Industry 4.0: survey from a system integration perspective

Manuel Sanchez , Ernesto Exposito & Jose Aguilar

INTERNATIONAL JOURNAL OF COMPUTER INTEGRATED MANUFACTURING
https://doi.org/10.1080/0951192X.2020.1775295

ARTICLE

Industry 4.0: survey from a system integration perspective

Manuel Sanchez [a,b,c], Ernesto Exposito [b] and Jose Aguilar [c,d]

[a]Informatics Engineering, Universidad Nacional Experimental del Táchira, San Cristóbal, Venezuela; [b]E2S UPPA, LIUPPA, Universite de Pau et des Pays de l'Adour, Anglet, France; [c]CEMISID, Universidad de Los Andes, Mérida, Venezuela; [d]GIDITIC, Universidad EAFIT, Medellín, Colombia

ABSTRACT

In recent years, a revolution named Industry 4.0 has arisen. Industry 4.0 is presented as the integration of new advances in areas such as Cyber-Physical Systems, the Internet of Things and Everything (IoE), Cloud computing, the Internet of Services, Big Data Analysis, Smart Factories, Augmented Reality, among others. Industry 4.0 is not only a new industrial revolution, but also a crucial integration challenge that involves several actors from the IoE, which are people, data, services, and things. This paper proposes an approach to analyze the integration challenges in the context of Industry 4.0 using five integration levels, which are connection, communication, coordination, cooperation, and collaboration (5 C). In that sense, this paper presents a state of the art of recent studies in Industry 4.0 from an integration perspective, categorized according to the 5 C integration levels versus the four actors of IoE. Specifically, this paper considers several works intended to solve problems of autonomic integration in Industry 4.0 at the highest levels of the 5 C integration stack (coordination, cooperation, and collaboration). Also, this paper presents a case study from an integration perspective, which contemplates autonomy, self-organizing, among other aspects, in order to turn a traditional industry into a smart factory regarding the Industry 4.0 concept.

ARTICLE HISTORY
Received 27 December 2018
Accepted 17 May 2020

KEYWORDS
Industry 4.0; integration; interoperability; IoE; 5C

1. Introduction

Because of the digital revolution, the boundaries between the physical and digital worlds are shrinking to give life to a more interconnected and smart factories in which employees, machines, processes, and products, interact to give a better organization of all the productive means, to empower the entire company itself to achieve higher levels of efficiency and productivity. In that sense, the concept of Industry 4.0, is used to designate the new generation of connected, robotics, and intelligent factories. Fundamentally, the vision of Industry 4.0 is to give smart capabilities to the production and physical operations in order to create a more holistic and better-connected ecosystem. Figure 1 present the technologies typically used to bring solutions in Industry 4.0, such as (see section 2.2 for details):

- System Integration: It refers to link together system components (vertical integration), two or more systems (horizontal integration), or to provide interfaces to link physical and virtual objects of a system (end to end integration). See (Suri et al. 2017; Pisching et al. 2018) for details
- The Internet of Things (IoT). It is a concept that refers to the connections between physical objects, such as sensors or machines, and the Internet (Sengupta, Gupta, and Vinayak 2017; Riggins and Keskin 2017).
- Internet of Everything (IoE). It is an evolution of IoT that refer to connect not only things, but also people, processes, and data, all connected to the Internet (D. Lee, Choi, and Kim 2017).
- Human-Machine Interaction (HMI). It defines the interfaces that allow humans to take part in a system but removing the risk that operations can represent for their lives.
- X-Mining (Everything mining). It refers to any data analytics technique that could be applied to the system actors (people, things, processes and data), in order to get a better understanding of the system. Techniques as data mining, semantic mining, ontological mining, process mining, services mining, social mining, big data analytics, machine learning, among others, enter under this concept.
- Smart factory. It is a factory that invests and benefits from the technologies, solutions, and

CONTACT Manuel Sanchez mbsanchez@unet.edu.ve Informatics Engineering Universidad Nacional Experimental Del Táchira, San Cristóbal, Venezuela

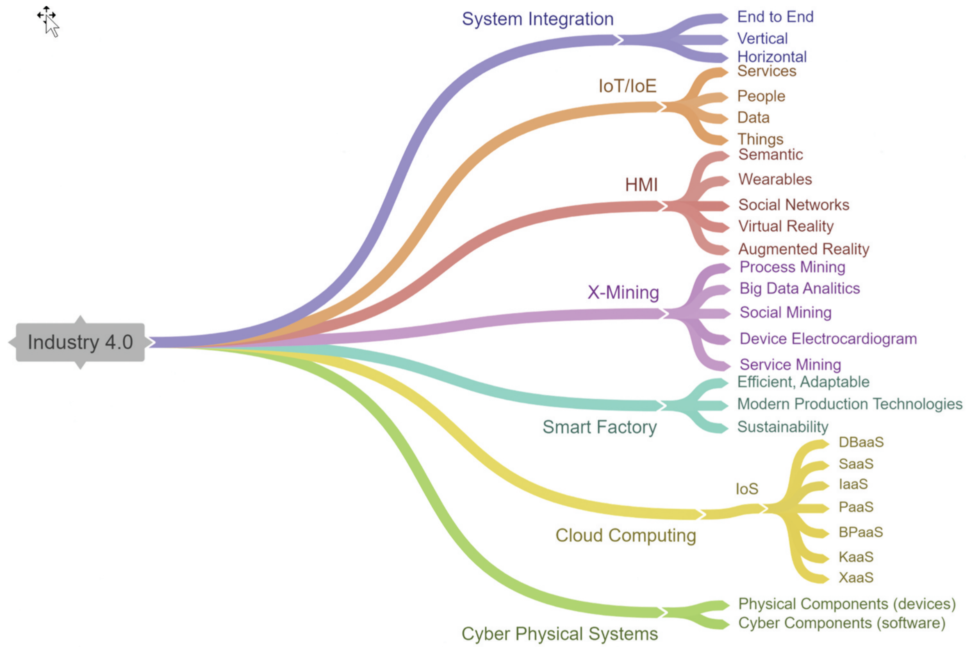

Figure 1. Typical technologies in the Industry 4.0.

approaches of Industry 4.0 (Liu et al. 2017). Smart Factories are developed into intelligent environments in which the real and digital are fully-interconnected (Weyer et al. 2015).

- Cloud computing. It consists of using interconnected remote servers hosted on the Internet to store, manage, and process information, using a service-oriented architecture (SOA) (Shila et al. 2017; Vaquero et al. 2008).
- Cyber-physical systems (CPS). It consists of the characterization of each physical object using a cyber component, so that this last can act as the smart part, in order to make decisions, interoperate, and execute actions in representation of the physical object associated with it (Goossens and Richard 2017).

In general, form Figure 1 can be deduced that solutions in Industry 4.0 use commonly Data mining techniques, Big Data Analytics, Social mining, Service mining, among other mining techniques to build knowledge-bases oriented to make autonomous and smarter decisions. Particularly, the application of these technologies in Industry 4.0 allows the management of the production process autonomously and to increase the factory productivity, flexibility, adaptability, and efficiency (X. Li et al. 2017a; Santos et al. 2017). Moreover, the Industry 4.0 enables to reconfigure factories in shorter cycles than the traditional ones, making an efficient use of human and physical resources (Suri et al. 2017) while increasing the effective communication between the actors involved in the production process (X. Li et al. 2017a). Particularly, Figure 1 shows that Industry 4.0 is a concept that allows the integration of a vast diversity of Artificial Intelligence (AI) techniques and automation technologies within the manufacturing domain to make smarter organizations (Suri et al. 2017; X. Li et al. 2017a; Khan et al. 2017; Gökalp, Şener, and Eren 2017).

Essentially, as Industry 4.0 is an emerging concept, there are a multitude of challenges, risks and barriers limiting its implementation that need to be solved (Hofmann and Marco 2017; Schwab 2016; Lu 2017; Preuveneers and Ilie-Zudor 2017; X. Li et al. 2017a; Liao et al. 2017; Suri et al. 2017). In that sense, in Figure 2, it can be seen the most common challenges around Industry 4.0., such as the complexity of the planning, for which it must be created explanatory models for managing complex products and production systems (Liao et al. 2017). Another challenge related to Industry 4.0 corresponds to standardization, which means to develop common standards to support 5 C processes of connection, communication, coordination, cooperation, and collaboration (Liao et al. 2017). Another challenge is related to privacy and security of data, due that sensors and smart

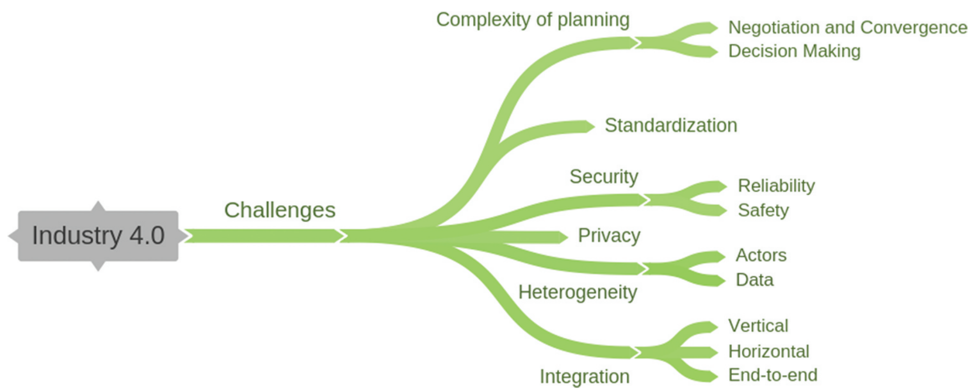

Figure 2. Common challenges in industry 4.0.

devices are continuously collecting information from the environment, and it is necessary to protect that information and avoid unauthorized users to access that data, or still worse, to gain access to control the system (Preuveneers and Ilie-Zudor 2017; X. Li et al. 2017b; Liao et al. 2017). Additionally, the heterogeneity of data and actors is considered a big challenge (Lu 2017; Liao et al. 2017) in Industry 4.0, due that devices from different manufacturers can generate data in a diversity of formats and might communicate using protocols that are incompatible with other brands. Notably, in this paper, the integration and interoperability challenges throughout the 5 C stack levels are considered. Integration is related to link together system's components or sub-systems to allow them to act as a whole and unique system (Drăgan, Selea, and Teodor-Florin 2017).

On the other hand, interoperability is the ability of two systems to understand each other and using functionalities of one into another (Lu 2017), in such a way that they can work together to produce useful results adjusted to the integration goals. In other words, interoperability allows exchanging information between devices, business processes, interfaces, people, among others. (Santos et al. 2017; Lu 2017; Khan et al. 2017), in order to solve conflicts and achieve agreements in the execution of their tasks. Fundamentally, integrability and interoperability requires from the entities involved to be able to connect (to join each other), to communicate (to exchange information between each other), to coordinate (to follow the orders of a central entity in order to achieve a global goal), to cooperate (to work with others to achieve individual goals) and to collaborate (to work with others to achieve common goals). That supposes another challenge within the Industry 4.0 due to the heterogeneity of entities that generate a large amount of heterogeneous data that is not easy to homogenize, which consist of producing relevant information (especially in real-time). Another significant challenge, related to integrability and interoperability issues, is how to provide autonomy to the production process, in order to accomplish global production goals. That means that entities involved in the production processes should be able to make emerging autonomous coordination, cooperation, or collaboration processes (processes that have not been explicitly specified). In this context, a central challenge is how to discover the coordination, cooperation, and collaboration necessities, and how to create a management plan to deploy these processes, to allow autonomous integration processes at the 5 C highest levels for manufacturing.

In general, the authors believe that the integration and interoperability challenges can be analyzed according to the 5 C integration stack so that they can be incrementally solved. For instance, issues related to how to connect heterogeneous actors should be studied at the connection level, but issues related to the autonomous interoperability of actors might be studied at the coordination, cooperation, and collaboration levels, depending on the actors' interaction. In that sense, this paper presents a survey regarding integrability and interoperability of actors in the Industry 4.0 context. Besides, this paper discusses the challenges that might be solved in order to achieve integration and interoperability of actors, and finally, it discusses the technologies that are commonly used in order to solve those challenges. Consequently, the research works discussed in the state of the art section of this paper, are categorized according to the 5 C integration level that most fit them. It was made in that way because our goal is related to solving integration and interoperability issues incrementally using the integration 5 C stack.

This paper is organized as follows. Section II presents as the first point, the evolution of the industry towards the Industry 4.0, as well as the concepts and technologies related to it. Likewise, an evolution of the IoE definition initially proposed by Cisco is presented in order to allow expanding and generalizing this paradigm. Subsequently, in section III, a short state of the art focusing mainly on the integration and interoperability of the actors of IoE within the Industry 4.0 versus the 5 C levels (Connection, Communication, Coordination, Cooperation, and Collaboration), is presented. Moreover, in this section is introduced a definition of these 5 C levels from our point of view. In Section IV, a discussion of the challenges in Industry 4.0 versus the 5 C, is presented, finishing with some conclusions in Section V.

2. Background

In this section is given a brief review of the evolution of the industry towards the fourth industrial revolution, and introduces several fundamental concepts in this context.

2.1. Introduction to industry 4.0

In ancient times of history, all aspects related to production, such as agriculture, transport, or the textile area, among others, were carried out manually, and the development of a product took a considerable amount of time. An essential fact in the history that had improved this situation considerably was the emergence of the first industrial revolution.

The first industrial revolution started from the second half of the century XVIII and took until the mid of century XIX. It was driven by the creation of the water pump and the steam engine, which allowed to mechanize the production and to transform manual production processes into manufacturing processes (Santos et al. 2017; X. Li et al. 2017a; Molano et al. 2017; Huber and Weiss 2017). In such a way, the manufacturing process allowed to transform raw materials into products with the help of steam machines, reducing production times considerably.

Subsequently, a second remarkable transformation of the industry, known as the second industrial revolution, started. This transformation process began at the end of the century XIX until the beginning of the century XX (Santos et al. 2017; X. Li et al. 2017a; Molano et al. 2017). According to (Santos et al. 2017; X. Li et al. 2017a; Molano et al. 2017; Huber and Weiss 2017), the elements that drove the second industrial revolution were the electricity and the division of labors. Those elements allowed manufacturing products through assembly lines. Moreover, this revolution drove many changes, like the invention of the internal combustion engine, the discovery of new sources of energy (electricity, oil, gas, among others.), the telegraph, and the airplane, among others.

Industry 3.0 started in the 1960 s and extended until the beginning of the century XXI (Santos et al. 2017; Molano et al. 2017). This revolution is also known as the Digital Revolution (Santos et al. 2017) because it was centered on the use of the information technology (IT), electronic circuits and the Internet to improve the production processes (Santos et al. 2017; X. Li et al. 2017a; Huber and Weiss 2017). In this revolution, the Programmable Logic Circuits (PLC) made possible, together with the Industrial Automation (basically, directed by the AI), the integration of automatic machines into the production lines, allowing to reduce human errors and to increase the development of products and services dramatically. Likewise, Industry 3.0 allowed the creation of more efficient, safer, and less polluting means of transport, besides, the use of renewable energy was expanded, and the use of intelligent objects begun.

In recent years, the Industry 4.0 or Fourth Industrial revolution term was announced at the Hanover Trade Fair, in 2011 (Santos et al. 2017; Romero et al. 2017). However, some authors affirm that the Fourth Industrial Revolution started at the beginning of the century XXI (Santos et al. 2017; Molano et al. 2017). Santos et al. (2017) affirm that this revolution is characterized by the integration of artificial intelligence solutions within the production machines. Moreover, X. Li et al. (2017a) affirm that the primary objective of Industry 4.0 is achieving high levels of operational efficiency and productivity. In the Industry 4.0 context, new technologies, such as Cyber-Physical Systems (CPS), Internet of Everything (IoE), Cloud computing, Augmented Reality, Big Data Analysis, among others, are expected to play a crucial role in order to enable factories to self-organize and self-control, in a distributed way and in real-time. Notably, that conjunction of technologies has allowed the creation of Smart Factories (Molano et al. 2017; Romero et al. 2017; Riel and Flatscher 2017), which can autonomously create smart products through smart processes and procedures (Molano et al. 2017).

2.2. Conceptual framework of the industry 4.0

This section presents some fundamental concepts involved in Industry 4.0.

2.2.1. Smart factory

A Smart Factory defines innovative production mechanisms, which are suitable for a diversity of applications in different industrial branches involving modern production technologies (Liu et al. 2017). Strozzi et al. (2017) affirm that factories become smarter, more efficient, safer, and more environmentally sustainable, thanks to the intelligent combination and integration of production technologies and devices, information and communication systems, data and services, and network infrastructures. Also, Syberfeldt, Danielsson, and Gustavsson (2017) say that the smart factory concept is intended to enable extremely flexible, and self-adaptable production processes, with machines and products that act both intelligently and autonomously, by implementing concepts such as IoT and CPS. Moreover, Deloitte Consulting (2017) defines the smart factory as one of the main features of Industry 4.0, which focuses on integrating various industrial devices to establish a networked manufacturing system. Those industrial devices interoperate autonomously in order to achieve the manufacturing goals. Mainly, a Smart Factory is a fully integrated industry (Romero et al. 2017) that combines many technologies, such as 3D Printing, AR, Radio-frequency identification (RFID), Enterprise Resource Planning (ERP), IoT, Smart predictive decision support tools, etc. (X. Li et al. 2017a; Strozzi et al. 2017), which use the AI to increase the productivity and efficiency of factories (Molano et al. 2017). Smart factories combine several smart devices that are coordinated, collaborate, and cooperate autonomously in order to achieve the production objectives. The main features of a smart factory are (Deloitte Consulting 2017):

- Connected: The actors involved in the production process can connect and communicate.
- Optimized: the production time is reduced, and the use of human and physical resources is optimized.
- Transparent: new tools are used to support quick, transparent, and consistent decision-making processes, as well as to track the orders appropriately.
- Proactive: early identification of quality issues and anomalies allows self-planning and rescheduling in real-time.
- Agile: adaptable layouts and equipment.

2.2.2. Cyber-Physical Systems (CPS)

CPS has been defined some time ago. This section considers some recent definitions about this concept. CPS was defined by Zanero (2017) as a set of computational and physical interconnected resources, which uses a smart control loop in order to adapt and improve the autonomy and efficiency of the whole system. In the same sense, Qiu et al. (2017) affirm that CPSs are characterized by strong interactions among cyber components (software) and physical components (devices). Both elements combine artificial intelligence, automation, and communication technologies tightly, in order to achieve high levels of performance, reliability, efficiency, and robustness in a physical environment (Goossens and Richard 2017). Likewise, Elattar, Wendt, and Jasperneite (2017) define CPS using a service-oriented vision: 'a CPS consists of one or more interconnected components or units, where services of each unit are visible to the other units of the system and allow them to cooperate.' Jazdi (2014) affirms that a CPS connected to the cloud is often referred to as the 'Internet of Things.' On the other hand, a CPS is essential in the context of Industry 4.0, because it helps to achieve production goals of the manufacturing processes while improving the effectiveness and efficiency of the entire industry autonomously.

2.2.3. Cloud computing and the Internet of Services (IoS)

Cloud computing has emerged as a new computing paradigm that offers excellent potential to share networked computing resources. Shila et al. (2017) define Cloud computing as a revolutionary paradigm to deliver computing resources, ranging from data storage/processing to software, as a service over the network, typically using Internet technologies. Additionally, (Shila et al. 2017; Vaquero et al. 2008) present the US National Institute of Standards and Technology (NIST) referential architecture that has categorized cloud computing into three service models: Infrastructure as a service (IaaS), Platform as a service (PaaS), and Software as a service (SaaS), which allow users to access software, operating systems, tools, and hardware, as a service over the Internet. Shila et al. (2017) affirm that the IoS facilitates the organization of various applications into interoperable services, as well as the use of semantics for the understanding, combination, and processing of data and information from different service providers, sources, and formats. On the other hand, Vaquero et al. (2008) affirm that the main target of IoS is to present everything as a service on the Internet, including software applications (SaaS), the platform to develop and deliver these applications (PaaS (Exposito and Diop 2014)), and the underlying infrastructure (IaaS (Vizcarrondo et al. 2012)). In that sense, everything as a service (XaaS (Perera et al. 2014)) refers to delivering anything as a service and includes the vast number of products, tools and technologies that vendors can deliver to users as a cloud computing service.

2.2.4. Internet of Things (IoT) and Internet of Everything (IoE)

IoT is related to a network of physical devices and other items, with installed capabilities to allow the connectivity. (Chen et al. 2017a; Mezghani, Expósito, and Drira 2017a; 2017b). The authors of (Sengupta, Gupta, and Vinayak 2017; Riggins and Keskin 2017) affirm that the purpose of IoT is to provide wireless communication to various physical objects that we use daily. On the other hand, Gupta et al. (2016) expand this definition, saying that some of those mobile devices are semi-autonomous or autonomous (smart), and can actuate in their surroundings to provide services to users, who may or may not be in the physical proximity of devices. On the other hand, Cisco defines the IoE as an era in which unprecedented value is created by real-time interaction between actors, including not only things, but also people, processes, and data, all connected to the Internet (D. Lee, Choi, and Kim 2017). (Yang, Martino, and Zhang 2017; Martino et al. 2018; Shaikh et al. 2017; Chen et al. 2017b) introduce IoE as the Internet that connects people, data, processes, and objects, giving connectivity of anything-anytime-anyplace for more intelligent health, smarter energy-efficient cities, smart transportation, among others. IoE is considered as an evolution of IoT, which consists of fourth main elements (people, data, processes, and data), in contrast with IoT, which consist of one part: 'things'. (Aazam and Huh 2016; Mohamudally 2017). However, we consider that the definition of Cisco for IoE is quite limited and must be extended to include the services dimension. For instance, in IoE, cloud computing services like storage services, clustering services, among others, are commonly used in order to outspread the limited capabilities of physical devices. Thus, by using Cisco's IoE definition, there is no place for services, because a service is not always a process neither data nor people or things.

On the other hand, a process (industrial or not) can be offered as a service using the XaaS concept of the cloud computing paradigm. In this sense, this paper proposes to enhance Cisco's IoE framework by including the service dimension. In other words, IoE is redefined as the interconnection of (see Figure 3):

- People: Humans behind a device using a human-machine interface, a wearable device, or social networks.
- Data: Databases, unstructured data, or raw data produced by things, services, or humans.
- Things: It represents anything with connectivity capabilities, like sensors, actuators, smartphones, smart vehicles, computers, among others.
- Services: This is related to the XaaS model of cloud computing, which means anything that can be accessed using a web service interface, like a Database (DBaaS), Knowledge (KaaS), Software (SaaS), Business Processes (BPaaS), among others.

2.2.5. System integration

Systems Integration is related to link together system components (Auger, Exposito, and Lochin 2017) like software, hardware, or other systems and subsystems. Those components interoperate and provide solutions according to their goals (collective or individuals) (Drăgan, Selea, and Teodor-Florin 2017). In the context of Industry 4.0, systems are usually integrated using technologies like IoT (Khan et al. 2017; Mezghani, Expósito, and Drira 2017a; 2017b), enabling the interoperability between things, data, people, services, and, and allowing them to connect, communicate, coordinate, collaborate and cooperate. According to (Suri et al. 2017; Pisching et al. 2018), integration is given in three ways:

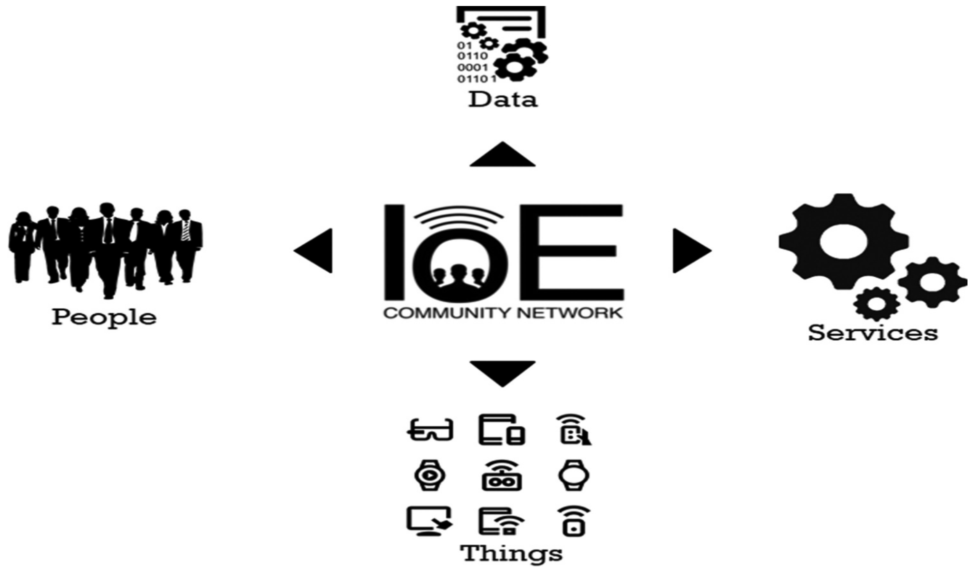

Figure 3. Actors of IoE.

- Horizontal Integration (inter-company integration): This is based on the collaboration or cooperation between two or more companies, to achieve individuals or common goals (Khan et al. 2017; Suri et al. 2017; Pisching et al. 2018).
- Vertical Integration (intra-company integration): The vertical integration brings together the system components within an enterprise, like production business process (BPaaS), applications (SaaS) devices, people, data, in order to allow them to coordinate, cooperate or collaborate (Khan et al. 2017; Suri et al. 2017; Pisching et al. 2018).
- End-to-End Integration: The end-to-end integration mix the digital and real worlds in such a way that real entities can interact with the cyber components of the system. For instance, devices that connect to the network can send information to the cloud, or people that communicate with the system using a Human Machine Interface (HMI) (Pisching et al. 2018).

In this paper is proposed an incremental approach to deal with the integration challenges in Industry 4.0. This approach is called the 5 C integration stack and consists of solving the issues on the specific layer of the 5 C to which they correspond. In that sense, connection issues must be solved in the first level. Next, the communication issues must be dealt in the second level. Once those actors can connect and communicate, the coordination, cooperation, and collaboration issues can be treated according to the integration needs of the manufacturing process. Coordination processes will allow a vertical integration between actors; however, cooperation and collaboration will allow integration in both sides (horizontal and vertical).

2.2.6. Modern human interactions

This sub-section refers to the ways people can interact with a system. In the context of Industry 4.0, Modern Human Interactions try to answer the question: how can people interact with actors like devices, data, and services?

2.2.6.1. Augmented Reality (AR). AR is defined by Kipper and Rampolla (2012), as the overlapping of virtual information on the real worldview. Besides, Syberfeldt, Danielsson, and Gustavsson (2017) say that applying this concept makes it possible to enhance a human's perception of reality. In the context of Industry 4.0, operations less efficient and potentially dangerous to technicians during their work might be driven using AR as an option to support the manufacturing processes (Pierdicca et al. 2017), and reduce risk. The usages of AR in Industry 4.0 are various and can be potentially applied to all activities taking place in the companies, like production, quality control, safety management, maintenance, and remote assistance, training, logistics, and design (Pierdicca et al. 2017; Büttner et al. 2017). AR for Industry 4.0 provides many advantages, such as design optimization, plant maintenance, and control, operator training, assistance and resolution of incidents, among others, with the goals of improving processes, reducing waiting times, increasing security and saving costs that are valuable characteristics in Industry 4.0.

2.2.6.2. Social networks. Cheung, Chiu, and Lee (2011) define social networks as 'virtual communities that allow people to connect and interact over a particular subject synchronously or asynchronously, or just to hang out together online.' On the other hand, (Liu et al. 2017) highlight social networks as sources of social and collective intelligence, from which is possible, for instance, to perform sentiment analysis and to even create recommendation systems (RS) based on people's discussions and opinions. Moreover, in Industry 4.0, the mining of social networks could allow the manufacturing system to get useful information about people, in order to decide their preferences about a product, or their requirements, among others.

2.2.6.3. Wearables. Basically, it is a computing device that people can wear (McCann and Bryson 2009). Besides, a wearable is an integral part of IoT (Hao and Helo 2017), which allows tracking and monitoring human activities (Mezghani, Expósito, and Drira 2017b). Frequently, it uses Machine-to-Machine communication (M2 M) to interoperate with other computing devices autonomously (e.g., smartwatches, glasses, or gloves). Mainly, Hao and Helo (2017) say that wearables can be helpful in the manufacturing industry for increasing the human-machine interactions and for connecting them to the production process as human resources.

2.2.6.4. Semantic. According to (Obitko and Václav 2015; Grangel-González et al. 2016), semantic allows data or documents to be understandable by machines (computers, devices, services, etc.), by making their meaning more explicit. In this sense, populating the data with semantic information will increase the interoperability between the actors of IoE, which is essential to allow the coordination, cooperation, and collaboration processes, to reach their design goals.

2.2.7. Big data analytics

In Industry 4.0, the integration of multiple manufacturing processes has generated a deluge of data from different sources, which requires new approaches for its management (Khan et al. 2017). In this sense, Big Data deals with this problem in production processes by pre-processing the data generated mainly by sensors, effectors, devices and people, looking for insights and knowledge that allow the humans involved in the production process to make better decisions. In general, Big Data can be defined using the five 'V' as follows (Obitko and Václav 2015; Jirkovský, Obitko, and Vladimír 2017; Chang and Wills 2016): Volume refers to the large volumes of information that are generated daily. Velocity refers to the speed of how the data are produced and must be processed to meet the demands. Variety refers to the different types of information formats, whether structured and unstructured. Veracity refers to the reliability of the data. Finally, Value refers to the meaning of the data in the operational context, that is, what is the real benefit that can be derived from them. Consequently, Big data analytics allows the collection and analysis of a large number of data from different sources, in order to support decision-making (Pierdicca et al. 2017). It is fundamental in the context of Industry 4.0 to identify useful patterns, production models, (Santos et al. 2017; Jirkovský, Obitko, and Vladimír 2017) as well as to ease the cleaning, formatting, transforming, and processing the technical data (Khan et al. 2017). Mainly, techniques like machine learning, text mining, data mining, process mining, service mining, semantic mining, and massively parallel data processing like map-reduce and Hadoop, cloud computing, databases oriented to graphs and events, databases without schema, etc., are necessaries for the analysis of the vast amount of data.

This section discussed the more familiar concepts regarding the Industry 4.0 concept, which are essential to adopt this new industrial revolution. The next section offers a state of the art around Industry 4.0, focusing on the integration and interoperability challenges.

3. State of the art of industry 4.0 from the integration perspective

In this section, a selection of articles related to Industry 4.0 is presented. This state of the art is organized according to the actors/dimensions of the IoE (people, data, things, services) versus the five levels of integration, to identify the integration levels and actors more studied. From our point of view, the 5 C levels can be defined as:

- Connection: it allows entities of IoE to be linked to the network and to share a standard media or a channel for the communication. That means it allows the actors to contact each other. The connection is essential to allow communication.
- Communication: Once entities are connected, they can exchange messages, allowing them to establish a conversation and interactions. Also, communication means that the entities can understand each other. Connection and Communication are essentials to achieve interoperability of the system, as well as to allow the coordination, cooperation, and collaboration processes.
- Coordination: Basically, the coordination is an activity carried out by a central entity (or orchestrator) that allows coherently to harmonizing the execution of the tasks of a system (intra-systems integration or vertical integration). In terms of services, the coordination is closely related to the concept of intra-system orchestration (internal to a business process or system).
- Cooperation: It consists of a negotiation process that allows the entities of the same system (intra-system integration or vertical integration) or entities of two or more systems (inter-systems integration or horizontal integration) achieving agreements in the execution of their tasks, in order to accomplish individual objectives. Cooperation is related to inter-system orchestration; however, it does not rely on a central coordinator.
- Collaboration: refers to entities of two or more systems (inter-system) that work together in order to achieve a common goal that participants would not be able to accomplish working alone. Collaboration is related to inter-system choreography (interactions between autonomous processes). Collaboration does not rely on a central coordinator.

According to this classification, a survey of research works mainly focused on the levels of integration of the IoE actors was elaborated. In that sense, Figure 4 shows a summary of the recent researches organized by the integration levels. In this case, a blue bar indicates the number of research works dealing with the integration of Things, an orange bar means the number of research works that focus on the integration of Data, the gray bar specifies the number of researches that considered the integration of people, and a yellow bar

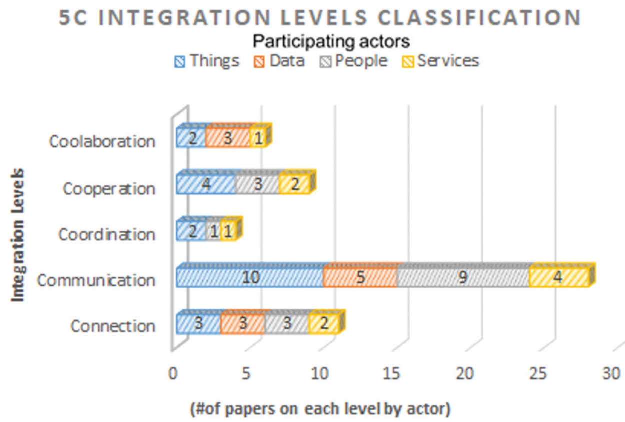

Figure 4. Existing works classified by the four actors of IoE vs. the 5 C integration levels.

corresponds to the number of papers dealing with the integration of services. For instance, at the connection level, three research works consider the connection of things, the other three researches consider the connection of data, three the connection of people, and two researches the interconnection of services.

Furthermore, at the coordination level, two researches worked with the coordination of Things, only one paper considered the coordination of people, and one research is about the coordination of services. Also, in the literature review, it was found only one paper dealing with the integration challenges in more than one level. It means that any solution provided by previous researches can allow all actors to connect, communicate, coordinate, cooperate, and collaborate.

In the next sub-sections, these research works are analyzed according to the 5 C level that best suited to each work. The works have been selected because they cover several aspects of the proposed classification model, or they have some relationship with the problem of autonomous integration in Industry 4.0, mainly for the highest 5 C levels (coordination, cooperation, and collaboration). In this classification, it can be noticed which integration level has been in recent years the most studied, as well as the actors involved at each integration level.

3.1. Connection

Research works positioned at this level focus mainly on the interconnection of entities, using a shared medium, but without defining explicit mechanisms for communication, coordination, cooperation, or collaboration.

Molano et al. (2017) describe an architecture for IoT applied to the industry (denoted as IIoT, for Industrial Internet of Thing), which integrates IoT, sensors, actuators, social networks, and cloud computing. The prototype architecture contains five layers. The Sensing layer comprises several types of devices, and it is responsible for collecting data from sensors or other devices, as well as to manage the manufacturing and logistics processes. The Database layer contains the physical (SQL and NoSQL databases) and virtual databases (logical links to the databases in the network nodes). The Network layer support all the infrastructure (physical devices), allowing devices to connect using wireless or wired networks.

Moreover, the network layer allows sharing the data with other devices connected to the system, enabling the interaction between the Sensor layer and the User layer. Similarly, the Data Response layer represents a data set whose goal is to keep the persistence of other layers. The User layer contains the API used by ERP applications, in order to monitor the raw material, the equipment failures, the quality control and programming of the production. This layer is a Middleware that provides several services, such as data compilation, transmission, data processing, IoT services, etc. Molano et al. (2017) focused on the interconnection of data with things through services, which access databases in the cloud computing and make data available to each device. It means that devices are connected through the data. However, this work does not include the coordination topic between the integrated actors. Because of that, this paper considers it to be positioned between the connection and communication levels.

On the other hand, Jirkovský, Obitko, and Vladimír (2017) use Semantic Web technologies mixed with a Big Data approach for data integration for CPS. They use a Semantic Web approach to deal with the semantic and platform heterogeneity issues. The authors propose an ontology (called SHS ontology) for the description of the industrial data. The SHS ontology contains structures that allow modeling different observations: the physical qualities, the units of measurements, or the external data sources. The architecture is divided into four parts. First, the *Data acquisition layer* collects data from sensors, other systems (MES/ERP systems), and some relevant external data sources. Besides, this layer is in charge of solving platform heterogeneity issues. Next, the *Transformation layer* converts data to a unified semantic form, according to SHS ontology (it corrects the damaged data if needed).

Moreover, on this layer, the semantic heterogeneity is solved, and RDF triples are created in order to populate the data with semantic information. The *Data storage layer* is in charge of storing the triples in the RDF format. Finally, the *Analytic layer* provides direct access to the storage layer for analysis tasks or customizing the user queries. The authors affirm that the main advantages of the integration using the SHS ontology is that the ontology describes the reality in its representation, and data can be easily queried in SPARQL. Same as previous works, this research is focused on put data available to other actors and dealing with the data heterogeneity issues. They allow the connection between actors. For that reason, this paper classifies it as belonging to the connection level.

Notably, (Molano et al. 2017; Jirkovský, Obitko, and Vladimír 2017) are relevant for our research because they describe how to connect actors of Industry 4.0 through data. Other works in this domain allow the inter-connection of actors using techniques like Big Data (Khan et al. 2017), AR (Pierdicca et al. 2017; Syberfeldt, Danielsson, and Gustavsson 2017), Network protocols like TCP/IP (Bohuslava, Martin, and Igor 2017; Exposito 2013), or works that present architectures for CPS integration (J. Lee, Bagheri, and Kao 2015).

3.2. Communication

Most of the studied works are classified at this level because they allow entities to communicate, making abstraction of underling connection details, and without proposing explicit processes for coordination, cooperation, or collaboration.

Román-Ibáñez, Jimeno-Morenilla, and Pujol-López (2018) propose a communication layer aimed to retrieve data of robotic arms manufactured by different firms. The proposed system allows monitoring the status of robotics cell in a footwear factory and displays a 3D visor that shows a simulation of the movements of robotic arms. Essentially, this research work unifies the different communication protocols used by manufacturers into a single one. Moreover, they have defined a custom communication protocol over TCP/IP to retrieve the data from the monitoring system. This protocol supports 128 types of messages, but only five have been defined (MSG_TIME, MSG_NOTIFY, MSG_DOF, MSG_JOINTS, and

MSG_SELECT). MSG_TIME is used to maintain the timeline of the monitored data. MSG_NOTIFY allows sending notification messages from servers to clients. MSG_DOF is used to change the number of degrees of freedom of the robot arms' joints. MSG_JOINTS allows maintaining the angle value of each joint in the robotic arm chain. Finally, MSG_SELECT allows a client to collect data from a specific robotic arm. The communication messages are protected from unwanted attackers. Thus, all the data shared between servers and clients is encrypted to avoid man-in-the-middle attacks. This paper corresponds to the communication layer due that its goal is to allow robotic arms from different manufacturers to communicate using a standard protocol.

Santos et al. (2017) propose a Big Data Analytics architecture that includes layers dedicated to deal with data needs, from the collection to the analysis and distribution. The proposed architecture is divided into seven layers. Components define each layer, and each component can be associated with some technological tool. The *first layer* represents the Big Data producers and consumers' entities; these entities are usually consumers of raw data, indicators, or metrics. The *second layer* (Data sources layer) represents the different sources of data, including components such as Databases (operational/transactional databases), files, ERPs, E-Mail, sensors, among others. All this data will feed the ETL layer (extraction, transformation, and loading processes). The *third layer* corresponds to the process of extracting data from data sources and storing it into the Big Data Warehouse (BDW), using several technologies to implement the ETL process and to integrate data from multiple data sources. The *fourth layer* is the Data Storage layer. This layer was divided into two sub-layers, which contain different components that must be used according to the context. Consequently, the data storage sub-layer stores data into a NoSQL database like Cassandra or HBase-streams in real-time.

On the other hand, The Hadoop BDW sub-layer is in charge of preserving the historical data. Once the data was stored in the BDW, it will be available for data analytics through the SQL query engine. The *fifth layer*, the Raw Data Publisher, enables access to the data by providing Web Services for the data stored in the Data Storage layer. The *sixth layer*, the Big Data Analytics, includes components to facilitate the analysis of the data, making available different data analysis techniques like Data Visualization, Data Mining, Reporting, etc. The *seventh layer* applies mechanisms for Security, Administration, and Monitoring.

Moreover, this layer includes components needed in the other layers in order to guarantee the proper operation of the whole infrastructure. In general, this work allows the data to be available to other actors, letting them communicate indirectly through it. However, this research does not study coordination processes, nor proposes processes for cooperation and collaboration directly. For this reason, it is considered to be positioned at the communication level. Also, it considers only the data dimension of IoE. Moreover, even if the author claims this works are adapted to Industry 4.0 (Santos et al. 2017), they did not present a precise application on this domain.

Similarly, Suri et al. (2017) provide a solution for the modularity and interoperability issues related to Industry 4.0 from a systems integration viewpoint, focusing on the 'vertical integration' of system using the model-driven engineering (MDE) approach. This approach enables heterogeneous systems to communicate in a low-coupled manner. In particular, this approach is oriented to industrial robots, which perform standard repetitive tasks. The communication model consists of two layers. The *model-based behavior layer*, in which the task execution model is created using an activity diagram in UML 2.0; and the *robot's implementation layer*, which is in charge of transforming the activity diagram designed in the previous layer into instructions recognized for robots by using some available frameworks designed for this purpose (i.e., Papyrus). The execution of the robots is made using API calls through the execution model (on-line execution), rather than deploying the source code on the system (off-line execution). In this sense, this approach allows the creation of complex systems of sensors and actuators, with low computational power and low energy usage.

Consequently, the main objective of the previous research is to allow things to communicate transparently and in a loose-coupled way. Due to this reason, it has been classified in the communication level. This paper is relevant for our research because it shows how to integrate and communicate actors of Industry 4.0 using an MDE based approach, to send orders to devices.

On the other hand, Bohuslava, Martin, and Igor (2017) enable communication based on the standard Ethernet (IEEE 802.3) for the control of the robotic cell.

The communication protocol used in this model of production robot cells is TCP/IP. The Control application is divided into several parts, consisting of a server running the control task, and some client subprograms running on each robot. All the requirements of the cells, as well as the instructions from the control center, will be processed as TCP/IP sockets. Complete communication with the sockets takes place only through the central unit, which coordinates the communication among the robot cells. This coordination is based on the messages exchanged thought the sockets according to two variants: a) Confirmed coordination, where the completion of each operation is notified to the central unit b) Unconfirmed coordination, in this case, the continuity of the activity is not conditioned to receive a confirmation message from a superior object. In this sense, robot cells can communicate using the TCP/IP protocol, with a central unit making the coordination of the whole communication process. This paper deals with problems of connection, communication, and coordination of robotic cells; however, the authors of this research work said that the primary goal of it is to allow those robots to communicate. It is the reason why this paper considers it to be in the communication level. This paper is essential for our research because it describes how to incorporate an existing low-level communication protocol in new devices, to allow them to communicate appropriately.

Additionally, Lee, Bagheri, and Kao (2015) propose a unified 5-level architecture as a guideline for the implementation of CPS. The proposed 5-level architecture provides a step-by-step guide for developing and deploying a CPS in manufacturing environments. The first level, the *Smart connection level* is in charge of acquiring the data directly from the sensors, or of collecting it from the controller or the enterprise manufacturing systems, such as ERP, MES (Manufacturing Execution System), SCM (Software Configuration Management) and CMM (Capability Maturity Model). The second level, the *Data-to-information conversion level*, infers useful information from the data using several tools and methodologies. The *Cyber level* acts as a central information hub. The information is sent from every connected machine in the network to the Cyber level.

Moreover, specific analytics tasks are used to extract additional information that provides better insights regarding the status of each machine. The cyber level uses a machine–cyber interface (CPI) in order to allow the interconnections between machines. On the other hand, the *cognition layer* generates detailed knowledge of the monitored system, and makes it available to experts, allowing them to make the correct decisions. According to the authors, this level requires proper user interfaces/ dashboards in order to transfer the acquired knowledge to the users completely. The *configuration level* allows self-configuration and self-adaptation of the devices, by getting feedback from cyberspace to physical space, acting as supervisory control. That configuration allows applying the corrective and preventive decisions (defined in the cognitive level) to the monitored system. In that sense, this system acts as a resilience control system (RCS). This research presents an intelligent middleware, which allows the coexistence of devices and people, facilitating the collection and transformation of data between them. Due to that, this research is positioned at the level of communication. Consequently, this research work is relevant for our research because it describes how to deploy a CPS and how to communicate and share information among things.

Sanchez et al. (2018b) have developed a solution for the interoperability between MAS and the Software Oriented Architecture (SOA) paradigm for intelligent environments (MAS-SOA Integration). Mainly, Sánchez, Aguilar, and Exposito (2018b) allow bidirectional communication between the agents of a MAS and the web service deployed in cloud computing, to give support to the actors of an intelligent environment. Principally, the agents of the middleware characterize people, devices, and services involved in the intelligent environment, which interact and exchange data. Cloud computing services process this data in order to let agents using it and make decisions oriented to support the activities of the users in an intelligent environment. The critical aspect of the solution provided by Sánchez, Aguilar, and Exposito (2018b) is the incorporation of an SOA-MAS communication sub-system, which is in charge of transforming messages from web services to a language that agents can understand, such as FIPA-ACL, and vice versa. Also, in Sanchez, Aguilar, and Exposito (2018a), the fog computing paradigm was added to the solution proposed in Sánchez, Aguilar, and Exposito (2018b), to avoid the issues of the cloud computing-based solutions. In that sense, in Sanchez, Aguilar, and Exposito (2018a), the authors combine the fog-computing paradigm with the MAS-SOA integration sub-system in order to solve issues of geolocation, real-time, and low-latency. Mainly, these works are essential in the Industry 4.0 context, because they allow the interoperability of actors in any cloud computing-based intelligent environment, like smart cities, smart factories, etc. Moreover, Sánchez, Aguilar, and Exposito (2018b) and Sanchez, Aguilar, and Exposito (2018a) are focused on solving issues related to the communication layer, which allows the actors to exchange information among them.

Other works in this domain allow explicitly or implicitly communications between actors, applying a variety of techniques, like MAS (Romero et al. 2017), IIoT (Molano et al. 2017; Wan et al. 2016), Big Data (Jirkovský, Obitko, and Vladimír 2017), human-robot interaction (Huber and Weiss 2017; Nelles et al. 2016), AR (Pierdicca et al. 2017; Longo, Nicoletti, and Padovano 2017), or Middleware (Ferrera et al. 2017).

3.3. Coordination

At this level, this work considers only those paper that allows coordination process using a central coordinator, according with the requirements defined previously (see section II) for the coordination level (centralized intra-system coordination). In that sense, Orellana and Torres (2019) propose a procedure to transform a legacy manufacture process into a smart factory level 2, according to Industry 4.0. Essentially, this proposal allows vertical integration, which guarantees the actors involved in the internal production process to share information. Notably, the remarkable point of this proposal is that it grants integration without buying new machinery. Moreover, their proposal uses Industrial IoT to achieve its integration goals. The procedure comprises eight steps that are executed continuously until the industrial process works correctly.

(1) Define management indicators. Define the indicators that will be used for evaluating the process. The authors propose to use the ISO 22,400 standard (Kang et al. 2016) for this purpose.
(2) Define the process's inputs, signal, and sensors. This step helps to determine which measurement instruments the machinery requires, and how to link them with other machinery's sensors.
(3) Identify and choose data sources based on the corrective and preventive maintenance. In this step, the data source associated with each indicator is defined.
(4) Link equipment of new and old machines. Determine the proper equipment required for each machine being automated in order to allow it to operate autonomously.
(5) Create standalone networks. The machinery might communicate using a dedicated and independent network in order to avoid communication conflicts.
(6) Generate alerts when processes' variation is detected. An alarm must be generated when the system encounters a fault, such as the shutdown of a motor, actuators, among others.
(7) Improve feedback and follow up processes. The production orders in which operators are working, as well as operation's errors and problems, are captured using a data collection software and send to an ERP software, such that all the information about the process can be available when it is requested for failure diagnosis.
(8) Test and validate the system. Verify if the system operates correctly or needs to be tuned up.

The case study for Orellana and Torres (2019) was conducted in an enterprise where the machinery had more than 47 years of operation. The results show that after the production process was transformed into a smart factory level 2, the production line was able to reduce the average production time from four days to three hours. This paper is positioned at the coordination level because it improves the coordination of the whole production process.

Soto, Tavakolizadeh, and Gyulai (2019) present an orchestration framework that combines IoT and machine learning for failure detection in production lines. The solution comprises three fundamental elements. Firstly, the production line is exposed using an IoT Connector that is responsible for transforming the data from different production protocols into network protocols or message queue systems. Secondly, the connector propagates the data using a Broker according to the IoT standards. Thirdly, the data is processed using a learning agent that orchestrates all the components' behavior and selects the learning algorithm depending on the data characteristics and the current use case.

Moreover, this component uses python to build the machine-learning model for decision-making.

This framework was evaluated holistically, using a realistic simulation. However, in a real production line, issues not covered by this solution might happen. This research work is positioned at the coordination level because it can orchestrate the behavior of the production line. However, there is still a significant amount of work to do in order to promote autonomous interoperability.

Ivanov, Sokolov, and Ivanova (2016) introduce the dynamic control concept and a dynamic model to coordinate activities in cyber-physical supply chains, based on the smart manufacturing concept. The authors propose a scheduling approach based on making a temporal decomposition of the scheduling problem to allow the dynamic execution of the jobs. They use a dynamic structure control (SDC) approach model, which is a dynamic interpretation of planning, in concordance with the execution time. Additionally, SDC is combined with the optimal program control (OPC) theory and mathematical programming (MP). The dynamic of planning is because the decisions on supply chain planning are taken for specific intervals of structural constancy. In this sense, a static optimization problem is solved with the help of MP for each time interval, while OPC is used in order to define and to model the transitions between the time intervals.

Moreover, the supply chain is modeled mathematically as a networked system described through control models M1-M2 (schedule for material supply processes, schedule for services, respectively). Then, when the manufacturing process starts, the M1-M2 process assigns services to business operations in sequential order. Next, M2-M3 (M3: schedule for resources) assigns and schedules services to information resources. Finally, M3-M4 (M4: schedule for information systems modernization) is launched in order to reconfigure the system. The coordination happens in the system's interconnections; for instance, the output of M1 is used in the constraints of M2; Analogously for M2, M3, and M4. This research is positioned at the coordination level because a central entity executes the coordination process. Also, this paper is essential for our research because it shows how the coordination processes can be deployed autonomously in the industrial domain.

Pierdicca et al. (2017) develop an AR Android application, in the context of Industry 4.0. This application assists an operator in order to allow assembling an object composed of several components that must be linked together in a specific order. At the end of the assembly phase, the application makes a verification of some parts of the final object. In this sense, the application displays the assembly instructions one by one using the head-mounted display (HMD) that the user wears. Moreover, the application uses textual information and 3D models of the real scene in order to help the operator to finish the task quickly. That means that for implementing this application, some 3D models for each real component must be created; those models must keep the same dimensions and components as the real scene.

Moreover, the 3D model of the real object is created using different colors for each component to allow users to recognize them easily. This research connects people with things in a coordinated way, in which the android app is the coordinator that displays information through the HMD interface to allow users to assemble an object more comfortably. This paper is positioned at the coordination level because it allows achieving a global goal using a central coordinator. Moreover, (Pierdicca et al. 2017) present an unusual approach that combines AR with devices and people to enable coordination, which can be very useful in the context of Industry 4.0.

Another research work with some level of coordination is (Bohuslava, Martin, and Igor 2017); however, that work is focused mainly on the connection of things.

3.4. Cooperation

The papers positioned at this level promote a specific mechanism for cooperation. For example, Huang et al. (Huang et al. 2017) propose a community energy system planning (CESP) model based on a Multi-Agent Systems (MAS), in order to improve the energy utilization within a specific community. In the solution, each participant is viewed as an agent. Furthermore, the stakeholders are represented as CESP agents too. Four types of stakeholders were considered into the model: Governments, People, Energy firms, and Energy facilitators. Additionally, the spatial location is also considered into the model, due to the transmission cost of hot and cold water. In this sense, all agents are organized in a spatial hierarchy and divided into different groups based on whether they have similar interests or not.

The negotiation process is only performed between agents of the same group, in order to improve the negotiation efficiency and to reduce the negotiation time. The information needed for the negotiation process, like price, supply and demand, policies, and other agents' initial planning, etc., is available to all agents. That is, they share their belief-desire-intention data within the group. Mainly, this research allows agents to build a decision-making system, which lets agents performing negotiations in order to improve the energy consumption within a community. Thus, each agent of the platform can find potential partners, negotiate and construct its decision-making model, with the primary goal of making an optimal decision related to the energy consumption within the community. The information needed by the agents to build their decision-making model includes databases, as well as negotiation models (such as persuade, threaten, inducements, and promise). Every agent uses a specific format that the other agents know to upload the negotiation models. However, in order to guarantee the privacy of the data, private information is only visible to interrelated agents. These agents cooperate without a central coordinator, in order to achieve the objectives discussed previously; because of that, it is classified at the cooperation level. In the same way, this paper shows how enterprises can offer their services as cloud computing services, and how customers can select the service with the best benefits autonomously. Particularly, this paper is significant for our research because it shows how the MAS paradigm can be used to make autonomous decisions and achieve a specific grade of efficiency cooperatively.

Also, D. Li et al. (2017) focus on developing a MAS that can deal with the complexity of the cooperative processes in smart manufacturing, using a structure consisting of intelligent agents with cloud computing-based feedback and coordination assistance. The negotiation mechanism allows a smart product (instantiated as an agent) to act as manager, while the smart machines and smart conveyor belt (instantiated as agents too) acts as contractors, competing by tasks. In this case, an RFID tag is used for the communication of the agents, by reading/writing it. Smart machine agents or smart conveyor belt agents initiate the negotiation process. The smart product agent publishes a task, and the smart machine agents receive it, deciding whether to bid for the task or not. The product agent uses a rule-based decision system in order to calculate the performance indicators that allow deciding which contractors are awarded or rejected. The contractor (smart machine) that wins the bid will execute the task. After the smart machine agent is selected, it is necessary to start moving the smart product from the current position to the target one, by constructing a conveyor belt route chain. Again, a new negotiation round is required in order to create the route chain from the start point to the target point. This research is focused on the cooperative process to organize smart products and smart devices into a smart factory, by using the MAS paradigm where each agent has individual objectives. This research is classified at the level of cooperation because the process of coordination is not centralized, like was defined in section 2. Besides, this work is relevant for our research because it gives us a vision of how smart objects can drive a cooperative process.

Other works in this domain propose cooperation processes using technologies like MAS (Romero et al. 2017), model-driven engineering (Suri et al. 2017), or human-robot interactions (Nelles et al. 2016).

3.5. Collaboration

In this sub-section, work focused on the study of the explicit collaborative process is presented. That means interactions between system actors in order to achieve a common goal. In that sense, Romero et al. (2017) propose a social factory architecture based on adaptive, collaborative, and intelligent MAS. Moreover, they explore the role of what they name a social operator 4.0 in the context of smart and social factory. Mainly, people, devices, and software systems socialize together (cooperate or collaborate) in real-time, to support manufacturing and services operations. The authors define a *social operator 4.0* as a type of operator that combines smart wearable solutions in conjunction with advanced human-machine interaction (HMI) technologies to promote cooperative/collaborative processes with other social operators, social machines, and social software systems. The MAS is used in order to simplify the communication between the cyber-physical elements, that means, humans, machines (real world), and software entities, as well as to distribute tasks (based on their competencies) and share & trade control in collaborative tasks.

Moreover, the MAS keeps as much as possible human inclusiveness within the manufacturing process, without compromising production goals and efficiency. Finally, the MAS can improve the skills of the human and machines through learning and practice, for what it must record and track their evolution. The social factory MAS is composed of human agents that characterize humans and their skills; artificial agents (machines) that characterize the machines and their capabilities; interface agents that characterize interaction rules and conditions for assisting humans and machines interfacing with the rest of the system. Similarly, Broker agents characterize the levels of automation available in the system and the rules for sharing and trading control in human-machine cooperation, in order to efficiently allocate and distribute tasks between the cyber part and the humans at the workstations of the manufacturing system. This research provides a suitable mechanism for facilitating collaborative tasks in smart factories, due to this reason, it is positioned at the collaboration level. This work is relevant for our research because it shows how a MAS can be an excellent solution to deal with collaboration issues autonomously.

On the other hand, Riel and Flatscher (2017) deal with the creation of a structured methodological approach to strategic production planning (SPP), intending to establish an integrated manufacturing road-mapping process. The essential idea is that the stakeholders involved in an integrated design process shall run a series of stages of divergent and convergent thinking. At each stage of divergence, the ideas about the design process are generated out-of-the-box thinking. Then, in the convergence stage, the ideas are consolidated and evaluated, with the primary goal of deciding how to proceed with every single idea. Typically, multiple parallel paths are created, where each path represents a particular set of ideas being worked. For the particular design problem of the SPP, the authors proposed a schema with three phases (each phase involves divergence and convergence stages). The first phase is in charge of identifying the most relevant topics, based on the use of techniques like brainwriting, extreme scenarios, etc. In the second phase, the participation of the top management representatives is required to prioritize the topics, according to the company strategy. The third phase uses the ranked topic list as input, to deal with the specific challenges linked to each topic. Next, the experts are involved in the process to identify and group each selected topic focusing on what has to be done rather than on when.

Consequently, the goal of the final phase is to define a concrete plan addressing the requirements and problems detected for each challenge. Finally, this paper is a proposal for a strategic method for collaboration among industries. The authors of (Riel and Flatscher 2017) have designed a use case to demonstrate how this proposal fits in Industry 4.0. However, this is a manual process that does not involve any kind of automation. This research is fundamental for our purposes because it shows a method that could be automatized to allow autonomous collaboration processes in Industry 4.0.

Likewise, Richert et al. (2016) make an empirical study of the collaborative problem in human-robot -teams. The method uses virtual reality in order to simulate a task that can only be accomplished through teamwork between robots and humans. The participants are immersed in a virtual scenario developed in Oculus Rift (a virtual reality system). The chief objective of this experiment is to analyze how the appearance of robots affects teamwork outcomes. In that sense, a humanoid robot is used in one experiment and an industrial robot in another. The human forms a team with each robot, and his physical reactions are studied while the team develops a task collaboratively. A set of instructional commands is provided beforehand to the human, in order to allow the communication with the robot.

On the other hand, Oculus Rift collects all the data generated during the study. The authors suggest using big data analytics in order to understand the nature of the collaborative process better; however, they consider that these experiments are only the stepping-stone to much more detailed research. Although the authors of (Richert et al. 2016) say that this research is linked to Industry 4.0, they do not clarify how this method can be used in this context to increase production, reduce costs, among other things. Essentially, our interest in this paper is because they measure the impact of mixing robots and people collaboratively.

The next section presents a discussion regarding the integration challenges in Industry 4.0, as well as a summary of the aspects covered in the solutions presented in the current section at each integration level.

4. Discussion

4.1. Integration challenges in industry 4.0

Industry 4.0 is a concept still in development, so there are many challenges to solve. Figure 5 shows the main current challenges of Industry 4.0 and their relationships with the 5 C levels. It can be seen that the Standardization challenge is presented at all levels. Also, in the last three levels, there are more challenges related to planning, decision making, and negotiation, that are oriented to allow actors to autonomously interoperate in order to coordinate, cooperate, and collaborate during the manufacturing processes. Those challenges are detailed as follows:

- The standardization throughout the 5 C integration levels means that standardized protocols, data & format, etc. are essential to allow a good understanding of the information shared by the actors, to allow autonomous 5 C processes.
- The definition of different integration styles, horizontal (between companies), vertical (intra-company), end-to-end (mixing digital and real-world), etc. (Huber and Weiss 2017; Terán, Aguilar, and Cerrada 2017; Yang, Martino, and Zhang 2017). Mainly, horizontal integration is needed in order to allow collaboration or cooperation among enterprises. Vertical integration is also required to allow coordination, cooperation, and collaboration between actors involved in the production processes, and the End-to-end integration is required to allow people to participate in the production process in a more natural and less invasive way.
- The specification of negotiation and convergence mechanisms must be proposed with the intention of allowing actors to achieve agreements in the execution of their tasks. Particularly, some works are proposing autonomic negotiation mechanisms for the 5 C

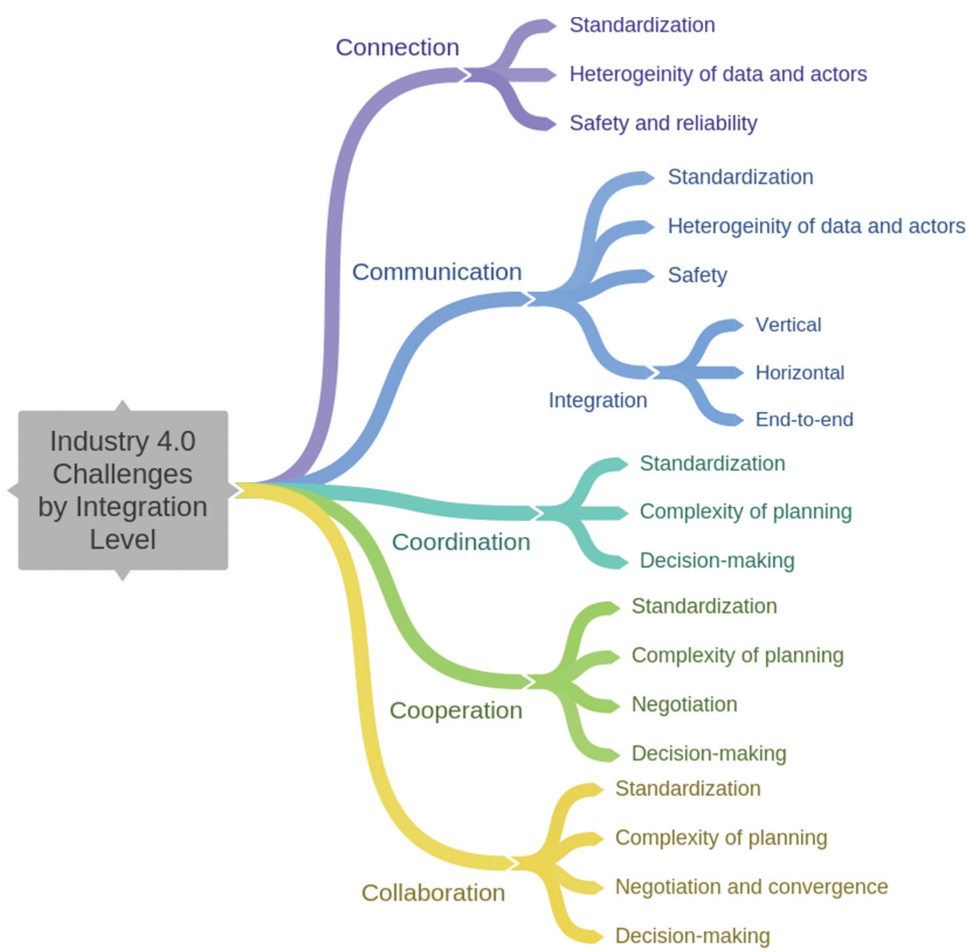

Figure 5. Integration challenges in industry 4.0 by integration level.

highest levels of integration (coordination, cooperation, and collaboration), to autonomously integrate the diverse actors that take place in Industry 4.0, and especially, data, people and services (see Figures 4 and 5).

- The definition of security and privacy of data mechanisms to allow a robust integration of the actors (Molano et al. 2017; Jirkovský, Obitko, and Vladimír 2017; Huber and Weiss 2017). It is essential to provide some mechanism that preserves the security and the privacy of the data in order to avoid an unwanted attacker to gain access to the information of the production process.
- The management of the heterogeneity of data and actors (X. Li et al. 2017a; Molano et al. 2017). Different actors generate a large amount of data, information, and knowledge in different formats that should be semantically integrated in order to allow actors to understand the messages correctly.
- The management of the complexity of the planning, to allow self-configuration of the production process (X. Li et al. 2017a; Huber and Weiss 2017).
- The management of the decision-making process (Molano et al. 2017) to make optimal decisions related to fit the goals of the manufacturing process.

4.2. *Studied researches*

The research works presented in Section III shows some of the main proposals addressing the integration challenges in Industry 4.0. However, there is not a complete solution that covers all the integration aspects through the 5 C levels in a production process (see Figure 4). Figure 3, illustrates that all actors in the production process must be able to connect, communicate, coordinate, cooperate, and collaborate in order to achieve the production goals efficiently. However, Figure 6 shows that the most studied integration level is communication, followed by the connection and cooperation levels, leaving at the last place the collaboration and coordination levels.

At the level of connection, the presented studies try to connect the actors, using technologies like Semantic Web, Big Data, among others, as connection medium. However, as can be seen in Figure 6, more research works are focused mainly on the interconnection of things, and there is not a solution that allows to interconnect all the actors, leaving many challenges still to be addressed, for instance, security, semantic, integration, and heterogeneity. From the case study can be noticed that connecting actors are a significant feature, in order to allow them to communicate; that means, allow people, services and things to have access to the data, allow people to have access to services or to connect to the system using a device, etc.

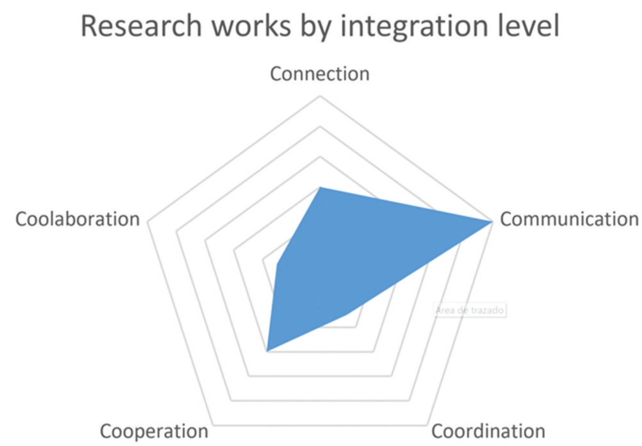

Figure 6. The research works by integration level.

On the other hand, at the *communication level*, research works are focused on allowing interoperation of actors by using a variety of methods, some of them use a service-oriented architecture, while others allow communication using low-level protocols. In the same sense, Figure 4 shows that some works focus on communicating things and people, while others are focused on communicating data and services. Furthermore, it does not exist a complete solution that allows all the actors to communicate correctly. The communication between actors is fundamental to make possible the 5 C highest levels. From the case study, if the actors are not able to communicate, then the production process will be limited because coordination, collaboration or cooperation processes would not be possible in an efficient way, and the actors will not know what, how and when to perform a task.

At the *coordination level*, most of the research works deal with this topic mainly following an implicit approach, and only services and things are explicitly coordinated, leaving much work to perform in this area. However, as illustrated in our case study, smart production asks for automatic discovery and coordination with an emphasis on allowing autonomous coordination of production processes.

On the other hand, the *level of cooperation* has been moderately worked (not as much as the connection and communication levels, see Figure 6) using techniques such as human-machine interfaces or MAS. However, a complete solution covering the cooperation of all the actors does not exist, leaving still much work to do at this level. One example of these works is how to make decisions or plan new activities while everything is cooperating. In that sense, our case study illustrated the importance of offering cooperation between internal or external actors, allowing turning a traditional production process into a smart production process. In such a way, the smart production process can reason in order to discover the raw materials needed to complete the orders.

Similarly, at the *collaboration level*, several works have been presented, but less than in the cooperation, connection, and communication levels (see Figure 6). The proposed solutions mainly include mixing of HMI technologies with MAS, SPP, among others; studies on specific scenarios and possible solutions are proposed, in order to allow collaboration, mainly of things, and in some cases of people. As can be seen from our case study, collaboration is fundamental in the production process, in order to allow actors to achieve the general goals of the manufacturing process. However, enabling autonomous cooperation (by discovering or creating a collaboration plan) is essential in the context of Industry 4.0, to increase the efficiency of the production process.

From Figures 4 and 5, it can be deduced that there is a need for an integration solution involving all actors along all levels of 5 C. In particular, this work thinks that most of the integration issues should focus on the heterogeneity of actors that take place in Industry 4.0, which need to be able to communicate in different ways and to process large and heterogeneous amount of data, information, and knowledge.

In the same way, the autonomous coordination, cooperation, and collaboration processes need to be further studied in the context of the Industry 4.0 concept. In particular, semantic integration between actors to allow sharing a common understanding is required.

In Summary, there is not a complete solution that allows the integration of all actors of Industry 4.0 and enables autonomous mechanisms for coordination, cooperation, and collaboration.

4.3. Integration technologies

Figure 7 shows a summary of the commonly used technologies that allow the integration and interoperability of actors in Industry 4.0.

At the connection level, it can be seen that the technologies used to allow actors to get in touch between them are: Augmented Reality, Industrial Internet of Thing, Semantic Web, and TCP/IP. It means that connection not necessarily indicates a network connection; it implies that actors can contact each other. E.g., Augmented Reality makes it possible to connect people with other actors of a production process; however, it can also allow communication or coordination.

Besides, as it was discussed in the previous subsection, communication was the level most studied by researchers in past years. It explains the variety of technologies used at that level, as shown in Figure 7. Starting from low-level protocols like TCP/IP, medium level protocols like FIPA, until more high-level protocols such as the service-oriented one. Furthermore, technologies as Big Data Warehouse allows communication indirectly, by letting actors getting and sending information through data, that also can be used for future coordination and learning analytical processes.

Accordingly, at the Coordination, Cooperation, and Collaboration levels, it can be noticed that the techniques are more related to AI. This work believes it is due that on those levels, actors need to incorporate negotiation and convergence protocol in order to resolve conflicts in the execution of their task. Moreover, actors must deal with the complexity of planning and decision-making, and AI helps to solve those challenges.

4.4. Case study

To illustrate the results of this research, we will use the case study described by Vachálek et al. (2017). The case study corresponds to a production line manufacturing of pneumatic cylinders. This production line consists of six stations: Distribution, Test, Processing, Handling, Sorting, and Assembling. At the first station, the operator supplies the line (put the components to the system), according to the production plan. An arm takes the components from the tray and put it to the next station. The second station is the test, which checks the size of each component. The process station performs the drilling and control the size of the hole after drilling. At the handling station, a manipulator puts each processed

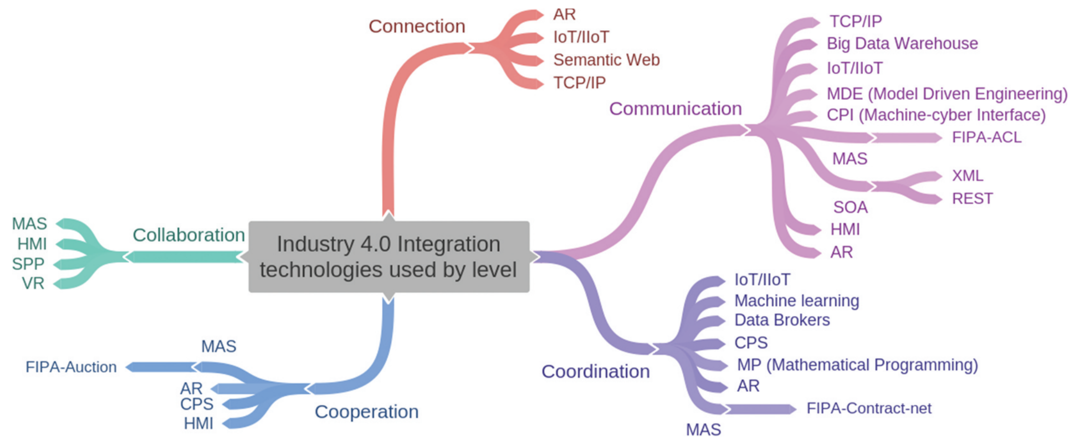

Figure 7. Commonly used integration technologies by level.

component into the sorting section, on which these components are sorted in different conveyor belts, according to the type of piece being produced. Finally, in the Assembling station, an operator combines the components (the piston, the spring, the cylinder body, and the lid), and packed them with the corresponding information. Additionally, a quality control test process is launched, in order to remove erroneous cylinders. This assembly line produces three different kinds of cylinders, one with a metal body and two with a plastic body. They have differences in the size of the drilled holes between the types of pistons.

As can be seen from the previous paragraph, this case study corresponds to a production line that has some kind of automation, but with low autonomy. This case study corresponds to a factory using Industry 3.0 concept. To transform this production line into the Industry 4.0 context, we can proceed as follows:

(1) Firstly, it is needed to transform all the devices, like the drillers, the conveyor belts, the robot arms, the manipulators into smart devices with capabilities of connectivity, communication, and reasoning, among others. The actors in this production process can be represented as cyber components. A Multi-agent system that correctly characterizes each actor and can control the sensors and effectors of the devices might be useful for this purpose.

(2) Secondly, the people involved in the production line will be changed into devices that can accomplish their same functionality, entirety, or by using some kind of HMI. It must reduce risk to people by keeping them away from the production line.

(3) At this point, we found the integration challenge, because it is necessary to put all the actors in the production line to share information and act autonomously, in order to produce each kind of cylinders. This process is as follows:

a. At the connection and communication levels, it is selected standards for connection, communication, and data format, in order to deal with the standardization and heterogeneity challenges. Each actor in the production process must have its cyber component, characterized as an intelligent agent. In this case, the standards FIPA (2005) for connection and communication can be useful, due that they are well defined and widely tested in industry. However, it could pose another challenge: ¿How to integrate agents and cloud computing services? In this case, Sanchez, Aguilar, and Exposito (2018b; (2018a)) have worked around this issue, interconnecting the agents with services deployed in the cloud, in order to extend their capabilities with cloud computing services. Additionally, there are needed some mechanisms to ensure that the data being shared among devices is protected against unauthorized access.

b. The coordination, cooperation, and collaboration levels must be added, depending on the production process characteristics. For the case study previously presented, it needs some coordination mechanisms, in order to allow:

i. The planning of the production strategy (self-planning).
ii. The execution of the plan (self-manage).
iii. The redefinition of the plan in case of failures (self-supervising and self-healing).

c. Mining techniques can be useful to deal with the complexity of planning and decision-making challenges regarding the coordination process described above. Essentially, the Mining techniques will allow creating knowledge-bases needed for smart decisions and planning. For instance, the process mining techniques applied to the current production process will be useful to get insights about how to coordinate the actors in the production of the cylinders around a production plan that defines how and when each actor will execute his tasks. Big data analytic techniques and, more precisely, machine learning algorithms are essential to predict the quality. They will help to check whether or not a cylinder is going to fail the test before it enters the production line. In such a case, the coordination and production plan must be redefined to avoid failure. It will considerably reduce the number of erroneous cylinders (Xu et al. 2017).
d. The negotiation challenge must be solved by using the multi-agent system negotiation protocols (see (Calvaresi et al. 2020)). It will help to solve conflicts during the executions of the cyber component's tasks.

5. Conclusions

Industry 4.0 is a concept still in development that arises from the integration of technologies such as Artificial Intelligence, smart factories, CPS, Cloud computing and IoS, IoT and IoE, Systems Integration, Modern Human-Computer Interactions, and Big Data Analysis, among others. In that sense, Smart Factory is an essential feature because it endows autonomy to the production process, allowing it to self-configuring, self-supervising, self-healing, among others. In a Smart Factory, devices interoperate autonomously intending to achieve manufacturing goals, taking care of efficiency, and resource usage. Besides, CPS is another crucial technology used in Industry 4.0 to bring autonomy to the production process, due that CPS uses a smart control loop that allows adapting and improving the efficiency of the whole system. In this case, a CPS let services and devices to interoperate in order to achieve production goals, as well as to improve the effectiveness and efficiency of the entire industry.

IoT/IoE is used as an integration layer, which not only allows the actors of the production process to communicate and interoperate but also to extend their capabilities by using services deployed through the cloud computing paradigm (as is detailed in the case study). In this sense, devices, people, data, and services can connect and communicate using the standards provided by IoS and cloud computing. That characteristic is essential to promote autonomous processes for coordination, cooperation, and collaboration, in order to drive the interoperability of actors and allow them to achieve, intelligently and efficiently, collective and individual goals.

As can be seen, Industry 4.0 is fully integrated, so, System Integration is a crucial aspect in this context because it allows integrating recent technologies (as is discussed in the case study) and putting them to work together in order to increase the autonomy of the production process. In the same sense, Modern Human-Computer Interactions is very useful in Industry 4.0, because it allows people to be integrated into the manufacturing process transparently. For instance, in the case study, people are separated from the production line, in order to reduce the occupational accident risks. Technologies like wearables, AR, etc. allow people to interoperate with other actors in a more intuitive way, increasing cooperation, collaboration, and coordination of those actors to improve production processes, reducing waiting times, increasing security, and saving costs, which are valuable characteristics in Industry 4.0. Finally, Big Data Analysis is essential in Industry 4.0, because it allows dealing with the heterogeneity of data and actors by pre-processing large volume of data in looking for knowledge, identifying useful patterns, production models, among others.

However, as is shown in the case study, a traditional industry cannot be turned into the Industry 4.0 concept only by integrating all the technologies described above. Industry 4.0 needs to endow autonomy to production processes. That means, not only autonomous interoperability of actors, autonomous decision-making, autonomous negotiation, etc., but also, self-configuring, self-healing, and self-supervising, among other properties that bring autonomy to the production process. In that sense, autonomous coordination, cooperation, and collaboration processes will be useful to let actors organizing, conjointly act, and efficiently drive the production processes.

The future works are oriented to design and implement a framework that addresses the integration and interoperability issues throughout the 5 C stack, in order to allow the production processes to self-configuring, self-manage, self-healing, and self-supervising. Specifically, the authors are going to develop a solution for the coordination of actors related to the case study presented in section 4. Besides, our solution must be easily coupled to references architectures for Industry 4.0 like RAMI 4.0 (Pisching et al. 2018; Platform Industry 4.0 2018) and IIRA (Lin et al. 2015) in order to extend the standardized solution that already exists for Industry 4.0.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Manuel Sanchez http://orcid.org/0000-0002-3310-3394
Ernesto Exposito http://orcid.org/0000-0002-3543-2909
Jose Aguilar http://orcid.org/0000-0003-4194-6882

References

Aazam, M., and E.-N. Huh. 2016. "Fog Computing: The Cloud-IoT\/IoE Middleware Paradigm." *IEEE Potentials* 35 (3): 40–44. doi:10.1109/MPOT.2015.2456213.

Auger, A., E. Exposito, and E. Lochin. 2017. "Survey on Quality of Observation within Sensor Web Systems." *IET Wireless Sensor Systems* 7 (6): 163–177. doi:10.1049/iet-wss.2017.0008.

Bohuslava, J., J. Martin, and H. Igor. 2017. "TCP/IP Protocol Utilisation in Process of Dynamic Control of Robotic Cell According Industry 4.0 Concept." In *2017 IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI)*, 000217–22. Herl'any, Slovakia: IEEE. doi:10.1109/SAMI.2017.7880306.

Büttner, S., H. Mucha, M. Funk, T. Kosch, M. Aehnelt, S. Robert, and R. Carsten. 2017. "The Design Space of Augmented and Virtual Reality Applications for Assistive Environments in Manufacturing: A Visual Approach." In *Proceedings of the 10th International Conference on PErvasive Technologies Related to Assistive Environments*, 433–440. PETRA '17. New York, NY, USA: ACM. doi:10.1145/3056540.3076193.

Calvaresi, D., K. Appoggetti, L. Lustrissimi, M. Marinoni, P. Sernani, A. F. Dragoni, and M. Schumacher. 2020. "Multi-Agent Systems' Negotiation Protocols for Cyber-Physical Systems: Results from a Systematic Literature Review." 224–235. doi:10.5220/0006594802240235.

Chang, V., and G. Wills. 2016. "A Model to Compare Cloud and Non-Cloud Storage of Big Data." *Future Generation Computer Systems* 57 (April): 56–76. doi:10.1016/j.future.2015.10.003.

Chen, K., S.-T. Hsu, J.-S. Jhang, and C.-S. Lin. 2017a. "Internet of Things Security Appliance." United States Patent Application 20170289176 Kind Code: A1, filed March 31, 2016, and issued October 5, 2017. http://www.freepatentsonline.com/y2017/0289176.html

Chen, X., P. Yang, T. Qiu, H. Yin, and J. Jianwei. 2017b. "IoE-MPP: A Mobile Portal Platform for Internet of Everything." *Journal of Intelligent & Fuzzy Systems* 32 (4): 3069–3080. doi:10.3233/JIFS-169250.

Cheung, C. M. K., P.-Y. Chiu, and M. K. O. Lee. 2011. "Online Social Networks: Why Do Students Use Facebook?" *Computers in Human Behavior*, Social and Humanistic Computing for the Knowledge Society, 27 (4): 1337–1343. doi:10.1016/j.chb.2010.07.028.

Deloitte Consulting. 2017. "The Smart Factory." Delloite University Press. https://www.google.co.ve/url?sa=t&rct=j&q=&esrc=s&source=web&cd=3&ved=0ahUKEwjN3eWstv_XAhWKOxQKHfk8AaIQFghHMAI&url=https%3A%2F%2Fdupress.deloitte.com%2Fcontent%2Fdam%2Fdup-us-en%2Farticles%2F4051_The-smart-factory%2FDUP_The-smart-factory.pdf&usg=AOvVaw3XZS9-BuP0iQ9EL7EHPRgw

Drăgan, I., T. Selea, and F. Teodor-Florin. 2017. "Towards the Integration of a HPC Build System in the Cloud Ecosystem." In *Complex, Intelligent, and Software Intensive Systems*, 916–925. Advances in Intelligent Systems and Computing. Cham: Springer. doi:10.1007/978-3-319-61566-0_87.

Elattar, M., V. Wendt, and J. Jasperneite. 2017. "Communications for Cyber-Physical Systems." In *Industrial Internet of Things*, 347–372. Springer Series in Wireless Technology. Cham: Springer. doi:10.1007/978-3-319-42559-7_13.

Exposito, E. 2013. *Advanced Transport Protocols: Designing the Next Generation*. London, UK: John Wiley & Sons.

Exposito, E., and C. Diop. 2014. *Smart SOA Platforms in Cloud Computing Architectures*. Networks And Telecommunications. Hoboken, NJ, USA: Wiley-ISTE. doi:10.1002/9781118761489.

Ferrera, E., A. J. Rosaria Rossini, S. E. Baptista, G. G. Hovest, M. Holgado, E. Lezak, et al. 2017. "Toward Industry 4.0: Efficient and Sustainable Manufacturing Leveraging MAESTRI Total Efficiency Framework." In *Sustainable Design and Manufacturing 2017*, 624–633. Smart Innovation, Systems and Technologies. Cham: Springer. doi:10.1007/978-3-319-57078-5_59.

FIPA. 2005. "FIPA Available Specifications." FIPA Specifications. http://www.fipa.org/specifications/

Gökalp, E., U. Şener, and P. Erhan Eren. 2017. "Development of an Assessment Model for Industry 4.0: Industry 4.0-MM." In *Software Process Improvement and Capability Determination*, 128–142. Communications in Computer and Information Science. Cham: Springer. doi:10.1007/978-3-319-67383-7_10.

Goossens, J., and P. Richard. 2017. *Handbook of Cyber-Physical Systems*. Multiprocessor Real-Time Scheduling. http://hdl.handle.net/2013/ULB-DIPOT:oai:dipot.ulb.ac.be:2013/250127

Grangel-González, I., L. Halilaj, G. Coskun, S. Auer, D. Collarana, and M. Hoffmeister. 2016. "Towards a Semantic Administrative Shell for Industry 4.0 Components." In *2016 IEEE Tenth International Conference on Semantic Computing (ICSC)*, 230–237. doi:10.1109/ICSC.2016.58.

Gupta, H., A. V. Dastjerdi, S. K. Ghosh, and R. Buyya. 2016. "IFogSim: A Toolkit for Modeling and Simulation of Resource Management Techniques in Internet of Things, Edge and Fog Computing Environments." *Software: Practice & Experience* 47 (9): 1275–1296. doi:10.1002/spe.2509.

Hao, Y., and P. Helo. 2017. "The Role of Wearable Devices in Meeting the Needs of Cloud Manufacturing: A Case Study." *Robotics and Computer-integrated Manufacturing*, Special Issue on Ubiquitous Manufacturing (UbiM), 45 (June): 168–179. doi:10.1016/j.rcim.2015.10.001.

Hofmann, E., and R. Marco. 2017. "Industry 4.0 And the Current Status as Well as Future Prospects on Logistics." *Computers in Industry* 89 (Supplement C): 23–34. doi:10.1016/j.compind.2017.04.002.

Huang, Z., Y. Hang, Z. Peng, and Y. Feng. 2017. "Planning Community Energy System in the Industry 4.0 Era: Achievements, Challenges and a Potential Solution." *Renewable and Sustainable Energy Reviews* 78 (Supplement C): 710–721. doi:10.1016/j.rser.2017.04.004.

Huber, A., and A. Weiss. 2017. "Developing Human-Robot Interaction for an Industry 4.0 Robot: How Industry Workers Helped to Improve Remote-HRI to Physical-HRI." In *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, 137–138. HRI '17. New York, NY, USA: ACM. doi:10.1145/3029798.3038346.

Ivanov, D., B. Sokolov, and M. Ivanova. 2016. "Schedule Coordination in Cyber-Physical Supply Networks Industry 4.0." *IFAC-PapersOnLine*, 8th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2016, 49 (12): 839–844. doi:10.1016/j.ifacol.2016.07.879.

Jazdi, N. 2014. "Cyber Physical Systems in the Context of Industry 4.0." In *2014 IEEE International Conference on Automation, Quality and Testing, Robotics*, 1–4. doi:10.1109/AQTR.2014.6857843.

Jirkovský, V., M. Obitko, and M. Vladimír. 2017. "Understanding Data Heterogeneity in the Context of Cyber-Physical Systems Integration." *IEEE Transactions on Industrial Informatics* 13 (2): 660–667. doi:10.1109/TII.2016.2596101.

Kang, N., C. Zhao, L. Jingshan, and J. A. Horst. 2016. "A Hierarchical Structure of Key Performance Indicators for Operation Management and Continuous Improvement in Production Systems." *International Journal of Production Research* 54 (21): 6333–6350. doi:10.1080/00207543.2015.1136082.

Khan, M., W. Xiaotong, X. Xiaolong, and W. Dou. 2017. "Big Data Challenges and Opportunities in the Hype of Industry 4.0." In *2017 IEEE International Conference on Communications (ICC)*, 1–6. doi:10.1109/ICC.2017.7996801.

Kipper, G., and J. Rampolla. 2012. *Augmented Reality: An Emerging Technologies Guide to AR*. 1 ed. Amsterdam; Boston, MA: Syngress.

Lee, D., K.-H. Choi, and H. Kim. 2017. "Editorial: Smart Devices & Smart Spaces in Wireless Internet of Everything (Wireless-ioe)." *Wireless Personal Communications* 94 (2): 145–147. doi:10.1007/s11277-017-4103-9.

Lee, J., B. Bagheri, and H.-A. Kao. 2015. "A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems." *Manufacturing Letters* 3 (Supplement C): 18–23. doi:10.1016/j.mfglet.2014.12.001.

Li, D., H. Tang, S. Wang, and C. Liu. 2017. "A Big Data Enabled Load-Balancing Control for Smart Manufacturing of Industry 4.0." *Cluster Computing* 20 (2): 1855–1864. doi:10.1007/s10586-017-0852-1.

Li, X., L. Di, J. Wan, A. V. Vasilakos, C.-F. Lai, and S. Wang. 2017a. "A Review of Industrial Wireless Networks in the Context of Industry 4.0." *Wireless Networks* 23 (1): 23–41. doi:10.1007/s11276-015-1133-7.

Li, X., L. Di, J. Wan, A. V. Vasilakos, C.-F. Lai, and S. Wang. 2017b. "A Review of Industrial Wireless Networks in the Context of Industry 4.0." *Wireless Networks* 23 (1): 23–41. doi:10.1007/s11276-015-1133-7.

Liao, Y., F. Deschamps, E. D. F. R. Loures, and L. F. P. Ramos. 2017. "Past, Present and Future of Industry 4.0 - a Systematic Literature Review and Research Agenda Proposal." *International Journal of Production Research* 55 (12): 3609–3629. doi:10.1080/00207543.2017.1308576.

Lin, S.-W., B. Miller, J. Durand, R. Joshi, P. Didier, C. Amine, R. Torenbeek, et al. 2015. "Industrial Internet Reference Architecture." Tech. Rep 2017-01–25. Industrial Internet Consortium (IIC). https://www.iiconsortium.org/pdf/SHI-WAN%20LIN_IIRA-v1%208-release-20170125.pdf

Liu, H., H. Ning, M. Qitao, Y. Zheng, L. T. Jing Zeng, R. H. Yang, and M. Jianhua. 2017."A Review of the Smart World." *Future Generation Computer Systems*, September. doi:10.1016/j.future.2017.09.010.

Longo, F., L. Nicoletti, and A. Padovano. 2017. "Smart Operators in Industry 4.0: A Human-Centered Approach to Enhance Operators' Capabilities and Competencies within the New Smart Factory Context." *Computers & Industrial Engineering* 113 (Supplement C): 144–159. doi:10.1016/j.cie.2017.09.016.

Lu, Y. 2017. "Industry 4.0: A Survey on Technologies, Applications and Open Research Issues." *Journal of Industrial Information Integration* 6 (Supplement C): 1–10. doi:10.1016/j.jii.2017.04.005.

Martino, B. D., L. Kuan-Ching, L. T. Yang, and A. Esposito. 2018. "Trends and Strategic Researches in Internet of Everything." In *Internet of Everything*, 1–12. Internet of Things. Singapore: Springer. doi:10.1007/978-981-10-5861-5_1.

McCann, J., and D. Bryson. 2009. *Smart Clothes and Wearable Technology*. New York, NY, USA: Woodhead Publishing Limited and CRC Press LLC.

Mezghani, E., E. Expósito, and K. Drira. 2017a. "A Model-Driven Methodology for the Design of Autonomic and Cognitive

IoT-Based Systems: Application to Healthcare." *IEEE Transactions on Emerging Topics in Computational Intelligence* 1 (3): 224–234. doi:10.1109/TETCI.2017.2699218.

Mezghani, E., E. Expósito, and K. Drira. 2017b. "An Autonomic Cognitive Pattern for Smart IoT-Based System Manageability: Application to Comorbidity Management." https://hal.laas.fr/hal-01651945/document

Mohamudally, N. 2017. *Smartphones from an Applied Research Perspective*. Rijeka, Croatia: InTech.

Molano, J. I. R., J. M. C. Lovelle, C. E. Montenegro, J. J. R. Granados, and R. G. Crespo. 2017. "Metamodel for Integration of Internet of Things, Social Networks, the Cloud and Industry 4.0." *Journal of Ambient Intelligence and Humanized Computing*. February 1–15. doi:10.1007/s12652-017-0469-5.

Nelles, J., S. Kuz, A. Mertens, and C. Schlick. 2016. "Human-Centered Design of Assistance Systems for Production Planning and Control. The Role of the Human in Industry 4.0." In *IEEE International Conference on Industrial Technology (ICIT)*, 2099–2104. Taipei, Taiwan: IEEE. doi:10.1109/ICIT.2016.7475093.

Obitko, M., and J. Václav. 2015. "Big Data Semantics in Industry 4.0." In *Industrial Applications of Holonic and Multi-Agent Systems*, 217–229. Lecture Notes in Computer Science. Cham: Springer. doi:10.1007/978-3-319-22867-9_19.

Orellana, F., and R. Torres. 2019. "From Legacy-Based Factories to Smart Factories Level 2 according to the Industry 4.0." *International Journal of Computer Integrated Manufacturing* 32 (4–5): 441–451. doi:10.1080/0951192X.2019.1609702.

Perera, C., A. Zaslavsky, P. Christen, and D. Georgakopoulos. 2014. "Sensing as a Service Model for Smart Cities Supported by Internet of Things." *Transactions on Emerging Telecommunications Technologies* 25 (1): 81–93. doi:10.1002/ett.2704.

Pierdicca, R., E. Frontoni, R. Pollini, M. Trani, and L. Verdini. 2017. "The Use of Augmented Reality Glasses for the Application in Industry 4.0." In *Augmented Reality, Virtual Reality, and Computer Graphics*, Vol. 10324: 389–401. Lecture Notes in Computer Science. Cham: Springer. doi:10.1007/978-3-319-60922-5_30.

Pisching, M. A., M. A. O. Pessoa, F. Junqueira, D. J. Dos Santos Filho, and P. E. Miyagi. 2018. "An Architecture Based on RAMI 4.0 To Discover Equipment to Process Operations Required by Products." *Computers & Industrial Engineering* 125 (November): 574–591. doi:10.1016/j.cie.2017.12.029.

Platform Industry 4.0. 2018. "Reference Architectural Model Industrie 4.0 (RAMI4.0) - An Introduction." Platform Industry 4.0. https://www.plattform-i40.de/PI40/Redaktion/EN/Downloads/Publikation/rami40-an-introduction.html

Preuveneers, D., and E. Ilie-Zudor. 2017. "The Intelligent Industry of the Future: A Survey on Emerging Trends, Research Challenges and Opportunities in Industry 4.0." *Journal of Ambient Intelligence and Smart Environments* 9 (3): 287–298. doi:10.3233/AIS-170432.

Qiu, M., S. Garg, R. Buyya, Y. Bei, and H. Shiyan. 2017. "Special Issue on Scalable Cyber–Physical Systems." *Journal of Parallel and Distributed Computing*, Special Issue on Scalable Cyber-Physical Systems, 103 (Supplement C): 1–2. doi:10.1016/j.jpdc.2017.01.025.

Richert, A., M. Shehadeh, S. Müller, S. Schröder, and S. Jeschke. 2016. "Robotic Workmates – Hybrid Human-Robot-Teams in the Industry 4.0." In International Conference on e-Learning, 127–31. Kuala Lumpur, Malaysia: Academic Conferences International Limited.

Riel, A., and M. Flatscher. 2017. "A Design Process Approach to Strategic Production Planning for Industry 4.0." In *Systems, Software and Services Process Improvement*, 323–333. Communications in Computer and Information Science. Cham: Springer. doi:10.1007/978-3-319-64218-5_27.

Riggins, F., and T. Keskin. 2017. "Introduction to Internet of Things: Providing Services Using Smart Devices, Wearables, and Quantified Self Minitrack." In *Proceedings of the 50th Hawaii International Conference on System Sciences*. doi:10.24251/HICSS.2017.166.

Román-Ibáñez, V., A. Jimeno-Morenilla, and F. A. Pujol-López. 2018. "Distributed Monitoring of Heterogeneous Robotic Cells. A Proposal for the Footwear Industry 4.0." *International Journal of Computer Integrated Manufacturing* 31 (12): 1205–1219. doi:10.1080/0951192X.2018.1529432.

Romero, D., T. Wuest, J. Stahre, and D. Gorecky. 2017. "Social Factory Architecture: Social Networking Services and Production Scenarios through the Social Internet of Things, Services and People for the Social Operator 4.0." In *Advances in Production Management Systems. The Path to Intelligent, Collaborative and Sustainable Manufacturing*, 265–273. IFIP Advances in Information and Communication Technology. Cham: Springer. doi:10.1007/978-3-319-66923-6_31.

Sanchez, M., J. Aguilar, and E. Exposito. 2018a. "Fog Computing for the Integration of Agents and Web Services in an Autonomic Reflexive Middleware." *Service Oriented Computing and Applications* 1–15. doi:10.1007/s11761-018-0238-0.

Sánchez, M., J. Aguilar, and E. Exposito. 2018b. "Integración SOA-MAS En Ambientes Inteligentes." *DYNA* 85 (206): 268–282. doi:10.15446/dyna.v85n206.68671.

Santos, M. Y., J. O. E Sá, C. Costa, J. Galvão, C. Andrade, B. Martinho, F. V. Lima, and E. Costa. 2017. "A Big Data Analytics Architecture for Industry 4.0." In *Recent Advances in Information Systems and Technologies*, 175–184. Advances in Intelligent Systems and Computing. Cham: Springer. doi:10.1007/978-3-319-56538-5_19.

Schwab, K. 2016. *La cuarta revolución industrial*. Madrid, España: Penguin Random House Grupo Editorial.

Sengupta, S., N. Gupta, and N. Vinayak Advisor. 2017. *Firewall for Internet of Things*. New Dehli: Indraprastha Institute of Information Technology. https://repository.iiitd.edu.in/xmlui/handle/123456789/587

Shaikh, S. F., M. T. Ghoneim, G. T. Sevilla, J. M. Nassar, A. M. Hussain, and M. M. Hussain. 2017. "Freeform Compliant CMOS Electronic Systems for Internet of Everything Applications." *IEEE Transactions on Electron Devices* 64 (5): 1894–1905. doi:10.1109/TED.2016.2642340.

Shila, D. M., W. Shen, Y. Cheng, X. Tian, and X. S. Shen. 2017. "AMCloud: Toward a Secure Autonomic Mobile Ad Hoc

Cloud Computing System." *IEEE Wireless Communications* 24 (2): 74–81. doi:10.1109/MWC.2016.1500119RP.

Soto, J. A., C. F. Tavakolizadeh, and D. Gyulai. 2019. "An Online Machine Learning Framework for Early Detection of Product Failures in an Industry 4.0 Context." *International Journal of Computer Integrated Manufacturing* 32 (4–5): 452–465. doi:10.1080/0951192X.2019.1571238.

Strozzi, F., C. Colicchia, A. Creazza, and N. Carlo. 2017. "Literature Review on the 'Smart Factory' Concept Using Bibliometric Tools." *International Journal of Production Research* 55 (22): 6572–6591. doi:10.1080/00207543.2017.1326643.

Suri, K., A. Cuccuru, J. Cadavid, S. Gérard, W. Gaaloul, and S. Tata. 2017. "Model-Based Development of Modular Complex Systems for Accomplishing System Integration for Industry 4.0." In *5th International Conference on Model-Driven Engineering and Software Development*, 487–495. doi:10.5220/0006210504870495.

Syberfeldt, A., O. Danielsson, and P. Gustavsson. 2017. "Augmented Reality Smart Glasses in the Smart Factory: Product Evaluation Guidelines and Review of Available Products." *IEEE Access* 5: 9118–9130. doi:10.1109/ACCESS.2017.2703952.

Terán, J., J. Aguilar, and M. Cerrada. 2017. "Integration in Industrial Automation Based on Multi-Agent Systems Using Cultural Algorithms for Optimizing the Coordination Mechanisms." *Computers in Industry* 91 (October): 11–23. doi:10.1016/j.compind.2017.05.002.

Vachálek, J., L. Bartalský, O. Rovný, D. Šišmišová, M. Morháč, and L. Milan. 2017. "The Digital Twin of an Industrial Production Line within the Industry 4.0 Concept." In *2017 21st International Conference on Process Control (PC)*, 258–262. doi:10.1109/PC.2017.7976223.

Vaquero, L. M., L. Rodero-Merino, J. Caceres, and M. Lindner. 2008. "A Break in the Clouds: Towards A Cloud Definition." *SIGCOMM Computer Communication Review* 39 (1): 50–55. doi:10.1145/1496091.1496100.

Vizcarrondo, J., J. Aguilar, E. Exposito, and A. Subias. 2012. "ARMISCOM: Autonomic Reflective Middleware for Management Service Composition." In 2012 *Global Information Infrastructure and Networking Symposium (GIIS),* 1–8. Choroni, Venezuela.

Wan, J., S. Tang, Z. Shu, D. Li, S. Wang, M. Imran, and A. V. Vasilakos. 2016. "Software-Defined Industrial Internet of Things in the Context of Industry 4.0." *IEEE Sensors Journal* 16 (20): 7373–7380. doi:10.1109/JSEN.2016.2565621.

Weyer, S., M. Schmitt, M. Ohmer, and D. Gorecky. 2015. "Towards Industry 4.0 - Standardization as the Crucial Challenge for Highly Modular, Multi-Vendor Production Systems." *IFAC (International Federation of Automatic Control)* Hosting by Elsevier Ltd 48 (3): 579–584. doi:10.1016/j.ifacol.2015.06.143.

Xu, Y. A. N., Y. A. N. M. I. N. G. Sun, J. I. A. F. U. Wan, X. I. A. O. L. O. N. G. Liu, and Z. H. I. T. I. N. G. Song. 2017. "Industrial Big Data for Fault Diagnosis: Taxonomy, Review, and Applications." *IEEE Access* 5: 138–146. doi:10.1109/ACCESS.2017.2731945.

Yang, L. T., B. D. Martino, and Q. Zhang. 2017. "Internet of Everything." *Mobile Information Systems* 2017: 1–3. doi:10.1155/2017/8035421.

Zanero, S. 2017. "Cyber-Physical Systems." *Computer* 50 (4): 14–16. doi:10.1109/MC.2017.105.