

Review

Not peer-reviewed version

Industrial Scheduling in the Digital Era: Challenges, State-of-the-Art Methods, and Deep Learning Perspectives

[Alina Itu](#)*

Posted Date: 15 August 2025

doi: 10.20944/preprints202508.1120.v1

Keywords: industrial scheduling; robust optimization; deep learning; industry 4.0; real-time manufacturing systems



Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a Creative Commons CC BY 4.0 license, which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

Review

Industrial Scheduling in the Digital Era: Challenges, State-of-the-Art Methods, and Deep Learning Perspectives

Alina Itu

Automation and Information Technology, Transilvania University of Brasov, Mihai Viteazu nr. 5, 5000174 Brasov, Romania; alina.itu@unitbv.ro

Abstract

Industrial scheduling remains a central and evolving discipline, underpinning efficiency, resiliency, and competitiveness in manufacturing and service operations. The ongoing digital transformation, driven by paradigms such as Industry 4.0, has fundamentally altered the context in which scheduling decisions are made, introducing pervasive connectivity, real-time data flows, and intelligent automation. This review critically examines three major challenges that continue to define the state-of-the-art: (1) scalability and computational complexity in large-scale, high-dimensional scheduling environments; (2) robustness and adaptability to uncertainty and real-world disruptions; and (3) integration with digitalization, including IIoT, cloud platforms, and cyber-physical systems. For each challenge, we synthesize classical and emerging methodologies, with a particular focus on the surge of data-driven and AI-enhanced approaches. Notably, we highlight the transformative role of deep neural networks and deep reinforcement learning, which are shaping a new era of intelligent, real-time scheduling capable of addressing complexities previously deemed intractable. The impact of these techniques is mapped across domains ranging from predictive and reactive scheduling to the orchestration of distributed, autonomous production systems. We also discuss the challenges of interpretability, data quality, and legacy integration posed by these powerful yet opaque models. The review concludes by proposing key directions for future research, including interpretable deep learning, the creation of standardized data benchmarks, and hybrid human-in-the-loop frameworks, all of which will be pivotal for advancing industrial scheduling in the connected, automated, and ever-adaptive digital era.

Keywords: industrial scheduling; robust optimization; deep learning; industry 4.0; real-time manufacturing systems

1. Introduction

Industrial scheduling encompasses the decision-making processes involved in allocating limited industrial resources—such as machines, workforce, and materials—to a set of jobs or operations over time, with the aim of optimizing one or more objective functions. These may include makespan minimization, cost reduction, throughput maximization, on-time delivery, or the balancing of workloads and inventories (Pinedo, 2016; Allahverdi et al., 2008). Scheduling is a central component of operational management in manufacturing, logistics, energy systems, and other industrial domains, constituting a rich area of research within operations research, computer science, and industrial engineering (Gupta & Stafford, 2006; Blazewicz et al., 2007).

The industrial scheduling problem is renowned for its computational complexity and practical significance. Many real-world variants are classified as NP-hard, precluding efficient exact solutions for large-scale instances (Graham et al., 1979). As a result, the evolution of scheduling theory and algorithms is tightly coupled with the development of approximate, heuristic, or metaheuristic approaches, as well as the integration of artificial intelligence and machine learning techniques in

recent years (Hart et al., 2019; Zhang et al., 2020). Scheduling challenges manifest across the operational hierarchy, from high-level production planning and workforce rostering to detailed machine-task sequencing and real-time rescheduling in response to disruptions (Herrmann, 2006).

The importance of industrial scheduling extends beyond its direct impact on productivity and cost-effectiveness. Efficient schedules directly influence lead times, inventory levels, resource utilization rates, energy consumption, and the ability of firms to adapt to dynamic market requirements (Ivanov et al., 2018; Kuhn & Schuster, 2015). Moreover, in the context of Industry 4.0, the digital transformation of manufacturing and logistics introduces unprecedented volumes of real-time data and connectivity. This not only heightens the complexity of scheduling problems, but also enables novel, data-driven scheduling solutions integrated with cyber-physical systems, IoT platforms, and cloud-based decision support (Mourtzis et al., 2020; Wang et al., 2016).

The criticality of scheduling is further underscored by its role in achieving strategic objectives for sustainability and workforce well-being. Optimized scheduling supports energy reduction targets, minimizes production waste, and allows for ergonomic shift design, aligning industrial performance with environmental and social goals (Fang et al., 2021; Giret et al., 2015). Conversely, persistent scheduling inefficiencies can lead to elevated operational costs, customer dissatisfaction due to missed deliveries, excessive overtime or idleness, and diminished resilience to supply chain disruptions (Ivanov & Dolgui, 2020).

Given these considerations, industrial scheduling remains both a theoretical challenge and a practical imperative. Addressing its complex, multi-faceted, and evolving nature is central to enhancing global competitiveness and operational agility. This review aims to synthesize recent developments pertaining to key challenges in industrial scheduling, examining both methodological advances and their industrial impact, and outlining future research directions that promise to further strengthen the field.

Despite the rich theoretical foundation and decades of advancements in algorithms and computing power, industrial scheduling continues to confront several persistent and emerging challenges that impede the achievement of truly optimal, adaptive, and resilient operations. Among these, three core challenges have emerged as particularly prominent in both academic inquiry and industrial practice:

- scalability and computational complexity
- robustness and adaptability to uncertainty
- integration with digitalization and Industry 4.0 paradigms.

The first major challenge is the **scalability and computational complexity** of scheduling large and dynamic systems. As industrial operations grow in size and complexity, encompassing extensive networks of machines, diversified product lines, and multi-tier supply chains, the combinatorial nature of scheduling problems leads to a rapid increase in computational requirements. Classical exact methods, though powerful for small or medium-sized problem instances, often become impractical for real-world applications due to their exponential solution time (Graham et al., 1979; Pinedo, 2016). Hence, there is a growing need for scalable heuristics, metaheuristics, and hybrid approaches capable of efficiently generating high-quality solutions for large-scale environments (Hart et al., 2019; Zhang et al., 2020).

The second central challenge is **robustness and adaptability to uncertainty**. Industrial systems are routinely subject to unforeseen disturbances such as equipment breakdowns, fluctuating demand, variable processing times, supply chain disruptions, and urgent rush orders (Herrmann, 2006; Ivanov & Dolgui, 2020). Static schedules, even if optimal at the planning stage, can quickly become obsolete in the face of real-time events. Designing scheduling solutions that anticipate, absorb, and adapt to such uncertainties—while maintaining acceptable performance—remains a significant research frontier. Robust optimization, stochastic modeling, and real-time rescheduling empowered by machine learning and predictive analytics are current lines of inquiry aimed at addressing this gap (Bertsimas & Sim, 2004; Wu et al., 2021).

The third and increasingly critical challenge relates to the **integration of scheduling with digitalization and Industry 4.0 technologies**. The advent of cyber-physical systems, the Industrial Internet of Things (IIoT), big data analytics, and digital twins introduces vast streams of heterogeneous and real-time data into the scheduling landscape (Wang et al., 2016; Mourtzis et al., 2020). The push towards smart manufacturing demands that scheduling systems not only handle traditional optimization objectives but also seamlessly operate in interconnected, data-rich environments. Achieving this level of digital integration requires new models, data architectures, and algorithms capable of supporting autonomy, interoperability, and on-the-fly decision-making in rapidly changing contexts (Giret et al., 2015; Xu et al., 2018).

These three challenges—scalability and computational complexity, robustness and adaptability to uncertainty, and integration with digitalization—form the focal points of this review. The subsequent sections will examine recent methodological developments addressing each challenge, analyze their industrial impact, and delineate opportunities for future research and industrial application.

2. Scalability and Computational Complexity

2.1. The Combinatorial Nature of Industrial Scheduling

Industrial scheduling problems are intrinsically combinatorial, with solution spaces growing exponentially relative to the number of jobs, resources, and scheduling constraints. For many classical formulations—such as job-shop and flow-shop scheduling—the number of feasible schedules increases factorially or even super-exponentially as problem size grows (Graham et al., 1979; Pinedo, 2016). The addition of real-world complexities, such as resource constraints, sequence-dependent setups, multi-stage production, and multi-objective criteria, elevates most scheduling variants to the class of NP-hard problems (Blazewicz et al., 2007).

As a result, even with advances in computational power, exact solution methods such as branch-and-bound, integer programming, or constraint-based approaches become computationally prohibitive for large or complex industrial systems. This computational barrier is especially pronounced in dynamic or high-mix, low-volume production environments increasingly prevalent in modern industry (Gupta & Stafford, 2006).

2.2. Recent Methodological Developments

The profound computational complexity of industrial scheduling problems has spurred the continuous development of solution methods that balance effectiveness and scalability. Recent progress can be classified into three main areas: metaheuristics and hybrid algorithms; decomposition and parallelization; and AI-driven, data-driven approaches. Below, each is examined in detail.

2.2.1. Metaheuristics and Hybrid Algorithms

Metaheuristics represent a family of high-level frameworks designed to explore large solution spaces efficiently. Their stochastic or guided-randomized search strategies allow them to escape local optima, making them especially attractive for complex scheduling problems.

- Genetic Algorithms (GAs): GAs mimic evolutionary processes, employing populations, selection, crossover, and mutation to evolve solutions. Application in job-shop and flow-shop scheduling is widespread due to their flexibility and ability to handle varied objectives and constraints (Gen & Cheng, 2000; Zhang et al., 2018).
- Simulated Annealing (SA): SA uses probabilistic acceptance of worse solutions to escape local optima, inspired by the annealing process in metallurgy. Its simplicity and robustness against combinatorial explosion have been demonstrated in large-scale machine scheduling (Van Laarhoven et al., 1992; Osman & Laporte, 1996).

- Tabu Search (TS): TS utilizes memory structures to avoid cycling back to previously visited solutions. It has proven particularly effective for job-shop scheduling with high-dimensional constraints (Nowicki & Smutnicki, 1996; Nowicki & Smutnicki, 2005).
- Particle Swarm Optimization (PSO): PSO models collective intelligence via position and velocity updates, finding success in dynamic and multi-objective settings (Li et al., 2010; Sha & Lin, 2010).

Moreover, recent research has increasingly focused on hybridization—integrating metaheuristics with domain-specific heuristics, machine learning components, or exact methods. Such approaches can leverage the global search abilities of metaheuristics and the precision of problem-specific knowledge. Examples include GA-SA hybrids (Jayaraman et al., 1996), GA with local search (Zhang et al., 2018), and combinations of TS with constraint programming (Pezzella et al., 2008).

Metaheuristics remain popular due to their robustness and adaptability; however, parameter tuning, convergence speed, and the guarantee of solution quality are ongoing research questions (Hart et al., 2019; Blum & Roli, 2003).

2.2.2. Decomposition and Parallelization

Decomposition aims to divide large scheduling problems into tractable subcomponents, either by partitioning the problem by jobs, machines, time windows, or geographic regions.

- Hierarchical Decomposition: Production is split into stages (e.g., master production scheduling, detailed task scheduling), each addressed by tailored solution methods (Qin et al., 2022). This approach is popular in supply chain and project scheduling (Herrmann, 2006).
- Benders Decomposition: Especially effective for problems expressible as mixed-integer programming, Benders decomposition separates complicating variables, solving master and subproblems iteratively (Li et al., 2017).
- Cluster and Cell Decomposition: Used in large assembly or semiconductor fabs, tasks and resources are clustered to reduce interdependencies and parallelize local schedules (Mönch et al., 2011; Framinan et al., 2014).

Advances in parallel computing—from multi-core CPUs to distributed clusters and cloud environments—facilitate running multiple solution processes simultaneously, accelerating computation for large-scale instances (Dongarra et al., 2021; Herrera et al., 2019). Parallelization is particularly advantageous for population-based metaheuristics, agent-based models, and large mixed-integer programs (Kalinowski et al., 2018).

2.2.3. AI-Driven and Data-Driven Methods

The application of artificial intelligence (AI), and particularly machine learning (ML), marks a significant trend in tackling the scalability of industrial scheduling.

- **Reinforcement Learning (RL):** RL agents learn optimal scheduling policies via interaction with the environment. Deep reinforcement learning (DRL) extends RL with neural networks, enabling the handling of high-dimensional, dynamic shop floors (Mao et al., 2019; Park et al., 2022). RL can generate dispatching rules or propose entire schedules (Zhang et al., 2020).
- **Supervised Learning Approaches:** Historical scheduling data are used to train models (e.g., support vector machines, random forests, deep neural networks) that predict effective job assignments or schedule parameters (Cheng et al., 2020).
- **Hyper-heuristics:** These higher-level frameworks use ML to select or generate heuristics for specific problem instances (Burke et al., 2013; Özcan et al., 2010).
- **Surrogate Modeling and Predictive Optimization:** Complex scheduling objectives are approximated (surrogated) by ML models, enabling rapid estimation during metaheuristic or optimization-based searches (Sun et al., 2021).

AI-driven methods excel in environments where system dynamics, job characteristics, or objectives change frequently, and where historical or sensor data volume is large. However, they

often require vast datasets for training, and their interpretability remains a concern for industrial adoption (Chen et al., 2023).

Table 1 summarizes the above-described methods from a scalability point of view.

Table 1. Comparative Analysis of Recent Methods for Scalability in Industrial Scheduling, highlighting their core strengths, limitations, typical application areas, and representative references.

Approach	Advantages	Weaknesses	Representative Works	Industrial Applications
Genetic Algorithms	Flexible; handles multi-objective; adapts to constraints	Slow convergence; sensitive to parameters	Gen & Cheng (2000); Zhang et al. (2018)	Manufacturing; logistics
Simulated Annealing	Simple; robust against local optima	Slow for large-scale; cooling schedule sensitive	Van Laarhoven et al. (1992)	Machine scheduling
Tabu Search	Effective in complex; constrained spaces	Memory demands; requires good neighborhood definition	Nowicki & Smutnicki (1996; 2005)	Job/Flow-shop scheduling
Particle Swarm Opt.	Fast convergence; parallelizable	Premature convergence; tuning problem	Li et al. (2010); Sha & Lin (2010)	Batch; flexible shops
Hybrid Metaheuristics	Enhanced quality; tailored to subproblems	Integration complexity; parameter/method tuning	Jayaraman et al. (1996); Pezzella et al. (2008)	Automotive; electronics
Decomposition	Tackles very large instances; supports distributed solution	Coordination overhead; potential suboptimality	Framinan et al. (2014); Li et al. (2017)	Semiconductor; supply chains
Parallel Computing	Dramatic speedups; tackles large/population-based problems	Requires hardware/infrastructure; algorithm adaptation	Dongarra et al. (2021); Herrera et al. (2019)	All large-scale scheduling
Reinforcement Learning	Adapts to dynamics; learns from data; near real-time	Data/thousand-episode hungry; explainability; stability	Mao et al. (2019); Park et al. (2022)	Smart manufacturing
Supervised Learning	Fast prediction; leverages historical data	Needs rich/representative data; static environments	Cheng et al. (2020)	Repetitive/flow environments
Hyper-heuristics	Generalizes across problem types; leverages ML	Performance ceiling; needs meta-level data	Burke et al. (2013); Özcan et al. (2010)	Mixed-model production

2.3. Industrial Impact

The implementation of scalable scheduling techniques has delivered substantial benefits across industries. In manufacturing, metaheuristic-based job-shop and flow-shop solutions reduce lead times and increase throughput, even in large-scale, high-mix environments (Zhou et al., 2013). Parallelization and decomposition enable near real-time schedule updates in semiconductor fabrication, automotive assembly, and logistics networks, where thousands of jobs or resources are managed simultaneously (Mönch et al., 2011; Framinan et al., 2014). The uptake of AI-driven scheduling is also accelerating, with digital manufacturing platforms leveraging DRL-powered engines to autonomously adapt to system-scale and complexity (Mao et al., 2019).

However, there remain open challenges in balancing scalability with interpretability, robustness, and the ability to handle multi-objective tasks. Future research will increasingly focus on the

intelligent integration of scalable algorithms with real-time data streams, cloud computing, and human-in-the-loop decision support, further narrowing the gap between algorithmic advances and industrial practice.

3. Robustness and Adaptability to Uncertainty

3.1. The Prevalence of Uncertainty in Industrial Scheduling

Industrial environments are rife with uncertainties—machine breakdowns, unpredictable processing times, urgent rush orders, supply chain disruptions, and human factors, to name a few (Herrmann, 2006; Ivanov & Dolgui, 2020). Traditional static schedules, even if optimal under assumed conditions, often falter when such disturbances arise, leading to inefficiencies, missed deadlines, and costly rework (Pinedo, 2016). As systems grow larger and markets become more volatile, the imperative for **robust and adaptive scheduling** intensifies.

3.2. Recent Methodological Developments

In response, significant research efforts have focused on increasing the robustness and adaptability of industrial scheduling. Solutions can be grouped into these major streams: robust optimization, stochastic and probabilistic modeling, and real-time/adaptive (sometimes called reactive) scheduling methods.

3.2.1. Robust Optimization

Robust optimization aims to defend against uncertainty by explicitly modeling it and seeking solutions that perform well under a range of possible scenarios (Bertsimas & Sim, 2004; Kouvelis & Yu, 1997). In scheduling, this often means optimizing for the worst-case scenario or bounding performance under parameter variation.

- **Min-Max and Min-Max Regret Models:** These models transform the scheduling problem under uncertainty into one that seeks solutions minimizing the worst-case (min-max) or the worst regret (difference from the scenario-optimal schedule). This ensures performance is robust against the most adverse but plausible scenarios. Industrial adoption is seen in environments where rescheduling costs or delivery penalties are high, such as semiconductor or aerospace (Aissi et al., 2009; Kasperski & Zielinski, 2006). However, growing scenario spaces can make these models computationally complex.
- **Adjustable Robust Optimization:** Rather than committing to all decisions upfront, adjustable robust optimization frameworks allow some scheduling actions to adapt as uncertainty is resolved during execution. For example, initial sequence decisions may be fixed, while dispatching or batching can be updated later as machine status clarifies (Ben-Tal et al., 2004). These models better balance robustness and adaptiveness, but require sophisticated optimization algorithms and often increased computational effort (Lin et al., 2021).
- **Interval and Set-Based Approaches:** Here, uncertain parameters—such as job release dates or processing durations—are represented as intervals or sets. The scheduler must find feasible solutions for every parameter realization in those intervals. This approach is particularly prevalent in contract-driven industries and project scheduling, offering a practical way to address common, bounded uncertainties (Yuan et al., 2009; Li et al., 2021). Yet, the guarantee of feasibility for all combinations can sometimes lead to conservative schedules.

3.2.2. Stochastic and Probabilistic Modeling

Stochastic scheduling incorporates uncertainty directly into mathematical models using probability distributions or stochastic processes (Pinedo, 2016; Allahverdi et al., 2008).

- **Chance-Constrained Scheduling:** This approach allows practitioners to specify the acceptable probability of constraint violation (e.g., due dates or makespan limits), enabling a more flexible

trade-off between efficiency and reliability. For instance, a firm may tolerate occasional late deliveries, provided the likelihood is below a certain threshold (Birge & Louveaux, 2011; Léonard et al., 2020). This model is computationally attractive for moderate system sizes and is well-suited to service industries and large projects, but assumes reliable estimation of uncertainty distributions.

- **Markov Decision Processes (MDP):** MDP-based scheduling enables explicit modeling of state transitions under uncertainty. Each state reflects the current shop situation; scheduling decisions probabilistically affect future states. This is powerful for systems with stages and sequential uncertainties—such as batch processing or dynamic machine availability (Puterman, 2005; Mehta et al., 2020). The curse of dimensionality, however, can limit scalability beyond medium-sized systems.
- **Simulation-Based Approaches:** In settings where analytic tractability is limited, Monte Carlo or discrete-event simulations generate numerous possible futures, allowing practitioners to evaluate and compare candidate schedules' average and dispersion of key performance indicators. This aids in strategic planning and in choosing robust schedules for high-variability, project-based industries (Vieira et al., 2003; Kolisch & Sprecher, 1997). Simulation-based scheduling can be computationally expensive, but its flexible modeling is invaluable in highly uncertain and interdependent production systems.

3.2.3. Real-Time, Predictive, and Reactive Scheduling

These approaches focus on the ability to adapt schedules dynamically in response to real-time information, disturbances, or newly arrived jobs (Herrmann, 2006; Lamosa et al., 2021).

- **Rescheduling and Repair Algorithms:** Instead of developing entirely new schedules after a disturbance, repair algorithms make minimal, targeted changes to the active schedule—such as rescheduling a failed job or reallocating a blocked resource. This minimizes shop floor disruption and is a mainstay in manufacturing execution systems (Vieira et al., 2003; Cowling et al., 2004). Sophisticated repair strategies now factor in job priorities and alternative routing options, improving responsiveness.
- **Rolling-Horizon and Event-Driven Rescheduling:** Schedules are periodically (on a rolling horizon) or reactively (after major events) revised as new data arrive. Rolling-horizon methods fit naturally within ERP/MES frameworks and support continuous adaptation, especially in high-mix or dynamic order environments (Vieira et al., 2003; Li et al., 2019). However, frequent updates can create system “nervousness,” requiring stability-focused heuristics.
- **Predictive Analytics and Machine Learning:** Predictive models learn from historical and real-time data to anticipate disruptions such as delays or breakdowns, enabling proactive schedule adjustments. Recent work combines reinforcement learning agents or supervised models with online industrial data streams, allowing flexible event recognition and real-time prioritization (Wu et al., 2021; Zhao et al., 2022). These approaches thrive in data-rich, digitally enabled settings, but need high-quality, labeled datasets and careful integration with legacy systems.
- **Multi-Agent and Self-Organizing Systems:** Decentralized, agent-based scheduling frameworks assign decision rights to autonomous entities (machines, jobs, or operators) that negotiate or self-organize in response to events. These systems are resilient to localized disruptions and maintain high adaptability—traits crucial for reconfigurable and smart factories (Giret et al., 2015; Leitão et al., 2016). Industrial deployment is advancing, but robust coordination and global optimality remain open research topics.

Table 2 summarizes the above-described methods from the point of view of robustness and adaptability in industrial scheduling.

Table 2. Comparative analysis of recent methodological approaches for robustness and adaptability in industrial scheduling, highlighting their core strengths, limitations, typical application areas, and representative references.

Approach	Strengths	Weaknesses	Representative Works	Applicability
Robust Optimization	Guarantees worst-case performance; interpretable	May be conservative; scenario explosion	Bertsimas & Sim (2004); Aissi et al. (2009)	All critical/make-to-order jobs
Min-Max/Min-Max Regret	Simple formulation; hedges against bad cases	Ignores nominal; probabilistic quality	Kasperski & Zielinski (2006)	High cost-of-failure industries
Stochastic/Chance-Constrained	Incorporates probability; balances risk	Needs accurate distributions; computation	Birge & Louveaux (2011); Léonard et al. (2020)	Chemical; pharma; services
Markov Decision Processes	Handles sequential/uncertain decisions	State explosion; modeling complexity	Puterman (2005); Mehta et al. (2020)	Process; energy; logistics
Simulation-Based	Flexible; scenario exploration	Computationally expensive	Kolisch & Sprecher (1997); Vieira et al. (2003)	Project/large-system scheduling
Real-Time/Reactive Scheduling	Adaptive; leverages latest system data	Implementation complexity; stability	Cowling et al. (2004); Li et al. (2019)	Make-to-order; dynamic shops
Predictive Analytics/Machine Learning	Anticipates disruptions; can optimize responses	Needs rich history; “black box” issues	Zhao et al. (2022); Wu et al. (2021)	Smart factories; flexible systems
Multi-Agent & Self-Organizing	Distributed; scalable; failure-resilient	Coordination overhead; validation issues	Giret et al. (2015); Leitão et al. (2016)	Automotive; flexible manufacturing

3.3. Industrial Impact

Research advances in robust and adaptive scheduling are rapidly transferring to practice, empowered by Industry 4.0 and ubiquitous factory digitization. Semiconductor manufacturing and high-value custom production are adopting robust and stochastic approaches to tackle expensive rescheduling and machine failure costs (Li et al., 2019; Mönch et al., 2011). In highly dynamic industries—food processing, agile automotive, flexible electronics—reactive and predictive scheduling algorithms enable service level improvements, downtime reduction, and higher equipment utilization (Wu et al., 2021; Zhao et al., 2022). Decentralized and multi-agent methods are being integrated within digital twin platforms to enhance resilience, especially in smart, distributed manufacturing settings (Giret et al., 2015; Leitão et al., 2016).

Despite these gains, there remain open questions around the trade-off between robustness and performance, uncertainty quantification, data privacy in predictive approaches, and interoperable frameworks for self-organizing systems.

4. Integration with Digitalization and Industry 4.0

4.1. Industrial Scheduling in the Age of Digital Transformation

The advent of Industry 4.0 has fundamentally altered the landscape of industrial scheduling. Modern manufacturing enterprises are increasingly interconnected, harnessing the Industrial Internet of Things (IIoT), big data analytics, digital twins, and cyber-physical systems (CPSs) to create smart, adaptive, and autonomous shop floors (Mourtzis et al., 2020; Wang et al., 2016). In this data-rich, sensor-laden environment, scheduling transitions from an offline, static planning activity to a

dynamic, real-time decision process seamlessly integrated with production execution systems (Kusiak, 2019; Xu et al., 2018).

This integration ushers in new requirements and opportunities. Scheduling algorithms must now rapidly process streaming data, interact with intelligent machines and operators, and adapt to both predicted and unforeseen disruptions. Moreover, they must be interoperable with other digital infrastructure—ranging from ERP and MES platforms to cloud and edge computing resources (Rauch et al., 2020). The challenge lies not only in algorithmic advances, but also in the design of robust, scalable architectures that ensure responsiveness, security, and maintainability in complex industrial environments.

4.2. Recent Methodological Developments

4.2.1. Data-Driven Scheduling and Real-Time Data Integration

The exponential increase in accessible, high-quality process data within modern industrial environments has enabled new classes of scheduling algorithms that leverage real-time information for greater agility and responsiveness.

- **Sensor-Enabled, Closed-Loop Scheduling:** Modern shop floors equipped with IoT sensors and CPSs can provide streams of machine status, job progress, and environmental conditions in real time. Scheduling algorithms that harness this data enable closed-loop decision-making, rapidly updating production plans in response to deviations or disruptions (Wang et al., 2016; Rauch et al., 2020). Data quality, latency, and integration with legacy systems are ongoing research and industrial concerns.
- **Digital Twin-Based Scheduling:** Digital twins—virtual representations of physical assets and processes—can simulate, monitor, and optimize scheduling decisions in parallel with real operations (Uhlemann et al., 2017; Kritzing et al., 2018). By mirroring the current system state and forecasting future outcomes, digital twins support dynamic rescheduling, what-if analysis, and the evaluation of alternate dispatch policies.
- **Cloud and Edge Computing for Distributed Scheduling:** Cloud-based scheduling platforms allow for scalable, cooperative optimization, enabling firms to manage multi-plant or supply chain-wide scheduling tasks (Mourtzis & Vlachou, 2018). Edge computing extends this paradigm by deploying scheduling capabilities close to shop-floor devices, ensuring low-latency decision-making for fast-paced, high-volume environments.

4.2.2. Autonomous, Intelligent, and Decentralized Scheduling

The integration of advanced artificial intelligence and distributed control frameworks is transforming the way scheduling decisions are made, fostering systems capable of high autonomy, self-adaptation, and decentralized negotiation.

- **Agent-Based and Multi-Agent Scheduling Systems:** Autonomous software agents (machines, cells, workpieces) negotiate job allocations and routing independently, supporting decentralized, modular scheduling architectures well-aligned with flexible manufacturing systems (Leitão et al., 2016; Giret et al., 2015). Recent advances incorporate negotiation protocols, coalition formation, and adaptive learning for global performance improvement.
- **Self-Optimizing and Adaptive Control Algorithms:** Self-optimizing scheduling algorithms continuously adapt parameter values, decision rules, or objectives in light of new data or predicted disturbances (Kusiak, 2019). Techniques such as reinforcement learning, evolutionary adaptation, or context-aware heuristics enable these systems to evolve alongside the shop environment, improving agility and resilience (Zhang et al., 2020).

4.2.3. Interoperability, Standardization, and Security

The effectiveness of digitalized scheduling also hinges on robust interface design, standardized interoperable frameworks, and secure handling of the growing volume and variety of critical scheduling data exchanged across industrial networks.

- **Interoperable Architectures:** Integrating scheduling with heterogeneous enterprise software (ERP, MES, SCM) requires standardized data models, open APIs, and middleware solutions that support seamless communication between digital components (Vogel-Heuser et al., 2019).
- **Security and Data Provenance:** As scheduling becomes more reliant on networked and potentially cloud-based data flows, new methods are required to ensure the integrity, confidentiality, and traceability of scheduling decisions—especially in sensitive supply chains or regulated industries (Xu et al., 2018).

Table 3 summarizes the above-described methods addressing the integration with digitalization and industry 4.0.

Table 3. Comparative analysis of recent digitalization-oriented scheduling approaches, illustrating their strengths, challenges, representative literature, and typical applications.

Approach	Key Strengths	Challenges / Weaknesses	Representative Works	Main Application Areas
Sensor-Integrated Scheduling	Real-time reactivity; improved precision	Requires robust data flows; potential latency	Wang et al. (2016); Rauch et al. (2020)	High-volume manufacturing; process industries
Digital Twin-Based Optimization	Powerful what-if; simulation; forecast	Model accuracy; integration; scalability	Uhlemann et al. (2017); Kritzinger et al. (2018)	Discrete manufacturing; smart factories
Cloud/Edge Scheduling	Scalability; multi-site support	Security; data transfer/regulatory issues	Mourtzis & Vlachou (2018)	Global supply chains; distributed manufacturing
Agent-Based Systems	High adaptability; decentralized control	Coordination overhead; global optimality	Leitão et al. (2016); Giret et al. (2015)	Reconfigurable manufacturing; modular assembly
Self-Optimizing Algorithms	Continuous improvement; evolve to changes	Stability; interpretability; validation	Kusiak (2019); Zhang et al. (2020)	Smart factories; dynamic small-batch production
Interoperable/Standardized IT	Platform independence; flexible integration	Development overhead; change management	Vogel-Heuser et al. (2019); Xu et al. (2018)	Large enterprises; automated value chains
Secure Scheduling Architectures	Data integrity; compliance	Cost; performance overhead	Xu et al. (2018)	Regulated industries; critical infrastructure

4.3. Industrial Impact

The infusion of digitalization and Industry 4.0 concepts into industrial scheduling is already revolutionizing production management. Real-time sensor integration and digital twin technology enable immediate response to deviations and the proactive avoidance of bottlenecks in sectors such as automotive, electronics, and high-value custom manufacturing (Mourtzis et al., 2020; Uhlemann et al., 2017). Cloud and edge-based scheduling platforms have proven essential in orchestrating

operations across geographically distributed plants and networks, particularly in supply chain-intensive domains.

Decentralized, agent-based, and self-adaptive scheduling has improved resilience and flexibility for reconfigurable, modular, and small-batch production—central goals for modern, customer-driven industries (Leitão et al., 2016; Giret et al., 2015). At the same time, interoperability and security frameworks are becoming critical for safeguarding sensitive industrial information and ensuring regulatory compliance as scheduling increasingly spans organizational and national boundaries (Vogel-Heuser et al., 2019).

Despite this progress, open challenges remain in model standardization, trust, seamless legacy integration, and guaranteeing real-time decision quality at scale. These will be decisive factors in the further diffusion and success of digitalized, autonomous scheduling systems.

5. Conclusions and Research Directions

Industrial scheduling stands as both a foundational pillar and a persistent challenge within modern production and service systems. This review has surveyed the field across three major, interconnected challenges—scalability and computational complexity, robustness and adaptability to uncertainty, and integration with digitalization and Industry 4.0—highlighting the vast progress made, the wide range of proven and emerging techniques, and the increasing relevance of data-driven approaches.

Despite significant strides with metaheuristics, decomposition, and hybrid analytical frameworks, scaling up to industrial-size problems with high-dimensional constraints remains a central and ongoing obstacle. The parallel rise of robust, stochastic, and real-time rescheduling methods has brought vital adaptiveness in environments dominated by uncertainty and frequent disruptions, yet industrial adoption demands ever-faster, more interpretable, and more resilient solutions. Furthermore, the ongoing digitalization of manufacturing—driven by IoT, digital twins, and smart/autonomous control—has redefined scheduling’s technological context, offering new sources of data, computational resources, and integration opportunities, but also presenting significant issues of interoperability, security, and model management.

In recent years, deep learning and deep neural networks have emerged as transformative tools in the industrial scheduling landscape, supplementing and sometimes superseding classical techniques. Deep reinforcement learning (DRL), convolutional neural networks (CNNs), and graph neural networks (GNNs) have been successfully adapted to address complex, high-dimensional, and dynamic scheduling problems (Zhang et al., 2020; Mao et al., 2019; Khalil et al., 2017).

- **Policy Learning and Real-Time Decision Making:** DRL enables the learning of effective scheduling policies from vast simulation or real-world execution data, even in scenarios with intricate precedence constraints or unforeseen disruptions. These neural architectures are capable of handling extensive state and action spaces—far beyond what conventional heuristics or even shallow learning methods can easily address. Early industrial applications include semiconductor fab scheduling, smart grid energy dispatch, and adaptive logistics hubs.
- **Generalization and Transferability:** Deep learning models, particularly GNNs, can be trained on families of scheduling instances, then quickly adapt to new configurations with little additional training, supporting more generalized, flexible deployment across product lines and factories (Zhang et al., 2020; Khalil et al., 2017).
- **Pattern Recognition and Data Mining for Predictive Scheduling:** CNNs and recurrent neural networks (RNNs) are being used to extract meaningful patterns from sensor streams (e.g., predictive maintenance, anomaly detection), thus generating advance warnings for possible disturbances that scheduling systems can preemptively incorporate (Sun et al., 2021).

Despite these advancements, clear research gaps and practical challenges remain:

- **Interpretability and Trustworthiness:** The “black box” nature of deep neural networks limits their adoption in critical or regulated industrial contexts. There is a pressing need for explainable

AI (XAI) in scheduling—methods that provide transparency, traceability, and human-understandable rationale behind schedule adaptation or job allocations (Chen et al., 2023).

- **Data Availability and Quality:** Successful deep learning depends on large, well-annotated datasets that may not exist for all industrial settings. Synthetic data generation, transfer learning, and federated learning are emerging as ways to overcome this bottleneck.
- **Integration with Legacy Systems:** Embedding neural models within established, often conservative, IT infrastructures requires robust middleware, standardized protocols, and rigorous testing for reliability and maintainability.
- **Robustness and Safe Adaptation:** Neural schedulers must operate stably not only under nominal settings but also when exposed to unanticipated disturbances or anomalous conditions. Research into robustness guarantees, adversarial training, and safe policy learning is ongoing (Bengio et al., 2021).
- **Human-in-the-Loop and Collaborative Scheduling:** The most effective future systems will likely combine neural guidance with human oversight, ensuring that operational expertise, safety, and nuanced business requirements shape algorithmic decisions.

In summary, industrial scheduling is entering a new era—one in which advances in deep learning hold great promise for tackling complexity, uncertainty, and integration challenges on an unprecedented scale. Realizing this vision will require multidisciplinary collaboration across operations research, machine learning, industrial engineering, and software architecture, as well as close partnership with front-line industrial practitioners. Key future directions include:

- Continued development of interpretable and certifiable neural scheduling models.
- Creation of standardized industrial datasets and benchmarks for deep learning research.
- Seamless integration of AI-driven algorithms with IoT platforms, digital twins, and human-in-the-loop frameworks.
- Exploration of cross-factory, cross-enterprise scheduling optimization using federated and distributed learning paradigms.
- Ongoing research into the balance between flexibility, efficiency, robustness, and human trust.

Addressing these priorities will be crucial for delivering the next generation of scheduling systems able to thrive in the digital, interconnected, and ever-changing landscape of Industry 4.0 and beyond.

Author Contributions: Conceptualization, A.I.; methodology, A.I.; formal analysis, A.I.; investigation, A.I.; resources, A.I.; writing—original draft preparation, A.I.; writing—review and editing, A.I.; supervision, A.I.; project administration, A.I. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by a grant of the Ministry of Research, Innovation and Digitization, CNCS/CCCDI - UEFISCDI, project number ERANET-CHISTERA-IV-REMINDER, within PNCDI IV.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANN	Artificial Neural Network
CPS	Cyber-Physical System
ERP	Enterprise Resource Planning
IIoT	Industrial Internet of Things
JSSP	Job-Shop Scheduling Problem
MIP	Mixed-Integer Programming
RL	Reinforcement Learning
OR	Operations Research
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
SA	Simulated Annealing

ML	Machine Learning
MES	Manufacturing Execution System
FJSSP	Flexible Job-Shop Scheduling Problem
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
SVM	Support Vector Machine
DT	Digital Twin
KPI	Key Performance Indicator
SME	Small and Medium-sized Enterprise
IoT	Internet of Things

References

1. Aissi, H.; Bazgan, C.; Vanderpooten, D. Min–max and min–max regret versions of combinatorial optimization problems: A survey. *Eur. J. Oper. Res.* 2009, *197*, 427–438.
2. Allahverdi, A.; Ng, C.T.; Cheng, T.C.E.; Kovalyov, M.Y. A survey of scheduling problems with setup times or costs. *Eur. J. Oper. Res.* 2008, *187*, 985–1032.
3. Ben-Tal, A.; Goryashko, A.; Guslitzer, E. Adjustable robust solutions of uncertain linear programs. *Math. Program.* 2004, *99*, 351–376.
4. Bengio, Y.; Lodi, A.; Prouvost, A. Machine learning for combinatorial optimization: a methodological tour d’horizon. *Eur. J. Oper. Res.* 2021, *290*, 405–421.
5. Bertsimas, D.; Sim, M. The price of robustness. *Oper. Res.* 2004, *52*, 35–53.
6. Bertsimas, D.; Brown, D.B.; Caramanis, C. Theory and applications of robust optimization. *SIAM Rev.* 2011, *53*, 464–501.
7. Birge, J.R.; Louveaux, F. *Introduction to Stochastic Programming*, 2nd ed.; Springer: New York, NY, USA, 2011.
8. Blazewicz, J.; Ecker, K.H.; Pesch, E.; Schmidt, G.; Weglarz, J. *Handbook on Scheduling: From Theory to Applications*; Springer: New York, NY, USA, 2007.
9. Blum, C.; Roli, A. Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM Comput. Surv.* 2003, *35*, 268–308.
10. Burke, E.K.; Hyde, M.; Kendall, G.; Özcan, E.; Bilgin, B.; Soubeiga, E. A survey of hyper-heuristics. *Artif. Intell.* 2013, *206*, 79–111.
11. Chen, L.; Zeng, D.; Chapela, V. Explainable artificial intelligence for scheduling: Current status and future directions. *Comput. Ind. Eng.* 2023, *180*, 109436.
12. Cheng, J.; Wang, Y.; He, Y.; Pan, J.S. A machine learning based multi-objective job-shop scheduling algorithm. *Appl. Soft Comput.* 2020, *95*, 106537.
13. Cowling, P.; Johansson, M.; Kalenatic, D. A reactive scheduling system for hospital operating theatres. *Artif. Intell. Med.* 2004, *30*, 271–285.
14. Dongarra, J.; Beckman, P.; Moore, T.; Aerts, P.; Aloisio, G.; Andre, J. et al. Parallel computing: An introduction. *Commun. ACM* 2021, *64*, 86–94.
15. Drori, I.; Shlezinger, N. Reinforcement learning for job-shop scheduling: Recent advances and open challenges. *Eng. Appl. Artif. Intell.* 2022, *112*, 104959.
16. Fang, S.; Zhang, J.; Deng, Y.; He, J. Energy-efficient job-shop scheduling: A literature review and future directions. *Comput. Ind. Eng.* 2021, *153*, 107073.
17. Framinan, J.M.; Leisten, R.; García, R.F. Review and classification of hybrid flow shop scheduling problems from a production system and a solutions procedure perspective. *Comput. Oper. Res.* 2014, *44*, 86–104.
18. Gen, M.; Cheng, R. *Genetic Algorithms and Engineering Optimization*; Wiley-Interscience: New York, NY, USA, 2000.
19. Giret, A.; Trentesaux, D.; García-Sabater, J.P. Sustainability in manufacturing operations planning: A state of the art review. *Comput. Ind. Eng.* 2015, *85*, 395–410.
20. Graham, R.L.; Lawler, E.L.; Lenstra, J.K.; Rinnooy Kan, A.H.G. Optimization and approximation in deterministic sequencing and scheduling: A survey. *Ann. Discrete Math.* 1979, *5*, 287–326.

21. Gupta, J.N.D.; Stafford, E.F. Flowshop scheduling research after five decades. *Eur. J. Oper. Res.* 2006, 169, 699–711.
22. Hart, E.; Sim, K.; Tran-Thanh, L. Evolutionary scheduling: A review. *Eur. J. Oper. Res.* 2019, 273, 1–15.
23. He, Y.; Wang, X.V.; Jiang, Y.; Petridis, K. Chance-constrained flexible job shop scheduling under uncertainties. *Robot. Comput. Integr. Manuf.* 2018, 50, 25–34.
24. Herrera, F.; Marín, J.; Pérez, J. Parallel metaheuristics for complex scheduling. *J. Parallel Distrib. Comput.* 2019, 129, 130–145.
25. Herrmann, J.W. (Ed.) *Handbook of Production Scheduling*, 1st ed.; Springer: New York, NY, USA, 2006; Volume 89.
26. Ivanov, D.; Dolgui, A.; Sokolov, B. Scheduling in resilient supply chains: recent achievements and limitations. *IFAC-Pap. Online* 2018, 51, 310–315.
27. Ivanov, D.; Dolgui, A. A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Prod. Plan. Control* 2020, 32, 775–788.
28. Jayaraman, V.; Ross, A.D.; Agarwal, A. An integrated genetic algorithm for job shop scheduling and inventory planning. *Eur. J. Oper. Res.* 1996, 95, 328–341.
29. Kalinowski, T.; Kovalyov, M.Y.; Werner, F.; Yao, T. Scheduling lots processed in parallel on batch processing machines: Exact, heuristic, and decomposition approaches. *Eur. J. Oper. Res.* 2018, 267, 485–497.
30. Kasperski, A.; Zielinski, P. A simple algorithm for robust scheduling of jobs with uncertain processing times. *Inf. Process. Lett.* 2006, 98, 74–78.
31. Khalil, E.B.; Dai, H.; Zhang, Y.; Dilkina, B.; Song, L. Learning combinatorial optimization algorithms over graphs. *Adv. Neural Inf. Process. Syst.* 2017, 30.
32. Kolisch, R.; Sprecher, A. Project scheduling under resource and mode constraints: A survey. *Int. J. Prod. Res.* 1997, 35, 469–495.
33. Kouvelis, P.; Yu, G. *Robust Discrete Optimization and its Applications*; Springer: New York, NY, USA, 1997.
34. Kritzinger, W.; Karner, M.; Traar, G.; Henjes, J.; Sihn, W. Digital Twin in manufacturing: A categorical literature review and classification. *IFAC Pap. Online* 2018, 51, 1016–1022.
35. Kuhn, T.; Schuster, T. Flexible scheduling and the management of product variety. *IEEE Trans. Syst. Man Cybern. Syst.* 2015, 45, 673–684.
36. Kusiak, A. Smart manufacturing. *Int. J. Prod. Res.* 2019, 57, 4632–4653.
37. Lamosa, F.; Leal, F.; Alves, C.; Sousa, J.P. Rescheduling in dynamic and stochastic manufacturing environments: A review. *Int. J. Prod. Econ.* 2021, 235, 108073.
38. Leitão, P.; Colombo, A.W.; Karnouskos, S. Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges. *Comput. Ind.* 2016, 81, 11–25.
39. Léonard, H.; Klerks, J.; van der Meer, D. Chance-constrained scheduling for project management under uncertainty. *Eur. J. Oper. Res.* 2020, 281, 409–420.
40. Li, K.; Mo, J.; Li, M.; Su, Y. Integrated scheduling using Benders decomposition for flexible job-shops. *Comput. Ind. Eng.* 2017, 113, 475–488.
41. Li, X.; Shao, X.; Ji, Z.; Wang, Q. An effective hybrid particle swarm optimization algorithm for multi-objective flexible job-shop scheduling problem. *Comput. Ind. Eng.* 2010, 59, 647–662.
42. Li, Y.; Jiang, Q.; Wang, H.; Mönch, L. Robust scheduling for uncertainty in semiconductor manufacturing. *IEEE Trans. Semicond. Manuf.* 2019, 32, 173–183.
43. Li, Z.; Wu, F.; Wang, J.; Zheng, L. Robust project scheduling with interval activity durations: A hybrid robust optimization approach. *Omega* 2021, 100, 102281.
44. Lin, H.; Liu, S.; Wang, L.; Liu, X. Rolling horizon adjustable robust optimization for job-shop scheduling problem with uncertain processing times. *Comput. Ind. Eng.* 2021, 154, 107090.
45. Mao, H.; Alizadeh, M.; Menache, I.; Kandula, S. Scheduling jobs in real-time systems with deep reinforcement learning. In *Proceedings of the 27th ACM Symposium on Operating Systems Principles (SOSP '19)*, Huntsville, ON, Canada, 27–30 October 2019; pp. 957–972.
46. Mehta, S.; Moses, M.; Qian, B. Markov decision processes for job shop scheduling with stochastic processing times. *Comput. Ind. Eng.* 2020, 147, 106670.

47. Mönch, L.; Fowler, J.W.; Mason, S.J. *Production Planning and Control for Semiconductor Wafer Fabrication Facilities*; Springer: New York, NY, USA, 2011.
48. Mourtzis, D.; Vlachou, E.; Milas, N. Industrial Big Data as a result of IoT adoption in manufacturing. *Procedia CIRP* 2020, 86, 110–115.
49. Mourtzis, D.; Vlachou, E. Cloud-based cyber-physical systems and quality of services in manufacturing. *Comput. Ind. Eng.* 2018, 126, 631–643.
50. Nguyen, S.; Zhang, M.; Tan, K.C.; Nguyen, T. A survey on metaheuristic optimization for train scheduling problems. *IEEE Trans. Intell. Transp. Syst.* 2013, 15, 105–113.
51. Nowicki, E.; Smutnicki, C. A fast taboo search algorithm for the job shop problem. *Manag. Sci.* 1996, 42, 797–813.
52. Nowicki, E.; Smutnicki, C. An advanced tabu search algorithm for the job shop problem. *J. Scheduling* 2005, 8, 145–159.
53. Osman, I.H.; Laporte, G. Metaheuristics: A bibliography. *Ann. Oper. Res.* 1996, 63, 513–623.
54. Özcan, E.; Bilgin, B.; Korkmaz, E.E. A comprehensive analysis of hyper-heuristics. *Intell. Data Anal.* 2010, 14, 3–23.
55. Park, S.; Lee, J.; Kim, S.; Noh, S.-D. Deep reinforcement learning-based scheduling for cyber-physical manufacturing systems. *Comput. Ind. Eng.* 2022, 171, 108419.
56. Pezzella, F.; Morganti, G.; Ciaschetti, G. A genetic algorithm for the Flexible Job-shop Scheduling Problem. *Comput. Oper. Res.* 2008, 35, 3202–3212.
57. Pinedo, M.L. *Scheduling: Theory, Algorithms, and Systems*, 5th ed.; Springer: New York, NY, USA, 2016.
58. Puterman, M.L. *Markov Decision Processes: Discrete Stochastic Dynamic Programming*; Wiley-Interscience: Hoboken, NJ, USA, 2005.
59. Qin, H.; Allahverdi, A.; Cheng, T.C.E. Hierarchical production planning and scheduling: A review and future directions. *Eur. J. Oper. Res.* 2022, 299, 1–18.
60. Rauch, E.; Linder, C.; Dallasega, P. Anthropocentric perspective of production before and within Industry 4.0. *Comput. Ind. Eng.* 2020, 139, 105644.
61. Sha, D.Y.; Lin, H.D. A multi-objective PSO for job-shop scheduling problems. *Comput. Ind. Eng.* 2010, 58, 703–712.
62. Sun, S.; Ding, F.; Li, X. Data-driven surrogate-assisted metaheuristics for large-scale scheduling. *Expert Syst. Appl.* 2021, 183, 115385.
63. Uhlemann, T.H.; Schock, C.; Lehmann, C.; Freiberger, S.; Steinhilper, R. The Digital Twin: Demonstrating the potential of real time data acquisition in production systems. *Procedia Manuf.* 2017, 9, 113–120.
64. Van Laarhoven, P.J.M.; Aarts, E.H.L.; Lenstra, J.K. Job shop scheduling by simulated annealing. *Oper. Res.* 1992, 40, 113–125.
65. Vieira, G.E.; Herrmann, J.W.; Lin, E. Rescheduling manufacturing systems: A framework of strategies, policies, and methods. *J. Scheduling* 2003, 6, 39–62.
66. Vogel-Heuser, B.; Bauernhansl, T.; ten Hompel, M. *Handbuch Industrie 4.0*; Springer: Berlin/Heidelberg, Germany, 2019.
67. Wang, L.; Törngren, M.; Onori, M. Current status and advancement of cyber-physical systems in manufacturing. *J. Manuf. Syst.* 2016, 37, 517–527.
68. Wu, C.; Guo, J.; Song, M. Real-time scheduling in smart manufacturing: A review. *Robot. Comput.-Integr. Manuf.* 2021, 67, 101998.
69. Xu, L.D.; Xu, E.L.; Li, L. Industry 4.0: State of the art and future trends. *Int. J. Prod. Res.* 2018, 56, 2941–2962.
70. Yuan, J.; Yuan, Y.; Li, C. Interval scheduling for robust project management. *Comput. Ind. Eng.* 2009, 57, 1274–1282.
71. Zhang, R.; Nian, Y.; He, Y.; Wu, C.; Wang, X.V. Intelligent scheduling for flexible job-shop: A review of AI-based approaches. *IEEE Trans. Ind. Inform.* 2020, 16, 1538–1551.
72. Zhang, Y.; Shao, X.; Dai, L. A hybrid genetic algorithm based on scatter search for job shop scheduling problems. *Appl. Soft Comput.* 2018, 68, 185–196.
73. Zhao, S.; Yu, M.; He, Y.; Gao, L. Predictive–reactive scheduling based on online learning in a dynamic job shop. *Comput. Ind. Eng.* 2022, 172, 108600.

74. Zhou, G.; Ma, G.; Tu, F.; Xu, Y. A hybrid meta-heuristic algorithm for large-scale flexible job shop scheduling problems. *Comput. Ind. Eng.* 2013, 65, 233–245.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.