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A Review of Green Workshop Scheduling Problems Based on Algorithmic Structures

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Abstract: As a major energy consumer, China faces significant challenges from environmental pollution and resource scarcity, which critically impact sustainable social development. With the national "dual carbon" goals established, the manufacturing sector must integrate green transformation principles into corporate development. Currently, under the framework of green manufacturing, workshop green scheduling has emerged as a prominent research focus in this field. Therefore, this paper integrates recent cutting-edge research and future prospects in this field. It addresses green scheduling in assembly lines, flexible manufacturing workshops, and distributed scheduling systems. The discussion primarily focuses on green workshop scheduling within algorithmic frameworks, thoroughly examining the strengths and weaknesses of different algorithms. It highlights innovative developments such as novel algorithms and hybrid approaches tailored to solve specific problems. The aim is to tackle challenges in green workshop scheduling, including energy conservation and emission reduction, efficient resource utilization, and effective coordination among complex workshops. This paper provides a systematic review of past research achievements and summarizes current mainstream algorithms. It identifies shortcomings in existing studies and points toward future research directions.

Keywords: Workshop Scheduling; Green Scheduling; Intelligent Manufacturing; Optimization Algorithms.

1. Introduction

With advancements in modern information technology, the mechanical manufacturing industry has evolved significantly. Since the 21st century, global energy crises and ecological challenges have hindered human development, prompting the sector to shift towards green technologies. China, under the Paris Agreement, aims to achieve "carbon peak" by 2030 and "carbon neutrality" by 2060. In workshop scheduling, green technology transformation reduces consumption and enhances efficiency, making it a key pathway for sustainable manufacturing.

This paper analyzes algorithms for green workshop scheduling in parallel, flow, and flexible workshops. First, it reviews heuristic algorithms (e.g., ACO, NSGA-II) and their limitations in adaptability. Next, it explores the core elements of green workshop algorithms, including encoding methods, search strategies, fitness functions, and control parameters. It introduces modern algorithms (e.g., NSGA-III-TV, WOA, HMOEA/D) for green workshop scheduling, highlighting their advantages over traditional algorithms. Finally, it outlines research gaps and suggests future directions, including integrating AI to optimize green workshop scheduling.

2. Common Green Workshop Problem Categories and Distinct Characteristics

Common green workshop problems are categorized into parallel workshop scheduling, flow workshop scheduling, flexible workshop scheduling, and distributed workshop scheduling. Details follow:

2.1. Green Scheduling for Parallel Machines

Parallel machine scheduling is divided into related and unrelated categories. Pan Zixiao et al. proposed PNSGA-II for the distributed low-carbon parallel machine scheduling problem, demonstrating superior performance in minimizing delay time and energy consumption [1]. They developed a mathematical model and compared PNSGA-II with other algorithms.In the research by He Yujie et al. the Hybrid Discrete Teaching-Learning-Based Optimization (HDTLBO) algorithm was proposed along with its model[2]. It outperformed previous algorithms by replacing the core operations with species sorting operations, thereby significantly enhancing search performance and providing a developmental direction for intelligent scheduling algorithms.

They proposed an approximate dynamic programming algorithm to minimize maximum completion time and energy cost, outperforming a 0-1 programming model.

These examples highlight significant attention to parallel machine scheduling, though challenges remain, especially the conflict between processing efficiency and load utilization.

2.2. Green Scheduling for Assembly Lines

Assembly lines are categorized into conventional, displacement, and hybrid types. Various classifications have emerged due to the complexity of the problems. M. Faraji Amiri et al proposed a distributed estimation algorithm for the multi-objective green assembly line scheduling problem, addressing completion time and energy consumption under uncertainty[3].

Hybrid assembly lines present greater complexity than conventional assembly lines. More thorough research is required, necessitating consideration of more sophisticated green energy-saving solutions to reduce carbon emissions, completion time, labor hours, and other issues.

Xiaoyuan Lian et al proposed IMOEA/D for minimizing completion time and optimizing scheduling in steel plant energy-efficient processing, demonstrating significant reductions in energy consumption[4].

Green scheduling for flow shops has been more widely studied than for parallel shops, though external emissions remain underexplored. Most research focuses on internal issues like completion time, energy conservation, and resource allocation. Future research should prioritize practical implementation.

2.3. Green Flexible Job Shop Scheduling Problem

The Green Flexible Job Shop Scheduling Problem (GFJSP) advances flexible machining processes in job shops, with research focusing on reducing carbon emissions and completion times under complex conditions.

S Jia et al. developed an MILP model to address idle energy consumption in parallel machines, saving energy by eliminating idle time. This model, combined with a hybrid genetic algorithm (HGA), optimizes scheduling [5].

NSGA-III, as the most widely used foundational algorithm, also requires further refinement to adapt to more complex scenarios. NSGA-III to address the multi-objective flexible workshop scheduling problem concerning completion time, total energy consumption, and total load, establishing a corresponding model. Experimental comparisons demonstrated enhanced overall efficiency and energy utilization.

NSGA-III-TV further refines NSGA-III to address poor initial solution quality and low local search efficiency. A brainstorming optimization algorithm was proposed for machine tool setup time in traditional green workshops, optimizing machine selection and sequencing to enhance global search capabilities. However, practical issues such as excessive parameters and complexity remain.

Li Yibing et al. proposed an improved artificial bee colony algorithm to optimize carbon emissions and waste in flexible workshop scheduling[6].

In summary, Green scheduling for workshops continues to evolve, with flexible workshops receiving the most attention in distributed settings. While energy consumption remains a key focus, there is limited attention to green metrics like carbon emissions, indicating a future research gap. Moreover, workshop scheduling has not been sufficiently applied to practical scenarios, with energy consumption in cross-regional transportation and internal scheduling between workshops being critical areas for future study.

2.4. Distributed Workshop Green Scheduling Problem

The emergence of distributed green scheduling problems arises from the limitations of traditional single-factory production models. More enterprises are transitioning to distributed workshop configurations, which include various types such as Green Distributed Identical Parallel Machine Scheduling Problem (GDIPMSP), Green Distributed Flow Shop Scheduling Problem (GDFSP), Green Distributed Permutation Flow Shop Scheduling Problem (GDPFSP), Green Distributed Hybrid Flow Shop Scheduling Problem (GDHFSP), and Green Distributed Flexible Job Shop Scheduling Problem (GDFJSP). Despite their diversity, all involve multiple interconnected workshops.

As green workshop scheduling evolves, with increasing focus on energy consumption and green objectives, flexible workshops in distributed settings receive the most attention, followed by hybrid assembly lines, while parallel machine workshops remain largely unexplored. Energy consumption is a key focus, but there is limited attention to green metrics like carbon emissions, highlighting a significant future research direction. Despite extensive theoretical work, workshop scheduling has not been sufficiently integrated into practical scenarios. Addressing energy consumption in cross-regional transportation and internal scheduling between workshops is a critical research priority.

3. Structural Framework of Green Workshop Scheduling Algorithms and Characteristics/Limitations of Traditional Approaches

The framework integrates several components—encoding methods for scheduling problems, relevant search schemes, adaptive functions, and control parameters—to enhance the algorithm's adaptability to diverse scenarios and requirements. Key aspects are detailed below.

3.1. Core Structure of the Algorithm

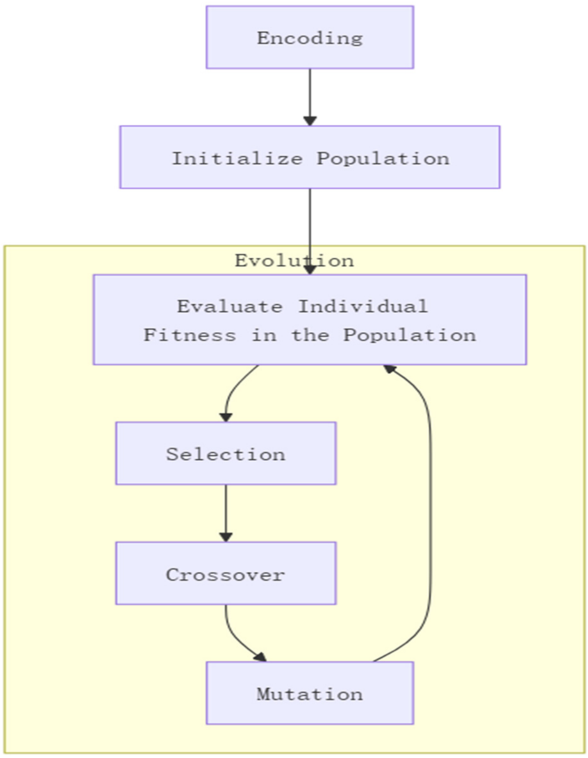

Figure 1. flow chart

Genetic Algorithms (GA) simulate biological evolution to search for optimal solutions by mimicking natural selection. GA treats all individuals within a population as objects, employing randomization techniques to guide efficient searches of encoded parameter spaces. Selection, crossover, and mutation constitute the genetic operations of these algorithms. Five core elements define GA: parameter encoding, initial population setup, fitness function design, genetic operation design, and control parameter configuration.

To address multidimensional optimization problems, the Segmented Encoding Genetic Algorithm (SE-GA) was developed. As shown in the figure 1, based on GA, SE-GA divides chromosome encoding into three segments, offering a more effective solution for complex, high-dimensional problems.

In summary, encoding methods are crucial in algorithms. For example, the flexible encoding approach in GA allows for solving diverse problems with tailored formats. Building on GA, the hybrid segmented encoding genetic algorithm combined with discrete particle swarm optimization (H-SE-GA-DPSO) was developed. This hybrid algorithm incorporates fundamental parameters to define its operational framework, combining GA and particle swarm characteristics. The encoding scheme divides chromosome and particle encoding into three segments for multidimensional optimization scheduling.

Relevant Search Schemes: These play a crucial role within the algorithm, primarily encompassing global search, local optimization, and balanced search capabilities.

The genetic algorithm is a heuristic search method that simulates biological evolution. By replacing old solutions with new ones, it progressively improves solution quality in search of optimal solutions. Its core logic mimics the "selection-replication-mutation" mechanism of biological evolution, gradually approaching the optimal scheduling scheme.

Similarly, PSO finds global solutions through inter-particle information exchange. When combined with GA, it leverages GA's crossover and mutation operations to enhance diversity and avoid local optima.

The fitness function connects the scheduling plan with the optimization objective, guiding the algorithm's search and translating business goals (e.g., reducing costs, meeting deadlines) into computable expressions.

To ensure the search direction aligns with practical requirements, core principles such as goal consistency, constraint compatibility, and computational efficiency are typically followed in scenarios. Primary objectives include minimizing total process time and minimizing total delay time (sum of positive values of "Finish Time - Delivery Date" for all workpieces.

Control Parameters: In workshop scheduling, control parameters are central to adjusting an algorithm's search efficiency and methodology. Previous research has discussed search directions and capabilities, but core parameter differences vary significantly across algorithms.

Taking the genetic algorithm as an example, its control parameters directly determine its ability to find the most efficient optimization solution, balancing population diversity and convergence efficiency. The following example illustrates this using a scheduling scenario aimed at minimizing completion time.

The population size (N) controls initial solution diversity, with a recommended range of 100-200 for large workshops to balance convergence and computation time. Maximum iterations (G) set the termination condition, with 100-200 generations for simple problems and 200-500 for complex ones. Crossover probability facilitates gene exchange to generate new solutions, with "Operation Order Crossover (OX)" commonly used in workshop scheduling.

Mutation Probability (MP) randomly modifies genes to avoid premature convergence and help escape local optima. For "process sequence encoding" scheduling problems, "swap mutation" or "reverse mutation" are commonly used, with Pm recommended between 0.01 and 0.05. Pm should be minimally adjusted based on workshop scale; excessively high values degrade the algorithm to "random search," negating GA's evolutionary advantage.

3.2. Single-Feature Heuristic Algorithms

Below are several single-feature heuristic algorithms: Mayfly Algorithm (MA), Non-Dominated Sorting Genetic Algorithm II (NSGA- II), and Ant Colony Optimization (ACO).

The NSGA-II It introduces a selection operator that combines parent and offspring populations and selects the optimal pair. Simulation results on challenging test problems demonstrate that, for most problems, it can find better solution distributions and achieve superior convergence near the true Pareto optimal frontier.

As shown in the Table 1, test problems comparing NSGA-II with PAES and SPEA performance.

Conclusion: We propose a computationally efficient elite MOEA algorithm based on non-dominated sorting. Compared with two other elite MOEA algorithms, PAES and SPEA, the proposed NSGA-II maintains a better solution distribution and converges more effectively to the obtained non-dominated frontier across nine distinct challenging test problems.

The introduction of NSGA-II has advanced green scheduling in flexible manufacturing workshops. Zhang et al. designed an extended process-based encoding and active decoding mechanism, along with initial solution generation, crossover, and mutation operations[7]. An improved version of NSGA-II was developed to address limitations in ranking and selection strategies, yielding Pareto solutions for scheduling.

Furthermore, it is suggested that future work could integrate decision-maker preferences with multi-objective evolutionary algorithms to eliminate irrationality within the population during genetic operations in the workshop, thereby enhancing the utilization of NSGA-II.

ACO, inspired by ants' pheromone-tracking behaviors is a meta-heuristic algorithm for solving combinatorial optimization problems. The Hyper-Colony Optimization (HCO) algorithm, based on ACO, improves performance.

ACO constructs solutions by iteratively adding components, using heuristic information and dynamic pheromone trails that reflect agents' search experience. Ant colony algorithms are widely applicable and can solve any discrete optimization problem with a defined solution mechanism.

Consequently, ant colony algorithms can be fused with other metaheuristics. One example is using tabu search to enhance ant solutions for the quadratic assignment problem. More complex hybrid algorithms have been proposed, commonly featuring faster solution construction and the ability to directly utilize partial iterations of solutions[8].

Summary: Since its inception in the 1990s, the ant colony algorithm has evolved into a mature meta-heuristic, supported by extensive experimental and theoretical research, establishing its significance in optimization.

3.3. Structural Limitations of Traditional Algorithms

The algorithms mentioned above, as single metaheuristic approaches, exhibit certain limitations worthy of attention. It is precisely the identification of these shortcomings that enables better algorithmic improvements.

Table 1. Comparing NSGA-II with PAES and SPEA performance

Problem	n	Variable bounds	Objective functions	Optimal solutions	Comments
SCH	1	$[-10^3, 10^3]$	$f_1(x) = x^2$ $f_2(x) = (x-2)^2$	$x \in [0,2]$	convex
FON	3	$[-4, 4]$	$f_1(\mathbf{x}) = 1 - \exp\left(-\sum_{i=1}^{3}\left(x_i - \frac{1}{\sqrt{3}}\right)^2\right)$ $f_2(\mathbf{x}) = 1 - \exp\left(-\sum_{i=1}^{3}\left(x_i + \frac{1}{\sqrt{3}}\right)^2\right)$	$x_1 = x_2 = x_3$ $\in [-1/\sqrt{3}, 1/\sqrt{3}]$	nonconvex
POL	2	$[-\pi, \pi]$	$f_1(\mathbf{x}) = \left[1 + (A_1 - B_1)^2 + (A_2 - B_2)^2\right]$ $f_2(\mathbf{x}) = \left[(x_1+3)^2 + (x_2+1)^2\right]$ $A_1 = 0.5\sin 1 - 2\cos 1 + \sin 2 - 1.5\cos 2$ $A_2 = 1.5\sin 1 - \cos 1 + 2\sin 2 - 0.5\cos 2$ $B_1 = 0.5\sin x_1 - 2\cos x_1 + \sin x_2 - 1.5\cos x_2$ $B_2 = 1.5\sin x_1 - \cos x_1 + 2\sin x_2 - 0.5\cos x_2$	(refer [1])	nonconvex, disconnected
KUR	3	$[-5, 5]$	$f_1(\mathbf{x}) = \sum_{i=1}^{n-1}\left(-10\exp\left(-0.2\sqrt{x_i^2 + x_{i+1}^2}\right)\right)$ $f_2(\mathbf{x}) = \sum_{i=1}^{n}\left(\lvert x_i\rvert^{0.8} + 5\sin x_i^3\right)$	(refer [1])	nonconvex
ZDT1	30	$[0, 1]$	$f_1(\mathbf{x}) = x_1$ $f_2(\mathbf{x}) = g(\mathbf{x})\left[1 - \sqrt{x_1/g(\mathbf{x})}\right]$ $g(\mathbf{x}) = 1 + 9\left(\sum_{i=2}^{n} x_i\right)/(n-1)$	$x_1 \in [0,1]$ $x_i = 0$, $i = 2, \ldots, n$	convex
ZDT2	30	$[0, 1]$	$f_1(\mathbf{x}) = x_1$ $f_2(\mathbf{x}) = g(\mathbf{x})\left[1 - (x_1/g(\mathbf{x}))^2\right]$ $g(\mathbf{x}) = 1 + 9\left(\sum_{i=2}^{n} x_i\right)/(n-1)$	$x_1 \in [0,1]$ $x_i = 0$, $i = 2, \ldots, n$	nonconvex
ZDT3	30	$[0, 1]$	$f_1(\mathbf{x}) = x_1$ $f_2(\mathbf{x}) = g(\mathbf{x})\left[1 - \sqrt{x_1/g(\mathbf{x})} - \frac{x_1}{g(\mathbf{x})}\sin(10\pi x_1)\right]$ $g(\mathbf{x}) = 1 + 9\left(\sum_{i=2}^{n} x_i\right)/(n-1)$	$x_1 \in [0,1]$ $x_i = 0$, $i = 2, \ldots, n$	convex, disconnected
ZDT4	10	$x_1 \in [0,1]$ $x_i \in [-5,5]$, $i = 2, \ldots, n$	$f_1(\mathbf{x}) = x_1$ $f_2(\mathbf{x}) = g(\mathbf{x})\left[1 - \sqrt{x_1/g(\mathbf{x})}\right]$ $g(\mathbf{x}) = 1 + 10(n-1) + \sum_{i=2}^{n}\left[x_i^2 - 10\cos(4\pi x_i)\right]$	$x_1 \in [0,1]$ $x_i = 0$, $i = 2, \ldots, n$	nonconvex
ZDT6	10	$[0, 1]$	$f_1(\mathbf{x}) = 1 - \exp(-4x_1)\sin^6(6\pi x_1)$ $f_2(\mathbf{x}) = g(\mathbf{x})\left[1 - (f_1(\mathbf{x})/g(\mathbf{x}))^2\right]$ $g(\mathbf{x}) = 1 + 9\left[\left(\sum_{i=2}^{n} x_i\right)/(n-1)\right]^{0.25}$	$x_1 \in [0,1]$ $x_i = 0$, $i = 2, \ldots, n$	nonconvex, nonuniformly spaced

First The MA algorithm, inspired by the flight and mating behavior of mayflies, incorporates parameters such as flight step size, attraction constant, and visual range. Improper settings can slow search speeds, requiring cumbersome debugging. Additionally, when faced with complex local minima, the algorithm struggles to find a globally optimal solution. As dimensions increase, search directions become dispersed, leading to slower convergence and reduced accuracy. Designed for monocular optimization, it can be combined with other algorithms but lacks an inherent structure to address diversity issues.

NSGA-II finds broad application in multi-objective optimization but retains limitations:

In high-dimensional multi-objective optimization, the algorithm's efficiency declines as the proportion of non-dominated solutions increases, requiring repeated dominance comparisons that slow it down, making real-time optimization challenging. Additionally, NSGA-II relies on genetic operations but lacks high-precision local search capabilities. Its constraint handling requires integration with other algorithms, and its performance depends on hidden parameters, requiring extensive tuning, which increases the difficulty and cost of applications.

Finally, there is ACO, which simulates ants collaborating through pheromones to find optimal paths, making it more suitable for scheduling problems. However, it has certain limitations.

Initial information imbalance and increased search randomness slow convergence in the early stages. ACO uses global and local pheromone updates, but determining optimal coefficients is challenging—too large risks discarding valuable information, while too small leads to redundancy. As dimensionality increases, the number of search paths grows exponentially, weakening pheromone guidance and reducing efficiency, accuracy, and computational costs. Spatial optimization requires discretization, leading to accuracy loss, and grid partitioning's effectiveness depends on experience, limiting its use in continuous optimization.

Summary: MA should focus on parameter sensitivity and high-dimensional scenarios to improve search accuracy. NSGA-II's limitations require further optimization for modern multi-objective problems. Derivative algorithms like NSGA-III, MOEA/D, and adaptive NSGA-II variants have emerged to address these challenges. The ACO algorithm faces limitations due to its bio-inspired mechanism, with pheromone updates and parameter tuning complicating its application in high-dimensional problems.

4. Innovations in Algorithm and Structure Improvements

Today, to address the diverse challenges faced by different workshops, there is a need to develop and refine new, efficient workshop algorithms to better achieve objectives such as minimizing completion time, reducing machine load, and lowering costs.

4.1. Recent Improvements to Algorithm Structures

First, The Multi-Objective Sparrow Search Algorithm (MOSSA), proposed by Zhang Fu et al. is designed to optimize completion time, machine load, and processing cost in flexible workshop production[9]. Unlike previous approaches that reduced multi-objective problems to single-objective ones, MOSSA simultaneously optimizes multiple objectives, offering better solutions for complex, real-world scenarios.

The workshop production scheduling problem can be summarized as follows: A workshop contains n workpieces to be processed and m processing machines. Each workpiecej_i includes r_i (r_i ≥1) operations, processed according to a specified process route. Each operationO_{ij} can be performed on different machines. Due to varying processing capacities among machines, the processing time for operation O_{ij} depends on the assigned machine.

In flexible manufacturing workshops, completion time is the most critical metric. Green manufacturing issues have gained importance under new production models, prompting MOSSA to focus on maximizing efficiency, minimizing processing costs, and optimizing completion time, with total processing cost as the objective.

$$f_1 = min\left\{\max_{1\le i\le n} CT_i\right\} \tag{1}$$

$$f_2 = min\left\{\sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{r_i} t_{ijk}x_{ijk}\right\} \tag{2}$$

$$f_3 = min\left\{\sum_{i=1}^{n}\sum_{j=1}^{r_i}\sum_{k=1}^{m} t_{jjk}x_{ijk}E_k\right\} \tag{3}$$

(1)The start time and processing time of a workpiece must be less than its completion time, i.e.,

$$ST_i + \sum_{j=1}^{r_i}\sum_{k=1}^{m} t_{ijk} \le CT_i \tag{4}$$

(2) The end time of the previous operation must be less than the start time of the next operation, i.e.

$$CT_{ijk} \le ST_{ij+1} \tag{5}$$

(3) The completion time for each workpiece should precede the overall completion time, i.e.,

$$CT_i \le maxCT_i \tag{6}$$

Table 2. Symbol description

Symbol	Meaning
r_i	Number of processes for the i-th workpiece
CT_i	Final processing completion time for workpiece i
t_{ijk}	Processing time for operation Oij on machine k
ST_i	Start time for machining workpiece i
ST_{ij}	ProcessO_{ij} start time
CT_{ijk}	ProcessO_{ij} completion time on machine k
x_{ijk}	ProcessO_{ij} : Variable value is 1 if processed on machine k, otherwise 0
E_k	Operating cost of machine k

The solution is discrete, while the Sparrow Search Algorithm uses continuous position vectors, requiring a conversion mechanism. The sequence chromosome's length is used for iteration, and the smaller value between the calculated and process chromosome lengths is selected as the number of positions (s) to modify. During population update, s nodes are randomly swapped in the process chromosome and machine segment.

The multi-objective MOSSA integrates non-dominated sorting and sparrow search to minimize completion time, workshop load, and cost, providing an efficient solution for multi-objective flexible workshops.

Beyond MOSSA, the Wolf Pack Algorithm (WPA) was introduced in 2013 by Wu Husheng, Zhang Fengming, Wu Lushan et al. Results demonstrate that this algorithm exhibits strong global convergence and computational robustness, particularly suited for solving complex functions with high-dimensional, multi-peak [10].

(1)Maximum completion time

(2)Total energy consumption of the machine

(3)Each process can only be performed once:

(4)A machine can only process the next operation after completing the current one:

Summary: The improved Wolf Pack Algorithm (IWPA) optimizes scheduling in flexible manufacturing workshops by balancing completion time and energy consumption. It identifies optimal workpiece sequencing and machine allocation to minimize both maximum completion time and energy usage. Large-scale testing shows that IWPA outperforms GA in minimizing maximum completion time while reducing overall machining time, making it particularly effective for large-scale operations.

4.2. Hybrid Algorithm Structure Integration

Hybrid algorithms provide an innovative solution for multi-objective green workshop scheduling. Luo Cong and Gong Wenyin introduced HMOEA/D for the permutation flow-shop scheduling problem (PFSP), combining three initialization strategies to ensure population diversity and solution quality. The algorithm uses Tabu Search for local optimization and an energy-saving strategy that reduces machine idle time by delaying workpiece processing start times, optimizing energy consumption without increasing completion time.

HMOEA/D integrates green objectives to minimize energy consumption and emissions. Using reference vectors and a neighborhood structure, it optimizes energy use. Genetic operations and tabu search improve efficiency, while an energy-saving strategy reduces consumption without increasing makespan. The Chebyshev function updates solutions, prioritizing energy reduction. Experiments validate its superior performance in reducing computational time and enhancing stability.

Additionally, Bilal Khurshid et al. proposed an improved hybrid simulated annealing evolutionary strategy for solving mixed-flow assembly workshops[11]. By integrating I.E.S. with S.A., it minimizes the maximum completion time of PFSSP.

By integrating two algorithms, the Hybrid Evolution Strategy (HESSA) minimizes the maximum completion time of the PFSSP and is validated on the Taillard benchmark PFSSP. Within HESSA, an improved evolutionary strategy is combined with the simulated annealing algorithm to find the optimal schedule for the PFSSP.

Experiments demonstrate that HESSA is a robust technique applicable to small, medium, and large-scale problems. A new upper bound of 54 instances was discovered, while the improved maximum completion time value was found to be 38 instances.

These examples show that hybrid algorithm fusion efficiently solves multi-objective problems, achieving breakthroughs in optimizing completion time, energy consumption, and algorithm stability, and paving the way for future advancements.

4.3. Innovation in Multi-Objective Processing Capabilities

NSGA-III is widely applied in handling multi-objective problems. However, solving high-dimensional multi-objective problems suffers from poor initial solution quality and inefficient local search. Therefore, proposed an improved algorithm, NSGA-III-TV, representing a new research direction for multi-objective scenarios[12].

Comparative experiments on NSGA-III-TA, NSGA-III-VNS, and NSGA-III-TV were conducted, focusing on HV values. NSGA-III-TA, based on the original NSGA-III, uses TA initialization and includes multi-point mutations in machine chromosomes and crossover mutations in process chromosomes.

Thus, in multi-objective processing, enhancing algorithmic capabilities through innovative modifications can better address diverse requirements under different objectives. In this regard, NSGA-III-TV demonstrates significant innovation in the field of local search[13].

WOA uses three operators to simulate humpback whale behaviors: prey search, encirclement, and bubble net feeding.

The WOA assumes the current best candidate solution represents the target prey or approaches optimality. Once the best-searching agent is identified, other search agents attempt to update their positions toward the optimal search agent.

Additionally, they established detailed multidimensional mathematical models. The algorithm comprises three operators simulating humpback whale behaviors: prey search, prey encirclement, and bubble net feeding.

Based on this, Kong Zhi and colleagues proposed the Adaptive Weight Optimization Algorithm (AWOA), featuring adaptive weight adjustment and search strategy[14]. They designed a method to adjust weights based on changes in the whale population, improving convergence speed. An adaptive search strategy was also developed to help escape local optima, addressing issues of slow convergence, low accuracy, and susceptibility to local optima.

Through repeated comparisons, the proposed improved algorithm better addresses the shortcomings of low convergence accuracy and susceptibility to local optima. It selects different search strategies to update the position, balancing the algorithm's global and local search capabilities.

5. Analysis of Green Workshop Scheduling Impacts Under Different Algorithms

Research shows that various algorithms have optimized real-world scheduling problems in green production. While traditional scheduling issues have been addressed, new challenges require the development of improved algorithms.

Under Single Algorithms: The MA algorithm struggles with poor global search and weak adaptability, leading to the proposal of an enhanced MIWMA for better performance.

NSGA-II is widely used but struggles with reduced efficiency in high-dimensional multi-objective optimization. Its reliance on genetic operations limits local search precision, and its constraint handling requires integration with other algorithms. Scholars have enhanced NSGA-II by combining it with other algorithms or improving it with variants like NSGA-III and NSGA-III-TV to boost adaptability in complex scenarios.

In multi-objective scenarios, WOA employs a spiral-shaped algorithm for global search, adapting to higher dimensions. However, it suffers from slow convergence, low accuracy, and susceptibility to local optima.

These examples show that different algorithms impact green workshop scheduling in various ways. By addressing these challenges, algorithms can be refined for more effective green workshop production.

6. Conclusion, Current Research Gaps, and Future Research Directions

6.1. Conclusion

This paper explores scheduling problems in green workshops, including parallel, flow and flexible workshops, focusing on the development and comparative advantages of scheduling algorithms. The second part concludes that different algorithms suit distinct application scenarios based on their structures and classifications. For example, single-objective heuristic algorithms are suited for simple scheduling problems but struggle with optimization accuracy and complexity in more advanced scenarios. While NSGA-II is widely applied, it lacks high-precision local search capabilities, requiring further innovation for optimization.

Subsequently, improved algorithms are introduced. As societal and technological advancements continue, green workshop scheduling has expanded from single scenarios to complex and diverse contexts. These innovative algorithms, through modifications and fusion, offer enhanced search and control capabilities, outperforming previous approaches and aligning better with modern applications. They also show superior performance in multi-objective scenarios. Therefore, selecting the most suitable algorithm for specific practical problems is crucial. By analyzing real-world contexts and researching algorithm implementation, green workshop advancements can be further driven.

6.2. Current Research Gaps

Current algorithms have made significant advances, but several issues need attention. Firstly, most algorithms still lack practical application, with limited real-world examples to support theoretical research. Literature shows that many studies focus on improving algorithmic capabilities, yet only a few substantiate these improvements with practical problem-solving, which is crucial for green workshop scheduling. Future research should incorporate real-world scenarios to better demonstrate the practical applicability of these algorithms.

Secondly, although computational capabilities have greatly improved, rapid societal development means that the search capacity of some algorithms still falls short of current requirements, necessitating further research and development to meet these challenges.

6.3. Future Research Directions:

Quantum Algorithms: Future research could integrate quantum algorithms with classical methods like GA and simulated annealing to tackle more complex multi-objective scenarios, offering solutions with better efficiency and precision.

AI Integration: Combining AI algorithms with existing complex scenario algorithms can address dynamic environments, particularly those prone to frequent equipment failures. Integrating AI could elevate green workshop scheduling, making it more suitable for future-oriented applications, but further validation through research is needed.

Green workshop scheduling holds immense potential for development. As society advances, continuous optimization in areas such as energy consumption, time management, and cost reduction is necessary. Ongoing research and adaptation will be key to maintaining progress in this field.

References

[1] Pan, Z.-X., & Lei, D.-M. (2020). Study on a distributed low-carbon parallel-machine scheduling algorithm based on problem characteristics. Acta Automatica Sinica, 46(11), 2427–2438.

[2] He, Y. J., Qian, B., & Hu, R. (2020). Solving complex parallel machine scheduling problems using a hybrid discrete teaching-learning algorithm. Acta Automatica Sinica, 46(4), 805-819.

[3] Amiri, M. F., & Behnamian, J. (2020). Multi-objective green flowshop scheduling problem under uncertainty: Estimation of distribution algorithm. Journal of Cleaner Production, 251, 119734.

[4] Lian, X., Zheng, Z., Wang, C., & Gao, X. (2021). An energy-efficient hybrid flow shop scheduling problem in steelmaking plants. Computers & Industrial Engineering, 162, 107683.

[5] Jia, S., Yang, Y., Li, S., Wang, S., Li, A., Cai, W., ... & Hu, L. (2024). The green flexible job-shop scheduling problem considering cost, carbon emissions, and customer satisfaction under time-of-use electricity pricing. Sustainability, 16(6), 2443.

[6] Yibing, L. I., Weixing, H., & Rui, W. U. (2020). Research on Multi-objective Green Flexible Job-shop Scheduling Based on Improved ABC Algorithm. China Mechanical Engineering, 31 (11).

[7] Zhang, C. Y., Dong, X., Wang, X. J., Li, X. Y., & Liu, Q. (2010). Multi-objective flexible job shop scheduling based on an improved non-dominated sorting genetic algorithm. Journal of Mechanical Engineering, 46(11), 156-164.

[8] Stützle, T., & Hoos, H. H. (2000). MAX–MIN ant system. Future generation computer systems, 16(8), 889-914.

[9] Zhang Fu, Wu Lei, Hui Jizhuang, Shao Shujun, & Du Chao. (2022). A flexible workshop production scheduling method based on multi-objective sparrow search algorithm. Journal of Beijing University of Technology, 48(11), 1132–1140.

[10] Wu, H. S., Zhang, F. M., & Wu, L. S. (2013). A new swarm intelligence algorithm: Wolf pack algorithm. Systems Engineering and Electronics, 35(11), 2430-2438.

[11] Khurshid, B., Maqsood, S., Omair, M., Sarkar, B., Ahmad, I., & Muhammad, K. (2021). An improved evolution strategy hybridization with simulated annealing for permutation flow shop scheduling problems. IEEE Access, 9, 94505-94522.

[12] Xu, Y., Chen, Y., Wang, C., & Peng, Y. (2024). Improving NSGA-III Algorithm for Solving High-dimensional Many-objective Green Flexible Job Shop Scheduling Problem. Journal of System Simulation, 36(10), 2314-2329.

[13] Seyedali, M., & Andrew, L. (2016). The whale optimization algorithm. Advances in Engineering Software, 95, 51-67.

[14] Kong, Z., Yang, Q. F., Zhao, J., & Xiong, J. J. (2020). Whale Optimization Algorithm Based on Adaptive Weight Adjustment and Search Strategy Using the Base-. Journal of Northeastern University (Natural Science Edition), 41(1), 35.