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Future-Proof Production Scheduling and Control

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A B S T R A C T

Traditional production scheduling and control are increasingly inadequate in light of the rapid evolution of manufacturing technology, the growing impact of unforeseen disruptions, and the generally increasing complexity of production. A framework for future-proof production scheduling and control is introduced to close this gap, providing a comprehensive overview of future requirements and the necessary technologies and approaches. Robust decision criteria are derived, explained and filled with major recent advances in production scheduling and control, digital twins, artificial intelligence, and knowledge formalisation. Emerging trends are discussed, and an outlook for future research and decision-making is derived.

1. Introduction

The vast majority of products and goods in our economic systems are produced in factories, i.e., physical facilities where they are manufactured through machinery and humans, driven by specific production processes. The transformation of raw materials or components into finished products follows a series of organised steps that are necessarily integrated with different classes of operations, including material handling, quality control, packaging, and many others. Decisions related to operating these organised steps are, without any doubt, the most important to be taken in a factory. They define what, when and how to act on the products, and directly influence the overall profitability, effectiveness, and efficiency of factories.

The characteristics of modern factories have drastically evolved in recent years, driven by advancements in technology, increasing product complexity and variety, and growing demands for quality [237]. As current production paradigms are no longer limited to mass-producing standardised goods, highly complex personalised products often require specialised components, advanced materials, and sophisticated and flexible production and assembly processes matching dynamic market demand [53]. Furthermore, efficient coordination of information flows, cooperation and synchronisation of various stakeholders [252] are keys to establishing new ways to effectively address diverse market needs [237]. For example, the automotive and electronics industries almost always involve intricate production systems with interconnected automated equipment, sensors, and control systems, adding layers of complexity to the factory environment. Instrumental goods, such as advanced machinery, have also increased in technical sophistication, necessitating more precise decisions and control techniques. Furthermore, modern factories face stringent traceability and quality assurance requirements, with every stage of production needing to be monitored and documented for compliance and customer satisfaction. This means that decisions related to production scheduling and control, resource allocation, and quality control are increasingly complex, as their impact on efficiency, cost, and product quality is more challenging to predict. These factors make the governance of modern factories more intricate [65], requiring sophisticated decision-making tools and strategies to manage this complexity.

Production systems are also increasingly challenged by uncertainty arising from external and internal factors. External ones, such as the fluctuating availability of raw materials and components, volatile material and energy prices [17,120], unpredictable delivery schedules, variable demand patterns, and the sudden influx of rush orders, create a highly dynamic environment. Internally, production is affected by unforeseen machine failures, equipment downtime, and workforce availability issues, all of which can disrupt planned operations. These uncertainties make it difficult to maintain a steady production flow, requiring production scheduling and control approaches capable of handling unpredictable events to minimise delays, optimise resource utilisation, and ensure timely delivery of products [6,171].

The described challenges and requirements drive the need for a class of production scheduling and control approaches capable of making effective decisions as the state of the manufacturing system and the boundary conditions evolve by anticipating and mitigating the impact of these changes. These approaches must also be designed with features and capabilities that can adapt to the characteristics of the factories and production technologies, to conditions of use, and to decisions and their driving criteria, to minimise the risk of ineffectiveness and obsolescence. Production scheduling and control approaches with these

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desired characteristics, labelled as *future-proof*, are investigated in this paper through a comprehensive framework for their characterisation and classification, considering the formulation of robust decision criteria, the definition of uncertainty models supporting decisions, data and models describing the current state and the behaviour of the factory, and the modelling of external factors.

An overview of recent technologies and advances in production scheduling and control [14] is also provided, while considering the limitations of conventional approaches [134], to give an overview of the evolving technologies and functionalities supporting short-term decision-making in modern manufacturing environments. In this perspective, the integration with the capability to leverage large and big data [65], the integration of digital twins [155], artificial intelligence [102] and knowledge formalisation [9], and the potential impact of environmental, social and governance factors [204] are considered, as essential ingredients for future-proof production scheduling and control.

The described framework for characterising future-proof production scheduling and control is introduced, motivated, and described in Section 2. Starting from this framework, the requirements, functionalities and characteristics of future-proof production scheduling and control approaches are analysed in relation to the available contributions in the literature. In this perspective, Section 3 addresses the exploitation of data to support the definition and instantiation of uncertainty models, Section 4 provides a comprehensive overview of robust decision criteria in production scheduling and control, Section 5 addresses the integration with digital twin models of factories and related approaches. Additional considerations and analyses are provided in Section 6, addressing specific trends in the manufacturing industry with particular impact on production scheduling and control. Finally, a summary and an outlook for future research trends are provided in Section 7.

2. Future-proof production scheduling and control

Production planning and scheduling mechanisms refer to the coordinated processes used to plan and execute the flow of production activities in a manufacturing system. This entails deciding what has to be produced, when, and how it should be carried out, ensuring that produced goods are delivered on time and production resources, such as machinery and human workers, are optimally utilised.

Production planning and scheduling follow a hierarchical decision structure, typically divided into three levels: strategic, tactical, and operational. At the strategic level, long-term decisions are made, such as facility location, capacity planning, and technology investments, which set the foundation for production capabilities. The tactical level focuses on medium-term planning, including aggregate production planning, material requirements planning (MRP), and workforce management, ensuring efficient resource allocation within the strategic constraints. At this stage, resources and their capabilities are treated at an aggregate level. These details, and their impact on decisions, are managed at the operational level, addressing scheduling, lot sizing, and execution within a short-term horizon [61].

The production of goods in a factory is driven by an *order*, i.e., a request to produce something. This request is issued at the tactical decision level and can be driven by a customer request, or internally generated according to specific policies for inventory management. An order usually contains the request to have a certain amount of parts, in other words, products. A *part* has a specific design, production process, and bill of materials (i.e. list of raw materials, components, sub-assemblies, and the quantities needed to produce a part). A *part type* identifies a class of products sharing the same design, bill of materials, and process plan. As an order could provide the request for multiple part types, these requests are commonly structured in jobs. A *job* is a specific unit of work representing the production of parts in a given quantity. Thus, an *order* typically aggregates multiple jobs to be scheduled and executed. The production process for a part type is described through a *process plan*, i.e., a sequence of operations (or process steps or tasks) to produce a part (of a specific part type). An *operation* is an indivisible portion of a process, described in terms of input part(s) and/or component(s), output part(s), tools and resources needed (operators, machines, tools, fixtures, etc.), processing time, and precedence relations with other operations. A *resource* is an asset (e.g. machine, human operator, tools, fixture) needed to execute one or more operations of a job. As the number and availability of resources are limited, jobs to be processed usually have to wait. This waiting happens in a *buffer*, i.e., an element or area used to host parts, possibly work-in-progress.

Thus, the execution of a job can usually be decomposed into a set of operations, each of which is the smallest piece of work that is convenient to consider. Multiple operations, structured according to a process plan and the associated requirements for resources, define what is needed to produce a part.

The focus of this work is on production scheduling and the related control mechanisms, making decisions on when and where to process the jobs using the available production resources. These decisions are defined according to the following nomenclature that will be used in the next sections:

- *sequence:* a permutation of jobs or the order in which jobs are to be processed on a given machine or system.
- *schedule:* a prescription of the start and finish of the processing of jobs on machines.
- *scheduling policy:* a policy prescribes an appropriate action for any state the system may be in. Referring to scheduling and sequencing, given the state of the system, they provide a rule by which to make decisions on the next job to be processed. Scheduling policies are specifically relevant in stochastic scheduling since, in deterministic cases, they reduce to simple sequencing and/or scheduling rules.
- *assignment:* decision on the resources to process a job.
- *routing:* sequence of resources to be visited.
- *(manufacturing) system:* a set of resources (machines) processing jobs, arranged according to a specific scheme, e.g., single machine, parallel machines, flow shop, job shop, open shop, etc. [69].

Scheduling problems are typically formulated as optimisation problems with specific objective functions and constraints that reflect the goals and limitations. Constraints represent the rules and limitations that must be respected during scheduling. These can include machine availability, job precedence relations, resource/workforce capacities and limitations, due dates, and production-specific requirements like setup times or batching restrictions.

Objective functions define the performance criteria to be optimised and can vary depending on the context. Common objectives in production scheduling include minimising the makespan (total completion time), minimising the tardiness or earliness of jobs, maximising resource utilisation, minimising production costs, or reducing energy consumption. In multi-objective scheduling problems, several objectives might be optimised simultaneously, often requiring trade-offs. An extensive classification and characterisation framework for scheduling problems based on the addressed set of machines, the considered constraints, and the objective function to be pursued has been established and consolidated for scheduling problems [47,69].

Constraints and objective functions drive the characteristics of the solution obtained. Thus, properly designed objective functions can drive the generation of schedules embedding a certain degree of robustness and/or stability (see Section 4. Alternatively, constraints can be defined to take into consideration the uncertainty affecting the variables defining the problem (see Section 3) or to pursue the mitigation of extreme scenarios or the stability of the schedule (see Section 4). As in most constrained optimisation problems, the interplay between objective functions and constraints determines the complexity of the scheduling problem [109], influencing the feasibility of algorithms and methods used for its solution (see Section 2.5).

2.1. Production scheduling and control matching the evolution and characteristics of manufacturing systems

The evolution of modern manufacturing systems is characterised by a significant increase in complexity and a higher degree of automation, which have transformed traditional production lines into interconnected, intelligent networks of production units. With the proliferation of sensors and smart devices, data is continuously generated and captured at every stage of the manufacturing process on an unprecedented scale. This wealth of data holds immense potential that should be harnessed to optimise production efficiency, improve product quality and reduce operational costs.

In addition, the need to deal with high variability has become increasingly important. As market dynamics change rapidly, manufacturing systems must cope with high variability in processes and materials, influenced by supply chain fluctuations, resource availability, and technological upgrades. To address this, manufacturers use flexible and robust production systems that swiftly adapt to changes. This flexibility includes adopting modular equipment, agile production methods, employees trained to manage and operate a wide range of processes and equipment, alternative processes, etc. Embracing such adaptability requires production scheduling and control approaches capable of operating while considering the constantly changing state of the system.

Consequently, production scheduling and control approaches can no longer rely on predefined static criteria. On the contrary, decisions must be made, considering the current state of the manufacturing system and external factors, and they must be aligned with future events and constraints. This has led to adopting model-based approaches [166], i.e., approaches leveraging a system model to predict its future behaviour based on specific decisions and, consequently, identify the best ones. This cyber-physical approach has been gradually incorporating data and ultimately further enhanced by the increasing availability of digital twins in factories [171,227]. A digital twin is a virtual replica of a physical manufacturing system that mirrors its operations in real-time and is driven by data and analytics. By leveraging these virtual models, decision-makers can predict and assess the impact of production scheduling and control decisions in different scenarios before implementing them in the real factory [171,230]. This predictive capability is invaluable for optimising production flows. Furthermore, digital twins can utilise the constantly updated data from the real factory to continuously update and improve the models used to control and support decisions.

Production scheduling and control approaches that provide the following functionalities are essential to match the characteristics of modern manufacturing systems (see Figure 1).

- **Data-driven**. As large volumes of data are generated and collected in manufacturing systems, it is essential to leverage them to support production scheduling and control decisions. Future-proof scheduling must incorporate data analytics to make informed decisions based on data. This includes updating parameters supporting decisions, exploiting data for anomaly detection and predictive analytics, and triggering the need to take or modify production scheduling and control decisions.
- **Digital Twin based**. Incorporate advanced decision support systems capable of leveraging 'daydreaming' or 'what-if' analyses, utilising the knowledge and models embedded in digital twins to predict and assess different scenarios and outcomes.
- **Adaptive**. As the variety of influences affecting manufacturing systems increases, production scheduling and control approaches must be able to adapt to the variability of products and processes. They must be flexible and able to recalibrate quickly to accommodate variability and changes in production requirements and the state of the system.

2.2. Production scheduling and control facing uncertainty and variability to support robust decisions

Despite the possibility of continuously updating decisions, the capacity to develop production schedules and control policies that can withstand future uncertainty is paramount. In fact, besides deciding what to produce, when and how, production schedules and control policies are also critical to the transparency and visibility of what is happening in a factory. Thus, while the capability exists to update decisions, doing so continuously may not always be advantageous. Frequent alterations to schedules and policies can lead to unrest that spreads through the factory, disrupting workflows and affecting the nearest processes and downstream activities. For these reasons, establishing a well-thought-out baseline schedule that can absorb minor deviations without constant adjustments is often more beneficial [242]. This provides a stable operation framework and supports mutual visibility and synchronisation within the production environment. This emphasises the importance of a balanced approach to scheduling and control, where adjustments are made thoughtfully and only when the benefits outweigh the costs of implementing changes and the associated impact.

The capability to manage future uncertainties is grounded in the ability to model them to the best extent possible, given the information available and the general predictability of internal and external events. To this end, the data collected in manufacturing systems presents a remarkable opportunity to derive sophisticated models for uncertainty for various phenomena, both external and internal, such as equipment failures, demand fluctuations, or delivery delays. Depending on the availability, accuracy and granularity of the data, a whole spectrum of uncertainty models can be developed. This spectrum ranges from creating scenarios and using probabilistic and stochastic models to integrating fuzzy logic and neural networks, tailored to the specific characteristics of the data. Leveraging machine learning and statistical analyses allows uncertainty models to be dynamically refined and improved through continuous updates and improvements [171,195].

Nevertheless, uncertainty models alone do not provide complete support for decision-making, especially in complex and complicated environments such as factories, which are governed by constraints and complex behaviours. In addition to predicting future events and

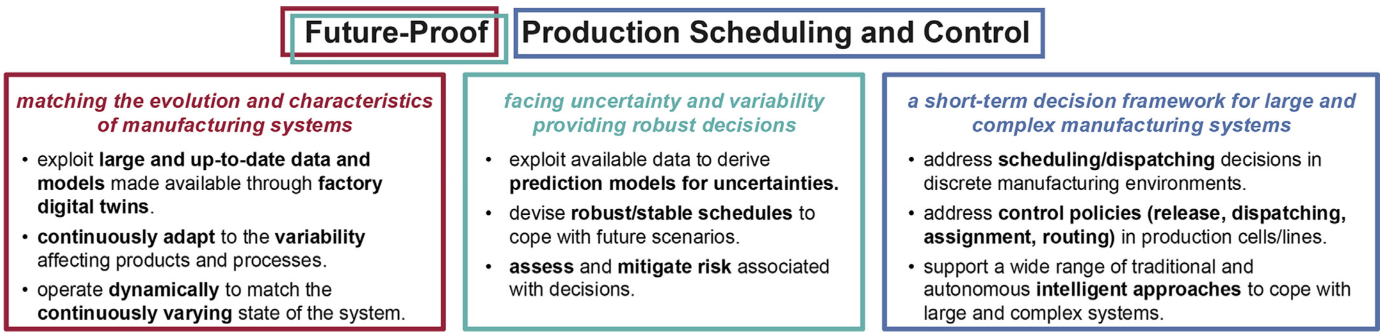

Fig. 1. Characteristics of future-proof production scheduling and control approaches.

outcomes, assessing their impact and magnitude is crucial. This underscores the need to incorporate the concept and evaluation of risks into the decision-making process. This involves not only identifying potential events, but also assessing the significance of these possible outcomes and their capacity to disrupt operations within a factory.

This approach involves considering less likely scenarios that, despite their rarity, could lead to severe consequences. The aim is to balance the likelihood of various events and their potential impacts, particularly to assess their capacity to cause significant disturbances. Adopting this risk-aware strategy ensures that scheduling and control decisions safeguard the execution of production activities against infrequent but potentially high-impact events. Ultimately, this emphasises the need for robust scheduling and control approaches that can absorb and mitigate the effects of unforeseen disruptions. Such approaches are vital to maintaining the system's effectiveness and reliability amidst uncertainty and ensuring its stability and performance are not compromised.

By harnessing uncertainty models to forecast future outcomes and utilising the flexibility and adaptability inherent in modern manufacturing systems, alongside the insights provided by digital twins of factories and their embedded models and data, these approaches can develop production schedules and control policies that are both adaptable and stable. They are designed to absorb disruptions without constant recalibration while maintaining the desired production performance levels.

Rather than relying on a single strategy for robustness, a thorough analysis and assessment of the risks enables the adoption of a broader and more diversified range of approaches. These may include establishing time or resource buffers, diversifying assignments to equipment and routing paths, and strategically delaying or advancing operations. At the same time, the choice of strategy-whether proactive, reactive, or a hybrid proactive-reactive approach-should be tailored to the specific characteristics of the production system in question and the particular uncertainty model.

Therefore, the following requirements for production scheduling and control approaches are defined (see Figure 1).

- **Uncertainty models**. Exploit available production data to derive prediction models for uncertainties supporting decisions.
- **Risk-based**. Identify and assess risks associated with uncertain events by modelling their impact on the operations in the production system.
- **Robust/stable**. Devise robust/stable schedules by mitigating risks associated with decisions and pursuing diverse strategies.

2.3. Production scheduling and control as a short-term decision framework for large and complex manufacturing systems

Short-term decision-making usually covers tactical actions and adjustments made within a relatively short period of a few days to a few weeks. Adopting advanced automation technologies also means that many short-term decisions are directly shaped by, or even delegated to, the control policies that govern the behaviour of these pieces of equipment. These systems, embedding pre-set algorithms and real-time data analytics, manage a wide range of operations, from orchestrating the flow of materials to optimising production processes and adapting to immediate operational changes. As a result, automated control policies become an important aspect to consider when making short-term decisions [99,144].

Furthermore, various decision-making approaches can support scheduling and control decisions. Algorithms ranging from classical optimisation to autonomous agents and machine learning are examined to provide a comprehensive overview of the evolving landscape of production scheduling and control in modern manufacturing systems.

From this perspective, this work will cover (see Figure 1):

- **Scheduling and control**. The focus will be on both production scheduling and control policies such as release, dispatching, assignment, and routing, which dictate the decision-making process in automated manufacturing lines and cells.
- **Short-term decisions**. It will cover short-term decision-making over a time horizon ranging from a few days to weeks.
- **Algorithm-agnostic**. No constraints are imposed on the class of algorithms included in the analysis, including agent-based systems and artificial intelligence [167].

2.4. A framework for future-proof production scheduling and control

Based on the requirements and scope defined in the previous sections, an analysis and classification of production scheduling and control approaches will be conducted to identify those that match the defined requirements and specifications summarised in Figure 1. Incorporating these requirements into scheduling and control approaches ensures that manufacturing systems are equipped for current demands and prepared for future challenges and innovations, enabling them to operate efficiently despite the complexity and uncertainties of modern manufacturing systems and adapt to the evolving operating scenarios.

The framework in Figure 2 will be used to structure the analysis and classification of these approaches with a particular focus on the following elements and functionalities.

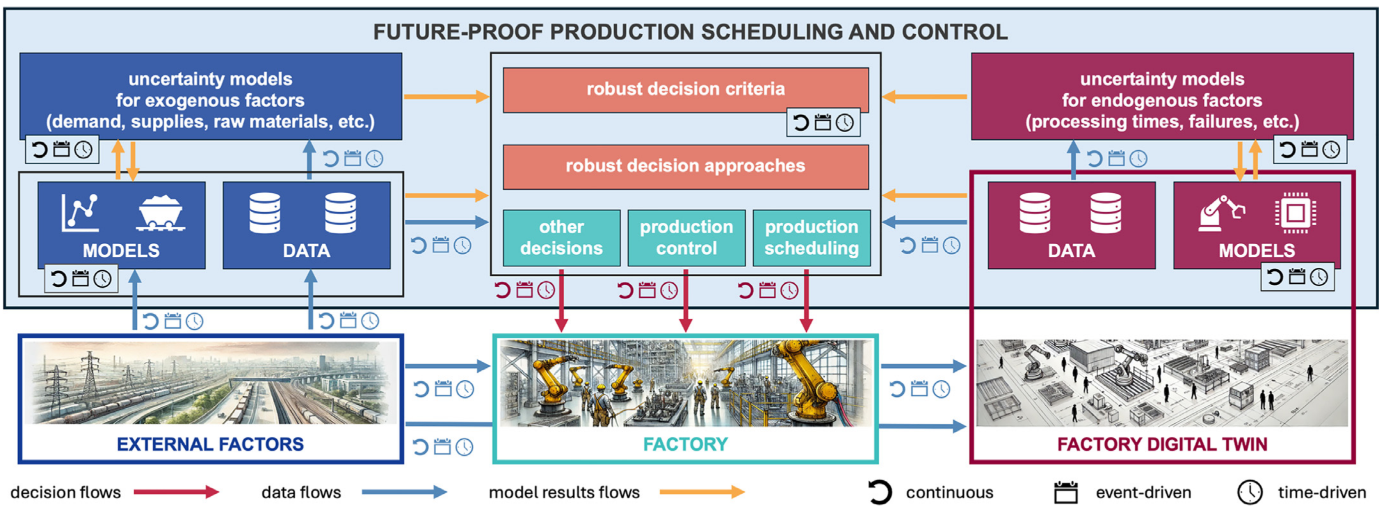

Fig. 2. Future-proof production scheduling and control framework.

A *digital twin* of a factory is an essential component to support production scheduling and control [227]. It acts as a container for factory data and embeds models of the factory behaviour to assess the benefits and impacts of different decisions, and propagate them to the real factory. These models range from analytical ones to classical performance evaluation (e.g., analytical models, discrete event simulation models) and artificial intelligence (AI), with machine learning (ML) in particular.

The capability to model and understand the uncertainties affecting the factories to be managed entails the need for *uncertainty models* of both endogenous and exogenous factors, e.g., processing times, availability of resources and related failures, supplier delivery times, etc. These will provide models for the uncertainty affecting scheduling variables (e.g., probabilistic distributions for processing times), characterise the responses of the system to internal end external disturbances (e.g., assessing risk measures associated to the outcome of decisions), and support the monitoring of the factory (e.g., through anomaly detection).

Pursuing robustness entails protecting scheduling and control decisions against the impact of uncertain events. Different classes of manufacturing systems and the way they operate may require different types of protection. *Robust decision criteria* will be covered, ranging from those aimed at protecting factories from the need to modify decisions already made to cases where changing decisions is not an issue if doing so could bring clear benefits. Furthermore, alternative indicators will be considered based on the uncertainty model available, from traditional statistics (e.g., mean and variance) to worst-case mitigation and risk-related ones.

While pursuing robustness, different strategies can be used to identify the right decision and when and how to modify it. Several classes of *decision approaches and paradigms* to support the optimal selection of scheduling and control decisions will be covered.

Production scheduling and control are primarily supported by data. As described in Figure 2, data is generated during the operation of the factory and ideally stored in the digital twin of the factory. This flow is operated according to various possible mechanisms and triggers. One option is a continuous update, so that the digital twin of the factory is continuously aligned to its real counterpart. Alternatively, the update can be time-based (e.g., every minute or hour) or triggered by the occurrence of specific events related to the factory (e.g., a product is completed) or the data (e.g., a given number of data updates are waiting to be operated). The data in the digital twin can be used to define uncertainty models for endogenous factors. In this case, the data flow can also be operated according to the three schemes described. Data originating from external factors, e.g., the planning of future deliveries from suppliers or the forecasted prices of raw materials, must also be considered. Some of this data propagates to the factory and, consequently, are stored in the digital twin. Alternatively, external data repositories will be available for storing them (top-left part of Figure 2) and support the definition of uncertainty models for exogenous factors. Data also supports decision-making approaches, as production scheduling and control often consider the current state of the system.

Furthermore, as models may support decisions, they can also be updated if the behaviour of the factory or external factors changes or if the data changes significantly. This is presented in Figure 2 for the different models considered, i.e., covering the factory and its components, external factors, uncertainty, and robust criteria and decision approaches. The models can also be updated according to different patterns, e.g., on a regular basis, when specific changes occur, or continuously to match the updated pattern of the associated data. As the goal of production scheduling and control is to support decisions to be implemented in the factory, this is modelled by the red arrows in Figure 2. Similar to the data flows and updates, these decisions can be enforced continuously, or regularly or triggered by specific events.

2.5. Complexity of scheduling problems

Scheduling problems are characterised by significant computational complexity, often classified as NP-hard, indicating that the effort to determine an optimal solution increases more than polynomially with the problem size [66]. This complexity stems from various factors, including the number of jobs, machines, and resources involved, and the presence of additional constraints such as sequence-dependent setup times, precedence relations, release and due dates [23,109]. Different problem variants, such as job-shop, flow-shop, and flexible scheduling, exhibit varying degrees of complexity [24]. The combinatorial nature of scheduling problems renders exact methods computationally feasible only for relatively small instances, while larger, more complex cases require approximation techniques to achieve practical and efficient outcomes. As most scheduling problems with real-world sizes are already NP-hard, their extension to consider uncertainty almost always necessitates using heuristic, metaheuristic, and machine learning-based methods and models to obtain near-optimal solutions within reasonable computational times.

3. Data-driven uncertainty models for production scheduling and control

A large variety of stochastic factors influence manufacturing systems. This is particularly noticeable when human workers are involved in the process, resulting in varying processing times [100]. Additionally, stochastic variability may occur due to the fluctuating availability of raw materials or resources. As a result, disturbances in the production process appear, and developed schedules might not even be feasible anymore [132]. To address this issue, numerous research projects have been conducted in recent years focusing on scheduling problems under uncertainty by providing methods for integrating varying processing times or due dates into production control models [291].

To classify uncertain scheduling approaches, tools for modelling uncertain factors can be applied [260]. Different characterisations of these methods exist. A more frequent differentiation is made between stochastic scheduling, fuzzy scheduling, and robust scheduling [261,291], which focuses on scheduling and the applied methods. Thus, this categorisation based on the applied methods is insufficient for future-proof production scheduling and control. It omits the connection between the method used and the available data. Therefore, this paper proposes a more detailed classification regarding data-driven uncertainty models for production scheduling and control. As shown in Figure 3, it consists of the three layers of available data, processing data and modelling uncertainty and is independent of the applied methods.

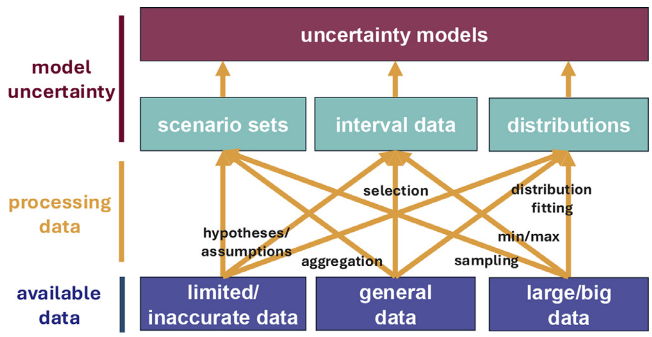

Fig. 3. Data-driven uncertainty models for production scheduling and control.

The basis here is provided by the existing data and described by the first layer. Based on specific data availability, different methods can be used to process the data and prepare it for the production scheduling and control model. This process is the foundation of the second level. At last, the uncertainty existing in the data is integrated into the model. The choice of a specific method is based on the two previous levels. In the following sections, each layer is explained in more detail.

3.1. Available data

Referring to Figure 3, the bottom level of the categorisation scheme focuses on the availability and type of data, which form the foundation for modelling uncertainty. This is fundamental as the scope and detail of available information are crucial for constructing rich and accurate models for uncertainty.

Although the trend towards Industry 4.0 and IoT has been pushing for collecting, storing and exploiting data in manufacturing systems, the availability of structured, updated and reliable data is a common issue in manufacturing companies [103]. In these cases, labelled as *limited data availability*, standard scheduling-related variables, e.g., processing times, delivery times, etc., are assigned ideal or standard values and/or are updated upon periodic assessments and reviews [68,297].

When structured approaches exist for monitoring factories, more meaningful amounts of data are collected and made available for analysis. This is referred to as *general data availability*, which can be considered the general case for modern factories. Historical records for relevant scheduling-related variables are available in this situation, possibly enriched and fused with estimates and/or constraints provided by managers and/or technicians (e.g., minimum and maximum values, mode, etc.) [38].

Finally, recent advancements in information technologies and their application to manufacturing have led to collecting, structuring, and storing vast amounts of data from numerous sources through various sensors, tools and methods, labelled as *large/big data availability* [297].

3.2. Modeling uncertainty

In contrast, different classes of models exist to represent and structure information and assumptions on uncertainty.

The selection of an appropriate method depends on many reasons, first of all, the type and amount of data available, as described in the previous section, but also on matching the characteristics and requirements of production scheduling approaches to be used.

A simple and well-established approach for modelling uncertainty is the definition of scenarios. Using scenarios is a common method for conducting what-if analyses to assess situations that have not yet occurred. Leveraging uncertainty models based on scenarios is an extremely common approach in scheduling, especially for those approaches based on simulation [298]. Scenario sets can be generated through assumptions, aggregations, or samples.

In cases where only limited data are available, the definition of scenarios is usually the only possible approach. As described in Section 3.1, possible observable values of relevant scheduling-related variables can be obtained through periodic reviews of the available data, or based on hypotheses and assumptions [106]. Additionally, missing data or further relevant inputs can be based on hypotheses and assumptions.

If general data is available, one standard processing method is through aggregation, i.e., using discrete scenarios to represent ranges of values for non-deterministic variables, e.g., processing times [67,260]. Scenarios can be obtained through sampling approaches, e.g., Monte Carlo sampling methods [216], quantisation-based approaches [79,242], quasi-Monte Carlo sampling [159], and quadrature rules based on sparse grids [37].

A more structured model for uncertainty is the definition of interval data. This is typically used when the available data are insufficient to support the definition of a probabilistic distribution [76]. Still, it is possible to establish a lower and upper bound to form an interval of possible values [132]. Both general and big data can serve as the basis for developing intervals through a selection process, i.e., choosing individual data points to represent an interval or min/max estimation. These intervals can then be leveraged in scheduling approaches to support both the definition of extreme cases [107], or to evaluate the obtained solutions against the possible variability of the input parameters [222,279]. Uncertainty models based on intervals can also be derived in the case of limited data availability, but this entails the explicit formulation of hypotheses and assumptions, typically by experts [106].

Finally, probabilistic distributions can be used to represent uncertainty, thus providing possible values for scheduling-related variables and the associated occurrence probability. To derive a probabilistic distribution from data, at least general data availability is needed. In the case of general data availability, a distribution can be obtained through imputation, i.e., leveraging available data, together with specific assumptions, e.g., using triangular distributions based on minimum, maximum and mode values [137,191]. Alternatively, if enough data is available, a distribution fitting method can be used. Numerous examples in the literature incorporate distributions in uncertainty models [26,239].

In the cases of large/big data availability, the selection of the proper model for uncertainty is driven by the requirements of the scheduling and control approach to be used or by constraints on computational complexity [26].

Besides the simple modelling of single variables, modelling uncertainty in complex systems entails the formalisation of constraints and links among the involved variables, together with incorporating the time variables, as factories are dynamically evolving environments. This requires defining complex uncertainty models incorporating these features but preserving the stochastic properties of the original phenomena and/or distributions [202]. The definition of this class of complex uncertainty model can be accomplished through the definition of structured scenarios [78] and the associated scenario reduction techniques [51], complex stochastic models integrating risk measures and decision making under risk [190], models based on interconnected distributions and decision models also exploiting Markov chains and phase-type distributions [8,43,123,201]. Addressing correlation and autocorrelation is also crucial for realistic shop floor data modelling, as they impact simulation accuracy and predictions. Properly incorporating these dependencies ensures models accurately reflect real-world manufacturing system behaviour [7].

3.3. Machine learning for uncertainty modelling and prediction

As scarcity of data is one of the main concerns in building uncertainty models, data-driven models are an alternative option. Among these, AI/ML techniques, characterised by their ability to learn a function that maps inputs to outputs based on example input-output pairs, can be effectively used in uncertainty modelling and prediction, even with minimal data [64,102,297]. Besides ML approaches, knowledge graphs and ontologies are also relevant tools to model and structure uncertainty [149], as well as process mining to create the data necessary for modelling uncertainty from simple log files [153]. Supervised learning methods can be used to estimate the value of uncertain variables, such as processing times and lead times, also for complex manufacturing systems [30,39], by leveraging data and information on the state of the system under study[19], but also related to the availability of raw parts and components [30], and the characteristics of the products [169], providing an alternative solution to the data-driven uncertaity models based on scenarios, interval data or distributions (see Figure 3).

Machine learning approaches are also exploited to predict the occurrence of specific events in the system, e.g., related to the availability of material and resources, triggering constraints for production scheduling and control [154,208] Unsupervised learning can also be used to reconstruct data or behaviour and map from observations to a surrogate model based on scenario sets, interval data, distributions (see Figure 3), or alternative patterns [91]. In this perspective, ML-based approaches can also integrate and complement traditional techniques, e.g., discrete event simulation [189], or queuing networks [74]

Adopting supervised learning in modelling manufacturing timings represents an essential shift from reliance on static, rule-based algorithms to more dynamic, data-driven methods. It allows for the incorporation of real-time data inputs and the continuous refinement of prediction models as new data becomes available, thereby enhancing prediction accuracy and responsiveness to changes [73,262]. A significant focus of this class of research is on the semiconductor manufacturing industry, where cycle time and lead time prediction are critical for efficient production planning [117,158]. Thus, exploring approaches in AI/ML is a promising option to improve uncertainty modelling to support production scheduling and control.

4. Robust decision approaches and criteria for production scheduling and control

The following section derives robust decision criteria based on the general definition and interrelation between robustness and relevant similar yet not identical terms in Section 4.1. Then, Section 4.3 derives future-proof robust production scheduling, while Section 4.4 introduces robust production control.

4.1. Robustness, stability, resilience

Robustness typically refers to the quality of being strong, stable, and capable of withstanding or adapting to challenges and adverse conditions without significant degradation in performance.

Concerning production scheduling and control, the concept of robustness must be adequately detailed. Production scheduling and control primarily decide what has to be produced/processed and when. Thus, two classes of results must be considered when referring to a schedule and its capability to deliver what has been promised. The first is achieving what is decided, i.e., that a production activity has been started and possibly reached its end, to complete the scheduled product/processes through the expected effort. The second one is the timing associated with this achievement, usually in terms of starting and finishing time. Thus, the term *stability* or *solution robustness* refers to the insensitivity of a plan or a schedule, in terms of the start times of activities, in response to changes in the input data or constraints [81]. On the contrary, the term *quality robustness* is used when referring to the insensitivity of the schedule performance in terms of the objective function, e.g., the total or maximum tardiness [81]. Pursuing the same reasoning, the two points of view on robustness are also referred to as *robustness in the solution space* and *robustness in the objective function space*, respectively [211]. The term *resilience* is also used to refer to this class of properties, as the capacity to recover quickly from difficulties, and to avoid major disruptions. This term is more general as it relates to the resilience of the manufacturing system itself, or even for the whole supply chain. It also encompasses the notion of reacting actively to control the effects of difficulties. For this reason, the robustness concepts described above are considered more accurate with respect to scheduling and will be used in the following sections.

Robustness can be pursued in two main directions. The first involves incorporating a robustness criterion as the objective function, with various such criteria being proposed, which are discussed and analysed in detail in Section 4.2. Additionally, since robustness aims at managing uncertainty, strategies which can be employed are explored in Section 4.3.

4.2. Robust decision criteria

An essential element in pursuing robust scheduling and control decisions is the criteria driving the selection of decisions. As robustness addresses the need to cope with uncertainty affecting the decisions to be taken, these criteria should be able to catch how this uncertainty impacts plans and results. A straightforward approach is reasoning in terms of expectation over possible outcomes, rather than only evaluating a single possibility. This leads to simple decision criteria aimed at optimising the expected value of an objective function. This entails the need to define a statistical model for the uncertainty that could be leveraged to assess how this impacts the objective function and its probabilistic description and, consequently, support the estimation of the values for a decision criterion (see Section 4.2.1). Nevertheless, as it is not always possible, alternative criteria are available, leveraging a less structured model for the data, e.g., domains for variables, minimum and maximum values, and a reduced or sampled set of scenarios (see Section 4.2.2).

4.2.1. Statistical robust decision criteria

Robust decision criteria can be based on a statistical model for the scheduling problem to be addressed.

According to the notation used in [200], a scheduling problem can be modelled through a vector of decision variables $\mathbf{x}$ defining the schedule and a vector of random variables $\mathbf{y}$ governed by a probability measure P on Y that is independent of x. For example, $\mathbf{x}$ could define the positions of the jobs in the sequence or can be used to identify precedence relations between the jobs. The values of $\mathbf{x}$ and $\mathbf{y}$ univocally determine the value of a performance indicator z defined in Eq. 1.

$$z = f(x, y) \quad (1)$$

For a given set of values for x, the resulting cumulative distribution function for z is defined in Eq. 2.

$$\Psi(x, \zeta) = P(f(x, y) \leq \zeta) \quad (2)$$

Thus, while pursuing the optimisation of a given objective function, Equation 2 can calculate its distribution for a given schedule $\mathbf{x}$.

The availability of the distribution of a scheduling objective function, as defined in Eq. 2, paves the way to a wide range of indicators and approaches, also involving the concept of risk, derived from different research fields, first of all, the financial area. These indicators are based on the reasoning that, given an objective function to be optimised, specific values are less acceptable than others. An example is provided in Figure 4, representing the distribution associated with a general objective function that has to be minimised. In this perspective, looking for the best schedules clearly aims at deciding the values in $\mathbf{x}$ that result in a distribution Ψ whose values are as much shifted towards the left. Statistics like the mean, variance, quantiles, as well as specific measures of risk associated with Ψ are aimed at supporting this and will be further described in the following subsections.

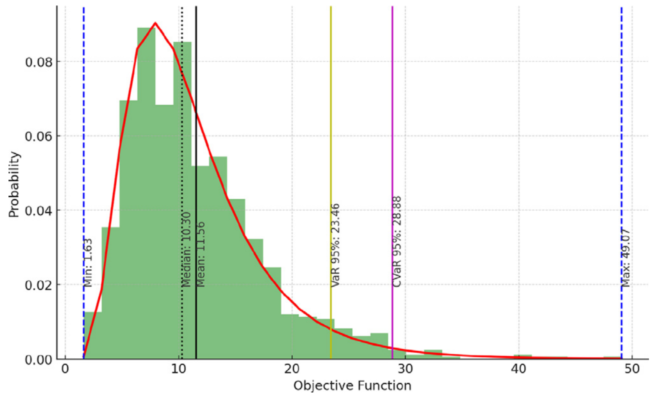

Fig. 4. Example of the distribution of an objective function associated with a schedule and a subset of related statistics.

Nevertheless, it must be noted that the estimation of Ψ is a computationally expensive task unless specific and strong hypotheses are enforced on the distributions in $\mathbf{y}$.

Mean-Variance and other trade-offs Managing uncertainty requires a comprehensive approach that balances expected benefits or performance with potential negative outcomes due to unexpected events. As a result, decision-making under uncertainty often involves evaluating tradeoffs. In this context, a mean-variance tradeoff is commonly used to navigate uncertainty, where the mean represents the expected performance or benefit. At the same time, the variance quantifies the uncertainty associated with those expectations. Mean-variance tradeoff approaches, as well as other classes of similar trade-offs, are common in many scientific areas addressing risk, as in portfolio management, logistics, transport, and energy [111]. Still, results are less popular in scheduling, as the estimation of the variance of a scheduling objective function quite often entails considerable computational effort [142].

Value-at-Risk and Conditional-Value-at-Risk Considering the distribution of an objective function as defined in Equation 2, a possible indicator for robustness is the use of well-established risk measures.

As defined in [11] and using the notation in [200], the *value-at-risk* α (VaR_α) of the value of the performance indicator z associated with the decision x can be defined through Eq. 3.

$$\zeta_\alpha(x) = min\{\zeta|\Psi(x,\zeta)\geq\alpha\} \tag{3}$$

If the random variables in y are discrete, $z = f(x,y)$ is concentrated in finitely many points, and $\Psi(x,\cdot)$ is a step function. This applies to scenario-based models. In such cases, the definition of the VaR in Eq. 3 must be rephrased [200].

Given x, if we assume that the different possible values of $z_k = f(x, y)$ can be ordered as $z_i < z_2 < \cdots < z_N$ so that $P(z = z_k) = p_k$ and k_α is an integer value matching the conditions in Eq. 4, then the VaR_α can be defined as in Eq. 5.

$$\sum_{k=1}^{k_\alpha} p_k \geq \alpha \geq \sum_{k=1}^{k_\alpha - 1} p_k \tag{4}$$

$$\zeta_\alpha(x) = z_{k_\alpha} \tag{5}$$

The VaR optimisation has seen increasing popularity for scheduling problems [161]. Various contributions have been proposed addressing single machine scheduling problems [12,246], flow shops [123–125,247], job shops [275]

Nevertheless, as a risk measure, the VaR has some issues and drawbacks [223], e.g., it does not provide any guarantee on the values exceeding the VaR, and a reduction of the VaR may lead to stretching the tail exceeding VaR with a possible increase of the maximum values.

To overcome these limitations, the conditional-value-at-risk (CVaR) has been proposed in the financial literature, also referred to as the expected shortfall. Thus, the α-tail distribution of $z = f(x,y)$ can be defined according to Eq. 6 and, consequently, the CVaR-α ($\phi_\alpha(x)$) calculated as the expected value of $\Psi_\alpha(x,\zeta)$ using Eq. 7.

$$\Psi_\alpha(x,\zeta) = \begin{cases} 0 & \text{for}\,\zeta < \zeta_\alpha(x) \\ [\Psi(x,\zeta) - \alpha]/[1-\alpha] & \text{for}\,\zeta \geq \zeta_\alpha(x) \end{cases} \tag{6}$$

$$\phi_\alpha(x) = \mathbb{E}[\Psi_\alpha] \tag{7}$$

Similarly to the case of the VaR, if the random variables in y are discrete, $z = f(x,y)$ is concentrated in finitely many points and $\Psi(x,\cdot)$ is a step function. Then, considering Eq. 4, the CVaR in Eq. (7) is rephrased [200] as shown in Eq. 8.

$$\phi_\alpha(x) = \frac{1}{1-\alpha}\left[\left(\sum_{k=1}^{k_\alpha} p_k - \alpha\right) z_{k_\alpha} + \sum_{k=k_\alpha+1}^{N} p_k z_k\right] \tag{8}$$

The definitions in Equations (7) and (8) do not provide any hint of how to compute this measure. Still, an equivalent linear programming problem has been demonstrated to serve to optimise Eq. (8) in scenario-based models [200].

The use of CVaR to support robust scheduling approaches is reasonably limited due to the intrinsic computational difficulty [60,160]. Nevertheless, approaches leveraging this class of risk measures have been proposed for various scheduling problems, ranging from single machine [36] to more complex ones [25,57,206,241].

Other criteria As robustness could also be focused on the stability of the devised schedule, similar performance measures have also been defined to capture the difference between the baseline schedule and the one executed, e.g., the expected difference or its variance [203]. Furthermore, due to the difficulty of estimating the VaR and, consequently, the CVaR, various risk measures have been used to assess the risk associated with a schedule in relation to various sources of uncertainty. These measures could be conventional ones applied to scheduling, but also specifically designed to match the characteristics of a particular scheduling problem [274]

4.2.2. Non-statistical robust decision criteria

Modelling uncertain variables in probabilistic terms often presents significant challenges, particularly where precise data and clear patterns are elusive. Probabilistic models typically rely on specific distribution assumptions and require accurate data for parameter estimation, which could create significant constraints and barriers when dealing with real manufacturing data. These challenges arise from various factors, including incomplete data, dynamic system behaviours, and the inherent unpredictability of certain variables. Alternative criteria can be used, based on the concept of interval probability [71], not assigning probability distributions to variables, but simply defining ranges or intervals within which the possible values lie.

Worst-case optimisation Minimax or maximin approaches minimise the worst possible (maximum or minimum) values of the objective function associated with scheduling decisions [36]. By emphasising the worst-case scenario, these techniques ensure that, even under the least favourable circumstances, the schedule is still feasible or maintains a level of performance that is as close as possible to the optimal. Focusing attention on worst-case scenarios surely reduces the computational complexity of the optimisation problem [224], but it is a conservative approach that could lead to overcautious decisions. Nevertheless, this class of approaches is beneficial in highly variable and unpredictable manufacturing environments, where the cost of major disruptions can far outweigh the benefits of maximising efficiency in the best-case scenario [44,286].

Regret-based criteria A different approach to mitigating the impact of uncertainty is operated through the concept of *regret*. In decision theory, regret measures the disparity between the outcome of a chosen action and the best possible outcome that could have been achieved with perfect foresight. In other words, it is a way to measure the lost opportunities and can be used to evaluate decisions under uncertainty.

Thus, the regret of a decision is calculated by comparing its result with the result of the optimal decision that could have been made if the future outcome of uncertain events had been known. This concept can be adopted in scheduling problems by minimising the expected regret (although this would entail assessing the associated probability) or, much more often, the maximum regret [114,132].

Other criteria Non-statistical robust decision criteria also exist for stability robustness, addressing the difference between the baseline and actual schedules using worst-case analyses, or regret-based performance [203].

4.3. Robust production scheduling strategies

Production scheduling approaches can be broadly classified into two categories based on their decision-making processes. The first category involves approaches that define and implement a baseline schedule as planned, usually referred to as scheduling approaches. Within this class, some approaches are typically more rigid, as they do not allow these decisions to be modified. In return for this rigidity, this ensures consistent visibility of the activities to be executed within the scheduling horizon. Different approaches exist that also define a baseline schedule but retain the possibility of modifying it while it is executed if necessary. This balances predictability and adaptability, allowing for adjustments in response to changes or unforeseen events [81]. The second category consists of dynamic scheduling approaches, where decisions are made dynamically as soon as a decision must be taken, e.g. when the processing of a job is completed, and continuously adapted as needed. Within these categories, scheduling approaches can be deterministic or consider the uncertainty affecting the production environment in which they operate. A summary of these classes of approaches is provided in Table 1, specifying whether they generate a baseline schedule and/or modify it, the capability of considering uncertainty and the

Table 1
Production scheduling approaches.

	Baseline Schedule	Incorporate Uncertainty	Modify Baseline Schedule	optimisation Criterion
Deterministic Scheduling	YES	NO	NO	OF
Online Scheduling	NO	NO	NO	OF
Reactive Scheduling	YES	NO	YES	OF/Stability
Proactive Scheduling	YES	YES	NO	Robustness/Stability
Proactive-Reactive Scheduling	YES	YES	YES	Robustness/Stability
Dynamic Scheduling	NO	YES	NO	Robustness

optimisation pursued. Concerning the last one, as introduced in Section 2, most scheduling approaches aim to optimise a specific objective function (*OF*). As robustness is taken into account, the same criterion is optimised (minimising or maximising), pursuing quality robustness (see Section 4.1). Differently, some approaches consider stability, alone or with the objective function. Hence, they aim to minimise an objective function considering deviations with respect to the baseline schedule [80].

4.3.1. Production scheduling approaches devising a baseline schedule

Planning and scheduling approaches, in general, are aimed at defining a baseline schedule, consisting of the planned start and finish time of the jobs to be scheduled on the considered resources [47]. It serves important functions within a company: it supports allocating resources to activities and jobs, plans future events, triggers subsequent processes in the manufacturing plant, makes commitments to due dates and deliveries to the customers, provides managers with visibility on future activities, and supports the estimation of performance measures and indicators. Thus, the baseline also plays a supporting role in the planning of external activities (e.g., material procurement and supply, maintenance) and is relevant to both the inbound and outbound supply chains.

Proactive scheduling

Proactive approaches involve planning, sequencing, and organising tasks in advance to optimise efficiency and productivity. Rather than reacting to events as they occur, proactive scheduling attempts to anticipate their potential negative impact by sequencing tasks and allocating them to resources according to the available knowledge about uncertainty [80]. Proactive approaches address robustness through time- or resource-buffers to absorb the impact of uncertain events [104,256]

Reactive scheduling

Reactive scheduling approaches involve adjusting plans and allocating tasks to resources in response to unexpected events or changes. Instead of adhering to a predetermined schedule, reactive scheduling allows flexibility in adapting to unforeseen circumstances. It requires the ability to assess the status of the system quickly, assess the proper modifications to be implemented, and make decisions on the fly. While proactive scheduling aims to prevent issues by mitigating their possible impact in advance, reactive scheduling focuses on effectively dealing with them as they arise [80,203].

Proactive-Reactive scheduling Proactive-reactive approaches combine elements of both proactive and reactive strategies. The idea is to have a well-planned baseline schedule in place (proactive), but also to be agile and adaptable to handle unexpected events or disruptions (reactive). This hybrid approach aims to balance the stability of proactive planning and the flexibility of reactive responses [47]. In a proactive-reactive approach, the baseline schedule, generated through a proactive approach, indicates what to do, how, and when. However, when unforeseen events occur, the proactive-reactive approaches allow for deciding whether and how the baseline schedule has to be modified. This flexibility allows for a more dynamic response to changes without altogether abandoning the benefits of proactive planning [104]. This class of approaches have been investigated for machine scheduling [119,131,197] and project scheduling problems [97,251].

Scheduling nervousness Scheduling nervousness refers to the degree of instability in a schedule caused by frequent and significant changes, as in the case of the adoption of reactive or proactive-reactive approaches. Multiple strategies can be adopted to mitigate nervousness. Frozen zones or time fencing can be used, where the scheduling horizon is divided into frozen, slushy, and liquid zones, with limited or no schedule changes permitted in the frozen zone to ensure short-term stability. Similarly, rolling horizon scheduling can reduce nervousness by updating schedules regularly rather than continuously reacting to minor changes [236].

A change impact analysis can be employed to evaluate the downstream effects of adjustments and, based on this, decide whether to implement the modified schedule. Finally, the use of robust scheduling criteria, aiming at mitigating the impact of uncertain events, can help create schedules that can absorb variability and require less frequent adjustments.

4.3.2. Production scheduling approaches not devising a baseline schedule

Online scheduling approaches involve adjusting and optimising schedules based on the current state of the system, in other words, based on changing conditions within and outside of the system. As new events occur, e.g., the completion of a job, the arrival of a new job to be put into production, a failure affecting the resources, etc., a new decision is made. Thus, online scheduling allows for making decisions when needed, as soon as new information becomes available or circumstances change. Dispatching policies fall in this class, i.e., rules or strategies used to select the next tasks or jobs to be executed on a set of resources and when. These policies are crucial in optimising the efficiency and performance of factories in near real-time [62,135,209,210,212,213]. Furthermore, they are also relevant in the design, configuration and tuning of automatic equipment [45].

Focusing on problems considering uncertainty, these are labelled as dynamic scheduling problems, whose solutions are generally referred to as *scheduling policies* [163] or *scheduling strategies* [86]. Additionally, fast search algorithms, often tree-based, are regularly applied to solve these scheduling problems dynamically, for instance, with a Monte Carlo tree search [82]. A scheduling policy dynamically makes scheduling decisions (sub-policies) upon specific events (e.g., the completion time of a job) or at specific times.

The robustness of dynamic scheduling approaches is somewhat different to analyse. Theoretical results demonstrate the dominance of a class of policies compared to others or that an optimal policy must be searched within a given class [86,164]. Alternatively, robustness can be assessed ex-post, testing the candidate policies in different scenarios and selecting the ones that perform better [45,87].

4.3.3. Machine learning for production scheduling

Machine learning in general, and reinforcement learning (RL) in particular, are gaining significant interest in production scheduling [266]. The dynamic and complex nature of these domains necessitates the implementation of agile learning algorithms capable of managing uncertainty and adapting to changing circumstances in real-time. Various recent research studies have been diving into the deployment of RL, particularly deep RL, in scheduling and control systems within the manufacturing industry, demonstrating the crucial advantages offered by these advanced techniques while acknowledging the gap between simulated results and real-world applications.

Applications of RL to manufacturing have been comprehensively reviewed [185], identifying diverse application areas, such as scheduling, dispatching, and execution. Key benefits have been identified, i.e., the superiority in handling dynamic and complex environments

[110], and the capability to outperform traditional heuristics [31] but, despite promising results in simulations, real-world applications and validations of these techniques are still limited. A significant concern is possibly missing explainability and the consequent lack of trust [102] for these approaches. AI and ML have also been applied to achieve optimal and near-optimal scheduling solutions [266] and to assess processing and lead times, failures, and delivery times for materials and components [29,55,266] for different problems (single machine, flow shop, job shop), job and machine characteristics, objectives, and benchmark methods [95].

Actor-critic models with deep RL and a duelling double Deep Q-network have been used for job shop scheduling problems facing unforeseen events like machine breakdowns and material shortages [75,118]. This class of approaches leverages reinforcement learning to adaptively select heuristic rules, obtaining near-optimal solutions for large-scale problems. Deep RL approaches provide large degrees of flexibility and can be adapted to different classes of complex scheduling problems [183,263]. Weighted Q-learning and dual Q-learning algorithms have been applied in job shop scheduling [101,271], handling two levels of learning: The top level focuses on local targets to minimise machine idleness and balance machine loads, while the bottom level targets global objectives to optimise the overall scheduling problem. Q-learning has also been integrated with hard c-means clustering to generalise to a broader range of scenarios [13].

Deep RL has also been integrated with models of the dynamic evolution of the manufacturing system, e.g., discrete-event simulation [217] or Petri nets [85] to implement dynamic scheduling. Integrating neural network models with agent-based architectures and decentralised decisions has also shown good performance for complex scheduling problems, such as those stemming from the semiconductor industry [186].

4.4. Robust production control policies

When considering automated equipment, such as production cells or lines, it is important to recognise that their automation control systems fundamentally govern their operation. Decisions regarding what to produce, when to produce it, and on which equipment are not made through external scheduling approaches. Instead, they are determined by control policies that are embedded within the control systems of the equipment [126]. Consequently, it becomes crucial to focus on these classes of policies:

1. *Release control policies* deciding if a job (part) is allowed to enter a manufacturing system or a portion of it (e.g., a shop, a manufacturing cell, a subset of machines, etc.). They can also be integrated with dispatching policies to decide which job (part) will be processed.
2. *Routing control policies* deciding the path that materials, components, or products should take through a production process.

Similarly to dynamic scheduling, the robustness of control policies can be assessed theoretically or ex-post, i.e., by testing policies on a range of scenarios and cases to identify the ones that perform better [45,87,115]. In the analysis of the performance of control policies, the term *stability* is used to address both the feasibility of the decisions taken, and the robustness to disturbances in terms of performance. Approaches based on real-time data analysis to adapt to varying conditions have also been proposed for release control policies [96,225]

Machine learning for production control policies

Machine learning technologies also offer a promising approach to tackle production control, providing complex decision-making and real-time adaptability while managing uncertainty. Q-learning techniques have been proposed for dispatching in single machine [270], parallel machines [293], job shops [214], and more complex manufacturing environments [116,219,272]. Also, for production control policies, ML-based algorithms and models have been integrated with different classes of models. In particular, Markov decision processes (MDP) [133,221] have been used to structure a complex set of nested decisions while an RL agent is used to take them (e.g., selecting a dispatching rule) based on the state of the system, or hybrid Monte Carlo tree search [82]. This class of approaches has been proposed for complex system architecture (e.g., flexible job shops [133], semi-automated systems [182]), as well as for different manufacturing sectors, e.g., semiconductor [221] and automotive [182].

5. Factory digital twin to support production scheduling and control

The concept of the digital twin (DT) has evolved into a transformative paradigm that redefines the interface between the physical and digital worlds. A DT is a virtual representation of a physical entity characterised by bidirectional information flow mirroring the real-world state and its digital counterpart, enabling real-time monitoring and simulation, offering predictive capabilities and analysis while supporting operational decision-making that guides actions in the physical system [181].

Implementing DT in manufacturing systems gives rise to the concept of the *factory digital twin* [227,228,301]. This concept extends beyond a simple digital replica of the physical infrastructure of the factory, offering a comprehensive representation encompassing machines, processes, and behavioural models, both at the individual component level and for the factory as a whole, including human interactions [226]. These models encompass a wide spectrum, from multiphysics models representing the physical properties of materials, processes, and equipment, to models that simulate the dynamic interactions of processes, workflows, and machine operations within the system. The latter can be based on different technologies, with analytical tools and discrete event simulation being among the most commonly employed methods [227,231]. Based on the results obtained from these models, the best set of decisions can be identified and implemented in the real factory through a feedback mechanism provided by the DT. Leveraging data and models, the factory digital twin is a powerful tool for optimising production, enhancing efficiency, and forecasting potential disruptions [129,227,231].

5.1. Data and knowledge formalisation

Two of the fundamental components of the DT of a factory are data and knowledge. These require defining a data model, i.e., a conceptual framework that describes how data is structured, stored, and manipulated.

Ontologies allow knowledge to be represented in a machine-readable form [218], providing formal definitions, integrating heterogeneous data, and supporting modularity and data distribution. Ontology-based frameworks have been proposed for production planning and control [218] and scheduling [162], as well as approaches based on knowledge graphs [127,149,294,295]. Ontologies designed to structure knowledge related to scheduling and control policies have been addressed [126,232,245] using a modular OWL ontology [258] that integrates various heterogeneous data models, such as the Semantic Sensor Network (SSN) and the Sensor Observation Sample and Actuator (SOSA) ontologies promoted by the World Wide Web Consortium (W3C) [88,93], Industry Foundation Classes [188], and Unified Modeling Language (UML) Statecharts [21].

The structuring of data through ontologies not only provides a standardised framework for defining concepts, relationships, and properties within a domain but also facilitates the implementation of higher-level approaches for representing and organising knowledge, such as knowledge graphs (KGs) [278]. By establishing a shared vocabulary and a formal schema, ontologies enable knowledge graphs to integrate diverse data sources, linking entities and relationships into a unified, interconnected representation [304]. This structured foundation allows knowledge graphs to leverage semantic relationships, enabling advanced reasoning, inference, and querying capabilities that can support a wide range of functions in a factory [58].

5.2. Approximate and surrogate models, ML-based models

Modelling the complexity of modern manufacturing systems and processes involves a significant level of computational demand, both in their formulation, implementation, and execution. Surrogate models act as stand-ins for detailed simulations, enabling faster analysis and optimisation by capturing essential system behaviours without requiring exhaustive computations. Approximate and surrogate models have been thus exploited to mitigate the computational complexity of complex scheduling problems, supporting the definition of near-optimal schedules [15,105], but also to support the modelling of complex manufacturing systems to assess the impact of short-term decisions [171,193,229] ML-based models have emerged within this class of models due to their ability to approximate intricate phenomena with reduced computational effort. ML techniques, such as neural networks, support vector machines, and Gaussian processes, have been proposed and investigated to tackle complex industrial problems in general and for scheduling [195,264].

5.3. Interlinking digital twins with production scheduling and control

The primary function of the DT of a factory in supporting production scheduling and control is to provide reliable, continuously updated information for many factory objects. A key capability of the DT is its ability to mirror the state of the real factory in real time through continuous monitoring and data collection. Although industrial information and communication technology (ICT) systems can collect and provide extensive information about the current state of production [103], the DT of a factory offers a more structured and comprehensive source of data, integrating and organizing data from various sources into a unified, semantically enriched representation of the factory [227].

Production scheduling and control approaches that require access to updated data about the state of the system can take advantage of this structured information to enable more efficient data analysis, better-informed decision-making, and more effective control of production processes. These approaches, e.g., online, reactive, proactive-reactive and dynamic scheduling (see Section 4.3) can be referred to as *digital twin-based* as they use dynamic input data, i.e., updated information about the actual state of the system provided by the DT [126].

Furthermore, some of the approaches addressed in Section 4 base decisions on predicting future variable values and events by estimating future states of the system to be controlled. In some cases, these estimations are performed using simple functions and calculations. However, for large and complex manufacturing systems, or when the widespread impact of uncertainty factors has to be estimated, the capabilities offered by a factory digital twin and its associated models (See Figure 5), are likely the most effective tools to support such approaches [230]. Production scheduling and control approaches with these characteristics can be referred to as *digital twin-enhanced* [126], as they can take advantage of the digital twin and, in particular, the embedded models describing the behaviour of the manufacturing system and the associated uncertainty.

5.3.1. Future states estimation and prediction

The DT can support the assessment of the impact of alternative decisions on the future performance of the plan/schedule (e.g., completion time, number of parts in a queue, etc.). This can be used for the identification of optimal or near-optimal production scheduling solutions, or control/dispatching rules [146,149,193,229,230]. Building on these prediction capabilities, schedule sensitivity can be estimated to enable preemptive mitigation strategies and robust scheduling frameworks for uncertain scenarios [172,285]. The practical value of these approaches is demonstrated in several real-world implementations where optimisation is combined with simulation [234,281,290], leveraging DT-enhanced approaches to conduct extensive evaluations before executing scheduling decisions.

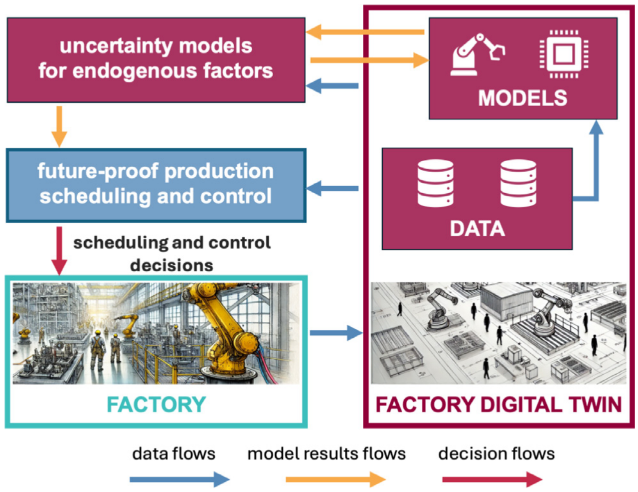

Fig. 5. Digital twin integration with scheduling and control policies.

5.3.2. Advanced analytics

Furthermore, advanced analytics capabilities can enhance decision-making through anomaly detection, system health monitoring, and knowledge-based reasoning, enabling proactive responses to potential issues.

While simulation provides the foundation, advanced analytics further expand scheduling capabilities through DTs. Integrating multi-level production process monitoring enables anomaly detection [174,245,268], possibly combined with real-time scheduling optimisation [113]. This monitoring capability, enhanced by future state prediction [151,296,300], enables intelligent scheduler training through deep reinforcement learning [277]. The resulting adaptive scheduling approaches excel in environments with the dynamic behaviour of both systems and human operators [155].

The power of advanced analytics is most evident in modern scheduling systems that simultaneously consider multiple factors such as machine failure and maintenance [283], tool wear, product quality [198], energy consumption [70], complex routings and transportations [56,267].

5.3.3. Operational enhancements

Finally, the DT of a factory can provide real-time adaptation mechanisms to improve system efficiency. Online, reactive and dynamic scheduling approaches can be integrated with the DT of a factory to enable production optimisation, also considering uncertainty [255,269]. This real-time capability becomes particularly important in environments involving humans to cope with unpredictable behaviour [3]. Support for the implementation of distributed computation to cope with computational complexity can also be supported by a factory DT (see Section 2.5) [265,289]. Also, decentralised decision mechanisms can benefit from the functionalities of a factory DT to support the dynamic handling of local disturbances [130,282]. To effectively implement distributed scheduling and control in digital twin-enhanced environments, multi-agent systems (MAS) can be employed to form hierarchical frameworks that combine both local autonomy and global coordination. [49,177,273] While individual agents maintain local autonomy for real-time scheduling decisions, digital twins provide a centralised learning and optimisation environment that can guide agent behaviour towards global objectives [136,176,238,257,280]. The DT, therefore, serves as both a simulation environment for policy development and a facilitator for balancing local responsiveness with system-wide performance objectives [171].

6. Emerging trends for production scheduling and control

The design of future-proof production scheduling and control approaches aims to guarantee effectiveness and reliability in the face of future changes affecting the operating environment, the driving criteria and the evolution of external factors and constraints. Emerging trends are expected to impact and influence the planning and control of production in factories. First, the integration of production scheduling and control in the hierarchy of decisions in a factory is addressed in Section 6.1, then optimisation objectives and constraints related to sustainability and human-machine interactions are considered in Section 6.2 and 6.3. Finally, specific characteristics and operating conditions are taken into consideration, i.e., complex and high-automation systems (Section 2.5), matrix production (Section 6.6), and remanufacturing (Section 6.7).

6.1. Integrated process planning, production planning and scheduling

Production and process planning decisions are traditionally addressed separately from production scheduling (see Section 2, although a clear interlink exists among them. Production planning defines quantities, delivery dates and lot-sizes, while process planning determines the operations, precedence constraints, technologies, and resources for producing part types. The integration of process planning and production scheduling can be leveraged to increase efficiency and utilisation of resources [253], especially when alternative process plans can be used, i.e., different technologies, process parameters and resources to achieve the same result [179]. As the complexity of this integrated problem exponentially increases in the number of alternatives, decomposition and heuristic techniques can be used [16,128]. Approaches focusing on DT-based functionalities leverage near-real-time process models in dynamic scheduling, to estimate the variance of relevant variables [290].

Integrated process planning and scheduling is relevant for many discrete manufacturing processes, ranging from traditional machining [179], to assembly operations [94,240], but also for emerging processes like additive manufacturing.

In additive manufacturing, process planning and scheduling are inherently coupled through nesting and resource allocation decisions. Nesting refers to creating jobs by batching individual parts in a single manufacturing process on the same machine [180,302]. Batching is based on process and geometric similarities, also involving optimising build sequences, defined through process planning [41]. Batching and the consequent process planning decisions must consider geometric dependencies, material compatibility, and heat dissipation. Then, production scheduling aims to minimise idle time and enhance overall production efficiency through resource allocation and sequencing[46]. Additionally, scheduling strategies are crucial to cope with machine failures, and material availability, ensuring that the production schedule remains feasible and effective [48]. To pursue these objectives, pre- and post-processing steps, such as quality control and assembly, have to be considered [48]. As additive manufacturing especially supports rapid prototyping, managing rush orders is also a relevant aspect [112], especially with the emergence of digital platforms [237].

An integration with production planning can address infeasibility at the scheduling phase due to the impossibility of meeting due dates given the constraints imposed by the process plans, resources and materials. Project scheduling approaches have been proposed, capable of considering precedence relations among aggregate activities, already at the production planning phases [5,139,170]. Robust approaches based on project scheduling have also been suggested to provide better integration with material requirement planning [4,138,140,194,233], order management and due date definition [10,28], management of variable availability of resources [140,241,243].

Integrated production planning and scheduling can also address the batching and splitting of orders to define jobs to be scheduled [143]. Scheduling approaches have been proposed addressing the *interstage batch delivery* problem [1], integrating scheduling and batching decisions [40]. In this class of problems, optimisation criteria usually consider the point of view of the customers receiving the delivery of product batches after the production phase, e.g., minimising a function of the completion times of the batches [175,259]. A related scheduling problem is *lot streaming*, where a lot is split into sub-lots to allow process overlapping and reduce the makespan [54,205]. Also, in this case, integrating multiple decision problems entails a considerable increase in computational complexity [192]. For these reasons, approaches in this area matching the future-proof requirement are extremely limited, leveraging heuristics [184] or theoretical results to support mitigating the impact of extreme scenarios [244].

6.2. Sustainability in production scheduling and control

Production scheduling is increasingly influenced by Environmental, Social, and Governance (ESG) considerations [204], reflecting the growing importance of sustainable and ethical manufacturing practices. From an environmental perspective, scheduling must account for energy efficiency, waste reduction, and carbon footprint minimisation [215], captured by the absolute perspective of sustainability, i.e., the critical boundaries of finite natural resources and the limited capacity of the environment to absorb pollution [77].

Based on the wide adoption of industrial information systems and factory DT architectures (see Section 5), manufacturing companies are increasingly adopting the latest advanced technologies in measuring, analyzing, and quantifying the environmental impacts of the processes, to leverage these quantified measures in production scheduling [287].

Future-proof production scheduling approaches in this context aim at finding the best balance between the energy supply and demand trade-offs, minimising use fluctuation by proper job sequencing and utilising the potential of renewable energy sources when and where possible [238,288]. Besides this, sustainability-aware production scheduling considers the complex relations between the dynamic pricing of renewable energy and the consumption by manufacturing resources, especially in low-volume production scenarios, profiling resource utilisation by even switching off unused ones. This goes beyond simple energy reasoning, addressing sustainability aspects to a greater extent, contributing to extending asset life, thus lowering the overall carbon footprint [2].

Recent reviews have investigated sustainability-related impacts on scheduling with a broad perspective, including different architectures of production systems, classes of scheduling problems, objectives, KPIs, and solution approaches [63]. Beyond the environment-related benefits, integrating sustainability considerations into production scheduling can also contribute to the reputation of a company, meet regulatory requirements, and contribute to long-term cost savings [204].

Concerning solution approaches and modelling hypotheses, sustainability-related scheduling problems can benefit from conventional scheduling approaches with modified constraints, objectives and related data sources [27]. Time windows associated with energy prices, supply and availability can be captured with constraint programming approaches, where energy is often modelled as a cumulative resource with a corresponding availability profile [187]. However, to consider the volatility of energy prices and the disturbances affecting the production environment, combined and multi-level scheduling approaches are needed that can adjust or re-schedule production, triggered by changes in key environmental parameters [187,215].

Besides purely mathematical optimisation approaches, several models combine forecasting and simulation techniques to address the overall complexity of the problems [148,220].

These approaches rely on a hybrid discrete-continuous simulation to capture the physical energy consumption behaviour and the discrete behaviour scheduling and control decisions in a factory. Thus, the local energy system optimisation is coordinated with overall global system management. As the complexity of scheduling is already NP-hard for many problems, heuristic approaches are often used to solve this class of problems in a reasonable time [22,50,220].

6.3. Scheduling human-machine collaborative environments

Modern manufacturing environments leverage advanced robotics to automate repetitive tasks and streamline production processes while integrating human operators for tasks that require creativity, problem-solving skills, and adaptability [145]. The deriving production scheduling problems thus address general scheduling and sequencing tasks with special, additional resource constraints and precedence relations, often combining assembly planning and task sequencing to match safety and ergonomics regulations, productivity targets, and thrive in high uncertainty circular manufacturing environments [52]. Workforce planning is also tightly related to scheduling in collaborative systems, as alternative process execution modes require different human labour extent [248].

Sequencing and allocating tasks to humans and machines must be operated, satisfying precedence constraints, capabilities and skills constraints, and soft factors such as fatigue. Future-proof scheduling approaches leverage predefined or in-situ-generated alternative process plans and decisions [35,285], incurring high computational complexity [178]. Thus, traditional solution approaches are often combined with numerical or event-based simulations [254], or simplified problem formulations [165]. The interaction between human operators and scheduling approaches is another crucial aspect of human-machine collaboration in factories, as it determines the scope of possible decisions and the level of human autonomy in production scheduling. Traditional systems create a single schedule to follow, typically after approval of the production control expert, so the human is a key part of the scheduling loop [42]. The rationale behind this is simply that one can never put all domain constraints and factory-specific local knowledge into a model (or only at the price of enormous computational complexity). In this setting, rescheduling is triggered event-based, periodically, or in a hybrid combination of these [83], to minimise the deviation from the original schedule [59]. In advanced and future-scheduler systems, scenario-driven decision-making, and what-if capabilities of the scheduler system will be essential to address responsiveness and robustness criteria, typically employing prediction data analytics and/or simulation models [173,284,303].

6.4. Scheduling highly automated and complex systems

State-of-the-art industrial environments are characterised by high degrees of automation, leveraging fixed and mobile robots for material transportation, parts handling, and/or process execution [34]. This entails additional classes of constraints, where temporal and spatial synchronisation of equipment involves process planning and task scheduling decisions [249].

In flexible automation, adopting AGVs involves significant complexity in scheduling and control techniques, as the size of AGV fleets can exceed a magnitude of hundreds [33,72]. Scheduling AGVs involves considering transportation capacities, capability, and status of the system such that possible traffic jams and deadlock situations should be avoided [155].

Industry-scale task scheduling problems with AGV assignment constraints have been solved through combined Benders decomposition and heuristics [199]. Other approaches leverage prescriptive analytics, e.g., deep Q-networks [84], and multi-agent RL [136] for optimal real-time scheduling of AGV systems, selecting suitable dispatching rules and candidate AGVs in response to variable states of the system. Future-proof approaches also consider changes in production and automation, for instance, when the volume or mix of products changes, impacting the feasibility and effectiveness of automation rules in fleet sizing or dispatching logic. This triggers a review of fleet management and related allocation policies, to maintain synergy between control and execution of production and automation systems [72].

Scheduling with automation aspects is especially crucial in semiconductor manufacturing, where automation-related constraints and the high complexity of industrial facilities pose extremely challenging requirements to future-proof production scheduling and control approaches. In semiconductor manufacturing, production scheduling has to cope with high work-in-progress, long manufacturing lead times (in wafer fabrication, lead time is called cycle time), and many concurrent processes [90]. The front end (silicon wafer manufacturing) is operated in huge job shops, while the back end (chip assembly and packaging) facilities are often structured as flow shops. A typical wafer fab may include several thousand machines (tools) that perform hundreds or even thousands of repetitive steps on a single wafer to make the final structure layer by layer, leading to a re-entrant flow [250]. Furthermore, semiconductor manufacturing equipment has super-high (even nanometer) precision, which is associated with extremely high tool costs. Therefore, effective load balancing and job scheduling are important in achieving high machine utilisation [154].

Regarding the automation of these systems, both fixed conveyors and mobile robots (AGVs) are applied to reduce or even replace manual job transfers [151]. Continuous load and perfect utilisation of the machines is an unrealistic ultimate objective; however, even if machine scheduling and load were perfect, automation can only degrade and cannot positively contribute to machine utilisation [72]. To address the overall complexity, DT models and ML-based predictors are combined with optimisation models and search heuristics. Dynamic scheduling and AGV dispatching can be combined with automation by assigning lot transfer jobs to AGVs, and monitoring the status, position and traffic of the robot fleet and the process status. A prescriptive AGV fleet scheduling approach is illustrated in Figure 6, where transportation lead times, as a result of alternative AGV schedules, are predicted by an ML model (parameter predictor). The input variables of this model are the AGV fleet attributes (e.g., vehicle position) and the status of manufacturing jobs (states space denoted by X). The output estimates the task lead times (LT), enabling dynamic AGV scheduling, rescheduling and matching manufacturing constraints. Other relevant scheduling examples include RL [102], digital twin rollouts [151], and risk quantification for scheduling decisions [152]. From a future-oriented scheduling perspective, semiconductor manufacturing, where thousands of machines operate within a single system, presents a compelling opportunity for advancing digital twin and production scheduling research, particularly in the autonomous generation of digital twins using black-box models to minimise human intervention [18].

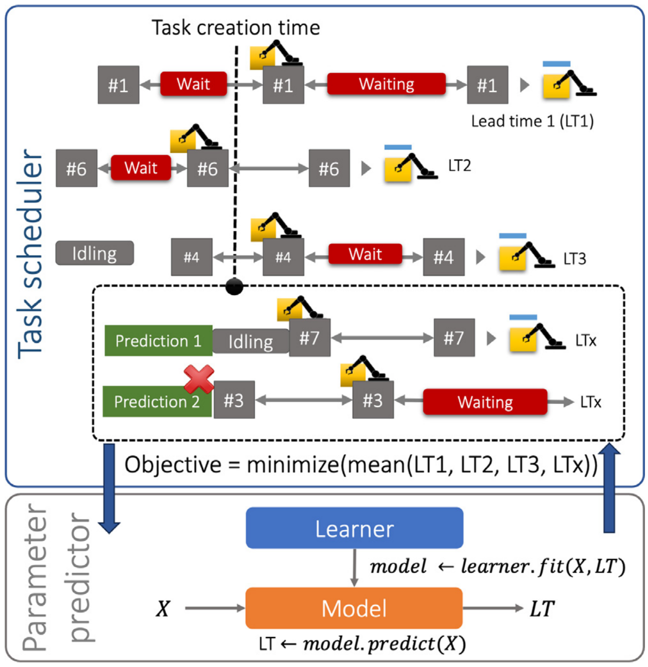

Fig. 6. Dynamic task scheduler with predictive AGV (grey squares) task lead times (LT) in semiconductor manufacturing.

6.5. Multi-agent systems for production scheduling and control

Multi-agent systems (MAS) in production planning and control involve decentralised, autonomous agents collaborating and negotiating to manage manufacturing processes dynamically [32]. Unlike traditional centralised or hierarchical approaches, MAS distribute decision-making across autonomous agents that interact and make decisions locally, allowing the system to respond dynamically to unexpected events such as machine breakdowns, supply delays, or shifting demand [32]. These characteristics are especially relevant for future-proof production scheduling and control approaches, enabling real-time responsiveness and adaptability to disturbances and integrations with data and models [176,299]. This decentralised coordination enhances flexibility and resilience in complex environments, but can lead to coordination complexity, communication overhead and stability of the decisions taken [196]. For these reasons, a larger emphasis on the protocols that govern information and decision exchange in multi-agentic systems is needed [196]. Economic model bidding systems are emerging where individual production agents interact based on price dynamics to maximise revenues [150]. Particularly relevant in current research is the application of smart contracts, which embed decision-making rules that are allocated dynamically, and often need to be verified to avoid malicious actors from taking advantage of such interactions [108]. MAS are particularly advantageous in complex, dynamic, and flexible manufacturing systems where high variability and frequent changes trigger a very large set of decisions to be rapidly taken, also considering the possibility to leverage AI/ML to support the reasoning of the agents [49,136,292]. MAS may, on the contrary, be less effective in highly repetitive, stable environments such as flow lines, where simpler, centralised control may be more suitable [257]. However, even in such environments, MAS may provide resilience benefits when unexpected disruptions occur [32].

6.6. Scheduling matrix production systems

Matrix production systems become increasingly popular in discrete manufacturing [207], breaking up the concept of rigid production lines into individual manufacturing cells, automatic or manual, that exhibit multiple process capabilities and no routing constraints [150]. Matrix production systems are thus characterised by a higher degree of flexibility, enabling the possibility of rescheduling, rerouting and reassigning jobs to resources in response to the occurrence of uncertain events [147,148,157].

This entails the need for more sophisticated production scheduling approaches to exploit these degrees of flexibility dynamically [20]. In contrast, further reasoning is required to manage these degrees of flexibility effectively. As discussed in Sections 4.2 and 4.3, both the criteria and strategies for robustness are based on the fact that corrective actions to mitigate the impact of previous decisions come with a cost. Therefore, making informed decisions that account for their impact is crucial. However, in matrix production systems, decisions are rarely irreversible due to the inherent flexibility of these systems, and the penalties for modifying decisions tend to be minimal.

As a result, the need for robust scheduling approaches (e.g., proactive-reactive) is less critical in such systems. Nonetheless, there remains a need for advanced scheduling techniques to determine when and if existing decisions should be altered, leveraging state-based control policy approaches [89], while also considering the importance of preserving the stability of schedules [150].

6.7. Scheduling re-manufacturing activities

Increasing attention is being devoted today to enhancing the sustainability of manufacturing processes by reducing the consumption of resources and critical materials, energy consumption, and environmental footprint while also reducing costs and increasing competitiveness in the global market [77,92,235]. Remanufacturing is the process of repairing or refurbishing a used product to restore its characteristics and functionalities, matching the original equipment manufacturer (OEM) specifications [235].

Scheduling remanufacturing activities presents a complex problem due to the inherent uncertainties and unique challenges associated with the characteristics of used products (core) and the associated remanufacturing process. Unlike traditional manufacturing, remanufacturing must contend with the unpredictable timing and quantity of returned products, the variable quality and condition of these products, and the complexities involved in disassembly and reassembly operations [123,235]. These factors introduce significant variability, complicating the scheduling process [121,123,168]. Due to the unpredictable and variable conditions of incoming parts, the associated remanufacturing process can vary in terms of the number and type of operations and their precedence relations, the associated processes and requirements [141], and processing times.

Furthermore, remanufacturing processes also entail the need to make operational decisions at the shop-floor level based on the progress of operations and their outcome, e.g., deciding upon the opportunity to operate reworks [125], or aborting the remanufacturing process based on technical feasibility and/or economic considerations. Robust and effective scheduling is crucial to optimise resource utilisation, minimise lead times, and meet customer demand cost-effectively [124]. Researchers have developed various models and approaches to addressing these challenges, including stochastic modelling [122], heuristic algorithms, and a wide range of optimisation techniques [156,276] and machine learning [98].

7. Summary and Outlook

Manufacturing systems are under an ever-increasing evolutionary process to reconcile the traditional trade-offs between economic efficiency and versatility in terms of the large variety and the ability to cope with great uncertainty. As a result, the mechanisms steering such increasingly complex factories, namely production scheduling and production control, need to be ready to match the characteristics and functionalities of manufacturing systems and cope with the described requirements for robustness and decision-making under uncertainty.

From this perspective, the traditional hierarchical structure of planning and scheduling, partitioning decisions both across time and within organisational levels, can introduce significant constraints, although providing a clear and standardised procedure framework. This particularly emerges in complex and rapidly evolving environments, where it may become necessary to revisit previous decisions, and adjust subsequent ones accordingly, to adapt to new conditions. Moreover, dynamically reconsidering decisions introduces significantly higher computational complexity, requiring advanced models and algorithms capable of real-time adjustments while maintaining overall system coherence. Robust methods, while providing solutions that account for uncertainty and variability, often require extensive computational resources, making them impractical for real-time decision-making or large-scale systems. As a result, more straightforward scheduling approaches are frequently adopted at the price of incurring suboptimal performance or unexpected disruptions.

In the medium term, the push to integrate multiple decision problems will be a major challenge. While it can enhance effectiveness and efficiency, this integration also introduces significant challenges. One key drawback is the lack of a clear decision hierarchy, which can cause local infeasibilities to propagate upward, potentially leading to nervousness and inconsistencies across the entire planning, scheduling and control. This highlights the need for a carefully structured and more complex decision hierarchy, one that accounts for the sources of infeasibility, the extent of their impact, and the available degrees of freedom for adjustments.

At the same time, as automation in both equipment and decision-making systems advances, the role of human decision-making must be redefined. It is essential to equip humans in factories with the tools and competencies necessary to understand operations, the scope of their decision authority, and the potential impact of their choices. This empowerment is crucial for maintaining control over highly complex, automatically-controlled systems, whose behaviour may become too intricate to fully model or predict, and that could drift into unpredictable and uncontrollable scenarios, posing significant operational and safety risks. To address these challenges, future-proof approaches can be crucial by leveraging real-time data, uncertainty models, and factory digital twins to simulate, support, and validate decision strategies. However, the high computational complexity associated with integrated and complex decision-making approaches represents a significant long-term challenge to their widespread adoption in manufacturing systems.

A path forward is the use of model-based approaches, particularly those leveraging digital twin models of both the uncertainty and the behaviour of the manufacturing system. Digital twins enable more accurate representation and prediction of system dynamics, allowing for improved decision-making under uncertainty. However, selecting appropriate models considering factors such as dimensionality, complexity, and their specific capabilities remains a challenging task [171]. A promising direction to overcome these challenges is the development of approximate or surrogate models. These models simplify the representation of the manufacturing system while maintaining sufficient accuracy, allowing for faster computations and making them an attractive solution for real-time and large-scale scheduling problems.

Finally, scheduling and control are and will be significantly impacted by the emergence of artificial intelligence (AI) and machine learning (ML) as transformative tools, offering powerful predictive capabilities, such as estimating lead times, forecasting future events, and modelling the behaviour of highly complex systems[64]. AI/ML algorithms can analyse vast amounts of historical and real-time data, uncover patterns, and provide predictions that can help optimise operations and reduce downtime.

However, while AI and ML can enhance decision-making by generating insights from data, they do not always guarantee high accuracy. The inherent uncertainty in data-driven models must be considered, as their predictions are often based on statistical inferences and may not fully capture the nuances of complex manufacturing environments. To this aim, it is crucial to integrate them with traditional (analytical, simulation, etc.) or physics-informed machine learning models that can incorporate domain-specific understanding, such as the characteristics of products, production flows, and capability and performance of resources, which may not always be readily extractable from data alone. This class of hybrid models outlines a promising direction for future research and also the potential to implement a new generation of approaches for production scheduling and control.

CRediT authorship contribution statement

Marcello Urgo: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation. **Gisela Lanza:** Conceptualization, Methodology, Validation, Investigation. **Rok Vrabič:** Conceptualization, Methodology, Validation, Investigation. **Dávid Gyulai:** Conceptualization, Methodology, Software, Formal analysis, Validation, Investigation.

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