An order batch scheduling method based on fuzzy model for cold rolling plant

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Abstract: This paper proposes an orders batch scheduling method for cold rolling plant, which firstly groups the available orders into the batches, and predicts their production time by means of fuzzy mode. To enhance the order delivery satisfaction, a fuzzy job shop scheduling model, in which each order batch is viewed as a fundamental scheduled job, is established to represent the production logistics of a cold rolling plant in Shanghai Baosteel. Considering the existent inventory in front of each machine, the calculation rules for the manufacturing time on each machine are defined based on the various production scenarios. For solving the proposed model, a partheno-genetic algorithm is employed. And, the application results of the proposed model and algorithm show that the order delivery satisfaction is greatly improved, and the scheduling working time is reduced.

Keywords: order batch scheduling; fuzzy model; delivery satisfaction; partheno-genetic algorithm

1. INTRODUCTION

Cold rolling line is an important finishing process in steel industry, whose products belong to the technology-condensed and capital-condensed commodities in the trade market. For the profit of steel enterprise, the advanced production scheduling technique has been paid more attentions nowadays. Some studies related to the production scheduling for tandem cold rolling line had been carried out, which focused mainly on a certain of single machines or processes. Both Moon et al. (1999) and Liu et al. (2005) reported the scheduling solutions concerning the bell-type annealing process in a cold rolling line, in which Moon et al. (1999) gave a mixing integer linear programming using a time slot method, and Liu et al. (2005) presented an optimization based on the discrete event simulation technique for the charging optimization and scheduling of the annealing process. In addition, Wang et al. (2002) proposed a scheduling method for the optimal operational parameters of tandem cold mill, and Zhao et al. (2008) optimized the production planning via a combination of coil-merging operation and assigned an optimal rolling sequence for tandem cold mill. With respect to the intermediate storage of cold rolling line, the related scheduling problem was also studied in Leisten (1990). Recently, Verdejo et al. (2009) addressed a sequencing problem in a continuous galvanizing line of the Spanish Steel Company, which was solved by a heuristics based tabu search. Tang et al. (2009) studied the scheduling problem of a single crane in annealing process of a cold rolling line, and mentioned a two-phase heuristics to minimize the last coil stack completion time.

Although the mentioned studies exhibited a great promotion to the manufacturing of cold rolling line or had been partly applied to the production practice, we discover that there is a potential structure for the production scheduling of cold rolling line (see Fig.1), which consists of not only the single machine scheduling, but the orders batch scheduling as well. As for the whole scheduling framework, the scheduling for single machine is on the basis of the orders batch scheduling solution, i.e. the results of orders batch scheduling provide the single machine scheduling with the input or the boundary condition. However, the studies in literatures for the orders batch scheduling are rather few now. It is worth noting that such practical optimization solution is intensively being required in current steel industry. Although Zhao et al. (2008) presented an order batch scheduling model for cold rolling line, that model completely viewed the order batch as a basic job shop scheduling model. Nevertheless, such model was somewhat inconsistence with the manufacturing practice that cannot be entirely dealt with by a discrete production mode.

Fig.1. The potential structure of production scheduling in cold rolling line
In this study, the order batch scheduling problem of a cold rolling plant in Shanghai Baosteel Co. Ltd., China is studied, in which different product categories and the corresponding due time are considered. A scheduling model with fuzzy batch manufacturing time and fuzzy due time is established by considering the uncertainty of batch production on machines. This model is summarized as a specific fuzzy Job Shop problem, to which a triangular fuzzy number is used to denote the manufacturing time of each batch. To evaluate the orders scheduling quality, we take the maximized delivery satisfaction as the objective function of the scheduling model, and define a series of calculation principles for the orders completion time. A partheno-genetic algorithm (PGA) is then employed to solve the fuzzy model. In the simulation, the real production data from Baosteel is finally used to verify the proposed model and algorithm.

2. ORDER BATCHES SCHEDULING MODEL

2.1 Problem description

Taking a cold rolling plant of Baosteel Co. Ltd. as an example, the production machines in the whole cold rolling line consists of pickling line (PL), tandem cold mill (TCM), degreasing line (DL), annealing line (AL), skin passing line (SPL), double-reduced rolling (DCR), coating line (CL) and finishing line (FL) (see Fig.2). And, each machine has its own front inventory as a material buffer of process. The products and the corresponding manufacturing paths can be listed as follows:

1) Hard rolled coil: PL—TCM
2) Cold rolled coil (plate): PL—TCM—DL—AL—SPL
3) Super thin coil (plate): PL—TCM—DL—AL—SPL—DCR
4) Coated coil (plate): PL—TCM—DL—AL—SPL—CL—FL

Since the production requirements of the various products are extremely different, the device parameters or operation pattern has to be changed if continuously producing the different categories of products. In order to maintain the production continuity and reduce the adjustment cost on the machines and the setup time, the order grouping is just to group the orders into some batches based on the product category constraints. At present, the order grouping and scheduling depends mainly on the manual handling by the experienced workers. However, with the production development, the Baosteel is nowadays adopting the week delivery mode to meet customers’ demands, improve the delivery ability and heighten the competition level of enterprise. Thus, the manual scheduling usually exhibits a poor capacity to fulfill the complicated requirements, and lead to a low order delivery satisfaction.

2.2 Order batches scheduling model

In this study, an order grouping method that combines product category with the order delivery week is presented. According to the week delivery mode, we designate the due time as Week I, Week II, Week III and etc. Then, a grouped order batch can be denoted as \(B_{ijw}\), where \(p\) denotes the product category \((p=1, 2, 3, 4, 5)\) and \(w\) denotes the due week \((w=I, II, III \ldots)\). Such order grouping will be the foundation of the order batch scheduling model.

The manufacturing time of orders is very hard to be accurately predicted because of some uncertain events in production, therefore it is difficult to reasonably reflect the practical situation only by the fixed scheduling parameters. For example, the completion time of an order may be prolonged due to an unexpected machine malfunction or material delay. So, using fuzzy conception could be an appropriate attempt to solve such practical scheduling problem. We view the grouped orders as a scheduling job and map the production of cold rolling plant into a job shop scheduling problem (JSSP). Considering the uncertain factors in production, the manufacturing time of each job on a machine is represented by a triangular fuzzy number \(\tilde{A}_{ijk}\) where, \(i=1, 2, \ldots, n\) denotes the index of jobs; \(j=1, 2, \ldots, m\) denotes the index of machines; \(k\) denotes the current sequence number of the whole process of job \(i\), which means the \(k\)-th step of job \(i\) is processed on machine \(j\); \(l\) denotes the current job is the \(l\)-th job of machine \(j\). The variables, \(a_{ijk}^L\), \(a_{ijk}^M\) and \(a_{ijk}^U\), represent the shortest manufacturing time, the possible time and the longest time of a job, respectively. And, the membership curve is illustrated as Fig.3. In addition, we specify the due time of an batch is denoted by a trapezoid fuzzy number \(\tilde{D}_i\) where

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\(d_i^O\) and \(d_i^P\) denote the optimistic due time and pessimistic time of job \(i\), respectively. (See Fig.4)

\[
\text{Fig.3 Membership function of manufacturing time of an order batch}
\]

\[
\text{Fig.4 Membership function of due time of an order batch}
\]

To evaluate the order delivery quality of the scheduling, an objective addressed by the average delivery satisfaction is adopted in this paper (Masatoshi et al., 1999). The model for batch scheduling of the cold rolling plant reads as follows.

\[
M \text{ max: } J = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{\text{area} \widetilde{F}_i \cap \text{area} \widetilde{D}_i}{\text{area} \widetilde{F}_i} \right)
\]

Subject to:

\[
\begin{align*}
\widetilde{S}_{ikl} & \geq 0 & l &= 1, k = 1, i = 1, 2, \ldots, n, j = 1, 2, \ldots, m & (2) \\
\widetilde{S}_{ikl} & \geq \widetilde{F}_{j(l-1)} & l & \neq 1, k = 1, i = 1, 2, \ldots, n, j = 1, 2, \ldots, m & (3) \\
\widetilde{F}_{i} & \geq \widetilde{S}_{i} + \widetilde{A}_{i} & i = 1, 2, \ldots, n, j = 1, 2, \ldots, m & (4)
\end{align*}
\]

where, \(\text{area} \widetilde{F}_i\) denotes the area of fuzzy completion time of job \(i\); \(\text{area} \widetilde{D}_i\) denotes the area of fuzzy due time of job \(i\); \(\widetilde{S}_{ikl}\) is the fuzzy start time of job \(i\) on machine \(j\); \(\widetilde{F}_{j(l-1)}\) is the fuzzy completion time of \((k-1)\)-th step of job \(i\); \(\widetilde{F}_{j(l-1)}\) is the fuzzy completion time of \((l-1)\)-th step of machine \(j\); \(\widetilde{F}_{i}\) is the fuzzy completion time of job \(i\) on machine \(j\); \(\widetilde{A}_{i}\) is the manufacturing time of job \(i\) on machine \(j\).

Eq.(1) is the objective to maximize the average delivery satisfaction of a grouped batch. We define the delivery satisfaction of a batch as the intersection area between the completion time \(\widetilde{F}_i\) and the due time of the batch \(\widetilde{D}_i\) (see Fig.5). Eq.(2) denotes that the earliest start time of job \(i\) is just the initial time of the schedule if it is the first job of the grouped batches and the first work on machine \(j\). Eq.(3) denotes that the earliest start time of job \(i\) is the completion time of the previous job on machine \(j\) if it is the first step of job \(i\), which means the succeeding job can be started on machine \(j\) only if the previous job has been done. Eq.(4) denotes that the completion time of each job is the fuzzy sum of the start time and the manufacturing time of the job.

\[
\text{Fig.5 The calculation of delivery satisfaction of each batch}
\]

In general JSSP, the earliest start time of job \(i\) on machine \(j\) is usually the larger one between the completion time of the previous step of job \(i\) and the previous job on machine \(j\), represented as: \(\widetilde{F}_i \geq \widetilde{D}_i\). However, to the proposed scheduling model, the calculation has to be redefined since the produced steel coils may be continuously transported into the inventory of next machine when the batch of orders is still produced on current machine. The start time of job \(i\) on machine \(j\) cannot be only calculated by \(\widetilde{F}_i \geq \widetilde{D}_i\), and the start time of previous step of job \(i\) should be further considered meanwhile.

2.3 Fuzzy calculation principle

2.3.1 Ranking a triangle fuzzy number

According to the theorem of fuzzy arithmetic definition (Kaufman et al., 1988), the ranking calculation rules can be viewed as a ranking criterion for a triangle fuzzy number.

Rank calculation 1: \(R_i(u) = \frac{u^L + 2u^M + u^U}{4}\).

Rank calculation 2: \(R_i(u) = u^M\) if \(R_i(u)\) is unavailable to evaluate two triangle fuzzy numbers.

Rank calculation 3: \(R_i(u) = u^U - u^L\) if both \(R_i(u)\) and \(R_2(u)\) are unavailable.

Here is a calculation example. Four triangle fuzzy numbers are \(u_1 = (2, 4, 6)\), \(u_2 = (1, 4, 7)\), \(u_3 = (3, 6, 7)\) and \(u_4 = (2, 3, 8)\), respectively. Using the above ranking rules, then
\[ R_i(u_1) = R_i(u_2) = R_i(u_3) = 4, \quad R_i(u_4) = 5.5. \]
So, \[ u_{\text{max}} = u_3 \; \text{and} \; u_{\text{min}} = u_2 \; \text{and} \; u_{\text{max}} = u_4 \]
Then, the descending order of the fuzzy numbers becomes
\[ \text{Rank}(u_3) \geq \text{Rank}(u_2) \geq \text{Rank}(u_4) \geq \text{Rank}(u_1). \]

2.3.2 Time calculation principle for order batch

Given a class of circumstance as an example, there might be a part of steel coils of job \( i \) that have been already produced from the previous machine, but this job still are not completely finished; whereas, the machine \( j \) is available at that time. Therefore, we propose the following three production scenarios to determine in this study.

Scenario 1: \( \text{Rank}(\tilde{t}_C) \), which means that the completion time of \((l-1)\)-th job on machine \( j \) is later than that of \((k-1)\)-th step job \( i \). (See Fig.6 (a))

Scenario 2: \( \text{Rank}(\tilde{t}_C) = \text{Rank}(\tilde{t}_C) \), which means that the completion time of \((l-1)\)-th job on machine \( j \) is the same as the start time of \((k-1)\)-th step of job \( i \), but earlier than its completion time. (See Fig.6 (b))

Scenario 3: \( \text{Rank}(\tilde{t}_C) < \text{Rank}(\tilde{t}_C) \), which means that the completion time of \((l-1)\)-th job on machine \( j \) is earlier than the start time of \((k-1)\)-th step of job \( i \). (See Fig.6 (c))

We assume that the manufacturing and setup time of a single steel coil can be neglected. Taking the three scenarios into account, the calculation of the start time of an order batch (job \( i \) on machine \( j \), \( S_{ijkl} \), can be determined by the following rules.

Rule 1: If the Scenario 1 is in the case (all steel coils in job \( i \) have been placed into the inventory of machine \( j \) before the previous job on machine \( j \) is finished), then \( S_{ijkl} = F_{ijkl} \).

Rule 2: If the Scenario 2 is in the case (a part of steel coils in job \( i \) have entered into the inventory of machine \( j \) before the previous step of job \( i \) is totally finished), then \( S_{ijkl} = S_{ijkl} \lor F_{ijkl} \). The operator \( [ \lor ] \) is to obtain the larger one of the two values.

Rule 3: If the Scenario 3 is in the case (the previous step of job \( i \) just starts after the previous job on machine \( j \) has been totally finished), then \( S_{ijkl} = S_{ijkl} \lor F_{ijkl} \).

2.4 Parameters of membership function

We give an experience based manufacturing time calculation depended upon the size of steel coils (see Eq.(5)).

\[ t = \beta(W_g \times \theta_h \times \omega_d \times Q \times V + C) \]  \hspace{1cm} (5)

where, \( \beta \) is the coefficient; \( W_g \) is the weight of the steel coil; \( \theta_h \) is coil thickness; \( \omega_d \) is coil width; \( Q \) is density of steel; \( V \) is the strip velocity of production; and \( C \) is the compensation value of manufacturing time.

Note that the experience based time prediction only shows the normal production condition. Some abnormal situation should be also considered such as machine maintenance, malfunction and so forth. Thereby, the mentioned time prediction will be applied to describe the shortest manufacturing time, \( a_{ijkl}^L \). As for the possible time \( a_{ijkl}^M \), it should be determined by the average production capacity (see Eq.(6)), where \( \sum W_{ijkl} \) is the accumulative time of current type of product on machine \( j \); \( \sum W_{ijkl} \) is the accumulative turnout of the product category on machine \( j \); and \( W_i \) is the weight of batch \( i \). Eq.(7) gives the longest manufacturing time \( a_{ijkl}^U \) calculation considering the machine breakdown, where \( T_{ijkl} \) is the longest breakdown time of machine \( j \) that includes the regulative or malfunction machine shutdown.

\[ a_{ijkl}^M = \frac{\sum W_{ijkl}}{\sum W_{ijkl}} \cdot W_i \]  \hspace{1cm} (6)

\[ a_{ijkl}^U = a_{ijkl}^M + T_{ijkl} \]  \hspace{1cm} (7)
3. SOLVING FOR THE ORDER BATCH SCHEDULING

The proposed scheduling model can be regarded as an asymmetrical traveling salesman problem, which is with the characteristics of NP-hard. As it was known, it is very hard for such problem to obtain an optimal solution within an acceptable computation time only by the generic mathematic programming, even some intelligent optimization. In this paper, we propose a partheno-genetic algorithm (PGA) to solve this combinatorial optimization.

3.1 partheno-genetic algorithm

Partheno-genetic algorithm is a class of special evolution algorithm that eliminates the infeasibility of crossover between two chromosomes organized by ordinal strings, and has been applied to some research fields (Katayama et al., 2001). In this study, we encode the scheduling solution by a string of integers, and the sequence of the integer in the string denotes the manufacturing sequence of the corresponding order batch for the cold rolling plant. We design the gene swap as the chief parthenogenetic operator on each individual, associated with the substring move. Here is an example.

Operator of gene swap:
Sequence number: 1 2 3 4 5 6 7
Parent: 5 7 3 4 1 2 6
Child: 5 2 3 4 1 7 6
Operator of substring move:
Substring: 3 4 5
Parent: 1 2 3 4 5 6 7
Child: 1 2 6 7 3 4 5
After creating the new individuals, the tournament selection is applied to establish the new generation as usual.

3.2 Solving step of the scheduling

The solving step of order batch scheduling for the cold rolling plant is as follows.

Step 1: Group the available orders to form a few of batches based on the order due time and product category.

Step 2: Calculate the fuzzy manufacturing time of each batch on the machines, and determine the fuzzy membership function of manufacturing time and due time.

Step 3: Initiate the status of the machines in the cold rolling plant, and randomly generate a number of n-bit strings represented as a set of initial solutions.

Step 4: Calculate the fuzzy completion time and the delivery satisfaction of each batch by the proposed computation principles, and obtain the average satisfaction of each solution and the current optimal solution.

Step 5: Use the evolution operator to create the new individual, and obtain the best-so-far of the fuzzy scheduling solution.

Step 6: Check whether the iteration number is arrived. If so, output the optimized order batch scheduling solution; otherwise, go back to step 5.

4. DATA EXPERIMENTS AND RUNNING ANALYSIS

A large number of experiments with real data from the cold rolling plant of Baosteel have been employed. To verify the effect of the proposed fuzzy scheduling model, we present an example to indicate the study for order delivery satisfaction compared to the manual scheduling. Table 1 illustrates a group of four-week production data in detail. Using the proposed method, the result of the instance has been confirmed to be effective by the experienced scheduling workers of the cold rolling plant in Baosteel.

<table>
<thead>
<tr>
<th>Batch No.</th>
<th>Product category</th>
<th>Due week</th>
<th>Order amount</th>
<th>Batch weight (t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I</td>
<td>22</td>
<td></td>
<td>6270.0</td>
</tr>
<tr>
<td>2</td>
<td>II</td>
<td>25</td>
<td></td>
<td>7980.0</td>
</tr>
<tr>
<td>3</td>
<td>III</td>
<td>19</td>
<td></td>
<td>5900.0</td>
</tr>
<tr>
<td>4</td>
<td>IV</td>
<td>36</td>
<td></td>
<td>8200.0</td>
</tr>
<tr>
<td>5</td>
<td>I</td>
<td>58</td>
<td></td>
<td>2900.0</td>
</tr>
<tr>
<td>6</td>
<td>II</td>
<td>71</td>
<td></td>
<td>5315.0</td>
</tr>
<tr>
<td>7</td>
<td>III</td>
<td>84</td>
<td></td>
<td>4634.0</td>
</tr>
<tr>
<td>8</td>
<td>IV</td>
<td>86</td>
<td></td>
<td>5335.0</td>
</tr>
<tr>
<td>9</td>
<td>I</td>
<td>10</td>
<td></td>
<td>1570.0</td>
</tr>
<tr>
<td>10</td>
<td>II</td>
<td>9</td>
<td></td>
<td>2004.0</td>
</tr>
<tr>
<td>11</td>
<td>IV</td>
<td>7</td>
<td></td>
<td>720.0</td>
</tr>
<tr>
<td>12</td>
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<td>42</td>
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<td>1920.0</td>
</tr>
<tr>
<td>13</td>
<td>II</td>
<td>34</td>
<td></td>
<td>1385.0</td>
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<tr>
<td>14</td>
<td>III</td>
<td>42</td>
<td></td>
<td>1815.0</td>
</tr>
<tr>
<td>15</td>
<td>IV</td>
<td>59</td>
<td></td>
<td>2310.0</td>
</tr>
<tr>
<td>16</td>
<td>I</td>
<td>20</td>
<td></td>
<td>765.0</td>
</tr>
<tr>
<td>17</td>
<td>II</td>
<td>13</td>
<td></td>
<td>559.0</td>
</tr>
<tr>
<td>18</td>
<td>IV</td>
<td>18</td>
<td></td>
<td>465.0</td>
</tr>
</tbody>
</table>

In addition, we exhibit here a comparative result for the fuzzy JSSP by using the intelligent algorithms, involving the discrete differential evolution (DDE) (Storn et al, 1997), Tabu Search (TS) and the proposed PGA. The result by experience based manual scheduling (MS) is altogether addressed. We select DDE because its solution quality and computational time are becoming more and more attractive to researchers and practitioners. The statistic comparisons are listed in Table 2, where four groups of real data from Baosteel are used. In the statistics, we make 10 times independent experiments for each algorithm, and obtain the average values of the solution. From the table, the intelligent search algorithms, whose average delivery satisfactions fundamentally exceed 90%, get the fairly better solutions than that by the manual scheduling. Furthermore, MS always takes the experienced worker over two hours to complete
such kind of scheduling work, which is a rather high labour force to humans. As for the order delivery satisfaction, the proposed PGA gets the best scheduling solution than the other algorithms. For the computational time respect, although the TS is somewhat faster than the proposed PGA, the solving difference can be completely accepted in the practice of production scheduling process. All in all, one can conclude that the proposed PGA presents a sound solving performance.

Table 2. The statistics comparison using four methods to solve the proposed model

<table>
<thead>
<tr>
<th>No.</th>
<th>Batches amount</th>
<th>Average Delivery Satisfaction</th>
<th>Computational Time (on average)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MS</td>
<td>PGA</td>
</tr>
<tr>
<td>1</td>
<td>17</td>
<td>81.3%</td>
<td>93.2%</td>
</tr>
<tr>
<td>2</td>
<td>18</td>
<td>80.1%</td>
<td>94.4%</td>
</tr>
<tr>
<td>3</td>
<td>19</td>
<td>77.5%</td>
<td>92.9%</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>78.2%</td>
<td>93.9%</td>
</tr>
</tbody>
</table>

4. CONCLUSIONS

In this study, a rule-based JSSP model with fuzzy manufacturing time is established for the order batch scheduling problem in the cold rolling plant of Baosteel. An evolution algorithm is designed to solve the fuzzy scheduling model. The running results using the real production data from Baosteel show that the proposed model and its algorithm exhibit a better delivery satisfaction of the orders than manual scheduling or some other intelligent optimizations. The average delivery satisfaction of orders reaches above 90%, which greatly meets the customer timing demands in the market. Furthermore, since the scheduling solution can be obtained within a dozen of seconds, the work efficiency of production scheduling will be largely heightened compared to the former experience based manual method.

ACKNOWLEDGEMENTS

This work is supported by the National Natural Science Foundation of China (61034003). The cooperation from the cold rolling plant of Shanghai Baosteel Co. Ltd., China in this work is greatly appreciated.

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