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SURVEY

Scheduling Under Uncertainty for Industry 4.0 and 5.0

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ABSTRACT This article provides a review about how uncertainties in increasingly complex production and supply chains should be addressed in scheduling tasks. Uncertainty management will be particularly important in Industry 5.0 solutions that will require the close integration of operators and technical systems. To prepare for these challenging developments, this work reviews the sources of uncertainty and the scheduling algorithms that deal with the different types of models developed to handle the uncertain nature of the elements and the environment of complex technological systems. The paper not only identifies the challenges, but also the main building blocks that can help to manage and reduce uncertainties based on the I4.0 and I5.0 solutions. We hope that this study will serve as a starting point for R&D projects and algorithm developments, which will be needed primarily in the field of multi-agent, multistage and inverse optimizations.

INDEX TERMS Scheduling, optimization, Industry 4.0, Industry 5.0, decision support.

I. INTRODUCTION

This article reviews the challenges of managing the different types and aspects of uncertainty in scheduling tasks to develop Industry 4.0 and Industry 5.0 solutions.

With the advent of new technologies brought about by Industry 4.0 [1], [2], the complexity of production systems continues to increase to ensure a high degree of adaptability [3], flexibility [4], reconfigurability [5], [6] and robustness against the increased level of uncertainty [7]. The challenges brought about by increased complexity are inherent in Industry 4.0 solutions [8]. The envisioned concept of Industry 5.0 carries the aims beyond efficiency and productivity by placing the worker at the center of the production process [9] and emphasizing sustainability [10]. Consequently, the complexity and uncertainty of the resultant system of systems further increase the difficulties concerning optimization and the scheduling of problems.

Thanks to the advent of new technologies of Industry 4.0, it is possible to handle these challenges. The importance of flexibility largely determines the ability of a system to deal effectively with a variety of uncertainties and their consequences [8].

Our aim is to overview the different types of uncertainties that can arise in the manufacturing industry and highlight what kind of Industry 4.0 solutions are available to address these uncertainties.

Although we recently provided an overview of how optimization algorithms should be developed according to the Industry 4.0 paradigm [11], but the detailed analysis of how scheduling algorithms should provide good solutions in line with Industry 4.0 principles, especially in handling the increased uncertainty, is missing. Our literature review concluded that the uncertainties inherent in Industry 4.0 and the opportunities arising from the concept have not yet been

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used to address the uncertainty issue. Our goal is to provide an overview of how uncertainty affects the solutions to the problems that occur in Industry 4.0 and to review the solution methods that play an important role in solving this problem area. Then, we present how to use these solution methods to achieve results that stand their ground in manufacturing and how they can be used to formulate long-term opportunities for future research.

The Industry 4.0 guiding principle did not initially focus on providing solutions to the ecological problems faced by production, but on boosting productivity, revenue growth, and competitiveness [12], as it built on the digital transformation and AI-driven technologies to increase the efficiency and flexibility of production systems [13]. Nowadays, digital transformation is also motivated by the necessity of production within environmental constraints in order to be geared towards sustainability.

The transformed industry will change the role of industry workers. Workers will be empowered in their industrial work and attracted to work in new high-tech environments [14]. The increased integration and complexity will require robust planning and scheduling solutions.

As a result of these trends, the Fifth Industrial Revolution builds on the pairing of humans and machines, so that man and machine work together wherever possible. Man contributes to productivity by providing the creativity needed to carry out tasks, while machines do the rest of the work. The implementation of Industry 5.0 consists of two visions [15]. One is 'human-robot co-working', where machines and humans work together. The other is the bioeconomy, where the clever use of biological resources for industrial purposes helps maintain a balance between economy, industry and ecology. The prerequisites for Industry 5.0 are the fulfillment of the objectives set out in Industry 4.0 in addition to the requirements to achieve the previously mentioned objectives [16], which mainly consist of the Data Interoperability of Networked Sensors, Multiscale Dynamic Modeling and Simulations: Digital Twins [17], Shop-floor Trackers, Virtual Training, Advances in Sensor Technologies and Machine Cognition [18], Intelligent Autonomous Systems and Deep Learning Methods [19].

The motivation of this work is to systematically explore scheduling algorithms that should be developed to handle uncertainty in human-centered and sustainability-oriented technological systems.

The major contribution of the paper is highlighted as follows:

- We have studied the nature and types of the scheduling problems and have highlighted that these optimization tasks significantly affect the efficiency of a manufacturing system.
- We have overviewed the uncertainties occurring in production systems and affecting the scheduling tasks.
- An Industry 4.0 focused review is presented about the scheduling algorithms from the last ten years which can handle uncertainties.
- The new requirements of Industry 5.0 are investigated according to how uncertainties should be handled to ensure sustainability and improve the working environment of the operators.
- We have summarized the challenges and have identified the most promising scheduling-related research directions.

The article is organized as follows: In Section II, a review is given of the scheduling problems and types of uncertainty related to complex production systems occurring in the Industry 4.0 and Industry 5.0 concepts as well as their impact on scheduling tasks. Section III reviews and presents in detail the scheduling solutions that address the issue of uncertainty and provides a good solution basis. Section IV takes a look at how the areas presented in the previous chapters appear in the complexity of the Industry 4.0 and 5.0 concepts, the challenges that need to be addressed, and the opportunities available to address them properly in order for the whole system to work effectively.

II. SCHEDULING PROBLEMS AND TYPES OF UNCERTAINTY

A. FORMALIZATION OF SCHEDULING PROBLEMS

Scheduling problems appear almost everywhere from the management of public transportation through CPU time allocation to the manufacturing industry. Although scheduling problems differ in terms of their characteristics, their aim is to assign resources and time intervals to all tasks. Different classifications of scheduling problems are found in the literature. A categorization of batch-scheduling plants based on 13 different parameters is presented in Fig. 1, which is mainly used by chemical production plants [20].

- Although the process topology describes the structure of manufacturing, which is sequential in most cases, recipes containing the mixture and splitting of operations (network topology) are present.
- The assignment of equipment can be fixed or variable, which means that only one piece of equipment or multiple pieces are available for each task, respectively.
- The pieces of equipment can be fully connected, i.e., materials can be transferred between pieces directly, but can also be partial, e.g., a pipe network between the pieces that are not connected directly to each other.
- Scheduling problems can be classified based on the storage policy of the intermediate material. The most common case is unlimited storage of the intermediate material, where storing materials between tasks is unrestricted. When intermediate materials are not stored, such materials can only be stored in the unit that produced them. Finite intermediate storage means that storage units, where materials can be stored, are available. The zero-wait policy means the intermediates must be used immediately after their production.
- The transfer of materials between units can occur instantaneously or over a period of time.

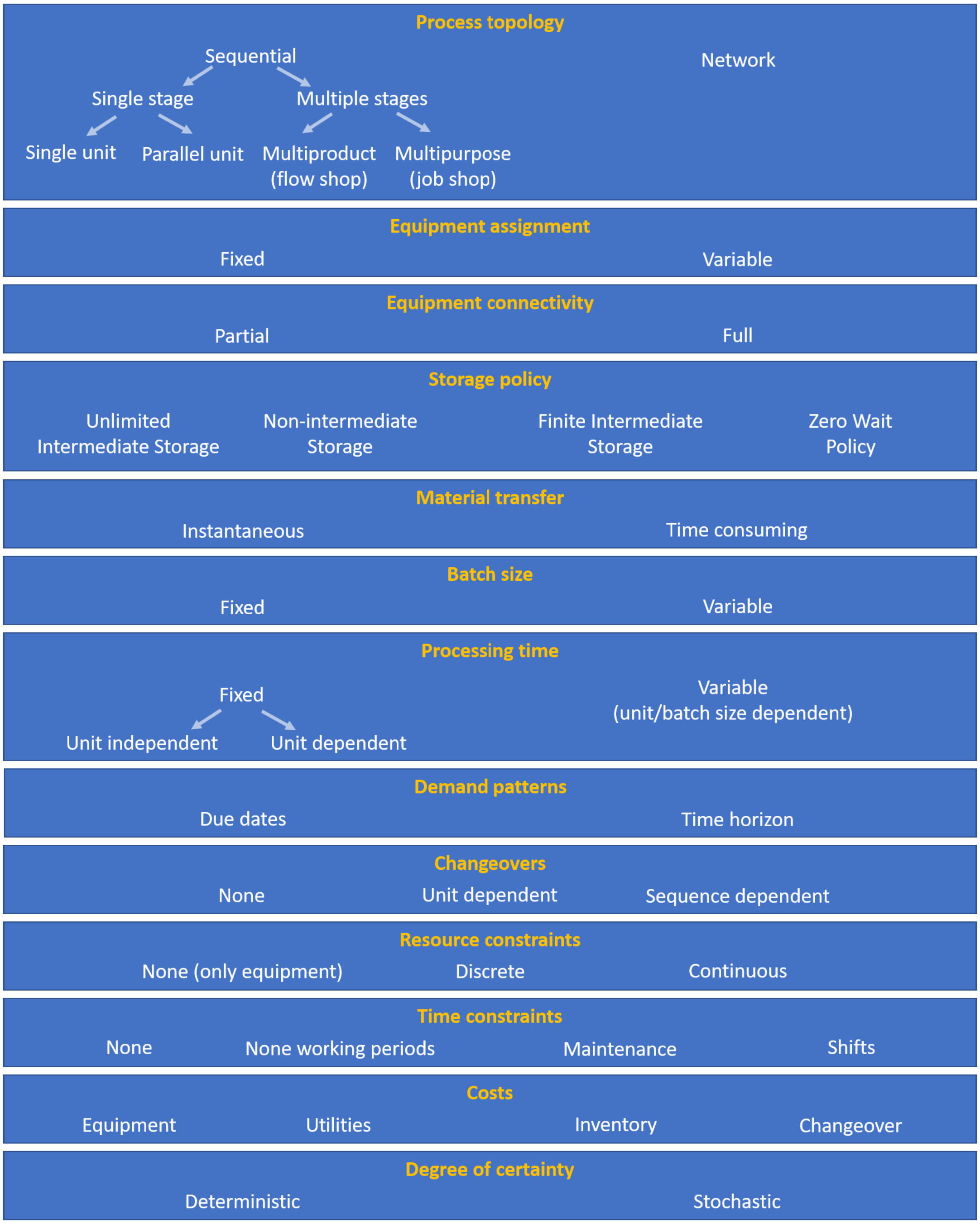


FIGURE 1. **Classification of the scheduling problems of batch plants [20].**

- The amount of material (batch size) can be fixed or it can be a decisive factor for a scheduling problem.
- The processing time of a task can be constant, or depend on both the unit used and the size of the batch.
- Each product may have deadlines by which the product must be finished or a time horizon can be given, during which all products must be finished.
- The units of equipment should be exchanged between the use of different materials. The time of such a changeover can be zero, vary for different units and depend on the order of materials.
- Even though a unit of equipment must be assigned to each task in order to perform the task, additional resources might be needed. These resources can be discrete (e.g. human resources) or continuous (e.g. water).
- A scheduling problem can be subject to some natural time constraints. Working hours or shifts can define time intervals for manufacturing and units being serviced are unavailable.

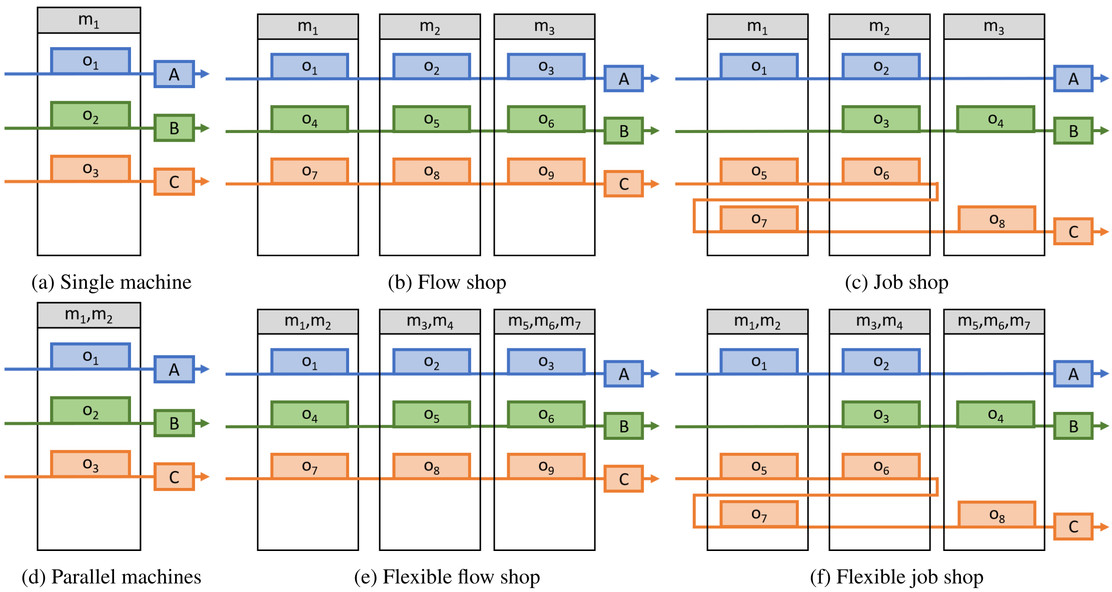


FIGURE 2. Topologies of shop-scheduling problems ($m_1, m_2, \ldots, m_7$ denote machines, $o_1, o_2, \ldots, o_9$ denote operations and A, B, C denote jobs).

- Besides time parameters, cost is also an important factor when scheduling problems. Costs can be incurred due to the storage, changeover and operation of units as well as the consumption of utilities.
- Last but not least, the parameters of a scheduling problem can be deterministic or stochastic.

As can be seen, scheduling problems can be described in great detail, but this is unnecessary in this paper. Therefore, we use the concept of shop-scheduling (machine-scheduling) problems and their classification, which is widely used in operations research.

In shop-scheduling problems, a set of jobs J is present, which contains n jobs. Job j belongs to a set of operations O_j consisting of c_j operations. A set of machines M containing m machines which can be operated. (In manufacturing systems, jobs, operations and machines are equivalent to products, tasks and operating units, respectively.) The topology of jobs is sequential, i.e., the order of the operations of a job is fixed (except for open-shop problems). Each operation of a job has to be performed to complete the job. Each operation is uninterruptible and an operation can be processed by only one machine. At a specified time, each machine is only able to process one operation. According to the topology of the jobs, the scheduling problems can be classified in following ways:

Single machine Only one machine is available ($m = 1$) and each job consists of one operation ($c_j = 1, j \in J$). An optimal permutation of the jobs has to be defined. (Fig. 2a)

Parallel machines There is more than one machine ($m > 1$) and each job consists of only one operation ($c_j = 1$, $j \in J$), i.e., every machine has the same functionality. Each operation has to be assigned to a machine and the optimal order of operations for each machine must be defined. (Fig. 2d)

Flow shop Each job consists of the same number of operations ($c_j = c, j \in J$) and the order in which the machines are used is the same for each job, i.e., the number of machines is equal to the number of operations in a job ($m = c$). Moreover, the first operation of each job can be performed by the first machine, the second operation can be performed by the second machine, and so on. These steps are also often referred to as stages. The optimal order and timing of operations for each machine have to be defined. (Fig. 2b)

Flexible flow shop Similar to the flow-shop problem, but more than one machine is available for each stage (integration of flow shop and parallel machines). Each job consists of c stages and there are identical machines in parallel at each stage. Each operation has to be assigned to a machine, moreover, the optimal order and timing of operations for each machine must be defined. (Fig. 2e)

Job shop Each job can consist of a different number of operations and the order and type of operations can vary for different jobs. A machine may be used more than once to complete a job or it may not be used at all. Furthermore, only one machine is available for each operation. The optimal order and timing of operations for each machine have to be defined. (Fig. 2c)

Flexible job shop This is an extension of the job shop problem. In this case, more than one machine may be available to perform an operation. The processing time of an operation can depend on the machine used for processing. Each operation has to be assigned to a machine and the optimal order as well as the timing of operations for each machine must be defined. (Fig. 2f)

Open shop The order of the operations for a job is not defined in advance. To complete a job, all of its operations have to be processed exactly once in an arbitrary order. The optimal order and timing of operations for each machine must be defined.

In addition to topology, the definition of a scheduling problem contains data about tasks, jobs and machines. In general, tasks and jobs are characterized by the following data [21]:

- p_{ki} denotes the **processing time** needed to complete operation k with machine i. The transportation time between machines and the period of time required to set up a machine are included in the processing time.
- a_j denotes the **arrival time** (ready time) when job j arrives in the system. The job cannot be started earlier.
- d_j denotes the **due date** by which job j should be completed. Failure to meet the due date usually results in some kind of penalty.
- l_j denotes the **deadline** by which job j must be completed. It cannot be violated.
- w_j denotes the **weight** (priority) expressing the relative urgency of job j.

The aforementioned characteristics describe the input of a scheduling problem. To measure the quality of a solution, additional attributes are needed which can be used to minimize (or maximize) their values during optimization. The most commonly used attributes are summarized below [22]:

- S_j denotes the **starting time** of job j when the first operation of the job starts.
- C_j denotes the **completion time** of job j when its last operation finishes. The objective might be to minimize the maximum completion time (makespan, C_{max}) or the average completion time (mean completion time, $\bar{C}$).
- F_j denotes the **flow time** of job j while the job is in the system (shop), i.e., is the difference between the starting and completion times of the job ($F_j = C_j - S_j$). The objective might be to minimize the maximum (F_{max}) or average flow times (mean flow time, $\bar{F}$).
- T_j denotes the **tardiness** of job j, by which the job is delayed according to the due date, i.e., the positive difference between the completion time and due date of the job ($T_j = \max\{0, C_j - d_j\}$). Lateness is penalized and the early completion of jobs goes unrewarded. The objective might be to minimize the sum of the tardiness time (total tardiness, $\sum_{j \in J} T_j$), the average tardiness time ($\bar{T}$) or the number of tardy jobs.
- L_j denotes the **lateness** of job j equating to the difference between the completion time and due date ($L_j = C_j - d_j$). The lateness is penalized and the early completion of jobs goes unrewarded. The objective might be to minimize the maximum lateness (L_{max}).
- W_i denotes the **workload** of machine i, which is the sum of its processing times ($W_i = \sum_{j \in J} \sum_{k \in o_j} p_{ki}$). The objective might be to minimize the total workload ($\sum_{i \in M} W_i$) or maximize the workload (critical machine workload, $\max_{i \in M}\{W_i\}$).

B. UNCERTAINTIES ACCORDING TO THE DYNAMIC SCHEDULING CONCEPT

In the previous subsection, the classification of scheduling problems with regard to the topology of jobs as well as the characterization of tasks and jobs according to inputs and attributes were presented. This chapter presents the different types of uncertainties that can be approached from several perspectives, according to the goal to be achieved, knowledge and information available, depth of uncertainty to be investigated and events that can lead to uncertainty.

In reality, various other confounding factors can be present that affect the existing schedule, e.g., emergency order, inaccurate processing and arrival time predictions, which can cause an already completed schedule to become obsolete. Therefore, in view of the current circumstances, a dynamic schedule is required, in which changes to a process necessitate the schedule to be changed in order to continue to meet new challenges [23]. The static schedule differs from the dynamic schedule in that the jobs to be performed are ready for execution and, depending on the goal to be achieved, the schedule is completed so it does not need to be modified later [24].

These solutions for a static schedule have a significant disadvantage, namely that they do not pay enough attention to the consequences of the impact of various events, as a result of which the established schedule may even become invalid. In reality, the specified conditions must be met in order for the processes and characteristics of the real physical system to remain within the defined behavioural limits. Initially, its execution requires a baseline that retains the desired characteristics to guarantee its execution. The importance of the offline and online phases may vary depending on the factors influencing the behaviour. To properly address these two phases, a broader interpretation of the schedule is worthwhile by taking two aspects into consideration: the static subproblem (a set of activities and a set of constraints) and the dynamic subproblem (monitoring the implementation of the schedule and improving the current solution). A review is required when the occurrence of some exogenous events affects the success of the schedule. Consequently, each event can be placed in a two-dimensional space (Fig. 3) with dimensions of the offline and online components relative to the applied solution method. By implication, no scheduling solution lies entirely on the offline axis, for which the result could only be interpreted in terms of a deterministic execution environment that is unrealistic [25].

The methodology with the smallest online component is the Robust Solution [26]–[28], where some information on occurring exogenous events is used, thereby masking environmental uncertainties.

In the case of Partially Defined Schedules, uncertainty is not taken into account but it consists of partially ordered activities, thus maintaining the possibility to re-establish the relationship between tasks in time in the light of new events that occur and the consequences they result.

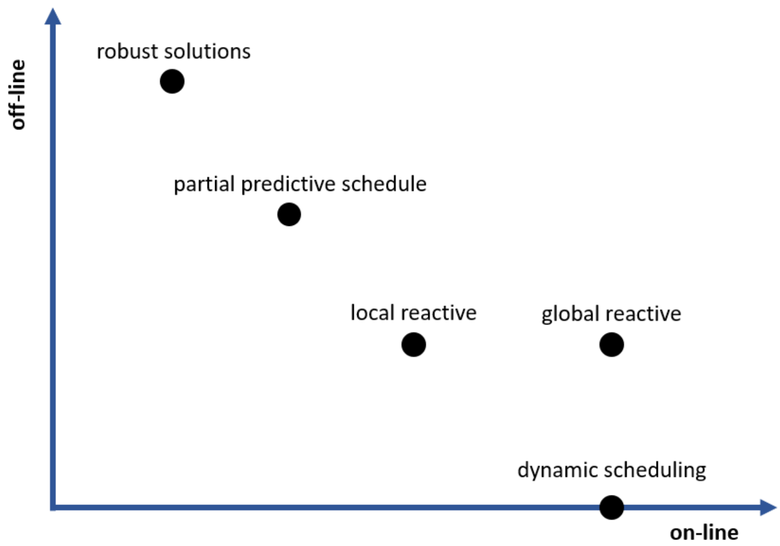


FIGURE 3. Scheduling approaches regarding the offline and online phases.

The online phase of the Reactive Scheduling approach requires more effort as rescheduling must be performed during implementation when exogenous events occur so as not to compromise the consistency of the result. Depending on the set of activities involved, the strategy can be local [29], [30] or global [31]. In the case of the former, a limited number of tasks must be rescheduled, and in the case of the latter, a completely new reschedule must be drawn up with regard to the tasks. It can be seen that the two techniques require different levels of effort, therefore their results are also mixed.

Dynamic Scheduling does not include an offline component, meaning that all decisions are made online. Therefore, instead of an initial schedule, a dynamic schedule is executed depending on the circumstances.

The different scheduling processes that occur in the manufacturing industry provide a good breeding ground for the analysis of different stochastic occurrences and their effects. During the performance of a task, various factors may change over time, which may lead to the rescheduling of the existing production schedule to continue to meet goals under changing conditions. These changes can influence the performance either positively or negatively [32]. Of the parameters considered in a schedule, those that provide constraints with regard to the schedule determine a good starting point for examining the dynamic perspective. These constraints can be categorized by criteria and thus grouped according to whether organizational goals and rules or physical, general, availability and preference constraints are being discussed. These stochastic factors can, by their nature, dynamically disrupt scheduling. These types of events that occur in dynamic scheduling can be divided into the following four classes as follows [33], [34]:

- Workpiece-related events: processing time is uncertain, workpiece arrives randomly, delivery time changes, dynamic priority and order change.
- Machine-related events: damage to the machine limits its available load, conflict between production capacity and the actual utilization of the machine.
- Process-related events: process is delayed, quality is objectionable and production is unstable.
- Other events: absence of the operator, late arrival of raw materials, defects in raw materials, etc.

There are also a number of uncertainties that can occur in real life as a result of certain activities that must be identified in order to deal with them. One way to do this is to first identify these cases as events and then classify them into classes as seen above. Factors that may cause such real-life disturbances include: breakdown of machines, cancellation of orders, changes in delivery times, uncertain due dates, uncertain processing times, overhaul of equipment and addition or removal of operations [35]. More examples are shown in Table 1, where the type of events and the sources of uncertainty are the reasons for the occurrence of uncertainty factors during scheduling.

C. EXTENSION OF THE TYPES OF UNCERTAINTIES FOR COMPLEX PRODUCTION SYSTEMS

The management of uncertainties in complex production systems requires a more thorough understanding and management of the uncertainties. The aim of this chapter is to break down the types of uncertainties according to their sources in more detail.

The causes of uncertainties in complex production systems can result from different sources, e.g., outputs and parameters of the model. Knowledge uncertainty can be defined based on the cause of various sources, e.g., parameters, input data and the unknown errors, overall. However, it does not have to be interpreted due to the lack of knowledge. A model can have imprecisions, since it always somewhat simplifies reality by arranging viewpoints in different ways. Inaccuracies may also be caused by the lack of knowledge or simply because known

TABLE 1. Dynamic event classes.

Events	Source of uncertainty	Examples
Workpiece-related events	Processing time	[35]–[52]
	Workpiece arrives randomly	[53]–[56]
	Delivery time changes	[57], [58]
	Order changes	[59]–[62]
Machine-related events	Machine is damaged	[8], [35], [54], [63], [64]
	Capacity and utility conflict	[65]–[67]
Process-related events	Process is delayed	[68]–[71]
	Quality objection and production unstable	[72]–[75]
Other events	Operator is absent	[76]–[79]
	Raw material arrives late	[80]
	Raw material is defective	[81], [82]

errors are introduced for practical reasons. Natural variability may arise from the conditions determined by the available environment, the degree of which cannot be reduced. In the case of decision uncertainties, when future decisions made by other actors and factors cannot be predicted, the consequences they cause can not be predicted.

To address uncertainty, first it is worth exploring the reasons that contribute to its occurrence, on the basis of which the delimitation into three categories can be made. Based on this, it is possible to narrow down the approaches needed to manage it. Examining Fig. 4 can help determine the source needed for identification. To identify the type of uncertainty variable, the trigger for a different event or variability due to some causes must be determined. These events or variations can be down to behavioural variability, workpiece or machine-related events, or a technological surprise, which can occur not only locally but also globally (societal randomness, inherent randomness of nature, amongst other events). These triggers can result in multiple uncertainties at once, each of which can be addressed by a workaround or treatment solution. To deal with one, it must be known exactly what type of variability it is, namely temporal, spatial or discrete, and how to reduce or eliminate the negative consequence it causes. In some cases, such a consequence cannot be avoided, in which case, an appropriate policy must be developed to manage it, e.g., technological surprise; social, economic and cultural dynamics or the inherent randomness of nature. In the case of Knowledge uncertainty, the triggers can be divided into two categories: structural uncertainty (conflicting evidence, reducible ignorance, interdeminancy, irreducible ignorance) and unreliability (inexactness, lack of observations / measurements, practically immeasurable). As can be seen, these sources stem from inadequate knowledge or some kind of ignorance. The consequences can be the choice or creation of an inappropriate model (model, parameter uncertainty), from which potentially misleading erroneous conclusions can be drawn that can result in serious consequences. Furthermore, identifying the source in itself can present significant difficulties at this level that can in some cases be reduced to some extent by expanding knowledge (if possible), therefore in other cases, this is not possible, its occurrence needs to be adapted and strategies are to be developed to avoid the damage it can cause. The third category is Decision uncertainty, the source of which is difficult to identify as it can result from the combined participation of several different factors, including variability and knowledge uncertainty, but it can also result from internal events (process-related) and external independent ones. Goals (goals - objectives, values - preferences) may change, which may arise not only from actors inside the company, but also from outside (external security as well as social, economic and cultural dynamics).

Uncertainties can also be distinguished according to whether we are related to the aleatoric or epistemic type of uncertainty [83]. Epistemic or epistemological uncertainty results from the lack of knowledge or data. This type of uncertainty can be reduced by collecting more data or using more advanced scientific principles. Aleatoric uncertainty results from the internal randomness of a phenomenon. In a sense, the randomness carried by human nature can be categorized into aleatoric uncertainty derived from nature.

The aforementioned classifications and categorizations will be explained in detail in the following sections.

1) VARIABILITY

Random or stochastic uncertainty can result from the unpredictability of human nature or natural systems. The variability in human nature may stem from individual bias [84] towards some benefits or from certainty in the correctness of their own views [85]. The variability of natural systems is free from intentional bias, derived from the chaotic features of nature. Based on time series data, good approaches can be made. These usually consist of historical data, which also include historical conditions. Uncertainties deduced from environment with natural endowments usually cannot be reduced by improving the structure of the model, therefore the degree of variability remains unchanged. The measurement of errors does not always lead to accurate results. Furthermore, there is no guarantee that the measured historical data can accurately adumbrate future data or that the difference between past and future results can have a significant deviation, potentially causing major effects. Usually, the output of the model is consistent with the model input, but the extent of the variability is affected by the varied errors and measured mismatches.

By examining the system, it can be seen that different behaviours may occur, which may take on different names,

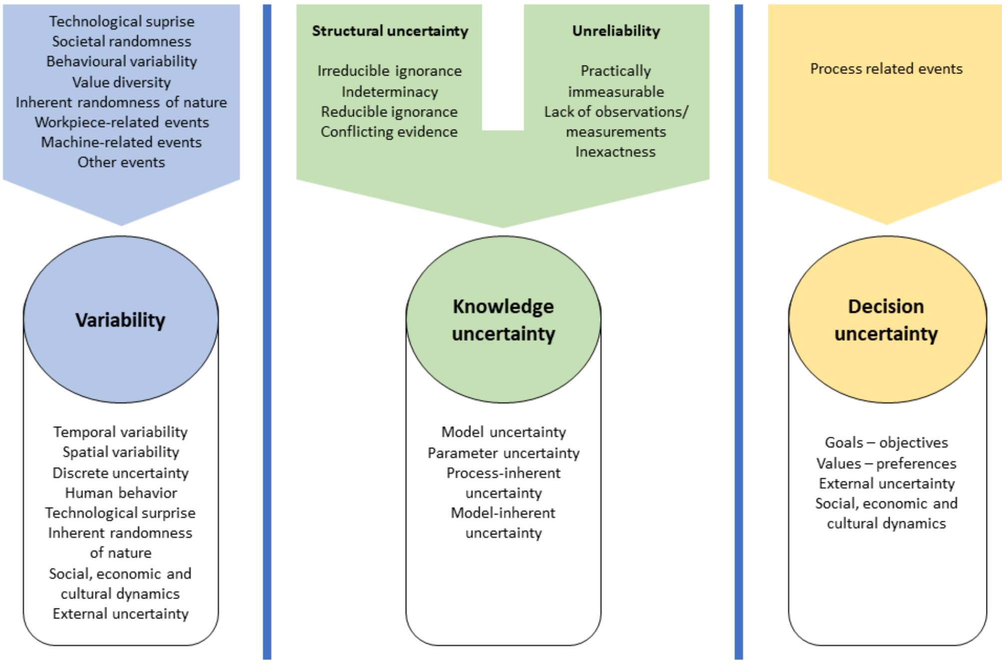


FIGURE 4. **Typology of uncertainties and their sources.**

like 'stochastic uncertainty' [86], 'objective uncertainty' [87], 'external uncertainty' [88] or 'random uncertainty' [89]. Empirical quantities can vary uncontrollably, simply because of their nature. In such cases, the uncertainty may be an inherent randomness or caused by occurrences related to the input data, functions or parameters.

According to a classification [90], two varieties can be classified in terms of variability:

- External uncertainty, including the availability of feed streams, product demands, prices and environmental conditions;
- Discrete uncertainty such as the availability of equipment and other random discrete events, e.g., the absence of operational personnel. Machine breakdown is considered as an uncertainty that may occur during job processing [91].

The following categorizations, which are distinguishable from sources [92], fit into the variability-type uncertainty:

- Inherent randomness of nature: processes that occur in nature that are unpredictable and difficult to predict.
- Human behaviour: characteristic forms of human behaviour, which are not rational when there is no overlap between what the individual has to say and their actual action (cognitive dissonance), or when the behaviour is characterized as "different than expected".
- Social, economic and cultural dynamics: Scenarios of processes in society, which are inconsistent or can pose serious threats.

Although all of these sources can be classified as uncertainties of variability [93], how they are handled is less clear, as it is not always possible to reduce the uncertainty depending on the environmental properties and origin of the source [94]. However, due to the lack of reducibility, it is still crucial for the policy decision to expand the information available so that as much detail as possible is available in the decision-making process. During the modelling process, a frequency distribution can be used if a property resulting from the absence of some information is uncertain in order to represent this uncertainty [95]. This allows the resulting parameters (mean, deviation, median) to represent the uncertainty of that particular property accurately.

However, it is a common mistake that the uncertainty resulting from sampling, which is the uncertainty of variability, is not equivalent to the epistemic uncertainty, i.e., when the uncertainty arises from a knowledge gap [96], both can be present at the same time, as well [97]. In addition, by focusing on their input functions, they can also exhibit variability. These may be part of the model structure but also appear as external inputs [98], [99], which may act as inputs to the model, as well, or as an element of its structure that can contain statistical or scenario uncertainty [100], recognized or completely ignored. If the purpose of the applied model is to predict a future case, i.e., the circumstances and experience during the development of the model did not serve the same purpose, their application to the aforementioned method may be of concern.

2) LIMITED KNOWLEDGE

Limited knowledge is a quality that investigators may possess or the state of our current knowledge (epistemological). Like the previous one, this can have different appellations, e.g., 'subjective uncertainty' [86], [101], 'internal uncertainty' [88], 'secondary uncertainty' [102] or 'informative uncertainty' [87], [101]. This form of uncertainty can take many forms such as limited and inaccurate data [103], measurement errors, limitations of understanding, lack of knowledge and inappropriate models. The NUSAP method [104] can be used to derive a concept (the concept of pedigree) that allows the assessment of deficiencies, which in turn allows the extent to which various uncertainties are reduced to be determined. Increasing the pedigree may also increase the degree of uncertainty, as research can shed light on the details of our perception of a particular area, which can increase the level of complexity.

Modeling is the process of understanding processes, which attempts to predict responses and supports the decision-making process [105]. The initial conceptualization stage develops into a numerical or computational representation [106], which is the most important stage and where uncertainties may spread further during the rest of the modelling. Given that the features consisting of multiple factors and their dependencies are complex, they need to be simplified, where oversimplification can lead to the omission of essential details but undersimplification can result in an overly complex model [107]. A proportion of the items from the classification belongs to limited knowledge [90]:

- Model-inherent uncertainty (model mismatch) such as kinetic constants, physical properties and mass/heat transfer coefficients. There are cases, when different parts are assembled to create a product. The properties of these parts can deviate geometrically, where the inaccuracy can cause the final products to fail [108]. When the parts are lighter because of the material(s) they are composed from, they can be as flexible, as sheet metals. The variability in or the uncertainty of these products results in a need for consolidated methodologies, which can predict these properties during the design stage [109].
- Process-inherent uncertainty such as variations in the flow rate and temperature fluctuations in the quality of the stream, processing time [35], [52] and the availability of equipment [110], like in the case of squeeze casting, where the temperatures of the shot sleeve, punch and smelting can be non-uniform [111].

Based on the level of knowledge, the degree of uncertainty can be categorized as follows: Although the two extremes are complete certainty and complete ignorance [112], a transition between these two sides as shown in Fig. 5 can occur. This transition also needs to be broken down into several levels, to which a separate procedure can be provided to deal with uncertainty in decision-making properly [113].

- We start from the point of complete certainty (that cannot be achieved), which is the state in which everything is known exactly, i.e., we are in possession of proper knowledge. At the levels of uncertainty in Case 1 (Fig. 5a), it is recognized that something cannot be completely certain and it is impossible or undesired to measure this uncertainty [114]. Such a case is treated by sensitivity analysis, so that the effects of different disturbances on the results can be assessed by examining the parameters belonging to the model.
- Uncertainty at Level 2 (Fig. 5b) consists of knowledge generated through processes, facts that can be used to infer contingencies, which are uncertain but statistically derivable. These can be associated with the probability of them occurring in the form of a single or multiple prediction or confidence intervals.
- In the case of the next level (Fig. 5c) of uncertainty, several probabilities can be listed before being ranked based on how likely they are to be detected. Therefore, the set of input and output parameters of the model also includes alternative options that can be ranked according to their probabilities. Although these alternatives are often recorded in scenarios in order that they can be ranked according to their perceived probabilities, probabilities are not assigned to them [115], [116].
- Level 4 uncertainty (Fig. 5d) is referred to when these scenarios can still be produced but not ranked. The lack of this ability may be due to the fact that an insufficient amount of knowledge or data is available to establish the necessary criteria, against which we could produce the perceived probabilities. In the absence of these (which may also result from the lack of a convention required to establish the ranking), it becomes very difficult to determine the uncertainties associated with the key parameters of the model.
- The last level (Fig. 5e) is total uncertainty, which is the case when the unknown is known. It is important to point out that this uncertainty can already be recognized, as it will identify the outcomes of scenarios that could have dire and unacceptable consequences. This level of uncertainty rarely occurs, which is why it is treated more in principle like absolute certainty is.

3) DECISION UNCERTAINTY

Uncertainty in process operations can originate from many aspects, including internal and external factors. Uncertainties arising during modeling may also result from an unexpected turn of events in the future. The occurrence of these events can originate from sources such as the environment, nature, an individual's personal goals and interests, activities, needs, limitations and various impacts [117]. For example, a change in the standard operating procedure affects existing processes, more precisely, the effect on the process changes its subsequent outcome and consequences. Even though the construction of the model is greatly influenced by the measured data, if the policies determining the implementation of the measurement change [118], the results obtained after this can affect the result of the model in unexpected ways. For systems, where the interrelationship requires a serious degree of cohesion, it is important to estimate the effects of changes, so that the system can be properly prepared for the consequences. These changes may result from individual decisions. In the case of complex integrated production systems, the

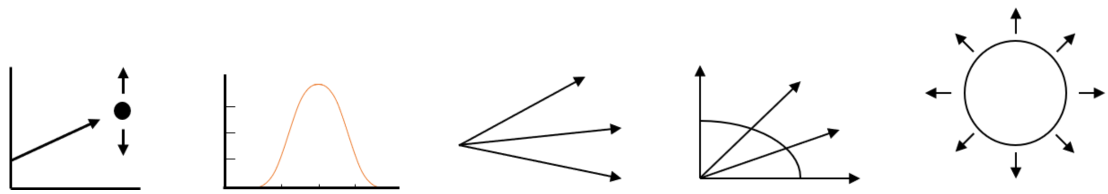


FIGURE 5. Levels of uncertainty.

impact of individual decisions and the changes they cause are of great and paramount importance, which need to be addressed.

There are sources in the categories differentiated by sources that also apply to decision-type uncertainty [90], [92]:

- Social, economic and cultural dynamics: Social events that have a significant effect on parts or all of the operation, from partial transformation to complete cessation, or even on the operation of the entire system [119]–[121].
- External uncertainty: Organizational or operational changes required as a result of external decisions (sales, policy decision or changed operating principles) [122]. The relationship between decision and external uncertainty can be determined when a government's (economic) policy decision has significant consequences or a policy change triggered by some external effect results in a changing environment in the banking sector [123]. The theory of precautionary saving is similar, where a larger degree of economic policy uncertainty forces more capital to be accumulated, thereby reducing the consequences of the risks arising from uncertainty [124], [125].

In heuristic approaches, decision uncertainty is a factor, where the treatment of which contributes greatly to the exploration of the appropriate outcome. An interpretation is that certain criteria, methods or principles are used to decide which alternative method promises to be the most appropriate or effective to achieve a goal [126]. Consequently, if the problem is divided into subproblems, a decision tree can be constructed, from which the next most advantageous step must be decided. To achieve this, the consequences of each decision option must be assessed. Ideally, the exact consequences of each decision are known, therefore the desired result can be achieved following a series of appropriate decisions. In reality, however, the consequences of decisions are uncertain, which is why it is extremely important to apply the appropriate method [127] that takes into account the goal to be achieved as well as the associated conditions, aspects and guidelines when dealing with decision uncertainty. By examining heuristic approaches from a different perspective, cases that use random numbers for the purpose of avoiding local optimal jams should be mentioned. These uncertain values may affect the result of the method, or alternatively, different implementations may result in different timelines with different objective values [128].

III. SCHEDULING ALGORITHMS THAT HANDLE UNCERTAINTIES OF PRODUCTION SYSTEMS

The aim of the first attempt was to solve deterministic scheduling problems. The first attempt to solve a problem which contained uncertainty was published in 1957 [23]. In that publication, a distinction between static and dynamic scheduling was made. In static scheduling, all data is known in advance and the schedule is fixed, i.e., it cannot be modified later.

In industrial environments, many unexpected events occur, e.g., machine breakdown, the arrival of emergency orders, etc. (as has been shown in Section II-B). To handle these unexpected events, the schedule must be modifiable, which is referred to as dynamic scheduling. Although static scheduling has already been classified as an NP-hard problem, dynamic scheduling is more complex and more difficult to solve. That is why specialized scheduling algorithms have been developed to solve specific problems.

There are four fundamental ways to tackle production scheduling that is subject to uncertainty [129]:

- **Proactive approach** It constructs solutions by modelling uncertainties [130], [131] or optimizing the performance in different scenarios [132]. Such an approach can be viewed as a form of under-capacity scheduling in order to maintain the robustness in different scenarios. (Fig. 6b)
- **Reactive approach** It changes the schedule during manufacturing. Usually it is based on simple rules, therefore the computational cost is low and easy to understand. As a result of only using local information to generate a new schedule, it may not provide a globally optimal solution. (Fig. 6c)
- **Predictive-reactive approach** It is a two-step process. Firstly, a predictive schedule is generated over the time horizon by typically using a static scheduling method. Secondly, the schedule is modified during its execution in response to unexpected events. (Fig. 6d)
- **Proactive-reactive approach** In the first step, an initial schedule is generated considering future disruptions like the robust approach. Nevertheless, reactive steps also

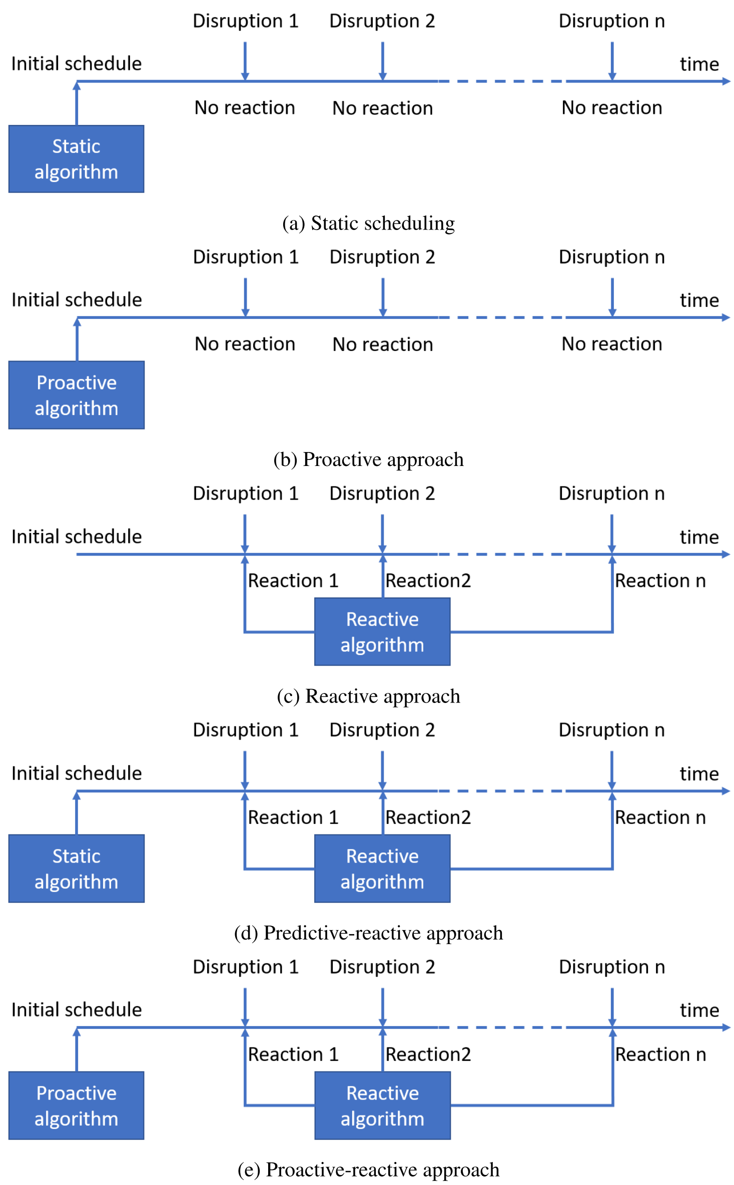


FIGURE 6. **Scheduling approaches.**

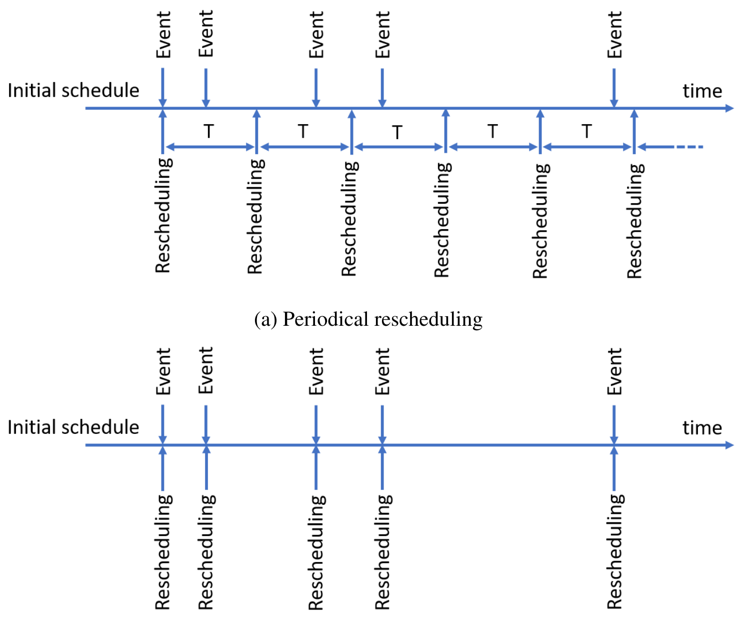
take place but usually less modification is necessary because of the robustness of the schedule. (Fig. 6e)

Fig. 6 summarizes the differences between the different approaches. Furthermore, Fig. 6a shows the static scheduling approach, which does not take uncertainties into account. Static scheduling algorithms can be used to generate the initial schedule for the predictive-reactive approach. Therefore, in this section, a short outlook on static scheduling methods is provided before enumerating the most commonly used approaches for uncertain scheduling problems.

A. STATIC SCHEDULING

As typical in operations research, exact heuristic methods are used to solve static scheduling problems [133]. Exact methods can provide the globally optimal solution. Given the NP-hard nature of the problem, its approach needs a lengthy CPU time for large-scale problems. The most commonly used approaches are the following [134]:

- Most of the papers formulate a Mixed-Integer Linear Programming (MILP) model for the problem and apply a general purpose solver like CPLEX or GuRoBi. According to the representation of time, two groups of models are available. The first one is the so-called time point-based formulation, where the time horizon is discretized by a predefined number of time points and binary variables belonging to these points [135]–[137]. The second one is the precedence-based formulation, where the orders of the operations are represented by binary variables [138]–[140].
- There are some graph-based approaches, where a directed graph represents the problem and a branch and bound algorithm determines the optimal solution. The



(a) Periodical rescheduling

(b) Event-driven rescheduling

FIGURE 7. Execution of reactive scheduling.

S-graph relies on such tools and has been developed with acceleration techniques and generalizations [141]. Alternative graphs apply a similar mathematical model and branching strategy [142].

- It is worth mentioning the space enumeration-based methods, which also use graphs. These approaches use Linearly Priced Timed Automata [143] or Timed Petri Nets [144].

Although heuristic methods cannot guarantee the global optimality of a problem, they are relatively fast compared to exact methods. These approaches also involve uncertainties (decision uncertainty) as has been noted in Section II-C3.

- There are lots of high-level metaheuristic methods that can solve job-shop problems, for example, simulated annealing, tabu search and genetic algorithms. Moreover, they can be used in parallel with exact algorithms guiding the search.
- Heuristic rules-based approaches use rules that can help to choose the next job to manufacture on a specific machine, e.g., a rule can choose the task, which has the shortest processing time and the machine with the smallest workload. These rules are usually based on local information and do not take into account the result of the decision. Since these methods are widely used in the literature, there are numerous different rules for different objectives [145]. The advantages of heuristic rules are that they are easy to understand and to apply and they are relatively fast, as well.
- Artificial intelligence is a broadly used approach, which cannot guarantee optimality, either. The most widely used method is to use a neural network that simulates the operation of a human neural network [146]. A neural network consists of individual neurons with weighted connections. Each neuron receives weighted inputs and uses an activation function on the sum of them. The weight of the inputs can be adjusted according to the current problem, moreover there are other artificial intelligence methods that can be used to solve scheduling problems like knowledge-based systems, fuzzy logic and case-based reasoning [147].

B. REACTIVE SCHEDULING

For reactive scheduling, an initial schedule has to be generated beforehand. During reactive scheduling, this schedule is modified or re-optimized upon the realization of the uncertain parameters or occurrence of unexpected events. The term 'rescheduling' is also widely used in the literature. The majority of papers not only focuses on the reactive scheduling algorithm but on the method to determine the initial schedule (predictive-reactive approach), as well.

Rescheduling can occur periodically, where the length of the periods can be constant or variable (Fig. 7a). The length of the period is not trivial, researches have been conducted to try and determine the optimal value. In the case of the event-driven approach, rescheduling is executed when an unexpected event occurs like a machine breakdown or the arrival of a new important job (Fig. 7b). Furthermore, hybrid solutions exist, where the periodical approach is used but for a few particular events, rescheduling also takes place.

Reactive scheduling can be full or partial. In full scheduling, all tasks and resources are rescheduled, while in partial scheduling only a part of the schedule is modified. Full rescheduling is not viable because it is time-consuming

TABLE 2. Reactive scheduling, rescheduling.

Problem	Uncertainty	Method	Paper
Flexible job shop	breakdown, arrival of a new job	genetic algorithm	[148]
Single machine	job duration	own heuristic algorithm	[38]
Precast production	breakdown	genetic algorithm, simulation	[149]
Cellular manufacturing systems	arrival of new jobs	mathematical model	[150]
Gasoline blending and product delivery	demand, component uncertainties	graphical genetic algorithm	[69]
Air separation units	electricity price	own heuristic algorithm	[151]
Flexible job shop	processing time	machine learning	[152]
Crude oil	tank unavailability	genetic algorithm	[153]
Steelmaking and continuous casting	processing time	mathematical model	[39]
Single machine	due date	own heuristic algorithm	[57]
Aircraft assembly	material delivery	mathematical model	[154]
Hybrid flow shop	dispatching rule set	artificial neural network, fuzzy interference system, VIKOR	[155]
Job shop	machine failure	heuristic rule	[156]
Flexible job shop	energy availability, supply and costs	multi-objective genetic algorithm	[157]
Job shop	disturbed (deleted) batches, breakdown	genetic algorithm	[158]
Crude oil	crude carrier delay, increase in demand	genetic algorithm	[159]
Flexible job shop	breakdown	particle swarm optimization	[160]
Two-machine flow shop	processing time, machine failure	heuristic rules	[35]
Short-period continuous reactors	product demand	mathematical model	[161]
Flexible job shop	processing time, new job insertion	artificial bee colony algorithm	[53]
Procurement	supply, demand	mathematical model	[162]
Flexible job shop	task duration	own heuristic algorithm	[36]
Crude oil	shipping delay, demand, tank unavailability	mathematical model	[68]
Flexible job shop	processing time, breakdown	genetic algorithm	[163]
Flexible manufacturing system	power consumption	mathematical model	[164]
Flexible manufacturing system	power consumption	mathematical model	[165]
Flow shop	breakdown, arrival of a new, ready time of job	own heuristic algorithm	[166]
Job shop	breakdown, rush job	own heuristic algorithm	[49]
Flexible job shop	breakdown, due date	evolutionary algorithm, genetic algorithm, particle swarm optimization	[58]
Tomato processing	supply	simulation model	[167]
Industrial environment	breakdown, arrival of a rush batch, batch cancellation	mathematical model	[168]
Moulds production	process duration	genetic algorithm	[40]

and often has to be performed. As a result, fast heuristic approaches are very common for reactive scheduling.

Table 2 provides a summary of the reactive scheduling (rescheduling) applied in papers concerning manufacturing systems. The topic, the examined uncertainty and the method used are presented. Although reactive scheduling is sometimes integrated with other problems (e.g. control, planning), this is beyond the scope of this paper.

C. STOCHASTIC SCHEDULING

Stochastic scheduling has two meanings in the literature. The first meaning is a scheduling problem containing some kinds of uncertainty and the second is a solution method which can solve this type of problem. In this chapter, the second meaning will be investigated.

A deterministic scheduling model can be solved by traditional mathematical programming methods. A stochastic scheduling model is a modification of a deterministic one treating the uncertainties using stochastic variables. The method is based on a probability-based description of uncertainties. It can be used in cases when information about the behaviour of uncertainties is available. The uncertainties can be described by the probability of unexpected events, where the frequency of occurrence of an event can equate to the probability of occurrence.

In modeling, the continuous probability distribution function is usually discretized, which is referred to as scenario generation, and can result in a large number of scenarios as well as it can affect the tractability of a solution. Therefore, it is necessary to compile a subset of initial scenarios without the loss of generality, which is usually referred to as scenario reduction.

The aim of a stochastic model is to minimize or maximize the expected value of an objective function. To solve a stochastic model, special techniques are required. There are two main types of stochastic models, the two-stage (multi-stage) stochastic programming and the chance-constrained programming-based approach. In two-stage (multi-stage) stochastic programming, the decision horizon is separated into two (more) parts, referred to as stages. The first-stage variables are determined before an uncertainty occurs, and the second-stage variables are determined after the realizations of uncertainties are observed.

Stochastic programming is one of the most popular methodologies to solve uncertain scheduling problems. Table 3 provides an overview of papers that apply a stochastic programming approach for scheduling problems of manufacturing systems.

D. FUZZY PROGRAMMING

Fuzzy programming can handle uncertainties when no historical data is available and probability distributions are unknown. Instead of using stochastic variables, fuzzy

TABLE 3. Stochastic scheduling.

Problem	Uncertainty	Method	Paper
Multi-modal cargo logistics distribution	demand, transit time, unloading time	two-stage programming (golden search algorithm, sample average approximation method, scenario decomposition method, Lagrangian decomposition)	[169]
Job scheduling	processing time, resource consumption	multi-stage programming (branch and bound algorithm, sampling-based approximation method)	[50]
Steel making	(day-ahead) electricity price	two-stage programming (progressive hedging algorithm)	[170]
Sugar-cane supply chain	harvest	two-stage programming (compromise programming)	[171]
Hazardous materials supply chain	demand	chance-constrained programming	[172]
Kitting facility	demand, yield	two-stage programming (moment-matching method, fast forward selection)	[173]
Chlor-alkali plant	electricity price	two-stage programming (CPLEX (Pyomo))	[174]
Multi-product, multi-period and capacitated lot-sizing and scheduling	cost of processing overtime	two-stage programming (sample average approximation)	[175]
Parallel machine scheduling	release time, processing time	two-stage programming (sample average approximation, scenario-reduction-based decomposition)	[52]
Parallel machine scheduling	processing time, release time	two-stage programming (sample average approximation, enhanced sample average approximation)	[42]
Two-level disassembly	lead time	scenario-based stochastic linear programming model (CPLEX)	[176]
Flow shop	processing time	chance-constrained programming (brain storm optimization, stochastic simulation)	[43]
Wafer fabrication manufacturing	demand	multi-stage programming (CPLEX)	[177]
Single machine	processing time	two-stage programming, recoverable robustness	[41]
Single-item multi-period disassembly	yield, demand	chance-constrained programming (outer approximation, BONMIN)	[178]
Cyclic personnel scheduling	demand	two-stage programming (CPLEX), Benders decomposition	[179]
Workover rig fleet sizing and scheduling	intervention time	two-stage programming (Monte Carlo, scenario reduction, quasi-Monte Carlo)	[180]
Braking equipment manufacturing plant	demand	multi-stage programming (fast forward selection)	[181]
Flow shop	wind energy supply	two-stage programming	[182]
General lot-sizing and scheduling	demand	two-stage programming (Monte Carlo sampling)	[183]
Day-ahead electricity commitment and production scheduling	breakdown	two-stage programming (CPLEX)	[184]
Single machine, multi-product shop floor lot-sizing and scheduling	demand, market, workforce efficiency	two-stage programming (Gurobi)	[185]
Master scheduling	demand	two-stage programming	[186]
Lot-sizing and scheduling	demand	two-stage programming (fast forward selection)	[187]
Job shop	processing time	two-stage programming (pseudo particle swarm optimization, Monte Carlo method)	[44]
Steelmaking continuous casting	demand	two-stage programming	[188]
Integration of scheduling and dynamic optimization	process uncertainties	tow-stage programming (Benders decomposition)	[189]
Engineer-to-order, make-to-order	duration	two-stage programming (CPLEX)	[45]
Manpower planning and scheduling	demand	two-stage programming	[190]
Crude oil	demand	chance-constrained programming (LINGO)	[191]
Multiple resource-constrained scheduling	processing time, due date, resource consumption and availability	two-stage programming (Benders decomposition)	[51]

programming approaches use fuzzy numbers to model uncertain parameters and fuzzy sets as well as membership functions for constraints. Although complicated integration schemes are needed in this type of models for continuous probability models, a large number of scenarios as the discrete probabilistic representations of uncertainties is not needed [192].

A classical set S is a collection of elements, which is well-defined, where an element x may or may not belong to S. For a fuzzy set, the membership function is not binary-valued (0 or 1) but can take on any value between 0 and 1: the higher its value, the higher the degree of membership is [193]. A fuzzy set $\tilde{A}$ is specified by a membership function $\mu_{\tilde{A}}(x)$. For element x, the value of $\mu_{\tilde{A}}(x)$ defines the degree to which x belongs to $\tilde{A}$. A fuzzy number is a convex and normalized fuzzy set with a piecewise-continuous membership function [194], where the value of the number is not limited to the [0, 1] interval.

To understand this more clearly, triangular fuzzy numbers (TFN) are presented. A TFN is defined by a triplet of points $\tilde{A} = (A_1, A_2, A_3)$ where the value of the fuzzy number $\tilde{A}$ can be between A_1 and A_3. A_1 is the most optimistic, A_2 is the most likely and A_3 is the most pessimistic value for $\tilde{A}$. $\mu_{\tilde{A}}(x)$ is the membership function of the TFN $\tilde{A}$, where the highest degree of membership belongs to A_2 (Fig. 8a).

Fuzzy numbers can represent uncertain variables in the form of an interval. Moreover, by using membership functions, some constraints can be violated and the satisfaction of such a constraint can be measured by a [0, 1] fuzzy number, which represents the degree of fulfilment. Objective functions are treated as constraints with lower and upper bounds defining some expectations.

The aforementioned ordinary or type-1 fuzzy number membership functions characterize the type-1 fuzzy sets. Type-2 fuzzy sets exist, whose membership functions are fuzzy themselves, which are also used to model uncertainties [195]. For element x' there is exactly one membership value ($\mu_{\tilde{A}}(x')$) in case of type-1 fuzzy sets (Fig. 8a) and there are more possible values for $\mu_{\tilde{A}}(x')$ in case of type-2 fuzzy sets (Fig. 8b). For a type-2 set the membership function is extended to three dimensions to handle this uncertainty.

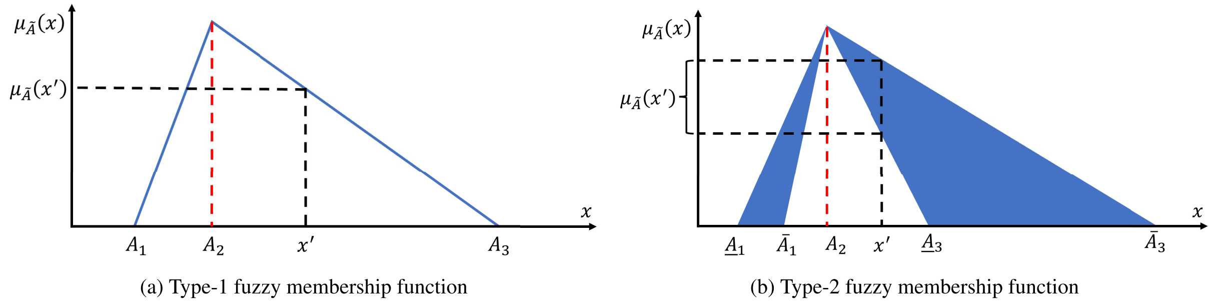


FIGURE 8. Triangular fuzzy number membership function.

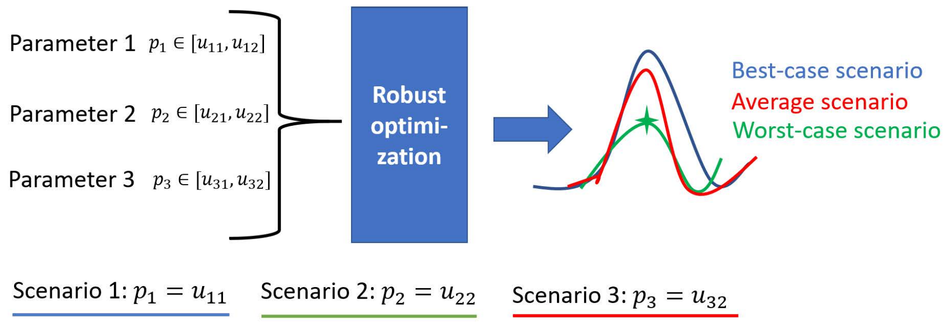


FIGURE 9. Schematic figure of the Solution Robust Optimization.

Both type-1 and type-2 fuzzy sets can be used for different types of scheduling problems. For example, to schedule the tasks of real-time embedded systems to achieve energy efficiency, type-1 [196] and type-2 [197] solutions exist.

One of the first papers about scheduling using fuzzy programming was published in the 1970s [198], [199]. Table 4 provides an overview of the works using the fuzzy approach for scheduling problems of manufacturing systems.

E. ROBUST SCHEDULING

One of the most important goals of robust scheduling is to incorporate uncertainties into the model describing the scheduling task, making the scheduling less sensitive to various confounding factors. During robust scheduling steps, the effects of disruptions on the performance measure are to be minimized and optimized schedules must not differ drastically. The two basic aspects of robust optimization are solution robustness and quality robustness [236]. The former approach examines the effect of changes in input data on optimal scheduling. In that case, the order changes are examined when the input data change slightly. In Fig. 9, the goal is to make a decision that is feasible and optimal for the worst-case objective function. The values of the various parameters can be taken from predefined intervals, resulting in different scenarios. Among these scenarios, the goal is to make a decision that is feasible and optimal for the worst-case objective function.

The purpose of the latter that is, quality robustness, is to ensure that the value of the objective function deteriorates slightly in the event that it is disturbed by uncertainties. In robust optimization, not only is the value of the objective function considered when determining the optimal solution, it is also important to consider how the expected value of the objective function changes in the optimal environment. As can be seen in Fig. 10, while in the traditional optimization, the red point provides the best solution, in robust optimization, the green point yields a more stable, robust optimum [237]. The example also proves that variability is an important consideration in the optimization process.

Robust optimization can be applied in many areas of practical tasks: flexible manufacturing, energy systems, job-shop scheduling, refinery and resource leveling problems, etc. (see Table 5). The range of uncertain parameters is wide, namely time, market demand and price, as well as machine breakdowns and failures are all determinant factors. Due to the diversity of the optimization models described, the modeling and solution methods may also differ.

Given that robust scheduling is an essential part of many application areas, many illustrative examples are found in Industry 4.0, software and various scheduling projects, as well as in the energy and industrial sectors. Some featured articles are shown in Table 5.

F. THE TOLERANCE SCHEDULING PROBLEM

Many scheduling, production and related optimization tasks require effective responses to unexpected events during their execution. Measuring the impacts of these unexpected events determines whether intervention and/or rescheduling is necessary to implement the given operations effectively. The study of such tasks is the subject of tolerance scheduling, which is an intensively studied area in optimization theory.

For many practical optimization and scheduling problems, little information is available about the uncertain parameters of the model. For example, the distribution functions of these

TABLE 4. Fuzzy scheduling.

Problem	Uncertainty	Method	Paper
Integrated supply, production and supply-chain distribution	demand, product price	evolutionary algorithm	[200]
Prefabricated building construction	execution time	cooperative co-evolutionary algorithm	[201]
Distributed hybrid flow shop	processing time, setup time	brain storm optimization	[202]
Integrated process planning and scheduling	processing time, due date	multi-layer collaborative optimization, genetic algorithm	[203]
Production planning and scheduling	startup time, processing time	particle swarm optimization	[204]
Multiproduct multistage scheduling	processing time	backtracking search algorithm	[205]
Job shop	duration, due date	hybrid evolutionary tabu search	[206]
Flow shop	processing time	weighted distance-based approximation	[207]
Distributed hybrid flow shop	processing time, due date	estimation of distribution algorithm, iterated greedy algorithm	[208]
Distributed two-stage hybrid flow shop	setup time	collaborative variable neighbourhood search	[209]
Assembly line worker assignment and balancing	processing time	genetic algorithm	[210]
Flow shop	machine degradation	genetic algorithm	[211]
Assembly job shop scheduling	processing time, delivery time	genetic algorithm	[212]
Flexible job shop	processing time	backtracking search based hyper-heuristic	[213]
Flexible job shop	processing time	flower pollination algorithm	[214]
Single machine scheduling and flexible maintenance planning	human resource availability	genetic algorithm	[215]
Single machine scheduling and flexible maintenance planning	human resource availability	genetic algorithm	[216]
Single machine	processing time	chance constrained programming	[217]
Parallel machine	processing time, release time, setup time	ant colony optimization	[218]
Flow shop	processing time, setup time	MILP	[219]
Flow shop	processing time, due date	genetic algorithm	[220]
Flow shop	machine degradation	variable neighbourhood search	[221]
Flow shop	processing time	own heuristic algorithm	[222]
Flexible job shop	processing time	artificial bee colony algorithm	[223]
Flexible job shop	processing time, new job insertion	artificial bee colony algorithm	[53]
Job shop	processing time	adaptive neuro-fuzzy inference system	[224]
Parallel machine	processing time, due date	fuzzy chance-constrained programming	[46]
Job shop	processing time	discrete harmony search algorithm	[225]
Open shop	processing time	particle swarm optimization	[226]
Flexible job shop	processing time	genetic algorithm, tabu search	[227]
Job shop	processing time, due date	genetic algorithm	[228]
Job shop	processing time	genetic algorithm	[229]
Open shop	processing time	particle swarm optimization	[230]
Open shop	processing time, setup time	fuzzy mixed integer linear programming	[231]
Parallel machine	processing times, release dates, setup times, due dates	particle swarm optimization, genetic algorithm	[232]
Job shop	processing time	tabu search	[233]
Parallel machine	processing time, due date	particle swarm optimization	[47]
Job shop	processing time	genetic algorithm [234]	
Flow shop	processing time	quantum evolutionary algorithm, particle swarm optimization	[235]

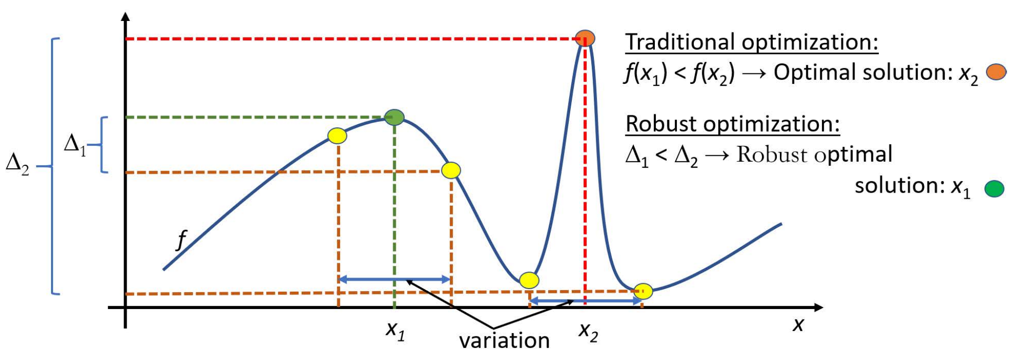


FIGURE 10. Schematic diagram of the Quality Robustness Optimization.

uncertain parameters are unknown and only lower and upper bounds on their possible values can be given. There are several ways to formalize uncertain parameters, for example, $p_1 \in [u_{11}, u_{12}]$ or $|p_1 - \hat{p}| \leq \epsilon$, where p_1 denotes the 'exact'

TABLE 5. Robust scheduling.

Problem	Uncertainty	Method	Paper
Flexible manufacturing	disruption caused by machine failures	mixed-integer linear programming (MILP) - CPLEX algorithm	[238]
Resource-constrained project scheduling	time and reworks	tabu search algorithm	[239]
Resource levelling problem	activity duration	genetic algorithm	[240]
Thermal, cooling, electrical hub energy system	market price	mixed-integer linear programming (GAMS)	[241]
Flexible job shop scheduling	machine breakdown	multi-objective genetic algorithm	[242]
Framework of a predictive job scheduling technique	machine failure	Theory of Markov processes and auto-regressive integrated moving average models	[243]
Classification of major sources of uncertainty in projects	duration of activities	detailed review paper including several methods	[244]
Robust self-scheduling for generation companies	electricity price	Box, Ellipsoidal, Polyhedral, Conditional Value-at-Risk stochastic programming, and Information-Gap Decision Theory models	[245]
Refinery, crude-oil scheduling	demand	nonconvex MINLP deterministic optimization model	[246]

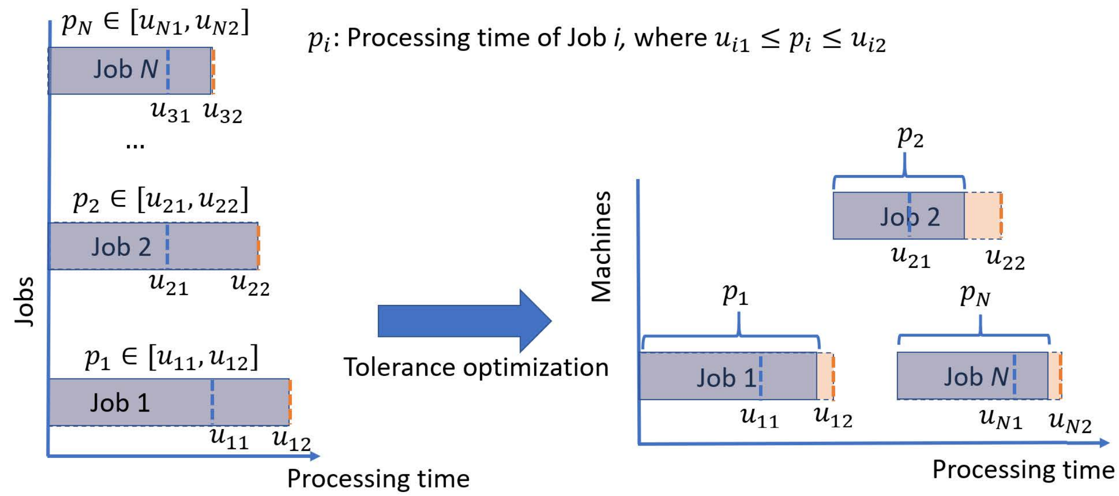


FIGURE 11. Schematic diagram of Tolerance Optimization.

value, $\hat{p}$ stands for the nominal value and ϵ represents the given uncertainty level. In order to handle such cases, interval arithmetic, which requires knowledge only of the feasible ranges of the uncertain parameters, can often be used effectively. Within these limits, the uncertain parameter can take any value. The lower and upper bounds can be determined by analyzing historical data.

The tolerance scheduling problem is based on an initial optimal or near-optimal solution, where the accepted tolerance values of the operating characteristics are known.

A schematic description of tolerance optimization is shown in Fig. 11. For each job, the upper and lower bounds with regard to the processing times of the job are known, which define an interval. The blue vertical dashed lines refer to the lower bound, while the red vertical lines refer to the upper bound of the processing times of the jobs. The result of tolerance optimization is the assignment and scheduling of jobs as well as machines where the processing times of the jobs fall within the given intervals.

In the case of a production scheduling problem, such tolerance values can apply to, for example, execution times, where the variation in parameters can strongly influence the quality of the overall production process. Features that fall outside of the tolerance range may induce a complete rescheduling of the original plans and processes, which could yield a different optimal solution. However, for each rescheduling, the costs involved must be taken into account. A dominant class of tolerance scheduling tasks focuses on fault tolerance. The uncertainty resulting from failures and its modelling can determine both the execution and completion times of jobs, therefore, it is a key factor in scheduling algorithms. Table 6 highlights some of the results on scheduling and uncertainty published in recent years.

G. INVERSE SCHEDULING PROBLEM

Adaptation of the solution techniques developed in inverse optimization started in the early 2000s [253]. In a traditional scheduling task, all parameters are given and the goal is to identify the job sequences, for which the completion time is minimal. In contrast, in inverse scheduling, the exact values of the processing times are unknown and the task is to specify their values within given bounds so that the predefined job

TABLE 6. Tolerance scheduling.

Problem	Uncertainty	Method	Paper
Dynamic Fault-Tolerant Elastic Scheduling	Uncertainty of task execution time in clouds	Own heuristic algorithm	[247]
Smart scheduling problems	Delivery dates of jobs	-	[248]
Fault tolerance and dynamic voltage scaling	Fault occurrences and task execution times	Own heuristic algorithm	[249]
Electric vehicle charging involving renewable energy	Energy requests and elastic charging property of electric vehicles	Two-stage model	[250]
General job shop scheduling problem	–	Ant Colony Optimization with constraint-handling approach	[251]
General stochastic job shop scheduling problem	Success (or failure) of a manufacturing job and its effect on jobs	Simulation	[252]

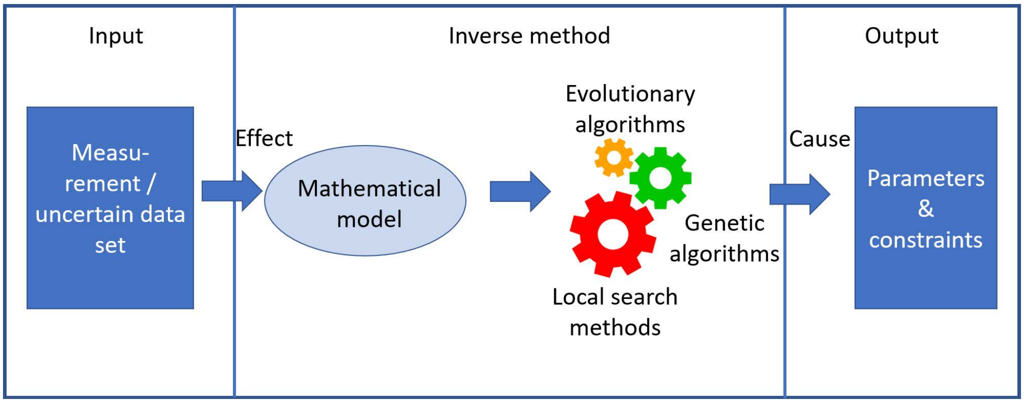


FIGURE 12. Schematic diagram of Inverse Optimization.

sequences are optimal. In some cases, the parameters of inverse scheduling tasks focus on the determination of the coefficients associated with the objective function, while in scheduling tasks, the unknown features are mainly related to various parameters of the jobs such as processing times, due dates, release times, job arrivals, machine breakdowns, etc. A schematic diagram of the steps comprising the inverse optimization can be seen in Fig. 12. Using the uncertain input data, a mathematical model can be built, which will form the basis for inverse optimization. Several solving algorithms may be suitable for solving this model, e.g., traditional LP solvers, local search methods, genetic algorithms or evolutionary algorithms can be used effectively. These steps yield the parameters within the searched constraint or objective function.

The tasks considered may also differ in terms of the way they are solved. Solving the problem with traditional optimization tools requires the investigation of complex models, while evolutionary-based algorithms can often yield valuable results. The given problems become even more complex when they have to be solved in uncertain environments. Table 7 shows examples of such problems, including the solution methods used by the authors and the uncertain parameters.

H. SCHEDULING WITH AGENT AND MULTI-AGENT SYSTEMS

Agent and multi-agent systems are often used to solve planning and scheduling problems. Planning and scheduling problems in manufacturing have to adapt to changing events. In many cases, traditional solutions are unable to handle the dynamic properties of the modelled systems effectively. However, using multi-agent systems can serve as a good alternative approach, which has been widely applied in numerous papers.

The concept of agent-based, multi-agent systems is based on distributed artificial intelligence. Intelligent autonomous entities help to solve various scheduling tasks, where cooperation between these entities implements a distributed AI-based approach. In the solutions, agents can be regarded as software modules that solve a predefined task, while being sufficiently intelligent to solve the task autonomously and communicate with the environment.

In a multi-agent system, three types of agents can be distinguished. The User Interface Agent is responsible for the communication tasks as well as monitoring and providing information to the Job Agents and Resource Agents. The User Interface Agent is also responsible for generating the required number of jobs and resource agents, which depends on the number of jobs and machines in the scheduling job. In addition, the agent is also responsible for assigning the appropriate Job Agent to each job. The Job Agents process the information of the different jobs and are responsible for supervising their execution, while Resource Agents are responsible for producing the appropriate schedules. The schematic structure of all these agents is shown in Fig. 13, where green and red boxes indicate job and resource agents, respectively.

TABLE 7. Inverse scheduling.

Problem	Uncertainty	Method	Paper
Single machine-shop environment with weighted completion time	–	Improved genetic algorithm (IGA)	[254]
Single machine-shop environment	Due dates, processing times	Hybrid multi-objective evolutionary algorithm	[255]
Dynamic flow shop inverse scheduling problem	Job arrivals, breakdown	Genetic algorithm with adaptive local search	[256]
Multi-objective flow shop scheduling problem	Processing parameters	Hybrid multi-objective evolutionary algorithm	[257]
Flexible job shop inverse scheduling problem	Processing time	Hybrid multi-objective evolutionary algorithm based on decomposition and particle swarm optimization	[258]
Smart scheduling problems	Delivery dates of jobs	-	[248]

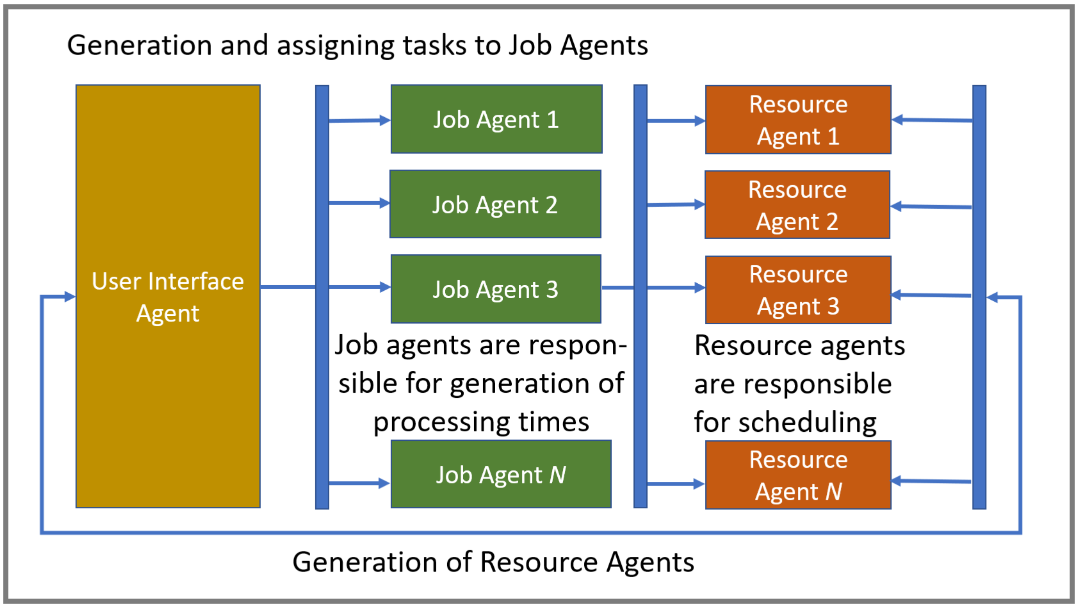


FIGURE 13. Model of a multi-agent scheduling system [259].

Several publications provide agent-based solutions for solving scheduling problems with an Industry 4.0 focus. A summary of these relevant works is presented in Table 8.

I. SUMMARY

Table 9 summarizes the information of Tables 2-8 according to the uncertainties. As can be seen, the most examined uncertainties are related to activity times, like processing time, execution time, and setup time.

IV. REQUIREMENTS OF THE 5th INDUSTRIAL REVOLUTION

The first four industrial revolutions focused primarily on technological solutions / developments and their collaboration. While in the case of Industry 5.0 - in addition to technological issues - other focal points emerge such as social, ecological, sustainability and psychological issues. A set of complex systems, such as smart materials with embedded bio-inspired sensors, comprises the enabling technologies of Industry 5.0. It is also clear from this brief introduction that the next industrial revolution will create even more complex, more uncertain and often multi-purpose systems, in which the importance of assistive technologies, such as scheduling, will continue to grow [281].

The aim of this chapter is to present the requirements of the Fifth Industrial Revolution as well as to highlight why and what uncertainties emerge in addition to what effects they can have. Enabling technologies of I5.0 and their requirements for the development of scheduling algorithms will be introduced first. Next, the tasks and challenges of Industry 4.0 solutions related to the management of uncertainty will be discussed. Finally, potential solutions will be proposed and further recommendations will be made.

A. ENABLING TECHNOLOGIES OF INDUSTRY 5.0 AND THEIR REQUIREMENTS FOR THE DEVELOPMENT OF SCHEDULING ALGORITHMS

Industry 4.0 has brought about important advances in terms of approach and technology. Industry 4.0 deals with sustainability and the people involved in the production process to a limited extent. Therefore, the focus points of Industry 5.0 have been rethought and are the following.

- Rather than taking an emergent technology as a starting point and examining its potential for increasing efficiency, a human-centered approach in industry places core human needs and interests at the heart of the production process. We want to use technology to adapt the production process to suit the needs of the workers.

TABLE 8. Agent and multi-agent systems in scheduling.

Problem	Uncertainty	Method	Paper
Hybrid energy system with price bidding-based demand response	Dynamic characteristics of intermittent energy and load demand	Event-Triggered Multi-agent Optimization	[260]
Production scheduling	Several risk factors are given	Genetic algorithm and multi-agent model	[261]
Risk-aware energy scheduling problem	Unpredictable energy generation from renewable and non-renewable sources	Multi-agent deep reinforcement learning	[262]
Production scheduling and control in remanufacturing	Unknown conditions of the used products	Simultaneous scheduling of machines using Constraint Programming	[263]
Adaptive and online control of the hybrid microgrids	Wind and solar power	Multi-agent Reinforcement Learning	[264]
Resource allocation and scheduling in a smart grid	Renewable energy sources	Review paper including many methods	[265]
Multi-project scheduling	Task duration, starting time	Agent-based simulation system	[266]
Resource scheduling in wireless sensor networks	Resources of wireless sensor network	MATLAB simulation tool	[267]
Distributed maintenance scheduling	Release date of activity, processing time, tardiness penalty, qualification level	Auction-based negotiation mechanism among the agents	[268]
Multi-agent coordination	Communication	Simple temporal networks with uncertainty model	[269]
Schedules patients and resources in outpatient clinics	Uncertainty and variability in waiting times and under-utilization of resources	Intelligent Real-time Scheduler by multi-agent system	[270]
Real-time residential load scheduling	Energy prices, renewable energy output	Deep reinforcement learning framework	[271]
Multi-project (re)scheduling	Task durations, resource demands	Agent-based Simulation	[272]
Multi-period dynamic emergency resource scheduling	Traffic	Multi-agent genetic algorithm	[273]
Two-agent scheduling problem	Processing time, weights of the jobs	Fuzzy simulation with genetic algorithm	[274]
Optimization model for truck appointment	Arrival time of trucks	Real-time multi-agent system	[275]
Scheduling of steel-making and continuous casting process	Customer orders, inaccurate estimate of processing time, unpredictable machine breakdown	Neuron-based stochastic dynamic programming	[276]
Parallel machines scheduling for electro-etching	Machine failure, urgent orders	Agent-based multi-agent negotiation mechanism	[277]
Railway container hub scheduling	Operation time, high coordination demand of facilities	Multi-agent systems	[278]
Interoperable dynamic scheduling for manufacturing	Production environment	Reinforcement learning (Q-learning) with agents	[279]
Job shop problems	Processing time and manufacturing environment	Multi-agent-based proactive–reactive scheduling algorithms	[49]
Flexible job shop problem with dynamic events	Job arrivals, uncertain processing times, breakdowns	Multi-agent scheduling system based on pheromone-based approach	[280]

TABLE 9. The number of publications in the last 10 years about uncertain scheduling in Industry 4.0.

Uncertainty	Reactive scheduling	Stochastic scheduling	Fuzzy programming	Robust scheduling	Tolerance scheduling	Inverse scheduling	Agent and multi-agent systems	Total
Processing, execution and setup times	8	11	32	3	1	3	8	66
Demand	4	14	1	1	1	0	1	22
Machine breakdown/failure	11	1	2	3	1	1	3	22
Supply/resource availability	6	4	2	0	0	0	6	18
Due date	2	1	7	0	1	2	0	13
Arrival of new job	5	0	1	0	0	1	4	11
Electricity price	2	2	0	1	0	0	1	6
Resource consumption	2	1	0	0	0	0	0	3
Market/product price	0	1	1	1	0	0	0	3
Deleted batches	2	0	0	0	0	0	0	2
Release time	0	2	0	0	0	0	0	2
Workforce efficiency	0	1	0	0	0	0	0	1
Failure of manufacturing	0	0	0	0	1	0	0	1
Total	42	38	46	9	5	7	23	170

- Industrial production needs to be sustainable, namely it should develop circular processes as well as reduce waste and the environmental impact. Technologies like AI can play a significant role here by optimizing resource efficiency and minimizing waste.
- Resilience refers to the need to develop a higher degree of robustness in industrial production, enabling it to deal with disruptions better as well as making sure it can provide and support critical infrastructure in times of crisis.

Each of the aforementioned points requires the treatment of uncertainty. These are explained in more detail below.

It is important to manage human-machine interactions properly for social, psychological and humanitarian reasons it is essential to integrate humans into modern production in the Industry 5.0 concept. On the other hand, it is important to learn as much as possible about this segment as it involves many uncertainties. This can only be achieved if an individualized human-machine interaction is present. One major part of this kind of interaction is the mental and physical tracking of employees, because this is the source of essential information that scheduling and other algorithms/techniques can make use of. In this changed work environment, many solutions become natural. A good example of this is when humans work with cooperative robots (cobots) in a common workspace. The roles depend on the specific work phase. The human and the cobot could play assistive and/or subordinate roles. It is important that a human should never be placed in a subordinate role; there are currently numerous examples of this, e.g., feeding raw material, and moving a finished workpiece. However, it should also be noted that the uncertainties present in scheduling processes increase as the human role is strengthened. This is why the use of technologies that can provide feedback to people and systems needs to be strengthened to decrease this effect. Examples of this are augmented, virtual or mixed reality technologies. Expanding human (physical and other) skills is also an important area to remain competitive in the new work environment. Their stable application is only possible if new human-machine interfaces are developed that can be used to control, for example, exoskeletons efficiently. In addition to physical abilities, enhancing cognitive abilities is also of paramount importance. To bring about this, a new integration and development level is needed between decision support systems and people. This is only possible if appropriate scheduling algorithms are used that handle the uncertainty adequately. Many papers have dealt with this [282]–[285].

In Industry 5.0, scheduling problems have different attributes than usual shop problems, which are presented in Section II-A. In a shop problem, each operation is executed by a single machine, while in I5.0, a human also has to be assigned to the operation in addition to the machine. The majority of scheduling algorithms has to be modified to be capable of making this type of decision. Furthermore, the handling of uncertainties becomes more important because human operations are not as strict as machine operations. For example, the operating time varies for a human but is fixed for a robot.

In Industry 4.0, the concept of 'digital twin' has already emerged, meaning a digital pair of real processes. A number of options for running simulations in this environment is available to increase the accuracy of digital twins with the help of continuous feedback. Finally, all functions and elements - including all uncertainties - are included in the digital twin. In Industry 5.0, the importance of the digital twin is increasing with the advent of human-centered thoughts. Since many different alternatives can be tested, including workplace safety issues, the scope and modelling of simulation and scheduling tasks go beyond mere technology issues. It is worth noting that as complexity and multi-purpose optimization challenges increase, multi-scale dynamic modelling and simulation need to be used more and more frequently. This in turn brings about the need to build scheduling tasks on top of each other. Ultimately, the goal is to create a well-designed and functioning cyber-physical system as well as a digital twin, where all maintenance and manufacturing processes operate below a certain level of risk, which is still a topic of research: [286]–[289].

Furthermore, in the case of Industry 5.0, the transmission, storage and analysis of data are key areas as on the one hand, a lot of data is generated due to networked sensors, but on the other hand communication between cooperating (autonomous) systems / modules is essential. The generated data should be stored efficiently as well as securely and the authorized device / entity must have secure access to them. This can only be addressed effectively with a scalable solution for such complex systems as I5.0 that can adequately handle multi-level cyber security, cloud computing infrastructure, big data management, traceability and edge computing. Communication and traceability are particularly critical areas in terms of uncertainty [10], [290]–[293].

Artificial intelligence is a dynamically evolving field, whose potential capabilities are also needed in Industry 5.0. Nowadays, advanced correlation analysis technologies are often referred to as AI. This is important because AI strongly influences the future and opportunities of Industry 5.0 [10], [15], [294]–[296]. However, to be truly implementable, the following areas need to be further developed:

- Individual, human-centered Artificial Intelligence, where the main goal of AI is to determine the best solution for the operator.
- Swarm intelligence, where communication and shared information are essential parts of the operation.
- Informed deep learning, where AI is combined with expert knowledge.
- In addition to correlation-based AI, causality-based AI must also evolve.
- New kinds of effective interfaces between humans and AI, for example, the brain-machine interface.
- Ability to handle, find as well as to discover abstract and complex relationships between different dynamic systems.
- Ability to react to new and/or unexpected conditions without human interaction/support.
- Safe, reliable and energy-efficient AI.

Modern technology is primarily powered by electricity and many methods are known to produce it. Sources of electricity can be renewable or non-renewable. It is important that the share of renewable resources increases in the future and, at the same time, be used as economically as possible. Many energy sources (such as wind energy) show pulsed energy production, that is, energy is not generated when consumers want to use it. Therefore, electricity storage networks can improve energy efficiency. However much Industry 5.0 is implemented, its energy demand will be high. Any effort to use renewable energy is a big step towards sustainability [10], [295], [297].

Although the type of energy usage is important, it must not be forgotten that not only electricity is used in the industrial process, therefore the resources used in the whole process must be taken into account. This is a serious problem because the resources of our Earth are finite. Moreover, there are many signs that current human activities are unsustainable and potentially catastrophic. Responsible action can only be taken if industrial processes become sustainable. The circular economy paradigm seeks a solution to this. One solution could be, for example, to introduce a CO_2 footprint label that makes it clear to the customer how much and what kind of resources have been used in the production of a given product. A greater amount of responsibility lies with people as far as power and resources are concerned. An average person can also do a lot to make a difference, therefore full integration of customers throughout the value chain is needed to inform them about the environmental and/or social value created. People incorporate this into their choices and willingness to pay. In order to achieve this goal, it is essential that professionals and scientists working in different fields work together throughout the life cycle of products, thereby formulating important ideas and expectations for products that put industrial processes on a more sustainable path. The selection of sustainable alternatives can be effectively supported with the help of the Industry 5.0 toolkits such as digital twins and simulations. Some papers have dealt with the relationship between Industry 5.0 and sustainability [9], [16], [292], [297], [298].

For such complex systems as those implemented in Industry 4.0 or 5.0, scalability is important and essential in terms of operability. In practice, the expectations of Industry 4.0 may not be met, especially in SMEs or across entire value chains, for many reasons ranging from financial problems to the introduction of conscious multiphases. Whatever path a company chooses to take with regard to Industry 4.0, it is important to pay attention to scalability as this is how it can be developed in the light of needs and resources [298]–[301].

In summary, the complexity of the systems and the potential uncertainty increases. Sources of uncertainty can range from a human to an algorithm, which are subject to uncertainties in terms of their operation, e.g., genetic algorithms. As the complexity of systems as well as the number of communication events/technologies increase and multipurpose objective functions emerge, the number of sources of uncertainty can only increase. In addition to identifying uncertainties and integrating them into models, it is important to integrate our social and natural environment as well as the resources more effectively to make the whole process sustainable and reduce the unwanted impact of uncertainty to a manageable level. Traceability processes as well as collecting, storing and processing as much information as possible is therefore important. Above a certain level, data processing is a big challenge, where Artificial Intelligence can be an important tool, which is capable of providing a solution for these kinds of complex systems.

B. TASKS, CHALLENGES RELATED TO UNCERTAINTY MANAGEMENT IN I4.0 SOLUTIONS

Although the challenges seen earlier in Industry 5.0 raise a number of issues, it is important to clarify that identifying and addressing uncertainty in Industry 4.0 also poses significant challenges because it will bring to the fore the use of technologies with a high degree of adaptability, increasing the efficiency of their collaboration and application of the paradigm. As a consequence, the effect of an unexpected event can influence the operation of multiple elementary modules. Due to the complex system and interconnection between the elements, the effect can spread like a chain reaction between the elements, causing serious unexpected consequences [302].

Industry 4.0 technology has enabled new manufacturing strategies, especially through the application of cyber-physical systems, which require highly customized solutions. The ultimate goal of this concept is to facilitate flexible, customized manufacturing to approach the typically lower costs of mass production. In addition to the personalization and regionalization trends that have become commonplace today, platform-type, modular products supporting both directions can emerge, which in most cases are non-consumer products. However, industrial products are built from modules and the manufacturers seek to standardize and produce the components by mass production. In general, a 'reversing' trend is also observed, with a declining product range and a particularly large product volume. Partly due to existing 'old-style' mass-production capabilities, and partly due to the more expensive production costs than traditional equivalents, a 'reversing' trend can also be observed with a decreasing product range, in case of a particularly large volume of products. These trends can be seen in Fig. 14. In summary, the current industrial processes show an increase in complexity, variability and the number of cooperating (autonomous) subsystems in the new trends. The consequence of these processes is that uncertainty also increases. The purpose of this subsection is to identify the sources of uncertainties and their effects.

OEE (Overall Equipment Effectiveness) is the primary measure of the efficiency of production systems with regard to where losses are systemized based on time. These losses can be linked to unplanned events, the flexible management of which involves a scheduling task. In these cases, the significant - unplanned - events that take place in the production area necessitate the immediate review and rewriting of plans. A flexible manufacturing environment is one aim of Industry 4.0, which effectively reduces these losses and increases productivity. Our approach is based on the OEE methodology in a similar way because the primary goal is to increase productivity by reducing uncertainties.

Considering the time available during production, efficiency can be increased by increasing the ratio of production time to other time components. In the process, it is very much beneficial if the factors that influence and reduce the

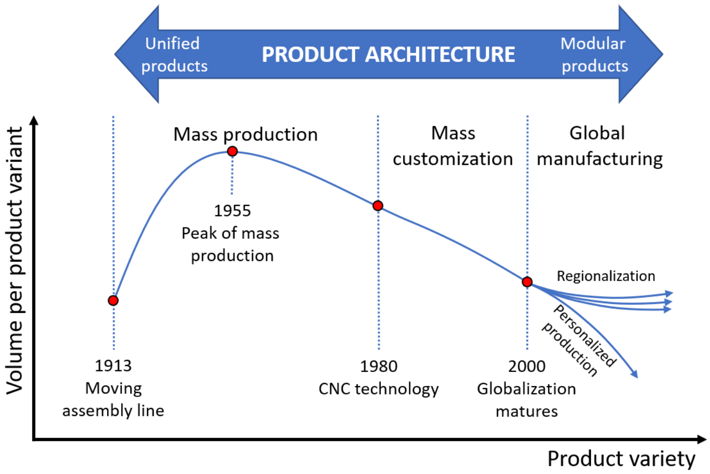


FIGURE 14. Changes in the variety and quantity of products. New paradigms are driven by the needs of the market and society. [303].

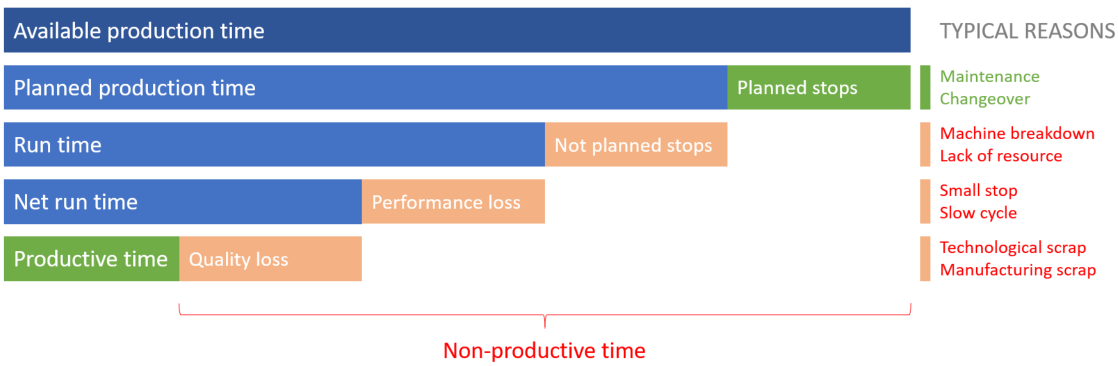


FIGURE 15. Time classification of production.

production time can be identified and their impact minimized. Fig. 15 shows the time components of production.

In most (real) production systems, conditions, such as the constant arrival of new tasks and/or unexpected downtime are constantly changing. Unexpected real-time events are divided into three categories, as was seen in Chapters II-B and II-C.

As has been seen, production time is the most significant when defined as the total time required for production. Although the time duration of many components of production can be planned and scheduled, as the complexity of systems increases, the number of uncertainties also rises. A number of ways to address these types of challenges was mentioned earlier such as flexible and dynamic scheduling.

In general, the risks in the manufacturing area of the Industry 4.0 are the following [304]:

- Manufacturing process management (Information risk associated with data losses, loss of integrity and available information.)
- Maintenance (Problem with the availability and integrity of data for maintenance)
- Operation methods and tools used (Errors in data processing)
- Machines and manufacturing technologies (Sensitivity and vulnerability of data problems related to cyber-attacks)
- Human sources (Low number of qualified workers)
- Machine environments (Attacks from the Internet network, problems related to electromagnetic compatibility and electromagnetic emissions affecting manufacturing machines.)

Industry 4.0 has some requirements and characteristics that include inherent uncertainties that occur directly or indirectly during optimization and / or scheduling tasks as outlined in Table 10.

The most appropriate scheduling strategies for Industry 4.0 and 5.0 problems should be determined based on their characteristics. The most important aspect is that the problem has to be solved offline or online. In addition, based on the available information, it has to be determined whether a deterministic or stochastic approach should be followed. Finally, the type of uncertainty is also a crucial characteristic, which can effectively determine how to solve the problem. All these characteristics restrict the set of possible solution strategies. All of these aspects are illustrated in Fig. 16, which

TABLE 10. Uncertainties of the requirements of Industry 4.0.

Requirements	Task	Challenges	Uncertainties
End-to-end engineering	This is a process that describes a system or service from beginning to end and offers a complete functional solution.	complexity	technological surprise, inexactness, lack of observation/measurements
Smart factory	It is a highly digitized and fully connected solution that relies on smart manufacturing, where the final goal is to organize production without human intervention.	regulated and controlled environment	inherent randomness of nature, behavioural variability, technological surprise, lack of observation/measurements, conflicting evidence
Product personalization	It is a customization process for unique goods and services based on the needs and desires of customers.	defining the limits of flexibility	societal randomness
Decentralization	It is a structural and approach mode, where the activities of an organization, mainly the planning and decision-making, are distributed or delegated away from a centralized infrastructure.	stable communication, security issues	behavioural variability, technological surprise, conflicting evidence
Flexibility	It is a capability to react cost-effectively and in a timely manner to changes within a predetermined limit of requirements.	create the right set of rules, choose the right information to collect, setting the data analysis frequency and response time	behavioural variability
Real-time capability	It is the capability of a system or device to collect and analyze data as well as respond instantaneously to an event, input or command.	keeping response time within limits, maintaining continuous communication	value diversity, inexactness, lack of observation/measurements, indeterminacy
Modularity	It is a concept that determines which independent and interlocking subsystems the system is comprised of based on their functionality.	formalization/provision of communication interfaces, independent stable operation	technological surprise, reducible ignorance
Interoperability	It is the capability of systems or components to exchange information.	formalization/provision of communication interfaces	value diversity, inexactness, lack of observation/measurements
Smart product	It is a data processing object/product, which has numerous interactive functions. The physical and software interfaces are combined, moreover, the application of a smart product is interactive.	regulated and controlled environment	inherent randomness of nature, behavioural variability, technological surprise, lack of observation/measurements, conflicting evidence
Autonomy	It is the capacity to make an uncoerced, informed decision. Autonomous units - that could be, for example, institutions, machines, organizations or systems - are independent or self-governing.	collect information needed to make a decision, making the right decision	inherent randomness of nature, behavioural variability, societal randomness, technological surprise, reducible ignorance
Agility	It is a capability of firms to sense environmental change and readily respond to it.	stable maintenance of signalling/the information system	inherent randomness of nature, societal randomness
Service orientation	It is a capability to offer a service (of humans, smart factories or cyber-physical systems) via the IoS (Internet of Services).	ensuring a high degree of availability, scalable operation	technological surprise

TABLE 11. Additional requirements of Industry 5.0.

Requirements	Task	Challenges	Uncertainties
Corporate social responsibility (CSR) and sustainability	It is a self-regulating business model that helps a company to be socially accountable to itself, its stakeholders and the public. Sustainability focuses on meeting the needs of the present without compromising the ability of future generations to meet their needs.	harmonization of socially and economically useful objective functions	societal randomness
Human-centric	People must be put back into industrial processes in a humane way. The masses need place in modern industrial processes and they carry out useful activities there.	find a large number of useful and humane jobs within modern industrial production	technological surprise, societal randomness, behavioural variability, inexactness, reducible ignorance
Wellbeing of the worker	It puts the wellbeing of workers at the heart of the production process and uses new technologies to create wellbeing beyond jobs and growth while respecting the production constraints of the planet.	create wellbeing with the help of modern technology in sustainable way	technological surprise, societal randomness, behavioural variability, inexactness, reducible ignorance
Advanced employees skills and training management	It empowers employees and addresses the evolving skills and training needs of employees. It increases the competitiveness of the industry and helps attract the best talent.	effective human development and its application	technological surprise, societal randomness, behavioural variability, inexactness, process related events
Social stability	Human-centric and the wellbeing of workers can help this process, but it is essential for the industry and the people to create and maintain a stable social background.	creating a stable, long-term sustainable society	societal randomness, inherent randomness of nature
Resilient against external shocks	A review of existing value chains and energy consumption practices could also make industries more resilient to external shocks.	minimize operational, manufacturing and supply risks	technological surprise, behavioural variability, value diversity, inherent randomness of nature, other events, inexactness, process related events
Responsive supply chain (RSC)	The responsive supply chain has three main components, namely the value chain, information technology and systems and knowledge management. The interaction between them leads to a supply chain that is responsive, flexible and speedy.	create stable and robust RSC in practice	technological surprise, behavioural variability, value diversity, machine-related events

defines three decision levels for choosing the right solution strategy for scheduling problems. Although the complexity of scheduling tasks may increase for Industry 5.0-related problems, the mathematical and algorithmic solution to these problems requires similar considerations as the solution methodologies presented earlier.

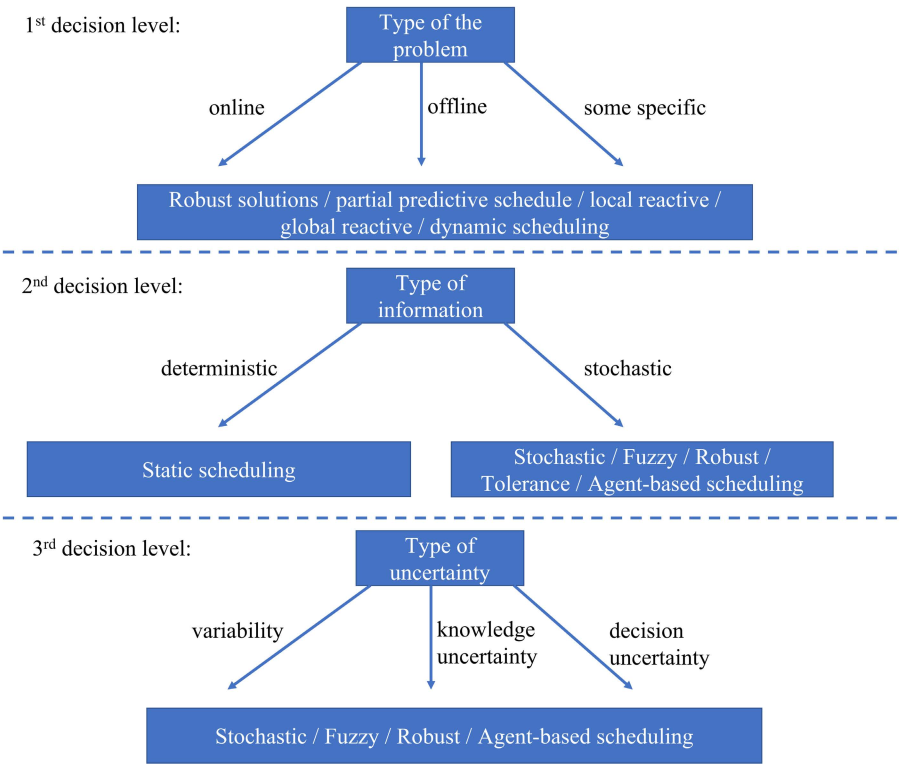


FIGURE 16. **Decision levels for selecting proper algorithms for scheduling problems.**

In summary, the Industry 4.0 paradigm is creating increasingly complex systems made up of autonomous modules that are able to communicate with each other. As a result, the number of elements of uncertainty will inevitably increase. Integration processes can somewhat compensate for the aforementioned negative effects. These can be organized into two large groups, namely the vertical and the horizontal integration.

C. TOOLKIT OF SOLUTION OPTIONS, INHERENT POSSIBILITIES IN HORIZONTAL AND VERTICAL INTEGRATION

Vertical integration focuses primarily on the internal processes. The structure of the ISA-95 standard helps to understand this flow as depicted in Fig. 17.

Vertical integration creates a clear connection between data transfer flow and the levels. This is necessary in the Industry 4.0 paradigm, because it works with smart products and smart resources that have to communicate with, for example, other entities as well as IT systems.

Fig. 17 clearly shows the solutions, decision times and communication techniques for each level. Since Level 0 is closest to the physical intervention, in this case, the least amount of time is available to make a decision, in extreme cases, this might only be a few microseconds. At the next level, the logical units are the first to process the incoming information and, if necessary, instruct the interveners on Level 0. A PLC is a typical logical unit that is located this level. Given that the time response is also important in this case, the equipment uses field network solutions. Level 2 is a distinct level in several respects. On the one hand, field communication communicates/replaces IP-based communication at this level, but on the other hand the number of human-machine interfaces has increased at this level, e.g., the simple HMI or complex SCADA systems. The primary task of the next level is the structured collection of data from the entire factory/company. Special data analysis and forecasting solutions have already been developed at this level. Importantly, the reaction rate of this layer slows down further. In practice, this means that making a decision can take minutes or even hours, depending on the method, hardware environment and amount of data which is processed. MES is the most popular solution at this level. Business logic takes place at the top level, which deals with aggregated data in many cases and its primary task is to support strategic decisions. ERP and PLM are good examples of tools at this level. The reaction time slows down further, it can even take months, due in part to the fact that certain decisions/forecasts can only be made with a sufficient amount of data.

It is easy to see in this solution that a minimum of 7 different systems must work harmoniously by communicating with a minimum of 2 different solutions. The used systems are usually made by different manufacturers, which equates to additional risks during their integration. The proper implementation of vertical integration reduces the number of uncertainties to a manageable level.

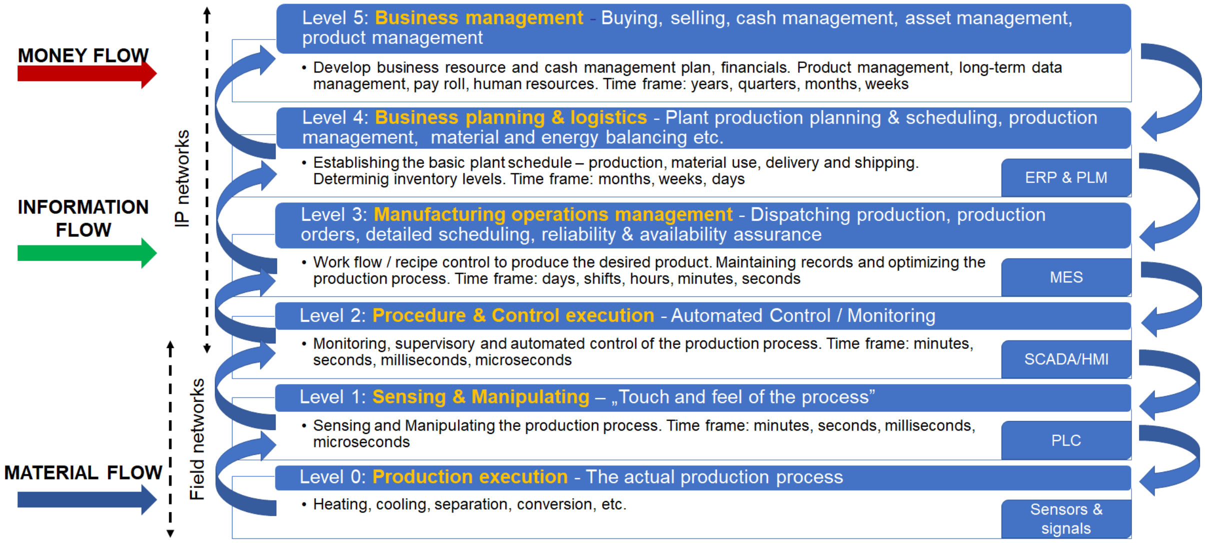


FIGURE 17. The structure of the ISA-95 standard for constructing vertical integration.

While vertical integration focuses primarily on internal processes, horizontal integration focuses more on external ones as it may include the whole supply chain. Practically, this means that the integration process covers all components of the supplier and customer networks. It is important to realize that this process is so complex and multi-stakeholder that the information flow can often only be solved by a cloud-based service.

In terms of uncertainty, similar problems arise in this case as have previously been seen, because countless systems work together using several communication solutions. The main difference is that in this case, (software) systems operating at the same level communicate with each other and although the communication network is the same, these share information through numerous kinds of interfaces and solutions. Another significant difference between the two kinds of integration is that while vertical integration in many cases can be considered closed/local, horizontal communication occurs over the open Internet, where important open services (also available on the Internet) are often used. This results in another uncertainty concerning the operation of systems. Since the system is open, one of the most important challenges are security issues. In this case, since, integration can also mitigate the negative effects of the resulting uncertainty, it is important and indispensable.

In the following list, the main causes of uncertainty have been collected, which can be normalized by integration:

- Large and complex systems
- Wide variety of cooperating systems
- Multiple communication solutions
- Different response times
- Security issues
- Open system

It is important to note that both types of integration processes have similar uncertainties and the biggest difference between them is whether they can be considered as external or internal processes for a given company. Based on this consideration, the integration process organizes the uncertainties into two large groups. Vertical integration contains the internal uncertainties, while horizontal integration includes the external ones.

Virtualization techniques are another important area that can help handle uncertainty. To be able to create the digital twin, that is, the virtual equivalent of manufacturing, a fully digitized factory is needed in addition to knowledge and modelling of processes in great detail. The process of creating a digital twin is already capable of exploring and/or correcting any errors and uncertainties. The parallel operation of virtualization and real production provides an opportunity to check the accuracy of one's modelling continuously, resulting in a system that is very close to reality and accurately identifies and manages the uncertainties in the system. Furthermore, this is an advantage for large and complex systems that can ensure stable and predictable operation in the long run.

In summary, both integration and virtualization techniques use a procedure in their design that identifies uncertainties in different areas and, where appropriate, eliminates or mitigates their effects. Such complex systems can only be operated efficiently and as expected if the uncertainties are managed well. Table 12 shows which techniques are suitable for reducing the impact of uncertainties in different situations.

D. DISCUSSION - RECOMMENDATIONS FOR TOOLS THAT SHOULD BE APPLIED AND DEVELOPED

Responsible thinking, rational use of resources, materials recycling, and social discipline and stability are all part of sustainable thinking. Industry 5.0 is opening up strongly in this direction, and (next to the Industry 4.0's technology-driven goals) sustainability and a livable society are the most prominent new focal points. It is important to note that these new directions increase potential uncertainties significantly.

TABLE 12. Possibilities to solve / manage uncertainties.

Technique	Industry 4.0 as a solution	Source of uncertainty	Solved/managed uncertainty
Vertical integration	managing uncertainty between internal systems	large and complex system	behavioural variability, technological surprise
		wide variety of cooperating systems	technological surprise
		multiple communication solutions	behavioural variability, technological surprise, value diversity, inexactness
		different response times	value diversity
		security issues	conflicting evidence, indeterminacy
		open system	inherent randomness of nature, societal randomness, technological surprise
Horizontal integration	managing uncertainty between external systems	large and complex system	behavioural variability, technological surprise
		wide variety of cooperating systems	technological surprise
		multiple communication solutions	behavioural variability, technological surprise, value diversity, inexactness
		different response times	value diversity
		security issues	conflicting evidence, indeterminacy
		open system	inherent randomness of nature, societal randomness, technological surprise
Virtualization	handling uncertainties in manufacturing processes	wide variety of applied technologies	behavioural variability, technological surprise
		incomplete knowledge	inexactness, lack of observations/measurements, practically immeasurable, conflicting evidence, reducible ignorance

The challenges, characteristics, and uncertainties of Industry 4.0 were discussed previously, which are summarized in Table 10. Although Industry 5.0 has the problems of Table 10, there are some new challenges in addition, and we need to address them. These requirements are the following: corporate social responsibility and sustainability; human-centric thinking; the wellbeing of the worker; advanced employees skills and training management; social stability; resilience against external shocks; responsive supply chain. These are shown in detail in Table 11. Since the Industry 5.0 is mainly accredited with bringing sustainability requirements, these goals can be linked with Sustainable Development Goals (SDGs), which were adopted by all United Nations Member States in 2015. Of the seventeen SDGs, SDG#7 'affordable and clean energy', SDG#9 'industry, innovation and infrastructure', SDG#12 'responsible consumption and production' and SDG#13 'climate actions' are related to environmental issues. As stated in [12], technologies that enable Industry 4.0, like digitization (IoT and CPS), real-time monitoring and data collecting, and big data analytics, can create new opportunities to achieve sustainability targets.

SDG#8 'decent work and economic growth', SDG#9 'industry, innovation and infrastructure', SDG#12 'responsible consumption and production' are strongly connected to the human-centric aspect of Industry 5.0. that puts human needs and interests at the heart of the production process.

That is why, the development of Industry 5.0 solutions demands the handling of the uncertain societal goals to become a resilient provider of prosperity by making production respect the sustainability boundaries and placing the well-being of the industry workers at the centre of the production process. The integration of economical, ecological and societal aspects further increases the necessity of handling uncertainty (see Fig. 18). This requirement urges the development of tools applicable for the analysis of interrelations and communicating uncertainty, methods that can be applied for the systematic reduction of the uncertainty, and models and simulators that can be used in digital twins. In the following subsections we will discuss the details of these suggested development directions.

1) TOOLS FOR THE ANALYSIS AND COMMUNICATING UNCERTAINTY

This problem should be described in several ways (mathematical risk analysis, quantitatively, qualitatively and verbally) and shared with all the relevant groups (e.g., managers, relevant members of the public and partners). It can also be observed that different methods have proven to be effective for different groups of participants. Qualitative information is generally more effective for stakeholders and the public than quantitative information. However, it is worth noting that quantitative uncertainty analysis often serves as a basis for qualitative information.

One approach to make risks/uncertainties more understandable is to compare risks/uncertainties. However, it is important to understand that this should be done with caution and, wherever possible, monitored, especially if the comparison is intended to demonstrate/achieve reductions in risks/uncertainties [305]. A graphical representation of uncertainties is usually useful and aids the communication process.

2) SYSTEMATIC REDUCTION OF UNCERTAINTIES - SIX SIGMA PROJECTS

Uncertainties can be reduced by examining the environment in which they occur and taking the necessary steps to adapt to it. In the case of performance measures, a target value

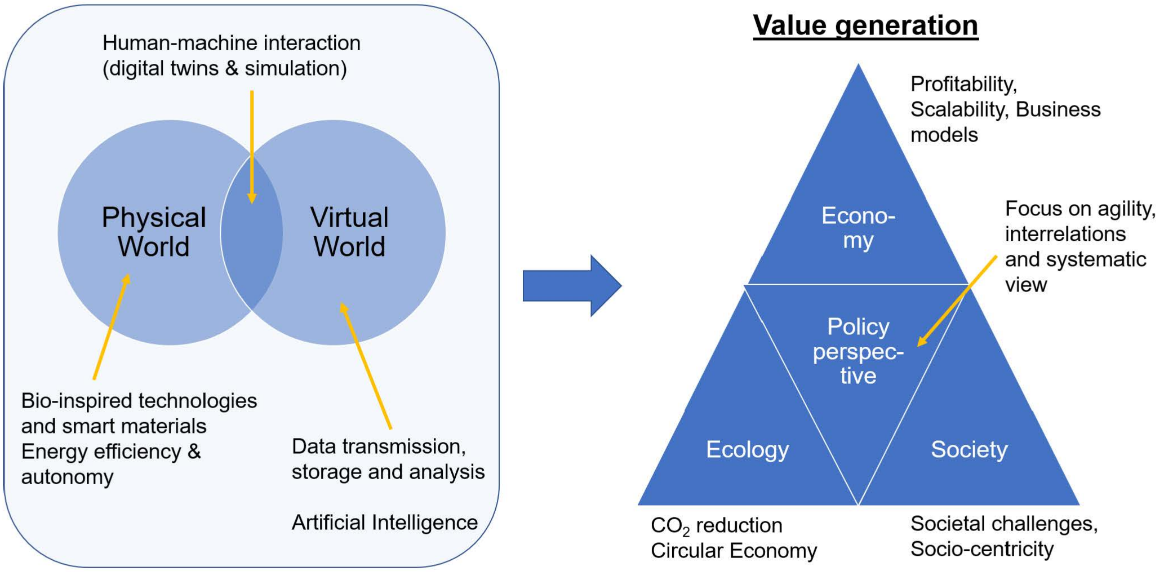


FIGURE 18. The concept of Industry 5.0 requires the integration of economical, ecological and societal aspects that further increases the necessity for handling uncertainty.

is needed. Defining this target value is paramount, but not always clearly feasible. There are several ways to identify this target value, which can be used to express the uncertainty associated with different values. The goal is to assign a distribution to the possible target values subjectively. This distribution then can be examined using trade-off analysis.

Six Sigma competitive business strategies increase the sensitivity of employees to quality and provide a rational framework for measuring and improving them by taking into account the control of costs. This solution has been introduced by many companies [306]–[308], whereupon they produce a more robust and desirable product that contributes greatly to revenue growth by improving internal productivity growth as well as reducing costs and warranties [309]. The Six Sigma methodology usually includes the following programs: Quality Function Deployment, Failure Modes & Effects Analysis, Statistical Distributions & Process Capability, Design of Experiments (DOE) & Response Surface Methods, Statistical Process Control and Robust Design Optimization [310]. Although applicable techniques are widespread, their application is often based on a deterministic model [311]. It is particularly important to consider the uncertainty concerning the transmission functions between inputs and outputs and to examine the uncertainty of the quality characteristics of the products with regard to the performance and cost of the product [312]. In the case of complex process characteristic of production systems and supply chains, the loss due to process uncertainty is much more significant than that resulting from changes in production processes. By ignoring variance or uncertainty, modifications can be made that can result in adequate performance but yield misleading results. By taking uncertainty into account, the occurrence of quality properties outside the specification limits can be reduced, thereby increasing confidence and examining variability, which can be offset by robustness to achieve significantly more efficient results [313], [314].

By using Six Sigma/Lean tools effectively, companies can remain competitive and increase their production efficiency. This also requires the need to appear in the schedules of various manufacturing tasks. To make the supply chain customizable and lean, manufacturing in smaller batches can be a good solution. The downside of this is the frequency of changeovers (due to the production of different products) and that downtime increases significantly, the cost of which can be more significant than previously estimated [315]–[317]. This challenge [318] requires policies for increasing sustainable manufacturing and competitiveness [319]. To achieve this, the Single-Minute Exchange of Die (SMED) system, which is a Lean and Six Sigma device, is a good solution to reduce the changeover times of machines [320]. Changes in consumer demand and the increase in demand for variable products require manufacturers to produce different parts quickly. SMED is becoming crucial to meet these requirements [321]–[323] and imperative in any organization.

A Manufacturing Execution System (MES) is an information system that meets the needs of production management which collects, processes and analyzes data with regard to manufacturing processes. It can be used to increase the efficiency of processes, yields and delivery properties. MES is widely used in, for example, the automotive, pharmaceutical, petrochemical and aerospace industries. To increase the efficiency of MES, the implementation of DMAIC (Define, Measure, Analyze, Improve, Control) achieves significant results, as well [306], [324], [325]. Integrating MES can reduce the cycle time and unnecessary processes while increasing value-added production. There are five stages in the implementation of DMAIC [306].

During the first phase, the purpose, boundary, schedule and direction of the project as well as various other areas of project management are defined, thus the financial benefits are also estimated. When combined with the MES tracking database, it contributes greatly to the rapid and accurate identification of process problems.

During the Measurement phase, basic information about the situation is collected (such as a control diagram, estimation of process performance, capability indicators and a Pareto diagram) and problem areas are delineated [326], [327]. This is the most complex phase of DMAIC [328].

The third phase is Analysis, where the root causes of the problems are identified. Information can be described statistically by discovering important factors and solutions. MES contributes to statistics with information derived from work in process (WIP).

During the Improvement phase (proactive analysis), solutions or suggestions for change are implemented to address the root causes identified during the analysis. MES provides and analyzes repair information during the design of experiments (DOE) and also accesses the best operational variables of the response surface methodology (RSM). MES with embedded statistical process control (SPC) can track production time and quantities as well as contribute to control processes with markings.

The Control phase additionally improves documents with information and the state-of-the-art business process management stays in the Improvement phase, which is integrated into the daily routine. In this phase, MES is connected to ERP and other application softwares. Linking MES and ERP provides access to production data so companies can leverage their ERP investments more [329]–[331]. It also allows for quick inspection with regard to plant capacity upon receipt of a new order, progression, cost and profitability control, manpower used, amongst other resources. Linking other software to MES provides analytical capabilities for internal operations, thereby contributing to the dissemination of information [332].

Industry 4.0 has a major impact on the future development of MES, as the paradigm shift with I4.0 brings about changes and requirements in complex processes that are of paramount importance to MES engineers and researchers [333]. Given the I4.0 maturity model, 2 of the 6 stages are prerequisites for I4.0, while the other 4 are part of it. Computerization is the first step that is a prerequisite for digitization where different forms of information technology are used. The second step is connectivity, where interconnections between these different technologies must be present in order for the entire production chain to be ready to accommodate the development of Industry 4.0. The remaining 4 stages are visibility, transparency, predictive capacity and adaptability [334]. The so-called digital shadow of a company is required for proper maintenance and monitoring of various data requires the company's so-called digital shadow, therefore decision-making processes can be done based on completely real data. A complete overview alone is insufficient, as causal relationships carry high-quality knowledge, therefore knowing the root of the root causes contributes greatly to decision-making processes. Given that the Big Data paradigm contributes greatly to this, it is an essential part of MES solutions. After analyzing the collected data, the predictive ability can be used to run simulations, based on which the best cases can be identified, thereby ensuring the most appropriate solution is applied in the future. An adaptable company is able to conform quickly and efficiently to changing conditions, thanks to the automated operation of the entire system and previously mentioned features [335], [336]. Therefore, a new generation of MES is required to meet with new challenges of I4.0 [337].

3) DEVELOPMENT OF FORECASTING MODELS AND DIGITAL TWINS

Managing uncertainty is also a priority for forecasting models, since the proper handling and mapping of uncertainty has a significant impact on the quality of the models prescribed. Such forecasting models can include price, inventory and consumption planning, for which a number of methodologies are known [338].

Generally speaking, in both scheduling and optimization problems the uncertainty of their optimal solutions can be reduced by using more accurate mathematical models. On the one hand, the accuracy of models can be achieved by increasing the reliability of their input data, but on the other hand it is necessary to choose such problem-solving techniques that support the handling of models with uncertainty. Data science solutions can help to reveal unknown relationships between input data, thereby reducing the level of uncertainty in the inputs [339], while machine learning techniques can further reduce the uncertainty in the solutions of complex optimization models. Fuzzy and stochastic models are of particular importance that can be used to describe uncertainties in optimization problems efficiently. One such modelling approach is survival analysis, which can be effectively applied to scheduling problems by introducing non-linear models [340]. Here, survival functions represented by the Weibull distribution describe the uncertainty of each activity as a function of time. Survival analysis as a data-driven method can also be used to identify frequent sets of events in such cases, where the occurrence of a set of events and their combinations may result in some critical events [341]. Hybrid semi-mechanistic models take advantage of the integration of discrete event models, related to process simulators and data-based models. The hybrid semi-mechanistic models consist of a white-box model based on mechanistic relationships and black-box substructures to describe less defined parts.

Digital twins are often based on such mathematical models that require very high computational demand. Such models may include modules for various optimization, scheduling and management tasks, in which missing knowledge and uncertain information make it difficult to manage the tasks accurately. Surrogate models can be used to replace black-box models, which are computationally expensive to evaluate [342]. These special surrogate models can be used to describe the given optimization problems and solve them approximately. Surrogate models can be used to study many engineering problems. The descriptive model itself can be a neural network, polynomial function, radial basis function, support vector machine, linear regression, fuzzy model, etc. The most important step in the application of surrogate modelling is to develop a surrogate that describes the target area sufficiently and accurately and requires just a few calculation steps when evaluating the simulation results [343].

Multi-stage models take uncertainty in the tasks into account at several levels. Different scenarios can be used to account for the characteristics of uncertainties in the task. The drawback of this approach is the large number of computational steps, as the number of scenarios can grow exponentially, which greatly increases the time required to solve the problem [344], [345].

E. OPEN RESEARCH CHALLENGES AND LIKELY EMERGING RESEARCH DIRECTIONS

The initial goals of control engineers were to develop unmanned factories, however, for ethical, social and impracticable reasons anthropocentric cyber-physical systems (ACPS) have become the focus [346]. As a result, all related physical components (PCs), cyber components (CCs) and human components (HCs) must be displayed at each operational level.

In another approach, the connected CC and PC are managed by humans [347]. In any case, in production, the context of CPS in Industry 4.0 can be observed in three components: HC, CC, and PC. Furthermore, HC-CC, CC-PC, and HC-PC interfaces play an important role in interconnecting components to become a unified system. Due to the growing demand for customized products and changes in machines/systems in CPS-based manufacturing in Industry 4.0, the manufacturing process requires a shorter product life cycle and the rapid application of new innovative solutions. Replacing traditional components with dynamic and intelligent CPS requires a broader expertise of the human worker, which necessitates faster learning techniques [348], [349]. This also includes interactive user guides based on work-based learning [350] and augmented reality (AR) [351]. A human-centered approach is also a significant requirement in Industry 5.0, as shown in Table 11. A human being is a significant component in the processes, therefore human-centered solutions and those that put human well-being first play a key role. In addition, empowering employees with evolving skills and trainings is needed to increase the competitiveness of the company.

The challenges facing CPS can be divided into four categories: production improvement, dynamic reconfiguration, standard and information technology. Sudden changes in customer requirements and unsatisfactory design can cause CPS to fail. Flexible and efficient manufacturing systems [348], [352] and efficient human-machine interaction are always inevitable in reducing machine control and maintenance time [353], as well as raising the issue of adaptation to new technology [350], [354]. Uncertainties regarding the quality and quantity of product returns are becoming an inevitable problem [355]. Efficient data and storage management is required for intelligent monitoring and intelligent control [356] and also increases interoperability [357]. Cloud-based data storage is a solution to this problem, but it also presents three challenges: resource management virtualization, cloud resource scheduling and lifecycle management (LCM) [358].

Having formal methods is a serious problem in defining and controlling interactions between industrial equipment and machines [359]. The emergence of dynamic reconfigurability affects several areas. A new modular, flexible, data-intensive reconfigurable manufacturing [360], [361] for on-demand, customizable products is in high demand [362], [363]. Flexibility also manifests itself in the need for easily programmable industrial robots, and minimizing time due to increasing product life cycle uncertainty, increasing product variability and globalization [364]. The challenge is to manufacture industrial robots [365] and to integrate self-optimization into the mechatronic system [366]. Human-machine interface and machine-to-machine interaction are required for the evolution from computer integrated manufacturing to Industry 4.0 [367]. Cryptographic authentication and secure storage are important in automated manufacturing [368] to avoid any deception. The development of new and flexible industry-oriented middleware is also a challenge to deal with a dynamically changing market [369]. The introduction and ramp-up of a new product can often cause several different unforeseen failures, which require formidable failure management systems [370].

Using CPS in manufacturing is an emerging technology, which requires standardization. Several challenges have already been addressed, such as seamless process integration [371], seamless data aggregation and disaggregation [372], standardization compliance [373], product-service innovation, product variety, quality standards, support devices and immediacy or order satisfaction [374]. Industrial automation systems are being developed using IEC 61131 standard [347], with Vision 2.0 addressing the new challenges of complex industrial automation systems, however further work on standardization is needed.

Information technology (IT), which is an important part of CPS, can be divided into two main types: people-centric and cyber-centric. Holistic production control is required [375] to control and optimize production. Due to the frequent changes in the intelligent space, the need for a broader range of skills to understand and manage the wide range of interactions between physical objects and digital equivalents is paramount [349]. Cyber components are becoming key challenges in the development of model management software design methodologies, Sense Compute-Control applications [376], software-compatible hybrid solutions [377] and enterprise vision prediction [378]. Furthermore, real-time optimization of hardware using cyber components is an essential and significant task [379], [380].

It is also necessary to mention the convergence of Industry 4.0 and the circular economy approach, for which the potentials are available to varying degrees. Sustainability also poses a challenge to Industry 5.0, which needs to be addressed in conjunction with a human-centric approach and liveable society goals. The main barriers to inhibiting the circual economy (CE) are process digitalization, semantic interoperability, sensor technology, CPS standards and specifications as well as design challenges [381]. Through Integrated Industry 4.0-CE, the manufacturing industry can gain promising solutions such as monitoring waste and natural resources, transforming closed-loop supply chains into technological supply chains, regulating coal and energy consumption.

V. CONCLUSION

Scheduling is one of the most important optimization research areas, which has a significant effect on the efficiency of a manufacturing system. In classical scheduling problems, all data are known in advance and do not change during the manufacturing process. In real-life problems, unexpected events can occur and the forecast data can be inaccurate, which has to be taken into account.

In this review, uncertainties which can occur in Industry 4.0 and 5.0 systems have been investigated.

First, a brief overview of the classical scheduling problems of manufacturing industries from the literature has been presented and a classification of uncertainties that occur in real-life problems given. Then, the most common approaches, which can solve scheduling problems, were surveyed focusing on the cases of uncertainties published since 2010. Finally, Industry 4.0 and 5.0 concepts were examined in the light of uncertainties and scheduling.

We have shown that uncertainty is an unmissable aspect of scheduling under the I4.0 and I5.0 paradigms. I4.0 solutions rely on horizontal and vertical integration that significantly increase the complexity of the scheduling problems. The increased complexity and the requirement of robustness and self-organising behaviour motivate the development of meta-heuristic optimisation algorithms. With the concept of I5.0, the integration of societal, economical, ecological and societal aspects further increases the necessity for handling uncertainty. This requirement urges the development of:

- tools applicable for the analysis of interrelations and communicating uncertainly,
- methods that can be applied for the systematic reduction of uncertainty,
- models and simulators that can be used in digital twins.
- preference for sustainable solutions when modelling optimisation problems and determining the best solution.

As I5.0 places the industry workers into the centre of the production system, the integration of the models and solutions that represent the uncertain human nature of the workers defines the most important research direction to the future.

Industry 5.0 provides new opportunities to achieve Sustainable Development Goals (SDGs), especially that are related to SDG#7 'affordable and clean energy', SDG#8: 'decent work and economic growth', SDG#9 'industry, innovation and infrastructure', SDG#12 'responsible consumption and production' and SDG#13 'climate actions'.

The issue of sustainability has an impact on the optimization and scheduling of tasks at several points. Corporate social responsibility and sustainability require the harmonization of socially and economically sound objective functions. The wellbeing of the worker needs the sustainable use of modern technologies. Social stability raises further aspects to be highlighted in the context of optimization, which requires, among others, the consideration of societal randomness in the modeling and the optimization steps.

By the synthesis in this paper, we hope to encourage more researchers and decision-makers to take a further step in developing and applying goal-oriented robust scheduling algorithms that can result in efficient, resilient, and sustainable production systems.

The role of scheduling tasks will be further enhanced by Industry 5.0 requirements. We reviewed the enabling technologies and scheduling requirements impacting Industry 5.0 considerations. We highlighted the role of agents and multi-agents in scheduling tasks, we have provided a systematic summary of the most important related methods and the nature of the uncertainties addressed. We reviewed the publications of the last 10 years on scheduling tasks methods used to manage scheduling tasks, taking into account the different types and nature of uncertainty. In particular, we highlighted the requirements of Industry 5.0, which need to be addressed in the context of scheduling tasks.

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