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Review of digital twin about concepts, technologies, and industrial applications

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ABSTRACT

Various kinds of engineering software and digitalized equipment are widely applied through the lifecycle of industrial products. 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 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. With the development of new-generation information and digitalization technologies, more data can be collected, and it is time to find a way for the deep application of all these data. As a result, the concept of digital twin has aroused much concern and is developing rapidly. Dispute and discussions around concepts, paradigms, frameworks, applications, and technologies of digital twin are on the rise both in academic and industrial communities. After a complete search of several databases and careful selection according to the proposed criteria, 240 academic publications about digital twin are identified and classified. This paper conducts a comprehensive and in-depth review of these literatures to analyze digital twin from the perspective of concepts, technologies, and industrial applications. Research status, evolution of the concept, key enabling technologies of three aspects, and fifteen kinds of industrial applications in respective lifecycle phase are demonstrated in detail. Based on this, observations and future work recommendations for digital twin research are presented in the form of different lifecycle phases.

1. Introduction

1.1. The origin of digital twin

Digital manufacturing has brought considerable values to the entire industry over the last decades. Through virtually representing factories, resources, workforces and their skills, etc., digital manufacturing builds models and simulates product and process development [1]. The progress in information and communication technologies (ICTs) has promoted the development of manufacturing greatly. Computer-aided technologies are developing quickly and playing more and more critical as well as typical role in industry, including CAD, CAE, CAM, FEA, PDM, etc. Big data, Internet of things (IoT), artificial intelligence, cloud computing, edge computing, the fifth-generation cellular network (5G), wireless sensor networks, etc. are developing rapidly and show big potentials in every aspect of the industry field [2–5]. All these technologies provide opportunities for the integration of the physical world and the digital world, which is an inevitable trend for addressing growing complexities and high demands of the market. However, the full strategic advantage of this integration is not exploited to its full extent. The process of this integration is a long way to go and the newest developments focus on digital twin.

NASA's Apollo space program was the first program to use the 'twin' concept. The program built two identical space vehicles so that the space vehicle on earth can mirror, simulate, and predict the conditions of the other one in space. The vehicle remained on earth was the twin of the vehicle that executed mission in the space [6]. The first use of the "digital twin" terminology appeared in Hernández and Hernández's work [7]. Digital twin was used for iterative modifications in the design of urban road networks. However, it is widely acknowledged that the terminology was first introduced as "digital equivalent to a physical product" by Michael Grieves at University of Michigan in 2003 [8]. The concept of "product avatar" was introduced by Hribernik et al. [9] in 2006, which is a similar concept to digital twin. The product avatar concept intended to build the architecture of information management that supports a bidirectional information flow from the product-centric

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Table 1
Amount of search results in different databases.

Time	google search	google scholar	WebofScience (topic)	WebofScience (title)	Scopus (topic)	Scopus (title)
before 2003	755	74	2	1	3	2
2003 – 2009	5310	96	1	0	6	1
2010	2210	22	1	0	1	1
2011	4080	34	1	1	1	1
2012	4400	44	0	0	10	6
2013	6390	60	2	2	7	5
2014	9180	70	2	1	2	1
2015	13,600	91	4	0	6	1
2016	20,500	235	17	4	23	7
2017	31,100	805	69	26	110	50
2018	69,900	2220	224	84	324	156
2019- 2019.9	90,200	2120	239	129	361	177

perspective. Research regarding product avatar can be found before 2015 in [10–12]. However, it seems that the product avatar concept was replaced by digital twin since then.

The initial detailed definition of digital twin was given by NASA in [13]. Since then, digital twin has been a hot spot in the aerospace field. In 2014, Michael Grieves published a white paper to detail the connotation further. The digital twin concept model, fulfillment requirements, and use cases were discussed in depth in [8]. In 2017, the Gartner company listed digital twin as top 10 strategic technology trends, ranking No. 5. They predicted that billions of things would have digital twin representations within three to five years [14]. It's worth noticing that Gartner did not conceive the concept in the manufacturing field specifically. Instead, they took facilities and environments as well as people, businesses, and processes into account. In the next two years, Gartner kept listing digital twin as top 10 strategic technology trends, ranking No. 4 [15,16].

The concept was descriptive and lacked auxiliary technologies when it was first proposed. However, the development of advanced information technologies makes preparations for the rise of digital twin. Table 1 shows the number of results searching 'digital twin' in different databases. It shows a tremendous rise of digital twin as the concept is arousing more and more interests both in industry and academia, especially since 2015.

1.2. Related review works

Since Dr. Grieves presented the concept, and NASA gave the first specific definition, large amount of literatures regarding digital twin have been published, including six reviews.

Holler et al. [17] analyzed 38 articles. The review results provided an overview of established concepts, classified the existing body of literature, provided a lifecycle perspective on applications, and suggested directions for further research. Negri et al. [18] conducted a comprehensive literature review to answer two questions: 'How does scientific literature define the digital twin?' and 'What role does it play in Industry 4.0?'. The review presented three possible uses of digital twin: analyzing health conditions to plan maintenance activities, managing the whole lifecycle of the physical object, and improving decision-making through engineering and numerical analysis. Kritzinger et al. [19] reviewed digital twin in manufacturing from a categorical perspective. To clarify integration level of digital twin in existing researches, the author proposed three subcategories of digital twin according to data integration levels. The classified subcategories were Digital Model, Digital Shadow, and Digital Twin.

Tao et al. [20] reviewed the state-of-the-art of the digital twin researches thoroughly. The authors focused on the key components, the up-to-date development, and the major applications of digital twin in industry. They divided the development trend of DT research into three stages, which is formation stage (2003–2011), incubation stage (2011–2014), growth stage (2014-now). The paper reviewed the most relevant theories: (1) DT modeling, simulation, verification, validation, and accreditation (VV&A), (2) data fusion, (3) interaction and collaboration, and (4) service. Liu et al. [21] compared and analyzed the DT models in the scientific publications. Digital twin models were retraced from the initial one to the most up-to-date one to find some principles of DT modeling. The paper reviewed relevant information on DT models according to the application purpose, model level, and model representation. For the analysis of Digital Twin applications, Enders and Hoßbach [22] proposed a classification scheme with six dimensions to describe the applications identified. The six dimensions include industrial sector, purpose, physical reference object, completeness, creation time, and connection.

Problems and pieces of advice about future development directions given in the previous review papers have been reflected in the latest developments of the digital twin. Table 2 provides a comparison of these six papers.

1.3. Intention of this paper

Digital twin has shown considerable potential in different fields and arouses plenty of industry and academic concern. However, the development of digital twin is still at its infancy. No universal definition, implementation framework, and protocol are available. It can be found that there lacks comprehensive and in-depth analysis of digital twin from the perspective of concepts, technologies, and industrial applications in the existing researches. Thus, through a comprehensive and in-depth review, the paper intends to:

- Analyze the status of digital twin research.
- Research the key technologies needed to apply digital twin.
- Give a complete summary of industrial application of digital twin in respective lifecycle phase.
- Recommend future research directions of digital twin.
- Give some potential solutions to address the existing problems.

The rest of the paper is organized as follows. Section 2 introduces literature classification criteria and literature review approach. Section 3 analyses the status of digital twin research. Section 4 reviews concept, key technologies, and industrial applications of digital twin. Some observations and future work recommendations are made in section 5 and summary and conclusion are drawn in section 6.

2. Research method

2.1. Classification criteria

The primary literature classification criterion in this research is based on different lifecycle phases of the objects. Here, 'the objects' refers to digital twin's counterpart in the physical world, i.e. the physical twin. Definitions of different lifecycle phases in this research

Table 2
Comparison of digital twin literature reviews.

Ref.	Time scope of considered papers	Num. of considered papers	Review purpose	Main conclusion
[17]	2001 – 2016	38	- To enhance transparency and understand digital twin concepts. - To supply ideas and directions for future work.	Not mentioned.
[18]	2012 – 2016	33	- To analyze the definitions of digital twin in academic publications. - To explore the role of digital twin for Industry 4.0.	Three possible uses emerged: - Analyzing health conditions to plan maintenance activities. - Managing the whole lifecycle of the physical object. - Improving decision-making through engineering and numerical analyses. Two ways on DT's relationship with simulation: - DT is a model that represents the system that varieties of simulations can be based upon. - DT is the simulation of the system itself.
[19]	Mainly 2014 – 2017	43	- To clarify integration level of digital twin in existing researches.	- The primary focus of recent research concerning the DT in manufacturing was dealing with production planning and control, maintenance and layout planning followed. - The development of the DT was still at its infancy as literature mainly consisted of concept papers without concrete case-studies.
[20]	2003.1 – 2018.4	50 papers and 8 patents	- To understand the development of digital twin applications in industry. - To outline challenges and some potential directions for future research.	- PHM is the most popular application area. - Modeling is the core of DTs. - Cyber-physical fusion is challenging for applying DT in industry. - Join forces between control and DTs is a promising area.
[21]	Mainly 2017 – 2018	21	- To compare and analyze the DT models in academic publications. - To emphasize several principles of the DT model technology.	- The recent studies discussed the great advances and auxiliary technologies of DT Model in different fields, but the representation form of the DT model was far from unified and completed. - Three relevant fields needed to be studied in-depth: a) Fusion of the DT model and reference architecture model, b) Uniform representation of the DT model, c) Modeling tool software and automated software.
[22]	Mainly 2016 – 2018.11	152	- To help researchers and practitioners get an overview of current Digital Twin applications to better understand and describe Digital Twins.	- A classification scheme with six dimensions was identified to define the digital twin applications.

Table 3
Classification properties and criteria.

Property	Classification criteria
Product lifecycle phase [23,24]	● Design phase: product design, process design, and plant design. ● Manufacturing phase: production of artifacts and relevant internal plant logistic. ● Service phase: external logistic, use, maintenance, and repair. ● Retire phase: disassembling, remanufacturing, reusing, disposal, etc.
Content of literature	● Concept: focus on concepts, definitions, capabilities of digital twin. ● Technology: descriptions or details of digital twin's enabling technology. ● Paradigm: general descriptions of digital twin applications in respective fields, no in-depth analysis, no detailed case study. ● Framework: general descriptions of digital twin applications in respective fields, with in-depth analysis, implementation framework, and a rather detailed case study. ● Application: detailed descriptions of digital twin applications in specific fields, with technical details and detailed case study.
Level of integration [19]	● Digital model: no self-driven data interaction between the physical entity and the digital entity. ● Digital shadow: there exists a self-driven unidirectional data flow between the physical entity and the digital entity. ● Digital twin: the data interaction between the existing physical entity and the digital entity is fully integrated bi-directionally.
Time of literature	● For journal paper: time of paper being accepted ● For conference paper: time of the conference ● For book chapter: time of publication ● For thesis: time of completion

follow the descriptions given by Kiritsis et al. [23] and Terzi et al. [24]. Design phase comprises product, process, and plant design. Manufacturing phase includes the production of the artifacts and relevant internal plant logistic. Service phase comprises distribution (external logistic), use, and support (in terms of repair and maintenance) of the artifacts. Retire phase means operations such as disassembling, remanufacturing, reusing, disposal, etc.

To clarify a particular case in this research, manufacturing resources, such as machine tools, fixtures, can be classified into manufacturing phase or service phase, depending on the application purpose. For example, a digital twin of machine tool regarding its own predictive maintenance is in service phase, while it is classified into manufacturing phase if its digital twin is used for process evaluation or improving parts' quality. Classifications of product lifecycle phases only adapt to industrial applications. Other digital twin applications, such as health care, traffic, smart city, are beyond the scope of this paper.

Other literature properties used for classification include the content of literature, level of integration, time of literature. Detailed classification properties and criteria are shown in Table 3.

2.2. Literature review approach

This review is based on scientific peer-reviewed papers and some technical reports or whitepapers from experts in this field. The review focuses mainly on digital twin concepts, key technologies, and industrial applications. A literature review of digital twin was carried out, comprising four stages: (a) search several databases with relevant keywords, (b) exclude irrelevant papers by reading abstracts, (c) read full-text of relevant papers and classify them according to criteria mentioned in subsection 2.1,(d) carry out in-depth analysis based on different literature properties such as lifecycle phases, content of literature, publication time, then the development trend of concepts, technologies, and industrial applications in different lifecycle phases are identified. Databases, search strings, and time scope of the literature review are presented in Table 4.

Table 4
Search field of the literature review.

Search field	Content
Databases	Web of Science, Scopus, Google Scholar
Search strings	digital twin, digital twins, digital replica, product avatar, virtual twin, etc.
Time scope	2003.1–2019.9

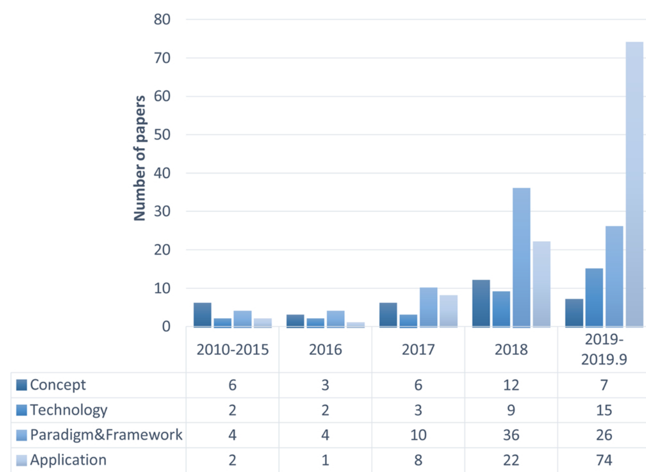


Fig. 1. Content type of digital twin literatures.

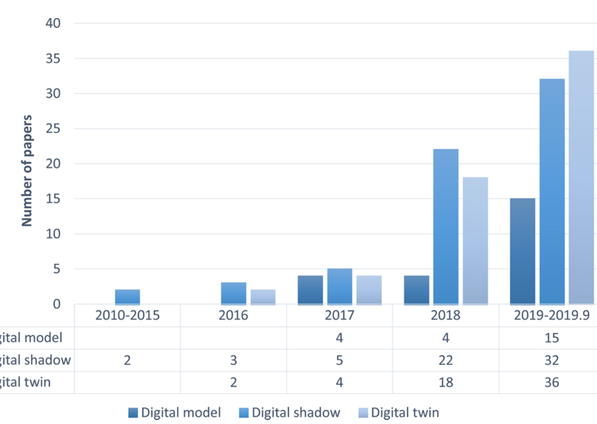
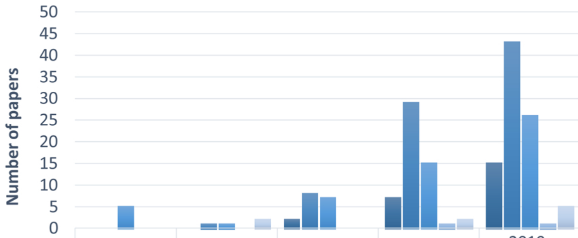


Fig. 2. Level of integration in digital twin literatures.

3. Status analysis of digital twin research

Totally, 240 academic publications are found after eliminating the irrelevant publications. To demonstrate the overall development trend of digital twin, the distributions of these papers are shown in Figs. 1–3.

The development of digital twin in academia is rather slow before 2017. However, after 2017, the number of academic publications of digital twin experienced an explosive growth. It can be seen in Fig. 1 that the number of literatures regarding concept, paradigm, and



	2010-2015	2016	2017	2018	2019-2019.9
Design			2	7	15
Manufacturing		1	8	29	43
Sevice	5	1	7	15	26
Retire				1	1
Full lifecycle		2		2	5

Fig. 3. Lifecycle phases of digital twin objects.

framework of digital twin grew continuously before 2018 but began to decrease in 2019. On the contrary, the number of literatures regarding technology and application of digital twin keeps growing, among which the number of digital twin application literatures experienced a huge growth in 2019. This indicates the fact that digital twin is gradually stepping out of its infancy and stepping into a stage of rapid development where researchers start to explore real practices and technologies in industry.

Among all the reviewed academic publications in this work, there are 176 papers that are explicit about the digital twin object. Thus, according to the classification criteria in Table 3, the distributions of integration level and lifecycle phases of digital twin objects are shown in Figs. 2 and 3.

From the distribution of level of integration in digital twin literatures in Fig. 2, it can be seen that over half of literatures described and studied digital model or digital shadow, although the authors all claimed a digital twin in their papers. In those digital twin related literatures, usually there are three kinds of twins, i.e. 'claimed twin', 'described twin', and 'actual twin'. The 'claimed twin' is according to the authors' statement in the papers. The 'described twin' is according to the definition and description given in the papers and is classified based on criteria in Table 3. The 'actual twin' is according to the actual application in case studies of the papers and is classified based on criteria in Table 3. The statistics in Fig. 2 refer to the 'described twin'. The rise of digital twin as 'described twin' in literatures indicates academia's growing interest in bidirectional data flow between physical object and its digital twin. However, taking 'actual twin' into consideration, most implementations of the 'claimed digital twin' in literatures are actually digital model or digital shadow.

The digital twin objects of the 176 papers stem from digital twin application and case studies of digital twin frameworks or paradigms. Some of them may involve two phases, and they are counted in different phases repeatedly. If the paper involves three phases, it is classified into 'full lifecycle'. From Fig. 3, it is clearly shown that most digital twin objects in literatures focus on single lifecycle phase, while only 5% consider full lifecycle. Manufacturing phase and service phase are the most common phases that researchers concern about, but retire phase is neglected by most researchers. During the review process, kinds of digital twin applications in different product lifecycle phases are identified and will be analyzed in section 4.

4. Concepts, technologies, and industrial applications

4.1. Digital twin concepts

To have a complete view of digital twin concept in literature, Table 5 provides some definitions appeared in academic publications, ordered by paper accepted time to illustrate development of the concept. Then different understandings about digital twin and digital twin conceptual models are reviewed.

Table 5 summarizes the key points of these definitions, which shows an evident tendency. In the earlier years, most of papers defined digital twin as high fidelity model or multidisciplinary simulation, without considering real-time connection with the physical object. As these research works went deeper, lots of researchers started to attach importance to dynamic and bidirectional mapping to the physical object. However, most of researchers did not distinguish DT from general computational models and simulations.

Zheng et al. [46] discussed the concept, characteristics of digital twin from the narrow sense and the broad sense. The proposed application framework consisted of three parts, physical space, virtual space, and information-processing layer. In the application process, the digital twin can implement full-scale system mapping, dynamic modeling throughout lifecycle, and real-time optimization of whole process. Grieves and Vickers [30] defined two types of digital twins: digital twin prototype (DTP) and digital twin instance (DTI) and DTs were in a digital twin environment (DTE).

Schluse and Rossmann [27] proposed a new concept of "Experimentable Digital Twins" and described how this "Experimentable Digital Twins" can perform the core of simulation-based development processes to simplify the processes, enable system-level detailed simulations, and implement smart systems. Two researches [32,47] followed regarding Experimentable Digital Twins (EDTs). Madni et al. [43] discussed the advantages of combining digital twins with IoT and system simulation to support model-based system engineering (MBSE). Four levels of virtual representation were defined, namely pre-digital twin, digital twin, adaptive digital twin, intelligent digital twin. Bao et al. [48] defined three types of digital twin models from the perspective of manufacturing process on the shop floor, which were Product Digital Twins, Process Digital Twins, and Operation Digital Twins. Ullah [49] proposed three types of digital twins: object twins, process twins, phenomena twins. Despite different explanations, the characteristics of digital twin have reached a consensus. Many industry fields may widely adopt digital twin, thus some publications tried to keep a large number of systems within the scope of digital twin concept, which caused some misunderstandings and confusions.

The basic idea of digital twin is simple, that is linking physical object and digital object in an accurate and real-time manner. However, it is hard to define the concept architecture. Lots of digital twin conceptual models or reference models have been proposed. Stark et al. [50] developed a "Digital Twin 8-dimension model" to plan the boundary and type of DT. Four dimensions represented the DT behavior capability richness while the other four dimensions represented the area of DT environment and context. The digital twin concept model presented by Grieves [8] contained three main parts: physical products, virtual products, their connections of data and information. The digital twin capability supported three of the most potent tools: conceptualization, comparison, and collaboration. Schleich et al. [51] addressed capabilities of the digital twin reference model, such as interoperability, expansibility, scalability, and fidelity. They also addressed different operations on this reference model along the product lifecycle, such as conversion, evaluation, composition, and decomposition. Tao et al. [52,53] put forward a five-dimension digital twin model, which comprised physical entity, virtual entity, services, digital twin data, and connection. Based on the five-dimension model, typical applications in different fields were explored.

Many research works discussed the connotation, definition of digital twin concept, independent of industry field. The concept is explained from different perspectives and each explanation makes sense. However, none of the explanations can be proved to be better than others. Through in-depth analysis, a conclusion is drawn that digital twin is a digital entity that reflects physical entity's behavior rule and keeps updating through the whole lifecycle. The conclusion is both

Table 5
Definitions of digital twin in academic publications.

No.	Refs.	Time	Definition of Digital Twin	key points
1	[13]	2010.11	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 simulation
2	[25]	2014.4	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 history to enable high-fidelity modeling of individual aerospace vehicles throughout their service lives.	fidelity modeling
3	[26]	2015	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	[27]	2016	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	[28]	2017	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 being globally available in real-time.	digital copy
6	[29]	2017	Faster optimization algorithms, increased computer power and 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	[30]	2017	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	[31]	2018.1	Digital Twins stand for a specific engineering paradigm, where individual physical artifacts are paired with digital model that dynamically reflects the status of those artifacts.	dynamic reflection
9	[32]	2018.2	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	[33]	2018.5	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	[34]	2018.7	DT is a multi-domain and ultrahigh fidelity digital model integrating different subjects such as mechanical, electrical, hydraulic, and control subjects.	fidelity model
12	[35]	2018.8	Digital twin represents a dynamic digital replica of physical assets, processes, and systems, which comprehensively monitors their whole life cycle.	dynamic replica
13	[36]	2018.9	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	[37]	2018.11	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	[38–40]	2018.12	BIM (Building Information Model) is digital twin.	
16	[41]	2018.12	Digital twin represents physical entities with their functions, behaviors, and rules dynamically.	dynamic representation
17	[42]	2019.1	The new technology, accessing to realistic models of the current state of the process and their behaviors in interaction with their environment in the real world is called the “Digital Twin”.	realistic model
18	[43]	2019.1	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
19	[21]	2019.2	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
20	[44]	2019.6	DT is defined as a digital copy of a physical asset, collecting real-time data from the asset and deriving information not being measured directly in the hardware.	real-time data
21	[45]	2019.8	Digital twin can be regarded as a paradigm by means of 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

Table 6
Technologies and software used in literatures.

No.	Refs.	Time	Data related technologies	High-fidelity modeling technologies	Model based simulation technologies
1	[54]	2017.5	Various sensors	Modelica models, reduced order models	ANSYS Simplorer
2	[55]	2017.11	3D scanning	Big data modeling	Finite Element Analysis software
3	[56]	2018	AutomationML	Modelica multiphysics modeling	–
4	[57]	2018.2	MTConnect	–	–
5	[34]	2018.7	OPC UA	Modelica models, Machine learning	MWorks
6	[58]	2018.7	–	3D animation model, Discrete event simulation model	Siemens plant simulation
7	[48]	2018.9	AutomationML	Model-based Definition	–
8	[59]	2018.10	–	Deep learning, Machine learning, Edge/fog computing	SUMO
9	[60]	2018.11	OPC UA, Kepware	Unity 3D model, Discrete event simulation model	Siemens plant simulation
10	[61]	2018.11	–	Big data, Machine learning	–
11	[62]	2019	AutomationML	Discrete event simulation model, Functional mock-up unit,	–
12	[63]	2019	–	Open modelica	MATLAB
13	[64]	2019	OPC UA, ZigBee, XML	–	–
14	[65]	2019.1	–	Computer vision algorithm, Principal component analysis	–
15	[66]	2019.2	–	Reverse engineering, Image processing, parametric modeling	–
16	[67]	2019.3	–	Markov chain	Monte Carlo simulation
17	[68]	2019.4	OPC UA, MTConnect	–	–
18	[69]	2019.5	–	Genetic algorithm, Non-rigid variation modeling	ANSYS
19	[70]	2019.5	–	Deep extreme learning machine	–
20	[71]	2019.6	3D scanning	Hertz contact theory, Hybrid particle swarm optimization	–

general and ambiguous, but this is the core of digital twin concept. Digital twin is not a specific technology, but an idea that can be implemented with many advanced technologies. Thus, future work should provide enough clarity and specificity regarding different industry field. Then the architecture, model of digital twin can lie on concrete industry practice and the advantages can be fully exploited.

4.2. Key technologies for digital twin

Plenty of technical challenges remain to be addressed to implement digital twin applications. To better grasp the development of digital twin key technologies, Table 6 lists technologies that academic publications used to build digital twin, ordered by paper accepted time to illustrate technology development. The following parts discuss key technologies for digital twin from three perspectives: data related technologies, high-fidelity modeling technologies, and model based simulation technologies. Fig. 4 presents the technology architecture for digital twin.

4.2.1. Data related technologies

Data is the basis of digital twin. Sensors, gauges, RFID tags and readers, cameras, scanners, etc. should be chosen and integrated to collect total-element data for digital twin. Data then should be transmitted in a real-time or near real-time manner. However, data that digital twin needed are usually of big volume, high velocity, and great variety, which is difficult and costly to transmit to digital twin in the cloud server. Thus, edge computing is an ideal method to pre-process the collected data to reduce the network burden and eliminate chances of data leakage and real-time data transmission is made possible by 5 G technology. Data mapping and data fusion are also needed to understand the collected data. The most common data mapping technology used in literatures is XML.

He et al. [35] surveyed the practical industrial IoT and signal processing algorithms in digital twin for real-time and multisource data collection. Ala-Laurinaho [72] examined which application layer protocols and communication technologies are the most suitable for the sensor data transmission from a physical twin to a digital twin. The developed platform allowed easy addition of sensors to a physical twin and provided an interface for their configuration remotely over the Internet. The examined application layer protocols were HTTP, MQTT, CoAP, XMPP, AMQP, DDS, and OPC UA. The examined communication technologies were 4 G, 5 G, NB-IoT, LoRaWAN, Sigfox, Bluetooth, 802.11 ah, 802.11n, ZigBee, Z-Wave, and WirelessHART. Angrish et al. [73] used document type unstructured schemas (MongoDB) to store streaming data from various manufacturing machines. It can be found that the used data related technologies, including data collection, data mapping, data processing, data transmission, varied with different applications in literatures. In addition, static data are of different types and formats in different fields. Standard data interfaces are required to transform these initial data into data catering to digital twin.

4.2.2. High-fidelity modeling technologies

Model is the core of digital twin. Models of digital twin comprise semantic data models and physical models. Semantic data models are trained by known inputs and outputs, using artificial intelligence methods. Physical models require comprehensive understanding of the physical properties and their mutual interaction. Thus, multi-physics modeling is essential for high-fidelity modeling of digital twin. In literatures, the most common multi-physics modeling language is Modelica.

One key issue that digital twin model should address is the contradiction between simplified virtual model and complex behavior of the physical object. A compromised approach is to implement flexible modeling in a modular way. Negri et al. [62] proposed to add black-box modules to the main simulation model. Different behavior models of digital twin were activated only when needed. The modules interacted with the main simulation model through standard interfaces. To balance computational effort and accuracy [63], before creating digital twin model of a complex system, engineers should identify which components are crucial for the system's functionality and define the modeling level of each component. Thus, high-fidelity model of digital twin can be built according to different modeling level.

For complex manufacturing phenomenon, Ghosh et al. [67] addressed the construction of digital twins using hidden Markov models. The models encapsulated the dynamics underlying the phenomenon by using some discrete states and their transition probabilities. Sun et al. [74] fused theoretical model and physical model to commission high precision products' assembly. The theoretical model was based on Model Based Definition (MBD) techniques and the physical model was built by point cloud scanning. For complex manufacturing systems, Lu and Xu [75] studied resource virtualization as a key technology to create digital twin of a smart factory. Semantic web languages, OWL and Jena were recommended as the modeling languages. Digital twin modeling can usually start with physics-based modeling. Black-box modeling using data or grey-box modeling using a combination of physics and data are also feasible.

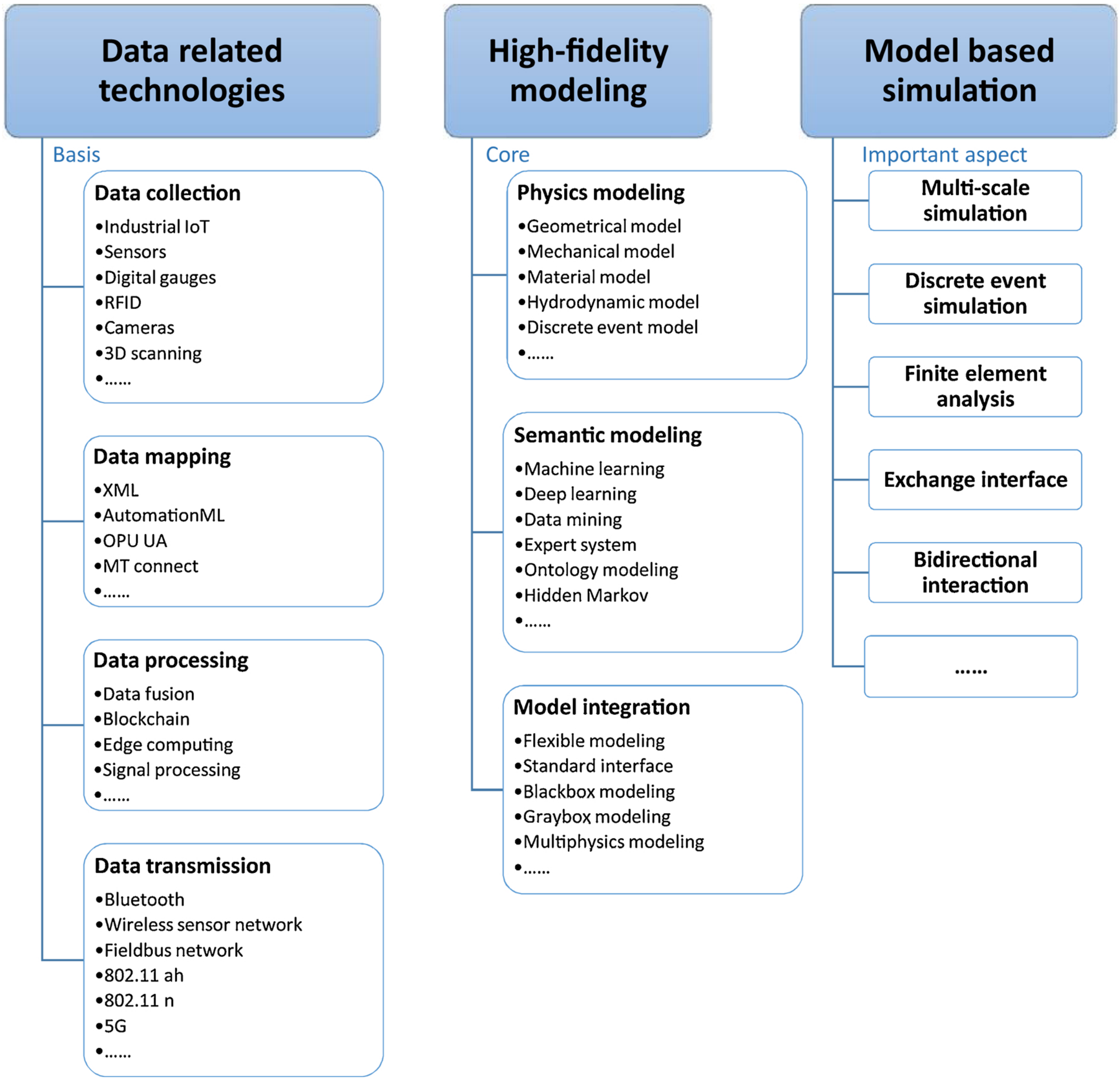


Fig. 4. Technology architecture for digital twin.

4.2.3. Model based simulation technologies

Simulation is an important aspect of digital twin. Digital twin simulation enables virtual model to interact with physical entity bi-directionally in real-time. To realize bidirectional interaction, Schroeder et al. [76] presented a high level model based on AutomationML for easily exchange data between heterogeneous systems. The attributes necessary to exchange data were put in an IoT middleware and other systems can have access to this attributes. Talkhestani et al. [77] defined Anchor-Point as the data of a mechatronic component from interdisciplinary domains. Based on a PLM IT-Platform and an Anchor-Point method, variances of the mechatronic data structure between the digital models and the physical system can be systematically detected. Different from traditional simulation, digital twin simulation uses real-time data of the physical system that are collected and recorded from physical space via IoT [78]. Qi et al. [79] recommended using image recognition and laser measurement technology to measure the parameters of the physical world, and using electrical control, programmable control, embedded control, and network control technology to control the physical world. Through in-depth literature review, it can be found that most of the existing works focus on unidirectional data flow, which is from physical to digital. The data flow from digital to physical after executing digital twin simulation requires deeper research.

Multi-physics, multi-scale simulation is one of the most important visions of digital twin. Thus, quantitative uncertainties and interfaces between different simulations are to be researched. Simulation models over different levels of detail, over all involved disciplines, and over lifecycle phases must be integrated [6]. Digital twin should provide an interface to different models and data in different granularities and keep them consistent. To solve multi-scaled, multi-physics problems, one strategy is to partition the solution domain along disciplines, and each domain exchanges data through an interface [80]. The existing work regarding digital twin multi-physics simulation usually treat integration of different models as simple input-output, showing better results than traditional methods. However, in some application scenarios, the mutual influence between different disciplines cannot be neglected and the problem of different temporal and spatial scales should be addressed appropriately.

4.3. Industrial applications of digital twin

Through in-depth analysis and summary, kinds of digital twin applications in different lifecycle phases are identified, including three applications in design phase, seven applications in manufacturing phase, and five applications in service phase (see in Fig. 5). Research on digital twin application in retire phase is insufficient in the existing literatures. Analyses on these applications are conducted in subsections.

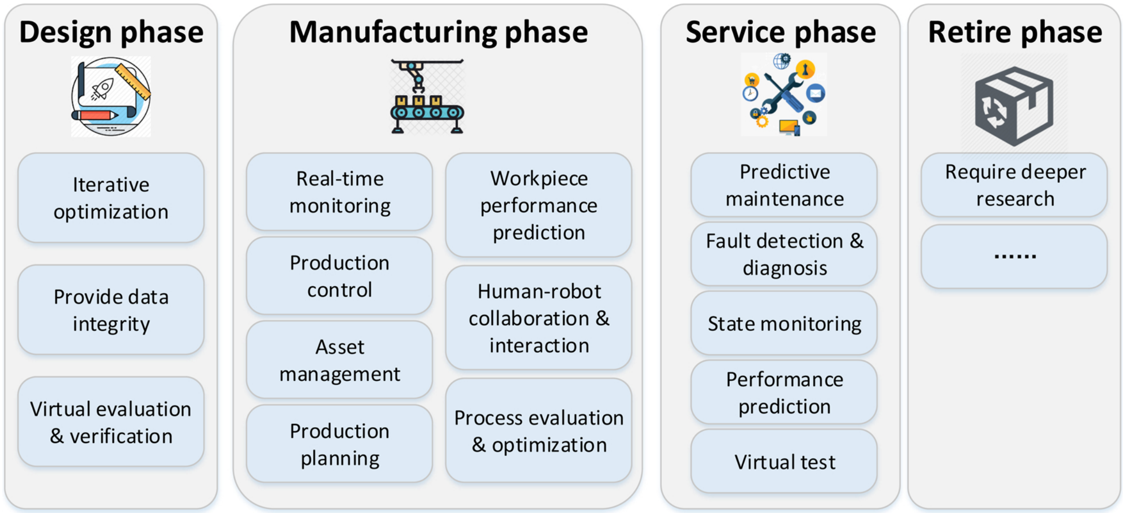


Fig. 5. Industrial applications of digital twin in different lifecycle phases.

4.3.1. Applications in design phase

Digital twin enables fusion between information model and product physical model and their iterative optimization, thereby shortening the design cycle and reducing rework cost [81]. Commonly, the design process comprises four steps: a) task clarification, b) conceptual design, c) embodiment design, and d) detail design [82]. Terzi et al. [24] took a village cobbler as an example. The cobbler was responsible for everything throughout the design, manufacture, repair, and recycle of the shoes, in which way data integrity, product traceability, and knowledge accessibility were enhanced. In this simple 'cobbler model', the cobbler knew customers' requirements and design constraints. He also knew which material was required for the type of product and the process to operate on it. Digital twin is a possible replacer for 'the cobbler's mind' in the current trend of products' complexity and variability.

Tao et al. [83] claimed that digital twin made designers have a complete digital footprint of products through design. It served as an 'engine' to convert big data into useful information. The information can be directly utilized by designers to make informed decisions at different design phases. The paper envisioned DT's capabilities at task clarification, conceptual design, and virtual verification. Schleich et al. [51] stated that digital twin allowed the check for conformance of the product specifications with the design intent and customer requirements. A comprehensive reference model for the digital twin in design and production engineering was proposed. Howard [84] discussed how digital twin might facilitate virtual validation of hardware to achieve optimized designs. The gap between EDA (engineering design automation) tools and digital twin was discussed. Xiao et al. [85] described a digital twin of solid rocket motor to promote the traditional experience based and semi-experience based design mode to a data based and model based design mode. Table 7 lists some of the literatures regarding digital twin applications in design phase.

- **Iterative optimization**: Good design is achieved by constant improvement towards the product specification throughout conceptual design to detail design. Digital twin can track down historical footprints of product design as well as track up improvement so as to realize iterative optimization. Digital twin based methodology can realize iterative design optimization between static configuration and dynamic execution [[86]], improve the accuracy and efficiency for product material selection [[87]], and reflect the evolution of dynamic parameters [[91]]. Digital twin is able to predict product or system performances and identify potential problems to indicate the optimization direction, which traditional simulation may neglect.
- **Provide data integrity**: As mentioned above, the 'cobbler model' doesn't adapt to today's paradigm of collaborative design. Processes that formerly used to be performed by a single person are fragmented into several pieces, which brings about a fragmentation of product and process knowledge and leads to the silos of knowledge situation [[24]]. Thus, lots of useful information that helps decision making is dispersed in different stakeholders. The next generation often has similar problems with the predecessor, but these problems could have been avoided by using knowledge about the predecessor [[30]]. Digital twin is a concept that origins from product lifecycle management (PLM). Digital twin constantly collects, analyses, and accumulates data from physical space [[83]] to provide sufficient basis for decision making in the design phase. For different perspectives and stakeholders, digital twin supports completely digital

Table 7
Digital twin applications in design phase.

Application	Refs.	Time	Proposed idea
Iterative optimization	[86]	2018.4	Iterative design optimization was achieved by considering both static configuration and dynamic execution.
	[87]	2019	By high-fidelity virtual models, the digital twin-driven method can optimize and evaluate the performance of material and predict significant indicators, and then iterative optimization between predicted properties and expected properties was implemented.
Provide data integrity	[88]	2018.10	Digital twin had unlimited access to all the data to provide an insightful basis for decision making for all the perspectives and stakeholders involved.
	[89]	2019.6	Digital twin enabled system integrators to have sufficiently detailed information on components without requiring LED suppliers to disclose proprietary information.
Virtual evaluation & verification	[90]	2019.1	Digital twin based framework minimized the time necessary to develop and design a new assembly line.
	[58]	2018.7	By using flexible digital twin, designer can quickly evaluate different designs and find design flaws in an easy way.
	[89]	2019.6	With the help of the luminaires' digital twins, different versions of complete luminaire designs were tested in different application scenarios by means of computer simulation.

workflows, so that detailed data is provided without disclosing proprietary information [[88]]. This requires the development of digital twin security strategy.

- **Virtual evaluation & verification**: The purpose of evaluation is to reduce the inconsistencies between the actual and expected behavior [[83]]. While the traditional emphasis has been on verifying and validating requirements (the Predicted Desirable) and eliminating problems and failures (the Predicted Undesirable), the digital twin model is also an opportunity to identify and eliminate the Unpredicted Undesirable [[30]]. Another advantage of digital twin method over traditional evaluation and verification method is that digital twin provides a high-fidelity model of the product and its operating environment. Thus, a multi-disciplinary, multi-scale interaction between the product and its future operating environment is obtained. In the design phase, digital twin supports virtual prototyping and tests different versions of products in different application scenarios.

4.3.2. Applications in manufacturing phase

Traditionally, manufacturing refers to an industrial production process through which raw materials are transformed into finished goods [92]. However, with the development of high demands on product qualities and rapid market response, manufacturing is shifted from primary processes to smart processes [93]. Modern manufacturing requires physical and digital interaction in a closed-loop manner. The core of digital twin is to realize the communication and interaction between the physical world and the digital world. Grieves envisioned three use cases of digital twin. We can conceptualize the actual manufacturing processes visually, compare the formation of the physical product to the virtual product to ensure what we are producing is what we want to produce, and finally collaborate with others to have up-to-the-minute knowledge of the products that are producing [8]. In the past decades, with the development of advanced mechanical technology and electrical technology, manufacturing automation is achieved. Fixed, carefully engineered sequences of actions are executed automatically [94]. Nowadays, manufacturing elements are becoming context-aware by communicating with their surroundings and are able to make intelligent decisions without explicitly being programmed. Digital twin is the key enabling factor towards this vision.

A lot of new concepts, paradigms, and frameworks are being proposed in manufacturing phase. Rosen et al. [26] showed how digital twin worked to transform a cyber-physical production system to an autonomous system. Tao and Zhang [53] explored a novel concept of digital twin shop-floor (DTS), which included four key components, i.e., physical shop-floor, virtual shop-floor, shop-floor service system, and shop-floor digital twin data. Park et al. [95] designed and implemented a digital twin to solve problems of personalized production and distributed manufacturing system. The digital twin was designed to monitor the present in real-time, track information from the past, and support operational decision-making for the future. Table 8 lists some of the literatures regarding digital twin applications in manufacturing phase.

- **Real-time monitoring**: The monitoring of manufacturing process in factory has been around for a while. However, digital twin provides real-time monitoring in a different and better way. First, digital twin integrates all the needed data with 3D models visually. Second, digital twin fuses historical data, real-time data, and predicted data to track the past, monitor the present, and predict the future. Total-elements information perception technology [46], augmented reality technology [96], three-dimensional visualization monitoring technology [108], etc. are studied to implement digital twin for real-time monitoring in the manufacturing phase. Digital twin for real-time monitoring is not just a presentation of current data and status of physical object, the high fidelity model of digital twin also helps understand situation and make optimization decision.
- **Production control:** Manufacturing systems need to perform pre-scheduled operations and react to disturbances continuously. Normally, the manufacturing system is controlled by a central Manufacturing Execution System based on static assumptions [26]. Digital twin can link the physical system with its virtual equivalent to perform intelligent control in real-time through a holistic perspective. By real-time data perception of dynamic environment and high accuracy model, digital twin implements timely smart control strategy in complex context, which caters to today's complex and demanding manufacturing system. However, most of research works were only on a theoretical level or were implemented in a laboratory environment. Digital twin for real-time smart control that runs in complex manufacturing environment is still a long way to go.
- **Workpiece performance prediction:** In manufacturing phase, disturbances exist both internal and external to the factory, such as degradations of machines, variations of raw materials [109]. Thus, it is promising but also difficult to predict workpiece performance. To predict the workpiece's performance before real manufacturing, digital twin should provide computable virtual abstractions of complex manufacturing phenomena and sufficient data. However, sometimes it is hard to identify the scientific rules of some manufacturing phenomena, such as surface roughness, complex product assembling. Digital twin computable abstraction integrates known physical rule, AI algorithms, and multidisciplinary models. The continuously updated models improve the prediction accuracy.
- **Human-robot collaboration & interaction**: Traditionally, the human and the robot motion planning were created in open-loop fashion. Therefore, any form of changes or perturbations in the assembly environment or object geometry requires re-calibration of both human and robot motions. Human and robot are blind to each other [80]. Digital twin can operate a closed-loop simulation so that human and robot update their path or actions simultaneously. Digital twin of a human-robot collaborative work environment supports human-robot task allocation, workstation layout optimization, human ergonomic analysis, and robot program test [81].
- **Process evaluation & optimization**: The increasing manufacturing complexity makes it difficult to do process planning in the traditional way. Planners are not able to consider the actual processing conditions when designing the process [42,110]. Dynamic changes of machining process and uncertain conditions of manufacturing resources have a great influence on product quality. Real-time data acquisition and data mapping in workshop enable digital twin aware of actual machining process and equipment condition. Digital twin collects measured data, deviation data, process planning data and integrates these data with geometric model, mechanical model, material model. Then the digital twin interacts with its manufacturing environment through interoperability interfaces, evaluating and optimizing the combination of process and parameters.
- **Asset management**: Traceability and visibility of assets play a critical role in the process of improving shop-floor performance, and contribute to better control, planning, and scheduling decisions [111]. The digital twin of manufacturing assets not only helps to achieve their business logic, but also enables interactive and collaborative work with other manufacturing assets. Digital twin supports the asset-related decision-making process, including assets configuration, reconfiguration, planning, commissioning, and condition monitoring [104]. In literatures, digital twin served to dynamically, realistically, and accurately mirror the working progress and status of manufacturing assets [105,112], manage the asset degradation [106].
- **Production planning**: As mentioned above, the increasing disturbances in manufacturing phase call for intelligent dynamic production planning. Digital twin makes it possible for a globally optimized production plan according to real-time status change. In the Digital Twin Shop-floor (DTS) paradigm proposed by Tao and Zhang [53], production plan is supported by sensor data, simulation data,

Table 8
Digital twin applications in manufacturing phase.

Application	Refs.	Time	Proposed idea
Real-time monitoring	[96]	2019	AR was used to visualize the digital twin data of a CNC milling machine in a real manufacturing environment.
	[49]	2018.11	Computable virtual abstraction of complex manufacturing phenomena was denoted as phenomena twin. The phenomenon twin of cutting force was used to visualize, optimize, and monitor a material removal process.
	[97]	2019.8	Digital twin was implemented to monitor industrial multi-effect evaporation process. Digital twin allowed for deeper understanding of the actual states of the analyzed system through estimation of variables.
Production control	[33]	2018.5	Digital twin-driven manufacturing cyber-physical system (MCPS) enabled a bi-level intelligence between local decentralized self-organizing and holistic online parallel controlling.
	[98]	2019.1	A digital twin model of micro punching system was proposed to perceive the context of the punching process and thus to form self-adaptive control actions catering to the physical environment.
	[99]	2019.4	A functional digital twin model of the steelmaking process was proposed based on flue-gas analysis to control the final blowing point.
Workpiece performance prediction	[100]	2017.6	A digital twin of additive manufacturing process can provide accurate predictions of the spatial and temporal variations of metallurgical parameters that affect the structure and properties of components.
	[67]	2019.3	Digital twin of successive grinding operations was constructed using hidden Markov models to predict the surface roughness.
Human-robot collaboration & interaction	[101]	2018.7	Digital twin of a human-robot collaborative work environment was tested for human-robot task allocation, workstation layout optimization, human ergonomic analysis, and robot program.
Process evaluation & optimization	[102]	2017	Digital twin for geometry assurance was supported by a concept that active part matching and self-adjusting equipment improve geometric quality without tightening the tolerances of incoming parts.
	[42]	2019.1	A digital twin-based machining process evaluation framework contained three phases: real-time data collection, establishment of digital twin-based process model, machining process planning evaluation and optimization.
	[103]	2019.7	Digital twin was used to improve the quality and reliability of control programs for CNC machines. Digital twin was used to perform virtual testing of a given grinding cycle for the possibility of defect occurrence at some combination of variable technological factors.
	[74]	2019.7	The digital twin model for the assembly-commissioning process mainly included dynamic iterative optimization of the process-parameters and real-time iterative optimization of the assembly-commissioning processing.
Asset management	[104]	2018	Digital twin supports the asset-related decision-making process, including asset configuration, asset reconfiguration, asset planning, asset commissioning, asset condition monitoring and health assessment.
	[105]	2018.12	Assembly shop-floor digital twin can dynamically, realistically, and accurately map the working progress and working status of manufacturing assets into the virtual space.
	[106]	2018.11	Digital twin for grinding wheel integrated the wheel production, process, end of life, and conditioning information to trace the wheel degradation, enable timely dressing, select wheel according to the work material.
Production planning	[107]	2018	Digital twin-driven smart shop-floor supports real-time data acquisition and dynamic simulation for dynamic resource allocation optimization. In the mode of dynamic resource allocation, the initial production plan can be changed at any time before production or during production.
	[36]	2018.9	Digital twin was implemented to enable the optimization of the planning and commissioning of human-based production processes by means of sensor data fusion, motion recognition, and knowledge management mechanism.

and EIS (Enterprise Information System) data. The production plan produced by production plan service is given to Virtual Shop-floor for verification. If the real-time states of resources change, modification advice will be given back to production plan service.

4.3.3. Applications in service phase

In the service phase, products are usually decentralized and out of control from manufacturers and suppliers. As a result, it is difficult to manage and gain access to their data, or to realize closed-loop data stream. In addition, the existent virtual model may be an accurate representation of the product's design, but it has no link to a specific manufactured part [113]. Furthermore, a manufactured part has no link to a specific used product, meaning that products of the same batch may perform differently in different service environments. In this phase, users are mainly concerned with the reliability and convenience of the product, while manufacturers and suppliers are mainly concerned with real-time product operation state, maintenance strategies, and so on.

Tao et al. [114] argued that with the digital twin methodology, degradation and anomalous events could be understood and unknowns could be foreseen previously. Tuegel et al. [80] proposed an aircraft structural life prediction process that utilized an ultrahigh fidelity model of individual aircraft by tail number (a digital twin). A reasonable estimate of the flight trajectory and maneuvers that would be flown during the mission was established. Then the likelihood of the airframe satisfactorily surviving the demands of the mission could be considered to decide whether to send that particular aircraft on that specific mission. NASA's vision [115] is that digital twin integrates various best-physics models with one another and with on-board sensor suites. As a result, decision-makers will understand physical processes related to degradation at the material, structural, and system level throughout the whole lifecycle. The systems onboard the Digital Twin are also capable of mitigating damage or degradation by activating self-healing mechanisms or by recommending changes in mission profile to decrease loadings. Table 9 lists some of the literatures regarding digital twin applications in service phase.

- **Predictive maintenance**: What is safe and what is dangerous or destructive for products are usually determined at the design phase, regardless of how the specific product is manufactured and used. Sometimes, engineers take safety factors into account and propose scheduled maintenance, which leads to high cost and low utilization of product performance. Digital twin is a real-time high-fidelity reflection of physical entities. Digital twin integrates multidisciplinary model (geometric, mechanical, material, electrical, etc.) to accurately compute the physical object's response to its using environment. Predictive maintenance is the most popular digital twin application both in academic research and industry practice from the beginning of digital twin development to the present. However, the current applications mainly focus on the high-value equipment, and many literatures neglect the effect that design process and manufacturing process have on the product's performance.
- **Fault detection & diagnosis**: For data-based fault diagnosis, the volume of data is not enough to train a reliable model because these physical entities operate normally for the most time. For physics-based fault diagnosis, it works well for pre-known anomalies but has no idea for unpredicted anomalies. Digital twin combines both, where multi-physics model cooperates with data of the specific product. Researchers leverage deep transfer learning [41], dynamic

Table 9
Digital twin applications in service phase.

Application	Refs.	Time	Proposed idea
Predictive maintenance	[63]	2019	Digital twin was enabled by advanced physics-based modeling. The digital twin of an industrial robot combined the digital replicate with degradation models to calculate the Remaining Useful Life of each machine components.
	[54]	2017	Simulation-based digital twin combined different modeling formalisms into an integrated model of an automotive braking system to support heat monitoring and predictive maintenance.
	[116]	2018.8	Digital twin combined installed base data with sensor data to maintain high machine availability and reduce downtimes.
Fault detection & diagnosis	[41]	2018.12	Deep transfer learning was used in a two-phase digital-twin-assisted fault diagnosis method to discover the potential problems that were not considered at design time.
	[37]	2018.11	A digital twin reference model for rotating machinery was constructed to enable accurate diagnosis and adaptive degradation analysis. The digital twin model was updated based on parameter sensitivity analysis.
State monitoring	[117]	2019.1	The proposed virtual monitoring method for hydraulic supports was based on digital twin theory. Information fusion algorithm was used to monitor the attitudes of the hydraulic supports.
	[118]	2019.5	The geometric digital twin of an existing reinforced concrete bridge monitored real geometries of the infrastructure components as well as a comprehensive set of semantic information, including materials, functions, and relationships between the components.
Performance prediction	[119]	2017.1	Digital twin-based procedure is capable of accurate real-time predictions of damage size and safe load carrying capacity for structures with complex damage configurations.
	[120]	2019.1	A digital twin representation of a quadcopter improved the estimates of the metrics of interest to the end-user.
	[70]	2019.5	A digital twin of ship used Deep Extreme Learning Machines to detect a deviation in the speed performances during real operations, and to estimate the speed loss due to marine fouling.
Virtual test	[121]	2018	An identical, simulated environment can be freely explored and tested by security professionals, without risking negative impacts on live systems.
	[122]	2018	Digital twin of old machines used an emulation model to support a reconditioning project. Virtual confidence can be obtained before starting the physical reconditioning work.
	[123]	2019	A digital twin of a IEEE 1451 smart sensor was constructed to have a large-scale simulations of sensor networks. Building a similar physical one would be cost and logistically prohibitive in the real world.
	[124]	2019	Digital twins of helicopter dynamic system can compute all the loads that the mechanical parts undergo without introducing significant maintenance burdens and bulky sensor cables.

Bayesian network [125,126], nonlinear dynamics [37] to model the behavior of physical product. Xu et al. [41] used simulation data to supplement insufficient training data. However, whether the simulation data and the physical measured data are of the same distribution remains a problem and requires deeper research.

- **State monitoring**: In addition to monitor the deviations between collected data and expected values, digital twin can interpret collected data from other perspectives. Comparison between digital twin simulated data and collected data can help determine the failure mode. Digital twin provides high-fidelity accurate model and keeps updating through the product lifecycle, thus digital twin can reproduce the current state of physical object in the virtual space with less data (compared to traditional state monitoring). The work of Xie et al. [117], Lu and Brilakis [118] applied information fusion algorithm to monitor a comprehensive set of semantic information of the physical object. Another advantage digital twin state monitoring over traditional method is that digital twin incorporates a unique identifier of one product and users can monitor the product state from any remote locations through this identifier.
- **Performance prediction**: Design that had been considered optimal at the beginning may not cater to changes in operating conditions in service phase [127]. Digital twin is “as-designed”, “as-manufactured”, “as-used” equivalent of the physical twin. The total element and full lifecycle data make digital twin aware of every bit of the physical twin’s performance. In this case, digital twin helps to better optimize and predict product performance. However, none of the existing research works take fully advantage of digital twin approach. The first to note is the same as mentioned in predictive maintenance that they neglect the effect of design process and manufacturing process. Secondly, knowing the product performance, digital twin should provide optimal using strategy to fully exploit the potential performance.
- **Virtual test**: As a digital counterpart of the physical entity, digital twin can test certain operations under circumstances that the failure of physical operation leads to great loss and damage. From this perspective, digital twin is like simulation, but more realistic and accurate. Digital twin provides identical, simulated environment that can be freely explored and tested without risking negative impacts on physical systems [121].

4.3.4. Applications in retire phase

Retire phase is often ignored as an actual phase. Knowledge about a system’s or product’s behavior is often lost when it is retired. The next generation of the system or product often has similar problems that could have been avoided by using knowledge about the predecessor [30]. In retire phase, digital twin contains the whole lifecycle information of the physical twin and can be retained at little cost in virtual space.

Our review work finds two papers regarding digital twin in the retire phase. Wang and Wang [128] presented a novel digital twin-based system for the WEEE (Waste Electrical and Electronic Equipment) recovery to support the manufacturing/remanufacturing operations throughout the product’s life cycle, from design to recycle. The product information models were developed from design to remanufacturing based on international standards. Liu et al. [129] aimed at the uncertainties in the process of remanufacturing and constructed architecture for digital twin-based remanufacturing shop-floor. The remanufacturing operation paradigm for automobile based on digital twin in future was also explored.

5. Observations and recommendations

5.1. For design phase

Most of the literatures regarding digital twin in design phase are about redesigning existing physical objects, or evaluating performances of the designed objects. No literature studies designing a new object from scratch. The proposed applications in existing literatures focused on industry fields that digital design has been widely adopted. However, the level of digital design in many industries is relatively low. The basic mathematical model and simulation model needed to support the construction of digital twin technology system are lacking, especially the digital simulation capability of key core components or process is lacking. Future work requires efforts on filling the gap between low digital design level and high demand of digital twin.

In redesign process, the product of previous version and the product of current version have considerable similarities. The comparison between digital twin of the previous product and digital twin of the current product can decide what to abandon and what to inherit.

Design of complex products usually involves various stakeholders. Many papers claim to provide seamless access to all the data. However, this is not easy. The data formats and professional software tools adopted by various stakeholders are often different. Platform that integrates heterogeneous data resource should be studied to enable digital twin. To protect intellectual property and ensure seamless data access for various stakeholders, the blockchain technology should be used to create digital twin. In this way, data is distributed among different stakeholders but can be linked together and remain accessible and un-editable.

In virtual verification, high-fidelity and multi-physics modeling of the product and its using environment are required. A sensible approach is to model according to the required granularity and modules to avoid unnecessary model complexity and long runtime, but low model accuracy also reduces the likelihood of discovering unpredicted undesirable, which is a huge potential for digital twin based virtual verification. Some literatures discussed modeling of product's interaction with its future using environment descriptively. Future work requires detailed quantitative modeling.

5.2. For manufacturing phase

In manufacturing phase, a considerable amount of data is produced along with manufacturing process of the product. Every process involves 5M1E (Man/Manpower, Machine, Material, Method, Measurement, Environment) data that affects product quality. To create digital twin, enormous manufacturing data should be integrated with the product's digital twin to support applications in the service phase. Some existing works have studied the modeling of complex manufacturing phenomena, such as cutting force, grinding surface roughness, additive manufacturing structure, but the digital twin modeling of complex manufacturing systems phenomena remains to be studied. External factors such as orders and supply chains, internal factors such as machine degradation, workers' skills, should be considered to understand complex manufacturing systems. Another deficiency in the existing researches is that human factor is not considered in digital twin of manufacturing system. Significant research effort needs to be made on the topic of digital twin for people in the manufacturing phase.

5.3. For service and retire phase

In service and retire phase, products have experienced operations of multiple stakeholders, which hinders data integration between different stakeholders and between different lifecycle phases. The decentralized products also make it difficult to connect digital twin with physical twin. Manufacturers and suppliers often pay much attention to high-value equipment. As a result, all the existing works focused on digital twin of high-value equipment or big infrastructures. No paper studies the digital twin of general products. In addition, even for high-value equipment, data is still insufficient, because some data cannot be measured in the actual situation. Thus, a promising direction is to make digital twin serve as "soft sensors" to extend the measurement range.

5.4. For full lifecycle phases

In the manufacturing, service, and retire phase, products of the same design start to undergo different manufacturing, service, and retire processes. The current existent virtual model may be an accurate representation of the product's design [113]. However, the individualized manufacturing, service, and retire processes are absent from the product's original model. Establishing a digital twin model for each individualized product takes a considerable amount of time, and a lot of digital twin models will result in huge workload. Grieves and Vickers defined Digital Twin Prototype (DTP) and Digital Twin Instance (DTI). DTP contains the informational sets necessary to describe and produce a physical version that duplicates or twins the virtual version. DTI describes an individual digital twin that corresponds to a specific physical product throughout the lifecycle of that physical product [30]. In this regard, a changeable parameterized model should be established in advance to describe behavior rules and data of the physical object. When the physical twin changes, the digital twin will change accordingly based on the pre-defined tolerances and variations. Except for the specified limits, digital twin should also learn from its physical twin and update core of its model to adapt unpredicted behavior rules. The idea is kind of similar to the way object-oriented programming uses classes as tools to create instances of objects.

From product lifecycle perspective, any change in one phase will have some effect in another phase because there is an association between each other. Therefore, digital twin should not only consider the current data, but also include historical data. Although the current literatures may achieve real-time connection between digital twin and physical object, there are few literatures that realize information flows throughout the entire lifecycle. A promising direction is to update and improve digital twin model along with the physical object's lifecycle.

6. Summary and conclusion

6.1. Summary

This paper analyzed the status of digital twin research and reviewed the state-of-the-art of digital twin from the perspective of concepts, key technologies, and industrial applications. The current digital twin concept is general and ambiguous. The concept should evolve towards more clarity and specificity and rely on industry practice. In terms of key technologies for digital twin, data related technologies, high-fidelity modeling technologies, and model based simulation technologies were reviewed and analyzed. Digital twin applications were summarized in respective lifecycle phase. Observations and future work recommendations for digital twin research were also presented in the form of different lifecycle phases.

In design phase, digital twin is used for product design and production system design in the forms of optimizing iteratively, providing data integrity, evaluate and verify virtually, etc. The main application is virtual evaluation & verification. Digital twin provides high-fidelity, multi-disciplinary model that can not only verify the design result's consistency with the design intention, but also discovery unpredicted undesirables. However, most of the literatures regarding digital twin in the design phase were about redesigning existing physical objects, or evaluating performances of the designed objects. Researches on designing a new object from scratch using digital twin are insufficient. What's more, low digital design level in some industries hinders the implementation of digital twin.

In manufacturing phase, applications of digital twin are also in various forms, such as real-time monitoring, production control, production planning, etc. The objects of digital twin are mainly manufacturing systems and manufacturing processes. Less attention is focused on products in the workshop because information of the products' manufacturing process will be of use in the service phase. Essentially, the role of digital twin in the manufacturing phase is to improve processing quality and reduce production cost in an efficient, dynamic, and intelligent manner, which is not available in the traditional method. However, the problems of data integration and complex phenomena modeling remain to be solved in future works.

Service phase is where digital twin originates. In service phase, digital twin is used for predictive maintenance, fault detection &

diagnosis, state monitoring, etc. Only two paper researched digital twin in the retire phase, indicating the need for more attention. Some literatures may achieve real-time connection between digital twin and its physical counterpart, but full-lifecycle information flow is lacking in existing researches.

6.2. Conclusion

It has been 17 years since Dr. Grieves proposed the terminology in 2003, and recent five years have witnessed the quick development of digital twin. However, up till now, no formal or widely-accepted definition has been achieved, and no unified creating and deploying process, too. Different industries and application fields have different perspectives and methods. Through an in-depth review, it is found that digital twin is gradually stepping out of its infancy and stepping into a stage of rapid development where researchers start to explore real practices and technologies in industry. The original yet grand vision to fully understand and reflect every aspect of the physical twin is still a long way to go. The application fields of digital twin are widely distributed, showing great vitality. Through in-depth analysis, conclusion can be drawn that the connotation of digital twin concept includes:

- **Individualized**: This means that digital twin is one-to-one with the individual physical twin. In other words, digital twin is as designed, as manufactured, as used, as maintained as the physical twin.
- **High-fidelity**: This means that digital twin can simulate the physical twin's behavior in the virtual space as exact as possible, which requires multi-physics modeling and continuous model updating through the whole lifecycle.
- **Real-time**: This means that digital twin responds to physical twin with relatively low latency, which is made possible by current development of mobile communication technology and IoT technology.
- **Controllable**: This means that changes on digital twin or physical twin control the other twin. This is the last step that closes the loop between digital twin and physical twin and realizes digital-physical convergence.

Overall speaking, each paper focused on development of a few digital twin components and the implementations were fundamentally different from each other. All of them adapted to the needs of respective application field using multiple tools. Some researches adopt modeling oriented view that stems from technical engineering issues, aiming at simulating the precise physical behavior. Others adopt information management oriented view, focusing on semantic connections and seamless information flow [130]. A variety of frameworks, reference models of digital twin were proposed, but none of them become industry consensus. As a result, it is difficult to conduct systematic research. The existing work cannot be inherited by other researchers, which may cause repeated research. It is urgent that researchers cooperate to form a systematic architecture of digital twin research.

Author contributions

Mengnan Liu mainly collect and analyze the reviewed literatures and prepare the manuscript. Shuiliang Fang and Huiyue Dong propose the idea of the research and discuss and recommend modifications. Cunzhi Xu helps to collect the needed literatures.

Declaration of Competing Interest

No potential conflict of interest was reported by the authors.

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