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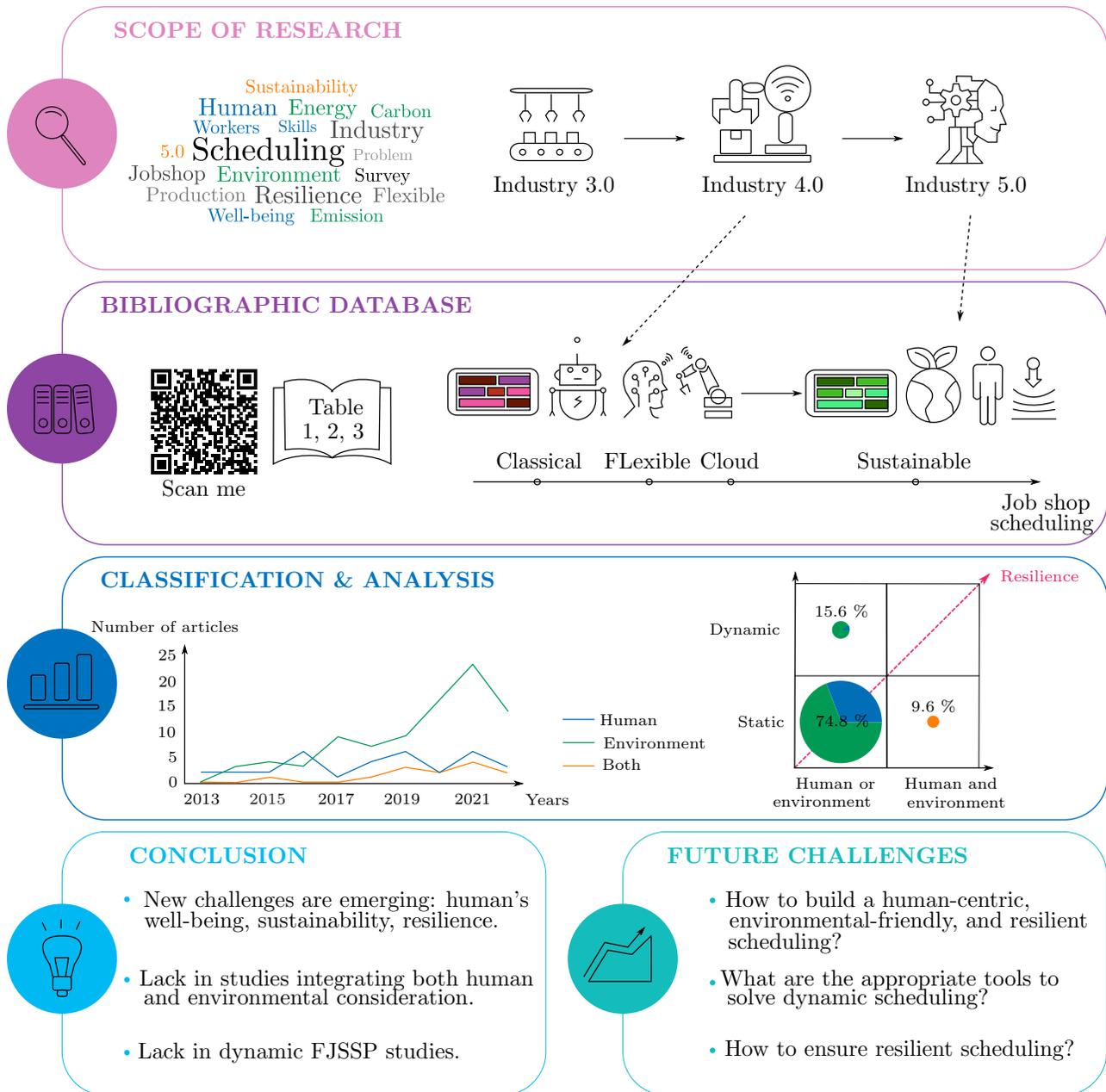


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Graphical Abstract

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Highlights

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- Human Centric Manufacturing
- Environmental consideration
- Resilience

Flexible Job Shop Scheduling Problem under Industry 5.0: A survey on Human Reintegration, Environmental Consideration and Resilience Improvement.

Candice Destouet^a, Houda Tlahig^a, Belgacem Bettayeb^a, Bélahcène Mazari^a

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Abstract

The Job Shop Scheduling Problem (JSSP) has been widely studied in recent decades. Various approaches have been proposed to support scheduling decisions according to the evolving production environment. The emergence of technological advancements in the context of Industry 4.0 has brought many changes and made production scheduling more and more efficient. Today's Industry 5.0 environment pays much attention to human considerations, sustainability, and resilience. These modern production environments can be accurately represented by the flexible shop floor scheduling problem in which various coordinating machines (with many alternative routing possibilities) and different operators are challenging. Recent literature on JSSP, which considers the human in the loop, has shown that the well-being and skills of workers significantly affect scheduling performance. In addition, knowing that industries are responsible for a significant part of the world's energy consumption and greenhouse gas (GHG) emissions, new studies in scheduling focus on environmental factors. This paper introduces the Sustainable Flexible Scheduling Problem (SFJSSP) as a human and energy-efficiency-centered scheduling problem. First, we review the last decade's literature on Flexible Job Shop Scheduling Problems (FJSSP) with human and/or environmental considerations. Next, we analyze the development trends in manufacturing scheduling problems. Finally, we discuss future research challenges to move towards scheduling 5.0 and suggest a mathematical model that considers human and environmental factors (in addition to the factors considered by the Classical Flexible Job Shop Scheduling Problem (CFJSSP)).

Keywords: Industry 5.0, Flexible job-shops Scheduling Problem, Literature review, Dynamic Scheduling, Human Centric Manufacturing, Environmental consideration, Sustainability, Resilience

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1. Introduction

In recent years, manufacturing systems have undergone many changes thanks to new technologies, especially with the emergence of Industry 4.0 (I4.0). I4.0 combines revolutionary new information and communication technologies (ICT) with real-time production and virtual simulation approaches to make operations management increasingly efficient. Cyber-Physical (Production) System CP(P)S, Internet of Things & Services (IoT&S), Horizontal and Vertical Integration, Adaptive Manufacturing, Big Data and Cloud are the major I4.0's concepts and technologies. They have been introduced into factories to increase automation and, thus, the production systems' efficiency. These concepts and technologies impact scheduling the most (Parente et al., 2020). To complement and expand the I4.0 industrial revolution, a new paradigm called Industry 5.0 (I5.0) is emerging. I5.0 focuses on decisive factors, not only from an economic and technological point of view but also concerning environmental and social dimensions. This relatively rapid transition from I4.0 to I5.0 is driven by the ever-changing customers' needs and aspirations and the new economic, societal, and environmental pressing challenges worldwide. Indeed, I5.0 aims to develop and reinforce mainly three characteristics: human-centricity, sustainability, and resilience. These characteristics are defined as the literature's three interconnected core values for I5.0 (Xu et al., 2021c).

Production systems of the I5.0 era should, first of all, be centered on humans. The latter are considered as a central element of a Human-Cyber-Physical Production System (HCPPS), which is part of a global ecosystem value chain. This systemic approach is essential to meet the ever-increasing aspirations for sustainability and to increase the resilience of HCPPS in the face of increasingly frequent and diverse disturbances. Thus, Operator 5.0 is introduced as “*a smart and skilled operator who uses human creativity, ingenuity, and innovation, aided by information and technology, to overcome obstacles on the way to developing new,*

cost-effective solutions for ensuring manufacturing operations' long-term sustainability and workforce well-being in the face of difficult and/or unexpected conditions (...)" (Wang et al., 2022a). These new needs and objectives of human-centricity, sustainability, and resilience are the concern of all functions of any company (HR, Design, Production, Marketing, Logistics, Finance, *etc.*) and at the different decision-making levels, *i.e.* operational, tactical, and strategic. Production scheduling is at the forefront of achieving these objectives at the operational level. However, these new concerns of I5.0 will induce additional variables, constraints, and criteria to be considered in scheduling problems, which are already generally very difficult to solve.

Scheduling problems have been widely studied in the literature of all industrial sectors, especially the manufacturing industry, with various production workshops. In this paper, we focus only on Flexible Job-Shop Scheduling Problems (FJSSP) incorporating human factors, environmental factor, or both in connection with I5.0. This is in line with the flexible durable scheduling problem (SFJSSP) paradigm as recently defined in the literature, *e.g.* Hongyu and Xiuli (2021). We review recent publications to analyze new trends in scheduling problems and solutions considered in the context of I5.0. We highlight current issues and future research challenges in FJSSP. The remainder of the paper is organized as follows. Section 2.1 describes scheduling problems and their trends through the different industries' evolution. Section 3 explains our literature search methodology. Section 4 presents and analyzes articles integrating human and/or environmental factors. Then, future research directions and challenges are discussed in Section 5.

2. Problem description

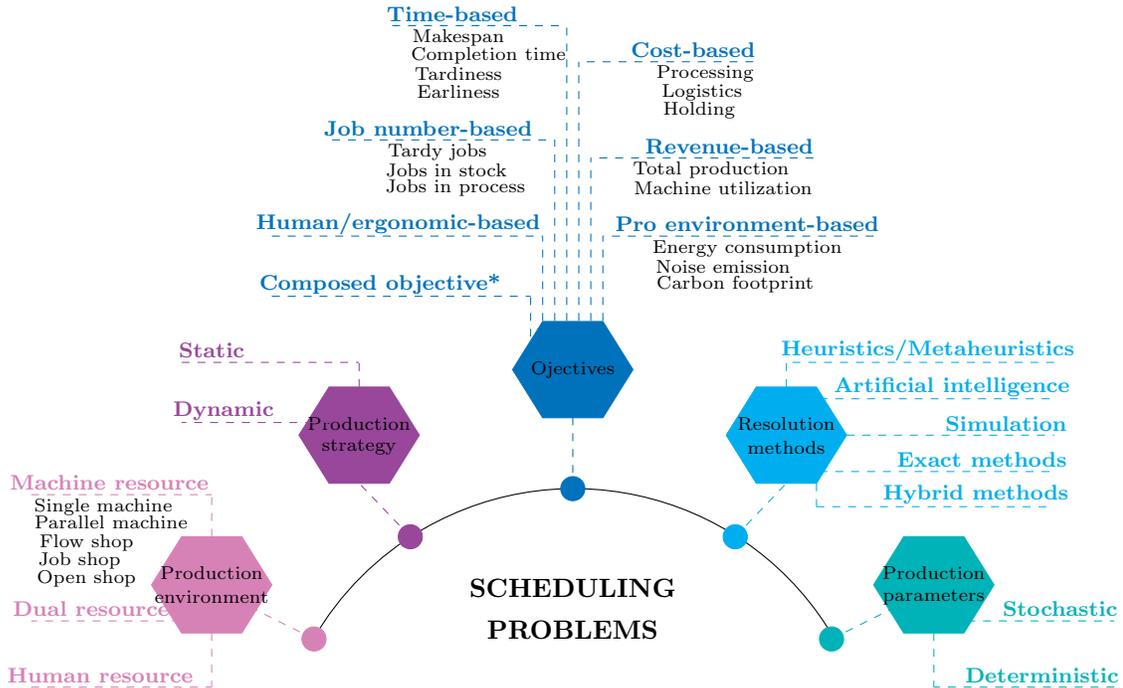
2.1. Scheduling problems introduction

Scheduling problems emerged in the 1950s as a decision-making process to accompany the advent of mass production. Because of the direct impact of scheduling on production efficiency, much research has focused on this problem since 1956 (Zhang et al., 2019a). In the scheduling problems, tasks are assigned to resources, and their execution is sequenced under different constraints to optimize one or more objectives (that will be detailed later in this section). Scheduling problems occur in various domains, such as manufacturing, transportation, services, or finance.

Several criteria, illustrated in Figure 1, characterize scheduling problems. The first criterion is the objective function, which can be time-related (*e.g.* minimizing the makespan or the tardiness), cost-related (*e.g.* minimizing resources operating costs), jobs number-related (*e.g.* minimizing the number of late jobs). It can also be robustness-related (*e.g.* maximizing the robustness of the scheduling), or quality-related (*e.g.* maximizing the number of tasks successfully realized). The time-related objective function minimization is the most studied in literature due to customers' demand. Recently, new objectives have emerged: pro-environment-based (*e.g.* minimizing energy consumption or carbon emission) and human-based (*e.g.* minimizing workers' risks or maximum workload). These objectives can be considered separately (single optimization objective) or in conjunction with each other (multi-objective optimization). The second criterion is the scheduling environment/strategy, which can be static or dynamic. Dynamic scheduling considers hazards, such as machine breakdowns or new job insertions, which makes the problem formulation closer to reality but more challenging to solve. The third criterion is related to the nature of the scheduling problems' parameters which can be stochastic or deterministic. Deterministic production ensures that parameters are known, unlike stochastic production, where one or more parameters, such as processing time or machine availability, are random variables revealed as production proceeds. Another criterion for classifying scheduling problems is the production environment, specifically characterized by the numbers and types of resources used and the way they are arranged to perform the different steps of the production process. In the case of a single-step process, there is either the single-machine environment, where a single machine processes all tasks, or the parallel machine environment, where several similar machines can do the step. When the process is multi-step, *i.e.* tasks are divided into operations that have to be processed on different machines, we talk about the workshop environment. Depending on the routing constraints of the process steps of different products, a workshop can be configured as a flow shop, a job shop, or an open shop. In a flow shop, the sequence of operations to execute is fixed and is similar for all tasks. In a job shop, the sequence is fixed but can differ from task to task. In an open-shop environment, the sequence is not set. Jiang et al. (2021) reported that the most studied production environments in literature are the flow shop and the job shop, due to their many applications in real-life manufacturing systems. Beyond these classical environments, the literature contains studies of specific industrial scheduling problems that have been formalized and solved, and whose solutions are effectively applied. The specificities of these problems can be related to: i) production process (reentrant/reverse flow, batch manufacturing, continuous/discrete flow, *etc.*), ii) resources (setup time, availability, degradation, learning, *etc.*), iii) products (perishability, handling, quality, *etc.*), or iv) decision approach (single/multi-objective, distributed/centralized, single/hybrid, *etc.*)

Scheduling problems can be solved in different ways using exact and approximate methods. However, most of the scheduling problems are NP-Hard and exact methods are not efficient in terms of computation time and memory consumed. In this sense, simple and hybrid approximate approaches based on heuristic, metaheuristic, simulation, and artificial intelligence methods allow finding suitable solutions close to the optimum in a reasonable time.

To summarize, scheduling problems can take many forms depending on the resources, the available data, and the requested objective. Moreover, they continue to evolve with the development of new technologies and the appearance of new challenges changing the production environment and/or the objectives. These new scheduling problems, which we focus on the most in this article, will be detailed in the following sections. We are particularly interested in two key aspects of I5.0: the human and the environment.



*composed objective: multi-objective composed with those mentioned above.

Figure 1: Scheduling problems characterization.

2.2. Scheduling challenges in the I5.0 era

2.2.1. Towards more flexibility

Classical Job Shop Scheduling Problem (CJSSP) is the most basic JSSP. In the CJSSP, we are given a set of n jobs $J = \{J_1, J_2, \dots, J_n\}$ and a set of m machines $M = \{M_1, M_2, \dots, M_m\}$. Each job j consists of n_j operations $O_j = \{O_{1j}, O_{2j}, \dots, O_{n_j j}\}$, which have to be processed in a predefined unique sequence, where each operation must be processed on a predefined machine. All machines are different, and their processing times are constant. The total number of machines of each type is equal to one. The objective of CJSSP is to decide the start time of each job on each machine it must visit, while optimizing a targeted performance requirement. This problem is characterized by two classical constraints related to the precedence between the operations of the same job and the impossibility of simultaneously executing several operations on the same machine. Even though the CJSSP model could be considered a typical “academic” case, it is often used to approximate real-world problems and is very useful to understand and develop solutions/approaches to scheduling problems. Therefore, this model has always attracted significant attention from academic researchers.

A production workshop is said to be “flexible” when it allows some or all operations to be processed by a set of machines, instead of only one in the case of a classical “non-flexible” environment. FJSSP can be defined (as the CJSSP) by a set of jobs divided into operations to be processed on a set of machines in a given sequence. Unlike the CJSSP, some operations in the FJSSP can be processed on a set of machines. The goal is to find the optimal machine assignment for each operation and an optimal operations sequence on each machine to minimize or maximize one or several desired performance criteria. The targeted criteria can

be: (1) time-based (makespan, completion time, tardiness, earliness, *etc.*), (2) Job-Number-based (number of tardy jobs, number of jobs in stock, number of jobs in the process, *etc.*), (3) cost-based (processing cost, logistics cost, holding cost, *etc.*), (4) revenue-based (machine utilization, total production revenue, *etc.*) or (5) energy- and/or pro-environment-based (noise emission, carbon footprint, *etc.*). FJSSP should consider different constraints, the main ones related to the precedence between operations, the availability of resources, and the release and/or due dates of the jobs considered.

Figure 2 gives an example illustrating the difference between CJSSP and FJSSP. In this figure, solid arrows mean that the machine for the next operation is fixed, while dashed arrows mean that the next operation can be assigned to one of several possible machines. FJSSP does not contain the restriction of one production resource per operation, which extends the size of the feasible solutions space, making the FJSSP a stronger NP-hard problem than the CJSSP. Moreover, many FJSSP studies assumed that scheduling is carried out in a static production environment. However, today’s production workshops are dynamic and subject to multiple random events (random arrival of jobs, machine breakdowns, insertion of urgent orders, *etc.*). In this case, scheduling must be dynamically updated in real-time. For this purpose, the dynamic version of the FJSSP (DFJSSP) can respond effectively to fluctuations in demand and possible unexpected disruptive events. Currently, dynamic scheduling problems, which better represent real manufacturing systems (subject to randomness), are receiving more and more attention from scientists and industrialists in terms of models and solution approaches suitable for fast, real-time decision-making.

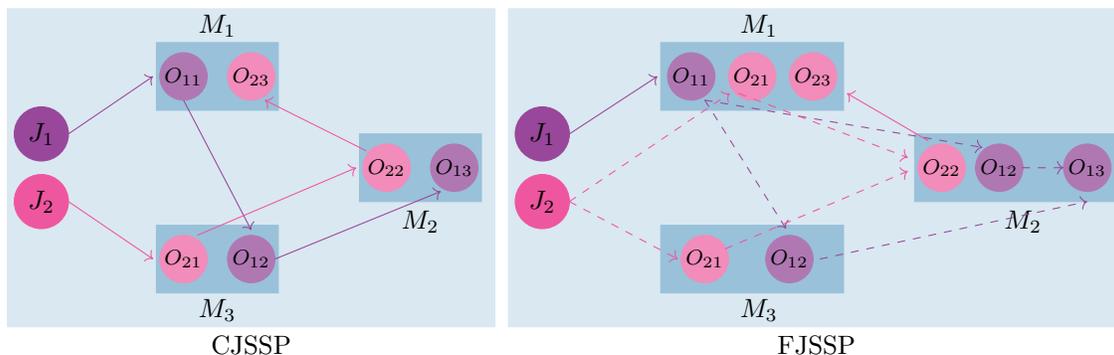


Figure 2: CJSSP vs. FJSSP.

Several exact and approximate approaches can be used to solve the FJSSP. Exact methods such as mixed integer programming, branch and bound, or constraint programming are used to guarantee solution optimality. However, due to the NP-Hardness of the problem, this kind of method is only efficient with small instances. As shown in Xie et al. (2019), most research has focused on solving this problem by applying heuristics or metaheuristics (genetic algorithm, simulated annealing, *etc.*) to find near-optimal solutions. Artificial intelligence methods represent another approach to deal with FJSSP, especially in a dynamic environment (Luo, 2020; Luo et al., 2021). In particular, machine learning techniques can handle NP-complete optimization problems with an extensive data set and improve the resolution of NP-hard manufacturing problems (Wuest et al., 2016). These techniques can learn from dynamic events and react automatically, thus helping to solve dynamic scheduling problems in a production system equipped with “smart” connected components and commonly referred to as an intelligent manufacturing system.

2.2.2. Towards more responsiveness

Throughout the transition from Industry 3.0 (I3.0) to I4.0 (from the 90’s onwards) and thanks to several technological advances, scheduling techniques have undergone many changes to improve responsiveness in the face of not only internal technical and organizational hazards (machine breakdowns, workers absence, process drifts, *etc.*), but also external hazards and constraints (fluctuations in demand, supplier disruptions, logistical incidents, *etc.*). Intelligent scheduling, also known as smart scheduling, arises to support the evolution of the industrial environment using smart manufacturing tools. The traditional job shop scheduling of the I3.0 era is based on centralized or semi-distributed control architecture. With the I4.0 revolution, decentralized scheduling is enabled by new and emerging industrial ICT-based manufacturing technologies, thus allowing the development of innovative approaches of intelligent distributed and parallel scheduling.

As shown in Figure 3 adapted from Jiang et al. (2021), production scheduling before the 3rd industrial revolution was mainly concerned with mass production lines, making high volumes of standardized products. Following the market trends with the increasing demand for customized products, mass production evolved into mass customization, giving customers a wider choice of products (Alemão et al., 2021).

Indeed, if in mass production the product market is segmented and usually only one product is offered in each market segment, mass customization classifies customers into different segments and groups customers' needs into the same market segment. Then, based on these grouped needs, customers are offered different product configurations within a predefined product family (Tseng et al., 1996). Hu (2013) gives a comprehensive review and discusses the enabling technologies development allowing the evolution of manufacturing paradigms from mass production to personalization. Mass customization focuses on products made only for individuals, at scale, to meet the requirements of those individuals without compromising environmental, economic and social impacts (Aheleroff et al., 2021). In a recent study, Aheleroff et al. (2022) point out that in mass customization, customers have a wide choice of products but are not fully involved in the design phase because the designer predetermines the choice of combinations. Today the demand for personalized products (color, size, fit, *etc.*) has never been higher and personalization is the main challenge for companies to meet customers' needs. Mass customization then evolved into the paradigm of mass personalization by combining the new technologies of I4.0 and the human creativity brought back with I5.0 to production. To go beyond mass customization, mass personalization paradigm represents "a personalized experience based on cocreation" (Baranauskas, 2019). In mass personalisation, customer's needs are satisfied at the personal level. The basic product design and features can change to provide unique products tailored to each individual (Tseng et al., 2010). Mass personalization differs from mass customization by expanding the design space, improving the customer experience and enhancing the creativity and innovation by customers (Sikhwil and Childs, 2021). While mass customization offers a choice from a range of available products, mass personalization allows customers to create their own unique products. Moreover, as mentioned by Aheleroff et al. (2021), mass personalization is primordial to meet the main challenges of I5.0.

From a manufacturing systems perspective, the traditional manufacturing of the I3.0 era turned into smart manufacturing, becoming increasingly flexible and dynamic to face new production challenges. This evolution has been possible thanks to new technologies and paradigms developed during the late 20th - early 21st centuries, such as IoT, CPS, Cloud Computing, Digital Twin, Agent-based systems, Artificial Intelligence, and Big Data. These technologies and techniques indicate the birth of I4.0 era. With I4.0, centralized scheduling has become a decentralized one, where autonomous agents are connected to each other and to the decision center, as presented in Leusin et al. (2018). In this system, each agent can make its own decision and interact with the other agents continuously, which allows for real-time production monitoring and control. In addition, big data tools make it possible to collect and store a large amount of data throughout the production process, giving the possibility to analyze and understand the system and continuously improve its performance (Rossit et al., 2019; Zhang et al., 2019a). With cloud computing, cyber-physical-system, and the internet of things, manufacturing systems can be seen as the fusion of the physical process and the virtual world, which led to the birth of the cloud manufacturing (CMfg) paradigm, including a scheduling service (Wu et al., 2013; Zhang et al., 2014). In the virtual world, the process is simulated and adapted continuously with real-time data collected in the physical process, which simulation improves in case of disturbance. These technologies bring to the scheduling function the possibility to be more and more dynamic and flexible, being able to react and adapt the production process in real-time. Adopting these new technologies is inevitable to make scheduling solutions as efficient and robust as possible. Although CMfg has been around for several decades already, scheduling problems in CMfg have only gained significant interest in the last decade. The majority of published research in this area deals with dynamic scheduling problems using the multi-agent systems paradigm combined with artificial intelligence tools (Liu et al., 2019a; Rashidifar et al., 2022; Zhou et al., 2019; Wang et al., 2022c; Zhang et al., 2022; Liu et al., 2023). Two recent articles by Liu et al. (2019a) and Rashidifar et al. (2022) give a more complete review of this subject.

2.2.3. Towards more sustainability

The rising concern for sustainability in the I5.0 context has led to a renewed focus on energy efficiency and re-humanization of production systems (Grabowska et al., 2022). Nowadays, the impact of environmental and social aspects on scheduling in manufacturing plants should be studied with the same importance, if not more, than economic and technological aspects, given the rapidity of catastrophic climate and demographic changes worldwide. This paper focuses on the FJSSP which considers the human and/or environmental factors. In our survey, we refer to this problem as the Sustainable Flexible Job Shop Scheduling Problem (SFSSP). In fact, even though I4.0 brought new approaches and tools to improve, among other things, the efficiency and robustness of scheduling solutions, new types of challenges emerged in production systems and value chains in general, in line with the economic, societal, and environmental changes worldwide. A new type of scheduling appears with I5.0: sustainable scheduling, described in the following subsections.

Nowadays, the environmental aspects and the preservation of the planet's health facing to the population increase and the depletion of natural resources represent one of the most interesting challenges for the I5.0.

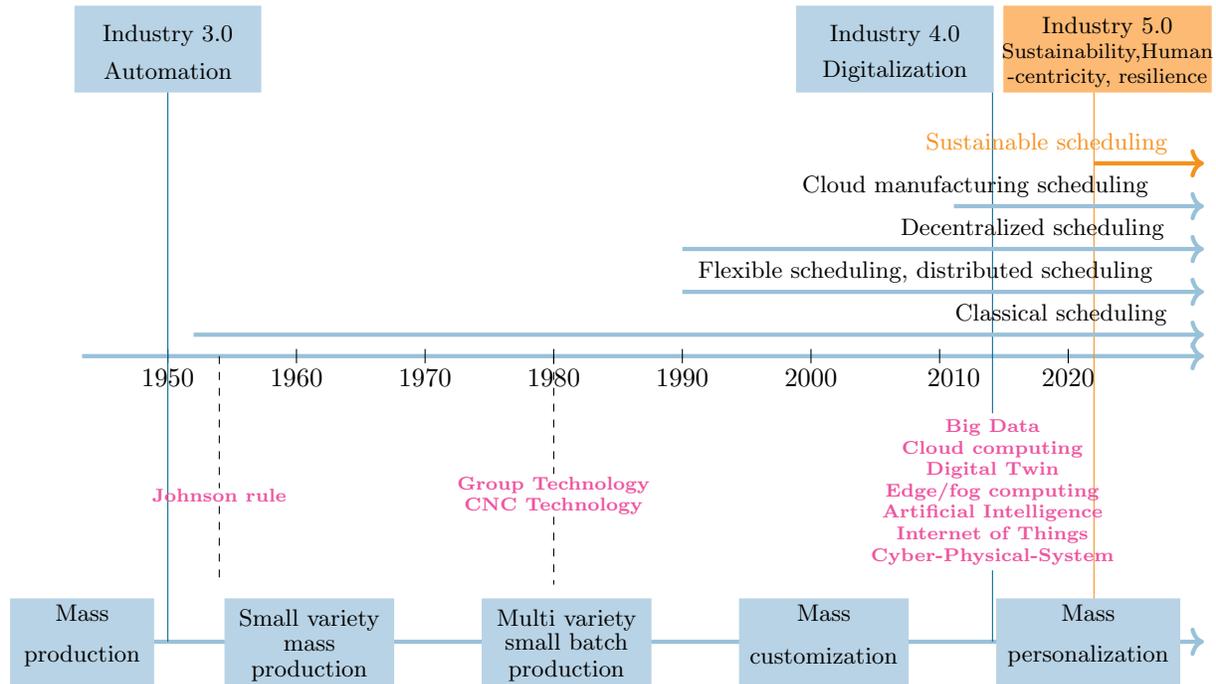


Figure 3: History of production scheduling, based on the one in Jiang et al. (2021) completed with Industry 5.0.

The main reason for this interest is the impact of industrial processes, energy consumption, and carbon emission on the planet (Dai et al., 2019). For many years, industries have been focused almost exclusively on the economic aspects, but this no longer viable perspective must change. Alaouchiche et al. (2020) reported that the industrial sector is responsible for 31.7% of the world’s energy consumption (see Figure 4). Moreover, industries use resources that are not always renewable, and whose price becomes increasingly higher as they become scarcer.

Reducing energy consumption and carbon emissions is a significant challenge to preserve the planet and achieve considerable savings for industries. Sindhvani et al. (2022) provides examples of fields such as agriculture, food, medicine, or surgery that need to shift into green industries.

Considering environmental factors in scheduling problems has gained interest in the last years with the emergence of the I5.0 era. Scheduling problems in job shops are related to energy consumption. In order to improve the energy efficiency of industrial plants, it is now necessary to take environmental factors into account when developing scheduling strategies. In scheduling problems, environmental factors have been studied in the last few years, as proved in Xiong et al. (2022). In this article, the authors review 297 articles from 2016 to 2021. 54 of them consider environmental parameters, minimizing energy consumption, carbon, or noise emission. The studied papers represent only 18 % of the literature, but this objective of green production is increasingly studied, combined with efficiency objectives. The increasing number of articles published, in the last few years, on energy-efficient scheduling problems makes our review a relevant topic.

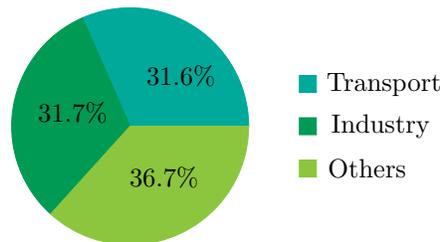


Figure 4: Total world energy consumption (Alaouchiche et al., 2020).

2.2.4. Towards more human-centricity

One of the most significant challenges raised by scheduling problems in the context of I5.0 is the human reintegration into the manufacturing environment, which has been greatly transformed by the increased

automation and the use of some advanced, sometimes intriguing technologies such as VR/AR, AI, Blockchains, *etc.* In fact, for many decades, most research on production scheduling has focused only on machine resources while ignoring or simplifying the presence of operators in the process model. However, in most real-life cases, the machines are operated by one or several workers and/or share with them the same workspace.

First, the complexity of adding human factors to a system model may partly explain this oversight. A machine can be modeled as a resource, characterized by quantitative and qualitative attributes such as availability, skills, speeds, *etc.* A worker is more difficult to analyze and model (Zhang et al., 2021b): he (or she) may have different costs, skills, learning rates, *etc.*, but above all, each worker has his (or her) own behavioral patterns related to his private life, personality, age, morphology, or any other type of factor that may directly or indirectly affect the performance of the production system. He (she) also presents various constraints of unavailability associated with breaks, days off, training, sick leaves, *etc.* It has often been reported in the literature that human operators impact the performance of production systems, primarily through their skills and abilities (Rinaldi et al., 2022). Thus, despite the difficulty of modeling, human behavior patterns must be considered to have the most realistic scheduling possible while optimizing resource utilization and reducing the gap between theoretical and effective performance.

Secondly, with the advent of I4.0 new technologies, industrialists and researchers have focused on the automation process, placing the objective of making machines more connected and more “intelligent” at the center of research while almost ignoring the human aspect and the environmental aspect as well. Consequently, industrial workers showed dissatisfaction and distrust of I4.0 and I5.0, seeing their jobs replaced by machines and impacting their social prosperity (Nahavandi, 2019). As Rosenbrock (1990) mentioned, “Humans should never be subservient to machines and automation, but machines and automation should be subservient to humans”. As a result, operators and machines should work together, and a new generation of operators appeared to meet the changing needs in the industry. An operator 4.0 can not only use and co-work with new technologies but can also work helped, even augmented, by them (Romero et al., 2016). The objective is to give repetitive and tedious tasks to machines and robots and transform them into “ideal companions”, while workers operate more complex and high-value-added tasks that require thought and creativity (Nahavandi, 2019). This is possible with cobots, designed to work with humans and enable proper human-machine interaction. This collaboration combines human creativity and machine efficiency, making mass personalization more feasible. This is why cobots are considered as a fundamental element for a resilient I5.0 taking better advantage of the relationship between machines, technology and human mind (Aheleroff et al., 2022).

Human centricity and environmental efficiency-related new challenges have led to the birth of the I5.0 era, which will bring back the human touch (Maddikunta et al., 2022) and will be conscious of the future generation by integrating sustainability as a primary decision criterion during the design and operation of production systems. As mentioned by Breque et al. (2021), I5.0 recognizes “the power of industry to achieve societal goals beyond jobs and growth, to become a resilient provider of prosperity, by making production respect the boundaries of our planet and placing the worker well-being at the center of the production process”. The industry needs to focus on integrating human values and environmental factors to take care of current and future generations. Note that human, social and societal aspects are usually confused, which is why the term “sustainable scheduling” is often used to refer to scheduling problems that consider the environmental factor associated with human and/or social and/or societal factors.

2.2.5. Towards more resilience

The third value when discussing I5.0 is resilience (Xu et al., 2021c). The resilience of a system is its ability to overcome alterations caused by one or more disruptive elements and return to its initial state with normal functioning or even by improving it. Breque et al. (2021) define resilience as “the ability to cope flexibility with change”.

Resilience is an essential property of systems, closely related to reliability, robustness and recoverability. In the scheduling domain, reliability refers to the probability that a schedule will be executed correctly (as planned) under given conditions for a specific period. Robustness defines the ability to perform well under external disruptions and to sustain good scheduling performance. Therefore, scheduling resilience can be defined as the ability to recover and maintain the scheduling performance after the occurrence of a disruptive event. It is a post-disruption property that focuses on re-optimizing and maintaining production scheduling performance.

Despite various existing methods to solve the JSSP, it is still challenging to implement these methods in the real-time manufacturing system due to complex dynamic occurring events. The proactive, predictive and reactive approaches were widely used in the production shops to deal with complexity. Proactive scheduling considers the current predictable changes in advance when generating the original schedule. Reactive

scheduling emphasizes adjustments to current scheduling when uncertain events occur. Predictive scheduling considers uncertainties in generating the original schedule. In real systems, dynamic scheduling can be completely-reactive, predictive reactive, or robust proactive (Ouelhadj and Petrovic, 2008). The differences between the static and the different dynamic scheduling types are illustrated in Figure 5.

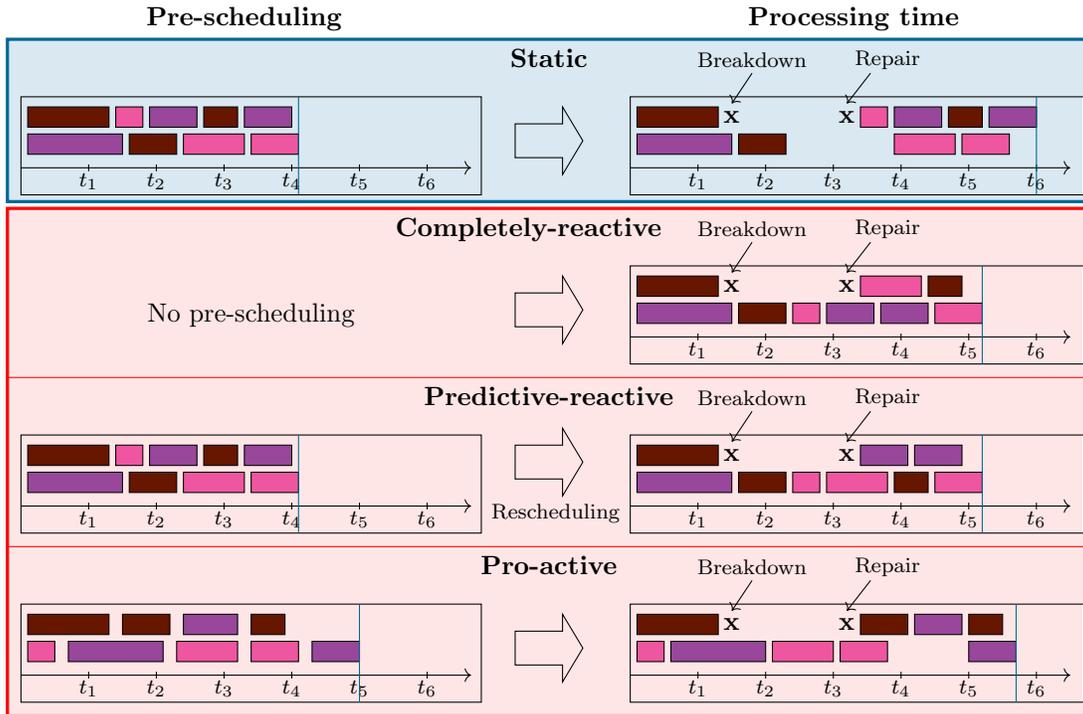


Figure 5: Static and dynamic scheduling.

In the illustrative example of Figure 5, the objective is to schedule three jobs represented with three different colors (pink, violet, and brown). Each of these jobs is composed of three operations, subject to precedence constraints, *i.e.* an operation cannot start before the previous operation of the same job is finished. We compare the efficiency of four different types of schedules when a disruption occurs. In this example, the disruptive event is a breakdown of the first machine between t_1 and t_2 , making the machine unavailable until it is repaired. The impact of this machine failure is illustrated in Gantt charts showing the difference between the pre-planning and what actually happens during the processing time. In a static case, the pre-scheduling is applied no matter what. Thus, the process must wait for the machine to be repaired before restarting. The difference between the pre-scheduling and the reality is significant. In a dynamic completely-reactive case, there is no pre-scheduling, and the scheduling is done as tasks come into the system. The breakdown of the machine has less impact on the process, which avoids that machine until its repair. In predictive-reactive scheduling, when the machine breaks down, a rescheduling adapts to the hazard. Finally, robust pro-active scheduling considers in the pre-scheduling the disruptions that may occur during the process. Operations are sequenced one after the other with a short time interval between each one to allow more time in case of trouble. In addition, robust proactive scheduling calculates the probability of a hazard occurring so that scheduling is done accordingly. Thus, the gap between the two end dates is reduced. As shown in the Figure, static scheduling is strongly impacted by disturbances, while dynamic scheduling can return quickly to its initial state.

Proactive and reactive scheduling paradigms aim to reduce the impact of the disturbances but some disruptive events' impact may exceed, sometimes, the ability of the rescheduling to restore the system performance. In this case, scheduling resilience should retain attention when solving the dynamic scheduling problem. To the best of our knowledge, resilience is less considered in the literature than the proactive and reactive scheduling approach and still needs more consideration. Recently, some papers deal with this new paradigm. For example, Wang et al. (2019) examine the concept of resilient scheduling for manufacturing systems and propose a three-layer resilient scheduling paradigm to divide the control policy into three modes: processing sequence regulation, system parameter adjustment, and structure change. The authors designed a big data-driven framework to protect manufacturing systems from these changes.

Thanks to new technologies arising in the I4.0 era, production is digitized and synchronized, and the system becomes intelligent and capable of reconfiguring itself. More precisely, data processing enables the

prediction of hazards that can occur, such as machine breakdown, new job insertion, missing operator, *etc.* Also, artificial intelligence methods help the system learn from past events and permit real-time scheduling. It allows the system variability adaptation while maintaining its quality and customer satisfaction objective.

Most studies in the literature deal with static scheduling because dynamic scheduling is more complex. Moreover, solving the scheduling problem dynamically with new technologies will help the system to improve its resilience and should be investigated more in the future. We can further enhance resilience by considering the workers and environmental aspects. Restoring the human factor will lead to smart manufacturing integrating human brains and the ability to think and react in an unexpected cases. Humans can manage disaster recovery strategies while machines cannot (Maddikunta et al., 2022). Sindhwani et al. (2022) adds “Good resiliency can only exist once people are incorporated in areas where the human touch is essential”. Regarding environmental aspects, minimizing pollution and energy consumption in scheduling will lead to cleaner production to preserve our planet and environment. Since most resources are non-renewable, encouraging recycling and slowing consumption will lead to a more stable system.

I5.0 presents new challenges, and a trade-off must be made between ecology and society (Xu et al. (2021c); Ahleroff et al. (2022)). The objective is to achieve sustainable, human-centric, and resilient manufacturing. The following sections will describe and analyze these aspects in more detail.

3. Research method

This paper focuses only on FJSSP due to their various real-world applications (Weng et al., 2022). We limit our review to articles published from 2013 onward, which marked the beginning of the I4.0 (Jiang et al., 2021). I4.0 rhymes with digitalization, new technologies, smart manufacturing, and thus production efficiency. We choose to examine the articles from the beginning of the fourth revolution to determine approximately when human and environmental consciousness began to appear in the literature. We conducted our research on two search engines, namely “Google Scholar” and “Scinapse” completed with papers found through “Connected Papers”. The keywords used were Flexible Job Shop Scheduling Problem (FJSSP) combined each time with a word related to the human factor (human, workers, dual resources, ergonomic) or the environmental factor (green, energy, carbon, sustainable).

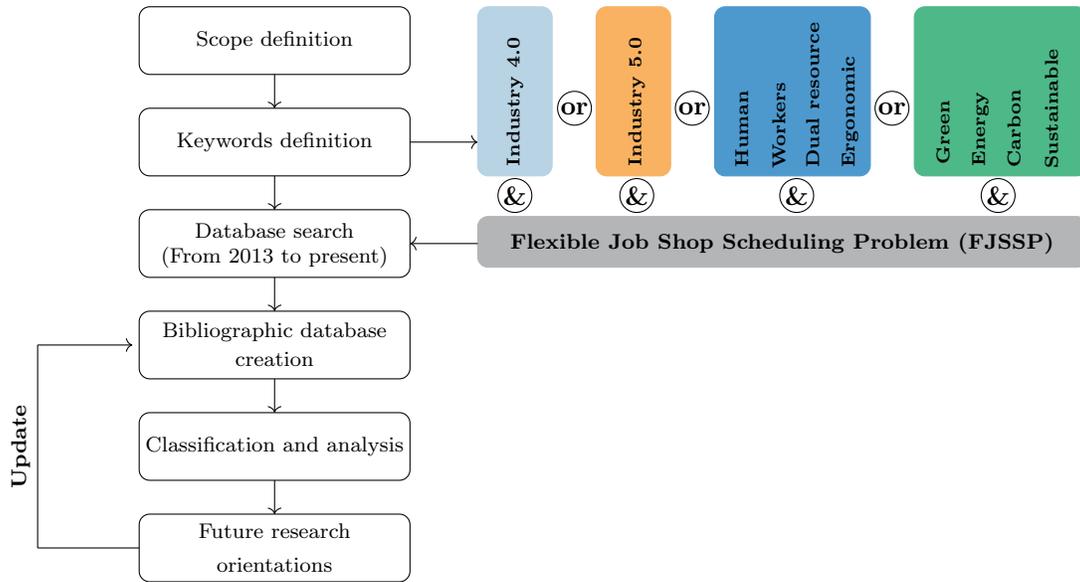


Figure 6: Research Method

After applying these keywords, another sorting was done. In the first stage, we retained only the papers concerning FJSSP and eliminated the others. In the second step, we kept either the papers integrating workers as a resource, the papers considering environmental concerns, or the papers combining both. After a final screening to identify precise and reliable articles, 135 papers were selected for this survey. We also chose to keep only the articles redacted in English. With this selection, we obtained articles that consider one or more aspects of FJSSP in I5.0, namely the human factor or the environmental factor, thus towards more sustainable and human values-based production scheduling. The studied articles are presented and analyzed in the next section.

4. Results and Analysis

In this section, we consider the 135 earlier selected articles. The selected papers are classified according to three criteria: the environmental factor (Table 2), the human factor (Table 1) and the two factors simultaneously (Table 3).

The papers considering the human factor are mentioned by the following metrics: Skills (Sk), Cost (Co), Learning rate (Lr), Ergonomic risks (Er), Rest (Re) and Age (Ag).

Papers taking into account the environmental factor are specified in the "Environmental factor" column by the following parameters: Energy consumption (Ec), Carbon emission (Ce), Noise emission (Ne), or Recycling (Re).

In most reviewed articles, the time or economic objective is associated with the energy objective. Only few papers consider simultaneously the economic, environmental, and human factors. Once again, regarding the growing importance of the human factor in the current manufacturing systems, this emphasizes the importance of taking the human factor into account in future research.

References	Human Factors						Objective(s)		
	Ag	Lc	Er	Lr	Re	Sk	Eco.	Env.	Hum.
Berti et al. (2021)	×					×	Cmax		
Xixing and Yi (2018)		×				×	Cmax, C, mW		
Liu et al. (2021b)		×				×	Cmax, mW, Lc		
Ren et al. (2016)		×				×	Js,C		
Li et al. (2016a) ; Zhang et al. (2013)		×				×	Cmax, C		
Wu et al. (2018)				×		×	Cmax		
Tan et al. (2021)					×	×	Cmax		F
Sun et al. (2019)					×		Cmax, mW		
Xiao et al. (2019)						×	Cmax, R		
Müller and Kress (2021); Kress and Müller (2019); Zheng and Wang (2016); Gong et al. (2020); Farjallah et al. (2022); Zhang et al. (2021b); Peng et al. (2018); Guevara et al. (2015); Lei and Guo (2014); Madenoğlu and Baykasoğlu (2019); Yazdani et al. (2015)						×	Cmax		
Paksi and Ma'ruf (2016)						×	E/T		
Andrade-Pineda et al. (2020)* Kress et al. (2019); Lei and Tan (2016)						×	Cmax, E/T		
Huang et al. (2014)*						×	Rd		
Gnanavelbabu et al. (2021)						×	Cmax, Rd		
Vital-Soto et al. (2022)						×	Cmax, mW, E/T		
Yazdani et al. (2019); Gong et al. (2018b)						×	Cmax, mW		
Luo et al. (2022)						×	Cmax, mW		wW
Zhongjie et al. (2013)**							Cmax, C		
Zhang et al. (2017b)**							Cmax		
Sano et al. (2016)**							T, Wip		wW

Table 1: Articles on FJSSP integrating the human factor from 2013 to 2022.

Ag: Age; Lc: labor cost; Er: Ergonomic risks; Lr: Learning rate; Re: Rest; Sk: Skill; Cmax: makespan; mW: Machine workload; C: Cost; R: Reliability; E/T: Earliness/Tardiness; wW: Workers workload; Rd: Rescheduling disruptions; Js: Job satisfaction; Wip: Work in process; *: dynamic scheduling; **: Human is considered as a dual resource and no specific factor is indicated.

References	Env. factors				Objective(s)		
	Ce	Ec	Ne	Rc	Eco.	Env.	Hum.
Yin et al. (2017b)	×	×	×		Cmax	Ec; Ne	
Hemmati Far et al. (2019)	×	×			C; E/T;		
Xu et al. (2021b)	×	×			Cmax; C; Q;	Ce	
Liu et al. (2021a)	×	×			Cmax; C; E/T	Ce	
Liu et al. (2017)	×	×			Cmax	Ce	
Seng et al. (2018)	×	×			Cmax	Ec	
Wang et al. (2020)*	×	×			Cmax; mW;		
Li et al. (2020d) ; Liang et al. (2021); Ning and Huang (2021); Sun et al. (2020); Ning et al. (2021)	×	×			Cmax; mW	Ce	
Gu (2021)	×	×			Cmax; mW	Ec	
Zhou et al. (2022)*	×	×			Cmax; R	Ec	
Huo et al. (2020) ; Wen et al. (2021)	×	×			Cmax; E/T	Ce	
Zhang et al. (2015)	×	×			Cmax; Wip; mW	Ce	

Jiang and Deng (2018)	× ×	EC; E/T
Piroozfard et al. (2018)	× ×	E/T Ce
Yin et al. (2017a)	× ×	Cmax Ec; Ne
Wang et al. (2018)	×	C Ec
Barak et al. (2021)	×	C; EC Ec
Song et al. (2014)	×	Cmax; C Ec
Xu et al. (2016)*	×	Cmax; C; mW; Q Ec
Jiang et al. (2014)	×	Cmax; C; Q Ec
Mokhtari and Hasani (2017)	×	Cmax; C; R
Wu and Sun (2018);Gong et al. (2022)	×	Cmax Ec; IO
He et al. (2015); Dai et al. (2015); Zhang et al. (2018); Luo et al. (2019); Yang et al. (2016); Li et al. (2020b); Wu et al. (2019); Zhang et al. (2019b); Zhang et al. (2021a) ; Dai et al. (2019); Li et al. (2021b); Li et al. (2021a); Ren et al. (2021); Wu et al. (2021); Li et al. (2022b); Li et al. (2022d); Wang et al. (2022d); Du et al. (2021); Wang et al. (2022b); Wei et al. (2022) ; Nouiri et al. (2018)* ; Li et al. (2020c)* ; Nouiri et al. (2020)* ; Duan and Wang (2021)*; Li et al. (2022c)*; Naimi et al. (2021)*	×	Cmax Ec
Liu et al. (2019b); Zhang et al. (2017a) ; Grosch et al. (2021) ; Park and Ham (2022)	×	Cmax; EC
Plitsos et al. (2017)	×	Cmax; Ft; IT
Luo et al. (2020) ; Zhang et al. (2017d)*; Wang et al. (2021a)	×	Cmax; mW Ec
Ayyoubzadeh et al. (2021)*	×	Cmax; mW; E/T
Sang and Tan (2022b) ; Sang and Tan (2022a)	×	Cmax; mW; E/T; Q Ec
Wu et al. (2020)* ; Duan and Wang (2022)*	×	Cmax; Rd Ec
Caldeira et al. (2020)*	×	Cmax; R Ec
Lei et al. (2019)	×	Cmax; E/T
An et al. (2020)	×	Cmax; E/T; C Ec
Shi et al. (2020)* ; Karim Ahangar et al. (2021)*; Li and Lei (2021)*	×	Cmax; E/T Ec
Li et al. (2019)	×	Cmax; E/T; mW Ec
Meng et al. (2020); Zhang et al. (2017c); Meng et al. (2019a) ; Ambrogio et al. (2020) ; Jiang et al. (2020) ; Rakovitis et al. (2022) ; Ham et al. (2021); Jiang et al. (2022) ; Garcia-Santiago et al. (2015)*	×	E
Ebrahimi et al. (2020)	×	EC; E/T
Lei et al. (2017)	×	mW Ec
Liu et al. (2014) ; Alotaibi et al. (2016)*	×	T Ec
Xu et al. (2021a)*	×	T; IT

Table 2: Articles on FJSSP integrating the environmental factor from 2013 to 2022.

Ce: Carbon emission; Ec: Energy consumption; Ne: Noise emission; Rc: Recycling; C: Cost; EC: Energy cost; Cmax: makespan; Q: Quality; R: Reliability; Wip: Work in process; mW: Machine workload; E/T: Earliness/Tardiness; Ec: Energy consumption; Ce: Carbon emission/footprint; Ne: Noise emission; Rd: Rescheduling disruptions; IO: Turn On/Off; Js: Job satisfaction; *: dynamic scheduling

References	Human Factors						Env. factors				Objective(s)		
	Ag	Lc	Er	Lr	Re	Sk	Ce	Ec	Ne	Rc	Eco.	Env.	Hum.
Lei and Guo (2015)						×	×	×			Cmax	Ce	
Gong et al. (2018a)	×				×		×	×	×		Cmax; Lc	Ec; Ne; Rc	S
Coca et al. (2019)		×					×	×	×		Cmax	Ce	Lr
Gong et al. (2019)	×				×		×				Cmax; EC; Lc; mW		
Meng et al. (2019b)					×		×					Ec	
Li et al. (2020a)					×		×					Ec	
Zhu et al. (2020)	×	×		×	×	×	×	×			Cmax; Lc	Ce	
Gong et al. (2021)	×				×		×	×	×		Cmax; Lc	Ec; Ne; Rc	S
Hongyu and Xiuli (2021)		×			×		×				Cmax	Ec	Lr
Li et al. (2021c)	×				×		×				Cmax; E/T; Lc; IT	Ec	
Peng et al. (2021)			×		×		×	×			Cmax	Ec; Ne	
Hajibabaei and Behnamian (2022)		×			×			×			Cmax	Ne	
Liu et al. (2022)	×				×		×	×	×		Cmax; Lc	Ec; Ne; Rc	S

Table 3: Articles on FJSSP integrating both human and environmental factors from 2013 to 2022.
 Ag: Age; Lc: labor cost; Er: Ergonomic risks; Lr: Learning rate; Re: Rest; Sk: Skill; Ce: Carbon emission;
 Ec: Energy consumption; Ne: Noise emission; Rc: Recycling; EC: Energy cost; IT: Idle time ; Cmax: makespan;
 mW: Machine workload; C: Cost; E/T: Earliness/Tardiness; Ce: Carbon emission/footprint; Ec: Energy consumption;
 Ne: Noise emission; Rc: Recycling; S: Safety.

The 135 referenced articles have been published in 67 different journals or books. However, about 50 % of these publications have been found in only 10 journals, as shown in Figure 7.

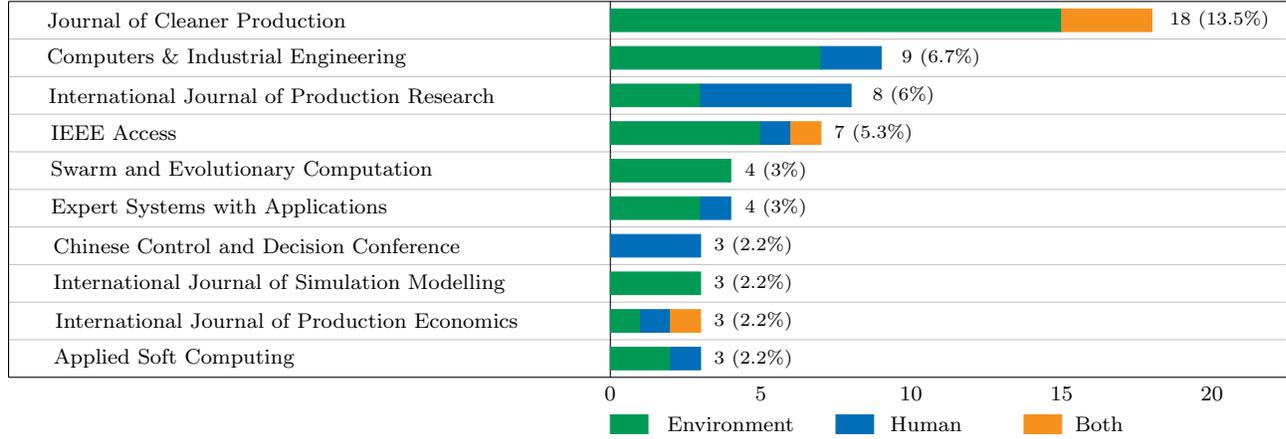


Figure 7: Top 10 journals publishing about FJSSP with human and/or environmental factors.

Figure 8 presents a chronological sorting of the reviewed articles. The Figure highlights the growth of interest for green production. The articles that first considered the environmental factor in the FJSSP date back to 2014. Over the last six years, at least eight papers per year consider energy consumption in their study. The consideration of the human factor in FJSSP varies over the years. In 2013, only a few articles were already considering the workers. Based on this graph, one can notice the lack of articles considering both environmental and human factors. Therefore, moving towards the I5.0 and more resilient production systems requires that research works focus more on integrating environmental and human factors.

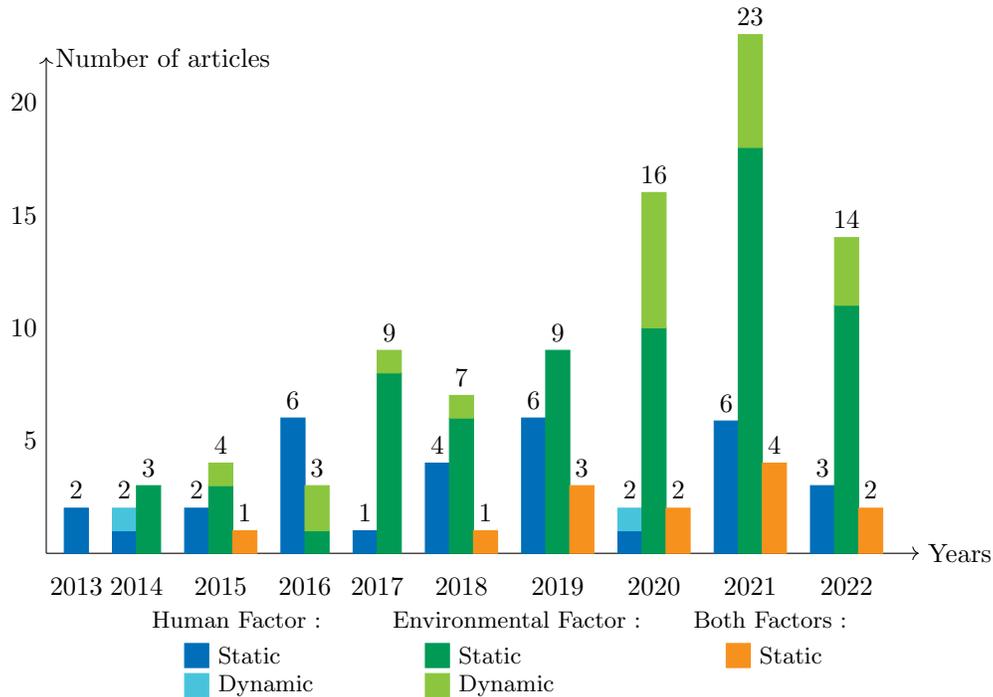


Figure 8: Enumeration of the surveyed literature integrating human and/or environmental factors.

Figure 9 details the proportion of articles incorporating the environmental and human factors separately or

simultaneously in the two cases of static and dynamic FJSSP. As previously mentioned, there is a correlation between these two dimensions and resilience. The Figure shows that most papers integrating at least one of the two factors solve the problem in a static production environment. Specifically, 69% of the reviewed papers consider the environmental factor, while 31% consider the workers. Only 9.6% integrate both factors, and only 15.6% deal with a dynamic environment. Furthermore, papers including both factors always solve static scheduling. Once again, the graph proves the lack of studies integrating workers and the environment simultaneously and any such study solving the problem dynamically. The lack of research studies integrating environmental and human factors in the case of dynamic FJSSP, demonstrates a real need to integrate these aspects while improving the performance of today’s industrial systems. To achieve an increasingly sustainable, human-value-based, and resilient industry, we must study the FJSSP in these directions. The following two subsections provide more details on integrating human and environmental factors in the FJSSP.

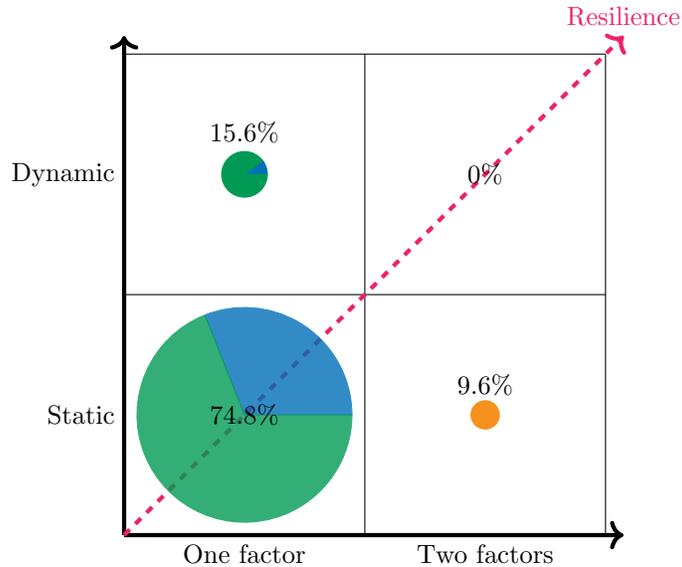


Figure 9: Proportion of articles integrating one or two factors (Human and Environment), considering static or dynamic scheduling.

4.1. Human Factor

In most cases, an FJSSP that considers the human factor is called a Dual Resource Constrained FJSSP (DRCFJSSP). It means that we consider both machines and workers as resources. One or more workers can operate the same machine, and a worker can operate one or more machines simultaneously. Figure 10 illustrates a DRCFJSSP, highlighting the difference between an FJSSP with only machine consideration, as seen in Figure 2, and a DRCFJSSP. For each operation, a worker has to be assigned to the corresponding machine to process it. Workers are also flexible, meaning that they can operate different machines. Workers’ consideration adds complexity to the model, as we have even more possibilities to make decisions. The three sub-problems in a DRCFJSSP are: (1) allocating each operation on the optimal machine, (2) assigning an optimal worker to process it, and (3) finding the optimal operation sequence on each machine. We can apply the dual resource-constrained problem to automobile manufacturing, equipment manufacturing and electronic products manufacturing, *etc.*, see for example Wu et al. (2018).

Generally, workers are difficult to represent in a mathematical model. The complexity of providing an accurate decision or action that a worker would make is very high, and operator errors are responsible for about 60-90 % of failures in a system (Kumar et al., 2020). In the literature, we notice various criteria for modelling a worker. First, some articles identify a worker by his skills (Lei and Tan, 2016; Zheng and Wang, 2016; Tan et al., 2021). With this characterization, a worker can have different skills, meaning that he can be more or less efficient depending on the machine. These skills vary from one worker to another and change the processing time of a task, thus impacting the scheduling. Directly linked to the worker’s qualifications, some papers take into account the worker’s learning rate (Wu et al., 2018; Zhu et al., 2020; Peng et al., 2021). In these models, workers’ skills evolve as they spend more time on a machine. Therefore, a worker who spends a lot of time on a machine will quickly increase his competence and thus reduce the processing time of the tasks he performs on this one. On the other hand, if he varies and spends time on several machines, he will be more versatile, which improves the production system’s flexibility. During his/her working time, a worker

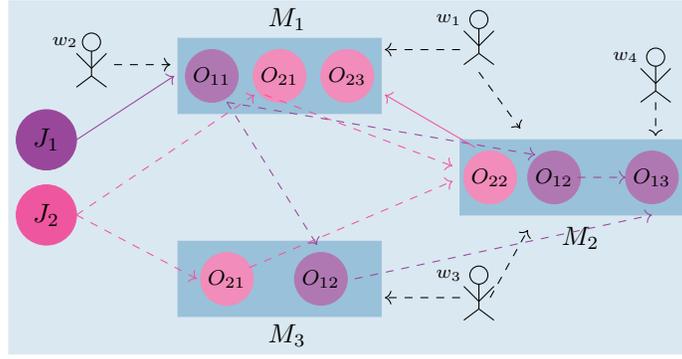


Figure 10: Dual Resource Constrained Flexible job-shop Scheduling Problem.

is exposed to different kinds of health risks, often called ergonomic risks (Coca et al., 2019; Hongyu and Xiuli, 2021; Hajibabaei and Behnamian, 2022). In a production process, ergonomic risks can be exposure to temperature and noise, vibrations affecting tendons, muscles, bones, or the nervous system, physical and mental effort, or bad postures that can cause musculoskeletal disorders. Different methods such as OCRA, RULA, REBA or EAWS were proposed in the literature to measure the human-related work risks. These methods, among others, are summarized in Table 4 (adapted from Savino et al. (2016)). The upper limbs correspond to the neck, trunk, waist, wrist, arms, and forearms, and the lower limbs correspond to the knees and legs (Savino et al., 2017).

Method	Body part	Parameters considered
RULA	Upper limb	Posture, muscle use, weight, task duration, frequency
OCRA	Upper limb	Rest, frequency, strength, posture, temperature, vibration
REBA	Upper and lower limb	Posture, muscle use, weight, task duration, frequency, hand coupling
OWAS	Full body	posture, lifted weight
EAWS	Full body	posture, strength, manual material handling

Table 4: Ergonomic methods description.

The ergonomic methods presented in Table 4 are used in particular in assembly line problems due to the repetitiveness of worker’s movement (Bautista et al., 2016) or workforce assignment problems (Rinaldi et al., 2022), but also in some FJSSP (Hongyu and Xiuli, 2021). For example, the OCRA index provides results such as “no risk”, “low risk” or “high risk” on the worker regarding the achieved task. We often model the ergonomic risk as a not-to-exceed limit in the constraints. Workers must therefore be assigned tasks that do not expose them to too many risks. For instance, if a machine requires an awkward posture, the same worker will not be assigned to this one for too long during the day. Also, we can consider the fatigue and rest time of the workers (Sun et al., 2019; Berti et al., 2021; Tan et al., 2021). Fatigue can be calculated as in Berti et al. (2021) with energy expenditure during the work process and the workers’ rest time. Tan et al. (2021) implements a worker-dependent recovery parameter to model workers’ fatigue reduced during rest time. Workers’ fatigue influences the scheduling as the more an operator is tired, the less efficient he will be (Savino et al., 2017), affecting processing times. Including rest time during a schedule can change tasks order or tasks beginning. For example, if no pre-emption is allowed, a worker cannot start to process an operation if the latter cannot be over before the worker’s rest time. Berti et al. (2021) also considers workers’ age, influencing workers’ fatigue and physical condition. Finally, the cost of workers can be considered, as in Li et al. (2016a); Gong et al. (2018a); Liu et al. (2022). The cost to employ a worker depends on his skills and experiences. It can be calculated as an hourly wage or a sum for each task processed, depending on the task. Thus, we can model workers with many parameters that greatly influence the schedule.

Figure 11 summarizes the most taken-into-account parameters based on the 47 selected articles and considering the human factor. Almost all found papers distinguish workers’ skills, whereas about a quarter consider labor cost, and only a few of them take into account learning rate, rest time, ergonomic risk, or age. What emerges from this figure is that most of the models treat workers almost as if they were machine resources. A machine has a capacity and a processing cost, and so do the workers. However, human operators are much more complex, and workers’ differences (age, gender, anthropometry, etc.) and well-being should be considered more. A worker feeling safe, healthy, well surrounded (machines, teams, managers), valued,

and involved is more motivated at work. Thanks to that, the production process is improved, and the system becomes more resilient, employing operators feeling good in their work environment and therefore more likely to perform better. Lu et al. (2022) proposes an Industrial Human Needs Pyramid which links everyday human needs with the manufacturing system. This pyramid highlights the parameters needed to model the operators. Five levels are presented: safety, health, belonging, esteem, and self-actualization. The authors conclude that manufacturing should consider workers personally, considering their differences on all levels, from physical to psychological. The goal is to create a system where “individual well-being and sustained manufacturing growth are mutually reinforcing” (Lu et al., 2022). In addition, nowadays and for years to come, the active population is ageing, which should increase the need to reduce ergonomic risks at work (Otto and Battaia, 2017).

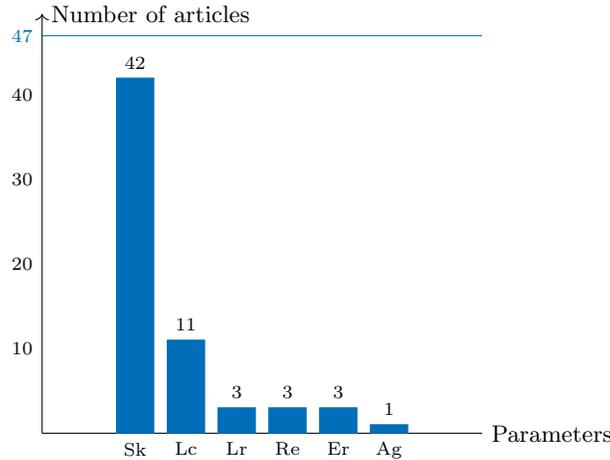


Figure 11: Distribution of the reviewed papers regarding human’s parameters. Sk: skill, Lc: Labor cost, Lr: learning rate, Re: rest, Er: Ergonomic risks, Ag: age.

To go further, we can divide the articles integrating human factors into two families: the ones considering the human factor in the objective function and those considering the human in the constraints. Only 28% of these articles measure the human factor in the objective function. In the other types of objectives, the most repeated are minimizing the makespan, the production cost, or the total tardiness. As detailed in Figure 12, papers adding human factors to the objective function optimize the workers’ cost most of the time. On the same time, some papers minimize ergonomic risks (Hongyu and Xiuli, 2021; Coca et al., 2019), worker’s fatigue (Tan et al., 2021) or worker’s workload (Luo et al., 2022; Sano et al., 2016).

Regarding resolution methods, different exact, heuristic, meta-heuristic and hybrid methods are widely explored in the literature. In our analysis, we focus only on the papers considering the Human or/and environmental factors and try to analyze the trends in the FJSSP regarding the resolution methods. Most papers use a hybrid method, composed of meta-heuristics combined with local search, as shown in Figure 13. Most often, the genetic algorithm or an improvement of it is used.

As previously mentioned, 28% of the papers integrating human parameters also consider environmental parameters, such as energy consumption, carbon emission, or noise emission. Meng et al. (2019b) has proven that workers’ skills can impact energy consumption in production. A worker with high skills will be more

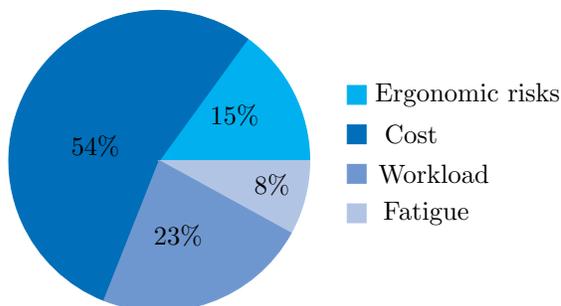


Figure 12: Human parameters considered in the objective function.

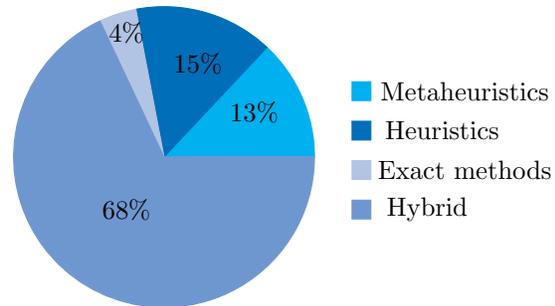


Figure 13: Resolution method used based on the 47 articles integrating human factor.

efficient, decreasing processing time and thus energy consumption. As seen in this Section, bringing back the human touch in manufacturing leads to many changes in the scheduling problems, especially in the FJSSP, creating challenges for future research. Future studies must focus more on ergonomic risks and differences between workers to ensure human well-being.

4.2. Environmental Factor

According to Li and Wang (2022), green production has started to attract attention since 2013. From this date, this topic’s research has increased, especially during the last three years. FJSSP follows this trend as shown in Figure 8. The industry is responsible for a third of energy consumption in the world (Alaouchiche et al., 2020), so being aware of energy saving in manufacturing could help reduce pollution emissions and improve resource utilization. Green production can pay attention to energy consumption, carbon emission, noise emission, or even recycling. The challenge here is to provide “environment-friendly” scheduling, while trying to optimize economic aspects and satisfy customers. For instance, if a machine is very efficient but needs lots of power to work, there is a trade-off between speeding up the production process and reducing pollution. Generally, the age of machines is heterogeneous in factories. New ones use less energy than older ones, which use more energy and emit more pollutants (Li et al., 2016b). As a result, the choice of machines for production must be adapted.

Concerning FJSSP, we collected 101 papers integrating environmental parameters in their models since 2013, detailed in Table 2. Figure 14 shows which factors are the most used. Undeniably, energy consumption is the one that has received the most attention, present in 100 articles on 101. Besides, carbon emission has attracted attention in 22 articles directly linked to energy consumption. Most of the time, the models measure environmental parameters in the objective function. 98% of these 101 articles try to maximize green production, and 89% of them are multi-objective, meaning that there is a trade-off between several objectives.

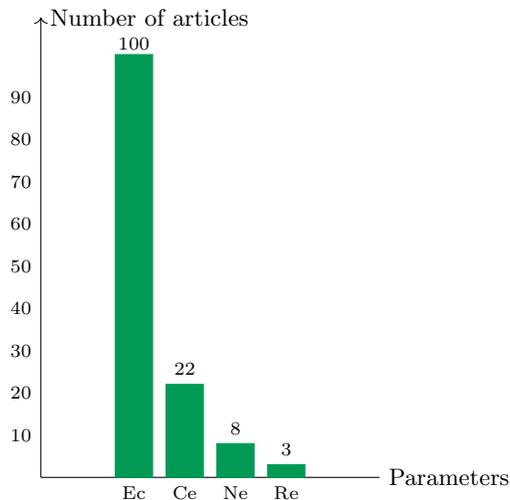


Figure 14: Environmental parameters considered in the literature. Ec: energy consumption, Ce: carbon emission, Ne: noise emission, Re: recycling.

Among all these articles, we notice different ways of modeling energy consumption. First, as described in Figure 15, the machines go through various stages during the process. These stages don’t use the same quantity of energy. For instance, Wu and Sun (2018) proposed an approach to simultaneously reduce the makespan, the energy consumption and the number of turning-on/off machines. Other works consider the idle state of a machine, *e.g.* Meng et al. (2019a). A set-up or a maintenance intervention can be carried out on a machine before or after the execution of an operation, consuming another amount of power, as considered in Li and Lei (2021) and Mokhtari and Hasani (2017). Finally, when a machine processes a task, it can have different energy consumption, linked with the operation’s type and duration (Gong et al., 2018a). In addition, a machine can have different speeds during the process, leading to a variation in energy consumption or even noise emission (Duan and Wang, 2021). Some articles schedule the shutdown of a machine if idle times are too long to reduce consumption (Zhang et al., 2017c).

At the same time, other activities in the factory also need power, such as transport, loading and unloading (Dai et al., 2019; Zhang et al., 2017c). In fact, when a product goes from one machine to another, it has to be transported, loaded on the machine, and therefore unloaded, which is energy-consuming. In this way, transport can have an impact on the schedule. For instance, the machine chosen for an operation can depend

on the previous machine selected for the same job while trying to limit transport time and thus the power consumed. Finally, the lighting, the heating, the air conditioning, *etc.* are auxiliary energies used during a production process, which are also considered in FJSSP literature, *e.g.* Ham et al. (2021). These energies are related to the makespan because the longer it takes to produce, the more power is required. Figure 15 summarizes all the activities that consume energy within a production workshop. We can model different parameters associated to these activities to optimize the overall energy consumption, without deteriorating other performance indicators related to customers' satisfaction. However, this is still a significant challenge for future research in the scheduling domain, especially the dynamic FJSSP.

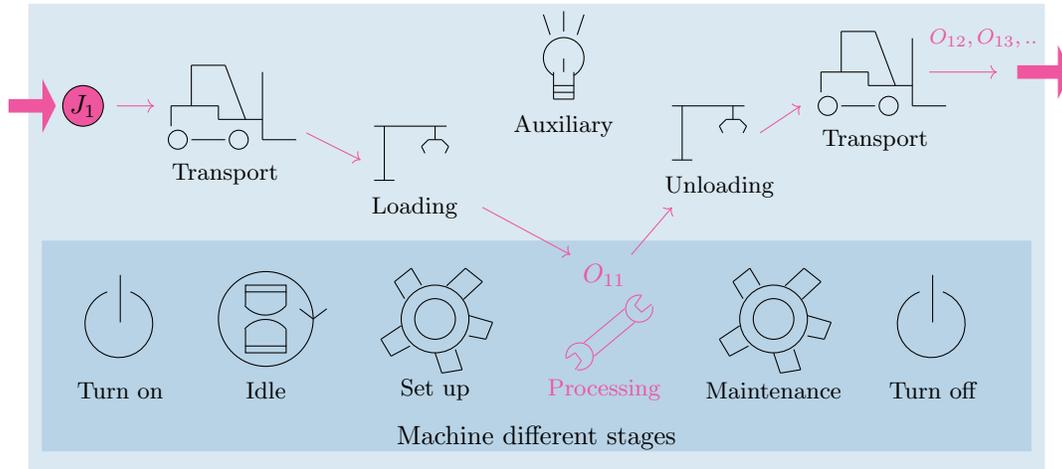


Figure 15: Energy consumption in a workshop.

The parameters described previously are not always considered in mathematical models. Figure 16 details how much articles integrate them in their studies, based on those optimizing energy consumption. The power consumed during the processing time is always considered. Most of them take into account the idle times of the machines but apart from these two, the other parameters are less studied in the literature.

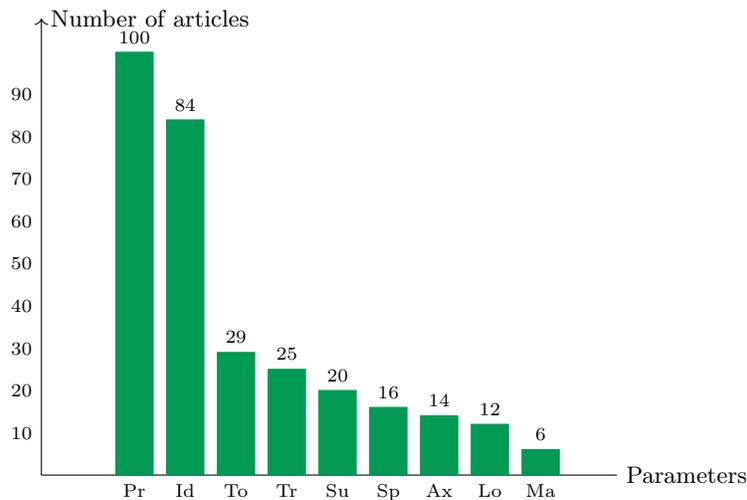


Figure 16: Energy parameters considered in flexible job-shops. Pr: processing time, Id: idle time, To: turn on and off, Tr: transport, Ax: auxiliary, Su: set-up, Sp: machine speeds, Lo: loading and unloading, Ma: maintenance.

Regarding resolution methods, most papers use hybrid methods to solve the green scheduling as shown in Figure 17. These hybrid methods are composed of meta-heuristics combined with local search or artificial intelligence methods. The latter can improve the solution by learning the system the right or wrong solutions. Moreover, artificial intelligence methods can deal with a dynamic environment. The rest of the studies use meta-heuristics (*e.g.* genetic algorithm), heuristics, artificial intelligence methods (*e.g.* agent-based methods, Q-learning) or exact methods.

To summarize, energy consumption during the production process is increasingly studied in the literature, often including the consumption of processing time and idle time. However, few studies have worked on energy

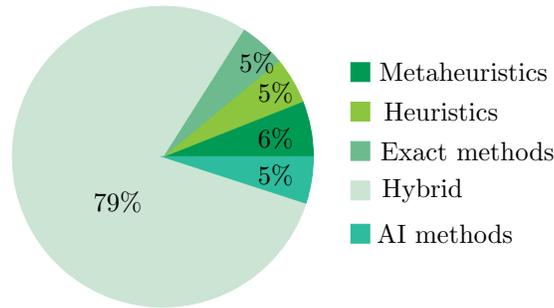


Figure 17: Resolution method used based on the 101 articles considering environmental factor.

consumption during transport, set-up, loading, unloading, and maintenance times. Similarly, auxiliary energy needs, such as lighting or air conditioning, need to be further considered. This environmental awareness helps factories to become more sustainable and to take the first step towards Industry 5.0. Then, the human factor should be increasingly considered as same as the economic and environmental factors. In fact, based on the 101 articles trying to maximize green production in FJSSP, only 13 of them integrate the human factor in their models. Nevertheless, the majority of reviewed papers emphasize the necessity for research to be conscious of both human and environmental values to improve the manufacturing systems' performance and the well-being of the present generation as well as future generations.

5. Future research

This paper reviewed and analyzed how human and environmental factors are considered in the literature of FJSSP. The scheduling models and methods were transformed by the arising of Industry 4.0 concepts and technologies and are nowadays challenged by the new concerns related to the human-centricity and environment efficiency of the current Industry 5.0 context. Looking at our analysis, only few papers consider the sustainable (economic-human-environment) scheduling problem, and efforts still need to be directed towards this problem exploration. In this section, we suggest a mathematical model to solve a Sustainable Flexible Job Shop Scheduling Problem (SFJSSP) with Dual Resource Constraint, aiming to minimize the total energy consumption. Our model should limit the worker's exposure to repetitive upper limb movements based on the standard OCRA index. The following subsections briefly described our model and provide the general mathematical model. Future extensions of the model are also discussed.

5.1. Problem statement

In our model, we consider both human and machine resources. For this purpose, we divide the tasks into four categories: the ones managed by both workers and machines (human-robot collaboration), the ones handled by either workers or machines, the ones operated only by workers (*e.g.* customized item), and the ones processed only by machines (*e.g.* difficult tasks). In addition, multiple workers can handle one operation, and a resource cannot perform several tasks simultaneously. Thus, we must specify the number of workers needed for each task. Obviously, both resources are not always available. Each operation allocated to a resource must wait until the previous task on that resource is completed. In addition, set-up times must be executed on machines when two consecutive jobs require different settings. Added to this is the maintenance time, whether it is predictive maintenance to anticipate breakdowns or repair. These procedures cause the unavailability of the machines that should be considered in the model.

For workers' availability, we must take into account more parameters. As mentioned earlier in this paper, recovery times and maximum workload must be included in the model to prevent and reduce workers' fatigue. In parallel, the ergonomic risks for each worker must be limited, affecting their health and efficiency. It can be calculated by an index such as OCRA, EAWS, RULA, *etc.* Several uses of these indexes in the same model can help to consider the problem entirely. These ergonomic constraints will impact the distribution of workers' tasks. Directly linked, the sequence of tasks that the worker performs can influence his efficiency (Rinaldi et al., 2022), affecting resource allocation. In addition, when a worker moves from one machine to another, there is an additional time involved, namely travel time. Moreover, the workers have different skills that can evolve along the production process according to their learning rate. The model must consider these aspects. Finally, the operators have different costs (wages) depending on their skills and experience. These costs must be integrated into the model, affecting the total production cost.

All these parameters will make the model more complex but more conscious of resource availability and efficiency. So, first, we integrate them as constraints. Then, we can easily adapt the model to maximize workers' well-being in the objective function, placing humans at the center of the problem.

Our choice is to minimize the total energy consumption. The first reason for this choice is that the environment is one of the two topics we want to focus on to move towards an I5.0. Second, defining energy as a constraint is complex because we don't have a clear idea of the limit not to be exceeded during the process. If we set the energy in the objective, the model will provide the most energy-efficient scheduling, regardless of the energy consumption limit.

5.2. Mathematical modelling

5.2.1. Assumptions

The following assumptions are made to model the considered SFJSSP:

- Each operation is processed by one operator on one machine;
- An operator can execute only one operation at a time;
- An operator rests 12.5% of his worked time when he wants during the day. It can be adapted according to factory rules;
- A period is equal to 7h or 8h, and a worker is assigned to one period to two (A worker is assigned every morning, afternoon, or night. These constraints can be adapted according to factory rules).

5.2.2. Objective function

We suggest a mono-objective formulation of the SFJSSP to minimize the total energy consumption as follows:

$$\min ET + EM + EC$$

ET corresponds to the energy linked to transport. EM denotes the machines' related energy and EC refers to the auxiliary energy. The latter is directly related to the makespan: the longer the production process, the more energy is consumed for lighting, heating, *etc.* Thus, by minimizing energy consumption, the makespan should also be minimized. Through this objective, the environmental factor is considered. Human factors, on its side, will be considered in the constraints.

5.2.3. Constraints

We consider three family constraints: workers-related, precedence-related, and tasks-related. First, the workers' constraints are defined as follows:

- $OCRA \leq 2.2$ → OCRA index respected for all workers;
- Rest time $\geq 12.5\% \times$ work time → Rest time respected for all workers;
- Period + next period = 1 → A worker can't be assigned on two consecutive periods.

Besides, we have three types of precedence constraints. The first type is related to tasks of the same job, as a task can't start before the completion time of the previous task added to transport time and waiting time. Waiting time can be for example cooling or drying. The second type of precedence constraint concerns the precedence of tasks assigned to the same worker, as a task can't start before the completion time of the previous task added to travel time and rest time for the chosen worker. Finally, the third type is related to tasks executed on the same machine and states that a task can't start before the completion time of the previous task added to the set-up time. The precedence-related constraints are defined as follows:

- Completion time + Transport + Waiting \leq Starting time of the next task;
- Completion time + Transport + Rest \leq Starting time of the next task;
- Completion time + Set-up \leq Starting time of the next task.

Finally, the task-related constraints ensure respecting due dates, starting time and completion time in the period the task is assigned on. We define these constraints as follows:

- Completion time \leq End time of the period;
- Starting time \geq Starting time of the period;
- Completion time \leq Due date.

5.3. Perspectives

In this study, we propose a mono-objective model to minimize energy consumption. Our model considers the human factor in the constraints by limiting workers’ repetitive movements. However, the human factor can be modeled as an objective function making our model multi-objective, for example, one considers to:

- Maximize the workers’ flexibility: the purpose is to reinforce the worker’s multi skills. In this sense, the system would be more flexible, allowing the operators to use more machines.
- Maximize the worker’s well-being, thanks to ergonomic indexes as mentioned previously. For example, we can minimize the maximum ergonomic index, thus reducing the ergonomic index of each worker.

By combining these objectives, we should be able to measure how much the workers and the environmental factors can impact the performance of the shop floor. We can imagine a multi-objective human-environment-economic model.

The SFJSSP we suggest in this paper is static. For small instances, our model can be solved with an exact method. Besides, the objective will be to provide a dynamic SFJSSP able to deal with uncertainties that can occur during the production process. The resilience will also be enhanced by improving the system’s ability to react to disruptive events. We may use, among others, the triangular fuzzy number to represent uncertainties in manufacturing systems as presented by Li et al. (2022a). In the last few decades, several methods have been used to solve the dynamic FJSSP. The two most used are metaheuristics and dispatching rules; however, these later are ineffective in finding an optimal solution (Luo, 2020). Metaheuristics deal with the dynamic scheduling problem by decomposing it into several static sub-problems, which leads to a time-consuming solution (Luo, 2020). On the contrary, artificial intelligence methods have proved their efficiency in dealing with real-time scheduling problems. To confirm this point, regarding the 135 articles selected in our studies, we notice differences between the resolution methods used in static and dynamic cases. Figure 18a shows that exact methods can solve static FJSSP, and on the contrary, Figure 18b demonstrates that no study has used these methods to solve dynamic scheduling. Moreover, artificial intelligence methods are used in dynamic cases while no static scheduling is solved with them. Hybrid methods used in dynamic cases most of the time combine meta-heuristics and artificial intelligence methods.

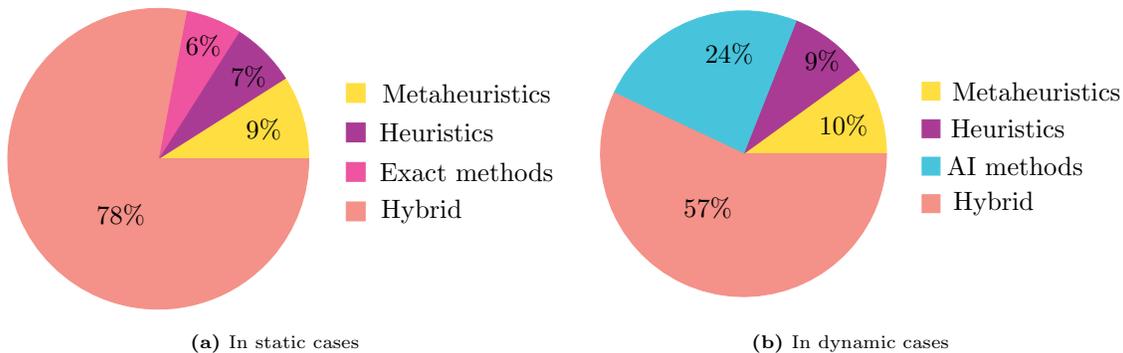


Figure 18: Resolution method used in case of static or dynamic FJSSP, based on the 135 articles selected.

We plan to solve our model using machine learning methods. In particular, we are interested in the deep reinforcement learning technique. Wang et al. (2021b) assures that “deep reinforcement learning can give immediate action for the problem if the model is well trained” and can handle combinatorial optimization problems. Further, Ansari and Bakar (2014) states that the fuzzy logic method can optimize multiple goals. In that sense, we will study the fuzzy logic to solve our multi-objective model. To go further in our approach, we plan to test our model on a real industrial case to improve it.

6. Conclusion

This paper presents a survey of FJSSP considering the environmental and human factors. We start by introducing the evolution of scheduling problems, particularly in the last decade from the emergence of Industry 4.0 to now. Scheduling problems have been widely studied in the literature under different production types, characteristics, environments, and objective functions. This interest is due to the high impact that scheduling has on the production process. FJSSP is the most encountered in the real-world case. For decades, research focused on economic aspects, minimizing the makespan or the production cost as an evaluation criterion. Recently, I4.0 has brought new technologies that increase production efficiency, driving

the research on solving the scheduling problem in this new context. Today new challenges are emerging, namely human's well-being, sustainability, and resilience. They tend to move towards an I5.0, filling in the gaps of I4.0. The objective is to use technologies in an intelligent way, placing humans at the head of the system and being conscious of our planet.

Most of the articles reviewed primarily consider economic and energy consumption objectives. Few papers consider, at the same time, the economic, environmental, and social dimensions. Growing importance is increasingly accorded to the sustainable FJSSP. Also, most previous studies consider the makespan as the main and single objective. Considering multi-objective models which take into account the three pillars of sustainability, is becoming trend research. Regarding resolution methods, most papers use hybrid methods to solve the scheduling problem considering human or environmental factors. These hybrid methods are composed of meta-heuristics combined with local search or Artificial Intelligence (AI) methods.

This survey proved a lack of studies integrating both factors linked to I5.0, namely human and environmental consideration, and a lack of dynamic FJSSP studies. These gaps provide a direction for future work to keep up with the manufacturing trend towards Industry 5.0.

References

- Aheleroff, S., Huang, H., Xu, X., Zhong, R., 2022. Toward sustainability and resilience with Industry 4.0 and Industry 5.0. *Frontiers in Manufacturing Technology* 2, 951643. URL: <https://www.frontiersin.org/articles/10.3389/fmtec.2022.951643/full>, doi:10.3389/fmtec.2022.951643.
- Aheleroff, S., Mostashiri, N., Xu, X., Zhong, R., 2021. Mass Personalisation as a Service in Industry 4.0: A Resilient Response Case Study. *Advanced Engineering Informatics* 50, 101438. URL: <https://www.sciencedirect.com/science/article/pii/S1474034621001907>, doi:10.1016/j.aei.2021.101438.
- Alaouchiche, Y., Ouazene, Y., Yalaoui, F., 2020. Economic and Energetic Performance Evaluation of Unreliable Production Lines: An Integrated Analytical Approach. *IEEE Access* 8, 185330–185345. doi:10.1109/ACCESS.2020.3029761.
- Alemão, D., Rocha, A., Barata, J., 2021. Smart Manufacturing Scheduling Approaches—Systematic Review and Future Directions. *Applied Sciences* 11. URL: <https://www.mdpi.com/2076-3417/11/5/2186>, doi:10.3390/app11052186.
- Alotaibi, A., Lohse, N., Vu, T.M., 2016. Dynamic Agent-based Bi-objective Robustness for Tardiness and Energy in a Dynamic Flexible Job Shop. *Factories of the Future in the digital environment - Proceedings of the 49th CIRP Conference on Manufacturing Systems* 57, 728–733. URL: <https://www.sciencedirect.com/science/article/pii/S2212827116312860>, doi:10.1016/j.procir.2016.11.126.
- Ambrogio, G., Guido, R., Palaia, D., Filice, L., 2020. Job shop scheduling model for a sustainable manufacturing. *International Conference on Industry 4.0 and Smart Manufacturing (ISM 2019)* 42, 538–541. URL: <https://www.sciencedirect.com/science/article/pii/S2351978920305837>, doi:10.1016/j.promfg.2020.02.034.
- An, Y., Chen, X., Zhang, J., Li, Y., 2020. A hybrid multi-objective evolutionary algorithm to integrate optimization of the production scheduling and imperfect cutting tool maintenance considering total energy consumption. *Journal of Cleaner Production* 268, 121540. URL: <https://www.sciencedirect.com/science/article/pii/S0959652620315870>, doi:10.1016/j.jclepro.2020.121540.
- Andrade-Pineda, J., Canca, D., Gonzalez-R, P., Calle, M., 2020. Scheduling a dual-resource flexible job shop with makespan and due date-related criteria. *Annals of Operations Research* 291, 5–35. URL: <https://doi.org/10.1007/s10479-019-03196-0>, doi:10.1007/s10479-019-03196-0.
- Ansari, A., Bakar, A., 2014. A Comparative Study of Three Artificial Intelligence Techniques: Genetic Algorithm, Neural Network, and Fuzzy Logic, on Scheduling Problem, in: *2014 4th International Conference on Artificial Intelligence with Applications in Engineering and Technology*, pp. 31–36. doi:10.1109/ICAJET.2014.15.
- Ayyoubzadeh, B., Ebrahimnejad, S., Bashiri, M., Baradaran, V., Hosseini, S., 2021. Modelling and an improved NSGA-II algorithm for sustainable manufacturing systems with energy conservation under environmental uncertainties: a case study. *International Journal of Sustainable Engineering* 14, 255–279. URL: <https://www.tandfonline.com/doi/full/10.1080/19397038.2021.1923083>, doi:10.1080/19397038.2021.1923083.

- Barak, S., Moghdani, R., Maghsoudlou, H., 2021. Energy-efficient multi-objective flexible manufacturing scheduling. *Journal of Cleaner Production* 283, 124610. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0959652620346540>, doi:10.1016/j.jclepro.2020.124610.
- Baranauskas, G., 2019. Mass Personalization vs. Mass Customization: Finding Variance in Semantical Meaning and Practical Implementation between Sectors.
- Bautista, J., Batalla-García, C., Alfaro-Pozo, R., 2016. Models for assembly line balancing by temporal, spatial and ergonomic risk attributes. *European Journal of Operational Research* 251, 814–829. URL: <https://www.sciencedirect.com/science/article/pii/S0377221715011819>, doi:10.1016/j.ejor.2015.12.042.
- Berti, N., Finco, S., Battaia, O., Delorme, X., 2021. Ageing workforce effects in Dual-Resource Constrained job-shop scheduling. *International Journal of Production Economics* 237, 108151. URL: <https://www.sciencedirect.com/science/article/pii/S0925527321001274>, doi:10.1016/j.ijpe.2021.108151.
- Breque, M., De Nul, L., Petridis, A., 2021. Industry 5.0: towards a sustainable, human-centric and resilient European industry. Luxembourg, LU: European Commission, Directorate-General for Research and Innovation. doi:10.2777/308407.
- Caldeira, R.H., Gnanavelbabu, A., Vaidyanathan, T., 2020. An effective backtracking search algorithm for multi-objective flexible job shop scheduling considering new job arrivals and energy consumption. *Computers & Industrial Engineering* 149, 106863. URL: <https://www.sciencedirect.com/science/article/pii/S0360835220305593>, doi:10.1016/j.cie.2020.106863.
- Coca, G., Castrillón, O., Ruiz, S., Mateo-Sanz, J., Jiménez, L., 2019. Sustainable evaluation of environmental and occupational risks scheduling flexible job shop manufacturing systems. *Journal of Cleaner Production* 209, 146–168. URL: <https://www.sciencedirect.com/science/article/pii/S0959652618332153>, doi:10.1016/j.jclepro.2018.10.193.
- Dai, M., Tang, D., Giret, A., Salido, M.A., 2019. Multi-objective optimization for energy-efficient flexible job shop scheduling problem with transportation constraints. *Robotics and Computer-Integrated Manufacturing* 59, 143–157. URL: <https://www.sciencedirect.com/science/article/pii/S0736584518305222>, doi:10.1016/j.rcim.2019.04.006.
- Dai, M., Tang, D., Xu, Y., Li, W., 2015. Energy-aware integrated process planning and scheduling for job shops. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 229, 13–26. URL: <http://journals.sagepub.com/doi/10.1177/0954405414553069>, doi:10.1177/0954405414553069.
- Du, Y., Li, J.q., Luo, C., Meng, L.l., 2021. A hybrid estimation of distribution algorithm for distributed flexible job shop scheduling with crane transportations. *Swarm and Evolutionary Computation* 62, 100861. URL: <https://linkinghub.elsevier.com/retrieve/pii/S2210650221000225>, doi:10.1016/j.swevo.2021.100861.
- Duan, J., Wang, J., 2021. Energy-efficient scheduling for a flexible job shop with machine breakdowns considering machine idle time arrangement and machine speed level selection. *Computers & Industrial Engineering* 161, 107677. URL: <https://www.sciencedirect.com/science/article/pii/S0360835221005817>, doi:10.1016/j.cie.2021.107677.
- Duan, J., Wang, J., 2022. Robust scheduling for flexible machining job shop subject to machine breakdowns and new job arrivals considering system reusability and task recurrence. *Expert Systems with Applications* 203, 117489. URL: <https://www.sciencedirect.com/science/article/pii/S0957417422008181>, doi:10.1016/j.eswa.2022.117489.
- Ebrahimi, A., Jeon, H., Lee, S., Wang, C., 2020. Minimizing total energy cost and tardiness penalty for a scheduling-layout problem in a flexible job shop system: A comparison of four metaheuristic algorithms. *Computers & Industrial Engineering* 141, 106295. URL: <https://www.sciencedirect.com/science/article/pii/S0360835220300292>, doi:10.1016/j.cie.2020.106295.
- Farjallah, F., Nouri, H., Belkahl, O., 2022. Multi-start Tabu Agents-Based Model for the Dual-Resource Constrained Flexible Job Shop Scheduling Problem, in: Nguyen, N., Manolopoulos, Y., Chbeir, R., Kozierekiewicz, A., Trawiński, B. (Eds.), *Computational Collective Intelligence*, Springer International Publishing, Cham. pp. 674–686.

- Garcia-Santiago, C., Del Ser, J., Upton, C., Quilligan, F., Gil-Lopez, S., Salcedo-Sanz, S., 2015. A random-key encoded harmony search approach for energy-efficient production scheduling with shared resources. *Engineering Optimization* 47, 1481–1496. URL: <http://www.tandfonline.com/doi/full/10.1080/0305215X.2014.971778>, doi:10.1080/0305215X.2014.971778.
- Gnanavelbabu, A., Caldeira, R.H., Vaidyanathan, T., 2021. A simulation-based modified backtracking search algorithm for multi-objective stochastic flexible job shop scheduling problem with worker flexibility. *Applied Soft Computing* 113, 107960. URL: <https://www.sciencedirect.com/science/article/pii/S1568494621008826>, doi:10.1016/j.asoc.2021.107960.
- Gong, G., Chiong, R., Deng, Q., Gong, X., 2020. A hybrid artificial bee colony algorithm for flexible job shop scheduling with worker flexibility. *International Journal of Production Research* 58, 4406–4420. URL: <https://doi.org/10.1080/00207543.2019.1653504>, doi:10.1080/00207543.2019.1653504. publisher: Taylor & Francis.
- Gong, G., Chiong, R., Deng, Q., Gong, X., Lin, W., Han, W., Zhang, L., 2022. A two-stage memetic algorithm for energy-efficient flexible job shop scheduling by means of decreasing the total number of machine restarts. *Swarm and Evolutionary Computation* , 101131URL: <https://www.sciencedirect.com/science/article/pii/S2210650222001018>, doi:10.1016/j.swevo.2022.101131.
- Gong, G., Deng, Q., Gong, X., Huang, D., 2021. A non-dominated ensemble fitness ranking algorithm for multi-objective flexible job-shop scheduling problem considering worker flexibility and green factors. *Knowledge-Based Systems* 231, 107430. URL: <https://www.sciencedirect.com/science/article/pii/S0950705121006924>, doi:10.1016/j.knosys.2021.107430.
- Gong, G., Deng, Q., Gong, X., Liu, W., Ren, Q., 2018a. A new double flexible job-shop scheduling problem integrating processing time, green production, and human factor indicators. *Journal of Cleaner Production* 174, 560–576. URL: <https://www.sciencedirect.com/science/article/pii/S0959652617324952>, doi:10.1016/j.jclepro.2017.10.188.
- Gong, X., De Pessemier, T., Martens, L., Joseph, W., 2019. Energy- and labor-aware flexible job shop scheduling under dynamic electricity pricing: A many-objective optimization investigation. *Journal of Cleaner Production* 209, 1078–1094. URL: <https://www.sciencedirect.com/science/article/pii/S0959652618333225>, doi:10.1016/j.jclepro.2018.10.289.
- Gong, X., Deng, Q., Gong, G., Liu, W., Ren, Q., 2018b. A memetic algorithm for multi-objective flexible job-shop problem with worker flexibility. *International Journal of Production Research* 56, 2506–2522. URL: <https://doi.org/10.1080/00207543.2017.1388933>, doi:10.1080/00207543.2017.1388933. publisher: Taylor & Francis.
- Grabowska, S., Saniuk, S., Gajdzik, B., 2022. Industry 5.0: improving humanization and sustainability of industry 4.0. *Scientometrics* , 1–28.
- Grosch, B., Kohne, T., Weigold, M., 2021. Multi-objective hybrid genetic algorithm for energy adaptive production scheduling in job shops. *The 28th CIRP Conference on Life Cycle Engineering*, March 10 – 12, 2021, Jaipur, India 98, 294–299. URL: <https://www.sciencedirect.com/science/article/pii/S2212827121001360>, doi:10.1016/j.procir.2021.01.106.
- Gu, X., 2021. Application Research for Multiobjective Low-Carbon Flexible Job-Shop Scheduling Problem Based on Hybrid Artificial Bee Colony Algorithm. *IEEE Access* 9, 135899–135914. URL: <https://ieeexplore.ieee.org/document/9557290/>, doi:10.1109/ACCESS.2021.3117270.
- Guevara, G., Pereira, A., Ferreira, A., Barbosa, J., Leitão, P., 2015. Genetic algorithm for flexible job shop scheduling problem - A case study. *AIP Conference Proceedings* 1648. doi:10.1063/1.4912426.
- Hajibabaei, M., Behnamian, J., 2022. Reducing noise pollution by flexible job-shop scheduling with worker flexibility: Multi-subpopulation evolutionary algorithm. *Scientia Iranica* URL: http://scientiairanica.sharif.edu/article_22674.html, doi:10.24200/sci.2022.57813.5431.
- Ham, A., Park, M.J., Kim, K.M., 2021. Energy-Aware Flexible Job Shop Scheduling Using Mixed Integer Programming and Constraint Programming. *Mathematical Problems in Engineering* 2021, 8035806. URL: <https://doi.org/10.1155/2021/8035806>, doi:10.1155/2021/8035806. publisher: Hindawi.

- He, Y., Li, Y., Wu, T., Sutherland, J., 2015. An energy-responsive optimization method for machine tool selection and operation sequence in flexible machining job shops. *Journal of Cleaner Production* 87, 245–254. URL: <https://www.sciencedirect.com/science/article/pii/S0959652614010464>, doi:10.1016/j.jclepro.2014.10.006.
- Hemmati Far, M., Haleh, H., Saghaei, A., 2019. A fuzzy bi-objective flexible cell scheduling optimization model under green and energy-efficient strategy using Pareto-based algorithms: SATPSPGA, SANRGA, and NSGA-II. *The International Journal of Advanced Manufacturing Technology* 105, 3853–3879. URL: <https://doi.org/10.1007/s00170-019-03797-w>, doi:10.1007/s00170-019-03797-w.
- Hongyu, L., Xiuli, W., 2021. A survival duration-guided NSGA-III for sustainable flexible job shop scheduling problem considering dual resources. *IET Collaborative Intelligent Manufacturing* 3, 119–130. URL: <https://onlinelibrary.wiley.com/doi/10.1049/cim2.12003>, doi:10.1049/cim2.12003.
- Hu, S.J., 2013. Evolving paradigms of manufacturing: From mass production to mass customization and personalization. *Procedia Cirp* 7, 3–8.
- Huang, Y., Yan, X., Li, J., 2014. Dual Resource Constrained Job Shop Dynamic Scheduling with Local Time Window. *Advanced Materials Research* 933, 708–713. URL: <https://www.scientific.net/AMR.933.708>, doi:10.4028/www.scientific.net/AMR.933.708. publisher: Trans Tech Publications Ltd.
- Huo, D.X., Xiao, X.J., Pan, Y.J., 2020. Multi-Objective Energy-Saving Job-Shop Scheduling Based on Improved NSGA-II. *International Journal of Simulation Modelling* 19, 494–504. URL: http://www.ijssimm.com/Full_Papers/Fulltext2020/text19-3_C012.pdf, doi:10.2507/IJSIMM19-3-C012.
- Jiang, T., Deng, G., 2018. Optimizing the Low-Carbon Flexible Job Shop Scheduling Problem Considering Energy Consumption. *IEEE Access* 6, 46346–46355. doi:10.1109/ACCESS.2018.2866133.
- Jiang, T., Zhu, H., Deng, G., 2020. Improved African buffalo optimization algorithm for the green flexible job shop scheduling problem considering energy consumption. *Journal of Intelligent & Fuzzy Systems* 38, 4573–4589. URL: <https://www.medra.org/servlet/aliasResolver?alias=iospress&doi=10.3233/JIFS-191370>, doi:10.3233/JIFS-191370.
- Jiang, T., Zhu, H., Liu, L., Gong, Q., 2022. Energy-conscious flexible job shop scheduling problem considering transportation time and deterioration effect simultaneously. *Sustainable Computing: Informatics and Systems* 35, 100680. URL: <https://www.sciencedirect.com/science/article/pii/S2210537922000233>, doi:10.1016/j.suscom.2022.100680.
- Jiang, Z., Le, Z., E, M., 2014. Study on multi-objective flexible job-shop scheduling problem considering energy consumption. *Journal of Industrial Engineering and Management (JIEM)* 7, 589–604. URL: <http://hdl.handle.net/10419/188621>, doi:10.3926/jiem.1075. place: Barcelona Publisher: OmniaScience.
- Jiang, Z., Yuan, S., Ma, J., Wang, Q., 2021. The evolution of production scheduling from Industry 3.0 through Industry 4.0. *International Journal of Production Research* , 1–21 URL: <https://doi.org/10.1080/00207543.2021.1925772>, doi:10.1080/00207543.2021.1925772. publisher: Taylor & Francis.
- Karim Ahangar, N., Khalili, M., Tayebi, H., 2021. The Three-Objective Optimization Model of Flexible Workshop Scheduling Problem for Minimizing Work Completion Time, Work Delay Time, and Energy Consumption. *Tehnički glasnik* 15, 76–83. URL: <https://hrcak.srce.hr/253025>, doi:10.31803/tg-20200815184439.
- Kress, D., Müller, D., 2019. Mathematical Models for a Flexible Job Shop Scheduling Problem with Machine Operator Constraints. 9th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2019 52, 94–99. URL: <https://www.sciencedirect.com/science/article/pii/S2405896319310936>, doi:10.1016/j.ifacol.2019.11.144.
- Kress, D., Müller, D., Nossack, J., 2019. A worker constrained flexible job shop scheduling problem with sequence-dependent setup times. *OR Spectrum* 41, 179–217. URL: <https://doi.org/10.1007/s00291-018-0537-z>, doi:10.1007/s00291-018-0537-z.
- Kumar, P., Gupta, S., Gunda, Y., 2020. Estimation of human error rate in underground coal mines through retrospective analysis of mining accident reports and some error reduction strategies. *Safety Science* 123, 104555. URL: <https://www.sciencedirect.com/science/article/pii/S0925753519321666>, doi:10.1016/j.ssci.2019.104555.

- Lei, D., Guo, X., 2014. Variable neighbourhood search for dual-resource constrained flexible job shop scheduling. *International Journal of Production Research* 52, 2519–2529. URL: <https://doi.org/10.1080/00207543.2013.849822>, doi:10.1080/00207543.2013.849822. publisher: Taylor & Francis.
- Lei, D., Guo, X., 2015. An effective neighborhood search for scheduling in dual-resource constrained interval job shop with environmental objective. *International Journal of Production Economics* 159, 296–303. URL: <https://www.sciencedirect.com/science/article/pii/S0925527314002436>, doi:10.1016/j.ijpe.2014.07.026.
- Lei, D., Li, M., Wang, L., 2019. A Two-Phase Meta-Heuristic for Multiobjective Flexible Job Shop Scheduling Problem With Total Energy Consumption Threshold. *IEEE Transactions on Cybernetics* 49, 1097–1109. doi:10.1109/TCYB.2018.2796119.
- Lei, D., Tan, X., 2016. Local search with controlled deterioration for multi-objective scheduling in dual-resource constrained flexible job shop, in: 2016 Chinese Control and Decision Conference (CCDC), pp. 4921–4926. doi:10.1109/CCDC.2016.7531874. journal Abbreviation: 2016 Chinese Control and Decision Conference (CCDC).
- Lei, D., Zheng, Y., Guo, X., 2017. A shuffled frog-leaping algorithm for flexible job shop scheduling with the consideration of energy consumption. *International Journal of Production Research* 55, 3126–3140. URL: <https://doi.org/10.1080/00207543.2016.1262082>, doi:10.1080/00207543.2016.1262082. publisher: Taylor & Francis.
- Leusin, M., Frazzon, E., Uriona Maldonado, M., Kück, M., Freitag, M., 2018. Solving the Job-Shop Scheduling Problem in the Industry 4.0 Era. *Technologies* 6. URL: <https://www.mdpi.com/2227-7080/6/4/107>, doi:10.3390/technologies6040107.
- Li, H., Duan, J., Zhang, Q., 2021a. Multi-objective integrated scheduling optimization of semi-combined marine crankshaft structure production workshop for green manufacturing. *Transactions of the Institute of Measurement and Control* 43, 579–596. URL: <http://journals.sagepub.com/doi/10.1177/0142331220945917>, doi:10.1177/0142331220945917.
- Li, H., Zhu, H., Jiang, T., 2020a. Modified Migrating Birds Optimization for Energy-Aware Flexible Job Shop Scheduling Problem. *Algorithms* 13. doi:10.3390/a13020044.
- Li, J., Huang, Y., Niu, X., 2016a. A branch population genetic algorithm for dual-resource constrained job shop scheduling problem. *Computers & Industrial Engineering* 102, 113–131. URL: <https://www.sciencedirect.com/science/article/pii/S0360835216303813>, doi:10.1016/j.cie.2016.10.012.
- Li, J.q., Deng, J.w., Li, C.y., Han, Y.y., Tian, J., Zhang, B., Wang, C.g., 2020b. An improved Jaya algorithm for solving the flexible job shop scheduling problem with transportation and setup times. *Knowledge-Based Systems* 200, 106032. URL: <https://www.sciencedirect.com/science/article/pii/S0950705120303270>, doi:10.1016/j.knosys.2020.106032.
- Li, J.q., Liu, Z.m., Li, C., Zheng, Z.x., 2021b. Improved Artificial Immune System Algorithm for Type-2 Fuzzy Flexible Job Shop Scheduling Problem. *IEEE Transactions on Fuzzy Systems* 29, 3234–3248. doi:10.1109/TFUZZ.2020.3016225.
- Li, K., Zhang, X., Leung, J.T., Yang, S.L., 2016b. Parallel machine scheduling problems in green manufacturing industry. *Journal of Manufacturing Systems* 38, 98–106. URL: <https://www.sciencedirect.com/science/article/pii/S0278612515001296>, doi:10.1016/j.jmsy.2015.11.006.
- Li, M., Lei, D., 2021. An imperialist competitive algorithm with feedback for energy-efficient flexible job shop scheduling with transportation and sequence-dependent setup times. *Engineering Applications of Artificial Intelligence* 103, 104307. URL: <https://www.sciencedirect.com/science/article/pii/S095219762100155X>, doi:10.1016/j.engappai.2021.104307.
- Li, M., Lei, D., Xiong, H., 2019. An Imperialist Competitive Algorithm With the Diversified Operators for Many-Objective Scheduling in Flexible Job Shop. *IEEE Access* 7, 29553–29562. URL: <https://ieeexplore.ieee.org/document/8626145/>, doi:10.1109/ACCESS.2019.2895348.
- Li, M., Wang, G.G., 2022. A review of green shop scheduling problem. *Information Sciences* 589, 478–496. URL: <https://www.sciencedirect.com/science/article/pii/S0020025521013438>, doi:10.1016/j.ins.2021.12.122.

- Li, R., Gong, W., Lu, C., 2022a. Self-adaptive multi-objective evolutionary algorithm for flexible job shop scheduling with fuzzy processing time. *Computers & Industrial Engineering* 168, 108099. URL: <https://www.sciencedirect.com/science/article/pii/S0360835222001693>, doi:10.1016/j.cie.2022.108099.
- Li, R., Gong, W., Wang, L., Lu, C., Jiang, S., 2022b. Two-stage knowledge-driven evolutionary algorithm for distributed green flexible job shop scheduling with type-2 fuzzy processing time. *Swarm and Evolutionary Computation*, 101139 URL: <https://www.sciencedirect.com/science/article/pii/S2210650222001092>, doi:10.1016/j.swevo.2022.101139.
- Li, W., He, L., Cao, Y., 2021c. Many-Objective Evolutionary Algorithm With Reference Point-Based Fuzzy Correlation Entropy for Energy-Efficient Job Shop Scheduling With Limited Workers. *IEEE Transactions on Cybernetics*, 1–14 doi:10.1109/TCYB.2021.3069184.
- Li, Y., Gu, W., Yuan, M., Tang, Y., 2022c. Real-time data-driven dynamic scheduling for flexible job shop with insufficient transportation resources using hybrid deep Q network. *Robotics and Computer-Integrated Manufacturing* 74, 102283. URL: <https://www.sciencedirect.com/science/article/pii/S0736584521001630>, doi:10.1016/j.rcim.2021.102283.
- Li, Y., He, Y., Wang, Y., Tao, F., Sutherland, J.W., 2020c. An optimization method for energy-conscious production in flexible machining job shops with dynamic job arrivals and machine breakdowns. *Journal of Cleaner Production* 254, 120009. URL: <https://www.sciencedirect.com/science/article/pii/S0959652620300561>, doi:10.1016/j.jclepro.2020.120009.
- Li, Y., Huang, W., Wu, R., Guo, K., 2020d. An improved artificial bee colony algorithm for solving multi-objective low-carbon flexible job shop scheduling problem. *Applied Soft Computing* 95, 106544. URL: <https://www.sciencedirect.com/science/article/pii/S156849462030483X>, doi:10.1016/j.asoc.2020.106544.
- Li, Y., Yang, Z., Wang, L., Tang, H., Sun, L., Guo, S., 2022d. A hybrid imperialist competitive algorithm for energy-efficient flexible job shop scheduling problem with variable-size sublots. *Computers & Industrial Engineering* 172, 108641. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0360835222006295>, doi:10.1016/j.cie.2022.108641.
- Liang, X., Chen, J., Gu, X., Huang, M., 2021. Improved Adaptive Non-Dominated Sorting Genetic Algorithm With Elite Strategy for Solving Multi-Objective Flexible Job-Shop Scheduling Problem. *IEEE Access* 9, 106352–106362. URL: <https://ieeexplore.ieee.org/document/9492149/>, doi:10.1109/ACCESS.2021.3098823.
- Liu, C., Yao, Y., Zhu, H., 2022. Hybrid Salp Swarm Algorithm for Solving the Green Scheduling Problem in a Double-Flexible Job Shop. *Applied Sciences* 12. doi:10.3390/app12010205.
- Liu, Q., Gui, Z., Xiong, S., Zhan, M., 2021a. A principal component analysis dominance mechanism based many-objective scheduling optimization. *Applied Soft Computing* 113, 107931. URL: <https://linkinghub.elsevier.com/retrieve/pii/S156849462100853X>, doi:10.1016/j.asoc.2021.107931.
- Liu, Q., Zhan, M., Chekem, F.O., Shao, X., Ying, B., Sutherland, J.W., 2017. A hybrid fruit fly algorithm for solving flexible job-shop scheduling to reduce manufacturing carbon footprint. *Journal of Cleaner Production* 168, 668–678. URL: <https://www.sciencedirect.com/science/article/pii/S0959652617320255>, doi:10.1016/j.jclepro.2017.09.037.
- Liu, Y., Dong, H., Lohse, N., Petrovic, S., Gindy, N., 2014. An investigation into minimising total energy consumption and total weighted tardiness in job shops. *Journal of Cleaner Production* 65, 87–96. URL: <https://www.sciencedirect.com/science/article/pii/S0959652613005258>, doi:10.1016/j.jclepro.2013.07.060.
- Liu, Y., Ping, Y., Zhang, L., Wang, L., Xu, X., 2023. Scheduling of decentralized robot services in cloud manufacturing with deep reinforcement learning. *Robotics and Computer-Integrated Manufacturing* 80, 102454.
- Liu, Y., Wang, L., Wang, X.V., Xu, X., Zhang, L., 2019a. Scheduling in cloud manufacturing: state-of-the-art and research challenges. *International Journal of Production Research* 57, 4854–4879.

- Liu, Y., Zhang, L., Sun, T., 2021b. An Improved Nondominated Sorting Genetic Algorithm-II for Multi-objective Flexible Job-shop Scheduling Problem Considering Worker Assignments, in: 2021 International Conference on Communications, Information System and Computer Engineering (CISCE), pp. 837–843. doi:10.1109/CISCE52179.2021.9445969. journal Abbreviation: 2021 International Conference on Communications, Information System and Computer Engineering (CISCE).
- Liu, Z., Guo, S., Wang, L., 2019b. Integrated green scheduling optimization of flexible job shop and crane transportation considering comprehensive energy consumption. *Journal of Cleaner Production* 211, 765–786. URL: <https://www.sciencedirect.com/science/article/pii/S0959652618336345>, doi:10.1016/j.jclepro.2018.11.231.
- Lu, Y., Zheng, H., Chand, S., Xia, W., Liu, Z., Xu, X., Wang, L., Qin, Z., Bao, J., 2022. Outlook on human-centric manufacturing towards Industry 5.0. *Journal of Manufacturing Systems* 62, 612–627. URL: <https://www.sciencedirect.com/science/article/pii/S0278612522000164>, doi:<https://doi.org/10.1016/j.jmsy.2022.02.001>.
- Luo, Q., Deng, Q., Gong, G., Guo, X., Liu, X., 2022. A distributed flexible job shop scheduling problem considering worker arrangement using an improved memetic algorithm. *Expert Systems with Applications* 207, 117984. URL: <https://www.sciencedirect.com/science/article/pii/S095741742201212X>, doi:10.1016/j.eswa.2022.117984.
- Luo, Q., Deng, Q., Gong, G., Zhang, L., Han, W., Li, K., 2020. An efficient memetic algorithm for distributed flexible job shop scheduling problem with transfers. *Expert Systems with Applications* 160, 113721. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0957417420305455>, doi:10.1016/j.eswa.2020.113721.
- Luo, S., 2020. Dynamic scheduling for flexible job shop with new job insertions by deep reinforcement learning. *Applied Soft Computing* 91, 106208. URL: <https://www.sciencedirect.com/science/article/pii/S1568494620301484>, doi:10.1016/j.asoc.2020.106208.
- Luo, S., Zhang, L., Fan, Y., 2019. Energy-efficient scheduling for multi-objective flexible job shops with variable processing speeds by grey wolf optimization. *Journal of Cleaner Production* 234, 1365–1384. URL: <https://www.sciencedirect.com/science/article/pii/S0959652619321110>, doi:10.1016/j.jclepro.2019.06.151.
- Luo, S., Zhang, L., Fan, Y., 2021. Dynamic multi-objective scheduling for flexible job shop by deep reinforcement learning. *Computers & Industrial Engineering* 159, 107489. URL: <https://www.sciencedirect.com/science/article/pii/S0360835221003934>, doi:10.1016/j.cie.2021.107489.
- Maddikunta, P.K.R., Pham, Q.V., B, P., Deepa, N., Dev, K., Gadekallu, T.R., Ruby, R., Liyanage, M., 2022. Industry 5.0: A survey on enabling technologies and potential applications. *Journal of Industrial Information Integration* 26, 100257. URL: <https://www.sciencedirect.com/science/article/pii/S2452414X21000558>, doi:10.1016/j.jii.2021.100257.
- Madenoglu, F., Baykasoglu, A., 2019. Dual-Resource Constrained Flexible Job Shop Scheduling Problem with Weighted Superposition Attraction Algorithm, in: International Congress on Human-Computer Interaction, Optimization and Robotic Applications Proceedings, SETSCI. pp. 167–170. URL: http://www.set-science.com/?go=d1001a2417e2b87d5b7c53e16c5e1675&conf_id=73&paper_id=33, doi:10.36287/setsoci.4.5.033.
- Meng, L., Ren, Y., Zhang, B., Li, J.Q., Sang, H., Zhang, C., 2020. MILP Modeling and Optimization of Energy-Efficient Distributed Flexible Job Shop Scheduling Problem. *IEEE Access* 8, 191191–191203. URL: <https://ieeexplore.ieee.org/document/9233355/>, doi:10.1109/ACCESS.2020.3032548.
- Meng, L., Zhang, C., Shao, X., Ren, Y., 2019a. MILP models for energy-aware flexible job shop scheduling problem. *Journal of Cleaner Production* 210, 710–723. URL: <https://www.sciencedirect.com/science/article/pii/S0959652618334218>, doi:10.1016/j.jclepro.2018.11.021.
- Meng, L., Zhang, C., Zhang, B., Ren, Y., 2019b. Mathematical Modeling and Optimization of Energy-Conscious Flexible Job Shop Scheduling Problem With Worker Flexibility. *IEEE Access* 7, 68043–68059. doi:10.1109/ACCESS.2019.2916468.

- Mokhtari, H., Hasani, A., 2017. An energy-efficient multi-objective optimization for flexible job-shop scheduling problem. *Computers & Chemical Engineering* 104, 339–352. URL: <https://www.sciencedirect.com/science/article/pii/S009813541730203X>, doi:10.1016/j.compchemeng.2017.05.004.
- Müller, D., Kress, D., 2021. Filter-and-fan approaches for scheduling flexible job shops under workforce constraints. *International Journal of Production Research* , 1–23 URL: <http://dx.doi.org/10.1080/00207543.2021.1937745>, doi:10.1080/00207543.2021.1937745. publisher: Informa UK Limited.
- Nahavandi, S., 2019. Industry 5.0—A Human-Centric Solution. *Sustainability* 11. doi:10.3390/su11164371.
- Naimi, R., Nouri, M., Cardin, O., 2021. A Q-Learning Rescheduling Approach to the Flexible Job Shop Problem Combining Energy and Productivity Objectives. *Sustainability* 13. doi:10.3390/su132313016.
- Ning, T., Huang, Y., 2021. Low carbon emission management for flexible job shop scheduling: a study case in China. *Journal of Ambient Intelligence and Humanized Computing* URL: <https://link.springer.com/10.1007/s12652-021-03330-6>, doi:10.1007/s12652-021-03330-6.
- Ning, T., Wang, Z., Duan, X., Liu, X., 2021. Research on flexible job shop scheduling with low-carbon technology based on quantum bacterial foraging optimization. *International Journal of Low-Carbon Technologies* 16, 761–769. URL: <https://academic.oup.com/ijlct/article/16/3/761/6122866>, doi:10.1093/ijlct/ctab005.
- Nouri, M., Bekrar, A., Trentesaux, D., 2018. Towards Energy Efficient Scheduling and Rescheduling for Dynamic Flexible Job Shop Problem. 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018 51, 1275–1280. URL: <https://www.sciencedirect.com/science/article/pii/S2405896318314824>, doi:10.1016/j.ifacol.2018.08.357.
- Nouri, M., Bekrar, A., Trentesaux, D., 2020. An energy-efficient scheduling and rescheduling method for production and logistics systems †. *International Journal of Production Research* 58, 3263–3283. URL: <https://www.tandfonline.com/doi/full/10.1080/00207543.2019.1660826>, doi:10.1080/00207543.2019.1660826.
- Otto, A., Battaia, O., 2017. Reducing physical ergonomic risks at assembly lines by line balancing and job rotation: A survey. *Computers & Industrial Engineering* 111, 467–480. URL: <https://www.sciencedirect.com/science/article/pii/S0360835217301572>, doi:10.1016/j.cie.2017.04.011.
- Ouelhadj, D., Petrovic, S., 2008. A survey of dynamic scheduling in manufacturing systems. *Journal of Scheduling* 12, 417. URL: <https://doi.org/10.1007/s10951-008-0090-8>, doi:10.1007/s10951-008-0090-8.
- Paksi, A.B.N., Ma'rif, A., 2016. Flexible Job-Shop Scheduling with Dual-Resource Constraints to Minimize Tardiness Using Genetic Algorithm. *IOP Conference Series: Materials Science and Engineering* 114, 012060. URL: <http://dx.doi.org/10.1088/1757-899X/114/1/012060>, doi:10.1088/1757-899X/114/1/012060. publisher: IOP Publishing.
- Parente, M., Figueira, G., Amorim, P., Marques, A., 2020. Production scheduling in the context of Industry 4.0: review and trends. *International Journal of Production Research* 58, 5401–5431. URL: <https://doi.org/10.1080/00207543.2020.1718794>, doi:10.1080/00207543.2020.1718794. publisher: Taylor & Francis.
- Park, M., Ham, A., 2022. Energy-aware flexible job shop scheduling under time-of-use pricing. *International Journal of Production Economics* 248, 108507. URL: <https://www.sciencedirect.com/science/article/pii/S0925527322001001>, doi:10.1016/j.ijpe.2022.108507.
- Peng, C., Fang, Y., Lou, P., Yan, J., 2018. Analysis of double-resource flexible job shop scheduling problem based on genetic algorithm, in: 2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC), pp. 1–6. doi:10.1109/ICNSC.2018.8361360. journal Abbreviation: 2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC).
- Peng, Z., Zhang, H., Tang, H., Feng, Y., Yin, W., 2021. Research on flexible job-shop scheduling problem in green sustainable manufacturing based on learning effect. *Journal of Intelligent Manufacturing* URL: <https://doi.org/10.1007/s10845-020-01713-8>, doi:10.1007/s10845-020-01713-8.

- Piroozfard, H., Wong, K., Wong, W., 2018. Minimizing total carbon footprint and total late work criterion in flexible job shop scheduling by using an improved multi-objective genetic algorithm. *Resources, Conservation and Recycling* 128, 267–283. URL: <https://www.sciencedirect.com/science/article/pii/S0921344916303688>, doi:10.1016/j.resconrec.2016.12.001.
- Plitsos, S., Repoussis, P., Mourtos, I., Tarantilis, C., 2017. Energy-aware decision support for production scheduling. *Decision Support Systems* 93, 88–97. URL: <https://linkinghub.elsevier.com/retrieve/pii/S016792361630166X>, doi:10.1016/j.dss.2016.09.017.
- Rakovitis, N., Li, D., Zhang, N., Li, J., Zhang, L., Xiao, X., 2022. Novel approach to energy-efficient flexible job-shop scheduling problems. *Energy* 238, 121773. URL: <https://www.sciencedirect.com/science/article/pii/S0360544221020211>, doi:10.1016/j.energy.2021.121773.
- Rashidifar, R., Bouzary, H., Chen, F., 2022. Resource scheduling in cloud-based manufacturing system: a comprehensive survey. *The International Journal of Advanced Manufacturing Technology* 122, 4201–4219.
- Ren, H., Xu, H., Sun, S., 2016. Immune genetic algorithm for multi-objective flexible job-shop scheduling problem, in: 2016 Chinese Control and Decision Conference (CCDC), pp. 2167–2171. doi:10.1109/CCDC.2016.7531344. journal Abbreviation: 2016 Chinese Control and Decision Conference (CCDC).
- Ren, W., Wen, J., Yan, Y., Hu, Y., Guan, Y., Li, J., 2021. Multi-objective optimisation for energy-aware flexible job-shop scheduling problem with assembly operations. *International Journal of Production Research* 59, 7216–7231. URL: <https://www.tandfonline.com/doi/full/10.1080/00207543.2020.1836421>, doi:10.1080/00207543.2020.1836421.
- Rinaldi, M., Fera, M., Bottani, E., Grosse, E.H., 2022. Workforce scheduling incorporating worker skills and ergonomic constraints. *Computers & Industrial Engineering* 168, 108107. URL: <https://www.sciencedirect.com/science/article/pii/S0360835222001772>, doi:<https://doi.org/10.1016/j.cie.2022.108107>.
- Romero, D., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fasth, F.B., Gorecky, D., 2016. Towards an Operator 4.0 Typology: A Human-Centric Perspective on the Fourth Industrial Revolution Technologies.
- Rosenbrock, H.H., 1990. *Machines with a Purpose*. Oxford University Press.
- Rossit, D., Tohmé, F., Frutos, M., 2019. Industry 4.0: Smart Scheduling. *International Journal of Production Research* 57, 3802–3813. URL: <https://doi.org/10.1080/00207543.2018.1504248>, doi:10.1080/00207543.2018.1504248. publisher: Taylor & Francis.
- Sang, Y., Tan, J., 2022a. Intelligent factory many-objective distributed flexible job shop collaborative scheduling method. *Computers & Industrial Engineering* 164, 107884. URL: <https://www.sciencedirect.com/science/article/pii/S0360835221007889>, doi:10.1016/j.cie.2021.107884.
- Sang, Y., Tan, J., 2022b. Many-Objective Flexible Job Shop Scheduling Problem with Green Consideration. *Energies* 15. doi:10.3390/en15051884.
- Sano, M., Nagao, M., Morinaga, Y., 2016. Balancing setup workers load of flexible job shop scheduling using hybrid genetic algorithm with tabu search strategy. *International Journal of Decision Support Systems* 1, 1. URL: <http://dx.doi.org/10.1504/IJDSS.2016.10000521>, doi:10.1504/ijdss.2016.10000521. publisher: Inderscience Publishers.
- Savino, M., Battini, D., Riccio, C., 2017. Visual management and artificial intelligence integrated in a new fuzzy-based full body postural assessment. *Computers & Industrial Engineering* 111, 596–608. URL: <https://www.sciencedirect.com/science/article/pii/S0360835217302632>, doi:10.1016/j.cie.2017.06.011.
- Savino, M., Mazza, A., Battini, D., 2016. New easy to use postural assessment method through visual management. *International Journal of Industrial Ergonomics* 53, 48–58. URL: <https://www.sciencedirect.com/science/article/pii/S0169814115300329>, doi:10.1016/j.ergon.2015.09.014.
- Seng, D.W., Li, J.W., Fang, X.J., Zhang, X.F., Chen, J., 2018. Low-Carbon Flexible Job-Shop Scheduling Based on Improved Nondominated Sorting Genetic Algorithm-II. *International Journal of Simulation Modelling* 17, 712–723. URL: http://www.ijstimm.com/Full_Papers/Fulltext2018/text17-4_712-723.pdf, doi:10.2507/IJSIMM17(4)C018.

- Shi, D.L., Zhang, B.B., Li, Y., 2020. A Multi-Objective Flexible Job-Shop Scheduling Model Based on Fuzzy Theory and Immune Genetic Algorithm. *International Journal of Simulation Modelling* 19, 123–133. URL: http://www.ijssimm.com/Full_Papers/Fulltext2020/text19-1_C01.pdf, doi:10.2507/IJSIMM19-1-C01.
- Sikhwal, R., Childs, P., 2021. Towards Mass Individualisation: setting the scope and industrial implication. *Design Science* 7, e16. URL: <https://www.cambridge.org/core/article/towards-mass-individualisation-setting-the-scope-and-industrial-implication/A0405DD7174D657EE5CD597B6D7D0646>, doi:10.1017/dsj.2021.18. edition: 2021/10/05 Publisher: Cambridge University Press.
- Sindhvani, R., Afridi, S., Kumar, A., Banaitis, A., Luthra, S., Singh, P., 2022. Can industry 5.0 revolutionize the wave of resilience and social value creation? A multi-criteria framework to analyze enablers. *Technology in Society* 68, 101887. URL: <https://www.sciencedirect.com/science/article/pii/S0160791X22000288>, doi:10.1016/j.techsoc.2022.101887.
- Song, W., Zhang, C., Lin, W., Shao, X., 2014. Flexible Job-Shop Scheduling Problem with Maintenance Activities Considering Energy Consumption. *Applied Mechanics and Materials* 521, 707–713. URL: <https://www.scientific.net/AMM.521.707>, doi:10.4028/www.scientific.net/AMM.521.707.
- Sun, X., Guo, S., Guo, J., Du, B., 2019. A Hybrid Multi-Objective Evolutionary Algorithm With Heuristic Adjustment Strategies and Variable Neighbor-Hood Search for Flexible Job-Shop Scheduling Problem Considering Flexible Rest Time. *IEEE Access* 7, 157003–157018. doi:10.1109/ACCESS.2019.2948057.
- Sun, X., Wang, Y., Kang, H., Shen, Y., Chen, Q., Wang, D., 2020. Modified Multi-Crossover Operator NSGA-III for Solving Low Carbon Flexible Job Shop Scheduling Problem. *Processes* 9, 62. URL: <https://www.mdpi.com/2227-9717/9/1/62>, doi:10.3390/pr9010062.
- Tan, W., Yuan, X., Wang, J., Zhang, X., 2021. A fatigue-conscious dual resource constrained flexible job shop scheduling problem by enhanced NSGA-II: An application from casting workshop. *Computers & Industrial Engineering* 160, 107557. URL: <https://www.sciencedirect.com/science/article/pii/S0360835221004617>, doi:10.1016/j.cie.2021.107557.
- Tseng, M., Jiao, J., Merchant, M.E., 1996. Design for Mass Customization. *CIRP Annals* 45, 153–156. URL: <https://www.sciencedirect.com/science/article/pii/S0007850607630364>, doi:10.1016/S0007-8506(07)63036-4.
- Tseng, M., Jiao, R., Wang, C., 2010. Design for mass personalization. *CIRP Annals* 59, 175–178. URL: <https://www.sciencedirect.com/science/article/pii/S0007850610000983>, doi:10.1016/j.cirp.2010.03.097.
- Vital-Soto, A., Baki, M.F., Azab, A., 2022. A multi-objective mathematical model and evolutionary algorithm for the dual-resource flexible job-shop scheduling problem with sequencing flexibility. *Flexible Services and Manufacturing Journal* URL: <https://link.springer.com/10.1007/s10696-022-09446-x>, doi:10.1007/s10696-022-09446-x.
- Wang, B., Zheng, P., Yin, Y., Shih, A., Wang, L., 2022a. Toward human-centric smart manufacturing: A human-cyber-physical systems (HCPS) perspective. *Journal of Manufacturing Systems* 63, 471–490. URL: <https://www.sciencedirect.com/science/article/pii/S0278612522000759>, doi:10.1016/j.jmsy.2022.05.005.
- Wang, H., Jiang, Z., Wang, Y., Zhang, H., Wang, Y., 2018. A two-stage optimization method for energy-saving flexible job-shop scheduling based on energy dynamic characterization. *Journal of Cleaner Production* 188, 575–588. URL: <https://www.sciencedirect.com/science/article/pii/S0959652618309351>, doi:10.1016/j.jclepro.2018.03.254.
- Wang, J., Liu, Y., Ren, S., Wang, C., Wang, W., 2021a. Evolutionary game based real-time scheduling for energy-efficient distributed and flexible job shop. *Journal of Cleaner Production* 293, 126093. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0959652621003139>, doi:10.1016/j.jclepro.2021.126093.
- Wang, J., Yang, J., Zhang, Y., Ren, S., Liu, Y., 2020. Infinitely repeated game based real-time scheduling for low-carbon flexible job shop considering multi-time periods. *Journal of Cleaner Production* 247, 119093. URL: <https://www.sciencedirect.com/science/article/pii/S0959652619339630>, doi:10.1016/j.jclepro.2019.119093.

- Wang, J., Zheng, P., Qin, W., Li, T., Zhang, J., 2019. A novel resilient scheduling paradigm integrating operation and design for manufacturing systems with uncertainties. *Enterprise Information Systems* 13, 430–447. doi:10.1080/17517575.2018.1526322.
- Wang, J., Zhu, K., Peng, Y., Zhu, K., 2022b. Energy-efficient scheduling for flexible job shop under multi-resource constraints using non-dominated sorting teaching-learning-based optimization algorithm. *Journal of Intelligent & Fuzzy Systems* 43, 409–423. URL: <https://www.medra.org/servlet/aliasResolver?alias=iospress&doi=10.3233/JIFS-212258>, doi:10.3233/JIFS-212258.
- Wang, L., Hu, X., Wang, Y., Xu, S., Ma, S., Yang, K., Liu, Z., Wang, W., 2021b. Dynamic job-shop scheduling in smart manufacturing using deep reinforcement learning. *Computer Networks* 190, 107969. URL: <https://www.sciencedirect.com/science/article/pii/S1389128621001031>, doi:10.1016/j.comnet.2021.107969.
- Wang, X., Zhang, L., Liu, Y., Li, F., Chen, Z., Zhao, C., Bai, T., 2022c. Dynamic scheduling of tasks in cloud manufacturing with multi-agent reinforcement learning. *Journal of Manufacturing Systems* 65, 130–145.
- Wang, Y., Peng, W., Lu, C., Xia, H., 2022d. A Multi-Objective Cellular Memetic Optimization Algorithm for Green Scheduling in Flexible Job Shops. *Symmetry* 14. doi:10.3390/sym14040832.
- Wei, Z., Liao, W., Zhang, L., 2022. Hybrid energy-efficient scheduling measures for flexible job-shop problem with variable machining speeds. *Expert Systems with Applications* 197, 116785. URL: <https://www.sciencedirect.com/science/article/pii/S0957417422002445>, doi:10.1016/j.eswa.2022.116785.
- Wen, X., Wang, K., Li, H., Sun, H., Wang, H., Jin, L., 2021. A two-stage solution method based on NSGA-II for Green Multi-Objective integrated process planning and scheduling in a battery packaging machinery workshop. *Swarm and Evolutionary Computation* 61, 100820. URL: <https://linkinghub.elsevier.com/retrieve/pii/S2210650220304739>, doi:10.1016/j.swevo.2020.100820.
- Weng, W., Chen, J., Zheng, M., Fujimura, S., 2022. Realtime scheduling heuristics for just-in-time production in large-scale flexible job shops. *Journal of Manufacturing Systems* 63, 64–77. URL: <https://www.sciencedirect.com/science/article/pii/S0278612522000061>, doi:10.1016/j.jmsy.2022.01.006.
- Wu, D., Greer, M.J., Rosen, D.W., Schaefer, D., 2013. Cloud manufacturing: Strategic vision and state-of-the-art. *Journal of Manufacturing Systems* 32, 564–579.
- Wu, M., Yang, D., Zhou, B., Yang, Z., Liu, T., Li, L., Wang, Z., Hu, K., 2021. Adaptive Population NSGA-III with Dual Control Strategy for Flexible Job Shop Scheduling Problem with the Consideration of Energy Consumption and Weight. *Machines* 9, 344. URL: <https://www.mdpi.com/2075-1702/9/12/344>, doi:10.3390/machines9120344.
- Wu, R., Li, Y., Guo, S., Xu, W., 2018. Solving the dual-resource constrained flexible job shop scheduling problem with learning effect by a hybrid genetic algorithm. *Advances in Mechanical Engineering* 10, 168781401880409. URL: <http://journals.sagepub.com/doi/10.1177/1687814018804096>, doi:10.1177/1687814018804096.
- Wu, X., Li, J., Shen, X., Zhao, N., 2020. NSGA-III for solving dynamic flexible job shop scheduling problem considering deterioration effect. *IET Collaborative Intelligent Manufacturing* 2, 22–33. URL: <https://onlinelibrary.wiley.com/doi/10.1049/iet-cim.2019.0056>, doi:10.1049/iet-cim.2019.0056.
- Wu, X., Shen, X., Li, C., 2019. The flexible job-shop scheduling problem considering deterioration effect and energy consumption simultaneously. *Computers & Industrial Engineering* 135, 1004–1024. URL: <https://www.sciencedirect.com/science/article/pii/S0360835219303791>, doi:10.1016/j.cie.2019.06.048.
- Wu, X., Sun, Y., 2018. A green scheduling algorithm for flexible job shop with energy-saving measures. *Journal of Cleaner Production* 172, 3249–3264. URL: <https://www.sciencedirect.com/science/article/pii/S0959652617326483>, doi:10.1016/j.jclepro.2017.10.342.
- Wuest, T., Weimer, D., Irgens, C., Thoben, K.D., 2016. Machine learning in manufacturing: Advantages, challenges, and applications. *Production & Manufacturing Research* 4, 23–45. doi:10.1080/21693277.2016.1192517.

- Xiao, S., Wu, Z., Yu, S., 2019. A two-stage assignment strategy for the robust scheduling of dual-resource constrained stochastic job shop scheduling problems. 9th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2019 52, 421–426. URL: <https://www.sciencedirect.com/science/article/pii/S2405896319310328>, doi:10.1016/j.ifacol.2019.11.092.
- Xie, J., Gao, L., Peng, K., Li, X., Li, H., 2019. Review on flexible job shop scheduling. IET Collaborative Intelligent Manufacturing 1, 67–77.
- Xiong, H., Shi, S., Ren, D., Hu, J., 2022. A survey of job shop scheduling problem: The types and models. Computers & Operations Research 142, 105731. URL: <https://www.sciencedirect.com/science/article/pii/S0305054822000338>, doi:10.1016/j.cor.2022.105731.
- Xixing, L., Yi, L., 2018. Approach of Solving Dual Resource Constrained Multi-Objective Flexible Job Shop Scheduling Problem Based on MOEA/D. International Journal of Online Engineering (iJOE) 14, 75. URL: <http://online-journals.org/index.php/i-joe/article/view/8966>, doi:10.3991/ijoe.v14i07.8966.
- Xu, B., Mei, Y., Wang, Y., Ji, Z., Zhang, M., 2021a. Genetic Programming with Delayed Routing for Multiobjective Dynamic Flexible Job Shop Scheduling. Evolutionary Computation 29, 75–105. URL: <https://direct.mit.edu/evco/article/29/1/75-105/97343>, doi:10.1162/evco_a_00273.
- Xu, W., Hu, Y., Luo, W., Wang, L., Wu, R., 2021b. A multi-objective scheduling method for distributed and flexible job shop based on hybrid genetic algorithm and tabu search considering operation outsourcing and carbon emission. Computers & Industrial Engineering 157, 107318. URL: <https://www.sciencedirect.com/science/article/pii/S0360835221002229>, doi:10.1016/j.cie.2021.107318.
- Xu, W., Shao, L., Yao, B., Zhou, Z., Pham, D., 2016. Perception data-driven optimization of manufacturing equipment service scheduling in sustainable manufacturing. Journal of Manufacturing Systems 41, 86–101. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0278612516300486>, doi:10.1016/j.jmsy.2016.08.001.
- Xu, X., Lu, Y., Vogel-Heuser, B., Wang, L., 2021c. Industry 4.0 and Industry 5.0—Inception, conception and perception. Journal of Manufacturing Systems 61, 530–535. URL: <https://www.sciencedirect.com/science/article/pii/S0278612521002119>, doi:10.1016/j.jmsy.2021.10.006.
- Yang, X., Zeng, Z., Wang, R., Sun, X., 2016. Bi-Objective Flexible Job-Shop Scheduling Problem Considering Energy Consumption under Stochastic Processing Times. PLOS ONE 11, e0167427. URL: <https://dx.plos.org/10.1371/journal.pone.0167427>, doi:10.1371/journal.pone.0167427.
- Yazdani, M., Zandieh, M., Tavakkoli-Moghaddam, R., 2019. Evolutionary algorithms for multi-objective dual-resource constrained flexible job-shop scheduling problem. OPSEARCH 56, 983–1006. URL: <https://doi.org/10.1007/s12597-019-00395-y>, doi:10.1007/s12597-019-00395-y.
- Yazdani, M., Zandieh, M., Tavakkoli-Moghaddam, R., Jolai, F., 2015. Two meta-heuristic algorithms for the dual-resource constrained flexible job-shop scheduling problem. Scientia Iranica 22, 1242–1257. URL: http://scientiairanica.sharif.edu/article_3715.html.
- Yin, L., Li, X., Gao, L., Lu, C., Zhang, Z., 2017a. Energy-efficient job shop scheduling problem with variable spindle speed using a novel multi-objective algorithm. Advances in Mechanical Engineering 9, 168781401769595. URL: <http://journals.sagepub.com/doi/10.1177/1687814017695959>, doi:10.1177/1687814017695959.
- Yin, L., Li, X., Gao, L., Lu, C., Zhang, Z., 2017b. A novel mathematical model and multi-objective method for the low-carbon flexible job shop scheduling problem. Sustainable Computing: Informatics and Systems 13, 15–30. URL: <https://www.sciencedirect.com/science/article/pii/S221053791630049X>, doi:10.1016/j.suscom.2016.11.002.
- Zhang, C., Gu, P., Jiang, P., 2015. Low-carbon scheduling and estimating for a flexible job shop based on carbon footprint and carbon efficiency of multi-job processing. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 229, 328–342. URL: <http://journals.sagepub.com/doi/10.1177/0954405414527959>, doi:10.1177/0954405414527959.

- Zhang, H., Dai, Z., Zhang, W., Zhang, S., Wang, Y., Liu, R., 2017a. A New Energy-Aware Flexible Job Shop Scheduling Method Using Modified Biogeography-Based Optimization. *Mathematical Problems in Engineering* 2017, 7249876. URL: <https://doi.org/10.1155/2017/7249876>, doi:10.1155/2017/7249876. publisher: Hindawi.
- Zhang, H., Xu, G., Pan, R., Ge, H., 2021a. A novel heuristic method for the energy-efficient flexible job-shop scheduling problem with sequence-dependent set-up and transportation time. *Engineering Optimization* , 1–22URL: <https://doi.org/10.1080/0305215X.2021.1949007>, doi:10.1080/0305215X.2021.1949007. publisher: Taylor & Francis.
- Zhang, J., Ding, G., Zou, Y., Qin, S., Fu, J., 2019a. Review of job shop scheduling research and its new perspectives under Industry 4.0. *Journal of Intelligent Manufacturing* 30, 1809–1830. URL: <https://doi.org/10.1007/s10845-017-1350-2>, doi:10.1007/s10845-017-1350-2.
- Zhang, J., Wang, W., Xu, X., 2017b. A hybrid discrete particle swarm optimization for dual-resource constrained job shop scheduling with resource flexibility. *Journal of Intelligent Manufacturing* 28, 1961–1972. URL: <https://doi.org/10.1007/s10845-015-1082-0>, doi:10.1007/s10845-015-1082-0.
- Zhang, J., Wang, W., Xu, X., Jie, J., 2013. A multi-objective particle swarm optimization for dual-resource constrained shop scheduling with resource flexibility, in: *2013 IEEE Symposium on Computational Intelligence for Engineering Solutions (CIES)*, IEEE, singapore, Singapore. pp. 29–34. URL: <http://ieeexplore.ieee.org/document/6611725/>, doi:10.1109/CIES.2013.6611725.
- Zhang, L., Luo, Y., Tao, F., Li, B.H., Ren, L., Zhang, X., Guo, H., Cheng, Y., Hu, A., Liu, Y., 2014. Cloud manufacturing: a new manufacturing paradigm. *Enterprise Information Systems* 8, 167–187.
- Zhang, L., Tang, Q., Wu, Z., Wang, F., 2017c. Mathematical modeling and evolutionary generation of rule sets for energy-efficient flexible job shops. *Energy* 138, 210–227. URL: <https://www.sciencedirect.com/science/article/pii/S0360544217311799>, doi:10.1016/j.energy.2017.07.005.
- Zhang, L., Yang, C., Yan, Y., Yaoguang, H., 2022. Distributed real-time scheduling in cloud manufacturing by deep reinforcement learning. *IEEE Transactions on Industrial Informatics* 18, 8999 – 9007.
- Zhang, S., Du, H., Borucki, S., Jin, S., Hou, T., Li, Z., 2021b. Dual Resource Constrained Flexible Job Shop Scheduling Based on Improved Quantum Genetic Algorithm. *Machines* 9. URL: <https://www.mdpi.com/2075-1702/9/6/108>, doi:10.3390/machines9060108.
- Zhang, X., Ji, Z., Wang, Y., 2018. An improved SFLA for flexible job shop scheduling problem considering energy consumption. *Modern Physics Letters B* 32, 1840112. URL: <https://www.worldscientific.com/doi/abs/10.1142/S0217984918401127>, doi:10.1142/S0217984918401127.
- Zhang, Y., Wang, J., Liu, Y., 2017d. Game theory based real-time multi-objective flexible job shop scheduling considering environmental impact. *Journal of Cleaner Production* 167, 665–679. URL: <https://www.sciencedirect.com/science/article/pii/S0959652617317845>, doi:10.1016/j.jclepro.2017.08.068.
- Zhang, Z., Wu, L., Peng, T., Jia, S., 2019b. An Improved Scheduling Approach for Minimizing Total Energy Consumption and Makespan in a Flexible Job Shop Environment. *Sustainability* 11. doi:10.3390/su11010179.
- Zheng, X.L., Wang, L., 2016. A knowledge-guided fruit fly optimization algorithm for dual resource constrained flexible job-shop scheduling problem. *International Journal of Production Research* 54, 5554–5566. URL: <https://doi.org/10.1080/00207543.2016.1170226>, doi:10.1080/00207543.2016.1170226. publisher: Taylor & Francis.
- Zhongjie, W., Mingming, Z., Miao, H., 2013. Study of the immune simulated annealing algorithm and dual-resource job shop order scheduling, in: *2013 25th Chinese Control and Decision Conference (CCDC)*, IEEE, Guiyang, China. pp. 2375–2379. URL: <http://ieeexplore.ieee.org/document/6561335/>, doi:10.1109/CCDC.2013.6561335.
- Zhou, G., Chen, Z., Zhang, C., Chang, F., 2022. An adaptive ensemble deep forest based dynamic scheduling strategy for low carbon flexible job shop under recessive disturbance. *Journal of Cleaner Production* 337, 130541. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0959652622001834>, doi:10.1016/j.jclepro.2022.130541.

- Zhou, L., Zhang, L., Ren, L., Wang, J., 2019. Real-time scheduling of cloud manufacturing services based on dynamic data-driven simulation. *IEEE Transactions on Industrial Informatics* 15, 5042–5051.
- Zhu, H., Deng, Q., Zhang, L., Hu, X., Lin, W., 2020. Low carbon flexible job shop scheduling problem considering worker learning using a memetic algorithm. *Optimization and Engineering* 21, 1691–1716. URL: <https://doi.org/10.1007/s11081-020-09494-y>, doi:10.1007/s11081-020-09494-y.