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Condition Monitoring Technology for Steel Making Facilities Utilizing Data Science

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Abstract:

In integrated steel making process, the influence of equipment troubles on production operation is significant. Therefore, it is strongly required to find out faults in the equipment at an early stage and to prevent the damages. New endeavors toward condition monitoring technology of the steel making facilities utilizing data science, such as ICT (Information and Communication Technology) and AI (Artificial Intelligence) are introduced.

1. Introduction

In coastal-type integrated steel works, the series of facilities from raw material unloading and storage through ironmaking, steelmaking, rolling and other steel making processes to shipment is arranged on a large plant site. Because many of the steel works in Japan were constructed during the era of high economic growth, the level of equipment maintenance required in these steel production facilities varies widely, from equipment which is now undergoing progressive deterioration due to aging to newly-introduced state-of-the-art equipment.

Because equipment trouble has a huge impact on production operation in an integrated steel making process, early discovery of equipment anomalies and prevention of damage in advance are demanded. Moreover, as a steel works is operated basically by a 24 hour-a-day system, signs of anomaly must be detected and corrected by constantly monitoring equipment under operating conditions.

In raw material yards, where iron ore, coal and other raw materials for steel making are unloaded, stored and transported, the handling machinery for stacking and reclaiming raw materials and a large number of belt conveyors are arranged in a large site, and equipment monitoring and maintenance are difficult because operation is performed under a poor environment, which includes outdoor conditions, dust and other problems.

At the hot rolling mill, where thin strip coils are produced from heated slabs, precision mechanical equipment is arranged in series, and products with various specifications are manufactured sequentially. For this reason, equipment sensing is performed under constantly changing operating conditions, and diverse types of data are collected, making it difficult to judge the signs of anomalies.

JFE Steel is promoting infrastructure construction and technology development for application of data science technologies such as state-of-the-art ICT (Information and Communication Technology) and AI (Artificial Intelligence)[1, 2]. This paper introduces new efforts in equipment condition monitoring applying data science to steel making equipment in which a high order of monitoring and anomaly diagnosis is demanded, as outlined above.

2. Condition Monitoring of Raw Material Yard Equipment

2.1 Belt Conveyor Monitoring System

Equipment control of raw material belt conveyors is extremely important, as the loss if conveyor trouble occurs is large. Although there is a high need for monitoring by installation of numerous sensors of various types, a large number of belt conveyors are arranged over a large site in raw material yards, and in some

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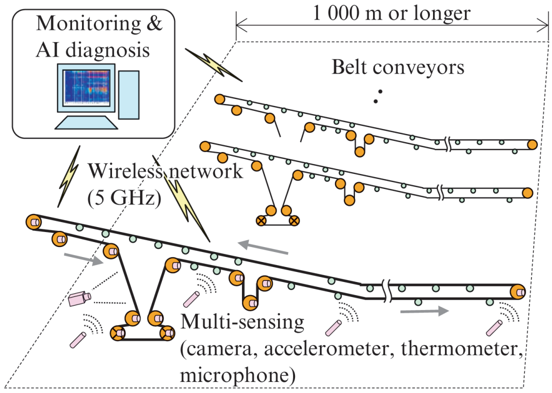

Fig. 1 Belt conveyor monitoring system

cases their total length reaches several 10 km or even several 100 km. Since the cost of installing cables for data collection would be prohibitive, wireless monitoring utilizing recent ICT rather than sensor cables is demanded.

A demonstration test of a belt conveyor monitoring system was conducted at JFE Steel East Japan Works (Chiba), and centralized monitoring of multiple types of data and anomaly diagnosis by use of image data were verified. An outline of the belt conveyor monitoring system is shown in **Fig. 1**. The object of the system is the multiple belt conveyors of the ore and coal systems in the raw material yards. Centralized anomaly analysis is performed at the raw material yard center by wireless communication of information from sensors installed at each belt conveyor. The installed sensors include visible light cameras for detection of conveyor belt defects such as breakage of the belt edge, longitudinal ripping, holes, cuts, etc., and vibrometers, thermometers and microphones for detection of anomalies of the drive system and pulley bearings, and visible light cameras, microphones, thermometers and vibrometers for monitoring the condition of raw material clogging in chutes.

2.2 Construction of Wireless Network

2.2.1 Network design in raw material yard environment

A wireless communication scheme[3, 4] for implementing a wireless network in the raw material yard environment was studied. The features of each of the frequency bands in wireless communication are shown in **Table 1**. The speed and distance of wireless transmission generally change depending on the frequency band. At low frequencies, the transmission speed is slow, but transmissions are relatively unaffected by obstacles and the communication range is long. Conversely, at high frequencies, the transmission speed is fast, but obstacles tend to interfere with transmissions

Table 1 Wireless communication scheme

	ZigBee IP, Wi-SUN	ZigBee	Wireless LAN (Wi-Fi)	
Frequency band	900 MHz	2.4 GHz	2.4 GHz	5 GHz
International standard	IEEE 802.15.4	IEEE 802.15.4	IEEE 802.11 b/g	IEEE 802.11 ac
Transmission speed (max)	100 kbps	250 kbps	54 Mbps	6.9 Gbps
Communication range	700 m	50 m	100 m*	100 m*

* Approx. 1 000 m with directional antenna

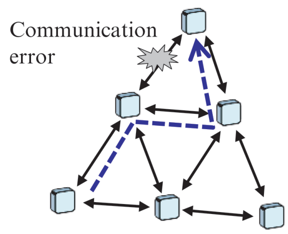

Fig. 2 Multi-hop networks

and the communication range is short. The transmission speed and range are also influenced by the transmission power of the wireless standard and the characteristics of the antenna. For example, when using a high-directional antenna in wireless transmission by Wi-Fi, the transmission direction is limited, but long distance transmission with a range of approximately 1 000 m is possible.

In monitoring of belt conveyors, it is necessary to transmit the video data acquired by photographing the belt surface with visible light cameras. For this, a 5 GHz band wireless LAN which enables large-volume transmission was considered effective. Since 5 GHz wireless transmission has high linearity, more stable transmission is possible by constructing a multi-hop network, as illustrated in **Fig. 2**, at locations where the equipment is complicated and it is necessary to provide multiple access points. In other words, when monitoring multiple conveyors, it is desirable to design a configuration that enables reliable transmission by one-to-one P2P (Peer-to-Peer) connection over long distances along raw material piles, and transmission by optimizing the transmission route by multi-hop connection in case access points are concentrated in a certain area.

2.2.2 Basic verification test of wireless transmission

A basic verification test was carried out to investigate the wireless transmission environment in the raw material yards. The test conditions are shown in **Table 2**, and the test environments are shown in **Fig. 3**. The transmission speed of 5 GHz band wireless was

Table 2 Test conditions of wireless communication

Condition		Straight P2P	Straight 1 hop	Over pile
A	High-directional antenna (3 dB beamwidth: 9°)	200-1 000 m	–	–
B	Medium-directional antenna (3 dB beamwidth: 30°)	200-1 000 m	–	57 m
C	Non-directional antenna	100-1 000 m	100 m+100 m 200 m+200 m 500 m+500 m	–

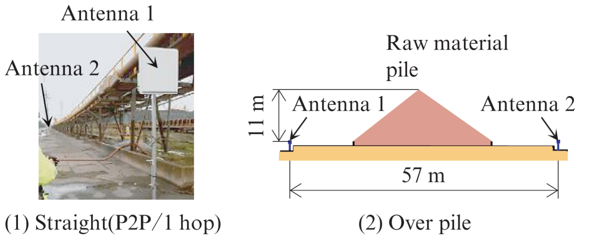

Fig. 3 Wireless communication test in raw material yard

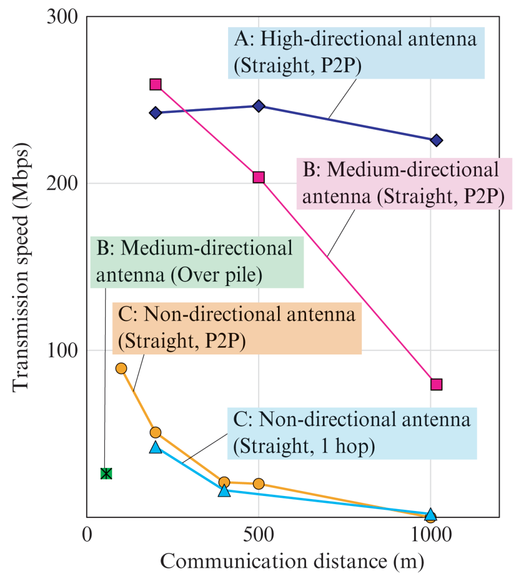

Fig. 4 Measurement results of transmission speed

measured under different antenna conditions in a straight test along a raw material pile and an over pile test, in which the antennas were located on the two side of a raw material pile having a height of 11 m.

Figure 4 shows the measurement results of transmission speed against communication distance, which is shown on the x-axis. The transmission speed changed remarkably depending on the directionality of the antenna. When a high-directional antenna was used, it was possible to secure an extremely fast transmission speed even over a long distance of 1 000 m, but with the medium-directional antenna and non-directional antenna, which have inferior directionality, a distinctive characteristic of slower transmission speeds depending on distance could be seen. When one-to-one P2P connection and a hop connection having one relay point were compared, a slight decrease in transmission speed was confirmed in the system with the relay. Furthermore, in over pile transmission, in which there was an obstacle (raw material pile) between the two wireless access points, an extreme decrease in transmission speed was observed, even when the communication distance was short.

In monitoring of belt conveyors, a trial calculation showed that the necessary transmission speed per conveyor is 20 Mbps. However, by using high-directional antennas, it is possible to construct a communication network with a considerable speed margin of more than 10 times the required speed in the large area of raw material yards. Moreover, since 5 GHz band wireless transmission is easily affected by obstacles, as confirmed in the over pile test described above, it is important to secure transmission stability by using relays in cases where access points are concentrated in an area of 200 m.

2.3 Belt Anomaly Detection by Image

A model of detection of belt shape defects by photographing the surface of a conveyor belt with a visible light camera was created, and its accuracy was verified.

The condition of photography of the belt is shown in **Fig. 5**. A network camera with dustproof and waterproof performance was used as the camera, and the shutter speed was set so as to enable blur-free photography, considering the speed of the conveyor belt. Because brightness would be inadequate if a fast shutter speed was used, multiple lights were set up so as to secure the necessary light intensity and were adjusted so that the brightness of the belt surface was uniform.

Based on the recorded image data, an anomaly judgment model that considered the diversity of defect shapes was constructed. Verification of the anomaly judgment model was performed by constructing a model using 80% of the image data recorded in advance, and judging the remaining 20%, which was unknown to the model. Judgment accuracy was evalu-

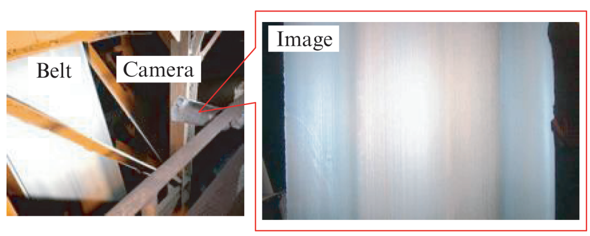

Fig. 5 Taking images of conveyor belt

ated by the percentage of correct answers concerning whether an actual shape defect existed or not and agreement with its properties in the results of judgments of the various image data by the model. As a result, the percentage of correct answers for all the data used in the evaluation was an average of 87%, confirming sufficient accuracy as an initial stage model.

3. Anomaly Sign Detection of Hot Rolling Mill

3.1 Anomaly Sign Detection by Data Science

Equipment stability is indispensable for maintaining superior cost competitiveness. Until now, JFE Steel had adopted the approach of constructing monitoring models specialized for the type of trouble in order to prevent the recurrence of that trouble. However, in some cases, the percentage of equipment in service for several decades since introduction has increased. At these plants, unexpected trouble has also increased, and it is no longer possible to respond by the conventional approach. On the other hand, in post-analysis of operational data after trouble, there are many examples that appear to be signs of potential anomalies. Therefore, JFE Steel developed an anomaly sign detection system for the hot rolling process which also makes it possible to detect the signs of unexpected trouble by incorporating big data analysis technology for efficient and comprehensive analysis of an enormous volume of data.

3.2 Outline of Anomaly Sign Detection System for Hot Rolling Mill

As distinctive features of the hot rolling process, this process consists of diverse types of devices and equipment, and it is a hierarchical structure. Therefore, as shown in **Fig. 6**, the anomaly sign detection system comprises monitoring by level at the sensor level, facility level and entire process level, and appropriate techniques are adopted for each level.

At the sensor level, which is the lowest level, monitoring is possible by the conventional upper and lower limit checks. For the intermediate facilities level, pattern monitoring using principal component analysis (PCA), and inter-variable correlation monitoring using a data driven model were introduced as the main monitoring techniques[5, 6]. However, in the top level, i.e., the entire process level, the number of variables treated is enormous, reaching more than several hundred. Therefore, a technique based on Lasso regression[7] was introduced as a type of sparse model that is useful for big data analysis. In all cases, the deviation from the standard under the normal operation condition was indexed as an anomaly score.

Due to the huge number of targets of monitoring, the time change in the anomaly score by monitoring target was shown by a heat mapping display corresponding to its magnitude to enable efficient monitoring. An example of a heat mapping display is shown in **Fig. 7**. The y-axis shows the targets of monitoring, and the x-axis shows the sequence of rolling. One cell shows the score (average value or other statistical quantity) of the anomaly score calculated for each rolling operation.

The configuration of the anomaly sign detection

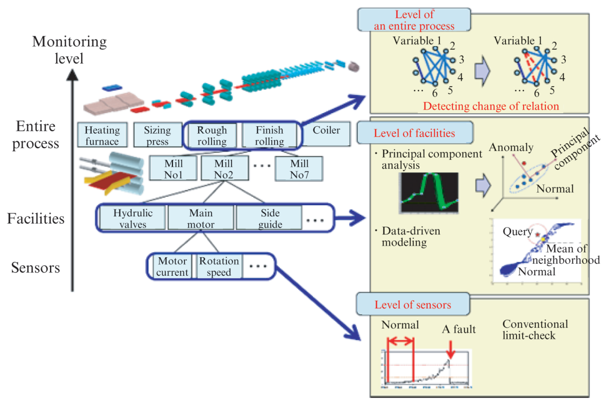

Fig. 6 Concept of anomaly sign detection by hierarchy level of a manufacturing process

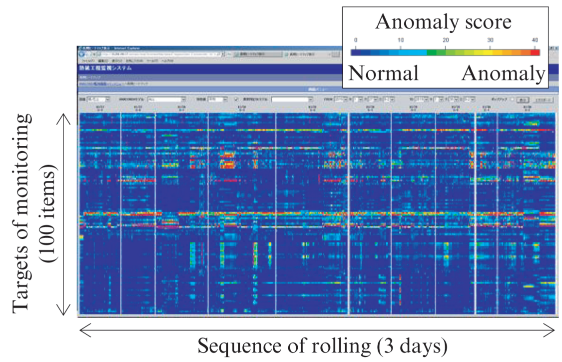

Fig. 7 An example of heat mapping display

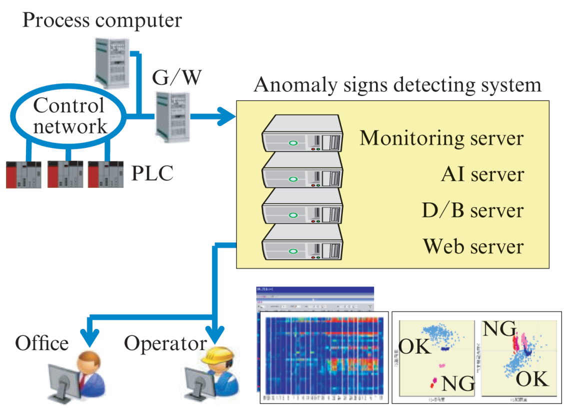

Fig. 8 System configuration of anomaly signs detection

system is shown in **Fig. 8**. Heat maps can be monitored from the operation room, office or elsewhere via the internet, and automatic creation of graphs such as scatter diagrams, etc. is also possible when necessary, since the target variable can be designated. Comparison of normal operations and trouble-affected operations can be performed easily by using a scatter diagram.

3.3 Monitoring of Entire Process Level

A large reduction in unnecessary explanatory variables is possible by using lasso regression in monitoring of hot rolling at the entire process level, as variables with very small influence coefficients are reduced to zero. **Figure 9** shows an outline of the lasso regression method. Prediction models are constructed for individual variables under normal operation, which are prepared in advance, and prediction error is calculated against the actual values newly obtained during monitoring judgment. Since the prediction error is small if the data for the target of judgment are normal and large if the data are anomalous, the anomaly score for each variable can be calculated based on the prediction error.

An example of anomaly sign detection for the finish rolling process is shown in **Fig. 10**. Among the targets of monitoring, this figure is a chart of the anomaly score for items that indicate the condition of mechanical accuracy of the rolling mill. A decrease in the anomaly score, which had shown a rising tendency, can be seen after repair.

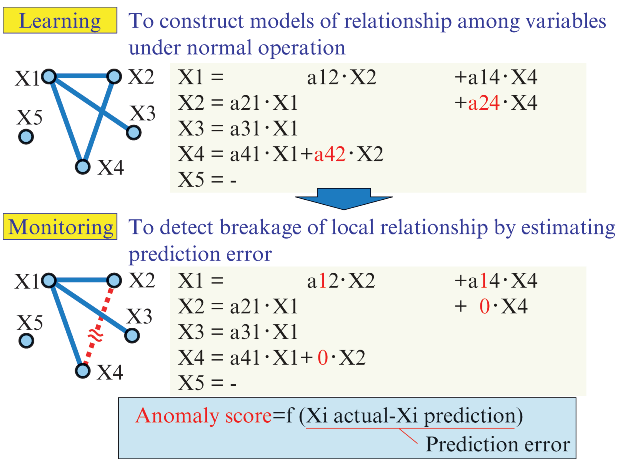

Fig. 9 Application of lasso regression method to detecting anomaly signs of the entire process

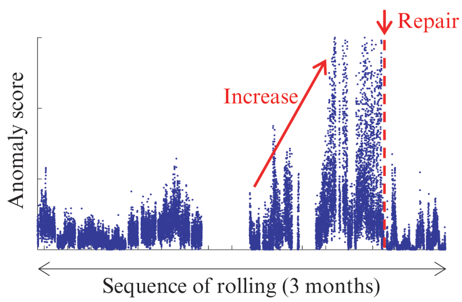

Fig. 10 An example of detecting anomaly signs by the level of the entire process

3.4 Monitoring of Facility Unit Level

The following explanation will be limited to pattern monitoring by PCA. When operation of a unit of equipment is constant, the pattern of the signals indicating the condition of that equipment is also constant. However, when operation is anomalous, there are many disturbances in the pattern, and these are considered to be signs of anomaly. Therefore, a method for anomaly diagnosis by detection of pattern disturbances by PCA was developed[6]. Positioning motors are typical equipment that shows constant operation. **Figure 11** is a diagram that shows the patterns of the amounts of movement of the equipment driven by a positioning motor. If the sampling points comprising patterns are defined as k points, one pattern corresponds to one point in k-dimensional space. Because there is a correlation between neighboring sampling points, the pattern under normal operation is distributed in a form in which those points show a mutual correlation in the k-dimensional space. Here, it is possible to extract the normal operation pattern as the principal component by applying PCA. When a disturbance in the pattern occurs due to hunting or some other anomaly, as shown in Fig. 11, that pattern deviates from the principal component. Therefore, the anomaly score defined by the vertical component to the principal component is calculated, and an anomaly sign can be detected by monitoring that deviation.

The results of monitoring the equipment operation pattern immediately after the start of coiling are shown in **Fig. 12** as an example of sign detection in the finishing coiler. Here, a decrease in the anomaly score, which

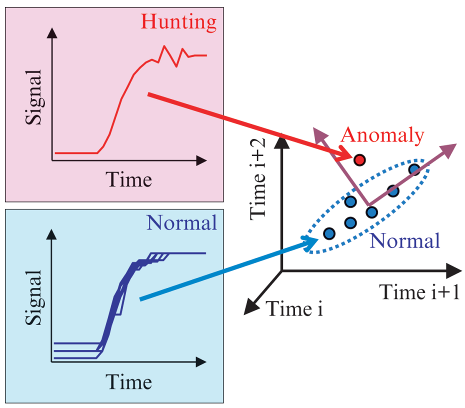

Fig. 11 Application of PCA method to detecting anomaly signs in a facility

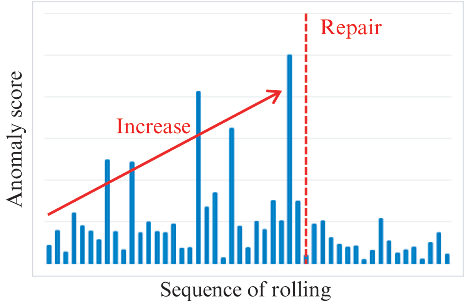

Fig. 12 An example of detecting anomaly signs by the level of facilities

had shown a rising tendency, can be confirmed after repair.

4. Conclusion

New efforts in equipment condition monitoring applying data science technology were introduced. In monitoring of raw material yard equipment, a demonstration test of belt conveyors was conducted, and the specifications necessary in wireless networks, which are indispensable for wide-area data collection, and the practicality of image judgment of belt shape defects were confirmed. In monitoring of hot rolling mill equipment, a monitoring system by levels was proposed for sensor and facilities, which is a hierarchical structure, and a system which is capable of comprehensive anomaly sign detection was constructed by applying appropriate anomaly score analysis techniques corresponding to each level.

In the future, we plan to expand these technologies to various types of equipment in order to promote stable production by advance prevention of equipment anomalies.

References

1) Kazama, A.; Tsuda, K. Bulletin of The Iron and Steel Institute of Japan. 2018, vol. 23, p. 696–699.
2) IIzuka, Y.; Shigemori, H.; Tomiyama, S.; Koshihara, T. Bulletin of The Iron and Steel Institute of Japan. 2018, vol. 23, p. 700–705.
3) Yamada, A.; Nojima, D.; Asai, T. IEICE communications society magazine. 2016, vol. 10, no. 2, p. 74–79.
4) Fukui, K.; Fukunaga, S. OKI Technical Review. 2011, vol. 78, no. 1, p. 104–107.
5) Hirata, T.; Kawahara, Y.; Sugiyama, M.; Asano, K. A Fault Detection Technique for the Steel Manufacturing Process Based on a Normal Pattern Library. IFAC-PapersOnLine. Paris, 2015, vol. 48, issue 21, p. 871–876.
6) Naruse, T.; Takada, M.; Hirata, T.; Hagio, Y.; Akechi, Y. Condition Monitoring Technologies Developed and Introduced for Use in Steel Works. Journal of Japanese Society of Tribologists. 2017, vol. 62, no. 11, p. 671–678.
7) Tibshirani, R. Regression Shrinkage and Selection via the Lasso. Journal of the Royal Statistical Society, Series B (Methodological). 1996, vol. 58, issue 1, p. 267–288.