The International Journal of Advanced Manufacturing Technology (2022) 121:5677–5692
https://doi.org/10.1007/s00170-022-09717-9

CRITICAL REVIEW

Digital twin applications in aviation industry: A review

Minglan Xiong[1] · Huawei Wang[1]

Received: 23 November 2021 / Accepted: 7 July 2022 / Published online: 28 July 2022

Abstract
As a highly secure and reliable system, aviation faces challenges including digital transformation, high production operation costs, low maintenance efficiency, and intensive technology. One of the most beneficial technologies is the digital twin (DT), which can solve the above issues. This paper investigates aviation industry DT from government authorities, industry, and academia. Firstly, it surveys the development of the definition of DT and compares its concepts with the Internet of Things, cyber-physical systems, and digital thread etc. Next, it shows the research timeline of aviation DT in the past 10 years by authorities such as Air Force Research Laboratory and National Aeronautics and Space Administration. Then, this paper reviews the state-of-the-art research status of DT in the whole lifecycle of the aviation system and concludes that aviation DT is the most widely used in manufacturing and maintenance, and should pay attention to the application of UAV DT. Finally, it summarizes that data fusion, high-fidelity modeling, integration with New IT, and human–machine interaction are the key technologies of aviation DT. The future possible research directions could be digital process twin risk control, interactive DT, and DT data learning.

Keywords Digital twin · Aviation industry · Life cycle management

1 Introduction

The aircraft has a complex system structure, including airframe, engines, flight control surface, instruments, pressurization, hydraulics, chassis, and other systems. In addition, the aircraft has many parts, large size, poor rigidity, complex shape, and high-precision requirements. Meanwhile, the operating environment of the aircraft is random and changeable, and the adaptability of different aircraft types to the operating environment is different. The weather, airport facilities, route, and other factors affect whether the aircraft can complete the flight mission safely. However, the aircraft will generate a great deal of data during the operation [1], which makes it possible to digitally manage the entire lifecycle of the aircraft to reduce operating costs and improve system reliability.

With the introduction of "Intelligent Manufacturing" [2], "Industry 4.0" [3], and "Made in China 2025" [4], intelligent transformation has become the development goal of all trades. Under the promotion of the internet of things (IoT), artificial intelligence (AI), cloud computing, edge computing, big data, 5G, etc. it is possible to manage the products and business processes from cradle-to-grave in each field [5, 6].

The development of DT benefits from the support of the abovementioned advanced technologies; meanwhile, it is listed as one of the top ten emerging technologies by Gartner [7], and it shows significant potential value in many fields [8, 9]. DT can provide a real-time, high-fidelity virtual model for its aviation counterparts [10]. This means, with the development of DT technology, the physical aircraft and its DT will be delivered simultaneously [11].

Both academia and industry are actively conducting research on DT, with exponential growth in the number of related papers [12]. However, it comes with problems such as misuse of the DT concept in research and application, neglect of data and model visualization, etc. Therefore, a systematic review of state-of-the-art research is required to support the efficient application and development of DT in the aviation industry, thereby improving the reliability and safety of aircraft. This paper systematically reviews the research status of the complete lifecycle of aviation industry

✉ Huawei Wang
wang_hw66@163.com

1 School of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, People's Republic of China

DT, and the following objectives have been formulated to help complete the work:

- Discuss the conceptual difference between DT and other technologies;
- Investigate the history of aviation industry DT;
- Explore the application status and possible challenges of aviation industry DT.

The rest of the paper is structured as follows: Sect. 2 introduces the development and differentiation of the DT concept. Section 3 briefly describes the main course of the aviation industry DT concept development. Section 4 outlines the application status of aircraft DT, including design, assembly, manufacturing, operation and maintenance, UAV filed, and others. Section 5 presents the key technologies. Section 6 suggests some research directions, and finally Sect. 7 summarizes the contributions of this work.

2 DT and clarification

At present, there is no clear definition of DT in academia, industry, or politics. In addition, with the development of other emerging technologies in recent years, it is easy to confuse their concept. Therefore, it is necessary to investigate and distinguish the concept of DT, which is the key to the rapid development of the aviation industry DT.

2.1 DT concept development

The application of DT can be traced back to 1970s; in the Apollo program, two identical space vehicles were built by the National Aeronautics and Space Administration (NASA); the first one, left on earth, would map the working status of the second vehicle [14]. In 2002, Professor Grieves first put forward the concept of DT in product lifecycle management [13]. In 2010, NASA pointed out that a DT consists of physical products, virtual products, and communications between the two vehicles. DT integrates multi-physics, multi-scale, and probabilistic simulations to map the state of the physical vehicle in real-time through sensor updates and service historical data [15]. In 2012, the Air Force Research Laboratory (AFRL) considered the Airframe DT (ADT) an integrated system composed of data, models, and analysis tools. This system can express the aircraft fuselage in the whole lifecycle, and make decisions on the whole fleet and single fuselage according to uncertain information [16]. Tao et al. added two dimensions based on NASA's definition, and that DT compose of five parts, namely, physical, virtual, connections, data, and services [8].

Suppose that CAD, CAE, CAM, traditional systems engineering, and other technologies lay a solid foundation for the development of the DT; in that case, the rapid growth of advanced technologies such as Cyber-Physical Systems (CPS), IoT, big data, AI, cloud computing, edge computing, sensor networks, radio frequency identification, and 5G cellular networks are providing breakthroughs for the development of DT in all fields [18, 19]. In recent years, various fields have gradually realized the significance and benefits of DT and have begun to research it [20]. The application of DT is diversified, and a lot of companies continuously update the development of DT concept according to their products and needs (the specific research results are shown in Table 1). For example, GE believes that the DT represents the software form of assets and processes and can be employed to understand, predict, and optimize performance. Its purpose is to improve the performance of assets and processes [21]. Siemens put forward the concept of comprehensive DT, and pointed out that ideal products can be delivered through accurate mapping among DT products, production, and management. Dassault's new concept is 3DEXPEROENCER TWIN, which emphasizes the experience consistency, subject consistency, single data source, and macro and micro unity between physical products and twins. PTC puts forward the concept of "DT + VR" by focusing more on the sense of reality and scene of products. ESI believes that the hybrid twin solution enables companies to virtually provide predictive maintenance and optimize the auxiliary operations of products by connecting current IoT information and past big data information, combined with possible future interpretations.

2.2 DT's concept clarification

2.2.1 DT, CPS, and IoT

Although the above literature shows that definitions of the DT are different in academia and industry, there are still some features in common: (1) use physical assets to represent reality; (2) the constructed DT can be improved or updated based on the mutual feedback between physical and virtual assets; and (3) evolution [27, 28]; and high-fidelity models are essential for the realization of DT [29]. These features are similar to the elements of simulation, CPS, and IoT. It is worth mentioning that there are differences and connections among them. The relationship between them is shown in Fig. 1. Simulation is the foundation of DT [30], DT is the prerequisite for the development of CPS [31], and IoT is the infrastructure of DT and CPS [32].

Simulation is the primary technology to realize DT, which can create and run DT. And it is also a core technology to ensure that DT and corresponding physical entities can achieve an effective closed loop. The main difference between DT and traditional simulations is that DT requires continuous iteration between physical and virtual entities.

Table 1 Diversified application of DT [22]

Institution	Physical twin	DT		DT+	DT++	Research results
Siemens	Physical prototype		DT	DT Product/Production/ Performance	Comprehensive DT	[23]
Dassault	Physical resources		Virtual twin	Product Lifecycle Twin	3DEXPEROENCER TWIN	[24]
PTC	Physical Product		DT	DT + Knowledge System	DT + Augmented Reality	[25]
ESI	Physical assets		Physically based Virtual twin	Data-driven Virtual twin	Hybrid twin	[26]
Beihang University	Physical Entity		Virtual Model	VE = {Gv, Pv, Bv, Rv} Geometric model + Physical model + Behavior model + Rule model	DT = {PE, VE Ss, DD, CN} Physical Entity + Digital Entity + Digital Data + Service + Connect	[8, 9]

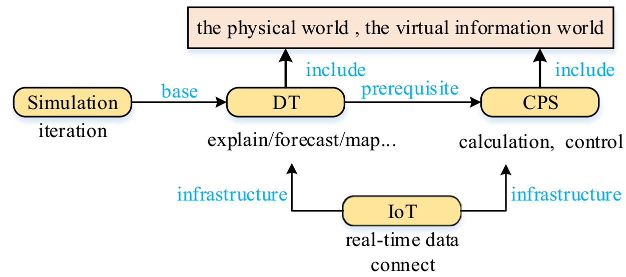

Fig. 1 The relationship between DT, CPS, IoT, and Simulation

The virtual digital entities constructed by DT need to use high-frequency, constantly iterative evolving simulations, and accompany the whole lifecycle of entities.

In the manufacturing scene, both CPS and DT include two parts: the real physical world and the virtual information world. The physical world performs the actual production activities, while various applications and services achieve intelligent data management, analysis, and calculation in the virtual information world. DT emphasizes the real-time mapping of physical entities and virtual models, while CPS is for information collection, processing, and control of the entire system. Therefore, DT is the premise of CPS implementation [33]. IoT realizes information identification and tracking between entities through network data [35]; provides comprehensive data collection, transmission, and connection [34]; and realizes effective interconnection between virtual models and physical entities, which is one of the core elements of DT and CPS.

2.2.2 DT, digital engineering, digital systems model, and digital thread

Digital engineering is an integrated digital method that uses the authoritative model source and data source of the system to support all activities from concept development to scrap handle [36]. Build a digital engineering ecosystem that leverages digital advances and technological innovations to complete a model-centric paradigm shift [37, 38].

The digital system model uses data to represent the elements and information of the system. It is based on the data model of the system and is the foundation of digital engineering. As such, the amount and types of data in the digital systems model will grow as the system is matured throughout its lifecycle. Use the classification defined by the digital systems model to provide digital engineering with systematic engineering data, project, and system supporting data [39, 40].

The digital thread is an enterprise-level analytical framework with the attribute of extensibility, configurability, and component. Based on the digital systems model template, it can transfer accurate information to the right object at the correct time and place during the system lifecycle. The digital thread should be realized in the DT environment [39, 41].

The core of the digital engineering ecosystem is the digital systems model, digital thread, and DT, and their interaction can improve the efficiency, agility, and flexibility in the whole purchasing process, enabling better decision-making in the lifecycle [42].

3 Aviation industry DT history

Traditional simulation techniques, such as computational fluid dynamics, finite element method, Monte Carlo simulation, etc., can reproduce the continuous-time history of flight and generate a wealth of simulation data to assess the flight performance, then predict the upcoming maintenance requirements and invasion by using simulation techniques based on varieties of applications [43]. However, compared with traditional modeling and simulation, DT has the following advantages: short design cycle, high reliability, frequent overhaul, and low maintenance cost [44]. It can not only shorten the times and duration of aircraft certification tests, eliminate accidental cracks and failures, but also reduce the times and frequency of structural maintenance inspections.

In 2011, the U.S. AFRL proposed a redesign life prediction process of the aircraft structure in order to take full advantages in very high-performance digital computing. The U.S. Air Force pointed out that in 2025 it would deliver the first new type of airplane and a digital model of the airplane at the same time. They thought that DT was the reconstruction of structural life prediction and management and it also stated the required technologies, including [11]:

- Multi-physics modeling;
- Multiscale damage modeling;
- Integration of structural finite element method and damage models;
- Uncertainty quantification;
- Modeling and control;
- Manipulation of large;
- Shared databases; and
- High-resolution structural analysis capability.

In 2012, AFRL first proposed the concept of ADT: the ADT is an aircraft structural model, which can meet the mission requirements of aircraft in the whole lifecycle. It is a sub-model including electronics, flight control, propulsion system, and other subsystems. ADT can meet the following goals: (1) more efficient design and certification can not only reduce the number of design changes after aircraft certification testing, but also shorten the number and time of certification testing, to reduce the acquisition cost; (2) eliminate accidental cracking and failure, and increase the availability and reliability of aircraft; (3) minimize the number and frequency of structural inspections and reduce maintenance and support costs.

Besides, the AFRL pointed out that there are still many physics and engineering modeling challenges in the implementation of ADT. These challenges can be divided into the following categories 10 [16]:

- Establishment of initial conditions;
- The application of flight load;
- Selection and integration of submodels; and
- Management and reduction of uncertainty.

In the same year, NASA cooperated with the Air Force Office of Scientific Research (AFOSR) and held the view that compared with the present generation, the future would need lighter mass, and at the same time, it would bear higher loads and more extreme services conditions in a longer time [17]. To make up for the shortcomings of traditional methods, a fundamental paradigm shift is needed. This paradigm shift, namely DT, emphasizes the combination of ultra-high-fidelity simulation, health management system, and collecting as much historical data as possible to reflect the life span of its flying twin, finally achieve safety and reliability level as never before. This is also the most widely used definition of DT [16].

In 2013, the AFRL developed ADT Spiral 1 program, in which a probabilistic individual aircraft fatigue tracking process is being developed and demonstrated. A large number of sources of uncertainty, such as fatigue crack growth properties, initial crack size, and loads, are captured in the form of probability distributions which are used in the fatigue crack growth predictions. The demonstration framework includes applied loads and environments, geometry and material data, physics-informed multi-scale, multi-discipline models, range of structural response and reliability, and physical aircraft.

In 2014, to better integrate the DT and sensory materials, NASA had researched how to model the manufacturing geometry and microstructure of components as degree as possible. This research aims to develop the concept of sensory materials such that they can be used within the DT framework. By combining DT and sensing materials technology, automatic evidence-based inspection and maintenance of aerospace vehicles can be realized [45]. Based on NASA's definition of DT, the U.S. Department of Defense (DoD) proposed that DT was a system enabled by a digital thread. The digital thread can feed data back to the original computer model of the part [36].

There is a need to update the physical model with the highest fidelity by using flight record data, airborne monitoring system data, and fleet history data, to realize predictable fault diagnosis and fatigue evolution [46–48]. The National Research Council of Canada (NRC) defines ADT based on DoD, reviews and evaluates the ADT proposed by the U.S. AFRL, and emphasizes the role of DT in individual aircraft tracking [49]. The framework describes 5 projects [49]: common fleet database, individual DT, quantitative risk assessment, individual physical aircraft, Bayesian inference.

In 2019, the U.S. Air Force proposed the "The digital air force" plan to face the complex security environment, which emphasized the network advantages of sensors and analysis tools. By comprehensively using the "Trinity" tools of modular open system architecture, agile software development, and digital engineering, the fighter is upgraded every 4 years with high frequency, thus realizing "spiral-up" research and development. DT can be used for maintenance optimization and inspection progress based on a quantitative risk assessment, and to manage the aircraft structural lifecycle with dramatically reduced costs while maximizing availability.

Therefore, the DT aircraft closely combines DT technology with the crucial links, crucial scenes, and crucial objects in aeronautical engineering. The aircraft engineering in physical space is simulated, monitored, and reflected in real-time based on models and data, then analyzed, evaluated, predicted, managed, and optimized utilizing algorithms, management methods, expert knowledge, and software. The functions include the service application of various scenes and objects in the spatial dimension and the system engineering management in the time dimension. Table 2 lists the definition of DT aircraft by each institution.

4 Aviation industry DT application

DT applies to the entire lifecycle of aircraft. High-fidelity model and rich data are vital conditions to ensure the implementation of DT, which can better serve the safe activities of the aircraft. This paper reviews the application status of DT in the aircraft industry from 2010 to August 2021. Its application includes five aspects: structural optimization design, product assembly, product manufacturing, operation and maintenance, and other aviation-related fields.

4.1 Design

The aircraft has a highly complex structure, and its structural design concept has undergone the evolution from static strength [50], safe life [51], damage tolerance to stand-alone tracking [52]. The design still has problems such as a high degree of coupling of variables, lack of data, and difficulty in obtaining indicators. [53]. How to realize the structural optimization design of aircraft is of great significance to the

Table 2 The main experience of DT aircraft concept development

No	Time	Proposer	Definition or explanation
1	2011	AFRL	Object: individual aircraft structure; Highlights: reengineer of structural life prediction and management; Expectation: ultrarealistic in geometric details and material details; Phase: full lifecycle [30]
2	2012	AFRL	Object: individual aircraft structure; Highlights: specific computational model; Expectation: enhance management methods; Phase: the entire lifecycle [11]
3	2012	NASA/AFOSR	Object: an as-built vehicle or system; Highlights: all-round simulation; Method: update and integration of model and data; Expectation: mirror the life of the corresponding flying twin; Phase: the entire lifecycle [13]
4	2014	NASA	Object: individual aerospace vehicles; Highlights: life management and certification paradigm; Method: simulation consists of as-built vehicle state, as-experienced loads and environments, and other vehicle-specific histories; Expectation: high-fidelity modeling; Phase: during the entire service life [31]
5	2014	DoD	Object: an as-built physical entity or system; Highlights: combined with DTh provides comprehensive simulation; Method: use the best available models, sensor information, and input data; Expectation: reflect and predict activities/performance of physical entity; Phase: lifecycle [36]
6	2018	NRC	Object: Individual airframe system; Highlights: digital representation of as-built/as-maintained system; Expectation: reflect and predict activities/performance of physical entity; Phase: lifecycle [49]

safety and reliability of aircraft [54, 55]. The development of DT technology can solve the above problems.

The purpose of ADT is to develop and demonstrate a probabilistic, risk-based, flight-by-flight individual aircraft tracking framework to replace the current one. The prognostic and probabilistic individual aircraft tracking framework proposed by Rudd [56] added more functions than the traditional individual aircraft tracking method: probability (or uncertainty), diagnosability, and predictability. In 2017, Airbus presented the strategy of creating aircraft fatigue model and DT, which pushed aircraft fatigue analysis to a digital age [57]. This strategy requires continuous review of aircraft design and operational parameters.

DT of aircraft structure can be expressed by multi-source data from online sensor monitoring, offline ground inspection, and flight operation history. Then, react and predict the behavior and performance of the corresponding aircraft structure entity during the whole lifecycle. According to the characteristics of virtual-real mapping, timeliness, multi-discipline/multi-physics, multi-scale/multi-fidelity, and probability/uncertainty [58], the basic framework of aircraft structure DT is designed as shown in Fig. 2. As a vital load bearing and maneuverability component of aircraft, aircraft landing gear bears high static and dynamic loads [53]. After adopting the DT technology, lots of tests, actual measurement, and calculation cases are synthesized to produce design simulation and integrate the historical test environment parameters into the design of the landing gear model, which generates structural optimization design scheme.

Ice deposition on wings, tails, and instruments is one of the most dangerous risks for aircraft flying at different altitudes. Developing a model-based aircraft deicing system can prevent or reduce icing on aircraft safety–critical components and ensure the operational safety of aircraft [59].

Assist the aerodynamic design process of components through interactive visualization of performance and geometry [60], non-destructive techniques for thermal barrier coatings estimation [61]. And high-fidelity, high-performance polymer composite data and new developments in digital modeling are combined to create a DT, which will prolong the life and improve the safety of key aircraft engine components [62].

4.2 Assembly

As a key technology of the aircraft manufacturing industry, assembly collaboration technology is of great matter of improving competitiveness and manufacturing level. Aircraft is a complex product, and its assembly process involves high complexity, strong dynamics, uncertainty, and frequent maintenance, so the quality control requirements for aircraft assembly are extremely strict. Traditional aircraft quality data is scattered in numerous business and management systems, manual processing is often used to locate quality problems, and its closed-loop management is weak [63, 64].

The assembly process is divided into three phases: workshop scheduling, on-site assembly, and problem feedback [64]. Combining DT with digital thread can create a cooperative and interconnected information cycle, which is called closed-loop manufacturing and enables companies to sync and optimize production among design, production schedule, manufacturing, automation, and use [65]. Real-time

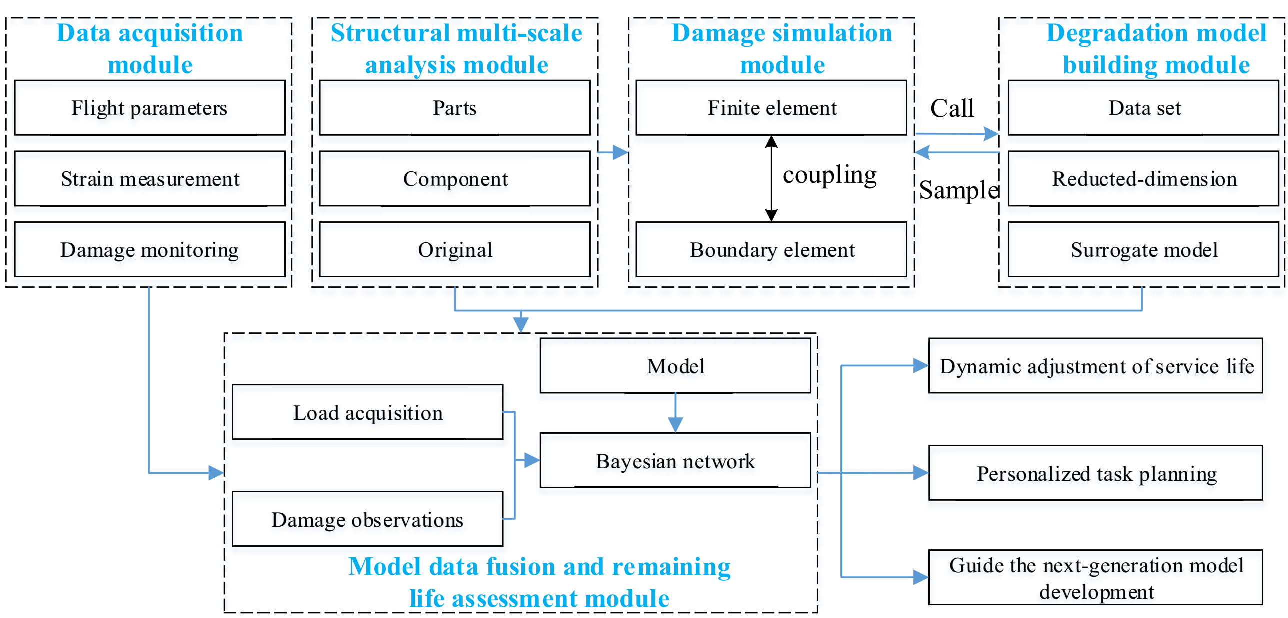

Fig. 2 Basic framework of an ADT [58]

acquisition, processing, and management of physical assembly data are contributed to establishing assembly DT and big data-driven predict, and complete assembly production management and control services based on DT [66].

The work mode based on digital coordination can accurately obtain the size, shape, spatial position, coordination accuracy, and other information of products [67], and an assembly coordination model can be established based on measurement data to control the quality of aircraft assembly [69], which greatly increases the efficiency of assembly. DT can achieve the integration of aircraft assembly quality data and use aircraft 3D model, to realize the synchronization of the virtual-physical world of the assembly process [68], and improve the efficiency and accuracy of assembly quality in the physical world. The combination of online multi-point displacement monitoring with matrix completion theory can realize real-time displacement perception of aircraft assembly [70]. DT provides a knowledge-supported for the intelligent design of the aircraft assembly line to improve efficiency, performance, and visibility [71]. The blockchain-based system provides a management platform for accurately recording the traceability data of aircraft spare parts, realizes the information integrity in the process of transaction operation, and improves the quality of traceability data and reliable information sharing in spare parts supply chain [72]. An integrated application platform for intelligent assembly based on DT is proposed in [73]. The platform consists of a hardware layer, software layer, and application layer, which can intelligently optimize and control the assembly process of aerospace products.

The aircraft assembly DT can collect comprehensive quality data [63], to realize the synchronous modeling of the product assembly process and assembly data package generation, which makes the process of complex products traceable [64], and effectively improves the quality management ability of the aircraft final assembly process, assembly quality, and efficiency [74].

4.3 Manufacturing

Currently, DT technology is the most active in intelligent manufacturing. Airbus and Boeing are building digital twin aircraft, and GE is developing digital twin engines. The digitalization of manufacturing accelerates the practical application of complex virtual product models, throughout the entire cycle of product generation. Particularly, the high-fidelity models of manufactured products are essential for reducing the gap between design and manufacturing and reflecting the real-virtual world [75]. Airbus and Boeing are constructing DT aircraft [28], and GE is developing DT engines [76]. The DT can effectively shorten the new product development cycle by 10 ~ 75% [77], and reduce the time originally spent on aerospace material testing and verification by 80% and 25% respectively [78].

Since the milling of the fan blade is easily deformed and the processing time is long, the processing accuracy and efficiency of the fan blade are affected. Milling processes DT model integrates relevant data from the machining process and cutting force models, which makes it possible to recognize trajectory deviation directly in the machining process, optimization of the machining process [79]. The processing efficiency and accuracy of blades can be improved by parameter optimization methods [81, 82], which integrates intelligent algorithms with processing databases and is ultimately be applied to blade manufacturing. By constructing DT of an aero-engine fan blade and simulating its manufacturing process and quality inspection process, the goals of reducing machining time, improving machining accuracy, and heightening manufacturing capability are achieved [80].

Optimization of the aircraft manufacturing process can also effectively raise its efficiency and safety. However, during additive manufacturing with DT, there are uncertainty material performance and instability process [83], which realize uncertainty management and control of the manufacturing process through controller design for DT. The machining process is simulated in virtual space, and in real-time precision machining. The computer numerical control monitors signals and sends out an early warning for the problematic process [84]. System simulation and model parameter optimization are carried out through data interaction and recording. DT module receives real-time feedback data from manufacturing measurement and performance testing and makes corrections during the whole optimization process [85]. The three-axis optimized machining simulation algorithm of [86] has been tested and verified by Commercial Aircraft Corporation of China Ltd.; it can follow the actual machining process efficiently. [87] put forward a DT modeling method based on the principle of bio-mixing, and developed a variety of DT models, such as geometric model, behavioral model, and process model, which could interact with each other to form a comprehensive real representation of the physical processing process, thus ensuring the multi-physicality, dynamics, and integration of the product processing process.

Combined with DT technology, it can handle large-scale discrete optimization problems in the workshop and improve the search efficiency of the workshop [88]. Ensure the quality and cost control of the additive manufacturing process of aviation industry metal components to guarantee that all parts installed on each aircraft meet the safety conditions [89]. Based on the specific function data of the 3D visualization process and support the use of web-based business analysis dashboards to help operators make correct decisions [90]. By integrating the corresponding virtual manufacturing resources into the cyber-physical production system, a variety of manufacturing services can be packaged and defined in a standardized format [91].

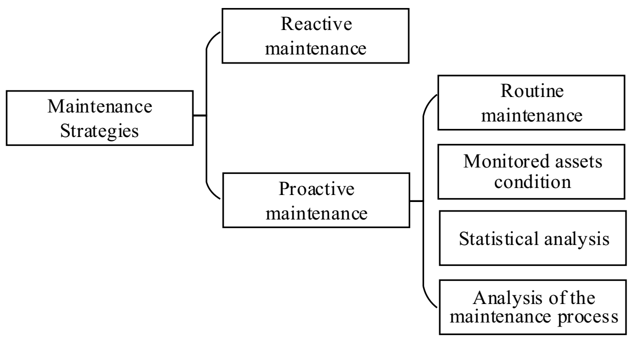

Fig. 3 Maintenance strategies diagram [94]

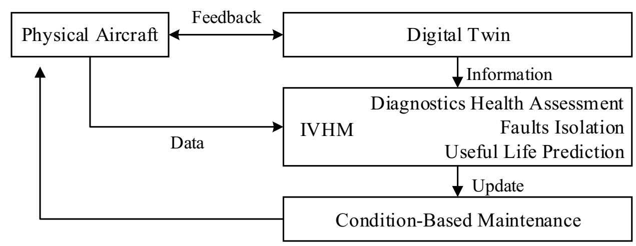

Fig. 4 DT in an IVHM framework [95]

4.4 Operation and maintenance

The development of maintenance has undergone the transition from "post-event maintenance" and "preventive maintenance" to "predictive maintenance," and the future development direction is precise maintenance. Planned maintenance activities are the foundation of implementing maintenance strategy [92]. By monitoring assets, information can be obtained in real-time, so that the behavior of assets can be analyzed. As shown in Fig. 3, the maintenance strategies can be divided into reactive maintenance and proactive maintenance. Proactive maintenance consists of four parts: routine maintenance, monitored assets condition, statistical analysis, and analysis of the maintenance process. The creation of common methodologies is very critical for the use of DT technology for the prediction of the machines' health status [93]. It offers great potential for digitalization maintenance with the following advantages [94].

Integrated vehicle health management (IVHM) is the paradigm shift to support condition-based maintenance for vehicles. DT combined with IVHM technology can more accurately assess the health of complex systems. IVHM technology is based on the continuous interaction and update of spacecraft data to achieve the effect of diagnosis, prediction, and failure mitigation [95]. The framework is shown in Fig. 4. Researchers have developed a variety of aircraft DT models by this idea. Especially in the research and development of engine DT [96–101], environmental control system DT, and fuel system DT [102], combined with real-time updated engine operation data, line maintenance data, workshop data, and other information [97], DT has significant advantages on fault parameter identification [96, 98] and line fault unit isolation [100], and then makes failure analysis and life prediction [97–101] for the degradation of core components, forming a network early warning system [99] to forecast and evaluate engine operating conditions, and reduce operating risks.

The fatigue crack detection of aircraft is very important for flight safety. For example, the use of dynamic Bayesian networks to integrate physical models, random conditions, and sources of uncertainty is helpful to the realization of DT [103]. By designing the finite element model of the key area and embedding the sub-structure analysis technology, it can help the operator detect the fatigue cracks that appear nearby [104]. The probability distribution of aircraft tire sinking rate, wear degree, yaw angle, and landing speed can all be described by DT model [105].

Nonlinear reduced-order models are being investigated for use as DT for advanced aircraft and spacecraft. A novel approach of computing analytical gradients of nonlinear normal mode solutions concerning system parameters using the multi-harmonic balance method [107] simplifies the high-fidelity model, greatly saves the calculation time, and provides an updated scheme for accurately describing aircraft behavior, component maintenance, or aging in time [108]. Integrating the digital models of the electromechanical actuator and anti-skid braking system and realizing various failure modes in electromechanical actuator digital model are helpful to strengthen the overall health management system of an electric braking system of multi-electric aircraft [109]. Comprehensive experimental verification of the DT of the developed aircraft environmental control system can realize the accurate diagnosis of the component-level simulation of the civil aircraft environmental control system [110]. Augmented reality, 3D models, and other technologies can realize the remote cooperation function of aircraft maintenance and improve the efficiency of aircraft maintenance [111]. These are conducive to the continuous safe operation of the aircraft, damage assessment, diagnosis, and prediction [106]. Significantly reduce the calculation cost and time cost.

4.5 Other aviation DT research

4.5.1 UAV field

UAV is one of the most active fields in the aviation industry in recent years. The scale, participants, and traffic volume of UAVs are increasing. With the rapid development and popularization of UAV, it has been widely applied to agricultural plant protection, land and resources planning, emergency rescue, forest fire-prevention, smart city, military politics, leisure tourism, and other fields.

At present, there are a few targeted types of research on UAV DT, and they mostly appear in the form of auxiliary functions in other DT fields. Taking advantage of the UAV's high space/time resolution, high measurement frequency, flexibility, and fast deployment time provide a convenient way to establish the target DT [112–117]. For example, the UAV can form a 3D model of the bridge and integrate it into the bridge's DT to monitor the health of the bridge in real-time [112], and combined with big data, IoT, and AI can connect specific site data with regional or global agricultural views to help develop site-specific protection and agricultural management practices [113]. At the same time, its high-resolution aerial satellite imagery advantage can map the digital elevation model of the map to maximize economic and environmental benefits [114], to help the efficient construction of smart cities [115]. Provide technical advantages for the intelligent security construction of DT cities [117].

The complexity and coherence of intelligent cooperation among UAVs greatly hinder its application development. The collaborative framework of the UAV swarm based on DT technology is intelligent and high-fidelity, to monitor the entire lifecycle of the UAV swarm. Further combine machine learning methods to achieve optimal solution exploration and control drone behavior [118]. The reliable UAV DT products include optimization loops, digital model parameterization, etc. [121], and the reduced-order model library of components can be combined with Bayesian state estimation [119], making it possible to train pilots and plan paths in a virtual environment [120]. These methods provide opportunities to reduce risks and losses in flight.

4.5.2 Others

In addition to the above applications, aviation DT is also doing well in aircraft airspeed measurement [122], airport product verification [123], wind tunnel measurement [124], flight education training [125, 126], aircraft maintenance training [127], airport capacity increase [100, 128], and more.

5 Key technologies

DT provides a standardized platform for the development of the intelligent aviation industry, realizes the consistent and seamless exchange of technical information and cross-domain interoperability, and at the same time reduces the risk of aircraft operation and improves the safety and efficiency of aircraft operation [129]. The construction of DT model of the aviation industry involves three key technologies: data fusion technology, multi-dimensional and multi-scale high-fidelity modeling technology, and fusion with New Information Technology (New IT). At the same time, considering the close relationship between the safe operation of aircraft and human factors [130], this section discusses the necessity of DT human–machine interaction(HMI) technology.

The relationship between each key technology is shown in Fig. 5. The fusion of the collected data can provide a basis for multi-dimensional and multi-scale high-fidelity modeling, integration with New IT, and HMI analysis. At the same time, HMI and New IT can promote multi-dimensional and multi-scale high-fidelity modeling. The four key elements work together to enable the aviation industry DT to provide better intelligent services.

5.1 Data fusion

Traditional data fusion technologies include probability fusion (e.g., Bayesian fusion), evidence belief reasoning fusion (e.g., Dempster-Shafer theory), and rough set-based fusion [131]. However, the DT data in the aviation industry has the attributes of multi-source and heterogeneous. It is necessary to ensure the data quality, reduce data uncertainty, unify data standards [132], improve data availability, eliminate data information islands, and enhance the information management ability of DT [133]. From the computational perspective, the "data and information fusion" is the key technology to propel a DT, which promotes the flow of information from raw sensory data to advanced comprehension and insights [106], and enhances the efficiency and application effect of data fusion by using big data, machine learning [134], and deep learning methods [135]. The role of data fusion in DT ecosystem is illustrated in Fig. 6. The advantages of the fusion operations are listed as follows [106]:

1. Sensor fusion can provide better signal quality;and
2. Both physical model fusion and data model fusion can improve model performance;
3. The fusion of sensor and physical model can form an adaptive physical model;

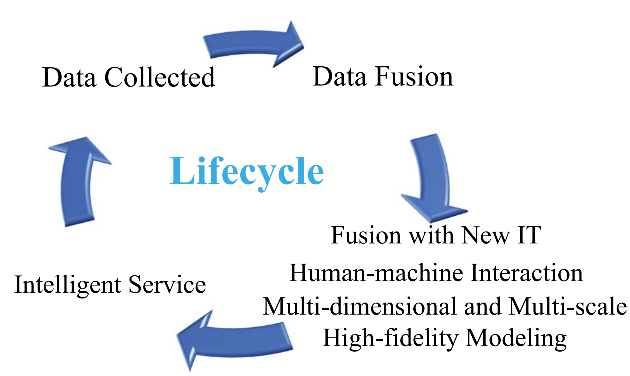

Fig. 5 The relationship between key technologies

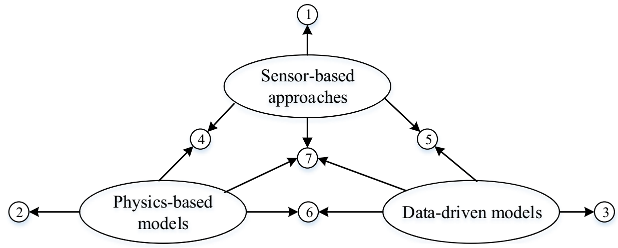

Fig. 6 Possible data fusion operations in DT development

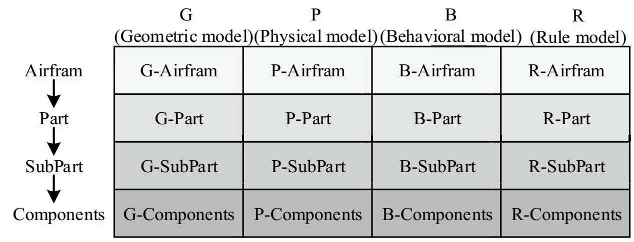

Fig. 7 Multi-dimensional and multi-scale model of civil aircraft

4. The fusion of sensor and data model enhances the robustness of data-driven model;
5. The accuracy of prediction is improved by the fusion of the data model and the physical model;
6. The integration of sensors, physics, and data models enables managers to make more reliable decisions.

5.2 Multi-dimensional and multi-scale high-fidelity modeling

Aircraft can be divided into four scale levels: airframe, part, sub-part, and components. And physical entities at different levels correspond to respective DT models. Through simulation verification and iterative optimization, the unit DT, subsystem DT, system DT, and complex systems DT are respectively realized and, at last, make mutual support and system integration at different level DT come true.

At the same time, the DT aircraft completes virtual modeling of physical entities from four dimensions: geometrical (G), physical (P), behavioral (B), and rules (R). All dimensions are associated, combined, and integrated to form an interconnected digital space model with high fidelity, which provides technical support for realizing multi-dimensional fusion simulation of “geometry-physics-behavior-rules” with multi-discipline, multi-mode, and multi-scale.

Through the establishment of the association relationship of the various dimensional models, a comprehensive virtual aircraft DT is formed, and the visual operation and simulation of the model are realized in the form of three-dimensional representation. In the information world, the real-time functions and performance of each system level of the physical civil aircraft are completely mapped, and the maintenance object information of the civil aircraft is analyzed level by level. It can be modeled and simulated with high efficiency and precision, and the maintenance of civil aircraft systems can be carried out from multi-scale. The correlation between the models is shown in Fig. 7.

5.3 Fusion with New IT

The integration of DT in the aviation industry and New IT contribute to the in-depth integration of all-elements, whole-process, and whole-business data of physical entities and realize the accurate construction of the entire lifecycle model of the physical products of the aviation industry, the comprehensive and real perception of the physical scene, and the completion of the comparison dynamic real-time interaction and intelligent services of aviation industry products, related personnel, and related environments [20]. Table 3 displays the integration advantages of DT and New IT.

Table 3 Advantages of DT and integration of New IT [20]

Combination	Benefits
DT + IoT	IoT provides technical support for the overall perception of the physical world and helps the real-time, reliable, and efficient transmission of twin data through wired or wireless networks.
DT+AR/VR/MR	To provide multi-dimensional and multi-time scale high-fidelity digital mapping for aviation physical entities. Realize the integration of visualization and virtual reality, make the virtual model truly present a physical entity, and enhance the functions of the physical entity.
DT + Edge computing	Edge computing technology can filter, specify and process some data collected from the physical world in real-time on the edge side, thus realizing the immediate decision-making, quick response, and timely execution of users. Cloud-edge data collaborative processing for different needs is realized, which improves data processing efficiency, reduces cloud data load and data transmission delay, and provides a guarantee for the real-time performance of DT.
DT+ cloud computing	Cloud computing can dynamically meet the different computing, storage, and operation requirements of aviation DT.
DT +5G	The 5G communication technology has the features of high speed, high-capacity, low delay, and high reliability, which can meet the data transmission requirements of the DT in the aviation industry, thus better promoting the application of the DT in the aviation industry.
DT + Big Data	Big data can extract more valuable information from the massive data generated by the aviation industry DT at high speed, to better explain and predict the result and process of the aviation industry DT.
DT + Blockchain	Blockchain can provide a reliable guarantee for the security of the aviation industry DT, and ensure that twin data can be retained and tracked throughout the whole process.
DT + AI	AI automatically performs data preparation, analysis, and fusion through intelligent matching of the best algorithm. Perform in-depth knowledge mining on twin data to generate various types of services. Significantly enhance the value of data and the responsiveness and accuracy of services.

5.4 Human–machine interaction

Humans play a vital role throughout the whole lifecycle of an aircraft, especially in operation and maintenance, where unpredictable emergency behaviors often occur [13]. DT can alleviate this problem, attain a more flexible interaction mode, analyze complex scenes of human existence [138], improve aircraft efficiency and operational safety [136], and support more effective and safer HMI [137]. The way of DT-enhanced HMI in design, manufacturing, and service is shown in Table 4.

6 Future research directions

Although DT has achieved excellent performance in the aviation industry, there is still a large potential for improvement and optimization, especially for practical application. Accordingly, some research trends and potential directions are given as follows.

1. **Digital process twin risk control**

The research of the aviation industry DT covers the whole lifecycle, which improves the ability of aircraft to operate efficiently and safely but also increases the risk and control difficulty of digital process twin. Once the risk occurs, it will bring property losses and even endanger life safety. Therefore, in the process of aircraft digital transformation, it is necessary to pay attention to the risk research of digital process twin, reduce the uncertain factors in the twin process, improve the robustness of the system, and realize intelligent aviation safety.

2. **Interactive DT research**

DT aircraft cannot live without people from research and development to retirement, and human behavior is more subjective, and unpredictable. Therefore, to realize the physical-virtual world interaction of DT aircraft, it is necessary to solve the problem of human–machine interaction under the framework of DT aircraft. Comprehensively consider information, calculation, and control, and construct an abstract model of aircraft DT with the man in the loop, to realize the optimal coordination between human and aircraft to improve flight safety capability.

3. **Data learning**

Machine learning, deep learning, and reinforcement learning have good performance in classification, clustering, and task generation, which can improve the adaptability of the aircraft digital twin, so that the aircraft digital twin can evolve, perceive, remember, and solve problems. Conversely, the DT model can accelerate the training phase of learning by creating suitable training datasets and simulating automatic labeling of toolchains, improving aircraft diagnostic, manufacturing, and decision-making capabilities.

Table 4 Methods of DT-enhanced HMI [137]

Methods of DT-enhanced	Phase	Results
Methods of DT-enhanced HMI in design	Conceptual design	Interactively. Designers can measure the performance of the aircraft in terms of design specifications, dimensions, comfort, and safety in use
	Design verification	Based on the DT data, designers can modify design program iteratively in the virtual environment, and then the design scheme can be optimized at an early phase
	Redesign	Based on the DT data, the shortcomings of current design are deeply analyzed, and then the design scheme is modified and optimized to meet the new user needs and product functions
Methods of DT enhanced-HMI in manufacturing	Task allocation,	Potential problems can be first, and then a better allocation scheme will be calculated, improve the efficiency of human–machine cooperation
	Assembly process	Workers can accurately locate small components and parts in the virtual model, which is a more realistic, accurate mapping environment
	Process control	Based on the DT data, engineers can quickly detect the occurrence of abnormal events and take timely measures to control failures, providing a safe interactive environment for workers
Methods of DT-enhanced HMI in service	Training	New operators are trained with the help of DT technology. The virtual space provides trainees with precise and visual guidance on the machine, and can quickly become familiar with the operating methods of the machine
	Maintenance	Combined with DT, engineers can directly find damaged parts and provide targeted maintenance guidance. Therefore, the maintenance work can complete the interaction accurately, intuitively and conveniently

Besides the above fields, aviation industry DT can also be researched in airport operation planning, low-altitude corridor safety digitization, UAV clusters, real-time tracking, and remote collaborative control.

7 Conclusion

The application of DT in different industries has surged. This article summarizes the research and application status of aviation industry DT by government authorities, industry, and academia. The main contributions of this article are summarized as follows.

1. The development process of DT concept is summarized, and clarifies the concepts of DT and design engineering, digital systems model, digital thread, IoT, and CPS.
2. This paper reviews the history of the aviation industry DT by various authoritative organizations (including NASA, AFRL, Department of Defense, AFOR, and NCR), and on this basis, summarizes the characteristics of the aviation industry DT.
3. The application status of aviation industry DT in the whole lifecycle is reviewed, including optimization design, assembly, manufacturing, operation and maintenance, UAV, and others. On this basis, it is concluded that aviation DT is the most widely used in manufacturing and maintenance, and the research in the UAV field is less but necessary.
4. Summarize the key technologies of aviation industry DT. Data fusion is the key, while multi-dimensional and multi-scale high-fidelity modeling is the core, New IT fusion is the driving force, and HMI is necessary. Discuss future research trends and development directions, including digital process twin risk control, interactive DT research, and data learning.

Although DT has become a research hotspot, aviation industry DT still has many problems to be solved urgently to enhance the feasibility of its engineering application. Therefore, through this paper, researchers can have a clear understanding and comprehending of aviation industry DT, and provide a reference for further research.

Acknowledgements Thanks for the editors, referees, and all the workmates who dedicated their precious time to this research and provided insightful suggestions. All their work contributes greatly to this article.

Author contribution Minglan Xiong: background research, methodology, validation writing—original draft, editing. Huawei Wang: review and editing, supervision.

Funding This work was supported by National Natural Science Foundation of China (Grant No. U1833110).

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

1. Badea V, Zamfiroiu A, Boncea R (2018) Big Data in the Aerospace Industry. Informatica Economică 22(1):17–24
2. Lee J, Bagheri B, Kao H (2015) A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manuf Lett 3:18–23
3. Lasi H, Fettke P, Kemper, HG et al (2014) Industry 4.0. Bus Inf Syst Eng 6:239–242. https://doi.org/10.1007/s12599-014-0334-4
4. Ling L (2018) China's manufacturing locus in 2025: with a comparison of 'Made-in-China 2025' and 'Industry 4.0.' Technol Forecasting Soc Change 135:66–74
5. Qi Q, Tuegel E (2018) Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison". IEEE Access 6:3585–3593
6. Mabkhot M, Al-Ahmari A, Salah B, Alkhalefah H (2018) Requirements of the smart factory system: a survey and perspective. Machines 6(23). https://doi.org/10.3390/machines6020023
7. Zhou M, Yan J, Feng D (2019) Digital twin framework and its application to power grid online analysis. CSEE J Power Energy 5(3):391–398
8. Tao F, Zhang H, Liu A, Nee A (2019) Digital twin in industry: state-of-the-Art. IEEE Trans Ind Informatics 15:2405–2415
9. Kritzinger W, Karner M, Traar G, Henjes J, Sihn W (2018) Digital Twin in manufacturing: a categorical literature review and classification. IFAC- PapersOnLine 51(11):1016–1022
10. Li L, Aslam S, Wileman A, Perinpanayagam S (2021) Digital twin in aerospace industry:a gentle introduction. IEEE Access 10:9543–9562
11. Tuegel E, Ingraffea A, Eason T, Spottswood S (2011) Reengineering aircraft structural life prediction using a Digital Twin. Int J Aerosp Eng. https://doi.org/10.1155/2011/154798
12. Melesse T, Pasquale RS (2020) Digital twin models in industrial operations: a systematic literature review. Procedia Manufacturing 42:267–272
13. Grieves M, Vickers J (2017) Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. Transdisciplinary perspectives on complex systems, Springer, Cham, pp 85–113
14. Boschert S, Rosen R (2016) Digital twin—the simulation aspect. Mechatronic Futures, Switzerland, Springer, Cham, pp. 59–74. https://doi.org/10.1007/978-3-319-32156-1_5
15. Shafto M, Conroy M, Doyle R, Glaessgen E, Kemp C, LeMoigne J, Wang L (2010) NASA technology roadmap: modeling, simulation, information technology & processing roadmap technology area 11. 2019–04–13
16. Tuegel E (2012) The airframe digital twin: some challenges to realization. In 53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA, pp. 1812. https://doi.org/10.2514/6.2012-1812

17. Glaessgen E. Stargel D (2012) The digital twin paradigm for future NASA and US Air Force vehicles", in *Proc.* In 53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA
18. Syafrudin M, Alfian G, Fitriyani N, Rhee J (2018) Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing. Sensors -Basel 18(9):2946
19. Darko A, Chan A, Adabre M, Edwards D, Hosseini M, Ameyaw E (2020) Artificial intelligence in the AEC industry: scientometric analysis and visualization of research activities. Autom ConStruct 112:103081
20. Tao F, Zhang H, Liu Q, Zhang M, Liu W et al (2010) Ten question towards digital twin: analysis and thinking. Comput Integr Manuf Syst 26(1):1–17
21. Parris C (2017) Digital twin Predix, GE. China. https://www.ge.com/cn/sites/www.ge.com.cn/files/8-15-4%20Predix-Digital-Twin-Technology.pdf
22. Zhao M, Ning Z (2020) Software definition and digital twin. Casting the Soul: Software defined manufacturing. China Machine Press, Beijing, China, pp 226–230
23. SIEMENS (2017) Digital twin of respiratory products. https://new.siemens.com/global/en/company/stories/industry/digitaltwin-simulation-vyairemedical. Accessed 15 Feb 2022
24. Dassault Group (2019) South Australia to share vision for the future economy. https://govinsider.asia/digital-gov/south-australia-share-vision-future-economy/. Accessed 15 Feb 2022
25. PTC Group (2019) PTC digital center. https://www.ptc.com/cn/industry-insights/zhongtai. Accessed 15 Feb 2022
26. ESI Group (2019) Hybrid Twin™ by ESI in Composite Factory 4.0. https://www.esi-group.com/resources/webinar/transformation-towards-the-industry-4-0-with-hybrid-twintm. Accessed 15 Feb 2022
27. Talkhestani BA, Jung T, Lindemann B, Sahlab N, Jazdi N, Schloegl W, Weyrich M (2019) An architecture of an intelligent digital twin in a cyber-physical production system. at-Autom 67(9):762–82
28. Tao F, Cheng J, Qi Q, Zhang M, Zhang H, Sui F (2018) Digital twin-driven product design, manufacturing and service with big data. Int J Adv Manuf Technol 94:3563–3576
29. Zhang H, Liu Q, Chen X, Zhang D, Leng J (2017) A digital twin-based approach for designing and multi-objective optimization of hollow glass production line. IEEE Access 5:26901–26911
30. Lu Y, Liu C, Kevin I, Wang K, Huang H, Xu X (2020) Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics Com-Int Manuf 61:101837. https://doi.org/10.1016/j.rcim.2019.101837
31. Uhlemann T, Lehmann C, Steinhilper R (2017) The digital twin: realizing the cyber-physical production system for industry 4.0. Procedia CIRP 335–40
32. Bagheri B, Lee J (2015) Big future for cyber-physical manufacturing systems. Design World 23. http://www.designworldonline.com/big-future-for-cyber-physical-manufacturing-systems/
33. Li H, Wei M, Huang J et al (2019) Survey on cyberphysical system. A CTA Automatica Sinica 45(1):37–50
34. Tao F, Liu W, Liu J et al (2018) Digital twin and its potential application exploration. Comput Integr Manuf Syst 24(01):1–18
35. Zhao Z, Liu F, Cai Z, Xiao N (2018) Edge com putting: platforms, applications and challenges. Journal of Computer Research and Development 55(2):327–337
36. Systems Engineering Initiatives (2021) http://www.acq.osd.mil/se/initiatives/init_de.html. Accessed 8 Jun 2021
37. Liu Y (2018) Digital clue helps US Air Force equipment development. Measurement & Control Technology 37(9):1–4
38. Zhang B, Li X, Wang X (2019) From digital twin to digital engineering modeling and simulation entering a new era. Journal of System Simulation 31(03):369–376
39. Glossary of Defense Acquisition Acronyms and Terms (2019) Defense Acquisition Portal, Defense Acquisition University, Fort Belvoir, VA. https://dap.dau.mil/glossary/Pages/Default.aspx. Accessed 27 Jun 2021
40. Zweber J, Kolonay R, Kobryn P, Tuegel E (2017) Digital thread and twin for systems engineering: Pre-MDD through TMRR. In Proceedings of the 55th AIAA Aerospace Sciences Meeting. http://arc.aiaa.org. https://doi.org/10.2514/6.2017-0875
41. Margaria T, Schieweck A (2019) The Digital Thread in Industry 4.0. In: Ahrendt W., Tapia Tarifa S. (eds) Integrated Formal Methods. IFM 2019. Lecture Notes in Computer Science, vol 11918. Springer, Cham. https://doi.org/10.1007/978-3-030-34968-4_1
42. Kobryn P, Tuegel E, Zweber J, Kolonay R (2017) Digital thread and twin for systems engineering: EMD to disposal. In Proceedings of the 55th AIAA Aerospace Sciences Meeting. http://arc.aiaa.org, https://doi.org/10.2514/6.2017-0876
43. Phanden R, Sharma P, Dubey A (2021) A review on simulation in digital twin for aerospace, manufacturing and robotics. Mater Today: Proc 38:174–178
44. Wang L (2020) Application and development prospect of digital twin technology in aerospace. IFAC-PapersOnLine 53(5):732–737
45. Hochhalter, Jacob D et al (2014) Coupling damage-sensing particles to the digitial twin concept. NASA/TM–2014–218257, National Aeronautics and Space Administration, Langley Research Center, 2014. http://www.sti.nasa.gov
46. Tuegel E, Kobryn P, Henderson D (2016) The Airframe Digital Twin Spiral 1 Program. In 2016 Aircraft Airworthiness and Sustainment Conference, March 21–24, pp 9032. http://www.meetingdata.utcdayton.com/agenda/airworthiness/2016/agenda.htm
47. Wang L, Asher I, Ryan K, Khan G, Ball D (2016) AIRFRAME DIGITAL TWIN (ADT) Delivery Order 0001: Scalable, Accurate, Flexible, Efficient, Robust, Prognostic and Probabilistic Individual Aircraft Tracking (SAFER-P2IAT) 1. The General Electric Company Niskayuna United States
48. Anagnostou E, Engel S, Madsen J, Engel K, Nardiello J et al (2016) Developing the Airframe Digital Twin Prognostic & Probabilistic Individual Aircraft Tracking Paradigm. In 2016 Aircraft Airworthiness and Sustainment Conference, March 21–24, pp 9038. http://www.meetingdata.utcdayton.com/agenda/airworthiness/2016/agenda.htm
49. Liao M, Guillaume R, Yan B (2020) Airframe digital twin technology adaptability assessment and technology demonstration Eng Fract Mech 225. https://doi.org/10.1016/j.engfracmech.2019.106793
50. Qiu Z, WANG X, (2012) Comprehensive design ideas of modern aircraft structure. Fundamentals of aircraft structural strength analysis and design, Beijing. University of Aeronautics and Astronautics Press, China, pp 5–7
51. Du Y (2014) Research on probabilistic damage tolerance analysis system and key technologies. Ph.D. dissertation, Dept. Solid mechanics, Northwestern Polytechnical University, Xi'an, Shanxi, China 1–2
52. Lee H, Cho H, PARK S, (2012) Review of the F-16 individual aircraft tracking program. J Aircraft 49(5):1398–1405
53. Tao F, Liu W, Zhang M et al (2019) Five dimension digital twin model and its ten applications. Comput Integr Manuf Syst 25(1):1–18
54. Besch H (2015) Large aircraft landing gears—a brief overview. In Proceedings of the 6th International Munich Chassis Symposium 2015, Berlin, Germany: Springer-Verlag 685–15

55. Kuruppu K, Hettiarachchi C (2018) Case study on aircraft tyre wear in Y12 aircraft tyres. Aeronaut J 122:1–22
56. Rudd J (2013). Airframe digital twin. In Proceedings of the 27th Symposium of the International Committee on Aeronautical Fatigue and Structural Integrity, Jerusalem, Israel 5:15
57. Graham K, Artim M, Daverschot D (2017) Aircraft fatigue analysis in the digital age. In Proceedings of the 29th Symposium of the International Committee on Aeronautical Fatigue and Structural Integrity (ICAF2017), pp. 61
58. Dong L, Zhou X, Zhao F et al (2021) Key technologies for modeling and simulation of airframe digital twin. Acta Aeronautica et Astronautica Sinica 42(3):113–141
59. Bachelor G, Brusa E, Ferretto D, Mitschke A (2019) Model-based design of complex aeronautical systems through digital twin and thread concepts. IEEE Syst J 14(2):1568–1579
60. Tadeja S, Seshadri P, Kristensson P (2020) AeroVR: An immersive visualisation system for aerospace design and digital twinning in virtual reality. Aeronaut J 124(1280):615–1635
61. Unnikrishnakurup S, Dash J, Ray S, Pesala B, Balasubramaniam K (2020) Nondestructive evaluation of thermal barrier coating thickness degradation using pulsed IR thermography and THz-TDS measurements: a comparative study. NDT and E Int 116:102367. https://doi.org/10.1016/j.ndteint.2020.102367
62. Seon G, Nikishkov Y, Makeev A, Ferguson L (2020) Towards a digital twin for mitigating void formation during debulking of autoclave composite parts Eng Fract Mech 225. https://doi.org/10.1016/j.engfracmech.2019.106792
63. Cai H, Zhang W, Zhu Z (2019) Quality management and analysis of aircraft final assembly based on digital twin. In IEEE 2019 11th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC) 1:202–205
64. Zhuang C, Gong J, Liu J (2021) Digital twin-based assembly data management and process traceability for complex products. J Manuf Syst 58:118–131
65. Demartini M, Galluccio F, Mattis P, Abusohyon I, Tonelli LR, F, (2019) Closed-loop manufacturing for aerospace industry: An integrated PLM-MOM solution to support the wing box assembly process. IFIP International Conference on Advances in Production Management Systems. Springer, Cham, pp 423–430
66. Zhuang C, Liu J, Xiong H (2018) Digital twin-based smart production management and control framework for the complex product assembly shop-floor. Int J Adv Tech 96:1149–1163
67. Guo F, Zou F, Liu J, Wang Z (2018) Working mode in aircraft manufacturing based on digital coordination model. Int J Adv Tech 98(5):1547–1571
68. Cai H, Zhu J, Zhang W (2021) Quality deviation control for Aircraft Using Digital. Twin J Comput Inf Sci Eng 21(3). https://doi.org/10.1115/1.4050376
69. Jiang Y, Huang X, Li S, Deng Z (2019) A coordination modelling approach for assembly of multi-constrained objects based on measured skin model. Assembly Autom. 39(2). https://www.emerald.com/insight/content/doi/https://doi.org/10.1108/AA-04-2018-058/full/html
70. Liang B, Liu W, Liu K, Zhou M, Zhang Y, Jia Z (2020) A displacement field perception method for component digital twin in aircraft assembly. Sensors 20(18). https://doi.org/10.3390/s20185161
71. Chang X, Jia X, Liu K, Hu H (2020) Knowledge-enabled digital twin for smart designing of aircraft assembly line. Assembly Autom. https://www.emerald.com/insight/content/doi/https://doi.org/10.1108/AA-09-2020-0133/full/html.
72. Ho GTS, Tang Y et al (2021) A blockchain-based system to enhance aircraft parts traceability and trackability for inventory management Expert Syst Appl 179. https://doi.org/10.1016/j.eswa.2021.115101
73. Li S, Liang Y, Bai S, Zhuang C, Cao Y (2021) Research on intelligent assembly modes of aerospace products based on digital twin. J Phys: Conf Ser 1756:26–29
74. Sun X, Bao J, Li J, Zhang Y, Liu S, Zhou B (2020) A digital twin-driven approach for the assembly-commissioning of high precision products. Robot Cim-Int Manuf 61. https://doi.org/10.1016/j.rcim.2019.101839
75. Schleich B, Anwer N, Mathieu L, Wartzack S (2017) Shaping the digital twin for design and production engineering. CIRP Ann 66(1):141–144
76. GE (2021) Digital Twin Software, GE Digital. https://www.ge.com/digital/applications/digital-twin. Accessed 15 Feb 2022
77. GE (2021) Compressing Time-to-V alue for Digital Industrial Companies. https://www.ge.com/digital/sites/default/files/download_assets/The-Digital-Twin_Compressing-Time-to-Value-for-Digital-Industrial-Companies.pdf. Accessed 15 Feb 2022
78. Bolcavage A, Brown P, Cedoz R, Cooper N, Deaton C, Hartman D, Keskin A, Ma K, Matlik J, Modgil G, Stillinger J (2014) Integrated computational materials engineering from a gas turbine engine perspective. Integrating Mater Manuf Innov 3(1):181–204
79. Hänel A, Schnellhardt T, Wenkler E, Nestler A, Brosius A, Corinth C, Fay A, Ihlenfeldt S (2020) The development of a digital twin for machining processes for the application in aerospace industry. Procedia CIRP 93:1399–1404
80. Zhan X, Zhu W (2019) Application framework of digital twin-driven product smart manufacturing system: a case study of aeroengine blade manufacturing. Int J Adv Robot Syst 16(5). https://doi.org/10.1177/1729881419880663
81. Qu S, Zhao J, Wang T (2017) Experimental study and machining parameter optimization in milling thin-walled plates based on NSGA-II. Int J Adv Manuf Technol 89:2399–2409
82. Xu G, Chen J, Zhou H et al (2019) Multi-objective feedrate optimization method of end milling using the internal data of the CNC system. Int J Adv Manuf Technol 101:715–731
83. Stavropoulos P, Papacharalampopoulos A, Michail C, Chryssolouris G (2021) Robust additive manufacturing performance through a control oriented digital twin. Metals 11(5):708. https://doi.org/10.3390/met11050708
84. Wang Z, Wagner T, Guo C (2020) Smart machining process monitoring enabled by contextualized process Profiles for Synchronization. Smart Sustain Manuf Syst 4(2):199–209
85. Xu Z, Ji F, Ding S, Zhao Y, Zhou Y, Zhang Q, Du F (2021) Digital twin-driven optimization of gas exchange system of 2-stroke heavy fuel aircraft engine. J Manuf Syst 58:132–145
86. Cao X, Zhao G, Xiao W (2020) Digital Twin–oriented real-time cutting simulation for intelligent computer numerical control machining. In PI Mech Eng B-J Eng. https://doi.org/10.1177/0954405420937869
87. Liu S, Bao J, Lu Y, Li J, Lu S, Sun X (2021) Digital twin modeling method based on biomimicry for machining aerospace components. J Manuf Syst 58:180–195
88. Zhang Z, Guan Z, Gong Y, Luo D, Yue L (2020) Improved multi-fidelity simulation-based optimisation: application in a digital twin shop floor. Int J Prod Res 1–20
89. Mandolla C, Petruzzelli A, Percoco G, Urbinati A (2019) Building a digital twin for additive manufacturing through the exploitation of blockchain: a case analysis of the aircraft industry. Compu Ind 109:134–152
90. Zörrer H, Steringer R, Zambal S, Eitzinger C (2019) Using business analytics for decision support in zero defect manufacturing of composite parts in the aerospace industry. IFAC-PapersOnLine 52(13):1461–1466
91. Zhang H, Yan Q, Zheng H (2020) Information modeling for cyber-physical production system based on digital twin and AutomationML. Int J Adv Manuf Technol 10:1927–1945
92. Matyas K, Nemeth T, Kovacs K, Glawar R (2017) A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. CIRP Ann Manuf Technol 66:461–464

93. Aivaliotis P, Georgoulias K, Alexopoulos K (2019) Using digital twin for maintenance applications in manufacturing: State of the Art and Gap analysis. In 2019 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) (pp. 1–5). IEEE
94. Errandonea I, Beltrán S, Arrizabalaga S (2020) Digital twin for maintenance: a literature review Compu Ind 123. https://doi.org/10.1016/j.compind.2020.103316
95. Ezhilarasu C, Skaf Z, Jennions I (2019) Understanding the role of a digital twin in integrated vehicle health management (IVHM). In 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC). IEEE 1484–91
96. Zaccaria V, Stenfelt M, Aslanidou I, Kyprianidis K (2018) Fleet monitoring and diagnostics framework based on digital twin of aero-engines. In Turbo Expo: Power for Land, Sea, and Air, American Society of Mechanical Engineers 51128 https://doi.org/10.1115/GT2018-76414
97. Kraft J, Kuntzagk S (2017) Engine fleet-management: the use of digital twins from a MRO perspective. In Turbo Expo: Power for Land, Sea, and Air American Society of Mechanical Engineers 50770. https://doi.org/10.1115/GT2017-63336
98. Wang J, Ye L, Gao R, Li C, Zhang L (2018) Digital twin for rotating machinery fault diagnosis in smart manufacturing. Int J Prod Res 1–15
99. Liu Z, Chen W, Zhang C, Yang C, Chu H (2019) Data super-network fault prediction model and maintenance strategy for mechanical product based on digital twin. IEEE Access 7:177284–177296
100. Ezhilarasu C, Jennions I (2020) A system-level failure propagation detectability using anfis for an aircraft electrical power system. Appl Sci 10(8). https://doi.org/10.3390/app10082854
101. Ellis M, Bojdo N, Filippone A, Clarkson R (2021) Monte Carlo predictions of aero-engine performance degradation due to particle ingestion. Aerospace 8(6). https://doi.org/10.3390/aerospace8060146
102. Ezhilarasu C, Skaf Z, Jennions I (2021) A generalised methodology for the diagnosis of aircraft systems. IEEE Access 9:11437–11454
103. Li C, Mahadevan S, Ling Y, Choze S, Wang L (2017) Dynamic Bayesian network for aircraft wing health monitoring digital twin. AIAA J 55(3):930–941
104. Bielefeldt B, Hochhalter J, Hartl D (2015) Computationally efficient analysis of SMA sensory particles embedded in complex aerostructures using a substructure approach. In Smart Materials, Adaptive Structures and Intelligent Systems, American Society of Mechanical Engineers, Colorado Springs. 57298:V001T02A007
105. Zakrajsek A, Mall S (2017) The development and use of a digital twin model for tire touchdown health monitoring. In 58th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, pp 08637. http://arc.aiaa.org/, https://doi.org/10.2514/6.2017-0863
106. Liu Z, Meyendorf N, Mrad N (2018) The role of data fusion in predictive maintenance using digital twin. In AIP Conference Proceedings, AIP Publishing LLC 37(1):1–6
107. Damme C, Allen M, Hollkamp J (2020) Updating geometrically nonlinear reduced-order models using nonlinear modes and harmonic balance. AIAA J 58(8):3553–3568
108. Guivarch D, Mermoz E, Marino Y, Sartor M (2019) Creation of helicopter dynamic systems digital twin using multibody simulations. CIRP Ann 68(1):133–136
109. Garza P, Perinpanayagam S, Aslam S, Wileman A (2020) Qualitative validation approach using digital model for the health management of electromechanical actuators. Appl Sci 10:10217809. https://doi.org/10.3390/app10217809
110. Chowdhury S, Ali F, Jennions I (2019) A methodology for the experimental validation of an aircraft ECS digital twin targeting system level diagnostics. In Annual Conference of the PHM Society 11(1):21–26
111. Utzig S, Kaps R, Azeem S, Gerndt A (2019) Augmented reality for remote collaboration in aircraft maintenance tasks. In 2019 IEEE Aerospace Conference, IEEE 1–10
112. Rashidi M, Samali B (2021) Health monitoring of bridges using RPAs. In: Wang C.M., Dao V., Kitipornchai S. (eds) EASEC16. Lecture Notes in Civil Engineering 101:209–218. Springer, Singapore. https://doi.org/10.1007/978-981-15-8079-6_20
113. Delgado J, Short N, Roberts D, Vandenberg B (2019) Big data analysis for sustainable agriculture on a geospatial cloud framework. Front. Sustain. Food Syst, 3(54). https://doi.org/10.3389/fsufs.2019.00054
114. Tsolakis N, Bechtsis D, Bochtis D (2019) Agros: a robot operating system based emulation tool for agricultural robotics. Agronomy 9(7). https://doi.org/10.3390/agronomy9070403. ISSN 20734395
115. Deng T, Zhang K, Shen Z (2021) A systematic review of a digital twin city: a new pattern of urban governance toward smart cities. J Manag Sci Eng 6(2):125–34
116. Fan C, Zhang C, Yahja A, Mostafavi A (2021) Disaster City Digital Twin: a vision for integrating artificial and human intelligence for disaster management. Int J Inf Manage 56:102049. https://doi.org/10.1016/j.ijinfomgt.2019.102049
117. Hollenbeck D, Chen Y (2020) Characterization of ground-to-air emissions with sUAS using a digital twin framework. In 2020 International Conference on Unmanned Aircraft Systems (ICUAS), IEEE 1162–1166
118. Lei L, Shen G, Zhang L, Li Z (2020) Toward intelligent cooperation of UAV swarms: when machine learning meets digital twin. IEEE Network 35(1):386–392
119. Kapteyn M, Knezevic D, Huynh D, Tran M, Willcox K (2020) Data-driven physics-based digital twins via a library of component-based reduced-order models. Int J Numer Meth Eng. https://doi.org/10.1002/nme.6423
120. Zohdi T (2020) A digital twin framework for machine learning optimization of aerial fire fighting and pilot safety. Comput Method Appl M 373:113446. https://doi.org/10.1016/j.cma.2020.113446
121. Gusev M, Nikolaev S, Papulov A, Belov S, Padalitsa D, Uzhinsky I (2019) Optimization-driven product development to support digital twin creation on the small UAV case study. In Proceedings of the 2019 Summer Simulation Conference 1–12
122. Alvarez O, Zeaa L, Bilb C, Napolitano M, Fravolini M (2019) Digital twin concept for aircraft sensor failure. In Transdisciplinary Engineering for Complex Socio-technical Systems: Proceedings of the 26th ISTE International Conference on Transdisciplinary Engineering, IOS Press10:370–80
123. Yu Z, Zhang Y (2020) An evolution-simulation-verification framework of aviation products in the future. In 2020 IEEE 2nd International Conference on Civil Aviation Safety and Information Technology (ICCASIT), IEEE 1004–7
124. Renganathan S, Harada K, Mavris D (2020) Aerodynamic Data Fusion Toward the Digital Twin Paradigm. AIAA J 58(9):3902–3918
125. Borgen K, Ropp T, Weldon W (2021) Assessment of augmented reality technology's impact on speed of learning and task performance in aeronautical engineering technology education. Int J Aerospace Psychol 1–11
126. Jonkers R, Shahroudi K (2020) A Design Change, Knowledge, and Project Management Flight Simulator for Product and Project Success. IEEE Syst J 15(1):1130–1139

127. Siyaev A, Jo G (2021) Towards aircraft maintenance metaverse using speech interactions with virtual objects in mixed reality. Sensors 21(6):2066. https://doi.org/10.3390/s21062066
128. Ahmed S, Pawar S, San O, Rasheed A, Tabib M (2021) A nudged hybrid analysis and modeling approach for realtime wake-vortex transport and decay prediction. Comput Fluids 221:104895. https://doi.org/10.1016/j.compfluid.2021.104895
129. Piroumian V (2021) Digital twins: universal interoperability for the digital age. Computer 54(1):61–69
130. Walter D (2000) Competency-based on-the-job training for aviation maintenance and inspection–a human factors approach. Int J Ind Ergonom 26(2):249–259
131. Castanedo F (2013) A review of data fusion techniques. Sci World J 1–19
132. Tao F, Qi Q (2019) Make more digital twins. Nature 573:490–491
133. Singh S, Shehab E, Higgins N, Fowler K, Erkoyuncu J, Gadd P (2021) Towards Information Management Framework for Digital Twin in Aircraft Manufacturing. Procedia CIRP 96:163–168
134. Alexopoulos K, Nikolakis N, Chryssolouris G (2020) Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. Int J Comput Integr Manuf 33:429–439
135. Meng T, Jing X, Yan Z, Pedrycz W (2020) A survey on machine learning for data fusion. Inform Fusion 57:115–129
136. Ma X, Tao F, Zhang M, Wang T, Zuo Y (2019) Digital twin enhanced human-machine interaction in product lifecycle. Procedia CIRP 83:789–793
137. Oyekan J, Hutabarat W, Tiwari A, Grech R, Aung M, Mariani M et al (2019) The effectiveness of virtual environments in developing collaborative strategies between industrial robots and humans. Robot CIM-Int Manuf 55:41–54
138. Brunner P, Denk F, Huber W, Kates R (2019) Virtual safety performance assessment for automated driving in complex urban traffic scenarios. In 2019 IEEE Intelligent Transportation Systems Conference (ITSC) IEEE 679–85