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Fitting optimization of steel product quality based on cubic splines

Wenjing Wang*

College of Electrical and Control Engineering, Liaoning Technical University, Huludao, 125105, China
**Corresponding author: 15690950068@163.com*

Abstract: *At present, iron and steel enterprises have higher requirements for the stability of product quality, and there is an urgent need to establish a data-driven online monitoring model for strip product quality. In this paper, cubic splines are used and the standardized dimensionless data are fitted, and the standardized mean value of carbon content is 0.5932 and the STD value is 0.09775. The normalized average temperature of the soaking furnace is 0.2814 and the STD value is 0.1887. It can be seen that the correlation coefficient between the temperature and hardness of the soaking furnace is very large, and the correlation between carbon content and hardness is weak. Finally, the detection model that can realize the online detection of steel belt quality was successfully established, which made up for the shortcomings of the previous detection mode.*

Keywords: *Data-driven, On-line monitoring model of strip product quality, standardization, Dimensionless data, Cubic spline interpolation*

1. Introduction

Cold-rolled strip, as an important product in the steel industry, is used in many industries. The stability of its quality directly affects the performance of the final product. Therefore, the demand for quality monitoring of cold-rolled steel strip production in the production process of iron and steel enterprises is gradually increasing. In actual production, the existing methods such as offline sampling inspection and visual inspection are difficult to meet the needs of real-time quality control due to their lag.

In recent years, with the continuous progress of technology, academia and industry have conducted in-depth research on the quality monitoring technology of cold-rolled strip production, and a series of progress has been made. In the field of machine vision, the surface defect detection technology of cold-rolled strip based on image processing has become a research hotspot. By utilizing a high-resolution camera and advanced image processing algorithms, this technology enables online, fast and accurate detection of surface defects in cold-rolled strip. Some studies have improved the accuracy and robustness of defect recognition by introducing deep learning algorithms, which has further promoted the practical application of this technology. In addition, the prediction model based on big data and artificial intelligence also provides new ideas for the quality monitoring of cold-rolled strip production. Through the mining and analysis of historical production data and real-time monitoring data, these models are able to predict and optimize the production process of cold-rolled strip, thereby improving product quality and production efficiency.

In summary, although the quality monitoring technology of cold-rolled strip production has made significant progress, it still needs to be further developed and improved to meet the actual production demand. In order to solve the problem that the previous model could not cope with real-time detection, the relationship between the factors of the strip process and the strip quality with different parameters was considered. Through the strip specification data, process parameters and performance index data, as well as the huge relationship between the indexes and the mechanical properties of the strip, the data dimensionality reduction was considered again, and the data-driven model was constructed to complete the index selection, and then the cubic spline fitting model was used to fit the data by selecting the connection between the index data. In order to better study and analyze the online strip detection model proposed in this paper, this paper is divided into the following chapters. The first chapter is an introduction, which discusses the background and research status of the whole detection model, as well as the contribution points of this paper. The second chapter is related theories, which introduces the theoretical knowledge that needs to be used in the subsequent models. Chapter 3 is the experimental part, which introduces the whole process of building the model. Chapter 4 is the conclusion, which introduces the output of the model and the analysis of the results. Chapter 5 is a summary, which summarizes the work of the whole paper and gives ideas for improving the model. The contribution of this paper is to realize the dynamic online inspection of the strip model.

2. Related Theories

2.1 Data-driven models

A data-driven model is a type of model that relies on data for analysis and decision-making. It is based on patterns and information extracted from large datasets, rather than predefined theories or rules. Data-driven models generate predictive or classification models by collecting, processing, and analyzing data.

The operation of this model typically includes the following steps: First, data is collected and cleaned to ensure its completeness and accuracy[1]. Then, algorithms analyze the data to extract key features and relationships. Finally, a predictive or decision-making model is built based on these features and relationships. In practical applications, data-driven models can adaptively adjust parameters to better fit the patterns in the data, resulting in more accurate outcomes.

2.2 Cubic spline fitting model

The cubic spline fitting model is a method that connects data points with a piecewise cubic polynomial. It is used to generate a continuous and smooth curve between multiple given data points[2].

Its operation works as follows: First, the intervals between each pair of adjacent data points are determined, and a cubic polynomial is constructed for each interval. To ensure the smoothness of the curve, these polynomials are required to have equal function values at the boundary of the intervals, as well as continuous first and second derivatives[3]. Through this approach, cubic splines can smoothly connect data points, avoiding discontinuities or abrupt fluctuations, thereby producing a smooth fitted curve.

3. Experiment

3.1 The establishment of data-driven model

To facilitate the development of a robust data-driven model, Figure 1 outlines a systematic approach. This flowchart illustrates the various stages involved, starting from the identification of business objectives to the deployment of the model[4]. Each phase is crucial in ensuring that the model effectively meets the specific needs of the application, with the detailed process shown in Figure 1.

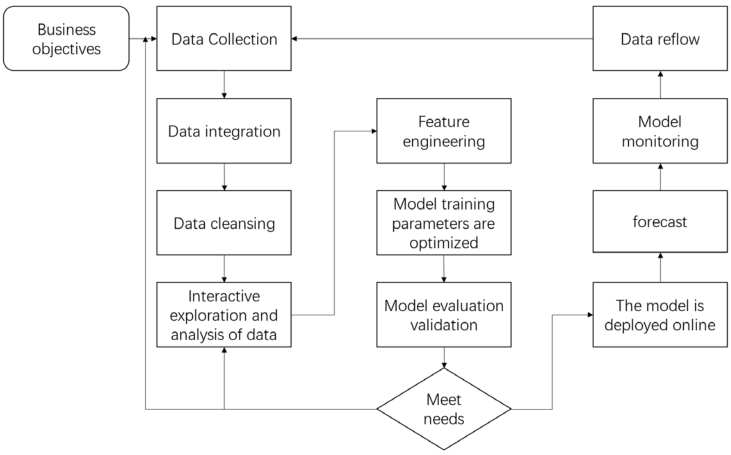

Figure 1: Data-driven model flowchart

The systematic approach illustrated in Figure 1 not only provides a clear framework for the development of a data-driven model, but also highlights the key activities and considerations at each

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stage to ensure that the final deployed model is both robust and aligned with business needs[5]. By following this systematic approach, it is possible to more effectively develop data-driven models that are both tailored to business needs and highly accurate and reliable, and the following is a detailed extension of this process.

Data collection gathers relevant data from various sources. Integration and cleansing ensure high-quality input. Interactive exploration and analysis deepen understanding of the dataset, informing feature engineering and optimizing model training parameters[6]. Validated models are monitored for performance and forecasts are made, leading to online deployment. This approach highlights the importance of each step for a successful data-driven solution.

3.2 The establishment of cubic spline fitting mode

Cubic spline fitting is a commonly used interpolation method in numerical analysis, and the cubic spline fitting process is to construct a smooth curve to fit a given set of data points. According to the characteristics of cubic polynomials, the method of differential interval is used to approximate the data in segments, and special connection conditions are set at the intersection to ensure the continuity and smoothness of the whole curve. Tri-spline fitting is a numerical analysis method used to fit a smooth continuous function curve from a set of scattered data. It is widely used in data approximation and interpolation problems in engineering, science and mathematics.

The system approach shown in Figure 2 not only provides a smooth curve fitting method in theory, shows the various steps of the fitting process, but also highlights its important role in data processing and analysis. By producing accurate and smooth data curves, meeting high-order continuity and smoothness requirements, providing powerful data approximation ability, and widely used in many fields, triple spline fitting is an indispensable part of numerical analysis. Moreover, in practice, it has become an important tool in data processing and analysis through flexible boundary conditions and efficient calculation methods. The detailed extension of the process is shown in Figure 2.

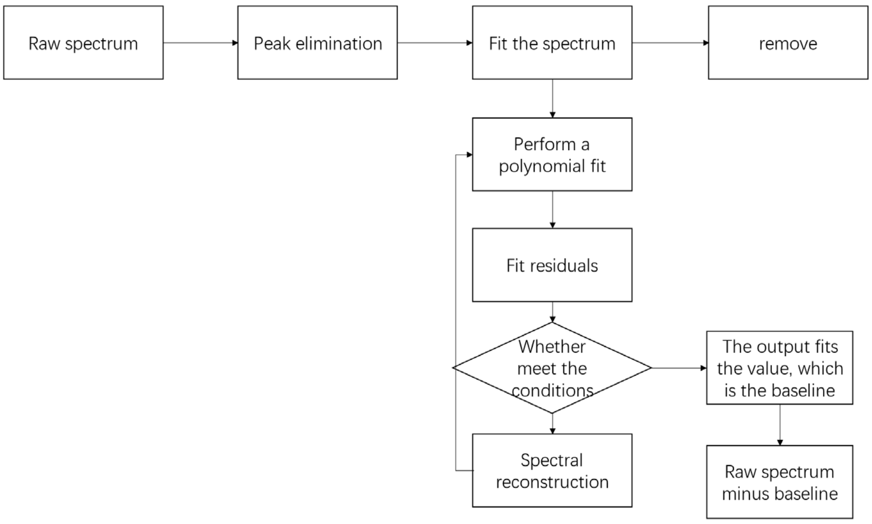

Figure 2: Flow chart of cubic spline fitting method

To better understand the underlying principles of cubic spline fitting, it is important to recognize that a cubic spline is a function composed of piecewise cubic polynomials[7]. Within the intervals between each data point, the spline function achieves smooth transitions between segments by ensuring continuity at the data points as well as the continuity of the first and second derivatives. The specific formulas are as follows:

$$S\left(x_j\right)=y_j\left(j=0,1,\ldots,n\right) \tag{1}$$

$$S'\left(X_0\right)=f_0' \tag{2}$$

$$S'\left(X_n\right)=f_n' \tag{3}$$

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$$S''(X_0) = f_0'' \tag{4}$$

$$S''(X_n) = f_n'' \tag{5}$$

$$S''(X_0) = S''(X_n) = 0 \tag{6}$$

The function S_x is defined as a cubic polynomial on each interval $[x_j, x_{j+1}]$, where $a = x_0 < x_1 < \cdots < x_n = b$ are given nodes. A cubic spline function is defined over the nodes if the function values are specified at each node and certain continuity and boundary conditions are satisfied. These conditions ensure that the spline function maintains smoothness and continuity across the intervals, including the values of the first and second derivatives at both ends[8]. In specific cases, this spline function is referred to as a cubic spline interpolation function. Based on findings from experiments, derivations, and analytical research, it can be concluded that the corresponding hardness can be accurately determined by inputting the carbon content and the temperature of the soaking furnace.

4. Results

Based on the previous modeling, we identified a strong correlation among the temperatures of the heating furnace, soaking furnace, and slow cooling furnace. Recognizing this relationship, we adopted a dimensionality reduction approach in our analysis. Specifically, we selected the soaking furnace temperature as a representative substitute for the other two furnace temperatures. This choice was made to simplify the model while still capturing the essential characteristics that influence the hardness of the cold-rolled strip steel.

In addition, we noted that the correlation between carbon content and other industrial parameters was weak. As a result, we treated carbon content as an independent variable. Thus, this study focuses on two primary independent variables: the soaking furnace temperature and carbon content. The performance indicator, hardness, serves as the dependent variable. This approach not only facilitates dimensionality reduction but also allows for effective variable selection, ensuring that our model remains manageable while still capturing critical factors that influence the product's quality.

Following this decision, we established a data-driven model and proceeded with data normalization to standardize our input variables. After normalization, the average value of carbon content was calculated to be 0.5932, with a standard deviation of 0.09775. Similarly, the average value of the soaking furnace temperature was found to be 0.2814, with a standard deviation of 0.1887. These statistics highlight the distribution of our variables and lay the groundwork for subsequent analysis.

To evaluate the model's performance, we calculated the sum of squared errors (SSE), which was determined to be 1.21. This low SSE indicates a good fit of the model to the data. Furthermore, the reliability index of the model was reported as 0.9372, reflecting a high level of accuracy in predicting the hardness based on the selected parameters. This level of reliability suggests that the model can effectively capture the underlying relationships between the independent variables and the dependent variable.

In the next phase of our analysis, we constructed cubic polynomials between each data point. This construction was done carefully to ensure that continuity was maintained at each data point, as well as continuity of the first and second derivatives. By ensuring these continuity conditions, we guarantee the smoothness of the curve. This attention to detail is critical, as it helps to avoid the Runge phenomenon, which can occur when too many high-order differences are used in polynomial interpolation, leading to oscillations at the boundaries of the interpolation interval. By employing cubic spline fitting, we achieve a more stable and accurate representation of the relationship between our independent variables and the performance indicator, thereby enhancing the overall reliability of our predictive model. Finally, to determine the cubic spline function, it was necessary to solve the corresponding system of equations, applying differential characteristics, continuity conditions, and boundary conditions for the first and second derivatives, thus obtaining the cubic spline fitting results, as shown in Figure 3.

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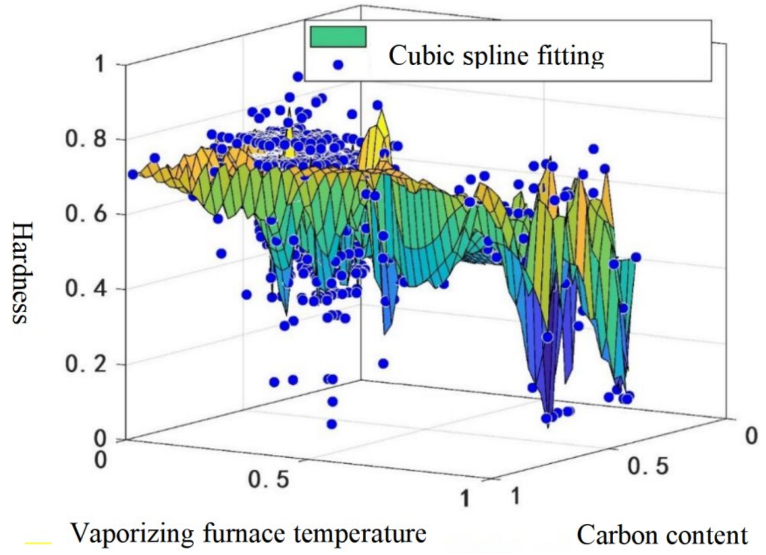

Figure 3: Cubic spline fitting results

The results indicate a robust relationship between the selected parameters and the hardness of the cold-rolled strip steel. The high reliability index suggests that the model effectively captures the underlying trends, allowing for accurate predictions of hardness based on the soaking furnace temperature and carbon content. The smoothness of the cubic spline fitting enhances the model's predictive capabilities, making it a valuable tool for online monitoring and quality control in steel production. Additionally, the insights gained from the dimensionality reduction approach can facilitate further optimization of the production process.

5. Conclusion

The paper develops a data-driven online monitoring model to improve the quality control of cold-rolled strip steel. Current methods are insufficient for real-time inspection, prompting this paper to analyze the relationship between process parameters and performance indicators using standardized dimensionless data. By applying cubic spline interpolation, the model improves the accuracy of fitting, focusing on key factors like carbon content and soaking furnace temperature. The study identifies the strong correlations between certain process variables and the resulting steel hardness, while establishing an efficient method for predicting product quality. Ultimately, the paper successfully creates an online detection model capable of real-time monitoring, addressing the limitations of previous models and enhancing the stability and accuracy of steel production quality control.

At the same time, in the future, cubic spline interpolation can still be used for engineering experiments, surveys and designs, providing accurate design and construction data through numerical interpolation and fitting. In the field of data analysis, cubic spline fitting models are also used to process noisy data and improve the fitting quality of the data through smoothing spline techniques.

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