International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Review Article)

Multi-objective dynamic job shop scheduling optimization in manufacturing systems: A short review

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International Journal of Science and Research Archive, 2025, 17(02), 885–894

Publication history: Received 13 October 2025; revised on 19 November 2025; accepted on 21 November 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.17.2.3123

Abstract

The growing emphasis on accountability and sustainability, along with the recent push to manage sudden disruptions, has added new layers of complexity to modern Job Shop Manufacturing Systems (JSMs). Even small reductions in conflicting objectives can have ripple effects throughout these systems. This review brings together current research on the use of Multi-Objective Optimization (MOO) methods in dynamic scheduling, with particular attention to how energy cost optimization (ECO) is incorporated into real-time decision-making frameworks. A critical review of current methodologies reveals that achieving sustainability necessitates balancing the inherent time versus cost/energy trade-off, driving the adoption of metaheuristics like Genetic Algorithms (GA) and advanced Deep Reinforcement Learning (DRL) for adaptive policy generation. We detail the indispensable role of integrated digital architectures, including Digital Twin (DT) frameworks for virtual validation and the Internet of Things (IoT) for real-time data acquisition. This synergy facilitates the shift from static planning to autonomous, resilient control, demonstrating proven effectiveness in reducing total tardiness, carbon emissions, and operational costs. Finally, outlining key challenges particularly computational scalability and model generalization and proposing future research directions focused on hybrid optimization, edge computing, and comprehensive Industry 5.0 integration for truly sustainable manufacturing concludes the paper.

Keywords: Dynamic Scheduling; Multi-Objective Optimization. Energy Cost; Digital Twin

1. Introduction

The modern industrial landscape, especially within Job Shop Manufacturing Systems (JSMs), is defined by a high degree of product customization that leads to intricate production flows, unpredictable job arrivals, and considerable operational uncertainty. Achieving effective scheduling in such a dynamic setting demands continuous real-time adaptation and swift, data-driven decision-making frameworks (Destouet et al., 2023). This need for responsiveness lies at the core of high-tech manufacturing systems, where continuous process optimization becomes achievable through the implementation of dynamic scheduling (Ghasemi et al., 2024). The multidimensional nature of modern scheduling is further intensified by the need to manage situations that involve pursuing multiple, and sometimes conflicting, objectives simultaneously (Long, 2024). Traditionally, time management in manufacturing primarily cantered on improving production efficiency, focusing on metrics such as minimizing makespan or reducing tardiness. However, this paradigm has shifted toward sustainability, a transformation aligned with the principles of Industry 5.0.

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The objectives (Destouet et al., 2023) in the article are not traditional since they include the reduction of environmental damage and containment of operational costs. Consequently, scheduling must now integrate the optimization of core production performance with better resource utilization and adaptive management of fluctuating factors—particularly energy consumption. The challenge of this real time optimization task is escalated by operational disturbances, e.g., deteriorating of machines or changes in electricity prices (Mingorance et al., 2025). This professional report seeks to investigate and summarize the method of introducing and encompassing enhanced multi-objective optimization (MOO strategies) systems into dynamic job setup frameworks in the job shop celebrated. Very specific emphasis is put on methodologies which have a tendency to minimize the energy costs, limit the carbon emissions without compromising core production indicators. The accomplishment of scalable, resilient and sustainable manufacturing activities is clarified in the report by reviewing the application of enabling technologies including Digital twins and Deep reinforcement learning. It is essential to note that the shift towards optimization as an autonomous mechanism of dynamic control as opposed to a classical exercise of planning is the key to the ability to sustain cost-effective industrial operations (Lee, 2023). The growing sophistication of the dynamic and sustainable scheduling has led to novel research thrust in the recent couple of years as indicated by the dispersion of the related publications. The table below demonstrates the vivid increase in the relevant publications with the peak in 2023 and 2024 and the potential existence of a strong contemporary interest in the given domain of the problem. The trend of the publications over the years is depicted in Figure 1.

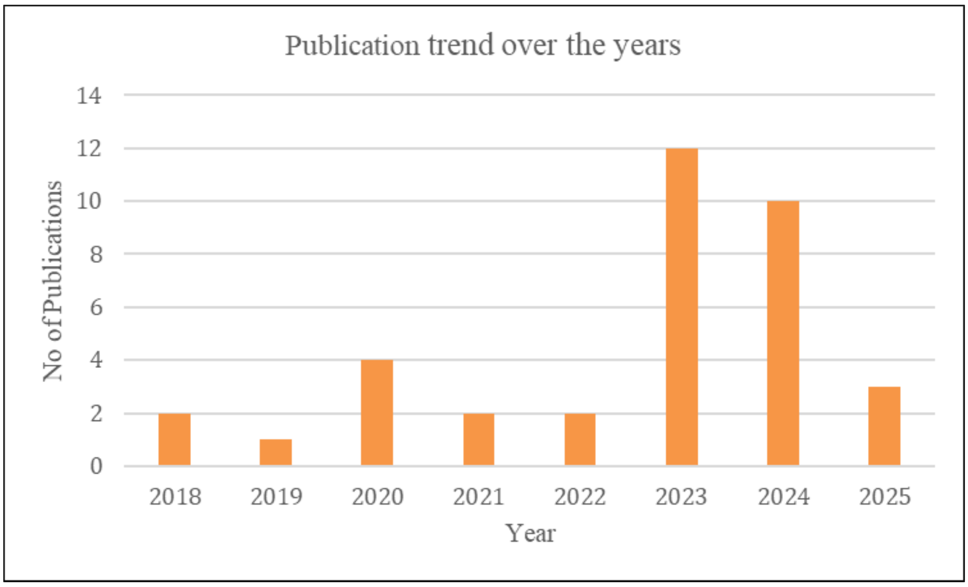

Figure 1 Articles publications over the years (2018-2025)

2. Dynamic Scheduling in Job Shop Manufacturing

Dynamic scheduling is the act of responding to production sequences and resource allocations in real-time or close to real-time as a result of some form of unforeseen activity or interference on the shop floor (Villalonga et al., 2021). This technique is essential in JSMs, which by definition presuppose the process of flexible routing and resource allocation, which stands highly against fixed planning assumptions in which problem sets of jobs and the availability of machines are fixed following the schedule generation.

2.1. Challenges of Handling Uncertainty

Dynamic scheduling of job shop manufacturing system (JSM) has an important role of operating with pervasive uncertainty, a factor that is essential in ensuring that systems are lightweight and resilient (Tariq et al., 2024). Random influx of jobs is one of the key problems that create an unceasing disruption to the system (Wong et al., 2022). As new jobs arrive, often unexpectedly and urgently, the existing schedule can quickly become infeasible or suboptimal due to these sudden changes (Z. Wang et al., 2020). This situation demands rapid resource reallocation and system adjustments, as traditional scheduling models may no longer perform efficiently under such conditions. Therefore, dispatching systems must be capable of generating practical scheduling policies within a short time frame to manage these disruptions effectively.

Moreover, resource limitations and random processing times further increase the complexity of scheduling. In job shop environments, overlapping activities, machine interdependencies, and shared resource constraints, along with issues related to machine reliability, make developing an efficient schedule even more challenging. To handle such uncertainties, especially variable operation times, scenario-based modeling becomes essential. This approach enables the application of advanced and adaptive methods to effectively manage dynamic production conditions (Nessari et al., 2024).

Another critical challenge arises from machine malfunctions and equipment failures, which can severely reduce productivity (Hector and Panjanathan, 2024). Unreliable machines often require costly and time-consuming repair-after-failure maintenance, disrupting overall operations. To mitigate these issues, implementing Predictive Maintenance (PdM) strategies becomes crucial. Technologies such as Internet of Things (IoT) sensors play a key role by detecting early signs of equipment faults, thereby enhancing system stability and reliability (Yousuf et al., 2024). In complex logistics environments such as container terminals, where similar uncertainties prevail, sudden fluctuations can create cascading effects that render traditional schedules ineffective. Addressing these challenges requires computational methods capable of balancing exploitation, which refines the best-known solutions, and exploration, which searches for robust alternatives that can adapt to dynamic changes within the system (Nessari et al., 2024).

2.2. Foundational Dynamic Scheduling Paradigms

To address the challenges of dynamic scheduling, systems are typically managed through a two-stage framework that distinguishes between proactive and reactive strategies in real time (Hendaoui et al., 2025). Proactive-reactive scheduling represents one such framework, where the initial proactive phase focuses on developing a robust baseline schedule capable of withstanding potential disruptions, followed by a reactive phase that adapts the schedule in response to real-time changes (Bahroun et al., 2024). Flexibility including the job slack times has been included in this schedule to cushion any small disturbance that might be experienced. Once the system exceeds the predefined threshold, it transitions into the reactive stage, where real-time information is utilized to modify the schedule in response to recent disturbances. This approach helps maintain continuous feasibility without causing significant disruption to the initial plan, as the system can adapt to unexpected events while preserving overall operational efficiency (Bahroun et al., 2024). The proactive stage provides stability by establishing a reliable foundation, whereas the reactive stage ensures flexibility, allowing the schedule to adapt smoothly to uncertainty and maintain optimal performance (Bahroun et al., 2024).

The other strategy is the Event-Driven Rescheduling, which only optimization is triggered by an important event, leaving the machine out of commission; or unforeseen energy costs influx. It minimizes to a minimum redundant computational load and instead targets key disruptions which deserve an immediate investigation (Fathollahi-Fard et al., 2024). The event-based approach presents an effective strategy for energy optimization, allowing the system to respond dynamically to temporary external factors such as fluctuations in energy prices. By adjusting operations in real time, the system can reduce energy consumption during non-critical periods, leading to more efficient resource utilization (Liang et al., 2024). Enhancing machinery dependability through the integration of Predictive Maintenance (PdM) and Mixed-Integer Programming (MIP) models also plays a vital role in managing energy costs. One practical method to minimize unplanned downtime involves scheduling preventive maintenance during the production planning phase, enabling maintenance tasks to be assigned to available idle periods (Maierhofer et al., 2025). This approach reduces the need for energy-intensive emergency scheduling during peak cost intervals, aligns maintenance with favorable energy price windows, and ultimately improves both energy efficiency and operational reliability (Fathollahi-Fard et al., 2024).

3. Multi-Objective Optimization in Job Shop Scheduling

Modern Job Shop Scheduling (JSS) is inherently complex because it requires balancing multiple, often conflicting, objectives that must be optimized simultaneously. Multi-Objective Optimization (MOO) methods are specifically designed to address this challenge, extending beyond single-objective approaches such as makespan minimization. Instead of identifying a single best solution, MOO methods generate a set of Pareto non-dominated solutions, each representing an optimal trade-off in which improving one objective can only be achieved by compromising another. The trade-off space in the dynamic and time-stable scheduling becomes even more complex, where systems are interested in integrating the opposing parameters such as time, expense, and energy efficiency. In dynamic scheduling, the most recent studies have paid more and more attention to the multi-criteria optimization problems, and the primary objectives have become highly emphasized. The information provided in the literature reviewed indicates that seemed to have high importance in optimizing time, cost, and energy metrics as their importance is emphasized in modern research on scheduling.

The number of objective functions considered in the selected studies can be seen in Figure 2.

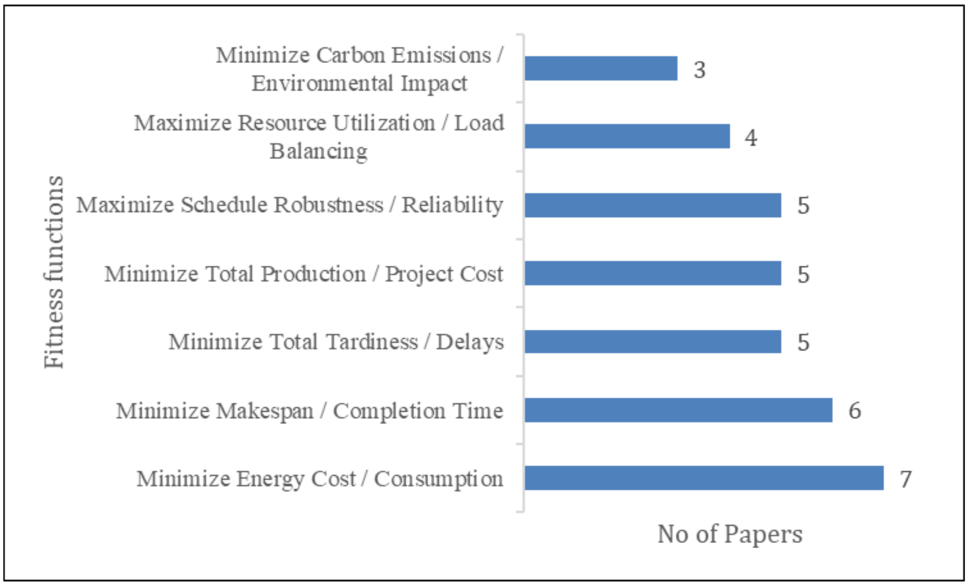

Figure 2 Objective functions considered in the selected publications

3.1. Objectives and Conflict in Sustainable Scheduling

Major production goals, including minimization of makespan, overall tardiness, and full use of resources are also nowadays being complemented with strict sustainability conditions in contemporary scheduling models. The environmental goals are part of these sustainability objectives; attempts are to reduce total (carbon) emissions and complete energy use (J. Wang et al., 2020). As an illustrative case, a single digital twin (DT)-based procedure led to a 5% decrease in carbon dioxide emissions in the case study with a manufacturing facility (Mingorance et al., 2025). Economic objectives are also a determinant with the aim being to reduce the total production costs and distribution costs and in the specific case the costs in relation to changing energy prices. Moreover, such aspects as human and quality are starting to receive an increased role in priority, particularly in the presence of Industry 5.0, which incorporates non-traditional goals such as the need to achieve stability in quality of products and to ensure the minimal harm to personnel by production, each including the consequences associated with the learning and forgetting process in a multi-memory (Maierhofer et al., 2025).

The incompatibility of the Multi-Objective Optimization (MOO) is characterized by the contrasts between time and cost (Razi and Ansari, 2024). Finding the minimum possible makespan may mean continuous high-power consumption use by the machines resulting in a higher consumption of energy. Alternatively, reducing administrative expenses by changing the schedule to off-peak shifts or idle time can decrease the duration of the entire project or add job lateness (Cui et al., 2020). Also, the schedule robustness (reduction of the cascading impact of disturbance) is complex, a complicated task that also turns the problem into bi-objective optimization problem, the weighting of makespan and schedule robustness becomes important.

3.2. Optimization Techniques for Multi-Objective Dynamic Scheduling

Due to the complexity of the Job Shop Scheduling (JSS) problems of large scale, primarily, metaheuristic and evolutionary algorithms are used to effectively identify a large set of high-quality Pareto solutions (Benaissa et al., 2024). The use of Genetic Algorithms (GA), specifically the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Optimization (MOO) scheduling is highly widespread in terms of scheduling. This is widely used due to capabilities to address non-linear formation of a wide range of solutions, which are well-distributed and non-dominated known as Pareto Fronts. Application NSIO2 has been used in bi-objective models, including optimization of makespan and index of the anti-cascade effect in multi-equipment scheduling that is robust. Often, hybrid algorithms combine GA with field-specific methods such as bi-directional scheduling methods or the simulation methods (so-called Simheuristics) to face stochastic multi-objective optimization problems arising under uncertainty (Nessari et al., 2024).

Results based on the variants of the Particle Swarm Optimization (PSO), such as Multi-Swarm PSO, are also used in the large-scale satministration of scheduling. Such algorithms are developed to reduce the performance measures (maximum completion time, and response time) with the load balancing mechanisms used frequently. They have especially been useful in the scheduling optimization in data center management corresponding to the supply chain sustainability. Modern scheduling issues are increasingly challenging with high-dimensional objective space to preclude multiple parallel objectives, including makespan, cost, carbon emissions, and quality stability, making the exploration to discover convergent and high-quality solutions with a single metaheuristic much more difficult. This growing complexity has driven a shift toward more adaptive and computationally efficient approaches, leading to increased reliance on Machine Learning (ML) and Deep Reinforcement Learning (DRL). The key advantage of these techniques lies in their ability to learn generalized scheduling rules offline, enabling rapid and effective implementation in real-time dynamic environments such as production scheduling.

4. Energy Cost Optimization in Modern jsms

Energy Cost Optimization (ECO) has become a critical concern in the manufacturing sector, as it directly influences operational costs, economic sustainability, and environmental preservation. Achieving effective ECO requires moving beyond the simple minimization of energy consumption (measured in kWh) to address the complex, time-dependent nature of energy costs. These costs fluctuate based on factors such as time-of-use tariffs and real-time market variations, resulting in dynamically changing financial impacts that must be carefully modeled and managed,

4.1. Strategies for Energy-Aware Scheduling

Energy-aware scheduling aims to leverage operational flexibility to optimize machine power usage and reduce overall energy expenditures. One of its key strategies is load shifting, which involves adjusting high-energy-consuming operations to periods when electricity prices are lower. By aligning production activities with fluctuating energy rates, this approach minimizes costs while maintaining operational efficiency. A number of studies have been devoted to lowering the total energy rates along with the total tardiness and minimization of disruptions that in many cases are caused by the emergence of new urgent occupations. These disturbances necessitate complicated time-table modifications in order to equal energy use and efficiency in working.

State of the art models in energy-conscious scheduling also include ideals of describing detailed energy conditions of machines. These models explicitly take into account different modes of operations of the machine including idle or standby mode, and different speeds of the processing including manual and automatic modes (Fathollahi-Fard et al., 2024). These scheduling models can reduce energy wastage when there is a switch in externalities (idle time minimization) and also choose energy-saving operating speeds (Gao et al., 2018). Low-carbon job shop scheduling is also another emerging practice, in which Low-Carbon Flexible Job Shop (LFJS) concept envisions actively combining carbon emissions reduction and classical scheduling goals (Destouet et al., 2023). These solutions employ new optimization models, including infinitely repeated game optimization, to ensure that production plans meet environmental commitment and evidences that these solutions are effective at minimizing the amount of energy used using real-time IoT data (J. Wang et al., 2020).

4.2. Algorithmic Integration and Impact

Certain special algorithms will be necessary to enable the effective incorporation of ECO (Energy Consumption Optimization) in dynamic conditions. One of them is through metaheuristic applications in which, the dynamic energy-sensitive job shop scheduling problem may be solved by applying heterogeneous, island parallel genetic algorithms. The strategy of parallelization will be able to generate solutions very fast, reduce the overall tardiness, overall energy expenditure, and inconvenience caused to the existing schedule, which shows that it is efficient in dynamic situations.

The second approach is the Deep Reinforcement Learning (DRL) which has shown a lot of usefulness in overseeing dynamic complex systems. Indicatively, a Clustering-Aided Multi-Agent DRL approach to semiconductor manufacturing will successfully result in decreased total job tardiness and consumption of machine energy, and proved the ability of DRL to address high-frequency scheduling needs and dynamic arrivals in energy-sensitive systems (Zhang et al., 2025).

Real time system awareness results in accurate cost reduction of energy. Although reducing the energy use (KWh) is also a vital environmental objective, to reduce the dynamic energy cost ($), external data feeds, including real-time data on the energy market, must also be incorporated. This need has led to the adoption of Digital Twin (DT) frameworks, which enable simulation and forecasting of the financial impacts associated with various scheduling policies while considering real-time energy pricing. The DT serves as a virtual testbed, allowing the optimization engine to continuously refine its strategies based on projected financial outcomes. In doing so, it functions as a critical infrastructure for enhancing both financial efficiency and environmental sustainability (Mingorance et al., 2025).

5. Advanced Enabling Technologies and Case Studies

The robust and scalable execution of Multi-Objective Dynamic Scheduling (MODS) relies on the interplay of three key technologies: the Digital Twin for integrated modeling, Deep Reinforcement Learning for adaptive control, and the Internet of Things for real-time data acquisition.

5.1. Digital Twin (DT) Frameworks for Adaptive Control

At its core, the Digital Twin (DT) is an enabling technology that bridges the physical world with the intelligent optimization layer known as the Cyber-Physical System (CPS). One of its key applications lies in providing real-time decision support, where operating strategies are dynamically adjusted through optimization techniques. The DT also facilitates automated decision-making by simulating various disruptions within the production process, such as component degradation or fluctuations in electricity prices, allowing the system to anticipate and respond effectively to changing conditions. One of the applications made its measurable results 5 percent cost savings on a per-tonne basis 5 percent carbon dioxide emissions reduction, and 30 percent better demand response (Mingorance et al., 2025).

The other thing that matters is building of a virtual workshop to be validated. The Digital Twin would allow engaging in simulation, optimization, and testing of intricate dynamic schedules paths, i.e. the ones regulating machine failures and worker memory systems, and deploying them on the real manufacturing areas. It is essential that this physical-digital convergence is important in conducting testing strategies that are capable of reducing carbon emissions and reducing cost of production at the same time. Also, rescheduling and monitoring, which happen to be integrated, represents another vital aspect of the Digital Twin. It gives a decentralized but connected procedure of making decisions through integrating condition based observing of the local Digital Twins of individual assets and by assessing the lead rate using a global Digital Twin. The system tracks the development in the production cycle automatically and initiates the relevant rescheduling to ensure the processes remain efficient and the operations are at minimal costs (Villalonga et al., 2021).

5.2. Deep Reinforcement Learning (DRL) for Policy Evolution

Deep Reinforcement Learning (DRL) is being adopted to address the computational constraints and generalization of poor performance common to fixed dispatching directions and the classic metaheuristics under areas of dynamic scheduling. This has been used in one notable task of adaptive scheduling policy generation, in which DRL is used to train an agent offline to learn valuable scheduling policies (SPs) that can be deployed online quickly. When the agent identifies real-time state features of the production system by applying Convolutional Neil Networks (CNNs), the process helps more attentively towards minimizing overall tardiness by the agent and can select the best dispatching rule.

One more important advantage of DRA is that it addresses generalization and dynamism of resource management. DRL models with Graph Neural Networks (GINs) cannot only encode the job shop structure (disjunctive graph) in a state representation. It is a structure that enables the model to be extended to large-scale instances and to build upon a dynamically varied quantity of machines essential in the case of any abrupt breakdowns or service recovery. An example of a multi-objective application case study is CA-MADRL which uses DRL to multi objective multi-paralleled batch processing scheduling, which does not consider certain dynamism issues such as job arrival and job family incompatibility. This method or approach to scheduling is able to produce much less job tardiness and machine power consumption as well as achieve scheduling needs on a high frequency by shaping DRA reward activities based on offline algorithm (MS-NSGA-II) cluster of pareto fronts (Zhang et al., 2025).

5.3. Role of Internet of Things (IoT) and Real-Time Data

IoT offers the real-time and high-resolution data stream that can be used to make responsive scheduling decisions. It is also used when real-time data acquisition is required as an application, as the IoT technology can allow manufacturers to access real-time data about resources and processes. This is core to the execution of low-carbon flexible job shop (LFJS) real-time scheduling strategies through which the present scope could be limited to lowering energy usage and improving production efficiency (J. Wang et al., 2020).

The Internet of Things (IoT) also plays a vital role in enabling Predictive Maintenance (PdM). PdM strategies rely on IoT sensor data to anticipate mechanical equipment failures and schedule preventive maintenance before breakdowns occur. This approach reduces unnecessary downtime and contributes to more stable and predictable energy consumption patterns. Beyond maintenance, IoT data is also valuable for optimizing logistics and transportation operations. It supports the dynamic coordination of Automated Guided Vehicles (AGVs) within factory logistics systems. Algorithms such as the Discrete Jaya Algorithm use real-time IoT data to minimize transportation costs, including travel, penalty, and vehicle expenses, by adapting to changing conditions such as variable unloading times. This integration of IoT-driven optimization enhances both cost efficiency and operational responsiveness in modern manufacturing environments.

The architecture brings performance to the three technologies which in turn has led to the successful implementation of MODS (Multi-Objective Dynamic Scheduling) and ECO (Energy Consumption Optimization). The real-time state vectors and the measurement data are provided by the IoT, and applied by the Digital Twin (DT) to the creation of a risk-free, simulated test environment, in which MOO policies can be tested and assessed against actual dynamics, like dynamic energy prices. The DRA player will make use of the DT to acquire the best adaptive policies giving the required low-latency control system in dynamic scheduling choices. Programs such as this coordination will be essential in the preservation of sustainable manufacturing as well as financially sound manufacturing operations. The table below gives an overview of the major research initiatives indicating the use of fully developed frameworks on MODS, whose focal points were placed on sustainability and cost agendas.

Table 1 Integrated Frameworks for Multi-Objective Dynamic Scheduling

Research Title	Method	Objectives	Sustainability Focus
A methodology leveraging digital twins to enhance the operational strategy of manufacturing plants in unexpected scenarios (Mingorance et al., 2025).	DT, Reinforcement Learning, Neuronal Networks	Cost Reduction, Efficient Production, Demand Adjustment	5% Cost Reduction, 5% Lower CO2 Emissions
A clustering-aided multi-agent deep reinforcement learning (Zhang et al., 2025)	CA-MADRL (DRL), MS-NSGA-II	Total Job Tardiness, High-Frequency Scheduling	Machine Energy Consumption Reduction
Solving the dynamic energy aware job shop scheduling problem (Luo et al., 2020).	Heterogeneous Parallel GA, Event-Driven Strategy	Total Tardiness, Disruption Minimization, Quick Response	Minimize Total Energy Cost
Dynamic scheduling of multi-memory process flexible job shop problem (Li and Chen, 2023).	Digital Twin, Virtual Workshop, Multi-Objective Optimization	Makespan, Total Production Cost, Quality Stability	Minimize Total Carbon Emissions
Infinitely repeated game based real-time scheduling for low-carbon flexible job shop (J. Wang et al., 2020).	Infinitely Repeated Game Optimization, IoT	Production Efficiency Improvement	Reduce Energy Consumption (Low-Carbon JSS)
Dynamic Scheduling and Preventive Maintenance in Small-Batch Production: A Flexible Control Approach for maximising Machine Reliability and Minimising Delays (Maierhofer et al., 2025).	Mixed-Integer Programming, Adaptive Maintenance Strategy	Maximize Machine Reliability, Minimize Delivery Delays	Reduces unplanned downtimes (Indirect cost/energy saving)

6. Computational Challenges and Future Directions

The field of multi-objective dynamic scheduling, particularly when incorporating complex metrics like energy cost and resilience, faces significant architectural and algorithmic hurdles that dictate future research trajectories. A critical challenge remains the computational complexity and scalability of dynamic scheduling solutions. Flexible Job Shop Problems (FJSSP) are notoriously NP-hard, and when uncertainty (stochastic processing times, random arrivals) and multiple conflicting objectives are added, the time required to find high-quality solutions rapidly escalates. While DRL approaches offer fast online execution, the initial training time and model complexity must be managed. The challenge is delivering results quickly, sometimes requiring millisecond-level response capability for low-cost emergent scheduling, forcing techniques to move away from computationally burdensome exact optimization methods. Furthermore, dynamic scheduling systems are fundamentally reliant on high-quality data acquisition and integration. Real-time decision-making requires accurate, comprehensive data feeds from smart manufacturing environments. Successfully incorporating novel elements such as complex human-centric data particularly factors like workers' learning and forgetting processes into the Digital Twin (DT) modeling environment introduces substantial challenges related to data integration and modeling uncertainty. Moreover, within Deep Reinforcement Learning (DRL)-based solutions, achieving model generalization and robustness remains a critical area of ongoing research. Although DRL can develop scheduling policies (SPs) that surpass traditional approaches in controlled training environments, these policies must demonstrate strong generalization to perform effectively in new and unseen scheduling contexts. Ensuring this adaptability is essential for the practical adoption of DRL-driven scheduling systems in industrial applications.

Future research will focus on developing hybrid, adaptive, and geographically distributed architectures capable of handling the latency-sensitive nature of real-time energy consumption optimization (ECO). Hybrid optimization and adaptive policy evolution will see the increased use of hyper-heuristics and coevolutionary genetic programming to generate generalized scheduling policies (SPs) through extensive offline learning. The given ability enables the system to identify better heuristics than those present in fixed, human-generated dispatching rules, which results in the evolved SPs being sound and very reusable in a set of various, unknown scheduling conditions. Other studies are being done in the area of developing hybrid optimization methods in order to utilize both the advantages of efficient search algorithms (such as those found in metaheuristics) and the real-time decision-making capability of machine learning (ML). These may include extending DRA with tailored clustering and digital algorithms (e.g., CA-MADRL) to effectively adapt to intricate objective functions while maintaining search efficiency and responsiveness to high-frequency variations (Zhang et al., 2025). In addition, proactive prediction models such as ensemble learning algorithms (e.g., Gradient Boosting Decision Tree, GBDT) can be employed to enable forecasting of machine utilization and infrastructure states (e.g., healthy or faulty machines) during task execution. This predictive layer enhances robustness, reduces task dropouts, and improves resource load balancing in constrained environments.

Integrating IoT, DT, and decentralized control for sustainability will also be a critical research direction. The transition from optimizing energy consumption to optimizing energy cost requires responsiveness to transient data such as real-time electricity pricing. Achieving this necessitates a shift toward cloud–edge computing frameworks. To ensure low-latency, real-time responsiveness, decision-making agents (e.g., DRL policies) should be decentralized and deployed at the edge within local DTs or machine controllers to minimize communication delays and enable ECO decisions to exploit short-lived, favorable energy windows effectively.

Additionally, as manufacturing systems become more complex and interconnected (e.g., integration of production and logistics), disturbances in one area can cascade throughout the system. Future work must develop robust optimization strategies, utilizing novel indices (such as complex network structure entropy) to evaluate and minimize the anti-cascade effect of scheduling decisions, ensuring resilience alongside efficiency and sustainability. Finally, future multi-objective optimization (MOO) models will fully integrate the broader sustainability mandate of Industry 5.0, explicitly modeling and optimizing human factors (e.g., job rotation, skill assignment) alongside environmental criteria (carbon emissions) and economic costs, moving toward a truly sustainable flexible job shop scheduling problem (SFJSSP) (Destouet et al., 2023).

7. Conclusion

Multi-objective dynamic scheduling has evolved from being an academic challenge to a practical necessity in modern Job Shop Manufacturing Systems. The review highlights a significant shift in manufacturing research and development, where traditional scheduling metrics like makespan and tardiness are now expanded to include crucial environmental and economic factors, primarily energy cost and carbon emissions optimization. The integration of advanced technologies such as the Internet of Things (IoT), Digital Twin (DT), and Deep Reinforcement Learning (DRL) has become essential in addressing the growing complexity of modern manufacturing systems. The combination of these technologies enables manufacturers to respond effectively to dynamic events such as random job arrivals, unexpected machine breakdowns, and fluctuations in electricity prices leading to enhanced efficiency and substantial cost savings.

Future research will focus on developing hybrid optimization systems that integrate the robustness of metaheuristics with the learning capabilities of machine learning and the adaptability of real-time decision-making. These systems must be dynamic and capable of maintaining real-time responsiveness while simultaneously optimizing multiple objectives in continuously changing environments. As computational demands increase, the focus will shift toward edge-based and decentralized decision-making frameworks, enabling low-latency and real-time adaptive scheduling. Such frameworks will allow manufacturers to respond promptly to abrupt variations in production and energy conditions.

The incorporation of predictive models, including ensemble learning approaches, will further enhance resilience by anticipating potential disruptions. This predictive capability will improve resource management, reduce task failures, and achieve balanced workload distribution in constrained environments.

Future scheduling models must also embrace sustainability-driven objectives that integrate environmental and human-centric factors to align with the vision of Industry 5.0. This includes balancing economic performance with human well-being, skill development, and carbon reduction fostering a more holistic and adaptive perspective on flexible job shop scheduling.

The synergistic integration of IoT, DT, and DRL technologies represents a key milestone, empowering manufacturers to optimize energy consumption, minimize emissions, and enhance production efficiency in unstable and dynamic environments. This convergence forms the foundation for sustainable digital manufacturing, offering the computational framework necessary to address complex, multi-objective, and dynamic scheduling challenges. Ultimately, this review underscores the critical role of these technologies in jointly achieving operational excellence and environmental sustainability, ensuring that future manufacturing systems remain resilient, adaptive, and cost-effective in an increasingly competitive and energy-conscious global landscape.

Compliance with ethical standards

Acknowledgment

The authors are thankful to Universiti Malaysia Pahang Al-Sultan Abdullah for supporting this research.

Disclosure of conflict of interest

The authors declared that they do not have any conflict of interest.

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