Int J Adv Manuf Technol (2018) 94:3563–3576
DOI 10.1007/s00170-017-0233-1

ORIGINAL ARTICLE

Digital twin-driven product design, manufacturing and service with big data

Fei Tao [1] · Jiangfeng Cheng [1] · Qinglin Qi [1] · Meng Zhang [1] · He Zhang [1] · Fangyuan Sui [1]

Received: 10 January 2017 / Accepted: 1 March 2017 / Published online: 16 March 2017

Abstract Nowadays, along with the application of new-generation information technologies in industry and manufacturing, the big data-driven manufacturing era is coming. However, although various big data in the entire product lifecycle, including product design, manufacturing, and service, can be obtained, it can be found that the current research on product lifecycle data mainly focuses on physical products rather than virtual models. Besides, due to the lack of convergence between product physical and virtual space, the data in product lifecycle is isolated, fragmented, and stagnant, which is useless for manufacturing enterprises. These problems lead to low level of efficiency, intelligence, sustainability in product design, manufacturing, and service phases. However, physical product data, virtual product data, and connected data that tie physical and virtual product are needed to support product design, manufacturing, and service. Therefore, how to generate and use converged cyber-physical data to better serve product lifecycle, so as to drive product design, manufacturing, and service to be more efficient, smart, and sustainable, is emphasized and investigated based on our previous study on big data in product lifecycle management. In this paper, a new method for product design, manufacturing, and service driven by digital twin is proposed. The detailed application methods and frameworks of digital twin-driven product design, manufacturing, and service are investigated. Furthermore, three cases are given to illustrate the future applications of digital twin in the three phases of a product respectively.

✉ Fei Tao
ftao@buaa.edu.cn

[1] School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, People's Republic of China

Keywords Digital twin · Product lifecycle · Design · Manufacturing · Service · Big data · Cyber and physical convergence

1 Introduction

Product lifecycle management (PLM) is the business activity of managing, in the most effective way, a company's products all the way across their lifecycles, from the very first idea for a product all the way through until it is retired and disposed of. PLM is the activity that enables a company to grow revenues by improving innovation, reducing time-to-market for new products, and providing superb support and new services for existing products, as well as enables better support of customers' use of products [1].

Nowadays, along with the application of new-generation information technologies in industry and manufacturing, e.g., internet of things technology and devices are employed to collect various data generated in the entire produce lifecycle [2], cloud technology is used to realize the data management and processing [3], and artificial intelligence is used for data mining and realizing added-value [4], the big data-driven manufacturing era is coming. For PLM, many researchers have carried out numerous studies on product data management [5], product information modeling [6], product information tracking [7], integration framework [8], knowledge management [9], supply-demand matching on product manufacturing [10], product assembly [11], and so on. However, although various big data in the entire product lifecycle, including product design, manufacturing, and service, can be obtained, it can be found that several research gaps still exist in PLM as follows:

1. The current research on product lifecycle data mainly focuses on physical products rather than virtual models.

2. Even if concerned with data from virtual models, there is lack of convergence between product physical and virtual space. Besides, due to the lack of the convergence, the data in PLM is usually isolated, fragmented and stagnant.
3. On one hand, it is difficult for a company to keep control when a product is at a customer location, on the other hand, even realized control, it is difficult to response for the upcoming demand or failure in advance and to guide product design, manufacturing, and maintenance.

These problems lead to low level of efficiency, intelligence, sustainability in product design, manufacturing, and service phases. Therefore, new ways are needed to handle above problems. Digital twin is an integrated multi-physics, multi-scale, and probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin. The idea and concept of digital twin, which is composed of physical product, virtual product, and connected data that ties physical and virtual product, can realize the convergence between product physical and virtual space. Therefore, how to generate and use converged cyber-physical data to better serve product lifecycle, so as to drive product design, manufacturing, and service to be more efficient, smart, and sustainable, is emphasized and investigated based on our previous study on big data in product lifecycle management [5].

The remainder of this paper is organized as follows. In Section 2, the concept of product lifecycle and related data in PLM are introduced, and the existing shortness in PLM is discussed. Section 3 introduces the concept of digital twin, as well as its industrial application. The potential applications of digital twin in the three phases of a product lifecycle, i.e., (1) digital twin-driven product design, (2) digital twin-driven product manufacturing, and (3) digital twin-driven product service, are investigated in Section 4, as well as the case study in each phase. Section 5 concludes this study and points out the future works.

2 Product lifecycle and related data

2.1 Product lifecycle and data

The concept of product lifecycle was proposed by Dean [12] in 1950 and was used in product marketing strategy research by Levitt [13]. The product lifecycle initially referred to the process from acceptance by the market to the final elimination. A biologically inspired lifecycle of the product was divided into four stages, i.e., introduction, growth, maturity, and decline [14]. With the rise of concurrent engineering [15], the product lifecycle was extended to the engineering field. And the product lifecycle was redefined to cover the entire process from product demand analysis, design, manufacturing, sales, and after-sales service to recycle [16].

When a specific product lifecycle is understood from the perspective of the manufacturer [17], it refers to the whole process from concept generation, design, procurement, manufacturing to use, and recycle. As shown in Fig. 1, each stage of the product lifecycle has its specific activities, involves the relevant staff and departments, and generates large amount of data [5].

1. Concept generation: Based on customers' demands, market information, investment planning, and other data, the concept of new product or product design improvements is defined, as well as the esthetics and main functions of the product. At this stage, a variety of data needs to be processed, such as various forms of customers' demands including comments, complaints and videos on the Internet, market information including volume of product sales, customer satisfaction, investment planning, and so forth.
2. Product design: Product development team completes product design work collaboratively through exchanging and sharing design data and ideas. The data involved in product design includes description of product function and appearance, product configurations, design parameter and test data, etc. And even historical fault data of similar products will improve the product design.
3. Raw material procurement: At this stage, appropriate procurement plan is drawn up for the purchasers by analyzing the availability, quotations, substitutes, potential suppliers of materials, or parts. The data considered at this stage includes manufacturer's data, such as the type, quantity, performance of raw materials, as well as supplier data such as price, distance, inventory, and so on.
4. Manufacturing: According to design specifications, the raw materials or components are processed or assembled into products, and then products are inspected through quality testing. At this stage, the dynamic manufacturing execution process needs to be monitored and managed. Therefore, the attributes, performance, parameters, and process conditions of production factors (e.g., human-machine-material-environment) are collected in real-time and recorded to monitor the production process.
5. Transportation: After finishing the production, products are transported to the point of sale in accordance with market demand and orders. At the same time, after the product is sold, delivery services are provided to users. In order to transport products accurately and timely, logistics arrangements must be optimized based on inventory data, order data, location data, etc.

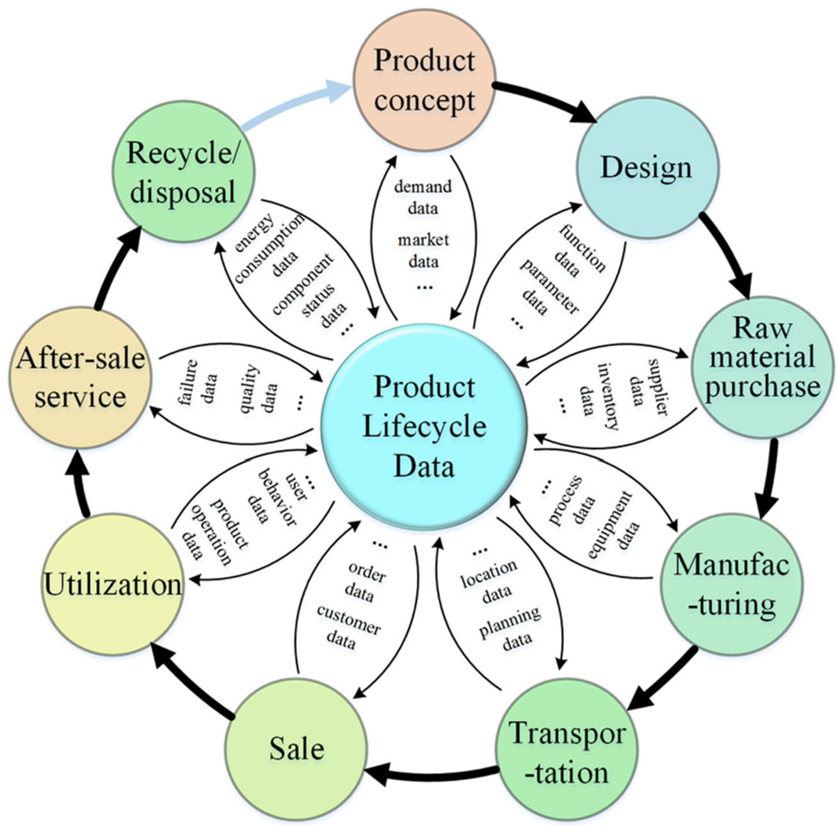

Fig. 1 The product lifecycle and related data

6. Sales: At this stage, product launch and marketing are carried out based on orders data, customers' data, inventory data and suppliers' data. In the sale process, customers' preferences, preferences crowd, location distribution of orders and other information can improve product design, production, logistics, and sale progress.
7. Utilization: Based on the information from user manual, customer can operate product normally. During use-phase, a large amount of data is generated, such as product status data, operational environment data, user behavior data. These data can be used not only for product maintenance and repair but also to improve product design.
8. After-sales service: This stage is responsible for product maintenance, service, and repair. According to the data acquired from products, appropriate maintenance and service solutions are generated and transmitted to manufacturers. As a result, efficient and accurate services are provided to users. In this process, failure data and causes, maintenance data, component quality, and status data are recorded and managed to predict product lifetime and other product failures.
9. Recycle/disposal: When a product is recycled, the remaining value of individual components are analyzed to determine when, how, where, and what to recycle or disposal based on product status data and historical maintenance data. In order to maximize product recycling benefits, the cost of recycling and disassembly, the reusable state, value, and remaining time of components, needs to be considered.

Product lifecycle engineering is an iterative process. At any stage of the product lifecycle, a large amount of data is collected, processed, and used, thus big data is formed [5].

2.2 Problems about product lifecycle data

The advances in information technology are driving the manufacturing industry toward big data era. Data analysis and mining are gradually playing a more and more significant role in manufacturing enterprise management. Big data can provide systematic guidance for related production activities through effectively collecting and analyzing a variety of data generated in the entire product lifecycle [5]. Furthermore, it can help enterprises' managers to solve the problems related to operation and decision-making. The value of manufacturing big data can be explored adequately to enhance the manufacturing efficiency. At present, smart manufacturing is driven by big data through three steps, which are association, forecast and control [18]. It is to find the new value from relationship and statistical characteristics of various data.

However, some problems affecting product data management and application in PLM still exist as follows: (1) Due to the different purposes and tasks, the data generated in various phases of the entire product lifecycle may form the information island between different phases of product lifecycle. (2) There is a lot of duplicate data in different phases of product lifecycle. These duplicate data may cause a lot of waste of resources and data sharing problem. (3) The interaction and iteration between big data analysis and various activities in the entire product lifecycle are relatively absent. Therefore, the big data analysis and the actual manufacturing process cannot be compared in parallel. (4) The current applications of big data prefer to put emphasis on the analysis of physical product data rather than the data from virtual models.

In response to the above problem, digital twin is viewed as an effective approach. The implementation of digital twin is a mutual promotion process between virtual and physical space of product lifecycle. Digital twin can directly compare and analyze the theoretical values of big data and the real values of product lifecycle activities. As a result, it can optimize iteratively various activities in the entire product lifecycle. In the virtual space of digital twin, various activities in the entire product lifecycle can be simulated, monitored, optimized, and verified. As well as, the seamless coordination of the entire product lifecycle can be realized. Therefore, information islands and data duplication can be effectively avoided.

3 Digital twin and its applications

3.1 Concept of digital twin

The concept of digital twin was firstly presented by Grieves at one of his presentation about PLM in 2003 at University of Michigan [19]. Up to now, several explanations and definitions of digital twin have been proposed.

For example, Hochhalter et al. [20] believe that digital twin is a life management and certification paradigm whereby models and simulations consist of as-built vehicle state, as-experienced loads and environments, and other vehicle-specific history to enable high-fidelity modeling of individual aerospace vehicles throughout their service lives. Reifsnider and Majumdar [21] hold the view that the digital twin is a kind of ultra-high fidelity simulation integrating with an on-board health management system, maintenance history, and historical vehicle and fleet data. It can mirror the whole life of a specific flying physical twin (or tail number), which enables significant gains in safety and reliability.

A general definition of digital twin which has been recognized and used by most people till now was given by Glaessegen and Stargel in 2012 [22]: digital twin is an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin. Meanwhile, digital twin consists of three parts: physical product, virtual product, and connected data that tie the physical and virtual product.

According to these explanations and definitions of digital twin, the following characteristics of digital twin are summarized: (1) Real-time reflection. Two spaces exist in digital twin, physical space and virtual space. The virtual space is the real reflection of the physical space, and it can keep ultra-high synchronization and fidelity with the physical space. (2) Interaction and convergence. This characteristic can be explained from three aspects. (a) Interaction and convergence in physical space. Digital twin is a kind of full-flow, full-element, and full-service integration. So the data generated in various phases in physical space can connect with each other. (b) Interaction and convergence between historical data and real-time data. Digital twin data is more comprehensive. It not only depends on expert knowledge but also collects data from all deployed systems real-timely. Therefore, the data can be mined deeply and used more fully through the convergence. (c) Interaction and convergence between physical space and virtual space. The physical space and virtual space are not isolated in digital twin. There exit smooth connection channels between the two spaces, which makes them interact easily [23]. (3) Self-evolution. Digital twin can update data in real time, so that virtual models can undergo continuous improvement through comparing virtual space with physical space in parallel [24].

3.2 Applications of digital twin

Since the concept of digital twin was proposed, it has been applied in many industrial fields and has demonstrated its great potential.

Structural Sciences Center at US Air Force Research Laboratory employed digital twin to build a realistic high-fidelity flight model and combine virtual model data with physical data to make a more accurate fatigue life prediction [24]. The Air Force Research Laboratory created a framework, in which the model integrates various data and has a high fidelity to physical space to simulate and assess the confidence in aerothermal model predictions for the coupled aero thermoelastic problem [25]. Bielefeldt et al. [26] also established a model based on digital twin to detect and monitor the damage in aircraft structure, and they used the case of aircraft wings to prove that the model was more effective. Hochhalter et al. [27] proposed to combine digital twin with sensory particles technology to realize real-time detection and aerospace vehicles' inspection, repair, and replacement as necessary. Based on digital twin, Tuegel [28] put forward the concept of Airframe Digital Twin (ADT) to achieve the goal of decreasing aircrafts' maintenance costs. And he also pointed out the challenges during realization process. Cerrone et al. [29] built the model of digital twin specimens and made the simulation implementation to solve crack path ambiguity. Simulation result shows using digital twin can reduce the inaccurate prediction under shear loading. Besides, PTC is trying to establish a virtual space as one-to-one representation of a unique physical product to be used in the product design process. And many other global famous companies (e.g., Dassault Systèmes, Siemens PLM Software) also express great interests in application of digital twin [30].

According to the applications of digital twin mentioned above, digital twin currently is primarily applied to the field of aeronautics and astronautics for failure prediction and is mainly applied to product service and maintenance phase. With the concluded characteristics of digital twin, especially synchronous linkage and ultra-high fidelity between physical product and corresponding virtual product, digital twin has high potential to solve above problems existing in PLM. This paper will emphasize its potential applications in product design, product manufacturing and product service.

4 Digital twin-driven production design, manufacturing, and service

4.1 Digital twin-driven product design

4.1.1 Existing product design processes

It is well known that the product design process refers to the entire process of a specific design from start to finish and the work steps of every stage it contains. Traditional product design process takes professional knowledge and experience of the individual as the center. Under the circumstance, the designers must carry out various tests to constantly prove the validity and usability of the design at the designing stage. In comparison, modern product design turns out to increasingly trend to set the customers as the center and enhance the participation of customers. Meanwhile, the product design process becomes more and more virtualizing, networking, and visualizing. Therefore, the modern big data-driven product design process and cloud manufacturing come into being.

However, these processes definitely still have some problems. For instance, the big data-driven product design process mainly puts emphasis on the analysis of physical data rather than the data from virtual models, namely that the convergence between product physical and virtual space is usually absent. While the cloud manufacturing-based process cannot make a quick response to the real-time changes due to lacking of the interaction and iteration between big data analysis and various activities. And the crowdsourcing-based process requires users with professional knowledge to comment, but not every user can participate in the review.

4.1.2 Digital twin-based product design

In allusion to the above problems, a new product design process based on digital twin is put forward. Digital twin is an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin. It can correctly map all kinds of physical data of the product to a virtual space. The virtual product can reflect the whole lifecycle process of the corresponding physical product. Based on digital twin, the product design process can be divided into conceptual design, detailed design, and virtual verification, as shown in (Fig. 2).

Conceptual design Conceptual design is the first and also the most important step of product design process, in which designers need to determine the future designing direction of the entire product. In this stage, designers will define the concept, esthetics, and the main functions of the new product. Meanwhile, designers need to deal with various kinds of data such as customer satisfaction, product sales, product competitiveness, investment plans, and many other information. These data is huge and scattered, which makes it difficult for designers to collect. Through utilizing digital twin, which can integrate all kinds of data in the product's physical space and easily integrate all the information [19], designers can make a quick understand on where should be improved with its characteristic of having single information source. What's more, digital twin is a faithful mapping of the physical product and can make the communication between clients and designers more transparent and faster by using the real-time transmission data. It can perfectly guide the improvement of the new product by making full use of customers' feedback and various problems appeared in customers' usage of the previous generation.

Detailed design After finishing the conceptual design, the next stage is detailed design. In this stage, designers should complete the design and construction of the product prototype, as well as the development of tools and equipment used in the commercial production. Designers need to further refine the product design scheme which includes product functions and appearance, product configuration, design parameters, and test data on the basis of the former stage. The detailed design stage requires repeated simulation tests to ensure that product prototype can achieve the desired performance. However, because of a lack of real-time data and environmental-impacted data, the effect of simulation tests is not obvious. Fortunately, digital twin technology can solve this problem well as it exists in the whole lifecycle of physical objects and can always coevolve with them. It can record all data of the product and the influence of environment. [31].

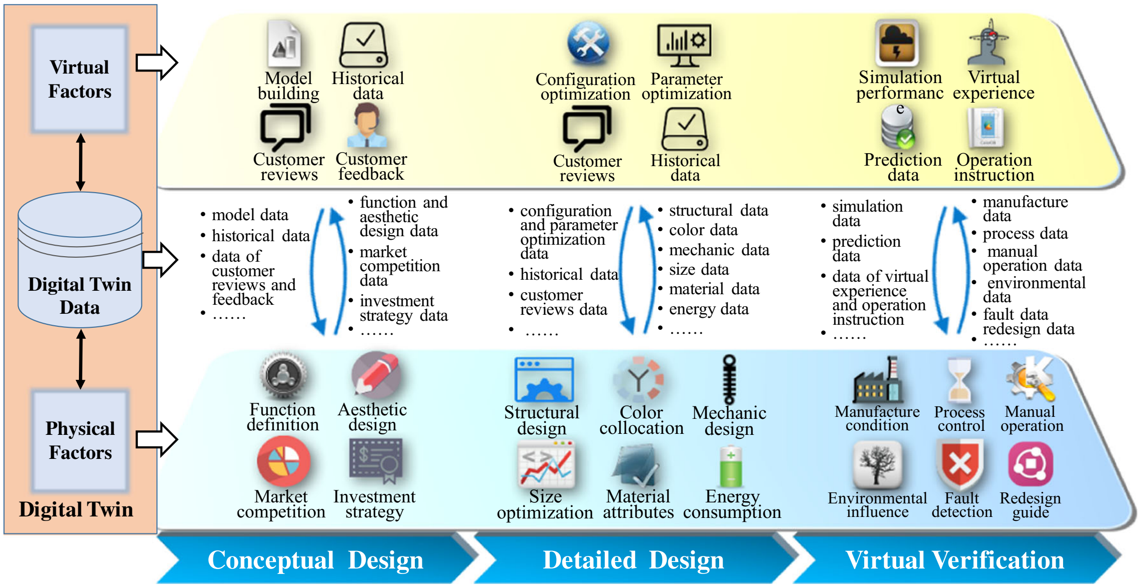

Fig. 2 Digital twin-based product design

Virtual verification The last stage is the virtual verification. In the traditional model, the validity and feasibility of design scheme cannot be evaluated until carrying out small batch production after finishing product design. It will not only extend the production cycle but also greatly increase the cost of time and money. If designers choose to use digital twin model, any accessories' quality will be predicted before they are actually produced by debugging and predicting directly in the model of digital twin. Digital twin-driven virtual verification can take full use of the data of equipment, environment, material, customers' physical characteristics, and history data of the last generation. This method can test whether there is a design defect and find the cause of it, and then the redesigning will be fast and convenient. Also, it can greatly improve the design efficiency by avoiding tedious verification and testing.

What's more, digital twin cannot only describe the behaviors but also propose solutions related to the real system. In other words, it can provide operation and service to optimize the auxiliary system and predict the physical objects based on virtual models. Therefore, by using digital twin technology, designers can create vivid simulation scenarios to effectively apply simulation tests on prototypes and accurately predict the actual performance of the physical products as far as possible.

4.1.3 A case of bicycle design based on digital twin

A bicycle is taken as an example to illustrate one of the future application modes of digital twin-driven product design. As shown in Fig. 3, the prototype will be finally obtained after going through three stages (conceptual design, detailed design, and virtual verification), and digital twin technology takes effect throughout the entire process.

In conceptual design of the bicycle, designers can integrate the physical properties of the bicycle such as color, material, size, mechanical properties, and the various data of its environment like temperature and geographic information by using digital twin technology to install assembly sensor on the bicycle. And it can correctly map all kinds of physical data of the product to a virtual space. Further, designers can get the riding habits of users and improve the design scheme by analyzing the information integrated by digital twin, such as riding speed, riding time, and braking habits. For the designers, online customer reviews are also an important class of reference information, which can no doubt support the concept generation in esthetic design and market competition strategy. At this stage, another important issue needs to be determined is the product cost control, which is directly related to corporate profits. With the help of the historical data integrated by digital twin, designers can analysis the product sales, market demand, user groups, and the characteristics of the similar products in the market. Taking the investment plan into consideration, designers can guide the product material selection, manufacturing process and pricing, etc., so as to ensure the maximization of profits.

In the detailed design stage, designers will further refine the design scheme on the basis of customers' feedback, test data, and various problems appeared in consumers' usage of the previous generation. For example, designers can be led to choose the appropriate color collocation to reduce the probability of accident by gathering the probability statistics of traffic accidents on bicycles with different colors. Also, improvement should be made according to the different usage habits, frame materials, tire size, and braking performance. Designers will choose appropriate frame form and frame size, relative position between handlebars and seat, relative position

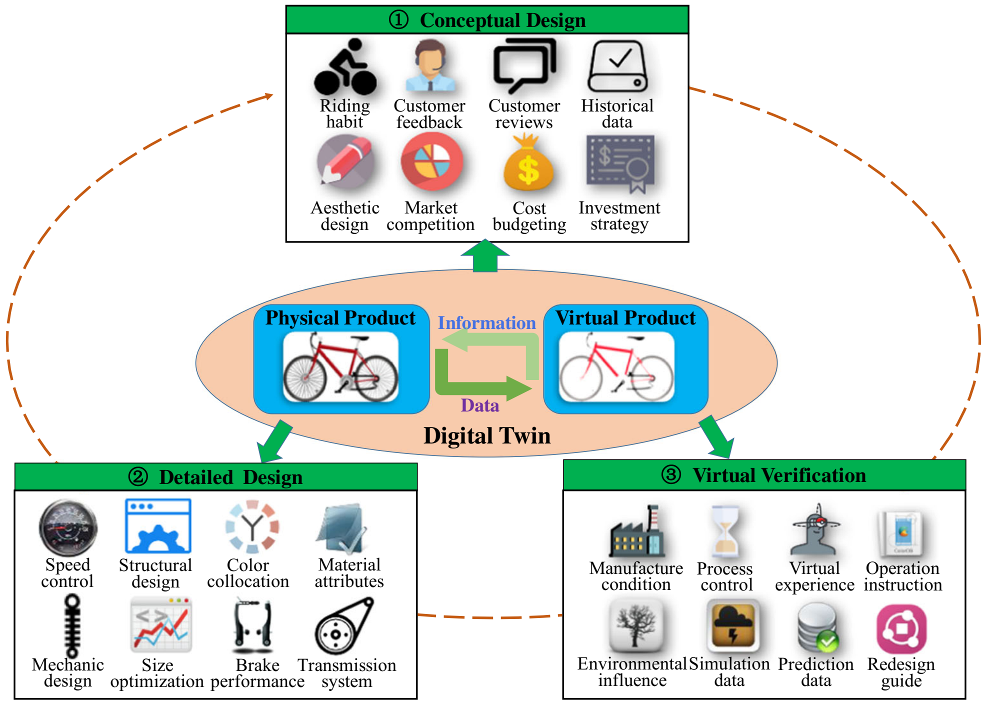

Fig. 3 Digital twin-driven bicycle design in future

between the cushion and pedal, width of the cushion, and angle of the seat surface according to the heights and shape characteristics of the riders. In detailed design stage, designers always need to carry out simulation verification to ensure that the design scheme is feasible, such as whether the parts can cooperate well, whether the color collocation is beautiful, whether the energy transmission system is effort-saving, whether the setting of the velocity gradient is reasonable and so forth. Designers can timely solve all these design defects and provide a relatively mature product prototypes for the next stage's virtual test.

In virtual verification stage, the designer can use digital twin technology to predict and test product performance directly by simulating design scheme, manufacturing process and environmental factors. They can also give operation instructions on the basis of the actual production conditions. In this stage, designers can use historical data to carry out simulation test according to users' body characteristics, and riding habit, so as to improve the comfort and convenience in practical use, such as the relative height of the seat, the sensitivity of the brake, and the position of the bells. This method can accurately find the defect of design and take rapid changes, so as to improve the design scheme efficiently and avoid tedious verification and testing.

4.2 Digital twin-driven product manufacturing

Product manufacturing refers to the whole process from the input of raw materials to the output of finished products. During the process, three aspects are mainly included, namely resource management, production plan, and process control. Firstly, according to the target product, the resources such as materials, equipment, tools, operators, etc. should be prepared and allocated. Secondly, to achieve objectives like reducing cost, shortening time, and improving quality, a production plan should be devised to predefine the manufacturing process, including machining, assembling, logistics, etc. Then in the execution stage, real-time states, such as the production schedule, material storage, product quality, and need to be monitored and controlled to ensure the accuracy, stability, and high efficiency of this process. To realize product manufacturing, shop floor is the basic performer, which provides the resources and organizes them orderly to yield the finished products.

Judging from the development of shop floor, it roughly experienced three stages, including "everything depending on physical space," "information space appearing and being stronger," and "physical space and information space beginning to interact" [32]. After these stages, the tie between physical space and information space is enhanced. However, due to the lack of data in the two sides as well as the data fusion and interaction, a series of problems still exist in shop floor, such as the lack of global optimization capacity in resource management, the divergence between production plan and actual production, and the inaccuracy in manufacturing process control.

Digital twin is an emerging and effective method for real-time interaction and further convergence between physical space and information space. To solve the problems mentioned above, digital twin-driven product manufacturing will be discussed in this section.

4.2.1 Method of digital twin-driven product manufacturing in shop floor

Based on digital twin, Digital Twin Shop Floor (DTS) [32], a new paradigm for product manufacturing is proposed. As shown in Fig. 4, DTS is composed of Physical Shop Floor (PS), Virtual Shop Floor (VS), Shop Floor Service System (SSS), and Shop Floor Digital Twin Data (SDTD). PS is an objective entities set, responsible for receiving production tasks and predefined orders and executing the orders strictly to yield final products. VS, an ultra-high-fidelity and full-digitalized mapping of PS, can carry out simulation and forecast for the production plans and process, give optimization strategies to SSS, and also monitor and regulate the manufacturing process in real time. SSS is the set of service systems, providing supports and services for the product manufacturing. SDTD refers to all the data related to PS, VS, and SSS, as well as the derived data through data fusion of the above three parts, and provides driving force for DTS.

As shown in Fig. 4, through convergence of SDTD, the three components of DTS (i.e., PS, VS, and SSS) interact with each other to realize the iterative optimization for resource management, production plan, and process control. To study the operation mechanism of DTS in detail, the process is given as follows.

1. When a new production task is coming, under the driving of SDTD, initial resource allocation plans for the equipment, materials, tools, human, etc. that meet the task requirements and constraints are generated. Specifically, SDTD involves data from PS (such as the capacity, quantity, real-time states of resources), data from VS (such as history records, simulation data, forecast data of resources), data from various service systems (such as enterprise plan data, product data), and the fusion data through data association, mining, combination, etc. Benefited from these data, the resource allocation plans are produced from a more comprehensive and practical perspective, which are related to the current state, the future state of the resources, as well as the global interest of the whole enterprise. The resource allocation plans can be produced in the form of services which provide orders of allocation, so as to set resources to appropriate states. Meanwhile, due to the real-time changes in PS, the services of resource allocation need an iterative adjustment and optimization.
2. According to the resource allocation plans, services in SSS generate production plans predefining the actual product manufacturing process, like equipment machining plan, manual operation plan, and tools scheduling plan. These plans are transmitted to VS, which is comprised of element models, behavior models and rule models, etc. VS carries out simulations in virtual space based on the plans and finds out the potential conflicts before the actual manufacturing process. VS can also feedback optimization strategies to services through analyzing simulation data, forecast data, and rule data generated by various models. Services in SSS make corrections according to the optimization strategies and transmit the revised plans back to VS for another verification. This process is finished until the production plan is verified completely by VS.

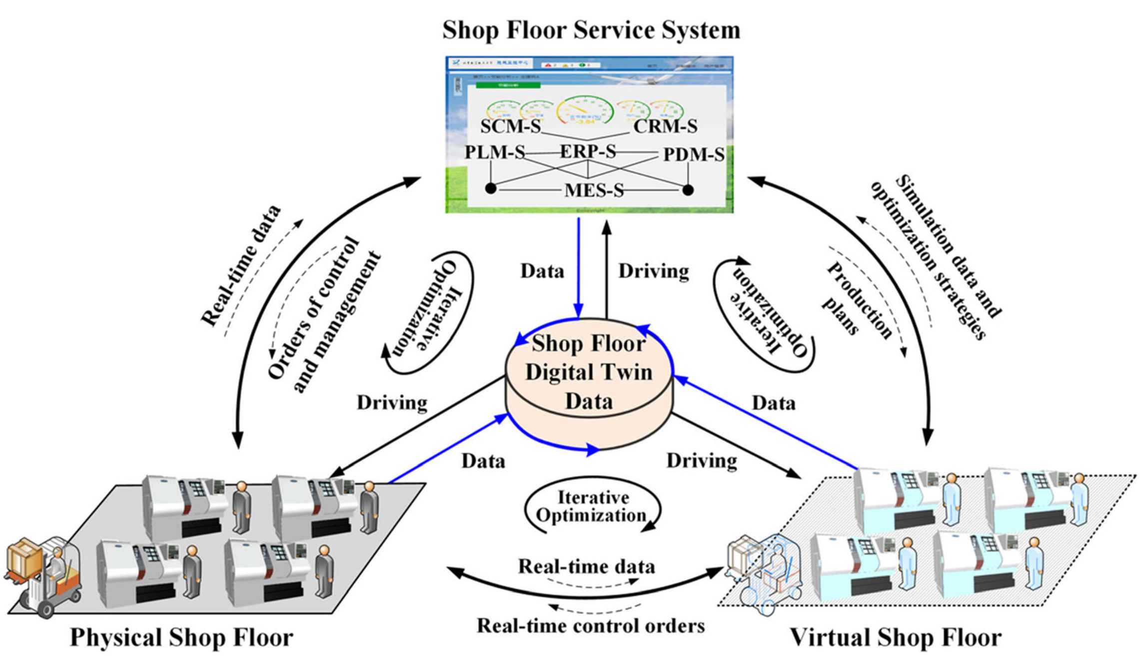

Fig. 4 The composition and operation mechanism of DTS [32]

3. PS receives orders based on production plans from VS and organizes the product manufacturing process strictly in accordance with the orders. During manufacturing, PS transmits the real-time state data to VS, which updates itself to flow up the physical changes. Meanwhile, VS compares the current production process with the predefined plans in virtual space. If the actual production is not inconsistent with the production plans, SSS can provide services to find out the existing problems and judge which part should be adjusted based on the physical disturbance data, simulation conditions data, environment data, etc. According to the results, VS can produce real-time strategies to adjust the production plans or real-time orders, so as to regulate the production process to ensure the consistence of the two parts and realize the optimization and precision of the process control. When the production task is completed, the final products are yielded and the shop floor prepares for the next operation.

4.2.2 A case of digital twin-driven drive shaft manufacturing in future

Drive shaft is a mechanical component for transmitting torque and rotation, commonly applied in speed reducer. The raw materials of drive shaft are steel bars, which have different types, reflecting in diameter, grade, strength, etc. Before machining, the NC code should be edited to predefine the manufacturing process. During machining, the machine tool processes the steel bars with center bore, groove, chamfering in accordance with the NC code through lathing, milling, polishing, etc. The finished drive shaft should be tested on the aspects of dimensional accuracy, surface roughness, balance, etc.

This section mainly discusses the future possible mode of digital twin-driven product manufacturing, and takes the drive shaft machining process as an example to illustrate the mode. As shown in Fig. 5, the digital twin refers to the physical production factors (i.e., steel bars, CNC machine, finished/semi-finished drive shaft, machine operator, shop floor environment), their corresponding models (i.e., virtual production factors), and the digital twin data. Digital twin data includes the physical data collected from sensors or numerical control systems installed in the physical machining shop floor, the virtual data read from the virtual models as well as the existing information systems (i.e. MES, ERP, PLM), and the data ties the two parts together. The optimization of resource management, production plan, and process control is discussed as follows:

Firstly, according to the production task of drive shaft, the raw materials and machining equipment should be allocated. The physical data, including the steel bars attributes, the CNC machine process capacities, and availability, etc. can be collected through RFID in real time. Virtual data, like the steel bars mechanical/thermal analysis data, machine performance prediction data, and failure statistical data can be achieved from virtual models of steel bars as well as the CNC machines. And other virtual data, like the production task management data, and enterprise interest data, can be read from information systems. Driven by the above data, as well as the processed data through association, clustering, regression, etc., services from SSS can devise plan of allocating steel bars and CNC machines for the current production task.

Secondly, based on resource allocation, services in SSS produce NC code as machining plan according to the machining size, tolerance, characteristics, so as to predefine the machining process, including the spindle speed, the feed rate, the position of groove, etc. Before the actual execution, the plan is transmitted to virtual CNC machine for verification. Through the simulation, the existing problems, such as the interference and collision between the tools and workpiece, can be found out. Meanwhile, as the simulation can be carried out repeatedly with little cost, the machining plan can be optimized through iterative test to achieve lower energy consumption, shorter processing time, and higher machining accuracy, etc. Based on the simulation results, services in SSS revise the machining plan.

Thirdly, driven by the machining plan, the CNC machine starts to operate. During this process, the real-time state of workpiece/tool position, spindle speed, feed rate, etc. can be read from numerical control system. Meanwhile, the tool wear, spindle vibration, workpiece surface roughness, etc. can be collected from external sensors. Virtual models of CNC machine and workpiece get these data to update their states; meanwhile, the models compare the current states with the predefined plan. If the inconsistence is existed, services in SSS will evaluate the machining process to find out whether problem is caused by physical disturbance, like the spindle vibration, tool wear, material defect, or by unreasonable factors of plan simulation, like parameter setting and boundary and initial conditions. Based on the result, virtual CNC machine will generate real-time order to regulate the machining process or adjust the machining plan to ensure the consistence between the two sides.

When the manufacturing process is completed, the finished drive shaft should be tested in size, accuracy, balance, etc. If they are satisfied with the indicators defined in virtual product, the drive shaft is qualified, otherwise a repair is needed.

4.3 Digital twin-driven product service

The product service described in this paper refers to the phases after sale, including product utilization and maintenance phases. In the two phases, users are mainly concerned with reliability and convenience of product, while manufacturers are mainly concerned with real-time product operation state, maintainability, when to maintain, what strategies to employ, and so on.

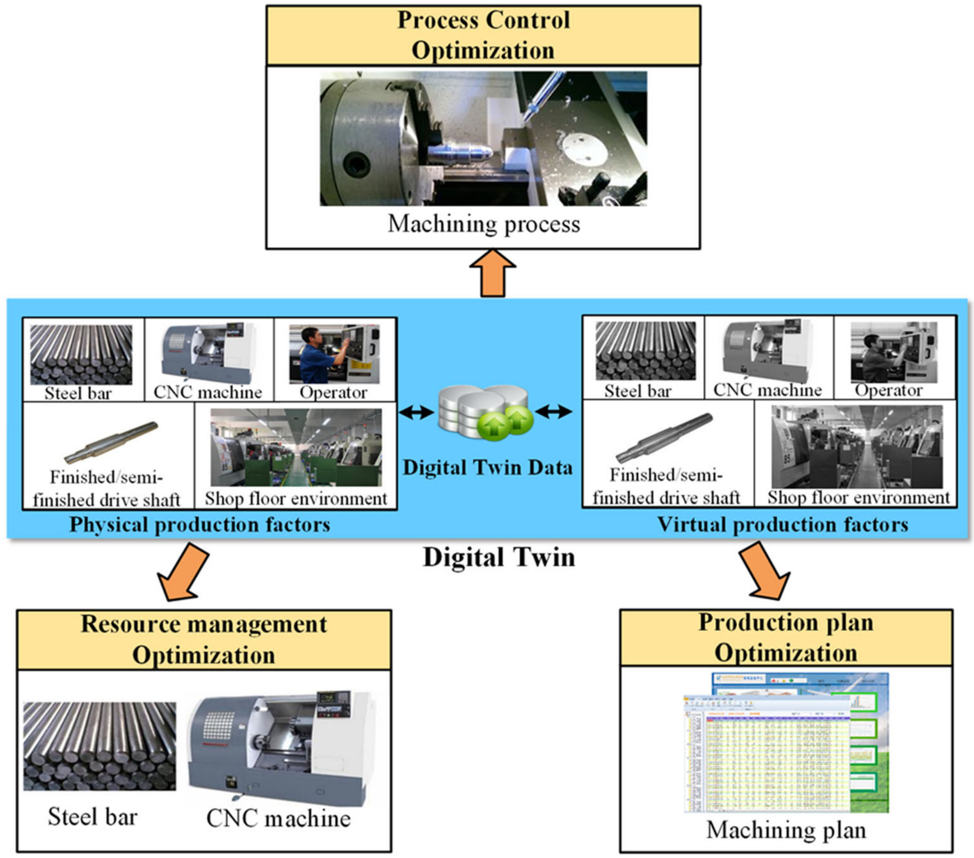

Fig. 5 The drive shaft manufacturing based on digital twin

4.3.1 Method of digital twin-driven product service

For complex products, such as aircraft, automobile and electric power equipment, they are characterized by complex structure, multiple parts, heterogeneous and multi-functional materials, and inconsistent degradation of material function. Any one of the defects and damages may lead to unnecessarily malfunction of the product, even serious safety accidents. Thus, it is particularly important for complex products to carry out daily maintenance.

Current existing maintenance methodologies for complex products are largely based on similitude and a heuristic understanding of the effects of operational and anomalous conditions on the structural health, safety, and performance of a complex product. The probabilistic or reliability methodologies are inadequate because they are based on assumed similitude between the circumstances in which the underlying statistics are obtained and the environment in which the complex product operates. However, the conventional approaches tend to be reactive rather than proactive and are often based on heuristic experience, worst-case scenarios rather than on the specific material, structural configuration, and usage of an individual complex product [22].

As the definition and characteristics of digital twin, it consists of three parts: physical product, virtual product, and connected data that tie the physical and virtual product, as shown in Fig. 6. With the digital twin methodology, degradation and anomalous events can be understood, and unknowns can be foreseen previously. On this basis, relevant services about complex product will be provided to product users and manufacturers, including the following nine categories of services, as shown in Fig. 6.

1. Service of real-time state monitoring. Based on the methodology of digital twin, advanced sensor and communication technology is employed to update the twin of physical product in real time. Product's real-time state data is transmitted to the constructed virtual product model to realize the synchronous linkage and ultra-high fidelity between physical product and corresponding virtual product. The real-time state data includes product position information, energy consumption information, user operation and setting data, product running information, material structure information, parts wear information, and so on. With the acquired real-time data and history data, product manufacturer can understand the operation state of the product in real time, and following services can be conducted with the extra virtual product data and connected data.

2. Service of energy consumption analysis and forecast. With the ultra-high fidelity between physical product and virtual product, the energy consumption

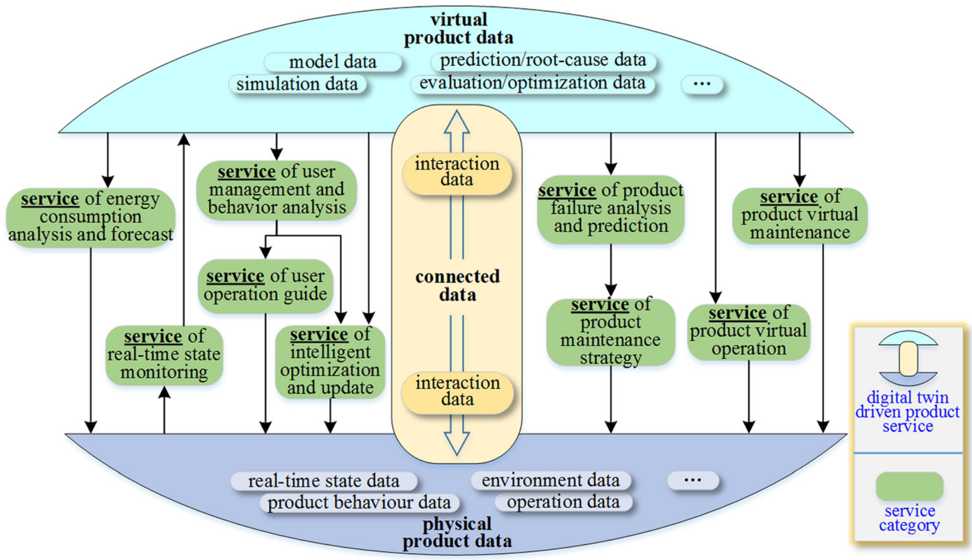

Fig. 6 Digital twin-driven product service

information of product or key parts can be monitored in real time. Based on the real-time and history energy consumption data, relevant statistical analysis can be made, such as energy consumption proportion of each key part, energy consumption per day/week/month. Besides, with the forecast algorithm library and knowledge library, future energy consumption can also be forecasted. Considering the energy consumption analysis and forecast, relevant activities of PLM can be carried out, such as green material selection [33] and large-scale process planning [34].

3. Service of user management and behavior analysis. Each user has its own operation habits. With the real-time monitoring of digital twin, all the operations of users can be obtained. Through analyzing the operation habits, the influence of poor operation on product performance and life can be computed on the one hand, and on the other hand, it can help manufacturers to update systems and improve product performance.
4. Service of user operation guide. With the high-speed computing in virtual product space, on the one hand, digital twin-driven user operation guide can guide users to operate product, and on the other hand, it can correct the users' poor habits in real time. Meanwhile, based on the analysis of users' operation habits, product health information, system update, etc., the operation manual library will also be updated in order to satisfy users' different demand.
5. Service of intelligent optimization and update. The operating habits of users are different, as well as application environment and service objects of each product. Through analyzing users' operation data and product behaviors data, and mining prediction/root-cause/evaluation/optimization data, new product running modes which are more fit the needs of users are proposed and can be loaded into the product through rewriting the internal functional program.
6. Service of product failure analysis and prediction. The virtual product model is not only composed of geometric models of product parts but also includes material properties, parts linkage coupling model, parts mechanics/temperature/flow coupling model. Through running relevant failure prediction algorithms with the virtual product model, real-time state data, and history data, product failure prediction is provided to users and manufacturer.
7. Service of product maintenance strategy. With digital twin technology, the ultra-high-fidelity virtual product model can faithfully reflect the mechanical structure of parts and the coupling between each other. When a fault occurs, faulty part can be detected with the service of product failure analysis. Then, corresponding maintenance strategy will be provided to the manufacturer and users, such as the position of faulty part, corresponding disassembly sequence, part specifications that need to be replaced.
8. Service of product virtual maintenance. The virtual maintenance cannot be implemented without the constructed ultra-high-fidelity virtual product model and virtual reality technology. While product failure occurs, and the maintenance strategy is provided, users or manufacturer can carry out virtual maintenance based on virtual reality and augmented reality technology, before conducting practical maintenance.
9. Service of product virtual operation. As a complex product often means complex operation, the operator needs a long time training and learning. Based on the constructed ultra-high-fidelity virtual product model and relevant data, the service of product virtual operation provides a platform where training and learning can be performed, thus shortening the train time, improving the training efficiency and accuracy.

Under product digital twin circumstance, and based on the physical product data, virtual product data, and connected data that ties the physical and virtual product, above nine smart services have the potential to improve the intelligence level of product, reduce product failure rate, improve maintenance effectiveness, and improve product utilization efficiency.

4.3.2 A case of digital twin-driven power transformer service

A power transformer is taken as an example to illustrate one of the future application modes of digital twin-driven product service, as shown in Fig. 7. The ultra-high-fidelity virtual power transformer can be depicted through modeling material properties, parts mechanics/temperature/flow coupling model and updating real-time physical power transformer data. Through adding sensors to the power transformer, as shown in Fig. 7, data of real state of physical power transformer can be fully synchronized to the virtual model. Meanwhile, relevant performance, such as parts structure and conversion efficiency, is employed to update knowledge library. Digital twin can timely analyze and evaluate whether maintenance is needed, whether it can bear the subsequent task and so on, according to the existing performance situation and the knowledge. The information of decision-making schemes is fed back to the physical power transformer. Meanwhile, the decision-making result can also be employed to update knowledge library.

On this basis, the digital twin-driven power transformer service is constructed with the physical transformer, virtual transformer, and connected data that tie the physical and virtual power transformer. After that, relevant services about the power transformer are analyzed as follows: (1) Real-time state monitoring of power transformer. Specific monitoring information includes basic information of the power transformer, equipment current status assessment score, power transmission capacity statistics, and contribution of each measuring point. (2) Energy consumption of power transformer itself. In addition to the power transmission and conversion capacity, the energy consumption of transformer itself also needs to be measured. Relevant statistics includes daily/weekly transformer self-consumption of energy, and follow-up energy consumption forecast. (3) Output power quality prediction and analysis. Power quality plays an important role in the operation of the power grid. Therefore, monitoring of real-time output power quality is necessary. Multiple point information is measured firstly, such as oil level, temperature, and pressure. And then, based on the multi-points linkage-dynamic bias threshold method, the bias of detection value is analyzed. Meanwhile, a plane is created in real time, and a variable dummy (evaluation value) for each measuring point with other measuring points is constructed. Based on the multiple nonlinear regression method, output power quality can be analyzed and predicted.

5 Key technologies and challenges ahead

The key technologies that need to be researched for implementing digital twin-driven product design, manufacturing, and service can be classified to the following five aspects:

1. Intelligent perception and connection. Related technologies to implement intelligent perception and connection include heterogeneous resources real-time perception and access technology, multi-source/modal data fusion and encapsulation technology, multi-source data communication and distribution technology, sensor co-measurement, and layout optimization technology.
2. Virtual modeling, running simulation and verification. The following technologies need to be addressed: “factor-behavior-rule” multi-scale modeling technology, virtual product running simulation technology, virtual production operation simulation and verification technology, virtual maintenance technology, virtual reality, and augmented reality technology.
3. Digital twin data construction and management. Related technologies include multi-granularity/scale data planning and cleaning technology, interpretable-operable-traceable heterogeneous data fusion technology, data clustering storage technology, virtual-real convergence and data collaboration technology, and virtual-real bidirectional mapping technology.
4. Digital twin-driven operation technology. The operation of digital twin-driven product design, manufacturing and service takes the following technologies as the prerequisite: high-performance computing technology, machine learning technology, real-time virtual-real interactive technology, self-organizing/adaptive dynamic scheduling technology, production factors configuration, production planning, and production process iterative operation and optimization technology.
5. Smart production and precision service. Related technologies include smart production and operation optimization services technology, collaborative production analysis technology, material intelligent tracking and distribution technology, production factors failure prediction and maintenance strategy technology, product lifecycle energy consumption optimization and forecasting technology, and product quality real-time analysis technology.

Meanwhile, there are many challenges that need to be addressed before digital twin can be accepted as a viable choice in product lifecycle, such as the following:

1. Ultra-high synchronization and fidelity between the virtual and physical space needs the breakthrough of virtual modeling technology and ultra-high-speed transmission technology.

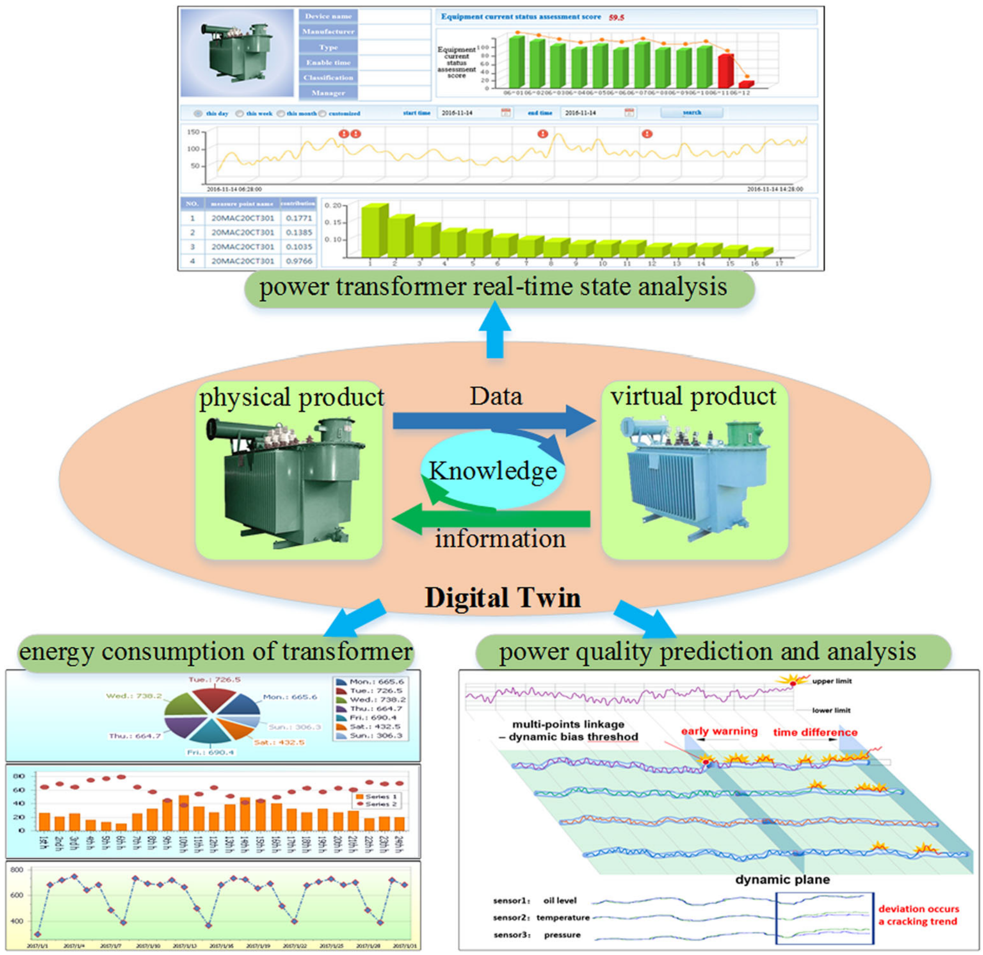

Fig. 7 Digital twin-driven power transformer services

2. High-performance computing and multi-physics/multi-scale interdisciplinary need to be addressed and improved to realize real-time smart analysis and prediction.
3. Deep learning in digital twin-driven product design, manufacturing, and service is another challenge that urgently needs to be addressed. And how to employ deep learning to undergo continuous improvement through the integration and convergence between virtual data and physical data is also a huge challenge.
4. Regulation at the personal, enterprise, local, national, and international level is another challenge hindering the implementation of digital twin-driven product design, manufacturing, and service, as well as the ideology constraints and cost limitations from part enterprise, especially small and medium enterprises. In addition, there is a lack of standards and criteria.

6 Conclusion and future works

With the coming of big data-driven manufacturing era, many new technologies, such as internet of things (IoT), big data, service-oriented technology, and cloud computing, have been employed in PLM. However, the current technologies mainly focus on physical product data rather than the data from virtual models. On the one hand, data generated in various phases of the whole product lifecycle may form the information island between different phases of product lifecycle. And on the other hand, a lot of duplicate data exists in different phases of product lifecycle and leads to resources waste and data sharing inefficiency. Besides, the interaction and iteration between big data analysis and various activities in the whole product lifecycle are relatively absent. To solve the problems, digital twin, with the characteristics of ultra-high synchronization and fidelity, convergence between physical and virtual product, etc., has high potential application in product design, product manufacturing, and product service.

The main contributions of this paper are concluded as follows: (1) To solve the problems about data in product lifecycle, a new method for digital twin-driven product design, manufacturing and service is proposed. (2) The detailed application methods and framework of digital twin-driven product design, manufacturing, and service are investigated. (3) Three cases are given to illustrate the practical applications of digital twin driven the three phases of a product respectively.

This paper preliminarily investigated the application methods and frameworks of digital twin-driven product design, manufacturing, and service. At present, the research is in the initial stage and still needs a lot of research work. Future work will concentrate on the following aspect: (1) intelligent perception and connection technology, (2) digital twin data construction and management, (3) smart service analysis method based on digital twin data, and (4) more applications on digital twin-driven PLM.

Acknowledgements This work is financially supported in part by National Natural Science Foundation of China (NSFC) under Grants 51522501, National Key Research and Development Program of China (No.2016YFB1101700), and Beijing Nova Program (Z161100004916063) in China. The authors thank Dr. Shizhong Mou from Donghua Software Co., LTD for providing information and data in Section 4.3.2. Thanks to Mr. S Gu and Miss K Chen for proofreading of this paper.

References

1. Stark J (2015) Product lifecycle management. Springer International Publishing, Switzerland
2. Xu LD, He W, Li S (2014) Internet of things in industries: a survey. IEEE Trans Ind Informat 10(4):2233–2243
3. Jiang L, Xu LD, Cai H et al (2014) An IoT-oriented data storage framework in cloud computing platform. IEEE Trans Ind Informat 10(2):1443–1451
4. O'Leary DE (2013) Artificial intelligence and big data. IEEE Intell Syst 28(2):96–99
5. Li J, Tao F, Cheng Y, Zhao L (2015) Big data in product lifecycle management. Int J Adv Manuf Technol 81(1–4):667–684
6. Matsokis A, Kiritsis D (2010) An ontology-based approach for product lifecycle management. Comput Ind 61(8):787–797
7. Kiritsis D, Bufardi A, Xirouchakis P (2003) Research issues on product lifecycle management and information tracking using smart embedded systems. Advd Engng Inf 17(3):189–202
8. Srinivasan V (2011) An integration framework for product lifecycle management. Comput Aided Des 43(5):464–478
9. Vezzetti E, Moos S, Kretli S (2011) A product lifecycle management methodology for supporting knowledge reuse in the consumer packaged goods domain. Comput Aided Des 43(12):1902–1911
10. Tao F, Cheng J, Cheng Y et al (2017a) SDMSim: a manufacturing service supply–demand matching simulator under cloud environment. Robot Comput Integr Manuf 45:34–46
11. Xu LD, Wang C, Bi Z et al (2012) AutoAssem: an automated assembly planning system for complex products. IEEE Trans Ind Informat 8(3):669–678
12. Dean J (1950) Pricing policies for new products. Harv Bus Rev 28(6):45–53
13. Levitt T (1965) Exploit the product life cycle. Harv Bus Rev 43(6): 81–94
14. Rink DR, Swan JE (1979) Product life cycle research: a literature review. J Bus Res 7(3):219–242
15. Nevins JL, Whitney DE (1989) Concurrent design of products and processes: a strategy for the next generation in manufacturing. McGraw-Hill Companies, New York
16. Ryan C, Riggs WE (1996) Redefining the product life cycle: the five-element product wave. Business Horizons 39(5):33–40
17. Cao H, Folan P (2012) Product life cycle: the evolution of a paradigm and literature review from 1950–2009. Prod Plan Con 23(8): 641–662
18. Zhang J, Gao L, Qin W et al (2016) Big-data-driven operation analysis and decision-making methodology in intelligent workshop. Comput Integr Manuf Sys 22(5):1221–1229
19. Grieves M (2014) Digital twin: manufacturing excellence through virtual factory replication. http://www.apriso.com
20. Hochhalter J, Leser WP, Newman JA et al (2014a) Coupling damage-sensing particles to the digital twin concept. NASA Center for AeroSpace Information
21. Reifsnider K, Majumdar P (2013) Multiphysics stimulated simulation digital twin methods for fleet management. 54th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference 1578
22. Glaessgen E, Stargel D (2012) The digital twin paradigm for future NASA and US Air Force vehicles. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference 20th AIAA/ASME/AHS Adaptive Structures Conference 14th AIAA 1818
23. Gabor T, Belzner L, Kiermeier M et al (2016) A simulation-based architecture for smart cyber-physical systems. IEEE International Conference on Autonomic Computing (ICAC) 2016:374–379
24. Tuegel EJ, Ingraffea AR, Eason TG et al (2011) Reengineering aircraft structural life prediction using a digital twin. Int J Aeros Eng. doi:10.1155/2011/154798
25. Smarslok B, Culler A, Mahadevan S (2012) Error quantification and confidence assessment of aerothermal model predictions for hypersonic aircraft. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference 1817
26. Bielefeldt B, Hochhalter J, Hartl D (2015) Computationally efficient analysis of SMA sensory particles embedded in complex aerostructures using a substructure approach. ASME 2015 Conference on Smart Materials, Adaptive Structures and Intelligent Systems V001T02A007-V001T02A007
27. Hochhalter J, Leser WP, Newman JA et al (2014b) Coupling damage sensing particles to the digital twin concept. https://ntrs.nasa.gov/search.jsp?R=20140006408
28. Tuegel E (2012) The airframe digital twin: some challenges to realization. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference 20th AIAA/ASME/AHS Adaptive Structures Conference 14th AIAA 1812
29. Cerrone A, Hochhalter J, Heber G et al (2014) On the effects of modeling as-manufactured geometry: toward digital twin. Int J Aerosp Eng. doi:10.1155/2014/439278
30. Stackpole B (2015) Digital twins land a role in product design. http://www.digitaleng.news/de/digital-twins-land-a-role-in-product-design/
31. Boschert S, Rosen R (2016) Digital twin—the simulation aspect. In: Mechatronic futures. Springer International Publishing, Switzerland, pp 59–74
32. Tao F, Zhang M, Cheng J et al (2017b) Digital twin workshop: a new paradigm for future workshop. Comput Integr Manuf Syst 23(1):1–9
33. Tao F, Bi LN, Zuo Y et al (2016a) A hybrid group leader algorithm for green material selection with energy consideration in product design. CIRP Ann - Manuf Technol 65(1):9–12
34. Tao F, Bi LN, Zuo Y et al (2016b) A cooperative co-evolutionary algorithm for large-scale process planning with energy consideration. J Manuf Sci Eng Trans ASME. doi:10.1115/1.4035960