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An Industry 4.0 approach to Assembly Line Resequencing

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Abstract

Contemporary assembly line systems are characterized by an increasing capability to offer each client a different product, more tuned to her needs and preferences. These assembly systems will be heavily influenced by the advent of Industry 4.0 technologies, enabling to propose business models that allow the late customization of the products, i.e. the customer can modify attributes of its product once started the production of it. This business model requires the manufacturing tools able to make decisions online and negotiate with the customer the changes that can be carried out, according to the workload flowing through the production system. In this work we analyze the possibilities and limitations of this new paradigm. First, we show that industry 4.0 systems can autonomously manage the production management process, and then we present a framework based on tolerance planning strategies (Tolerance Scheduling Problem), to determine which changes can be carried out. The ability of resequencing the production process is also implemented in the case that the operations associated with late customization allow it (i.e., when intermediate buffers are available). This establishes a parallelism with the problem of non-permutation Flow Shop. We finally discuss future developments necessary to implement these procedures.

Keywords: Assembly line; resequencing; Industry 4.0; customization; cyber-physical Systems; Tolerance Scheduling Problem; decision-making

1. Introduction

The development of new industrial production technologies has triggered a new industrial revolution, Industry 4.0 (Hermann et al., 2016). These technologies promise to modify the production paradigm, allowing the current robotic systems to achieve greater autonomy in the process of managing production (Monostori [2014]; Yao et al. [2017]; Rossit & Tohmé [2018]) These advances lend manufacturing systems the ability to respond flexibly to the changing conditions of the market (Hermann et al. 2016). Technologies such as Cyber-Physical Systems (CPS) and Additive technologies further enhance the flexibility of production processes, inducing a potential new industrial revolution. CPS are systems consisting of physical components with computational functionalities, as for instance mechanisms that are controlled or monitored by algorithms running on computers (Lee 2008). These systems constitute the adequate tools for Additive Manufacturing (AM), a process in which layers of material are joined as to generate products following the patterns found in databases of 3D models. In comparison to traditional fabrication processes, AM exhibits significant advantages, as for instance the reduction of delays between designing, producing in a just-in-time way and delivering products to consumers (Mueller 2012).

These technologies contribute to improve the flexibility of the production process, leading to a larger variety of products available to customers. In this sense, Yao & Lin (2016) claim that the synergy between Industry 4.0 environments and those technologies will intensify business strategies of mass customization (customers will face a large variety of options) and mass personalization (each customer defines her own product, Kumar (2007)). The wide possibilities of increasing the variety of products and their characteristics pose technological challenges which require an increasing complexity of the information systems associated to the production processes. Managing the production of personalized or customized goods will be quite demanding, given their different requirements. It will be necessary to assess the alternative costs, the different production stages, the dispatch of finished products, as well as the materials involved and the due dates of the processes. CPS are fundamental pieces in this structure, since they have access to all this information and can play some roles proper of Decision Support Systems (DSS), involving many business functions related to production (Rossit et al. 2018b). Therefore, it is natural to think that the entire flow of tasks in these mass customized production processes, involving the planning of operations and their implementation, can be handled in a decentralized and autonomous way by the CPS themselves. This means that CPS could collect information and specifications from the clients and, on the basis of records of processes and operations carried out in the past and with the aid of 3D design tools, develop a production plan for every specific product.

The Assembly Line (AL) production systems will also be influenced by this increase in flexibility in production. Bortolini et al. (2017a) state that the products produced in ALs may not only be personalized, but also that late customization will be possible. That is, customers not only get involved in the definition and design of the product and its specifications as in the case of mass customization products (Pine et al. [1993]; Singer et al. [2014]; ElMaraghy & ElMaraghy [2016]), but also once started in a late customization mode. This production mode implies that during the production of the customized product, customers will be able to monitor the advance of the production of its product through technologies linked to the Cloud and propose modifications to the initial customized product. This allows companies to offer their clients an unprecedented level of personalization.

Late customization can be seen as a postponenment production strategy (Bucklin 1965) as well as been a leagile framework (Naylor et al. 1999). The former kind of strategies intended to maximize benefits and minimize risks by postponing as much as possible future investments in a product. This translates in the production of basic or standard goods delaying the stage of differentiation as to adjust the differences to satisfy as much as possible the real demand of the goods (Van Hoek 2001). A leagile framework, in turn, is a production structure able to implement efficiently, according to the type and the market, the differentiation of goods (Naylor et al. [1999]; Nieuwenhuis & Katsifou [2015]). A leagile framework includes non-differentiated production stages (i.e. the fabrication of generic or standard products) running under a lean strategy (Shah & Ward 2003), while the stages in which the differentiation is generated run under an agile strategy (Yusuf et al. 1999).

In this paper we develop and deepen the analysis of the links between late customization and production planning. In particular we intend to show how late customization may be implemented in a production plan. We have to note that the advantages of a late customization processes can be achieved only if the system is autonomous and able to keep running the fabrication process. The client needs real-time information about the evolution of the production of his personalized good, as well as assurances that his late modifications will be accepted and implemented by the manufacturer. This kind of interaction is possible in an Industry 4.0 environment, as pointed out by Bortolini et al. (2017a), requiring full operational versions of IoT, CPS (able to collect real-time information) and Cloud linkages.

However, this extreme flexibility in product differentiation requires a considerable increase in the effort to achieve an efficient sequencing of the products to be produced by the AL (Boysen et al., 2009). Since the products can not only have differences from the beginning of production which would imply working with mixed-model systems (Faccio et al., 2018), but as the production advances, modifications will be incorporated to them, generating new differentiations among products. In this sense, Resequencing strategies for AL will be a key element in addressing this issue (Boysen et al., 2012). Traditionally, the field of Resequencing in AL is associated with solving problems due to unforeseen events arising from unexpected disruptive events such as breakings of machines, delays in the delivery of materials, differences in processing times, among others. However, under a business model that allows late customization, the events that modified the initial scenario (with which production was initially scheduled) are of another nature: these events are modifications of operations and specifications.

Our work contributes in the generation of scheduling tools that support late customization business strategies for AL processes. This proposal works combining problems of Tolerance Scheduling problem (Rossit et al., 2018b) and of non-permutation sequences (Rossit et al., 2018a), and allows the company's management system analyzing the late customizations of customers regarding the state of its production system. Our approach allows us to provide a tool to define when a late customization of the customer is possible to be accepted and when it is not, depending on the production sequence in execution, and when it is possible to apply a resequencing to incorporate the late customizations.

The rest of the work is organized as follows, Section 2 presents Industry 4.0 technologies and their implementations in AL. Section 3 describes Late Customization manufacturing and planning considerations. In Section 4, we present the capabilities and limitations of Industry 4.0 technologies to manage autonomously the production planning. In Section 5 we present our sequencing proposal for late customization. In Section 6 we analyze future developments needed.

2. Assembly Line problems and the Industry 4.0 approach

In this section we present a brief description of the main assembly line concepts to introduce the core problem of the paper. Then, we present succinctly some Industry 4.0 notions and review the main contributions of Industry 4.0 in AL systems found in the literature to set our contribution in context.

2.1. Assembly line concepts

An AL is a manufacturing process in which the parts (usually interchangeable parts) are added as the semi-finished assembly moves from one workstation to another work station, where the parts are added in sequence until the final assembly is produced. In this production system, the productive units or workstations that carry out the operations are aligned in serie. The workpieces visit the stations successively as they move along the line generally by means of some form of transport system, for example, a conveyor belt (Boysen et al., [2007]; Boysen et al. [2009]). The design of an AL is a complex process where many issues must be taken into account to achieve efficiency, among them: the line balancing (Boysen et al., 2007), the sequencing in mixed-model productions (Boysen et al. al., 2009), the feeding material (Faccio et al., 2014) and also the ergonomic risks of the workstations (Bortolini et al., [2017b]; Bortolini et al. [2018b]) are of particular importance.

Sequencing problems are present in ALs that produce more than one model of products (mixed-model lines), i.e., the AL is not intended to produce a single type of products, but a family of products (Bard et al. 1992). In these ALs, the tasks of different models are performed in the same workstation during consecutive cycles. Therefore, the sequencing problems in these AL, aim to minimize the sequence-dependent work overload in a workstation (it occurs when several models that require an intensive use of the same workstation are processed consecutively), and also to comply with the criteria of the Just-in-Time philosophy (JIT) like the balance in the use of parts (Bard et al., 1994).

To address these problems Boysen et al. (2009) state in their review of the topic, that there are three possible resolution approaches: mixed-model sequencing, car sequencing) and level scheduling. Another problem that arises from these mixed-model environments is when it is necessary to solve unforeseen problems raised during production by implementing resequencing methods (Boysen et al., 2012). In AL environments, Boysen et al. (2012) identifies that it can be resequenced in two different ways: physically (the order of production model is altered using some intermediate buffer) or virtually (the sequence of production is maintained, but the assignment of orders to the customers is altered). Resequencing is a subject that has been extensively studied in the scheduling literature in general (Vieira et al. [2003], Ouelhadj & Petrovic [2009], Rossit et al. [2018b]), and the main strategies to approach them are reactive or proactive ones. In the reactive strategy, the production sequenced is modified after the disruption of an event that prevents the further normal processing of the programmed sequence. While, in the proactive approach, it is sought to foresee possible disruptions, adding sufficient time to resequence in the case of disruptive events (Boysen et al., 2012).

The material feeding into the assembly process is another vital issue for the efficiency of AL (Bortolini et al., 2016). The material feeding, or AL logistics part, tries to provide the right type and quantity of components to the correct workstation at the right time. To achieve this, the main issues to be analyzed are the type of storage to be used and the feeding policy (Battini et al., [2009], Faccio et al., [2015]). The type of storage depends mainly on the type of packaging and the dimensions to store the components along the AL (Bortolini et al., 2016). Meanwhile, the feeding policy refers to how the material is supplied, from which three main policies can be identify: lateral storage, feeding by kitting and kanban feed. In the Kanban policy, containers are formed in a supermarket area, while they are stored in defined amounts at the station level. When the components in a container are depleted, the related kanban is released and material replenishment occurs (Faccio et al., 2014).

Recent contributions in the literature suggest including ergonomic risk in the AL design. Assembly workers are intrinsically prone to musculoskeletal disorders, due to strenuous operations that recur with high frequency (Bortolini et al., 2017b). The latest developments in legislation (EU Machinery Directive, 2006/42 / EC, 89/391 / EEC, Occupational Safety and Health Law) and the aging of the workforce in developed countries require that ergonomic design be included in the design AS (Bortolini et al., 2018a). These advances can also contribute to reduce worker absenteeism (Cohen [2012]; Bukchin & Cohen [2013]).

2.2. Assembly lines in the Industry 4.0 literature

We will present, first, some basic notions of Industry 4.0, and then, we review the main contributions to the literature on assembly lines in Industry 4.0 environments.

The increasing relevance of studies of Industry 4.0 environments is mostly due to the penetration of internet connectivity in production systems, fundamentally through the Internet of Things (IoT). The data collected by production machines is fed into physical control units through a SCADA (Supervisory Control and Data Acquisition) or similar systems. With the enhanced connectivity of production systems this information can be transmitted to processing centers with higher capacity, endowing Decision Support Systems (DSS) with data traditionally restricted to control levels and thus becoming useful for CPS (Wang et al. [2015]; Yao et al. [2017]; Rossit & Tohmé [2018]). This connectivity and the ensuing capabilities applied to production systems have led to the concept of Cyber-Physical Production Systems (CPPS) (Monostori 2014). Data collected through a Wireless Sensor Network (WSN) gets compiled by IoT, yielding a better picture of the state of the system. This assessment gets even more precise if a connection with Cloud Computing is established, increasing considerably the data processing capacities. Notice that manufacturing generates large volumes of data, which require, in turn, of large data processing facilities (Zhong et al. 2016). This connection between Manufacturing Systems and Cloud Computing has given rise to the concept of Cloud Manufacturing, in which computers and system production resources get assembled through the Cloud (Xu [2012]; Zhou & Yao [2017a]). This allows the scalability of the activities of the firms. Then, a central issue is the selection of the cloud services required by companies (Zhou & Yao [2017b]; Zhou & Yao [2017c]). IoT links cyber and physical systems making fabrication processes intelligent, connecting all the participants, eliminating the barriers between producers and consumers and supporting online communities for the design, creation and sale of products. While all these uses of the Internet are already in use, they will become even faster and cheaper facilitating closer interactions between customers and production units, connected through platforms (Porter & Heppelmann 2015).

We will now review the main contributions in the literature on the application of Industry 4.0 features to AL systems. In this sense ElMaraghy & ElMaraghy (2016) presents a brief review of the topic, and clarify that in these Industry 4.0 systems, intelligence is embedded in the products, workstations and the system. This embedded intelligence allows a greater autonomy in the communications between the entities of the system and improve its adaptability to the production flow. Pfeiffer (2016) analyzes manual work in ALs, carrying out a field study tracking the non-routine tasks of the operators. This study provides important conclusions for the design and development of a system with greater autonomy, by focusing on those tasks that are not routine but contribute significantly to the overall efficiency of the system. In this sense, the contribution of Hedmann & Almström (2017) reviews the use of data in manual assembly systems. These authors point out the difficulty of incorporating into the company's information system data generated in the manual assembly workstations, highlighting the loss of efficiency that this entails. Their proposed solution involves a digital manufacturing system in which data is collected and turned over to the general information system of the company. Xu et al. (2017) propose the incorporation of visualization technologies for the analysis of this type of information in AL systems. Their proposal uses the real-time analysis of information to, by comparing with historical records, detect anomalies, inefficiencies and infer their possible causes, all through the use of Visual Analytics. Gewohn et al. (2018) extend the reach of visualization techniques by developing a quality control system that allows the user to obtain high quality information. In Gewohn et al. (2017) such system is developed allowing the user to maintain a quality control of a vehicle assembly line in real time.

From a more integrative perspective, Cohen et al. (2017) evaluate the impact of Industry 4.0 technologies on different AL configurations. Bortolini et al. (2017a) propose a framework to develop AL systems in Industry 4.0 environments and the future production paradigm of "personalized production", allowing the customer to participate both in the design stage of the product and in the incorporation of modifications to the final product.

Our contribution takes these ideas on late customization to propose a design for its future implementation.

3. The late customization model

Industrial systems of production have traditionally being specialized on mass production, i.e. the provision of standard and undifferentiated products minimizing costs. But, with increasing competition among firms, product differentiation became a key issue for the organization of industrial activities since the 1990s (Vollmann et al. 2005). From then on, products tend to address the specific and clearly non-massive requirements of customers, giving raise to the production model of mass customization (Pine et al [1993]; Kumar [2007]). These are considered to be “long tail” markets (Anderson [2004]; Anderson [2008]). According to Anderson (2008), those are markets in which the goal is to sell smaller volumes for a larger number of products, unlike the traditional objective of selling large amounts of a few products. The expression “long tail” is used to represent probability distributions in which observations in the tails have still a fair amount of weight. Anderson uses this term to distinguish the traditional market strategies oriented to generate a very concentrated production, from the new approaches in which a demand for variety can be satisfied, as shown in Figure 1 (Anderson 2004). In the last two decades the widespread use of the internet (e.g. IoT) and the digitalization of retail markets have laid the grounds for long tail production systems (Anderson 2008).

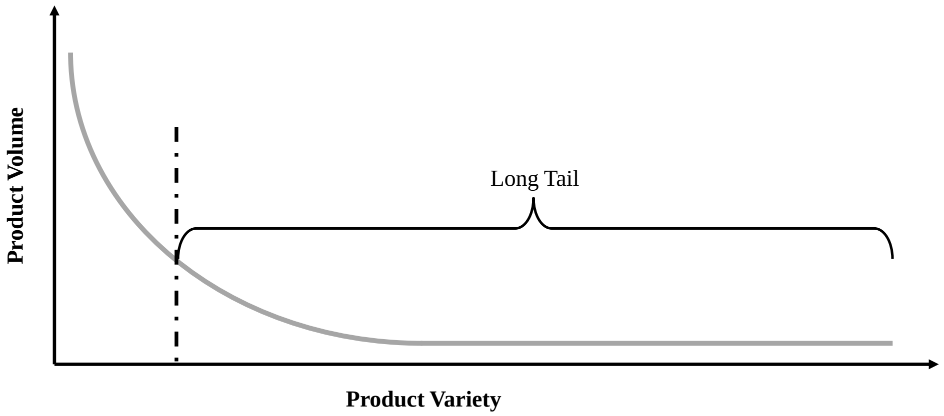

Fig. 1 Long tail market.

3.1. Late customization in manufacturing planning

The strategy of providing differentiated products lead to a paradigm change in manufacturing planning, posing new challenges for industrial activities. To satisfy the new kind of markets, industries had to adopt agile models, exploiting the competitive advantages of each organization (Yusuf et al. 1999). These manufacturing models intend to face the uncertainty of the market by increasing the response capability of the organization in order to satisfy the customers with similar costs to mass production industries (Yusuf et al. 2004).

Handling the production of large amounts of customized products presents a tough challenge, since product differentiation hampers scale economies. In this sense, the concept of leagile frameworks (Naylor et al. 1999), showed a way to address this problem.

The foundations of leagile systems are analogous to the theory of postponement (Alderson 1950, reedited in Alderson 2006). The idea of basing a business on postponement involves the maximization of benefits while minimizing risks by producing generic goods, delaying the differentiation of products as much as possible (Bucklin 1965). This reduces the risk of storing products prone to obsolescence (Van Hoek 2001). Leagile production implements postponement in the production plan, by applying two different strategies. One amounts to lean production previous to the differentiation of goods, while the other is an agile strategy to produce after differentiation (Naylor et al. 1999). Thus, leagile systems get the best of lean and agile production processes, for both the generic components and the customized final products (Mason-Jones et al. 2000). Then, leagile systems face two kinds of demand: one is an initial and rather stable one of generic modular components, guided by medium and long term forecasts; the other demand is for end products, following the short term market trends. The system transitions from a demand to the other, at the differentiation point (Nieuwenhuis & Katsifou 2015).

Advanced manufacturing technologies empower leagile systems, as recently shown in (Ghobakhloo & Azar 2018). These authors surveyed the Iranian auto part sector of almost 200 companies, finding that the lean and agile systems have a high synergy, strengthen by data intensive advanced manufacturing technologies. In general the leagile strategy has been widely applied by industries, since it shields their first stages of production from external noise, while being flexible enough to respond to an ever changing market. Industry 4.0 technologies increase considerably the use of information and facilitate designing and executing plans based on that information. Bortolini et al. (2017a) indicate that this opens the possibility to offer the client the possibility of late customizing her product since the availability of real-time information on the state of the production process allows late modifications (i.e. after placing the order).

As said, in the leagile scheme, the late customization operations would be carried out way after the differentiation point, while the lean ones remain stable. The differentiation point arises when the customer places her order. After that, the basic components are assembled in a final product in an assembly-to-order mode, according to the requirements of the customer. Bortolini et al. (2017a) indicate that in Industry 4.0 environments, the database in the Cloud of the firm allows the customer to monitor the assembly process and validate, at specified stages, the configuration of the customized product.

3.2. Late customization in the shop floor

These production modalities, which provide the customer the opportunity of participating in the design of the product, have been well developed in recent years in the AL systems, as mentioned (Hu et al. [2009]; Aljorephani & ElMaraghy [2016]). The main premise is to offer products as personalized as possible to customers but at the cost of mass production products (Kumar 2007). The developments in modular production offer more options to the client, keeping productions processes as standard as possible (Hu et al., 2009). Product platform developments have allowed the client to access an increasing variety of products achieving efficiency in production. Product platforms are defined as groups of functions, components, modules and subsets that are shared across a product family (Aljorephani & ElMaraghy 2016). The latter, in turn, is defined as a set of related products that share common components, modules or sub-assemblies (Simpson et al. [2014], Abbas & ElMaraghy [2018]).

Product platforms offer a wide range of products to customers while maintaining the advantages of economies of scale and at the same time increasing the flexibility and responsiveness of the company (Simpson 2004). Production costs tend to be proportional to the number of models or variants available (Aljorephani & ElMaraghy 2016). Nevertheless, a product platform is able to generate final products by adding, removing and / or replacing one or more components of the platform as to satisfy a certain segment of the market. In this sense, recent technological developments in manufacturing allow a more efficient assembly and disassembly process (intelligent materials, glues that lose their effect in response to external stimuli such as freezing or overheating) allow to postpone the point of differentiation in an AL (ElMaraghy & ElMaraghy 2016). In this way the product platform, by handling materials or components in late customization scenarios, improves the efficiency of the process. Another interesting aspect in this regard is the use of multiplatform systems to reduce the number of variants that arise from the same platform (postponing the point of differentiation), although in this case an excessive number of platforms leads to losing the benefits of economies of scale (ElMaraghy & Abbas 2015).

Besides, AM systems are perfectly able to make single-unit products o industrial productions with very low volumes (Mueller 2012). One of the main impacts of implementing these technologies is the reduction of costs in single-unit products. Yao & Lin (2016) illustrate this with the example of the AM production of a plastic gear, which has a cost of $55 per unit. The traditional injection production of these gears has a cost of only $5 per unit, but requires a matrix that costs $10000. These authors calculate the equilibrium point and indicate that if less than 200 gears are needed, AM can provide them at a lower cost. This indicates that the new technologies allow producing low volumes or even single units without increasing the costs over mass production. This is a strong incentive for making long tail markets commonplace.

However, from the point of view of planning and sequencing, the problem can become extremely complex as pointed out by (ElMaraghy & ElMaraghy [2016]; Manzini et al. [2018]; Abbas & ElMaraghy [2018]; Pereira & Álvarez-Miranda [2018]). In addition, if the goal is to offer an agile and effective late customization service for the client, it is necessary to endow the company with the capacity to respond autonomously and online to the customer's queries, calculating possible delivery dates or production costs (Monostori 2014). In this sense, Industry 4.0 poses the potential for this level of autonomy and agility (Rossit et al., 2018b). Industry 4.0 or Smart Manufacturing environments can address these business strategies in an efficient way, based on the use of CPS and AM. They collect updated information about physical objects and processes through IoT/CPS, improving the productivity and flexibility of already existing mass production processes. This empowers the customers, allowing them to contribute to the attributes of the product or service in which they are mostly interested (Yao & Lin 2016). These closer interactions with customers can be handled thanks to the larger flexibility of Industry 4.0 environments, endowed with intelligent production systems that can be autonomously configured to optimize production, yielding a higher level of service and larger returns.

4. Production planning and control in Industry 4.0 environments

In order to make autonomous a production system based on Industry 4.0 technology they have to be able to handle the planning and control functions autonomously. This means that these technologies have to handle production orders and the flow of material, as well as program production operations, execute the orders, control the execution, etc. These functions are usually hierarchically structured, with higher level functions, restricting lower level functions, according to standards as for instance ANSI/ISA 95 or ISA 95. This standard provides 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 yields a common ground for the communication among 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 SCADA and Programmable Logic Controllers (PLC), for instance. 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 communication scheme among the the different levels; in traditional production settings each level interacts only with its adjacent levels (Rossit & Tohmé 2018).

4.1. Decision making in CPPS

As discussed in (Rossit & Tohmé 2018), CPPS will have an impact on decision-making activities in the area of industrial planning and control. This will be due to the ability of CPPS to carry out a wide spectrum of activities, ranging from the physical operations of production (level 0) to planning, evaluating and managing the entire production process (level 3), by controlling the actions and systems on levels 1 and 2 (i.e. the measurement and sensing instruments as well as the control systems). This approach is illustrated in

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

Figure 2, in which the levels of ISA 95 that should be incorporated to CPPS are highlighted.

Some of the direct benefits of this integration of functionalities are, for instance, the increased flexibility to respond to unexpected events, or faster transmission of information through the entire system. These advantages are due to the fact that CPPS can translate the data obtained at level 1 to the higher order language used at level 3, eluding the adjacency limitations inherent in PERA, generating faster answers to unforeseen events.

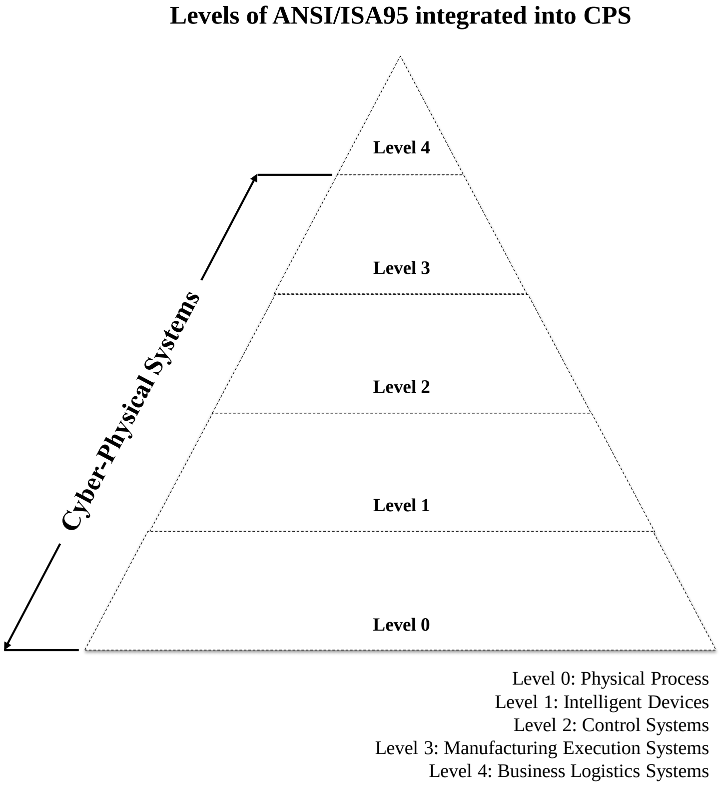

Fig. 2 Levels of ANSI/ISA95 integrated into CPS

This, in turn, directly affects the way in which decisions are made in production planning, which in terms of PERA will be managed by both ERP (Enterprise Resource Planning) and the CPPS. Figure 3 shows this.

Figure 3 indicates that only the decisions at the aggregate level (as for instance the goals of the company) will be handled by ERP systems, already adapted to smart manufacturing environments. All other decisions will automatically be made and executed by CPPS. In this way, current Manufacturing Execution Systems (MES) will be absorbed by CPPS, which will also take care of integrating the dispatch of work orders and their schedule in the shop floor. This will improve the quality of the information at this level, increasing the flexibility and the ability to respond to changing circumstances (Rossit & Tohmé 2018).

A good deal of the decisions made by ERP systems (like 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 (Rossit et al. 2018b).

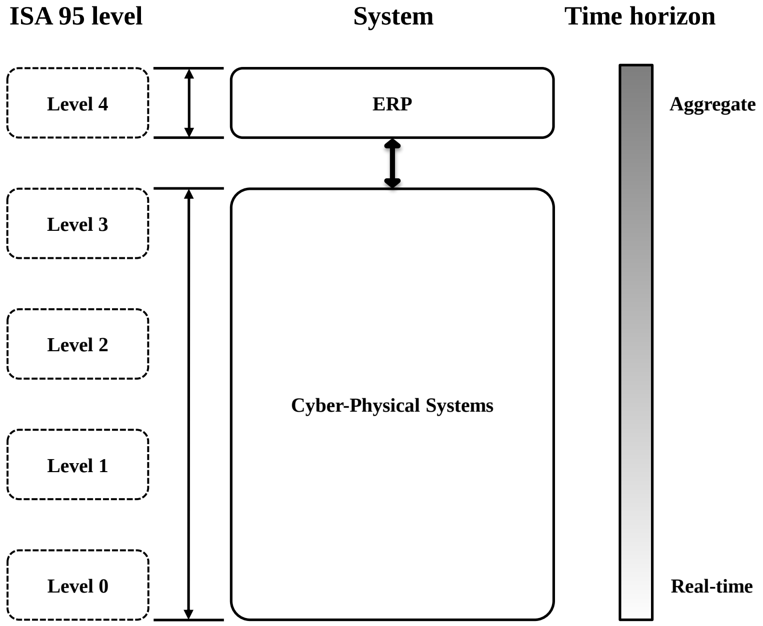

Fig. 3 Distribution of ISA 95 levels between ERP and CPPS.

4.2. Sequencing decision making process

This proposed structure of decision making affects the sequencing process, since it involves ISA-95 levels where production sequences are programmed. We have shown that CPPS can autonomously handle several levels of ISA-95 from the physical process to the master production plan. In this sense, the scheduling process gets embedded in those levels, indicating that CPPS could solve autonomously the scheduling problem. Up to this point we have consider the capabilities of CPPS from the point of view of their hardware or the global structure of the network. This allows us to affirm that the scheduling process can be managed technologically by the CPS. It is however necessary to design advanced tools to generate online schedules allowing enough flexibility to market demands (Rossit & Tohmé [2018]; Rossit et al. [2018b]). This requirement is intensified when a strategy of late customization is offered to the client, changing the operations and the materials once the production process has begun. It is necessary to provide CPS with appropriate tools for facing autonomously these modifications or late scenarios.

These tools must give the system the ability to negotiate autonomously with the customer, or at least provide the proper support to the human being who oversees the negotiation. Once the production for a given customer has begun, there are specifications of the designed product that will become real by the execution of the planned operations. This concretization of the specifications will limit the space for late customization, and the autonomous system has to be "conscious" of this reduction on the late personalization freedom to negotiate future modifications. In turn, the production of that good is immersed in an industrial production environment that also influences the possibility of "freely" modifying the product. A mixed-model sequence of production makes modifications, once the production process has begun, highly inefficient due to the sequence-dependent work overload on some workstations, or due to unforeseen excessive consumption of some component or material. Therefore, exposing the system to late modifications requires appropriate methods, establishing margins of action or negotiation for late customization, so that the system keeps the proper efficiency corresponding to an industrial system, and not to an artisanal one. In this regard, the Tolerance Scheduling problem raised in Rossit et al. (2018b) provides an adequate approach to deal with this type of problem.

4.2.1. The Tolerance Scheduling problem

The Tolerance Scheduling problem involves looking for the margins or tolerances for which an initial solution (schedule) is still optimal or good enough for the planner. It was originally designed to solve problems derived from unexpected disruptive events in production such as breakups of machines or delays in standard production times, such as those defined in Boysen et al. (2012). Thus, an autonomous system could incorporate a tool to analyze not only the nature of the event (whether it is a rescheduling-triggering event or not), but also its magnitude and analyze its impact on the performance of the system, helping to reduce its nervousness, avoiding constant reschedules (Rossit et al. at

2018b). In this case we will use the same concept, but for a different problem, the proposing an AL scenario where the customer can be offered the option of late customization while maintaining the desired efficiency in the performance of the production system.

This *Tolerance Scheduling* problem starts with an initial solution (optimal or near-optimal). The goal is to generate a range of tolerances, mainly for the parameters of the model. As with the specification of tolerances for manufactured goods that allow for a range within which the good is still considered appropriate, here we allow for certain degree of imperfection in the plan actually carried out. Consider for instance situations in which the actual processing times differ from the specifications used to solve the original scheduling problem. This event has an impact on the performance of the production process (e.g. worsening the makespan), which would call for rescheduling the plan. But it is worth to ponder whether the gains of doing this outweigh the costs of rescheduling.

The theoretical foundation of the optimization process on which the Tolerance Scheduling problem is based, is in the Inverse Scheduling (Koulamas [2005]; Brucker & Shakhlevich [2009]). While in the traditional scheduling problem all the parameters are known, in the inverse scheduling problems those parameters are assumed to be unknown and have to be determined in order to make optimal a given schedule (Brucker & Shakhlevich 2011). The determination of the values of the unknown parameters is usually restricted to certain intervals. For example, an Inverse Scheduling problem arises when we seek to find the adjusted delivery dates, d_j, of each job j, in order that a given schedule π becomes optimal making minimal adjustments to the delivery dates and the schedule as to ensure a certain range of values for the objective function (for deeper explanations see Koulamas (2005) and Brucker & Shakhlevich (2009)). In the case of the Tolerance Scheduling problem, we seek tolerances for the parameters ensuring that the original schedule remains acceptable and thus no rescheduling is necessary.

Formally, given an optimal or near-optimal schedule π, $F(\pi) \approx F^*$, (where $F(\pi)$ is the objective function value for π and F^* is the optimal objective function value) and the families of parameters d_j and p_{ij} (being p_{ij} the processing time of job j at stage i), we seek a maximal interval of variations for them, we also incorporate an *inertia factor*, δ, expressing the weight given to the stability of the system. A high δ indicates that the design favors a high stability (high inertia), meaning that fewer events can trigger reschedules. Then, in the case of minimizing the objective function F :

$$\max\|\hat{d} - d\|$$

$$s.t. \quad F_{max}(\pi, \hat{d}) \leq F_{max}(\sigma, \hat{d}) \cdot (1 + \delta),$$

$$F_{max}(\pi, \hat{d}) \leq F^{*} \cdot (1 + \delta),$$

$$\text{For any schedule } \sigma,\ \underline{d}_j \leq \hat{d}_j \leq \overline{d}_j, \delta \geq 0,\ j \in N.$$

That is, the goal is to maximize the distance between the *d* parameters, while ensuring that schedule π increases the original *F** objective function value up to an inertia factor $\delta \geq 0$. That is, obtain the set of parameters $\hat{d}$ such that for that set of parameters $\hat{d}$, the sequence π is better than any feasible order σ affected by δ. This provides a tool that not only detects possible rescheduling events but also determines whether or not to proceed with the rescheduling process. The choice of δ is not arbitrary: it must be proportional to the weight given to the *inertia* of the production process. That is, if the idea is to reschedule only at high levels of disruption (high inertia), δ must be large. On the contrary, a low inertia system should be readier to react, which requires a lower *δ*.

This procedure is rather easy to automatize, providing another tool to be added to the DSS embedded in the CPPS, making the latter more prone to autonomous behavior. The value of δ should, in that case, be set at the design stage

5. Resequencing Assembly lines in Industry 4.0 environments

Our proposed resequencing strategy to allow late customization in ALs in Industry 4.0 environments is based on two principles, one applicable to the line segments where there are consecutive workstations and the other applicable to locations where buffers exist.

For the first case, of consecutive workstations, the customer should have the possibility of modifying the product within the tolerances defined by the Tolerance Scheduling problem. In this way it is possible to translate the late customization of the customer into either operations time or in consumption of components. These late customizations may imply, for example, varying the operating times on a workstation, according to the tolerances defined by the system when solving the Tolerance Scheduling problem at the beginning of production. If the variation is within the defined tolerances, the customer is informed that its late customization can be accepted. While, if that variation falls outside of tolerance range, the request for late customization is rejected.

The second case of late customizations contemplated in our design is when the product arrives in an intermediate storage buffer. In these cases, the customer would have (potentially) greater freedom to customize the product with respect to the operations that follow downstream of the buffer.

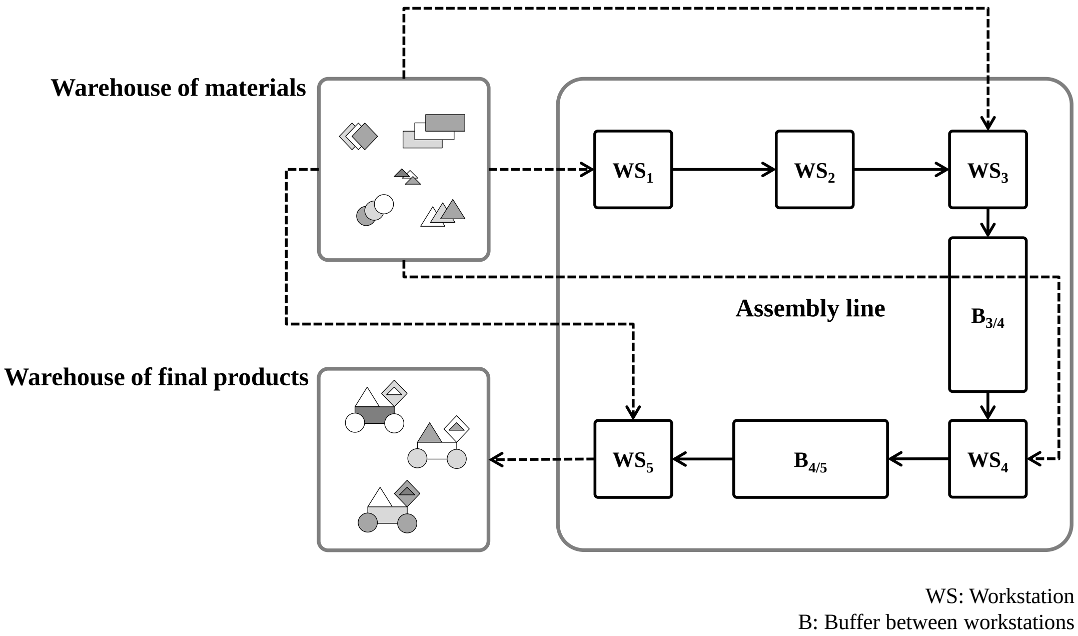

Fig. 4 Assembly line with intermediate buffer.

To better illustrate our proposal, we present Figure 4, where a generic AL system is presented. The System of Figure 4 has five workstations (WS_i) and two intermediate buffers ($B_{i/i+1}$), a materials warehouse and one of finished products. The products begin to be processed in the first WS_1 workstation, then move to the second WS_2 workstation, then to the third WS_3. From this station the products pass to Buffer $B_{3/4}$, from where they are sent to the workstation WS_4 and again pass to a buffer of intermediate storage, the $B_{4/5}$. From this buffer the products are sent for final processing in the WS_5 workstation and then sent to the final product warehouse. The materials required in each workstation are provided by the Materials Warehouse. The feedinf policy is not specified, represented by a dotted line.

The system works as follows. The customer makes a demand for a customized product, specifying its characteristics. The system arranges with the customer a delivery date (taking into account the rest of the demands and the workload of the system) and the cost. If the client confirms this negotiation, it is considered a placed order, and any subsequent modification that the customer may want to make is classified as late customization. The system sends the order to be scheduled for production. The sequence is calculated together with its corresponding tolerances by solving the Tolerance Scheduling Problem.

Then, if the customer, after having agreed to place the order, wants to make a modification to its product can choose the option of late customization. The customer defines a new specification or particular condition of its product, and the company's management system analyzes whether it is possible to satisfy the new modification. For this, the first analysis that the system must perform is whether the modification is still physically possible, i.e., if the modification does not imply operations already executed on the product, preventing the incorporation of the new modifications desired by the customer. If it is physically impossible to perform them, then the system notifies the customer that it is impossible to make the required modification. If it is physically possible to perform the modification, the productive viability of implementing these late modifications can be evaluated. For this, the production sequence must be analyzed according to the two principles mentioned at the beginning of this section.

The first thing that the system analyzes, after determining that the modification is physically viable, is to verify to which workstation corresponds to perform the late modified operations. In particular, it has to check whether it is before or after an intermediate storage buffer. If the operations must be performed on a Workstation prior to the next intermediate buffer, the system has to analyze their impact on the current production sequence according to the tolerances calculated for the current sequence. For example, suppose in Figure 4 that the customer’s product is currently being processed by the WS_1 workstation and the operation included in the late modification corresponds to the WS_3 workstation. The new modification must then be translated in terms of operation times and material consumption, and the tolerances of the current sequence must be evaluated to see whether they allow absorbing the modification of the customer or not. If they allow absorbing the modifications of the customer, she gets notified that her late request can be granted. Otherwise, if the modifications exceed the tolerances, the customer's late request is rejected.

Now suppose that the customer's product is again in the WS_1 workstation of Figure 4, and the operations required by the late customization are performed in the WS_4 workstation. Between the current processing workstation and where the late modifications will be made is the intermediate buffer $B_{3/4}$. In this case, the evaluation of the requirements is more extensive. As in the previous case, the tolerances of the current sequence are evaluated. If they allow absorbing the late requirement, the customer's order is accepted. However, even if the current tolerances cannot absorb the customer's late requirement, it is passed to a second evaluation instance: resequencing the products in the intermediate buffer (in our example, reordering the production sequence from the buffer $B_{3/4}$). This reordering seeks to generate a new sequence of products in such a way that they can meet the late requirements of the customer, without negatively influencing the rest of the products in production process.

This framework can be implemented on an online system and offer the customers an interactive late customization system. These strategies of analysis of the late requirements of the customers allow offering an adequate level of service maintaining a level of production according to an industrial environment.

6. Future work

To advance in the design and implementation of a framework to offer late customization services to the customer, it is necessary to develop further two aspects of this framework: on the one hand, the assignment of tolerance to any given production order, and on the other, generating efficient calculation tools for resequencing the production process.

The allocation of the tolerance to a given order is not a trivial issue, since the tolerance corresponds to the current sequence of production. The ongoing sequence produces more than one product for more than one customer. Therefore, if a customer wants to make a modification, and that modification could be absorbed by the tolerances, it is very likely that the residual tolerance will be reduced. This leaves a smaller margin for future late modifications by other customers. Faced with this situation, it is necessary to define mechanisms to assign tolerances to different customers. These mechanisms will depend on the company, which may opt for an auction, where all customers bid to obtain the margin of tolerance to make their late modifications. Another option would be that the contract for manufacturing the product includes the payment of a fee enabling future late modifications. A vital aspect in all these analyses will be the value of the factor δ for the calculation of the tolerance, since a high value will allow more slack to the company for the incorporation of late modifications of the customers, but at the expense of the efficiency of the sequence for that δ (the larger δ the larger the difference between the optimal sequence and the selected one) (Rossit et al., 2018 b).

The other aspect to consider is in the case of resequencing at some intermediate buffer. The AL problem with resequencing has a direct similarity with the scheduling problem of non-permutation Flow shop (NPFS), in which jobs can be processed for some station in a different order from that at the previous stations (Rossit et al. [2016]; Rossit et al. [2018a]). The space of feasible solutions for cases in which the intermediate buffers are bounded depends on the size of the intermediate buffers (Brucker et al., 2003) and is a NP-hard problem, even for two stages (Papadimitriou & Kanellakis 1980). Therefore, incorporating strategies to resequencing the production plan so that the conditions imposed by late modifications can be met is not a trivial task. Even more so when these modifications depend on the processing times that are not known beforehand. In this sense, robust optimization methods can be applied (Ritt et al. [2016]; Pereira & Álvarez-Miranda [2018]). Also, critical path analyses as in Rossit et al. (2018c) are of particular interest, where the combinatorics of the critical paths allows the independence of the values of the processing times, bounding the search space.

7. Conclusion

In this work a framework was presented that allows supporting late customization strategies in AL systems. This framework presents as an innovation the possibility of implementing it on an autonomous system, since it can determine whether a late modification required by a client can be processed by the AL given the current production conditions, without requiring a scheduler to manage the system. At the same time, it also allows incorporating the possibility of resequencing the workflow when possible, increasing the possibility of incorporating late modifications.

On the other hand, future developments required for an effective implementation of the proposed framework were analyzed. These developments range from mechanisms of allocation of production tolerances to efficient calculation methods for resequencing.

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