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Review

A review of challenges and solution approaches in smart manufacturing: a view on scheduling in the Industry 4.0 era

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Abstract: In this systematic literature review, we addressed the critical gap in smart manufacturing scheduling research by developing an integrated framework that bridges problem evolution characteristics with solution method suitability. First, we identified that Industry 4.0 technologies fundamentally transform production scheduling through three defining characteristics: Distributed decision-making, Dynamic adaptability, and Flexible operations, collectively termed the DDF paradigm. Second, employing a PRISMA-guided methodology, we analyzed 44 problem-solving studies published between 2016 and 2025 to systematically evaluate existing solution approaches. Our analysis revealed that only 16% of the reviewed studies simultaneously address all three DDF characteristics, highlighting a significant research gap. Furthermore, we demonstrated distinct performance trade-offs among three major methodological families: mathematical programming (including optimal control), simulation and multi-agent systems, and heuristic/metaheuristic algorithms. Mathematical programming, particularly optimal program control, offers rigorous handling of structural dynamics but faces scalability challenges. Simulation and multi-agent systems provide high real-time suitability for decentralized environments, while metaheuristics remain the most frequently applied approach due to their flexibility in complex search spaces. Based on these findings, we proposed a comprehensive research roadmap that extends the DDF framework to incorporate emerging Industry 5.0 requirements for resilience, sustainability, and human-centricity. This review provides practitioners with actionable guidance for method selection and offers researchers a structured agenda for advancing toward more integrated, adaptive, and human-centric scheduling systems in the era of intelligent manufacturing.

Keywords: scheduling; smart manufacturing; industrial management; Industry 4.0; systematic review
Mathematics Subject Classification: 90-02, 90B35

1. Introduction

Manufacturing scheduling, the allocation of limited resources to tasks over time to optimize one or more objectives, has been a cornerstone of operational efficiency since the 1950s [1]. Classical problems such as the job-shop (JSP) and flow-shop (FSP) are known to be NP-hard, and their study has produced a rich body of knowledge grounded in deterministic, centralized, and static models. However, the emergence of Industry 4.0, characterized by Cyber-Physical Systems (CPSs), the Internet of Things (IoT), and Artificial Intelligence (AI), is fundamentally disrupting this paradigm. CPSs enable real-time data exchange, decentralized intelligence, and dynamic reconfiguration, capabilities that render traditional scheduling models and were designed for predictable and hierarchical environments, increasingly inadequate [2]. This creates a critical gap: The scheduling literature has not developed a unified framework that simultaneously captures how problem characteristics have evolved and provides structured guidance on matching solution approaches to these new challenges.

The concept of production has evolved through successive industrial revolutions. Industry 1.0 introduced mechanical manufacturing, Industry 2.0 enabled mass production, and Industry 3.0 brought automation through information technology. Industry 4.0 introduces a fourth paradigm shift: From automated to interconnected and intelligent manufacturing. This evolution is mirrored in manufacturing processes themselves, as exemplified by advanced techniques like electrostatic atomization minimum quantity lubrication machining, which demonstrates how precision manufacturing technologies have co-evolved with scheduling requirements. At its core are CPSs, transformative technologies that integrate computation, networking, and physical processes [3]. Connected via IoT and augmented with cloud computing and AI, CPSs create “smart factories” where physical assets and their digital twins communicate, cooperate, and make decentralized decisions in real-time [4]. Moreover, the vision of Industry 5.0 has extended this foundation by explicitly emphasizing human-centricity, resilience, and sustainability [5,6]. For scheduling, this evolution means moving beyond the hierarchical, ANSI/ISA-95 pyramid of Industry 3.0 toward collaborative networks of CPSs, where scheduling must become adaptive, distributed, and capable of incorporating human factors and sustainability metrics.

The evolution of smart manufacturing has generated substantial research interest in production scheduling, with studies highlighting various dimensions of this transformation. For instance, research on cyber-physical production systems demonstrates the challenges of integrating distributed decision-making in manufacturing environments, while sustainability-focused investigations reveal how environmental considerations are reshaping scheduling objectives. Concurrently, studies on resilient manufacturing systems emphasize the need for adaptive scheduling approaches that can withstand disruptions, and human-centric perspectives call for the integration of ergonomic and cognitive factors into scheduling algorithms.

Several valuable reviews have examined scheduling in the Industry 4.0 context (see Table 1 for a comprehensive comparison). Early reviews assessed traditional techniques from an I4.0 perspective [7]. Subsequent works classified scheduling characteristics [8,9], reviewed solution techniques [10], or focused on specific enablers such as digital twins [11] or particular algorithmic classes like metaheuristics [12,13]. Recent contributions have begun addressing Industry 5.0 dimensions [6,14] and simulation-based optimization [15]. Despite this growing body of work, no review systematically and simultaneously addresses two fundamental questions:

- *RQ1:* How have the core characteristics of scheduling problems been redefined or intensified in the CPS-enabled Industry 4.0 environment?
- *RQ2:* What optimization approaches and solution methodologies have been developed to address these new challenges, and how do they compare in terms of applicability, strengths, and limitations?

This gap is significant because understanding the transformation of problem characteristics is a prerequisite for selecting or developing appropriate solution methods, yet these two dimensions are typically treated separately in the literature. This review makes three distinct contributions to bridge this gap:

1. *A unified framework:* We propose the distributed, dynamic, and flexible (DDF) paradigm as a novel characterization of smart scheduling in Industry 4.0, grounded in a systematic analysis of 44 primary studies.
2. *A critical classification:* We provide a comprehensive classification and critical assessment of solution approaches, mathematical programming (including optimal control), simulation and multi-agent systems, and heuristic/metaheuristic algorithms, with explicit attention to their suitability for addressing DDF characteristics.
3. *A research roadmap:* We reveal patterns in the literature, including the striking finding that only 16% of studies address all three DDF characteristics simultaneously, and we outline a concrete, eight-point research agenda that integrates emerging Industry 5.0 requirements (resilience, sustainability, and human-centricity) to guide future investigations.

Table 1. Comparison of literature reviews on scheduling in the Industry 4.0 context.

Research	Review focus	Problem type	Solution methods
Waschneck, Altenmüller [7]	Functional areas of I4.0	JSP	Assessment of traditional techniques from an I4.0 perspective
Molins and de Mesquita [16]	Research type and themes	Scheduling (General)	Overview of techniques used in the I4.0 era
Zhang, Ding [9]	Problem characteristics and structures	JSP	Classification and analysis of techniques for smart JSP
Parente, Figueira [10]	Critical development areas	Scheduling (General)	Techniques addressing I4.0 challenges and opportunities
Coelho and Silva [13]	Computer architectures for parallelism	Scheduling (General)	Parallel Meta-heuristics
Liaqait, Hamid [17]	Problem characteristics	JSP	Overview of decentralized JSP techniques
Serrano-Ruiz, Mula [11]	Digital Twin (DT) technology	Scheduling for Zero-Defect Manufacturing	Systematic Literature Review (SLR) of DT-based scheduling

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Research	Review focus	Problem type	Solution methods
Bakon, Holczinger [6]	Scheduling under uncertainty for I4.0 & I5.0	Scheduling (General)	Taxonomy of uncertainty modelling and solution methods
dos Santos, Costa [18]	Systematic literature review on multi-objective optimization for distributed manufacturing scheduling	Distributed manufacturing scheduling	Review of multi-objective optimization methods
Jiang, Yuan [19]	Technology evolution (I3.0 to I4.0)	Scheduling (General)	Techniques and future trends in I4.0
Mourtzis [12]	Multi-objective metaheuristics	Scheduling in I4.0 & I5.0	Metaheuristic algorithms for multiple objectives
Prashar, Tortorella [20]	Morphological analysis of production scheduling literature in Industry 4.0	Scheduling (General)	Morphological analysis and classification of methods
Shakeri and Benfriha [21]	Overview of smart scheduling in MES for Industry 4.0	Scheduling in MES (General)	Overview of smart scheduling techniques
Varela, Putnik [22]	Systematic review of manufacturing scheduling for Industry 4.0	Manufacturing scheduling (General)	Systematic review of techniques
Chen, Lee Kong [23]	Review of production planning and scheduling methods for manufacturing in I4.0	Scheduling (General)	Literature review of methods
Shakeri, Halawi-Ghoson [24]	Systematic review of intelligent scheduling in MES for Industry 4.0	Intelligent scheduling in MES (General)	Systematic review of intelligent scheduling techniques
Tan, Kong [25]	Analysis and systematic review of scheduling and control in IoT environment for I4.0	Scheduling in IoT environment (General)	Systematic review of metrological data and techniques
Ghasemi, Farajzadeh [15]	Adaptive scheduling	Dynamic and flexible scheduling	Methods for real-time adaptation to changes
Groth, Schumann [26]	Review of machine learning algorithms for production scheduling	Production scheduling (General)	Review of ML algorithms
Zahid, Leclaire [27]	Review of smart scheduling for sustainable manufacturing	Smart scheduling for sustainable manufacturing	Review of smart scheduling approaches for sustainability
Zhang, Bao [14]	Metaheuristics for multi-objective problems	Production scheduling in I4.0 & I5.0	State-of-the-art survey of metaheuristics and Digital Twins

Despite significant advances in smart manufacturing scheduling, research faces critical technical bottlenecks that limit practical implementation. Approaches often struggle with the dynamic, distributed, and data-intensive nature of modern production environments, failing to adequately address real-time adaptability and scalability challenges. In this paper, we address these limitations by proposing a novel Data-Driven Framework (DDF) that systematically integrates Industry 4.0

technologies with advanced scheduling methodologies. Our approach not only bridges the gap between theoretical models and practical applications but also provides a structured pathway for transitioning toward the emerging Industry 5.0 paradigm. The remainder of this paper is organized as follows: In Section 2, we detail our systematic review methodology following PRISMA guidelines. In Section 3, we establish the theoretical foundations of Industry 4.0 and smart manufacturing. In Section 4, we introduce the DDF paradigm by analyzing core characteristics of smart scheduling. In Section 5, we offer a critical review and comparative assessment of solution approaches. Finally, in Section 6, we synthesize key findings, discuss implications for Industry 5.0, and propose a concrete research agenda to advance the field.

2. Research methodology

In this section, we detail the systematic methodology employed to conduct the literature review on scheduling evolution in the Industry 4.0 era. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, we outline a rigorous, multi-stage process designed to ensure comprehensive coverage and methodological transparency. First, we describe the search strategy employed across major academic databases (2.1). Next, we present the explicit inclusion and exclusion criteria that guided study selection (2.2). We then detail the multi-stage screening and selection process, visualized through a PRISMA flow diagram (2.3). Finally, we explain the data extraction and synthesis framework used to analyze the selected studies, which directly informs the characterization of smart scheduling presented in Section 4 (2.4). This structured approach ensures the review's reproducibility and provides a solid foundation for identifying key trends and characteristics in the literature.

2.1. Search strategy

The literature search was performed on November 8, 2025, across three major academic databases: Scopus, Web of Science, and Google Scholar. These databases were selected to provide comprehensive coverage of peer-reviewed journal articles and relevant conference proceedings. The following search string was applied to titles, abstracts, and keywords: "scheduling" AND "Industry 4.0". In addition to the database searches, backward and forward citation chasing was conducted on key seminal and recent high-impact papers [14,15] to ensure saturation and capture any potentially missed studies.

2.2. Inclusion and exclusion criteria

To ensure the relevance and quality of the selected studies, a set of inclusion and exclusion criteria was defined, as detailed in Table 2.

2.3. Study selection and screening

The study selection process followed a multi-stage screening protocol. The complete workflow is documented in the PRISMA-compliant flow diagram (see Figure 1). A total of 156 records were identified from the database searches. After removing seven duplicate records, 149 unique records progressed to the title and abstract screening stage. At this stage, 68 records were excluded as they were out of scope (e.g., studies not focused on production scheduling) based on the criteria search engine reason (SER), without full-text (WF), and non-related (NR). The full text of the remaining 80 articles was assessed for eligibility. During this detailed assessment, 15 articles were excluded with documented justifications mapped to criterion loosely related (LR) in Table 2 (e.g., books and conceptual articles without a clear problem-solving or review contribution). This process resulted in a final corpus of 65 studies included in the qualitative synthesis, comprising 44 closely related (CR) problem-solving articles and 21 partially related (PR) review articles.

Table 2. Criteria of exclusion and inclusion.

In/Ex		Criterion	Explanations
Exclusion		Search engine reason (SER)	Non-English article
		Without full-text (WF)	Lack of access to the text of the article/ Citation article
		Non-related (NR)	Article not related to manufacturing scheduling
		Loosely related (LR)	Book, report, or presentation (LR1), conceptual article (LR2)
Inclusion	Partially related (PR)	Literature review article	
	Closely related (CR)	Problem-solving article	

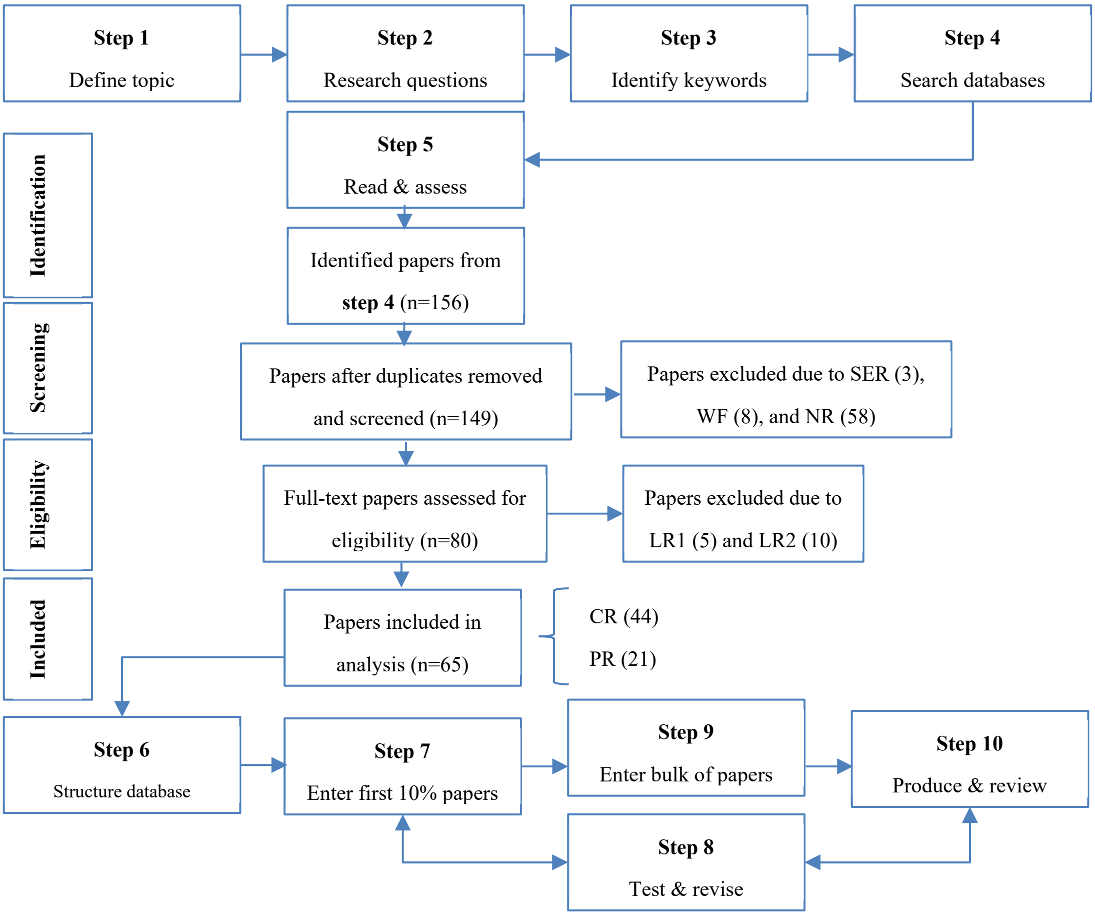

Figure 1. The PRISMA-compliant flow diagram.

2.4. Data extraction and synthesis

From the final set of 65 included studies, we extracted key information, including authors, year, problem type, solution approach, performance metrics, and the study's focus. This information was systematically organized to enable cross-study analysis and comparison. The extracted data formed the basis for identifying the core characteristics of smart scheduling (Section 4) and for classifying and critically assessing the solution approaches (Section 5).

The DDF classification presented in Table 4 was independently verified by two researchers to ensure consistency. Any discrepancies in classification were resolved through discussion and consensus, following the operational definitions provided in Section 4.4. This verification process enhanced the reliability of our literature analysis and classification framework.

3. Theoretical foundations and definitions

In this section, we establish the conceptual framework for this review by defining the key paradigms and technologies that constitute the foundation of smart manufacturing scheduling in the Industry 4.0 environment.

CPSs represent the foundational technology paradigm of Industry 4.0, characterized by the deep integration of computational, networking, and physical processes. Unlike traditional embedded systems, CPSs are distinguished by their ability to monitor, coordinate, control, and integrate physical operations through real-time feedback loops between the physical and digital worlds [3]. The "Physical Element" refers to tangible assets on the shop floor, machines, robots, AGVs, workpieces, and sensors, each augmented with a "Cyber Twin" that possesses computational and communication capabilities. This cyber counterpart can collect data, create virtual representations, and execute algorithms.

The IoT provides the communication infrastructure enabling connectivity, enabling manufacturing assets to interact and share information. Cloud computing offers scalable storage and computational power for processing the vast data streams generated by CPSs, enabling advanced analytics and hosting digital models. AI serves as the brain of this connected ecosystem, enabling predictive maintenance, quality control, and intelligent scheduling by extracting meaningful patterns from industrial data [28].

Industry 4.0 leverages CPSs and IoT to create smart factories where decentralization, interoperability, and real-time data access transform production management. The core vision is to create manufacturing systems that can adapt in real-time to changing conditions, optimize performance across objectives, and connect assets horizontally (across the supply chain) and vertically (from shop floor to enterprise planning). Moreover, Industry 5.0 extends this vision by explicitly emphasizing human-centricity, environmental sustainability, and resilience against disruptions [5].

The realization of smart manufacturing occurs within the smart factory. Wu and Xu [4] decribed the smart factory as a flexible system that can self-optimize performance across a broader network, self-adapt to and learn from new conditions in real or near-real time, and autonomously run entire production processes. This goes far beyond automation, embedding intelligence into every asset and process. Translating advanced scheduling algorithms into practical, operational tools for the smart factory remains a key challenge. The implementation framework proposed by Wu and Xu [4] offers a concrete pathway for bridging this gap. Their work highlights the critical role of data integration, interoperability, and user interface design in ensuring that sophisticated scheduling solutions are adopted and effectively used on the shop floor. This operational perspective moves beyond algorithmic performance to consider the socio-technical system within which the schedule must function. Zheng and Ardolino [29], through a systematic review, further clarify the applications of these technologies, showing that IoT and CPSs are most prevalent for real-time monitoring and control, while cloud computing and big data analytics facilitate large-scale data processing and decision support, all of which are essential for the smart factory's operation.

Within this context, production scheduling, the allocation of limited resources to tasks over time to optimize one or more objectives, must fundamentally evolve. The theoretical underpinnings of traditional scheduling are well-established in foundational works [1,30,31], which document classical problem types (job-shop, flow-shop, parallel-machine), optimization criteria, and algorithmic strategies. These principles remain relevant but are being redefined and extended within the Industry 4.0 paradigm to incorporate new capabilities and complexities. A pivotal contribution bridging classical theory with the new paradigm is the monograph scheduling in Industry 4.0 and cloud manufacturing [32], which systematically conceptualizes the shift from traditional, hierarchical scheduling to dynamic, cloud-based approaches.

Table 3. Mapping CPS capabilities to scheduling characteristics.

CPS Capability	Enabled Scheduling characteristic	Mechanism
Embedded computation and machine-level intelligence	Distribution	Decentralized decision entities (agents) evaluate local conditions, negotiate with peers, and commit to schedules without central orchestration
Real-time sensing and continuous state monitoring	Dynamics	Production disturbances (machine failures, rush orders) are detected immediately, triggering schedule revisions at the operational level
Wireless communication and interoperability	Distribution/ Coordination	Assets share status, intentions, and constraints across the network, enabling distributed consensus and coordinated local optimization
Virtualization and digital twinning	Flexibility/ Reconfiguration	Physical assets are represented virtually, allowing simulation of alternative configurations and logical reassignment of functions
Data analytics and learning from historical data	Proactivity	Patterns in disruptions, maintenance needs, and demand variability are predicted, enabling anticipatory scheduling
Human-machine collaboration interfaces	Human-centricity	Human operators provide contextual knowledge, with the system adapting to human preferences and cognitive load

A rigorous and in-depth analysis of algorithmic solutions for complex scheduling problems is provided by Brucker [33] in "Scheduling Algorithms." This book is renowned for its formal and mathematical treatment of the field, covering a broad spectrum of problem classes from single-machine environments to complex job-shops and resource-constrained project scheduling. It serves as a key reference for understanding the fundamental algorithms, exact and heuristic, that form the backbone of scheduling research. This theoretical foundation is essential for evaluating and developing the advanced metaheuristics and distributed algorithms required to tackle the integrated and dynamic scheduling challenges posed by smart manufacturing systems.

To establish clear causal logic linking technology to scheduling transformations, we must understand how specific CPS capabilities enable new scheduling characteristics. Table 3 maps these capabilities to the scheduling characteristics they support, along with the mechanisms through which this enablement occurs.

To understand how Industry 4.0 transforms scheduling, it is instructive to consider the evolution from the hierarchical model of Industry 3.0, as defined by the ANSI/ISA-95 standard, to the integrated, collaborative model enabled by CPSs. In the traditional pyramid (Figure 2), decisions flow sequentially from business planning (Level 4, e.g., ERP) down to the physical process (Level 0). Scheduling typically resides at Level 3, isolated from real-time shop-floor data.

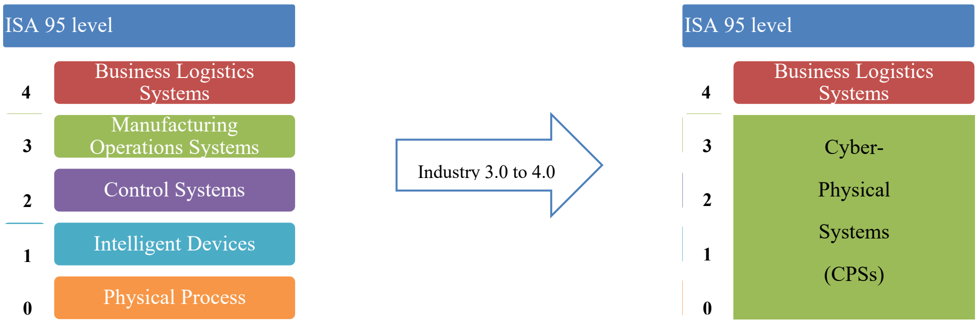

Figure 2. Decision-making processes in Industry 3.0 and Industry 4.0 (adapted from Guizzi and Vespoli [34] and Rossit and Tohmé [35]).

Industry 4.0 collapses these rigid hierarchies. Levels 0 to 3 are integrated into a network of CPSs, where physical assets and their cyber counterparts communicate and cooperate via IoT and cloud computing. This architectural shift fundamentally redefines scheduling problems, imbuing them with three core characteristics: distribution, dynamics, and flexibility. The interplay between these characteristics is crucial; distribution enables more dynamic responses to disruptions, while flexibility in resources is a prerequisite for leveraging distribution and dynamics.

4. Characteristics of smart scheduling

Building upon the systematic literature review detailed in Section 2, in this section, we synthesize the core characteristics that define “smart scheduling” in the context of Industry 4.0. Our analysis reveals that contemporary scheduling systems are increasingly characterized by three interconnected dimensions: Distribution, Dynamics, and Flexibility, collectively termed the DDF paradigm. We systematically examine each dimension in turn. First, we explore the architectural shift from centralized to distributed decision-making enabled by Cyber-Physical Systems (4.1). Second, we analyze the requirement for temporal adaptability and responsiveness to real-time disruptions (Dynamics, 4.2). Third, we investigate the need for system reconfigurability to accommodate product and process variety (Flexibility, 4.3). To provide a comprehensive overview, Table 4 cross-references the reviewed studies against these three characteristics, mapping the literature’s focus and identifying prevailing trends. In this structured analysis, we aim to clarify the defining features of next-generation scheduling systems and guide future research directions.

4.1. Distribution of decision-making

The decentralized architecture of CPSs transforms scheduling from a centralized, top-down activity into a distributed process. In this paradigm, autonomous agents representing machines, jobs, or other resources interact locally to negotiate and generate schedules. This approach contrasts sharply with traditional centralized models, where a single entity requires global information, creating bottlenecks for scalability and reactivity. The literature reveals three predominant approaches to handling distribution:

1. *Systematic Architectures:* Many researchers propose semi-centralized or fully decentralized architectures. Ivanov and Dolgui [2], Ivanov and Dolgui [36], Ivanov and Sokolov [37], and Dolgui and Ivanov [38] model the dynamic distribution of operation execution and machine availability over time, demonstrating how large-scale scheduling problems can be decomposed into smaller sub-problems solved at different points in time.
2. *Optimal Control Models:* This approach models scheduling as a dynamic control problem, where schedules are represented as trajectories, which are particularly well-suited for distributed systems with continuous-time dynamics.
3. *Agent-Based Models:* Multi-agent systems (MAS) align naturally with the CPS philosophy. Leusin and Frazzon [39] embedded MAS into CPSs to create frameworks where intelligent production resources interact directly to achieve scheduling goals, enhancing dynamism and flexibility. The concept of distributed scheduling is fundamentally rooted in multiagent systems [40]. This perspective is crucial for understanding smart manufacturing systems, which are inherently decentralized. In such systems, CPSs can be viewed as intelligent agents that negotiate and cooperate to achieve scheduling objectives, moving beyond traditional centralized control paradigms. The multi-agent framework provides formal grounds for analyzing the performance of such distributed decision-making processes, a cornerstone of the Industry 4.0 scheduling paradigm.

As indicated in Table 4 (Column B_1), nearly half of the reviewed studies incorporate a distributed perspective, underscoring a move away from monolithic scheduling systems toward more agile, collaborative networks.

4.2. Dynamics of real-time response

The real-time connectivity of CPSs via IoT, combined with their decentralized nature, drastically increases the dynamism of the scheduling environment. Scheduling is no longer a static plan created in advance but an adaptive process that continuously reacts to real-time events. These disturbances mostly originate from orders (e.g., new rush orders and cancellations) and resources (e.g., machine breakdowns and tool unavailability). The strategies for managing this dynamism range from purely reactive to highly proactive are:

- *Fully Reactive:* Real-time decisions with no pre-computed schedule, often using simple dispatching rules.
- *Predictive-Reactive:* A baseline schedule generated offline, modified in response to real-time disruptions [41].

- *Robust Predictive-Reactive:* Initial schedule designed to be inherently robust, with rescheduling only when performance deviates significantly.
- *Robust Proactive:* Schedule engineered from the outset to absorb potential disruptions.

A critical evolution noted in the literature is the concept of structural dynamics, which requires deeper theoretical treatment. The concept of dynamics requires precise articulation to distinguish what is genuinely novel in the CPS context. We propose a distinction between two fundamentally different types of dynamics:

- Event dynamics refers to changes in state variables while the production system's underlying structure remains fixed. Classical reactive scheduling falls within this category: When a machine breaks down, the scheduler reassigns affected jobs to other machines. The production system's configuration, which machines exist, how they are connected, what functions they perform, is treated as static.
- Structural dynamics refers to changes in the configuration of the production system, machine assignments, routing structures, logical connections among resources, and the formation or dissolution of temporary production coalitions. The system's structure becomes a decision variable.

The CPS enables structural dynamics through several mechanisms. First, cyber twins provide virtual representations that can be reconfigured logically: A machine's function can be reassigned to another machine with similar capabilities, not merely as a fallback but as a routine operational choice. Second, software-defined functionality means machine behaviors are governed by programmable logic that can be updated in real-time. Third, dynamic coalition formation enables groups of resources to temporarily collaborate on complex tasks, then dissolve and reconfigure.

The foundational work by Ivanov et al. [2,36,37] provides essential grounding. Moreover, Ivanov and Dolgui [2] demonstrated how dynamic reconfiguration of supply chain structures can absorb disruptions more effectively than buffer-based approaches. Ivanov and Dolgui [36] showed that CPS-enabled production systems can reroute material flows not just through alternative paths within a fixed network, but by altering the network topology. Ivanov and Sokolov [37] introduced "structural resilience," where system structure adapts proactively based on predictive analytics.

A concrete example clarifies the distinction: In a classical flexible manufacturing cell, if a milling machine fails, jobs are rerouted to another identical milling machine (event dynamics). In a CPS-enabled structurally dynamic system, if a milling machine fails, its control logic could be migrated to a different machine type, a multifunctional machining center, which temporarily performs milling operations while its original functions are suspended. This is not merely alternative routing within a fixed topology but a change to the topology. This distinction has profound implications: Scheduling expands from a resource allocation problem to a combined system configuration and allocation problem.

The dynamic nature of smart manufacturing, where processing times vary due to learning effects, deterioration, or disruptions, requires moving beyond static models. This aligns with the field of time-dependent scheduling, where job processing times are functions of their start times or sequence positions [42]. The models and algorithms from this field are essential for mathematically representing and managing the real-time adaptability and temporal dependencies inherent to Industry 4.0 environments.

4.3. Flexibility for adaptive execution

To achieve high levels of dynamism in a distributed environment, scheduling systems must possess maximum flexibility. From a scheduling theory perspective, this translates to studying flexible shop configurations. A Flexible Job-Shop (FJS) or Flexible Flow-Shop (FFS) extends classical problems by enabling multiple parallel machines at each production stage with different capabilities, providing alternative routing choices.

Researchers have tackled flexible scheduling within Industry 4.0. Ghaleb and Zolfagharinia [43] and Li and Goga [44] developed models for the Dynamic Flexible Job-Shop Scheduling Problem (DFJSP), explicitly considering real-time events. Ivanov and Dolgui [2] and Ivanov and Dolgui [36] used optimal control theory to model FFS and FJS problems with time-varying processing speeds.

However, a notable gap in the literature is that most researchers focus exclusively on machine flexibility (using different machines for an operation). There is comparatively less emphasis on process flexibility (producing different product types on the same machines) or routing flexibility (changing the sequence of operations). A truly smart scheduling system would need to integrate these dimensions.

The three characteristics, the DDF Paradigm, are deeply intertwined. Distribution provides the architectural framework for localized, rapid decision-making. Dynamics is the operational reality demanding such a distributed response. Flexibility is the inherent capability making effective response possible. Table 4 presents a comprehensive mapping of the reviewed literature against these characteristics, demonstrating how researchers address distribution (B_1), dynamics (B_2), and flexibility (B_3). As Table 4 reveals, only 16% of the reviewed articles simultaneously address all three characteristics (see Figure 3), highlighting a significant area for future research. A smart scheduling problem in the Industry 4.0 era is, therefore, best defined as a DDF scheduling problem, where solutions must harmonize these interconnected facets.

4.4. Operationalization of DDF classification criteria

To ensure reproducibility and enable consistent future extensions of the corpus, we formally operationalize the DDF classification criteria as follows:

- *Distribution (B1):* A scheduling system is classified as “distributed” when decision-making authority is allocated across at least two distinct computational entities that operate with some degree of autonomy, without requiring centralized coordination for all operational decisions. This includes hierarchical, federated, or fully decentralized architectures where local agents can make scheduling decisions based on local information and objectives.
- *Dynamics (B2):* A system exhibits “dynamic” characteristics when it can respond to either event-driven dynamics (real-time changes in the production environment) or structural dynamics (changes in system configuration or objectives). Specifically:
    - *Event-driven dynamics:* Response to disturbances including machine breakdowns (affecting ≥5% of operational capacity), urgent order arrivals (exceeding 10% of planned workload), material shortages, or quality deviations, with adaptation within one production cycle.
    - Structural dynamics: Adaptation to changes in system configuration such as addition/removal of resources (≥10% change in resource pool), modification of production objectives (e.g., shifting from makespan minimization to due date

adherence), or changes in organizational structure (e.g., merging production lines or outsourcing operations).

- *Flexibility (B3):* “Flexibility” is operationalized as the system’s capacity for reconfiguration to accommodate at least two of the following: (1) Product mix changes (ability to handle ≥3 different product types without major retooling), (2) routing flexibility (alternative processing paths for ≥20% of operations), (3) volume flexibility (scaling production by ±25% without structural changes), or (4) expansion flexibility (integrating new resources with ≤48 hours of downtime).

These operational definitions provide clear thresholds for classification, ensuring that future studies can be consistently evaluated against the DDF framework and facilitating comparative analysis across the smart scheduling literature.

Table 4. Comprehensive analysis of smart scheduling studies by DDF characteristics.

Study	Problem type	DDF Characteristics			Performance metrics	Focus of the study
		B_1	B_2	B_3		
Ivanov, Dolgui [2]	Flow-Shop	*	*	*	Cost, service level	Dynamic reconfiguration absorbs disruptions
Ivanov, Dolgui [36]	Job-Shop	*	*	*	Makespan, utilization	Optimal control for flexible assembly
Leusin, Frazzon [39]	Job-Shop	*	*	*	Flow time, tardiness	MAS embedded in CPS enhances adaptability
Dolgui, Ivanov [38]	Flow-Shop	*	*	*	Multiple	OPC foundation for dynamic scheduling
Ivanov, Sokolov [37]	Job-Shop	*	*	*	Robustness, reactivity	Proactive-reactive control framework
Kocsi, Matonya [45]	Job-Shop	*	*	*	Throughput, delay	Real-time DSS for customized production
Ramadan, Salah [46]	Job-Shop	*	*	*	Lead time, WIP	I4.0 scheduling in lean systems
Guizzi, Vespoli [34]	Job-Shop	*	*		Throughput	Decentralized CPS outperforms hierarchical
Zaayman and Innamorato [47]	Job-Shop	*	*		Multiple	Simio for real-time scheduling
Vespoli, Grassi [48]	Flow-Shop	*	*		WIP, tardiness	WLC in decentralized architecture
Marangé, Lemoine [49]	Parallel	*	*		Robustness	Robust optimization with model-checking
Grassi, Guizzi [50]	Flow-Shop	*	*		Multiple	Semi-heterarchical architecture evaluation
Li, Goga [44]	Job-Shop	*		*	Makespan	Scheduling-centric workflow for FJS
Nahhas, Lang [51]	Flow-Shop		*	*	Robustness	ISBO for stochastic machine breakdowns
El Mouayni, Demesure [52]	Job-Shop		*	*	Fatigue, reliability	GRASP with human factors

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Study	Problem type	DDF Characteristics			Performance metrics	Focus of the study
		B_1	B_2	B_3		
Liu and Liu [53]	Parallel		*	*	Profit, NPV	Stochastic programming with cash flow
Zhang, Ding [9]	Job-Shop		*	*	Makespan	MPGA-CP for DFJSP
Ghaleb, Taghipour [8]	Flow-Shop		*	*	Multiple	Real-time maintenance-production
Ghaleb, Zolfagharinia [43]	Job-Shop		*	*	Makespan, stability	DFJSP with job arrivals/breakdowns
Ortíz-Barrios, Petrillo [54]	Job-Shop		*	*	Multiple	Fuzzy AHP-TOPSIS dispatching
Wenzelburger and Allgöwer [55]	Job-Shop		*	*	Tracking error	MPC with Petri net for FJS
Sokolov, Zakharov [56]	Job-Shop		*	*	Proactiveness	Investigated combined models and algorithms for modern proactive intellectual scheduling under the Industry 4.0 environment.
Mimouni and Jalid [57]	Flow-Shop		*	*	Energy, makespan	Multi-objective green scheduling
Azab and Pourvaziri [58]	Job-Shop		*	*	Efficiency	Proposed a Digital Twin-based approach for scheduling and smart material-handling considerations.
Rossit and Tohmé [59]	Single	*			Lateness	ATCS in knowledge architecture
Fu, Ding [60]	Flow-Shop		*		Makespan, energy	FWA with learning/deteriorating effects
Ferreirinha, Baptista [61]	Single		*		Multiple	Dynamic dispatching rule selection
Rossit, Tohmé [62]	Single		*		Tardiness	Tolerance scheduling logic
Rossit, Tohmé [35]	Single		*		Tardiness	Tolerance & inverse scheduling
Rossit, Toncovich [63]	Flow-Shop		*		Makespan	Missing operations in FSP
Rossit, Toncovich [64]	Flow-Shop		*		Makespan	Non-permutation with missing ops
Kianpour, Gupta [65]	Job-Shop		*		Tardiness	Project management, integer programming
Rossit, Toncovich [66]	Flow-Shop		*		Makespan	SA/GA for missing operations
Rossit and Tohmé [67]	Single		*		Max lateness	Tolerance for maximum lateness
Fernandez-Viagas and Framinan [41]	Flow-Shop		*		Multiple	Real-time information integration
Tarazona, Mula [68]	Parallel		*		Multiple	Hybrid metaheuristic optimization
Sun and Zhang [69]	Job-Shop		*		Real-time Performance	Proposed a real-time production scheduling method for an RFID-enabled semiconductor back-end shopfloor in Industry 4.0.

Continued on next page

Study	Problem type	DDF Characteristics			Performance metrics	Focus of the study
		B_1	B_2	B_3		
Babaeimorad, Fattahi [70]	Job-Shop		*		Maintenance & Production Cost	Addressed integrated optimization of production and preventive maintenance scheduling in Industry 4.0.
Kosse, Betker [71]	Job-Shop		*		Efficiency	Developed a semantic digital twin for dynamic scheduling of Industry 4.0-based precast concrete element production.
Lopez-Salazar, Ekwaro-Osire [72]	Job-Shop		*		-	Proposed a Reinforcement Learning approach for production scheduling in Industry 4.0 considering limited data.
Salatiello, Vespoli [73]	Job-Shop		*		Multiple Objectives	Proposed long-sighted dispatching rules for manufacturing scheduling problems in Industry 4.0 using a hybrid approach.
Leite, Pinto [74]	Parallel			*	Multiple	VND for integrated planning-scheduling
Rossit, Toncovich [75]	Flow-Shop			*	Makespan	Examined flow shop scheduling problems with missing operations in Industry 4.0 production environments.
Rossit, Nesmachnow [76]	Flow-Shop			*	Multiple Objectives	Developed a multi-objective evolutionary algorithm based on decomposition for a flow shop scheduling problem in the context of Industry 4.0.

5. A review of smart scheduling approaches

The unique characteristics of smart scheduling, distribution, high dynamics, and high flexibility, necessitate specialized solution approaches. In this section, we provide a critical review of the principal methodologies employed, moving beyond a mere description of individual papers to analyze the mutual relationships between results, highlight application contexts, and guide the reader toward deeper exploration via key bibliographic references.

Three dominant methodological approaches are identified in the literature (Table 5): Mathematical Programming, Simulation and Multi-Agent Systems, and Heuristic and Metaheuristic Algorithms. The choice among these often involves a trade-off between solution quality, computational speed, and the ability to handle real-time disruptions, a central challenge in Industry 4.0 (see Table 6).

Table 5. Classification and critical analysis of smart scheduling solution approaches.

Methodological family/ Subcategory	Representative studies	Key limitations
Mathematical Programming		
Optimal Control	Ivanov, Dolgui [2]; Ivanov, Dolgui [36]; Ivanov, Sokolov [37]; Dolgui, Ivanov [38]; Sokolov, Zakharov [56]	Computational complexity for large instances
Mixed-Integer Programming	Rossit, Tohmé [62]; Rossit, Tohmé [35]; Rossit and Tohmé [67]; Kianpour, Gupta [65]; Babaeimorad, Fattahi [70]	Scalability for real-time response
Stochastic Programming	Liu and Liu [53]; Marangé, Lemoine [49]	Distribution assumptions
Multi-objective Mathematical Models	Mimouni and Jalid [57]	Trade-off complexity
Simulation and Multi-Agent Systems		
Discrete-Event Simulation	Guizzi, Vespoli [34]; Yang and Takakuwa [77]; Zaayman and Innamorato [47]	No inherent optimization
Simulation for Decision-Support	Fernandez-Viagas and Framinan [41]	Requires extensive scenario definition
Multi-Agent Systems	Leusin, Frazzon [39]	Coordination overhead
Hybrid Simulation-MAS	Vespoli, Grassi [48]; Grassi, Guizzi [50]	Design complexity
Petri Net Based	Wenzelburger and Allgöwer [55]	State explosion
Digital Twin-based	Azab and Pourvaziri [58]; Kosse, Betker [71]	Requires robust infrastructure and accurate digital models
Simulation for Validation	Rossit, Toncovich [75]	Lacks inherent optimization capability
Heuristic and Metaheuristic Algorithms		
Dispatching Rules	Nahhas, Lang [51]; Ferreirinha, Baptista [61]; Ramadan, Salah [46]; Rossit and Tohmé [59]; Salatiello, Vespoli [73]	Myopic optimization
Multi-Criteria Dispatching	Ortíz-Barrios, Petrillo [54]	Weight sensitivity
Genetic Algorithms	Zhang, Ding [9]; Ghaleb, Taghipour [8]; Ghaleb, Zolfagharinia [43]; Kocsi, Matonya [45]; Li, Goga [44]	Parameter tuning
Simulated Annealing	Rossit, Toncovich [63]; Rossit, Toncovich [64]; Rossit, Toncovich [66]; Rossit, Nesmachnow [76]	Slow convergence
Fireworks Algorithm	Fu, Ding [60]	Relatively new, fewer studies
GRASP	El Mouayni, Demesure [52]	Greedy bias
Variable Neighborhood Descent	Leite, Pinto [74]	Neighborhood structure design
Hybrid Metaheuristics	Tarazona, Mula [68]	Integration complexity
Reinforcement Learning (RL)	Lopez-Salazar, Ekwaro-Osire [72]	Requires extensive training data

Table 6. Comparative assessment of solution approaches for smart scheduling in Industry 4.0.

Approach category	Scalability (Empirical)	Typical solution quality	Real-time Suitability	Primary I4.0 application context
Optimal Control (OPC)	Moderate (≤ 50 jobs)	Optimal for continuous-time model	Moderate (seconds)	Dynamic flow-shop/ job-shop, structural dynamics, supply chain
MIP/ Stochastic/ Fuzzy	Low (≤ 20 jobs)	Optimal (for modelled uncertainty)	Low (minutes to hours)	Offline predictive scheduling, robust baseline generation
Discrete-event simulation	Very high (full factory models)	Policy-dependent, feasible	High (event-driven)	Validation, what-if analysis, decision support
Multi-Agent Systems (MAS)	Very high (distributed, scalable)	Feasible, locally optimal	Very high (milliseconds)	Decentralized control, real-time dispatching, CPS coordination
Dispatching rules	Very high (1000+ jobs)	Suboptimal, feasible	Very high (microseconds)	Real-time scheduling, low-complexity decisions
Metaheuristics	High (≤ 500 jobs)	Near-optimal	Moderate (seconds–minutes)	Periodic rescheduling, complex multi-objective problems
Hybrid metaheuristics	Moderate–High (≤ 300 jobs)	Near-optimal, often improved	Moderate	Balancing global optimization with problem-specific constraints

5.1. Mathematical programming

Mathematical programming approaches formulate scheduling problems using mathematical models and seek optimal or near-optimal solutions. In the context of Industry 4.0, Optimal Control Theory has emerged as a particularly significant branch of mathematical programming, offering a dynamic and continuous-time perspective that aligns well with the real-time, evolving nature of smart factories.

- *Optimal Program Control (OPC) and the Maximum Principle:* A pioneering and influential stream of research, led by Ivanov and Dolgui [2], Ivanov and Dolgui [36], Ivanov and Sokolov [37], and Dolgui and Ivanov [38], applies OPC. This approach models schedules as dynamic trajectories rather than static sequences. The core advantage lies in its ability to handle structural dynamics, where job sequencing and machine configuration decisions are made simultaneously and can change over time. The methodology decomposes the large-scale scheduling problem into smaller, more manageable sub-problems at each time instant using a modified maximum principle. This is particularly effective for flexible flow-shop and job-shop problems with time-varying constraints, providing a theoretical foundation for dynamic rescheduling that is more deeply integrated than simple reactive adjustments. For readers seeking a comprehensive foundation, the work of Dolgui and Ivanov [38] serves as an excellent review of OPC applications in production and supply chains.
- *Other Mathematical Models:* Alongside OPC, other mathematical programming formulations are used to encapsulate Industry 4.0 challenges. For instance, stochastic programming is employed by Liu and Liu [53] to manage uncertainties in processing times within parallel-machine environments. Mixed-Integer Programming (MIP) models are widely used; for example, Rossit and Tohmé [35] and Rossit and Tohmé [62] developed MIP models for tolerant

and inverse scheduling, creating schedules that are inherently robust to minor disruptions. Kianpour and Gupta [65] innovatively combined integer programming with project management concepts to integrate real-time data into job-shop schedules.

- *Relationships and Applications:* The relationship between these methods is hierarchical in complexity. While MIP and stochastic programming are powerful for predictive scheduling under uncertainty, OPC models extend this into the reactive and proactive domains by providing a continuous-time framework for control. A practical application of this is seen in supply chain scheduling, where Ivanov and Dolgui [2] demonstrated how OPC could dynamically reschedule flows in response to supplier delays or machine failures, thus maintaining system viability.

5.2. Simulation and multi-agent systems

This paradigm is crucial for validating and operating in the decentralized, event-driven environment of Industry 4.0. These approaches are less about finding a provably optimal solution and more about evaluating performance, enabling adaptability, and facilitating coordination among distributed entities.

- *Simulation for Validation and Decision-Support:* Discrete-event simulation is extensively used as a virtual testbed for scheduling strategies. Researchers like Guizzi and Vespoli [34] and Yang and Takakuwa [77] used simulation (e.g., with Simio) to compare the performance of traditional hierarchical scheduling against novel, decentralized CPS-based architectures. Their work quantitatively demonstrated the superiority of decentralized approaches in handling unexpected events like rush orders. Simulation also acts as a core component in decision-support systems, as seen in Fernandez-Viagas and Framinan [41], where it was used to test combinations of predictive and reactive strategies in a flow shop with real-time information, providing managerial insights into which strategy performs best under different disruption scenarios.
- *Multi-Agent Systems for Distributed Control:* MAS provides a natural architectural model for the distributed characteristic of smart scheduling. In the MAS, autonomous agents (representing machines, jobs, and transporters) interact through negotiation and cooperation to achieve a global scheduling objective. Leusin and Frazzon [39] embedded MAS within CPSs, demonstrating how intelligent resources could interact in real-time to achieve dynamism and flexibility, effectively dealing with local disturbances without central intervention. This approach directly enables the fully reactive and robust predictive-reactive strategies. The work of Vespoli and Grassi [48] and Grassi and Guizzi [50] further exemplifies this by combining simulations with agent-based dispatching rules (like WorkLoad Control) in a semi-heterarchical architecture, showing how local decisions can lead to efficient global outcomes.
- *Relationships and Applications:* Simulation and MAS are highly complementary. MAS defines the rules of interaction and autonomy, while simulation models the environment and evaluates the emergent system behavior. A key industrial application area is in high-mix, low-volume production, as studied by Kocsi and Matonya [45], where a real-time scheduling system must constantly adapt to new, customized orders.

5.3. Heuristic and metaheuristic algorithms

Given the NP-hard nature of most scheduling problems, which is further exacerbated by the dynamic and flexible constraints of Industry 4.0, heuristic and metaheuristic algorithms are the most frequently employed approach (as seen in Figure 3-c). They sacrifice guaranteed optimality for the sake of obtaining good-quality solutions within computationally feasible timeframes, making them suitable for real-time or frequent rescheduling.

- *Metaheuristics for Complex Search Spaces:* Population-based metaheuristics like Genetic Algorithms (GA) are exceptionally popular due to their flexibility. For example, Zhang and Ding [9] combined a Multi-Population GA with Constraint Programming (MPGA-CP) to solve dynamic flexible JSPs, effectively embedding exact reasoning within a metaheuristic search. Other metaheuristics like Simulated Annealing (SA) are often used in hybrid models, as seen in the works of Rossit and Toncovich [63], Rossit and Toncovich [64], and Rossit and Tohmé [67], where a GA provides an initial solution that is subsequently refined by SA for problems with missing operations. The Fireworks Algorithm (FWA), a more recent metaheuristic, was applied by Fu and Ding [60] to a stochastic FSP with deteriorating and learning effects, showing competitive performance against established algorithms like NSGA-II. The trend toward hybridization continues to dominate the field, with researchers combining the strengths of different algorithms to overcome the limitations of individual methods. The critical review by Tarazona and Mula [68] provides a valuable taxonomy of hybrid metaheuristics, classifying them by their architecture and level of coupling. Their analysis goes beyond a simple catalog to examine the conditions under which hybrid strategies are most effective, offering crucial guidance for future algorithm design.
- *Heuristics and Dispatching Rules for Real-Time Control:* For scenarios requiring immediate decisions, sophisticated heuristics and dispatching rules are developed. Dispatching rules (e.g., ATCS and FIFO) are extremely fast and scalable, handling hundreds of jobs in real time, but they produce schedules that are often far from optimal [46,61]. Nahhas and Lang [51] proposed an Integrated Simulation-Based Optimization (ISBO) heuristic to handle stochastic machine breakdowns. Ortíz-Barrios and Petrillo [54] developed a dynamic dispatching rule for flexible JSPs by fuzzy AHP and TOPSIS, enabling multi-criteria decision-making that considers machine status and job priorities in real-time. Rossit and Tohmé [59] applied the Apparent Tardiness Cost with Setups (ATCS) rule within a knowledge architecture for a smart single-machine system.
- *Relationships and Applications:* There is a trend toward hybridization, where the strengths of metaheuristics are combined, or metaheuristics are integrated with other techniques like simulation (simulation-based optimization) or mathematical programming. The application of a Tabu Search by Bezoui and Olteanu [78] to solve flexible JSPs in the Industry 5.0 context underscores the continued relevance of these methods for evolving industrial paradigms, especially when incorporating human-centric constraints. For a broader perspective on the integration of simulation and optimization in this domain, the review by Ghasemi and Farajzadeh [15] offers a valuable roadmap.

In summary, the landscape of smart scheduling approaches is diverse. Mathematical programming, particularly OPC, provides a strong theoretical foundation for dynamic control. Simulation and MAS offer indispensable tools for designing, validating, and operating decentralized systems. Finally, heuristics and metaheuristics represent the practical workhorses for solving the complex, real-world instances of these problems. The most promising future directions lie in the further integration of these approaches, such as embedding simulation within metaheuristics for fitness evaluation or using MAS to coordinate the execution of schedules generated by optimal control models. Each approach exhibits distinct trade-offs between solution quality, computational speed, and real-time capability. Hybridization, embedding simulation within metaheuristics or using MAS to coordinate optimal control models, represents the most promising direction.

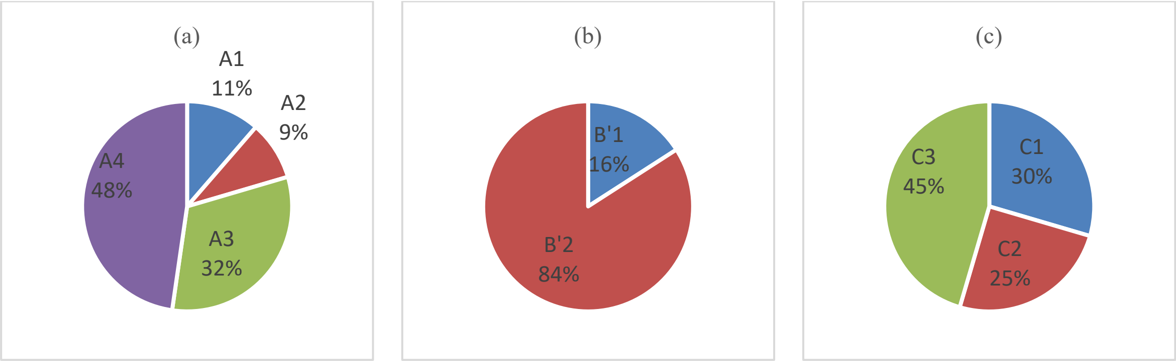

Figure 3. Problems, characteristics, and approaches in the literature. Problem types: A_1. single-machine, A_2. parallel-machine, A_3. flow-shop, and A_4. job-shop. Key characteristics: B_1. distributed, B_2. dynamic, and B_3. flexible B'_1. distributed, dynamic, and flexible, B'_2. other than B'_1. Primary approach: C1. mathematical programming (MP), C2. simulation (SIM) and multi-agent systems (MAS), and C3. heuristic (H) and metaheuristic algorithms (MH).

Based on the defined categories in Table 4 and Table 5, the circular graphs of Figure 3 show the coverage of areas of problems, characteristics, and approaches. It can be seen that job shops (48%) are the most prominent problem area for Industry 4.0 scheduling. Moreover, among the 44 included articles, only 16% of them have a contribution to distributed dynamic flexible scheduling in the manufacturing systems of the Industry 4.0. The category of heuristic and metaheuristic algorithms is the largest one in the approach area.

6. Conclusions and research agenda

In this systematic literature review, we analyzed the transformation of manufacturing scheduling in the Industry 4.0 era, addressing how problem characteristics have been redefined and what solution methodologies have emerged. In this section, we synthesize key findings, discuss implications for Industry 5.0, outline a future research agenda, and acknowledge limitations.

6.1. Summary of findings

Our analysis reveals that Industry 4.0 fundamentally transforms scheduling along three interconnected dimensions, the DDF paradigm:

- Distributed decision-making shifts from centralized hierarchical control to decentralized networks of autonomous CPS agents that negotiate and coordinate locally. Over 30% of reviewed studies incorporate distributed approaches, ranging from systematic architectures to agent-based systems, with only 16% simultaneously addressing all three DDF characteristics.
- Dynamic scheduling evolves from static off-line planning to adaptive real-time processes responding to disruptions. We distinguish event dynamics (reactive adjustments within fixed structures) from structural dynamics (reconfiguration of the production system). While 89% of studies address dynamics, most focus on event dynamics, leaving structural dynamics underexplored.
- Flexible scheduling leverages machine capabilities, routing options, and process plans. Flexible job-shop and flow-shop problems dominate, yet research emphasizes machine flexibility over process or routing flexibility.

Critically, only 16% of reviewed studies address all three DDF characteristics simultaneously, indicating a significant research gap. Three solution approach families dominate the literature:

- *Mathematical Programming (30% of studies):* Optimal Control Theory, particularly Optimal Program Control (OPC), uniquely suits structural dynamics by modeling schedules as continuous-time trajectories. Mixed-integer, stochastic, and fuzzy programming address robustness and uncertainty but remain mostly predictive and off-line.
- *Simulation and Multi-Agent Systems (25% of studies):* Discrete-event simulation validates decentralized architectures, while MAS provide natural architectural models for distributed scheduling. Their combination enables rigorous testing of interaction protocols.
- *Heuristic and Metaheuristic Algorithms (45% of studies):* Genetic algorithms dominate, often hybridized with constraint programming or local search. Dispatching rules enable ultra-fast real-time decisions but sacrifice global optimality.

Each approach exhibits distinct trade-offs between solution quality, computational speed, and real-time capability. Hybridization, embedding simulation within metaheuristics or using MAS to coordinate optimal control models, represents the most promising direction.

6.2. Implications for Industry 5.0

The emerging Industry 5.0 paradigm extends Industry 4.0's technological foundation through three pillars [5], with direct implications for scheduling:

- *Resilience:* Structural dynamics, identified as a critical gap, is foundational for resilience. Systems that dynamically reconfigure their structure, not merely adjust parameters, can better absorb disruptions. In future studies, researchers must integrate optimal control with digital twins for real-time reconfiguration.
- *Sustainability:* Beyond energy efficiency [57], sustainability requires incorporating material circularity, waste reduction, and lifecycle considerations into multi-objective DDF frameworks.
- *Human-centricity:* Scheduling systems must incorporate human factors, fatigue, skill levels, and cognitive load, as explicit decision variables, with CPS augmenting rather than replacing human capabilities [52,78].

The DDF paradigm provides a foundation, but must extend to encompass resilience, sustainability, and human-centricity (DDF-RSH).

6.3. Research gaps and future directions

Our findings of this review, together with the Industry 5.0 outlook, point to several persistent gaps and promising research avenues:

- *Decentralized decision-making.* Despite growing attention, most studies remain centralized. Adapting multi-factory scheduling concepts to smart shop floors with human-in-the-loop architectures remains an open challenge.
- *Structural dynamics.* Nearly all dynamic researches treat event dynamics; structural dynamics, reconfiguring production systems, requires closer integration of control theory (OPC) with scheduling.
- *Multiple flexibility dimensions.* Machine flexibility dominates, while process, routing, and product mix flexibility are neglected. Future models should integrate these dimensions to unlock adaptive potential.
- *Holistic DDF treatment.* Only 16% of studies address DFF simultaneously. Understanding their interdependencies is urgent, especially as Industry 5.0 adds resilience, sustainability, and human-centricity.
- *Rapid versus exact methods.* Context-specific guidelines for selecting appropriate methods are lacking. Benchmarking on standardized industrial datasets is needed for evidence-based choices.
- *Sustainability and human-centric objectives.* Models incorporating energy, waste, circular economy, and human factors are rare and seldom combined with DDF characteristics.
- *Real-world validation.* Most studies are simulation-based; case studies in actual smart factories are scarce. Thus, collaborative industry research is essential to test practical relevance and scalability.
- *Emerging frontiers.* Digital twin-based scheduling [11,19], reinforcement learning for dynamic policies, federated learning for distributed privacy-preserving coordination, and edge-cloud collaborative architectures represent transformative directions.

In future studies, researchers should bridge classical scheduling theories with I4.0/I5.0 capabilities, adopt open benchmarks, and report solution quality alongside computational performance, robustness, and implementation effort. Only through such integrative research can we realize truly adaptive, resilient, and human-centric smart scheduling.

Author contributions

All authors have read and approved the final version of the manuscript.

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Fariborz Jolai: Supervision, Validation, Writing – review & editing.

Frank Werner: Validation, Writing – review & editing.

Use of Generative-AI tools declaration

The authors declare that they have used Artificial Intelligence (AI) tools in the creation of this article. Specifically, the DeepSeek AI tool was employed for final editing of the Abstract and Conclusion sections to enhance clarity, coherence, and overall writing quality, as well as for English language editing throughout the manuscript draft to improve readability and linguistic accuracy. The authors take full responsibility for the content of this manuscript, including any portions produced with the assistance of AI tools.

Conflict of interest

Frank Werner is an editorial board member/guest editor for Journal of Industrial and Management Optimization and was not involved in the editorial review or the decision to publish this article.

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