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Digital Twin in Industry: State-of-the-Art

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***Abstract*— Digital Twin (DT) is one of the most promising enabling technologies for realizing smart manufacturing and Industry 4.0. DTs are characterized by the seamless integration between the cyber and physical spaces. The importance of DTs is increasingly recognized by both academia and industry. It has been almost 15 years since the concept of DT was initially proposed. To date, many DT applications have been successfully implemented in different industries, including product design, production, prognostic and health management, and some other fields. However, at present, no paper has focused on the review of DT applications in industry. In an effort to understand the development and application of DTs in industry, this paper thoroughly reviews the state-of-the-art of the DT research concerning the key components of DTs, the current development of DTs, and the major DT applications in industry. This paper also outlines the current challenges and some possible directions for future work.**

***Index Terms*— Digital Twin, data fusion, industry application, modeling.**

I. Introduction

SMART manufacturing is one of the strategic priorities shared by all the major manufacturing initiatives such as Industry 4.0 and Industrial Internet. Sensors and data transmission technologies are increasingly used to collect data throughout different stages of a product's lifecycle, including product design, manufacturing, distribution, maintenance, and recycling. Big data analytics can make full use of the data to discover failure causes, streamline a supply chain, optimize product performance, and enhance production efficiency [1]. One of the key challenges for smart manufacturing is to connect the physical and virtual spaces. The rapid development of simulation, data acquisition, data communication, and other advanced technologies have triggered greater interactions, than ever before, between the physical and virtual spaces. The importance of Digital Twin (DT), which is characterized by the cyber-physical integration, is increasingly emphasized by both academia and industry. DTs and big data analytics are mutually reinforcing technologies on account of smart manufacturing. DTs can integrate the physical and virtual data throughout a product lifecycle, which leads to a huge volume of data that can be processed by advanced analytics. Then the analysis results can be used to improve the performance of product/process in the physical space [2]. This paper aims to review the state-of-the-art of DTs in industry.

DTs are being applied in more and more areas of different industries [3]. This is evidenced by the increasing publications and patents on DTs during the past few years. DTs enable manufacturers to make more accurate predictions, rational decisions, and informed plans. Tao et al. suggested 13 potential DT applications in the areas such as product design, production planning, assembly, man-machine interaction in a workshop, etc. [4]. DTs can supply a cyber-physical manufacturing system with information about a real-world situation and operating status. Such information can enhance a manufacturing system's intelligence regarding analytical assessment, predictive diagnosis, and performance optimization. DTs can, therefore, be regarded as an important driver of the paradigm of smart manufacturing. Moreover, DTs can trigger the next wave in simulation. The development of simulation has gone through three stages to date: (1) the simulation of a specific device based on special tools; (2) the simulation of a generic device based on standard tools; and (3) the multi-level and multi-disciplinary simulation. The advent of DTs presents an exciting possibility of real-time simulation throughout a product lifecycle [5].

Despite the increasing popularity of the DT research, no efforts have been devoted to reviewing the DT applications in industry. The concept of DTs was initially introduced in 2003 [6], and this paper covers all the relevant journal and conference articles published from January 2003 to April 2018. The concept of DT was initially introduced in 2003 [6]. This paper covers all the relevant journal and conference articles published from January 2003 to April 2018. Table 1 summarizes the reviewing methodology in terms of the searching criteria, search strings, paper selection procedure. To further improve reliability, three searchers independently searched the aforementioned databases for three times. Then the three researchers compared and compiled their findings. As a result, more than 100 papers were initially found. Next, the authors evaluated the relevance of every paper to the research topic (i.e., the applications of DTs in industry) based on the contents of abstract, introduction, and conclusion of every paper. For example, although certain papers contained

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the keywords of "digital" or "twin", they unnecessarily meant "digital twin" as a whole. Therefore, such papers were excluded from the further review. In this way, a total of 50 papers were included in this paper. Eight patents were found in a similar way. The authors read through all the included papers and patents to summarize their common grounds and unique propositions.

TABLE I
METHODOLOGY ON SCREENING PAPERS

Searching Index	Specific Content
Database	ProQuest, ScienceDirect, Scopus, IEEE Xplore, and Google Scholar.
Article Type	Scientific/technical articles published in peer-reviewed journals and conferences
Search Strings	"Digital twin", "digital twin design", "digital twin manufacturing", "digital twin control", "digital twin optimization", "digital twin service", "digital twin prognostic", etc.
Search Period	From January 2003 to April 2018
Screening Procedure	The relevance with the research topic as judged by the contents of abstract, introduction, and conclusion of every papers.
Classification Scheme	Framework of current development of DTs in industry (as shown in Section III) and industrial applications of DTs (as shown in Section IV)

Completeness is the priority of a review work. An iterative process has been followed to produce a complete list of keywords. The highly cited articles were leveraged to build an initial list of keywords. Next, new keywords were added to the list according to search process when the keyword list could not find more relevant articles in the corresponding research area. Multiple databases were searched to increase the variety of data source. The keywords were all abstracted by the authors who are experts in cyber-physical system, smart manufacturing, and manufacturing service, which is useful for reducing the bias.

Based on a comprehensive review of 8 patents, 50 articles, and the best practices of 6 leading companies that are collected from ProQuest, ScienceDirect, Scopus, Google Scholar, IEEE Xplore, Google Patent, this work aims to converge different perspectives to answer five research questions: (a) What is DT? (b) What is the current development of DTs? (c) Which industrial areas are most applicable for DTs? (d) How to implement DTs? (e) What are the main challenges in deploying DTs?

The rest of this paper is organized as follows. Section II reflects the history of DTs. Section III outlines the current development of DTs. Section IV presents the DT applications in industry. Section V summarizes the state of the art and draws some provisional conclusions. Section VI summarizes the contributions of this work.

II. CONCEPT AND A BRIEF HISTORY OF DTS

A. *The concept of DTs*

The first appearance of the DT dates to 2003, when Grieves introduced the concept, for the first time, in his course on "Product Lifecycle Management (PLM)" [6]. Although the concept was insufficiently specific at that time, a preliminary form of the DT was proposed to include three parts: physical product, virtual product, and their connections. The enabling technologies of DTs experienced exponential growth since then. In 2010, the concept of DTs was revisited by NASA (National Aeronautics and Space Administration), which defined the DT as a multi-physics, multi-scale, probabilistic, ultra-fidelity simulation that reflects, in a timely manner, the state of a corresponding twin based on historical data, real-time sensor data, and physical model [7]. DTs become a popular research topic. According to Gabor et al. [8], the DT is a special simulation, built based on expert knowledge and real data collected from the existing system, to realize a more accurate
simulation in different scales of time and space. According to Maurer [9], the DT is a digital representation that can depict the production process and product performance. The meaning of DTs becomes increasingly concrete since then, leading to some special notions such as the Airframe Digital Twin (ADT) and Experimental Digital Twin (EDT) [10, 11].

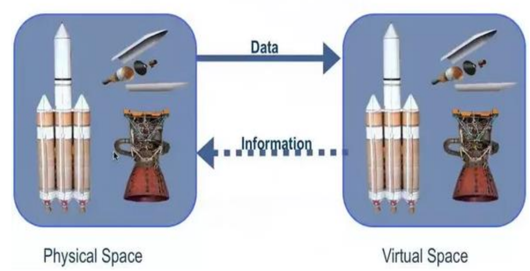

Fig.1. Three parts of the DT [6]

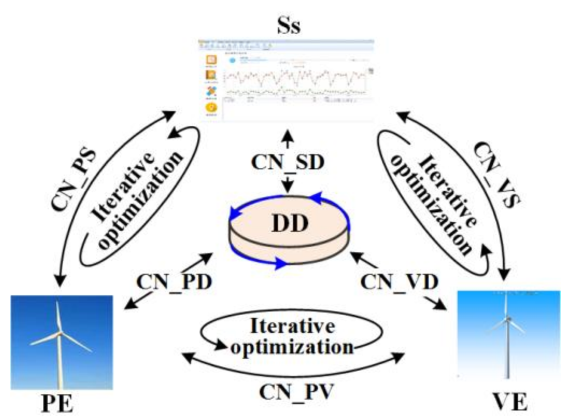

Fig.2. Five parts of the DT [12]

There are different understandings of DTs. Some researchers [5,8,9] believe that the DT research should focus on simulation. Others [2-4,6] argue that the DT contains three parts: physical, virtual, and connection parts. Fig 1 illustrates the basic framework, in which, the virtual space is mapped to the physical space through the connection part that exchanges data and information [6]. On the basis of the three parts, Tao and Zhang proposed that a complete DT should include five parts: physical part, virtual part, connection, data, and service [12]. The framework is shown in Fig 2, where PE represents the physical entity; VE represents the virtual entity; Ss

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represents the services for both PE and VE; DD stands for the DT data; CN means the connection of different parts. The five parts are equally important for DTs. The physical part is the basis of building the virtual part. The virtual part supports the simulation, decision-making, and control of the physical part. Data lies in the center of DTs, because it is a precondition for creating new knowledge. Furthermore, DTs lead to new services that can enhance the convenience, reliability, and productivity of an engineered system. Finally, the connection part bridges the physical part, virtual part, data, and service.

B. History of DTs

The history of DTs is rather brief, which is largely due to the technological limitations during its early development. The theoretical development of DTs went through three stages: formation, incubation, and growth. The first appearance of DTs could date to the presentation made by Grieves in 2003, which was deemed to be the origin of DTs [6]. Few articles were published in this period. Hence, it is classified as the formation stage. From 2003 to 2011, the rapid development of communication technology, Internet of Things (IoT), sensor technology, big data analytics, and simulation technologies contributed to the rise of DTs. In 2011, the first journal article was published, which elaborated how DTs were useful for predicting the aircraft structural-life [13]. In 2012, NASA formalized the definition of DTs and envisioned its prospects in the aerospace industry [7]. More and more efforts were devoted to the DT research since then. Therefore, this period is regarded as the incubation stage. In 2014, the first white paper was published, which reflected the growth of DTs from one conceptual idea to numerous practical applications [6]. The finding that DTs would be applicable to many different industries beyond the aerospace industry further promoted its development. In 2017 and 2018, Gartner classified DTs as one of the top ten most promising technological trends in the next decade.

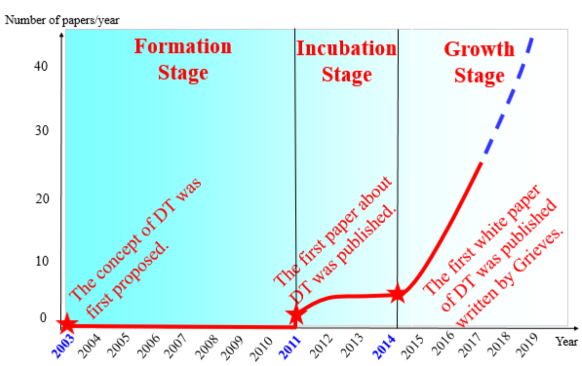

Fig.3. Development Trend of DT Research

Fig. 3 illustrates the number of conference and journal papers on DT since 2011, which reflects the history of DTs. At first, the concept was proposed in 2003. From 2003 to 2011, the technological foundations were far from mature to support the development of practically viable DTs. On the other hand, however, cloud computing, big data, IoT, and sensor technologies experienced a rapid growth. In other words, the revival of DT research was triggered by the technological advancement in other areas. Moreover, the significance of DTs was underestimated at the time largely due to the lack of long-term visions of how DTs would influence, if not revolutionize, industrial applications. Because of the aforementioned reasons, there were few publications on DT from 2003 to 2011. In 2012, NASA showed the superiority of DTs and gave a more specific definition. More and more DT applications have appeared since then. As illustrated in Fig 3, the research on DTs is drawing increasing attention in the academia. Considering the current momentum, it is expected that the research and application on DTs will experience another surge during the next 3-5 years. Therefore, it is argued that the DT research now enters the rapid growth stage.

III. Current development of DTs in industry

A. Theoretical foundations of DTs

The theoretical foundations of DTs come from different disciplines such as information science, production engineering, data science, and computer science. The most relevant theories are reviewed as follows, which are divided into four parts: (1) DT modeling, simulation, verification, validation, and accreditation (VV&A), (2) data fusion, (3) interaction and collaboration, and (4) service.

DT modeling, simulation, and VV&A: DT modeling involves physical modeling, virtual modeling, connection modeling, data modeling, and service modeling. Theories of physical modeling are useful for extracting, defining, and describing the key features of a physical object. Theories of virtual modeling are useful for building a virtual representation of a physical entity, which will depict the same features and behaviors in the virtual space. The virtual model should be a mirror-reflection of the physical model. Theories of connection modeling are useful for maintaining a constant connection between the physical model, virtual model, data model, and service model. A typical connection model includes data transmission, data format conversion, data source protection, etc. Theories of data modeling are useful for data definition, operation procedure definition (e.g., security checks), data storage, etc. Through data modeling, data is stored according to certain criteria and logic, which can facilitate data processing. Theories of service modeling are useful for the identification, analysis, and upgrade of services. Simulation theories are useful for operation analysis (e.g., structural strength analysis and kinetic analysis) in a simulation environment. VV&A can validate the veracity of a virtual model and provide a confidence level by checking model error, algorithm error, and hardware error.

Data fusion: data fusion involves three processes -- data pre-processing, data mining, and data optimization. Firstly, DTs must handle a massive volume of data, including physical data, virtual data, and fusion data between them. Therefore, it is necessary to perform a data pre-processing that includes data cleaning, data conversion, and data filtering. Next, the pre-processed data is mined through fuzzy sets, rule-based reasoning, intelligent algorithm, and other advanced data analysis methods. Finally, theories of data optimization are useful for dealing with the iterations of physical data, virtual data, connection data, service data, and data fusion, to discover the data evolution laws.

Interaction and collaboration: all DT parts must interact and collaborate with each to tackle complex problems. DTs involve three kinds of interaction and collaboration: physical-physical, virtual-virtual, and virtual-physical. Through physical-physical interaction and collaboration, multiple physical entities can communicate, coordinate, and collaborate with each other to perform a complex task that cannot be performed by any individual device. Through virtual-virtual interaction and collaboration, multiple virtual models can be connected to form a network for information sharing. Through virtual-physical interaction and collaboration, the virtual model can be optimized in synchronization with the physical object, while the physical object can be dynamically adjusted based on direct orders from the virtual model.

Service: relevant theories of service include service encapsulation, service matching and searching, quality of service (QoS) modeling and evaluation, service optimization and integration, and fault-tolerance management. Service encapsulation enables DTs to invoke different functions by using a uniform information template or interface. Service matching and searching enable DTs to choose a suitable service based on client requirements. QoS modeling and evaluation, including quantitative evaluation algorithms and dynamic updating techniques, enable DTs to evaluate service quality. Service optimization is useful for selecting the best service. Service fault-tolerant management includes fault detection, fault determination, and fault-tolerant management approach [14]. Based on the service theories, DTs can prescribe the most suitable service, such as maintenance, to the client.

B. DT modeling and simulation

DT modeling and simulation are the basis of implementing DTs in practice. The prior studies of DT modeling framework, methodology, and technique are summarized as follows.

To build a digital model of a physical object, it requires information about geometry and material property. Emuakpor et al. integrated a nondestructive material determination technique, a water displacement method, and an iterative Ritz method for the DT to measure the material property. The technique was verified through an experiment on nickel alloys [15]. Majumdar et al. studied the behavior of synergistic materials based on the multi-physics modeling, which was used as the foundation for building the DT model [16].

Various researchers proposed different modeling architectures. Schroeder et al. proposed a new DT modeling architecture, which included five layers (i.e., device layer, user interface layer, web service layer, query layer, and data repository layer) to manage the DT data. They also developed an augmented reality system to display real-time information [17]. Schroeder et al. also proposed a DT data modeling method to exchange data between heterogeneous systems via AutomationML. The method includes three modeling stages: creating a model, defining the model, and developing an information system. A case study on industrial valves was conducted to validate the method [18]. Yun et al. proposed a modeling architecture for large-scale DT platforms that included a distributed cooperation framework and a communication mechanism [19].

Some researchers studied the workflow of building DTs. Moreno et al. used a commercial punching machine to showcase a step-by-step process of how to build a DT model. The process consists of five steps: (1) 3D modeling, (2) behavior extraction, (3) modeling of the interaction between a punching machine and moving elements, (4) operation modeling, and (5) simulation [20]. Haag and Anderl argued that DT is the digital representation of a physical object. They built the DT of a bending test bench, together with some specific modeling methods of a physical entity, digital entity, and connection [21]. DebRoy et al. proposed some applications of the DT of a 3D printing machine, such as heat transfer modeling, solidification modeling, property prediction, residual stress modeling, and distortion modeling [22].

DT model should be properly assessed to ensure its accuracy of reflecting the physical and virtual realities. Therefore, Smarslok et al. proposed a framework for error quantification and confidence assessment, including a set of metrics to measure the fidelity of DT models [23].

To date, no consensus has been reached regarding the DT modeling. None of the previous studies have considered all the five parts of DTs: physical part, virtual part, data, connection, and service modeling. Therefore, some generic modeling methods and processes are critically needed.

C. Data fusion

Data fusion is another key enabling technology because DTs must process a massive volume of data collected from a variety of channels such as machine, physical environment, virtual space, historical database, etc.

Tao et al. studied the data fusion for the DT of a shop-floor concerning the data of physical equipment, virtual model, data, and service. They also suggested some enabling technologies for the data fusion, including data generation, modeling, cleaning, clustering, mining, and evolution [24].

To realize data fusion, it is necessary to reduce the dimensionality of massive data. Ricks et al. proposed an order-reduction technique for DTs, which were applied in the High-Fidelity Generalized Method of Cells to enhance the efficiency of data processing [25]. Data integration is another key challenge. Cai et al. developed a method to integrate sensor data and manufacturing data as the basis of building the DT of a vertical milling machine, where sensor data was used to monitor machining operations and predict surface roughness [26].

Although there are many studies of data fusion, few of them were conducted in the context of DTs. Therefore, it is a promising direction to integrate data fusion and DT modeling.

D. Interaction and collaboration

At present, there are few studies on the interaction and

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collaboration for DTs, and only two papers were found. Rosen et al. argued that DTs could be used to make a production system continuously react to dynamic changes in physical space. Because the virtual space can gather all available data, such as, system sensors' data, surface properties, etc., in the physical space. At the same time, simulation can be used to validate operational procedures in virtual space. Thus, production units could execute orders automatically according simulation results [27]. According to Vachálek et al. [28], DTs could respond to an unexpected change in a manufacturing process more rapidly based on constant interactions between the virtual and physical spaces.

E. Service

The data-driven DT can reinforce services such as structure monitoring, lifetime forecasting, in-time maintenance, etc.

Above all, DTs can suggest service based on information. Seshadri and Krishnamurthy used the guided wave responses to make real-time predictions. They integrated sensor data, input data, and virtual data to depict a physical object and diagnose the damage size, location, and other failure information [31]. Cai et al. used the fused data from sensor and manufacturing process to monitor machine operation and predict surface roughness [26].

Bielefeldt et al. proposed a non-destructive evaluation (NDE) method to detect fatigue cracks. A case study on aircraft wings indicated that the method can effectively reduce the amount of calculations [29]. Bazilevs et al. developed the DT framework to predict fatigue damages, for which, the physical data and sensor data were integrated to improve prediction accuracy. The framework was validated based on a case study on wind-turbine blades [30].

The integration between DTs and service is a promising research direction. Not only new services can be enabled by DTs, but also existing services can be enhanced by the new data supplied by DTs. Many research problems, such as service searching & matching, QoS modeling & evaluation, and service optimization, should be addressed towards the future paradigm of DT-driven servitization.

IV. Industrial Applications of DTs

This section summarizes the industrial applications of DTs that have been reported through publications, patents, and the best practices of leading companies.

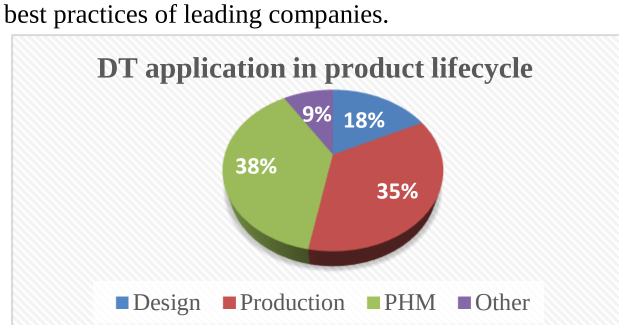

Fig.4. Distribution of DT publications in different areas

A. DTs in product lifecycle

Industrial applications of DTs focus on the areas of design, production, prognostic and health management (PHM), etc. where DTs demonstrate superiority over traditional solutions. Fig. 4 illustrates the distribution of publications.

1) DTs in product design

DTs can be used to design new products in a more responsive, efficient, and informed manner. Six papers were found in this area.

DTs are useful for product design. Zhuang et al. explored the application of DTs in product design and suggested some relevant theories and tools to implement the design-oriented DT [32]. Canedo considered DTs as a new way of managing the Industrial IoT. They argued that product design could be notably improved by adding the data feedback from DTs [33].

Design and production can be synchronized through DTs. Yu et al. proposed a new DT model to manage the 3D product configuration. They believed that the application of DTs in design could reinforce the collaboration between design and manufacturing [34]. Tao et al. proposed a DT-driven design framework because most of the design decisions were made without adequate interactions among the expected, interpreted, and external spaces. They envisioned some potential DT applications in different design phases such as product planning, conceptual design, and detailed design. A case study on bicycle design was conducted to instantiate the framework [35]. Schleich et al. put forward a new DT model to manage geometrical variations. They argued that the DT enabled designers to evaluate the quality of a product even at the early stage [36]. Zhang et al. proposed a DT-based approach to design production lines. A case study on the glass production line was used to validate the effectiveness of the approach [37].

2) DTs in production

DTs can make a production process more reliable, flexible, and predictable. The relevant applications are summarized as follows.

Above all, DTs can visualize and update the real-time status, which is useful for monitoring a production process. Weyer et al. predicted that DTs represent the next generation of simulation. Hence, DTs play a critical role in developing advanced cyber-physical production systems. They argued that, since DTs can synchronize the physical and virtual spaces, human operators can depend on DTs to monitor a complex production process, make timely adjustments, and optimize the process [5].

DTs can facilitate the adjustment of production operations based on both practical situation and simulation. Rosen et al. discussed the application of DTs in production operations. Since DTs could integrate a variety of data (e.g., environment data, operational data, and process data), autonomous systems can respond to state changes even during an ongoing operation [27]. Bielefeldt et al. combined the techniques of shape memory alloy (SMA), sensory particles, and finite element analysis to detect, monitor, and analyze the structural damage of commercial aircraft wings [29].

DTs are useful for the digitalization of production facilities and paradigm shift. Brenner and Hummel investigated the hardware and software requirements for implementing the DT in the European School of Business (ESB) Logistics Learning Factory to realize smooth interactions among human, machine, and product [38]. Tao and Zhang developed the DT of a shop-floor, which included the physical shop-floor, virtual shop-floor, shop-floor service system, and production data. Besides, they envisioned how DTs could serve intelligent manufacturing [12]. Ameri and Sabbagh described how a "digital factory", the DT of a physical factory, was developed in terms of capability extraction, supply chain, and digitalization process [39].

DTs can facilitate production optimization. Konstantinov et al. discussed how to adapt existing tools to enable DTs and applied vueOne (a set of virtual engineering tools) to optimize a magnet insertion process [40]. Uhlemann et al. reported that DTs had certain advantages, over the Value Stream Mapping, in production optimization [41]. Soderberg et al. discussed the DT application in real-time geometry assurance during the pre-production and production phases, based on a case study of the sheet metal assembly station [42]. Vachálek et al. focused on the DT-driven optimization of production lines. By connecting computer simulation with the physical system, the DT could reduce material waste and prolong machine lifetime [28].

DTs can also facilitate control. Uhlemann et al. presented a data acquisition approach to implement DTs in production systems. In this way, it realized the effective production control in real time [43]. Schluse et al. introduced the EDT to achieve a tight integration between the virtual and physical spaces and enhance simulation technology. They also considered the EDT as an enabler of simulation-based system engineering, optimization, and control [44].

3) DTs in PHM

At present, most of the DT applications are related to PHM. DTs were firstly applied in the PHM of aircraft. Tuegel et al. applied the DT to predict the structural-life of aircraft through multi-physics modeling, multi-scale damage modeling, integration of structural FEM and damage models, uncertainty quantification, and high-resolution structural analysis. They reported that the DT could facilitate the management of aircraft service life [13]. Tuegel also proposed a new concept, namely ADT, to maintain airframe, reduce uncertainty, and improve robustness. Besides, they suggested some technological challenges of implementing ADT, such as how to assign initial conditions, integrating different models, reducing uncertainties, etc. [10]. Li et al. built a DT model based on the Dynamic Bayesian Network to monitor the operational state of aircraft wings. A probabilistic model was built to replace the deterministic physical model. The DT model led to more accurate diagnosis and prognosis based on a case study of the leading edge of aircraft wings [45]. Zakrajsek and Mall built a DT model to predict the tire touchdown wear and the probability of failure. The DT model demonstrated many advantages over the traditional model in predicting the probability of failure for the varying sink rate, yaw angle, and speed [46]. Glaessgen and Stargel pointed out that the conventional methods used by the US Air Force were inadequate to meet the demand for real-time monitoring and accurate prediction. Therefore, they called for new DTs that could integrate historical data, fleet data, and sensor data. Moreover, they summarized some attributes of DTs (e.g., the ultra-high-fidelity model, the high computational and data processing ability, and vehicle health management system) as well as the benefits for PHM (e.g., increase of reliability, and timely assessment of mission parameters) [7].

The application of DTs in PHM is not limited to aircraft. Gabor et al. developed a simulation-based DT model to predict the behaviors of a cyber-physical system. The model has four tiers: physical necessity, machine-environment interface, immediate reaction, and planned reaction [8]. Knapp et al. applied the DT in an additive manufacturing process to predict the cooling rate, temperature gradient, micro-hardness, velocity distribution, and solidification parameters. As a result, it led to more accurate predictions of the cooling rate and melting rate than the Level Set Method and heat conduction models [47].

Compared to the traditional PHM, the DT-driven PHM has many advantages. Hochhalter et al. combined the DT with sensory materials to overcome the shortcoming of the traditional methods, which were overly dependent on empirical data and hence less responsive to uncertainties. A case study on a non-standard specimen demonstrated that the DT led to more accurate predictions of repairing and replacement [48]. Reifsnider and Majumdar built a high-fidelity DT model, based on the multi-physics simulation, to perform fault diagnosis without damage initiation. Besides, the method demonstrated high sensitivity to fracture development and was therefore useful for PHM [49]. Cerrone et al. presented the as-manufactured geometry to predict crack paths. A specimen DT model was created to deal with the ambiguity of crack paths under the shear loading, which led to more accurate predictions [50].

What is more, some researchers have conducted other work related with the DT in PHM. Tao et al. investigated the application of DTs in product utilization and maintenance. They prescribed nine principles to improve maintenance efficiency and reduce maintenance failure [51]. Tao et al. also explored the potential application of DT-driven PHM [4]. Gockel et al. built the DT of an aircraft structure by using the models of Finite Element Model (FEM) and Computational Fluid Dynamics (CFD). They suggested that the DT could reduce cost and improve reliability, which were the two priorities of the US Air Force [52].

4) DTs in other areas

Apart from the aforementioned applications in design, production, and PHM, the DT was occasionally applied in other areas. Schluse and Rossmann introduced the notion of EDT that integrated the DT and virtual testbed. EDT can be used to streamline a development process and conduct detailed simulations [11]. Schluse et al. claimed that EDT could reduce the complexity of simulation and increase the flexibility of a driver-assistance system [53]. Alam and Saddik proposed the DT model to depict cloud-based cyber-physical systems. The model was proven effective for making recommendations based on a telematics-based driver-assistance system [54].

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B. DT-related Patents

General Electric (GE) owns four patents that are directly related to DTs. Two of them are concerning wind farms. GE [55] invented the DT of a wind farm, which included two communication networks. The first network connects the control systems of wind turbines in a wind farm. The second network connects the digital models of wind turbines in the cloud. The digital models are constantly updated based on data collected from the first network. The system can monitor the running states of wind turbines through sensors, and control their operations through the digital models. Furthermore, GE developed a DT interface [56] to manage multiple digital models at the same time. The proposed interface has a graphical user interface (GUI) to display the digital mirror of a wind farm. The interface includes a control icon that contains information about the latest operating conditions of each wind turbine, and some control features that can be (re)configured to optimize the performance of the wind farm. Besides, the patent introduces some new methods to develop the wind farm DT and assess the operating state based on the DT. Lastly, Shah et al. applied the DT to control the cooling system of a power system based on the health score and the simulated operation [57].

Hershey et al. invented an apparatus to implement the DT of a twinned physical system. Sensors are used to collect data of designated parameters in the twinned system. A computer processor is installed to receive data from sensors, monitor conditions of the system, and assess the system's remaining life. In this way, the assessments could be more automatic and accurate [58].

Siemens also owns four DT-related patents that focus on machine-human interface, DT implementation method, energy efficient asset maintenance, and collision detection.

Siemens invented a human-programming interface (HPI) that enables a machine to interact with human and interpret human behaviors. At present, automation systems mostly are lack of concerning the important roles of humans in the automation environment. The HPI can be used to generate the DT of human which is brought into an autonomous system. Hence, the autonomous system could become more intelligent [59].

Johnson invented a systematic flow for creating the DT of a room, including obtaining point cloud data through scanning, building digital models, and matching the models with corresponding objects in the room. The patent is also useful for building a digital factory [60].

Song and Canedo applied the DT for energy efficient asset maintenance. The DT was employed to gather structured data from a product lifecycle, and to improve product quality and maintenance efficiency through simulation [61].

Krautwurm invented a DT-based method to avoid collisions within a distributed autonomous production system. [62].

C. DT applications by industry leaders

Apart from the aforementioned patents, some leading companies have applied DTs in various fields such as aerospace engineering, electric grid, car manufacturing, petroleum industry, healthcare, etc.

Siemens applied DTs for power system and wastewater plant. It developed the DT for the planning, operation, and maintenance of a power system in Finland, which significantly improved the automation, data utilization, and decision making [63]. Siemens also developed the DT of a wastewater treatment plant to monitor pipes in real time, save energy, and forecast fault tendencies in advance [64].

GE [65,66] proved that the DT can change the paradigm of how a wind farm is developed, operated, and maintained. Compared to the traditional paradigm without DTs, the new paradigm can increase the operation efficiency by 20%. GE also developed the hardware and software for establishing the wind farm DT. Furthermore, GE applied the DT in other fields such as locomotive and healthcare. The DT was applied to track a locomotive's lifecycle, including design, configuration, establishment, operation, etc. In particular, because the conditions of each component can be obtained in real time, operations of the locomotive can be optimized timely [67]. GE Healthcare applied the DT to streamline the operation of a hospital in terms of bed planning and work allocation [68].

British Petroleum (BP) [69, 70] applied the DT to address the challenge of monitoring and maintaining oil/gas facilities located in remote areas. For example, BP deployed the DT to improve the reliability of an oil exploration and production facility in Alaska.

Airbus aims to realize the digitalization of factories through DT-based solutions. It developed an assembly line DT to monitor the production process and optimize the operation efficiency [71].

SAP SE (Systems, Applications & Products in Data Processing) believes that some failures of subsea equipment can be avoided by the DT-driven PHM services. For example, a digital inspection is much more cost-effective than any physical inspection. The DT can simulate a practical situation and predict its future evolvement. As a result, the security of equipment can be improved as well [72].

IBM (International Business Machines Corporation) applied the DT in automatic vehicles to analyze the engine speed, oil pressure, and other critical parameters. In this way, not only breakdowns can be effectively prevented, but also a more efficient engine can be developed [73].

V. Observations and Recommendations

Based on a thorough review of 50 papers, 8 patents, and the best practices by industry leaders, some observations are obtained, and some recommendations are raised.

A. PHM: The most popular application area

Based on the above summary, it is clear that DTs have been extensively applied in the context of PHM. Thirteen articles reported the application of DTs in PHM, which is significantly more than the other areas. Moreover, DT-driven PHM shows great advantages over the traditional PHM methods in terms of four respects i.e., model, data, interaction, and decision-making.

(1) The traditional PHM mainly focuses on the geometric

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modeling and physical modeling, while it rarely considers the behavior modeling and rules modeling. As a result, the model cannot achieve high precision. In contrast, the DT-driven PHM can integrate the four kinds of modeling (i.e., geometric, physical, behavior, and rule modeling) to depict a practical situation more accurately. The ultra-fidelity can enhance the effectiveness of PHM.

(2) The traditional PHM is mainly driven by historical data and some static physical data, while it rarely considers the simulation data, real-time data, and data fusion between physical and virtual data. In contrast, the DT-driven PHM holistically merges physical data and virtual data, real-time data and historical data, as well as the data fusion. In this way, it corresponds to the sweeping trend that smart manufacturing is driven by the big data.

(3) The traditional PHM cannot support the back-and-forth interactions between a physical entity and its virtual model. In contrast, the DT-driven PHM connects the physical and virtual spaces. In this way, not only the physical entity can be better controlled, but also the virtual model can be progressively optimized and upgraded.

(4) Made possible by DTs, the decision making of maintenance will be driven by the high-fidelity virtual models on top of the traditional optimization algorithms, which will lead to a more rational maintenance strategy.

As for the application of DTs in PHM, different aspects of aircraft were the primary research subjects, such as wings, structural-life, and touch-down wear [12,41,47]. Other subjects included geometry assurance, cyber-physical system, and additive manufacturing, wind farm [46,7,40,65,66]. Through DTs, the historical data and real-time data can be integrated to build an enhanced prediction model. The articles reviewed in Section IV.A.3) *DTs in PHM* mostly follow this direction.

However, the current research on PHM still has some limitations. For example, the current applications mainly focus on the high-value equipment, which limits the broader applicability of DTs. Furthermore, not only DTs are useful for fault diagnosis and lifetime prediction, but also applicable for equipment maintenance and repair.

B. Modeling: Core of DTs

Regarding the implementation of DTs, a critical question is how to build a practically viable DT model. On the one hand, almost every paper [3,4,6,9-12,26-28,31-53] acknowledged the importance of DT modeling. On the other hand, no consensus has been reached regarding how to build a DT model in a generic way. Nine papers and one patent specifically discussed different methods of DT modeling [14-22,61], such as the five-layer structure, the three-step process, and the five-dimension modeling [11,16,17].

Based on the above review, it is clear that a unified DT modeling framework is needed urgently. Furthermore, it is equally important to develop more modeling tools for the DT. Therefore, DT modeling is a promising direction of DT research and application.

C. Cyber-physical fusion: the difficulty of DT applications

Another challenge of implementation is how to realize the effective cyber-physical fusion. Cyber-physical fusion involves many technologies such as data acquisition, data transmission, data mining, and collaborative control, etc. Cyber-physical fusion is a relatively new topic, for which, no universal framework is readily available. Besides, the fault tolerance theory is far from mature at the moment.

Many issues should be addressed to realize the cyber-physical fusion for DTs. Firstly, the fusion algorithms should be improved regarding robustness and applicability. Secondly, parallel computing can be applied to improve the computation efficiency and meet the demand of mass data processing. Thirdly, because of the cyber-physical fusion, DTs are exposed to security threats from both cyber and physical spaces. Therefore, the security of the DT should be carefully studied. Lastly, it is essential to standardize the connection and communication protocols.

D. Other recommendations

In addition to the aforementioned areas, DTs can be applied in certain new areas such as dispatching optimization and operational control in the workshop.

DTs can realize more accurate planning and more efficient dispatching. The physical model can monitor production status in real time. Meanwhile, the virtual model can analyze, evaluate, and optimize a scheduling scheme through self-organizing and self-learning.

Control plays a vital role in industry. A good control strategy can notably enhance the production efficiency and productivity. The relevant control theories include Proportion Integration Differentiation (PID) control, fuzzy control, neural network control, optimum control, robust control, etc. Few of the existing control theories have considered the cyber-physical connection, which is a distinguishing feature of DTs. Given a new task, DTs can automatically propose a novel control plan and adjust the control plan based on operation conditions. In this way, the control system is made more adaptable and robust. It is a promising direction to join forces between DTs and control.

VI. Conclusions

There has been a surge of the DT research and application in different industries. This is evidenced by the fact that many new articles and patents have been published during the past two years. What is more, some industrial leaders begin to introduce DTs into their product offering. This paper reviews a total of 50 previous publications, 8 patents and some worldwide famous companies' outcomes to summarize the state-of-the-art of the DT research and application. The main contributions of this work are summarized as follows:

(1) It outlines the key enabling technologies for the DT modeling, data fusion, interaction and collaboration, data, and service. Moreover, it summarizes the current studies on the DT implementation.

(2) It reviews the current applications of DTs in different industries, based on which, it concludes that DTs are most

popular in PHM, the core of DTs is modeling, and the most pressing issue is cyber-physical fusion.

(3) It outlines two promising application areas, DT in dispatching optimization and operational control, which are currently underexplored.

Despite the rapid growth, digital twin remains a rapidly evolving concept. Many pressing issues should be addressed to enhance its viability in practice. For example, a unified DT modeling method is critically needed. In that regard, this paper can guide more researchers to address the future directions of the DT research and application.

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