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Research on Actual Mixed Flow Production Line Scheduling Considering Shift and Machine State Constraints

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Abstract: Based on the actual production requirements, this paper studies the key issues of the mixed flow production line scheduling in the digital machine shop. Considering the shift constraints and machine state constraints, a robust scheduling algorithm is proposed. For the shift constraint, that is, the process must be arranged to the corresponding shift time of the machine, a time slice mapping mechanism is proposed to improve the efficiency of the algorithm. The algorithm considers the availability of the machine and the currently determined machine load in the machine allocation for the deterministic state constraint. The deterministic state requires that the current machine state be considered when arranging the machine. There are mainly three states: good, damaged and time-limited maintenance. Only when the machine is in good or non-maintenance state at the current time, the processing can be arranged on the machine. Non-deterministic state refers to the uncertainty machine load. Uncertain machine load refers to the load caused by the arrival of random orders, machine failures and scheduling changes. The uncertain machine has a non-negligible effect on the scheduling results. The efficiency of a robust scheduling algorithm that considers shift constraints, predicted non-deterministic machine load components, and deterministic machine load components is verified by the simulation. Applying the scheduling method proposed in this paper to the actual machine shop mixed-flow production line scheduling, it can adjust the production cycle, rationally assign tasks, balance production load and avoid bottleneck machines, realize efficient operation of production lines, maximize resource utilization and meet the actual production management needs of manufacturing enterprises.

Keywords: mixed-flow production line scheduling; machine state constraints; shift constraints; time slice mapping mechanism.

1. Introduction

In the current customized production mode, the environment and resource conditions of the production workshop are more flexible, and managers pay more attention to the uncertainties in production and their impact on production such as the arrival of emergency orders and machine failure. As well as the changes in the workshop environment, the scheduling system must be adjusted to a certain extent. Therefore, in order to cope with real-time changes in the production environment, the scheduling system must have some adaptability. To this end, the production workshop should monitor the production factors in real time to control the real-time production schedule and workshop environment, improve the ability to prevent and respond to emergencies, minimize the impact of uncertainty and quickly make production smooth[1]. This kind of uncertainty causes the constraints of the scheduling system to change. In addition to static constraints, dynamic constraints must be considered when scheduling. Since some workpieces are large workpieces and the processing time is long, the production workshop may arrange for production over a long period of time in one production scheduling. However, with the arrival of orders and machine failures during this period, it is necessary to consider the future when scheduling production. Factors such as machine load at the moment to produce a flexible and efficient scheduling solution.

The resource conditions of the production workshop have changed a lot. In the past, some production scheduling under the premise of information determination cannot meet the current needs. The production scheduling determined by the information has certain scheduling tasks, deterministic task time, machine time and status. However, in actual production, the influence of factors such as equipment failure, emergency orders and delivery time changes caused by changes in process, equipment, raw materials and personnel has shown random dynamic changes. When an emergency occurs, if the dispatching system does not have a certain degree of robustness, it will cause discontinuity in production, thus affecting the delivery date.

In summary, the current production workshop environment and scheduling requirements have undergone great changes. It is very urgent for manufacturing companies to study the scheduling system that adapts to the current environment. This paper is to study and solve the mixed flow production line scheduling of digital machine shop in this context. Key issues to meet the actual production management needs of manufacturing companies. The multi-machine machine shop mixed flow production line scheduling is a flexible job shop scheduling problem [2]. In this paper, the research status of the domestic and international workshop scheduling and the actual needs of the current manufacturing enterprises are fully investigated. On this basis, the key problems of the mixed flow production line scheduling in the digital machine shop are studied. The purpose is to solve the dispatching system and production workshop that the enterprise is currently facing. The actual informatization level does not match the problem, and truly realizes the informationized scheduling and intelligent scheduling of the production workshop, and improves the production efficiency, which is of great significance and significance for promoting the informationization of the manufacturing industry.

The mixing machine production line in the digital machine shop means that a variety of workpieces can be produced on the same production line. The process of each workpiece is different. The machines that can be used in each process are different. It belongs to the flexible job shop scheduling problem and is an extension of the job shop scheduling problem[3].

Compared to job shop scheduling problems, the flexible job shop scheduling problem relaxes constraints such as routing constraints, allowing one machine to machine the same workpiece multiple times, and adding additional operations to an optional machine set (all machines or In some machines, choose a machine to process and other conditions. Since the flexible job shop scheduling problem is closer to the current actual production shop scheduling requirements, it has received extensive attention and research by scholars in recent years[4][5][6][7][8]. Kacem I[9] et al. proposed a genetic algorithm to optimize the maximum time of completion of the flexible job shop, the workload of critical machines, and the total workload of all machines. Wang J F et al [10] proposed an improved genetic algorithm for flexible job shop scheduling problem, and designed improved chromosome representation method and crossover and mutation operator. Akhshabi M et al. [11] applied a clone selection algorithm to solve flexible job shop scheduling problems. The Clonal Selection Algorithm (CSA) is a group-based random algorithm designed by the principle of random immune clone selection. This paper analyzes the optimization mechanism of CSA and proposes a general optimization model. It is verified by experiments that CSA can effectively solve the FJSP problem. Pan Y et al [12] combined with the phase correlation characteristics of the flexible Job-shop scheduling problem (FJSP) and the evolution characteristics of genetic algorithm (GA), an adaptive genetic algorithm was proposed, which was verified by an example. This method can speed up the convergence process, improve search efficiency and solution accuracy, and avoid falling into local optimum. Cwiek M and Nalepa J[13] discuss how to identify solution populations to effectively guide the search and make the algorithm highly convergent. Gao KZ et al. [14] proposed an improved Artificial Bee Colony (IABC) algorithm for flexible job shop scheduling problems with fuzzy processing time, with the goal of maximizing fuzzy completion time and maximum fuzzy machine work. The quantities are minimized separately, and a simple and effective heuristic rule is designed to initialize the population. Li X and Gao L[15] proposed an effective hybrid genetic algorithm and tabu search hybrid algorithm for FJSP, with the goal of optimizing the maximum completion time. Gao KZ et al [16] proposed an effective Discrete Harmony Search (DHS) algorithm to solve the multi-objective FJSP problem by weighted sum method, and designed a new initial machine allocation method and mixed locality. Search methods to improve the efficiency of the algorithm. Jamrus T et al. [17] combines particle swarm optimization with genetic operators to solve flexible job shop scheduling problems with uncertain processing times.

The actual production workshop environment has dynamic characteristics, and many scholars have studied real-time and dynamic scheduling problems[18][19][20][21][22][23]. Kulak O[24] proposes an efficient hybrid genetic algorithm to optimize the maximum completion time for dynamic events such as random job arrivals, machine failures and processing time changes in the production environment. Liping et al. [25] proposed a rescheduling method based on hybrid genetic algorithm and tabu search to solve the dynamic job shop scheduling problem of random job arrival and machine failure. The simulator is used to generate real-time events, and both scheduling efficiency and stability are considered to improve the robustness and performance of the scheduling system. Ning T et al [26] established a simulation model for optimizing the maximum completion time and stability of flexible job shop dynamic scheduling problem, and proposed an improved hybrid multi-stage quantum particle swarm algorithm, which designed a machine including A double-chain structure coding method for distribution chains and sort chains. Su N et al [27] designed a super heuristic based on multi-objective genetic programming to generate the Pareto frontier. Nahavandi N et al [28] proposed a multi-agent genetic algorithm to solve the dynamic job shop scheduling problem based on improving the efficiency of bottleneck resource utilization. Zai-Xin WU et al [29] In order to deal with dynamic events quickly and efficiently in the job shop scheduling process, an improved hybrid particle swarm optimization algorithm combining genetic algorithm (GA) and simulated annealing algorithm (SA) is proposed. GSPSO) is used to solve the dynamic job shop scheduling problem based on event-driven scheduling strategy. Aydin Teymourifar[30] proposes a hybrid distributed algorithm that uses multiple algorithms distributed on different machines to simultaneously search the solution space to achieve high efficiency of the algorithm. The literature [31] proposes a greedy stochastic adaptive search job shop scheduling mechanism to optimize the average delay, stability, maximum completion time and average flow time.

In summary, after several decades of development, the mixed flow production line scheduling of the machine shop has achieved many research results and is widely used in actual production workshops. In the investigation, it is found that in order to obtain the optimal solution in a limited time, most of the current meta-heuristic algorithms are used to solve the problem of complex mixed-flow production line scheduling. Most of the scheduling models are simplified. Although it is convenient for theoretical research, it is difficult to apply. Actual production workshop mixed flow production line scheduling with dynamic, random and multi-target requirements. In order for the dispatching system to better promote the application, it must be closely aligned with the actual production shop scheduling requirements. The existing research is closely integrated with the actual production workshop, and there are not many constraints considering the shift constraint and the real-time machine state. In order to make the production scheduling closer to the actual production process, this paper combines the actual needs of the production workshop, the research purpose is to truly solve the actual production problems and improve production efficiency. The research background of this paper is that China's manufacturing enterprises are carrying out the integration of informationization and industrialization. The informationization capability has been greatly improved, the information level of production equipment has been significantly improved, and the scheduling constraints and targets have also been improved. The change, while the existing production scheduling system cannot adapt to the current production needs, it is urgent to carry out the research on the mixed flow production line scheduling to meet the current needs. The data of the mixed-flow production line dispatching system of the machining shop in this paper is derived from the real-time production workshop, and the scheduling target with high attention in the actual production workshop is selected, and the shift and machine state problems of the actual production workshop are deeply studied to meet the actual situation. Scheduling needs of the production floor.

The remaining contents of this paper are arranged as follows: the second section establishes the mathematical model of the actual mixed flow production line scheduling considering shift and machine state constraints. The actual mixed flow production line scheduling algorithm is proposed in the third section. The simulation experiment is carried out in the fourth section. The last section summarizes the content of the full paper.

2. Problem model

The main symbol definition is shown in the Table 1.

Table 1. Symbol definition

i	Workpiece ($i \in \mathrm{J}$)
j	Process ($j \in \mathrm{O}$)
k	Machine ($k \in \mathrm{M}$)
n	Number of workpieces
m	number of machines
l_i	Number of operations for the *ith* workpiece
O_{ij}	The *jth* process of the *ith* workpiece
t_{ijk}	Processing time of process O_{ij} on *kth* machine
S_i	The start time of the *ith* workpiece
D_i	Expiration time of *ith* workpiece
J	Workpiece collection
M	Machine collection
M_{ij}	Processable machine collection for operation O_{ij} , $\mathrm{M}_{ij} \subseteq \mathrm{M}$
O_i	The process set of the workpiece i , where $O_{if_{(i)}}$ is the first process of the set, $O_{il_{(i)}}$ is the last process
T_k	The processable time slice set of the *kth* machine
M_s	Machine state collection, $U = 0,1,2$, where 0: damaged, 1: good, 2: limited time maintenance
L_k	Load of the *kth* machine
Ld_k	Deterministic load of the *kth* machine
Lr_k	Uncertainty load of the *kth* machine

S_{ijk}	Start processing time of the process O_{ij} on the *kth* machine
C_{ijk}	The completion time of the operation O_{ij} on the *kth* machine
C_i	Completion time of the *ith* workpiece
C_{max}	Maximum processing completion time for all workpieces (*makespan*)
T_{total}	Total delay time for all workpieces

The scheduling problem is described below.

Processing conditions: A processing system has m device $M=\{m_k\}_{k=1}^{m}$, processing n artifacts $J=\{j_i\}_{i=1}^{n}$, the i artifact contains the l_i process, specifying the j of the i artifact The process O_{ij} can be processed by selecting a machine k in the machine collection $M_j \subseteq M$, processing time is t_{ijk}, and each workpiece is i Given a start processing time S_i and an expiration time of D_i.
Optimization goal: Considering that the actual mixed flow production line scheduling requirements have higher time efficiency, the weighted sum method is used to optimize the maximum completion time and the total delay time, as shown in the formula Eq. 1.

$$F=\min\left(w_1C_{max}+w_2T_{total}\right). \quad (1)$$

Among them, w_1, w_2 are the weights of the maximum completion time C_{max} and the total delay time T_{total}.
The maximum completion time is calculated according to the formula Eq. 2., and the total delay time is calculated according to the formula Eq. 3.

$$C_{max}=\max\left(C_i\right),\ i=1,\dots,n. \quad (2)$$

$$T_{total}=\sum_{D_i<C_i}(C_i-D_i),\ i=1,\dots,n. \quad (3)$$

The following constraints need to be considered:

1) Each workpiece contains a specific sequence of operations, which must be processed in the order of the sequence. For example, the operation set of job i is O_i, which must be followed from the first process. $O_{if_{(i)}}$ to the last process $O_{il_{(i)}}$ is processed in sequence, and there is no dependency between the processes of different workpieces;
2) At the same time, the same workpiece cannot be processed on multiple machines at the same time;
3) Each process O_{ij} can be processed one or more times on a device in the corresponding optional device collection M_{ij}, or it can be processed on the device , each device in the equipment collection processes the same workpiece at different times;
4) Each machine can only process one process of one workpiece at a time. Once the process starts processing on one device, it cannot be interrupted. It must wait until the process being processed can complete another process.
5) Each workpiece i must be processed at the specified start processing time S_i;
6) Shift time constraints. Every machine must work according to the specified shift time every day. Therefore, it is necessary to arrange the processing start time and end time of the process into the shift schedule of the corresponding machinery and equipment. For example, if the process O_{ij} is processed on the machine k, the process O_{ij} must be processed on the machine k for the processing time k and the processing completion time C_{ijk} is scheduled to be within the time slice of the machine's k processable time slice collection S_k.
7) Machine state constraints. There are two types of machines, one is a deterministic machine state and the other is a non-deterministic machine state. The deterministic machine state includes the current state of the machine and the determined machine load Ld_k, each machine has three deterministic machine states, taken in the machine state set M_s Values: good, damaged and time-limited maintenance. The non-deterministic machine state mainly refers to the uncertainty machine load Lr_k caused by the arrival of random orders. When assigning a machine, the operation must be scheduled to the time slice T_k of the currently available machine. Also try to balance the machine load L_k, L_k is the sum of the deterministic load Ld_k and the uncertainty load Lr_k.

3. Actual Mixed Flow Production Line Scheduling Algorithm

This paper presents a new dual-population hybrid particle swarm optimization (PSO) algorithm which searches solutions of the most popular index firstly, that is the maximum completion time, and then searches the optimal solutions set for the average flow time and machine idle time successively.

3.1 Time slice mapping mechanism considering machine state constraints

The equipment is not available for a certain period of time during the planning period due to unpredictable faults or maintenance plans. As with the shift problem, the working time is not continuous. Therefore, the time slice mapping mechanism can also be used for processing. The determined machine status mainly includes three types: available, unavailable, and time-limited maintenance status. The usable state means that the state is good and the process can be arranged on the machine for processing, so it can be treated as a normal machine during the scheduling. The unavailable state means that the machine cannot be arranged for production due to other reasons such as damage, and the machine with the unavailable state is removed from the processable machine assembly during the scheduling to avoid the process being arranged on the machine that is not available. Time-limited maintenance is that the machine needs to be repaired and maintained within a certain period of time. It is not available during the maintenance period. For this case, a similar shift processing method can be used to map the status time data of each machine to the time series linked list. . This is done by comparing the start time of the machine's time-limited maintenance period, P_1, and the end time, P_2, with the time slice chain, and removing the machine maintenance status time period from the time slice chain. , update the time slice chain. For example, the original time slice chain is as shown in Figure 1. When mapping the machine's time-limited maintenance time period to the time slice chain, the start time and end time of the current time slice cursor and time slice chain need to be re-established. Adjustments, as shown in Figure 2, where the shaded portion is the time-limited maintenance unavailable time.

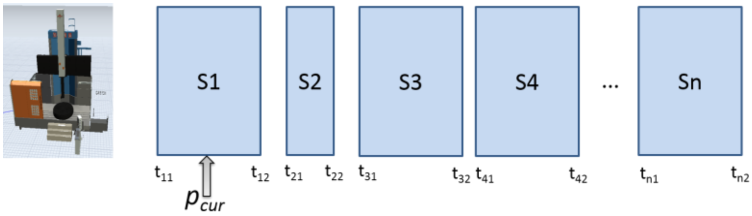

Figure 1. Time chain

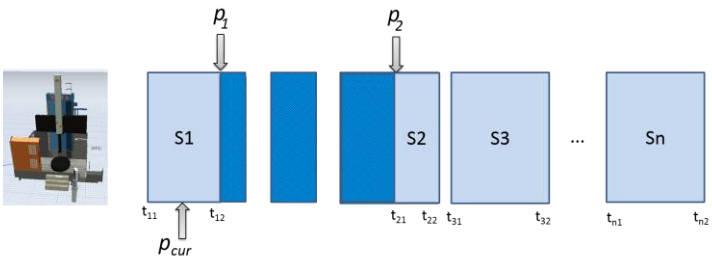

Figure 2. Time slice chain considering machine state constraints

3.2 Mixed flow production line scheduling algorithm

On the basis of machine load forecasting, research on mixed-flow production line scheduling considering state constraints is to balance machine load as much as possible in machine allocation, including deterministic load and uncertainty load, and need to consider the processing method of machine state time and scheduling algorithm. How to combine the determined machine state and the uncertain machine load obtained by prediction.

This paper proposes an adaptive GA algorithm (NAGA) that considers machine state constraints. The key steps are as follows:

Step 1. Initialize the parameters;

(1) Parameter and variable settings: population size P_{size}, maximum iteration number G_{max}, crossover and mutation probability p_g, local search probability p_l, current population fitness value variance V_f, iterative loop variable g, temperature variable T, local search length L;

(2) Randomly generate the initial population P, the number of individuals in the group is P_{size};

(3) Initialize the initial temperature parameter for local search T_s

Step 2. Perform a selection operation to perform the crossover operation and the mutation operation according to the variable probability p_g;

Step 3. Calculate the individual's fitness value;

Step 4. Perform a local search by probability p_l, and the local search length L is inversely proportional to the variance V_f;

(1) generating new individuals from the neighborhood of the current solution and calculating individual fitness values;

(2) Update the current solution according to formula (4-18);

(3) Update the current temperature parameter: $T \leftarrow 0.97 \cdot T$;

(4) Repeat the local search steps (1)-(3) until the number of local search cycles is greater than L.

Step 5. Calculate the fitness value of the new individual;

Step 6. The population evolves to the next generation, increasing the number of iterations: $g = g + 1$;

Step 7. Repeat algorithm steps 2-6 until the algorithm meets the end condition: $g > G_{max}$.

The algorithm first performs the initialization operation. The main initialization parameters are: population size P_{size}, maximum iteration number G_{max}, local search probability p_l and so on. The initial population is randomly generated on the basis of the initialization parameters, the solution is randomly distributed throughout the solution space, and then the initial temperature parameter T_s is initialized. After initialization, the algorithm performs selection operations, mutations, and crossover operations as described in the paper [32]. The mutation probability and crossover probability are variable and are calculated according to the formula (5). k is a constant, mainly considering that the evolution speed decreases with the number of iterations, so in order to make the group have a certain diversity in the late stage of evolution, the crossover rate and the mutation rate increase with the number of iterations. . In order to prevent the algorithm from falling into the local optimal value, step 4 performs a local search based on the simulated annealing algorithm. Considering that the local search will take time and cost, in order to improve the efficiency of the algorithm, a variable neighborhood local search algorithm is adopted, and the local search length is used. Calculated by (7), where c is a constant, the larger the variance V_f, the smaller the local search length. Conversely, the smaller the variance, the larger the local search length.

For the machine selection problem, due to the three states of the machine: good, damaged and time-limited maintenance, it is necessary to assign the machine to the undamaged machine at the start of the scheduling, and generate the time of each machine according to the time slice mapping mechanism. The linked list then maps the time period set of the time-limited maintenance machine to the time slice linked list, and arranges the operations in the time slot chain of the corresponding machine in the subsequent process scheduling. The machine selection during the scheduling process needs to take into account the machine's load $L_k(t)$, including the determined load $Ld_k(t)$ and the predicted load $Lr_k(t)$. In order to balance the machine load, this paper arranges the process to the machine with less machine load when the machine is selected. This paper defines the machine load as the sum of the machining time of all the workpieces on the machine, according to the formula (8) The calculation, where N is the number of operations scheduled to the k machine, and $t_j(k)$ is the processing time for the j process scheduled to the k machine.

$$\Delta F = f(S') - f(S) \tag{4}$$

$$s^* = \begin{cases} s', & if\, \Delta F < 0 \; or \min(1, \exp(-\frac{\Delta F}{T})) \geq r, \\ s, & otherwise. \end{cases} \tag{5}$$

$$p_g = k \cdot g \tag{6}$$

$$L = \frac{c}{V_f} \tag{7}$$

$$L_k(t) = Ld_k(t) + Lr_k(t) = \sum_{j=1}^{N} t_j(k) + Lr_k(t) \tag{8}$$

4. Simulation

The parameters are set as follows: population size P_{size} is 120, generation gap is set to 0.9, initial temperature parameter T_s is 1000, maximum iteration number G_{max} is 2000, order quantity, shift information, The weights of worker proficiency, equipment status, and date type are w_1, w_2, w_3, w_4, and w_5, depending on their importance. Set to 0.2, 0.3, 0.1, 0.2, and 0.2, the maximum completion time C_{max} and the total delay time T_{total} are set to 0.6 and 0.4 according to their importance.

In order to verify the performance of the adaptive GA algorithm (NAGA) proposed in this paper considering machine state constraints, the NAGA algorithm is used to solve 10 standard flexible job shop scheduling examples, and is proposed in the literature [33] Improved PSO algorithm (EPSO) and literature [34] proposed in the improved GA algorithm (pGA), literature [35] for solving flexible job shop scheduling problems The frog leap algorithm (SFLA) and the literature [36] proposed the Elite Quantum Heuristic Evolutionary Algorithm (EQEA) for FJSP. The results are shown in the Table 2. Where the degree of relative deviation is used. Dev is the evaluation criterion of the algorithm, as shown in the formula (9), where S_{NAGA} refers to the solution obtained by the adaptive GA algorithm (NAGA) proposed in this paper, S_{best} refers to the optimal solution obtained by the four algorithms pGA, EPSO, SFLA and EQEA. It can be seen from the table that the adaptive GA algorithm (NAGA) proposed in this paper is superior to other algorithms in the quality of the solutions obtained from the 10 examples.

$$Dev = (S_{NAGA} - S_{best}) / S_{best} \times 100\% \tag{9}$$

Table 2. Algorithm performance comparison

Instance	Size	pGA	EPSO	SFLA	EQEA	NAGA	Dev(%)
MK01	10×6	40	40	40	40	40	0
MK02	10×6	26	26	26	26	26	0
MK03	15×8	204	204	204	204	204	0
MK04	15×8	63	62	63	61	59	-3.3
MK05	15×4	175	174	173	173	173	0
MK06	10×15	67	65	66	64	60	-6.3
MK07	20×5	143	141	141	141	140	-0.7
MK08	20×10	525	524	524	525	523	-0.2
MK09	20×10	310	309	309	309	308	-0.3
MK10	20×15	230	228	226	225	223	-0.9

The time performance comparison of the algorithm is shown in the Table 3. It can be seen from the table that the adaptive GA algorithm (NAGA) proposed in this paper is superior to other algorithms in the time performance of the solutions obtained from the 10 examples.

Table 3. Algorithm time performance comparison

Instance	Size	pGA	EPSO	SFLA	EQEA	NAGA	Dev(%)
MK01	10×6	3	2.8	2.6	2	1.8	-10
MK02	10×6	6	5	5	3	2	-33
MK03	15×8	8	7	7	5	4	-20
MK04	15×8	10	9	7	5	4.2	-16
MK05	15×4	7	7	6	6	5	-16.7
MK06	10×15	15	14	14	12	11	-8.3
MK07	20×5	17	16	15	15	14	-6.7
MK08	20×10	22	20	18	18	17	-5.6
MK09	20×10	21	19	18	17	16	-5.9

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Instance	Size	pGA	EPSO	SFLA	EQEA	NAGA	*Dev*(%)
MK10	20×15	35	33	30	26	23	-11.5

In order to verify the effect of the solution result considering the machine load factor on the optimization target, the result of scheduling the balance of the machine load is compared with the result of not considering the balance of the machine load. The algorithm proposed in this paper is used for actual production workshop scheduling. The workshop has 17 machines, the machine number range is Equip01-Equip17, processing 50 workpieces, and a total of 9 processes. The shift of the device is set to single shift by default, and the shift information of non-single shift is as shown in the table Table 4. Machine status information is shown in the Table 5. The starting time is: 2017-03-01 00:00:00, the deadline is: 2017-08-15 08:00:00, which does not consider the balance of the machine load, the Gantt chart is shown in the figure Fig.3, and the Gantt chart is considered to balance the load of the machine Fig.4 shown. It can be seen that the graph Fig.4 is more balanced than the machine in the diagram Fig.3, the scheduling efficiency is higher, and the maximum completion time is earlier. The completion time is not considered when the machine load is: 2017-08-16 15:38:00, the total delay time is 1 day, 7 hours and 38 minutes. When the machine load is considered, the completion time is: 2017-08-13 15:38:00, completed 1 day, 16 hours and 22 minutes. Therefore, from the experimental results, it can be known that the maximum completion time and the total delay time can be reduced in consideration of balancing the machine load.

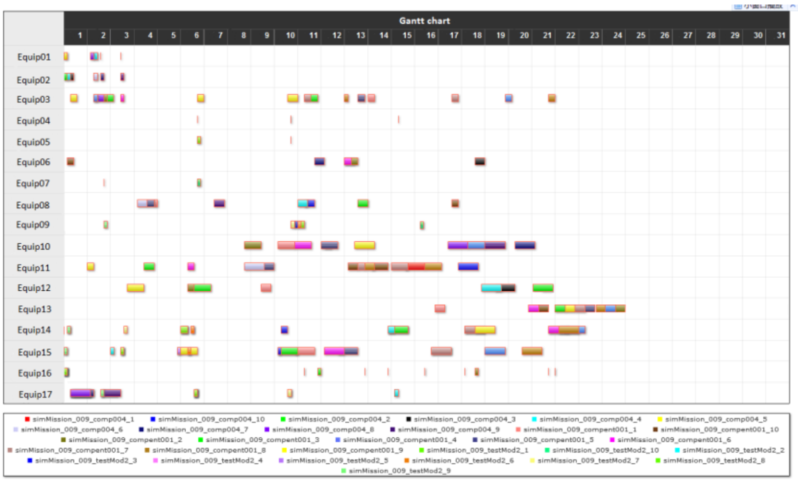

Figure 3. Scheduling Gantt chart without balancing machine load

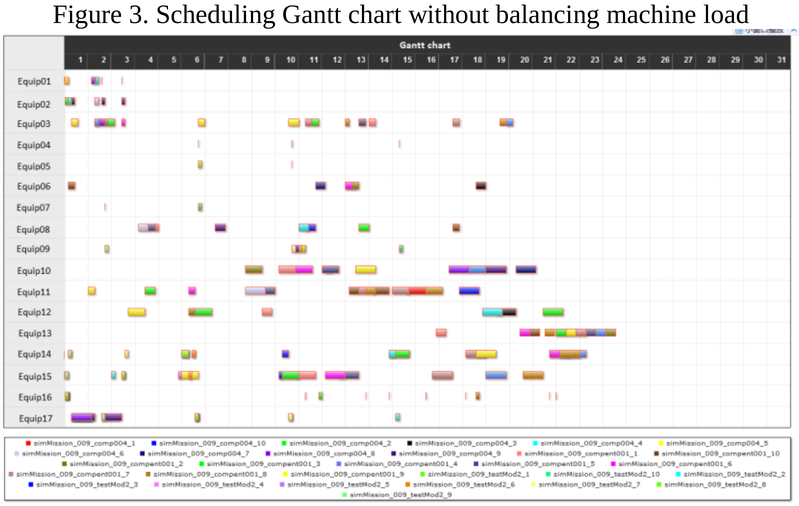

Figure 4. Scheduling Gantt chart considering balancing machine load

Table 4. Shift information

ID	Machine ID	Shift	Starting time	Finish time
1	Equip03	Double Shift 1	2017-03-01 08:00:00	2017-03-04 08:00:00
2	Equip10	Double Shift 2	2017-04-05 08:00:00	2017-04-20 08:00:00
3	Equip06	Three Shifts	2017-05-10 08:00:00	2017-05-08 08:00:00
4	Equip08	Overtime Shift 1	2017-06-04 08:00:00	2017-06-12 08:00:00
5	Equip11	Overtime Shift 2	2017-07-15 08:00:00	2017-07-18 08:00:00
6	Equip16	Three Shifts	2017-08-01 08:00:00	2017-08-02 08:00:00

Table 5. Machine status information

ID	Type	Machine ID	Starting time	Finish time
1	Maintain	Equip03	2017-03-04 09:00:00	2017-03-06 12:00:00
2	Damage	Equip06	2017-04-02 15:00:00	2017-04-03 08:00:00
3	Damage	Equip11	2017-04-21 10:00:00	2017-04-23 08:00:00
4	Maintain	Equip03	2017-05-06 15:00:00	2017-05-07 09:00:00
5	Maintain	Equip15	2017-06-11 14:00:00	2017-06-13 08:00:00
6	Damage	Equip16	2017-07-25 08:00:00	2017-07-27 08:00:00
7	Damage	Equip06	2017-08-08 08:00:00	2017-08-09 08:00:00

5. Summary

This paper studies the problem of mixed-flow production line scheduling with machine state constraints, and divides the machine state into two types, one is the deterministic machine state, and the other is the machine load. For deterministic machine states, the machine is placed on an available machine when the machine is assigned. Machine loads include deterministic machine loads and uncertain machine loads. Aiming at the uncertain machine load, a machine load forecasting method based on least squares support vector machine is proposed. The improved particle swarm optimization algorithm is used to select the parameters and predict the machine load. On this basis, the problem of scheduling of mixed-flow production lines considering the state of the machine is studied. The machine state is integrated into the time slice mechanism. The machine load is determined in the machine allocation and the predicted machine load is taken into account. The simulation experiment is carried out and the actual production is carried out. The shop floor example verifies that the scheduling algorithm that considers machine state balances machine load and optimizes maximum completion time and delay time.

References

[1]. Li X., Gao L., Zhang C., et al. A review on integrated process planning and scheduling. Int J Manuf Res, 2010, 5:161－180.
[2]. Guo Quanjie. Simulation and optimization of aluminum alloy door and window mixed flow production line based on digital factory [Master's thesis]. Jinan: Shandong University, 2015.
[3]. Tian Zhipeng. Research and application of stamping shop scheduling and assembly line sequencing method for automotive mixed flow production [PhD thesis]. Wuhan: Huazhong University of Science and Technology, 2016.
[4]. Lin J, Luo D, Li X, et al. Differential Evolution Based Hyper-heuristic for the Flexible Job-Shop Scheduling Problem with Fuzzy Processing Time. Simulated Evolution and Learning. 2017:75-86.
[5]. Nouiri M, Bekrar A, Jemai A, et al. An effective and distributed particle swarm optimization algorithm for flexible job-shop scheduling problem. Journal of Intelligent Manufacturing, 2018:1-13.
[6]. Azzouz A, Ennigrou M, Said L B. A hybrid algorithm for flexible job-shop scheduling problem with setup times. International Journal of Production Management \& Engineering, 2017, 5(1):23-30.
[7]. Devassia J V, Salazaraguilar M A, Boyer V. Flexible job-shop scheduling problem with resource recovery constraints. International Journal of Production Research, 2017(11):1-18.

[8]. Lu P H, Wu M C, Tan H, et al. A genetic algorithm embedded with a concise chromosome representation for distributed and flexible job-shop scheduling problems. Journal of Intelligent Manufacturing, 2017:1-16.
[9]. Kacem I. Genetic algorithm for the flexible job-shop scheduling problem. Computers \& Operations Research, 2008, 35(10):3202-3212.
[10]. Wang J F, Du B Q, Ding H M. A Genetic Algorithm for the Flexible Job-Shop Scheduling Problem. Elsevier Science Ltd. 2008.
[11]. Akhshabi M, Akhshabi M, Khalatbari J. Solving flexible job-shop scheduling problem using clonal selection algorithm. Indian Journal of Science \& Technology, 2011, 4(10).
[12]. Pan Y, Xue D J, Gao T Y, et al. A Modified Adaptive Genetic Algorithm for the Flexible Job-Shop Scheduling Problem. Applied Mechanics \& Materials, 2013, 401-403:2037-2043.
[13]. Cwiek M, Nalepa J. A fast genetic algorithm for the flexible job shop scheduling problem. Companion Publication of the 2014 Conference on Genetic and Evolutionary Computation, ACM, 2014:1449-1450.
[14]. Gao K Z, Suganthan P N, Pan Q K, et al. Discrete harmony search algorithm for flexible job shop scheduling problem with multiple objectives. Journal of Intelligent Manufacturing, 2016, 27(2):363-374.
[15]. Li X, Gao L. An effective hybrid genetic algorithm and tabu search for flexible job shop scheduling problem. International Journal of Production Economics, 2016, 174:93-110.
[16]. Gao K Z, Suganthan P N, Pan Q K, et al. An improved artificial bee colony algorithm for flexible job-shop scheduling problem with fuzzy processing time. Expert Systems with Applications An International Journal, 2016, 65(C):52-67.
[17]. Jamrus T, Chien C F, Gen M, et al. Hybrid particle swarm optimization combined with genetic operators for flexible job-shop scheduling under uncertain processing time for semiconductor manufacturing. IEEE Transactions on Semiconductor Manufacturing, 2017, PP(99):1-1.
[18]. Shen X N, Yao X. Mathematical modeling and multi-objective evolutionary algorithms applied to dynamic flexible job shop scheduling problems. Information Sciences, 2015, 298:198-224.
[19]. Hosseinabadi A A R, Siar H, Shamshirband S, et al. Using the gravitational emulation local search algorithm to solve the multi-objective flexible dynamic job shop scheduling problem in Small and Medium Enterprises. Annals of Operations Research, 2014, 229(1):1-24.
[20]. Wang L, Luo C, Cai J. A Variable Interval Rescheduling Strategy for Dynamic Flexible Job Shop Scheduling Problem by Improved Genetic Algorithm. Journal of Advanced Transportation, 2017, 2017(3):1-12.
[21]. Wei Z. Multi-objective dynamic scheduling algorithm for flexible job-shop problem based on rule orientation. Systems Engineering-Theory \& Practice, 2017, 37(10):2690-2699.
[22]. Pei J, Liu X, Fan W, et al. Minimizing the makespan for a serial-batching scheduling problem with arbitrary machine breakdown and dynamic job arrival. International Journal of Advanced Manufacturing Technology, 2016, 86(9-12):3315-3331.
[23]. Nguyen S, Zhang M, Johnston M, et al. Automatic programming via iterated local search for dynamic job shop scheduling. IEEE Transactions on Cybernetics, 2017, 45(1):1-14.
[24]. Kulak O. Hybrid genetic algorithms for minimizing makespan in dynamic job shop scheduling problem. Pergamon Press, Inc. 2016.
[25]. Li Ping. Research on mixing and job shop scheduling under uncertain conditions [PhD thesis]. Wuhan: Wuhan University of Science and Technology, 2013.
[26]. Ning T, Huang M, Liang X, et al. A novel dynamic scheduling strategy for solving flexible job-shop problems. Journal of Ambient Intelligence \& Humanized Computing, 2016, 7(5):1-9.
[27]. Su N, Zhang M, Johnston M, et al. Dynamic Multi-objective Job Shop Scheduling: A Genetic Programming Approach. 2013, 505:251-282.
[28]. Nahavandi N, Zegordi S H, Abbasian M. Solving the Dynamic Job Shop Scheduling Problem using Bottleneck and Intelligent Agents based on Genetic Algorithm. International Journal of Engineering Transactions B Applications, 2016, 29(3).
[29]. Zai-Xin W U, Gao S C, Jie Q I. An improved particle swarm optimization algorithm for dynamic job-shop scheduling problem. Electronic Design Engineering, 2016.
[30]. Aydin Teymourifar, Gurkan Ozturk. A Hybrid Distributed Algorithm for Multi-Objective Dynamic Flexible Job Shop Scheduling Problem. International Journal of Industrial and Manufacturing Engineering, 2018,12(2).

[31]. BaykasoäŸLu A, Karaslan F S. Solving comprehensive dynamic job shop scheduling problem by using a GRASP-based approach. International Journal of Production Research, 2017, 55(11):3308-3325.
[32]. Qiaofeng Meng, Linxuan Zhang, and Yushun Fan. Approach of hybrid GA for multi-objective job-shop scheduling. International Journal of Modeling Simulation & Scientific Computing, 2016, 07(4).
[33]. Ida K, Oka K. Flexible job-shop scheduling problem by genetic algorithm. Electrical Engineering in Japan, 2011, 177(3):28－35.
[34]. Xu Y, Wang L, Wang S. An effective shuffled frog-leaping algorithm for the flexible job-shop scheduling problem[C]// IEEE, 2013:128-134.
[35]. Teekeng W, Thammano A, Unkaw P, et al. A new algorithm for flexible job-shop scheduling problem based on particle swarm optimization. Artificial Life & Robotics, 2016, 21(1):18-23.
[36]. Wu X, Wu S. An elitist quantum-inspired evolutionary algorithm for the flexible job-shop scheduling problem[J]. Journal of Intelligent Manufacturing, 2017, 28(6):1441-1457.