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基于改进单亲遗传算法的炼钢最优炉次计划模型

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摘要: 炉次计划在炼钢生产计划的编制过程中扮演着重要角色, 优化的炉次计划对炼钢厂的高效、稳定运行产生深远影响. 基于已有文献, 并根据小方坯连铸过程的特点, 考虑了钢种、断面、交货期等因素, 建立了新的炉次计划模型, 以期通过优化生产合同的组合而降低生产费用. 炉次计划问题是复杂的组合优化问题, 不可能在列举所有可能的求解结果. 因而, 采用了改进的单亲遗传算法寻求问题的最优/近优解. 在求解过程中, 通过分析比较, 得到了合理的算法参数. 最后, 通过采用遗传算法、单亲遗传算法和改进的单亲遗传算法对模型求解结果的比较, 验证了改进后单亲遗传算法的优越性.

关键词: 炼钢; 最优炉次计划模型; 改进单亲遗传算法; 仿真

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Optimal charge plan model for steelmaking based on modified partheno-genetic algorithm

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Abstract: The charge plan plays an important role in compiling the production plan for steelmaking, and an optimized charge plan will have a far-reaching effect on the stability and efficiency of a steelmaking workshop. According to the characteristics of billet continuous casting process, a new charge plan model is developed by taking into account three constraints: steel grades, dimensions, and due dates. By using this model, we reduce the production cost by optimizing the sequencing of the contracts. The problem is combinatorial in nature; the complete enumeration of all its possibilities is computationally prohibitive. Therefore, a modified partheno-genetic algorithm (PGA) is employed to search optimum/near-optimum solutions. During the solving process, reasonable algorithm parameters are acquired through the analysis and comparison of different relative parameters. Furthermore, a comparative analysis of the results obtained by implementing the genetic algorithm (GA), PGA and modified PGA on the proposed model reveals that modified PGA outperforms GA or PGA in solving the charge planning problem.

Key words: steelmaking; optimal charge plan model; modified PGA; simulation

1 Introduction

The steel industry is one of the basic industries for the national economy. High ore reserves, low production costs, extensive use and recycling utilization allow the steel industry to provide raw materials for numerous other important industries. The manufacturing process is a multi-stage process that can roughly be divided into three phases.

1) Ironmaking: the production of molten iron, mainly from iron ore and reductants such as coke.

2) Steelmaking-continuous casting: processing the hot metal into steel with a well-defined chemical composition and solidifying the liquid steel into billets.

3) Rolling: the production of finished products.

At present, most of the production in the steel plant is limited to market ability, and multiple grades, small lots and high quality characterize customers' demands for steel products. However, mass production is necessary in the organizing process in a steel workshop. So only through making and carrying out the rolling plan,

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the charge plan, the cast plan and the scheduling plan, and then fulfilling production, can the contract products be finally transferred to the final products. Thus, it can be seen that the charge plan plays an important role in the production. So contract products with the same steel grade and small differences in due dates should be grouped into charges in the production process[1]. A reasonable charge plan is able to reduce the production costs, decrease the amount of open orders (redundant products belonging to none of the contracts), raise the production efficiency and ensure on-time deliveries. So in order to provide high level of charge plans for the steelmaking workshop, the charge planning problem is studied in this paper.

The rest of this paper is organized as follows. Section 2 presents a literature review. In Section 3, the optimal charge plan model is established. The solution algorithm is discussed in Section 4. Section 5 presents simulation results, and a conclusion is outlined in Section 6.

2 Literature review

In recent years, with the goal of helping planners improve efficiency, precision and reliability, a large quantity of research has been done on the production planning problem in the steel industry. In view of the charge planning problem, Tang et al established a mixed integer programming model of furnace charge plan and adopted a genetic algorithm (GA) to solve this model[2]. Chen et al also described the use of GA for the dynamic advanced planning and scheduling problem and demonstrated that the production idle time and tardiness/earliness penalties for both original orders and new orders could be minimized at each rescheduling point[3]. Based on the connections between different parts in the production process, Huang et al developed some mathematic models to optimize the charge design[4], and then a dynamic programming algorithm was proposed to solve these models. In addition, a decomposition strategy for solving large scheduling problems using mathematical programming methods was presented by Harjunkoski and Grossmann[5]. To solve the steelmaking charge planning problem, an improved particle swarm algorithm was proposed by Xue et al[6]. And to optimize the order planning, a component-based approach was adopted by Azevedo and Sousa[7]. Tonshoff et al developed a mediator-based approach for decentralized production planning, scheduling and monitoring[8]. In order to adequately tackle the customer-order planning problem, Azevedo et al proposed a multi-agent system architecture for real-time planning in distributed manufacturing enterprises[9]. To meet the requirements for the mid- to long-term planning of a steel producer, Witt and Voss used a simple mathematical model, and some standard software products, namely, the 'ILOG OPL-Studio' from IBM and the 'Advanced Planner and Optimizer' (APO) from systems applications and products in data processing (SAP), were applied to solve this model[10]. Liu et al presented a heuristic algorithm based on rules to solve the scheduling problems for the casting-rolling process in basic oxygen furnace (BOF) special steel plants[11].

From above, it's known that the researchers have solved the planning problem with different methods, but the solutions are difficult to obtain and the processes have turned out to be inefficient. The charge planning problem is a quite complicated combinatorial optimization problem. If the scale of the problem is larger, it's difficult to obtain the optimal solution in shorter time. So it's necessary to find an intelligent algorithm to obtain the near-optimum solution. The GA, which is a non-numerical computing method based on the biological principle of natural selection and population genetics, is able to make an individual (each candidate solution) move to the optimal solution by means of a 'the survival of the fittest' mechanism. GA is an iterative search procedure, which has been successfully used for a variety of combinatorial optimization problems, e.g. the job-shop scheduling problem[12-15]. The main operations of GA involve changing the solutions from iteration to iteration by applying a crossover operator, which combines two chromosomes to obtain offspring, and a mutation operator, which modifies a single chromosome. However, based on several experiments in the research, GA is quite complicated to use for solving the actual charge planning problem due to multiple constraints.

Although partheno-genetic algorithm (PGA) is a kind of GA, in the operation of PGA, the crossover operator in the traditional GA is removed, and all of the operations are carried out using an individual. Thus, the operations of PGA can simplify the genetic operations and improve the computing efficiency. In particular, no initial population diversity is required in PGA, and the problem of immature convergence does not exist. Moreover, PGA has been successfully used to solve combinatorial optimization problems. Li[16] described PGA in detail. Bai et al[17] proposed an immune partheno-genetic algorithm (IPGA) for solving the winner determination problem in combinatorial auctions, and the simulation results showed that the IPGA achieved good performance in large size problems and the immune operator could improve the searching ability and greatly increase the converging speed. Zhu and Duan[18] developed an intelligent dynamic restoration algorithm for multiple services in WDM (wavelength division multiplexed) networks based on PGA. Their simulation showed that the algorithm was able to improve the restoration efficiency under high loads and reduce the service disruption ratio on the basis of fully utilizing the resources of the network. Kang et al[19] proposed a virus coevolutionary partheno-genetic algorithm (VEPGA) to determine the optimal placement of sensors on a large space structure for the purpose of modal identification, and the simulation results showed that the VEPGA outperformed the sequential reduction procedure (SRP) and PGA. Moreover, considering that the GA may lose solutions and substructures as a result of the disruptive effects of the genetic operators and it is not easy to regulate the convergence, Wang and Tang[20] presented an improved adaptive genetic algorithm (IAGA) and adopted partheno-genetic operation (PGO) to ensure a feasible solution.

PGA can simplify the process of solving a combinatorial optimization problem, and the charge planning problem in steelmaking is a typical combinatorial optimization problem. Thus, a modified PGA (MPGA) is developed to solve the charge plan model in this study.

3 Optimal charge plan model in steelmaking process

3.1 Problem description

Generally speaking, the charge (or heat) is the basic unit for the steelmaking process, and a charge represents the whole process, which starts with smelting in an electric arc furnace (EAF) or BOF and ends in casting or ingot casting. The plan-making of the charge plan is the process of resolving and grouping the contract products into semi-finished steel products, and then grouping these semi-finished steel products into charges. The constraints of steel grades, dimensions and due dates are all considered in the planning process. Therefore, the charge planning problem is a complicated combinatorial optimization problem subjected to several constraints.

The notation used in this paper is as follows:

m is number of charges (unknown beforehand);

n is number of contract products;

i, j is serial number of contract products, $i, j = 1, 2, \cdots, n$;

k is serial number of charges, $k = 1, 2, \cdots, m$;

t is ton;

d is day;

$V_{\max}(V_{\min})$ is maximum (minimum) furnace capacity, t;

G_i is steel grade of contract product i;

w_i is weight of contract product i, t;

W_i is width of contract product i, mm;

c_1 is penalty coefficient for differences in contract products' steel grades, $\yen/\mathrm{t}$;

c_2 is penalty coefficient for differences in contract products' widths, $\yen/\mathrm{t}$;

c_3 is penalty coefficient for contract products unselected into any of the charges, $\yen/\mathrm{t}$;

c_4 is penalty coefficient for open order, $\yen/\mathrm{t}$;

c_5 is penalty coefficient for differences in contracts' due dates, $\yen/(\mathrm{day}\cdot\mathrm{t})$;

P_{ij}^1 is penalties for differences in contract products' steel grades, $\yen$;

P_{ij}^2 is penalties for differences in contract products' widths, $\yen$;

P_k^3 is penalties for contract products unselected into any of the charges, $\yen$;

P_k^4 is penalties for open order in charge k, $\yen$;

P_{ik}^5 is penalties for differences in contract products' due dates in charge k, $\yen$;

d_{ik} is due date of contract product i in charge k;

d_{ek} is earliest due date of contract products in charge k.

3.2 Grouping requirements and modelling hypothesis

In the billet continuous casting process, the requirements for grouping contract products into charges are listed as follows:

1) The steel grades of the contract products in a charge should be in the same steel grade class.

2) The dimensions of the billets' sections in a charge should be the same.

3) The total weight of the contract products in a charge should not surpass the maximum furnace capacity.

4) The due dates of the contract products in a charge should be similar.

According to the actual production, the following modelling hypothesis can be obtained:

1) The final number of grouped charges is unknown beforehand.

2) The contract products are allowed to remain unselected in any of the charges.

3) The total weight of the contract products in a charge is allowed to vary between 95% and 100% of the furnace capacity.

4) The steel grades and dimensions of the contract products are determined beforehand.

3.3 Model of problem

Based on the above grouping requirements and modelling hypothesis, the following model is developed:

$$\min z = \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n}(P_{ij}^1 + P_{ij}^2)x_{ij}x_{ik} + \sum_{k=1}^{m}(P_k^3 + P_k^4) + \sum_{k=1}^{m}\sum_{i=1}^{n}P_{ik}^5 x_{ik}, \tag{1}$$

subject to

$$\sum_{k=1}^{m} x_{ik} \leqslant 1,\ i = 1, 2, \cdots, n, \tag{2}$$

$$x_{ik} = \begin{cases} 0, \text{ contract product } i \text{ exists in charge } k, \\ 1, \text{ else}, \\ i = 1, 2, \cdots, n, \ k = 1, 2, \cdots, m, \end{cases} \tag{3}$$

$$P_{ij}^1 = \begin{cases} c_1(G_i - G_j), & \text{contract product } i, j \text{ belongs to the same steel grade class}, \\ +\infty, & \text{else}, \end{cases} \tag{4}$$

$$P_{ij}^2 = \begin{cases} c_2(W_i - W_j), & \text{the width of contract product } i, j \text{ belongs to } [W, W'], \\ +\infty, & \text{else}, \end{cases} \tag{5}$$

$$P_k^3 = \begin{cases} c_3 \cdot \sum_{i=1}^{n} w_{ik} x_{ik}, & \sum_{i=1}^{n} w_{ik} < V_{\min}, \\ 0, & \text{else}, \end{cases} \tag{6}$$

$$P_k^4 = \begin{cases} c_4(95\% V_{\max} - \sum_{i=1}^{n} w_{ik} x_{ik}), & V_{\min} \leqslant \sum_{i=1}^{n} w_{ik} x_{ik} \leqslant 95\% V_{\max}; \\ 0, & 95\% V_{\max} \leqslant \sum_{i=1}^{n} w_{ik} x_{ik} \leqslant V_{\max}; \\ +\infty, & V_{\max} \leqslant \sum_{i=1}^{n} w_{ik} x_{ik}, \end{cases} \tag{7}$$

$$\sum_{i=1}^{n} w_{ik} \leqslant V_{\max}, \ k = 1, 2, \cdots, m, \tag{8}$$

$$P_{ik}^5 = c_5(d_{ik} - d_{ek}) w_i. \tag{9}$$

In the above equations, equation (1) is the objective function of the optimal charge plan model based on the lowest penalties, including three parts. The first part contains the penalties for the differences in the contract products' steel grades and the widths of adjacent contract products in a charge. The second part contains the penalties for open orders or ungrouped contract products, and the last one contains the penalties for the differences in the due dates of the contract products in a charge. The corresponding constraint conditions of the objective function are listed in equation (2) to equation (9). Equation (2) indicates that a contract product can only be grouped into a charge. Equation (3) is a function to judge the contract products and charges, if a contract product belongs to a charge, the function equals 1; otherwise, it equals 0. Equation (4) is the method of computing the penalties of the steel grades of the adjacent contract products in charge k. In the actual production process, the steel grade of the adjacent contract products in the same charge should be in the same steel grade class, and the value of equation (4) equals c_1 multiplied by the difference of steel grades. Or else the contract products can't be grouped in a charge, and the value of equation (4) is $+\infty$. Equation (5) calculates the penalties for differences in the widths of the contract products in a charge. The widths of the adjacent contract products in the same charge should be in a range $[W, W']$, and the value of equation (5) equals c_2 multiplied by the difference of widths. Or else the contract products can't be grouped in a charge, and the value of equation (5) is $+\infty$. Equation (6) indicates the penalties for a charge where the total weight of the contract products is less than $V_{\min}$. Equation (7) is a function for computing the penalties for an open order in a charge. Equation (8) indicates that the total weight of the contract products in a charge must be less than $V_{\max}$. Finally, equation (9) calculates the penalties for contract products with different due dates.

For the billet continuous casting process, the steel grades and dimensions of the contract products are generally classified before grouping them into charges. Thus, the penalties for the contract products' widths and steel grades can be removed from the model, and a simplified model can be easily deduced as below.

$$\min \ z' = \sum_{k=1}^{m} (P_k^3 + P_k^4) + \sum_{k=1}^{m} \sum_{i=1}^{n} P_{ik}^5 x_{ik}. \tag{10}$$

4 Solution algorithm

In this section, the algorithm parameters and evaluating indicators are discussed, and then the solution steps are described. Especially, the modification of PGA is introduced in Section 4.2.

4.1 Discussion of algorithm parameters

The study object in this paper is a 75-ton (practical tapping amount) BOF in the steelmaking workshop of Fangda Special Steel Technology Co., Ltd. The evolutionary generation, searching method, population size and penalty coefficient should be set in the solving process of MPGA.

Usually, the optimal solution is unknown in the solving process of the optimization problem, making it is necessary to set the stopping criteria of the algorithm beforehand. Liu et al[21] proposed the stopping criteria used in GA. The algorithm terminates if one or more of the criteria are met: a) the evolutionary generation exceeds a predefined number; b) the difference between the fitness functions in the preceding generations is less than a very small number; c) the population diversity is less than a very small number; and d) the best fitness function difference between two consecutive generations is less than a very small number. The stopping criteria of GA are also suitable for MPGA. In this paper, a near-optimum solution is obtained by setting the evolutionary generation (the first criterion). Through numerous tests, it was found that the simulation results could almost meet the accuracy requirements when the evolutionary generation reached the 100th generation. After the 100th generation, the results improved little; however, the calculating time increased greatly. Thus, the evolutionary generation is set to 100, and the other parameters are analyzed in the following research.

1) Searching method.

The searching method (the gene-exchanging method) of PGA is classified as a one-point searching method and multi-point searching method. The former is used to exchange the position of two genes, while the latter is used to exchange $m(m \geqslant 2)$ pairs of genes. According to a related study[16], the searching methods for PGA may be different for different problems. As to the charge planning problem, the convergence curves under different searching methods are shown in Fig.1. From Fig.1, it is easy to see that the one-point searching method is the optimal searching method by comparing the convergences of the different searching methods. Therefore, the one-point searching method is adopted to solve the problem discussed.

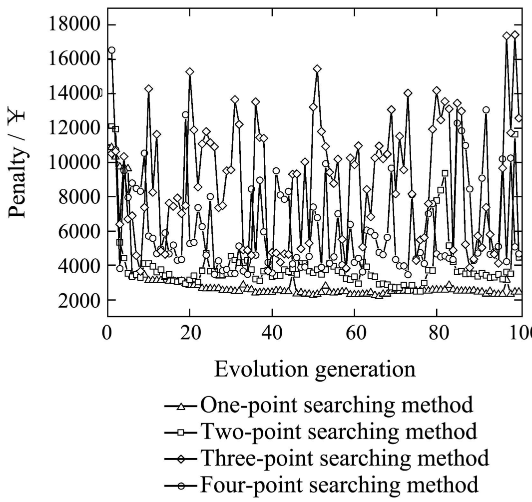


Fig. 1 Comparison of different searching methods

2) Population size.

The population size is an important parameter that will profoundly influence the computational efficiency. If the size is too small, the searching efficiency will be low and the algorithm will run into a locally optimal solution; otherwise, if the size is too large, the amount of calculation will be big, and the computation will be ineffective. A few tests are carried out to acquire a near-optimum population size. The convergence curves under different population sizes are shown in Fig.2, from which we can see that the evolution performs best with a size of 40.

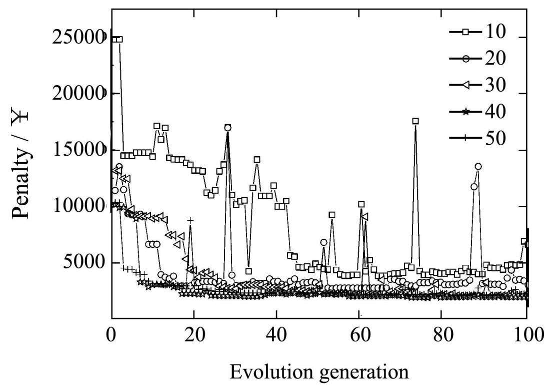


Fig. 2 Comparison of different population sizes

3) Penalty coefficient.

The goal of the optimal charge plan model is to minimize the penalties under the premise of the fewest number of charges and the least open order amount. Therefore, the weights of c_4 and c_3 should be larger than c_5. Through numerous tests, it was found that when c_5 is equal to 2 $￥/(\mathrm{day} \cdot \mathrm{t})$ or 1 $￥/(\mathrm{day} \cdot \mathrm{t})$, the results are able to reach the goal of the model.

When c_4 = 100 $￥/\mathrm{t}$ and c_5 = 2 $￥/(\mathrm{day} \cdot \mathrm{t})$ or 1 $￥/(\mathrm{day} \cdot \mathrm{t})$, the open order amount and number of charges under different c_3 are as shown in Table 1 and Table 2. We found that the number of charges and open order amount varied between tests for different parameters. Comparing the above data, it is not difficult to recognize that the open order amount is the lowest and the number of grouped charges is the fewest when c_3 = 130 $￥/t$ and c_5 = 1 $￥/(\mathrm{day} \cdot \mathrm{t})$. Hence, we chose c_3 = 130 $￥/\mathrm{t}$ and c_5 = 1 $￥/(\mathrm{day} \cdot \mathrm{t})$.

Table 1 Number of charges and open order amount while c_5 = 2 $￥/(\mathrm{day} \cdot \mathrm{t})$

$c_3/(￥\times\mathrm{t}^{-1})$	50	60	70	80	90	100	110	120	130
Open order amount/t	8.118	4.259	4.403	0.876	1.558	2.370	3.608	7.497	0.810
Number of charges	18.095	18.045	18.045	18.000	18.000	18.023	18.045	18.091	18.000
Sample size	21	22	22	22	22	44	22	22	19

Table 2 Number of charges and open order amount while c_5 = 1 $￥/(\mathrm{day} \cdot \mathrm{t})$

$c_3/(￥\times\mathrm{t}^{-1})$	50	60	70	80	90	100	110	120	130
Open order amount/t	0.740	0.932	0.907	3.748	3.889	3.745	0.678	0.842	0.650
Number of charges	18.000	18.000	18.000	18.045	18.045	18.045	18.000	18.000	18.000
Sample size	21	22	22	22	22	22	22	23	22

4) Final optimized algorithm parameters.

The final optimized algorithm parameters were obtained through the above analysis and comparison of different parameters, as shown in Table 3.

Table 3 Parameters of MPGA

Parameter	Searching method	Population size	$c_3/(¥\times t^{-1})$	$c_4/(¥\times t^{-1})$	$c_5/(¥\cdot(\text{day}\cdot t)^{-1})$
Value	One-point searching method	40	130	100	1

4.2 Fitness function of individual

As in GA, the fitness function is adopted to evaluate the individuals in PGA. The value of the fitness function represents the environmental adaptability of the individual. An individual with a bigger fitness has more chance to pass on an inheritance to the next generation. The fitness function can be converted from the objective function.

In the fitness function of PGA, the fitness of all the individuals in each generation is calculated, and then the offspring generation is obtained through the crossover or mutation of the individuals in the parent generation. Because the amount of calculation is great, the efficiency will be decreased. It is not necessary to use some individuals with high penalties. Therefore, in this study, only some optimal individuals with low penalties are selected to calculate the fitness. However, if the number selected is too small, a locally optimal solution may be obtained because of the lack of diversity in the population. For a population with 40 individuals, the five optimal individuals in each generation are selected to ensure the diversity. The fitness function is shown as follows:

$$f(x_i)=\frac{\dfrac{1}{z(x_i)}}{\sum\limits_{i=1}^{5}\dfrac{1}{z(x_i)}}, \tag{11}$$

subject to

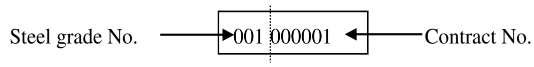
$$\sum_{i=1}^{5} f(x_i)=1, \tag{12}$$

where, x_i represents individual i in the population of a generation and $z(x_i)$ is the penalty of individual i. The individuals with higher penalty indicates that the grouping result of the contract products in the charges are less optimized, so they will be inherited to the offspring in a lower probability, i.e. they have lower fitness. Through equation (11), the individuals with higher fitness in each generation can be calculated easily and rapidly, and then the optimized individuals are evolved to the next generation.

4.3 Solution procedure

On the basis of the above analysis, the solving steps of MPGA are designed as follows.

Step 1 Encoding. The real encoding method and ordinal encoding method are two familiar methods. The former is generally used in solving a combinatorial optimization problem, while the latter is used to solve a complicated engineering optimization problem. In this study, the steel grades and contracts are encoded to sequential number strings (chromosomes). The encoding method is shown as follows.



Step 2 Define the individual evaluation method, which is the fitness function (equation (11)). The fitness function is employed to evaluate the individuals of each generation.

Step 3 Set the algorithm parameters, population size, evolutionary generation and penalty coefficients.

Step 4 Generate the original population, and then compute the individuals' penalties in the population.

Step 5 Select the five optimal individuals with the lowest penalties, calculate these individuals' fitnesses, reproduce until the number of individuals is equal to the population size and carry out the one-point cross operation. Then, these new individuals are used to make up the next population.

A sort of one-point genes exchanging operation of MPGA is shown as follows:

Parent generation: $x_1, x_2, x_3, x_4, x_5, x_6$.

Offspring generation: $x_1, x_2, x_6, x_4, x_5, x_3$.

The offspring generation exchanges the positions of gene x_3 and gene x_6 on the basis of the parent generation.

Step 6 Loop, until the end of the evolution.

At the end of the calculation, if there are solutions not meet the constraints, we put the unselected contract products together with the new ones for the next planning.

To reduce the destruction of the optimal individuals, the elites of each generation are kept and passed on to the next generation in the algorithm. The optimal individuals are reproduced and the genes are exchanged to make the model quickly converge to the optimal solution.

The flow chart of MPGA is shown in Fig.3.

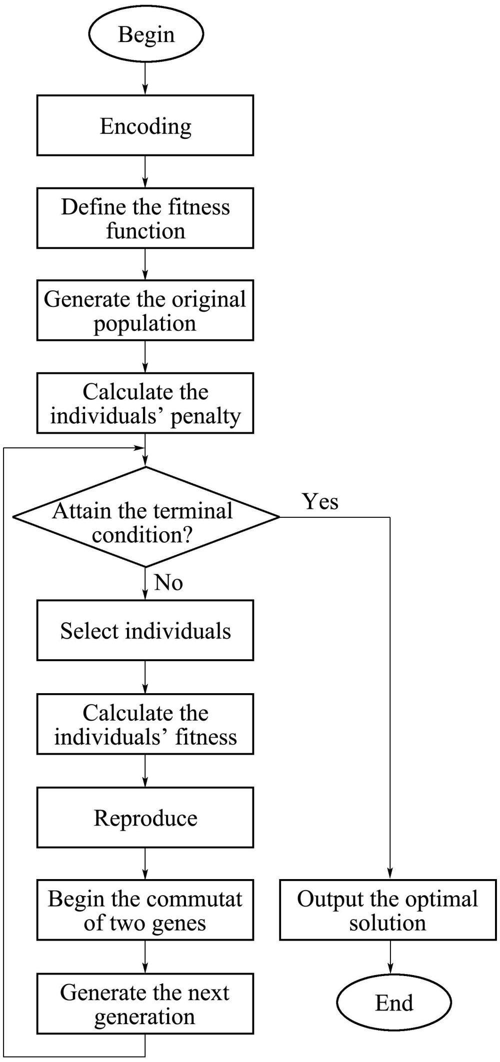


Fig. 3 Flow chart of MPGA

Table 4 Grouped results by using MPGA

Charge No.	Contract products' weight/ t	Real weight/ t	Open order amount/ t	Penalty/ ￥
1	71.868	71.875	0.007	672.410
2	71.868	71.875	0.007	338.360
3	71.868	71.875	0.007	306.915
4	71.868	71.875	0.007	647.605
5	71.868	71.875	0.007	275.480
6	71.868	71.875	0.007	312.970
7	72.493	72.493	0.000	0.000
8	72.493	72.493	0.000	156.235
9	74.366	74.366	0.000	0.000
10	73.117	73.117	0.000	0.000
11	74.367	74.367	0.000	0.000
12	71.868	71.875	0.007	516.275
13	72.492	72.492	0.000	0.000
14	74.368	74.368	0.000	0.000
15	71.868	71.875	0.007	410.035
16	71.868	71.875	0.007	406.715
17	73.117	73.117	0.000	259.350
18	73.742	73.742	0.000	0.000

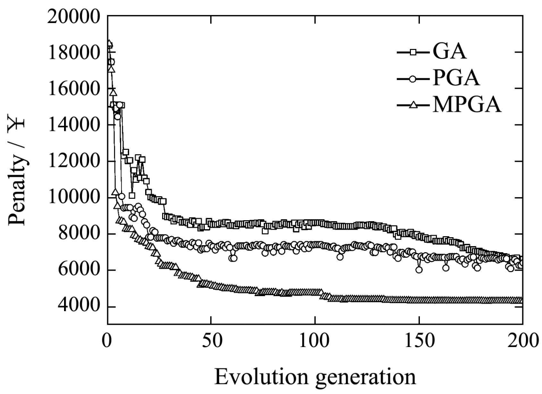


Fig. 4 Comparison of GA, PGA and MPGA

5 Simulation results

On the basis of the above analysis, an actual charge planning case with 240 contracts in Fangda Special Steel Technology Co., Ltd is used to verify the model and algorithm. Microsoft Visual C # is adopted to solve the problem. The experimental environment is a Pentium (R) Dual-Core CPU/ 3.20HZ/2.00GB/Windows 7. To acquire better solutions, the evolution generation is set to 200 in this experiment. As shown in Table 4, the penalty reaches the lowest value when the algorithm evolves to the 198th generation. The results show that all of the contract products are grouped into 18 charges, the open order amount is 0.063 t, and the penalty is ￥4302.35.

By comparing GA and PGA with MPGA in Fig.4, the superiority of MPGA is not difficult to recognize. As can be seen from the curve, with an increase in the evolutionary generation, the penalty tends to decrease. The simulation results are able to meet the requirements of minimizing the number of charges and open order amount.

To test the generality of the proposed method, a 100-ton BOF at another steelmaking workshop is used in another experiment. As presented in Fig.5, during the first 23 generations, the penalty curve converges at high speed, and then the curve becomes smooth. These results certify the generality of the algorithm.

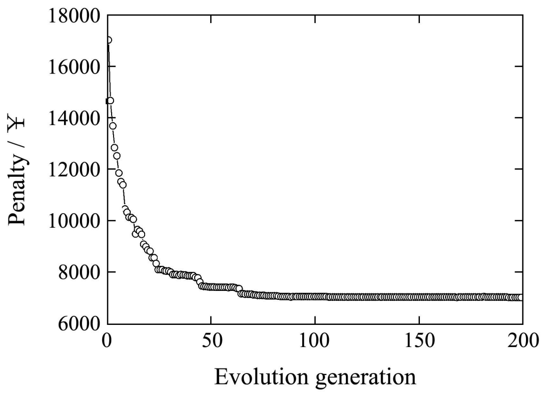


Fig. 5 Relation between penalty and evolutionary generation for 100-ton BOF

Obviously, the major benefits of MPGA are its simplicity and feasibility. Therefore, it is convenient to apply to the charge planning problem in an actual production environment. In addition to shortening the programming period for the charge plan, the use of the proposed algorithm can also minimize the number of charges and the open order amount. Therefore, the production and inventory costs can be decreased.

6 Conclusions

In this paper, the charge planning problem that exists in a steelmaking workshop was described. Aiming at this problem, an optimal charge plan model was developed, in which the final number of grouped charges was unknown beforehand. Then, this model was simplified based on the characteristics of the billet from the continuous casting process. To solve the model, MPGA was applied. Meanwhile, the optimized algorithm parameters were obtained through analysis and comparisons. The research showed that the penalty decreased gradually with an increase in the evolutionary generation. Finally, the optimal solution was developed, which achieved the fewest charges and the smallest open order amount. The results showed the efficiency and simplicity of the model and algorithm, and the proposed methodology will have a great influence on the charge plan organization in a steelmaking workshop.

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