TRENDS AND PROSPECTS OF DIGITAL TWIN TECHNOLOGIES: A REVIEW

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Abstract. The plethora of technologically developed software and digital types of machinery are widely applied for industrial production and the digitalization of building technologies. The fourth industrial revolution and the underlying digital transformation, known as Industry 4.0 is reshaping the way individuals live and work fundamentally. However, the advent of Industry 5.0 remodels the representation of industrial data for digitalization. As a result, massive data of different types are being produced. However, these data are hysteretic and isolated from each other, leading to low efficiency and low utilization of these valuable data. Simulation based on the theoretical and static model has been a conventional and powerful tool for the verification, validation, and optimization of a system in its early planning stage, but no attention is paid to the simulation application during system run-time. Dynamic simulation of various systems and the digitalization of the same is made possible using the framework available with Digital Twin. After a complete search of several databases and careful selection according to the proposed criteria, 63 academic publications about digital twin are identified and classified. This paper conducts a comprehensive and in-depth review of this literature to analyze the digital twin from the perspective of concepts, technologies, and industrial applications.
Keywords: *digital twin, smart infrastructures, digital asset management, literature review*

Introduction

The fourth Industrial Revolution (Industry 4.0) framework indicates the creation and intersection of advanced technologies, such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), cloud computing, and digital twins, which are pervasive. These technological advancements are critically required for efficiently improved systems that reduce human imperfections and mediation (Nguyen et al., 2022). Over the last decade, the terms physical internet (PI), digital twin (DT), and their related innovations have gained much attention among scholars. PI is defined as a seamless global logistics and distribution infrastructure incorporating physical objects (e.g., sensors) and interfaces to digitally interconnect (Kamble et al., 2022). It is expected to help overcome the inefficiencies of the current logistics paradigm in the global volatile market context (Brenner and Hummel, 2017). Indeed, significant efforts have been made to explore various applications and advanced techniques of PI in transportation and distribution aspects such as material handling systems (Govindaraju and Putra, 2016; Hozdić, 2015; Rosen et al., 2015), interconnected modular containers (Tao et al., 2019), informational dimensions of PI-container (Sallez et al., 2016), and auction logistics (Kong et al., 2016). Its applications are also reaching the operations of well-known firms such as Amazon, UPS, and FedEx (Delbrügger et al., 2017). *Table 1*, identifies selected definitions of digital twin from cited publications, and the corresponding citation keywords.

***Table 1**. Definition of digital twin in journal article publications.*

S/N	Citation	Definition of digital twin	Keywords
1	Shafto et al. (2012)	A digital twin is 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.	Integrated simulations
2	Hochhalter et al. (2014)	A digital twin is a life management and certification paradigm whereby models and simulations consist of as-built vehicle state, as-experienced loads and environments, and other vehicle-specific histories to enable high-fidelity modeling of individual aerospace vehicles throughout their service lives.	Fidelity modeling
3	Söderberg et al. (2017)	Very realistic models of the current state of the process and their behaviors in interaction with their environment in the real world–typically called the “Digital Twin”.	Realistic model
4	Grieves and Vickers (2017)	Digital twins are 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.	Virtual substitutes
5	Bruynseels et al. (2018)	The term digital twin can be described as a digital copy of a real factory, machine, worker, etc., that is created and can be independently expanded, automatically updated as well as globally available in real-time.	Digital copy
6	Schluse et al. (2018)	Faster optimization algorithms, increased computer power, and the amount of available data can leverage the area of simulation toward real-time control and optimization of products and production systems-a concept often referred to as a Digital Twin.	Real-time control and optimization
7	Leng et al. (2019)	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.	Virtual information
8	Zhou et al. (2021); Zhou et al. (2020)	Digital Twins stand for a specific engineering paradigm, where individual physical artifacts are paired with a digital model that dynamically reflects the status of those artifacts.	Dynamic reflection
9	Kaewunruen and Lian (2019); Kaewunruen et al. (2018); Kaewunruen and Xu (2018)	A digital twin is a one-to-one virtual replica of a “technical asset” (e.g., machine, component, and part of the environment).	Virtual replica
10	Xu et al. (2019)	The digital twin model is an exact and real-time cyber copy of a physical manufacturing system that truly represents all of its functionalities	Cyber copy
11	Zhou et al. (2021); Zhou et al. (2020)	DT is a multi-domain and ultrahigh fidelity digital model integrating different subjects such as mechanical, electrical, hydraulic, and control subjects.	Fidelity model
12	Leng et al. (2019)	Digital twin represents a dynamic digital replica of physical assets, processes, and systems, which comprehensively monitors their whole life cycle.	Dynamic replica
13	Luo et al. (2019)	This rich digital representation of real-world objects/subjects and processes, including data transmitted by sensors, is known as the digital twin model	Digital representation
14	Wang et al. (2019)	Digital Twin is essentially a unique living model of the physical system with the support of enabling technologies including multi-physics simulation, machine learning, AR/VR and cloud service, etc.	Living model
15	Ojolo et al. (2010)	The technology accesses realistic models of the current state of the process and their behaviors in interaction with their environment in the real world are called the “Digital Twin”.	Dynamic representation realistic model
16	Madni et al. (2019)	A digital twin is a virtual instance of a physical system (twin) that is continually updated with the latter’s performance, maintenance, and health status data throughout the physical system’s life cycle.	Updated virtual instance
17	Leng et al. (2019)	DT refers to a virtual object or a set of virtual things defined in the digital virtual space, which has a mapping relationship with real things in the physical space.	Mapping
18	Fotland et al. (2020)	DT is defined as a digital copy of a physical asset, collecting real-time data from the asset and deriving information not being	Real-time data

		measured directly in the hardware.	
19	Wang et al. (2019)	A digital twin can be regarded as a paradigm using which selected online measurements are dynamically assimilated into the simulation world, with the running simulation model guiding the real world adaptively in reverse.	Dynamic, bidirectional

Results and Discussion

Digital twin technologies in additive manufacturing

The Fourth Industrial Revolution (Industry 4.0) is a strategic vision toward the use of sensors, data analytics, and automation, to streamline and optimize manufacturing processes (Tao et al., 2018). Smart Manufacturing has emerged from Industry 4.0 as a key concept to imbue automated manufacturing processes with machine intelligence; real- time data monitoring, planning, control, and optimization (Kusiak, 2019). These concepts very much intersect with each other, with the digital twin as one of the key enabling tools. Digital twins are generally applied at two different scales: the enterprise management scale as commonly seen in Industry 4.0/ Smart Manufacturing frameworks (Hozdić, 2015) and the individual asset scale (Macchi et al., 2018; Schleich et al., 2017). Most of the conceptual and generic frameworks for Industry 4.0 focus on the enterprise scale, which provides a simulated replica of the manufacturing process, factory, operations, and related logistics (Macchi et al., 2018; Tao et al., 2018). The large-scale nature of these twinned systems has led to the development of hierarchies that explain how smaller units of the digital twin compose together from the component level to the factory level, to the operations level, and finally to the enterprise management level. Examples of such a hierarchy are the automation pyramid (Alcácer and Cruz-Machado, 2019; Govindaraju and Putra, 2016). At the enterprise management scale, hierarchical frameworks have been proposed for large-scale data management of a distributed metal Additive Manufacturing (AM) system, to improve product quality and production efficiency (Liu et al., 2020); or toward a methodical approach for metal AM design, printing, and validation (Bonnard et al., 2019).

In contrast, at the asset scale, a digital twin simulates the complex physics of an individual system such as a robotic arm or spacecraft, to predict, maintain and control the system. Hierarchies have also emerged at this scale to distinguish a digital twin's modelling, sensing and control capabilities (Madni et al., 2019; Kritzinger et al., 2018). This review paper focuses on reviewing and formulating an asset scale digital twin hierarchy specific for metal additive manufacturing (AM). Metal AM's sensitivity to small process changes can have a significant impact on mechanical performance (Gong et al., 2015; Wycisk et al., 2014), which in many cases is unacceptable for biomedical or aerospace applications (Liu et al., 2020; Lowther et al., 2019). Reviews on the processing science of metal AM underscore the complexity of multiple processing parameters and the need for quality control (Sames et al., 2016). Part qualification often relies on the interrogation of an exhaustive design of experiments to identify optimal machine parameters (Chen et al., 2021; Zhang et al., 2021; Zhou et al., 2021; Yong et al., 2020), or the use of post-build Computed Tomography (CT) scans or micrograph imaging (Mindt et al., 2018). Early conceptualizations of metal AM digital twins were initially proposed to address this heavy reliance on trial-and-error.

Challenges and future works

Although Digital Twin (DT) is a revolutionizing technology of industry 4.0 to test new systems before manufacture, improve efficiency and productivity, forecast the future behavior of the systems, buildings, and infrastructures, and provide better service, still there are challenges regarding the use of these models in real cases. As part of Industry 4.0, developing methods for the application of DT models for some industrial applications and domains particularly production, predictive maintenance, and after-sales services is still in its infancy. Many kinds of literature consist of papers with conceptual frameworks with very few case studies and detailed methodologies. However, some applied case studies already exist in the literature (Zhou et al., 2020). Although it is challenging, data processing architectures are still in their infancy, and the development and implement the DT models in real cases is still ongoing though with promising gains. Therefore, further research needs real case studies in developing methods to implement DT in industrial environments to enhance its possible roles in industrial operations. Regarding implementation, construction, understanding, and control of the machine with an accurate multiscale DT model of work-in-process are still challenging because the real-time changes during the machining process are hard to be perceived and simulated. These challenges can be solved through the continuous fusion of manufacturing technologies and new-generation information technologies (Kritzinger et al., 2018).

These days, the focus is given to the realization of DT models on specific products and machines instead of the whole manufacturing system. Other challenges in the implementation of the DT models include insufficient possibilities for synchronization between the physical and the digital world, the missing of high reliability for simulation models and virtual testing on different scales, the difficulties in the prediction of complex systems, as well as the challenges with gathering and processing large data sets (Schleich et al., 2017). Moreover, challenges related to enormous data collection, model creation, lack of awareness of the model and methodology, and resistance companies to change are still unsolved issues in the realization of DT models (Lohtander et al., 2018). More disputes on the applications of DT have been indicated by manufacturers including high cost and data security questions (Kunath and Winkler, 2018). The data acquisition problem is another challenge in the realization of DT models in small and medium-sized companies to fulfill the real-time requirements for DT applications. Moreover, now days missing standardization is a big issue that should be solved to implement DT across companies. Therefore, these problems are believed to be the main reason behind the slow adaptation of DT technology by companies. Therefore, still, there is further research that needs to develop standards and improve methods for DT modeling that can be used in real- case applications to extend its role in industrial operations. Moreover, intensive research works are expected on feasible solutions to adapt the DT models in complex manufacturing systems.

Review of different trends in digital twin

Tao et al. (2019) proposed the Correlation and Comparison between Digital Twins and Cyber-physical Systems (CPS) towards Smart Manufacturing and Industry 4.0. The method proposed discussed the origin and evolution of CPS and DTs from traditional IT to new IT transforming existing manufacturing systems and business models. Both CPS and DTs form a closed loop between the cyber/digital and physical worlds based on state sensing, real-time analysis, scientific decision-making, and precise execution, but a DT provides a more intuitive means of improvement in engineering. CPS implements sensors and actuators as its main modules, while DTs follow a model-based systems-engineering approach that emphasizes data and models. CPS and DTs were further compared and correlated based on Origin, Development, Category, Composition, etc. The result identified the similarities and differences between CPS and DTs, as promising technologies that emphasize cyber-physical integration. The key features of the development of the digital twin were recently presented (Neto et al., 2021). The method proposed consists of two phases. The initial phase addressed the execution of a literature review; the last phase addressed the expert interviews. The literature review began with a parameterized search to identify potentially relevant documents in a comprehensive academic database. Next, a filtering process was executed, in which the identified documents were evaluated to reach a final portfolio for content analysis. Lastly, to retrieve insights from the gathered documents, an analysis of content was carried out to identify key features of manufacturing digital twins. A wide range of logical search operators enabled the execution of a more precise search query, reducing the efforts spent during filtering.

Ante (2021) presents the studied overview of the intellectual discourses of DT Research. The proposed method objectively identifies explorative factor analysis, seven strands of research. These comprise DT as the paradigm for the virtual representation of real systems, DT for manufacturing processes and human-robot collaboration, Cyber-physical systems for coordination between physical and computational elements, Industry 4.0 for the automation of manufacturing and industrial practice, relationship extraction and matching in a social manufacturing context, advances in computing and communication technologies and optimization of geometrical variation in spot welding sequences. Seven scientific discourses were identified using empirical co-citation analysis, which represents 62% of the research environment. Research streams and their high-impact publications are described and their prevalence over time is presented. The results show that DT is being considered in the face of various scientific themes, most of which fit under the scope of Industry 4.0 or smart manufacturing. In Karagiannis et al. (2020), iterated the architecture for emotions-aware digital twins was proposed for manufacturing. The method proposed imbibes an architecture that would allow humans to keep the locus of control by better comprehending, communicating relevant data, and promoting situational awareness. Background of manufacturing systems adopts emotion theories such as the Neurological approach, Conditioned response theory, appraisal theory, and Thayer’s emotion which uses multiple scales for classifications. The emotion-awareness capability allows DTs to respond better to industry needs and requirements of manufacturing enterprises of the future, contributing to improved information delivery, ergonomics, professional development, and other application at the enterprise scale. The emotional state affects the speed of perception and decision-making and improves the delivery of visual information. This work can contribute to the reduction of hazardous situations on the production floor, increase product quality, and facilitate innovation and creativity in design tasks.

Shao and Helu (2020) present the synthesis of different perspectives on the digital twin to understand its framework in manufacturing. The method proposed to differentiate the digital twin from traditional notions of modeling and simulation. Assessment of the scope and constraints of a digital twin framework depends on factors such as Application, Viewpoint, and Context. The method highlighted the potential of digital twin usage at all levels of manufacturing (e.g. machine, cell, line, facility, or supply chain). A standardized framework can help enable manufacturers to leverage digital twins for decision-making and control by providing the means to navigate the complex set of standards, technologies, and procedures that can be used for implementation. The goal of the framework study is to provide a generic development framework for the use of digital twin in manufacturing that can be instantiated for case-specific implementations. Four parts have been proposed for the standard: (1) overview and general principles, (2) reference architecture, (3) digital representation, and (4) information exchange. The integration of Cyber-physical Systems and Cyber-physical power systems was published in (Kunath and Winkler, 2018). The method proposed describes Decision Support System (DSS) as one major element which is an automatic model generator that builds simulation models, using information from the Digital Twin of the manufacturing system. The manufacturing system is subdivided into the manufacturing equipment system, the material flow system, the value stream system, the operating materials system, and the human resource system. Each element of each subsystem of the manufacturing system is represented in the information world and linked to its physical element by the information system. Using intelligent and self-learning search algorithms, the decision support system can improve the overall performance of a company and the whole supply chain. Integration of the Digital Twin of the manufacturing system into a decision support system will improve the order management process. Until now, only a few companies are using technologies for the identification and localization of products, machines, and especially workers. The reasons are the supposed high costs and unsolved questions regarding data security. The method achieved implementation of the Digital Twin with dynamic simulation-based scheduling, dynamic calculation of delivery dates, and pricing.

Coronado et al. (2018) present the development and implementation of a new Manufacturing Execution System (MES) powered by android devices and cloud computing tools. The method proposed that CPS along with cloud computing, web apps, mobile devices, sensors, and Digital Twins contribute to MES. The shop floor digital twin components include both machinery and discrete sensing devices which transmit data to the cloud platform using MTConnect; and tooling, products, materials, and people, whose information is supplied directly to the cloud platform using the MES. The combination of MES and MTConnect data can enable not only the evaluation of machine efficiency but can also provide a means to analyze the state of a part as it moves from raw material to final product. While the MTConnect capability of a machine can provide a wealth of valuable process information, some data are either not collected by the machine or not supported by the MTConnect standard. The web app provides access to a table with more details on each piece of material, such as supplier and bar diameter. The visualization updates each 500 ms to reflect any changes in material availability or procurement. The Design and development of qualitative and quantitative evaluations of the advantages of a synchronized digital twin for the reconfiguration of a manufacturing system were recently published (Talkhestani et al., 2020). The proposed method explained by the Anchor-Point- Method is a method to synchronize the anchor points of a DT in domain mechanic, electric, and software. To synchronize the models of the DT, the Anchor-Point Method consists of three phases with seven steps, which can be applied in an assistance system. The first phase, automated change detection, consists of three steps. First, the Programmable Logic Controller (PLC) code of the system at the reference point and the current version is uploaded from a repository. The second and third steps of the sequence diagram describe the formalization and abstraction of the PLC code based on a central control software metamodel.

Rasor et al. (2021) present the development of a specification technique that combines Model-Based systems engineering with Product Life-cycle Management. The proposed method and language are used to serve as a guideline and support for the requirements definition and architecture design of DTs. The process consists of 3 phases. The first phase (macro-level) identifies the use cases of the DT in a value chain network, and the second phase (micro-level) sequentially formalizes and details the identified use cases from abstract to concrete. The final phase consolidates the DT use cases. The result analyzes the feedback from the application workshop and integrates suggested improvements and finally examines the usability of the specification technique in a broad network of industrial suppliers. Singh et al. (2021) proposed the development of an Information Management Framework (IM-Framework) for DT in aircraft manufacturing. The proposed method studies the integration of IM for DT. Challenges of big data, information sharing & organization, and scalability for DT are discussed in the IM context. The existing ways of managing an industrial asset show the different dependencies and constraints that DT may put on the overall system. The proposed IM framework is constructed based on four IM phases. With the understanding of IM phases and information flow, a multi-layered framework is proposed based on common requirements from IM & engineering views. Further, a case study for aircraft structure damage tolerance has been formalized for the framework. The cost of development and maintenance as well as scalability must be driven by both economic and business models. The framework targets mainly to support DT development activities in the manufacturing and in-service phases of the aircraft life-cycle. It is also targeting to support some design feedback loop DT development activities with some calibrations.

Jiang et al. (2021) reviewed articles in the civil engineering sector to clarify the ambiguity related to Building Information Modelling (BIM) and Cyber-physical systems. The proposed method reviewed 468 articles on the Digital Twin to clarify whether it is being misinterpreted as BIM or CPS. The research includes a two-step literature review to define the DT and its constituents based on a first-round review. The method classified the papers and their keywords using labels from the list of DT constituent's i.e. physical parts, and virtual parts. The method also reviewed 134 papers related to DT in the civil engineering sector out of 468 papers in detail. DT promotes smart construction. When virtual models are connected with target physical parts in BIM applications or CPS applications, when making corresponding 3D models for target physical parts, DTs usually emerge. The paper after reviewing 134 articles put out an appropriate definition for the DT and differentiates a DT from BIM and CPS mainly based on the physical part, virtual model, connections between physical and virtual models, and the twin relationship between the physical part and the virtual model. DT can be applied to buildings, facilities and equipment, and construction sites from the physical part perspective. Sacks et al. (2020) proposed the development of a DTC information system workflow including information stores, information processing functions, and monitoring technologies. The proposed method builds on existing concepts of Building Information Modeling (BIM), lean project production systems, automated data acquisition from construction sites and supply chains, and artificial intelligence to formulate a mode of construction that applies digital twin information systems to achieve closed-loop control systems. The method develops the core concepts for the development and implementation of a data-driven planning and control workflow for the design and construction of buildings and civil infrastructure that is founded on digital twin information systems. The result derived a coherent, comprehensive, and feasible workflow for planning and controlling of design and construction of buildings and other facilities using digital twin information systems.

Ito (2019) reviewed Digital Twin as an advanced fusion of technology from cyberspace (virtual space) and physical space (real space). The proposed method discussed in "Society 5.0" is based on a system that highly integrates cyberspace and physical space (i.e, real space). Society 5.0 is a concept proposed as the target at which future society should be aimed. Industry 4.0, a concept from Germany, notes the importance of establishing a Cyber- physical system (CPS) in which cyberspace and physical space are deeply linked to each other; hence, it can be said that this concept is similar to Society 5.0. The result realized that a Digital Twin requires reproducing a sophisticated digital building model in a virtual space and using it to simulate complex physical phenomena that may occur in the real world with high accuracy and high calculation speed. The development of a dynamic digital twin model using the Cambridge Campus as a case study was published (Qiuchen Lu et al., 2019). The proposed method presents system architecture for developing dynamic DTs at building levels this architecture is brought to life through the development of a dynamic DT demonstrator of the West Cambridge site of the University of Cambridge. Specifically, this demonstrator integrates an as-is multi-layered IFC Building Information Model (BIM), building management system data, space management data, real-time Internet of Things (IoT)-based sensor data, asset registry data, and an asset tagging platform. The demonstrator also includes two applications: (1) improving asset maintenance and asset tracking using Augmented Reality (AR); and (2) equipment failure prediction.

Delbrügger et al. (2017) proposed the framework development of a Building Information Model detailing 3D geometry and semantic annotations for Digital Twins of Factories. The proposed framework adopted the use of a small set of different IFC data and is the first published uniform navigation approach that combines Building Information Models, additional dynamic interior equipment, the environment outside, and different movement types. An evaluation of public toilet ventilation design schemes through a digital twin was recently published (Bao et al., 2022). The proposed method seeks to determine the most effective scheme for reducing indoor pollutant concentrations using Autodesk Revit to create a digital twin BIM of different ventilation systems. The method simulated the diffusion of pollutants in these models using computational fluid dynamics (CFD)-based methods and used DesignBuilder to simulate building energy consumption. The experience of architectural designers is often vague and difficult to grasp, so this experience is difficult to use as the basis for accurate judgments. The airflow of different ventilation systems was simulated to verify the accuracy of the computational model simulation. Kaewunruen and Xu (2018) reviewed DT for railway station buildings using a Revit-based simulation of construction work with a specific BIM application for King’s Cross station in London. The proposed method highlights the adoption and transformation of the 3D model of the King's Cross station building into a 6D building information model. The 6D model contains a time and cost schedule with carbon emissions calculation, and renovation assumptions using Revit. The method seeks to understand BIM and BIM tools, 3D modeling of King's Cross station building via selected software, information modeling simulation including schedule, cost estimation, carbon emissions, and renovation simulation.

Zhang et al. (2021) studied the expansion of the digital twin in building life cycle management. The proposed method explored the benefits and shortcomings of DT in buildings implementation. In four rounds of experimentation, more than 25,000 sensor reading instances were collected, analyzed, and utilized to create and test a limited digital twin of an office building facade element. Using a test bed, the method collected data and created a WSN that was installed on the building facade to collect light, ambient temperature, and relative humidity measurement data of the environment. The result pointed out the method of implementation, highlight the benefits gained from the digital twin, and uncovered some of the technical shortcomings of the current Internet of Things systems. The development of emerging technologies facilitating the evolution of BIM to Digital Twins in built environment applications was recently reviewed systematically (Deng et al., 2021). The proposed method reviewed a total of 123 relevant journals and court proceedings and developed a five-level ladder categorization system based on the building life cycle to reflect the current state-of-the-art in Digital Twin applications. In each level of this taxonomy, applications were further categorized based on their research domains (e.g., construction process, building energy performance, indoor environment monitoring). Prior studies have not fully exploited or realized the envisioned concept of the Digital Twin. Based on the analysis of the reviewed work and the trends in ongoing research, the authors propose a concept of an advanced Digital Twin for building management as a baseline for further studies.

La Russa and Santagati (2020) investigated the application of the DT approach to get Sentient buildings to perceive external inputs and support management and conservation. The proposed method foresees the integration of an H-BIM model with a DSS based on AI for the management of museum collections in historical architectures and addresses the management of the thermo-hygrometric conditions for the preventive conservation of museum collections in buildings with high historical value. The method modeled the whole building, gathered meteorological data, analyzed and labeled data, and trained and validated the ML algorithm. The method achieved the 3rd level of maturity according to Evan's definition. Shirowzhan et al. (2020) reviewed scholarly articles covering “lean” and “BIM” concepts in construction. The proposed method acquired journals from Scopus and filtered 48 journals using thematic analysis to synthesize and compare the qualitative data aiming to identify important recurring themes. Network analysis was carried out to identify the bibliometric network of co-authorship and the relationship of co-occurrence of keywords within the data set. Expert opinions were also gathered to verify the findings of the current systematic review. The result showed that the interaction between lean and BIM has not been documented before 2009. The shift in themes and discussions in the early years of the last decade (2010-2013) and the last three years of the decade (2018-2020) were compared. Findings revealed a large synergy between lean and BIM in control interactions and reduction in variations. Macchi et al. (2018) reviewed and analyzed the development of state-of-the-art research and industry standards that impact BIM and asset management within the operation and maintenance phase. The method proposes the hierarchical architecture of the DT-enabled asset management framework. Four aspects of requirements, intelligence, efficiency, integration, and interoperability were considered for the successful implementation of DT-enabled asset management. DT and AI-supported decision-making systems would highly improve the intelligence and integration of the whole system.

Conclusion

This research forms a literature review that led to a digital twin paradigm targeted at assessing which are the application contexts, the life cycle phases, the functionalities, the architectures, and the components of existing digital twins technologies. A detailed picture of the main features of existing scientific research on DT's, highlighting on the different application domains and the related technologies. The idea of Digital Twin as a virtual representation of a physical asset repetitively corressponds with the physical operating scenario is accurately presented presented from varrious research articles. The reviewed literatures also indicated that the development of the Digital Twin technology is still at its infancy as literature mainly consists of concept papers without concrete case-studies. Nevertheless, some research have had pragmatic case-studies already in existance particularly the lower levels of integration Digital Model and Digital Shadow. The main focus of recent research in Digital Twin in manufacturing as been aimed at production planning and control as it is a main data-sink within a production system that ties the entire manufacturing plant systems together. Hence, it has a mid-level time-horizon, simulation is often used in order to exploit the models at their best. However, the DT can also be used in domains with higher time-frequencies as e.g. process control and condition based maintenance, without using time intense simulation, but using other data driven approaches. For the continous development of the digital twin technology there is a need for further developments of different casestudies and industrial environments in order to evaluate the prospective advantages of digital twin technologies.

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Conflict of interest

The authors declare the literature review research was conducted in absence of any conflict of interest.

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