

A self-learning method for improving the hot-rolled plate shape

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Abstract. In the multi-standard rolling process of multi-steel production lines, frequent changes in specifications lead to slow self-learning and inaccurate learning, which makes the index of thickness deviation on plate out of target. To solve this problem, a quick self-learning method was designed and proposed. By calculating the crown deviation value of the current rolled steel strip, the bending roll force variation value and the plate shape feedback compensation value. The control parameters in the model are compensated accordingly to compensate for control deviations caused by changes in rolling conditions and the multi-standard steel. Experiments show that the rapid self-learning method can effectively improve the shape index.

Keywords: Hot rolling, Shape Set Up, Self-learning.

1. Introduction

In the hot rolling process of strip steel, the shape control is an important part of the dimensional accuracy control of hot strip, which has been increasingly valued by steel companies. The excellent plate shape is not only restricted by factors such as equipment, process, and management, but also high-precision plate shape control system is indispensable [1,2]. According to the theory of roll elastic deformation and strip plastic deformation, the formation mechanism of the plate shape is very complicated. Hot-rolling profile control is a complex process with multi-variable, fast-time-varying, strong-coupling, and non-linearity. Plate-shaped influencing factors such as rolling force, bending force, roll wear, and thermal crown will change with time and space. And mutual influence and coupling [3,4]. Therefore, most of the shape control mathematical models are based on a large number of simplifications and assumptions, and the calculation results often fail to meet user requirements.

The following problems exist in the current line production:

- 1) In order to ensure the surface quality of stainless steel strips and increase the production rate, mixed rolling must be implemented. Compared with carbon steel, stainless steel is a material that is difficult to roll. It has high deformation resistance and strict surface quality requirements at high temperatures. From the aspect of control, the key is to improve the adaptability of the control model and improve the control accuracy of the model under the condition of frequent switching of steel specifications.
- 2) In the way of scheduling by order quantity, it is difficult to formulate a standard operation plan on a rolling basis. At present, the specification of steel grades in the plan is frequently switched and the



rolling stability is poor. According to the statistics of the strips with the same control characteristics, the operation plan of the small batch and multiple steel grades directly affects the hit rate of the slab shape index.

3) The original plate shape rapid self-learning is not ideal for use in mixed rolling and small lot sizes, and the statistical data shows that the initial processing of the strip shape index hit rate is the lowest, and thus the overall shape index hit rate Have a greater impact.

4) For crown control, dynamic feedback control is not available in mill equipment, process control computer systems, and basic automation systems.

5) The original self-study only compensates the plate shape based on the actual data of the first strip head. When the temperature difference between the head and tail of different heating furnaces or the same slab is large, it is easy to cause self-learning disorders.

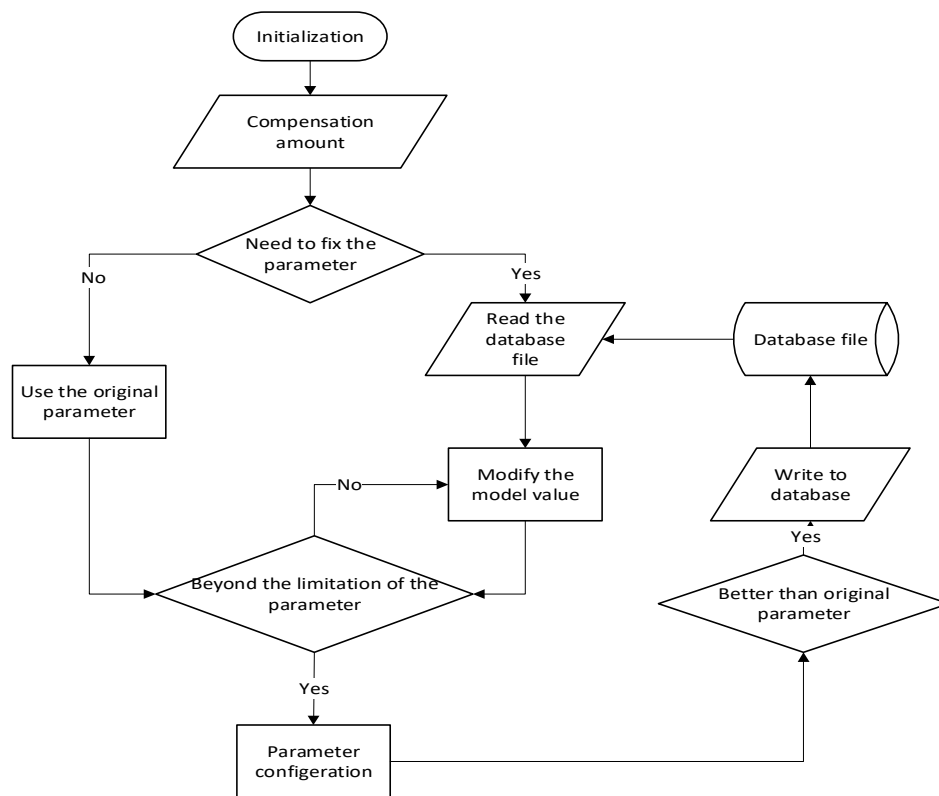
In order to solve the above problems, a method for rapid self-learning of a plate shape is designed and implemented.

2. Rapid Plate-shaped self-learning method

The strip hot continuous rolling control model is the most critical and the most important control technology in strip production. It determines and determines the control parameters of each equipment, and realizes the quality indexes such as strip thickness, width, plate shape and temperature through the basic automation system. control. However, there are inevitable deviations in the control process due to factors such as production conditions, model calculation accuracy, and equipment control accuracy. Self-learning can use the previous control experience of the control system to automatically adjust the control parameters according to the deviation of the measurement data from the measurement system and the target value, so that the control system can work in the optimal state according to the set target value, thereby improving the system performance index [5].

Plate shape rapid self-learning by calculating the crown deviation value of the rolled strip, bending roll change value, and plate shape feedback compensation value, the control parameters in the model are compensated accordingly to make up for the control caused by the rolling condition and other changes. Deviation, to achieve rapid improvement of strip shape, and improve the model's control accuracy. The short-term adaptation calculates the compensation after the last working stand has bitten steel, and this compensation value will be used for the calculation of the strip shape setting of the strip to be rolled at the next moment.

The main design ideas include: Subdividing and improving control features, improving statistical methods, and saving slab shape compensation data in real time.

**Fig. 1** Data flow

2.1. Data initialization stage.

First of all, taking into full consideration the influence of strip rolling properties and heating characteristics on the strip shape, using them as the key control characteristics of slab shape compensation, the strip shape compensation data can be obtained by evaluating the deviation of strip actual and target values after strip rolling. Then, according to the control features coupled and processed by the function to adapt the compensation amount, as the subsequent compensation of the same characteristics of the estimated strip. Finally, the latest compensation data is saved in real time. When the strip steel with the same characteristics is rolled later, the latest compensation data is read and submitted to the setting calculation model to avoid the initialization phenomenon after switching the steel specifications, and to improve the shape control model. Adaptive capabilities.

The plate shape compensation data can be obtained by judging the actual deviation from the target value after strip rolling. Then, according to the control features coupled and processed by the function to adapt the compensation amount, as the subsequent compensation of the same characteristics of the estimated strip. Finally, the latest compensation data is saved in real time. When rolling the strip with the same characteristics in the future, the most recent compensation data is read and submitted to the setting calculation model to avoid the initialization phenomenon after switching the specifications of steel grades and to improve the adaptive capacity of the strip shape control model.

The new fast self-learning features data processing, saving, restoring, and extending. Through the function processing and selection of appropriate parameters to meet the requirements of rapid self-learning sensitivity, stability, rapidity, accuracy, with strong adaptive capabilities.

2.2. Data update stage.

First, calculate the record number according to the control feature of the strip, determine the storage address in the data file, and read the most recent set of compensation amount estimates from the data file; then, use the formula (1) to get the current latest deviation amount. Deal with the previous set of

deviations to generate a new estimate of compensation for the next strip. Function 1 not only considers the state change during the rolling process, but also avoids the oscillation caused by the random error of the detection system, thus ensuring the stability, sensitivity and accuracy of the self-learning.

$$G_{n+1} = \sum_{i=n}^1 a_i G_i \quad (1)$$

In the formula, G_{n+1} is the estimated value of the compensation amount of the next block ($n+1$ block); $G_i (i=n \sim 1)$ is the nearest group ($n, n-1, n-2, \dots$) The estimated value of strip compensation; a_i is the weight coefficient of G_i . Finally, the data is updated using a FIFO (first-in-first-out) method, and the plate-shaped compensation data processed by the function are saved in real time.

2.3. Data process stage.

First, the record number is calculated according to the characteristics of the steel strip to be rolled, thereby determining the storage address in the data file. Read this record and restore the most recent shape compensation data to the memory variable. For crown compensation, the formula (2) should be used for comprehensive processing. Because the water cooling is delayed after biting the steel, the temperature of the rolling head is relatively high, resulting in a low strip crown. Therefore, the compensation coefficient β should be used to adjust the crown compensation proportionally, that is, by integrating the estimated value of the full-length average crown compensation value C_{n+1} of the same characteristic steel strip and the crown deviation value C_{nTop} of the same characteristic strip steel in the temporary storage zone. As the final crown compensation of the strip, the strip crown is reduced. The scaling function expression is

$$C_{Final} = C_{n+1} + bC_{nTop} \quad (2)$$

In the formula (2), b is the head crown compensation coefficient of the strip; C_{n+1} is the estimated value of the latest full-length average crown compensation; C_{nTop} is the crown compensation amount of the n th strip head; C_{Final} is the n +th The final crown compensation of one strip.

2.4. Extension.

In order to improve self-adaptive self-learning, self-study will automatically write the compensation data into the storage space of the data file with different heating characteristics and the same features. It provides reference compensation data for the same feature strips to be rolled in other furnaces to avoid initial processing and improve self-learning efficiency.

3. Experiments and analysis

The new self-learning model reflects its good application effect. The hit rate of the shape index, especially the flatness, has been significantly improved. Reduced the workload of model maintenance personnel and operators and played a positive role in improving strip shape.

3.1. Comparison of effects.

Compared with 102 steel grades rolled before application, there were 218 control group numbers, and steel grades and specifications expanded faster after application (see Table 1). Rolled over 124 steel grades with 379 control group numbers. The number of batches in the rolling plan is counted. The results show that the proportion of batch rolling with the same control group number increased from 24.31% to 28.42% before application, which shows that the shape control after application is relatively more complicated.

Table 1. Comparing of effects

Phase	Steel grade	Control group	Rate
before	102	218	24.31%
after	124	379	28.42%

3.2. Effectiveness analysis.

After adopting the new plate shape for rapid self-learning, the crown and straightness hit rate indicators have been improved under the condition that the shape control conditions have become more complicated (see Table 2). The hit rate of stainless steel crown increased by 6.53%, the overall crown rate of strip steel exceeded 94%, the hit rate of carbon steel flatness increased by 14.52%, and the hit rate of strip flatness exceeded 86%.

Table 2. Shape plate index hit rate

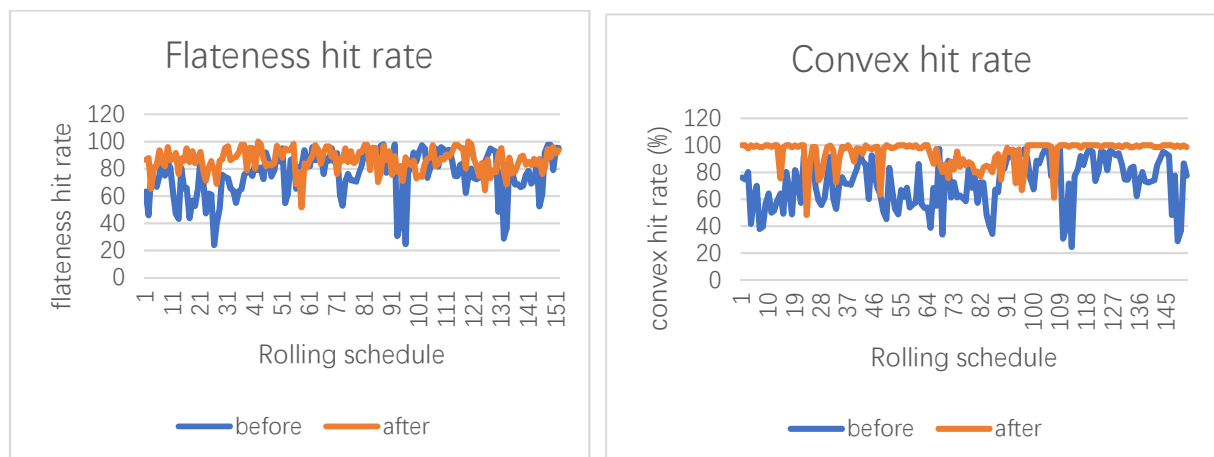
Phase	Average convex hit rate	Average flatness hit rate
before	87.75%	72.12%
after	94.28%	86.64%

3.3. Control stability

Figure 2 and Table 3 shows that the new plate-shaped rapid self-learning model significantly improves the large fluctuations in the front-end and middle-segment shape indicators of the operation plan. The flat-shaped indicators show a steady upward trend and remain at a high level. The standard deviation of convex is 17.56, Before applying the fast self-learning method, the standard deviation of crown was 17.56, after application was 9.24, as well as the standard deviation of flatness.

Table 3. Shape plate index stability

Phase	Standard Deviation of convex	Standard Deviation of flatness
before	17.56	16.26
after	9.24	8.36

**Fig. 2** shape index

4. Summary

The control model is the close combination and application of rolling process technology and computer technology, and it should continue to meet the requirements of production and quality. With the expansion of specifications and the increase of production capacity, it is an inevitable trend to improve

the accuracy of model control and expand the scope of application. Aiming at the difficulty of shape control under the condition of mixed rolling production process and small-volume and multi-variety specification operation planning in hot rolling mill. The design, development and application of the new plate-shaped rapid self-learning not only satisfies the accuracy requirements of the plate shape control under the multi-steel, small-batch, and multi-standard operation plans. In addition, a shape control technology with the characteristics of 1580 hot-rolling mixed rolling was also formed, which also marked the transition of the 1580 hot-rolling control model from digestion and absorption to application innovation. Strengthening the application innovation of the control model will enable the process control computer to achieve better performance, thereby increasing the level of automation of the production process, improving product quality, and ultimately increasing the competitiveness of the product.

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