

Batch Scheduling Method – A Fuzzy Model for Rolling Mill

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Abstract– Many uncertain factors in job shop scheduling problems are significant for the scheduling procedures. This paper proposes an orders batch scheduling method for a rolling mill and estimates the production time by means of fuzzy form. A mathematical model is proposed to enhance the average order delivery satisfaction and maximize min satisfaction of fuzzy job shop scheduling model. Each order of a batch is viewed as a fundamental scheduled job. Mixed integer algorithm and genetic algorithm is employed for solving the proposed model. The results of the proposed model are promising.

Keywords- Rolling mill, Fuzzy schedule, Genetic algorithm.

I. INTRODUCTION

Scheduling is widely defined as the process of assigning a set of jobs to resources over a period of time. Effective scheduling plays a very important role in today's competitive manufacturing environment. Performance criteria such as machine utilization, manufacturing lead times, inventory costs, meeting due dates, customer satisfaction, and quality of products are all dependent on how efficiently the jobs are scheduled in the system. Hence, it becomes increasingly important to develop effective scheduling approaches that help in achieving the desired objective. The scheduling and planning of a production order have an important role in the manufacturing system. The diversity of products, increased number of orders, the increased number and size of industries and expansion of factories have made the issue of scheduling production orders more interesting, hence the traditional methods of optimization are unable to solve them (Z. Othman, K. Subari and N. Morad, 2007) [9]. Genetic algorithms are stochastic global optimization methods inspired by the biological mechanisms of evolution and heredity, which have been widely used for scheduling problem (Storn 1997) [3].

Rolling mill is an important finishing unit in steel industry, which is a captive industry. Because of tough competition industries are preferring more on made to order production strategy. In rolling mills production takes place on campaign basis. Similar product only can be rolled during particular campaign. Preparation time is required for changing campaign as it involves set up time for preparing the rolling lines. Time for calculation of process time cannot be calculated exactly as it cannot be predicted.

An effort is made in this paper to prepare rolling sequence based on customer orders. Rolling sequence means the sequence of orders to be carried out in a campaign. Customer orders are grouped into lots and later lots into batches again within each batch order sequences (i.e., rolling sequence) are optimized for customer satisfaction. Integer programming and heuristic techniques are applied to solve the problem. The paper is organized as follows. Literature survey at section 2. Section 3 deals with basic model and calculation of processing time. Section 4 with genetic algorithm and steps followed for calculation of optimization. Results and conclusion in section-5 and -6 respectively.

II. LITERATURE REVIEW

The advanced production scheduling techniques are drawing more attentions currently. The production scheduling for tandem cold rolling line had been carried out by many studies, Moon et al. (1999) [5] and Liu et al. (2005) [7] reported the scheduling solutions in a cold rolling line, in which an integer linear programming, and discrete event simulation technique were applied for the charging optimization. Wang et al. (2002) [6] proposed a scheduling method for the optimal operational parameters of tandem cold mill, and Zhao et al. (2008) [10] found an optimal rolling sequence for cold mill. With respect to the intermediate storage of cold rolling line, the related scheduling problem was also studied in Leisten (1990) [2]. Verdejo et al. (2009) [13] addressed a sequencing problem in a continuous galvanizing line and was solved by a heuristics based tabu search. Tang et al. (2009) [12] studied the scheduling problem of a single crane in annealing process of a cold rolling line,

Although the mentioned studies exhibited a great promotion to the manufacturing of cold rolling line or had been partly applied to the production practice, there is a potential structure for the production scheduling of rolling line.

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) [11] presented an order batch scheduling model for rolling line, that model completely viewed the order batch as a basic job shop scheduling model. To evaluate the order delivery quality of the scheduling, an objective addressed by the delivery satisfaction is adopted in the paper (Masatoshi et al. 1999 [4]. M. Omare et al. 2006) [8]. A novel objective function for job-shop scheduling problem with fuzzy processing time and fuzzy due date is solved using differential evolution algorithm (Yanmei Hu et al. 2011) [14]. Batch order processing was applied in cold rolling mill by Jun Zhao (2011) [15]. An effective genetic algorithm is applied for job shop with fuzzy satisfaction by Akeela M. Al-Atroshi 2013 [16] flexible job-shop scheduling problem as the research object, and constructed mathematical model aimed at minimizing the maximum makespan. The same was solved by genetic algorithm and case study was done in an automobile gear transmission shop by Erming Zhou et al. 2017 [17].

III. SCHEDULING MODEL

Customers place orders on steel mills through marketing management department with due dates and product specifications. Production planning department bunches these orders into batches in a homogeneous way taking into consideration quality, deliver date, etc. Based on the information after finalizing sequence machine scheduling and subsequent production will take place. The information is shared among various units. (see Figure 1) But in reality often production unit encounters difficulty in following the sequence as time cannot be predicted correctly, inventory builds up on intermediate machines and thereby process delaying.

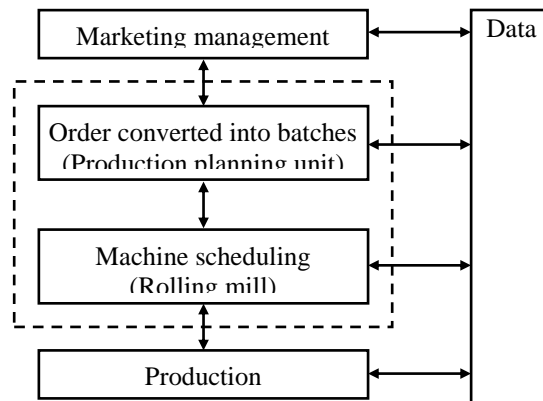


Figure 1. Flow of information

A scheduling model with fuzzy batch manufacturing time and fuzzy due time is proposed hereby considering the uncertainty of batch production time on machines. This model resembles a typical Job Shop problem, to which a triangular fuzzy number is used to denote the process of each batch. The orders are evaluated keeping the objective function as maximum average order delivery satisfaction and minimum satisfaction of the fuzzy job shop scheduling model, mathematical formulation is done and solved by applying heuristic genetic algorithm.

Since the production requirements of the various products are extremely different, the device parameters or operation pattern has to be changed. 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 such as quality, grade, lead time, etc.

Generally such order grouping and scheduling is done manually. However, with the production development, rolling mill adopts generally the week delivery mode to meet customers' demands, improve the delivery ability. Thus, the manual scheduling usually exhibits a poor capacity to fulfill the complicated requirements.

In this paper orders are grouped into homogeneous batches using integer linear programming model. Later the orders in each batch are optimized for delivery satisfaction using fuzzy model.

3.1 Integer linear programming –

Based on the weight of order and campaign production target orders are formed into groups, let

O_i = i -th order [$i = 1, \dots, m$]

B_b = b -th lot [$b = 1, \dots, N$]

S = number of lots to be formed

R = maximum number of batches allowed

Max_w, min w= maximum product weight and minimum product weight allowed in a lot

w_i = product weight of i-th order

Objective function(P): minimization of number of lots

$$\text{MIN}(P) = \sum_{i=1}^M B_i \tag{1}$$

$$\sum_{b=1}^N O_i B_b \leq 1 \quad \text{for all Orders}(i=1, \dots, m) \tag{2}$$

Constraint satisfies each order is assigned to a particular batch.

$$\sum_{i=1}^M O_i B_b \times w_i \leq \max w \quad \text{for all } B_b(b=1, \dots, n) \tag{3}$$

$$\sum_{i=1}^M O_i B_b \times w_i \geq \min w \quad \text{for all } B_b(b=1, \dots, n) \tag{3}$$

Constraint satisfies that a lot is within the weight limits.

B_i = Integer value. Its value is 1 if at least one order is allotted otherwise its value is 0.

$$B_i + z \left(1 - \sum_{i=1}^M O_i \cdot B_i \right) \geq 1 \tag{4}$$

$$B_i + z \left(1 - \sum_{i=1}^M O_i B_i \right) \leq 1 \tag{4}$$

where z = big value

Eqs.(3 and 4) ensures whether B_i = lot assigned or not.

$$\sum_{i=1}^N B_i \leq 25 \tag{5}$$

B_{i+1} ≤ B_i for all i = 1, ..., M - 1

$$\sum_{i=1}^M B_i > 0 \tag{6}$$

Number of lots are formulated by solving the above equations.

3.2 Fuzzy delivery satisfaction –

Considering the uncertain factors in production, the manufacturing time of each job on a machine is represented by a triangular fuzzy number $\tilde{A}_{ikjl} (a_{ikjl}^L, a_{ikjl}^M, a_{ikjl}^U)$ where, i = 1, 2, ..., n denotes the index of jobs; j = 1, 2, ..., m denotes the index of machine; 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_{ikjl}^L , a_{ikjl}^M and a_{ikjl}^U , represent the shortest manufacturing time, the possible time and the longest time of a job, respectively. And, the membership curve is illustrated as Figure 2. In addition, we specify the due time of a batch is denoted by trapezoid fuzzy number $\tilde{D}_i(d_i^o, d_i^p)$, where d_i^o and d_i^p denote the optimistic due time and pessimistic time of job i, respectively (see Figure 3).

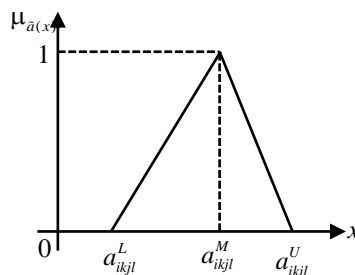


Figure2. Membership function of manufacturing time of an order batch

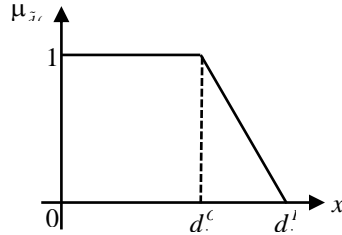


Figure 3. Membership function of due date

The model for batch scheduling of the rolling plant reads as follows. Delivery satisfaction (J) is maximized as follows:

Objective function:

$$\text{Max } J = w_1 \times \text{Max } z_1 + w_2 \times \text{Max } z_2 \quad (7)$$

Where

$$z_1 = \frac{1}{n} \sum_{i=1}^n K$$

$$z_2 = \min[k_1, k_2, \dots, k_i, \dots, k_n]$$

$$K = \frac{\text{area } \tilde{I} \cap d}{\text{area } \tilde{I}}$$

and

w_1 and w_2 are weight for objective function respectively. Sum of weights is one where $\text{area } \tilde{I}$ denotes the area of fuzzy completion time of job i ; \tilde{d} denotes the area of fuzzy due time of job i ; k = delivery satisfaction. z_1 =average delivery satisfaction and z_2 = min of delivery of satisfaction.

Subject to:

$$\tilde{S}_{ikjl} \geq 0, \quad l = 1 \text{ and } k = 1, i = 1, 2, \dots, n, j = 1, 2, \dots, m \quad (8)$$

$$\tilde{S}_{ikjl} \geq \tilde{F}_{j^{(l-1)}} \quad l \neq 1 \text{ and } k = 1, i = 1, 2, \dots, n, j = 1, 2, \dots, m \quad (9)$$

$$\tilde{F}_{ij} \geq \tilde{S}_{ij} + \tilde{A}_{ij} \quad i = 1, 2, \dots, n, j = 1, 2, \dots, m \quad (10)$$

\tilde{S}_{ikjl} is the fuzzy start time of job i on machine j ; $\tilde{F}_{i^{(k-1)}}$ is the fuzzy completion time of $(k - 1)$ -th step of machine j ; \tilde{F}_{ij} is the fuzzy completion time of i on machine j ; \tilde{F}_i is the fuzzy completion time of job i ; and \tilde{A}_{ij} is the manufacturing time of job i on machine j .

Eq.(7) is the objective to maximize the delivery satisfaction of batch. We define the delivery satisfaction of a batch as the intersection area between the completion time \tilde{I} and the due time of the batch \tilde{d} (see Figure 4). Eq.(8) 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.(9) 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.(10) denotes that the completion time of each job is the fuzzy sum of the start time and the manufacturing time of the job.

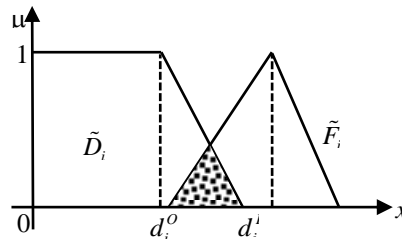


Figure 4. Delivery satisfaction

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 . However, to the proposed scheduling model, the calculation has to be redefined since the product may be continuously transported into the inventory of next machine when the batch of orders is still produced on current machine.

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(FN).

3.3 Fuzzy ranking adopted in this paper –

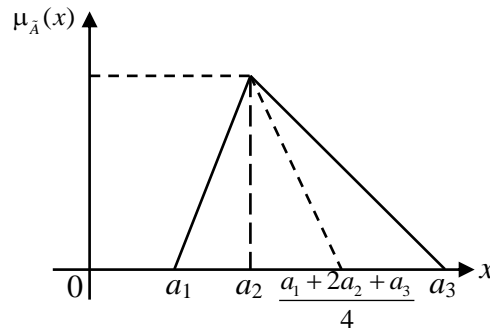
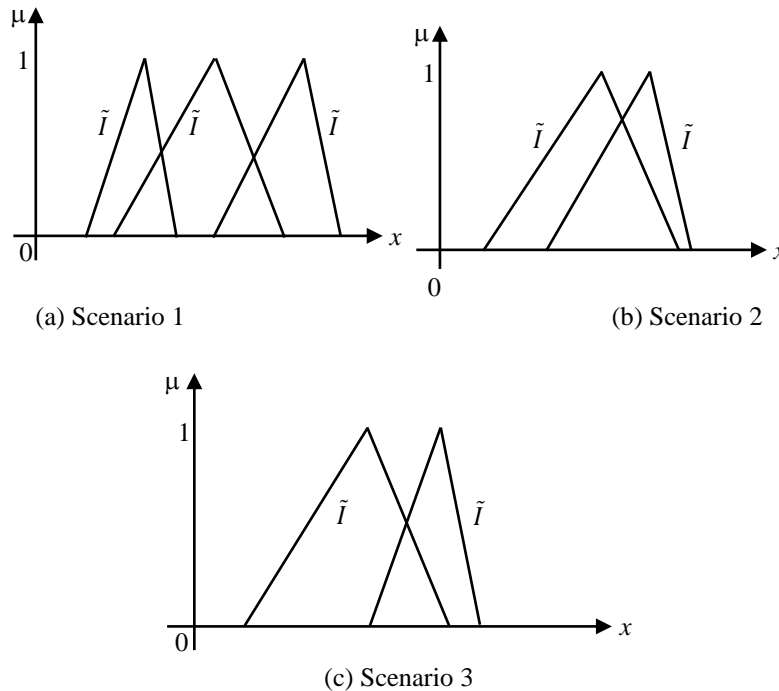


Figure 4. The greatest associate ordinary number of A

Criterion 1: If $C1(A) = [(a1 + 2a2 + a3)/4] > (<) C1(B) = [(b1 + 2b2 + b3)/4]$, then $A > (<) B$;

Criterion 2: $C1(A) = C1(B)$, then $C2(A) = a2$ is compared with $C2(B) = b2$ to rank them;

Criterion 3: If they have the identical $C1$ and $C2$, the difference of spreads $C3(A) = a3 - a1$ is chosen as a third criterion. According to these three criteria, it becomes possible to rank all FNs. Among FNs $A_i, i= 1, 2, \dots, n$. the maximum and minimum FNs are respectively denoted by A_{max} and A_{min} . For example, according to these three criteria, determine the order of FNs of $S = \{A1, A2, A3, A4\}$, where $A1 = (2, 5, 8), A2 = (3, 4, 9), A3 = (3, 5, 7), A4 = (4, 5, 8)$. Using the first criterion $C1, C1(A4) = 5.5$ and $C1(A1) = C1(A2) = C1(A3) = 5.0$. Hence $A_{max} = A4$. By the second criterion $C2, C2(A3) = C2(A3) = 5$ and $C2(A2) = 4$. Thus $A_{min} = A2$. The third criterion $C3$ shows $C3(A1) = 6$ and $C3(A3) = 4$. In this way, the decreasing order of FNs of S becomes $A4, A1, A3, A2$.



(c) Scenario 3
 Figure 5. Different scenarios

We assume that the manufacturing and setup time of a single steel product 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_{ikjl} , can be determined by the following rules.

Rule 1: If the Scenario 1 is in the case (all steel production job i have been placed into the inventory of machine j before the previous job on machine j is finished), then $S_{ikjl} = F_j(l-1)$.

Rule 2: If the Scenario 2 is in the case (a part of steel product) in job i have entered into the inventory of machine j before the previous step of job i is totally finished), then $S_{ikjl} = S_i(k-1) \vee F_j(l-1)$. The operator [V] 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 $S_{ikjl} = S_i(k-1) \vee F_j(l-1)$.

3.4 Calculation of fuzzy processing time parameters –

Manufacturing time calculation depended upon the size of steel product

$$\text{Manufacturing time } t = (\text{weight of product} * \text{slip coefficient} / (\text{volume of product} * \text{density} * \text{speed}) + \text{compensation factor} \quad (11)$$

The time is calculated based on normal situation. Sometimes abnormal situation such as malfunction of equipment and machine maintenance may take place, the mentioned time prediction will be applied to describe the

shortest manufacturing time, a_{ikjl}^L .

As for the possible time a_{ikjl}^M , it should be determined by the average production capacity possible time = a_{ikjl}^M
 = average product weight on that machine till the period
 * weight of batch / accumulated production (12)

Eq.(13) gives the longest manufacturing time a_{ikjl}^U calculation considering the machine breakdown,
 $a_{ikjl}^U = a_{ikjl}^M + \text{breakdown expected time}$ (13)

IV. Solving for the Order Batch Scheduling

The order batch scheduling model is 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 mathematical programming, even some intelligent optimization. Genetic Algorithm is a class of evolutionary algorithm that eliminates the infeasibility of crossover between two chromosomes organized by ordinal strings. 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 rolling plant.. Here is an example, (the sequence number is orders in each batch).

Example: 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 roulette wheel selection is applied to establish the new generation as usual. The solving step of order batch scheduling for the rolling plant is as follows.

Step 1: Group the available orders to form a few lots based on product tonnages and minimum lots. Which is nothing but order conversion into lots say for large batches.

Order conversion into lots decision – find out which jobs of the same family are to be included in each lot, using integer linear programming as mentioned at section 3.1

Step 2: again the lots are regrouped into small batches based on the orders product category as well as delivery time. Calculate the fuzzy manufacturing time of each job of batch on the machines, and determine the fuzzy membership function of manufacturing time and due time mentioned at section 3.2.1, 3.2.3

Step 3: Initiate the status of the machines in the rolling plant, and randomly generate a number of n-bit strings represented as a set of initial solutions. Sequencing decision – determine the order in the jobs within each batch are to be processed,

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 (see section 3.2)

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.

The steps are shown in flow chart (Figure 6).

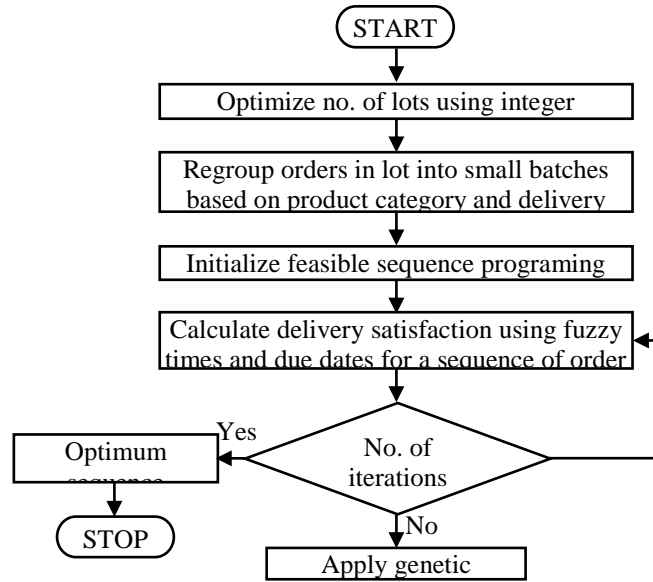


Figure 6. Flow chart indicating methodology adopted

V. DATA ANALYSIS AND RESULTS

To verify the effect of the proposed fuzzy scheduling model, a study was conducted for order delivery satisfaction with data obtained from a rolling mill and compared to the manual scheduling.

1 Data is obtained for product category, delivery period of the item, quantity of products in the order, weight of products in the order. Each rolling mill tries to optimize the productivity using minimum batches and maximum production as far as possible in order to minimize set up time, tool wear outs, integer linear programming is used to select minimum lots with orders placed.

2 The data is again regrouped in terms of product category and within product category delivery period are target is taken to form a rolling batch and the algorithm is applied. Sample data is shown in Table 1. Such data is obtained from step 5.1.

Table 1: The data is calculated from a rolling mill

Order Sl. No.	Product category	Delivery period(in week) (from current date)	Order qty. (Nos.)
1	1	1	14
2	2	2	13
3	3	3	15
4	3	4	16
5	2	1	18
6	2	2	14
7	3	3	10
8	4	3	14
9	4	2	15
10	4	3	16
11	1	2	14
12	2	4	15
13	3	2	13
14	1	1	14
15	1	3	12

3 w_2 value is taken as 0.2 in delivery satisfaction objective function.

The statistic comparisons are listed in Table 2, where four groups of real data from rolling mills is presented.

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 delivery satisfaction (objective function) fundamentally exceed 70%, get the fairly better solution than that by the manual scheduling. Furthermore, manual

scheduling always takes more time even for the experienced worker. As for the order delivery satisfaction, the proposed GA gets the best scheduling solution.

Table 2: The results for delivery satisfaction in each batch is follows

Batch qty.	Manual schedule (objective function)	GA (objective function)
54	0.78	0.8
60	0.75	0.76
12	0.64	0.70

VI. CONCLUSION

The product lots (large batches) are formed for maximum campaign production for optimum number of orders that can be planned. To optimize this integer programming is used as the processing times cannot be accurately determined fuzzy processing times are calculated. Finding out the order sequence in a regrouped batch for scheduling when such fuzzy processing time appears is a complicated task when it is done manually. Hence a model is proposed to verify the effect of the proposed fuzzy scheduling model and compared the study for order delivery satisfaction with 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 rule-based JSSP model with fuzzy manufacturing time is established for the order batch scheduling problem in the rolling plant. And evolution algorithm is designed to solve the fuzzy scheduling model.

The average delivery satisfaction of orders reaches above 70%, which greatly meets the customer timing demands in the market. It is better than manual method.

Future research plans to extend this model to solve the problem using different programming method under different uncertain environments.

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