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Digital twin for smart manufacturing: a review of concepts towards a practical industrial implementation

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ARTICLE

Digital twin for smart manufacturing: a review of concepts towards a practical industrial implementation

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ABSTRACT
Latest trends and developments in digital technologies have enabled a new manufacturing model. Digital systems can monitor, optimize and control processes by creating a virtual copy of the physical world and making decentralized decisions. This paradigm relies on the development of a digital counterpart, the Digital Twin, for each production resource taking part to the whole manufacturing process. Although real applications of Digital Twin may differ in technical and operational details, in the past years, a huge effort has been done in order to identify and define focal functionalities and properties, as well as main challenges for the practical implementation within real factories. This paper is intended to review and analyse principles, ideas and technological solutions of the Digital Twin vision for production processes focusing on the practical industrial implementation. The purpose of this document is therefore to summarize the current state-of-art on Digital Twin concepts, and to draw their up-to-date state for application and deployment in real industrial processes. Finally, future directions for further research are discussed.

1. Introduction

Computer integrated manufacturing, digital information technologies, data analytics and data-driven services, are all examples of solutions that, if properly integrated and combined with the actual production resources, can improve the production process in terms of efficiency productivity and flexibility (Tao and Zhang 2017; Schleich et al. 2017; Rosen et al. 2015). Intelligent production systems are expected to cognitively interpret the surrounding environment, and to autonomously plan and act strategies to achieve the best performance in any condition. In this context, *Cyber-Physical Systems* (CPS) are described as intelligent systems that integrates hardware with computational, communication and control capabilities (Monostori 2018). From a broader perspective, policies known as *'Industry 4.0'* were specifically defined with the aim of accelerating all those disruptive technological and organizational changes that can potentially create a significative gap of performance in the manufacturing ecosystem (Koh, Orzes, and Jia 2019). The Industry 4.0 plan was firstly outlined by the German Government as a strategy for integrating latest advances in technology, as Internet of Things (IoT) and CPS, into production processes. Industry 4.0 vision enables a new manufacturing model, based on the concept of the Smart Manufacturing, where digital systems can monitor and control physical processes, creating a virtual copy of the physical world and making decentralized decisions (Chen et al. 2020). The core of the Smart Manufacturing model is this tight integration between cyber and physical worlds, that permits to achieve greater efficienc and competitiveness for the manufacturing processes (Davis et al. 2012).

From a practical point of view, the biggest challenge is about the definition and implementation of holistic models and architectures able to effectively integrate the Industry 4.0 vision into factories shopfloors. In particular, the main focus is on the technological enablers for the interconnection and cooperation of the different production resources, based on computational intelligence and control logic, which are no more centralized in a single production entry point but distributed all over the network (Rejikumar et al. 2019). The final goal is the achievement of higher product quality, higher product personalization, real 'Just in Time' production,

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process flexibility and reconfigurability, maximum Overall Equipment Effectiveness avoiding downtime and failures.

From this context, the notion of Digital Twin comes straightforward, meaning a digital replica of a physical component, always connected and synchronized with it (Negri, Fumagalli, and Macchi 2017). The described vision reveals the emerging importance of developing a digital complement, i.e. a virtual counterpart, for each production resource taking part to the whole manufacturing process. In fact, the virtual element is the way to achieve the independent management of the associated production resource, fundamental feature to implement the decentralized approach underlying the Industry 4.0 philosophy (Kang et al. 2016). The virtual element can get access to properties, behaviours and rules of the physical entity, using this information to monitor its real counterpart, but also to continuously evolve itself. It could also record historical data and working performances of the physical counterpart, as well as carry out optimization and prediction for it (Barenji et al. 2020).

Thus, Digital Twin concepts have been universally acknowledged as a promising and innovative research field, as well as a strategical approach for improving modern production processes. However, up to now, the term Digital Twin has been used with different meanings and objectives, most of the time declined to the needs of a specific context or a particular application domain. For this reason, several Digital Twin definitions have been proposed in literature, some of them even showing opposing ideas (Kritzinger et al. 2018). Indeed, application aims are vast and integration levels may differ considerably.

Therefore, the purpose of this paper is to analyse the different ideas and concepts introduced in literature so far, with special focus on the different methodologies proposed for the implementation of Digital Twins in production processes. On the path of a research stream that generated a large variety of definitions, perspectives and models for the integration of Digital Twins (as also described by Enders and Hoßbach 2019), this review paper picks up the invitation for a possible next step being the analysis of the frameworks and architectures proposed in literature for correspondences and diversities into real production scenarios. This will permit to develop and acquire a deeper methodology and knowledge on the practical implementation of Digital Twins into manufacturing processes, highlighting industrial frameworks and technologies to achieve effective solutions.

The paper is organized as follows: Section 2 gives an introduction on Digital Twin terminology, definitions, notions, and presents a review of the research works that can be currently found in literature providing an overview of the enabling technologies and key concepts for the practical implementation of a Digital Twin; Section 3 presents an architecture for adoption of Digital Twins into real Smart Manufacturing production processes, derived by the convergence of the models proposed in the literature; finally, Section 4 describes challenges and open points still to be tackled for the effective and prolific adoption of Digital Twins.

2. The notion of digital twin

2.1 The evolution of the manufacturing scenario

Highly competitive markets, mass customization of products, short time to market and performance improvements can be considered the main drivers leading the development and adoption of new production technologies. In the last decades, the paradigm has left the traditional serial path of design and production activities, linked to rigid and static manufacturing systems, to schemes characterized by more feedbacks and iterations, as depicted in Figure 1 (Thilak, Devadasan, and Sivaram 2015).

However, one of the main challenges of modern manufacturing processes is the capability of increasing products variety with small production batches. Current manufacturing processes require production resources able to quickly adapt and react to changes in production environment, providing flexibility, reconfigurability, resistance to disturbances and more efficienc to the overall production process. Phases such as simulation, code generation, commissioning and testing need to be continuously performed 'on the fly', avoiding waste of time which are not compatible with continuously changing products and relative requirements. Thus, thanks to Industry 4.0 technologies, such phases are virtualised and incorporated in the process itself, being a real-time simulation and control counterpart of the physical process itself. Therefore, industry is experimenting a new scenario, depicted in Figure 2, based on

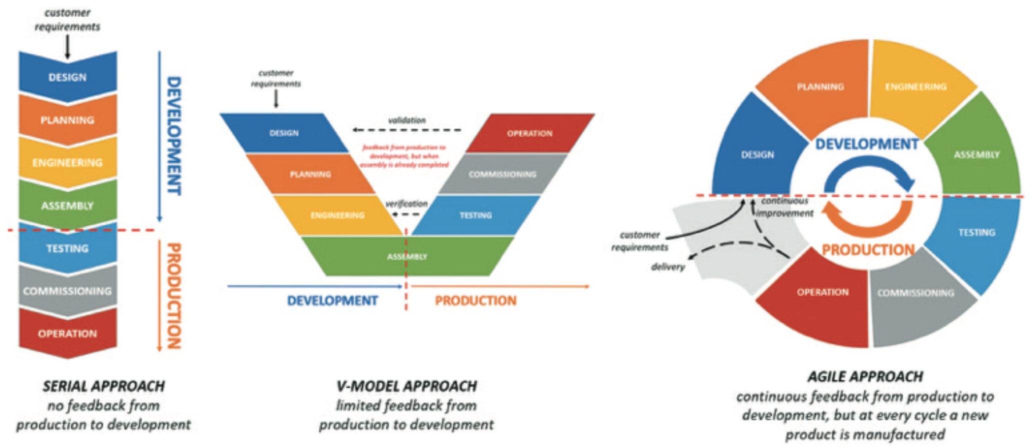

Figure 1. Different production paradigms adopted so far for manufacturing processes.

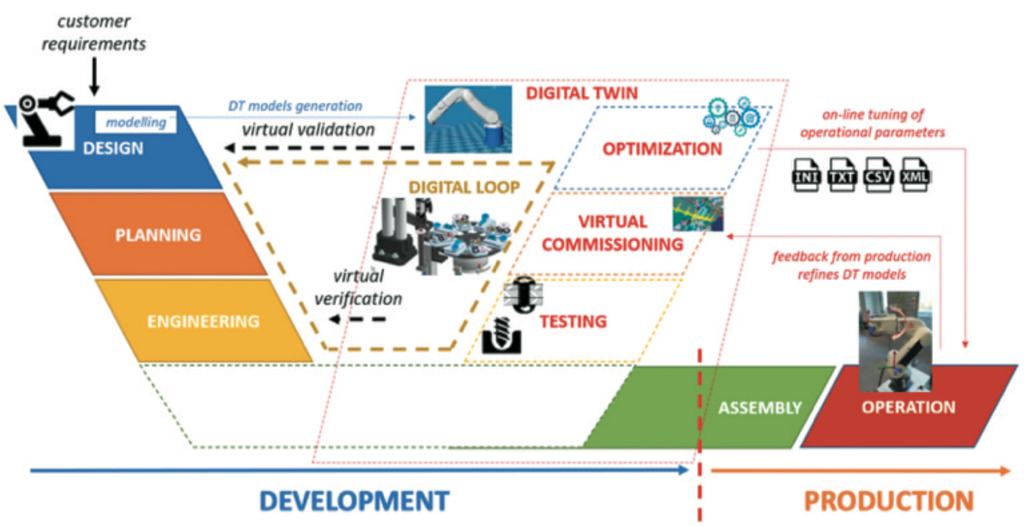

Figure 2. The Smart Manufacturing vision characterized by a tight integration of optimization, commissioning and testing in the development-production loop enabled by the Digital Twin.

feedbacks from a digital manufacturing layer even before production. According to this vision, reactions from production refines Digital Twins' models; optimization algorithms allow on-line reconfiguration; and virtual commissioning reduces delivery time of dedicated manufacturing systems.

2.2 The digital twin concept in the industry

The first well-known definition of Digital Twin was given by NASA in their integrated technology roadmap (Shafto et al. 2010), where it was stated that *'a Digital Twin is 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'*. In fact, NASA's Apollo program was the first case in history about producing a copy of a product. However, the twin ground vehicle remained a hardware copy of the space module, not a digital one.

Similarly, another form of 'hardware' twin is the Iron Bird (Airbus Group 2020), a giant ground-based test rig developed by Airbus Industries in 2015 used to incorporate, optimize and validate vital aircraft systems. It allows testing parts and elements in earlier development cycles, even when some physical components are not yet available and before the aircraft actual first flight. Due to the increasing power of simulation technologies, in the last years more and more physical components have been replaced by virtual models in the Iron Bird. Further extending this idea, the path leads to a complete digital model of the physical system, i.e. the Digital Twin of a complete aircraft.

Beyond these two relevant precursors, the Digital Twin originates as a virtual element acting as a copy of the corresponding hardware resource (Jones et al. 2020), leveraging the advances in computer technologies. Extents and targets for Digital Twin technologies span from virtual replicas of single objects (digital representations of mere geometrical assets of a product or production equipment), to digital entities of virtual production resources and equipment supporting reconfiguration and flexibility (Zhang et al. 2019), to virtual models of the complete production process supporting enterprise resource planning (Zhang, Zhang, and Yan 2019; Jones et al. 2020).

The Digital Twin can be seen as the next wave in simulation technology. The digital models can serve for design evaluation and validation before realizing the physical artefact, adopted by the *'Simulation-based System Design'* paradigm, mainly exploited in R&D and design phases. However, in a more general and complete sense, the term Digital Twin implies a pairing, or a bridge, between an asset in the real physical world and an entity in the digital domain, being the two elements closely tied and integrated in a reciprocally beneficial interaction (Kritzinger et al. 2018). Disturbances and uncertainties in the physical world or inaccuracies in the virtual space can cause differences and inconsistency between the two elements. Depending on the level of intelligence and on the application domain, this information can also be used to eliminate disturbances and uncertainties or to refine and re-calibrate the virtual element in order to get a more accurate and higher-fidelity model.

Digital Twin also provides a platform able to assist operators by means of simulation-driven forecasts, as well as by calculating control and service decisions. In order to achieve this vision, models and parameters must be able to evolve in an automatic way over the lifetime of the product or system, mirroring at each point in time operating and behavioural conditions of the real physical twin (e.g. updating model parameters of the virtual copy to represent wearing due to use). Then, the Digital Twin model is *'a set of virtual information that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level'* (Grieves and Vickers 2017). Ultimately, a Digital Twin can be considered a special virtualization of a physical system, built based on the expert knowledge and real data collected, that allows accurate simulation at different time and space scales, becoming a virtual substitute of its real-world counterpart.

Functionalities and roles can extend to the complete product lifecycle (Ma et al. 2020; Lim et al. 2020), including design, manufacturing (Zhang, Zhang, and Yan 2019), service (Aivaliotis, Georgoulias, and Chryssolouris 2019), maintenance and end-of-life (Wang and Wang 2019; Tao et al. 2019). The large number of works targeting the service and maintenance phase, typically referred as *'Prognostic and Health Management'* (PHM) domain, is also proved by the need of a sector-specific survey of the different definitions, features and viewpoints (Xiaodong et al. 2020). In addition, it can be noticed that so far research mainly considered Digital Twins for products and tools. As stated by Lu et al. (2020), 85% of practical Digital Twin applications developed up to now refer to manufacturing devices, while only 11% to the overall production process and flow

Therefore, the virtual element should not just work in an offlin mode. As explained by Negri, Fumagalli, and Macchi (2017), the offlin twin could simulate the behaviour of the physical product, replicating the characteristics of the device in a very accurate way (Figure 3). However, for more advanced scenarios, relevant in the context of manufacturing systems, such as *Cyber-Physical Production Systems*, the Digital Twin is always available to the system, managing communication to the physical device. In this sense, it acts as a specific and unique 'entry point': other resources on the network directly communicate with the digital counterpart of the production resource, and not with its physical part (Snide and Harriman 2018).

In the Industry, Digital Twin concepts and technologies have gained, over the years, more and more interest, as they could have a significant impact on automation systems, eventually providing value to businesses throughout the whole product manufacturing lifecycle. Digital Twin was cited by Gartner[1] among the Emerging Technologies in 2017 (Figure 4).

In iSCOOP (2020) Gartner predicted that by 2021 half of large industrial companies will gain a 10% improvement in effectiveness thanks to embracing

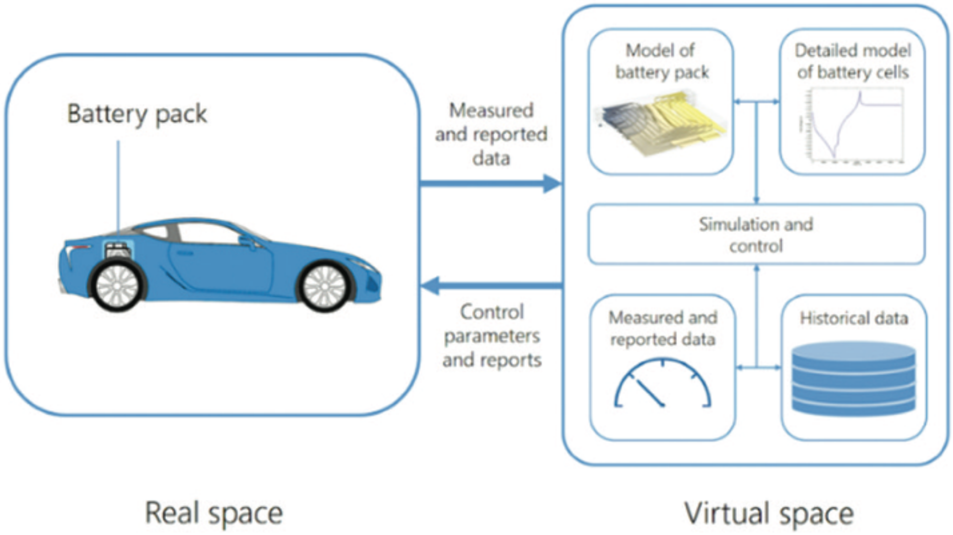

Figure 3. Exchange of data and information by process virtualization (COMSOL 2019).

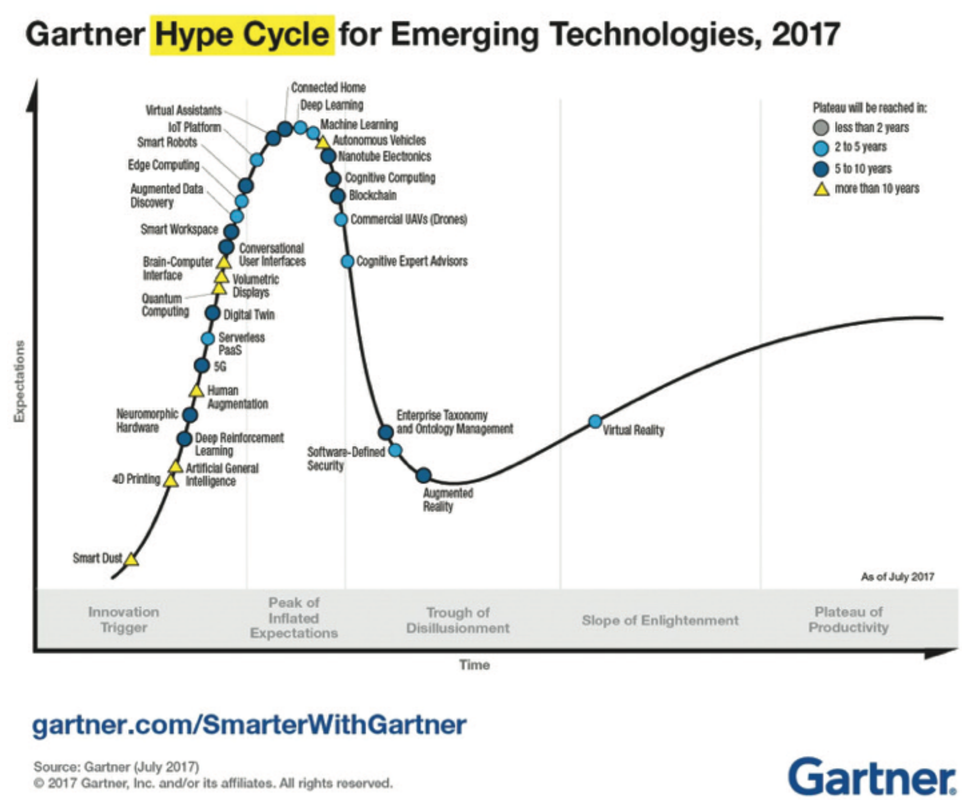

Figure 4. Gartner Hype Cycle 2017 (Gartner 2017).

Digital Twin technologies (the report was produced in 2018). Same importance to Digital Twin technologies is confirmed by more recent reports (Gartner 2019a), where it is stated that *'Hyper-automation (Strategic Technology Trend #1) often results in the creation of a digital twin of the organization'*. The mentioned prediction seems to be confirmed in a survey by Hughes (2018) involving about 300 manufacturing companies. Results showed that about 40% of companies had already integrated Digital Twin technologies in their process or at least in a pilot use-case (Figure 5). Considering the active integration in the Digital Twin technologies of Product Lifecycle Management (PLM) or Industrial IoT platforms, the

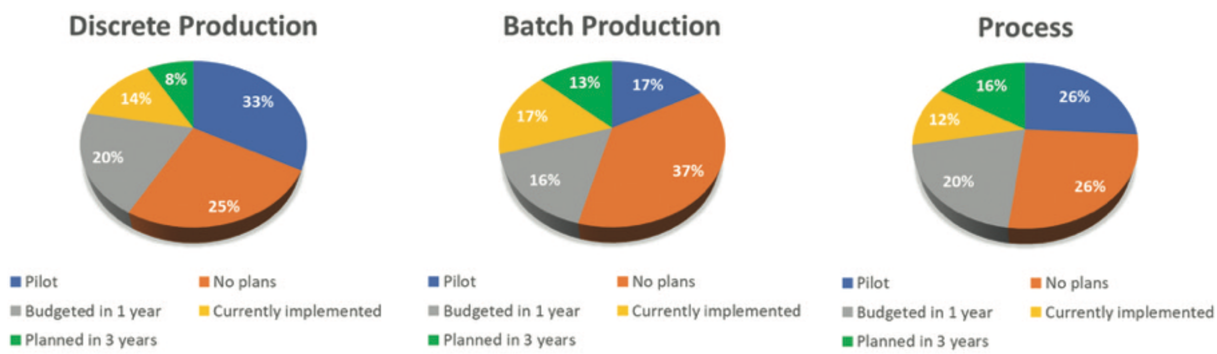

Figure 5. Digital Twin initiatives in industry (Source: Hughes 2018).

number of adopter grows to about 60%. Also Gartner (2019b) agrees on this, stating that *'24% of organizations that either have Internet of Things (IoT) solutions in production or IoT projects in progress already use digital twins; another 42% plan to use twins within the next three years'*.

2.3 Structures and behaviours

The evolution of concepts and definitions around the Digital Twin vision permits to focus on its basic and fundamental elements. Basically, a Digital Twin model is composed by the following three parts (Grieves 2014):

- a physical product in the real world;
- a virtual product in the digital space;
- data connection mapping the two spaces together.

The physical part is therefore connected to a high-fidelity virtual companion during its whole lifecycle. This requires the capability to integrate and combine data from multiple sources, e.g. sensor data, model data and domain knowledge, to generate more accurate and comprehensive information. Different models can be developed in the digital space and associated to the physical resource, depending on the desired objective (Wright and Davidson 2020). In particular, a distinction can be made between a model with the purpose of a realistic simulation of the associated physical asset and a model targeting an effective and functional coupling with the physical world.

Considering current literature on Digital Twin concepts, a major distinction can be made among the terms *'Digital Model'*, *'Digital Shadow'* and *'Digital Twin'* depending on the degree of integration between the physical resource and its virtual copy (Kritzinger et al. 2018). Nature and frequency of data flow and information exchange between the two entities are the fundamental criteria for this classific -tion (Figure 6). In particular:

- a *'Digital Model'* only permits to exchange data manually, and no online status update and synchronization is possible between the two objects. This is the typical concept associated with the design phase;
- in a *'Digital Shadow'* the automated data flow only happens in one direction, specifically from the physical entity to the virtual one, so no feedback is given to the real system from its virtual counterpart. This model is adopted at most in service and maintenance phase, to track and predict the behaviour of a product in its usage phase;
- the *'Digital Twin'* is characterized by a full, automated, bi-directional data flow between the physical and digital worlds. This vision is the most suitable to manufacturing applications, as product quality prediction, production planning or human-robot collaboration.

Therefore, the distinctions are not only limited on integration level but also on the overall objective. In the first two cases, as in a simulation aiming at capturing in the best possible way the physical behaviour, the model permits to understand and replicate at different detail levels the performance of the product from the operational status point of view. For example, it can describe the temperature trend, or the speed profile of a fluid at each instant of time. In this case, the final objective of the Digital Twin is to verify and prove the effectiveness of the design, or to optimize the working performance, for example, adjusting the value of some parameters. Therefore,

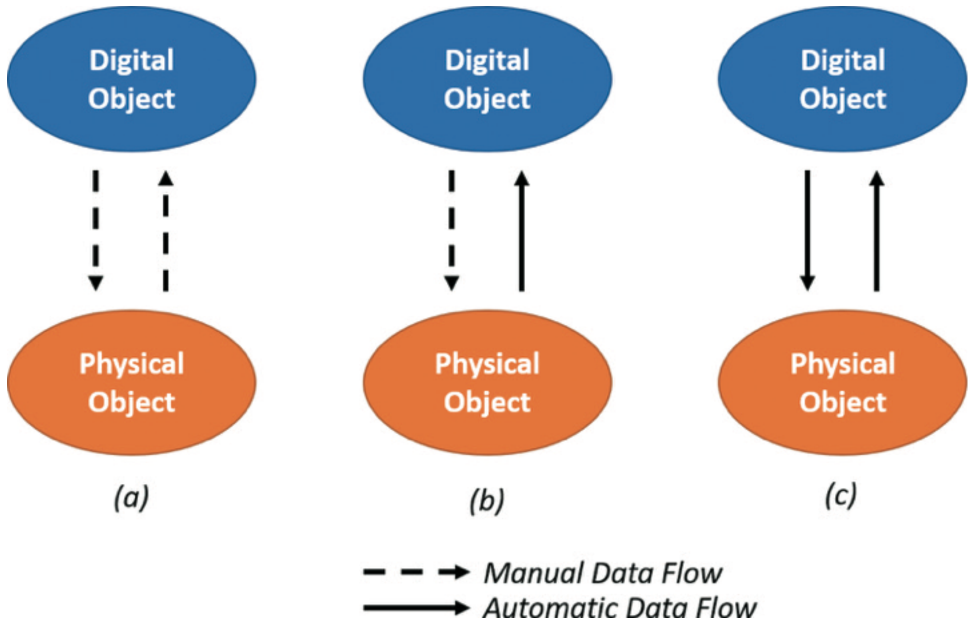

Figure 6. Data and information flow for Digital Model (a), Digital Shadow (b) and Digital Twin (c) systems (Source: Kritzinger et al. 2018).

the computational time is not significant because the ultimate purpose is the accuracy and completeness of the simulation. As an example, an emerging trend in the area of *'Digital Model'* or *'Digital Shadow'*, is represented by systems for the programming and commissioning of robotic cells (Burghardt et al. 2020; Kousi et al. 2019; Pellicciari, Vergnano, and Berselli 2014; Pérez et al. 2020). The programming phase can be performed in an off-line mode, and the generated program can be transferred to the real system at a later time (Gadaleta, Pellicciari, and Berselli 2019). Same approach is valid for the design of production cells, where accurate simulations can drive layout definition and support design choices (Bevilacqua et al. 2020; Caputo et al. 2019; Gadaleta, Berselli, and Pellicciari 2017; Peruzzini et al. 2017).

On the other hand, a *'Digital Twin'* of the third type aims at primarily describing how the associated physical product behaves when integrated with other elements. The model contains information about the interaction towards other systems, how the physical resource affects the behaviour of the entities it relates to, and how its own behaviour is affected by the environment around it. According to the Digital Twin vision, the physical product or process is connected to an ideally high-fidelity virtual companion, able to fully replicate its behaviours and characteristics. Therefore, the computational speed becomes a fundamental factor, as the virtual element not only has to model the internal state of the physical resource but also its 'dynamic' behaviour, e.g. the 'reaction time' when a particular event occurs. In this case, the main target is the realization of a virtual element that can fully replace the physical product, behaving according to the same identical patterns when interacting with any other resource in the physical world (Zheng et al. 2020). If needed, simplifications and approximations are adopted when defining the internal model in order to improve the computational time, as long as these simplifications do not affect the digital representation of the interactive behaviour of the physical object.

Finally, as reported by Talkhestani et al. (2019), an additional level is required, enriched with Artificial Intelligence, giving to the system autonomy, adaptability and self-awareness capabilities. The Digital Twin becomes what the authors call *'Intelligent Digital Twin'*, a system exposing advanced elements, bidirectional communication and control between the two domains, interfaces and services like data analytics and semantic models' descriptions (Figure 7).

2.4 Digital twin for manufacturing in the literature

Literature has provided definitions and visions on the Digital Twin, as emerges from several papers on the topic The queried databases include Scopus, Emarald Insight, Science Direct, and IEEE Xplore. Works were collected by searching for the following keywords: *'Digital Twin', 'Industry 4.0', 'Smart Manufacturing'*. Only the period between 2010 and 2020 was considered, since the term *'Digital Twin'* was coined in 2010 in the aforementioned draft strategic roadmap of NASA. The keywords were identified based on a preliminary review of works and researches considered as reference sources in the considered domain. A first check on the pertinence of the papers to the reference keywords was performed by reading titles and abstracts. This permitted to downsize the analysis to a selection of 115 documents.

Table 1 summarizes the most important Digital Twin definitions that have been found in literature, together with the lifecycle phase and application level they mainly refer to. As can be noticed from the table, first notions of Digital Twin already appeared in 2010, but the most abundant contributions can be found starting from the year 2016. The interest on the subject can be considered world-wide, as researchers from countries all over the world addressed the Digital Twin topic.

Several works addressed the task of presenting a thorough categorical review on the available literature about Digital Twin (Kritzinger et al. 2018; Enders and Hoßbach 2019; Jones et al. 2020; Melesse, Di Pasquale, and Riemma 2020). The high number of existing review works attests the increasing interest of the research community towards the topic, but on the other hand, clearly shows the differences and discrepancies about concepts and application domains. Kritzinger et al. (2018) categorized papers based on their scope, considering four main paper typologies: *'concept', 'case-study', 'review', 'definition'*. Results clearly demonstrated that Digital Twin technologies and applications were still at their early stage, as contemporary publications (year 2018) mainly focused on conceptual ideas with very limited practical case-studies and industrial applications. As Figure 8 shows, up to 2019 literature work mainly

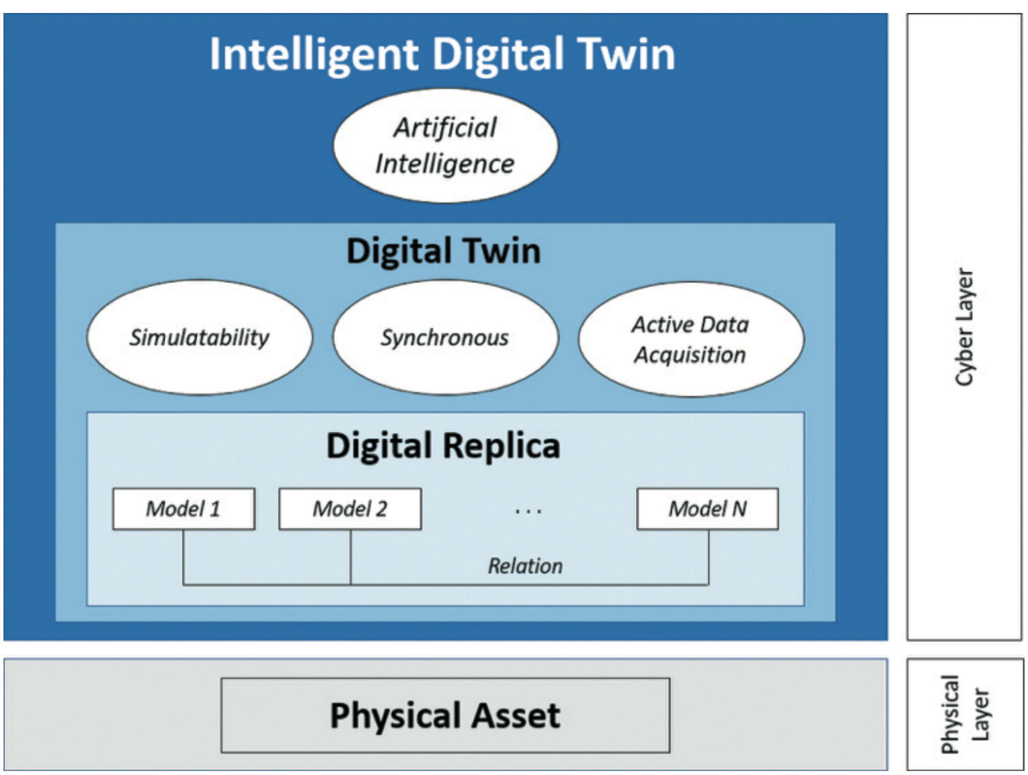

Figure 7. Schematic architecture for the 'Intelligent Digital Twin' (Talkhestani et al. 2019).

Table 1. Definition and application object of digital twin (Source: Enders and Hoßbach 2019; Rejikumar et al. 2019).

Year	Author(s)	Country of the research	Definition	Addressed Phase	Application Level
2010	Shafto et al.	USA	An integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin (Shafto et al. 2010)	Utilization phase	Product
2012	Gockel et al.	USA	A cradle-to-grave, ultra-realistic model of an aircraft structure's ability to meet mission requirements, which is explicitly tied to the materials and manufacturing specifications, controls, and process used to build and maintain the aircraft (Gockel et al. 2012)	Design and utilization phase	Product
2014	Grieves	USA	The Digital Twin concept model contains three main parts: a) physical products in Real Space, b) virtual products in Virtual Space, and c) the connections of data and information that ties the virtual and real products together (Grieves 2014)	Lifecycle	Product
2015	Rosen et al.	Germany	Very realistic models of the current state of the process and their own behaviour in interaction with their environment in the real world (Rosen et al. 2015)	Production phase	Process
2016	Bielefeldt et al.	USA	Ultra-realistic multi-physical computational models associated with each unique aircraft and combined with known flight histories (Bielefeldt, Hochhalter, and Hartl 2015)	Utilization phase	Product
2016	Boschert and Rosen	Germany	The vision of the Digital Twin itself refers 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 all – the current and subsequent – lifecycle phases (Boschert and Rosen 2016)	Lifecycle	Product, Process, System
2016	Schluse and Rossmann	Germany	Virtual substitutes of real world objects consisting of virtual representations and communication capabilities making up smart objects acting as intelligent nodes inside the internet of things and services (Schluse and Rossmann 2016)	Design phase	Product
2016	Schroeder et al.	Brazil	Virtual representation of a real product in the context of Cyber-Physical Systems, which can monitor and control the physical entity, while the physical entity can send data to update its virtual model (Schroeder et al. 2016)	Lifecycle	Product
2016	Kraft	USA	An integrated multi-physics, multi-scale, probabilistic simulation of an as-built system, enabled by Digital Thread, that uses the best available models, sensor information, and input data to mirror and predict activities and performance over the life of its corresponding physical twin (Kraft 2016)	Lifecycle	Process
2016	Bajaj et al.	USA	A unified system model that can coordinate architecture, mechanical, electrical, software, verification, and other discipline specific models across the system lifecycle, federating models in multiple vendor tools and configuration-controlled repositories (Bajaj, Cole, and Zwemer 2016)	Lifecycle	Process
2017	Negri et al.	Italy	The Digital Twin consists of a virtual representation of a production system that is able to run on different simulation disciplines that is characterized by the synchronization between the virtual and real system, thanks to sensed data and connected smart devices, mathematical models and real time data elaboration (Negri, Fumagalli, and Macchi 2017)	Lifecycle	System
2017	Grieves and Vickers	USA	The Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin (Grieves and Vickers 2017)	Lifecycle	Product
2018	Kritzinger et al.	Austria	Based on the given definitions of a Digital Twin in any context, one might identify a common understanding of Digital Twins, as digital counterparts of physical objects (Kritzinger et al. 2018)	Utilization phase	Product
2018	Demkovich et al.	Russia	A Digital Twin of a production system is a multi-level digital layout that describes the product, processes and resources in the environment of their functioning, i.e. allowing to simulate the processes taking place in the real system, as well as collecting and displaying in real time data on the status of objects obtained from the PLC and sensors installed in the production system both on industrial equipment and in its environment (Demkovich, Yablochnikov, and Abaev 2018)	Production phase	System
2018	Autiosalo	Finland	Digital Twin is the cyber part of a Cyber-Physical System (Autiosalo 2018)	Utilization phase	Product
2018	Tao et al.	China	A complete Digital Twin should include five parts: physical part, virtual part, connection, data, and service (Tao et al. 2018)	Lifecycle	Product
2019	Zheng et al.	Singapore	In a broad sense, the Digital Twin is an integrated system that can simulate, monitor, calculate, regulate, and control the system status and process (Zheng, Yang, and Cheng 2019)	Utilization phase	System
2019	Ding et al.	China	As the key technology of Cyber-Physical Systems, Digital Twin provides a clear and feasible way to realise the functions of Cyber Physical Systems. [. . .] It builds a virtual twin of a physical entity (or system) to transparentise the geometrical/physical/behavioural status of the physical entity (or system) and provide the real-time simulation optimisation and control of the corresponding performance of the physical entity (or system) (Ding et al. 2019)	Production phase	Product, System
2020	Alexopoulos et al.	Greece	. . . the DT that represents the virtual model of the physical system or process, it is linked with CPS entity through data communication channel and it is capable of replicating aspects of the behaviour of the CPS system (Alexopoulos, Nikolakis, and Chryssolouris 2020)	Production phase	System

(*Continued*)

Table 1. (Continued).

Year	Author(s)	Country of the research	Definition	Addressed Phase	Application Level
2020	Jones et al.	United Kingdom	A complete virtual description of a physical product that is accurate to both micro and macro level (Jones et al. 2020)	Lifecycle	Product
2020	Melesse et al.	Italy	DT is a living model of the system or physical asset that can continually adapt to operational changes based on the collected online data and information, to forecast the future of the corresponding physical twin (Melesse, Di Pasquale, and Riemma 2020)	Lifecycle	System
2020	Lu et al.	New Zealand	Digital Twin has evolved into a broader concept that refers to a virtual representation of manufacturing elements such as personnel, products, assets and process definitions, a living model that continuously updates and changes as the physical counterpart changes to represent status, working conditions, product geometries and resource states in a synchronous manner (Lu et al. 2020)	Lifecycle	Product, Process

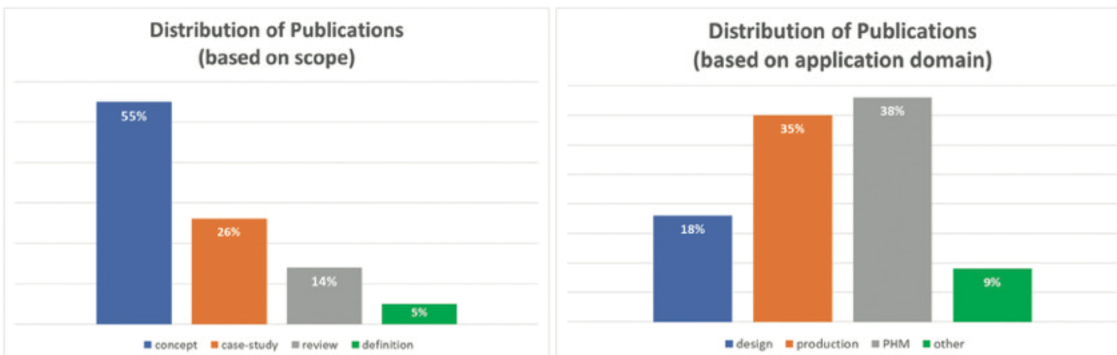

Figure 8. Distribution of DT publications based on scope (left, Enders and Hoßbach 2019) and targeted phase (right, Tao et al. 2019).

concentrated on production of *'concept papers'*, first essential step in order to make possible the concrete application of Digital Twin in practice. Lu et al. (2020) reached the same conclusion, remarking that most of the research done up to year 2020 is *'conceptual work'*, and concrete implementation into real use–cases is still at an early stage. Most recent reviews addressed both the theoretical foundations (Jones et al. 2020) and applicative domains (Enders and Hoßbach 2019; Melesse, Di Pasquale, and Riemma 2020). All the reviews highlight the prolific publication activity around the topic in the years 2017-2020: year 2017 registered an increase of about +300% in the number of publications with respect to the previous year (from 12 in 2016 to 36 in 2017), year 2018 +239% (from 36 to 86 in 2018). As mentioned in all the reviews, the most common format, around 56% of the total papers, is the publication as a Journal article. This percentage grows up to more than 60% for works on research on theoretical concepts.

Considering the capacity of integration, in the last couple of years researchers are more focused on Digital Twin scenarios where the connection between virtual physical worlds is tightly coupled and information exchange is bidirectional and automated. This is due on one side to progresses and advances in the research fields, with an increasing numbers of proposed novel and innovative frameworks for Digital Twin systems (e.g. Damjanovic-Behrendt and Behrendt 2019), and on the other side to rapid developments of suitable digital technologies that made more efficien and functional the practical implementation of the Digital Twin vision (Alexopoulos, Nikolakis, and Chryssolouris 2020). In fact, if the review of available literature work in the year 2018 (Kritzinger et al. 2018) showed that only a very low percentage of case-studies were related to *'Digital Twin'* integration level (Table 2), a more recent review (Enders and Hoßbach 2019) revealed that the number of applications at *'Digital Twin'* integration level has rapidly increased, as evident in Figure 9.In conclusion, literature review unquestionably demonstrates that although Digital Twin development can be still

Table 2. Distribution of literature work based on scope and integration level (Source: Enders and Hoßbach 2019).

	Concept	Case-Study	Review	Definition
Undefined	11.90%	4.76%	2.38%	0.00%
Digital Model	14.29%	11.90%	0.00%	0.00%
Digital Shadow	26.19%	7.14%	2.38%	0.00%
Digital Twin	2.38%	2.38%	9.52%	4.76%

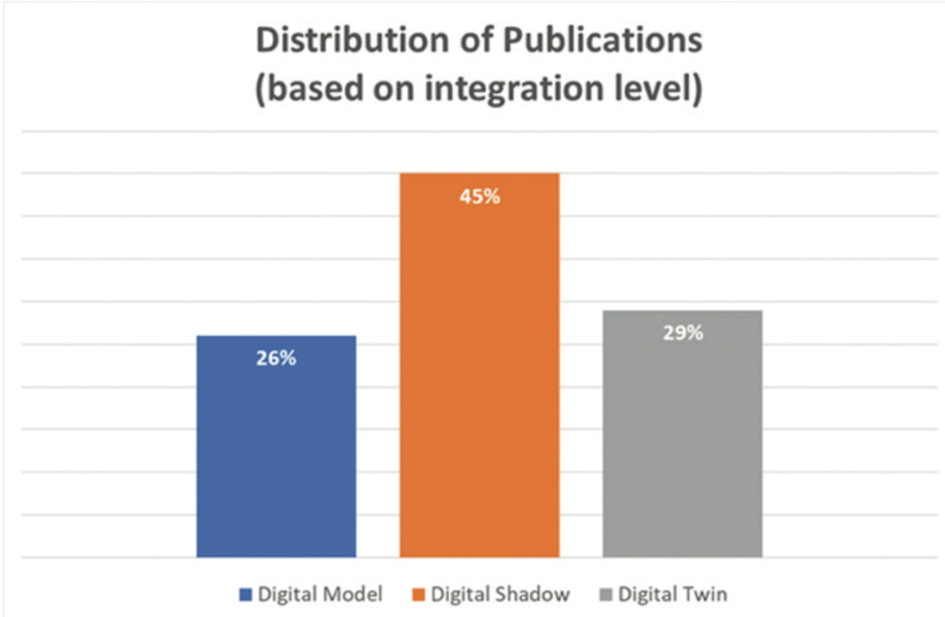

Figure 9. Distribution of literature work based on targeted integration level (Enders and Hoßbach 2019).

considered at its beginnings, a massive work has been done so far from the research community in the definition of conceptual basis and theory. However, up to now, a high number of papers still focuses on concept definitions, while manufacturing *'Digital Twin'* systems still present research areas to be further developed and open challenges to be tackled.

In this context, this paper mainly focuses on the *'Digital Twin'* integration level, with particular attention to methodologies and solutions for its effective implementation in production scenarios. In the following sections, architectures for the Digital Twins into a Smart Manufacturing production process will be discussed and possible models for the integration of Digital Twins into Smart Manufacturing processes is proposed. Key elements driving the future vision of Digital Twins are derived, and the main challenges to this vision are finally presented.

2.5 Main components of a digital twin

The Digital Twin descriptions and classifications given in the previous Section permit to identify a set of enabling technologies underlying the practical implementation and application of the relative concepts to real factory shop-floors. Interconnection and interaction capabilities between physical and virtual worlds are required, implying standardization and harmonization of communication protocols and interfaces. Data processing capabilities are needed, e.g. data cleaning, data mining and data fusion, as well as computational skills in order to implement optimization, decision-support and prediction about the production behaviour. Finally, data security is another fundamental aspect (Rymarczyk 2020) ensuring the normal operation of physical and virtual worlds against malicious attacks (Gehrmann and Gunnarsson 2020). In fact, digital ecosystems can only function efficiently if all parties involved can trust in the security of their data and communication, as well as in the protection of their intellectual property.

Nowadays, new developments and advances in information technologies in the context of the Industry 4.0 offer a prolific and sound base for practical Digital Twin implementation:

Internet-of-Things (IoT) solutions, in particular Industrial IoT, provide ubiquitous sensing ability to collect data from different shop-floor resources, factories and processes;

Cyber-Physical Systems (CPSs) integrate the computational and physical capabilities, which make physical resources able to compute, communicate and control;

Cloud computing provides powerful computing capability for operating sophisticated models;

Edge computing provides computational capabilities to decentralized resources, whenever latency, data security, and bandwidth issues may hinder the adoption of cloud-based solutions;

Big Data and Artificial Intelligence give intelligence to entities, models and systems.

Although Digital Twin shares concepts and principles with IoT and CPSs, it represents something different and complementary to them. As Lu et al. (2020) clearly highlighted, a Digital Twin mainly lives in a virtual space, though it needs a physical product to be associated to. CPSs, in contrast, are characterized by a physical entity and its digital counterpart, while IoT acts as the connection and communication space that links together the different resources. However, how to integrate these assets in a functional, consistent and coordinated 'intelligent unit' still represents an open issue. Some work has been done on the definition of suitable architectures (Talkhestani et al. 2019; Stark, Fresemann, and Lindow 2019; Damjanovic-Behrendt and Behrendt 2019), but so far no Digital Twin integration into real industrial use cases based on established frameworks can be found in literature.

2.6 A practical example of manufacturing digital twin

One of the first applicative cases targeting the implementation of a Digital Twin at the shop-floor level was proposed by SIEMENS in 2015 (Rosen et al. 2015). Through a clear and intuitive example, it illustrates from a practical standpoint the elements, capabilities and the challenges of a Digital Twin for manufacturing contexts. Although the case seems to limit the role of the Digital Twin to a scheduler, it still permits to infer the potential and the contribution in terms of benefits that can be achieved through a deep integration applying digitalization, modelling and simulation concepts to an intelligent production system. In particular, a *Cyber-Physical Production System* (CPPS) is considered, consisting of four *Cyber-Physical Production units* (Figure 10):

a Robotic Cell performing loading/unloading operations with a Carousel Buffer

a CNC Drilling Machine;

a CNC Milling Machine;

a Transport System.

Each production resource can rely on a virtual copy that stores general and specific information, e.g. configuration data, current states, functions and capabilities. In addition, a Digital Twin for every single product is available, storing relevant information for the part production, such as part ID, part program files, production history. The Digital Twin can be located either on a physical memory integrated into the pallet carrying the physical part or on any other memory device distributed along the IT infrastructure. The complete production process is managed and

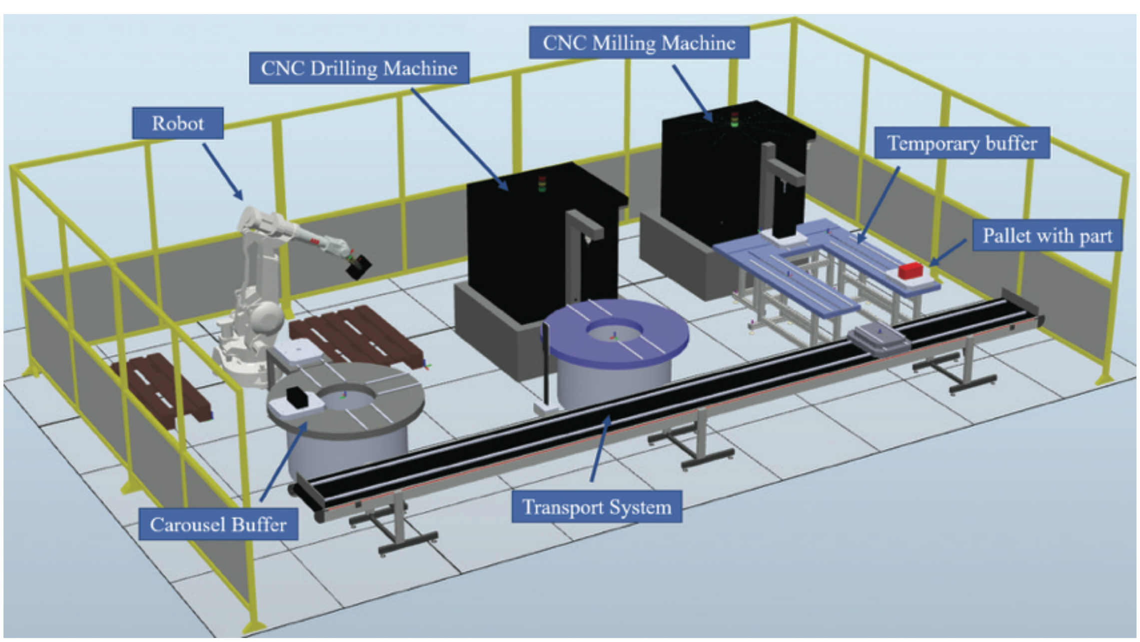

Figure 10. Cyber-Physical Production System example (elaborated from a layout proposed by Rosen et al. 2015).

controlled by a central Manufacturing Execution System (MES).

The Digital Twins of parts and resources allow to increase the level of modularity and autonomy: the knowledge on the current state of the production system resources enables the production units to autonomously react to disturbances during operation, e.g. respond to new orders or modify order priorities. In this context, the different Cyber-Physical Production units can manage and supervise the part flow independently from the MES, through communication and negotiation routines. Each production resource can perform queries to the other machines in order to optimize the production flow. They can perform scheduling tasks, enriching the job with data and information gathered in real-time during the production process.

As an example, considering the layout of Figure 10, once the milling operation on the part has been completed, the Milling Machine can query the production units directly involved in the following production steps thanks to the fact that the Digital Twin of the part contains information on next operations to be performed, e.g. drilling. In particular, the Milling Machine can send a request to all production units having a 'drilling capability', in order to continue the part production process, since the skills of the production units are known thanks to their own Digital Twins. Replies are then evaluated according to specific rules and criteria, e.g. cost vs. time, and the part is assigned to the available production resource. Three situations could happen as a consequence of the Milling Machine query:

the Drilling Machine is available: the Milling Machine sends a request to the Transport System, in order to bring the part to the Drilling Machine;

the Milling Machine itself gets selected (e.g. the Drilling Machine has a long waiting queue): it proceeds with the drilling operation on the part;

no production resource gets selected (e.g. the Drilling Machine is down and the Milling Machine does not have a suitable tool): the Milling Machine sends a request to the Transport System, in order to bring the part to the Carousel Buffer

Digital Twins also enable effective and robust reactive behaviours in case of faults: for example, in the case of a breakdown of the Carousel Buffer, the Milling Machine can re-configure itself in order to act as a temporary buffering unit through its input/output legs. This information, stored in the Digital Twin, can be accessed by the Transport System: it will move the finished parts to the input leg of the Milling Machine for buffering, rather than to the Carousel unit. CPPS can then go on with production (semi-finished parts can still be drilled, as the Drilling Machine is now free), and in the meanwhile maybe the Carousel Buffer could be repaired. Once the Carousel Buffer will be operational again, the finished parts waiting in the Milling Machine legs can be unloaded and the production returns to the normal state.

Despite the convincing and sound approach, the proposed concept has not yet been actually applied to a real use-case. In fact, the proposed model only considers an illustrative case, and only preliminary work has been carried out so far for its implementation.

2.7 Standardization of the interface

A promising approach is the adoption and adaptation of the *'Asset Administration Shell'* architecture, proposed in the German government program Industry 4.0, i.e. the *'Reference Architecture Model Industrie 4.0 – RAMI4.0'* (DIN SPEC 91345:2016-04 2016), even if it is still under investigation and development. It defines guidelines and rules for the development of a standardized interface, the Administration Shell, managing the connection of production resources, devices and tools in an Industry 4.0-compliant way. Proposing definitions and vocabulary for the related production asset, the Administration Shell could also represent a defined interface for the Digital Twin (Figure 11). Practically, it includes all the relevant information for representing the asset and its technical functionality. As an example, it stores all data and information about the asset providing also controlled access to them, and it permits network addressing and unambiguous asset identification. An asset could also be represented by multiple Industry 4.0-compliant Administration Shells, thus having more than one Administration Shell for different purposes. In this case, the different Administration Shells must be able to refer to each other. Finally, the Administration Shell approach considers the whole asset lifecycle stages according to *IEC 62890* (Figure 12). Iñigo et al. (2020) demonstrated the feasibility and benefits of the Administration Shell approach,

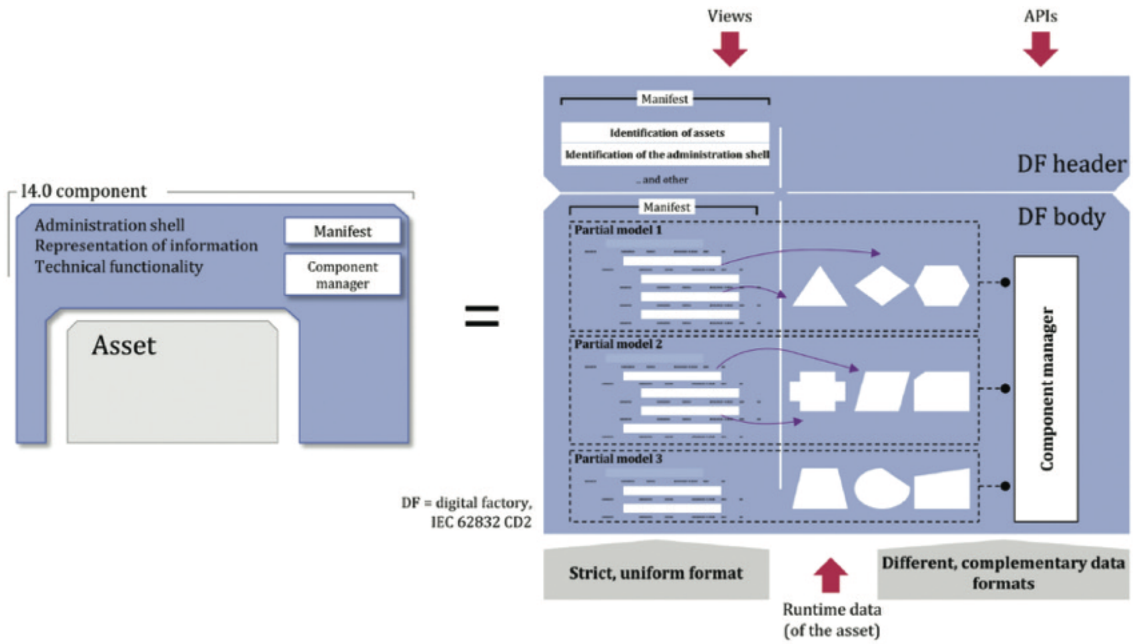

Figure 11. Administration Shell structure as defined in the 'Reference Architecture Model Industrie 4.0 – RAMI4.0' (DIN SPEC 91345:2016-04 2016).

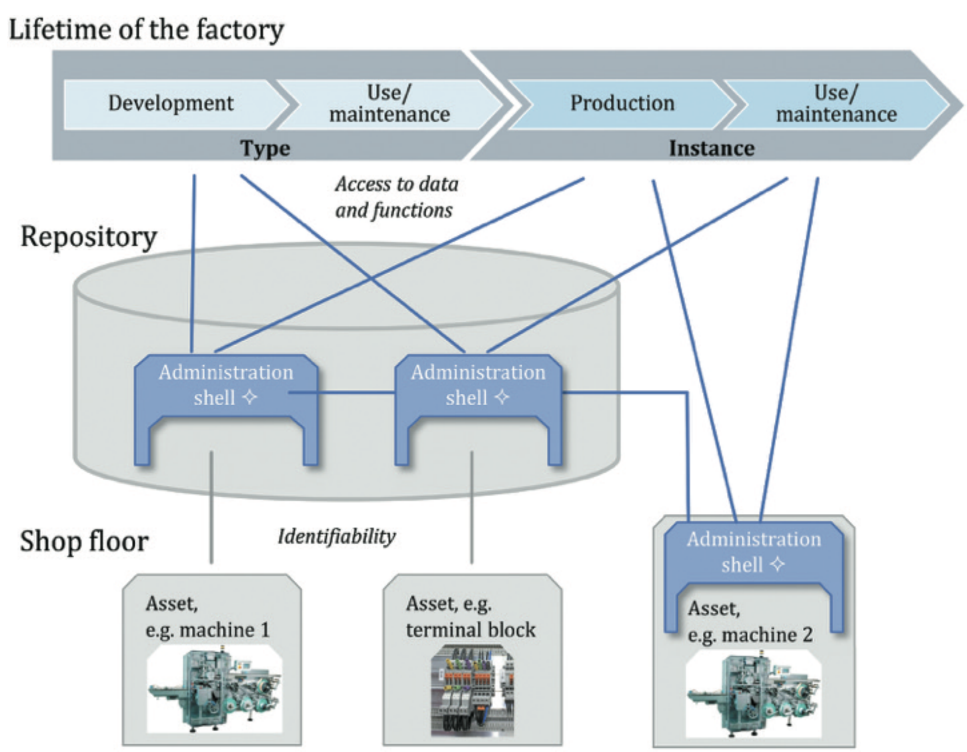

Figure 12. Different allocations for Administration Shells in an I4.0 network (DIN SPEC 91345:2016-04 2016).

integrating it into a real industrial scenario that considered a robotic arm and a grinding machine.

Despite all the important and productive work done so far, there are still some critical aspects not yet covered for the complete adoption of the Administration Shell as the Digital Twin reference architecture. In particular, it provides no means to perform synchronization to the physical asset, triggered by changes in the real world. In addition, the two main elements composing the Administration

Shell, the *'Component Manager'* and the *'Manifest'*, only focus on physical asset information storage and access, through a service-oriented architecture system. *'Intelligent coordination and supervisory units'* (for example, implementing artificial intelligence techniques, optimization services, predictive maintenance methods) necessary for the practical realization of an *'Intelligent Digital Twin'* are not considered. Security is another aspect not fully covered by the Administration Shell approach: as remarked by Iñigo et al. (2020), the Administration Shell does not integrate communication security measures, and does not offer solutions for their implementation. For this reason, its adoption turns out to be still unpractical for all those applications where information and data security is essential.

2.8 Digital twin for human-centric manufacturing

The so-called 'Human Digital Twin Computing' is another emerging application area for Digital Twin concepts (Saariluoma, Cañas, and Karvonen 2021; Kawamura 2019). Several research works can be found in literature, addressing ideas and challenges related to the creation of digital copies of human beings (Truby and Brown 2021; Barricelli et al. 2020). From a general point of view, human users are connected, via ambient or wearable sensors and IoT transmission technologies, to their digital copy in the virtual space, which is not only able to replicate movements and actions but also to reproduce states and behaviours, and recently to identify individuality and emotions (ToshiToshima et al. 2020). With particular regard to the manufacturing context, the Industry 4.0 vision allows new solutions and interfaces for the interactions between workers and production resources, paving the way to a novel 'Operator 4.0' (Peruzzini, Grandi, and Pellicciari 2020). The role of a Human Digital Twin in industrial environments can be beneficial to production and efficienc by addressing, among the others, ergonomics (Greco et al. 2020; Grandi et al. 2020), layout design (Rueckert, Niemann, and Kam 2020) and human-machine collaboration (Malik and Brem 2021; Yi, Liu, and Ni 2020). Vergnano, Berselli, and Pellicciari (2017) introduced the importance of Digital Twin for simulation-based training. Big Data and Artificial Intelligence algorithms acquire and process human knowledge, creating models that can replicate and anticipate human intentions, skills and interaction preferences. Research on Human Digital Twin is still at its early stage, but the potential and possibilities are unquestionably clear. However, an important point to be addressed and clarified is related to possible ethical and legal issues that could arise from digitally cloning human data.

3. Industrial implementation

Different understandings of the Digital Twin concepts can be observed in industrial practice, with different targets and implementation strategies, as introduced in Section 2.2. Examples can be found in the aircraft manufacturing domain, where Digital Twin concepts have been applied to the management of aircrafts service life (Tuegel et al. 2011), to the monitoring of operational state of wings (Li et al. 2017), to the simulation of helicopter dynamic systems (Guivarch et al. 2019), to the prediction of tire touchdown wear, as well as to the prediction of components failure probability (Zakrajsek and Mall 2017). However, the contribution of Digital Twin ideas to prognostic is not only related to aircraft industry: additive manufacturing domain (Knapp et al. 2017), crack paths prediction (Cerrone et al. 2014), and fault diagnosis (Reifsnider and Majumdar 2013) are just some other examples of pioneering works on Digital Twin-driven applications. Finally, rare applications have been investigated for the end-of-life phase (Wang and Wang 2019).

3.1 Digital twin architecture for shop-floor integration

In the following, ideas, concepts, guidelines and architectural models for Digital Twin implementation and deployment into factories shop-floors are analysed and discussed. Few approaches have been proposed at theoretical level, one of these being the *'Digital Twin Shop-floor'* (DTS) architecture, discussed in Tao and Zhang (2017) and in Tao et al. (2017). Similarly, the *'Product Manufacturing Digital Twin'* (PMDT) model, proposed by Zhang, Zhang, and Yan (2019), targets the application of Digital Twins to the production phase. Recently, additional work has been done in the definition of suitable architectures targeting manufacturing scenarios, such as approaches based on a *'Tri-Model'* definition by Zheng and Sivabalan (2020), and on a *'P4R information model'* by Park et al. (2020). Wu et al. (2020) proposed a five-dimensional digital twin framework, targeting the representation of the complex relationship between digital twin objects and their attributes. Xu et al. (2020) presented a framework for the application of Digital Twin concepts to manufacturing environments based on Industrial Cloud Robotics (*'Digital Twin-Based Industrial Cloud Robotics Framework'*–DTICR).

Although all the architectures share common foundations and sometimes even structures, some minor differences can be identified. Almost all the models agree on the definition of the following main components:

Physical Shop-floor: it embraces all the factory production resources that exist in the physical world e.g. human operators, machines and materials;

Virtual Shop-floor: it contains the different descriptor models, also built in multiple dimensions e.g. geometric models, manufacturing attribute models, behaviour rule models, data fusion models. It evolves together with the Physical Shop-floor, therefore synchronization and consistency between *Virtual Shop-floor* and *Physical Shop-floor* become of fundamental importance. The *'Product Manufacturing Digital Twin model'* proposed by Rejikumar et al. (2019) highlights also the role of an additional element, the *Shop-floor Network Layer*, responsible for the communication between the physical and virtual world;

Shop-floor Service System: a service platform integrated with shop-floor application systems, offering decision support services, e.g. job scheduling optimization, real-time monitoring of manufacturing resources, quality monitoring, material delivery optimization. It combines models and algorithms with functions from Enterprise Information System (EIS), computer-aided tools, and IT network infrastructure. It exposes services for specific queries and requests from both the *Physical Shop-floor* and the *Virtual Shop-floor*. The *Shop-floor Service System* element encapsulates the logic that orchestrates and manages the whole production process, representing the intelligent core of the architecture. It requires connections and interfaces towards all the other elements in order to access and exchange data and information. Given the wide range of different interfaces (e.g., RS232, CAN and ZigBee) and communication protocols (e.g., Profibus, TCP/IP and Modbus), the *Shop-floor Service System* also integrates proper interface modules;

Shop-floor Digital Twin Data: it includes data from both the physical and virtual worlds, e.g. production data, tooling data, material data, quality data, cost data. Data generated from both physical entities and digital mirrors, as well as the fused data are used to support the activities in the shop-floor. To this aim, the PMDT also adds the definition of the virtual elements associated to each production resource. In particular, the *Virtual Shop-floor* is seen as a combination and interaction of five different models:

Product Definition Model: it conveys product design and manufacturing information, e.g. geometric tolerances, material specifications, bill of material through an integrated 3D model;

Geometric and Shape Model: it describes geometric dimensions and shape of the associated Smart Shop-floor element, e.g. weight or length;

Manufacturing Attribute Model: it describes the non-geometric attributes, e.g. cost, energy consumption;

Behaviour and Rule Model: it includes behaviours and rules, e.g. activities, actions of operators, process constraints. Different implementations could be possible in order to describe behaviours (*Unified Modelling Language* or *Petri Nets*, for instance), while rules can be expressed using different methods (neural networks, fuzzy logic, Pareto optimization);

Data Fusion Model: it describes and models relationships among production data.

The different models can interact through an appropriate communication layer, the so-called *'Digital Thread'* (Figure 13) which permits to keep the synchronization between the physical world and the virtual space, making the PMDT a unique, reversible, faithful model of the corresponding *'Cyber Physical Production System'*.

Park et al. (2020) proposed a different information model, the P4R, that provides abstraction for data at *'product'*, *'process'*, *'plan'*, *'plant'* and *'resource'* level. Although the considered architectures define diffe - ent hierarchical models for the elements (Figure 14), and a different number of layers for the architecture, they still agree on the general data flow among the elements.

In particular, the *'Digital Twin Shop-floor'* (Tao and Zhang 2017) and the *'Digital Twin-Based Industrial Cloud Robotics Framework'* (Xu et al. 2020) propose an interconnected model, where each element is connected with any other. The PMDT, the P4R and the *'Tri-model-based'* (Zheng and Sivabalan 2020) models, on the other hand, rely on a hierarchical architecture

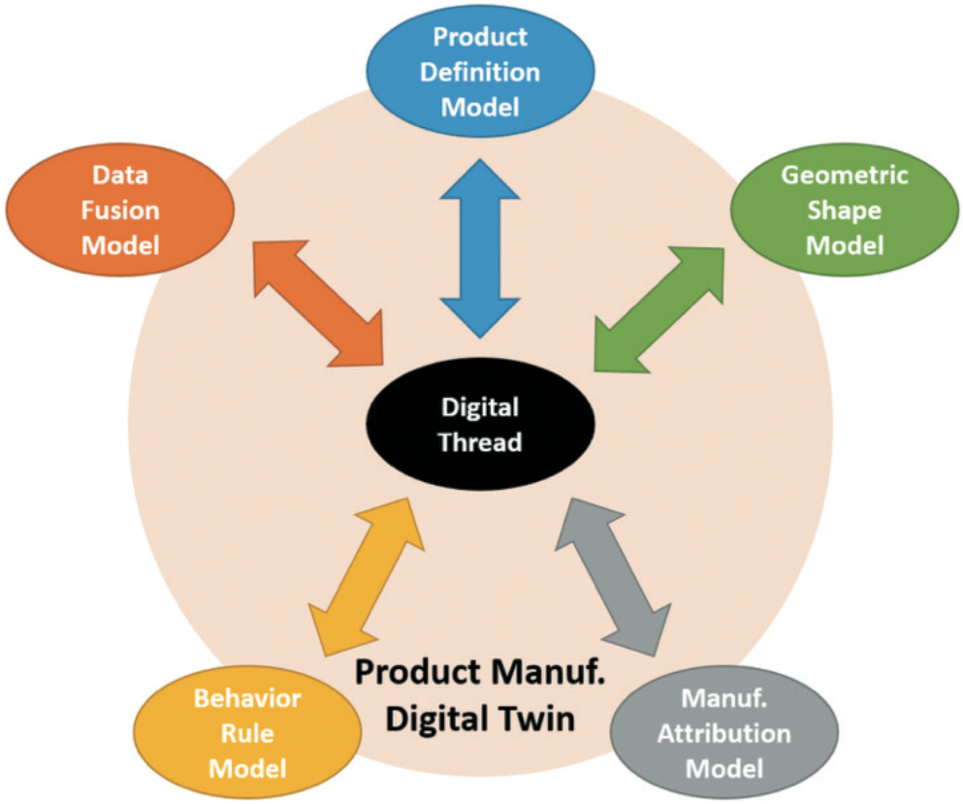

Figure 13. Basic components of a Product Manufacturing Digital Twin (Zhang, Zhang, and Yan 2019).

based on 4 or 5 layers, identified by different names but with the same operational behaviours. In this case, each layer of the architecture can only interact with the adjacent layers.

Production data acquired in the *Physical Shop-floor* layer are managed and stored in the *Shop-floor Digital Data* layer. Data mainly include factory data, production process data and environment data, directly generated by physical entities without further processing. They are made available to the *Virtual Shop-floor* layer to build, or refine, the descriptor models. The *Virtual Shop-floor* layer requires access to data to get information about model parameters and model operation states and to store information from simulation, evaluation, optimization and prediction.

The *Shop-floor Service System* exposes and executes 'intelligent' services implemented through cognitive algorithms, e.g. genetic algorithms, differential evolution algorithms, simulated annealing algorithms, that require as inputs virtual data and aim to optimize production scheduling and process flow. As an example, in the case of a failure of the production plan at the *Physical Shop-floor* level, e.g. equipment breakdown or material shortage, real-time shop-floor data regarding unexpected behaviours are collected and transferred to the virtual space, in order to update the *Virtual Shop-floor* model status. Data are also passed to the *Shop-floor Service System* layer, where the 'intelligent' algorithms refine and optimize again the models. The optimization results are then analysed and evaluated to decide whether a production rescheduling would be required or not. If yes, the new scheduling will be transferred to the physical shop-floor. Therefore, even if the PMDT and the P4R architectures do not provide a direct link between the *Shop-floor Service System* and the *Shop-floor Digital Data* (called, respectively, 'Application Layer' and 'Data Layer' in the bottom architecture in Figure 14), they result to be connected through the *Virtual Shop-floor* layer. Services exposed by the *Shop-floor Service System* can also be supported by various sub-services, like data services, algorithm services, model services and visualization services.

It must be noticed that data coming from the *Physical Shop-floor* and the *Virtual Shop-floor* elements are usually encoded with different protocols and communication interfaces. In addition, information can also be stored using various formats, types and

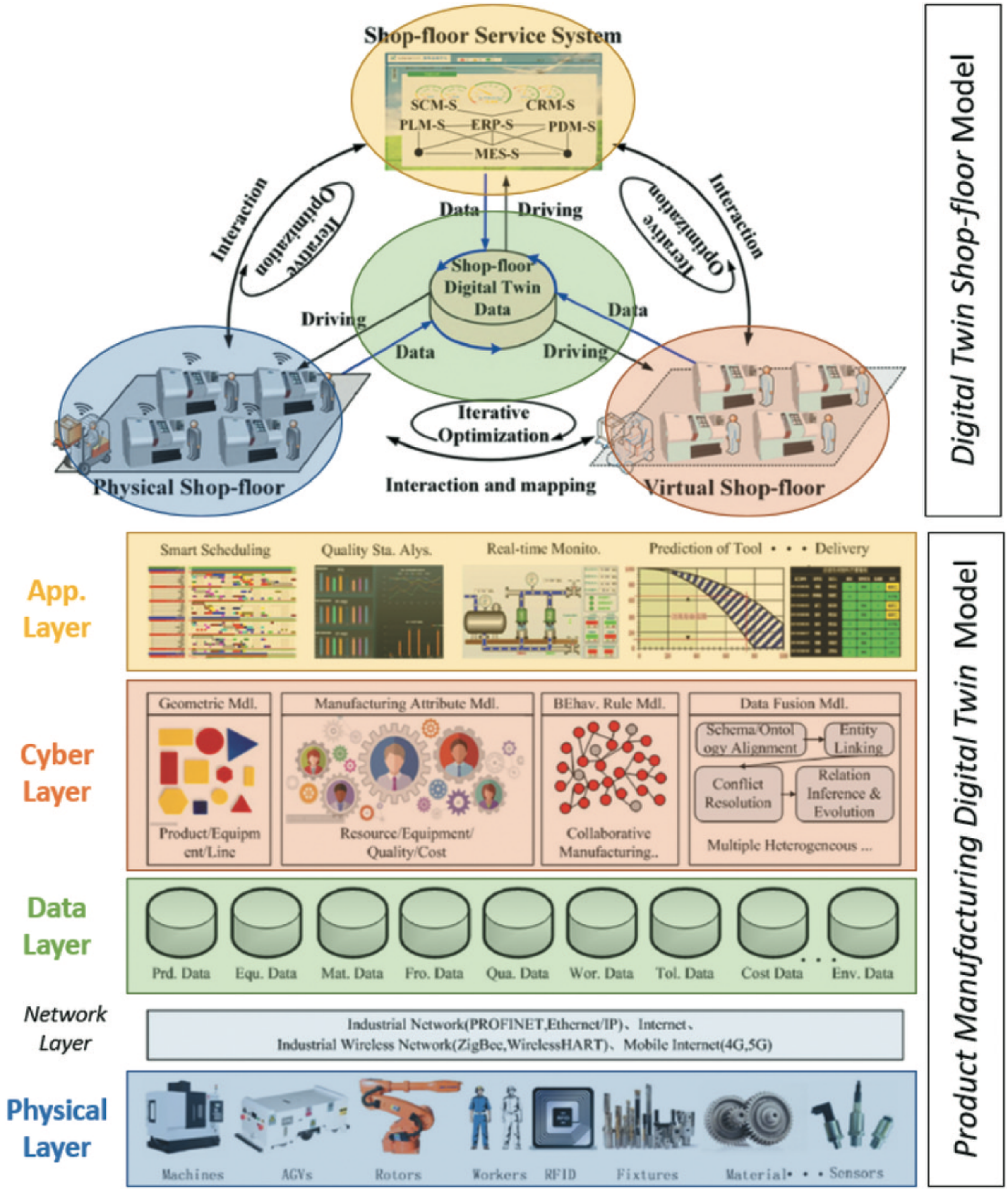

Figure 14. Comparison between *'Digital Twin Shop-floor'* (above, Tao and Zhang 2017) and other Digital Twin architectures (below, Zhang, Zhang, and Yan 2019) architectures.

structures. For this reason, appropriate interfaces able to uniform data access are implemented. These interfaces permit to convert the heterogeneous data into a unified information model, also applying data cleaning and fusion algorithms (e.g. Kalman filter, neural network and Bayesian inference). In this way, the unified physical fused data and the unified virtual fused data become coherent and consistent, and can then be processed and elaborated by the *Shop-floor Service System*.

The mapping between the physical and the virtual worlds will accompany the physical resource through its whole lifecycle, e.g. production, maintenance and recovery phases, being also used for the dynamic optimization of the shop-floor (Zhang, Zhang, and Yan 2018). As an example, storing data and information about a tool, its lifetime can be optimized by predicting the tool wear index. Searching optimal solutions by mathematical methods always turns out to be a difficul and computational intense problem. However, as the virtual equipment provides a digital mirror in high fidelity with the physical one, the optimization can be performed in the cyber environment through parameters modifications and testing. As the virtual equipment can be adjusted with little cost, the equipment operation can be validated in the cyber environment first, then performed on the physical one, which reduces the risks of the actual production process.

In conclusion, the definition and identification of a reference architecture for the practical implementation of Digital Twins at shop-floor level is becoming paramount. A promising work is the development of an international standard, the *ISO 23,247 'Digital Twin Manufacturing Framework'* (ISO23247 ISO23247 2020). In particular, Part 2 specifically targets the definition of a reference framework for the adoption of Digital Twin-related technologies into modern manufacturing processes. At present, the standard is still in its genesis (DIS ballot phase). Additional work is required, considering not only research of architectures for the Digital Twin implementation but also collection of feedback and inputs from manufacturing companies. This *'Digital Twin Integration Framework'* should act as a reference model providing principles and standard definitions but also directions and instructions for the proper application of theoretical concepts into real-world use-cases. On the other hand, it should be general and flexible enough to permit customization, so that it could be easily adapted and tuned according to specific requirements and scopes of different companies with diffe - ent needs and targeting different integration levels or production areas.

3.2 Operational flo

As highlighted in the *'Digital Twin Shop-floor'* model (Tao and Zhang 2017), the logical flow of Digital Twin operations can be decomposed in three main phases: before, during and after production (Figure 15).

Before production, the *Shop-floor Service System* elaborates a production plan, that is passed to the *Virtual Shop-floor* for validation. and then passed to the *Physical Shop-floor* for execution. During production, simulated data from the *Virtual Shop-floor* are continuously compared to actual production data from the *Physical Shop-floor*. If data inconsistency is found, a specific service will determine the cause of data misalignment: disturbances in the physical world, e.g. equipment failure, or inaccuracies in the virtual models. In case of disturbances in the *Physical Shop-floor*, specific services in the *Shop-floor Service System* will elaborate corrective actions aiming at eliminating or reducing them. The 'recovery strategies' identified by these services will be first validated at the *Virtual Shop-floor* level, and then transformed into control orders to correct *Physical Shop-floor* behaviours. If data inconsistency is caused by the virtual models, new model calibration will be performed. Actual production plan will be then verified again and the production process will be adjusted accordingly.

It is important to highlight a 'behavioural diffe - ence' between the *Virtual Shop-floor* and the *Physical Shop-floor* when querying services to the *Shop-floor Service System*: while the output of *Virtual Shop-floor* queries is directly transmitted to the virtual models, the output of *Physical Shop-floor* queries is first conveyed to the *Virtual Shop-floor* layer for verification, and only then to the physical resource for execution. Moreover, a difference in queries content can be also noticed. Services invoked from the *Physical Shop-floor* layer mainly concern production planning and scheduling, aiming at solving existing problems quickly and preventing possible faults during production. On the other hand, queries from the *Virtual Shop-floor* layer mainly refer to calibration and test, in order to support model operation and evolution. It must be noted that not all the proposed architectures agree on the fact that the *Physical Shop-floor* can directly query services at the *Shop-floor Service System* level. For example, the hierarchical organization of the PMDT does not allow direct data exchange between the two layers (Figure 14).

Once production is completed, history production data are stored and archived, expanding the 'knowledge database' to be used for models building and

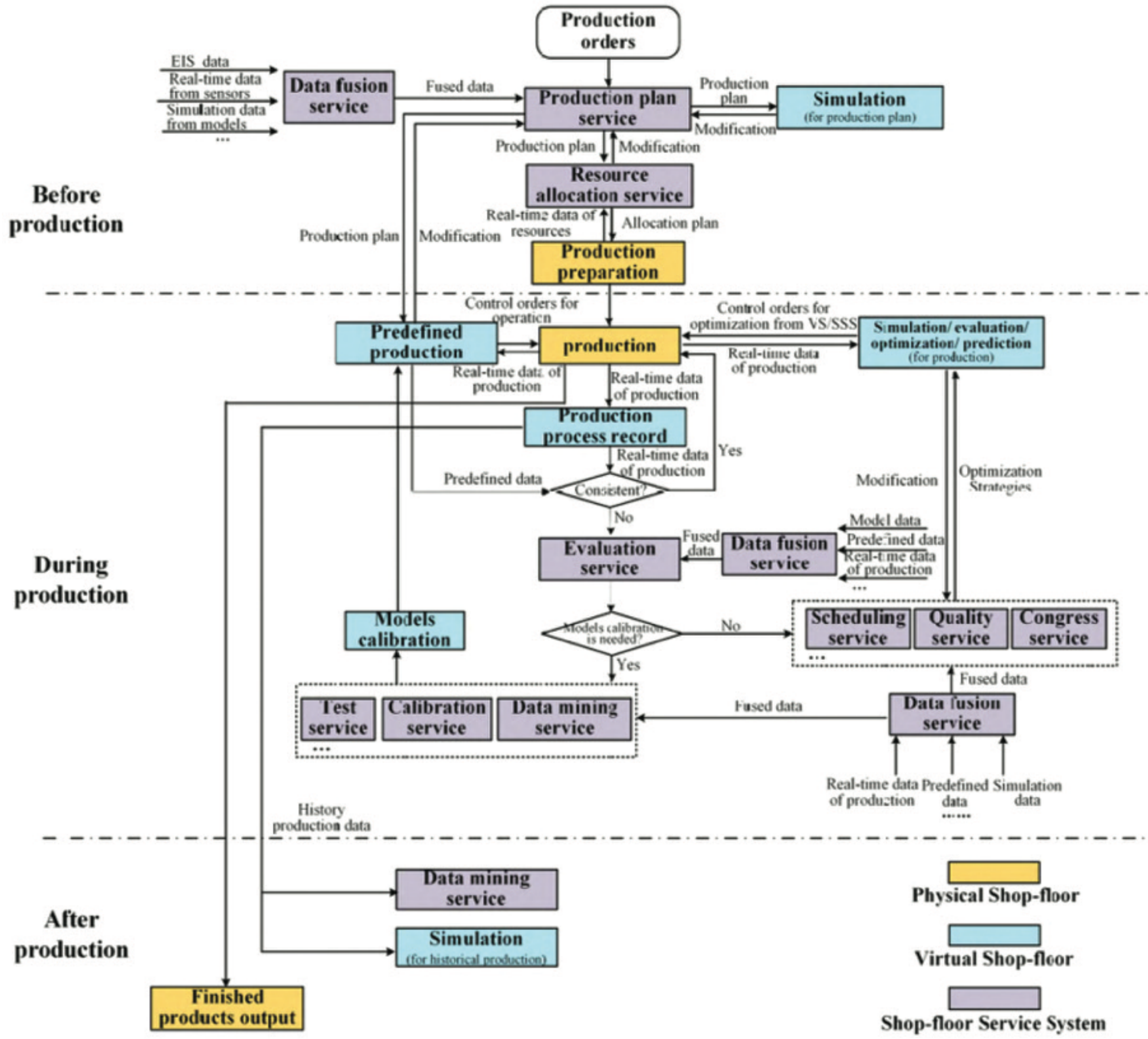

Figure 15. Operational mechanism of the *'Digital Twin Shop-floor'* model (Tao and Zhang 2017).

calibration. Moreover, the *Virtual Shop-floor* could also playback the stored historical data, to self-adjust and self-optimize its internal models, for instance minimizing production defects. From this point of view, the Digital Twin implementation turns out to be a constant evolution process, along with different production cycles.

3.3 Digital infrastructures and data fusion

The Digital Twin approach can be extended to integrate not only physical production resources that are connected through the same local area communication network but also systems that exhibit cloud connection capabilities. In fact, cloud connection and technology provide the Digital Twin architecture with high performance infrastructure resource and data analytics functionalities (Liu et al. 2019).

Nowadays, off-the shelf cloud IoT platforms are available: *Mindsphere*[2] by SIEMENS and *Thingworxs Kepware*[3] among the others are examples of 'platforms as a service' systems that offer enhanced connectivity services towards automation applications. They provide open application interfaces to obtain data from production resources and plants. Supporting bi-directional data flow between the production process and the cloud, they can be considered important enablers for the practical implementation of a Digital Twin for Smart manufacturing processes. *Vuforia Spatial Toolbox*[4] is a recent research platform to leverage Augmented Reality to visualise and help programming connected applications.

Several works investigated the cloud-based manufacturing system approach (Liu, Jiang, and Jiang 2020), considering Web Applications hosted in IoT platforms and web protocols, e.g. WebSocket, to exchange data with the shop-floor. Cheng et al. (2020) proposed a cloud-based reference framework, the *'DT-II framework'*. It supports the Digital Twin integration considering three perspectives: product lifecycle level, intra-enterprise level and inter-enterprise level. The framework adopts a hierarchical architecture similar to the ones presented by Zhang, Zhang, and Yan (2019), Zheng and Sivabalan (2020), and Park et al. (2020), but the connections between the layers are based on a *'Cloud Service Bus'*.

According to the *'Cloud-based Cyber Physical System Architecture'* (C2PS), sensory information collected in the real physical layer is stored in its own data store, but it is also transferred to a data store in the cloud-based cyber layer (Alam and El Saddik 2017). Interactions among production resources are possible either through direct ad-hoc communication in the physical layer, or through the cloud layer adopting peer-to-peer communications among the hosted cyber objects. To keep layers synchronization, data transfer and update are fundamental (Figure 16).

The proposed architecture has been successfully applied in a telematics-based driving assistance

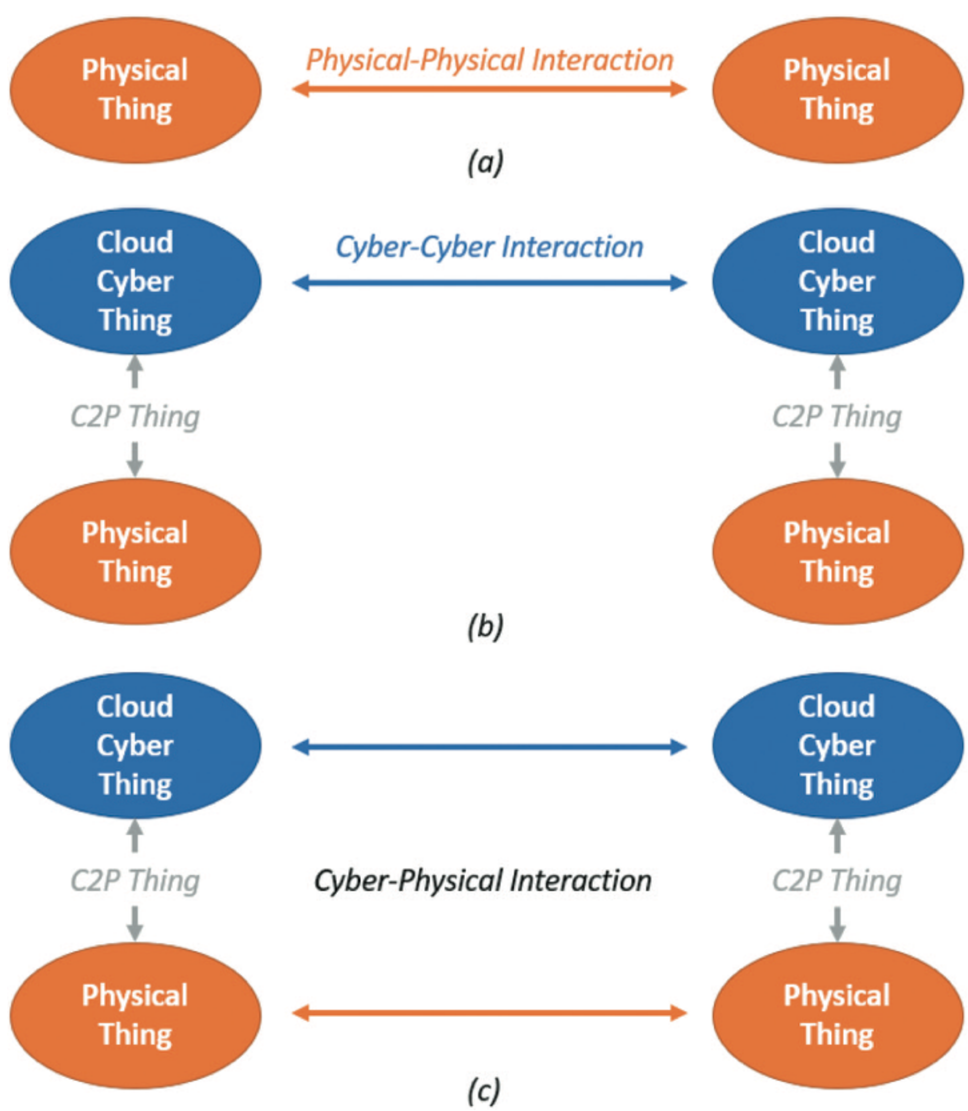

Figure 16. Possible interactions between two C2PS resources: physical-physical (a), cyber-cyber (b), and hybrid cyber-physical (c) (Source: Alam and El Saddik 2017).

application. The C2PS framework is used to determine whether the vehicle is in a city, village or any other areas, and to provide the driver with warnings, such as speed-wise possible fines, demerit points or even accident statistics of the upcoming road segment. In this context, sensors and fusion services permit to identify various driving events, based on which driving-related situational recommendations for drivers are inferred. Three possible types of data fusions are possible for this situational driving support recommender system. At physical level, sensors only manage data related to near real-time driving events detection mainly speeding and turn events detection. At cyber level, Cloud-based services provide delay-tolerant services, e.g. nearby parking or restaurant information, as well as accident statistics. However, the main key point of the C2PS architecture is the possibility to combine and perform data fusion among the services hosted in the two physical and cyber levels, making available 'hybrid-sensor' services. As an example, a speeding event detected by sensors at the physical layer level can further be fused with the location and weather services information available in the Cloud. As a result, the system can provide information on possible fines related to location-specific speed limits.

Despite the promising results obtained by the application of C2PS approach to assisted driving, its efficien implementation into factory shop-floors still requires some work and additional effort to adapt the architecture to current production processes.

3.4 Examples of implementations in the industry

Companies use Digital Twin to increase the manufacturing flexibility and competitiveness, while in some other cases, e.g. General Electric, the Digital Twin understanding focuses on forecasting the health and performance of their products over lifetime. Notably, General Electric developed the Digital Twin of a wind farm, with the aim of improving its control, operation and maintenance (Lund et al. 2016). In a different domain, General Electric applied the Digital Twin to locomotives' lifecycle monitoring (Miller 2016), and in the healthcare sector they developed a Digital Twin for bed planning and work allocation optimization in a hospital. In addition, General Electric also proposed a general-purpose Digital Twin platform called *PREDIX*[5] for production asset performance prediction.

SIEMENS commitment is on improving efficienc and quality in manufacturing and in power generation plants as well as in wastewater plants (SIEMENS 2017), whereas TESLA aims at developing a Digital Twin for every built car, hence enabling synchronous data transmission between the car and the factory (Fourgeau et al. 2016). International Business Machines Corporation developed a Digital Twin to analyse critical parameters, e.g. oil pressure, of their automatic vehicles. British Petroleum uses Digital Twins for monitoring and maintenance of oil and gas facilities located in remote and difficul to reach areas (McCannel 2018; AUCOTEC 2017), while Haier has integrated the Digital Twin approach in its 'Internet Factory'[6] in China.

ABB[7] and Microsoft (2019) also have developed their own software tools and platform, to adapt their product portfolio to Digital Twin concepts and vision. Always in the manufacturing domain, Digital Twin concepts have found applications for simulation, prediction and decision-making in iron and steel manufacturing process (Xiang, Zhi, and Jiang 2018).

Moreover, as discussed in Section 2, Digital Twin has been nowadays applied in aerospace applications for aircraft real-time monitoring, diagnosis and prognosis, maintenance, etc. (Koh, Orzes, and Jia 2019; Tuegel et al. 2011; Tuegel 2012). In this context, Airbus Group also claims that the digitalization of their plants will largely adopt Digital Twin-based solutions (Liu 2017). In 2018 Rolls-Royce introduced their *'Open Simulation Platform'*, with the aim of creating a digital platform for product design (Rolls-Royce 2018), within their roadmap towards services digitalization (SAE 2019). Finally, Digital Twin application scope has also been extended to the monitoring and supervision of power system control centres (Brosinsky, Westermann, and Krebs 2018) and Equipment Energy Consumption Management (Zhang, Zuo, and Tao 2018).

3.5 Discussion on practical implementations

Despite the promising and sound foundations of the Digital Twin implementation models proposed so far, few practical validations into a real-world manufacturing process has been attempted. For instance, the *'Digital Twin Shop-floor'* model has been applied to equipment energy consumption monitoring, analysis and optimization, aiming at improving energy efficienc of production (Zhang, Zuo, and Tao 2018). Work on this point is still ongoing, as some challenges and issues related to the practical application of DTS concepts have not yet been solved (Tao and Zhang 2017; Tao et al. 2017).

Also, the PMDT model has only been tested into a 'theoretical use-case', representing the case of a blisk machining application, where the Digital Twin acted essentially as a job scheduler. The interconnection and interaction between the physical and virtual spaces was not implemented, but still recognized as an important future step to be tackled. In the same way, when Tao and Zhang (2017) proposed the *'Digital Twin Shop-floor'* architecture, their main effort was focused at establishing a theoretical model and at providing guidelines for its implementation. A convincing architecture was thus defined and thoroughly presented, and the need to target the practical implementation of an effective two-way connection between the Digital Twin and the physical shop-floor was clearly outlined as a future step.

The *'Tri-based-model'* was a first step in this direction: it was developed and tested in a controlled laboratory environment, and still some limitations were remarked, especially related to communication latency. The P4R approach was validated in a real manufacturing system, also in this case under controlled operating conditions, and the results achieved were really promising, but some open points must still be solved in order to fully integrate the Digital Twin architecture into the manufacturing process. Following this direction, several works tried to implement a real Digital Twin demonstrator (Rolle, Martucci, and Godoy 2020; Židek et al. 2020), showing an increasing interest and a slow shift of the research community from more theoretical concepts to more practical aspects.

4. Future challenges in implementation

The implementation of the Digital Twin vision into factories shop-floors can open up opportunities in order to achieve a new level of productivity, paving the way towards Smart and Intelligent Manufacturing. However, the deployment of Digital Twins into current production processes still raises questions and open points, which can be grouped in four main directions (Tao and Qi 2019) as in the following sections.

4.1 Communication protocols

A first issue in deploying the Digital Twin vision is related to production resources data access. Synchronization and consistency between the physical and the virtual worlds must be ensured. How to implement proper two-way communication protocols still represents an open issue, strictly related to the need for standardized connection and communication means, so to unify data formats, as well as their representation and exchange. *OPC Unified Architecture* (OPC-UA) is a well-known and widespread machine-to-machine communication protocol for information exchange among industrial automation systems and equipment, that targets the defin -tion of an integral information model for data collection and control.

AutomationML is another powerful data format targeting efficien exchange of engineering information, that can be extended and adapted to model Digital Twins (Schroeder et al. 2016; Zhang, Yan, and Wen 2020). In the same way, several industrial communication protocols have been already widely adopted and can be roughly divided into three main categories (Lu et al. 2020): Fieldbus Networks, Ethernet-based Industrial Networks and Industrial Wireless Networks. All the three categories rely on the ISO Open System Interconnection (OSI), properly modified so to meet real-time and reliability constraints of production shop-floors. However, to fully cover all the application requirements, information models from different Standards need to be harmonized and integrated. In fact, so far, different Industrial Ethernet Standards are not compatible with each other. Interesting and promising research on standard interfaces, modelling and simulation (IEEEP1451 IEEEP1451 2020, IEEE1516; IEEE1516 2020) is currently ongoing (Song et al. 2019).

In conclusion, up to now no solutions that allow a completely automated synchronization between the physical asset and its virtual counterpart have been proposed. Heterogeneity and differences in communication interfaces and protocols can hinder or even make not feasible the collection of data. Therefore, customized access modules must be implemented and deployed, through which data from different sources are transformed into a unified and uniformed interface. At the same time, since data may be represented in different formats and types, data integration routines including cleaning and format conversion must be developed. Recently, first steps towards the definition and development of possible semantic models able to support the most promising architectures for Digital Twin implementation into manufacturing shop-floors is appearing in the literature (Li et al. 2020).

4.2 Fidelity models generation and integration

The second important issue to be considered is the high-fidelity generation and synchronization of models at *Virtual Shop-floor* level. Two main strategies are usually adopted: detecting changes in the physical asset or taking 'pictures' of the asset status at regular time intervals. Several methodologies and approaches have been proposed in literature, for example exploiting multicast functionality of EtherNet/IP, but they all turn out to be only partially automated (Talkhestani et al. 2019).

Models rules can be built exploiting Artificial Intelligence techniques, e.g. data mining algorithms; independently of the techniques used for model construction, the accuracy of the model must be checked and verified through appropriate Verification Validation and Accreditation (VV&A) routines. How to build practically viable Digital Twin models as well as how to develop high-fidelity models based on data from physical resources, which are affected by variability, disturbances and uncertainties, are still active research topics, and so far no consensus has been reached for a unified Digital Twin modelling framework. Several well-known Standards already exist and can be used for describing physical assets, but so far no one of them has reached the full consensus as a reference model for Digital Twins. Figure 17 shows an overview of the evolution of the most popular current standards (Lu et al. 2020). Common ontology and semantics must also be defined, as a fundamental step towards the development and acceptance of a consolidated vocabulary and a universal language that could be generally adopted to model objects and attributes of a Digital Twin.

ISO technical committees are also working on the development of a dedicated standard for the definition of a Digital Twin framework for manufacturing (ISO23247 ISO23247 2020), including terms, principles and vocabulary. At present, multi-domain modelling and simulating methods mainly consists of software interfaces (Wang 2003), High-Level Architecture (Pedrielli et al.

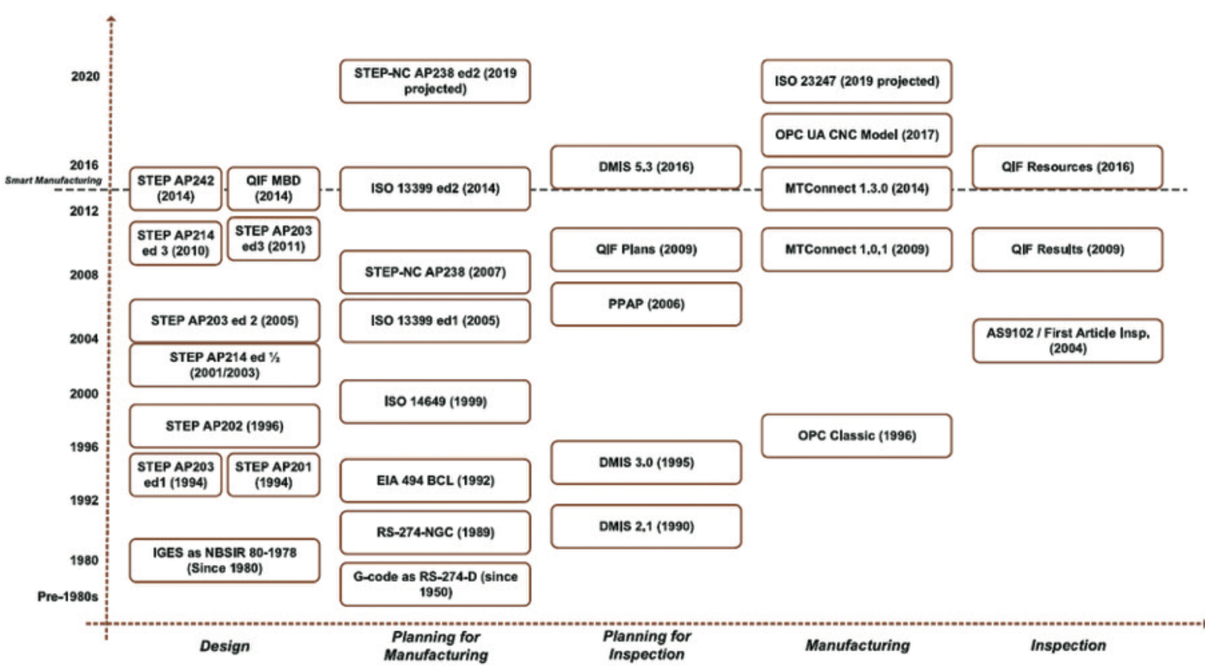

Figure 17. Evolution of standards for Digital Twin in the manufacturing domain (Lu et al. 2020).

2011) and *Unified Modelling Language* (UML), based on *Modelica* modelling language (Mattsson and Elmqvist 1997). Unfortunately, so far, no method is able to fully overcome interface compatibility issues between different software applications. Detail level of models is another major challenge: while an excessive simplified model may not unveil the full potential of Digital Twin applications, a very accurate approach might lead to unbearable complexity of electrical equipment data, measurement devices and massive amount of signals. A possible solution could be represented by *Model Order Reduction* techniques, which simplify the high-fidelity original model preserving all the important model properties, making it suitable for fast and close to real-time simulation (Hartmann, Herz, and Wever 2018).

Commercial tools able to generate reduced order models are so far available (e.g. *Ansys* software by CADFEM[8]), but they are mainly conceived for linear model cases. However, many real-world physical effects are described by nonlinear equations and the application of standard commercial software to these equations results in poor results.

Finally, some other issues on modelling are here highlighted. Interdisciplinary model fusion and coherence is to be considered: current cross-domain analysis techniques are not yet ready for direct implementation on a Digital Twin, as they still lack fully automated operation. Moreover, the ability to correct and adjust virtual model inaccuracies based on inconsistencies between virtual resources and physical entities is another topic that remains still unanswered, despite current research efforts carried out in this direction (Zipper et al. 2018). The development of novel data cleaning and identification methods is also still required for treating the corresponding noisy, highly oscillatory data as usually collected by sensors in the physical space. The application of Digital Twin on early detection and prediction of faults raises an additional side challenge related to model knowledge: in order for the virtual model to be able not only to identify the system state but also to diagnose possible faults, the faults themselves must be modelled. Therefore, possible faults must be known in advance, maybe from experience, and this represents a crucial limiting factor for Digital Twin deployment.

4.3 Different domains integration

The third factor that is deeply related to the *'Digital Twin Shop-floor'* practical deployment is about data management and fusion. *Shop-floor Digital Twin Data* consists of physical data and virtual information, that are combined and fused together through data comparison, association and clustering techniques. Data dimensionality reduction plays an important role in making data fusion easier, by cleaning massive and redundant information. As an example, considering a machine tool, wear data retrieved from physical space can be combined with simulation data about stress and deformation, as well as service data about scheduling and maintenance records from information systems to form the fused data.

The realization of an effective cyber-physical fusion also requires the integration of many different technologies, such as fusion algorithms and data mining aiming at a holistic approach for storage, management, examination and validation of Digital Twin data. Some preliminary work has been already carried out, analysing benefits and positive impacts of complementing Digital Twin with Big Data in order to foster the deployment of Smart Manufacturing into real-world production scenarios (Qi and Tao 2018). From a practical point of view, several platforms are already available in the market (e.g. *Mindsphere, Thingworxs Kepware, Vuforia Spatial Toolbox*, etc.), offering different functionalities and levels of integration. These solutions incorporate the IoT vision and offer a good starting point for cross-domain data integration. On the other hand, the main challenge still consists in the harmonized integration into a unified platform of different and heterogeneous legacy systems.

4.4 Implementation cost analysis

Finally, cost-benefit analysis must be considered, in order to guarantee economic and financial interests for factories when investing in the infrastructure development for the Digital Twin realization. Although this issue is not strictly 'technical', it is worthy to mention it: as for every technology, its adoption, dissemination and widespread application in production and manufacturing environments can only happen if it brings tangible and significant improvements and benefits to Capital Expenses (CapEx) or Operating Expenses (OpEx) for the final process (Boehm and Valerdi 2007; Honour and Jenkins 2013).

The global maturity level of the company needs to be considered, meaning the degree of digitalization inside the company, the level of integration among different platforms storing the data, but also the innovation capacity of the company organization itself. Studies and analyses on benefits and values brought by the adoption of Digital Twins in shop-floor environments (Breillat 2020) turn out to be fundamental in order to endorse the development and integration of Digital Twin systems into real production scenarios. Indeed, the return on costs deriving from investments strongly depends on the company's ability to reap the benefits brought by the new technologies.

5. Conclusions

So far, no clear and unanimous view on methods and tools to implement Digital Twin concepts into real production environments has been identified. Several issues still need to be overcome as reported in the previous section. This discourages companies, especially small and medium enterprises, from planning investments on the adoption and integration of Digital Twin-based solutions, even if many machines and plants newly acquired incorporates sensors and communication capabilities. As highlighted by Hughes (2018) in its industrial survey, almost 60% of the companies declared their expectations to regain their initial investment on Digital Twin technologies within 1 year. Considering the early stage of many Digital Twin components, this objective looks quite unreachable for the moment.

However, Digital Twin is undoubtedly one of the major innovation trends which is appearing in the design, management and optimization of production facilities. The big and widespread efforts posed by the research community and industrial players to define standards, architectures, approaches and deployable systems attest the recognized importance given to the topic and suggests that the current issues will be overcome in a few years.

Notes

1. .https://www.gartner.com/en
2. .https://siemens.mindsphere.io/en
3. .https://www.kepware.com/en-us/products/thingworx-kepware-edge/
4. .https://www.ptc.com/en/products/augmented-reality/vuforia-spatial-toolbox#
5. .https://www.ge.com/digital/iiot-platform
6. .http://factory.haier.com
7. .https://new.abb.com/abb-ability
8. .https://www.cadfem.net/gb/en/our-solutions/cadfem-ansys-extensions/model-reduction-inside-ansys.html

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