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Application of Deep Learning in Parameter Optimization of Automatic Production Process in Hot Rolling Production Line

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Abstract. China is a major producer of steel and a pillar industry of the national economy, with huge coal consumption. With the increasingly prominent problem of energy shortage, traditional industrial models are constantly being transformed and upgraded using information technology, and a comprehensive energy information management system is being constructed. This article focuses on the production scheduling optimization problem of steel hot rolling production process. Firstly, based on the hot rolling process flow, the operation and maintenance time consumption of hot rolling equipment and the conversion time between hot rolling equipment are fully considered. The mathematical model of production scheduling for the hot rolling production process is established with the goals of minimizing work order completion time and balancing equipment working hours. Then, the classic NSGA-II algorithm is used as the basis for multi-objective solving. To solve the problems of the algorithm being prone to falling into local optima, insufficient distribution, and long solving time, the algorithm is improved by combining deep reinforcement learning ideas. Finally, through simulation experiments, the superiority of the improved algorithm in the convergence process is verified. At the same time, real hot rolling cases are used as scheduling objects to complete scheduling optimization and provide scheduling solutions.

Keywords: hot-rolling, scheduling model, NSGA-II, deep reinforcement learning

1 Introduction

The steel industry is a pillar industry of China's national economy. With the improvement of domestic steel production level, China's steel industry is accelerating its transformation towards high-end, green and intelligent industries. With the accelerated promotion of green technologies such as ultra-low emissions and extreme energy efficiency in the steel production process, the speed of green transformation in the steel industry is gradually increasing. At the same time, digital technologies such as digital twins, the Internet of Things, and big data are also gradually being promoted in steel production enterprises.

However, with the accelerated development of China's steel industry and global economic integration, although advanced production equipment is rapidly entering production workshops, the disadvantages of Chinese steel enterprises in production management and scheduling are gradually emerging. Most of the existing steel enterprises in China are facing problems such as overcapacity, supply-demand imbalance, insufficient product innovation, fierce market competition, and ecological environment. At the same time, the demand for steel products from customers is diversified, requiring shorter product delivery cycles and higher quality requirements for steel products. Therefore, in order to meet the needs of national development and customer demands, steel enterprises must improve traditional production management models, strengthen efficient connections between various processes, ensure the continuity of the production process, improve management and information automation levels,

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enhance production efficiency and product quality, reduce energy consumption, accelerate upgrading and transformation, and achieve sustainable development of energy for both the enterprise itself and society.

The entire steel production process mainly includes processes such as ironmaking, steelmaking, continuous casting, hot rolling and cold rolling, acid rolling, etc. Add raw materials such as iron ore to the blast furnace, refine them into molten iron, pour the molten iron into the ladle, pour the ladle into the converter, and then transport the ladle to the continuous casting machine for solidification, cooling, drawing, and cutting into solid slab of predetermined specifications. Hot rolling refers to rolling carried out above the recrystallization temperature of the metal.

The meaning of the so-called hot rolling production scheduling is that steel enterprises, based on meeting various production constraints such as hot rolling operation priority and equipment capacity during the production process, achieve effective allocation and use sequence of shared resources such as manpower, materials, and machines, in order to achieve optimal performance indicators. In short, production scheduling is the allocation of resources and optimization of some production indicators by completing specific production tasks within a certain period of time. Therefore, if the production scheduling plan is not mature, it will increase the waiting time of processing equipment on the production line, thereby increasing energy consumption, affecting product quality and equipment utilization. Therefore, how to make the production scheduling plan of steel enterprises scientifically and reasonably is of great significance for coordinating production and energy conservation and consumption reduction in enterprises. Developing a scientifically reasonable production scheduling plan in the steel production process plays a crucial role in energy conservation and consumption reduction. This article focuses on the key processes of continuous casting and hot rolling in the steel production process. Based on the production mode of each process, the production constraints and scheduling requirements of each process are analyzed, and corresponding scheduling models are established, which can effectively play a role in energy conservation and consumption reduction. Therefore, after analyzing the typical process of hot rolling technology, the main innovative work of this article regarding the hot rolling scheduling problem is as follows:

1) Firstly, the current situation of hot rolling production scheduling in China was analyzed and summarized

2) For the production process of the workshop, a scheduling function is established with the goal of minimizing production completion time and achieving time balance among various equipment. The scheduling function includes multiple parameters and establishes relevant constraints.

3) For multi-objective optimization problems, this paper uses NSGA-II to solve them. In order to address the shortcomings of the algorithm, such as getting stuck in local optima, insufficient distribution, and long solving time, this paper integrates deep reinforcement learning algorithms on the basis of existing algorithms to improve the performance of the algorithm.

4) A simulation experimental environment was constructed to verify the performance of the algorithm, and corresponding scheduling schemes were provided to guide enterprises in completing production scheduling.

The chapter arrangement of this article is as follows: Chapter 1 is the introduction section, which explains the research background and research object of this article. Chapter 2 mainly introduces the existing related research results. Chapter 3 constructs a hot rolling production scheduling model based on production practice, fully considering the relevant constraint conditions, which is closer to the real production process. Chapter 4 uses improved deep learning methods to solve the hot rolling scheduling model. Chapter 5 sets up a simulation experimental environment to verify the model and algorithm, and completes the scheduling of relevant cases. Finally, the conclusion section summarizes the research results of this article and summarizes further research directions.

2 Related Work

Many scholars have conducted research on the scheduling of hot rolling production processes. Dengju Zhou from Anhui University of Technology, based on the characteristics of a hot rolling production line in a domestic steel plant, considered the constraint of limited heating furnace capacity and established a heating furnace hot rolling integrated scheduling model with the goal of minimizing the total completion time, minimizing the total residence time of steel billets, and minimizing the total standby time of rolling mills. Then, the NSGA-II algorithm was designed and improved according to the characteristics of actual scheduling problems. The solution was characterized by chromosome hierarchical coding, and a conflict detection repair module was introduced to ensure the feasibility of the solution. Finally, multiple sets and scales of experimental samples were designed based on the actual production data of a domestic steel plant. The final experimental results showed that the model and solving method could effectively shorten the processing time of steel billets, reduce the energy consumption of heating furnaces, and be more effective than manual methods. More efficient scheduling Energy saving [1].

Wei Zhao from Anshan Iron and Steel Group established a multi-objective optimization model for the contract scheduling problem within a hot rolling plan cycle, designed an improved differential evolution algorithm (TMS-MODE) to solve the model, and adopted adaptive mutation strategies for different individuals to improve the search depth and breadth of the algorithm. Finally, the model and algorithm were validated through actual contract cases, and the results showed that the proposed algorithm had significant advantages in medium and large-scale problems, with greater diversity, convergence, and uniformity, all of which were superior to the commonly used non dominated sorting genetic algorithms (NSGA-II). And basic MODE [2].

Yidi Wang from Beijing University of Science and Technology proposed a hot rolling rescheduling optimization method to address the dynamic event of emergency order insertion during the hot rolling scheduling process. The method analyzed the impact of order disturbance factors on the scheduling plan and established a mathematical model for the hot rolling rescheduling problem with the optimization objective of minimizing the weighted sum of order delay penalty and slab jump penalty. Then, a hot rolling rescheduling distribution estimation algorithm (EDA) was designed. The algorithm proposed an integer encoding scheme based on insertion position for the insertion processing of emergency orders, and a probability model was designed based on the model characteristics. The fitness function based on the penalty value was defined by comprehensively considering the objectives and constraints. Finally, simulation experiments were conducted on actual production data to verify the feasibility of the model and algorithm. And effectiveness [3].

Lan Chen investigated the energy oriented scheduling problem generated by hot rolling production under flexible time of use (TOU) electricity prices. The surveyed objects received electricity from power plants owned by enterprises and state-owned power grids. Based on the survey results, the studied scheduling problem was modeled as a multi-objective prize collection vehicle routing problem with special constraints. The scheduling model selected slabs from the order pool and sorted them to form rolling units, while minimizing the transition costs of strip specifications, penalty costs, and electricity costs. Then, an adaptive reassembly program and a local reinforcement program based on shortest path search were introduced, and a knowledge-based NSGA-II algorithm was developed. Finally, after experimental verification, a more flexible hot rolling scheduling was provided. Scheduling plan [4].

Shiji Song, in response to the matching scheduling problem of molten iron transportation from ironmaking blast furnaces to steelmaking furnaces, establishes the time correspondence between iron production and steelmaking demand in blast furnaces, the weight correspondence between torpedo tankers and molten iron, and the composition correspondence between molten iron and molten steel. Based on the real-time monitoring of material flow and equipment status by production process machines, the process route of molten iron and the schedule of each process are determined. At the same time, for the dynamic scheduling problem of continuous casting production process, the furnace schedule and pouring schedule of steelmaking continuous casting production process are formulated. A mixed integer programming model for key processes such as steelmaking continuous casting and continuous casting hot rolling process in steel production line is established, and the accurate solution algorithm or efficient and intelligent approximate solution algorithm for the model is given [5].

3 Establishment of Hot Rolling Analysis and Scheduling Model

This section first analyzes the process flow of hot rolling production, and then establishes a production scheduling mathematical model for the hot rolling production process based on the process flow. At the same time, equipment maintenance time is taken into account, and the balance between the shortest time to complete the work order and the total equipment usage time is used as the main optimization objective. A complete mathematical model is established, and corresponding constraint conditions are established.

3.1 Description of Hot Rolling Process Problems

Hot rolling is an important link in strip steel production, with a continuous and uninterrupted production process without waiting time. The hot rolling stage is mainly equipped with a hot rolling mill. If there is only one hot rolling unit in the hot rolling stage, the production environment can be abstracted as a single machine environment. When the order information is obtained from the upper level manufacturing control process and the specification attributes of the strip steel in the order are known, the production plan can be prepared according to the order data, and the actual strip length of each rolling unit can be obtained. The difference between the actual length of each rolling unit and the upper limit of the unit rolling unit length is the surplus length of the rolling unit. The goal of preparing the rolling plan is to minimize the surplus length of each rolling unit to achieve the goal of minimizing the total surplus length. The preparation of the rolling plan can obtain the configuration of multiple rolling units, and then the production of the prepared rolling units can be sorted. The hot rolling unit is only allowed to process one rolling unit at a time, and in the production process, a flexible equipment maintenance plan should be formulated to ensure production quality. Finally, a minimum maximum completion time is obtained. Production sequence [6]. The process flow of hot rolling is shown in Fig. 1.

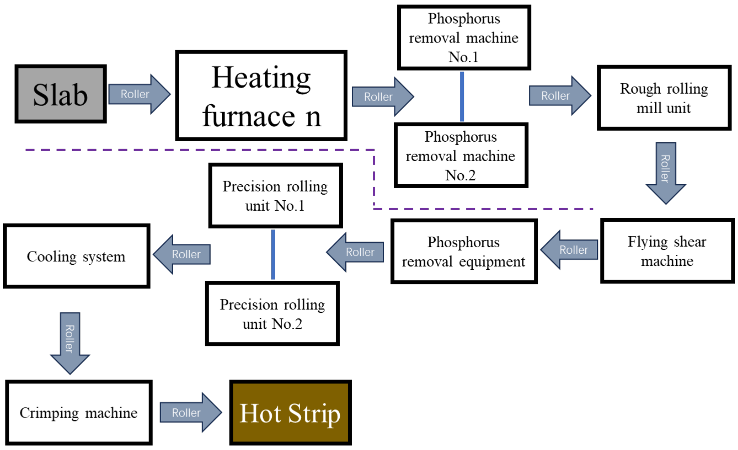

Fig. 1. Hot rolling process flowchart

Step 1: Slabs: slabs produced by furnace rolling method are stored in specific stacking positions in the slab warehouse, slabs produced by carbon steel insulation pit hot charging rolling method are stored in designated stacking positions in the insulation pit, and slabs produced by direct hot charging rolling method are directly sourced from the high-temperature continuous casting workshop.

Step 2: Heating: The slab is lifted onto the roller conveyor by a clamp crane. Then it is transported by roller conveyor to the heating furnace for heating.

Step 3: Phosphorus removal: The heated slab is transported by roller conveyor to the high-pressure water phosphorus removal machine for phosphorus removal. The water pressure is maintained at 40Pa.

Step 4: Fixed width: After phosphorus removal, the slab is transported by a conveyor roller to a fixed width press for side pressure to achieve the required width.

Step 5: Rough rolling: The slab with a fixed width is transported backwards through a roller conveyor, and is subjected to rough rolling in a two roll rough rolling mill and a four roll rough rolling mill in sequence.

Step 6: Flying shear: The rough rolled slab is sent to the flying shear machine through a roller conveyor.

Step 7: Phosphorus removal: After the slab is sheared, it is transported by a roller conveyor to a high-pressure water phosphorus removal machine for further phosphorus removal.

Step 8: Precision rolling: After phosphorus removal, the slab is transported backwards through a roller conveyor and sequentially processed by two four-roll precision rolling mills.

Step 9: Cooling: The finished strip steel obtained by precision rolling is transported to the laminar cooling system through a roller conveyor.

Step 10: Coiling: The cooled strip steel is sent to the coiling machine via a roller conveyor to be coiled into steel coils [7].

The formulation of hot rolling plans and scheduling schemes generally consists of two steps: the first step is to split and combine the steel strips in the order, and combine the steel strips with different sizes in different orders into the same batch. Then, the steel strips in the same batch are configured according to the upper limit of the rolling unit length constraint to minimize the total scrap length and obtain multiple rolling units. The second step of scheduling is to determine the processing sequence of the rolling units formed in the planning stage on the hot rolling mill based on constraints such as order delivery time and machine adjustment time. Then, based on the completion time of the last rolling unit in each rolling planning cycle, the start time of equipment preventive maintenance in that rolling planning cycle is determined to minimize the maximum completion time [8]. The schematic diagram of hot rolling plan formulation and scheduling is shown in Fig. 2.

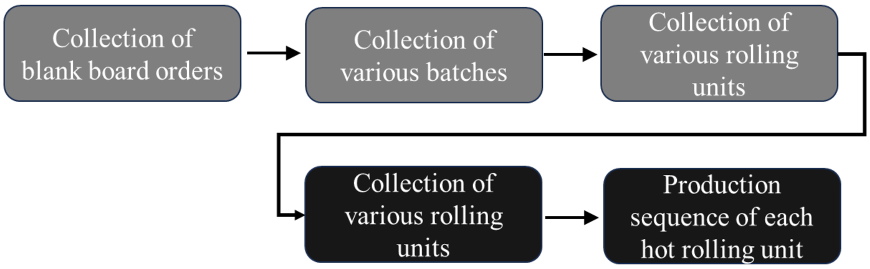

Fig. 2. Schematic diagram of hot rolling plan formulation and scheduling

3.2 Quantitative Model of Equipment Maintenance Factors

Preventive maintenance of machines can be divided into two types: flexible and non flexible. The preventive maintenance of flexible equipment in this article is fixed in duration, but the specific start and end times of the maintenance vary within time window [T_{sN}, T_{eN}]. The subscript represents the maintenance plan number, T_{sN} represents the earliest start time of the N-th preventive maintenance, and T_{eN} represents the latest end time of the N-th preventive maintenance. The duration T_N of preventive maintenance is a fixed constant, the period of preventive maintenance time window is T, and the length T_{CL} of preventive maintenance time window is equal to the difference between T_{eN} and T_{sN}, which is also a fixed constant.

Consider the schematic diagram of the scheduling plan for flexible equipment maintenance. The time period between the end of the previous preventive maintenance and the end of the next preventive maintenance is a rolling plan cycle, and there is a correlation between adjacent rolling plan cycles. That is, the end time of the previous rolling plan cycle determines the start processing time of the first rolling unit in the next rolling plan cycle. There is no idle time before the first preventive maintenance of the equipment in the picture, and there is idle time before the second preventive maintenance of the equipment. Within the preventive maintenance time window, under the premise of not exceeding the upper limit of [T_{sN}, T_{eN}], the preventive maintenance time can be arranged arbitrarily to ensure that the equipment preventive maintenance starts after the completion of the last rolling unit in each rolling plan cycle [9], without idle time. The schematic diagram is shown in Fig. 3.

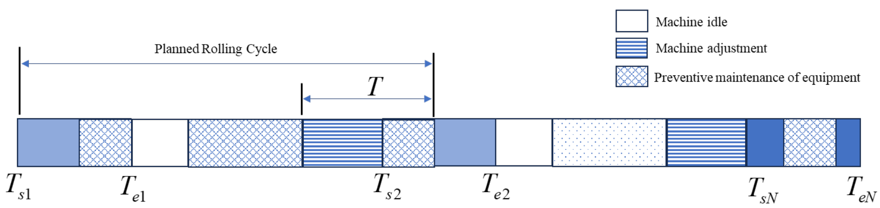

Fig. 3. Schematic diagram of hot rolling scheduling plan cycle

3.3 Quantification of Machine Adjustment Time

During the rolling process, once production begins, the rolling mill runs continuously. Assuming there are m slabs to be processed, each slab must go through $X(X \geq 2)$ stages of processing in sequence. At least one stage in all processing stages has multiple parallel devices. The number of equipment in the processing stage is. Hot rolling mixed flow workshop scheduling is to determine the processing sequence and equipment allocation of slabs in each processing stage based on the quantity of slabs, process information, equipment quantity, processing capacity, etc., in order to optimize one or more scheduling indicators. In order to uniformly describe the parameters involved in the article [10], the parameter list involved in the article is shown in Table 1:

Table 1. List of all parameters in the quantification process of rolling production parameters

Parameter	Parameter meaning
m	Total number of processed slabs
X	Total number of processing stages
S_x	The number of parallel devices in the processing stage
$S_{xi,i\in[i\min,i\max]}$	Equipment numbering for parallel processing stages
$Q,Q\in[1,m]$	The position of the slab to be processed on the equipment at each processing stage
$M_{x,s}$	The total number of slabs processed on equipment s in processing stage x
$T_{start,x,n,s}$	The start time of processing slab n on equipment s in processing stage x
$T_{end,x,n,s}$	End time of processing of slab n on equipment s in processing stage x
$F_{x,n,s}$	Determine whether slab n is allocated to equipment s in processing stage x for processing

For any slab, if the completion time of processing at a certain stage is equal to the start time of processing plus the processing time, the quantified result of the processing equipment is as follows:

$$\begin{cases} F_{x,n,s}=0 & \text{Equipment assigned} \\ F_{x,n,s}=1 & \text{Device not assigned} \\ \sum_{y=1}^{xi} F_{x,n,y}=1 & xi\in\left[i\min,i\max\right] \end{cases} \quad (1)$$

For each processing stage, the total number of slabs processed on all equipment should be equal to the total number of slabs, in other words, each slab must undergo processing from stage $1-X$ to stage. The representation method is as follows:

$$\sum_{y=1}^{xi} M_{x,s}=m\ \ x\in\left[0,X\right] \quad (2)$$

For any slab, the processing time at a certain stage is calculated by subtracting the processing start time from the processing end time, expressed as follows:

$$T_{x,n,s}=T_{end,x,n,s}-T_{start,x,n,s},\ x\in\left[0,X\right],s\in\left[0,S_x\right],n\in\left[0,m\right] \quad (3)$$

For any slab, it can only proceed to the next stage of processing after the completion of the previous stage, which can be quantified as:

$$T_{end,x,n,s}\le T_{start,x+1,n,s},\ x\in\left[0,X\right],s\in\left[0,S_x\right],n\in\left[0,m\right] \quad (4)$$

For any device, it can only process the next slab after completing the processing of the current slab, which can be quantified as follows:

$$T_{end,x,n,s}\le T_{start,x,n+1,s},\ x\in\left[0,X\right],s\in\left[0,S_x\right],n\in\left[0,m\right] \quad (5)$$

In addition, there are other fixed constraints, such as parameters and variables related to time that should satisfy non negative constraints.

3.4 Description of Hot Rolling Process Problems

For the scheduling problem in the hot rolling workshop, it is necessary to judge the quality of the scheduling plan through the objective function. This article selects the maximum completion time as the scheduling objective, as well as the relatively less studied but extremely important equipment work hour balance for the relevant projects of this research topic, as the scheduling research objectives of this article.

1) Minimum maximum completion time

Choosing the maximum completion time $T_{\max}$ of the entire processing process as the objective function means that the total time to complete all slab processing is smaller, which is of great significance for improving the utilization rate of workshop equipment, saving workshop production time, shortening production cycles, and increasing enterprise production capacity.

2) Minimum balance of equipment working hours

During the manufacturing process, each device in the workshop may have processed multiple tasks, resulting in multiple processing times. The equipment working hour balance index refers to the average standard deviation of the processing time of all equipment in the workshop. The average value is represented by N_{av}. The smaller the difference in processing time between each section, the less jumping, which is conducive to reducing equipment wear and tear, extending the service life of equipment, and further reducing production costs for enterprises.

3) Matrix coding for hot rolling process

This article has m workpieces and X processing stages. Each row of the matrix corresponds to a workpiece, and the first to last rows correspond to workpieces 1 to m, respectively. Each column of the matrix corresponds to each processing stage, from the first column to the last column corresponding to processing stages 1 to X. The hot rolling matrix is constructed as follows:

$$MATRIX_{hot-rolling} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1x} \\ a_{21} & a_{22} & \cdots & a_{2x} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mx} \end{bmatrix} \quad \textbf{(6)}$$

Convert the virtual matrix into row vectors, which have the same features as the corresponding positions of the virtual matrix. Then, generate the initial population based on the transformed row vector features, which can be converted back into the virtual matrix during decoding. Finally, perform genetic operations on the original row vectors. Decoding refers to determining the order in which each workpiece is processed at each processing stage and the equipment selected [11]. The formula for converting virtual matrices and row vectors is as follows:

$$MATRIX_{hot-rolling} \Leftrightarrow [a_{11}, a_{12}, \cdots a_{1x}, \cdots, a_{n1}, \cdots, a_{nx}] \quad \textbf{(7)}$$

4) Establishment of the overall objective function

This article establishes a solution objective based on the shortest completion time and the most balanced equipment working hours. In actual production, the smaller the maximum completion time, the smaller the total time required to complete all slab processing. This is of great significance for saving production time, shortening production cycles, improving equipment utilization, and increasing production capacity for enterprises. At the same time, select the equipment working hour balance indicator for the entire processing process, which is the average of the standard deviation of the processing time of each equipment in each processing stage. The overall objective function is defined as $f(x)$ and expressed as follows:

$$f(x) = \alpha \cdot \min T_{\max} + \beta \frac{1}{X} \sum_{x=1}^{X} \sqrt{\frac{\sum_{x=1}^{S_x} \left(\sum_{l=1}^{M_{x,s}} \left(T_{end,x,n,s} - T_{start,x,n,s} \right) \right)^2}{S_x}} \quad \textbf{(8)}$$

In the formula, a and β represent the weights between the completed work hours and the equipment balance value. Under the premise of knowing the information of slab, equipment and process and satisfying various constraints, determine the processing sequence of slab and the equipment allocation at each stage to ensure the minimum completion time. Under the premise of knowing the information of slab, equipment and process and satisfying various constraints, determine the processing sequence of slab and the equipment allocation at each stage to achieve the minimum value of the objective function equipment balance.

4 Intelligent Algorithm for Solving the Objective Function

This article uses the NSGA-II algorithm [12] to solve the objective function, but classical constrained multi-objective optimization problems require simultaneous consideration of both objectives and constraints, especially when the constraints are extremely complex. Relying solely on the NSGA-II algorithm has many drawbacks, such as getting stuck in local optima and slow solving speed. The integrated problem model of hot rolling plan and heating grate production requires balancing all objective functions within the feasible region, which may result in a slow convergence speed of the population. However, it is expected that each individual in the population will eventually reach the optimum. Therefore, based on the classic algorithm, this article improves the algorithm framework by adding a deep Q-learning module to the algorithm. Through the improvement of deep Q-learning, it avoids local optima and improves the solving speed of the algorithm. The improved framework is called [13] $i-$ *Framework*.

The initial solution part has a certain impact on the effectiveness of the algorithm in solving the optimal solution of the hot rolling production scheduling problem. The encoding part is based on the real number encoding of the slab, and in this encoding chromosome, the serial number of each slab is represented as the rolling sequence number of the slab in the rolling unit. Before encoding, the slabs are arranged in order of width from small to large, and then individuals that meet the conditions are selected based on their individual function values. The better individuals can enter the heating furnace, and finally the difference between the actual heating time and the ideal heating time of the slabs is obtained. The penalty value between each slab is calculated based on the final individual function value.

Modeling with Markov decision process [14], designing state space, action space, reward function, etc. This article takes the ratio of current convergence to initial convergence and the ratio of current diversity to initial diversity of population 1 and population 2 as the state space. At the same time, using the changes in migration parameters as the action space, corresponding reward values are designed based on the state. The specific details are as follows:

1) Obtain three migration parameter values based on the actions of the intelligent agent, and perform corresponding migration operations in the environment according to the parameter values to obtain the convergence and diversity values of the current population 1 and population 2;

2) Design the action space of the intelligent agent, which mainly completes the modification of the migration function;

3) The design purpose of the return function is to achieve the optimal value of the migration function, and the design of the return function is as follows:

$$R_i = \begin{cases} 0 & V_{\text{Intelligent agent}} = 1 \\ 0.5 & V_{\text{Intelligent agent}} < 1 \\ -1 & V_{\text{Intelligent agent}} > 1 \end{cases} \tag{9}$$

In the formula, $V_{\text{Intelligent agent}}$ represents the migration value obtained by the intelligent agent.

Due to the similarity between the weight vectors of individual $i-Framework$, it is possible to find a uniformly distributed Pareto solution at a lower computational cost. In this paper, $i-Framework$ is used as the basis for improving the algorithm. Based on $i-Framework$, the population is decomposed into t sub problems, with the scale function using the Chebyshev method, and then cross mutation operations are performed on each sub problem. Choose to adopt the elite retention strategy, mix the father and son generations, and select the optimal t populations as new populations. Finding a neighborhood is better. Aggregate it and calculate the aggregation function value to update the parent population. The flowchart for improving the algorithm is shown in Fig. 4.

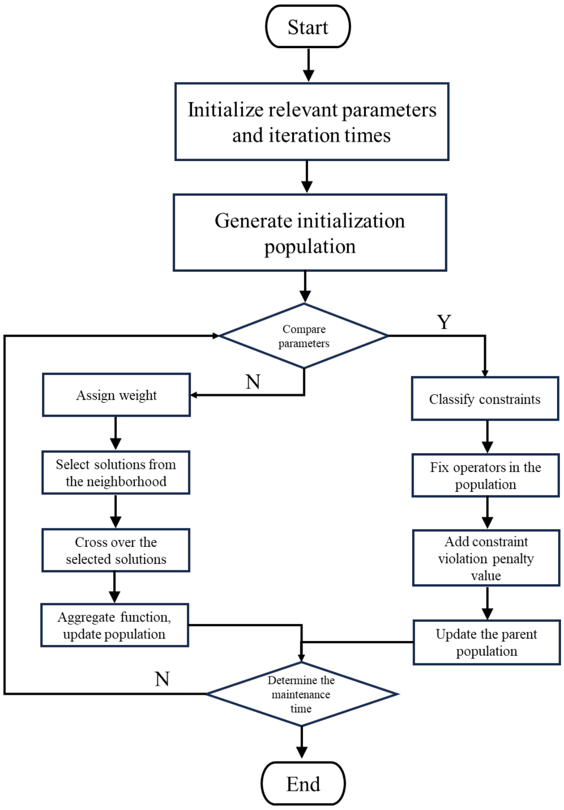

Fig. 4. Algorithm solving flowchart

The algorithm expression is as follows:

$$Min\ g^{te}\left(x\middle|\lambda, z^*\right) = \max\left\{\lambda_i \middle| f_i\left(x\right) - z_i^*\right\} \quad \textbf{(10)}$$

In the formula, z^* is the algorithm reference point, providing a gene library to quickly encode fitness values from individuals. As the number of iterations increases, if the generated individual is in the gene pool, its fitness value is directly output. If the generated individual is not in the gene pool, the calculated fitness value is added to the gene pool for subsequent individuals to use. The algorithm process is as follows:

Step 1: Initialize relevant parameters, iteration times, and reference points, etc;

Step 2: Generate initialization population;

Step 3: Determine if b is less than epsilon. If so, proceed to Step 4; otherwise, proceed to Step 8;

Step 4: Assign weights to each sub problem;

Step 5: Adopt the strategy of retaining elites in the selection process. As the roulette algorithm may lose the best individual from the previous generation, assign the best individual directly to enter the new generation population to prevent losing the best individual;

Step 6: Cross the population and perform mutation operator operations on the solution;

Step 7: Aggregate function values update parent population

Step 8: Classify the constraints, which are used to determine the constraints to be processed in each stage;

Step 9: Satisfy weak constraint problems with lower priority and repair operators in the population; Satisfy high priority strong constraint problems and add constraint violation penalty values;

Step 10: Update the parent population;

Step 11: Determine the number of iterations;

Step 12: End and output.

The pseudo code representation of the algorithm is as follows:

i − *Framework* NSGA-II Algorithm

1. Start
2. Establish an optimized network structure *Q* and initialize the network parameters;
3. Establish a target network and ensure that the parameters of the target network are consistent with those of the *Q* network;
4. Set relevant parameter values, such as maximum iteration times, maximum exploration steps per iteration, learning rate, etc
5. Initialize the experience pool
6.for (int episode=1; episode<=m; episode+=1) {
7. Initial state reset
8. for (int t=1; t<=T; t+=1){
9. Action selection: Select an action a according to the s-greeny strategy
10. Environmental status update: The agent executes action *a*, receives reward *r*, and the next state s'
11. Experience storage: Store (s, a, r, s') in the experience pool
12. Randomly select batches of learning samples from the experience pool
13. Perform network training
14. Update the parameters of the target *Q* network every x steps, and copy the parameters of the target *Q* network to be consistent with those of the *Q* network}}
End for
15. Obtain the values of three migration parameters, *p*, *q*, and *m*, based on the selected action
16. Calculate the convergence and diversity of the initial population
17. Use the main body of the dual population NSGA-II algorithm as feedback to the environment and perform genetic operations
18. Determine whether the current generation is a migrant based on the values of the p and q parameters. If so, perform the corresponding migration operation according to the value of the m parameter, exchange the corresponding individuals, and proceed to step 6; Otherwise, proceed to step 4
19. Determine whether the current generation is the last generation to migrate. If so, the migration ends and proceed to step 7; otherwise, proceed to step 4;
20. Calculate the convergence and diversity of the current population after the migration ends, determine whether the target state has been reached, calculate the reward for this action, and return to the main program.
End

5 Simulation Experiment and Result Analysis

This chapter simulates the production scenario of a domestic steel enterprise, whose ironmaking plant has four blast furnaces, namely 1 # BF, 2 # BF, 3 # BF, and 4 # BF. The two steel mills of the steel enterprise each have one molten iron pretreatment station, namely the first steel mill molten iron pretreatment station and the second steel mill molten iron pretreatment station. The molten iron pretreatment equipment and steel production time corresponding schedule of these two molten iron pretreatment stations are shown in Table 2 and Table 3.

Table 2. Steel production schedule

Steel tank number	Loading weight of molten iron	Start time
10021	310	07:17
20014	310	07:39
20017	310	08:11
30028	310	09:02
40003	310	09:36
10017	310	10:21
30018	310	10:38
20012	310	11:27
30011	310	12:05
30006	310	12:59

10021	310	13:20
40019	310	14:06
40007	310	14:58
20020	310	16:03
10009	310	17:26

Table 3. Preprocessing process

Steel tank number	Pre slag removal treatment	Desulfurization and dephosphorization treatment	After slag removal treatment
10021	27	34	35
20014	21	33	34
20017	30	32	32
30028	21	30	32
40003	24	31	34
10017	32	37	32
30018	26	36	33
20012	25	38	35
30011	30	29	36
30006	21	34	33
10021	23	33	34
40019	28	36	35
40007	27	35	34
20020	32	33	32
10009	19	32	36

When generating test cases, for the convenience of setting the initial properties of the slab, the density of the slab is uniformly set to $7.93g/cm^3$. The width range of the slab is $[1500mm, 2500mm]$, and the thickness range of the slab is $[15mm, 300mm]$. To verify the effectiveness of the proposed optimization problem and algorithm, simulation experiments were conducted from different perspectives on test cases with different numbers of heating furnaces and slab quantities. In the test case, the number of heating furnaces is fixed at 8 devices, and the slab sizes are ($m = 5 - 25$) respectively. The test data for different slab sizes are shown in Table 4.

Table 4. Test data for slab size ($m = 5 - 25$)

Quantity of slabs	Solution duration (s)	Non essential furnace stay time (s)
5	0.2392	16.8783
6	0.4216	13.9879
7	0.5028	16.5276
8	0.6871	17.8983
9	0.6648	15.9873
10	0.7084	18.0932
11	0.9283	17.8733
12	1.4219	17.0396
13	1.9074	19.0023
14	2.9897	14.3904
15	4.8972	13.2293
16	6.8978	14.5687
17	9.1024	15.0994
18	16.3096	16.4307
19	36.7086	17.2123
20	39.0982	18.5604
21	47.8017	17.7682
22	50.0901	14.0894
23	50.1038	20.0012
24	50.3927	15.7897
25	50.7084	16.5432

From the above data table, it can be seen that the solution time of the model increases rapidly before reaching the upper limit of the solution time. For the optimization objectives of the model, due to the setting of certain weights for different optimization objectives in the simulation experiment, it can be seen from the data that with a constant number of heating furnaces, as the number of slabs increases, the non essential dwell time of the slabs continues to increase, that is, the total processing completion time increases, but it does not show a linear growth trend, but rather a local up and down floating overall upward trend.

In order to more vividly depict the scheduling situation of the integrated production scheduling problem of heating furnace hot rolling, in this case, there are 20 slabs to be processed, with slab numbers 1-20; Each slab needs to go through 4 processing stages, numbered 1-4; From the first processing stage to the last processing stage, the number of equipment in each stage is 2, 1, 2, and 3, with a total of 8 devices. Provide a visualized transmission scheme for experimental simulation scheduling, as shown in Fig. 5.

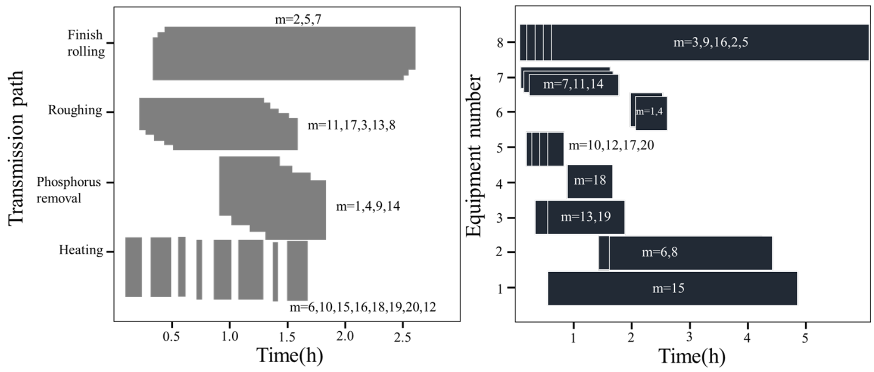

Fig. 5. Schematic diagram of slab transmission path

Use the improved NSGA-II algorithm to solve the case. The software platform for algorithm operation is Matlab 2023b, and the hardware platform is a computer: Intel (R) Core (M) i7-8800 processor, with a frequency of 3.06 GHz; 16.00GB of RAM, Windows 11 system. The values of some algorithm parameters need to be given in advance: the number of population individuals is set to 100, the maximum number of iterations is set at 1000, and the maximum completion time considering time constraints is set. As the number of iterations increases, the minimum maximum completion time gradually decreases from 217 minutes to 186 minutes. When the number of iterations reaches 482 to 1000, the value of completion time stabilizes and converges to 154, and no longer changes. From the trend of curve changes, the algorithm presented in this article demonstrates excellent optimization ability when solving scheduling cases, and can quickly converge to the optimal value. The convergence effect is shown in Fig. 6. The scheduling Gantt chart is shown in Fig. 7.

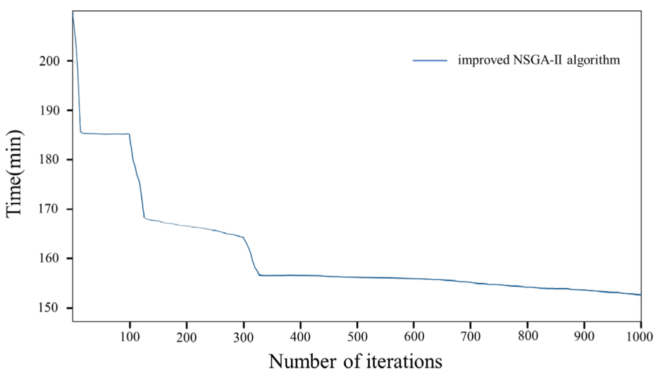

Fig. 6. Algorithm convergence effect diagram

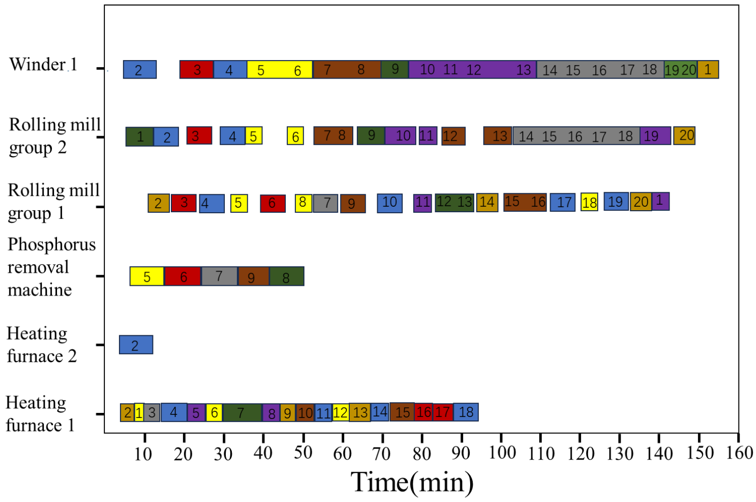

Fig. 7. Hot rolling scheduling gantt chart

From the above process, it can be concluded that in processing stage one, slabs 1-25 are processed on heating furnace 1 and heating furnace 2 respectively according to the coding scheme. Before the 30th minute after the start of processing, slabs 1, 3, 12, 4, 8, 14, and 19 have completed the processing of processing stage one. Following the principle of completing first, proceeding to the next processing, and processing in order of coding priority if all are completed, slabs 1 and 3 have completed processing stage two on the high-pressure water phosphorus removal machine. During the period from the 30th minute to the 50th minute after the start of processing, the high-pressure water phosphorus removal machine in processing stage two is in maintenance status. At this time, although slabs 12, 4, 8, 10, 20, 5, 14, 19, 9, and 11 have completed processing stage one between the 30th and 50th minutes, due to the maintenance shutdown of the high-pressure water phosphorus removal machine during this time period, and the fact that there is only one equipment available for processing stage two, these slabs cannot enter processing stage two during the 30th to 50th minutes and can only wait in the buffer zone. After the 50th minute, the high-pressure water phosphorus removal machine finished maintenance and resumed normal operation. At this time, the processing stage one of the blank plates 12, 4, 8, 10, 20, 5, 14, 19, 9, and 11 had been completed. According to the coding priority order, after the 50th minute, the blank plate 4 began processing process 2 on the high-pressure water phosphorus removal machine first, and the other blanks completed stage two processing on the high-pressure water phosphorus removal machine in sequence.

6 Conclusion

The rationality of hot rolling scheduling determines the production cycle and the efficiency of completing production orders. This article focuses on the optimization of production scheduling for steel hot rolling production processes, analyzing the pre-processing, hot rolling and other process flows in the hot rolling production process. Then, the operation and maintenance time consumption of hot rolling equipment and the conversion time between hot rolling equipment are analyzed. A mathematical model of production scheduling for the hot rolling production process is established with the goal of minimizing work order completion time and balancing equipment working hours. Finally, deep learning algorithms are used to improve the efficiency and performance of NSGA-II function in solving multi-objective models. Finally, a simulation experimental platform is built with real production cases to solve the Gantt chart of production scheduling and guide enterprises to improve production efficiency.

At the same time, there are also shortcomings in the research methods used in this article. With the rapid development of intelligent manufacturing technology and the increasing demand for intelligent manufacturing systems, the hot rolling scheduling production simulation system still needs a lot of improvement. The prospects for further research directions are summarized as follows:

1) In the actual scheduling production of the hot rolling workshop, there are often many and complex factors that need to be considered, and they may change dynamically. For example, during the scheduling process, users change orders or new users urgently insert orders. The production process needs to consider logistics time cost constraints, buffer capacity constraints, etc. How to consider these factors and establish a more comprehensive scheduling model has significant practical significance.

2) The production of hot rolling workshops consumes a large amount of energy and has an impact on the environment. Against the backdrop of energy conservation and emission reduction becoming a hot topic of concern in countries around the world, combining the scheduling of production, energy consumption, and emission mechanisms in hot rolling workshops, proposing and establishing reasonable green manufacturing scheduling goals, will be the next research focus.

3) In the existing hot rolling mixed flow workshop scheduling production simulation system, the three-dimensional model of the object is static. The next step is to model the workshop object more finely and add motion and shape changes to the object, such as allowing gears, shafts, and cutting tools on the machine tool to simulate motion, and the processed blanks to "flow" on the production line and undergo shape and appearance changes with the processing progress, in order to make the simulation workshop more realistic and vivid. In addition, more functional modules should be developed in the system to meet the usage needs of different scenarios and populations, such as developing teaching functional modules for school education or factory employee training.

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