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High-Precision Process Control Technology for Steel Plant through Just-In-Time Modeling: Recent Developments and Applications†

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Abstract:

JFE Steel has developed a new process control technology using locally weighted regression model, a type of Just-In-Time modeling. Just-In-Time modeling is the following method: A large volume of past input and output data is accumulated, and a local prediction model is constructed by prioritizing the past data near the query point each time a prediction is required. This technology can improve the quality control accuracy significantly, and has been used in various manufacturing processes and in various steel works in JFE Steel. This paper discusses the outline of this technology and examples in commercial plants.

1. Introduction

Customer requirements for the quality of iron and steel products are becoming increasing strict and diverse, and high-precision manufacturing conditions have been applied accordingly. Moreover, even when manufacturing the same product, it is necessary to change the manufacturing conditions in response to changes in raw material prices so as to avoid the increase of manufacturing costs while maintaining quality. In addition, since the relationship between quality and manufacturing conditions changes due to progress in manufacturing technologies, changes in manufacturing equipment, changes in the characteristics of manufacturing equipment over time and other factors, appropriate modification of manufacturing conditions corresponding to those changes is also necessary. Thus, the establishment of technologies which can maintain the quality of diverse kinds of products and further improve quality, while responding quickly to the environmental changes mentioned above, has been demanded[1)].

In a steel works, a large number of computers are used to operate various manufacturing equipment, and automation by computerization to improve labor productivity has a long history. The volume of software has increased rapidly since the 1980s, and accompanying this, the number of process models implemented to perform feedforward control and optimization has also grown dramatically. Because the increase of model maintenance load has now become a problem, simultaneously with the development of advanced control technologies, the necessity of technical development to reduce the maintenance load is also increasing[1)].

With progress in computer technology, large volumes of manufacturing results are now collected in databases at many sites in manufacturing industries for quality control and operational improvement. The technique called Just-In-Time modeling[2, 3)] has attracted considerable interest in recent years as a technology in which more precise models are constructed by effective utilization of that data. Just-In-Time modeling is a method in which the values of model parameters are not specified in advance, but a large volume of past input and output data is collected, and a local prediction models is constructed by prioritizing the past data near the query point each time a prediction is required[1)].

This paper discusses research in connection with practical application of material property design and material property control of products in steel plants using locally weighted regression[4)], which is one type of Just-In-Time modeling, in order to solve the above-mentioned problems. Following this, innovations in order to expand the application of the developed tech-

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nology to various processes and workplaces are discussed.

2. Material Property Design and Material Property Control of Steel Products

2.1 Object Manufacturing Processes and Quality Indexes

The object processes are processes to build material properties into products. These include the steelmaking process, in which the chemical composition of the product is adjusted; the heating process, where the semi-finished products called slabs, which are manufactured in the steelmaking process, are heated to the specified temperature; rolling processes, in which the material is formed to the specified dimensions and shape; and cooling processes, in which the product is cooled to the specified temperature[1)].

Although the quality indexes for steel products include dimensions, shape, material properties, etc., the object discussed in this paper is material properties, which are one key index in the quality of steel products[1)].

2.2 Material Property Design

Material property design is a decision-making process in which manufacturing conditions which will satisfy the product specifications related to the customer's required material properties are decided. The product specifications required by customers include strength (Tensile strength, Yield point, and Elongation), toughness (Absorbed energy, Transition temperature), and others. Manufacturing conditions include chemical composition, and respective temperatures at the heating process, rolling process and cooling process, etc.[1)].

Until recently, material property design was performed by design engineers who possessed a wealth of knowledge and experience. A knowledge-based system using If-Then rules and fuzzy logics was proposed for the purpose of automating material property design and improving its accuracy[5)]. However, since it is difficult to implement the knowledge and experience of design engineers into a knowledge database quickly in response to changes in the environment, it gradually becomes more and more difficult to obtain appropriate manufacturing conditions from a knowledge-based system. For this reason, it became inconvenient to use the knowledge-based material property design system. Therefore, model-based material property design was demanded[1)].

A design engineer must not only satisfy the customer's material property requirements, but must also decide the manufacturing conditions so as to minimize manufacturing costs. Thus, it can be said that material property design involves solving a kind of optimization problem. In performing this optimization with a computer, a technique which enables precise prediction of product quality from manufacturing conditions becomes necessary[1)].

2.3 Material Property Control

In the stage of material property design before manufacturing, the standard values of each manufacturing condition are determined so as to satisfy the customer's material property requirements. However, as no technique for accurate prediction of material properties from manufacturing conditions has been established, it is difficult to calculate the manufacturing conditions for obtaining the target material properties with high precision. Since there are limits to the accuracy of the standard values decided by the design engineer, variations occur in the material properties of the product. Although regulation control is performed so as that the manufacturing conditions conform to the standard values during operation in the manufacturing stage, the actual values may diverge from the standard values due to disturbances, resulting in variations in the material properties of the product[1)].

Feedforward control has been performed to reduce control errors in material properties. In this technique, the cause-and-effect relationship between manufacturing conditions and material properties is modeled, and the material properties of the product are made to converge on the target values by calculating appropriate manufacturing conditions for the processes where production has not yet begun, based on that model and the actual values of the manufacturing conditions where production has already been completed, and operating based on the calculated results[1)].

2.4 Conventional Material Property Design Techniques and their Problems

As material property prediction models, construction of physical models simulating metallurgical phenomena has been an object of research in the past. However, for various reasons, it is difficult to construct and maintain practical physical models. Problems include the fact that no technology which enables online measurement of the metallic microstructure has been established, the difficulty of constructing a model which strictly expresses metallurgical phenomena, etc.[1)].

Therefore, black-box modeling came to be used at manufacturing sites. This is a technique in which a prediction model is created directly from input data and output data. Among black-box techniques, linear regression models, in which a simple parameter identification method by the least square method has been established, are widely used as material property prediction models[1].

However, for processes which are both complex and non-linear, it is difficult to express the relationship between diverse manufacturing conditions and product quality by a simple formula with fixed model parameters, and as a result, adequate prediction accuracy cannot be obtained[1].

Therefore, in order to secure the accuracy of the model, the general practice was to divide the manufacturing conditions into multiple divisions and provide model parameters for each division. The values of the parameter table in this type of prediction model had been decided by using a database in which a large volume of actual manufacturing result data was accumulated. However, in cases where environmental changes occur frequently, sufficient prediction accuracy cannot be obtained, since the objects of prediction cannot be expressed appropriately by a model that was constructed based on past data. It is possible to respond to changes over time if the divisions can be reviewed and the values of the model parameter table can be adjusted at regular intervals. However, as a problem of this approach, adjustments of the model must inevitably depend on human intervention, which involves a heavy work load; as a result, frequent adjustments are not possible and it is difficult to maintain accuracy. Moreover, there were also limits to the accuracy of material property design and material property control because models with low accuracy were used[1].

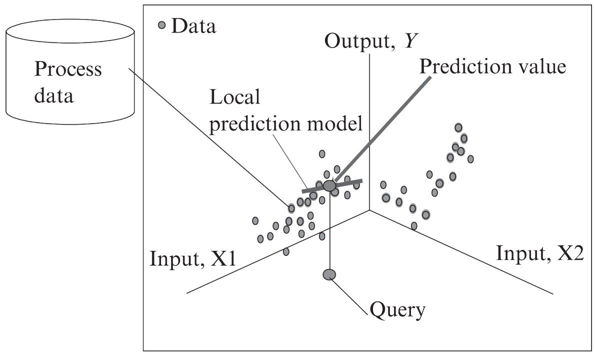

Fig. 1 Locally weighted regression model (Reproduced from reference 6))

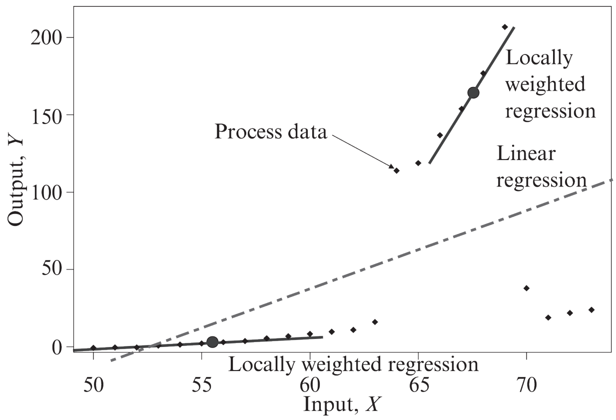

Fig. 2 Linear regression and locally weighted regression (Reproduced from reference 6))

3. Material Property Design and Material Property Control System Using Just-In-Time Modeling

In order to solve the problems mentioned above, material property design and material property control systems were developed using a locally weighted regression model, which is a type of Just-In-Time modeling.

3.1 Locally Weighted Regression Model

Locally weighted regression, as shown in **Fig. 1**, is a method in which local models are constructed by prioritizing the past data near the query. As the local model, the linear equation shown below is used.

$$\hat{y} = b + \sum_{m=1}^{M} a_m x_m \quad \text{......} (1)$$

Where, $\hat{y}$ is the predict of the output, x_m ($m=1, ..., M$) are inputs, and b and a_m are model parameters. A numerical example for comparison with linear regression is shown in **Fig. 2**. For simplicity of explanation, the number of input variables is assumed to be 1. The horizontal axis shows the input variable, and the vertical axis shows the output variable. As can be understood from the plots of the actual input and output data, a non-linear relationship exists between the input and output. If fitting of these data is performed by linear regression, the result is as shown by the chain line, and accurate fitting is not possible. In contrast to this, in locally weighted regression, a local model is created by prioritizing the past data in the vicinity of the query. Figure 2 shows the locally weighted regression model and the predicts when 55.5 and 67.5 are given as queries. In locally weighted regression, it is necessary to revise the prediction model each time the value of the query changes, but it can be understood that this technique gives good prediction accuracy, even for non-linear objects. In addition, appropriate calculation of the coefficient for the vicinity of the query is also possible[6].

3.2 Evaluation of Material Property Prediction Accuracy

In locally weighted regression, it is not necessary to determine the numerical expression for expressing the causal relationship between the input and output in advance. Therefore, this technique is suitable for modeling of complex and non-linear objects such as material property prediction[1].

The object variables of a dataset for material property prediction are the characteristic values of mechanical tests such as tensile strength, yield point, elongation, absorbed energy, etc. The explanatory variables are manufacturing conditions that display a clear physical cause-and-effect relationship with the object variable. As input variables, ten-plus items are selected from among chemical composition, heating conditions, rolling conditions and cooling conditions. Due to the extremely diverse range of products manufactured, the correlation between input variables can be considered small[1].

Regarding the number of samples collected in the dataset, the samples were selected from the manufacturing cycle so that substantially all the data for manufacturing conditions are in the dataset. To enable construction of new prediction models using recent data, the system was designed so that datasets are updated by first-in first-out method (FIFO). Although the data collected in the dataset are measurements by sensors, an allowable range is set for the values of each sensor, and values which exceed the allowable range are not collected in the dataset so as to prevent collection of anomalous data. Predicts are calculated by the material property prediction model, and when the difference between those results and the actual values exceeds the control range, those calculated values are excluded from the dataset. Defective data are also excluded from the dataset[1].

The prediction error by the linear regression model which was used in the past and the prediction error of the proposed locally weighted regression model were evaluated for three types of products, namely, controlled-rolling steels for plates, tempered steel for plates and hot-rolled steel for pipes. It was found that the root mean square error (RMSE) of the prediction error for tensile strength and yield stress by the locally weighted regression model is reduced by approximately 40–60% in comparison with the linear regression model. These evaluation results confirmed that prediction accuracy is greatly improved in comparison with the conventional linear regression method by using locally weighted regression in the material property prediction model[7, 8].

3.3 Practical Application of Material Property Design System

Because a large improvement in material property prediction accuracy by using the locally weighted regression model could be confirmed, a material property design system was constructed using that model.

The functions of the constructed material property design system are as follows. First, the design engineer inputs the manufacturing conditions. The material properties under those manufacturing conditions are then predicted by the locally weighted regression model based on the actual result data accumulated in the past, and those prediction results are visualized for the design engineer. In material property design, it is not sufficient simply to satisfy the customer’s property requirements; it is also necessary to reduce the risk of occurrence of nonconforming products and other problems. It is necessary to determine the manufacturing conditions while considering these secondary evaluation indexes. Therefore, visualization for the design engineer, who will adjust these items, is also necessary. For this, linkage to a database of risk information is necessary. The design engineer reviews and judges the visualized results, and inputs changes in the manufacturing conditions to satisfy the material property requirements and also adequately reduce manufacturing costs and risk. This process is repeated until manufacturing conditions which satisfy the design engineer are obtained[7].

In predicting material properties by a locally weighted regression model, a large volume of past actual manufacturing data is necessary. Attention must be given to the following two points when collecting that actual result data. First, due to the diversity of the product manufacturing process, it is necessary to couple data between multiple processes. Next, the data items required in product quality prediction change due to various environmental factors, such as progress in manufacturing technology, changes in the manufacturing equipment, changes in the customer’s property requirements, changes in the characteristics of the equipment over time, fluctuations in the cost of raw materials, etc. Therefore, it must be possible to collect the necessary data quickly and easily, including these environmental changes. Moreover, although design engineers are highly skilled in metallurgical phenomena and manufacturing processes, they are not experts in computer science and programming. For this reason, it is necessary to construct a system which enables easy improvement and maintenance of models even by persons who are novices in computer technology. To satisfy this requirement, the material property design system was constructed by using a multi-purpose data mining tool[7].

Use of a data mining tool enables quick and easy data coupling between processes. Furthermore, by using the visual programming function (**Fig. 3**) of the data mining tool, it is also possible to modify the program which edits data for use in model creation quickly and flexibly, including changes in process characteristics accompanying environmental changes, etc.[7].

As programming to enable general-purpose use of the functions of the locally weighted regression model with various objects, prediction models for other objects

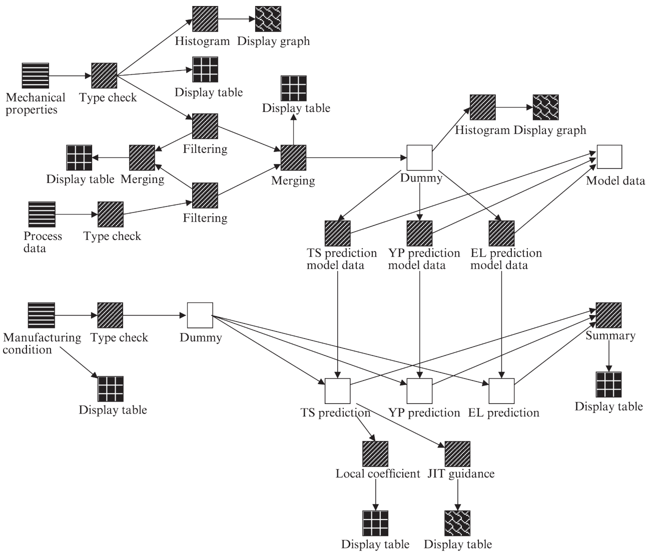

Fig. 3 Use of visual programming

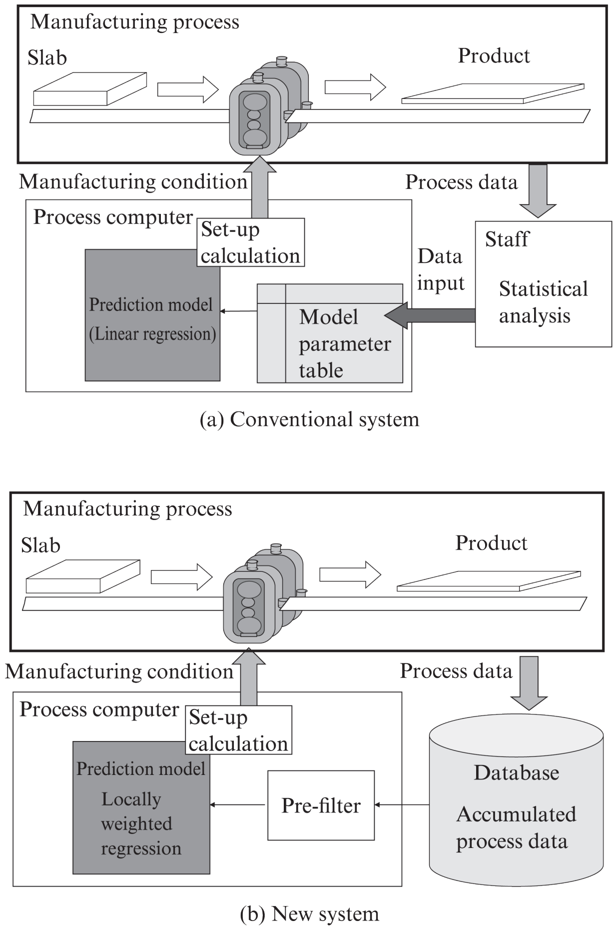

Fig. 4 Mechanical property control system (Reproduced from reference 6))

can be created by registering icons in the data mining tool and simply copying and pasting the icons. In case of environmental changes such as changes in manufacturing conditions, changes in quality characteristic values, etc., in the past, prediction models were prepared by experienced persons with a thorough knowledge of the object process. However, this was time-consuming work. In contrast, this tool makes it possible to construct new models in minimal time[7)].

Material property design accuracy was compared in conventional design using a linear regression model and design by the new system utilizing the locally weighted regression model. The RMSE of the material property design error of the new system was reduced by approximately 50% in comparison with the conventional system, demonstrating that a large improvement in material property design accuracy in comparison with the conventional method is possible[7)].

3.4 Practical Application of Material Property Control System

As a large improvement in material property prediction accuracy by using the locally weighted regression model was confirmed, a material property control system utilizing this model was constructed.

The conventional control system is shown in **Fig. 4**(a), and the newly-constructed system is shown in Fig. 4(b). The values of the manufacturing conditions for obtaining the required material properties are calculated in the process computer and set to the equipment of the manufacturing process. Conventionally, offline statistical analysis and maintenance of the model parameter table, which consisted of multiple divisions, by the steel works staff was necessary. However, with the new system, actual result data for measured input variables and output variables are accumulated automatically in the database when each product is manufactured, old data in the database are eliminated automatically, and a locally weighted regression models are constructed automatically using the actual result data in that database. As a result, a large reduction in the model maintenance load was possible[6)].

The RMSE of the material property control error of the new system was reduced by approximately 20–40% in comparison with the conventional system, showing that a substantial improvement in material property control accuracy is also possible in comparison with the conventional system[8)].

3.5 Summary of Material Property Design and Material Property Control Systems

Practical techniques and systems for material property design and material property control were developed by using a locally weighted regression model. Design error and control error in the material properties of products were reduced by applying the developed systems to material property design and material property control in an actual plant, thereby contributing to improvement of product quality. These systems also contributed to reduction of the load of model maintenance, which had been performed by staff in a time-consuming process. The material property design system has been used since March 2003, and the material property control system has been used since November 2002. Since both of the developed systems have been used continuously in JFE Steel for more than 10 years, it is considered possible to respond to environmental changes. As described above, the effectiveness of the proposed techniques and developed systems was verified in actual plants[1].

4. Company-Wide Development of High-Precision Process Control Technology by Just-In-Time Modeling

Because the process control technology using Just-In-Time modeling is a general-purpose technology, the range of application of this technique is currently being expanded to automatic control of product quality in various other processes for which it is difficult to construct physical models or it is difficult to maintain model accuracy due to environmental changes[6].

In practical application, it is necessary to gain the cooperation of those concerned at the manufacturing site by obtaining their understanding of the effectiveness of the proposed technique. This chapter describes innovations for this purpose[6].

4.1 Reason for Selecting Locally Weighted Regression Model

The proposed technique itself must be easy to be understood. All of those concerned at the manufacturing site do not necessarily understand modeling and computer science. Although there are various methods for creating models of complex and non-linear objects, the locally weighted method was selected from among those methods because it is an extension of the linear regression method, which is widely used in manufacturing sites. In linear regression, a line is drawn so as to minimize the sum of squares of prediction error. On the other hand, in the locally weighted method, heavier weight is given to samples near the query, and the weight of more distant samples is reduced; the weighted sum of squares is then calculated, and a line is drawn so as to minimize that value. In calculations by the linear regression method, the weights of all samples are assumed to be the same. The locally weighted regression method differs from the linear regression method only in that the weights of the samples are changed depending on their distance from the query. The fact that linear regression is widely used as a model by those concerned at manufacturing sites is because agreement with the prior knowledge regarding the physical characteristics of the object is confirmed based on the value of the partial regression coefficient. Models which agree with the physical characteristics of the object tend to be used with a sense of security. Like linear regression, the values of partial regression coefficients can also be calculated with the locally weighted method, and can be confirmed by those concerned at the manufacturing site[6].

4.2 Development of Just-In-Time Model Development Support Tool

4.2.1 Outline of functions of development support tool

In order to receive an intuitive understanding that the precision of the model is improved in comparison with the conventional method, a development support tool using a general-purpose data analysis tool was created. As shown in **Fig. 5**, the development support tool comprises three functions. The first is a function for importing actual results data for input variables and output variables from the actual results database. The next is a function for creating locally weighted regression models from the imported data and calculating predicts. Repeated calculations are performed by leave-one-out cross-validation[9]. The final function is a function for visualizing the results of evaluations of prediction accuracy. A scatter plot of the measurements and the predicts calculated by leave-one-out cross-validation and a histo-

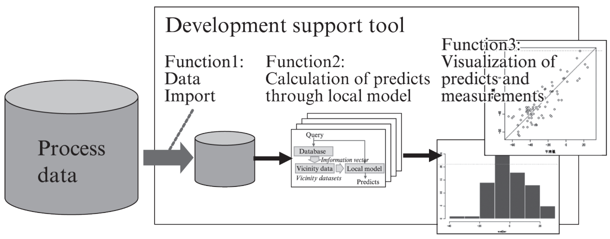

Fig. 5 Functions of development support tool (Reproduced from reference 6))

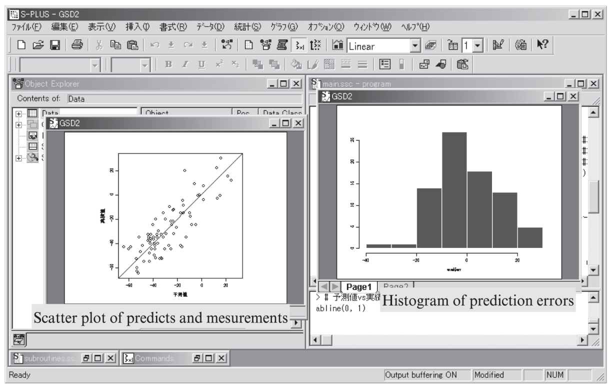

Fig. 6 Evaluation of prediction errors (Reproduced from reference 6))

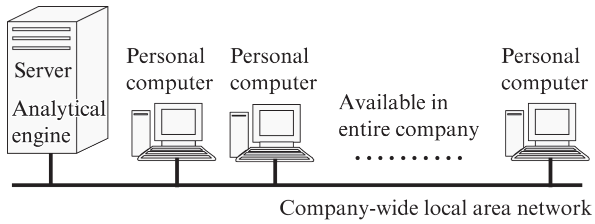

Fig. 7 Development support system based on web service

gram of prediction errors are drawn, and statistical quantities such as the mean and standard deviation of prediction errors, etc. are calculated (**Fig. 6**)[6].

4.2.2 Web-based systemization and in-company training

This development support tool was systemized as a web-based service, as shown in **Fig. 7**. With the conventional approach, a large amount of working time was required for software management because it was necessary to install software for each user. Knowledge and proficiency in the use of analytical software was also necessary, and as a result, the quality of the results depending on the user, in other words, deviations in the precision of the model, was a major problem. By adopting web-based systemization, simple use by anyone is possible via the company's internal local area network (LAN) by using a web browser, and deviations in the quality of results are slight because a standardized design procedure is supplied to users. Moreover, the fact that it is not necessary for users to install the software has greatly reduced the time required for software management. In addition to an outline of Just-In-Time modeling technology and examples of its practical application, training in the use of the development support tool is also given at in-house technical classes for young engineers in an effort to disseminate this technology in the company.

4.3 Development of Just-In-Time Model Standard Software

To enable easy transplantation to other systems, a calculation module of the locally weighted regression model was standardized. The material property design and material property control functions introduced in this paper were also packaged in the same program. As a result, it is possible to hold down development costs when the system is deployed to actual equipment for automatic control of other processes[6].

4.4 Examples of Applications of High-Precision Process Control Technology Using Just-In-Time Modeling

Process control technology using Just-In-Time modeling has been applied in JFE Steel's East Japan Works (Chiba, Keihin), West Japan Works (Kurashiki, Fukuyama), and Chita Works. This technology has been developed to various processes, including ironmaking, steelmaking, hot rolling, plates, pipes, cold rolling, etc. Although previous discussion described examples of practical application of material property design and material property control, other concrete examples of applications which have been publicly announced to date are a hot metal (molten iron) desulfurization control model[10] in impeller type desulfurizing equipment, a blowing control model for converters[11, 12], a tundish molten steel temperature model[13] for continuous casting, a width control model[14], cooling temperature control model[19] and plan view control model[15]for plates, a rolling load model[16] in the finishing mill of the hot strip mill, a material property control model[17] for cold-rolled steel strips and an alloying degree control model[18] for the continuous galvanizing line.

5. Conclusion

This paper has introduced successful examples in which modeling and control system development and maintenance were performed efficiently by effectively utilizing actual manufacturing result data that was collected automatically at iron and steel manufacturing sites and stored in large volume, contributing to a reduction in the deviations in the quality of iron and steel products[6].

At iron and steel manufacturing sites, model-based control has been widely implemented since an early date and is continuing to increase at present. Progress in technologies for efficiently modeling control objects with high precision, developing control systems, and maintaining and improving those systems is necessary and indispensable for improving product quality, and is also expected to become increasingly important in the future[6].

In the future, the author hopes to contribute to improvement of the manufacturing site, and simultaneously, to contribute to the development of this field of technology, by continuing the results of this research and expanding their application in the design and automatic control of various processes and product quality[1].

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