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Reduce Product Surface Quality Risks by Adjusting Processing Sequence: A Hot Rolling Scheduling Method

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Abstract: The hot rolled strip is a basic industrial product whose surface quality is of utmost importance. The condition of hot rolling work rolls that have been worn for a long time is the key factor. However, the traditional scheduling method controls risks to the surface quality by setting fixed rolling length limits and penalty scores, ignoring the wear condition differences caused by various products. This paper addresses this limitation by reconstructing a hot rolling-scheduling model, after developing a model for pre-assessment of the risk to surface quality based on the Weibull failure function, the deformation resistance formula, and real production data from a rolling plant. Additionally, Ant Colony Optimization (referred to as ACO) is employed to implement the scheduling model. The simulation results of the experiments demonstrate that, compared to the original scheduling method, the proposed one significantly reduces the cumulative risk of surface defects on products. This highlights the efficacy of the proposed method in improving scheduling decisions and surface quality of hot rolled strips.

Keywords: product surface quality; hot rolling process; scheduling; Weibull distribution; hot rolled strip



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1. Introduction

With the advancement of industrial technology and heightened market demands, elevated expectations have been placed on the surface quality of hot rolled strip steel. This requirement is particularly pronounced in aerospace, aviation, shipping, bridges, automotive manufacturing, and household appliances. The reason behind this phenomenon is that severe surface defects can lead to reduced product lifespan, durability, and reliability, potentially resulting in operational failures, fractures, or various safety hazards during usage [1]. Furthermore, such defects may necessitate production process adjustments or even shutdown and equipment replacement, thereby imposing substantial risks on production operations [2]. Consequently, there exists an urgent imperative for research focused on safeguarding the surface quality of hot rolled strip steel.

Theoretical research and practical experience have revealed that roll wear is a primary cause of product surface defects. Roll wear results from the combined effects of production factors such as rolling temperature, material properties, and rolling sequence during the rolling process. However, the underlying mechanism is intricate and challenging to elucidate, and there exists no definitive analytical formula to describe this relationship. Under identical process parameters and production tasks, varying degrees of roll wear can lead to differing surface quality outcomes. Consequently, surface quality is predominantly assessed post-rolling through subsequent inspections [3]. Due to this complexity, most models for hot rolling scheduling heavily rely on production trials and scheduling expertise to ensure product quality. On one hand, these models impose constraints artificially, such as limiting

the maximum rolling length or position of the rolled product in the scheduling sequence [4]. On the other hand, they minimize penalty scores as scheduling objectives to ensure that constraint violations remain within acceptable bounds [5]. For instance, setting a maximum rolling length about 100 km for a rolling unit, and scheduling high-quality products to be rolled within the first 30 km to 40 km of the primary rolling material [6]. Could scheduling schemes exceeding the setting rolling length produce products of acceptable quality? Could schedules with more constraint violations also meet quality requirements? Evidently, the traditional scheduling models face significant limitations in answering these questions. The fixed constraint parameters and subjective penalty score definitions lack the necessary precision to establish a comprehensive understanding of the intricate relationship between surface quality defects and the roll's wear processing. As a result, these models are unable to proactively minimize quality risks from a production task optimization perspective prior to rolling. Once surface quality defects exceed the customer's requirement, products can only be downgraded or remanufactured.

Could we unify various influencing factors during the rolling process into standardized rolling length to further explore the patterns governing surface defect risk occurrence during planning and scheduling before hot rolling? The advancement of intelligent manufacturing and big data platforms paves the way for data-driven methods to characterize the mapping relationship between surface quality risks and influencing factors in hot rolled strip steel. This might address the shortcomings of traditional scheduling models and mitigate the risk of surface defects by evaluating surface quality risk of products in advance, to reduce quality risk. With this notion, we have reconstructed the hot rolling scheduling model using rolling equivalent kilometers and the Weibull failure function [7], aiming to reduce the risk of surface defects as well as overcome the reliance on empirical constraint parameters and penalty values in traditional scheduling models, which could provide a reference for the digitized and intelligent transformation of steel production controlling, planning, scheduling and optimizing [8].

2. Theoretical Foundation

2.1. Hot Rolling Process

The hot rolling process is illustrated in Figure 1, with typically 5 to 7 sets of work rolls and supporting rolls in the finishing mill. When work roll wear reaches a certain level, roll changing is necessary to prevent the failure of product quality from customer specifications. Generally, steel plants often define a critical rolling length for products; rolling will be continued within the length until work roll changes. Supporting rolls have a longer lifespan, requiring changing operation every 15 to 20 days. The slab sequence rolled between two consecutive work roll changes is termed a rolling unit. Different rolling sequences result in different roll wear condition. To minimize roll wear for better quality, the slab sequence is arranged according to a specific profile, as depicted in Figure 2.

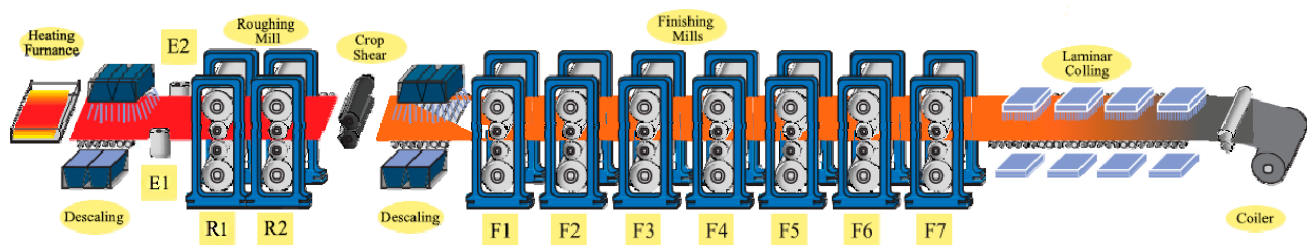


Figure 1. Hot rolling process.

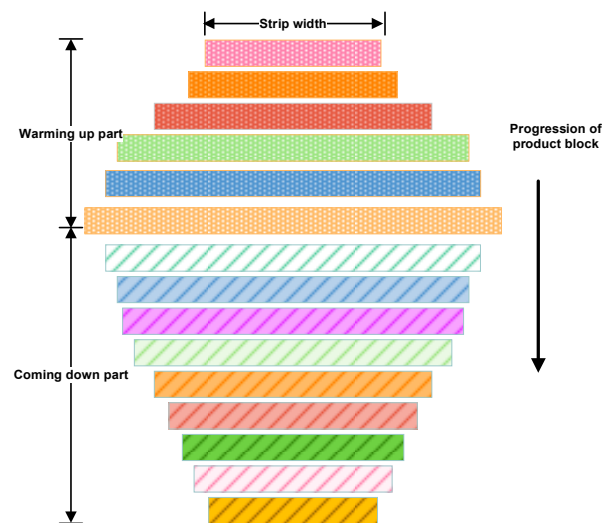


Figure 2. Specific profile for hot rolling.

As shown in Figure 2, where different colors and patterns represent different strips, the rolling unit consists of a warming up and a coming down part: a few general slabs for warming up should be rolled at first to heat up the rolls. Then the part which changes from wider to narrow for coming down should be rolled into higher-quality main rolled products [9]. For better surface quality, hot rolling plants often impose process constraints by regulating the rolling positions of the rolled strip in the scheduling sequence. Typically, with the hot rolling process progressing, the wear on the work rolls becomes increasingly severe, leading to more surface defects in the products. Therefore, hot rolling mills prioritize scheduling products with higher surface quality requirements before those with lower requirements. This is achieved by restricting the rolling positions and lengths of the products in the rolling plan. For example, products with a surface quality grade of grade I are rolled at the first 30~40 km of the coming down part. Other rolling length limits are set as illustrated in Table 1.

Table 1. Traditional rolling length restrictions for different surface levels.

Surface Quality Grade	Maximum Length for Rolling Position (km)
I	30~40
II	60~80
III	Not exceed total length limit of rolling unit

Table 1 specifies the positional ranges in the actual accumulated rolling lengths for strip products with different surface quality requirements, where higher surface quality grades indicate higher processing demands. Special limitations on rolling position and specific profile make its scheduling problem different from others. To ensure the feasibility of scheduling program and the stability of product quality, it usually needs to set up special constraints in scheduling model.

2.2. Hot Rolling Scheduling Model

Due to the complexity of special constraints, parameters for the hot rolling scheduling model heavily rely on production trials and scheduling expertise. On one hand, these models impose constraints artificially such as limiting the critical rolling length or position of products in the scheduling sequence like Table 1. On the other hand, they minimize penalty scores as objective functions to ensure constraint violations remain within acceptable bounds. Processing time constraints for guaranteed delivery, rolling location limitations as well as other process constraints are shown below:

Constraints of time window for rolled strip are given by:

$$T_1 \leq T_{start} + T_{i-1 \rightarrow i}^{Trans} + \sum_{k=1}^M \sum_{i=1}^n T_i y_{ik} \leq T_2 \quad (1)$$

Equation (1) signifies the time window constraint, which mandates that each slab must be rolled within the specified time range. $[T_1, T_2]$ signifies that the rolling of the slab i should not start earlier than T_1 and should not finish later than T_2 . T_{start} represents the scheduled start time, $T_{i-1 \rightarrow i}^{Trans}$ denotes the transfer time between slab $i - 1$ and slab i , and T_i signifies the rolling time for slab i .

Constraints to ensure that rolls can operate normally are given by Equations (2) and (3).

$$\sum_{j=1}^n Z_{ijk} l_j \leq W_{same} \quad (2)$$

Equation (2) represents the technological constraint for continuous rolling of products in similar width series, aimed at preventing damage to the work rolls caused by the continuous rolling of slabs with the same product width during the manufacturing process.

$$Z_{ijk} = \begin{cases} 1 & \text{adjacent products } i, j \text{ in the same unit are in similar width series} \\ 0 & \text{otherwise} \end{cases}$$

l_j represents the rolling length of product j , and W_{same} denotes the maximum rolling length for continuous rolling of products in similar width series.

$$\sum_{i=1}^n y_{ik} l_i < Q_k \quad (3)$$

Equation (3) represents the constraint on rolling length, preventing roll wear condition exceeding the permissible degree. $y_{ik} = \begin{cases} 1 & \text{rolling unit } k \text{ includes product } i \\ 0 & \text{otherwise} \end{cases}$. and Q_k represents the maximum rolling length of the main rolled products in rolling unit k .

Maximum allowable jump amount of width, thickness, and hardness between adjacent products in rolling sequence are given by Equations (4)–(6).

$$-W_{up} \leq W_{x_i} - W_{x_{i+1}} \leq W_{down} \quad (4)$$

Equation (4) indicates the hard constraint of width jump amount, which enforces certain limitations on width jumps between the two continuous rolling products. W_{x_i} represents the rolling width of the product x_i and $W_{x_{i+1}}$ represents the rolling width of the product x_{i+1} ; W_{down} signifies the lower limit of width jump amount between adjacent products in the same rolling unit, and W_{up} signifies the upper limit.

$$-H_{up} \leq H_{x_i} - H_{x_{i+1}} \leq H_{down} \quad (5)$$

Equation (5) denotes the hard constraint of thickness jump amount which enforces certain limitations on the thickness jumps between the two continuous rolling products. H_{x_i} represents the rolling thickness of the product x_i and $H_{x_{i+1}}$ represents the rolling thickness of the product x_{i+1} ; H_{down} signifies the lower limit of the thickness jump amount between adjacent products in the same rolling unit, and H_{up} signifies the upper limit.

$$-G_{up} \leq G_{x_i} - G_{x_{i+1}} \leq G_{down} \quad (6)$$

Equation (6) indicates the hard constraint of hardness jump amount, imposing certain restrictions on the hardness jumps between the two continuous rolling products. G_{x_i} denotes the rolling hardness of the product x_i and $G_{x_{i+1}}$ denotes the rolling hardness of

the product x_{i+1} , G_{down} represents the lower limit of the hardness jump amount between adjacent products in the same rolling unit, and G_{up} signifies the upper limit.

For solutions that violate constraints and length limits, different penalty scores are set based on the differences in the specifications that violate width, thickness, or hardness, or exceed rolling length limits. This type of traditional scheduling model is often applied in past single-variety mass production modes where the optimization objective is to minimize the total penalty of scheduling sequence. However, in current multi-variety production modes, different specifications, hardness levels, and quality objectives of products within a rolling unit result in varying degrees of roll wear.

Hence, using fixed parameters of rolling kilometer and penalty scores as constraints in the hot rolling scheduling model becomes less feasible. To address this limitation, we propose converting actual rolling lengths based on incorporating the deformation resistance formula and the Weibull failure function to characterize roll wear under different conditions. This approach could not only accommodate diverse materials and dynamically changing conditions but also further capture the evolving patterns of quality risk within the scheduling model.

2.3. Deformation Resistance

Under elevated temperatures, the electro-mechanical control system controls rolling forces of rolls, causing slab deformation. Simultaneously, the rolls experience wear due to the deformation resistance from the slab. Deformation resistance is the force required in per unit area for plastic deformation of a metal material under stress conditions [10], for which the study holds significant guidance for subjects such as developing rolling processes, formulating process systems, and developing new steel grades [11]. Its formula is the fundamental stone of rolling force models whose magnitude is influenced by internal factors such as chemical composition, microstructure, and grain size of product, as well as external factors like rolling temperature, rolling speed, and property jump amount of adjacent rolling piece arranged in the same rolling unit [12], given by Equation (7).

The formula [13] for deformation resistance is as follows:

$$\sigma = \sigma_0 \exp(a_1 T + a_2) \left(\frac{u}{10}\right)^{(a_3 T + a_4)} \left[a_6 \left(\frac{\gamma}{0.4}\right)^{a_5} - (a_6 - 1) \frac{\gamma}{0.4} \right] \quad (7)$$

where T represents the thermodynamic temperature, and $T = \frac{t+273}{1000}$. t is deformation temperature. σ_0 is the basic deformation resistance, under the condition where $t = 1000$ °C, $u = 10\text{s}^{-1}$, $\gamma = 0.4$. u is deformation velocity, and $a_1 \sim a_6$ are the model regression coefficients related to the steel grade. γ represents the extent of true deformation in the material, $\gamma = \ln \frac{h_0}{h_1}$, where h_0 and h_1 are the entrance and exit thicknesses of the strip. The degree of deformation can be considered as a measure of the change in steel thickness, which means the greater the variation in steel thickness, the higher the deformation resistance.

During rolling, speed is consistent within the same rolling unit. Hence, it can be inferred that slab attributes like steel grade, width, thickness, and temperature are the primary factors affecting deformation resistance, which are also the main factors contributing to roll wear. Ultimately, these factors influence surface quality via work rolls as rolling length accumulates. This paper utilizes the Sims rolling force formula [14] and the theoretical framework of hot rolled steel materials proposed by Zhou [13] as the theoretical foundation for analyzing roll wear and calculating rolling equivalent kilometers. This choice aims to standardize the measurement of various factors' impact on roll wear.

2.4. Weibull Distribution

With the advancements in sensing and data-storage technologies, collecting data from operating equipment and applying data science techniques have become effective means to study complex system [15]. Weibull distribution is widely used in life prediction, inspection, and reliability analysis due to its probabilistic nature. It plays a significant role in the analysis of cumulative wear-related failures in electromechanical equipment [16].

Weibull regression models exist in two forms, the Proportional Hazard Model (WPHM) and the Accelerated Failure Time Model (AFTM), which differ mainly in whether co-variables are introduced [17]. WPHM is a statistical regression model proposed by the British statistician D.R. Cox. Qiu et al. [18] proposed an integrated Remaining Useful Life prediction model combining GA, SVR, and WPHM, whose effectiveness was validated through bearing experiments. Zhang et al. [19] introduced a Mixed Weibull Proportional Hazard Model (MWPHM) to predict the failure time of mechanical systems with multiple failure modes. In comparison to traditional WPHM, MWPHM demonstrated superior system failure-prediction ability in experiments involving high-pressure water descaling pumps. Regarding AFTM, the team led by Yi-Chao Yin [20] presented a power-Weibull model based on imprecise probability statistical methods for accelerated life testing, which predicted random failure times tested under normal conditions. The process from roll changing to subsequent wear can be viewed as a reliability-decreasing failure process for the study of eventual impact on product quality. Weibull distribution, which is a holistic distribution, is well suited to consider the overall wear condition of rolling mill rolls from the perspective of product surface defects in the rolling unit. Therefore, we choose to use the two-parameter Weibull distribution to describe this evolutionary process. The following are the two main functions of the Weibull distribution.

$$f(t; \gamma, k) = \begin{cases} \frac{k}{\gamma} \left(\frac{t}{\gamma}\right)^{k-1} e^{-\left(\frac{t}{\gamma}\right)^k} & t \geq 0 \\ 0 & t < 0 \end{cases} \quad (8)$$

$$(t) = 1 - F(t) = \exp\left(-\left(\frac{t}{\gamma}\right)^k\right) \quad (9)$$

Equation (8) is the probability density function of the two-parameter Weibull distribution, and Equation (9) is the reliability function for the two-parameter Weibull distribution, where $k > 0$ denotes the trend of the function and $\gamma > 0$, which indicates a scaling of the function that does not affect the shape of the distribution.

3. Methodology

We aim to consider dynamic roll wear conditions in the scheduling model by characterization of the variation patterns of product surface quality as rolling length accumulates by evaluating the surface quality risk of products before rolling. Ultimately, the scheduling model with the objective of minimizing surface quality risk can be reconstructed.

Based on the above idea, we divided the technical approach into 5 steps as illustrated in Figure 3. Firstly, we collected data from product surface inspection, equipment condition, rolling plans, roll changing schedules, and production records. Secondly, we converted the influence of different factors on roll wear based on a deformation-resistance formula, thereby standardizing the actual accumulated rolling length into rolling equivalent kilometers. Thirdly, we analyzed product surface defect data and classified product quality level according to cumulative risk of surface defects. Then we created a pre-assessment risk model of products' surface quality based on the Weibull regression model, fitting risk curves for defect occurrence under varying roll wear conditions to evaluate the surface quality in advance. Finally, based on the product quality risk model, we constructed a hot rolling scheduling model with the objective of minimizing the cumulative risk of product defects to optimize the rolling plan. We employed ACO to optimize scheduling schemes with the lowest quality risk. Under this research framework, quality risks could be dynamically updated with roll wear conditions and environmental conditions by rolling data updating during production, further guiding scheduling optimization.

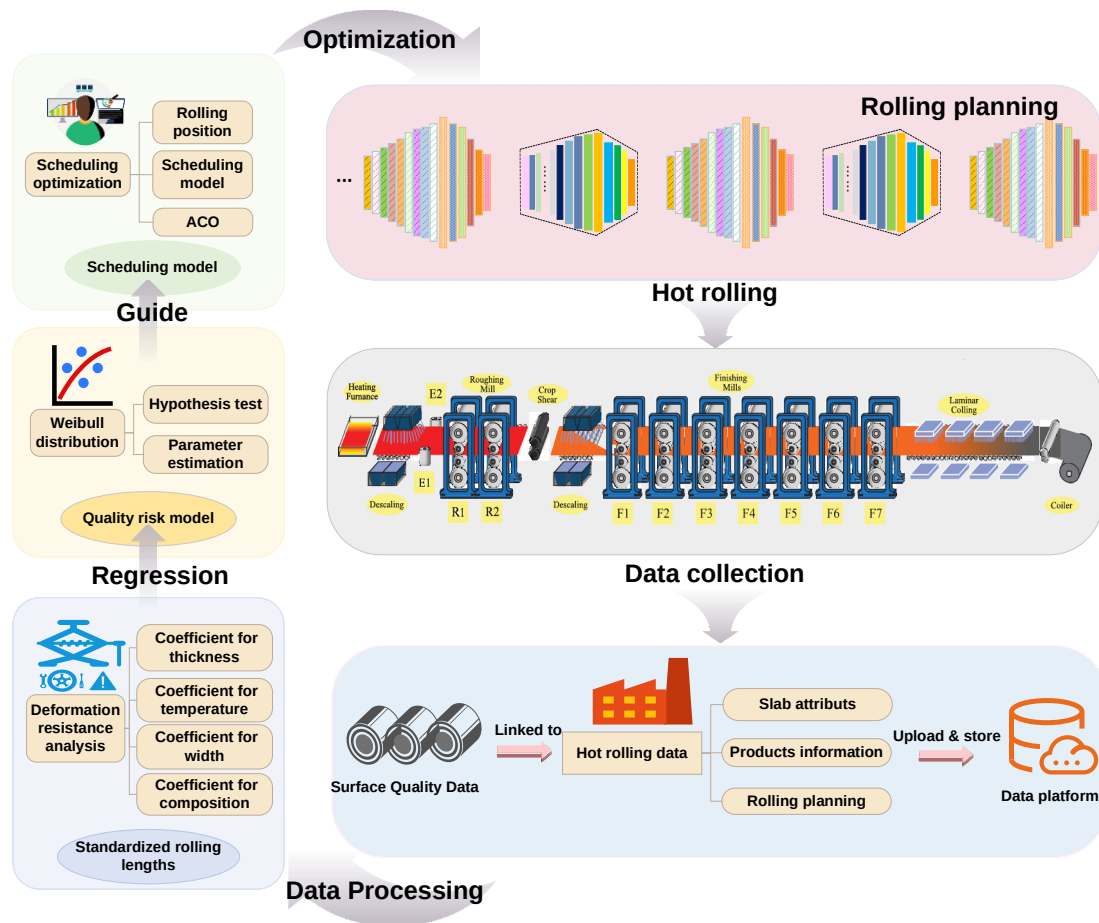


Figure 3. Research approach applied Weibull distribution analysis.

3.1. Rolling Length Standardization

Just like how cars need maintenance and servicing after a specified mileage [21], rolling mill rolls need to be managed by replacing and maintaining them once they wear to a certain extent. To uniformly assess the impact of various factors on roll wear, we opt for the deformation-resistance formula as the basis for converting into rolling equivalent kilometers. This enables the conversion of actual accumulated rolling lengths under different steel compositions, rolling temperatures, thicknesses, and widths into a unified variable, which ensures a better representation of surface quality risk in constructing the hot rolling scheduling model. According to Section 2.2, the calculation of rolling equivalent kilometers incorporates four influencing factors: rolling temperature, strip width, strip thickness, and rolling hardness. We designed the formula for calculating rolling equivalent kilometers in this study as $L^s = \nabla * L$, where L denotes the actual rolling kilometers, L^s represents equivalent kilometers, and ∇ signifies the equivalent coefficient.

In correspondence with the four influencing factors, Equation (10) is derived.

$$L^s = \nabla_1 * \nabla_2 * \nabla_3 * \nabla_4 * L \quad (10)$$

In Equation (10), ∇_1 represents the thickness equivalent coefficient, ∇_2 represents the temperature equivalent coefficient, and ∇_3 represents the width equivalent coefficient. For the factor of rolling hardness, we apply the carbon equivalent theory to calculate the equivalent coefficient ∇_4 , so ∇_4 represents the steel composition equivalent coefficient. We

employ the carbon equivalent formulas specified by Japanese JIS and WES standards as the basis for calculating the steel composition equivalent coefficient.

$$Ceq(JIS) = C + \frac{Mn}{6} + \frac{Si}{24} + \frac{Ni}{40} + \frac{Cr}{5} + \frac{Mo}{4} + \frac{V}{14} \quad (11)$$

In Equation (11), Mn , Cr , Mo , V , Ni , Cu , and Si , respectively, represent the compositional proportions of alloying elements manganese, chromium, molybdenum, vanadium, nickel, copper, and silicon, respectively.

3.2. Pre-Assessment Risk Model of Products' Surface Quality

The Weibull reliability curve is utilized to fit the curve of product quality changing with the increase of rolling equivalent kilometers, which is called the risk model as depicted in Figure 4. In Figure 4, the vertical axis represents roll reliability, which is equivalent to 1 minus the risk value. We converted the actual rolling lengths into a uniform dimension and defined rolling equivalent length for different risk levels $P(I)$, $P(II)$ and $P(III)$, which correspond to the rolling equivalent kilometers for each risk level $L(I)$, $L(II)$, and $L(III)$, where is shown in indifferent color in Figure 4.

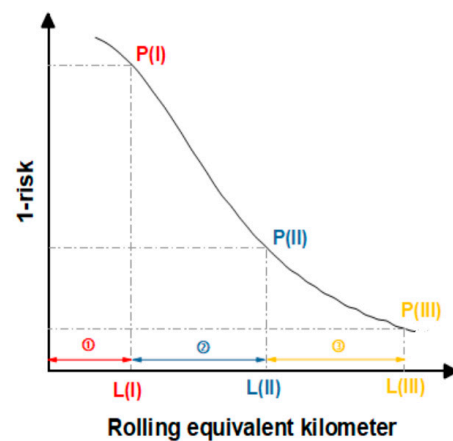


Figure 4. Curve between product quality risk and rolling equivalent kilometer.

In view of the changes in working conditions brought about by the changes in rolled products, we incorporate environmental factors as covariates into the Weibull distribution regression analysis as the pre-assessment risk model of product surface quality. The reason is that different operating environments (such as temperature, humidity, pressure, and other elements) or variations in processes and materials can influence the lifecycle of equipment. Therefore, it is necessary to analyze heterogeneous data from the environment and estimate these influences on a unified basis. We improved the probability density function of the two-parameter Weibull distribution in Section 2.3 as follows:

$$f(t, x; \gamma, k) = \begin{cases} \frac{k}{\exp(\sum_{i=1}^k \beta_i X_i)} \left(\frac{t}{\exp(\sum_{i=1}^k \beta_i X_i)} \right)^{k-1} e^{-\left(\frac{t}{\exp(\sum_{i=1}^k \beta_i X_i)} \right)^k} & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (12)$$

The parameters mentioned above are calculated using the maximum likelihood estimation with the Gauss–Newton estimation. Firstly, a hypothesis test is conducted to confirm the curve conforms to Weibull distribution. Subsequently, the Weibull distribution curves are fitted for each group of roll wear conditions, resulting in a pre-assessment risk model of product surface quality corresponding to roll wear condition.

3.3. Scheduling Model Description

On the basis of the Weibull reliability distribution, we have developed a hot rolling scheduling model that takes products' surface quality risk into account. On the one hand, the model aims to minimize the cumulative surface quality risk as the objective function, and on the other hand, the model constrains the rolling positions in rolling sequence for different surface grade demands. The proposed model retains hard constraints that must be adhered to in the process specifications to ensure the feasibility of the scheduling scheme, such as the maximum upper limit of rolling length, time window constraints for rolling, maximum limits on jump amount of width, thickness, and hardness between adjacent strips of the same rolling unit as Equations (1)–(6). The rest of the mathematical model is as follows.

Objective function

$$\text{Min} \sum_{k=1}^M \sum_{i=1}^n \sum_{j=1}^n q_{ij} x_{ijk} \quad (13)$$

Equation (13) serves as the objective function, aiming to minimize the cumulative surface defect risk for all rolling units and their respective steel coils, where M represents the number of rolling units; k denotes the index of the rolling unit; i and j denote material indices; n is the quantity of materials; q_{ij} signifies the quality risk between steel coils i and j .

Constraints

Except for Equations (1)–(6), there are hard constraints which ensure the feasibility of the scheduling sequence, given as Equations (14)–(16).

$$\sum_{k=1}^M y_{ik} \leq 1 \quad i = 0, 1, 2, \dots, n \quad (14)$$

Equation (14) ensures product i is scheduled once in one rolling unit. $y_{ik} =$
 $\begin{cases} 1 & \text{rolling unit } k \text{ includes product } i. \\ 0 & \text{Otherwise} \end{cases}$

$$\sum_{i=1}^n x_{ijk} = \sum_{j=1}^n x_{ijk} = y_{ik} \quad i = 1, 2, \dots, n \quad j = 1, 2, \dots, n \quad (15)$$

where $x_{ijk} = \begin{cases} 1 & \text{products } i \text{ and product } j \text{ are adjacent in rolling unit } k \\ 0 & \text{otherwise} \end{cases}$. Equation (15) ensures the uniqueness of product processing.

$$y_{0k} = 1 \quad k = 1, 2, \dots, M \quad (16)$$

Equation (16) indicates that virtual product 0 must be scheduled within each rolling unit.

Equations (17)–(19) are constraints imposed in conjunction with the proposed pre-assessment risk model of surface quality.

$$\sum_{p=1}^m S_{ip} = 1 \quad p = 1, 2, \dots, m; \quad i = 1, 2, \dots, n \quad (17)$$

In Equation (17), p represents the surface quality level index, $p = 1, 2, \dots, m$;

$$S_{ip} = \begin{cases} 1 & \text{Product } i \text{ has a surface quality level } p. \\ 0 & \text{Otherwise.} \end{cases}$$

Equation (17) ensures that a strip product has only one surface grade.

Constraints imposing surface quality risk by the rolling position limitations in scheduling sequences corresponding to different surface grades are given by Equations (18) and (19).

$$R_{kp} = \exp\left(-\left(\frac{l_{kp}}{\gamma}\right)^\beta\right) \begin{cases} l_{kp} = l_{k1} & \text{If } R \geq R_{k1} \\ l_{kp} = l_{k2} & \text{If } R_{k1} < R \leq R_{k2} \\ l_{kp} = l_{k3} & \text{If } R_{k2} < R \leq R_{k3} \end{cases} \quad (18)$$

In Equation (18), l_{kp} represents the maximum rolling length corresponding to surface quality level p within rolling unit k . This equation introduces roll reliability R and dynamically incorporates the change in l_{kp} . It is dynamically changing and varies with different roll conditions. Equations (17)–(19) differ from the static parameters of previous scheduling models, which associate the roll reliability for surface quality of products and transform hot rolling kilometer limitations in dynamic constraints.

$$w_{ik1} > w_{ik2} > w_{ik3} \quad (19)$$

where w_{ikp} represents the rolling priority of steel coil i with surface grade p in rolling plan k , where $p = 1, 2, 3$. This equation indicates that coils with higher surface grades should be rolled before those with lower surface grades.

3.4. Algorithm for Solution

According to the dynamic conversion of rolling length, we have improved the pheromone in the framework of the ACO algorithm to ensure it can be more adapted to this problem. Figure 5 illustrates the execution flow of the algorithm, with the detailed steps as follows.

Step 1: Initialize population and construct path. Initialize the ant colony population. Each ant would construct a path which represents a rolling scheduling solution corresponding to a sequence of products processing. Ants select strip products as nodes in their paths, starting from the warming up part in the rolling special profile. The initial starting point of the path is randomly chosen from among pre-heated products. Other nodes' selections adhere to the principle of placing products with higher surface quality requirements ahead of those with lower requirements, and hard constraints that adjacent products satisfy are feasible, like thickness, width, and hardness jumps. The ant colony traverses all nodes to form paths according to the above rules.

Step 2: Selection of the next node. Assuming that ant k is currently at node i , the probability of selecting the next node j is determined by the following formula.

$$p_k(i, j) = \begin{cases} \frac{[\tau(i, j)]^\alpha [\mu(i, j)]^\beta}{\sum_{u \in J_k(i)} [\tau(i, u)]^\alpha [\mu(i, u)]^\beta}, & j \in J_k(i) \\ 0 & \text{others.} \end{cases} \quad (20)$$

where $J_k(i)$ refers to the set of nodes that can be directly reached from node i and that ant k has not visited yet in its path. $\mu(i, j) = 1/d_{ij}$, where d_{ij} represents the quality pre-assessment risk of arranging node j after node i . $\tau(i, j)$ represents the amount of pheromone on the edge from node i to node j , and the initial $\tau(i, j)$ of all edges are the same. α represents the importance factor of the pheromone, and β represents the importance factor of the heuristic function. α and β need to be set with initial values.

Step 3: Update local pheromone. Ants visit nodes and release pheromones on the path they pass. Path pheromones $\tau(i, j)$ update according to the pheromone left behind by all ants. The update formula is given as:

$$\tau(i, j) = (1 - \rho) * \tau(i, j) + \sum_{k=1}^m \Delta\tau_k(i, j) \quad (21)$$

$$\Delta\tau_k(i, j) = \begin{cases} 1 / (\sum_{i,j}^n (q_{ij} x_{ijk})), & (i, j) \in R^k \\ 0 & \text{Others} \end{cases} \quad (22)$$

where m represents the number of ants; ρ denotes the pheromone evaporation rate, $0 < \rho \leq 1$. During algorithm iteration, the initial ρ needs to be set; $\Delta\tau_k(i, j)$ indicates pheromones released by the ant k on the path it traverses; $1/(\sum_{i,j}^n(q_{ij}x_{ijk}))$ represents the path length, which is the reciprocal of the accumulated risk of surface defects calculated according to scheduling sequence corresponding to the path. It is negatively correlated with the sum of quality risks R^k for all products of a rolling scheduling sequence.

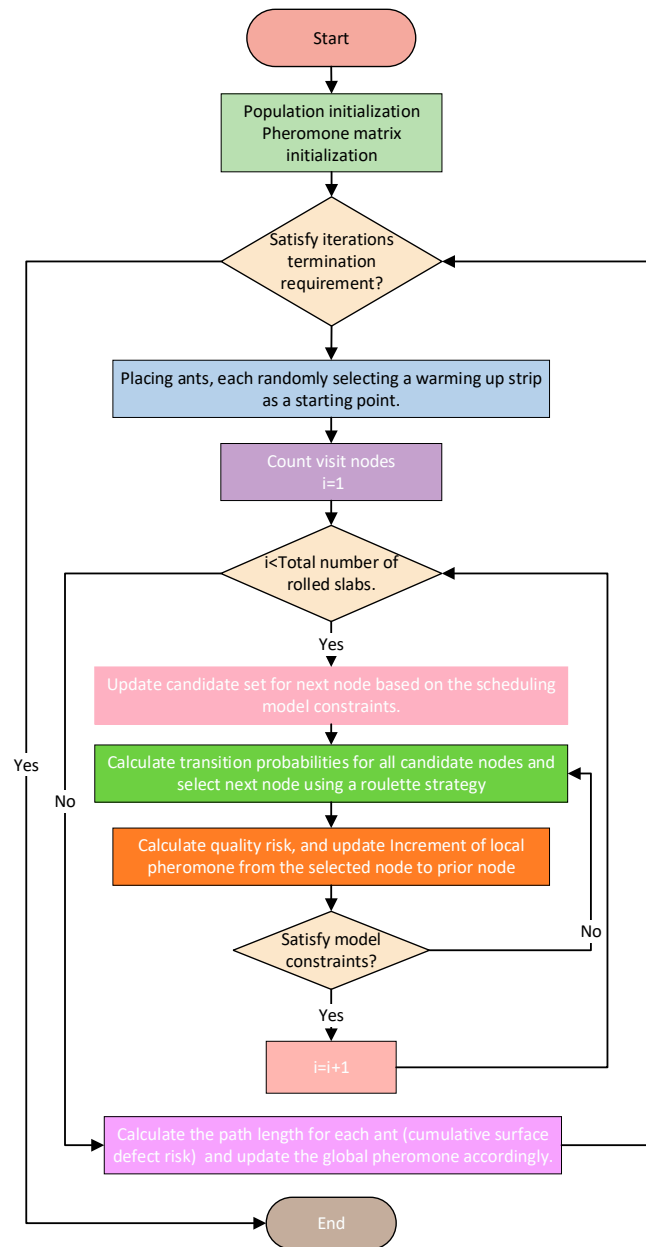


Figure 5. Flow chart of ACO.

Step 4: Update global pheromone. Upon completing a path, ants update their pheromone-associated defect risk based on its path as Equation (18). For $\Delta\tau_k(i, j)$, this is given by:

$$\Delta\tau_k(i, j) = \begin{cases} 1/(\sum_{i,j}^n(q_{ij}x_{ijk}))_{best} & (i, j) \in R^k \\ 0 & \text{Others} \end{cases} \quad (23)$$

$(\sum_{i,j}^n (q_{ij} x_{ijk}))_{best}$ refers to total surface defect risks of the best individual in the historical population.

Step 5: Repeat steps 1–4 until the iteration termination condition is satisfied.

4. Experiments

4.1. Data Preparation

The essence of the pre-assessment risk model of surface quality is to fit Weibull distribution curves for different roll wear conditions based on rolling data. Prior to this, data need to be processed, as in the following four steps. The first step involves distinguishing roll wear condition. The second step is to convert different rolling lengths in rolling units with the same wear condition into a unified dimension. The third step is to collect and record product surface defect data and define product surface quality risk. Finally, divide levels of surface quality based on statistics defect data. Finally, the method proposed in this paper is applied and compared with the original scheduling results to demonstrate the effectiveness of this method.

We collected production data from a 1780 mm hot rolling line at a steel plant over a continuous period of 30 days, primarily using a scheduling method that combines manual scheduling with a genetic algorithm, totaling 13,210 recordings. By considering roll changing times, we divided the data into 193 rolling units. Due to the various influencing factors of thickness jump, width jump, temperature, and steel composition, the wear of work rolls during the hot rolling process differs. According to the equivalent coefficient conversion in Equation (10) of Section 3.1, the deviation in work roll wear can be standardized using equivalent rolling kilometers. However, the wear of backup rolls must also be considered during rolling. Unlike the frequent replacement of work rolls, backup rolls are typically replaced every 15–20 days. To simulate the wear state within one cycle more precisely, we assume the wear state of backup rolls changes gradually over three consecutive days, dividing a 15-day cycle into five state groups. Consequently, a 30-day period includes ten different wear state groups, each representing different reliability levels. Each group, except the last one, which covers 13 rolling states, covers the hot rolling data of 20 rolling units, as illustrated in Figure 6.

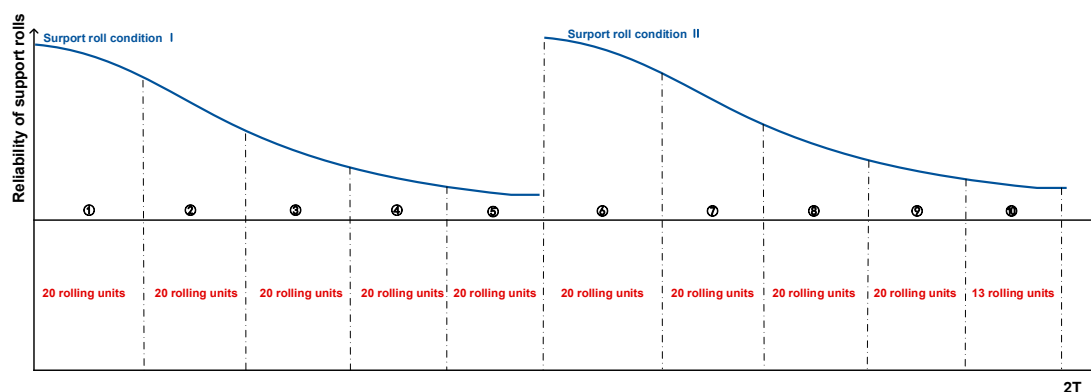


Figure 6. Data group diagram.

We believe that these rolling units within the same group are under similar roll wear conditions, forming the basis for Weibull reliability analysis.

4.2. Rolling Length Standardization

The greater the deformation resistance, the more severe the roll wear, and the higher product quality risk. Therefore, we convert rolling equivalent kilometers based on magnitude of deformation resistance for rolling length standardization. For execution, we apply the linear interpolation method to calculate the equivalent coefficient after obtaining the curve of deformation resistance. Linear interpolation refers to an interpolation method

where the interpolating function is a first-degree polynomial. The interpolation error at the interpolation nodes is zero. Geometrically, linear interpolation approximates the original function using a straight line passing through points A and B, as shown in the diagram. This method can be used to approximate the original function or to calculate values not explicitly listed in a table during lookup, as illustrated in Figure 7.

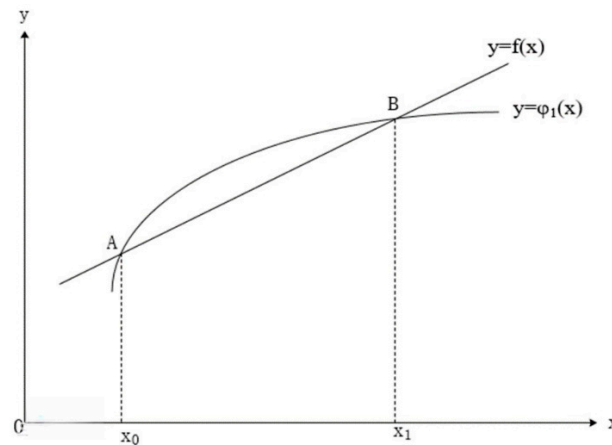


Figure 7. Linear interpolation method diagram.

For example, $(x_0, y_0), (x_1, y_1)$ represent the values at points A and B, then the equivalent coefficient for a certain factor can be calculated as follows:

$$\nabla_k = \frac{x - x_1}{x_0 - x_1} y_0 + \frac{x - x_0}{x_1 - x_0} y_1 \quad (24)$$

When the values at points A and B are known, we can find the value of y corresponding to any point x between them. Assuming the product thicknesses of 2.3 mm and 2.5 mm have equivalent coefficients of 1.3 and 1.5, respectively, the equivalent coefficient for a product thickness of 2.4 mm can be calculated as follows:

$$\varphi_1(x = 2.4 \text{ mm}) = \frac{2.4 - 2.3}{2.5 - 2.3} * 1.3 + \frac{2.4 - 2.5}{2.3 - 2.5} * 1.5 = 1.4$$

According to the equivalent kilometer conversion formula given by Equation (10) in Section 3.1, we calculate the equivalent coefficients for thickness, temperature, and width using the linear interpolation method based on the deformation resistance curves. The equivalent coefficients for the steel composition are primarily assumed based on prior knowledge.

4.2.1. Equivalent Coefficient for Thickness

According to Equation (1), assuming constant deformation temperature and deformation rate, deformation resistance varies nonlinearly with deformation degree, as shown in Figure 8a. From $\gamma = \ln \frac{1}{1-r}$, $r = \frac{h_0 - h_1}{h_0}$ in the deformation resistance formula. The compression ratio represents the change in product thickness. Therefore, if the initial slab thickness is roughly the same, a greater change in product thickness results in a higher true strain, producing thinner final products. Conversely, smaller changes in product thickness result in lower true strain, producing thicker final products. Thus, the relationship between steel product thickness and deformation resistance can be inferred: deformation resistance decreases as product thickness increases. Consequently, we transfer Figure 8a into Figure 8b and define coefficients depicting the variation in deformation resistance and strip thickness as shown in Table A1.

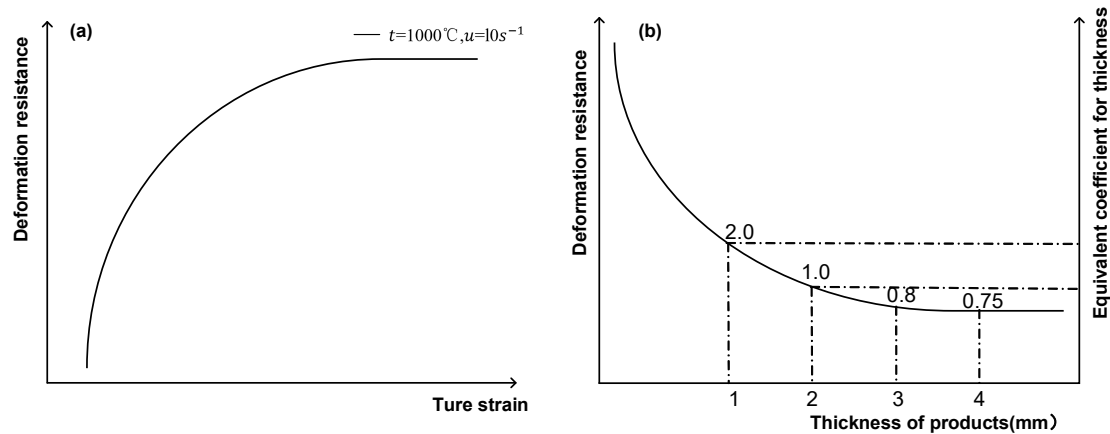


Figure 8. Curve between deformation resistance. (a) Line graph between deformation resistance and true strain; (b) Line graph of product thickness and deformation resistance.

4.2.2. Equivalent Coefficients for Temperature

When factors of deformation resistance and the parameter σ_0 are known, the deformation resistance formula can be calculated. When the strain rate $u = 10 \text{ s}^{-1}$ and strain $\gamma = 0.4$, we can calculate deformation resistance σ for different values of temperature. As the temperature increases, deformation resistance sometimes increases and sometimes decreases. For certain steel specifications, the change curves may differ slightly, depending on the internal structure of the rolled products at the time. Based on calculated deformation-resistance values, an approximate curve is plotted as shown in Figure 9. We assume the equivalent coefficients to be 1 and 1.1 at $T = 900^{\circ}\text{C}$ and $T = 1000^{\circ}\text{C}$, respectively. The linear interpolation method can calculate other coefficients, as shown in Table A2 of Appendix A.

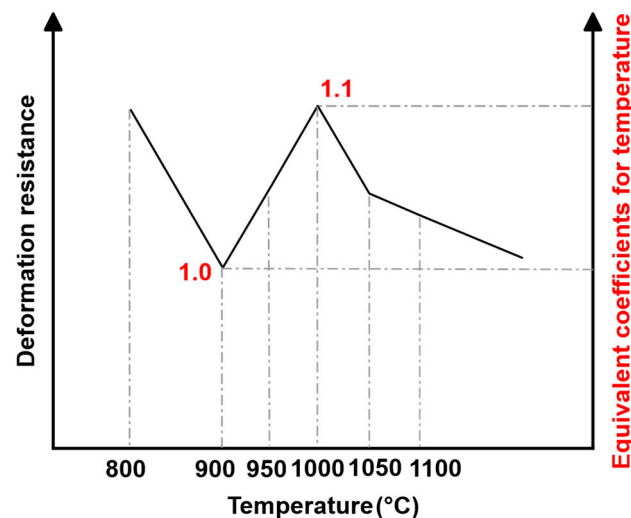


Figure 9. Line graph between deformation resistance and temperature.

4.2.3. Equivalent Coefficients for Width

According to the hot rolling mechanism, it is known that the width jump amount of the main rolled products can be categorized as increment and decrement. Typically, the positive jump falls within the range of 0 to 200 mm, while the negative jump also ranges 0–200 mm. However, due to the different impacts of positive and negative jumps on the wear of the rolls, their wear curves or equivalent coefficient variation curves exhibit an asymmetric “V” shape, as shown in Figure 10. As illustrated, under the same positive or negative width jump conditions, negative jumps often result in more significant roll wear. We assume the equivalent coefficients at the inflection points and use the interpolation

method to calculate the other equivalent coefficients. The results can be found in Table A3 of Appendix A.

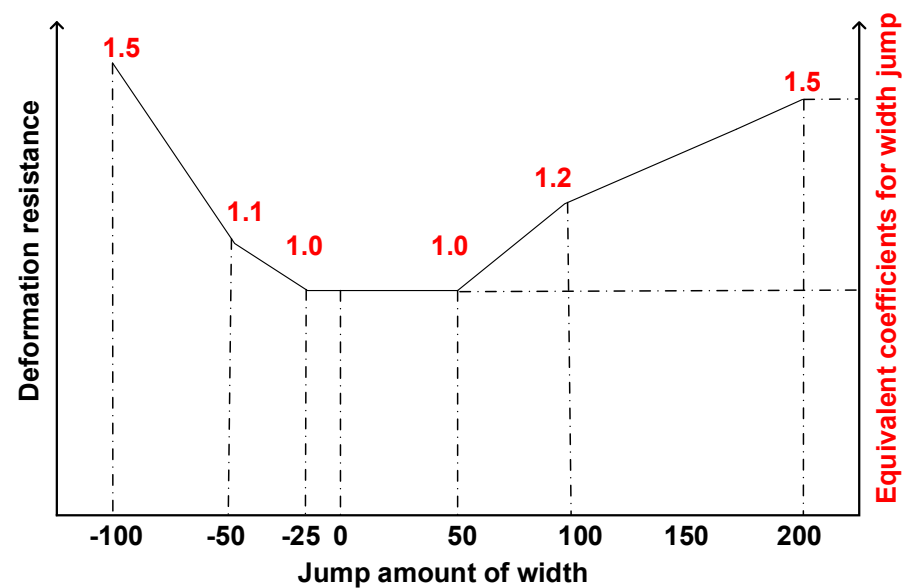


Figure 10. Line graph between deformation resistance and width jump.

4.2.4. Equivalent Coefficients for Composition

The higher the carbon equivalent, the harder the rolled strip and the greater the roll wear. Conversely, the lower the carbon equivalent, the less the roll wear. Therefore, we took 1.0 to 2.0 as a baseline and set its equivalent coefficient to 1.0. The specific settings of the four elements are as shown in Table A4.

4.3. Processing of Product Surface Defect Data

4.3.1. Surface Defect

We chose three types of defects directly related to roll wear to characterize the variation trend of surface defect risk within a rolling unit: temperature spots count, roll marks, and scratches. They are used as criteria for dividing the risk of surface defect occurrence. Figure 11 demonstrates the statistics of surface defects from the second rolling unit after the first support roll changing.

As shown in Figure 11, with the accumulated rolling length increasing, the more severe the roll wear, the lower the roll reliability, and the more product defects there are. Furthermore, it is observed that the influence degree of roll wear on these defects varies by comparing all rolling units. The correlations between defect type and roll wear from greatest to smallest are roll marks, temperature spots, and scratches. Based on the data statistics of surface defect data, we assigned weights of 0.5, 0.4, and 0.3 to the respective defects. The ratio of surface defect area size of strip to the total area is used to characterize surface defect risk for each strip, given by:

$$P = \sum_{i=1}^3 w_i \frac{S_i}{S} = p_1 w_1 + p_2 w_2 + p_3 w_3 = w_1 \frac{S_1}{S} + w_2 \frac{S_2}{S} + w_3 \frac{S_{i3}}{S} \quad (25)$$

In the equation, S_i represents the area of different types of defects, w_i represents the weights of different types of defects, and the ratio of the defect value to the steel strip area is denoted by P .

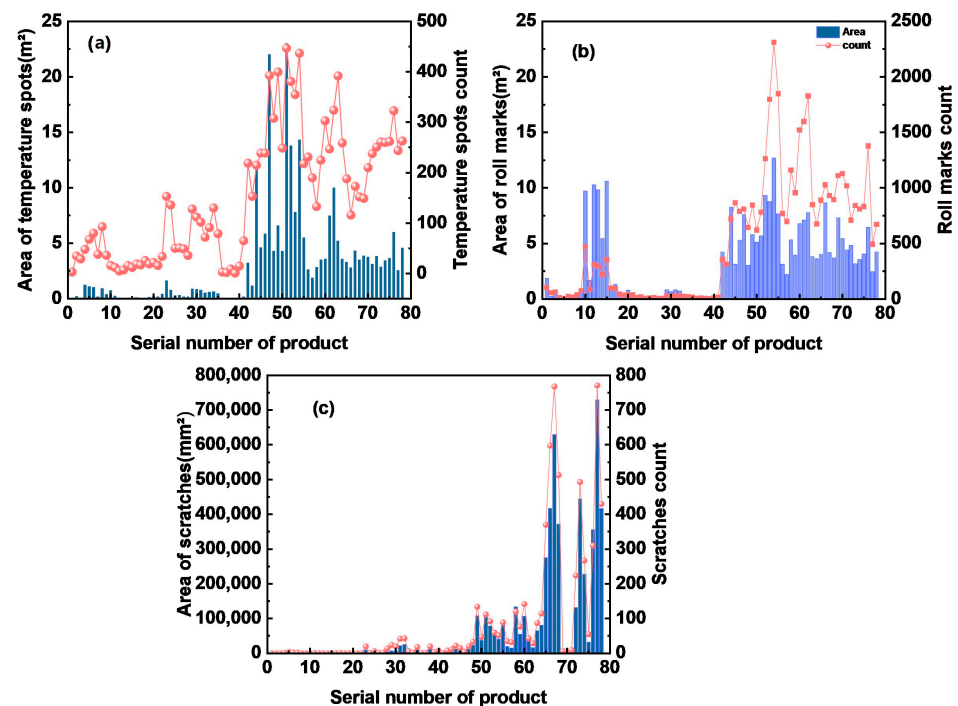


Figure 11. Statistics of strip defect quantities and areas in a specific rolling unit. (a) Temperature spots; (b) roll marks; (c) scratches.

4.3.2. Surface Defect Risk

Practical experience in hot rolling production indicates when the roll surface is in good condition, the reliability is higher and the risk of surface defects is lower; when roll surface wear is severe, the reliability is relatively low and the risk of surface defects is lower. It can be assumed that when the sample size is large enough, the defect ratio P would be considered as roll reliability and surface quality risk. We removed a small number of outliers from the defect proportion and scaled the overall defect proportion up by 100 times to define the surface defect risk R . R is divided into three levels, with reliability defined as $Q = 1 - R$, as shown in Table 2. By converting the actual defect proportions into defect risk and fitting them to the Weibull reliability curve, we can deduce the equivalent rolling kilometers for different defect scenarios under different roll wear conditions.

Table 2. Defect proportions for different surface grades and the reliability of rolls.

Surface Defect Risk	Risk Degree (R)	Defect Ratio $\times 100$	Roll Reliability (Q)
I	low	0~0.25	1~0.75
II	middle	0.25~0.6	0.75~0.4
III	high	>0.6	<0.4

In hot rolling scheduling, products with high surface quality requirements are scheduled to be rolled before those with lower requirements. Different surface quality levels correspond to different rolling length range restrictions. Length range with higher surface defect risks cannot roll products with higher quality requirements. While regions with lower defect risks can roll products with lower requirements. The relationship between rolling equivalent kilometers and the risk of defect occurrence $p_i(l_i)$, along with different grade inclusion relationships, is shown in Table 3. It signifies the position where products with higher surface quality grades can be rolled; products with lower grade quality can also be rolled.

Table 3. Inclusive relationship for rolling position among different quality grades.

Probability of Surface Defect Occurrence	Surface Quality Level of Steel Strip Allowed to Be Rolled
$P_I(l_I)$	I, II, III
$P_{II}(l_{II})$	II, III
$P_{III}(l_{III})$	III

The probability of defect occurrence $P_I(l_I)$ corresponding to surface quality level I, II, III, which means surface quality level allowed to be rolled in the position of rolling length where the probability of surface defect occurrence is $P_I(l_I)$.

5. Results and Discussion

In order to confirm that the overall distribution form of the surface defect risk data conforms to the Weibull distribution, we conducted hypothesis testing on the 10 groups of roll condition beforehand to ensure the reasonableness of the regression analysis. On this basis, the reliability functions of the 10 sets of the risk models were regressed. In addition, we discussed the introduced concept of rolling equivalent kilometers and verified whether this variable's conversion aligns with the actual hot rolling process in Sections 5.3 and 5.4.

5.1. Weibull Distribution

5.1.1. Hypothesis Testing

If it is unsure whether the roller wear data follow a Weibull distribution, we should perform a hypothesis test for the Weibull distribution. Here, the equivalent kilometers are used to represent roller failure time data. Since a roller is replaced at the end of each rolling unit, representing a complete lifecycle, equivalent kilometers can be used as an indirect measure when the lifetime is difficult to calculate. When n sets of equivalent kilometer data for the roller are known, the steps to perform the hypothesis test are as follows.

Step 1. Arrange the failure time data (here, equivalent rolling length data) in ascending order.

$$t_{(1)} < t_{(2)} < t_{(3)} < \dots < t_{(n)}$$

Step 2. Calculate $x_i, y_i, i = 1, 2, 3, \dots, n$, where

$$x_i = \ln(t_{(i)}) \quad (26)$$

$$y_i = \ln\left(-\ln\left(1 - \frac{i}{n+1}\right)\right) \quad (27)$$

The cumulative failure function of the Weibull distribution is expressed as follows. After performing an identity transformation and simplifying, we obtain:

$$F(t) = 1 - \exp\left(-\left(\frac{t}{\gamma}\right)^k\right) \quad (28)$$

That is,

$$\ln \ln\left(\frac{1}{1-F(t)}\right) = \beta \ln t - \beta \ln \gamma$$

If $x = \ln t$, $y = \ln \ln\left(\frac{1}{1-F(t)}\right)$, $B = -\beta \ln \gamma$, the above equation can be simplified to: $y = \beta x + B$.

The above equation reveals a linear relationship between x and y . When the failure data are complete, y can be calculated using y_i .

Step 3. Plot a scatter diagram of (x_i, y_i) and observe their trajectory. If the data points generally align along a straight line with a positive slope on the scatter plot, it indicates that the sample follows a Weibull distribution.

In the dataset comprising 193 rolling units, these units are divided into 10 groups, and a Weibull hypothesis test is conducted on these 10 groups of data.

Figure 12 shows the results of the hypothesis testing. After undergoing coordinate transformation for 10 roll wear condition, the data from the 10 groups of different conditions approximately align along a line with a positive slope. This alignment suggests that the data from these 10 groups conform to the Weibull distribution hypothesis testing. This also indicates that our assumption regarding the gradual change period for the backup rolls is appropriate.

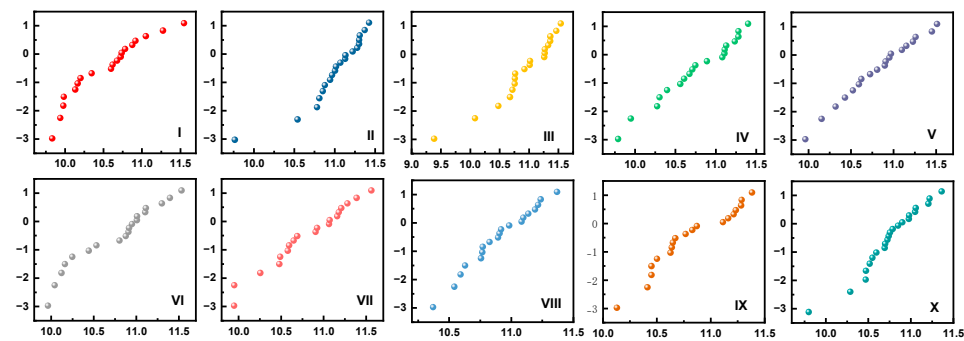


Figure 12. Hypothesis testing for Weibull distributions of roll wear conditions.

5.1.2. Parameter Estimation

A regression model (pre-assessment risk model of surface quality) with two covariates has parameters including the reciprocal of the shape parameter $\sigma = \sigma(k = \frac{1}{\sigma})$, covariate coefficients β_1 and β_2 . We established a Weibull regression model with initial parameter settings as follows $\sigma = 0.61$, $\beta_1 = 1$, $\beta_2 = 2$. After data fitting, the estimated parameter values for the 10 condition groups are shown in Table A5.

The reliability density function $f(t)$ and reliability function $R(t)$ for the 10 sets of Weibull models are presented in Figure A1.

5.2. Algorithm Execution

We selected rolling unit 128 in the second support roll change cycle (hereafter referred to as unit 128), which involves 82 pending rolled products for analysis. At this point, the production conditions of unit 128 were simulated using a Weibull distribution to derive the reliability function of the risk model-based regression in Table A5 in Appendix A.

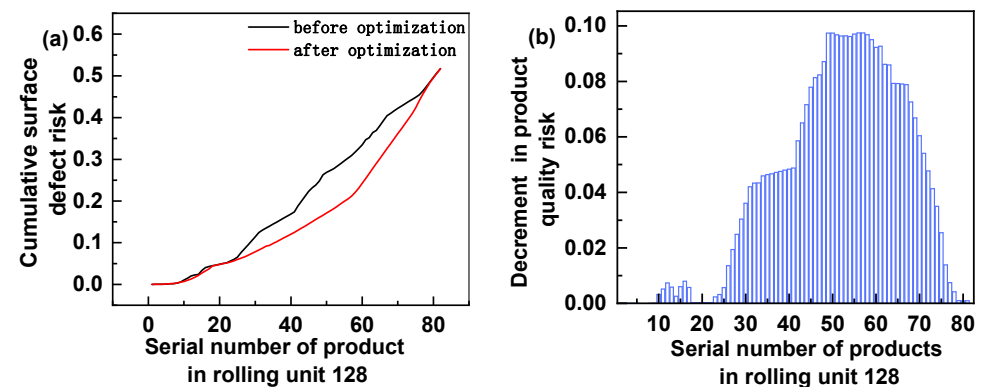
$$R = \exp\left(-\left(\frac{l}{127554.6}\right)^{1.6150}\right) \quad (29)$$

We applied the ACO introduced in Section 3.4 to schedule optimization. The constraint parameter values for the model were set as follows: $W_{same} \leq 30$ km, $Q_k \leq 160$ km, $W_{up} = W_{down} = 200$ mm, $H_{up} = H_{down} = 2$ mm, $G_{up} = G_{down} = 6$. The equivalent rolling length for the unit is 104.8 km, and the initial algorithm parameters are configured as shown in Table 4.

The algorithm iteration process has an iteration time of 38 s. The obtained optimal scheduling order scheme has an accumulated quality risk of 8.4016. Figure 13a displays the comparison of surface defect cumulative risk for unit 128 before and after the scheduling optimization. Figure 13b shows the decrement quality risk compared to the original plan for 82 hot rolled strips. These two demonstrate a significant reduction in defect risk in the optimized schedule, indicating the effectiveness of the proposed hot rolling scheduling model.

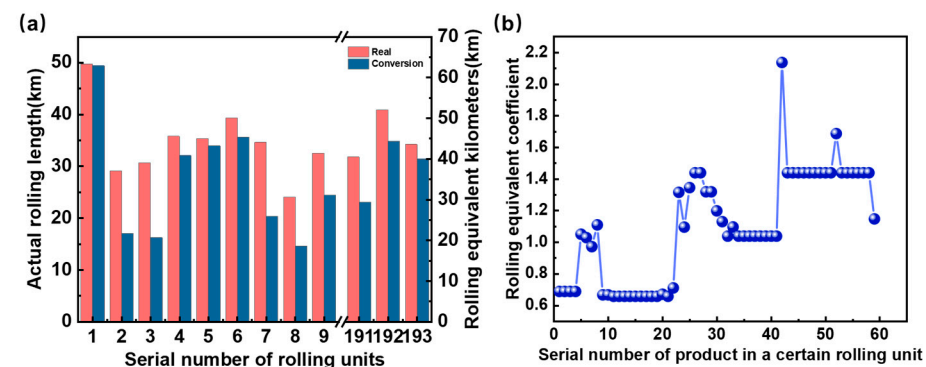
Table 4. Initial parameter settings for ACO.

Parameters	Symbolic Notation	Setting
Population size	m	50
Importance factor of pheromone	α	1
Importance factor of heuristic function	β	5
Evaporation factor of pheromone	ρ	0.1
Maximum epochs	E	500

**Figure 13.** Comparison before and after optimization of unit 128. (a) Cumulative risk difference; (b) decrement quality risk.

5.3. Rolling Equivalent of Rolling Units

Real rolling length and equivalent kilometers for rolling units are shown in Figure 14a. Comparing these two variables in (a), it can be observed that differences between the actual rolling kilometers and the equivalent kilometers vary for different rolling units, indicating that there are differences in the wear and tear on the rolls for different hot rolling operations. We further analyzed the data and found that each rolling unit exhibits a similar pattern in terms of its comprehensive equivalent coefficient. Figure 14b illustrates the variation in the comprehensive equivalent coefficient for unit 128.

**Figure 14.** Rolling length standardization. (a) Comparison of actual rolling length and rolling equivalent kilometers; (b) line graph of rolling equivalent coefficients for a rolling unit.

From the above graph, it can be observed that rolling equivalent coefficients are in a lower status for the 10th to 20th hot rolled strips in the main rolled. Investigating the reasons behind this, we found there is relatively little variation in factors such as thickness, width jump amount, temperature, and carbon equivalent. It can be inferred that the rolls used for this section of rolling have experienced relatively mild wear and are still in a phase of low cumulative wear.

Under unified dimensional units, the equivalent rolling kilometers can vary. When the wear state is more severe (e.g., rolling harder, thinner products), the equivalent rolling

kilometers are shorter than those corresponding to less severe wear states. Consequently, the rolling positions and lengths for products of different quality grades will also change. By using the pre-production surface quality risk-assessment model, the cumulative risk can be predicted, guiding the optimization of the rolling schedule and reducing product quality risk. Consequently, it is advisable to schedule products with higher surface quality requirements to be rolled within this range. As the number of rolled products increases, roll wear becomes more significant, and the fluctuations in the composite equivalent due to the factors mentioned above also become more pronounced. In subsequent positions in the scheduling, it is more appropriate to arrange the rolling of products with relatively lower surface quality requirements. This conclusion aligns with the scheduling experience of dispatchers in hot rolling operation practice.

5.4. Rolling Equivalent Kilometers for Different Quality Grades

After analyzing unit 128, we calculated the rolling ranges corresponding to different surface defect risk, as shown in Table 5.

Table 5. Equivalent length limits of rolling unit 128 for different grades.

Surface Quality Grade	The Maximum Rolling Equivalent Kilometers (km)
I	58.7
II	120.2
III	169.8

We convert the rolling equivalent kilometers for different product surface quality levels based on the Weibull fitting parameters from Section 4.3, as shown in Figure 15.

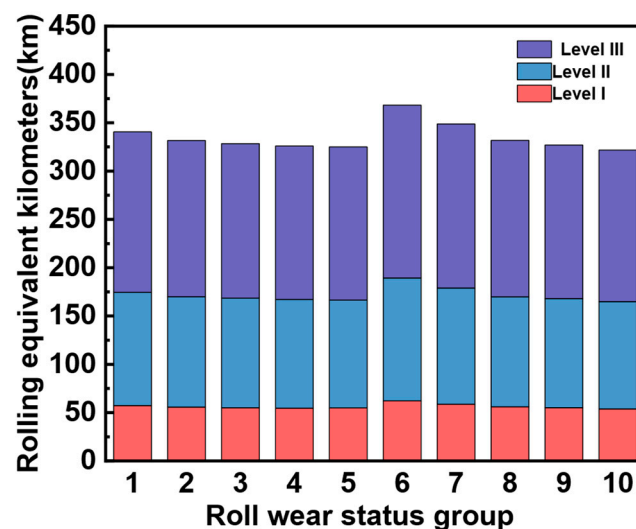


Figure 15. Rolling equivalent kilometers for different surface quality level.

According to Figure 15, it can be observed that for the same product surface quality level, there is little difference in the equivalent rolling kilometers under different roll conditions. The equivalent lengths for levels I, II, and III fluctuate around 50 km, 120 km, and 160 km. When the variation in physical quantities such as thickness, width, temperature, and hardness is gentle, the actual rolling length would be approximately equal to the rolling equivalent kilometers. Moreover, it is necessary to convert based on the equivalent coefficient for more deviation. Additionally, it can be seen that the rolling equivalent kilometers of the front support roll condition (from 1 to 5) for various surface grades are slightly longer than the behind (from 6 to 10). This also aligns with the actual rolling practice, where it is possible to roll a slightly longer length of products when the support roll condition is better.

6. Summary

Surface quality control of the hot rolled strip has attracted much attention. This paper is a research example of data mining on the rolling process in the steel industry, which on the one hand breaks the limitations of the past hot rolling scheduling model that relies on human experience to set up the rule parameters, and on the other hand associates the planning and scheduling with the product quality control, which provides a methodological reference for the application of massive data from the production process and product quality control. It helps to integrate equipment maintenance, product quality and planning and scheduling, and provides a new technical method for the future realization of Industry 4.0 on digitalization.

- (1) This study applied the Weibull distribution to establish the correlation between the influencing factors of hot rolled strip surface quality and roll reliability and constructed a pre-assessment risk model of surface quality risk for the rolled strip on the basis of unified dimensions. The hypothesis test results showed that the data from 10 groups of roll conditions approximately followed a straight line. This indicates that the Weibull distribution function can be used to simulate roll reliability.
- (2) The proposed scheduling model departs from the traditional approach of minimizing a penalty function, instead constructing a model that considers the surface defect risk of strips and hard constraints in hot rolling scheduling. Using actual production data from a hot rolling plant for the model test, the results verify that the developed scheduling method which introduced the proposed pre-assessment risk model of product surface quality can reduce the surface defect risk of the steel strip.
- (3) We have developed a solving algorithm based on the ACO for the proposed scheduling model. Testing the algorithm with real production data from a hot rolling plant showed that it can find optimized solutions within acceptable iteration time. Results indicate that this algorithm can be used to solve optimization models aimed at reducing the risk of hot rolled product surface defects.

Author Contributions: All authors agree to be accountable for all aspects of the work. T.J.: Conceptualization and Methodology; Data management; Data analysis and process; Code testing; and Writing (original draft, review, and editing). N.Z.: Data management; and Writing (review, and editing). Y.X.: Method application; Data analysis and process; and Coding. Z.L.: Data collection; and Writing (review, and editing); Superintendent and access to Funding. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: Author Yongyi Xie was employed by the company Automotive Intelligence and Control of China Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Table A1. Equivalent coefficients for thickness.

Serial Number	Thickness (μm)	Thickness Equivalent Coefficient ∇_1
1	<2.0	2.1
2	2.0	2.0
3	2.3	1.5
4	2.5	1.3
5	3.0	1.0
6	4.0	0.8
7	5.0	0.75

Table A2. Equivalent coefficients for temperature.

Serial Number	Temperature ($^{\circ}\text{C}$)	Temperature Equivalent Coefficients ∇_2
1	840~850	1.1
2	880~920	1.0
3	920~950	1.1
4	950~980	1.2
5	>980	1.3

Table A3. Equivalent coefficients for width.

Serial Number	Width Jump Amount of Adjacent Strips (mm)	Equivalent Coefficients ∇_3
1	<−300	2
2	−300	1.8
3	−200	1.7
4	−100	1.5
5	−50	1.1
6	−25~+50	1.0
7	+100	1.2
8	+200	1.5
9	+300	1.7
10	300	1.8

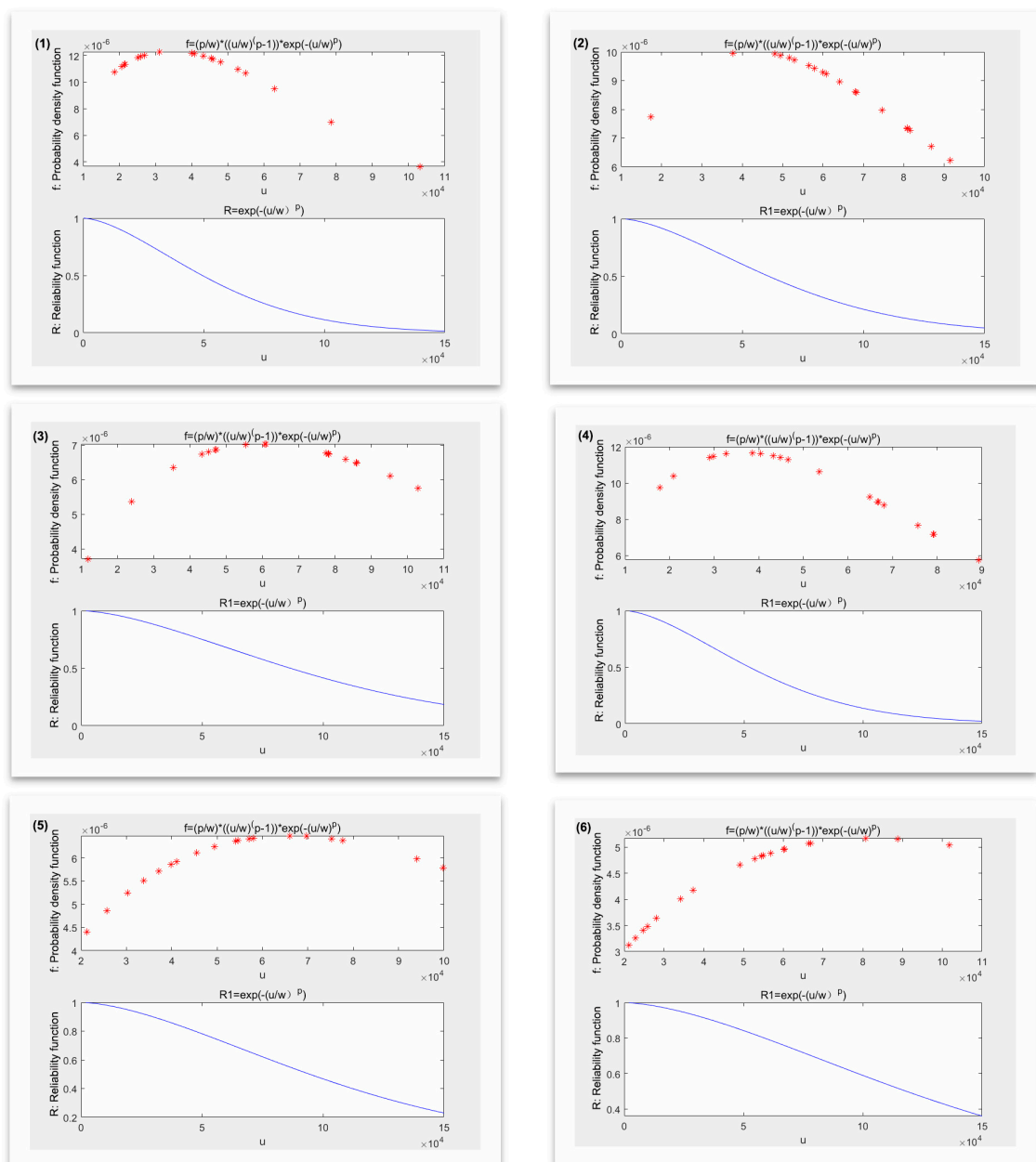
“+” represents a positive jump, and “−” represents a negative jump.

Table A4. Equivalent coefficients for steel composition.

Serial Number	Carbon Equivalent	Composition Equivalent Coefficient ∇_4
1	0~1.0	0.8
2	1.0~2.0	1.0
3	2.0~3.0	1.2
4	3.0~4.0	1.4
5	4.0~5.0	1.6
6	>5	1.7

Table A5. Parameter estimates for Weibull distribution of pre-assessment risk model.

Serial Number	σ	β_1	β_2
1	0.6174	0.5802	−29.5778
2	0.6172	0.8481	−48.1241
3	0.6195	0.4564	−20.3522
4	0.6154	1.2808	−77.5812
5	0.6154	1.2697	−77.7869
6	0.6155	0.4233	−17.7221
7	0.6192	0.9683	−56.0247
8	0.6127	0.7330	−39.6592
9	0.6140	−3.1591	232.6263
10	0.6153	1.3157	−80.7218

**Figure A1.** Cont.

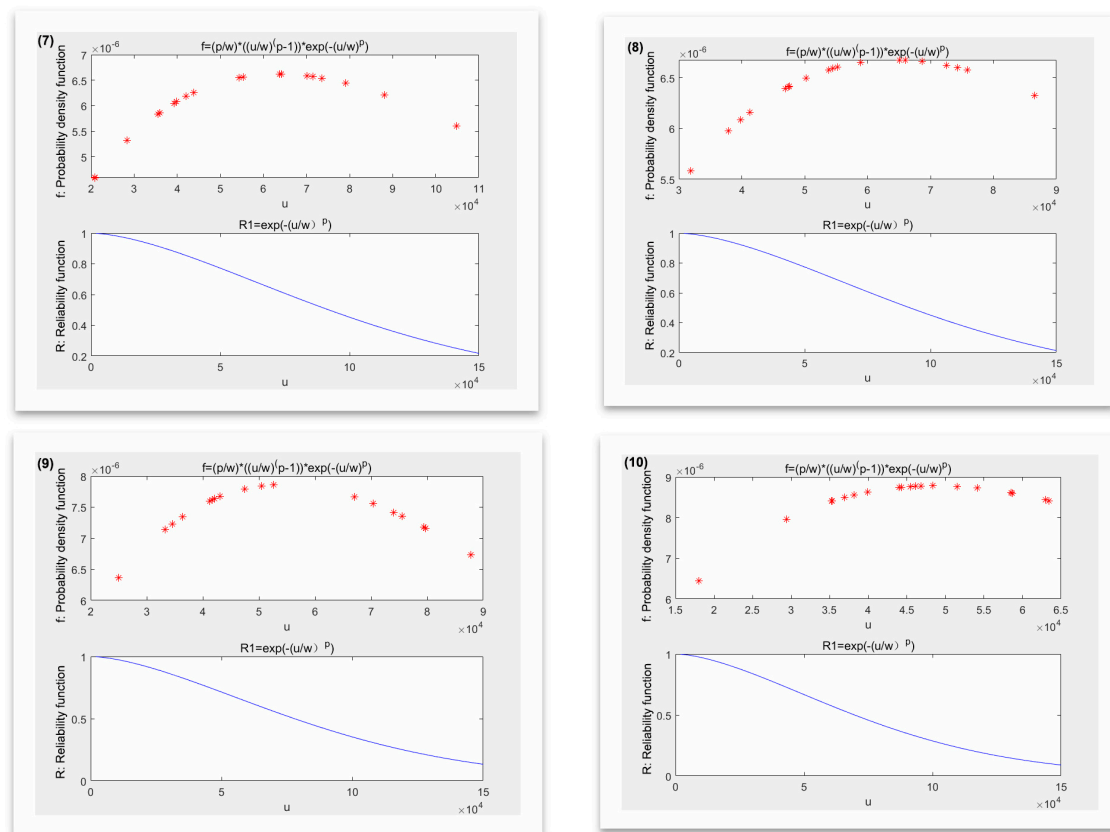


Figure A1. Quality risk model in different Weibull distributions (Line represents the relationship between reliability and equivalent rolling kilometers and * represents the relationship between probability density and equivalent rolling kilometers).

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