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Introduction of J-dscom™ to No. 4 CGL Welding Machine

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Abstract:

In the production line of hot-dip galvanized steel sheets used for automotive steel sheets, a welding machine is installed to weld the tail end and the leading end of the steel strip loaded on the entry side to enable continuous production. In a continuous line with a furnace, a failure of the welding machine not only causes a line stoppage but also results in breakage of the strip within the furnace due to welding anomalies, significantly impacting production. Therefore, by applying an equipment anomaly prediction detection system developed by JFE Steel to the welding machine in the hot-dip galvanized steel sheet production line, signs of equipment anomalies are detected and the impact on production is mitigated.

1. Introduction

In recent years, high tensile strength steel sheets with excellent strength, formability and lightweight properties and hot-dip galvanized steel sheets with corrosion resistance have been widely used as automotive steel sheets. These steel sheets are produced by the continuous annealing line (CAL) or continuous galvanizing line (CGL). At these automotive steel sheet production lines, the tail end and head end of steel strips charged at the entry side of the line are welded together to enable continuous production. However, a malfunction of the welding machine may cause a line stop. Since both the CGL and CAL have annealing furnaces for steel strips, line stops have an incalculable impact on production, as a lengthy period is necessary when cooling down the furnace and time is also required when starting up the furnace. Moreover, since equipment anomalies in the welding machine can also lead to welding defects, there is a large risk of weld breakage in the furnace at continuous lines with a furnace. Therefore, stable welding machine operation is demanded.

This paper describes an example of anomaly detection by applying an equipment anomaly prediction detection system (J-dscom™)[1,2] developed by JFE Steel to the welding machine at a CGL.

2. Background

2.1 Overview of Mash Seam Welding Machine

Mash seam welding machines, which are suitable for welding thin steel sheets, have been introduced at many automotive steel sheet production lines. Mash seam welding is a type of resistance welding in which the head and tail ends of two steel sheets are overlapped, and welding is performed using the heat input of the resistance heat of the sheets when a welding current is passed while applying pressure to the overlapped sheets with a pair of welding wheel electrodes traveling in the sheet width direction. Three main welding parameters are used in mash seam welding, the welding current, welding speed and electrode force. In welding using resistance heat, the input heat increases as the welding current increases. The welding current also increases as the welding speed of the moving electrode wheels decreases, due to taking a longer time when the current is applied. If the electrode force is small, the contact area between the electrodes and the sheets will decrease, and in this case, the heat input will increase as a result of the increased resistance of the sheets due to the decreased contact area where the current flows. The necessary heat input increases as the sheet thickness increases, and a higher electrode force is required as the material hardness increases.

Figure 1 shows a schematic drawing of a welding machine. In the welding operation, welding is performed as a U-shaped carriage on which the electrode

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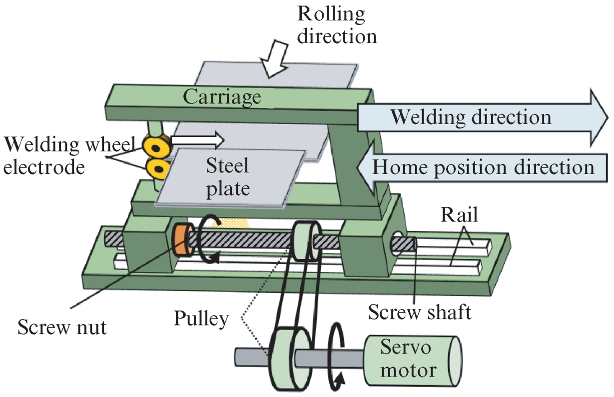

Fig. 1 Outline drawing of mash seam welding machine

Table 1 Welding machine operation equipment failure case

Year	Faulty component	Downtime (H)
2018	Screw nut	7.3
2019	Screw nut, Screw shaft, Pulley	13.8
2020	Screw nut	4.9

wheels are mounted travels in the strip width direction. Therefore, the welding speed is the same as the carriage travel speed.

2.2 Failure Cases of Welding Machine Carriage Traveling System

The carriage traveling system is driven by a servo motor, and the rotation of the motor is converted to axial motion by pulleys, the screw shaft and the screw nut. **Table 1** shows the failure record of the carriage traveling system of a welder at a certain continuous line. The drive part of the traveling system is prone to deterioration, as the ball screw nut, shaft and pulleys fail each year. The welding wheel electrodes are made of copper material, and the roughness of the wheel surface is repaired by grinding with a cutter after each welding is completed. Moreover, since the traveling system of welding machines is generally located under the welding machine itself, as shown in Fig. 1, copper chips generated during grinding of the wheel electrode fall into the drive part of the traveling mechanism, contributing to easier deterioration.

3. Detection of Anomaly Prediction Signs by Principal Component Analysis

Figure 2 shows the anomaly detection method using principal component analysis in this system. In this method, electrical signals acquired by CT, PLG and other sensors are received from the equipment control device, and multiple baseline waveforms are acquired

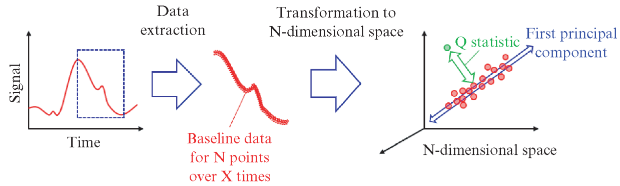

Fig. 2 Overview chart of principal component analysis

by dividing the monitoring sections. A principal component analysis of these baseline waveforms is then carried out, and the data for N points, where N is the number of data comprising 1 waveform, are plotted as 1 point in an N-dimensional space. When the number of times the baseline waveforms are acquired is as X, the direction with the largest width of the data distribution when plotted in the N-dimensional space in the same manner as the X waveform is determined as the first principal component, the direction which has the largest width and is orthogonal to the first principal component is determined as the second principal component, the direction which has the largest width and is orthogonal to the first and second principal components is determined as the third principal component, and so on in the same manner until an arbitrary N-th principal component is determined. At this time, the Q statistic, which is the amount of variation of the direction orthogonal to the principal components specified in the range of 1 to N, is used as an index of the degree of anomaly. Using Q statistics obtained from multiple normal data by this technique as reference, the early signs of waveform change accompanying equipment deterioration, that is, anomaly prediction signs, are visualized as the trend of the Q statistic by calculating the Q statistics. The object of judgments is the data during plant operation, and anomalies are detected by setting a threshold value. Although it is not possible to detect waveform changes within the normal range by the conventional monitoring technique using a threshold, waveform changes within the normal range can be captured as the Q statistic by principal component analysis.

4. Application to Welding Machine Traveling System

Since travel of the welding machine carriage is performed by conversion of the rotation of the motor to linear motion by the drive part, changes in the condition of the drive part appear as changes in the load current waveform of the motor. Two monitoring timings are conceivable, either during the welding operation by carriage travel or during homing (return to home position). However, in the welding operation, the

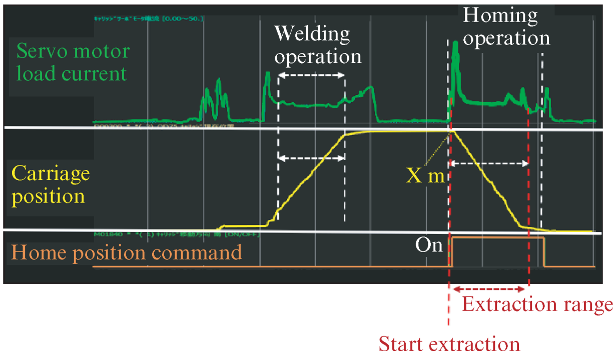

Fig. 3 Monitoring targets and timing

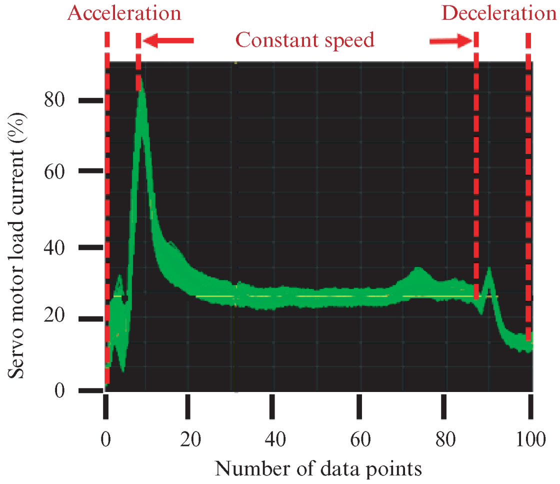

Fig. 4 Reference waveform created from multiple normal data

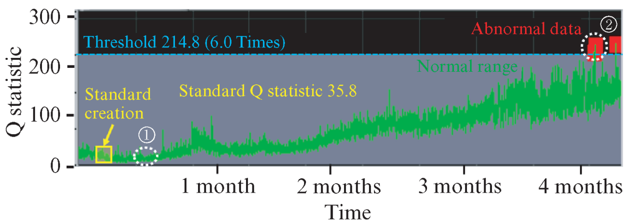

Fig. 5 Q statistics for 4 months since the creation of reference waveform

welding speed setting of each material is different, and the load current also changes due to those differences, making it difficult to evaluate anomalies in the operation. On the other hand, in homing operation after welding, the carriage travels its full stroke at a constant speed each time, suggesting that time-series changes in deterioration can be captured easily during homing. Therefore, motor operation during homing was selected as the timing of load current monitoring.

Figure 3 shows the load current waveform of the servo motor, that is, the object of monitoring, and the current position of the carriage and homing command used as the collection conditions. In monitoring carriage travel, the full width of the travel stroke must be considered as the object of monitoring in order to understand the position where an anomalous waveform occurs. Therefore, the monitoring conditions adopted here were from "Current position X m" immediately after the start of homing and "Homing command ON." The carriage operation time for data collection is calculated from the stroke range and the homing speed. With this system, it is possible to collect 300 data points per signal waveform at the maximum speed of 1 msec. In this example, monitoring was performed by collecting 100 data points in 150 msec.

Figure 4 shows the data for 100 welding runs collected as reference waveforms. During homing, the waveform rises and falls due to acceleration and deceleration of the traveling mechanism. However, since the timing of monitoring is the same, the waveforms generally overlap with some amount of variation. The principal components and Q statistic are calculated based on this variation, and the Q statistic increases in judgment data with different reference waveforms and shapes.

5. Example of Welding Machine Anomaly Detection

Figure 5 shows the transition of the Q statistic during the 4-month period after the creation of the reference waveform. Data that fall within the threshold range are plotted in green, and data that exceed the threshold are plotted in red. The Q statistic calculated from the reference was 35.8. Based on the failure record in Table 1, it was thought that failure would occur within a 1-year period. Therefore, in order to detect anomaly prediction signs before failure actually occurred, the increase after 10 months was estimated, and the threshold was set at 6 times the reference. In this example, the Q statistic rose once in the first month, continued to rise from an elapsed time of 2 months through the fourth month, and threshold exceedance occurred before 4 months had passed. In an inspection during scheduled maintenance 2 weeks after threshold exceedance, damage of the ball screw shaft and nut was discovered, confirming the consistency of the damage condition and the increase in the Q statistic.

In this case, by utilizing anomaly prediction by this system, unexpected failure could be prevented in advance by carrying out planned repairs.

Figure 6 shows the collected waveforms of the locations marked ① and ② in Fig. 5. The green waveforms are the reference waveforms, and the red waveforms are the representative waveforms of ① and ②, respectively. Focusing on the changes in the representative waveforms in the enlarged parts, the variability of the wave-

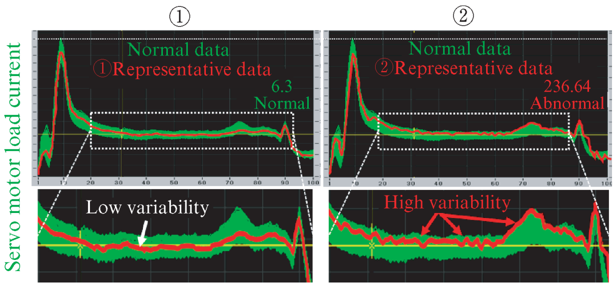

Fig. 6 Comparison of normal and representative data

form immediately after creation of the reference waveform in ① is low, but remarkable variability resembling fine wave-like undulations can be seen in the waveform from the fourth month in ②. It is considered that Q statistic rose accompanying the increase in this undulating variability. Where these waveform changes are concerned, since the fluctuations in the anomalous data occur within the distribution range of the normal waveform, anomalies cannot be discovered by the conventional monitoring method of threshold judgment of the load current. However, by using principal component analysis, it is possible to detect anomalies, even within the distribution range of normal data, because the Q statistic increases accompanying an increase in waveforms with shapes different from the normal data.

6. Conclusion

An anomaly prediction monitoring technique was introduced in a welding machine at a continuous production line, and it was found that anomaly prediction signs in the welder carriage travel system, which cannot be detected by conventional threshold monitoring, can be captured as changes in the Q statistic in an anomaly diagnosis by principal component analysis, enabling advance prevention of equipment failures. Although the example in this paper concerned a welding machine, since the anomaly prediction detection system (J-dscom™) can also be applied in a similar manner to all types of production equipment, not limited to welding machines, a reduction in the impact of a wide range of equipment problems on production can be expected.

References

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This paper reproduces the paper listed as reference 3), which was written by the same lead author, with revisions of some expressions.