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 the DT was initially proposed. To date, many DT applications have been successfully implemented in different industries, including product design, production, prognostics 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*—Data fusion, digital twin (DT), 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 the 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 14 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 multilevel and multidisciplinary 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. Table I summarizes the reviewing methodology in terms of the searching criteria, search strings, and paper selection procedure. To further improve the 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 the keywords of "digital"

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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)

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.

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 the 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, and Google Patent, this paper aims to converge different perspectives to answer the following five research questions. 1) What is DT? 2) What is the current development of DTs? 3) Which industrial areas are most applicable for DTs? 4) How to implement DTs? 5) 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. 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 "prod-

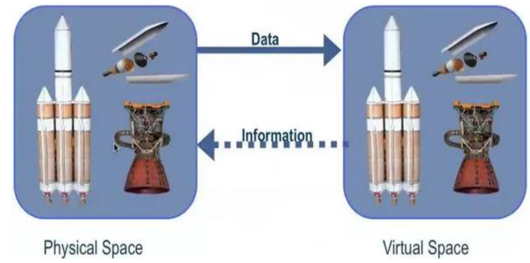

Fig. 1. Three-dimension model for the DT [6].

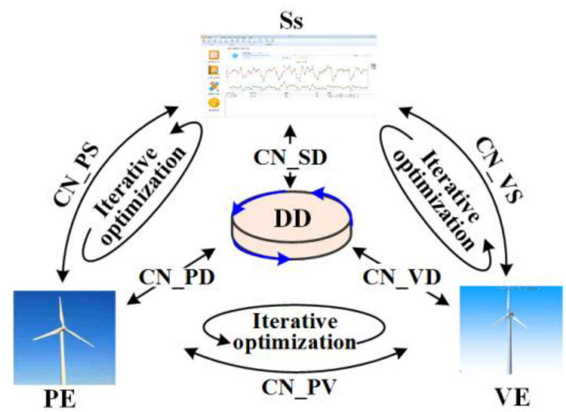

Fig. 2. Five-dimension model for the DT [74].

uct lifecycle management" [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 2012, the concept of DTs was revisited by the National Aeronautics and Space Administration (NASA), which defined the DT as a multiphysics, multiscale, probabilistic, ultrafidelity simulation that reflects, in a timely manner, the state of a corresponding twin based on the 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 the 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].

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 dimensions: 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-dimension model for the DT, Tao *et al.* proposed that a complete DT should include five dimensions: physical part, virtual part, connection, data, and service [12]. The framework is shown in Fig. 2, where PE rep-

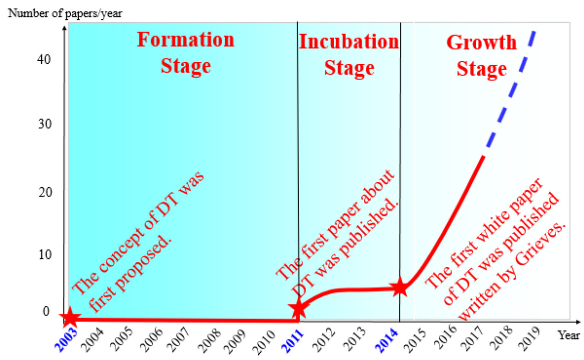

Fig. 3. Development trend of the DT research.

resents the physical entity; VE represents the virtual entity; Ss represents the services for both PE and VE; DD stands for the DT data; and CN means the connection of different parts [12], [74]. The five dimensions 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 lie 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 the 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, the 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 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 the 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 the DT from 2003 to 2011. In 2012, the 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 following four parts: DT modeling, simulation, verification, validation, and accreditation (VV&A); data fusion; interaction and collaboration; and service.

1) 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 entity. 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 are 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 the model error, algorithm error, and hardware error.

2) Data Fusion: Data fusion involves three processes—data preprocessing, data mining, and data optimization. First, 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 preprocessing that includes data cleaning, data conversion, and data filtering. Next, the preprocessed data are 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.

3) Interaction and Collaboration: All DT parts must interact and collaborate with each other 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.

4) 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 enables 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 the 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 the 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 multiphysics 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 the 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 following five steps: three-dimensional (3-D) modeling, behavior extraction, modeling of the interaction between a punching machine and moving elements, operation modeling, and 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 3-D printing machine, such as heat transfer modeling, solidification modeling, property prediction, residual stress modeling, and distortion modeling [22].

The 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 dimensions 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 were 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 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 the virtual space. Thus, production units could execute orders automatically according to 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 nondestructive 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 and matching, QoS modeling and evaluation, and service optimization, should be addressed toward 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.

A. DTs in the Product Lifecycle

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

1) DTs in the 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.

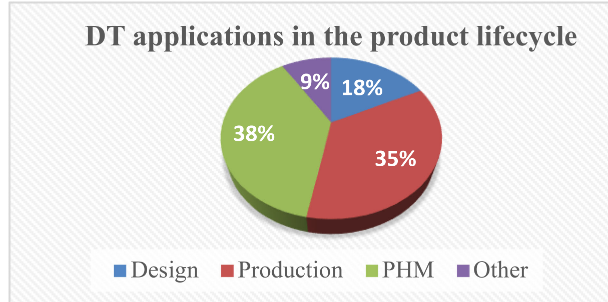

Fig. 4. Distribution of DT publications in different areas.

DTs are useful for the 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 the 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 3-D 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 the production lines. A case study on the glass production line was used to validate the effectiveness of the approach [37].

2) DTs in the 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, 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 preproduction 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 the simulation technology. They also considered the EDT as an enabler of the simulation-based system engineering, optimization, and control [44].

3) DTs in the PHM: At present, most of the DT applications are related to the PHM. DTs were first applied in the PHM of the aircraft. Tuegel *et al*. applied the DT to predict the structural life of the aircraft through multiphysics modeling, multiscale damage modeling, integration of the structural finite-element model (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 the 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 ultrahigh-fidelity model, the high computational and data processing ability, and vehicle health management system) as well as the benefits for the PHM (e.g., increase of reliability, and timely assessment of mission parameters) [7].

The application of DTs in the 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, microhardness, 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 nonstandard 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 multiphysics simulation, to perform fault diagnosis without damage initiation. Besides, the method demonstrated high sensitivity to fracture development, and was therefore, useful for the 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 the PHM. Tao *et al*. investigated the application of DTs in product utilization and maintenance. They prescribed nine principles to improve the maintenance efficiency and reduce maintenance failure [51]. Tao *et al*. also explored the potential application of the DT-driven PHM [4]. Gockel *et al*. built the DT of an aircraft structure by using the models of 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 the EDT that integrated the DT and virtual testbed. The EDT can be used to streamline a development process and conduct detailed simulations [11]. Schluse *et al*. claimed that the 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].

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 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. 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 the 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 the 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].

Systems, Applications & Products in Data Processing (SAP SE) 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 the equipment can be improved as well [72].

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 aforementioned summary, it is clear that DTs have been extensively applied in the context of the PHM. Thirteen articles reported the application of DTs in the PHM, which is significantly more than the other areas. Moreover, the 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 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 dimensions of modeling (i.e., geometry, physics, behavior, and rule modeling) to depict a practical situation more accurately. The ultrafidelity can enhance the effectiveness of the PHM.
2) The traditional PHM is mainly driven by the 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 the top of the traditional optimization algorithms, which will lead to a more rational maintenance strategy.

As for the application of DTs in the 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 [7], [40], [46], [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-A3 mostly follow this direction.

However, the current research on the 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-dimensional modeling [11], [16], [17].

Based on the aforementioned 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

The challenges of implementation include 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. First, the fusion algorithms should be improved regarding robustness and applicability. Second, parallel computing can be applied to improve the computation efficiency and meet the demand of mass data processing. Third, 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. Finally, 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 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. Conclusion

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 paper are summarized as follows.

1) It outlines the key enabling technologies for the DT modeling, simulation, and VV&A, data fusion, interaction and collaboration, 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 the 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, DT 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.

References

[1] A. Kusiak, "Smart manufacturing must embrace big data," *Nature*, vol. 544, no. 7648, pp. 23–25, 2017.
[2] Q. L. Qi. and F. Tao, "Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison," *IEEE Access*, vol. 6, pp. 3585–3593, Jan. 2018, doi: 10.1109/ACCESS.2018.2793265.
[3] F. Tao, M. Zhang, J. F. Cheng, and Q. L. Qi, "Digital twin workshop: A new paradigm for future workshop," *Comput. Integr. Manuf. Syst.*, vol. 23, no. 1, pp. 1–9, Jan. 2017, doi: 10.13196/j.cims.2017.01.01.
[4] F. Tao *et al.*, "Digital twin and its potential application exploration," *Comput. Integr. Manuf. Syst.*, vol. 23, no. 1, pp. 1–18, Jan. 2018, doi: 10.13196/j.cims.2018.01.001.
[5] S. Weyer, T. Meyer, M. Ohmer, D. Gorecky, and D. Zühlke, "Future modeling and simulation of CPS-based factories: An example from the automotive industry," *IFAC PapersOnLine*, vol. 49, no. 31, pp. 97–102, 2016, doi: 10.1016/j.ifacol.2016.12.168.
[6] M. Grieves, "Digital twin: Manufacturing excellence through virtual factory replication," White paper, 2014. [Online]. Available: http://www.apriso.com/library/Whitepaper_Dr_Grieves_DigitalTwin_ManufacturingExcellence.php
[7] E. Glaessgen and D. Stargel, "The digital twin paradigm for future NASA and U.S. Air Force vehicles," in *Proc. 53rd AIAA/ASME/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf.*, 2012. [Online]. Available: https://arc.aiaa.org/doi/pdf/10.2514/6.2012-1818.
[8] T. Gabor, L. Belzner, M. Kiermeier, M. T. Beck, and A. Neitz, "A simulation-based architecture for smart cyber-physical systems," in *Proc. IEEE Int. Conf. Autonomic Comput.*, Wurzburg, Germany, 2016, pp. 374–379, doi: 10.1109/ICAC.2016.29.
[9] T. Maurer, "What is a digital twin?" 2017. [Online]. Available: https://community.plm.automation.siemens.com/t5/Digital-Twin-Knowledge-Base/What-is-a-digital-twin/ta-p/432960
[10] E. J. Tuegel, "The airframe digital twin some challenges to realization," in *Proc. 53rd AIAA/ASME/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf.*, Honolulu, HI, USA, 2012, Art no. 1812.
[11] M. Schluse and J. Rossmann, "From simulation to experimentable digital twins: Simulation-based development and operation of complex technical systems," in *Proc. IEEE Int. Symp. Syst. Eng.*, Edinburgh, U.K., 2016, pp. 1–6, doi: 10.1109/SysEng.2016.7753162.
[12] F. Tao and M. Zhang, "Digital twin shop-floor: A new shop-floor paradigm towards smart manufacturing," *IEEE Access*, vol. 5, pp. 20418–20427, 2017, doi: 10.1109/ACCESS.2017.2756069.
[13] E. J. Tuegel, A. R. Ingraffea, T. G. Eason, and S. M. Spottswood, "Reengineering aircraft structural life prediction using a digital twin," *Int. J. Aerosp. Eng.*, vol. 2011, pp. 1687–5966. Aug. 2011, doi: 10.1155/2011/154798.
[14] F. Tao, Y. F. Hu, and L. Zhang, *Theory and Practice: Optimal Resource Service Allocation in Manufacturing Grid*. Beijing, China: China Machine Press, 2010, pp. 11–12.
[15] O. S. Emuakpor, T. George, J. Beck, J. Schwartz, C. Holycross, and J. Schwartz, "Material property determination of vibration fatigued DMLS and cold-rolled nickel alloys," *ASME. Turbo Expo: Power Land, Sea, Air*, Düsseldorf, Germany, 2014, pp. V07AT28A008–V07AT28A008.
[16] P. K. Majumdar, M. Faisalhaider, and K. Reifsnider, "Multi-physics response of structural composites and framework for modeling using material geometry," in *Proc. 54th AIAA/ASME/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf.*, Boston, MA, USA, 2013, Art. no. 1577.
[17] G. Schroeder *et al.*, "Visualising the digital twin using web services and augmented reality," in *Proc. IEEE 14th Int. Conf. Ind. Informat.*, Poitiers, France, 2016, pp. 522–527, doi: 10.1109/INDIN.2016.7819217.
[18] G. Schroeder, C. Steinmetz, C. E. Pereira, and D. B. Espindola, "Digital twin data modeling with automation ML and a communication methodology for data exchange," *IFAC PapersOnLine*, vol. 49, no. 30, pp. 12–17, 2016, doi: 10.1016/j.ifacol.2016.11.115.
[19] S. Yun, J. H. Park, and W. T. Kim, "Data-centric middleware based digital twin platform for dependable cyber-physical systems," in *Proc. 9th Int. Conf. Ubiquitous Future Netw.*, Milan, Italy, 2017, pp. 922–926.
[20] A. Moreno, G. Velez, A. Ardanza, I. Barandiaran, Á. R. de Infante, and R. Chopitea, "Virtualisation process of a sheet metal punching machine within the industry 4.0 vision," *Int. J. Interact. Des. Manuf.*, vol. 11, no. 2, pp. 1–9, May 2016, doi: 10.1007/s12008-016-0319-2.
[21] S. Haag and R. Anderl, "Digital twin-proof of concept," *Manuf. Lett.*, vol. 15, pp. 64–66, 2018, doi: 10.1016/j.mfglet.2018.02.006.
[22] T. DebRoy, W. Zhang, J. Turner, and S. S. Babu, "Building digital twins of 3D printing machines," *Scripta Mater.*, vol. 135, pp. 119–124, Jul. 2017, doi: 10.1016/j.scriptamat.2016.12.005.
[23] B. P. Smarslok, A. J. Culler, and S. Mahadevan, "Error quantification and confidence assessment of aerothermal model predictions for hypersonic aircraft," in *Proc. 53rd AIAA/ASME/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf.*, Honolulu, HI, USA, 2013, Art. no. 1817.
[24] F. Tao *et al.*, "Theories and technologies for cyber-physical fusion in digital twin shop-floor," *Comput. Integr. Manuf. Syst.*, vol. 23, no. 8, pp. 1603–1611, Aug. 2017, doi: 10.13196/j.cims.2017.08.001.
[25] T. M. Ricks, T. E. Lacy, E. J. Pineda, B. A. Bednarcyk, and S. M. Arnold, "Computationally efficient solution of the high-fidelity generalized method of cells micromechanics relations," in *Proc. 30th Tech. Conf. Amer. Soc. Composites*, East Lansing, MI, USA, 2015. [Online]. Avaliable: https://www.cavs.msstate.edu/publications/docs/2015/09/140441700_Ricks.pdf
[26] Y. Cai, B. Starly, P. Cohen, and Y. S. Lee, "Sensor data and information fusion to construct digital-twins virtual machine tools for cyber physical manufacturing," *Procedia Manuf.*, vol. 10, pp. 1031–1042, Jul. 2017, doi: 10.1016/j.promfg.2017.07.094.
[27] R. Rosen, G. V. Wichert, G. Lo, and K. D. Bettenhausen, "About the Importance of autonomy and digital twins for the future of manufacturing," *IFAC PapersOnLine*, vol. 48, no. 3, pp. 567–572, 2015, doi: 10.1016/j.ifacol.2015.06.141.
[28] J. Vachálek, L. Bartalský, O. Rovný, D. Šišmišová, M. Morháč, and M. Lokšík, "The digital twin of an industrial production line within the industry 4.0 concept," in *Proc. 21st Int. Conf. Process Control*, Štrbské Pleso, Slovakia, 2017, pp. 258–262, doi: 10.1109/PC.2017.7976223.
[29] B. Bielefeldt, J. Hochhalter, and D. Hartl, "Computationally efficient analysis of SMA sensory particles embedded in complex aerostructures using a substructure approach," in *Proc. ASME Conf. Smart Mater. Adaptive Struct. Intell. Syst.*, Colorado Springs, CO, USA, 2015, pp. V001T02A007-1–V001T02A007-10, doi: 10.1115/SMASIS2015-8975.
[30] Y. Bazilevs, X. Deng, A. Korobenko, F. L. di Scalea, M. D. Todd, and S. G. Taylor, "Isogeometric fatigue damage prediction in large-scale composite structures driven by dynamic sensor data," *ASME. J. Appl. Mech.*, vol. 82, no. 9, pp. 0091008–0091012, Jun. 2015, doi: 10.1115/1.4030795.
[31] B. R. Seshadri and T. Krishnamurthy, "Structural health management of damaged aircraft structures using the digital twin concept," in *Proc. AIAA/AHS Adaptive Struct. Conf.*, Grapevine, TX, USA, 2017, Art. no. 1675.
[32] C. B. Zhuang, J. H. Liu, H. Xiong, X. Y. Ding, S. L. Liu, and G. Weng, "Connotation, architecture and trends of product digital twin," *Comput. Integr. Manuf. Syst.*, vol. 23, no. 4, pp. 53–768, Apr. 2017, doi: 10.13196/j.cims.2017.04.010.
[33] A. Canedo, "Industrial IoT lifecycle via digital twins," in *Proc. 11th IEEE/ACM/IFIP Int. Conf. Hardware/Softw. Codes. Syst. Synthesis*, Pittsburgh, PA, USA, 2016, Art. no. 29.
[34] Y. Yu, S. T. Fan, G. Y. Peng, S. Dai, and G. Zhao, "Study on application of digital twin model in product configuration management," *Aeronaut. Manuf. Technol.*, vol. 526, no. 77, pp. 41–45, Jul. 2017, doi: 10.16080/j.issn1671-833x.2017.07.041.
[35] F. Tao *et al.*, "Digital twin-driven product design framework," *Int. J. Prod. Res.*, Feb. 2018. [Online]. Available: doi: 10.1080/00207543.2018.1443229
[36] B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack, "Shaping the digital twin for design and production engineering," *CIRP Ann. Manuf. Tech.*, vol. 66, no. 1, pp. 141–144, 2017, doi: 10.1016/j.cirp.2017.04.040.

[37] H. Zhang, Q. Liu, X. Chen, D. Zhang, and J. Leng, "A digital twin-based approach for designing and multi-objective optimization of hollow glass production line," *IEEE Access*, vol. 5, pp. 26901–26911, 2017, doi: 10.1109/ACCESS.2017.2766453.

[38] B. Brenner and V. Hummel, "Digital twin as enabler for an innovative digital shopfloor management system in the ESB logistics learning factory at Reutlingen - University," *Procedia Manuf.*, vol. 9, pp. 198–205, Apr. 2017, doi: 10.1016/j.promfg.2017.04.039.

[39] F. Ameri and R. Sabbagh, "Digital factories for capability modeling and visualization," in *Proc. IFIP Int. Conf. Adv. Prod. Manage. Syst.*, Iguassu Falls, Brazil, 2016, pp. 69–78.

[40] S. Konstantinov, M. Ahmad, K. Ananthanarayan, and R. Harrison, "The cyber-physical e-machine manufacturing system: Virtual engineering for complete lifecycle support," *Procedia CIRP*, vol. 63, pp. 119–124, 2017, doi: 10.1016/j.procir.2017.02.035.

[41] T. H. J. Uhlemann, C. Lehamnn, and R. Steinhilper, "The digital twin: Realizing the cyber-physical production system for industry 4.0," *Procedia CIRP*, vol. 61, pp. 335–340, 2017, doi: 10.1016/j.procir.2016.11.152.

[42] R. Söderberg, K. Wärmefjord, J. S. Carlson, and L. Lindkvist, "Toward a digital twin for real-time geometry assurance in individualized production," *CIRP Ann. Manuf. Technol.*, vol. 66, no. 1, pp. 137–140, 2017, doi: 10.1016/j.cirp.2017.04.038.

[43] T. H. J. Uhlemann, C. Schock, C. Lehmann, S. Freiberger, and R. Steinhilper, "The digital twin: demonstrating the potential of real time data acquisition in production systems," *Procedia Manuf.*, vol. 9, pp. 113–120, Apr. 2017, doi: 10.1016/j.promfg.2017.04.043.

[44] M. Schluse, M. Priggemeyer, L. Atorf, and J. Rossmann, "Experimentable digital twins—Streamlining simulation-based systems engineering for industry 4.0," *IEEE Trans. Ind. Informat.*, vol. 14, no. 4, pp. 1722–1731, Apr. 2018, doi: 10.1109/TII.2018.2804917.

[45] C. Li, S. Mahadevan, Y. Ling, S. Choze, and L. Wang, "Dynamic Bayesian network for aircraft wing health monitoring digital twin," *AIAA J.*, vol. 55, no. 3, pp. 930–941, Jan. 2017, doi: 10.2514/1.J055201.

[46] A. J. Zakrajsek and S. Mall, "The development and use of a digital twin model for tire touchdown health monitoring," in *Proc. 58th AIAA/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf.*, Grapevine, TX, USA, 2017, Art. no. 0863.

[47] G. L. Knapp *et al.*, "Building blocks for a digital twin of additive manufacturing," *Acta Mater.*, vol. 135, pp. 390–399, Aug. 2017, doi: 10.1016/j.actamat.2017.06.039.

[48] J. Hochhalter *et al.*, "Coupling damage-sensing particles to the digital twin concept," Langley Research Center, National Aeronautics and Space Administration, Hampton, VA, USA, *NASA/TM-2014-218257, L-20401, NF1676L-18764*, Apr. 01, 2014.

[49] K. Reifsnider and P. Majumdar, "Multiphysics stimulated simulation digital twin methods for fleet management," in *Proc. 54th AIAA/ASME/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf.*, Boston, MA, USA, 2013, Art. no. 1578.

[50] A. Cerrone, J. Hochhalter, G. Heber, and A. Anthoy, "On the effects of modeling as-manufactured geometry: Toward digital twin," *Int. J. Aerosp. Eng.*, vol. 2014, pp. 1–10, Aug. 2014, doi: 10.1155/2014/439278.

[51] F. Tao, J. F. Cheng, Q. L. Qi, M. Zhang, H. Zhang, and F. Y. Sui, "Digital twin-driven product design, manufacturing and service with big data," *Int. J. Adv. Manuf. Technol.*, vol. 2018, no. 94, Mar. 2017, Art. no. 3563, doi: 10.1007/s00170-017-0233-1.

[52] B. Gockel, A. Tudor, M. Brandyberry, R. Penmetsa, and E. Tuegel, "Challenges with structural life forecasting using realistic mission profiles," in *Proc. 53rd AIAA/ASME/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf.*, Honolulu, HI, USA, 2013, Art. no. 1813.

[53] M. Schluse, L. Atorf, and J. Rossmann, "Experimentable digital twins for model-based systems engineering and simulation-based development," in *Proc. IEEE Annu. Int. Syst. Conf.*, Montreal, QC, Canada, 2017, pp. 1–8, doi: 10.1109/SYSCON.2017.7934796.

[54] K. M. Alam and A. El Saddik, "C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems," *IEEE Access*, vol. 5, pp. 2050–2062, 2017, doi: 10.1109/ACCESS.2017.2657006.

[55] A. M. Lund *et al.*, "Digital wind farm system," U.S. Patent Application 15/075 231, Nov. 17, 2016.

[56] A. M. Lund *et al.*, "Digital twin interface for operating wind farms," U.S. Patent 9 995 278, Jun. 12, 2018.

[57] T. Shah, S. Govindappa, P. Nistler, and B. Narayanan, "Digital twin system for a cooling system," U.S. Patent 9 881 430, Jun. 30, 2018.

[58] J. E. Hersheyielsen *et al.*, "Digital twin of twinned physical system," U.S. Patent Application 15/087 217, Oct. 5, 2017.

[59] L. Wang and A. M. Canedo, "Human programming interfaces for machine-human interfaces," U.S. Patent Application 15/284 571, Apr. 20, 2017.

[60] R. Johnson, "Method for creating a digital twin of a room," Eur. Patent Application 16186640.5, Mar.7, 2018.

[61] Z. Song and A. M. Canedo, "Digital twins for energy efficient asset maintenance," U.S. Patent Application 15/052 992, Aug. 25, 2016.

[62] F. Krautwurm, "Method for collision detection and autonomous system," European Patent Application 16185493.0, Feb. 28, 2018.

[63] Siemens, "For a digital twin of the grid Siemens solution enables a single digital grid model of the Finnish power system," 2017. [Online]. Available: https://www.siemens.com/press/pool/de/events/2017/corporate/2017-12-innovation/inno2017-digitaltwin-e.pdf

[64] A. G. Siemens, "Siemens expands digitalization solutions for the process industries," 2018. [Online]. Available: https://www.siemens.com/press/en/pressrelease/?press=/en/pressrelease/2018/processindustries-drives/pr2018030215pden.htm

[65] GE Renewable Energy, "Digital wind farm-the next evolution of wind energy," 2016. [Online]. Available: https://www.ge.com/content/dam/gepower-renewables/global/en_US/downloads/brochures/digital-wind-farm-solutions-gea31821b-r2.pdf

[66] GE Look ahead, "The digital twin Could this be the 21st-century approach to productivity enhancements?", 2015. [Online]. Available: http://gelookahead.economist.com/the-digital-twin/

[67] J. Miller, "Why digital threads and twins are the future of trains," 2016. [Online]. Available: https://www.ge.com/digital/blog/why-digital-threads-and-twins-are-future-trains

[68] *Healthcare Solution Testing for Future | Digital Twins in Healthcare*, Science Service, Dr. Hempel Digital Health Network, 2017. [Online]. Available: https://www.dr-hempel-network.com/digital-health-technolgy/digital-twins-in-healthcare/

[69] D. C. McCannel, "What is a digital twin? (Plus 3 industries which already benefit)," 2018. [Online]. Available: https://www.llamazoo.com/what-is-a-digital-twin/

[70] AUCOTEC, "3 Industries being transformed by digital twins." 2017, [Online]. Available: http://news.aucotec.com/3-industries-transformed-digital-twins/

[71] Y. Liu, "Lockheed martin space systems company makes use of digital twins speed F-35 fighter production," 2017. [Online]. Available: http://www.sohu.com/a/212980157_613206

[72] V. Govindarajan, "Preventing disasters with a digital twin," 2017. [Online]. Available: http://www.digitalistmag.com/iot/2017/11/01/preventing-disasters-with-digital-twin-05486723

[73] G. Cline, "An engine can become a platform with a digital twin," 2017. [Online]. Available: https://www.ibm.com/internet-of-things/trending/digital-twin

[74] F. Tao, M. Zhang, Y. Liu, N.Y.C. Nee, "Digital twin driven prognostics and health management for complex equipment," CIRP Annals, vol. 67, no. 1, pp. 169–172, May. 2018.

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