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Production Planning and Scheduling in Cyber-Physical Production Systems: a Review

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The study of scheduling procedures has generated important contributions to the improvement of productivity in different industrial branches. In recent years, the incorporation of high technology to production systems brought the advent of a "fourth industrial revolution", *Industry 4.0*. One of the mainstays of Industry 4.0 is the application of Cyber-Physical Systems (CPS), which are physical production systems that incorporate sophisticated computational tools. This implies embedding computers, enabling a real-time connection between workstations and Decision Support Systems. It seems natural, in this setting, to associate scheduling schemes to CPS. This allows streamlining the decision-making process, allowing more flexible and lean production lines. We review here the most salient contributions on scheduling in these environments. We distinguish between work on the basic issues of scheduling and that on scheduling as part of higher level production planning activities. To frame correctly this distinction we analyze how CPS can embody the different levels of the ISA-95 structure and how this relates to the classical structure of production planning. Our review suggests that the real-time availability of information will have a significant impact in this area and that scheduling will be solved in the future in decentralized decision processes.

Keywords: Cyber-Physical Systems; Industry 4.0; Scheduling; Production Planning; Real-Time

Subject classification codes: include these here if the journal requires them

1. Introduction

Tech experts and pundits alike have predicted a new industrial revolution for the next decade. This so-called Industry 4.0 stage will imply a big shift in the manufacturing paradigm, with the Internet of Things (IoT) and Cyber-Physical Sistems (CPS) concepts playing major roles (Preuveneers & Ilie-Zudor [2017]; Uhlmann et al. [2017a]). The economic impact of Industry 4.0 is supposed to be large: for instance, the German GDP is forecasted to increase in more than 250 billion euros up to 2025, when the transition to

Industry 4.0 should have been completed (Heng 2014).

Lu (2017) claims that Cyber-Physical Systems (CPS) are the main engine of Industry 4.0, being able to achieve efficiency at all levels of industrial activities by integrating heterogeneous data and knowledge. This shows clearly that CPS are cornerstones of the new manufacturing paradigm. CPS are, in turn, defined as processing technologies with high interconnection between physical assets and computational tools (Baheti & Gil 2011).

Big expectations have been placed on CPS. Their potential advantages led the National Science Foundation (NSF) and the European Commission to fund research and development projects aimed to create new CPS technologies. In China a new strategic plan, Made in China 2025 (Chen 2017), exhibits also a strong interest in these new areas. Other countries have as well included them in their strategic plans of science and innovation.

Since CPS are controlled or monitored directly by algorithms running on computers, it is of interest for manufacturing purposes, to explore the possibility of incorporating scheduling schemes to them. Even more, if CPS are considered as networks of interacting elements with the aim of achieving some objectives (Ilie-Zudor et al. 2017), like for instance carrying out a production plan, the incorporation of scheduling becomes highly relevant. So, for instance, Yuan et al. (2017), review the application of these systems to the petrochemical industrial sector, showing how they can be used to improve production planning. Blunck et al. (2017) draw from both Game Theory and Operations Research to evaluate the capacity needed to achieve a given work flow. These and other applications of CPS have led to the wider concept of Cyber-Physical Production Systems (CPPS) (Monostori 2014), representing the ensemble of sub-systems connected to the environment and among them in these enhanced Industry 4.0 settings. One of the benefits of CPPS is the possibility of linking directly the shop floor with a high level Decision Support System (DSS) (Rossit & Tohmé 2018). This allows providing real time data to the DSS as well as giving the shop floor the ability to rapidly adapt to the output of the DSS.

These new manufacturing structures will induce changes in the way production planning is carried out. We propose here an approach to solving production scheduling problems autonomously, which are known for being NP-hard (Pinedo 2016). Since schedules are usually chosen for short time frames, the planning process has to be repeated frequently (sometimes even several times in a single week). The quality of the solutions has a direct economic impact on the benefits of companies, and thus on their long-term ability to thrive in competitive markets (Framinan et al. 2014). This intrinsic criticality of scheduling processes becomes even more salient in their incorporation to the Smart Manufacturing processes of Industry 4.0. As pointed out by Monostori (2014), scheduling processes constitute one the main challenges in the design of CPPS. Moreover, Qin et al. (2017) claim that the literature has not yet addressed the potential of CPPS to run self-optimization and self-configuration processes,.

Rossit & Tohmé (2018) discussed tools able to increase the autonomous capability to operate directly on a schedule generator, embedded in the production system. A growing number of publications have presented ways of solving the scheduling problem in these new production environments. Many of them address the problem in its classical presentation (Shime et al. [2016]; Framinan et al. [2017]; Leusin et al. [2018]; Rossit et al. [2018b]; Framinan et al. [2019]; Da Silva et al. [2019]), i.e. considering a series of tasks that must be allocated to production units, evaluating the solutions according to objective functions, as described by Pinedo (2016). There exists also another body of work in which scheduling is seen as embedded in a higher level of production planning, involving, for instance, the supply of resources, the demands of clientes or multi-factory allotments, etc (Badr [2016]; Ivanov et al. [2016a]; Frazzon et al. [2018a]; Pimentel et al. [2018]; Klein et al. [2018]). The latter line of work proposes systems and architectures for scheduling without being concerned with classical optimization issues as Pinedo (2016).

We intend to review the main contributions to both lines of analysis. We start by presenting the standard approach of Pinedo (2016), describing the main relations of scheduling with the rest of planning levels as well as with other functions of an organization. We intend to frame the different contributions in the structure of production planning. We will also address the way in which CPS are able to embed the different levels of decision making, using the ISA-95 standard as reference. We can then see how Industry 4.0 will impact on the decision making processes in the field of production, based on the technology of their components.

2. New scenario: Industry 4.0 technologies

In this section we will briefly review the technologies that may contribute to take production planning to a higher level. On one hand we consider the Industry 4.0 tools that may impact on production processes and, in particular, Cyber-Physical Production Systems (CPPS).

2.1. Industry 4.0 technologies

The main difference of Industry 4.0 with its predecessors is that, instead of traditionally hierarchical and centralized structures, it exhibits schemes in which autonomous agents interact in decentralized architectures. These agents are connected among them and with decision centers. The technologies that are mostly relevant for the process of decision-making are Cloud Computing, Internet of Things (IoT), Big Data and RFID connections.

Cloud Computing provides computing services over a network, usually the Internet. This allows virtualizing and scaling resources in a dynamic way. Its use provides firms the possibility of getting resources as they are needed, without incurring in sunken costs and paying only for the resources actually used (Wang & Wang [2018a]; Caggiano [2018]; Sunny et al. [2017]).

IoT is the portmanteau expression for the digital connection of objects to the Internet. It involves the different technologies that allow the smart integration of objects on line and thus to follow remotely the state of execution of work orders while collecting data and information in real time (Wang & Wang 2018b). This possibility of being remotely accessed, nevertheless, creates vulnerabilities that make cybersecurity a crucial aspect in these systems. (Preuveneers et al. [2016]; Preuveneers et al. [2017]).

Big data, in turn, refers to the techniques for processing large and inhomogeneous databases collected online. While these techniques can be seen as outgrows of Statistics, novel computational procedures facilitate the detection of patterns where no traditional methods could yield useful insights or even be applied (Uhlmann et al. [2013]; Uhlmann et al. [2017b]). This became only possible with the advent of fast and powerful hardware connected in networks. In the case of manufacturing, Big Data methods allow accessing and processing large amounts of data generated in production processes (Wang & Wang 2018b).

Radio-frequency identification (RFID) refers to procedures to store and recover data remotely using RFID labels, cards or transponders. The identity of an object (akin to its idiosyncratic serial number) can be transmitted to others through radio waves. This technology provides a way to exchange relevant information between fast moving objects at long distances (Ilie-Zudor et al. [2011]; Wang & Wang [2018b]).

2.2. CPS and CPPS

As briefly discussed in the Introduction, CPS are some of the main components of Industry 4.0 systems. CPS facilitate the confluence of physical and virtual spaces, integrating computational and communication processes in interaction with physical processes, adding new capabilities to physical systems (Wang et al. 2015). Unlike traditional embedded systems, in which components tend to be independent, CPS feature a network of interactive I/O physical elements. Later years have witnessed great advances in this area. New intelligent CPS spur innovation and competition in different industries (aerospace, automobile, chemical, energy, infrastructure, transportation, etc.). A relevant instance of CPS is constituted by intelligent manufacturing lines, in which a single machine can carry out a variety of procedures communicating with the other components (Wang & Wang 2018b).

A more precise description of CPS can be given in terms of the five-level architecture introduced in Lee et al. (2015). They define a 5C architecture outlining the main design levels of CPS: 1) *Connection* level, 2) *Conversion* level, 3) *Cyber* level, 4) *Cognition* level and 5) *Configuration* level. Table 1 represents this architecture and its main attributes

The Connection level is the one at which information from the environment is collected, coming from sensors, controllers or enterprise manufacturing systems (ERP, SCM, etc.). At this level it is necessary to have well designed protocols (managing different types of data) and select the proper sensors. Then, the Conversion level is the one at which data is transformed into useful information, bringing some sort of self-awareness to the machines. The Cyber level is the third one, playing a central role in the architecture, since it gathers information from all the components of the system. The fourth level is the Cognition level, at which a thorough knowledge of the system is generated. This knowledge can be used by expert users and supports the decision-making process. The final level is the Configuration level, where the information at the cyberspace is fed back to the physical space. This fifth level acts as a resilience control system (RCS).

Lee et al. (2015) apply this five-level architecture in a Prognostics and Health Management (PHM) application, aiming to ensure the correct maintenance of the physical assets. Beyond this, we consider this architecture as roadmap for the characterization of CPS and the study of new aspects of them, in our case, the incorporation of scheduling into them.

CPS with manufacturing-specific implementations have given rise to Cyber-Physical Production Systems (CPPS). According to Monostori (2014) CPPS consist of autonomous and cooperating elements and subsystems interconnected in such way that, depending on the setting, cover all the stages of the production process, from the shop floor to the logistic networks. One of the main challenges posed by these systems is the need to develop robust approaches to scheduling, in order to face adequately to the different and unforeseen stresses on distributed production processes.

2.3. Related works

The prospects of Industry 4.0 have spurred the interest of scholars, who have devoted effort to analyze, in particular, scheduling and decision making in production systems under the new paradigm. Recent reviews on these subjects have been published in the last couple of years (Dolgui et al. [2018]; Ivanov et al. [2018]; Liu et al. [2018]; Uhlmann & Frazzon [2018]; Waschneck et al. [2017]; Zhang et al. [2017]). Dolgui et al. (2018) e Ivanov et al. (2018) have focused on the application of control theory to planning and scheduling. The main issue is whether it is possible to generate tools for controlling the different links of the supply chain, integrating this information to schedules (Dolgui et al.

2018), improving the quality of the dynamic responses of the production systems (Ivanov et al. 2018). Both contributions also analyze further venues for the application of control theory to this new research field.

On the other hand, Waschneck et al. (2017) and Zhang et al. (2017) analyze the literature on job shop scheduling in Industry 4.0 environments according to classical approaches. They focus on the impact and challenges that these environments pose for traditional scheduling settings. Waschneck et al., consider the semiconductor industry and the way in which the autonomy in decision-making, the increase in flexibility and integration as well as questions related to the interactions in networks, may affect job shop production. Zhang et al., reviewing 120 articles on job shop scheduling, analyze how the advent of Industry 4.0 may lead to the study and development of scheduling in distributed systems.

Uhlmann & Frazzon (2018), analyze another aspect of scheduling and Industry 4.0, namely considering the problem of rescheduling, i.e. how to modify a schedule already in execution in the face of unexpected disruptions (more on rescheduling, below). Uhlmann & Frazzon's are in particular interested on rescheduling systems distributed over different organizations. On the other hand, Liu et al. (2018) study scheduling in cloud manufacturing. In Cloud Manufacturing, jobs are subdivided in subtasks, and since the industrial organization is in the cloud, organizing them becomes more complex than in the traditional case.

This paper intends to contribute to this literature by viewing CPS as production resources that may integrate different functions and acquiring progressively more accuracy.

3. Scheduling decision-process

Scheduling is the last stage of planning before the actual execution of the plan (Pinedo

2012), it involves the allocation of the available production resources in a work flow generated in a previous planning stage. The choice of a schedule demands a detailed description of the production process and amounts to handle a large volume of information (Framinan et al. [2014]; Rossit et al. [2018]). As it is intuitively evident, these decision problems have a strong combinatorial nature and consequently a high complexity.

Formally, a scheduling problem is the allocation of a family N of jobs, $N = \{1, 2, \ldots, n\}$ on a set M of machines, $M = \{1, 2, \ldots, m\}$. Each job j consists of a class O_j of operations, where operation O_{ij} of job j must be carried out on machine i. Each operation O_{ij} has an associated processing time $p_{ij} \in \mathbb{N}$ on machine i. Each job j will be associated to an ordering R_j of the operations of O_j, reflecting the precedence ordering among operations. The whole point of scheduling is to find a schedule π of jobs over machines yielding an optimal value $F(\pi)$, where F denotes some objective function.

Scheduling problems are highly dependent on the actual details of the production setting (Job Shop, Flow Shop, etc.). This implies that different parameters (delivery dates, preparation times, waiting times, etc.) and different objective functions (makespan, total tardiness, maximal tardiness, etc.) require alternative statements of the general problem.

3.1. Manufacturing Scheduling systems

Given the combinatorial nature and the complexity of most scheduling problems, Decision Support Systems (DSS) are usually needed to support the process of decision-making (Framinan et al. 2014a). These systems are called Manufacturing Scheduling Systems (MSS) and constitute a variant of Business Information tools, i.e., information systems supporting business functions. Framinan & Ruiz 2010 present a guideline for the design, implementation and testing of a MSS. The model of Pinedo (2016) provided a general description of a MSS (Figure 1).

The system is constituted by the following components: a Database Management module, an Automatic Schedule Generator, a Schedule Editor and a Performance Evaluator. Each of these last two components has its own Graphical User Interface (GUI). The Database Management module manages the information required to develop a production schedule. This information is generated on the basis of the production orders and the master production programs, as well as from shop floor data, which allows monitoring the state of the physical aspects of production. The output of the Database Management module feeds into the Automatic Schedule Generator.

The MSS, represented in Figure 1, is intended as a decision-making aide to the scheduler or the final user. The goal is produce a working schedule and also address events that arise in the dynamics of the production process (Pinedo 2016). The main tasks faced by the users of the system are the allocation of jobs to resources (in general, machines), handle problems affecting schedules (like changes in resources, dates, quantities, etc.) and anticipate future problems with the schedule (Framinan et al. 2014b). The field study of McKay & Buzacott (2000) showed that human schedulers usually follow a "script", independently of the production field in which they operate. It starts by evaluating the current situation, looking for critical issues or sources of conflict, as for instance a job that takes longer than planned or wrong uses of resources. Once identified, the scheduler has to determine whether to run a rescheduling process or reassign resources. Once done that, it updates the information on the schedule and runs again an analysis of possible critical issues.

MSS, being handled by a human, become affected by the idiosyncrasies of the user. One important shortcoming is a frequent myopic stance, under which the horizon of analysis is no longer than an hour ahead (Crawford & Wiers 2001). This can be attributed to two sources, on one hand, the high complexity of scheduling problems and the changing scenario in which these problems are defined.

One aspect in which schedulers are particularly skilled is in reducing considerably the size of problems, by applying criteria like Drum-Buffer-Rope's (Goldratt & Cox 1992) and focusing on bottlenecks (Webster 2001). This can be both an advantage and a complication. It simplifies drastically the solution-finding process while at the same time can eliminate optimal or at least valuable solutions. Another problematic feature is that schedulers working at different shifts may address similar situations differently (Framinan et al. 2014b). Finally, schedulers may pursue some goals in detriment of others. Field studies, like Vernon (2001), indicate that schedulers usually pursue production goals instead of service-oriented goals, sometimes contrary the expectations of managers.

3.2. Scope of Manufacturing Scheduling systems

The scope of MSS refers to the class of business functions that the system implements in support of the management of the production. Framinan & Ruiz (2010) postulate two levels, depending on the time horizon:

- A higher level that uses the output of production planning to set up the dates for the beginning of each job on each machine. This level is often referred as *release scheduling*. (Framinan et al. 2014a)
- A lower level which is involved with real-time item movement planning. This level is usually denoted as *reactive scheduling*. (Framinan et al. 2014a)

A MSS has to cover these two levels adequately. That is, the architecture of the system has to provide means to monitor and execute the planned schedules. Mckay & Wiers (1999) introduced the concept of "sustained control", which involves the way in which schedulers monitor the progress of production and address deviations from the plan. Schedulers may not have to reschedule but may have to solve smaller scheduling decision (optimization) problems. The MSS should provide support for both levels. The user may intervene more frequently at the lowest level, that of reactive scheduling.

Once the schedule has been generated, the fabrication operations can start. While managers and supervisors want the shop floor to run the schedule with precision, deviations can appear forcing operators to intervene. The largest deviations arise when unexpected events disrupt the normal execution of the schedule. Even if the schedule does not get updated, the execution differs from it due to the reaction of operators (Vieira et al. 2003).

Rescheduling is the process of updating the schedule in response to interruptions and other changes (Ouelhadj & Petrovic 2009). Some triggers of rescheduling are the arrival of new jobs, breaks and repairs of machines, delivery delays, etc. There exist different strategies to address the rescheduling in the face of events disrupting the production process. One class of strategies is purely reactive, making decisions all along the apparition of the events, for instance by dispatching jobs when production orders reach the shop floor, without starting with an initial schedule. Another kind of strategy has a predictive-reactive nature and is more commonly used in fabrication systems. This predictive-reactive scheduling is a multi-stage process in which schedules are revised in response to real time events. In the first (predictive) stage a schedule is generated as a solution to the problem without considering possible interruptions. In the next stages (reactive), the original schedule is modified to address unforeseen events, assuming that no further events will appear. This is repeated every time a rescheduling is required (Li, Pan & Mao 2015).

There exist strategies that start from assuming uncertainties in the decision-making process. This is the case of Robust Predictive-reactive Scheduling (Al-Hinai, & ElMekkawy 2011). This strategy makes the original schedule more robust as to ensure a lower impact on performance of eventual disruptions and the ensuing reschedules. Alternatively, Robust Pro-active Scheduling provides each operation with an extra processing time, shielding the schedule from certain type of uncertainty, reducing the number of potential reschedules.

An important aspect of Dynamic Scheduling is that it takes into account the fact that the production process will be already being carried out when the disruptions happen. Reschedules that disregard this aspect may incur in strong modifications that may generate unduly losses (arising, for example, from stopping ongoing jobs, modifying allocations already being implemented or moving jobs from a machine to another, etc.). A way to reduce such unwarranted changes is by incorporating into the objective function the minimization of the number of jobs that have to change the starting dates originally scheduled (Katragjini et al. 2013).

4. Standard Production Decision-making process: ANSI/ISA 95

The ANSI/ISA 95 is a standard that can provide a framework for an automated interface between production facilities and control systems. Officially is defined as[1]: " ISA-95 is the international standard for the integration of enterprise and control system. ISA-95 consists of models and terminology that can be used to determine which information has to be exchanged between systems for sales, finance and logistics and systems for production, maintenance and quality". It can yield a common ground for the

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[1] http://www.isa-95.com/

communication of all the participants in a production process and gives a representation of how information can be modelled and used. It organizes the different levels of decision-making hierarchically. It is based on the “Purdue Enterprise Reference Architecture” (PERA) which distinguishes five levels, as shown in Figure 2. Level 0 is associated to the physical process of manufacturing. Level 1 involves the intelligent devices that measure and manipulate the physical process are located. Typical instruments at this level are sensors, analyzers, effectors and related instruments. Level 2 represents the control and supervision of the underlying activities. Systems acting on ISA-95 Level 2 are Supervisory Control and Data Acquisition (SCADA), Programmable Logic Controllers (PLC), Distributed Control Systems (DCS) and Batch Automation Systems. Level 3 involves the management of the operations and the production work flow in the production of the desired products. Some of the systems comprised at this level are Batch Management, manufacturing execution/operations management systems (MES/MOMS), the laboratory, maintenance and plant performance management systems, data historians and related middleware. This level has special importance for our work, since it is here where the scheduling process takes place. Finally, level 4 is associated to the business activities of the entire firm. This architecture represents, in a synthetic way, the different activities and functions of a production system. Besides, it establishes the way in which the different levels communicate; in traditional productions settings in particular, each level interacts only with its adjacent levels (Rossit & Tohmé 2018).

4.1. Decision making in CPPS

CPPS change the way in which decisions are made in the realm of industrial planning and control. To introduce our view on this topic, we show in Figure 3 the levels of ISA 95 that should be incorporated into CPPS. This integration ensues from the capacities of CPPS, which can enact physical processes (level 0), measure and handle the instruments reading the physical processes (level 1) and implement control actions over its operations (level 2). Furthermore, given the computing power of CPPS, they will also be able to plan, evaluate and manage the entire production process (level 3).

This integration of functionalities will yield direct benefits, as for instance increasing the flexibility of the production system in response to unexpected events; or the higher integration and transmission of information, given that a CPPS by itself can translate the data obtained at level 1 into the higher-level language used at level 3, bypassing the adjacency constraints inherent in PERA.

On the other hand, decision-making, focused on production planning, will be also impacted by the development of Industry 4.0. This will give rise to a new structure, which, while keeping PERA's levels, will be managed by two large systems: ERP (Enterprise Resource Planning) and the CPPS. Figure 4 shows this.

Figure 4 shows that the decisions about both the aggregate level and the goals to be pursued will be handled by the Enterprise Resource Planning (ERP) systems (tuned to smart manufacturing environments). All other decisions will be automatically and systematically run by CPPS, including the execution of the production plan in real time. In this structure, the CPPS can be seen as a set of autonomous elements collaborating to reach the goals set by the ERP system. This means, in particular, that current Manufacturing Execution Systems (MES), which take care of dispatching work orders and their scheduling in the shop floor, will be absorbed by CPPS. This will yield information of better quality, useful for both making the decisions at this level and minimizing response times, increasing the flexibility of the entire system.

This structure, handled only by the ERP and CPPS systems, will redefine the way in which production will be planned. The traditional view, centralized and highly hierarchical, will make way for distributed features. This will, in turn, impact on the scheduling process, not only because decisions will be made collaboratively but also because the resources will be distributed (Wang & Wang 2018c), setting the stage for further developments. But the literature keeps treating the planning problem in a centralized and mostly static way. The MES is assumed to consider the entire set of distributed resources and dispatching orders according to that higher-level vantage point. But the new paradigm requires the decentralization and collaboration of the different components, exchanging information acquired in real time. The scheduling community will face the challenge of developing new strategies and methods tailored for this new setting. In this sense, Zhang et al. (2017), propose redefining the traditional methods and algorithms to the distributed framework. A particularly important contribution to these developments will arise from the incorporation of more complex structures, like those that appear in problems of non-permutation scheduling of manufacturing cells (Rossit et al. [2016]; Rossit et al. [2018]).

A good deal of the decisions made by ERP systems (as inventory control, management of databases, handling information about suppliers, etc.) will be managed by CPPS. But we leave them separated as to indicate at what point the system becomes autonomous and up to which human interventions may be needed, particularly in the area of production planning. The linkage with human decision-makers will be at the aggregate or strategic level. They will define the goals and guidelines for the firm and the system. An ERP system will get them and will translate these guidelines for the rest of the system, in particular to the CPPS that handle the production system. The latter are thus not completely autonomous since they keep an open loop with the ERP system, at least on production planning (see section 2.4.1.1 in Framinan et al. 2014c). Basically, this procedure plans and controls the fabrication tasks in a given manufacturing infrastructure, but not planning the infrastructure itself. In this line, Almada-Lobo (2016) postulates the absorption of Manufacturing Execution Systems in Industry 4.0 systems. On the contrary, higher levels of management, defining more general aspects of the fabrication, should not be included.

5. Review

As said, we will review the main contributions to the literature, in the light of two different perspectives. Section 5.1 considers the articles on the design of architectures and systems handling information on scheduling problems, emphasizing the integration of the different levels of planning by the use of CPS and Industry 4.0 in general. Section 5.2 is devoted to works that focus on the more traditional scheduling problems and how the form in which they should be addressed by the use of CPS and Industry 4.0 (real-time information, self-optimization, etc).

5.1. Review of the literature on production planning integrating scheduling and other levels and functions

The main difference between these contributions and those reviewed in Section 5.2 is that they analyze the *structure* of the scheduling process without seeking to optimize a particular objective function, or, when such function is presented (as in Ivanov et al. (2016a) and Ivanov et al. (2016b)) it is not a traditional one in the sense of Pinedo (2016).

Industry 4.0 will increase production flexibility, closing the gap between production capabilities and the requirements of customers, becoming closer to make-to-order systems (Badr 2016). In this latter work, an agent-based approach is applied to address the problem of customized production, specifically in multi-factory environments, in which each factory is an agent that generate schedules in goal-oriented negotiations. In turn, the sources of services (materials, transportation and storage), will be also independent of the factories. The approach yields generic solutions that are flexible enough as to solve the problem. Frazzon et al. (2018a), considering Industry 4.0 environments and the ensuing the possibility of increasing the transparency of information, integrates questions of transportation and supply chain to the problem of planning production processes. These authors indicate that the supply chain affects the schedule and, if a purveyor faces a perturbation transporting the goods the production planning system should be able to solve it. This should be achieved by a hybrid approach based on mixed-integer programming, discrete event simulation and a genetic algorithm. Among other advantages, this approach allows reducing the number of delayed orders. Frazzon et al. (2018b) addresses a similar problem but with a data-driven architecture. They develop a data exchange framework to generate dynamically schedules with dispatching rules. The comparison with static dispatching rules (without updating data) shows that the dynamic approach is an improvement. Pimentel et al. (2018), in the same sense, design an adaptive decision making system based on simulation for digital industries. These industries will gather, thanks to the CPS, the data relevant for scheduling, that through simulation will help to evaluate scenarios and support the decision making process. Mourtzis et al. (2017) profit from the capacity of CPS of monitoring the state of machines to design mobile applications to efficiently coordinate maintenance tasks. A maintenance worker will be able to inform on line to the scheduling center as to incorporate this information in the plan as well as to receive instructions in real time. Uhlmann et al. (2018) analyzes Contract Manufacturers, where the latter are able to take into account the requirements and conditions posed by the customers. This makes it difficult to evaluate, in general, scheduling processes, especially in the case of events requiring a reschedule. Uhlmann et al. present a model of the risks of rescheduling both in terms of the ability to deliver to customers as to schedule further production operations. In their exercise they used simulations based on real world information.

Another important approach to scheduling in supply chains with Industry 4.0 technologies is by the application of control theory (Ivanov et al. [2016a]; Ivanov et al. [2016b]). Ivanov et al. (2016a) considers short term planning in supply chain with smart production systems. A dynamic non-stationary view of the execution of jobs and the time decomposition of the problem are key components of the approach. They apply a modified form of the continuous maximum principle to determine the optimal amounts of goods and computational resources required to build a supply chain based on CPS (Ivanov et al. 2016b).

Cupek et al. (2016) present an agent-based approach the problem of scheduling short series of production. These authors consider an industry seen as a network of CPS, in which they seek to coordinate them to reach a contracted production level. Their agents are based on the ISA-95 standard while the architecture is completely heterarchical and decentralized. Klein et al. (2018) also deploy an agent-based approach to generate a scheduling-support system. These agents do not only represent the production units but also storage centers, transportation means and production orders. These agents interact through auction-based negotiations. In such an auction a production order-agent receives the bids of production units-agents. The rest of the agents align with the results of this auction. This is implemented in JADE (Java Agent Development Framework). Other AI tools have been applied to this kind of problem, as in Block et al. (2018), who develop a manufacturing ontology to build a decentralized MES. The decentralization approach takes up from an initial ISA-95 architecture, and through CPS the authors develop a decision making procedure. The ontology allows coordinating the CPS, where each of them runs the simulations and evaluates its own situation. The ontology assumes different levels in a hierarchy, using the computational ability of each CPS (as for instance, edge computing) and avoids to overcharging a central host. Shiue et al. (2018) use a learning-based to solve a scheduling problem in real time. Using reinforcing learning (RL) (considering multiple dispatching rules) they apply two mechanisms: an off-line learning module and an RL based on Q-learning. Comparing the response of their system to that of others, based on machine learning, the authors show that theirs is better.

5.2. Classical scheduling problems in Industry 4.0 environments

Here we consider the works with a more "local" perspective, trying to find schedules optimizing a traditional goal as defined in Pinedo (2016).

Luo et al. (2015) analyze a hybrid flow shop scheduling problem in which the jobs to schedule arrive dynamically and the operation on machines is not continuous. The information is provided in real time by RFID technologies. To solve the problem these authors present a multi-period hierarchical scheduling mechanism to divide the planning horizon in shorter periods. In this view divide hierarchically the decisions to make by the shop floor (shorter time) and the stage manager (longer horizon). At each level the decision makers optimize their schedule. Wang et al. (2016) introduce a scheduling method based on Petri Nets to build in an IoT-enabled hybrid flow shop system. They can thus address the real time scheduling problem with a modified Ant Colony Optimization algorithm, confining the pheromones to avoid getting stuck in the search of solutions. Shime et al. (2017) study a flexible flow shop problem focusing on sustainability in Industry 4.0 environments with sequence-dependent setups. They introduce heuristic algorithms based on dispatching rules and sizing the lot in order to minimize the total tardiness of the jobs. Framinan et al. (2017) study the impact of real time information to generate reschedules in flow shop environments trying to minimize the makespan. The study tries to quantify the advantages of gathering data in real time over the actual finishing time to reschedule the jobs that have to be processed. Their results show that the benefits of rescheduling over not rescheduling (keeping the initial schedule) are highly dependent on the variability of processing times. A larger variability in processing times leads to lower benefits of rescheduling. Framinan et al. (2019), elaborated on these results and presented rescheduling strategies that make the best out of real time information. Among these strategies the one that gave the best results is the one that uses the critical path as tool. Only if the difference between the actual and the expected processing time affects the critical path a reschedule is enacted. Fu et al. (2018) study a bi-objective flow shop problem with time-dependent processing times and uncertainty in Industry 4.0 environments. They solve this problem by applying their Fireworks algorithm.

Other contributions have been presented for job shop configurations. Cuihua et al. (2016) studied job shop scheduling problems in which the pieces to be processed are identified using RFID, and the piece itself requests the next operation to be executed on it. These authors present a genetic algorithm with double code improving the ability of scheduling of a single code algorithm. Ivanov et al. (2017) address a job shop scheduling problem in Industry 4.0 with a control theory approach. This allows the authors to solve efficiently scheduling problems in the fabrication of highly customized products, managing the intrinsic complexity of finding solutions. Leusin et al. (2018) consider a multi-agent system embedded in CPS to solve dynamic job shop problems. For this, they use a data exchange framework ensuring an efficient integration of the system. This allows them to exchange real time information on the IoT, with the capacity of self-configuring the system and managing the perturbations along the production line. These authors show that their proposal yields improvements in flexibility, scalability and efficiency in simulated cases based on industrial data. Another work based on the use of real time information provided by IoT in job shop scheduling problems is Wang et al. (2018b). It assumes again an agent-based architecture that optimally assigns tasks to machines according to their real time state. A bargaining-game-based negotiation system coordinates the agents to solve efficiently the problem. This method, implemented in JADE, yields better results than traditional dynamic programming strategies in terms of makespan, critical workload and total energy consumption. Zhang et al. (2017) also apply a game-theoretic approach to solving a job shop scheduling problem. The method seeks a subgame perfect Nash equilibrium in a two stage game, in which again the makespan, workload and energy consumption are optimized for a real-time multi-objective flexible job shop scheduling problem.

In Zhang et al. (2018), IoT is applied to the problem of remanufacturing car engines constituting an Internet of Manufacturing Things environment. The authors develop a real time scheduling methods seeking Pareto optimal solutions in the reduction of costs. The results, obtained in a case study, show that this method yield reductions of more than 30% both in costs and energy consumption. Rossit et al. (2018b) analyze different rescheduling strategies in the literature on Industry 4.0. The authors argue for inverse scheduling strategies for CPS-based systems through the formulation of a tolerance scheduling problem. This problem amounts to find the tolerances for a given schedule and up from them, to evaluate the magnitude of events that could trigger a reschedule. Da Silva et al. (2019) analyze the rescheduling problem in the case of a single machine. In this problem a dynamic environment is assumed in which the orders of the customers as well as their arrival order and the cancelation of orders change in time. At each event, the mathematical optimization problem is solved again. The results are compared to state of the art insertion methods and to an approach in which information is “perfect”. The latter model is based on the assumption that future events are known a priori. This yields a bound in the comparison with the proposed method. The results with this method are consistently better than with state of the art approaches and with respect to the perfect information bound.

6. Literature analysis and Future work

There are two promising future research lines on scheduling in Industry 4.0 that can be detected in the literature reviewed in this paper. One is the management of real time information and the other is the decentralization of decision making.

The use of real time information is a recurring topic in the articles discussed above. Industry 4.0 will drastically stimulate this, thanks to the use of CPS, IoT and related technologies. It is clear that decision making problems like scheduling will benefit from this development, since most performances metrics are directly associated to the management of time. Even those that are not directly related to that are indirectly associated to the efficient use of time, because resources are best used if delays and tardiness are avoided. In this sense, the literature reviewed provides valuable and pioneering contributions on the best use of real time information, improving the quality of rescheduling procedures.

The other main line of research that will be empowered by the advent of Industry 4.0 is the decentralization of decision making processes. In the literature the approaches based either on autonomous architectures, smart agents or game-theoretical methods decentralize the decisions. This yields a larger flexibility by enabling each CPS to decide on scheduling based on its own history and goals.

Very few of the contributions in the literature are based on real world cases. While this is understandable since Industry 4.0 is still in the making, it will be really significant to count on real world benchmarks of interests in industrial applications.

An important task that we leave for future development is the construction of testbed scenarios, on which different autonomous decision-making procedures can be tested. In previous works, Matt et al. (2014) and Seitz & Nyhuis (2015) present models of factories on which different developments in Industry 4.0 can be tested. Similar approaches are reviewed in Abele et al. (2017).

It is also of interest the possibility of implementing other knowledge-bases approaches. Running them on our test scenarios will allow evaluating and comparing them. So, for instance Francalanza et al. (2017) propose to design a CPPS from scratch with knowledge-based methods. Engel et al. (2018) present a declarative recipe description combined with an ontological model for industrial processes while Ye et al. (2018) postulate a knowledge-based method to plan the operation of an intelligent CNC Controller.

7. Conclusions

In this paper we presented a study of the impact of CPS and Industry 4.0 technologies on the solution of scheduling problems. We justified our claims in the ability of CPS to absorb most of the control structure ISA-95. We revised the main contributions on this issue, differentiating the works in which scheduling is part of a higher level of planning and those that address scheduling directly.

Of the contributions on the planning problems we found that the main approaches are agent-based or simulation-based. In the case of direct treatments of scheduling many contributions are aimed to generate rescheduling strategies using real time information. The game-theoretical approaches are also commonplace, providing a clear example of decentralized decision making.

We ended by pointing out the need to have benchmark instances as well as standard scenarios on which to compare and assess the different contributions.

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Table

Table 1. Cyber-Physical 5C’s Architecture.

Level	***Attribute***
I. Connection Level	• Plug-in • Tether-free communication • Sensor network
II. Conversion Level	• Data-to-information • Multi-dimensional data correlation • Smart analytics
III. Cyber Level	• Virtual modelling • Clustering information • Controllability
IV. Cognition Level	• Integrated simulation and synthesis • Collaborative diagnostics and decision making • Early awareness
V. Configuration Level	• Self-configuration • Self-optimization

Figures

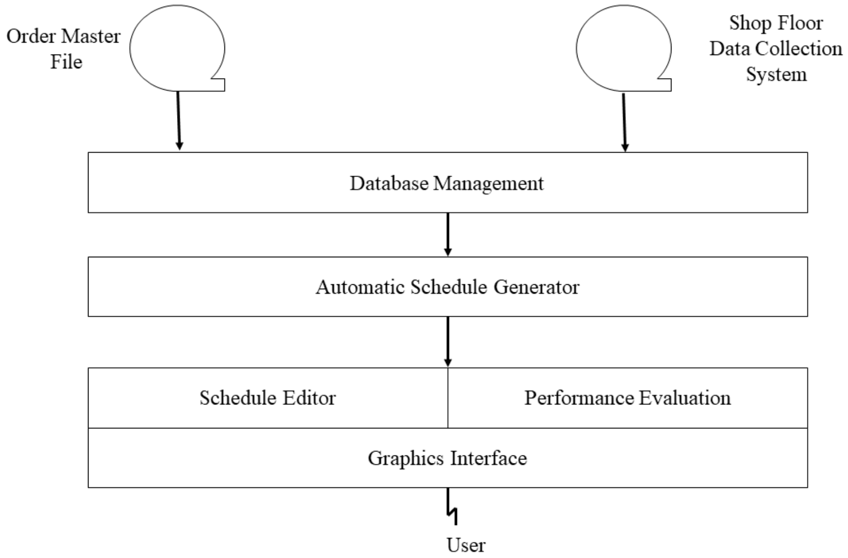

Figure 1. Scheduling System. Pinedo (2016)

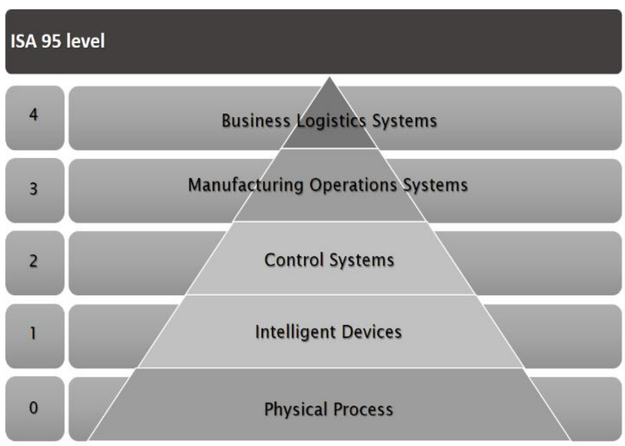

Figure 2. Control structure ANSI/ISA 95 (Rossit & Tohmé 2018)

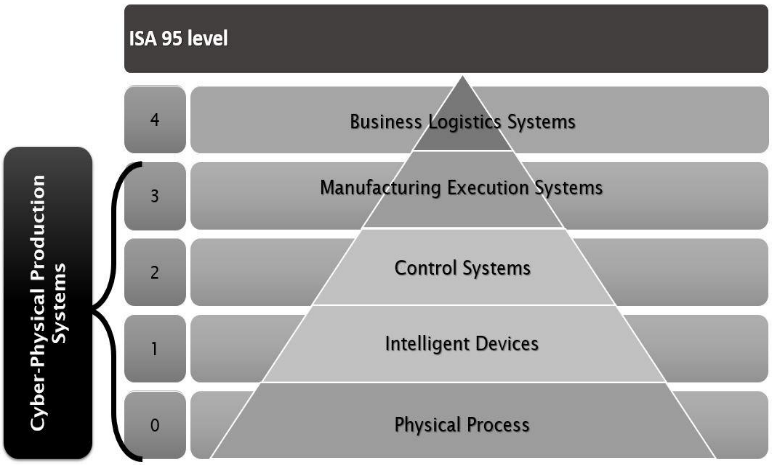

Figure 3. Control structure of a CPPS.

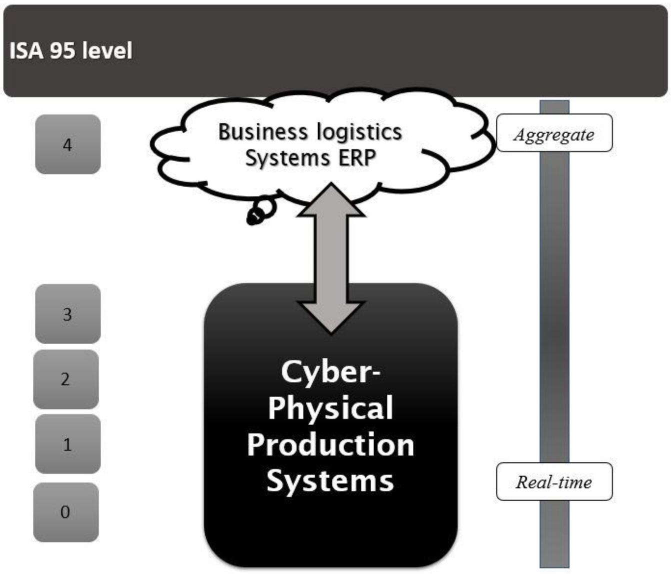

Figure 4. Distribution of ISA 95 levels between ERP and CPPS. The representation of time is drawn from the model of the Manufacturing Enterprise Solutions Association (MESA) International.