Research on Decision Support Method for Charge Batch Planning of Steelmaking-Continuous Casting under Lagrangian Framework

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Abstract: Charge batch planning is the bottleneck of production management planning in iron and steelmaking enterprises. The optimization of the charge batch planning process will directly influence the iron and steelmaking cost, production and energy consumption. In this paper, an effective mathematical model based on multi-objective weighting method is built up to describe the multi-performance indexes and the multi-constraints; an efficiency adaptive search algorithm based on linear augmented Lagrangian relaxation framework is proposed to alleviate the problem of sawtooth oscillation when the traditional Lagrangian algorithm searches within the feasible domain. The strategy proposed in this paper is verified based on the background of the actual steelmaking and continuous casting management process in China steelmaking plant. The optimization results guarantee the solution quality and speed of charge batch planning of steelmaking-continuous casting.

Keywords: charge batch planning; steelmaking and continuous casting production; Lagrangian relaxation algorithm; adaptive search algorithm

1. INTRODUCTION

The production operation control system of iron and steel enterprises becomes more and more complex with the increase of production scale. Steelmaking-continuous casting (SCC) charge batch planning is the bottleneck of Computer integrated manufacturing system (CIMS) of iron and steelmaking enterprises. The slab tends to be more and more personalized, and its function is more and more targeted, which leads to the high intensity and complexity of the combined slab, so that the optimization efficiency and the quality of the optimization results cannot be met at the same time. In addition, it is difficult to optimize the artificial composite slab from the global point of view, that is, it is easy to make the optimization results fall into local optimization, which makes it difficult to fully meet the important optimization indexes such as delivery time, flow direction, residual material quantity and so on. As a result, the executive manufacturing system is greatly affected, which in turn affects the production efficiency and production cost of the whole production process. It is of great significance for iron and steel enterprises to study how to ensure the slab production efficiency and the optimization quality of the algorithm, to meet the needs of customers and to meet the internal production operation mode at the same time, and to improve the comprehensiveness of the optimization index for iron and steel enterprises. In order to optimize the mode of production management and solve the problems caused by the constraints of production rules, how to establish a mathematical model to qualitatively describe the production process to quickly solve the optimization problem of charge batch planning is of great significance for iron and steelmaking enterprises to realize modern intelligent management system.

2. LITERATURE REVIEW

2.1 SCC process batch planning mathematical model

Li et al. (2009) used the distributed interactive simulation high-level architecture HLA to simulate the steelmaking process. Azadeh et al. (2010) established a simulation model for the main equipment and operation of the steel plant, integrated the output of the simulation model with the experimental design, and optimized the experimental parameters by emergency search algorithm. In the actual production process, the production process is complex and there are many coupling factors, so the established problem model is difficult to fully reflect the complexity of the actual production process or the problem needs to be idealized. Models for reducing waste and reducing flow balance have been proposed by Zhou (2014) to reduce the amount of waste. Based on a harmony search algorithm and a prediction model, Lin et al. (2015) proposed a comprehensive planning framework. The approach uses a rough predictive model to estimate the hot rolling plan (HRP) problem performance in the optimization of the steelmaking-continuous casting plan (SCP) problem, and the solution of HRP problem is obtained by using the knowledge-based simulation models. Lin et al. (2016) took the early/delay ratio, non-thermal loading ratio and capacity utilization imbalance ratio corresponding to SCC factory and HR factory as objective functions and a new concept called "order set" is introduced for modeling. A multi-objective integer programming model with known charge numbers is proposed by Hu et al. (2017) considering the combination of charging time constraints and capacity utilization and order properties differences. However, the model has some shortcomings, such as the formal description is too complex.

2.2 SCC process batch planning algorithm optimization

Huang et al. (2009) established two mathematical models for the charge batching problem, which are to minimize the amount of remaining material and replace the cost with a tapping mark, and to form the slab according to the dynamic programming method in order to obtain the optimal solution of the original problem. This method can significantly reduce the residual material of the charge batching problem and improve the production efficiency. Tang et al. (2009) established a mathematical model for the SCC batch planning and solved it by the integer programming method. For the SCC batch planning, Dong et al. (2010) established a mathematical model of multi-objective optimization, in which the objective function is to minimize the number of charges, the minimum cost and the maximum production capacity, and the guided variable neighborhood algorithm and simulation are used. The annealing method is combined with the variable neighborhood algorithm to solve it. Considering the relationship between the remaining capacity of the charge and the plate, flexible modeling based on the slab width, Ma et al. (2013) proposed the Variable Neighborhood Search Algorithm (VNS) as a local search hybrid algorithm in the Iterative Local Search Algorithm (ILS). Liu (2015) combines particle swarm optimization (PSO) with fast convergence and genetic algorithm (GA) to optimize the global optimization ability. A hybrid optimization algorithm combining PSO with GA, PSO-GA hybrid algorithm, is proposed. The linear programming model is established to solve the possible operational conflicts in the process, optimize the processing sequence of each charge, minimize the waiting time between processes, and obtain the final optimized production plan Gantt chart.

3. MATHEMATICAL FORMULATION OF THE PROBLEM

3.1 problem description

Charge is the smallest production unit in the steelmaking-continuous casting production process, we need to reasonably integrate the slab and the charge, in the combination process, every slab has its own index mandate, including priority, flow direction, pouring width range, steel grade, delivery date, specification, whether the same hot roll and so on. Therefore, in the process of modeling, because of the different physical properties of each slab the slab combination will produce the penalty factor. To reduce the penalty coefficient caused by the attributes, we should optimize the main goal, in addition, from the customer satisfaction to make the first production of the charge with high priority; from the point of view of energy saving of the production process, we should improve the utilization rate of furnace capacity. These three aspects are taken as optimization objectives. The related requirements for the slab combination should be considered (Tang et al. 2008).

3.2 Parameters definition

During the preparation of charge planning, N is the total number of contracts to be prepared, $N=\{1,2,...,n\}$; T is the furnace capacity; b_j is the cost of using the charge j. The weight of the *i*-th slab is g_i, the Priority of the *i*-th slab is h_i, the upper and lower limits of the casting width of the *i*-th slab are d_i^H and d_i^L ($\forall i \in N$). p_j represents the penalty value resulting from insufficient utilization of the charge j ($\forall j \in N$); allowing the width of the casting width to be adjusted is w_{max}; the sum of the penalty cost factors for slabs due to attribute differences is C_{ij}, $\forall i, j \in N$, $C_{ij} = C_{ij}^1 + C_{ij}^2 + C_{ij}^3 + C_{ij}^4 + C_{ij}^5 + C_{ij}^6$; The steel-level increase cost factor of contract *i* merged into contract *j* is C_{ij}^1 ; width penalty cost factor between contract *i* and contract *j* is C_{ij}^2 ; C_{ij}^3 is the contract delivery time difference cost factor for contract i and contract j ; C_{ij}^4 is the contract *i* and contract *j* flow differential cost coefficient (when the contracts *i* and *j* have the same flow direction, $C_{ij}^4 = 0$, otherwise, $C_{ij}^4 = +\infty$.); the difference cost factor caused by whether contract *i* and contract *j* are the same warm-up materials is C_{ij}^5 (when the contract *i* and *j* are both warm-up materials or the same non-warm-up materials, $C_{ij}^5 = 0$, otherwise, $C_{ij}^5 = +\infty$.); the difference between the contract *i* and the contract *j* component cost factor is C_{ij}^6 (when the contract *i* and *j* are the same, $C_{ij}^6 = 0$, otherwise, $C_{ij}^6 = +\infty$).

3.3 Decision variables

1) $X_{ij} = \begin{cases} 1, & \text{for the } i\text{-th contract belongs to the } j\text{-th charge} \\ 0, & \text{otherwise} \end{cases}$,

2) $X_{jj} = \begin{cases} 1, & \text{for the } j\text{-th contract is chosen as the charge center} \\ 0, & \text{otherwise} \end{cases}$,

$\forall i, j \in N, i \neq j$.

3.3 model

According to the production requirements of steelmaking-continuous casting, the optimization objectives are as follows:

$$\text{with } Z = \text{Min}\,(J_1 + J_2 + J_3 + J_4) \tag{1}$$

1) Minimize the cost of charge generation

$$J_1 = \min \sum_{j=1}^{N} b_j X_{jj} \tag{2}$$

2) Minimize the remaining capacity of the charge

$$J_2 = \min \sum_{j=1}^{N} p_j X_{jj} (T - \sum_{j=1}^{N} g_j X_{ij}) \tag{3}$$

3) Try to improve customer satisfaction, priority customers give priority to production (This reference Tang 2008)

$$J_3 = \min \sum_{i=1}^{N} \sum_{j=1}^{N} h_i X_{jj} (1 - X_{ij}) \tag{4}$$

4) Minimize the difference in physical properties of slabs in the same charge

$$J_4 = \min \sum_{i=1}^{N} \sum_{j=1}^{N} (C_{ij}^1 + C_{ij}^2 + C_{ij}^3 + C_{ij}^4 + C_{ij}^5 + C_{ij}^6) \cdot X_{ij} \tag{5}$$

It should be noted here that according to the principle of minimizing the objective function, two contracts of $C_{ij}^x = +\infty$ are not allowed to be programmed into the same charge (*x*=1, 2,…,5.).

The objective functions (2) (3) refer to Yang et al. (2014). According to the process specificity and mechanical equipment capacity in the actual production process of steelmaking-continuous casting, the following constraints are formulated:

1) Due to the constraints of the production process, they are not selected or can only be combined into one charge, and cannot be combined into two or more charges at the same time.

$$\sum_{j=1}^{N} X_{ij} \le 1, \forall i \in N \tag{6}$$

2) Slab width constraint in the same charge, slab charge generation in the production process, the slab width jump times and amplitude must meet the production regulations.

$$-w_{max} \le (\min(d_i^H, d_j^H) - \max(d_i^L - d_j^L)) \cdot X_{ij} \le w_{max} \tag{7}$$

$$\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \min(\theta, 1) \le 1, \forall i, j \in N, i \ne j \tag{8}$$

$$\theta = \max(0, \sum_{i=1}^{N} \sum_{j=1}^{N} (\min(d_i^H, d_j^H) - \max(d_i^L - d_j^L)) \cdot X_{ij}) \tag{9}$$

3) The weight of the slab in the charge is restrained, and the furnace capacity is higher than the total weight of the slab in the same charge.

$$\sum_{i=1}^{N} g_i \cdot X_{ij} \le T \cdot X_{jj}, \forall j \in N \tag{10}$$

4) Decision variable constraints, decision variables can only take 0 or 1.

$$X_{ij} \in \{0,1\}, \forall i, j \in N \tag{11}$$

$$X_{jj} \in \{0,1\}, j \in N \tag{12}$$

4. SOLUTION METHODOLOGY

4.1 Lagrangian relaxation algorithm

In the process of solving the original problem, we introduce a set of Lagrange multiplier relaxation constraints (7), and then decompose the original problem into a sub-problem represented by "the optimal value of each Charge". Use a set of Lagrange multipliers to relax the "only one Charge per slab group" constraint. The objective of the relaxed optimization problem is to minimize the Lagrange function.

1) The original problem is transformed into a dual problem by relaxing Coupling constraints.

$$Z_d = \max_{ui} \cdot \min_{X, Y_j(X)} (a_1 f_1(X) + a_2 f_2(X) + a_3 f_3(X) + a_4 f_4(X)) + \sum_{i=1}^{N} u_i (1 - \sum_{j=1}^{N} x_{ij}) \tag{13}$$

2) Simplify dual problems:

$$Z_d = \max_{ui} \cdot \min_{X, Y_j(X)} \sum_{i=1}^{N} \sum_{j=1}^{N} (C^*_{ij} - p_j \cdot g_i - h_i - u_i) \cdot X + \sum_{j=1}^{N} T \cdot p_j \cdot Y_j(X) + \sum_{i=1}^{N} h_i + \sum_{i=1}^{N} u_i \tag{14}$$

3) Parameter quantization:

Let $C^*_{ij} - p_j \cdot g_i - h_i = q_{ij}$, $i = 1, 2, \ldots, N$, $j = 1, 2, \ldots, N$, traverse *I*, *j* construct order cluster penalty value distribution matrix *Q*, calculate original When the optimal value of the problem is considered, each slab is considered as the charge centre, that is, $X_{jj} = 1$, $j = 1, 2, \ldots, N$, and the known parameters unrelated to the decision variable *X* are not considered, and the following results are obtained:

$$Z^{Dil} = \max_{\lambda_i} \cdot \min_{X_{ij}} \sum_{i=1}^{N} \sum_{j=1}^{N} (Q - u_i) X_{ij} + \sum_{i=1}^{N} u_i \tag{15}$$

4) According to formula (7) and formula (15), we can get:

$$X_{ij} = \begin{cases} X_{jj}, & \text{for } Q - u_i \le 0, \\ 0, & \text{otherwise.} \end{cases} \tag{16}$$

5) Treat each slab as the charge centre, the model in step (3) is transformed into a sub-model function only related to Lagrange multiplier, and the optimal value of the original problem is solved by solving the optimal value of the sub-model.

$$max\ Z^{Dil}(\lambda_i) = \sum_{j \in N} \min(0, Q - u_i) + u_1 \tag{17}$$

4.2 Model reference adaptive search algorithm

The combination of orders with different attributes will produce a penalty value. The combination of n orders will result in an order clustering penalty value distribution matrix due to the different attributes of the order. Different from the traditional Lagrangian search algorithm, it is necessary to find the subgradient direction for Lagrangian multiplier iteration. The search algorithm finds the optimal Lagrangian multiplier in the order clustering penalty value distribution matrix to optimize the optimal target value. The optimization process is divided into three steps: (1) firstly, the order clustering penalty value distribution matrix is constructed based on the different attributes between orders; (2) then the Lagrange multiplier sample space is constructed according to the data structure characteristics of the order clustering penalty value distribution matrix. (3) in the Lagrange multiplier space, the Lagrange multiplier is iterated based on the model reference adaptive search algorithm to find the Lagrangian multiplier which optimizes the objective value of the objective function.

The probability mass function $f(u : T_k)$ of Lagrangian multiplier is given by:

$$f(u : T_k) = \prod_{i=1}^{n} \prod_{j=1}^{n} T_k(i, j) I_{[u_i = u_{ij}]} \tag{18}$$

Where, if $u_i = U_{ij}$, then $I_{[u_i = U_{ij}]} = 1$; otherwise $I_{[u_i = U_{ij}]} = 0$. By constructing the Lagrange multiplier, the space of the dual function is maximized, and the search space of the Lagrange multiplier is greatly reduced. Then, we use a random search method to search in U^* to find the Lagrangian multiplier that minimizes the target function.

We describe the following methods for combining the MRAS method with the Lagrangian search method to find the optimal value of the objective function as follows:

Set $K = 0$, T_0 is evenly distributed over U^*.

Step 1: Properly transform the order cluster penalty value distribution matrix *Q* to ensure that each column has the fewest elements relative to a row.

Step 2: For each row i, design an index $J_i^{'}$ of the column containing the smallest multiplier element.

Step 3: Design a search space for Lagrangian multipliers that may take values, $\{U = \{u = [u_{1.};\ldots;u_{m.}] \mid u_{i.} \in \{u_{i.}^{0}, u_{i.}^{J_i'(N_i)}\}\}$. u is a Lagrangian multiplier matrix.

Step 4: Construct a probability matrix T_k and randomly generate N Lagrangian multiplier matrices $u^1, u^2, ..., u^n$ from the probability matrix T_k. For each i, the Lagrangian multiplier of the (i, j) -th multiplier element at U^* is sampled with probability $T_k(i, j)$.

Step 5: Calculate all target values $Z(u_i)$ for i and sort them from small to large, $Z_{[1]} \le ... \le Z_{[n]}$, set $\gamma_k = Z_{[[pn]]}$, P is the sample quantile of the target value and $P \in [0,1]$.

Step 6: Update the probability of the (i, j) -th element of the probability matrix in the k-th iteration by:

$$F_k(i,j) = \frac{\sum_{n=1}^{N} S(h(u^n))^k / f(u^n; F_{k-1}) I_{[h(u^n) \le v_k]} I_{[u_i^n \in T_{ij}]})}{\sum_{n=1}^{N} S(h(u^n))^k / f(u^u; F_{k-1}) I_{[h(u^n) \le v_k]}} \quad (19),$$

update $F_k := \psi F_k + (1-\psi) F_{k-1}, 0 < \psi \le 1$ at the same time.

Step 7: If the stop condition is not met, set $k = k + 1$, return to step 4, and jump to step 8 if the stop condition is met.

Step 8: Implement a random search algorithm to find a Lagrangian multiplier that produces an optimal solution to the original problem.

The Lagrangian relaxation algorithm is embedded in the engineering background process. After introducing a set of Lange multipliers to relax the "Each contract can only be classified as a charge" constraint, the optimal solution is solved independently due to all sub-problems. The optimum value for each charge, usually does not meet the relaxation constraints. By establishing a coordination mechanism, the optimal solution of all sub-problems is coordinated to satisfy these constraints to solve such problems (Shen et al. 2015). The Lagrangian multiplier in the sub-question is equivalent to the price, and the constraints are not When satisfied, the objective function of the subproblem is penalized. By solving the dual problem, the Lagrangian multiplier is updated, and the updated Lagrangian multiplier is substituted and iteratively solved the sub-problem, which can realize the coordination of the sub-problems. Converting the original problem into a dual problem,

$$Z_d = \max_{ui} \cdot \min_{X, Y_j(X)} (a_1 f_1(X) + a_2 f_2(X) + a_3 f_3(X) + a_4 f_4(X)) + \sum_{i=1}^{N} u_i (1 - \sum_{j=1}^{N} x_{ij}) \quad (20)$$

The dual function in equation (20) is a concave function and consists of multiple concave surfaces. Each concave surface corresponds to a batch scheme of a slack problem. Due to the combined nature of discrete optimization, the various possible implementations of uncertainties further exacerbate this characteristic, and the number of possible batch schemes increases dramatically as the size of the problem increases. So, for practical problems, the number of concavities is very large, and the dual function is close to the smoothing function, especially when it is close to the optimal value. The smoothing property of this dual function can be solved iteratively by improving the proxy subgradient method. For a given set of Lagrangian multipliers, the optimal subproblem solution is obtained, and then the iterative process is repeated based on the improved proxy subgradient update until some stopping criteria are met.

A feasible solution is constructed based on the center of the furnace that is sought after the problem of relaxation. Based on the Lagrangian relaxation problem, the heuristic rule is designed to adjust the original problem coupling constraint. $x_{ij}^k (i = 1, \ldots N. j = 1, \ldots, N)$ represents the parcel decision variable of the kth iteration, and C_{ij}^* represents the sum of the difference penalty fees between contract i and contract j. Let i=1, k=0, the heuristic steps are as follows:

Step 1: Determine whether $\sum_{j=1}^{N} x_{ij}$ is not greater than 1, ($i = 1, 2, \ldots, N$). If the condition is met, jump to step 3, otherwise go to step 2.

Step 2: Calculate $C_{i,j}^* = \min\{C_{ij}^* \mid x_{jj} = 1, C_{ij}^* \le 0\}$, let $x_{i,j} = 1$, $x_{i,j} = 0, (j = 1, \ldots, N. i \ne j)$. For a solution that does not satisfy the constraint, calculate a contract that produces a minimum difference penalty cost value with the charge center contract.

Step 3: $i = i + 1$, if $i \le N$, jump to step 1, otherwise stop.

4.3 Subproblem solving algorithm based on charge decomposition strategy

The original problem is decomposed into N independent subproblems, equation (17), each subproblem mean the optimal value of a charge, and x_{ij} is the only variable in the equation. Now we suppose that every contract is a cluster centre, $x_{jj} = 1, 2, \ldots, N$, because of different physical factors and other contracts, every contract will have different penalty values, and then the sub-problem will change. For the boxing combination problem. In this section, backward dynamic planning is used to solve subproblems (Bertsekas 2013).

The 0-1 knapsack problem is described as: there are N items and a backpack with a capacity of V. The weight of the i-th item is $w[i]$, and the value is $v[i]$, which items can be loaded into the backpack to make these items. The capacity of the backpack is higher than the total of the weights, and the largest is the sum of the values.

The state transition equation is:

$$f[i][v] = \max\{f[i-1][v], f[i-1][v - w[i] + v[i]]\} \quad (21)$$

$f[i][v]$ represents the total value of the items in the backpack after the item is placed. The equation indicates that when the i-th item is not placed, the first i-1 item is put into the backpack, and the total value is $f[i-1][v]$. When the i-th item is placed, the first i-1 item is placed in the backpack of the capacity $v-w[i]$, and the maximum value is $f[i-1][v-w[i]]$ plus the *i*-th item value.

The problem described in this section is to make the working converter as full as possible and to ensure that the sum of the penalty values generated by the charge center contract and other contracts is optimal, without exceeding the constraints of the furnace capacity, but the difference with the traditional knapsack problem is that the optimal value is not the "maximum value", but the total penalty value is the smallest. Further, it is determined that the contract is the match of the charge in the charge center, that is, the value of the variable x_{ij} ,then find the optimal value of the subproblem.

In this paper, the experiment is carried out by taking the contract 1 as the center of the furnace. The optimization process of the state transition matrix is performed in order from bottom to top and from left to right. Let the contract number be $\{n \mid n=1,2,\ldots,N\}$, the contract weight is $\{w_n \mid n=1,2,\ldots,N\}$, and each contract and contract 1 will generate a penalty value and the parameter is $\{v_n \mid n=1,2,\ldots,N\}$. The furnace capacity is $\{T_k \mid k=1,2,\ldots,K\}$. The state transition matrix is a $2n*k$ order matrix D, and $D(a,b)$ represents the value of the matrix a row b column, and the odd row of the matrix represents the sum of the optimal quantized parameters of converter does not exceed the furnace capacity, even rows Indicates the contract number corresponding to the optimal quantization parameter installed in the converter. $OPSM(v_1,v_2,v_3)$ indicates the sum of the optimal values of the contracted quantitative parameters of the converter under the condition of the furnace capacity. For example, the furnace capacity is 20, the contracts 1, 2, and 3 are all 10, and the quantitative parameters are respectively 3, 4, 5, then $OPSM(v_1,v_2,v_3)$ = 9. $OPNO(n_1,n_2,n_3)$ indicates the contract number corresponding to the optimum value of the furnace capacity without exceeding the furnace capacity, for example: $OPSM(v_1,v_2,v_3)$ = 9, $OPNO(n_1,n_2,n_3)$ =2 , 3.

We can use the following method to get the optimal value and the match of the subproblem with the contract 1 as the charge center:

Step 1: Set $n=N, k=1$;

Step 2: If $w_n > T_k$, jump to step 3, otherwise go to step 4.

Step 3: $D(2n,k)=0, D(2n-1,k)=0, n=n-1$. If $n>0$, jump to step 2, otherwise jump to step 5.

Step 4: $D(2n,k)=OPNO(n,n+1,\ldots,N)$, $D(2n-1,k)=OPSM(v_n,v_{n+1},\ldots,v_N), n=n-1$, if $n>0$, jump to step 2, otherwise jump to step 5.

Step 5: $k=k+1$. If $k \le K$, set $n=N$, jump to step 2, otherwise stop.

5 contract numbers are randomly selected as $\{n=1\ 2\ 3\ 4\ 5\}$; the contract weight is $\{w_n=26\ 26\ 26\ 23\ 23\}$; this paper sets the penalty value generated by contract 1 and five contract clusters to negative. $\{v_n=-100\ -75\ -23\ -55\ -67\}$, the quantization parameter is taken as its absolute value, so that it can solve the problem of "what contract can be loaded to minimize the total penalty value without exceeding the furnace capacity" It is converted into "what contract does not exceed the furnace capacity, so that the contract is loaded to maximize the quantization parameter"; the furnace capacity $\{T_K=100\}$. After the optimization, the charge loading contracts 1, 2, 4 and 5 can maximize the quantization parameter, that is, when the contract 1 is the center of the furnace, the combination of the contracts 2, 4 and 5 can obtain the subproblem optimal value.

5 TESTING AND SIMULATION RESULTS

In order to obtain the optimal solution and obtain the best performance and running time, we respectively experiment on the MRAS algorithm and the traditional Lagrangian relaxation algorithm method for different problem structures. The comparison of Lagrangian multiplier optimization strategy MRAS algorithm and LR algorithm iterative Process is given in Fig 1. The near-optimal solution for different algorithms is shown in Fig 2. The remaining number of slabs remaining at the same processing time is given in Table 1. The runtime of different problem sizes is shown in Fig 3.

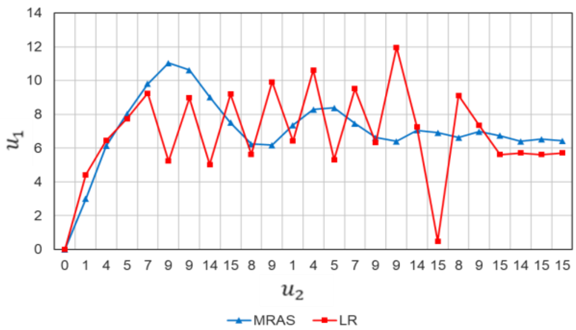

Fig 1. Comparison of Lagrangian Multiplier Optimization Strategy MRAS and LR algorithm Iterative Process

As can be seen that the longer the running time is, the iterative effect of MRAS is better and gradually stabilizes, while the traditional LR algorithm has larger fluctuations and the iterative effect is weaker.

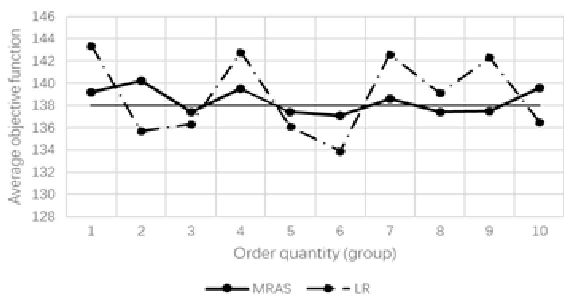

Fig 2. Near-optimal solution for MRAS and LR algorithm

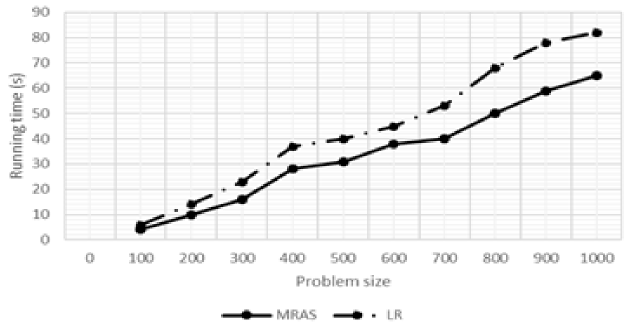

Fig 3. The runtime of different problem sizes

We can see from the curve trend, as the scale increases, the running time of MRAS algorithm is significantly smaller than LR algorithm.

Table 1. The remaining number of slabs remaining at the same processing time

MRAS algorithm			Traditional LR algorithm		
Charge No.	Slab No.	T.W.	Charge No.	Slab No.	T.W.
1	1\5\9\28	92	1	2\7\35	78
2	3\18\30	83	2	5\17\29	75
3	10\12\13\24	98	3	1\4\21\38	90
4	2\19\23\35	96	4	6\25\28\32	87
5	15\26\36\39	93	5	3\18\40	69
6	4\6\8\17	89	6	8\15\33	79
7	7\29\31\33	90	7	10\23\27\39	91
8	14\22\37\40	88	8	9\12\26\34	86
9	20\21\32	82	9	13\24\37	81
10	11\16\27\34	97	10	11\16\19\31	94
Residual slab 25\38			Residual slab 14\20\22\30\36		

(T.W. Total weight of slab in the charge)

From Table 1, we can conclude that under the same running time, under the optimization of MRAS algorithm, the total weight of slab in the charge is higher, and the residual slab is less.

6. CONCLUSIONS

In the study of decision support method of steelmaking-continuous casting charge batch planning, a model reference adaptive search algorithm under Lagrangian framework is proposed to solve the charge batch planning problem of steelmaking-continuous casting. The algorithm is proposed to solve the P-median problem. Different from the traditional Lagrangian algorithm, the algorithm designs the data matrix of the P median problem as an equivalent global optimization problem, and then through the search algorithm to lock in the corresponding to the original P value problem optimal solution of the Lagrange multiplier, namely tectonic order clustering matrix of value distribution of punishment , find the Lagrange multiplier, and the iterative update, in order to adjust the Lagrangian problem optimal solution, this algorithm can effectively solve the problem of Lagrange original easily plunged into local optimal problem, thus effectively solve the steelmaking - continuous casting charge batch planning problem. The experimental results show the effectiveness of the model and the algorithm.

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