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Review article

Simulation optimization applied to production scheduling in the era of industry 4.0: A review and future roadmap

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ABSTRACT

Production Scheduling (PS) is an essential paradigm within supply and manufacturing systems and an important element of sustainable development. PS, mainly known for its horizontal effects within the operational decision level, directly impacts both tactical and strategical levels of decision-making. In other words, an optimally designed and utilized PS module could bring efficiency towards the whole supply chain network of many manufacturing systems. Simulation Optimization (SO), as a growing Decision Support Tool (DST), provides a methodology required to drastically improve the efficiency of industrial systems. Thus, in this article, we review the existing research on SO Applied to PS (SOAPS), within the context of wider adaption of Industry 4.0 (known as the fourth industrial revolution). Firstly, relevant articles are examined and reviewed to position the research and develop research questions that enable the highlighting of research gaps. Then, a methodology was created based on: the studied PS problem features, proposed optimization frameworks, executed simulation tools, the SO architectures and the experimentation and validation strategies used. Finally, we investigate how Industry 4.0 could enhance the existing research on SOAPS to provide real-time and efficient SO-based DSTs for PS modules within modern manufacturing systems.

1. Introduction

A system is an "interconnected" group of elements (subsystems) "coherently organized" for a goal [1]. According to Anderson and Johnson [2], a system is a group of interacting/interrelated/interconnected/interdependent elements (subsystems) that constitute a complex and integrated whole. From the system architecture point of view, a manufacturing company consists of a set of multi-level hierarchical subsystems. At the top level, there is a supply chain system that includes networks of suppliers, manufacturing plants (the manufacturing system), retailers, and supply chain service providers [3]. The elements (subsystems) of the supply chain system are connected to a horizontal flow of material and information (see Fig. 1). Each element represents a system itself, that is, a subsystem of the central supply chain system. For example, each manufacturing plant consists of a set of workstations connected through the flow of material and information. The material flow between these workstations can follow any of the manufacturing type architectures such as a line, job-shop, or continuous flow manufacturing [4,5].

Consequently, we refer to a manufacturing system as "a subsystem for the main supply chain system of a manufacturing company that is primarily responsible for creating value through manufacturing operations". Taking into account this definition, the performance of a manufacturing system can be measured by evaluating its ability to produce products competitively and sustainably [6]. A manufacturing system consists of a network of manufacturing plants (or just one manufacturing plant), workstations inside each plant, and production steps within each workstation. Such hierarchical categorization is crucial, especially when it comes to the decision making process. Since, within the level of the supply chain system (interactions between

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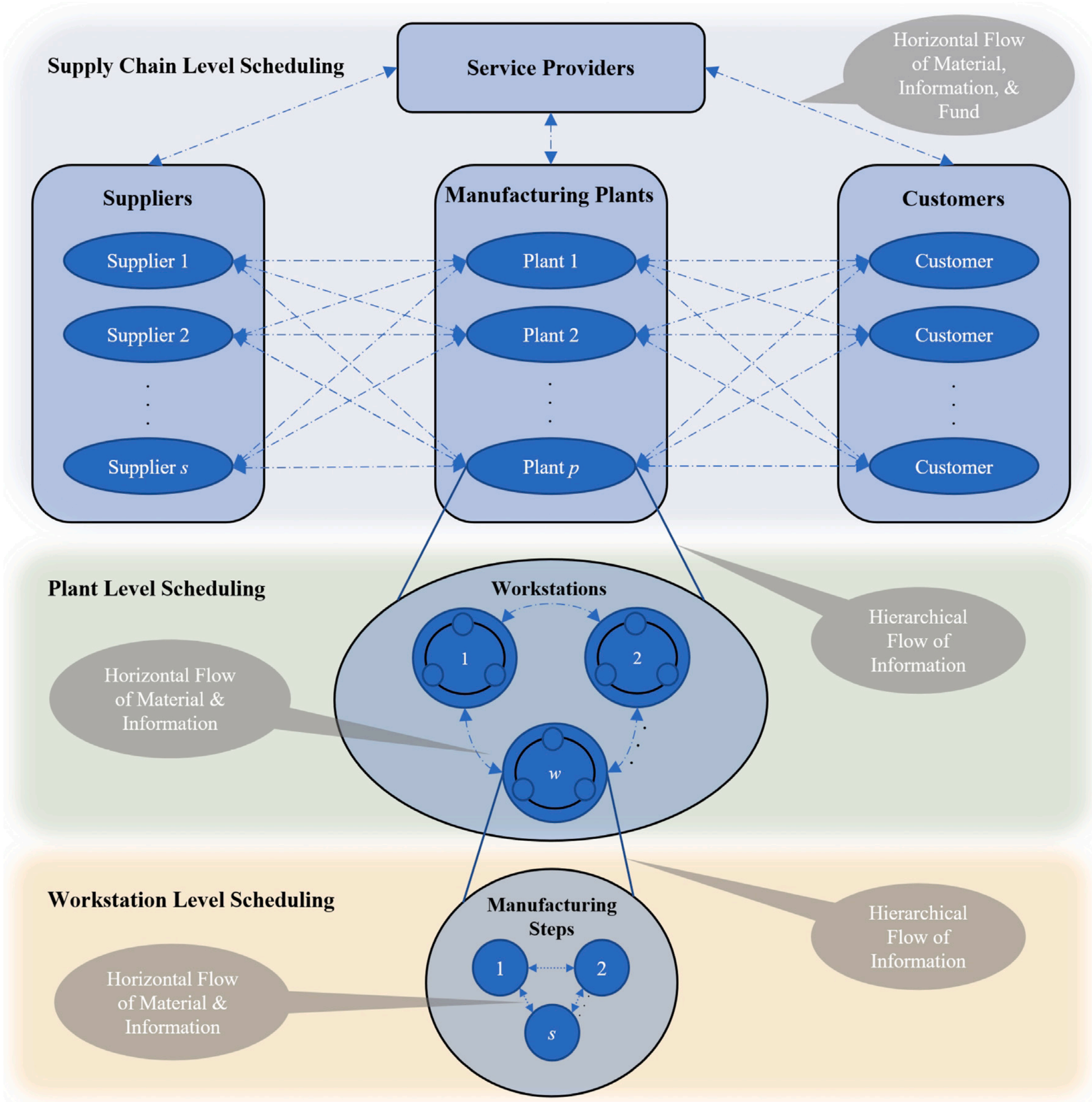


Fig. 1. Scheduling at different levels of manufacturing systems.

manufacturing plants and other suppliers), decisions are mainly concerned with macro-level business alternatives (long-term in terms of the planning horizon), known as strategic decisions [7]. However, decisions at the manufacturing plant level are mainly concerned with tactical production planning (mid-term in terms of planning horizon) [4]. On the contrary, at an operational decision-making level (short-term in terms of planning horizon), the production plan is translated into workstation plans (e.g., orders scheduling on machines). Thus, the process of decision making within each mentioned hierarchical level is clearly different (although they are hierarchically connected to each other).

According to the Cambridge Dictionary, the word "scheduling" refers to: the job or activity of planning the times at which particular tasks will be done or events will occur [8]. Within modern manufacturing systems, optimal scheduling plays a key role in enhancing the competitiveness of value creation processes [9]. Note that within manufacturing systems, the term scheduling is generally referred to as Production Scheduling (PS) [10]. Scheduling is required in the following hierarchical decision making levels:

- Supply Chain Level[1]: What processes are scheduled for each production plant based on the states of manufacturing plants, suppliers, service providers, and retailers that aim to perform optimal Key Performance Indicators (KPIs) (KPIs at the supply chain level refer mainly to how agile, resilient, sustainable, and synchronized the supply chain network is)?
- Plant Level[2]: What processes are scheduled to each workstation considering the workstations' technologies, resource capacities, and maintenance requirements aiming to obtain optimized plant-level KPIs (KPIs in the plant level mainly refer to how well a

[1] The multi-plant manufacturing system is commonly used to represent modern manufacturing industries aiming to benefit from geographical, social, political, economical, and logistical differences [11,12].

[2] The idea of multi-workstation (multi-shop) manufacturing is prevalent in many industries, such as semiconductor manufacturing, and well-supported within the literature of Job Shop (JS) and Flow Shop (FS) manufacturing. It aims mainly to provide flexibility within production plants to produce different categories of products [13,14].

plant performs within a network of plants to support the main manufacturing system goals)?
- Workstation Level: What processes are scheduled for each resource (e.g., manufacturing machines) within a workstation considering specific resource and process constraints (e.g., sequence-dependent setups) to obtain optimized workstation level KPIs (depending on Make-To-Order (MTO) or Make-To-Stock (MTS) strategies within the plant, different KPIs are defined for a workstation)?

With increased disruptions, such as the Covid-19 crisis and geopolitical conflicts all over the world, almost all manufacturing companies (from different industries) have been driven to be more resilient to deal with similar disruptions in the future. Furthermore, almost all industries are threatened by the effects of climate change (Global Warming), either directly or indirectly, forcing them to perform as lean and sustainable as possible. On the other hand, the traditional or physical manufacturing and supply chain planning focuses on product, financial, and information flow, which the modern/digitalized supply chain still focuses on, it also revolves around cyber/virtual networks, IT infrastructures, and data sharing procedures, introducing new risks independent of physical products or locations [15]. This is mainly known as the "Cyber Risk". In other words, by enhancing the level of digitalization, manufacturing companies face a new kind of vulnerability, called cybersecurity challenges [16]. Taking into account these facts, scheduling as an important factor is even more essential than before, as an efficient scheduling paradigm is an enabler of a resilient, lean and sustainable supply and manufacturing system [17,18]. A challenge is that scheduling-based decision-making is known as one of the most complex optimization problems, even in the case of simplified classical single-level manufacturing systems [13].

In scheduling, there are two main types, reactive and proactive scheduling strategies. In reactive scheduling, planners try to keep up with events in the field and adjust when operations deviate from the plan. However, in proactive scheduling, the planner(s) plans the future and then uses the scheduling plan by overseeing the events in the system while dynamically updating the scheduling plan according to the states of the system [19]. Consequently, the critical infrastructures required to execute efficient reactive/proactive scheduling plans are real-time data collection and processing [20]. The main question here is: How to collect and process data to run reactive/proactive real-time and dynamic schedules within different levels of a manufacturing system?

Efforts to improve the performance of manufacturing systems have spurred four industrial revolutions in the last two hundred years. In recent years, with the growing advances in manufacturing processes and technology, many new global concepts have emerged. The term "Industry 4.0" has become an increasingly important research topic in recent years. This concept appeared first in an article published in November 2011 by the German government that resulted from an initiative on a high-tech strategy for 2020 [21].

Industry 4.0, potentially marking the onset of the fourth industrial revolution, constitutes a sophisticated technological framework that has garnered extensive scholarly attention, driving significant progress in intelligent and interconnected manufacturing systems [22,23]. The primary objective of Industry 4.0 centers on digitalization [24], underscored by robust cybersecurity measures and economically viable considerations.

Fig. 2 represents the main concepts within the Industry 4.0 domain. As one of key advancements, the Internet of Things (IoT) facilitates seamless connectivity, enabling devices and systems to communicate and share data in real time. System integration (Integration) facilitates the orchestration of collaboration among various system components, ensuring an efficient and interconnected workflow. Additive manufacturing revolutionizes traditional production methods by enabling the creation of complex structures layer-by-layer, fostering flexibility and customization. Virtual Reality and Simulation provide environments for design, testing, and training to minimize errors and improve overall precision within manufacturing systems. Moreover, cybersecurity measures protect sensitive data and systems from potential threats in this interconnected landscape. Big data analytics utilizes the power of vast datasets, extracting valuable insights to inform decision making and optimize processes. Cloud Computing serves as the backbone, facilitating scalable and accessible storage and computing resources. Autonomous robots, equipped with advanced AI, navigate and execute tasks independently, improving efficiency and safety on the factory floor. Industry 4.0, through the integration of these technologies, revolutionizes manufacturing systems into a new era of connectivity, innovation, and productivity [25]. In this context, data become a critical asset, necessitating effective governance [26].

In fact, effective governance is crucial for successful decision-making in manufacturing systems transitioning to Industry 4.0. A Data Governance (DG) system is essential to establish capacities for shared decision-making, authority, and control over data assets. As the production model in manufacturing systems shifts toward data connectivity (as shown in Fig. 1 through both vertical and horizontal flows), a data-centric model is essential. DG should ensure that data are managed strategically, preventing the creation of data silos and enabling organizational-wide sharing. The complexity introduced by Industry 4.0, such as the adoption of third platforms and inter-company collaboration, requires a robust DG system. For further discussions on the DG aspects of implementing Industry 4.0 solutions in manufacturing systems, we refer to the comprehensive research by Zorrilla and Yebenes [27] that addressed these challenges by proposing a formal reference framework within the Industry 4.0 context, supported by third-platform technologies. From an ethical point of view, there is a crucial need to address the potential impact of autonomous systems on human workers and society on a large scale. Questions about job displacement, privacy concerns in data-driven environments, and the ethical use of AI should be meticulously addressed. Furthermore, as Industry 4.0 changes the interaction style between humans and machines drastically, establishing ethical guidelines becomes paramount [28]. On the ergonomic front, the introduction of advanced technologies requires a thoughtful design approach to enhance the work environment and prevent adverse effects on human health and well-being. Striking a balance between automation and preserving meaningful human roles is essential, as well as prioritizing user-friendly interfaces and considering the physical and cognitive aspects of human interactions with these advanced systems [29]. When all these advances and ideas are combined, the fourth industrial revolution radically changes the traditional PS paradigm within the industrial sectors [30].

Digital Twin (DT) is one of the revolutionary tools that emerged from Industry 4.0 [31,32]. A DT is a virtual model designed to accurately reflect the physical system. The physical system being studied, for instance, a manufacturing system, is outfitted with various sensors related to vital areas of functionality. These sensors produce data about different aspects of the performance of the physical system, such as energy consumption, production machine conditions, number of finished parts, and more. This data is then relayed to a processing system and applied to the digital copy. Within manufacturing systems, the data processing system is usually referred to as the Manufacturing Execution System (MES). The Internet of Things (IoT) guarantees a constant connection between the field and the virtual copy. An important component of a DT is real-time simulation model of the system typically stored within a cloud computing environment. In fact, such a tool is required to move towards improved reactive/proactive scheduling within manufacturing systems [33]. Although a real-time simulation model provided by DT is beneficial to monitor the manufacturing system in real-time, it does not provide any systematic comparison between different alternatives, which is required to distinguish between different scheduling alternatives within both reactive and proactive scheduling strategies.

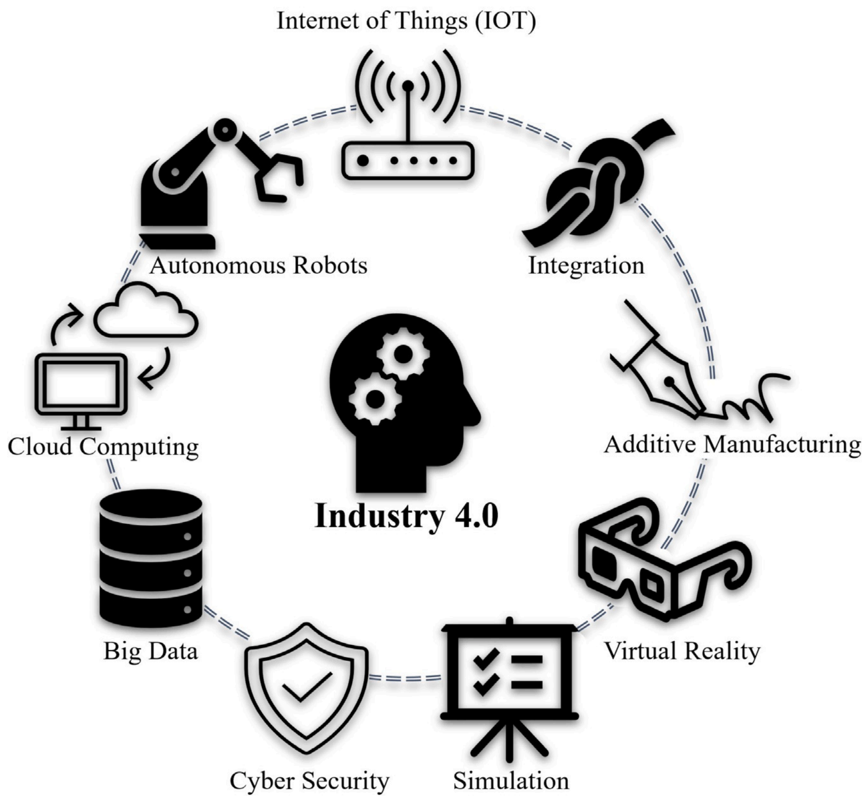


Fig. 2. Industry 4.0 concepts.

An important addition to simulation is an optimization which allows the choice of trade-offs between different factors in a system to achieve the best possible outcomes. The notion of various factors means that there are other solutions, and the idea of achieving desirable results declares that there is an objective to seek improvements in how to find the best solution. Optimization methods have been proposed for a wide range of production-related problems since the 1950s, addressing the issues of long-term aggregate production planning and detailed short-term PS [34].

Hybrid methods that combine simulation and optimization concepts within their architectures are of interest to enhance PS paradigms within manufacturing systems. Hybrid SO methods have been one of the most promising techniques to solve complex real PS problems [35, 36]. Integrating simulation models with optimization methods could establish promising Decision Support Tools (DSTs) benefiting from the advantages of both tools, which is the main idea to support proposing SO methods for different complex and stochastic industrial problems such as PS problems.

In this article, we first systematically review existing research on SO Applied to PS (SOAPS), an important aspect of a DT. To design a well-directed taxonomy, the existing literature on PS and SO is analyzed based on four main characteristics (dimensions) of the research work within the context of SOAPS. These characteristics are as follows: (1) problem and modeling environment referring to PS problem structures (Problem and Modeling Dimension), (2) SO methodology and application highlighting the SO methods architecture (Solving Methodology Dimension), (3) SOAPS real case studies (Real Applications Dimension), and experimentation methodology examining validation strategies (Experimenting Dimension). Different subcategories and alternatives are justified in each area of analysis, allowing us to reveal research gaps and highlight future research directions. Finally, considering industry 4.0 technologies, we examine the different research paths to enhance existing research on SOAPS. In general, this article presents the first review on the intersection of PS and SO (SOAPS) within the Industry 4.0 domain.

The remainder of this paper is organized as follows. To position the research in the current article, Section 2 analyzes existing related reviews and designs the research questions. Taking into account the research objectives and questions, Section 3 details the design of the research methodology used. Using the designed methodology, Section 4 reviews the literature on SOAPS. Then in Section 5 we highlight research gaps in the current literature in SOAPS to allow further development of these technologies within Industry 4.0. Finally, Section 6 concludes the paper.

2. Positioning and research questions

As mentioned, our prime goal in this research is to thoroughly explore the current body of knowledge on SOAPS and to suggest ways to enhance it in the context of Industry 4.0. It is worth mentioning that Industry 4.0 finds practical applications across various sectors, including domains such as healthcare [37] and food [38]. However, our primary emphasis in this study is on manufacturing systems, particularly in the realm of SOAPS. Consequently, the purpose of this section is to review selected literature, at a high level, to gain an understanding of how SOAPS is currently considered in published reviews. This will help us to understand the state-of-the-art contributions, derive relevant structures, and identify research questions. To identify relevant review articles concerning SOAPS, Industry 4.0, and their intersections, we conducted searches using various keywords such as “Simulation Optimization Production Scheduling”, “Production Scheduling Industry 4.0”, and “Simulation Optimization Industry 4.0” on the Google Scholar and Web of Science platforms.

Neither SO nor PS are isolated research domains. Specifically, within the literature, optimization, simulation, Machine Learning (ML), uncertainty, and Industry 4.0 are the main research concepts that have been widely integrated into both fields. Consequently, to review the literature related to PS and SO from the perspective of related concepts, certain evaluations of each concept should be considered. These evaluations are defined as follows:

- PS: production environments (e.g., flow shops, job shops, etc.), modeling methodologies, special constraints, scheduling strategies (reactive or proactive), and industrial case studies.
- SO: the architecture and implementation procedure of the SO technique(s) implemented.
- Optimization: objective function(s), constraints, and architecture of optimization modules.
- Simulation: simulation goal(s) (e.g., simulation for objective calculation) and simulation type (e.g., Discrete Event Simulation (DES)).
- Uncertainty: uncertainty source and uncertainty modeling (e.g., stochastic, fuzzy, etc.).
- ML: ML goal(s) and usage (e.g., metamodeling), ML techniques (e.g., Neural Networks (NNs)), and the architecture of implemented ML techniques.
- Industry 4.0: considered Industry 4.0 concepts such as DT, cybersecurity, and cyber resilience and their integration procedures.

The literature that we review in this section is shown in Table 1, where ✓and * signs show the primary and marginal focus of each idea, respectively. The concept referred to as a "primary focus" within this review article pertains to those concepts that are either directly addressed by the research questions or hold a distinct emphasis in the content analysis. Conversely, a concept categorized as having a "marginal focus" indicates instances where the concept is briefly mentioned but not extensively analyzed, such as a separate subsection or section in the content analysis. This classification framework ensures a clear differentiation between concepts that receive more in-depth attention and those that are touched upon with a lesser degree of scrutiny.

Generally, review articles are classified into two main categories: Literature related to PS, which are review articles focusing mainly on different types of PS problems and their features; Literature related to SO, review articles focusing on SO methodologies, their architectures, and their areas of application.

In the following, all the contents of Table 1 are detailed in line with the analysis of SOAPS-related review articles.

2.1. Literature reviews related to PS

In an early study, Chong et al. [39] classified different approaches for reactive PS. Their main focus is on the usage of DES as a tool for dealing with different production disturbances. Their research is not essentially a systemic review paper; however, they reviewed 30 articles and proposed taxonomies for both uncertainties in discrete manufacturing and reactive scheduling methods. Their main contribution lies in proposing a conceptual model towards dynamic reactive scheduling.

An interesting review on uncertainty sources, modeling approaches, and mitigation techniques within PS is presented by Aytug et al. [40]. They first examined the purposes of scheduling within manufacturing systems with a main focus on reactive scheduling, and then provided a taxonomy on different types of uncertainty by reviewing 113 articles. Their review mainly covered PS and uncertainty concepts (see Table 1). Their research does not provide a discussion of proactive scheduling and methodologies to solve PS problems.

Slotnick [41] reviewed the literature on PS from the perspective of order acceptance and scheduling on production machines. She examined deterministic and stochastic PS problems and presented a taxonomy based on production environments and optimization features by reviewing 130 articles. From the perspective of the concepts mentioned above, Slotnick [41] examined PS, uncertainty, and optimization mainly and marginally addressed SO concepts (see Table 1). Her research did not answer why each method is selected for each particular configuration of PS problems, which is essential to enable future applications.

Sun et al. [42] classified the intersection between multi-objective optimization and PS problems in flow-shop production environments. Their primary focus was investigating optimization algorithms applied to multi-objective flow shop scheduling problems (see Table 1). They reviewed and classified 137 articles based on objective functions, unique constraints, and solution algorithms considered in each piece. Their review focused only on the flow-shop production environment and did not cover other settings, such as job shops.

González-Neira et al. [43] presented a comprehensive review of PS problems under uncertainty in flow-shop production environments. By reviewing 170 research articles, they provided taxonomies on uncertainty source(s), modeling of uncertain parameters, and exciting optimization methods within the literature of flow shop scheduling research (see Table 1). However, research on their uncertainty and PS problems is limited to flow-shop production environments only.

In another review article, Fazel Zarandi et al. [44] examined the existing literature on intelligent methods applied to PS problems by reviewing 540 related research articles. They provided a taxonomy consisting of fuzzy scheduling, expert scheduling, ML in scheduling, local search methods, and constraint programming in scheduling. Moreover, in each category, they specified the technique used and the features of the production environment. Although their review is one of the most comprehensive surveys on intelligent PS, they only partially mentioned SO solution methods. Their study mainly covers the application of optimization and ML in PS (see Table 1).

Considering the operationalization of Industry 4.0 in manufacturing systems and its impacts on PS paradims, Parente et al. [45] conducted a two-stage cascade literature review. Their main objective was to identify Critical Scheduling Areas (CSA) influenced by Industry 4.0 implementation within manufacturing systems, from the point of view of PS by reviewing 61 articles. In the first stage, they analyzed opportunities and challenges posed by Industry 4.0, revealing common trends with production management. Their review also emphasized challenges related to Cyber Physical Systems (CPS) and adaptive manufacturing, stressing their relevance to PS. In the second stage, they evaluated the level of development of each CSA and proposed future research directions for them. Regarding SO, their analysis is limited to proposing SO as one of the future directions (existing gaps) to evaluate human–robot collaboration within manufacturing systems.

In another review article, [46] discussed the integration of ML approaches into Production Planning and Control (PPC) functions under the Industry 4.0 framework. Through a systematic review of the literature of 93 research articles, they mainly highlighted methodologies for the implementation of ML-aided PPC (ML-PPC) and proposed a classification framework for further research insights. Their review covered the ML techniques, tools, activities, and data sources necessary for ML-PPC and evaluated use cases and Industry 4.0 characteristics. Accordingly, they highlighted challenges such as the complexities of data collection through IoT technologies and adapting ML models to dynamic manufacturing environments. In particular, their review article indicated the dominance of MATLAB, R, Python, and RapidMiner as tools to develop ML-PPC. From the SOAPS point of view, they studied PS from a high-level perspective as one of the PPC domains. Moreover, their attention to SO is limited to considering simulation as a tool to train or evaluate ML models.

Seeger et al. [47] explored the application of data mining techniques in optimizing PS under the Industry 4.0 framework, focusing on the integration of CPS and digital transformation in production workshops. Through a review of the literature of 60 articles, the paper classified research based on the level of implementation of the CPS in PS and technological optimization techniques. Their review highlighted the need for a digital chain linking physical assets and decision-making processes and emphasized the challenges of employing data mining for optimizing PS problems, which are NP-hard and often non-deterministic. The study identified the role of simulation in addressing uncertainties and disturbances and emphasized the importance

Table 1
Summary of SOAPS-related review articles.

Category	Reference	PS	Uncertainty	Simulation	Optimization	SO	Industry 4.0	ML	Reviewed articles
Reviews related to PS	Chong et al. [39]	✓	*	✓	–	*	–	–	30
	Aytug et al. [40]	✓	✓	–	–	–	–	–	113
	Slotnick [41]	✓	✓	–	✓	*	–	–	130
	Sun et al. [42]	✓	–	–	✓	–	–	–	137
	González-Neira et al. [43]	*	*	–	✓	✓	–	–	170
	Fazel Zarandi et al. [44]	✓	–	–	✓	–	–	✓	540
	Parente et al. [45]	✓	–	–	–	–	✓	*	61
	Usuga Cadavid et al. [46]	*	–	–	–	–	✓	✓	93
	Seeger et al. [47]	✓	–	*	*	–	✓	*	60
	Guzman et al. [18]	✓	*	–	✓	–	–	–	60
Reviews related to SO	Akyol and Bayhan [48]	✓	–	–	*	*	–	*	186
	Barbati et al. [49]	✓	–	*	✓	✓	–	–	66
	Wang and Shi [50]	*	–	–	✓	✓	–	–	192
	Figueira and Almada-Lobo [51]	–	–	✓	✓	✓	–	–	73
	Amaran et al. [52]	✓	–	–	✓	✓	–	*	212
	Xu et al. [53]	*	–	–	✓	✓	–	*	170
	Xu et al. [54]	–	–	–	–	✓	✓	–	35
	Liu et al. [55]	*	–	–	✓	✓	–	–	122
	Ghasemi et al. [25]	*	–	–	–	✓	–	–	64
	Li and Zhang [56]	✓	–	–	–	*	–	–	26
	De Paula Ferreira et al. [57]	*	–	✓	–	*	✓	–	90
	Leng et al. [58]	–	–	*	–	*	✓	–	192
This review article		✓	✓	✓	✓	✓	✓	*	99

of building robust simulation models to bridge the gap between historical data and future expectations. They also underscored the growing interest in data-driven optimization in manufacturing and supply chain management and suggested potential research directions exploring real-time data processing, investigating DT implementations, addressing the connection between different CPS levels, and considering human involvement in the context of industry automation. From a SOAPS point of view, their review article analyzed simulation and optimization cores within studied methodologies from a high-level point of view. In other words, they did not provide details on the architecture of SO methods proposed to tackle PS problems in manufacturing systems.

The review article by Guzman et al. [18] studied PS within manufacturing companies, considering the challenges posed by changing market demands and the need to optimize resource utilization while ensuring high-quality products and rapid responsiveness. Through a systematic review of the literature, the article analyzed 60 articles in this field, categorizing studies based on methodology, modeling approaches, solution techniques, application areas, and data sets. The review highlighted research gaps and proposes future directions, including exploring hybrid and matheuristic algorithms, addressing sustainability parameters in models, considering collaborative inter-enterprise perspectives, and investigating nonlinear solvers for mathematical models. Although their review provided deep insight into PS problems from an optimization point of view, they did not examine methods that incorporate simulation models (such as SO) within their architecture.

2.2. Literature reviews related to SO

Tekin and Sabuncuoglu [59] reviewed 173 articles to evaluate the optimization cores within SO algorithms. They categorized optimization cores within SO methods into global and local techniques and provided a comprehensive literature analysis based on it. As shown in Table 1, their review focused mainly on SO and optimization concepts. However, discussions on the simulation cores and their architectures, which are one of the main parts of any SO algorithm, are missing in their research.

Akyol and Bayhan [48] examined the existing literature on the application of NNs to PS problems. They provided a taxonomy based on the architecture of NNs applied to PS and their area of implementation (production environments). In addition, they provided a taxonomy on hybrid methods that integrate NNs with a variety of optimization methods, including SO techniques. They reviewed 186 articles, focusing mainly on NNs and PS, while marginally examining other ML tools, optimization, and SO concepts (see Table 1). They did not provide a discussion of the data collection and processing procedures for training NNs.

Barbati et al. [49] reviewed the state-of-the-art agent-based models applied to optimization problems. Reviewing 66 research articles, Barbati et al. [49] stated that agent-based models and specifically agent-based simulations, among all research areas, have been applied primarily to PS problems (33 out of 66). They also provided a list of articles that address applications of agent-based models in PS while mainly focusing on optimization procedures applied to their presented case studies. (see Table 1). Their review mainly focused on the architecture of agent-based SO methods. It did not provide insights regarding the multi-methods created by combining agent-based simulation models with other simulation strategies (e.g., discrete event).

Wang and Shi [50] presented a review of SO methods applied to optimization problems. They categorized SO-related research work based on the optimization architecture associated with SO techniques implemented in the literature. When reviewing 192 research articles, as shown in Table 1, they focused mainly on SO methods and specifically the optimization module integrated with SO techniques while providing marginal information on SO applications to PS.

In another review article, Figueira and Almada-Lobo [51], who reviewed 73 articles, provided an analysis of the SO literature by examining SO methods based, first, on the simulation and optimization integration architecture within the SO methods and, second, on the purpose of the simulation (e.g., the simulation used for objective calculation). In addition, they provided information on the optimizers executed within different SO methods (see Table 1) but did not address the newly introduced concept of Industry 4.0.

Amaran et al. [52] considered SO an optimization method to deal with uncertain problems with complex and unknown problem structures. Accordingly, after providing different applications of SO methods, they focused on the optimization structure of SO techniques. They offered a taxonomy by reviewing 212 research articles (see Table 1). Their review of simulation architecture is limited to covering simulation software packages.

Xu et al. [53] reviewed the literature on SO methods by exploring areas of SO application and optimization strategies. They studied 170 articles focusing mainly on optimization strategies using SO methods and marginally addressing some PS applications,such as semiconductor manufacturing and some applications that integrated ML with SO, such as metamodeling (see Table 1). They provided some insight regarding the execution of SO algorithms on the cloud; however, they did not present alternatives for data acquisition and processing procedures to use SO as a DST (e.g., interactions with IoT tools). Moreover, they provided future paths for applying SO methods based on advances in big data and cloud computing research.

Xu et al. [54] examined application possibilities of SO methods in the era of Industry 4.0. Their article searches for different potentials of SO methods to become one of the leading DSTs to support Industry 4.0 practices. They argued that SO is essential for optimal control decisions in a highly dynamic and uncertain environment. A solution they highlight is multi-fidelity simulation optimization, where information provided by lower-fidelity models is used with high-fidelity models to lower computational expense. However, they did not provide test environments, such as designing DSTs for PS.

Taking SO methods as optimization techniques, Liu et al. [55] examined the optimization architecture within SO processes and provided application areas for each optimization category by reviewing 122 articles in SO research. Regarding PS, their review marginally mentions this, with the main focus on SO methods (see Table 1).

Ghasemi et al. [25] reviewed 64 research articles that focus on the application of SO in operational problems of semiconductor manufacturing. They first highlighted some semiconductor manufacturing challenges and attempted to address them using SO techniques. As shown in Table 1, their review focused mainly on SO applications, documenting possible solutions for PS sectors in semiconductor manufacturing systems.

In another study, Li and Zhang [56] provided a roadmap for designing SO-based DSTs for PS problems. Their article is not a review article; primarily, they highlighted some future applications of SO in PS problems considering the rapid improvement of computers' computational power.

In another review article, De Paula Ferreira et al. [57] focused on the intersection of simulation and Industry 4.0, highlighting the role of simulation in optimizing decision-making, system design, and operational performance within complex manufacturing systems. The study presented a conceptual framework for Industry 4.0 and systematically reviewed 90 articles using the PRISMA methodology, revealing an increasing trend in simulation-based research within Industry 4.0. Their review identified 10 simulation-based approaches and 17 Industry 4.0 design principles. Moreover, they suggested that simulation effectively captures Industry 4.0 design principles, particularly through hybrid simulation and DT approaches. However, from the SOAPS point of view, they marginally mentioned PS as one of the main simulation and Industry 4.0 application areas. In addition, they limited the applications of SO only to the design of smart factories.

By reviewing 192 research articles, Leng et al. [58] explored the integration of DT technologies into the design of smart manufacturing systems using a Function Structure Behavior Control Intelligence Performance Framework (FSBCIP). They highlighted the challenge of concurrently designing subsystems of complex (and smart) manufacturing systems and introduced DT as a solution for semi-physical simulations to detect design errors and flaws early on, reducing physical commissioning costs. The survey covered DT concepts, major design steps, blueprint models, enabling technologies, and design cases. From SOAPS point of view, they did not focus on PS problems. Moreover, within their review, the applications of SO methods are limited to DT-based optimization.

Considering the above analysis of PS and SO-related review articles, it is evident that no review article comprehensively addresses SO method applications in PS, with SO review articles applied to a range of application domains. From a conceptual point of view, SO methods are not technically optimization techniques. SO methods are hybrid DSTs designed to model and optimize decision-making problems at different managerial levels by integrating optimization and simulation cores. This shows the importance of evaluating SO architectures rather than just focusing on their optimization features.

Another critical point is that SO and PS are separate research fields. Therefore, studying SO applications within PS without considering other connected concepts, such as uncertainty, optimization, and the type of simulation, within the context of Industry 4.0 would not lead to accurate analysis. However, to our knowledge, most related review articles considering these concepts and their impacts still need to be included (see Table 1). Therefore, this paper addresses these gaps by:

- Presenting the first review on the application of SOAPS.
- Analyzing the architecture of implemented SO methods based on their implementation goals and simulation, optimization, and integration procedures.
- Studying the architecture and implementation of related research concepts consisting of uncertainty, simulation, optimization, and ML.

Moreover, we are highlighting a road map towards using SO as a DT-based DST within different levels of manufacturing systems dealing with scheduling problems (using Industry 4.0 technologies). The above analysis allows us to derive our research questions, which are detailed below.

2.3. Research questions

First, it is essential to understand the features of PS problems that have been tackled by SO methods up to now. Uncertainty is an indivisible part of most of the problems tackled by SO. Understanding the source(s) of uncertainty and modeling strategies in PS problems enables us to better understand why SO could be an appropriate method to tackle these problems. Moreover, it highlights the existing gaps by showing the missing sources of practically critical uncertainty in the SOAPS literature. Several optimization techniques consisting of both local and global methods have been integrated with different simulation methods, such as DES, to form SO procedures in the literature. Thereby, seven research questions, listed below, are defined to analyze the architecture of both simulation and optimization techniques that are developing in SO methods within the literature. Similar to other DSTs, SO results should be verified after each new application. Therefore, one needs to understand the validation strategies used to confirm an SO method. Undoubtedly, engineering is all about addressing real-world problems. Therefore, looking at existing industrial PS case studies managed by SO is essential. Therefore, the research questions are defined as follows:

1. What are the general characteristics of the PS problems addressed by SO methods up to now, and to what level of decision making (defined in Fig. 1) do these SO applications belong within a manufacturing system?
2. What are the main uncertainty sources and modeling strategies considered within the SOAPS literature? Is uncertainty a barrier or opportunity for SO applications in PS?
3. What are the main features of optimization cores used within SOAPS?
4. What are the common simulation strategies within SO methods applied to PS problems?
5. What are the common integration strategies to combine simulation and optimization cores in SO methods?
6. What validation strategies were performed within the literature to verify the results of SO applications to PS problems?
7. What case studies are considered within the literature of SOAPS?

The subsequent section outlines the research methodology utilized to address the aforementioned research questions. In this regard, we

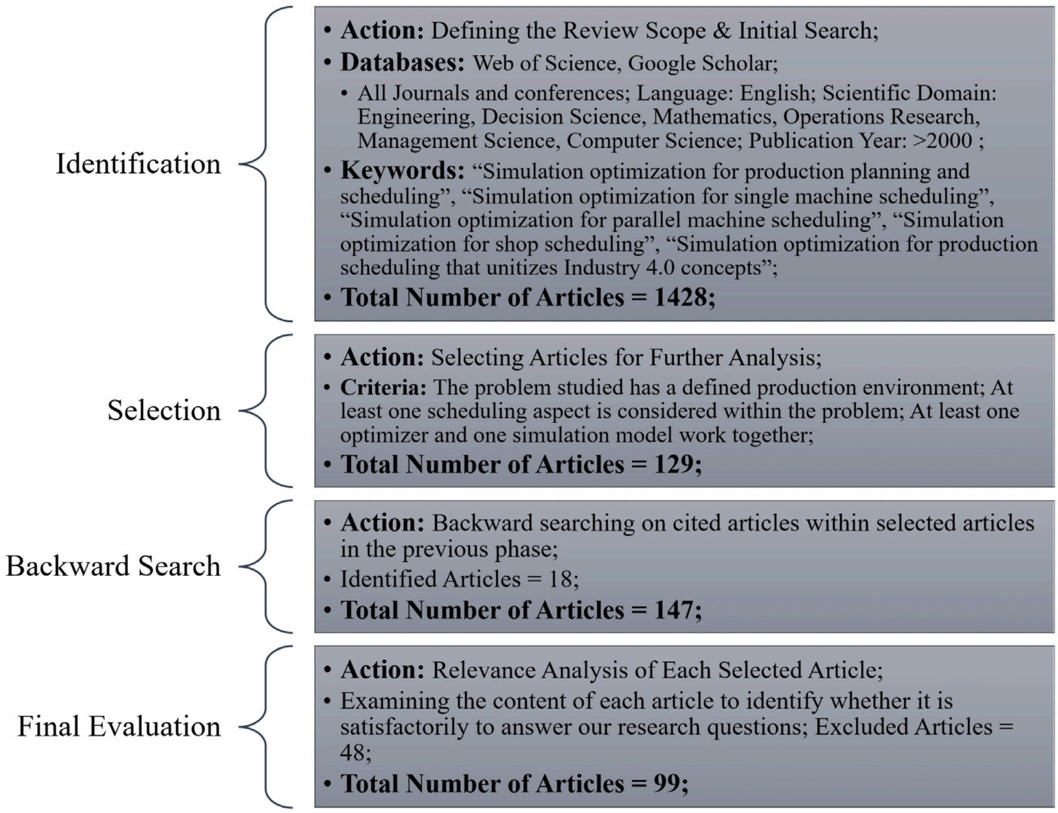


Fig. 3. Implemented structured literature review steps based on Seuring and Gold [60] and Guzman et al. [18].

employ four distinct dimensions for the content analysis of the literature. The first dimension (D1 in Fig. 4) addresses the initial two research questions, while the second dimension (D2 in Fig. 4) is dedicated to addressing questions three, four, and five. Additionally, the third dimension (D3 in Fig. 4) relates to research question six, and the fourth dimension tackles the final research question, stated earlier.

3. Research methodology

It is important to delimit the research using appropriate boundaries to conduct a useful review of the literature that can yield reliable results. In recent years, researchers have proposed different structures to design systematic literature reviews (e.g., 4-step methodology [60], PRISMA [57,61], and the two-stage cascading literature [45]). In this research, we implement the 4-step systematic literature review methodology proposed by Seuring and Gold [60]. Fig. 3 summarizes the steps taken to develop the review of the literature in this research.

As shown in the Identification phase of Fig. 3, to cover the SOAPS literature, the following search terms were applied to the Web of Science database and Google Scholar[3] [4]:

- Simulation optimization for production planning and scheduling.
- Simulation optimization for single machine scheduling.
- Simulation optimization for parallel machine scheduling.
- Simulation optimization for shop scheduling[5]
- Simulation optimization for production scheduling that unitizes Industry 4.0 concepts.

This search yielded 1428 individual results, of which only publications in English were retained. For the current review of the literature, it is worth noting that:

1. In this article, we focus on the applications of SO to PS problems in the context of Industry 4.0. Therefore, articles that solely address either of these concepts, SO or PS, are not considered in this research.
2. In order to provide the most recent trends in PS and SO-related research, in this study, research items published since 2000 are considered.

Consequently, in the selection phase, all articles published in peer-reviewed journals and conferences were subsequently selected using the following criteria:

- The problem studied has a defined production environment.
- At least one scheduling aspect is considered within the problem.
- At least one optimizer and one simulation model work together.

After filtering, 129 articles simultaneously satisfied all the above criteria and were included in the subsequent analysis.

Subsequently, during the Backward Search step, we conducted an examination of the articles cited within the selected publications from the previous phase, resulting in the identification of 18 additional articles.

Ultimately, in the Final Evaluation phase, each of the chosen articles underwent a comprehensive assessment to examine its alignment with the research questions addressed in this review. Following the completion of this stage, a total of 99 articles were selected for inclusion in this review.

[3] http://www.webofscience.com.

[4] http://www.scholar.google.com.

[5] To cover all shop scheduling research items, the term shop schedule is replaced by job shop scheduling, job shop scheduling, flow shop scheduling, flow shop scheduling, group shop scheduling, group shop scheduling, open shop scheduling, and open shop scheduling and different searches are performed.

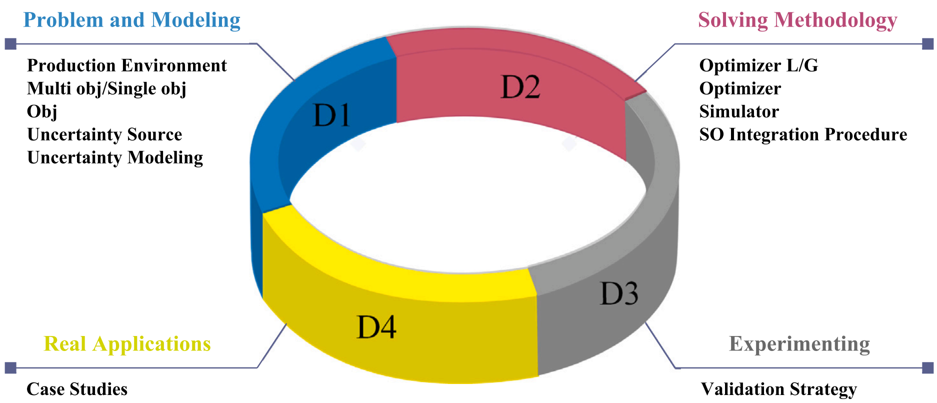


Fig. 4. Dimensions applied to the content analysis in research step 1.

Table 2
List of acronyms.

Abbreviation	Explanation	Abbreviation	Explanation
AB	Agent-Based	M Obj	Multi-objective
ACO	Ant Colony Optimization	Mspan	Makespan
AT	Arrival Times	Multi-M	Multi-Method Simulation
BC	Bee Colony	NTJ	Number of Tardi Jobs
BS	Beam Search	obj	Objective
BSO	Brain Storm Optimization	OCBA	Optimal Computing Budget Allocation
CCM	Chance Constrained Method	OO	Ordinal Optimization
CMW	Critical Machines Workload	Op	Optimizer
Com/P	Compromise Programming	Op/G	Global Optimizer
Com/T	Completion Times	Op/L	Local Optimizer
CT	Cycle Time	PE	Production Environment
CWDR	Comparison With Dispatching Rules	PIn	Process Interruption
CWES	Comparison With Exact Solution	PM	Parallel Machines
CWLB	Comparison With Lower Bound	PT	Processing Times
CWLM	Comparison With Literature Methods	QT	Queue Time
CWSH	Comparison With Standard Heuristics	SA	Simulated Annealing
CWSM	Comparison With Standard Metaheuristics	SAOR	Simulation Actualizing Optimization Results
DD	Due Date	SC	Special Constraint
DE	Differential Evolution	SDSTCVS	Simulating Data Sets To Create Virtual Shop
Dem	Demand	SEDR	Simulation Evaluating Dispatching Rules
Det	Deterministic	SetT	Sequence Dependent Setup Times
DOE	Design Of Experiments	SFOC	Simulation For Objective Calculation
DR	Dispatching Rules	Sim	Simulator
DT	Digital Twin	Sim/P	Simulated Part
EA	Evolutionary Algorithm	SM	Single Machine
Ea	Earliness	SO/IP	SO Integration Procedure
EDA	Estimation of Distribution Algorithm	S Obj	Single Objective
Eli	Eligibility	SPML	Simulation Performing Machine Learning
FS	Flow Shop	SPOP	Simulation Providing Optimization Parameters
FT	Flow Time	SS	System State
Fuz	Fuzzy	SSPL	Solving Standard Problems from Literature
G/P	Goal Programming	St	Stochastic
GPSO	Hybrid Genetic Particle Swarm Optimization	STASF	Simulation To Analyze Solutions Feasibility
GS	Group Shop	StT	Statistical Test
HS	Harmony Search	SVMESD	Simulation Visualizing MES Data
Inv	Inventory level	T&E	Trial and Error
JI	Job Insertion	Tar	Tardiness
LBc	Load Balance	Tht	Throughput
LO	Linear Optimization	TJ	Tardy Jobs
Mai	Maintenance	TS	Tabu Search
MAv	Machine Availability	TWO	Total Workload
MC	Monte Carlo	UM	Uncertainty Modeling
MF	Machine Failure	US	Uncertainty Source
MIP	Mixed Integer Programming	WIP	Work In Process

As presented earlier, Fig. 4 shows four main dimensions (D1, …, D4) and their subdimensions applied to the content analysis in this research. In the first stage, research papers are analyzed based on their problem features and modeling strategies (Problem and Modeling), including the Production Environment (e.g., job shops), number of objectives (Multi obj or Single obj), the purpose (obj), Uncertainty Source, and Uncertainty Modeling Strategy. In the second phase, research papers are analyzed based on their problem-solving methodology, including if the optimizer is local (L) or global (G), the optimizer type (Optimizer), simulator type (Simulator), and the architecture of the SO method (SO Integration Procedure). The research articles are analyzed in the next step based on their experimentation methodology (Experimenting). Consequently, the verification methods performed in each research (Validation Strategy) to validate their results are examined. Finally, to assess the real applications of SO in addressing PS problems, the case studies used to evaluate the methodology are analyzed. In the following sections, each taxonomy is detailed.

4. Review of SO applied to PS (SOAPS)

In this section, the retrieved articles are examined by the defined research goals and questions, which consist of, first, descriptive analysis and, second, content analysis based on the dimensions detailed within the research methodology in Section 3.

4.1. Descriptive analysis

This section analyzes the retrieved publications based on their publication time and keyword co-occurrence. The complete list of articles reviewed in this research is provided in the first column of Table 3.

Fig. 5 presents the distribution of articles published each year, revealing fluctuations in the range of six to 17 publications within two-year intervals. Notably, a significant portion of the selected articles, comprising more than 52% of the total, fall within the 2015–2022 time-frame. Furthermore, specific time intervals; namely, (2014, 2016], (2018, 2020] and (2016, 2018]; emerge as periods with notably high inclusion rates, featuring 17, 15, and 11 published articles, respectively.

One way to analyze the reviewed articles is to examine the keywords used. Although there is no way to standardize keywords, it would help to some extent to validate the research questions asked. Fig. 6 shows the network of co-occurrence of keywords created for articles examined in Table 3 generated using the VOSviewer science mapping software [158].

In the graph, the size of a node defines a specific keyword's occurrence ratio. Furthermore, the distance between the nodes refers to the strength of the agreement between two keywords. VOSviewer uses a clustering algorithm to highlight keyword clusters based on their concurrence ratios. For example, on the right bottom, industry 4.0, big data, internet of things, and supply chain management are in one cluster (shown in green). Keywords emphasize the analysis method used (i.e. genetic algorithm, metaheuristics, mathematical programming, etc.), the type of manufacturing environment used (i.e., job-shop, flow-shop, etc.) with the methods used to capture using the terms stochastic job-shop and stochastic process.

Accordingly, job-shop scheduling, simulation optimization, scheduling, and industry 4.0 were the dominant keywords in the examined articles. Moreover, the digital twin keyword is mainly connected to the research domain through dynamic scheduling and big data (right side of the graph). Analysis of the keywords shows that the job-shop environment seems to be the most studied production environment within this research domain.

This analysis is further enriched by Fig. 7, which illustrates the temporal trends of keyword co-occurrence. In particular, concepts such as industry 4.0, big data, digital twin, and smart manufacturing have emerged as prominently addressed keywords in the reviewed literature, particularly post 2019.

In the following, according to the research questions defined in Section 2 and the research methodology detailed in Section 3, a detailed analysis of the articles examined in this review is provided. The following provides a content analysis for each designed dimension.

4.2. Problem and modeling (content analysis dimension 1)

In this section, the content analysis of column "Problem Modeling" in Table 3 is discussed. There are two subsections, with the first detailing the Production Environment (PE), Single Objective (S Obj), or Multiple Objective (M Obj), and the second subsection describing the Uncertainty Source (US) and Uncertainty Modeling (UM).

4.2.1. PE and objective function analysis

Regarding PE, most are classified into the following categories:

Single Machine (SM): In Single Machine Scheduling Problems (SMSPs), all jobs must be processed on one single machine. Additionally, precedence constraints between jobs may be given [109]. Within the literature, SM environments are denoted by $1/\beta/\gamma$ [13]. Within the context of SOAPS, the SM scheduling domain has predominantly served as a platform for the development of sophisticated methodologies, exemplified by the use of reinforcement learning (RL), as demonstrated by Yang et al. [156]. This emphasis arises from the inherent simplicity of SM scheduling, enabling researchers to concentrate their efforts on advancing complex methodologies to effectively address various intricate production scheduling challenges.

Parallel Machines (PM): Parallel Machine Scheduling Problems (PMSPs) can be divided into three groups that contain: (i) identical machines in parallel, (ii) machines in parallel with different speeds, and (iii) unrelated machines in parallel [148]. In the literature, PM environments are denoted by $P_m/\beta/\gamma$, $Q_m/\beta/\gamma$, and $R_m/\beta/\gamma$ referring to m identical machines in parallel, m machines in parallel with different speeds, and m different machines in parallel, respectively [13]. PM has been considered as the PS environment in different articles, such as works by Persson et al. [75], Yang [88], Balin [97], Xu et al. [115] and Expósito-Izquierdo et al. [148].

Flow Shop (FS): In FSSPs, all jobs have the same processing order through the machines, while the order of positions on each device can be different. There are exceptional cases for FSSPs, where, in at least one stage, there are multiple machines capable of processing a specific operation (Flexible Flow Shop Scheduling Problem (FFSSP)) or jobs could skip a particular step of production (Hybrid Flow Shop Scheduling Problem (HFSSP)) [44]. Within the literature, the FS environment with m machines in series and the Flexible Flow Shop (FFS) environment with c stages in series have been represented by $F_m/\beta/\gamma$ and $FF_c/\beta/\gamma$, respectively [13]. FS has been the considered PS environment in several research within the SOAPS domain (for the full list of FS environments within SOAPS see Table 3).

Job Shop (JS): In JSC, the operations of a job are ordered, each job follows a predetermined route, and a machine may be visited more than once by a job. A particular case of JSSP is a Flexible Job Shop Scheduling Problem (FJSSP), where, at least at one stage, multiple machines are capable of processing a specific operation [159]. Within the literature, the JS environment with m machines in series and the Flexible Job Shop (FJS) environment with c stages have been represented by $J_m/\beta/\gamma$ and $FJ_c/\beta/\gamma$, respectively [13]. JS has been the dominant PS environment within the SOAPS literature, as shown in Table 3.

Group Shop (GS): The Group Shop Scheduling Problem (GSSP) is a generalization of the classical JSSPs. In the GSSP, each job consists of operations that must be processed on specified machines without preemption. The functions of each position are divided into groups in which a total precedence order is given [91]. Within the SOAPS context, research on GS PS environments is limited. Ahmadizar et al. [91] is one of the examples of considering GS as the PS environment within the SOAPS context.

In Table 3, the PE is provided for each article. To analyze this data, Fig. 8(a) shows the frequency of each PE within the retrieved papers. As shown, JS has been the PE most considered within the SOAPS literature with a total of 50 out of the 99 articles, with FS, PM, SM, and GS in 36, eight, four, and one articles, respectively.

Table 3
The retrieved articles and their content analysis. Note that all terms used are detailed in Table 2.

References	Problem and modeling						Solution methodology					Real applications	Experi-menting
	PE & Objective function analysis				Uncertainty		Optimization type			Simulation type	Integration type		
	PE	S Obj	M Obj	Obj	US	UM	Op/L	Op/G	Op	Sim	SO/IP	Case study	Validation strategy
Hsieh et al. [62]	JS		✓	CT	WIP, MF	St	✓		OO	DES	SFOC	Semiconductor	CWDR
Sivakumar [63]	FS		✓	Tar,CT	PT, SetT	St		✓	LO	DES	SFOC	Semiconductor	Case Study
Cave et al. [64]	FS		✓	Mspan, Cost		Det	✓		SA	DES	SFOC		SSPL
Gupta and Sivakumar [65]	JS		✓	CT, Utilization		Det	✓		Pareto	DES	SFOC	Semiconductor	Case Study
Finke et al. [66]	FS	✓		Ear, Tar		Det	✓		TS	DES	SFOC		CWES
Kacem et al. [67]	JS		✓	Mspan, Workload		Det	✓		GA	DES	SFOC		CWLB
Yang et al. [68]	FS		✓	Tar, Flow Time	PT, DD	St	✓		TS	DES	SFOC	Ceramic	Case Study, CWSH
Allaoui and Artiba [69]	FS		✓	Tar, Com/T, NTJ	MAv, Mai	St	✓		SA, DR	DES	SFOC		CWLM
Gupta and Sivakumar [70]	SM		✓	Tar, CT	PT, SetT	St	✓		Com/P	DES	SPOP	Semiconductor	CWSH
Wang et al. [71]	FS	✓		Mspan	PT	St	✓		GA, OO, OCBA	DES	SFOC		CWSM
Rosen and Harmonosky [72]	FS	✓		Cost	PT	St	✓		SA, OO	DES	SFOC	Semiconductor	Case Study
Tavakkoli-Moghaddam and Daneshmand-Mehr [73]	JS	✓		Mspan		Det	✓		DR	DES	SFOC		CWSH
Wang et al. [74]	FS	✓		Mspan	PT	St	✓		GA, STs	DES	SFOC		CWSM
Persson et al. [75]	PM		✓	Tar, LBc	PT	St	✓		GA	DES	SFOC	Postal service	Case Study
Priore et al. [76]	FS		✓	Tar, FT	PT, SS	St	✓		DR	DES	SFOC, TMLT		CWSH
Chong et al. [77]	JS	✓		Mspan		Det	✓		BC	DES	SFOC		CWSM
Ang and Sivakumar [78]	SM		✓	Tar, CT	PT, SetT	St	✓		GA	DES	SFOC	Semiconductor	Case Study
Hsieh et al. [79]	JS		✓	CT	PT	St	✓		DR, OO	DES	SFOC		CWDR
Zribi et al. [80]	JS	✓		Mspan		Det	✓		TS, GA	DES	SFOC		CWLM
Andersson et al. [81]	FS		✓	Tht, Inv, SetT	PT, SS	St	✓		GA	DES	SFOC	Car Engines	Case Study
Alfieri [82]	FS		✓	Tar	PT, SetT, JI	St	✓		TS	DES	SFOC	Cardboard	Case Study
Klemmt et al. [83]	JS	✓		Mspan	SetT, Tar	Det	✓	✓	GA, MIP	DES	SFOC, SFBG		CWES
Zhang et al. [84]	JS		✓	CT, WIP		Det	✓		DR,RSM	DES	SFOC	Semiconductor	Case Study, CWDR
Gholami et al. [85]	FS	✓		Mspan	SetT, MAv	St	✓		GA	DES	SFOC		StT
Goren and Sabuncuoglu [86]	JS		✓	Tar, FT, Com/T	PT, MAv	St	✓		BS	DES	SFOC		CWLM
Xing et al. [87]	JS		✓	Mspan, TWo, CMW		Det	✓		ACO	DES	SFOC		StT
Yang [88]	PM	✓		FT	AT, SetT, MAv	St	✓		GA	DES	SFOC	Semiconductor	Case Study
Mouelhi-Chibani and Pierreval [89]	FS	✓		Tar	PT, AT	St	✓		SA	DES	TMLT, SFOC		SSPL
Azadeh et al. [90]	JS		✓	Tar, Mspan	PT	St		✓	G/P	DES	TMLT	Textile	Case Study
Ahmadizar et al. [91]	GS	✓		Mspan	PT, AT	St	✓		ACO	DES	SFOC		SSPL
Gu et al. [92]	JS	✓		Mspan	PT	St	✓		GA	DES	SFOC		CWSM
Azadeh et al. [93]	FS	✓		Mspan	PT, SetT	St, Fuz	✓		T&E	DES	TMLT, SFOC	Ceramic	CWLM, Case Study
Nicoară et al. [94]	JS	✓	✓	Mspan		Det	✓		GA	DES	SFOC	Pharma	CWLM, Case Study
Lang and Li [95]	JS	✓		Cost, EC	PT, MAv	St	✓		NSGA-II	DES	SFOC		
Liu et al. [96]	JS		✓	Cost	PT, MAv	St	✓		NSGA-II	DES	SFOC	Semiconductor	Case Study
Balin [97]	PM	✓		Mspan	PT	Fuz	✓		NSGA-II	DES	SFOC		CWDR
Frantzén et al. [98]	FS		✓	Tht, SetT, Mspan	St	MAv	✓		T&R	DES	SFOC	Automotive	Case Study
Azzi et al. [99]	FS		✓	Mspan, Utilization		Det	✓		Heuristics	DES	SFOC	Rotor shaft	CWDR
Guo et al. [100]	JS	✓		Mspan		Det	✓		ACO	DES	SFOC	Semiconductor	Case Study, StT
Shahzad and Mebarki [101]	JS	✓		Tar		Det	✓		DR, TS	DES	TMLT, SFOC		StT
Kaban et al. [102]	JS		✓	WIP, QT	PT	St	✓		DR	DES	SFOC, SEDR	Automotive	Case Study, CWLM
Löhndorf and Minner [103]	SM	✓		Cost	Dem	St		✓	DP	MC	SFOC		CWDR
Moon et al. [104]	PM		✓	Mspan, Cost		Det	✓		GA	DES	SFOC		StT
Hao et al. [105]	JS	✓		Mspan	PT	St	✓		EDA	MC	SFOC	Semiconductor	Case Study, CWLM
Korytkowski et al. [106]	JS		✓	Tar, FT	PT, SetT	St	✓		DR, ACO	DES	SFOC	Printing	Case Study
Korytkowski et al. [107]	JS		✓	Tar, FT	PT, SetT	St	✓		DR, GA	DES	SFOC	Printing	Case Study
Zhang et al. [108]	PM		✓	Tar, Cost	PT, SetT, MAv	St	✓		DE	DES	SFOC		CWES
Löhndorf et al. [109]	SM		✓	Cost	PT, Dem, SetT	St	✓		DR	DES	SFOC		CWDR
Pérez-Rodríguez et al. [110]	JS	✓		WIP	AT, PT	St	✓		EDA	DES	SFOC	Steel Doors	CWSM, Case Study
Yang et al. [111]	JS		✓	Tar, Ea	PT	St	✓		OO, OCBA	MC	SFOC		CWLM
Kulkarni and Venkateswaran [112]	JS	✓		Mspan		Det		✓	LP	DES	SFOC, SPOP		SSPL
Marichelvam et al. [113]	FS	✓		Mspan	PT	St	✓		EDA	DES	SFOC		CWLM, StT
Morady Gohareh et al. [114]	JS		✓	Tar, Ea	PT	St	✓		Heuristics	DES	SFOC		StT, CWLM
Xu et al. [115]	PM	✓		CT	AT	St	✓		GA	DES	SFOC		CWLM
Lin and Chen [116]	FS	✓		FT	PT	St	✓		GA, OCBA	DES	SFOC	Semiconductor	Case Study
Lin and Chen [36]	FS	✓		FT	AT, PT	St	✓		GA	DES	SFOC	Semiconductor	Case Study
Mokhtari and Dadgar [117]	JS	✓		TJ	PT, DD, MAv	St	✓		SA	MC	SFOC		StT
Shen and Yao [118]	JS		✓	Tar, Mspan	AT	St	✓		EA	DES	SPOP		StT, CWSM
Bard et al. [119]	JS		✓	Mspan, Tht		Det	✓		GRASP	MC	SPOP		StT, Case Study
Shen and Yao [118]	JS		✓	Tar, Mspan	AT	St	✓		EA	DES	SPOP		StT, CWSM
Horng and Lin [120]	JS	✓		Mspan	PT	St	✓		ACO	DES	SFOC		StT
Hao et al. [121]	FS		✓	WT, PIn	AT, PT	St	✓		PSO	DES	SFOC	Steel manufacturing	CWLM, Case Study
Azadeh et al. [122]	FS	✓		Cost	PT	St	✓		DR	DES	TMLT, SFOC	Food	CWLM, Case Study
Azadeh et al. [123]	JS	✓		Mspan	PT	Fuz	✓		DR	DES	TMLT, SFOC		CWLM
Frazzon et al. [124]	JS	✓		Tar	PT	St	✓		GA	DES	STASF		SSPL
Aurich et al. [125]	FS		✓	Tar, Mspan		Det	✓		SA, TS	DES	SFOC, SPOP	Semiconductor	Case Study
Kulkarni and Venkateswaran [126]	JS	✓		Mspan		Det	✓		TS	DES	SFOC		CWLM
Kuck et al. [127]	JS	✓		CT	PT, SetT, MAv	St	✓		DR	DES	SFOC	Semiconductor	Case Study
Ahmadi et al. [128]	JS		✓	Mspan, Stability	MAv	St	✓		NSGA-II	DES	SPOP		CWSM
Fazayeli et al. [129]	FS	✓		Mspan	MAv	St	✓		GA, SA	DES	SPOP		CWLM
Nouiri et al. [130]	JS	✓		Mspan	MAv	St	✓		PSO	DES	SPOP		CWLM, StT
Yuan et al. [131]	FS	✓		Mspan	PT	St	✓		GA	DES	SFOC		CWSM
Jiang et al. [132]	FS		✓	Tar, Ea		St	✓		EDA, OCBA, OO	DES	SFOC	Steel manufacturing	CWLM, Case Study
Nasiri et al. [133]	OS	✓		WT	AT, PT	St	✓		DR	DES	TMLT, SPOP		CWLM
Rahmanidoust [134]	FS		✓	Tar, Mspan		Det	✓		NSGA-II	DES	SFOC		StT

(continued on next page)

Table 3 (*continued*).

Fu et al. [135]	FS		✓	Tar, Mspan	PT	St	✓		FwA	MC	SFOC		StT, CWLM
Waschneck et al. [136]	JS	✓		WIP	PT, SetT, MAv	St	✓		DR	DES	TMLT, SFOC	Semiconductor	Case Study
Yang and Gao [137]	JS		✓	Cost, Mspan	PT	St	✓		EA	DES	SFOC		CWSM
Jamrus et al. [138]	JS	✓		Mspan	PT	Fuz	✓		GA	DES	SFOC	Semiconductor	Case Study, CWSM
Rahmati et al. [139]	JS	✓		Mspan	MAv	St	✓		HS	DES	SFOC		CWSM
Fu et al. [140]	FS		✓	Tar, Mspan	AT, PT	St	✓		EA	Multi-M	SFOC		CWLM, StT
Fu et al. [141]	FS		✓	Com/T, Energy		St	✓	✓	CCM, BSO	MC	SFOC		CWLM
Lin et al. [142]	JS	✓		Mspan	PT	St	✓		GA, OCBA	DES	SFOC		CWLM
Peng et al. [143]	FS		✓	Mspan, Energy	PT, SetT	St	✓		EA	MC	SFOC	Cylinder manufacturing	Case Study, StT
Amiri et al. [144]	JS		✓	FT, Mspan, NTJ	PT	St	✓		EA, DOE	DES	TMLT, SFOC		StT
Fu et al. [145]	FS	✓		Mspan	AT, PT	St	✓		EA	DES	SFOC		StT
Han et al. [146]	FS		✓	Com/T, Mspan	PT	St	✓		EA	MC	SPOP		SSPL
Gong et al. [147]	JS		✓	Mspan, Energy, Cost		Det	✓		NSGA-II	DES	SFOC		CWLM
Expósito-Izquierdo et al. [148]	PM	✓		Com/T	SetT	St	✓		EA	AB	SPOP		StT
Turker et al. [149]	JS		✓	Tar, Ea, WIP	AT, PT	St	✓		DR	DES	SFOC		CWSH
Negri et al. [150]	FS		✓	Mspan	PT, MAv	St	✓		GA, DT	DES	SVMESD, SFOC	Production lab	Case Study
Ghasemi et al. [151]	JS		✓	Tar, Ea	PT	St	✓		EA, OO, OCBA	MC	TMLT, SFOC		CWLM, StT
Gheisariha et al. [152]	FS		✓	Com/T, Tar	SetT	Det	✓		HS	DES	SFOC		CWLM, StT
Zhang et al. [153]	JS	✓		Mspan	PT, MAv	St	✓		T&E, DT	DES	SPOP	Hydraulic valves	Case Study
Wang et al. [154]	JS	✓		Mspan	PT	St	✓		DR, GA	DES	SPOP, TMLT		CWLM, StT
Caldeira and Gnanavelbabu [155]	JS	✓		Mspan	PT	St	✓		Jaya Algorithm	MC	SFOC		CWLM, StT
Yang et al. [156]	SM	✓		Cost	PT	St	✓		Heuristics	Multi-M	SPOP, TMLT		StT
Morady Gohareh and Mansouri [157]	JS	✓		Tar, Ea	PT	St	✓		ACO	DES	SFOC		CWSH

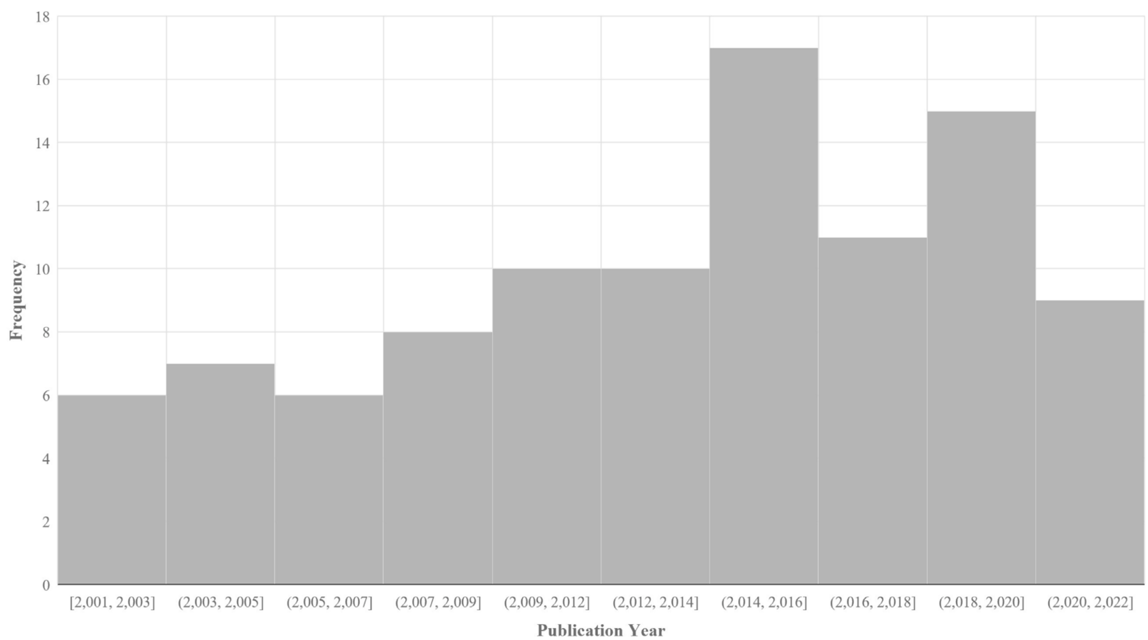


Fig. 5. Histogram of articles examined within this review.

One of the main parts of an optimization problem is the objective function, which essentially refers to the value(s) planned to be either minimized or maximized over the set of feasible alternatives (solutions). The features of the objective(s) (e.g., the number of goals) have a direct impact on the architecture of any optimization problem [160] (here, PS problems). Within the PS literature, the completion time (Com/T), positions and profit, throughput (Tht), make span (Mspan), cycle time (CT), early delay (Ea), tardy delay (Tar), and flow Time (FT) have been the main objectives considered by researchers [161]. On the other hand, strategies to deal with single-objective PS problems are different from multi-objective ones. Accordingly, Table 3 shows whether a PS problem within the retrieved articles is modeled as a single-objective or multi-objective optimization problem. It also highlights the objective(s) considered in each investigation. To assess this information, Fig. 8(a) shows the number of articles that considered whether Single Objective (S Obj) or Multi Objectives (M Obj) for each PE. Furthermore, in Fig. 8(b), the frequency of each objective in both single-objective and multi-objective PE problems within the articles. As shown in Fig. 8(a), the number of PS problems with a single objective and multiple objectives is virtually equal. For instance, in articles with a JS Production Environment (PE), there are 26 and 24 articles with single-objective and multi-objective functions, respectively. The main objectives in PS optimization problems are detailed in the following.

Within the classic machine scheduling literature, Mspan, Com/T, Tar, and Number of Tardy Jobs (NTJ) are the targets considered [162]. In the following, frequently used classic objectives within the SOAPS literature are detailed:

Mspan: within the literature on PS, Makespan refers to the completion time of the last job to leave the system. Due to its importance, from the practical point of view, minimizing Makespan has been the main objective within several PS problems studied to achieve high machine utilization ratios [163]. Accordingly, Kacem et al. [67], Chong et al. [77], Gholami et al. [85], Hao et al. [105], Azadeh et al. [123], Peng et al. [143] and Caldeira and Gnanavelbabu [155] are some examples of considering Makespan as the objects within the SOAPS literature.

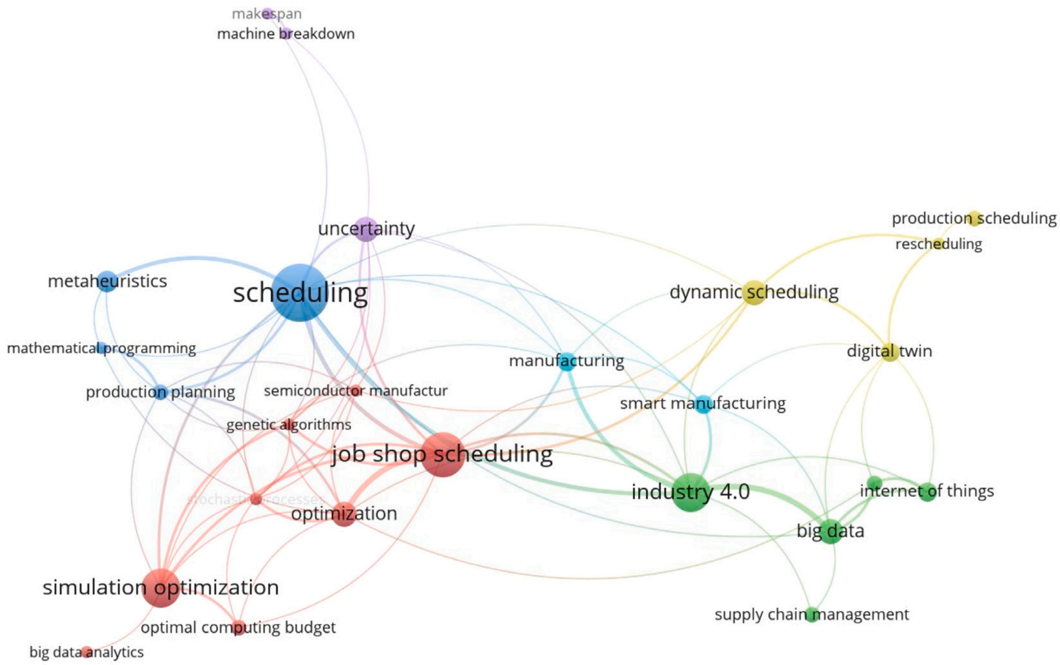


Fig. 6. Keyword co-occurrence map including keyword clusters.

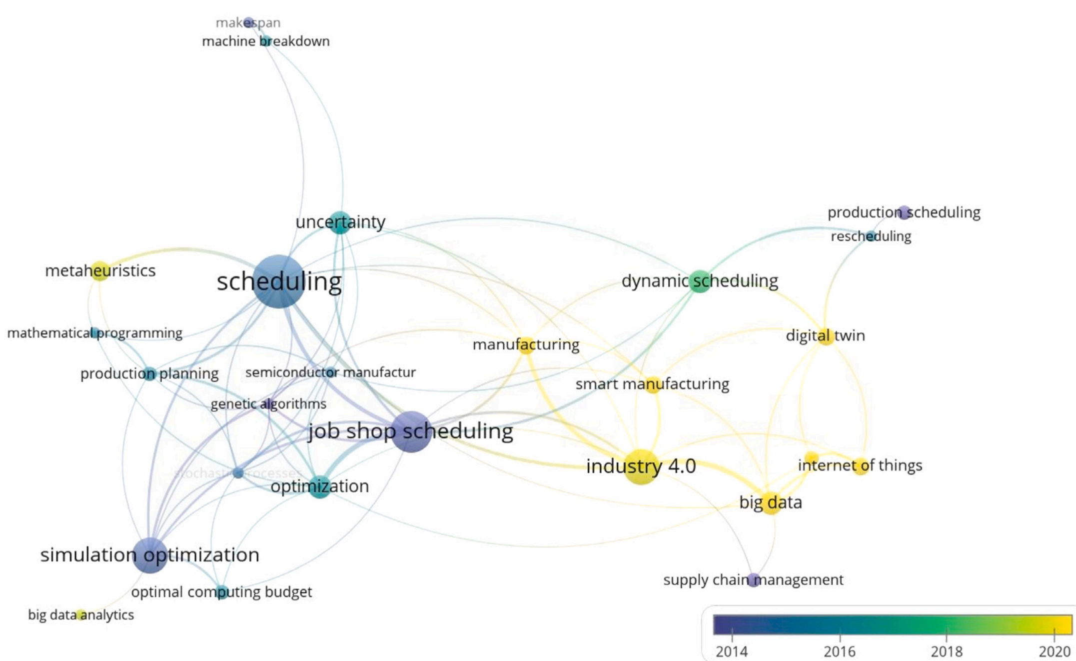
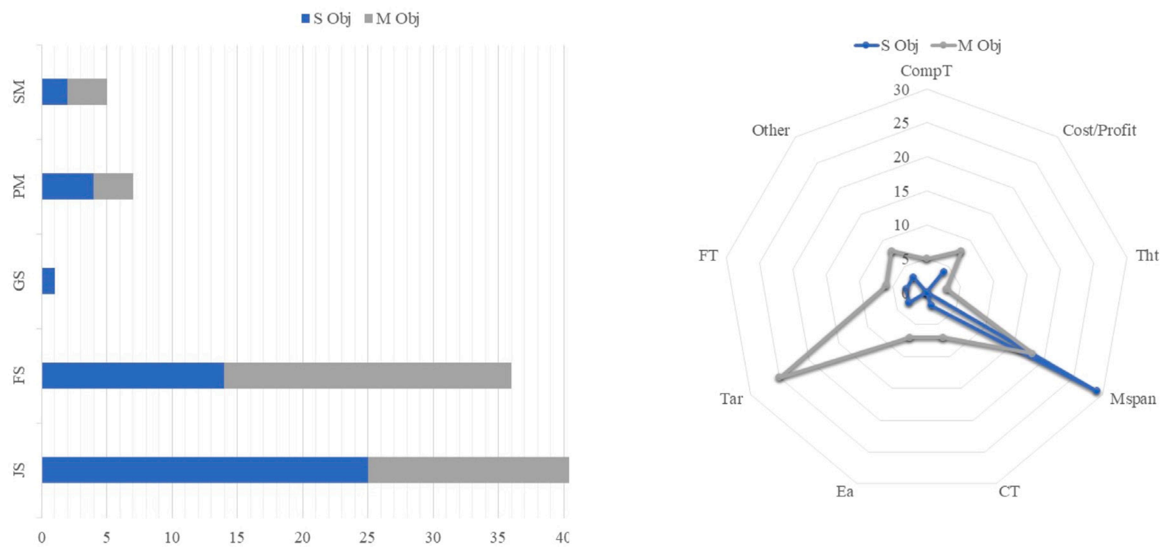


Fig. 7. Keyword co-occurrence map including keyword trends over time.

Within the machine scheduling literature, problems aimed at optimizing Mspan time have been represented by $\alpha/\beta/C_{max}$ [13].

Com/T: The completion time refers to the moment that processing of a job/order/operation is finished at a considered PE. Researchers have considered Com/T in different forms, such as the mean of completion times [69] and total completion times [86,148]. In the machine scheduling literature, problems aimed at minimizing the real weighted completion time have been represented by $\alpha/\beta/\sum w_j C_j$ [13].

Ea/Tar: Earliness and Tardiness are generally calculated based on the difference between the completion time of an order/job/operation with its Due Date. Ea is of interest when holding a finished order/job/operation is a critical factor (e.g., considerable holding costs). At the same time, Tar calculates the difference between the Com/T and Due Dates to monitor delivery delays. To balance the trade-off between holding and uncertainty costs, Ea and Tar are mostly considered together [151]. Sivakumar [63], Gupta and Sivakumar [70], Yang et al. [111], Ghasemi et al. [151] and Morady Gohareh et al. [114] are examples of research that think Ea/Tar-based objectives functions. Within the machine scheduling literature, problems that aim to minimize the total weighted earliness and tardiness times are represented by $\alpha/\beta/\sum w_j E_j$ and $\alpha/\beta/\sum w_j T_j$, respectively [13].



(a) Production environments and single or multi objectives.

(b) Objective functions.

Fig. 8. Objective considered and single or multi objectives.

In addition to those mentioned above, classical objective representations and several hybrid objective functions are proposed within SOAPS. Hybrid objective functions are mainly built based on classical objective functions by creating new combinations and adding new calculations. In the following, frequently-used hybrid objective functions within SOAPS literature are detailed:

Cost/Profit: Financial feasibility is one of the main purposes of PS in every industry. Thus, some researchers have attempted to calculate the cost and/or profit values within PEs as an objective of PS. For instance, to calculate the objective of cots/profit, Rosen and Harmonosky [72] considered Work In Process (WIP), labor, machine, and tardiness costs, Moon et al. [104] and Gong et al. [147] considered electricity costs, and Zhang et al. [108] considered production operations costs and the cost related to due date performances. In fact, any PS problem could be transformed to a cost minimization/profit maximization problem by defining certain cost/profit metrics and combining them with scheduling-related decisions.

Tht: Throughput essentially refers to the number of jobs/operations finished by their due dates in a PS problem. In other words, maximizing is similar to a critical member of jobs with Tar equal to zero. For example, Frantzén et al. [98] calculated throughput as maximum theoretical system capacity minus actual throughput, and Bard et al. [119] calculated throughput directly and maximized weighted throughput.

CT: People in operations management typically refer to Cycle Time (CT) as the time from start to finish of operational work. While people from lean manufacturing typically refer to Cycle Time as the average time between two successive units exiting the work process. CT has often been used in the literature as the PS objective, as in [62,79,84,127], to name a few. Com/T and Mspan are used to calculate according to these descriptions.

FT: Flow Time (FT) refers to the mean flow time, which refers to the average time spent by the jobs/tasks/order in a specific production unit (e.recent workstation, line, plant, and fab). FT, similar to weighted CT, is one of the main factors that could support tactical and strategic decision-making in production units by providing high-level information. Yan and Wang [164], Korytkowski et al. [106], Lin and Chen [36] and Amiri et al. [144] are some examples of considering FT as a PS objective function within the literature of SOAPS.

Other: There are other objectives such as Number of Tardy Jobs (NTJ) [69,144], Utilization [99], and WIP [84,149]. Note that, as they have rarely been applied within the literature of SOAPS, here, we categorize them as Other.

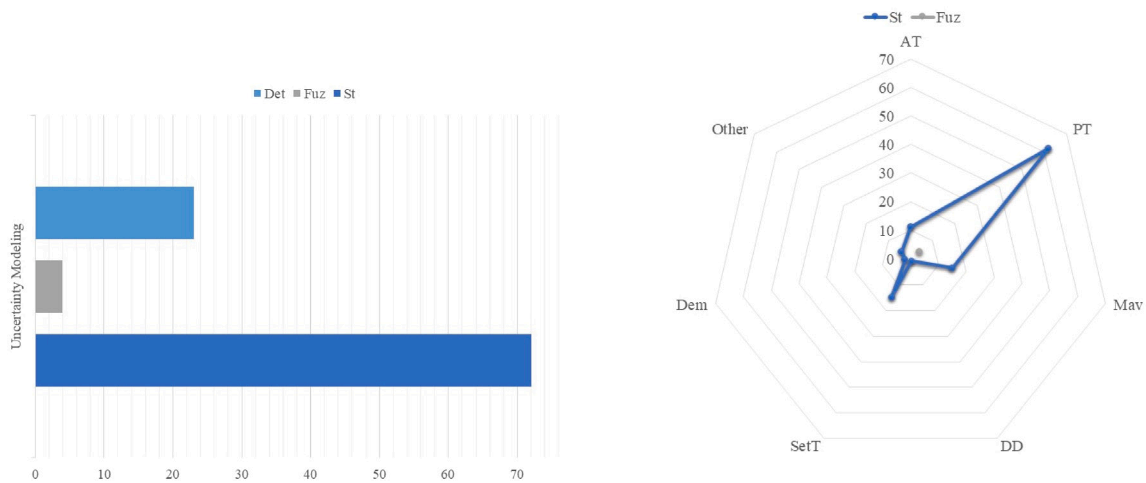
As shown in Fig. 8(b), within the articles studied, the objective function for single-objective PS problems has been mainly Mspan (37 pieces). However, in multi-objective PS problems, the frequency of Tar, Mspan, CT, Cost/Profit, FT, and Ea based objective functions are 16, 13, seven, seven, six, and five, respectively. To conclude, the analysis provided within this section on PE and objective characteristics is in line with **First Research Question**, which is addressed in the following.

JS and FS have been the most often considered PEs. On the one hand, one of the main reasons for this finding is that in the modern world, the desire for complex products has increased exponentially, requiring more complex production technologies and steps. On the other hand, SO methods are generally complicated and time intensive, limiting their usage to simple optimization problems that can be solved efficiently using more straightforward techniques. Accordingly, considering the high complexity of more attention that must be pampered to SM and PM scheduling, they are more appropriate to model modern production units. Moreover, tackling them using more complex optimization tools such as SO has been of interest.

Mspan has been the main objective considered within single-objective problems, while in multi-objective issues a variety of objectives have been presented by researchers. To justify it, we focus on the features of Mspan minimization. As mentioned previously, Mspan refers to the completion time of the last job to leave the system. Consequently, minimizing it indirectly reduces job completion times and improves machine load balance. In other words, the capability of Mspan minimization in improving other factors of a PS problem makes it a suitable objective for single-objective optimization problems.

4.2.2. Uncertainty

Uncertainty is an inseparable part of many production processes, and the source and modeling are described here. An important note here is that to consider the uncertainty within PS, there are factors that



(a) Uncertainty modeling. (b) Uncertainty source.

Fig. 9. Uncertainty source and modeling method used.

should be considered, such as the fluctuation significance of a production parameter/variable to decide whether it is uncertain. Moreover, PS problems are generally firmly NP-Hard, while adding uncertainty to them increases the complexity exponentially. Here, we analyze the literature of SOAPS based on uncertainty modeling strategies and uncertainty sources.

Accordingly, Table 3 highlights Uncertainty Source (s) (US) and the Uncertainty Modeling (UM) strategies considered within the articles retrieved in this research. Before analyzing this data, it is essential to discuss the differences between stochasticity and fuzziness as the main UM strategies.

Fuzziness describes the event ambiguity. It measures the degree to which an event occurs, not whether it occurs. Stochasticity (randomness) describes the uncertainty of the occurrence of the event. In fact, whether an event occurs is "Stochastic" and to what degree it occurs is "Fuzzy". Stochasticity is an objective form of indeterminacy whose distribution functions of random variables are deduced by application of statistical methods and fuzziness is a subjective form of indeterminacy that is distinguished by the degree of belongingness to a set [165]. Although almost all production events involve a certain level of uncertainty, due to specific reasons such as reducing complexity or the nonexistence of critical accuracy required forms; many researchers have solved PS problems in a deterministic structure.

To analyze the related information in Table 3, Fig. 9(a) shows the frequency of stochastic, fuzzy, and deterministic PS problems in the retrieved literature. Accordingly, in 72, 23, and four articles, the PS problems are considered Stochastic (St), Deterministic (Det), and Fuzzy (Fuz), respectively.

Within a PS problem, there are different parameters/variables that could be the source of uncertainty. Fig. 9(b) shows the frequency of the uncertain parameters/variables considered within the literature of SOAPS for both stochastic and fuzzy problems. Clearly, Processing Time (PT) has been regarded as an uncertain factor with stochastic and fuzzy PS with 56 and five articles, respectively. Furthermore, the other main stochastic parameters/variables considered are arrival time (AT), machine availability (MAv), and setup time (SetT) with 13, eight, and 17 references, respectively. In the following, the PS environments with uncertain parameters/variables are detailed.

PT: Processing times have been the most commonly considered part of uncertain PS problems, which refers to the amount of time spent on a specific process/operation/job. In fact, PT fluctuations have a great impact on several critical PS modules, such as dispatch strategies [120], since a slight change in the PT of an operation could make the entire production shift schedule plan infeasible. Several investigations such as [63,74,86,95,131,143,151,164] considered PTs stochastic within their PS problems. Other research modeled the uncertainty of PTs using fuzzy sets such as [93,97,123,138].

MAv: Availability of production sources such as machines is always a critical factor in PS. There are several reasons to change the state of a machine from available to unavailable, such as preventive or emergency maintenance and the unavailability of complementary sources (e.g., masks, filling materials, and labor). Hsieh et al. [62], Allaoui and Artiba [69], Gholami et al. [85], Goren and Sabuncuoglu [86], Yang [88], Frantzén et al. [98], Liu et al. [96], Zhang et al. [108], Kuck et al. [127], Nouiri et al. [130], Rahmati et al. [166] and Zhang et al. [153] are some examples of considering stochastic MAv within their PS problems.

DD: The due date of an order/job/operation essentially refers to its expected ready-to-deliver time. Several internal (e.g., condition change in dependent products) and external (e.g., customer decisions) factors could fluctuate the DD of an order/job/operation, directly and indirectly impacting PS decisions. Yang et al. [68] and Mokhtari and Dadgar [117] are examples of considering stochastic DDs in PS problems.

SetT: In PS, there are two types of setup times, sequence-dependent and sequence-independent SetTs. The sequence-dependent SetT refers to a certain amount of delay required to proceed from one process to the next for a specific reason, such as changing masks. While the sequence-independent, the sequence-independent SetT could occur for any reason unrelated to the process succession (e.g., setup after breakdown). Sivakumar [63], Gupta and Sivakumar [65], Gholami et al. [85], Korytkowski et al. [106], Kuck et al. [127] and Expósito-Izquierdo et al. [148] are some examples of considering SetT in the literature.

Dem: Within production systems, demand uncertainty of a specific product occurs for two reasons, which could be caused by internal and/or external events. Internal events are related to the manufacturing system, such as the expiration of an assembly part's inventory. Customer decisions are one of the most familiar examples of external demand uncertainty. Considering the literature of SOAPS, Löhndorf and Minner [103] and Löhndorf et al. [109] solved PS problems with demand uncertainty assumptions.

AT: Arrival time at a production step for an operation is a critical factor that influences the PS plan. There are several reasons, such as uncertainties in previous production steps that cause AT fluctuations. Yang [88], Mouelhi-Chibani and Pierreval [89], Shen and Yao [118] and Fu et al. [140] are some examples of considering AT uncertainties within the literature.

Other: There have been other uncertain factors influencing PS such as WIP [98], Job Insertion (JI) [82], and shipping times [124] that are considered within the Other category of uncertainty sources in this research.

To conclude, the information provided in this section on uncertainty modeling strategies and sources that address the **Second Research Question**, with the following summary. Most PS problems considered within the SOAPS literature have at least one uncertain parameter/variable (76 articles). It is worth mentioning that simulation models are essentially used to mimic production features in SO techniques applied to PS [51], where uncertainty is an inseparable part of most production systems. Thus, it seems logical to see that SO methods mainly solve PS problems with at least an uncertain parameter/variable. Within this context, PT has been the primary source of uncertainty within the SOAPS literature.

Considering that most PS problems are naturally firmly NP-Hard, adding uncertainty factors increases the complexity exponentially. Thus, most researchers intend to include uncertain elements within their PS problems, trying to keep it as simple and efficient as possible by choosing a limited number of uncertain parameters/variables, enabling them to solve their problems in a reasonable time. Between these uncertainty factors and parameters, PT is the primary source of uncertainty included in PS problems in many research articles [120,167]. Thus, we conclude that due to the complexity of uncertainty in PS problems, there is a limitation in proposing SO methods describing production systems in detail, a gap that could be addressed through possible solutions from Industry 4.0, such as the application of ML techniques to capture uncertainty, cloud computing to overcome lack of computing power and wider use of sensors to collect data.

Furthermore, it is important to recognize that in addition to the benefits of digitization, there are associated costs and vulnerabilities, commonly known as cyber risks. Therefore, while advancing the research landscape concerning the use of advanced Industry 4.0 technologies to solve PS problems within manufacturing systems, there is the need for an equal attention to cybersecurity strategies. An important aspect is the cyber resilience of these solutions to ensure robustness against potential threats.

4.3. Solution methodology (content analysis dimension 2)

The reviewed literature is examined in the previous sections based on production environments, problem objectives, and uncertainty strategies. This section focuses on analyzing the SO structure. As mentioned above, SO techniques mainly integrate a simulation model with an optimizer(s). Here, we examine the architecture of the optimization and simulation methods performed within the SOAPS literature. Then, their integration procedure to form SO techniques is studied. Finally, we highlight the existing gaps within this context.

4.3.1. Optimization type

There are two main categories to classify optimization techniques: global and local optimizers. Global optimization refers to finding the optimal value of a given objective function among all possible solutions. In contrast, local optimization finds the optimal value within the neighboring set of candidate solutions [168]. According to this definition, exact optimization methods, such as linear programming, are global optimizers, while heuristic and metaheuristic optimization techniques are local optimizers [169].

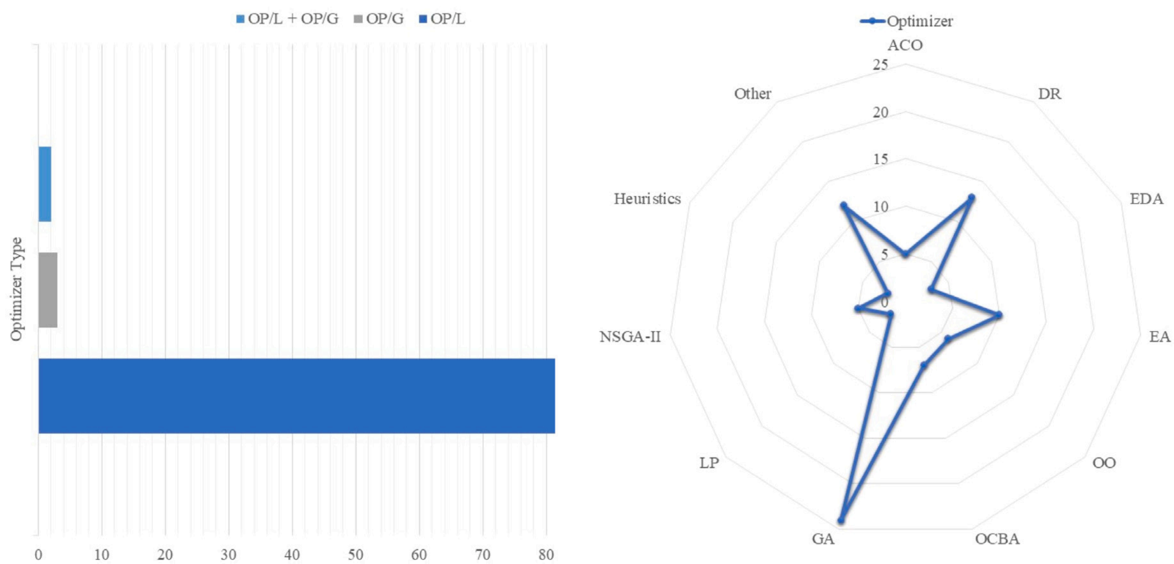
To examine optimization techniques within the reviewed literature, Table 3 classifies the optimizers used as local (Op/L) or global (Op/G). In addition, details on the type of optimizer(s) used in each SO method are defined. To examine these data, Fig. 10(a) shows the frequency of each optimizer type within the retrieved articles. As demonstrated, most optimizers are considered local (94 references). In contrast, in three papers, the optimizers are global, and in two, they are a combination of both local and global optimizers (OP/L + OP/G).

Fig. 10(b) shows the specific type of optimizer used in the SO methods. The genetic Algorithm (GA) has been the mainly used optimizer within SO methods (29 references). Accordingly, other optimizers such as Ant Colony Optimization (ACO), Dispatching Rule (DR), Estimation of Distribution Algorithm (EDAs), Ordinal Optimization (OO), Optimal Computing Budget Allocation (OCBA), Linear Programming (LP), Non-dominated Sorting Genetic Algorithm (NSGA-II), Heuristics, and Other Evolutionary Algorithms (EAs) are used five, 14, four, four, seven, two, four, two, and eight times, respectively. In the following, these optimization types are briefly discussed.

GA: Genetic Algorithms (GA) are randomized search algorithms that have been developed to mimic the mechanics of natural selection and natural genetics. GAs operate on string structures, like biological structures, that evolve according to the survival rule of the fittest by using a randomized yet structured information exchange. Therefore, in every generation, a new set of strings is created, using parts of the best members of the old group [170]. GAs with modified operators have been widely used as an optimizer within SO methods applied to PS problems, Kacem et al. [67], Wang et al. [74], Yan and Wang [164], Klemmt et al. [83], Korytkowski et al. [107], Lin and Chen [36], Fazayeli et al. [129], Jamrus et al. [138] and Negri et al. [150] are some examples of such applications.

ACO: Ant Colony Optimization (ACO) is based on the natural behavior of ant colonies and their worker ants. When ants forage, they naturally find a logical and practical route between their nest and the food source. In other words, they determine an optimum way. This behavior is the basis of ACO [171]. According to Bianchi et al. [171], the ACO algorithm contains three main steps that make up the central optimization loop of the algorithm: (1) Construction of ant solutions, which is a procedure in which 'ants' incrementally create paths, i.e., solutions in the broader optimization context. (2) Evaporate pheromone is a process in which the pheromone for specific solutions is decreased using local information; therefore, this step is also often referred to as local update. (3) Daemon actions, a step that refers to decisions made based on global information relating to the optimization problem. These three steps are repeated until the optimization problem has converged or is otherwise terminated via a specified termination condition. To address PS problems using SO methods, some research, such as [87,91,100,120] used ASO as an optimization tool.

DR: Dispatching Rules (DR) have been used as solution tools for many problems of theoretical and practical relevance. They are generally simple rules (e.g., operation with the Shortest Processing Time (SPT) starts first) designed explicitly for a PS problem aiming to optimize an objective(s). Various multi-attribute dispatching rules have been developed to allocate tasks to the appropriate sources, using mainly mathematical modeling, queuing networks, and simulation to evaluate them. They have been applied primarily in manufacturing, and only a few implementations can be found in container terminals and warehousing [172]. DRs have been integrated within SO methods to tackle PS problems in various research such as [69,73,76,102,123,127,136].



(a) Optimizer type: Local or global. (b) Specific type of optimizer used.

Fig. 10. Optimizer type and specific optimizer used.

EDA: Estimation of Distribution Algorithms (EDA) are evolutionary algorithms that work with a population (P) of candidate solutions. An initial P is generated, and its members are evaluated using the objective function. Those with better function values are selected to build a probabilistic model of P, and a new set of points is sampled from the model. The process is iterated until a termination criterion is met [173]. In some research, EDA has been used as the optimization strategy within SO methods to solve PS problems, such as [105,110,132].

OO: Within Ordinal Optimization (OO), instead of optimizing problems in the global solution space Θ, OO is divided into two phases [174]. In the first phase, a sample set of solutions Ψ is selected from the global space, with the solutions ranked using a solution method with a short computation time. In the second phase, a smaller set of solutions is selected from Ψ and optimized using a longer computation method. The aim is to find the optimal or, if not, the best set of solutions from Θ with the shortest computation time. OO has been used as the basis for designing SO methods to tackle PS problems in some research such as [62,72,79,111,151].

OCBA: Optimal Computing Budget Allocation (OCBA) is used when limited computing availability is allocated to different optimization solutions. Consequently, in OCBA, more computation budgets are assigned to solutions with more potential to achieve the optimal point [111]. To solve PS problems using SO methods, OCBA has often been implemented within the second phase of OO, as in [71,111,132,151].

LP: An essential element of Linear Programming (LP) models is the set of assumptions required. These assumptions are linearity, certainty, and continuity. It is optional to assume a single objective, although it must be realized that the optimal solution obtained is only optimal with respect to the function used as the objective. LP methods require the assumption of certainty. If coefficients involve some risk, this introduces a form of non-linearity. Stochastic programming is a form of nonlinear programming where the non-linearity is due to uncertainty in model coefficients [175]. The Chance Constrained Method (CCM) is a specific form of stochastic programming in which constraints are viewed as satisfying a specified proportion of time. In fact, CCM enables LP to solve stochastic problems at a specific confidence level. Sivakumar [63] and Kulkarni and Venkateswaran [112] are examples of using LP as the optimization core within SO methods to solve PS problems.

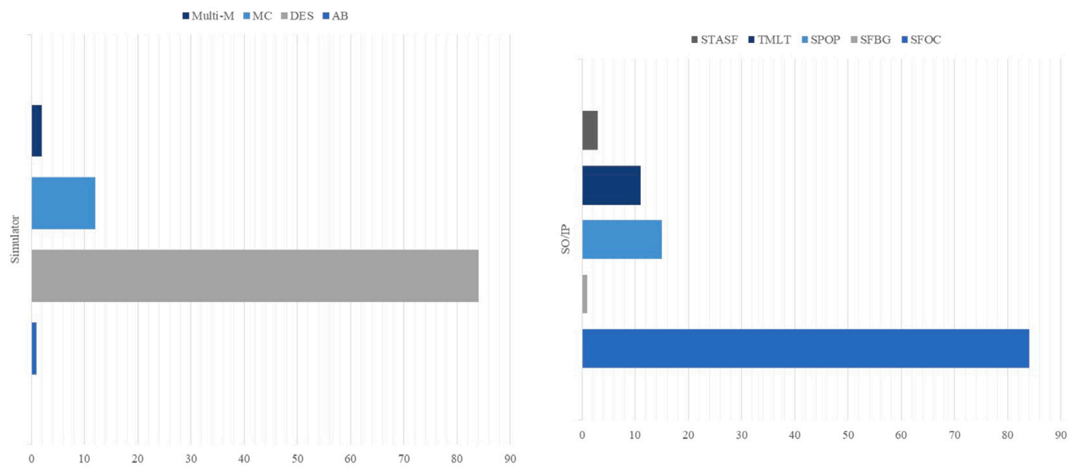
NSGA-II: Non Dominated Sorting Genetic Algorithm (NSGA-II) is one of the most popular multi objective optimization algorithms with three special characteristics: fast non-dominated sorting approach, fast crowded distance estimation procedure, and simple crowded comparison operator [176]. To solve PS problems, Liu et al. [96], Lang and Li [95], Ahmadi et al. [128] and Rahmanidoust [134] used NSGA-II within the context of SO methods.

Heuristics: Heuristic algorithms approximate the global optimum to find a satisfactory solution. Heuristics are essentially novel rules derived from the nature of an optimization problem to obtain the optimal or near-optimal point [177]. Azzi et al. [99] and Morady Gohareh et al. [114] are two examples of designing heuristic algorithms integrated within SO procedures to solve PS problems.

EA: Evolutionary Algorithms (EAs) are efficient heuristic search methods based on Darwinian evolution with powerful characteristics of robustness and flexibility to capture global solutions of complex optimization problems. Using EAs, the probability of finding a near optimum in an early stage of the optimization process is very high [178]. Both GA and ACO are EAs, which are detailed above. Here, all other EAs are classified within the EA category. Accordingly, Shen and Yao [118], Yang and Gao [137], Fu et al. [140], Fu et al. [145] and Ghasemi et al. [151] are some examples of the development of EAs as optimizers within the SO structure to solve PS problems.

To conclude, the information provided in this section on the type of optimizer integrated within SO methods to address PS problems is used to address the **Third Research Question**, detailed below.

Local methods have been the main optimizers used for SO methods to solve PS problems. The main reason to justify it lies in the fact that the majority of PS problems are highly complex (mostly NP-Hard),



(a) Simulator type.

(b) SO integration.

Fig. 11. Simulation type and SO integration.

thus global optimizers are not capable of solving them in a reasonable amount of computational time, resulting in the use of local optimization methods (i.e., sacrificing accuracy for computation feasibility).

GA has been the most widely used optimizer within SO methods to tackle PS problems. GA has a special architecture consisting of chromosome-based solutions and highly flexible operators, making it a suitable choice for any large-scale optimization problem with just a few modifications from the original format. These could clearly justify the considerable interest in using GA as the optimization core within SO structures to tackle PS problems.

One of the key elements to enhance the reactive/proactive scheduling plans within a manufacturing system is to perform dynamic optimal decisions (e.g., using mentioned optimization techniques). This requires an efficient data exchange, sharing, and processing procedure between the system being controlled and the decision making tools. On the other hand, within smart manufacturing systems, the concept of smart agents has recently been proposed [179]. This refers to computer agents replacing humans in decision making procedures, optimizing PS in our case. Such advances also require a well-developed data sharing and processing system within manufacturing systems. Thus, it is essential to examine the required features of optimization cores to be integrated efficiently within the advanced data sharing and processing systems; however, it has not yet been addressed. This is also essential for manufacturing systems that aim to use SO as a tool to move toward Industry 4.0 [54]. Accordingly, in Section 5, we highlight some possible paths to address this gap within the context of Industry 4.0.

4.3.2. Simulation type

In the past, simulation models were classified into one of the following categories: Monte Carlo (MC), Discrete Event (DES), and Continuous Event [180]. Recently, the need to consider unique composition and complex relationships of individual entities within models has motivated researchers to use a new class of simulation models named Agent Based (AB) models [181]. In addition, there are also examples of where multi-simulation methods are used, which we denote as Multi-Method Simulation (Multi-M).

Table 3 shows the type of simulation model used in each retrieved article (see the Sim column) in this research. Accordingly, to analyze this data, Fig. 11(a) shows the frequency of using each simulation type. As shown, DES models have been the main used technique with 87 references using this simulation type. Moreover, MC, AB, and Multi-M methods are used within nine, one, and one research papers, respectively. In the following, all mentioned terms are detailed.

MC: Monte Carlo (MC) simulation methods can be used to numerically evaluate the expectations of functions of random variables (e.g., posterior moments of parameters of interest) for which no analytical expressions are available. They consist of generating lucky draws from the relevant distribution and replacing expectations by arithmetic means across such draws [182]. In several articles, MC has been used as the simulation type to tackle PS problems such as Azzi et al. [99], Hao et al. [105], Löhndorf and Minner [103], Marichelvam et al. [113], Yang et al. [111], Mokhtari and Dadgar [117], Fu et al. [141], Peng et al. [143] and Ghasemi et al. [151], to name a few.

DES: Discrete event simulation involves tracing the state conditions of processes over time. This form of simulation is perfect for modeling input details and identifying detailed system outputs. DES is entity driven, with entities typically representing orders arriving at some service facility or a job coming at a manufacturing machine [183]. DES has been widely implemented within SO methods to tackle PS problems such as in [66,67,74,75,80,82,92,101,119,133,150,152], to name a few.

AB: An Agent-Based (AB) simulation model refers to a computer model that consists of a collection of agents/variables that can take on a group of states. The state of an agent at a given point in time is determined through an array of rules that describe the agent's interaction with other agents. These rules may be deterministic or stochastic. The agent's state depends on the agent's previous state and the state of a collection of other agents with whom it interacts [184]. Expósito-Izquierdo et al. [148] is an example of using AB simulation models within the structure of SO methods to solve PS problems.

Multi-M: Multi-Method (Multi-M) simulation models are designed to integrate different modeling and simulation methods to overcome the drawbacks of individual approaches and obtain the advantages from each type. Within the literature, Fu et al. [140] is an example of using Multi-M simulation by using DES and AB models within a simulation structure.

The information provided here documents the simulation type integrated within SO methods to tackle PS problems and deals with the **fourth Research Question**. The following points are highlighted in the above description. DES has been the primary simulation approach used within SO methods to tackle PS problems. This is because PS problems practically involve operational decision-making within a short-term planning horizon. DES is a well-known tool for short-term to mid-term decision-making. This makes DES an appropriate tool to deal with PS problems.

AB simulation is a new approach to simulating systems with interacting autonomous agents. AB models have been used mainly to simulate interactions of autonomous agents to identify, explain, generate, and design emergent behaviors. Considering the digital transformation caused by Industry 4.0 applications in manufacturing sectors, AB simulation is an essential tool for creating and improving Business Models (BMs) by examining interactions of agents (machines, people, and processes) in a business that implements digitization. Although PS modules within manufacturing companies are one of the sectors mainly influenced by Industry 4.0, considering the above analysis, AB or Multi-M that includes AB simulation [57] have rarely been used within SO procedures to tackle PS problems [185,186]. It is an open research area to explore.

4.3.3. Integration type

Another critical factor within SO methods is the integration of simulation and optimization. This refers to how the simulation and optimization cores are connected to each other to form an SO method.

Table 3 shows the SO Integration strategy in the SO/IP column. To analyze this data, Fig. 11(b) provides information on the frequency of SO/IP approaches in the reviewed articles. Accordingly, Simulation For Objective Calculation (SFOC) has been the main SO/IP approach used with 86 references. Moreover, Simulation To Analyze Solution Feasibility (STASF), Training Machine Learning Tool (TMLT), Simulation Providing Optimization Parameters (SPOP), and Simulation For Bound Generation (SFBG) have been referenced in five, nine, 11, and one articles, respectively. In the following, we provide a brief overview of these approaches.

SFOC: In this category, simulation models are used to calculate the objective value(s) within the optimization procedure. This could occur within either an iterative or a sequential basis. There are several articles that use this strategy such as [36,67,69,73,76,83,91,99,104,109,125,138,144,150,151,164], to name a few.

STASF: This strategy is mainly useful where the optimization procedure ignores some critical constraints (assumptions) due to its complexity. Then, the simulation model checks the feasibility of the solution(s) obtained considering all critical assumptions and constraints. Werner et al. [187], Azadeh et al. [93], Lang and Li [95] and Frazzon et al. [124] are some examples that use STASF within their SO architecture to tackle PS problems.

TMLT: In this strategy, SO methods benefit from ML tools by replacing some of their modules with a trained ML tool. In other words, ML tools help SO methods by reducing the computation intensity and/or enhancing the quality of the solutions. For example, Ghasemi et al. [151] used an ML tool to replace simulation replications within their SO method to reduce the computation time intensity of their SO method. Priore et al. [76], Mouelhi-Chibani and Pierreval [89], Azadeh et al. [93], Shahzad and Mebarki [101], Azadeh et al. [123], Nasiri et al. [133] and Waschneck et al. [136] are some examples of TMLT in SO methods applied to PS problems.

SPOP: This refers to a group of SO methods where the simulation module mainly provides problem parameters. Then, the optimizer is implemented on the parameterized problem. This procedure could occur sequentially or iteratively within the architecture of the SO method. Gupta and Sivakumar [70], Kulkarni and Venkateswaran [112], Shen and Yao [118], Fazayeli et al. [129], Nouiri et al. [130], Expósito-Izquierdo et al. [148] and Zhang et al. [153] are some examples of implementing SPOP-based SO methods to PS problems.

SFBG: In this strategy, the simulation model is executed to generate upper and/or lower bounds of an optimization problem. This enables the optimizer to be utilized in a more targeted manner within the solution space. Klemmt et al. [83] is an example of using the SFBG strategy within the SO method developed to solve PS problems.

The material reviewed here addresses **fifth Research Question**, with the following summarizing the above description. Within the architecture of most SO methods applied to PS problems, the optimization core is used to explore different solutions, while the simulator is executed to calculate the fitness value for each solution (SFOC). One of the main advantages of such integration is that it guarantees the practical efficiency of SO results, since simulation models are essentially built to reflect real-world environments, ensuring the quality of solutions evaluated by them. Another advantage lies in the integration simplicity, since in SFOC the information trade-off between optimizer and simulator occurs at just one point, which is the fitness calculation.

Computational complexity of detailed (accurate) manufacturing simulation models are usually considerably high. This causes in most SFOC research works in sacrificing the accuracy (reducing simulation replications) for obtaining solutions in a reasonable time (e.g., [99,144]). Another approach has been the use of TMLT strategy to use trained ML tools (simulation metamodels) instead of detailed simulation models. For instance, recently, Ghasemi et al. [151] proposed a novel SO algorithm named Evolutionary Learning Based Simulation Optimization (ELBSO) and applied it to a Stochastic Job Shop Scheduling Problem (SJSSP). ELBSO is developed based on the Ordinal Optimization (OO) Theorem for solving complex optimization problems in two main phases. In the first phase of ELBSO, sets of solution vectors are improved using an evolutionary optimization procedure integrated with a pre-trained ML-based metamodel (Genetic Programming (GP) with supervised learning strategy is used as the ML tool in their research). GP was used as an ML tool, as it performed well in previous applications to metamodel simulation models of complex systems, such as in the research by Can and Heavey [188]. In the second phase, a large number of simulation experiments are implemented to the improved solutions from the first phase. Their results showed a huge amount of execution time efficiency while keeping the final solution's quality, caused by integrating the ML-based simulation metamodel within the architecture of the SO algorithm. This research work was the first attempt to design such a TMLT strategy to tackle SO's computational complexity issues in solving PS problems. Thus, a gap exist in integrating other ML methods within the ELBSO. Moreover, modifying the architecture of ELBSO itself is another interesting research path to explore.

4.4. Experimenting validation strategy (content analysis dimensions 3 & 4)

Another challenging step in designing an SO method to address PS problems is experimentation and validation. In this section, the considered strategies for experimenting and validating SO methods applied to PS are discussed. In addition, related case studies within the literature are examined.

Table 3 defines the experimentation (validation strategy) for each article in this investigation. To examine this data, Fig. 12 shows the frequency of using each validation strategy within the retrieved articles. These we classify into, Case Study, Comparison With Literature Methods (CWLM), Comparison With Standard Metaheuristics (CWSM), and Statistical Tests (StT), with these being used as the main utilized validation strategies with 36, 25, 15 and 24 references, respectively. Moreover, other strategies such as Solving Standard Problems from Literature (SSPL), Comparison With Exact Solutions (CWES), Comparison With Dispatching Rules (CWDR), and Comparison With Lower Bound (CWLB) are referenced in six, three, seven, and one articles, respectively. The mentioned terms are detailed in the following:

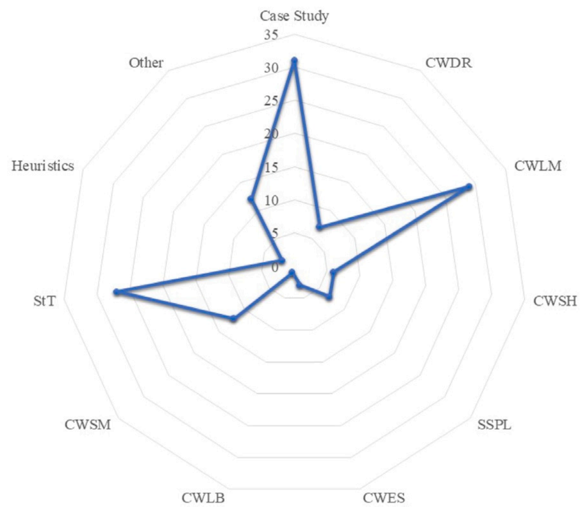


Fig. 12. Validation strategies.

Case Study: As previously mentioned, PS is one of the main challenges in many industries. Table 3 details where case studies (real applications) were used to validate SO methods for PS. Semiconductor manufacturing is the main type of manufacturing system covered for applying SO methods to PS problems, with Hsieh et al. [62], Sivakumar [63], Gupta and Sivakumar [65], Rosen and Harmonosky [72], Gupta and Sivakumar [70], Ang and Sivakumar [78], Zhang et al. [84], Yang [88], Liu et al. [96], Hao et al. [105], Lin and Chen [36], Kuck et al. [127], Aurich et al. [125], Waschneck et al. [136] and Jamrus et al. [138] being some examples of implementing SO methods. Moreover, SO has been applied to other industrial PS problems such as in the automotive industry [98,102], cardboard industry [82], ceramic industry [68,93], cylinder manufacturing [143], food industry [122], textile industry [93], steel manufacturing [110, 121,132], and pharma [94].

CWSM: There are several well-known metaheuristics available to solve optimization problems, such as GA and ACO. Accordingly, articles that use Comparison With Standard Metaheuristics (CWSM) compare their SO method(s) with the results of well-known metaheuristics are categorized within this experimenting classification. Wang et al. [74], Wang et al. [71], Chong et al. [77], Gu et al. [92], Marichelvam et al. [113], Pérez-Rodríguez et al. [110], Shen and Yao [118], Yuan et al. [131] and Rahmati et al. [166] are some examples that use this approach to validate their SO methods applied to PS problems.

StT: Statistical Testing (StT) has always been an alternative to validate experiment results, especially methods such as hypothesis testing, regression, Design Of Experiments (DOE) and sampling [189]. Many StTs have been utilized to validate SOAPS, such as Chong et al. [77], Xing et al. [190], Gholami et al. [85], Shahzad and Mebarki [101], Mokhtari and Dadgar [117], Horng and Lin [120], Rahmanidoust [134], Fu et al. [140], Fu et al. [135] and Gheisariha et al. [152], to name a few.

SSPL: Solving standard PS problems and benchmarks has always been a standard method to validate optimization results. Consequently, articles that use Solving Standard Problems from Literature (SSPL) [64,89,91,96,112,124] are some examples of validating SO methods applied to PS using benchmarks and standard PS problems.

CWES: SO methods are applied to large-scale PS problems that are not typically solvable using exact solvers in a reasonable time. However, it is always of interest to see how an SO method performs on small-sized instances in comparison with exact results, which we denote the Comparison With Exact Solution (CWES). Finke et al. [66], Klemmt et al. [83] and Zhang et al. [108] are articles that validate SOAPS results by comparing them with exact solutions.

CWDR: Another method to validate SO methods applied to PS is to compare the results with the Comparison With Dispatch Rules (CWDR). Hsieh et al. [62], Hsieh et al. [79], Zhang et al. [84], Balin [97], Azzi et al. [99], Löhndorf and Minner [103] and Löhndorf et al. [109] are some examples of validating SO results in solving PS problems with DR-based scheduling results.

CWLB: Although discovering lower bounds for PS problems is not a simple task, comparing the difference of the SO solutions with the lower bounds is a logical method to validate them, which we denote as Comparison With Lower Bound (CWLB). Kacem et al. [67] is an example of using lower bounds to evaluate SO solutions for PS problems.

CWLM: All research that compares SO results in solving PS problems with results reported within the literature is classified in this category, Comparison with Literature Methods (CWLM). Benmansour et al. [191], Zribi et al. [80], Goren and Sabuncuoglu [86], Azadeh et al. [93], Azadeh et al. [90], Nicoară et al. [94], Kaban et al. [102], Hao et al. [105], Xu et al. [53], Nasiri et al. [133], Lin et al. [159] and Gheisariha et al. [152] are some examples of comparing SO results with methods extracted from the literature.

To conclude the information provided in this section on SOAPS experimentation and case study applications, addresses the **Sixth and Seventh Research Questions**. Most researchers have used real PS case studies to validate their proposed SO methods, with semiconductor manufacturing being the most common industry.

The following points are provided to highlight the importance of both semiconductor manufacturing in the modern world and optimizing PS in semiconductor manufacturing. Semiconductors lead to the transition of the 21st century to an information society by triggering new innovations in Industry 4.0, such as 5G Networks and the industrial IoT [192]. On the other hand, PS modules are one of the most crucial elements in bringing efficiency to semiconductor manufacturing systems [14].

5. SOAPS in the era of Industry 4.0

In this section, we discuss the opportunities to enhance the existing research on SOAPS using Industry 4.0 methods. In practice, production facilities are dynamic and subject to several disruptions, unforeseen events, and uncertainties. Examples of such disruptions and uncertainties are discussed within Section 4.2 (e.g., random processing times, arrivals, order cancellations, random machine breakdowns, and due date changes). One goal of Industry 4.0 is to enable schedules to be adapted to such events by performing rescheduling on a continuous basis, using real-time information on a manufacturing system. This is the basis for real-time reactive scheduling. However, adding predictive models to this strategy leads to proactive scheduling. This level of connectivity and real-time information sharing can be achieved with the help of advanced Industry 4.0 technologies such as CPS, IoT, and Internet of Services (IoS) [193,194]. To fully realize the potential of such technologies, decision models that can utilize real-time information should be present in all aspects of the manufacturing process. This includes PS, which is a core component of the manufacturing process, as discussed above in Section 1. A key tool here is a manufacturing simulation model that enables real-time production monitoring and information visualization. This refers to the recently established concept of a Digital Twin (DT). Accordingly, a DT encompasses a simulation model built on a virtual environment (i.e., a cloud) visualizing and monitoring the real-time captured production information (Data). Within this context, DT is supported by IoT-based data capture and acquisition (using in-field sensors), cloud computing and CPS technologies.

An important component to achieve the above is to develop efficient exchange of data to/from a system with a DST. An important concept here is the data pipeline designing. Data pipeline design is a formalized process of creating a series of steps or stages for extracting, transforming, and loading data from various sources to a destination for further analysis or storage. It is a key aspect of data engineering and involves the integration of data management, data processing and data integration techniques [195]. Recently, researchers have designed different data pipeline architectures for DTs in manufacturing systems (e.g., [196,197]). On this topic, [198] proposes an efficient Application Programming Interface (API) for manufacturing DTs with the following components:

- A Driver: a hardware/software machine adaptor that handles communications using IoT between the physical field controller and the network.
- A Database: recording the transactions between the system and the virtual machine.
- A Generic Machine Access Library (GMAL): a set of API functions which allow end-users to build third-party applications impacting the field (e.g., an online simulation tool such as DT).

Within these elements, database design plays a key role in providing computationally feasible data sharing infrastructure, especially in the case of online decision making for complex manufacturing systems [198]. Angrish et al. [198] compared alternatives for designing a MongoDB database to simulate the additive manufacturing process. However, there is still no research examining an optimal database design for online reactive/proactive scheduling in manufacturing systems using DTs and/or SO methods.

In general, there is no research examining the data engineering aspects (e.g., data pipeline and database designing) of PS in manufacturing systems using online DSTs such as DTs and/or SO methods. Therefore, we highlight this as one of the main research paths to be explored.

After designing the required data sharing infrastructures, the next desirable phase would be to upgrade such a DT to enable it to interact with the production unit by acting as a DST. To do so, two main add-ons are required: 1- A decision-making element that predicting future production events using the obtained data and providing optimized scheduling decisions; 2- A physical side that implements the optimized decisions from the brain core to the field.

One possibility is that such an add-on could be established using an integrated ML optimization tool, where the ML tool assists the online simulation tool by being trained from the captured data and predict the future status of the production system. Moreover, the optimizer could provide optimized reactive/proactive rescheduling decisions considering the current state visualized by the simulation model and the predicted events performed by the ML tool. That is an integrated ML-based SO tool. An example of such decision making tools for PS problems is proposed by Ghasemi et al. [151]. In this article, an Evolutionary Learning Based Simulation Optimization (ELBSO) method within Ordinal Optimization was presented for a Stochastic Job Shop Scheduling Problem (SJSSP). A novel aspect of the ELBSO method was the use of an ML-based meta model (Genetic Programming (GP)) as part of the solution procedure that resulted in fast execution, which could allow this solution method to be used as a real-time decision support tool. In fact, ELBSO is one of the first attempts by researchers to design ML-based SO methods for PS problems. That is one of the key paths to explore within this research domain.

The second add-on is provided by IoT. IoT assures that all related devices and units are connected to the DT, while all decisions from DT could directly influence the production system in real-time. Indeed, designing and executing such a DT-based DST requires a huge amount of effort from computing resources. In recent years, there has been some research attempting to design such an online smart DST framework. For instance, Negri et al. [150] designed an on-cloud DES model from the captured data from CNC machines using IoT in a research lab in Italy. They integrated a GA based optimizer within their DT framework to provide optimized future decisions. Using IoT, they also implemented their optimized decision on the CNC machines. However, there is a significant lack of standardization for such approaches as they are considerably new. Thus, here, we would like to direct attention towards the new emerging generation of SO methods which use Industry 4.0 such as cloud computing.

Another research topic is AB simulation. AB Simulation offers a decisive asset that facilitates modeling of complex systems and provides assistance to manufacturing systems in the implementation of targeted and effective strategies [199,200]. Within the scheduling context, both the scheduler and the scheduled element can be defined by agents. In other words, an agent, within a simulation model, is capable of simulating the behaviors of the decision-maker (scheduler), while, another agent simulates the behaviors of the object in reaction to the decision maker's decisions. The design for each of these agents are different due to their different functionalities within the manufacturing system. A potential research path lies in examining different designs for such agents to be integrated within SO methods in solving PS problems.

A critical aspect within the context of SOAPS in the Industry 4.0 environment is Cyber Resilience. Corallo et al. [16,201] emphasize that cyber-attacks targeting manufacturing systems can result in a range of detrimental business consequences. These include severe impacts such as (i) disruption of critical infrastructure or the compromise of key machines and components, (ii) disruption of network and computer services, (iii) theft of invaluable industrial trade secrets and intellectual property, (iv) breaches of safety and environmental regulations, and (v) even posing life-threatening risks to workers. Such complex scenarios can cause disruption of existing PS parameters within manufacturing systems, resulting in substantial financial losses while restoring normal operations, which leads to a decrease in productivity. Another crucial concept within this domain is Data Governance in manufacturing systems referring to the systematic management and control of data assets, encompassing policies, processes, and standards to ensure data quality, integrity, security, and compliance. The strategic integration of governance should effectively navigate the value chain for manufacturing system stakeholders, balancing benefits, risks, and resources to optimize business process goals, particularly within the context of information security as defined by industry standards such as ISO27001 [202] and COBIT 5 [203] throughout the information lifecycle. As the design of innovative SO solutions for PS in manufacturing systems discussed in this research, we would like to draw attention to the paramount importance of incorporating robust cyber security and data governance measures to enhance the robustness in manufacturing system data/information infrastructure. This area of research within the context of SOAPS is very much open for further research.

Finally, we highlight that modern manufacturing is all about supply chain-supply chain competition between different companies [204]. Thus, an improvement within either the plant or workstation level (e.g., using the above-mentioned SOAPS in the Industry 4.0 direction) does not benefit a manufacturing company unless it enhances the supply chain competences. Surprisingly, as is discussed in the previous section, almost all research within the SOAPS domain mainly focuses on a single system, focusing mainly on a workstation or a plant, with a lack of analysis in terms of hierarchical integration, as shown in

Fig. 1. On the other hand, implementing the technologies and ideas mentioned above potentially enhances the level of integration between different decision-making levels by providing a higher level of data integration between different elements within the value chain. However, as supply chain systems span multi disciplines there is also a need for tools such as Model-Based System Engineering methodologies as demonstrated in [205]. Such methodologies will be necessary for the development of online data sharing infrastructure, scheduling decisions at the supply chain level (strategic), plant level (tactical), and workstation level (operational) allowing for better integration. This integration enables decision makers at the supply chain level to have an accurate/detailed overview on both tactical and operational states as demonstrated in Section 1. Therefore, a potential research direction is exploring hierarchical PS using SO and Industry 4.0 methods within value chains.

6. Conclusion

In this article, a systematic review of SO methods applied to PS problems has been conducted. It initially examines the existing review articles related to SOAPS, and highlights the research gaps. The article then employed a methodology to conduct a comprehensive and systematic content analysis. A four dimension taxonomy was designed for this review: 1- Problem and Modeling; 2- Solution Methodology; 3- Experimenting; 4- Real Applications. Within each dimension, related subcategories are discussed and used to analyze the content. The main contribution of this current review is that, for the first time, it provides a detailed analysis on SOAPS-related concepts such as production environments, uncertainty modeling strategies, optimizers, simulators, SO integration architectures, validation methods, and case studies.

This article found that JS production, Makespan objective function, and stochastic randomness are the main features of PS problems considered within the SOAPS literature. Moreover, local optimizers, GA, DES, and SFOC are the concepts used mainly within the architecture of SO methods applied to PS problems. We also found that the majority of articles used case studies to validate their proposed SO methods applied to PS, where semiconductor manufacturing is the most widely used case research. The article shows clearly that the literature since 2018 has incorporated Industry 4.0 concepts (see Fig. 7), such as smart manufacturing, digital twin, big data, with the goal of developing scheduling systems to act more intelligently to react to disruptions. Lastly, in Section 5 we also highlighted some future directions on how Industry 4.0 could improve the efficiency of SO methods in addressing industrial PS problems in modern production systems.

The research is limited in that it was focused on the application of SO applied to production scheduling (i.e. SOAPS), with the review carried out between 2000 and 2022 using Google Scholar and Web of Science. Production scheduling, however, is an essential part of a supply chain scheduling, as shown in Section 1.

As stated, DT stands as one of the main outcomes of Industry 4.0 technologies, particularly within the domain of manufacturing systems digitization. As a sophisticated replication of physical assets, DT incorporates sensor data, simulation models, and real-time analytics to provide a virtual representation of the manufacturing environment. This convergence of digital and physical dimensions empowers Industry 4.0 manufacturing systems with predictive capabilities, fostering an efficient reactive/proactive approach to manufacturing and supply chain resilience [206]. However, the interoperability of DT subsystems such as data pipelines, simulation cores, and optimization modules, faces challenges arising from diverse data formats, communication protocols, and semantic interpretations across interconnected systems (e.g., ERP and MES systems), taken into account cyber security and data governance issues. On the other hand, DT synchronization in manufacturing systems encounters different challenges, such as real-time alignment of virtual and physical entities and integration with existing decision-making tools. Therefore, the development of standardized frameworks, common data models, and robust SO modules is necessary to establish a well-synchronized and interoperable DT in supply chain and manufacturing systems. Consequently, in order to enhance the level of standardization within this domain, this review article comprehensively examined the SO architecture to address PS manufacturing problems (SOAPS) in the context of Industry 4.0.

CRediT authorship contribution statement

Amir Ghasemi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Fatemeh Farajzadeh:** Data curation, Formal analysis. **Cathal Heavey:** Funding acquisition, Project administration, Writing – original draft, Writing – review & editing. **John Fowler:** Supervision, Writing – original draft. **Chrissoleon T. Papadopoulos:** Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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