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Operation Guidance Technique of Blast Furnace Using Data Science

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Abstract:

In a blast furnace operation under low percentage of reducing materials, which intends to rationalize, the furnace condition easily falls into unstable. Therefore, it is important to operate the furnace with a better understanding of the current condition. However, information obtained from sensors is not still enough. Accordingly, techniques for particle size measurement of charging coke in real time, prediction of pig iron temperature based on blast furnace physical model, and furnace condition detection based on inner pressure data of the blast furnace have been developed by utilizing data science technique. These techniques contribute to the detecting the anomaly causing troubles in advance with the guidance to operator for preventing a blast furnace from falling into serious trouble, and to continuous stable operation. In this paper, the outline of these techniques and various guidance systems are described.

1. Introduction

The blast furnace is a process in which coke and iron ore are charged alternately from the top of the furnace, hot blast is blown into the furnace from tuyeres located in the lower part of the furnace, and molten pig iron is produced by reduction of the iron ore by the carbon in the coke. Blast furnaces are being operated at a low reducing agent ratio (RAR), which has the effect of reducing emissions of carbon dioxide. Here, "reducing agent" refers to the coke charged from the furnace top and the pulverized coal injected through the tuyeres, and "reducing agent ratio" is defined as the amount of reducing agents used in the production of 1 ton of pig iron by the blast furnace. Among reducing agents, coke also plays the role of a spacer in the furnace in order to secure permeability when the high temperature gas blown from the tuyeres in the lower furnace rises through the furnace. The reaction between the oxygen contained in the iron ore (or sintered ore) and the carbon in the coke under the high temperature environment in the blast furnace, generates heat, together with carbon monoxide (CO) or carbon dioxide (CO_2). The iron ore is melted and the reduction reaction proceeds with good efficiency as a result of this heat. Similar to the RAR, the coke ratio is defined as the amount of coke necessary in the production of 1 ton of pig iron. Although reducing the coke ratio has the large environmental merit of reducing the amount of CO_2 emitted from the blast furnace, the smaller amount of coke may be inadequate to perform the essential function of coke as a spacer, as mentioned above. Because the narrower gas flow paths under this condition reduce furnace permeability, and heat generation also decreases, there is a risk that low coke operation may prevent the reduction reaction.

JFE Steel is targeting the development of a cyber physical system (CPS) for the blast furnace, as shown schematically in **Fig. 1**. This paper presents an overview of the coke particle size meter, operation guidance based on hot metal temperature prediction and permeability anomaly detection guidance developed as precursor technologies for CPS.

2. Coke Particle Size Distribution Sensor

Although the coke charged into a blast furnace

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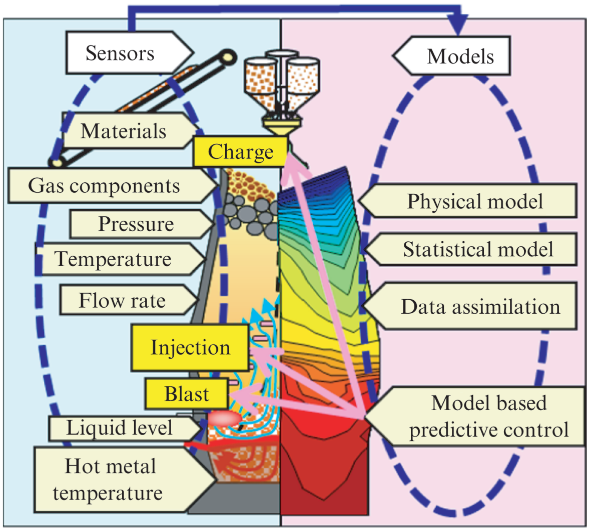

Fig. 1 Schematic diagram of CPS blast furnace

includes particles of various sizes, if the amount of small coke increases, gas flow paths will be narrower, and the furnace condition will become unstable. Conventionally, coke was sampled before charging into the blast furnace and analyzed off-line once or twice each week in order to control the tendency of the particle size distribution of the charged coke.

However, the particle size of coke drifts with a shorter cycle, and if it is possible to detect these increases in the proportion of small size coke, it will also be possible to take action in advance to prevent deterioration of the furnace condition. Therefore, JFE Steel developed a coke particle size distribution sensor which makes it possible to monitor the particle size distribution in real time.

2.1 Algorithm of Particle Size Meter Using Laser Range Finder

In the developed particle size distribution sensor, profile measurement is performed on the coke transport conveyor using a laser range finder. Because the profile is measured as distance data, the distance data are translated into luminance values and image data are generated, and the particle size distribution is obtained by processing the image as described below.

① Input image

The height data of each data point of the laser range finder are translated into luminance value, and an image file is generated. Although an image file may contain some vacancies, the vacancies are filled by linear interpolation from the surrounding data.

② Particle edge detection (binarization) and particle separation

Next, particle edges are detected by binarizing the image file translated into luminance information from the distance data obtained in ①. Since the particle periphery is not necessarily extracted completely in the binarized particle images, additional separation processing of the individual particles is performed.

③ Exclusion of lower layer particles and particles at the edge of images

When piled coke on a conveyor is observed from above, only the particles on the surface can be measured, but it is not possible to accurately measure the particle size of the lower layer particles which are buried under other particles and can only be seen through gaps in the piled coke. Therefore, these lower layer particles are excluded by using the height data. In addition, particles which are only partially visible at the edge of images are also excluded, as their particle size cannot be determined.

④ Analysis of particle size distribution

The area of the extracted particles is obtained from their number of pixels. Assuming that the diameter of a true circle having the same diameter as the pixel number represents the diameter of a particle, it is possible to determine the number of particles of each particle size in units of 1 mm. Therefore, the wt% distribution of each particle size is calculated from this information.

Assuming the particle area is A (mm^2), the number of pixels of a particle is n (pixel), the vertical size of a pixel is L_v (mm/pixel), and the horizontal size of a pixel is L_h (mm/pixel), the particle area A and particle size D can be calculated from Eq. (1) and Eq. (2), respectively.

$$A = n \cdot L_v \cdot L_h \qquad \text{(1)}$$

$$D = 2\sqrt{\frac{A}{\pi} \cdot L_h} \qquad \text{(2)}$$

Figure 2 shows the results arranged by the image processing algorithm in ① to ③. The image on the left is a raw image obtained in ①, where the color tone differs depending on the distance. The image in the center is an image obtained as the result of the processing in ②, in which the individual particle has been separated. The image on the right is the result of the processing in ③, and shows that it is possible to extract only the particles in the uppermost layer of the conveyor.

2.2 Correction of Particle Size Distribution

In the particle size distribution measurements based on image analysis described in the previous section, direct measurement of the sizes of particles in the interior of the conveyor coke pile is difficult. Therefore, the particle size distribution obtained by image processing

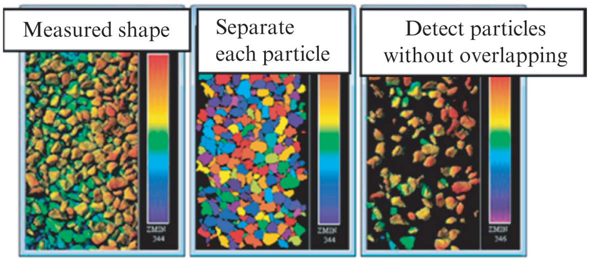

Fig. 2 Schematic diagram of algorithm for calculation of particle size

is corrected by a statistical method.

The cumulative frequency distribution of oversize particles (particles above the screen) is known to follow a logarithmic Gaussian distribution with respect to particle size [1]. Accordingly, the slope and intercept of a line (when both the vertical and the horizontal axis are logarithmic axes, a straight line is obtained) approximating the cumulative frequency distribution of the particle size obtained through a large number of measurements were averaged, and the correction was performed so that the percentage of small particles fit the particle size analysis data. This had the effect of considering small particles which were buried in the lower part of the conveyor and had been excluded because they could not be measured accurately. The data measured by this sensor were compared with the results of a manual analysis by sampling. **Figure 3** shows the results of this comparison. As a result of correction, good agreement between results measured by the particle size meter and the particle size distribution analyzed manually could be confirmed.

2.3 Online Measurement

A coke particle size distribution sensor was installed at the blast furnace charging conveyor of No. 3 blast furnace at JFE Steel's West Japan Works (Kurashiki District), and an online test was performed. As shown in **Fig. 4**, the measurement results confirmed that the device satisfied the target precision. In the first half of the operation, coke piled in the raw material yard was loaded, and when this was switched to coke conveyed directly from the CDQ (Coke Dry Quench) unit in the second half, a difference in the particle size of the two batches of cokes could be confirmed. Because the development of the coke particle size meter makes it possible to determine the particle size of the charged coke in real time, as demonstrated in this test, appropriate blast furnace operation has become possible.

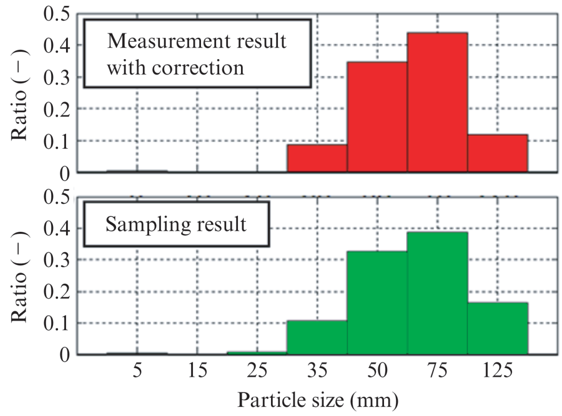

Fig. 3 Comparison of results of measurement by particle size meter and manual analysis by human

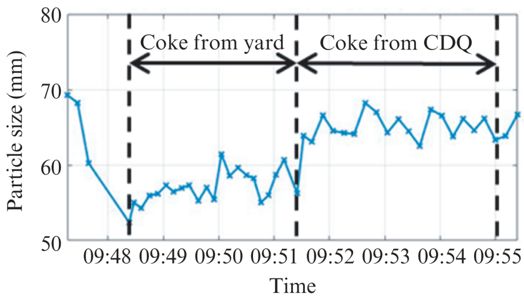

Fig. 4 Result of measurement by particle size meter

3. Operation Guidance on Hot Metal Temperature Control

Due to the large heat capacity of a blast furnace, the response of the hot metal temperature (HMT) to changes in manipulated variables is slow. Operators change the manipulated variables based on future predictions of HMT, but they tend to perform excessive control actions. As a result, large control errors of HMT occurred frequently and it caused an increase in the reducing agent ratio. Therefore, HMT prediction by a model that can reproduce the time lag until the effect of control actions appears was necessary. An algorithm to derive the appropriate control actions based on the prediction was also required.

Various statistical models and physical models for the future prediction of HMT have been proposed in the past. In this research, we selected the physical model-based approach. Conventionally, physical blast furnace models for process control had been limited to one-dimensional transient models of the furnace height direction. In this research, we created a two-dimensional transient model that also calculates the radial distribution of state variables and applied the developed model to the actual operation.

In the developed thermal control guidance system (operation guidance on hot metal temperature control) [2–5], the two-dimensional transient model predicts the future evolution of HMT assuming that the manipulated variables at present are kept constant, and the non-linear model predictive control derives appropriate control actions to achieve the target HMT.

3.1 Overview of Blast Furnace Two-Dimensional Transient Model

The two-dimensional transient model comprises 12 differential equations that express the solid flow and gas flow, reactions in the furnace, and heat transport phenomena. As the manipulated variables, it is possible to set the blast volume, blast temperature, blast moisture, pulverized coal injection rate, and radial distribution of the ore to coke ratio at the furnace top. As the disturbances, it is possible to set the reducibility of the iron ore, slag ratio, coke water content, particle sizes of the coke and iron ore, *etc*.

In a blast furnace, it normally takes about eight hours for the influence of the change of burden materials on HMT to appear. Since it is necessary to express this time lag in the physical model of the blast furnace, the process of burden descent was expressed in detail by dynamically generating calculation cells conforming to the burden layer structure. **Figure 5** shows the calculation cells. In the initial condition shown in Fig. 5(a), the number of cells in the height direction was set at 33, assuming the case in which solid ore and coke are charged in layers in an actual furnace. Fig. 5(b) shows the condition after the cells converged. In the lower part of the furnace, the cells contracted due to the melting of the ore and gasification of the coke, resulting in 43 cells in the height direction. The number of meshes in the radial direction was set at three to express the radial distribution of the ore to coke ratio while minimizing the calculation time. The differential equations were discretized by the finite volume method, the above-mentioned manipulated variables and disturbance were set as the input conditions, and a convergence calculation was performed at each time step. **Figure 6** shows the flowchart of the calculation by the two-dimensional transient model.

3.2 Model Calculation Considering Effect of Disturbance

When the transient model is used for the process control in the long term, estimation errors occur due to disturbances which are difficult to measure directly. These disturbances include drift in raw material properties such as the carbon content of the coke, iron content of the ore, and reducibility of the ore. To incorporate the effects of disturbances in model calculations, successive corrections are made in the model parameters to reduce the estimation error between the actual values and the calculated values of main process variables such as the furnace-top gas composition, and the HMT, *etc*. However, owing to the long time constant of the blast furnace process, appropriate consideration of the effect of disturbances in the model calculation is an issue. For example, the effect of disturbance originating from the burden materials appears in the composition of the furnace top gas two to six hours after the burden materials are charged.

As a countermeasure for this problem, the coke ratio, reduction equilibrium, and the heat loss are corrected retroactively in time (here, 72 hours retroac-

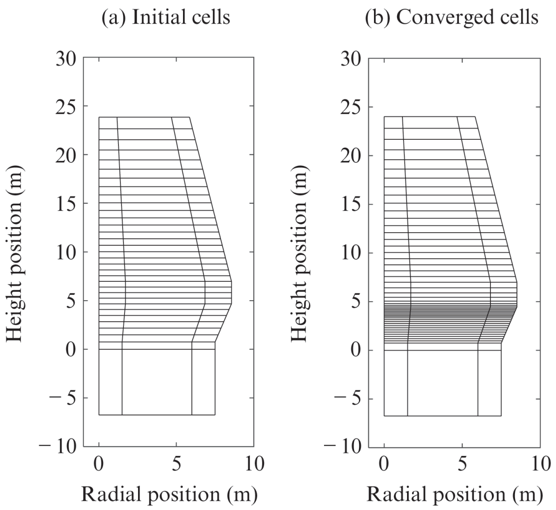

Fig. 5 Calculation cell of 2D transient model

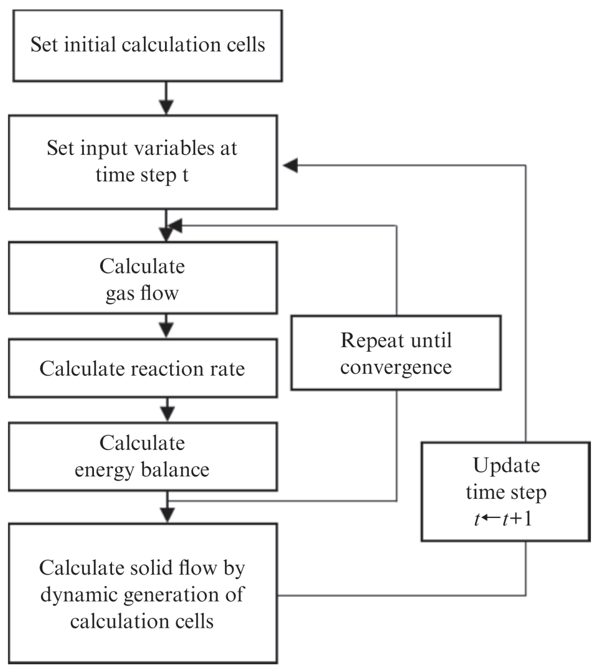

Fig. 6 Flowchart of 2D transient model

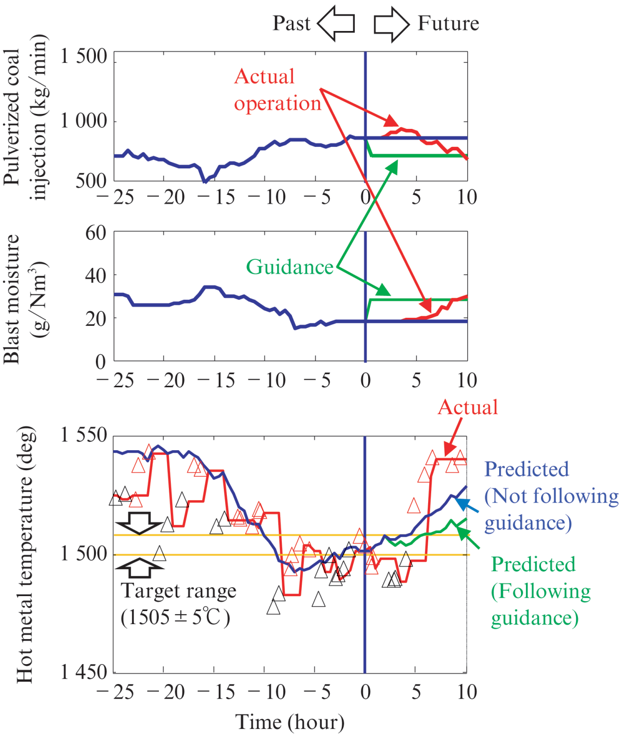

Fig. 7 Predicted hot metal temperature using 2D transient model
(Comparison between guidance and actual operation)

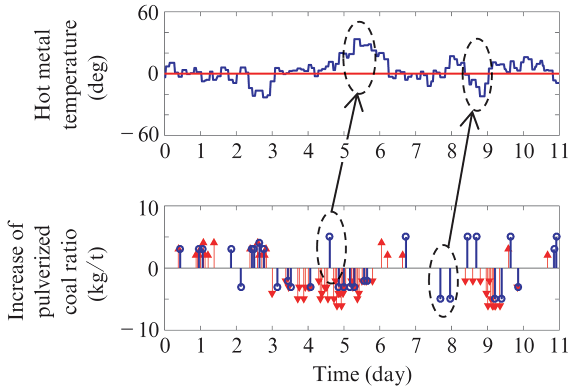

Fig. 8 Result of operation guidance
(○ actual operation, △ guidance)

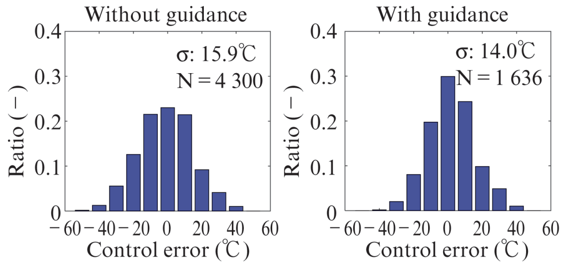

Fig. 9 Control accuracy of hot metal temperature

tively) so as to minimize the errors of the main process variables. The state variables 72 hours earlier are given as the initial condition, and the parameter corrections are made successively while moving the timeframe forward every 30 minutes. This technique is called moving horizon estimation (MHE) [6], and made it possible to reduce the estimation errors of the main process variables by approximately 30 to 50%.

3.3 Hot Metal Temperature Control Guidance

Figure 7 is a comparison of operation based on guidance and operation based on the judgment of the operator. Because HMT was predicted to become excessively high eight hours from the present time, the guidance system presented a reduction of the pulverized coal injection rate and an increase in blast moisture. In the example of manual operation based on the operator's judgment, the actual HMT (shown by the triangles in the bottom section of Fig. 7) exceeded the target value by 40°C. If the guidance had been followed by the operator, HMT would have been controlled near the target value.

A guidance system that provides the operator with the recommended operational amount of the pulverized coal ratio (PCR) and blast moisture in this manner was installed at an actual plant. **Figure 8** shows the daily operational data for eleven days. The upper part of the figure shows the deviation from the target HMT, and the lower part shows the change in PCR, where the circles indicate actual operation and the triangles show the recommendation by the guidance system. The operator mostly manipulated PCR following the guidance, and HMT was successfully controlled to the vicinity of the target value except for several points. A deviation exceeding 30°C occurred at around day 4.7 because the operator increased PCR contrary to the guidance, and HMT dropped at around 7.5 days because the operator decreased PCR contrary to the guidance to keep the present PCR. The fact that the control error of HMT occurs due to the control actions different from the guidance also supports the validity of this guidance.

The results of a long-term guidance operation test confirmed that guidance had the effect of reducing the control error of HMT by 1.9°C in comparison with the conventional manual operation, as shown in **Fig. 9**. This system is demonstrating its effectiveness at multiple blast furnaces in JFE Steel.

4. Permeability Anomaly Detection Guidance

In recent years, blast furnace operation oriented toward low RAR has increased the possibility of poor permeability in the furnace, as well as the possibility of the trouble called channeling, that is, a non-uniform distribution of hot blast pressure in a furnace, in which the upward flow is locally concentrated due to further deterioration of permeability. In particular, because even small channeling trouble can lead to burden collapse and can become a cause of serious trouble in the future, it is desirable to take action such as reducing the blast volume, *etc*. in advance. However, it is difficult to capture signs that may lead to channeling by only the conventional technique of monitoring the trend in ventilating resistance, and operators may be late in recognizing the anomaly, or may miss it entirely. Therefore, in this research, we studied an anomaly detection technique utilizing Q-statistics, which is one technique of multivariate statistical process control (MSPC) [7, 8], in the data of the shaft pressure gauges installed in the height and circumferential directions of the furnace body, and developed a permeability anomaly detection system for detection of the signs of channeling trouble.

4.1 Overview of Principal Component Analysis

Figure 10 shows the behavior of shaft pressure obtained from multiple shaft pressure gauges. During normal operation, all the pressure data show synchronized behavior (Fig. 10, left), but when the furnace condition deteriorates, the pressure distribution in the furnace becomes disordered and some of the pressure data change asynchronously (Fig. 10, right).

In the example in **Fig. 11**, only two of the multiple pressure data are used in order to simplify the explanation. During normal operation, the pressure data are distributed in the ellipse in Fig. 11. The long axis direction of the ellipse is called the first principal component (T^2-statistic) and expresses the magnitude of data drift. The short axis direction perpendicular to the long one shows the second principal component; this is called the Q-statistic and expresses the degree of deviation from the normal conditions. The Q-statistic increases when the pressure data deviate from normal behavior, even before actual trouble such as shaft pressure drift or channeling occurs accompanying deterioration of permeability. Therefore, it is possible to detect permeability anomalies by successively calculating the Q-statistic and setting its threshold value.

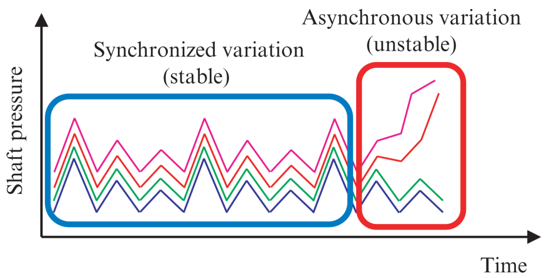

Fig. 10 Normal/Abnormal change of shaft pressure

4.2 Anomaly Detection by Q-Statistic

Figure 12 shows an example of anomaly detection by Q-statistics in off-line analysis of pressure drift which actually occurred in the shaft of a blast furnace. The top of Fig. 12 shows the shaft pressure trend data, and the bottom shows the Q-statistic trend corresponding to the trend of the shaft pressure. As the shaft pressure gradually drifts, the Q-statistic also increases and exceeds the threshold (criterion for judging anomaly) approximately 10 minutes before the first pressure drift in the shaft (anomaly state). After the first pressure drift in the shaft, the Q-statistic value continues at a comparatively high level, and the Q-statistic exceeds the threshold about 5 minutes before the second pres-

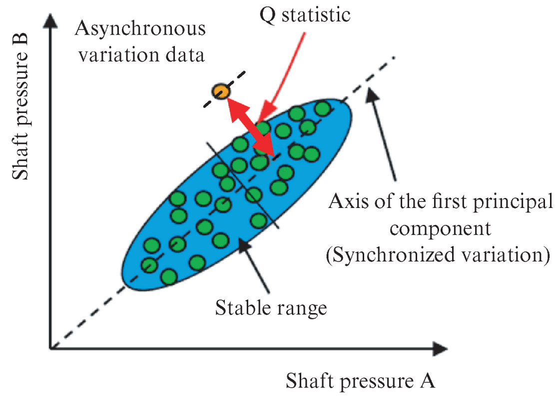

Fig. 11 Anomaly detection of shaft pressure using Q statistics (Example of using only two shaft pressure data)

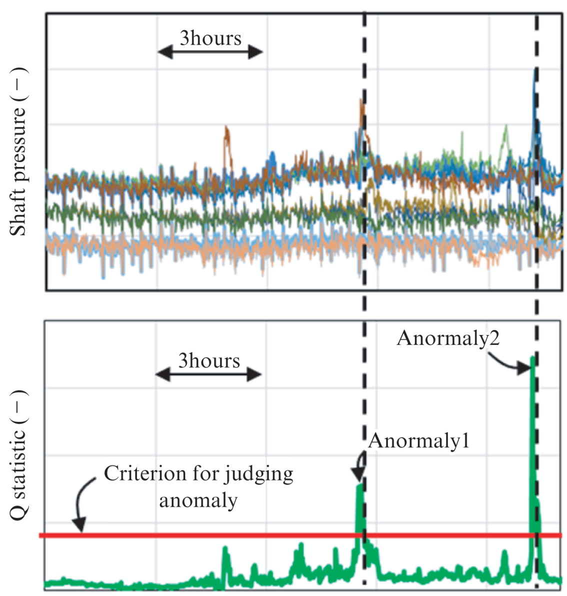

Fig. 12 Example of anomaly detection by Q statistics (Top: Shaft pressure data, Bottom: Q statistics data)

sure drift. This shows that it is possible to capture the anomaly state of the blast furnace before permeability problems develop into serious trouble such as channeling. A system which provides guidance to the operator indicating reduction of the volume of hot blast blown into the furnace through the tuyeres when an anomaly is detected by the Q-statistic in actual operation has been constructed and is now in operation.

5. Blast Furnace CPS

Development of the data science technologies described above is continuing, envisioning implementation of a cyber physical system (CPS) for the blast furnace. In the CPS blast furnace, a high-order virtual process is constructed, in which sensor data from the actual production process are collected and analyzed, and the process is modeled in real time based on those data. Introduction of the virtual process will make it possible to grasp the internal condition of the blast furnace, which is often described as a “black box,” and predict its future condition. In addition to realizing stable operation by monitoring the soundness of the blast furnace and feeding back the results of anomaly predictions to operational actions in the actual process, the virtual process is also expected to improve productivity by identifying bottlenecks in the process.

The operational processes of blast furnace are complex, and the technologies described in this paper are only the first step toward the creation of a true CPS. In the future, the authors aim to develop a CPS for the various events that occur in the blast furnace and will reflect the results in future predictions and operational judgments through linkage between the actual process and the virtual process.

6. Conclusion

A coke particle size distribution sensor for measurement of the coke size before charging into the blast furnace was developed, and an operation guidance system based on hot metal temperature control and an anomaly detection guidance system were also implemented.

(1) The coke particle size sensor makes it possible to measure the coke particle size distribution before charging in real time, and take advance action so that increases in small-sized coke will not affect the condition of the furnace.

(2) The hot metal temperature control guidance system predicts the hot metal temperature eight hours in the future based on a two-dimensional transient model, and it provides appropriate control actions of the pulverized coke ratio and blast moisture to achieve the target hot metal temperature.

(3) The permeability anomaly detection guidance system performs principal component analysis (PCA) of the shaft pressure data from multiple pressure gauges, detects pressure anomalies based on the Q-statistic and provides guidance on blast volume reduction to the operator.

Use of these technologies supports stable and efficient blast furnace operation.

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