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Anomaly-Sign Detection Techniques for Steel Manufacturing Facilities Utilizing Data Science

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Abstract:

In steel making processes, influence of an equipment fault on production operation is significant. It is strongly required to detect an equipment fault at an early stage and to prevent the damage. Therefore, techniques to detect fault signs utilizing data science are developed in a hot rolling process. In this paper, two techniques, the one possible to monitor an entire process and the other specified to monitoring hundreds of run-out table motors, are mentioned.

1. Introduction

In steel manufacturing processes, early detection and prevention of equipment anomalies is strongly required because equipment faults have a significant impact on production operations. However, there are limits to the conventional approach of constructing monitoring logics for individual equipment due to the extremely large number and diverse types of equipment that should be monitored. As an additional problem, the percentage of equipment which has been in operation for several decades since introduction has increased in recent years, and as a result, unexpected trouble has also shown an increasing tendency. To solve these problems, two different anomaly-sign detection systems targeting application of data science technology were developed for the hot rolling process. The first is a monitoring system which can comprehensively monitor the entire process based on various types of operational data while also realizing general applicability. With this system, monitoring at the entire process level, facility level and sensor level is possible, and the different techniques, such as big data analysis technology, statistical techniques, *etc*. are applied corresponding to the level. In addition, use of AI technology in monitoring at the entire process level makes possible to narrow down the range of anomaly sources. This approach has high general applicability, enabling development to processes other than hot rolling. The second anomaly-sign detection system is a specialized system for designated equipment. This paper reports an example of the development of a specialized anomaly-sign detection system for the hundreds of motors used in the run-out table, which is a product conveying device located between the finish rolling mill and the coiler. In this system, which has a proven record of eliminating the need for maintenance, individual monitoring logics are constructed for each motor by using a statistical technique to eliminate the machine differences that occur between several hundred motors. This paper presents examples of these two systems, which were developed to satisfy different aims.

2. Entire Process Monitoring Technology

2.1 Overview

As a distinctive feature of the hot rolling process, the process consists of diverse types of devices and equipment, which also have a hierarchical structure. Therefore, as shown in **Fig. 1**, monitoring was configured by level, that is, at the sensor level, facility level and entire process level, and appropriate techniques were applied to each level.

The lower sensor level is monitoring that can be

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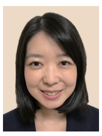

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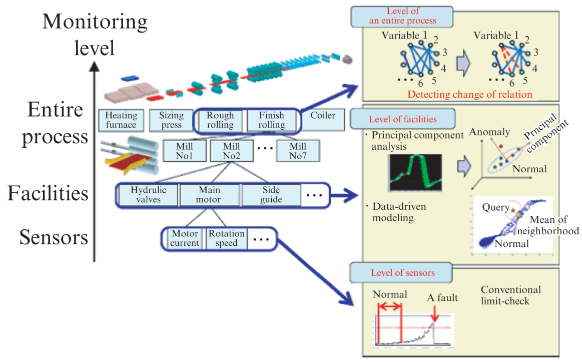

Fig. 1 Concept of anomaly signs detection by hierarchy level of a manufacturing process

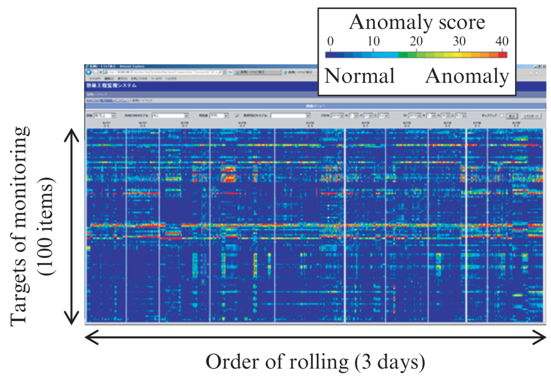

Fig. 2 Example of heatmapping display

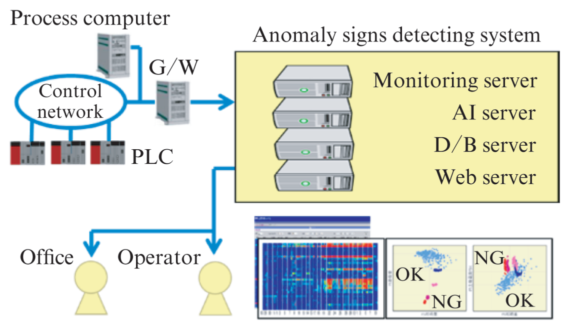

Fig. 3 System configuration of anomaly signs detection

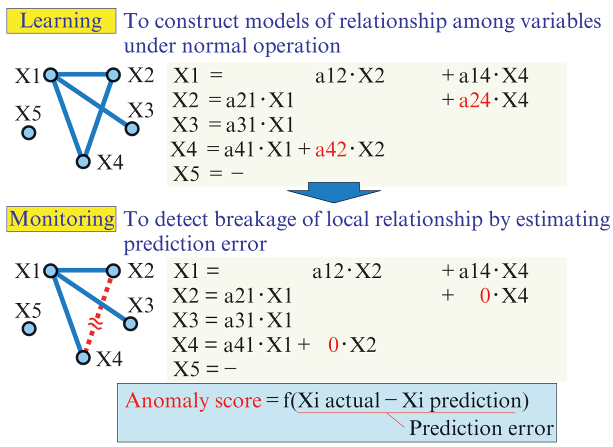

Fig. 4 Application of Lasso regression method to detecting anomaly signs of the entire process

performed by the conventional technique of upper and lower limit checks. For the intermediate facility level, pattern monitoring using principal component analysis (PCA) and intervariable correlation monitoring using data driven model were introduced as the main monitoring technique [1,2]. At the upper level of entire process monitoring, a technique based on Lasso regression [3], which is one type of sparse modeling, was introduced considering the enormous number of variable items to be handled, which total several hundred or more. In all cases, the degree of deviation with respect to criteria for normal operation was indexed as an anomaly score.

Due to the extremely large number of monitoring targets, the magnitude of the temporal changes in the anomaly scores of each monitoring target is expressed by a heatmapping display to enable efficient monitoring. An example is shown in **Fig. 2**, where the vertical axis represents the monitoring targets and the horizontal axis represents the rolling order. Here, one cell shows the anomaly score (average value or other statistical quantity), which is calculated in rolling coil units.

An overview of the system configuration is shown in **Fig. 3**. Heatmaps can be accessed via the internet from the operation room, offices or other locations. Moreover, because variables that require attention are designated, automatic creation of graphs such as scatter diagrams is possible when necessary. Normal products and anomaly products can be compared easily by using scatter diagrams.

2.2 Monitoring of Entire Process Level

Use of Lasso regression, which is applied to monitoring of the hot rolling process at the entire process level, greatly reduces the number of unnecessary explanatory variables because small influence coefficients are reduced to zero. **Figure 4** shows an overview of the Lasso regression method. Prediction models are constructed by variable for data under normal operation, which are prepared in advance, and the prediction error for actual values which are newly acquired during monitoring and judgment are calculated. Because prediction error is small when the data of the judgment target are normal and large when the data are anomaly, the anomaly scores of individual variables can be calculated based on the prediction error.

Figure 5 shows an example of detection of anomaly signs in the finish rolling process. The figure shows a chart of the anomaly score, which is an index showing the condition of mechanical accuracy of a rolling mill. Although the anomaly score had shown an increasing trend, a large reduction can be seen after repair.

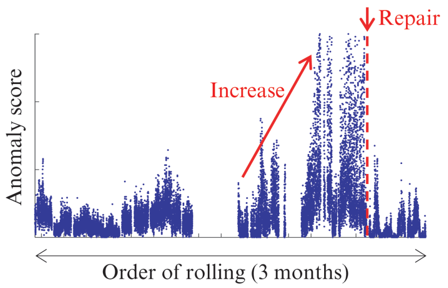

Fig. 5 Example of detecting anomaly signs by the level of the entire process

2.3 Monitoring of Facility Level

The main monitoring techniques introduced for monitoring at the facility level were pattern monitoring using PCA and intervariable correlation monitoring using a data-driven model. First, pattern monitoring by PCA will be explained. When equipment shows a constant repeated action, the waveform (pattern) of the signals showing the condition of that equipment is also constant. During anomaly operation, disturbances occur in the waveform, and these are captured as anomaly signs. Therefore, a method for detection of waveform disturbances and diagnosis of anomalies using PCA was developed [1,2]. Positioning motors are a typical example of equipment that displays a constant repeated action. **Figure 6** shows the waveform of the amount of movement of equipment driven by a positioning motor. If sampling points comprising a waveform are k-points, one waveform corresponds to one point in k-dimensional space. Because there is a correlation between adjacent sampling points, waveforms for normal operation are distributed in a pattern in which a mutual correlation exists in k-dimensional space. Here, it is possible to extract waveforms for normal operation as principal components by applying PCA. As shown in Fig. 6, because the waveform deviates from the principal component when a disturbance in the waveform occurs due to hunting, *etc*., anomaly signs can be detected by calculating and monitoring the degree of deviation, which is defined as the distance from the component perpendicular to the principal component. The calculation formula is shown below [4,5], where the statistical quantity T^2 is an index of the direction of the principal component, and the statistical quantity Q is an index of the direction perpendicular to the principal component.

$$T^2 = \sum_{r=1}^{R} \frac{t_r^2}{\sigma_{tr}^2} \qquad Q = \sum_{p=1}^{P} \left(x_p - \hat{x}_p \right)^2 \quad \cdots\cdots\cdots\cdots\cdots\cdots (1)$$

σ_{tr} : standard deviation of r-th principal component score t_r

R : number of principal components

P : number of data items

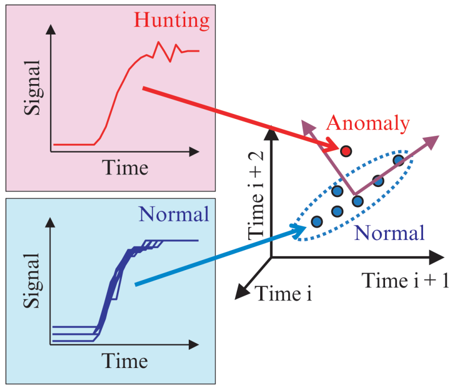

Fig. 6 Application of PCA method to detecting anomaly signs in a facility

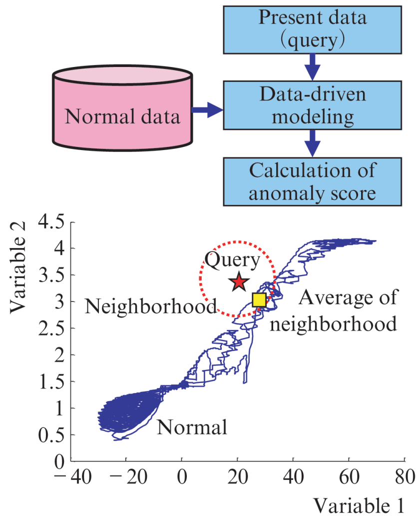

Fig. 7 Application of data-driven modeling method to detecting anomaly signs in a facility

Next, intervariable correlation monitoring using a data-driven model will be explained. In this method, as illustrated in **Fig. 7**, in cases where a certain correlation exists between variables showing the condition of equipment during normal operation, the normal data from the past are registered in a database in advance, and when measured values for a judgment target are acquired, the distance between the present data (query) and the past data registered in advance in the database is calculated, and this distance is defined and monitored as the degree of deviation. Provided a certain relationship exists between variables in the equipment, monitoring is possible irrespective of the type of equipment. The calculation formula for distance d is shown below.

$$d \sqrt{\sum_{p=1}^{P} \left(x_p - q_p \right)^2} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (2)$$

P : number of data items

As an example of anomaly-sign detection in the fin-

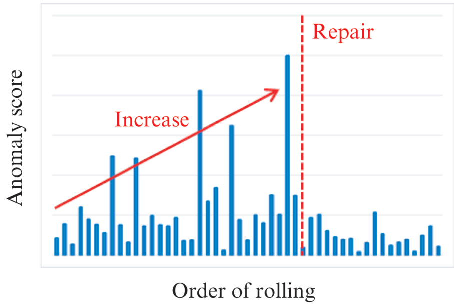

Fig. 8 Example of detecting anomaly signs by the level of facilities

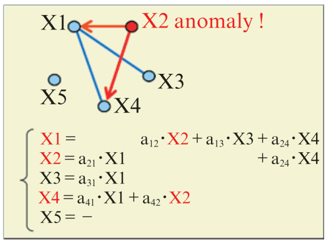

Fig. 9 Image of propagation of anomaly source

ishing coiler, **Fig. 8** shows the results of monitoring of the action waveform using PCA method immediately after the start of coiling. Here, the anomaly score, which had shown an increasing tendency, decreased after repair.

2.4 Estimation technique of anomaly source using AI

As a problem in the monitoring of the entire process level discussed above, source anomalies propagate to other variables through the regression model, and as a result, anomalies are observed in multiple variables. To simplify the explanation, **Fig. 9** shows an example consisting of only five target variables. Assuming the source anomaly is X_2, the anomaly scores of X_1 and X_4 will also increase because X_2 is the explanatory value of those variables. In actuality, the model includes more than 100 variables, and anomalies sometimes occur simultaneously in multiple different variables. Since it is difficult to identify the anomaly source in such cases, an estimation method utilizing AI was developed. In this method for estimating anomaly sources, learning is performed by deep learning using various combinations of data to which small anomalies are added artificially. **Table 1** shows the results of AI estimations of five faults that occurred in the past. Because the hit rate (ratio of the number of items estimated to be anomaly sources to the number of items whose anomaly score exceeds a predetermined threshold) is 7 to 33 %, and the number of missed variables that must be detected, as judged by fault analysis, were zero, the estimations are considered valid.

Table 1 Result of AI estimation

	Fault A	Fault B	Fault C	Fault D	Fault E
Number of variables whose anomaly score exceeded the threshold	45	15	39	17	10
Number of variables estimated as anomaly sources	3	5	5	3	3
Number of missed variables that must be detected	0	0	0	0	0
Number of variables not valid as anomaly sources	0	3	3	0	1

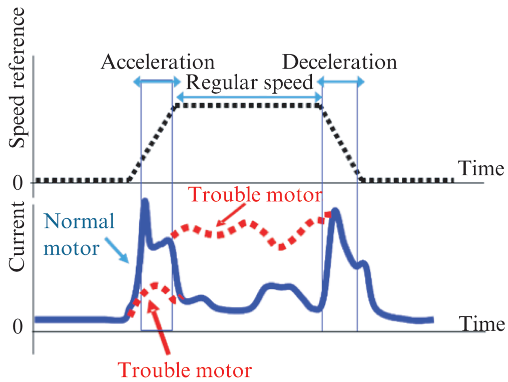

Fig. 10 Speed reference and current of motor

3. Conveying Motor Monitoring Technology

The run-out table is located between the finishing rolling mill and the coiler, and is a conveying device which cools hot strips toward the target temperature before coiling. The table consists of several 100 rolls and the same number of motors driving each roll. Therefore, if a roll fails to rotate due to a coupling anomaly or an anomaly load on the motor, the strip being conveyed will be damaged, and a lengthy line stop will be necessary. **Figure 10** shows the behavior of the load current with respect to the speed reference of a motor. In normal conveying operation, peaks in the load current with respect to the speed reference of the motor occur during acceleration and deceleration, and the current is approximately constant under the constant (regular) speed condition. However, if fault occurs in the motor, a waveform deviating from that in normal operation will be observed.

As conventional techniques for advance detection of motor fault, motor sound detection and anomaly detection when the measured current exceeds a threshold value have been used. However, the former requires sound detection of several 100 motors by the control and maintenance staff within a limited period of time,

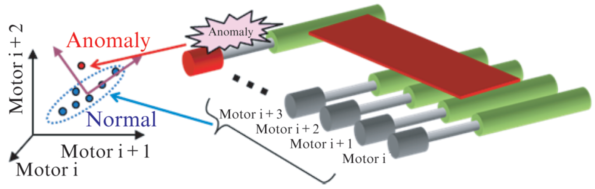

Fig. 11 Application of PCA method to monitoring run-out motor current

and because sound detection depends heavily on long years of experience by the personnel involved, there is a possibility that anomalies may be overlooked. The latter method makes it possible to detect anomalies in real time, but it is necessary to set threshold values considering the characteristics of each motor after determining the behavior of the motor current during acceleration, regular speed operation, and deceleration, and depending on the case, misdetection of anomalies is possible.

Based on these issues, a new monitoring technique for run-out table motors using PCA was developed[6], as described in the following. Because basically the same operation is performed between adjacent motors, the motor current of adjoining motors shows a high correlation. In applying PCA to this, as shown in **Fig. 11**, normal operation, including machine differences between motors, can be expressed as a principal component. In case a motor anomaly occurs, the degree of deviation, defined as the distance from the component perpendicular to the principal component, is calculated, and anomaly signs can be detected by monitoring this value. As a result, it is not necessary to adjust the threshold for each motor. It should be noted that this method is different from the method of using PCA in pattern monitoring described in section 2.3 "Monitoring of Facility Level," since the deviation from the correlation between motors is monitored in this method.

Next, the monitoring system will be described. **Figure 12** shows the system configuration. The actual current values are collected in a data server by Hall CT sensors installed on the run-out motors. The motors of the run-out table are divided electrically into a total of three groups of approximately 100 motors each from the first part of the table, and the reference speeds given to each group are different, depending on the strip passing position. Furthermore, the current waveforms of the motors differ depending on the speed pattern, that is, acceleration, regular speed and deceleration, as shown in Fig. 10. Based on these considerations, in applying the PCA system to current monitoring, models were constructed for each speed pattern and group, in which the reference speed is different.

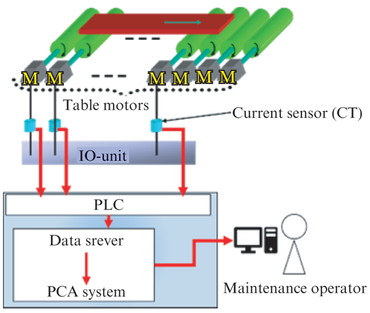

Fig. 12 Run-out motor current monitoring system

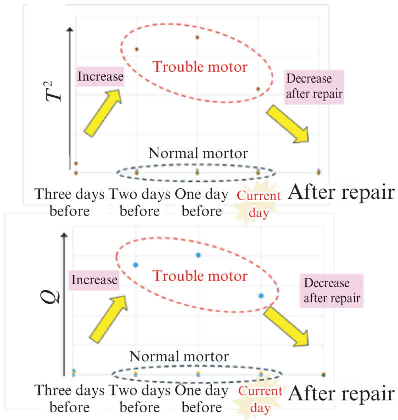

Fig. 13 T^2 and Q statistics of failed motor and others

Figure 13 shows the statistical quantities T^2 and Q in the data collected during regular speed operation for a case of failure of one of a total of 329 motors, in which the roll failed to rotate due to breakage of the coupling between the roll and the motor. It can be understood that the values of the statistical quantities T^2 and Q of the failed motor changed greatly from those of other normal motors beginning 1–2 days before failure. This example demonstrates the usefulness of the PCA technique, in which motor anomalies are expressed by the statistical quantities T^2 and Q.

4. Conclusion

New approaches to anomaly-sign detection technology for the hot rolling process utilizing data science technology were introduced. The first is an anomaly-sign detection technique which enables monitoring at the entire process level, while also achieving general applicability to other manufacturing processes. A monitoring system by level was proposed for facilities and equipment, which have a hierarchical structure, and a system which enables comprehensive anomaly-sign detection was implemented by applying appropriate techniques for analysis of the degree of anomaly corresponding to each level. The second is a specialized monitoring technique for the product conveying motors of the run-out table. For high efficiency implementation of logic for monitoring the several 100 motors of the table, a technique using the PCA method was applied. Although these two systems were developed for different steel works, the authors plan to construct a single system integrating the functions of the two systems and promote further stabilization of production by advance prevention of equipment anomalies.

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