Ontologies for Industry 4.0

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Abstract

The current fourth industrial revolution, or 'Industry 4.0' (I4.0), is driven by digital data, connectivity, and cyber systems, and it has the potential to create impressive/new business opportunities. With the arrival of Industry 4.0, the scenario of various intelligent systems interacting reliably and securely with each other becomes a reality technical systems need to address. One major aspect of I4.0 is to adopt a coherent approach for the semantic communication in between multiple intelligent agents, which could be human and/or artificial (software or hardware) ones. For this purpose, ontologies can provide the solution by formalizing the smart manufacturing knowledge in an interoperable way. Hence, this paper presents the few existing ontologies for industry 4.0, along with the current state of the standardization effort in the factory 4.0 domain and examples of real-world scenarios for Industry 4.0.

1   Introduction

1.1   What is Industry 4.0?

Industry 4.0 (I4.0) is a term coined to represent the fourth industrial revolution based on the latest technological advances. While it represents an application of the concept of cyber-physical systems (CPS), understood as its core (Lee et al., 2015), it goes far beyond CPS, involving advanced data communication systems (Wollschlaeger et al., 2017), embedded intelligence (Wang et al., 2016), and data semantics standardization (Fiorini et al., 2017).

Industry 4.0, which was initiated at the beginning of this decade by national programs (Haupert et al., 2014) called *Smart Manufacturing* Leadership Coalition[1] in the US and *Industrie 4.0*[2] in Germany, has already proven to be a no-way-back trend that has the potential to take today's Industry to a higher level of efficiency, performance, and productivity and it has started to be used by companies such as ABB and Siemens(Drath and Horch, 2014).

Indeed, Industry 4.0 scenarios can present e.g. physical objects manipulated by means of their virtual representations, which by their turn provide services, that at the end support applications for highly detailed product customization, precise and timely accurate logistics supply chains, and efficient product delivery. Everything related to the production could be represented in the cyberspace, from the smallest and least significant raw material or component up to the complete product and all the machinery involved in its production (Rosen et al., 2015). This setup relies on fast and efficient data transmission, supported by wireless communication technologie, e.g. based on 5G (Rappaport et al., 2013), in which part of the products could decide autonomously their best and most optimized way through the production process, exchanging data with other components and elements of the industrial environment.

Hence, in an Industry 4.0 scenario, the manufacturing process is the main activity and, among several equipments, autonomous robots are extensively used towards manufacturing performance and revenue improvements (Kattepur et al., 2018), (Zhang et al., 2019). This helps to explain why power consumption related to motors represents 2/3 of the electrical power consumed by the industry sector (Saidur, 2010). Combined with currently available techniques of data analysis and cognition, this creates new possibilities of interoperability, modularity, distributed processing and integration in real time with other systems for industrial processes. In fact, those possibilities constitute the core concept of Industry 4.0 (Hermann et al., 2016).

1.2   Technologies for Industry 4.0

Industry 4.0 or smart factory (Kannengiesser and Muller, 2013) is based on new and radically changed processes in manufacturing industry. It represents a number of contemporary automation, data exchange, and manufacturing technologies (Hermann et al., 2016), such as virtual enterprise (Smirnov et al., 2010), cloud manufacturing (Xie et al., 2017), *Internet of Things* (IoT), also named by Cisco as *Internet of Everything* (Zheng et al., 2014), and its emerging concepts *Industrial Internet of Things* (IIoT) (Civerchia et al., 2017), or *Industrial Internet* as used in the US by General Electric (GE) to represent the realization of IoT for Industrial applications.

In particular, data is gathered from suppliers, customers and the plant/factory itself and evaluated before being linked up with real production. The latter is increasingly using new technologies such as smart sensors, 3D printing, next-generation robots, cloud computing, and data analytics. This results in flexible and adaptive production processes that are fine-tuned, adjusted, or set up differently in real-time (Hermann et al., 2014).

Traditional industry relies on a well-defined 5-layer automation architecture. The machine level (field devices such as sensors and actuators) is at the lowest level and sends data via analog signals to logical controllers such as the Programmable Logic Controller (PLC) in the station level. Supervisor Control and Data Acquisition (SCADA) systems in the cell level perform (remote)

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[1]http://smartmanufacturingcoalition.org/
[2]http://www.hightech-strategie.de/de/59.php

control tasks. Manufacturing Execution Systems (MES) in the process control level allow users to perform complex tasks such as production scheduling. Top-level Enterprise resource planning (ERP) or factory operation management level allows the management reporting and shares manufacturing data such as the order status with other systems (Wollschlaeger et al., 2017).

The fourth industrial revolution Industry 4.0 represents a new paradigm shift from the *centralized* to the *decentralized* industry, relying on the cyber-physical-based automation, where sensors send data directly to the cloud and where services such as monitoring, control, and optimization automatically subscribe to the necessary data in real-time. Hence, I4.0 involves flexible production networks that require horizontal integration across the company, while any production-related information exchanged in the network must be vertically forwarded to the corresponding service endpoints of the local production system (Wally et al., 2017). The ultimate goal of this emerging technology is to improve the work conditions and to increase productivity, speed, precision, repeatability, reliability, flexibility and competitiveness. In the coming years these technologies will be seen as a viable alternative to the current manufacturing processes, and will enable mass customization, faster production, better quality, increased productivity, and improved decision making (Da Xu and He, 2014).

It is worth noting that mass customization can allow the production of small lots at reasonable cost due to the ability to rapidly configure machines in order to adapt to the customer-supplied specifications and additive manufacturing (Wang et al., 2016). On the other hand, data-driven supply chains can speed up the manufacturing process by an estimated 120% in terms of time needed to deliver orders and by 70% in time to get products to market (Davies, 2015). Thence, Industry 4.0 technologies aims to improve the product quality and dramatically reduce the costs of scrapping or reworking defective products. Predictive maintenance and self-healing technologies in Industry 4.0 intend to enable plants/factories to keep running in order to guarantee the productivity. Industry 4.0 technologies could allow individuals and companies to share access to products, services, and experiences, enabling 'sharing economy' as a new business model. With access to factory and cross-market data, decision makers can predict, response, and adapt to factory needs and market trends in an accurate and timely manner. Some estimates indicate that smart factory technology will have global market size of 62.98 billion USD by 2019 and 74.80 Billion USD by 2022 (Markets and Markets, 2016).

1.3 Challenges of Industry 4.0

Industry 4.0 is opening the door for a new industrial revolution. In order to understand the contributions and challenges of I4.0, and how it will influence life at different level of development, it is important to keep in mind how revolutionary industrial changes took place and their contribution to the evolution of technology since the first industrial revolution. Britain was the birthplace of the first technological revolution which emerged in late 18th century with the invention of the steam engine and the introduction of new mechanical production facilities. The second industrial revolution encompassed at the end of the 19th century the development of electrical, chemical, and motor-vehicle engineering sectors, while the third industrial revolution came up with developments in the electronic and aerospace sectors, leading to the omnipresence of IT systems and production automation (MacDonald, 2016).

The fourth industrial revolution is initiating the use of Cyber Physical Systems (CPS) (Lee et al., 2015) and is focused on the development of new generation of intelligent and integrated technologies for smart manufacturing (Ivezic and Ljubicic, 2016), seeking to optimize its planning and usage across different industrial domains such as oil and gas industry (Du et al., 2010), (Guo and Wu, 2012), mining (Xue and J.Chang, 2012), energy (Teixeira et al., 2017), steel production (Dobrev et al., 2008), construction (Sorli et al., 2006), aviation (Hoppe et al., 2017), (Lehmann et al., 2018), automotive industry (Phutthisathian et al., 2013), electronic industry (Liu et al., 2005a), chemical industry (Natarajan et al., 2011), process engineering (Wiesner et al., 2010), etc.

In addition, the concept of virtual production is considered to be the key for modelling production aiming for zero defects (MacDonald, 2016).

Hence, the driving force behind the development of I4.0 is the rapidly increasing digitization of the economy and society, in the sectors of agriculture (Jayarathna and Hettige, 2013), production (Meridou et al., 2015), and services, e.g. banking (Atkinson et al., 2006), telecom (Agrawal et al., 2008), tourism (Fang et al., 2016), or insurance (Koetter et al., 2019).

I4.0 aim is to integrate the state of the art of communication technologies such as cloud (Xu, 2012),(Xie et al., 2017), IoT (Wan et al., 2018a), (Cagnin et al., 2018) with the new trends of evolved intelligent industrial technologies, such as new-generation intelligent agents (Kannengiesser and Muller, 2013), Internet of Robotics Things (IoRT) (Ray, 2016), Augmented Reality (AR) and Virtual Realty (VR) (Flatt et al., 2015), (Ivaschenko et al., 2018).

Despite the benefits and advances promised by Industry 4.0, the players in this arena have a wide range of challenges to cope with, from human-robot interaction (HRI) (Jost et al., 2017), (Calzado et al., 2018) to data analysis (Xu and Hua, 2017), (Li and Niggemann, 2018). On the other hand, wireless communication are also an important factor in I4.0. With 5G networks still under development (Nordrum and Clark, 2017), other wireless technologies are being adopted in the meantime, leading to the need for networks coexistence solutions (de Moura Leite et al., 2017). Furthermore, I4.0 requires the understanding of data heterogeneity in the context of cyber-physical systems integration (Jirkovsky et al., 2017), (Matzler and Wollschlaeger, 2017) as well as the interoperability (Salminen and Pillai, 2007), (Nilsson and Sandin, 2018) within the agent-based ecosystem (Kao and Chen, 2010) for unambiguous communication (Zhang et al., 2018), efficient collaboration (Olszewska, 2017) and cooperation (Hildebrandt et al., 2017). Thence, information and data used for smart manufacturing should follow a semantic standard (Macia-Perez et al., 2009) throughout the whole industrial environment.

In particular, ontologies are a powerful solution to capture (Liandong and Qifeng, 2009) and to share the common knowledge (Hoppe et al., 2017) among the distributed partners of the I4.0 technology, leading e.g. to Context-as-a-Service (CaaS) platforms (Hassani et al., 2018). Indeed, ontologies aim to make domain knowledge explicit and remove ambiguities, agree on the same definitions, be designed in a modular way, enable machines to reason, and enable knowledge sharing between machines and humans (Persson and Wallin, 2017) and in between machines (Olszewska and Allison, 2018). Moreover, ontologies for the Industry 4.0 are required to be business focused, promote cooperation with customers and partners (Persson and Wallin, 2017) and, on the other hand, meet ontological, autonomous robotic requirements (Bayat et al., 2016). Furthermore, ontologies need to analyze and reuse domain knowledge by using present ontologies (Persson and Wallin, 2017).

Focusing on those characteristics, this paper approaches the Industry 4.0 theme by an ontological perspective, in which the consistent and standardized data semantics mandatory requirement has to be met. The goal of our work is to contribute towards the effort of unambiguously representing domain knowledge in order to assist I4.0 practitioners in the development of coherent and efficient systems. The contribution proposed in this paper is an ontological perspective of the Industry 4.0 domain, with a highlight on the Autonomous Robotic facet of I4.0.

The rest of the paper is structured as follows. Section 2 presents existing ontologies for the Industry 4.0 domain, along with a literature overview about relevant standardization efforts in the smart manufacturing field, with an emphasis on its Autonomous Robotic aspect. Section 3 describes real-world case studies providing potential applications for the use of I4.0 ontologies, while Section VI concludes the work with reflections and future directions.

2 Industry 4.0 Ontologies

2.1 I4.0 Ontological Frameworks

Ontologies consist in a formal conceptualization of the knowledge representation and provide the definitions of the concepts and relations capturing the knowledge of a domain in an interoperable way (Wang et al., 2010).

The domain of *Industry 4.0* or *Factory 4.0* or *Smart manufacturing* consists of concepts related, on one hand, to business services (Wally et al., 2017), encompassing automatization of the project management (Martin-Montes et al., 2017), organizational management (Izhar and Apduhan, 2017), customer satisfaction management (Kim and Lee, 2013), (Daly et al., 2015), risk management (Atkinson et al., 2006), virtualization of operations (Jiang et al., 2004), (Smirnov et al., 2010), such as billing (Agrawal et al., 2008), ticketing (Vukmirovic et al., 2006), generation of recommendations (Lorenzi et al., 2011), and decision-making aids (Koetter et al., 2019).

On the other hand, production services (Wally et al., 2017) involve abstractions of manufacturing processes (Brodsky et al., 2016), (Tang et al., 2018), such as production management (Yusupova et al.), product compliance (Disi and Zualkernan, 2009), resource reconfiguration (Wan et al., 2018b), decision support (Arena et al., 2017), and intelligent-based automatization of chain processes (Muller et al., 2018), such as assembly (Merdan et al., 2008), (Cecil et al., 2018) and/or diassembly (Koppensteiner et al., 2011), packaging (Wan et al., 2019), shipping (Phutthisathian et al., 2013) as well as system diagnosis (Bunte et al., 2016), product control (Bunte et al., 2016), safety controls (Akbari et al., 2010), and security inspections (Mozzaquatro et al., 2016).

For this purpose, in the last decade, ontologies have been developed for one specific industrial domain such as aviation (Keller, 2016), aeropsace (Kossmann et al., 2009), construction (Liao et al., 2009), steel production (Dobrev et al., 2008), chemical engineering (Vinoth and Sankar, 2016), (Feng et al., 2018), oil industry (Du et al., 2010), (Guo and Wu, 2012), energy (Santos et al., 2018), electronics (Liu et al., 2005a). On the other hand, ontologies have been used for one specific manufacturing process such as packaging (Liu et al., 2005b), process engineering (Wiesner et al., 2010), process compliance (Disi and Zualkernan, 2009), risk management (Atkinson et al., 2006), safety management (Hooi et al., 2012), customer feedback analysis (Kim and Lee, 2013), (Daly et al., 2015), organizational management (Grangel-Gonzalez et al., 2016), (Izhar and Apduhan, 2017), project management (Cheah et al., 2011), product development (Zhang et al., 2017), maintenance (Haupert et al., 2014), resource reconfiguration (Wan et al., 2018b), production scheduling (Kourtis et al., 2019). Other ontologies have been focused on one service, e.g. ticketing (Vukmirovic et al., 2006), or on one manufacturing concept, e.g. information flow (Bildstein and Feng, 2018), information security (Mozzaquatro et al., 2016), data integration (Yusupova et al.).

More recently, two ontological framework tending to cover the wider domain of smart manufacturing have been proposed. On one hand, Cheng et al. (2016) provided a model of the production line using a combination of five ontologies, namely, device ontology (with concepts such as Machine), process ontology (with a taxonomy of the different Operations performed by the technical equipment), parameter ontology (with concepts such as Quality of Service), product ontology (with the product information), and the base ontology (integrated the four other and defining the concept Order). On the other hand, Engel et al. (2018) proposed a three-layer ontology for batch process plants. The first layer, or application layer, contains the operations; the second layer, or domain layer, the architecture, while the third layer, or upper layer, refers to an upper ontological model, describing general system characteristics and relations.

These ontologies have been proven to bring some advances in the field, but they have a limited scope and/or a basic vocabulary. Hence, the effort to standardize the whole domain is a huge enterprise, and some current results of these standardization work are reported in Section 2.2.

2.2 I4.0 Ontological Standards

2.2.1 Ontological Standard Effort

As Industry 4.0 relies heavily on robotic agents which have to evolve and perform the main operations in smart manufacturing environment and which are solicited to communicate with human operators, customers, or with diverse distributed partners, the standardization of knowledge representation is a key element facing I4.0 development and is required to be addressed quickly and efficiently to avoid accumulated difficulty at later stages of development. Hence, the ontological standardization effort for I4.0 builds upon the IEEE 1872-2015 Standard Ontologies for Robotics and Automation (IEE, 2015), which establishes a series of ontologies about the Robotics and Automation (R&A) domain (Fiorini et al., 2017) that can be extended to the Industry 4.0. by incorporating new I4.0-specific ontological concepts, as described in the next paragraphs.

CORA Ontology The Core Ontology for Robotics and Automation (CORA) (Prestes et al., 2013) developed within the IEEE 1872-2015 Standard Ontologies for Robotics and Automation (IEE, 2015) is a core ontology for robotics. A core ontology specifies concepts that are general in a whole domain such as Robotics. In the case of CORA, it defines concepts such as Robot, Robot Group, and Robotic System. Its role is to serve as basis for other more specialized ontologies in R&A, currently developed within IEEE P1872.1 and P1872.2 standardization efforts, and focused on Robot Task Representation and Autonomous Robotics, respectively. Moreover, it determines a set of basic ontological commitments, which should help robot developers and other ontologists to create models about robots (Bayat et al., 2016).

ROA Ontology The Ontology for Autonomous Robotics (ROA) (Olszewska et al., 2017) defines robotic notions identified as fundamental (Ivezic and Ljubicic, 2016) for Autonomous Robotics. Hence, ROA provides the definitions of behavior, function, goal, and task concepts and re-uses ontologies such as the SUMO upper-ontology, the CORA core ontology, and specialized ontologies such as the Spatio-Temporal Visual Ontology (STVO) (Olszewska, 2011).

ORArch Ontology The Ontology for Robotic Architecture (ORArch) specifies notions related to hardware and software, as well as how these can be represented together in mixed architecture descriptions. Moreover, ROA aims to allow one to describe multiple architectural viewpoints on the same robots, combining hardware and software devices.

Figure 1 depicts the main concepts of this ontology. The top concepts are part of the top-level ontology. The ontology divides the reality in endurants, perdurants and abstracts. Endurant and perdurants are entities that are situated in time, while abstract entities are not. Perdurants have temporal parts, such as processes and events, while endurants have no temporal parts, such as physical and social objects. Abstract entities are formal entities, such as logical and mathematical entities.

The main aspect of the ontology is the separation between physical and virtual endurants. Physical endurants are objects of everyday life. Virtual endurants are endurants that emerge from computational devices in operation. Computation devices are any entity that computes a computable function. Examples of virtual endurants are typical entities related to running software, such processes, threads, components, objects and procedures, but also include virtual reality entities.

The ontology also imports the notion of Robot from CORA. We introduced some concepts (and axiomatization) such as Artifact to align its meaning with CORA/SUMO.

The concepts dealing with architecture is shown in Fig. 2. ORArch includes DnS ontology for describing architecture. DnS allows the representation of descriptions without the need for second-order languages. It has two main concepts, namely Description and Situation. A Situation is an entity similar to a collection which aggregates (i.e. is setting for) some entities that should
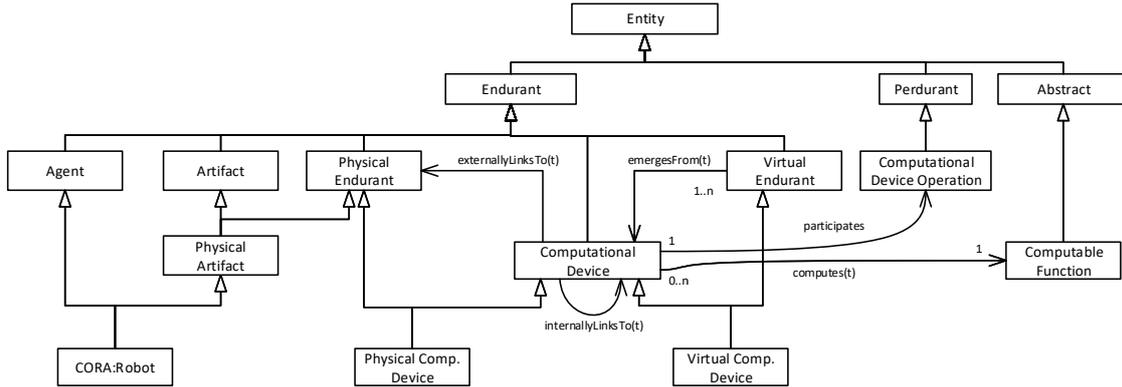
Figure 1: Concepts about hardware and software and ORArch.

be taken into consideration together for a given reason. Examples of situations is the plant or a navigation context for a robot. A situation satisfies one or more descriptions. A descriptions defines concepts and roles that classify elements of a situation. A description of a plant would define the concepts of type-A product and type-B product, which classify instances of products. A descriptions of a robot context defines concepts such as objective and obstacle, which classify object and regions in different situations. It is important to note that instances of Concept are distinct of the concepts that form the ontology itself. Consider the concept Mobile Robot. It might appear in the ontology as a subclass of CORA:Robot and also an instance of RobotType. These both entities are treated as different. In ORArch, we consider that the notion of robot architecture has two sides. It can refer to a selection of components in a given, constructed robot, but it can also refer to an architectural model, or description of an architecture that might be present in different robots. These two notions are captured by the concepts (Robot Architecture) Viewpoint and (Robot Architecture) Description.

O4I4 Ontology   The Ontology for Industry 4.0 (O4I4) is dedicated to capture the I4.0 specific domain concepts, while re-using CORA, ROA, and ORArch ontologies for the robotic facet of smart manufacturing. It is worth noting that CORA used SUMO as the upper ontology. However, in the light of the requirements of the suite of standardization ontologies (Fiorini et al., 2017), it is planned that SUMO becomes optional as a top-level ontology in P1872.2. One reason is that some users of IEEE 1872 (IEE, 2015) voiced their desire to use CORA with other top-level ontologies. On the hand, SUMO is too big and complex for customizable projects. Hence, with O4I4 which aims to be a business-focused ontology, we began defining a minimal top-level ontology to support our development. Such top-level ontology is also optional, but also should be easier to map to other top-level ontologies, if needed.

The new I4-specific concepts appear in Fig 1 and their definition is as follows:

- *Computable Function* is an Abstract entity representing a given computable function with defined inputs and output.
- *Computational Device Operation* is a Perdurant denoting the functioning of a computational device.

Moreover, in the ontological standard, the concept of *Computable Service* is defined as a Computational Device Operation which captures the notion of the process in which an agent has to compute a external request (with a possible input) and to deliver a result (output). It exists from the moment in which the requester starts being served not from the moment in which the agent is requested. However, a Computable Service can only exist if the agent has the capability of performing that service. It is worth noting that a Computable Service is a sort of service from
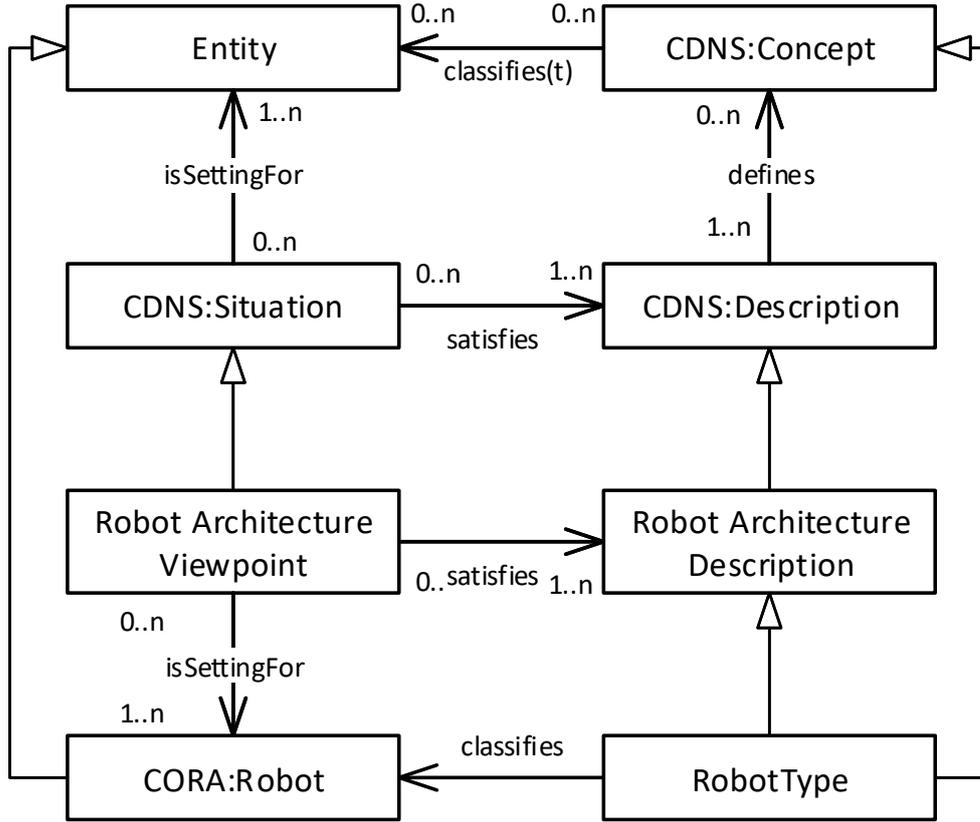
Figure 2: Concepts about robot architecture viewpoint and description in ORArch.

a computational science point of view. Other classes of services could be developed in the future to cover notions related to robotic service, etc.

2.2.2 Ontological Standard Roadmap

To sum up, the standard design using formal models consists of (i) the development of standard vocabularies for robotic concepts; (ii) the development of a functional ontology for Autonomous Robotics; (iii) the validation of relationship using functions as a basis for relationship checking; and (iv) the use of developed vocabularies and ontology for Industry 4.0 applications.

The benefits of such design are twofold. On one hand, academics can discuss concepts unambiguously on the topic which will pave way for further research and investigation on the topic (Bermejo-Alonso et al., 2018). On the other hand, Industry practitioners can use these to conceptualize implementation scenarios (Olszewska et al., 2018). Indeed, as every scenario considered within the framework of the Industry 4.0 includes different entities which communicate and cooperate with each other, the main role of the presented ontological standard is to facilitate that exchange, as exemplified in Section 3.

3 Industry 4.0 Scenarios

3.1 Smart-Rapid Prototyping Scenario

In Industry 4.0, 3D printing/additive manufacturing is a key-technology enabler for smart factories. This technology is also known as rapid prototyping, digital fabrication, solid imaging, solid free form fabrication, layer based manufacturing, laser prototyping and free form fabrication. The process involves building prototypes or working models in a relatively short time to help the
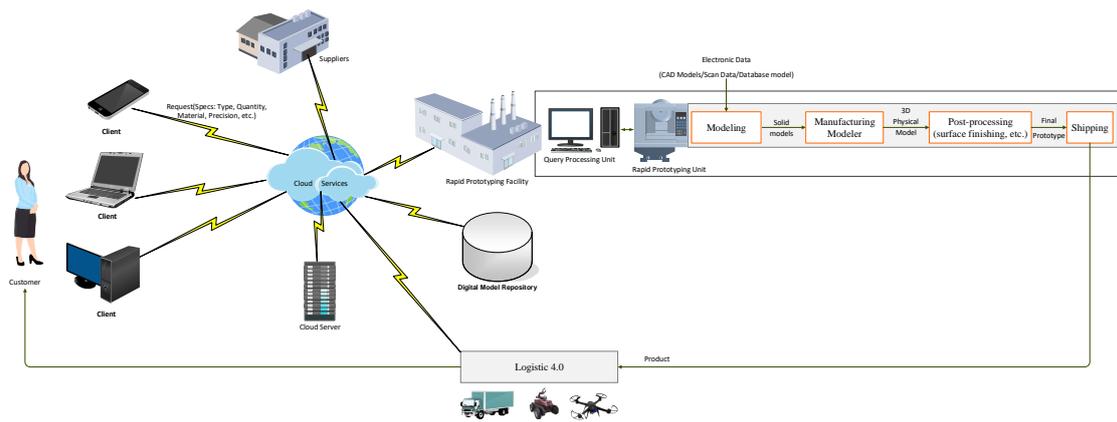
Figure 3: Overivew of the Smart Rapid Prototyping scenario.

creation and the testing of various design features, ideas, concepts, functionality, and in certain instances, the outcome and performance (Bagaria et al., 2011). Nowadays, there is a growing need and expectation of more rapid bespoke production in order to both deliver the rapid prototyping of more products and variants and to support specialist products and obsolete parts globally and locally. Rapid prototyping provides a viable way to quickly and cost effectively deliver components or complete products and decrease the holding and transporting stock (and obsolescence concerns) (Burke et al., 2015).

In a smart rapid prototyping scenario (Fig. 3), a customer with predefined profile accesses a web service to send a query to the manufacturing facility. This query contains the specifications of the part to be manufactured by the smart rapid prototyping facility including the digital model uploaded by the customer or selected from an online digital model repository, as well as the material, the color and the number of units required. The customer's query is then parsed and directed to the rapid prototyping unit that generates or retrieves the solid model to be sent to the manufacturing modeler that create the 3D physical model. Post-processing such as surface finishing is then applied to create the final prototype that is shipped to the customer via logistic 4.0 technologies such as connected trucks, autonomous ground, or aerial vehicles. Moreover, the customer is able to track all the manufacturing steps from the receipt of the request to the delivery of the final prototype.

In this scenario, the exchange of information and resources among those entities becomes crucial to obtain a good performance of the system as a whole, and the ontology approach can facilitate this exchange of information through the use of the defined concepts like Computable Function, Computational Device Operation, and Computable Service. Moreover, the ontology contributes towards the uniformization of the attributes required within the process as well as their unambiguous interpretation by both the machines and the customer.

3.2 UAV's Good Delivery Scenario

Another crucial element of Industry 4.0 is the efficient good delivery. Thence, let's consider a scenario where an operator has to supervise goods' deliveries via unmanned aerial vehicles (UAVs), assigning different UAVs to different delivery tasks. These UAVs have a fault detection system that can detect and inform the operator about degradation in performance. Based on that information, the operator has to infer if that particular drone can be kept in operation or it has to be brought back for maintenance. This kind of reasoning requires considerable amount of expertise, since it has to be precise and relatively quick. This might hinder the adoption of UAVs by non-specialized business, such as pizza delivery, for instance.

An ontological approach can help this human-robot system in many aspects and as a consequence, enable the business to grow. For example, the ROA ontology (Olszewska et al., 2017) (described in Section 2.2) provides formal concepts such as of tasks, functions, and behaviors as well as brings spatio-temporal relations. In this scenario, this can aid, on one hand, the robot to unambiguously communicate the status information about itself to a human operator and, on the other hand, this can aid the operator's decision making. Indeed, through automated reasoning, the robotic system can display more meaningful and simpler information. For instance, consider that the malfunctioning UAV was designed with the function of delivering packages in confined places, such as corridors. As its motors degrade, it starts to display different behaviors, such as small, but sudden changes in its trajectory, which it is able to correct if enough space is available. In a non-intelligent system, the operator alone has to check if displayed behavior is compatible with the designed function of the robot and decide about grounding it or not. Depending on the knowledge or workload of the operator, these can become expansive/dangerous operations. With an ontology representing the robot architecture, the system can also autonomously classify the erratic movements and infer whether they fulfill the designed function of delivering pizza. This system can them inform the user directly of this fact, unloading the operator of having to decode low-level warning signals and decide the best course of action, which improves the operator's general situation awareness.

4   Conclusions

The use of robotic agents in context of Industry 4.0 has triggered, among others, the need to develop an interoperable communication model to interconnect them efficiently as well as an unambiguous, semantic knowledge conceptualization of the smart manufacturing domain to ensure a coherent and effective human-robot collaboration. For this purpose, ontologies have been identified as a possible solution for the representation of the vocabulary describing the key concepts related to this fourth industrial revolution. Thence, this paper presents the current state of ontologies for Industry 4.0, covering both existing ontological frameworks and ontological standardization efforts in that field. Moreover, illustrative I4.0 scenarios have been provided to raise the awareness of practitioners about the potential of using ontologies for Industry 4.0.

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