Temperature field modeling of the plate during hot rolling based on inverse heat conduction problem

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Abstract. In the established temperature field model of plate hot rolling process, the heat transfer coefficients of each stage are solved by empirical formula, but due to the complexity of the production environment, temperature field models tend to be less accurate. In order to solve this problem, this paper designs a rolling experiment, collects the actual temperature data, and combines with genetic algorithm, simulated annealing algorithm and particle swarm optimization algorithm to correct the heat transfer coefficients of air-cooling zone, and the three algorithms are compared. Finally, the particle swarm algorithm is selected to establish the temperature field model of the hot rolling process. The average error of the final temperature field model calculation is within 14℃.

Keywords. Inverse heat conduction problem, Particle swarm optimization algorithms, Rolling experiment, Temperature field model

1. Introduction

In heat transfer, the inverse heat conduction problem is relative to the positive heat conduction problem. The positive heat conduction problem is the process of obtaining the temperature field by solving the Fourier differential equation of heat conductivity numerically, while the thermophysical parameters, the initial temperature conditions, and the heat transfer coefficients of the plate are known [1]. In the process of solving, due to the complex field conditions, the heat transfer coefficients are often affected by the influence of oxide scale, rolling pressure and impurities between the contact surfaces, and thus affecting the calculation accuracy of the temperature field.

The idea of the inverse heat transfer problem is to compare the actual temperature measured by the experiment with the temperature calculated by the positive problem model, and correct the heat transfer coefficients by a specific algorithm, so that the temperature calculated by the temperature field model is gradually close to the real temperature measured by the experiment. The solution idea is shown in Fig. 1.
In this paper, the rolling experiment of plates is designed, and the temperature values during the rolling process are measured by the plug-in method. The application of genetic algorithm, simulated annealing algorithm and particle swarm optimization algorithm to modify the heat transfer coefficients in the inverse heat conduction problem are studied. The accuracy and time of the three methods are compared with the experimental data, the particle swarm algorithm with better effect is selected to establish the temperature field model of the rolling process.

2. Experimental Design
To measure the temperature curves of the plate internal temperature points during hot rolling, the experimental platform build in this paper includes three parts: plate heating zone, rolling deformation zone and data acquisition system, as shown in Fig. 2.

   Fig. 2 The experimental system schematic

The method of inserting a thermocouple into the plate is used for measurement. Since the plate rolling temperature is generally 1000~1100℃, the final cooling temperature is 600~650℃, and the K-type nickel-chromium-nickel silicon thermocouple temperature range meets this temperature range, so this thermocouple is used. In order to reduce the measurement error caused by thermocouple, this paper selects a 3mm thermocouple with a smaller diameter, and the selected thermocouple is calibrated before the experiment. In the temperature range of this experiment, the maximum error of the thermocouple does not exceed 1.1℃, meet the experimental accuracy requirements.

The plug-in method used in the experiment requires drilling the side of the experimental specimen, and then inserting the thermocouple after the specimen is heated and discharged. Installing the thermocouple after punching the experimental plate will affect the original temperature field, in order to reduce the temperature loss caused by punching and plugging, the pore size is minimized on the basis of considering the specimen thermal expansion and the thermocouple manufacturing process; In order to reduce the shear force of specimen on thermocouple during the rolling process, a stepped drilling method is used instead of the common cylindrical drilling method, a chamfer transition is used at the junction of the measurement point aperture and the outer aperture. There is also a chamfer at the orifice to reduce the destructive power on the thermocouple. The innermost diameter of the temperature...
measuring hole of this experiment is 4mm, the outer diameter is 5mm, and the drilling depth is 75mm. Three effective temperature measurement points are selected on the specimen for the experiment. In order to avoid the interruption or failure of the temperature measurement process caused by the damage of the thermocouple, in addition to the three measuring points, two alternative temperature measuring points are added at the location of the vulnerable measuring points. The schematic diagram of the final feasible specimen production plan is shown in Fig. 3.

![Fig. 3 Schematic diagram of the punching scheme of the specimen](image)

In order to test the feasibility of the experimental scheme, this paper uses the domain point probe method to compare the numerical error size of the measurement points of the porous model and the non-porous model. Take the central measuring point as an example, the model with thermocouple inserted after drilling is compared with the model without drilling, and the results are shown in Fig. 4.

![Fig. 4 Comparison of temperature drop before and after thermocouple in central measuring point](image)

It is shown in the above figure that when the thermocouple is inserted into the temperature measuring hole, it firstly exchanges heat with the high temperature test piece to reach equilibrium, and then as time goes on, the temperature changes tend to be consistent with the original temperature field, and finally the difference is within 1°C. This shows that the temperature influence caused by the insertion of the thermocouple is gradually eliminated with the passage of time, and the same precision as the original temperature field can be achieved, indicating that the design of the scheme is feasible.

The specific experimental steps are as follows:
1. Place the specimen in a heating furnace, heat to 1200 ℃ for 2 hours.
2. Connect the temperature acquisition device and debug it.
3. After the furnace is opened, the test piece is taken out, and before being transported to the rolling mill through the roller conveyor, insert the thermocouple sequentially into the specimen, and the collection system records the data in real time.
4. Let the specimen cool in air for 100 seconds and then enter the mill for three passes of reciprocating rolling. Each reduction is 10mm.
3. Comparison and Selection Of Inverse Calculation Algorithms

In this paper, the temperature values are known, and the heat transfer coefficients in the boundary condition are the required variables. The heat transfer coefficients after solving the inverse heat conduction problem are substituted into the positive problem for calculation, and the obtained temperature must be consistent with the known temperature. Therefore, the inverse heat conduction problem becomes an optimization problem that can be calculated by different algorithms [2].

At present, various inversion algorithms are mainly divided into gradient-based optimization algorithms and non-gradient optimization algorithms. The accuracy of non-gradient optimization algorithm is often higher than that of gradient-based optimization algorithm. Therefore, this paper mainly analyzes three non-gradient optimization algorithms: genetic algorithm, simulated annealing algorithm and particle swarm optimization algorithm.

3.1. genetic algorithms

The genetic algorithm starts by a set of randomly generated initial solutions. The adaptive search process for optimal solutions is achieved through the selection, intersection, variation and operation of biological inheritance and evolutionary processes [3].

The heat transfer coefficients to be back-calculated are taken as variables, and the optimization objective function is determined by comparing the calculated value with the measured value, and the optimal value of the heat transfer coefficients are obtained by minimizing the function [4][5].

3.2. simulated annealing algorithms

Simulated annealing algorithms is a stochastic optimization algorithm based on Monte Carlo iterative solution strategy. Its main idea is to randomly select points in the search interval, and use the Metropolis sampling criterion to make the random points move closer to the optimal solution. The Metropolis sampling criterion algorithm is: When the system changes from one energy state 1 to another energy state 2, the corresponding energy changes from E1 to E2, the probability that state 2 is accepted is:

$$p(1 \rightarrow 2) = \begin{cases} 1, & E_2 < E_1 \\ \exp\left(-\frac{E_2 - E_1}{T}\right), & E_2 \geq E_1 \end{cases}$$

After several iterations, the system gradually tends to be in a stable distribution state.

3.3. particle swarm optimization algorithms

Particle swarm optimization is a swarm intelligence algorithm proposed by American scholars Eberhart and Kennedy [6]. In the particle swarm algorithm, the solution of each optimization problem can be regarded as a point in the search space, that is, particle. In addition to a fitness value determined by the objective function, all particles have a velocity to determine the direction and distance, and the particles follow the current optimal particle to search in the solution space [7].

3.4. Comparison of inverse results

In this paper, the temperature data obtained in the above experimental process are processed by the above three algorithms, to inversely correct the heat transfer coefficients of the air-cooling process and the rolling process. Considering that during the hot rolling process, the air cooling period is the longest after the specimen out of the furnace, and the number of data samples during this process is large, so, three kinds of algorithms are used to solve the air-cooling heat transfer coefficient of this stage, then the characteristics of the three algorithms are analyzed, and an algorithm will be selected to calculate the heat transfer coefficients between the deformation zone and the inter-pass.

In this paper, the initial value of air cooling heat transfer coefficient is determined according to Newton's cooling formula, integrating the thermal convection, contact with the roller table et into the emissivity ε:
h=εδ(T^2+T_0^2)(T+T_0)                           (2)

Where, \( \delta \) is the Stefan-Boltzmann constant, \( \delta=5.67\times10^{-8}\text{W/(m}^2\text{K}^4) \); \( T \) is the temperature of the plate surface; \( T_0 \) is the temperature of the fluid near the surface of the plate, \( h \) is the convective heat transfer coefficient.

Emissivity \( \epsilon \) is a constant between 0 and 1, and the parameter to be identified for this stage, in this paper, the surface oxide scale, air convection, contact with the roller table and other heat dissipation factors are considered, so the initial value of the emissivity is set to 0.8. The genetic algorithm, particle swarm optimization algorithm and simulated annealing algorithm are used to solve the emissivity of the upper and lower surfaces \( \epsilon_1, \epsilon_2 \) respectively. The results are shown in the following table.

**Table 1.** Air-cooled heat transfer coefficient inversely calculated by different algorithms

| algorithms                        | \( \epsilon_1 \) | \( \epsilon_2 \) |
|-----------------------------------|-------------------|-------------------|
| genetic algorithm                 | 0.871             | 0.722             |
| simulated annealing algorithm     | 0.870             | 0.723             |
| particle swarm optimization algo  | 0.871             | 0.722             |

The results calculated by the three algorithms are substituted into the original model and compared with the experimental data for error analysis. The maximum error values of each algorithm are shown in Table 2.

A comparison of the error rates of the three algorithms is shown in Fig. 5.

**Table 2.** Maximum error value of different algorithms (%)

| algorithms                        | Point 1 | Point 2 | Point 3 | Calculation time(min) |
|-----------------------------------|---------|---------|---------|-----------------------|
| genetic algorithm                 | 1.16    | 3.09    | 0.17    | 44.4                  |
| simulated annealing algorithm     | 1.66    | 3.27    | 1.35    | 81                    |
| particle swarm optimization algo  | 1.20    | 3.11    | 0.17    | 42.6                  |

**Fig. 5** Comparisons of Solving Errors of Different Algorithms

It can be seen from Table 2 that the particle swarm algorithm has the fastest convergence rate and is similar to the genetic algorithm. It can be seen from Fig. 5 that the error of the particle swarm algorithm is smaller than the other two algorithms. Therefore, the particle swarm optimization algorithm is used to modify the heat transfer coefficients.
4. Particle Swarm Optimization Algorithm and Its Calculation Results

4.1. Particle swarm optimization algorithm

The steps of solving the inverse heat conduction problem based on the standard particle swarm optimization algorithm are as follows:

1. Initialize the particle swarm, including swarm size $M$, randomly initialize the initial position and speed of the search point $x_i, v_i$; variable range of search space; learning factor $c_1$ and $c_2$; maximum particle speed $v_{\text{max}}$; the optimal position that each particle has experienced so far $g_{\text{best}}$, find the global extremum from the individual extremum, the best value of the particle is set to $z_{\text{best}}$.

2. Updates the best position each particle experiences $g_{\text{best}}$, based on the fitness value calculated by the following formula, updating the best position the group has experienced $z_{\text{best}}$.

$$J(h) = \sum_{i=1}^{M} \left( T_i^m - T_i^c \right)^2$$  (3)

3. Where, $M$ is the temperature value sequence length; $T_i^m$ is the measuring temperature values for different measuring points, $T_i^c$ is the calculating temperature values for different measuring points.

Update the speed and position of the current particle according to the following formula.

$$v_{id}(t+1) = wvid(t)+c_1r_1(pid-xid(t))+c_2r_2(pgd-xid(t))$$  (4)

$$xid(t+1) = xid(t)+vid(t+1)$$  (5)

$$v_{id}^{\text{max}} = \begin{cases} v_{\text{max}}, & v_{id}^{\text{max}}(t) > v_{\text{max}} \\ -v_{\text{max}}, & v_{id}^{\text{max}}(t) < -v_{\text{max}} \end{cases}$$  (6)

Where, $c_1$ and $c_2$ are learning factor, Non-negative acceleration constant, the value are usually between [0, 2]; $r_1, r_2$ are uniformly distributed random number in [0,1]; $t$ is the current iteration; $w$ is the inertia weight.

4. Verify whether the result reaches the end condition. If the end condition is met, stop the operation, output the optimal particle and the corresponding optimal value.

4.2. deformation zone coefficient correction result

The temperature change of the plate in the deformation zone mainly comes from the plastic deformation heat generation, the friction heat generation and the heat lost in contact with the roll.

Based on the previous experience, experimental conditions and solution results, the formula model selected in this paper is[8]:

$$h=(a \cdot p+b) \cdot v^{0.5}$$  (7)

Where, $h$ is the contact heat transfer coefficient; $p$ is the average unit rolling pressure; $v$ is the rolling speed; $a, b$ are the model coefficients.

The correction results of the particle swarm optimization algorithm contact heat transfer coefficient in the deformation zone are as shown in the table 3, and the initial value of the contact heat transfer coefficient is calculated by the following formula [9]:

$$h_r = \lambda/\sqrt{\pi \alpha}$$  (8)
Where, \( t \) is the length of contact between the rolled piece and the roll; \( \alpha \) is the thermal diffusion coefficient.

**Table 3.** Parameters of Contact Heat Transfer Coefficient Model in Deformation Zone

| Deformation Zone | \( a \)  | \( b \)  |
|------------------|--------|--------|
| Upper surface    | 37.32  | 1836   |
| lower surface    | 38.44  | 1275   |

4.3. *inter-pass heat transfer coefficient correction result*

The plate loses a lot of heat when it comes into contact with the roll. After leaving the roll, the internal heat conduction continues, and the heat of the core continues to conduct to the lower temperature surface, therefore, the heat transfer coefficient of this interval is greater than 1. The particle swarm algorithm solves the heat transfer coefficient at this stage as follows:

**Table 4.** Parameters of Inter-pass Heat Transfer Coefficient Model

| contact heat transfer coefficient | first pass | second pass | third pass |
|----------------------------------|------------|-------------|------------|
| Upper surface                    | 1.81       | 2.14        | 2.51       |
| lower surface                    | 1.96       | 2.29        | 2.45       |

5. **Verification Of Temperature Field Model**

In the previous paper, the heat transfer coefficients of the air-cooling and rolling stages are obtained by the thermal inverse problem algorithm combined with the experimental data, the temperature field of the hot plate in the experimental conditions can be calculated by substituting the heat transfer coefficients into the positive temperature field model. In order to verify the accuracy of the model, the calculation results of the two measurement points from the model are compared with the experimental values. The result is shown in Fig. 6.

![Fig. 6 Comparisons between calculated and measured values](image)

It can be seen from the figure that the model generally conforms to the changes of the actual experimental law.

In this paper, the precision of the model with back-calculated correction by particle swarm optimization algorithm and the model without back-calculated correction is compared. The maximum deviation values of the two models are counted at the measurement points, it can be seen from table 5, the error of the corrected model is smaller than that of the uncorrected model, and the deviation of each point are reduced by more than 10 °C.
Table 5. Comparison of the maximum deviation of the calculated results at the temperature measuring points before and after the model correction (℃)

| Zone              | Corrected model | Uncorrected model |
|-------------------|-----------------|-------------------|
|                   | Point 1 | Point 2 | Point 1 | Point 2 |
| Air cooling zone  | 2.38     | 2.34     | 13.24   | 25.20   |
| Deformation zone  | 5.76     | 4.12     | 19.16   | 33.45   |
| Rolling air cooling zone | 11.07 | 13.79 | 31.85 | 35.81 |

The average error of the temperature field calculated by substituting the modified heat transfer coefficients is 14℃, the temperature field model established in this paper is greatly improved accuracy compared to the original temperature field.

6. Conclusion
1. This paper designs and completes the experiment of measuring temperature. The temperature data during the rolling process are measured, which provide a basis for solving the inverse problem.
2. In this paper, the inverse heat conduction problem model of genetic algorithm, simulated annealing algorithm and particle swarm optimization algorithm are established respectively. By comparing and analyzing the results of air-cooling heat transfer coefficient, the accuracy and time cost of particle swarm optimization algorithm are better than the other two algorithms. So the heat transfer coefficients between the deformation zone and the inter-pass are solved by the particle swarm inversion method.
3. This paper verifies the accuracy of the temperature field. The difference between the calculated values of the model and the measured values at the experimental temperature measuring points are compared, the air-cooling deviation ≤3.38℃, the deformation zone deviation ≤7.56℃, and the rolling inter-pass deviation ≤13.79℃ are better than the empirical formula, which proves the accuracy of the obtained model.

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