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Innovative Application of Gradient Descent to Optimize Strip Process Parameters

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Abstract: Cold-rolled steel strip, renowned for its high strength, excellent toughness, and other superior properties, is extensively utilized across various industries. However, coupling parameters in the continuous annealing process poses significant challenges for quality control. To address this issue, this study employs the gradient descent algorithm to optimize the process parameters. By defining clear objectives, identifying key parameters, establishing a loss function, as well as iteratively updating the parameters, an optimal parameter combination is identified, thereby enhancing product quality and production efficiency. Experimental results demonstrate that the algorithm exhibits outstanding performance in optimizing hardness errors, with a notably low MSE value. Looking ahead, research will focus on developing adaptive or real-time optimization systems to propel the intelligent development of the steel industry.

1. Introduction

Cold-rolled steel strip is a pivotal product in the steel industry, and optimizing its process parameters poses a significant challenge. In actual production, the parameters of each stage of continuous annealing are tightly coupled, with the heating furnace temperature influencing subsequent soaking, cooling, and strip travel speed, posing difficulties for constructing mechanical models and complicating online quality control and optimization.

Recent technological advancements have prompted academia and industry to delve deeply into the optimization of cold-rolled steel strip process parameters, yielding significant results. In mathematical modeling and simulation, sophisticated techniques are employed to construct more precise cold-rolling models, enabling the simulation of cold-rolling processes under various parameters for optimization. In the realm of intelligent control, machine learning, neural networks, and other intelligent algorithms are introduced to automatically optimize parameters and intelligently regulate the cold-rolling process based on real-time data feedback, thereby enhancing production efficiency. In terms of new materials and technology applications, materials tailored for cold rolling are developed, while innovative technologies such as ultrasonic testing and laser measurement are utilized to improve product quality and production efficiency.

Although technological innovations have enabled the optimization of strip steel process parameters to meet standards, the pursuit does not stop there. To overcome the limitations of previous models in real-time detection and considering the correlation between process parameters and strip quality, this paper focuses on using the gradient descent algorithm to explore the optimal solution for an online quality detection model of strip products. To comprehensively elaborate on the optimization model of strip steel process parameters, this paper is divided into five chapters. The first chapter serves as an introduction, summarizing the entire paper. The second chapter delves into the theoretical framework, laying the foundation for modeling. The third chapter details the experimental procedures. The fourth chapter presents the experimental results. The fifth chapter provides a systematic conclusion.

2. Related theorie

The key to applying the gradient descent algorithm in optimizing the process parameters of steel strip production lies in first defining the optimization objectives, such as enhancing the mechanical properties of the steel strip or reducing energy consumption, and identifying the critical process parameters that influence these objectives, including heating temperature, rolling speed, cooling rate, among others[1]. Subsequently, a loss function related to the objectives is established, which quantifies the deviation between the parameter settings and the target values. The algorithm then initiates from a set of initial parameters and calculates the gradient of the loss function, which indicates how the parameters should be adjusted to minimize the loss.

In each iteration, the parameters are updated in the opposite direction of the gradient, with the aim of gradually reducing the value of the loss function until convergence criteria are met. Through this process, the gradient descent algorithm identifies a set of optimized parameters for the steel strip process, resulting in improved production efficiency and product quality[2]. This model is closely integrated with the actual conditions of steel strip production and leverages the iterative optimization characteristics of the gradient descent algorithm to achieve efficient optimization of process parameters.

3. Experiment

3.1 Gradient Descent Optimization of Process Parameters for Steel Strip Production

The present experiment is aimed at precisely tuning the critical process parameters in steel strip production, such as heating temperature, rolling force, rolling speed, and cooling rate, through the application of the gradient descent algorithm[3]. This endeavor is undertaken to maximize product quality attributes including strength, toughness, and surface quality, as well as production efficiency. Article hypothesize that by meticulously adjusting these parameters, essay can significantly reduce the defect rate and enhance product consistency and yield.

In traditional steel strip processes, parameter optimization is crucial for enhancing product quality and production efficiency. However, due to the complexity of the processes, challenges such as local optima and inefficient optimization are often encountered[4]. The adoption of gradient descent optimization for steel strip process parameters enables precise adjustments of parameters like rolling temperature and speed, thereby improving production efficiency and product quality. Through optimization, the grain size and morphology of the steel can be more effectively controlled, leading to enhanced plasticity, toughness, and strength. Furthermore, the gradient descent algorithm aids in identifying the optimal parameter combination, further reducing production costs and energy consumption. Consequently, the optimized steel strip products can better meet the demands for high performance and high added value, and even further expand their application scope in fields such as engineering machinery and aerospace, enhancing market competitiveness.

Therefore, based on prior research and production experience, several process parameters with the most significant impact on steel strip performance are identified[5]. Reasonable initial values are set for each selected parameter, according to the standard operating conditions of the existing production line, serving as the starting point for the gradient descent algorithm. In each experimental round, the settings of each parameter and the corresponding steel strip performance indicators, such as tensile strength, yield strength, elongation, and surface roughness, are meticulously recorded. The collected data is then cleaned to remove outliers and noise, ensuring accuracy and reliability for subsequent analysis.

A comprehensive evaluation index is defined as the objective function, based on the steel strip's performance indicators. This objective function should comprehensively reflect the quality and production efficiency of the steel strip, such as the total defect rate, cost-benefit ratio, or overall performance score. Numerical differentiation or analytical methods are utilized to calculate the gradient of the objective function with respect to each selected parameter. This typically involves first-order differentiation of the objective function to obtain the sensitivity of each parameter's impact on it. Parameter values are adjusted according to the gradient descent formula, with a preset learning rate. The choice of learning rate should balance convergence speed and stability, avoiding excessive values that lead to oscillation or insufficient values that result in slow convergence. The process of gradient calculation and parameter updating is repeated until predefined stopping conditions are met. These conditions may include the gradient falling below a threshold, reaching the maximum number of iterations, or no significant performance improvement[6]. During the iteration process, close attention should be paid to the changes in the objective function value and the impact of parameter adjustments on steel strip performance. The specific steps for gradient descent optimization of steel strip process parameters are illustrated in the figure 1.

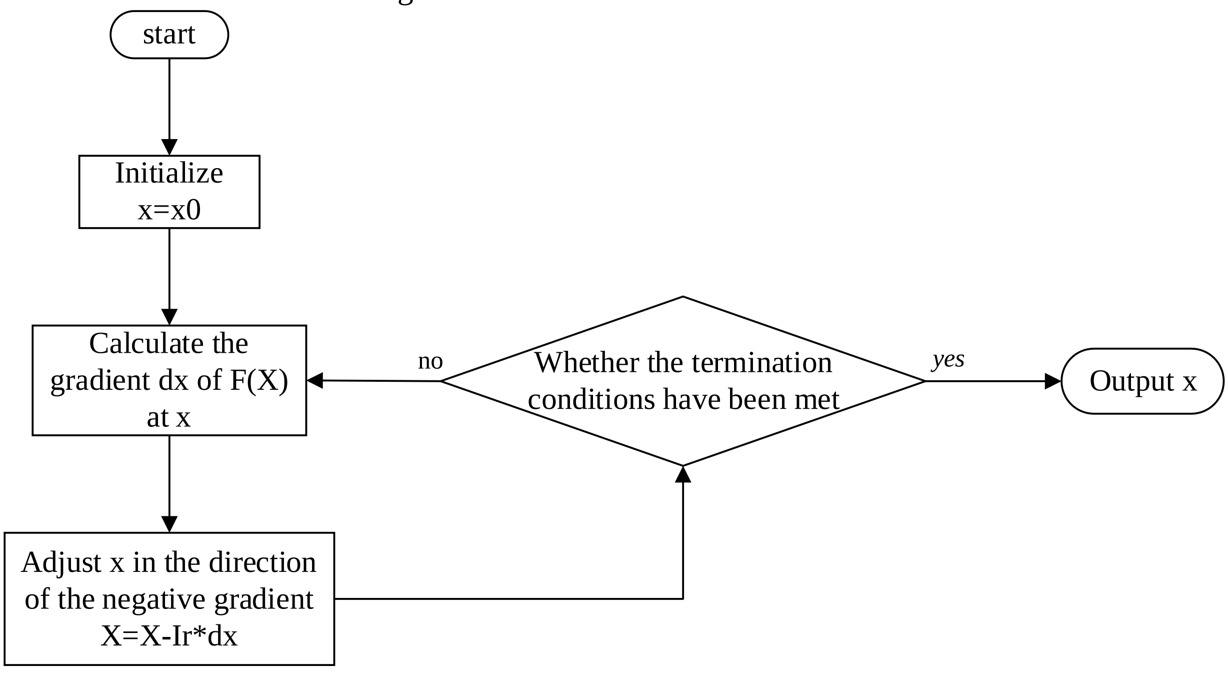

Figure 1. Flow diagram of gradient descent optimization process parameters

Gradient descent algorithm, through iterative updates of parameter values, rapidly converges to the optimal solution, significantly enhancing optimization efficiency compared to traditional methods. Furthermore, when confronted with high-dimensional parameter spaces and complex coupling relationships, the algorithm effectively navigates to find global or near-optimal combinations of process parameters[7]. In the optimization of steel strip process parameters, the adoption of gradient descent aids steel enterprises in improving product quality, optimizing production processes, and reducing costs. The application of this algorithm contributes to the intelligent and refined development of the steel industry.

3.2 Gradient descent determines the optimal strip process parameter analysis

This paper designates the product quality index function of the steel strip as $Q(T,F,V,R)$, the production efficiency index function as $E(T,F,V,R)$, and the production cost index function as $C(T,F,V,R)$, where T represents the rolling temperature, F denotes the rolling force, V signifies the rolling speed, and R indicates the rolling ratio.

(1) Product Quality Index Function $Q(T,F,V,R)$

Product quality is primarily influenced by factors such as hardness H, strength S, surface quality Sq, internal stress σ, and crack occurrence rate Cr. It can be formulated as follows:

$$Q(T,F,V,R)=\alpha_1 H(T,F,R)+\alpha_2 S(T,F,R)+\alpha_3 Sq(F,V)+\alpha_4(1-Cr(T,F))+\alpha_5(1-\sigma(T,F)) \quad (1)$$

Where: The hardness $H(T,F,R)$ can be expressed as

$$H(T,F,R)=h_0+h_1T+h_2F+h_3R \quad (2)$$

Where h_0,h_1,h_2,h_3 are coefficients obtained through extensive experimental data fitting, indicating a linear relationship between rolling temperature, rolling force, rolling ratio, and hardness. A higher rolling temperature, within a certain range, may promote grain refinement, thus increasing hardness; variations in rolling force and rolling ratio also alter the material's microstructure, subsequently affecting its hardness[8]. Similarly, the strength $S(T,F,R)$ can be formulated as

$$S(T,F,R)=s_0+s_1T+s_2F+s_3R,s_0 \quad (3)$$

s_0,s_1,s_2,s_3 satisfy the temperature change of the fitting coefficient, rolling force, and rolling ratio influence the material's microstructure, such as dislocation density and grain orientation, thereby impacting its strength. The surface quality $Sq(F,V)$ can be represented as

$$Sq(F,V)=sq_0-sq_1F-sq_2V^2 \quad (4)$$

sq_0,sq_1,sq_2 are coefficients. A larger rolling force may lead to surface defects like scratches, while excessive rolling speed can cause issues like steel strip vibration, affecting surface flatness, hence the negative correlation. The internal stress $\sigma(T,F)$ is given by

$$\sigma(T,F)=\sigma_0+\sigma_1T+\sigma_2F \quad (5)$$

$\sigma_0,\sigma_1,\sigma_2$ as coefficients. Inappropriate rolling temperatures and forces can result in uneven deformation, leading to increased internal stress[9]. The crack occurrence rate $Cr(T,F)$ is assumed to be

$$Cr(T,F)=cr_0+cr_1T+cr_2F \quad (6)$$

cr_0,cr_1,cr_2 are coefficients. Excessively high rolling temperatures may cause thermal embrittlement, while excessive rolling forces can lead to localized stress concentrations, both prone to inducing cracks.

(2)The production efficiency index function $E(T,F,V,R)$

The production efficiency index function $E(T,F,V,R)$ is primarily related to the operational stability St of the production line, capacity Ca, and material springback B, which can be constructed as:

$$E(T,F,V,R)=\beta_1 St(V,F)+\beta_2 Ca(V,R)+\beta_3(1-B(F)) \quad (7)$$

Where: Operational Stability $St(V,F)$: It is assumed that $St(V,F)=st_0-st_1V-st_2F^2$, st_0,st_1,st_2 being coefficients. Excessive rolling speed may lead to unstable equipment operation, and excessive rolling force can also impact the stability of the equipment. Capacity $Ca(V,R)$: For instance,

$$Ca(V,R)=ca_0+ca_1V+ca_2R \tag{8}$$

Where ca_0,ca_1,ca_2 are coefficients. Higher rolling speeds and appropriate rolling ratios contribute to increased production output per unit time[10]. Material Springback $B(F)$: It is postulated that

$$B(F)=b_0+b_1F \tag{9}$$

b_0,b_1 as coefficients. Proper setting of the rolling force can reduce material springback, thereby enhancing production efficiency, as springback results in adjustments and time wastage in subsequent processing steps.

(3) Production Cost Index Function $C(T,F,V,R)$

The production cost is primarily associated with energy consumption En and equipment wear W, and can be formulated as follows:

$$C(T,F,V,R)=\gamma_1En(T,V)+\gamma_2W(F,V) \tag{10}$$

Where: Energy Consumption $En(T,V)$: It is assumed that

$$E(T,V)=en_0+en_1T+en_2V^3 \tag{11}$$

en_0,en_1,en_2 as coefficients. Higher rolling temperatures and speeds typically consume more energy. Equipment Wear $W(F,V)$: It is postulated that

$$W(F,V)=w_0+w_1F+w_2V^2 \tag{12}$$

w_0,w_1,w_2 are coefficients. Greater rolling forces and higher rolling speeds accelerate equipment wear.

(4) Optimization Objective Function $O(T,F,V,R)$

The optimization objective is to enhance production efficiency and reduce production costs while ensuring product quality. The objective function can be constructed as:

$$O(T,F,V,R)=\lambda_1Q(T,F,V,R)+\lambda_2E(T,F,V,R)-\lambda_3C(T,F,V,,R) \tag{13}$$

Where $\lambda_1,\lambda_2,\lambda_3$ are weight coefficients determined based on the importance of product quality, production efficiency, and cost in actual production. By adjusting the values of rolling temperature T, rolling force F, rolling speed V, and rolling ratio R, and utilizing methods such as experimentation and simulation, the objective function $O(T,F,V,R)$ is continuously optimized to achieve its maximum value, thereby determining the optimal combination of steel strip process parameters.

4. Results

This study conducted a comparative analysis of the accuracy of four optimization algorithms—Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing, and Gradient Descent—for a data-driven online quality inspection model for steel strip products. The aim was to validate through systematic experimental analysis that the Gradient Descent algorithm is sufficiently precise and can serve as a viable solution for optimizing the model's performance.

The dataset utilized in the experiments was sourced from the actual production environment of a steel enterprise, comprising extensive quality inspection data for steel strip products. After preprocessing, the dataset was divided into training and testing sets for model training and validation. In terms of model architecture, study adopted a Deep Neural Network as the base model, with the number of layers and nodes adjusted according to the experimental requirements. The optimization objective was set to minimize the model's prediction error, thereby enhancing prediction accuracy.

For optimizing the error in predicting the hardness of cold-rolled steel strips, MSE value obtained using the Gradient Descent algorithm was 772.2521. Given this low MSE value, by selecting the Gradient Descent algorithm as the model for seeking the optimal solution for the steel strip quality inspection model.

Initially, Experimentation employed the Genetic Algorithm to select the most suitable process parameters based on their fitness within the problem domain, approximating the optimal solution. The Particle Swarm Optimization algorithm was used as an auxiliary model to complement the primary model, and a comparative analysis of the results from both models was conducted to obtain an approximate solution. The Simulated Annealing algorithm, based on probability, was employed to iterate through different parameter indicators and find the optimal state of steel strip performance under specific parameters. Considering that the Gradient Descent algorithm finds the values of the independent variables that minimize the objective function by computing its derivative, a comparison chart of the accuracy of four optimization algorithm models was derived based on their solutions, as shown in Figure 2.

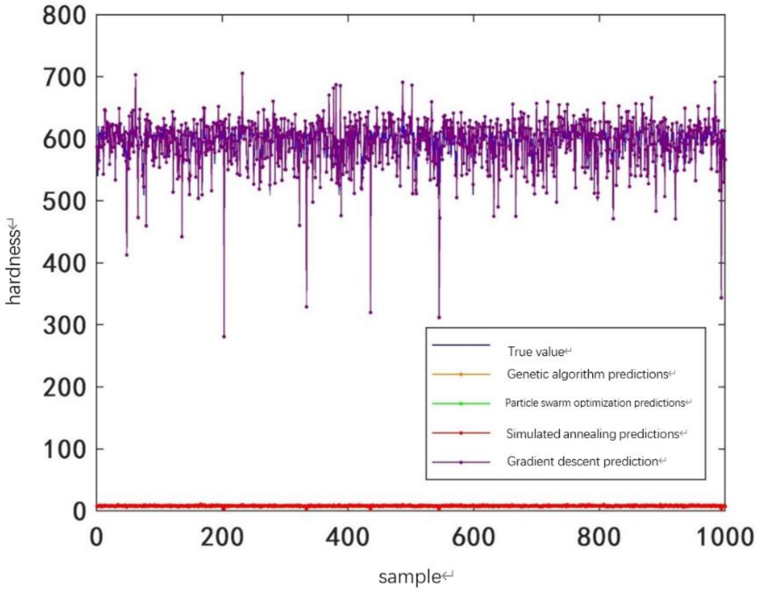

Figure 2. Comparison of the accuracy of the four optimization algorithms

Based on the comprehensive analysis of quality prediction models and continuous casting process parameter optimization, to conduct a meticulous analysis of optimization algorithms such as gradient descent and obtain a data-driven optimal online detection model for steel strip product quality, this paper developed a solution for optimizing the process parameters of steel strips. Furthermore, the MSE of the gradient descent optimization algorithm was calculated and is presented in the table 1 below.

Table.1. Gradient descent optimization error analysis

MSE / Optimization algorithms	
Gradient descent	772.2521

The analysis of the MSE for the gradient descent optimization algorithm yielded a result of

772.2521 for the MSE value of the gradient descent method. It was found that, in terms of optimizing the hardness error of cold-rolled steel strips, the gradient descent algorithm performed best, with a sufficiently low MSE. Consequently, the optimal parameter combination after optimization was determined to be [0.0543, 0.1386, 0.2193, 0.1418, 0.1546, -0.0026, 0.1486, 0.0713, 0.0899, 0.0072, 0.1762, 0.0575].

5. Conclusions

This paper delves deeply and comprehensively into the optimization of process parameters for cold-rolled steel strips. Given the intricate coupling relationships among various parameters in the continuous annealing process, constructing an accurate mechanistic model undoubtedly poses a formidable challenge. In response to this predicament, the present study diligently investigates and implements the application potential of the gradient descent algorithm in this field. By clearly defining optimization objectives, meticulously screening and identifying key parameters, scientifically constructing a loss function, and conducting multiple rounds of iterative optimization, this paper has achieved precise adjustment and control of parameters during the experimental stage. Particularly in optimizing the core indicator of hardness error in cold-rolled steel strips, the employed gradient descent algorithm has demonstrated exceptional performance. While maintaining a low MSE value, it has successfully uncovered the optimal parameter combination and validated its remarkable effectiveness through practical verification. This achievement not only enhances the product quality of cold-rolled steel strips but also lays a solid foundation for subsequent research.

Looking ahead, the research on optimizing the process parameters of cold-rolled steel strips can be further deepened on this basis.

References

[1] Cao Mengchuan, Wu Dan, Du Pengxuan. Comparative Analysis of Convergence Rates of Stochastic Gradient Descent and Batch Gradient Descent in Optimization of Lycium Barbarum Growth Model [J]. Modern Agricultural Machinery, 2024, (06): 75-77.

[2] Fang Su, Jia Jinwei, Yu Ling, et al. Optimal design method of wire bundle cross-section layout based on gradient descent continuous optimization algorithm [J]. Electric Power and Energy, 2024, 45 (05): 580-583+598.

[3] Liu Bing, Qiu Xu, Ding Yumin, et al. Research on Strip Production Process Optimization and Quality Control Based on Mathematical Model Analysis [J]. Journal of Liaoning University of Science and Technology, 2024, 26 (05): 13-17.

[4] Liu Jiaxu, Chen Song, Cai Shengze, et al. Design of Adaptive Fractional Gradient Optimization Algorithm Based on Robust Control [J]. Control Theory & Applications, 2024, 41 (07): 1187-1196.

[5] Chen Yan, Lei Xuejing, Yang Mei. Research on Optimal Valve Opening Scheme for Air Conditioning Control System Based on Gradient Descent [J]. China Machinery, 2024, (16): 8-12.

[6] Hao Zeyong. Research on collaborative optimization of process parameters of hot-rolled strip plate shape in multiple processes [D]. Yanshan University, 2024.

[7] Xing Haiyan, Yi Ming, Duan Chengkai, et al. Edge Recognition Model of Pipeline Defects Based on Magnetic Gradient Tensor Combined Invariant Algorithm Optimized by Improved Gradient Descent Algorithm [J]. China Mechanical Engineering, 2023, 34 (16): 1915-1920.

[8] Guo Zhuangzhuang. Research on Model Compression and Implicit Gradient Optimization Algorithm in Federated Meta-learning Framework [D]. Nanjing University of Science and Technology, 2023.

[9] Tian Zhiwei. Optimization of process parameters for cold-rolled galvanizing cleaning section [J]. Metallurgical Management, 2020, (19): 55-56.

[10] Yang Jie, Hu Qi, Xiao Ting, et al. Energy Efficiency Modeling, Process Parameter Optimization and Ranking Modeling Optimization of Cold Rolling Continuous Retirement Unit Based on Energy Consumption [J]. China Mechanical Engineering, 2020, 31 (14): 1724-1732.