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CRITICAL REVIEW

Industry application of digital twin: from concept to implementation

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Abstract
With the development of artificial intelligence, big data, Internet of Things, and other technologies, digital twin has gained great attention and become a current research topic. Using digital twin technology, the digital twin model can be constructed in the cyber space that is fully equivalent to the physical entity. It is always consistent with the physical entity in the operation process, which greatly improves the dynamic perception and prediction ability of the real world. After the development in recent years, digital twin has gradually changed from the initial concept discussion to the study of model framework and implementation method. However, because the research objects in different industries have great differences in their own composition, service conditions, and application scenarios, they have personalized characteristics in modeling strategies and usage methods. Therefore, based on different industries, this paper reviews the current articles on digital twins and distinguishes the focus of digital twin modeling research; subsequently, the relevant supporting techniques and methods are summarized according to their different importance for digital twin modeling. Based on the review in this paper, future researchers can conduct targeted research on digital twin technology in term of the characteristics of the objects in their industry.

Keywords Digital twin · Literature review · Industry applications · Modeling method

1 Introduction

1.1 The origin of digital twin

With the rapid development of information technology, all industries are striving towards the goal of digitalization, informatization, and intelligence. In recent years, due to the emergence of technologies such as fifth-generation wireless cellular networks (5G), the Internet of Things (IoT), edge computing, and artificial intelligence (AI), digital twin (DT) technology has become a new approach to solve various problems arising from products in various industries.

DT is a virtual model of a physical entity that is created in a digital approach. It relies on real-world monitoring data to be applied to the virtual model to simulate the behavior of the physical entity in the real environment. With the help of DT technology, functions such as state prediction and decision optimization of physical entities can be realized, which can reflect the full lifecycle process of physical equipment.

DT was first proposed by Professor Michael Grieves of the University of Michigan in 2003, but at the time, he called it a virtual digital representation equivalent to a physical product. Subsequently, he called this conceptual model the "mirrored space model" in 2005 [1] and the "information mirroring model" in 2006 [2, 3]. However, these two terminologies cannot perfectly explain their ideas. Until 2016, he and John Vickers jointly proposed the concept of the "digital twin" [4]. The terminology was then widely accepted by researchers until now. The National Aeronautics and Space Administration (NASA) was the first to try to put the idea of DT into practical applications. From 2011 to 2016, with aircraft wings as the research object, NASA conducted exploratory research on DT technology while proposed the key technical problems to be solved by DT technology [5]

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and the solution method of some of the problems [6–8]. This is an important step for the further development of DT.

Since then, DT technology gradually gained attention. Gartner listed DT as one of the top 10 strategic technology development trends in 2016 and 2017. Lockheed Martin regarded DT as one of the top six technologies affecting the national defense and military industry in 2018. In 2020, the China Association for Science and Technology (CAST) will also list DT as a "2020 major scientific problem and engineering problem." By integrating existing technologies, Siemens has launched software platforms such as PlenSight, Teamcenter, and PLM to realize the development and verification of DT model. Meanwhile, Dassault, Microsoft, and others company have also launched their own DT solutions, using DT technology in complex products and smart buildings.

1.2 Related review

Currently, many review articles on DT have been published. Kritzinger et al. [9] categorized a review of articles on DT by distinguishing the degree of information interaction between virtual and physical models. This paper clarifies the differences and connections between DT and similar concepts. Lu et al. [10] discussed in detail the core concepts, reference models, related technologies, and application scenarios of manufacturing driven by DT, which can provide a direction for the research of DT in intelligent manufacturing. Qiu et al. [11] discussed the possibility that the combination of augmented reality (AR) and DT technology can improve the quality and efficiency improvement of complex product assembly, while arguing that AR is an important method to achieve DT. Qi et al. [12] reviewed in detail the applications, possible technologies, and tools of DT and provided guidance for the building of five-dimensional DT models. Boje et al. [13] discussed the concept and application of DT in the building information modeling (BIM) and gave a technical route to be studied in the future. Errandonea et al. [14] focused on the review of product maintenance, followed by an in-depth discussion of the synergy between DT and maintenance. Jones et al. [15] classified the DT model into 13 features for discussion. Khan et al. [16] also discussed the application of DT technology in product maintenance. At the same time, he discussed the role of AI in the maintenance process based on DT. Phanden et al. [17] reviewed the application of DT in aerospace, manufacturing, and robot simulation. Liu et al. [18] discussed the concept, technology, and industrial application of DT on the basis of product lifecycle stages. He believed that DT should have the characteristics of individuality, high fidelity, real time, and controllability. Lo et al. [19] reviewed the research progress of DT in the product design process. Opoku et al. [20] reviewed the current research status of DT in the construction industry. Wang et al. [21] proposed a framework for building a DT model of the offshore wind turbine. which can provide research guidance for the application of DT in the field of ocean engineering. Onile et al. [22] reviewed the application of DT in the energy field and the current problems encountered. Jiang et al. [23] discussed the application of DT in civil engineering. Davila Delgado and Oyedele [24] suggested the use of DT model for manufacturing to facilitate the research process on DT in the built environment.

1.3 Intention of this paper

In recent years, the research on DT has shown an explosive upward trend. By comparing the research in different fields, it is found that the understanding of DT in various fields has their own characteristics. From the existing research results, there is a lack of comparison of the conceptual understanding and building methods of DT in each industry, which leads to the existence of DT information islands between different fields and hinders the overall development process of DT technology. Therefore, this paper intends to:

(1) Review the development history of DT from three aspects: concept, framework, and implementation technical methods.
(2) Taking industries as the division, review the current application scenarios of DT technology and its advantages.
(3) Summarize the focus of current research on DT model building methods in various industries.
(4) The implementation technology of DT is divided into three levels: the basic, the core, and the advanced, which provides potential solutions for future research.

The rest of this paper is arranged as follows. Section 2 introduces the sources and classification criteria of the literature collected in this paper and analyzes the current DT research trends. Section 3 introduces the status of DT research. Section 4 introduces the research progress and building methods of DT technology in various industries. Section 5 categorizes the relevant implementation technical method that can be used in DT technology. Section 6 proposes the future direction of the DT, while summarizing the whole paper.

2 Literature review research method

2.1 Literature classification criteria

In this paper, the title keyword "digital twin" was used to search the literature in ScienceDirect.com. The restricted literature types were review articles and research papers, which included journals and conference papers. Subsequently, the research content of the literature was checked, and some obviously irrelevant documents were eliminated, such as "digital" and "twin" as two independent words in the title. In the search results, the total number of articles is 370, of which 14 are review papers.

2.2 Status analysis of digital twin research

Figure 1 shows the annual number of papers published about DT. The trend in the number of papers published shows that the number of papers on DT was relatively small until 2017, and most of them were conference papers. This indicates that researchers were not aware of the potential and advantages of DT technology currently. Since 2018, papers have shown explosive growth. In 2018 alone, the number of papers published in 1 year is equivalent to the total amount of papers published before. In subsequent years, the volume of publications in each year was almost 2 to 3 times that of the previous year. This indicates that DT technology is entering a phase of rapid development.

Subsequently, the concept explanation, the model framework establishment, and the technical approach to implement the DT were used as the article division criteria, as shown in Fig. 2. The papers before 2017 mainly researched the concept of DT. After that, the research on the building of the framework of DT has become a research topic. Each industry has studied different DT model building methods for their respective research objects. Since 2019, research on implementation methods has also shown rapid growth. The number of related papers is almost twice that of the previous year. This shows that the DT has entered the actual building stage, and different solutions are proposed for different problems.

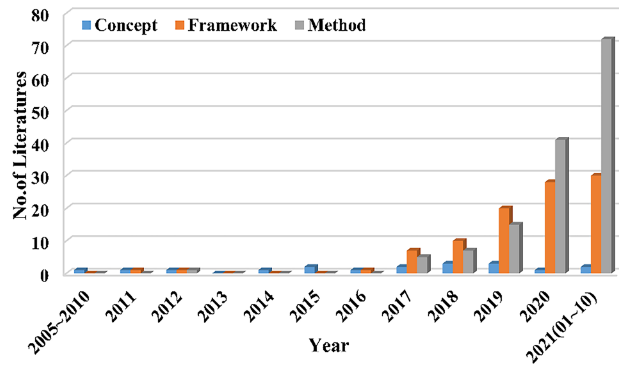

Fig. 2 Number of papers with different research content

3 Development routes of DT

Since Grieves first proposed the concept of DT, many achievements have emerged from research on DT. According to the categories of research results, this paper considers that the following three problems are mainly solved: (1) What exactly is the DT concept? (i.e., the DT concept refinement stage); (2) how to build a DT model? (i.e., the DT framework building stage); and (3) what methods are used to implement the functions in the model framework? (i.e., the DT method research stage). It is worth noting that the periods of these three stages are intersecting, as shown in Figs. 3 and 4. Since these three stages are developing at the same time,

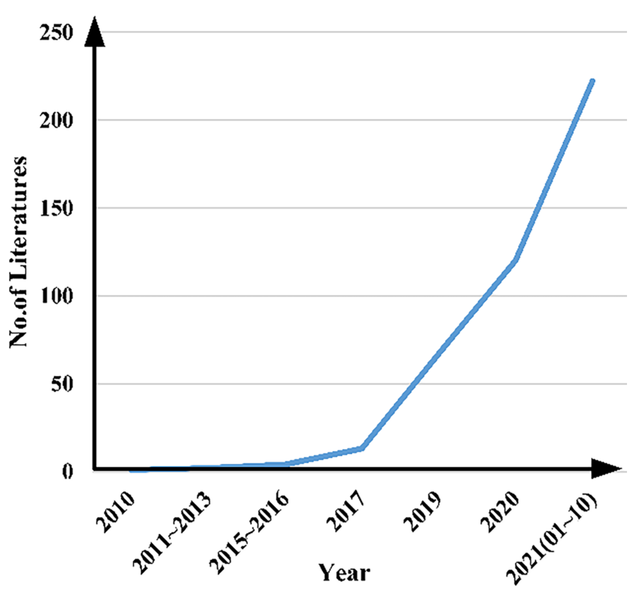

Fig. 1 Number of papers on DT per year

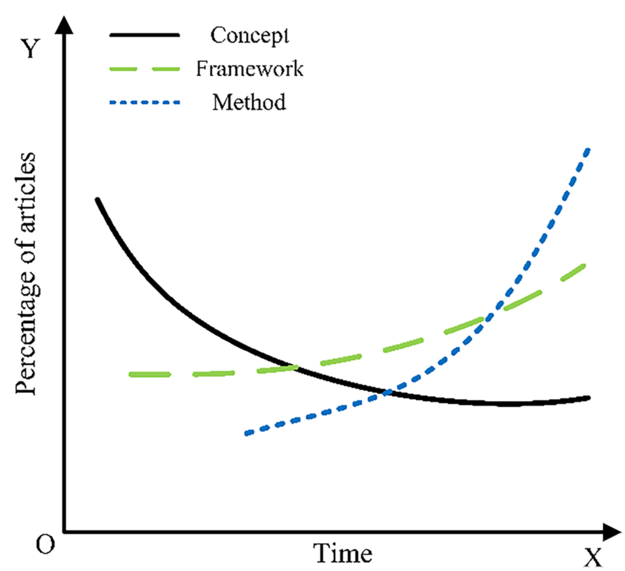

Fig. 3 Stages of development of DT

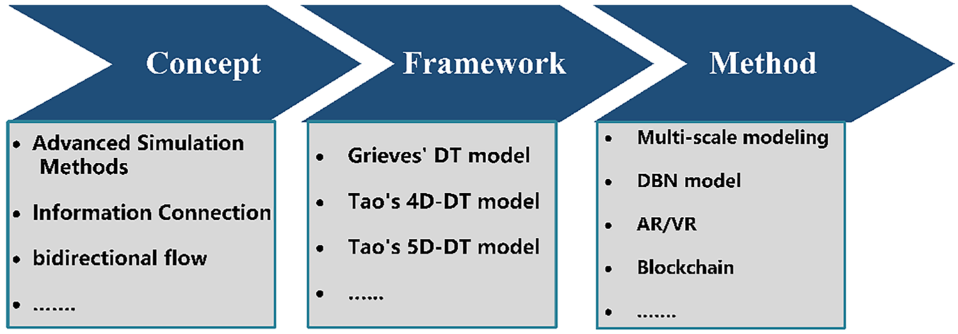

Fig. 4 Evolution process of DT

the classification basis of this paper is based on the different focus of the researcher at the time. Therefore, this section will review the current development routes of DT in these three categories.

3.1 The DT concept refinement stage

Grieves initially explained that DT is a mirrored virtual model corresponding to a physical entity. This explanation is very vague, but it also emphasizes one of the most important characteristics of DT, that is, the need to maintain consistency between the physical entity and the virtual model. Subsequently, based on this understanding, researchers from different industries have enriched the concept of DT based on the research characteristics of the field. During the research process to build a DT model of the aircraft, NASA concluded that "the DT is an integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, feet history, etc., to mirror the life of its corresponding flying twin" [25]. Therefore, DT was mainly regarded as a special "simulation" method at this time. Compared with the traditional simulation in the past, the DT can use multi-source data to correct its simulation results, so that the simulation model can be consistent with the actual physical model in real-time and ultimately improves the accuracy of the simulation. Some scholars also share this view; for example, Yeratapally et al. [26] proposed that "the DT is a digital replica of an arbitrarily complex system that is continuously updated to match its real-world counterpart." As a way to digitally create virtual models of physical entities, Tao et al. [27] proposed DT can simulate the behavior of physical entities in the real environment with the help of data and add or extend new capabilities to physical entities through virtual-real interaction feedback, data fusion analysis, and iterative optimization of decisions.

All of the above concepts consider whether the model uses the data collected in the physical entity when it runs as the biggest difference between the DT model and previous approaches. Subsequently, Tchana et al. [28] proposed that the essence of DT is the connection and synchronization between the data related to the physical product and the information contained in the virtual model. Therefore, real-time data collection and synchronization between virtual and physical models was important features of the DT model. For example, Negri et al. [29] proposed DT can be used to simulate physical systems for various purposes using real-time, synchronized sensing data from the field. Rabah et al. [30] considered DT as a simulation process for various purposes, and the process needs to ensure real-time synchronization of data.

Another important feature in the DT is the fluidity of the data between the physical entity and the virtual model. Based on the degree of data transfer between them, Kritzinger et al. [9] proposed that there are three categories of current DT models: (1) digital model (DM), no data flow; (2) digital shadow (DS), there is a one-way data flow; and (3) digital twin (DT), there is a two-way data flow, so the whole system can be closed-loop operation. These three models illustrate how the DT differs from previous approaches where it allows for two-way real-time data interaction.

Each industry has different research subjects. Therefore, the researchers explained the definition of DT in more detail based on the characteristics of the research objects in the industry. In the manufacturing industry, Grieves proposed "the DT 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" [31]. Urbina Coronado et al. [32] proposed that DT is a digital model that can be used for offline simulation and analysis and then can be used to control the entire manufacturing process. Lohtander et al. [33] considered DT as a way to digitally display static and dynamic objects in all machining process, and the idea can also be used in the study of DT of arbitrary objects. In the automation industry, Ayani et al. [34] defined DT as a multi-physics and multi-scale simulation model reflecting the corresponding physical model, with emphasis on the promotion of DT high-fidelity simulation to the industry. In the production process, due to the integration of multiple disciplines, Negri et al. [29] proposed that the production system represented by DT is able to run on different simulation disciplines, and its characteristic is the synchronization between virtual systems. In the field of IoT, as an intelligent node in the IoT and services, DT is a virtual substitute for real-world objects [35]. At the same time, DT is also an information platform based on advanced sensor, high-performance computing, intelligent data analysis, and other technologies to simulate physical entities [36]. In the combustion process of automobile internal combustion engines, DT was considered to be an organized collection based on physics models that are used to model the current state of the power system [37]. Therefore, DT is also regarded as a theoretical modeling method that can simulate its related mechanism. In the application of marine engineering, the DT model focused on the simulation of the real marine environment and the elimination of the influence of uncertain factors [21].

3.2 The DT framework building stage

As the understanding of the concept of DT has gradually deepened, researchers have turned to the study of methods for building DT frameworks. The first framework of the DT model was also proposed by Grieves. He proposed that the foundation of DT model should include three main parts: (a) physical products in real space; (b) virtual products in virtual space; and (c) the connections of data and information between the virtual and physical models [38]. This includes two important features of DT, virtual model and physical entity consistency and two-way real-time interaction. Virtual model and physical entity consistency is to maintain consistency with the physical entity in real time during the operation of the DT model, including its geometric appearance consistency, material property consistency, and change mechanism consistency. Only by maintaining this consistency can the concept of "twin" in DT be achieved. The meaning of "digital" is not only reflected in the model being established in the digital space, but also reflects the data exchange between the two. This data exchange also determines the functions that the DT model can achieve: (1) through the virtual model to predict and diagnose the state of the physical entity by using the generated data and (2) realize the correction and gradual evolution of the virtual model to itself through the data transmitted by the physical entity. However, the DT framework proposed by Grieves is relatively simple and does not directly show the characteristics and functions of DT.

Subsequently, to complete the content of the model framework, Tao and Zhang [39] proposed a four-dimensional DT framework, which more specifically describes the composition structure of the DT. The framework includes four parts: physical entity, virtual model, service, and DT data. Physical entities refer to all entities related to the object to be studied. Virtual model is a model constructed from multiple dimensions, such as geometry, physics, behavior, and rules.

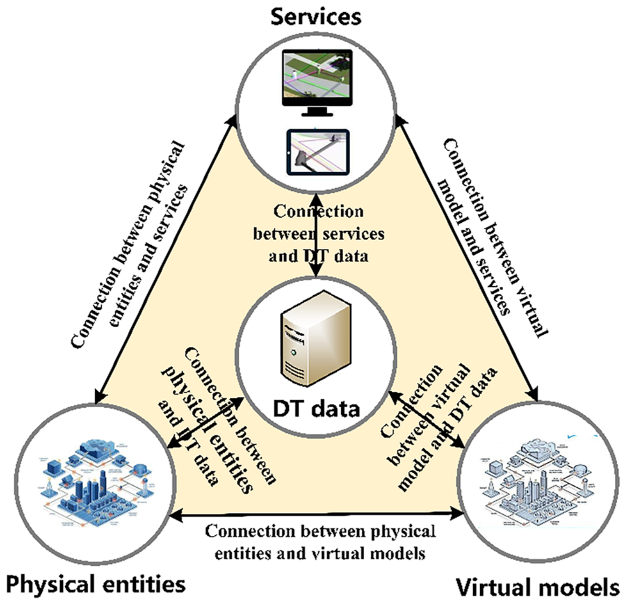

Fig. 5 Five-dimensional DT model framework

Services is an integrated service platform, such as enterprise information systems, computer-aided, and tools. DT data is a data module, which mainly collects DT data for processing and fusion and then serves other modules. In the framework of this model, the mutual communication between the data generated by each module is emphasized. Subsequently, Qi et al. [12] proposed that the data flow between each module should also be regarded as an important feature of the DT model, so this data connection was set to a single dimension, and finally the five-dimensional DT model framework was established, as shown in Fig. 5.

According to the own characteristics of the research object in the industry, the researcher proposed the modeling method of DT applicable to this industry based on the five-dimensional model, the details of which will be discussed and summarized in Sect. 4 of this paper.

3.3 The DT method research stage

When researching the DT model of the aircraft, NASA proposed a detailed method to building DT in the aerospace industry, such as a load spectrum generation method for aircraft simulation models [40] and the use of Bayesian updating to achieve the fusion of multi-source data such as inspection data and simulation data [41]. However, it also raises some problems that could not be solved at that time [42, 43], such as multi-physical field simulation, real-time and accurate data storage and transmission technology, and full lifecycle simulation technology.

With the study of DT concepts and model frameworks, more and more implementation methods for building DT models have been studied and proposed. The research on DT has also evolved from conceptual studies to framework studies to detailed methods, achieving a facet-to-point evolution. The current technical approaches and the possible implementation of certain features of the DT framework are discussed in detail in Sect. 5 of this paper.

4 Industry applications of DT

DT provides a new solution to the problems faced by various industries. Therefore, DT technology has been applied in several industries. This section will review and summarize the application status of DT technology, the advantages it brings to the development of the industry, and the modeling focus of each industry, as shown in the Fig. 6.

It is worth noting that since the manufacturing industry is the most intensively studied for DT, the manufacturing industry is divided into six parts for a detailed review according to the full product lifecycle process, as shown in Fig. 7.

Fig. 7 The full product lifecycle process of the manufacturing industry

4.1 Manufacturing industry

4.1.1 Product design

As the first step in the entire product manufacturing process, the product design process is not only constrained by user requirements and manufacturing equipment capabilities, but also the design results will affect the production cycle and cost of the entire manufacturing process. However, traditional design methods have problems such as unclear demand transmission and difficulty in coordination of manufacturing equipment, which leads to various unexpected problems in the actual production process of the product, for example, product performance defects and unreasonable operation steps in the production process. To address the problems with product design, it is crucial to have information on production data. Stark et al. [44] proposed a DT model for modular design of cyber-physics production systems. By integrating production resources into the construction tool module, users can create, verify, and optimize product design results. Wang et al. [45] proposed to extend the design process of intelligently formulated products by letting customers provide the data needed for DT models, but the method needs to consider the security and confidentiality of the data exchange process. The above research can effectively solve the problem of unclear design requirements, and how to use real-time data from the production of parts, such as geometric deviations and unreasonable machining processes, is the key to optimize product design. Söderberg et al. [46] considered the necessary functions of DT in maintaining the real-time geometric quality of the product, such as geometric quality, tolerance, locator position, clamping strategy, and welding sequence. Zhou et al. [47] used reinforcement learning method to determine the optimal structure and machining process of centrifugal blade. This method effectively avoids the problem of product performance defects

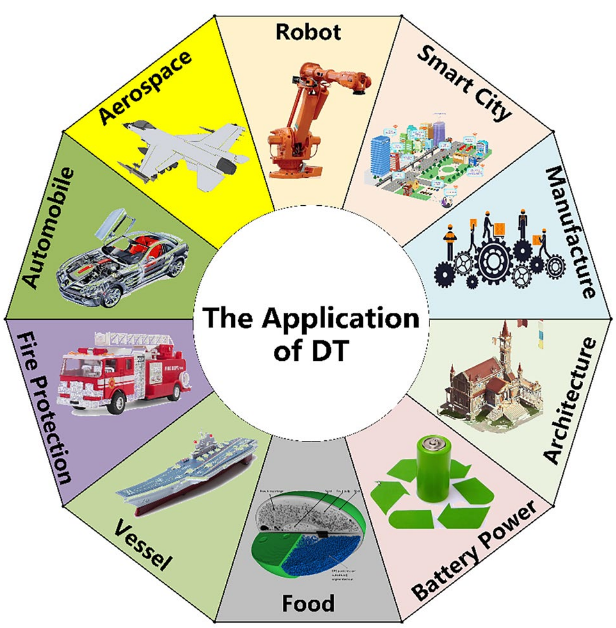

Fig. 6 Industry applications of DT

caused by design errors, but does not achieve real-time data interaction between virtual and physical models.

In summary, by generating the corresponding DT model while designing the product and putting it into the real environment for manufacturing simulation, we can identify and solve the problems that were not found at the beginning of the design, ensuring the maximum benefit of the manufacturing and also speeding up the design cycle.

4.1.2 Product manufacturing

Product manufacturing process is a complex system engineering. It is necessary not only to consider the configuration and assembly process of the production line in the actual manufacturing process, but also to consider the product priority allocation scheme due to the different order quantity in the production process. At the same time, the current production mode of enterprises has gradually changed from mass manufacturing to small batch individualized manufacturing, which also puts forward higher requirements for the transformation speed of product design and manufacturing process. In the current DT research, to respond to the rapid change demand of the production line, Zhang et al. [48] integrated the system modeling based on physics and the real-time process data of the manufacturing process to realize the rapid design scheme of hollow glass production line. Leng et al. [49] proposed that the DT model can reduce the time required for order switching by analyzing the variability between the two products, but the method needs to focus on the impact of episodic events. Through the above studies, the rapid conversion process of production lines at a low cost can be realized, and the manufacturing efficiency of products can be improved.

Due to the increasing number of product types, order management in manufacturing companies has become more complex than ever. However, some force majeure factors will cause great interference to product order management, such as customer demand changes and machine failures. Therefore, the real-time consistency-maintaining feature of the DT can provide a new guidance for the solution of this kind of problem. Kunath and Winkler [50] proposed a DT model framework for an AI-based order management decision systems by combining order management oriented data with the DT of the manufacturing system. By fusing real-time information from the DT model with the manufacturing system to get the order decision results, the enterprises can maintain flexible operation capability.

Product assembly in the manufacturing process has always been an important factor restricting the efficiency of enterprises. Especially for the assembly of high-precision and complex products in the aerospace and other industries, there is a lack of assembly methods that always maintain high quality and high efficiency. Using the high-fidelity of DT in the simulation process, Malik and Bilberg [51] proposed a DT model consistent with the physical system, which improves the efficiency of human–machine collaborative assembly. Caputo et al. [52] built a DT assembly model based on a concurrent engineering approach by correcting the errors associated with the assembly process as soon as it is in the design phase. Franciosa et al. [53] integrated physical sensors, deep learning, and CAE simulation to simulate the product defects caused by various factors. This method can lead to a right first rate of > 96% in product production. Therefore, how to improve the simulation ability of DT in the assembly process and make it better consistent with the actual situation has become the key solution to achieve higher assembly efficiency and better accuracy.

4.1.3 Manufacturing equipment

Manufacturing equipment is the most basic part of the product manufacturing process. At present, the manufacturing industry's requirements for the development of equipment tend to be more intelligent, digital, and visual. Through the establishment of DT model of related manufacturing equipment, the possible failures or deviations of the machine can be predicted in advance, and related remedial operations can be carried out to ensure the processing quality of the products, the yield rate, and the production efficiency of the enterprise.

For machine tool, Scaglioni and Ferretti [54] developed a DT model incorporating several modules to improve machining accuracy, such as the cutting process module, the drive chain module, and the control system module. This method is mainly based on finite element method (FEM) to build the DT model of manufacturing equipment. Zhu et al. [55] proposed a AR application for real-time monitoring and data management of CNC milling machines, but the program only provides relatively simple control functions.

Wei et al. [56] proposed the consistency maintenance method between the DT model and its physical entity while verifying the slide wear to obtain a consistency deviation of only 9.8%. This method can realize the wear reproduction of FE model for simple structure, but the complex structure needs further study. Akintseva et al. [57] built a corresponding DT model for the bearing wear of circular grinding machine tools. Luo et al. [58] used the solution of integrating DT physical model and data-driven method to predict the remaining useful life of machine tools, which can improve the prediction accuracy by 68%. It can show that the fusion of virtual and physical model data can effectively improve the performance of the DT model.

Tools and clamping equipment, as part of the machine tool, are directly related to the quality of product production in terms of wear and tear and clamping performance. To determine the appropriate clamping parameters, Liu et al.

[59] achieves accurate dynamic clamping positioning by obtaining real-time simulation data and production data. This method relies on the accuracy of key data acquisition for manufacturing units. Xie et al. [60] proposed a DT model that can accurately predict tool damage state by fusing tool damage data. However, the prediction accuracy of this method depends on the richness of the damage data, so the practical use has certain requirements for the amount of data.

4.1.4 Manufacturing workshop

The manufacturing workshop is a collection of personnel, equipment, products, production materials, and production data. How to arrange and manage each element of the workshop more efficiently as well as analyze and process data from different sources has become a key issue in the study of DT on the manufacturing workshop. To achieve efficient assignment arrangements for personnel, Graessler and Poehler [61] builds DT model to automate employee assignment decisions by automatically considering information such as employee skill levels and personal characteristics. Zhang and Ji [62] proposed a DT manufacturing workshop model oriented to carbon emission prediction as well as low-carbon control, which can help to achieve the goal of "carbon neutrality." Kong et al. [63] proposed a data construction method for DT workshop, which effectively described the manufacturing data. However, the stability of the data structure can be further improved if big data techniques are used in this method to mine the intrinsic relationships of manufacturing process data.

To generate relevant product processes quickly during production, Liu et al. [64] proposed an intelligent process scheduling method combining the advantages of DT model and hyper-network, which realized the rapid correspondence of multi-source correlation information between machine tools. The verification results show that the method can effectively shorten the production cycle by up to 23%. Therefore, the fast data classification capability of the hyper-network model provides a solution for efficient scheduling of process plans.

4.1.5 Product service

Once the product is on the market, it is necessary to provide follow-up services for the product. This is due to (1) self-monitoring of the product's own state to prevent damage to the user; (2) monitoring data can also be reflected in the product design stage, that is, by improving some unreasonable design to improve the quality of the next generation of products.

In the study of this problem, Ayani et al. [34] used Simumatik3D to build the DT of the old machine and found the problems of the machine through simulation, but the method relies on the accurate reproduction of the damage in the model. Qi et al. [65] introduced in details the various types of services that can be provided by DT, while illustrating the role that each service can play at different product stages. Zhang et al. [66] compared the data generated by the virtual model and the physical model in real-time to exclude various checking interference information, and the verification showed that this method could increase the average utility rate of the machine by 14.9%. However, the virtual model of the method needs to be updated in real-time, so the time cost is large. Mi et al. [67] proposed the use of the NSGA-II algorithm in the DT model to consider the problem of uncertain parameters in the model to improve the accuracy of fault diagnosis and prediction. In conclusion, for problems such as the interference of uncertainty factors in the virtual model, using actual data to make corrections an effective solution.

4.1.6 Product lifecycle

The product lifecycle is the whole process from the demand for a product to its obsolescence and disposal. Therefore, the product lifecycle is composed of the five parts mentioned above, and the ultimate purpose of DT is to serve the whole lifecycle management of the product. The product design is completed through user requirements, and the DT model is used to find defects in the design process. Subsequently, enterprises can then adjust their production processes to improve yields and production efficiencies, resulting in faster time to market. During the product use period, product maintenance is carried out by collecting relevant inspection data, and then the data is returned to the design side for product improvement. This allows the entire product lifecycle to form a closed loop, allowing DT technology to be applied to all aspects of the product.

To better utilize the various data generated throughout the product lifecycle, Tao et al. [68] proposed the key technologies to realize DT-driven product design, manufacturing, and service. Subsequently, Tao et al. [27] further illustrated the data fusion approach in the DT while illustrating an example of gearbox health management for a wind turbine with up to 30% improvement in the identification of relevant faults. Macchi et al. [69] discusses the role of DT in asset management decision support. Schleich et al. [70] illustrated the value that DT can create within the different phases of the product lifecycle. The above literature can better illustrate the role and value of the DT in the product lifecycle and provide an impetus for the corresponding research.

4.1.7 DT building method in manufacturing industry

When reviewing the DT application for the manufacturing industry, it can be argued that the DT building method focused on three parts: data, simulation, and services. As shown in Fig. 8, the relationship between them can be

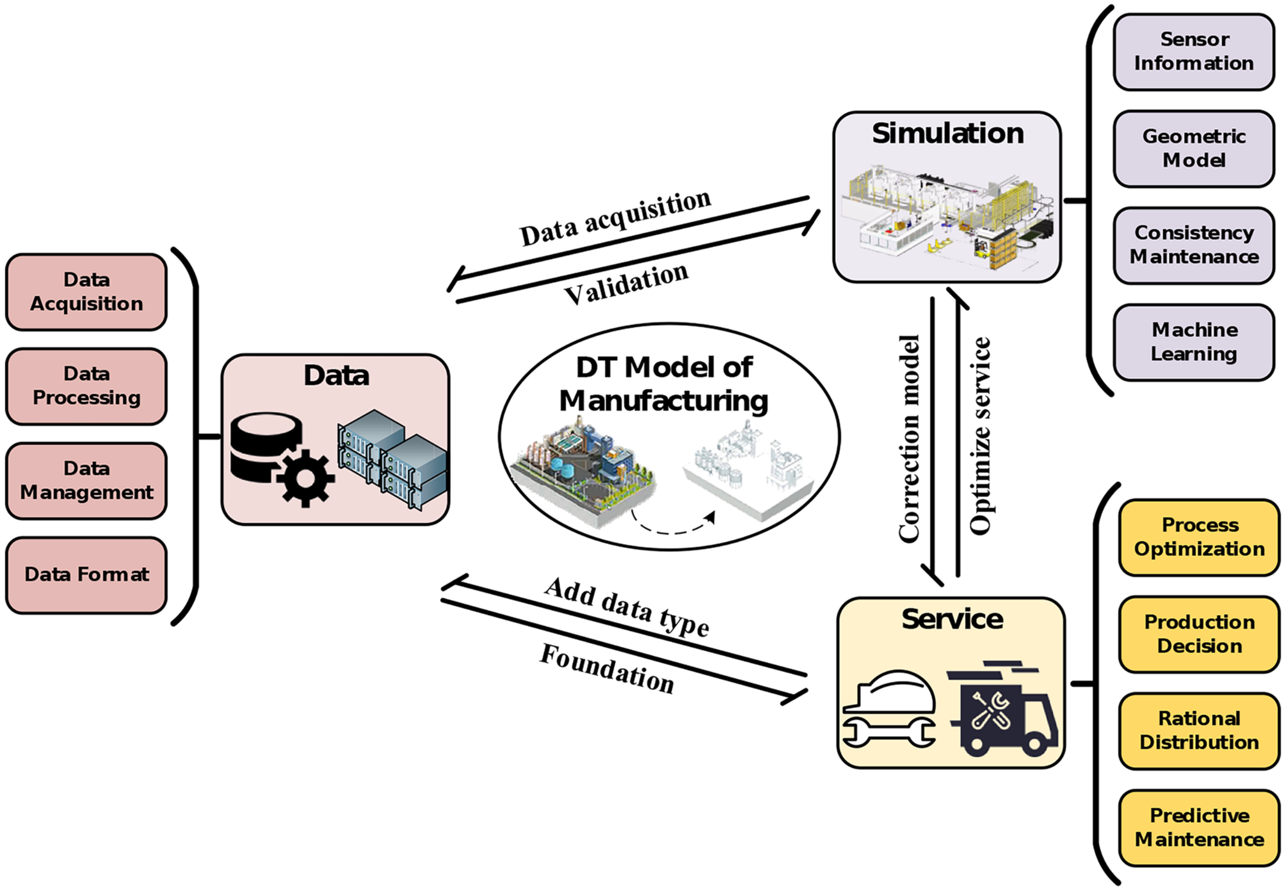

Fig. 8 DT building method for manufacturing industry

described as follows: manufacturing process data can be used to verify the validity and correctness of manufacturing process simulation, while various types of data (such as equipment status data, maintenance data, etc.) are the basis for implementing services; the simulation in the manufacturing process can be used to guide the type of data acquired to target the completion of critical data collection. At the same time, the simulation can also obtain the data that are difficult to monitor, and the support for the service process is more comprehensive and accurate; the service of this product can provide the data in the operation and maintenance and increase the richness of the data. For simulation, the service can play a role in error correction of the simulation model and improve the accuracy of the simulation model. The current research progress of these three parts is as follows.

Data In the manufacturing industry, there are many devices in just one workshop, such as various machine tools, production lines, and sensors. These devices constantly output inspection data or production data, which contains key information that affects the production process. At the same time, the data format output by each device is different, which poses a challenge to the integration of multi-source data. Therefore, to build a DT model in the manufacturing industry, it is necessary to focus on data processing-related issues.

Firstly, standardizing the format type of data can improve data transmission and recognition more efficiently. Therefore, Botkina et al. [71] used the international standard ISO-13399 as the data transfer format of a cutting tool, which can effectively reduce the difficulty of data manipulation during the manufacturing and use of cutting tool data. Subsequently, to respond to emergencies faster, the DT puts forward higher requirements for data acquisition and processing efficiency. Uhlemann et al. [72] demonstrates the advantages that real-time data acquisition and data processing in DT bring to production systems based on the concept of learning factories, which can be implemented to help companies improve transparency and manufacturing process optimization. Liu et al. [73] and Wang et al. [45] improved data analysis by transferring the data generated in the DT model to the cloud management model. D'Amico et al. [74] proposed that each module in the DT model needs to have its own data management repository, which can improve the efficiency of data management. Although multiple databases can realize the classification and processing of data, the data connection between databases also needs to be considered in depth. Finally, the data fusion between different models can make the DT function more powerful and avoid dealing with information islands. Therefore, Min et al. [75] and Xia [76] also used a machine learning approach to achieve data fusion between physical entities and virtual models, and this method is more prominent for multi-dimensional and multi-quantity data processing.

Simulation Simulation is the most important function in the DT model, which is inseparable at any stage of the manufacturing process. For this module, Kousi et al. [77] built a 3D workshop model to simulate the production of personalized products through sensors and CAD models. Negri et al. [78] considered modeling some of the more critical parts and behaviors of the production system (e.g., energy consumption prediction and motion behavior) separately and activating the use of the needed parts during actual use to improve the efficiency of the model. The advantage of this method is the high computational efficiency of a single model, but it may increase the risk of model errors. Aivaliotis et al. [79] builds the virtual model of manufacturing equipment by combining geometric model, virtual sensor model, and model uncertainty parameters. Adjusting the model to the state of the real machine by sensor data can keep the virtual model consistent with the physical entity. Yi et al. [80] decomposed the assembly model into several models for simulation verification of the assembly process, such as 3D model, assembly process information model, and accuracy information model. The application of this method requires attention to the accurate modeling of sub-models and the connection of information between models.

Service The goal of DT model is to provide various types of services for the manufacturing process, such as improving product design, predictive maintenance of manufacturing equipment, and reasonable task allocation of production lines. The results can eliminate unnecessary factors in reducing production efficiency. Zhang et al. [81] proposed optimal control methods to enable DT models to formulate optimal path objectives in real-time based on the information in the production system. The application of this method helps to keep the production operation in the best condition in real-time, avoiding the interference of external factors to the production process. Guo et al. [82] used an event-based mechanism and multi-objective optimization decoupling approach for a flexible cellular manufacturing DT model, which enables optimization of production layout, production scheduling, and logistics distribution behaviors. However, the method needs to consider the access to metrics that cannot be directly measured by sensors.

4.2 Aerospace industry

As the first industry to apply DT technology, Aerospace believes that the method can be used for research in data management and health state prediction for the design and manufacture of aircraft structures, as shown in Fig. 9. By introducing DT into the whole lifecycle of an aircraft, it will not only improve the intelligence of the aircraft at all stages, but also realize the closed-loop optimization of aircraft design, manufacturing, and maintenance. Firstly, to build a DT model of an aircraft, it is necessary to synthesize the data related to the aircraft in the manufacturing process, which can find the key information to improve and optimize the aircraft design process. Liu et al. [83] proposed a DT model

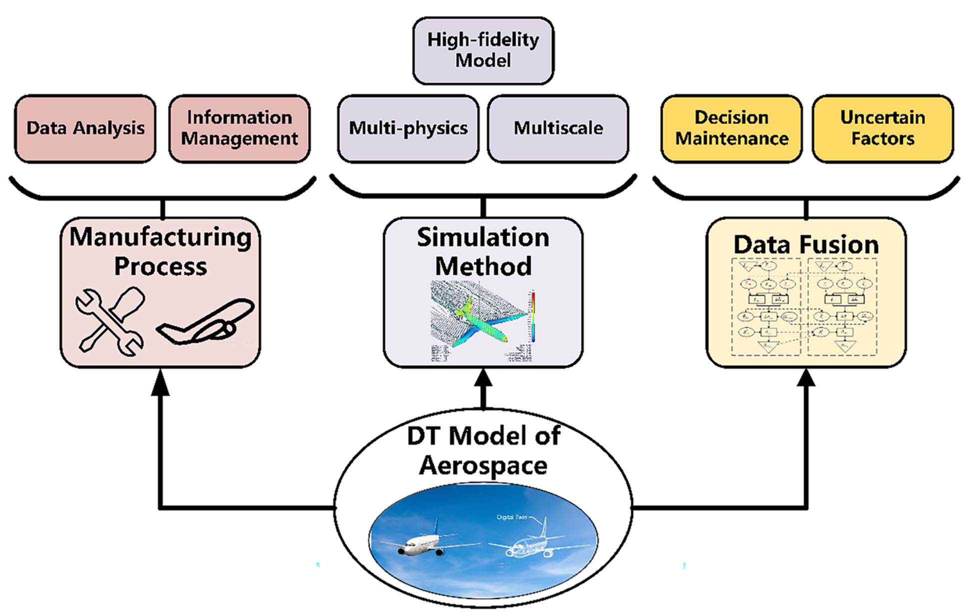

Fig. 9 DT model building method for the aerospace industry

to simulate the machining process of aircraft parts from multiple levels, which can reflect the machining performance of parts and the related decision-making ability. However, this method needs to consider the problem caused by simulation lag. Dai et al. [84] used ontology-based information modeling method to study the data management of aircraft in the manufacturing process, which enables fast information search and reasoning. Singh et al. [85] proposed an information management framework for the DT-based aircraft manufacturing industry. The continuous exchange of information among the multi-layers of the framework helps to understand the different stages of information management from data identification to retrieval and then to reservation.

During the flight, the aircraft are subjected to complex and irregular alternating loads, so it is prone to damage, such as fatigue cracks and pits. The traditional method of inspection and maintenance requires a thorough inspection of the aircraft at regular intervals to eliminate potential problems, but this results in significant maintenance costs. DT collects various types of sensor information and historical data and combines them with structural dynamics and finite element theory, thus building a multi-scale, multi-physical field, high-fidelity finite element simulation model. It realizes the reproduction of fatigue cracks, wear, creep, and other failure modes.

To support aircraft use and maintenance decisions, the DT model building process needs to consider multiple sources of uncertainty throughout its lifecycle, integrating multiple data sources from models and physical entities to reduce the impact of uncertainty on the structural health state assessment. Therefore, how to better integrate multiple sources of data into the DT model is a current research focus on the aircraft industry. Li et al. [86] used the dynamic Bayesian network (DBN) to deal with the uncertainty factors in the operation of the aircraft and realized the accurate prediction of the crack state on the aircraft wing. This method can reduce the influence of uncertainty factors on the DT, but the method requires high measurement accuracy of the sensor. Considering the complexity of the helicopter dynamical system, Guivarch et al. [87] built the DT model of the helicopter dynamic system by building multiple local models, which realized the accurate estimation of the actual displacement results. Considering the uncertainty conditions affecting fatigue crack growth, Yeratapally et al. [26] and Leser et al. [26, 88] proposed to reduce the influence of this uncertainty factor by inputting the actual crack data to the model. Ye et al. [89] proposed a DT model to evaluate the health of reusable spacecraft structural health state assessment, which can be applied to both offline and online types with good applicability. Wang et al. [90] proposed a DT model of the aircraft based on the combination of FEM and Monte Carlo simulation to achieve optimal estimation of the crack state with modified particle filtering. In future research, DT can achieve such goals as accurate perception of the aircraft's own state, autonomous mission planning, decision on the optimal flight path, and provision of safe and timely maintenance strategies. It can achieve the aircraft operation goals of higher efficiency, longer life and lower cost.

4.3 Smart city

With the increasing population density in cities, the unreasonable, untimely, and inadequate distribution of public resources in cities has aggravated the conflicts among people. The DT is applied to the construction of smart city, which is based on the BIM and the 3D geographic information model, using the IoT to digitize all the objects in the city, such as buildings, transportation facilities, underground pipelines, and other entities, and finally build a completely corresponding virtual city in cyberspace. Through the establishment of DT smart city, urban traffic will be smoother, urban management will be more efficient, and urban services will be more convenient.

Among the issues related to the establishment of DT smart cities, there are two that deserve attention. One is how to build a virtual model of the many complex buildings in the city with high precision and efficiency; the other is the data sources in the process of urban management are wide, and the amount of data that needs to be processed at the same time is huge. Therefore, how to process these data reflects the true laws of the city's operation, as shown in Fig. 10.

For the problem of building modeling in DT city, the current research focuses on how to achieve fast and accurate modeling of complex buildings while adding as much detail to the buildings as possible while ensuring better simulation results. In the current research, the use of image recognition has a promising application. The overall efficiency can be improved by identifying the main structural features of the building and subsequently automating the modeling process. Lu et al. [91] used optical symbol recognition techniques to extract features of buildings from images and CAD drawings, followed by a neuro-fuzzy algorithm to achieve rapid creation of physical models of buildings. This method enables semi-automatic modeling of buildings, but the components of the building model need to be continuously expanded, and attention needs to be paid to buildings with complex structures. Angjeliu et al. [92] proposed that the main structural features of the building should be identified, followed by parametric modeling of the main structure to deal with the complex structure. This method can achieve better simulation results at a smaller modeling cost. Kaewunruen et al. [93] used the Net Zero Energy Buildings (NZEB) metric to assess the energy demand of buildings. This method can be used in energy and environmental studies of buildings to help support the global goal of achieving carbon neutrality.

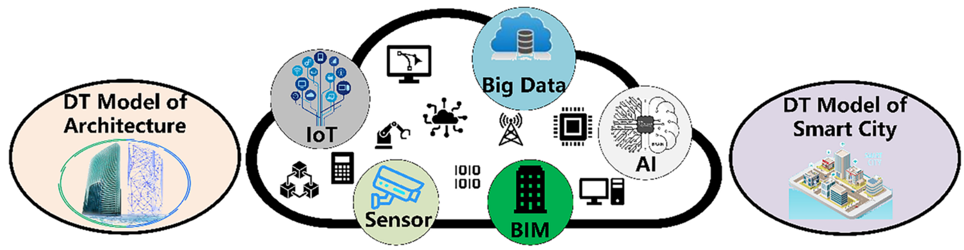

Fig. 10 DT model building method for smart city

The city can collect a variety of information in management, such as traffic signals and congestion, the working state of underground pipelines, and air and weather information. With the increasing scale of cities, the intelligent use of data is becoming a key solution to this complex management problem. To solve the data processing problem in the DT city, O'Dwyer et al. [94] proposed to divide the city into multiple regions for fast data processing and then integrate the regional data processing results based on a holistic perspective and obtain the corresponding solutions. This framework can greatly reduce the amount and difficulty of data processing, while the research focus needs to be on multi-regional data fusion. Fan et al. [95] divided the data processing problem of the DT into four steps: (1) multi-data sensing for data collection, (2) data integration and analytics, (3) multi-actor game-theoretic decision-making, and (4) dynamic network analysis. White et al. [96] combines BIM with IoT sensors widely deployed in cities to build DT model of smart cities. Bartos et al. [97] fused sensor data with DT model to monitor and predict the state of urban drainage network in real time. Faced with the huge amount of data in the city, big data analysis has become a very effective means to cope with it and achieve efficient management of the city by analyzing the potentially effective information in the data. Li et al. [98] used big data analysis technology to analyze relevant data in cities and used deep learning network to achieve the extraction of key data features, which greatly improved the ability of data analysis. Therefore, it is necessary to make comprehensive use of machine learning and big data analysis technologies when building DT models for city to improve the capability in urban operation assurance.

4.4 Battery technology

With the development of technology, electric vehicles are gradually accepted by the market, and their market share is increasing year by year. As the main means of energy storage in electric vehicles, the performance of battery is directly related to the overall performance of electric vehicles. Due to the current widespread use of lithium battery technology, with changes in the external environment, the continuous charging and discharging of the battery, and other factors, there are bound to be safety, reliability, performance degradation, and other issues. Therefore, the DT model built by the current battery technology focuses on predicting the current performance state of the battery and making maintenance and replacement decisions, without too much involving the structural design of the battery, as shown in Fig. 11. Qu et al. [99] proposed a DT model of lithium-ion battery by deep learning and determined the health factor of the battery by some measurable parameters (e.g., cell terminal voltage, current, and sampling time). The method is intuitive to evaluate the performance degradation degree by actual discharge capacity, but it is more practical to study the overall discharge simulation of battery pack. Li et al. [100] proposed a battery management system based on a cloud system, which can accurately monitor the battery status while improving the data storage capacity by embedding the

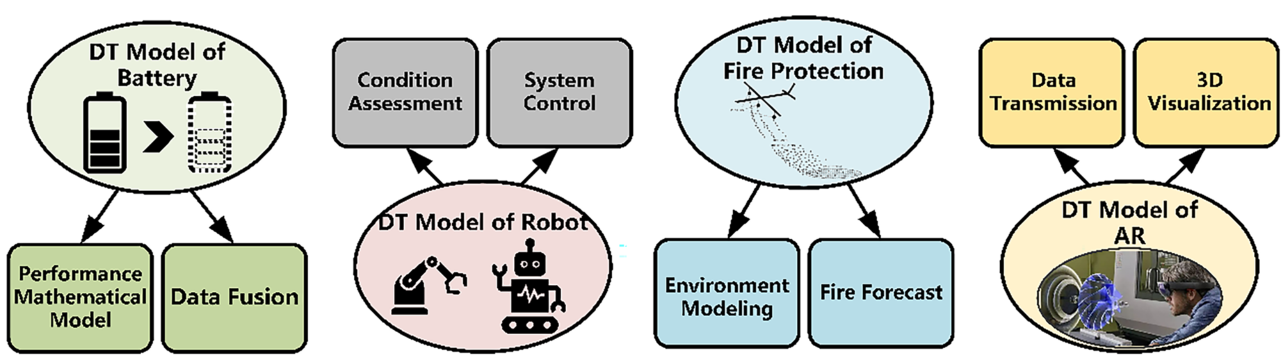

Fig. 11 DT model building method for the other industries

adaptive extended H-infinite filters and particle swarm optimization algorithms in the cloud. Under the support of 5G technology, this method can greatly improve the prediction speed and provide real-time monitoring and protection for the battery safety of electric vehicles. However, this method lacks the ability of battery life prediction. Meraghni et al. [101] fused a physical performance model of the battery and a deep transport model to build a DT model for battery performance state assessment with features such as real-time updates and online measurement. The validation found that the method can achieve a prediction accuracy close to 92%. This method enables the construction of a model for battery performance by considering the uncertainty between different operating conditions and the initial parameters of battery performance.

In current research, more literature is to consider how to use the relevant detection data of battery physical entities to establish or modify the virtual model in DT to complete the prediction of battery performance status. In the previous discussion, it is known that an important feature in DT is the two-way data interaction between physical entities and virtual models. Therefore, in the future, when applying DT to batteries, the high-fidelity virtual simulation capability of DT can be used to achieve optimization of battery arrangement for the purpose of improving the safety and reliability of electric vehicles while also providing a powerful verification tool for the battery research process.

4.5 Robot

The use of robots is becoming more and more common, such as industrial robots, household robots, service robots, and robots with special applications. The emergence of these robots has greatly improved the efficiency of people's work.

The traditional concept of robot is regarded as a kind of equipment entity that strictly follows the code to work, which only makes people get rid of repetitive and dangerous work. With the rapid development of AI technology, data are regarded as the key element for robots to complete the last puzzle. The robot perceives the real physical world through various types of sensors, uses 3D modeling technology to model the surrounding environment in real time, and forms a high-precision semantic model of the 3D environment. The model enables the robot to truly behave accordingly to the ever-changing environment. Therefore, the development of DT technology in robotics equipment research is an important way to improve robot reliability and intelligent development.

The building method of the DT model of industrial robots for path planning is mainly to study its obstacle avoidance method. Dröder et al. [102] proposed a control strategy using augmented machine learning, which combines the nearest neighbor approach for path planning and the use of cluster analysis for obstacle detection. This method can effectively respond quickly to obstacles and people in any space. Aivaliotis et al. [79] implemented the health state assessment of a robot by converting its components into a physical model for simulation, which mainly draws on the sub-model concept in FEM. Erdős et al. [103] improved the tightness of the DT through a multi-level calibration method to ensure sufficient operating accuracy during the offline process of the robot and improve the working quality of the offline robot. However, this method cannot do the offline process for the processing of unexpected events and model correction. Xu et al. [104] fused the data detected by multiple sensors to establish the DT model of intelligent detection robot. This multiple sensor data can effectively modify the digital model to reflect the more real state of the robot.

The above literature has conducted in-depth research on the DT method of robots, and the intelligent improvement of robots will inevitably put forward higher requirements for the calculation ability of the DT model. Therefore, in the future, it is still necessary to study fast calculation methods such as reduced-order model to adapt to the DT modeling method for robots.

4.6 AR and VR

AR and VR technology is an important part of DT and also an important medium to connect people with DT model. In the application of AR, the DT focuses on the development of its service and visualization functions, where the challenges can be divided into (1) real-time transmission of physical entity data; (2) fusion processing of physical and virtual data; and (3) 3D visualization. Zhu et al. [55] proposed that using AR to visualize DT data requires 5 steps: physical data acquisition, virtual model simulation of the data, geometric correction of the 3D model to the physical entity, AR device to provide visualization to the user, and finally the user can use the DT data for decision-making and control of the physical system. Cai et al. [105] derived the transformation matrix to determine the spatial relationships of individual objects in the system, so that the location information of physical entities can be quickly deployed in the DT model. Validation proves that the method is effective in laying out entities in both directions in the physical system and DT space.

4.7 Other applications

DT has also emerged within various other fields. In the vessel industry, Coraddu et al. [106] proposed that data collected by sensors on board can be used to build a data-driven

DT of the ship. This model can estimate the speed loss due to attachment. In the fire protection industry, it is mainly to realize the rapid modeling of the fire environment and quickly generate the optimal fire extinguishing path and scheme. For example, Zohdi et al. [107] considered the use of meshless particles to build the DT model in the fire scene. After the real-time fire data observed by simulation and practice, the optimal fire extinguishing path can be quickly determined by the machine learning algorithm. In the automobile industry, the main focus of research is on the fuel consumption problem of car engines, such as Guan et al. [108] who used genetic algorithms applied to DT models to implement and optimize the fuel consumption and Nox emissions of car engines. Aversano et al. [109, 110] combined orthogonal decomposition for data compression with Kriging for interpolation to design a reduced-order model (ROM) for the combustion system to predict the combustion data under arbitrary operating conditions, which greatly improves the computational speed. In the food transportation industry, Defraeye et al. [111] and Shoji et al. [112] proposed a DT model for the preservation of fruits during transportation. The freshness of mangoes was predicted quantitatively by measuring the external ambient temperature based on a temperature-dependent finite element model of biochemical degradation reactions. For the biopharma industry, Sokolov et al. [113] mainly used DT technology to explore the impact of uncertain factors on the biopharmaceutical environment.

There are also some studies for some engineering equipment or application systems, such as condition monitoring of crane booms [114], 3D printing devices [115], railroad turnout systems [116], cooling performance sensing of coolers [117], electro-optical systems [118], plasma radiation detection systems [119] and Disease transmission simulation[120].

4.8 DT research comparison between different industries

Researchers from different industries have their own understanding of how DT technology can contribute to the progress of industries. For the manufacturing industry, DT is seen as a revolutionary technology to enhance the overall manufacturing process intelligence and visualization. DT can effectively eliminate the problem of information island in each stage of the manufacturing process, which makes the product form a closed-loop connection from the design stage to the use stage and improves the connectivity and applicability of the manufacturing industry data. Therefore, in addition to focusing on high-fidelity simulation models and methods, the manufacturing industry also focuses on the research on the fusion method applicable to the DT model, which includes the data-data, model-model, and data-model integration process. The deep integration of manufacturing process data and model is realized by using DT technology, which provides a powerful power source for the development of the manufacturing industry. Finally, the digitization and virtualization of the total factor of the manufacturing plant, the real-time and visualization of production management, and the collaborative and intelligent equipment operation and maintenance are realized. The above will help the industrial enterprises realize digital operation.

For the aerospace field, DT can be regarded as an advanced tool to improve the aircraft design and research process, manufacturing assembly and operation and maintenance capabilities. By realizing the effective integration of the whole lifecycle of the aircraft, DT can greatly improve the operation and maintenance efficiency of the aircraft and the prediction ability of the remaining life under the premise of reducing the aircraft manufacturing cost. Therefore, DT research in aerospace has focused more on DT modeling techniques for complex systems such as aircraft to achieve coupled analysis of multiple physical fields. At the same time, in order to predict the remaining useful life of aircraft more accurately, the multi-sensor monitoring data is effectively fused to reduce the interference of multiple uncertain factors on aircraft life prediction. Therefore, DT can provide more intelligent management and maintenance methods for aerospace industry and support its digital transformation.

For the construction of smart cities, DT technology can be considered as a necessary path for its development. Using the high-precision three-dimensional visualization technology of DT, the spatial information of the city is more comprehensive, and the true appearance of the city can be restored to the greatest extent. Therefore, the DT study of smart cities pays more attention to the research of 3D modeling technology to achieve more lightweight and fast modeling while accurately describing urban buildings. At the same time, with the help of IoT and other technologies, the traffic and public security problems existing in the operation of the city are monitored in real time in the DT model, and the high-fidelity simulation characteristics are used to improve the interactivity of the intelligent city DT model and the management ability of the city.

Machine learning, big data analysis, and cloud computing play an important role in the research of battery energy industry, while DT can closely combine the above methods for the study of performance degradation of highly nonlinear systems such as batteries. Therefore, in this field of DT research, more attention is paid to the integration and connection between different methods to achieve effective management of battery systems.

For the robotics industry, DT is considered to be the key to give robots "self-awareness" by using real-time sensor data collection to build a deep learning model that allows machines to adjust to changes in the environment on their own. Therefore, the industry is focusing more on the integration of traditional deep learning methods with DT modeling.

Ocean engineering is an emerging field of DT applications. DT is considered to be an important step in its digital and intelligent transformation. Considering the complexity of the marine environment, the current DT research in the field of marine engineering mainly focuses on the consistency maintenance and correction of the simulation model and the effective integration of multi-source data to achieve the predictive maintenance of marine engineering equipment.

For applications such as fire protection, food transportation, and epidemic disease transmission prevention, DT is more concerned about how to use high-fidelity simulation methods to obtain high-precision prediction results while intelligently generating response methods.

5 Key implementation technologies for DT

The establishment of DT model requires the support of various technologies and methods (Fig. 12). According to the importance of different technical methods for the building of DT, this paper divides the technical methods for modeling into three categories: (1) the basic technology of DT, (2) the core technology of DT, and (3) the advanced technology of DT. The adequate sensing of the physical world and presentation of the DT model to people are the prerequisites for realizing the DT. Therefore, the basic technologies of DT mainly include the perception of physical entities and the presentation of the DT model results, such as sensor technology, IoT technology, data management and storage technology, data transmission technology, and DT visualization technology. The accuracy of virtual model building directly affects the performance of the DT model. An effective virtual model should not only ensure the accurate prediction of physical entity performance, but also need to be consistent with the changing physical entities. Therefore, the core technology of DT should be directed to the establishment of virtual models, such as the modeling and simulation technology of virtual models, data analysis, and virtual-physical data fusion technology. Subsequently, to improve the efficiency and intelligence of DT models, advanced technologies of DT need to be explored, such as cloud computing, edge computing, big data analytics, machine learning and AI, mobile-connected technologies, and blockchain technologies.

5.1 The basic technology of DT

The DT model cannot be built without the development of related fundamental technologies. This section will introduce the basic technologies in the process of DT research, the continuous development of which constitutes the cornerstone of DT research.

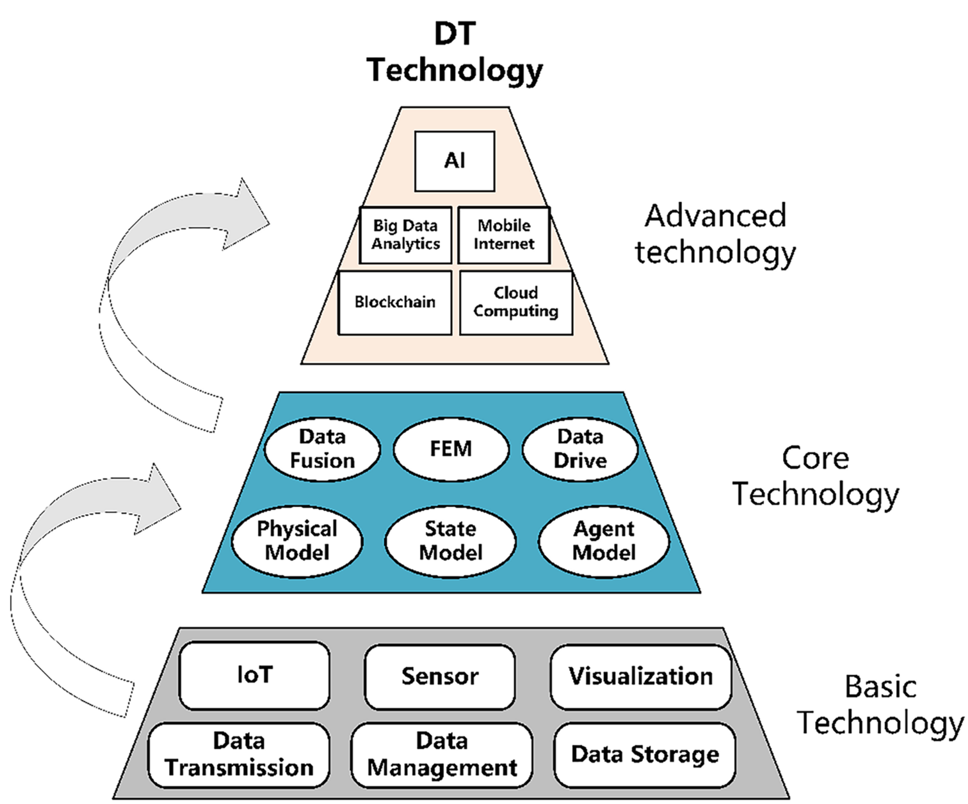

Fig. 12 Key technologies and methods for DT

5.1.1 Sensor technology

Data is the basis for the realization of DT, and sensors are important devices for sensing data from the physical world. In the industrial IoT, sensors are the windows that connect production equipment to the outside world. The development of sensors has gone through three stages: the first stage of structural sensors, which uses changes in structural parameters to transform the signal, such as commonly used pressure sensors and resistance strain sensors; the second stage of solid-state sensors, commonly used in semiconductors, dielectrics and other fixed components, such as hot spot couples sensors and Hall sensors; and the third stage is the development of intelligent sensors, the most suitable type of sensor for use in DT. This type of sensor usually has certain detection, self-diagnosis, data processing, and self-adaptation capabilities for the external information it receives. By combining sensor information with a microchip, the sensor has a certain artificial intelligence. In DT applications, a large amount of data is often detected in the physical entity module. If all these data are input to the main computer for analysis, it is easy to cause excessive waste of resources. Therefore, the data is filtered and processed in one step by smart sensors to extract the feature signals for transmission to the computer and improve the overall model calculation efficiency. However, the current approach to full sensing of physical entities is achieved by increasing the number of sensors, which increases the overall cost of the system and may result in reduced reliability. Therefore, the development direction of sensor technology for the DT should be towards more integration and multifunctional development. By integrating multiple purpose sensors in one sensor, it is possible to reduce costs while increasing the stability and reliability of the sensor. At the same time, the future development also needs to continue to increase the degree of intelligence of the sensor.

5.1.2 IoT technology

The IoT is an extended network based on the Internet that collects real-time information such as sound, light, mechanics, biology, and location of objects that need to be monitored or connected through various information sensors. Through the network access, it can realize the information exchange and communication between things and things and things and people and also realize the intelligent sensing, identification, tracking, monitoring, and management of objects and processes. Because the devices and sensors that make up the IoT can collect exactly the types of data needed to build DT model, the IoT can make the DT even more diverse and complex. With the gradual improvement of IoT devices, DT can be applied in smaller and simpler objects while bringing high revenue to enterprises. Therefore, since the DT model can significantly reduce the complexity and improve the efficiency of the IoT ecosystem, it can be said that the IoT is the carrier of the DT, and the DT is the underlying logic of the IoT.

5.1.3 Data storage and management technologies

The complexity, heterogeneity, and quantity of current data are constantly increasing, DT requires data to be processed in a short time as possible. At the same time, the diversity of data, the decentralization of equipment, and the protection of data also put higher demands on the management of data. Therefore, traditional data storage and management methods are no longer applicable. The storage and management methods of big data are more suitable for DT. The current common big data storage mainly consists of distributed file storage (DFS), NoSQL database, in-memory database, and cloud database technology. Common storage devices include flash memory and phase change memory. DFS is characterized by the ability to interconnect and collaborate through computer networks to assign tasks, thus allowing faster and better processing of large-scale data analysis problems. This characteristic plays an important role in the establishment of DT models for the smart city. NoSQL database can support well when facing a large amounts of data storage. The benefits of in-memory databases are good performance and speed. The advantages of a cloud database are high scalability, high availability, high performance, and maintenance free. Compared to traditional magnetic storage media, flash memory has high transfer rates, low latency, and low energy consumption. Phase-change memory is a nonvolatile memory that can read and write and recover data up to 100 times faster than flash memory but at a relatively high cost [121].

5.1.4 Data transmission technology

After the physical entity collects the data and the virtual model generates the data, they need to be transmitted to the data processing module for analysis. Therefore, the process needs to be realized by using the corresponding data transmission technology. The data transfer technology for DT consists of two parts, one is the data transfer format and the other is the data transfer method. Since the DT model contains different devices and models, the adoption of an appropriate data transfer format plays an important role in the mutual communication between devices and models. Several data exchange formats are currently in use, including Extensible Markup Language (XML), Standard for the Exchange of Product Model Data (STEP), Asset Administration Shell Format (AAS), Computer Aided Exchange (CAEX), JavaScript Object Notation (JSON), and Yet Another Markup Language (YAML). Schroeder et al. [122] used AutomationML to build DT model, placing the data in an XML file format for exchange in the middle layer. This method allows effective information exchange from the field to the enterprise level. Haag and Anderl [123] proposed a method to improve the consistency between physical entities and virtual models based on STEP. This format can effectively describe the format of object geometric features, while the data can be seamlessly integrated in multiple CAD systems. Platenius-Mohr et al. [124] used the AAS format to handle the exchange of asset information data in IoT. This method can facilitate the interoperability of information between DT models of different organizations.

Data transmission methods are mainly divided into wired transmission and wireless transmission. Wired transmission is characterized by good transmission signal, high stability, and fast transmission rate. It is not easily affected by objective conditions such as natural weather and transmitting devices in the transmission process. Usually, the transmission media used are fiber optic cable, optical fiber and cable, etc., but the cost is higher compared to wireless transmission. Wireless transmission technology is relatively simple to implement and can effectively save costs, but the transmission quality is not as good as wired transmission methods. Common wireless transmission methods include Bluetooth, wireless broadband, 5G, near-field communication (NFC), satellite communication, global positioning system (GPS), and shortwave communication.

5.1.5 Visualization technology

Human–computer interaction is an important way to realize DT, and a good human–computer interaction experience cannot be achieved without the support of data visualization technology. Visualization techniques can be divided into 2D visualization and 3D visualization techniques. 2D visualization techniques mainly use the form of graphs and tables, such as bar charts, pie charts, time series charts, and error tables. 2D visualization can represent the correlation between data very well. However, when confronted with high-dimensional data, the method will not be able to track this information, which will result in the relationships between data points being partially obscured. 3D visualization can be a good solution to this shortcoming. The current 3D visualization technologies are mainly virtual reality (VR), augmented reality (AR), and mixed reality (MR). Zhu et al. [55] developed an AR application for CNC milling machines to monitor and control the machines. Cai et al. [105] used AR technology to communicate with the DT of a robotic arm and its manufacturing process. Ke et al. [125] built an interaction framework based on VR, AR, and MR to facilitate physical space and virtual space information interaction. By using all three technologies together in the visualization of DT, the immersive, multi-aware interactive experience of DT can be enhanced.

5.2 The core technology of DT

The core technology of the DT is an important component to realize the function. By organically integrating these parts into a whole, a basic DT model can be built.

5.2.1 Modeling

Building a digital virtual model of the physical world is the core technology for building DT model. Currently, the most applied is the physics-based modeling method, which can directly describe the geometric shape of the application object, the physical properties, and the intrinsic connection of the object. By transferring the environmental information collected by sensors and related changes to the physically based model, the virtual model is guaranteed to accurately simulate the changes in the physical entity. In physics-based modeling approaches, multi-domain multi-scale fusion modeling approaches for the DT are very important because the application object is not in a single environment. Multi-scale modeling can connect physical processes at different time scales, and therefore, such computational models can have higher accuracy.

While physics-based modeling approaches can describe the external changes of objects, modeling for intrinsic rules is often done using semantic-based approaches. The semantic network model is a kind of symbolic network in knowledge representation; by pre-storing the knowledge composed of the connections inherent in the model in semantic knowledge, it can be searched along with the connection when the object to be applied needs to make some changes according to the rules. Commonly used semantic modeling approaches have ontology-based modeling method, such as Li et al. [126] proposed a framework structure for semantic indexing and retrieval of manufacturing tasks based on ontologies. Erkoyuncu et al. [127] used ontologies to capture diverse data over the asset lifecycle, thus enabling collaborative change of DT models with complex engineering systems.

Simulation is closely related to modeling, and the role of simulation is to allow us to better understand the changes of physical entities, so the simulation technology of DT is the core method to ensure that the DT and physical entities form an effective closed loop. Traditional simulation is based on the FEM of ANSYS, ABAQUS, and other simulation software. By building a simulation model consistent with the physical entity and inputting complete environmental information into the model, the characteristics and parameters of the physical world can be correctly reflected. However, when large deformations such as metal stamping process and dynamic crack growth are encountered across the simulation, the calculation results of the traditional FEM depend excessively on the mesh generation method, which causes many inconveniences in the simulation process. Therefore, many scholars have studied many more advanced simulation methods, such as computational fluid dynamics (CFD) [110], coupled Eulerian–Lagrangian (CEL) method, extended finite element method (XFEM) [128], discrete element method (DEM) [129], and smooth particle method (SPH) [130]. The above methods show great results in their various applications. In addition, ANSYS also provides the professional module ANSYS Twin Builder for DT modeling and simulation. This module is an integrated system simulation tool that can reduce the order of 3D models of ANSYS electromagnetic field, structure, fluid, and thermal analysis modules, providing a high-precision and high-speed system simulation environment. At the same time, the module can also be connected to an industrial Internet platform to access test data and real-time data. For example, ANSYS and Hewlett-Packard have cooperated with HP's IoT EL20 edge computing system to build a DT for pumps. By combining the pressure and flow data collected at the outlet and inlet of the pump with finite element simulation, it is accurately to identify the cause of the pump failure. In addition, Simulink is a multi-domain simulation tool for dynamic and embedded systems, where the simulation objects can be communication, control, and signal processing. Therefore, the tool can be applied to DT modeling in the above fields.

Although the traditional simulation methods can accurately represent the laws of the physical world operation, the speed of simulation calculation is usually limited by the computer's capability. At the same time, traditional simulation methods require a large amount of a priori knowledge and a comprehensive grasp of the fundamental laws in the system, which makes the model building process relatively complex and difficult. Therefore, traditional simulations cannot achieve the output of prediction results with real-time physical world data input. At the same time, for applications with short time periods such as cutting and tool wear, the traditional simulation method cannot achieve real-time results. The data-driven agent-based modeling approach is applied to the DT technology, which involves only the input and output data of the process and does not have to analyze the internal detailed records. Therefore, the method is used to model engineering systems for simulation under nonlinearity and uncertainty. The current commonly used data-driven surrogate models are support vector machines, neural networks, and Gaussian process (GP). Chakraborty et al. [131] explored the role of surrogate models in DT and validated it with a GP surrogate model as an example. However, although this method can avoid the problems caused by large-scale calculation, the quality and quantity of samples play a vital role in the actual application. Therefore, to better apply this method, it is also necessary to study how to quickly obtain accurate samples.

5.2.2 Data fusion

There are often many types of sensors in the physical entity of the DT model. Therefore, it is necessary to filter, analyze, and fuse the data collected by different sensors. At the same time, it is often difficult to build models that can accurately represent physical entities when faced with research objectives that have complex system mechanisms. Therefore, DT modeling also requires a combination of historical and real-time data of the system structure to update and correct the virtual model, so that the virtual model can always be synergistically consistent with the physical entity. All of the above processes require relevant data fusion means to achieve, and there are currently more results in data fusion for DT. Lv et al.[132] believes that multi-physics information fusion can achieve self-adaptive and intelligent development for the grinding process for the environment. Azcarate et al. [133] describes the process and framework of data fusion from the perspective of data structure. Yavari et al. [134] combines the theory of temperature sensor and thermal simulation data to predict the defects of workpiece in additive manufacturing. Klingaa et al. [135] takes the gas transformation of additive manufacturing process as an important parameter of data fusion. Therefore, data fusion has become an essential process in the study of DT.

The current data fusion methods are mainly divided into 3 types: (1) data layer fusion that directly processes on the original data layer collected; (2) feature layer fusion that first extracts the feature signals of the data layer and then processes the feature information; and (3) the signals acquired by each sensor that are processed at a basic level to establish relevant preliminary conclusions, followed by decision-level fusion with correlation processing for decision-level judgments. The difficulty and complexity of the above three methods are gradually increasing, and most of the current research is mainly focused on the first type.

Specific data fusion methods can be considered as statistical-based and information-based methods. In statistical-based methods, there are mainly Kalman filter (KF), particle filter (PF), Bayesian inference, and so on. It is mainly based on probability theory to estimate the data and obtain better data fusion results according to probability distribution characteristics. Kienzlen et al. [136] uses KF to predict coupled signals. Yu et al. [118] used Bayesian network to update the uncertainty parameters of the photoelectric system in real time and realized the effective integration of various data. Fang et al. [137] uses PF to fuse the crack information detected by the sensor with the calculated results of the crack growth rate model to reduce the interference of uncertainty factors on the prediction results.

Statistical-based fusion methods require obtaining a large amount of data with high accuracy, such as Bayesian estimation that also requires obtaining the prior distribution probabilities of parameters, which sets a greater difficulty for the implementation of this method. In response to the above problems, many scholars have proposed information-based data fusion methods, which are mainly based on information theory, including such as ontology methods, fuzzy inference rules, D-S evidence theory. Yu et al. [138] uses an ontology to achieve the integration of data, objects, and knowledge for cities, and its rule-based reasoning method can effectively identify the cause of faults and give maintenance measures. He et al. [139] used D-S evidence theory to fuse inspection data to achieve accurate predictions for robot performance states. Machine learning approaches have received much attention in recent years due to their specific autonomous learning capabilities and advantages such as high data tolerance. Wang et al. [140] build a backpropagation neural network (BPNN) algorithm using wireless sensor data, which can achieve better data fusion quality.

5.3 The advanced technology of DT

As technology continues to advance, DT can accommodate more advanced technologies to improve its performance, so that DT technology can develop in the direction of more intelligence, speed, and security. This section briefly introduces the advanced technology methods that have been applied in the current DT technology.

5.3.1 Cloud computing and edge computing

When DT is used in cities, workshops, and other fields, because some devices and sensors need to be monitored, if a large amount of data is all transmitted to the main computer for processing, it may cause a heavy burden on the computer and make the calculation time longer. As a type of distributed computing, cloud computing can decompose huge data processing programs into multiple small programs through a network cloud and then process and analyze these small programs through a system composed of multiple servers and return them to users. Hu et al. [141] proposed a knowledge resource center based on cloud computing, which reduces the computational resource occupation and enables efficient interaction between users and machines. To achieve the real-time rapid response required by DT, it is necessary to develop wireless data transmission technology to achieve rapid data transmission between the device and the cloud.

Unlike cloud computing, which is a centralized approach to data processing, edge computing is another solution. By processing the data directly in the vicinity of the sensor or physical entity and then using the network to transfer the processed data to the main server for computation, its improves computational efficiency and responsiveness. Lin et al. [142] used cloud computing and edge computing to work together for large-scale online analysis, achieving efficient DT model building with low resource consumption. By combining edge computing with cloud computing, it can greatly improve the data processing ability of DT.

5.3.2 Big data analysis

Faced with a large amount of data from various sources, how to better analyze and process these data is the key to achieve DT models with stronger decision-making ability, more accurate prediction ability, and faster processing speed. Big data analysis usually includes four steps: (1) data acquisition, (2) data preprocessing, (3) data storage, and (4) big data analysis mining. Data acquisition is achieved mainly by sensors. Data preprocessing is done to fill, smooth, merge, and normalize the collected raw data. Data storage is to store the processed data and build up a corresponding database for management and recall. The most critical aspect of big data analytics is the analysis and mining of the data to find potentially useful information and intrinsic laws from the data. Kaewunruen and Lian [116] relied on a big data platform to build a full lifecycle model of railway turnout systems that can be used for system visualization as well as prioritization of maintenance. Min et al. [75] used a real-time petrochemical industry big data network to train and optimize the DT model. Therefore, big data analysis can provide intelligent enhancement for DT, which can greatly improve the efficiency of enterprise production operation.

5.3.3 Mobile internet technology

Mobile connected technology for industry refers to real-time monitoring of industrial equipment and logistics information in manufacturing processes through mobile devices such as cell phones and tablets while sharing real-time information for decision-makers. By transferring the results generated by the DT model to mobile devices, real-time solutions can be generated for problematic devices while being quickly sent to workers to operate the devices. As a new generation of mobile communication technology, 5G can not only bring a good mobile Internet experience, but also provide key technology for smart manufacturing, smart cities, and autonomous driving. By applying 5G and industrial Internet technology to DT, the capability of DT can be greatly enhanced. Urbina Coronado et al. [32] built an android application to collect relevant data for supporting the DT of the workshop while providing cloud access, data backup, and computational capabilities.

5.3.4 Blockchain

As a kind of shared database, the data and information stored in blockchain have the characteristics of "unforgeable," "traceable," and "open and transparent," so it is possible to adopt blockchain technology that can be used to protect the data collected from the physical world. At the same time, the cryptographic properties of the blockchain are used to ensure the data invariance of the DT. As a digital asset for enterprises, the decentralized transaction mechanism provided by blockchain can well support digital asset trading and always maintain transparency during the transaction process. The advantages of such transactions can accelerate the commercialization of DT. Huang et al. [143] used blockchain technology to data management issues in DT while illustrating its advantages with case studies. Shen et al. [144] used blockchain to build a security sharing framework to solve the security problems in data exchange. Therefore, blockchain can provide a security approach for DT in asset management. However, blockchain technology has just begun, and it is still necessary to explore the fusion method between blockchain and DT in the future.

6 Future outlook and conclusion

6.1 Future outlook

At present, the research on DT is gradually reaching a new height and has begun to play its own value in many industries. In future applications, DT can be used to realize the digital transformation in all fields and industries with the demand for building digital capabilities, such as health care and sports. For most industries that have applied DT, the current level of digitalization is still low, and the major achievements are mainly concentrated in the new framework and new system construction. However, there is a lack of core simulation tools and digital integration technologies for the most important basic digital modeling. Therefore, the breakthrough for these problems has become a major bottleneck for the development of DT.

The future development of DT is facing the direction of big scenarios, such as DT city and industrial parks. Since the constructed scene is large, the scale of the DT model is also large. The development of the method focuses on the reproduction of three-dimensional visualization and the logical relationship of internal components. The technical method is mainly based on rapid scene construction, online monitoring and fusion of data, and intelligent decision support. At the same time, the future research needs to focus on the small-scale research, which mainly focuses on the physical characteristics and properties of the research object, such as mechanical properties, kinematic characteristics, or smaller microscopic characteristics. The purpose of this study is to be more suitable for the actual situation through simulation.

6.2 Conclusion

Since 2018, DT technology has entered a phase of rapid development. And as can be seen in the numerous papers on DT research, researchers from different industries have conducted many studies on the concepts, frameworks, and detailed methods of DT for the research characteristics of their industry objects. Therefore, this paper mainly divides industries, reviews, and summarizes the conceptual evolution, modeling methods, industrial applications, and related technical methods that may be used in the modeling process of DT. Firstly, the current research status of DT is reviewed in terms of DT concept refinement, DT framework building, and DT method research, and the history of development and future development trends are summarized; subsequently, the application of DT in manufacturing industry, aerospace, smart city, battery energy, robot, and AR/VR industry is reviewed in detail, and the focus of DT modeling that is concerned by different research objects is discussed. At the same time, industries with less research are briefly summarized, such as fire protection, food transportation, and marine engineering; to better support the development of DT, the current relevant technical methods are divided into three categories according to their importance for DT modeling, which provides researchers with guidance for the establishment of DT models; finally, the future directions of DT technology in terms of concepts, methods, and applications are discussed. In conclusion, for the study of DT technology, researchers need to build the corresponding DT model framework for the specific characteristics of the research object and need to focus on the relevant detailed methods.

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