Research on Flexible Flow-shop batch scheduling based on improved Genetic Algorithm

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Abstract. In this paper, the batch scheduling problem of multi-stage flexible flow shop in mixed-flow production is studied. Considering the factors of parallel machine scheduling and equipment adjustment time, an integrated equal and variable optimal batch strategy is proposed. On this basis, a batch scheduling model is constructed to minimize the completion period, maximum load and total tardiness, and an improved genetic algorithm based on two-layer search framework is designed to solve the problem. In order to obtain a better scheduling scheme, the algorithm adopts three-stage coding and decoding considering adjustment time, and introduces the critical chain method and the minimum critical ratio rule through the integrated iterative process of inner algorithm and outer batch. The example results show that compared with the original scheme, the optimized scheduling scheme can effectively reduce the completion cycle by 10.35% and the order delay ratio by 40%. At the same time, the production line adjustment frequency is reduced by 22.45% compared with the scheme under equal division strategy. According to the above results, the applicability and effectiveness of the optimized batching strategy and the improved algorithm are verified.

Keywords: Flexible flow shop; Optimized batching strategy; Improved genetic algorithm with two-layer frame

1 Introduction

Under the current multi-variety market demand, considering the increasingly important requirements of product response speed, delivery punctuality and enterprise economy, enterprises are more using batch flow technology to accelerate output efficiency, reduce process time and reduce the phenomenon of procrastination. The Flexible Flow shop scheduling problem with lot Streaming involves process sequencing, equipment allocation, sub-batch quantity and batch setting. Therefore, the research on it can guide the actual production scheduling more effectively.

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Previous literatures have studied equal batch strategy and variable batch strategy. Wang et al. [1] adopted equal batch strategy to build scheduling model and proposed an adaptive difference algorithm based on parallel chromosome coding. Wong et al. [2] and Chakaravarthy et al. [3] used the equal batch strategy to divide the batch into smaller batches for parallel processing between multiple stages. Wang et al. [4] established a batch scheduling model considering batch transfer and sublot mixing, and used a two-stage discrete water wave optimization algorithm to solve it. Cheng et al. [5], taking into account the batching characteristics and constraints, constructed a mixed integer linear programming model with variable batching strategy, and proposed a mixed coding genetic algorithm to solve it. This paper proposes an optimal batch strategy, that is, flexibly adjust the number of sub-batches of each order under the equalization strategy, which is called flexible equalization strategy.

Parallel machines have been widely used in various processing stages of flow shop in order to improve workshop production flexibility and output rate. CHENG et al. [6] proposed the TSHF-LSP(I) model to study the equipment allocation problem under single operation. Wang et al. [7] optimized the batch scheduling problem by improving the crossover and mutation modes in the global search process of differential evolution algorithm, but did not consider the influence of adjustment time. DAI et al. [8] applied Internet of Things (IOT) technology to build a scheduling optimization model based on variable batch strategy for capacitor manufacturing shop scheduling, and proposed an improved distribution estimation algorithm without considering the influence of adjustment time. The above researches on FFSSP-LS mostly focus on solving the problem of single process scheduling. Although such researches can achieve the optimization effect well, they do not conform to the production reality of the close connection of multiple processes in general workshops, so it is difficult to be directly applied to the optimization of shop scheduling.

For the solution method of batch scheduling model, T. C. E. et al. [9] studied the replacement FSSP with deteriorating workpiece, established a planning model with the goal of minimizing the maximum completion time, and solved it by using GA of improved population initialization. Jian Feng Zhao et al. [10] established a corresponding scheduling model and proposed an improved adaptive GA for the multi-stage FFSSP with parallel batch processors in the intermediate stage. Lei W [11] proposed an adaptive GA embedded in local search, and designed the adaptive probability automatically adjusted along with the algorithm process, so as to ensure the quality of the solution at the later stage of iteration. Reference [5] designed a hybrid coding GA to solve multi-stage FFSSP-LS. In addition, many experts and scholars have applied improved GA to multi-scene scheduling optimization, which shows that GA has strong compatibility, multiple improvement angles and is suitable for dealing with combinatorial optimization problems.

The comprehensive consideration of partial strategy, parallel machine scheduling, equipment adjustment factors such as time, for more products made in the mixed flow phase partial study of scheduling problem of flexible flow shop, construction to completion of the cycle, maximum load and the target of minimizing the total tardiness, scheduling model, and puts forward an improved GA algorithm to double search framework. The algorithm adopts three-stage coding and decoding considering adjustment time, combines the inner layer algorithm with the outer layer batching strategy, introduces the critical chain method and the minimum critical ratio rule, and tries to get the best scheduling scheme in the limited schedule period.

2 Problem description and model construction

2.1 Problem Description

The FFSSP-LS studied in this paper can be described as: n orders of flexible flow shop ($n = \{1,2 \dots N\}$) need to be continuously installed on i workstations ($i = \{1,2 \dots I\}$), the production process is fixed (the sequence of flow through each stage is consistent and cannot be skipped), each workstation has M_i parallel machine available ($M_i \geq 2$) and the processing time of each parallel machine for the same order may be different (heterogeneous parallel machine). In order to better analyze problems and build models for FFSSP-LS, the following assumptions are made:(1) At any workstation, different sub-batches of each order can be simultaneously produced on multiple equipment;(2) using the optimized batch strategy in this paper, the batch difference between sub-batches Should be guaranteed to be $\{0,1\}$ for each order. (3) At the same time, each processing equipment can only process one process of a single sub-batch, and the processing process without interruption and other dynamic changes;(4) At the same time, each sub-batch process can only be processed in the same processing equipment, and cannot be preempted; (5) The processing time of each order process and the adjustment time of each equipment batch change are known and fixed in advance;(6) Each order contains only one type of product, and the product types are different.

2.2 Model Construction

2.2.1. Parameter setting.

n—order set, $n = \{1,2 \dots N\}$;j—set of sublots,$j = \{1,2 \dots J\}$;i—workstation set,$i = \{1,2 \dots I\}$;i_m—set of devices on workstation $i, m = \{1,2 \dots M_i\}$;M—total number of equipment in the workshop;

2.2.2. Variable setting.

$Sum(n)$—represents the total quantity of order n; $Sum(nj)$—represents the lot of sublot j of order n; S_n—indicates the number of sublots of order n; D_n—indicates the delivery date of order n; ω_1—represents the weight to minimize the maximum completion period; ω_2 —represents the weight of minimizing total delay time; ω_3—represents the weight to minimize the maximum load of the equipment; C_{max} —represents the maximum completion time for all orders; $IT_{nj}^{i_m}$—represents the processing time of a single product on the m-th equipment of workstation i for sublot j of order n; PT_{nj}^{i}—represents the total processing time of sublot j of order n at workstation i; ST_{nj}^{i}—represents the processing start time of sublot j of order n at workstation i; FT_{nj}^{i}—represents the processing completion time of sublot j of order n at workstation i; CT—equipment adjustment time;

2.2.3. Decision variables.

$U_{i_m}^{nj\rightarrow n'j'}$—If the processing order of sublot j of order n is earlier than that of sublot j' of order n', the value is 1; otherwise, the value is 0; $V_{i_m}^{nj\rightarrow n'j'}$—If the sublot j of order n processed on the m-th equipment of workstation i and the sublot j' of order n' do not belong to the same order, the value is 1; otherwise, the value is 0; $W_{nj}^{i_m}$—The value is 1 if the m-th equipment is selected on workstation i by sublot j of order n; otherwise, the value is 0;

2.2.4. Objective functions and constraints.

Minimize the maximum completion cycle:

$$f_1 = minC_{max} \tag{1}$$

Minimize total tardiness:

$$f_2 = min\sum_{n=1}^{N} max(FT_{nj}^{I} - D_n, 0) \tag{2}$$

Minimize the maximum load of equipment:

$$f_3 = min\left(max\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{i=1}^{I} PT_{nj}^{i} W_{nj}^{i_m}\right) \tag{3}$$

$$f = \omega_1 f_1 + \omega_2 f_2 + \omega_3 f_3 \tag{4}$$

$$M = \sum_{i=1}^{I} M_i \tag{5}$$

$$Sum(n) = \sum_{j=1}^{J} Sum(nj) \tag{6}$$

$$Sum(nj) = \begin{cases} \lfloor Sum(n)/S_n \rfloor & MOD(Sum(n)/S_n) < j \le J \\ \lfloor Sum(n)/S_n \rfloor + 1 & 1 \le j \le MOD(Sum(n)/S_n) \end{cases} \tag{7}$$

$$Sum(nj) \in [Sum(nj)_{min},\ Sum(nj)_{max}],\ \forall n,\ j \tag{8}$$

$$\sum_{m=1}^{M_i} W_{nj}^{i_m} = 1,\ \forall n,\ j \tag{9}$$

$$PT_{nj}^{i} = Sum(nj) \cdot IT_{nj}^{i_m},\ \forall n,\ j,\ \mathrm{i},\ \mathrm{m} \tag{10}$$

$$\mathrm{ST_{nj}^{i}} + \mathrm{Sum(nj)} \cdot \mathrm{IT_{nj}^{i_m}} \le \mathrm{FT_{nj}^{i}} \le \mathrm{ST_{nj}^{i+1}} \tag{11}$$

$$ST_{nj}^{i} + PT_{nj}^{i} + CT \cdot V_{i_m}^{nj\rightarrow n'j'} \le ST_{n'j'}^{i} + Q\left(1 - U_{i_m}^{nj\rightarrow n'j'}\right) \tag{12}$$

$$PT_{nj}^{i},\ ST_{nj}^{i},\ FT_{nj}^{i},\ CT \ge 0,\ \forall n,\ j,\ \mathrm{i} \tag{13}$$

Equation (5) represents the constraint of the total number of workshop equipment; Equation (6) represents the batch constraint of each order. The sum of the sub-batches of an order is equal to the total batch of the order. Equation (7) and (8) represent the constraint of sublots. MOD is a complementary function, which cannot ensure that the maximum value of the difference of each sublot is 1. The maximum and minimum values of each sublot are set according to the actual workshop. Equation (9) represents the restriction of equipment selection. Only one equipment can be selected for processing in the same workstation for each sub-batch of orders. Equation (10) represents the constraint of equipment processing time, which is equal to the product of sub-batch quantity and unit processing time on the equipment; Equation (11) represents the process constraints of the sub-batches of each order. The start time of the process after the sub-batches of the same order shall be longer than the completion time of the previous process. Equation (12) represents equipment resource constraints. The task starting condition after tightening the same equipment is that whether to add adjustment time is considered on the basis of completing the task before tightening, and the equipment is allowed to be idle during the processing. Equation (13) represents a non-negative constraint.

3 Algorithm Design

After the genetic algorithm was proposed in 1975, Goldberg et al. [12] made a comprehensive summary and summary of it. Due to its strong compatibility, multiple improvement angles and applicability to combinational optimization problems, it has been widely used in multi-scene scheduling optimization by many experts and scholars.

3.1 Improved genetic algorithm of bilayer frame

The efficiency of traditional genetic algorithm is low because of the study of FFSSP-LS multiple batch schemes and machining paths. Aiming at the optimization model of FFSSP-LS, this paper designs an improved GA algorithm based on double-layer frame, and its main improvements are as follows: 1) In order to enhance the search scope of the algorithm, a two-layer algorithm framework is designed, which uses the reasonable sublot generated by the outer layer under the batch-constraint as the initial solution of GA algorithm. Meanwhile, the inner layer searches for the optimal device allocation and sublot sorting through the iterative optimization process of the algorithm. 2) In order to improve the search performance of the algorithm, the coding method [13] is used for reference and the decoding strategy considering the adjustment time is adopted, and the critical chain method in TOC is combined with the introduction of the minimum critical ratio rule to continuously optimize the completion time of each task.

3.1.1. Encoding and decoding.

A three-paragraph coding method based on real numbers is selected, which is expressed as [(LHS)(MHS)(RHS)]. Each paragraph refers to the coding of batch segmentation, process sequencing and equipment selection respectively, and the middle is separated by "00".

The decoding process considers the equipment adjustment time: (1) Sequential reading of LHS segment chromosome, and according to the corresponding MHS, RHS segment gene to obtain the order sub-batch, sub-batch and equipment allocation information; (2) According to the process constraints, calculate the start and finish time of each process; (3) Judge whether the adjacent sub-batches processed by each equipment belongs to the same order. If so, it is not necessary to adjust the time; otherwise, it is necessary to add adjustment time.

3.1.2. Selection operation.

Each iteration process will select according to the evaluation result of individual fitness value, and the selected individual will be substituted into the subsequent iteration optimization to improve the objective function value. In this paper, roulette method is adopted to ensure the participation probability of excellent individuals in the population as much as possible. The specific fitness function is defined as follows:

$$F = \frac{1}{f} \tag{14}$$

Equation (14) select the general fitness function to transform the value of the comprehensive objective function f from the minimum to the maximum, so as to increase the difference of the objective function appropriately for the convenience of subsequent iterations.

3.1.3. Cross operation.

For each pair (two) of paternal chromosomes, a crossover operation is performed to provide a combination of genetic material by exchanging parts of the genetic material of the two. This paper refers to the crossover operator POX in reference to literature [14] to operate on the section of process sequencing (MHS) and equipment selection (RHS).

3.1.4. Conflict detection.

Conflict detection is aimed at the cross validity of process sequencing. Due to the strict technological constraints between the processes of each sub-batch in the same operation, it is necessary to test the children C_a and C_b generated in the MHS section, and swap their positions if sequence conflict (process error) is found.

3.1.5. Mutation operation.

The mutation operation is different from the crossover operation, which adjusts the processing sequence of different job sublots and the allocation equipment of each job sublot to assist the generation of new populations, so as to further improve the local search performance and reduce the occurrence of premature convergence to ensure diversified populations.

3.2 Improve GA algorithm flow

The improved GA algorithm is used to solve the scheduling model and the optimization scheme based on related scheduling objectives can be obtained quickly. The specific algorithm flow is as follows:

Step1 Set population size N, iteration times of outer batching G_{out} and iteration times of inner algorithm G_{in}.

Step2 Adopt three-stage coding method to encode the initial batch scheme, and add equipment adjustment time into the decoding process;

Step3 According to the results of individual fitness function calculation, roulette method was used to evaluate and select the operation to generate the initial population.

Step4 Select crossover probability P_c to perform corresponding crossover operation on MHS and RHS segments, and generate legitimate new populations through conflict detection.

Step5 Select the mutation probability P_c and carry out corresponding mutation operation on the newly generated MHS and RHS segments after crossover to obtain the new population.

Step6 If the inner algorithm reaches the maximum number of iterations, output the solution; otherwise, return to step3;

Step7 Generate a new batch scheme and substitute it into the algorithm for solving, output the current solution at the end of iteration, select the optimal solution of the batch scheme before and after, and guide the batch direction adjustment;

Step8 Output the scheduling results under the optimal batch scheme at the end of the outer batch iteration;

Step9 Determine the key chain of the current scheduling scheme based on TOC theory [15];

Step10 Use the minimum critical ratio rule to continuously optimize the critical chain and output the final scheduling scheme.

4 Case Analysis

The example data adopted in this paper are as follows: THE PCB assembly workshop of H Company is divided into 3 workstations and there are 8 available production lines. A total of 10 kinds of order tasks need to be completed, and each order flows through all workstations in sequence. It is reasonable for sub-batches of each order to be more than 180pcs. Algorithm parameters are set as follows: Population size N is 85, crossover probability P_c and mutation probability P_m are 0.8 and 0.05 respectively, outer batting iteration times G_{out} is 80, inner algorithm iteration times G_{in} is 300, ω_1, ω_2 and ω_3 are 0.5,0.3 and 0.2 respectively. MATLAB2016a software is used for programming simulation. For details, see Table 1-2.

Table 1. Basic information of processing line

The workstation	Line number	The number of production line	The number of production line
SMT	L1, L2, L3	3	0.5

AI	L4, L5, L6	3	0.5
MI	L7, L8	2	0.5

Table 2. Processing time corresponding to available production line of each workstation

The order information		Production line processing time (s)			The date of delivery
Serial number	Batch size	SMT	AI	MI	Unit (h)
P1	780	28/29/45	49/37/57	41/36	34
P2	570	25/20/30	61/48/69	29/25	35
P3	810	29/21/43	63/51/74	32/28	28
P4	720	36/27/55	51/43/55	11/10	45
P5	600	25/25/49	33/29/35	14/13	37
P6	900	19/17/23	42/37/46	18/16	30
P7	690	28/26/51	41/34/49	35/31	38
P8	720	35/23/47	44/35/50	30/27	28
P9	600	29/18/37	42/38/46	18/16	36
P10	660	36/27/55	37/33/40	13/11	36

In this paper, genetic algorithm is used to generate shop scheduling. Gantt diagram is shown in 1 (shaded area represents equipment adjustment time). At the same time, the optimal scheduling scheme is calculated by using the optimized batching strategy and the improved genetic algorithm, as shown in Gantt diagram 2:

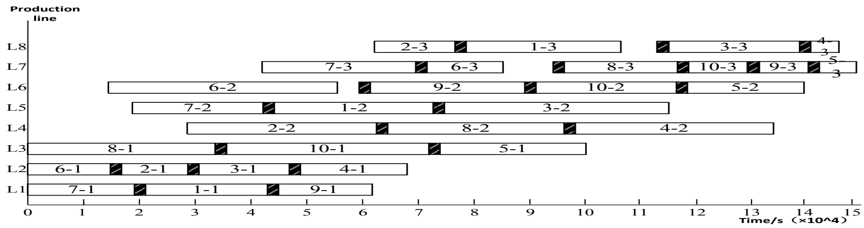

Fig. 1. Gantt chart of initial scheduling

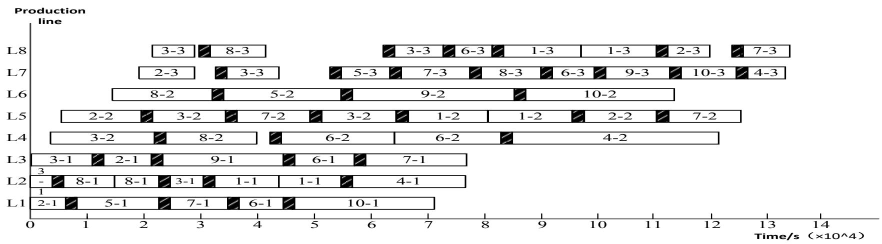

Fig. 2. Optimized batch scheduling Gantt diagram

Through comparative analysis, it is found that the completion cycle is reduced by 10.35%. The production line balance of each workstation has reached a better level; In addition, it also reduced the proportion of delayed orders by 40%, saving 23.90 hours of total delay time.

5 Conclusion

In this paper, multi-stage FFSSP-LS is studied, and an optimized batching strategy is proposed after analyzing the advantages and disadvantages of common batching. Based on the consideration of completion period, delivery time, equipment load balance and other factors, a batch scheduling model was constructed to minimize the maximum completion period, the total delay time, and the maximum load of equipment. The proposed two-layer search framework was used to improve the GA algorithm to solve the problem. Finally, based on the EXAMPLE of PCB assembly workshop of H Company, it is shown that the proposed method can not only ensure on-time delivery and improve the balance of production line, but also effectively reduce the completion cycle, reduce the frequency of production line adjustment and improve the effective utilization of production line.

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