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Enabling technologies and tools for digital twin

Qinglin Qi [a], Fei Tao [a,*], Tianliang Hu [b], Nabil Anwer [c], Ang Liu [d], Yongli Wei [b], Lihui Wang [e], A. Y.C. Nee [f]

[a] School of Automation Science and Electrical Engineering, Beihang University, Beijing, 100083, China
[b] School of Mechanical Engineering, Shandong University, Jinan, 250061, China
[c] LURPA, ENS Paris-Saclay, Universite Paris-Sud, Universite Paris-Saclay, 94235, Cachan, France
[d] School of Mechanical and Manufacturing Engineering, University of New South Wales, Sydney, 2053, Australia
[e] Department of Production Engineering, KTH Royal Institute of Technology, Stockholm, Sweden
[f] Department of Mechanical Engineering, National University of Singapore, Singapore, Singapore

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ABSTRACT

Digital twin is revolutionizing industry. Fired by sensor updates and history data, the sophisticated models can mirror almost every facet of a product, process or service. In the future, everything in the physical world would be replicated in the digital space through digital twin technology. As a cutting-edge technology, digital twin has received a lot of attention. However, digital twin is far from realizing their potential, which is a complex system and long-drawn process. Researchers must model all the different parts of the objects or systems. Varied types of data needed to be collected and merged. Many researchers and participators in engineering are not clear which technologies and tools should be used. 5-dimension digital twin model provides reference guidance for understanding and implementing digital twin. From the perspective of 5-dimension digital twin model, this paper tries to investigate and summarize the frequently-used enabling technologies and tools for digital twin to provide technologies and tools references for the applications of digital twin in the future.

1. Introduction

Currently, digitalization has become a consensus, especially digital twin, precise virtual copies of machines or systems, is revolutionizing industry [1]. Many companies and fields already use digital twin to spot problems and increase efficiency [2]. With the advancement of information technologies, especially the emergence of new generation of information technologies (New ITs) such as Internet of things (IoT), cloud computing, big data analytics, and artificial intelligence (AI), the digitalization process is greatly accelerating. Through the convergence of the physical and virtual worlds, digitalization is becoming one of the main drivers of innovation in all sectors [3]. As shown in Fig. 1, the evolution of digitalization has gone through four progressive stages: digital enablement, digitalization assistance, digital control and link, and cyber-physical integration. Digital enablement refers to the process of converting paper document into digital forms without making any different-in-kind changes to the process itself [4,5]. Due to the limitation of digitalization tools, initially, only the most essential information is digitalized for storage, processing, and transfer. With the extensive applications of CAX technologies (e.g., CAD, CAE, and CAM) in the 1980s, the paradigm of digitalization shifted toward assisting engineers to work with computers effectively. With the development of Internet and advanced control technologies in the 1990s, business digitalization provided new revenue and value-producing opportunities for enterprises [5]. After entering the 21 st century, the New IT (e.g., IoT, cloud computing, big data, and AI) makes it possible to progressively converge the physical and virtual worlds (i.e., the cyber-physical integration [6]) toward the digitalization of industrial ecology.

Digital twin (DT) provides a unique means to achieve the cyber-physical integration, which is a notion embraced by more and more enterprises [7]. DT means an organic whole of physical asset (or physical entity) as well as its digitized representation, which mutually communicate, promote, and co-evolve with each other through bidirectional interactions [8]. Through various digitization technologies, the entities, behaviors, and relations in the physical world are digitized holistically to create high-fidelity virtual models [9,10]. Such virtual models depend on real-world data from the physical world to formulate their real-time parameters, boundary conditions, and dynamics, leading to a more

* Corresponding author.
E-mail address: ftao@buaa.edu.cn (F. Tao).

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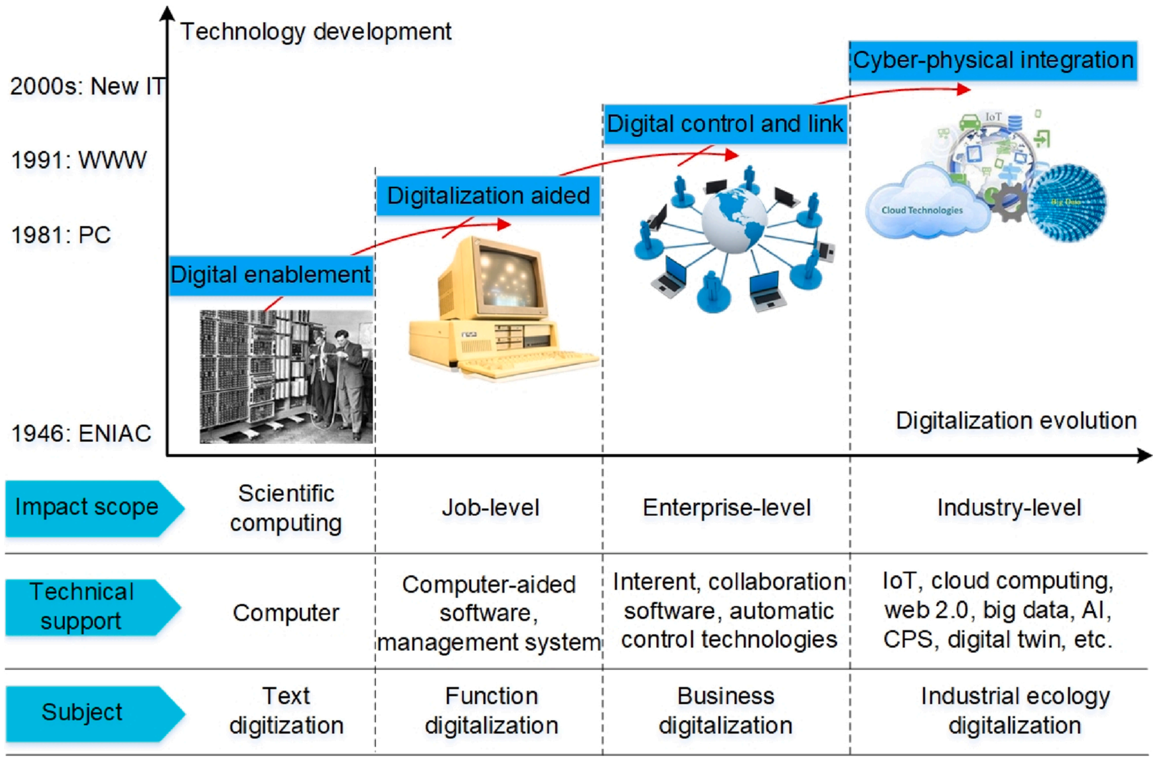

Fig. 1. Evolvement of digitalization paradigm.

representative reflection of the corresponding physical entities [10,11]. DT is attracting attention from both academia and industry. Gartner classified DT as one of the top 10 technological trends with strategic values for 3 years from 2017 to 2019 [12]. In 2018, Lockheed Martin listed DT as one of the six game-changing technologies for the defense industry [12].

DT has many strategic benefits. In particular, DT provides a unique way to reflect a physical entity in the digital world with respect to its shape, position, gesture, status, and motion [13]. Together with the sensory data acquisition, big data analytics, as well as AI and machine learning, DT can be used for monitoring, diagnostics, prognostics and optimization [14,15]. Through the assessment of ongoing states, the diagnosis of historical problems, and the prediction of future trends, DT can provide more comprehensive supports for the decision-making of a wide spectrum of operations. Once integrated with the digital representation of facilities, environments, and people, DT can be used for the training of users, operators, maintainers, and service providers [16]. Through DT, it is also possible to digitize expert experience, which can be documented, transferred, and modified throughout an enterprise to reduce the knowledge gap. Through simulation tools and virtual reality tools, DT can deepen the operator's understandings of complex physical entities and processes.

DT is an effective means to improve enterprises productivity and efficiency, as well as to reduce cost and time [17]. The current studies mainly focus on the macro level in terms of framework, process, and know-what as opposed to the micro level in terms of specific technologies, tools, and knowhow. Despite a strong desire from small and medium-size enterprises (SMEs) to incorporate DT into their daily businesses, most of the SMEs are unfamiliar with the key technologies and tools of DT. Moreover, DT is a highly complex system that requires a long-term process to orientate, operate, and optimize. To facilitate researchers and practitioners to implement DTs, this paper presents a summary of the key enabling technologies and tools for DT.

The rest of this paper is organized as follows. Section 2 presents a brief overview of DT. Section 3 analyzes the ideal potential functions and practice emphasis. Sections 4 and 5 present the key enabling technologies and tools for DT. Finally, Section 6 draws conclusions and outlines future work.

2. A brief overview of digital twin

2.1. History of digital twin

Strictly speaking, DT is not a completely new concept. It is rooted in some existing technologies [18], such as 3D modeling, system simulation, digital prototyping (including geometric, functional, and

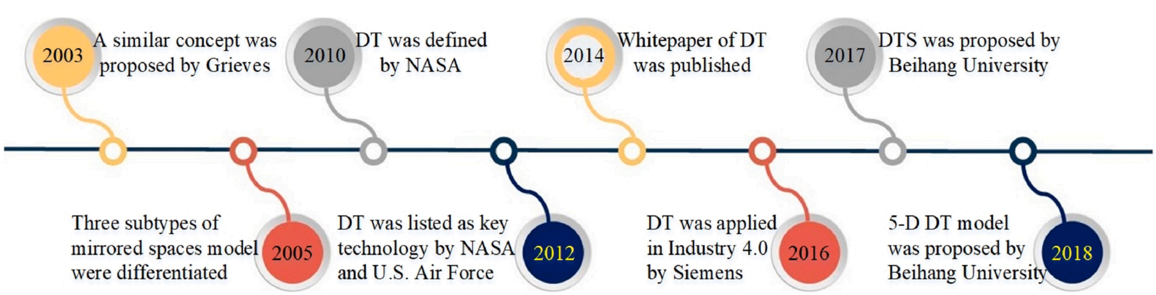

Fig. 2. The milestones of DT development.

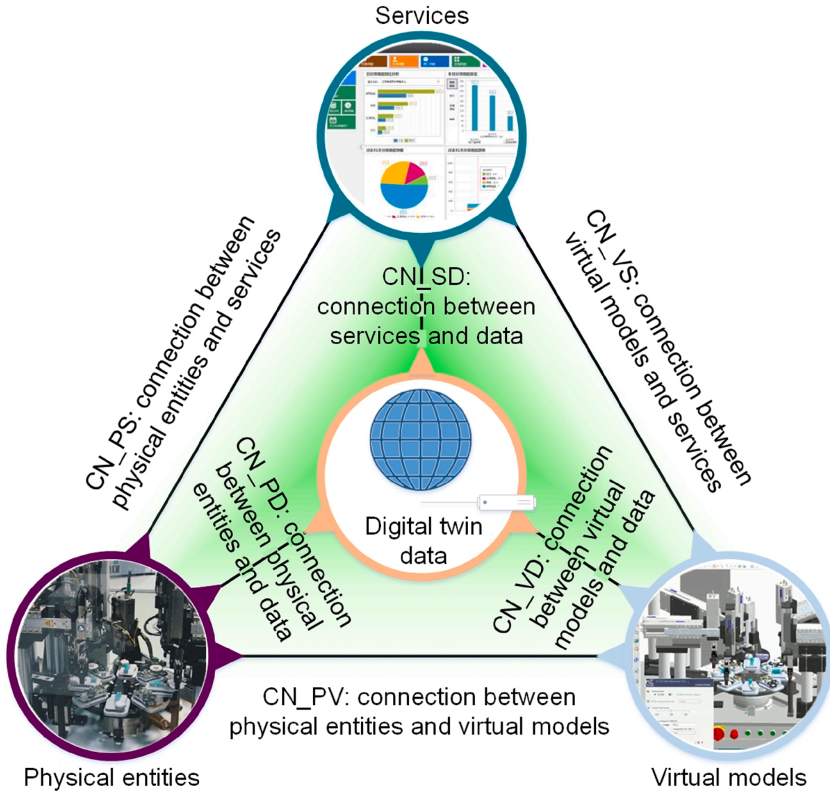

Fig. 3. Five-dimension digital twin model.

behavioral prototyping), etc. The increasing popularity of DT reflects the inevitable trend that the virtual world and the physical world are becoming increasingly linked to each other and integrated as a whole. From the conception of "a virtual, digital equivalent to a physical product" by Grieves [11] to the debut of DT thanks to national aeronautics and space administration (NASA) and air force research laboratory (AFRL) [10], DT represents the breakthrough of numerous limitations (e.g., data acquisition, digital description, and computer performance and algorithms, etc.). Then, DT was applied in Industry 4.0 by Siemens in 2016. As more and more researchers devoted to the research of DT, the number of relevant publications begun to grow exponentially [19]. Tao et al. [20] proposed the concept of DT shop-floor in January 2017 and discussed the characteristics, composition and operation mechanism and key technologies of DT shop-floor, which provided theoretical support for the application of DT in the manufacturing. Later then, to promote the further applications of DT in more fields, Tao et al. [21] extended the existing 3-dimension DT model and added two dimensions (DT data and services) to propose a five-dimension DT model. Some milestones of DT development are shown in Fig. 2.

Various definitions of DT appeared, which are reviewed by Tao et al. [19] and Negri et al. [22]. At present, the two most widely accepted definitions were given by Grieves and NASA. NASA defined DT for a space vehicle as "*A Digital Twin is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin*" [23]. In 2014, Grieves published the white paper about DT, according to which, the basic DT model consists of three main parts: *(a) physical products in Real Space, (b) virtual products in Virtual Space, as well as (c) the connections of data and information that tie the virtual and real products together* [11]. In essence, DT involves creating a virtual model for a physical entity in the digital form in order to simulate entity behaviors, monitor the ongoing status, recognize internal and external complexities, detect abnormal patterns, reflect system performance, and predict future trend [24]. Currently, the three-dimension DT model originally defined by Grieves is most applied. However, with the continuous expansion and upgrading of application requirements, the development and applications of DT present new trends and demands. For example, the applications of DT have gradually expanded into the civilian fields in recent years from the military and aerospace fields in the initial stage. With the expansion of the application fields, DT is faced with more service demands from different fields, different levels of users, and different businesses. Meanwhile, the Internet of everything provides conditions for realizing the cyber-physical interaction and data integration of DT. Therefore, on the basis of the DT model proposed by Grieves, Tao et al. [21] proposed the five-dimension DT model to promote the further applications of DT in more fields.

2.2. Five-dimension digital twin model

The five-dimension digital twin model can be formulated as formula (1) [25].

$$M_{DT} = (PE,\ VM, Ss, DD, CN) \tag{1}$$

where PE are physical entities, VM are virtual models, Ss are services, DD is DT data, and CN are connections. According to formula (1), the 5-dimension DT model is shown in Fig. 3.

2.2.1. Physical entities in digital twin

DT is to create the virtual models for physical entities in the digital way to simulate their behaviors [8]. The physical world is the foundation of DT. The physical world may consist of device or product, physical system, activities process, even an organization. They implement activities according to physical laws and deals with uncertain environments. The physical entities can be divided into three levels according to function and structure, which are unit level, system level, and system of system (SoS) level [6].

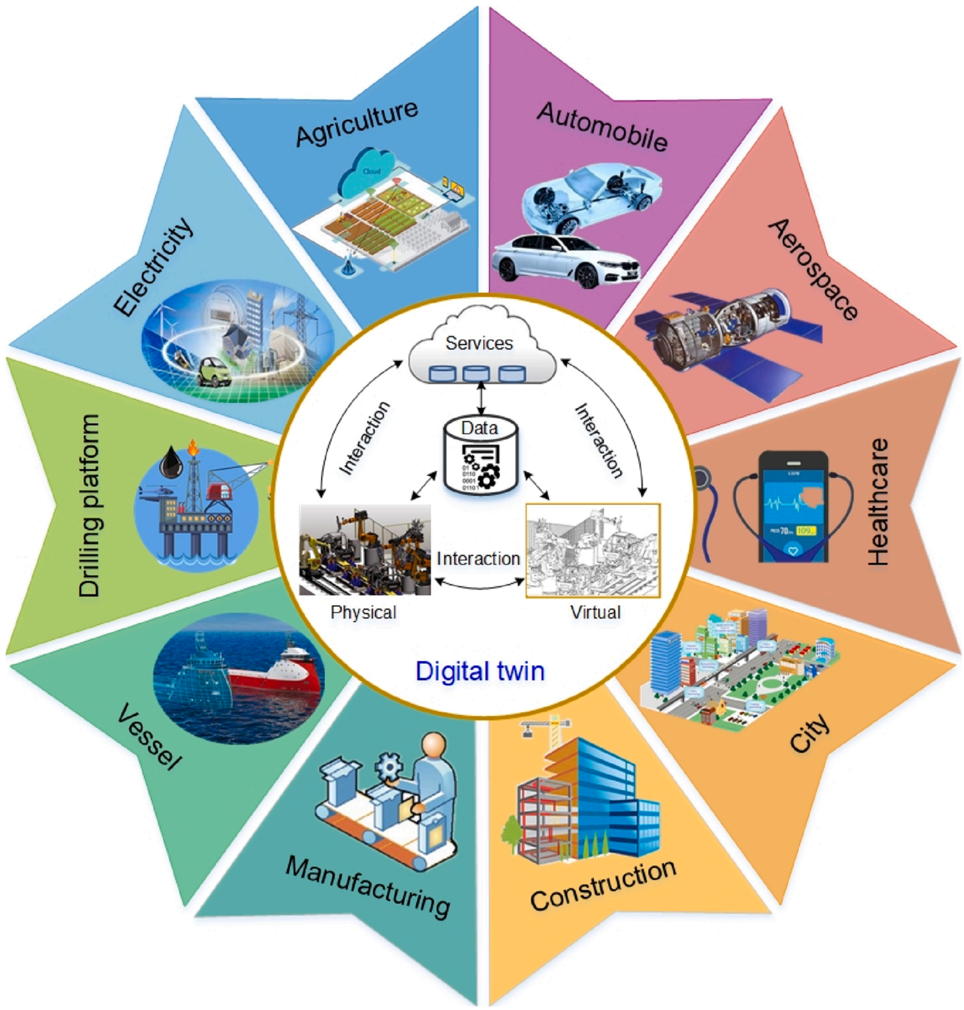

Fig. 4. Different application fields of digital twin.

2.2.2. Virtual models in digital twin

Virtual models ought to be faithful replicas of physical entities, which reproduce the physical geometries, properties, behaviors, and rules [26]. The 3-dimension geometric models describe a physical entity in terms of its shape, size, tolerance, and structural relation. Based on physical properties (e.g. speed, wear and force), physics model reflects the physical phenomena of the entities, such as the deformation, delamination, fracture and corrosion. Behavior model describes the behaviors (e.g., state transition, performance degradation and coordination) and responding mechanisms of the entities against changes in the external environment. The rule models equip DT with logical abilities such as reasoning, judgement, evaluation, and autonomous decision-making, by following the rules extracted from historical data or come from domain experts.

2.2.3. Digital twin data

Twin data is a key driver of DT [12]. DT deals with multi-temporal scale, multi-dimension, multi-source, and heterogeneous data. Some data is obtained from physical entities, including static attribute data and dynamic condition data. Some data is generated by virtual models, which reflects the simulation result. Some data is obtained from services, which describes the service invocation and execution. Some data is knowledge, which is provided by domain experts or extracted from existing data. Some data is fusion data, which is generated as a result of fusion of all the aforementioned data.

2.2.4. Services in digital twin

Against the background of product-service integration in all aspects of modern society, more and more enterprises begin to realize the importance of service [27]. Service is an essential component of DT in light of the paradigm of Everything-as-a-Service (XaaS). Firstly, DT provides users with application services concerning simulation, verification, monitoring, optimization, diagnosis and prognosis, prognostic and health management (PHM), etc. Secondly, a number of third-party services are needed in the process of building a functioning DT, such as data services, knowledge services, algorithms services, etc. Lastly, the operation of DT requires the continuous support of various platform services, which can accommodate customized software development, model building, and service delivery.

2.2.5. Connections in digital twin

Digital representations are connected dynamically with their real counterpart to enable advanced simulation, operation, and analysis. Connections between physical entities, virtual models, services, and data enable information and data exchange. There are 6 connections for DT, which are connection between physical entities and virtual models (CN_PV), connection between physical entities and data (CN_PD), connection between physical entities and services (CN_PS), connection between virtual models and data (CN_VD), connection between virtual models and services (CN_VS), connection between services and data (CN_SD) [25]. These connections enable the four parts to collaborate.

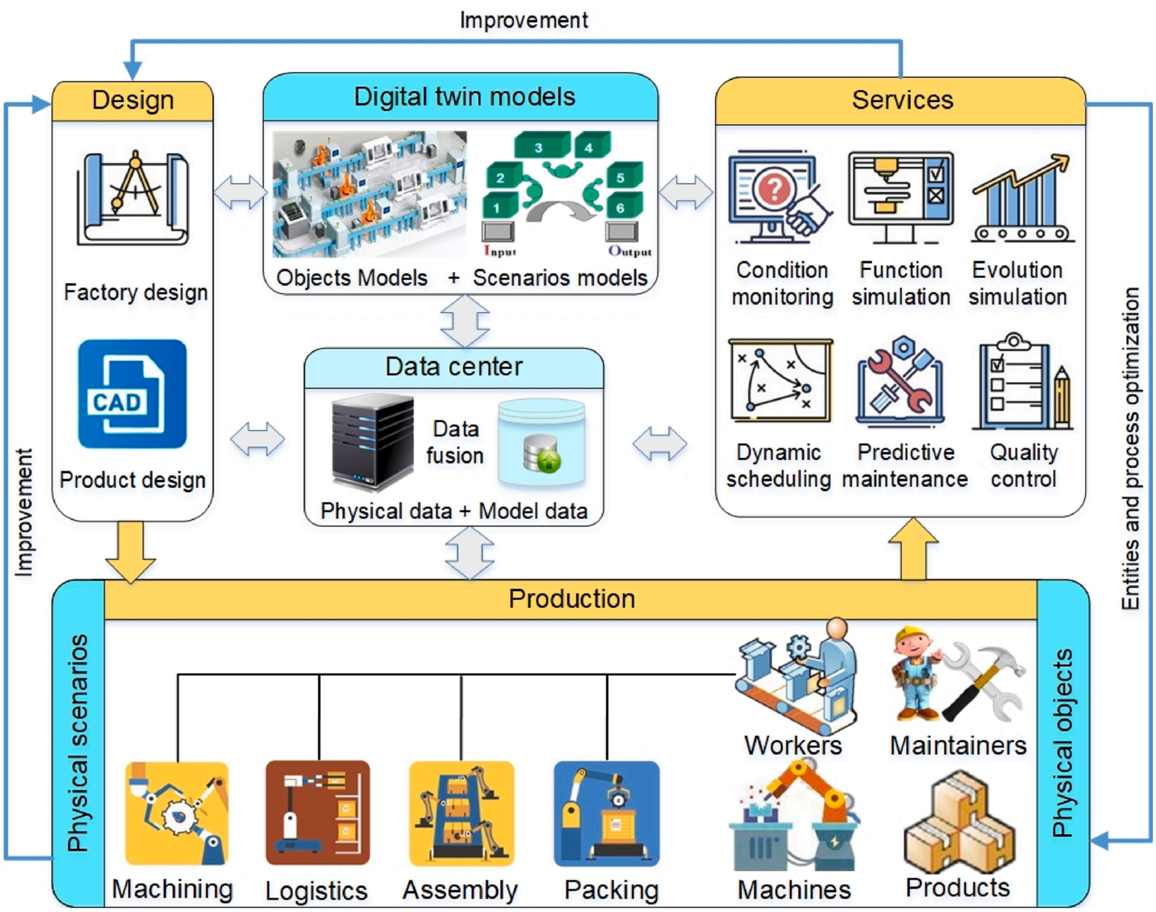

Fig. 5. Composition and application of digital twin.

2.3. *Application fields of digital twin*

Through the integration with mobile Internet, cloud computing, big data analytics and other technologies, DT is potentially applicable for many fields where it involves the mapping, fusion, and co-evolution between the physical and virtual spaces. As shown in Fig. 4, the DT applications can be found in smart city, construction, healthcare, agriculture, cargo shipping, drilling platform, automobile, aerospace, manufacturing, electricity, etc. [2]. As a relatively new technology, the application of DT was pioneered by the leading enterprises (e.g., GE, PTC, Siemens, ANSYS, Dassault, etc.) [28,29]. For civil engineering, Dassault used its 3D Experience Platform to build a "Digital Twin Singapore" to support urban planning, construction, and service [30]. Intellectsoft is exploring the DT applications on construction site to detect potential problems and prevent dangerous operations. In the healthcare field, Sim&Cure developed patient-based digital twin for treating aneurysms [31], and Dassault conducted a "Living Heart Project (LHP)" toward a human heart DT [32]. According to the whitepaper about DT by Microsoft, DT has the power to accelerate agricultural business and support agricultural sustainability [33]. DNV GL established a "virtual sister ship" (i.e., a vessel DT) to increase reliability, reduce operational cost, and improve safety throughout the vessel's lifecycle [34]. A drilling platform DT for the Blue Whale #1 in China enabled the visualization display, operational monitoring, and design training. Tesla attempted to develop a DT for each electric car to enable the simultaneous data transfer between car and plant [28]. In the aviation industry, Airbus, Boeing, AFRL, and NASA used DT to mirror actual conditions, identify defects, predict potential faults, and solve the problem of airframe maintenance [29]. LlamaZOO used DT to enable mine supervisors to monitor their operators' vehicles [35]. Based on the Predix platform, GE built a digital wind farm, by creating a DT for every wind turbine, to optimize maintenance strategy, improve reliability, and increase energy production [36]. Finally, many DT applications can be found in the manufacturing field. For example, SAP and Dassault relied on DT to reduce the deviation between functional requirement and actual performance. Siemens and PTC relied on DT to improve manufacturing efficiency and quality control. GE, ANSYS, TESLA, and Microsoft focused on the real-time monitoring, prognostics and health management, and manufacturing services [12].

3. Functions and practice emphasis of digital twin

3.1. *Category and product lifecycle application of digital twin*

DT reflects the virtual-reality integration and mapping relations between the physical and virtual worlds [6]. By recording, simulating, and predicting the running trajectory of entities and processes in the physical and virtual worlds, it can achieve the efficient exchange of information, optimal allocation of resources, analytical reduction of cost, and prevention of fatal failures [26]. Physical entities exist in specific scenarios to achieve their own functions and provide targeted services. Therefore, DT can be divided into entity DT and scenario DT, as shown in Fig. 5. Based on the 3D geometric models, entity DT functions to integrate different information such as monitoring information, sensing information, service information, and behavior information regarding a physical entity toward ubiquitous tracking of the entity throughout the whole lifecycle [9,37]. Physical entity would have a virtual twin that is exactly the same as its status, running trajectory, and behavioral characteristics. As for the DT scenarios, the physical scenarios are represented in the virtual space with static and dynamic

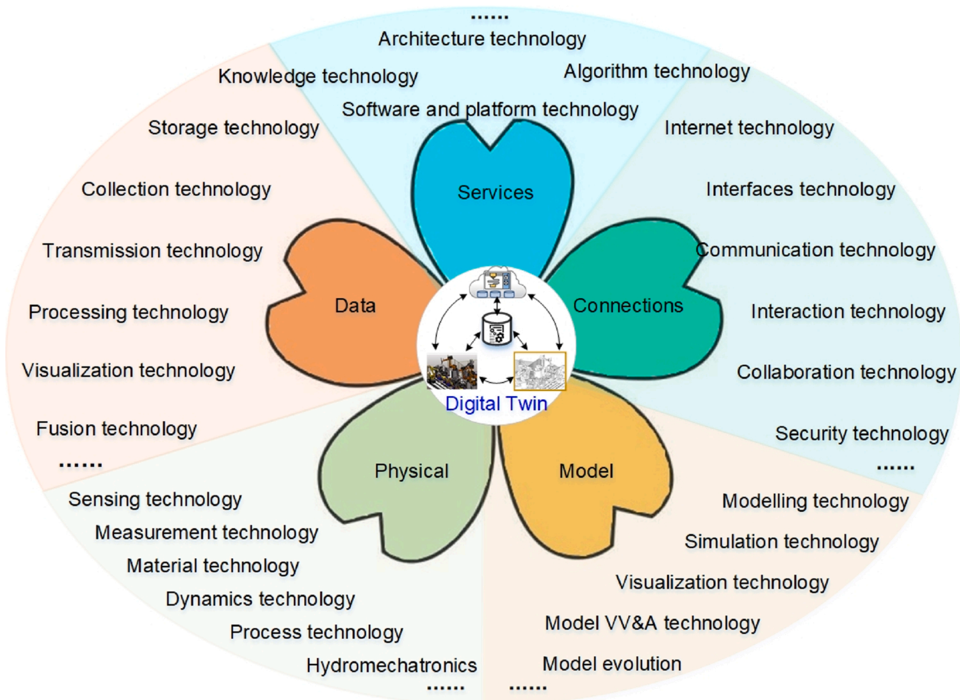

Fig. 6. Framework of enabling technologies for digital twin.

information. Static information includes spatial layout, equipment, and geographic location [29,38]. Dynamic information involves environment, energy consumption, equipment operation, dynamic process, etc. [29,38]. The activities in the physical scenario can be simulated by DT.

Some DT applications focused on the entity in terms of functional modeling, concept verification, behavior simulation, performance optimization, status monitoring, diagnosis and prediction, etc. Such applications can be found in areas such as healthcare, cargo shipping, drilling platform, automobile, aviation, aerospace, and Internet of Things. Some other DT applications focused on the scenario (i.e., the ideal conditions at its best to achieve specific functions). For example, production scenario is to produce the target product in optimal way. Construction is the production process of constructing the buildings, and manufacturing is the production process of turning raw materials or parts into products. Usage scenario refers to where, how, and when a product is utilized by end users, which could impact product status and lifetime. For a shop-floor or factory, it could be a production scenario for a product or a usage scenario for machine tools. The full potentials of DT can only be enabled through integration between entity DT and scenario DT.

According to the product lifecycle, the applications of DT can be attached to the design, production and use phases, as shown in Fig. 5. Above all, at the product design stage, DT enables designers to digitalize, visualize, and materialize the intangible concepts of complex systems (e.g., ship, aircraft, and factory) that have numerous components and implicit couplings [38,39]. Besides, the quality of design schemes can be evaluated, compared, and validated through DT without building expensive physical prototypes [39]. By virtually running the design scheme in production and usage scenarios, the manufacturability and all the expected functions of the target entity can be simulated to verify whether the design meets all the requirements. In this way, the design and production departments can collaboratively identify design flaws, quality defects, and improve solutions [24]. Guo et al. [38] and Zhang et al. [40] demonstrated that DT could enable the designers to simulate the whole factory design process with respect to factory layout, equipment configuration, material handling, buff ;er capacity, etc. Zhang et al. focused on the development of simulation-based approach for plant design and production planning [41]. Their modeling and simulation approaches can be applied to develop digital twin models of plant. Next, at the production stage, from the perspective of production management, through the simulation, verification, and confirmation of process planning and production scheduling, DT could enable the optimal (re)configuration of on-site resources, equipment, work-in-progress, and workers [42]. From the perspective of control and execution, DT functions to keep track of everything occurring in the physical world, based on which, to perform operational forecasting, to optimize control strategy [43,44], and to align actual process with planning [45]. For example, the DT of construction site can detect and predict potential issues in the virtual space before they actually occur in the physical space. The shop-floor DT can optimize process planning, resources allocation, manufacturing process, and process control, etc. [26,46]. Besides, Zhang et al. proposed an architecture of using cloud-based ubiquitous robotic systems for smart manufacturing of customized product. They also developed an implementation procedure for the development of a cloud-based ubiquitous robotic system [47]. Wang et al. used holon, which possesses a logical part and a physical part, to mimic the cyber and physical entities of CPS [48]. Their study is the implementation of digital twin technology. Lastly, at the service stage, since the same physical entity behave differently in various usage scenarios for different purposes, DT is used to simulate the usage scenarios. DT can lead to new insights for diagnosis and prognosis of wear [49], remaining life [9], damage location [50], etc., so that most of problems can be eliminated in the bud, reducing costs and downtime [51]. When problems occur, iterative experiments can be conducted in the digital environment to generate the best maintenance solution [8]. For example, DT is used to monitor and simulate the performance of aircraft engines in terms of wear coefficient and pressure tolerance [14], and DT is also used to drive PHM for wind turbines [25].

3.2. Practice emphasis for digital twin

In the practical applications of DT, the following key points need more attention. Firstly, the core of any DT is a high-fidelity virtual model. To this end, it is critical to fully understand the physical world.

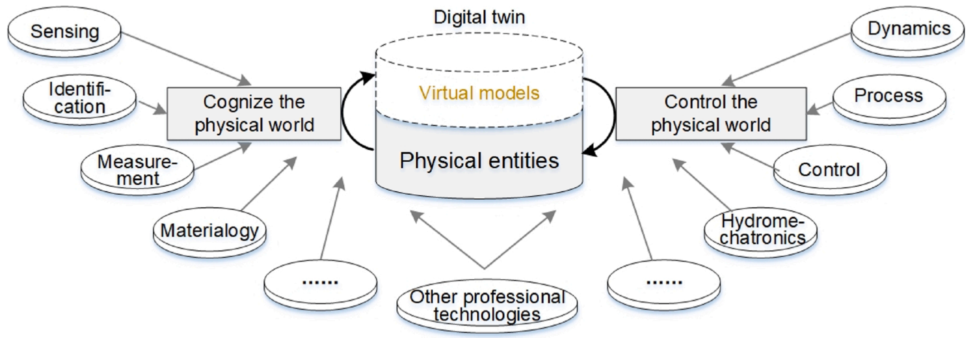

Fig. 7. Enabling technologies for cognizing and controlling physical world.

Otherwise, the virtual model cannot correspond effectively with the physical world. Secondly, while the virtual model is a key part of DT, DT modeling is a complex and iterative process. A good virtual model is characterized by high standardization, modularization, lightweight, and robustness [2]. The standardization of encoding, interface, and communication protocol is intended to facilitate information sharing and integration. Modularization increases the flexibility, scalability, and reusability through the separation and recombination of individual models. Lightweight reduces information transfer time and cost. Besides, the robustness of models is indispensable to deal with various uncertainties. Thirdly, the operations of models and services are all driven by data. From raw data to knowledge, the data must go through a series of steps (i.e., data lifecycle) [52]. Each step needs to be restructured based on the characteristics of DT. Moreover, DT is unique in a way that not only it processes data from the physical world, but also it fuses data generated by the virtual models to make the results more reliable. Fourthly, the ultimate goal of DT is to provide users with value-adding services, such as monitoring, simulation, verification, virtual experiment, optimization, digital education, etc. [15,19]. DT services are delivered through various mobile apps. Besides, DT can accommodate some third-party services such as resources service, algorithm service, knowledge service, etc. Therefore, service encapsulation and management are both important parts of DT. Lastly, the physical world, virtual models, data, and services are not isolated. They constantly interact with each other through connections among them towards collective evolution.

4. Enabling technologies for digital twin

According to the 5-dimension model, as shown in Fig. 6, a variety of enabling technologies are required to support different modules of DT (i.e., physical entity, virtual model, DT data, smart service, and connection). For the physical entity, the full understanding for the physical world is a prerequisite for DT. DT involves multidisciplinary knowledge, including dynamics, structural mechanics, acoustics, thermals, electromagnetism, materials science, hydromechatronics, control theory, and more. Combined with the knowledge, sensing, and measurement technologies, the physical entities and processes are mapped to the virtual space to make the models more accurate and closer to the reality. For the virtual model, various modeling technologies are essential. Visualization technologies are of the essence for real-time monitoring of physical assets and processes. The accuracy of virtual models directly affects the effectiveness of DT. Therefore, the models must be validated by verification, validation & accreditation (VV&A) technologies and optimized by optimization algorithms. Besides, simulation and retrospective technologies can enable rapid diagnosis of quality defects and feasibility verification. Since the virtual models must co-evolve with constant changes in the physical world, model evolution technologies are needed to drive the model update. During the operation of DT, a huge volume of data is generated. To extract useful information from raw data, advanced data analytics and fusion technologies are necessary. The process involves data collection, transmission, storage, processing, fusion, and visualization. DT-related services include application service, resource service, knowledge service, and platform service. To deliver these services, it requires application software, platform architecture technology, service oriented architecture (SoA) technologies, and knowledge technologies. Finally, the physical entity, virtual model, data, and service of DT are interconnected to enable interactions and exchange information. The connection involves Internet technologies, interaction technologies, cyber-security technologies, interface technologies, communication protocols, etc.

4.1. Enabling technologies for cognizing and controlling physical world

The physical world of 5-dimension digital twin model is often complex. There are intricate attributes and connections (including explicit and invisible ones) between the various entities in the physical world. The creation of virtual models is based on the entities in the physical world, as well as their key internal interaction logic and external relationships. It is very difficult to virtually reproduce such a complex system. Therefore, the establishment and improvement of DT is a long process. On the one hand, the virtual model corresponding to the physical entity is not perfect. As shown in Fig. 7, virtual models need to evolve to gradually improve the correspondence with physical entities [26], which requires a full understanding and perception for the physical world. On the other hand, after the physical entities are digitized, many implicit associations can be discovered, which can be used to promote the evolution of physical entities to control the physical world [53].

To create high-fidelity models, it is imperative to cognize the physical world and perceive data. As shown in Fig. 7, the first step to reflect the physical world is to measure the parameters, such as size, shape, structure, tolerance, surface roughness, density, hardness, etc. The existing measurement technologies include laser measurement, image recognition measurement, conversion measurement, and micro/nano-level precision measurement. To synchronize a virtual model with its real-world counterpart, real-time data (e.g., torque, pressure, displacement speed, acceleration, vibration, voltage, current, temperature, humidity, etc.) must be collected. To this end, sophisticated digital twins continuously pull real-time sensor and system data to represent a near real-time as-is state of physical entities [54]. Structural analysis models, evolution models, and fault prediction models may vary significantly for different industries, which require the expertise. For example, smart manufacturing involves knowledge and technologies about mechanical engineering, material engineering, control and information processing, etc. Especially, how to automatically control manufacturing equipment in an adaptive and effective manner is one major issue [55]. Since methods, technologies, and tools for DT are forward-looking, it requires effective collaboration between different industries.

Furthermore, DT serves to improve the performance of physical entities in the physical world. When the entities in physical world carry out the intended functions, the energy is controlled by control system to

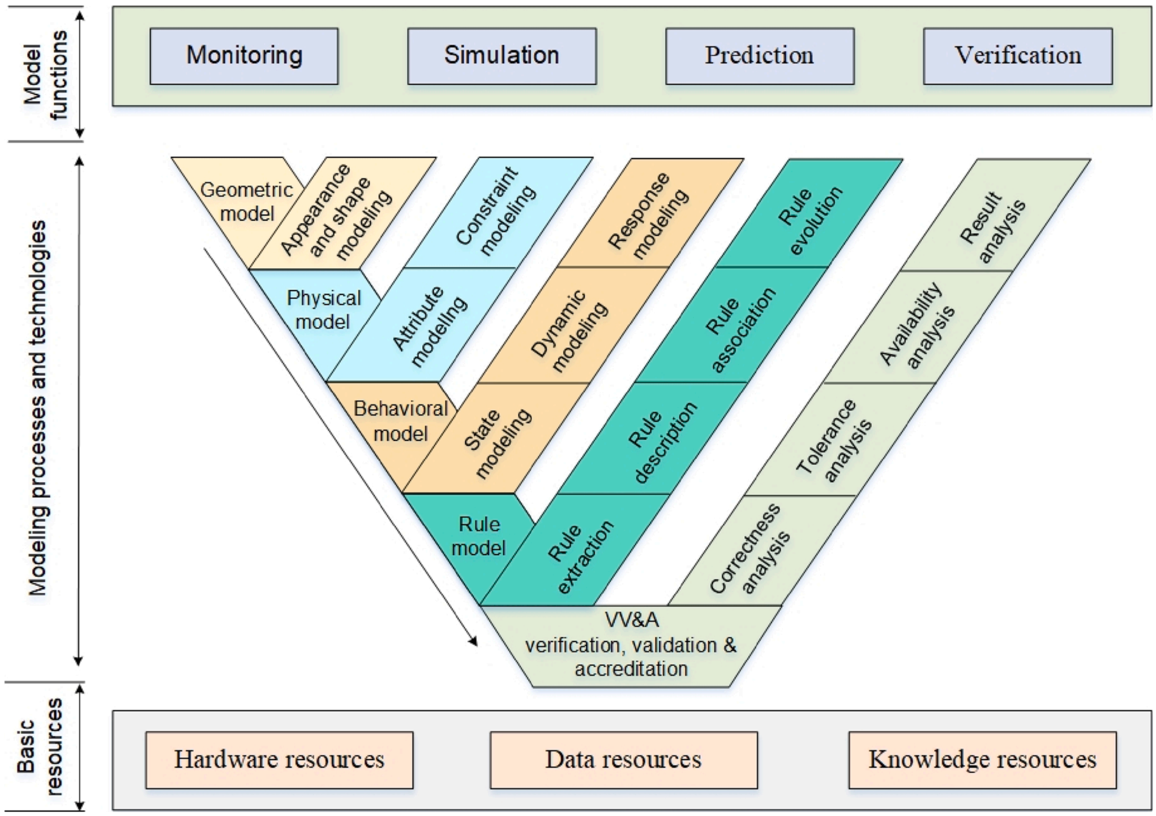

Fig. 8. Enabling technologies for modeling.

drive their actuators to accurately complete the specified actions. This process involves power technologies (e.g., hydraulic power, electric power, and fuel power), drive systems (e.g., shaftless transmission, bearing transmission, gear transmission, belt transmission, chain transmission, and servo drive technologies), process technologies (e.g., process planning, design, management, optimization, and control), and control technologies (e.g., electrical control, programmable control, hydraulic control, network control, and interdisciplinary technologies such as hydromechatronics.

DT applications call for new technologies to better perceive the physical world. Big data refers to large amounts of multi-source, heterogeneous data, which is characterized by 5 Vs, i.e., high volume, variety, velocity, veracity, and value. Big data analytics provides a new approach to understand the physical world. Valuable information can be found from complex phenomena through data analysis, which is suitable for various industries. As an interdisciplinary technology that integrates neurobiology, image processing, and pattern recognition, machine vision can extract information from images for the purposes of detection, measurement, and control. In addition, the cutting-edge technologies of various disciplines and industries are all worthy of further study to make the model more accurate, and the simulation and prediction results more in line with the actual situation. For example, for the manufacturing industry, new special processing technologies, manufacturing processes and equipment technologies, and smart robotic technologies can all help DT to control the smart manufacturing process. For the construction industry, emerging technologies (e.g., new materials, construction machinery, and shock absorption technologies) are transforming the construction industry. For now, it is recommended to use image recognition and laser measurement technologies to measure the parameters of the physical world, and use electrical control, programmable control, embedded control and network control technologies to control the physical world, as well as use big data analytics technologies to mine the implicit laws and knowledge.

4.2. Enabling technologies for digital twin modeling

Modeling refers to the process of representing a physical entity in digital forms that can be processed, analyzed, and managed by computers. Modeling is arguably the cornerstone of DT, which provides information representation method for product design, analysis, computer numerical control (CNC) machining, quality inspection, production management, etc. As shown in Fig. 8, DT-related modeling involves geometric modeling, physical modeling, behavioral modeling, and rule modeling.

Geometric model describes a physical entity in terms of its geometric shape, embodiment, and appearance with appropriate data structures, which are suitable for computer information conversion and processing. The geometric model includes geometric information (e.g., points, lines, surface, and bodies) as well as topological information (element relations such as intersection, adjacent, tangent, vertical, and parallel). Geometric modeling includes wireframe modeling, surface modeling, and solid modeling. Wireframe modeling uses basic lines to define the ridgeline portion of the target to form a stereoscopic frame. Surface modeling describes each surface of an entity and then splice all surfaces to form a holistic model. Solid modeling describes the internal structure of a three-dimension entity, which includes information such as vertices, edges, surfaces, and bodys, etc. Besides, to increase the sense of reality, developers create appearance texture effects (such as wear, cracks, fingerprints, and stains, etc.) with bitmaps that represent the surface details of the entity. Texture techniques mainly are texture blending (with or without transparency) and lightmaps.

Geometric model describes the geometric information of an entity, but do not describe entity features and constraints. The physical model adds information such as accuracy information (e.g., dimensional tolerance, shape tolerances, position tolerance, and surface roughness), material information (e.g., material type, performance, heat treatment requirement, hardness, etc.), and assembly information (e.g., mating relationship and assembly order). Feature modeling includes interactive

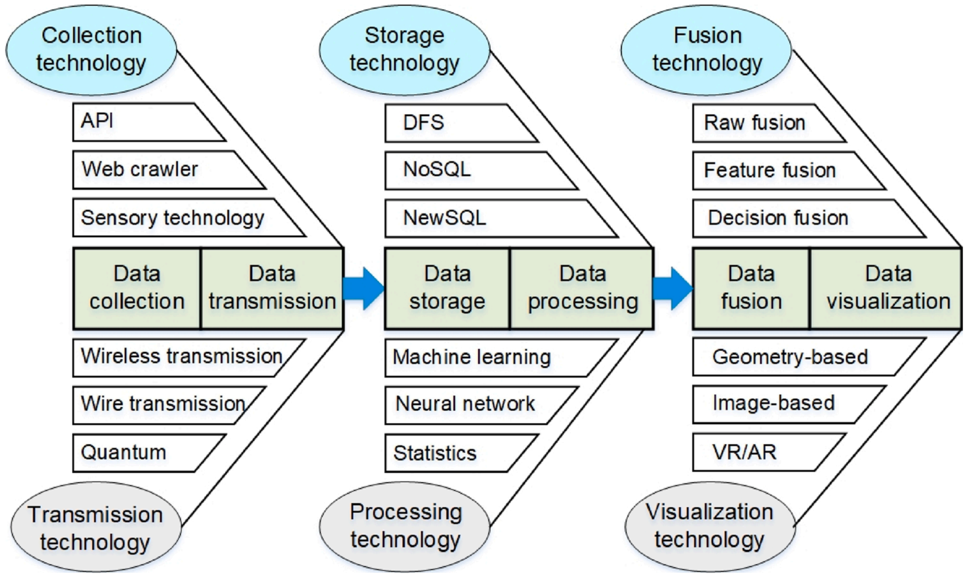

Fig. 9. Enabling technologies for digital twin data management.

feature definition, automatic feature recognition, and feature-based design.

Behavioral model describes various behaviors of a physical entity to fulfill functions, respond to changes, interact with others, adjust internal operations, maintain health, etc. The simulation of physical behaviors is a complex process that involves multiple models, such as problem model, state model, dynamics model, evaluation model, etc. These models can be developed based on finite state machines, markov chains, and ontology-based modeling methods, etc. State modeling includes state diagram and activity diagram. The former describes the dynamic behaviors of an entity over its lifecycle (i.e., the representation of a sequence of states), whereas the latter describes activities required to complete an operation (i.e., the representation of a sequence of activities). Dynamics modeling deals with rigid body motion, elastic system motion, high-speed rotating body motion, and fluid motion.

Rule model describes the rules extracted from historical data, expert knowledge, and predefined logic. The rules equip the virtual model with an ability to reason, judge, evaluate, optimize, and predict. Rule modeling involves rule extraction, rule description, rule association, and rule evolution. Rule extraction involves both symbolic methods (e.g., decision tree and rough set theory) and connectionist methods (e.g., neural network). Rule description involves methods such as logical notation, production representation, frame representation, object-oriented representation, semantic web notation, XML-based representation, ontology representation, etc. Rule association involves methods such as category association, diagnostic/inferential association, cluster association, behavior association, attribute association, etc. Rule evolution includes application evolution and periodic evolution. Application evolution means the process of adjusting and updating the rules based on feedback obtained from the application process, and periodic evolution means the process of regularly evaluating the effectiveness of current rules over a certain period of time (the time varies depending on the application). The recommendations of key modeling technologies are solid modeling technologies for the geometric model, texture technologies for increasing the sense of reality, finite element analysis technologies for the physical model, finite state machines for the behavioral model, XML-based representation and ontology representation for the rule model.

Model VV&A can improve model accuracy and simulation confidence [56]. Model VV&A is intended to analyze whether and to what extent the correctness, tolerance, availability, and running result meet the requirement. Model VV&A involves both static methods and dynamic methods. Static methods are used to evaluate the static aspect of modeling and simulation, including grammatical analysis, semantic analysis, structural analysis, causal maps, control analysis, etc. Dynamic methods are used to validate the dynamic aspects of modeling and simulation, including black box test, white box test, execution tracking, regression testing, statistical technique, and graphical comparison.

The current modeling technologies focus on the construction of geometric and physical models. There is a lack of “multi-spatial scale models” that can represent the behaviors, features, and rules from different granularities of different spatial scales. There is a lack of "multi-time scale models" that can characterize the dynamic process of physical entities from different time scales. From the system perspective, it remains a challenge to integrate various models with different dimensions, different spatial scales, and different time scales. As a result, the existing virtual models cannot describe physical entities in a realistic and objective manner. The future modeling technologies are characterized by multidisciplinary and multifunctional synthesis. The DT modeling process is an interdisciplinary synthesis process, which involves mechanical science, hydraulics, aerodynamics, structural mechanics, fluid mechanics, acoustics, thermals, electromagnetism, and control theory. Modeling should be optimized for multi-objective and full-performance, to reach high accuracy, reliability, and reproduce both dynamic and static characteristics. Moreover, combined with the historical usage, maintenance, and upgrade data, various DT models (e.g., structural analysis model, thermodynamic model, product failure and life prediction and analysis models, etc.) can be progressively optimized through bayesian, machine learning, as well as other data mining methods and optimization algorithms.

4.3. Enabling technologies for digital twin data management

Data-driven digital twin can perceive, respond, and adapt to the changing environment and operational conditions. As illustrated in Fig. 9, the whole data lifecycle includes data collection, transmission, storage, processing, fusion and visualization [52].

The data sources include hardware, software, and network [24]. Hardware data includes the static attribute data and dynamic status data. Barcodes, QR codes, radio frequency identification devices (RFID), cameras, sensors, and other IoT technologies are widely used for information identification and real-time perception. Software data can be collected through software application programming interfaces (APIs), and open database interfaces. Network data can be collected from the

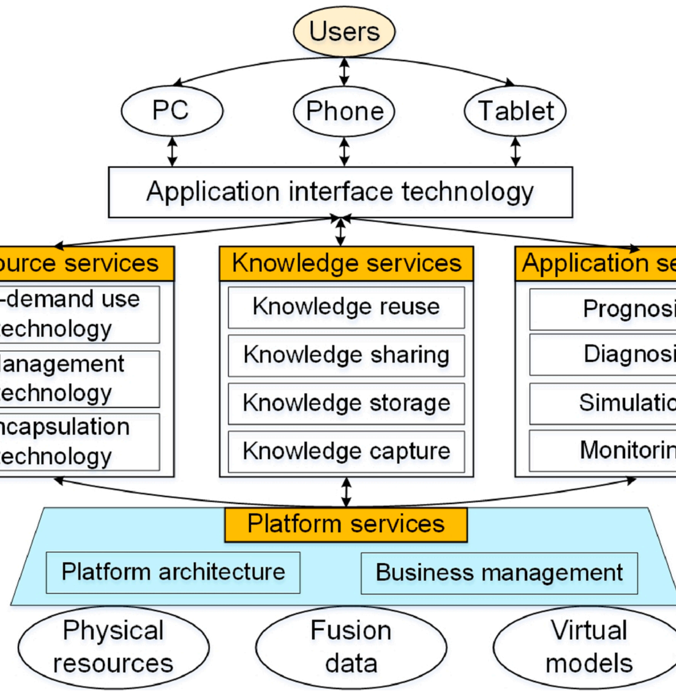

Fig. 10. Enabling technologies for digital twin services.

Internet through web crawlers, search engine, and public APIs.

Data transmission technologies include wire and wireless transmissions. Wire transmission technologies include twisted-pair cable transmission, symmetric cable transmission, coaxial cable transmission, fiber optic transmission, etc. Wireless transmission includes short-range and long-distance technologies. The widely used short-range wireless technologies include Zig-Bee, Bluetooth, Wi-Fi, Ultra-Wideband (UWB), and Near Field Communication (NFC) [57]. Long-distance wireless technologies include GPRS/CDMA, digital radio, spread spectrum microwave, wireless bridge, satellite communication, etc. Both wire and wireless transmissions depend on transmission protocols, access methods, multi-access schemes, channel multiplex modulation and coding, and multi-user detection technologies.

Data storage is to store the collected data for further processing, analysis, and management. Data storage is inseparable from database technologies. However, due to the increasing volume and heterogeneity of multisource DT data, traditional database technologies are no longer unfeasible. Big data storage technologies, such as distributed file storage (DFS), NoSQL database, NewSQL database, and cloud storage, are drawing growing attention. DFS enables many hosts to access shared files and directories simultaneously over the network. NoSQL is characterized by the ability to scale horizontally to cope with massive data. NewSQL denotes new scalable and high-performance databases, which not only has storage and management capability for massive data, but also supports ACID and SQL of traditional database. NewSQL implements replication and failback by using redundant machines.

Data processing means extracting useful information from a large volume of incomplete, unstructured, noisy, fuzzy, and random raw data. Firstly, data is carefully preprocessed to remove redundant, irrelevant, misleading, duplicate, and inconsistent data. The relevant technologies include data cleaning, data compression, data smoothing, data reduction, data transformation, etc. Next, the pre-processed data is analyzed through statistical methods, neural network methods, etc. Relevant statistical methods include descriptive statistics (e.g., frequency, central tendency, discrete tendency, and distribution analysis), hypothesis testing (e.g., u-test, t-test, $\chi 2$ test, and F-test), correlation analysis (e.g., linear correlation, partial correlation, and distance analysis), regression analysis (e.g., linear regression, curve regression, binary regression, and multiple regression), clustering analysis (e.g., partition clustering, hierarchical clustering, density-based clustering, and grid-based clustering), discriminant analysis (e.g., maximum likelihood, distance discriminant, bayesian discriminant, and fisher discriminant), dimension reduction (e.g., principal component analysis, and factor analysis), time series analysis, etc. Neural network methods include forward neural network (i.e., neural network based on gradient algorithm such as BP network, optimal regularization method such as SVM, radial basis neural network, and extreme learning machine neural network), feedback network (e.g., Hopfield neural network, Hamming network, wavelet neural network, bidirectional contact storage network, and Boltzmann machine), and self-organizing neural network (e.g., self-organizing feature mapping and competitive learning). Besides, deep learning provides advanced analytics technology for processing and analysing massive data [58]. Database methods include multidimensional data analysis and OLAP methods.

Data fusion copes with multisource data through synthesis, filtering, correlation, and integration. Data fusion includes raw-data-level fusion, feature-level fusion, and decision-level fusion. Data fusion methods include random methods and artificial intelligence. Random methods (e.g., classical reasoning, weighted average method, Kalman filtering, Bayesian estimation, and Dempster-Shafer evidence reasoning,) are applicable for all three levels of data fusion. Artificial intelligence methods (e.g., fuzzy set theory, rough set theory, neural network, wavelet theory, and support vector machine) are applicable for the feature-level and decision-level data fusions.

Data visualization serves to present data analysis results in a straightforward, intuitive, and interactive manner [52]. Generally speaking, any method intended to make explicit the underlying principles, laws, and logics contained in data by means of graphics is called data visualization. Data visualization is manifested in various ways such as histogram, pie chart, line chart, map, bubble chart, tree chart, dashboards, etc. According to the principle of its visualization, these methods can be divided into geometry-based technologies, pixel-oriented technologies, icon-based technologies, layer-based technologies, image-based technologies, etc.

As the volume of data continues to increase, the existing data technologies are bound to advance. For data collection, the future data

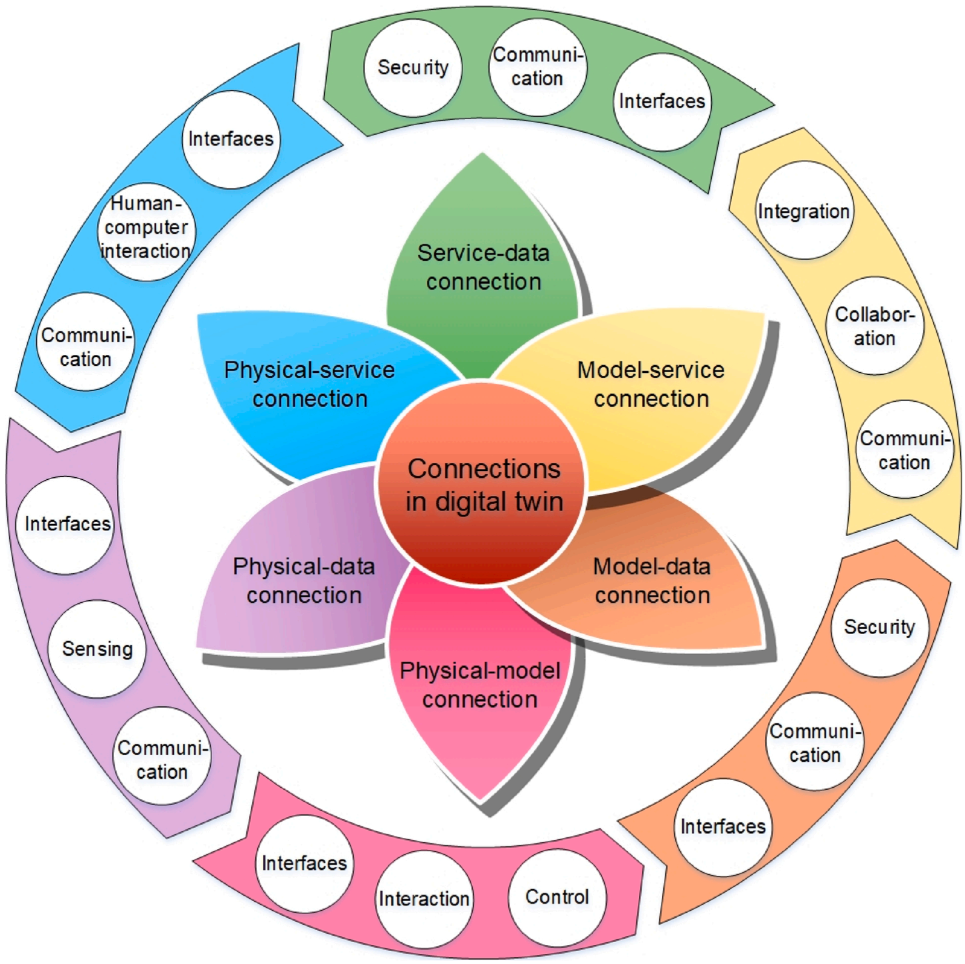

Fig. 11. Enabling technology for connections.

acquisition technologies should focus on real-time status data collection. Therefore, it is necessary to explore smart identification technologies, advanced sensor technologies, machine vision technologies, adaptation and access technologies, etc. For data transmission, it is necessary to explore the applicability of the high-speed, low-latency, high-performance, and high-secure data transmission protocols (e.g., fibre channel protocol and 5 G), and their corresponding devices. Besides, quantum transmission technology is potentially applicable for DT as well, including quantum key distribution (QKD), quantum teleportation, quantum secure direct communication (QSDC), quantum secret sharing (QSS). Data storage can be improved by adopting new storage media (e.g., inductive thin film and magnetic random access memory) and restructuring storage architecture (e.g., time series, distributed, and MPP architecture). As algorithms become increasingly complex, new data processing architectures (e.g., edge computing and fog computing [59]) can address the issue of massive data processing. Moreover, new data processing technologies such as graph processing and domain-oriented data processing technologies should be developed. The future directions of data fusion include real-time data fusion, online data and offline data fusion, physical data and simulation data fusion, structured and unstructured data fusion, big data fusion, object-based data fusion, similarity fusion, cross-language data fusion, etc. Currently, it is difficult to visualize explicitly the large-scale and high-dimensional data. In the future, multiple models should be adopted to customize the data visualization outcomes through parallel visualization technologies, complex data dimensionality reduction visualization technologies, unstructured data visualization techniques, etc. The recommendation of key technologies for data lifecycle management includes sensors and other IoT technologies for data collection, 5 G technology for data transmission, NewSQL technology for data storage, edge-cloud architecture computing technology for data processing, artificial intelligence technology for data fusion. The data visualization technologies vary depending on the applications.

4.4. Enabling technologies for digital twin services

DT integrates multiple disciplines to achieve advanced monitoring, simulation, diagnosis and prognosis. Monitoring requires computer graphics, image processing, 3-D rendering, graphics engine, virtual-reality synchronization technologies, etc. Simulation involves structural simulation, mechanics (e.g., fluid dynamics, solid mechanics, thermodynamics, and kinematics) simulation, electronic circuit simulation, control simulation, process simulation, virtual test simulation, etc. Diagnosis and prognosis are based on data analysis, which involves statistical theory, machine learning, neural network, fuzzy theory, fault tree, etc.

As shown in Fig. 10, some hardware and software resources and even knowledge can be encapsulated into services. The lifecycle of resource services can be divided into three stages: service generation, service management, and on-demand use of services [60]. Service generation technologies include resource perception and assessing (e.g., sensors, adapters, and middleware), resource virtualization, and resource encapsulation technologies (e.g., SOA, web services, and semantic services), etc. Service management technologies include service searching, matching, collaboration, comprehensive utility evaluation, quality of service (QoS), scheduling, fault tolerance technologies, etc. On-demand

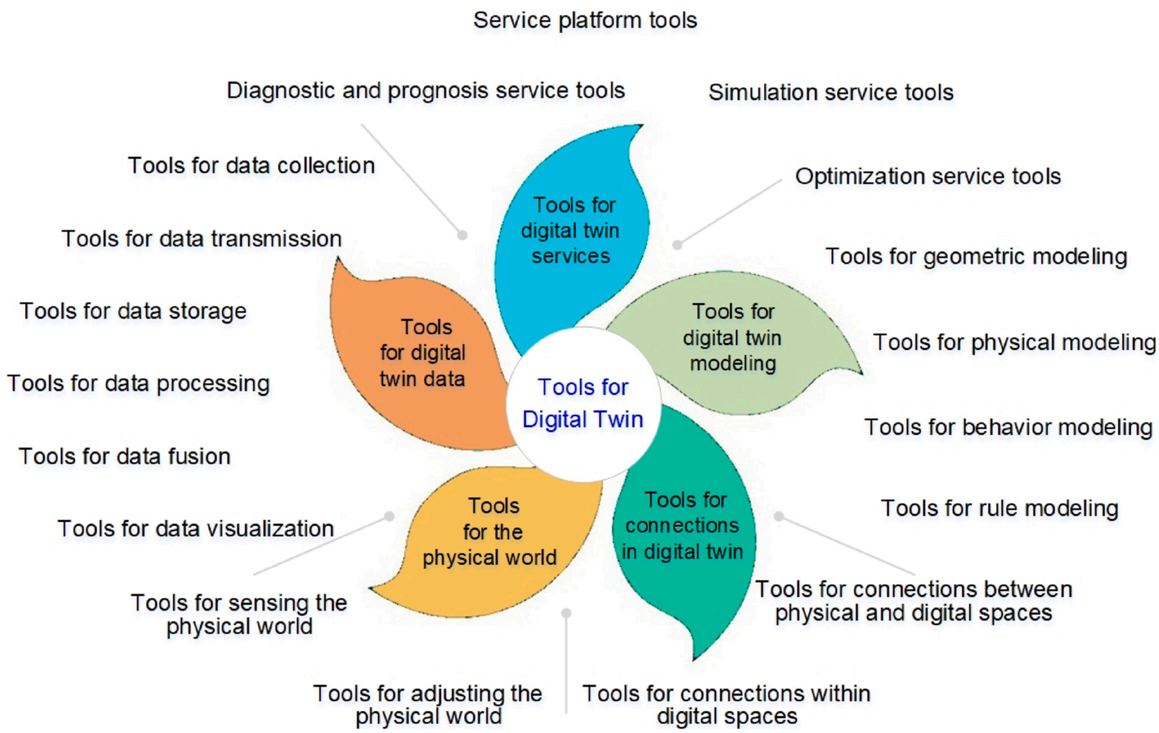

Fig. 12. Framework of tools for digital twin.

use technologies consisted of transaction and business management technologies, etc. to provide supporting for realizing automatic matching, transaction process monitoring, comprehensive evaluation, optimal scheduling of services and users' business. Knowledge services involve the process of knowledge capture, storage, sharing, and reuse, etc. Common technologies for knowledge capturing include association rule mining, statistical methods, artificial neural network, decision tree, rough set method, case-based reasoning method, etc. Knowledge storage, sharing, and reuse are implemented in the form of services.

Resource and knowledge services, application services can be managed through the industrial IoT platform. Platform provides some supporting functions such as service publishing, querying, searching, smart matching and recommendation, online communication, online contracting, service evaluation, etc. Platform-related technologies include platform architecture, organization mode, operation and maintenance management, security technologies, etc.

In addition, the creation of virtual models is complex and specialized project, so are the data fusion and analysis. For users who do not have relevant knowledge, it is difficult to build and use the DT. Therefore, it is imperative that models and data are able to be shared and used by users. Because service can shield the underlying heterogeneity, the DT components can be encapsulated to services to be managed and used in service platform. As a result, the DT components that cannot be easily developed in-house can be purchased, shared, and reused in a convenient "pay-as-you-go" fashion through services [12]. Benefited from comprehensive servitization, the DT can be managed in a service platform uniformly. Among the enabling technologies for digital twin services, service-oriented architecture is the most important.

In the future, moving target detection is significant for smart monitoring. Moving target detection, classification, tracking and other high-level behavioral analysis algorithm improvements are research route. For multi-state, multi-physics, multi-scale and complex coupling simulations, they are required to be more precise, more detailed, and have continuous dynamic optimization capabilities. As DT is complex system integrating multiple engineering disciplines, the future research includes multi-domain simulation, joint simulation of multi-simulation systems coupling. Besides, future simulations also need to enhance high-performance computing and parallel scalability capabilities. The generation of massive operational data poses new challenges for diagnosis and prognosis. Big data-based diagnosis and prognosis will be the mainstream research, including algorithm design, feature extraction, performance improvement, etc. Service transactions involve the service provider, demander and operator. How to consider the interests of all participants, and balance their utility is the bottleneck, which still needs to be solved. Services work together to complete tasks. Collaborative services are exposed to more uncertainties, which affect the smooth completion of the task. For knowledge extraction, there is a lack of resources in natural language processing, especially dictionaries, which is worth of future research. Efficiency and security are the two basic elements of the platform. Architecture, algorithms and standards of security and reliability without compromising performance are the top priority of research.

4.5. *Enabling technologies for connections in digital twin*

As shown in Fig. 11, based on the real-time data exchange through CN_PV, not only the running state of the physical entities is reflected dynamically in the virtual world, but also the analysis results of the virtual models are sent back to control the physical entities. Through CN_PD, DT is used to manage the entire product lifecycle, which laid data foundation for analysis, prediction, quality tracing, and product planning. Through CN_PS, services (e.g., monitoring, diagnostics, and prognosis) are linked to physical entities to receive data and feed the service outcome back. In the connections of physical entities with models, data and services, identification, sensing and tracking of physical entities are crucial. Therefore, RFID, sensor, wireless sensor network, and other IoT technologies are necessary. Data exchange requires communication technology [61], unified communication interfaces, and protocol technologies, including protocol parsing and conversion, interface compatibility, and common gateway interface, etc. Since human interacts with DT in both physical and virtual worlds, human-computer interaction technologies (e.g., VR, AR, MR) should be incorporated, as well as human–robot interaction and collaboration [62]. Given many different models, CN_VD needs communication,

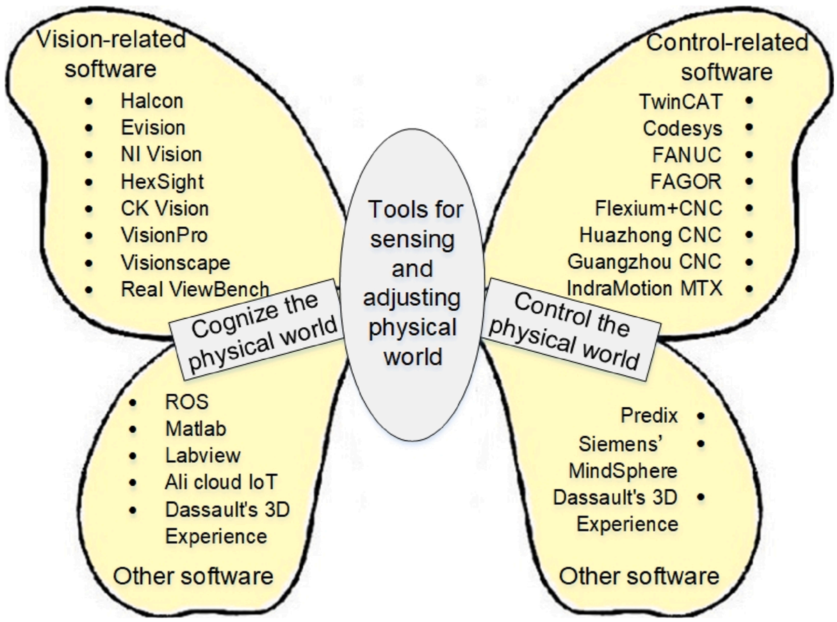

Fig. 13. Tools for cognizing and controlling physical world.

interfaces, protocols, and standard technologies to ensure smooth data interaction between virtual models and data. Similarly, the connections between services and virtual models (CN_VS) as well as data (CN_SD) also require communication interface, protocol, standard technologies, and collaboration technologies. Finally, security technologies (e.g., device security, network security, information security) must be incorporated to protect the security of DTs. In the connections in digital twin, the communication interfaces and protocol technologies, human-computer interaction technologies, as well as security technologies should be pay more attention.

The connection part serves to ensure real-time interaction among different parts of DTs. At present, the inconsistency of interfaces, protocols, and standards is the bottleneck of DT connection. It is necessary to investigate the general interconnection theories, standards, and devices with heterogeneous multi-source elements. As data traffic continues to grow exponentially, research hotspots such as multi-dimensional multiplexing (e.g., time division, wavelength division, frequency division, code division, and modularization) and coherent technologies, can provide more bandwidth and lower latency access services. Facing the massive incoming data, a promising solution is to build ultra-large-capacity routers with tens of millions of small routing entries to provide end-to-end communications. It is necessary to develop new network architectures in order to achieve the flexible control of network traffic and make the network (as pipelines) more intelligent. Given the increase of communication bandwidths and energy consumption, it is necessary to develop new strategies and approaches toward green communication.

5. Tools for digital twin

As shown in Fig. 12, based on the 5-dimension digital twin model, functional requirements and enabling technologies of digital twin, some tools are prescribed, including tools for cognizing and controlling physical world, tools for digital twin modeling, tools for digital twin data management, tools for digital twin services applications, and tools for connections in digital twin.

5.1. Tools for cognizing and controlling physical world

The tools for physical part of DT can be divided into tools for cognizing physical world and tools for controlling physical world. Cognizing different aspects of the physical world is the foundation of digitalization. IoT is one of the drivers of digital twin. When the physical entities are hooked up to data sensing and gathering systems, digital twin turn the data into insights and ultimately into optimized processes and business outcomes. For example, Ali Cloud IoT provides secure and reliable device sensing capacity, enabling fast access to multi-protocol, multi-platform, multi-regional devices. Besides, the virtual models run in parallel to the physical assets. Driven by sensors data, digital twin flags operational behavior that deviates from simulated behavior. For example, a petroleum company may stream sensor data from offshore oil rigs that operate continuously. IoTSyS is an IoT middleware, which provides a communication protocol stack for the communication between smart devices. IoTSyS supports multiple standards and protocols, including IPv6, oBIX, 6LoWPAN, and efficient XML exchange formats. Moreover, most tools for cognizing the physical world are vision-related. For example, in an uncharted workshop environment, AGV (automated guided vehicle) cars can use LIDAR (light detection and ranging), depth camera, GPS (global positioning system), and maps established through the ROS (robot operating system) software architecture, to optimize the path [63]. Similar software tools are shown in Fig. 13.

A tool for controlling the physical world can make physical entities run more efficiently and securely based on feedback information, which is analysis and processing of perceived physical entity state information in virtual world. Digital twin is to adjust the physical world mainly through controlling the operations with feedback. Therefore, the tools for changing the physical world mostly are control-related. For example, TwinCAT software system can turn almost any compatible PC into a real-time controller with a multi-PLC system, NC axis control, programming environment and operating station [64]. SAP provides vehicle maintenance and remote diagnosis services for Trenitalia (i.e., the primary train operator in Italy) through real-time data analysis. Besides, it provides an optimal operation plan for the health state and train running state through the dispatching system [65]. Similar software tools are shown in Fig. 13.

5.2. Tools for digital twin modeling

ANSYS Twin Builder containing extensive application-specific libraries and features third-party tool integration is an appropriate software tool for digital twin modeling, which allows for multiple modeling domains and languages. Twin Builder can enable engineers to quickly

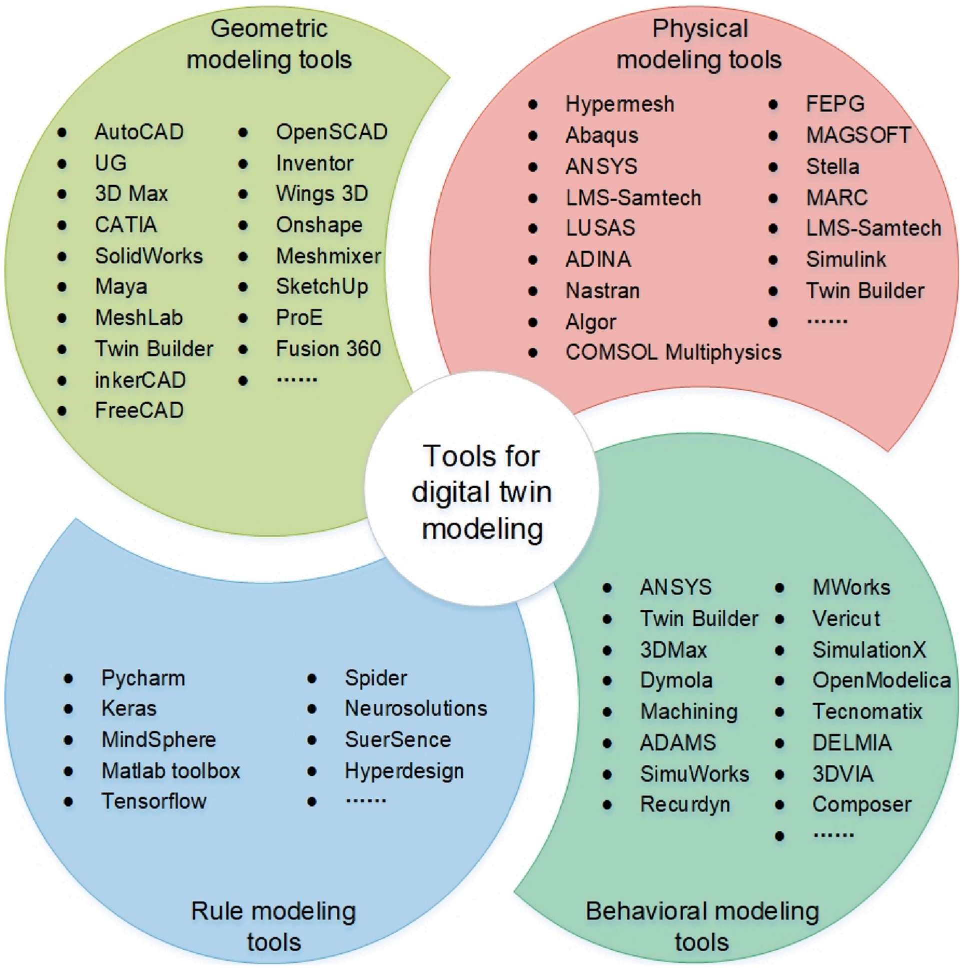

Fig. 14. Tools for digital twin modeling.

build, validate and deploy the digital models of physical assets. Twin Builder's built-in libraries provide rich components to create the desired system dynamics models at an appropriate level of detail, which include models from multiple physical domains and multiple levels of fidelity. Besides, Twin Builder couples with ANSYS' physics-based simulation technology to bring the detail of 3D into the systems context. Moreover, Twin Builder readily integrates embedded control software and HMI design to support testing the performance of embedded controls with models of the physical system. In addition, Siemens NX software, a flexible and powerful tool, can enable companies to realize the value of the digital twin. NX software can deliver the next generation of design, simulation, and manufacturing solutions through integrated toolset, to support every aspect of product development, from concept design through engineering and manufacturing.

Moreover, virtual models reproduce the physical geometries, properties, behaviors, and rules. The models include geometry models, physical models, behavior models and rule models. Therefore, the tools for DT modeling include geometry modeling tools, physical modeling tools, behavior modeling tools, rule modeling tools.

The geometric modeling tools serve to describe the shape, size, position and assembly relationship of entities, based on which, to perform structural analysis and production planning. For example, a performance test device for the DT model of CNC machine tool is established in SolidWorks. Besides, 3D Max is software for 3D modeling, animation, rendering and visualization. 3D Max is used to shape and define detailed environments, objects (person, place, or thing) and widely used in advertising, film and television, industrial design, architectural design, 3D animation, multimedia production, games, and other engineering fields. The common geometric modeling tools are shown in Fig. 14.

The physical modeling tools are used to build physical model by endowing physical characteristics of physical entities into geometric models, then physical state of physical entities can be analyzed through this physical model. For example, through the finite element analysis (FEA) software by ANSYS, sensor data can be used to define real-time boundary conditions for the geometric models and integrate wear coefficient or performance degradation into the models [66]. Besides, Simulink can be used to create physics-based model using multi-domain modeling tools. Physics-based modeling with Simulink involves multiple models, including mechanical, hydraulic, and electrical components. Similar software tools for physical modeling are shown in Fig. 14.

The behavior modeling tools are used to establish a model that responds to external drivers and disturbance factors and improves the simulation service performance of DT. For example, based on the soft PLC platform CoDeSys, the motion control system of CNC machine tool can be designed. The motion control system can interact information with the multi-domain model of three-axis CNC machine tool established in the software platform MWorks, through the socket communication. In this way, it can realize the motion control of single-axis and three-axis interpolation of CNC machine tool. Besides, the multi-domain model can respond to the external drive. Similar software tools are shown in Fig. 14.

The rule modeling tools can improve the service performance by modeling the logics, laws, and rules of physical behaviors. For example, the machine learning ability by PTC's Thingworx upon the HP EL20 edge computing system can monitor sensors to automatically learn the normal state of the pump while it is running. Based on the learned rules,

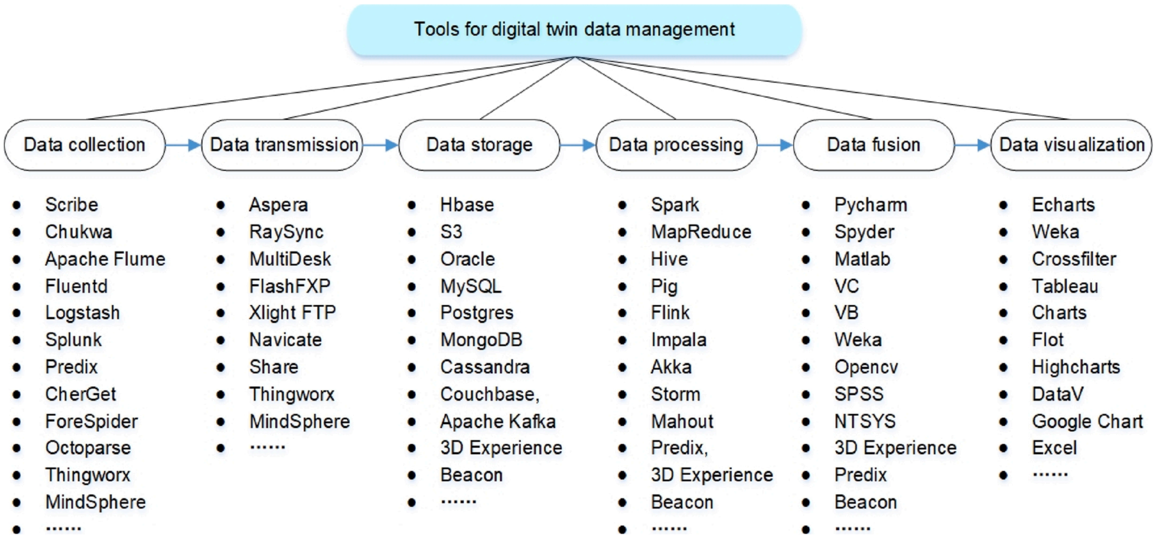

Fig. 15. Tools for digital twin data management.

DT can recognize abnormal operating conditions, detect abnormal patterns, and predict future trends [67]. Similar software tools are shown in Fig. 14.

5.3. Tools for digital twin data management

Data is the carrier of information and the key driver of DT. As shown in Fig. 15, the tools for DT data management include data collection tools, data transmission tools, data storage tools, data processing tools, data fusion tools, and data visualization tools.

Data collection tools can obtain complete, stable and effective data through reasonable sensor placement. For example, DHDAS signal acquisition and analysis system is a set of signal analysis and processing software. The software can be used with a variety of models to complete the real-time acquisition and analysis of different signals. The software also has signal analysis processing capabilities. Similar software tools are shown in Fig. 15.

The purpose of data transmission is to realize real-time data transmission while ensuring that data information is not missing or damaged, and to maintain the authenticity of data to the greatest extent. With the advent of the big data era, traditional FTP solutions are inadequate to meet the data transmission needs in terms of speed or reliability. A representing tool is Aspera that is known for the ability to transmit large size file, over long transmission distance, and under poor network condition. Aspera uses the existing WAN infrastructure to transmit data in a much faster speed than FTP and HTTP. Without changing the original network architecture, it supports the Web interface, client, command line and API for transmission, as well as PC, mobile devices, MAC, and Linux devices. Alternative data transmission tools are shown in Fig. 15.

Data storage is the guarantee of subsequent operations, which realizes the classification and preservation of data, and responds to data calling in real time through efficient read-write mechanism. The data storage technology has experienced a rapid development in recent year. A representing example is HBase based on the Hadoop platform. HBase is a highly reliable, high performance, column-oriented, scalable, real-

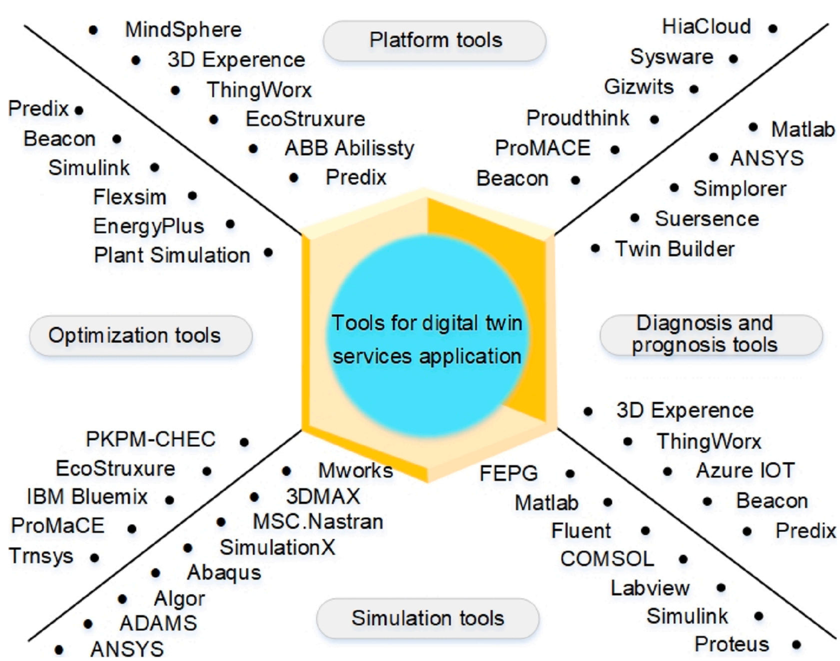

Fig. 16. Tools for digital twin services applications.

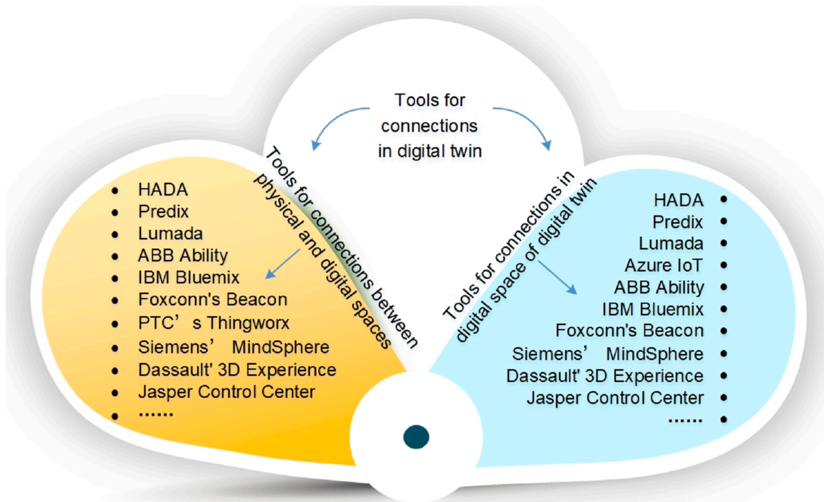

Fig. 17. Tools for connections in digital twin.

time read-write distributed database. It can support the storage of both semi-structured and unstructured data, as well as independent indexing, high availability, and large instantaneous writes. The alternative data storage systems are shown in Fig. 15.

Data processing eliminates interference and contradictory information, making data available for efficient use. For example, Spark is an open source cluster computing software, which has the real-time data processing ability. Spark supports applications written in multiple languages such as Java, Scala and Python, greatly reducing the user's threshold. Spark also supports SQL and Hive SQL for data query. Similar data processing software is shown in Fig. 15.

Data fusion integrates, filters, correlates and synthesizes the processed data to aid in judgment, planning, verification and diagnosis. For example, Spyder is a commonly used data fusion tool that supports Python programming. Another data fusion software, Pycharm, can improve productivity in debugging, syntax highlighting, project management, code jumping, smart prompting, auto-completion, unit testing, and version control. Other tools that are equipped with the data fusion ability are shown in Fig. 15.

Data visualization provides neat, intuitive and clear data information to personnel for real-time monitoring and rapid capture of target information. For example, the open-source software Echarts can run smoothly on PCs and mobile devices, and is compatible with most current browsers. Echarts provides intuitive, vivid, and customized data visualizations for huge-volume and dynamic data. It can accommodate a variety of data formats without extra conversions. Similar tools are shown in Fig. 15.

5.4. Tools for digital twin service applications

The tools for digital twin service applications can be classified into platform service tools, simulation service tools, optimization service tools, diagnostic and prognosis service tools, as shown in Fig. 16.

Service platform tools integrate emerging technologies such as the Internet of things, big data, artificial intelligence. For example, the Thingworx platform can connect the DT model to the products in operation, to display sensor data, and analyze results through web applications. ThingWorx platform could provide industrial protocol conversion, data acquisition, device management, big data analysis and other services. HIROTEC, a premier automation manufacturing equipment and parts supplier, realized the connection between CNC machine operation data and ERP system data based on the ThingWorx platform, effectively reducing equipment downtime. Siemens launched the MindSphere platform. The platform can transmit industrial field devices data collected by sensors, controllers and various information systems to the cloud in real time through secure channels, and provide big data analysis and mining, industrial APPs, and value-added services for enterprises. Similar tools are shown in Fig. 16.

The application service tools include monitoring service tools, optimization service tools, diagnostic and prognosis service tools, etc. The diagnostic and prognosis service tools can provide intelligent predictive maintenance strategy for equipment and reduce equipment downtime, etc., by analyzing and processing the twin data. For example, the ANSYS simulation platform helps customers design the IIoT-connected assets themselves and analyze the operational data created by these smart devices, versus design data to enable troubleshooting and predictive maintenance. In addition, integrated with data-driven methods (machine learning, deep learning, neural networks, and system identification, etc.), MATLAB can be used to determine remaining useful life to inform operations on the most opportune time to service or replace equipment. For example, Baker Hughes, a large service company providing products and services to the oil development and processing industry, has developed predictive maintenance alarm system based on MATLAB. Similar diagnostic and prognosis tools are shown in Fig. 16.

Using twin data like sensor data, energy costs, or performance factors, the optimization service tools are triggered to run hundreds or thousands of what-if simulations to evaluate readiness or necessary adjustments to current system set-points. This enables system operations to be optimized or controlled during operation to mitigate risk, reduce cost and energy consumption, and increase system efficiencies. For example, the Plant Simulation software by Siemens can optimize the production line scheduling and factory layout [68]. And in digital twin electric grid, Simulink receives measured data from the grid, then runs thousands of simulation scenarios to determine if the energy reserve is sufficient and whether grid controllers need adjustment. Similar tools are shown in Fig. 16.

Advanced simulation tools not only can perform diagnostics and determine the best benefits of maintenance, but also capture information to refine the next-generation design. For example, if lack of appropriate FEM simulation analysis, in the design of CNC machine tool, the machine will fail in vibration. On the other hand, if extra material is added to increase the strength and to reduce vibration then the cost of machine would escalate due to the over-designing of the CNC machine tool. However, carry out corresponding structure simulation analysis in the finite element software ANSYS and then auxiliary to the appropriate evaluation function, which will take into account the performance and cost, and meet the lean design requirements of CNC machine tool [69]. Similar simulation tools are shown in Fig. 16.

Table 1
Comprehensive tools and their roles in different aspects of DT (√ denotes it can be used in this part).

Various parts \ Comprehensive tools		Predix	PTC's Thingworx	Siemens' MindSphere	ANSYS	Dassault' 3D Experience	Foxconn's Beacon
DT evolution	Knowing the physical world				√	√	
	Changing the physical world	√		√			
Modeling	Geometry modeling					√	
	Physical modeling				√	√	
	Behavior modeling				√		
	Rule modeling		√				
DT data management	Data collection	√	√	√			√
	Data transmission		√	√			
	Data storage		√			√	√
	Data processing	√				√	√
	Data fusion	√				√	√
	Data visualization					√	√
Services	Simulation services	√		√	√	√	√
	Optimization services	√		√			√
	Diagnosis and prognosis services	√	√	√	√		√
	Platform services	√	√	√		√	√
Connections	Connection in digital world	√		√		√	
	Connection between digital and physical world	√	√	√		√	√

5.5. Tools for connections in digital twin

The tools for DT connections are used to connect the physical and virtual worlds, as well as to connect different parts of DT. The core of any DT is to map between physical and virtual worlds and break the boundaries between physical and virtual realities. For example, PTC Thingworx can act as a gateway between sensors and digital models to connect various smart devices to the IoT ecosystem [67]. MindSphere is a cloud-based, open IoT operating system from Siemens that connects products, plants, systems, and machines. MindSphere uses advanced analytics to enable the wealth of data generated by the IoT. Jasper Control Center from Cisco Jasper can better manage connected devices using NB-IoT technology. Jasper Control Center continuous monitor network conditions, device behavior, and IoT service status to ensure high service reliability through real-time diagnostics and proactive monitoring of connection status. The connections within DT mean the communication, interaction, and exchange of information among physical entity, data center, service, and virtual model. These information connections are necessary to help develop problem diagnostics and troubleshooting, determine the ideal maintenance plan based on the characteristics of each physical asset, and optimize the performance of physical assets, etc. For example, the Azure IoT Hub by Microsoft enabled Rolls-Royce to build engine models and perform data analysis based on machine learning. In this way, it can detect anomalies of about-to-fail components and prescribe suitable solutions [70]. Similar tools are shown in Fig. 17.

There are a number of comprehensive tools that play multiple roles in DT applications, such as FEA software ANSYS not only modeling, but also providing simulation services, troubleshooting services, and so on. Similar comprehensive tools include Predix, Siemens' MindSphere, ANSYS, Dassault's 3D Experience, Foxconn's Beacon, PTC's Thingworx, etc., as shown in Table 1.

Implementing digital twin is a complex system and long-drawn process, which requires multiple technologies and tools to work together. For example, reproducing a wind turbine requires monitoring of various data (e.g., vibration signals, acoustic signals, electrical signals, etc.) of the gearbox, generator, blades, bearings, shafts, tower and power converter, as well as environment conditions (e.g. wind speed, wind direction, temperature, humidity and pressure). In addition, digital twin includes virtual representation of physical asset. Many models need to be built to reproduce a wind turbine, including geometric models, functional models, behavioral models, rules models, finite element analysis models, fault diagnosis models, life prediction models, and so on. All of the above need one of the enabling technologies and tools. For example, the data collection of various signals from wind turbine need sensor technologies. The data transmission, storage, processing and fusion may use 5 G, NewSQL, edge-cloud architecture and artificial intelligence technologies, etc. And the geometric models can be built through tools such as SolidWorks, UG, AutoCAD, CATIA, etc. Finite element analysis models can run in ANSYS, MARC, ADINA, etc. Moreover, Dymola, MWorks, SimulationX and others can support system modeling and simulation. From the above, digital twin involves a wide range of technologies and tools that are invented or developed by different companies. There are different protocols and standards, about these technologies and tools. To enable these technologies and tools to work together, data and models should be standardized and delivered in common formats, protocols and standards. Through common formats, protocols and standards, these technologies and tools work together for a particular objective.

6. Conclusion

DT represents an advancement of digitalization. It is increasingly applied in more and more areas, such as smart manufacturing, building management, smart city, healthcare, oil & gas, and many more. Because DT is a complex system integrating multiple engineering disciplines, many companies and researchers are unfamiliar with the key technologies and tools of DT. The 5-dimension digital twin model has good practicability and scalability, and can provide a common reference model support for applications of digital twin in different fields. Combined with 5-dimension digital model, this paper investigated and summarized the enabling technologies and tools for DT, which could provide guidance for DT practices. However, due to different formats, protocols and standards, current tools may not be integrated and used simultaneously for a particular objective. Therefore, in the future, the universal design and development platforms and tools for digital twin are required to be developed. Besides, infrastructure that is suitable for industrial practices and has high reliability, is required to meet the requirements of digital twin. Besides, the practice of DT is closely related to specific objects. For example, DT city and DT shop-floor are quite different in terms of model size, operational rules, data management, etc. Therefore, this paper provides general directions for enabling technologies and some examples of tools. The technology research about DT and the selection of tools require the participants in academia and industry to judge and decide according to specific fields and objects.

Declaration of Competing Interest

Qinglin Qi, Fei Tao, Tianliang Hu, Nabil Anwer, Ang Liu, Yongli Wei, Lihui Wang, and A.Y.C. Nee declare that they have no conflict of interest or financial conflicts to disclose.

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