does not change, and it can be determined from the control output that a change in state is occurring. There are many different failure modes for the same parts, and installing sensors for different factors and devising different detection methods was exactly the path taken by the previous generation of AI. Even if there is no change on the surface, if a change in the internal state can be detected, signs of an anomaly can be detected. Rather than just looking at the signals from the sensors, determination is made based on events of the heat treatment equipment in the background. We believe that this is the reason why heat treatment equipment manufacturers should implement IoT for our heat treatment equipment.

3. Implementation Examples of Detection of Anomaly Signs

Figure 1 shows a schematic diagram example of a batch carburizing furnace (“batch furnace” below) that illustrates its operation. The products to be treated are placed on a tray and are inserted into the heating chamber by a pusher that moves on a skid rail. A fan is installed in the heating chamber to equalize the temperature and atmosphere inside the furnace, and treatment is performed using a predetermined heat treatment pattern. When the treatment is completed, the products are carried out to the elevator above the oil quenching chamber, lowered into the oil quenching chamber for quenching, and then returned to the transport surface to be carried out of the furnace. Each chamber is separated by a door to maintain the treatment atmosphere, and the doors are opened and closed only when the treated products are moved.

The current data acquisition parameters are about 80 parameters for batch furnaces, and more than 200 parameters for continuous furnaces in some cases. There is a wide range of uses, from simply using the signal as a monitor to deterioration and treatment quality prediction, but as explained in **section 2**, instead of using the sensor signal as is, it is observed after some processing. This section presents some examples that may be unique to heat treatment equipment.

3. 1 Deterioration Diagnosis of Tray Pusher Transport Systems

In a tray pusher transport system, a metal rod (pusher) pushes a tray loaded with treated products and moves it on a transport rail (skid rail). This section presents an example of deterioration diagnosis for a tray pusher transport system in a batch furnace. In a batch furnace, the products to be treated may change from batch to batch, and so the profile of the transport force may vary in size and shape each time. In addition to the state of the skid rails, the bottom surface condition of transport tray also has a significant impact, and so it is almost impossible to have the same profile for each batch. Therefore, we defined several features from the profile of the transport force and modeled them using machine learning. In **Fig. 2**, Ⓐ is the period from the discovery of strain in the skid rail of the transport to its replacement, and Ⓑ is the period after the replacement with the new one. The data for each period were labeled as NG (Fail) or OK (Pass) and divided into classes. Each point is the anomaly score for each batch, and the continuous line is the moving average of the anomaly scores. When the anomaly score became equal to the period Ⓐ, the rail strain was measured and found to be equivalent to Ⓐ. Therefore, this continuous line can be said to represent the deterioration progress over time.

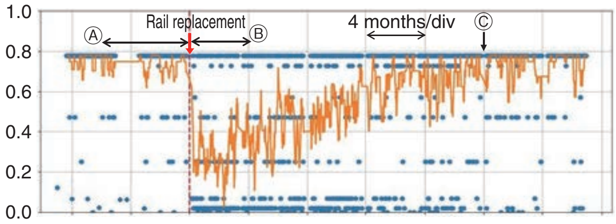

Fig. 2 Deterioration diagnosis of the tray pusher transport device

3. 2 Deterioration Diagnosis of Oxygen Sensors

In carburizing, the carbon concentration on the steel surface and the carburizing depth are controlled based on the carbon potential ("CP" below)[3]. An oxygen sensor[4] is used to measure the CP, but the output value of the oxygen sensor changes as it deteriorates. Since the value of the reference sensor changes, the CP value that was set cannot be obtained. On the other hand, if the CP value generates an error due to changes in the characteristics of the oxygen sensor, then the behavior of the enriched gas valve opening ("MV value" below) that controls it should also change. For this reason, we try to estimate the change in the characteristics of the oxygen sensor from the behavior changes of the MV values. Because it is difficult to make a determination based on the instantaneous MV values, we perform a type of filtering as a time-series signal within a batch to obtain the features of MV values for each batch (called "arrMV"). **Figure 3** shows a time series plot of this arrMV for a batch furnace. In (a), where all treatments are aligned, all conditions such as the CP target value, treatment temperature, and treated product are included and there are large fluctuations, while in (b), which is filtered for specific treatment conditions only, the changes in the oxygen sensor (= deterioration behavior) are clearly visible. If a regression analysis of arrMV and the treatment conditions is performed for one to two months after replacement of the oxygen sensor, the true CP value can be estimated from the arrMV value even when the oxygen sensor is deteriorated, and the CP target value can be corrected to obtain a given CP.

3. 3 Signs of Anomalies in Area around the Fan

The furnace atmosphere agitation fan is the mechanical component in the most severe environment of the carburizing furnace as shown in **Fig. 4**.

Vibration analysis is commonly used to analyze rotating bodies. However, vibration sensors and analyzers are expensive, and their communication traffic is

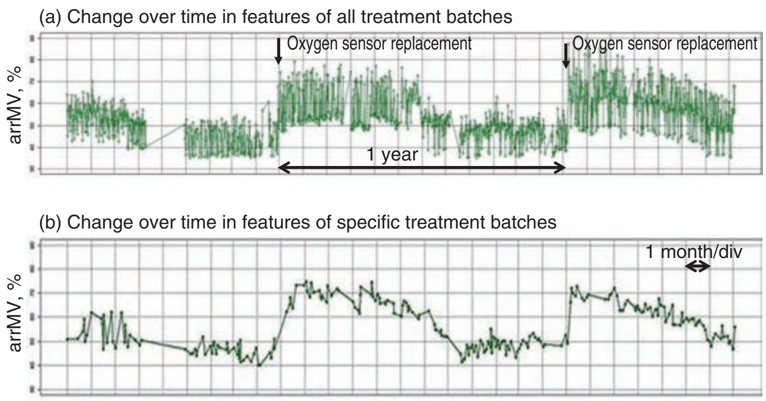

Fig. 3 Degradation behavior of oxygen concentration sensor

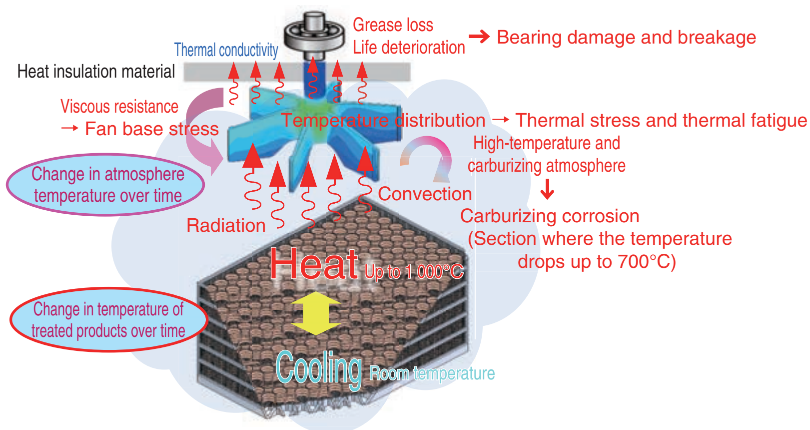

Fig. 4 Ambient environment of agitation fan in a carburizing furnace

extremely high. Therefore, various methods of predicting failure without using vibration were investigated, and by using the torque of the motor that drives the fan, it was possible to detect signals that seemed to be signs of failure from about two days before bearing failure. However, considering the seriousness of the damage when the fan stops, the signs of failure must be detected more in advance, and to solve the problems of cost and communication traffic, we started by developing a new vibration sensor using an inexpensive MEMS three-axis accelerometer sensor (“vibration sensor” below) and a signal processor. Because data processing is performed at the endpoint of signal generation, we call this the End Point Processor, or EPP for short. The EPP decomposes the frequency of the vibration sensor signal once and sends out only the calculated vibration energy and features that show the frequency characteristics. The final processing is performed by an analysis platform in the cloud to analyze signs of anomalies. The MEMS three-axis accelerometer sensor is inexpensive, but its signal output uses the SPI (Serial Peripheral Interface) system, which has a transmission distance of around 20 to 30 cm. Consequently, the SPI signal is isolated by a pulse transformer and converted to the isoSPI system, which can extend the transmission distance to 10 m, and the signal is connected using a RJ45 LAN connector with a built-in pulse transformer so that any commercially-available LAN cable can be used. Because the isoSPI system has a maximum transmission clock of 1 MHz, the sampling frequency of the vibration sensor was limited to 1.6 kHz (signal bandwidth of 800 Hz), but since the target rotation speed in the heat treatment system is around 1 000 min^{-1}, there is no wide-ranging variable speed operation, and so the necessary frequency band can be obtained. By narrowing the specifications in this way, we were able to significantly reduce the cost of the vibration measurement system (EPP is shown **Fig. 7**).

Figure 5 shows the process of bearing failure due to lubrication failure of the furnace atmosphere agitation fan using an in-house experimental furnace with EPP. The lower section shows the motor torque, and the upper section shows the time series for the EPP output signal obtained by applying the MT method. Bearing failure is not a simple increase in vibration energy. Instead, internal damage causes spectral shifts and increased vibration, but this is mitigated after a while. This phenomenon is repeated several times and eventually leads to a failure stop. This shows that, while the state of the signal just before failure changes for the motor torque, the vibration measurement using EPP captures the change even before the failure. The jump in the value in the first half of the torque graph is due to the change in the furnace temperature and is not a signal of an anomaly. The signal interruptions are due to equipment stoppages during holidays.

3. 4 Deterioration Diagnosis of Heaters

Generally, the electrical resistance of heater wires

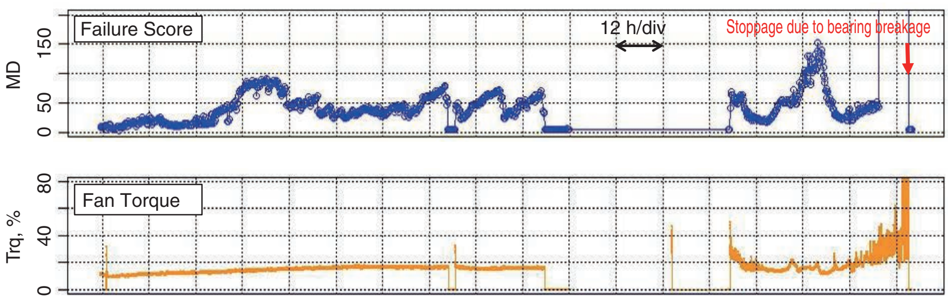

Fig. 5 Signs of agitating fan failure

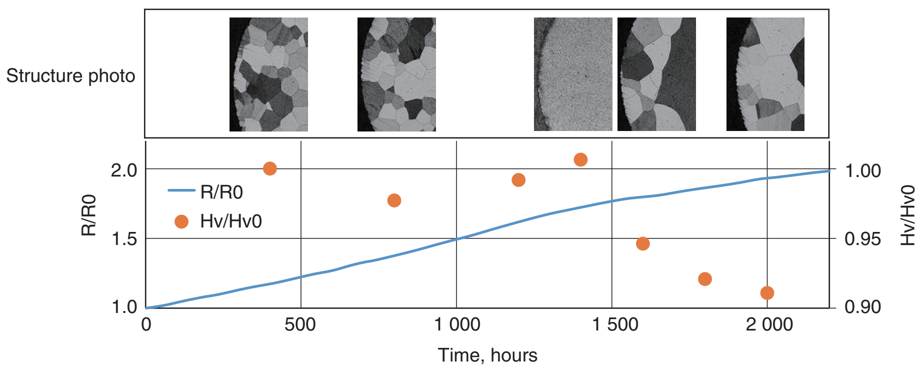

Fig. 6 Characteristic changes of heater wire in accelerated life test

(“resistance value” below) increases with use. This is due to the repeated formation and peeling of the oxidation film on the surface of the wire, which causes it to become thin and narrow. On the other hand, observing the metallurgical structure of the wire revealed that the structure becomes coarser as it is used, and at some point it becomes recrystallized, and then coarsens again. Hardness measurements show that the initial hardness is maintained until recrystallization, but after recrystallization, the hardness rapidly decreases. In other words, the metallic structure becomes osteoporotic and prone to fracture. There is a correlation between the change in microstructure and the resistance value and hardness, but it varies depending on the wire material. **Figure 6** shows an example of heater resistance, metallurgical structure, and hardness changes during an accelerated deterioration test of a heater. In this heater wire, recrystallization occurs when the resistance value is about 1.7 times the initial value, and once that happens, the hardness decreases, and the probability of wire breakage increases rapidly.

Next, the change in the resistance value of the heater can be found as follows.

The heater resistance value R_n when the heater resistance value is observed every fixed time interval L and repeated n times can be expressed as shown in Equation (1) using the Arrhenius equation.

$$ln(R_n/R_0)=L\cdot K_0\sum_{i=1}^{n} exp(-E_a/\kappa_B T_i) \quad (1)$$

Where, E_a: Activation energy of heater wire deterioration

κ_B: Boltzmann constant

T_i: Operating temperature of the i th section (K)

K_0: Deterioration characteristic value (constant)

The change in resistance value of a heater depends largely on the usage conditions, but if temperature data is recorded, it can be divided into periods L, and the distribution of the representative temperature T_i (approximately the maximum temperature) for each interval can be found to indicate the usage state of the heater. The distribution of this T_i may also be indicative of the future usage state. In other words, if we generate random numbers that follow the past distribution of T_i and simulate them with Equation (1), we can predict the future resistance value. In this way, although it is not possible to predict when the heater will break, it is possible to predict when a breakage is likely and the necessary power would be unable to be generated.

When Koyo Thermo Systems, a manufacturer of heat treatment equipment, started IoT, we spent many hours investigating heater wires. The reason for this is that basic data on heater wires is not published or available.

The wires listed here are examples of wires whose properties could be quantified, but there were also wires that showed completely different properties or whose data could not be reproduced, and so this led us to stop using these wires. In the age of IoT, heaters suitable for IoT are necessary, and we would like to request cooperation from wire manufacturers that includes disclosure of basic data on their materials.

4. Data Acquisition System

Figure 7 shows the data acquisition system. In the system configuration, special attention was paid to security measures. Various types of data for industrial equipment are integrated in control devices such as PLCs, and it is only rational to use them. However, the system is immediately exposed to security risks when it tries to send this data to the outside world. The greatest fear in industrial facilities is that an intrusion from outside will cause the facility to stop or operate abnormally. In order to avoid this problem, the gateway of our system blocked access to the input port from the outside by hardware, and prevented intrusion from the outside by allowing only unidirectional communication to the outside. The cloud applications, which serve as the platform for data acquisition and analysis, have undergone a cloud application vulnerability assessment in accordance with the “Information security management guidelines for the use of cloud computing services” formulated by the Ministry of Economy, Trade and Industry (METI), and these applications are subject to rechecks. This security assessment will also be conducted at periodic intervals in the future.

Also, the EPP can be used not only for vibration measurement but also for many other applications by connecting to various devices used in heat treatment equipment in combination with optional boards. This enables implementation of IoT without remodeling of old or existing devices that do not have PLCs, and because it does not pass through the control system of the device, it avoids the problem of security risks.

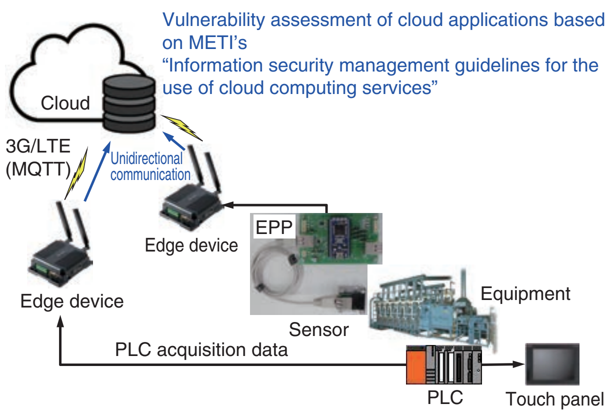

Fig. 7 Overview of data acquisition system

5. Conclusion

As we enter an era where AI is changing the world, information technology has become the source of new concepts and services that are completely different from those of the past. To cite a familiar example, in the world of passenger cars, automatic brakes have already begun to take the place of humans in avoiding hazards, and it will not be long before automated driving becomes the norm. IoT in the field of industrial machinery is still only a word in a certain sense, but the first step is to avoid hazards in production operations. As an equipment manufacturer, it goes without saying that the reliability of our equipment comes first and foremost, but what kind of value we can add to it and what kind of innovation we can bring about will depend on our software. Keeping in mind the question, “What kind of valuable services can we provide through our products?”, we will continue to take on the challenge of developing a system that supports our customers by enabling them to continue their production operations with a constant sense of security.

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