

Review

Advanced Planning Systems in Production Planning Control: An Ethical and Sustainable Perspective in Fashion Sector

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Featured Application

This research enables AI-driven APS systems in manufacturing industries, especially fashion, enhancing real-time scheduling, optimizing resource use, and aligning production with dynamic market demands. It supports sustainable, agile manufacturing aligned with the Industry 5.0 paradigm.

Abstract

In the shift toward sustainable and resource-efficient manufacturing, Artificial Intelligence (AI) is playing a transformative role in overcoming the limitations of traditional production scheduling methods. This study, based on a Systematic Literature Review (SLR), explores how AI techniques enhance Advanced Planning and Scheduling (APS) systems, particularly under finite-capacity constraints. Traditional scheduling models often overlook real-time resource limitations, leading to inefficiencies in complex and dynamic production environments. AI, with its capabilities in data fusion, pattern recognition, and adaptive learning, enables the development of intelligent, flexible scheduling solutions. The integration of metaheuristic algorithms—especially Ant Colony Optimization (ACO) and hybrid models like GA-ACO—further improves optimization performance by offering high-quality, near-optimal solutions without requiring extensive structural modeling. These AI-powered APS systems enhance scheduling accuracy, reduce lead times, improve resource utilization, and enable the proactive identification of production bottlenecks. Especially relevant in high-variability sectors like fashion, these approaches support Industry 5.0 goals by enabling agile, sustainable, and human-centered manufacturing systems. The findings have been highlighted in a structured framework for AI-based APS systems supported by metaheuristics that compares the Industry 4.0 and Industry 5.0 perspectives. The study offers valuable implications for both academia and industry: academics can gain a synthesized understanding of emerging trends, while practitioners are provided with actionable insights for deploying intelligent planning systems that align with sustainability goals and operational efficiency in modern supply chains.

Keywords: optimization; advanced planning system; cyber-physical systems; metaheuristic algorithms; machine learning; human-centered manufacturing; sustainable production



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1. Introduction

Until now, production has focused on boosting productivity by enhancing sales volume, which has led to overproduction. With the transition towards more sustainable

and environmentally responsible production, it is essential to extend product lifecycles by refurbishing components and products [1]. Interest in Artificial Intelligence (AI) has surged recently due to its wide-ranging applications in areas such as modeling, classification, optimization, and prediction. AI systems are designed to stimulate human cognitive functions by learning, adapting, processing language, and performing intelligent tasks rationally [2]. As big data and analytics continue to evolve, market demands for product manufacturing have escalated, needing greater personalization, quicker delivery times, and reduced costs. To support and enhance decision-making, a larger range of data fusion is essential for scheduling, allowing the integration of information from heterogeneous sources to encompass nearly all aspects of manufacturing, whether derived from expert insights, Internet of Things (IoT) systems, or external data [3]. Traditional techniques such as infinite capacity scheduling present the great limitation of not providing a realistic production plan according to the real availability of resources, materials, or equipment for production systems. As a results, they are rather ineffective for complex optimization problems with vast solution spaces, such as assembly line balancing, production planning, and fashion sales forecasting.

Applying AI in supply chain operations, such as in production scheduling and control, can overcome the limitations provided by traditional scheduling techniques. Moving towards finite-capacity scheduling adds value by identifying future critical issues in advance and providing corrective actions that can be implemented on time. Moreover, finite-capacity scheduling aims to identify an effective and feasible production plan making the best use of available resources, minimizing production time in compliance with the internal and external deadlines.

This work highlights how introducing AI into Advanced Planning and Scheduling (APS) systems can resolve optimization challenges where traditional techniques often fail, especially in decision-making based on more informed resource management. AI-based APS systems not only enhance the precision and flexibility of scheduling processes but also support human intervention in executing tasks more efficiently, reducing errors and improving outcomes. The primary objective of this research is to explore how AI and metaheuristic techniques can be leveraged within APS systems to manage the growing complexity of production scheduling—particularly in dynamic sectors like fashion. By integrating AI models such as Deep Reinforcement Learning and Artificial Neural Networks with metaheuristics like Ant Colony Optimization and Genetic Algorithms, the study demonstrates how hybrid, self-adaptive models can tackle complex scheduling problems such as Job Shop Scheduling Problems (JSSPs). These solutions improve adaptability, sustainability, and operational efficiency in high-variability contexts such as small-batch or custom-order production. Furthermore, they offer scalable and low-configuration alternatives suitable for real-time rescheduling and enhanced decision-making, in alignment with Industry 4.0 and Industry 5.0 principles.

Therefore, this research aims to bridge a significant gap in the scientific literature by consolidating fragmented insights into a unified framework. It contributes by contextualizing AI-enhanced APS approaches within production planning and control (PPC) while also embedding human-centric and ethical considerations. Practically, the findings offer companies actionable insights to modernize production systems without large infrastructure investments, improving responsiveness, energy efficiency, and alignment with volatile demand patterns—especially in sectors like fashion manufacturing.

We started from the following Research Question (RQ): “How can AI algorithms and metaheuristic techniques enhance production and scheduling control in manufacturing contexts such as the fashion industry?” In order to guide this research, some research areas are defined in the Research Methodology (Section 2), as well as appropriate search

keywords. The areas of analysis are as follows: (i) an overview of production planning, control, and scheduling; (ii) AI and Machine Learning (ML) techniques to support APS systems; (iii) metaheuristic optimization techniques; (iv) hybrid metaheuristics; (v) ethical and sustainability perspectives in manufacturing contexts, with a particular focus on the fashion industry, addressing recent trends and challenges in responsible AI use.

Section 2 describes the research methodology applied to carry out this work. Section 3 provides a preliminary overview of production planning and control (PPC) in order to introduce the literature review analysis by covering the abovementioned key areas of analysis of the relevant sources. In Section 4 a structured framework for AI-based APS systems supported by metaheuristics is proposed. It consolidates the strategic role of APS systems powered by AI in manufacturing contexts according to both an Industry 4.0 (I4.0) and a human-centric perspective. In Section 5 the results of the literature review are discussed with some final remarks. Finally, this research work ends by providing relevant implications from both managerial and academic perspectives. Practitioners and researchers can benefit from this analysis for future research and implementations.

2. Research Methodology

This study aims to provide the comprehensive state of the art of AI and metaheuristic techniques applied to finite-capacity scheduling systems in order to fill the knowledge gap among researchers, ML practitioners, and production planners. Moreover, highlighting the ethical and sustainability perspectives of the introduction of such approaches in manufacturing contexts like the fashion industry aims to construct a stepping stone toward data-driven APS systems.

Although several review strategies have been proposed [4], the research approach adopted in this study was a Systematic Literature Review (SLR). An SLR is a transparent, scientific, and replicable methodology used to effectively synthesize a body of literature, thereby providing a validated, reliable, and replicable procedure [5,6]. It allows for the identification, selection, and critical evaluation of existing research to answer a clearly defined Research Question (RQ) [7]. The SLR procedure consists of four main steps (in Figure 1): (i) review planning; (ii) search execution; (iii) analysis of documents; (iv) reporting of results [6].

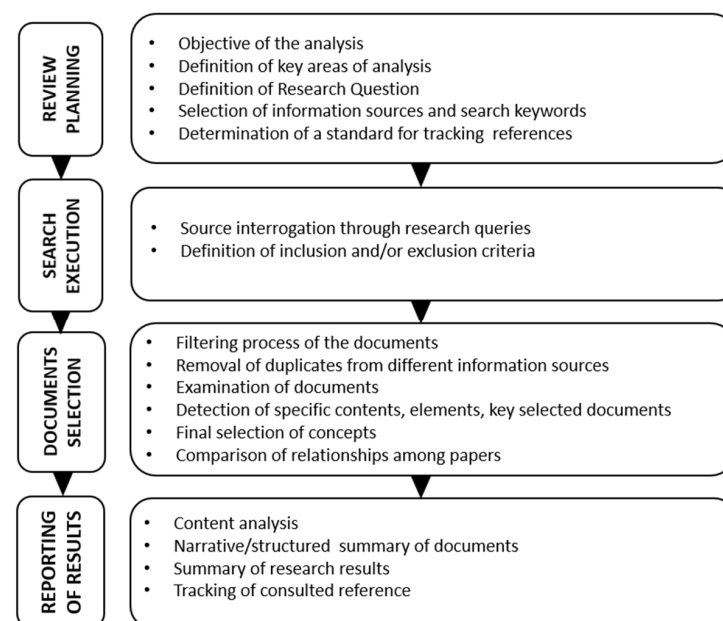


Figure 1. SLR protocol. Adapted from [6].

2.1. Review Planning

The review planning phase started with the analysis objective of finding what advantages the introduction of AI-based finite-capacity planning tools, called APS systems, can bring in manufacturing with respect to traditional solutions in terms of decision-making in resource allocation in order to enhance manufacturing from ethical and sustainability points of view. This study aims to explore how AI-driven metaheuristic techniques can solve combinatorial optimization problems in production. Key areas of analysis were identified to address the RQ: (i) production planning, control, and scheduling overview; (ii) AI and ML techniques to support APS systems; (iii) metaheuristic techniques; (iv) hybrid metaheuristics; (v) ethical and sustainability perspectives in manufacturing contexts, mainly in fashion.

These analysis areas were built through consulting information sources using appropriate search keywords. The following RQ was defined:

“How can AI algorithms and metaheuristic techniques enhance production and scheduling control in manufacturing contexts such as the fashion industry?”

In line with the objectives and RQ of the study, the search criteria were based on combining some keywords. Such keywords were used, exploiting the use of the Boolean operators (“AND”, “OR”) to compose the entire search string query (Q) that was implemented when querying the databases [8].

2.2. Search Execution

The search execution was conducted in January 2025 on Elsevier’s Scopus (<https://www.scopus.com/>) and Web of Science (WoS) (<https://www.webofknowledge.com>), the largest abstract and citation databases of peer-reviewed literature [9].

The first step was to implement the advanced search string, detecting only the title, abstract, and keywords fields through the following query:

TITLE-ABS-KEY ((“production planning” OR “production scheduling” OR “advanced planning system” OR “scheduling optimization” OR “finite scheduling”) AND (“Artificial intelligence” OR “machine learning” OR “deep learning” OR “generative ai” OR “cutting-edge”) AND (“metaheuristic*” OR “algorithm*”) AND (“fashion” OR “textile” OR “apparel” OR “manufacturing”)).

This SLR was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [10], which consist of evidence-based standards that promote the transparent, rigorous, and complete reporting of systematic reviews across various disciplines. Starting from an initial sample of 424 papers identified, a process of filtering was carried out by defining the inclusion and exclusion criteria in order to select the most relevant papers for the topic under consideration. Specifically, four inclusion criteria were identified (in Table 1) that are widely used in systematic reviews to ensure the selection of relevant, high-quality, and recent literature aligned with the research scope. They help maintain the rigor, reproducibility, and manageability of the review process. Specifically, as English is the dominant language for scientific publications worldwide, ensuring accessibility and consistency, restricting included papers to those in English avoided translation errors and makes the review feasible within resource constraints [11]. Selecting peer-reviewed journals and recognized conference proceedings ensured scientific rigor and quality. Reviews provide comprehensive insights, while articles present original research. Excluding other types of papers (e.g., editorials, theses) maintained our focus on validated contributions [12]. Focusing on relevant subject areas (e.g., Engineering, Computer Science, Mathematics, Decision Science) ensured the inclusion of papers aligned with the research’s scope and domain expertise with respect to unrelated disciplines [13]. Finally, limiting the publication period to recent years (2017–2024) ensured that the review captured the latest

advances and trends, especially important in fast-evolving fields like AI and scheduling optimization [14]. After that, the sample was screened and further reduced by eliminating duplicated results (exclusion criteria) from both databases, avoiding overcounting and ensuring accuracy in the sample [15].

Table 1. Selection inclusion criteria.

Filter Type	Description	Database
Language	English	Scopus, WoS
Document type	Journal, conference proceedings	Scopus
	Article, review article, proceeding papers	WoS
Subject area	Engineering, Computer Science, Mathematics, Decision Science, Business, Management and Accounting	Scopus
	Engineering, Computer Science, Mathematics, Operations Research, Management Science	WoS
Total	2017–2024	Scopus, WoS

2.3. Document Selection

Based on these inclusion criteria, and after deleting 59 duplicated results that overlapped between the WoS and Scopus databases, the number of papers was reduced to 195 results (shown in Figure 2). Moreover, a further skimming was carried out, reducing the sample to 133 results by reading the papers' title, abstract, and keywords during the eligibility phase. A sample of 66 papers did not further conform to the research scope and were eliminated. Finally, 67 papers were found to be relevant to our research topics and so they were full-text analyzed.

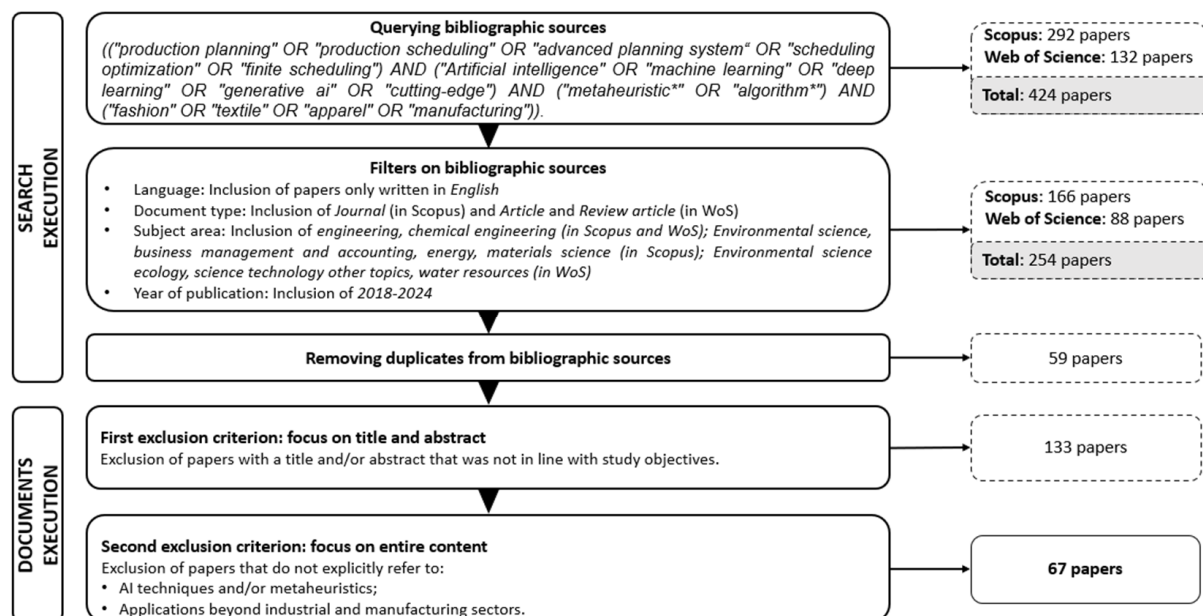


Figure 2. Document filtering process, adapted from PRISMA guidelines.

The research was conducted directly using the abovementioned set of keywords, as using the acronym “APS” would have led to different meanings not relevant to the topic in question. Moreover, within the chosen set of keywords, two of them (“generative ai”) did not provide any results. Even if these two forms of AI have a large number of applications at present, they have still not been applied to Job Shop Scheduling Problems (JSSPs) to optimize resource use.

2.4. Reporting of Results

The last stage of the SLR methodology consists of the reporting of the 68 results that were full-text analyzed in order to answer the planned research objectives and to build the content analysis in Section 3. The following section will be divided following the areas of analysis identified at the beginning of the Research Methodology.

3. Analysis of Literature Resources

This section presents in detail the main findings of the SLR, organized into thematic subsections that reflect the core research areas and methodologies identified: (i) production planning, control, and scheduling, highlighting foundational concepts and approaches (Section 3.1); (ii) an in-depth exploration of the AI techniques (i.e., Machine Learning, Reinforcement Learning, and Deep Learning techniques) used to support APS systems. Section 3.3 delves into metaheuristic techniques, while Section 3.4 discusses hybrid metaheuristics, reflecting the integration of multiple approaches for enhanced performance. Finally, Section 3.5 considers the ethical and sustainability perspectives in manufacturing and, more specifically, the fashion sector, addressing recent trends and challenges in responsible AI use. Table 2 summarizes the 67 studies included in the SLR, outlining their main objectives, identified research gaps, and the industrial sectors they address.

Table 2. Synthetic presentation of SLR results.

ID	Reference	Aim of Paper	Research Gap	Industrial Sector
R1	Kaven et al. [1]	Propose Multi-Agent Reinforcement Learning (MARL) approach for online layout planning and scheduling in flexible assembly systems	Limited exploration of MARL in real-time applications for layout planning and scheduling in flexible assembly systems	Manufacturing (flexible assembly systems)
R2	Chen et al. [3]	Present human–cyber–physical data fusion method based on Reinforcement Learning (RL)	Lack of comprehensive frameworks for human–cyber–physical data fusion using RL across various applications	Steel manufacturing
R3	Chagas et al. [16]	Conduct bibliometric and systemic analysis of production planning optimization	Limited integration of Digital Twins (DTs) with ML in adaptive production planning and control systems	Manufacturing (production planning)
R4	Chiurco et al. [17]	Discuss data modeling and ML practices to enable intelligent DTs in adaptive production planning and control	Gaps in understanding scalability of DRL approaches for dynamic scheduling in sustainable manufacturing	Manufacturing (DTs)
R5	Zhang et al. [18]	Provide systematic review of DLR-based dynamic scheduling for resilient and sustainable manufacturing	Insufficient theoretical and practical exploration of smart master production scheduling frameworks in diverse supply chains	Sustainable manufacturing
R6	Serrano-Ruiz et al. [19]	Develop conceptual framework for smart master production schedule in supply chain	Lack of tailored ML techniques specific to various industrial applications and challenges	Supply chain management
R7	Bertolini et al. [20]	Offer comprehensive literature review of ML applications in industrial contexts	Limited empirical studies on effectiveness of smart machine monitoring systems in different I4.0 contexts	Manufacturing

Table 2. Cont.

ID	Reference	Aim of Paper	Research Gap	Industrial Sector
R8	Singh et al. [21]	Evaluate smart machine monitoring system under I4.0 concept	Need for further investigation into application of big data analytics in production scheduling optimization	Manufacturing (I4.0)
R9	Shen [22]	Optimize production scheduling of intelligent manufacturing systems for clothing using association rule algorithm	Insufficient examination of tailored ML techniques for production planning and control in I4.0 contexts	Clothing manufacturing
R10	Usuga Cadavid et al. [23]	Explore ML applications in production planning and control in I4.0 era	Gaps in empirical research on challenges of synergistic and intelligent process optimization in complex manufacturing environments	Manufacturing (production planning)
R11	Harjunkoski et al. [24]	Present initial results and open challenges in synergistic and intelligent process optimization	Limited exploration of improved GAs based on ML in practical production scheduling scenarios	Chemical production
R12	Guo et al. [25]	Research application of improved GA based on ML in production scheduling	Need for further studies on integration of memetic algorithms and RL in sociotechnical production scheduling	Manufacturing (production scheduling)
R13	Grumbach et al. [26]	Propose memetic algorithm with RL for sociotechnical production scheduling	Gaps in understanding of average reward adjustments in DRL for order release planning	Discrete manufacturing (assembly)
R14	Schneckenreither et al. [27]	Develop average-reward-adjusted DRL approach for order release planning	Need for more empirical studies on application of DRL in chemical production scheduling	Chemical production
R15	Hubbs et al. [28]	Present DRL approach for scheduling	Limited exploration of exact methods and ACO in single-machine scheduling problems with periodic maintenance	Chemical production
R16	Qamhan et al. [29]	Propose exact method and ACO for single-machine scheduling problem with time window periodic maintenance	Few models handled periodic maintenance simultaneously, with scheduling often treated separately	Manufacturing
R17	Bindi et al. [30]	Analyze impact of supply chain strategy in luxury fashion industry on performance indicators	Need for more empirical studies evaluating impact of supply chain strategies in luxury fashion industry on performance indicators	Fashion industry / supply chain
R18	Fani et al. [31]	Develop data-driven decision-support tool for production planning, combining association rules and simulation	Limited frameworks integrating association rules and simulation in production planning decision-support systems	Fashion industry / supply chain
R19	Kuhnle et al. [32]	Explore RL for opportunistic maintenance optimization	Lack of exploration into application of DRL in different industrial contexts for production scheduling	Manufacturing (maintenance optimization)
R20	Waschneck et al. [33]	Optimize global production scheduling using DRL	Need for systematic review that addresses both theoretical and practical applications of AI in production scheduling	Semiconductor manufacturing

Table 2. Cont.

ID	Reference	Aim of Paper	Research Gap	Industrial Sector
R21	Del Gallo et al. [34]	Conduct SLR on application of AI to solve production scheduling problems in real industrial settings	Insufficient research on energy management considerations in Job Shop Scheduling Problems	Manufacturing (production scheduling)
R22	Kawaguchi et al. [35]	Address Job Shop Scheduling Problems, considering energy management using parallel Reactive TS	Gaps in understanding how RL can be effectively applied to minimize makespan in assembly processes	Manufacturing (job shop scheduling)
R23	Ying and Lin [36]	Minimize makespan in two-stage assembly additive manufacturing using RL-iterated greedy algorithm	Need for empirical validation of AI and ML applications in reshaping manufacturing processes	Manufacturing (additive manufacturing)
R24	Priyanga et al. [37]	Discuss how AI and ML reshape manufacturing processes in smart factories	Limited research on robust scheduling techniques in hot rolling production environments	Smart manufacturing
R25	Zhang et al. [38]	Develop robust scheduling method for hot rolling production using local-search-enhanced ACO algorithm	Need for more comprehensive methodologies that integrate smart production planning and control systems in I4.0	Steel manufacturing
R26	Oluyisola et al. [39]	Design and develop smart production planning and control systems in I4.0 era through methodology and case study	Lack of detailed guidance on how to translate system-level requirements—such as scalability, flexibility, and real-time responsiveness—into low-level architecture components (like algorithms)	Semiconductor manufacturing
R27	Fani et al. [40]	Apply data mining and augmented reality to enhance decision-making in production	Limited application of data mining and augmented reality techniques in fashion industry for decision-making processes	Fashion industry
R28	Göppert et al. [41]	Predict performance indicators with ANNs for AI-based online scheduling in dynamically interconnected assembly systems	Gaps in understanding of potential of ML in optimized production planning using hybrid simulation	Automotive/industrial assembly
R29	Sobottka et al. [42]	Investigate potential of ML in optimized production planning with hybrid simulation	Need for empirical validation of ambient intelligent-based decision-support systems in production planning and control	Discrete manufacturing
R30	Gomes et al. [43]	Develop intelligent-based decision-support system for production and control planning	Limited understanding of cycle time prediction in textile manufacturing using Neural Networks (NNs)	Textile manufacturing
R31	Onaran and Yanık [44]	Predict cycle times in textile manufacturing using ANNs	Gaps in energy estimation techniques and production scheduling methodologies for job shops using ML	Textile manufacturing
R32	Pereira et al. [45]	Estimate energy consumption and production scheduling in job shop environments using ML	Limited research on application of NNs for predicting manufacturing lead times, particularly extrusion tools	Job shop energy estimation

Table 2. Cont.

ID	Reference	Aim of Paper	Research Gap	Industrial Sector
R33	Sajko et al. [46]	Predict manufacturing lead times for extrusion tools using NNs	Need for further exploration of innovative hybrid approaches for FJSS that incorporate preventive maintenance	Plastic/metal tool-making
R34	Grumbach et al. [47]	Propose robust–stable scheduling in dynamic flow shops based on Deep Reinforcement Learning (DRL)	Lack of comprehensive studies on integration of ML and augmented reality in production planning	Assembly manufacturing
R35	Jung and Park [48]	Study DL-based prediction of production demand using Long Short-Term Memory (LSTM) under data sparsity conditions	Limited empirical evidence on effectiveness of data-driven decision-making tools in fashion industry	Manufacturing/supply chain management
R36	Huang et al. [49]	Predict product completion times using hybrid approach combining DL and system modeling	Insufficient research on scalability of RL techniques for large-scale production scheduling	Discrete manufacturing
R37	Zareian Beinabadi et al. [50]	Address sustainable supply chain decision-making in automotive industry using data-driven approach	Need for more diverse case studies to validate application of AI in production control across different manufacturing sectors	Automotive
R38	Riemer-Sorensen and Rosenlund [51]	Apply DRL for long-term hydropower production scheduling.	Gaps in understanding challenges of implementing intelligent scheduling systems in real-world manufacturing environments.	Energy (hydropower)
R39	Kuhnle et al. [52]	Explore explainable RL in production control for job shop manufacturing systems.	Limited exploration of impact of data quality on effectiveness of ML algorithms in production scheduling.	Manufacturing (maintenance optimization)
R40	Zhao et al. [53]	Develop dynamic job shop scheduling algorithm based on DQN	Insufficient theoretical frameworks for integrating various AI techniques in supply chain management	Flexible job shop/supply chain management
R41	Zhu et al. [54]	Propose DRL-based online real-time task scheduling method with ISSA strategy	Need for more research on interaction between human operators and AI systems in production environments	Flexible job shop
R42	Wang et al. [55]	Discuss design patterns for DRL models addressing Job Shop Scheduling Problems	Gaps in the understanding of the role of big data analytics in enhancing production efficiency and decision-making	Flexible job shop
R43	Du and Li [56]	Present DRL-based algorithm for distributed precast concrete production scheduling	Limited exploration of real-time data integration techniques for improved scheduling in manufacturing	Construction
R44	Wan et al. [57]	Explore FJSS using DRL with meta-path-based heterogeneous graph NNs	Need for empirical studies focusing on application of AI in optimizing energy consumption in manufacturing processes	Manufacturing
R45	Zhang et al. [58]	Investigate distributed real-time scheduling in cloud manufacturing using DRL	Insufficient examination of impact of Machine Learning (ML) on reducing lead times in production systems	Cloud manufacturing

Table 2. Cont.

ID	Reference	Aim of Paper	Research Gap	Industrial Sector
R46	Waschneck et al. [59]	Apply DRL for semiconductor production scheduling	Gaps in research on how to effectively combine traditional scheduling methods with modern AI techniques	Semiconductor manufacturing
R47	Zhou et al. [60]	Use multi-agent-based hyperheuristics for multi-objective FJSS in aero-engine blade manufacturing plant	Limited understanding of benefits and challenges of using cloud-based solutions for production scheduling	Aero-engine Manufacturing
R48	Tremblet et al. [61]	Estimate makespan in flexible job shop scheduling environments using ML	Need for further exploration of ethical implications of AI in manufacturing and production planning	Manufacturing (flexible job shop scheduling)
R49	Górnicka et al. [62]	Optimize production organization in packaging company using ACO	Insufficient research on effectiveness of hybrid algorithms in solving complex scheduling problem	Packaging
R50	Peiris et al. [63]	Discuss production scheduling in modular construction using metaheuristics and future directions	Gaps in empirical evaluation of smart factory concepts in enhancing operational efficiency	Transportation
R51	Rubaiee and Yildirim [64]	Present energy-aware multi-objective ant colony algorithm to minimize total completion time and energy costs in single-machine preemptive scheduling	Limited studies addressing integration of maintenance strategies with production scheduling	Discrete manufacturing
R52	Ghasemi et al. [65]	Demonstrate feasibility of real-time application of Machine Learning in production scheduling	Need for more comprehensive frameworks that consider entire supply chains in production scheduling	Semiconductor manufacturing
R53	Liu and Li [66]	Examine progress of business analytics and knowledge management for enterprise performance using Artificial Intelligence and human-machine coordination	Insufficient research on role of IoT in enhancing production planning and control systems	Business management
R54	Qiu et al. [67]	Propose hybrid ML and population knowledge mining method to minimize makespan and total tardiness for multi-variety products	Gaps in understanding of impact of variability in production processes on scheduling effectiveness	Manufacturing
R55	Delgoshaei and Ali [68]	Present method for scheduling temporary and skilled workers in dynamic cellular manufacturing systems using hybrid ACO and TS algorithms	Limited exploration of potential of RL in adaptive manufacturing systems	Manufacturing
R56	Ren et al. [69]	Design and implement business management system for Dongfeng plate-making	Need for empirical validation of simulation models used in production scheduling decisions	Packaging industries
R57	Tarigan et al. [70]	Schedule production in flexible packaging industry using mathematical models and Genetic Algorithms	Insufficient examination of how organizational culture influences adoption of AI in manufacturing	Packaging manufacturing

Table 2. Cont.

ID	Reference	Aim of Paper	Research Gap	Industrial Sector
R58	El Khoukhi et al. [71]	Introduce “Dual-Ants Colony,” novel hybrid approach for FJSS with preventive maintenance.	Gaps in research on integration of sustainability considerations into production scheduling methodologies	Manufacturing (job shop scheduling)
R59	Aungkulanon et al. [72]	Explore manufacturing and production planning via fish swarm optimization method and its hybridizations	Limited studies on application of AI in SMEs for production management	Manufacturing (optimization)
R60	Kato et al. [73]	Propose new approach to solve FJSSP based on hybrid particle swarm optimization and random-restart hill climbing	Need for more case studies to illustrate practical challenges of implementing AI in production systems	Manufacturing (job shop problems)
R61	Alamin et al. [74]	Present SMART-IC for smart monitoring and production optimization for zero-waste semiconductor manufacturing	Insufficient research on relationship between supply chain resilience and advanced scheduling techniques	Semiconductor manufacturing
R62	Adjogble et al. [75]	Discuss advanced intelligent manufacturing in process industry using AI	Gaps in understanding of role of ML in predictive maintenance for manufacturing equipment	Process industry
R63	Zhang et al. [76]	Develop dynamic job shop scheduling method based on DRL for multi-agent manufacturing systems	Limited exploration of use of multi-agent systems in collaborative production scheduling	Manufacturing (job shop scheduling)
R64	Zhou et al. [77]	Use RL with composite rewards for production scheduling in smart factory	Need for empirical studies on effectiveness of ML models in dynamic production environments	Smart manufacturing
R65	Antons and Arlinghaus [78]	Explore data-driven and autonomous manufacturing control in CPPSs	Insufficient research on impact of training and skill development on successful AI implementation	Autonomous manufacturing
R66	Para et al. [79]	Survey and critically assess energy-aware, multi-objective job shop scheduling optimization in manufacturing, highlighting state-of-the-art metaheuristics and their results	Gaps in existing literature regarding energy considerations in scheduling; lack of comparative profiles and future directions for energy-aware multi-objective approaches	Manufacturing
R67	Wang et al. [80]	Provide comprehensive review of RL approaches applied to intelligent scheduling in manufacturing systems.	Prior reviews lacked depth in RL applications in scheduling; this paper compiles RL methods, challenges, and insights.	Manufacturing

3.1. Production Planning, Control, and Scheduling

Production planning represents a core component of manufacturing systems that handle several production operations, such as scheduling orders, determining batch sizes, and managing capacity planning, typically over a medium-term horizon. However, the infinite-capacity scheduling, the traditional PPC approach, has the limit of not providing a realistic production plan according to the actual availability of a company’s system, whether in terms of resources, materials, or equipment. Recently, companies have faced increasing pressure to meet short delivery times and high customization demands, which require more responsive and reconfigurable systems. Effective planning is a critical strategic decision that directly impacts a company’s efficiency, demanding significant computational effort due to its complex nature [16]. Since the rapid industrial evolution, reconfigurable manufacturing systems have needed to be able to adapt in real time to operational and

strategic environments, increasing demand for customized products, and supply chain interruptions or resource fluctuations [17,18].

PPC's main operations (e.g., job scheduling, performance optimization, and dynamic control) are strongly supported by several I4.0 technological pillars [19,20], such as cyber-physical systems (CPSs), cyber-physical production systems (CPPSs), sensors, big data analytics (BDA), the Industrial Internet of Things (IIoT), and cloud computing [19,21]. For instance, PPC uses Information and Communication Technologies (ICTs) by the horizontal and vertical integration of some manufacturing technologies into the software and tools of production scheduling processes [22]. The capabilities explored for BDA based on AI include real-time optimization integrated into sales and operations planning (S&OP) processes, enterprise resource planning (ERP), and material requirements planning (MRP) to predict material flows and shop floor operations behavior [19], and lastly master production scheduling (MPS) to enhance forecasting, scheduling, and decision-making along the supply chain [19,23]. In the I4.0 context, PPC—together with the management of maintenance, quality, and supply chain processes—considers functions determining the production plan, such as the global quantities to be produced in order to satisfy production objectives in terms of profitability and productivity, allowing the real-time synchronization of resources as well as product mass-customization [20]. The overall objective of PPC is the creation of reliable production plans whose deployment is facilitated by the increased computing power of AI solutions [23]. Prediction-based solutions outperform traditional planning methods—whether based on static historical data or real-time resource measurements—by providing a global, batch-level perspective. Designed for large-scale manufacturing systems, they leverage cloud infrastructure to handle high-volume data streams, enabling real-time optimization, scalability, and fault tolerance [24].

In order to respect production constraints as much as possible, these approaches need to determine production items (sequence, time, and machine) and accomplish the request for each of them within a time horizon [16,25]. Moreover, production planning often intersects with complex challenges such as uncertain capacities, fluctuating demand, hybrid flow shops, load balancing, and the integration of scheduling in dynamic industrial settings [16]. Indeed, in the production planning field, scheduling problems generally refer to short-term planning at the operational level, particularly focusing on coordinating resources use by planning processing times, sequencing operations, and ultimately optimizing overall production time and resource utilization [25]. Sometimes various unforeseen disturbances (e.g., machine breakdowns, worker illnesses, procurement risks) may occur during production planning, which may cause inconsistencies between planning and reality.

Therefore, mathematical formulations and algorithms are needed to solve timely sequencing in production problems in order to avoid the occurrence of production accidents and unexpected deviations representing bottlenecks along the production system [25]. For this reason, scheduling problems can be defined as Resource-Constrained Project Scheduling Problems (RCPSPs), aiming to find optimal plans with minimal makespan for each activity based on precedence relationships, while respecting resource availability restrictions [26]. In order to achieve the scheduling objective, it is necessary to consider constraint conditions and scheduling results as first-level information in production operations, while raw material supply and real-time equipment data are considered as second-level information.

However, production environments are dynamic, often influenced by disturbances such as machine failures or supply chain disruptions. As a result, production scheduling must consider the following:

1. Complexity: Scheduling must handle multiple factors such as the timing of each production operation (including arrival, start-up, loading, unloading, processing, waiting between machines, and transport times) as well as external factors like the availability of material and human resources, such as skilled operators. With the increasing complexity of the scheduling problems, the computational effort as well as the time required to find an optimal solution—or a sub-optimal one—rises [25].
2. Randomness: Dynamic environments and conditions (e.g., machine breakdowns, order changes, etc.) affect stability [25].
3. Multiple constraints: Sequence-dependent setup times, varying process types (e.g., single jobs vs. batch processing), and fluctuating process times complicate scheduling and operations [25,27]. Indeed, relevant uncertainties such as production delays, plant shutdowns, rush orders, price fluctuations, and shifts in demand can distort previously optimal or sub-optimal schedules [28]. Single-machine scheduling often overlooks maintenance, assuming constant system availability, an approach that raises the risk of breakdowns and disrupts optimal production performance [29].
4. Multi-objective requirements: Balancing productivity, cost-efficiency, and customer satisfaction under competing Key Performance Indicators (KPIs) [25,30–32]. This involves minimizing losses and inventory costs while maximizing output and efficiency. However, achieving these goals is challenging due to their interconnected nature and operational constraints [25]. A core challenge in production scheduling lies in reconciling conflicting priorities; e.g., customers demand lower costs, higher efficiency, and better service, while manufacturers aim to simplify production and maximize profit [3].

Therefore, finite capacities and the emergence of Work-In-Process effects add to this complexity, which is often underestimated by traditional ERP tools due to high human dependency [3,27,33]. Hence, integrating real-time data through CPPS and AI-driven systems is essential for predictive, flexible, and adaptive PPC [24].

Therefore, the data-driven integration of various PPC modules, e.g., MPS, MRP, Capacity Requirements Planning, which work in a synchronic manner is essential for predictive capacity planning and the real-time traceability of machine and product status [19].

Production scheduling and planning directly impact on business performance in terms of efficient scheduling which means that both plant maintenance and resource availability are met within their required timeframes, ensuring a high level of quality in production control [29]. Production scheduling problems, particularly Job Shop Scheduling Problems (JSSPs) and Flexible JSSPs (FJSSPs), are classified as NP-hard due to their combinatorial complexity [18,34,80]. Traditional heuristics and rule-based systems can approximate solutions but often fall short in accuracy, scalability, and adaptability.

Since exact solutions cannot be computed in polynomial time, heuristics and rule-based methods are typically used to obtain approximate solutions. However, these approaches have some drawbacks, as achieving greater accuracy often demands high computational effort and is time consuming, while relying on general rules may lead to oversimplifications [18]. Thus, the implementation of Advanced Planning and Scheduling (APS) systems enhanced by Artificial Intelligence (AI)—especially Machine Learning (ML) and metaheuristics—is strongly recommended.

In the next sections a particular subset of AI, Machine Learning (ML) [26] and its related techniques, together with metaheuristic techniques will be discussed regarding their application in manufacturing production contexts to solve challenging combinatorial optimization problems. These approaches offer dynamic optimization, reduced manual intervention, and improved responsiveness in high-variability manufacturing contexts.

3.2. AI Techniques to Support APS Systems

AI is emerging as a powerful tool for gaining advantages in dynamic markets [81] where customers' increasing demand and product variety challenge manufacturers' capacity to innovate and remain competitive [37]. The I4.0 paradigm integrates technologies, particularly AI and ML, to support production planning and control by generating optimal or near-optimal production plans within a feasible timeframe [16]. I4.0 technologies enable cost reductions in production and management through machine-to-machine communication, data-driven decision-making, and automation. However, the growing complexity and dynamism within production systems, driven by horizontal and vertical integration and automation, have introduced new challenges [16]. Before automated data collection, variables in production planning were limited due to manual handling [38]. Nowadays, the smart factory concept—based on real-time data sharing and seamless connectivity—allows machines to autonomously process large datasets, extract insights, and optimize operations [37].

Indeed, ML algorithms are central to this shift as they can be trained on available datasets, relying on sufficient high-quality input data to identify patterns and predict continuous values [30,32,39]. Typically, ML algorithms can be classified according to the type of PPC task and the input and output data given [30], improving with experience, rather than being specially programmed manually by humans [32,39].

ML techniques are commonly categorized into three categories [20] (supervised learning, unsupervised learning, and RL) and are applied in PPC for forecasting, fault detection, production optimization, shop floor control, and quality improvement [32]. Supervised and unsupervised ML techniques can predict supply disruptions by exploiting historical data, while RL has been explored to support real-time adaptive and decentralized control scheduling in response to unpredictable events [18,23,33]. ML helps manage uncertainty in medium-term planning, enhancing inbound logistics and overall supply chain performance. Inbound logistics, involving internal material flows, benefits from continuous tracking and integration enabled by ML [1,21,33].

This paper investigates the potential of ML, particularly RL, to improve lead time planning in job shop manufacturing [23]. Continuous training and re-training of models are often required depending on the approach used [21,39]. However, implementing AI-driven APS systems remains a major industry challenge. Effective APS requires managing job orders and production flows to avoid bottlenecks and ensure timely deliveries [23,30,31]. Traditional systems such as ERP handle large volumes of production planning data, but lack operational effectiveness [23]. While a traditional production system makes difficult or even prevents human production scheduling, APS aims to assist decision-makers by delivering optimized production schedules in real-time, and therefore must be flexible, robust, and responsive to changing solutions [16,32].

To pursue this, metaheuristics and AI techniques come into play and the synergism between AI and APS is introduced. This study focuses first on RL (discussed in Section 3.2.1), while metaheuristics and hybrid techniques are addressed in Sections 3.3 and 3.4.

3.2.1. Supervised ML Techniques

Among supervised ML algorithms, there are several Deep Learning (DL) Neural Networks (NNs) that can effectively address multi-objective FJSSPs, ensuring production continuity and stability in dynamic environments [32]. Artificial Neural Networks (ANNs), inspired by the human brain, are well-suited for the optimization of PPC due to their ability to manage continuous action-state spaces through interconnected nodes with adaptive weights [41–44]. In industrial contexts, ANNs support tasks such as fault detection, quality improvement, forecasting, and shop floor control. They are particularly effective in predicting energy consumption [45] and flow time [46] by enhancing efficiency and due date

accuracy, as well as integrating sustainability perspectives on production processes. By updating weight parameters rather than each input, as in traditional probabilistic methods which lack learning capabilities [32,42–44,47], they can learn from large datasets without manual heuristics and support both online and offline operation [39,42,43].

Variants of NNs include Recurrent Neural Networks (RNNs), which model sequential data by maintaining information from the previous step [48,49]. However, they struggle with long-term dependencies due to the vanishing gradient problem, which is mitigated by LSTM networks [48–50].

Another type of algorithm belonging to this category is Convolutional Neural Networks (CNNs), which often operate in hybrid models with LSTM or RNNs [48–50]. Despite their effectiveness, deploying CNNs and RNNs can require high computational power and domain expertise, posing challenges for organizations with limited resources [50].

3.2.2. Reinforcement Learning and Deep Learning Techniques

Reinforcement Learning (RL) is a subfield of ML that has gained attention for its ability to solve complex decision-making problems through trial-and-error interactions with dynamic environments [3,36,47]. Unlike supervised learning, which relies on labeled data but enables an agent to learn optimal actions by maximizing cumulative rewards based on feedback from past experiences—similar to how humans or animals learn [1,32]—in RL, an agent observes a state (S_t), takes an action (A_t), receives a reward (R_{t+1}), and transitions to a new state (S_{t+1}) [32,38]. The goal is to learn an optimal policy $\pi: S \rightarrow A$ that maps states to actions to maximize long-term returns, often guided by value functions like $V\pi(s)$ and $Q\pi(s, a)$ [3,32,38,80]. RL excels in its ability to handle environments with uncertainty, making it particularly suitable for real-time control tasks in manufacturing, production scheduling, and maintenance planning [28,32]. Effective RL implementation requires the careful design of state representation, the action space, and the reward function [32]. A typical RL setup includes an agent, a process representing the real system (e.g., a factory), and an optimizer that mediates decision-making [24]. Multi-Agent RL (MARL) has proven effective in decentralized settings, where agents manage local tasks like order dispatching or machine scheduling [1]. Despite its strengths, RL faces challenges such as reward design, convergence, and computational demands [32]. It performs best when environmental patterns are at least partially deterministic, improving learning efficiency [28,51].

Modern DRL integrates RL with Deep Neural Networks (DNNs), allowing agents to learn from high-dimensional, unstructured data [22,41,47]. Algorithms such as Q-learning, Monte Carlo methods, and SARSA are widely used to approximate optimal policies without full environment models [52]. While powerful, RL is best viewed as complementary to traditional optimization methods [51]. Hybrid approaches that combine RL with classical stochastic optimization or heuristic methods have been shown to improve performance in complex industrial scenarios [28,32]. Overall, RL offers a flexible and adaptive framework for dynamic industrial environments, particularly when integrated with Deep Learning to enhance state representation and generalization [18,22,32,53].

Deep Learning (DL) is a branch of ML that uses ANNs to map complex, high-dimensional input data to meaningful outputs, making it particularly well-suited for decision-making in unstructured industrial environments [19]. While DL was previously limited by insufficient data and computational power, recent advancements in big data (e.g., IoT sensors) and high-performance computing have unlocked its full potential, especially in tackling NP-hard problems common in manufacturing [54].

ML and DL techniques are increasingly being applied in smart manufacturing to extract actionable insights, optimize processes, and improve productivity. A significant advancement in this area is DRL, which combines DL's capacity for handling unstructured data

with RL's adaptive decision-making [19,47]. DRL is particularly effective in dynamic and uncertain environments, such as supply chain and production systems. One promising application is in Zero Defect Management, where DRL dynamically adjusts MPS to maximize service levels while minimizing inefficiencies [13].

By leveraging DNNs, DRL eliminates the need for manual feature engineering or predefined state spaces [18,47,56,57]. This makes it suitable for autonomous planning and scheduling in complex industrial settings. However, DRL is still challenged by high data and computational requirements, limited real-world deployment, and difficulties in generalizing across different environments [28,51]. To address these limitations, hybrid approaches are being explored that integrate DRL with classical optimization methods or embed domain knowledge to improve learning performance and generalization. In job shop scheduling, DRL agents interact with evolving schedules—known as Temporary Scheduling—and use DNNs to approximate value functions, enabling informed real-time decisions [55,58].

A prominent DRL algorithm is the Deep Q-Network (DQN), which integrates Q-learning with DNNs to solve complex, dynamic problems like job scheduling [54,59].

In applying DRL to production scheduling in complex job shops, cooperative DQN agents, derived from one of the most widely used RL techniques, are employed [33]. The DQN agents are trained in an RL environment, using DNNs to make real-time decisions. The DQN agents learn from historical data and aim to maximize efficiency by optimizing production scheduling and resource allocation even in NP-hard problems according to user-defined, flexible objectives [18,53]. QN agents operate in uncertain environments without manual objective decomposition, allowing for global optimization and autonomous scheduling. In practice, cooperative multi-agent DQN systems are trained offline in simulations using historical data and then deployed online once optimal solutions are embedded in trained networks [33]. Each DQN agent manages its assigned workstation, refining decision rules based on observed outcomes and peer agent behaviors. Lot positions are randomized during training to ensure data diversity, though the quality of results can still depend on data sufficiency [33,54]. Despite being computationally intensive, the approach offers strong scalability and flexibility, allowing legacy systems to be updated within hours and adapting to changing objectives without manual reprogramming [33,56]. DQN agents also enable decentralized, self-learning production systems, which align well with Industry 4.0 goals. By leveraging a cooperative Multi-Agent Structure (MAS), DQN solutions effectively tackle the complexity and local optimization challenges of job shop scheduling [18,33,60].

3.3. Metaheuristic Techniques

Exact algorithms could solve optimization problems by just obtaining the optimal solutions, but these require too long a computation time and typically fail to solve complex problems with many decision variables and constraints. Heuristic models seem to be a good option to provide the best schedules, although they are quite slow and lack scalability for dealing with large-scale problems. This is the reason why, when there is a relatively high number of decision variables (nearly thousands of products), the introduction of metaheuristic algorithms allows for the finding of sub-optimal solutions [61].

Metaheuristics represents a class of optimization techniques that aim to find near-optimal solutions through approximation strategies. These methods are particularly effective as they are able to solve challenging combinatorial optimization problems, such as minimizing product delivery times under multiple constraints [35]. Unlike exact algorithms, metaheuristics strikes a balance between solution quality and computational efficiency, enabling the resolution of problems within a reasonable time frame [62]. By

exploring a broad space of feasible solutions, they can then identify high-quality outcomes with significantly less computational cost compared to traditional optimization methods, iterative procedures, or simple heuristics.

Metaheuristics can be classified into two macrocategories: (i) single-state metaheuristics, (ii) population methods [60,63]. Single-state metaheuristics aims to enhance an algorithm's ability to exploit existing solutions by encompassing various local search techniques, including Simulated Annealing (SA) and Tabu Search (TS), whereas the population-based methods can be divided into two main categories: Evolutionary Algorithms (EAs) and Swarm Intelligence (SI). Today, they have been applied in various manufacturing domains [64], e.g., the steel manufacturing industry [3,38], semiconductor manufacturing [65], chemical manufacturing [28], fashion [30,31,40], and a modular construction approach for the transportation sector [63].

3.3.1. Single-State Metaheuristics

Simulated Annealing (SA) is an approximate method based on Monte Carlo design which accepts a worse solution than the current solution by the Metropolis criterion, enabling the system to jump out of local optimal solutions to reach the global optimal solution [67]. These systems tend to organize themselves into minimum-energy and stable configurations, i.e., the ones in the thermodynamic process from which it takes its name. The energy is assimilated to the objective function, which is therefore minimized.

This approach resorts to the use of local search techniques in optimization problems to define and explore the surroundings of the current solution according to the following procedure: the initial solution, a representation of the solution, the definition of the neighborhood, and the evaluation of the neighbors. The admissible solutions of optimization problems have the advantage of converging to optimal solutions. Thus, the best solution in the neighborhood becomes the new current solution and the procedure is iterated.

However, the acceptance of worst-case moves is a “probabilistic law” (randomization of neighborhood exploration). In particular, the algorithm terminates when a predetermined number of iterations is reached, if the optimality of the current solution is proved, or sometimes after a certain number of iterations without solution improvement.

Tabu Search (TS) is a metaheuristic technique able to solve various combinatorial optimization problems, including scheduling and routing. The core concept of TS relies on its memory structures—specifically, short-term and long-term memory—to guide the local search process. Short-term memory prevents the algorithm from revisiting recently explored or rejected solutions, while long-term memory can restrict moves that have been repeatedly unproductive [68]. The efficiency of TS is heavily influenced by the length of the tabu list, which is typically fixed but must be manually adjusted before each simulation. As a result, the traditional TS approach is not well-suited for modern production environments characterized by a sort of production variety in small batches [35]. To improve local search performance, TS marks previously visited or rule-violating solutions as “tabu” (i.e., temporarily forbidden), thereby encouraging the exploration of new areas in the solution space [68]. However, maintaining effective diversification remains a challenge. TS relies on memory-based functions to avoid re-exploring regions of the solution space that have yielded little improvement. To address this, a capacity-constrained long-term memory is updated at each iteration. When the memory is full, the oldest entry is replaced with a new candidate solution, supporting broader exploration [68]. Variants such as Parallel TS and Parallel Reactive TS seems to be suitable for improving solution quality in JSSPs, especially under energy management constraints [35]. In response to these limitations, Reactive Tabu Search (RTS) has been proposed for JSSPs, particularly in the context of small-batch production. Unlike conventional TS, RTS does not require predefining the tabu list length as

it dynamically adjusts its length using adaptive reaction and escape mechanisms. The tabu list length is stored as a real number and truncated to an integer when applied, allowing RTS to escape from cyclic paths and explore a wide search space. RTS's effectiveness has been validated in both load distribution problems and JSSPs influenced by the demands of small quantity production [35].

3.3.2. Population-Based Metaheuristics

The population-based methods are categorized into two main categories. Firstly, the EAs include Genetic Algorithms (GAs) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II).

GAs are optimization techniques inspired by the principles of natural selection and genetics. They operate on a population of candidate solutions and simulate biological processes such as reproduction, crossover, and mutation to iteratively evolve toward an optimal solution. In this context, each individual in the population (also called a chromosome) encodes a potential solution, typically represented through binary or real-valued gene sequences that map the specific characteristics of the problem. Its operation is based on a fitness function, which measures the quality of a solution according to defined performance metrics. The most fit individuals are selected to reproduce, combining their genetic material to form a new generation through crossover and mutation. This process continues across iterations until a stopping criterion is met, such as convergence to an acceptable solution or a fixed number of generations [69]. In job shop scheduling environments, GAs are employed to estimate energy consumption and minimize makespan by encoding and exploring the solution space efficiently [45]. To enhance performance, GAs are often combined with local search algorithms, especially in energy-efficient Job Shop Scheduling Problems (JSSPs), to refine candidate solutions [67]. At each step of the process, individuals with higher fitness are more likely to be selected for the next generation. Through continuous evolution, the population gradually improves, with each successive generation achieving better performance. Eventually, the algorithm converges to a near-optimal or optimal solution, which is decoded from the best-performing individuals in the final generation [25].

Another multi-objective optimization algorithm called the NSGA-II is an EA designed to find a diverse set of solutions within complex optimization problems involving multiple conflicting objectives. It operates by simulating the process of natural selection, where the population is composed of a set of genes that represent all the operations to be scheduled and the set of candidate solutions is represented by chromosomes or individuals [70]. The solution evolves over generations to approximate the Pareto front—the set of all solutions based on non-dominance and elitism criteria [45,70]. JSSPs, in particular, often involve objectives such as minimizing makespan, total tardiness, and machine changes. Due to the conflicting nature of these objectives, JSPs are commonly formulated as multi-objective optimization problems, where the aim is not to find a single optimal solution but a diverse Pareto set that balances these competing goals. Accurately approximating this Pareto front increases the complexity of designing efficient and scalable optimization techniques [79]. NSGA-II is a robust and efficient algorithm able to find a diverse set of high-quality solutions, making it a valuable tool in many practical applications. If you are working on a problem that involves multiple conflicting objectives, NSGA-II is worth considering. However, since the algorithm lacks a great local search capability, it can be inefficient, being unable to quickly solve optimization problems [67,70].

On the other hand, Swarm Intelligence (SI) refers to Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and the Fish Swarm Algorithm (FSA).

Ant Colony Optimization (ACO) is a metaheuristic algorithm designed to solve discrete optimization problems [71], including multi-objective optimization tasks [63]. Originally introduced as the Ant System (AS), the ACO algorithm evolved into the more effective Ant Colony System, which improved solution feasibility by guiding the ants' path construction [38].

Inspired by the natural foraging behavior of ants, ACO uses pheromone trails and problem-specific heuristics to probabilistically guide search processes [63,68]. Ants initially explore randomly, but over time, they converge on shorter, more efficient paths as stronger pheromone trails reinforce better solutions [29,62]. Among the Swarm Intelligence methods, ACO is the most effective and efficient solution for high-complexity combinatorial optimization problems [67,71]. ACO is especially well-suited for high-complexity scheduling problems, which resemble routing problems where tasks must be optimized based on a defined "distance" metric, such as penalty costs c_{ij} [38,67]. Solutions are built incrementally in chronological order, allowing the algorithm to preserve high-quality partial sequences during its search, rather than relying on fixed sequences.

In a scheduling context, each ant represents a potential solution, and the paths they take correspond to different scheduling strategies. These are evaluated using a fitness function, typically the makespan, where shorter makespans receive more pheromone reinforcement, increasing their selection likelihood in future iterations [51,62].

Particle Swarm Optimization (PSO) is a population-based algorithm designed for solving continuous optimization problems. Inspired by the collective behavior of bird flocks and fish schools, PSO models particles explore a solution space by combining cognitive learning (based on individual experience) and social learning (influenced by neighbors) [63,72,73]. This dual-learning approach enables PSO to converge efficiently toward high-quality solutions. Indeed, it seems to be more effective than single-state metaheuristics like GAs [63].

PSO is widely applied in Flexible Job Shop Scheduling Problems (FJSSPs), especially in multi-objective settings. Particles adjust their positions and velocities based on both their own best-known solutions (local optima) and the global best-known solution within the swarm. Velocity bounds are set to keep particles within the solution space, and the process continues until a stopping criterion—like iteration limit or stagnation—is reached [73]. While PSO's strength lies in its hybrid search strategy, combining exploration and exploitation, it can suffer from premature convergence and a loss of diversity. To counter this, duplicate particles are detected and mutated using a roulette wheel selection method, promoting diversity [73]. Although PSO is considered one of the most effective Swarm Intelligence techniques, it faces challenges such as slow convergence, high computational cost, and limited global–local search balance. To improve performance, hybrid variants—such as Hybrid PSO—have been proposed, combining PSO with other metaheuristics for better optimization [63,72]. Therefore, hybrid techniques will be discussed in the next section.

3.4. Hybrid Metaheuristics

One particularly effective hybridization strategy involves integrating single-state metaheuristics, such as Tabu Search or Simulated Annealing, with population-based methods, such as GAs or Particle Swarm Optimization. While single-state methods excel at intensifying the search around promising areas of the solution space (exploitation), population-based algorithms provide greater exploration capabilities across the global search space.

By hybridizing these approaches, researchers and practitioners can design optimization algorithms that achieve a more balanced search process, improving convergence speed, solution quality, and robustness. This section explores some successful hybrid metaheuristics for addressing NP-hard scheduling and optimization problems.

Tabu Search (TS), known for its effective use of short-term and long-term memory strategies, has proven highly capable in tackling NP-hard problems. This strength has led to its frequent integration into hybrid metaheuristic algorithms, where it complements other optimization techniques. A notable example is its hybridization with ACO, commonly referred to as ACTS. This hybrid algorithm ACTS combines the global search capabilities of ACO with the local refinement power of TS, resulting in a more robust optimization method. The ACTS algorithm builds upon the classical ACO framework, enhancing it with TS features to improve performance in solving both discrete optimization problems—such as identifying shorter paths in graphs—and more complex continuous problems with multiple objectives. A critical parameter in ACTS is the number of colony members: while increasing the number can improve solution quality, it also significantly raises computational demands. In ACTS, the total system cost, used as the objective function, determines the amount of pheromone deposited by each colony member. A higher objective function value leads to more pheromone being spread, increasing the probability that the corresponding path will be selected in subsequent iterations. This mechanism helps ACTS deliver solutions with lower variance, indicating greater reliability and consistency. Generally, ACTS outperforms traditional Branch and Bound (B&B) algorithms, especially in large-scale problems where B&B approaches struggle to produce feasible solutions. Unlike B&B, ACTS can escape local optima effectively due to its memory structures, consistently producing superior solutions within the same number of iterations. However, while ACTS generally offers better performance, its convergence speed is not always guaranteed [68].

Moreover, ACO is also involved in another hybrid metaheuristic, where it is combined with GA, a single-state metaheuristic technique, to leverage the strengths of both approaches in solving complex optimization problems. Through a comparative analysis of both GA and ACO, it emerged that employing a hybrid model named Genetic Ant Colony (GA + ACO) allows for the combination of the strengths of both metaheuristic approaches, achieving better scheduling outcomes in terms of robustness and adaptability than either method used independently [63].

GAs are renowned for their robust global search capabilities, effectively exploring vast solution spaces to identify optimal solutions. However, they often struggle with complex problems due to their tendency to become trapped in local optima and the inefficiency arising from redundant iterations when nearing a solution. This limitation stems from GA's reliance on population-based search mechanisms without incorporating sufficient feedback mechanisms to guide the search process effectively [69]. This is unlike ACO which, inspired by the foraging behavior of ants, excels in adaptive search strategies. Despite having underdeveloped vision, ants can find the shortest path from a food source to their nest by following pheromone trails, which are updated dynamically based on the quality of the path. ACO leverages this positive feedback mechanism, using pheromone levels to probabilistically guide the search towards promising regions of the solution space [25]. However, ACO can be slow to converge and may require extensive computational resources to explore the solution space adequately [69]. To address these limitations, the hybrid GA–ACO algorithm combines the strengths of both methods: the GA generates a diverse initial population, while ACO refines solutions using pheromone trails. This synergy improves convergence speed, avoids local optima, and enhances overall optimization performance in production [62] and resource allocation problems [69]. For instance, in production scheduling problems, the hybrid GA-ACO algorithm has been implemented using MATLAB, integrating with scheduling examples to optimize production cycles. The results indicate that the hybrid algorithm not only meets production scheduling requirements but also improves search efficiency and convergence performance compared to standalone GA or ACO methods [25].

The advantage of the combination of NGSa with SA can be demonstrated when applied to a random initial population under varying iteration numbers and initial population sizes [60].

All the algorithms for solving the permutation-based combinatorial problems which emerged from this review are shown in Table 3. This table summarizes both the supervised ML and RL techniques as well as the metaheuristic algorithms and the hybrid ones which have been discussed, respectively, in Sections 3.2–3.4.

Table 3. Summary of algorithms.

Algorithm Category	Algorithm Name	Features (References)
Supervised ML	Artificial Neural Network (ANN)	• Learns from large datasets without manual heuristics [42,43]; • Fast and scalable processes [32]; • Flexible in supporting real-time decisions in different industrial problems [41,44]; • Improves energy efficiency and scheduling accuracy [45,46]; • Low learning speed [39]; • Performance highly depends on data quality and architecture [44,45].
	Recurrent Neural Network (RNN)	• Well-suited for sequential and time-dependent data [40]; • Capable of learning patterns in temporal or ordered data [41,42]; • Struggles with long-term dependencies [40]; • Computationally intensive training [40]; • May underperform without enhancements like LSTM [48].
	Convolutional Neural Network (CNN)	• Very layered structure [20,48]; • Requires hybrid approach combined with LSTM [48] or RNN [50]; • Significant computational resources and specialized expertise [50].
Reinforcement Learning (RL)	Deep Learning (DL)	• Can be combined with ANNs to solve tasks in complex decision-making problems [19]; • Particularly well-suited for high-dimensional and unstructured datasets [19]; • Insufficient data and inadequate computational resources limits its power [54]; • Able to extract insights to solve NP-hard problems applied in manufacturing industry [54].
	Deep RL (DRL)	• Enhancement of learning directly from high-dimensional, unstructured input data [22,41,47]; • Promising application in industrial domains, especially when paired with traditional optimization techniques (e.g., DL [18,22,32,53] or DNN [22,41,47]); • Hybrid approaches improve performance in complex industrial environments [28,32,51]; • Powerful for decision-making in dynamic and uncertain contexts [32,52]; • Good training has high computational costs and needs large amounts of data [54].

Table 3. Cont.

Algorithm Category	Algorithm Name	Features (References)
Reinforcement Learning (RL)	Deep Q-Network (DQN)	• Q-learning commonly used to approximate optimal policies without explicitly modeling the environment [52]; • Achievement of global efficiency through multi-agent cooperation [18,33,60]; • Potential sub-optimality with insufficient data [33,54]; • Offline training by learning from historical and randomized data due to high computational demand [33]; • Enables flexible, self-learning, and decentralized control for NP-hard problems [18,53]; • Reduced need for manual tuning [59]; • Flexibility of decentralized, self-learning, and self-optimized systems [33,54].
	Simulated Annealing (SA)	• Minimization of objective function and its energy; • Able to escape local optima; • Limit of iterations and slow training; • No guarantee of finding global optimum [67].
Single-State Metaheuristics	Tabu Search (TS)	• Local searching guided by LSTM [68]; • Heavily affected by tabu list length [68]; • Need for manually adjustment before each simulation [35]; • Not well-suited for small-batch production or high variance [35]; • Reactive TS suitable for improving solution quality in JSSPs under constraints [35]; • Dynamic adjustment of Reactive TS length [35].
	Genetic Algorithm (GA)	• Inspired by natural selection, works on population of candidate solutions (chromosomes) [69]; • Fitness function guides selection of best solutions for next generation [69]; • Applied in job shop scheduling to minimize makespan and energy use [45]; • Often combined with local search for better performance [67]; • Iteratively evolves toward near-optimal solutions [25]; • Stops when convergence reached or after set number of generations [25].
Population Method Metaheuristics	Non-Dominated Sorting Genetic Algorithm II (NSGA-II)	• EA for quickly solving multi-objective problems [70,79]; • Finds diverse set of high-quality solutions for problems with conflicting objectives [70]; • Simulates natural selection using genes and chromosomes to represent operations and candidate solutions [45,70]; • Robust in generating diverse and effective solution sets [67,70]; • Weak local search capability [67,70].
	Ant Colony Optimization (ACO)	• Well-suited for solving complex and heavily constrained scheduling problems [38,63,71]; • Mimics natural foraging behavior of ants (Swarm Intelligence) to construct paths [63,68]; • Ants build solutions incrementally, preserving high-quality sub-solutions [38]; • Adaptively improves solutions through iterative learning [67,71]; • Pheromones updated dynamically [63]; • Weaker paths decay over time, favoring optimal or shorter routes [62]; • No guarantee of reaching global optimum [62,79]; • Most widely used and validated approach in energy-aware JSP research over last decade [79].

Table 3. Cont.

Algorithm Category	Algorithm Name	Features (References)
Population Method Metaheuristics	Particle Swarm Optimization (PSO)	- Inspired by collective behavior of bird flocks or fish schools to explore solution space [63,72]; - Among most used algorithms for FJSSPs, especially in multi-objective contexts [73]; - Two key learning mechanisms (cognitive and social learning) to efficiently convergence toward high-quality solutions [63,73]; - More effective than single-state metaheuristics like GAs [55].
	Fish Swarm Algorithm (FSA)	- Based on social behavior of fish (or bird) swarms [72]; - Slow convergence speed [72]; - Simple to implement with few control parameters [72]; - Limited ability to explore new potential solution points [72].
Hybrid Metaheuristics	Ant Colony Tabu Search (ACO+TS)	- Combines ACO's global search with TS's local refinement; - Suitable for both discrete and continuous multi-objective optimization; - More robust and reliable than standalone algorithms; - Escapes local optima more effectively; - More likely to find feasible solutions in fewer iterations; - High computational cost when colony size increases; - Convergence speed not always guaranteed [68].
	Genetic Ant Colony (GA+ACO)	- Combines GA's global search with ACO's adaptive, feedback-driven refinement [63]; - Improves convergence speed [62]; - Avoids local optima better than standalone methods [25]; - Enhances solution robustness and adaptability [63]; - Proven effective in production scheduling and resource allocation tasks [62,69]; - Better performance than GA or ACO alone [25].
	Non-Dominance Sequencing Genetic Algorithm + Simulated Annealing (NGSA)	This combination benefits in applications with random initial populations under varying iterations [60].

3.5. Ethical and Sustainability Perspectives in Manufacturing and Fashion Sector

Traditionally, planning and scheduling operations have been carried out by humans, who provided high-level estimates of total monthly product demand as inputs to decision-making models [28]. A significant source of variability in processing times arises from uncertainties introduced by human operators [1]. As conventional approaches, mathematical optimization and heuristics struggle to adapt effectively to modern manufacturing challenges, including increased uncertainty, smaller batch sizes, greater product variety, and the simultaneous demand for maximum efficiency and productivity [34]. These traditional methods also rely heavily on human intervention to break down complex scheduling problems into manageable parts, with workers updating schedules daily as new information becomes available. Moreover, while forecasts aiming to predict specific order entries or shipment dates tend to be unreliable, aggregate monthly demand can still be reasonably estimated [51].

Production scheduling in manufacturing contexts illustrates a common challenge: the clash between customer expectations—lower costs, faster delivery, better service—and the manufacturer's priorities, such as simplifying production and maximizing profit. These opposing goals converge at the scheduling stage, where misalignment is often worsened by poor communication across the supply chain. While information systems like ERP or

scheduling software exist, they struggle to resolve these human-centered conflicts, as successful scheduling still heavily relies on negotiation, compromise, and communication [3]. Automation allows human workers to focus on higher-level tasks that require advanced cognitive skills such as analysis, synthesis, and problem solving [37]. In such a way, the paradigm of I4.0 finds its integration in Industry 5.0 (I5.0).

Moreover, ML also empowers Anomaly Detection processes facing two key challenges: (i) limited user trust due to the lack of labeled data, which hinders proper validation; (ii) the inability to link anomalies to their root causes. The former often results in blind reliance on or complete rejection of the algorithm, while the latter limits the usefulness of AD for troubleshooting. Both issues can be addressed through eXplainable Artificial Intelligence (XAI), which enhances transparency and insight into model decisions [74].

ML and AI applications empower machine-intelligent PPC systems to exploit self-optimizing algorithms for data analytics by providing insights and recommendations that enhance decision-making, efficiency, and business sustainability [39,75]. Advanced algorithms can also help businesses to tailor their marketing strategies, identify high-value customers, and boost customer retention [75]. AI-empowered planning systems offer a significant advantage by enabling real-time decision-making, predictive analytics, and intelligent automation across the entire supply chain. These platforms serve as the digital core of enterprises within the intelligent clothing ecosystem.

The fashion ecosystem is one of the manufacturing industries most affected by the complexity of a supply chain that includes a lot of actors such as suppliers, designers, manufacturers—often Small and Medium Enterprises (SMEs)—governments, logistic providers, trade associations, retailers, and consumers [66]. In today's fast-moving and highly competitive clothing industry, there is a growing need to implement planning and scheduling systems powered by AI. By now traditional methods are no longer capable of handling the complexity and speed required to meet dynamic market demands, especially as consumers increasingly expect personalized products, rapid delivery, and greater transparency. They not only communicate demand to suppliers with greater accuracy but also coordinate decisions among all stakeholders.

Moreover, AI enables platforms to optimize every operation thanks to human-computer interactive systems which enhance customer trust by offering responsive, data-driven, and personalized support.

By integrating AI into planning and scheduling, clothing companies can address some really relevant sustainability goals such as reducing waste, shortening lead times, increasing responsiveness, and ensuring better alignment between supply and demand. This leads to greater operational and cost efficiency, improved sustainability, and a stronger competitive position in the market [37].

In manufacturing contexts, and specifically in a clothing fabrics one, using association rule mining based on AI-based scheduling algorithms enhances production efficiency, economic performance, and energy savings for businesses [28,76–78]. An intelligent clothing factory can be designed by exploiting these technological pillars, providing a more efficient and interactive experience for all the actors involved in its very complex supply chain, bringing benefits all the way to the end consumers [22].

4. A Summary Structured Framework

AI-enhanced APS systems bridge the gap between researchers and practitioners by enabling real-time responsiveness, adaptability, and system resilience—key goals in both the I4.0 and I5.0 paradigms.

In addition to operational gains, the integration of AI and metaheuristics into production planning also raises important ethical considerations, particularly under the emerging

principles of I5.0, which emphasizes human-centric, sustainable, and resilient production systems. The ability of AI-powered systems to make autonomous decisions must be aligned with ethical standards related to transparency, accountability, and inclusiveness. For example, algorithms that affect work schedules can impact employee well-being and job satisfaction, making it critical to design systems that respect human factors and organizational fairness. This perspective reinforces the shift toward human–machine collaboration rather than substitution, with AI serving as a decision-support tool rather than a replacement for human judgment.

AI-based scheduling systems also support social and environmental sustainability. They contribute to improved job satisfaction by distributing workloads more evenly, enabling more predictable shifts, and enhancing responsiveness to individual needs. In the fashion industry, these technologies help reduce overproduction, cut lead times, and align output more precisely with actual consumer demand—thereby reducing environmental impact and building consumer trust through transparency and personalization [30,37].

Figure 3 presents a conceptual framework that consolidates the discussed components—AI-driven APS systems supported by metaheuristic techniques—highlighting their strategic role in modern manufacturing.

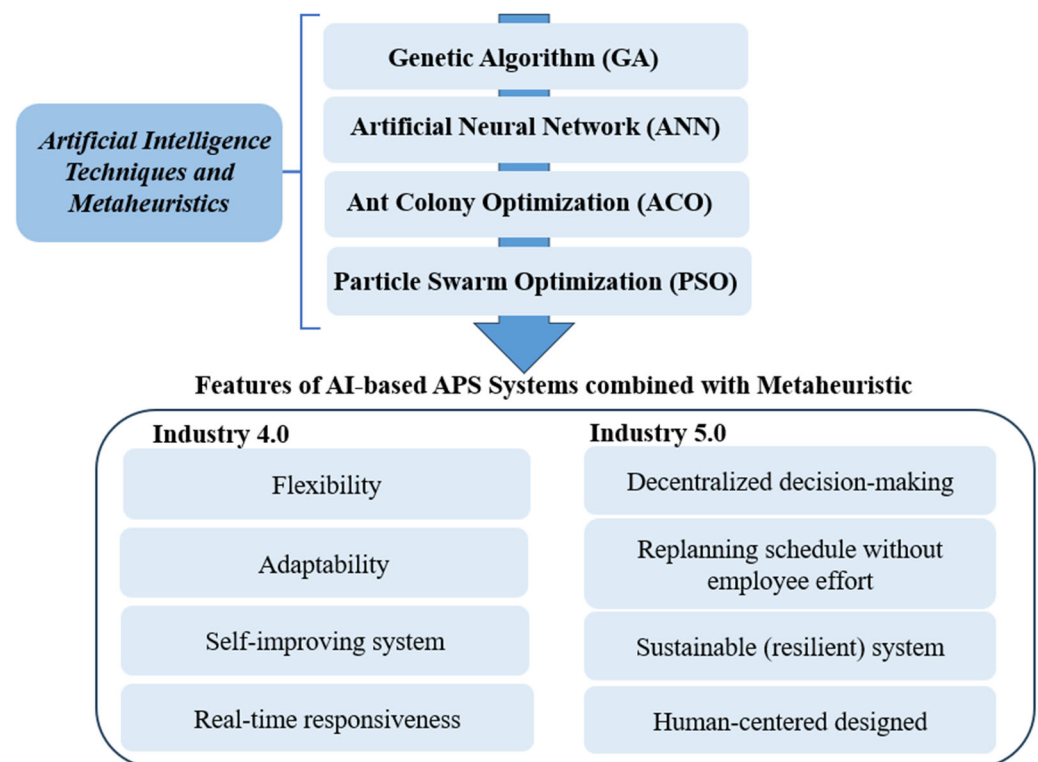


Figure 3. Proposed framework for AI-based APS systems supported by metaheuristics [3,18,23,25,28,30,32,33,37–39,41–46,51,53–56,62–64,67–69,71–73,79,81].

5. Discussion and Conclusions

This study offers a comprehensive and integrative view of how Artificial Intelligence (AI) and metaheuristic techniques can be leveraged within Advanced Planning and Scheduling (APS) systems to address the growing complexities of production scheduling in manufacturing—particularly in dynamic sectors like fashion. By combining the strengths of AI models such as DRL and ANNs with metaheuristics approaches like ACO and GAs, it becomes possible to manage complex, multi-objective scheduling problems such as Job Shop Scheduling Problems (JSSPs) by exploiting greater efficiency, adaptability, and sustainability perspectives. Therefore, metaheuristics approaches like ACO show strong

performance in solving large-scale combinatorial scheduling problems, offering fast convergence and effective use of problem-specific heuristics. Enhanced ACO variants, including elitist strategies and hybrid models like GA-ACO, further improve solution quality by balancing exploration and exploitation. These methods also reduce the need for detailed system modeling and extensive configuration, making them well-suited to high-variability contexts such as small-batch or custom-order production. Similarly, DRL aligns with I4.0 and I5.0 visions by enabling self-optimizing production systems, while ANNs have proven useful in tasks like cycle time prediction.

From an academic standpoint, this study contributes to the literature by highlighting the potential of hybrid optimization models and self-adaptive algorithms. It demonstrates how AI not only improves the configuration and performance of metaheuristics but also facilitates autonomous learning and decision refinement in production environments. Techniques such as Simulated Annealing and Tabu Search, while effective, depend heavily on manual parameter tuning and often lack the flexibility to adapt to rapidly changing conditions. In contrast, AI can support automatic parameter optimization and leverage historical production data to enable adaptive learning and schedule refinement with minimal human intervention. Theoretically, the primary value of this study lies in providing a unified framework that consolidates and contextualizes diverse approaches to AI-driven scheduling optimization. Unlike the fragmented literature, which tends to focus either on specific algorithms or narrow application domains, this work maps the intersection between AI and metaheuristics specifically in the context of production planning and control (PPC) within manufacturing. While existing studies have examined AI in broader manufacturing environments or assessed individual techniques in isolation, this study goes further by highlighting how hybrid, self-adaptive models can be tailored to the unique constraints of fast-moving, demand-volatile sectors such as the fashion sector. This not only fills a gap in the literature but also establishes a novel contribution by focusing not only on algorithmic adaptability but also on responsiveness and ethical considerations, reflecting the priorities of modern, digitally transformed production systems in real-world and high-variability contexts.

From a practical perspective, the findings have direct implications for companies aiming to modernize their production control systems without heavy infrastructure investment. Production scheduling faces several core challenges: (i) ensuring stable and cost-effective operations; (ii) managing the inherent complexity of job shop environments, where machines, time, and human resources must be optimally allocated; (iii) adapting to dynamic market conditions that introduce instability and uncertainty into production workflows. To address these issues, ERP systems can be tightly coupled with APS solutions in order to provide planners with robust decision support in order to significantly reduce workflow complexity, limit dependence on manual tools like spreadsheets, and enhance coordination across organizational units. By demonstrating how AI-enhanced metaheuristics can improve scheduling responsiveness through a more flexible response to dynamic changes, reduce manual overhead, and support energy-efficient operations, the study provides actionable insights for decision-makers. For instance, fashion manufacturers can use these techniques to dynamically group products, reduce transition losses, and better align production with customer demand—even in short-run or custom-order scenarios. Moreover, the study emphasizes that AI-based scheduling tools are not only technically effective but also operationally viable: they require minimal manual configuration, are scalable across different production sizes, and can evolve over time through adaptive learning. Companies reading this study can thus gain both a strategic and operational understanding of how to transition toward intelligent scheduling systems that support both efficiency and sustainability objectives.

The integration of AI and metaheuristics into APS systems yields both operational and strategic benefits. These include enhanced flexibility to respond to disruptions (e.g., machine breakdowns or urgent orders), real-time rescheduling capabilities, and the ability to group similar products to minimize transition costs. Such capabilities are particularly relevant in sectors like fashion manufacturing, characterized by volatile demand, short product lifecycles, and complex, multi-stakeholder supply chains. In these environments, traditional ERP and scheduling tools often fall short of aligning production with customer requirements. AI-enhanced scheduling systems offer adaptive and scalable alternatives that support energy-efficient operations and improve scheduling accuracy without requiring costly infrastructure changes.

In conclusion, this research agenda aims to extend these findings by achieving the following:

- Bridging the gap between technological innovation and real-world decision-making, ensuring that AI tools are designed as effective decision-support systems that empower human planners rather than replace them;
- Embedding human-centric values into production scheduling, consistent with I5.0's emphasis on collaboration, fairness, and employee well-being, ensuring ethical and inclusive automation;
- Advancing the ethical, sustainable, and inclusive vision of I5.0 by promoting transparency, accountability, and environmental responsibility in AI-driven production systems;
- Providing sector-specific solutions for complex, multi-actor ecosystems such as fashion, addressing the unique challenges of fast-changing markets, short product lifecycles, and diverse supply chain participants.

Therefore, this research bridges a critical gap between theory and practice in the field of intelligent production scheduling by aligning the related strategies with both operational objectives and emerging ethical expectations. It contributes to the academic dialogue by consolidating knowledge and advancing hybrid AI/metaheuristic frameworks tailored to industry needs while also offering clear, applicable insights for manufacturers navigating the challenges of I5.0. Moreover, it provides actionable insights for manufacturers seeking more adaptive, efficient, and ethically grounded production planning solutions.

While the study presents a comprehensive literature-based framework, it lacks empirical validation through real-world industrial applications. As such, the practical effectiveness and generalizability of the proposed approaches remain to be tested across diverse manufacturing environments. In addition, further work should also explore how emerging AI paradigms, such as generative AI, could be integrated into APS systems to unlock new capabilities in dynamic, high-variability production contexts.

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Abbreviations

The following abbreviations are used in this manuscript:

ACO	Ant Colony Optimization
ACTS	Ant Colony Tabu Search
AI	Artificial Intelligence
ANN	Artificial Neural Network
APS	Advanced Planning and Scheduling
BDA	Big Data Analytics
CNN	Convolutional Neural Network
CPPS	Cyber–Physical Production System
CPS	Cyber–Physical System
DL	Deep Learning
DNN	Deep Neural Network
DQN	Deep Q-Network
DT	Digital Twins
EA	Evolutionary Algorithm
ERP	Enterprise Resource Planning
FJSSP	Flexible Job Shop Scheduling Problem
FSA	Fish Swarm Algorithm
GA	Genetic Algorithm
GA-ACO	Genetic Algorithm–Ant Colony Optimization
I4.0	Industry 4.0
I5.0	Industry 5.0
ICTs	Information and Communication Technologies
IIoT	Industrial Internet of Things
IoT	Internet of Things
JSSP	Job Shop Scheduling Problem
KPIs	Key Performance Indicators
LSTM	Long Short-Term Memory
MARL	Multi-Agent Reinforcement Learning
ML	Machine Learning
MPS	Master Production Scheduling
MRP	Material Requirements Planning
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
NGSA	Non-Dominance Genetic Simulating Annealing
NNs	Neural Networks
NP	Non-Deterministic Polynomial-Time
PPC	Production Planning and Control
PSO	Particle Swarm Optimization
Q	Query
RCPSP	Resource-Constrained Project Scheduling Problem
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RQ	Research Question
RTS	Reactive Tabu Search
SA	Simulated Annealing
SC	Supply Chain
SI	Swarm Intelligence

SLR	Systematic Literature Review
S&OP	Sales And Operations Planning
SMEs	Small and Medium Enterprises
TITLE-ABS-KEY	Title–Abstract–Keywords
TS	Tabu Search
WoS	Web of Science
XAI	eXplainable Artificial Intelligence

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