Characteristics of Adaptable Control of Production Systems and the Role of Self-organization Towards Smart Manufacturing

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Abstract. Self-adaptive control of production systems has attracted a lot of research during last years. Nevertheless, most of these approaches are still unable to tackle current manufacturing expectations, they are very particular for the case study, are in an initial stage of research or do not apply the concept of self-organization and their properties in its strong sense. Thus, leaving the systems without enough robustness, adaptability, or emergence that are highly desirable considering current market requirements. Therefore, the purpose of this work to identify some of the important characteristics that have been applied in past studies and that can be considered together as a baseline to build future manufacturing frameworks.

Keywords: Self-organization · Smart manufacturing · Cyber-physical production systems · Manufacturing requirements

1 Introduction

In past decades, the high dynamicity of markets and high rate of personalization of products has brought the need for companies to change their internal business and manufacturing structure to stay competitive. This situation entails the proposition of novel production strategies where resources have to be ready to change, in such a way that no delays can be allowed, operations have to be continuous and opportunities to increase performance should be part of a constant manufacturing evolution [1]. This new level of agility is envisioned by the 4th industrial revolution that applies current emerging technologies offering a more efficient and adaptable manufacturing scenario [2]. This level of adaptability introduces the need of having systems that can dynamically self-organize, with agents that have no global vision of the system and with a global awareness that is the result of a high interaction and cooperation.

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However, such level of self-organization is not simple to implement [3]. Several design constrains and safety issues have to be considered due to the high level of decentralization required. Thus, making the self-organization process as a field of continuous research considering manufacturing expectations [4].

Self-organization in the strong sense does not mean just the dynamic organization of manufacturing resources, functionalities, or services. Considering its basic definition in biology or software engineering, there are several characteristics that support this concept e.g. emergence, learning, robustness, etc. [5]. However, most studies rarely apply all these characteristics together due to the difficulty of its formalization in control architectures and due to the high level of abstraction that these concepts have. Therefore, it is main interest of this work to discuss some of these characteristics from the literature in such a way that can contribute to build future manufacturing solutions. It is also envisaged that the research findings can build a solid foundation for better developing in the research phase of the PhD dissertation, which is generically guided by the following research question.

Q. *What could be a suitable set of interaction patterns, methods, and tools to promote adaptability and evolvability in cyber-physical production systems, namely the self-organization of manufacturing resources and the introduction of experienced based knowledge and control principles to assist this adaptability in the context of smart manufacturing?*

The rest of this paper is organized as follows: Sect. 1 described the objective of the work. Section 2 links the content of this paper with applied artificial systems. Section 3 provides a brief overview of Smart manufacturing and of the concept of self-organization. Section 4 presents and integrated vision of current requirements and characteristics; and Sect. 5 concludes summarizing main findings and future works.

2 Relation to Applied Artificial Intelligence Systems

Smart manufacturing is the result of a digital transformation accompanied with the design and implementations of more complex and sophisticated production systems, highly needed to overcome current manufacturing expectations. Thus, new technologies are influencing the introduction of smart and autonomous Cyber-Physical Production Systems (CPPS).

In order to support this smartness and autonomy, Artificial Intelligence (AI) and more specifically distributed AI solutions have paved the way towards the introduction of tools and technologies that are reshaping traditional production design principles for several reasons. First, by providing a highly distributed infrastructure. While traditional production environments are mostly centralized, such level of centralization implies rigidity in the decision making and poor levels of adaptability [6]. Additionally, centralized systems are failure-prone due to the high dependency in one central decisional element. If this element fails, the whole system automatically crashes. While in distributed systems, elements can make individual decisions.

Thus, novel solutions should be decoupled and decentralized. Distributed AI and more specifically multi-agent systems (MAS) have been highly applied in last decades to overcome such challenge. These distributed computerized systems can support the instantiation of adaptable and distributed solutions and thus create intelligent entities to facilitate the emergence of a global behavior [6]. Additionally, current data availability, as well as the high number of sensors and Information and communication infrastructures inside and outside the shop floor, improve the integration with the supply chain and provide necessary information to adapt and optimize processes in real time. Finally, AI provides the necessary methods and tools to promote experience-based knowledge, reasoning, and learning. Novel AI solutions are attracting a considerable set of applications and undoubtedly will pursue the development and optimization of adaptable production systems. Furthermore, a preliminary research in these fields has shown an increasing attention in the application of bio-inspired AI. Indeed, several manufacturing paradigms towards agile manufacturing such as Bionic Manufacturing Systems (BMS), Holonic Manufacturing Systems (HMS) [7], or Evolvable Production Systems (EPS) [8] have found inspiration in the patterns provided by natural systems. Those have been an interesting source of research to provide novel mechanisms to fulfill current smart manufacturing vision taking advantage of information and enabling high flexibility and connectivity in the physical process.

3 Smart Manufacturing and Cyber-Physical Production Systems

Traditional manufacturing plants following the mass production paradigm have relied to a large extend into dedicated production lines. These production systems even though highly capable of generating standardization and fast and cost-effective solutions were not able to manage the new era of high product personalization. The need of a higher product variety and its high heterogeneous requirements introduced a new conception of production development [9]. Thus, the emergence of new production paradigms i.e. Flexible Manufacturing Systems (FMS) and Reconfigurable Manufacturing Systems (RMS) to increase flexibility, agility and reconfigurability [9]. Such approaches, aimed to provide rapid adaptation to market changes, increasing usability of hardware, personalization, decentralization and decreasing engineering effort and time [10]. In addition to this, novel solutions took advantage of enabling technologies like AI, robotics, high sensor availability and high levels of computation and networking to introduce digitalization in factories with the aim of make them smarter. Thus, generating the concept of smart manufacturing where CPPS are main enablers. CPPS have high capabilities of computation and communication [11]. Their main expectations include self-x properties i.e. self-adaptation, self-organization, self-learning [12] and are therefore a focus of continuous research. Even though there is narrow applicability of self-organization, it is highlighted here because of the tremendous number of benefits for future industries e.g. to achieve the idea of lights-out manufacturing philosophy where processes and machines are fully automated and require no human intervention.

3.1 Self-organization in Smart Manufacturing

The self-organization plays a very important role in current production systems. Self-organization can be described as the set of structural or behavioral changes that arise in response to an external input, or variations in the conditions of a system. This continuous variations and evolution can cause instability due to the inappropriate process synchronization with the decentralized units [13]. Due to this reason, self-organizing systems should maintain an adequate level stabilization and equilibrium. While classical systems have normally an external control, self-organization occurs spontaneously [14]. In this case "*…spontaneous means that no internal or external agent is in control of the process: for a large enough system, any individual agent can be eliminated or replaced without damaging the resulting structure…*" [14]. This makes self-organization a truly collective process characterized by robustness and adaptability.

Although all units in a self-organizing system should have only local vision and be able to communicate just with their closer neighbors, such interactions can be propagated to distant regions of the system [14].

In self-organizing systems, the whole is the result of the sum of their parts. Such interaction brings several emerging behaviors i.e. behaviors that were not directly preprogrammed. In manufacturing, this is translated to the no need to specify a production sequence or flow. Thus, a manufacturing system can automatically self-organize without previous models or rules. A high level of robustness and adaptability because of self-organization is still a continuous research endeavor. Therefore, it is worth examining some of previous works to understand how manufacturing paradigms and enterprises can enhance or adopt common characteristics, integrating new technologies and thus being ready to change generating more benefit to companies, increasing quality, and reducing cost of production.

4 Characteristics of Adaptable Production Systems Towards Smart Manufacturing

In the control of self-adaptable manufacturing systems, there are different characteristics that allow the system to run efficiently. While there have been approaches that asses this objective successfully, such implementations are highly constrained by knowledge-based models that somehow neglects the idea of adaptability in the system at least in its strong sense. A collection of works mainly from popular databases (Web of science, Scopus, and Google scholar) has been included in this study, considering key words like self-adapt, evolve, organize and manufacturing, being main interest of such research effort to extract and discuss main characteristics and requirements as will be shown in Sect. 4.1. A summary of the works considered is presented in Table 1.

4.1 Characteristics Description

In smart manufacturing, the control of adaptable production systems should be highly **decentralized**. Even though centralized systems can be considered as essential for data collection, logging or interfacing the benefits from distributed systems pushes more agility and reactivity in presence of environmental changes and disturbances. The decision-making should not rely on centralized control units with a global vision [6]. Instead, single units should be independent and should have the ability to make autonomous decisions. Nevertheless, high levels of decentralization imply also high levels of myopia and perhaps non-optimal behavior. Myopia refers to the efficiency in decision making considering the close environmental vision of individual entities; it can cause global degradation due to the lack of a central supervisory element.

Therefore, an equilibrium between adequate levels of centralization and decentralization are necessary as shown by some examples in the literature where hybrid control architectures report and adequate performance. In addition, adaptability implies the existence of **modularization** of resources.

Modularization promotes reconfigurability and granularity in terms of hardware and software [15]. The finer the **granularity**, the finer the level of engineering design and abstraction. Coarser levels of granularity advocate entire shop floors, while finer granularity levels represent sensors or grippers. This results in higher levels of **complexity** in the control of a production plant, higher levels of **composability** and possibly communication delays. Factories need to be highly **scalable** and their constituent elements **pluggables**. Such elements should have minimal cost of reconfiguration and if possible null re-engineering effort. Aforementioned levels of scalability are achieved by compatible modules in terms of mechanical and software design [16]. This results in systems that are highly **adaptable or robust** i.e. that can maintain certain conditions regarding external changes or modifications [17]. Adaptability is normally applied in runtime to provide a set of alternative strategies, structural changes and behaviors that allow continuous work of the system.

Despite the decentralization needed, manufacturers require a certain level of **optimization**. The optimization process might have different visions. It might refer to the capability components, machines or devices to change their behavior with the aim of improving the overall process efficiency [32]. Also, it might refer to a reconfiguration process with the objective of maximizing resource utilization [33] and to the needed strategies that can improve the overall process performance [34]. This means the reduction of due times, energy consumption, etc. considering also the avoidance of queues or bottlenecks. It is possible to find optimization strategies in dispatching and scheduling operations [35]. Dispatching decisions might improve the sequential resource operation i.e., routing a product to the most suitable resource. It is not easy no find fully optimized systems in self-organizing control architectures since this means the need for having global vision. Thus, it is important to introduce **hybrid architectures** that allow hierarchies or supervisory entities to have control of the overall performance of the process.

Emergence plays an important role in self-organizing control architectures. In engineering, emergence brings the chance of finding novel structural self-organizing patterns. Such emerging patterns are not pre-defined; thus, giving the system the ability to autonomously find alternatives of organization to unexpected situations. This is one of the most important differences with classical knowledge-based approaches, where most of the behavior is predefined and makes systems unable to cope with unexpected situations. The myopia caused by the high level of decentralization of individual units can result in instability. The result of this instability is consequence of very unpredictable environments and sometimes uncontrolled emerging properties [17]. In engineering systems, this is caused by conflicting policies or rules due to the lack of a centralized unit. With such possibility of system degradation, it is essential to provide a **stability** mechanism that can guide the whole adaptability process and provide the necessary evolution and

Table 1. Selected works in the context of self-adaptable production systems.

Reference, year	Adaptation driver and description
Frei et al. [18], 2011	Self-organization of tasks in creation time (chemical reaction basis) and adaptation in runtime. Automatic layout generation according to available modules and ontological based decision-making
Onori et al. [19], 2012	Presents the concept of EPS and more specifically the concept of plug & produce. A multi agent architecture allows the communication between resources, products and transport systems
Leitao et al. [20], 2012	Routing of a product (dynamic task allocation) according to product availability through a mechanism of potential fields
Rocha et al. [21], 2014	Plug and produce of components using and agent based data model. It supports monitoring, data analysis and human machine interaction
Barbosa et al. [22], 2015	2-dimensional self-organization: structural and behavioral. Composed of hybrid architecture: (hierarchical and heterarchical) and modules for learning (behaviors) and nervousness stabilizer
Ribeiro et al. [23], 2015	Agent based architecture for focused on runtime topological changes in the routing of products. Measurement of transport cost and path computation. Transport cost is used to quantify stability
Ferreira et al. [24], 2016	Fully bio-inspired architecture. Self-organization based on the firefly algorithm. Resources attract mobile parts based on an attraction mechanism (each resource has a template of available operations)
Wang et al.[25], 2016	Self-organization of a conveying route based on agent based negotiation and rules. Self-organization is supported by big-data analysis using a coordinating entity that has global vision of the system. There are mechanisms that prevent deadlocks
Zhang et al. [26], 2017	Self-organization consists on optimal task matching of services of resources and tasks. Self-adaptation is implemented in run time. Mechanisms presented are conflict resolution and optimal configuration model (based on metrics evaluation)
Jimenez et al. [27], 2017	Dynamic hybrid control system that integrates a switching mechanism to alter between hierarchical and heterarchical architectures according to a governance parameter

(*continued*)

Table 1. (*continued*)

Reference, year	Adaptation driver and description
Zhang et al. [28], 2018	Cooperation between production and logistics. Tasks and resources are virtualized as services and a self-organizing configuration layer based on an intelligent task and logistics decomposition process based on a ATC model
Sanderson et al. [29], 2019	This approach is based on the design of an ontological modelling of the system based on a function-behavior-structure methodology. The product development relies on a recipe that formalizes its design features
Ding et al. [30], 2020	Autonomous manufacturing task orchestration. Based on a Hidden Markov model to determine the most optimal machine sequence after a production task has been launched. Based on probabilities to perform an adequate autonomous work in progress
Guo et al. [31], 2021	The work proposes a collaborative control for adaptive and smart production logistics. It uses the hybrid automata to model the relation of physical components and data processing and adaptive strategies to deal with production exceptions

support in presence of dynamic changes [13]. Natural systems are continuously changing because of continuous **learning** from external and internal modifications. In control architectures, the role of learning might depend on the level of granularity to which it is referred. P. Neves et al. [36] define three learning levels in a multi-agent architecture considering module (finer granularity), group (coalitions) and global learning level. Because of such mechanisms, parameters, logical behavior, and structural modifications can be improved e.g., regulation of the speed of conveyor, self-organization of the functionalities of components and even structural changes. Naturally, all these mechanisms need to be in constant evaluation and adjustment, by the operator or by predefined goals or experience so that learning mechanisms can take effect. Additionally, manufacturing systems can take advantage of **data driven approaches** and high availability of data to reinforce their production adaptability. Under this continuous evaluation, it is important to note the **measurement of various metrics** examining variables that have strong influence in the manufacturing process. Few works consider such evaluation as part of the adaptation, and therefore, keep their adaptability tied to very general drivers. Some examples are: cost of production, quality, time and flexibility [37]. The reduction time for self-organizing processes is highly desirable. Such minimization can typically be done by reducing the setup, processing, transport and waiting times [38].

4.2 Self-adapting and Self-organizing Manufacturing Applications

Despite the manufacturing industry having a wide scope of subfields, a considerable number of works make use cases in the assembly line. Most likely due to the simplicity of abstracting modules or engineering steps and because it makes simpler the engineer reductionist process in this type of applications. Different types of adaptation applications have been recognized from this overview. First, the manufacturing **scheduling and planning** influences the utilization of resources and clearly provides an optimal or near optimal manufacturing task sequence to fulfill plan specifications. This is highly related to the **autonomous task allocation** of resources, which describes which machines' services are available to fulfill specific jobs. In run time, this generally results in transportation from one resource to another from shipment to final production. The **transportation** e.g., in conveyors, automated guided vehicles (AGVs) or cranes provides the means of **routing** a product to the adequate resource or **re-routing** it in case of disruptions or when trying to optimize the process (reducing transportation time, distributing weight, etc.).

During the run time operation, different modules can be added or replaced without extra engineer effort (**plug and produce**) which includes not just hardware adaptation but also the dynamic organization of the digital entities. This clearly increases hardware re-usability, facilitating also process customization. In terms of hardware composability, and more precisely fine granularity modules, the **composability of skills** or the adequate functionalities re-arrangement (self-organization) provide a variety of different compound services from very simple ones, adding more complex capabilities to the system. Figure 1 presents a summary of characteristics and applications of self-adapting and self-organizing manufacturing applications and characteristics.

4.3 The Role of Self-organization Towards Smart Manufacturing

Main challenges and requirements in the context of CPPS converge in the inappropriate assumption that a strong predefined knowledge should be available about the system behavior, which is not always feasible considering the high dynamism of markets and high level of unexpected situations.

In this context, the adaptability of manufacturing process should not rely on the application of model-driven approaches since they are mostly static and therefore not able to overcome unanticipated events.

Several approaches have introduced self-organization mechanisms to increase adaptability in manufacturing. Nevertheless, the term is sometimes misused, considering its original roots in software engineering and natural and biological systems. Thus, most current implementations lose the real essence of self-organization and end up developing traditional systems with hard-coded knowledge or modelling-based techniques and relying into some extend to having external control. Consequently, the consideration of main self-organization emerging requirements can assist in overcoming the pitfall of making CPPS highly adaptable and at the same time bringing a set of necessary engineering considerations. However, despite such assumptions and benefits, a high-distributed system in the strong sense of self-organization has many drawbacks, too. The high level of myopia may cause a chaotic behavior and even process inefficiency. This is of course not desired by industrial practitioners and consequently can cause aversion to its industrial adoption. In such case, it is unavoidable the consideration of hybrid architectures as shown for example by implementations of the holonic paradigm, which by the way does not contradicts the main definition of self-organization [5].

Thus, we believe that the future of self-organizing manufacturing systems should be a holistic and interdisciplinary process. Clearly, it does not mean the creation of new frameworks or architectures from scratch; but the convergence of a set of architectural patterns and methodologies from different fields and works i.e. biological self-organizing patterns, control and stability of distributed architectures, machine learning and a strong baseline of concepts especially from EPS, HMS and CPPS. Additionally, we believe that the consideration of the studied requirements and characteristics would push this research endeavor for future implementations.

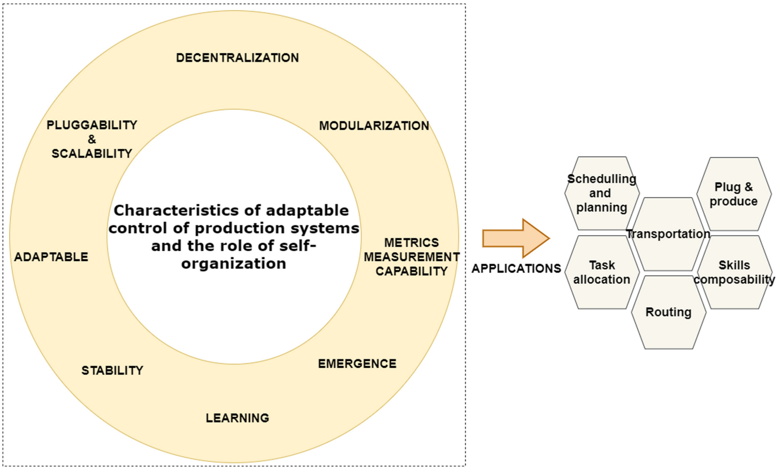

Fig. 1. Self-adapting and self-organizing manufacturing applications and characteristics.

5 Conclusions and Further Work

This paper conducts a short review of characteristics of self-adaptable production systems that may be consider together to develop a generic framework. Most of works are specific for the case study and therefore neglect the consideration of a high scope of requirements. Thus, some challenges emerge because of the lack of a fully extensive solution. In addition, the concept of self-organization even though introduced to some extent in few works, does not seem to be fully exploited; for example, with biological or software foundation. This does not mean to develop fully distributed solutions, but to take advantage of such patterns and adapt them to the production context and their needs.

Within such ideas, we believe that novel solutions should take advantage of current research, methodologies, and technologies to provide a holistic and robust approach. Of course, a benchmarking of such concepts and ideas is important before implementing them. This becomes critical nowadays to fulfill current manufacturing expectations, taking advantage also of fully digitalized factories and high data availability.

Future works need to consider these ideas and connect them. Additionally, it is important to note how self-organizing patterns can improve the process adaptability and how holistic solutions based on these characteristics can be implemented. For example, considering the work proposed in [24] where a fully distributed bio-inspired solution is presented. It would be interesting to include in this approach learning techniques for dynamic adaptation or the inclusion of control-based models or metrics evaluation for an enhanced self-organized process. In addition, it is important to consider and analyze managerial implications of this research. This will push the industrial adoption of self-organizing systems. Future work of this research will also include practical applications in use cases like material handling, transporting and routing where concepts of self-organization and emergence are easy to analyze.

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