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A Review of Multi-objective Green Flexible Job Shop Scheduling Based on Intelligent Optimization Algorithms

Zihan Li[1,*]

[1]Southwest Petroleum University, Chengdu 610500, China

*Corresponding author email: 1536703796@qq.com

Abstract

The flexible job shop scheduling problem (FJSP) is a representative and complex optimization problem in production scheduling because it simultaneously involves operation sequencing and machine assignment. With the rapid development of green manufacturing and intelligent manufacturing, research on FJSP has gradually shifted from traditional efficiency-oriented objectives, such as makespan and machine utilization, toward multi-objective green optimization that considers energy consumption, carbon emissions, energy cost, processing cost, and resource balance. From the perspective of industrial engineering and management, this paper reviews recent studies on multi-objective green flexible job shop scheduling. First, it clarifies the basic characteristics and research evolution of FJSP. Second, it summarizes the main research progress from three aspects: green objective modeling, realistic constraint scenarios, and intelligent optimization algorithms. Third, it evaluates the applicability of genetic algorithms, NSGA-II, memetic algorithms, hybrid metaheuristics, and deep reinforcement learning. Finally, it identifies current limitations in green indicator systems, model realism, algorithm interpretability, and engineering implementation, and proposes future research directions. The review indicates that multi-objective green FJSP has moved beyond the stage of simply comparing algorithmic performance and is increasingly becoming a comprehensive optimization problem for complex manufacturing systems. Future research should strengthen systematic modeling of green objectives, dynamic scenario representation, and integration with real enterprise production systems.

Keywords

Flexible job shop; Green scheduling; Multi-objective optimization; Intelligent optimization algorithm; Literature review.

1. Introduction

The flexible job shop scheduling problem (FJSP) is an important extension of the classical job shop scheduling problem. In FJSP, decisions must be made not only on the processing sequence of operations but also on the assignment of each operation to one of several eligible machines. This additional routing flexibility significantly expands the solution space and makes FJSP more complex than the traditional JSP [1]. For industrial engineering and management, the significance of FJSP lies not only in its computational difficulty, but also in its direct connection with resource allocation, operation organization, bottleneck coordination, and production efficiency improvement. In this sense, FJSP is both an optimization problem and a typical production management problem.

For a long period, research on FJSP mainly focused on efficiency-oriented objectives such as makespan, total tardiness, and machine workload. These studies laid a foundation for modeling and algorithm design. However, with increasing pressure for green transformation in

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manufacturing enterprises, a scheduling model based only on time efficiency can no longer fully meet practical production requirements. Energy-oriented FJSP research has gradually become a relatively independent branch [2], and green scheduling increasingly emphasizes the coordination between production objectives and environmental objectives rather than simply adding an energy-consumption term to an existing model [3]. Therefore, the key question has shifted from how to schedule faster to how to balance efficiency, cost, resource utilization, and green performance.

In addition, time-of-use electricity prices, real-time energy tariffs, equipment maintenance, transportation coordination, machine breakdowns, and dynamic orders have been incorporated into scheduling models. As a result, FJSP research is moving from static and idealized models toward more realistic manufacturing environments. This transition indicates that multi-objective green FJSP is no longer merely a comparison of algorithmic performance. It is increasingly becoming a comprehensive optimization and decision-support problem for manufacturing systems. Against this background, this review reorganizes the literature on multi-objective green FJSP and discusses its research logic, methodological applicability, and practical value from the perspective of industrial engineering and management.

2. Research Foundation of Multi-objective Green FJSP

The core feature of FJSP is flexibility. Specifically, the same operation can be processed on different candidate machines, and different machines usually differ in processing time, energy consumption, processing cost, and resource occupation [1]. This flexibility makes the problem more difficult than the classical JSP, but it also makes FJSP more representative of real manufacturing systems, where parallel equipment, alternative process routes, and resource reconfiguration are common. From an industrial engineering perspective, this means that scheduling is not only a question of time arrangement but also a question of resource allocation and system efficiency.

In terms of objective functions, FJSP has evolved from single-objective efficiency optimization to multi-objective green collaborative optimization. Earlier studies mainly minimized makespan, total processing time, or machine workload. The central concern in this stage was to improve production efficiency and shorten delivery cycles. With the development of green manufacturing, researchers have gradually introduced total energy consumption, energy cost, carbon emissions, idle energy consumption, and transportation energy consumption into scheduling models [1-3]. This transformation indicates that scheduling evaluation is becoming more systematic. It is no longer sufficient to obtain a fast schedule; a desirable schedule should also be energy-saving, low-carbon, cost-effective, and balanced.

Chinese studies also show a clear development trajectory in this direction. Zheng et al. established a multi-objective green FJSP model considering makespan, total workload, and total energy consumption, and proposed an improved NSGA-II algorithm [4]. Zhao et al. further incorporated total machine energy consumption and total carbon emissions into a multi-objective green FJSP model and improved the solution quality by using an enhanced dual-population genetic algorithm [5]. These studies indicate that domestic research has gradually expanded from energy optimization toward the coordination of makespan, energy consumption, and carbon emissions.

It should be noted that multi-objective green FJSP is not simply a matter of adding more objective functions. The real challenge lies in the conflicts among efficiency objectives, resource objectives, and environmental objectives. For example, shortening makespan may require more intensive machine operation and higher power consumption, while excessive emphasis on energy saving may prolong production cycles. Therefore, valuable research should focus on the

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trade-off relationships among different objectives rather than pursuing the optimum of a single indicator.

3. Research Progress in Multi-objective Green FJSP

3.1. Green Objectives and Multi-objective Modeling

In green objective modeling, international studies have paid early attention to energy cost and dynamic energy environments. Shen et al. studied energy-cost-efficient scheduling in flexible job-shop manufacturing systems under time-of-use electricity tariffs, closely linking energy cost with the scheduling process [6]. Burmeister et al. further considered real-time energy tariffs and proposed a memetic NSGA-II approach to optimize both makespan and energy cost [7]. These studies show that green scheduling research is shifting from minimizing energy consumption to optimizing energy-related economic and environmental performance under realistic price mechanisms.

Domestic research shows a progressive expansion of green objectives. Energy-oriented FJSP research has formed modeling ideas around total energy consumption, idle energy consumption, peak power, and energy cost [2]. Green shop scheduling research also emphasizes that multiple production and environmental objectives should be coordinated rather than treated separately [3]. The work of Zheng et al. [4] and Zhao et al. [5] further demonstrates that Chinese scholars have extended the research focus from total energy consumption to the integrated optimization of makespan, energy consumption, and carbon emissions.

Overall, green objective modeling shows three major trends. First, the objective system is becoming richer, extending from energy consumption to energy cost, carbon emissions, processing cost, and workload balance. Second, dynamic energy environments have received increasing attention. Third, the trade-off among multiple objectives has become a central issue. This development should be understood not only as an increase in the number of objectives but also as the systematization of scheduling evaluation.

3.2. Complex Constraints and Realistic Manufacturing Scenarios

The expansion of realistic scenarios is another important feature of recent multi-objective green FJSP research. Zhang et al. studied green distributed flexible job shop scheduling considering transportation time and established a mixed-integer programming model with the objectives of minimizing makespan and total energy consumption [8]. This study is meaningful because transportation is treated as an explicit constraint instead of an implicit condition, making the model closer to real production systems.

Li et al. incorporated preventive maintenance into an energy-saving optimization model for FJSP, showing that equipment health, maintenance activities, and scheduling decisions are closely related [9]. Compared with models that focus only on processing operations, such studies better reflect the systems-thinking logic of industrial engineering and management. Production scheduling should not be separated from equipment management, maintenance planning, and shop-floor operational constraints.

International research has also incorporated many realistic factors. Duan and Wang considered machine breakdowns, idle time arrangement, and machine speed-level selection in energy-efficient FJSP [10]. Wei et al. examined hybrid energy-saving measures under variable machining speeds [11]. Yao et al. introduced mobile robot transportation into energy-efficient FJSP and developed a knowledge-based multi-objective evolutionary algorithm [12]. Tian et al. investigated dynamic energy-efficient scheduling for multi-variety and small-batch production in an aerospace manufacturing case [13]. These studies no longer regard the shop floor as a

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static system composed only of jobs and machines. Instead, transportation, maintenance, breakdowns, dynamic orders, and process variability are incorporated into integrated models.

Nevertheless, the increasing complexity of constraints also creates a new challenge. Many studies continuously add new factors, but they do not always explain the managerial meaning of these factors. In other words, the models appear more realistic, but the question of why these constraints matter for production management and how they support managerial decisions is not always sufficiently discussed.

3.3. Solution Methods and Algorithmic Evolution

Because multi-objective green FJSP is discrete, nonlinear, and strongly coupled, solution methods have always been central to this research field. The NSGA-II proposed by Deb et al. provides a classical framework for multi-objective optimization. Its fast non-dominated sorting mechanism, elitist strategy, and crowding-distance operator make it widely applicable in multi-objective scheduling [14]. Many subsequent studies have improved algorithms based on this framework.

Different studies emphasize different algorithmic improvements. Zheng et al. improved NSGA-II by introducing adaptive crossover and mutation strategies and learning mechanisms [4]. Burmeister et al. and Gong et al. improved algorithmic structures through memetic ideas and operation-sequence flexibility to enhance solution quality under multi-objective and complex constraints [7,15]. Yao et al. embedded knowledge-driven mechanisms into a multi-objective evolutionary algorithm for energy-efficient scheduling with mobile robot transportation [12]. These studies indicate that evolutionary algorithms are evolving from general-purpose search tools toward problem-specific and knowledge-enhanced optimization methods.

Deep reinforcement learning represents a newer research direction. Zhang et al. introduced deep reinforcement learning into energy-saving FJSP and transformed the scheduling process into a Markov decision process using a deep Q-network [16]. This suggests that data-driven methods may play an increasingly important role in complex dynamic production environments. However, current reinforcement-learning-based studies remain exploratory and still face challenges in training sample requirements, model stability, parameter tuning, and result interpretability.

4. Review of Intelligent Optimization Algorithms

Intelligent optimization algorithms remain the main technical route for solving multi-objective green FJSP. However, different algorithms have different strengths and limitations in problem representation, search mechanism, applicable scenarios, and engineering implementation. Existing reviews show that because FJSP is characterized by discreteness, nonlinearity, and multiple coupled constraints, exact methods often encounter computational difficulties in medium- and large-scale problems [1-3]. Therefore, metaheuristic algorithms and their improved variants dominate the field.

Genetic algorithms and their multi-objective extensions are among the most widely used algorithm families. Their advantage lies in flexible encoding, which can represent operation sequencing and machine assignment simultaneously. They can also be combined with Pareto-based multi-objective frameworks to generate a set of trade-off solutions. For industrial engineering and management research, genetic-algorithm-based methods provide a relatively mature computational tool for resource allocation and multi-objective trade-off analysis. However, they are often sensitive to parameter settings, may converge prematurely, and may have limited adaptability to dynamic environments.

Traditional metaheuristic methods such as particle swarm optimization, ant colony optimization, and simulated annealing also have application value [1-3]. Particle swarm

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optimization usually converges quickly and has relatively few parameters, but it requires additional discrete representation mechanisms for complex scheduling problems. Ant colony optimization is suitable for sequence construction and path-search problems and has relatively interpretable heuristic logic, but it often requires considerable computational effort. Simulated annealing has strong local search ability and can help escape local optima, so it is often embedded into other algorithms as a local improvement module. These methods are generally more suitable as complementary mechanisms than as the only solution framework for complex multi-objective green FJSP.

Memetic algorithms and hybrid metaheuristics have shown greater potential in recent years. Studies by Burmeister et al. [7] and Gong et al. [15] indicate that, under multi-objective, complex-constraint, and dynamic energy scenarios, hybrid algorithms usually achieve better convergence and solution distribution than single algorithms. This is because hybrid algorithms can combine global search, local improvement, knowledge guidance, and problem-specific heuristic rules. However, their structures are becoming increasingly complex, with more parameters and higher reproduction difficulty. A gap still exists between academic algorithm design and enterprise application.

Deep reinforcement learning has introduced a new perspective into green FJSP. Compared with traditional metaheuristics, reinforcement learning can update decision strategies through interaction with the environment, making it potentially suitable for dynamic disturbances, real-time response, and rolling optimization. However, this approach remains immature for broad industrial use. Its real value for industrial engineering and management depends not only on whether it can compute a good result, but also on whether it can use shop-floor data, real-time status information, and management rules to support dynamic production decision-making.

Table 1. Representative intelligent optimization algorithms for multi-objective green FJSP

Algorithm type	Main advantages	Main limitations	Typical role in green FJSP
GA / NSGA-II	Flexible encoding and mature multi-objective framework	Parameter sensitivity and possible premature convergence	Mainstream framework for Pareto-based multi-objective scheduling
PSO / ACO / SA	Fast search, sequence construction, or strong local improvement	Discrete representation difficulty, computational cost, or limited global search	Often used as auxiliary or local improvement mechanisms
Memetic and hybrid algorithms	Balance between global search and local exploitation	Complex structure and high reproduction cost	Suitable for complex constraints and dynamic energy environments
Deep reinforcement learning	Potential for dynamic decision-making and real-time response	High data demand, training instability, and limited interpretability	Promising direction for dynamic and data-driven shop-floor scheduling

5. Research Gaps and Future Directions

Although multi-objective green FJSP research has made considerable progress, several limitations remain. First, the green indicator system is still incomplete. Existing studies have widely considered energy consumption, energy cost, and carbon emissions, but the systematic integration of peak power, logistics energy consumption, multi-energy coordination, and life-cycle environmental impacts remains insufficient [2,3,5].

Second, the realism of models needs further improvement. Many studies have introduced transportation, maintenance, machine breakdowns, and dynamic orders, but most of them still rely heavily on standard benchmark instances and static assumptions. There is still a gap between these models and real shop-floor randomness, management rules, and enterprise decision processes [8-13].

Third, algorithmic studies often emphasize performance indicators while paying less attention to interpretability and deployment feasibility. Many papers can demonstrate that an improved algorithm performs better in terms of convergence, Pareto-front quality, or solution diversity, but they rarely explain why this improvement is meaningful for enterprise production management. This issue becomes more prominent as reinforcement learning and complex hybrid algorithms are increasingly introduced.

Future research can be deepened in four directions. First, researchers should construct a more comprehensive green objective system including energy consumption, carbon emissions, energy cost, logistics energy, and resource utilization efficiency. Second, production, transportation, and maintenance should be modeled in a more integrated way to improve the representation of real manufacturing systems. Third, deep reinforcement learning, knowledge-driven optimization, and digital twins may be combined with traditional scheduling optimization to enhance adaptive decision-making in dynamic environments. Fourth, industry case studies and enterprise-level validation should be strengthened to improve the engineering value of research findings.

6. Conclusions

Overall, FJSP research has evolved from traditional single-objective efficiency optimization to multi-objective green optimization that considers makespan, energy consumption, energy cost, carbon emissions, processing cost, and resource coordination. Scholars have accumulated substantial research achievements in green objective expansion, complex-scenario modeling, and intelligent algorithm improvement. Recent studies on improved NSGA-II, dual-population genetic algorithms, hybrid metaheuristics, and deep reinforcement learning indicate that the field has entered a stage of joint innovation in modeling and solution methods.

From the perspective of industrial engineering and management, the most important challenge is not simply how many new algorithms can be designed, but how models can better reflect real manufacturing systems, how algorithms can become more interpretable for managers, and how research results can support enterprise production decisions. The value of multi-objective green FJSP ultimately depends on its ability to improve production organization, resource allocation, energy efficiency, and management performance in real manufacturing systems.

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