


REVIEW

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Digital Twin for Integration of Design-Manufacturing-Maintenance: An Overview

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Abstract

Traditional design, manufacturing and maintenance are run and managed independently under their own rules and regulations in an increasingly time-and-cost ineffective manner. A unified platform for efficient and intelligent design-manufacturing-maintenance of mechanical equipment and systems is highly needed in this rapidly digitized world. In this work, the definition of digital twin and its research progress and associated challenges in the design, manufacturing and maintenance of engineering components and equipment were thoroughly reviewed. It is indicated that digital twin concept and associated technology provide a feasible solution for the integration of design-manufacturing-maintenance as it has behaved in the entire lifecycle of products. For this aim, a framework for information-physical combination, in which a more accurate design, a defect-free manufacturing, a more intelligent maintenance, and a more advanced sensing technology, is prospected.

Keywords: Digital twin, Design-manufacturing-maintenance integration, Artificial intelligence, Deep learning, Information fusion, Cyber-physical systems

1 Introduction

Traditionally, the design and manufacturing of equipment are run and managed independently, and relatively disconnected with each other, resulting in low reusability of design information, and manufacturing and maintenance data cannot effectively support the optimized design of equipment. This disconnection results in virtual mapping, cyclic iteration and integrated development of equipment design, manufacturing and maintenance not being achieved, and consequently, companies will have the problems with long development cycles and high maintenance costs. On the other hand, traditional maintenance scenarios include safety assessment [1], life prediction [2–4], structural integrity monitoring [5, 6], and online monitoring [7, 8]. These traditional measures

are mainly based on physical mechanisms and laws, and is highly relied on simplified models. The integration of design-manufacturing-maintenance of engineering equipment is a huge challenge due to the difficulty of creating accurate physical models for the design of complex equipment.

In engineering practice, the intelligent operation and maintenance needs to consider the monitoring of operation [9], warning of sudden failure [10], timely start and pause of control systems [11], feedback of maintenance status [12] and the visualization of maintenance [13]. With the development of virtual technologies such as the Internet, VR and AR, the design-manufacturing-maintenance of mechanical equipment has gradually diversified [14–16]. It is urgent to explore and improve sustainable and intelligent design-manufacturing-maintenance integration technology for mechanical equipment and systems, and create a fast, efficient and visualized industrial equipment intelligent design-manufacturing-maintenance platform [17–20].

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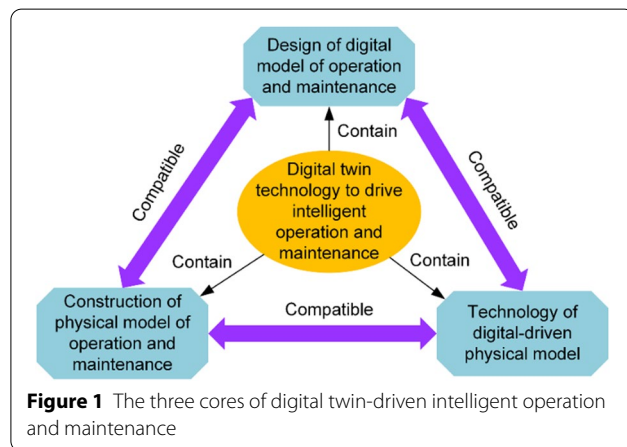
The emerging digital twin concept may offer a possible solution [21–25]. The digital twin can provide real-time feedback from the virtual world to engineers [26–29], who can combine information from the virtual world with information from expert databases to make maintenance decisions, which will significantly reduce time and costs. The combination of the digital twin with the design-manufacture-maintenance of equipment can help to make more efficient, cost-effective and convenient steps in new product development and in-service equipment management.

There are three cores of digital twin in intelligent design-manufacturing-maintenance, as shown in Figure 1, mainly including the design of digital models, the construction of physical models and the techniques for fusing digital and physical models, which should be compatible with each other. The construction of a physical model includes program design, program execution and data feedback. Design-manufacturing-maintenance

involves cross-industry, cross-platform, human-machine interaction and collaboration, and machine-machine interaction and collaboration throughout the product lifecycle. As such, digital twin technology plays a key role in driving the development of industrial clustering.

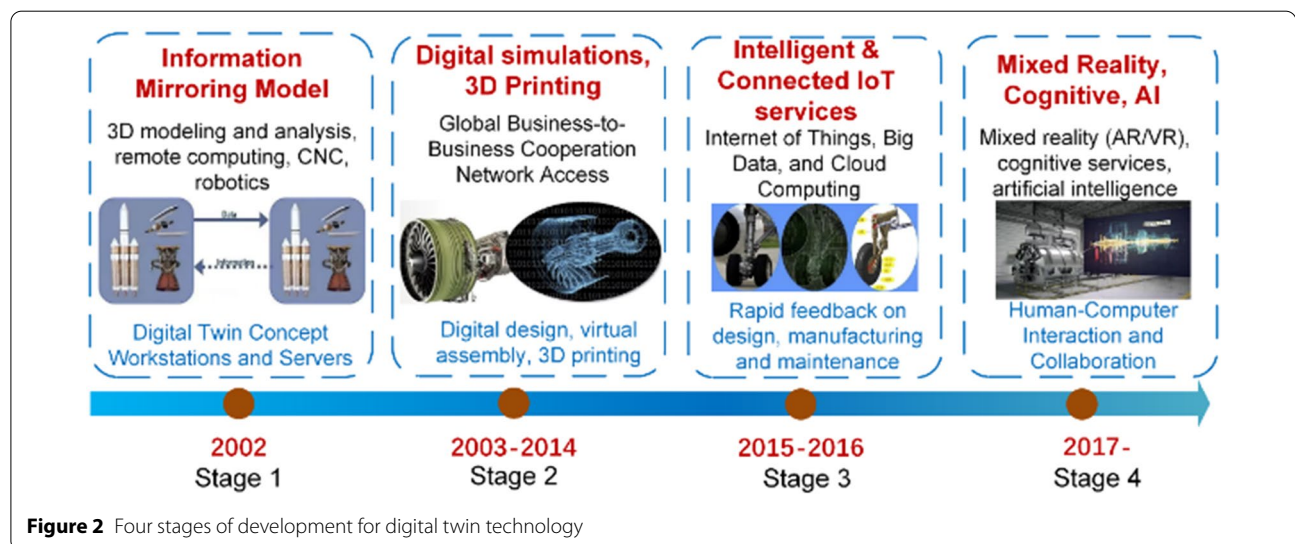
On the other hand, the convergence of human-cyber-physical systems is the core factor of digital twin technology applied to the intelligent operation and maintenance of industrial equipment [30, 31]. Currently, there are few studies on the application of cyber-physical systems to the intelligent design-manufacturing-maintenance of industrial equipment. To address the fundamental issue of sensor-model-diagnostic high-fidelity system fusion, a scientific basis for edge intelligence-based lifecycle management is required.

This paper is an overview of the integration of digital twin with equipment design-manufacturing-maintenance, by highlighting the challenges including design solution determination, digital scene construction and the fusion of the physical world with the virtual model, and by paying attention to the progress and prospects for digital twin application into the real world.



2 Digital Twin: Definition

Though the digital twin is attracting more and more attention, its definition has evolved for a long time. The concept of digital twin is retroactive to 2003, when Professor Grieves of the University of Michigan introduced the concept in a course on total product lifecycle management. The four stages of digital twin development are shown in Figure 2. The digital twin was defined as physical products, virtual products and the convergence between the two [32, 33]. Glaessgen et al. [34] raised digital twin as an integrated multi-physical, multi-scale,



high-fidelity twin system through physical models, sensor upgrades, and historical data, as shown in Figure 3. Abdulmoteleb et al. [35] proposed digital twin as a virtual copy of an organism or non-organism physical entity, while allowing information interoperability between the physical and virtual entities. Söderberg et al. [36] considered digital twin as an optimization of digital copies of physical entities. Bolton et al. [37] thought of digital twins as virtual representations of physical objects across life cycle that can be understood, learned and reasoned with real-time data. Negri et al. [38, 39] proposed the concept of model engineering and related techniques, and a set of measurement criteria for a correct digital twin, i.e., a digital twin is defined as a simulation model that acquires data from the field and triggers the operation of physical devices. The digital twin is a virtual simulation that integrates multiple data, dimensions, attributes and application possibilities in the context of new-generation information technology, industrial Internet technology and smart manufacturing concepts [40–42]. It is believed that, digital twin is a virtual entity that creates physical entities digitally, making full use of data such as physical models, sensor updates and operational histories to

integrate multi-disciplinary, multi-physical quantity, multi-scale and multi-probability simulation processes and complete mapping in virtual space, thus reflecting the full life-cycle processes of the corresponding physical equipment for simulation, monitoring, evaluation, prediction, optimization, control and other fields.

One of the features of digital twin is to create virtual models of physical objects digitally to simulate the behavior of physical objects [32]. Virtual models can understand the state of physical entities by sensing data to predict, evaluate and analyze the dynamic changes of simulated objects. In turn, the physical object will respond according to the optimized solution in the simulation. By closing the cyber-physical loop [43], the digital twin can achieve optimization of the entire production process. This interactivity between the real and digital worlds of a product or process provides a rich set of models and data for manufacturing process analysis and optimization, enabling more realistic and comprehensive measurements of system unpredictability [44].

The big data technology is often involved in digital twin for accurate calculation, as it can effectively mine the hidden and effective data, which greatly improves the

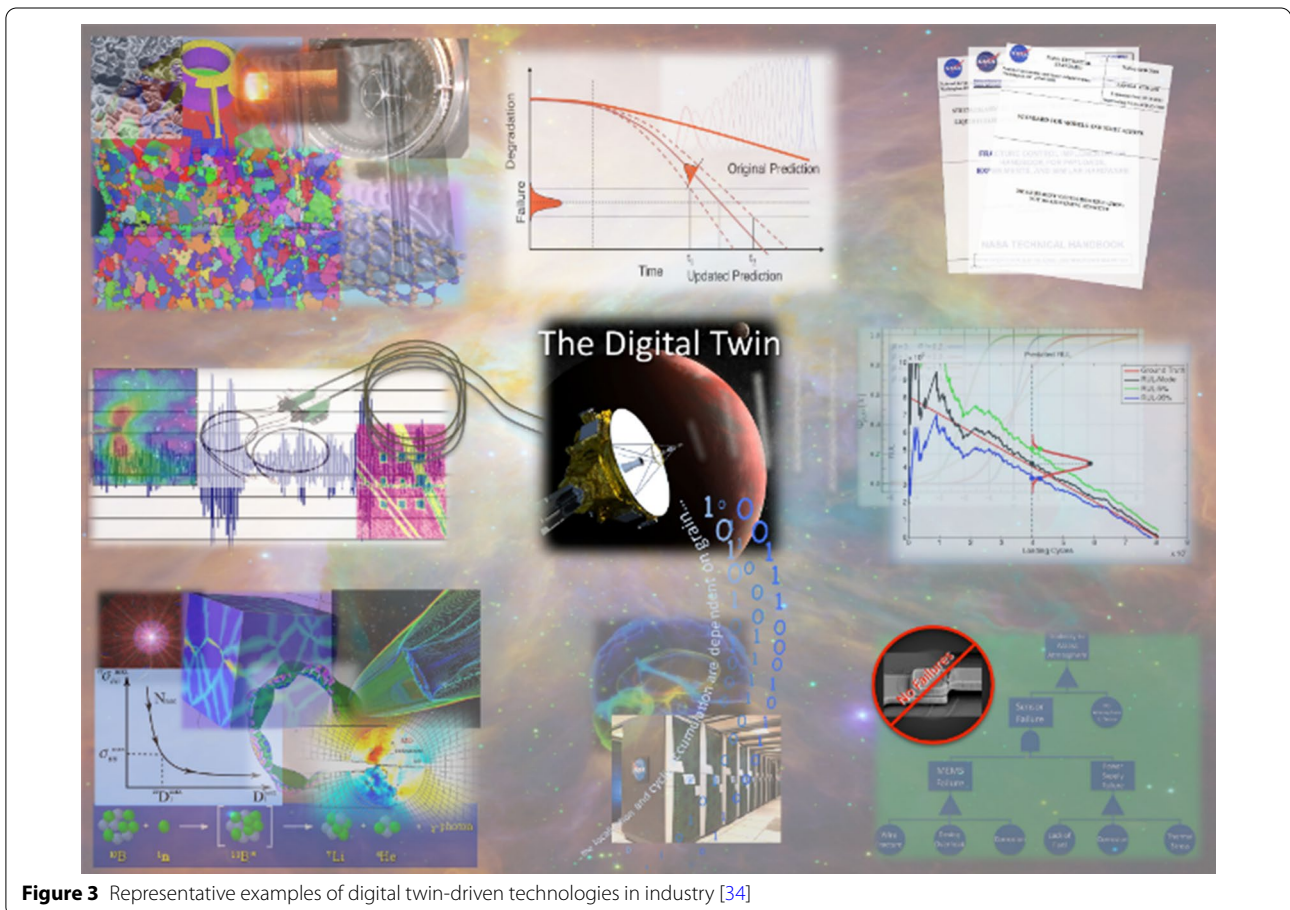


Figure 3 Representative examples of digital twin-driven technologies in industry [34]

intelligence of digital twin [45] and the applicability. Digital twin as a new technology has been applied in various fields, such as aerospace [46–50], industry manufacturing [51–53], 3D printing [54, 55], medical services [56–59], bio-manufacturing [60], agricultural machine [61], robots [62–64], power industry [65, 66], smart city [67], pressure vessel [68], machining [69–72], automatic transportation [73], roads infrastructure [74], construction system [75], as listed in Table 1.

3 Digital Twin for Design

Digital twin has gained widespread attention in the aerospace field [76, 77, 120]. For example, the U.S. Air Force Laboratory proposed a study to predict structural life and ensure structural integrity of aircraft using digital twin technology in 2011. It seems the digital twin is a new paradigm in the age of information and data revolution. The digital twin can combine physical equipment data, virtual equipment data, and connecting data of physical and virtual equipment to support the design, manufacturing and maintenance of equipment.

Digital twin is a multidisciplinary crossover technology that allows designers in plant for quick evaluation and identification of design flaws [106]. A hybrid design approach of data science and physical mechanisms is the main avenue for future research on large high-end devices. Zhuang et al. [108] proposed an implementation framework for designing and applying shop-floor digital twin. The digital twin design adopts advanced sensing equipment, industrial internet, big data, cloud computing and other science and technology. It has the characteristics of high fidelity, cross-dimensional integration, and high reliability. It can realize functions such as status detection, life prediction, and data tracking [34, 121]. It follows that the digital twin is a holistic system model of objects and environments with multiple software, relying on data transmission from sensors to address the operational conditions of physical entities in the virtual world, and the feedback from the virtual world to design and improve the operational quality and efficiency of the physical world and enhance economic efficiency.

In 2016, the U.S. Air Force developed and applied a digital twin analysis framework to provide engineering analysis capabilities and decision support for the entire lifecycle of aeronautical system. The digital twin merges physics-based modeling and experimental data to generate an authoritative digital representation of the system at each stage of the weapon system acquisition and sustainment process. As a result, the digital twin can save the development time and cost of the aeronautical system design [82], as shown in Figure 4. In 2017, Tao et al. [104] proposed the concept of the digital twin workshop, explaining in detail the main components

and operational mechanism of digital twin workshop. In 2018, Bohlin et al. [95] presented a digital twin-based active part matching and self-adjustment device to improve geometric quality without tightening incoming part tolerances, which provided the framework for implementing digital twin-driven Smart Assembly 4.0. Xu et al. [122] designed a digital cam servo motion system based on digital twin. Utilizing multi-dimensional simulation software, the trajectory planning, state monitoring and precise control of the electronic cam motion were realized by employing the virtual-real interaction capability of the digital twin technology. Guo et al. [106] proposed a modular approach to help build flexible digital twins and make changes accordingly. With this flexible digital twin, designers can quickly evaluate different designs and easily identify design defects, thus time-saving, as shown in Figure 5.

For intelligent design, digital twin needs to be combined with next generation of information technology, such as machine learning, deep learning, cloud computing and big data [123]. Machine learning can be the result of a digital twin simulation with simple learning capabilities. Cloud computing can provide digital twin with multi-dimensional data computing technology and cloud data storage technology. Integrating cloud technology in digital twin can effectively reduce the computation time of complex systems and overcome the difficulties of storing large amounts of data [124], as shown in Figure 6. In this regard, manufacturing companies such as General Electric, Siemens and Tesla have already started to create application scenarios that enrich the digital twin through next-generation information technology [102].

In addition to the application of digital twin technology in industry, digital twin technology is also being explored in agriculture and animal husbandry to promote smart agriculture [116] and smart animal husbandry [125, 126]. Therefore, a real-time, bi-directional, transparent and systematic consideration of design-manufacture-performance is only possible by using full digital twin technology to build a large number of surreal models and data, including digital product models, digital design models, digital manufacturing models, and digital performance models [127].

4 Digital Twin for Manufacturing

4.1 Evolution of Manufacturing Mode

Since 1970s, the manufacturing industry has been changing from product manufacturing to service-oriented manufacturing. Traditional manufacturing industry includes three stages for development, i.e., labor-intensive mainly in light textile industry, technology and capital-intensive mainly in electromechanical and high-tech industries, and knowledge, technology, capital

Table 1 List of current major digital twin technologies in the past decade

Year	Author/affiliation	Field	Overview	Refs.
2011	Eric J. Tuegel U.S. Air Force Research Laboratory	Aviation	A conceptual model for predicting the lifetime and ensuring the structural integrity of aircraft structures using digital twin technology is proposed	[48], [49], [76]–[78]
2012	E. H. Glaessgen Durability and Damage Tolerance Branch NASA Langley Research Center	Aviation and aerospace	Combining digital twin technology with ultra-high fidelity simulation, an integrated vehicle on-board health management system, maintenance history and all available historical and fleet data to reflect the lifespan of its on-the-fly digital twin	[34], [46], [47]
2014	Albert Cerrone Cornell University	Structural fracture damage	By applying the concept of digital twins, the diagnosis of ambiguity in crack paths indicated the need to consider fabricated specimens	[79]–[81]
2016	Dr. Edward M. Kraft United States Air Force	Aviation	The USAF is developing and applying a Digital Thread/Digital Twin analysis framework to provide engineering analysis capabilities and support for decision making throughout the lifecycle of a vehicle	[82]
2016	Schroeder, Greyce N Federal University of Rio Grande do Sul	Future manufacturing and product services	In the context of cyber-physical systems for implementing digital twins for future manufacturing and product service systems, a method is proposed for modelling the attributes associated with digital twins using AutomationML	[83]–[88]
2017	Alam, Kazi Masudul University of Ottawa	Cyber-physical system	A reference model for a cloud-based CPS, the digital twin architecture of C2PS, is proposed, in which the key attributes of C2PS are described analytically	[30], [35], [63], [89]–[92]
2017	Banerjee, Agniva University Of Maryland	Industrial production lines	A simple method for formulating knowledge from industrial production line sensors into digital twin models is presented. A method for extracting and inferring knowledge from large-scale production line data is presented	[93], [94]
2017	Robert Bohlin Fraunhofer-Chalmers Centre Chalmers Science Park	Smart assembly	The infrastructure, components and data flows required for the digital twin to enable Smart Assembly 4.0 are detailed and highlighted	[95], [96]
2017	Yuan-Shin Lee North Carolina State University	Machine tools	Techniques for deploying sensors to capture specific features of machines are discussed, and data and information fusion analysis techniques for modelling and developing digital twin virtual machine tools are presented	[97]–[101]
2017	T. DebRoy The Pennsylvania State University	Additively manufactured	The perspectives of researchers from several organisations provide the current status and research needs of the main building blocks of first generation digital twin additive manufacturing	[51], [54], [55]
2017	Benjamin Schleich Friedrich-Alexander-Universitaät Erlangen-Nürnberg	Design and production engineering	A comprehensive reference model based on the skin model shape concept is proposed which acts as a digital twin of the physical product in design and manufacturing	[36], [102]

Table 1 (continued)

Year	Author/affiliation	Field	Overview	Refs.
2017	Fei Tao Beihang University	Smart shop-floor	The concept of the digital twin-based Digital Twin Shop is explored and the four key components of digital twins are discussed, namely the physical shop, the virtual shop, the shop service system and the shop digital twin data	[23], [43], [70], [103]–[108]
2018	Lohtander, Mika Lappeenranta University of Technology	Micro manufacturing unit	The Micro Manufacturing Unit (MMU) used is a digital twin research environment that investigates how digital twins are constructed and what information is needed to describe the real behaviour of the digital model of the MMU	[109], [110]
2018	Macchi, Marco Department of Management	Asset lifecycle management	Examines the role of Digital Twin in supporting decision making in asset lifecycle management	[111]–[113]
2018	Moussa, Cynthia Electrical Engineering Department École de Technologie Supérieure Montreal	Hydro generator	A digital twin concept based on a finite element simulator for large hydro generators is proposed	[114]
2019	Qingfei Min Dalian University of Technology	Petrochemical Industry	A framework and method for building a digital twin model based on the petrochemical industry IoT, machine learning and a practical cycle of information exchange between the physical plant and the virtual digital twin model is proposed to enable production control optimisation	[115]
2020	Roman Bambura Technical University in Zvolen	Engine block manufacturing	The framework for the implementation of the digital twin of the engine body manufacturing process consists of a physical layer, a virtual layer and an information processing layer	[71]
2020	Yu N Bulatov Bratsk State University	Generation Plant	The concept of a digital twin of a distributed generation unit with automatic voltage regulation and automatic speed regulation of a fuzzy self-tuning unit on the basis of a synchronous generator is presented	[65], [66]
2020	A E Burov Institute of Computational Technologies SB RAS	Composite pressure vessel	Development of a composite over-wrapped pressure vessel digital twin device for spacecraft electric propulsion engines	[68]
2020	Kirill Nemtinov Tambov State Technical University	Agricultural machine	A method for building a digital twin model or e-model of complex agricultural machinery is presented and its structure is proposed as a set of frameworks	[61], [116]
2020	Sungshin Kim Pusan National University	Microgrid	An operational scheduling model for energy storage systems applied to virtual space is proposed for building microgrids using digital twin technology	[117]
2020	Yang Peng Shanghai Construction No. 4 (Group) Limited Company	Smart buildings and smart city	A successful project case of a large hospital in China is reported by presenting both technical and managerial innovations—a “continuous lifecycle integration” approach based on the digital twin concept and “early movement” of the general contractor	[57], [67], [74], [75]

Table 1 (continued)

Year	Author/affiliation	Field	Overview	Refs.
2021	Carina L. Gargalo Technical University of Denmark	Bio-manufacturing industry	Biomanufacturing and other process industries now have the opportunity to participate in the latest industrial revolution, also known as Industry 4.0. In order to achieve this successfully, an information loop from physical to digital and back again should be carefully developed	[60]
2021	Brendan Kochunas University of Michigan	Nuclear power	Some areas of the existing modelling and simulation infrastructure around nuclear power systems are suitable for digital twin development, while recent efforts in advanced modelling and simulation are less appropriate at this time	[118]
2022	Yongli Wei Shandong University	Manufacturing system	An implementation strategy for the physical entities of a manufacturing system digital twin is investigated. The strategy begins with an application-oriented requirements analysis of the physical entities of the manufacturing system digital twin, followed by a study of the optimal requirements deployment scheme using axiomatic design theory	[119]

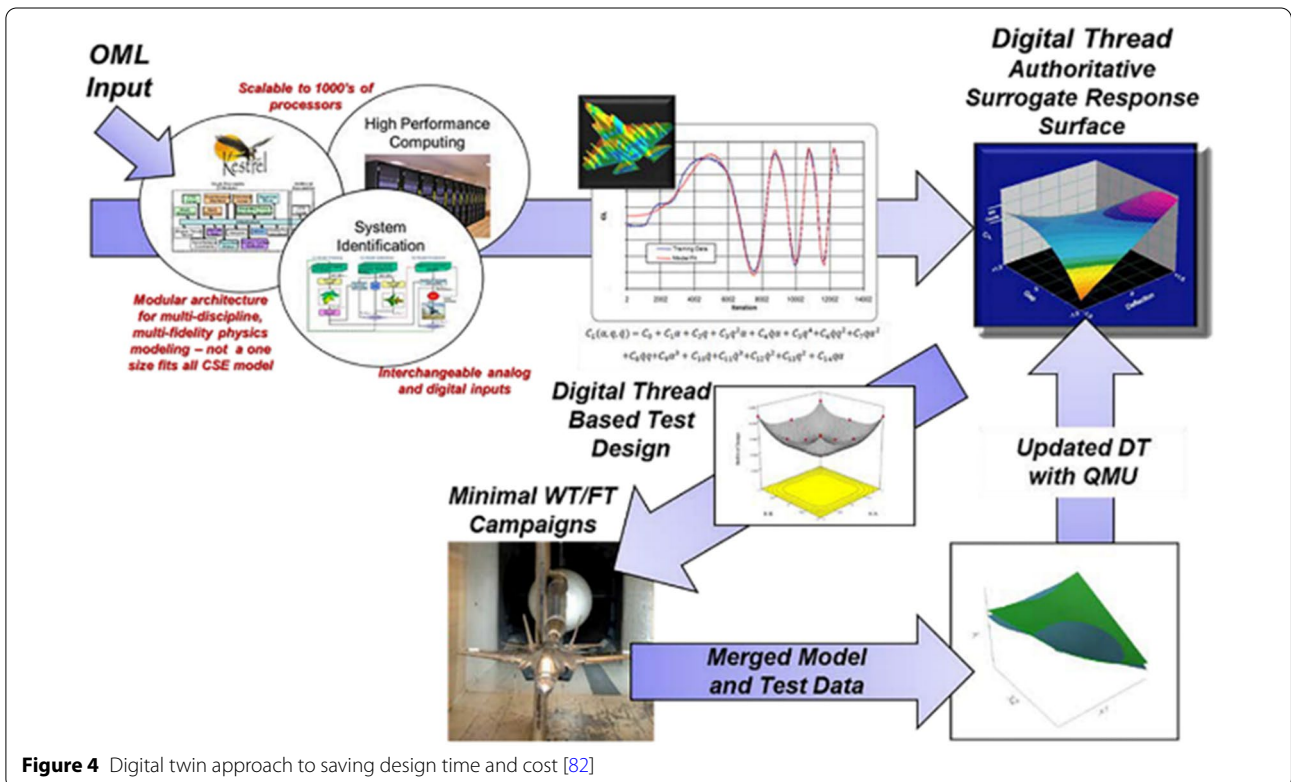


Figure 4 Digital twin approach to saving design time and cost [82]

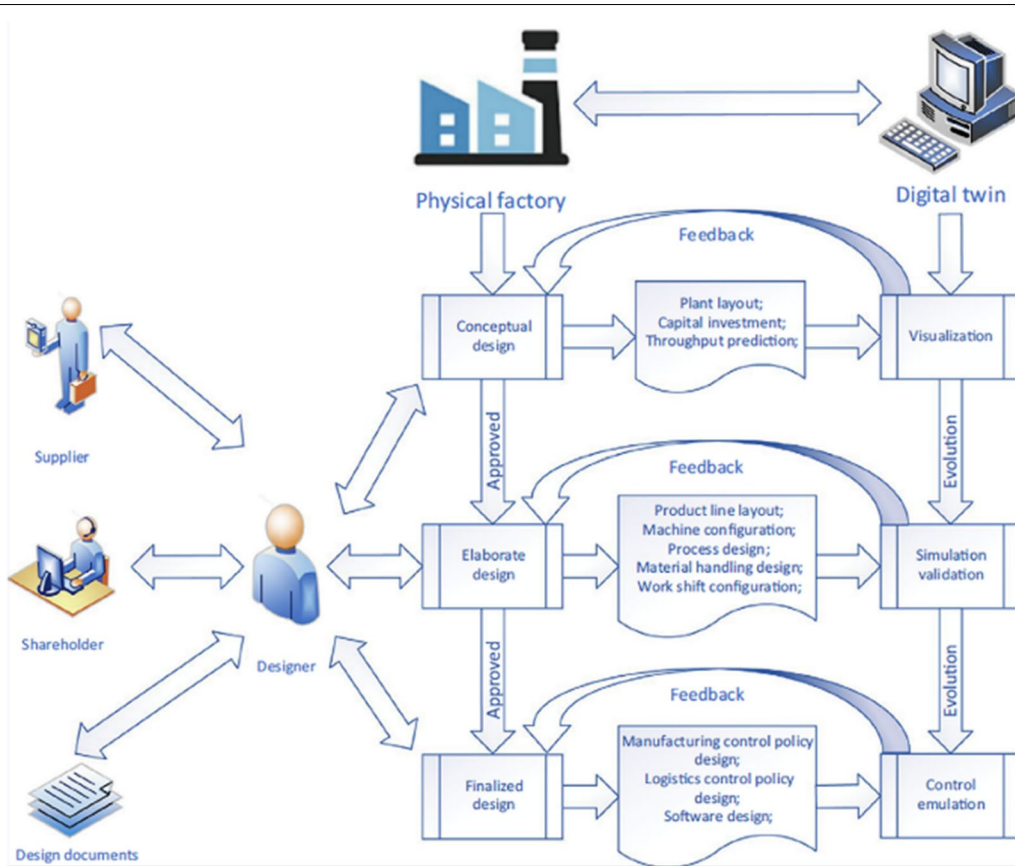


Figure 5 Framework for digital twin application in plant design [106]

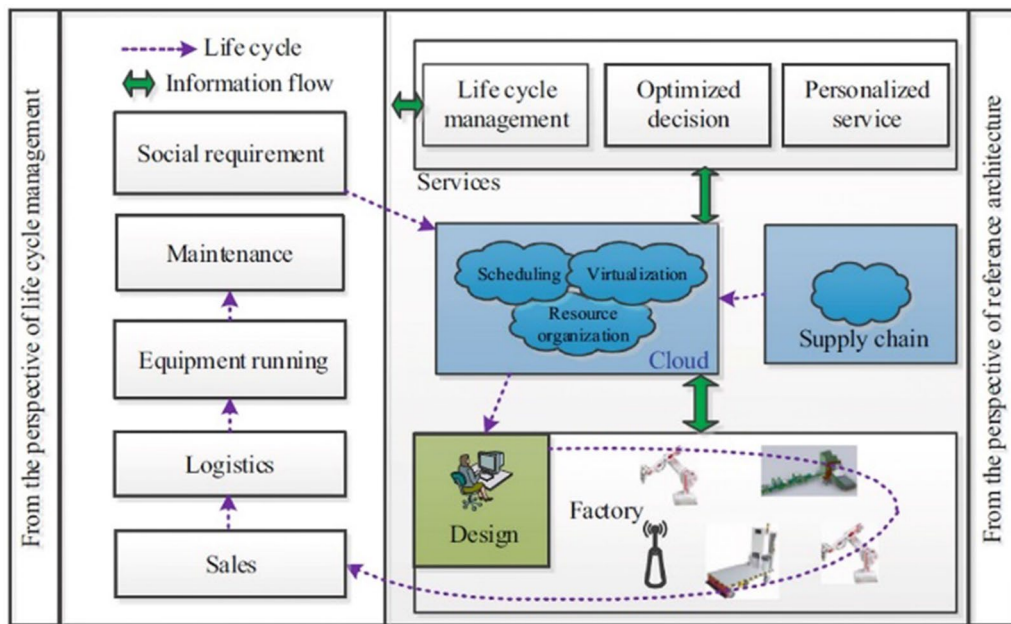


Figure 6 Cloud-integrated cyber physical systems for complex industrial applications [124]

and service intensive towards equipment manufacturing. Recently, intelligent manufacturing has gradually become dominant with the introduction of big data, artificial intelligence and digital twin concept [128]. As a result, intelligent manufacturing systems such as electronic manufacturing, digital manufacturing and virtual manufacturing, have become the new paradigm for improving manufacturing operations in manufacturing environments [129]. Traditional manufacturing is an online process where product designs and drawings are forwarded to the shop floor for manufacturing prototypes. Digital technology, on the other hand, is a cyclical process of conceptual design and innovation of products in computer-aided design software. These designs and processes are simulated to verify the feasibility of product production. Products are inspected at each stage of the manufacturing process using inspection techniques and computer-aided quality control methods.

The rising of cyber-physical system and digital twin simulation is also updating the manufacturing industries. For example, Negri et al. [92] proposed a production system separated from the core simulation to allow flexibility in deciding whether to activate copies of specific behaviors only when needed. Similarly, the petrochemical industry will also undergo intelligent transformation and upgrading. Min et al. [115] proposed a framework and method for building a digital twin model based on the petrochemical industry IoT, machine learning, and a practice cycle of information

exchange between physical plant and virtual digital twin model for control optimization, as shown in Figure 7.

Nowadays, more and more countries are investing in manufacturing capacity to increase productivity to offset costs, and manufacturers are being forced to develop advanced manufacturing technologies to achieve greater capacity with faster and more complex mechanical systems [130]. Hu et al. [131] proposed a scheme including automatic creation of mechanical, electrical, and plumbing systems that included modules for logic chains, equipment grouping, labeling schemes, and conversion of building information model information into geographic information system maps, as shown in Figure 8.

In addition, artificial intelligence technology has impact on enterprises, and enterprise IT operation and maintenance management is also moving towards intelligent and advanced pace [132]. Liu et al. [46] proposed a technical framework for intelligent solution design, simulation verification and in-orbit analysis using digital twin and digital ties. Wang et al. [133] proposed a digital twin-based aero-engine low-pressure turbine unit body docking technology by modeling the physical objects in the environment and process, and using multiple sensors to achieve physical fusion, model fusion, and data fusion based on a 3D virtual docking simulation process. Zhang et al. [134] constructed of a spacecraft digital twin model to represent the process, state, and behavior of the spacecraft as it completed its in-orbit assembly. The emerging

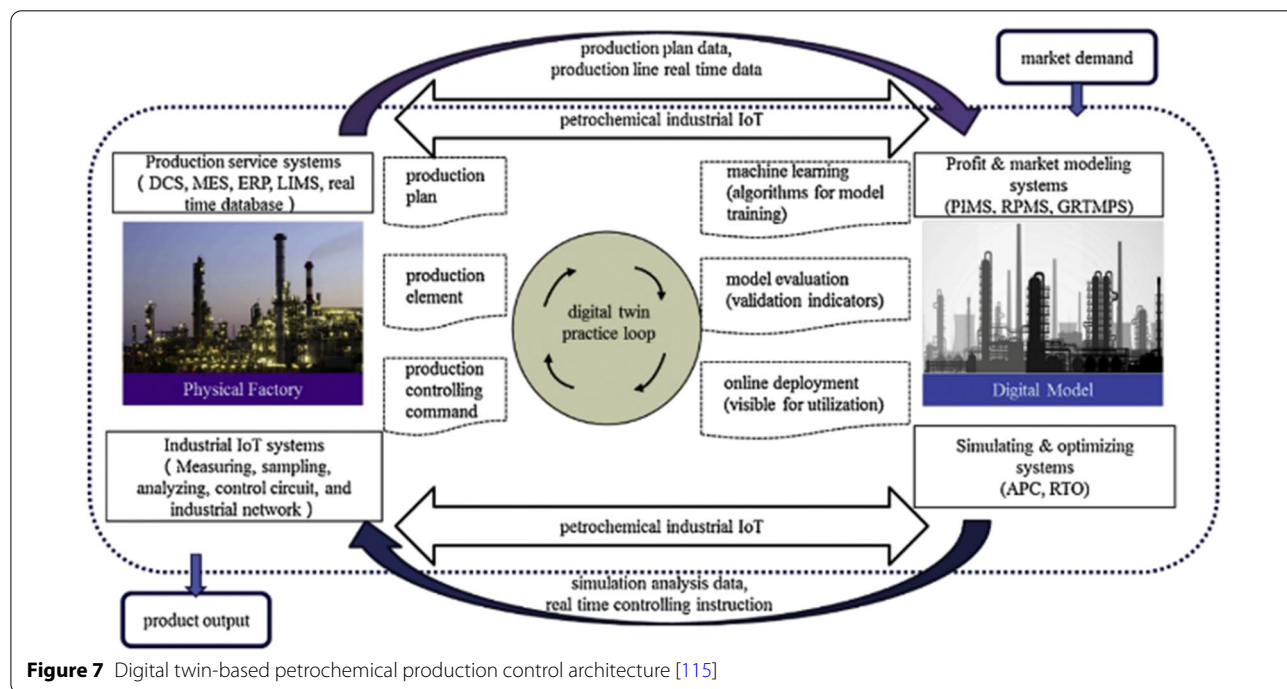


Figure 7 Digital twin-based petrochemical production control architecture [115]

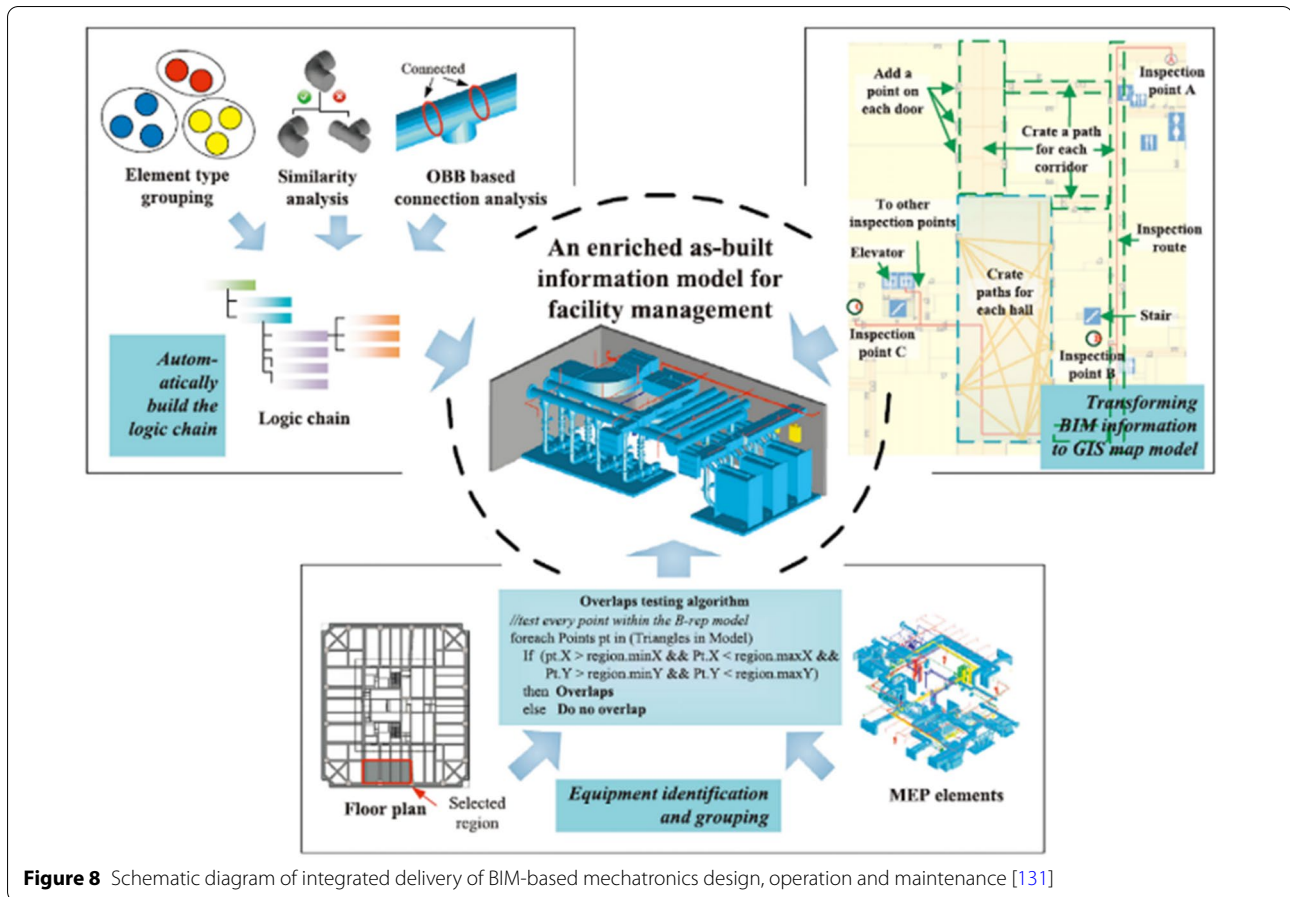


Figure 8 Schematic diagram of integrated delivery of BIM-based mechatronics design, operation and maintenance [131]

technologies such as cloud computing, IoT, are expected to combine information technology with manufacturing.

4.2 Digital Manufacturing Based on Digital Twin

The aim of data-driven manufacturing is to transform data acquired throughout the product lifecycle into manufacturing intelligence in order to provide data solutions for the development of manufacturing [135]. In data-driven manufacturing, the data generated by manufacturing systems is experiencing explosive growth and has reached over 1000 EB per year [136]. Systematic computational analysis of manufacturing data will lead to more informed design solutions, which in turn will increase the effectiveness of data-driven manufacturing [137]. In other words, data-driven manufacturing can be seen as a necessary condition for smart manufacturing. As a result, data is becoming a key enabler of manufacturing competitiveness [138] and manufacturers are beginning to recognize the strategic importance of data.

Data-driven value does not depend only on the amount of data under consideration, but on the information and knowledge hidden within. New information technologies such as IoT, cloud computing, mobile internet and AI can

be strategically leveraged and effectively integrated to support data-driven manufacturing [139]. A large body of research has emerged in recent years examining data-driven manufacturing, including industrial automation [140]. Galletti et al. [141] studied big data as a driver of industrial competitiveness. Dubey et al. [142] illustrated the unique role of big data analytics in sustainable manufacturing. Zhang et al. [143] proposed big data analytics architecture for clean manufacturing and maintenance processes. Lohtander et al. [110] constructed digital twins of micro-manufacturing cells by using production components and simulation software, which allowed the immediate integration of the machine into the industrial environment and allowed the subsequent control of all parameters of the production system.

The digital twin provides a state-of-the-art technical framework for smart manufacturing in the manufacturing industry [144], and has a supporting role in securing the industrial internet and the smart manufacturing 2025 strategy with cyber physical systems at its core as well as innovative value [91, 130, 145, 146]. Zhuang et al. [147] raised that digital twin helped to solve the problem of effective convergence and management of heterogeneous

dynamic data from multiple sources in the whole product lifecycle, and proposed a digital twin implementation framework for product manufacturing.

In summary, digitally driven manufacturing technologies enable manufacturers to manage real-time, bi-directional and co-evolving mappings between physical objects and their digital representations, which paves the way for deep cyber-physical integration. Combined with the digital twin, data-driven smart manufacturing will become more responsive, adaptive and predictive.

5 Digital Twin for Maintenance

5.1 The Significance

Maintenance has evolved from “maintenance after the fact” and “preventive maintenance” to “predictive maintenance”. Precision maintenance is the way of the future, with the aim of ensuring operational safety and reducing synergistic optimization targets and operational costs [127]. The digital-twin-based maintenance include five key technologies: data collection technology, data modelling technology, twin data application, artificial intelligence technology and human-machine interaction technology. The scientific principles of intelligent operation and maintenance of industrial equipment include sensing and damage perception, damage evolution and prediction models, and diagnosis and decision intelligence, as shown in Figure 9. The prediction of damage mainly involves the description of evolutionary laws and the development of predictive models, the coupling of multiparameter quantities and mechanisms, multi-scale

and multi-level simulations and experimental reproduction. Lifetime intelligent maintenance includes the fusion of multi-physics big data, artificial intelligence and internet diagnostics, system diagnostics based on component-level data, intelligent diagnostics and diagnostic intelligence issues.

The use of intelligent operation and maintenance technology in the automatic verification system of energy meters can improve efficiency and produce better economic and social benefits [20]. The application of intelligent technologies such as artificial intelligence, robotics, augmented reality, and online monitoring to traditional substations to achieve visibility of the station situation, risk penetration, power consumption, one-touch operation, and integrated command can significantly improve the operation and maintenance costs of traditional power stations [148–150]. Through high-capacity mobile communication network, high-speed wireless network and various mobile terminals, the operation and maintenance mode of relay protection and circuit breakers equipment are changing towards portability, efficiency and intelligence [151–156]. Therefore, digital twin is an important way to achieve equipment health status monitoring and provides a new paradigm for equipment fault diagnosis. For example, Gregor et al. [157] described the design ideas for an integrated reconfigurable maintenance system. Xu et al. [113] proposed a two-stage digital twin-assisted fault diagnosis method based on deep migration learning to achieve fault diagnosis in the operation phase and maintenance phase, as shown in Figure 10.

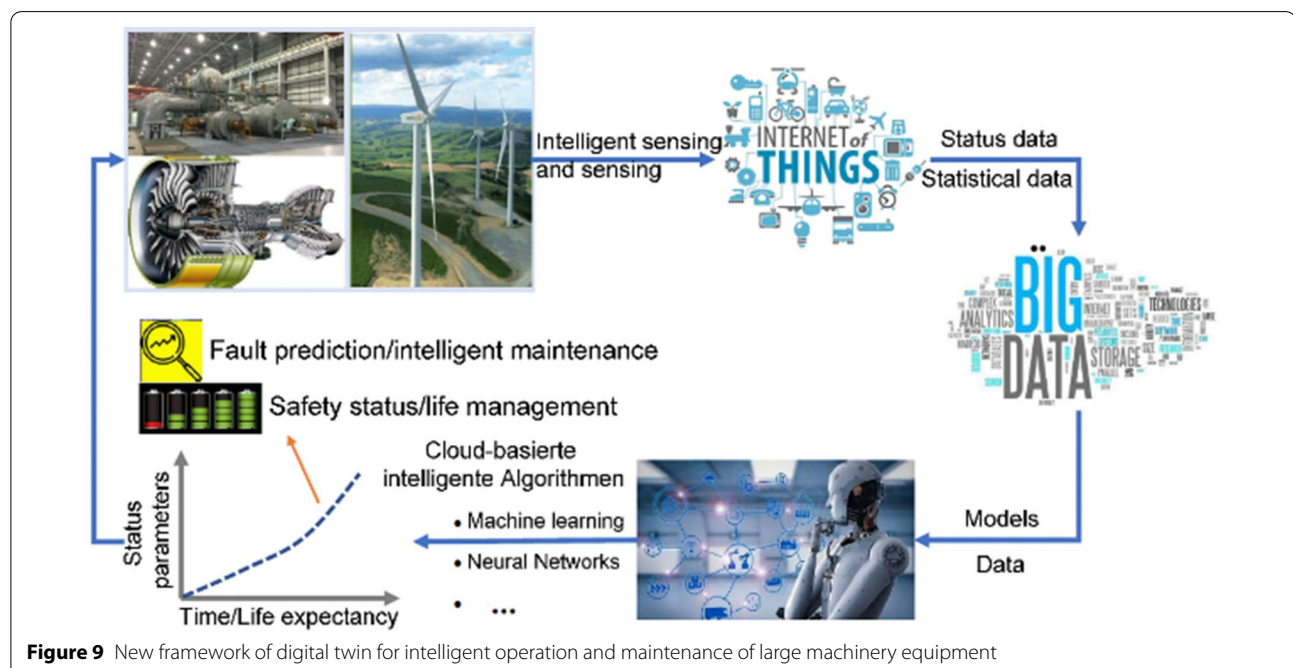
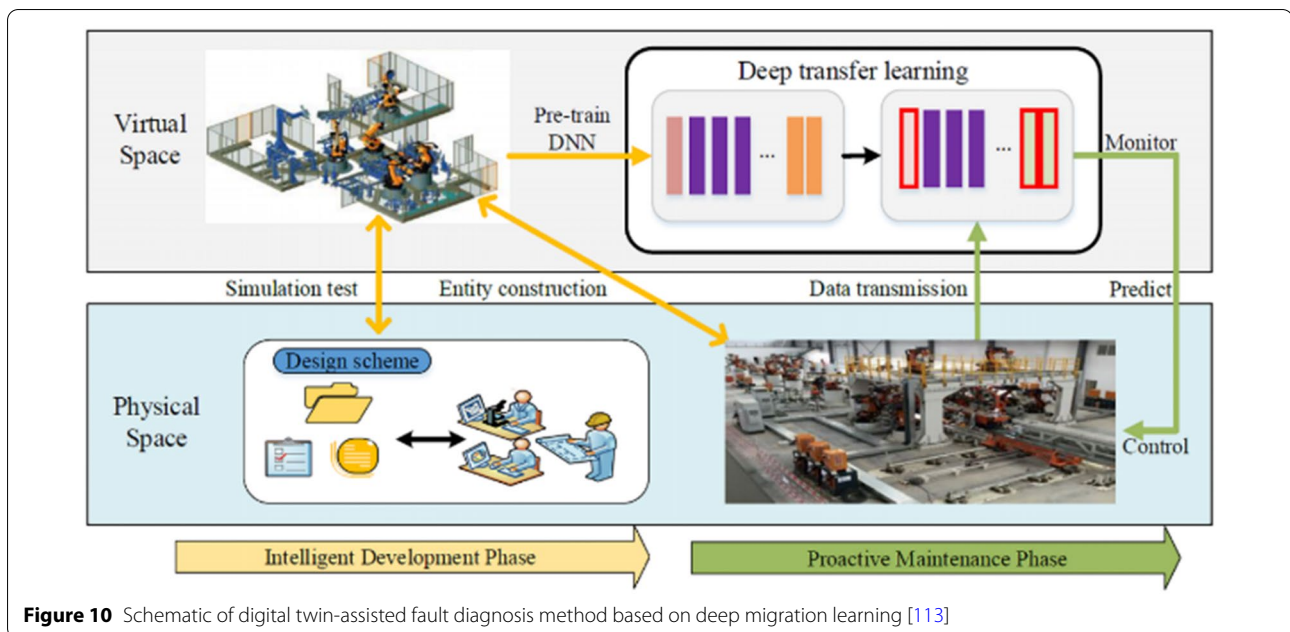


Figure 9 New framework of digital twin for intelligent operation and maintenance of large machinery equipment



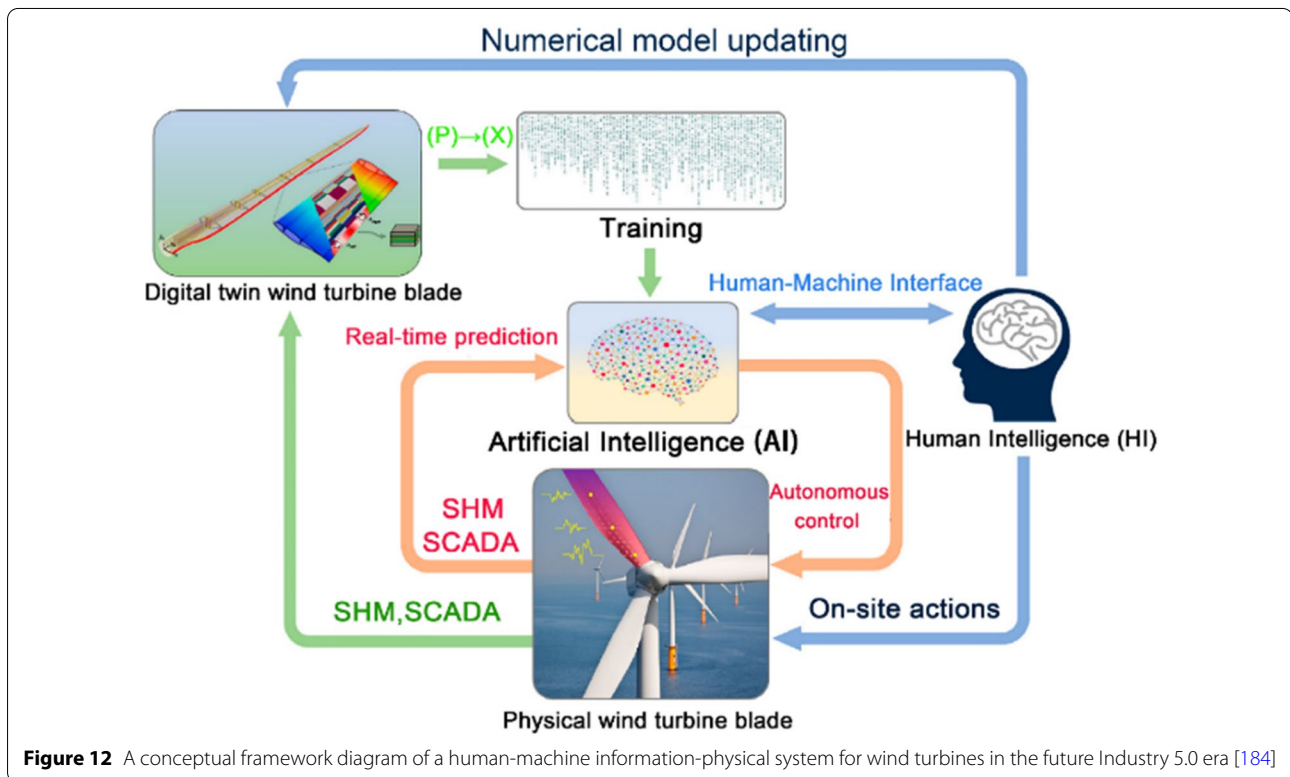
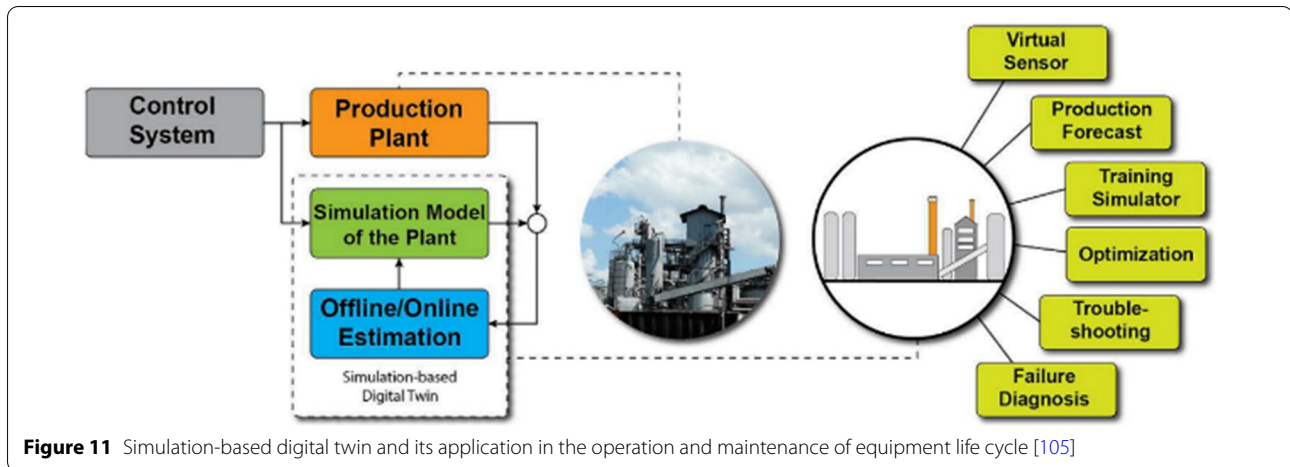
5.2 The Applications

Intelligent operation and maintenance of industrial equipment is an important part of Industry 4.0 [158]. Intelligent operation and maintenance has been penetrated into various fields with the development of information technology, such as intelligent power station [159], intelligent network [160], engineering vehicles [161], green buildings group [162], micro-grid technology [163], communication network [164], nuclear power [118, 165–168], alleviation photovoltaic [169], bridge maintenance [170].

In machinery industry, the operation and maintenance of machine tools require regular inspection and adjustment by human beings. The diversification and complexity of industrial requirements make CNC machine tools more and more automated and networked. And remote monitoring and intelligent fault diagnosis system is the foundation and indispensable unit of machine tool automation and networking [99, 171]. Luo et al. [100, 172, 173] established a multi-domain unified modeling approach for digital twins, explored the mapping strategy between physical and digital spaces, and proposed a self-prediction and self-maintenance method for digital twins. If machine tools can be built with a digital twin in virtual space that can monitor the health status and operating history of machine tools at any time, unnecessary losses caused by unexpected events can be greatly avoided [101, 174–177]. Scaglioni et al. [98] developed a dynamic model of the Mandelli M5 machine tool. The dynamic behavior of the digital twin was verified by installing the required sensors on the machine.

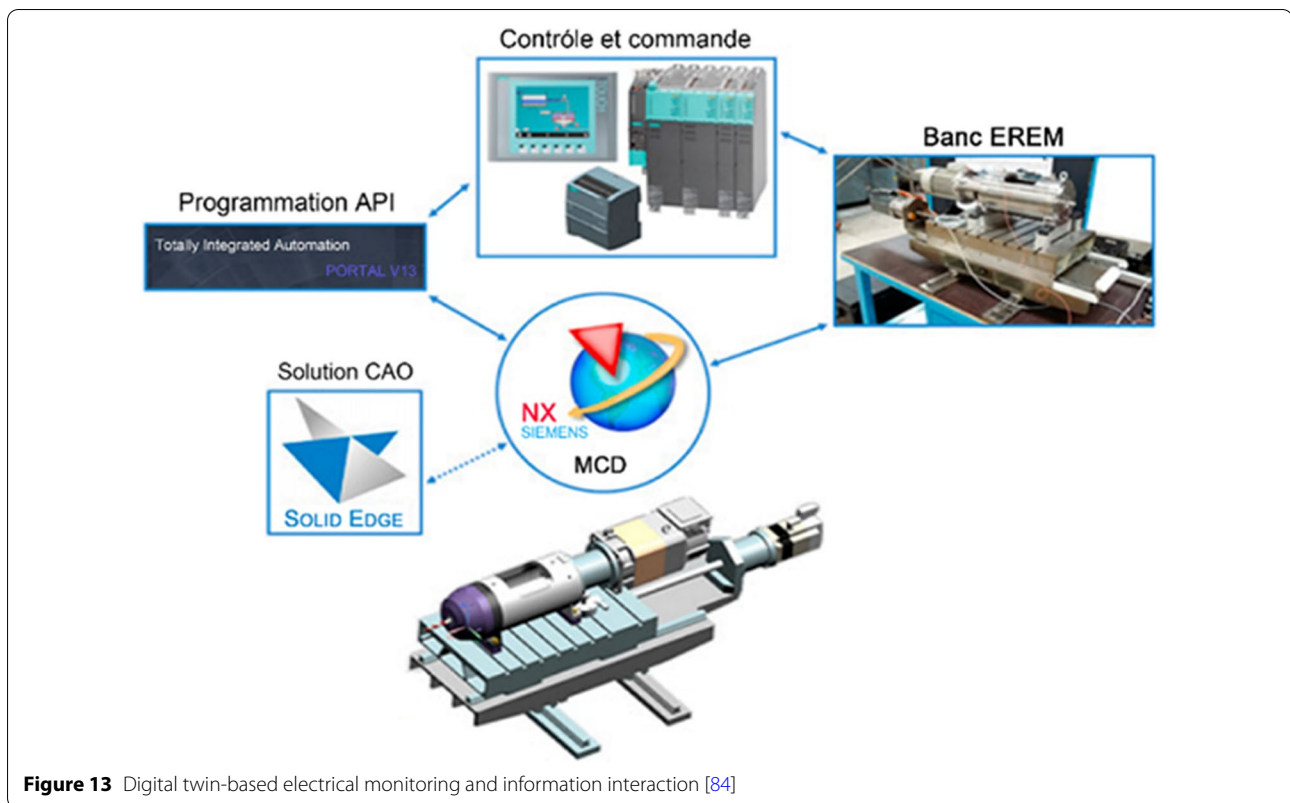
In other industries, Martínez et al. [105] proposed a method for generating a simulation-based digital twin from an automatically generated first-principles model that can be used for operation and maintenance of the equipment life cycle, as shown in Figure 11. Liu et al. [178, 179] proposed an intelligent management platform for coal mine electromechanical equipment based on the IoT, effectively reduces the probability of equipment failure, improves the level of equipment refinement management, and realizes the whole life cycle management of equipment. Moussa et al. [114] proposed a digital twin model for large hydroelectric generators. To improve the accuracy and efficiency of prediction and health management of wind power, Tao et al. [112, 180–183] proposed a digital twin failure prediction model for complex equipment, which effectively utilized the interaction mechanism of digital twin and data fusion techniques. Chen et al. [184] proposed a future-oriented intelligent, semi-autonomous human-cyber-physical system fusion wind turbine under this new concept, as shown in Figure 12. Xiao et al. [185] developed an intelligent ultrasonic inspection system with defect tracking and defect simulation analysis for the characteristics of defects in the welded joints of hydraulic turbine runners. By embedding virtual 3D models, the use of AI technology can precisely combine virtual and reality. In addition, there is a need to develop predictive maintenance solutions for industrial equipment that combine digital twins with augmented reality [84], as shown in Figure 13.

To realize the intelligent operation and management of microgrid and intelligent micro network group [186],



Fu et al. [163] established a microgrid fault diagnosis model based on advanced Petri net theory by studying the microgrid operation and maintenance knowledge base, and proposed an intelligent diagnosis and analysis method of microgrid faults. Park et al. [117] proposed an operational scheduling model of energy storage system applied to virtual space for building microgrids using digital twin technology. Mu et al. [165] leveraged virtual reality technology to establish a virtual environment for existing nuclear power plants, and an intelligent nuclear

power immersion system was developed by integrating data monitoring and fault analysis, and providing operation and maintenance assurance, equipment management, fault analysis, operation and maintenance demonstration, and intelligent simulation training. Liu et al. [187] proposed a new concept of combining digital twin model with steel structure operation and maintenance safety by taking spoke type cable truss as an example. Liao et al. [188] developed a new data-driven approach to machine performance evaluation and prediction in order



to reduce the problem of reaching the shortest possible downtime during machine maintenance.

In overview, in the area of digital twin-based maintenance, transforming maintenance decisions from reliance on downtime inspection to a combination of online testing and simulation. In particular, it is important to note that digital twin technology is not simply a simulation, but requires a focus on underlying technological innovation, including sensing technology, sensing networks, digital model building and so on.

6 The Challenges and Solutions

6.1 The Challenges

A large amount of data information will appear in the design process of mechanical equipment, but there are currently barriers to share this data information between peers, with inadequate use of data and inconsistent data standards. The needs of users are developing in the direction of diversification and personalization, which presents a huge challenge to the design of mechanical equipment.

To achieve high fidelity, high precision and visualization in the manufacture of mechanical equipment, the support of digital twin technology is urgently needed. The current use of digital twin technology for manufacturing is still mainly based on finite element simulation

[189], thus requiring improvements in digital twin manufacturing technology to achieve high fidelity and high precision manufacturing of mechanical equipment.

The whole life cycle management of the product based on virtual model is often carried out to achieve real-time and intelligent operation and maintenance of equipment. As for complex structures of large equipment, real-time data from internal components that are closely related with each other are limited. In this case, the concept of digital twin can capture, locate and clarify faults, and assess the state of equipment for predictive maintenance. Digital twin-based maintenance requires comprehensive view of multi-physics structures and establishment of system-level modeling under multi-physics field. Nevertheless, the challenge is, to correct the key characteristic parameters, to develop accurate mechanistic and lifetime models of the equipment based on various verification tests.

6.2 Design-Manufacturing-Maintenance Integration

Although traditional design can be closed-loop, i.e., a top-down decomposition process aiming for a bottom-up structure, it is relatively static, does not indicate processing, manufacturing, testing, repairing and prediction of the physical product, and thus cannot reflect the dynamic state in different stages, and is unable to guide

the full lifecycle management. Currently there exists the inability of feedback of real-time manufacturing testing and assembly, and end-user's data to the product design process. In addition, the conventional design, manufacturing and maintenance are independently run and managed with various rules. Such kind of disconnection results in low availability of design information for reuse, ineffectiveness of manufacturing data to support optimal design, and poor guidance of maintenance data for design and manufacturing, and thus hinder optimization and integration of design, manufacturing and maintenance, and increase the time and cost for product development.

Digital twin technology provides a feasible solution for this integration as it spans the full lifecycle of product design-manufacturing-maintenance. The utilizing of digital twin helps unification of modeling standards and rules as geometric parameters, manufacturing and maintenance data are well represented. Only in a complete digital twin can a large number of surreal models and data be built, including digital product models, digital manufacturing models, and digital maintenance models. Design, manufacturing and maintenance are real-time, bi-directional, transparent, and need systematic considerations. Therefore, the application of digital twin technology to the integration of optimal design, intelligent manufacturing and efficient operation and maintenance is promising. For example, a digital bus based on the product model data interaction specification was exploited by Boeing. By improving existing virtual prototypes, a manufacturing-oriented digital twin design model was created, which initially enabled design and manufacturing collaboration [190].

The digital-twin-based integration of design-manufacturing-maintenance needs a framework for information-physical combination, which can describe and manage the heterogeneous, polymorphic, and massive data generated at different stages of product development and application. This has sound physical basis as it is a cross-discipline, personalized, and data-focused process [191, 192]. In terms of design, scientific modeling is required to maximize uncertainty control and thus determine reasonable safety intervals, which requires consideration of interaction of different failure mechanisms and development of physics-based accurate lifetime prediction methods. On the manufacturing side, achieving defect-free and residual stress-free manufacturing is being a long-time pursuit. The emerging technology of additive manufacturing is being improved to control internal defects and quantify its impact on mechanical performance. The life enhancement from surface strengthening is significant, while needs to be further quantified in extreme conditions. For maintenance, the focus is on digital twin technology to shift maintenance decisions from reliance

on downtime inspection to a combination of online testing and simulation. Nevertheless, note that the digital twin technology is highly relied on sensing technology and its network. As the application of digital twin technology for industrial equipment requires the extraction of relevant operational data from physical entities, this requires high-fidelity, high-precision data sensors to achieve this. In addition, it is a challenge to transfer these massive amounts of data to the digital twin of the equipment in real time, which requires a latency-free, high-speed wireless network.

7 Summary and Outlook

In this overview, the definition of digital twin, and its development in design, manufacturing and maintenance of engineering components and equipment were summarized. Key challenges including convergence, standardization, long life, and high fidelity need to be addressed accordingly for a better digital twin technology. The development of feedback between design and manufacturing, and better standardization of repair data through physical inspection of mechanical equipment, and use of artificial intelligence-enabled repair data analysis, will greatly aid in the integration of design-manufacturing-maintenance based on digital twin concept. For this aim, there needs a framework for information-physical combination, in which a more accurate design, a defect-free manufacturing, a more intelligent maintenance, and a more advanced sensing technology, are prospected.

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