SIMULATION OF BATCH PRODUCTION SCHEDULING IN DISCRETE MANUFACTURING WORKSHOP BASED ON IMPROVED GENETIC ALGORITHM

Junhui Song¹*, Hua Xie² and Jianmei Rou¹

¹ Xinyang Normal University, College of Computer and Information Technology, Xinyang 464000, China
² Xinyang Vocational and Technical College, president’s Office, Xinyang 464000, China
E-mail: 85141727@qq.com

ABSTRACT: A proper batch scheduling method for discrete manufacturing workshops can transform the complex multi-objective overall scheduling into simple single-objective batch scheduling, which can significantly reduce production cycle and control production cost, and it is a hot topic in current research. Taking production cost and production cycle as the optimization targets, this paper constructed a simulation model for the multi-objective batch production scheduling of discrete workshops, meanwhile, it also improved the traditional Non-dominated Sorting Genetic Algorithm (NSGA), at first, an object-oriented algorithm was introduced into NSGA, which reduced the coding length and the number of iterations in the algorithm; and then the segmentation crossover and mutation methods were applied to optimize the original NSGA’s crossover and mutation operations, and to repair the product processing sequence coding and processing equipment coding in the genetic chromosomes, so as to ensure that the genetic offspring individuals would have feasible solution(s). At last, the improved algorithm had been applied to the solution of the model, and with practical production examples, the feasibility of the proposed model had been verified. The research conclusions can provide a new idea for the scheduling optimization of large-scale discrete workshops.

KEYWORDS: discrete manufacturing workshop, production scheduling optimization, simulation, batch scheduling strategy, improved genetic algorithm (Improved-GA).

1 INTRODUCTION

For automobiles, ships, electronic products, and other intensive manufacturing industries, the production process is generally to break down the main task into several sub-tasks, and then the sub-tasks are manufactured and processed independently. This manufacturing process consisting of multiple parts processing tasks is called discrete workshop manufacturing (Huang et al., 2018; Völker and Gnilkowsky, 2003; Fattahi et al., 2013).

Due to the large number of products and the complicated processing techniques, factors such as processing equipment damage, product processing delay, and production cost increase would occur in the production process of discrete workshops (Chi et al., 2014). For large-scale manufacturing workshops, the traditional single optimization target production scheduling can no longer meet the actual needs. Studies on multi-objective workshop production scheduling have been reported, and existing researches of multi-objective optimization include processing cost, processing batch, completion time, and delay time, etc., there are constraints and even contradictions between the above optimization targets. In order to reduce the optimization difficulty, most researchers convert the multi-objective optimization function into the weighting of the single-objective functions. However, the weighting of objective functions in the existing research are mostly determined based on experience, lacking of theoretical basis (Yang and Wang, 2012; Bandyopadhyay and Bhattacharya, 2013); various uncertainties such as machine failures, new product orders, and product processing blockages can also cause complexity in production scheduling (Aghezzaf et al., 2010; Liu et al., 2015).

Another way to lower the difficulty of production optimization is to perform scheduling in batches, by direct batching, minimum batching and other methods, the complex multi-objective overall scheduling is converted into simple single-objective batching scheduling, which can significantly reduce the production cycle. The difficulty lies in the batch division and scheduling optimization strategy (José and Yoon, 2013; Marimuthu et al., 2009; Defersha, 2012; Low et al., 2004; Huang, 2010; Quanke and Jianying, 2004; Congbo, 2017). Distributed
optimization and integrated optimization are common methods for solving batch division and scheduling optimization strategies. Distributed optimization is to divide the overall task according to a certain rule in the planning stage, and then perform scheduling in sequence, it is a local optimization method which can hardly obtain the global optimal solution of scheduling (Chang, 2015; Shengyao et al., 2012; Wang et al., 2013; Hans et al., 2007); Integrated optimization is to perform comprehensive processing of task batching and scheduling optimization, so as to obtain the global optimal solution through the integrated optimization method, however, at present, there are few studies on multi-objective integrated optimization scheduling of discrete manufacturing workshops (Li et al., 2018; Xia and Wu, 2005; Wu and Ierapetritou, 2007).

Aiming at the above defects, this paper constructed a multi-objective batch production scheduling simulation model of discrete manufacturing workshops based on integrated optimization scheduling method with production cost and production cycle as the optimization targets; at the same time, the traditional NSGA had been improved and applied to the solution of the simulation model. In the end, the proposed method had been verified by practical examples. The research conclusion can provide a theoretical reference for the scheduling optimization of large-scale discrete workshops.

2 DISCRETE MANUFACTURING WORKSHOP MULTI-OBJECTIVE BATCH SCHEDULING MODEL

2.1 Problem description and optimization targets

Assume there are a total of M processing equipment and N kinds of products to be processed in a manufacturing workshop; each equipment can only process one product at a time, the several batches of sub-tasks broken down from a whole process task have the same processing priority; The processing equipment starts processing of next-batch products right after it finished the processing of previous-batch products, and there’s no idle or lag time in-between; the handling time of the products is ignored, and the processing time and procedures of each product are fixed.

Given the above assumptions, this paper established a multi-objective batch scheduling model for discrete manufacturing workshops with minimizing processing time \( T \) and production cost \( C \) as the optimization targets. The objective function can be expressed as:

\[
\min \text{Makespan} = \min \left( \frac{1}{\max_{i=1}^{N} T_i} \right)
\]

\[
\min \text{Cost} = \min (C_c + C_s) = \min \left( \sum_{i=1}^{M} \sum_{j=1}^{N} X_{ijk} \times P_{ijk} \times S_{ijk} + \sum_{i=1}^{M} \sum_{j=1}^{N} X_{ijk} \times P_{ijk} \times C_{ijk} \times L_{ij} \right)
\]

(2)

In above formula, \( C_c \) and \( C_s \) represent the processing cost of the product and the additional cost due to external disturbance factors, respectively; \( P_{ijk} \) and \( S_{ijk} \) represent the processing cost and adjustment cost caused by external disturbance factors of the \( j \)-th product in the \( k \)-th processing procedure on the \( k \)-th equipment, respectively; \( S_{ijk} \) is the corresponding adjustment time of \( P_{ijk} \); \( C_{ijk} \) is the processing time required for the \( j \)-th procedure on the \( k \)-th equipment of the \( i \)-th product; \( L_{ij} \) represents the divided processing batch in the production process.

The constraints for Formulas 1 and 2 are:

\[
E_{ijk} - E_{(j-1)k} \geq S_{ijk} + C_{ijk} \times L_i
\]

if \( X_{ijk} = X_{(j-1)k} = 1, k = m \) \hspace{1cm} (3)

\[
E_{ijk} - E_{(j-1)k} \geq C_{ijk} \times L_i
\]

if \( X_{ijk} = X_{(j-1)k} = 1, k \neq m \) \hspace{1cm} (4)

\[
E_{ijk} - E_{ijk} \geq S_{ijk} + C_{ijk} \times L_f
\]

if \( X_{ijk} = X_{ijk} = 1, R_{ijk} = 1 \) \hspace{1cm} (5)

\[
E_{ijk} - S_{ijk} \geq S_{ijk} + C_{ijk} \times L_i
\]

if \( X_{ijk} = 1 \) \hspace{1cm} (6)

\[
\sum_{i=1}^{M} X_{ijk} = 1, i \in (1, H), j \in (1, n_i)
\]

(7)

Formula 3 means that for one equipment, the processing of next-procedure can only be started after the processing of previous-procedure is completed, and \( S_{ijk} \) and \( E_{ijk} \) are the start time and completion time for the \( j \)-th procedure on the \( k \)-th equipment of the \( i \)-th product; Formula 4 represents that when a previous-procedure and a next-procedure are not processed on the same equipment, it needs to wait; Formula 5 stipulates that the processing equipment can only perform one procedure at the same time; Formula 6 indicates that the difference between \( E_{ijk} \) and \( S_{ijk} \) must be greater than the required time of the procedure; Formula 7 states that all procedures must be processed by the \( M \) equipment in the workshop.

2.2 Simulation model construction

Figure 1 shows the discrete manufacturing workshop multi-objective batch scheduling policy model constructed in the paper. The simulate scheduling management system \( S_P \) first allocates the product \( P_i \) to the corresponding buffer area. When the equipment for processing \( P_i \) is idle, \( P_i \) is
transported to the corresponding processing equipment \( M_i \), and is processed according to the planned path. After the processing is completed, the product is transported to the next buffer area and wait for subsequent processing.

![Discrete manufacturing workshop multi-objective batch scheduling policy model](image)

**Fig. 1** Discrete manufacturing workshop multi-objective batch scheduling policy model

\[ P_i \text{'s batch scheduling times } B_i \text{ is:} \]

\[ B_i = \frac{P(i)Q}{P(i)Lv(Iorder(i))} \]  \hspace{1cm} (8)

\( Q \) is the production quantity of product \( P_i \); \( Lv \) is the batch scheduling vector; \( Iorder \) is the processing batch sequence coding of the \( P_i \). \( H \) is the sum of batch scheduling of \( N \) products, denoted as:

\[ H = \sum_{i=1}^{N} B_i \]  \hspace{1cm} (9)

According to Formulas 8 and 9, \( OT \) is the number of procedures for all products, denoted as:

\[ OT = \sum_{i=1}^{N} B_i \times P(i) \times PN_i \]  \hspace{1cm} (10)

\( PN_i \) is the number of procedures of \( P_i \).

### 3 SOLUTION ALGORITHM OF MULTI-OBJECTIVE BATCH SCHEDULING MODEL

#### 3.1 Algorithm flow

This paper improved the traditional NSGA, reduced the coding length and iteration number in the algorithm, and optimized the crossover and mutation calculation in the GA, so as to guarantee the feasibility of the genetic offspring and the validity of the global solution. The improved algorithm flow is shown in Figure 2. In the figure, Epoc and Maxgen represent the number of iterations and the maximum number of iterations, respectively.

Optimize the coding method in the NSGA. According to the characteristics of the multi-objective batch scheduling model, introduce the object-oriented batch scheduling model into NSGA, and divide the objects to be optimized in Figure 1 into processing equipment \( Mach \), product batch \( J \) and genetic chromosome \( Chrom \). Among them, \( Chrom \) included product processing sequence coding (\( Jorder \)) and processing equipment coding (\( Morder \)).

Initialize the algorithm’s initial population, population size, crossover operator, genetic operator, product processing sequence coding, and processing equipment coding. The initialized populations obtained by the object-oriented algorithm have shorter coding lengths and feasible individuals.

![Calculation process of improved NSGA](image)

**Fig. 2** Calculation process of improved NSGA

#### 3.2 Crossover and mutation optimization

Aiming at coding features of the NSGA, the original NSGA crossover operation was optimized by the segmentation crossover method. The crossover target is the transformation of the product processing sequence coding and the processing
equipment coding. Order the crossover segments of the two genetic chromosomes Chrom (i) and Chrom (j) to be Z_{i1} and Z_{i2}, according to Formula 11, the segments Z_{i1} and Z_{i2} after crossover were obtained as:

\[
\begin{align*}
Z_{ic} &= rZ_{i1} + (1-r)Z_{i2} \\
Z_{sc} &= (1-r)Z_{i1} + rZ_{i2}
\end{align*}
\]  (11)

Taking Figure 3 as an example, the crossover optimization of chromosome Chrom is explained.

**Fig. 3** Schematic diagram of algorithm chromosome crossover optimization

After the crossover operation, the initial planned product processing batch and the number of procedures would change. Therefore, the product processing sequence coding and processing equipment coding should be repaired. The repair process of the two is shown in Figure 4.

Through the above repair process, it is ensured that the genetic offspring individuals would have feasible solution(s).

The mutation optimization process is similar to the optimization of crossover operation, the mutation targets are also the product processing sequence coding and processing equipment coding. The mutation process of the genetic chromosome Chrom (i) can be performed according to Formula 12:

\[
\nu_{\text{Chrom}(i)} = J(m) \times B_l + r(J(m) \times B_u - J(m) \times B_l)
\]  (12)

The mutation operations of Jorder and Morder are both single-point mutation modes.

### 3.3 Decoding optimization

The devised decoding optimization method is shown in Figure 5. The decoding operation can prepare the products waiting in the buffer area or the next procedure in advance, thereby saving the total production time.

**Fig. 5** Schematic diagram of decoding optimization of the NSGA

The process of the decoding operation is: firstly, select a certain procedure j from \textit{Jorder}, and find the \textit{Morder} equipment number corresponding to the procedure, and then retrieve the processing process of the equipment, find an idle time period y that j can insert, when j is the first processing procedure, the earliest processing time allowed is \(a = S_{ijk}\), otherwise: \(a = E_{ijj-1} \), b and c are the start time and end time of the idle time period y of the equipment, respectively.

### 4 SIMULATION EXAMPLE VERIFICATION

Use simulation analysis to verify the proposed model and the improved NSGA. Assume there are 4 kinds of products \(P_1-P_4\), the production quantity of \(P_1\) is 65, the number of procedures is 5, the number of batches is 5; the production quantity of \(P_2\) is 65, the number of procedures is 5, the number of batches is 5; the production quantity of \(P_3\) is 45, the number of procedures is 4, the number of batches is 4; the production quantity of \(P_4\) is 65, the number of procedures is 4, the number of batches is 5.

To simplify the calculation, the multi-objective optimization function processing time T and production cost C of this paper are converted into a single-objective optimization function, and the expression defining the efficiency coefficient \(f\) is:

\[
f = \sqrt{e^{-\frac{(\text{Makespan}-T_1)}{T_0-T_1}} \cdot e^{-\frac{(\text{Cost}-C_1)}{C_0-C_1}}}
\]  (13)

It can be seen from the above formula that, the closer the \(f\) value is to 1, the better the optimization effect of the algorithm.

According to Formula 13, calculate the variation curve of \(f\) under different iteration times, shown as Figure 6. It can be seen from the figure...
that $f$ exceeds 0.8 when the number of iterations reaches 25 generations; when the number of iterations reaches 250 generations, the value of $f$ exceeds 0.9, indicating that the improved NSGA proposed in this paper has significant optimization effect.

**Fig. 6** Variation curve of $f$-value of the model with the number of iterations

Simulation of the optimized scheduling schemes of the above 4 kinds of products was carried out, and three types of batch integrated optimization scheduling results were obtained and defined as scheme A, scheme B and scheme C, respectively. The typical scheduling Gantt charts of the three schemes are shown in Figure 7.

**Fig. 7** Batch integrated optimization scheduling Gantt charts of three schemes

Figure 8 shows the Pareto solution sets statistics for schemes A, B, and C.

**Fig. 8** Pareto solution sets of schemes A, B, and C

Combing with Figures 7 and 8 we can know that, the production cost of scheme A was lower, but the total production time was longer; the production time of scheme B was shorter, but the production cost was higher; scheme C combined the advantages of scheme A and scheme B, its production cost and production time were controlled at an appropriate level. By analyzing the reasons we can see that, the number of batches divided in scheme A was less, and the adjustment time was the shortest, but the processing time of each procedure was longer, and the waiting times for subsequent
procedures and other processing equipment were also prolonged; meanwhile, less batch number would result in greater processing loads for some processing equipment, while for other equipment, the processing loads were too small (as shown in Figure 7(a)). This production scheduling method is not conducive to long-term operation of the equipment and it would result in low production efficiency. In scheme B, the number of divided batches was larger, and the production time of each processing batch was shorter, therefore, the idle waiting times of products and processing equipment were significantly reduced, at the same time, larger batch number made the processing load of each equipment more balanced, and the production efficiency was higher, but correspondingly, the equipment production cost and product processing adjustment cost were also increased significantly.

Scheme C combined the advantages of scheme A and scheme B, it realized proper division of product processing batches, and made the production cost and production cycle reach a dynamic balance, and then the optimal solution(s) of production optimization scheduling had been obtained by the algorithm proposed in this paper.

5 CONCLUSION

Based on the integrated optimization scheduling method, this paper took production cost and production cycle as the optimization targets and constructed a multi-objective batch production scheduling simulation model for discrete manufacturing workshops. At the same time, it also improved the traditional NSGA and applied it to the solution of the simulation model. In the end, through practical production examples, the proposed method had been verified. The research conclusions are as follows:

(1) The object-oriented algorithm had been introduced into NSGA, so that the coding length and iteration number in the algorithm had been reduced; by using segmentation crossover and mutation methods, the original NSGA crossover and mutation operations had been optimized, and the product processing sequence coding and processing equipment coding in the genetic chromosome had been repaired to ensure the genetic offspring individuals would have feasible solution(s).

(2) The simulation results showed that the proper division of product processing batches can make the idle waiting time of products and processing equipment less, the processing load of equipment more balanced, production efficiency higher, so that the production cost and production cycle could reach a dynamic balance. The research conclusion can provide a new idea for the scheduling optimization of large-scale discrete workshops.

6 ACKNOWLEDGEMENTS

Henan Province Teacher Education Curriculum Reform Project: Network Training Model for Primary and Secondary School Teachers under the Background of Large Data (NO. 2018-JSYYB-029); Henan Province Teacher Education Curriculum Reform Project: Research on the curriculum reform of teachers' Informatization in primary and secondary schools under the mode of "Internet + education"(NO.2019-JSYYB-118)

7 REFERENCES


