Autonomic computing in manufacturing process coordination in industry 4.0 context

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Industry 4.0 is defined as a paradigm that integrates the latest technological inventions in Artificial Intelligence (AI), Communication, and Information technologies, among other domains. This integration is made to increase the levels of automation, efficiency, and productivity of production, in manufacturing and industrial processes. In particular, the actors of the production processes (Things, Data, People and Services) should autonomously be able to act and make decisions, to implement self-* properties, such as self-configuration, self-management, and self-healing. In that sense, the Industry 4.0 revolution introduces many new challenges and issues that need to be solved. Some of those challenges are related to the integration of the heterogeneous actors that carry out the manufacturing process's task. Moreover, it is crucial to determine how to permit the actors to self-manage the production processes. In this paper, we present a framework for the integration of autonomous processes based on the needs for coordination, cooperation, and collaboration. Notably, we define three autonomic cycles that allow the actors of manufacturing processes (Data, People, Things, and Services) to interoperate. These autonomic cycles can create a coordinated plan for self-configuration, self-optimization, and self-healing during the manufacturing process. In this way, the actors could be appropriately coordinated, oriented to autonomously manufacture Smart Products, detect failures, and recover from errors or failures, among other things.

KEYWORDS:
Industry 4.0; Autonomic Computing; Everything Mining; Internet of Everything; Autonomous Coordination.

1. Introduction

In recent years, Industry 4.0 is taking more and more relevance, and many new kinds of research are taking place around it (Sanchez et al., 2020). Lee et al. (2014) affirm that the "transformation from today's industry into more intelligent smart factories requires further advancement in advancement in science by tackling several fundamental issues". In that sense, Artificial Intelligence (AI) will play a crucial role in Industry 4.0, because it permits the adoption of a variety of techniques that can be used to create smart societies (Lu, 2019). Besides, Lu argues that future AI researches will produce a high impact on human society due that they are oriented to promote smart solutions and bring independence to machines in areas like healthcare services, education, logistics, financial systems, customer services, etc.

However, Xu et al. (2018) confirm that there are still many issues and challenges that must be solved to make Industry 4.0 a reality. Some of these issues are related to the integration between two or more factories (*Horizontal integration*) (Khan et al., 2017; Suri et al., 2017). Bringing together the internal actors of a single factory (People, Things, Data, and Services) is another crucial issue. It implies the necessity of dealing with issues related to the *heterogeneity of the data* and *actors,* the *complexity of the planning*, among others (*Vertical integration*) (Hofmann & Rüsch, 2017; Lee et al., 2017; Li et al., 2017b; Liao et al., 2017; Lu, 2017a; Preuveneers & Ilie-Zudor, 2017; Suri et al., 2017; Truszkowski et al., 2010b). Particularly, Lu (2017b) argues that the integration of different technologies and actors present a problem at different levels of operability. One vital point to consider is the necessity of new approaches to ensure the interoperability and active self-organization of actors within Industry 4.0.

Specifically, coordination, cooperation, and collaboration processes (3C) are of high significance to allow humans and robots to accomplish a large number of intelligent tasks (Lu, 2019). Those processes are vital to deal with issues, such as integration and interoperability of actors in production processes. Moreover, the 3C processes will allow actors to negotiate and to achieve goals that cannot be accomplished by a unique actor. The previous statement leads us to consider that 3C processes are the central mechanisms for integration and interoperability in Industry 4.0. Essentially, these mechanisms will allow enhancing autonomy in manufacturing processes. For instance, they can help to solve issues related to the heterogeneity of the actors, distributed decision making, negotiation of production goals, among others.

In general, Peruzzini & Stjepandić (2018), affirm that manufacturing processes in the context of Industry 4.0 require proactive and analytics capabilities in order to transform manufacturing into an intelligent and self-managed environment. It means that autonomy is a desired feature in the context of Industry 4.0. Particularly, Santos et al. (2017) affirm that Industry 4.0 must have the autonomy to schedule maintenance, predict failures, and adapt themselves to new requirements and unplanned changes in the production processes. Also, Li et al. (2017a) consider that Industry 4.0 requires high agility, rapid changes in the customized production style, and fast reconfiguration of the manufacturing system. Consequently, autonomy requires that the system or process can detect needs, make decisions, and deploy solutions with minimal human interaction (Collier, 2002; Truszkowski et al., 2010b). Moreover, (Morris, 1982; Sterritt & Hinchey, 2005; Truszkowski et al., 2010a) suggest that autonomy means self-governance/self-direction because it is a specialized form of self-management (that means, self-heal, self-protect, self-configure, self-optimize, self-* of the process).

At this point, IBM presented in 2001 the Autonomic Computing paradigm (IBM, 2004; Lalanda et al., 2013; Parashar & Hariri, 2005; Sterritt & Hinchey, 2005; Vizcarrondo et al., 2012), oriented to endow autonomic properties to systems based on an intelligent control loop, known as MAPE (Collier, 2002; Vizcarrondo et al., 2017). This loop collects, aggregates, and filters data of the managed resource (Monitor phase), provides mechanisms to study complex situations and analyze future situations (Analysis phase), defines the set of operations that must be executed to achieve the system's goals (Planning phase), and provides mechanisms to carry out the plan (Execution phase). The MAPE loop requires a good understanding of the system to make the best decisions, in order to accomplish the goals for which the autonomic cycle was designed. This system uses knowledge bases and implements data analysis tasks for its operation. In that sense, Peruzzini & Stjepandić (2018) argue that the data analytic helps to improve the agility of the decision-making processes, bringing information about the manufacturing processes. Accordingly, as described in Aguilar et al. (2016, 2017b) and Koubaa (2017), an autonomic cycle of data analysis tasks (ACoDAT), is a type of intelligent control loop for supervision that allows reaching strategic objectives around a problem (it is a MAPE loop). An ACoDAT integrates a set of data analysis tasks that act autonomously and collectively, in order to achieve the strategic objectives pursued by it. Each task interacts with the others and has a specific role in the cycle (Aguilar et al., 2016, 2017b; Koubaa, 2017): Observing the supervised process, analyzing and interpreting what happens in it, and making decisions that allow reaching the objective for which the MAPE cycle was designed. In general, Aguilar et al. (2016, 2017b) and Koubaa (2017) think that the data analysis tasks must be based on *everything mining techniques*, such as data mining, semantic mining, ontological mining, process mining, service mining, sentiment analysis, social networks mining, among others.

Based on the previous context, we made a review of the literature, and we found that it exists a variety of researches that are intending to solve the challenges of Industry 4.0, using mostly coordination or cooperation processes. Moreover, some of those researches have incorporated data mining techniques intending to improve the manufacturing processes. However, the proposed solutions consider mostly the "device" actor of the manufacturing processes, but in fact, there are three more actors that are generally omitted: people, services, and data. In that sense, these researches are missing some vital information that could be gathered from those actors for a better understanding of the whole manufacturing process. In addition, although there exist some standardized reference architectures for Industry 4.0, like RAMI 4.0 (Platform Industry 4.0, 2018), and IIRA (Lin et al., 2015), they are still in immature state respect to the interoperability and standardization of the actors involved in manufacturing processes (Yli-Ojanperä et al., 2019).

Furthermore, according to Xu et al. (2018), developing incremental approaches for the integration of the growing technologies around Industry 4.0 is of high importance to ensure the integration of actors in manufacturing processes. However, no previous works details how to incrementally integrate actors and technologies.

According to the problem presented previously, this paper shows how to combine the Everything Mining, the Autonomic Computing and the Internet of Everything (Chen et al., 2017b; Martino et al., 2018; Shaikh et al., 2017; Yang et al., 2017) paradigms to solve the integrability and interoperability issues in a manufacturing process, based on a method that incrementally uses the 3C processes. Principally, this research tries to increase the autonomy of a manufacturing process by enabling autonomous coordination processes based on three autonomic cycles. These three autonomic cycles allow autonomic coordination processes by enabling self-planning, self-optimization, and self-healing in the manufacturing processes. Notably, this paper is based on previous researches (Sanchez et al., 2020), in which, they have detected challenges and future directions in Industry 4.0 from a system integration perspective. Consequently, our contributions are:

- An architecture for an autonomous integration of actors in Industry 4.0, using technologies/paradigms like the Autonomic Computing, the Internet of Everything, and the Everything Mining.
- The autonomic capabilities could be incrementally added to the system. In that sense, the self-coordination, self-cooperation, and self-collaboration process can be enabled incrementally (one by one). However, in this paper, we deal only with the coordination level.
- We present three autonomic cycles that manage the self-coordination process, intending to allow the integration and interoperability of actors in Industry 4.0. It means that data, people, things, and services can autonomously work together (using coordination processes) to achieve the production goals.
- This paper shows how the proposed framework could be easily coupled to other standardized reference architecture, like RAMI 4.0 (Platform Industry 4.0, 2018).
- Finally, this paper presents and discusses the applicability of the proposed framework in a traditional industry, so that it is possible to transform it into a smart factory.

This paper is organized as follows: Section 2 presents the related works. Section 3 shows the proposed framework for autonomous integration and interoperability of actors in the industry 4.0 context. Moreover, in Section 3, the concept of autonomic cycles of data analysis tasks is introduced. Then, section 4 describes the specification of three autonomic cycles for autonomous coordination in Industry 4.0. Additionally, Section 5 presents a case study that shows how the autonomic cycles are instantiated in a factory. Finally, Section 6 shows a comparison with previous works, finishing with conclusions in Section 7.

1. Related works

This section presents a brief state of the art of the autonomic coordination and mining tasks in production processes.

1.1 Industry 4.0 and Coordination problem

For the coordination problem in Industry 4.0, Haupert et al. (2017) propose the aggregation of semantic information to the data collected in a Smart Factory production line, to allow the creation of a service orchestration planning within a manufacturing process. Also, Syberfeldt et al. (2017) say that a Smart Factory enables an extremely flexible production, and self-adaptable production processes, with machines and products that act both intelligently and autonomously. In that sense, the actors involved in the production line are provided with services that allow interoperability among them. In this case, the functionality of the manufacturing process is represented as a composition of different services. The authors affirm that the process can be easily improved by using a dynamic approach, which consists of adding semantic information to the services provided by the devices. Likewise, the object (being manufactured) must provide a semantic description of how to produce itself. In this way, the orchestrator can use the semantic information attached to services, to create a dynamic orchestration of services, by adequately selecting the devices that will produce the object more efficiently. On the other hand, Haupert et al. (2017) test their proposal using the following metrics: a) how to endow a centralized orchestration process to an automated CPS production line; b) how a CPS can be self-maintained; c) how a service orchestration process can ensure that objects are produced efficiently.

Also, Leal et al. (2019) develop an ontology for interoperability assessment. The goal of this paper is to show which elements must be considered concerning the interoperability assessment. The developed ontology is divided into two sub-ontologies: the assessment core and the systemic core. The assessment core permits the evaluation of the system's design. The systemic core describes concepts that enabled the design of different kinds of assessments. In the systematic core, the system is defined using characteristics of quality, which also can be related to the system's requirements. In counterpart, the assessment core contains concepts like the problem, the evaluation criteria, assessment scope, and assessment processes. Those concepts allow defining the reasons for what the assessment is made, as well as the quality attributes to consider, type of assessments, etc. The system interoperability is evaluated by defining the quality characteristics and the evaluation criteria, which must be rated to get a result that identifies the problems.

Lucas et al. (2018) use different communication technologies in a hierarchical architecture for communication and data management. The global operability of the system is guaranteed thanks to a central orchestrator. This orchestrator defines the data and communications protocols used by each sub-network, according to their requirements of latency and reliability. This work proposes the grouping of the devices into subnets or cells, which implement various technologies throughout the entire industrial plant. Each cell can use different communication technologies according to their needs. In this context, the orchestrator is responsible for the coordination of the resources assigned to different cells. The results of Lucas et al. (2018) show that the decentralized method can guarantee the delay necessities of the applications, and significantly outperforms a centralized approach.

A conceptual framework that allows achieving integrability, coordination, and orchestration capabilities in a CPS was introduced by Rojas et al. (2017). The framework is composed of five layers. The Control layer is an intermediate layer between the physical system and cyber units, which allows proper integration of them. The Operational layer includes analytical tasks for monitoring, optimizing, and diagnosing the system, in order to empower the interoperability of the hardware in the control layer (The Operational layer is still under development). The Information layer is in charge of collecting data from all layers and provides high-level data analysis techniques oriented to feed the knowledge bases. The Application layer is where APIs and User Interfaces are implemented. Finally, the Business layer refers to components of the upper layers of the automation pyramid (Hollender, 2010), like the Enterprise Resources Planning (ERP) and the decision making systems. In the framework proposed by Rojas et al. (2017), no autonomic coordination and orchestration mechanisms have been defined.

Cavalieri et al. (2019) propose a solution that uses the *Open Connectivity Foundation (OCF)* communication standard to allow an OPC-UA server that uses a publish/subscribe pattern to transfer all the information stored in it towards an OCF device over IoT. The OCF device translates the message and publishes it to other OCF devices in its ecosystem. The proposed architecture is straightforward, but functional. However, the translation OCF to OPC-UA was not treated in that research work.

1.2 Industry 4.0 and Mining Tasks

Xu & Duan (2019) developed a survey related to the connection between CPS and big data in Industry 4.0. This study reveals that most researches are putting their efforts on the use of big data in the conception of CPS, but fewer researches focus on using the data analytic techniques to make CPS more efficient and effective. Furthermore, Xu and Duan affirm that most researches do not cope with the collaboration and cooperation of CPSs inter companies. Xu & Duan (2019) conclude by saying that using different data analytics applications will generate a high impact on the management of the whole Industry.

Qin et al. (2016) propose some mining tasks in the context of Industry 4.0. They have implemented a multi-layered framework of manufacturing for Industry 4.0. In the Integration layer, the Internet of Things (IoT) (Chen et al., 2017a; Mezghani et al., 2017a, 2017b) and CPS are used as technologies for the combination of the elements involved in the manufacturing process. On this level, sensors and machines are in charge of collecting the data produced in the supply chain, as well as receive customer feedback. Moreover, this level applies different data analytic technologies to discover useful information from data that can help to improve the manufacturing process. Furthermore, technologies like Advanced Data Mining and Big Data Analysis are applied to the Intelligence layer to create a knowledge base that serves as a support for the planning and decision-making processes. Notably, the Intelligence layer enables the manufacturing system to be self-aware, self-optimized, self-configured, and in general, self-*. The Automation layer is composed of physical components like machine and factories' processes. On this layer, technologies like a PLC (Programmable logic controller), a numeric controller, and statistical probability analysis, are used to optimize the production process.

Seeger et al. (2018) develop a solution that allows dealing with the scalability and performance issues generated in a system that has been dynamically configured by using IoT. For this purpose, a set of recipes is created. According to Seeger et al. (2018), a recipe is just a set of semantic descriptions of the configurations of the devices created in IoT. Moreover, a recipe describes the data flow between devices through ingredients that interact and exchange information. Likewise, these recipes allow the specification of restrictions that will impact the autonomous selection of the offer that best suits the instantiation of the recipe. Seeger et al. have verified that the scalability of the system is guaranteed due that the recipes are executed as a dynamic and distributed choreography, rather than as a centralized orchestration (Seeger et al., 2018). In this context, the choreographies are dynamically created according to the system requirements. The reliability of the system is guaranteed by a mechanism of failure detection and automatic recovery. In this case, when a device fails, then it is removed, and a recipe is run to find a replacement.

Finally, Wang et al. (2016) focus on describing how MAS can be used in smart factories in order to allow autonomic coordination and cooperation processes. A negotiation mechanism leads agents to cooperate, allowing them to determine a route of agents to transport and elaborate the product. This negotiation mechanism is based on the contract net protocol, where the product acts as a manager. The MAS is supported by a Big data mechanism, which is used to solve the agent deadlocks and decision making.

2. Proposed Integration Framework

This section presents the proposed architecture for autonomous integration and interoperability of actors in Industry 4.0. This is one of the main contributions of our work.

2.1 Autonomic Integration Framework for the Industry 4.0 (AIFI)

In this research, we propose an autonomic integration framework for Industry 4.0 (see Fig. 1).

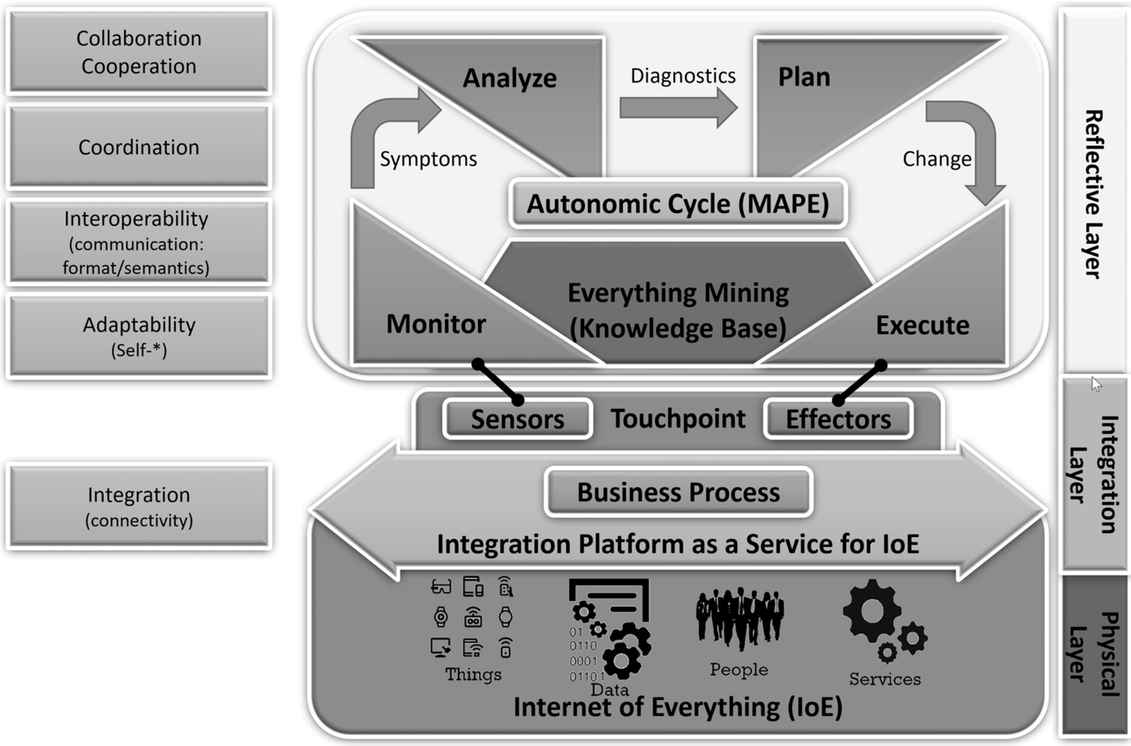

Figure 1: Autonomic Integration framework for the Industry 4.0 (AIFI 4.0)

This framework uses the Autonomic Computing Paradigm (Lalanda et al., 2013; Parashar & Hariri, 2005; Vizcarrondo et al., 2012), as an essential element that guarantees the autonomy and adaptability of the production process. Autonomic properties, like self-configuration, self-healing, self-optimizing, self-protecting, self-coordination (any self-* property), are developed in order to endows autonomy in manufacturing processes. Consequently, the Managed Resource is the Business Process, which means, it is the element that will be controlled to increase its autonomy. The Business Process is offered as a Service (BPaaS), which means that the Internet of Services (IoS) (Shila et al., 2017) is another essential paradigm integrated into this framework.

Moreover, the communication among the actors involved in the Production Process is possible thanks to IoS, especially, by the incorporation of the Internet of Everything (IoE), which considers the integration of all the manufacturing process actors known as Things, Data, People, and Services. Typically, in other frameworks, like CPPS (Qiu et al., 2017; Zanero, 2017), only Thing and Data are explicitly considered as part of the production processes. However, People and Services are quite crucial because they not only can address essential tasks (like decision-making, data-processing, and others), but they also produce valuable information about the production process that must be incorporated into the knowledge bases used to make decisions. For instance, mining of the Business Process is essential to get production goals, help to detect failures or bottlenecks, among others. It means that mining the Business Process can help in the development of self-supervising capabilities.

Consequently, IoE acts as the integration media for actors (Things, Data, People, Services), the Business Process itself, and the autonomic cycles in the Reflective Layer. Besides, it helps to solve issues related to the heterogeneity of actors and platforms. Furthermore, the Business Process is monitored continuously by the Reflective Layer in order to collect useful information for the creation of the knowledge bases needed by the autonomic cycles.

Expressly, the autonomic coordination, cooperation, and collaboration processes are incorporated as self-* properties of the Business Process. In this sense, the knowledge bases needed by the autonomic cycles are created and updated by the Everything Mining component. This element is fundamental to allow our framework to learn from the Business Process and to encourage self-configuring, self-management, and self-healing of the manufacturing process.

From this perspective, it is necessary to introduce the concept of "Everything Mining" as the mining of any actor, such as the process mining, big data mining, service mining, things mining, and people mining (sentiment analysis, opinion mining, etc.), with the primary goal of getting a better understanding of the system and learn from it. So, Everything-mining includes not only data mining technology, but also process and service mining (mining from events rather than only data), or whatever other kinds of mining technology.

In essence, "Everything Mining" serves all the knowledge needed by self-configuration, the self-healing, self-optimization, self-protection, self-* capabilities, to endow autonomy to the system, making it more proactive, reflective and robust. For instance, the self-configuration would allow the system to reconfigure itself according to its needs and objectives. On the other hand, self-optimization would help to improve the resources and raw material utilization. Also, the self-healing would allow detecting and repairing failures — for instance, the detection of delays in whatever stage of a production process. In the same sense, the self-protection characteristic would help to ensure system safety, for example, improving the security and privacy of the data. From this example, it is easy to notice how the autonomy of the production process increases each time that a new self-* property is incorporated into the system. The fundamental feature of this framework is that it empowers autonomic integrability and interoperability of actors in manufacturing processes. This characteristic is possible thanks to the inclusion of self-coordination, self-cooperation, and self-collaboration (self-*) properties to the system.

Moreover, the proposed framework is based on the idea of adding autonomic cycles of Everything Mining. That means that the self-* properties are added incrementally. For instance, we can start adding the self-coordination property. Next, we can add the self-supervising property, to finish with the self-reconfiguration property. It is simpler than adding all the self-* properties at the same time.

Thus, the "Everything Mining" tasks can generate knowledge of the processes in the Industry 4.0, in particular, for the automation of the coordination, collaboration and cooperation processes (3C Processes) in the Reflective Layer (see Fig, 1). In this sense, extracting information from different actors helps to improve the autonomy of the manufacturing process, using the data generated by them. In that sense, everything mining allows getting useful information from the actors of the manufacturing process, such as data, things, people, and services. Moreover, that information is used to create the knowledge bases that are used by the autonomic cycles to make decisions. This knowledge is essential to promote autonomic coordination, cooperation, and collaboration in manufacturing processes. In particular, this paper proposes three autonomic cycles with the primary goal of enabling autonomic coordination in production processes. Section 3.3 presents these autonomic cycles.

2.2 **Integration with RAMI 4.0.**

Sanchez et al. (2020) proposed an approach for solving the integration & interoperability issues in Industry 4.0, using the levels of connection, communication, coordination, cooperation, and collaboration (5C). This approach was called the 5C integration stack levels. The idea is to start solving the challenges at the connection level, next to the communication level, to finish in the levels of coordination, cooperation, and collaboration, depending on the system's needs. In the present paper, we continue that work, by proposing a framework for autonomous integration and interoperability of actors in Industry 4.0, which allows incrementally adding autonomous 5C processes as autonomic cycles. This framework was described in the previous section. Moreover, in this section, we will show how this architecture can be coupled to other reference architectures for Industry 4.0, as RAMI 4.0 (Platform Industry 4.0, 2018). This is one of the main contributions of this work.

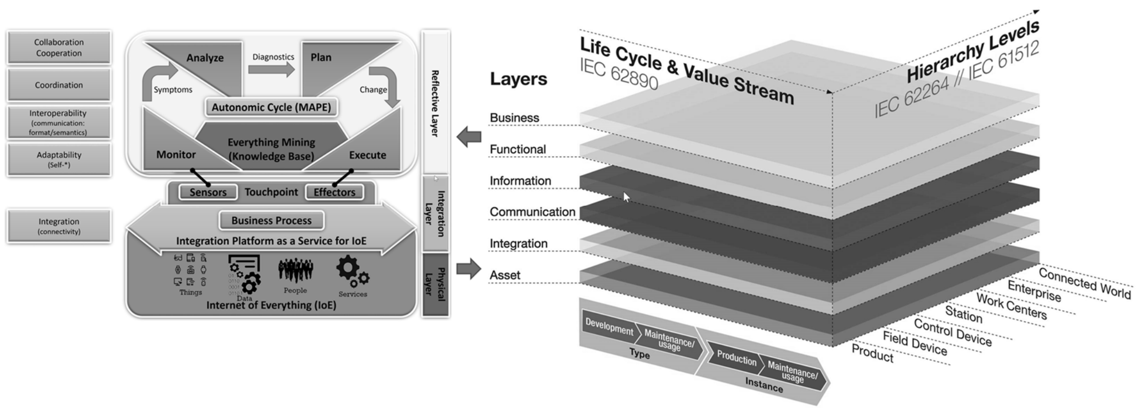

Figure 2: Compatibility AIFI 4.0 and RAMI 4.0

Fig. 2 describes how AIFI 4.0 and RAMI 4.0 can be integrated. First, the physical layer of AIFI and the Asset layer of RAMI are the same. It means that all the physical elements in a production process (actors) are deployed at this layer. Second, the Integration Layer of AIFI is managed by the Internet of Everything. In consequence, all the physical actors are characterized as cyber components (digital twins), which are in charge of interact and make decisions. Besides, the Integration layer of AIFI corresponds to the Integration and Communication layers of RAMI, and allow the actors to connect and communicate transparently. Third, the components that made part of the Information, Functional, and Business layers of RAMI have access to all the knowledge bases built using the everything mining paradigm. These knowledge bases ensure a proper understanding of the production environment and allow the cyber component to make decisions for themselves. For instance, the manufacturing process actors can use the processes for self-coordination, self-cooperation, and self-collaboration created in the AIFI's reflective layer, to self-organize the manufacturing process to achieve the production goals.

2.3 Autonomic Cycles of Data Analysis Tasks

The main objective of the data analytic autonomic cycle is to gather useful knowledge from actors, to facilitate the decision-making processes (Aguilar et al., 2017a, 2017b). In general, an autonomic cycle generates descriptive, diagnostics, and predictive models, among others, in order to endow autonomic capabilities to the system.

On the other hand, an "Autonomic Cycle of Data Analytics Tasks" is a concept defined in (Aguilar et al., 2017a, 2017b), which consists of a set of Data Analysis tasks that work together, in order to achieve an objective in the process that they supervise. Those tasks interact with each other and have different roles in the cycle. The roles could be: Observing the process, analyzing and interpreting what happens in it, and making decisions, which allow reaching the objectives for which the cycle was designed.

The integration of Data Analytics tasks in a closed-loop allows solving complex problems. In this sense, it is essential to integrate the Data Analytics tasks coherently, to generate useful and strategic knowledge for the achievement of the objectives. The detailed description of the roles of each task is (Aguilar et al., 2017a, 2017b):

- Monitoring: Tasks in charge of observing the supervised system. They must capture data and information about the system's behavior. Besides, they are responsible for the preparation of the data for the next steps: preprocessing, selection of the relevant features, etc. See Aguilar et al. (2017a, 2017b) for more details.
- Analysis: These tasks interpret, understand, and diagnose what is happening in the monitored system, using the data. Besides, these kinds of tasks allow building knowledge models from the dynamics observed in the system, oriented to know what is happening in it.
- Decision making: These tasks define and implement the necessary actions based on the previous analyses, in order to improve, correct failures, among other things, in the supervised system. These tasks impact the dynamics of the system to improve it. The effects of the decision-making tasks are again evaluated in the monitoring and analysis steps, restarting a new iteration of the cycle.

The concept of "Autonomic Cycles of Data Analysis Tasks" has been used in different domains. For instance, it has been used in the context of Smart Classroom (Aguilar et al., 2017b; Sanchez et al., 2020), among others.

3. Autonomic Coordination in Industry 4.0

This section discusses the design of the AcoDAT in order to enable autonomic coordination in manufacturing processes. The connection and communication processes (2C) are not treated in this paper, due that other previous researches already dealt with them, as was shown in the survey conducted by Sanchez et al. (2020). In this paper, we focus on dealing with processes linked to the highest three levels of the 5C stacks. Specifically, we start with the coordination process, leaving cooperation and collaboration outside of the scope of this paper.

3.1 Specification of the Autonomic Cycles for the coordination in the Industry 4.0

The Autonomic Cycle for Coordination in Industry 4.0 (ACCI40) proposed in this paper defines a set of data analysis tasks. The main goal of this cycle is to allow self-planning, self-supervising, and self-configuring the manufacturing process. In this context, the actors involved in the process can make decisions using the knowledge bases to improve the efficiency and productivity of the factory, detect failures, and repair the system, among other things. Consequently, a Smart Product is aware of guiding its production (that means, the Smart Product is smart enough to coordinate the actors to its manufacture).

In general, a self-coordination process in Industry 4.0 requires a set of autonomic cycles of data analysis tasks, in order to create (self-configuring), supervise (self-supervising), and reconfigure (self-repairing) the production process. The autonomic cycles must use Everything Mining tasks to get useful information that helps in solving the coordination needs that arise in the production processes. In such sense, data and semantic mining tasks can be used to determine the objectives of the coordination process. In the same way, people and things mining tasks are useful to determine the elements that must be coordinated, as well as their availabilities, status, and roles. Furthermore, process and service mining tasks can help to determine failures in the production process, and contribute to self-healing, and self-optimizing of the production process. In conclusion, the concept of Everything Mining allows developing methods, tools, and strategies for the autonomic coordination in the production processes, within the context of Industry 4.0.

Notably, in this article, we propose a set of autonomic cycles for self-coordinate a production process (these autonomic cycles were named ACCI40). Specifically, the goal of each Autonomic Cycle is the following:

- ACCI40-1 (Build the coordination plan): This cycle is responsible for obtaining useful information for the creation of a coordination plan adjusted to the objectives and needs of the manufacturing process. The coordination plan considers the availability of entities, their characteristics, roles, among others, in such a way that all the actors can be perfectly synchronized. The outcome of this autonomic cycle is the prescriptive model of the coordination plan. A prescriptive model is a structured set of operations that describe how to achieve the objectives as efficiently as possible (Heldal et al., 2016). Moreover, prescriptive models are usually represented in a format that is readable by a machine or smart object.

- ACCI40-2 (Supervise the process): In this case, the data analytical tasks are oriented to supervise the manufacturing process, to detect failures, and ensuring that the coordination plan is being properly executed, among other things. Mainly, this autonomic cycle must analyze and predict actions, roles, along with others, more suitable for the coordinated process. The input of this cycle is the prescriptive model of the coordination plan, and its outcome is the system's diagnostic model.
- ACCI40-3 (Self-configuration of the coordination plan): this autonomic cycle is responsible for the reconfiguration of the coordination plan when an abnormal situation is detected by the self-supervision cycle. In that sense, the coordination plan can be reconfigured in order to solve the issues. The final solution contemplates the current execution context (for example, if a device is out of service, then it must not be considered in the new plan, and its role will be reassigned to another device). Notably, this cycle generates a prescriptive model for the reconfiguration of the current coordinated process. The input of this cycle is the system's diagnostic model and the prescriptive model of the original coordination plan, and its outcome is a new prescriptive model for coordination, adjusted to the new needs and context.

The data sources for the previous autonomic cycles are the organization's databases (Inventory Systems, Organization Social Networks, ERP systems, and the rest), the business process models, among others. In the next sections, each autonomic cycle will be described.

3.2 Specification of the ACCI40-1: Build the coordination plan

The goal of this autonomic cycle is to build the coordination plan of the production process, based on the production goals and the current context. Mainly, this cycle is composed of six tasks (see Fig. 3):

1) Determine the objectives of the coordination process.
2) Determine the production tasks and the roles required.
3) Determine the actors that must/can participate in the process.
4) Determine the activities for each actor based on its roles and competences.
5) Determine the requirements (technological or not).
6) Design the coordination plan.

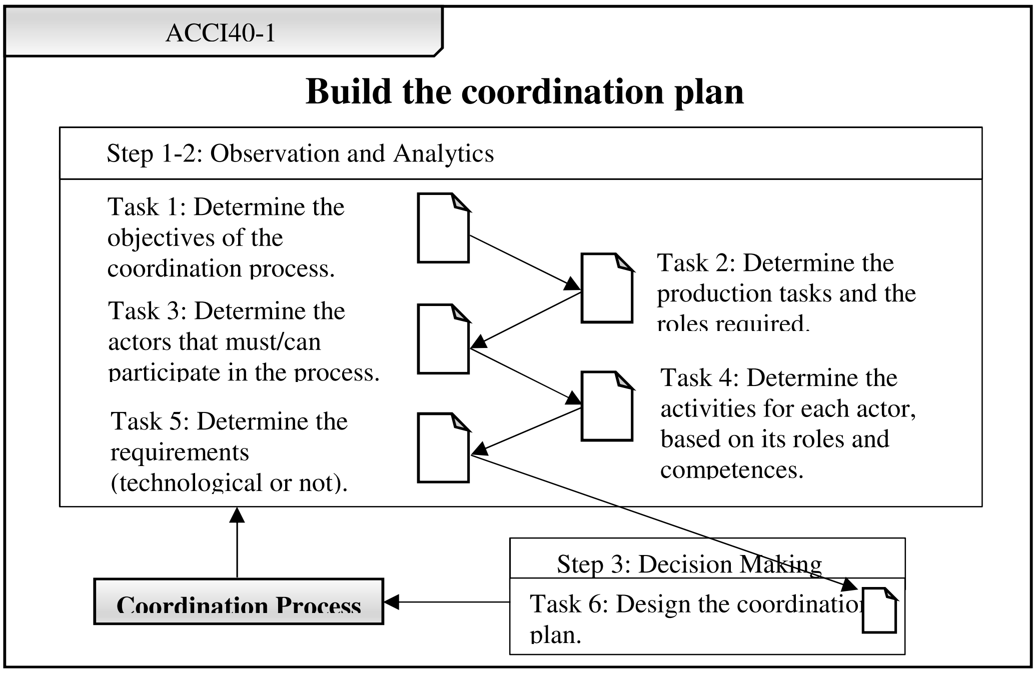

Figure 3: Structure of the ACCI40-1

The first five tasks involve observations and data analysis operations based on the actors' data. In that sense, these tasks are in charge of extracting and analyzing the useful information about the production process. Additionally, it must detect the elements needed to build a specific product, as well as the actors that must be involved in its production, the roles, and tasks to be carried out by each actor, among others. The structure of this ACCI40-1 is shown in Fig. 3.

Table 1: Description of the Tasks of the ACCI40 1

Task Name	Some of the Everything Mining Techniques	Data Sources
Determine the objectives of the coordination process	Process Mining, Data Mining	BPEL, Organization BD
Determine the production task and the roles required	Process Mining	BPEL
Determine the actors that must/can participate in the process	Thing Mining, People Mining, Service Mining, Data Mining	UPnP Services, BPEL Social network, SOA platform, Organization BD
Determine the activities for each actor, based on its roles and competences	Thing Mining, People Mining, Service Mining	UPnP Services, Bpel, Social network, SOA platform
Determine the requirements (technological or not)	Data Mining, Service Mining	Organization BD, SOA platform
Design the coordination plan	Data Mining	Previous Results

Table 1 shows the data sources used in this autonomic cycle for each task. Besides, the tasks for this autonomic cycle are described as follows:

4.4.1 Steps 1-2: Observation and Analysis.

Task 1. Determine the objectives of the coordination process: this task determines the specific production objectives of the production process. For instance, it can determine new product requirements, detects if the products fit its requirements, and recognize if the production objectives have been met, among other things. For this purpose, the process, data, and semantic mining techniques can be used on data sources, such as organizational social networks and databases, business process models, etc.

Task 2. Determine the production tasks and the roles required: this task determines what production tasks should be carried out to manufacture the product, as well as the roles to be played by the actors of the process. In the same sense, this task must discover new and more effective ways to build products. Besides, this task will improve the mode of how the production tasks are assigned to each actor. For this purpose, process mining techniques may be used on business process models (BPEL, Petri nets, etc.) and event logs of the production processes, as data sources.

Task 3: Determine the actors that must/can participate in the process: this task looks for available actors to develop the production tasks. Additionally, this task can use predictive models to determine when the actors are available to synchronize and link to the production chain. In this case, it is necessary to use various mining techniques, such as thing mining, people mining, service mining, and data mining, on different data sources, such as the business process models, social networks, organizational databases, among others. For instance, it can use service mining over the SOA platform to infer the services available in the production environment.

Task 4: Determine the activities for each actor based on its roles and competencies: Task 4 assigns the production tasks to the manufacturing process' actors, in concordance with their availabilities, roles, competencies, etc. Similarly, several mining techniques are required, such as things, people, and services mining. Also, learning techniques can be useful to learn from the production processes about how actors work more efficiently.

Task 5: Determine the requirements (technological or not): The goal of this task is to analyze the technical aspects required by the production process to manufacture a product. For instance, it can predict whether the amount of raw material in the inventory is enough to produce the products in the current production order. This task performs data mining or service mining tasks in organizational databases and business process models, among other mining techniques.

4.4.2 Step 3: Decision Making.

Task 6. Design the coordination plan: This task builds a prescriptive coordination model using the information obtained in the previous steps, in order to associate activities, actors, tasks, roles, the production process sequence, and requirements. That means that this plan describes how to assign the tasks to each actor based on the information collected from tasks 1 to 5, like roles, availability, and other characteristics and requirements of the production process.

3.3 Specification of the ACCI40-2: Supervise the process

The goal of this autonomic cycle, called ACCI40-2, is to supervise the execution of the previous coordination plan, in order to ensure that it is executing correctly. This autonomic cycle consists of 3 tasks:

- Determine how each actor is executing its tasks.
- Determine the general performance of the plan.
- Determine which actors guarantee the production process.

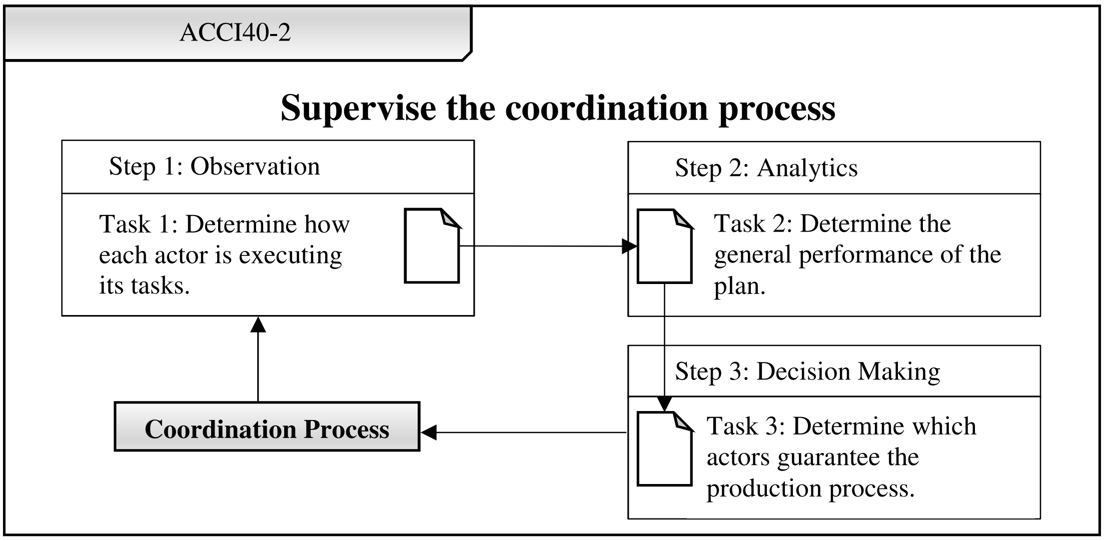

Figure 4: Structure of the ACCI40 2

Now, we are going to describe the tasks of this cycle. Table 2 shows the tasks, data sources, and mining techniques for this cycle. The first task monitors how the process' actors are working. The second task is a data analytical task that determines the general performance and status of the coordination plan. Finally, the third task is a decision-making task that makes a diagnosis of the system using information from tasks 1 and 2. The structure of ACCI40-2 is shown in Fig. 4.

4.4.3 Step 1: Observation.

Task 1. Determine how each actor is executing its tasks: The goal of this task is to monitor the production process, oriented to detecting how each actor is working (detect failures, delays, needs, task complexity, computational resources, etc.). This goal can be accomplished by applying things, people, processes, and service mining techniques, among other techniques.

Table 2: Description of the Tasks of the ACCI40-2

Task Name	Some of the Everything Mining Techniques	Data Sources
Determine how each actor is actors executing its tasks	Thing Mining, People Mining, Service Mining	BPEL, Organization BD
Determine the general performance of the plan	Process Mining	BPEL
Determine which actors guarantee the production process	Data Mining, Thing Mining, People Mining, Service Mining	UPnP Services, Bpel, Social network, SOA platform, Organization BD

4.4.4 Step 2: Analysis

Task 2. Determine the general performance of the plan: This task is responsible for analyzing the general performance of the plan, based on the information provided by task 1, as well as by applying real-time process mining on the current production process.

4.4.5 Step 3: Decision Making

Task 3. Determine which actors guarantee the production process: The main goal of this task is to discover, based on the information received from the previous tasks, the most reliable actors that guarantee to achieve the production goals successfully, with the lowest amount of failures or delays. Reliability, in this case, implies that the information received from these actors is valid and trusted, as well as the fact that the actors finish their tasks in the estimated time, among other things. Once this task has been completed, it generates a diagnostic model of the manufacturing process.

3.4 Specification of the ACCI40-3: Self-configuration of the plan

The goal of ACCI40-3 is to use the information provided by the previous autonomic cycles, in order to detect issues and re-design the coordination plan according to the current needs. Notably, this cycle is composed of six tasks (see Fig. 5):

- Determine the state of the coordination process.
- Determine the production tasks and roles required.
- Determine the availability of actors.
- Determine the activities for each actor based on its roles and competences.
- Determine the requirements (technological or not).
- Re-design the coordination plan.

Mainly, most of the tasks performed by this autonomic cycle are the same tasks performed by ACCI40-1. In this cycle, specifically, tasks 1 and 6 are different. Task 1 defines the current state of the coordination process, while task 6 designs the new coordination plan based on the current information provide by tasks 1-5. Table 3 shows the information about these tasks, as well as the data sources used by each autonomic cycle to extract knowledge. Tasks 1 and 6 are described below:

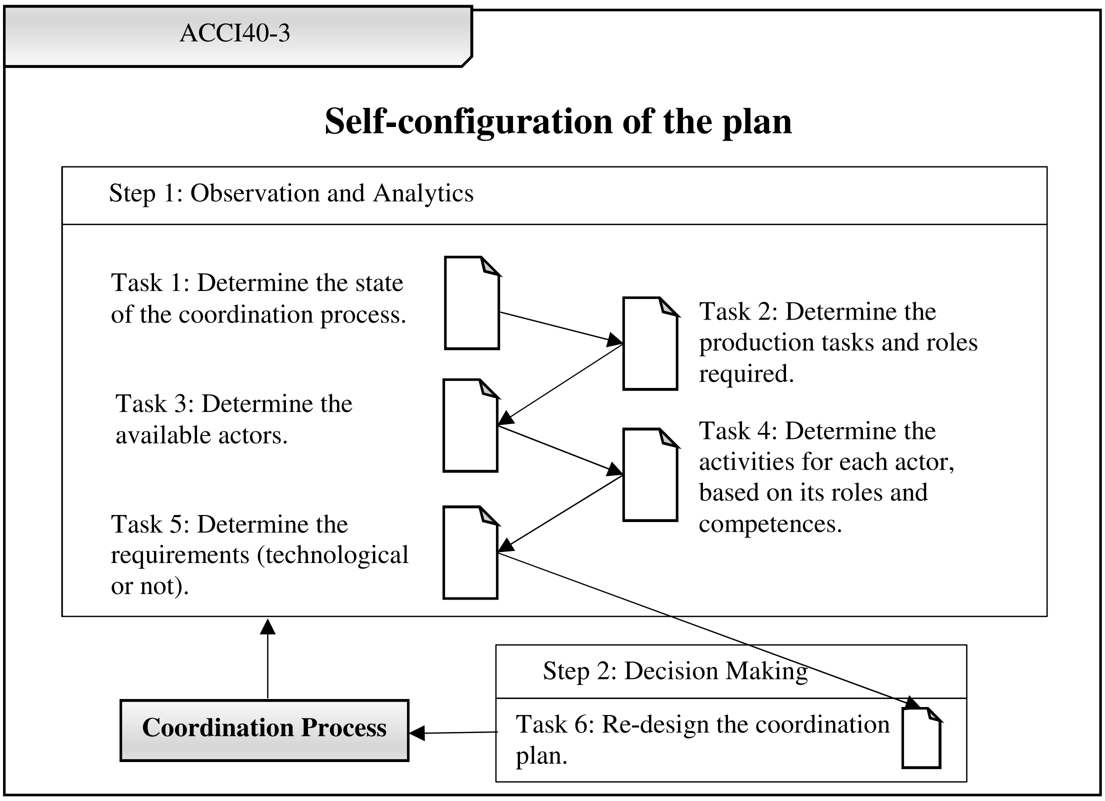

Figure 5: Structure of the ACCI40-3

4.4.6 Step 1: Observation and Analysis

Task 1. Determine the state of the coordination process: The main goal of this task is to observe the environment, in order to get information about the current state of the process (detect failures, delays, needs, task complexity, computational resources, among other aspects). The information collected by ACCI40-2 is essential for this task. Principally, the process mining techniques on the BPEL and event logs of the production process must be executed in order to achieve the goals of this task.

4.4.7 Step 2: Decision Making

Task 6. Re-design the coordination plan: This task performs similar activities as task 6 of ACCI40-1. However, it differs because this task is executed in real-time. Additionally, in ACCI40-1, the outcome is a prescriptive model for coordination, which allows starting the production process appropriately. In this case, the outcome is a new prescriptive model for coordination adjusted to the changes in the environment.

Table 3: Description of the Tasks of the ACCI40 3

Task Name	Some Everything Mining Techniques	Data Sources
Determine the state of the coordination process	Process Mining	BPEL
Re-design the coordination plan	Data Mining, Service Mining	Organization BD, SOA platform

4. Case Study

4.1 Experimental Context

To illustrate the functionality of the autonomic cycles described in the previous section, we are going instantiate them into a generic and traditional production process (the factory is not smart), using the next scenario:

Suppose a company disposes of one assembly line with several devices (see Fig. 6). Likewise, the consumers place orders to request customized products, with the specific delivery time as a requirement. The company must prudently accept the elaboration of the products, in order to not incur in delaying the production process. Additionally, Smart Products coordinate their production. In this sense, to allow the Smart Product to act autonomously, the company requires several integration mechanisms in the levels of coordination, cooperation, and collaboration:

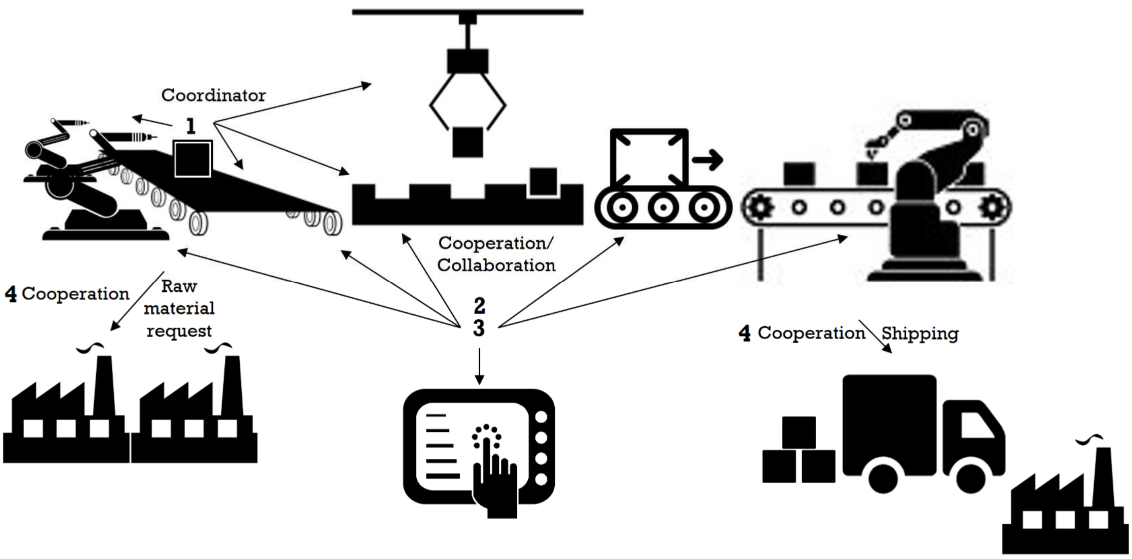

Figure 6: Industry 4.0 scenario with the 3C processes.

1) Smart products self-coordinate their production. Accordingly, *coordination mechanisms* driven by the Smart Product are essential, in such a way that in each phase of the production process, new elements are added to the product, according to the specific requirements of it, which generally differ from one Smart Product to another.
2) In the same way, the Smart Objects (things) must use *cooperative mechanisms*, in order to interact with other actors, to allow carrying out the production process in an efficient manner. Each Thing actor has specific objectives; for example, the objective of the assembly belt is to transport the product from a starting place to a destination one, knowing that multiple origins and destinations can exist. The objective of a robotic arm may be to add a layer to the final product, and so on. In this way, the cooperation between all the actors will allow them to create the final product properly.
3) The objective of the whole production process is to manufacture Smart Products efficiently, minimizing production time, costs, and making an efficient use of human and physical resources. The elements of the production process must consider this common goal, and *collaborate* among them to achieve it, without neglecting their particular objectives; that is, they must deal with multiple objectives.

4) On the other hand, the smart factory can *cooperate* with other organizations, in order to make automatic requests of raw materials and avoid stopping the production process. Finally, the Smart Product can *cooperate* with the shipping organization, so that the products reach the final consumer in time.

In this Industry 4.0 scenario, the 3C processes are fundamental to achieve the manufacturing process goals. In this research, we consider only the coordination process, the collaboration and cooperation processes will be treated in future researches.

In the same sense, we are going to instantiate the general scenario describe above (see Fig. 6) into a particular case study. This case study corresponds to a production process for the production of sandwich bread, where the client can customize the wrapper (logo, name, and other details), the quantity, the type of bread (white bread, grain bread, with raisins, with sesame, among others), among other things. The production process involves devices like the smart conveyor belt that route the bread to the least busy device, smart slicers that slice the bread, wrapping machine to pack the bread using the correct wrapper, the smart kneader machines, the smart printers, etc. Mostly, the production process is launched as a service using BPEL. Also, the organization has event logs and databases related to the production process, inventory of raw materials, among others.

In this scenario, the coordination problem consists in how to produce the sandwich bread and customize orders for each customer (like logo, quantity, etc.), without increasing the production cost. Additionally, parameters like quality and resource consumption must be considered. Moreover, the selling price must be the same for big and small customers' orders. This requirement can be achieved by grouping small orders among them, or by grouping small order with big orders. However, the coordinator must be aware of separating them for distribution.

Formally, in this case-study, the Smart Product is the sandwich bread, and it is the coordinator of the production process. In that sense, the coordination process is based on autonomic cycles, according to the next steps:

1) The smart sandwich bread instantiates the ACCI40-1 to build the coordination plan. This plan contains information about the devices selected for the manufacturing process, the tasks assigned to each device, the sequence order that must be followed by the smart sandwich bread, the time for each device to accomplish its tasks, etc. With this information, the smart sandwich bread can guide its production.
2) Once the production process is started, the smart sandwich bread launches the second autonomic cycle (ACCI40-2), to start the self-supervising of the process and detect problems during the manufacturing of the sandwich bread.
3) If some issues are detected by the ACCI40-2 (i.e., a malfunction of some device, one untrusted actor was detected, etc.), the ACCI40-3 is started to self-heal the manufacturing process and continue with the production.

The autonomic cycles create the knowledge bases needed for decision making, by using the Everything Mining techniques that allows gathering information from transactional databases (containing information about orders, customer, inventory, recipes with information about how to prepare each type of bread, etc.), as well as the event logs generated by previous executions of the manufacturing process, among others data sources.

According to the AIFI 4.0 architecture, all devices in the production line are deployed at the physical layer. Moreover, for this case study, we use ROS Industrial to characterize each actor of the bread factory as cyber units (Koubaa, 2017), and ROSLink (Koubaa et al., 2017) as a message queue that enables IoE as a communication platform (see Figure 7). This configuration covers the two first levels of the 5C stacks. ROSLink allows the devices of the bread production line to connect and communicate through the Internet. The ROSLink Bridge is in charge of translating all messages from ROS Specific format to JSON format and vice versa. Moreover, The ROSLink Cloud Proxy allows the incorporation of other actors that are far from the production line. For instance, the manager can connect from his office and change the production goals. The baker can connect and change some production conditions, etc.

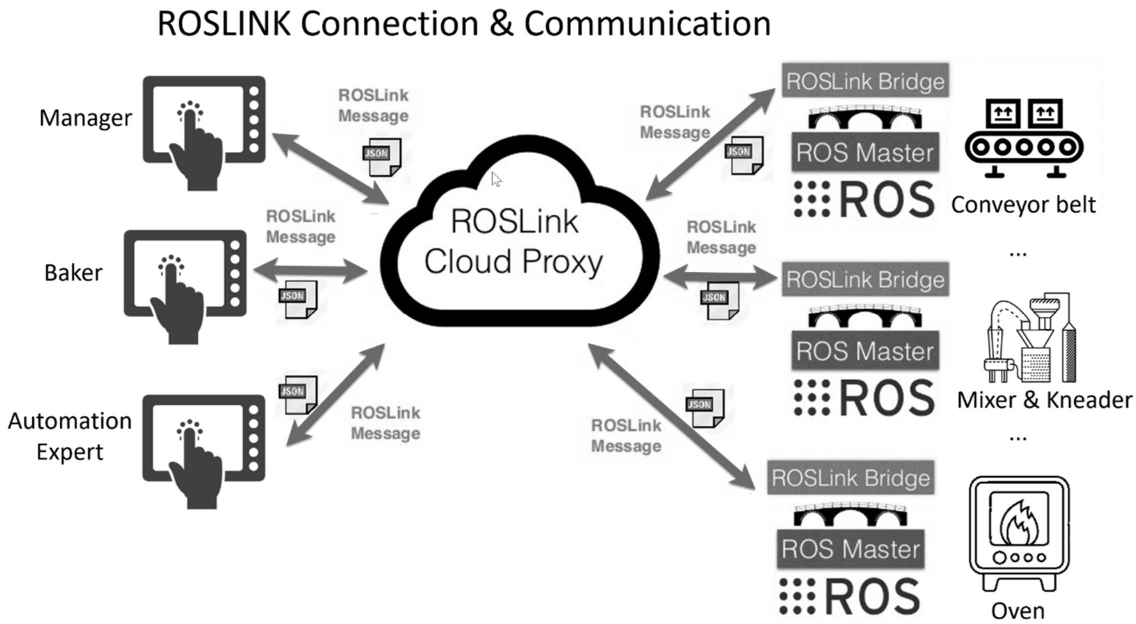

Figure 7: RosLink connection and communication approach.

In the next subsections, the instantiation of the autonomic cycles is detailed. Those cycles are deployed in the reflective layer of the AIFI architecture.

4.2 Instantiation of the ACCI40-1: Build the coordination plan

At the beginning of the production process (before starting the manufacturing process), the Smart Product must configure the production environment, according to the current context. Moreover, it must consider the customizations requested by the customers as well as the availability of devices, among other things. The next steps describe how the ACCI40-1 is instantiated in this case study.

1) The Smart Product (smart sandwich bread) launches the first task of the autonomic cycle, in order to discover its production goals. It gets information about the production process (using process mining techniques) and the purchase orders (using the organization's databases). For instance, this step may discover that the objectives are to produce 1000 units of white bread, where 200 must be wrapped with logo A, 500 must be wrapped with logo B,

and 300 with logo C. Another customer requires 400 units of grain bread, where 200 must be wrapped with logo B, and 200 with logo D.

2) The second task uses the information collected in the previous step in conjunction with the event logs, and the business process model in BPEL, in order to determine the activities that must be involved in the production process, as well as the roles and production tasks that must be carried out by each actor. For instance, this process must return specific information like mix 15min, bake 45 min, stamp logo A, package, slice, transport, among others.
3) The Smart Product must determine the availability of the actors. For instance, in our case study, it can discover that the smart conveyor belt must transport the products through the diverse phases of the process and that the smart slicer machines must slice the bread, but only two of three are available. Also, it determines if it is necessary to request authorization for one specific actor, among other things.
4) The previous information is used to define the criteria to assign activities correctly to each actor. Mainly, the information gathered in the previous tasks is used in order to associate roles and tasks with the actors that might be involved in the production process. Everything-mining techniques must be used as support to set the assignment. One example of the result of this task is: (smart conveyor belt, transport), (smart slicer 1, slice), (smart slicer 2, slice) (smart printer 1, print logo A), (smart printer 3, print logo B), (smart printer 3, print logo C), (manager, authorize shopping of raw material), etc.
5) Next, the Smart Product determines the requirements for its production. For instance, this task defines the communication language and protocols between the devices and other actors. One example of the results is: (smart printer, XML-SOAP), (smart slicer, JSON-REST), etc.
6) All the knowledge base collected in the previous steps is combined to define the coordination plan, which includes information about the task assignment, actors, sequence of tasks, among other things. For instance, the prescriptive model that represents the coordination is shown in Table 4. With that information, the Smart Product can start the production process. Also, as the devices are smart, they can make some decisions, and communicate with the people (Actor) when they need decisions that only the manager can make, among other things.

The final result is shown in Table 4. It is a prescriptive model that indicates the tasks to be executed in order to achieve the production goals defined in task 1. Additionally, it contains information about the time required to finish each task, tasks' dependencies, as well as the actors assigned to execute each task. For instance, the task number 3 (cut 1000 units of white bread) requires 30 min to be accomplished, should start after task 1 (see Table 4), and might be executed by the Smart Cutter actor. The schedule plan can be generated using a Manufacturing Scheduling System (MSS) approach, as described by Rossie et al. (2019). The architecture of the automatic schedule generator is shown in Fig. 8.

Table 4: Coordination Plan generated by ACCI40-1

Nº	Task	Time (min)	Dependencies	Actor
1	Mix & Knead (1000 white bread)	45		Smart Kneader
2	Transport (Though Cutter)	30	1	Smart Conveyor Belt
3	Cut Bread (1000 white bread)	30	1	Smart Cutter
4	Transport (To Oven)	30	1	Smart Conveyor Belt
5	Bake (1000 white bread)	60	4	Smart Oven
6	Transport (thought slicer)	30	5	Smart Conveyor Belt

7	Slice (1000 white bread)	30	5	Smart Slicer 1; Smart Slicer 2
8	Transport (thought wrapping)	45	5	Smart Conveyor Belt
9	Wrap (1000 white bread)	45	5	Smart Wrapping
10	Transport (thought packer)	50	5	Smart Conveyor Belt
11	Pack (orders)	50	5;15	Smart Packer
12	Print (200 Logo A)	50		Smart Printer 1
13	Print (500 Logo B)	125		Smart Printer 2
14	Print (300 Logo C)	75		Smart Printer 3
15	Transport (to Packer)	5	12;13;14	Smart Conveyor Belt
16	Print (200 Logo B)	50	12	Smart Printer 1
17	Print (200 Logo D)	50	14	Smart Printer 3
18	Transport (to Packer)	5	16;17	Smart Conveyor Belt
19	Mix & Knead (400-grain bread)	30	1	Smart Kneader
20	Transport (Though Cutter)	20	19	Smart Conveyor Belt
21	Cut Bread (400-grain bread)	20	19	Smart Cutter
22	Transport (To Oven)	20	19	Smart Conveyor Belt
23	Bake (400-grain bread)	60	5;22	Smart Oven
24	Transport (thought slicer)	20	23	Smart Conveyor Belt
25	Slice (400-grain bread)	20	23	Smart Slicer 1; Smart Slicer 2
26	Transport (thought wrapping)	30	23	Smart Conveyor Belt
27	Wrap (400-grain bread)	30	23	Smart Wrapping
28	Transport (thought packer)	35	23	Smart Conveyor Belt
29	Pack (orders)	35	18;23	Smart Packer

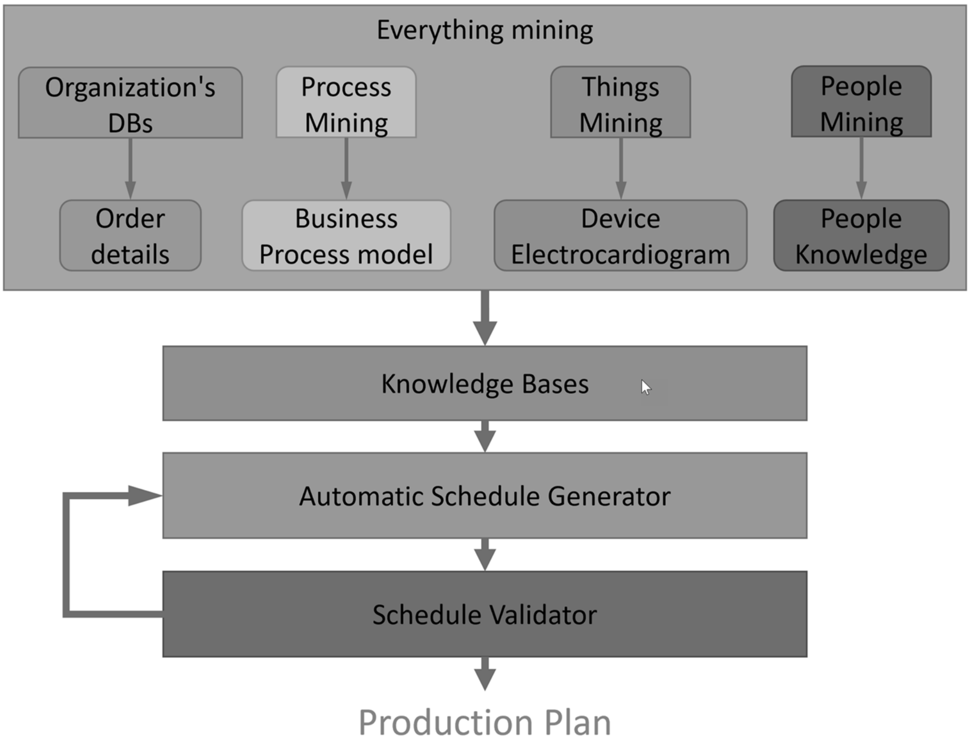

Figure 8: Automatic Schedule generator (Rossit et al., 2019).

The everything mining layer represents the tasks (1), (2), (3), and (5) of this autonomic cycle. This layer collects the information needed by the schedule generator to create the plan (this information is described in the steps above). Besides, this layer feeds the knowledge base needed for decision making. The automatic schedule generator layer uses the information stored in the knowledge bases, and apply the MSS approach, to generate the plan, as described in tasks (4) and (6). This plan is sent to the Schedule Validator layer, in which an expert checks, adjusts, and approves the plan. The schedule validation process can be automated to check the plan, and if it is not approved, then it is forwarded to the Automatic Schedule Generator in order to make the corresponding fixes.

4.3 Instantiation of the ACCI40-2: Supervise the coordination process

Once the process has started, the Smart Product must control the correct execution of the process, detect failures, among other things. In this sense, it executes the autonomic cycle ACCI40-2, in order to allow self-supervising. Notably, the steps followed by this autonomic cycle are:

1) The first step is to collect information from the actors of the production process using Everything Mining tasks. They reveal useful information to determine how each actor is working. Notably, it can determine what actors are delaying the process, what is the cause of the delay, among other things. For instance, it can discover that smart printer 3 is delaying the process because it took more time to print the logos than other printers. In this step, the process mining technique applied to historical event logs is used to create a knowledge model that contains information about the historical time used by each machine to accomplish their tasks.
2) In this step, process mining techniques are applied in order to measure the general performance of the production process. As in the previous step, the model created using the process mining contains information about the global time employed to produce each order. This information is compared to the current execution, in order to determine if the performance of the current process is delayed respect to the historical production data.
3) The third step is to detect what actors are executing their tasks correctly. Additionally, it can detect if the data sent by the actors are trusted, or if there are communication failures, using everything mining techniques. For example, this step can use a predictive model built using historical production data, in order to detect if given the current conditions a product will pass the control test or not. One example of the output of this task is: (Slice 1, trusted), (Slice 2, trusted), (Printer 3, untrusted), etc.

Table 5: Diagnostic Model generated by ACCI40-2

Actor	Status	Trusted
Smart Kneader	Alive	true
Smart Conveyor Belt	Alive	true
Smart Cutter	Alive	true
Smart Oven	Alive	true
Smart Slicer 1	Alive	true
Smart Slicer 2	Alive	false
Smart Wrapping	Alive	true
Smart Packer	Delayed	true
Smart Printer 1	Alive	true
Smart Printer 2	Alive	true
Smart Printer 3	Failure	true

Each time that a new knowledge model is added to the self-supervising autonomic cycle, the system gains more autonomy, and more failures can be detected.

Table 5 shows an example of the diagnostic model generated for this case study. It shows that almost all actors are working without issues, but the smart packer is generating some delays in the production process, and Smart Printer 3 presents a failure. That means, the production process requires to be reconfigured.

4.4 Instantiation of the ACCI40-3: Self-configuration of the plan.

This cycle takes the diagnostic model produced by ACCI40-2 as input, in order to decide about starting or not the reconfiguration of the production process. The tasks of this autonomic cycle are very similar to those of ACCI40-1, and the output as well. In this case, we are going to obtain a new plan similar to the one showed in Table 4, but containing new actors, new timing, among other things, depending on the current production process' needs.

Also, it could generate a new prescriptive model in order to improve the production process. This prescriptive model contains useful information to reconfigure the system. This model deletes the actors that are causing delays, failures, etc., in the process. Moreover, synchronization times are adjusted according to the time that actors currently take to execute their tasks.

Thus, smart factories can gain autonomy in their coordination processes, as well as solve integration and heterogeneity issues, by including the cycles of data analysis tasks described in this section.

5. Comparison with previous works

In this section, we show how the integration of actors arises in our proposal, through the coordination process defined by the autonomic cycles. Furthermore, some premises are proposed to study the integration issue. Next, we make a comparison with previous works in order to show the advantages of using our proposal.

5.1 General premises for the integration of actors in the context of the Industry 4.0

We propose the next premises, to determine the capabilities of our autonomic cycle for coordination in Industry 4.0:

- *First Premise*: Actors belonging to the production process attain their vertical and horizontal integrations by coordinating their interactions.
- *Second Premise*: Actors of the production process (data, people, things, and services) can communicate among them (interoperate), by sending and receiving data during the coordination process. This premise only checks the communication of actors.
- *Third Premise*: the coordination is managed by the autonomic cycles of data analytical tasks.
- *Fourth Premise:* All actors involved in the manufacturing process should work together (interoperate), each one performing its specific tasks.

Now, we describe like the premises are reached by our approach:

- Regarding the first premise, our proposal allows the integration at different levels thanks to the Integration and Reflective layers. Vertical integration is reached by the autonomic coordination of actors within the same Industry, while that the Horizontal integration is reached by the autonomic cooperation and collaboration processes that take place between industries (see Fig. 6). In our case study, vertical integration allows manufacturing the smart bread, thanks to the coordination plan discovered by ACCI40-1. In the same way, horizontal integration allows this Industry to cooperate/collaborate with other companies in order to deliver orders, get raw materials, etc. It will be analyzed in further works.
- For the second premise, the interaction of actors is guaranteed due to the Internet of Everything paradigm. Moreover, the People actor can interact with other actors using the HMI devices disposed within the production process. In general, the framework allows the exchange of data between actors and their understanding, which guarantees that they can communicate (see Fig. 1).
- Concerning the third premise, the Smart Product invokes ACCI40-1 in order to coordinate all the activities that need to be developed by other actors involved in the manufacturing process. In the case study, the smart sandwich bread invokes the ACCI40-1 to start the coordination process. Next, when the production process begins, it launches the ACCI40-2; and when this last autonomic cycle detects a problem in the production process, then it invokes the ACCI40-3.
- Finally, for the fourth premise, the coordination plan defined by the ACCI40-1 assures that all actors work together, in order to achieve the production goal. Moreover, the ACCI40-2 and ACCI40-3 allow reconfiguring the manufacturing process when a fault is detected. They ensure the continuity of the production process. In our case study, the smart sandwich bread controls its production, and the autonomic cycles gather all the information that is needed to assign tasks to other actors. This premise allows for the completion of the manufacturing process successfully.

5.2 Comparison of results

In this sub-section, a qualitative comparison with related works is made. In the first place, we verify if related works comply with the four premises defined in the previous sub-section (see Table 6).

Table 6: Comparison with previous works based on the premises

	First Premise	Second Premise	Third Premise	Fourth Premise
(Haupert et al., 2017)	×	✓	×	✓
(Lucas-Estañ et al., 2018)	✓	✓	✓	✓
(Rojas et al., 2017)	✓	✓	✓	✓
(Qin et al., 2016)	✓	✓	×	✓
(Seeger et al., 2018)	✓	✓	✓	✓
(Wang et al., 2016)	×	✓	✓	✓
This work	✓	✓	✓	✓

As can be noticed from Table 6, almost all the previous works comply with all premises, except Haupert et al. (2017), Qin et al. (2016), and Wang et al. (2016). Substantially, Haupert et al. (2017) and Wang et al. (2016) do not comply with the first premise because they only allow vertical integration. On the other hand, the works Haupert et al. (2017) and Qin et al. (2016) do not act following the third premise, because they do not use data analytical tasks.

Now, we present a qualitative comparison based on some specific characteristics that indicate the grade of autonomy reached by the autonomic cycles. The next characteristics are used for this comparison:

1) Integration of the four actors of the production process (data, services, people, and things).
2) Support Everything Mining.
3) Support the self-configuration of the production process.
4) Support the self-optimization of the production process.
5) Support the self-healing of the production process.
6) Support processes of self-coordination, self-cooperation, and self-collaboration.
7) Autonomic properties can be added incrementally.

Table 7 shows the result of this comparison. As can be seen, most of the related works do not satisfy all the characteristics.

Table 7: Comparison with previous works based on the characteristics that indicate the grade of autonomy reached

	1	2	3	4	5	6	7
(Haupert et al., 2017)	×	×	✓	✓	×	×	×
(Lucas-Estañ et al., 2018)	×	×	×	×	×	×	×
(Rojas et al., 2017)	×	×	×	×	×	×	×
(Qin et al., 2016)	×	×	✓	✓	×	×	×
(Seeger et al., 2018)	×	×	✓	✓	✓	×	×
(Wang et al., 2016)	×	×	×	×	×	×	×
This work	✓	✓	✓	✓	✓	✓	✓

Specifically, the works Haupert et al. (2017), Qin et al. (2016), Wang et al. (2016), Lucas et al. (2018), Rojas et al. (2017) and Seeger et al. (2018) do not allow integration of the four actors of a production process (1), because most of them use IoT as an integration framework what only consider Things and Data. That fact is the first weak point in those works because when services, people, data, and things are integrated, the framework can get a better comprehension of the production process, and the autonomy of the whole system can be increased. Additionally, Haupert et al. (2017), Qin et al. (2016), Wang et al. (2016), Lucas et al. (2018), Rojas et al. (2017) and Seeger et al. (2018) do not support everything mining (2). This element is a second weak point of those works because the data component is not the unique actor that can bring information to the process. Everything Mining permits getting information from social networks (people mining), sentiment analysis (people mining), process, and service mining, among other sources, which allows us to have a better understanding of the context. For instance, people mining can retrieve information about the conditions in which people produce the most; the process mining could get information about how a product is produced (tasks that need to be accomplished, actors involved in the production process, among others).

Regarding the self-configuration of the production process (3), only Wang et al. (2016), Lucas et al. (2018), and Rojas et al. (2017) do not comply with it. These works do not allow the system to be self-configured, a characteristic that is essential in the Industry 4.0 context (Bahrin et al., 2016; Qin et al., 2016; Xu et al., 2014). Additionally, Wang et al. (2016), Lucas et al. (2018) and Rojas et al. (2017) do not support self-optimization of the production process (4), in that sense, they are not able to supervise the process to detect tasks that could be optimized, and launch the self-configuration autonomic cycle to repair the system. Besides, Haupert et al. (2017), Wang et al. (2016), Lucas et al. (2018) and Rojas et al. (2017) do not support self-healing of the production process (5), which means, they are not able to supervise the process to detect failures and reconfigure it when an error occurs in the system. Finally, none supports self- coordination, self-cooperation, and self-collaboration (6). In particular, Haupert et al. (2017) support self-planning, but it is not based on coordination, cooperation, and collaboration processes, and do not apply processes and services mining tasks. The autonomy of the research works presented in Section 2 is not good enough to let actors of the production process manufacturing a product according to the requirements of the Industry 4.0. Finally, our proposed framework lets incrementally add self-* capabilities to the system. It means that the self-configuration process can be added as the first step. Next, the self-supervising capability can be incorporated, finishing with the self-reconfiguration process. Moreover, the other 3C functions can be added later, like the self-cooperation and self-collaboration, which will highly increase the autonomy of the system. In this sense, the scalability of the framework is guaranteed. This property was not found in previous research works.

6. Conclusion

This paper focuses on providing a solution for the integrability and interoperability challenges in production processes regarding the Industry 4.0 context. The proposed framework can deal with the heterogeneity of actors and integration issues, thanks to the adoption of IoE as integration media, and the use of the "autonomic cycle" concept. While the autonomic cycles can create/discover a coordination plan, in order to allow actors to self-organize, and to coordinately manufacture a product, the IoE serves as the glue that joins all the actors together; that means, that it allows them to connect, communicate and exchange data, in order to execute their tasks properly.

Additionally, the Autonomic computing paradigm brings autonomy to the system, supported by the knowledge created by the Everything Mining component, which is in charge of applying a variety of mining techniques, like data mining, sentiment analysis, social network analysis, service mining, process mining, among others, to determine useful information that might improve the system integration and interoperability. In that sense, the autonomic cycles represent an essential characteristic of this framework, in the first place, because they allow the autonomic configuration of the production process, enabling actors to interoperate and work coordinately to produce Smart Products. Additionally, the autonomic cycles apply an intelligent loop that supervises the whole system, in order to know whether or not the actors are working correctly and to reconfigure the process autonomously when any issue is detected.

Mainly, the autonomic cycles for coordination presented in this work, use the information collected by the Everything Mining tasks, to autonomously create/discover, supervise, and optimize/repair the production process. The autonomic cycles allow our proposal to increase the autonomy of the manufacturing process, which is an essential feature in the Industry 4.0 context (Bahrin et al., 2016; Lu, 2017a; Qin et al., 2016; Xu et al., 2014).

Future work is oriented to implement this framework in a simulated environment that allows verifying the functionalities of our solution. In that sense, we plan to use Arcadia methodology (Roques, 2016) to design a Capella-based autonomic manufacturing system for Industry 4.0, and then, implement a digital twin based on this design, using the ROS Industrial (Koubaa, 2017; ROS Industrial, 2018) middleware. Additionally, the required dataset will be the event logs and BPEL diagrams of the organization. Finally, it will be applied some everything mining techniques like service, and process mining tasks, sentiment analysis, using the previous datasets. Another important future work is related to the development of the specific autonomic cycles to allow autonomic processes for cooperation and collaboration in the context of Industry 4.0.

7. References

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