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A TWO-STAGE PROCESS BAT ALGORITHM FOR SOLVING THE STEELMAKING AND CONTINUOUS CASTING SCHEDULING PROBLEM WITH ENERGY CONSTRAINTS

Nan Zhang[1] and Zhimin Lv[2,*]

[1]Institute of Engineering Technology
[2]Collaborative Innovation Center of Steel Technology
University of Science and Technology Beijing
No. 30, Xueyuan Road, Haidian District, Beijing 100083, P. R. China
b20150443@xs.ustb.edu.cn; *Corresponding author: lvzhimin@nercar.ustb.edu.cn

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Abstract. *In steel companies, the energy cost is one of the main costs of steel products, and it provides new targets for companies to consider the internal consumption and conversion of energy and reduce production costs. As one of the three key processes in steel production, steelmaking and continuous casting process plays an important role in energy optimization. In this paper, taking account of the impact of tiered electricity prices and converting gas to electricity, we developed a new model for steelmaking and continuous casting with the above energy constraints to reduce the production of slab costs. For the case of unknown casting sequence in advance, coexistence of continuous and discrete production process, a novel two-stage process bat algorithm is developed. In this algorithm, the casting sequence on the continuous casting machine is determined first, followed by the heating sequence on the converter and refining furnace. By solving the practical scheduling problem, it can be concluded that the proposed algorithm can find the optimal solution for the different objectives quickly. In conclusion, the improved two-stage process bat algorithm is effective, and the scheduling model with gas and electricity constraints can reduce enterprise costs and increase its profits.*
Keywords: Iron and steel industry, Steelmaking and continuous casting scheduling problem, Gas and electricity, Energy constraints, Two-stage process bat algorithm

1. **Introduction.** The iron and steel industry is a pillar industry in China and an important symbol of the country's economic level. According to the statistics of the World Steel Association, China's crude steel production reaches 1.053 billion tons in 2020, up 5.2% year-on-year [1]. And the energy intensity was 20 GJ per ton of crude steel. The increase of crude steel output and energy intensity will lead to huge total energy consumption of iron and steel enterprises. Energy efficiency improvement or energy saving is the most controllable factor affecting energy consumption in the steel industry [2]. Therefore, considering the impact of energy and saving energy in the steel plant scheduling process can reduce the energy consumption of enterprises, further effectively reduce production costs and increase profits. In the process of steel production, raw materials are processed into final products through coking, sintering, iron making, steel making, continuous casting, and rolling, forming the material flow. In the process of material flow operation, energy flows such as by-product gas (blast furnace gas, coke oven gas, converter gas, etc.), electricity, steam, and water are generated and consumed. The total resources of the three kinds of gas among the above-mentioned energy can account for 50% of the total energy

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consumption, which plays a very important role in the energy balance of iron and steel enterprises.

In China, a large amount of steel is produced through steelmaking and continuous casting process, and much converter gas is generated. In addition to supplying the gas to each production unit as fixed consumption, the surplus gas can be stored in the gas cabinet for future needs or directly into the combined cycle power plant (CCPP) unit to generate electricity, which can be supplied to the consuming users for consumption, and the surplus can also be sold back to the grid to generate revenue for the enterprise [3]. The process of steelmaking and continuous casting, in addition to the generation and conversion of gas, is also accompanied by the consumption of electricity. Both of them have a great impact on the steelmaking cost. Therefore, considering the internal consumption and transformation of energy while ensuring production plays a great role in reducing slab costs and increasing enterprise profits.

As a result, steel companies are in urgent need of energy optimization. Self-generation of electricity is very important to protect their production under the power restriction initiative. Therefore, the conversion of gas-to-electricity can not only ensure the production of enterprises but also promote the optimization of energy costs. Therefore, studying how to optimize the gas-to-electricity conversion can maximize the efficiency of the enterprise. On the other hand, influenced by the tiered electricity price, steel companies would like to adjust their production patterns by scheduling more production when electricity prices are low and, conversely, reducing production when electricity prices are high. This optimization operation also helps to reduce production costs.

At present, production scheduling and energy scheduling in iron and steel enterprises mostly operate independently, and production optimization and scheduling focus more on material flow without considering the influence of energy flow, which is not conducive to achieving lower cost and better gas-to-electricity profit in enterprises [4,5]. Therefore, the study of planning and scheduling in steel enterprises considering energy constraints such as gas and electricity can not only reduce the cost of enterprises, but also improve the executability of order scheduling, ensure the production of enterprises, and increase their profit. It can be said that the quality of production planning and scheduling considering energy constraints and the cost of energy consumption plays a significant role for steel companies.

Based on the characteristics of continuous and discrete production, unknown casting schedule in advance and the energy constraints to be considered, this paper proposes a new steelmaking and continuous casting scheduling model and presents a two-stage process bat algorithm to solve this model. The improved two-stage algorithm divides the steelmaking and continuous casting problem into casting solution and heats solution. Casting solution determines the casting sequence and processing time, while heat solution defines the final scheduling plan for the overall steelmaking and continuous casting model.

The experimental results show that the improved bat algorithm is effective for solving the steelmaking and continuous casting scheduling problem under energy constraints. The enterprise can use this overall production and energy scheduling optimization to rationalize the production to save cost and improve the enterprise profit.

The rest of this paper is organized as follows. The literature review on related papers is introduced in Section 2. Section 3 establishes the model of steelmaking and continuous casting scheduling with energy constraints. Section 4 introduces a two-stage process bat algorithm for the proposed scheduling model. Then, Section 5 presents some experiments and reports the computational results. Section 6 gives some discussions on the proposed model. Finally, the paper is concluded in Section 7.

2. **Literature Review.** For the traditional planning and scheduling problems of steel enterprises, the focus is more on production planning optimization and process operation scheduling [6]. Mattik et al. [7] proposed a mixed integer planning model based on the block planning principle in order to solve the joint scheduling problem of hot rolling and continuous casting in steel enterprises. Zhao et al. [8] studied a new single-machine scheduling problem arising from an industrial wire rod and bar rolling process and proposed a two-stage decomposition method to solve the industrial scale problem. However, these papers mostly study production planning and scheduling optimization, with less consideration of energy constraints. Such a model may have bottlenecks in practical application, which makes it difficult to implement planning and scheduling accurately.

Energy intensity is one of the most commonly used indicators for comparing the comprehensive energy utilization efficiency of different countries and regions. In steel companies, it has a direct impact on production costs and thus on the competitiveness of the company. The reduction in energy intensity is evidence of the improvement in efficiency. There are two basic technologies used for the production of steel: the blast furnace and basic oxygen furnace (BF+BOF) and the electric arc furnace (EAF) [9]. The first one uses coal and iron ore for production, and the other one uses waste products and electricity. Obviously, the former will consume more energy. World leaders in steel production (i.e., China, Japan, Russia, Korea, Germany, Brazil, and Ukraine) mostly use BF+BOF technologies [10].

Many studies deal with analyses of energy intensity in the steel industry. For example, Gajdzik et al. [10] analyzed the energy intensity of steel production in Poland as a function of investments made in the steel industry in the years 2000-2019. Their research results show that with the increase of technological investment in electric steel plants in Poland, the energy consumption of steel produced by electric furnaces decreased during the analysis period. Worrell et al. [11] provided "world best practice" energy intensity values for the production of iron and steel, aluminum, cement, pulp and paper, ammonia and ethylene. The "best practice" figures for energy consumption provided in their report should be considered as indicative, which may vary over time depending on the availability, costs, characteristics and quality, as well as product type and quality. Reddy and Ray [12] studied the physical energy intensity indicators of the steel industry in India in the years 1991-2005. The intensity effect of the steel industry is negative, indicating that energy efficiency has improved. Arens et al. [13] analyzed the development of the specific energy consumption (SEC) in the German steel sector between 1991 and 2007. And they found that the total SEC declined by 0.4%/year. All of the above shows that the study of energy in iron and steel enterprises is very important for enterprise costs and profits.

Therefore, the research on energy scheduling in steel enterprises is important for reducing waste, lowering costs, and increasing the efficiency of enterprises. For gas energy, Zhao et al. [14] proposed a data-based predictive optimization (DPO) method to carry out real-time adjusting for the gas system. Zhao et al. [15] proposed a two-stage online prediction method based on an improved echo state network to realize forecasting in the BFG system. The results demonstrate that the prediction system exhibits high accuracy and can provide effective guidance for balancing and scheduling the byproduct energy. Most of the above-mentioned scholars focus on the production and consumption forecasting of a single process, and few papers consider gas energy in the production plan and generate an integrated model.

In fact, electricity is one of the most important energy sources after gas in steel enterprises. Under the current situation of electricity rationing, it is urgent for enterprises to save and optimize electricity consumption. Scholars have studied the application of electric power and found that it plays a significant role in improving the power grid balance and reducing the cost of enterprises. In [16], a model predictive control method based on finite control set (FCS-MPC) is designed for power imbalance and the cost function is optimized using the least squares method. The simulation results show that the proposed method has good results and advantages in stabilizing the DC bus voltage, reducing regulation time and speeding up the load response. Santos and Almada-Lobo [17] described the production planning and scheduling problem for integrated pulp and paper mills. They propose a new model that integrates the critical production processes of pulp, paper, and energy mills, and explore the advantages of integrating the above three stages. Their research results may help companies to increase their competitiveness and reactiveness in dealing with demand pattern oscillations.

Analyzing the current situation of material flow and energy flow in the steel industry, it is found that most industries are currently scheduling material and energy separately. In recent years, how integrating material flow and energy flow modeling and adding energy constraints into production planning and scheduling has become the focus of research in process industries such as steel, petrochemical, and pulp. Tan et al. [18] developed a two-stage model to test the optimization of the actual problem in a steel mill, and the results showed the effectiveness of the proposed method for reducing power spending and optimizing the production of the enterprise considering the production scheduling problem in the continuous casting stage of steelmaking with variable power prices. Castro et al. [19] studied the production scheduling problem considering time-varying energy prices. They proposed a new discrete-time aggregate formulation, and all models rely on the resource-task network (RTN) process representation. Compared to the manual scheduling process, the method achieves approximately 20% reduction in electricity consumption costs by shifting production from peak to low periods.

The above-mentioned modeling of the integration of material and energy flow involves multiple industries and phases. For the steel industry, due to the actual situation of long production lines and insufficient equipment capacity, the theoretical studies on the coordinated operation of material and energy flow in the production operation process are still relatively few, and most of them focus on time-varying electricity price as a constraint, and seldom involve the constraint of gas energy. Based on the traditional RTN, Li and Lv [20] proposed an extended resource task network (ERTN) for the collaborative scheduling of material and energy flows in steel production. And the ERTN model is carried out for gas and electricity consumption of the steelmaking continuous casting system. The dispatching of 70 heats in a steel company under discrete slots and solved by CPLEX has achieved good results. However, discrete slots do not apply to the actual production scheduling for some processing time is not an integer multiple slot duration, and the solution for 70 heats does not apply to the large-scale scheduling of steel mills.

Therefore, this paper intends to consider the scheduling optimization problem of multiple heats in iron and steel mills with constraints of gas and electricity under continuous time, in order to realize the effective utilization of gas and electricity in enterprises and obtain greater profits.

3. Modeling.

3.1. **Problem description and assumptions.** The steelmaking and continuous casting include three main stages: steelmaking, refining, and continuous casting. Each heat passes through the above processes in turn according to its unique process path and finally combines into a continuous casting in the continuous casting machine, constituting a complex production network. Because of the above process characteristics, the steelmaking continuous casting problem of a steel mill can be regarded as a multi-process parallel machine hybrid flow shop scheduling problem in the last stage of continuous production.

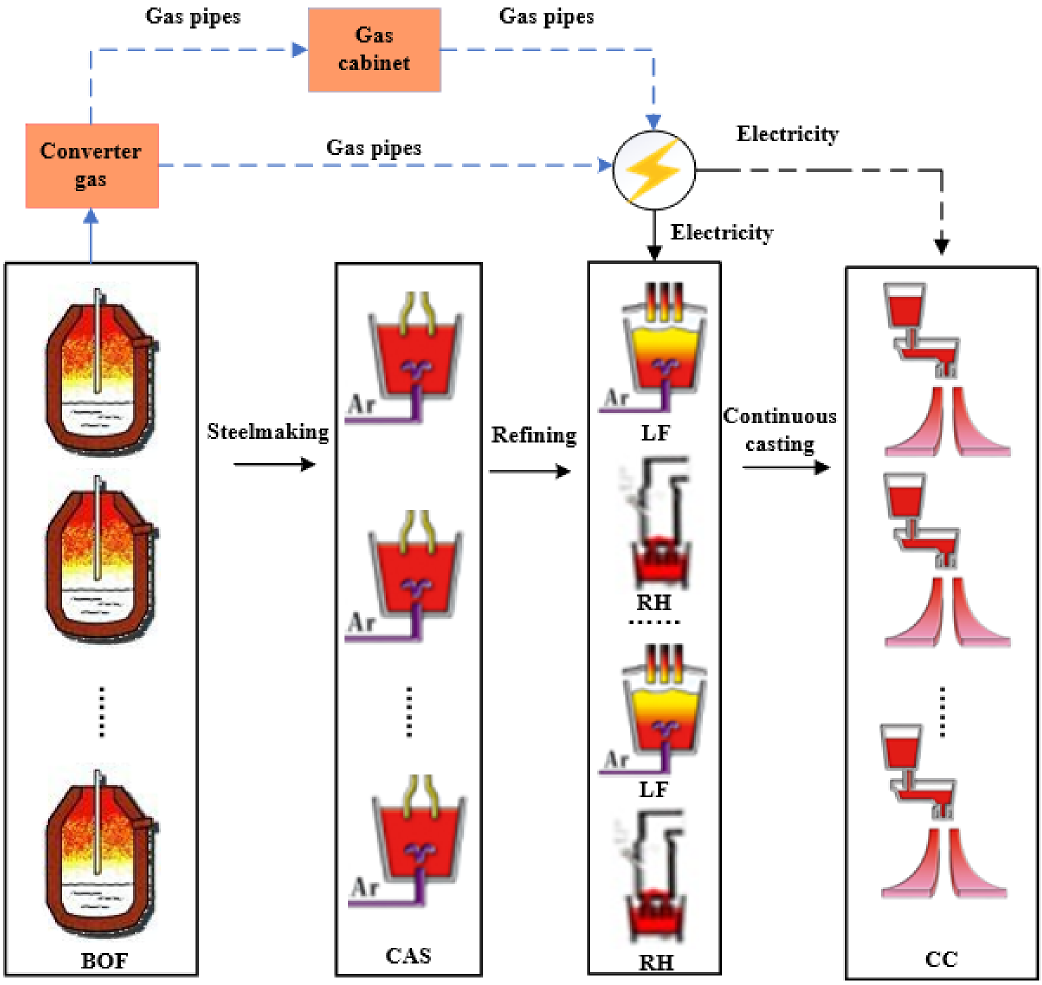

FIGURE 1. Steelmaking and continuous casting production process

As shown in Figure 1, a large amount of converter gas is produced in the basic oxygen furnace (BOF). In addition to satisfying the production requirements of the steel process, the surplus gas can be stored in the gas cabinet for later use or directly into the CCPP unit for power generation. There are three kinds of refining equipment in the steel plant: composition adjustment by sealed argon bubbling (CAS), rheinstahl and heraeus (RH) furnace, and ladle furnace (LF). The RH, LF and continuous casting (CC) stages all consume electricity during the production process, especially the LF furnace, which consumes a large amount of electricity during the refining process. When the gas cabinet level exceeds the upper safety limit, the surplus converter gas is burned and discharged into the atmosphere.

Most of the existing studies on the scheduling of steelmaking and continuous casting have focused on the case where the casting sequence is known [21-23]. It is often assumed in these studies that the execution sequence of the casting has been obtained by advanced planning and scheduling system (APS). However, most of the current APS focus on material flow production planning and do not consider energy constraints. Therefore, this precondition that the casting sequence and the execution equipment are known is not suitable for solving the actual problem of steelmaking and continuous casting with energy constraints in this paper. Therefore, in the modeling, it mainly studies the steelmaking and continuous casting scheduling when the casting sequence and equipment are unknown in this paper.

As mentioned earlier, the steel industry has a mixed model of continuous and discrete production. Moreover, regarding the above analysis of gas and electricity energy in the steelmaking and continuous casting system, it can be known that the different steel grades and the uniqueness of the steelmaking process route led to different amounts of energy consumed in their production. Based on the above characteristics, simple mathematical models or models based on small-scale problems are not sufficient to describe the actual production planning requirements of large steel companies. Therefore, we need to study gas and electricity consumption under different production process paths, and establish a planning and scheduling model with energy constraints. The ultimate goal is to improve customer satisfaction and obtain the maximum benefit for the company. Thus, the steelmaking and continuous casting scheduling problem with energy constraints can be described as follows. Given C casts composed of H heats (the casting sequence on the caster is unknown), we expect to schedule the heats and casts to steelmaking, refining, and continuous casting equipment, respectively, so as to minimize energy cost and meet the requirements of delivery time.

In the modeling process of steelmaking and continuous casting, the following assumptions are used.

1) Energy scheduling mainly considers by-products of gas and electricity, and other energy sources such as steam and heat are not considered. The gas generated from the steelmaking process can be used for electricity generation or other process consumption. The refining and continuous casting stages mainly consume electricity. Therefore, electricity and gas resources are important energy sources in the steelmaking and continuous casting production process and should be given priority consideration.
2) The amount of electricity and gas consumed per unit of time for each process is known. Since converter gas supplies multiple users in the whole steel production process, the fixed consumption of converter gas can be regarded as a black box model, which is assumed to be a fixed value.
3) In order to control the drop of molten steel temperature caused by process waiting, the waiting time is required to be no greater than the maximum waiting time for the process if the equipment for the next process is occupied.
4) The transportation time between processes is not considered separately, and is spread to the process processing time.
5) The processing time of the heat on each process is known. The partial casting schedule is known, i.e., the number of casts and the heat information within each cast are known. However, the processing sequence of each cast and its start time in the continuous casting machine is unknown.
6) In the process of changing casts, it is necessary to change the tundish, mold, width adjustment, and other operations, and the changeover time between different casts is not exactly the same. To simplify the model, it is assumed that the changeover time between different casts on the same equipment is the same.

3.2. **Model for steelmaking and continuous casting with energy constraints.** Since the first two stages (the steelmaking and refining stages) are dispatched by heats, they are discrete stages, while the continuous casting stage is based on casting, which is a continuous stage. Therefore, steelmaking and continuous casting is a continuous and discrete production process. If a discrete mathematical model is established, as the number of heats increases, the total number of variables and constraints involved increases, making the solution very difficult to meet the actual production needs. So, the model presented in this paper is a continuous time scheduling problem with a minimum timing unit of minutes. The continuity of scheduling makes the definition of practical problems more clearly defined and flexible. The established model is as follows.

Description of symbols and variables.

Sets:

H: the number of heats;

C: the number of casts;

$C(h)$: heat h is a subset of relevant cast C;

$L(C, H)$, $F(C, H)$: the last or first heat h in cast C;

M: equipment;

K: production stage;

M_k: the set of all equipment in production stage k.

Parameters:

$T_{h,m}$: processing duration of heat h on equipment m;

$Setup_m$: maximum waiting time of heat h after production stage k;

$Wait_{h,k}^{\max}$: waiting time of heat h after production stage k;

$GH^{\max}$, $GH^{\min}$: maximum and minimum value of gas holder position;

$Q^{EL\max}$, $Q^{EL\min}$: maximum and minimum capacity limit of CCPP unit;

P_t: purchase price of electricity at time t;

S_t: selling price of electricity at time t;

C_{EM}: penalty cost of discharging gas.

Variables:

$t_{m,h}^{s}$, $t_{m,h}^{f}$: starting and finishing time of heat h on equipment m;

$X_{m,h}$: true when heat h is produced on equipment m;

$V_{m,h,h'}$: true when heat h' is produced after h on equipment m;

$Q_{m,t}^{Pro}$: gas produced by the equipment m at time t;

$Q_{m,t}^{\text{con}}$: power consumption by the equipment m at time t;

π_t^{Cons}: gas consumption of fixed consumption users at time t;

GH_t: position of gas holder at time t;

Q_t^{GH}: the change of gas holder position at time t, which can be positive or negative, when negative, it means that the gas holder level drops;

Q_t^{EL}: generation capacity of CCPP units at time t;

Q_t^{EM}: the amount of gas discharged at time t.

From the analysis in the previous sections, it can be seen that energy constraints such as gas and electricity are very important for the production scheduling of iron and steel enterprises. Therefore, considering the changes of electricity costs and gas-to-electricity conversion on the production profits, in order to maximize the profits of enterprises, the objective function of the steelmaking and continuous casting system can be divided into three parts as follows.

Minimize steelmaking and continuous casting electricity costs Obj1. In the production process, many processes need to consume electricity, such as refining, continuous casting, and hot rolling. In order to maximize profits, it is necessary to control costs. Therefore, minimizing power costs has become one of the goals pursued by enterprises.

$$\min \sum_{m \in M_k} \sum_{t \in T} Q_{m,t}^{\text{con}} \times T_{h,m} \times P_t, \quad k \neq 1 \tag{1}$$

Maximize profits from gas-to-electricity conversion Obj2. Gas-to-electricity conversion not only reduces gas emissions and the greenhouse effect, but also reduces the amount of electricity purchased by companies, and the surplus electricity sold back to the grid can also increase additional profits. Therefore, increasing the conversion profit is one of the means to increase the total profit of steel companies.

$$\max \sum_{t\in T} Q_t^{EL} \times S_t \tag{2}$$

Maximize total profits Obj3. For cost minimization and conversion profit maximization, the total profit function is used to comprehensively evaluate the cost and profit objectives.

$$\max \left(\sum_{t\in T} Q_t^{EL} \times S_t - \sum_{m\in M_k} \sum_{t\in T} Q_{m,t}^{\text{con}} \times T_{h,m} \times P \right), \quad k \neq 1 \tag{3}$$

The constraints are as follows.

Production constraints

As a binary variable, $X_{m,h}$ is true only when a given heat h is produced on equipment m. Therefore, Equation (4) shows that one heat can only be produced on one machine in each stage.

$$\sum_{m\in M_k} X_{m,h} = 1, \quad \forall h \in H,\, k \in K \tag{4}$$

Equation (5) is defined as the end time of heat h on equipment m is equal to its start time plus its processing time.

$$t_{m,h}^{f} = t_{m,h}^{s} + X_{m,h} \times T_{h,m}, \quad \forall h \in H,\, m \in M \tag{5}$$

There is a maximum wait time limit. Therefore, when the heat is processed in a certain stage, the start time of the next stage minus the finish time of the previous stage is less than its maximum waiting time. The production flow in the connected stages is shown in Equation (6).

$$0 \le t_{m',h}^{s} - t_{m,h}^{f} \le Wait_{h,k}^{\max}, \quad \forall h \in H,\, m \in M_k,\, m' \in M_{k+1},\, k < 3 \tag{6}$$

Equation (7) ensures that when the casting of the current heat is completed, the next heat will start immediately, that is, the continuity of the casting stage shall be ensured.

$$t_{m,h'}^{s} = t_{m,h}^{f}, \quad \forall h, h' \in C(h),\, V_{m,h,h'} = 1,\, m \in M_k,\, k = 3 \tag{7}$$

In the continuous casting phase, for different casting, there should be a setup time between the finish time of the previous casting and the start time of the next casting.

$$t_{m,h'}^{s} \ge t_{m,h}^{f} + Setup_m, \quad \forall h \in L(C,H),\, h' \in F(C+1,H),\, m \in M_k,\, k = 3 \tag{8}$$

Equation (9) indicates that multiple heats within the same casting must be assigned to the same caster.

$$X_{m,h} = X_{m,h'}, \quad \forall h, h' \in C(h),\, m \in M_k,\, k = 3 \tag{9}$$

Energy constraints

According to the above analysis of energy generation and consumption, the energy constraints in the steelmaking stage are as follows.

The generation of converter gas is equal to the sum of the consumption of fixed users, gas holder, gas-to-electricity conversion and the gas discharged.

$$\sum_{m\in M_k} Q_{m,t}^{Pro} = \pi_t^{Cons} + Q_t^{GH} + Q_t^{EL} + Q_t^{EM}, \quad \forall t \in T,\, k = 1 \tag{10}$$

Among them, the actual production of CCPP units has minimum and maximum power generation requirements.

$$Q^{EL\min} < Q_t^{EL} < Q^{EL\max}, \quad \forall t \in T \tag{11}$$

The constraint of gas holder position is

$$GH_t = GH_{t-1} + Q_t^{GH}, \quad \forall t \in T \tag{12}$$

For gas holder resources, the resources available at time t should be within the range allowed by the safety upper and lower bounds.

$$GH^{\min} < GH_t < GH^{\max}, \quad \forall t \in T \tag{13}$$

According to the tariff policy of the State Grid of China, three different electricity prices are generally used for industrial electricity consumption: peak, flat, and trough, as shown in Figure 2. The electricity prices for the three stages are 0.8334, 0.5760, and 0.3256 [RMB/KWh] [24]. The daily electricity price changes can be divided into 6 time periods: 0:00-8:00, 8:00-11:00, 11:00-15:00, 15:00-18:00, 18:00-22:00, and 22:00-24:00.

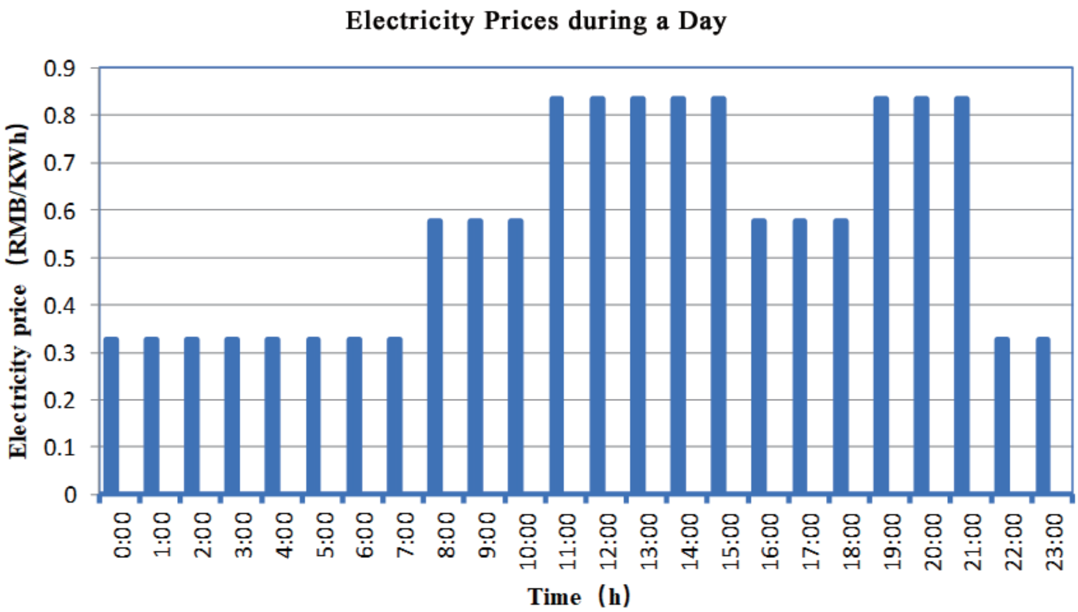

FIGURE 2. Change in electricity prices during a day

4. **Model Encoding and Two-Stage Process Bat Algorithm.**

With the increase in the number of heats in the steelmaking process, the difficulty of solving the problem also increases. At the same time, the coexistence of heats and casts, unknown casting sequence and execution equipment also make the solution more complex. In this paper, we propose a novel two-stage process bat algorithm to solve the above technical difficulties. The scheduling of the steelmaking and continuous casting process is also divided into two stages: the casts determination and the heats solution.

4.1. **Model encoding.**

As mentioned earlier, the steel industry has a mixed model of continuous and discrete production. In order to better solve this multi-objective and multi-constrained continuous-discrete coexistence mathematical model, the encoding strategy should be defined first.

As we all know, the different casting sequences of continuous casting stage can lead to a great difference in operation schedules. And once the casting sequence is determined, the overall production plan can be launched by the backward scheduling strategy from the casting sequence of the continuous casting machine to the heats sequence of the steelmaking-refining process, combined with the constraints of the steelmaking-refining process. Therefore, it can be said that in the process of steelmaking-continuous casting plan scheduling, different casting sequence has an important influence on the overall scheduling, i.e., the determination of the casting sequence becomes especially important. Therefore, when establishing the encoding strategy of steelmaking and continuous casting scheduling model, this paper first takes the casts as the encoding unit to determine the sequencing and processing time of continuous casting process. Then the casts are divided into corresponding heats in the steelmaking and refining process to determine the heats schedule.

Here, creating two encoding matrices, the casts and heats are used as the row vector of the matrix, respectively. For the cast model, create an $M \times n$ matrix, defined as $x = (x_{1,1}, x_{1,2}, x_{1,3}, \ldots, x_{1,n}; x_{2,1}, x_{2,2}, x_{2,3}, \ldots, x_{2,n}; \ldots; x_{M,1}, x_{M,2}, x_{M,3}, \ldots, x_{M,n})$, where M is the total number of casts and n is the total number of processes in steelmaking and continuous casting. For the heat model, establish an $m \times n$ matrix, defined as $y = (y_{1,1}, y_{1,2}, y_{1,3}, \ldots, y_{1,n}; y_{2,1}, y_{2,2}, y_{2,3}, \ldots, y_{2,n}; \ldots; y_{m,1}, y_{m,2}, y_{m,3}, \ldots, y_{m,n})$, where m is the total number of heats and n is the total number of processes in steelmaking and continuous casting. The real numbers in the matrix above are the machine numbers used for the process of the cast/heat. Taking the heating model as an example, the encoding strategy is shown in Figure 3. In this paper, each heat in the steelmaking and continuous casting stage has to go through three processes: converter, LF/RH refining furnace, continuous casting machine, and for the convenience of the solution, the total number of processes $n = 4$ (converter steelmaking, LF refining, RH refining, continuous casting) is set. It is stipulated that all heats are assigned to machines according to the above processes, and processes that do not go through (e.g., no RH refining process) are encoded with their machine codes set to 0.

In summary, we have combined the casts/heats, processes, and machines that need to be considered in the steelmaking and continuous casting system into a matrix that clearly and concisely expresses the logical connection between the three. Therefore, with

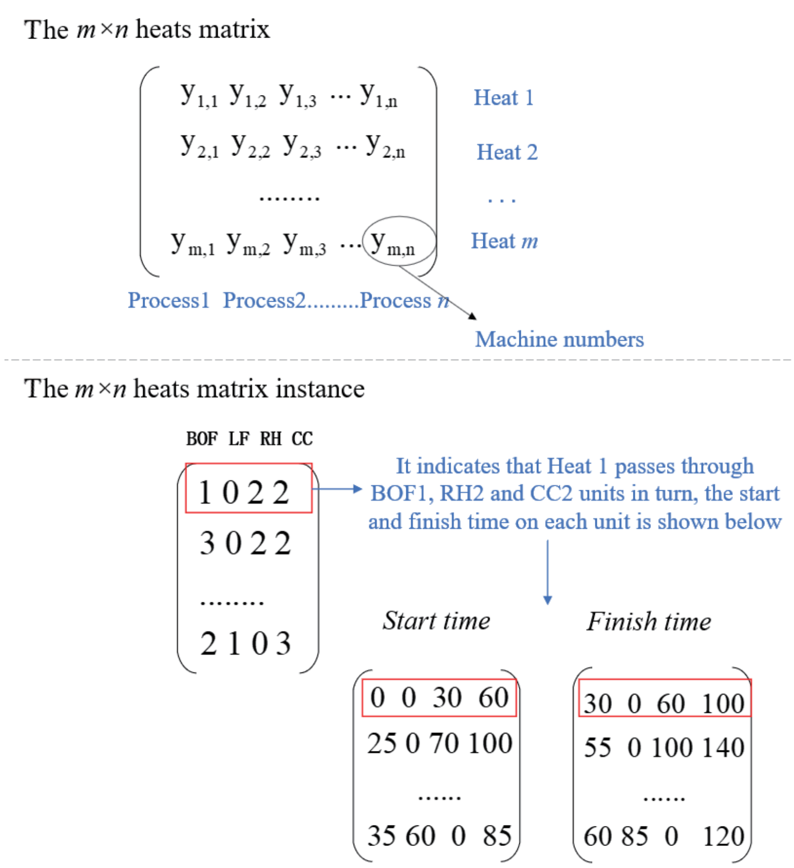

FIGURE 3. Encoding strategy for heats scheduling

the above encoding strategy, the actual steel plant scheduling problem can be transformed into a clear mathematical expression for easy recognition and solution.

4.2. **Two-stage process bat algorithm.** The steelmaking and continuous casting model mainly use the bat algorithm [25] to optimize the casting and heats sequence to finally obtain an optimal solution to the problem. The bat algorithm is proposed primarily to solve large-scale continuous problems, where each bat moves continuously in its search space according to the position function [26,27]. In contrast, for the solution of discrete problem in this paper, the equations of the bat algorithm for individual bat velocity and position are no longer applicable. Therefore, an improved bat algorithm is proposed in this paper, which retains the basic idea of the bat algorithm, and on this basis, the definition of bat groups and an optimal group of casts are added, and the bats' velocity and position are updated and modified to make it more applicable to the solution of the actual steel mill problem.

Here, we define a two-stage process bat algorithm that solves the continuous casting schedule problem and the discrete heats schedule problem separately.

Stage 1: Define the casting as the scheduling unit and propose the concept of optimal casting groups. Using the grouping and evolution of bats, the optimization of the casting is realized. Through repeated iteration, the optimal casting and the current optimal solution are found.

However, the production schedule obtained at this moment is not necessarily the optimal schedule for the model, and there is still space for optimization of the steelmaking-refining process. Therefore, the next stage is needed.

Stage 2: When the casting schedule is determined, the casting schedule is split into heats schedule, and the heat is used as the minimum scheduling unit. Under the condition that the casting sequence of the continuous casting machine is known, the heats schedule in the steelmaking-refining stage is calculated iteratively to further optimize, and finally, a better optimized feasible solution of the steelmaking and continuous casting model is obtained.

During the solution process, it involves bat group definition, and the update of bat velocity and position, as shown below.

4.2.1. *Definition of bat groups and an optimal group of casts.* As mentioned above, the determination of the casting sequence is of great importance in the planning and scheduling of the steelmaking and continuous casting model. This subsection proposes a method to define the optimal group of castings to obtain the current optimal solution faster.

Here, the bats are divided into groups, and each group stores multiple individuals with similar casts. The Hamming distance was used to evaluate the cast similarity of individuals in the population. Hamming distance is a concept that indicates the number of different characters in the corresponding positions of two strings. In this subsection, a smaller Hamming distance indicates that the more similar the two casting encoding matrices are, the higher the probability that they exist in a group.

The casting encoding matrix mentioned here comes from the casting sequence machine matrix in the previous section. Each row represents the processing machine and sequence of the casts. If the same row of two casting matrices has the same row vector, it means that the two casts are similar and the corresponding Hamming distance is reduced by 1.

For example, as shown in Figure 4, for two 10×2 matrices, if the two matrices are completely different, the initial Hamming distance is 10. If three of the row vectors are the same, it means that the matrices are similar in three casts and the Hamming distance becomes 7.

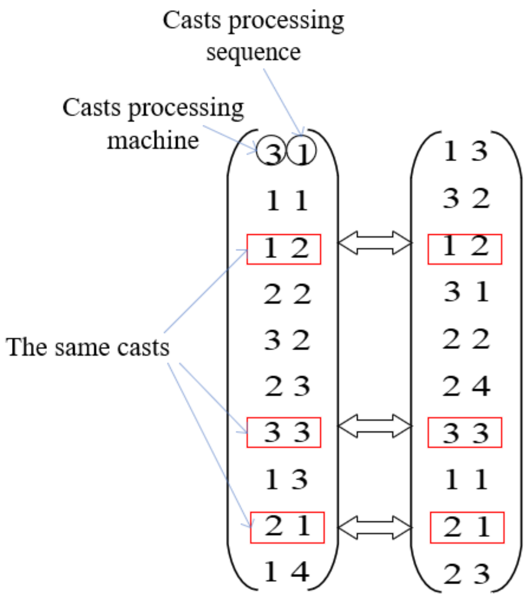

Figure 4. Hamming distance between casting matrices

After the bats are classified by casts similarity, the casts in the current optimal group can be considered superior. Then, if the bats in other groups are allowed to learn from this superior group, there is a high probability to get a better casting sequence. This learning mode makes the casting continuously updated and finally gets the current optimal solution.

4.2.2. *Velocity and position updating.* The velocity v_i^t is defined as the distance between the bat's current position x_i and the current optimal bat x_*.

For the casting schedule stage: from the encoding strategy of the model, it is known that the real number of matrix row vectors of each bat individual x_i represents the machines used in different casts. Since the concept of an optimal group is introduced, the x_* here is slightly changed, and it is taken from the optimal bat group or the current optimal bat individual with 50% probability each.

$$x_{*1}^{t-1} = \begin{cases} Group\left(x^{t-1}\right), & \text{if } 0 < rand < 0.5 \\ x_*^{t-1}, & \text{if } 0.5 \leq rand < 1 \end{cases} \tag{14}$$

The operation is defined as the cross-substitution of bat position, so as to express the update of bat individual velocity.

$$v_i^t = P \oplus \left[AR\left(x_i^{t-1}, x_{*1}^{t-1}\right)\right] \tag{15}$$

In Equation (15), the random integer P denotes the number of row vectors replaced between bat individuals, and $AR\left(x_i^{t-1}, x_{*1}^{t-1}\right)$ denotes the random replacement of row vector genes between x_i^{t-1} and x_{*1}^{t-1}.

For the heats schedule stage: when the current optimal casting schedule is determined, the real number of matrix row vectors of each bat individual x_i represents the machines used in different heats. The x_* here is taken from the current optimal bat individual. The operation is defined as the cross-substitution of bat position, so as to express the update of bat individual velocity.

$$v_i^t = P \oplus \left[AR\left(x_i^{t-1}, x_*^{t-1}\right)\right] \tag{16}$$

For a defined set of mixed flow shop scheduling discrete encodes, the velocity expresses the substitution between two groups of steelmaking and continuous casting scheduling schemes x_i^{t-1} and x_*^{t-1}. When the encoding replacement is completed, a random variation matrix x_w $(w \times n)$ is generated, and a local variation of the velocity variable is performed to produce a new location solution for the bat individual. The location solution is expressed as

$$x_i^t = W \oplus VA\left(v_i^t, x_w^{t-1}\right) \tag{17}$$

In Equation (17), the random integer W represents the number of row vectors of individual bat variants, and $VA\left(v_i^t, x_w^{t-1}\right)$ expresses the process of replacing the individual velocity with the variation matrix to produce a new bat position.

Taking Figure 5 as an example, during the casting schedule stage, if there are two different casts of bat individuals x_1 and x_*, as shown below, when the random integer $P = 2$, the random adjacent two rows of vectors in x_* are replaced by the same position vector in x_1 to obtain the new individual velocity v_i. Then, a random matrix x_w is generated based on the random integer W, and the individual bat velocity v_i is locally mutated to produce the new bat position x_i. If the current optimal value of the casting schedule is obtained, save the fourth column vector of this matrix. In the second stage, the heats bat individuals X_1 and X_* are shown below, and the new velocity V_i is obtained by replacement optimization. The final heats schedule X_i is obtained by varying with a random matrix X_w. Thus, the final function value is obtained, and the conversion is considered complete.

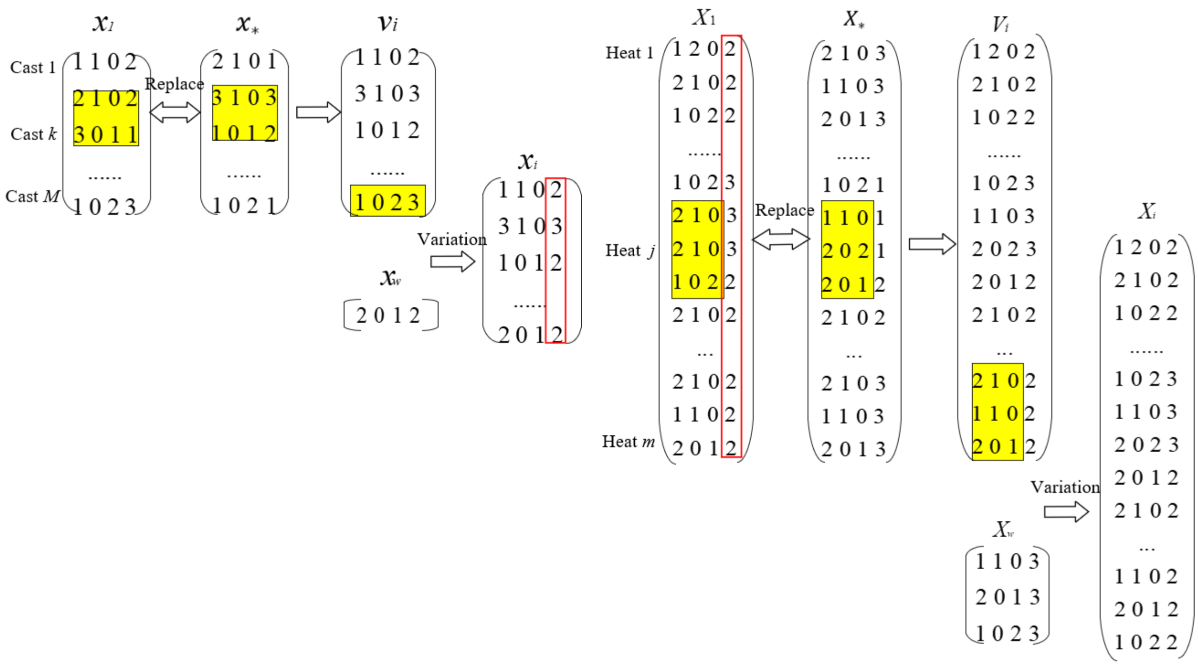

FIGURE 5. An example of the bat algorithm update

4.2.3. *Adjusting the pulse emission rate and the loudness.* It can be considered that the r_i and A_i are affected by the number of iterations. In basic bat algorithm, the loudness is only related to the previous iteration, which may lead to some limitations. Here, a new definition is proposed to further improve the performance of the algorithm.

$$A_i^{t+1} = A_i^t \times \frac{iter\_\max - t/8}{iter\_\max - iter\_\min} \tag{18}$$

$$r_i^{t+1} = \left(1 + \exp\left(\frac{8}{iter\_\max} \times \left(\frac{iter\_\max}{2} - t\right)\right)\right)^{-1} \tag{19}$$

As Equations (18) and (19), the definitions of r_i and A_i are related to the number of iterations, where $iter\_max$ and $iter\_min$ represent the maximum and minimum iterations of the algorithm. By using the above-mentioned equations, each bat has a greater probability of local search near the current optimal solution at the early stage of iteration, which will accelerate the convergence of the algorithm. At the same time, it effectively prevents the algorithm from falling into a local optimum solution.

In summary, the two-stage process algorithm is shown in Figure 6.

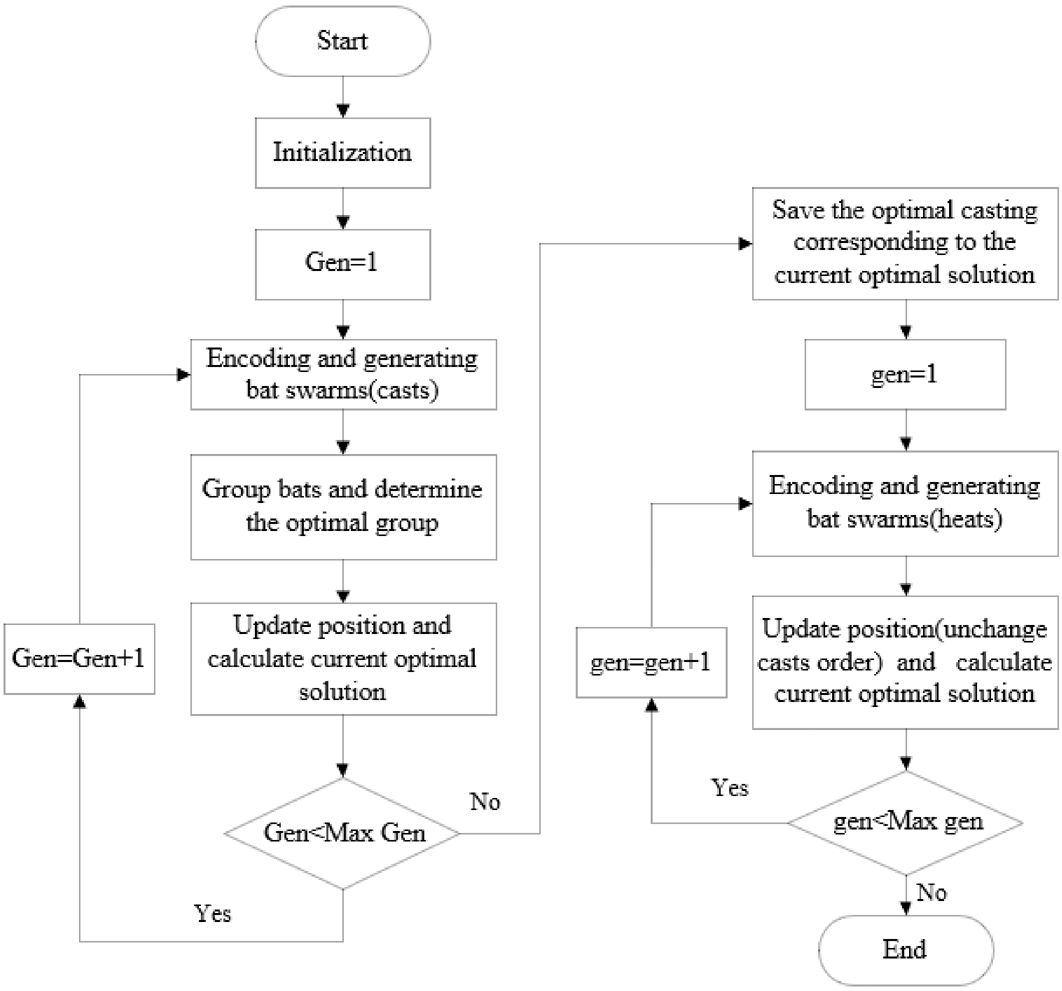

FIGURE 6. Two-stage process bat algorithm

5. **Numerical Results and Performance Comparison.** The steelmaking and continuous casting model developed in this paper comes from an actual plant that contains three BOFs, one LF, two RH refining furnaces, and three CC machines. In this process, the converter produces a large amount of converter gas and the refining, and continuous casting processes consume electricity.

In this paper, the production scheduling time is set to two days, and the relevant parameters of the bat algorithm used in this paper are

Casting schedule stage: population size = 50, number of iterations = 200, initial loudness $A \in [0.7, 1]$, initial pulse firing rate $r \in [0, 0.3]$.

Heats schedule stage: population size = 30, number of iterations = 500, initial loudness $A \in [0.7, 1]$, initial pulse firing rate $r \in [0, 0.3]$.

Here, the setting of $A \in [0.7, 1]$ and $r \in [0, 0.3]$ is more conducive to increasing the speed and effectiveness of bat iterative optimization.

5.1. **Validity and advantages of the model.** In order to verify the feasibility and effectiveness of the two-stage process bat algorithm and continuous-time steelmaking and continuous casting scheduling model proposed in this paper, this section applies the method to the solution of the 70 heats scheduling model and compares it with the discrete slot ERTN model solved with CPLEX in [20]. The data used in this section are consistent with the ERTN model, and the results of solving for different objectives are shown in Table 1.

Table 1. Comparison of different objectives

	CPLEX			Two-stage bat algorithm		
	EC (CNY)[1]	CP (CNY)[2]	TP (CNY)[3]	EC (CNY)	CP (CNY)	TP (CNY)
Obj1	187728	1442517	1254789	159500	1497400	1337900
Obj2	215163	2001136	1785973	197750	2100600	1902850
Obj3	211480	1999206	1787725	174530	2084700	1910170

[1] EC: electricity costs; [2] CP: gas-to-electricity conversion profits; [3] TP: total profits

From the comparison results, it can be seen that the algorithm proposed in this paper can find better solutions when solving for minimizing electricity cost, maximizing gas-to-electricity conversion profit, and maximizing total profit. The literature can only solve up to 70 heats, and the discrete slot model does not apply to the actual steel mill. In comparison, the intelligent improved bat algorithm can solve more heats, which makes the planning and scheduling problem more in compliance with the actual steel mill, and the solution time of the algorithm is much shorter than that of CPLEX (when calculating 60 heats, the CPLEX CPU running time reaches 1100 s, while the two-stage bat algorithm only uses 70 s). Therefore, the feasible solution to the problem can be found quickly under different constrained objectives. In summary, the advantages of the new model proposed in this paper are shown in Table 2. Therefore, the two-stage bat algorithm can be considered as effective for steel mill scheduling.

Table 2. Comparison of the two methods

	CPLEX	Two-stage bat algorithm
Model classification	Discrete time model	Continuous time model
Running time	1100 s	60 s
Heats number	Max. 70	More than 170
Results	The valid solution can be found	The solution obtained is better

5.2. **Effect of casting machine operating rate.** In the steelmaking and continuous casting process, under the condition that three converters are produced at the same time, the different numbers of heats will lead to different machine operating rates (MOR) of each process, which will affect gas production and power consumption. Therefore, it is meaningful to discuss the increase or decrease of the objective function when the number of heats and the MOR are changed.

In this chapter, the casting MOR is used as the evaluation criterion. For the same operating conditions, different heat numbers and different casting MOR are used to explore the gas generated and electricity consumed in the steel plant, so as to investigate the effect of different operating rates on the optimization of the steel scheduling model. To verify the effect, 100, 130, 150, and 170 heats are taken for testing, and the results are shown in Tables 3 and 4.

Table 3. Optimization results of minimizing electricity cost

Heats	MOR (%)	Obj1 (CNY)	CP (CNY)	TP (CNY)	Growth rate (%)
100	60.27%	240850	2811800	2570950	
130	70.55%	344850	4127000	3782150	47.11%
150	75.16%	398430	4961400	4562970	20.64%
170	84.13%	511590	5782200	5270610	15.51%

Table 4. Optimization results of maximizing gas-to-electricity conversion profit

Heats	MOR (%)	EC (CNY)	Obj2 (CNY)	TP (CNY)	Growth rate (%)
100	65.38%	332550	3750600	3418050	
130	73.44%	420920	5078700	4657780	36.27%
150	79.67%	505180	5859600	5354420	14.96%
170	85.36%	578840	6529800	595096	11.14%

It can be seen that the increase in the number of heats has an impact on the optimization results of the steelmaking and continuous casting scheduling model, the more the heat numbers, the higher the operating rates and the increasing total profit.

However, as the total operating rate becomes larger, the utilization rate of steelmaking scheduling equipment becomes greater, even to the point of reaching near or full load, which will definitely lead to less flexibility in equipment scheduling and less space for total profit improvement. The analysis of the numerical experimental example of the two objective functions shows that when the number of heats changes from 100 to 130, the profit growth rate is the largest, reaching 47.11% and 36.27%, respectively. When the number of heats grows to 170, the profit only increases by 15.51% and 11.14% compared to 150 heats. In the process from 100 to 130, 150 to 170 heats, although the total profit is increasing, the growth is getting slower and slower, and the profit growth rate is decreasing. Therefore, when setting the amount of equipment in each workshop and the number of heats processed per day, steel mills need to take account of the MOR and profit, in order to optimize the profitability of the mill while making full use of each equipment.

5.3. **Impact of different LF on electricity costs.** LF refining equipment consumes a lot of electricity during production, which has a large impact on the electricity costs of the steel mill. With the same number of total heats, the number of heats that pass through LF refining varies can lead to different electricity costs. When LF is produced at full capacity, the electricity cost remains the same no matter how it is scheduled; therefore, the LF production in this section does not reach full capacity. This part is tested by the different number of heats passing through LF to explore the change of LF on the electricity cost of the steel mill.

In Table 5, the minimum completion time (MCT) represents the current cost of electricity when considering only the minimized completion time constraint for the steelmaking and continuous casting process, without considering the cost of electricity and the profitability of gas-to-electricity conversion. It can be seen that with the increase in the number of heats that pass through LF refining, the electricity cost is gradually increasing and the space available for LF scheduling becomes smaller. Compared with the optimization results considering only the minimization completion time, the electricity cost reduction rate when optimizing the minimized electricity cost (Obj1) shows a trend of increases first and then decreases. This is because when the number of heats passes through LF is relatively few, LF scheduling did not reach full capacity and the scheduling space is large, and as the LF number increases to a certain level, the scheduling range begins to decrease. Therefore, the number of heats passing through LF has an important impact on electricity cost reduction.

Table 5. The electricity cost optimization results under different LF

Heats	Pass through LF	MCT (CNY)	Obj1 (CNY)	Reduction rate (%)
150	40	321930	303510	5.72%
	50	381260	335870	11.91%
	60	416070	371490	10.71%
	70	434780	409420	5.83%

In order to clearly compare the effect of LF on electricity cost, an experiment was set up to compare the effect on electricity cost when the number of LF machines is 1 or 2 for the case of 150 heats, and the results are shown in Table 6.

Table 6. The electricity cost under different LF machines

Heats	LF machines	Pass through LF	Obj1 (CNY)	Saving rate (%)
150	1	70	409420	
150	2	70	367770	10.17%

Since the number of 70 heats passing through LF is already close to the full capacity of the equipment, the minimized electricity cost can be calculated as 409420 when the number of equipment is one. At this time, if two machines are set up, the space available for heat scheduling increases, and the electricity cost is greatly reduced by 10.17%. Therefore, when construction cost is not considered, the number of LF refining machines can be considered to increase, which is conducive to reducing the production cost of enterprises.

5.4. **The effect of variable electricity prices on the objective function.** In order to verify the impact of energy constraints on the steelmaking and continuous casting scheduling of steel mills, this chapter solves the multi-furnace scheduling problem and explores the changes in scheduling schemes under different optimization objectives. Table 7 shows the results of optimizing different objective functions. Figures 7 to 9 show the Gantt charts of the optimization results for Obj1, Obj2, and Obj3. One color in the figure represents one cast.

Table 7. Comparison of different objective functions

	EC (CNY)	Gas discharge (CNY)	CP (CNY)	TP (CNY)
Obj1	340630	0	5634100	5293470
Obj2	468220	0	6636700	6168480
Obj3	429740	0	6608400	6178700

Obj1 is used to optimize and minimize the cost of electricity, the LF is shifted to the area of low electricity price. However, it does not optimize the profit of gas-electricity conversion, so the profit is low. Obj2 optimizes the profit of gas-electricity conversion and production is shifted to the area of high electricity price, so the conversion of gas-electricity in this area is increased. The results are shown in Figures 7 and 8. Therefore,

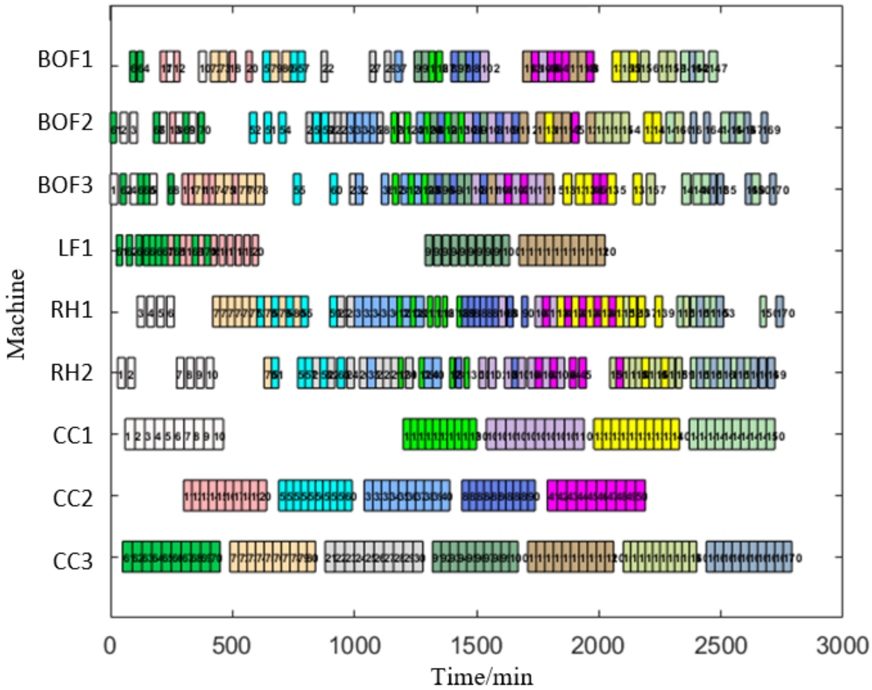

Figure 7. (color online) Gantt chart of Obj1

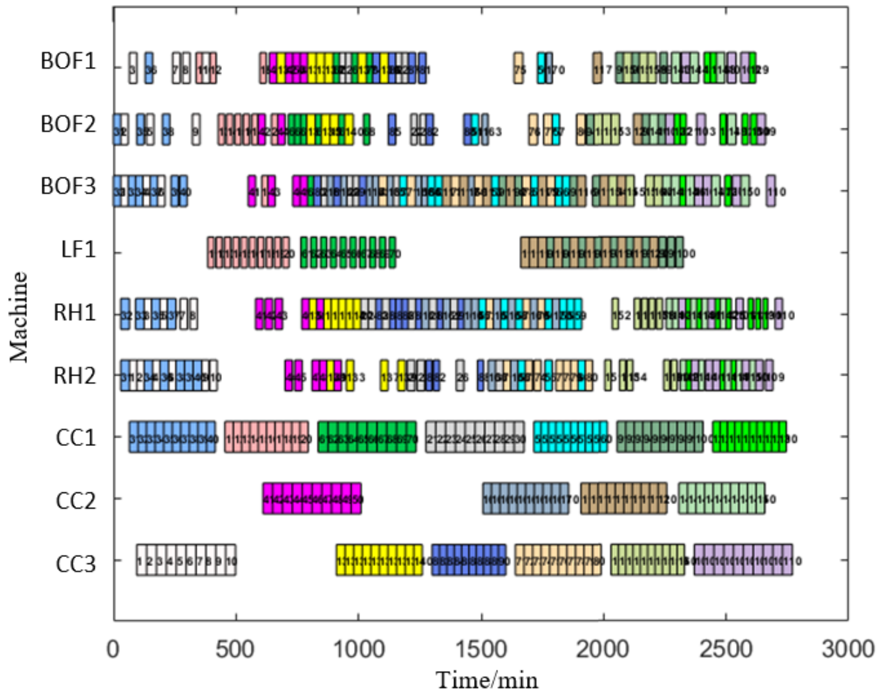

Figure 8. (color online) Gantt chart of Obj2

compared with Obj1 results, Obj2's gas-electricity conversion profit increases by 17.80%, and total profit increases by 16.53%. Obj3 integrates electricity cost and gas-to-electricity conversion profit, LF production moves to low electricity price, and most of gas-electricity generation is in middle and high electricity price region, so electricity cost is less than Obj2, and gas-electricity conversion profit is relatively lower, but total profit increases compared with Obj2, as shown in Figure 9.

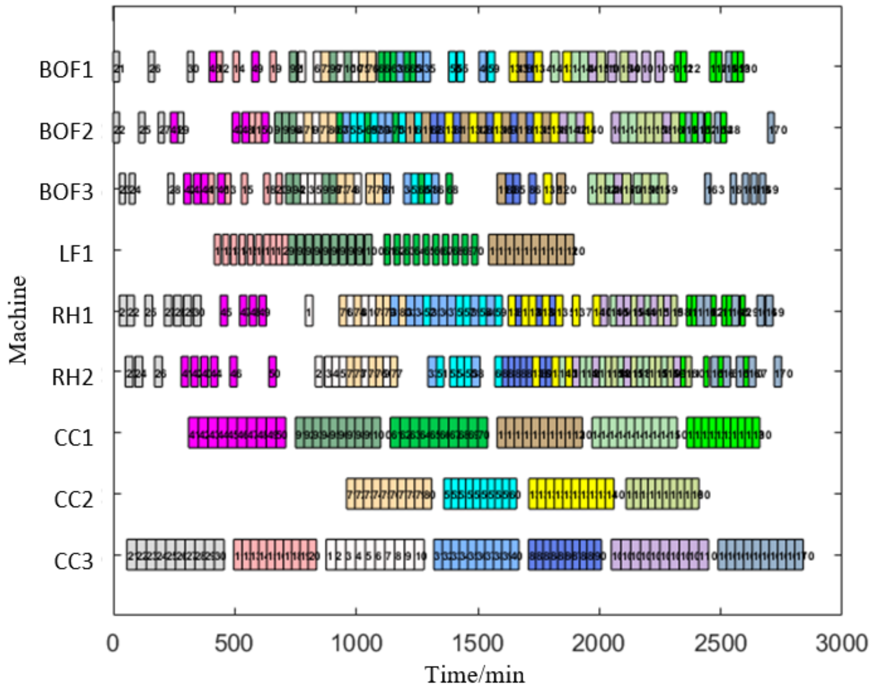

Figure 9. (color online) Gantt chart of Obj3

In summary, considering different objective functions have different effects on production scheduling, by making the right choices when scheduling production, the mill can reduce production costs and increase total profits, improving its competitiveness in the increasingly competitive market environment.

6. **Discussion.** The model proposed in this paper is solved using a novel two-stage process bat algorithm. The algorithm is coded in MATLAB R2016b, and performed on an Intel Core i7 laptop, with 2.6GHz and 8GB RAM. According to the actual situation of the steel plant, the conditions for implementing the model are as follows:

1) The processing time of the heat on each process, the number of casts, and the heat information within each cast are known in advance;
2) The amount of converter gas produced, electricity and gas consumed per unit of time for each process can be obtained through the central control system;
3) No shutdown and no unexpected conditions of all machines during the scheduling process.

In summary, the steelmaking and continuous casting model established in this paper has the following strengths. Firstly, it can quickly solve the scheduling problem of multiple heats in a few days; Secondly, it uses minutes as the minimum scheduling unit for flexible scheduling, and is more suitable for actual production in enterprises; Thirdly, the unknown casting sequence is added to the scheduling, which makes the solution more practical; Finally, it adds the energy constraints of gas and electricity to the traditional scheduling process, which helps enterprises reduce production costs and increase profits. However, the model used in this paper does not take account of the unexpected conditions of the machines, such as downtime for maintenance.

However, the model established in this paper does not take account of the unexpected conditions of the machines, such as equipment failure, and expedited orders, or the shutdown caused by daily maintenance. Therefore, the model also has some limitations, which can be considered and improved in future research.

7. **Conclusion.** In this paper, a new model is established for the steelmaking and continuous casting scheduling problem which considers energy constraints. It considered the characteristics of the continuous and discrete production processes and the related electricity and gas constraints. Under the influence of gas production, consumption, and variable electricity price, the model proposed in this paper has the objective function of minimizing electricity costs, maximizing gas-to-electricity conversion profits, and maximizing total profit. In this way, the internal consumption and transformation of energy can be achieved, and companies can reduce production costs and increase corporate profits. In the solving process, taking the expanded number of heats, the unknown casting sequence and execution equipment, and the special process condition into account, a two-stage process bat algorithm is developed. In the two-stage method, first, we use the casting as the scheduling unit, and the casting sequence and start time on the continuous casting machine are determined. Then, keeping the casting sequence unchanged, the next step is to determine the heats sequence on the converter and refining furnace. Since the steel plant is actually a case where continuous and discrete coexist, the traditional bat algorithm for solving the continuous problem is modified to make it more applicable to solving the steelmaking and continuous casting model. During the modification process, the position and velocity functions of the bat individuals are redefined and the pulse emission rate and loudness formulations are adjusted. The improved algorithm can quickly narrow down the search scope and calculate a feasible solution under different objectives. The improved bat algorithm can solve multi-heat scheduling problems, and it takes less time than the CPLEX method. During the instance validation stage, it can solve the scheduling problem for 170 heats in a short time and verify that different casting machine operating rates and different LF numbers have different effects on costs and profits. On the whole, the modeling and solving algorithm proposed in this paper are effective for solving the actual problems of iron and steel enterprises. The operators can set their own process equipment numbers and processing heats as needed to minimize costs and maximize profits.

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Author Biography

Nan Zhang joined the Institute of Engineering Technology at the University of Science and Technology Beijing as a Ph.D. student in Fall 2015. She received her B.Sc. and M.Sc. degrees from the University of Science and Technology Beijing in 2013 and 2015. Her research focuses on production planning and scheduling of iron and steel industry, and energy scheduling management.

Zhimin Lv is a Professor in the Collaborative Innovation Center of Steel Technology of the University of Science and Technology Beijing. He received his B.Sc. and M.Sc. degrees in Mechanical Engineering from Hebei University of Technology in 1992 and 1995 and a Ph.D. in Electrical and Computer Engineering from the University of Science and Technology Beijing in 1999. His research interests include enterprise information technology, production planning optimization and scheduling method, manufacturing process quality modeling and diagnosis technology, and data mining method.