



INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X

Impact Factor: 6.078

(Volume 12, Issue 5 - V12I5-1251)

Available online at: <https://www.ijariit.com>

Application of Operations Research in Production Planning

Dr. Richa Kalpesh Saxena

richa.saxena@nmims.edu

NMIMS, Anil Surendra Modi
School of Commerce, Mumbai
Campus

Vaibhav Shah

vaibhav.shah191@nmims.in

NMIMS, Anil Surendra Modi
School of Commerce, Mumbai
Campus

Vansh Sanghavi

vansh.sanghavi666@nmims.in

NMIMS, Anil Surendra Modi
School of Commerce, Mumbai
Campus

Vihaan Jain

vihaan.jain620@nmims.in

NMIMS, Anil Surendra Modi
School of Commerce, Mumbai
Campus

Viraj Kothari

viraj.kothari138@nmims.in

NMIMS, Anil Surendra Modi
School of Commerce, Mumbai
Campus

ABSTRACT

The present review is a systematic literature review-cum-bibliometric analysis of the application of operations research (OR) to production planning and optimisation in manufacturing. The data for the review was procured from Elsevier's Scopus database using the keywords "Production Planning", "Optimization" and "Manufacturing", and was screened using the PRISMA framework. The final database comprises 1,591 articles and review papers published between 2016 and 2026. Using Biblioshiny, the study examines publication trends, leading sources, authorship and the thematic structure of the field. Annual output rose from 75 documents in 2016 to 273 in 2026, an annual growth rate of 13.79%, spread across 568 sources and 5,270 authors. Production control and optimisation, and smart manufacturing and Industry 4.0, were found to be the dominant themes, while sustainability-oriented multi-objective decision making is emerging. The review identifies eight research priorities, including common benchmarks, fair comparison of learning-based and classical OR methods, digital twins, human-centric planning and integrated, resilient planning.

Keywords: Operations Research, Production Planning, Optimisation, Manufacturing, Bibliometric Analysis.

1. INTRODUCTION

Production planning is an important part of manufacturing because it helps businesses decide what to produce, how much to produce, when to produce it and how to use available resources. Companies must manage workers, machines, raw materials, inventory and delivery deadlines at the same time. Poor planning can lead to higher costs, delays, unused resources and excess stock. Since these decisions are connected, production planning can be difficult, especially when a company has limited resources and changing customer demand (Lindahl et al., 2023).

Operations research (OR) provides a systematic way to deal with these challenges. It uses mathematical models, data and analytical methods to compare different options and support decision-making. Techniques such as linear programming, mixed-integer programming, inventory models and scheduling can help manufacturers allocate resources, control costs and meet production targets. These methods do not replace managerial judgement, but they can help managers make decisions based on evidence rather than relying only on experience (Saxena et al., 2024).

The importance of OR has increased as manufacturing has become more technology-driven and competitive. Industry 4.0 has introduced connected machines, automation and digital systems that provide information about production, orders and inventory. Such information can help businesses make better decisions and update their plans when conditions change. Research on smart factory design has also shown how digital technologies can influence the way production systems are organised (Pei et al., 2017). At the same time, these developments create a need for planning approaches that can respond quickly to new information.

Manufacturers must also consider several objectives at once. Along with reducing costs, they need to maintain quality, deliver products on time, reduce waste and use energy efficiently. These objectives may sometimes conflict. For example, faster delivery could require overtime and increase operating costs, while reducing energy use could affect production time. Multi-objective optimisation helps researchers examine these competing goals together (Ojstersek et al., 2020). Uncertainty adds another challenge because demand, prices and supplier deliveries may not follow expectations. Robust optimisation, stochastic models and simulation-based methods have therefore been studied to help production plans cope with changing conditions (Ardjmand et al., 2016; Escuin et al., 2017; Amiri et al., 2019).

Artificial intelligence and machine learning are also receiving growing attention in production planning. These approaches can identify patterns in data and support decisions such as scheduling, quality control and production control. Recent research has explored learning-based methods alongside traditional optimisation techniques, rather than treating them as complete replacements for established OR methods (Burggraf et al., 2021; Mayerhoff & Schmidt, 2026). However, as the number of studies increases, it becomes harder to understand the overall direction of the field, compare the methods being developed and identify the gaps that still remain.

This study therefore reviews research on the application of operations research to production planning and optimisation in manufacturing. It uses a systematic literature review supported by bibliometric analysis to examine publication trends, leading sources, authorship and collaboration patterns, and the main themes in the literature. The study also considers how interest in areas such as artificial intelligence, digital twins, sustainability and resilience has changed over time. By bringing these areas together, the review aims to provide a clearer picture of the field and identify priorities for future research.

The review is organised as follows. The next section presents the literature review, followed by the research methodology. The data analysis and results are then discussed, followed by the future research agenda, and the paper closes with the conclusion and limitations.

2. LITERATURE REVIEW

Production planning has been widely studied, and many mathematical approaches to optimisation have been discussed (Lindahl et al., 2023). With advances in areas such as artificial intelligence (AI) and operations research, production planning optimisation has become a dynamic area in which researchers and scholars can apply such concepts and create new methods. Operations research is a scientific approach to solving problems in the management of complex systems, which enables decision-makers to make better, logic-backed decisions (Saxena et al., 2024). Industry 4.0 is one such concept, describing how digitisation, automation and new technologies can transform processes in businesses around the globe (Guerrero et al., 2025a). It is a set of technologies, organisational concepts and management principles that can improve the performance of manufacturing supply chains, driven by production cost optimisation, mass customisation requirements, connectivity and the digitisation of factories. Closely aligned with Industry 4.0 and operations research are concepts such as multi-objective optimisation, digitisation, simulation, smart manufacturing and reinforcement learning.

Multi-objective optimisation, in the context of this topic, refers to the systematic process of optimising several objectives of a business process at the same time. It is a well-known research field in production planning and scheduling (Ojstersek et al., 2020). AI is another concept that is being readily adopted in areas such as scheduling and quality control, and it is expected to become a major part of production planning processes in the coming years (Burggraf et al., 2021). Reinforcement learning, considered a subset of AI, has offered innovative solutions to dynamic production planning and control (PPC) by improving key performance indicators (KPIs) through autonomous learning (Mayerhoff & Schmidt, 2026).

Such concepts show that new advancements in production planning are significant and that these advances are beneficial to businesses. The evidence from the literature further supports this claim, and the optimisation of production planning therefore remains a progressing field in which scholars and researchers continue to work. Table 1 indicates the scope of some of the literature reviewed for this paper.

Table -1: Scope of papers reviewed

Authors	Scope of Study	Year
Ma et al.	Review of process planning from an operations research perspective	2026
Mayerhoff & Schmidt	Reinforcement learning for autonomous production planning and control	2026
Pei et al.	Research on design of the smart factory for forging enterprise in the Industry 4.0 environment	2017
Ardjmand et al.	A robust optimisation model for production planning and pricing under demand uncertainty	2016
Escuin et al.	Inventory replenishment policies with time-varying stochastic demand for the paper industry	2017
Amiri et al.	Multi-objective simulation optimization for uncertain resource assignment and job sequence in automated flexible job shop	2019

3. RESEARCH METHODOLOGY

Traditional literature reviews often lack thoroughness and rigor and are conducted ad hoc, rather than following a specific methodology (Snyder, 2019). The authors have therefore followed a specific and widely used methodology. A Systematic Literature Review (SLR) is used as the method to review past studies and strengthen the foundation of knowledge on a broad topic (Paul & Rialp-Criado, 2020). The current study employs bibliometric analysis under the SLR to build a strong foundation for the chosen topic, using data obtained through a keyword search and citation analysis of peer-reviewed journal articles and review papers (Saxena et al., 2024). Aggregated data analysed through bibliometric analysis allows one to understand the structure of a field, its

social networks and its topical interests easily and efficiently (Zupic & Čater, 2015). For this purpose, literature databases are used as a tool to assess publications in a specific subject, discipline, country or region of the world (Alryalat et al., 2019).

3.1 Article selection, inclusion and exclusion criteria

The data was obtained from Elsevier's Scopus database using the keyword search method. This method helped the authors obtain a relevant sample space from the very start of the process of building a dataset for bibliometric analysis.

The inclusion and exclusion of records was based on the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement. PRISMA is a systematic process that helps reviewers document what was done, why the review was done and what the authors found (Page et al., 2021). It has well-established steps, namely Identification, Screening, Eligibility and Inclusion, which ensure that the research methodology is documented efficiently and effectively.

Initially, the keywords "Production Planning" AND "Optimization" were used, which returned 22,212 documents. To obtain a more niche and smaller sample space, the authors added the keyword "Manufacturing". This led to a result of 4,916 documents. The exact search string finally used in Elsevier's Scopus was "Production Planning AND Optimization AND Manufacturing". Thus, in the Identification step of PRISMA, a total of 4,916 documents were included in the sample space.

The authors then applied a time span filter. Research papers were found to start from 1968 and extend to 2027, but the early years contained far fewer publications. To ensure an adequate time span for analysis, the previous ten years (2016 onwards) were retained and papers from 1968 to 2015 were excluded. The authors also checked for skipped years, since gaps would have prevented uniformity in the data, and no skipped years were found in the period selected. This filter excluded 2,018 papers.

Next, the authors excluded conference papers, book chapters, conference reviews, books, retracted documents, notes, errata, editorials, short surveys and data papers, so that the sample space was limited to articles and reviews. This step was important because it made the bibliometric analysis of the topic more convenient and consistent, and it removed 1,185 documents.

The remaining papers were written in a range of languages, which would have been an obstacle to further analysis. It was therefore decided to exclude languages such as Chinese, Russian and German and to retain only English, as it is widely accepted globally. This excluded 111 papers, which also shows that most of the articles and review papers on the chosen topic are written in English.

Finally, a filter was added on the source type. The database showed three categories, namely journal, trade journal and book series. After careful analysis, the authors excluded trade journals and book series, which removed a further 5 papers. The resulting 1,597 documents formed the final sample space. Figure 1 documents all inclusion and exclusion criteria applied in refining the sample space, in accordance with the PRISMA 2020 statement (Page et al., 2021).

3.2 Bibliometric analysis

Bibliometric reviews analyse an extensive body of published research using statistical tools, in order to identify trends and citations and/or co-citations of a particular theme by year, country, author, journal, method, theory and research problem (Paul & Rialp-Criado, 2020). The authors have used bibliometric analysis for the same purpose on the topic chosen in this paper. After the keyword search in Elsevier's Scopus database and the application of the above filters, the remaining papers were exported as an .ris file and imported into Mendeley Desktop, a reference manager. The papers were then exported from Scopus as a BibTeX file (.bib), the format required for further analysis.

The authors used the "bibliometrix" package in RStudio and imported the BibTeX file into its web interface, Biblioshiny (Aria & Cuccurullo, 2017). Biblioshiny restricted the data to the 2016 to 2026 timespan and converted it into a spreadsheet-compatible (.xlsx) file for further analysis in Microsoft Excel. Performance indicators and thematic mapping were then used to examine publication trends, sources, authorship and the conceptual structure of the field.

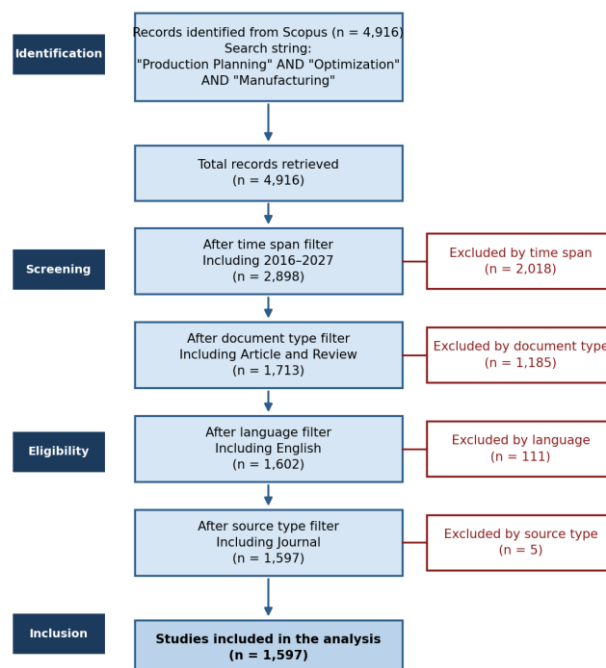


Figure -1: PRISMA flow diagram of the screening process (author's work).

4. DATA ANALYSIS AND RESULTS

4.1 Overview

This section analyses 1,591 documents on optimisation in manufacturing production, covering production planning, scheduling and production control, published between 2016 and 2026. The data was exported from Scopus on 10 September 2026 as a BibTeX file of 1,597 records (1,522 articles and 75 reviews, all in English). After Biblioshiny restricted the data to the 2016 to 2026 timespan, 1,591 documents remained for analysis.

The analysis was carried out with the bibliometrix R package through its web interface, Biblioshiny (Aria & Cuccurullo, 2017). Bibliometrix supports the full science-mapping workflow, from importing and cleaning data to performance analysis and conceptual mapping (Aria & Cuccurullo, 2026). Following Zupic and Čater (2015), the analysis combines performance indicators (documents, sources and authors) with science mapping (the thematic map) to describe both how much is published and what the field is about.

4.2 Main Information

Table -2: Main information about the dataset

Indicator	Value
Timespan	2016–2026
Sources (journals, books, etc.)	568
Documents	1,591
Annual growth rate	13.79%
Authors	5,270
Authors of single-authored documents	66
International co-authorship	26.34%
Co-authors per document	3.88
Author's keywords (DE)	4,783
References	0
Document average age	3.68 years

Table 2 summarises the dataset. Over eleven years, 1,591 documents were published in 568 different sources by 5,270 authors. The field is clearly team-based, with 3.88 co-authors per document and only 66 authors writing alone. The average document is only 3.68 years old, which means most of the literature is recent and the topic is still developing.

Optimisation of manufacturing production is a core application area of operations research. It covers problems such as production planning, job-shop and flow-shop scheduling, process planning and maintenance planning. The most frequent author keywords in the dataset (production planning, optimization, scheduling, Industry 4.0 and genetic algorithm) confirm that the collection is centred on these classical operations research problems, increasingly solved in a smart-factory context.

4.3 Annual Growth Rate

The number of publications on optimisation in manufacturing production grew at 13.79% per year between 2016 and 2026. This is a compound rate: it compares the output of the first year with the output of the last year and spreads the change evenly over the ten intervals.

$$\text{Annual Growth Rate} = (N_{2026} \div N_{2016})^{1/10} - 1$$

As Table 4 shows, 75 documents were published in 2016 and 273 in 2026, a rise of more than three and a half times. A growth rate close to 14% a year is high for a field built on long-established methods such as linear and integer programming. It shows that manufacturing optimisation is still attracting new research interest.

There are several likely reasons. First, Industry 4.0, digital twins and smart manufacturing have created new planning and scheduling problems with real-time data. Second, machine learning, reinforcement learning and metaheuristics such as genetic algorithms give researchers new ways to solve large problems that exact methods cannot handle. Third, pressure to cut energy use and emissions has added sustainability objectives to classical cost and time objectives.

Two cautions apply. The data was exported in September 2026, so the 2026 figure covers only part of the year and the true growth rate is probably slightly higher. In addition, the growth rate is an average for the whole period and does not show in which years growth was faster or slower.

4.4 Sources

The 1,591 documents were published in 568 different sources, an average of about 2.8 documents per source. Research on manufacturing optimisation is therefore spread across many outlets rather than concentrated in a few journals.

This spread reflects the interdisciplinary nature of the topic. Optimisation of production draws on operations research, industrial engineering, manufacturing technology, computer science, automation and sustainability studies. Researchers from each discipline tend to publish in journals that belong to their own field, which increases the number of sources.

One implication is that a researcher who wants to follow this topic needs to watch a wide range of journals. At the same time, the low average number of documents per source suggests that many sources publish only one or two papers on the topic. A small group of core journals carries a large share of the output, as the analysis of the most relevant sources below shows.

4.5 Authors

A total of 5,270 authors contributed to the 1,591 documents, which is about 3.3 authors for every document in the dataset. Each document has on average 3.88 co-authors. This large author base shows that many research groups around the world are working on manufacturing optimisation problems.

Teamwork is natural in this field. A typical study combines a mathematical model, a solution algorithm, computational experiments and often a real industrial case. Each of these steps needs different skills, from modelling and programming to knowledge of the shop floor, so the work is usually shared among several researchers.

4.6 Single-Authored Documents

Only 66 of the 5,270 authors, about 1.25%, have written single-authored documents. Almost all research in the dataset is therefore produced by teams rather than by individuals. This very low share fits with the high figure of 3.88 co-authors per document. It suggests that the field has moved away from the individual theoretical contribution typical of early operations research towards group-based work that joins modelling, computation, data analysis and industrial application. In the Scopus export, 65 of the 68 single-authored documents are research articles and only 3 are reviews, so individual researchers still make original contributions, but they are rare.

4.7 Other Indicators

International co-authorship accounts for 26.34% of documents, so roughly one paper in four involves authors from more than one country. This level of collaboration suggests that manufacturing optimisation problems are of shared global interest, with universities and industry partners working across borders. The documents contain 4,783 different author's keywords. This large vocabulary reflects the many production problems, solution methods and application settings covered, from flow-shop scheduling and process planning to digital twins and additive manufacturing. The literature is also recent, with an average document age of 3.68 years.

Finally, the number of references is shown as 0, which means that no cited-reference data was included in the export. Analyses that depend on references, such as co-citation and bibliographic coupling, could therefore not be performed, and citation-based results should be read with caution.

4.8 Most Relevant Sources

Table -3: Twelve most relevant sources by number of documents

Rank	Source	Documents	% of 1,591
1	Computers and Industrial Engineering	68	4.3%
2	International Journal of Production Research	66	4.1%
3	International Journal of Advanced Manufacturing Technology	60	3.8%
4	Applied Sciences (Switzerland)	47	3.0%
5	Journal of Manufacturing Systems	40	2.5%
6	Journal of Cleaner Production	36	2.3%
7	Sustainability (Switzerland)	31	1.9%
8	International Journal of Production Economics	28	1.8%
9	IEEE Access	25	1.6%
10	Journal of Intelligent Manufacturing	24	1.5%
11	IEEE Transactions on Automation Science and Engineering	22	1.4%
12	European Journal of Operational Research	21	1.3%
	Total (12 sources)	468	29.4%

The most productive source is Computers and Industrial Engineering with 68 documents (4.3% of the dataset). It is followed closely by the International Journal of Production Research (66) and the International Journal of Advanced Manufacturing Technology (60). Together the top three sources account for 194 documents (12.2%), and the top five for 281 documents (17.7%).

The differences between the leading sources are small, so no single journal dominates the field. However, the twelve sources listed make up only 2.1% of the 568 sources, yet they publish 468 documents, almost 30% of the total. The field therefore has a clear core of journals and a long tail of sources that publish only a few papers each, as Bradford's law would predict.

4.8.1 Observations on publication venues

The twelve sources fall into four broad groups:

- **Operations research and industrial engineering:** Computers and Industrial Engineering, International Journal of Production Research, International Journal of Production Economics and European Journal of Operational Research. Their presence confirms that production planning and scheduling are treated as classical operations research problems.
- **Manufacturing technology and systems:** International Journal of Advanced Manufacturing Technology, Journal of Manufacturing Systems and Journal of Intelligent Manufacturing. These focus on applying optimisation on the shop floor and in smart factories.
- **Automation and computing:** IEEE Transactions on Automation Science and Engineering and IEEE Access, which reflect the role of control, automation and data-driven algorithms.
- **Sustainability:** Journal of Cleaner Production and Sustainability (Switzerland), which show that energy and environmental objectives are now part of production optimisation.

Three of the twelve sources, Applied Sciences, Sustainability and IEEE Access, are fully open-access journals. Together they published 103 of the 468 documents (22%), which suggests that researchers value the speed and visibility of open-access publishing. Even so, established subscription journals such as the International Journal of Production Research and the European Journal of Operational Research remain central outlets.

4.9 Sources Production over Time

Cumulative documents of the five most relevant sources, 2016–2026

Together: 22 documents in 2016, 281 by 2026

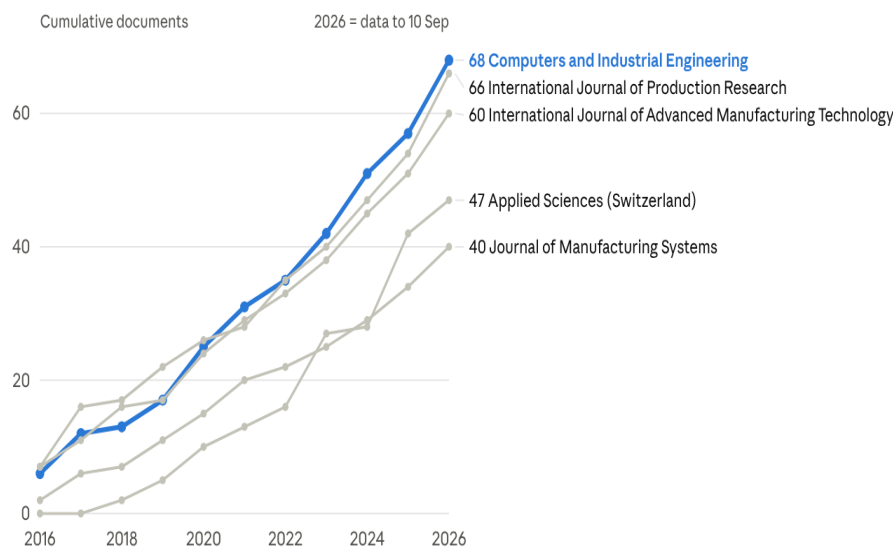


Figure -2: Sources production over time (cumulative documents of the five most relevant sources, 2016–2026)

Figure 2 shows how the output of the five most relevant sources built up year by year. The values are cumulative, so each line can only rise or stay flat, and the 2026 values (68, 66, 60, 47 and 40) equal the totals in Table 3. The steeper a line, the more documents that source published in that year.

The five sources together published only 22 documents in 2016 but reached 281 by 2026, 17.7% of the whole dataset. By the end of 2021 they had a combined 121 documents; the remaining 160 (57%) appeared in the five years from 2022 to 2026, so production has clearly accelerated in recent years.

The International Journal of Production Research led from 2016 to 2020. Computers and Industrial Engineering moved ahead in 2021 (31 against 28), the two were tied at 35 in 2022, and Computers and Industrial Engineering has led ever since, adding 11 documents in 2026 alone. Applied Sciences (Switzerland) shows the most striking rise: it published nothing on the topic until 2018, then grew to 47 documents, with its largest jump in 2025 (+14). This matches the wider growth of open-access publishing noted in the sources analysis. The Journal of Manufacturing Systems grew more steadily, from 2 documents in 2016 to 40 in 2026. Because the data was exported in September 2026, the final year is incomplete, and the true 2026 figures for each source are likely to be higher.

4.10 Thematic Map

The thematic map groups keywords into clusters (bubbles) and places each cluster by its centrality, meaning how strongly it links to the rest of the field, and its density, meaning how well developed it is internally. Each bubble shows its three most frequent keywords, and its size is proportional to how often those keywords occur.

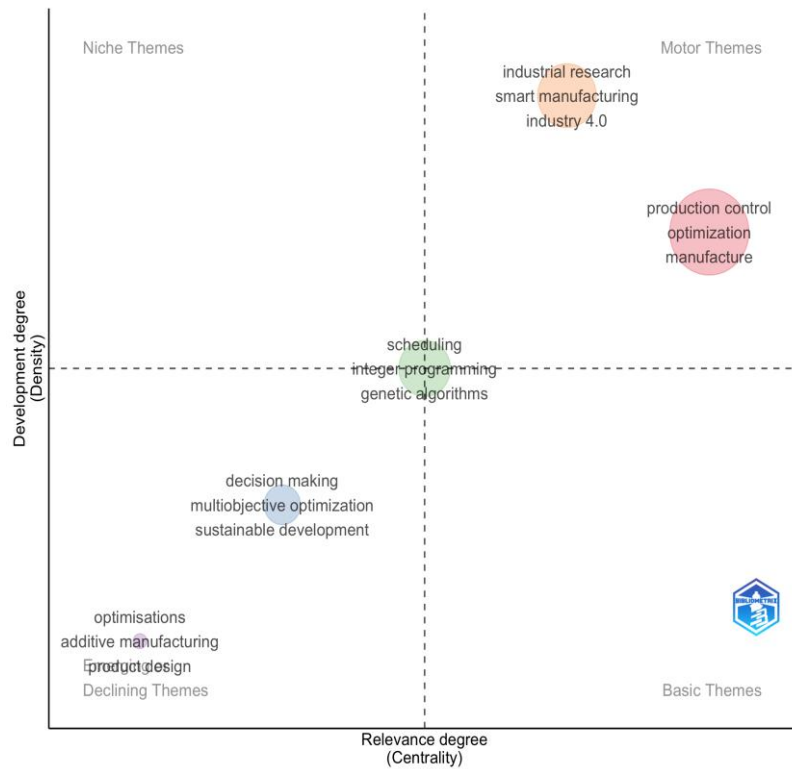


Figure -3: Thematic map on the basis of relevance (centrality) and development (density)

The four quadrants are read as follows:

- **Motor themes (upper right):** central to the field and well developed.
- **Basic themes (lower right):** central but not yet well developed; general topics that support many others.
- **Niche themes (upper left):** well developed internally but specialised and weakly linked to the rest of the field.
- **Emerging or declining themes (lower left):** weakly developed and weakly linked; either new or fading.

4.10.1 Production Control, Optimization and Manufacture

This is the largest bubble on the map and sits far to the right in the upper-right quadrant, so it is a motor theme. Its size shows that these keywords are the most frequent in the dataset, and its position shows that they connect strongly to every other theme. This cluster is the backbone of the field: it describes the core operations research task of controlling and optimising manufacturing production.

4.10.2 Industrial Research, Smart Manufacturing and Industry 4.0

This cluster has the highest density on the map and is also clearly central, making it the most developed motor theme. Research on smart factories, connected machines and real-time data has built a tight and mature body of work. Its strong position matches the rapid growth in output since 2020 and the prominence of journals such as the Journal of Manufacturing Systems and the Journal of Intelligent Manufacturing.

4.10.3 Scheduling, Integer Programming and Genetic Algorithms

This cluster sits almost exactly where the two dividing lines cross, so it lies on the border between all four quadrants. It represents the classical operations research toolkit: scheduling problems formulated as integer programmes and solved with exact methods or metaheuristics such as genetic algorithms. Its central position suggests that these methods are moderately developed and moderately connected; they serve as a bridge between the core production-control theme and more specialised topics.

4.10.4 Decision Making, Multiobjective Optimization and Sustainable Development

This cluster is in the lower-left quadrant, but close to the centre, so it is classed as an emerging or declining theme. Given the young average document age of 3.68 years and the strong presence of the Journal of Cleaner Production and Sustainability among the top sources, it most likely reflects an emerging interest. Researchers are increasingly balancing several objectives at once, such as cost, time, energy use and emissions. If this research keeps growing, the cluster is likely to move towards the centre of the map.

4.10.5 Optimisations, Additive Manufacturing and Product Design

This is the smallest bubble and it lies in the far lower-left corner, with the lowest centrality and density on the map. Additive manufacturing (3D printing) is a newer production technology, and optimisation of its process and product design is still a small, loosely connected topic within this dataset. It is therefore best read as an emerging theme, although the map alone cannot confirm whether it is rising or fading.

4.11 Annual Scientific Production

Annual scientific production rose more than three and a half times, 2016–2026

75 documents in 2016 → 273 in 2026 · 1,591 in total · peak 273

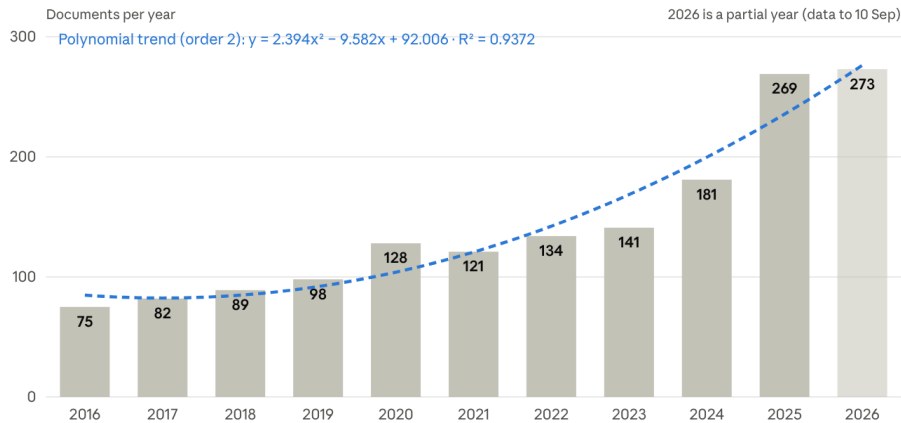


Figure -4: Annual scientific production, 2016–2026 (2026 is a partial year, data to 10 September)

Table -4: Annual scientific production

Year	Documents	Change from previous year
2016	75	—
2017	82	+9.3%
2018	89	+8.5%
2019	98	+10.1%
2020	128	+30.6%
2021	121	−5.5%
2022	134	+10.7%
2023	141	+5.2%
2024	181	+28.4%
2025	269	+48.6%
2026	273	+1.5%
Total	1,591	

Table 4 shows that annual output rose from 75 documents in 2016 to 273 in 2026, an increase of about 3.6 times. 2026 recorded the highest value even though it covers only part of the year. In total, 1,591 documents were published over the period, and the overall increase matches the annual growth rate of 13.79%.

The growth pattern can be divided into three phases. In the first phase (2016–2019), output grew slowly but steadily, from 75 to 98 documents a year, with increases of 8–10% each year. These four years produced 344 documents, about 21.6% of the dataset.

In the second phase (2020–2023), output jumped to 128 documents in 2020 (+30.6%), dipped slightly to 121 in 2021 (−5.5%) and then rose again to 141 in 2023. This phase produced 524 documents (32.9%). The jump in 2020 and the small dip in 2021 may reflect the COVID-19 period, when supply-chain disruption raised interest in production planning while slowing some research activity.

In the third phase (2024–2026), production accelerated sharply: +28.4% in 2024 and +48.6% in 2025, reaching 269 documents. These final three years account for 723 documents, almost half (45.4%) of the whole dataset. This rise is likely linked to the spread of Industry 4.0, digital twins and AI-based optimisation methods, together with the growth of open-access journals publishing on the topic.

4.11.1 Trendline

A second-order polynomial trendline was fitted to the annual output, with $x = 1$ for 2016 up to $x = 11$ for 2026:

$$y = 2.394x^2 - 9.582x + 92.006, R^2 = 0.9372$$

The positive coefficient of the squared term shows that output has been increasing by a larger amount each year. The R^2 of 0.9372 means the curve explains about 94% of the variation in annual output, so it is a good fit. The curve dips slightly at the start and reaches its lowest point around 2017, where growth was slowest.

The curve does not match every observed value. It lies above the actual values in 2022, 2023 and 2024 and well below the actual value in 2025 (about 236 fitted against 269 actual), which shows that real growth came in sudden jumps rather than smoothly. The fitted value for 2026, about 276 documents, is very close to the observed 273. Because 2026 is a partial year (data up to 10 September), the small increase from 2025 to 2026 (+1.5%) should not be read as a slowdown. The fact that 2026 has already passed

the 2025 total suggests that growth is continuing. A polynomial trendline is a descriptive tool and should only be used to describe output within the period studied, not to forecast future years.

5. FUTURE RESEARCH AGENDA

This paper aggregates a body of evidence for a rapidly expanding field. From 75 papers in 2016, the volume of research output in manufacturing production optimisation increased to 273 papers in 2026 (an annual growth rate of 13.79%), distributed across 568 sources in total, in 1,591 papers. The increase in the number of publications is not synonymous with a growing and connected understanding, of course. The commonest pattern to emerge from reading the thematic map in combination with the evidence base presented in the literature review is that the technologies and techniques are growing more diverse and numerous, faster than the evidence that tests and compares them with one another, links them across planning levels, and verifies them in real production environments. The research priorities given below attempt to fill this gap. Research priorities 1–7 concern production planning and scheduling itself, and research priority 8 is more discursive, concerning the limitations of the evidence base itself.

Two notes about the figures are needed. The first is that several of the shares indicated below are the results of a keyword search of titles, abstracts and key terms in the Bibliometrix export, and are provided for the early period (2016–2020, 472 documents) compared with the recent period (2024 onwards, 727 documents, which includes four early-view documents carrying 2027 dates). These reflect the direction of the evidence and are not necessarily exact measures. The second is that the statements about how studies in the evidence base are validated are the results of a reading of the title and abstract. They are not counted evidence and should be verified by full-text coding.

Table -5: Summary of future research priorities

Priority	Finding in the corpus	Core research question	Suggested approach	Contribution to knowledge base
1. From case studies to common benchmarks	Production control, optimization and manufacture is the biggest motor theme; benchmark and real-world terms still in the minority	Are the improvements reported significant on the same instances, and in real plants?	Open instance libraries; common reporting standard; replication studies	Comparative evidence of what works
2. Learning-based planning versus classical OR	Reinforcement learning from 0.6% to 8.5% of documents; tests between algorithms are rare	Where is learning better than MILP and metaheuristics, and where is it not?	Controlled tests with equal data, time and KPIs; hybrid OR–ML models	Clear criteria for when the extra complexity is worth it
3. Digital twins and closing the planning loop	The Industry 4.0 cluster has the highest density in the thematic map; digital twin terms from 0.8% to 9.9% of documents	Does real-time evidence lead to better or more stable plans in practice?	Ablation experiments; value-of-information tests; pilot-line research	Evidence on the benefits of live data for planning
4. Sustainability as a real decision problem	Sustainability terms doubled to 21.7% of documents; the cluster is in the emerging/declining quadrant	How should energy, emissions and cost be traded off in practice?	Preference-based multi-objective and bilevel models; scenario analysis	More realistic sustainable production plans
5. Human-centric planning and explainability	Human-centric terms from 4.2% to 9.6% of documents; explainability in only 11 documents	Can planners understand, question and override a model?	Decision experiments; field studies; human-in-the-loop tools	Principles for designing usable planning tools
6. Integration, uncertainty and resilience	Resilience terms from 1.5% to 10.2% of documents; most problems solved at a single planning level	What is lost by treating planning, maintenance, quality and logistics as separate decisions?	Integrated models; decomposition; disruption stress tests	Robust, joined-up planning approaches
7. Additive manufacturing and peripheral themes	Additive manufacturing cluster has the lowest centrality and density in the thematic map	How can build-job decisions be connected to the production planning model?	Nesting–batching–scheduling models; economic comparisons	Connects an isolated topic to the main field
8. Limitations of the evidence base	No reference data; Scopus only; partial 2026; noisy scope and keywords	How can cleaner and fuller data be obtained for future bibliometric research?	Multi-database search; keyword cleaning; full-reference exports	A more reliable source for citation analysis

5.1 Research Priority 1: From case studies to common benchmarks and real validation

The biggest bubble in the thematic map (production control, optimization and manufacture) and the classical tool set for scheduling, integer programming and genetic algorithms together encapsulate the essence of the field. Mixed-integer programming terms are in about 12% of recent documents and genetic algorithms in about 10%. Evidence of testing beyond a single case is growing but is still in the minority: benchmark-related terms rose from 3.2% to 10.6% of documents between the two periods, and real-world or industrial-case terms from 6.6% to 14.0%. It is telling that a recent review of process planning from an operations research perspective includes benchmarks in its title (Ma et al., 2026), which indicates that the lack of common test beds is recognised.

The gap here is comparability. In our reading of titles and abstracts, many papers appear to create their own instances, so that a new algorithm is not easily compared with an older algorithm. This is an interpretation and not counted evidence, and it needs to be supported by full-text coding.

Questions worth asking:

- Do reported improvements survive when the same method is tested on instances from other plants, other sizes and other product mixes?
- Can the field find agreement about benchmark sets for production planning, and not just for scheduling?
- Are the solution time, optimality gap and solver settings reported openly enough for the results to be repeated?

Suggested approach: Build open instance libraries from anonymised industrial data, agree a short reporting standard (instance size, solver, time limit, gap and KPIs) and encourage replication studies. A common test bed would allow exact methods, metaheuristics and learning-based methods to be compared on equal terms for the first time.

5.2 Research Priority 2: Learning-based planning versus classical OR

Machine learning and reinforcement learning have gone from the fringes to the mainstream in a few short years. Reinforcement learning appears in 3 of 472 documents (0.6%) in 2016–2020 but in 62 of 727 (8.5%) from 2024 onwards, and machine learning in 1.3% and 10.0% respectively. Reviews have followed in the direction of these findings: deep reinforcement learning in production systems (Panzer & Bender, 2022), reinforcement learning for autonomous production planning and control (Mayerhoff & Schmidt, 2026) and deep learning perspectives on industrial scheduling (Itu, 2025). Applications such as dynamic job shop scheduling with multi-agent deep reinforcement learning (Zhang et al., 2022) show why researchers are excited. Large language models and generative AI are still very new, with only about 30 documents in the whole data set.

The gap here is that learning-based and classical methods tend to be discussed in separate papers. Few studies seem to compare them on the same data, the same KPIs and the same budget of computing time. Without this, no one can say when the added complexity, training cost and risk of overfitting to a simulator are worth it.

Questions worth asking:

- Where does reinforcement learning beat mixed-integer programming and metaheuristics, and where does it fall behind?
- How do learned policies behave when disrupted by events that look nothing like their training data?
- Can hybrid designs, such as learning to warm-start a solver or estimate parameters while OR guarantees feasibility, combine the strengths of the two methods?

Suggested approach: Controlled comparisons of exact, metaheuristic and learning-based methods on shared instances, including disruption scenarios and a report of the time taken to train and the gap between the simulation and the shop floor. Hybrid OR–ML designs deserve a place in the same comparison.

5.3 Research Priority 3: Digital twins and closing the planning loop

The cluster of industrial research, smart manufacturing and Industry 4.0 has the highest density in the thematic map, which means it is the most advanced cluster. The data reflects this: terms for digital twins rose from 0.8% to 9.9% of documents, data-driven terms from 0.6% to 9.6% and dynamic or real-time terms from 22.2% to 39.5%. Reviews now look at the combination of AI and digital twins from an optimisation point of view (Karkaria et al., 2025), building on the concept of knowledge-driven twin cells (Zhou et al., 2020), alongside more general surveys of AI in manufacturing (Gao et al., 2024).

The gap here is that a dense cluster can develop its own vocabulary and become somewhat inward-looking. It is not clear how much live data actually improves the plan compared with data that is provided at regular intervals, or what it costs in latency, synchronisation and plan instability when the plan is re-optimised too often.

Questions worth asking:

- How often should a plan be re-optimised, and when does frequent re-planning create nervousness on the shop floor?
- What is the value of real-time information compared with a rolling-horizon plan that is updated once a shift?
- Which types of data quality problem matter most for planning decisions?

Suggested approach: Ablation experiments that turn the data feeds on and off, value-of-information tests and pilot-line research that reports plan stability and deployment cost in addition to the usual KPIs for cost and time.

5.4 Research Priority 4: Sustainability as a real decision problem

The cluster of decision making, multiobjective optimization and sustainable development sits in the lower-left quadrant close to the centre, so it can be read as an emerging area. Sustainability terms appear in 10.4% of early documents and 21.7% of recent ones, energy terms in 10.8% and 19.7%, and carbon or emissions terms in 7.4% and 11.1%. Reviews now trace sustainable optimisation for production planning and control towards the concept of Industry 5.0 (Guerrero et al., 2025b), scheduling with a view to waste minimisation (Le Hesran et al., 2019) and bilevel modelling with a sustainability perspective (Caselli et al., 2026). By contrast, terms for circular economy and remanufacturing dropped slightly, from 4.9% to 3.4%.

The gap here is that sustainability is still often added as yet another objective or constraint, and the energy and emission data is often assumed. Less is known about how decision makers choose from a set of trade-off solutions, where the boundary of carbon accounting should lie and how the decisions of individual companies interact with policy, such as carbon prices.

Questions worth asking:

- How do planners actually choose from a Pareto front of cost, time, energy and emissions?
- How do plans change when real energy tariffs and measured emission data replace assumed values?

- Can the link between regulation and company planning be captured in a bilevel model?

Suggested approach: Preference-based multi-objective models; bilevel formulations for policy questions; and scenario analysis with measured energy data. Studies should report clearly what choice of emission boundary and data assumptions were used.

5.5 Research Priority 5: Human-centric planning, explainability and trust

Industry 5.0, human-centric, operator and similar terms rose from 4.2% to 9.6% of documents. Reviews on human-aware logistics and manufacturing systems (Prunet et al., 2024), ergonomics-aware task allocation (Bao et al., 2026) and cognitive decision making for reconfigurable production (Song & Jiao, 2026) show growing interest. Yet explainability appears in only 11 documents in the whole data set, all from 2024 onwards.

The gap here is that many models treat workers as just another resource, and the planner is usually a user who is content simply to take the output. Whether the planner can understand, question and safely override a recommendation is rarely tested, yet a black-box plan that fails on the shop floor is expensive.

Questions worth asking:

- What kinds of explanation help the planner rely on a model the right amount, neither blindly nor never?
- How much of a difference do ergonomics, skill and fatigue of the workforce make to plan cost and quality?
- Who is responsible if an automated plan fails?

Suggested approach: Decision experiments in which planners work with various levels of explanation and override rules, measuring plan quality, frequency of overriding and workload, followed by field studies in plants that already use automated planning.

5.6 Research Priority 6: Integration across planning levels, uncertainty and resilience

Resilience and disruption terms rose from 1.5% to 10.2% of documents, with uncertainty remaining a steady presence at about 16% in the two periods. Robust optimisation grew from 8.5% to 15.7%, whereas stochastic terms (12.1% to 9.2%), fuzzy terms (5.1% to 4.1%) and lot-sizing terms (5.5% to 1.9%) are slightly less visible. A number of reviews point to the need for integration: a taxonomy of sourcing, making and delivering problems (Mengual-Recuerda et al., 2026), integrated scheduling of distributed manufacturing including assembly and distribution (Fu et al., 2026), the integration of production, maintenance and quality AI systems (Mota et al., 2025) and flexibility in manufacturing system design (Weckenborg et al., 2024).

The gap here is that planning, scheduling, maintenance, quality and logistics problems are still largely solved one at a time, and disruptions are often handled with a single scenario. It is also not clear whether classical stochastic and fuzzy techniques are being replaced or are only being relabelled as robust or data-driven.

Questions worth asking:

- How much is lost when planning, maintenance and quality decisions are made one after the other instead of together?
- How do robust, stochastic and data-driven methods compare when the same disruptions are tested?
- Can integrated models remain solvable at industrial size?

Suggested approach: Integrated models solved with decomposition methods or matheuristics, tested under a common set of disruption scenarios such as machine breakdowns, supply delays and demand shocks. A thematic evolution analysis over time slices would reveal whether uncertainty modelling is fading or only changing its name.

5.7 Research Priority 7: Additive manufacturing and other peripheral themes need links to planning

The cluster of optimisations, additive manufacturing and product design has the lowest centrality and density in the thematic map. Additive manufacturing is an author keyword in 62 documents and appears in about 110 documents when titles and abstracts are included. Much of the work concerns process parameters and part geometry, and a recent classification of nesting problems shows just how specialised the questions have become (Tang et al., 2026). Quantum computing is a tiny signal, with five documents, and a recent review of its implications in advanced manufacturing (Salawu & Glen, 2026).

The gap here is that the planning side of additive manufacturing, such as which parts to batch together in a build job, how to schedule build jobs and when printing should replace conventional production, is rarely linked to planning models.

Questions worth asking:

- How does additive manufacturing change the lot sizes, inventory and lead times in a planning model?
- Can the nesting, batching and scheduling of build jobs be solved together with the production plan?
- Is quantum computing relevant for production planning, or is it too soon to tell?

Suggested approach: Models that connect build-job nesting and batching with capacity and inventory decisions, and economic comparisons with conventional processes. Quantum approaches should be a watch item until they are applied in studies.

5.8 Research Priority 8: Limitations of the evidence base

A limitation of this study is that the evidence base relies on the coverage and quality of the bibliometric data. These constraints do not invalidate the patterns found, but they do affect how far the patterns can be generalised. Future research can take several of them on board.

- **No reference data.** The export has no cited references, so co-citation and bibliographic coupling could not be run. The citation-based statements have to be taken with some care. A database export with full references would remedy this.
- **One database.** Only Scopus was used. If Web of Science is added, the picture would be wider and fairer.
- **Noisy scope.** The keyword search also retrieved documents on construction, dental and biomedical printing, hydrogen and drug manufacturing. The most cited review in the export deals with additive manufacturing in construction and not with production planning. Domain filters or a more refined search string would make the maps cleaner.

- **Noisy keywords.** The data set contains 4,783 different author keywords with spellings such as optimization and optimisation, or genetic algorithm and genetic algorithms. Merging synonyms before mapping, as recommended in the bibliometrix guidelines (Aria & Cuccurullo, 2017), would make the thematic map easier to read.
- **A partial year.** The data was exported on 10 September 2026, so the 2026 count is incomplete, and a few early-view documents carry 2027 dates. The review set is also small, with 75 reviews of which many are outside production planning.
- **Collaboration.** International co-authorship is 26.34% and the average document has 3.88 co-authors. A later study could test whether cross-country and cross-discipline teams, for example operations research with computer science, produce better connected research.

6. CONCLUSION AND LIMITATIONS

This study reviewed the application of operations research in production planning and manufacturing optimisation using 1,591 articles and review papers indexed in Scopus from 2016 to 2026. The findings show that research activity increased considerably during the period, with annual output rising from 75 documents in 2016 to 273 in 2026. The literature is spread across many journals and involves researchers from different disciplines, reflecting the broad nature of production planning. Traditional methods such as mathematical programming and scheduling remain important, while newer topics including machine learning, digital twins, sustainability, human-centred planning and resilience have become more visible. Overall, the findings suggest that OR continues to be useful, but future progress depends not only on developing new techniques but also on comparing them fairly and testing whether they work in practical manufacturing settings.

The study has some limitations. The data were collected from Scopus only, so research indexed in other databases may not have been included. The dataset was exported in September 2026, meaning the publication count for 2026 is incomplete. In addition, keyword-based analysis can indicate which topics are discussed, but it cannot fully measure the depth or quality of every study. Future research could use multiple databases, improve keyword standardisation and examine the full text of selected papers in greater detail. Researchers should also test different methods using common benchmarks and real industrial cases. Such steps could make the evidence easier to compare and help manufacturers choose planning approaches that are effective, reliable and suitable for changing production conditions.

REFERENCES

- [1] Alryalat, S.A.S., Malkawi, L.W. and Momani, S.M. (2019) 'Comparing bibliometric analysis using PubMed, Scopus, and Web of Science databases', *Journal of Visualized Experiments*, 2019(152). Available at: <https://doi.org/10.3791/58494>.
- [2] Amiri, F., Shirazi, B. and Tajdin, A. (2019) 'Multi-objective simulation optimization for uncertain resource assignment and job sequence in automated flexible job shop', *Applied Soft Computing Journal*, 75, pp. 190–202. Available at: <https://doi.org/10.1016/j.asoc.2018.11.015>.
- [3] Ardjmand, E., Weckman, G.R., Young, W.A., Sanei Bajgiran, O. and Aminipour, B. (2016) 'A robust optimisation model for production planning and pricing under demand uncertainty', *International Journal of Production Research*, 54(13), pp. 3885–3905. Available at: <https://doi.org/10.1080/00207543.2016.1161251>.
- [4] Aria, M. and Cuccurullo, C. (2017) 'bibliometrix: An R-tool for comprehensive science mapping analysis', *Journal of Informetrics*, 11(4), pp. 959–975. Available at: <https://doi.org/10.1016/j.joi.2017.08.007>.
- [5] Aria, M. and Cuccurullo, C. (2026) *Science Mapping Analysis: A Primer with Biblioshiny*. New York: McGraw-Hill. ISBN: 978-88-386-2297-7.
- [6] Bao, Q., Zhang, X., Su, S. and Guo, F. (2026) 'Ergonomics-aware task allocation for human-centric collaborative assembly: A systematic review', *Machines*, 14(8). Available at: <https://doi.org/10.3390/machines14080894>.
- [7] Burggraf, P., Wagner, J. and Heinbach, B. (2021) 'Bibliometric study on the use of machine learning as resolution technique for facility layout problems', *IEEE Access*, 9, pp. 22569–22586. Available at: <https://doi.org/10.1109/ACCESS.2021.3054563>.
- [8] Caselli, G., Iori, M. and Ljubić, I. (2026) 'Bilevel optimization with sustainability perspective: A survey on applications', *European Journal of Operational Research*, 332(2), pp. 357–375. Available at: <https://doi.org/10.1016/j.ejor.2025.08.051>.
- [9] Escuin, D., Polo, L. and Ciprés, D. (2017) 'On the comparison of inventory replenishment policies with time-varying stochastic demand for the paper industry', *Journal of Computational and Applied Mathematics*, 309, pp. 424–434. Available at: <https://doi.org/10.1016/j.cam.2016.03.027>.
- [10] Fu, Y., Li, Z., Gao, K., Fathollahi-Fard, A.M. and Zhang, Z. (2026) 'Integrated scheduling of distributed manufacturing with assembly and distribution: State of the art, challenges, and future directions', *International Journal of Production Research*, 64(11), pp. 4669–4710. Available at: <https://doi.org/10.1080/00207543.2025.2602898>.
- [11] Gao, R.X., Krüger, J., Merklein, M., Möhring, H.-C. and Váncza, J. (2024) 'Artificial intelligence in manufacturing: State of the art, perspectives, and future directions', *CIRP Annals*, 73(2), pp. 723–749. Available at: <https://doi.org/10.1016/j.cirp.2024.04.101>.
- [12] Guerrero, B., Mula, J. and Poler, R. (2025a) 'Sustainable operations management towards Industry 5.0', *Dirección y Organización*, (85), pp. 85–92. Available at: <https://doi.org/10.37610/85.692>.
- [13] Guerrero, B., Mula, J. and Poler, R. (2025b) 'Sustainable optimisation approaches for production planning and control to evolve towards Industry 5.0', *International Journal of Production Research*, 63(21), pp. 8091–8123. Available at: <https://doi.org/10.1080/00207543.2025.2507794>.
- [14] Itu, A. (2025) 'Industrial scheduling in the digital era: Challenges, state-of-the-art methods, and deep learning perspectives', *Applied Sciences*, 15(19). Available at: <https://doi.org/10.3390/app151910823>.

- [15] Karkaria, V., Tsai, Y.-K., Chen, Y.-P. and Chen, W. (2025) 'An optimization-centric review on integrating artificial intelligence and digital twin technologies in manufacturing', *Engineering Optimization*, 57(1), pp. 161–207. Available at: <https://doi.org/10.1080/0305215X.2024.2434201>.
- [16] Le Hesran, C., Ladier, A.-L., Botta-Genoulaz, V. and Laforest, V. (2019) 'Operations scheduling for waste minimization: A review', *Journal of Cleaner Production*, 206, pp. 211–226. Available at: <https://doi.org/10.1016/j.jclepro.2018.09.136>.
- [17] Lindahl, S.B., Babi, D.K., Gernaey, K.V. and Sin, G. (2023) 'Integrated capacity and production planning in the pharmaceutical supply chain: Framework and models', *Computers and Chemical Engineering*, 171. Available at: <https://doi.org/10.1016/j.compchemeng.2023.108163>.
- [18] Mayerhoff, J. and Schmidt, M. (2026) 'Reinforcement learning for autonomous production planning and control: A systematic literature review', *Journal of Manufacturing Systems*, 86, pp. 546–568. Available at: <https://doi.org/10.1016/j.jmsy.2026.03.023>.
- [19] Ma, Y., Luo, K., Zhao, Q. and Zheng, L. (2026) 'A review of process planning from an operations research perspective: Models, algorithms, and benchmarks', *International Journal of Production Research*. Available at: <https://doi.org/10.1080/00207543.2026.2703758>.
- [20] Mengual-Recuerda, A., Andres, B., Mula, J. and Poler, R. (2026) 'A comprehensive taxonomy of sourcing, making and delivering problems for production planning', *International Journal of Production Research*, 64(16), pp. 6992–7018. Available at: <https://doi.org/10.1080/00207543.2026.2639745>.
- [21] Mota, B., Faria, P., Ramos, C. and Vale, Z. (2025) 'Review of manufacturing integration between production, maintenance and quality artificial intelligence systems', *Journal of Industrial Information Integration*, 47. Available at: <https://doi.org/10.1016/j.jii.2025.100910>.
- [22] Ojstersek, R., Brezocnik, M. and Buchmeister, B. (2020) 'Multi-objective optimization of production scheduling with evolutionary computation: A review', *International Journal of Industrial Engineering Computations*, 11(3), pp. 359–376. Available at: <https://doi.org/10.5267/j.ijiec.2020.1.003>.
- [23] Page, M.J. et al. (2021) 'The PRISMA 2020 statement: an updated guideline for reporting systematic reviews', *BMJ*, 372, n71. Available at: <https://doi.org/10.1136/bmj.n71>.
- [24] Panzer, M. and Bender, B. (2022) 'Deep reinforcement learning in production systems: A systematic literature review', *International Journal of Production Research*, 60(13), pp. 4316–4341. Available at: <https://doi.org/10.1080/00207543.2021.1973138>.
- [25] Paul, J. and Rialp-Criado, A. (2020) 'The art of writing literature review: What do we know and what do we need to know?', *International Business Review*, 29(4), 101717. Available at: <https://doi.org/10.1016/j.ibusrev.2020.101717>.
- [26] Pei, F., Tong, Y., He, F. and Li, D. (2017) 'Research on design of the smart factory for forging enterprise in the Industry 4.0 environment', *Mechanika*, 23(1), pp. 146–152. Available at: <https://doi.org/10.5755/j01.mech.23.1.13662>.
- [27] Prunet, T., Absi, N., Borodin, V. and Cattaruzza, D. (2024) 'Optimization of human-aware logistics and manufacturing systems: A comprehensive review of modeling approaches and applications', *EURO Journal on Transportation and Logistics*, 13. Available at: <https://doi.org/10.1016/j.ejtl.2024.100136>.
- [28] Salawu, G. and Glen, B. (2026) 'Quantum computing as a disruptive technology: Implications for advanced manufacturing and Industry 5.0', *Applied Sciences*, 16(10). Available at: <https://doi.org/10.3390/app16104856>.
- [29] Saxena, R.K., Garg, A., Jain, A., Mittal, A., Y, B. and Kachhara, D. (2024) 'The Applications of Operations Research in Insurance and Management', *International Journal of Management and Social Sciences Research*, 10(02), pp. 45–66.
- [30] Scopus (2026) *Bibliographic export of documents on optimisation in manufacturing production, 2016–2026* [Data set, BibTeX file]. Exported 10 September 2026.
- [31] Snyder, H. (2019) 'Literature review as a research methodology: An overview and guidelines', *Journal of Business Research*, 104, pp. 333–339. Available at: <https://doi.org/10.1016/j.jbusres.2019.07.039>.
- [32] Song, M. and Jiao, R.J. (2026) 'A positioning review of cognitive-intelligent decision-making for reconfigurable production systems in digital transformation toward Industry 5.0', *The International Journal of Advanced Manufacturing Technology*. Available at: <https://doi.org/10.1007/s00170-026-18244-w>.
- [33] Tang, A., Fu, G., Zhang, T., Song, P., Xiao, X., Peng, Q., Mo, T., Zhang, A. and Zhang, Z. (2026) 'Nesting problems in additive manufacturing: Classification and review', *Journal of Computing and Information Science in Engineering*, 26(3). Available at: <https://doi.org/10.1115/1.4070330>.
- [34] Weckenborg, C., Schumacher, P., Thies, C. and Spengler, T.S. (2024) 'Flexibility in manufacturing system design: A review of recent approaches from operations research', *European Journal of Operational Research*, 315(2), pp. 413–441. Available at: <https://doi.org/10.1016/j.ejor.2023.08.050>.
- [35] Zhang, Y., Zhu, H., Tang, D., Zhou, T. and Gui, Y. (2022) 'Dynamic job shop scheduling based on deep reinforcement learning for multi-agent manufacturing systems', *Robotics and Computer-Integrated Manufacturing*, 78. Available at: <https://doi.org/10.1016/j.rcim.2022.102412>.
- [36] Zhou, G., Zhang, C., Li, Z., Ding, K. and Wang, C. (2020) 'Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing', *International Journal of Production Research*, 58(4), pp. 1034–1051. Available at: <https://doi.org/10.1080/00207543.2019.1607978>.
- [37] Zupic, I. and Čater, T. (2015) 'Bibliometric methods in management and organization', *Organizational Research Methods*, 18(3), pp. 429–472. Available at: <https://doi.org/10.1177/1094428114562629>.