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Digital twin-driven product design framework

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With the advent of new generation information technologies in industry and product design, the big data-driven product design era has arrived. However, the big data-driven product design mainly places emphasis on the analysis of physical data rather than the virtual models, in other words, the convergence between product physical and virtual space is usually absent. Digital twin, a new emerging and fast growing technology which connects the physical and virtual world, has attracted much attention worldwide recently. This paper presents a new method for product design based on the digital twin approach. The development of product design is briefly introduced first. The framework of digital twin-driven product design (DTPD) is then proposed and analysed. A case is presented to illustrate the application of the proposed DTPD method.

Keywords: digital twin; product design; framework; design theory; data lifecycle; big data

1. Introduction

Recently, a new paradigm of data-driven product design has emerged. The design process is becoming more digitalised than ever before, as indicated by the universal application of digital design package (e.g. CAD, FEA, CAE, CAM, etc.). Made possible using the Internet of Things (IoT), data are directly collected from smart products, transmitted to the ‘cloud’ in real-time and analysed using big data analytics. Against such a background, this study focuses on the synergy between a pair of virtual product and physical product. In the virtual world, products are created in laboratories to visualise product structure, simulate product behaviour and optimise product performance. In the physical world, when products are utilised by end users, their performance, behaviour and interaction with the users are captured by sensors and controlled by actuators. Traditionally, the virtual and physical products are built, analysed and upgraded, somehow in separation from each other. In the light of the data-driven product design, it calls for a new framework that can effectively converge, integrate, and synchronise the increasingly ‘bigger’ data that are related to the virtual product, the physical product and their back-and-forth interactions.

To date, the most commonly used definition of digital twin was proposed by Glaessegen and Stargel in 2012: ‘digital twin means an integrated multiphysics, multiscale, probabilistic simulation of a complex product, which functions to mirror the life of its corresponding twin’. Digital twin (DT) consists of three parts: physical product, virtual product and the linkage between physical and virtual product (Glaessgen and Stargel 2012). It serves as a bridge between the physical world and the digital world. Different from CAD (that exclusively focuses on the digital world) and IoT (that heavily concentrate on the physical world), DT is characterised by the two-way interactions between the digital and physical worlds, which can possibly lead to many benefits. On one hand, the physical product can be made more ‘intelligent’ to actively adjust its real-time behaviour according to the ‘recommendations’ made by the virtual product. On the other hand, the virtual product can be made more ‘factual’ to accurately reflect the real-world state of the physical product.

In the past, digital twin is mostly used for fault diagnosis, predictive maintenance and performance analysis. To date, few efforts have been devoted to exploring the applicability of digital twin for product design, with respect to, how and in what ways the communication, synergy and coevolution between a physical product and its digital representation (virtual product) can lead to more informed, expedited and innovative design process. Furthermore, so far, digital twin is

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merely used for the design, operation and maintenance of complex systems (e.g. aircraft engine, wind turbines, power plant and so forth), while few efforts have been devoted to exploring the values of DT to consumer product design.

This study presents a digital twin-driven product design (DTPD) framework, which can guide manufacturers to create a digital twin, and utilise the information provided by the digital twin to support the product design process. The remainder of this paper is organised as follows. Section 2 reviews some previous studies relevant to the proposed DTPD framework. Section 3 formally presents the DTPD framework with respect to its theoretical formulation and systematic process. Section 4 presents a case study of a bicycle design to showcase the possible application of DTPD in design practice. Section 5 draws conclusions and outlines future work.

2. The development of product design and prospect forecast

2.1 *New era of data-driven product design and manufacturing*

Nowadays, the success of product design hinges increasingly on the manufacturer's capability to handle data. Data can be accumulated through different phases of a product's lifecycle including design, production, distribution, usage, maintenance, upgrade and recycle. Some data are related to the product's status, behaviour and performance (e.g. state sampling data in utility, maintenance and failure information, upgrade information, degradation status, remaining values and recycle scheduling records). Some data are related to the context in which a product is being used with respect to, for example, when, where, how, by whom and under what circumstances the product is used. Some data are related to customers in regards to their demographics information (e.g. income, education, gender, etc.), behaviours (e.g. online browsing, searching and purchasing history), and preferences (e.g. product rating, reviewing history, repeated purchase, etc.). The technological backbones of data-driven product design are IoT and big data analytics.

The enabling technologies of IoT include sensors, software, electronics, actuator, etc. The applications of IoT can be found in many fields such as healthcare (Catarinucci et al. 2015), transportation (Pyykönen et al. 2013), and smart city (Jin et al. 2014). IoT can lead to countless benefits, such as significantly enhanced automation, accuracy, efficiency and productivity. Made possible using the IoT technologies, data can be collected directly from the physical products in real-time; a group of physical products can communicate and collaborate directly with each other; a physical product connected to IoT can interplay with an intangible service on the Internet; a physical product can be monitored, controlled, and upgraded remotely.

Big data are valuable information assets that are characterised by high volume, velocity and variety. Big data analytics aims to abstract useful information to facilitate a certain human creativity out of an enormous amount of highly unstructured and seemingly unrelated data. Design-related big data are richly available on the Internet and the Internet of Things. On one hand, some big data are generated by customers from the Internet. For example, countless text-heavy customer reviews are published on e-commerce platforms (e.g. Amazon.com) and social platforms (e.g. Facebook.com). On the other hand, made possible using advanced sensor technologies, big data can be collected from the physical products using Internet of Things.

Despite the sweeping trend, there are some major challenges ahead of data-driven product design: (1) How to effectively convert an enormous amount of data towards a small selection of useful information that can be directly queried by designers to support their design decisions-making at different phases of the design process? (2) How to effectively integrate a variety of different data about product, customer, and environment, which are collected from diversified sources (both Internet and IoT) using different methods, in order to discover the deeply hidden game-changing patterns? (3) How to rapidly respond to a current event that is happening in the real-world based on the real-time data, and how to predict a future event that will occur based on historical data?

2.2 *Call for data-driven design framework*

Quality Function Deployment (QFD) is widely used in the product planning phase to translate customer voices to product requirements (functional and quality requirements). QFD can be combined with many other design methods such as Analytic Hierarchy Process (AHP), TRIZ, Taguchi, Failure Mode and Effects Analysis (FMEA) and Kano Model. When QFD is employed to design complex products or systems such as automobiles, it is common that even the most experienced designers could lose track easily of the information flow over time. Recently, there emerged some studies that aim to abstract useful customer voices from online customer reviews that are published by motivated users on the Internet (Hadi-Vencheh and Mohamadghasemi 2013; Hanumaiah, Ravi, and Mukherjee 2013; Liu et al. 2013).

Axiomatic Design (AD) was proposed by Suh to establish a scientific foundation for engineering design (Brown 2008). There are many applications of AD in product design (Hirani and Suh 2005; Lee and Suh 2005). AD is known for the two famous design axioms. Nowadays, when more and more products become increasingly interconnected with each other, functional couplings exist not only within a single product but also between different products that are connected to the Internet and IoT. Take a smartphone, for example, its function <play video> is not only affected by the smartphone's internal parameters such as screen, processor and battery, but also by many external parameters of its 'connected' product/service such as wireless transmitters, Internet bandwidth, video format, etc. In light of the continuous expansion of the Internet and IoT, the diagnosis of functional couplings is becoming too overwhelming to be manually handled by human designers.

TRIZ is one of the most well-known problem-solving methods in engineering design, and it is widely used in product design (Altshuller 1999; Zusman, Zainiev, and Clark 1999; Mann et al. 2003). The design thinking behind TRIZ is highly analogous to that behind the big data analytics, and both intend to uncover the hidden patterns, general principles, and unknown correlations, under the surface of an enormous amount of data. The TRIZ matrix was manually created by Altshuller (Altshuller 1999) based on his personal interpretation and abstraction of hundreds of thousands of product patents. Recently, there appeared some studies about combining TRIZ with big data analytics to automatically discover the hidden patterns behind massive amount of product patents. Furthermore, many of the TRIZ parameters can be measured precisely using sensors in real-time, leading to the possibility of automatically recognising system contradictions.

The Function–Behaviour–Structure (FBS) framework was proposed by Gero in 1990, based on which, Gero and Kannengiesser (Gero and Kannengiesser 2004) situates functions, behaviours and structures in three worlds (i.e. expected world, interpreted world and external world). The interpreted world plays the critical role in bridging the expected world (that is too ideal since it only exists in the designer's mind) and the external world (that is too overwhelming because it involves countless variables, uncertainties and constraints). Traditionally, the interpreted world is constructed by designers based on their subjective experience, understanding and knowledge about the physical world. As a result, it is oftentimes difficult to clearly differentiate the interpreted world from the expected world and make the interpreted world reflect accurately the dynamically changing physical world. Moreover, the three worlds are lacking real-time linkages.

The traditional design methods cannot be directly employed to support the data-driven product design. Firstly, they are not intended to accommodate the big data. Traditionally, designers depend heavily on their experience to identify high-value data, convert data to useful information, and make sense of the data using relevant knowledge. In order to increase efficiency, in practice, designers often follow the lead user theory and ethnography to improve the quality of input data in the first place. Nevertheless, such a strategy is no longer feasible, in front of the big data. Secondly, the traditional design methods are developed to process structured information that is characterised by a high degree of organisation, clarity and consistency. Therefore, they are not suitable for dealing with the unstructured information generated without any predefined models or formats. Lastly, the traditional design methods are not capable of responding rapidly to the dynamically changing data and emerging new situations. It should be made explicit though, by no means, the authors propose to abandon the existing design theory and methodologies (DTMs) and develop completely new ones. But rather, the authors propose to adapt those existing design methods and make them more capable of coping with for a massive amount of highly and dynamically changing data coming from diversified sources.

In addition, with the development of technology, design is oriented towards virtualisation, functionality-driven, data-driven and better use of distributed resources. Goswami et al. connected product design and commercial objectives, promoting manufacturers to frame product line design strategy by offering right product attributes (Goswami, Daultani, and Tiwari 2017). Battaïa et al. presented a method for designing reconfigurable machining systems used for family part production, offering a rapid and cost-effective response to production fluctuations (Battaïa, Dolgui, and Guschinsky 2017). Yin et al. focused on the relationships between product supply and customer needs (Yin, Stecke, and Li 2017). Chen et al. proposed a method for the optimal conceptual design synthesis based on the distributed resource environment to promote the design efficiency and innovation (Chen and Xie 2017). Zhang et al. presented a graph-based approach to knowledge reuse for knowledge-driven decision-making in new product development (Zhang et al. 2017). Szejka et al. proposed a review to analyse the main researches on semantic interoperability field (Szejka et al. 2017). Hoedt et al. paid attention to the effect of virtual training for manual assembly tasks (Hoedt et al. 2017). These works improve design performance around one or some of points. DTPD can almost meet all of the above requirements.

3. Digital twin and its applications

The concept of digital twin can date back to Grieves's presentation about Product Lifecycle Management (PLM) in 2003 (Grieves 2014). However, at that time the concept of digital twin is not mature enough because of technology limitations. Along with the data acquisition technology (e.g. IoT), processing technology (e.g. cloud computing), simulation technology and many other related technologies development, the concept of digital twin becomes more mature and specific.

Industry and academic define digital twin in many different ways, it is generally accepted that a digital twin is an integrated multiphysics, multiscale probabilistic ultra-realistic simulation of systems or products which can mirror the life of its corresponding twin using available physical models, history data, real time data, etc. developed by NASA (Glaessgen and Stargel 2012). Rosen et al. believe that digital twin is the model which can interact between autonomous system behaviours and the environment in the physical world (Rosen et al. 2015). There are many other definitions in particular fields. In our opinion, digital twin is a real mapping of all components in the product life cycle using physical data, virtual data and interaction data between them.

Because the digital twin can allow companies or users to have a complete digital footprint of the product they concerned from design and development through the end of the product lifecycle, so digital twin has increasing attention by both industry and academic. Existing primary applications of digital twin in industry are briefly summarised as follows.

The concept of digital twin was first proposed and primarily used in product or equipment prognostics and health management (PHM). Typical applications are described in the following paragraph. Tuegel et al. used a digital twin to predict the reengineering aircraft structural life (Tuegel et al. 2011). Seshadri and Krishnamurthy proposed a damage characterisation method based on digital twin for aircraft structural health management, which demonstrated great advancement in predicting the damage location, size and orientation (Seshadri and Krishnamurthy 2017). Gockel et al. proposed Airframe Digital Twin (ADT) to assess the flight state which helps find the subsequent damage in a real-time way (Gockel et al. 2012). Besides aircrafts, General Electric pays attention to using digital twin to forecast product health in product lifecycle, which can make operations and maintenance more accurate.

The notion of digital twin should be differentiated from cyber twin. Cyber twin is based on the conception of CPS. Generally speaking, the notion of cyber twin is derived based on the development of cyber physical system (CPS). Cyber space is defined as a networked space that consists of multiple interconnected cyber twins of critical objects (Lee, Bagheri, and Kao 2014; Liu and Xu 2017; Xu 2017). In other words, cyber twins purely exist and are merely meaningful within the cyber space. In sharp contrast, a complete DT must include a physical model, a virtual model, and connections between the physical and virtual models. In other words, it emphasises interaction, communication and collaboration between physical space and cyber space.

Nowadays, as the application of new IT in manufacturing, the smart manufacturing era has arrived. DT can be regarded as a critical milestone towards smart manufacturing and smart industry, while cybernetics provides the theoretical basis for DT. Cybernetics studies the concepts of control and communication in living organisms, machines and organisations, including self-organisation. It studies how a system (either biological system or artificial system) processes information and depends on information to make decisions and take actions, with respect to automatic control and communication (Novikov 2016). Cybernetics provides the theoretical foundation for developing smart systems that are capable of collecting, processing and understanding various contextual information, based on which, DT can make more contextually smart decisions. In short, relevant studies about cybernetics can be regarded as the technological backbones of DT.

Some countries proposed their national strategies such as Industry 4.0, CPS-based manufacturing(Wang, Törngren, and Onori 2015), service-oriented manufacturing(Tao, Zhang, and Laili 2015), and Made in China 2025. Throughout the above national manufacturing strategies, one common goal is smart manufacturing (Kang et al. 2016). In order to realise the integration and fusion of manufacturing physical world and information world, for realising smart production and intelligent management, digital twin was introduced into manufacturing stage. For example, the concept of digital twin shop-floor (DTS) (Tao, Zhang et al. 2017) was proposed, and DTS characteristics, architecture, system composition, operating mechanism, and enabling key technologies are studied in detail (Tao, Cheng et al. 2017). Vachálek et al. investigated the application of digital twin in an industrial production line and analysed its superiority (Vachálek et al. 2017). Knapp et al. studied additive manufacturing's digital twin and used it to make predictions about properties and serviceability of components (Knapp et al. 2017). Recently, Soderberg et al. studied digital twin-based real-time geometry assurance in individualised production (Söderberg et al. 2017). DXC company tries to build digital twin model to improve manufacturing efficiency and flexibility.

Furthermore, some researchers have studied the application of digital twin in engineering optimisation. Rosen et al. introduce digital twin application in optimising equipment operation (Rosen et al. 2015); and Bantégnie created a pump's digital twin to optimise its performance in physical world. What's more, Gabor et al. yielded an architectural framework of the digital twin for complex systems to optimise the system behaviours (Gabor et al. 2016).

The above-mentioned digital twin applications stay primarily in the production stage and after-product stage, and are heavily dependent on the product digital twin mode. Not much attention was paid to make use of digital twin in the first stage of product creation (i.e. the design stage). As pointed out and stated by Dassault, there is huge potential of digital twin in product design (Digital Twins 2015). In addition, if one could establish the product digital twin mode from the design phase, then more related design data, marketing data, user experience data, etc., can be integrated into the product digital mode, and this will result in better serve for the production stage and after-product stage.

Therefore, the application of digital twin in product design is emphasised in this paper. The aim of this paper is try to provide a reference framework for digital twin-driven product design (DTPD).

4. Digital twin-driven product design methodology

4.1 *General digital twin mode for a product*

As shown in Figure 1, the general digital twin mode for a product consists of three parts, which are the physical entities in physical space, the virtual models in virtual space, and the connected data that tie physical and virtual worlds. The physical entities are the real product that can be operated by the users. They are manufactured from raw materials or parts, through machining, assembly and other processes. The physical entities have different characteristics, behaviours and performance in the course of manufacturing, use, Maintenance, Repair & Overhaul (MRO), disposal, and other operations, and a lot of data are generated. The virtual models are the mirror images and mapping of the physical products in the virtual space. They could reflect the whole lifecycle process, as well as simulate, monitor, diagnose, predict and control the state and behaviours of the corresponding physical entities. The virtual models include not only the geometric models, but also all rules and behaviours, such as material properties, mechanical analysis, health monitoring. The connected data include the subsets of physical data and virtual data, as well as some 'new data' that are acquired after the integration, fusion and analysis of physical data and virtual data. In the process of design and production, the parameters of the virtual models are passed to the production line and the virtual models are processed into real physical products. Through digital detection or measurement, the product attributes, operating status and other data are fed back to the virtual models, achieving a two-way data transmission process. By constructing the product models in the virtual space, as well as the feedback of the digital models to the physical space, the digital twin mode achieves a closed-loop process.

The digital twin mode for a product can collect and accumulate the data continuously and knowledge on the entire lifecycle process, such as design, manufacturing, quality inspection, MRO. And these data and knowledge could continue to be reused and improved. As a result, the digital twin mode could enable the management, tracking and consistency maintenance of product by dynamically sensing, storing and presenting the whole product lifecycle data.

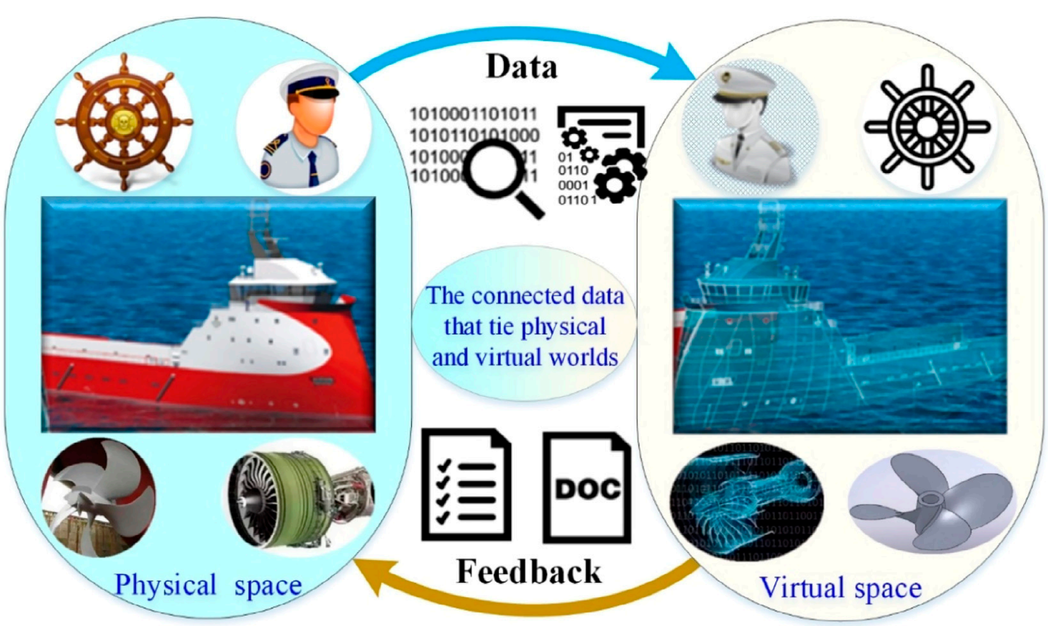

Figure 1. General digital twin mode for a product.

4.2 *Process of building a functional digital twin*

As shown in Figure 2, given an existing physical product, in general, it takes six steps to create a fully functional digital twin. It should be made explicit though, in practice, manufacturers may not strictly follow the sequence to build DTs. It is also possible that these steps can be carried out concurrently.

4.2.1 *Step (1): Build the virtual representation of the physical product*

The enabling technologies of this step are computer-aided design (CAD) and 3D modelling. Both are commonly used technologies in product design. The virtual product includes three aspects: elements, behaviours, and rules (Tao, Cheng et al. 2017). At the level of elements, the virtual product model mainly includes the geometric model and physical model of the product, user and environment, etc. At the level of behaviours, the authors not only analyse the behaviour of products and users, but also focus on the analysis of the product and user interaction generated by the behaviour and modelling. At the rules level, it mainly includes the evaluation, optimisation and forecasting models established following the law of product operation.

4.2.2 *Step (2): Process data to facilitate design decision-making*

Data collected from different sources (i.e. mainly from the physical product, and also from the Internet) are analysed, integrated and visualised. Firstly, data analytics is necessary to convert data into more concrete information that can be directly queried by designers for decision-making. Secondly, since product data are collected from diverse sources, data integration is useful for discovering the hidden patterns that cannot be uncovered based on a single data source. Thirdly, data visualisation technologies are incorporated to present data in a more explicit fashion. Finally, advanced artificial

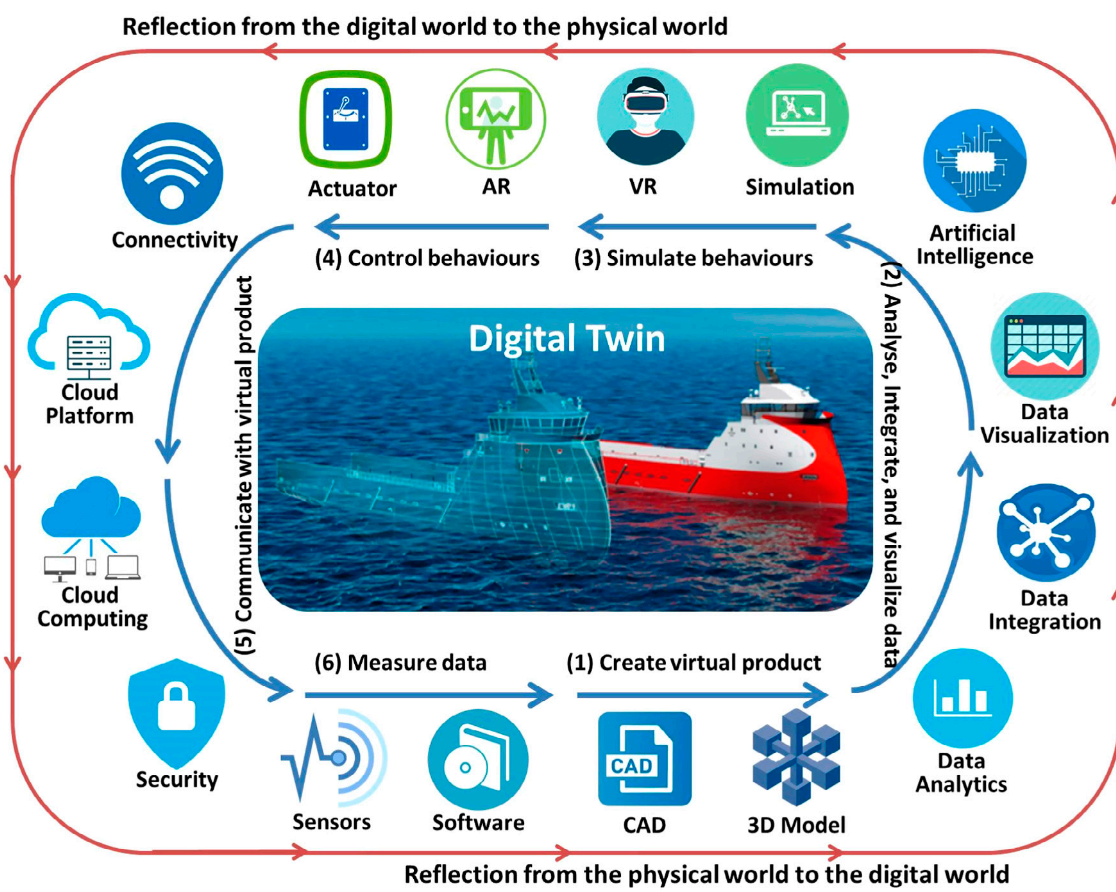

Figure 2. Enabling technology of digital twin.

intelligence techniques can be incorporated to enhance a DT's cognitive ability (e.g. reasoning, problem solving and knowledge representation), so that certain relatively simple recommendations can be made automatically.

4.2.3 *Step (3): Simulate product behaviours in the virtual environment*

The enabling technologies of this step include simulation and virtual reality (VR). The former is used to simulate key functions and behaviours of the physical product in the virtual world. In the past, simulation technologies are widely used in product design. On the other hand, virtual reality (VR) technologies play the role of involving designers and even users to 'directly' interact with the virtual product in the simulated environment. Recently, VR technologies are increasingly employed to support virtual prototyping and product design (Stark, Israel, and Wöhler 2010). Many readily available VR hardware devices can be directly adopted for digital twin.

4.2.4 *Step (4): Command the physical product to perform recommended behaviours*

Based on the recommendations of DT, the physical product is equipped with a capability, by means of various actuators, to adaptively adjust its function, behaviour and structure in the physical world. Sensors and actuators are the two technological backbones of a digital twin. The former plays the role in sensing the external world, whereas the latter plays the role in executing the desirable adjustments requested by DT. In practice, the commonly used actuators that are suitable for consumer products include, for example, hydraulic, pneumatic, electric, and mechanical actuators. In addition, augmented reality (AR) technologies can be used to reflect some parts of the virtual product back to the physical world. For example, AR enables end users to view the real-time state of their products. Recently, AR technologies are increasingly applied in the factory domain production engineering (Nee and Ong 2013).

4.2.5 *Step (5): Establish real-time, two-way, and secure connections between physical and virtual product*

The connections are enabled using a number of technologies, such as network communication, cloud computing and network security. Firstly, networking technologies enable the product to send its ongoing data to the 'cloud' to power the virtual product. The feasible networking technologies for consumer products include, for example, Bluetooth, QR code, barcode, Wi-Fi, Z-Wave, etc. Secondly, cloud computing enables the virtual product to be developed, deployed and maintained completely in the 'cloud', so that it can be conveniently accessed by both designers and users from anywhere with an Internet access. Lastly, since product data are directly and indirectly concerning user-product interactions, it is critical to guarantee the security of connections. In light of the Internet of Things, much effort has been devoted to connecting the physical and virtual product, which can be adapted for the DT research.

4.2.6 *Step (6): Collect all kinds of product-related data from different sources*

Generally speaking, there are three types of product-related data that should be processed by DT. For ordinary products, physical product data is usually divided into product data, environmental data, customer data and interactive data. Product data contains customer comments, viewing and download records. Interactive data consist of user-product-environment interaction, such as stress, vibration, etc. Using the sensor technology and IoT technology can collect some of the above data in real time, and analyse from the product manual, web page customer browsing records, download records, evaluation feedback, etc., can obtain the rest of the data. The collected data are fed to the Step (1) in order to close the loop towards building more functional virtual product.

4.3 *Framework of digital twin-driven product design (DTPD)*

Once a digital twin is successfully built, it can facilitate designers to perform different design activities. According to the design theory and methodology (DTM) classification by CIRP (Nee and Ong 2013), DTM plays the role in 'generating new solutions', 'enrich functional information of design solutions', and 'represent design knowledge'. New solutions are generated based on creativity, combination and modification (Tomiyama et al. 2009). DT is expected to be most useful for the combination-based design. The most commonly used combination-based DTM is the systemic design approach prescribed by Pahl and Beitz (Pahl and Beitz 2007; Pahl et al. 2007), which divides the design process into four phases: *task clarification, conceptual design, embodiment design* and *detail design*. Each phase can be further divided into multiple sub-steps. Relevant DTMs can be incorporated into different phases of the systemic design process. For example, during the conceptual design phase, Axiomatic Design, TRIZ, Robust Design and Adaptable Design

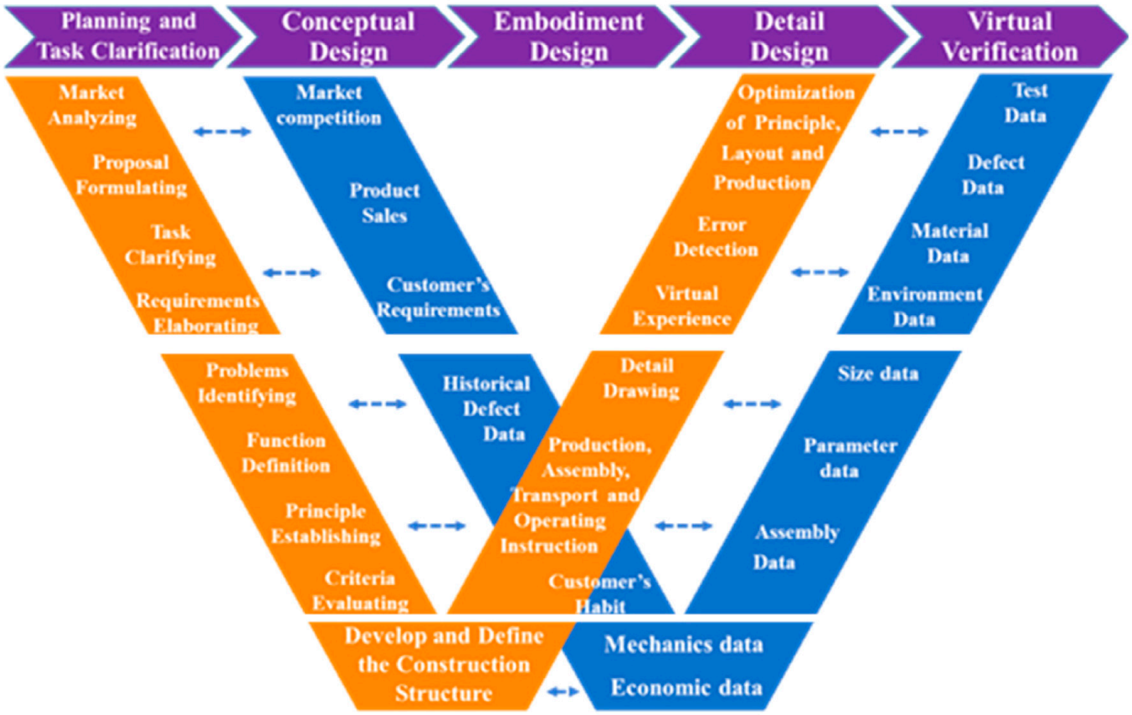

Figure 3. Framework of DTPD.

can be incorporated to reduce unnecessary design complexities (Lu and Suh 2009), resolve undesirable design contradictions (Chen and Liu 2001), make a product less sensitive to uncertainties, and increase a product's adaptability to changing requirements (Gu, Hashemian, and Nee 2004), respectively. Since DTPD is characterised by the ability to make full use of data to build a virtual model, a specific design phase called virtual verification is proposed as the last phase of the design process. The complete process is shown in Figure 3. Various design activities and their associated data are divided into five parts, which correspond to the five design phases.

4.3.1 *Theory support for DTPD*

As illustrated in Figure 4, the proposed framework DTPD integrates relevant design theory and methodology (DTM), data lifecycle management (DLM), and digital twin (DT).

Firstly, DTPD develops based on existing DTMs. They are included to structure the design process and decide where, how, and in what ways different kinds of data are exploited for various design activities. In addition, DTMs explains the internal conflict and contact among the various design phases, which are conducive to coordinate the relationship between the design factors.

Secondly, design process becomes increasingly digital. DTPD depends on the massive amounts of historical and real-time data, etc., relevant studies about DLM can deal with the data throughout the product lifecycle. DLM can collect, transfer and storage the date from physical world. It also motivates the DTPD by integrating and processing the data, which promotes the communication and interaction of different kinds of data. In addition, it can make sure the purity and accuracy by cleaning, analysing and mining the data.

Thirdly, relevant studies about DT are included to explain how to build a digital twin to serve the data-driven design of consumer products. It can also make designers have a complete digital footprint of products through design. It should be noted that DTPD is essentially a design framework, in which, digital twin serves as an 'engine' to convert big data managed by DLM into useful information that can be directly utilised by designers to make informed decisions at different design phases as prescribed by DTM.

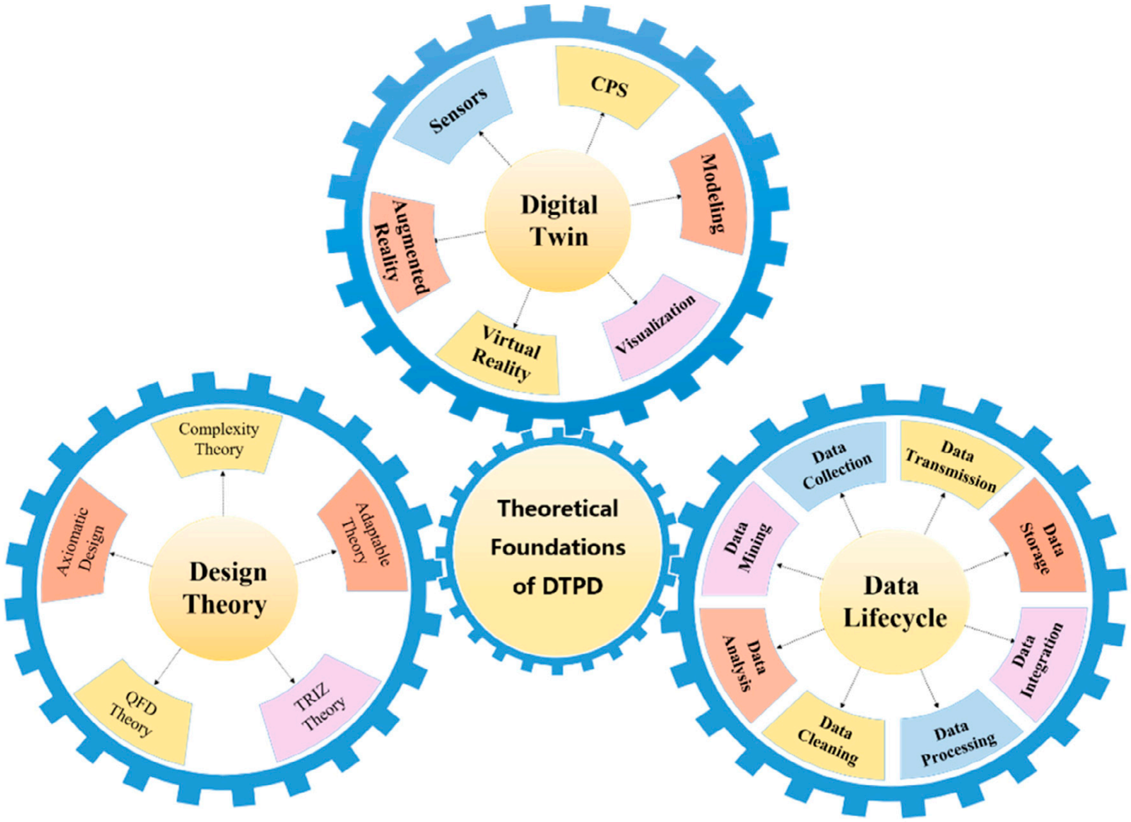

Figure 4. Theoretical formulation of DTPD.

4.3.2 *Collaborative design between designers and digital twin in DTPD*

From the perspective of design, DT can be regarded as a special kind of 'intelligent design machine', which is capable of providing designers with information, recommendation, and assessment throughout a product design process. If the 'design language' is used to describe digital twin, it can be regarded as an overlapped representation of both designer's intentions and real-world realities. According to the situated FBS framework (Gero and Kannengiesser 2004), design involves back-and-forth interactions between three worlds: *expected world*, *interpreted world* and *physical world* as shown in Figure 5.

A product can be described with respect to its function, structure and behaviour in all three worlds. When a product is projected from the expected world to the interpreted world, and eventually to the physical world, more details and specifics are gradually added to the product. The product is moved to the physical world from the digital world (in the designer's mind), because practical uncertainties and constraints have been imposed on the product. The essence of digital twin is to create a digital representation of the physical product in the interpreted world. Note that this virtual product should be seen as a dual-reflection from both the expected world and the physical world. On one hand, as much as possible, the virtual product should reflect the designer's expectations on how the product ought to function, behave, interact with customers, respond to uncertainties, and be physically structured. On the other hand, as accurate as possible, the virtual product should reflect the real-time state of the physical product in the real world. Moreover, digital twin also enables the physical product and virtual product to communicate with each other in real-time and coevolve with each other over time.

Figure 5 illustrates the role played by DT in data-driven product design. In the expected world, based on their understanding of customers (i.e. arrow 1 in Figure 5) and knowledge of the physical world (i.e. arrow 2 in Figure 5), designers propose a product's expected function, behaviour and structure (i.e. arrow 3 in Figure 5). Next, the expectations are visualised, simulated, analysed and optimised in the interpreted world (i.e. arrow 4 in Figure 5), by means of CAD, FEM, 3D modelling, virtual prototyping and so forth. Then the product is projected from the interpreted world to the physical world (i.e. arrow 5 in Figure 5). Traditionally, as the product enters the physical world, the designers will grad-

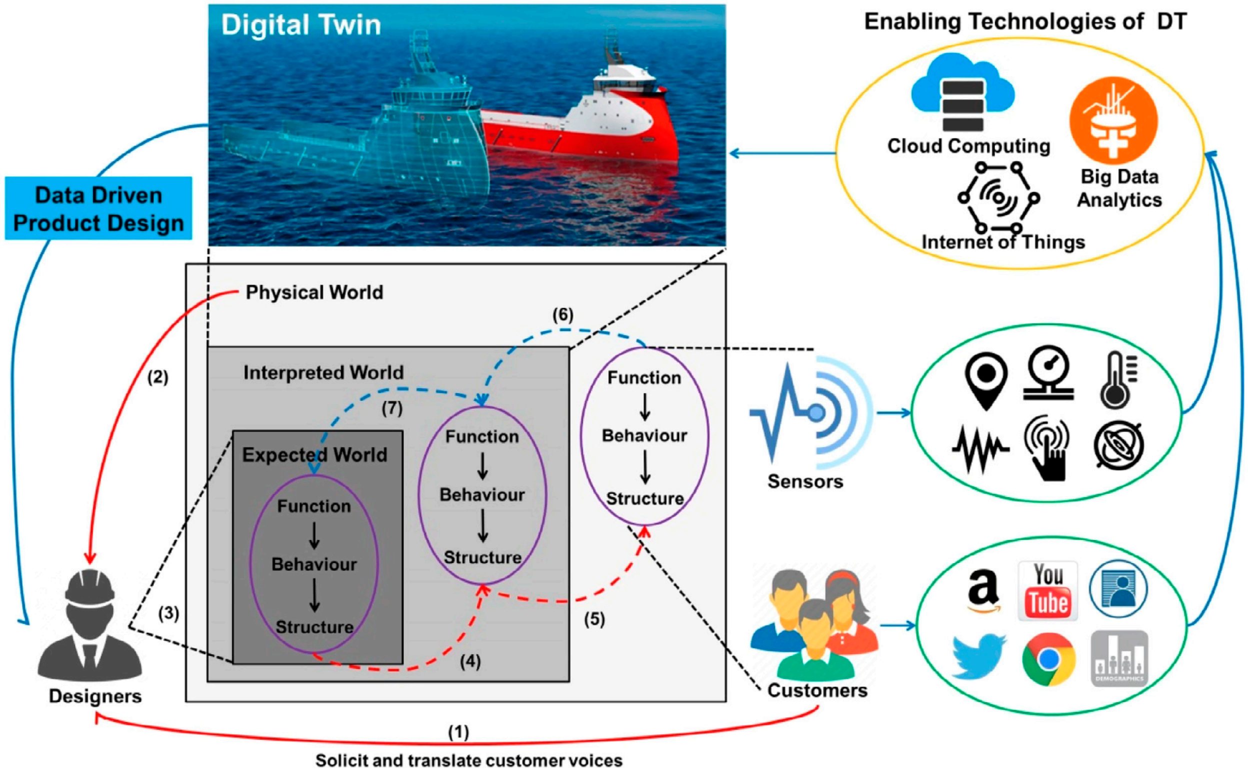

Figure 5. Understanding of digital twin in the FBS framework.

ually lose track of the various product-related information. In particular, while a product is manufactured in outsourced factories, distributed by the third-party retailors, purchased by globally distributed customers, and maintained by third-party dealers. As a result, designers have to employ design methods (e.g. survey, interview, lead-user theory, ethnography, etc.) to solicit feedbacks from customers, which are probably divided into two-ways, one is to collect the user's online comments on the website, like Amazon and YouTube, to understand the user's demand for the product; another is to collect product running data through the sensors to analyse the users' habits and preferences. The essence of digital twin is to create a digital representation of a physical product in the interpreted world (i.e. arrow 6 in Figure 5) and then reflect from the interpreted world back to the expected world (i.e. arrow 7 in Figure 5).

Figure 6 illustrates some new values created through the communication between designers and digital twin, as well as the synergy between the virtual product and physical product (the subscript number indicates the product generations). The designers are guided to adjust their expectations based on those 'facts' that are cross-examined in both interpreted and physical worlds, and hence make more informed design decisions. The inconsistency among the expected product, virtual product, and physical product (with respect to their function, behaviour and structure) are gradually minimised. Lastly, the physical product is made more personalised and intelligent through various 'lessons' learned from the virtual product. Last but not least, the zigzagging interactions between the virtual product and physical product lead to a coevolution for the digital twin.

It should be noted that, unlike the complex systems, consumer products involve intensive back-and-forth interactions between product and user. Since DT is a real-time digital representation of the physical product, it can directly interact with end users and provide not only real-time product state information but also timely recommendations of utilisation, maintenance and upgrade services. In that regard, Thorsten et al. proposed the notion of 'product avatar', which is a digital representation of the physical product (Hribernik et al. 2006), in order to interact with the end user on Facebook. Moreover, rich information is readily available on the Internet to build user profiles. In some sense, a user profile can be regarded as the digital representation of a certain user in the digital world. Therefore, it is also interesting to investigate the interplay between user profile with digital twin.

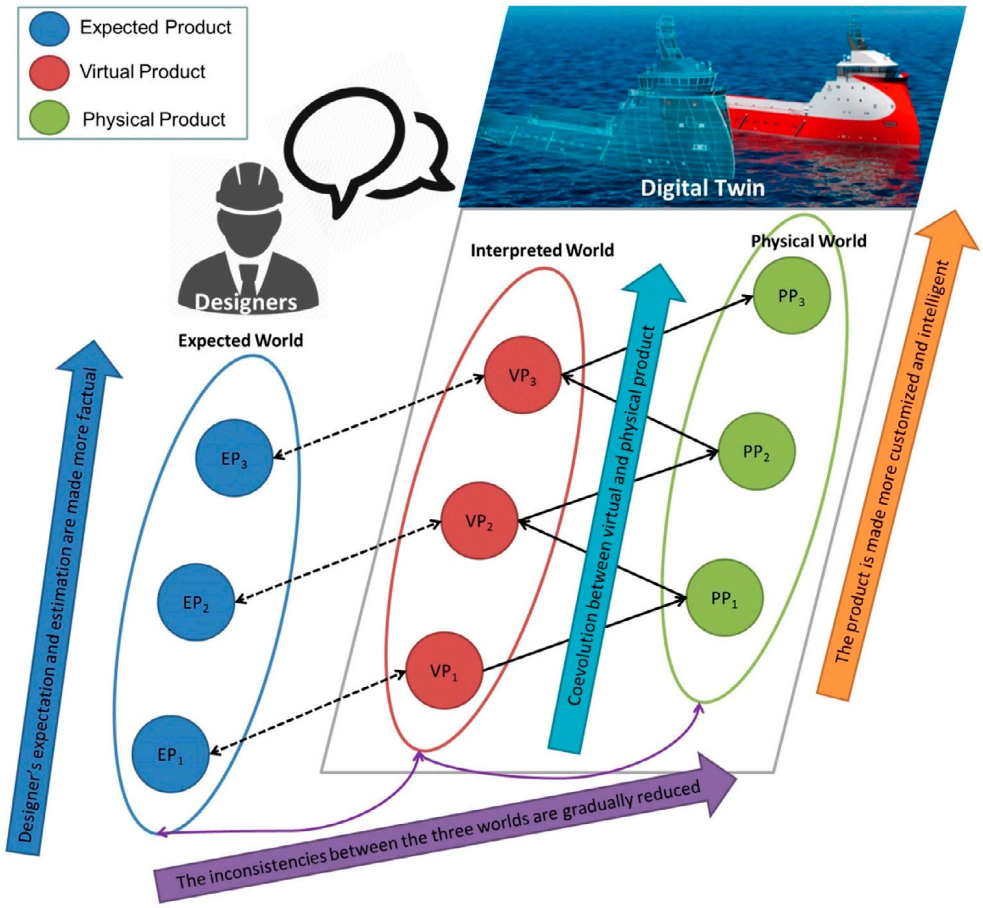

Figure 6. Collaborative design between designers and digital twin in DTPD.

4.3.3 *Data lifecycle management in DTPD*

From the perspective of data science, digital twin can be regarded as an information filtering and integration system. On one hand, DT functions to filter the massive amount of data towards useful information that can be directly queried for design operations. On the other hand, DT functions to integrate different types of data to discover hidden patterns and cross-check analysis results. As illustrated in Figure 4, a typical data lifecycle includes data collection, data transmission, data storage, data integration, data processing, data cleaning, data analysis and data mining. Through such a lifecycle, raw data are converted to useful information that can be directly queried by designers to support their design decision-making. Some steps relevant to DTPD are illustrated as follows.

4.3.3.1 *Data collection.* Data collection is the first step of the whole process. In DTPD, the physical product data are collected by sensors from both consumers and products or extracted through interviews, downloads from online sources or reading documentation (Jin et al. 2015).

4.3.3.2 *Data integration.* According to the definition of DT, data from different sources, formats and characteristics must be integrated for next step. Data integration involves combining data that reside in different sources and providing users with a unified view (Lenzerini 2002).

4.3.3.3 *Data cleaning.* Data cleaning means the process of identifying, removing and correcting various kinds of errors included in the data-set of DTPD. Some common tasks of data cleaning include record matching, identification of inaccurate data, evaluation of overall quality, deduplication and column segmentation (Baheti and Gill 2011).

4.3.3.4 *Data mining.* The goal of the data mining process in DTPD is extracting information from a data-set and transforming it into a visualisation structure for further use (Keivanpour and Ait Kadi 2017). Aside from the raw analysis step, it involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualisation and online updating (Chakrabarti et al. 2006).

4.4 *Digital twin-driven product design*

4.4.1 *DT-driven task clarification*

In the task clarification phase, customer needs are translated into functional requirements under design constraints, where DT serves as an 'interpreter' to facilitate the 'translation' process.

Firstly, DT serves to deepen designers' understandings about target customers and customer voices. So far, the vast majority of customer-related data are collected from various e-commerce, social and searching platforms based on the Internet. Increasingly, customer-related data (e.g. bio activities and personal habits) can be directly collected from various smart devices (e.g. smartphone, smart watch, smart coffee machine) based on the Internet of Things. The customer-related information is useful for enhancing product personalisation and adaptability. The massive customer voices must be processed to be useful for task clarification (Xue et al. 2012). For example, a function recommender system can be incorporated into DT to recommend exciting new functions for a target product through analysis of readily available customer reviews published on e-commerce platforms.

Secondly, DT serves to guide designers to rationally formulate functional requirements. Functions can be represented as the input–output transformation of energy, materials and signal, all of which can be possibly detected by different sensors and analysed by DT. Furthermore, DT can provide key information such as how often the function is used, how long it is used every time, how many customers use the function, etc. According to the Axiomatic Design Theory, the information content of a product or its components can be calculated by measuring the overlapping area between the system curve and design range. The design range is determined by designers based on their estimations of the system curve. Based on the information directly collected from the physical product, a system curve (i.e. variance, mean value, bias) can be drawn in a much more precise manner. As a result, designers can adjust the design range accordingly.

Thirdly, DT serves to provide designers with affordance information. By definition, affordance refers to a possible action on a product performed by users in the real world. A fundamental difference between affordance and function is that the former is necessarily dependent on a particular artefact, whereas the latter can be artefact-independent (new functions can be formulated purely based on customer needs or abstracted entirely based on artefact behaviours). Traditionally, designers can only obtain affordance information through the time-consuming ethnographic observations and contextual inquires. Since affordance concerns with product–customer interactions, made possible by the DT, certain affordance information can be directly collected from various smart products. In the future, through the VR technologies, it is even possible to obtain affordance information based on customer behaviours in a completely virtual environment.

Last but not least, DT serves to clarify various design constraints imposed on a particular product. Since DT is oriented from product lifecycle management, it is potentially capable of synthesising a comprehensive collection of design constraints imposed by all the relevant stakeholders. Some examples of constraints include weight, size, budget, schedule, manufacturing capability, environmental standards, safety standards and government regulations. In the following conceptual design phase, designers can further validate whether and to what extent a new concept complies with various constraints through virtual verification. In the future, it is also interesting to explore how and in what ways constraint information can be collected by means of sensors directly from the physical product. For example, it is possible to utilise a car's rear camera to detect various parking constraints in the physical world.

4.4.2 *DT-driven conceptual design*

In the conceptual design phase, the functional requirements are mapped to the design parameters, working principles and physical structures. Conceptual design involves concept generation and concept evaluation. A good design concept must be logically feasible, functionally simple and physically certain. DT plays the role in identifying design opportunities and evaluating new design concepts.

Firstly, DT serves to facilitate designers to identify system contradictions within a product. In TRIZ, Altshuller prescribed 39 parameters (e.g. weight, speed, force, pressure, temperature, illumination, energy, etc.), and many of them can now be precisely measured by advanced sensors. Based on the correlation analysis of data collected from different sensors that essentially represent different TRIZ parameters, designers are enabled to understand not only where the contradictions are but also how bad the contradictions are. Compared to the current practice of letting designers manually identify contradictions purely based on their abstract thinking (Cavallucci and Khomenko 2006), DT enables designers to identify contradictions in a more informed fashion.

Secondly, DT serves to capture various uncertainties associated with a product. Uncertainties are caused by incomplete and/or unknown information. Any product's actual performance in the physical world can be affected by a number of uncertainties, which could arise at different phases throughout a product's lifecycle (e.g. production, distribution, usage, maintenance, recycle, etc.). In particular, the aggregation of many uncertainties may significantly affect a product's function, behaviour, and structure. DT serves to capture various uncertainties in the physical world and simulate them in the digital world, so that more robust design solutions can be generated and virtually validated against the uncertainties. In addition, once the DT is capable of interacting with customers, the uncertain information can also be provided to the end users in real-time.

Thirdly, DT serves to identify and diagnose various complexities associated with a product. According to Suh's classification (Suh 1999), there are four types of complexities that are resulted from unwise design decisions, namely time-independent real complexity, time-independent imaginary complexity, time-dependent combinatorial complexity and time-dependent periodic complexity. It should be noted that Suh considered complexity as a measure of uncertainty of fulfilling functional requirements. Since time is utilised as a differentiating factor to categorise complexities, it is possible for DT to detect different kinds of complexities based on their correlations with real-time data. For example, if a complexity is commonly experienced by all customers at all times, it is likely to be a time-independent real complexity. In contrast, if a complication is only reported by a limited number of customers all the time, it is likely to be a time-independent imaginary complexity. Moreover, based on the real-time data, DT can suggest corresponding actions to resolve complexities, for example, by resetting the functional periodicity (e.g. electrical periodicity and information process periodicity (Suh 1999)).

Finally, DT serves to incorporate a variety of contextual information into concept generation. For the consumer products, some generally applicable contextual information include, for example, time (i.e. when the product is being used), location (i.e. where the product is being used), how (i.e. the activities the product is used to perform), who (i.e. profile of the user) and environmental conditions (e.g. temperature, light, sound, humidity). By comparing the virtual context and physical context, designers can deepen their understandings of the ideal and real contexts in which a product is used, and such understandings are especially important for designers to improve a product's adaptability.

4.4.3 *DT-driven virtual verification*

The purpose of evaluation is to reduce the inconsistencies between the actual and expected behaviour, making the actual behaviour of the product as consistent as possible with the expected behaviour. The DT-based virtual verification involves various data from the physical world. Physical data are collected based on various sensors installed on a real product. Physical data include both historical data and real-time data. Driven by the incoming physical data, the virtual model is progressively upgraded and optimised. Because of the abundant historical data and iteratively upgraded virtual model, a small batch of production is no longer needed. Traditionally, new products need to be repeatedly tested before mass production. With digital twin, designers can easily forecast product behaviour through virtual verification without having to wait until the product is produced to modify the design scheme, which makes it more effective to reduce inconsistencies between expected behaviour and actual behaviour, and greatly shorten design cycles and reduce costs.

However, a working structure cannot be assessed until it is transformed into a more detailed representation which usually involves selecting raw materials, producing a rough dimensional layout and considering technological possibilities (Pahl et al. 2007). Only then, in general, is it possible to evaluate the essential aspects of a solution principle. It will not be a constraint when employing the digital twin.

In virtual verification, designers can debug and predict directly in digital twin model by taking full use of various data. Taking this method can accurately find the defect of design and take rapid changes which make the improvement of the design efficiently by avoiding tedious verification and testing. In the traditional model, the effectiveness and feasibility of the design can't be evaluated until the small batch is finished. It will not only extend the design cycle, but also greatly increase the cost of time and money. If the designers select the digital twin model, the quality of any accessory will be predicted by direct prediction of the digital twin model. Digital twin-driven verification of virtual products can take full advantage of equipment, the environment, the material, and the historical data of the previous generation. This method can test for the existence of design flaws and find the cause, making sure that the redesign will be quick and easy. Moreover, it can greatly improve design efficiency by avoiding lengthy verification and testing.

Constrained by many factors such as time, cost and human resources, it is difficult for one to conduct a comprehensive testing of the product under various environments before the product is released in the traditional design model. So, the designers define product performance in terms of product performance in general to simplify the testing condition, which may result in a limitation in product's performance and scope of application. Digital twin can reflect the physical space to virtual space, and the virtual space can keep ultra-high synchronisation and fidelity with the physical space. Therefore, digital twin records all the historical data of product life cycle, including data generated from the using process and the environment. As a result, the designers can quickly and conveniently know the product performance and guide the product design comprehensively using the data referred above to set-up all kinds of testing conditions in virtual space and testing virtual product in various environments.

In addition, digital twin cannot only describe the behaviour, but also propose solutions related to real systems, in other words, it can provide operations and services to optimise the auxiliary system and predict physical objects based on virtual models. Thus, using digital twin technology, designers can create vivid simulation scenarios, effectively apply simulation tests to prototypes, and accurately predict the actual performance of physical products as accurately as possible.

5. Case study: digital twin application in bicycle design

5.1 *Bicycle-sharing: a new paradigm for bicycle use under new IT background*

Recently, a new paradigm for bicycle use is rising in China, which is called 'Bicycle-sharing'. The most famous companies are OFO and Mobike bicycle. They provide the users with bicycle as a kind of public service, and charge some cycling fee at a very cheap price, e.g. 0.5 RMB one time. The working flow of shared-bicycle paradigm is shown in Figure 7. When a user wants to find a shared bicycle, he only needs to open the Mobike apps in his IPhone, then he will be told where to get a bicycle because of the automatic positioning function service. Next, after the shared bicycle is found, he scans the QR code on the plate. The password will be sent to his app interface, or the smart lock of the bicycle will automatically unlock. Then, he could ride the bicycle to his destinations. Last, when the user arrives at the destination, he just locks the bicycle lock and pays for riding via app. 'Bicycle-sharing' is a success case using New IT

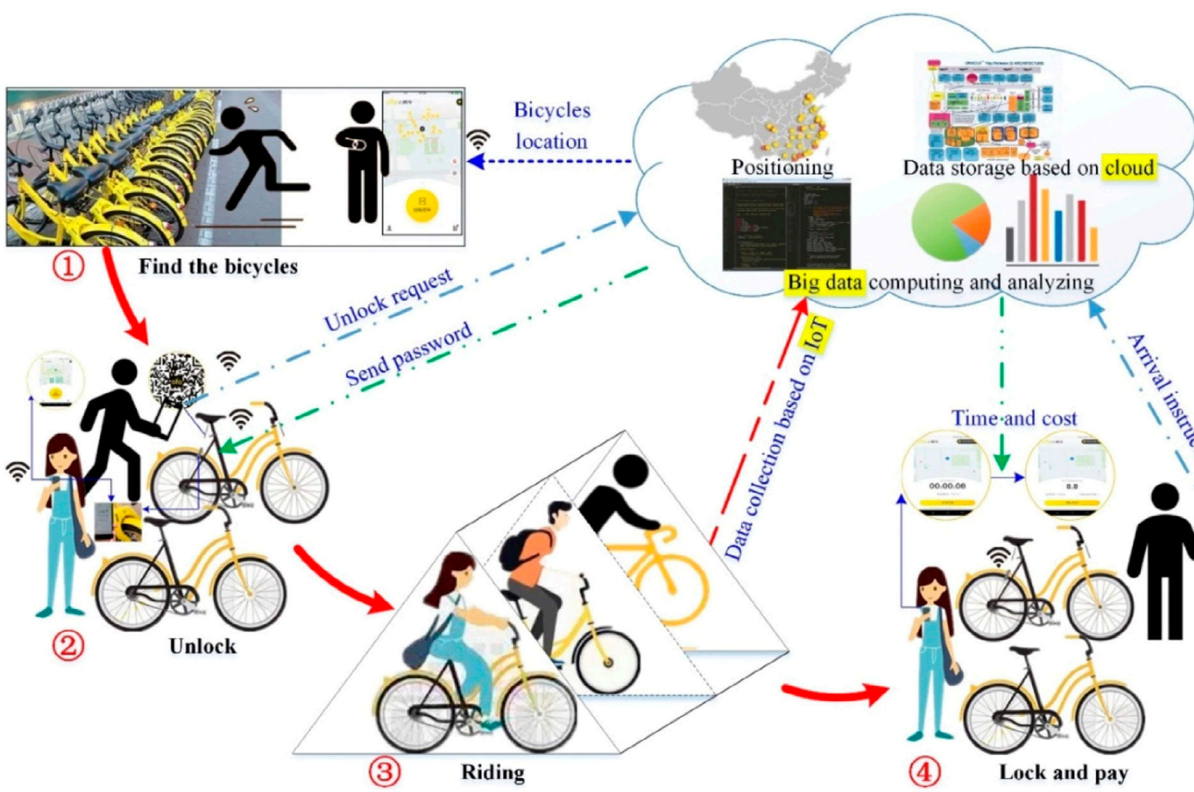

Figure 7. The use flows and interaction mode of shared bicycles.

in public transportation. A lot of new ITs are used in 'Bicycle-sharing'. For example, the real-time and physical-related bicycle data (e.g. location, route, status, etc.) can be collected and communicated using IoT during riding. Based on cloud computing, all the shared bicycles' data storage, processing and analysis (such as computing, statistics and positioning, etc.) are implemented and finished in a 'Sharing Cloud'. Mobile Internet connects the users, shared bicycles and 'Sharing Cloud'. For instance, the users send the unlock request and arrival instruction to the 'Sharing Cloud'. The 'Sharing Cloud' would feed the location, the password, as well as the time and cost back to the users. The user comments are also collected from apps through smart terminals (e.g. smart phones, PADs, etc.). With big data analysis, the bicycles are becoming smart, and are used more conveniently and efficiently. New IT has injected fresh energy to bicycles. Massive data of bicycles are acquired and analysed via New IT in the new paradigm of 'Bicycle-sharing'. These data would help build the digital twin for bicycles and support designer for bicycle redesign.

5.2 *Digital twin-driven bicycle redesign*

Traditional bike design methods are mostly based on designers' knowledge and experience. However, the digital twin paves a new way for bicycle design. As shown in Figure 8, the digital twin for bicycle primarily consists three parts:

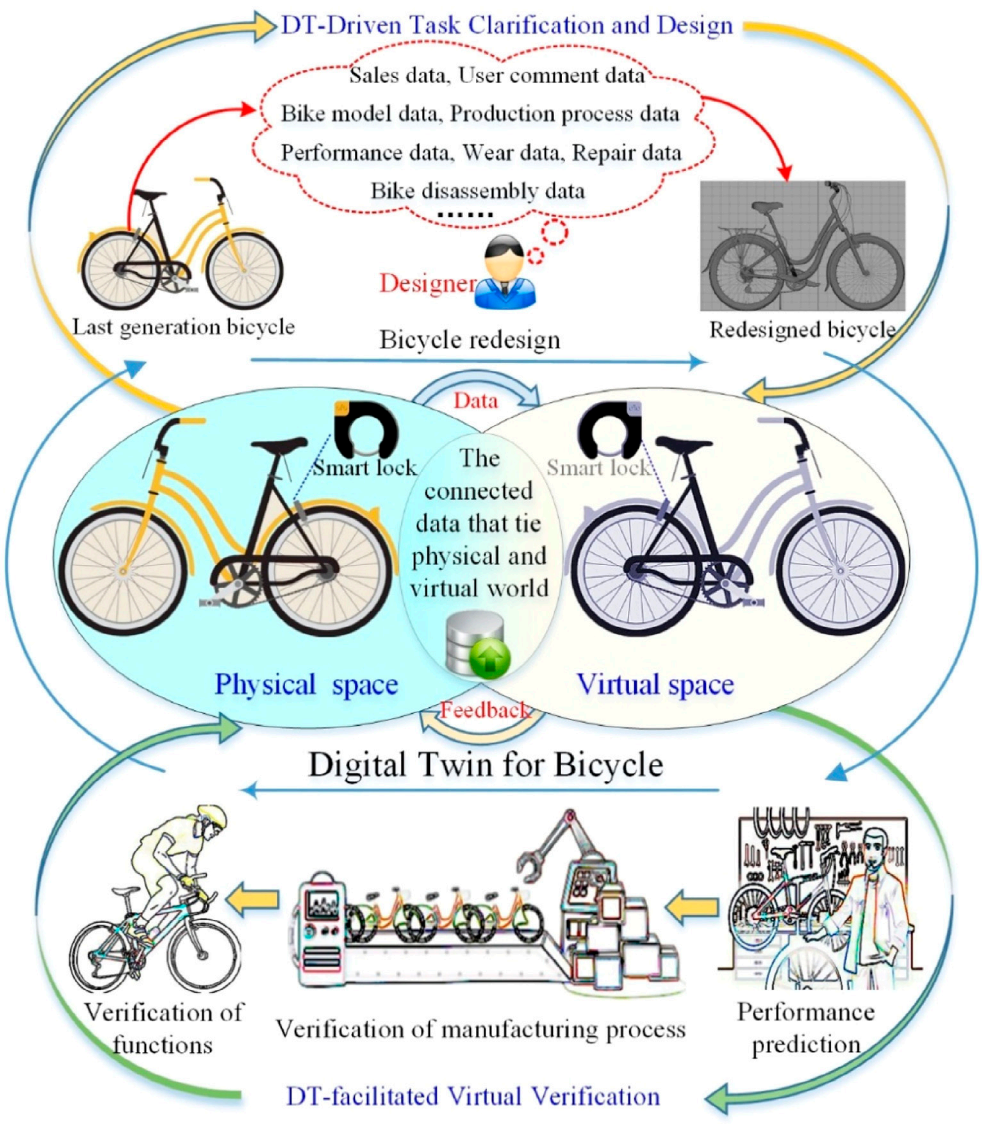

Figure 8. DT-driven bicycle design and virtual verification under DTPD.

the virtual bicycle in the virtual space, the real bicycle in the physical space, and the interactive data between virtual and real bicycle. Based on IoT and mobile Internet, the virtual space could obtain a lot of data for the real bicycle, such as the speed, acceleration, wheel pressure, user comments, as well as the relevant environment data, etc. With these data, a virtual model can be established in the virtual space, which is the real mapping and reflection of the real bicycle. During the entire bicycle lifecycle, the virtual space would coevolve with the physical space. The virtual space would constantly collect, analyse and accumulate the data from the physical space, which could be used for the design or redesign of next generation bicycle.

The lifecycle of bicycle includes the design, manufacturing, sales, maintenance and retirement, etc. As shown in Figure 8, designers can obtain all the data of the last generation bicycle through the digital twin, to redesign the next generation. In the *task clarification phase*, the designers could easily access the online user comments, rather than the questionnaire or telephone interview. By analysing these comments, the designers can discover the design flaws of the bicycle, the particular needs of the users, and the vision for the future development. Through the translation process based on the digital twin for the bicycle, the user demands are interpreted into functional requirements. For example, most of the shared bicycles do not have the backseats. So many users may make a request for the backseats, which are useful for carrying something or a friend. As a result, the designers would have a basic judgement that the design of the backseats should be considered.

Once the functional requirements are confirmed by the designers, they would be mapped to design parameters, working principles, and physical structures based on the digital twin for the bicycle. Taking the backseat design as example, the designers would compare the difference between the actual and the expected backseat, to deepen their understandings of the ideal and real contexts. With the digital twin-driven product design method, the designers could comprehensively compare and analyse the parameters of the bicycle, the height distribution of the user crowd, and the user comments about the use purpose. Eventually, the bicycle's backseat is designed to be an appropriate height based on the digital twin for the bicycle. Besides, as the backseat should be able to bear a certain weight, so the material selection of the backseat should be considered at the same time, as well as the shape, area, etc.

As shown in Figure 8, bicycle is still taken as an example to illustrate the virtual verification in DTPD, which includes three steps, namely *performance prediction, verification of manufacturing process and verification of functions*. In the performance prediction, the designers use the maintenance and failure history information, as well as the knowledge of engineering and material science, to simulate the various operations and predict the change of the performance indicators. For example, the digital twin for the bicycle could predict the change of the backseat wheels and tyre pressure, etc., when more weight is put on the backseat. Next, in the verification of manufacturing process, designers use the digital twin model to simulate the manufacturing process of bicycles. On one hand, the specific links are optimised. Through simulation in virtual space, designers could determine the optimum process with the shortest time and print out the production instructor. On the other hand, the high defective rate steps would be reduced by accurate simulation. For example, through the simulation about key steps and a data relation mapping about material and equipment, the fractures of some components could be reduced. At last, the designed functions are verified. For one thing, the ergonomics of the bike is verified by integrating the customer's physical data, and possible problems in design would be found. For another, the functions of the bicycles under different circumstance are verified by integrating various environment data. For example, the brake distance, tyre wear speed, backseat life, etc., are tested in different weather condition through the digital model. In the virtual verification, once the unqualified problems are found, the design scheme would be improved through iteration of design process.

The digital twin for bicycle would facilitate the iterative optimisation of bicycle design. The design cycle, cost, etc., would be greatly decreased, and the design efficiency, satisfaction, security, etc., would be generally improved.

6. Conclusion and future works

Over the last decade, dramatic advances have taken place in the capabilities and technologies of the data collection of the physical product as well as the creation and representation of the virtual product. However, the connection between the two data sources has lagged far behind their respective development, which hinders the applicability of the digital twin to various activities in industry and manufacturing.

Motivated by this need, this paper presents a comprehensive design framework that focuses on connecting the physical product and virtual product. DTPD is expected to be most useful for the iterative redesign of an existing product instead of the novel design or a completely new product. It should be noted that most of the selected design methodologies (e.g. FBS and TRIZ) that constitute DTPD are proven to be more useful for redesigning existing products. Nevertheless, it unnecessarily means that DTPD cannot be adapted for designing completely new products, which is one direction of future work.

Digital twin enables designers to fully customise, easily compare and effectively assess. Designers can better understand customer requirement through the data and information of customer reviews and usage habits. Moreover, they can compare the performance of virtual products under different circumstances to ensure the inconsistency between the actual behaviour and the desired actual of the manufactured product is decreased to the minimum. Finally, digital twin can accelerate design cycle by avoiding lengthy testing attributed to the assessment of virtual product.

This paper investigated the framework and application of DTPD. Future work will concentrate on the following aspects:

(1) Data storage and transfer in Digital Twin: It is quite a hard and serious job to ensure intact data storage and transfer in DT since any small lack may contribute to severe mistakes, in which circumstance, the speed of data transmission becomes particularly important as new data is generated every time and the data source is also extremely large. In addition, it is equally important to ensure the correctness and security in the process of transmission process.
(2) Visualisation of digital twin: Data are the constituent element of the digital twin, and the results obtained by analysing the data are indispensable. However, it is more important to translate useful information into intuitive expressions. For example, building a digital twin model in the virtual space based on a real bicycle, when someone sits on the bike, the sensors can detect the changes in tyre pressure, whether can the changes occur on the virtual bike to show the corresponding of the deformation with the real bike changes is more interesting research issue.
(3) Collaboration based on digital twin: Collaborative design has long been a challenge for manufacturers (Wang et al. 2002), while digital twin paves the way for new modes of design collaboration. Firstly, DT will greatly facilitate customer involvement (i.e. the endeavour of engaging customers in product design) by presenting customers with both physical and virtual products. Secondly, DT will support global product development by the virtual design teams, through the collection, convergence and integration of physical data obtained from the same product sold to different markets. Finally, product-oriented DT and production-oriented DT can collaborate with each other to enhance the effectiveness of ‘design for manufacturing’.

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