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Optimization Study on Hardness of Cold Rolled Strip Steel Based on a Data-Driven Approach

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Abstract. As a key index to measure product quality and processability, the hardness of cold-rolled strip steel has an important influence on the production efficiency of iron and steel enterprises. However, due to the coupling between the process parameters at each stage of the continuous annealing process, and the setting of traditional process parameters depending on the experience of the operator, the lack of scientific and systematic optimization methods, which easily leads to the problem of high hardness fluctuation and low resource utilization. In this study, the data-driven method is used to conduct a preliminary correlation analysis to further clarify the optimal combination of process parameters for achieving the target hardness. The Pearson correlation coefficient is used to determine that carbon content, quenching furnace temperature, and strip speed significantly affect strip hardness. To further clarify the optimal combination of process parameters to achieve the target hardness, a Genetic Algorithm (GA) was tried in this study. The results show that the optimized process parameter combination can effectively improve the stability and consistency of strip hardness, and provide a scientific basis for the process parameter setting in the cold rolled strip production process, which is helpful for enterprises to improve product quality, reduce cost, and enhance market competitiveness.

Keywords: Cold rolled strip steel, Hardness optimization, Pearson correlation coefficient, Genetic Algorithm.

1. Introduction

Cold-rolled strip steel is an important product in the steel industry, and its mechanical properties, especially hardness, are directly related to product quality and market competitiveness[1]. As a key index to measure the durability, service life, and processing performance of strip steel, hardness has a decisive impact on the application range and stability of the product. In actual production, process parameters such as carbon content, soaking furnace temperature, rapid cooling furnace temperature, etc. will have a significant impact on the hardness of strip steel. Due to the coupling between the process parameters at each stage of the continuous annealing process (the temperature setting of the heating furnace will affect the subsequent setting of the heat and cooling temperature, as well as the strip travel speed), it is difficult to establish the mechanism model of the process, which poses challenges for online product quality control and optimization[2]. However, the traditional process parameter setting often relies on the operator's experience judgment, and lack of scientific and systematic, which not only limits the further improvement of product quality but also may lead to the waste of resources.

With the rapid development of data science and the continuous progress of intelligent manufacturing technology, using big data analysis to optimize process parameters has become an important way to improve product quality. Pearson correlation coefficient, as an effective tool to quantify the degree of linear correlation between variables [3], helps us to identify the key process parameters that affect the hardness of cold rolled strip steel. Genetic algorithm, as a powerful optimization algorithm, can effectively search the global optimal solution in complex parameter space by simulating the natural evolution process and has been widely used in various industrial optimization problems. In recent years, the application of genetic algorithms in material science, mechanical engineering, and other fields has been increasing, which fully proves its effectiveness and feasibility in dealing with complex optimization problems [4]. Therefore, the combination of the Pearson correlation coefficient and genetic algorithm not only scientifically identifies the key parameters but also effectively improves the control accuracy of strip hardness through algorithm optimization, which provides a solid theoretical basis and technical support for the intelligent upgrading of the cold rolled strip production process.

The purpose of this study is to optimize the production process parameters of cold-rolled strip steel by using a data-driven modeling method [5], to control the hardness of strip steel and improve the quality of the product. Firstly, through an in-depth analysis of actual production data, the Pearson correlation coefficient was used to quantify the correlation between process parameters and strip hardness, and the key process parameters with significant influence on strip hardness were identified. Then, the process parameters were optimized with a genetic algorithm. By iteratively updating the population, the optimal combination of process parameters to achieve the target hardness is searched. This study not only provides a scientific basis for the process parameter setting of cold rolled strip production, but also provides strong support for enterprises to improve product quality stability, reduce production costs, and enhance market competitiveness.

2. Data Cleaning and Correlation

The data in this study is from https://cxcy.upln.cn/, which includes the specification data, process parameters, and performance indexes of a batch of strip steel products. First, to verify the integrity of the data set, check whether there are missing values. For missing data, appropriate data completion strategies should be used to ensure the accuracy of the data. Python code is used here to search and complement the whole process to ensure the integrity and accuracy of the data:

Table 1. Check for missing values

	Column	Non-Null	Count	Data type
0	strip steel thickness	1000	non-null	int64
1	strip steel width	1000	non-null	int64
2	carbon content	1000	non-null	int64
3	silicon content	1000	non-null	int64
4	strip steel speed	1000	non-null	int64
5	heating furnace temperature	1000	non-null	float64
6	soaking furnace temperature	1000	non-null	float64
7	slow cooling furnace temperature	1000	non-null	float64
8	over-aging furnace temperature	1000	non-null	float64
9	rapid cooling furnace temperature	1000	non-null	int64
10	quenching furnace temperature	1000	non-null	int64
11	flattening mill tension	1000	non-null	float64
12	hardness	1000	non-null	int64

After examination, as shown in Table 1, there is no missing value. To have a comprehensive understanding of the data, further descriptive statistical analysis was carried out.

Table 2. Data statistics

	Strip steel thickness	Strip steel width	Carbon content	Silicon content	Strip steel speed	Heating furnace temperature
mean	8600.5900	204.0390	382.0580	9.0570	613.2900	717.1758
std	341.4383	12.8424	55.8614	2.6730	44.5740	48.9958
min	8020.0000	180.0000	42.0000	0.0000	451.0000	81.2000
25%	8360.0000	201.0000	355.0000	7.0000	586.7500	708.3500
50%	8470.0000	202.0000	387.0000	9.0000	629.0000	718.7000
75%	8720.0000	203.0000	418.0000	10.0000	649.0000	730.0000
max	9570.0000	234.0000	615.0000	22.0000	679.0000	812.6000

Table 3. Continuation of Table 2

	Soaking furnace temperature	Slow cooling furnace temperature	Over-aging furnace temperature	Rapid cooling furnace temperature	Quenching furnace temperature	Flattening mill tension	Hardness
mean	647.5520	621.8845	353.2120	59.7830	41.6590	2365.4237	595.3500
std	30.5756	40.0717	24.1891	9.6037	5.1652	170.6408	23.7285
min	319.5000	232.0000	99.5000	28.0000	7.0000	1962.3596	490.0000
25%	636.5000	602.3750	344.5000	51.0000	38.0000	2255.8809	580.0000
50%	643.0000	618.5000	352.0000	57.0000	42.0000	2339.9572	600.0000
75%	652.0000	638.0000	359.5000	70.0000	45.0000	2438.6638	610.0000
max	725.0000	820.5000	416.5000	72.0000	60.0000	3064.7601	660.0000

Table 2 and Table 3 show that in terms of strip dimensional characteristics, the thickness data fluctuates in the range of 8020 to 9570 microns with a standard deviation of 341.44 microns, while the width is concentrated in the range of 180 to 234 microns with a smaller standard deviation of 12.84 microns. In chemical composition analysis, carbon content fluctuated significantly, ranging from 42 to 615 ppm, with a standard deviation of 55.86 ppm. silicon content is relatively stable with a standard deviation of only 2.67ppm, while silicon content in most samples is close to 10ppm. In terms of process parameters, strip steel speed fluctuates between 451 and 679 m/min with a standard deviation of 44.57. The furnace temperature parameters, especially the heating furnace and soaking furnace temperature [6], show a wide range of variations, with standard deviations of 48.99 and 30.58, respectively. flattening mill tension remained in the range of 1962.36 to 3064.76N with a standard deviation of 170.64N. Hardness is a key performance indicator, its value is between 490 and 660HV, with a standard deviation of 23.73HV, although it fluctuates but is generally more concentrated.

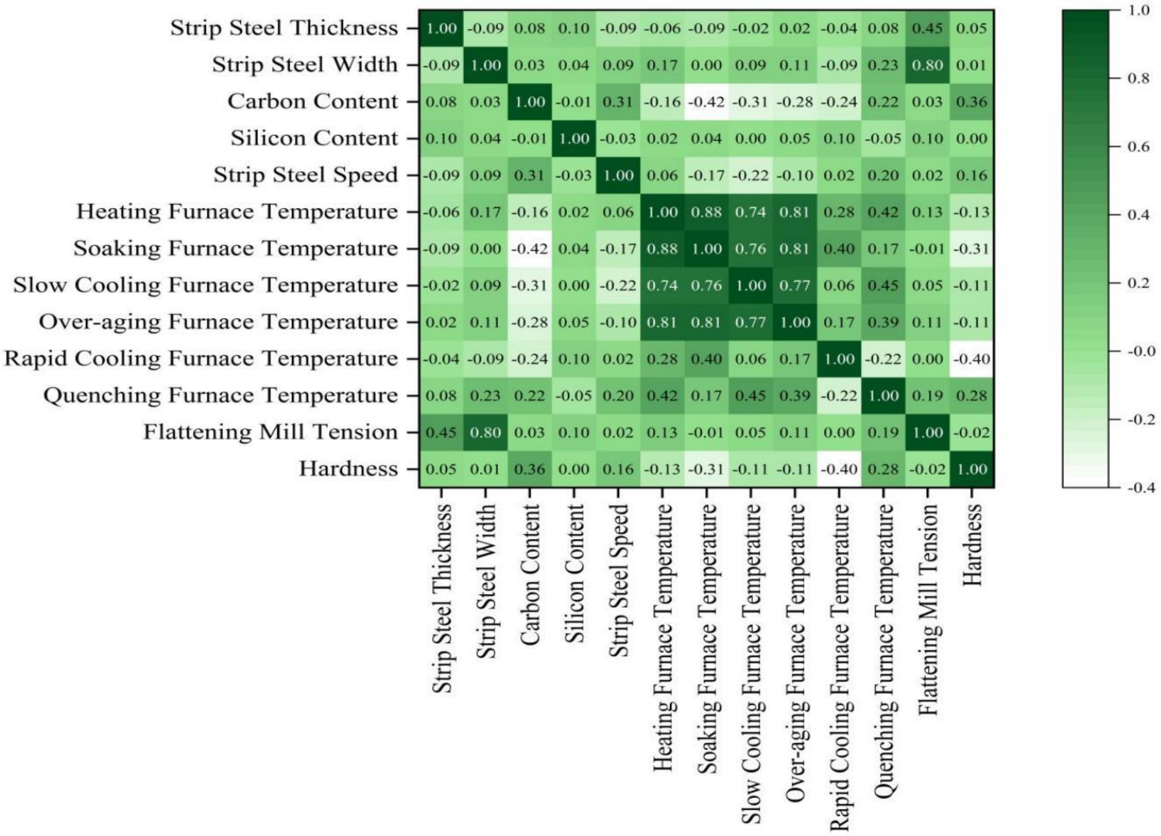

Figure 1. Thermal map of the correlation coefficient between each parameter and hardness

In the process of cold-rolled strip production, to improve product quality, the first task is to identify the process parameters that have a significant impact on the hardness of the strip. In this study, the Pearson correlation coefficient was used for data correlation analysis. The statistical index effectively quantifies the degree of linear correlation between process parameters (including strip steel thickness, width, carbon content, silicon content, speed, various furnace temperatures, and flattening mill tension) and strip steel hardness. Specifically, the Pearson correlation coefficient [7] is calculated based on the ratio of the covariance between two variables to the product of their respective standard deviations, which not only reveals the strength of the influence of each parameter on the hardness but also indicates the direction of the influence.

Table 4. Table of correlation coefficients between each parameter and hardness

Parameter	Correlation coefficient
carbon content	0.3553
quenching furnace temperature	0.2815
strip steel speed	0.1609
strip steel thickness	0.0498
strip steel width	0.0055
silicon content	0.0036
flattening mill tension	0.0206
slow cooling furnace temperature	0.1115
over-aging furnace temperature	0.1124
heating furnace temperature	0.1276
soaking furnace temperature	0.3122
rapid cooling furnace temperature	0.3985

Figure 1 and Table 4 show that carbon content (0.36) and quenching furnace temperature (0.28) are positively correlated to hardness, and strip steel speed (0.16) is also positively correlated. The results show that increasing carbon content, increasing quenching furnace temperature, or accelerating strip steel speed can effectively improve the hardness. On the contrary, slow cooling furnace temperature (-0.11), over-aging furnace temperature (-0.11), and heating furnace temperature (-0.13) were negatively correlated with hardness. Soaking furnace temperature (-0.31) and rapid cooling furnace temperature (-0.40) have a particularly significant and negative correlation to the hardness, and it is very important to control these temperature parameters to prevent the hardness from decreasing. In summary, carbon content, quenching furnace temperature, and strip steel speed should be the key objects of process optimization. rapid cooling furnace temperature, soaking furnace temperature, and heating furnace temperature need to be strictly regulated. Other parameters such as strip steel thickness, width, and silicon content have a relatively small impact on the hardness, but can not be ignored in the overall optimization process, and moderate adjustment is required to ensure stable product quality.

3. Quality Detection Model Development

Field operators often rely on personal experience to set the process parameters of strip products to achieve quality control. To improve the consistency and stability of strip product quality, it is necessary to build a data-based process parameter optimization scheme. The optimization goal focuses on adjusting the strip process parameters [8], aiming to make the product hardness close to the preset target value and striving to reduce resource consumption and cost in the process. Specific goals include precisely matching the hardness standards and ensuring the rationality and operability of the optimized process parameters in actual production, thereby improving the consistency and stability of product quality.

In the training process, we use the standardized training data, and the model form $y = sigmoid\,(X\beta)$, wh y ich represents the prediction result, X the input feature, β the model parameter to be learned, and sigmoid the logical function to map the linear combination to the probability value [9]. To achieve the target hardness, we use a genetic algorithm to search for the optimal combination of process parameters. Genetic algorithm (GA) draws on the mechanism of natural evolution and aims to find the global optimal solution. Its core processes include selection, crossover, and variation.

The fitness function is used to evaluate the merits and disadvantages of each individual (that is, the combination of process parameters), and obtains the fitness value of the individual through calculation. In this context, the smaller the fitness value, the better the individual.

$$\text{fitness}(\text{in divid}) = \left|\hat{y} - y_{\text{target}}\right| \tag{1}$$

Where, $\hat{y}$ is the predicted value of hardness, and y_{target} is the target value of hardness.

The series of optimization steps of fitness calculation, selection, crossover, and mutation are repeated until the combination of process parameters is found to make the predicted hardness value of the strip accurately reach or approach the preset target hardness value of 590 [10], which is the condition for the algorithm to stop.

After solving, we get the optimization results before the de-standardization, as shown in Table 5.

Table 5. Optimization results (before de-standardization)

Best solutions	[-0.28322051,0.86536561,0.95015729,-1.39364143,0.45232201,-0.73057661, 0.8130496,0.81960467,-0.73112452,-0.55116941,-0.71096378,-0.34009623]
Best Fitness	30

The actual available parameter values, that is, the optimal process parameter combination, can be obtained by de-normalization, as shown in Table 6.

Table 6. Actual available parameter values

Parameter	Available parameter value (original scale)
Strip Steel Thickness	8503.0400
Strip Steel Width	215.8666
Carbon Content	435.4027
Silicon Content	5.3014
Strip Steel Speed	634.0053
Heating Furnace Temperature	677.0964
Soaking Furnace Temperature	673.0684
Slow Cooling Furnace Temperature	655.8080
Over-aging Furnace Temperature	334.0687
Rapid Cooling Furnace Temperature	54.2154
Quenching Furnace Temperature	37.8918
flattening mill tension	2312.3106

The optimization results show that the strip thickness is set to 8503.04 microns, the width is 215.87 mm, the carbon content is 435.40ppm (parts per million), the silicon content is 5.30wt% (weight percentage), the strip speed is 634.01 m/min, and the heating furnace temperature is controlled at 677.10 degrees Celsius. The temperature of the soaking furnace is adjusted to 673.07 degrees Celsius, the temperature of slow cooling furnace is 655.81 degrees Celsius, the temperature of the over-aging furnace is set to 334.07 degrees Celsius, the temperature of fast cooling furnace is maintained at 54.22 degrees Celsius, the temperature of quenching furnace is determined to 37.89 degrees Celsius, and 2312.31 Newtons of flattening machine tension is applied. The optimal parameter combination reached the optimal fitness value of 30 in the iteration of the genetic algorithm, that is, the difference between the hardness predicted by the model and the target hardness was 30 hardness units (based on the Brinell hardness meter) [11], which verified the high precision and reliability of the model in prediction and optimization.

4. Conclusions

In this study, the optimization of production process parameters of cold rolled strip steel was deeply discussed through a data-driven modeling method and optimization algorithm, to achieve accurate control of strip hardness and optimization of process parameters, to improve the stability of product quality and economic benefits of iron and steel enterprises. The core findings of the study include two parts: first, through Pearson correlation analysis, it is clear that carbon content, quenching furnace temperature, and strip speed have a significant positive correlation on the hardness of the strip, while the rapid cooling furnace temperature, soaking furnace temperature and heating furnace temperature are negatively correlated. These findings provide a scientific basis for the optimization of subsequent process parameters. Secondly, the logistic regression model and genetic algorithm are used to optimize the process parameters, and the optimal parameter combination to make the strip hardness close to the preset target value is successfully obtained, and the feasibility and effectiveness of the combination in actual production are demonstrated through practical verification.

This study not only achieves accurate optimization of strip production process parameters at the technical level but also provides a scientific and reasonable process parameter setting basis for field operators through scientific modeling and optimization methods, which effectively improves the controllability of the production process and the consistency of product quality. At the same time, this study puts forward a systematic research idea and framework and emphasizes the feasibility and application potential of data-driven optimization algorithms in the field of metal material optimization. Future research can further improve the model and algorithm on this basis, improve the optimization efficiency and accuracy, and provide more scientific and reasonable solutions for quality control in the production process of steel and other metal materials, to help enterprises improve market competitiveness and economic benefits.

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