WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Application of Heuristics in Production Planning and Job Scheduling

Indranil Deb [a], *Ranjan Kumar Gupta* [b*]

[a] Research Scholar, Department of Management and Commerce, West Bengal State University, Barasat, Kolkata-700124, India
[b*] Assistant Professor, Department of Management and Marketing, West Bengal State University, Barasat, Kolkata-700124, India
DOI: https://doi.org/10.55248/gengpi.4.623.45166

ABSTRACT

In supply chain management, the production is a core process which converts raw material into finished goods in a timely manner. From the inception of industrial revolution, technological advancement, economical process, organizational model, market demand has evolved, which has influenced changes in mechanism of production planning and scheduling. Scheduling refers to the sequencing of tasks and their assignment to suitable resources. This paper focuses on the various types of production scheduling problem, where heuristics techniques have been applied to formulate and solve the problems. Emerging technologies like artificial intelligence, blockchain, cloud computing, internet of things (IoT) directly impact the planning and scheduling frameworks used in the production industry. Recent development in production scheduling has emerged further due to state-of-the art technology and its perspective to global orientation of manufacturing organization and their view towards green manufacturing schedule with enforced security during information sharing.

Key Words: Heuristics, production planning, job scheduling, green scheduling problem

1. Introduction

A production scheduling problem revolves around processing of jobs or parts on different machines and determining the sequence and timing of each operation on each machine such that some given performance criterion is maximized or minimized (Bhongade & Khodke, 2012). Efficient production scheduling is very critical for manufacturers to maximize high resource utilization, minimize delays while keeping production cost as low as possible. The majority of production shop scheduling problems can be classified into two classes (i) flow shop and (ii) job shop scheduling. In flow shop problem, machines are organized in order to process operation on the jobs, whereas in job-shop scheduling problem a set of jobs passes through different machines in any sequence. The two classes of production scheduling problems are accordingly named as assembly job shop problem (AJSP) and assembly flow shop problem (AFSP). The processing of jobs on different machines in same assembly or processing of parts in same assembly is carried out in parallel. The parameters influencing performance of the production system depends mainly on the complexity of the product structure, dispatching rule, and scheduling method.

Since the industrial revolution, technology and the global economy have developed rapidly. Driven by the market demand and the development of science and technology, the organisational model of the production system has evolved, which has in turn caused changes in the methods of production scheduling (Jiang et. al., 2021). The production scheduling mechanism has evolved from centralised/decentralised scheduling to distributed scheduling. Increasing product complexity, manufacturing environment complexity and an increased emphasis on product quality are the factors leading to uncertainties in production processes (Morton et. al., 1994). These uncertainties evolve from unplanned machine maintenance, rework, changes in product design, production modes, random demand, and random capacity etc.

Production scheduling has various variants of problem. It can be roughly divided into two categories, (a) general scheduling problem applicable in all industries and (b) real industry scenarios. The process overlapping or sequence dependent setup time is one of the realistic aspects in scheduling problem. With the rise of Industry 4.0 standards, which has led to a significant increase in data collection activities that is used to build larger and more complex models (Schlenkrich & Parragh, 2023). Newly emerging technologies such as internet of things, cloud computing and trend towards digitalization, automation and interconnection of systems operating at manufacturing floor has predominantly impacts production planning and scheduling frameworks. Industrial use cases consist of several thousand operations on a large variety of machines; therefore, it is necessary to identify and highlight approaches, which can meet the challenges of scheduling in the era of Industry 4.0 and are suitable to tackle large scale problems. For large scale scheduling problems advanced solution approaches belong to three categories, namely metaheuristics methods, constraint programming and machine learning.

To formulate different problem and solution approaches, mathematical programming methodology try to solve the underlying scheduling problem to optimality, heuristics and metaheuristics focuses on to find good solutions within reasonable computation times, whereas constraint programming is used to reduce the search space in the domain.

2. Literature review

The production scheduling approaches can be classified into categories; first type is generic extensions of classical scheduling problems, and the second type is specific solution approaches motivated by a certain industry. In the first category production scheduling problems are related to flexible job shop scheduling problem (Chaudhry & Khan, 2016; Xie et. al., 2019), assembly flow shop scheduling (Komaki et. al., 2019), non-permutation flow shop scheduling (Rossit et. al., 2018) or resource constrained project scheduling (Hartmann & Briskorn, 2010; Pellerin et. al., 2020). At the core of production scheduling problem there are two major tasks – the allocation of operations to suitable resources and defining their processing sequences. These tasks need to be executed by a scheduling method satisfying a set of constraints, such that an objective function is optimized. The set of constraints may vary significantly from one scheduling problem to another and reflect different aspects of the underlying real-world problem.

The classical scheduling problems consider few and simple restrictions like number of jobs to be processed on number of machines with fixed processing time, sequence of machines etc. Though classical job shop problem is a challenging optimization problem, real-world practical problems require to consider various other constraints like changing the setup of machines between jobs, processing sequence depending on time, varying processing time between multiple resources, characteristics of resources used to perform a given task, complex task relationships and constraints on their timing etc. The resources can be staff or machines. Due to variations in experience and skill level of staffs, and variations in the available technology; performing the respective production step varies with processing time by the resources. Xie et. al. (2019) proposed e flexible job shop scheduling problem (FJSSP) to capture more realistic aspect by choosing processing machine among the list of suitable machines. Kress et. al. (2019) introduced heterogeneous aspect of machine operator independent of processing time. There can be specific machines which might also be designed to produce two products in parallel which motivates incorporation of batch production constraints to the scheduling models. Ham (2017) investigated FJSSP with parallel batch processing machines, which was further developed by Mahmoodjanloo et. al. (2020) by formulating a model for reconfigurable machine tools for FJSSP. In this context Zhang & Wang (2018) explored flexible assembly job shop problem with sequence dependent setup times with part sharing. In production scheduling, sequence of tasks of resources has a significant influence on the setup time needed between two production tasks. To address this aspect, Shen et. al. (2018) developed a metaheuristic called tabu search algorithm in the context of the FJSSP with sequence dependent setup times. Relationship between different tasks is not always simple sequence, rather there can be different kind of relations between predecessor and successor. It can be overlapping of operations, no-wait constraint, transportation time, earliest and latest start or finish time, tardiness cost etc.

The four major categories of advanced solution approaches evolved to solve complex real-world scheduling problems, are mixed integer programming, metaheuristics, constraint programming, and machine learning. The first category of solution method is metaheuristics, which is used to tackle large scale production scheduling problems. Among various types of metaheuristics developed to solve scheduling problems, population based and nature inspired methods, trajectory-based approaches, decomposition algorithms or combination of these methods are significant. Population based and nature inspired metaheuristics follow principles that can be observed in natural phenomena observed in animal behaviour and natural selection in evolution. Genetic algorithms are popular examples for population-based metaheuristic that successively modify a set of solutions (also called population) under the principle of survival of the fittest. Defersha and Rooyani (2020) proposed a two-stage genetic algorithm for the FJSSP incorporating constraints sequence dependent setup time, release dates and lag time. Ali et. al. (2020) applied genetic algorithm with new virtual crossover operators for the dynamic job shop scheduling problem. Zhang et. al. (2019) developed hybrid particle swarm optimization along with genetic algorithm and simulated annealing. Particle swarm optimization (PSO) modifies a population of solutions in order to find the best solution within the search space. Simulated annealing is inspired by the process of annealing in metallurgy. Ant colony optimization (ACO) approach, which is inspired by the behaviour of ants travelling between their nest and potential food sources, applied by Zhang et. al (2020) to investigate multi-objective optimization in flexible assembly job shop scheduling to minimize makespan, total tardiness and total workload. Yang et. al. (2022) applied dragonfly metaheuristic, which is a method performing the phases of exploration and exploitation in a manner that is inspired by the behaviour of insects during their hunt for prey. To enhance the population initialization and generation jumping stage, the researchers incorporated dynamic opposite learning strategy into the algorithm to overcome the limitation of getting stuck in local optima.

There are several trajectory-based approaches which have been identified as suitable for large scale scheduling problems. The trajectory-based methods modify a single solution candidate that moves through the search space. Hajibabaei & Behnamian (2021) applied tabu search method for flexible job shop scheduling with unrelated parallel machines and resource dependent processing times. The researcher presented metaheuristic method in matrix-based solution containing information on the operation, sequence assignment of machines and flexible resources. In this approach initial solution is improved iteratively by performing modification of the solution, while keeping track of previous modification in the tabu list in order to prevent getting stuck in local optima. There are situations where jobs may block the machine after completion until the following machine becomes available. Mogali et. al (2021) investigated such blocking job shop problem. Rossit et. al. (2018) modified tabu search methods for job shop scheduling problems with routing, batching and release dates and then solved different neighborhood structures efficiently. To minimize the total weighted tardiness of flexible job shops, Sobeyko and Monch (2016) developed an iterative local search method using a simulated annealing acceptance criterion and hybridized the approach by means of the shifting bottleneck heuristic and a variable neighborhood search. To tackle complex scheduling problem having many real-world restrictions, such as sequence flexibility, resumable operations, sequence dependent setup times, partial overlapping between operations, unavailability of machines or fixed operations, Lunardi et. al. (2021) used combination of different metaheuristic solution approaches namely genetic algorithm, differential evolution, tabu search and iterated local search. From their research it is found that a combination of tabu search and differential evolution appears to be the most efficient method and it outperforms the other heuristics and a constraint programming approach.

The other metaheuristics approaches applied on large problem instances through decomposition by solving smaller subproblems efficiently and combining the results to an overall solution. El-Kholany et al. (2022) presented a method for decomposing a job shop scheduling problem into time windows, whose operations are then scheduled using a multi-shot form of declarative programming, called Answer Set Programming (ASP). It is observed that with larger instance size, the decomposition method delivered close result to the results provided by the constraint programming solver. The purpose of decomposing of job-shop scheduling problem into multiple time windows and solving the results is to optimize the total weighted tardiness and problem instances. Another programming methodology, for combinatorial optimization problems, called Constraint programming (CP) uses constraint propagation in order to reduce variable domains. This programming has drawn attention from the researchers due to its capability of solving extremely large scheduling problems. The constraint programming along with mixed-integer programming used to formulate to a challenging scheduling problems like online printing shop scheduling problem (Lunardi et. al., 2020).

Driven by the aim of Industry 4.0 to automate processes and the availability of large amounts of data, machine learning has grown very fast in the production context. The machine learning is another solution approaches for scheduling problems which consists of different learning-based methods, such as reinforcement learning and neural networks. The machine learning approaches suitable for dynamically changing scheduling environments, where frequently new jobs appear. In machine learning an agent repeatedly performs actions impacting an environment and receiving respective reward signals in order to learn a scheduling policy. Lei et. al. (2022) applied deep machine learning, where the agent was represented by a deep neural network, to the flexible job shop scheduling problem. To prioritize tasks various parameters can be optimized like earliest due date, shortest processing time etc. Zhang et. al. (2020) applied machine learning and developed Markov Decision Process model for priority dispatching. Han & Yang (2020) developed machine learning framework to solve job shop scheduling problems combining neural networks and machine learning.

3. Emerging concept in production planning – Green scheduling problem and blockchain technology

During the fourth industrial revolution, commonly known as Industry 4.0, with the high level of digitization, the concept of sustainability has evolved. Camarinha-Matos et. al. (2022) remarked that sustainable manufacturing represents the "integration of processes and systems capable to produce high-quality products and services using less and more sustainable resources (energy and materials), being safer for employees, customers and communities surrounding, and being able to mitigate environmental and social impacts throughout its whole life cycle". The manufacturing scheduling and its applications in manufacturing systems in term of sustainability, which is often termed as Green Scheduling Problems (GSP). From the economic viewpoint, sustainability in manufacturing in industrial contexts is aimed at reducing total setup times and energy consumption (Xin et. al., 2023). This is achieved through efficiently scheduled manufacturing operations, optimal jobs machine allocation, and job sequencing, which ensures optimal product quality. According to this viewpoint, manufacturing industries have become increasingly attracted to green manufacturing due to the recent huge increase in global energy consumption as well as the variations in energy costs (Ramezanian et. al., 2019). Hence, the quest for the reduction in the environmental degradation effects becomes as fundamental as the optimization of industrial production efficiency. In the context of Industry 4.0, smart manufacturing changes the traditional job shop scheduling problems into smart distributed scheduling problems. This shift provides increased flexibility, higher product quality, reduced lead times, and customized production (Liaqait et al., 2021). GSP could be defined as the problem of assigning multiple jobs to a given machine, which are to be processed at specific times, and gaining optimization of a given objective function. The GSP is an extension of the traditional Job Shop Scheduling Problem (JSSP), belonging to the family of NP-hard problems. The main characteristic of a traditional JSSP is an increased makespan, despite a high energy consumption, as well as the neglection of optimized resource allocation, operation methods, and job sequences. On the contrary, GSPs are aimed at lowering the cost of operations and reducing energy consumption. Moreover, in this kind of problem, resource allocation and operations sequence optimization are aimed to reduce pollutant emissions.

The typical problems, related to the GSP, are defined as modifying of the traditional flow shop scheduling problem to achieve opposite objectives, such as economic efficiency and sustainable efficiency. Li et al. (2022) developed a two-stage knowledge-driven evolutionary algorithm was proposed to solve a multi-objective distributed green flexible job shop scheduling problem. Lu et al. (2022) proposed a Pareto-based multi-objective hybrid iterated greedy algorithm to solve a Distributed Hybrid Flowshop Scheduling Problem (DHFSP) by minimizing makespan and total energy consumption (TEC). Zhao et. al. (2021) and Zhang et. al. (2019) formulated energy-efficient hybrid flow shop scheduling problems using artificial bee colony algorithms. Xin et al. (2021) proposed a modified whale swarm optimization algorithm for improving efficiency in a permutation flow shop scheduling problem with variable transportation time. Afsar et al. (2022) proposed an enhanced memetic algorithm combining a multi-objective evolutionary algorithm using e fuzzy numbers to manage processing time uncertainties. Gong et al. (2020) proposed a hybrid evolutionary algorithm to solve an energy-efficient flexible flow shop scheduling with worker flexibility. Cota et al. (2019) extended the adaptive large neighbourhood search metaheuristic to the multi-objective problem to improve the efficiency of the search process and extended to the problems related to large-scale instances. Han et. al. (2022) focused on balanced energy costs criterion and developed a model of a distributed blocking flowshop scheduling problem. Zhu et. al. (2022) proposed a distributed no-wait flow shop scheduling problem with due windows, with an efficient discrete knowledge-guided learning fruit fly optimization algorithm. Similarly, Guo et al. (2022) proposed a discrete fruit fly optimization algorithm based on a differential flight strategy to solve a DPFSP. Iterated greedy algorithms are used (Li et. al., 2022; Chen et. al., 2022; Huang et. al., 2020) to efficiently solve the DPFSP and enhance local search. The Non-Dominated Sorting Genetic Algorithms (NSGA) alone or combined with other algorithms has been applied in green scheduling manufacturing problems. To highlight few researchers namely Geng et. al. (2021), Dong & Ye (2022), Anghinolf et. al. (2021), Xue et. al. (2019), Fernandez-Viagas et. al. (2022) etc. Zeng et. al. (2022) used NSGA-II to solve a Multi-Objective Distributed Permutation Flowshop Scheduling Problem (MO-DFSP) by minimizing the makespan and carbon emissions, considering production and transportation constraints. Li et. al. (2021) used NSGA-II to solve an Energy-Efficient Distributed Permutation Flowshop Scheduling Problem (EEDPFSP) by minimize the total flow time and TEC. Huo et. al. (2020) formulated a multi-objective energy-saving job-shop scheduling process and optimized to minimize the maximum makespan, total carbon emissions, and total tardiness. In another study, Boufellouh et. al. (2020) used combined NSGA-II and Simulated Annealing (SA) to minimize the total carbon emission and maximum completion time in a Permutation Flowshop Scheduling Problem with Constrained Tool (PFS-CT) replacement activities. The NSGA-III-based proposed algorithm was efficiently used to optimize the disruption management model. In Zhang et al. (2020), a mathematical model for multi-objective optimization to minimize TEC, makespan, and peak power of the job shop was proposed, which used an integrated process planning and scheduling approach. The problem was efficiently solved by employing a hierarchical multi-strategy genetic algorithm based on a non-dominated sorting strategy.

Another recent trend in scheduling problem has emerged as collaborative distributed manufacturing scheduling problem. The collaborative distributed manufacturing scheduling (CDMS) has gained significant importance in extended, networked, and virtual manufacturing environments due to its adaptability and integration potential. In a distributed manufacturing environment, CDMS can occur within a single factory or across multiple companies in a dynamic and variable extended or virtual organization. For effective collaboration, the CDMS system must be secure, transparent, and trustworthy. Collaborative distributed manufacturing scheduling (CDMS) involves multiple entities working together and sharing resources to achieve their individual and collective goals (Putnik et. al. 2021). In the current complex and rapidly changing manufacturing environments, organizations such as extended manufacturing environments (EME) or virtual enterprises (VE) require collaborative distributed manufacturing scheduling (CDMS) to meet the demands of Industry 4.0 (Putnik & Ferreira, 2019). Scheduling problems that occur in distributed environments (Guo et. al., 2015) are complex, but CDMS can help companies tackle them effectively. The scheduling problems in CDMS (Varela et. al., 2012) are becoming increasingly complex due to the growing number of entities and resources involved. These entities and resources may be geographically dispersed and often involve combinatorial optimization problems (Varela & Ribeiro, 2014).

The emerging blockchain model has established its benefit in CDMS in the processing of manufacturing functions, specifically joint process planning and scheduling. Unlike existing solutions, which are specific to a particular production environment or programming method, the blockchain-based CDMS model makes a novel contribution to the field by integrating various techniques such as mathematical optimization, metaheuristics, machine learning, and agent-based approaches to solve basic scheduling problems. Blockchain technology, with its decentralized and distributed digital registry system, has seen widespread use in various industries over the past 15 years, including production planning, where it enhances efficiency and transparency through integration with management systems (Skowroński, 2019; Assaqty et.al., 2020). The key idea is to establish a peer-to-peer network between these enterprises using blockchain technology, enabling coordination and collaboration among them. Each enterprise has its own production facilities for manufacturing products. Distributed manufacturing systems (DMS) play a vital role in the current era of globalization since they can be used to manage and control distributed systems in organizations or networks. A popular approach called multi-agent systems (MAS) consists of a set of autonomous agents that can work together toward a common goal. To facilitate this, the MAS approach to CDMS uses specific architectures and protocols. These frameworks and protocols provide efficient communication and coordination between agents, enabling efficient management and control of the distributed system (Shen, 2002). CDMS is the most important part of the modern global manufacturing environment as it provides coordination and management of distributed production processes. Varela & Ribeiro (2014) proposed a model for dynamic planning based on a dynamic decision-making with multiple criteria. Their approach aimed to integrate strategies that allow for finding a compromise between different performance indicators such as cost, quality, and delivery time. Furthermore, various approaches, algorithms, tools, systems, and platforms support production planning from centralized to decentralized architectures. These approaches aim to integrate production planning as well as other management functions such as process planning, nesting, system balancing, and layout determination. The significant contributions made in this area by Vieira et. al. (2012), Varela et. al. (2012), Guo et. al. (2015), Ramakurthi et. al. (2021,2022). Zhou et. al. (2008) proposed an agent-based approach for distributed production scheduling to achieve global combinatorial scheduling optimization by integrating workflow scheduling in a distributed production environment. The proposed agent-based approach is adapted from the particle swarm optimization (PSO) algorithm, in which agents move toward a graph to find an optimal global time interval. Zhang et al. (2019) proposed a new task scheduling system in a production environment with multiple factories and workflows that consists of a set of rules that are considered necessary to meet the constraints of the production environment. In 2008, Wang et. al. proposed a different task scheduling method that uses a special type of computer algorithm called the discrete fruit fly optimization algorithm, designed to reduce costs and power consumption. In distributed production environment, communication and collaboration between the hubs should be efficient and effective. In 2017, Manupati et. al. used a telefacturing-based distributed manufacturing environment as a means of optimizing manufacturing services by enhancing the interoperability between various hub facilities. This approach led to enhance production outcomes and a more streamlined manufacturing service. In collaborative management process, integration of fundamental management functions require flexibility in process planning. Özgüven et. al. (2010) proposed a mathematical model for job-shop scheduling problems with routing which enables to integrate two management functions with a certain degree of flexibility. The task scheduling in a multi-factory manufacturing setting is crucial due to need to balance multiple objectives simultaneously. Fu et. al. (2019) built a task-scheduling approach with workflow constraints and utilized an integrated brainstorm optimization algorithm to balance multiple objectives simultaneously.

Many researchers explored and applied blockchain technology in distributed manufacturing scheduling. Kapitonov et. al. (2017) implemented blockchain model in autonomous object decision-making processes in an unconstrained environment, Sikorski et. al. (2017) leveraged blockchain technology to improve efficiency and to reduce cost in machine-to-machine communication, Skowronski et. al. (2019) applied blockchain in a multi-agent model for improved decision-making in intelligent production systems. Assaqty et. al. (2020) evaluates practical aspects of collaboration between the manufacturing environment through the blockchain that are suitable for smart manufacturing, Cambou et. al. (2020) focused on blockchain in additive manufacturing to eliminate attacks by intermediaries, Westerkamp et. al. (2019) evaluated potential of blockchain to improve the security aspects of production systems. There are many other researchers who used blockchain to improve the privacy and security of data transmission and communication on the Internet of Things (IoT); to develop a smart manufacturing security model to enhance security, privacy, and tamper protection; to prevent fraud scenarios and secure a logistics business etc. There are eminent researchers in the area of blockchain contributed significantly to improve coordination and collaboration in the smart manufacturing industry (Assaqty et. al., 2020), to create private systems to keep track of products and materials while maintaining privacy. Shahbazi and Bain (2021) proposed integrating blockchain technology and machine learning to address security and data management issues in smart manufacturing.

4. Relevance of the study

The relevance of this study is to explore development and formulation of job-shop scheduling problem over the years and how various methodologies have been applied to solve these problems. Our objective can be summarized as below:

- Review the literature of job-shop scheduling problem with many of its variations.
- Identify the types of job-shop scheduling problem and related constraints in various phases of production environment.
- Development of industry specific job-shop scheduling problem with in-built constraints.
- Identify the methodologies used by various researchers to optimize various constraints in different complex real-life situation.
- Application of different heuristics techniques which contributed to the solution of diversified and integrated job-shop scheduling problem.
- Influence of Industry 4.0 specification on job-shop scheduling problem.
- What a technological development and modern instruments influenced job-shop scheduling problem in distributed manufacturing environment.
- Application of emerging concept like green scheduling problem and blockchain technology in job-shop scheduling problem

5. Research Gap

Development of technology and change in aspects of doing business globally, has changed the dimension of job-shop scheduling problem from traditional one to complex scheduling problems. The world is now a globally integrated manufacturing hub. The globalisation of manufacturing and changes in production modes have compelled the development of production scheduling enabled by state-of-the-art technologies. From literature review, we find that there is future research opportunity in the following dimensions:

- Consideration of added complexities due to changes in product design and production methods brought by product personalization.
- Future expansion of the customer-centric value chain.
- Responsiveness of the scheduling system to new work.
- Integrating production scheduling with Manufacturing Execution and Control Systems.
- Use of artificial intelligence and blockchain concepts in simulation-based optimization techniques.
- Application of blockchain technology to improve manufacturing to control machines and to make sure they are doing the job correctly through secure data transactions.

The implementation of sustainable facility layout problem is an emerging concept to develop strategies to implement sustainable facility layout. Though blockchain technology has been applied in distributed manufacturing systems, there is an opportunity further focusing on the blockchain scheduling. Many researchers have proposed frameworks for scheduling, but blockchain-based smart contracts for scheduling in the context of distributed production, can be explored further. In production management, flexible and adaptive production planning is an excellent differential due to sustainability issues, big and complex data processing, and customization for enabling and supporting real-time decision-making in a dynamically changing production environment, under the constant transformation of the market. Thus, future production scheduling should be intelligent and flexible enough to the decision-maker to customize production decisions according to established priorities, either of the company and/or the customers' preferences. The dynamic production scheduling can be advanced by deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management to optimize resource utilization and enhance productivity in terms of enterprise decision-making.

6. Conclusion

This paper studies relevant articles on job-shop scheduling problem, an important domain of supply chain management. Our study reveals that, with the increasing complexity of supply chain management, the problems have shifted their nature from discrete to integrated environment. Initially the problems had been formulated in isolation where each stage was locally optimized. Growing demand and integrated natured of business environment have compelled to explore those in a different way. In these scenarios, the focus shifted from local optimization to global search and optimization. The integration of sub-systems was not much effective to achieve global optimization, where development of heuristics and combination of multiple methodologies have evolved and transformed the solution at optimum level. The dynamic scheduling which encompasses on-demand scheduling, should address optimal allocation of manufacturing resources to overcome uncertain number of manufacturing tasks in different scheduling periods.

Due to uncertain disruptions in the real-world manufacturing environment, it is difficult for traditional scheduling methods to effectively solve complex dynamic scheduling problems. While heuristic-based methodologies iteratively update solutions to find optimal result, artificial intelligent (AI)-based methods can quickly achieve near-optimal solutions. The AI greatly helps to adapt to dynamics based on their sequential decision-making. The AI-enabled data-driven predictive scheduling is increasingly gaining importance to enable the accurate prediction of various uncertain information which naturally figure out accurate uncertainty information from some given historical manufacturing data, that substantially improves the scheduling performance. There is a limitation of AI also, which cannot fully manage unrecognized disruptions due to the changes in customer needs or manufacturing capabilities. Thus, researchers should refocus on the interactions between humans and intelligent manufacturing systems during scheduling processes and should develop intelligent manufacturing systems to improve their ability to respond in a timely manner to various disturbances throughout the scheduling process.

The recent need for a compromise between production and energy-efficiency has led manufacturing industries to tackle the issues of sustainability linked to green manufacturing. Themes of costs, energy-efficiency, multi-objective optimization, and process control are trendy topics in GSP in manufacturing. Themes related to computational methods, cost reduction, energy storage, and optimal scheduling are emerging topics in the same field. The AI-enabled dynamic scheduling will play an important role to enable optimal decisions during the scheduling process in a low-carbon manufacturing environment, which will significantly contribute to the sustainability and resilience of our society's development.

7. References

1. Manuel Schlenkrich, Sophie N. Parragh, Solving large scale industrial production scheduling problems with complex constraints: an overview of the state-of-the-art, Procedia Computer Science, Volume 217, 2023, Pages 1028-1037, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2022.12.301.

2. Xin, X.; Jiang, Q.; Li, C.; Li, S.; Chen, K. Permutation flow shop energy-efficient scheduling with a position-based learning effect. Int. J. Prod. Res. 2023, 61, 382–409.

3. Qasim, M., Wong, K.Y. & Saufi, M.S.R.M. Production planning approaches: a review from green perspective. Environ Sci Pollut Res (2023). https://doi.org/10.1007/s11356-022-24995-2

4. Jiepin Ding, Mingsong Chen, Ting Wang, Junlong Zhou, Xin Fu, and Keqin Li. 2023. A Survey of AI-Enabled Dynamic Manufacturing Scheduling: From Directed Heuristics to Autonomous Learning. ACM Comput. Surv. Just Accepted (April 2023). https://doi.org/10.1145/3590163

5. Silva, D.M., Mateus, G.R. (2023). A Mixed-Integer Programming Formulation and Heuristics for an Integrated Production Planning and Scheduling Problem. In: Di Gaspero, L., Festa, P., Nakib, A., Pavone, M. (eds) Metaheuristics. MIC 2022. Lecture Notes in Computer Science, vol 13838. Springer, Cham. https://doi.org/10.1007/978-3-031-26504-4_21

6. Zengqiang Jiang, Shuai Yuan, Jing Ma & Qiang Wang (2022) The evolution of production scheduling from Industry 3.0 through Industry 4.0, International Journal of Production Research, 60:11, 3534-3554, DOI: 10.1080/00207543.2021.1925772.

7. Fernandez-Viagas, V.; de Athayde Prata, B.; Framinan, J.M. A critical path based iterated local search for the green permutation flowshop problem. Comput. Ind. Eng. 2022, 169, 108276.

8. El-Kholany, M., Gebser, M., Schekotihin, K., 2022. Problem Decomposition and Multi-shot ASP Solving for Job-shop Scheduling. Theory and Practice of Logic Programming 22, 623–639. doi:10.1017/S1471068422000217.

9. Yang, D., Wu, M., Li, D., Xu, Y., Zhou, X., Yang, Z., 2022. Dynamic opposite learning enhanced dragonfly algorithm for solving large-scale flexible job shop scheduling problem. Knowledge-Based Systems 238. doi:10.1016/j.knosys.2021.107815.

10. Lei, K., Guo, P., Zhao, W., Wang, Y., Qian, L., Meng, X., Tang, L., 2022. A multi-action deep reinforcement learning framework for flexible Job-shop scheduling problem. Expert Systems with Applications 205. doi:10.1016/j.eswa.2022.117796.

11. Ramakurthi, V.; Manupati, V.; Machado, J.; Varela, L.; Babu, S. An innovative approach for resource sharing and scheduling in a sustainable distributed manufacturing system. Adv. Eng. Inform. 2022, 52, 101620. https://doi.org/10.1016/j.aei.2022.101620.

12. Camarinha-Matos, L.M.; Rocha, A.D.; Graça, P. Collaborative approaches in sustainable and resilient manufacturing. J. Intell. Manuf. 2022, 1–21.

13. Sang, Y.; Tan, J. Intelligent factory many-objective distributed flexible job shop collaborative scheduling method. Comput. Ind. Eng. 2022, 164, 107884.

14. Li, Y.-Z.; Pan, Q.-K.; Ruiz, R.; Sang, H.-Y. A referenced iterated greedy algorithm for the distributed assembly mixed no-idle permutation flowshop scheduling problem with the total tardiness criterion. Knowl.-Based Syst. 2022, 239, 108036.

15. Li, W.; Chen, X.; Li, J.; Sang, H.; Han, Y.; Du, S. An improved iterated greedy algorithm for distributed robotic flowshop scheduling with order constraints. Comput. Ind. Eng. 2022, 164, 107907.

16. Zeng, Q.-Q.; Li, J.-Q.; Li, R.-H.; Huang, T.-H.; Han, Y.-Y.; Sang, H.-Y. Improved NSGA-II for energy-efficient distributed no-wait flow-shop with sequence-dependent setup time. Complex Intell. Syst. 2022, 9, 825–849.

17. Li, R.; Gong, W.; Wang, L.; Lu, C.; Jiang, S. Two-stage knowledge-driven evolutionary algorithm for distributed green flexible job shop scheduling with type-2 fuzzy processing time. Swarm Evol. Comput. 2022, 74, 101139.

18. Cambou, B.F.; Jain, S. Key Recovery for Content Protection Using Ternary PUFs Designed with Pre-Formed ReRAM. Appl. Sci. 2022, 12, 1785. https://doi.org/10.3390/app12041785.

19. Dong, J.; Ye, C. Green scheduling of distributed two-stage reentrant hybrid flow shop considering distributed energy resources and energy storage system. Comput. Ind. Eng. 2022, 169, 108146.

20. Lu, C.; Zhang, B.; Gao, L.; Yi, J.; Mou, J.A. Knowledge-Based Multiobjective Memetic Algorithm for Green Job Shop Scheduling with Variable Machining Speeds. IEEE Syst. J. 2022, 16, 844–855.

21. Afsar, S.; Palacios, J.J.; Puente, J.; Vela, C.R.; González-Rodríguez, I. Multi-objective enhanced memetic algorithm for green job shop scheduling with uncertain times. Swarm Evol. Comput. 2022, 68, 101016.

22. Han, X.; Han, Y.; Zhang, B.; Qin, H.; Li, J.; Liu, Y.; Gong, D. An effective iterative greedy algorithm for distributed blocking flowshop scheduling problem with balanced energy costs criterion. Appl. Soft Comput. 2022, 129, 109502.

23. Zhu, N.; Zhao, F.; Wang, L.; Ding, R.; Xu, T. A discrete learning fruit fly algorithm based on knowledge for the distributed no-wait flow shop scheduling with due windows. Expert Syst. Appl. 2022, 198, 116921.

24. Guo, H.-W.; Sang, H.-Y.; Zhang, B.; Meng, L.-L.; Liu, L.-L. An effective metaheuristic with a differential flight strategy for the distributed permutation flowshop scheduling problem with sequence-dependent setup times. Knowl.-Based Syst. 2022, 242, 108328.

25. Sadollah, A.; Nasir, M.; Geem, Z.W. Sustainability and optimization: From conceptual fundamentals to applications. Sustainability 2020, 12, 2027.

26. Hajibabaei, M., Behnamian, J., 2021. Flexible job-shop scheduling problem with unrelated parallel machines and resources-dependent processing times: a tabu search algorithm. International Journal of Management Science and Engineering Management 16, 242–253. doi:10.1080/17509653.2021.1941368.

27. Ramakurthi, V.; Manupati, V.; Machado, J.; Varela, L. A Hybrid Multi-Objective Evolutionary Algorithm-Based Semantic Foun- dation for Sustainable Distributed Manufacturing Systems. Appl. Sci. 2021, 11, 6314. https://doi.org/10.3390/app11146314.

28. Li, Y.-Z.; Pan, Q.-K.; Gao, K.-Z.; Tasgetiren, M.F.; Zhang, B.; Li, J.-Q. A green scheduling algorithm for the distributed flowshop problem. Appl. Soft Comput. 2021, 109, 107526.

29. Anghinolfi, D.; Paolucci, M.; Ronco, R. A bi-objective heuristic approach for green identical parallel machine scheduling. Eur. J. Oper. Res. 2021, 289, 416–434.

30. Lunardi, W., Birgin, E., Ronconi, D., Voos, H., 2021. Metaheuristics for the online printing shop scheduling problem. European Journal of Operational Research 293, 419–441. doi:10.1016/j.ejor.2020.12.021.

31. Mogali, J., Barbulescu, L., Smith, S., 2021. Efficient primal heuristic updates for the blocking job shop problem. European Journal of Operational Research 295, 82–101. doi:10.1016/j.ejor.2021.02.051.

32. Putnik, G.D.; Putnik, Z.; Shah, V.; Varela, L.; Ferreira, L.; Castro, H.; Catia, A.; Pinheiro, P. Collaborative Engineering definition: Distinguishing it from Concurrent Engineering through the complexity and semiotics lenses. IOP Conf. Ser. Mater. Sci. Eng. 2021, 1174, 012027. https://doi.org/10.1088/1757-899x/1174/1/012027.

33. Geng, K.; Ye, C. A memetic algorithm for energy-efficient distributed re-entrant hybrid flow shop scheduling problem. J. Intell. Fuzzy Syst. 2021, 41, 3951–3971.

34. Shahbazi, Z.; Byun, Y.-C. Integration of Blockchain, IoT and Machine Learning for Multistage Quality Control and Enhancing Security in Smart Manufacturing. Sensors 2021, 21, 1467. https://doi.org/10.3390/s21041467.

35. Liaqait, R.A.; Hamid, S.; Warsi, S.S.; Khalid, A. A critical analysis of job shop scheduling in context of industry 4.0. Sustainability 2021, 13, 7684.

36. Zhao, F.; He, X.; Wang, L. A two-stage cooperative evolutionary algorithm with problem-specific knowledge for en-ergy-efficient scheduling of no-wait flow-shop problem. IEEE Trans. Cybern. 2021, 51, 5291–5303.

37. Xin, X.; Jiang, Q.; Li, S.; Gong, S.; Chen, K. Energy-efficient scheduling for a permutation flow shop with variable transportation time using an improved discrete whale swarm optimization. J. Clean. Prod. 2021, 293, 126121.

38. Pellerin, R., Perrier, N., Berthaut, F., 2020. A survey of hybrid metaheuristics for the resource-constrained project scheduling problem. European Journal of Operational Research 280, 395–416. doi:https://doi.org/10.1016/j.ejor.2019.01.063.

39. Assaqty, M.I.S.; Gao, Y.; Hu, X.; Ning, Z.; Leung, V.C.M.; Wen, Q.; Chen, Y. Private-Blockchain-Based Industrial IoT for Material and Product Tracking in Smart Manufacturing. IEEE Netw. 2020, 34, 91–97. https://doi.org/10.1109/mnet.011.1900537.

40. Huang, J.-P.; Pan, Q.-K.; Gao, L. An effective iterated greedy method for the distributed permutation flowshop scheduling problem with sequence-dependent setup times. Swarm Evol. Comput. 2020, 59, 100742.

41. Huo, D.X.; Xiao, X.J.; Pan, Y.J. Multi-objective energy-saving job-shop scheduling based on improved NSGA-II. Int. J. Simul. Model. 2020, 19, 494–504.

42. Peron, M.; Fragapane, G.; Sgarbossa, F.; Kay, M. Digital Facility Layout Planning. Sustainability 2020, 12, 3349. https://doi.org/10.3390/su12083349.

43. Gong, G.; Chiong, R.; Deng, Q.; Han, W.; Zhang, L.; Lin, W.; Li, K. Energy-efficient flexible flow shop scheduling with worker flexibility. Expert Syst. Appl. 2020, 141, 112902.

44. Zhang, X.; Zhang, H.; Yao, J. Multi-objective optimization of integrated process planning and scheduling considering energy savings. Energies 2020, 13, 6181.

45. Mahmoodjanloo, M., Tavakkoli-Moghaddam, R., Baboli, A., Bozorgi-Amiri, A., 2020. Flexible job shop scheduling problem with reconfigurable machine tools: An improved differential evolution algorithm. Applied Soft Computing 94, 106416.

46. Ali, K., Telmoudi, A., Gattoufi, S., 2020. Improved Genetic Algorithm Approach Based on New Virtual Crossover Operators for Dynamic Job Shop Scheduling. IEEE Access 8, 213318–213329. doi:10.1109/ACCESS.2020.3040345.

47. Defersha, F., Rooyani, D., 2020. An efficient two-stage genetic algorithm for a flexible job-shop scheduling problem with sequence dependent attached/detached setup, machine release date and lag-time. Computers and Industrial Engineering 147. doi:10.1016/j.cie.2020.106605.

48. Boufellouh, R.; Belkaid, F. Green scheduling of permutation flow shop with tool deterioration and constrained tool replacement: A case study from metalworking industry. In Proceedings of the 2020 IEEE 13th International Colloquium of Logistics and Supply Chain Management (LOGISTIQUA), Fez, Morocco, 2–4 December 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1–6.

49. Zhang, C., Song, W., Cao, Z., Zhang, J., Tan, P.S., Xu, C., 2020a. Learning to dispatch for job shop scheduling via deep reinforcement learning, in: Proceedings of the 34th International Conference on Neural Information Processing Systems, Curran Associates Inc., Red Hook, NY, USA.

50. Zhang, S., Li, X., Zhang, B., Wang, S., 2020b. Multi-objective optimisation in flexible assembly job shop scheduling using a distributed ant colony system. European Journal of Operational Research 283, 441–460. doi:10.1016/j.ejor.2019.11.016.

51. Lunardi, W., Birgin, E., Laborie, P., Ronconi, D., Voos, H., 2020. Mixed Integer linear programming and constraint programming models for the online printing shop scheduling problem. Computers and Operations Research 123. doi:10.1016/j.cor.2020.105020.

52. Han, B.A., Yang, J.J., 2020. Research on adaptive job shop scheduling problems based on dueling double DQN. IEEE Access 8, 186474–186495. doi:10.1109/ACCESS.2020.3029868.

53. Assaqty, M.I.S.; Gao, Y.; Hu, X.; Ning, Z.; Leung, V.C.M.; Wen, Q.; Chen, Y. Private-Blockchain-Based Industrial IoT for Material and Product Tracking in Smart Manufacturing. IEEE Netw. 2020, 34, 91–97. https://doi.org/10.1109/mnet.011.1900537.

54. Xie, J., Gao, L., Peng, K., Li, X., Li, H., 2019. Review on flexible job shop scheduling. IET Collaborative Intelligent Manufacturing 1, 67–77. doi:10.1049/iet-cim.2018.0009.

55. Skowroński, R. The open blockchain-aided multi-agent symbiotic cyber–physical systems. Futur. Gener. Comput. Syst. 2019, 94, 430–443. https://doi.org/10.1016/j.future.2018.11.044.

56. Putnik, G.D.; Ferreira, L. Industry 4.0: Models, tools and cyber-physical systems for manufacturing. FME Trans. 2019, 47, 659– 662. https://doi.org/10.5937/fmet1904659p.

57. Fu, Y.; Wang, H.; Huang, M. Integrated scheduling for a distributed manufacturing system: A stochastic multi-objective model. Enterp. Inf. Syst. 2019, 13, 557–573. https://doi.org/10.1080/17517575.2018.1545160.

58. Sikorski, J.J.; Haughton, J.; Kraft, M. Blockchain technology in the chemical industry: Machine-to-machine electricity market. Appl. Energy 2017, 195, 234–246. https://doi.org/10.1016/j.apenergy.2017.03.039.

59. Cota, L.P.; Guimarães, F.G.; Ribeiro, R.G.; Meneghini, I.R.; de Oliveira, F.B.; Souza, M.J.; Siarry, P. An adaptive multi-objective algorithm based on decomposition and large neighborhood search for a green machine scheduling problem. Swarm Evol. Comput. 2019, 51, 100601.

60. Zhang, B.; Pan, Q.-K.; Gao, L.; Li, X.-Y.; Meng, L.-L.; Peng, K.-K. A multiobjective evolutionary algorithm based on decomposition for hybrid flowshop green scheduling problem. Comput. Ind. Eng. 2019, 136, 325–344.

61. Xue, Y.; Rui, Z.; Yu, X.; Sang, X.; Liu, W. Estimation of distribution evolution memetic algorithm for the unrelated parallel-machine green scheduling problem. Memetic Comput. 2019, 11, 423–437.

62. Ramezanian, R.; Vali-Siar, M.M.; Jalalian, M. Green permutation flowshop scheduling problem with sequence-dependent setup times: A case study. Int. J. Prod. Res. 2019, 57, 3311–3333.

63. Zhang, J., Wang, L., Xing, L., 2019. Large-scale medical examination scheduling technology based on intelligent optimization. Journal of Combinatorial Optimization 37, 385–404. doi:10.1007/s10878-017-0246-6.

64. Zhang, X.; Liu, X.; Tang, S.; Królczyk, G.; Li, Z. Solving Scheduling Problem in a Distributed Manufacturing System Using a Discrete Fruit Fly Optimization Algorithm. Energies 2019, 12, 3260. https://doi.org/10.3390/en12173260.

65. Komaki, G.M., Sheikh, S., Malakooti, B., 2019. Flow shop scheduling problems with assembly operations: a review and new trends. International Journal of Production Research 57, 2926–2955. doi:10.1080/00207543.2018.1550269.

66. Kress, D., Muller, D., Nossack, J., 2019. A worker constrained flexible job shop scheduling problem with sequence-dependent setup times. ¨ OR Spectrum 41, 179–217. doi:10.1007/s00291-018-0537-z

67. Skowroński, R. The open blockchain-aided multi-agent symbiotic cyber–physical systems. Futur. Gener. Comput. Syst. 2019, 94, 430–443. https://doi.org/10.1016/j.future.2018.11.044.

68. Rossit, D.A., Tohme, F., Frutos, M., 2018. The non-permutation flow-shop scheduling problem: A literature review. Omega 77, 143–153. ´ doi:https://doi.org/10.1016/j.omega.2017.05.010.

69. Zhang, S., Wang, S., 2018. Flexible Assembly Job-Shop Scheduling With Sequence-Dependent Setup Times and Part Sharing in a Dynamic Environment: Constraint Programming Model, Mixed-Integer Programming Model, and Dispatching Rules. IEEE Transactions on Engineering Management 65, 487–504. doi:10.1109/TEM.2017.2785774.

70. Shen, L., Dauzere-P ` er´ es, S., Neufeld, J.S., 2018. Solving the flexible job shop scheduling problem with sequence-dependent setup times. ` European Journal of Operational Research 265, 503–516. doi:10.1016/j.ejor.2017.08.021.

71. Ham, A., 2017. Flexible job shop scheduling problem for parallel batch processing machine with compatible job families. Applied Mathematical Modelling 45, 551–562. doi:10.1016/j.apm.2016.12.0

72. Kapitonov, A.; Lonshakov, S.; Krupenkin, A.; Berman, I. Blockchain-based protocol of autonomous business activity for multi- agent systems consisting of UAVs. In Proceedings of the Workshop on Research, Education and Development of Unmanned Aerial Systems (RED-UAS), Linkoping, Sweden, 3–5 October 2017; pp. 84–89. https://doi.org/10.1109/RED-UAS.2017.8101648.

73. Manupati, V.K.; Krishnan, M.G.; Varela, M.L.R.; Machado, J. Telefacturing based distributed manufacturing envi-ronment for optimal manufacturing service by enhancing the interoperability in the hubs. J. Eng. 2017, 9305989. https://doi.org/10.1155/2017/9305989.

74. Chaudhry, I.A., Khan, A.A., 2016. A research survey: review of flexible job shop scheduling techniques. International Transactions in Operational Research 23, 551–591. doi:10.1111/itor.12199.

75. Sobeyko, O., Monch, L., 2016. Heuristic approaches for scheduling jobs in large-scale flexible job shops. Computers and Operations Research ¨ 68, 97–109. doi:10.1016/j.cor.2015.11.004.

76. Guo, Z.; Ngai, E.; Yang, C.; Liang, X. An RFID-based intelligent decision support system architecture for production monitoring and scheduling in a distributed manufacturing environment. Int. J. Prod. Econ. 2015, 159, 16–28. https://doi.org/10.1016/j.ijpe.2014.09.004.

77. Varela, M.L.R.; Ribeiro, R.A. Distributed Manufacturing Scheduling Based on a Dynamic Multi-criteria Decision Model. In Recent Developments and New Directions in Soft Computing. Studies in Fuzziness and Soft Computing; Zadeh, L., Abbasov, A., Yager, R., Shahbazova, S., Reformat, M., Eds.; Springer: Cham, Switzerland, 2014; Volume 317. https://doi.org/10.1007/978-3-319-06323-2_6.

78. Bhongade, A.S., Khodke, P.M., Heuristics for production scheduling problem with machining and assembly operations, International Journal of Industrial Engineering Computations, 3 (2012) 185–198.

79. Varela, M.L.R.; Putnik, G.D.; Cruz-Cunha, M.M. Web-based Technologies Integration for Distributed Manufacturing Schedul- ing in a Virtual Enterprise. Int. J. Web Portals 2012, 4, 19–34. https://doi.org/10.4018/jwp.2012040102.

80. Vieira, G.; Varela, M.L.R.; Putnik, G.D. Technologies integration for distributed manufacturing scheduling in a virtual enter- prise. In International Conference on Virtual and Networked Organizations, Emergent Technologies, and Tools, Ofir, Portugal, 6–8 July 2011; Springer: Berlin/Heidelberg, Germany, 2012; pp. 337–347.

81. Hartmann, S., Briskorn, D., 2010. A survey of variants and extensions of the resource-constrained project scheduling problem. European Journal of Operational Research 207, 1–14. doi:https://doi.org/10.1016/j.ejor.2009.11.005.
82. Özgüven, C.; Özbakır, L.; Yavuz, Y. Mathematical models for job-shop scheduling problems with routing and process plan flexibility. Appl. Math. Model. 2010, 34, 1539–1548. https://doi.org/10.1016/j.apm.2009.09.002.
83. Zhou, R.; Chen, G.; Yang, Z.H.; Zhang, J.B. Distributed manufacturing scheduling using a novel cooperative system. In Proceed- ings of the 2008 IEEE International Conference on Service Operations and Logistics, and Informatics, Beijing, China, 12–15 October 2018; IEEE: New York, NY, USA, 2008; Volume 1; pp. 256–260.
84. Wang, C.; Ghenniwa, H.; Shen, W. Real time distributed shop floor scheduling using an agent-based service-oriented architec- ture. Int. J. Prod. Res. 2008, 46, 2433–2452. https://doi.org/10.1080/00207540701738052.
85. Shen, W. Distributed manufacturing scheduling using intelligent agents. IEEE Intell. Syst. 2002, 17, 88–94. https://doi.org/10.1109/5254.988492.
86. Frank W. Ciarallo, Ramakrishna Akella, Thomas E. Morton, (1994) A Periodic Review, Production Planning Model with Uncertain Capacity and Uncertain Demand—Optimality of Extended Myopic Policies. Management Science 40(3):320-332. https://doi.org/10.1287/mnsc.40.3.320