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To cite this article: Marzieh Khakifirooz, Michel Fathi, Alexandre Dolgui & Panos M. Pardalos (2024) Scheduling in Industrial environment toward future: insights from Jean-Marie Proth, International Journal of Production Research, 62:1-2, 291-317, DOI: 10.1080/00207543.2023.2245919

To link to this article: https://doi.org/10.1080/00207543.2023.2245919

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INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH
2024, VOL. 62, NOS. 1–2, 291–317
https://doi.org/10.1080/00207543.2023.2245919

Scheduling in Industrial environment toward future: insights from Jean-Marie Proth

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ABSTRACT

According to [Dolgui, Alexandre, and Jean Marie Proth. 2010. *Supply Chain Engineering: Useful Methods and Techniques*. Vol. 539. Springer.], advancing tactical levels in production systems has led to the disappearance of static scheduling in favour of dynamic scheduling. Additionally, the evolving challenges in the supply chain paradigm have significantly impacted the organisation of production systems. This shift has moved scheduling issues from the tactical to the strategic level, resulting in linear organisations encompassing scheduling decisions. [Proth, Jean Marie. 2007. "Scheduling: New Trends in Industrial Environment." *Annual Reviews in Control* 31 (1): 157–166. https://doi.org/10.1016/j.arcontrol.2007.03.005.] emphasised that real-time scheduling in production systems has become a pivotal area of research. He presented several open problems for researchers to address in this context, including (1) the development of real-time algorithms capable of handling multiple operations on the same product and unrelated resources, (2) adapting previous schedules with certain modifications, (3) addressing unforeseen actions that arise randomly in real-time planning, and (4) exploring cyclic scheduling problems with size limits as alternative solutions to heuristic approaches. This paper reviews the evolving trends in light of J.M. Proth's predictions and advice within the aforementioned domains.

ARTICLE HISTORY
Received 19 December 2022
Accepted 29 July 2023

KEYWORDS
Industry 4.0; dynamic scheduling; real-time assignment; supply chain scheduling; proactive-reactive scheduling; cyclic scheduling

1. Introduction

J.M. Proth's primary research areas encompassed mathematical optimisation, operations research, scheduling, and order management. His work in mathematical optimisation was predominantly focused on themes such as production control (Boulet et al. 1991; Nagi and Proth 1994) and job-shop scheduling (Dolgui and Proth 2010; Hillion and Proth 1989a). Scheduling, particularly concerning due dates (V. S. Gordon, Proth, and Chu 2002a, 2002b) and, in certain cases, tardiness and deadline-monotonic scheduling (Chu, Portmann, and Proth 1992; Duron, Louly, and Proth 2009), constituted a primary area of concentration for J.M. Proth. In the realm of operations research, he provided insights into the iterative method, group technology (Chauhan et al. 2006), manufacturing cell engineering (Chen, Chu, and Proth 1997; Hilger, Harhalakis, and Proth 1991), and supply chain engineering (Proth 2007). Job shop scheduling (Chen, Chu, and Proth 1998), dynamic priority scheduling, and flow shop scheduling (including fair-share scheduling, rate-monotonic scheduling, dynamic priority scheduling, and fixed-priority preemptive scheduling) received significant attention in his scheduling research (C. Wang, Chu, and Proth 1996, 1997; Chauvet, Herrmann, and Proth 2003). Furthermore, his research on order management challenges encompassed elements of microeconomics, outsourcing, and selection (Dolgui and Proth 2013). J.M. Proth's investigations in scheduling drew upon concepts from real-time computing (Chauvet et al. 2000), distributed computing, trace scheduling, industrial engineering, and systems theory (Hillion and Proth 1989b). Moreover, his exploration of job shop scheduling entailed computational complexity theory and heuristic concepts (Chu, Proth, and Sethi 1995; Harhalakis, Nagi, and Proth 1990). Petri net research by J.M. Proth encompassed bottlenecks, software engineering, and job shop planning, all of which featured interdisciplinary characteristics and relied on supply chain and manufacturing engineering (Hillion and Proth 1989c; Proth and Sauer 1998; Proth, Sauer, and Xie 1997; Proth, Wang, and Xie 1997). His studies on real-time computing principles intertwined with traffic flow (Awasthi, Parent, and Proth 2006), network analysis (Herrmann et al. 1996), dynamic network analysis (Herrmann et al. 1995), and flow network challenges (Awasthi et al. 2010). In his latest

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research on scheduling, J.M. Proth explored pooling, fleet management, cybernetics, and polynomial algorithms (Awasthi et al. 2011).

J.M. Proth's collaborations with Minsk's team led by V.S. Tanaev have been instrumental in scheduling research. These collaborations began with two INTAS projects, where Dr. Proth was the scientific coordinator. The first project, INTAS-96-0820, focused on discrete optimisation problems in scheduling and computer-aided design from 1997 to 2000. The second project, INTAS-00-0217, dealt with scheduling and assignment models under uncertainty and real-time constraints in various domains, such as manufacturing, communication, computer-aided design, and transportation, spanning from 2001 to 2004.

The contributions of these collaborations have resulted in significant research outcomes. Several notable papers emerged from these projects, shedding light on various aspects of scheduling and due date assignment. For instance, V. S. Gordon, Proth, and Chu (2002a) explored due date assignment and scheduling models, while V. S. Gordon, Proth, and Chu (2002b) conducted a comprehensive survey of the state-of-the-art research in common due date assignment and scheduling. Other publications delved into topics such as single-machine scheduling, lot-sizing and scheduling on parallel machines, and scheduling with precedence constraints.

Moreover, the collaborative projects extended beyond scheduling problems and encompassed related areas such as assembly line balancing, combinatorial design of machining lines, and power transmissions. Notable papers emerged from these endeavours as well, addressing the optimisation of multi-position machines and transfer lines (Dolgui et al. 2008), stability analysis of optimal balance for assembly lines (Y. N. Sotskov, Dolgui, and Portmann 2006), combinatorial design of minimum-cost transfer lines (Delorme, Dolgui, and Kovalyov 2012), and optimal design of machines processing pipeline parts (Battaïa et al. 2012).

To disseminate the research outcomes, special issues were edited to present the results of these collaborative projects. Three special issues were published, covering discrete optimisation methods in scheduling and computer-aided design (Dolgui, Gordon, and Proth 2002, 2003), and discrete optimisation methods in production and logistics (Dolgui et al. 2006).

These works of J.M. Proth and his collaboration with Minsk's team contribute to the broader field of scheduling research by exploring topics such as scheduling with positionally dependent processing times (V. S. Gordon and Strusevich 2009), unit-time job-shop scheduling (Y. Sotskov, Dolgui, and Werner 2001), multi-product lot sizing and scheduling (Dolgui et al. 2010), scheduling with due date assignment under special conditions (V. Gordon, Strusevich, and Dolgui 2012), understanding dependencies between jobs and the impact of job positions on processing times (Dolgui, Gordon, and Strusevich 2012), multi-level decomposition for efficiency and reliability of power transmission systems (Dolgui, Guschinsky, and Levin 2007), and a collection of research on line balancing problems (Battaïa and Dolgui 2013, 2022).

Given that we currently reside in the era of Industry 4.0, these ideas hold potential value for individuals seeking to leverage this foundational knowledge and gain insights into the intertwined scheduling and supply chain management domains. This study aims to disentangle the theories and research findings of J.M. Proth (referred to as the 'past industrial environment' in this context) from the recent trends influenced by the development of Industry 4.0 (referred to as the 'new industrial environment' in this context) and explore how is the impact of the past on the present landscape and identifies the principal trends.

1.1. *Past Industrial environment*

Real-time scheduling, a prominent topic in the scheduling literature, involves allocating jobs to system resources according to their emergence based on system needs. J.M. Proth worked when industries were transitioning into mass production with increased diversification, and the widespread adoption of supply chain concepts led to the emergence of real-time assignments (Duron, Louly, and Proth 2009). Proth (2006) and Dolgui and Proth (2010) identified two types of real-time assignments based on the nature of the problem. The first type, online assignment with an idle period (OAIP), involves assigning jobs to resources without modifying the existing schedule. The second type, online assignment with partial rescheduling (OAPR), allows limited adjustments to the current schedule. However, Proth (2007) did not recommend OAPR as a suitable solution for manufacturing, as he believed revisiting previous scheduling decisions could harm a company's reputation and competitiveness.

During J.M. Proth's industrial age, the variety of products involved in a project was constrained by the number of operation types (Duron, Proth, and Wardi 2005). The transition from job shops to assembly lines increased productivity and adaptability, prompting the need for real-time reassignment of activities in scheduling. Dynamic scheduling became valuable for mass production systems dealing with diverse products (Chauhan, Gordon, and Proth 2007). It is important to note that dynamic scheduling differs from real-time scheduling. Traditional production design relies on dynamic scheduling, aiming to establish a predetermined schedule at the start of the

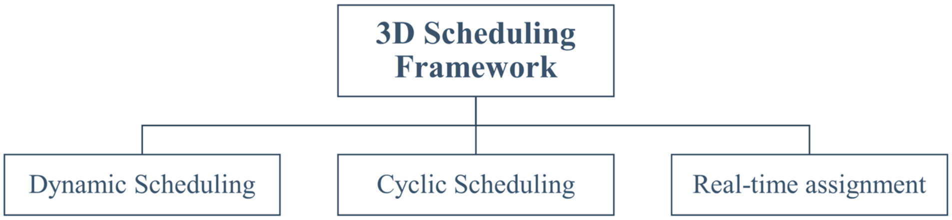


Figure 1. Three main scheduling challenges of the industrial environment from J.M. Proth point of view (Proth 2007).

management period and make adjustments in response to disruptions. Dolgui and Proth (2010) explains that dynamic scheduling is employed to modify the current schedule or reschedule remaining activities in unforeseen circumstances.

Furthermore, Proth (2007) emphasised the importance of flexible scheduling due to the integration of operations spanning from client requests to payment and the need to adapt to demand fluctuations. Disruptions and unexpected events were categorised by Dolgui and Proth (2010) as resource-related or operation-related. Resource-related disruptions include machine breakdowns, tool failures, unavailability of tools or personnel, lack of raw materials or components, and defective or insufficient materials or components. Operation-related events encompass changes in deadlines, order cancellations, delayed order arrivals, and alterations in production processes due to resource changes. Govil and Proth (2002) suggested that competitive market pressures, facilitated by advanced data processing, communication technologies, and international trade agreements, led to modifications in the organisation of production systems. This involved integrating operations from client requests to cash and adapting to demand variations.

In this paper, we sought to incorporate the esteemed perspective of J.M. Proth regarding the future of scheduling in industrial settings. To this end, we referenced his seminal paper, 'Scheduling: New trends in Industrial Environment' (Proth 2007), which highlighted dynamic scheduling, real-time assignment, and cyclic scheduling as the main challenges in the new industrial environment and provided valuable insights into the allocation of jobs to system resources based on emerging needs. In this paper, we referred to Proth's overview of the '3D scheduling framework' as a guideline for comparing the past, present, and future scheduling trends in industrial settings (see Figure 1). We also considered his notable book, 'Supply Chain Engineering: Useful Methods and Techniques', (Dolgui and Proth 2010) as a significant contribution to our understanding of his latest collection of thoughts and opinions in intersecting scheduling practices in a real-world environment. Therefore, this paper examines how scheduling solutions have evolved since J.M. Proth's works and explores the impact of new industrial developments, specifically the pillars of Industry 4.0, on scheduling management.

1.2. New Industrial environment

Industry 4.0 has ushered in a new era of digitalised production, characterised by interconnected technologies and the concept of the 'smart factory'. These advancements enable the seamless data flow for process analysis and control throughout the manufacturing process, providing increased flexibility and reactivity. In this context, the scheduling system is critical in connecting the physical and digital worlds (Ivanov et al. 2016).

Recent trends in scheduling literature have recognised the need to adapt scheduling theory to the requirements of Industry 4.0. Researchers such as D. A. Rossit, Tohmé, and Frutos (2019) and D. Rossit and Tohmé (2018) have explored the impact of this new manufacturing paradigm on scheduling theory. Additionally, J. Zhang et al. (2019) conducted an extensive survey on job shop scheduling research and its perspectives within the context of Industry 4.0. Several reviews, including Valledor et al. (2018), have classified scheduling methodologies using terms such as strategy, policy, and method.

In the context of Industry 4.0, Ghaleb, Zolfagharinia, and Taghipour (2020) identified the challenges of 'real-time scheduling and shop-floor disruptions' as emerging trends. However, the implementation of real-time scheduling in the advanced industrial environment differs from previous approaches (Dolgui and Proth 2010). The rescheduling process is defined by completely reactive, predictive-reactive, and proactive-reactive scheduling strategies. While previous literature focused on completely reactive and predictive-reactive approaches, recent years have witnessed the widespread adoption of predictive and proactive-reactive scheduling due to advancements in data analytics (Chargui et al. 2022; Peng, Lin, and Li 2023).

The scheduling policy determines when and how to trigger rescheduling and update the current schedule. Rescheduling methods vary and include continuous and periodic rescheduling (Angel-Bello, Vallikavungal, and

Alvarez 2021), event-driven rescheduling (He, Dong, and Zhao 2020), and hybrid rescheduling (A. Liu, Fowler, and Pfund 2016; Ghaleb, Taghipour, and Zolfagharinia 2021). While many of these policies have been explored in previous industrial environments, the new disruptive events and the emphasis on sustainable scheduling management (Akbar and Irohara 2018; L. Liu 2019) sets the current smart industrial environment apart.

Considering the differences between current and past trends in scheduling management, this paper aims to address two research questions based on the guidelines suggested by Proth (2007):

(1) Firstly, it explores how scheduling methodologies have evolved from the tactical to the strategic level through the increased implementation of cyclic scheduling, real-time assignment, and dynamic scheduling.
(2) Secondly, it investigates how scheduling solutions have been modified in response to the spread of the supply chain paradigm facilitated by advancements in data processing, communication systems, and international trade agreements.

The structure of this paper follows the priority set by Dolgui and Proth (2010) on dynamic scheduling, real-time assignment, and cyclic scheduling. Each section begins with a review of the latest works by J.M. Proth in the respective category. Subsequently, the scope expands to encompass advanced trends in each field, focusing on strategic scheduling and the supply chain-scheduling trade-off. Finally, the study concludes with recommendations for research and practice that consider the characteristics of the future industrial environment.

2. Dynamic scheduling

Dynamic scheduling systems play a crucial role in optimising production output by considering various factors such as machine workload, set-up times, available resources, incoming orders, and priorities. These systems can be categorised into two types: reactive and proactive scheduling.

Reactive scheduling involves performing work in response to immediate production requirements. As new work arrives, the shop floor dynamically adjusts to accommodate its completion. On the other hand, proactive scheduling, such as dynamic scheduling, takes a proactive approach by adjusting the schedule to optimise output. A dynamic scheduling system aims to adapt production processes to address resource-related challenges (e.g. machine breakdowns, tool failures, quality control issues) and job-related issues (e.g. rush jobs, cancellations) while maximising the utilisation of shop floor resources.

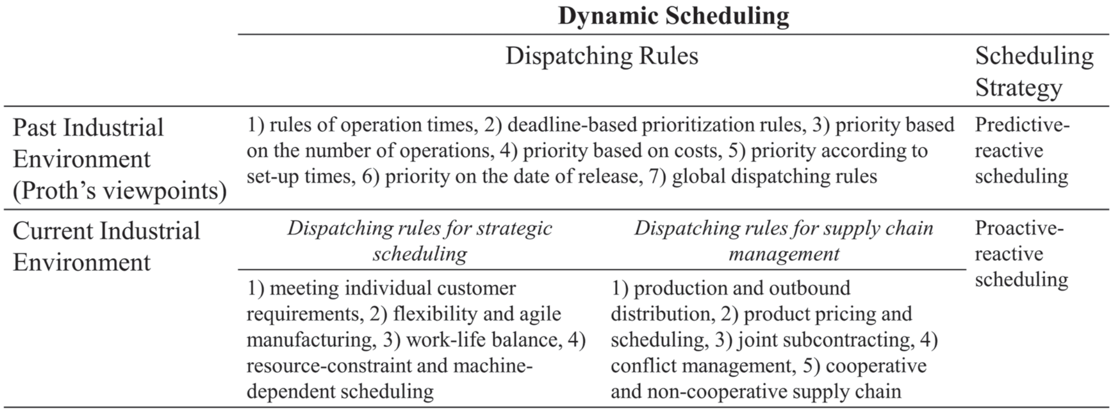
In the past industrial era, two commonly used methods have been identified in dynamic scheduling. The first method is based on dispatching rules, which provide guidelines for assigning jobs to resources based on certain criteria or heuristics. These rules help determine the order in which jobs should be processed to optimise overall performance. The second method is predictive-reactive scheduling, which combines predictive modeling with reactive adjustments. By utilising predictive models, the system can anticipate potential disruptions or changes and proactively adjust the schedule to mitigate their impact on production.

J.M. Proth explored these two methods in detail and highlighted their significance in dynamic scheduling. He emphasised the importance of effectively managing resources and addressing job-related challenges to achieve optimal shop floor performance. By incorporating dispatching rules and predictive-reactive scheduling, dynamic scheduling systems can effectively respond to changing conditions and optimise production output.

Dynamic scheduling systems consider machine workload and set-up times, resources, incoming orders, and priorities to arrange work for optimum output. The scheduling methods could be divided into two types: (1) reactive, with work performed in reaction to production requirements, in which as work arrives, the shop floor adapts to accommodate its completion; and (2) proactive, like dynamic scheduling, which adjusts the timetable to enhance output. A dynamic scheduling system should adapt production to reduce resource (machine breakdowns, tool failures, quality control difficulties) or job-related (rush jobs, cancellations) problems and maximise shop floor resource utilisation. Dolgui and Proth (2010) identified the two most usual methods for producing dynamic scheduling: dispatching rules and predictive-reactive scheduling (see Figure 2 for comparing the past and current scheduling trends in dynamic scheduling).

2.1. Dispatching rules

Dispatching rules, also known as priority rules, are employed when a decision needs to be made regarding which operation should be assigned to an available resource when conflicts arise. Unlike schedules that are prepared in advance, dispatching rules are implemented dynamically. In J.M Proth's works, a range of priority rules is presented, including (1) rules of operation times (such as shortest processing time, shortest operation time with set-up, and minimum remaining operation times), (2) deadline-based prioritisation rules, (3) priority based on the number of operations (such as most



	Dynamic Scheduling		
	Dispatching Rules		Scheduling Strategy
Past Industrial Environment (Proth's viewpoints)	1) rules of operation times, 2) deadline-based prioritization rules, 3) priority based on the number of operations, 4) priority based on costs, 5) priority according to set-up times, 6) priority on the date of release, 7) global dispatching rules		Predictive-reactive scheduling
Current Industrial Environment	*Dispatching rules for strategic scheduling*	*Dispatching rules for supply chain management*	Proactive-reactive scheduling
	1) meeting individual customer requirements, 2) flexibility and agile manufacturing, 3) work-life balance, 4) resource-constraint and machine-dependent scheduling	1) production and outbound distribution, 2) product pricing and scheduling, 3) joint subcontracting, 4) conflict management, 5) cooperative and non-cooperative supply chain	

Figure 2. Comparison of past (J.M. Proth's era) and current dynamic scheduling trends in industrial environment.

and fewest remaining operations), (4) priority based on costs, (5) priority according to set-up times (Chu, Proth, and Wang 1998), (6) priority dependent on the date of release (such as first in-first out, arrival time, and last in-first out) (V. S. Gordon, Proth, and Chu 2002b), and (7) priority based on the evaluation of the near future also known as global dispatching rules (including shortest queue, lowest load, the mixture of FIFO and operation time, and largest cost over time) (Herrmann et al. 1995).

In the new era of the industrial environment, dispatching rules play a crucial role in strategic planning and supply chain management. These rules provide a classification framework that enables efficient decision-making in scheduling tasks.

2.1.1. Dispatching rules under strategic scheduling

Strategic scheduling involves understanding the desired objectives and effectively utilising resources. In practical terms, if the budget represents the strategic plan, the schedule becomes the detailed plan that includes specific dates, times, and locations. This strategic scheduling approach integrates the tactical, operational, and strategic levels of planning. As a result, the following strategic rules are implemented in scheduling management influenced by Industry 4.0 initiatives:

(1) *Meeting individual customer requirements* (Fattahi, Dasu, and Ahmadi 2022; Yao and Liu 2009): In the context of Industry 4.0, customer-specific unique criteria can be incorporated throughout the product lifecycle, encompassing design, configuration, ordering, planning, manufacturing, and operation. Furthermore, the ability to accommodate last-minute modifications is a distinguishing feature of Industry 4.0. With the advancements in manufacturing capabilities, it is now feasible to produce customised items even in extremely small production numbers (batch size of 1) while still ensuring profitability (H. Zhou et al. 2018). Considering these modifications within the manufacturing process, certain priority rules, although not novel, have gained prominence in contemporary industrial development. These include:
   Rule 1: Prioritizing products with the greatest availability of resources.
   Rule 2: Assigning priority to products with the most interconnected critical tasks.
   Rule 3: Giving priority to products that require more warehouse space for their resources.

(2) *Flexibility and agile manufacturing*: Ad-hoc networking enables dynamic adjustments in various aspects of corporate operations, including quality, time, risk, resilience, price, and environmental friendliness. This capability fosters continuous supply chain optimisation and supports agile manufacturing practices. Several technologies, such as lean manufacturing, decentralised manufacturing, and cloud manufacturing, significantly influence dispatching rules. Within these manufacturing environments, the following priority rules have been defined:
   Rule 4: Open-loop dispatch control (Grassi et al. 2021) selects work for production without considering feedback from the production system. It relies on known system features and predetermined criteria to make these decisions.
   Rule 5: Closed-loop dispatch control (Grassi et al. 2021) selects work to be admitted to production based on the real-time status of the monitored production system.
   Rule 6: Online data-driven dispatching rules (W. Chen et al. 2013) learn dispatching rules from historical data and generate real-time dispatch solutions.

(3) *Work-Life Balance*: One of the crucial objectives for companies is to address the increasing need of employees to achieve a better balance between their work and personal lives, as well as between personal development and continuing professional development, which is commonly referred to as 'social sustainability' in the workplace (Akbar and Irohara 2018). Consequently, recent scheduling problems considering social sustainability, encompassing aspects such as quality of life, income stability, work environment, and the comprehensive impact of occupational risks (Coca et al. 2019), have incorporated new priority rules. These rules are applied to a domain that is typically associated with staff rostering problems (An et al. 2021; Frihat, Hadj-Alouane, and Sadfi 2022).

(4) *Different dispatching rules for each machine*: In practical scenarios, effective yet straightforward and intuitive rules-of-thumb are frequently utilised to develop rule-based priority approaches, relying on problem-specific knowledge to provide viable solutions within a relatively short timeframe. However, constructing effective priority rules is a complex undertaking. Even with extensive expertise and knowledge, professionals and researchers may explore numerous alternatives. Consequently, a key challenge is designing rules that generalise well when applied to unforeseen circumstances (Oukil and El-Bouri 2021). Moreover, understanding why specific rules perform successfully (or not) in different contexts does not necessarily facilitate straightforward decision-making regarding rule adoption for particular circumstances. In this regard, several studies have investigated the performance evaluation of priority rules for various scheduling problems and disruptive events. These include resource-constraint scheduling problems (Dumić and Jakobović 2021; Luo et al. 2022), dynamic unrelated machine scheduling problems (Durasević and Jakobović 2018), stochastic resource-constrained multi-project scheduling problems with new project arrivals (H. Chen et al. 2019), and dynamic multi-objective flexible job shop scheduling problems (Ozturk, Bahadir, and Teymourifar 2019).

2.1.2. Dispatching rules in supply chain scheduling

Supply chain scheduling integrates supply chain management and scheduling (Z.-L. Chen and Hall 2022). It addresses complex scheduling challenges within supply chains, driven by various real-world applications, such as:

(1) Coordinated decision-making in centralised supply chains, involving integrated production and distribution scheduling, joint scheduling, product pricing, and coordinated subcontracting and scheduling (Dawande et al. 2006).

(2) Coordination and competitiveness issues in decentralised supply networks, including cooperation and conflict among multiple partners' scheduling decisions in supply chains and cooperative and non-cooperative supply chain scheduling games (Z.-L. Chen and Hall 2007).

To define decision-making in supply chain scheduling, we can distinguish between (i) a single centralised agent who evaluates trade-offs between different operational decisions and their associated profits or costs within a supply chain and (ii) two or more decentralised agents whose self-interested decisions collectively impact the overall quality of supply chain solutions. In both cases, the fundamental question is:

How can the numerous operational tasks and decisions within the supply chain be coordinated to enhance overall performance?

Consequently, we propose the following categories to delineate the dispatching rules on the interactions and specifications of activities in the supply chain network. It is important to note that given the broad range of problems in each category, several hybrid or standard priority rules can be implemented for each problem. Here, we provide a brief indication of the nature of the problem in each category as a starting point for further discussion on potential dispatching rules.

Category 1: Integrated production and outbound distribution scheduling for offline and online problems, which addresses the integration of manufacturing and outbound distribution scheduling for made-to-order (MTO) or time-sensitive goods. This category encompasses the following key problems that influence the selection of dispatching rules:

- *Individual and immediate delivery* (Sawik 2016): In small-scale production, this scenario in supply chain distribution may involve a scheduling problem with a single machine. Challenges may arise due to limited or insufficient available vehicles in the delivery schedule. In larger-scale production, there could be a single specific customer while the production is planned with multiple machines.
- *Batch delivery to single/multiple customers* (K. Li, He, and Ram Kumar 2022): For batch delivery (not necessarily batch production), the production schedule needs to manage either a single machine or

parallel machine scheduling, while the delivery schedule requires planning involving direct shipping, routing, and a limited number of available vehicles.

- *Fixed delivery departure date* (Agnetis, Aloulou, and Kovalyov 2017; Leung and Long Chen 2013): The scheduling problem in this type of scenario typically pertains to delivery scheduling and the status of vehicles, which may involve heterogeneous or homogeneous vehicles.
- *Multiple plants* (Z.-L. Chen and Pundoor 2006): Managing multiple plants usually aims to minimise the total lead time (or minimise the maximum lead time among the plants) while also minimising the total costs of the supply chain.
- *Two-stage delivery* (Bushuev 2018; Xiao and Qi 2016): The primary scheduling challenge in this type of problem is to address delivery costs by minimising the total delivery cost (or minimising the maximum delivery cost across all delivery stages) while also minimising the total cost of the supply chain.

Category 2: Coordinated product pricing and scheduling decisions for MTO services involving single-period or multiple-period orders and product problems. While problems in this category are not new, most of the research in this field has focused on topics such as the problem's NP-hardness, computational complexity, and approximate solutions. However, what distinguishes these categories of supply chain scheduling problems in the new industrial environment are the allowable price ranges, which can be discrete or continuous. Therefore, certain dispatching rules can be incorporated into the scheduling problems considering this constraint. For more information, please refer to Sibdari and Pyke (2010) and Z.-L. Chen and Hall (2022).

Category 3: Joint subcontracting and scheduling decisions for tasks that require an internal processing facility and one or more subcontractors. The decision-maker must determine both the subset of work to be subcontracted and the internal processing timeline. In some cases, they may also need to design a schedule for subcontracted jobs. Problems in this category can be classified into the following major sub-problems:

- *Value of subcontracting* (Z.-L. Chen and Li 2008; Lee and Choi 2011): The main challenges in this area that significantly impact the selection of dispatching rules are evaluating the value of subcontracting in terms of total cost and the total cost plus the weighted sum of makespan.
- *Subcontracting budget constraint* (Sinha, Davich, and Krishnamurthy 2016): The budget constraint in the supply chain scheduling problem is similar to many traditional job-shop scheduling problems and involves challenges for dispatching rules related to total completion time, total tardiness, or maximum tardiness.
- *Delivery of subcontracted jobs* (S. Wang et al. 2022): Problems in this area pertain to scheduling the single in-house machine, the single subcontractor machine, and the two-stage flow shop.

Furthermore, additional problems such as the flow shop environment and lead time performance guarantee are emerging in this category of supply chain management. The existing literature in this field has primarily focused on investigating the NP-hardness of the problems, their complexity, heuristic analysis, and computational challenges Z.-L. Chen and Hall (2022).

Category 4: Optimization and conflicts arise due to the self-interest of different parties in the supply chain, leading to conflict costs experienced by one party when another party dominates the decision-making process. This broad category encompasses various traditional scheduling problems under conflict scenarios and new challenges. The most challenging conflict in supply chain scheduling is the *conflict in sequencing in the assembly line* (Ostermeier 2022). During the assembly process, conflicts may arise between suppliers and manufacturers, where either the suppliers dominate, the manufacturer negotiates, or the manufacturer dominates, and the suppliers negotiate or adjust. Conflicts can also arise when suppliers and manufacturers cooperate, and the dispatching rule aims to achieve cost savings from cooperation or other types of conflict costs. *Conflicts in scheduling and batching in the supply chain* (Agnetis, Aloulou, and Fu 2016) can occur in various situations, from incompatible components or conflicts with other batches to instances where one batch fits well but damages something else. These conflicts can arise on the supplier's or manufacturer's side, with or without cooperation between the parties.

For other types of conflicts in supply chain scheduling, such as the *conflict between the manufacturer and distributor* or the *conflict in re-sequencing in the supply chain*, the problem can arise on the supplier's side, the manufacturer's side, or both, with or without cooperation. Dispatching rules are selected based on maximising savings from cooperation or minimising the total cost (Manoj, Sriskandarajah, and Wagneur 2012).

Category 5: Cooperative and non-cooperative supply chain scheduling mainly involve game-theoretical solution approaches with complete or incomplete information (Mafakheri, Adebanjo, and Genus 2021). In this context, several scheduling concepts can be aligned with game-theoretical concepts, such as rescheduling games

(Z. Liu, Lu, and Qi 2018), batch sequencing games (Çiftçi et al. 2013), capacity allocation games (Cui and Zhang 2018), and project planning and execution. Similar to other theoretical game problems, in these scheduling games, the utility function typically considered is the cost function, and dispatching rules are defined based on this objective.

Consider a scenario where a single server must serve multiple customers, and each customer's pricing depends on their completion time (waiting time before service begins plus service time). The price is a non-decreasing function of the project completion time. In such cases, it is essential to address two issues: (1) how to find a sequence of customers that minimises the overall cost, and (2) how to allocate the total cost among customers in a stable manner such that no two customers would agree to swap their positions in the sequence. In most sequencing games, each customer may receive service at a different time. A typical, though not universal, assumption is that the cost to the customer is a linear function of the completion time. Under this assumption, it is straightforward to establish a rule that minimises the total cost, which is analogous to a result in classical scheduling theory (Y. Zhang, Zhang, and Liu 2020).

2.2. Scheduling strategy

The latest scheduling strategy introduced by Dolgui and Proth (2010) was 'predictive-reactive scheduling', in which a static scheduling procedure gives the ideal or near-optimal schedule at the beginning of the working day, which will be implemented throughout the whole time, assuming no unforeseen events occur. When an unanticipated incident disrupts the system, the schedule is updated using a technique known as a 'repair heuristic'. There are three sorts of heuristics for repair:

1. *The right-shift repair heuristics* consist of pushing forward in time those processes that were not finished during the disruption. The temporal shift must be significant enough to absorb the disruption.
2. *The match-up schedule repair heuristics* rearrange the remaining operations to align with the starting timetable. To achieve this objective, the production system must be sufficiently flexible to absorb the disturbance within a limited time frame.
3. *The partial scheduling heuristics* are defined based on the specification and characteristics of the problem.

Most of the research in scheduling over the past several years has concentrated on developing exact and heuristic procedures generating a workable baseline schedule, assuming complete information and a static and deterministic environment. During execution, however, considerable uncertainty may occur. 'Proactive-reactive scheduling' deals with the uncertainty by creating a baseline schedule protected against disruptions and deploying reactive scheduling procedures to revise or reoptimize this schedule when necessary. Proactive scheduling considers the worst-case uncertainty to avoid future changes to the initial schedule in the event of a disruption. The models under this strategy start by generating an initial schedule and then updating that schedule as needed. During project execution, dynamic scheduling choices are made at stochastic decision points, which often correspond to the completion times of activities. The choices are made using priority rules to determine which tasks should be dispatched over time. The policies are based on the observed history and a priori knowledge of the distribution of activities and resource attributes.

Proactive-reactive scheduling can be seen as an offline and online model, where all the unpredictable factors are predetermined or fixed in the offline model. In the online model, the factors are considered stochastic (Ghaleb, Zolfagharinia, and Taghipour 2020). There are three sorts of proactive scheduling techniques:

Redundancy-based strategies (Lou et al. 2012): The underlying principle of these strategies is to mitigate the effect of uncertainty. Such strategies as fault-tolerant real-time scheduling and slack-based protection rely on the intelligent insertion of redundancy to achieve a suitable trade-off between schedule quality and resilience.

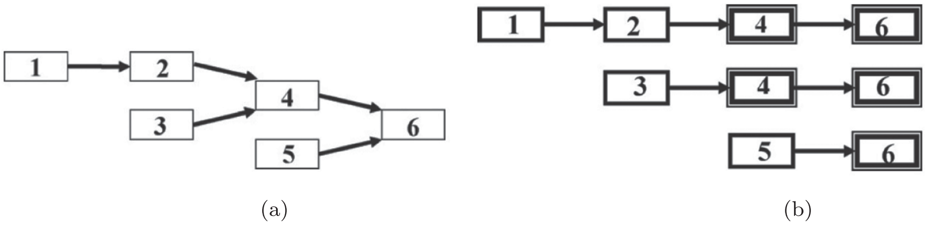
Probabilistic approaches (Chargui et al. 2022; Peng, Lin, and Li 2023): These strategies aim to generate stable and robust schedules by modeling uncertainty using probability density functions, for instance, establishing initial stable schedules under random machine breakdowns to maintain an acceptable degree of shop floor performance degradation or constructing preemptive parallel machine scheduling under random breakdowns with predictable process duration and due dates.

Contingent or policy-based strategies (Cardin, Mebarki, and Pinot 2013; Xie, Li, and Xu 2021): These policies do not provide a unified offline timetable. They prefer to build a branching or contingent schedule or a policy that decides when certain accidents happen, such as just-in-case scheduling and Markov decision-process-based policy.

3. Real-time assignment

3.1. Past trends in real-time scheduling

A decision is considered to be made in real-time if the time between the availability of the necessary data and the completion of the decision exceeds the time required



(a) (b)

Figure 3. Assembly process and its decomposition (Proth 2007). (a) An assembly process and (b) Linear production systems.

to process it. Consequently, the duration of this process can vary significantly across different cases. According to Dolgui and Proth (2010), real-time scheduling in supply chains is motivated by two objectives: (1) the ability to reschedule the entire production system 'online' in response to unforeseen events such as machine breakdowns, strikes, reworks, and fundamental changes in the market; and (2) the ability to respond instantly to customer demands.

Proth (2007) developed the first version of the real-time assignment in Chauvet et al. (2000) with the following assumptions:

- Projects are scheduled in the order in which they are received (i.e. FIFO).
- Each activity's processing time falls within two limitations.
- There is no wait time between successive activities.
- The project's manufacturing strategy is unique.
- A single resource cannot conduct two or more distinct activities for the same product, while two or more identical resources may execute the same activities.

Cases of linear production and assembly activities

Chauvet et al. (2000) considered two cases of linear production and assembly activities as shown in Figure 3 and developed an algorithm called 'S' (for more detail on the algorithm, refer to Section 3.2 of Chauvet et al. 2000) for the case of a linear production that minimised the completion of the product at hand with the complexity of $O(m \times n)$, where m and n denote the number of activities and the total period in a linear activity sequence, respectively.

Proth (2007) assumed the assembly process as depicted in Figure 3(a). The algorithm 'S''s goal is to decompose each assembly process into linear processes and to iteratively adjust the solution until each assembly activity that is distributed among several linear manufacturing processes is performed simultaneously.

Considering the sequence of activities connecting the tree's leaf to its base, we get a linear process, as shown in Figure 3(a), which can be broken into three linear processes, as depicted in Figure 3(b). In fact, a particular assembly activity is present in at least two linear processes. If we schedule these linear processes independently of one another, there is no need for the same assembly activity to be conducted at the same time by several linear processes. Then, Proth (2007) showed how to adjust these periods.

Adjustment of assembly activities

For the purpose of adjusting assembly operations, Chauvet et al. (2000) used the algorithm 'S' for each linear process. There are three different cases for each assembly activity in the solution, as follows:

- Case 1: Depending on the linear process, the activity is conducted during a variety of idle time windows. The highest rank of these windows is given to the assembly activity in this instance.
- Case 2: The activity is completed within the same time window with different starting times based on the linear process. In this situation, the rank of this window is allocated to the assembly activity, but its bottom limit is substituted by the activity with the longest starting time.
- Case 3: Regardless of the linear process, the activity is conducted inside the same time window, and the starting time is the same. In this situation, the window's rank is assigned to the assembly activity.

If every assembly activity falls under the third scenario, the algorithm terminates. Otherwise, the algorithm is restarted using the supplied windows as starting windows and the windows acquired in the previous iteration as initial windows for non-assembly operations. Also, Chauvet et al. (2000) proved that this approach minimises the makespan (i.e. the completion time).

Control of Work-In-Process (WIP)

Proth (2007) proposed two approaches for the control of WIP:

- Approach 1: At the end of each operation, the approach simply controls the storage time of each

product. The maximum storage time of a product at the end of each operation is a variable that the approach fixes the maximum storage duration at the exit of each operation.
- Approach 2: The approach controls the storage length and the number of components stored concurrently at the end of each operation. This approach permits managing the maximum WIP level and the production cycle.

For more detail about the approaches, refer to Section 3.4 in Proth (2007).

3.2. New trend in real-time scheduling

In the realm of Industry 4.0, manufacturing systems rely on a range of advanced technologies, including cyber-physical systems (CPS), the Internet of Things (IoT), and the Internet of Services (IoS). By integrating these principles into industrial systems, real-time communication, monitoring, and control capabilities are achieved. To fully capitalise on the potential of these technologies, decision models that can effectively utilise real-time data must be integrated into all facets of the production process.

In the subsequent sections, we delve deeper into the emerging trends in real-time scheduling, exploring its applications in supply chain scheduling, critical infrastructure resiliency, pandemic and supply chain stress testing, disruptive technologies and innovations, and other relevant domains. These discussions shed light on the evolving landscape of scheduling practices and their intersection with key areas of industrial environments.

3.2.1. Real-time supply chain scheduling

There is a rich body of literature on supply chain scheduling, encompassing various research studies. A few notable contributions in this domain are as follows.

Real-time supply chain scheduling with dynamic decision-making

Averbakh and Xue (2007) conducted research on real-time supply chain scheduling problems with *preemption*, proposing two competitive algorithms for addressing such challenges. V. S. Gordon and Strusevich Strusevich (2009) investigated a single-machine real-time scheduling problem and addressed the assignment of due dates considering *positionally dependent processing times*. Averbakh (2010) delved into the real-time integrated production-distribution scheduling problem, specifically considering *capacitated deliveries*. Han et al. (2015) investigated online supply chain scheduling for *single-machine and parallel-machine configurations* with a single customer, aiming to minimise the makespan and delivery cost.

Coordination and collaboration in real-time supply chain scheduling

Ruiz-Torres, Ho, and López (2006) focused on supply chain scheduling involving both *outsourced and internal parallel resources*. They developed several heuristics to generate Pareto-efficient scheduling solutions. Yeung, Choi, and Cheng (2011) examined coordination and scheduling aspects in a *two-echelon supply chain*, considering dual delivery modes and inventory costs. Yao (2013) developed a scheduling model for *co-operator selection and task allocation in a mass customisation* real-time supply chain. Their model incorporated collaborative benefits and risks to guide decision-making. Agnetis, Aloulou, and Fu (2014) focused on the coordination of production and *batch delivery* in the real-time supply chain, considering regular and express modes as well as outsourced distribution. G. Wang (2021) studied integrated real-time supply chain scheduling, considering *procurement, production, and distribution* activities and the spillover effects among them.

Optimization and decision-making in real-time supply chain scheduling

Naso et al. (2007) utilised a genetic algorithm to tackle the ready-mixed concrete *delivery scheduling problem*, which involved strict time constraints and requirements for no earliness and lateness of the supply. Ruiz-Torres et al. (2008) explored *outsourcing decisions* in supply chain scheduling, with a focus on minimising the average tardiness. Rasti-Barzoki and Hejazi (2013) focused on minimising the weighted number of tardy jobs in supply chains with due date assignments and *capacity-constrained deliveries* for multiple customers. Tang, Jing, and He (2013) utilised an ant colony scheduling algorithm to address scheduling challenges in *real-time manufacturing supply chain networks*. Chang, Chang, and Chang (2013) proposed an *integer programme and applied a column generation-based algorithm* to solve a supply chain scheduling problem. Ivanov, Dolgui, and Sokolov (2018) focused on *recovery action* scheduling in the supply chain, considering *resilience* constraints. They aimed to develop strategies for effective recovery from *disruptions* in the supply chain. Tang et al. (2023) employed simulation to evaluate a practical *order-merging strategy* for collaborative production scheduling. Zeng, Sadeghzadeh, and Xiong (2023) analysed *sustainable supply chain scheduling within the blockchain environment*, exploring the potential benefits and challenges associated with incorporating blockchain technology.

Choi, Yeung, and Cheng (2013) studied the scheduling and coordination of supply chains, considering *variable production rates and storage costs*. Ullrich (2013) analysed the integrated problem of *machine scheduling and vehicle* *routing with time windows*, considering the coordination between these two aspects. Selvarajah and Zhang (2014) developed a supply chain batch scheduling model to minimise the *sum of delivery and inventory costs*. They identified optimal batching strategies with a fixed job sequence. Mahdavi Mazdeh and Karamouzian (2014) applied game theory to evaluate strategic challenges in the supply chain, including scheduling and batch delivery of orders. They considered objective functions related to *batch delivery and total tardiness costs* and addressed coordination issues by developing a sharing mechanism, penalty determination, and threat strategies. Agnetis et al. (2015) proposed two fast algorithms for *coordinating production and batch delivery*. In summary, the objective functions considered in supply chain scheduling problems in the literature encompass a combination of various metrics, such as total, maximum, or weighted flow time, distribution cost, lateness, setup time, inventory cost, delivery time, completion time, tardiness, earliness, number of late jobs, and makespan (Cakici, Mason, and Kurz 2012).

On-Demand Delivery Service Systems

Scheduling models are crucial in shaping on-demand delivery service systems. The application of multi-source data-driven and machine-learning models holds the potential to enhance the accuracy of scheduling plans in these business models. Noteworthy examples of research in this domain include courier scheduling on crowdsourced delivery platforms (Behrendt, Savelsbergh, and Wang 2022), scheduling for vehicle-to-vehicle communications (Ko et al. 2020), and self-scheduling capacity in the on-demand economy (Gurvich, Lariviere, and Moreno 2019).

Integration of disruptive technologies and innovations

Disruptive technologies and innovations, including cloud manufacturing, 3D printing, autonomous vehicles, drones, wearable technology, blockchain, robotics and automation, and the IoT, have been integrated into supply chain design and operations management. These technologies facilitate transparent product flow and order tracking, enabling real-time supply chain control. Analytical foundations for real-time supply chain capabilities were explored by Oliveira and Handfield (2019). Furthermore, Dolgui and Ivanov (2022) highlighted the role of 5G in digital supply chain and operations management, emphasising its major capabilities: intelligence, visibility, transparency, dynamic networking, and connectivity. The emerging trend in scheduling models for new industrial environments necessitates dynamic collaboration with disruptive technologies in the supply chain to achieve supply-demand balance and resilience against disruptions. Integrating disruptive technologies with social media, big data analytics, predictive analytics, and inventory and network optimisation tools significantly enhance understanding consumer preferences and customisation levels in the global supply chain of industrial environments.

3.2.2. Real-time strategic scheduling

Critical infrastructure resiliency

Integrating the digital, physical, and human worlds continues to reshape industrial environments, reaching deep into society in the era of Society 5.0. The Industry 4.0 revolution, coupled with the IoT, big data, and the industrial Internet, has brought about transformative changes in product design, manufacturing processes, and the development of new products and services. These advancements also enhance the resilience of industrial environments (Bianco et al. 2022). As a result, a complex network of interconnected entities encompassing things and people has emerged, facilitating seamless communication and connectivity.

While these innovations hold immense potential for improving well-being and generating benefits, they also introduce new and unknown failure mechanisms, hazards, and risks. This is partly due to the emergence of functional and structural dependencies that significantly impact scheduling decisions. Therefore, it becomes essential to measure, assess, and enhance the resilience of industrial environments and their critical infrastructures, susceptible to disruptive events. Integrating simulation and analytics into scheduling decision-making problems allows for integrating scheduling models with infrastructure systems operations and their functional interdependencies within industrial environments.

Assessing the resilience of interdependent critical infrastructures and identifying vulnerabilities that threaten their continued operations would be a valuable addition to scheduling models. This approach enables the identification of critical areas for improvement, aiding policymakers and operations managers in making informed decisions to enhance the resilience of critical infrastructures. By incorporating scenario-based scheduling problems, policymakers can proactively address challenges and enhance the resilience of industrial environments.

Pandemic and supply chain stress testing

A significant aspect that J.M. Proth has not addressed in his studies on scheduling problems is the resiliency of critical industrial environments, particularly in the context of pandemics. The concept of stress tests for critical supply chains was introduced by Simchi-Levi and Simchi-Levi (2020), highlighting the need to assess and strengthen the resilience of supply chains during disruptive events.[1] During the COVID-19 pandemic, various challenges and shortages were observed in industrial environments, including a lack of personal protective equipment for healthcare workers and hospital ventilators. These shortages directly impacted the scheduling plans of supply chain participants across different levels, ultimately affecting the overall performance of the entire supply chain.

To prevent such problems when facing disasters, governments should consider implementing stress tests and developing new scheduling models for industrial environments that provide critical goods and services. These stress tests would resemble those established for banks by the U.S. government and the European Union following the 2008 financial crisis. The focus of these tests should be on assessing the resilience of industrial environments and their global supply chain networks, which form interconnected ecosystems (Ivanov and Dolgui 2022b).

Furthermore, other studies have explored the resilience of supply chains and disruptions during the COVID-19 pandemic, such as Salama and McGarvey (2023) and Hosseini and Ivanov (2021), shedding light on the importance of resilience in navigating and mitigating disruptions in supply chain operations.

Business models and order penetration point (OPP)

Industrial environments can be classified into different business models, such as MTO, make-to-stock (MTS), and hybrid MTO/MTS systems. MTO systems are rapidly growing due to the Internet, telephone, platform ordering, and quick response time requirements (Teimoury et al. 2011). However, MTS systems can fulfill customer orders quickly but face inventory risks associated with short product life cycles and unpredictable demands. MTS/MTO systems provide a combination of lean and agile paradigms within the global supply chain, and the strategic decision of determining the order penetration point (OPP) plays a crucial role in defining the boundary between MTO and MTS policies (Olhager 2003). Customizing incoming orders takes place at the OPP (Teimoury et al. 2012). Therefore, new scheduling models need to consider modern business models and the location of the OPP. Additionally, there is extensive literature on integrating operations, marketing, and finance perspectives in the supply chain, which can be effectively integrated through scheduling models (Teimoury and Fathi 2013).

3.2.3. Other new trends

Energy-efficient and real-time scheduling

One of the major challenges in the current industrial landscape is making energy-efficient and real-time scheduling decisions (M. Liu et al. 2020; S. Wang et al. 2020; Wu, Cheng, and Chu 2021). Parallel and distributed scheduling techniques and real-time pricing strategies are crucial in energy-related industrial settings. Research in this direction includes distributed scheduling in grids, scheduling energy flows with load-balancing constraints, real-time power balancing through energy scheduling and renewable sources, and optimal scheduling for electric vehicle charging in distribution grids. In general, developing low-energy and energy-efficient parallel scheduling algorithms, in collaboration with emerging technologies in the Industry 4.0 era, is instrumental in achieving success in the new industrial environment. Furthermore, creating digital twins and real-time scheduling and rescheduling simulations offers significant value, particularly in competitive settings like truck fleet assignments.

Markov decision processes and reinforcement learning

Many scheduling problems are dynamic and require sequential decision-making. Markov decision processes have been widely utilised for optimising such problems, as demonstrated by studies such as Yih and Thesen (1991) and Hermans, Leus, and Van Looy (2023). Additionally, reinforcement learning has found applications in scheduling, as evidenced by the work of Z. Wang et al. (2023).

Flexible and collaborative scheduling in healthcare facilities

In healthcare facilities, on-call duty and appointment scheduling play a crucial role, and there is a need for flexible and collaborative scheduling models that can handle dynamic priorities and multi-class scheduling. Notable studies in this area include Sauré, Begen, and Patrick (2020), Mahmoudzadeh, Mirahmadi Shalamzari, and Abouee-Mehrizi (2020), and Jiang, Abouee-Mehrizi, and Diao (2020).

Scheduling in the retail industry

The retail industry is experiencing disruptive technologies and innovations, which necessitate novel scheduling solutions. These solutions aim to optimise profit and customer relationship management by enabling automated pickup and delivery, personalised promotion scheduling, and more. The study by Chapados et al. (2014) explores the importance of scheduling in this context.

Scheduling in humanitarian logistics

Scheduling is also critical in humanitarian logistics, emergency management, and disaster relief programmes. During disaster events, interactive and collaborative scheduling and resource sharing is vital for effective response. Relevant studies in this area include Hu et al. (2019), Wex et al. (2014), and Shin, Kim, and Moon (2019). These works highlight the significance of scheduling in addressing emergencies and facilitating efficient resource allocation.

4. Cyclic scheduling

Dolgui and Proth (2010) defines 'cyclic scheduling' as a scenario where a set of tasks is continuously repeated using the same set of resources. In such a system, the decision-making process involves two steps: (1) assigning operations to resources and (2) scheduling operations based on the availability of different resources. In the upcoming section, we delve into the specific details and perspectives presented by Dolgui and Proth (2010) in each of these areas and explore new trends that have emerged in the current industrial environment. Figure 4 provides a classification of the common trends in each category.

4.1. Assignment of operations to resources

Assignment of operations to resources involves balancing the workload among the available resources. In the basic model proposed by Dolgui and Proth (2010), it is assumed that each product undergoes only one operation per machine to minimise the workload on the most critical machine (i.e. the bottleneck machine) among the available machines. The work by Dolgui and Proth (2010) primarily focuses on the traditional and fundamental version of the assignment problem. It is worth noting that the assignment problem has a rich historical background in scheduling management, and a comprehensive review of recent developments in this field would require independent research. This section briefly overviews variant assignment problems commonly encountered in supply chain or strategic scheduling contexts.

Assignment problem as a variant of transportation problem

The assignment problem is a special case of transportation problems that involve two key properties. First, the payoff matrix for the problem is required to be square, and second, the optimal solution always ensures that each row or column of the payoff matrix has only one assignment. The objective of scheduling in this context is to allocate an equal number of sources to an equal number of destinations at the lowest possible cost. While the assignment problem is commonly used to allocate individuals to tasks, it can involve other entities such as machinery, cars, plants, or assigned periods. Regardless of the type of assignee, the problem is typically approached with the following assumptions (Pentico 2007):

(1) The number of assignees is equal to the number of tasks.
(2) Each assignee is assigned exactly one responsibility.
(3) A single assignee must complete each task.
(4) A cost is associated with each task assigned to an assignee.
(5) The objective is to determine the assignment of tasks that minimises or maximises the total cost.

Unbalanced assignment problem

Unbalanced assignment problems occur when the number of tasks exceeds the available facilities. Since the Hungarian solution technique requires a square matrix, a common approach is to augment the given matrix with zero-cost fake rows or columns to make it square. Moreover, non-zero costs can be employed for assignments using dummy tasks or agents to indicate changes based on which agents or tasks are unallocated (Z. Wang and Zhang 2022).

Prohibited assignment problem

Sometimes, due to technological, spatial, legal, or other constraints, assigning a specific facility to a particular task is impossible. In such cases, the solution is to assign an infinite cost to the corresponding cell. This position should be excluded from further consideration when making assignments (Jansen and Rohwedder 2020).

Traveling salesman problem as an assignment problem

The traveling salesman problem shares similarities with the assignment problem, with the distinction that the traveling salesman must visit each city exactly once before returning to the starting point. When applying the assignment problem-based scheduling to the traveling salesman problem, if the assignment solution does not satisfy the additional constraint, the enumeration approach can be employed after addressing the problem using the assignment technique (Bai et al. 2013; Mosayebi, Sodhi, and Wettergren 2021).

Aircrew assignment problem

Aircrew assignment falls under assignment problems, where crew members are assigned to individual flight segments within a specific time frame. The objective of this problem is to optimally assign a given set of crew pairings to crew members while adhering to a set of constraints that can be divided into two subproblems. The first subproblem involves crew pairing, while the second pertains to constructing a timetable. The airline's strategy involves allocating tasks to crew members, to minimise travel time between states or cities. Additionally, they must consider the employees' limited stay periods while attempting to minimise the length of their stays. Another objective in the airline industry's assignment problem is to maximise profitability by considering seat costs and consumer demand (Kenan, Jebali, and Diabat 2018; Zeighami and Soumis 2019). A similar approach can be applied to crew assignment in the bus and railway industries, considering factors such as

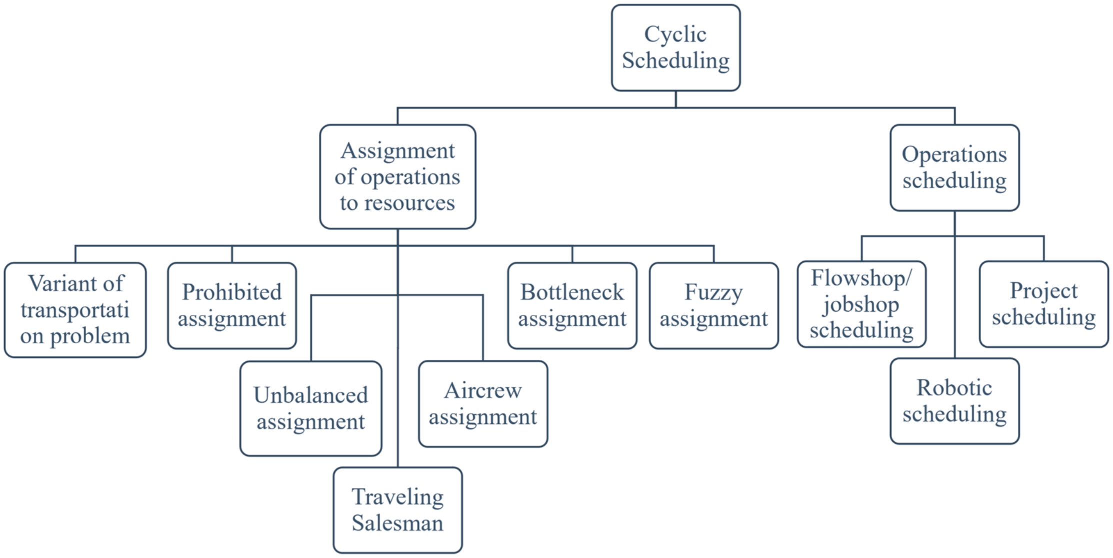


Figure 4. Classification of common cyclic scheduling.

journey time, passenger load, and schedules (Heil, Hoffmann, and Buscher 2020).

Bottleneck assignment problem

As a subset of the linear assignment problem, the linear bottleneck assignment problem deals with multiple agents and multiple tasks. Each agent can be assigned to perform any task, with the assignment cost varying depending on the agent-task combination. The objective is to assign exactly one agent to each task to minimise the total cost of the assignments. To reduce the latest completion time, linear bottleneck assignment problems have been introduced in allocating work to parallel processors. In this context, the cost coefficient represents the time each machine requires to complete a specific task (Karsu and Azizoğlu 2012).

Fuzzy assignment problem

When the parameters of an assignment problem are imprecise or challenging to define, it is referred to as an assignment problem with fuzzy parameters. By incorporating fuzzy logic into the assignment problem, fuzzy numbers can be converted into real numbers and processed using the Hungarian approach. Alternatively, the assignment problem can be solved without converting fuzzy numbers into real numbers while still allowing for the ranking of fuzzy numbers. A ranking algorithm can convert a fuzzy assignment problem into a crisp assignment problem (Singh 2014; Xu et al. 2018).

4.2. *Operations scheduling*

According to Dolgui and Proth (2010), the bottleneck resource in a cyclic production system can always be utilised up to its capacity. In other words, it is always possible to optimise the output of a cyclical production system by adding sufficient work-in-process (WIP). Therefore, the objective is to maximise productivity by employing the smallest feasible amount of WIP rather than maximising production. Several methods have been developed to determine the minimum WIP required and the initial placement of WIP components. These methods can be classified into two types of circuits:

(1) The production flow represents the manufacturing processes, and there is no limit to the number of jobs (WIP) that can be introduced into these cycles.
(2) The control cycle restricts resources from performing multiple operations simultaneously, requiring the input of exactly one WIP in a control circuit.

The cycle time of this production flow is determined by dividing the sum of transition firing times by the total number of WIP in the cycle.

Assume that each basic cycle includes at least one work-in-process, which triggers transitions immediately. Under this condition, the cycle duration of the highly linked event with the longest duration determines the firing rate of all transitions in a steady state. The optimal productivity of a cyclic production system can be attained by utilising the cycle time of the control cycle. Therefore, the scheduling objective is to introduce work-in-process (WIP) into the production flow until the control cycle of the bottleneck resource reaches the critical circuit while minimising the amount of WIP introduced into the system.

Operational cyclic scheduling can be categorised into several well-known scheduling models discussed in the following subsections. However, this field intrigues researchers primarily because of the computational complexity of the problems. J.M. Proth has significantly contributed to analysing and evaluating discrete event systems, production planning, and control. In his work, he employed Petri-net modeling to simulate manufacturing systems, including cyclic scheduling (DiCesare et al. 1993; Hillion and Proth 1989c; Proth and Minis 1995; Proth and Sauer 1998; Proth, Wang, and Xie 1997). Petri nets provide a comprehensive approach to production management and enable the reduction of problem complexity, albeit with certain constraints imposed on the decision-making system.

The most common cyclic operational scheduling problem is the cyclic job shop scheduling problem, which involves determining the processing sequence in which operations are repeated on each machine. Typically, assumptions about minimal setup, transit duration, and constant processing times are made, which may be negligible in a cyclic job shop scheduling problem. Various variations of the cyclic job shop problem exist, including those with restricted or infinite buffer capacity, parallel and series-parallel machines, and blocking or no-wait conditions. Several generic solutions for addressing the general cyclic scheduling problem include branch-and-bound, Lagrangean relaxation, mixed-integer linear programming, and interactive human-computer processes (Bożejko et al. 2017; Pempera and Smutnicki 2018; Quinton, Hamaz, and Houssin 2020).

Cyclic flow shop scheduling problem (Levner, Kats, and Levit 1997; Smutnicki et al. 2022)

This represents a specific case of the ‘cyclic job shop problem’ subclass. Some of these challenges assume that setup and transit periods are negligible, while others explicitly consider material handling devices with significant operating times. In the cyclic flow shop, the number of machines is predetermined. Each machine is arranged sequentially, and all tasks must follow the specified sequence when visiting the machines. A conveyor belt or another material handling device transfers tasks to and from fixed stations, where they undergo prescribed activities. Typically, transportation times are considered to be insignificant. The objective of the cyclic flow shop scheduling problem is to determine the order (i.e.task sequence for each machine) in which the machines repeatedly execute the jobs. In the permutation flow shop, the task processing sequences on each machine are identical.

Cyclic robotic scheduling problem (Elmi and Topaloglu 2016; Feng, Che, and Wang 2014)

Consider a manufacturing system of multiple machines organised as a flow shop or a job shop. In a flow shop scenario, all components follow the same predetermined order as they visit the machines. On the other hand, in a job shop setting, each part has its own specified technical path through the machines. Computer-controlled robots or other material-handling equipment are responsible for transporting the components to and from the stationary machines where the tasks are performed. In this problem, the duration of transportation operations and empty robot movements are considered unimportant. Therefore, the system’s performance and productivity heavily rely on the efficiency of the transportation devices. The cyclic robotic scheduling problem aims to determine how the machines process the parts (work sequence) and the routes the robots take to transfer the parts. Each robot can be seen as a specialised machine, making the robot-based production system a subset of the job shop model. These transportation technologies possess distinct physical properties, structures, and functionalities compared to other machines, leading to unique characteristics in the robotic scheduling problem.

Cyclic project scheduling problem (Vanhoucke 2012)

This problem involves determining the minimal cycle time for a cyclic industrial process in which precedence connections interconnect a series of operations. This issue can be described as the ‘cyclic PERT-shop’ (Bocewicz, Pawlewski, and Banaszak 2018). The algebraic method for calculating the minimal cycle time uses matrix multiplications and the ‘max’ operation in lieu of addition and ‘addition’ in place of multiplication. The minimal cycle time in this algebraic solution equals the eigenvalue of a given operation duration matrix. In contrast, the eigenvector provides the earliest start times of the operations within one cycle. Consequently, the cyclic scheduling issue is equivalent to the eigenvalue problem.

The activities within the cyclic project schedule are essential for completing the entire project. In addition, we can assume that another set of partially ordered generic operations needs to be performed simultaneously by an unlimited number of machines or operators. It is also assumed that a dedicated machine executes each operation, and there are a sufficient number of machines, eliminating the need for scheduling operations on machines. Each operation has a processing time, and the generic operations and their precedence relationships are depicted in a generic graph. Considering a periodic process where this graph repeats an infinite number of times, it implies that each operation must be carried out regularly and repeatedly within the same period.

The problem of cyclic project scheduling finds application in various real-world planning and scheduling scenarios. This category of cyclic problems is especially suitable for modeling and optimising the throughput of periodic processes in multi-product chemical manufacturing facilities, commonly known as 'scheduling for batch production' (Almasarwah and Süer 2021). These models involve dividing all products into batches and scheduling the processing of these batches. In addition to the cyclic timing constraints, challenges in this category may include equipment allocation, material balance, resource constraints, inventory management, demand-responsive limitations, batch size, production makespan, and cost reduction.

5. Conclusion

This paper discusses J.M. Proth's perspectives on scheduling models in industrial environments and explores research opportunities. The paper examines past and current industry challenges, focusing on dynamic scheduling, real-time assignment, and cyclic scheduling.

The advent of emerging technologies in new industrial environments poses numerous challenges for real-time supply chain management. Consequently, there is a pressing need for resilient and collaborative scheduling models to establish sustainable business practices. Furthermore, the decision-making process in scheduling should be automated and intelligent, incorporating human-AI collaboration-based models. This enables quick responsiveness in the face of disruptions and shortages.

Future industrial environments will be characterised by increased autonomy, collaboration, competitiveness, and social sustainability. Demand and supply dynamics and innovative technologies like 3D printing will influence these developments.

5.1. Scheduling trends in future industrial environment

In the future industrial environment, several scheduling trends are expected to emerge:

(1) *Artificial Intelligence (AI) and Machine Learning (ML) Optimization*: AI and ML technologies are increasingly utilised to optimise scheduling processes. These technologies can analyse large datasets, identify patterns, and make predictions, allowing for more efficient scheduling decisions. They consider various factors such as machine availability, worker skills, and production demand to minimise downtime or bottlenecks. Examples of research in this area include ML-based scheduling (Aytug et al. 1994; Karimi-Mamaghan et al. 2022; Morabit, Desaulniers, and Lodi 2021, 2023; S. Li et al. 2021; Tahir et al. 2021), deep-reinforcement-learning-based scheduling (Chi et al. 2022; Sun and Li 2021), and the use of ChatGPT for scheduling (Prieto, Mengiste, and García de Soto 2023) in future industrial environments.

(2) *Real-Time Adaptive Scheduling*: Dynamic and adaptive scheduling systems replace traditional static schedules. Real-time data from connected devices, IoT sensors, and production systems enable continuous operations monitoring. This information allows schedules to be adjusted online, respond to changing conditions, disruptions, or unexpected events, and ensure optimal resource allocation and production efficiency. Methods for scheduling and rescheduling that leverage data and adapt in real-time (L. Zhou et al. 2022), with learning (H. Wang et al. 2021), simulation-optimisation (Cai et al. 2022), and operational robustness analysis (Cheng et al. 2022), using technologies like open AI, robots, cyber-physical systems (CPS), and digital twins under unexpected disruptions and swift environmental shifts, will more common in future industrial environments.

(3) *Collaborative Scheduling*: Industrial environments embrace collaboration and stakeholder involvement in scheduling. There are several examples of collaborative scheduling in the literature, such as collaborative real-time scheduling (Cai et al. 2022; Gui et al. 2022) and centralised and decentralised scheduling (Minguillon and Lanza 2019; Tang et al. 2023). The future industrial environment will collaborate the collaborative scheduling of robots, smart automated technologies, and open AI paradigms in high automation and digital transformation. Additionally, using game theory for collaborative scheduling under job-splitting cooperative games in competitive industrial environments would be essential. The future industrial environment will witness the increased collaboration between humans and machines in scheduling tasks. Combining human judgment with machine-driven insights can lead to more effective scheduling strategies that balance efficiency, productivity, and worker well-being. Some problems may arise in human-machine collaboration, which requires an equitable multi-objective scheduling perspective (Heeger et al. 2022).

(4) *Predictive Maintenance Integration*: Predictive maintenance techniques, driven by IoT and data analytics, play a significant role in scheduling maintenance activities. By monitoring equipment condition and performance, organisations can anticipate maintenance requirements and schedule preventive actions to minimise unplanned downtime. Integrating predictive maintenance with scheduling systems ensures that maintenance tasks are efficiently

planned, reducing operational disruptions. Most predictive maintenance scheduling policies in future industrial environments will be data-driven problems that require ML and optimisation techniques (D'Ariano et al. 2019; Gerum, Altay, and Baykal-Gürsoy 2019; Grall et al. 2002).

(5) *Flexibility and Agile Scheduling*: In an era of rapidly changing customer demands and market dynamics, flexibility and agility in scheduling have become crucial. Industrial environments adopt agile scheduling approaches, enabling quick adjustments and accommodating short-term changes. This trend involves employing lean methodologies, implementing just-in-time principles, and embracing modular production systems that facilitate easy reconfiguration and adaptation to shifting requirements. Moreover, 3D printing is shaping the future of industrial environments by collaborating with robots and open-AI solutions. Some research papers in 3D printing scheduling can be found in (Elango et al. 2016; J. Zhang, Yao, and Li 2020; Kim and Kim 2021; S. Liu et al. 2021).

(6) *Sustainability Consideration*: Sustainable practices and environmental concerns are becoming integral to industrial operations. Scheduling systems are expected to incorporate sustainability considerations, such as energy optimisation, reduced waste, and eco-friendly production (Akbar and Irohara 2018; Yue and You 2013). By integrating sustainability into scheduling decisions, industrial environments can reduce their carbon footprint, comply with regulations, and improve their brand image. Moreover, future industrial environments rely on emerging technologies such as 4D Printing, 6G Telecommunications, Edge Computing Technology, Robots, and disruptive technologies like Web-based TV, Virtual Reality, Blockchain, Cryptocurrency, and AI.

(7) *Digital Supply Chain Scheduling*: Digital supply chain scheduling is a prominent scheduling trend in the future industrial environment. It utilises advanced technologies like AI, ML, IoT, and big data analytics to optimise the allocation of resources, tasks, and activities throughout the supply chain. By incorporating real-time visibility, predictive analytics, collaborative scheduling, and intelligent logistics, businesses can make data-driven decisions, improve efficiency, reduce costs, and adapt quickly to market changes. Digital supply chain scheduling enables agile operations, continuous improvement, and enhanced customer service, ultimately providing a competitive advantage in the evolving industrial landscape.

(8) *Hyper-heuristics Algorithms*: Many heuristics, meta-heuristics, and hyper-heuristics are used for solving scheduling problems (Drake et al. 2020). Several applications of hyper-heuristics in scheduling literature can be seen in (Asta, Özcan, and Curtois 2016; Bilgin et al. 2012; Burke et al. 2007; Mısır et al. 201311; Pour, Drake, and Burke 2018; Rahimian, Akartunalı, and Levine 2017; Y. Chen et al. 2017). Meta-heuristics and hyper-heuristics differ primarily in their search focus. Meta-heuristics directly explore the solution space of a problem, while hyper-heuristics explore the space of heuristics. Applying ML-based hyper-heuristics to solve scheduling problems and developing new dispatching rules can be considered more frequently in future industrial environments.

5.2. *Future research direction*

According to the review results provided in this paper, the following feature research directions are proposed based on the current and future industrial environment:

(1) In new industrial environments, various scheduling, batching, delivery, and resilience problems should be considered in supply chain networks where suppliers make deliveries to several manufacturers, who also make deliveries to customers. The objective is to minimise the overall scheduling and delivery costs using several classical scheduling objectives while maximising the supply chain's resilience. This is achieved by scheduling jobs and grouping them into batches, each delivered to the next downstream stage as a single shipment. The total system cost minimisation problem of suppliers and manufacturers who make cooperative decisions can be considered in supply chain scheduling.

(2) Another perspective in this area is coordinated supply chain scheduling in new industrial environments, such as joint production-inventory planning models, where the problem is how to coordinate the scheduling of production, supply, and assembly of products such that the total supply chain production, inventory, and transportation costs are minimised.

(3) The dynamic characteristics of new industrial environments based on uncertain demand and supply should be considered in scheduling modeling.

(4) In industrial environments, there are conflict and cooperation challenges among different echelons of supply chains with their ideal schedules based on optimal cost and capacity constraints. As these scheduling models are not coordinated, it would lead to poor performance.

(5) The circular economy improves the efficiency and resilience of business processes by removing waste, improving end-of-life resource management, and recycling materials. Applying the circular economy to new industrial environments makes supply chain resilience and scheduling more sustainable.

(6) The shortage economy occurs in different forms, such as temporary fluctuations, disruptions, extreme shocks, and long-lasting disruptions in uncertain situations in new industrial environments that significantly affect the global supply chain. Ivanov and Dolgui (2022a) classified the spread of shortages into acute (pandemic-induced reasons) and chronic (long-term reasons). The shortage of resources can be classified into labour, materials and components, energy, and capital, with inflation, price fluctuation of materials and energy, and high volatility of workforce and energy. The supply chain's ripple effect is critical to resiliency during the shortage economy. Operational decisions such as scheduling under workforce constraints, scheduling under material disruptions, scheduling under capital constraints, and scheduling under energy constraints would be examples of topics in industrial environments under resource shortages. Also, scheduling-related examples of the implications of the shortage economy on new industrial environments would be manufacturing control using situational and dynamic rescheduling approaches and consideration of container shortages in routing decisions. Operational management decisions on the planning level during the shortage economy would be developing models and frameworks on production, distribution, and sourcing planning with consideration of continuous shortages and long-term disruptions in material, energy, capital, and workforce resources to have continuous mass customisation production, equity in demand satisfaction, and secure ecosystem viability.

Note

1. https://www.youtube.com/watch?v=hhsDmTrD9e4

Acknowledgments

Dr. Jean-Marie Proth has made an immeasurable and enduring contribution to management science and operational research. His works influenced the research and study of many students, academicians, and practitioners.

Data availability statement

Data supporting the findings of this study are available on a reasonable request from the authors.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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