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Systematic Review

Scheduling and Controlling Production in an Internet of Things Environment for Industry 4.0: An Analysis and Systematic Review of Scientific Metrological Data

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Abstract: To review the present scenario of the research on the scheduling and control of the production process in the manufacturing industry, this comprehensive article has extensively examined this field's hotspots, boundaries, and overall evolutionary trajectory. This paper's primary goal is to visualize and conduct an organized review of 5052 papers and reviews that were published between 2002 and 2022. To reveal the "social, conceptual, and conceptual framework" of the production area, identify key factors and research areas, highlight major specialties and emerging trends, and conduct research, countries, institutions, literature keywords, etc., are all used. Additionally, research methodologies are always being improved. The aim of this work is to explore more references for research implementation by analyzing and classifying the present research status, research hotspots, and potential future trends in this field of research.

Keywords: CiteSpace; scientometrics; visualization; scheduling; control; manufacturing; job shop; lean construction

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1. Introduction

1.1. Background Information

"Industry 4.0 and smart manufacturing" are terms that play a major role in the "digitization", "process automation", and "the growing use of information and communications technology (ICT)" [1]. The term "Industry 4.0" means "Information and communication technology" is evolving quickly, and many disrupting tools have emerged, which influence the manufacturing industry through the use of "cyber-physical systems", at a time when market complexity and competition, as well as pressure to reduce costs and environmental impact, are all rising quickly. The industry is willing to look for more integrated solutions to realize the full economic potential of the entire production chain, while functioning sustainably and in accordance with environmental standards as a result of this driving force.

However, due to the increasing size of workshop production and increasingly fierce competition, managing the process production and integrated decision-making to achieve energy-savings, output maximization, and cost-efficient production is becoming a hot research topic. From the theoretical level, scheduling in job shop production [2] is a significant "decision-making process". For example, in a job shop method, the production rate must be well-decided to ensure the required tools, supplies, resources, workers, etc., are accessible when needed for the timely completion of the job. So, the scheduling goal is to assign a few resources to activities throughout time in the most effective way possible, ensuring that needs are satisfied and operations are successful. Scheduling problems can be modeled using the constraints and characteristics of the process, and several objective functions (such as profit maximization or makespan minimization) can be provided [3,4].

It is thus possible to determine the best task sequencing and resource allocation.

The "Job Shop Scheduling Problem (JSP)" is an optimization tool [5], having aims to find the best order of jobs to be performed on a group of machines, each of which is specially equipped to carry out a particular operation. The goal is often to reduce factors such as makespan, maximum tardiness, etc. The JSP considers that jobs may have diverse machine sequences, leading to an exponential number of possible schedules, in contrast to its specific instance. The "Flow Shop Scheduling Problem (FSP)" process control is also a type of decision-making that modifies the operating parameters of a process to regulate the qualitative characteristics of work streams. Maintaining constant quality parameters or monitoring time-varying set points for these metrics presents a challenge that may require modifying inputs and process variables. All large firms recognize the importance of advanced control techniques for energy conservation, throughput maximization, and cost-effective production as they continue to gain momentum across all industries. Additionally, because the two theories were developed independently, there is still a study gap in smoothing integration in job shop production, despite the recent focus of an increasing number of academics on the assimilation of "scheduling and control". The number of theoretical and empirical works on SC-related subjects has significantly increased. A sizeable corpus of research literature has been amassed on this topic since the first papers were published in the late 1970s. However, these assessments concentrated on specific viewpoints. In this paper, we attempt a thorough analysis of articles that were published between 2002 and 2022. Additionally, this review has been updated. This article is categorized into the following sections. "Section 2" of this document describes the data gathering techniques. The main body of this article's third section contains the data analysis results and graphs. It will be interpreted (analyzed mostly for co-occurrence and co-citation) from CiteSpace. This section summarizes information about the country, institution, author, and keywords, with keywords serving as the most important part of the research frontier analysis for planning and management. The existing study on job shop scheduling and control (JSSC) in manufacturing will be presented in Section 4, before the conclusions, limits, and recommendations for future work are discussed. The hot topics and future trends are covered in Section 5. The conclusion, which is the last section, will provide certain restrictions on the current research.

The assistance of the current study is explained as: First, we describe the interactions of collaboration, and highlight the lack of coordination and collaboration in the scheduling and control fields. Second, we explore the ideas and "research hotspots" of the "scheduling and control area". Furthermore, we can determine the future research frontier based on the spike in keyword searches and the time zone map. Third, we analyze the literature and build an author co-citation network to detect developing trends, significant turning points, top researchers, and the growth and evolution of the scheduling and control (SC) area.

1.2. Research Objectives

This field has advanced quickly since the original work shop scheduling and control problem was posed. It is an "NP-hard problem", and substantial research has been conducted to address its many classes and complexities.

However, few papers thoroughly examine the many methods created by earlier academics, and even fewer can summarize and assess it at the macro level. Therefore, this article aims to explore the most recent JSSCP literature to apply it to Industry 4.0 deployment. In this regard, this study has addressed the following points:

i Existing research status of JSSC.
ii Hotspots and frontiers of research in the JSSC field.
iii Research gaps in the JSSC field.

CiteSpace is the main instrument used in this study's scientometric literature review (SLR), which provides a systematic review and discussion of hotspots and frontiers that have emerged since 2002. CiteSpace software can help researchers quickly focus on the most important material and a specific knowledge area. We believe that this publication will offer researchers and professionals a thorough insight. We examined the records from the previous 20 years to make this analysis more trustworthy and impartial.

2. Research Method

Academic publications in the field were identified to meet this paper's research goals. The Scopus database was used to obtain the list of publications. A delineation of the research boundary is frequently required because it is challenging to search every related article [3]. Each publication's main points will be based on its research contents. We conducted a systematic literature review using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2009 guidelines to ensure the inclusion of all relevant studies.

2.1. Bibliometric Analysis

Due to the fact that it establishes the scientific papers from which any conclusions will be formed, the collection of data from the current literature is crucial to this study. Therefore, care is taken in selecting the database and searching strategy. Scopus was selected as the literature resource for this study because, in contrast to other databases, it has a broad coverage of construction-related research [4]. The Scopus database is best suitable for interdisciplinary research since it contains a larger range of journal publications than the databases previously indicated.

The existing literature on job shop scheduling and control in this database was then found by searching for terms such as "manufacturing", "flow shop", "plant factory", "production system", and "scheduling", as well as "control", "scheduling", and "retrieval". The selected articles were from 2002 to 2022, in light of JSSC's development history within construction-related research. Only articles from peer-reviewed English document proceedings were taken into account for the review process.

The titles and abstracts of the sources were checked as part of a further review procedure to remove irrelevant articles. The bibliometric analysis was applied to those that survived the screening process. More than 8000 documents were found during the initial search, but only 5052 remained after the manual screening. The widespread appropriation of the term "scheduling and control" in other contexts and scientific disciplines can be used to explain why so many irrelevant papers had to be removed.

2.2. Scientometric Analysis

Mulchenko [5] initially offered the definition of scientometrics as "a quantitative analysis of the research on the growth of science". On the basis of sizable academic datasets, it can be viewed as a strategy that "maps the current state of knowledge and its evolution in a field and analyses the influence and citation processes of research". It is unlikely that the discipline of computer vision in construction can be comprehensively described. A full overview of the study area is provided by manual review, but this method is still vulnerable to bias and has little room for individual interpretation [6]. The current work provides a thorough examination of "computer vision" inside "construction-related activities" [7] using the "scientometric technique" in order to facilitate the visualization, which is used to trace the structure and evolution of various themes [8]. It is based on the use of an extensive academic database to assess the intellectual environment through modeling and visualization.

It is necessary to use keywords to identify groups having an impact on research areas. In order to preserve the authors' opinions as much as possible, the literature on scheduling and control for the manufacturing industry was examined. To identify research trends, the following methodologies were used: "country co-occurrence, literature co-citation, and co-occurrence analysis, abstract term cluster analysis, co-occurrence analysis and clustering, co-author analysis, and burst detection". The abstract term clustering, and various specific research themes tied to the conceptual framework of the study, highlight the detailed research trends within the subject. These techniques have been recommended in past research of a similar nature [6,9].

3. Results and Discussion

All results and discussions will follow the process flow of the figure below. Figure 1 is an illustration of the systematic review process that includes searches of databases and registers. The diagram is designed to provide transparency and clarity in reporting the selection of studies for inclusion in this systematic review as exhibited the same in the PRISMA checklist in Supplementary Material.

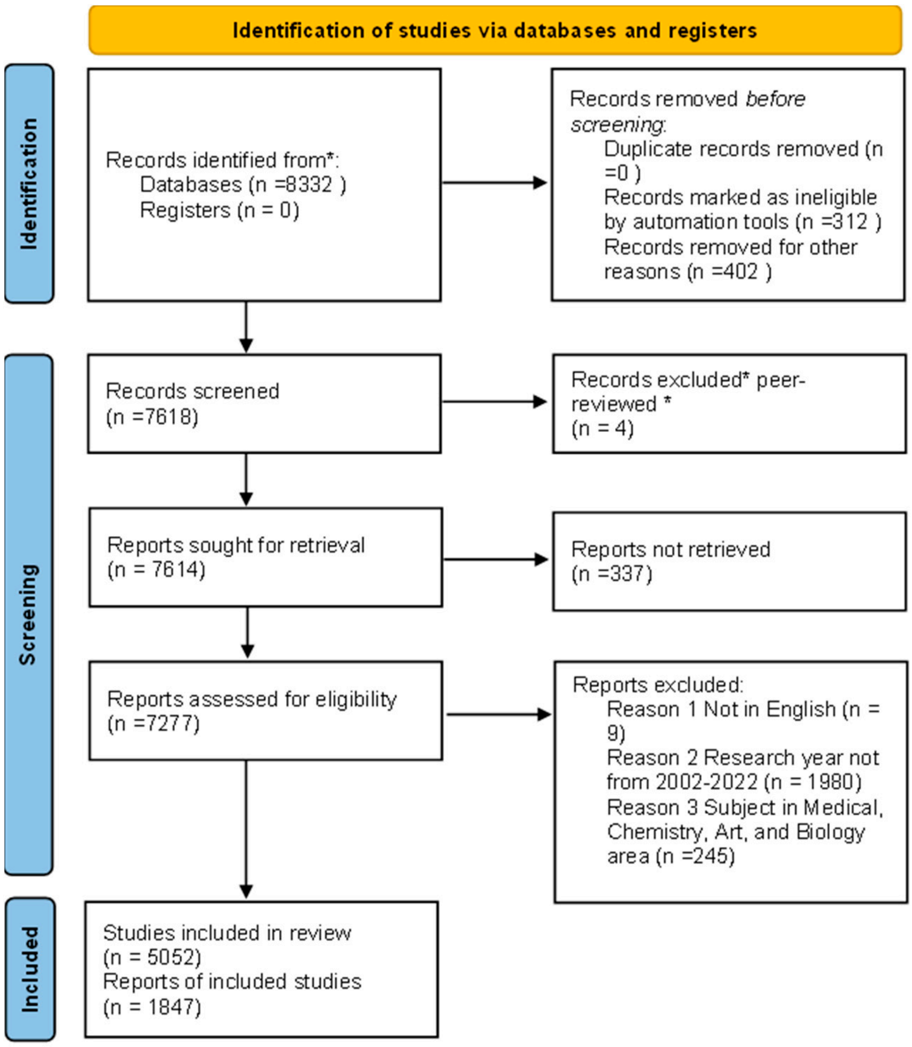


Figure 1. PRISMA 2020 flow diagram which included searches of databases and registers. * refers to the filter potions or key inclusive and exclusive criteria for systematic review.

The flow diagram begins with the identification of studies through database and register searches. This initial search results in a pool of potentially relevant studies, which are then screened based on their titles and abstracts. Studies that are clearly irrelevant are excluded at this stage. Afterwards, the remaining studies will be reviewed in full text. An analysis of a systematic review involves only studies that meet the inclusion criteria, whereas studies that do not meet these criteria are excluded from the analysis. The reasons for exclusion are documented and reported. The final step is to synthesize the research results from the relevant selected investigations, and report the findings of the systematic review. The PRISMA flow diagram serves as a useful tool for researchers to follow when conducting a systematic review, and provides a clear and concise visual representation of the study selection process as exhibited the same in the PRISMA checklist in Supplementary Material.

All results and discussions will follow the figure below to develop. The Figure 1 is a Illustrations of the systematic review process that includes searches of databases and registers. The diagram is designed to provide transparency and clarity in reporting the selection of studies for inclusion in a systematic review.

Figure 2 is a detailed overview of the systematic review process that covers searches exhibiting the analysis of information resources (datasets, records, archives), directories (documents), and related information sources. The diagram is designed to enhance the transparency and completeness of reporting the selection of studies for inclusion in this systematic review. The process flow diagram starts with the discovery of studies through a search of conference proceedings and reference lists. After being screened based on their titles and abstracts, the studies that emerged from this initial search are a pool of potential relevancy. It is at this point that studies that are obviously irrelevant are discarded. The remaining studies will then be read in full following that. Studies that don't fit the criteria are excluded, and the systematic review is only of studies that do. Documented and disclosed are the exclusionary factors. The systematic review's findings are reported after the information research outputs from the reviewed investigations have been synthesized. The PRISMA flow diagram offers a clear and concise visual representation of the study selection process, which is a useful tool for researchers to use when conducting a systematic review, which comprises analysis of databank information records, registries, and additional archives as exhibited the same in the PRISMA checklist in Supplementary Material. The use of the PRISMA flow diagram helps ensure that the systematic analysis is rigorous and transparent, thereby increasing the confidence and validity of the study findings. Figure 3 illustrates the overall research methodology to execute the critical review.

3.1. Data Acquisition

In order to obtain suitable articles, the keyword search methodology explained in Section 2.1 was used. These findings are summarized. Most scholarly works on JSSC can be found in journals that cover both fields, such as production research, advanced manufacturing technology, computers, and industrial engineering, "IFIP Advances in Information and Communication Technology", "Procedia CIRP, and Computers and Operations Research". Figure 4 illustrates the "annual variation in the number of publications on the study issue" under consideration. Research on production scheduling and control has been maintaining a slow upward trend since 2002; from 2012 to 2021, the number of research articles has been increasing gradually, the research field has been expanding, and the research content has been deepening, indicating that the field has attracted the attention of many scholars. While this trend may be influenced by some uncertain factors, the number of articles published during this period had a large decrease in 2013–2015, and after that, it has been rapidly and continuously increasing. In 2021, the number reaches the peak; this stage is the explosive period of production scheduling and control research. The overall trend indicates that the academic community has paid increasing attention to the production schedule as time changes. This field is still a hot topic for the future, and the number of annual publications may continue to increase.

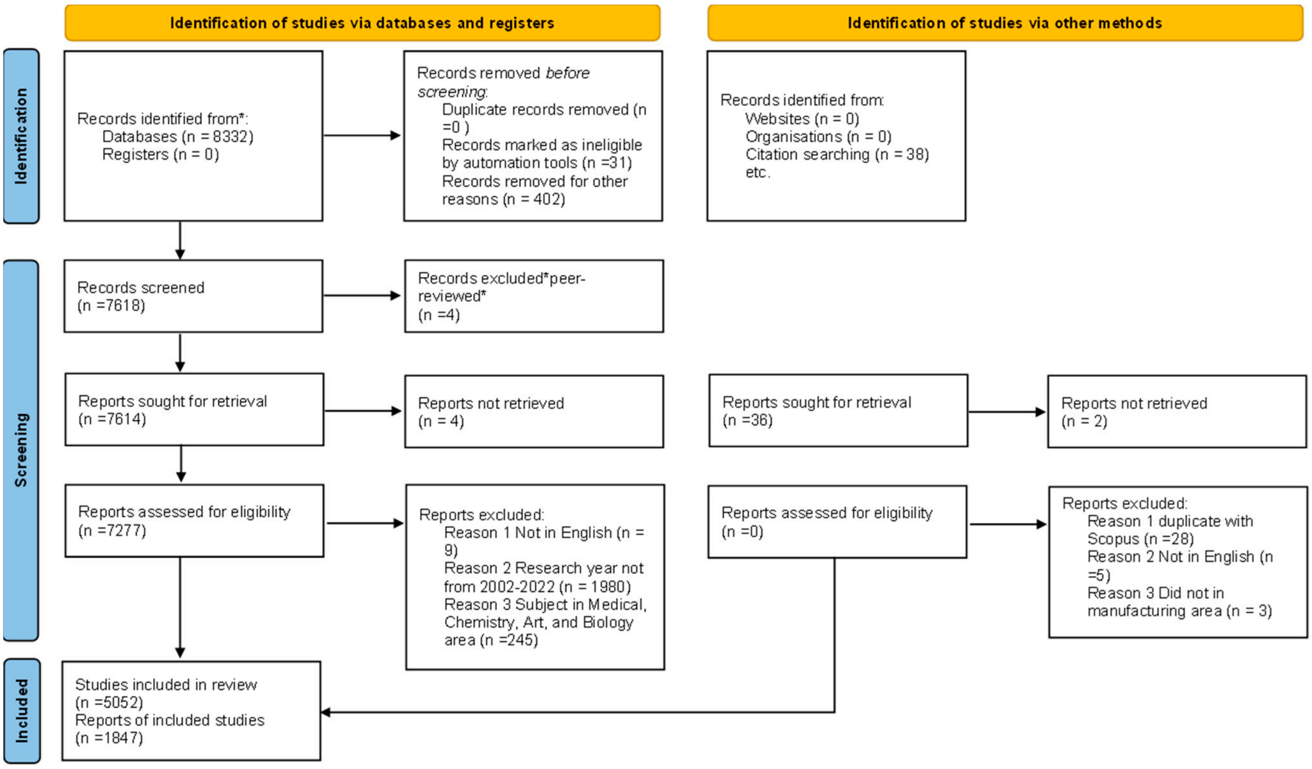


Figure 2. PRISMA 2020 flow diagram which included searches of databases, registers, and other sources. * refers to the filter potions or key inclusive and exclusive criteria for systematic review.

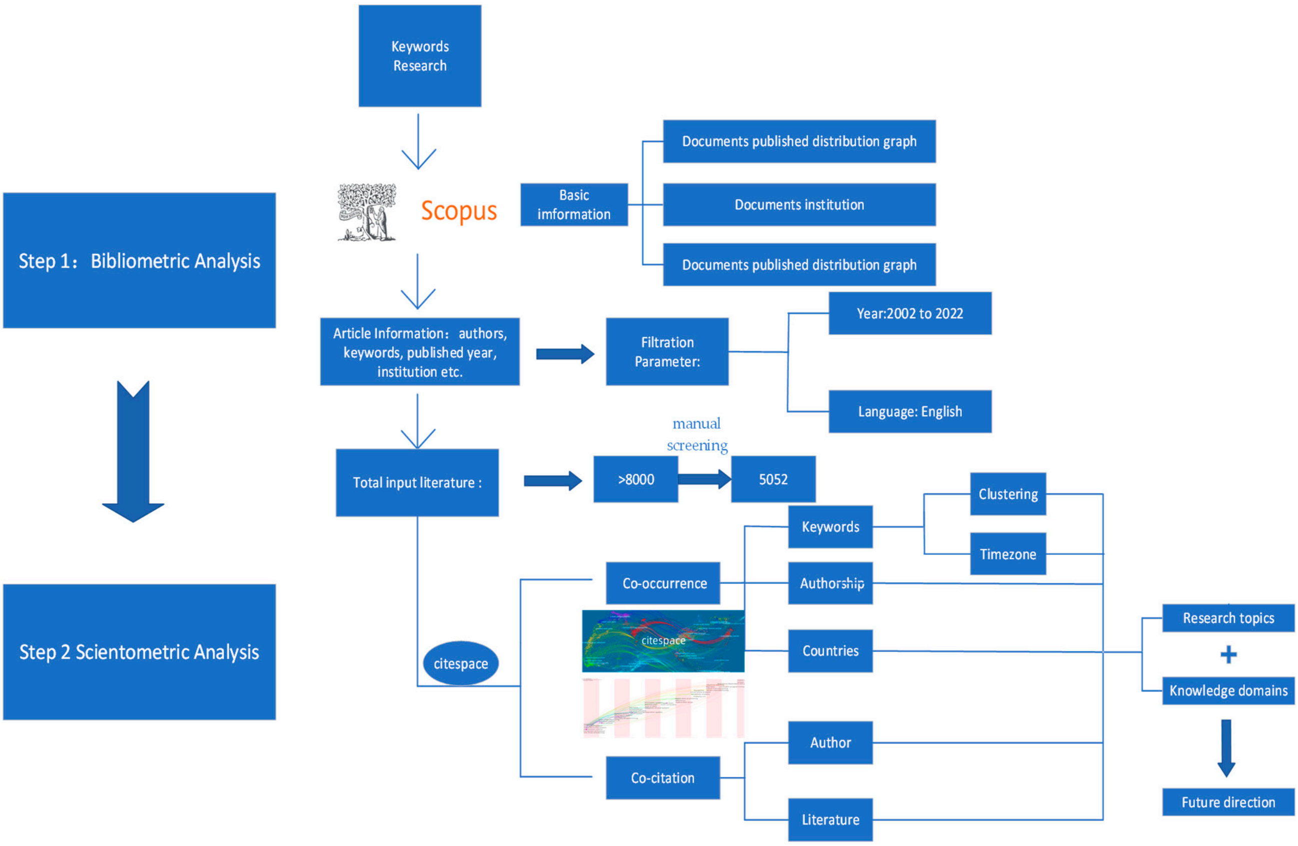


Figure 3. Overview of the research methodology.

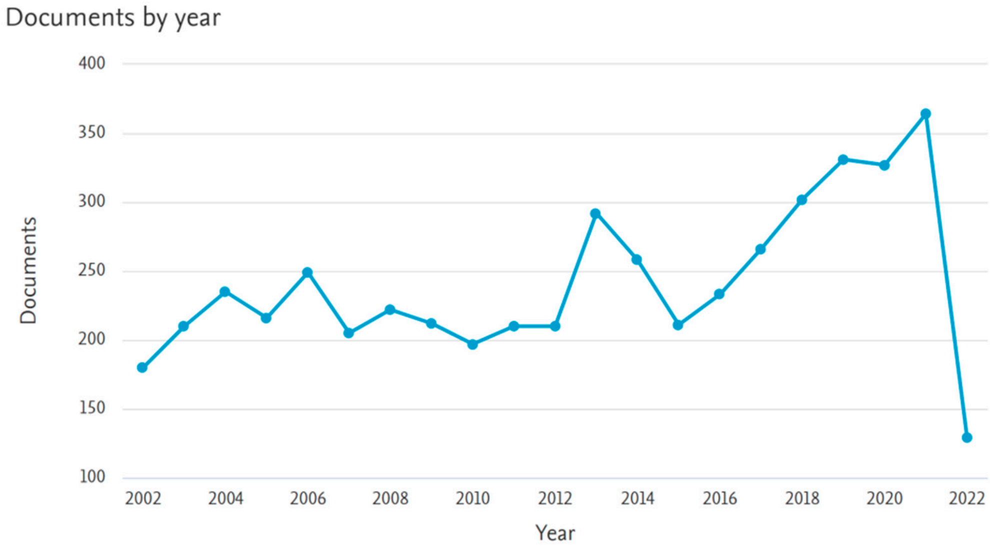


Figure 4. "Historical trend of published studies" in JSSC for manufacturing (period 2002–2022).

3.2. Keyword Co-Occurrence Analysis

As high-level descriptions of a document's information, keywords can help researchers identify the crux and substance of the investigation [10]. High-frequency and central terms can indicate the research discipline's key ideas. The hue of the keyword's links indicates the first occurrence of two keywords in a document. Brighter linking colors match the "initial year of co-occurrence" closest. CiteSpace provides keyword counts and importance. Thus, co-keyword analysis reveals the scheduling and control domain conceptual frameworks. The CreateSpace analysis settings: top 25 annually (2002–2022), LRF = 3, LBY = 5, and e = 1. Pathfinder pruned the sliced networks and co-occurrence network map. The 109-link, 97-node network is shown in Figure 5. In addition to frequency or count, the network centrality of a keyword can indicate its importance. Figure 6 shows the top five keywords with high counts or centrality.

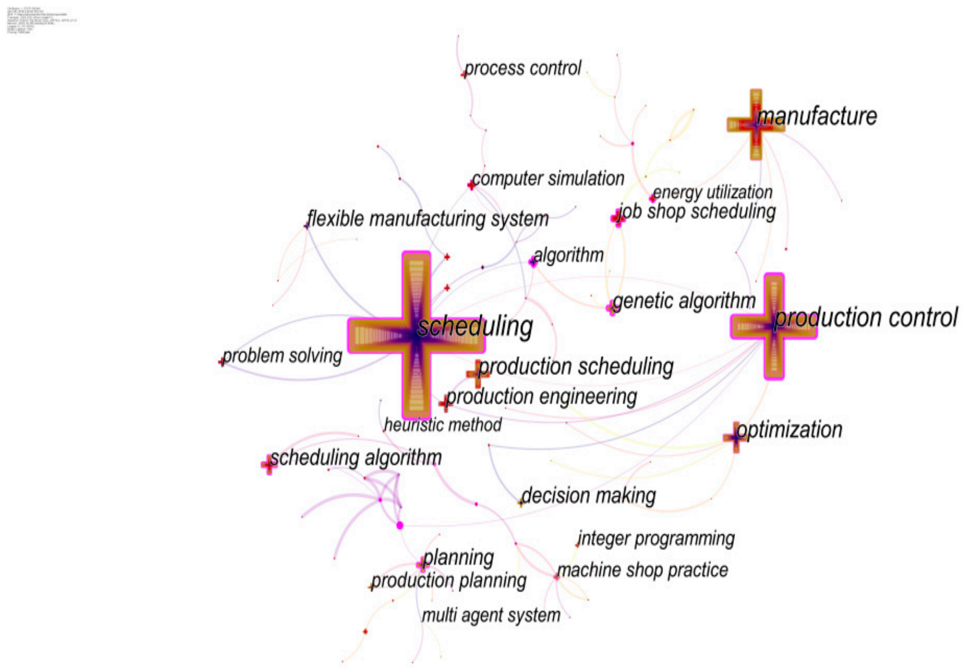


Figure 5. Network of "co-occurring keywords related to JSSC" in manufacturing (period 2002–2022).

No.	Frequency	Keywords
1	805	optimization
2	709	production scheduling
3	509	planning
4	461	genetic algorithom
5	459	decision making

No.	Centrality	Keywords
1	0.68	genetic algorithm
2	0.48	makespan
3	0.38	production control
4	0.28	energy efficiency
5	0.27	industrial application

Figure 6. Two lists of keywords.

From Figure 6, scheduling, production control, and manufacturing occupy the highest frequency and largest nodes, covering the entire research period; however, this paper used "manufacturing", "scheduling", and "production" for the initial search, thus, these three keywords occupy the highest frequency and largest nodes. After removing these words, the top five keywords were chosen and ranked by frequency and centrality (Figure 6): "Optimization", "production scheduling", "planning", "genetic algorithm", "decision making", etc. High-frequency keywords cannot conduct, but they are central. The keyword graph's inflection point is centrality ≥ 0.1, which may represent this field's research hotspots. From the centrality, the top 1 is "genetic algorithm" with 0.68; a combination conclusion, with frequency, scheduling, and control hotspots, is focused on using the algorithm to optimize production.

Even though the "JSS problem is NP-hard", these strategies can help get us closer to an ideal outcome. Meanwhile, from the centrality rank (Figure 6), we can conclude that controlling the whole job shop production process is important and attracts a lot of attention; many researchers are trying to optimize the source planning and scheduling [11]. Satake et al. [12] utilized a new method to decrease the production period. Thus, from all of these keywords, which are related to improving production and at the same time decreasing energy consumption, it is reasonable to provide a conclusion that, although many scholars are focused on the flexible job shop problem, little attention is given to the factors of energy and environment, which means that sustainability and green energy might be the next frontier and hotspot. Thus, we can know that in job shop production scheduling and control, many researchers are focused on different algorithms; researchers are not only focused on minimizing the production time, but the production energy as well. Moreover, we can find that production is changing from energy-consuming to green and sustainable production, and this change can reflect and support the innovation of Industry 4.0 [13–16].

3.3. Keywords Timeline

Keyword co-occurrence networks statically represent the research area. CiteSpace uses time zones to show JSSC keyword evolution [17–25]. Below is a Figure 7. showing the year that keywords first occurred. This graph shows keywords over time, as well as SC research trends. The key point is 2016. Industry 4.0 followed lean construction from 2002 to 2015. In this period, AI technology and big data were widely used in the whole working production process (design, fabrication, construction, and delivery) [26–34]. Morariu O. et al. [17] offer a "machine learning approach for reality awareness and optimisation in the cloud", and Waschneck B. et al. [18] said that "AI-based methods will replace mathematical models". Production problems were initially stochastic, not dynamic. Scholars then solve working process and inventory problems dynamically, closer to the actual production [35–40]. This transformation allows the entire production process to quickly adapt to market information changes, improving service levels [41–49].

In terms of the technologies used in Industry 4.0, the goal is to connect all objects in a factory through communication technology, and is varied depending on the four working processes [23–29]. For example, in the design period, BIM, AR, and VR are widely used in manufacturing [19–22,50–53]; during manufacturing, smart sensors and robots will provide great help [23–26,54–57]; in the construction stage, real-time location services, smart cranes, and virtual construction scheduling are widely used [27]; in the final delivery stage, BIM-based defect management (BIMDM) systems and building management systems (BMSs) are needed [28–31]. Generally speaking, in Industry 4.0 and smart construction since 2016, technologies such as "big data, AI, blockchain, E-business, and cloud computing", which are based on computer science, were widely utilized in job shop production and construction. From the supply chain perspective, the powerful calculation power of these technologies enabled the making, planning, and achieving of dynamic production muti-optimization [32] and working process integration [33]. Furthermore, with this powerful technology, modern job shop production can be reasonably regarded as smart mass customization, which means it can not only meet the industry's production needs, but can also meet the preferences of different customers [34].

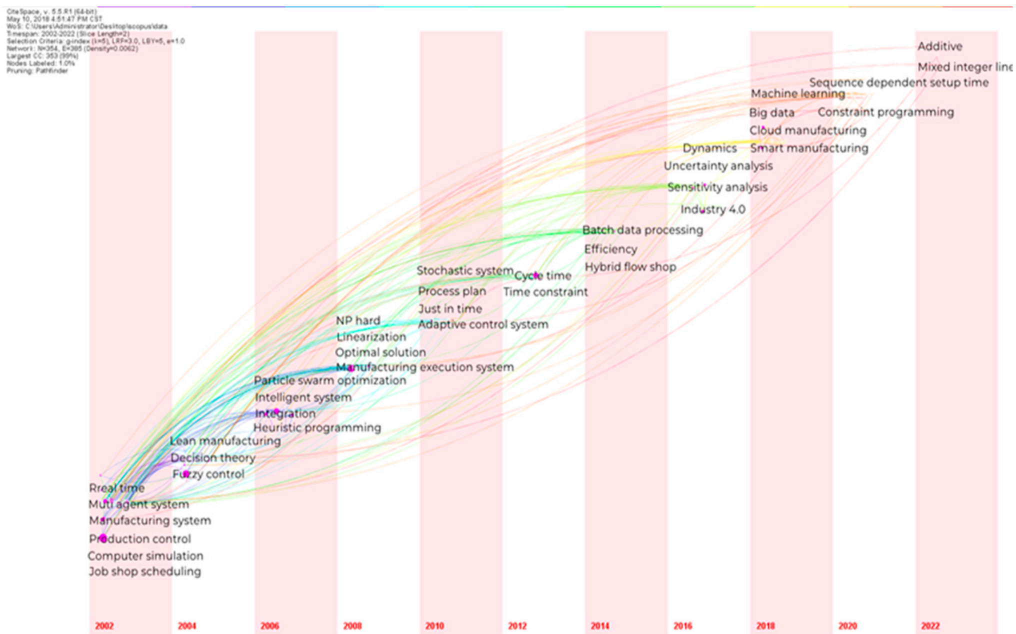


Figure 7. Keywords of the timeline related to JSSC in manufacturing.

3.4. Keyword Burst Analysis

The burst index can detect high-frequency keyword changes to determine research field frontier content, which will be chosen in CiteSpace to identify scheduling and control research hotspots [35]. Figure 8 shows 40 burst keywords; in chronological order, the burst keywords have been changing over the years from 2002 to 2022.

Manufacturing research has explored topics such as computer-aided manufacturing (2002–2006), heuristic methods (2002–2009), inventory control (2002–2007), optimal control systems (2002–2006), and intelligent manufacturing. Recent research hotspots include machine learning, deep learning, integer programming, and stochastic systems (2014–2022). Inventory control (65.56) is the strongest research topic, followed by Industry 4.0 (2017–2022), computer-aided manufacturing (25.61), multiobjective optimization (22.09), learning systems (21.01), and stochastic systems (20.02).

In 322 documents in our database, this keyword appeared 50 times in 2018, 87 times in 2019, and 126 times in 2020. Overall, we contend that studies of the circular economy and game theory are the current hot topics for SSCM research. Using CiteSpace [35], we explored "keyword burst detection" to find "research hotspots in the SSCM domain". Figure 9 displays 40 keywords with at least two-year peaks. From 2007 to 2021, these have been evolving in chronological order.

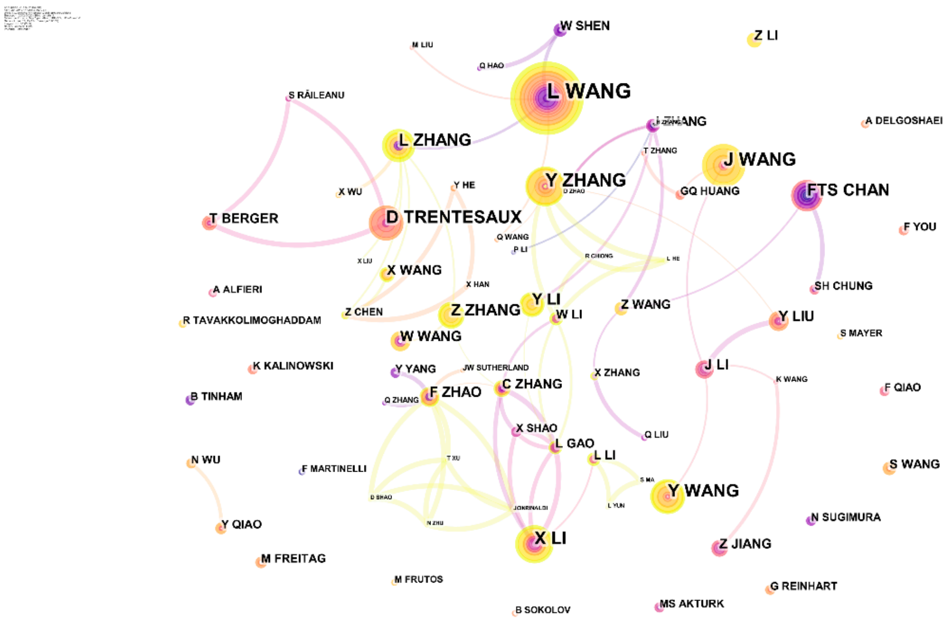
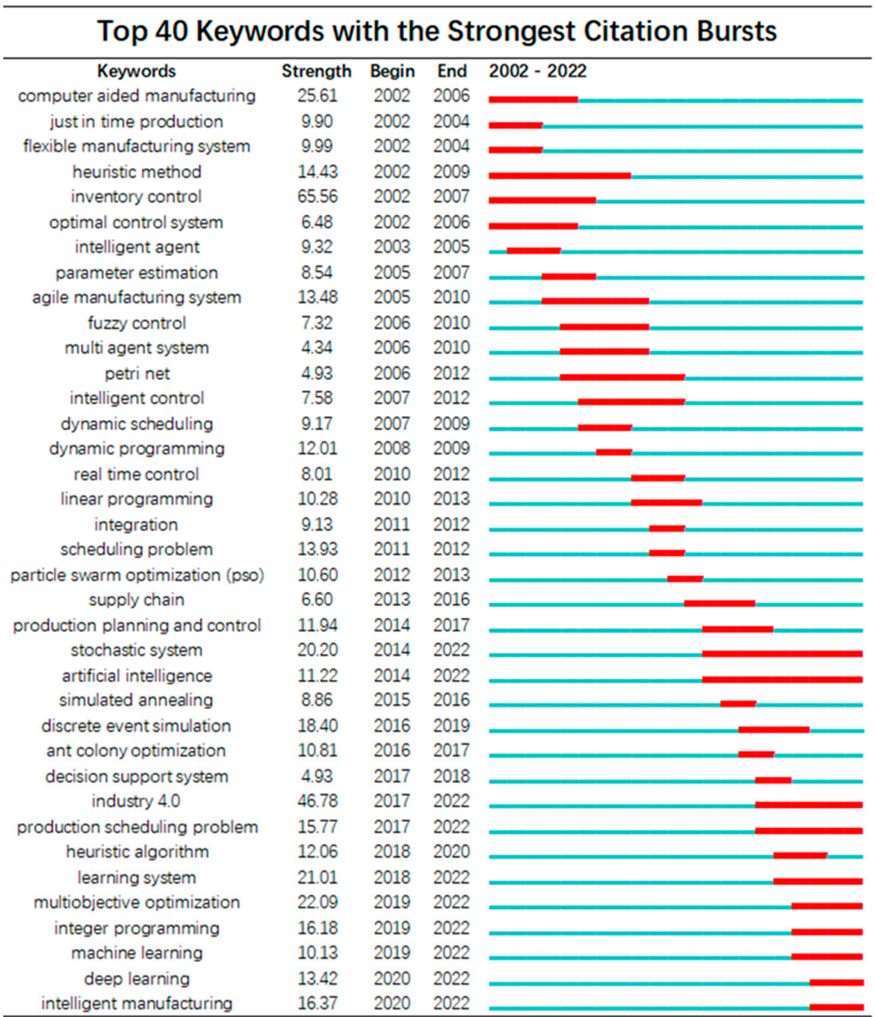


Figure 8. Network of co-authorship for JSSC-related manufacturing publications.


Top 40 Keywords with the Strongest Citation Bursts

Keywords	Strength	Begin	End	2002 - 2022
computer aided manufacturing	25.61	2002	2006	
just in time production	9.90	2002	2004	
flexible manufacturing system	9.99	2002	2004	
heuristic method	14.43	2002	2009	
inventory control	65.56	2002	2007	
optimal control system	6.48	2002	2006	
intelligent agent	9.32	2003	2005	
parameter estimation	8.54	2005	2007	
agile manufacturing system	13.48	2005	2010	
fuzzy control	7.32	2006	2010	
multi agent system	4.34	2006	2010	
petri net	4.93	2006	2012	
intelligent control	7.58	2007	2012	
dynamic scheduling	9.17	2007	2009	
dynamic programming	12.01	2008	2009	
real time control	8.01	2010	2012	
linear programming	10.28	2010	2013	
integration	9.13	2011	2012	
scheduling problem	13.93	2011	2012	
particle swarm optimization (pso)	10.60	2012	2013	
supply chain	6.60	2013	2016	
production planning and control	11.94	2014	2017	
stochastic system	20.20	2014	2022	
artificial intelligence	11.22	2014	2022	
simulated annealing	8.86	2015	2016	
discrete event simulation	18.40	2016	2019	
ant colony optimization	10.81	2016	2017	
decision support system	4.93	2017	2018	
industry 4.0	46.78	2017	2022	
production scheduling problem	15.77	2017	2022	
heuristic algorithm	12.06	2018	2020	
learning system	21.01	2018	2022	
multiobjective optimization	22.09	2019	2022	
integer programming	16.18	2019	2022	
machine learning	10.13	2019	2022	
deep learning	13.42	2020	2022	
intelligent manufacturing	16.37	2020	2022	

Figure 9. Keyword burst in the 2002–2022 period exhibiting with diverse colours.

3.5. Author Co-Occurrence Analysis

By using the bibliographic records, which contain information regarding the article's authors, it is possible to map both the collaborations between researchers and the identification of the top researchers in a given field. Afterward, a network of co-authors can be created. First, the five most prolific authors were identified. According to Figure 10, L WANG, J WANG, and Y ZAHNG held the third position. CiteSpace is capable of visualizing and analyzing scientific knowledge [35]. Consequently, networks of co-authorship can be generated in Figure 8. Such a strategy has been identified as an effective technique for uncovering the concealed propositioning of a large dataset. By methodically producing numerous accessible graphs, CiteSpace excels at mapping different knowledge domains [35]. To create abstract clustering, it was also used to generate and analyze the networks of co-authors, countries, and co-occurrences as unveiled in the Figures 8 and 11 respectively. CiteSpace's burst detection is built upon the Kleinberg algorithm [36]. The factors were determined as when the "co-authorship network" was generated: top N (N = 15), LRF = 3, LBY = 5, and e = 1 for the years 2002 through 2022. The pathfinder technique was used to prune sliced and combined networks, producing the 187 nodes and 154 linkages shown in Figure 11. The number of citations a scholar has is indicated by the size of each node; the later the time of appearance, the deeper the node color. The core author will be selected from Price's law. In this law "N is the total number of authors; M is the number of articles written by all authors; x_{max} is the number of articles written by the most prolific author in the selected group; m is the threshold of the prolific group, i.e., the number of articles written by the least prolific author in the group; y is the number of authors who wrote x articles". From Price's inference:

$$[\sum_{x=m}^{x_{max}} y_x \cdot x]/[\sum_{x=1}^{x_{max}} y_x \cdot x] = 1/2$$

Serial number	Frequency	Centrality	Year	Author
1	44	0.03	2005	L WANG
2	26	0.01	2011	J WANG
3	24	0.05	2011	Y ZHANG
4	23	0.02	2009	X LI
5	21	0	2013	Y WANG

Figure 10. The top five most prolific authors from 2002 to 2022.

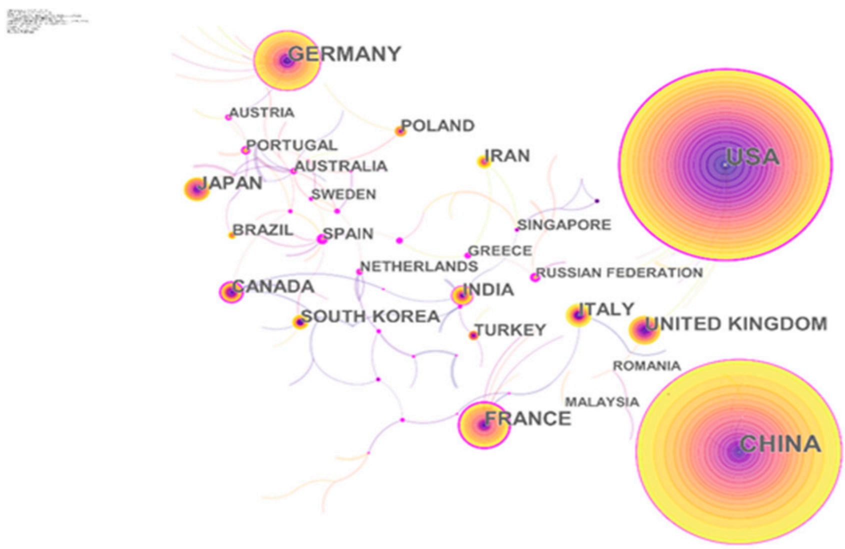


Figure 11. Network of countries.

The above formula indicates that the group of highly productive authors wrote half of all the papers.

$$\sum_{x=m}^{x_{max}} y_x \times x = [\sum_{x=1}^{x_{max}} y_x \times x]^{0.5}$$

In this formula, the left part is M.

M is exactly the starting point for 50% of the total number of papers with highly productive authors; the value of m is obtained by inference (process omitted):

$$m = 0.749(x_{max})^{0.5}$$

From the above formula ($m = 0.749 \times \sqrt{\text{Ncmax}}$), the minimum number of publications for the core author in this article is five, and there are 48 productive authors. We are focusing on the top five authors (Figure 8) in the following analysis.

The density of cooperative relationships in the network is 0.0089, and there are no scholars for which the centrality is more than 0.1 in the field of "production scheduling and control research", which means that the coordination is weak between different authors. In addition, these top five authors constitute their respective author groups. There are also some small collaborative teams with only one link between two nodes, and their networks do not unfold; thus, they are limited to two-person collaboration and their collaborative power is weak.

The top 10 nations (out of 150) that published papers in the scheduling and control area are shown in Figure 12 in terms of publications, total papers, and centrality. Figure 12 shows the visualization maps of the research nations that have produced literature; as can be seen, these nations constitute a loosely connected network of relationships [54]. Therefore, the more publications a nation has in common with other nations, the more central it is. A total of 5052 papers on this topic were obtained for the years 2002 through 2022 after using CiteSpace's "remove duplicates" function [37]. The visualization map for nations where ES research has taken place was created using the pruning option (pruning based on Pathfinder/Pruning sliced networks). Following software execution, the network gained 150 nodes, 164 linkages, and a density of 0.0147. Figure 13 lists the top ten producing nations.

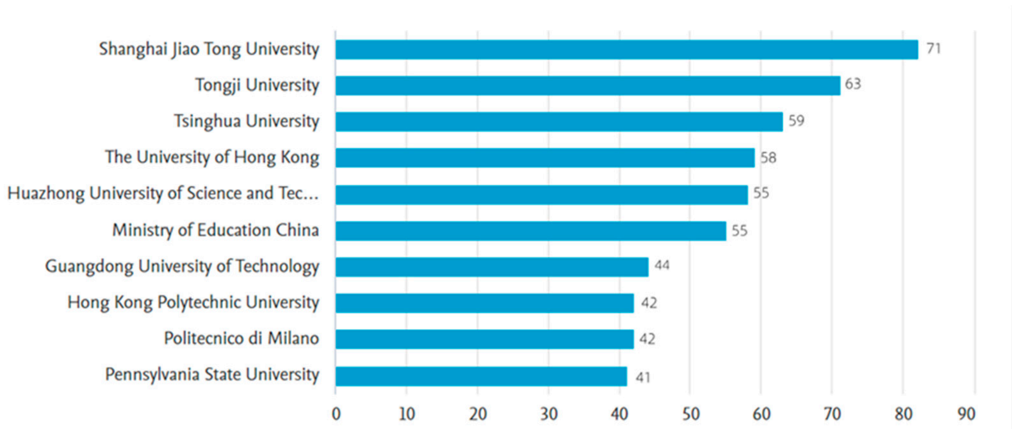


Figure 12. Top 10 most productive institutions in the 2002–2022 period.

Institutional contributions were also identified. Figure 12 shows that there are 50 nodes, 31 connected lines, and a density of 0.0253. The number of publications is indicated by the node size, with larger nodes indicating larger issuance, and vice versa. Centrality reflects the level of importance, with higher centrality indicating higher importance. The visualization results, from the 5052 documents selected for this study, allow identification of the main institutions in the field. The first ranking is Shanghai Jiao Tong University, with 71 articles on IoT-based manufacturing, resources management [38], job shop scheduling [39], etc. The next is Tongji University, with 64 articles focusing on the scheduling of semiconductor manufacturing [40], deadlock-free genetic scheduling algorithms [41], and real-time scheduling [42]. The number of publications from these two institutions accounts for approximately 25% of the top ten institutions, and has a high impact.

Rank number	Countries	Quantity	Centrality	Initial time
1	CHINA	1016	0.59	2002
2	UNITED STATES	838	1.35	2002
3	GERMANY	365	0.23	2002
4	FRANCE	278	0.74	2002
5	UNITED KINGDOM	208	0.17	2002
6	JAPAN	174	0	2002
7	ITALY	172	0.4	2002
8	CANADA	165	0.17	2002
9	INDIA	146	0.12	2003
10	SOUTH KOREA	130	0.78	2002

Figure 13. List of the top ten most productive countries between 2002 and 2022.

3.6. Author Co-Citation Network

Making an "author co-citation network" has the aim of identifying academics whose works are related to the SSCM research area. Whenever two academics are referenced in the same work, this is referred to as co-citation. As analytic objects, we used references from 9151 peer-reviewed papers. The CiteSpace configurations were: LRF = 3, LBY = 5, e = 1 (2002–2022), and top N (N = 50). The pathfinder algorithm pruned the sliced and merged networks, leaving 531 nodes and 848 links. More citations mean bigger nodes. The first author label is applied to nodes with more than 150 citations. Purple circles cover nodes with centralities above 0.1. From Figures 14 and 15, we can identify highly cited and/or central researchers.

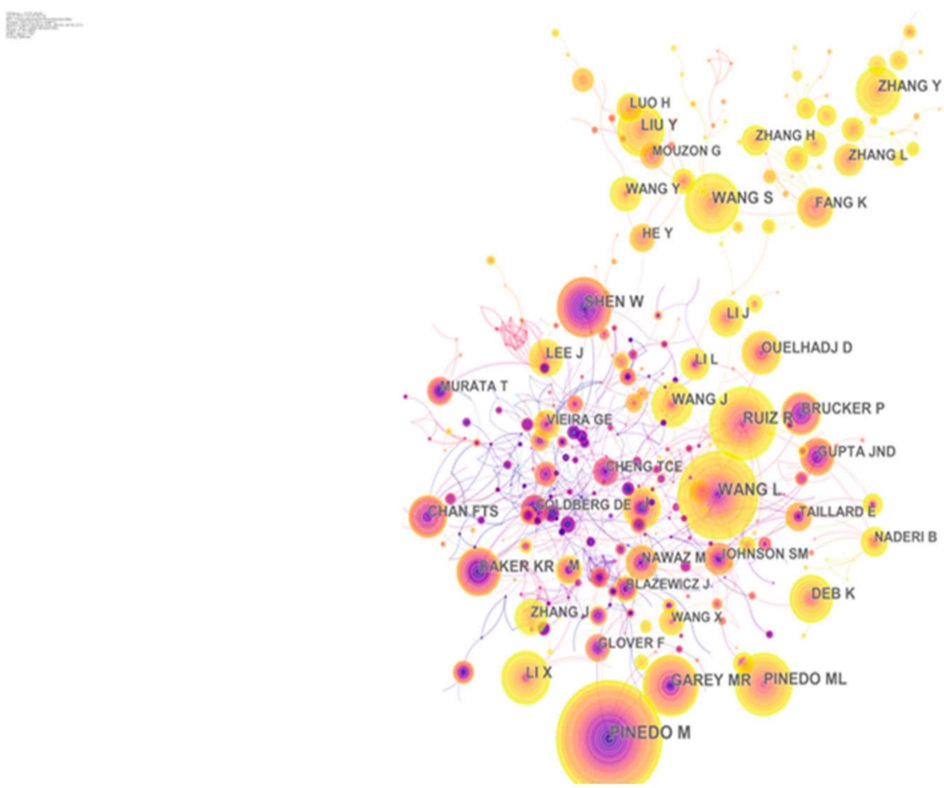


Figure 14. Network of author co-citation for publications related to JSSC in manufacturing.

Order	Count	Centrality	Author Name
1	282	0.06	Michael Pinedo
2	210	0.19	Lihui Wang
3	180	0.15	Rubén Ruiz
4	154	0	Michael R Garey
5	147	0	Weiming Shen

Figure 15. Top five most co-cited authors.

Figure 15 shows the top five most co-cited authors: Michael Pinedo (282 citations), Lihui Wang (210), Rubén Ruiz (180), Michael R. Garey (154), and Weiming Shen. Figure 16 shows the top five authors' citation distribution. Between 2002 and 2022, these five scholars' overall citations increased. Professor Michael R. Garey is cited the most every year, except 2021. Lihui Wang, who works on digital twins, smart manufacturing, human–robot collaboration, and more at Sweden's KTH Royal Institute of Technology, was first cited in 2003. In 2021, his citations surpassed Michael R. Garey's, putting him in first place. Professor Rubén Ruiz (Universitat Politècnica de València) studies scheduling, routing, optimization, and metaheuristics, and is cited increasingly. New York University professor Michael Pinedo specializes in financial services planning and scheduling. Weiming Shen, a National Research Council Canada and University of Western Ontario professor, has citation trends similar to Michael Pinedo.

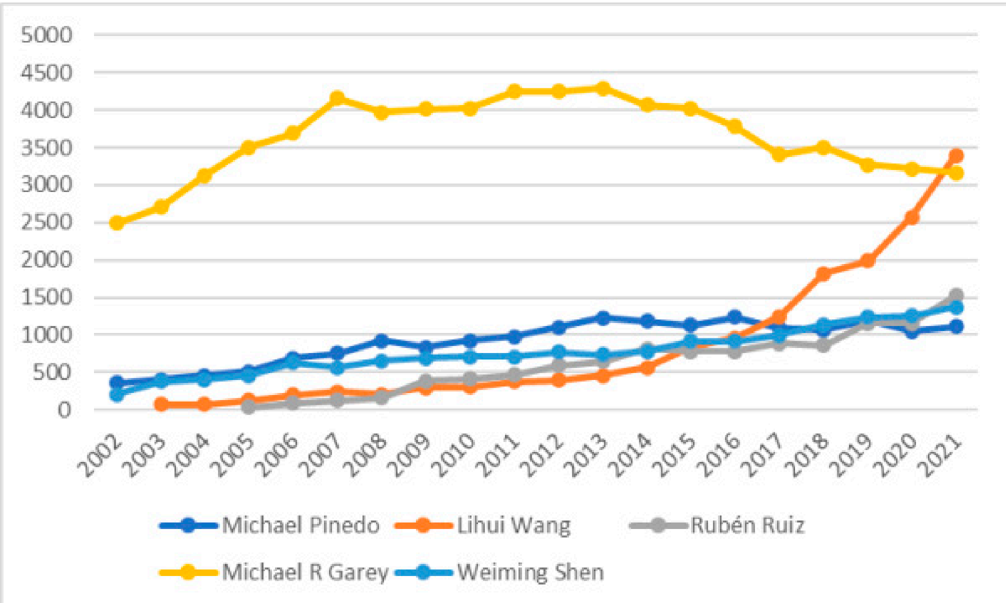


Figure 16. Citation distribution of the top five most cited authors.

There are six scholars whose centralities are greater than 0.2, implying that they are more influential than others, and have a substantial effect on the growth of scheduling and control research. These authors include GOLDBERG DE (centrality: 0.3), DAI M (centrality: 0.28), PRABHU VV (centrality: 0.26), HE Y (centrality: 0.25), ZHANG R (centrality: 0.25), and OGBU FA (centrality: 0.22). "When authors have a high number of citations and centrality, they can be considered influential or leading scholars" [43,44]. Lihui Wang, Rubén Ruiz, and Shiqiang Wang are regarded as leading researchers based on their citation counts and centralities, which exceed 500 and 0.1, respectively.

3.7. Document Co-Citation Network and Clustering

Document co-citation analysis shows a research field's intellectual structures by revealing the quantity and authority of references cited in publications. Citation relationships are represented by document co-citations. The literature's co-citation network was created by extracting references from the top 50 cited papers from each 1-year time slice between 2002 and 2022. Integrating and clustering co-citation networks produced 6580 nodes with modularity Q = 0.9656. The large number of isolated clusters lowered the mean value to 0.3647. Papers are the nodes in the network diagram, and the connecting lines show co-citation relationships, with colors indicating when they were established. Early SC research appears in the top right corner. Figure 12 illustrates the study's color distribution evolution. Co-citation network analysis shows clustering related to #1 cooperative manufacturing management framework, #3 future requirement, #4 research theme, #6 event-driven control architecture, and #7 power consumption uncertainty; #1, #3, and #6 have similar content. On the left side of the network as illustrated in the Figure 17, recent research papers include #0 flexible manufacturing systems, #2 manufacturing operation scheduling, and #5 service supply chain. Flexible manufacturing systems and manufacturing operation scheduling dominate the production scheduling research. Production scheduling and control research is also found in these clusters. Early SC research papers, on the right side of the co-citation network, focus on schedule and control job shop production; this is the co-citation network's trend and frontier. Mutations are dark-filled nodes in the co-citation network, according to Kleinberg's burst detection [36]. These burst event segments demonstrate the academic community's interest in the paper's research at the time, demonstrating changes in the paper's importance to related research. The network analysis reveals the emerging research areas and representative literature, as shown in Figure 11. Moreover, #0 and #1 are the largest clusters; combined with the color consideration, cluster 1 becomes grey, indicating it experiences a relatively long time from the statistical period, while cluster 2 is brightly colored, indicating that this cluster is the current popular research area. Thus, this article focuses on clusters #0 and #2 for the analysis: cluster #0 (flexible manufacturing system) indicates that a large number of studies refer to flexible manufacturing, and cluster #2 (manufacturing operation scheduling) indicates that a large number of studies refer to manufacturing operation scheduling. Figures 18 and 19 have exhibited the myriads of investigators/authors refer who have conducted studies on flexible manufacturing system (cluster #0), and manufacturing operation scheduling (cluster #2).

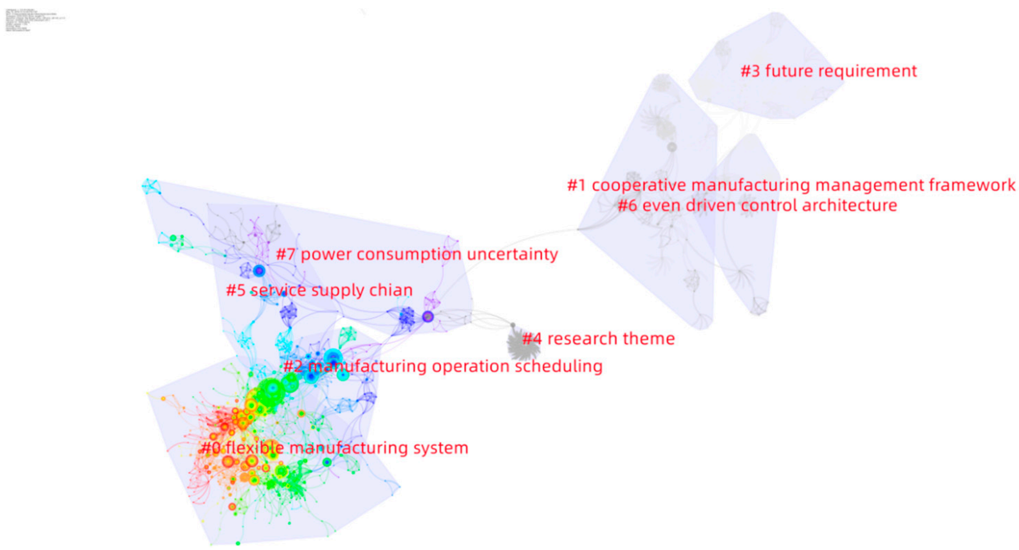


Figure 17. Document network of co-citation.

Cluster #0 flexible manufacturing system

Cited References							Citing articles
Cites	Author	(Year)	Journal	Volume	Page	Coverage%	Author (Year) Title
42	Shrouf F	2014	Optimizing the production scheduling of a single machine to minimize total energy consumption costs	67	197-207	25	Wang, X (2018) A comprehensive survey of ubiquitous manufacturing research.
36	Gahm C	2016	Energy-efficient scheduling in manufacturing companies: A review and research framework	248	744-757	20	Biel, K (2016) Systematic literature review of decision support models for energy-efficient production planning.
27	Luo H	2013	Hybrid flow shop scheduling considering machine electricity consumption cost	146	87-96	19	Li, M (2022) A review of green shop scheduling problem.
25	Zhang R	2016	Solving the energy-efficient job shop scheduling problem: a multi-objective genetic algorithm with enhanced local search for minimizing the total weighted tardiness and total energy consumption	112	423-439	18	Giret, A (2015) Sustainability in manufacturing operations scheduling: a state of the art review.
21	Mansouri SA	2016	Green scheduling of a two-machine flowshop: Trade-off between makespan and energy consumption	248	3361-3375	12	Cui, W (2020) Integrating production scheduling, maintenance planning and energy controlling for the sustainable manufacturing systems under tou tariff.
21	He Y	2015	An energy-responsive optimization method for machine tool selection and operation sequence in flexible machining job shops	87	18-23	11	Wang, J (2020) Infinitely repeated game based real-time scheduling for low-carbon flexible job shop considering multi-time periods.
21	Lee J	2015	A cyber-physical systems architecture for industry 4.0-based manufacturing systems	3	126-140	11	An, Y (2020) A hybrid multi-objective evolutionary algorithm to integrate optimization of the production scheduling and imperfect cutting tool maintenance considering total energy consumption.
21	Zhong RY	2017	Intelligent manufacturing in the context of industry 4.0: a review	3	245-254	10	Abedini, A (2020) A metric-based framework for sustainable production scheduling.
20	Zhang J	2019	Review of job shop scheduling research and its new perspectives under Industry 4.0	30	616-630	10	Gong, X (2016) A generic method for energy-efficient and energy-cost-effective production at the unit process level.
19	Mokhtari H	2017	An energy-efficient multi-objective optimization for flexible job-shop scheduling problem	104	228-238	10	Ghaleb, M (2020) Real-time production scheduling in the industry-4.0 context: addressing uncertainties in job arrivals and machine breakdowns.

Figure 18. Top 10 most cited authors in cluster #0 [58–77].

Cluster #2 manufacturing operation scheduling

Cited References							Citing articles
Cites	Author	(Year)	Journal	Volume	Page	Coverage%	Author (Year) Title
28	Fang K	2011	A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction	30	234-240	15	Trentesaux, D (2014) Sustainability in manufacturing operations scheduling: stakes, approaches and trends
26	Dai M	2013	Energy-efficient scheduling for a flexible flow shop using an improved genetic-simulated annealing algorithm	29	418-429	11	Prabhu, VV (2015) Energy-aware manufacturing operations.
22	Bruzzone AAG	2012	Energy-aware scheduling for improving manufacturing process sustainability: A mathematical model for flexible flow shops	61	459-462	9	Pach, C (2015) Reactive control of overall power consumption in flexible manufacturing systems scheduling: a potential fields model.
18	Duflou JR	2012	Towards energy and resource efficient manufacturing: A processes and systems approach	61	587-609	8	Chu, Y (2014) Moving horizon approach of integrating scheduling and control for sequential batch processes.
14	Fang K	2013	Flow shop scheduling with peak power consumption constraints	206	115-145	7	Duerden, C (2015) Genetic algorithm for energy consumption variance minimisation in manufacturing production lines through schedule manipulation.
12	Michael S	2020	Design of cyber physical system architecture for industry 4.0 through lean six sigma: conceptual foundations and research issues	20	110-124	7	Kucharska, E (2017) Almm-based methods for optimization makespan flow-shop problem with defects.
10	He Y	2012	A modeling method of task-oriented energy consumption for machining manufacturing system	23	167-174	6	Nguyen, S (2018) A hybrid genetic programming algorithm for automated design of dispatching rules.
10	Trentesaux D	2013	Benchmarking flexible job-shop scheduling and control systems	21	1204-1225	6	Duerden, C (2015) Minimisation of energy consumption variance for multi-process manufacturing lines through genetic algorithm manipulation of production schedule.
8	Chu Y	2015	Integrated planning and scheduling under production uncertainties: Bi-level model formulation and hybrid solution method	72	255-272	6	Liu, Y (2014) An investigation into minimising total energy consumption and total weighted tardiness in job shops.
5	Nie Y	2014	Extended discrete-time resource task network formulation for the reactive scheduling of a mixed batch/continuous process	53	17112-17123	6	Chu, Y (2014) Efficient decomposition method for integrating production sequencing and dynamic optimization for a multi-product cstr.

Figure 19. Top 10 most cited authors in cluster #2 [78–97].

4. Current Research

Since the first papers were published in this field in the late 1970s, a sizable body of research literature has accumulated. These reviews, however, emphasized particular viewpoints, such as analytical models or scheduling issues. In this paper, we attempted to review articles with broader methodological perspectives. This review has also been more recently updated. We examined the literature from a variety of angles: 1. model classification; 2. algorithms; 3. industry problems; 4. advantages and disadvantages. Moreover, the main scheduling and control methods are subdivided and categorized into several parts, the details for which are shown in Figure 20.

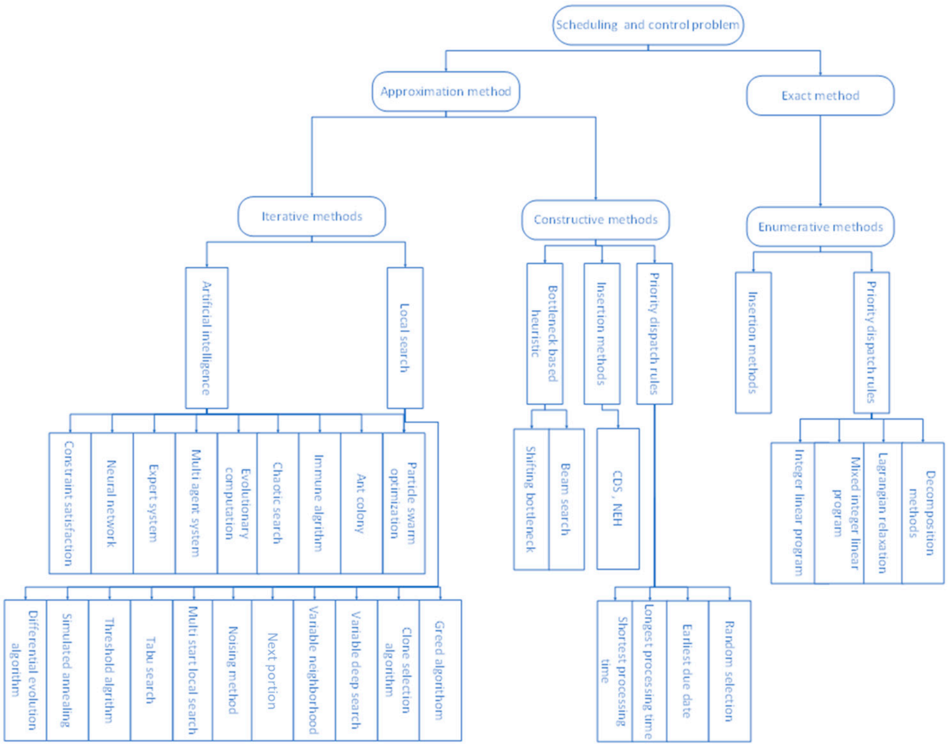


Figure 20. The main scheduling and control methods.

Exact methods, also known as optimization methods, can guarantee the global optimal solution, but these can only be used to solve "small-scale problems".

4.1. Exact Method

The precise methods are primarily based on operational research. Although the exact method can theoretically find the optimal solution, its practical application is limited.

4.1.1. Lagrange Relaxation

Lagrangian relaxation is an approach for finding the best answers to challenging optimization issues. This approach aims to optimally resolve complex problems in polynomial time by loosening some constraints in the problem and incorporating them into the "objective function" using "Lagrangian multipliers", followed by iteratively updating the multipliers using the gradient method to continuously raise the lower bound and lower the upper bound. Tang and Xuan [45] applied the "Lagrangian relaxation algorithm to the mixed flow job shop scheduling problem to minimize the total weighted completion time". Tang et al. [46] developed a "mixed integer programming model for the steel production scheduling problem and proposed a Lagrangian relaxation algorithm to solve it efficiently". Tang et al. [47] combined the "Lagrangian relaxation algorithm with the column generation algorithm for the optimization of the co-located batch decision-making in the steel industry".

4.1.2. Branch-and-Bound Method

This algorithm solves integer programming problems by partitioning feasible solution spaces, relaxing integer variables, and calculating upper and lower bounds, called bounding. Pruning deletes the worse solutions in order to reduce the search range until the upper bound equals the lower bound, resulting in an optimal solution. This approach reduces computational complexity by avoiding unnecessary searches. However, the algorithm requires large memory space to store root node information throughout the search process. In order to discover the best solution to the scheduling problem for up to 50 workpieces, Pots and Van Wassenhove [48] devised a branch delimitation algorithm for the single-machine production scheduling problem, and integrated it with the Lagrangian algorithm. Abdul-Razaq et al. [49] examined "branch-and-bound and dynamic programming" techniques and contrasted them using 50 workpiece instances. According to the experimental findings, this method can immediately identify the best solution to a small-scale problem, but it is impossible to quickly identify the best solution to a large-scale problem. This approach was utilized in a mixed-flow shop by Zhang W. [50] to reduce the overall drag time. In order to enhance performance, Néron E. et al. [51] integrated the ideas of inference (energetic reasoning) and global operations into the branch.

4.2. Approximate Method

The exact method is suitable for "small-scale problems". The production scheduling problems in manufacturing are usually complex and large-scale; moreover, the speed of solving problems is often demanding and important, so it is difficult to apply the above-mentioned exact algorithms to the actual production problems. Due to these limitations, approximation algorithms have received a lot of attention from both academics and industries. They have advantages such as simple structure, fast solution speed, and the ability to give an approximate optimal solution.

4.2.1. Intelligent Optimization Algorithm

Intelligent optimization algorithms are the most common methods because they do not seek to obtain the optimal solution, but obtain a satisfactory solution, which is more suitable for solving complex production problems. Additionally, intelligent optimization algorithms generally simulate a phenomenon or group behavior in the natural world, making them highly self-organizing, self-learning, and self-adaptive in the search process. They are easy to parallelize, which makes them different from the exact methods. In addition, this method can be subdivided into individual inspiration methods (tabu search algorithm, a simulated annealing algorithm, genetic algorithm, etc.) and population-based inspiration algorithms (ant colony algorithms, artificial bee colony, particle swarm optimization, differential evolutionary algorithm, etc.)

"Simulated Annealing Algorithm" (Individual Inspiration)

This algorithm was first suggested by "Metropolis", and its optimization approach alludes to the "physical annealing" procedure. "Job shop scheduling is a challenge that Matsuo [52] and Van Laarhoven [53] have addressed using the simulated annealing method. With the optimization goals of minimizing the completion time and the number of jobs with delayed completion, Chakraborty [54], Suresh [55], and others used the simulated annealing algorithm to solve the flow shop scheduling problem. The algorithm's effectiveness was shown by contrasting the algorithm's performance to the previous results. The fast simulated annealing process and quenching hybrid algorithm were used by Akram [56] and colleagues in 2016 to locate the global best solution and avoid falling victim to local optimizations. The job shop scheduling problem was optimized with the goal of minimizing completion time and compared against 88 benchmark cases; the ideal answer was 45 within a tolerable amount of time. Finally, it is shown that the algorithm can successfully identify the job shop scheduling problem's optimal solution". This approach can reach the global optimal value, since it needs a high beginning temperature and a slow cooling rate.

Tabu Search (Individual Inspiration)

The tabu search algorithm finds approximate optimal combinatorial solutions. Glover and Hansen proposed it in 1986, and Glover perfected it. It can solve some scheduling problems optimally. Tabu can solve many scheduling issues. The original solution, neighborhood structure, search approach, and table length are only a few of the issues with tabu search. Taillard used tabu search to schedule jobs for shops. "A critical path and block structure-based tabu search algorithm was presented by Nowicki et al. [57] to solve JSP. An N7 neighborhood-based tabu search technique was put forth by Zhang [98] in 2007. To overcome JSP difficulties, Sonawane et al. [99] combined the Genetic algorithm and the tabu search algorithm in 2014. For larger and more complicated scheduling issues, the tabu search method can achieve a faster average completion time. The tabu search algorithm is better. The tabu search algorithm has issues with the initial solution, the neighborhood structure, the search method, and the length of the tabu table". These issues can be resolved to benefit the tabu search algorithm.

Genetic Algorithm (Population-Based Algorithm)

The genetic algorithm, an intelligent optimization algorithm that simulates nature's evolutionary process, can search globally. Biogenetics selects fit individuals, crosses and mutates them to create new ones, and then replaces parents with better ones. Thus, everyone's fitness improves. Genetic algorithms self-organize and learn. Tabu search and annealing algorithms repeat one solution. Genetic algorithms are used in production scheduling, group optimization, machine learning, pattern recognition, optimal control, and other fields. Huang and Süer [100] examined an allocation rule-based hybrid multiobjective "genetic algorithm". Yang et al. [101] proposed a hybrid genetic algorithm for mixed-batch scheduling and planning. Goncalves [102] suggested incorporating local search into a hybrid genetic algorithm for production scheduling. " Figleska [103] investigated a special scheduling problem with multiple parallel machines in the first stage and one single machine in the second stage, and external resources are only available at a specific time". Muthiah and Rajkumar [104] proposed a genetic algorithm and an artificial bee colony algorithm for the job shop scheduling problem. The artificial bee colony algorithm performed better due to its local search ability. In practical production scheduling problems, Wong et al. [105] studied an integrated optimization problem of mould maintenance and production scheduling, taking into account maintenance cost, and proposed an effective legacy algorithm. Maimon and Braha [106] proposed a better genetic algorithm for single-machine circuit board production scheduling.

Ant Colony Optimization (ACO) Algorithm (Population-Based Algorithm)

Italian scholar Dorigo [107] proposed the ACO algorithm in 1991 to simulate ants' food-finding behavior. Ants leave "stigmergy" or "pheromone" as they search for food, which later, ants in the same colony can use to influence their behavior. Colorin et al. solved the workshop scheduling problem with the ACO algorithm, and many Chinese scholars have studied it. Despite slow convergence, the ACO algorithm solves complex combinatorial optimization better, such as robustness". Liao and Juan [108] used the "ant colony optimization algorithm" to reduce work time. Lin et al. [109] improved the flow shop scheduling ant colony algorithm. Yagmahan and Yenisey [110] proposed a multiobjective "ant colony optimization algorithm" for flow shop scheduling under multiobjective conditions, and tested it with standard problems. Cheng et al. proposed an efficient "ant colony algorithm" [99]. Mohammad et al. [111] improved the ant colony algorithm for automated car scheduling. Neto and Filho [112] reviewed the use of the ant colony algorithms in production scheduling, and suggested improvements.

Particle Swarm Optimization (PSO)

The PSO algorithm, proposed by "Kennedy and Eberhart" [113], simulates birds' self-organization, self-learning, and self-adaptation. In this algorithm, each particle represents a solution, and records its best solution so far (personal best solution). The population's best solution is the global best solution. Thus, the particle's next flight direction depends on three factors: the particle's original speed, which indicates search inertia; the individually best solution; and the population's best solution. In this way, the grains will keep their original direction while learning from both their individual best solution and the global best solution, improving search efficiency. It also has a fast convergence rate, but it tends to fall into local optimality. "JJ BAI et al. [114] proposed a method based on a particle swarm algorithm to solve MOFJSP batch scheduling, which introduces preference information to guide the particles to approach the Pareto front. G. Moslehi et al. [115], Liu et al. [116], Mostaghim et al. [117], and Tripathi et al. [118] used local search techniques, collaborative optimization techniques, the sigma method, and important parameter adaptive techniques to enhance the local optimization of the particle swarm algorithm to avoid local convergence. Shao et al. [119] proposed a hybrid algorithm based on discretized particle swarm and simulated annealing, which theoretically improved the application of the particle swarm algorithm in the field of MOFJSP discretization. The methods proposed in [114–116,118–120] all use the particle swarm algorithm based on the Pareto optimization technique. In general, the particle swarm algorithm has fast convergence and computational simplicity, but it easily falls into local optimum".

Differential Evolution Algorithm (Population-Based Algorithm)

This algorithm uses GA-like variation, crossover, and selection. From a randomly generated population, it uses the different vectors of two randomly selected individuals as one of the evolutionary directions for the third individual, and sums them according to certain rules to create a new variant. "The target is crossed with the new variant to create a new test. Selection takes place when the new one is better". The differential evolution algorithm uses these three processes because the selection operation keeps better solutions, and eliminates inferior ones to evolve the population towards the optimal solution. This algorithm solves group optimization problems, such as production scheduling, because it avoids local optimization and has strong global convergence. Deng and Gu [121] proposed a discrete differential evolution algorithm for the problem of the replacement flow shop scheduling without idleness, in which variation, crossover, and selection operations under discrete conditions are defined. For the same problem, Tasgetiren [122] combined a variable iterative greedy algorithm with a differential evolutionary algorithm to propose a highly efficient hybrid differential evolutionary algorithm. Liu [123] proposed a sequential differential evolutionary algorithm for the traditional flow shop scheduling problem, and used a rule to transform a continuous solution into a discrete scheduling solution.

Some of the approaches used to solve the scheduling problem are: ANN, multiagent system, Petri net, cultural algorithm, DNA algorithm, memetic algorithm, scatter search, and others. See Figure 12 for details. Each algorithm has pros and cons, so how to combine them is a hot topic. The following Table 1 summarizes and frequencies some common algorithms found in the 5052 documents selected for this research.

4.3. Production Control

Production control (PC) is the managerial responsibility for organizing, directing, and overseeing the procurement of raw materials and their processing within an organization. Based on the selected 5052 papers, we summarized them and classified them as the framework: 1. Regulated by orders; 2. Regulated by Inventory; 3. Flow-scheduled systems; 4. Hybrid control systems.

4.3.1. Regulated by Orders

Contract-Controlled System

The system essentially splits up large, complex contracts into many smaller orders for individual items. Additionally, the system establishes deadlines for each item's delivery or completion. The contract must be finished within the specified finishing date, so the work must be performed accordingly. As a result, it helps manage complicated project systems. Contrary to the majority of other SCO types, this system typically focuses on controlling production from the early stages of design.

Table 1. Common job shop scheduling and control algorithm classification and statistics table.

Category	Name of Methods	Exact or Approximate	Feature	Advantage	Disadvantage	Application	References	Quantity of Methods (%)
Enumerative methods	Decomposition method	Exact	The optimization problem transformed into a mathematical planning problem	Obtain the exact solution when the problem size is small	The solution time grows exponentially when the problem is an NP-Hard problem	Scheduling problem	[45–47]	1.13%
	Lagrangian relaxation method	Exact						14.29%
	Mixed integer linear program	Exact						0.40%
	Integer linear program	Exact						0.49%
	Branch and bound	Exact	Subdividing a problem into several subproblems and cutting out meaningless branches	Obtain the optimal solution and fast average solution speed	Takes up a lot of memory space	Integer planning problems, production schedule problems, site selection	[48–51]	0.20%
Local search	Greed algorithm	Approximate	The global optimal solution can be obtained by local optimal selection	Small code size, high operational efficiency, low space complexity	Cannot guarantee that the final solution obtained is optimal, cannot be used to solve maximum or minimum problems	Combinatorial optimization problems	[124–128]	2.24%
	Clone selection algorithm	Approximate	Distributed, adaptive learning, and parallel computation	Fast convergence and algorithmic diversity	Premature convergence and lack of cross-operation problems	Constrained optimization, dynamic optimization, time uncertainty scheduling problem	[129–135]	0.08%
	Variable neighborhood	Approximate	Changing the neighborhood structure	Versatility, robustness, few parameters	Long solution times for complex problems	Scheduling issues, vehicle path issues, color quantification, continuous optimization problems	[136–141]	3.48%

Table 1. *Cont.*

Category	Name of Methods	Exact or Approximate	Feature	Advantage	Disadvantage	Application	References	Quantity of Methods (%)
	Tabu search	Approximate	Avoid loops in the search process, only advancing and not retreat	Easy to obtain excellent solutions	Initial value sensitive	Displacement issues, scheduling issues	[57,98,99]	9.76%
	Simulated annealing	Approximate	Multiobjective optimization	Flexible, wide application, high operating efficiency	Longer optimization process	Neural networks, image processing, VLSI (very large-scale integrated circuit) optimal design, production scheduling	[52–56]	4.33%
	Differential evolution algorithm	Approximate	Group difference-based, heuristic, randomized search algorithm	Fewer undefined parameters, less likely to fall into local optimum, fast convergence	Search stagnates when the population is small	Data mining, pattern recognition, digital filter design, artificial neural networks	[121–123]	2.85%
Artificial intelligence	Genetic algorithm	Approximate	Simulating natural evolution to search for optimal solutions	Fast random search capability, scalability	Poor local search capability, easy to fall into "premature"	Combinatorial optimization, data mining, image processing, production scheduling	[100–106]	28.70%
	Ant colony algorithm	Approximate	Self-organization, positive feedback, global optimization	Excellent computing power and operational efficiency	Slow initial convergence	Multiobjective optimization, data classification, data clustering, pattern recognition	[107–112]	1.46%
	Particle swarm optimization	Approximate	Swarm intelligence, random search	Highly versatile algorithm, adjust few parameters, simple principle, easy to implement, fast convergence speed	Not enough search accuracy	Neural network training, image processing field, electric power system field, the field of mechanical design	[113–120]	9.36%

Table 1. *Cont.*

Category	Name of Methods	Exact or Approximate	Feature	Advantage	Disadvantage	Application	References	Quantity of Methods (%)
	Immune algorithm	Approximate	Swarm intelligence search algorithm, global convergence	Ensures population diversity, overcomes the 'early maturity' problem, and allows for a globally optimal solution	Easy to fall into local search, bad group diversity	Nonlinear optimization, combinatorial optimization, control engineering, robotics, fault diagnosis, image processing	[142–147]	1.80%
	Chaotic algorithm	Approximate	Randomness, traversal, regularity	High efficiency, confidentiality, and ease of use	Uneven traversal, high search density at boundaries, long search time	Image data encryption, secure communications, control systems, and optimization	[148–151]	1.23%
	Multiagent system	Approximate	Autonomy, interaction with other agents and people, time continuity, self-adaptability, mobility	Scalability and design flexibility and simplicity, reduces system complexity	Gossip problem, delay in information exchange	Large-scale complex problems	[152–159]	5.13%
	Expert system	Approximate	The combination of "knowledge base" and "inference machine"	High efficiency, flexibility, transparency	Narrow field of knowledge and possible disparity of opinion	Speech understanding, image analysis, system monitoring, chemical structure analysis, signal interpretation, etc.	[160–162]	1.68%
	Neural network	Approximate	Massively parallel processing, distributed storage, elastic topology, highly redundant and nonlinear operations	Self-learning, self-organizing, fast-solving speed, robustness	Requires large amounts of data, black box	Pattern recognition, intelligent control, combinatorial optimization, prediction	[163–171]	6.85%

4.3.2. Regulated by Inventory

CONWIP (Constant Work-in-Progress)-SLC System (Pull-Based)

Spearman et al. proposed the "CONWIP system" (1990). The quantity of cards sets a limit on the total amount of work being performed. The logic behind how this system operates is as follows: in order to authorize a job to enter the production line, a card that is available must be present. Numerous researchers, such as Papadopoulou et al. [172], Yang [173], and Krishnamurthy [174], have suggested that the CONWIP-SLC is suitable for a "flow shop repetitive environment". According to Li [175], this system allows for a greater variety of products than Kanban systems. Ryan [176] explained the procedure of using CONWIP in a job shop with multiple products. Slomp's recent study [177] demonstrates a practical application of CONWIP-SLC. According to Stevenson et al., a variation of the CONWIP system, known as "m-CONWIP", can be used in a setting with a greater variety of products. For every shop floor routing scenario, there are m (multiple)-CONWIP loops in this system.

Kanban-SLC System

This approach was defined as "Kanban variations that follow the PPC department's pull production from stock without central scheduling. The most common Kanban types are production (P-Kanban) and transportation (T-Kanban)". When both types are used, it is called dual-card Kanban. When only one type is used, it is called single-card. Arbulu's construction material procurement process uses Kanban [178]. Kumar and Panneerselvam [179] noted that supply chain management, CONWIP, and Kanban can help JIT initiatives succeed. The Kanban system reduces inventory by producing just-in-time to meet demand at each stage [179,180]. N. Singh and Kwok Hung Shek [180] used the general purpose simulation system to study the "Kanban system" in an assembly area. For repetitive flow shop systems, Snyder [181] recommends the "Kanban system". "The development of the Kanban system at a local manufacturing company in Malaysia" is presented by Naufal et al. [182]. This system is also a "key operations management tool" in "Lean manufacturing" [183].

Periodic-Review System

In this system, the inventory level (I) is checked at fixed intervals, called review periods. The quantity needed to make the inventory reach a predetermined level S is the size of the order. Two examples of studies discussing this system in the literature are the works by Maddah et al. [184] and Li Z. et al. [185]. Consider a periodic-review inventory system with erratic supply and demand. A periodic review inventory system with two resupply modes, a normal mode and an emergency mode [186], also creates processes to deal with the inventory issue in these two modes.

4.3.3. Flow-Scheduled Systems (FS)

There are several systems are based on flow scheduling, such as the PBC (period batch control) system, the MRP (material requirements planning) system, and the OPT (optimized production technology) system. Each of them has its own features and applications. For instance, the inventory between each production and demand stage is constrained in the base-stock system. In PBC, it is a cyclical process, which means that all of the needed components are to be prepared in the previous stage. Companies can determine when, how many, and what products to produce and purchase by using the MRP system. It runs on a preset cycle in which the components needed for a later period in the following stage are produced (Benders and Riezebos [187]). As a result, the previous stage of production is scheduled to include building and constructing the products in one session, which is based on the definition of final product production (semifinished products, components, and raw materials).

PBC System

In or around 1926, Mr. R. J. Gigli developed the PBC system. It is a cyclical system that runs on a fixed cycle or periods, during which, the components needed for a later period in the following stage are produced (Benders and Riezebos [187]). As a result, the previous stage of production is scheduled to include the building of all the components needed to construct the products in one session. According to Maccarthy and Fernandes [188], the repetitive and semirepetitive production systems are a good fit for the application of PBC. Tesic et al. [189] developed a new model to implement the "PBC system into a virtual manufacturing environment, to better integrate the production planning with the applications of group cells". Moreover, it is important to remember that Benders [187] thought the PBC system was a classic, and not out-of-date system. Stevanov B. et al. [190] used this system, combined with computational methods, to deal with the railway brake services [191].

MRP System

Since the 1970s, large corporations around the world have used MRP, a sophisticated SCO. MRP helps companies decide what, when, and how much to make and buy. It can handle complex situations, such as many products with a BOM, according to Velasco [192] and Arnold [193]. "Non-repetitive production systems" can use MRP [188,194]. Gupta and Snyder argue that MRP can be used with other SCOs due to its adaptability [181].

OPT System

Eliyahu Goldratt created the OPT (optimized production technology) system in the 1970s. The OPT system is made of two basic components: software, and a philosophy that is embodied in the well-known 10 OPT [195,196]. The BUILDNET module receives input data as part of OPT software's fundamental operation. The SERVE module then determines a resource's average utilization and load profile. "The SPLIT module divides the network into critical and noncritical resource areas" based on this capacity calculation. Additionally, time buffers are allotted where necessary. Finally, the OPT module creates a realistic master production schedule using a good heuristic. There is OPT parameterization in the work of Croci and Pozzetti [197].

4.3.4. Hybrid Systems

Apart from the above system, there also burst some new control systems which combined some of the former ones, and the typical example is the "POLCA (paired-cell overlapping loops of cards with authorization) system". In this system, POLCA cards are the name for production control cards. This process, which releases authorizations through a "high-level centralized material requirements planning system (HL/MRP)", controls the flow of orders through the various cells. Because of its operational logic, POLCA is a hybrid system. Regarding the field of application, according to Krishnamurthy et al. [198] and Suri [199], POLCA is a quick-response manufacturing strategy designed to address material control. "Lödding et al. [200] suggest POLCA for environments with a high number of variants and complexity of materials flow. Optimization of the POLCA system is found in Fernandes Braglia [201] and Santos et al. [202]. Chinet [203] gives an overview of POLCA research, as well as a relevant case study".

4.4. Integrated Scheduling and Control System

This system is the best solution to respond to the dynamic environment. Scheduling policy solving and control command computation are used as virtual objects, and automation devices as physical objects. One of the classic systems, such as parallel Petri nets [204], provides a feasible solution to achieve the interactive co-integration of the physical and information worlds [205]. In addition, digital twins can be applied to different layers of the production process, such as the equipment layer, the production line layer, and the factory layer, and achieve the interconnection of shop floor information and physical space.

Research on integrated scheduling and control in industry is currently focused on power grids [206], railroads [207], and elevators [208]. Baldea and Harjunkoski [209] systematically reviewed the theory of "integrated production scheduling and process control", and summarized the integrated model into the following types: top-down integration approaches, bottom-up approaches, and state-space scheduling.

4.4.1. Top-Down Approaches

Top-down approaches are scheduling frameworks with dynamics and control components such as time scale-bridging. Dynamic optimization can create good scheduling and control options using all relevant dynamic and economic data. They use open-loop control, but lack a feedback structure to ensure process stability and performance outside of the rated operating conditions (Mitra et al. [210]; Zhuge and Ierapetritou [211]). It has no explicit feedback structure for stability and performance, and is subject to scheduling and control disturbances (e.g., fluctuations in feed quality). Zhuge and Ierapetritou [211] proposed a scheduling mechanism that recomputes the plan and control actions for the remaining cycle time after a disturbance, building on Flores-Tlacuahuac and Grossmann [212]. "(Based on crossing a threshold between target and actual process states). Terrazas-Moreno et al. [213] discuss workload-reducing decomposition methods". Numerous cases [214–217] have shown that process system input–output dynamic behavior is slow, emerges over a time scale relevant to scheduling computation, and can be described by a low-dimensional model.

4.4.2. Bottom-Up Approaches

This strategy involves including "economic considerations in the design of the plant's overall control framework". Skogestad [218] suggested this consideration at the "level of the distributed control system", while Kadam and Marquardt [219] and Engell [220] recommended it as part of the supervisory controller. Reaidy [221] proposed integrating bottom-up and IoT to enhance the flexibility of warehouses in a dynamic environment.

4.4.3. State-Space Scheduling

The growth of state spaces has attracted the attention of researchers. This includes the existence of perturbations, and the necessity of updating control procedures and schedules in the event of perturbations. In the report by Gallestey et al. [222], for instance, hybrid MPC is applied to scheduling issues, and multiple authors have discussed multiparameter scheduling solutions. Several authors have talked about this approach [223–228].

5. Discussion and Future Trends

5.1. Overview

In order to review the body of knowledge on job shop production scheduling and control, this study uses scientometric analysis. The study of classical scheduling theory in the workshop started in the 1950s, and the first study was published in 1959. There were not more than 100 articles a year until the late 1980s. A general upward trend in publications over the past 20 years, with a peak in 2021, confirms the growing interest in the study of shop floor scheduling control issues. The articles, however, are primarily focused on the areas of engineering and computers, with 36.9% and 25.0%, respectively. This highlights the close relationship between product development and computers in modern engineering [229–231].

This network analysis study examined the relationships between research countries, key researchers, and published documents. The "co-citation network mapping" results presented in Sections 3.4–3.6 highlight global and homogeneous researcher interactions. First, China leads in research influence, along with the U.S.A. China keeps links with other countries in Figure 9, but Italy, the U.K., and France are weak. Most researchers co-cite influential JSSC scholars (Figure 8). This agrees with the observations in Sections 3.2 and 3.7 that scholars in this field, and in different national regions, do not communicate enough.

Overall, "the publication bottleneck in which manufacturing-related research is published on JSSC is more complicated [232–234]. A journal's value as a source of knowledge can be measured by the number of studies it publishes in its particular field [235–237]. In this regard, the *International Journal of Production Research* has published the most articles on the topic under review, a total of 279. In addition, it contains a greater number of citations than *Computers and Industrial Engineering* and the *International Journal of Advanced Manufacturing Technology* [238–240]. In summary, the *International Journal of Production Research* appears to be the leading journal in its field" [241–243]. Thus, based upon existing studies, this study has explored the research implementation by analyzing and classifying the present research status, research hotspots, and potential future trends in this field of "Lean Construction", "job shop scheduling and control (JSSC)", and "Information and Communication Technology" [244,245]. As organizations recognize the importance of scheduling control, an increasing number of them are adopting it as a means to attain social, environmental, and economic advantages [246].

5.2. Future Scope

Even though the knowledge appears to concentrate on all of the key themes in manufacturing, including "operational and management issues, resource optimization, better production scheduling, and activity tracking, it is possible to identify emerging issues in the field, and potential partnerships between research clusters. Some following topics, such as "smart manufacturing", "decision-making system" and "Integration of scheduling and control" are proposed to be added to the current research agenda in the field of scheduling and control in manufacturing" in this section. For example, smart manufacturing can benefit from real-time machine visibility, thanks to the application of augmented reality technology. The AR interface can reflect the status of a machine and its processing behavior through a visualized model in real-time using data from smart machines. Users can view projected machine data on a real machining scenes with AR-enabled real-time visibility [224]. In decision-making systems, cloud technology and big data will be used, which enable end users to conveniently pay as they go for services when they are needed [225], and could be set up on a cloud platform for easy end-user download and use in daily decision-making. Last, is the "Integration of scheduling and control", which is currently a new area of research interest. Because the two theories were created independently for a long time, there are numerous modeling, numerical, and organizational hurdles to their smooth integration. When combining their needs, the first thing to take into account is their various temporal horizons [226]. The synchronization of calculation and decision-making, on several time scales, is difficult because scheduling takes hours or days, and control takes minutes or seconds [227]. The scheduling model is usually static and must be upgraded to dynamic, while the control model is usually linear and must be upgraded to nonlinear [228]. Thus, integrated intelligent scheduling control requires fast dynamic and nonlinear model real-time computations. Thus, future research will continue to create a great integrated system.

6. Conclusions

Scheduling and control in production, particularly in uncertain environments, have garnered the attention of researchers. Acknowledging the significance of scheduling control, more and more companies are implementing it to achieve social, environmental, and economic benefits for their organizations. Similarly, recognizing the importance of lean construction, companies are increasingly adopting scheduling practices to achieve their organizational social, environmental, and economic goals. The increasing number of empirical and conceptual papers on job shop scheduling and control (JSSC) indicates that research in this area is gaining academic attention. However, a limited literature review on JSSC does not provide a better understanding and overview of developments in this field. To address this, the main objective of this study is to provide a visual and systematic scientometric review of 5052 articles and reviews published from 2002 to 2022. Research methods include co-authorship analysis, co-keyword analysis, and co-citation analysis.

This study aims to answer the following questions: What are the unique technologies in the scheduling control (SC) field? What are the development processes in the SC field? What are the future trends in the SC field? By focusing on key nodes with high frequency, centrality, and burst intensity, and the articles contained behind them, this report sheds light on key emerging trends that are of value to the reader. We find that there are some limitations regarding databases, search terms, methodology, and citation manipulation. Future research could retrieve data from other databases, cover papers with a wider variety of language, combine scientometric review with the conventional systematic review method, and focus on tracing and addressing issues with citation manipulation. Overall, this study aims to help researchers and practitioners better understand the developments in the field of job shop scheduling and control.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15097600/s1. PRISMA checklist [247].

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