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Review:

A review of the flexible job shop scheduling problems considering transportation vehicles*

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Abstract: The flexible job shop scheduling problem for processing machines and transportation vehicles (FJSP_PT) has garnered significant attention from academia and industry. Due to the inclusion of transportation vehicle scheduling in the scheduling problem of flexible manufacturing systems, solving FJSP_PT becomes more challenging and significantly more practically relevant compared to the flexible job shop scheduling problem. This paper summarizes the assumptions, constraints, objective functions and benchmarks of the FJSP_PT. Then, statistical analysis is conducted on relevant literature up to 2023, including journals, number of articles published each year, and solving algorithms. This paper analyzes recent literature on FJSP_PT, categorizing it based on algorithms into exact algorithms, heuristic algorithms, metaheuristic algorithms, and swarm intelligence-based algorithms. Finally, the research trends and challenges faced by the FJSP_PT problem are summarized.

Key words: Flexible manufacturing system; Transportation vehicle; Processing machine; Integrated scheduling; Review

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1 Introduction

With the upgrading of the consumption structure, the demand of markets and consumers for personalization and customization is increasing. Many countries are trying to promote the reform of manufacturing industries, such as Industry 4.0 (He and Xia, 2021) in Germany and Made in China 2025 (Zhang, 2021). The traditional production mode is being changed to a more flexible and intelligent manufacturing mode to accelerate the construction of a manufacturing power. With the widespread application of transportation equipment like cranes and automated guided vehicles (AGVs) (Zhang et al., 2023) as shown in Fig.1 in the flexible manufacturing system (FMS), the logistics procedures transporting jobs between machines have a significant impact on production efficiency and have been considered into the job shop scheduling problem. Compared with other traditional logistics devices like conveyor belts, transportation vehicles can accomplish the logistics tasks of processing jobs in a more efficient and flexible manner.

From a theoretical standpoint, as an extension of the flexible job shop scheduling problem

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a) Gantry crane b) Automated guided vehicle

Fig. 1 Common transportation equipment in FMS

(FJSP)(Wang et al., 2019; Chen et al., 2010), the flexible job shop scheduling problem for processing machines and transportation vehicles (FJSP_PT) is highly complex. In the production flow of a job, the transportation stages and the processing stages occur alternately. Correspondingly, the transportation time and the processing time together constitute the flow time of a job in FMS. In the past, most research on the traditional scheduling problem in FMS focused on the processing time and ignored the transportation time. However, flexible transportation procedures are seen playing more and more important roles in modern manufacturing systems. Due to the coupling between processing and transportation stages, the increase in types of scheduling entities makes solving FJSP_PT more difficult. From a practical perspective, FJSP_PT exists widely across manufacturing industries characterized by features such as diversified products and small batches, such as hardware products, as well as industries like automated container terminals. Therefore, FJSP_PT represents an optimization problem that is both practically significant and theoretically intricate.

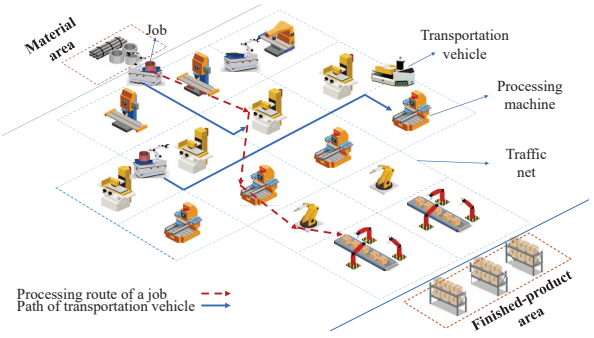

Fig. 2 FMS with transportation vehicles

An FJSP_PT can be described as follows: in an FMS such as the one depicted in Fig.2, there exists an order comprising N_J jobs. Each job has multiple operations to be processed. The FMS requires scheduling N_M machines and a finite number, N_A, of vehicles to effectively execute both the processing and transporting tasks for all jobs, optimizing the makespan or other related objectives. Throughout production, the transportation and processing procedures for each job will be carried out alternately. Consequently, the transportation time and processing time collectively impact the job-completion duration. Therefore, the FJSP_PT cannot be readily decoupled into the FJSP and logistics scheduling problems. The flexibility in this problem is evident in the following areas:

- Operation flexibility: Each operation can be processed by different machines.
- Machine flexibility: Each machine can process multiple operations.
- Vehicle flexibility: Each vehicle can transport all jobs for all operations.

Obviously, compared with other types of flexible job shop scheduling problems, the additional vehicle flexibility in FJSP_PT will lead to an expansion of the problem solution space, increasing the difficulty of problem solving.

At present, numerous related research studies focusing solely on FJSPs involving machines within the FMS have been extensively published and reviewed. The literature reviews in this domain primarily concentrate on problem analysis (Rathore and Chauhan, 2015; Balogun and Popplewell, 1999) and statistical analysis of solving algorithms such as dispatching rules (Gupta et al., 1989), genetic algorithms (GA) (Godinho Filho et al., 2014), neural networks (Rathore and Chauhan, 2015), machine learning (Priore et al., 2001), methodologies for multi-objective optimization (Türkyılmaz et al., 2020), and others (Gao et al., 2019; Xie et al., 2019; Chan and Chan, 2004). Simultaneously, research on logistics-scheduling problems involving transportation vehicles within the FMS has also received attention. Fazlollahtabar and Saidi (2015) have surveyed the literature concerning the scheduling and path-planning of automated guided vehicle (AGV) systems, distribution, transshipment, and transportation systems. However, apart from Nouri et al. (2016a), there have been few reviews specifically addressing FJSP_PT. Nouri et al. (2016a) introduced a new classification schema encompassing seven criteria: number of transport sources, type of transport

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sources, job complexity, routing flexibility, recirculation constraints, optimization criteria, and implemented approaches. This paper aims to provide the latest overview of the FJSP_PT problem, highlighting the following main contributions:

(1) This paper summarizes the common assumptions, constraints, objective functions, benchmarks, etc., related to the FJSP_PT.

(2) Using bibliometric methods, this paper conducts a statistical analysis of relevant literature up to 2023, encompassing journals, the number of papers published each year, and solution algorithms.

(3) This paper analyzes recent literature on FJSP_PT, categorizing it based on algorithms into exact algorithms, heuristic algorithms, metaheuristic algorithms, and swarm intelligence-based algorithms.

(4) The research status, gaps, trends and challenges of the FJSP_PT problem are summarized.

The rest of the paper is organized as follows: The model and benchmarks of FJSP_PT are sorted out in Section 2. In Section 3, we focus on analyzing publications related to FJSP_PT, surveying the solving methods and real-world applications. Section 4 discusses the research status, trends and future challenges of this problem.

2 Model of FJSP_PT

2.1 Problem positioning

This subsection primarily explains three scheduling subproblems essential in FJSP_PT. The typical flexible job shop scheduling problem comprises only two subproblems: job routing and operation sequencing. However, within FJSP_PT, there exists another scheduling subproblem concerning vehicles, the assignment of transportation tasks.

- Job routing: This subproblem involves planning feasible processing routes for jobs across machines. In a flexible job shop, machines can handle various operations. Each job necessitates the processing through multiple machines to complete different operations sequentially.
- Operation sequencing: This subproblem entails sequencing the operations to be processed on each machine. It does not affect the route of each job, but it determines the processing order of operations on the same machine.
- Transportation task assignment: In this subproblem, the transportation tasks of all operations will be allocated to different vehicles.

While FJSP_PT has been defined by the aforementioned three subproblems, it remains crucial to differentiate them from other similar problems as shown in Table 1. As given in Table 1, FJSP with transportation time does not schedule vehicles or does not consider their position changes during production. It only includes transportation time in makespan calculation or assumes that there are enough vehicles. Although some studies also consider vehicle path planning, this review will not cover those aspects.

Table 1 Differentiation from other similar problems

Problem	Description
Flexible job shop scheduling of machines and transport vehicles	Include the above subproblems (Zhang et al., 2019)
Flexible job shop scheduling with transportation time	Only consider the transportation time or enough transport vehicles[1](Dai et al., 2019)
Flexible job shop integrated scheduling and vehicle pathplanning problem	Besides the above three sub problems, include the vehicle path planning problem (Saidi et al., 2015)

[1] When there are enough transport vehicles, all jobs can be loaded immediately. In this case, subproblem (3) is not necessary to be considered and FJSP_PT will degenerate to FJSP with transportation time.

2.2 Mathematical Model of FJSP_PT

Since these scheduling problems rely on the actual production context, various scholars may model them to varying extents based on specific cases. Overall, their models, such as Petri net or integer programming models, consider the following common assumptions, constraints, and objectives. In this paper, we also introduce a fundamental integer programming model for minimizing makespan in Appendix A. The inclusion of transportation vehicles in flexible job shop scheduling problems introduces numerous new assumptions, constraints, decision variables, and optimization objectives that need to be considered.

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2.2.1 Common assumptions

In most literature, the following appropriate assumptions are usually made about FJSP_PT for grasping the key to the problem (Ulusoy et al., 1997; Erol et al., 2012):

(1) Sufficient buffer capacity for storing (un)finished jobs is ensured in each machine (Chaudhry et al., 2011). Adequate space for material storage areas is typically designated during the workshop layout-planning phase.

(2) The consideration of machine and vehicle malfunctions is omitted (Liu et al., 2013). Equipment malfunctions, often unpredictable and challenging to control, are generally treated as sudden events and dynamically accounted for.

(3) The processing and transportation durations cannot be interrupted (Kumar et al., 2011). In real production scenarios, many manufacturing processes run uninterruptedly. Interruptions can lead to decreased production efficiency, increased production costs, and potential resource wastage.

(4) The loading/unloading duration of vehicles is not considered(Homayouni and Fontes, 2021). The duration is usually short and relatively stable, constituting a secondary factor in this problem.

2.2.2 Decision Variables

For the mixed integer programming model of FJSP_PT, the definition of decision variables (Homayouni and Fontes, 2021) is as follows:

- X_{ji}^{m}: If operation O_{ji} is processed on the mth machine, then $X_{ji}^{m}=1$; otherwise, $X_{ji}^{m}=0$.
- $Y_{j_1i_1,j_2i_2}^{m}$: If the subsequent operation to $O_{j_1i_1}$ on the mth machine is $O_{j_2i_2}$, then $Y_{j_1i_1,j_2i_2}^{m}=1$; otherwise, $Y_{j_1i_1,j_2i_2}^{m}=0$.
- B_{ji}^{m}: If the operation O_{ji} is the first operation processed by the mth machine, then the binary variable B_{ji}^{m} is set to 1; otherwise, it is set to 0.
- L_{ji}^{m}: If the operation O_{ji} is the last operation processed by mth machine, then the binary variable is set to 1; otherwise, it is set to 0.
- U_{ji}: If the transportation task O_{ji} is the first task of a vehicle, then the binary variable is set to 1; otherwise, it is set to 0.
- R_{ji}: If the transportation task O_{ji} is the last task of a vehicle, then the binary variable is set to 1; otherwise, it is set to 0.
- $W_{j_1i_1,j_2i_2}^{k}$: If kth vehicle transports the operation $O_{j_1i_1}$ before $O_{j_2i_2}$, then $W_{j_1i_1,j_2i_2}^{k}=1$; otherwise, $W_{j_1i_1,j_2i_2}^{k}=0$.

where j, j_1 and j_2 are the job indexes; i, i_1 and i_2 are operation indexes; m is machine index; k is vehicle index, and O_{ji} represents the ith operaton of the jth job. Among these variables, U_{ji}, R_{ji}, and $W_{j_1i_1,j_2i_2}^{k}$ are the new decision variables not previously present in FJSP.

Remark 1 Soukhal et al. (2005) investigated two-machine flow job shop scheduling problems considering transportation constraints, explicitly accounting for both transportation capacity and times. The study analyzed the complexity of this class of problems, proving the strong **NP-hardness** of makespan optimization. With the consideration of transportation vehicles, the solution space complexity of FJSP_PT is at least $N_A^{N_O}$ times higher than that of traditional FJSP, where N_O represents the total number of operations for all jobs.

2.2.3 Generic constraints

We summarize the common constraints of FJSP_PT from previous literature as follows:

(1) Processing sequence constraint: The sequence of operations for each job must adhere to a specific technological route (Deroussi, 2014), like constraints (3) and (4). This constraint primarily stems from the inflexibility of altering the processing sequence of most jobs in actual production.

(2) Equipment utilization constraint: Machines and vehicles can handle only one job at a time(Kumar et al., 2011), like constraints (5) and (12).

(3) Job utilization constraint: Each job can only be present in a specific machine or vehicle at any time, like constraints (16) and (21).

(4) Equipment space constraint: Machines situated in different locations result in time consump-

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tion for vehicles traveling among them, like constraints (18) and (21). This constraint primarily arises from the layout of machines and limitations on vehicular movement space.

(5) Task logical constraint: Before each process is carried out, it needs to be transported to the designated machining machine by a vehicle, like constraints (16) and (21).

As shown in Appendix A, due to the transportation vehicles, constraints (12) - (21) are newly added or adjusted based on the FJSP model.

2.2.4 Objectives

There are numerous objectives in the existing literature regarding FJSP_PT for improving **efficiency** (about time), **stability** (about workload), or reducing **costs** (about energy). These objective functions include makespan, mean tardiness, total weight tardiness, total workload, workload balancing, total energy consumption, and mean flow time. From another perspective, various optimization objectives can also be classified as overall metrics, machine-specific metrics, and vehicle-specific metrics, as outlined in Table 2. Over 90% of the literature on single-objective FJSP_PT adopts makespan as the objective function.

For the multiobjective FJSP_PT, green production has increasingly attracted scholars' attention (Liu et al., 2019; Zhou and Liao, 2020) in recent years. FJSP_PT problems centered around green production typically aim to minimize total energy consumption as one optimization objective, while another objectives often involve enhancing production efficiency or workload balance (Zhou and Liao, 2020; Liu et al., 2019). Commonly, in multiobjective FJSP_PT, improvements in one objective value may negatively impact other objectives, making it more challenging than solving the single-objective problem.

2.3 Benchmark

The benchmark serves as a baseline for problem-solving and stands as a dependable standard for validating the effectiveness of algorithms. At present, there are several sets of benchmarks for FJSP_PT that are organized on the website `https://fastmanufacturingproject.wordpress.com/2019/04/11/fjspt-instances/`.

(1) Bilge set (Bilge and Ulusoy, 1995): The 82 instances are designed at different levels of the ratio $\bar{T}t/\bar{T}p$ of average traveling time $\bar{T}t$ to average processing time $\bar{T}p$, because a major parameter influencing the interaction of the vehicle and machine schedules is the relative magnitudes of the processing time and the traveling time.

(2) Deroussi set (Deroussi, 2014): The 10 instances are built by the 10 job sets and 4 layouts originally proposed in Bilge and Ulusoy (1995) and differ from the original ones in the sense that all machines have been duplicated. Thus, each operation can be performed in two alternative machines with the same processing time.

(3) Kumar set (Kumar et al., 2011): The 56 instances were created based on 7 job sets and 4 layouts designed by Bilge and Ulusoy (1995). Each instance in the first group has a $\bar{T}t/\bar{T}p$ ratio ≥ 0.25, whereas each instance in the second group has a $\bar{T}t/\bar{T}p$ ratio ≤ 0.25.

(4) Homayouni set1 (Homayouni et al., 2020): This dataset comprises 20 small- and medium-sized problem instances initially designed by Fattahi et al. (2007) for the flexible job shop scheduling problem, encompassing 2-12 distinct jobs, 4-48 operations, and 2-8 machines.

(5) Homayouni set2 (Homayouni et al., 2020): This dataset comprises 10 instances proposed by Brandimarte (1993), encompassing 55-240 operations, and 21 instances designed by Chambers and Barnes (1996), with the number of operations ranging from 100-225.

Overall, several scholars have proposed and utilized benchmarks for the FJSP_PT problem, covering various scales, $\bar{T}t$ and $\bar{T}p$.

Remark 2 The relative size of $\bar{T}t$ and $\bar{T}p$ has a significant impact on the characteristics of the FJSP_PT. When $\bar{T}t \gg \bar{T}p$, the processing time of operations can be ignored and the operations on which the machines are processed are no longer critical, except for the constraints of the machines' processing capabilities. FJSP_PT will degenerate to the vehicle routing problem. When $\bar{T}t \ll \bar{T}p$, FJSP_PT will degenerate to the traditional flexible job shop scheduling problem.

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Table 2 Description of objective functions

Type	Objective function	Interpretation	Reference
Overall metrics	Makespan	The time when all the jobs have been processed	Chetto et al. (1995); Bilge and Ulusoy (1995); Ulusoy et al. (1997); Gnanavel Babu et al. (2010)
	Mean flow time	The average time all the jobs spent in FMS	Reddy and Rao (2006); Anandaraman et al. (2012)
	Mean tardiness	The average difference between the completion time and the due date	Subbaiah et al. (2009); Anandaraman et al. (2012); Nageswararao et al. (2014)
	Total weighted tardiness or penalty cost	The weighted sum of the difference between the completion time and the due date	Poppenborg et al. (2012); Jerald et al. (2006)
	Total energy consumption	The energy consumption of all machines and vehicles	Liu et al. (2019); Wang et al. (2021); Xu et al. (2023); Xin et al. (2023a)
	Profit	The ratio of profits from completed jobs within a given time to all jobs	Yung et al. (2009)
Machine metrics	Total machine workload	The total working time among all machines	Liu et al. (2013)
	Balancing machine workload	The standard deviation of workload among all machines	Sawik (1996); Hoshino et al. (2008)
	Machine utilization	The ratio of total machine down time to total elapsed time	Jerald et al. (2006)
Vehicle metrics	Traveling time	The sum of nonloading and loading time of all vehicles	Yung et al. (2009)
	Distribution cost	The traveling energy-consumption cost and fixed cost of all AGVs used	Zou et al. (2021)
	Vehicle utilization rate	The ratio of traveling time to the elapsed time	Jerald et al. (2006)
	Total waiting time	The sum of waiting time for transportation tasks	Wang et al. (2022)
	Vehicle energy utilization	The total energy consumed by the vehicles	Yung et al. (2009)

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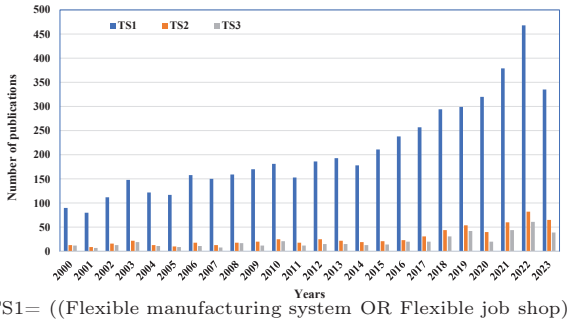
3 Literature reviews for FJSP_PT

3.1 Analyses of related publications

To gain a deeper understanding of the research progress in fields related to FJSP_PT, we set the words *flexible manufacturing system*, *flexible job shop*, *integrated*, *simultaneous*, *scheduling*, *automated guided vehicle*, *machine*, *transportation time*, and *handling time* as index keywords in the Web of Science database. A statistical analysis of publications from 2000 to 2023 is conducted to highlight recent trends and directions in research within this field, as shown in Fig. 3. The statistic results and analysis are as follows:

(1) As shown in Fig. 3, which is based on a topic search on three terms marked by TS1, TS2, TS3, the number of publications researching the FJSP_PT in flexible manufacturing systems increases steadily. However, compared with the whole research field of the flexible job shop scheduling problem, the research of this problem is relatively insufficient.



TS1= ((Flexible manufacturing system OR Flexible job shop) AND Scheduling) AND PY=Year
TS2= ((Flexible manufacturing system OR Flexible job shop) AND Scheduling AND (AGV OR Automated guided vehicle OR Handling)) AND PY=Year
TS3= ((Flexible Manufacturing System OR Flexible Job Shop) AND Scheduling AND (AGV OR Automated guided vehicle OR Handling) AND Machine) AND PY=Year

Fig. 3 Topic search results in Web of Science

(2) In total, nearly 100 publications have been analyzed, discussed, and synthesized until the present. *International Journal of Production Research*, *European Journal of Operational Re-*

search and *Computer & Industrial Engineering* published about 50% of the research articles.

(3) The proportion of publications with different methods to solve this problem is shown in Fig. 4. More than 60% of the publications focused on three approaches: neighborhood-based methods, genetic algorithms, and hybrid algorithms. The utilization of methods like artificial neural networks is comparatively low.

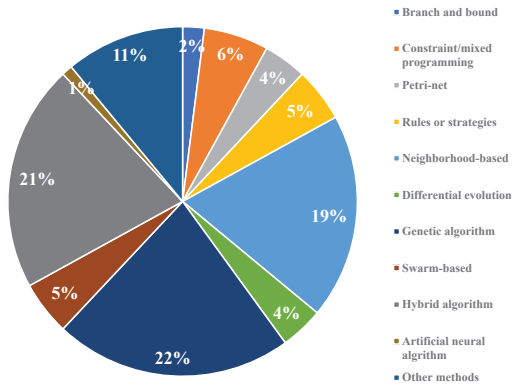


Fig. 4 Distribution of solving methods

3.2 Methods for FJSP_PT

Within this section, we have provided a brief review of the relevant studies on FJSP_PT, which have also been organized into Table A2 in Appendix B. The methodologies applied to FJSP_PT are classified into three categories, i.e., exact methods, heuristics, and meta-heuristics, and presented as shown in Fig. 5. The following section will introduce these methods in detail.

3.2.1 Exact methods

Lacomme et al. (2002) tackled the simultaneous job input sequencing and vehicle dispatching problems in FMS with a single AGV system using a branch and bound approach. Further, a discrete event simulation model evaluating the job sequence given instances is built in their subsequent research (Lacomme et al., 2005). Brucker et al. (2012) addressed cyclic job shop problems with a transport robot and blocking, and presented a superior integer programming formulation to minimize the cycle time. Chikhi et al. (2015) established a mixed-integer programming model for a two-stage robotic flow job shop scheduling problem to minimize makespan and solved it using CPLEX. Heger and Voss (2017) built a new mixed integer linear programming model for scheduling AGVs in a flexible reentrant job shop with blocking and tackled the model by GUROBI. Ham (2020) proposed two different constraint programming formulations for the first time for a flexible job shop scheduling problem with transports.

3.2.2 Heuristics

Lee and DiCesare (1993, 1994) modeled the centralized and distributed AGV system by Petri nets for global heuristic search. Later, Chetto et al. (1995) proposed a simulation-based approach to study a dynamic scheduling problem for evaluating different dynamic scheduling strategies such as short processing time, first comes first served and last came first served. Sawik (1996) presented a multilevel decision model, utilizing a bicriterion integer formulation for upper-level machine loading and part routing, and a period-by-period heuristic at the lower level. Abdelmaguid and Nassef (2010) developed a constructive heuristic based on Giffler and Thompson's algorithm and integrated different dispatching rules into the heuristic for minimizing makespan. Zeng and Tang (2014) proposed two integer nonlinear programming models and a two-stage heuristic algorithm incorporating the timetabling method and local search, which utilized a disjunctive graph model and feasibility principles for solving the blocking job shop problem with AGVs.

Baruwa and Piera (2016) used a timed colored Petri net (TCPN) approach for minimizing makespan and exit time objectives. The TCPN model enabled the evaluation of all feasible vehicle assignments, demonstrating the benefits of vehicle-controlled assignments in certain scenarios. Tabatabaei et al. (2018) focused on both offline and dynamic scheduling problems, developing a heuristic scheduler in MATLAB. The methodology involved applying the time frame to offline problems, producing dynamic scheduling scenarios, and mathematically modeling constraints and limitations.

Babu et al. (2018) employed the Nawaz-Enscore-Ham heuristic algorithm, analyzing 82 problems with the existing solutions for minimization of the makespan. Zheng et al. (2018) proposed a hormone regulation-based approach for online schedul-

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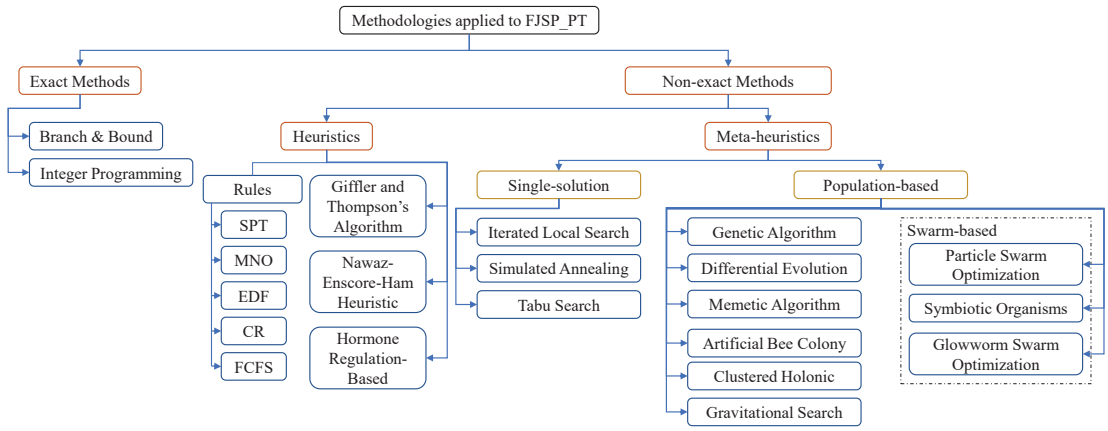

Fig. 5 Overview of research methods in FJSP_PT

ing of machines and AGVs within a distributed system for assigning emergent tasks and generating feasible schedules, demonstrating improved scheduling quality compared to existing methods in realtime environments. Tang et al. (2020) proposed a hormone regulation-based approach for online scheduling of machines and AGVs in a distributed system. The method assigned emergent tasks and generated feasible schedules using a task-allocation approach based on hormonal regulation.

3.2.3 Meta-heuristics

For the single-solution meta-heuristics, Ulusoy and Bilge (1993) proposed an iterative heuristic procedure where makespan is the performance criterion. Then, they built a nonlinear mixed integer programming model, and an iterative procedure was developed using the sliding time window method (Bilge and Ulusoy, 1995). Deroussi et al. (2006) combined the metaheuristic optimization and the discrete event simulation to efficiently handle algorithmic and structural complexity. Further, Deroussi et al. (2008) implemented an efficient neighboring system into iterated local search, simulated annealing and their hybridization and demonstrated the effectiveness of the approach. Chen et al. (2007) formulated the scheduling problem in a container terminal as a hybrid flow job shop scheduling problem with precedence and blocking constraints with the objective of minimizing makespan, and proposed a tabu search algorithm with developed mechanisms to ensure quality and efficiency. Poppenborg et al. (2012) addressed online scheduling in a flexible job shop with blocking, aiming to minimize total weighted tardiness, utilizing a mixed integer programming formulation for offline scenarios and an online tabu search algorithm. Elmi and Topaloglu (2013) addressed the robotic scheduling problem in blocking hybrid flow shop cells with multiple part types, unrelated parallel machines, robots, and machine eligibility constraints. They proposed a mixed integer linear programming model and developed a simulated annealing approach for minimizing makespan. Zheng et al. (2014) proposed a tabu search heuristic algorithm, featuring a two-dimensional solution representation and an innovative neighbor solution generation, to optimize makespan. Aldaihani (2015) proposed a tabu search and a greedy insertion algorithm for solving the scheduling problem in flexible manufacturing cells with nonidentical machines, a robot, and pallet handling.

As a highly popular and classic evolutionary optimization algorithm, GAs have been widely applied to solve this problem. Ulusoy et al. (1997) addressed the simultaneous scheduling of machines and identical AGVs in a flexible manufacturing system, minimizing makespan through a GA that utilizes chromosomes to represent operation sequencing and AGV assignment dimensions, incorporating a special uniform crossover operator and mutation operators. Abdelmaguid et al. (2004) introduced a new GA with a heuristic coding scheme, combining it with selected GA operators from scheduling literature. Reddy and Rao (2006) utilized GA based on the non-dominated sorting method and the crowding distance to minimize makespan, mean flow time, and mean tardiness

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objectives, recognizing the complexity of conflicting objectives in scheduling. Jerald et al. (2006) proposed an adaptive GA to minimize the penalty cost and machine idle time. Lv et al. (2011) proposed a mathematic model based on a specific FMS with a single AGV and a single buffer area and validated it using GA with appropriate parameters. Chaudhry et al. (2011) proposed a spreadsheet-based GA to solve the problem. A domain independent general purpose GA was used, which was an add-in to the spreadsheet software. An adaptation of the proprietary GA software was demonstrated to the problem of minimizing makespan.

Mostafa et al. (2012) introduced a job-based GA for AGV scheduling, enhancing it with a fuzzy logic controller to control GA operators (crossover and mutation rates) during optimization. Tuma et al. (2013) explored hybridizing a GA with tabu search to potentially achieve improved results in reactive scheduling production and examined a new GA chromosome structure with a higher correlation to the makespan. Sanches et al. (2015) proposed the use of an adaptive GA for production scheduling in FMS to minimize makespan with low running time. Zeng et al. (2015) proposed a two-stage heuristic algorithm, including a local search combined GA and a heuristic algorithm for lower makespan to solve part-scheduling problems. Umar et al. (2015) proposed a hybrid GA to optimize makespan, AGV travelling time, and penalty cost, incorporating a multiobjective fitness function with adaptive weight assignment and fuzzy expert system control of genetic operators. Lin et al. (2015) proposed a simulation optimization method and used discrete event simulation, and integrated computing budget allocation with GA for computational efficiency.

Nouri et al. (2016b,c,d, 2018) proposed a hybrid metaheuristic using a clustered holonic multiagent model, employing a neighborhood-based GA for global exploration and tabu search by cluster agents for targeted exploration. Considering the interruptions for multiple transports, Dang and Nguyen (2016) proposed a heuristic approach based on GAs to minimize the makespan. Dang and Nguyen (2016) addressed the efficient utilization of mobile robots in modern manufacturing environments and proposed a heuristic approach based on GAs to minimize the makespan. In their subsequent research, an adaptive large neighborhood search algorithm incorporating exploration/exploitation heuristics (Dang et al., 2019b) and a hybrid heuristic method combining GA and tabu search (Dang et al., 2019a) are proposed one after another.

Zhu and He (2019) proposed a novel GA to optimize production schedules and minimize makespan in manufacturing systems with shared resources. Wang and Xin (2019) tackled the flexible flow job shop scheduling problem with parallel machines and introduced a GA with efficient coding, decoding schemes, crossover and mutation operators. Kumar et al. (2019) employed two heuristics, namely priority dispatching rules and modified GA with a three-parent crossover to optimize the integrated scheduling problem. Gu et al. (2020) utilized a bio-inspired scheduling optimization approach inspired by the endocrine system's hormone secretion principle. Homayouni et al. (2020) proposed an operation-based multistart biased random key GA with greedy heuristics for efficient solution generation. Wang et al. (2021) proposed a multiobjective flexible job shop scheduling model optimizing total energy consumption and makespan. To solve this problem, they introduced a multiregion division sampling strategy-based multiobjective optimization algorithm integrated with a GA and a differential evolution algorithm. Chaudhry et al. (2022) introduced a solution using Microsoft Excel spreadsheet, utilizing the EvolverÂő proprietary GA for optimization. The model determines the simultaneous assignment of operations to alternative machines, sequences operations on each machine, and assigns transportation operations between machines to available AGVs. He et al. (2022) proposed a novel memetic algorithm combining GA and variable neighborhood search to handle dynamic events and obtain a new scheduling plan.

For the other population-based meta-heuristics, Gnanavel Babu et al. (2010) used a tackled new meta-heuristic differential evolution algorithm to solve the simultaneous scheduling of machines and two identical AGVs. Kumar et al. (2011) employed differential evolution, incorporating a machine selection heuristic and a vehicle assignment heuristic to minimize makespan by efficiently assigning tasks to machines and vehicles. Lacomme et al. (2013) introduced a framework based on a disjunctive graph for modeling the scheduling problem and applied a memetic algorithm to minimize makespan.

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Nageswararao et al. proposed a hybrid metaheuristic algorithm implemented in JAVA (Nageswararao et al., 2015) and gravitational search algorithm (Nageswararao et al., 2017), aiming to optimize the sequence, relative makespan, and AGVs schedule, demonstrating enhanced productivity, minimized delivery cost, and optimal fleet utilization compared to other algorithms. To maximize customer satisfaction while minimizing distribution costs, Zou et al. (2021) formulated a multiobjective mixed integer linear programming model and developed an effective multiobjective evolutionary algorithm. The algorithm included a constructive heuristic for population initialization, a multiobjective local search for exploitation, a novel two-point crossover operator to utilize non-dominated solutions, and a restart strategy to prevent local optima.

He et al. (2022) proposed an effective multiobjective evolutionary algorithm aimed to minimize makespan, total idle time of machines, and total energy consumption of both machines and AGVs. The algorithm incorporated an efficient encoding/decoding method, a new crossover operator, and an opposition-based learning strategy for balancing exploration and exploitation. Wang et al. (2022) developed a novel multi-state scheduling algorithm enhanced by a neural network-based travel time prediction for optimization of the AGV utilization rate and total processing makespan. The algorithm schedules more AGVs and tasks in each calculation, moving closer to global optimization. Xu et al. (2023) tackled the multiobjective green scheduling problem in integrated flexible job shops and automated guided vehicles. They introduced a multiobjective mixed-integer programming model, and proposed an efficient heuristic algorithm with population initialization method balancing the processing time and energy consumption. Xin et al. (2023a) proposed a genetic programming algorithm to evolve scheduling strategies to solve the dynamic large-scale collaboration problem for processing machines and AGVs in FMS and the evolved strategies had better adaptability and scalability for various scenarios.

3.2.4 Swarm intelligent methods

To minimize the makespan and total workload of machines, Liu et al. (2013) proposed a multiobjective micro artificial bee colony algorithm (MMABC) to tackle this problem, in which each solution corresponds to a food source and the bee population is divided in two parts: a replaceable bee part and a non-replaceable bee part. Nageswararao et al. (2014) proposed the binary particle swarm vehicle heuristic algorithm focusing on minimizing mean tardiness and improving solution quality. Deroussi (2014) investigated the hybridization of particle swarm optimization (PSO) with stochastic local search to experimentally determine the optimal balance between PSO's exploration ability and local search's exploitation ability, revealing that local search significantly enhances the basic PSO algorithm. Reddy and Reddy (2017) introduced the symbiotic organisms search algorithm for simultaneous scheduling of machines and AGVs in FMS to minimize makespan, demonstrating its effectiveness through comparisons with existing methods.

Hemmati et al. (2018) addressed a flexible cell scheduling problem considering time-of-use electricity tariffs and incorporating energy-conscious policies, setup time constraints, and part defect percentages. They employed an ant colony optimization (ACO) algorithm to minimize the total cost and introduced two hybrid algorithms (hybrid GA and hybrid ACO) for improved results. Liu et al. (2019) formulated a mixed-integer programming model considering comprehensive energy efficiency. An integrated GA-GSO-GTHS algorithm, combining GA, glowworm swarm optimization (GSO), and green transport heuristic strategy (GTHS), was proposed for and efficient solution. Zhou and Liao (2020) focused on the flexible job shop greening scheduling problem with crane transportation and introduced the efficient hybrid algorithm combining particle filter and Levy flight with decomposed multiobjective evolution and particle swarm optimization. Chen et al. (2022) established a dual-resource integrated scheduling optimization model with the objective of minimizing makespan. They introduced a hybrid discrete PSO algorithm, incorporating competitive learning and a random restart mechanism to mitigate premature maturation issues. From the path-related and operation-related nature of FJSP_PT, Xin et al. (2023b) employed a hybrid method combining two model-based algorithms, estimation of distribution algorithm and ACO algorithm, to solve the problem. Amirteimoori and Kia (2023) proposed a mixed-integer linear programming model and a

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parallel hybrid PSO-GA algorithm. The novel metaheuristic is designed for parallel computing, showcasing reduced run time.

3.3 Real-world applications

Although FJSP_PT has been extensively studied, the practical application of these research methods is relatively limited. Dai et al. (2019) developed an enhanced genetic algorithm in terms of the makespan and the total energy consumption and introduced a real-world case from a flexible workshop with several AGVs in Nanjing to demonstrate the effectiveness of the proposed algorithm. Among the Pareto solutions obtained, the most satisfying energy-efficient solution will shut down the machine with larger rate power and unload power. He et al. (2022) proposed a multiobjective scheduling model that considers sequence-dependent setup to simultaneously minimize the makespan, total idle time of machines, and total energy consumption, and developed an effective multiobjective evolutionary algorithm. A real-world intelligent manufacturing workshop integrated with AGVs for producing the components of security monitoring robots at a Chinese company was used to test the proposed algorithm. Xin et al. (2023b) proposed a hybrid algorithm combining ACO and the estimation of distribution algorithm from different problem perspectives. To validate the effectiveness, a practical case study was carried out in a hardware workshop covering a series of processes including lathing, planing, milling, cutting, bending, polishing, drilling, and spraying in the southern region of China.

4 Research status, trends, and future challenges

4.1 Research status

Based on the above content, it can be concluded that the research on the FJSP_PT problem is relatively comprehensive, but the following statuses and gaps still need to be noted.

(1) From the perspective of **problem modeling**, numerous scholars have proposed various modeling methods for different FJSP_PT problems based on different practical situations. However, most scheduling problems currently have too many assumptions. Sometimes, these assumptions can simplify problem complexity and even change the nature of the problem, e.g., when there are a sufficient number of transportation vehicles. In addition, the constraint-handling is relatively simple, and scheduling objective functions mainly focus on minimizing completion time. Optimization objectives for each scheduling entity are considered relatively less.

(2) From the perspective of **solution methods**, a wide range of solution methods has been proposed, from exact algorithms such as branch and bound to hybrid evolutionary algorithms. However, most algorithms currently are designed based on further adaptation and improvement of FJSP solving algorithms, lacking in-depth analysis of problem characteristics and operator design based on problem features. Furthermore, currently, the majority of solving methods are relatively classical. Approaches such as neural networks and reinforcement learning are less commonly designed and utilized.

(3) From the perspective of **experimental design**, several sets of instances have been proposed. The differences among these instances primarily manifest in scale, lacking specialized design for different values of key problem parameters. However, these values such as the processing time and energy consumption of processing machines and transportation vehicles in flexible manufacturing systems may be different significantly. The magnitude of this difference (e.g., $\bar{T}t/\bar{T}p$) is highly likely to affect the solution effectiveness of algorithms. Therefore, there is an urgent need to enrich the test instances.

(4) From the perspective of **practical application**, FJSP_PT is widely present in industries such as manufacturing and logistics management, and many solving methods have been proposed. However, they have not yet been widely applied in practice. To some extent, the scheduling of processing machines and transportation equipment depends on the workshop-production management mode. The practical application of algorithms requires scholars to consider more comprehensive and detailed factors in problem modeling. In some cases, it may even require integration with methods such as data mining and big data technology to ensure the effectiveness and robustness of algorithms in addressing practical problems.

In addition, the implementation of these approaches also imposes the following additional demands on workshop management: (a) Coordination: Ensuring

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coordinated operation between machines and vehicles to maximize the smoothness of manufacturing systems. (b) Real-time monitoring: It is essential to monitor the production process and equipment status, including vehicle battery level, in real-time, promptly adjusting scheduling strategies to respond to unforeseen circumstances. (c) Safety: Ensuring that scheduling schemes comply with safety standards to avoid equipment conflicts, material accumulation, or other safety risks. (d) Data support: Establishing a comprehensive data collection and analysis system to enable decision-making and optimize scheduling based on accurate production data.

4.2 Research trend

In future research on FJSP_PT, the following trends are worth paying attention to:

(1) **Small scale to large scale:** With the diversification of market demand and the flexibility improvement of processing machines, the factory scale and order scale will increase significantly. Therefore, the scheduling problem with more processing machines and more jobs is of practical significance. Due to the advantages of low cost, high reliability and high efficiency during operating, more and more intelligent vehicles like AGVs will be widely applied to intelligent workshop. The integrated scheduling problem with large-scale transport vehicles also needs to be paid attention to.

(2) **Centralized to distributed:** In the future, the machines will possess more powerful perception, communication and computing capabilities, which make the distributed collaboration possible. The distributed collaboration among machines can reduce the dependence on the centralized control and bring stronger scalability and robustness. Besides, the local communication during distributed collaboration requires a lower bandwidth and less computing resources than centralized scheduling. The distributed collaboration also does well in dealing with local conflicts, such as vehicle fault or the temporary changes of orders. The above advantages will be more obvious in large-scale integrated scheduling problems.

(3) **Single-objective to multiple-objective:** Most of the production problems can hardly be evaluated by only one objective. To achieve low-carbon and green production, a scheduling scheme considering both economic and social benefits needs to be made. Therefore, the multiobjective FJSP_PT needs to be studied. Besides, the integrated scheduling problem for machines and vehicles may be optimized based on the two kinds of objectives, such as minimizing the total workload for machines and minimizing the movement time for vehicles, respectively. Due to the coupling between the processing and transport stages, the integrated scheduling problem needs to be solved to improve their objectives simultaneously.

(4) **Certain to uncertain:** Many uncertain factors and events exist widely in the actual manufacturing system, such as inaccurate processing time of machines, an urgent order, and even the sudden failure of a vehicle. An efficient scheduling system must be able to make a rapid and accurate response to these uncertain factors and events, so as to ensure the smooth production by adjusting the production plan quickly.

4.3 Future challenges

With further research on the problem, the following difficulties and challenges may be encountered in the solving process.

(1) **Large-scale FJSP_PT:** Because FJSP_PT is NP-hard, the difficulty of solving this problem increases sharply with the problem scale. Exact algorithms and some swarm intelligence optimization algorithms can hardly find an acceptable solution in tolerable time. More efficient algorithms need to be designed. Further, some specific conditions which hardly occur in small-scale FJSP_PT may no longer be ignored. For example, the vehicle-congestion problem in large-scale cases will significantly affect the operation efficiency of the workshop. From the aspects of problem characteristics and algorithm feasibility, the large-scale integrated scheduling problem needs to be re-examined.

(2) **FJSP_PT with complex constraints:** In FJSP_PT, due to the strong dependency on vehicles, the influence and constraint relationships among different machines and even the workshop environment become more complex. For example, the operation sequencing of machines may be sensitive to the result of task assignment and path planning of vehicles, not to mention that the arrival of jobs for each machine may be affected by many dynamic factors such as

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vehicle failures, capacity loss, and traffic congestion. Obviously, the dependence implied in the processing-transport two-phase flow must be well handled before a feasible and even robust schedule can be made. From another viewpoint, the problem knowledge brought by constraints can also be used in the generation of a desirable and even optimal schedule.

(3) **Dynamic FJSP_PT:** In a complex workshop environment, many dynamic factors exist, such as vehicle failure, order change and so on. Due to the obvious differences in the type, frequency and mode of their influences on production, these factors usually need different mechanisms and methods to handle, such as the task reassignment and path re-planning for vehicles failures and the local rescheduling for order change. Generally, fast and accurate response is the basic requirement for dynamic processes, which creates the demands on anytime algorithms being able to provide satisfactory solutions in real-time. The stability of re-scheduling is also a necessity for the safety and smoothness of production.

(4) **Multi-objective FJSP_PT:** At present, the scheduling strategies for multiobjective optimization problems remain very challenging. The selection of appropriate objectives with diverse demands from production efficiency, safety, and comprehensive cost is still a crucial issue for FJSP_PT modeling, especially under the worldwide appeal of reducing carbon emission. Obviously, the intelligent and flexible scheduling in FJSP_PT relies on a well-balanced decision-making about multiple objectives from various aspects as well as the coordination of the local objectives about the operations of machines and vehicles.

Contributors

Sai LU designed the research, processed the data, and drafted the manuscript. Bin XIN, Qing WANG, and Fang DENG helped organize the manuscript. Sai LU revised and finalized the paper.

Conflict of interest

All the authors declare that they have no conflict of interest.

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References

Abdelmaguid TF, Nassef AO, 2010. A constructive heuristic for the integrated scheduling of machines and multiple-load material handling equipment in job shops. *Int J Adv Manuf Technol*, 46(9-12):1239-1251. https://doi.org/10.1007/s00170-009-2176-7

Abdelmaguid TF, Nassef AO, Kamal BA, et al., 2004. A hybrid ga/heuristic approach to the simultaneous scheduling of machines and automated guided vehicles. *Int J Prod Res*, 42(2):267-281. https://doi.org/10.1080/0020754032000123579

Aldaihani MM, 2015. Scheduling methodologies for a flexible manufacturing cell with non-identical parallel machines and a robot. *Int J Ind Syst Eng*, 21(4):499-514. https://doi.org/10.1504/IJISE.2015.072730

Amirteimoori A, Kia R, 2023. Concurrent scheduling of jobs and agvs in a flexible job shop system: a parallel hybrid pso-ga meta-heuristic. *Flex Serv Manuf J*, 35(3):727-753. https://doi.org/10.1007/s10696-022-09453-y

Anandaraman C, Vikram A, Sankar M, et al., 2012. Evolutionary approaches for scheduling a flexible manufacturing system with automated guided vehicles and robots. *Int J Ind Eng Comput*, 3(4):627-648. https://doi.org/10.5267/j.ijiec.2012.03.004

Babu K, Babu V, Medikondu N, 2018. Implementation of heuristic algorithms to synchronized planning of machines and agvs in fms. *Manage Sci Lett*, 8(6):543-554. https://doi.org/10.5267/j.msl.2018.5.001

Balogun O, Popplewell K, 1999. Towards the integration of flexible manufacturing system scheduling. *Int J Prod Res*, 37(15):3399-3428. https://doi.org/10.1080/002075499190112

Baruwa OT, Piera MA, 2016. A coloured petri net-based hybrid heuristic search approach to simultaneous scheduling of machines and automated guided vehicles. *Int J Prod Res*, 54(16):4773-4792. https://doi.org/10.1080/00207543.2015.1087656

Bilge Ü, Ulusoy G, 1995. A time window approach to simultaneous scheduling of machines and material handling system in an fms. *Oper Res*, 43(6):1058-1070. https://doi.org/10.1287/opre.43.6.1058

Brandimarte P, 1993. Routing and scheduling in a flexible job shop by tabu search. *Ann Oper Res*, 41(3):157-183. https://doi.org/10.1007/BF02023073

Brucker P, Burke EK, Groenemeyer S, 2012. A mixed integer programming model for the cyclic job-shop problem with transportation. *Discrete Appl Math*, 160(13-14):1924-1935. https://doi.org/10.1016/j.dam.2012.04.001

Chambers JB, Barnes JW, 1996. New tabu ssearch results for the job shop scheduling problem. *The University of Texas, Austin, Technical Report Series ORP96-06, Graduate Program in Operations Research and Industrial Engineering*, :1-20.

Chan FT, Chan HK, 2004. A comprehensive survey and future trend of simulation study on fms scheduling. *J Intell Manuf*, 15(1):87-102. https://doi.org/10.1023/B:JIMS.0000010077.27141.be

Chaudhry IA, Mahmood S, Shami M, 2011. Simultaneous scheduling of machines and automated guided vehicles in flexible manufacturing systems using genetic algorithms. *J Central South Univ*, 18(5):1473-1486. https://doi.org/10.1007/s11771-011-0863-7

Chaudhry IA, Rafique AF, Elbadawi IAQ, et al., 2022. Integrated scheduling of machines and automated guided vehicles (agvs) in flexible job shop environment using genetic algorithms. *Int J Ind Eng Comput*, 13(3):343-362. https://doi.org/10.5267/j.ijiec.2022.2.002

Chen J, Zhang Sy, Gao Z, et al., 2010. Feature-based initial population generation for the optimization of job shop problems. *J Zhejiang Univ SCI C (Front Inf Technol Electron Eng)*, 11(10):767-777. https://doi.org/10.1631/jzus.C0910707

Chen K, Bi L, Wang W, 2022. Research on integrated scheduling of agv and machine in flexible job shop. *J Syst Simul*, 34(3):461-469. https://doi.org/10.16182/j.issn1004731x.joss.20-0796

Chen L, Bostel N, Dejax P, et al., 2007. A tabu search algorithm for the integrated scheduling problem of container handling systems in a maritime terminal. *Eur J Oper Res*, 181(1):40-58. https://doi.org/10.1016/j.ejor.2006.06.033

Chetto H, Castagna P, Plot C, 1995. Performance evaluation of dynamic scheduling strategies for manufacturing systems. *IFAC Proc Vol*, 28(10):347-352. https://doi.org/10.1016/S1474-6670(17)51542-6

Chikhi N, Abbas M, Benmansour R, et al., 2015. A two-stage flow shop scheduling problem with transportation considerations. *4OR*, 13(4):381-402. https://doi.org/10.1007/s10288-015-0297-4

Dai M, Tang DB, Adriana G, et al., 2019. Multi-objective optimization for energy-efficient flexible job shop scheduling problem with transportation constraints. *Rob Comput Integr Manuf*, 59:143-157. https://doi.org/10.1016/j.rcim.2019.04.006

Dang QV, Nguyen L, 2016. A heuristic approach to schedule mobile robots in flexible manufacturing environments. *Procedia CIRP*, 40:390-395. https://doi.org/10.1016/j.procir.2016.01.073

Dang QV, Nguyen CT, Rudová H, 2019a. Scheduling of mobile robots for transportation and manufacturing tasks. *J Heuristics*, 25(2):175-213. https://doi.org/10.1007/s10732-018-9391-z

Dang QV, Rudová H, Nguyen CT, 2019b. Adaptive large neighborhood search for scheduling of mobile robots. Proc Genetic and Evolutionary Computation Conf, p.224-232. https://doi.org/10.1145/3321707.3321764

Deroussi L, Gourgand M, Tchernev N, 2006. Combining optimization methods and discrete event simulation: A case study in flexible manufacturing systems. Proc Int Conf on Service Systems and Service Management, p.495-500. https://doi.org/10.1109/ICSSSM.2006.320512

Deroussi L, Gourgand M, Tchernev N, 2008. A simple metaheuristic approach to the simultaneous scheduling of machines and automated guided vehicles. *Int J Prod Res*, 46(8):2143-2164. https://doi.org/10.1080/00207540600818286

Deroussi L, 2014. A hybrid pso applied to the flexible job shop with transport. Proc 1st Int Conf on Swarm Intelligence Based Optimization, 8472:115-122.

Elmi A, Topaloglu S, 2013. A scheduling problem in blocking hybrid flow shop robotic cells with multiple robots. *Comput Oper Res*, 40(10):2543-2555. https://doi.org/10.1016/j.cor.2013.01.024

Erol R, Sahin C, Baykasoglu A, et al., 2012. A multi-agent based approach to dynamic scheduling of machines and automated guided vehicles in manufacturing systems. *Appl Soft Comput*, 12(6):1720-1732. https://doi.org/10.1016/j.asoc.2012.02.001

Fattahi P, Saidi MM, Jolai F, 2007. Mathematical modeling and heuristic approaches to flexible job shop scheduling problems. *J Intell Manuf*, 18:331-342. https://doi.org/10.1007/s10845-007-0026-8

Fazlollahtabar H, Saidi MM, 2015. Methodologies to optimize automated guided vehicle scheduling and routing problems: a review study. *J Intell Rob Syst*, 77(3):525-545. https://doi.org/10.1007/s10846-013-0003-8

Gao KZ, Cao ZG, Zhang L, et al., 2019. A review on swarm intelligence and evolutionary algorithms for solving flexible job shop scheduling problems. *IEEE/CAA J Autom Sin*, 6(4):904-916. https://doi.org/10.1109/JAS.2019.1911540

Gnanavel Babu A, Jerald J, Noorul Haq A, et al., 2010. Scheduling of machines and automated guided vehicles in fms using differential evolution. *Int J Prod Res*, 48(16):4683-4699. https://doi.org/10.1080/00207540903049407

Godinho Filho M, Barco CF, Tavares Neto RF, 2014. Using genetic algorithms to solve scheduling problems on flexible manufacturing systems (fms): a literature survey, classification and analysis. *Flex Serv Manuf J*, 26(3):408-431. https://doi.org/10.1007/s10696-012-9143-6

Gu WB, Li YX, Zheng K, et al., 2020. A bio-inspired scheduling approach for machines and automated guided vehicles in flexible manufacturing system using hormone secretion principle. *Adv Mech Eng*, 12(2):1-17. https://doi.org/10.1177/1687814020907787

Gu WN, Li YX, Li Z, et al., 2019. An intelligent approach for dynamic agv scheduling problem in the discrete manufacturing system. Proc IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conf, p.1736-1739. https://doi.org/10.1109/ITNEC.2019.8729029

Gupta YP, Gupta MC, Bector C, 1989. A review of scheduling rules in flexible manufacturing systems. *Int J Comput Integr Manuf*, 2(6):356-377. https://doi.org/10.1080/09511928908944424

Ham A, 2020. Transfer-robot task scheduling in flexible job shop. *J Intell Manuf*, 31(7):1783-1793. https://doi.org/10.1007/s10845-020-01537-6

He LJ, Chiong R, Li WF, et al., 2022. A multiobjective evolutionary algorithm for achieving energy efficiency in production environments integrated with multiple automated guided vehicles. *Knowl-Based Syst*, 243:108315. https://doi.org/10.1016/j.knosys.2022.108315

Unedited

He YA, Xia MH, 2021. Research on mass personalization production model based on the industry 4.0. *Manuf Autom*, 43(01):25-29(in Chinese).
https://doi.org/10.3969/j.issn.1009-0134.2021.01.007

He YM, Xin B, Lu S, et al., 2022. Memetic algorithm for dynamic joint flexible job shop scheduling with machines and transportation robots. *JACIII*, 26(6):974-982.
https://doi.org/10.20965/jaciii.2022.p0974

Heger J, Voss T, 2017. Optimal scheduling for automated guided vehicles (agv) in blocking job-shops. Proc IFIP Int Conf on Advances in Production Management Systems, p.151-158.
https://doi.org/10.1007/978-3-319-66923-6_18

Hemmati FM, Haleh H, Saghaei A, 2018. A flexible cell scheduling problem with automated guided vehicles and robots under energy-conscious policy. *Sci Iran*, 25(1):339-358.
https://doi.org/10.24200/SCI.2017.4399

Homayouni SM, Fontes DB, Gonçalves JF, 2020. A multi-start biased random key genetic algorithm for the flexible job shop scheduling problem with transportation. *Int Trans Oper Res*, 30(2):688-716.
https://doi.org/10.1111/itor.12878

Homayouni SM, Fontes DB, 2021. Production and transport scheduling in flexible job shop manufacturing systems. *J Glob Optim*, 79(2):463-502.
https://doi.org/10.1007/s10898-021-00992-6

Hoshino S, Seki H, Naka Y, 2008. Development of a flexible and agile multi-robot manufacturing system. *IFAC Proc Vol*, 41(2):15786-15791.
https://doi.org/10.3182/20080706-5-KR-1001.02669

Jerald J, Asokan P, Saravanan R, et al., 2006. Simultaneous scheduling of parts and automated guided vehicles in an fms environment using adaptive genetic algorithm. *Int J Adv Manuf Technol*, 29:584-589.
https://doi.org/10.1007/s00170-005-2529-9

Kumar MVS, Janardhana R, Rao CSP, 2011. Simultaneous scheduling of machines and vehicles in an fms environment with alternative routing. *Int J Adv Manuf Technol*, 53(1):339-351.
https://doi.org/10.1007/s00170-010-2820-2

Kumar N, Chandna P, Joshi D, 2019. Integrated scheduling of part, tool and automated guided vehicles in a flexible manufacturing system using modified genetic algorithm. *Int J Ind Syst Eng*, 32(4):443-468.
https://doi.org/10.1504/IJISE.2019.101332

Lacomme P, Moukrim A, Tchernev N, 2002. A new lower bound for scheduling of fms based on agv material handling. 35(1):217-222.
https://doi.org/10.3182/20020721-6-ES-1901.00038

Lacomme P, Moukrim A, Tchernev N, 2005. Simultaneous job input sequencing and vehicle dispatching in a single-vehicle automated guided vehicle system: a heuristic branch-and-bound approach coupled with a discrete events simulation model. *Int J Prod Res*, 43(9):1911-1942.
https://doi.org/10.1080/13528160412331326450

Lacomme P, Larabi M, Tchernev N, 2013. Job-shop based framework for simultaneous scheduling of machines and automated guided vehicles. *Int J Prod Econom*, 143(1):24-34.
https://doi.org/10.1016/j.ijpe.2010.07.012

Lee DY, DiCesare F, 1993. Integrated models for scheduling flexible manufacturing systems. Proc IEEE Int Conf on Robotics and Automation, p.827-832.
https://doi.org/10.1109/ROBOT.1993.292247

Lee DY, DiCesare F, 1994. Integrated scheduling of flexible manufacturing systems employing automated guided vehicles. *IEEE Trans Ind Electron*, 41(6):602-610.
https://doi.org/10.1109/41.334577

Lin JT, Chiu CC, Chang YH, et al., 2015. A hybrid genetic algorithm for simultaneous scheduling of machines and AGVs in FMS. In: Gen M, Kim KJ, Huang XX (Eds.), Industrial Engineering, Management Science and Applications 2015.

Liu ZC, Guo SS, Wang L, 2019. Integrated green scheduling optimization of flexible job shop and crane transportation considering comprehensive energy consumption. *J Cleaner Prod*, 211:765-786.
https://doi.org/10.1016/j.jclepro.2018.11.231

Liu ZC, Ma S, Shi Y, et al., 2013. Solving multi-objective flexible job shop scheduling with transportation constraints using a micro artificial bee colony algorithm. Proc IEEE 17th Int Conf on Computer Supported Cooperative Work in Design, p.427-432.
https://doi.org/10.1109/CSCWD.2013.6581001

Lv YL, Zhang G, Zhang J, et al., 2011. Integrated scheduling of the job and agv for flexible manufacturing system. Appl Mech Mater, 80–81:1335-1339.
https://doi.org/10.4028/www.scientific.net/AMM.80-81.1335

Mishra A, Dash A, Bishoyee N, et al., 2009. Simultaneous scheduling of machines and agvs in fms environment using swarm optimization and comparison with genetic algorithm. Proc POMS 20th Annual Conf, p.172-181.

Mostafa B, Shamsuddin BS, Mohd K, 2012. Performance optimization of simultaneous machine and automated guided vehicle scheduling using fuzzy logic controller based genetic algorithm. *Int J Phys Sci*, 7(9):1461-1471.
https://doi.org/10.5897/IJPS11.407

Nageswararao M, Narayanarao K, Ranagajanardhana G, 2015. Hybrid meta heuristic algorithm for simultaneous scheduling of machines and agvs in flexible manufacturing environment. *Can J Basic Appl Sci*, 3(2):29-44.

Nageswararao M, Narayanarao K, Ranga G, 2017. Integrated scheduling of machines and agvs in fms by using dispatching rules. *J Prod Eng*, 20(1):75-84.
https://doi.org/10.24867/JPE-2017-01-075

Nageswararao M, Narayanarao K, Ranagajanardhana G, 2014. Simultaneous scheduling of machines and agvs in flexible manufacturing system with minimization of tardiness criterion. *Procedia Mater Sci*, 5:1492-1501.
https://doi.org/10.1016/j.mspro.2014.07.336

Nageswararao M, Narayanarao K, Rangajanardhana G, 2017. Scheduling of machines and automated guided vehicles in fms using gravitational search algorithm. Appl Mech Mater, 867:307-313.
https://doi.org/10.4028/www.scientific.net/AMM.867.307

Nouri HE, Driss OB, Ghédira K, 2016a. A classification schema for the job shop scheduling problem with transportation resources: state-of-the-art review. Springer, Cham.
https://doi.org/10.1007/978-3-319-33625-1_1

Unedited

Nouri HE, Driss OB, Ghédira K, 2016b. Hybrid metaheuristics for scheduling of machines and transport robots in job shop environment. *Appl Intell*, 45(3):808-828. https://doi.org/10.1007/s10489-016-0786-y

Nouri HE, Driss OB, Ghédira K, 2016c. Simultaneous scheduling of machines and a single moving robot in a job shop environment by metaheuristics based clustered holonic multiagent model. Proc 8th Int Conf on Agents and Artificial Intelligence, p.51-62. https://doi.org/10.5220/0005694300510062

Nouri HE, Driss OB, Ghédira K, 2016d. Simultaneous scheduling of machines and transport robots in flexible job shop environment using hybrid metaheuristics based on clustered holonic multiagent model. *Comput Ind Eng*, 102:488-501. https://doi.org/10.1016/j.cie.2016.02.024

Nouri HE, Driss OB, Ghédira K, 2018. Controlling a single transport robot in a flexible job shop environment by hybrid metaheuristics. Transactions on Computational Collective Intelligence XXVIII, Cham, 10780:93-115. https://doi.org/10.1007/978-3-319-78301-7_5

Poppenborg J, Knust S, Hertzberg J, 2012. Online scheduling of flexible job-shops with blocking and transportation. *Eur J Ind Eng*, 6(4):497-518. https://doi.org/10.1504/EJIE.2012.047662

Priore P, De LFD, Gomez A, et al., 2001. A review of machine learning in dynamic scheduling of flexible manufacturing systems. *AI EDAM*, 15(3):251-263. https://doi.org/10.1017/S0890060401153059

Rathore K, Chauhan NR, 2015. Fms scheduling using neural networks: A review. Proc Int Conf on Soft Computing Techniques and Implementations, p.39-44. https://doi.org/10.1109/ICSCTI.2015.7489601

Reddy BSP, Rao CSP, 2006. A hybrid multi-objective ga for simultaneous scheduling of machines and agvs in fms. *Int J Adv Manuf Technol*, 31(5):602-613. https://doi.org/10.1007/s00170-005-0223-6

Reddy KS, Reddy NS, 2017. Simultaneous scheduling of machines and agvs in fms by using symbiotic organisms search (sos) algorithm. *Int J Res Appl Sci Eng Technol*, 5(11):1780-1790. https://doi.org/10.22214/ijraset.2017.11258

Saidi MM, Dehnavi AS, Evazabadian F, et al., 2015. An ant colony algorithm (aca) for solving the new integrated model of job shop scheduling and conflict-free routing of agvs. *Comput Ind Eng*, 86:2-13. https://doi.org/10.1016/j.cie.2015.01.003

Sanches DS, da Silva Rocha J, Castoldi MF, et al., 2015. An adaptive genetic algorithm for production scheduling on manufacturing systems with simultaneous use of machines and agvs. *J Control Autom Electr Syst*, 26(3):225-234. https://doi.org/10.1007/s40313-015-0174-6

Sawik T, 1996. A multilevel machine and vehicle scheduling in a flexible manufacturing system. *Math Comput Modell*, 23(7):45-57. https://doi.org/10.1016/0895-7177(96)00028-3

Soukhal A, Oulamara A, Martineau P, 2005. Complexity of flow shop scheduling problems with transportation constraints. *Eur J Oper Res*, 161(1):32-41. https://doi.org/10.1016/j.ejor.2003.03.002

Subbaiah KV, Nageswararao M, Narayanarao K, 2009. Scheduling of agvs and machines in fms with makespan criteria using sheep flock heredity algorithm. *Int J Phys Sci*, 4(2):139-148.

Tabatabaei A, Torabi F, Paitoon T, 2018. Simultaneous scheduling of machines and automated guided vehicles utilizing heuristic search algorithm. Proc IEEE 8th Annual Computing and Communication Workshop and Conf, p.54-59. https://doi.org/10.1109/CCWC.2018.8301705

Tang DB, Zheng K, Gu WB, 2020. Hormone Regulation Based Approach for Distributed and On-line Scheduling of Machines and AGVs. In: Tang DB, Zheng K, Gu WB (Eds.), Adaptive Control of Bio-Inspired Manufacturing Systems. Springer, Singapore. https://doi.org/10.1007/978-981-15-3445-4_3

Tuma CCM, Morandin O, Caridá VF, 2013. Minimizing the makespan for the problem of reactive production scheduling in a fms with agvs using a new structure of chromosome in a hybrid ga with ts. Proc IEEE 18th Conf on Emerging Technologies & Factory Automation, p.1-6. https://doi.org/10.1109/ETFA.2013.6648079

Türkyılmaz A, Şenvar Ö, Ünal İ, et al., 2020. A research survey: heuristic approaches for solving multi objective flexible job shop problems. *J Intell Manuf*, 31(8):1949-1983. https://doi.org/10.1007/s10845-020-01547-4

Ulusoy G, Bilge Ü, 1993. Simultaneous scheduling of machines and automated guided vehicles. *Int J Prod Res*, 31(12):2857-2873. https://doi.org/10.1080/00207549308956904

Ulusoy G, Sivrikaya-ŞerifoÇğlu F, Bilge Ü, 1997. A genetic algorithm approach to the simultaneous scheduling of machines and automated guided vehicles. *Comput Oper Res*, 24(4):335-351. https://doi.org/10.1016/S0305-0548(96)00061-5

Umar UA, Ariffin M, Ismail N, et al., 2015. Hybrid multiobjective genetic algorithms for integrated dynamic scheduling and routing of jobs and automated-guided vehicle (agv) in flexible manufacturing systems (fms) environment. *Int J Adv Manuf Technol*, 81(9):2123-2141. https://doi.org/10.1007/s00170-015-7329-2

Wang HY, Zhao F, Gao HM, et al., 2019. A three-stage method with efficient calculation for lot streaming flowshop scheduling. *Front Inf Technol Electron Eng*, 20(7):1002-1020. https://doi.org/10.1631/FITEE.1700457

Wang H, Sheng BY, Lu QB, et al., 2021. A novel multi-objective optimization algorithm for the integrated scheduling of flexible job shops considering preventive maintenance activities and transportation processes. *Soft Comput*, 25(4):2863-2889. https://doi.org/10.1007/s00500-020-05347-z

Wang M, Xin B, 2019. A genetic algorithm for solving flexible flow shop scheduling problem with autonomous guided vehicles. Proc IEEE 15th Int Conf on Control and Automation, p.922-927. https://doi.org/10.1109/ICCA.2019.8899914

Wang XK, Wu WM, Xing ZC, et al., 2022. A neural network based multi-state scheduling algorithm for multi-agv system in fms. *J Manuf Syst*, 64:344-355. https://doi.org/10.1016/j.jmsy.2022.06.017

Unedited

Xie J, Gao L, Peng K, et al., 2019. Review on flexible job shop scheduling. *IET Coll Intell Manuf*, 1(3):67-77. https://doi.org/10.1049/iet-cim.2018.0009

Xin B, Lu S, He YM, et al., 2023a. Automatic design of dynamic collaboration strategies for machines and automated guided vehicles via multiobjective genetic programming. *Unmanned Syst*, (in press). https://doi.org/10.1142/S2301385025500153

Xin B, Lu S, Wang Q, et al., 2023b. Simultaneous scheduling of processing machines and automated guided vehicles via a multi-view modeling-based hybrid algorithm. *IEEE Trans Autom Sci Eng*, (in press). https://doi.org/10.1109/TASE.2023.3301656

Xu GJ, Bao Q, Zhang HL, 2023. Multi-objective green scheduling of integrated flexible job shop and automated guided vehicles. *Eng Appl Artif Intell*, 126:106864. https://doi.org/10.1016/j.engappai.2023.106864

Yung TW, Ponnambalam SG, Yogeswaran M, 2009. Multi-objective aco for integrated scheduling of machines and material handling equipment in flexible manufacturing systems. Proc IEEE Int Conf on Automation Science and Engineering, p.304-309. https://doi.org/10.1109/COASE.2009.5234130

Zeng CK, Tang JF, 2014. Blocking job shop cell scheduling with automated guided vehicles. Proc 11th World Congress on Intelligent Control and Automation, p.438-442. https://doi.org/10.1109/WCICA.2014.7052753

Zeng CK, Tang JF, Yan CJ, 2014. Scheduling of no buffer job shop cells with blocking constraints and automated guided vehicles. *Appl Soft Comput*, 24:1033-1046. https://doi.org/10.1016/j.asoc.2014.08.028

Zeng C, Tang J, Yan C, 2015. Job-shop cell-scheduling problem with inter-cell moves and automated guided vehicles. *J Intell Manuf*, 26(5):845-859. https://doi.org/10.1007/s10845-014-0875-x

Zhang GH, Sun JH, Liu X, et al., 2019. Solving flexible job shop scheduling problems with transportation time based on improved genetic algorithm. *Math Biosci Eng*, 16(3):1334-1347. https://doi.org/10.3934/mbe.2019065

Zhang L, 2021. Path selection of manufacturing transformation and upgrading under the background of made in china 2025. *China Collect Econ*, 4:9-10 (in Chinese).

Zhang RW, Dou LH, Xin B, et al., 2023. A review on the truck and drone cooperative delivery problem. *Unmanned Syst*, (in press). https://doi.org/10.1142/S2301385024300014

Zheng K, Tang DB, Giret A, et al., 2018. A hormone regulation-based approach for distributed and on-line scheduling of machines and automated guided vehicles. *Proc Inst Mech Eng Part B J Eng Manuf*, 232(1):99-113. https://doi.org/10.1177/0954405416662078

Zheng Y, Xiao YJ, Seo Y, 2014. A tabu search algorithm for simultaneous machine/agv scheduling problem. *Int J Prod Res*, 52(19):5748-5763. https://doi.org/10.1080/00207543.2014.910628

Zhou BH, Liao XM, 2020. Particle filter and levy flight-based decomposed multi-objective evolution hybridized particle swarm for flexible job shop greening scheduling with crane transportation. *Appl Soft Comput*, 91:106217. https://doi.org/10.1016/j.asoc.2020.106217

Zhu ZQ, He YY, 2019. An improved genetic algorithm for production scheduling on fms with simultaneous use of machines and agvs. Proc 11th Int Conf on Intelligent Human-Machine Systems and Cybernetics, 1:245-249. https://doi.org/10.1109/IHMSC.2019.00064

Zou WQ, Pan QK, Wang L, 2021. An effective multi-objective evolutionary algorithm for solving the agv scheduling problem with pickup and delivery. *Knowl-Based Syst*, 218:106881. https://doi.org/10.1016/j.knosys.2021.106881

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A Integer Programming Model of FJSP_PT

The variable notations of FJSP_PT are shown in Table A1.

Table A1 Description of Key Symbols

Symbol	Description	Symbol	Description
N_J	The number of jobs to be processed.	N_M	The number of machines in FMS.
N_A	The number of AGVs in FMS.	J	The index set of jobs, $J=\{1,2,...,N_J\}$.
J_j	The jth job, $j \in J$.	M	The index set of machines, $M=\{1,2,...,N_M\}$.
M_m	The mth machine, $m \in M$.	A	The index set of AGVs, $A=\{1,2,...,N_A\}$.
A_k	The kth AGV, $k \in A$.	N_j^{opr}	The total number of the operations of J_j, $j \in J$.
N_O	The total number of all the operations, $N_O = \sum_{j=1}^{N_J} N_j^{opr}$.	O_j^{opr}	The index set of the operations of J_j, $O_j^{opr} = \{1,2,...,N_j^{opr}\}$, $j \in J$.
O_{ji}	The i-th operation of J_j, $i \in O_j^{opr}$.	LU	The initial area index of all jobs and vehicles.
Ω_{ji}	The index set of machines which can handle O_{ji}.	t_{jim}^P	The processing time of O_{ji} on M_m, $m \in \Omega_{ji}$.
D	The position index set of the raw material area and machines, $D=\{0,1,...,N_M\}$.	D_d	The position set of the raw material area and machines, $d \in D$, D_0 means the position of raw material and M_m is located at D_m, $m \in M$.
$t'_{d_1d_2}$	The no-load time between two positions, $\forall d_1, d_2 \in D$.	$t_{d_1d_2}$	The transportation time between two positions, $\forall d_1, d_2 \in D$.
Tet_{ji}	The ending time of the transportation stage for O_{ji}.	Tep_{ji}	The ending time of the processing stage for O_{ji}.

The integer programming model is formulated as follows:

$$\text{Minimize } Cmax \tag{1}$$

$$\text{Subject to :}$$

$$Cmax \geq Tep_{jN_j^{opr}}, \forall j \in J, \tag{2}$$

$$\sum_{i_1<i\in O_j^{opr}} \sum_{m\in M} Y_{ji_1,ji}^m + \sum_{j_1\in J\setminus\{j\}} \sum_{i_1\in O_{j_1}^{opr}} \sum_{m\in M} Y_{j_1i_1,ji}^m + \sum_{m\in I} B_{ji}^m = 1, \forall j \in J; i \in O_j^{opr}, \tag{3}$$

$$\sum_{i_1>i\in O_j^{opr}} \sum_{m\in M} Y_{ji_1,ji}^m + \sum_{j_1\in J\setminus\{j\}} \sum_{i_1\in O_{j_1}^{opr}} \sum_{m\in M} Y_{j_1i_1,ji}^m + \sum_{m\in I} L_{ji}^m = 1, \forall j \in J; i \in O_j^{opr}, \tag{4}$$

$$\sum_{j\in J} \sum_{i\in O_j^{opr}} B_{ji}^m \leq 1, \forall m \in M, \tag{5}$$

$$\sum_{j_1\in J} \sum_{i_1\in O_j^{opr}} L_{j_1i_1}^m \leq \sum_{j_2\in J} \sum_{i_2\in O_{j_2}^{opr}} B_{j_2i_2}^m, \forall m \in M, \tag{6}$$

$$Y_{j_1i_1,j_2i_2}^m \leq X_{j_1i_1}^m, \forall j_1, j_2 \in J; i_1 \in O_{j_1}^{opr}; i_2 \in O_{j_2}^{opr}; m \in M; (if\ j_1 = j_2 : i_2 > i_1), \tag{7}$$

$$Y_{j_1i_1,j_2i_2}^m \leq X_{j_2i_2}^m, \forall j_1, j_2 \in J; i_1 \in O_{j_1}^{opr}; i_2 \in O_{j_2}^{opr}; m \in M; (if\ j_1 = j_2 : i_2 > i_1), \tag{8}$$

$$B_{j_1i_1}^m \leq X_{j_1i_1}^m, \forall j_1 \in J; i_1 \in O_{j_1}^{opr}; m \in M, \tag{9}$$

$$L_{j_1i_1}^m \leq X_{j_1i_1}^m, \forall j_1 \in J; i_1 \in O_{j_1}^{opr}; m \in M, \tag{10}$$

$$\sum_{m\in M} X_{ji}^m = 1, \forall j \in J; i \in O_j^{opr}, \tag{11}$$

$$\sum_{j\in J} \sum_{i\in O_j^{opr}} U_{ji} \leq N_A, \tag{12}$$

$$\sum_{j\in J} \sum_{i\in O_j^{opr}} R_{ji} = \sum_{j\in J} \sum_{i\in O_j^{opr}} U_{ji}, \tag{13}$$

$$U_{ji} + \sum_{i_1\in O_j^{opr}, i_1<i} W_{ji_1,ji}^k + \sum_{j_2\in J\setminus\{j\}} \sum_{i_2\in O_{j_2}^{opr}} W_{j_2i_2,ji}^k = 1, \forall j \in J; i \in O_j^{opr}; k \in A, \tag{14}$$

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$$R_{ji} + \sum_{i_1 \in O_j^{opr}, i_1 > i} W^k_{ji_1,ji} + \sum_{j_2 \in J \setminus \{j\}} \sum_{i_2 \in O_{j_2}^{opr}} W^k_{j_2 i_2, ji} = 1, \forall j \in J; i \in O_j^{opr}; k \in A, \tag{15}$$

$$Tep_{ji} - Tet_{ji} - t^p_{jim} \geq M(X^m_{ji} - 1), \forall j \in J; i \in O_j^{opr}; m \in M, \tag{16}$$

$$Tep_{j_1 i_1} - Tep_{j_2 i_2} - t^p_{jim} \geq M(Y^m_{j_2 i_2, ji} - 1), i_1 \in O_{j_1}^{opr}; i_2 \in O_{j_2}^{opr}; m \in M(if\ j_2 = j_1 : i_1 > i_2), \tag{17}$$

$$Tet_{ji} - Tep_{j(i-1)} - t_{m'm} \geq M(X^m_{ji} + X^{m'}_{j(i-1)} - 2), \forall j \in J; i \in O_j^{opr} \setminus \{1\}; m, m' \in M, \tag{18}$$

$$Tet_{j1} - t_{LUm} \geq M(X^m_{ji} + U_{j1} - 2), \forall j \in J; m \in M, \tag{19}$$

$$Tet_{j_1 i_1} - Tet_{j_2 i_2} - t_{m''m'} - t_{m'm} \geq M(W^k_{j_2 i_2, j_1 i_1} + X^m_{j_1 i_1} + X^{m'}_{j_1 (i_1 - 1)} + X^{m''}_{j_2 i_2} - 4), \tag{20}$$

$$\forall j_1, j_2 \in J; i_1 \in O_{j_1}^{opr}; i_2 \in O_{j_2}^{opr} \setminus \{1\}; k \in A; m, m', m'' \in I(if\ j_1 = j_2 : i_1 > i_2),$$

$$Tet_{j_1 1} - Tet_{j_1 i_1} - t_{m'LU} - t_{LUm} \geq M(W^k_{j_2 i_2, j1} + X^m_{j_1 1} + X^{m'}_{j_2 i_2} - 3), \tag{21}$$

$$\forall j_1, j_2 \in J; j_2 \neq j_1; i_2 \in O_{j_2}^{opr}; m, m' \in M, ; k \in A$$

$$B^m_{ji}, L^m_{ji}, X^m_{ji} \in \{0, 1\}, \forall j \in J; i \in O_j^{opr}; m \in M, \tag{22}$$

$$Y^m_{j_2 i_2, j_1 i_1}, W^k_{j_2 i_2, ji}, U_{j_2 i_2}, R_{j_2 i_2} \in \{0, 1\}, \forall j_1, j_2 \in J; i_1 \in O_{j_1}^{opr}; i_2 \in O_{j_2}^{opr}; k \in A, \tag{23}$$

$$Cmax, Tep_{ji}, Tet_{ji} \geq 0, \forall j \in J; i \in O_j^{opr}; m \in M. \tag{24}$$

where M is a sufficiently large positive integer. Expression (1) ensures that the optimization objective is minimizing the makespan, inequality (2) ensures its proper valuation related with the completion time of all jobs. Constraints (3) and (4) ensure that each operation has exactly one predecessor and one successor, except for the first and last operations of each machine. Constraint (5) ensures that each machine has at most one first operation, while constraint (6) ensures that each machine has an equal number of first and last operations. Constraints (7) and (8) ensure that consecutive operations on a machine are assigned to the same machine, constraints (9) and (10) ensure that the first and last operations of each machine are assigned to the corresponding machine, and constraint (11) ensures that each operation is assigned to exactly one machine.

Constraints (12) and (13) ensure that the number of first transportation tasks does not exceed the available number of vehicles and is the same as the number of last transportation tasks. Constraint (14) enforces that each transportation task is either the first task of a vehicle or immediately follows one and only one other transportation task, while constraint (15) ensures that each transportation task is either the last task of a vehicle or is immediately followed by one and only one other transportation task.

Each operation can only be completed when: (i) the corresponding job arrives assigned to the machine processing it, and its processing time has passed, ensured by constraint (16); (ii) the previous operation on the same machine has been completed, and its processing time has passed, ensured by constraint (17).

Regarding the arrival times of vehicles, a job can arrive at the corresponding machine and the respective transportation task can be completed only before processing its current operation, ensured by constraint (18); unless it is the first operation of the job, in which case the job must be transported from the LU area to the machine processing its first operation, ensured by constraint (19). It is noteworthy that constraint (18) applies only to cases where two consecutive operations of the same job are processed on different machines because no transportation is needed when consecutive operations are processed on the same machine, and the vehicle immediately becomes idle. Additionally, if the vehicle transported another job immediately before the current job, it is required to: (i) deliver that job to the corresponding machine; (ii) pick up the current job from the location of the previous operation or, if it is the first operation, from the loading area; and (iii) deliver it to the machine processing the current operation. This is ensured by constraints (21) and (20). Finally, constraints (22)-(24) describe the properties of the variables.

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B Literature Review of FJSP_PT

Table A2: Literature review of FJSP_PT

No.	Problem types	Objective	Method
Lee and DiCesare (1993)	Centralized and distributed AGVs systems	-	Petri net for modeling centralized and distributed AGVs
Lee and DiCesare (1994)	Centralized and distributed AGV systems	Makespan	Petri net for modeling centralized and distributed AGVs
Chetto et al. (1995)	Dynamic scheduling problem for machines and vehicles with constant speed	Multiple performance measures	Simulation approach for studying scheduling rules
Bilge and Ulusoy (1995)	Machines and two identical AGVs in FMS	Makespan	Nonlinear mixed integer programming model and heuristic procedure by time windows
Sawik (1996)	Machines and identical AGVs in FMS	Machine workloads and intermachine flows of parts	Period-by-period heuristic based a family of complex dispatching rules
Ulusoy et al. (1997)	Limited machines and identical AGVs in FMS	Makespan	Genetic algorithm with a special uniform crossover operator and two mutation operators
Lacomme et al. (2002)	Machines with finite buffers capacity and two AGVs with blocking in FMS	Makespan	Simulation-based branch and bound for small-and-medium-size problem
Abdelmaguid et al. (2004)	Machines and two identical AGVs in FMS	Makespan	Hybrid genetic algorithm and heuristic coding scheme
Soukhal et al. (2005)	Two-machine flow shop scheduling problem with transporters	Makespan	Complexity analysis
Lacomme et al. (2005)	Machines and a single AGV	Makespan	Branch-and-bound coupled with a discrete event simulation model
Reddy and Rao (2006)	Machines and two identical AGVs in FMS	Makespan, mean flow time, and mean tardiness	Hybrid multiobjective genetic algorithm
Deroussi et al. (2006)	Machines and AGVs in FMS	Makespan	Integrated local search by combining metaheuristic
Jerald et al. (2006)	Machines and AGVs in FMS	Penalty cost and machine idle time	Adaptive genetic algorithm
Chen et al. (2007)	Hybrid flow shop scheduling problem with precedence and blocking constraints of container terminal with quay cranes	Makespan	Tabu search
Deroussi et al. (2008)	Machines and AGVs in FMS	Makespan	New solution representation based on vehicles rather than machines and iterated local search, simulated annealing and their hybridization
Hoshino et al. (2008)	Multiple robots with various speeds in fluctuating low-volume and high-mix manufacturing system	Workload balancing	A flexible and agile multi-robot manufacturing system with AGVs and product-processing robots
Mishra et al. (2009)	Machines and material handling devices	Makespan	Particle swarm optimization with operation-based representation
Subbaiah et al. (2009)	Machines and AGVs with constant speed	Mean makespan and tardiness	Sheep flock heredity algorithm
Yung et al. (2009)	Six multi-operational machines and two AGVs in FMS	Machine utilization, profit made, AGV traveling time and AGV energy utilization	Ant colony optimization
Gnanavel Babu et al. (2010)	Machine and two identical AGV in FMS	Makespan	Meta-heuristic differential evolution
Abdelmaguid and Nassef (2010)	Machines and multiple-load material handling equipment in JSP	Makespan	Constructive heuristic based on Giffler and Thompson's algorithm and different dispatching rules
Lv et al. (2011)	Machines and a single AGV in FMS	Equipment utilization	Genetic algorithm
Kumar et al. (2011)	Machines and AGVs in FMS	Makespan	Machine-selection heuristic and a vehicle-assignment heuristic which are incorporated in the differential evolution approach
Chaudhry et al. (2011)	Machines and AGVs in FMS	Makespan	Spreadsheet-based genetic algorithm

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Anandaraman et al. (2012)	Machines, a single AGV and two identical robots in FMS	Makespan, mean flow time, and mean tardiness	Sheep flock heredity algorithm and artificial immune algorithm system algorithm
Brucker et al. (2012)	Machines and a single robot in cyclic job shop problem with blocking	Cycle time	Integer programming formulation
Poppenborg et al. (2012)	Machines and AGVs in flexible job shop with blocking	Total weighted tardiness	Mixed integer programming and online tabu search
Mostafa et al. (2012)	Machines and two identical AGVs	Makespan	Job-based GA controlled by fuzzy logic
Tuma et al. (2013)	Machines and two AGVs in FMS	Makespan	Hybrid genetic algorithm with tabu search
Liu et al. (2013)	Machines and AGVs in FJSP	Makespan and total workload of machines	Multiobjective micro artificial bee colony algorithm
Elmi and Topaloglu (2013)	Machines and AGVs in blocking hybrid flow shop cells	Makespan	Mixed integer linear programming and simulated annealing
Lacomme et al. (2013)	Machines and identical AGVs	Makespan	Framework based on a disjunctive graph and a memetic algorithm
Zeng et al. (2014)	Machines and AGVs in blocking job shop	Makespan	Two integer non-linear programming models and two-stage heuristic algorithm
Zeng and Tang (2014)	Machines and AGVs in FMS	Makespan	Two-stage heuristic algorithm combining an timetabling method and local search
Nageswararao et al. (2014)	Machines and identical AGVs in FMS	Mean tardiness	Binary particle swarm vehicle heuristic algorithm
Zheng et al. (2014)	Machines and AGVs in FMS	Makespan	Mixed integer linear programming model and tabu search
Deroussi (2014)	Flexible job shop problem with transport	Makespan	Hybridization of particle swarm optimization with stochastic local search
Sanches et al. (2015)	Machines and AGVs in FMS	Makespan	Adaptive genetic algorithm
Zeng et al. (2015)	Machines and single AGV in cell part scheduling problem	Makespan	Two-stage heuristic algorithm consisting of a local search combined genetic algorithm and a heuristic algorithm
Umar et al. (2015)	Machines and AGVs	Makespan, AGV travel time, and penalty cost	Genetic algorithm controlled by fuzzy expert system
Chikhi et al. (2015)	Three machines for two stages and a robot or a conveyor	Makespan	CPLEX
Nageswararao et al. (2015)	Machines and two identical AGVs	Makespan	Hybrid meta heuristic algorithm
Aldaihani (2015)	Non-identical parallel machines and a robot in a flexible manufacturing cell	Total completion time	Hybrid algorithm of tabu search and greedy insertion algorithm
Lin et al. (2015)	Machines and identical AGVs in FMS	Makespan	Optimal computing budget allocation embedded with genetic algorithm
Nouri et al. (2016c)	Machines and a single transport robot in job shop scheduling problem	Makespan	Hybrid metaheuristic approach based on clustered holonic multiagent model
Nouri et al. (2016d)	Machines and transport robots in flexible job shop scheduling problem	Makespan	Hybrid metaheuristics based on clustered holonic multiagent model
Nouri et al. (2016b)	Machines and many robots in job shop scheduling problem	Makespan	Hybrid metaheuristic approach based on clustered holonic multiagent model
Baruwa and Piera (2016)	Machines and AGVs in FMS	Makespan and exit time of the last job	Timed colored petri net
Dang and Nguyen (2016)	Machines and mobile robots in modern manufacturing models	Makespan	Heuristic approach based genetic algorithm
Heger and Voss (2017)	Machines and multi-AGVs in flexible reentrant job shop with blocking	Makespan	Mixed integer linear programming and GUROBI
Nageswararao et al. (2017)	Machines and two AGVs in FMS	Makespan	Meta-heuristic gravitational search
Reddy and Reddy (2017)	Machines and AGVs in FMS	Makespan	Symbiotic organisms search
Nageswararao et al. (2017)	Machines and AGVs in FMS	Completion time and mean tardiness	Meta-heuristic based on three initial scheduler algorithms

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Nouri et al. (2018)	Machines and single AGV in flexible job shop scheduling problem	Makespan	Hybrid metaheuristic approach based on clustered holonic multiagent model
Tabatabaei et al. (2018)	Machines and two identical AGVs in dynamic FMS	Cycle time	Heuristic method
Babu et al. (2018)	Machines and material control devices in FMS	Makespan	Nawaz-Ensocre-Ham heuristic algorithm
Zheng et al. (2018)	Machines and AGVs	Makespan	Hormone regulation-based approach
Hemmati et al. (2018)	Machines and AGVs in flexible cell scheduling problem	Total cost	Hybrid genetic algorithm and hybrid ant colony algorithm
Dang et al. (2019b)	Machines and identical AGVs	Makespan	A hybrid heuristic of genetic algorithm and tabu search
Liu et al. (2019)	Machines and single crane in flexible job shop scheduling problem	The total cost of the energy consumption and makespan	Genetic algorithm, glowworm swarm optimization and green transport heuristic strategy
Gu et al. (2019)	Multiple AGVs with constant speed in a dynamic AGV scheduling problem	Makespan	Biological intelligent approach
Dang et al. (2019a)	Automatic machines and material handling devices	Makespan	Hybrid heuristic method combining genetic algorithm and tabu search
Zhu and He (2019)	Machines and AGVs with constant speed in modern manufacturing systems	Makespan	Average distribution genetic algorithm
Wang and Xin (2019)	Parallel machines and identical AGVs in flexible flow shop	Makespan	Genetic algorithm with effective coding and decoding scheme and genetic operators
Kumar et al. (2019)	Part, tool and two automated guided vehicles in FMS	Makespan	Priority dispatching rules and modified genetic algorithm
Gu et al. (2020)	Machines and AGVs with constant speed in a dynamic scheduling problem	Makespan	Bio-inspired scheduling optimization approach inspired by hormone secretion principle
Ham (2020)	Machines and identical transports in FMS	Makespan	Two constraint programming formulations
Tang et al. (2020)	Machines and AGVs within a distributed online system	Makespan	Hormone regulation
Zhou and Liao (2020)	Machines and cranes for flexible job shop green scheduling	Total energy consumption and makespan	Levy flight-based decomposed multiobjective evolution hybridized with particle swarm
Homayouni et al. (2020)	Machines and transports in FMS	Makespan	Operation-based multistart biased random key genetic algorithm
Homayouni and Fontes (2021)	Machines and transports in FMS	Makespan	Local search
Wang et al. (2021)	Machines and transportation robots flexible job shop scheduling problem	Total energy consumption and total makespan	Multi-region division sampling strategy-based multiobjective optimization algorithm integrated with a genetic algorithm and a differential evolution algorithm
Zou et al. (2021)	Machines and AGVs in a matrix manufacturing workshop	Overall customer satisfaction and distribution costs	Effective multiobjective evolutionary algorithm with local search
He et al. (2022)	Machines and AGVs in job shop environment	Makespan	Effective multiobjective evolutionary algorithm with new crossover operator
Chaudhry et al. (2022)	Machines and AGVs in flexible job shop environment	Makespan	Genetic algorithm based on spreadsheet model
Chen et al. (2022)	Machines and AGVs in flexible job shop environment	Makespan	Hybrid discrete particle swarm optimization algorithm with a heuristic initialization method
He et al. (2022)	Machines and robots in flexible job shop	Makespan	Novel memetic algorithm combining genetic algorithm and variable neighborhood search
Wang et al. (2022)	Machines and AGVs in FMS	Makespan, AGV load rate, AGV utilization, and task execution time	Multi-state scheduling algorithm
Amirteimoori and Kia (2023)	Machines and AGVs in flexible job shop system	Makespan	Parallel hybrid partical swarm optimization and genetic algorithm
Xu et al. (2023)	Machines and AGVs in mulltiobjective green scheduling problem	Total energy consumption and makespan	Efficient heuristic algorithm with greedy insertion decoding method considering the selection of AGVs
Xin et al. (2023a)	Machines and AGVs in FMS	Total energy consumption and makespan	Genetic programming

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