

DX Technologies Supporting Steel Sheet Manufacturing

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Abstract:

In recent years, the steel industry has been required to produce high quality and high productivity steel sheets. Conventionally, management indicators for each process were measured and accumulated into databases to serve operational improvements. However, there were challenges in quality analysis using operational data, the performance of surface inspections, and equipment monitoring. Focusing on digital transformation (DX) technology, JFE Steel has utilized “J-astquadTM” to aggregate through-process operational data subdivided in the longitudinal direction of the steel sheets, and performs quality analysis to achieve expeditious operational improvements. Additionally, the performance of surface inspections has been improved by utilizing texture analysis and some visual inspections have been automated. With “J-dscomTM”, anomaly prediction monitoring of facilities has been conducted to enable prevention of facility troubles.

1. Introduction

Automobiles are an indispensable presence in modern life, and both high quality and high productivity are demanded in the manufacture of the steel sheet products used in automotive outer panels and other automobile parts. Therefore, in the steel sheet sector at JFE Steel, the manufacturing process is controlled strictly and efficiently, with the aim of ensuring a stable supply of steel sheet products with excellent reliability and cost competitiveness. As part of those efforts, conventionally, quality control indicators were established for problems such as surface defects, which are critical to the quality of steel sheets, and inspections were conducted in each manufacturing process (production line). In addition, operational data from each line was

also accumulated in databases and utilized in retrospective analyses of quality defects and equipment and operational troubles, and thus was useful in operational improvement. However, there were many challenges in this approach, as it was difficult to analyze large volumes of data by manual human work, automatic detection of low-contrast defects was desired, and there were limits to monitoring of individual problems due to the enormous number of units of equipment in a steel works.

To solve these problems, JFE Steel is proceeding with the introduction of DX (digital transformation) technologies. “J-astquadTM” realized operational improvement by reducing quality defects, which is achieved by aggregating granular operational data and quality data in the longitudinal direction of steel sheets and analyzing alignment-linked through-process data. JFE also developed a “surface inspection system with texture analyses” that improves defect detectability by image processing focusing on differences in texture (pattern), thereby automating visual inspections. For advance prevention of equipment and operational trouble, the company also developed “J-dscomTM”, which monitors anomaly signs at various levels (entire process level, unit equipment level, *etc.*). This paper describes the details of these DX technologies.

2. Analysis System for Through-Process Material Quality Data: “J-astquadTM”

In the steel sheet sector, increasingly high quality requirements are applied to steel sheets with each passing year. Once a quality defect occurs, it is necessary to conduct a retrospective analysis based on the data, and identify and improve the operational conditions that caused the defect.

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JFE Steel completed hierarchically-structured computer systems in its steel works in the 1980s. However, these systems traditionally had a pyramid structure, in which data were aggregated hierarchically to the higher levels¹⁾. As a result, the data granularity of the aggregated data, that is, the resolution of the information expressed by the data, was mainly limited to the level of steel sheets, and much data was inevitably discarded. Therefore, in recent years, JFE Steel has renovated those systems with cutting-edge computational infrastructure technology and data integration technology, and implemented a system in which the detailed granular data obtained at lower levels in the hierarchical structure are aggregated by edge servers and then stored and used in databases^{1,2)}.

As an example of development, this chapter introduces the analysis system for through-process material quality data “J-astquadTM”, which aggregates the huge volume of data in steel sheet manufacturing and performs quality analyses based on that data.

2.1 Background of Development

In quality analysis of steel sheets, diverse types of data for many processes are necessary, including data from the casting, hot rolling, cold rolling and surface treatment processes. In addition, in analyses of designated parts of steel sheets, it is desirable to use detailed granular data for each part of the sheet.

However, in the former computer systems mentioned in the Introduction, time and labor were required to collect and correlate the necessary volume of granular data, and due to the large volume of data, manual analysis itself was no easy matter. As a result, excessive time was required to identify the factors that finally led to quality defects and implement actions for operational improvements. Thus, speeding up this process was a challenge.

2.2 Developed Technology

To solve the above-mentioned problems, JFE Steel developed “J-astquad”, which contributes to identifying the factors in quality defects by automatically aggregating and performing advanced analyses of through-process granular data³⁾.

The concept of “J-astquad” is shown in **Fig. 1**. One key function of “J-astquad” is generation of through-process alignment-linked data by the longitudinal position in the steel sheet. This function aggregates granular operational data and quality data in the sheet longitudinal direction across the casting, hot rolling, cold rolling and surface treatment processes, and generates alignment-linked data. “J-astquad” also has a visualization function that maps granular information at each position on the steel sheet, as well as a function

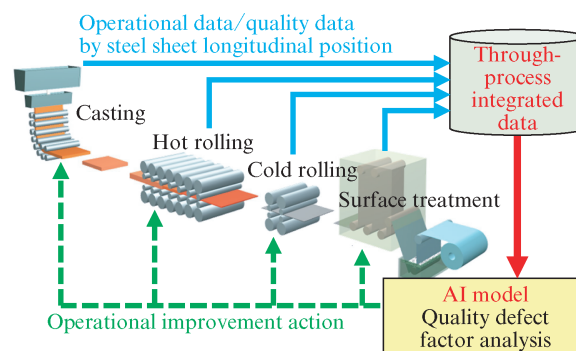


Fig. 1 Concept of “J-astquadTM”
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that utilizes AI (artificial intelligence) to analyze the factors in the occurrence of quality defects and a function that displays factor analysis results and related actual operational data in an integrated manner.

The following sections present detailed explanations of these functions.

2.2.1 Through-Process Data Alignment-Linking Function

JFE Steel developed a logic that precisely aligns longitudinal positions on steel sheets with high granularity across multiple processes, considering changes in the length of the steel sheet due to rolling in each process, inversion of the leading and tail ends of the sheet, *etc.*, and generates through-process alignment-linked data. For quality data that have coordinate positions in the longitudinal direction, the logic aligns and combines the positions of the operational data in each process, in which the total steel sheet length and data aggregation intervals are different. This linking function can also respond to the additional intermediate processing and longitudinal division of steel sheets that occur in some of target steel sheets.

Figure 2 shows the concept of linking, using the manufacturing process of a certain steel sheet as an example. For instance, at position A in the surface treatment process, linkage is performed by tracing back the process. Since the leading and tail ends of a steel

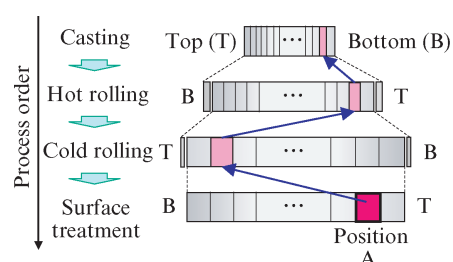


Fig. 2 Through-process longitudinal position alignment linking³⁾
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sheet are inverted by coiling and uncoiling between processes, the position in the cold-rolling process corresponding to A is inverted in surface treatment when seen from the leading edge side. The positions of the data before and after rolling are also aligned considering the change in the sheet length due to rolling in the cold-rolling process. Following this, the pairs of data corresponding to position A are linked by tracing back with the hot rolling process and casting process.

In comparison with conventional analyses, which had been limited to the use of representative value data in steel sheet units, this system enables a detailed analysis of the actual condition by using through-process data with granularity in the longitudinal direction.

2.2.2 Quality Analysis Based on AI Model and Screen Display

JFE Steel also developed a technology that identifies the operational conditions which influence quality and estimates the cause of quality defects using an AI model based on machine learning and statistical analysis. As shown in Fig. 3, the implemented system trains the AI model using data for longitudinal positions with through-process linkage, and then calculates the impact (degree of influence) of the operational variables on the quality obtained from the model. To support the quality of analysis targets, this system has a composition that enables an appropriate selection of the algorithm to be used in the model from among various techniques.

A function that compares the actual data for opera-

tional variables estimated to be factors in quality defects with the quality data, and displays the results on the screen was also implemented. One type of screen is used to check the general trends for large number of steel sheets. This screen displays the impact of operational variables based on the analysis, together with graphs showing the correlation of quality and variables with a high degree of impact. Screens used to individually check single steel sheets display quality maps visualizing the quality condition at each position on the sheet, and graphs comparing the longitudinal data for critical operational variables.

These analytical functions and screen display functions contribute to quick judgment and operational action for factors causing quality defects.

2.3 Application to Actual Equipment

This section describes the application of “J-astquad” to actual equipment. The heavy data processing load and huge amount of accumulated data resulting from granularity in the steel sheet longitudinal direction were challenges for the system. However, these problems were solved by aggregating the data on a JFE Steel’s private cloud environment, J-OSCloud⁴⁾, and constructing a computing environment with extensibility in line with the volume of data.

As an example of quality defect factor analysis and operational improvement after application to actual equipment, the factors responsible for a rapid increase in quality defects in a certain period were analyzed using this system. As shown in Fig. 3, an importance analysis of operational variables based on an AI model was conducted, and the quality defect occurrence rate could be reduced at an early timing by appropriately modifying operational variable x_n , which had the highest calculated importance.

As described above, implementation and use of this system for steel sheets is contributing to a stable supply of high-quality steel sheets. In the future, successive deployment to other product groups is also scheduled.

3. Surface Inspection System with Texture Analysis

Surface inspections of steel sheet products are carried out for quality assurance. Conventionally, surface inspections of products were performed by visual inspection by the operator, but in JFE Steel, inspections have been automated by the introduction of surface inspection systems, initially by methods using laser beams and subsequently by optical surface inspection systems using cameras⁵⁾.

Since the surface condition of steel sheets differs depending on the production line, product type, etc.,

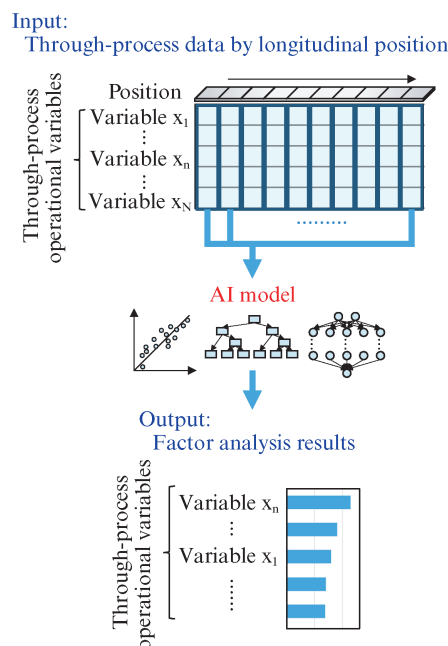


Fig. 3 Factor analysis of quality defects with through-process data and AI model³⁾

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and the defect patterns to be detected are diverse, it is difficult to detect all surface defects correctly with only one type of surface inspection system. Therefore, JFE Steel developed an original surface inspection system using a polarization method, *etc.*, which achieved highly reliable inspection^{6,7)}. On the other hand, automatic detection of the low-contrast defects that occurred with some steel grades has a high degree of difficulty, and had remained a challenge.

This chapter introduces an example of the development of a surface inspection system with texture analysis which has higher detection performance than the conventional technologies, resulting in successful automation of visual inspections.

3.1 Background of Development

This section explains the configuration and processing flow of optical surface inspection systems⁵⁾. **Figure 4** shows the processing flow of a general surface inspection system.

Optical surface inspection systems generally consist of a light source, camera and processing section. First, the light source and camera are installed above the production line, the light emitted by the light source is irradiated on the steel sheet at a certain angle, and image acquisition of the reflected light is performed by the camera. Next, the defect area is detected from the acquired image. Following this, the feature values of the image are calculated from the detected defect area, and finally, the types of defects, class of defects, *etc.* are classified.

Defects are generally detected based on differences in the brightness of normal areas and defect areas. Therefore, in order to detect defects correctly, it is necessary to correctly design the elements called the optical system, that is, the installation angle of the light source and camera, the wavelength to be used, and the polarization state.

However, as an additional challenge, even assuming that images acquired by a properly designed optical system are used, it may be impossible to detect the defects that occur in some steel grades due to a combi-

nation of excessive noise in the normal area caused by surface properties and low contrast in the defect area (i.e., a low signal-to-noise (S/N) ratio).

3.2 Developed Technology

To overcome this problem, JFE Steel developed a surface inspection system with texture analysis that can detect defects even when the signal of the defect area is buried in the noise of the normal area⁸⁾. Unlike the conventional technology, which uses the difference in brightness, this technology focuses on texture (pattern) for detection processing of defect areas, drawing on the idea of human visual perception.

Texture analysis surface inspection is broadly performed by two procedures. The details are explained in the following.

3.2.1 Calculation of Texture Feature Values

The first procedure is calculation of texture feature values by applying image filters.

Defects can be detected easily by applying the proper image filter to the image to emphasize the contrast of a designated defect. However, the effective filter differs depending on the orientation and size of the defect. Therefore, multiple Gabor filters are used, as these filters can extract a designated direction and designated frequency component.

Figure 5 shows the imaginary parts of the waveforms of 16 types of Gabor filters with different wavelengths (frequencies) and orientations as a grayscale map. By applying a Gabor filter to an image, it is possible to emphasize the component with the orientation and wavelength (frequency) of that filter. Since multiple filters are applied to the image, texture feature images corresponding to the number of filters can be obtained. It is also possible to add and select the filters to be applied, depending on the targeted defect.

3.2.2 Defect Detection

The next procedure is defect detection based on analysis of images. If n image filters are applied to each

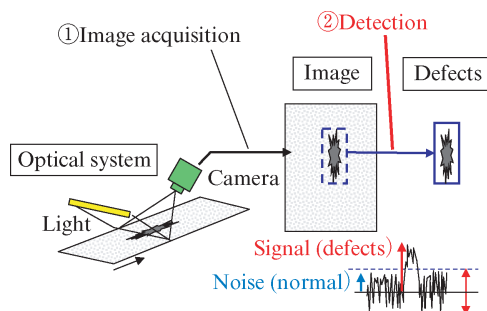


Fig. 4 Processing flow of surface inspection system

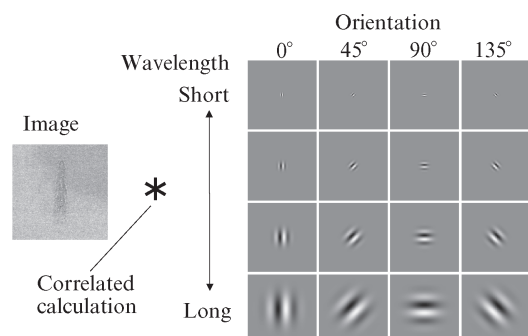


Fig. 5 Examples of Gabor filter

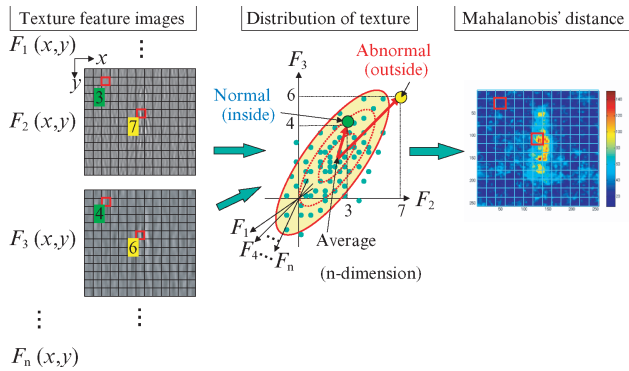


Fig. 6 Defect detection based on distance

pixel by the procedure in the previous item 3.2.1, n texture feature images are obtained. When the brightness distributions of those n texture feature images are plotted on an n -dimensional space, the normal area will have a designated feature, resulting in a distribution with the designated location as its center. On the other hand, since the filter emphasizes the contrast of the defect area, the defect area is plotted at a location that deviates from the distribution of the normal area in that dimension. Therefore, the distance from the center of the average distribution is defined as the anomaly score, and a threshold for judging defects is set based on probability.

Figure 6 shows an example of defect detection when the distance, that is, the anomaly score, is calculated from the texture feature images obtained in the examples in Fig. 5, and is then expressed by a color map. If binarization and denoise processing are applied to the anomaly score in the same way as in the conventional method, defects can be detected.

3.3 Application to Actual Equipment

Finally, application to actual equipment will be described⁹⁾. In the proposed method, the high computational load of image processing in texture feature calculations was particularly a problem. Therefore, in operations in which the filter size is increased, the computational load is reduced by downsampling the image. This problem was also solved by applying a GPGPU (General Purpose computing on Graphic Processing Unit) as the hardware for operations.

In application to actual equipment, the new system was installed at a production line where an existing surface inspection system was installed as shown in Fig. 7, and the light sources and cameras of the existing system were used, connected in parallel to each camera, and the results were aggregated in the texture analysis system. This enabled performance improvement and system integration without interference with the existing system, and achieved a system configuration with

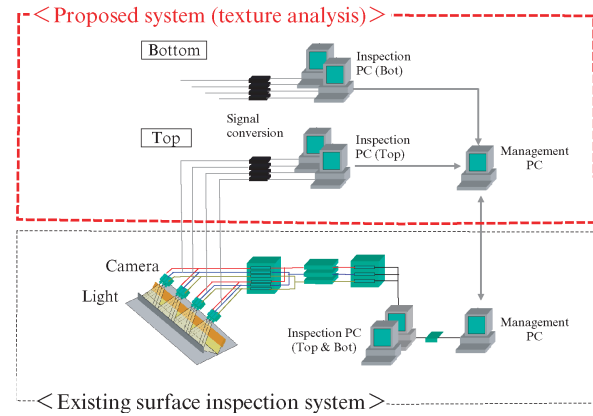


Fig. 7 System configuration of manufacturing line

high versatility and applicability, regardless of the product.

In the production line where the system was applied to the actual equipment, it was not possible to detect some defects with low contrast with the previous surface inspection system, and visual inspection by humans at regular sheet length intervals were still required. After introduction of the developed technology, automatic inspection of the full length and full width of products became possible, resulting in improvement of the quality control level. It is thought that this also contributed to improved customer satisfaction. The developed surface inspection system is also scheduled to be deployed at multiple other production lines in the future.

4. Equipment Anomaly Monitoring System: “J-dscom™”

In iron and steel manufacturing processes, equipment failures have a significant impact on operations. Therefore, technologies that enable early detection of equipment anomalies are essential for maintaining a stable supply of products. However, due to the large number and diversity of equipment in steel manufacturing facilities, conventional approaches—where monitoring logic is developed individually for each facility—have inherent limitations. In addition, in recent years, the proportion of aging equipment that has been in operation for several decades has increased. As a result, the frequency of unexpected failures has also tended to increase.

To address these issues, JFE Steel has developed an anomaly monitoring system utilizing data science techniques¹⁰⁾. This section presents an overview of the developed equipment anomaly monitoring system, “J-dscom™”, and describes its application in the hot rolling process.

4.1 Background of Development

The hot rolling process consists of diverse types of equipment arranged in a hierarchical structure, as shown in Fig. 8. To monitor such a structure effectively, monitoring targets are classified into three levels: the “sensor level”, “facility level”, and “entire process level”, and appropriate monitoring methods are applied to each level.

At the sensor level, signal-level control logic is applied to individual sensor data. At the facility level, temporal variation characteristics of single variables and correlations among multiple variables are analyzed using multivariate analysis techniques. At the entire process level, large-scale data correlations are monitored in a manner tailored to dynamic system behavior.

In this paper, facility-level monitoring, which has been particularly emphasized in the hot rolling process, is described in detail below.

4.2 Developed Technology

At the facility level, two monitoring methods have been introduced. One is waveform monitoring using principal component analysis (PCA), and the other is inter-variable correlation monitoring using data-driven models. These methods enable accurate detection of changes in equipment conditions and early identification of anomaly precursors. In both approaches, deviation from normal operating conditions is quantified as an anomaly score, which is used as a monitoring index.

Given the large number of monitoring targets, visualization using heatmaps is employed to efficiently capture temporal variations in anomaly scores. This enables intuitive understanding of trends and locations of anomalies, thereby contributing to faster maintenance actions.

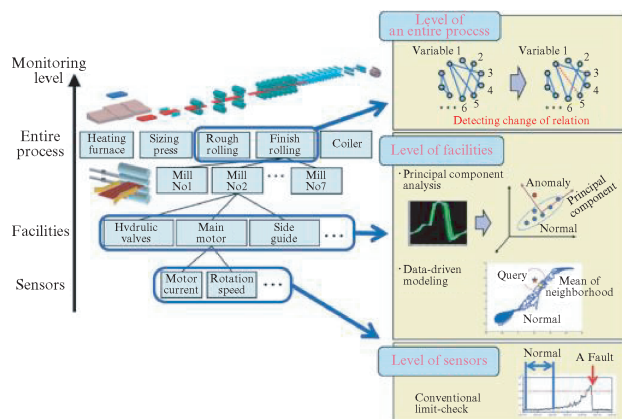


Fig. 8 Concept of anomaly signs detection by hierarchy level of manufacturing process

4.2.1 Monitoring of Signal Waveform

This section describes waveform monitoring based on PCA. For equipment characterized by repetitive operations, signal waveforms are generally stable under normal conditions. When anomalies occur, disturbances appear in these waveforms, which can be captured as early signs of abnormal behavior.

As shown in Fig. 9, a PCA-based method is used to detect waveform disturbances. Assuming that one waveform consists of k sampling points, each waveform can be represented as a point in a k -dimensional space. Due to correlations among neighboring sampling points, normal waveforms form a structured distribution in this space. PCA is applied to extract principal components representing normal patterns.

The Q-statistic in PCA is used to quantify the degree of deviation from the principal component space. It is defined as the sum of squared residuals not explained by the principal components. In this method, the Q-statistic serves as an index for detecting waveform disturbances (e.g., control hunting). Anomalies are identified by monitoring deviations in this index.

4.2.2 Monitoring of Variable Correlation

This section describes monitoring based on correlations among variables using a data-driven model. As shown in Fig. 10, this method is applicable when stable correlations exist among multiple variables under normal operating conditions.

In this approach, historical data under normal conditions are stored in advance. New observations are then compared with the reference data by calculating similarity. Specifically, the distance between new data and the reference dataset is computed, and this distance is used as an anomaly score.

Various statistical distance measures, such as Euclidean distance and Mahalanobis distance, can be applied. This method is highly versatile, as it can be used for different types of equipment as long as correlations among variables exist.

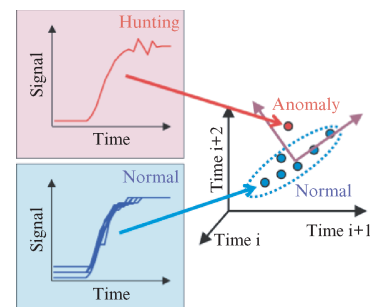


Fig. 9 Application of PCA method to detecting anomaly sign in facility

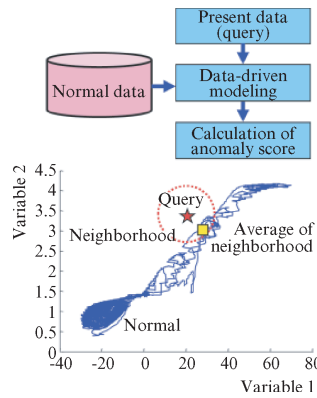


Fig. 10 Application of data-driven modeling method to detecting anomaly sign in facility

4.3 Application to Actual Equipment

Table 1 shows the implementation status of anomaly monitoring models across hot rolling lines at JFE Steel. A large number of models have been deployed for electric motor-driven equipment across all process sections, from reheating furnaces to coilers.

For electric motor-driven units, monitoring models utilize data from motor control panels, including motor current and rotational speed, as well as control command signals and operational conditions. For hydraulic cylinder-driven units, signal waveform monitoring models based on PCA have been implemented for specific operations.

After deployment, anomaly detection models have triggered maintenance actions several times per month, including inspections, part replacement, and equipment restoration. These activities have contributed to the proactive prevention of equipment failures. JFE Steel is continuing to expand the application of these monitoring models to further reduce unplanned downtime.

5. Conclusion

To strengthen operational improvement, JFE Steel has introduced and utilizes various DX technologies, including “J-astquadTM”, a texture analysis surface inspection system and “J-dscomTM”.

- “J-astquadTM” has speeded up operational improvement by quality analysis utilizing through-process data with alignment linkage in the steel sheet longitudinal direction.
- The surface inspection system was developed as an inspection technology utilizing texture analysis, and has achieved automation of some visual

Table 1 Introduction of anomaly sign detection model

Type of unit	Section	Num. of models
Electric motor drive unit	Reheating furnace	38
	Sizing press	16
	Rough rolling mill	43
	Finish rolling mill	98
	Coiler	39
	Table roll	564
Pump unit		22
Hydraulic drive unit		109
Total		929

inspections.

- “J-dscomTM” enables the proactive prevention of equipment failures through multi-level anomaly monitoring, including facility-level monitoring.

In the future, JFE Steel will continue to work to further improve customer satisfaction through horizontal scaling of DX technologies.

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