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Intelligent Optimization of Process Parameters in Limit Gauge Hot Strip Rolling

Fengwei Jing, Junliang Li, Shimeng Hao, Jie Li and Jing Wang *

National Engineering Research Center for Advanced Rolling Technology and Intelligent Manufacturing, University of Science and Technology Beijing, Beijing 100083, China
* Correspondence: wjing2022@yeah.net

Abstract: Aiming at the problems of large rolling deviation and low stability in limit specification of hot strip rolling, the optimal rolling suggestions were obtained based on back propagation (BP) neural network and genetic algorithm. According to equipment state and strip specification to select excellent sample set, in the sample set based on the data of application of neural network to build the mapping relationship between process parameters and the rolling stability, limit specifications of the mapping model is set up, and then using the genetic algorithm for the search of this mapping model, the search model of rolling stability of ideal point, determine a set of process parameters optimal advice accordingly. Taking the rolling of MRTRG00201_1276_3 as an example, a set of optimal process parameters are obtained by simulating rolling of MRTRG00201_1276_3. Then the sample distribution and rolling stability of each process are analyzed in turn. The results show that the process parameters obtained by optimizing the model accord with the distribution law of rolling samples, can obtain high rolling stability, and can play a guiding role in limit specification rolling.

Keywords: hot strip rolling; limit specifications; intelligent optimization; neural-network; genetic algorithm stability

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1. Introduction

The limit specification of hot strip rolling generally refers to the extremely wide or thin specification of a certain kind of steel in strip production. In actual production, the extremely thin specification is in the majority. In recent years, experts from some iron and steel production enterprises have carried out research on the production technology of extreme specifications based on the production site [1,2]. Studies have shown that extreme gauge rolling is characterized by: less rolling quantity, lower rolling stability than the conventional product specification, more preparation procedures (hot roll transition material, etc.), high equipment status requirements (rigidity, looper, mill adjustment), and special process requirements (adjusting load distribution and rolling speed, controlling rough rolling sickle bend, etc.). At the same time, some scholars have studied the control strategy and process system of the rolling process [3,4], and the research shows that the upper limit of limit specification width is not only related to the design specification of the rolling mill, but also related to the control technology, process system, and equipment working state; in addition to the design capacity of rolling mill unit, the lower limit of limit specification thickness is also closely related to control technology, process system, and equipment working status.

Before the production of limit specification in the current workshop, the process personnel generally formulates the production process and equipment status system. After the process specification is given by the process control system, the equipment and process are maintained, modified and confirmed item by item in combination with the current automatic data acquisition signal and equipment routine inspection results, and the production task is executed after meeting the production conditions. The problems in the whole process are: difficult analysis, complex production system and process, experience dependent rolling stability, unstable product quality, hidden danger of equipment damage, etc. [5]. In recent years, some scholars have put forward some experience and standards for the production of limit specifications of hot strip rolling, but they all put forward specific rolling suggestions for the specified specifications. These process parameters and equipment status have little guiding significance for other steel types and specifications [6,7]. At the same time, some scholars have analyzed the relevant equipment and technology of limit gauge rolling and believe that the current dimension control is a mature technology, and the key to improvement lies in the adjustment and maintenance method, while the artificial intelligence method is a powerful tool, which can fill the gap between the physical model and the actual data [8], and can be combined with the original rolling system to improve the performance [9].

Different from the traditional analysis methods, the artificial intelligence method can simulate the human brain to deal with the real process. Through data input, it can carry out self-learning training and simulation. It has a high degree of fitting and has significant advantages in dealing with non-linear relations. Liu, D. used a genetic algorithm to optimize the number of hidden layer nodes and network weights of the neural network, which improved the model accuracy and computational efficiency [10]. Yang, G. proposed a neural network control method integrating the genetic algorithm, which effectively improves the learning efficiency and convergence accuracy of the weight coefficients of the multi-layer feedforward neural network [11]. Yang, J. utilized the genetic algorithm to optimize the weight threshold of the multi-layer feedforward neural network, which improved the accuracy of the rolling force prediction model [12]. Rafael, M. compared various online training methods in computational experiments, and the results show that intelligent algorithms are superior to traditional algorithms in terms of computational efficiency and computational accuracy [13]. Wang, Z. studied the application status of artificial neural network in the field of rolling. His research shows that the artificial neural network has great advantages in single process parameter prediction, such as rolling force prediction, yield strength prediction, and coiling temperature prediction. The prediction accuracy of steel rolling related parameters can be significantly improved, and the quality of rolled products can be improved [14]. The artificial intelligence method can predict the rolling process based on field and experimental data, and can avoid the error caused by the assumption being divorced from reality and the simplification being too rough [15]. In the research of strip rolling, the commonly used artificial intelligence methods include artificial neural network (ANN) and support vector regression (SVR) [16]. Among them, the back propagation (BP) neural network is widely used in the research of various rolling models because of its high stability and high combination with other algorithms. The genetic algorithm is based on the widely existing natural selection and genetic mechanism in nature, and simulates the biological evolution mechanism on the computer to achieve the purpose of rapid search and optimization. It is simple and universal, and can maintain high optimization accuracy and efficiency [17]. By combining the two methods, the process optimization results with high reliability can be obtained when the number of test samples is small [18,19]. In this paper, an intelligent optimization method of rolling process parameters for hot strip rolling based on BP neural network and genetic algorithm is proposed, which intelligently recommends the optimal process parameter combination to guide the actual production and improve the rolling stability.

At present, the application of intelligent algorithms in the rolling field mainly focuses on the prediction of single process parameters, the optimization of neural network weight thresholds by genetic algorithm. Few authors discuss the problems that how to construct a sample set related to equipment status and how to use artificial intelligence models to optimize process parameter combinations. The author conducts a field study aimed at filling this research gap and closely integrated with the production site to provide instructive advice for production site technicians.

2. Preparation of Sample Set

2.1. The Basis for Evaluation of Rolling Stability

During the production and development of extreme gauge strip steel, the rolling stability is affected by many factors. For example, the thin gauge hot coil will have such apparent quality problems as unqualified strip steel size, unqualified flatness, poor final rolling temperature hit, and poor coil shape, which will lead to the forced interruption of steel stacking, tail flicking, and roll change [20]. In this study, taking the evaluation system of a steel plant as an example, combining theoretical research and field experience, the following factors are used to evaluate the rolling stability scores, as shown in Table 1.

Table 1. Rolling stability score.

Number	Scoring Items
1	Abnormal finish rolling head
2	Abnormal finish rolling body
3	Abnormal finish rolling tail
4	Rough rolling sickle bending deviation
5	Serious buckle warping during rough rolling
6	Coiler1 pinch roll winding steel stacking
7	Coiler2 pinch roll winding steel stacking
8	Coiler3 pinch roll winding steel stacking
9	Coiler1 loose coil
10	Coiler2 loose coil
11	Coiler3 loose coil

2.2. Preparation of Sample Set

In the database, there are samples of different steel grades, different specifications, different equipment states, different process systems, and different production times. It is necessary to select the sample set that meets the specific conditions according to certain rules to build the model. These conditions include: steel grade, thickness range, width range, equipment process status range, quality score range, rolling stability score range, etc. The sample set in this paper includes: the sample set of the same product specification, the sample set of the same product specification and equipment status, the excellent sample set of the same product specification and equipment status, and the sample set of the same steel and equipment status.

The sample set of the same product specification refers to the sample set that meets the limits of product thickness and product width at the same time under the limits of the specified steel type. The upper and lower limits of the thickness and width range can be flexibly configured. For example, the typical specification range limits are shown in Table 2.

Table 2. Specification range limitation.

Thickness/mm	Lower Thickness Limit/mm	Upper Thickness Limit/mm
τ	$\tau - 0.05$	$\tau + 0.05$
Width/mm	**Lower Width Limit/mm**	**Upper Width Limit/mm**
ω	$\omega - 25$	$\omega + 25$

The sample set of the same product specification and the same equipment status refers to the sample set in which the "Manhattan distance" of each sub item equipment status meets the specified range limit on the basis of meeting the restrictions of the same product specification. The upper and lower limits of Manhattan distance between the sample equipment status and the current equipment status can be flexibly configured.

The "Manhattan distance" between two n-dimensional vectors $A(x_{11}, x_{12}, \ldots, x_{1n})$ and $B(x_{21}, x_{22}, \ldots, x_{2n})$ is calculated as [21]:

$$d = \sum_{k=1}^{n} |x_{1k} - x_{2k}| \tag{1}$$

The above itemized equipment includes: descaling water, coiler, finish rolling automatic gauge control (AGC) system, finish rolling looper, finish rolling bending roll, temperature measuring instrument, thickness measuring instrument, rough rolling vertical roll, rough rolling side guide plate, cooling water between finish rolling stands, coiler side guide plate, finish rolling side guide plate, pressure measuring instrument, width measuring instrument, laminar flow cooling, finish rolling roll shifting, finish rolling roll gap lubrication, finish rolling stiffness, rough rolling stiffness, etc. Because the importance of the status of each sub-equipment is not consistent, based on the combination of rolling equipment and process and the rolling experience of field technicians, weights W_k are allocated to each sub-item, and flexible adjustment according to changes in rolling quality. The calculation formula of "Manhattan distance" after substituting the weight allocation value W_k is as follows:

$$d = \sum_{k=1}^{n} |x_{1k} - x_{2k}| \cdot W_k \tag{2}$$

The excellent sample set of the same product specification and equipment status refers to the sample set that meets the rolling stability and quality evaluation range on the basis of meeting the screening conditions of the same product specification and equipment status. The upper limit of the rolling stability and quality evaluation range is 100 points, and the lower limit can be flexibly configured according to the number of samples of the same product and equipment status in the field rolling history, but should not be lower than 80 points. For example, the range limits when the sample is small are shown in Table 3.

Table 3. Specification range limitation.

Lower Limit of Stability Evaluation	Upper Limit of Stability Evaluation
80	100
Lower Limit of Quality Evaluation	**Upper Limit of Quality Evaluation**
80	100

The sample set of the same steel and the same equipment status refers to the sample set that meets the restrictions of the same steel and the same equipment status at the same time. In this sample set, the mapping relationship between thickness parameters, width parameters and rolling stability index can be determined to facilitate modeling and optimization.

3. Neural Network Modeling

3.1. BP Neural Network Model

BP neural network is the most widely used neural network. Its basic idea is the gradient descent method, which uses the gradient search technology to minimize the error mean square deviation between the actual output value and the expected output value of the network [22]. BP neural network is an activation function model with linear weight. Input a vector, and then input the vector into the activation function of neurons in the hidden layer. Then, the output value of the function is weighted to obtain the value of the output layer. A typical BP neural network model is shown in Figure 1.

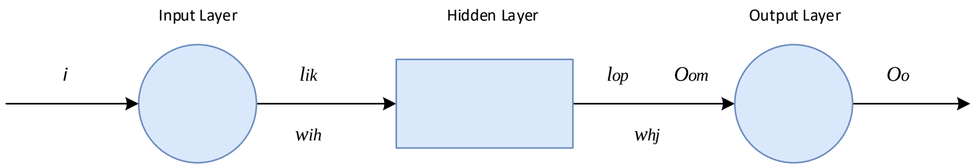


Figure 1. BP neural network model.

The input of the input layer is $i = (i_1, i_2, \cdots, i_n)$, and the input unit becomes the input l_{ik} of the hidden layer after weighting; the number of neural units in the hidden layer is p. After processing, the output of the hidden layer is l_{op}; the output result of the hidden layer becomes the input o_{om} of the output layer after weighted processing by w_{hj}; the number of neurons in the output layer is q, and the output of the output layer is o_o. When the error between the actual output and the expected output exceeds the specified accuracy, it enters the error back propagation stage. The error is corrected by the weight of each layer through the output layer in the way of error gradient descent, and is transmitted back to the hidden layer and the input layer [23].

3.2. Correlation Analysis of Rolling Data

In the actual production of rolled pieces, there are many production process parameters besides the rolling specification, such as the process parameters in the heating furnace area, including the discharge temperature, in furnace time, rolling rhythm, etc.; rough rolling area includes primary descaling, descaling between rough rolling passes, number of rough rolling passes and thickness of medium and thick billets; the finishing rolling area includes secondary descaling, final rolling temperature, descaling between stands, roll gap lubrication, load distribution, roll bending, rolling mileage, linear speed, etc. There are collinear variables in many rolling process parameters, and the number of neural network input variables will affect the effect and speed of model fitting, so these variables need to be eliminated before modeling. In this paper, the Adaptive-Lasso method [24] is selected for parameter estimation and variable selection. Lasso parameter estimation is defined as follows:

$$\hat{\beta}^{*(n)} = \arg\min_{\beta} \left\| y - \sum_{j=1}^{p} x_j \beta_j \right\|^2 + \lambda_n \sum_{j=1}^{p} \hat{\omega} |\beta_j| \tag{3}$$

where the weight is $\hat{\omega} = 1/|\hat{\beta}_j|^{\gamma} (\gamma > 0)$. $\hat{\beta}_j$ is the coefficient obtained by the least square method.

After preliminary screening by the Adaptive-Lasso method, according to the recommended requirements of rolling process on site, 7 items, such as width, thickness, rolling rhythm, intermediate slab thickness, final rolling temperature, furnace time, and rolling sequence in roll change cycle, are finally selected as neural network inputs, and the rolling stability score is taken as neural network output to build the neural network model of limit specification rolling. This is shown in Figure 2.

3.3. Data Standardization

BP neural network model learning is a mapping from input variables to output variables. For each variable, the size and distribution of the data extracted from the input space are different, and the input variables have different orders of magnitude, which means that the variables have different proportions, and the features with a large proportion will occupy a dominant position in the learning algorithm, resulting in the learner being unable to learn from other features. Therefore, in this study, the rolling data are standardized to improve the prediction accuracy and convergence speed of the model [25]. The standardization process is as follows:

$$x' = \frac{x - x_{mean}}{x_{std}} \tag{4}$$

where x' is standardized data; x is original data; x_{mean} means average of original data; x_{std} represents the standard deviation of original data.

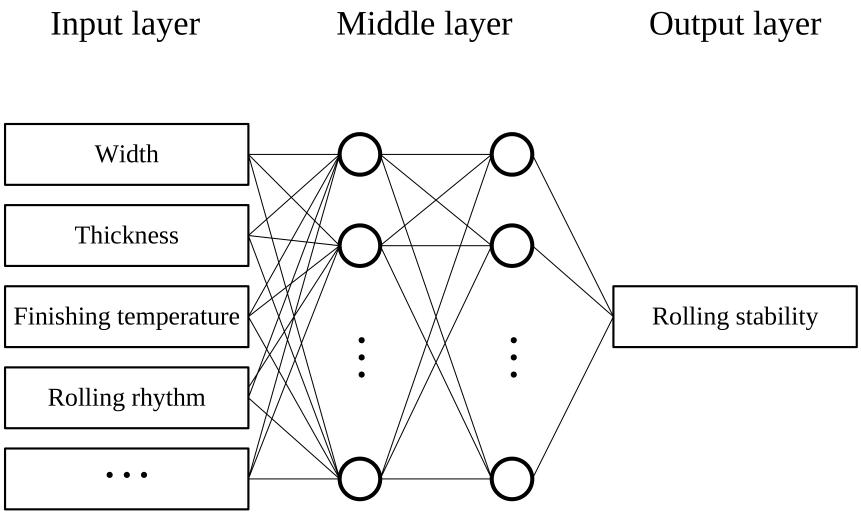


Figure 2. Neural network model of limit gauge rolling.

3.4. Activation Function Selection

In the neural network, because the full connection layer only makes affine transformation on the data, and the superposition of multiple affine transformations is still an affine transformation, the non-linear transformation of activation function is introduced to improve the approximation ability of the network model [26]. The selection of activation function requires the following properties:

(1) Continuous and differentiable (non differentiable on a few points is allowed). The derivable activation function can directly use the numerical optimization method to learn the network parameters;
(2) The activation function and its derivatives should be as simple as possible, which is conducive to improving the efficiency of network computing;
(3) The value range of the derivative of the activation function should be in a suitable range, which should not be too large or too small, otherwise it will affect the efficiency and stability of training.

In this study, rectified linear unit (ReLU) function is used as the activation function (see Figure 3). ReLU is the hard limit when $x < 0$, and the first derivative is 1 when $x > 0$. Therefore, the function can maintain the gradient without attenuation, alleviate the gradient disappearance problem, accelerate the convergence speed, and have the ability of network sparse expression.

3.5. Model Prediction Accuracy

The selected excellent sample set of the same equipment state and steel grade is divided into two parts: training set and test set. The training set is used to train the limit gauge rolling neural network, build the mapping relationship between process parameters and rolling stability, and establish the mapping model of limit gauge rolling. Then, the test set is brought in to predict the rolling stability score, and the fitting of the prediction results is shown in Figure 4.

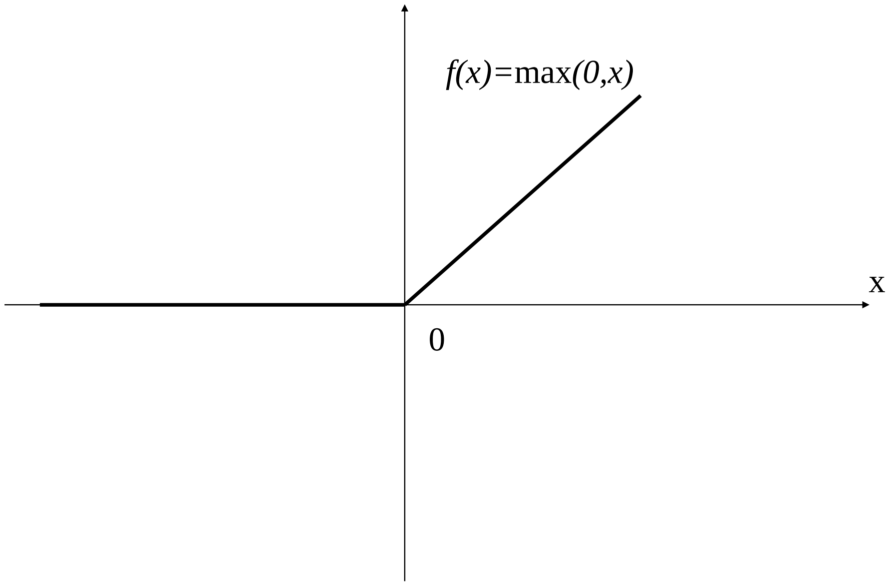


Figure 3. ReLU activation function.

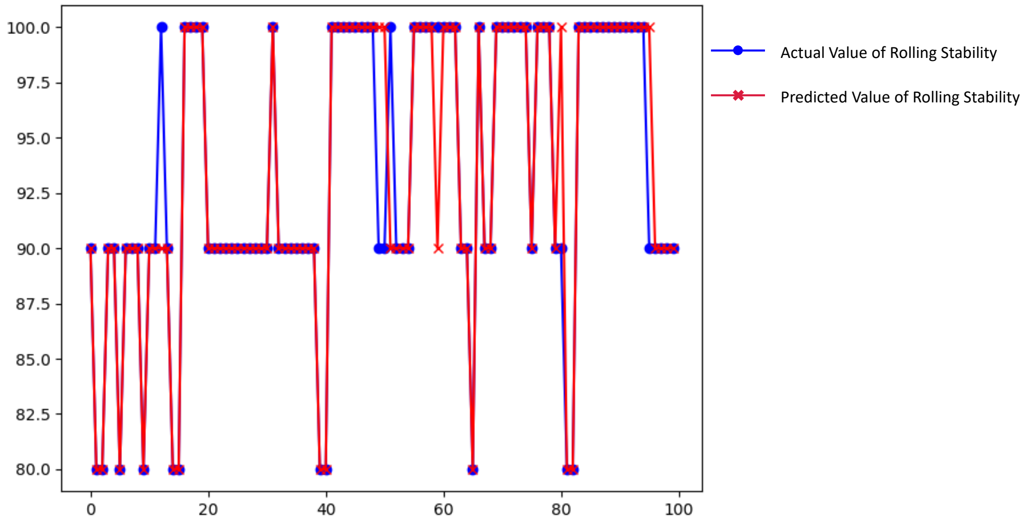


Figure 4. MRTRG00201_1276_3 Test set fitting.

The results show that the neural network has a high prediction accuracy, and can well predict the mapping relationship between the input process parameters (width, thickness, rolling rhythm, intermediate slab thickness, final rolling temperature, rolling sequence in furnace time and roll change cycle) and the output rolling stability score. Therefore, it can be used for the optimization of limit specification rolling process parameters.

4. Genetic Algorithm

4.1. Parameter Setting of Genetic Algorithm

The genetic algorithm (GA) is a parallel search algorithm which combines the evolution rule of organism and genetic mechanism. The optimization feature of the algorithm is multi-parameter and multi-combination. By simulating the natural law of "natural selection and survival of the fittest" in the process of natural evolution, the parameters to be optimized are encoded. The encoded parameters are called chromosomes. Through selection, crossover, mutation and other operations, the chromosomes are artificially screened. Through multiple data iteration operations, the optimal set of data chromosomes is finally obtained, So as to realize the global optimization function of process parameters [27,28].

The algorithm flow is shown in Figure 5.

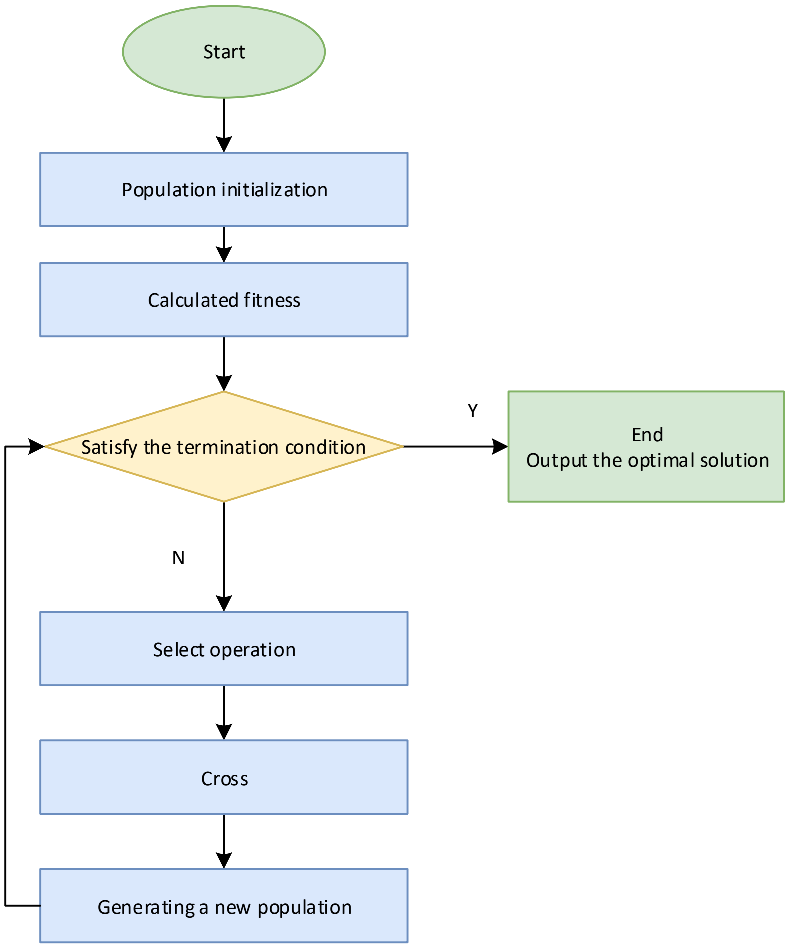


Figure 5. Genetic algorithm flow.

Based on the BP neural network constructed in this study, a coupling model is constructed by combining BP neural network and genetic algorithm to intelligently optimize the rolling process parameters of the limit specification of hot strip rolling. Some parameters of genetic algorithm are set as shown in Table 4. Run the program with Pycharm as the development tool to find the global optimal value of process parameters.

Table 4. Genetic algorithm parameter.

Parameters	Set Values
Population size	100
Maximum genetic algebra	30
Probability of variation	0.5
Crossover probability	0.5
generation gap	0.3

4.2. Optimization Objective Function and Constrained Condition

In order to ensure that the rolling process recommendations are reasonable and effective and meet the actual requirements of the production site, the optimization range of each recommended process item is limited in the process of genetic algorithm optimization. Taking the rolling of the same steel with the same equipment as the test example, select the excellent sample set of rolling of the same steel with the same equipment. The process range is shown in Table 5. Then, the maximum and minimum values of each process in the excellent sample set are floated by 1% as the optimization range, as shown in Table 6. By constantly updating the excellent sample set, the rolling suggestion of limit specification is constantly approaching the optimal process combination.

Table 5. Excellent sample set process range.

No.	Process Items	Minimum	Maximum	Units
1	Mill Pacing	6.5	32.92	(/h)
2	Thickness of Intermediate Billet	43.70	43.73	(mm)
3	Final Rolling Temperature	1103	1137	(°C)
4	Time in the Furnace	143.68	215.23	(min)
5	Roll Change Order	2	155	-

Table 6. Model optimization process range.

No.	Process Items	Minimum	Maximum	Units
1	Mill Pacing	6.44	33.25	(/h)
2	Thickness of Intermediate Billet	43.26	44.17	(mm)
3	Final Rolling Temperature	1091.97	1148.37	(°C)
4	Time in the Furnace	142.24	217.38	(min)
5	Roll Change Order	1.98	156.55	-

5. Optimization of Process Parameters and Result Analysis

5.1. Optimization of Process Parameters

Taking the rolling rhythm, intermediate slab thickness, final rolling temperature, in furnace time and rolling sequence in roll change cycle as recommended processes, taking the rolling stability score as the goal, the neural network model as the fitness function for global optimization. The genetic algorithm is used to search the trained neural network model, and the mapping relationship is optimized with the rolling stability score of 100 as the goal, until the rolling process suggestions that meet the conditions are found. The extreme specification rolling model constructed has the characteristics of many optimization parameters and high complexity. There are slight differences in the results of multiple optimizations, but all of them can achieve the simulation effect of 100 points of rolling stability. In field applications, the rolling rhythm requirements must be met while ensuring rolling stability. Therefore, the optimal process parameter combination obtained by optimization in the shortest time is used as the rolling recommendation. In order to ensure production safety, the rolling recommendation will be determined by the field technology. Personnel decides whether to accept or not.

The strip steel MRTRG00201 with width of 1276 mm in a steel plant is taken as the test object. There are 91 thin gauge samples with thickness less than 4 mm in the rolling history samples of strip steel with the same equipment status and product specification, of which the minimum thickness is 3.2 mm, the maximum thickness is 4 mm, the highest rolling stability score is 100 and the lowest is 80. However, the 3 mm thick strip has not been rolled. When the 3 mm thick strip needs to be rolled on site, there is no rolling history sample as a reference, and there is no way to obtain the setting of various process values and rolling stability. Therefore, taking the 3 mm thick strip as the test object, the rolling process parameters are optimized through the limit specification rolling model combined with neural network and genetic algorithm, and the optimal process values are proposed.

In the iteration process, the iteration operation of the crossover selection mutation crossover selection cycle is repeated [29,30], and the final optimization objective function value tends to be stable, and the individual with the highest rolling stability is output. The optimization results are as follows: the rolling rhythm is 30.86/h, the thickness of intermediate slab is 43.71 mm, the final rolling temperature is 1100.12 °C, the furnace time is 150.16 min, the serial number is 30.36 in the roll change cycle, and the rolling stability score is 100 points, as shown in Table 7:

Table 7. MRTRG00201_1276_3 Recommended rolling process.

Recommended Process Items	Recommended Process Values	Units
Mill Pacing	30.86	(/h)
Thickness of Intermediate Billet	43.71	(mm)
Final Rolling Temperature	1100.12	(°C)
Time in the Furnace	150.16	(min)
Roll Change Order	30.36	-
Rolling Stability Score	100	-

5.2. Result Analysis

The rolling process is a multivariate non-linear process with strong coupling characteristics. The recommended values of various process parameters are obtained through the optimization of the rolling model of extreme specifications. As shown in Table 7, under the coupling action of this group of process parameter values, a rolling stability effect of 100 points can be achieved. However, in field applications, in order to satisfy production equipment and process requirements and ensure production safety, the recommended values of various process parameters should conform to field production rules and satisfy the experience expectations of field technicians. Therefore, it is necessary to provide technical personnel with more intuitive and specific analysis to improve the practicability and security of the model.

The visualization process of multi-factor coupling effects is complex and requires the high analysis ability of field technicians. Therefore, in this study, the visualization process of multi-factor coupling effects is presented in the form of single-factor slices. Focusing on the distribution law of samples and the evolution law of rolling stability, it is recommended to analyze various process parameters of the roll change cycle, such as mill pacing, thickness of intermediate billet, final rolling temperature, time in the furnace, and roll change order. The rationality and feasibility of the proposed process value are verified based on the historical sample data on site.

5.2.1. Mill Pacing

As shown in Figure 6a, the previous rolling history samples of MRTRG00201_1276 steel strip are mainly distributed between (29, 31) and (31, 33), a total of 36 samples. The rolling rhythm value recommended by the model is 30.86/h, which is distributed in the interval (29, 31), in line with the sample distribution law of this steel strip rolling.

According to Figure 6b, the rolling stability score of the rolling rhythm interval (29, 31) is higher than that of the adjacent interval. Based on the sample distribution and rolling stability score, it is obvious that the rolling rhythm interval (29, 31) is easier to obtain high rolling stability.

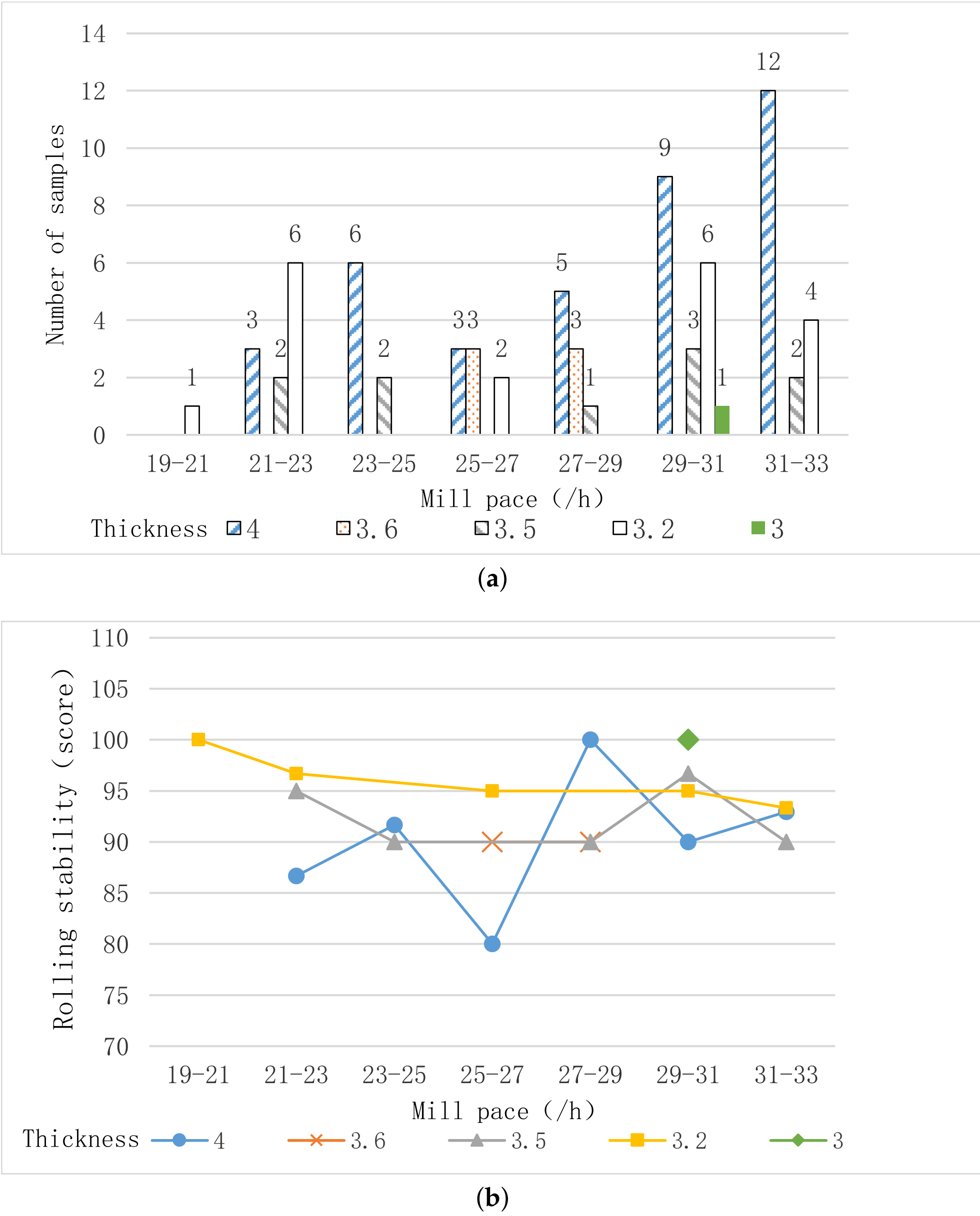
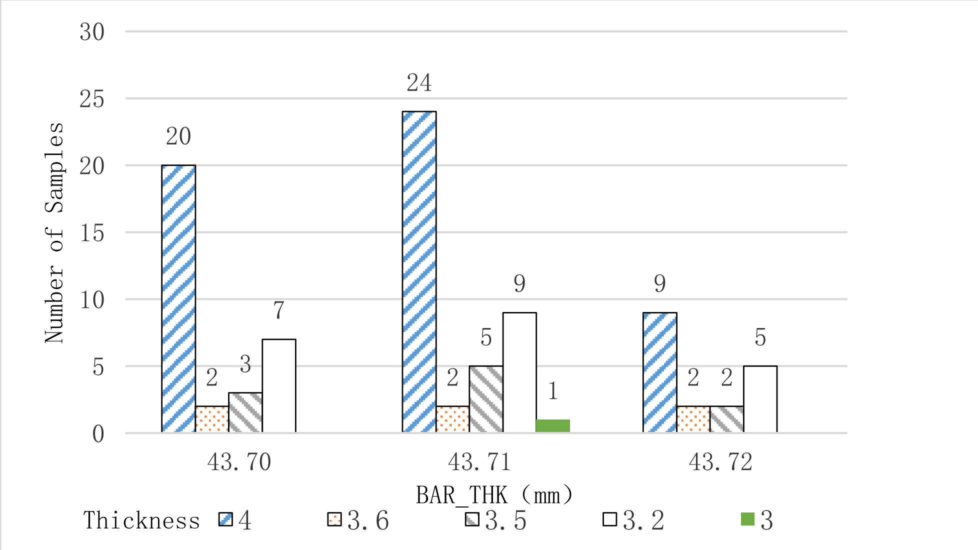


Figure 6. Rolling rhythm. (**a**) Sample distribution; (**b**) Stability score.

5.2.2. Thickness of Intermediate Billet

According to Figure 7a, in the rolling history samples of MRTRG00201_1276 strip, the thickness of the intermediate billet is mainly distributed around 43.7 mm, with the minimum of 43.70 mm and the maximum of 43.72 mm. The thickness of intermediate billet recommended by the model is 43.71 mm, which is at the position with the largest number of rolling samples, and conforms to the distribution law of rolling samples.



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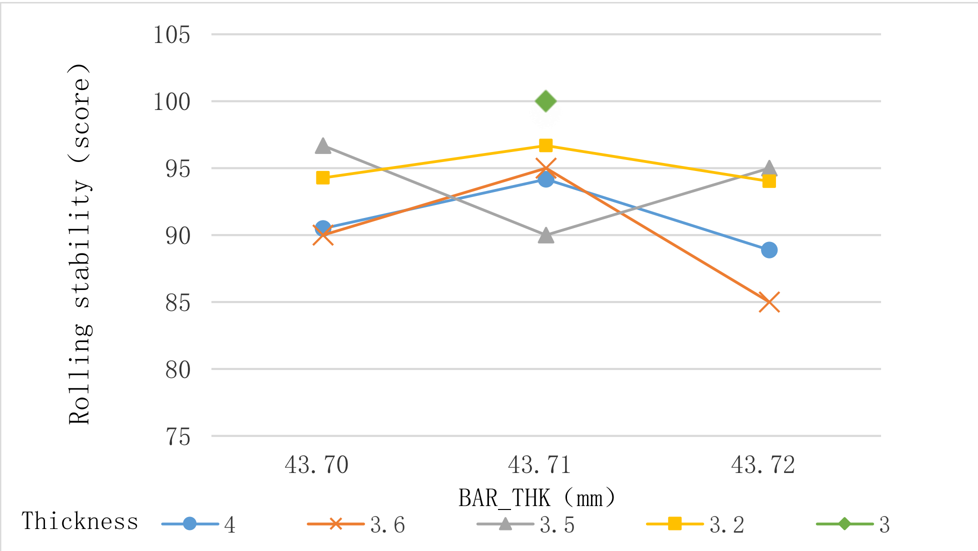


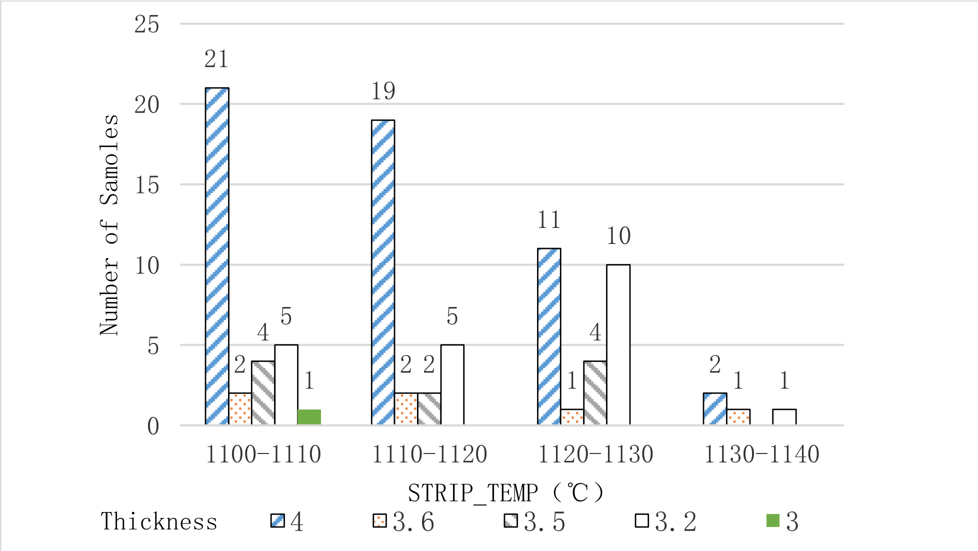
(**b**)

Figure 7. Thickness of intermediate billet. (**a**) Sample distribution; (**b**) Stability score.

According to Figure 7b, the rolling stability score when the thickness of intermediate billet is 43.71 mm is significantly higher than that when other values are taken, while the optimal parameter obtained through model optimization is 43.71 mm, which can obtain the highest rolling stability.

5.2.3. Finishing Temperature

According to Figure 8a, in the rolling history samples of MRTRG00201_1276 strip, the final rolling temperature is mainly distributed in the interval (1100, 1110), in which there are 33 samples, and the final rolling temperature obtained by model optimization is 1100.12 °C, which conforms to the sample distribution law.



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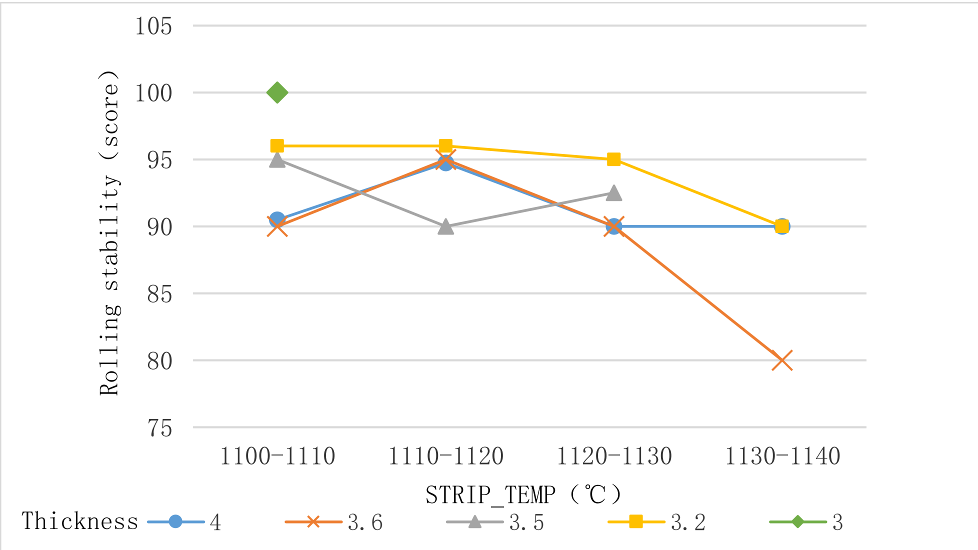


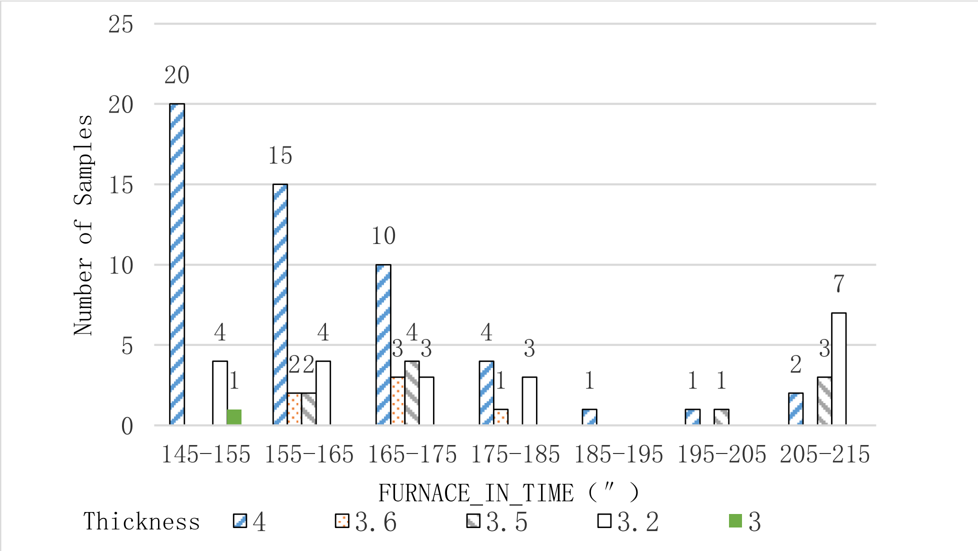
(**b**)

Figure 8. Finishing temperature. (**a**) Sample distribution; (**b**) Stability score.

According to Figure 8b, it is easy to obtain high rolling stability in the interval (1100, 1110), and the rolling stability tends to decrease with the increase in final rolling temperature. Therefore, the process value obtained through model optimization is helpful to obtain higher rolling stability.

5.2.4. Time in the Furnace

According to Figure 9a, in the rolling history samples of MRTRG00201_1276 strip, the furnace time is mainly distributed in the interval (145, 155) and the interval (155, 165), and the number of samples in these two intervals is 45, accounting for about half of the total number of historical samples, while the process value obtained by model optimization is 150.16 min, which is located in the interval (145, 155), which conforms to the sample distribution law.



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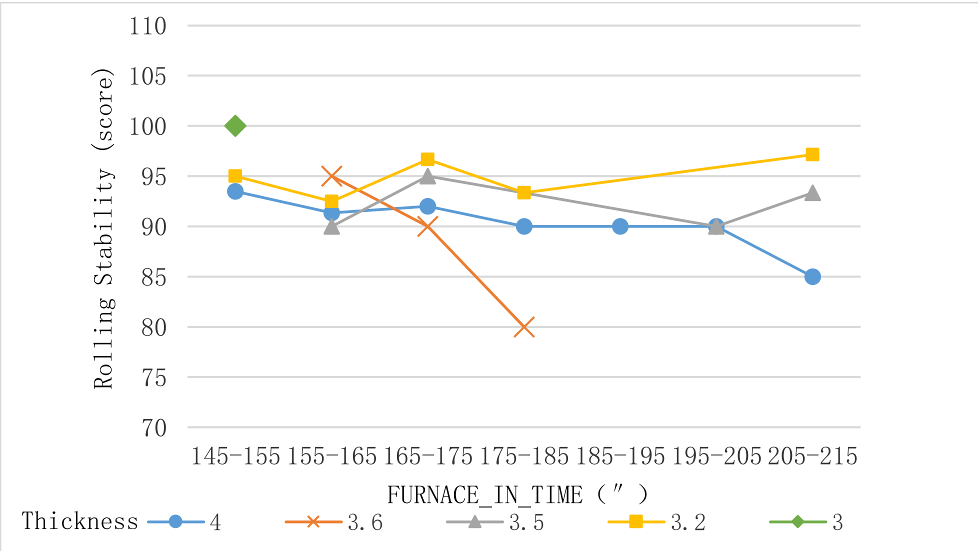


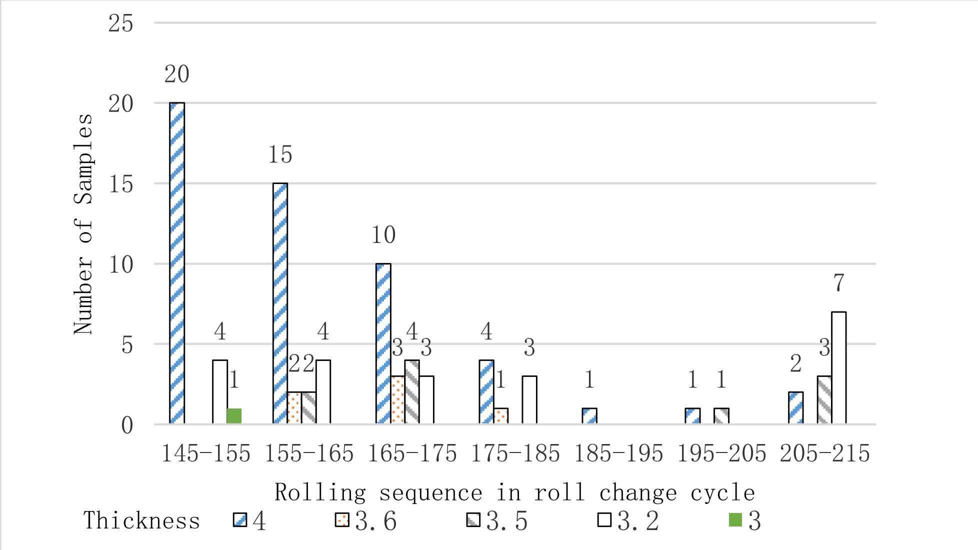
(**b**)

Figure 9. Time in the furnace. (**a**) Sample distribution; (**b**) Stability score.

As shown in Figure 9b, with the change of furnace time, the rolling stability scores of most thickness specifications are relatively stable, but for the interval with the largest sample distribution, it is easier to obtain high rolling stability within the furnace time interval (145, 155).

5.2.5. Rolling Sequence in Roll Change Cycle

According to Figure 10a, in the rolling history samples of MRTRG00201_1276 strip, the rolling sequence in the roll change cycle is mainly distributed in the interval (30, 60) and (60, 90), of which the number of samples in the interval (30, 60) is 24, and the number of samples in the interval (60, 90) is 31. The number of samples in the two intervals accounts for about 60% of the total number of samples. The rolling sequence in the roll change cycle obtained by model optimization is 30.36, which conforms to the sample distribution law.



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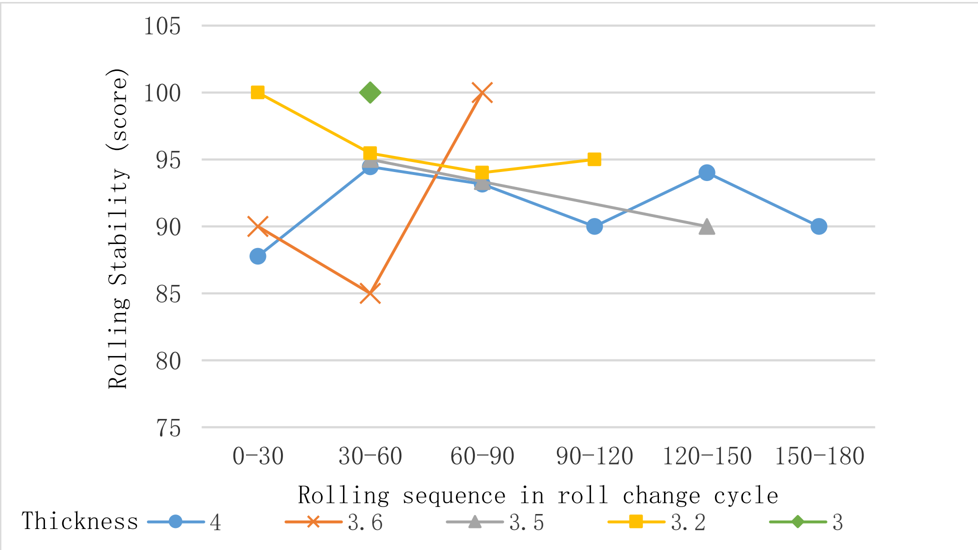

(**b**)

Figure 10. Time in the furnace. (**a**) Sample distribution; (**b**) Stability score.

According to Figure 10b, there are four thickness specifications in the rolling history sample, among which the strip steel (4 mm, 3.5 mm, 3.2 mm) with three thickness specifications has high rolling stability in the interval (30, 60), so the process value obtained through model optimization is helpful to obtain high rolling stability in rolling.

6. Conclusions

(1) The sample set is selected based on the similar equipment status and strip steel quality specification. This method can obtain the sample set that meets the current rolling status, improve the prediction accuracy of the model, and make the optimization results fall within the ideal range.

(2) In this research project, a rolling case of grade MRTRG00201_1276_3 is chosen to evaluate the practicability and reliability of the model. The rolling history of this product gauge strip is blank, and the on-site technicians lack the rolling experience of this product gauge. Their research can best reflect the advanced nature and practicability of the model. In this study, the single-factor slice display method is used in the multi-factor coupled action model to clearly and intuitively analyze the accuracy and practicability

of each process parameter suggestion. The results show that the suggested values of each process obtained through the optimization research model are in line with the field production laws and the experience expectations of field technicians.

(3) The coupling model of BP neural network and genetic algorithm can establish the mapping model between process parameters and rolling stability, search the ideal point of rolling stability in the model, and then determine a set of optimal suggestions for process parameters. Each process parameter in the rolling suggestion conforms to the distribution law of rolling samples, which can obtain high rolling stability and play a guiding role in rolling production. This research method can provide useful guidance for other complex and inexperienced rolling processes or similar industrial production processes. In future work, we can further improve the model optimization speed by optimizing the genetic algorithm.

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