

Optimum steel making cast plan with unknown cast number based on the modified discrete particle swarm optimization

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Abstract: An optimum furnace cast plan model with unknown cast number is presented. Based on the analysis of the difficulties in solving the problem, a pseudo traveling salesman problem(TSP) model is presented to describe the plan and scheduling model. Based on that the discrete particle swarm optimization(DPSO) can make the best of the particles' local and global optima, but it has the disadvantages of slow convergence and low search precision and the inver over operator is fast converged and high precise, but it is blindfold to learn from the other particles, a novel modified discrete particle swarm optimization algorithm based on the inver over operator(IDPSO) is presented. Experiments carried out on TSP show that IDPSO achieves good results comparing with the general DPSO. It can improve both the convergence speed and solution precision. IDPSO is used to solve the optimum cast plan problem. Simulations have been carried and the results show that the pseudo traveling salesman problem is very fit for describe the model. The computation with practical data shows that the model and the solving method are very effective.

Key words: discrete particle swarm optimization; inver over operator; steel making cast plan; traveling salesman problem

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基于改进离散粒子群算法的炼钢连铸最优浇次计划

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摘要: 提出了浇次数未知的最优浇次计划模型. 在分析该模型求解困难的基础上, 提出了用伪旅行商表示该模型的方法. 针对离散粒子群优化具有收敛速度、精度低, 但能充分利用各粒子的局部最优值和全局最优值信息的特点, 而序列倒置算子具有收敛速度和精度较高, 但学习具有盲目性的特点, 结合二者优点, 提出了一种基于序列倒置的改进离散粒子群优化算法. 实验研究表明, 该算法与普通离散粒子群优化算法相比, 不论是收敛速度和还是求解精度都有了较大提高. 基于该改进算法求解最优浇次计划模型的研究表明: 所提伪旅行商问题模型非常适合用于组浇模型描述. 应用实际生产数据的计算表明该模型及其求解方法均非常有效

关键词: 离散粒子群优化; 序列倒置算子; 炼钢连铸组浇计划; 旅行商问题

1 Introduction

The iron and steel industry is an essential and sizable sector for industrialized economies. It is capital and energy intensive, and companies have been putting consistent emphasis on increasing productivity and saving energy. The modern integrated process of steel making, continuous casting and hot rolling directly connects the steel making furnace, the continuous caster and the hot rolling mill with hot metal flow and makes a synchronized production. However, it also brings new

changes for production planning and scheduling. For steel making process, the main work is to arrange the charge plan and cast plan. The basic unit of steel making is the charge. In the steel making and continuous cast production process, each start of the caster needs to consume electricity, equipment adjustment time, and the costs of the tool(such as crystalizer) consumption and the accessorial material are very high. This requires that more charges to be casted continuously on the same caster so as to reduce the adjustment cost. But the

charge number in every cast is limited. There are three factors affecting the charge number: the life-span of the tundish, the difference of steel grades between the charges, the widths of the charges.

To form a cast, the charges must satisfy the following conditions:

- 1) Steel grades must be the same or similar;
- 2) Steel thickness of the charges must be equal;
- 3) The times of width change is limited;
- 4) Width should ideally change from wide to narrow;
- 5) The consignment dates of the charges must be near.

2 The mathematical model of optimum cast plan

To obtain the mathematical model, the following assumptions are made:

- 1) All the charges are to be arranged.
- 2) The tundish life-span is constant.

Usually, the cast number is known previously. In this paper we present a novel method to deal with this problem with unknown cast number. The mathematical model of the optimum cast plan is as follows^[1~3]:

$$\min J = \sum_{k=1}^P \sum_{i=1}^N \sum_{j=1}^N (C_{ij}^1 + C_{ij}^2 + C_{ij}^3) X_{ik} X_{jk}, \quad (1)$$

$$\text{s.t. } \sum_{j=1}^P X_{ij} = 1, \quad i = 1, 2, \dots, N, \quad (2)$$

$$2 \leq \sum_{i=1}^N X_{ij} \leq LA, \quad i = 1, 2, \dots, N, \quad (3)$$

$$X_{ij} \in (0, 1), \quad i = 1, 2, \dots, N, \quad j = 1, 2, \dots, P. \quad (4)$$

Where:

P : cast number which is unknown previously;

N : the charge number to be arranged;

LA : the tundish life-span;

C_{ij}^1 : annexed expense of steel making between the difference of steel grades and

$$C_{ij}^1 = \begin{cases} 0, & \text{Steel grades of charge } i \text{ \& } j \text{ are equal;} \\ F_1, & \text{Charge } i \text{ \& } j \text{ belong to the same steel grade serial and needn't be separated;} \\ F_2, & \text{Charge } i \text{ \& } j \text{ belong to the same steel grade serial and are separated with clapboard;} \\ \infty, & \text{Charge } i \text{ \& } j \text{ don't belong to the same steel grade serial;} \end{cases} \quad (5)$$

$$C_{ij}^2 = \begin{cases} 0, & W_i = W_j, \\ F_3 * |W_i - W_j|, & 0 < |W_i - W_j| \leq E, \\ \infty, & |W_i - W_j| > E. \end{cases} \quad (6)$$

$$C_{ij}^3 = \begin{cases} F_4 * |d_i - d_j|, & \text{if } d_i - d_j \geq 0, \\ F_5 * |d_i - d_j|, & \text{if } d_i - d_j < 0. \end{cases} \quad (7)$$

Where:

W_i : width of the i -th charge;

d_i : consignment date of charge i .

Objective function (1) assures the difference cost to be the smallest in steel-grades, widths and consignment dates in each charge. Constraint (2) ensures that every charge must be and only be arranged to one cast. Constraint (3) ensures that the charge number must be greater than or equal to 2 and cannot exceed the endurance capability of tundish.

3 Pseudo TSP model for cast plan

According to the cast plan model, it is natural to solve the problem by arranging the charge into an array and the array stores the cast number(see Fig.1). This is effective if the charge number is small. If the charge number is very big, the search algorithm will not be able to solve the problem effectively^[3]. Moreover, the cast number must be known previously if we use this array description. If the cast number is unknown previously, it will not take functions. In this paper, the traveling salesman problem(TSP) solution method is used to solve the cast plan model.

Charge number	N	$N-1$	\dots	3	2	1	0
Cast number	2	m	\dots	0	1	2	1

Fig. 1 Array description of cast plan model

3.1 The general description of TSP

Given N cities and a salesman, the TSP in discussion may be stated as follows. The salesman sets out from the same fixed city and finally comes back to the starting city to minimize total traveling distance. It is required that each city should be visited by the salesman exactly once.

3.2 The difference between TSP and the cast plan problem

Although the cast plan scheduling problem may be reduced to TSP, there are many obvious differences be-

tween the cast plan problem and the general TSP. A feasible tour of the salesman for TSP is a closed route. This means that for the salesman, if he starts from point i , then he must finally returns to point i . However, a schedule of a turn in the actual cast plan scheduling problem is an open path, that is, each charge is arranged exactly once.

3.3 Conversion of the cast plan scheduling problem into a normal TSP

To convert the cast plan scheduling problem into a TSP, assume that N charges are to be arranged into P casts and P is unknown previously. These N charges may be viewed as N nodes and a salesman may be regarded as the tour. Fig.2 shows the Pseudo TSP with 8 nodes. The first 4 charges are arranged in one cast and the second 3 are arranged in another cast. The last charge cannot be arranged into any cast. The dashed line represents that the two adjacent charges cannot be arranged in the same cast.

It must be pointed out that the distance with reasonable tour route is the sum for all the charges that can be arranged in the same cast. And the distance in the same cast can be calculated as follows:

$$L = L + 1, \tag{8}$$

$$C = \sum_{i=1}^m \sum_{j=1, i \neq j}^m (C_{ij}^1 + C_{ij}^2 + C_{ij}^3), \tag{9}$$

$i, j = 1, 2, \dots, m.$

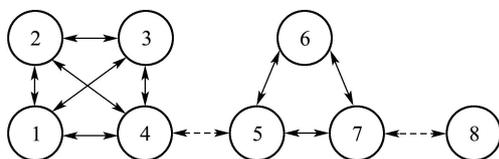


Fig. 2 Pseudo TSP model with 8 nodes

How do we decide that the charge can be arranged in the same cast?

Assume that the m charges have been arranged in the same cast. L and C are calculated with (8) and (9). And the $(m + 1)$ charge is to be arranged in the same cast. If

$$L + 1 \leq LA, \tag{10}$$

$$C + \sum_{j=1}^m (C_{j,m+1}^1 + C_{j,m+1}^2 + C_{j,m+1}) < \text{valve}. \tag{11}$$

Then the $(m + 1)$ -th charge will be arranged in

the same cast, otherwise, the cast will only arrange m charges. In (11), the “valve” is a threshold which can not be reached when the charges can be arranged in the same cast.

After all the charges have been arranged, we must decide which casts are necessary and which casts may be canceled. If the total cost in one cast is greater than or equal to the cost when all the charges in this cast are not arranged, then this cast is canceled.

4 An improved discrete particle swarm optimization with inver over operator

Particle swarm optimization(PSO) is a population-based evolutionary computation technique developed by Kennedy and Eberhart in 1995^[4]. PSO has been widely used because it can define search direction and search scopes only based on the fitness function converted from the objective function and doesn't need to know the differential of objective function and other auxiliary information. PSO is initialized with a population of random solutions of the objective function.

Traveling salesman problem is a well-known NP-hard combinatorial optimization problem. By now, TSP has been well studied by many meta-heuristic approaches, such as nearest neighborhood search, simulated annealing, tabu search, neural networks, ant colony system^[5], and genetic algorithm^[6]. Since 1995, particle swarm optimization has been proven to succeed in continuous problems. But for the combinatorial problems, it is still a new field.

For the TSP, the present position is the basic path. It is difficult to express its velocity. Here, we solve the problem based on the inver over operator^[7].

The main idea of the inver over operator is as follows: Given a particle population and a selection probability, with a low probability p the second city for inversion is selected randomly. This is necessary: without a possibility to generate new connections, the algorithm would search only among connections between cities present in the initial population. If $\text{rand}(\cdot) > p$, a randomly selected mate provides a clue for the second marker for inversion. In that case the inversion operator resembles crossover, as part of the pattern (at least 2 cities) of the second individual appears in the offspring.

Let's illustrate a single iteration of this operator in the following example.

Assume that the current individual S' is $S' =$

(2, 3, 9, 4, 1, 5, 8, 6, 7) and the current city c is 3. If the generated random number $\text{rand}(\cdot)$ does not exceed p , another city c' from the same individual S' is selected (say, c' is 8), and appropriate segment is inverted, producing the following offspring $S' = (2, 3, 8, 5, 1, 4, 9, 6, 7)$. Otherwise (i.e., $\text{rand}(\cdot) > p$), another individual is (randomly) selected from the population, assume, it is (1, 6, 4, 3, 5, 7, 9, 2, 8). This individual is searched for the city c' "next" to city 3 (which is 5), thus the segment for inversion in S' starts after city 3 and terminates after city 5. Consequently, the new offspring is $S' = (2, 3, 5, 1, 4, 9, 8, 6, 7)$.

Note again, that a substring 3~5 arrived from the "second parent". Note also, that in either case the resulting string is intermediate in the sense that the above inversion operator is applied several times before an offspring is evaluated. This process terminates when the next city c' (to the current city c) in randomly selected individual is also the "next city" in the original individual.

By analyzing the operator, it can be found that the inver over operator doesn't make use of any useful information it obtained before. It is well known that PSO can make use of the particle's local and global optima. It is nature to think that if we can benefit from the PSO and the inver over operator.

To introduce the new improved discrete particle swarm operation with inver over operator (in brief, IDPSO), two crossover probabilities are introduced into the IDPSO algorithm. One is called p_{best} crossover probability (p_{cp}) and the other is called g_{best} crossover probability (p_{cg}).

Based on the previous discussion, the improved IDPSO algorithm can be concluded as follows:

While (iterative number < largest iterative number)
do

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For  $j = 1 : n$ 
  produce a random number  $r_p$  in (0,1),
  if  $r_p < p_{\text{cp}}$ 
    the second city for inversion is selected
    randomly.
  else
    if  $r_p < p_{\text{cg}}$ 
      then crossover the other particle with  $p_{\text{best}}$ 
      using inver over operator,
    else crossover the particle with  $p_{\text{best}}$  using

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    inver over operator.
  end
end
Compute the fitness of every result particle,
If the new fitness smaller than that of the older
  accept the new path
else
  refused the new path,
end
If  $f(j) < p_{\text{best}}$ ,  $f(p_{\text{best}}) = f(j)$ 
  and  $p_{\text{best}} = j$ .
End For
Find out the  $f(g_{\text{best}})$  and  $g_{\text{best}}$ ;
End While
Output the  $f(p_{\text{best}})$  and  $g_{\text{best}}$ .

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In order to show the good performance of the IDPSO presented in this paper, a comparison experiment has been carried. The populations of IDPSO and the DPSO are 100 and 200 respectively. Order crossover(OX) is used as the crossover operator for DPSO. Table 1 lists the results of IDPSO and DPSO. 30 cities TSP is discussed. In Table 1, g , Ave, Opt N and t represent computation generation, average of the 10 runs, times of the optima to be found and the time needed for 10 runs respectively.

Table 1 Result comparison of DPSO and IDPSO

g	DPSO			IDPSO		
	Opt N	t/s	Ave	Opt N	t/s	Ave
500	0	646	438.9	5	57	424.1
800	1	1002	432.39	9	78	423.76
1000	2	1441	430.96	10	100	423.74

From Table 1, it can be seen that the performance of IDPSO is superior to that of DPSO even when the population of IDPSO is only half of that of DPSO. When $g = 500, 800, 1000$, the probabilities to find optima of DPSO are low, while the probabilities of IDPSO are very high and their time for 10 runs is much less than that of DPSO.

5 Application example

Now take the practical data in a steel and iron plant as an example. There are 30 charges to be arranged. The basic model parameters of each charge can be found

in [3]. If charge number i is greater than 15, its parameters are the same as those of charge number $i-15$. The other parameters are set as follows:

Maximum iterative number: 1000;

Population size: 100.

According to the cast model and the Pseudo TSP solution method, the search process is plotted in Fig.3 and the results are listed in Table 2. In Table 2, 0* represents that the charges cannot be arranged in any cast. In Fig.3, the solid line represents the search process of the IDPSO with fixed cast number and the dashed line represents the search process of the IDPSO with unknown cast number. From Fig.3, it can be seen that the optimum value with unknown cast number is much smaller than that with fixed cast number.

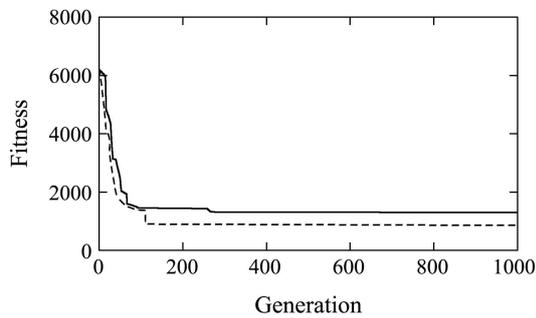


Fig. 3 Search process of IDPSO with fixed cast number and unknown cast number.

Table 2 Computation results

Fixed cast number		Unknow cast number	
Cast number	Charge number	Cast number	Charge number
1	2,3,17,18	1	2,3,17,18
2	12,15,27,30	2	12,15,27,30
3	8,23	3	6,21
4	6,7,21,22	4	5,7,20,22
5	11,26	5	11,26
6	9,10,24,25	6	9,10,24,25
7	13,14,28,29	7	13,14,28,29
8	1,4,16,19	8	1,4,16,19
0*	5,20	9	8,23
optimum value: 1210		optimum value: 776	

6 Conclusion

Based on the steel making process, a cast model with unknown cast number is presented by considering the effects of steel grade, width and charge date. This model is very practical and is easy to use. To solve the optimum cast plan, an improved DPSO is proposed. Simulation results with practical iron and steel plant data show that the model and computation method is very useful and effective and can make good charge plan.

References :

- [1] TANG L, WANG M, YANG Z. Model and algorithm of cast plan with unknown number of cast for steelmaking continuous casting scheduling[J]. *Iron and Steel*, 1997, 32(10): 19 – 21.
- [2] NING S, WANG W, PAN X. Integrated method of steel-making and continuous casting Planning[J]. *Control Theory & Applications*, 2007, 24(3): 374 – 379.
- [3] XUE Y, MEI Z, YANG Q. Optimum steelmaking cast plan with unknown cast number based on the pseudo TSP model[C] // *Proceedings of 2006 IEEE International Conference on Systems, Man and Cybernetics*. Taipei, Taiwan: IEEE, 2006: 3721 – 3726.
- [4] KENNEDY J, EBERHART R C. Particle swarm optimization[C] // *Proceedings of IEEE International Conference on Neural Networks*. Perth, Australia: IEEE, 1995: 1942 – 1948.
- [5] YANG J, SHI X, MARCHESE M, et al. An ant colony optimization method for generalized TSP problem[J]. *Progress in Natural Science*, 2008, 18(11): 1417 – 1422.
- [6] LIU F, ZENG J. Study of genetic algorithm with reinforcement learning to solve the TSP[J]. *Expert Systems with Applications*, 2009, 36(2): 6995 – 7001.
- [7] GUO T, MICHALEWICZ Z. Inver-over operator for the TSP[C] // *Proceedings of the 5th International Conference on Parallel Problem Solving from Nature*. Amsterdam, The Netherlands: Springer Press, 1998: 803 – 812.

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