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Synchronizing physical and digital factory: benefits and technical challenges

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Abstract

The Digital Twin is a representation of characteristics and behavior of a factory according to various levels of detail and the scope it addresses. Its full range of capabilities can be exploited when it is synchronized with the real world. Indeed, in this case, it can be used to mirror the real operating conditions for simulating the real-time behavior, and thus forecasting factory performances. However, we are still far from its large-scale diffusion. The purpose of this work is to analyze both the major challenges that still have to be faced and some potential solutions for each of the identified challenges.

Keywords: Digital twin; Physical twin; Virtual factory; Synchronization

1. Introduction

The idea of realizing the twin of a physical system is not a new concept, since it was already used by NASA over half a century ago during the Apollo program, where "at least two identical space vehicles were built to allow mirroring the conditions of the space vehicle during the mission" [1]. Another artifact exemplifying the concept of hardware twin is the *Iron Bird* [2], i.e., a ground-based engineering tool used in aircraft industries to incorporate, optimize and validate vital aircraft systems. The recent continuous evolution of information and communication technologies (ICT) is paving the way to the opportunity of realizing a Digital Twin (DT) instead of a Physical Twin (PT). Compared to the latter, DT has a lower realization cost since some or all of the complex real components can be virtually reproduced; in addition, the DT can be enhanced with simulation capabilities, thus making the DT more valuable and powerful than the PT. The term DT was brought to the general public for the first time in NASA's integrated technology roadmap [3], where it was defined as "an integrated multi-physics, multiscale simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin". By combining all this information, the DT continuously forecasts the health of the vehicle/system, the remaining useful life and the probability of mission success. In the field of manufacturing, the concept of DT has been used to refer to a "comprehensive physical and functional description of a component, product or system, which includes more or less all information, which could be useful in later lifecycle phases" [4]. In manufacturing, DT has been also seen as a digital avatar encompassing Cyber Physical System (CPS) data and intelligence: structure, semantics and behavior of the associated CPS, providing services to mesh the virtual and physical worlds [5]. In addition, DT can be seen as a complex system in high-dimensional spaces which requires handling large and noisy data, high-precision arithmetic, multi-model and multiscale algorithms [6].

Besides these well-known examples and definitions, the concept of DT is a result of the ongoing *digitization* process, i.e., the "integration of the digital technologies into everyday life by the digitization of everything that can be digitized" [7]. The digitization is making progress in various industrial fields

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besides aerospace, including also manufacturing. Particularly, the industrial Internet of Things, the Cyber-Physical Systems and Big Data technological solutions can be considered enabling technologies for the effective implementation of the DT. The potential of the DT in the field of manufacturing has been recently analyzed in several scientific articles and publications [8] [9] [10], showing how the digital twin can be enhanced thanks to further connections and synchronizations with the real factory. The relevance of the DT in the modern factories is also demonstrated by the inclusion of this topic in the scope of various strategic roadmaps of industrial and scientific research [11]. However, an up-to-date state of the art highlights how far we are from a large-scale diffusion of DT as "current approaches to the implementation of digital twins lack of a conceptual basis, which hinders the applicability of the digital twin vision to various activities in design and production engineering" [9]. Indeed, "there are many challenges that must be overcome in developing the DT. It is difficult to put together a comprehensive DT development plan that covers a decade or more of activities" [6]. In order to contribute to bridge this gap, the main goal of this paper is to investigate the major challenges that a manufacturing company has to face to implement the DT. This analysis is coupled with a review of the most important benefits deriving from the effective and efficient use of a fully-synchronized and faithful DT. In particular, by collecting, analyzing and synthesizing some of the major contributions on the theme of DT synchronization, this paper addresses the following research questions (RQ):

Q1. Which are the benefits and main motivations behind the concrete realization of the DT?
Q2. Which are the challenges to be faced in order to bridge the gaps currently hindering the concrete realization of the DT?
Q3. To what extend the current enabling technologies enable the proper synchronization of the DT?

The outcomes of this investigation will be exploited by a future second stage of our research, which aims at identifying valid solutions to support industrial companies while addressing the challenges mentioned above.

The remainder of this paper is organized as follows. Section 2 introduces a conceptual model for DT. Section 3 analyzes the major benefits deriving from the DT (RQ Q1). Section 4 summarizes the main challenges that need to be addressed to realize the DT (RQ Q2) and the corresponding enabling technologies (RQ Q3). Finally, the Section 5 draws the conclusions and summarizes the main outcomes.

2. Digital Twin conceptual model

The DT represents a new, captivating but still a blurry concept; for this reason, this section proposes a conceptual model, to enhance the understanding of the DT by highlighting its main entities and relations. Figure 1 provides a picture of the proposed model,that puts in evidence the continuous synchronization between the Real Factory and its digital counterpart, i.e., a constant mirroring of the two sides that can lead to the benefits described in the following sections. The synchronization is realized by means of two streams of data. The first one (from left to right) represents the real-time monitored data flow and includes all physical variables sensed at the factory shop floor level by ubiquitous sensors attached to various physical components of the factory (e.g., machines, automation systems, etc.) and transmitted with a high-frequency towards the digital space. Conversely, the second stream (from right to left) involves actions to be performed real-time or near real-time at shop floor level, representing the feedback returned from the digital space to the real factory, e.g., corrective actions and planning decisions that can be the result of the execution of control algorithms. In addition, it is generated a low-frequency wave returning back to factory floor (arrow in blue at the top), which implements all strategic decisions taken from company management and generates long-period benefits with proper return of investments along the whole factory's lifecycle.

The knowledge model underpinning the digital counterpart of the factory (the right part of the figure) is composed of three blocks: the *DT Component Logical Schema*, the *DT Component Instances* and the *Historical persisted Data*. The first one is a formal representation of a component used within the factory, i.e., an abstract characterization of the component with all its parts and logical relations existing between parts. Moreover, it also contains a description of the behavior of the component. Logical schema of different components integrate and contribute to create the schema of the entire factory floor, leveraging the modularity capabilities of the DT [4]. If the *DT Component Logical Schema* represents the intensional aspect of the model of any physical object, process and operation, the *DT Component Instances* block represents its concrete instantiation, i.e., the digital counterpart specific to the tail number of a product or component [4]. The third block of the DT model is the temporal (or historical) extension of the twin, i.e., all product or system historical data accumulated from the early phases of the production until its disposal.

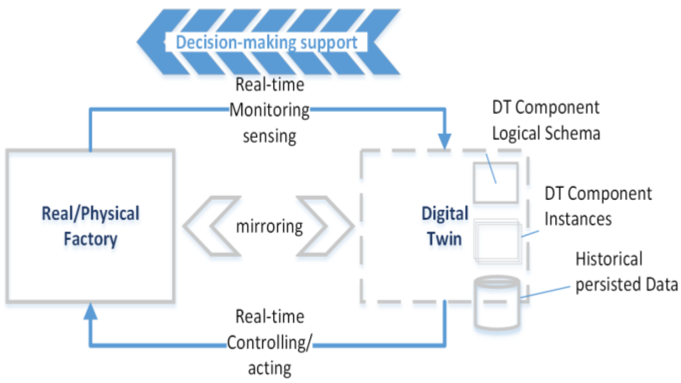

Fig. 1. The DT conceptual model.

3. Benefits deriving from real-virtual synchronization

In the following subsections, a list of benefits deriving from the fully synchronization between the Real Factory and its digital counterpart will be presented.

3.1. Support to the production process along the entire factory and product lifecycle

The advantages of the DT are not limited to a single product or factory lifecycle phase. Indeed, the DT can permeate the whole production process and affect the factory at different level (from single product to connected enterprises) and at different stages. In this regard, a significant example of advantage consists in the support of the *Digital Continuity*, a paradigm that guarantees the availability of information in all product and factory lifecycle stages. By virtue of the Digital Continuity, "information created in each stage of the product lifecycle is seamlessly made available to subsequent stage" [1], thus creating a "mutual promotion process between virtual and physical space of product lifecycle" [12], which "optimizes various activities in the entire product lifecycle, as they can be simulated, monitored, optimized, and verified in the digital space" [12].

Specifically concerning the product design phase, the DT can support the conceptual design, the detailed design, and the virtual verification. In the first stage, a designer can quickly understand how to improve the product characteristics by accessing to an integrated and complete source of information made possible by the DT. Furthermore, in representing a faithful image of the physical product, the DT makes the communication between clients and designers more effective, transparent and faster. The detailed design stage generally requires repeated simulation and tests to ensure that a product prototype can achieve the desired performance. In this case, since the DT can exist during the whole lifecycle of physical objects and coevolve with them, it is possible to cope with the lack of real-time data and data related to the environmental impact, which potentially affect the simulation tests results. Finally, regarding the virtual verification, designers can exploit the DT to create vivid simulation scenarios where the prototypes are tested to accurately predict the actual performance of the physical products as far as possible [12].

Beneficial effects also occur in the pre-production, production and product use and maintenance phase. For example, in the case of aircrafts production, "material state evolution models would be integrated into a single unified structural model that is tightly coupled to a DT. It can evolve as the usage of the vehicle and the age of the structure dictate; therefore, in addition to providing a structural life prediction tool, the DT also facilitates configuration control for an individual aircraft, thus enabling better management of an aircraft throughout its service life". Furthermore, this will allow better maintenance decisions to be made in a timely manner [6]. Benefits of DT go beyond the single factory life cycle since DT is independent of manifestations or specific realizations. For example, the equipment of a production system consists of different production units, which in turn can be seen as products provided by other companies. DTs of these products can be useful for the (virtual) commissioning of the productions system and also for the operation of the production system, e.g., for maintenance planning [4]. In addition, the DT evolves across the real system along the whole life cycle and integrates the currently available knowledge about it.

3.2. Closed loop between real and virtual factory worlds

As depicted in Figure 1, one of the major result of implementing a fully synchronized DT is the realization of a closed loop between the real and digital space. The closed loop is realized through a two-way communication: (1) the information transfer from the physical to the DT by means of the observation and sensing of the physical twin, (2) the information transfer from the digital to the physical twin originating from scientific assumptions, simulation, and virtual testing models [9]. Many are the advantages of closing the loop: feedback from virtual to real are used to apply corrective decision over the real factory (real plant, systems or product) over the whole product's life cycle as discussed in the previous subsection. In addition "DT can close the loop from operation and service back to design of new products or updated revisions" [4].

3.3. Support to Teaching Factory

The first concept of PT, as conceived in the NASA Apollo program, was exploited for training purposes, since it was used during flight preparations and for simulating alternatives. In general, the replication of real production environment in order to reproduce an authentic learning instructional setting for the training of workers is an inherent concept of the Learning Factory, conceived as real industrial site, which allows a direct approach to the product creation process [13]. Learning Factories are based on a didactical concept emphasizing experimental, problem-based and authentic learning [14]. The concept of Learning Factory has evolved into other notions like the Knowledge Factory, the Model Factory and, most importantly, the Teaching Factory, which are used to describe similar kinds of learning systems. The Teaching Factory uses the cutting edge technologies deriving from the visual approach to manufacturing (AR/VR) and e-enhanced learning tools (e.g. Virtual collaboration classroom, Computer-based Training, and so forth) in order to align manufacturing training and teaching to the need of an increasingly complex industrial scenario [15]. Due to the strict synchronization and the closed loop between the real and the digital factory, the DT enhances the collaboration between stakeholders, strongly supporting "the human knowledge toolkit, i.e., conceptualization, comparison and collaboration" [8], and thus contributing to the realization of the teaching factory.

3.4. Understanding data relationship, data consistency and integrity checks

By adopting proper formalisms to model enterprise information at different levels of details, DT can aid in understanding the relationship between a physical factory and its underlying information. Knowledge representation languages, which are based on first-order logics like description logics or ontologies, can be used to automatically infer new knowledge (in terms of axioms) starting from the axiomatized representation of the product, process and production process, also ensuring data and knowledge integration [16][17].

The unique digital model underlying the DT represents the systems, resources, and production processes to be used throughout the factory lifecycle. In addition, it ensures data consistency and integrity and prevents data loss or corruption when different software tools access or modify partial areas of the digital model in different time intervals [18]. Consistency and integrity checks are particularly relevant in regulated industries, such as food and beverage or pharmaceutical, where documentation and proof of processes, events and actions may be required. In these scenarios, it is essential the role of DT that "provides an interface to different models and data in different granularities and keeps them consistent." [4]

3.5. Decentralization of the production

The DT is an enabler of decentralization of production systems control and therefore a key for achieving a new level of flexibility in automation systems. Under these conditions, the DT flatten the automation pyramid, leading to large scale distributed automation solutions [5]. According to [1], DT can contribute to "turn automated systems into *autonomous* systems, which provides the production system with the ability to respond to unexpected events in an intelligent and efficient manner, without the need for re-configuration at the supervisory level". According to [5], the decentralization is guaranteed by a micro-services architecture, i.e., software development techniques where services are fine-grained and the protocols are lightweight [19]. This architecture brings the benefits of *Agility*, *Isolation* and *Resilience*, as machines have the ability of self-recovery after a failure, and *Elasticity*, as a platform can be subject to variable workloads especially on seasonal basis and is able to respond to workload changes provisioning or dismissing computational power [5]. Furthermore, the modularity of the DT, made possible by modular representation languages, as described in the previous subsection, makes the DTs of the product parts directly available to the production units, enabling the latter to orchestrate the part flow autonomously through, for instance, a process of negotiation [1].

3.6. Support to smart products

The advances in microchip, sensor and ICT paved the way for the advent of *smart products*, which track and communicate their operating conditions and thus allow to *feed* their product models with data about their status, such as environmental conditions and loads [9]. The general idea is that a DT approach can support smart products, thus extending the physical product with a kind of shadow of the product in the digital space. Such shadow enables: (1) the study of the effects of various parameters related to the product; (2) the study of the effect of various anomalies to be determined along with fault, degradation and damage mitigation strategies; (3) to perform in-situ forensics in the event of a potentially catastrophic fault or damage.

4. Challenges to exploit the DT in its full potential

On the basis of a literature review, it is possible to identify a list of major challenges that a manufacturing company has to face to effectively implement the DT in its full potential. This list, representing the contribution in response to the RQ Q2 posed in section 1, is presented in the following subsections. In addition, in response to the RQ Q3, a brief analysis of the available enabling technologies is proposed for each challenge (Figure 2).

4.1. Connection with the Real Factory

An updated state of the art of the methods for connecting the Real Factory with its DT in production systems highlights that these methods have not yet been fully standardized and they also often lack of key functionalities [20]. In particular, critical aspects of the connection with the Real Factory that have to be addressed are the data acquisition, validation and transmission. Related technologies to enable the first two stages include "heterogeneous resources real-time perception and access technology, multi-source/modal data fusion and encapsulation technology, multi-source data communication and distribution technology" [12]. Among the data communication technologies, the OPC Unified Architecture is a de-facto standard for the machine to machine communication protocol in industrial automation. Finally, concerning the stage of transmission, ultra-high-speed transmission is an enabling technology [12]

Whenever the acquisition of real measurements are not feasible for technical reasons, this acquisition can be performed with virtual sensors which simulate the data in motion coming from the Real Factory [4].

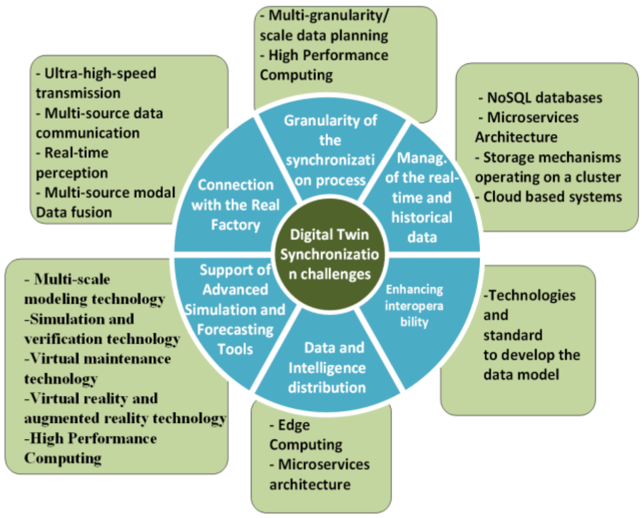

Fig. 2. The DT synchronization challenges and technological solutions.

4.2. Granularity of the synchronization process

DT is underpinned by "a digital model of the environment, which must be as precise and detailed as its real twin in order to execute accurate simulations and evaluations" [21]. If this model becomes indistinguishable from its real counterparts, then it can give a significant contribution to "bridge the gap between design and manufacturing" [9]. However, a detailed synchronization process can entail a significant processing cost, especially if paired with a high sampling frequency. For this reason, it is relevant to face the challenge to find the right compromise between the detail level of the DT and the efficiency of the synchronization process [22]. Enabling technologies related to this challenge include multi-granularity/scale data planning [12] and High Performance Computing. The detail level of the DT can be measured through its fidelity, i.e., the ability that describes the closeness of the DT to the physical world [9]. According to Grieves [23], the fidelity of the DT can be also evaluated through three specific tests: the Visual Test, the Performance test and the Reflectivity test.

4.3. Management of the real-time and historical data

The real-time monitoring of the current system capabilities enables to update the decisions about maintenance strategy, to predict failures, and to implement product lifecycle energy optimization strategies. In order to dynamically assess the performance of a production system, it is essential to connect to the latter (sect. 4.1) and then process its produced data in real-time. In particular, these data have to be managed within a circular process in the two directions (Figure 1): from the real factory to the DT for feeding the Online DT and from the DT to apply actions to the real factory. Under these conditions, the technological system supporting the DT must be endowed with scalable capabilities that enable to harvest real-time data which can be captured, processed and transformed into significant insights in an efficient manner. Another relevant challenge consists in the persistence and accumulation of the acquired data (historical data) for feeding the offline analysis. Referring to the common Big Data characterization of the three Vs, the handling of the real-time data affects mainly the data Velocity Dimension, while the accumulation of the historical affects the data Volume Dimension. The data Volume of the DT continues to increase during the whole factory lifecycle. In addition, in Small Medium Enterprise the database of production data "is extremely heterogeneous, and its quality regularly insufficient for the realization of the DT" [20].

Enabling technologies to cope with this challenge are the mechanisms for managing data leveraging databases and microservices to historicize and display the acquired data, and cutting-edge processing and storage mechanisms operating on cluster system (e.g., NoSQL databases) distributed on cloud. In this regard, cloud based systems have to be taken into account to ensure the horizontal scalability of storage, computation, and communication capabilities, and to decouple storage, data processing, and data management [24]. Finally, it is essential to investigate data security issues with the aim to ensure confidentiality, integrity and availability of sensible data [20] [5].

4.4. Support for Advanced Simulation and Forecasting Tools

DT not only enables to monitor information in real time but also collect and use this information in order to properly simulate the factory performance. In this way, DT offers the capabilities to perform the operations through a simulation environment where the various resources can be tested through different configurations. When a DT based simulation is used on the shop floor close to the modeled production resources, it gives a digital representation that looks and behaves exactly like the resources themselves. This approach can be realized only if the DT is fully supported by the various software tools that enable to model and simulate the complex dynamics of a manufacturing system (e.g., discrete or continuous simulators) where the system can refer to a single cell, a production line, or an entire factory. Another key success factor of this approach is the capability to set up the initial conditions of the simulation models through a true snapshot of the real system (e.g., based on the collected historical data) [25] [26]. The following technologies need to be addressed to support this approach: "multi-scale modeling technology, virtual production operation simulation and verification technology, virtual maintenance technology, virtual reality, and augmented reality technology" [12]. In addition, another major enabling technology that have to be addressed is High Performance Computing, which allows to answer to the demand of higher performance deriving from the advances in mathematical methods and algorithms within complex simulation models.

4.5. Data and Intelligence distribution

Another challenge consists in the study of valid strategies for distributing intelligence and data of the DT close to the various production resources, so that a data deluge from the shop floor toward the DT can be avoided. Indeed, the distribution of the intelligence can contribute to reduce the volume of data sent to the network by the involved resources, thus also reducing the transmission time and increasing the network availability. Such challenge can be tackled with the Edge Computing paradigm [27], which provides the processing and computation close the data sources and for this reason part of the computing power and storage space are moved near the place where data are generated. Another enabler to distribute the intelligence is the microservice based architecture, which can contribute to reduce the stratification and the separation in layers of the classical conception of the automation pyramid.

4.6. Enhancing the interoperability of the production resources

The DT concept requires a homogeneous perspective of the handled information that persists across the different functional boundaries. However, the realization of this perspective is hindered by the lack of interoperability between software systems that support the different aspects of the DT. In this regard, there are three major obstacles that need to be addressed. These obstacles are organizational siloing, knowledge of the physical world, and the number of possible states that systems can take [23]. Moreover, the lack of widely accepted standards and of architectural references to achieve interoperability contributes to worsen an already complex scenario [5][28]. A potential solution is a data model shared among the involved software. The data model should represent both static and dynamic characteristics of the real factory. Enablers for addressing this challenge are the languages, technologies and tools to develop the data model as well as available standards for modeling its contents.

5. Conclusion and future investigations

Starting from a focused literature review, this work has identified many benefits deriving from the realization of a fully-synchronized factory twin and numerous challenges to be addressed in order to make it a viable solution. An examination of the technological panorama to overcome such difficulties has been also provided. The major obstacles derive from the nature of the DT, as it represents a complex system in high-dimensional spaces, thus requiring integrated multi-physics, multi-domain, multiscale modeling technology and ultra-high synchronization and fidelity between the virtual and physical space. Many of the technological solutions addressing all these facets are at the cutting edge of corresponding enabling technologies: Big Data, High-Performance Computing, Cyber Physical Systems, in situ probabilistic simulation, knowledge-based modelling and representation, to cite a few. Thus, advances in many disciplines must to be expected before the DT can be fully realized. Meanwhile, current studies and use cases, although downscaling the problem, represent good examples towards the DT concept and can help to illuminate the path. Future lines of investigations will attempt to measure the maturity grade of a company in adopting and implementing the DT within the factory floor. In this regards, the evaluation tests for virtual systems developed in [23] can be adopted with proper modifications and applied to a specific study case. In addition, a future research will aim at supporting industrial companies in identifying valid solutions to address the challenges mentioned in this study.

References

[1] Rosen R, von Wichert G, Lo G, Bettenhausen KD. About the importance of autonomy and digital twins for the future of Manufacturing. IFAC-PapersOnLine 48.3; 2015; 567-572.

[2] Airbus Industries, Innovation. http://www.airbus.com/innovation/proven-concepts/in-design/iron-bird/. Retrieved 2018-02-22

[3] NASA Technology Roadmap. Modeling, Simulation, Information Technology & Processing Roadmap Technology Area 11, April 2012.

[4] Boschert S, Rosen R. Digital twin—the simulation aspect. Mechatronic Futures 2016; 59-74.

[5] Ciavotta M et al. A Microservice-based Middleware for the Digital Factory. Procedia Manufacturing 2017; 11: 931-938.

[6] Tuegel EJ et al. Reengineering aircraft structural life prediction using a digital twin. International Journal of Aerospace Engineering 2011.

[7] Business Dictionary 2015. Definition Digitalization. http://www.businessdictionary.com/definition/digitalizati on.html. Retrieved 2018-04-24.

[8] Grieves M. Digital twin: Manufacturing excellence through virtual factory replication. White paper; 2014.

[9] Schleich B et al. Shaping the digital twin for design and production engineering. CIRP Annals; 2017; 66.1: 141-144.

[10] Negri E, Fumagalli L, Macchi M. A Review of the Roles of Digital Twin in CPS-based Production Systems. Procedia Manufacturing 2017; 11: 939-948.

[11] EFFRA. Factories 4.0 and Beyond; 2016.

[12] Tao F et al. Digital twin-driven product design, manufacturing and service with big data. The International Journal of Advanced Manufacturing Technology 2018; 94.9-12 : 3563-3576.

[13] Caldarola EG, Modoni GE, Sacco M. Manulearning: A Knowledge-Based System To Enable The Continuous Training Of Workers In The Manufacturing Field. International Conference e-Learning, Madrid, Spain.

[14] Tisch M, Hertle C, Abele E, Metternich J, Tenberg R. Learning factory design: a competency-oriented approach integrating three design levels, International Journal of Computer Integrated Manufacturing; 2015; 29:12, 1355-1375.

[15] Chryssolouris G, Mavrikios D, Rentos L. The Teaching Factory: A Manufacturing Education Paradigm. Procedia CIRP 57; 2016; 44-48.

[16] Caldarola EG, Rinaldi AM. A Multi-strategy Approach for Ontology Reuse Through Matching and Integration Techniques. Quality Software Through Reuse and Integration. Springer, Cham, 2016. 63-90.

[17] Caldarola EG, Rinaldi AM. An approach to ontology integration for ontology reuse. Information Reuse and Integration (IRI), 2016 IEEE 17th International Conference on. IEEE, 2016

[18] Terkaj W, Urgo M. Virtual factory data model to support performance evaluation of production systems. In Proceedings of OSEMA 2012 workshop, 7th international conference on formal ontology in information systems 2012, Graz, Austria (pp. 24-27).

[19] Newman S. Building microservices: designing fine-grained systems. O'Reilly Media, Inc.; 2015.

[20] Uhlemann THJ, Lehmann C, Steinhilper R. The digital twin: Realizing the cyber-physical production system for industry 4.0. Procedia Cirp 61; 2017: 335-340.

[21 Terkaj W, Tolio T, Urgo M. A virtual factory approach for in situ simulation to support production and maintenance planning, CIRP Annals - Manufacturing Technology 2015; 64(1): 451–454.

[22] Modoni GE, Sacco M, Terkaj W. A telemetry-driven approach to simulate data-intensive manufacturing processes. Procedia CIRP 2016, 57, 281-285.

[23] Grieves M, Vickers J. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. Transdisciplinary Perspectives on Complex Systems 2017; 85-113.

[24] Shafto M et al. Modeling, simulation, information technology & processing roadmap. National Aeronautics and Space Administration; 2012.

[25] Kádár B, Lengyel A, Monostori L, Suginishi Y, Pfeiffer A, Nonaka Y. Enhanced control of complex production structures by tight coupling of the digital and the physical worlds. CIRP AnnalsManufacturing Technology 2010; 59.1: 437-440.

[26] Kuts V, Modoni GE, Terkaj W, Tähemaa T, Sacco M, Otto T. Exploiting Factory Telemetry to Support Virtual Reality Simulation in Robotics Cell. International Conference on Augmented Reality, Virtual Reality and Computer Graphics; 2017; p. 212-221. Springer, Cham.

[27] Shi W. et al. Edge computing: Vision and challenges. In: IEEE Internet of Things Journal 2016; 3.5: 637–646.

[28] Modoni GE, Doukas M, Terkaj W, Sacco M, Mourtzis D. Enhancing factory data integration through the development of an ontology: from the reference models reuse to the semantic conversion of the legacy models. International Journal of Computer Integrated Manufacturing 2017, 30(10): 1043-1059.