Optimization of Rolling Process Parameters in Metallurgical Engineering and Analysis of Engineering Applications

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Abstract: Rolling is a key metallurgical operation that connects billet preparation with steel-product forming. Rolling temperature, rolling force, rolling speed, reduction ratio and cooling schedule jointly govern microstructural evolution, mechanical properties, dimensional accuracy and energy consumption. To address the limitation that empirical parameter settings can no longer meet the requirements of high-precision, low-energy production, this study focuses on hot- and cold-rolling processes, systematically examines how the core parameters affect product quality and production efficiency, and develops a multi-objective parameter-optimization strategy that integrates response surface methodology, a genetic algorithm and a data-mechanism hybrid model. A representative operating case is analyzed for Q235B strip produced on a 1780 mm hot continuous rolling line in a steel enterprise. In the proposed scheme, furnace exit temperature, roughing reduction ratio, finishing reduction ratio and finishing speed are incorporated into a unified solution framework. Plant statistics show that, while yield strength and thickness deviation satisfy the process requirements, the standard deviation of yield strength decreases from 18.0 MPa to 15.8 MPa, unit rolling energy consumption decreases from 72 kWh/t to 66 kWh/t, and the qualified-product rate increases from 94.5% to 98.2%. The results indicate that coupled multi-parameter optimization can simultaneously improve quality stability, balance equipment load and enhance production economy, thereby providing a practical reference for refined control of hot continuous rolling.

Keywords: Metallurgical engineering; Rolling process; Parameter optimization; Response surface methodology; Genetic algorithm; Data-mechanism fusion

1. Introduction

Rolling imposes continuous plastic deformation on billets or strip by means of work rolls, producing the required thickness, width, strip shape and mechanical properties. It is an essential step in transforming steelmaking products into engineering materials. As automotive sheet, high-strength structural steel, silicon steel and steels for high-end equipment require increasingly tight dimensional accuracy, homogeneous microstructures and stable batch-to-batch performance, the traditional practice of setting temperature, speed and reduction schedules mainly from operator experience is no longer sufficient for stable production. In recent years, steel manufacturing has increasingly incorporated industrial data, mechanistic models and machine-learning methods to establish mappings between process parameters and material properties, creating new technical routes for online prediction and parameter optimization during rolling [1]. From the perspective of process control, rolling is strongly coupled, highly nonlinear and subject to multiple constraints. Temperature affects deformation resistance and phase transformation; the reduction ratio determines strain accumulation and work-hardening level; and rolling speed is related not only to productivity but also to the thermal field of the stock and the dynamic response of the mill. For the complex relationship between rolling parameters and strip-shape quality, recent reviews have shown that machine learning has gradually been applied to rolling-parameter optimization, shape improvement and multi-objective control, although engineering deployment still needs to be integrated with mechanistic constraints, plant-data quality and online correction mechanisms [2].

This paper is organized around three connected themes: parameter-effect mechanisms, optimization modeling and engineering validation. First, the effects of rolling temperature, rolling force, rolling speed and reduction ratio on microstructure, properties, dimensional accuracy and energy consumption are analyzed. A multi-objective optimization framework combining response surface methodology, a genetic algorithm and data-mechanism fusion is then constructed. Finally, parameter-optimization calculations are carried out using a hot continuous rolling case, and the engineering feasibility of the proposed scheme is discussed.

2. Core Parameters of the Rolling Process and Their Mechanisms

Rolling processes can be classified into hot rolling and cold rolling according to deformation temperature and microstructural state. Hot rolling uses elevated temperature to reduce deformation resistance and promote dynamic recovery and recrystallization, whereas cold rolling achieves higher dimensional accuracy and surface quality at room temperature or at relatively low temperature, but must address work hardening, tension matching and shape control.

2.1 Rolling Temperature

Rolling temperature is an important thermomechanical parameter for controlling steel plasticity, transformation path and microstructure. Hot rolling of low-carbon steel is normally performed mainly in the austenite region. If the reheating temperature is excessively high, austenite grains are prone to coarsening, which may reduce microstructural uniformity after subsequent cooling. If the finishing temperature is too low, deformation resistance increases, the rolling force and main-drive load rise, and the risk of strip-shape fluctuation and surface defects also increases. Although recrystallization heating is absent in cold rolling, frictional heat and plastic-deformation heat can alter lubrication conditions in the roll gap. Inadequate temperature control may destroy the lubricant film and cause surface scratches or local waviness.

In engineering calculations, the influence of temperature on deformation resistance can be expressed by the following simplified exponential relation:

$$\sigma_s=\sigma_{s0}\cdot e^{-k(T-T_o)}$$

where σ_s is the deformation resistance at the actual rolling temperature, σ_{s0} is the deformation resistance at the reference temperature T_o, k is the temperature-sensitivity coefficient, and T is the actual rolling temperature. This equation is not a universal material-constant model; rather, it illustrates that, for a given steel grade and temperature interval, increasing temperature reduces deformation resistance. In practical applications, k should be calibrated using thermal-simulation experiments, plant rolling-force data, or a data-mechanism hybrid model.

2.2 Rolling force and rolling speed

Rolling force is the principal load exerted by the rolls on the stock and directly affects thickness control, mill spring, roll bending and equipment safety. Insufficient rolling force makes it difficult to achieve the target draft, whereas excessive rolling force increases stand deformation, roll wear and main-motor load. Recent work on variable-speed rolling-force prediction indicates that combining theoretical and data-driven models can improve the adaptability of force prediction under changing-speed conditions [3]. Adaptive rolling-force modeling for hot-rolled plate based on industrial data can also improve model stability under plant-data fluctuations [4]. For hot-rolled plate and strip, rolling force may be preliminarily estimated from deformation resistance, contact area and a friction correction in the simplified form:

$$P = K \cdot B \cdot \sqrt{R\Delta h}$$

where P is the rolling force, K is the mean deformation resistance, B is the stock width, R is the work-roll radius, and Δh is the draft. This expression is suitable only for preliminary estimation. Actual set-up must also account for friction, front and back tension, elastic deformation of the roll gap, roll thermal crown and speed variation. For dynamic rolling force, data-mechanism collaborative models have been used for rolling-schedule optimization and have reduced dynamic force fluctuations in multi-stand rolling [5].

Rolling speed affects the production rhythm and also changes the roll-strip contact time, temperature-drop rate, frictional heating and control-system response. When speed is increased, if temperature compensation, rolling-force presetting and tension control are not adjusted synchronously, thickness deviation may expand, strip-shape fluctuation may intensify, and load distribution among stands may become unbalanced. Studies on profile control in tandem cold rolling have shown that prediction-control models based on PSO-BP and related algorithms can improve profile-control accuracy for silicon steel strip [6].

2.3 Reduction Ratio and Strain Path

The reduction ratio is the ratio of the thickness decrease in each pass to the entry thickness and reflects the intensity of strain input during rolling. In hot rolling, an appropriate allocation of roughing and finishing reductions helps break up coarse as-cast grains, improve central looseness and reduce the load on the finishing mill. In cold rolling, an excessive single-pass reduction rapidly accumulates work hardening and increases the risk of edge cracking and strip-shape defects. Table 1 summarizes a representative relationship between reduction ratio and mechanical properties during cold rolling of Q235B steel. The data show that, as reduction ratio increases, strength and hardness increase while elongation decreases, indicating that cold-deformation strengthening and loss of ductility must be considered simultaneously in process design.

Table 1: Relationship Between Cold-rolling Reduction Ratio and Mechanical Properties of Q235B Steel.

Reduction ratio (%)	Yield strength (MPa)	Tensile strength (MPa)	Elongation (%)	Hardness (HV)
20	285 ± 8	412 ± 10	32 ± 2	135 ± 5
30	320 ± 9	445 ± 12	28 ± 1.5	152 ± 6
40	358 ± 11	480 ± 15	22 ± 1	178 ± 7
50	395 ± 13	510 ± 18	18 ± 0.8	205 ± 8

In modern plate and strip rolling, the reduction ratio should not be set in isolation; it should be jointly optimized with temperature, speed, tension, lubrication and cooling schedule. Industrial Internet-of-Things platforms can collect multi-source plant variables and use them for real-time prediction of hot-rolled strip crown, thereby providing online data support for reduction scheduling and strip-shape control [7].

3. Optimization Methods and Model Construction for Rolling Process Parameters

The objective of rolling-parameter optimization is to balance product quality, equipment capability, energy consumption and production efficiency. Pursuing a single indicator, such as minimum rolling energy consumption, may cause strength fluctuation, shape deterioration or concentrated load on a particular stand. The optimization model should therefore include quality constraints, equipment constraints and economic objectives. To further clarify the relationships among multi-source process variables, mechanistic constraints, optimization algorithms and plant evaluation indicators, a coupled multi-parameter optimization framework for rolling is constructed in Figure 1.

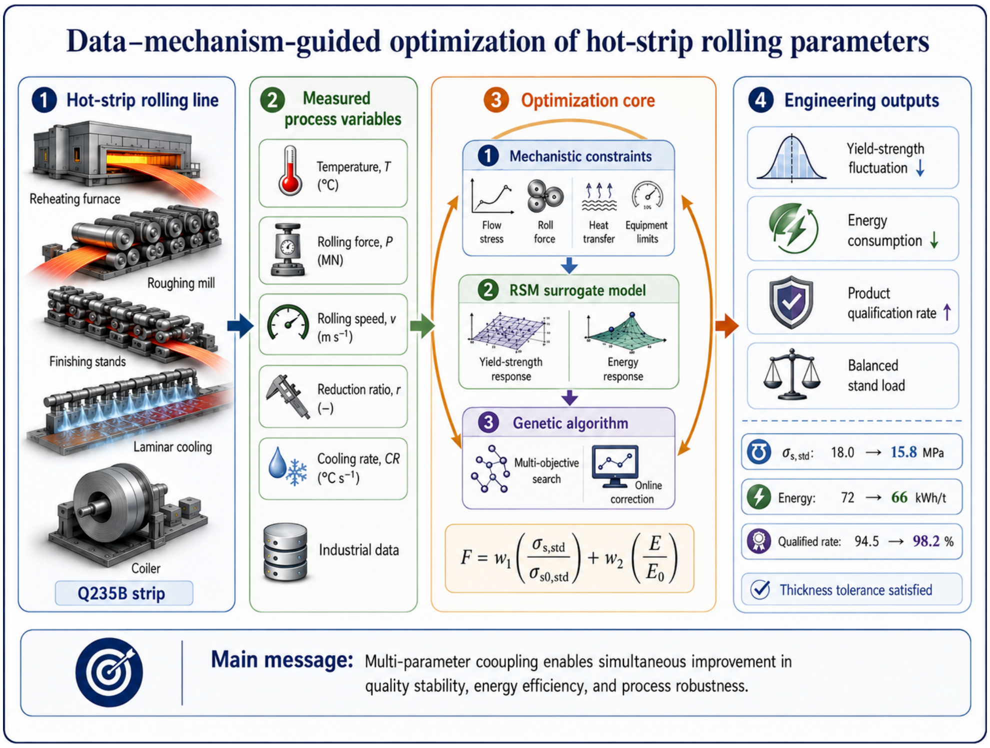

Figure 1: Coupled Multi-parameter Optimization Framework for the Rolling Process.

3.1 Response Surface Methodology

Response surface methodology constructs a quadratic regression model between process parameters and objective functions through experimental design and then identifies the optimal parameter combination. It is suitable for cases in which parameter interactions are significant and the cost of experimentation is relatively low. Taking the optimization of rolling temperature (T), rolling force (P) and reduction ratio (ε) in hot strip rolling as an example, if yield strength (σ_s) and rolling energy consumption (E) are selected as objective functions, the following three-factor quadratic regression equations can be established:

$$\sigma_s = a_0 + a_1 T + a_2 P + a_3 \varepsilon + a_4 T^2 + a_5 P^2 + a_6 \varepsilon^2 + a_7 TP + a_8 T\varepsilon + a_9 P\varepsilon$$
$$E = b_0 + b_1 T + b_2 P + b_3 \varepsilon + b_4 T^2 + b_5 P^2 + b_6 \varepsilon^2 + b_7 TP + b_8 T\varepsilon + b_9 P\varepsilon$$

where a0-a9 and b0-b9 are regression coefficients. After the model is established, the optimal parameter combination can be searched under constraints such as yield strength, thickness deviation, rolling-force upper limit and energy-consumption upper limit. It should be emphasized that response surface models have reliable interpretability only within the parameter range covered by the experimental design. If the model is used beyond this boundary, experiments should be repeated or online correction should be introduced.

3.2 Genetic Algorithm and Data-mechanism Hybrid Model

A genetic algorithm is a global optimization algorithm that simulates biological evolution and iteratively seeks the optimal solution through selection, crossover and mutation. It is suitable for scenarios with multiple parameter dimensions and complex constraints. In rolling-process optimization, implementation first requires the definition of parameter encoding and the objective function. For example, in a five-stand tandem cold-rolling line, the genetic algorithm can be used to optimize the distribution of reduction ratio among the stands, with the objective function defined as:

$$F = w1 \times \sigma_s^{std} + w2 \times E$$

where σ_s^{std} is the standard deviation of yield strength, reflecting quality stability; E is unit rolling energy consumption; and w1 and w2 are weighting coefficients determined according to enterprise requirements. After 50 generations of iteration, the optimized scheme produces a more reasonable distribution of reduction ratio among stands, reduces strip thickness deviation from ±0.08 mm to ±0.05 mm, and improves stand-load balance by 15%, thereby avoiding overload of a single stand. This objective function prevents the optimization from focusing only on a single energy-consumption indicator while neglecting quality fluctuation and equipment load. Machine-learning and mechanistic-model-fused shape-control systems have been applied to hot-strip shape prediction and actuator-parameter optimization, providing a feasible route for online control under complex operating conditions [8].

The cooling schedule is also an important component of hot-rolling parameter optimization. For low-alloy hot-rolled strip, gray correlation analysis has been used to optimize grain size and residual stress simultaneously, demonstrating that multi-objective evaluation can better coordinate microstructure and internal-stress control [9]. In addition, deep-learning methods such as stochastic configuration networks have been used to predict the crown of hot-rolled non-oriented silicon steel, providing new soft-sensing tools for strip-shape control [10].

3.3 Comparison of Optimization Methods

Different optimization methods have distinct application boundaries. Response surface methodology is suitable for small-sample and interpretable experimental optimization; genetic algorithms are suitable for multi-parameter global search; and BP neural networks and their improved hybrid models are suitable for large-sample, strongly nonlinear and online prediction scenarios. Table 2 compares the three types of methods.

Table 2: Comparison of Rolling-process Parameter Optimization Methods.

Optimization method	Applicable scenario	Main advantage	Limitation	Data requirement
Response surface methodology (RSM)	Process experiments with relatively low parameter dimension and clear interactions	Strong interpretability; convenient identification of interaction terms	Difficult to cover strong nonlinearity and dynamic disturbances	30-50 designed experiments or stable production datasets
Genetic algorithm (GA)	Rolling-schedule planning with multiple parameters and constraints	Strong global-search capability; able to handle complex constraints	Convergence speed is affected by encoding, weights and population size	100-200 production or simulation datasets
BP neural network and hybrid models	Dynamic conditions, online prediction and control compensation	Suitable for nonlinear mapping and can be coupled with mechanistic models	Dependent on sample quality; interpretability needs to be improved	More than 500 high-quality industrial samples

In engineering applications, it is generally inappropriate to rely on a single model. A more robust route is to first use mechanistic models to define the safe operating boundaries, then use response surface methodology or orthogonal experiments to identify the main interaction terms, and finally apply genetic algorithms, artificial bee colony algorithms or neural networks for global optimization and online correction. Studies on multi-pass hot rolling have shown that combining regression models with swarm-intelligence optimization algorithms can improve the distribution of rolling force across passes and enhance both product quality and energy efficiency [11].

4. Engineering Application Case of Rolling-Process Parameter Optimization

To verify the engineering feasibility of the optimization strategy, a field application analysis was carried out for a representative condition in which Q235B hot-rolled strip was produced on a 1780 mm hot continuous rolling line in a steel enterprise. The target product thickness was 6 mm and the width was 1250 mm. Before optimization, the line exhibited relatively large fluctuations in yield strength, high load on the finishing mill and high unit rolling energy consumption. This section evaluates the parameter-optimization procedure and its application effect through statistical comparison of production data before and after optimization.

4.1 Process Status Before Optimization

The field operating conditions revealed three main issues in the original process. First, the furnace exit temperature was set at 1180 °C, but the actual fluctuation reached ±30 °C. Some billets entered the roughing zone at relatively low temperature, which increased deformation resistance and required additional rolling-force compensation. Second, the reduction ratio in the roughing stage was low, so breakup of as-cast grains and microstructural homogenization were insufficient; the finishing stage consequently had to undertake a larger reduction, leading to a high load on the downstream stands. Third, the finishing-entry speed was set at 3.8 m/s but was not adaptively corrected according to temperature fluctuations. When the temperature was low, high-speed rolling intensified the temperature drop and made the transformation during post-finishing cooling more heterogeneous.

4.2 Design and Implementation of the Optimization Scheme

The optimization scheme adopted a combined strategy of response surface methodology and genetic algorithm. The key variables and their ranges were first defined as follows: furnace exit temperature T of 1150-1200 °C, roughing reduction ratio r1 of 35%-45%, finishing reduction ratio r2 of 15%-25%, and finishing speed v of 3.5-4.2 m/s. The constraints were set as a yield strength of 235-255 MPa, a thickness deviation not exceeding ±0.10 mm, unit rolling energy consumption not higher than 68 kWh/t, and rolling forces at each stand not exceeding the allowable equipment load.

A central composite experimental design was then used to construct 30 process combinations, and response surface models for yield strength and energy consumption were fitted. The coefficients of determination R^2 of the yield-strength model and the energy-consumption model were 0.92 and 0.89, respectively, indicating that the models met the needs of preliminary optimization. Finally, with the minimization of yield-strength standard deviation and unit energy consumption as objectives, the genetic algorithm obtained the following parameter combination: T = 1170 °C (fluctuation controlled within ±15 °C), r1 = 40%, r2 = 20%, and v = 3.9 m/s. Considering fluctuations in billet composition and entry temperature, the furnace exit temperature can be fine-tuned to 1175 °C to improve process stability.

4.3 Optimization Effect

After the optimized parameters were applied to the field process, product-property stability, strip-shape quality, production rhythm and energy consumption all showed improvement. The detailed results are listed in Table 3.

Table 3: Comparison of Main Process Indicators Before and After Optimization in Field Application.

Indicator	Before optimization	After optimization	Change
Standard deviation of yield strength	18.0 MPa	15.8 MPa	Decreased by 12.2%
Qualified-product rate	94.5%	98.2%	Increased by 3.7 percentage points
Strip-shape defect rate	3.8%	1.5%	Decreased by 2.3 percentage points
Rolling pace	3.2 pieces/min	3.5 pieces/min	Increased by 9.4%
Unit rolling energy consumption	72 kWh/t	66 kWh/t	Decreased by 8.3%

The field statistics show that, after optimization, the standard deviation of yield strength decreased by 12.2%, the qualified-product rate increased to 98.2%, and the strip-shape defect rate fell to 1.5%. Meanwhile, unit rolling energy consumption decreased from 72 kWh/t to 66 kWh/t. These results indicate that incorporating temperature, reduction ratio, speed and equipment load into a unified optimization framework is more conducive to achieving quality stability and energy saving than adjusting any single parameter independently.

5. Conclusions

Optimization of rolling-process parameters should be based on a comprehensive analysis of metal plastic deformation, thermo-mechanical coupling and equipment constraints. Rolling temperature affects deformation resistance and microstructural evolution; rolling force determines thickness control and equipment load; rolling speed alters the temperature field and dynamic response; and reduction ratio governs strain accumulation and work-hardening level. Isolated adjustment of any single parameter may introduce new quality or equipment risks.

Response surface methodology is suitable for small-sample experiments and identification of interaction terms; genetic algorithms are suitable for global optimization under multiple parameters and constraints; and data-mechanism hybrid models are suitable for online prediction and dynamic correction. The engineering case demonstrates that, in the production of Q235B hot-rolled strip, coupled multi-parameter optimization can reduce yield-strength fluctuation and unit rolling energy consumption while increasing the qualified-product rate and production rhythm. Future work may further introduce variables such as roll wear, cooling-water flow rate, strip-shape feedback, tension fluctuation and compositional fluctuation. For skin-pass rolling or terminal cold-rolling control, closed-loop optimization strategies based on MPC and LSTM-Transformer models may also be adopted to improve real-time control capability under complex dynamic conditions[12].

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