Study on Precise Temperature Control Method of Hot-rolled Ribbed Bar during Cooling Process

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Abstract. Aiming at the demand for performance control in the production process of hot-rolled ribbed bar, the finite difference method was used to establish a temperature prediction model during the cooling process. The calculation accuracy of the temperature model depends to a large extent on the selection of heat transfer coefficient. In this study, the industrial production data was cleaned and screened by the clustering algorithm to obtain training sample data, and based on BP neural networks, the mapping relationship between different influencing factors and heat transfer coefficient was established. According to the change of production conditions, the heat transfer coefficient is learned adaptively, which improves the prediction accuracy of the model. By comparing the predicted and actual temperature values over a period of time, the deviation between most predicted and actual values is less than 20°C, and the deviation is reduced by about 30°C compared with that before the BP network was used to study the heat transfer coefficient. Under the constraints of the target temperature and the temperature difference between the inside and outside of the section, the precise control of the cooling temperature of the hot-rolled ribbed bar is realized by the calculation of the temperature prediction model.

1. Introduction
At present, the economy in China is developing at a high speed, public infrastructure construction is constantly advancing, and hot-rolled ribbed bars have become the most widely used construction materials [1]. In order to meet the needs of national economic development, the new national standard for hot-rolled ribbed bar was officially implemented on November 1, 2018 [2]. The implementation of the new national standard put forward new requirements for the performance and metallographic organization of hot-rolled ribbed bar. During the hot rolling process, it is very important to control the temperature of the rolled piece. The precision of the rolled piece temperature control determines the microstructure and performance of the rolled product [3]. If the temperature of the hot-rolled ribbed bar can be accurately controlled during the cooling process, it will be of great significance to improve product performance and quality.

In the calculation of the temperature model, the selection of the heat transfer coefficient plays a decisive role in the calculation accuracy of the model. The production of hot-rolled ribbed bar is a complicated process. The production process is constantly disturbed by various random factors. The chemical composition, scale, contact conditions and other factors are constantly fluctuating, it is difficult to ensure the calculation accuracy of the temperature model using the heat transfer coefficient directly calculated by the traditional formula. In order to ensure the calculation accuracy of the model, this paper uses the BP neural network to establish the model to realize the adaptive learning of the heat transfer coefficient. The training data of the BP neural network are selected from the actual measurement data.
of the production line. Due to the complex and changeable conditions in the actual production, and the possible detection errors of the measurement equipment, there are inevitable outliers in the original production data collected. In this paper, the Mean Shift algorithm is used to cluster the data and remove the abnormal data to ensure the reliability of the data.

2. Establishment of temperature model

For the calculation of the temperature of hot-rolled ribbed bar, in order to simplify the modeling process, the cross-section can be simplified to a circular cross-section. Since the heat dissipation in the longitudinal and circumferential direction is much smaller than the radial, the heat conduction in the length and circumferential direction can be ignored, and the heat transfer process is simplified to a one-dimensional heat transfer process in the radial direction [4]. The heat conduction differential equation can be expressed by equation (1), and the boundary conditions are expressed by equation (2) and (3) [5].

\[
\frac{1}{r} \left( \frac{\partial T}{\partial r} + r \frac{\partial^2 T}{\partial r^2} \right) + \frac{\dot{q}}{k} = \frac{1}{\alpha} \frac{\partial T}{\partial t} \tag{1}
\]

in this, \(r\) is radius of section, \(\dot{q}\) is internal heat source strength of material, \(\rho\) is density, \(c\) is specific heat, \(k\) is thermal conductivity.

\[
k \frac{\partial T}{\partial r} + h(T - T_w) = 0 \tag{2}
\]

\[
r = R \tag{3}
\]

in this, \(h\) is heat transfer coefficient, \(T_w\) is average temperature of cooling water.

Figure 1. One-dimensional cylindrical coordinate node division.

In order to establish the finite difference formula, the section of steel bar needs to be divides the nodes in the radial direction, and take the center node of the circular section as 1, divide the radial into \(M-1\) segments, each segment is \(\Delta r\), the boundary point is \(M\), and set up a point \(M+1\) outside the section. For equation (1), the finite difference method is used to solve it, and the explicit difference formula of the internal nodes of the steel bar ignoring the internal heat source can be expressed by equation (4).

\[
T_i^{k+1} = (f_1 + f_2)T_{i+1}^{k} + (1 - 2f_1 - f_2)T_i^k + f_1T_{i-1}^{k} \tag{4}
\]

in the formula, \(f_1 = \alpha \Delta t / \Delta r^2\), \(f_2 = \alpha \Delta t / r \Delta r\), \(T_i^{k+1}\) is the temperature of the node \(i\) in the radial direction at time \(k+1\), \(T_{i+1}^{k}\) is the temperature of the node \(i+1\) in the radial direction at time \(k\), \(T_{i-1}^{k}\) is the temperature of the node \(i-1\) in the radial direction at time \(k\).

When \(i=M\), the difference calculation equation of the boundary point can be obtained by combining equation (2) and (4).

\[
T_M^{k+1} = (1 - f_1 - f_2)T_M^k + f_1T_{M-1}^k + f_2T_{M+1}^k \tag{5}
\]

in this, \(f_3 = (f_1 + f_2)h \Delta r / k\), \(T_M^{k+1}\) is the temperature of the node \(M\) in the radial direction at time \(k+1\), \(T_M^k\), \(T_{M-1}^k\) are the temperature of the node \(M\) and \(M-1\) in the radial direction at time \(k\).
When the initial value of the temperature at each node of the steel bar section is known, the temperature distribution of the steel bar section at any time can be iteratively calculated through equations (4) and (5).

3. Processing of sample data
The Mean Shift algorithm is an algorithm based on kernel density estimation. The multivariate kernel density estimation formula for a point \( x \) of the bandwidth matrix \( H \) of the kernel function can be expressed by equation (6) [6].

\[
\hat{f}(x) = \frac{1}{n} \sum_{i=1}^{n} K_{h}(x-x_i) \\
K_{h}(x) = |H|^{-1/2} K(H^{-1/2}x)
\]

in this formula, \( K_{h}(x) \) is kernel function.

The biggest advantage of the clustering algorithm is that there is no need to specify the number of cluster centers in advance, it automatically searches for clustering centers through iteration[7]. When clustering is completed, some categories can be eliminated automatically which contain fewer data points. The data can be filtered and cleaned by using the algorithm. The data of cooling water pressure, flow rate, water temperature and steel bar surface temperature of two sets of coolers on the hot-rolled ribbed bar production line is taken as input, and use the Mean Shift algorithm to perform the clustering algorithm test on the above data. The production line that carried out the study enabled two sets of coolers, and the data of the two sets of coolers are processed separately. Select 450 groups and 400 groups of data as initial data, after clustering processing, 283 sets and 256 sets of data are obtained.

4. BP neural network model
Based on the training of the BP neural network, the mapping relationship between the heat transfer coefficient and other influencing conditions is established to adapt to the change of production conditions. Therefore, the input parameters are water pressure, flow, water temperature, and specifications. The output parameter is the heat transfer coefficient. The neural network structure is shown in Figure 2.

\[\text{Figure 2. BP neural network structure.}\]

Using the previously filtered data, the neural network is trained to obtain a heat transfer coefficient learning model that is compatible with the two sets of equipment.

5. Application result analysis
The research is applied to actual production, and the production data of the hot-rolled ribbed bar during
cooling for a period of time is obtained. The temperature change of the surface layer of the steel bar at a certain temperature measurement point is calculated by the temperature model. Compare the calculated temperature with the measured temperature, and the comparison result is shown in Figure 3. When the data point is closer to the inclined solid line with a slope of 1, it means that the deviation between the calculated temperature and the measured temperature is smaller.

![Figure 3](image)

**Figure 3.** Overall fitting degree of measured temperature and calculated temperature.

It can be seen from the figure that the data points are distributed closer to the diagonal. The deviation between most predicted values and actual values is less than 20°C, which is 30°C smaller than before. Through the learning of heat transfer coefficient by BP neural network, a more accurate prediction of the temperature during the cooling process of hot-rolled ribbed bar can be realized.

![Figure 4](image)

**Figure 4.** The calculation result of the software based on the temperature model.

Through the calculation of the temperature model, the temperature distribution of the steel bar section can be obtained. By formulating a reasonable process to control the maximum temperature difference between the surface and the core, the stability of the performance can be guaranteed. Figure 4 is the calculation result of the software based on the temperature model. The temperature distribution of the cross section of steel bar at various times during the cooling process is obtained by calculation. The three temperature curves represent the temperature calculation results of the steel bar core, half radius and surface from top to bottom. The constraints are added to the maximum temperature difference of the steel bar section, the temperature difference constraint of the first group of coolers is 310°C and the temperature difference constraint is 300°C for the second group of coolers. The heat transfer coefficient of the first group of coolers calculated according to the temperature difference constraint is
6300W/m²·℃, and the heat transfer coefficient of the second group of coolers is 4795 W/m²·℃, and the final surface redness temperature is 790.2℃.

Based on the actual production conditions and the results of BP neural network training, under the premise of constant pressure and water temperature, the flow rate setting of each cooler can be calculated according to the heat transfer coefficient value. Then the valve status of each cooler is set according to the flow rate. Finally, the precise control of the temperature of the steel bar in cooling process is realized. This method is of practical significance for guiding the formulation of the cooling process and microstructure control of hot-rolled ribbed bar.

6. Conclusion
(1) Based on the related theory of heat transfer, the finite difference method is used to establish a high-precision temperature prediction model. It can predict the temperature drop process and section temperature distribution during the cooling process of hot-rolled ribbed bar after rolling.

(2) According to the characteristics of production data, Mean Shift algorithm is used for clustering processing. The production data is cleaned and screened by clustering. Based on the BP neural network, the mapping relationship between the heat transfer coefficient and other influencing factors is established, and the adaptive learning of the heat transfer coefficient is realized.

(3) Applying the data-driven temperature prediction model to production practice, the high-precision calculation of the temperature field of hot-rolled ribbed bar under different temperature constraints and the setting of the state of the cooling equipment can be realized. Finally, the precise control of the temperature during the cooling process of the hot-rolled ribbed bar is realized, which provides a numerical analysis method for formulating a reasonable microstructure and performance control process.

Acknowledgments
This work was supported by the national key research and development program of China (2017YFB0304203).

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