Review on Multi-objective Dynamic Scheduling Methods for Flexible Job Shops and Application in Aviation Manufacturing

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Abstract: Intelligent production is an important development direction in intelligent manufacturing, with intelligent factories playing a crucial role in promoting intelligent production. Flexible job shops, as the main form of intelligent factories, constantly face dynamic disturbances during the production process, including machine failures and urgent orders. This paper discusses the basic models and research methods of job shop scheduling, emphasizing the important role of dynamic job shop scheduling and its response schemes in future research. A multi-objective flexible job shop dynamic scheduling mathematical model is established, highlighting its complex and multi-constraint characteristics under different interferences. A classification discussion is conducted on the dynamic response methods and optimization objectives under machine failures, emergency orders, fuzzy completion times, and mixed dynamic events. The development process of traditional scheduling rules and intelligent methods in dynamic scheduling are also analyzed. Finally, based on the current development status of job shop scheduling and the requirements of intelligent manufacturing, the future development trends of dynamic scheduling in flexible job shops are proposed.

Key words: flexible job shop; dynamic scheduling; machine breakdown; job insertion; multi-objective optimization

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0 Introduction

The flexible job shop scheduling problem (FJSP) is a fundamental optimization problem that has extensive applications across both manufacturing and service industries. Intelligent manufacturing requires optimizing job shop scheduling to achieve complex system management, promoting the integration of industrialization and informatization in the development of "smart factories". Sisson[1] first explained the job shop, stating that the manufacturing units of different batches of processing orders in the job shop are independent of each other, meaning that there are constraints on the process path and processing steps. Scheduling is the process of organizing and executing production plans during the operation of a production system, and efficient production scheduling is the key to improving production efficiency[2]. Jackson[3] is the first to carry out job shop scheduling on the production line, optimizing the maximum order lead time to meet production requirements.

According to the characteristics of different job shops, job shop scheduling can be divided into single machine scheduling, parallel machine scheduling, job shop scheduling, flexible job shop scheduling, replacement flow shop scheduling, open job shop scheduling, and distributed job shop scheduling. Single machine and parallel machine scheduling are fundamental scheduling problems, which only need to consider the scheduling of one machine or one workpiece. Job shop scheduling has expanded in

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the scale of machines and processes, but processes can only be dealt on fixed machines without flexible features. The workpieces and machines in FJSP exhibit high flexibility, allowing processes to be carried out on any machine with varying processing times. Research on FJSP has begun in the 1950s. During this period, scholars had a vague concept of this job shop model, but the research object could be seen as a standard FJSP instance[4-6]. Brucker et al.[7] extended the "one to many" relationship between workpieces and machines to job shop scheduling theory, forming the basic definition of FJSP. Brandimarte[8] and Kacem et al.[9] generated MK and Kacem scheduling instances for job shops with different degrees of flexibility, which became the basic experimental dataset for subsequent researchers on FJSP. FJSP is a typical non deterministic polynomial problem, and a large amount of research has mainly focused on two aspects: Job shop models and scheduling methods[10-26]. Table 1 summarizes the relevant research on job shop scheduling. Blackstone et al.[10] summarized and compared the early scheduling rules for solving the job shop scheduling problems (JSP), and believed that these rules were highly effective in addressing complex and dynamic scheduling issues. Ramasesh[11] examined dynamic job shop scheduling problems (DJSP) with the focus on the development of job shop models and optimization objectives. The emergence of intelligent algorithms has provided a new direction for addressing the JSP. Blazewicz et al.[12] compared exact methods and approximate algorithms, and pointed out that approximate algorithms are more effective in solving large-scale problems.

Table 1 Classification of studies on job shop scheduling

Reference	Research objective	Research content
Blackstone[10]	Scheduling method	JSP scheduling rules
Blazewicz et al.[12]	Scheduling method	Accurate methods and approximate algorithms
Sellers[13]	Scheduling method	Neural networks and classical optimization methods
Qian et al.[15]	Scheduling method	Traditional methods and intelligent optimization methods
Xie et al.[22]	Scheduling method	Meta heuristic and classical optimization algorithms
Li et al.[25]	Scheduling method	Dynamic scheduling algorithms and reinforcement learning
Ramasesh[11]	Scheduling model	DJSP
Allahverdi et al.[14]	Scheduling model	JSP considering setting time
Gordon et al.[16]	Scheduling model	Single machine and parallel online scheduling
Allahverdi et al.[17]	Scheduling model	JSP considering setting time
Abdullah et al.[18]	Scheduling model	FJSP considering fuzzy time
Peng et al.[19]	Scheduling model	Multi-objective static FJSP
Dhiflaoui et al.[20]	Scheduling model	Dual resource JSP and FJSP
Gao et al.[23]	Scheduling model	Swarm intelligence algorithms and evolutionary algorithms
Xiong et al.[24]	Scheduling model	JSP and FJSP
Mohan et al.[21]	Model and method	Response scheduling of DJSP
Jiang et al.[26]	Model and method	Intelligent algorithms for FJSP and DFJSP

With the advent of the artificial intelligence and big data era, Sellers[13] provided a detailed introduction to the application of neural network algorithms in JSP, and categorized them into three mainstream methods along with heuristic rules and classical optimization methods. Allahverdi et al.[14,17] comprehensively summarized JSP that considers setting time (acquiring tools, locating work in process materials, etc.), enriching the basic model of job shop scheduling. Qian et al.[15] analyzed the pros and cons of traditional and intelligent scheduling methods, and believed that integrating the strengths of both approaches would be a new breakthrough in scheduling methods. Gordon et al.[16] compared single machine and parallel machine scheduling, mainly considering order delivery time and other optimization objectives. Abdullah et al.[18] summarized FJSP with fuzzy concepts, and divided it into fuzzy processing time and fuzzy delivery time, which were more in line with production reality. Peng et al.[19] summarized the research on multi-objective static FJSP, focusing on the application of intelligent search algorithms in multi-objective scheduling. Dhiflaoui et al.[20] distinguished between dual resource JSP and dual resource FJSP, considering both machine resources and worker resources in the scheduling category, extending the FJSP.

Mohan et al.[21] analyzed and compared the complete response scheduling and pre-response scheduling methods of DJSP, concluding that the latter can quickly handle dynamic events and exhibits stronger robustness. Xie et al.[22] classified the methods for solving FJSP into exact algorithms, heuristic algorithms, and metaheuristic algorithms. Metaheuristic algorithms perform well by relying on local search and optimization strategies. Gao et al.[23] comprehensively summarized the application of swarm intelligence algorithms and evolutionary algorithms on FJSP, providing detailed introductions to encoding, decoding, initialization, and search operators. Xiong et al.[24] analyzed the properties, assumptions, basic types, and performance metrics of JSP, and also introduced the general representation and overview of the JSP model. Li et al.[25] summarized various methods for handling DJSP, emphasizing the application of reinforcement learning in dynamic scheduling. Jiang et al.[26] analyzed the FJSP problem from both static and dynamic scheduling perspectives, and comprehensively summarized the current mainstream algorithms and scheduling models. A comprehensive analysis was conducted on preventive maintenance when dealing with machine fault interference in job shop scheduling, and it was believed that achieving real-time status monitoring of equipment is a prerequisite for improving fault prediction, fault diagnosis, and fault-tolerant control.

Based on the above research, the following conclusions can be drawn.

(1) Early research mostly focused on the JSP, where swarm intelligence algorithms, with their efficient optimization capabilities, have gradually replaced precise algorithms and traditional scheduling rules. Deep learning exhibits strong adaptability through data-driven approaches, yet its interpretability remains limited.

(2) The research has gradually shifted from theoretical methods to analyzing job shop models under multiple constraints, such as the green job shop considering carbon emissions, the multi-resource job shop expanding scheduling resources, the comprehensive job shop improving scheduling processes, and the fuzzy job shop with fuzzy processing time.

(3) Due to the continuous interference in the job shop production environment, the goal of dynamic scheduling is to maintain system balance and ensure the normal execution of production plans. Obviously, dynamic scheduling is more complex and difficult to solve.

We retrieved the keyword "dynamic flexible job shop scheduling" from the Web of Science (WoS) database and obtain 266 articles published in core journals from 2000 to 2024. We used Citespace to cluster its keywords. Fig.1 shows the top ten most frequently occurring keyword maps, and Fig.2 shows the clustered ten keyword maps. It can be seen that the research hotspots in this direction in-

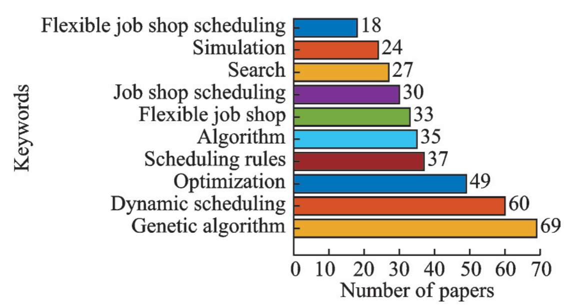

Fig.1 Keyword frequency for papers of "dynamic flexible job shop scheduling"

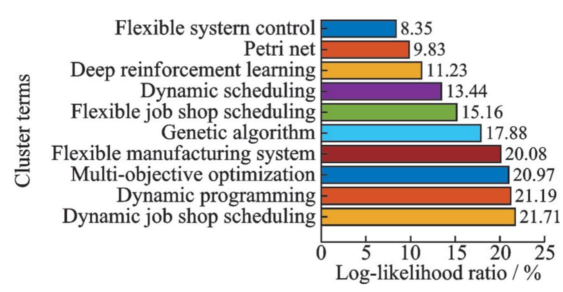

Fig.2 Clustering graph for papers of "dynamic flexible job shop scheduling"

clude dynamic scheduling, multi-objective optimization, etc.

In summary, this paper explores dynamic response methods for multi-objective dynamic flexible job shop scheduling problems (DFJSP) based on different dynamic events. The remaining chapters are arranged as follows: Section 1 elaborates in detail on the FJSP model, the multi-objective optimization model, and the multi-objective dynamic scheduling model for flexible job shop; section 2 compares the pros and cons of different dynamic response methods and rescheduling schemes for DFJSP under machine failures; section 3 discusses DFJSP under urgent orders, analyzes the effects of order arrival processing schemes and different insertion schemes; section 4 analyzes the application of fuzzy theory in dynamic scheduling for DFJSP under fuzzy processing time; section 5 summarizes DFJSP under mixed dynamic events and studies the mixed processing scheme for dynamic events; section 6 presents an application case of scheduling methods in aviation manufacturing; section 7 draws certain conclusions and provides direction for future research.

1 Problem Description

This section elaborates the basic FJSP mathematical model, the multi-objective optimization model, and the multi-objective dynamic scheduling model for flexible job shops.

1.1 Flexible job shop scheduling model

The classical FJSP can be described as: m machines processing n workpieces; any workpiece contains several processes; the process path of any workpiece is fixed; the processing time of any process on different machines is different; the purpose of scheduling is to select the appropriate process sequence and machine allocation to achieve the optimal scheduling goal. Table 2 shows the symbol definitions in the FJSP mathematical model.

Table 2 FJSP model variables

Symbol	Definition	Symbol	Definition
n	Total number of workpieces	O_{ij}	The jth process of workpiece i
m	Total number of machines	M_{ij}	The machinable machine set of O_{ij}
i	Workpiece index	T_{ij}^{S}	The starting processing time of O_{ij}
j	Process index	T_{ij}^{E}	The end processing time of O_{ij}
k	Machine index	t_{ijk}	The processing time of O_{ij} on M_k
C_i	Duration	x_{ijk}	Equals 1 when O_{ij} is machined on M_k, otherwise 0
n_i	Number of processes	z_{ijpqk}	Equals 1 when O_{ij} is processed before O_{pq}, otherwise 0
P_k^{I}	No-load power consumption	P_k^{P}	Load energy consumption

FJSP modeling needs to consider both workpiece constraints and machine constraints. Eq.(1) indicates that the process can only be processed on one machine. Eq.(2) indicates that there is a pre and post-relationship between the processes of the same workpiece. Eq.(3) indicates that the start time of any workpiece must be after time 0. Eq.(4) indicates that the machine's setting time is ignored. Eq.(5) indicates that the machine can only process one workpiece at a time.

$$\sum_{k=1}^{m} x_{ijk}=1 \qquad 1\leqslant i\leqslant n;1\leqslant j\leqslant n_i \tag{1}$$

$$\begin{gathered}T_{i(j+1)}^{\mathrm{S}}\geqslant T_{ij}^{\mathrm{S}}+t_{ijk}\cdot x_{ijk}\\ 1\leqslant i\leqslant n;1\leqslant j\leqslant n_i;1\leqslant k\leqslant m\end{gathered} \tag{2}$$

$$T_{ij}^{\mathrm{S}}\geqslant 0 \qquad 1\leqslant i\leqslant n;1\leqslant j\leqslant n_i;1\leqslant k\leqslant m \tag{3}$$

$$\begin{gathered}T_{ij}^{\mathrm{E}}=T_{ij}^{\mathrm{S}}+t_{ijk}\cdot x_{ijk}\\ 1\leqslant i\leqslant n;1\leqslant j\leqslant n_i;1\leqslant k\leqslant m\end{gathered} \tag{4}$$

$$\begin{gathered}(T_{ij}^{\mathrm{E}}-T_{pq}^{\mathrm{E}}-t_{ijk})x_{ijk}x_{pqk}(z_{ijqpk}(z_{ijqpk}+1))+\\ (T_{pq}^{\mathrm{E}}-T_{ij}^{\mathrm{E}}-t_{pqk})x_{ijk}x_{pqk}(z_{ijqpk}(z_{ijqpk}-1))\\ 1\leqslant i\leqslant n;1\leqslant j\leqslant n_i;1\leqslant k\leqslant m\end{gathered} \tag{5}$$

1.2 Multi-objective optimization model

The multi-objective optimization problem is described as

$$\min F(\boldsymbol{X})=[f_1(x),f_2(x),\cdots,f_n(x)]^{\mathrm{T}} \tag{6}$$

where $\boldsymbol{X}\in\boldsymbol{\Omega}, f_1(x), f_2(x),\cdots, f_n(x)$ represent n optimization objectives and $\boldsymbol{\Omega}$ the decision space corresponding to the scheduling scheme set.

Multi-objective optimization problems are usually solved by non-dominated sorting, and the superiority or inferiority of new solutions generated during the iterative process needs to be evaluated. For the two solutions $\boldsymbol{x}_1, \boldsymbol{x}_2 \in \boldsymbol{\Omega}$, the condition that $\boldsymbol{x}_1$ can dominate $\boldsymbol{x}_2$ is given by Eq.(7). If none of the solutions can dominate $\boldsymbol{x}_1$, it is a Pareto solution and given by Eq.(8). The Pareto solution corresponds to a set of scheduling schemes and is mapped as a Pareto front in n-dimensional space. Eqs.(9—12) provide conventional definitions for the minimizing completion time, the minimizing total machine load, the maximum machine load, and the minimizing job shop energy consumption.

$$f_i(\boldsymbol{x}_1) \leqslant f_i(\boldsymbol{x}_2) \quad i \in 1,2,\cdots,n \tag{7}$$

$$f_k(\boldsymbol{x}_1) < f_k(\boldsymbol{x}_2) \quad k \in 1,2,\cdots,n \tag{8}$$

$$\min(\max C_i) \quad 1 \leqslant i \leqslant n \tag{9}$$

$$\min \sum_{i=1}^{n} \sum_{j=1}^{n_i} \sum_{k=1}^{m} t_{ijk} \cdot x_{ijk} \tag{10}$$

$$\min\left(\max \sum_{i=1}^{n} \sum_{j=1}^{n_i} t_{ijk} \cdot x_{ijk} \right) \tag{11}$$

$$\min \sum_{i=1}^{n} \sum_{j=1}^{n_i} \sum_{k=1}^{m} t_{ijk} x_{ijk} P_k^{\mathrm{P}} + (C_i - t_{ijk} x_{ijk}) P_k^{\mathrm{I}} \tag{12}$$

Fig.3 shows common job shop scheduling optimization objectives, which can be divided into static indicators and dynamic indicators. Static indicators mainly involve order and job shop indicators, while dynamic indicators can mostly reflect the response effect of manufacturing systems to interference.

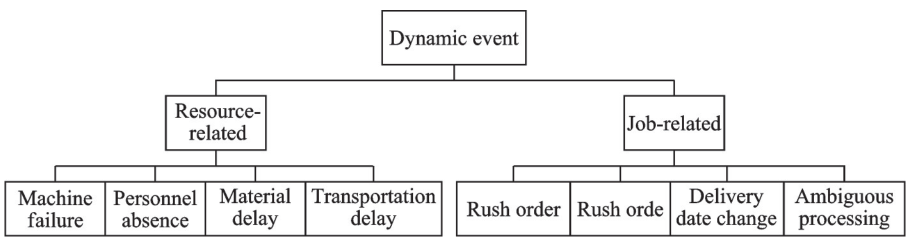

Fig.3 Job shop scheduling optimization objective classification

1.3 Multi-objective dynamic scheduling model for flexible job shop

In response to sudden disruptions in the production line, resources and workpieces need to be re-arranged or rescheduled. There are three common rescheduling strategies: Right shift rescheduling, partial rescheduling, and complete rescheduling. The characteristics of the three rescheduling schemes are given in Table 3. Based on the characteristics of interference, an appropriate rescheduling strategy should be selected to minimize interruptions and optimize resource utilization to the greatest extent possible.

Table 3 Comparison of rescheduling schemes

Rescheduling scheme	Characteristic
Right shift rescheduling	Good robustness; waiting for machine repairs significantly affects the delivery time of orders
Complete rescheduling	Poor robustness; complete resource reallocation effectively shortens maximum completion time
Partial rescheduling	Better robustness; ignoring machine failures results in low overall scheduling efficiency

Dynamic events in flexible job shops can be divided into two categories: (1) Resource related; (2) workpiece related. Fig.4 shows the process for building available machine sets. Based on different dynamic events, common flexible job shop dynamic scheduling models can be divided into the following categories.

DFJSP under machine failure: Machine failures occurring randomly during the production process and the unavailability of equipment due to regular maintenance activities are collectively regarded as machine failures. A machine failure can be described as follows: Machine M_k fails randomly at time t, the expected repair time is t_{r}, the process on the machine is O_{ij}, and the failed machine should be removed from the set of available machines until the failure is repaired. Right shift rescheduling is suitable for minor failures; complete rescheduling is effective in reducing the completion time when the failure has a long repair time. And partial reschedul-

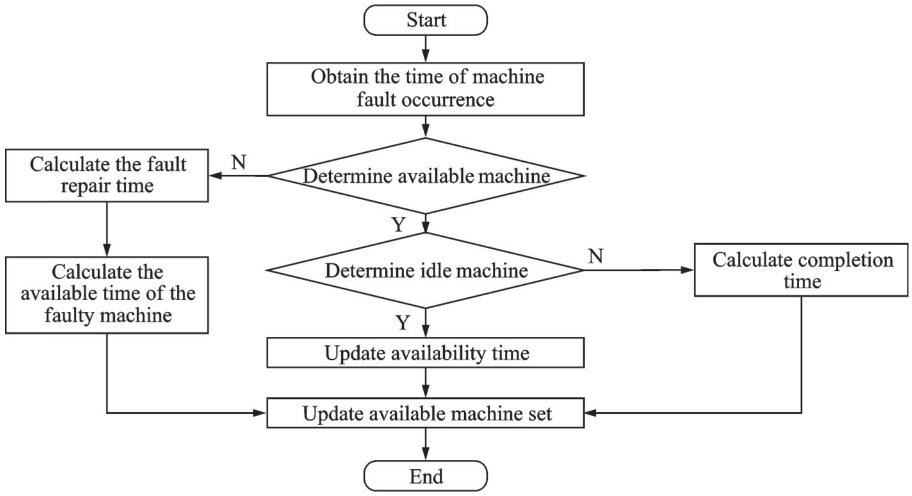

Fig.4 Process for building available machine sets

ing can reduce the impact of the failure on the overall production.

DFJSP under urgent order: Urgent orders have special delivery requirements compared to regular orders and have higher priority. An urgent order can be described as: A new batch of orders is added to the set of workpieces to be processed at time t, and the priority of the orders and workpieces needs to be evaluated. The workpieces with higher priority are inserted into the original processing schedule for production. The common insertion schemes include: Return insertion, extension insertion, and rearrangement insertion. Table 4 shows the characteristics of three types of insertion schemes.

Table 4 Comparison of insertion schemes

Insertion scheme	Characteristic
Return insertion	Ensure the delivery time of most orders, but affect the completion of regular orders
Extension insertion	Quickly responding to urgent orders, but causing delays in the completion of most regular orders
Rearrangement insertion	The cost of rearranging insertion orders is low, but the completion of urgent orders is delayed

DFJSP under fuzzy time: During the production process, the machining time of the workpiece fluctuates within a certain range due to factors such as changes in the machine's state and machining errors.

DFJSP under mixed dynamic events: With the increasing complexity of production scenarios, dynamic job shop scheduling needs to consider various dynamic event interferences, mainly including machine interference and workpiece interference.

2 DFJSP Under Machine Failure

There are three common ways to handle machine failures in DFJSP: Right shift rescheduling, partial rescheduling, and complete rescheduling. Fig.5 shows distribution of different rescheduling algorithms. Right shift rescheduling waits for machine availability to be restored before processing workpieces, partial rescheduling partially reallocates workpieces on faulty machines, and complete rescheduling reallocates all workpieces after the fault time.

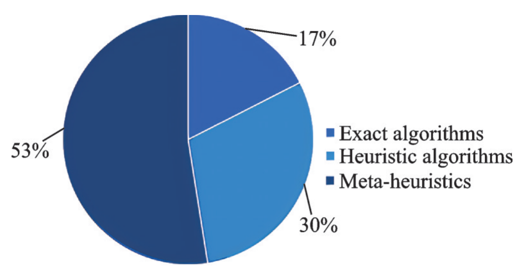

Fig.5 Distribution of approaches for FJSP

2.1 Intelligent-algorithm-based approaches

The dynamic job shop scheduling problem under machine failure continues to use the intelligent algorithms of static scheduling. Common intelligent algorithms include genetic algorithms, particle swarm algorithms, bee colony algorithms, etc.[27-32] Table 5 presents the classification of intelligent algorithms for handling job shop scheduling problems under machine failures. As illustrated in Fig.5, the distribution of these methods for single-objective FJSP reveals that meta-heuristic algorithms are the most prevalent, constituting roughly half of the total usage.

Table 5 Classification of intelligent algorithms for DFJSPs under machine failures

Method	Number of papers	Reference
Intelligent algorithm	7	[33-39]
Multi objective evolutionary algorithm	2	[40-41]
Particle swarm optimization algorithm	2	[42-43]
Knowledge optimization algorithm	1	[44]
Teaching optimization algorithm	1	[45]
Bird optimization algorithm	1	[46]

2.1.1 Genetic-algorithm-based approaches

The genetic algorithm(GA) is the earliest intelligent algorithm applied to job shop scheduling, and its basic idea is to achieve gene evolution through chromosomes to ultimately form stable species. With its characteristics of simple operation and easy implementation, GA has been widely used to solve complex systems and has become a conventional method for solving dynamic interference vehicle scheduling problems.

Gholami et al.[33] used genetic algorithm to solve DFJSP under machine failures, while optimizing the expected time span and expected average delay. The method adopts an event driven strategy to simulate the occurrence of machine failures, and determines the time of failure based on the schedule of machines in the job shop. They believe that attention needs to be paid to the machine failure interval and repair time in future research. Al-Hinai et al.[34] proposed a two-stage hybrid genetic algorithm, in which the first stage optimizes robustness and stability through multiple metrics, and the second stage integrates machine allocation and operation sequence with expected machine faults to verify the effectiveness of the optimization method. Meanwhile, they pointed out that multi-objective optimization was the research focus of DFJSP, and the Pareto optimization set could be used by decision makers to choose appropriate scheduling schemes. He et al.[35] proposed a new idle time insertion strategy to enhance the robustness and stability of scheduling schemes. This strategy improves the right shift rescheduling strategy by rearranging the workpieces during the maintenance period of the faulty machine, alleviating the delayed delivery. Based on the nature of different machine failures, a suitable rescheduling scheme is selected from idle time insertion, right shift rescheduling, and route switching scheduling to improve the efficiency of rescheduling. Wang et al.[44] designed a genetic algorithm with special chromosome encoding and optimized the encoding method and crossover mutation operator. This method achieves real-time machine allocation and scheduling rule adjustment, and comparative experiments with right shift rescheduling have shown that it can adapt to interference with minimal time. Li et al.[36] divided machine tools into two states: Processing and standby, and established an energy consumption optimization model for machine tools. They used a non-dominated sorting method to solve the dynamic scheduling under machine failures.

Yang et al.[40] proposed a dual objective optimization method combining an improved non-dominated sorting genetic algorithm and an extreme learning machine to improve the robustness and completion time of machine fault optimization scheduling. The robustness was measured by the position of fault probability and floating time in the extreme learning machine. Wang et al.[41] considered that preventive maintenance activities could cause machine unavailability, and incorporated the transportation process of workpieces into the DFJSP model, establishing a dual objective optimization model to optimize total energy consumption and total construction period. They combined genetic algorithm and differential evolution algorithm to design a multi-region partitioning sampling strategy to solve the model, achieving good optimization results.

In summary, genetic algorithms can effectively handle dynamic job shop scheduling problems, but further research is needed to improve the search performance of the algorithm, especially in terms of global and local search strategies.

2.1.2 Approaches based on other algorithms

The advancement of artificial intelligence has led to an increasing application of swarm intelligence algorithms in addressing job shop scheduling problems. Considering the probability, location, and time of machine failures, Xiong et al.[42] proposed a multi-objective robust scheduling algorithm to optimize the maximum completion time, and believed that dynamic scheduling under machine failures can be extended to handle disturbances such as time disturbances and workpiece arrivals. Shen et al.[45] developed a multi-objective evolutionary algorithm that can optimize the efficiency and stability of the job shop. Experiments have shown that the introduction of stability objectives is beneficial for improving job shop stability after machine failures occur, while ensuring production efficiency. In addition, they also designed a dynamic decision-making program that can provide different rescheduling solution sets for decision-makers to select.

Event driven response methods require efficient rescheduling strategies, and researchers have begun to combine machine states with job shop scheduling to achieve faster response times. Ahmadi et al.[37] studied a method for optimizing completion time and job shop stability to handle machine failures in DFJSP. On the basis of Al-Hinai et al.[34], stability was defined as the deviation of the average workpiece completion time. It is worth noting that they paid more attention to the state and conditions of the machine while dealing with machine failures, and achieved multi-objective optimization of DFJSP through an improved genetic algorithm. Nouiri et al.[47] proposed a two-stage particle swarm optimization algorithm, which performs better in robustness and stability compared to the hybrid genetic algorithm proposed by Al-Hinai et al[34]. Buddala et al.[38] designed a predictive schedule with minimum completion time, which can generate a stable rescheduling plan based on the schedule when a fault occurs.

As research deepens, more and more production line indicators are being considered. Fig.6 shows proportion of papers we summarize on dynamic scheduling optimization objectives under machine failures. The makespan remains the most fundamental indicator for measuring job shop performance, and robustness and stability performance reflect the response efficiency of dynamic events. In addition, machine utilization and processing energy consumption are also important indicators for dynamic scheduling under machine failures. Teymourifar et al.[39] used scheduling rules based on gene expression programming to solve dynamic scheduling under random faults, where limited buffering conditions enhance the complexity of the problem. They optimize the maximum completion time, maximum machine load and total machine load by taking the average value. Duan et al.[43] established a dynamic response strategy that considers the total energy consumption, completion time, and reusability of the system. They proposed a Pareto multi-objective particle swarm optimization algorithm that could achieve stable rescheduling in the event of machine failure. Wei et al.[46] proposed a multi-objective bird optimization algorithm based on game theory. In response to the game relationship between production efficiency and stability after interference occurs, they adopted an approximate Nash equilibrium solution to solve the problem and designed a neighborhood operator based on path re-linking and machine service age to enhance the search ability.

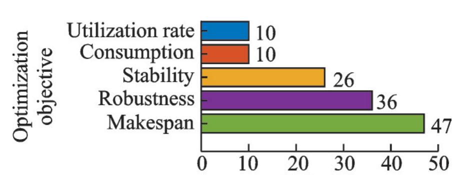

Fig.6 Proportion of papers on optimization indicators under machine fault rescheduling

2.2 Deep-learning-based approaches

With the flourishing development of deep learning, researchers have applied it to DFSJP. Table 6 presents the relevant literature on deep learning for solving DFJSP under machine faults in recent years.

Table 6 Deep learning for solving DFJSP under machine failure

Method	Optimization objective	Reference
Double layer deep Q-learning	Average latency, machine utilization	[48]
Convolutional neural network	Completion time, robustness	[49]
Deep Q-learning	Completion time, machine utilization, workpiece delay	[50]
Multi agent	Total order delay, machine utilization, machine load	[51]

Luo et al.[48] argued that conflicting objectives in DFJSP should be optimized, and they proposed an online scheduling framework that optimized weighted latency and average machine utilization through a two-layer deep Q-network . At each rescheduling point, the current job shop state is used as the state feature input, and a feasible target is selected to determine the Q-network behavior. In addition, they designed six composite scheduling rules to allocate available operations to feasible machines as candidate action sets for the network. Zhang et al.[49] proposed a two-stage algorithm based on convolutional neural networks to solve machine failure problems, and established a DFJSP model with completion time and robustness as the objectives. The first stage trains the prediction model through convolutional neural networks, and the second stage uses the model to predict the robustness of scheduling. The evaluation criteria for robustness include machine failures, machine loads, and the floating time of operations. Wang et al.[50] designed a dynamic multi-objective scheduling algorithm based on deep reinforcement learning to optimize the completion time, average machine utilization, and average workpiece delay rate of the job shop. This algorithm combines deep Q-learning with a real-time scheduling framework and uses an improved local search algorithm to optimize scheduling results. Experiments show that this method significantly improves all three objectives compared to scheduling rules. Luo et al.[51] designed a scheduling optimization scheme based on multi-agent near end strategies, which includes three types of agents based on different levels of near end optimization strategies: Optimization target agent, workpiece agent, and machine agent. The optimization target agent determines the target value at a fixed rescheduling cycle, and the workpiece and machine agents select the workpiece order and machine allocation at the rescheduling node.

Solving DFJSP under machine faults has high complexity and randomness, and can be well applied in modern Industry 4.0 and intelligent factories in the future. Common solving methods can be divided into scheduling rules, intelligent algorithms, and deep learning. Scheduling rules, as a traditional method, are gradually being replaced by intelligent methods. Intelligent algorithms are the main method for dealing with such problems, and deep learning has great potential in handling dynamic events with efficient learning. In terms of solving methods, the combination of deep learning algorithms under collaborative mechanisms and local search strategies has profound significance for dynamic scheduling under machine failures. In addition, real-time monitoring of machine status can greatly improve the efficiency of rescheduling and reduce the impact of interference.

3 DFJSP Under Urgent Orders

When receiving an urgent order, it is necessary to proactively rearrange the scheduling plan. Job insertion is the effective integration of new orders into existing plans to ensure job shop scheduling stability and progress. DFJSP for urgent orders considers the priority of orders based on the model in section 1.1, and usually adds the following workpiece constraints: New jobs need to have the characteristics of standard FJSP, that is processing flexibility; when inserting a new job, the procedure needs to complete it as soon as possible, and to consider the impact on the previous scheduling plan as well. That is stability.

There are three common methods for handling urgent orders: Extension insertion, return insertion, and rearrangement insertion. Return insertion requires sufficient processing time to be reserved for emergency orders, and urgent insertion allows for rescheduling of scheduling schemes.

3.1 Intelligent-algorithm-based approaches

Urgent orders have the highest priority, and intelligent algorithms can quickly respond to such dynamic events, demonstrating good stability in addressing such issues. Fattahi et al.[52] established a new workpiece arrival type DFJSP model for a manufacturing enterprise instance, which is actually a flexible job shop. They defined stability as the total deviation and penalty of the start time between the rescheduling scheme and the pre-scheduling scheme, and used Pareto optimal frontier collaborative optimization to improve the efficiency of the scheduling scheme. The limitation of this research is that it is difficult to obtain the optimal solution for medium to large-scale job shops. Nie et al.[53] pointed out that not all workpieces were available at the beginning of scheduling, and the arrival time of workpieces was unpredictable. They proposed a dynamic scheduling strategy based on gene expression planning for such dynamic events, achieving self-construction of scheduling strategies. This method effectively solves the dynamic arrival of workpieces in large-scale cases, jointly optimizing completion time, average flow time, and average delay time. Gao et al.[54-55] used new workpiece insertion as a constraint in DFJSP modeling and designed a two-stage artificial bee colony algorithm to optimize the maximum completion time. They improved the population initialization rules and introduced local search operators to improve the search efficiency of bee colonies and proved the superiority of their method in the pre-scheduling and rescheduling stages through three different rescheduling strategies. Zhang et al.[56] selected processing tasks based on the correlation between orders and achieved information transmission between tasks through multi-task genetic programming. Experimental results showed that the proposed algorithm can significantly improve the effectiveness of scheduling heuristic methods in multitasking scenarios.

The handling of urgent orders in actual production often relies on manual experience and expert knowledge. There is relatively little research on dynamic response under a single emergency order, and further research is needed on fast response methods under emergency orders.

3.2 Deep-learning-based approaches

The multi-agent state space can accurately reflect the real-time changes in the job shop, and deep learning is widely applied to dynamic scheduling of urgent orders.

Aydin et al.[57] are the first to use deep learning algorithms to solve job shop scheduling under urgent orders, and designed an improved Q-learning algorithm to train agents to select corresponding rules for processing workpiece insertion. Wang et al.[58] believed that reward machines in deep Q-learning can handle dynamic events to the maximum extent possible, and optimized the average delay by selecting appropriate scheduling schemes through intelligent agents. The job shop they studied does not have flexibility, but has greatly promoted subsequent research on emergency orders. Bouazza et al.[59] used deep learning to solve DFJSP, which can determine the most suitable machine selection rules and operation scheduling rules, thereby minimizing the weighted average waiting time in a dynamic and flexible job shop with workpiece insertion. Wang et al.[60] proposed a multi-agent optimization strategy with a buffer, which adopts a weighted Q-learning optimization with dynamic greedy search to penalize delivery time. Luo[61] modeled DFJSP as a Markov decision process, in which intelligent agents determine the next operation and machine allocation to be processed based on the production status of the current decision point. It is highly feasible to solve this problem through reinforcement learning methods.

The dynamic scheduling of job shops under urgent orders focuses more on the delay and completion rate of orders, and has higher robustness and stability compared to machine fault rescheduling. Deep learning performs efficiently on this problem, and intelligent algorithms can stably output rescheduling solutions when solving such problems. For delayed delivery of urgent orders, in addition to delivery penalties, targets such as production costs and energy consumption should also be considered.

4 DFJSP Under Fuzzy Time

Ambiguity is commonly present in flexible manufacturing systems, and fuzzy time refers to the fluctuation of workpiece processing time within a certain range due to unpredictable factors. In the fuzzy flexible job shop scheduling problem (FFJSP), workpieces have fuzzy start and finish times. Triangular fuzzy numbers are usually used to represent workpiece processing information, and the processing sequence between processes is based on fuzzy set operation rules.

Triangular fuzzy numbers are widely used membership functions in scheduling. The processing times t_1, t_2 and t_3 correspond to the earliest processing time, the highest probability processing time, and the latest processing time of the workpiece, respectively. Given two arbitrary triangular fuzzy numbers $\tilde{t}=(t_1, t_2, t_3)$ and $\tilde{s}=(s_1, s_2, s_3)$, the sum of fuzzy numbers can be expressed as $\tilde{t}+\tilde{s}=(t_1+s_1, t_2+s_2, t_3+s_3)$.

The fuzzy nature of FFJSP also results in differences in its performance on Gantt charts. Fig. 7 shows the FFJSP Gantt chart. Above the timeline of machine M_1 is the fuzzy completion time of the workpiece, and the below is the fuzzy start time of the workpiece. O_{11} is the first processed workpiece represented by a rectangle.

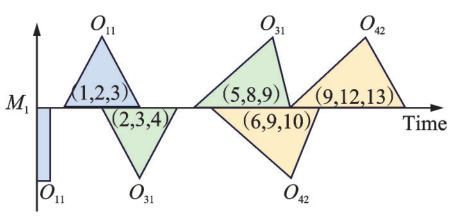

Fig.7 FFJSP Gantt chart

4.1 Single objective optimization

Fuzzy completion time is a commonly considered optimization metric in FFJSP. Lei et al.[62-63] used an effective decomposition integral genetic algorithm to solve the fuzzy job shop and optimize the fuzzy completion time, extending the decoding method in FJSP to FFJSP. Wang et al.[64] proposed a distribution estimation algorithm to solve FFJSP, which adopts a left shift strategy to optimize the scheduling scheme for idle machines and uses fuzzy number operations to optimize the completion time. Liu et al.[65] transformed dynamic FFJSP into FJSP, simplifying the solution process of fuzzy job shop and using distribution estimation algorithm to optimize fuzzy completion time. Xu et al.[66] used a new encoding method and improved scheduling efficiency through a two-stage search strategy based on teaching mechanism and local search. Lin[67] combined optimization algorithms based on biogeography with heuristic algorithms, and developed migration operations through path connections to obtain scheduling schemes. Lin et al.[68] proposed a hybrid multidimensional optimization algorithm for FFJSP, which introduced heuristic insertion rules and path re-linking techniques, greatly improving search efficiency. Sun et al.[69] proposed a hybrid co-evolutionary algorithm that combines particle swarm optimization and genetic algorithm under the collaborative mechanism to improve convergence ability. Li et al.[70] proposed an improved genetic algorithm for solving fuzzy job shops, which accurately solves the processing time using the triangular fuzzy number sorting criterion and introduces a simulated annealing mechanism to prevent local optima. Gao et al.[71] designed a new selection mechanism to enhance the effectiveness of differential evolution algorithm in solving fuzzy job shops, optimizing fuzzy completion time through various fuzzy instances.

4.2 Multi-objective optimization

Considering the characteristics of fuzzy job shops, researchers have innovated optimization objectives and research methods for such problems. Table 7 presents the studies on multi-objective optimization of FFJSP. Fuzzy processing time leads to uncertainty in equipment load, so machine load is a commonly considered optimization objective. The fuzzy multi-objective job shop scheduling model typically includes decision variables (such as operation start times and machine assignments), objective functions (such as minimizing fuzzy makespan and fuzzy tardiness), and constraints (such as operation sequence and resource limitations).

Table 7 Research classification of DFJSP under fuzzy time

Optimization objective	Method	Reference
Delivery time	Genetic algorithm	[72]
Machine load	Harmony search algorithm	[73]
Machine load	Adaptive multi-objective evolutionary algorithm	[74]
Total flow time	Multi-objective fuzzy linear programming	[75]
Robustness	Improved genetic algorithm	[76]
Machine load	Modified artificial bee colony algorithm	[77]
Power consumption	Artificial immune algorithm	[78]
Delivery time	Genetic algorithm	[79]
Power consumption	Dual population evolutionary algorithm	[80]
Machine load	Reinforcement learning	[81]
Machine load	Mixed integer linear programming algorithm	[82]

Sakawa et al.[72] established a fuzzy job shop scheduling model with fuzzy processing time and introduced the concept of Gantt chart similarity into genetic algorithms, which became the basis for subsequent fuzzy job shop research. Gao et al.[73] applied the discrete harmony search algorithm to FFJSP, enriching the population and optimizing the maximum fuzzy machine workload during the initialization phase. Wang et al.[74] proposed a decomposition-based hybrid adaptive multi-objective evolutionary algorithm that optimizes fuzzy completion time while reducing total workload. Saraçoğlu et al.[75] used multi-objective fuzzy linear programming to model cellular manufacturing systems, minimizing fuzzy completion time and total flow time by increasing the utilization rate of each stage. Wang et al.[76] combined non-dominated sorting genetic algorithm-Ⅱ with local simulated annealing algorithm to optimize the Pareto set through neighborhood operators, while optimizing fuzzy completion time and robustness. Zhong et al.[77] proposed a modified artificial bee colony algorithm to optimize machine workload. The algorithm incorporates a variable neighborhood search local search operator and crossover operator. The researchers designed a system that reflects the relationship between delivery time and completion time. Li et al.[78] proposed an improved artificial immune algorithm to optimize job shop energy consumption, designed four initialization heuristics for specific problems, and introduced simulated annealing mechanism in the algorithm to improve its search ability. Vela et al.[79] proposed a measurement method for evaluating expiration dates, which combines tabu search and genetic algorithm to optimize the fuzzy completion time and deadline of fuzzy job shops. Pan et al.[80] considered energy-saving FFJSP and designed a feedback-based dual population evolutionary algorithm to optimize fuzzy total energy consumption. They proposed an effective evaluation mechanism and adopted a feedback mechanism based on population quality to dynamically adjust the population. Li et al.[81] used reinforcement learning algorithms to optimize the completion time and total machine load of fuzzy job shops. Their contributions mainly include three aspects: Improved initialization strategy, parameter adaptive strategy based on Q-learning, and local search strategy based on reinforcement learning. Li et al.[82] established a mixed integer linear programming model for optimizing machine workload in fuzzy job shops. They improved efficiency by using specialized fuzzy number mixed initial rules and developed five different search methods to enhance search capabilities.

The difficulty of FFJSP lies in the complexity of fuzzy operations, and the flexibility of the job shop places higher demands on the algorithm's search ability. Fuzzy characteristics are more difficult to solve compared to random dynamic events such as machine failures and emergency orders. Fuzzy processing time can affect process sequencing and machine allocation, thereby affecting job shop production efficiency and costs. Fuzzy job shop should be deeply integrated with supply chain management, big data analysis and other fields to explore the reasons for processing time fluctuations and achieve intelligent and digital management of the entire production process.

5 DFJSP Under Mixed Dynamic Events

Job shop scheduling is influenced by factors such as the coupling relationship between equipment and processes, uncertain task arrival time and quantity, limited and uncertain resources, production equipment failures, order priorities and constraints, etc. These factors lead to the need to consider multiple uncertainties in the dynamic scheduling process to achieve efficient production[26]. At present, the handling of different dynamic events is independent, and it is of great significance to consider the synchronous occurrence of multiple dynamic events in production systems.

5.1 Intelligent-algorithm-based approaches

Gao et al.[83] studied DFJSP under new workpiece insertion and with workpiece fuzzy processing time constraints. They combined the characteristics of artificial bee colony algorithm to divide the process of solving DFJSP into pre-scheduling stage, execution stage, and rescheduling stage, and proposed three variant algorithms to optimize the maximum fuzzy completion time. Li et al.[84] developed a hybrid artificial bee colony algorithm based on a combination of bee colony algorithm and tabu algorithm for two dynamic events: Inserting new workpieces and canceling old jobs. They introduced clustering grouping during the initialization phase and used an adaptive strategy based on tabu search to ensure population diversity and prevent premature convergence. The local search strategy based on taboo search effectively improved the search ability of the algorithm. Li et al.[85] considered four different dynamic events: Machine failures, arrival of new jobs, job cancellation, and changes in workpiece processing time, and proposed a search algorithm based on Monte Carlo tree. Previous studies could not address the issue of rapid response to dynamic events. Instead, they gradually generated a subsequent processing schedule for unprocessed workpieces through a designed continuous time window. This method has shown efficient results in solving quality and scheduling efficiency issues. Lyu et al.[86] modeled the energy consumption of flexible manufacturing systems and described DFJSP as a mixed integer programming optimization problem. Based on a heuristic framework, they designed a rescheduling algorithm for machine failures and workpiece arrivals. The effectiveness of the proposed rescheduling scheme has been demonstrated through comparative case simulations in different scenarios. An et al.[87] considered machine preventive maintenance while solving workpiece insertion and established a multi-objective optimization model to jointly optimize production scheduling and maintenance plans. In order to obtain a comprehensive maintenance production scheduling plan, they constructed a local search mechanism based on critical path and studied the influence of parameters on the proposed non-dominated genetic algorithm through experiments.

5.2 Deep-learning-based approaches

Rajabinasab et al.[88] developed an information-based multi-agent scheduling system that combines dynamic events such as machine failures and random workpiece arrivals, and compared its effectiveness with multiple scheduling rules. This system optimizes job shop utilization, tight delivery time, fault level, and average repair time, and can be extended to open job shops and integrated production lines. Shahrabi et al.[89] considered the dynamic job shop scheduling problem with random job arrivals and machine failures, and optimized the scheduling scheme through Q-learning of optimal parameters and variable neighborhood search at any rescheduling point. Waschneck et al.[90] developed a multi-agent dynamic scheduling method for flexible job shops with machine failures and order insertion. In this method, each agent is represented by a deep Q-network and trained through deep Q-learning. Baykasoğlu et al.[91] studied dynamic events such as machine failures, new order arrivals, and changes in expiration dates, and proposed a constructive algorithm based on greedy random pose search. They focused on the instability of order progress, completion time, average delay, and average running time. The effectiveness of this method has been demonstrated by comparing the event driven rescheduling strategy with the periodic rescheduling strategy. Ghaleb et al.[92] considered real-time joint optimization of maintenance planning and production scheduling in intelligent manufacturing systems. A pre-reaction scheduling scheme based on genetic algorithm is proposed for new job arrivals, unexpected expiration date changes, machine degradation, and random failures. Experimental results have shown that this rescheduling scheme can effectively save costs. Zhang et al.[93] proposed a genetic-programming-based assisted evolutionary multi-task algorithm, which constructs tasks through multi-agent systems and evaluates scheduling rules based on phenotype characteristics. This method can not only improve the completion efficiency under dynamic events, but also be used for knowledge transfer in multi task-learning.

Mixed dynamic events require consideration of the complex relationships between different interferences and proposing targeted response strategies. Future research can expand existing scheduling models and consider more assumptions, such as material resources, human resources, and variable processing time.

6 Application in Aviation Manufacturing

To verify the application of scheduling methods in practical problems, simulations were conducted based on order data from an aviation manufacturing impeller production line at a certain research institute. Table 8 presents the specific processing information of the production line. The effectiveness of

Table 8 Processing information of aviation manufacturing impeller production line

Workpiece	Process	M_1	M_2	M_3	M_4	M_5	M_6
Impeller 1	Rough milling shape	5	6	8	—	5	9
	Precision milling shape	7	9	—	8	—	10
	Swarf machining	4		4	5	—	3
	Edge milling	—	4	6	7	2	—
	Round corner milling	6	7	9	—	8	8
	Precision milling flow channel	8	8	—	12	9	—
Impeller 2	Rough milling shape	7	8	10	—	7	—
	Precision milling shape	8	10	—	9	—	11
	Edge milling	—	5	7	8	3	—
	Point milling	5	7	—	—	6	7
	Round corner milling	7	8	—	9	—	9
	Precision milling flow channel	8		8	12	9	8
Impeller 3	Rough milling shape	4	5	7	—	4	8
	Precision milling shape	5	7	—	6		8
	Rough milling channel	8	—	8	12	9	8
	Point milling	5	7	—	—	6	7
	Round corner milling	6	6	9	—	8	7
	Precision milling flow channel	7	7	—	11	8	
Impeller 4	Rough milling shape	7	8	10	—	7	
	Precision milling shape	8	10	—	9	—	11
	swarf machining	4	—	4	5	—	3
	Edge milling	—	4	6	7	2	
	Point milling	5	7	—	—	6	7
	Rough milling channel	7	8	10	—	7	—
	Precision milling flow channel	8	—	8	12	9	8

the aviation manufacturing impeller production line was verified using a hybrid particle swarm algorithm based on the improved variable neighborhood search operation. Fig.8 shows the flowchart of the method.

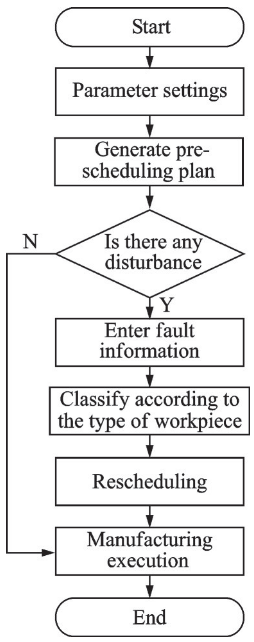

Fig.8 Rescheduling process diagram

To ensure the fairness of the experiment, the parameters of hybrid particle swarm optimization (HPSO) and dynamic particle swarm optimization (DPSO) are kept consistent: The maximum number of iterations is set to 100; the population size is set to 100; the mutation probability is set to 0.15; the acceleration factor and the update probability are set to 0.5 and 0.7, respectively, and each test question is independently run 20 times.

6.1 Dynamic scheduling of machine failures

In scenario 1, the faulty machine is machine 4 which holds two faults in the 20th and the 30th hours separately. In scenario 2, the faulty machine is machine 6 which holds two faults in the 30th and the 20th hours separately. The scheduling results of the three methods in the two scenarios are shown in Table 9, where the two values of each solution correspond to the completion time and energy consumption of the optimal scheduling scheme, measured in hours and kW·h, respectively.

Table 9 Comparison of three methods under machine faults

Scenario	NSGA Ⅱ		DJaya		HPSO	
	Solution/[h, kW·h]	Number	Solution/[h, kW·h]	Number	Solution/[h, kW·h]	Number
1	[70.0, 2 569.1]	4	[73.0, 2 253.1]	1	[67.0, 2 355.9]	12
2	[67.0, 2 388.6]	9	[69.0, 2 329.6]	0	[64.0, 2 100.4]	14

Figs.9, 10 show the scatter plots of the results for the two scenarios. In scenario 1, HPSO solved the scheduling instance and obtained 12 non-dominated solutions, NSGA Ⅱ obtained four non-dominated solutions, and DJaya obtained one non-dominated solution. In scenario 2, HPSO obtained 14 non-dominated solutions for scheduling instances, NSGA Ⅱ obtained nine non-dominated solutions, DJaya had no non dominated solutions, and HPSO obtained the highest number of non-dominated solutions with higher search accuracy, proving the effectiveness of the algorithm in dynamic scheduling problems.

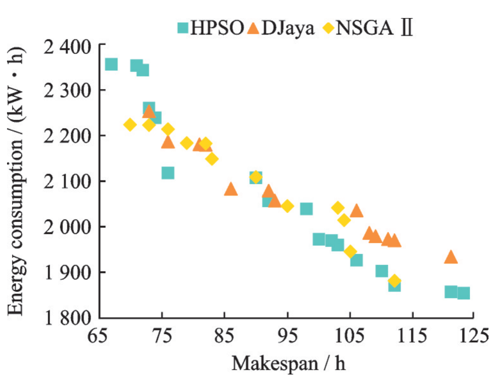

Fig.9 Dynamic scenario 1 scatter plot

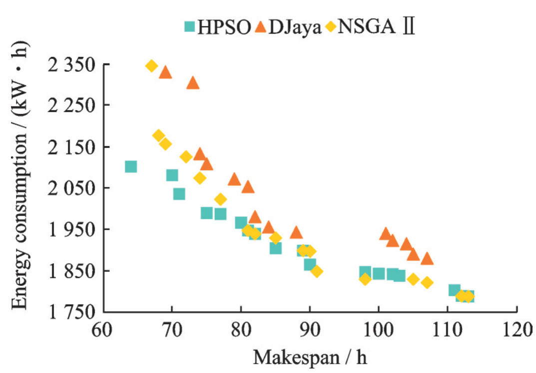

Fig.10 Dynamic scenario 2 scatter plot

Fig.11 shows the dynamic scheduling scheme for machine 4 after failure obtained by the HPSO algorithm, with corresponding maximum completion time and energy consumption of 67.0 h and 2 355.9 kW·h, respectively. Fig.12 shows the dynamic scheduling scheme for machine 6 after failure obtained by the HPSO algorithm, with corresponding maximum completion time and energy consumption of 64.0 h and 2 100.4 kW·h, respectively. The fault intervals are within the 30th hour and the 20th hour separately, and M_6 is unavailable from the 30th to the 50th hours.

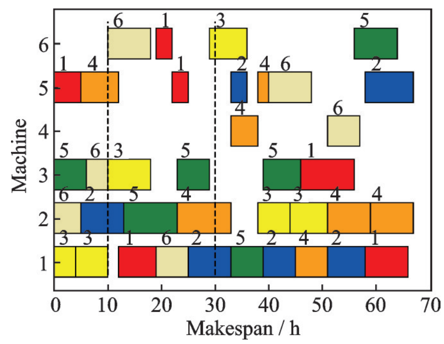

Fig.11 Machine allocation Gantt of scenario 1

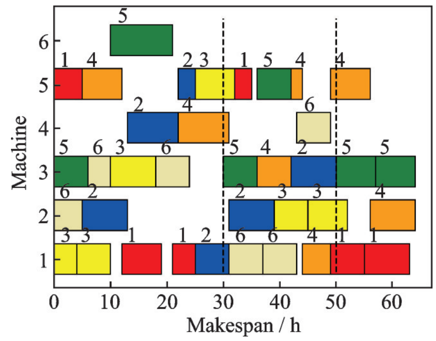

Fig.12 Machine allocation Gantt of scenario 2

6.2 Dynamic scheduling for random arrival of workpieces

In dynamic scenario 3, workpiece 2 arrives at an interval of the 10th hour. In scenario 4, workpiece 2 arrives at the 30 th hour. The scheduling results of the three methods in two scenarios are shown in Table 10, where the two values of each solution correspond to the completion time and energy consumption of the optimal scheduling scheme, measured in hours and kW·h, respectively.

Table 10 Comparison of three methods under random arrival

Scenario	NSGA Ⅱ		DJaya		HPSO	
	Solution/[h, kW·h]	Number	Solution/[h, kW·h]	Number	Solution/[h, kW·h]	Number
1	[80, 2 679.2]	2	[84, 2 729.4]	0	[78, 2 689.0]	21
2	[76, 2 581.4]	2	[79, 2 689.7]	0	[76, 2 581.4]	21

Figs.13, 14 show the scatter plots of the results for scenario 3 and scenario 4, respectively. In scenario 3, HPSO solved the scheduling instance and obtained 21 non-dominated solutions, NSGA Ⅱ obtained two non-dominated solutions, and DJaya did not have any non-dominated solutions. In scenario 4, HPSO obtained 21 non-dominated solutions for scheduling instances, NSGA Ⅱ obtained two, DJaya obtained zero, and HPSO obtained the highest number of non-dominated solutions with higher search accuracy, proving the effectiveness of the algorithm in dynamic scheduling problems.

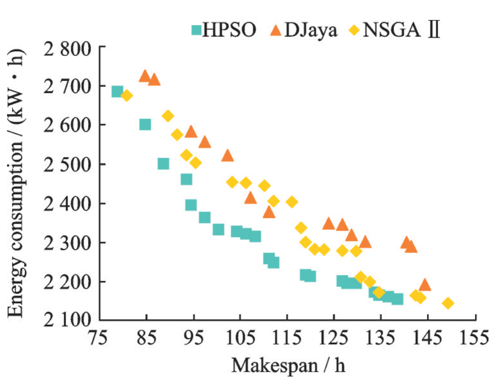

Fig.13 Scatter plot of dynamic scenario 3

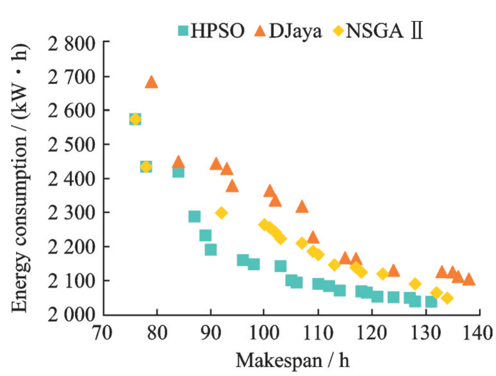

Fig.14 Scatter plot of dynamic scenario 4

Fig.15 shows the dynamic scheduling scheme for machine 4 after failure obtained by the HPSO algorithm, with corresponding maximum completion time and energy consumption of 67.0 h and 2 355.9 kW·h, respectively. Fig.16 shows a dynamic scheduling scheme for scenario 4 obtained by the HPSO algorithm, with corresponding maximum completion time and energy consumption of 76 h and 2 581.4 kW·h, respectively. This dynamic scheduling scheme adds new workpieces to the schedule at the 30th hour, which extends the maximum completion time by 15 units compared to the original scheme.

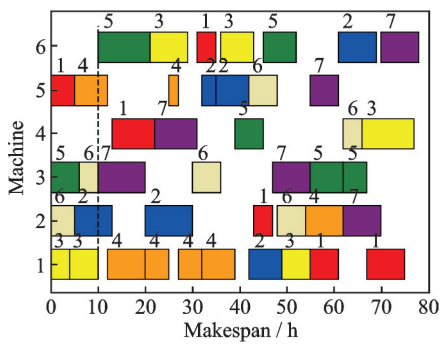

Fig.15 Gantt chart of scenario 3

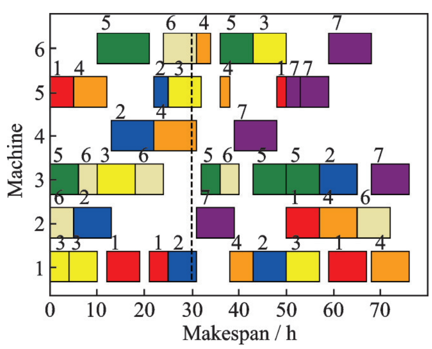

Fig.16 Gantt chart of scenario 4

6.3 Prototype system

We develop a cloud edge control platform for intelligent production lines in aviation manufacturing based on the SupOS system. Fig.17 shows the control platform, which includes safety monitoring, model management, quality management, impeller production line, shell production line, and planning and scheduling module. Fig.18 shows the relevant indicators of the impeller production line, including qualification rate, processing progress, job shop energy consumption, equipment operating time, equipment utilization rate, and capacity utilization rate indicators. The impeller production status can be obtained through it. Fig.19 shows the scheduling scheme corresponding to the impeller production line, and shows the running time of the production equipment. The scheduling scheme Gant is the Pareto optimal solution. Fig.20 shows

Fig.17 Control platform

Fig.18 Impeller production line

Fig.19 Pre-scheduling plan

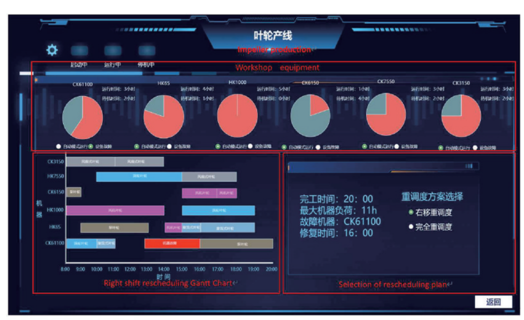

Fig.20 Right shift rescheduling scheme

the right shift rescheduling plan after the machine malfunctioned, with the completion time extended to 20:00. Fig.21 shows the complete rescheduling scheme after a machine failure, which reschedules the processing tasks after the failure time, reduces the impact of dynamic interference, and improves production efficiency. Fig.22 shows the scheduling scheme after inserting the turbine impeller order. The scheduling scheme is rescheduled using a sequential insertion scheduling scheme to ensure its robustness.

Fig.21 Complete rescheduling plan

Fig.22 Rescheduling plan for urgent orders

7 Conclusions and Outlook

This paper summarizes DFJSP, focusing on optimization objectives, job shop constraints, and dynamic response schemes and conducts in-depth research on scheduling under machine failures, emergency orders, fuzzy time, and mixed dynamic events.

By analyzing existing literature, the following conclusions can be drawn.

(1) Method and model: Classic FJSP is an academic optimization problem used to solve practical scheduling problems. A large number of swarm intelligence algorithms have been developed to solve FJSP, and deep learning methods have shown good performance in handling dynamic scheduling. A more comprehensive job shop scheduling model has been established, which extends the basic FJSP mathematical model to simulate actual production scenarios.

(2) Optimization objective: The completion time is the most important optimization indicator, but there are often multi-objective requirements in actual production. Multi-objective optimization is usually necessary in job shop scheduling, and dynamic scheduling focuses more on optimizing the two indicators of robustness and stability.

(3) Dynamic event: Machine failures are the most common dynamic disturbances in the job shop, and rescheduling and predictive maintenance are the main ways to reduce the impact of machine failures. The mixed dynamic interference increases the difficulty of job shop scheduling, and the fast response characteristics of deep learning provide a new direction for dealing with such problems.

Job shop scheduling has a wide range of applications in practical production, and future research can focus on the following directions.

(1) Optimize scheduling algorithm: Most intelligent algorithms have limitations, and deep learning algorithms have poor interpretability. Developing a new scheduling method by combining the advantages of two algorithms and considering the dynamic event processing mode under the collaborative mechanism is of great significance for improving scheduling performance and job shop production efficiency.

(2) Establish a dynamic model: Production scheduling radiates to many industries, including semiconductors, healthcare, military, etc. Analyzing the characteristics of different industries and extending the FJSP model can enrich the theory of job shop scheduling. A robust and predictive job shop model can be established using techniques such as state monitoring[94], risk mitigation[95], and data-driven[96]. More practical instance validations can be conducted and the DFJSP model can be combined with the assembly line job shop model and distributed job shop model.

(3) Collaborative fault diagnosis: Machine fail-

ures will seriously affect the efficiency of production systems. At present, most fault handling methods use pre-reaction scheduling, which requires high time and resource reallocation for reactions. Performing fault diagnosis using production line scheduling collaborative adaptive technology[97], fault-tolerant control[98], and distributed control[99], analyzing the mechanism of fault propagation, and establishing a fault knowledge base in the form of a knowledge graph[100] can reduce response time and resource waste.

(4) Develop prototype system: Conduct research on key technologies can be studied for precision control, dynamic scheduling, energy efficiency optimization, and equipment operation and maintenance in cloud edge collaborative production lines. Fig.23 shows the cloud edge collaborative optimization scheme for intelligent production lines. Based on this, a multi-objective dynamic control and optimization technology for intelligent production lines is established, and a prototype system integration verification new method and technology are developed.

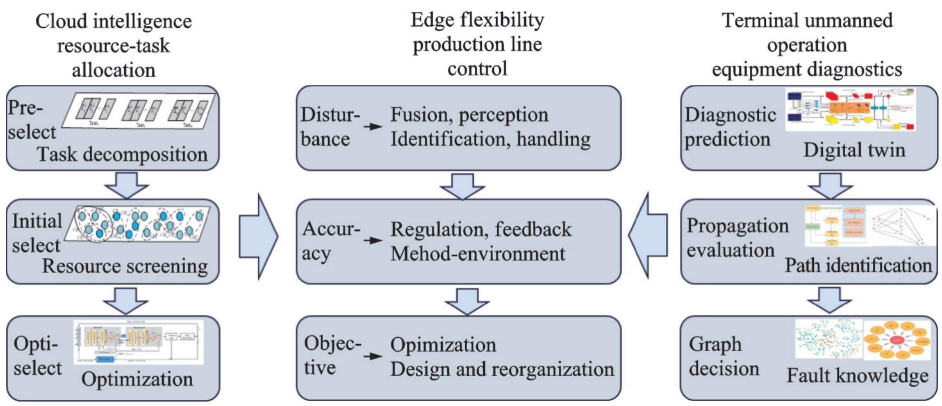

Fig.23 Collaborative optimization solution for cloud edge end of intelligent production line

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柔性车间多目标动态调度方法及其在航空制造中的应用综述

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摘要：智能生产是智能制造的重要发展方向，智能工厂是推动智能生产的关键因素。柔性车间作为智能工厂的主要形式，在生产过程中会不断地发生动态干扰，包括机器故障和紧急订单等。本文讨论了车间调度的基础模型与研究方法，强调了动态车间调度及其响应方案在未来研究中的重要地位；建立了多目标柔性车间动态调度数学模型，指出其在不同干扰下呈现出复杂多约束特性；针对机器故障、紧急订单、模糊完工时间和混合动态事件下 的动态响应方法及优化目标进行了分类讨论，分析了传统调度规则与智能方法在动态调度中的发展过程；根据车间调度发展现状与智能制造发展要求，给出了柔性车间动态调度未来发展趋势。

关键词：柔性车间；动态调度；机器故障；紧急订单；多目标优化