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Development of Blast Furnace Operation Data Visualization and Analysis Technology

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Abstract

In order to utilize operation data and sensor data of blast furnaces, we developed data visualization and analysis technology. For the visualization of data, a large amount of data on shaft pressure and stave temperature was visualized two-dimensionally, and then the spatial change rate and time change rate of the data were also visualized. As a result, the accuracy and speed of estimation of blast furnace operation was improved. In addition, the visualization technology of the blast furnace operation state was developed using CbLW-PLS. As for data analysis technology, a prediction model such as hot metal temperature was developed using "large-scale database online modeling" applying JIT (Just-In-Time) modeling and machine learning, and its predictability was evaluated.

1. Introduction

To grasp, estimate, and control the blast furnace operation, blast furnace data has been utilized. The basic work of blast furnace engineers is to examine, grasp, and analyze the operation of the blast furnace by referring firstly to the various operating conditions such as the blast volume and the pulverized coal injection rate through tuyeres, the amount of materials charged from the furnace top and the charging mode, the material conditions such as compositions and the particle sizes of materials, and the time-serial transition charts and the X-Y plot illustration of the various data such as the hot metal (pig iron) temperature, hot metal compositions, and slag compositions. Next, by utilizing these data, works such as statistical analysis, visualization with various methods, comparisons with mathematical model calculation result, and/or with model test result are executed, and the in-furnace status is grasped and the control method of the blast furnace is studied.

Furthermore, data pertaining to the blast furnace operation are not limited only to the basic operation data such as that of the blast condition and charging method, but data are obtained in a great quantity from various sensors installed on the blast furnace (**Fig. 1**[1]). However, a blast furnace is a high temperature, high pressure vessel, with a highly dusty internal atmosphere due to the use of crushed materials, and furthermore solid, gaseous, and liquid phases are existent therein. Therefore, the installation of sensors is taxing, and it is difficult to sufficiently obtain the truly required data for analysis. Accordingly, it is necessary to grasp, estimate, and predict the in-furnace phenomena by effectively utilizing the methods of visualization, statistical analysis, and further of late, machine learning and AI methods based on the acquired data.

2. Effort of Visualization of Blast Furnace Data

When viewed from the point of visualizing the in-furnace status, a blast furnace is a furnace having a spatial expanse not only in the height direction, but also in the circumferential and radial directions, and the operation status changes spatially and time-serially on a moment by moment basis. Accordingly, 2D and/or 3D data that are ceaseless timewise are to be obtained, and the visualization is basically required to be realized based on such data.

As shown in Fig. 1, various types of sensors are installed on the blast furnace, and the furnace operation status is grasped by them. However, most of the sensors provide only 1D-like point data, and many of the sensors of the shaft sonde, vertical sonde, belly sonde, and the furnace core sonde[2] that are capable of measuring the in-furnace status are used with low frequency, for instance only several times a day, or not so frequently, for example once a month. Then, by obtaining and utilizing the furnace cooling water temperature (stave temperature) data and the shaft pressure data transmitted continuously timewise from sensors installed in a 2D arrangement with

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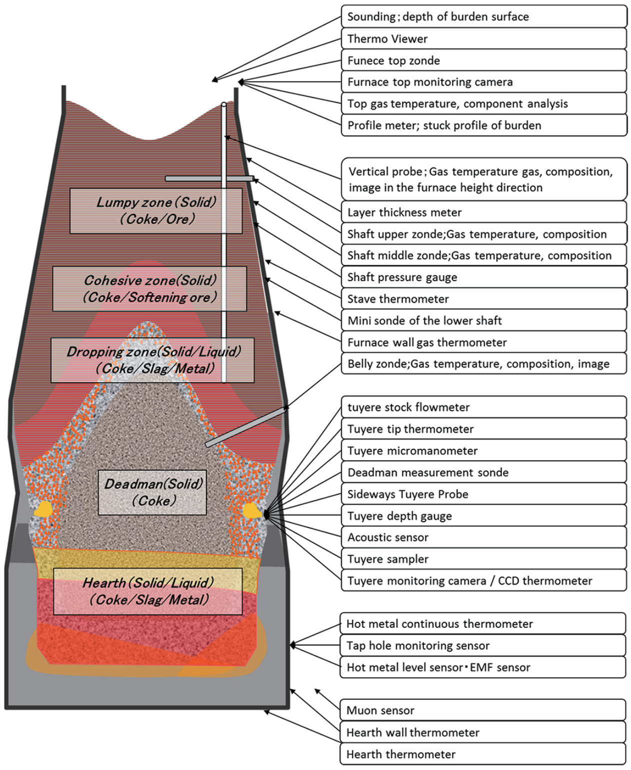


Fig. 1 Outline of sensor installed in blast furnace[1]

a 2D spatial expanse, the 2D visualization of the status of the blast furnace surface was developed.

2.1 2D visualizing systems[3–8]

In processing the data obtained by the sensors installed on the blast furnace, the following aspects are considered. The blast furnace is not simply cylindrical, but consists of a plurality of plane-intersected-cones, and therefore, to unfold the outer shell shape to a 2D plane form, certain attention is required. Basically, by paying attention to the blast furnace shape, the furnace outer shell shape and the sensor positions were projected to and developed on a 2D plane composed of the furnace height direction and the furnace circumferential direction, on which the sensor measurement data were drawn. Furthermore, where there were no data, data were complemented by linear interpolation, and thus, a 2D development elevation was obtained.

Figure 2 shows examples of the 2D visualization of the stave temperature and the shaft pressure. The figure in the upper left of Fig. 2 shows an example of the visualization of the stave temperature, and the figure in the top right shows an example of the visualization of the shaft pressure data. The horizontal axis denotes the furnace circumferential angle, and the vertical axis denotes the furnace height from the tuyere level to the furnace top, wherein the * marks show the positions of the sensors. In addition, by successively updating these 2D visualized images time-serially, monitoring on a real time-serial basis is possible. In the on-line system, data are updated routinely in one second cycles, and the data are accumulated.

Furthermore, as the various phenomena within the blast furnace are considered to vary accompanying time lag and/or spatial movement, in addition to the current time stave temperature and the shaft pressure, the spatial change rate and the time change rate were also calculated and 2D-visualized. The figure in the bottom left in Fig. 2 shows the development elevation of the time change rate of the stave temperature. By monitoring the image of the time change rate, it is possible to grasp the in-furnace status change earlier and more accurately than just by monitoring the temperature measurement. Defining the time change rate with respect to the shaft pressure is also possible.

The figure in the bottom right of Fig. 2 shows the differential of shaft pressure. The pressure is very sensitive to the changes of the burden structure and the gas flow, and reflects them. Therefore, in order to minutely observe the pressure information, the spatial change rate of pressure, or differential of pressure, has been conventionally monitored. In this system, the differential of pressure was visualized by calculating the generalized spatial change rate. Further, the spatial change rate is also definable with respect to the stave temperature.

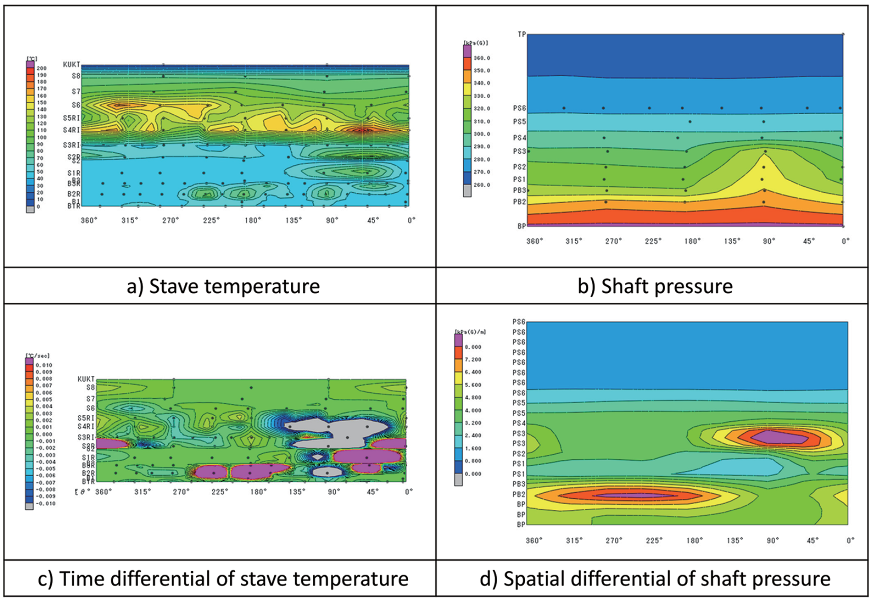


Fig. 2 Example of two-dimensional visualization of stave temperature and shaft pressure

By monitoring the result of the visualization time-serially, it is possible to grasp the change of the in-furnace status readily. Further, efforts to analyze the shaft pressure data are ongoing not only on the production furnace basis, but also on the basis of the model experiment simulated for a blast furnace shaft, and on the basis of computer simulation.[9, 10]

2.2 3D illustration function[11]

With the two-dimensionally developed visualized images, it is difficult to intuitively grasp the positional linkage among the shaft, the belly, and the bosh that all characterize the shape of a blast furnace. Further, with respect to the temperature information of the blast furnace hearth, it is necessary to monitor the 3D transitions of temperatures not only of the hearth wall but also of the hearth bottom as well. Accordingly, by using the surface data, a function to visualize the temperature of the entire furnace three dimensionally was developed.

(1) 3D illustration method

In the 3D illustration, a three-dimensional coordinate system was established, having its point of origin at the center of the hearth bottom of a blast furnace, and composed of the furnace height direction axis, furnace radial direction axis, and the furnace circumferential angle coordinate axis. Visualization was performed by means of perspective projection. In addition, with respect to the shaft pressure, the spatial change rate vector was defined on the development elevation plane composed of the tangential line in the height direction and the tangential line in the circumferential direction, and was made simultaneously drawable.

(2) Examples of 3D visualization of the shaft

Figure 3 shows examples of 3D visualization of the stave temperature, the shaft pressure, and its spatial change rate vector. By updating time-serially the measured data, the dynamic blast furnace behavior is monitored in the form of 3D moving image information. With this, the correlation between the fluctuation of the stave temperature and the shaft pressure on the furnace surface became more readily grasped, and the understanding of the in-furnace phenomena and the operation monitoring capability are enhanced.

(3) Examples of visualization of the temperatures of the hearth wall and the hearth bottom

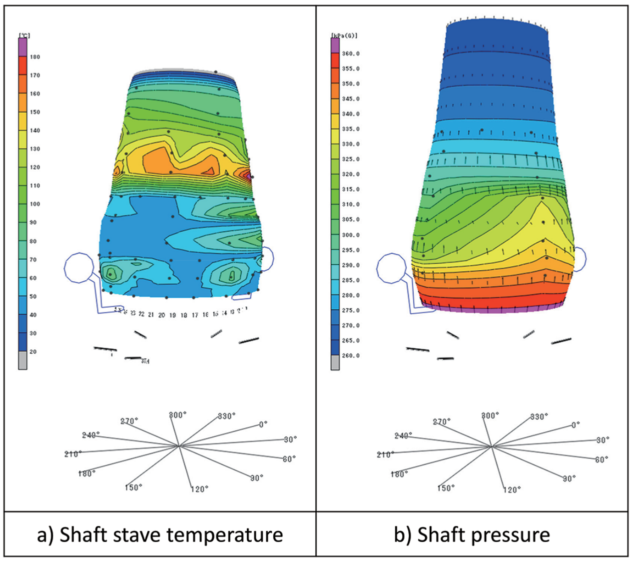


Fig. 3 Example of three-dimensional visualization of shaft region

Figure 4 shows examples of 3D visualization by using the temperatures of the hearth wall and the hearth bottom. From the figure, it is possible to grasp at what point the change of the rise or the descent of the temperatures of the hearth wall and the hearth bottom had happened, and from what direction and how it had progressed. Three dimensional changes are grasped; for example, in June, all temperatures had subsided; however, in August, the hearth side wall temperature rose, in November the hearth wall temperature subsided, while the hearth bottom temperature rose.

2.3 Monitoring function

It is possible to provide a monitoring function by utilizing the shaft pressure data, temperature data, and the secondarily processed data of the data such as the time change rate and the spatial change rate.

(1) Monitoring function of the shaft pressure fluctuation

The shaft pressure fluctuation can be monitored by utilizing the time change rate of the shaft pressure data. For example, prompt monitoring of the shaft pressure fluctuation is possible by monitoring the differential of the shaft pressure time change rate between that of the maximum value and that of the minimum value, or between the one in the region where shaft pressure changed most greatly and the one in the region where it changed least. **Figure 5** shows an example of the shaft pressure fluctuation monitoring screen. On the monitoring screen, the display has a function that a part of the screen changes from blue to flashing red, and sounds an alarm when the differential of the shaft pressure time change rate between its maximum value and its minimum value exceeds a threshold.

(2) Scaffold thickness monitoring function

With the stave temperature data, it is possible to estimate the scaffold thickness by estimating heat flux. To maintain sound operation of a blast furnace, monitoring of the gas flow on the furnace wall is necessary, and the control thereof is required to prevent the undesirable rise of the heat load and to suppress the formation of scaffold in front of the stave. By using the two thermocouples installed in the depth direction (horizontal direction) on a stave, the thickness of the scaffold can be estimated by assuming one-dimensional steady heat transmission and the physical properties of the scaffold.

An example illustration of stave temperature, heat flux, and the scaffold thickness is shown in **Fig. 6**. Although based on an assumption, by converting the stave temperature data to intrinsic numerical values representing the scaffold thickness, the in-furnace thermal status and the furnace wall status are more concretely visualized.

2.4 Utilization of stave temperature time change rate—estimation of root position of cohesive zone

There have been a number of reports issued in the past concerning the method of estimating the cohesive zone.[12, 13] This report estimates the root position of the cohesive zone based on the time change rate of the stave temperature. The cohesive zone root posi-

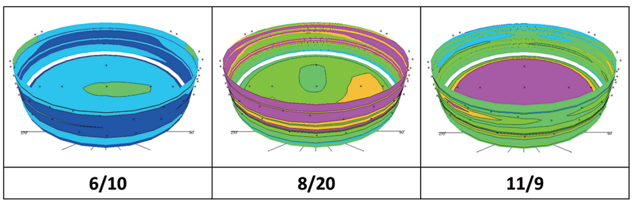


Fig. 4 Three-dimensional visualization example of temperature of hearth and hearth wall

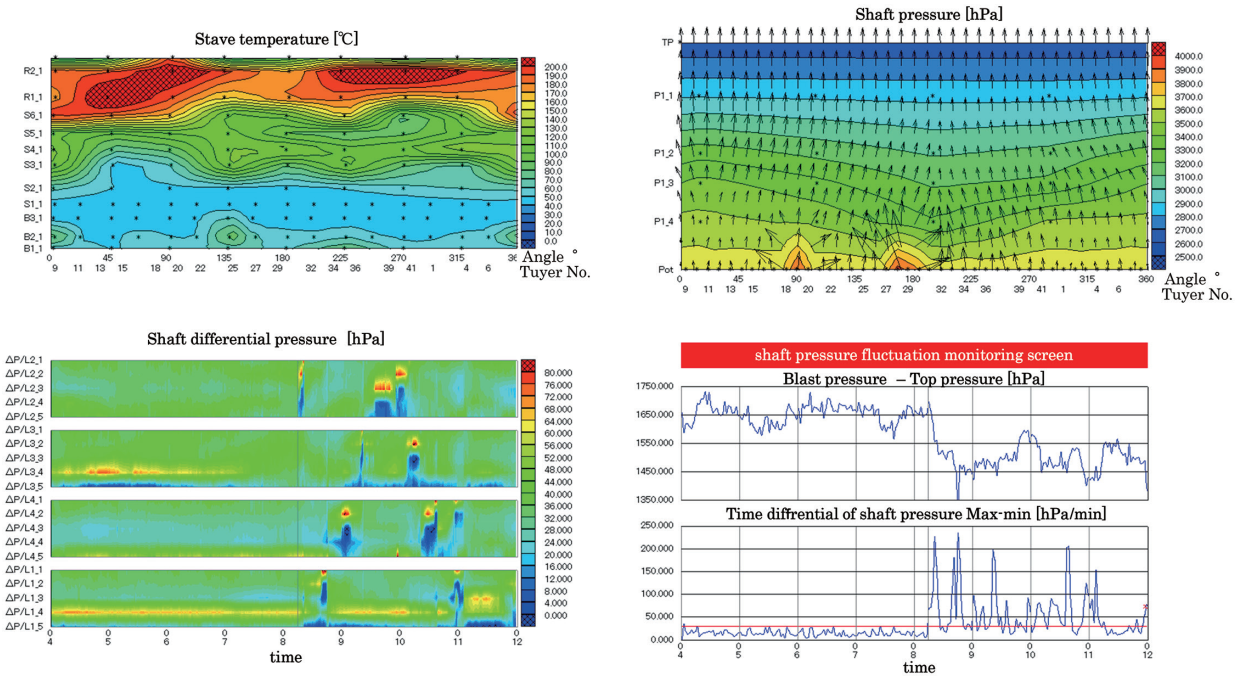


Fig. 5 Example of shaft pressure fluctuation monitoring screen

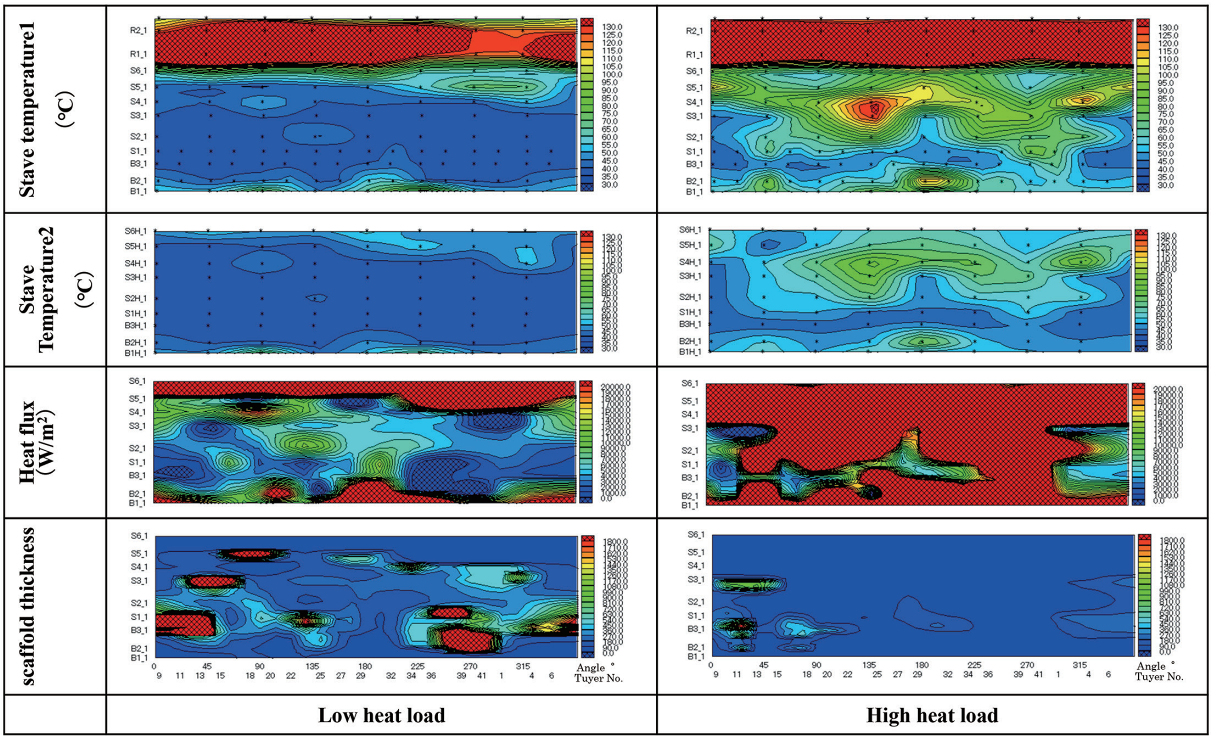


Fig. 6 Drawing example of stave temperature, heat flux, and scaffold thickness

tion can be estimated from the shaft pressure spatial change rate, or the differential of the shaft pressure. However, in the region where the root of the cohesive zone is considered to be existent, like the bosh for example, due to the problem of the half molten slag existent at the root clogging the gas-sampling hole of a shaft pressure gauge and less installed therein therefore, an estimation method was developed by utilizing the stave temperature obtained from a number of measuring points that are installed in the lower region of the blast furnace.

(1) Method of estimating root position of cohesive zone

The root position of the cohesive zone was estimated by utilizing the stave temperature based on the following concept. In the cohesive zone, it is considered that the resistance to the gas permeability is large and the packed burden structure fluctuates in the circum-

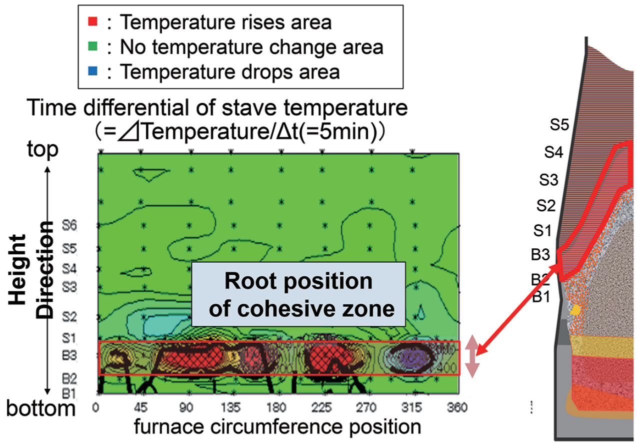


Fig. 7 Conceptual view of the estimation method of root position of cohesive zone

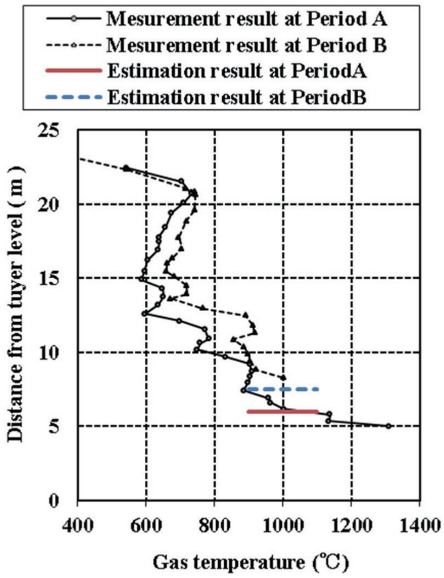


Fig. 8 Comparison of measurement results of furnace wall gas temperature by vertical sonde and estimation results of root position of cohesive zone by time differential of stave temperature

ferential direction. Therefore, the gas that flows through the cohesive zone does not always form a stable plug-flow, and the direction and the rate of gas flow fluctuate locally, and thus, what is termed as channeling may occur frequently. As a result, at the position corresponding to the root of the cohesive zone, the stave temperature is considered to fluctuate locally for a short period of time depending on the status of the formed root of the cohesive zone. The actual incidence of such phenomenon can be confirmed.

Accordingly, it was assumed that the region corresponding to the position of the root of the cohesive zone can be identified by selecting the region on the visualized image on the screen wherein the stave temperature change rate is large (**Fig. 7**).[14] However, since this estimation method employs a minute gas flow change in the vicinity of the cohesive zone root to detect the root position of the cohesive zone, the estimation is not possible when such a phenomenon does not actually occur. Furthermore, this method is not applicable when a large-scale channeling that exceeds the local condition fluctuation around the cohesive zone root takes place as such channeling is detected.

(2) Comparison of the estimated value and the value measured by the vertical sonde

Figure 8 shows an example of the comparison of the result of the furnace wall gas temperature measured by the vertical sonde and the estimation result of the root position of the cohesive zone by the time differential of stave temperature.[15] The root position of the cohesive zone level obtained from the time differential of the stave temperature was about 7.5 m during period A, and 6 m during period B. As the in-furnace temperature cannot be estimated by the stave temperature, only the height level is indicated. As compared with the measurement result of the vertical sonde, during both periods of A and B, the root position of cohesive zone levels agrees approximately with the 1 000°C level position, and it is suggested that the temperature position corresponds to the upper level of the cohesive zone even when the level is varied.

3. Blast Furnace Operation Estimation Model Utilizing Operation Data

When estimating the future blast furnace operation status and determining an action to be taken, it is routine practice to search the past operation status that is similar to the current operation status, and then reference the action taken at the time in the past and the transition of the operation status afterward. The search for the past operation status similar to the current one is conventionally practiced based on experience and/or memory; however, there are possibilities of not only a lack of experience but also of oversight and misjudgment. Therefore, the automated search for the past operation status similar to the current one (search for past similar data) for the effective utilization of the past data was studied. For the automated search for past similar data and for the estimation of the future operation status utilizing the result of the automated search, application of the "Just-In-Time Modelling"[16] method was studied.[17]

3.1 Automated search for past similar data and method of future estimation

The concept of the automation of the search for past similar data and the method of future estimation is as follows (**Fig. 9**). ①Select variables that contribute to the search for the desired variables from the blast furnace operation database ②Quantize the selected variables. ③Construct a quantized database for search. ④Search the quantized "neighboring" data of the "query" on the quantized database quantum by quantum. Further, ⑤Construct a local model that complements the output of the searched neighboring data. ⑥Estimate by the local model the output that corresponds to the "query". ⑦The local model is discarded, and whenever the query is changed, a new local model is constructed to handle the chronological change

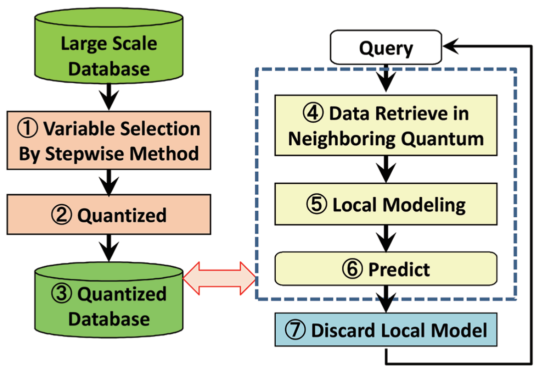
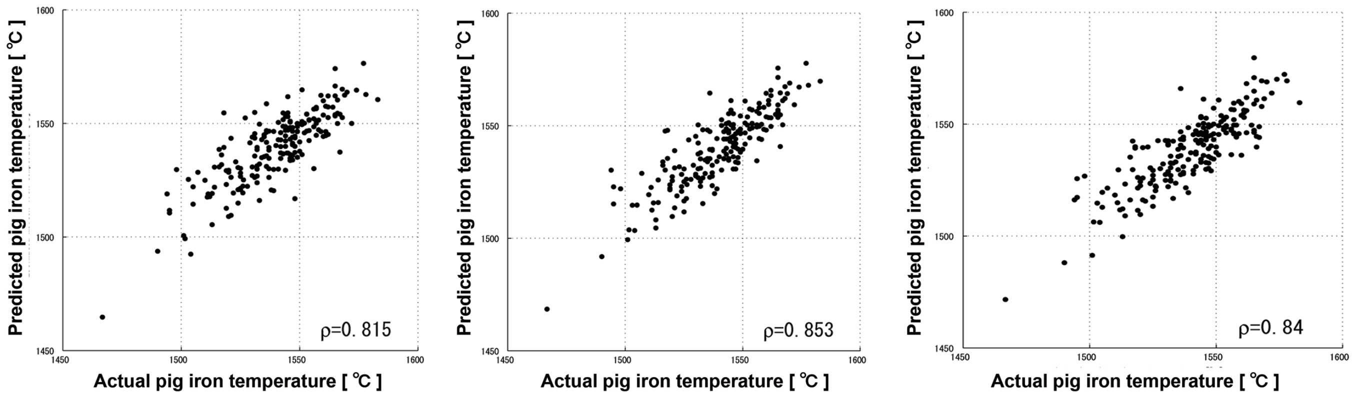
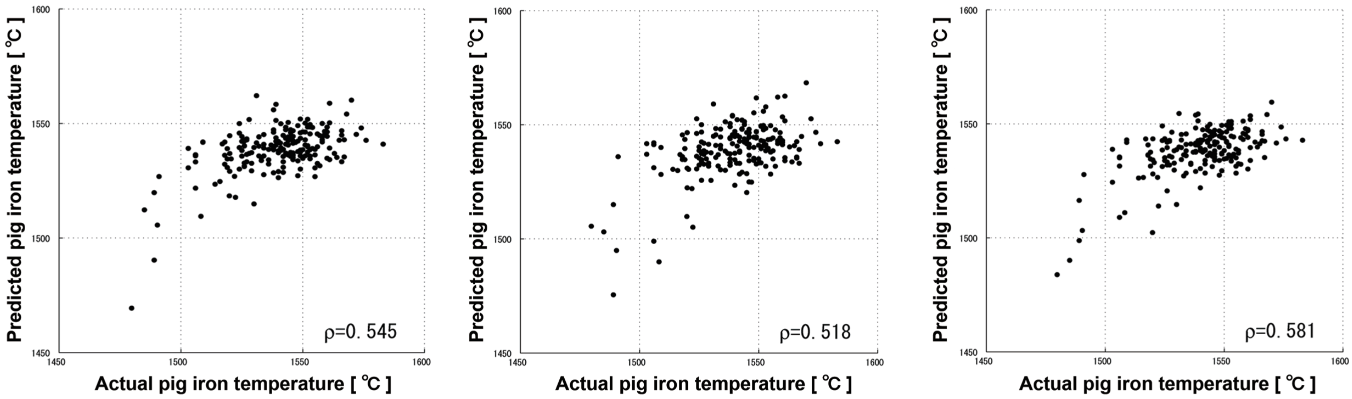


Fig. 9 Concept diagram of LOM



a) Arithmetic average model b) Multiple regression model c) On-line Bayesian learning

Fig. 10 Comparison of hot metal temperature estimation results after 1 hour by different local models



a) Arithmetic average model b) Multiple regression model c) On-line Bayesian learning

Fig. 11 Comparison of hot metal temperature estimation results after 6 hours by different local models[19)]

of the characteristics of the estimated variables and/or the target system. This method is called "Large database Online Modeling" (LOM).

(1) Comparison of the estimation accuracy by different local models

In LOM, when a query is given, a local model is constructed based on the set of the neighboring data of the query, and the estimated value is obtained by utilizing the local model so constructed. Originally, the arithmetic average method using the simple average of the neighboring data was used as the local model. However, to improve the estimation accuracy, the local multiple regression model and the on-line Bayesian learning model were developed, and the estimation accuracy was compared. The local multiple regression model is a model in which the multiple regression analysis is applied to the set of the neighboring data of the query, and a linear estimation model is constructed based on the obtained regression coefficient. The on-line Bayesian learning model is one in which a non-linear function is assumed and their parameters are determined by the Bayesian statics.[18, 19)]

Figures 10 and **11** show the comparisons of the actual hot metal temperature and the results of the estimation by the three types of local models. The results show that, in any model, the estimation accuracy after one hour is relatively high, while that after 6 hours deteriorates greatly.

Figure 12 shows the correlation coefficient relationship between the values estimated by the models and the actual values after one hour, two hours, four hours, and six hours. After one hour and two hours, the correlation coefficients of the arithmetic average model,

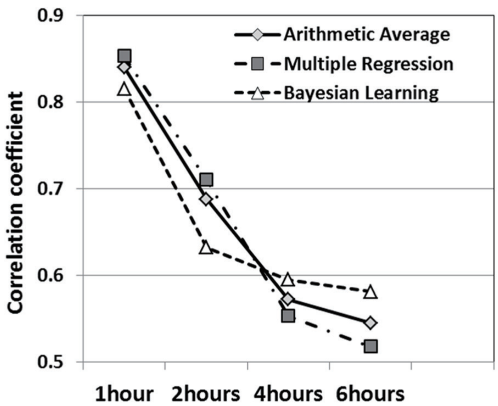


Fig. 12 Comparison of correlation coefficient between actual data and predicted data

the multiple regression model, and the Bayesian learning model do not differ greatly although the Bayesian learning model which considers nonlinearity shows the somewhat lowest values. However, in the estimation result after four hours and six hours, the correlation coefficient of the arithmetic average model significantly deteriorates, while that of the on-line Bayesian learning model that takes into account nonlinearity shows less degree of deterioration, and therefore relative improvement in the estimation accuracy is recognized. From the result, in the case of a short term estimation such as after one hour or two hours, the simple arithmetic average model and/or the local multiple regression model assuming linearity are acceptable. However, in the case of the long-term estimation after four hours or longer, the need for a model that takes into account nonlinearity is suggested.

(2) Combined use with the result of independent component analysis (ICA)

With respect to the data obtained from sensors installed in a blast furnace, relatively a large number of shaft pressure sensors and stave temperature sensors numbering as many as several tens to several hundreds are installed. However, although there are many sensors, depending on the sensor position, data of some of the sensors fluctuate with strong correlation with other sensors; therefore, it is not appropriate to handle all sensor data as independent variables. Accordingly, the extraction of characteristic variables from among the sensor data and the incorporation thereof to LOM as a new parameter was studied. Specifically, from the visualized images of the blast furnace 2D visualizing system, characteristic variables were extracted, and by employing the characteristic variables as the data for LOM instead of the original data, not only the reduction of order of the data dimensions and the reduction of the computational load thereby, but also the possible improvement of the estimation accuracy were promoted.

As the method to extract the characteristic variables from the 2D visualized image, the independent component analysis (ICA) was used.[20, 21] ICA is a technique to evaluate quantitatively the characteristics of multidimensional data by extracting statistically the independent components from the multidimensional data, and by evaluating the thus extracted independent components. An example of the comparison of the results of two cases with respect to the estimation of the blast furnace heat load estimation is introduced. In one case of the said two cases, the blast furnace heat load was estimated by applying ICA to the visualized stave temperature image and by extracting the independent components, and by incorporating the independent components in LOM as data. In another case of the said two cases, the original data were used as they were. The correlation coefficient was 0.699 when the actual values and the estimated values of the blast furnace heat load after one hour were compared. The correlation coefficient was 0.778 when ICA was applied. Therefore, by extracting the independent characteristic variables by ICA and utilizing as the LOM model data, improvement in the estimation accuracy is expected.[22]

3.2 Estimation model utilizing machine learning[23]

As a method to estimate the hot metal temperature, in the preceding chapter, a method in which the past similar data were selected and a local model was constructed therefor was developed. However, depending on the status of blast furnace operation, there are cases in which sufficient past similar data are not existent for constructing a model. In this chapter, a method of constructing an estimation model by utilizing all the data selected during the selection period is developed.

As for the modeling method, the Partial Least Squares (PLS), the Decision Trees, the Random Forest, and the Ensemble Pattern Trees were used for the study.

PLS is an analysis method that lies intermediately in nature in between the multiple regression analysis and the principal component analysis, and is an analysis method that does not use the input variables as they are, but uses the latent variables determined by the linear combination with the input variables, wherein the inner product of the output variable and the latent variable are maximized.

The Ensemble Pattern Trees is a robust nonlinear model construction method, in which a number of pattern tree models are integrated into one estimation model by utilizing bagging. Although it is not easy to realize high accuracy with a single pattern tree wherever there are data fluctuations and/or noise, this problem is solved with the Ensemble Pattern Trees.

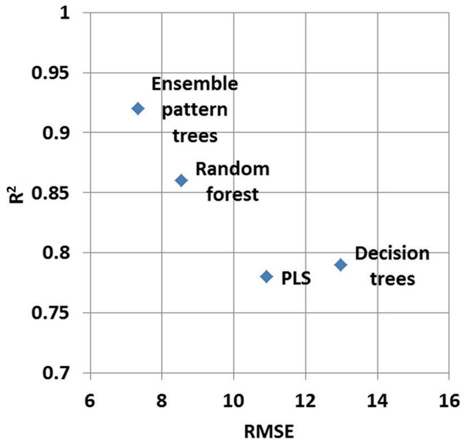


Fig. 13 Relationship between RMSE of predicted results and R^2

Figure 13 shows the result of estimating the hot metal temperature by using the above analysis methods. Figure 13 shows the relationship between the root mean square error (RMSE) and the coefficient of determination R^2 of the estimation result.

From this, the estimation accuracy of PLS and the Decision Trees is not high. Random Forest shows relatively high estimation accuracy, and the Ensemble Pattern Trees show higher estimation accuracy.

However, there is still room for optimization in adjusting the parameters of each model, and though the analysis method is important, models can be further improved by conducting analysis utilizing a great quantity of data.

3.3 Visualization and estimation of blast furnace operation status[24]

For blast furnace operation, maintaining the operation status in a stable condition is crucial. However, on account of the complexities of the in-furnace reactions and the duration required from charging of materials through the furnace top to tapping reaching as long as eight hours, it is difficult to grasp the operation status and its change. Therefore, in order to grasp the operation status of a blast furnace intuitively, visualization of the operation status was conducted by reducing the order of the multidimensional blast furnace operation data to the lower dimensions, and further, from the result of the visualization, the future operation based on the result of the visualization status was estimated by utilizing the Track-forecast method.

There are a number of proposed methods of visualization and dimensionality reduction, among which the Covariance-based Locally Weighted Partial Least Squares (CbLW-PLS) was used herein. The CbLW-PLS method evaluates the resemblance of samples by the Euclidean distance weighted based on the covariance between the input and the output in the LW-PLS, one of the Just-In-Time type modeling.[25] The visualization of data was realized by classifying and visualizing the high dimensional status derived from the multidimensional operation data into four operation status types of “very good”, “good”, “bad” and “very bad”.

Figure 14 shows the result of the visualization of the blast furnace operation status in a two-dimensional space. The horizontal axis shows the goodness/badness of the operation status and the ver-

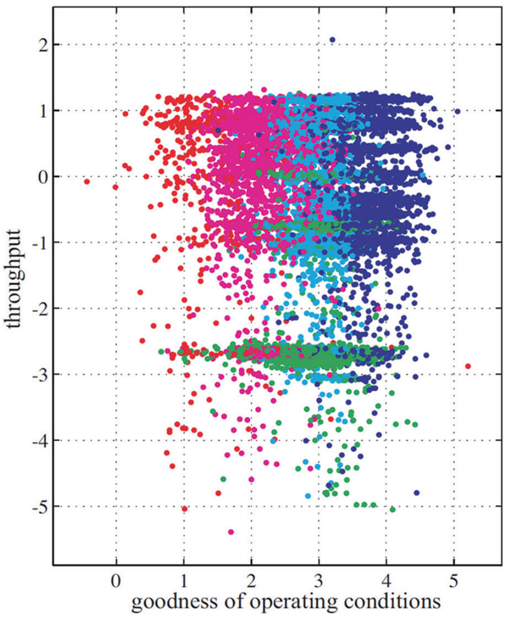


Fig. 14 Visualization of blast furnace operation status by CbLW-PLS[24)]

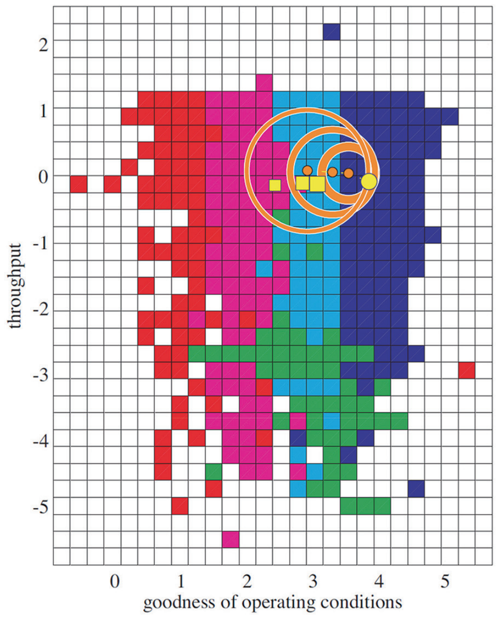


Fig. 15 Evaluation result operation status by the Track-forecast method[24)]

tical axis shows an index of the production amount. The color of the respective plot shows the result of the judgement of operators, wherein the dark blue, the light blue, the light red, and the dark red color denote "very good", "good", "bad", and "very bad", respectively. The green color shows the status of low production regardless of whether the status is good or bad. Thus, the goodness or the badness of the operation status based on the multidimensional data can be expressed as the result of reducing the order of the dimensions of the multidimensional data to the 1D low dimension by utilizing the CbLW-PLS.

The estimation of the operation status and the visualization was conducted by the Track-forecast method. The method is conducted in the following manner. Based on the past data, the position of the subject data after an elapse of time is shown by the circle. In the order-reduced low dimension 2D space, the neighboring samples at the current time are extracted, and each sample of the samples after the elapse of a certain period of time is acquired from the database. The center of the estimated circle is calculated by the weight average of the coordinates of the centers of the circles of the sample data, and the radius of the circle is defined as the distance that integrates to a fixed degree the calculated Euclidean distances between the centers obtained earlier after an elapse of time and the sample data.

Figure 15 shows the result of the estimation of the change of the operation status by utilizing the neighboring data in the database. The yellow dot circle shows the present operation status, the orange dot circles show the results of the operation status estimation after two, four, and eight hours, and the orange circles show the 70% reliability regions. The yellow dot square shows the transition of the actual operation status. As a result of the verification based on 5963 samples, either deterioration or improvement of the operation status could be correctly estimated with an accuracy of over 70%.

4. Conclusion

Utilizing mainly the stave temperature data and the shaft pressure data, the operation status of a blast furnace, the furnace wall region in particular, was visualized. By displaying a number of sensor data of the stave temperature and the shaft pressure in the form of an image two-dimensionally on a screen, the objective visualization of the shaft pressure fluctuation and/or the in-furnace spatial fluctuation due to the occurrence of slip has been realized. By combining the transition of the operation data with the spatial change rate, time change rate, and the like of data, the early detection of the shaft pressure fluctuation and so forth become possible. In addition, by utilizing the time change rate, spatial change rate, and the like of data, the estimation of the position of the cohesive zone root and/or the emission of an alarm signal against the shaft pressure fluctuation are also practiced. From the stave temperature data, it is possible to acquire the distributions of heat fluxes and the scaffold. Furthermore, by constructing a three-dimensional visualized image, visualizing the in-furnace status is more readily accessible. In addition to the shaft and the hearth temperature and pressure, other data that need to be monitored are also displayed on a single screen for the ease of monitoring, and the delay in taking actions due to missing the signs of an abnormal phenomenon or so forth was avoided, and the optimization of the operation status and prompt action taking could be promoted.

With respect to the analysis of the blast furnace operation data, the estimation model of the hot metal temperature or the like was developed by utilizing LOM and machine learning. Concerning LOM, the search for past similar blast furnace data was conducted and the future operation status was estimated, thus confirming the high possibility of it being a future status estimation model. Furthermore, by improving the local model, and by extracting characteristic variables by means of independent component analysis from the visualized image, and incorporating them into LOM as a variable, the further improvement of the estimation accuracy was confirmed. Concerning the machine learning, an estimation model utilizing the entire operation data was developed and the estimation accuracy was confirmed.

Furthermore, by utilizing CbLW-PLS, the multidimensional blast furnace operation data was visualized with the low-order dimensions, and additionally, by utilizing the Track-forecast method, the possibility of the estimation of the future operation status was revealed.

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