COOLING TEMPERATURE CONTROL FOR STEEL PLATES THROUGH LOCALLY WEIGHTED REGRESSION MODEL

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Abstract

A new control method is proposed for controlling cooling temperature in steel plate production process. The proposed method is based on a locally weighted regression model, which is a type of Just-In-Time models. The cooling temperature control system using the proposed method was developed and has been applied to actual plants. The proposed method determines the optimal manufacturing condition from the information of the pre-processes which has actual process data. Significant effects on reducing cooling temperature deviations and model maintenance load have been achieved in commercial production. The developed system has made contributions to improving yield and production rate.

Keywords: Just-in-time modeling, data based modeling, nonlinear model, optimum control, quality improvement

1. INTRODUCTION

Physical models are widely used to analyze the relation- ship between manufacturing condition and product quality in various processes. However, it is difficult to construct models that precisely reproduce physical phenomena observed in steel manufacturing processes, because the relationship between manufacturing condition and product quality is extremely complex and nonlinear. Therefore, it is not practical to incorporate control systems based on physical models into production systems. Data-oriented modeling techniques such as Just-In-Time modeling [1, 2, 3] and model-on-demand [4] have been the focus of interest in recent years, because progress in computer technology has made it possible to accumulate and rapidly search enormous volumes of data. In these methods, no model is constructed in advance. Rather, 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. To date, applied research has been conducted on Just-In-Time modeling for complex, nonlinear processes such as chemical and steel plants [1, 2, 3, 4]. Its applications include prediction of future trends and estimation of targets which are difficult to measure. However, the focus of past research was limited to improving the prediction or estimation accuracy of the models. Although various innovative methods have been developed, a problem of quality design or quality control using Just-In-Time modeling, in other words, how to determine the optimal manufacturing condition for securing the target quality, has not been solved yet.

The author has proposed a quality design method and an automatic process control method utilizing locally weighted regression [5], which is a type of Just-In-Time modeling. Quality design systems [6] and quality control systems [7, 8, 9, 10] using the methods have been developed and applied to commercial plants, and have been contributed to improving product quality, i.e. mechanical properties, dimensions, plan view pattern and chemical composition, and have been reducing manufacturing cost.

This paper discusses the application of the process control method to a steel plate production process to improve the accuracy of cooling temperature, i.e. one of manufacturing condition which affects quality indices of steel products. Its application at JFE Steel's steelworks is also presented.

2. OBJECT PROCESS AND CONVENTIONAL CONTROL TECHNIQUE

In the steelmaking process, the chemical composition of the materials is adjusted and intermediate products called stabs are cast. These slabs are heated to the specified temperature in the heating process; then they are subjected to plastic working in the rolling process to obtain the specified shape and dimensions. In the cooling process, the microstructure and mechanical properties of the steel materials are built into the product by cooling it to the specified temperature. As shown in **Fig. 1**, the object process is a cooling process. Temperature control of the process is essential to reduce the deviation of product quality.

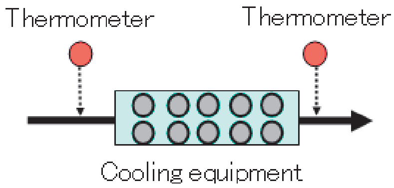


Fig. 1 Cooling process

Feed-forward control, in which material temperature after processing is made to converge on the target values, is performed based on the model, which describes the causal relationship between manufacturing conditions and material temperature after processing. The physical model for the temperature control is expressed as the following equations.

$$q = -k\frac{\partial T}{\partial x} \quad , \quad q = h\,\Delta T \tag{1}$$

where, q is amount of heat required (heat flux) [W m^{-2}] i.e., thermal power per unit area. k is material's conductivity [W m^{-1} K^{-1}], T is material temperature [K], x is distance, m, h is heat transfer coefficient, [W m^{-2} K^{-1}], ΔT is difference in temperature between material surface and surrounding water [K]. h is fitting parameter. Output variable of the predictive model is material temperature after processing. Input variables are the manufacturing conditions, that is, material temperature before processing, material thickness, water flow rate, material transfer speed, water temperature, material chemical compositions, and so on. Because the fitting parameter differs in the case of manufacturing condition, it is difficult to construct and maintain practical physical models.

To solve this difficulty, in actual manufacturing situations black-box models, directly derived from the input and output data, have been used rather than physical models. Among black-box models, linear multiple regression models have been widely used. However, linear models are not suitable for highly nonlinear processes. General practice to improve the prediction accuracy is the use of model parameter tables, which are derived by dividing the manufacturing condition into multiple classes and having different model parameters for different classes. Because of complex, nonlinear phenomena and diversified products, a large number of classes are necessary to obtain high precision models. In addition, the model parameter tables need to adapt to environmental changes over time by adjusting the model parameters and reviewing the classification periodically. This adaptation requires human intervention and increases workload of engineers and operators. In practice, therefore, it is difficult to frequently modify the prediction models and maintain their accuracy.

To solve this problem, a new control system is developed by using locally weighted regression, which is a type of Just-In-Time modeling. In the locally weighted regression, a local prediction model is constructed by prioritizing the past data near the query point each time a prediction is required. The locally weighted regression model can be successfully fitted into the data near the query for the nonlinear processes although it is difficult to make an accurate model by the conventional approaches.

3. DEVELOPED CONTROL SYSTEM USING LOCALLY WEIGHTED REGRESSION MODEL

The purpose of the developed control system through locally weighted regression model is to determine the optimum values of manipulated variables of the post-processes from the information of the pre-processes which has actual process data. This system consists of the following 4 modules.

3.1. Database

Actual values of manufacturing condition and the objective variable are stored in the database each time the manufacturing of the object process is completed. y^n and $\mathbf{x}^n \equiv [x_1^n \quad \cdots \quad x_M^n]^T$ are the *n*-th sample of an output and *M* inputs, respectively. The number of data stored in the database is *N*. In the object process, the sample size of the database is 10,000, and the number of input variables is 32. The number of data accumulated in the database is determined so that the data cover all manufacturing conditions in the production cycle of the plant. To build prediction models based on the most recent data, the database is updated by the FIFO method, i.e., the oldest data in the database are deleted when adding a new data.

3.2. Selecting initial values

The query $\tilde{\mathbf{x}} \equiv [\tilde{x}_1 \quad \cdots \quad \tilde{x}_M]^T$ in the next module described in Section **3.3** is decided in this module as follows. The input variables can be divided into 2 groups, the inputs of post-processes $\tilde{x}_1 \quad \cdots \quad \tilde{x}_K$ and the inputs of pre-processes $\tilde{x}_{K+1} \quad \cdots \quad \tilde{x}_M$. The actual values are used for the inputs of pre-processes because the actual process data exist. On the other hand, the standard values are used for the inputs of post-processes.

3.3. Generating locally weighted regression model

In this module, a local prediction model at the query is constructed by using the data stored in the database. The model parameters calculated in this module are given to the next module described in Section **3.4**.

The locally weighted regression model at the query $\tilde{\mathbf{x}}$ can be expressed by the following linear equation:

$$\hat{y} = b + \sum_{m=1}^{M} a_m x_m \tag{2}$$

where, $\hat{y}$ is the output predictive value, and $\boldsymbol{\theta} \equiv [b \quad a_1 \quad \cdots \quad a_M]^T$ are model parameters. To construct a local model which can be successfully fitted into data near the query for the nonlinear process, the coefficients of this local linear regression model are determined through the following procedure.

The coefficients of this model are obtained so as to minimize the weighted sum of squared errors $J = (\mathbf{y} - \Omega\boldsymbol{\theta})^T \Pi (\mathbf{y} - \Omega\boldsymbol{\theta})$ where, $\Pi \equiv diag(W^1 \quad W^2 \quad \cdots \quad W^N)^T$, Ω is $N \times (M+1)$ matrix, and the elements of the matrix Ω are as follows: $\Omega_{n1} = 1$ and $\Omega_{n(m+1)} = x_m^n$, $(m \geq 1)$.

The weight W^n is called similarity between the query and the *n*-th sample of inputs. It is defined by $W^n \equiv \exp(-\Gamma^n / p\,\sigma_\Gamma)$, where *p* is a tuning parameter. By using the similarity as the weight for locally weighted regression, a local prediction model can be successfully fitted into the data near the query. Γ^n is the distance between the query $\tilde{\mathbf{x}}$ and the *n*-th sample of inputs $\mathbf{x}^n$ in the database. It is defined by $\Gamma^n \equiv \sum_{m=1}^{M} |\lambda_m| \, |x_m - \tilde{x}_m|$, where λ_m is a weight for scaling different types of input variables such as temperature and dimensions. σ_Γ is the standard deviation of the distance Γ^n.

3.4. Deriving optimal manufacturing condition

The relationship between manufacturing condition and product quality around a query $\tilde{\mathbf{x}}$ as modeled in Section **3.3**. The next step is to optimize manufacturing condition of the post-processes $\mathbf{u}$ by solving the following quadratic programming problem.

$$\min_{\mathbf{u}} (\mathbf{u}-\tilde{\mathbf{u}})^T \Lambda (\mathbf{u}-\tilde{\mathbf{u}}) \qquad \textit{subject to} \qquad y^o = b + [a_1 \quad \cdots \quad a_K]\mathbf{u} + [a_{K+1} \quad \cdots \quad a_M]\tilde{\mathbf{v}} \tag{3}$$

where $\mathbf{u} \equiv [x_1 \quad \cdots \quad x_K]^T$ are the manufacturing conditions of post-processes, and they are the decision variables of the quadratic programming problem. $\tilde{\mathbf{u}} \equiv [\tilde{x}_1 \quad \cdots \quad \tilde{x}_K]^T$ are the given standard values of the manufacturing condition of post-processes. $\tilde{\mathbf{v}} \equiv [\tilde{x}_{K+1} \quad \cdots \quad \tilde{x}_M]^T$ are the given actual values of the manufacturing condition of pre-processes. y^o is the target value of output variable. The weight Λ is, for example, the weights for scaling different types of input variables.

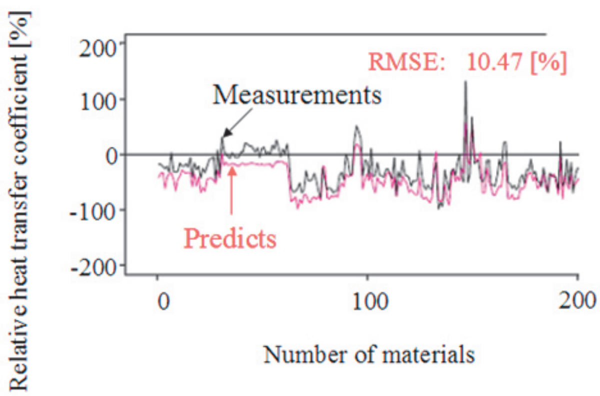
The calculated decision variable $\mathbf{u}$ is set up to the actual production processes.

4. APPLICATION TO AN ACTUAL PLANT

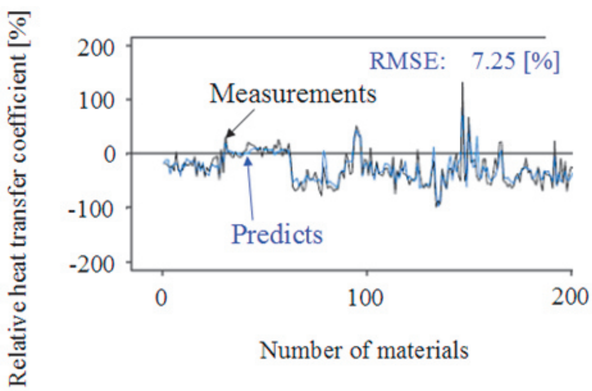
The application results of the developed system to the object process are described in this section.

4.1. Accuracy of heat transfer coefficient prediction

The fact that errors in the prediction of heat transfer coefficient are greatly reduced by using a locally weighted regression model was confirmed with data from an actual manufacturing process. The result of predictive accuracy on actual manufacturing data is shown for the conventional system and the developed system through locally weighted regression model. As shown in **Fig. 2**, the root mean square error (RMSE) with the developed predictive method was about 31% as large as that with conventional method.



(a) Conventional system



(b) Developed system

Fig. 2 Predictive accuracy of heat transfer coefficient

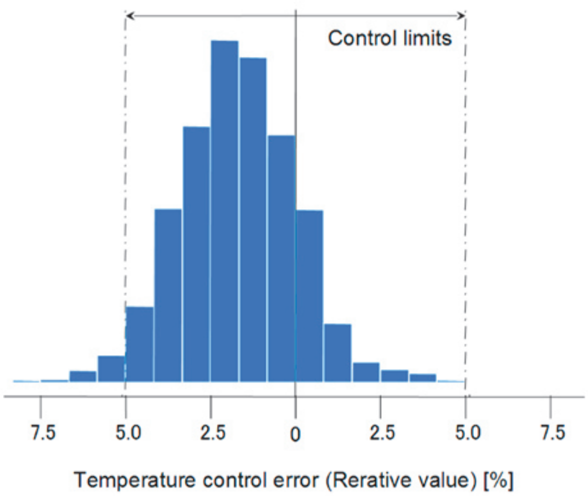
4.2. Material temperature control result

The following presents the results of a comparison of material temperature controlled error by the conventional control system and the developed control system as shown in **Fig. 3**. The controlled errors are relative values for the target material temperature. The RMSE of the developed control system has reduced by 29% in comparison with that of the conventional system.

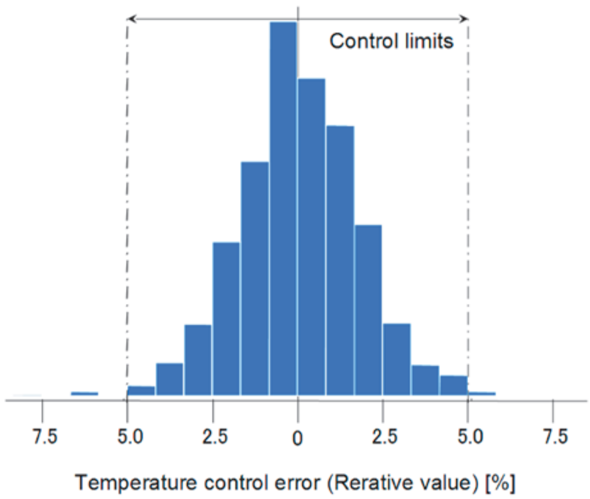
This system has been used in the production of products at JFE Steel Corporation's steelworks. It has been possible to improve the material property control accuracy. The probability to exceed the limits of the cooling temperature control of the developed system has become one third as large as that of the conventional system. The developed system has made contributions to improving yield and production rate.

Furthermore, the probability of quality defect could be reduced, as it was possible to improving yield and production rate. It is also possible to calculate the optimum model parameters automatically in real time. This has greatly reduced the enormous load of model parameter table maintenance work, which had necessarily been performed by staff, and thus made an important contribution to improving the job satisfaction of personnel.

Because this is a general-purpose technique, its scope of application is currently being expanded to automatic control of quality in various other processes where the construction of physical models or maintenance of model accuracy is difficult due to environmental changes.



(a) Conventional control system



(b) Developed control system

Fig. 3 Histogram of material temperature control errors

5. CONCLUSION

A control method for steel production process to determine the optimal manufacturing conditions for securing the target quality was developed. The proposed method is based on locally weighted regression, which is a type of Just-In-Time modeling. A quality control system based on the proposed method was developed and applied to quality control problems of various steel products. In this paper, the application result of the developed system for steel production process is reported.

This paper introduced a successful example in which modeling and control system development or maintenance were performed efficiently by effectively utilizing the actual manufacturing data that are collected automatically and accumulated in large volume in a steel manufacturing plant, thereby contributing to a reduction in manufacturing condition deviations in steel production process. In steel manufacturing plants, many model-based control systems have been implemented since an early date, and their number is continuing to increase. Because this is a general-purpose technique, its scope of application is currently being expanded to automatic control of quality in various other processes where the construction of physical models or maintenance of model accuracy is difficult due to environmental changes.

The developed system for steel production process has been used at JFE Steel Corporation's steelworks. It has functioned stably in spite of changes in manufacturing equipment and other environmental changes during this period. By determining the optimal manufacturing condition based on the proposed method, the product quality control accuracy was improved and the risk of quality defects was reduced.

To build a locally weighted regression model and make it effective, the tuning parameter p in the similarity function is adequately determined by taking account of both prediction errors and the suitability of model parameters. In addition, automatic calculation of the optimal model parameters in real time has become possible. As a result, the load of maintenance work for the enormous model parameter tables, which required manual work by the staff, has been significantly reduced. Thus, the developed system has made an important contribution to improving the job satisfaction of personnel.

The usefulness of the proposed system was confirmed through its industrial application; thus it is confidently expected that the system can be used for various purposes. Accordingly, the authors plan to expand the scope of application of this method to quality control problems in various other processes in which it is difficult to construct physical models or to maintain the accuracy of models due to environmental changes.

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