Digital twin-enabled smart industrial systems: a bibliometric review

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The aim of this study is to investigate the body of literature on digital twins, exploring, in particular, their role in enabling smart industrial systems. This review adopts a dynamic and quantitative bibliometric method including works citations, keywords co-occurrence networks and keywords burst detection with the aim of clarifying the main contributions to this research area and highlighting prevalent topics and trends over time. The analysis performed on citations traces the backbone of contributions to the topic, visible within the main path. Keywords co-occurrence networks depict the prevalent issues addressed, tools implemented and application areas. The burst detection completes the analysis identifying the trends and most recent research areas characterizing research on the digital twin topic.
Decision-making, process design and life cycle as well as the enabling role in the adoption of the latest industrial paradigms emerge as the prevalent issues addressed by the body of literature on digital twins. In particular, the up-to-date issues of real-time systems and industry 4.0 technologies, closely related to the concept of smart industrial systems, characterize the latest research trajectories identified in the literature on digital twins. In this context, the digital twin can find new opportunities for application in manufacturing, control and services.

Keywords: digital twin; smart industrial systems; literature review; co-occurrence network; burst detection; main path.

1. Introduction

Digital twin is a concept that dates back to the NASA Apollo program, when several identical vehicles were manufactured to allow the conditions of the vehicle travelling in space to be replicated during the mission. Later, in 2010, Shafto et al. (2010) provided the definition of the NASA digital twin: “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. It is ultra-realistic and may consider one or more important and interdependent vehicle systems”. In the aerospace sector, the product digital twin has been exploited to predict the life of aircraft structure and assure its integrity, to design and maintain airframes, and to address the shortcomings of conventional certification, fleet management and sustainment approaches (see among the others Tuegel et al. 2011; Glaessgen and Stargel 2012;

Tuegel 2012). Great interest in replicating digital aircraft counterparts for discovering and understanding emergent behaviours in dealing with product maintenance and service can be said to be related to the importance of ensuring proper behaviour of these systems, as enormous expense would be generated by undesired performances (Tao et al. 2018).

In an era of increasing market requirements, industrial systems have to respond quickly to unexpected events, ensuring proper system behaviour under different conditions, raising the issue of system flexibility. Flexibility is provided by the quick re-configurability of production, when the system is disrupted or needs to be re-organized as a result of interaction with customers (mass customization) and market changes, enabling enterprises to stay competitive in the marketplace (Morgan and O'Donnell 2017). Hence, identification of the proper management of industrial systems for flexibility is gaining more attention, extending the attractiveness of the implementation of the digital twin concept to the management of production systems (Lu et al. 2019; Park et al. 2019). Within the context of the fourth industrial revolution, smart industrial systems are expected to be cyber physical systems integrated through the Internet of Things (IoT) and utilizing cloud computing services (Sajid et al. 2016). This reconfigurable nature of decentralized systems is paramount in achieving flexibility (Morgan and O'Donnell 2017). Accordingly, smart industrial systems are expected to be an integral part of the enterprises that stay competitive in the marketplace.

As smart industrial systems overcome the limitation of central re-planning, shortening response times, and executing high-level tasks autonomously without human control, they greatly increase the system complexity (Rosen et al. 2015). Consequently, the digital twin of the smart industrial system, constituted by a virtual copy of the physical industrial system, reflecting its elements in real-time, based on IoT and synchronized information (Park et al. 2019), is a fundamental part of smart industrial systems (Lu et al. 2019; Nikolakis et al. 2019). In particular, with reference to process planning and execution in the context of smart industrial systems, a digital twin should represent the means to provide fast and advanced decision-making support for elements distributed within the system (see for example the planning and commissioning presented by Nikolakis et al. (2019)). Moreover, the development of digital twins seems to be the right way to overcome the limitations in the use of recent technologies in product lifecycle management (e.g. lack of convergence between the product physical and virtual space). Synchronization and fidelity of representation, in fact, provide a high potential application in product design, manufacturing, and service (Tao et al. 2018).

Given the opportunities offered by the digital twin concept, the goal of this paper is to depict a landscape of the related scientific literature, providing a knowledge base and directions for future research on the topic, with particular attention to its relationship with smart industrial systems. Hence, this paper aims to consider the following research questions (RQ1, RQ2 and RQ3):

- RQ1: What are the main contributions to the research on digital twins and what do these contributions address?
- RQ2: What are the topics the digital twin concept has been related to and what is the importance of smart industrial systems among them?
- RQ3: What have been the trends in research on digital twin and what are the recent research streams?

In order to achieve such a challenging objective, the present work adopts the dynamic literature review method called 'Systematic Literature Network Analysis (SLNA)' introduced by Colicchia and Strozzi (2012). The applied analysis is based on bibliographic network analysis, an approach that has proved to be successful in investigating related concepts such as Smart Factory and Lean (see Strozzi et al. 2017 and Ciano et al. 2019).

The paper is structured as follows. Materials and methods are presented in Section 2, while in Section 3 the results of the citation network and scores analyses are described. In Section 4 the results of the second phase of the SLNA methodology are outlined with particular reference to keyword clustering and analysis. The detection of bursts in the use of keywords over time is described in Section 5. In Section 6 the results are discussed, research directions are identified, and final remarks conclude the paper.

2. Materials and method

2.1. Materials

The papers used in this study were gathered from Scopus, the database with the largest scientific journal coverage (Mongeon and Paul-Hus 2016). In order to include most of the body of literature about the topic, the search was performed using a broad and general search field, i.e. TITLE-ABS-KEY. Regarding the keywords used in digital twin literature, the search referred to the review by Holler et al. (2016), suggesting "digital twin", "product avatar", "cyber-physical equivalence”, “product shadow” and “information mirroring model”. However, Scopus searches for “cyber-physical equivalence”, “product shadow” and “information mirroring model” did not provide any output as isolated title or keyword terms and no consistent output as abstract terms. Therefore, the search was limited to the first two keywords ("digital twin” and "product avatar") indicated by Holler et al. (2016). In fact these terms are often used as synonyms as they both refer to the product digital counterpart of a physical product (Rios et al. 2015). In Scopus, the keyword “digital shadow” appears as one of the most recurrent keywords associated with the former two. The link between the concepts is found in the core nature of “digital twin” that literature indicates as a “digital shadow” of a physical product and which includes all the information and knowledge about it (Schroeder et al. 2016; 2017).

In order to consider the link between the digital twin concept and process aspects, the Scopus search in TITLE-ABS-KEY of the keyword “process avatar” was performed but reported only the paper by Wan et al. (2011), not cited to date by other Scopus papers. For these reasons, the search was completed using the following string: TITLE-ABS-KEY ("digital twin*" OR "product avatar*" OR "digital shadow*"). This choice was made to encompass all the body of literature about digital twin and to understand what are the topics in this field, their weight and importance and, among them, to evaluate what is the role of the application of digital twin in the smart industrial system context. Moreover, only works written in the English language were considered. An additional filter on the publication year was applied, as the search outcome before 2004 consisted in only six papers published from the ‘70s to the ‘90s, whose content was not consistent with the scope of this study (i.e. depict a landscape of the related scientific literature, providing a knowledge base and directions for future research on the topic). Hence, the search was restricted to papers published from 2004. At the end of January 2019, the search output with the above-mentioned constraints was a set of 496 papers distributed over time as shown by Figure 1.

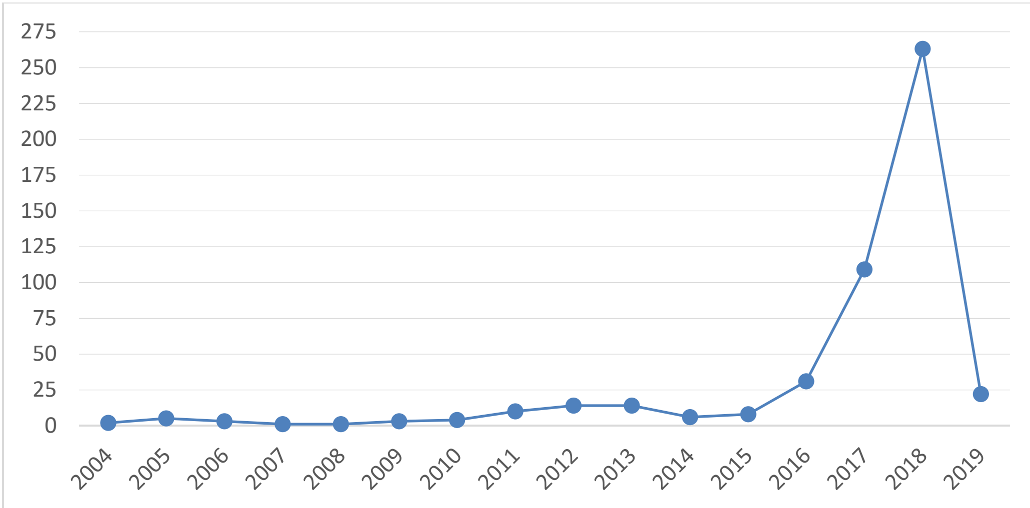

Figure 1. Publications about digital twin over time

2.2. Method

In order to provide a complete landscape of scientific literature on digital twin, the method used in this work is based on the bibliographic network analysis developed by Strozzi et al. (2017). In fact, the authors suggested that analyses built upon citations and keywords can enable a challenging result to be reached. The methodology is depicted in Table 1.

RQ1 is addressed exploring the main development trajectory of the digital twin research and analysing the papers in the network with the highest total citation score. Citations can be represented through a network composed of isolated nodes and connected components, i.e. groups of nodes representing publications connected by citations and graphically linked by arrows. The arrows' direction goes from the cited paper to the one that is citing it, thus from the oldest to the most recent one, representing the flow of knowledge. Within the connected components, it is possible to recognize the main development trajectory of the topic extracting the so-called "main path" (Hummon and Doreian 1989; Lucio-Arias and Leydesdorff 2008), defined also as the "backbone of the research tradition" (Lucio-Arias and Leydesdorff 2008, Colicchia and Strozzi 2012). The articles included in the main path are built on prior works and act as hubs for the following studies (Strozzi et al. 2017). From the possible methods used to detect the main path among the ones described by Liu and Lu (2012), this research focuses on the search path link count (SPLC), global, key-route main path. This choice implies the traversal count, i.e. the significance index for each link in a citation network, which is calculated based on all possible search paths originating from a start node, then selecting a path with the largest overall traversal counts and including the link that has the highest transversal count (Liu and Lu 2012). The extraction of the main path was performed using the Pajek software for large network analysis (Batagelj and Mrvar 1998) and following the procedure suggested by Colicchia and Strozzi (2012).

The main path analysis is completed by considerations about the papers in the network with the highest total citation score, i.e. key reference papers. In actual fact, as the focus of the main path is the traversal count, it may not include the paper with the highest citation score, while the citation is assumed to represent influence (Zhao and Strotmann 2015).

RQ2 is addressed through the keywords co-occurrence network analysis, based on the approach developed by Waltman et al. (2010). The approach consists of the clusterization and the mapping of bibliometric networks, obtained as output of the use of VOSviewer, the dedicated software for the implementation of this approach. Clusters are groups of keywords that are used most frequently together to classify papers, and their analysis can reveal the research areas within the topic. The map is the representation of the network, in which the nodes, namely the keywords, have various dimensions according to their occurrence weight and are marked by different colours reflecting how they belong to the different clusters.

RQ3 is tackled implementing Kleinberg's burst detection (Kleinberg, 2003). This analysis considers keywords recognizing the ones characterized by a "burst", i.e. a sudden increase in the frequency of use over time. Kleinberg's method uses an infinite state automaton to model the streams, in which bursts appear as state transitions; when the term becomes common, it reaches a kind of steady state and is no longer considered a burst (Pollack and Adler, 2015). Due to the effectiveness of this technique it is exploited by this work for the identification of the trends in publication. The algorithm is implemented on the normalized keywords in the Sci2 software (Sci2 Team, 2009) and the output is a temporal bar graph in which the keyword bursts are ranked according to the burst weight, i.e. the magnitude of the change in the keyword frequency.

As input data for both keywords co-occurrence network analysis and Kleinberg's burst detection analysis, this work considers all keywords, i.e. a combination of author keywords and different kinds of indexed keywords. Author keywords are chosen by the authors themselves, thus they encompass the specific extent of the study. Indexed ones are assigned to works by content supplier and they are based on vocabulary and thesaurus terms and encompass wider and more objective information, for instance, subject area, main topic, study typology, adopted methodology, sectors, etc. (Ciano et al. 2019; Pozzi and Strozzi 2018). In this work they are used together, as indexed keywords are updated only when a term becomes popular and could thus miss some recent and increasingly relevant topic, while considering only author ones could lead to overlooking broader and more complete features of the papers (Ciano et al. 2019; Pozzi and Strozzi 2018).

Table 1. Methodology adopted by this work

Research Question	Data	Representation	Tool for the analysis	Software
1) What are the main contributions to the research on digital twin and what do these contributions address?	Citations a. References b. Citations count	Citation network	a. global search of the key-route main path on the biggest connected component b. total citation score	a. Pajek software b. Scopus
2) What are the topics the digital twin concept has been related to and what is the importance of smart industrial systems among them?	All keywords: author keywords + indexed keywords	Co-occurrence networks of keywords.	Clusterisation of nodes using VoS clustering techniques	VoSviewer software
3) What have been the trends in research on digital twin and what are the recent research streams?	All keywords: author keywords + indexed keywords	Temporal bar graph	Kleinberg's Burst detection algorithm	Sci2 software

3. Citation network analysis

The citation network of the collected papers (Figure 2) presents many isolated nodes. The isolated nodes represent papers that are not cited: this can be due to the recent date of publication or to their slight different scope in comparison to the majority of the other papers. Anyway, they include the keywords of search, reflecting the belonginess to the macro subject of digital twin, but highlighting peculiar areas of application. The network includes also seven connected components in which papers are linked by arrows that represent the presence of a citation and whose direction goes from the cited paper to the one that is citing it. Precisely, the biggest connected component includes 147 nodes, while the other six consist of 3 or 2 nodes each. As connected components are made up of a large number of nodes and contain more information (Strozzi, Bono, and Gutierrez 2014), the citation network analysis can provide more significant results. Therefore, this study considers only the biggest connected component and extracts its main path to detect the development trajectory within the topic. The Pajek software, with the default rank numbers of key-routes, i.e. 1-10, extracts a key-route global main path consisting of 15 nodes (Figure 3).

3.1. Main path analysis

The 15 papers representing the main path nodes range from 2017 to January 2019, proving the recent development of the topic. Digital twin literature is just taking hold and the structure of the main path trajectory (Figure 3) mirrors the sudden increase in scientific production. In particular, there has been considerable growth in the last three years, with a significant rise in 2017 and then a strong surge in 2018, which more than doubled the outcomes of the previous year, as shown in Figure 1. Parallel to the increase in the number of papers published, the main path starts with a linear structure covering 2017 publications and develops into as a star network that includes papers published in 2018 and 2019. Retracing the main path structure, the content of the papers reveals two main evolutionary trends that reflect the consequences of the recent spread of the scientific production on the topic: on one hand, literature seeks consolidation, thus conceptual basis, reference models or frameworks; on the other hand, research is undertaking detailed studies on specific digital twin applications and features.

Analysing the nodes of the main path that contribute to the development of the conceptual basis, the first one in the trajectory is the work by Wärmefjord et al. (2017). This study presents an insight into the two main digital twin adoptions, namely the geometry assurance of an assembled product and the real-time optimization in the production phase. The analysis of such adoptions highlights the digital twin dependence on the input data quality: the correct selection of data can convert information to knowledge and exploit the Big Data potential (Wärmefjord et al. 2017). The authors recognize a lack of practical directions to deal efficiently and effectively with input data, therefore they contribute to the literature by providing a framework for the correct and smart selection of the necessary inputs for each production phase activity. As the second node of the main path, Schleich et al. (2017) attempt to fill a lack of conceptual basis in the widespread implementation approaches. Thus, they build a first reference model for the digital twin implementation in design and production. The authors define the essential properties for a digital twin model, such as scalability, expansibility, interoperability, and fidelity. Moreover, they classify a set of operations on the model along the product life-cycle. This paper highlights the digital twin application in the product life-cycle outlining the use of the model in the geometrical variation management, as well as the first node. Notwithstanding the traditional application of digital twin as regards the product, the development trajectory of the topic intrinsic to the main path reveals other adoptions. Similarly, the focus of the study by Zhang et al. (2017) shifts from the product life-cycle to the production line design. In this context, geometrical assurance is no longer the priority and the adoption refers to digital twin in designing both equipment configuration and execution system. This study enriches digital twin literature presenting a framework able to support engineering analysis and decision-making in the production line design and in the evaluation of the solutions. The final output is the entire line model complete with control scheme, motion script, data acquisition system and execution system, enhancing the digital twin ability to simulate the production line performance.

The main path then forks out into three nodes that contribute to the consolidation of digital twin literature as well. Liu et al. (2018) provide a digital twin-based method for reusing and evaluating process knowledge. The approach regards the creation of a digital twin-based process knowledge model framework which includes process requirement and constraints, the real-time status of process equipment and geometrical information. Tests with a prototype system proved that this method allows for an effective and precise process of knowledge reuse. Bao et al. (2018) propose an integrating manufacturing information model using digital twin. In particular, this study outlines the modeling approaches of product digital twins, process digital twins, and operation digital twins, enlarging the range of the application of the digital twin from the product only. With this aim, the authors highlight the need for data transmission and integration between different digital twins and propose AutomationML as a data exchange format. Since the digital twin has several adoptions in the life cycle, there is a shortage of clear definitions in literature and, above all, of its requirements (Durão et al. 2018). To fill this gap, Durão et al. (2018) analyse 19 papers and report interviews in industry focusing on the most frequently addressed digital twin requirements: real-time, integration, and fidelity. The studies by Durão et al. (2018), Bao et al. (2018) and Zhang et al. (2017) introduce the link between digital twin and industry 4.0 paradigm.

The three nodes establishing the link between digital twin and industry 4.0 paradigm merge in the study by Tao et al. (2018) to a node representing the central hub of a star network. Tao et al. (2018) contribute to the development of the theoretical and conceptual background of the topic through the detail of frameworks for the application of digital twin-driven product design, manufacturing, and, in addition to the other studies, product service. This study concludes the flow of knowledge on the conceptual basis, reference models and frameworks, providing the foundation for the widening of specific digital twin's applications and features.

Every host node in the star network studies in detail a specific digital twin aspect. For instance, the study by Zheng et al. (2018) details a digital twin-enabled design approach for Smart product-service system service innovation, focusing on the digital twin adoption in service. Other studies consider digital twin implmentation in specific contexts, such as in livestock farms in the agricultural industry (Jo et al. 2018), in carbon fibre composite parts manufacturing (Zambal et al. 2018) and in 3D printing (Mukherjee and DebRoy 2019). The study by Yun et al. (2018) further develop the focus on the digital twin specific requirements first detailed by Durão et al. (2018). Yun et al. (2018) present a software-defined networking control mechanism overcoming the limitations of communication and providing stable service in a digital twin context. The study by Taylor (2019) depicts the state-of-the-art of the literature about distributed simulation for operational research, identifying its major role in the digital twin context, compared to other tools. Finally, two further studies developed the role of digital twin as an enabler of smart production driven by industry 4.0 (Zhuang et al, 2018; Preuveneers et al. 2018). The miscellaneous subjects covered by the star network hosts demonstrate the possible declination of digital twin in various contexts, suggesting an even greater topic branching in the future. The recent broadening implementation is confirmed by the sources of the publications, ranging from conference proceedings to the *International Journal of Advanced Manufacturing Technology*, *Applied Materials Today* and the *Journal of Cleaner Production*.

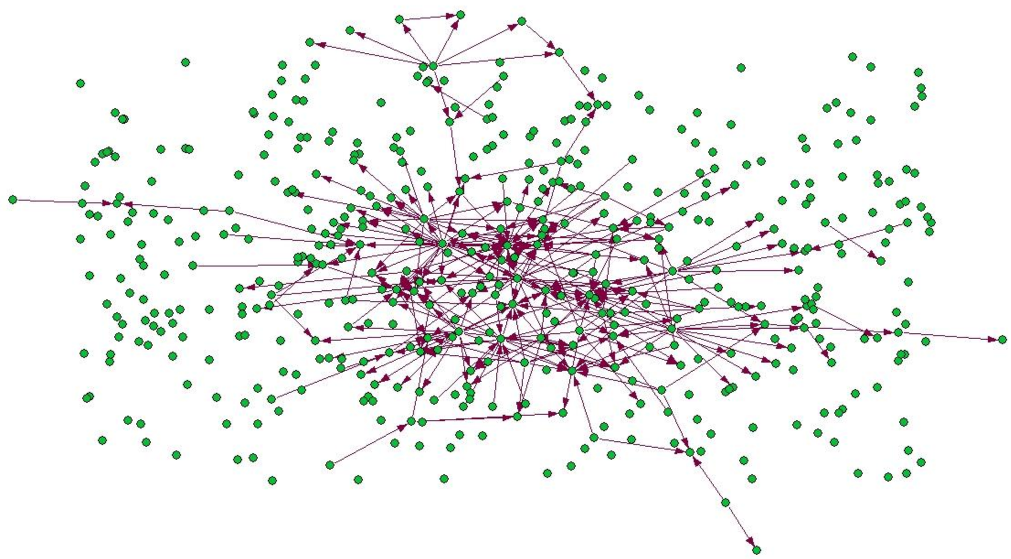

Figure 2. Citation network

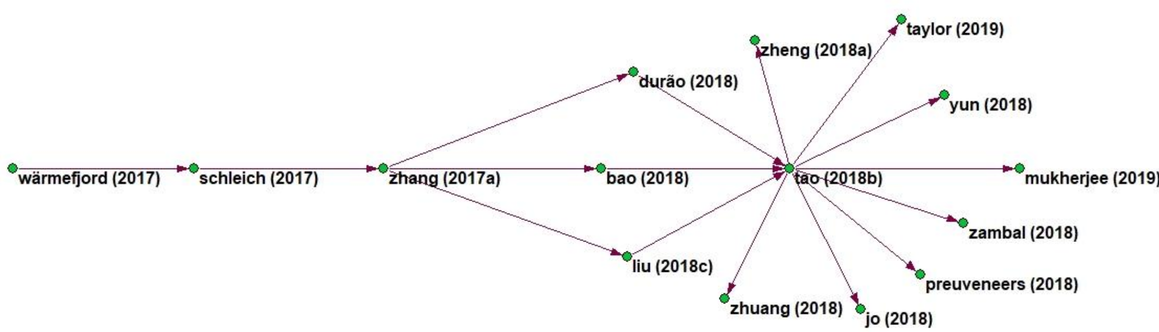

Figure 3. Biggest connected component main path

3.2. Total citations score

The applied algorithm to detect the global key-route main path is based on the citation traversal weights (Liu et al. 2012); this does not ensure that all the most cited papers are taken into account (Strozzi et al. 2017; Ciano et al. 2019 submitted) but only the ones that are important for understanding the development of the theory. Indeed, in this work among the five most cited papers in Scopus in the digital twin literature (Table 2), only the fifth belongs to the main path, the work by Tao et al. (2018). The most cited paper, the one by Sarma and Girão (2009), refers to the digital shadow as a possible method to cope with the diversifying of the Internet towards an Internet of things.

The work by Rosen et al. (2015) points out the importance of digital twin in the creation of an autonomous system, due to its ability to allow the communication between virtual and real worlds and the simulation in all the life cycle phases.

The paper by Tuegel et al. (2011) describes the digital twin adoption in the aircraft industry to integrate structural deflections and temperatures depending on flight conditions, in order to predict local damage and material state evolution.

Lee, Post, and Ishii (2011) present ZeroN, a tangible interface element used for physics simulation and education, which can be levitated and moved freely by computer in a 3D space. Here digital shadow provides users with visible links between ZeroN and other parts of the tabletop tangible interfaces. Despite the high citation score, this paper belongs to the specific research area of magnetic levitation, and the exclusion from the main path reflects its distance from the main topics addressed in the connected component, namely the ones related to the smart industrial system.

The five most cited papers have different scopes and there is not a common thread able to strongly link them. Except for the article by Tao et al. (2018), none of them is linked to the two main development trajectories identified in the main path. However, these articles and papers address a specific topic, making them the key reference in their research stream, demonstrating the potential of the digital twin concept before the increase in interest in recent years.

Table 2. The five most cited papers in the digital twin literature

Authors	**Title**	**Year**	**Source Title**	**Citation count**	**Document type**	**Main path**
Sarma A.C., Girão J.	Identities in the future internet of things	2009	Wireless Personal Communications	165	Conference Paper	No
Rosen R., Von Wichert G., Lo G., Bettenhausen K.D.	About the importance of autonomy and digital twins for the future of manufacturing	2015	IFAC-PapersOnLine	78	Conference Paper	No
Tuegel E.J., Ingraffea A.R., Eason T.G.,	Reengineering aircraft structural life prediction	2011	International Journal of Aerospace Engineering	75	Article	No

Spottswood S.M.	using a digital twin					
Lee J., Post R., Ishii H.	ZeroN: Mid-air tangible interaction enabled by computer controlled magnetic levitation	2011	UIST'11 - Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology	60	Conference Paper	No
Tao F., Cheng J., Qi Q., Zhang M., Zhang H., Sui F.	Digital twin-driven product design, manufacturing and service with big data	2018	International Journal of Advanced Manufacturing Technology	57	Article	Yes

4. **Keywords clusters analysis**

Setting the minimum number of a keyword occurrence at 10 and the resolution at 1.3, the network depicted in Figure 4 is the VOSviewer outcome. The network is composed of 51 nodes, i.e., keywords, corresponding to 8 clusters (Table 3; Figure 5). The following paragraphs comment on the content of the clusters through relevant articles and define the research areas within the literature about digital twins.

4.1. Digital twin for decision making

The biggest cluster of the keywords network concerns the importance of *decision making* in the *digital twin* literature. *Digital Twin* models adopt iterative simulation to *forecast* the possible impact of changes for the real world, empowering *decision-making* (Kuehn 2018). Liu et al. (2018) even stated that *decision-making* can be seen as the final objective of *digital twin.*

However, *digital twins* generate enormous databases of information, which are helpful in *decision-making* only if consistent and integrated. Therefore, several works underline the need for a proper *semantic* meta-model to structure information. A univocal *semantics* ensures the digital continuity of data along with all the phases of the production system, and their synthesis under a unified common environment (Kousi et al. 2019) providing a holistic view that empowers *decisions* (Negri et al. 2017). Moreover, a unique and consistent *data storage* reduces effort in collecting data to perform simulations (Negri et al. 2017).

The literature goes further into depth on the link between *digital twin* and *decision making* especially in the *aircraft* industry, the sector that witnessed the *digital twin* launch and development (Tuegel et al. 2011; Boschert and Rosen 2016; Kraft 2016; Liu et al.2018). D*igital twins* simulations, running virtually through all the flights corresponding to the projected usage, allow the user to understand what the *aircraft* has experienced and to *forecast* future maintenance needs and repair costs, often by using *Finite Element Methods* (Tuegel et al. 2011; Negri et al. 2017). In this research stream, some studies refer to the *digital twin*/digital thread binomial (see Kraft 2016; Boschert and Rosen 2016, and Mavris et al. 2018). In the same way as *digital twin*, digital thread describes an integrated *systems engineering* process that digitally manages the processes (Kraft 2016). However, digital thread and *digital twin* have different focuses: the digital thread concept is used to support and create informed *decisions* in the acquisition phase, and, as a consequence, in the design of new *aircraft*, while the digital twin should support *decisions* in its operation and service (Boschert and Rosen 2016). Using their combination, *uncertainties* can be more accurately identified, included and then reduced (Kraft 2016). Furthermore, *digital twin* can translate residual input *uncertainties* into probabilities of obtaining various outcomes, supporting better *decisions* (Tuegel et al. 2011). Moreover, by refining the digital thread/*digital twin* model with *structural dynamics* modelling on an individual *aircraft* basis, *fighter aircraft* can shift from fleet or squadron-based management to risk-based management (Kraft 2016).

4.2. Big data in production systems

The work by Wärmefjord et al. (2017), presented in the main path analysis (Section 3.1), described the dependency of the digital twin on the input data and the importance of the correct selection to exploit the *big data* potential. Their work introduces the central theme of this cluster, i.e., the focus of digital twin literature on the use of *big data* in *production systems*. *Big data* could be considered as an essential part of digital twin; indeed, *big data* makes it possible to express most of the digital twin functions, while digital twin puts the *big data* analysis and the actual manufacturing in parallel (Qi and Tao 2018). Furthermore, literature is paying close attention to this research area since both *big data* and digital twin are considered key enablers of the recent concept of *smart* manufacturing, namely a ‘dramatically and pervasive application of networked information-based technologies throughout the manufacturing and supply chain enterprise’ (Davis et al. 2012), and of its synonym *smart factory* (Qi and Tao 2018; Jeon and Suh 2018).

In this smart environment, *artificial intelligence*, characterized by self-*learning* ability, increases intelligence through data analytics (Qi and Tao 2018). *Big data* and *artificial intelligence* can transfer intelligence to entities, models and *systems*, establishing autonomous cooperation and negotiation between physical and virtual spaces and enabling digital twin application on the shop-*floor* (Tao and Zhang 2018). Zhuang et al. (2018) developed this concept tracing the evolution of shop-*floor* production management and control strategies. According to the authors, four stages characterize the evolution. After a first passive data collection via paperwork and offline input, a second stage involves a *real-time* collection through IoT technology. Then, a *real-time system* should associate *real-time* physical data with the assembly shop-*floor* digital twin, opening the way to the third stage. This consists in the predictive management and control characterized by the applications of machine *learning*, artificial neural networks, data mining and other *big data*-related technologies, able to predict potential shop-*floor* production disturbance, product quality, status and behavior of equipment, and improve human-robot collaboration (Dröder et al. 2018): a new approach for product and process *optimization* and decision-making. Finally, the fourth stage of the evolution path of shop-*floor* production management and control strategies is the proactive management and control, i.e. the systems autonomous optimization and decision-making based on prediction results.

4.3. Product design and life cycle

Some keywords belonging to this cluster, namely *product design, product life cycle management,* and *product avatar,* outline a research stream in the digital twin literature that focuses on the product. Indeed, it is proven that the digital twin remains the virtual counterpart of its physical twin across the entire product life cycle (Haag and Anderl 2018). Digital twin deals with both static and dynamic *information,* the former regarding geometrical dimensions, materials, and processes, the latter referring to the *information* that changes with time along the *product life cycle* (Schroeder 2016.b). Digital twin can be applied to all three phases of a *product life cycle*, i.e., *product design,* product manufacturing and product service (Tao et al. 2018). The need for early and efficient evaluations of the consequences of concept materialization makes digital twin essential in the *design* phase (Schleich et al. 2017). Tao et al. (2018) identified three stages within digital twin-based *product design*, i.e. conceptual *design*, detailed *design*, and virtual verification. In the conceptual *design* stage, designers define the concept, while a digital twin provides them with huge amounts of required *information*, such as customer satisfaction, product sales, investment plans, and much more, all integrated into a single source. The detailed *design* stage defines product functions and appearance, product configuration, and *design* parameters. Behavioural attributes can be integrated into the shape by storing them within the *computer-aided design* model, which can then be used as an index for information (Miller et al. 2018). Digital twin supports this stage allowing repeated simulations in order to refine the product prototype. In the last stage, virtual verification, digital twin can exploit data regarding equipment, environment, physical characteristics as well as historical data to test the behaviour of the product and eventually propose corrective solutions.

Wuest Hribernik and Thoben (2014) focused on the amount of *information* required by the *design* phase. According to the authors, the *product avatar* should be built upon (i) *product life cycle management*, implying *information* continuity, (ii) intelligent products, using IoT technologies to collect real-time data, and (iii) collaboration of stakeholders to tailor the product serving as an *information management* tool.

4.4. Digital twin towards industry 4.0

The link between the latest industrial paradigm, such as *industry 4.0*, and the *digital twin* concept has gained interest in the *industrial research* community. Indeed, the cluster that connects these two topics is the one with more keywords' occurrences (Figure 5). The *industry 4.0* paradigm is characterized by the physical-virtual connection and by the cyber physical systems networking (Lee et al. 2015; Negri et al. 2017; Uhlemann et al. 2017), and the *digital twin* exploits the real-time synchronization of the input data coming from the field (Fumagalli and Macchi 2017; Uhlemann et al. 2017; Vachálek et al. 2017; Haag and Anderl 2018).

Within the *industry 4.0* environment, the system view and the interrelation between all the development phases is crucial and *simulation* is an essential tool (Boschert and Rosen 2016). Therefore, a modern *manufacturing process* calls for new *simulation* modelling paradigm concepts such as database integration and online *automat*ed modelling; *digital twins* connected through Ethernet/IP communication protocol, sensor technologies, and ERP/MES data and standards can provide this (Moreno et al. 2017; Rodič 2017). Moreover, the *digital twin* can *simulate* the entire process due to the ultra-high-fidelity virtual models (Qi and Tao 2018).

Besides, *industry 4.0* and *digital twin* can be linked in reference to the flexibility demand of the newest *automation* systems (Rosen et al. 2015). Flexibility can be achieved by *industry 4.0* autonomous systems that receive prior knowledge on the product and the production process from the *digital twin*. Moreover, *digital twin* information and models can be exploited by *simulations* in the action planning of the autonomous system; the *simulations* foresee the consequences of actions in given scenarios enabling autonomous decisions and increasing the systems' flexibility even more.

4.5. Cyber physical systems

An *embedded system* is defined as a computer system dedicated to specific functions and *embedded* in a complete device or system (Park, Zheng and Liu 2012). *Cyber physical systems* are an evolution of *embedded systems* in which networking can coordinate and integrate computation and physical processes; the network contains various *embedded systems* with computational components that serve to monitor, detect and activate physical elements (Park, Zheng and Liu 2012). Their ability to collect the information, monitor it from the physical space and synchronize it with the cyberspace often led literature to see *cyber physical systems* as the actualisation of *Industrial Internet* (Li et al. 2017). Moreover, due to the high connectivity, *cyber physical systems* act as *distributed* computer *systems,* characterized by decentralised control (Wang, Törngren and Onori 2015; Yun, Park and Kim 2017).

Most of the contemporary research about *cyber physical systems* focuses on the link between the *embedded systems* of the physical layer and the application layer (Alam and El Saddik 2017). In this context, digital twins can act as a bridge between the physical and the application layers for all the physical objects (Rosen et al. 2015; Gabor et al. 2016; Alam and El Saddik 2017; Schroeder et al. 2017; Leng et al. 2018).

The digital twin contains all the information needed for production in a *cyber physical system*, e.g., part ID and part type, production order number and priority, production workflow information, program files, production history (Rosen et al. 2015). It can manage all this information in real time and possibly recommend control actions for the physical environment

(Uhlemann, Lehmann and Steinhilper 2017; Leng et al. 2018). The joint adoption of digital twin and *cyber physical systems* is essential for the control of smart manufacturing and a research area is devoted to this topic (see Section 4.8). Literature also highlights specific aspects of their combination. For instance, Alam and El Saddik (2017) focused on the importance of digital twins for the cloud-based *cyber physical systems*, while Gabor et al. (2016) addressed their research to the possibility of implementing planning into a *cyber physical system* using digital twin through the so-called “simulation-based planning”.

4.6. IoT and digital shadow

Industrie 4.0, the German term for industry 4.0 (Hermann, Pentek and Otto 2016), reflects the shift of *manufacture* from the centralized mode to the distributed mode (Wan, Cai and Zhou 2015). In this context, the value creation process changes, advocating *internet of things (IoT)* to link production and sales (Wan, Cai and Zhou 2015; Schuh, Jussen and Harland 2018). *Internet of things* technologies carry out online collection of real-time data through RFID tags and readers, smart sensors, bar codes, wireless networks, sensor networks, and Ethernet. Moreover, internet of things technologies can be applied to the majority of contexts, ensuring the timeliness of data (Zhuang, Liu and Xiong 2018). The digital twin concept, in the sense of *digital shadow* (Schroeder et al. 2016; 2017; Uhlemann, Lehmann and Steinhilper 2017), provides a new solution for managing such data (Misra, Simmhan and Warrior 2015; Schuh, Jussen and Harland 2018; Zhuang, Liu and Xiong 2018). Combining *internet of things* with data from ERP and systems or service management systems generates a comprehensive set of data in real-time, while the *digital shadow* creates the preconditions for the accumulation of diverse data of the enterprise and creates a base for further analyses and applications working with that data (Schuh, Jussen and Harland 2018). Moreover, the literature links the concepts of internet of things and digital shadow also referring to humans. Humans are active participants of internet of things, serving as sensors and actuators, and digital shadow helps in managing digital identities of humans using “things” (Misra, Simmhan and Warrior 2015; Sarma and Girão 2009). Indeed, digital shadow contains uses, sessions and the required information about the endpoint devices in communication and service provision, becoming a projection of a virtual identity (Sarma and Girão 2009).

4.7. Immersive technologies in robotics

Research interest reflects what is happening in the industry. In recent years, the adoption of immersive technologies, such as *virtual reality* and *augmented reality*, have seen a considerable rise in *robotics* (Kuts et al. 2018; Petković et al. 2019). *Virtual reality* creates a digital world in which users can be immersed and can interact with the various entities (Oyekan et al. 2019) through *digital devices*, such as headsets (Joordens and Jamshidi 2018). *Augmented reality* overlaps digital content on the real world (Schroeder et al. 2016) by means of transparent glasses, tablets or smartphones (Schroeder et al. 2016; Petković et al. 2019). Their use contributes to advantages, such as testing, troubleshooting, remote co-working, pre-evaluation of machine launch, monitoring, control, and education (Kuts et al. 2018) and their exploitation is usually enabled by a digital twin (Schroeder et al. 2016; Joordens and Jamshidi 2018; Kuts et al. 2018; Oyekan et al. 2019; Petković et al. 2019).

Literature on this topic ranges from considering the coupling between digital twin and *virtual reality* or *augmented reality* to works in which all the three technologies are combined. Some works explain how *virtual reality* allows the creation and testing of new scenarios, while the digital twin of the *robot* helps in the development of characteristics in those scenarios such as the sensor and control system of the real *robot (e.g.* Joordens and Jamshidi 2018). On the other hand, other works focus on the ability of *augmented reality* to display real-time information accessing digital twin model data via web services (e.g. Schroeder et al. 2016).

An example of research in which all three technologies are combined is the study by Petković et al. (2019), which focused on safe, flexible robotized warehouses. In this study augmented reality is proposed in order to track worker motion inside the warehouse and to display valuable information, e.g., products to pick, or instruction for repairing robots, while virtual reality and digital twin are exploited to construct virtual warehouses with realistic simulations of worker interaction.

4.8. Control in smart manufacturing

According to Ding et al. (2019), *smart manufacturing* is the concrete embodiment of the recent production mode shift from mass production to mass individualization and the consequent transformation of production systems from automated to autonomous (Ding et al. 2019). However, Tao and Zhang (2017) recognized a challenge in achieving *smart manufacturing*, namely the merging of the physical manufacturing world and the virtual world, in order to realize smart interconnection, smart interaction, and smart *control*.

In this context, several works on *smart manufacturing* identify its key enablers in *cyber physical* systems and digital twin (see among others Ding et al. 2019; Leng et al. 2019; Tao and Zhang 2017; Uhlemann, Lehmann and Steinhilper 2017). In particular, several research works deal with their adoption to achieve *control*, a key activity in *smart manufacturing* (Zawadzki and Żywicki 2016). Each physical device in the system has a cyber part as its digital representation, leading to the digital twin models. So, the digital twin can monitor and *control* the physical object, while the physical object can send data to update and synchronize its virtual counterpart (Leng et al. 2019; Haag and Arlen 2018). This approach allows for *control of* the entire *process* and all the interfaces of parts *flow* and production progress in a transparent and real-time way (Uhlemann, Lehmann, and Steinhilper 2017; Ding et al. 2019). The parts *flow* and production *process control* driven by *cyber physical* systems and digital twin not only fulfil monitoring purposes but can also be applied to predict system behavior, enabling manufacturing optimization and improvement (Leng et al. 2019).

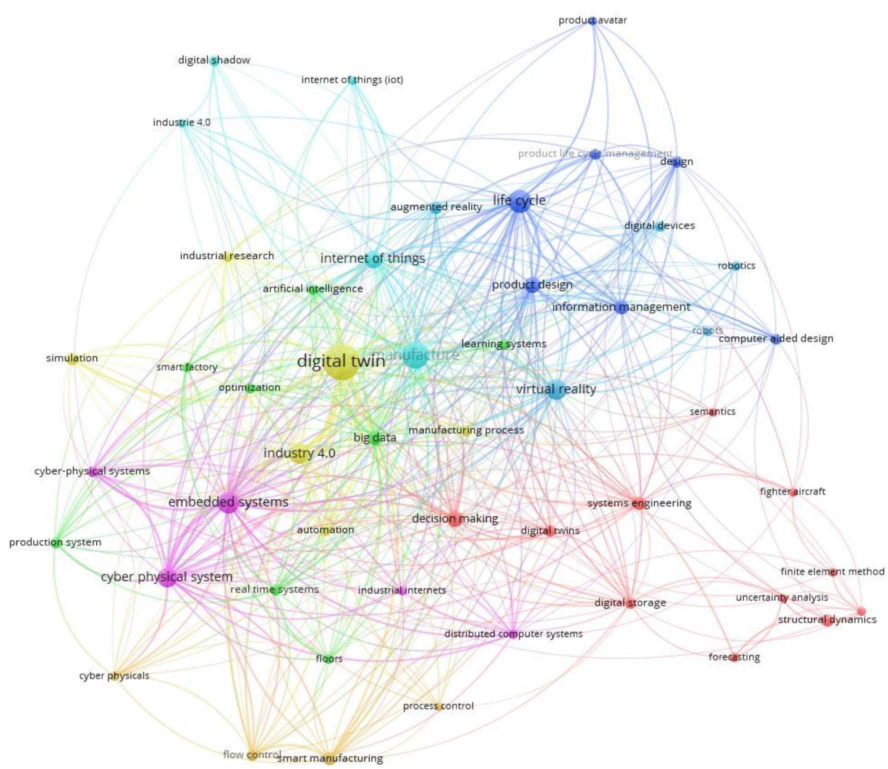

Figure 4. Keywords co-occurrence network

Table 3. Clusters of keywords

Digital twin for decision making	Big data in production systems	Product design and life cycle	Digital twin towards industry 4.0	Cyber physical systems	IoT and digital shadow	Immersive technologies in robotics	Control in smart manufacturing
decision making	big data	life cycle	digital twin	embedded systems	manufacture	virtual reality	smart manufacturing
systems engineering	learning systems	product design	industry 4.0	cyber physical system	internet of things	augmented reality	flow control
structural dynamics	artificial intelligence	information management	simulation	cyber-physical systems	digital shadow	digital devices	cyber physicals
digital twins	optimization	design	automation	distributed computer systems	industrie 4.0	robotics	process control
digital storage	real time systems	computer aided design	manufacturing process	industrial internets	internet of things (iot)	robots	
forecasting	production system	product life cycle management	industrial research				
aircraft	smart factory	product avatar					
fighter aircraft	floors						
finite element method							
semantics							
uncertainty analysis							

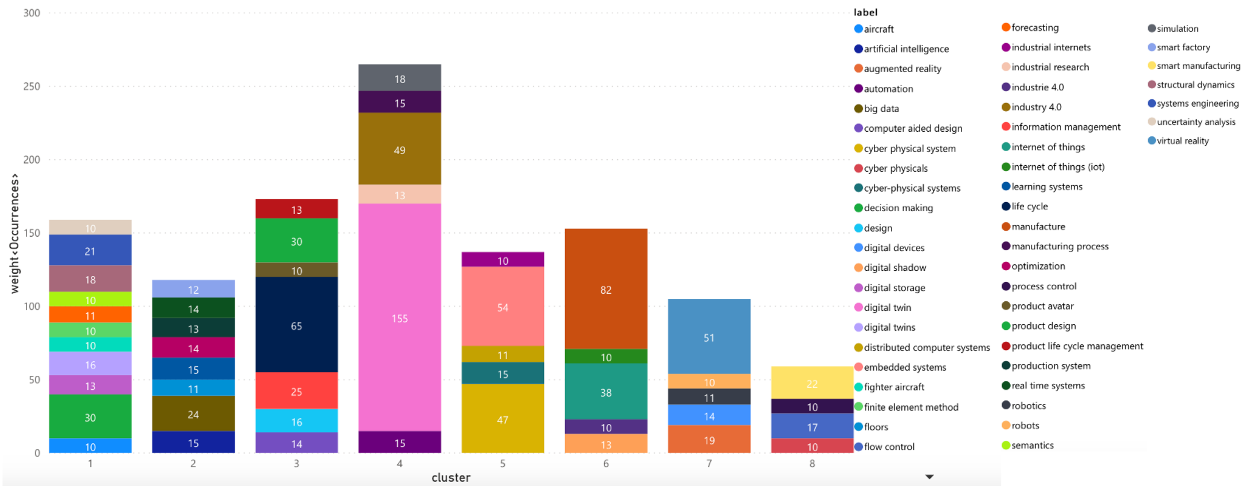

Figure 5. Representation of the weight (occurrence) of each keywords belonging to the eight clusters

5. Keywords burst detection analysis

Figure 6 depicts the temporal bar graph of Kleinberg's Burst detection, which provides insights into the popularity of keywords over time. The graph contains information about both the duration and the weight of a trend within the topic. Its analysis can confirm or add further information to what has emerged in the previous analyses of the citation network and of the keywords co-occurrence network. In particular, the latest trends can suggest future research directions.

The limited amount of scientific production between 2004 and 2011 (see Figure 1) is mirrored by the smallest bursts in the literature timeline. In addition, Kleinberg's Burst detection confirms the need for development of a conceptual basis, through the bursts of *shadow* and *avatar* (Figure 6), referring to digital twin synonyms *digital shadow* and *product avatar*.

The slight increase in the digital twin publications in 2012 (see Figure 1) is combined with a clear focus on the aircraft industry demonstrated by the bursts in the use of *airframe*, *aircraft* and *fleet* keywords. Indeed, the key paper by Glaessgen and Stargel (2012), addressing the shortcoming of traditional approaches to certification, fleet management and sustainment through the shift to the digital twin paradigm, was in fact published in 2012. In addition, the burst characterized by the highest weight is *dynam*, which can be linked to the keyword *structural dynamics*, adopted by articles and papers published in 2012. Besides the scope of the studies published in this year, this burst can be explained by the fact that four out of the eight original works published in 2012 were presented in the special session on the digital twin in the 53rd Structures, Structural Dynamics, and Materials Conference, all addressing aircraft issues. The bursts in this year confirm that the aircraft industry is the sector that has witnessed the real dawn of the topic, a context depicted by the keywords' cluster analysis. Moreover, the bursts of the keywords "*life"*, *which* started in 2012, and "*cycle*", in 2014, confirm the interest of research in studying the adoption of the digital twin concept along with the product *life cycle*, in accordance with Tao (2018).

Bursts that start in 2013 mirror the in-depth study of the implementation of the digital twin concept to the aircraft industry, through the focus on aircrafts physical issues. Parts of keywords depicted by Figure 6, such as "*composit*", "*materi*" and "*struct*", suggest the compound keyword *composite materials*, the main material implemented for aircraft *structural composites.* Issues in this context are represented by the parts of keywords "*crack*" and "*prop*", which can be understood as part of *fatigue crack propagation*, due to stress factors. These keywords are often associated with others such as "*damage detection*", for monitoring crack propagation, and "*Monte Carlo methods*", for its modelling, explaining the bursts "*damage*" and "*method*". Although these keywords are characterized by a sudden increase in use in 2013, they have been used together for describing research works in less than 10 cases; hence they are not detected by the VOSviewer keywords' clustering technique.

In accordance with the results of the citation networks and keywords clustering analyses, the sudden and high increase in the use of "*real"* and "*time"* can be detected in 2017 (Figure 6). These parts of keywords confirm the recent interest in real time systems, discussed in Section 4.2 and 4.6, in relationship with big data and IoT technologies.

In this context, the real time burst opens the way to the burst of the part of keyword "*industri*" in 2019, probably referred to the German name "industrie 4.0", a synonym of smart manufacturing (Strozzi et al. 2017). This last burst reflects the debate of digital twin adoption towards the newest industrial paradigms, discussed in Sections 3.1 and 4.4, commenting the works by Bao et al. (2018), Durão et al. (2018), and Zhang et al. (2017) and the fourth keywords' cluster.

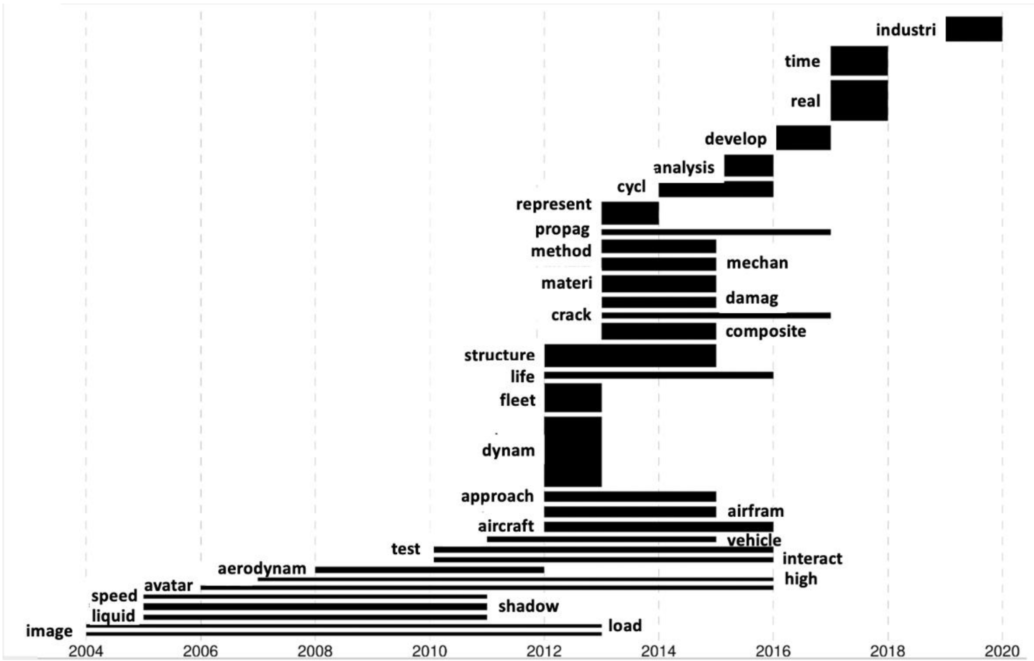

Figure 6. Keywords bursts temporal graph

6. Discussion

Answers to research questions can be given based on the analyses considering the citations and keywords used to characterize the research works. A synthesis of the elements discussed is presented in Table 4.

Table 4. Outcomes of the performed analyses

<table>
<tr><th colspan="2">Citation network analysis</th><th rowspan="2">Keywords' clusters analysis</th><th rowspan="2">Burst detection analysis</th></tr>
<tr><th>Main path analysis</th><th>Total citation score</th></tr>
<tr><td rowspan="4">Initial consolidation through conceptual models and frameworks</td><td rowspan="4">Rosen et al. (2015) (digital twin importance for autonomous systems)</td><td>Digital twin for decision making</td><td rowspan="4">Aircraft issues (until 2014)</td></tr>
<tr><td>Big data in production systems</td></tr>
<tr><td>Product design and life cycle</td></tr>
<tr><td>Digital twin towards industry</td></tr>
</table>

		4.0	
Subsequent exploration of new digital twin adoption, especially Digital twin as enabler of industry 4.0	Tao et al. (2018) (digital twin for product design, manufacturing and service)	Cyber physical systems	Real time systems (2017-2018)
		IoT and digital shadow	
		Immersive technologies in robotics	Industry 4.0 (from 2019)
		Control in smart manufacturing	

6.1. RQ1: What are the main contributions to the research on digital twin and what do these contributions address?

The development trajectory outlines the need for consolidation of the knowledge base and the exploration of new frontiers of digital twin. The consolidation issue is addressed by Wärmefjord et al. (2017), Schleich et al. (2017), Zhang et al. (2017), Liu et al. (2018), Durão et al. (2018), Bao et al. (2018) and Tao et al. (2018), who develop models and frameworks to answer the requirements for digital twin adoption. The new frontiers are presented by Jo et al. (2018), Preuveneers et al. (2018), Zambal et al. (2018), Zheng et al. (2018), Yun et al. (2018) Zhuang et al. (2018), Mukherjee and DebRoy (2019), Taylor et al. (2019). In these works, the digital twin is linked to new applications (e.g. agriculture and materials) and to the technologies of smart production driven by industry 4.0. Moreover, the use of digital twin for product design, manufacturing and services represents a central contribution to the development of the field. Besides, the representation of digital twin as an enabler of autonomy in manufacturing is central to recent developments in research (Rosen et al. 2015).

6.2. RQ2: What are the topics the digital twin concept has been related to and what is the importance of smart industrial systems among them?

With reference to RQ2, the interest of research in the application and link of the digital twin concept to decision making, big data, product design, and life cycle, industry 4.0, cyber physical systems, IoT and digital shadow, immersive technologies in robotics and control in smart manufacturing is detected. Among the identified topics, a strong link between the concept of digital twin and elements of smart industrial systems (big data, industry 4.0, cyber physical systems, IoT and smart control) emerges. Literature is paying close attention to linking big data and digital twin, key enablers of the recent concept of smart manufacturing and smart factory (Qi and Tao 2018; Jeon and Suh 2018). Industry 4.0 and digital twin can be linked to the achievement of flexibility in responding to demand from smart industrial systems (Rosen et al. 2015). Moreover, digital twin has recently been studied as acting as a bridge between the physical and the application layers for all the physical objects (Rosen et al. 2015; Gabor et al. 2016; Alam and El Saddik 2017; Schroeder et al. 2017; Leng et al. 2018), i.e. the focus of cyber physical systems (Alam and El Saddik 2017). The interest of research in combining IoT with data from ERP and systems or service management systems is in generating a comprehensive set of data in real-time, while the digital twin creates a base for further analyses and applications working with that data (Schuh, Jussen and Harland 2018). Moreover, literature about smart manufacturing identifies its key enablers in cyber physical systems and digital twin (see among others Ding et al. 2019; Leng et al. 2019; Tao and Zhang 2017; Uhlemann, Lehmann and Steinhilper 2017). Their combination allows for the control of systems in a transparent and real-time way (Uhlemann, Lehmann, and Steinhilper 2017; Ding et al. 2019). Thus, the importance of digital twin-enabled smart industrial systems in the research is clearly identified in the literature.

Among the industry 4.0 technologies, additive manufacturing does not appear within the list of keywords constituting the clusters and thus seems to be overlooked by research on the link between digital twin and smart technologies. However, the keywords constituting the network analyzed in this work may be limited and may not cover all the existing topics that have been addressed. As it does not meet the co-occurrence requirements, the research developed on additive technologies turns out to be underrepresented within the body of knowledge and represents a possible area for further study.

6.3. RQ3: What have been the trends in research on digital twins and what are the recent research streams?

With reference to RQ3, two main trends in research on digital twins can be identified. A strong and renewed focus on aircraft issues and features characterizes the papers and articles up to 2014. Recent interest is detected in modelling and realizing real time systems, i.e., smart industrial systems. The latest direction of research is represented by industry 4.0, the set of technologies known as a synonym of smart manufacturing (Strozzi et al. 2017). The digital twin-enabled smart industrial systems represent a clear research area for future development of the concept of digital twin. Indeed, as the achievement of smart industrial systems is needed more and more in order to compete in the market by adopting flexible industrial systems meant to respond quickly to unexpected events (Morgan and O'Donnell 2017), the identification of the proper management of industrial systems for flexibility is gaining more attention. In this context, the attractiveness of the combination of the digital twin concept and industry 4.0 technologies becomes essential.

7. Conclusions

The digital twin concept has proven to be a topic of central interest for research, and this study represents an attempt to outline the existing body of literature on this subject, clarifying its relationship with the recently emerged concept of smart industrial systems. The adopted methodology, i.e., quantitative bibliometric analyses based on citations and keywords, has allowed for the outline of interest in studies. From these analyses, the identification of research trajectories, central issues, reference studies, and of recent and future research streams has been obtained.

This study contributes to the body of knowledge through the analysis of the evolution of this field of research and identification of works that have studied it, most recent research trends, and an underrepresented topic, that could represent a direction for future research work. Concerning the applied methodology, considering both citations and the author and indexed keywords has offered some benefits. While citations provide a view of the main contributions to the evolution of the field, i.e., a link between main topics covered, the keywords give details on how the topics and issues have been debated and the areas of application. Moreover, their bursts over time provide insights into the temporal evolution of interest over time, identifying the rise of research streams through the detection of a sudden increase in the use of keywords.

In particular, the analysis of the main path of the citation network highlighted that in the last two years the scientific production regarding the topic is experiencing, on the one hand, the attempt to consolidate the topic through frameworks and reference models, on the other hand, the investigation of new possibilities for digital twin adoption, such as agriculture and materials, and its link with industry 4.0. This latter part of the development trajectory of the topic suggests that future works should update the results obtained by the former part. Therefore new frameworks and reference models should be formalised to grasp the role of and/or the way to adopt digital twin in the latest suggested contexts.

The keywords analysis identified eight clusters representing the research areas and clarified the focus that research on digital twin had led to so far. Moreover, the burst detection of the keywords identified the latest research trends in industry 4.0 and real time systems. In fact, six out of the eight clusters contain keywords referring to industry 4.0, smart manufacturing, or specific industry 4.0 technologies, and the cluster with more keywords' occurrences is the cluster 4, that links industry 4.0 paradigm and digital twin (Figure 5). Future works could investigate further the adoption of digital twin and industry 4.0 features and technologies concerning the two remaining research areas, i.e., decision making and product design and life cycle.

As a practical contribution, this study clarifies the importance of digital twin in realizing smart industrial systems, identifying, in particular, the role of digital twin in the realization of real-time systems and the combination of digital twin and industry 4.0 technologies as the latest opportunities and research directions. Indeed, the literature identifies in the digital twin a prerequisite of the cyber-physical production system, a core element of industry 4.0. Moreover, literature draws attention to the link between digital twin and big data, IoT systems, and immersive technologies, some of the industry 4.0 pillars.

However, additive technologies are an underrepresented topic among the industry 4.0 technologies. Indeed, even if the trajectory development of the topic demonstrates the interest in studying the interrelation between digital twin and new materials and 3D printings, this topic is missing in the keywords' clusters, suggesting that more industrial research and applications should be conducted to allow further contributions.

A limitation emerges as this study is based on the citations and co-occurrence of keywords that may be not completely representative of the importance of references and topics within the body of knowledge.

Despite this limitation, the value of this work is in how the citations and co-occurrence networks can be exploited as a research tool to support the dynamic analyses of research on a concept and for drawing up agendas to promote developments in further research.

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