Digital Twin Technologies for Turbomachinery in a Life Cycle Perspective: A Review

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Abstract: Turbomachinery from a life cycle perspective involves sustainability-oriented development activities such as design, production, and operation. Digital Twin is a technology with great potential for improving turbomachinery, which has a high volume of investment and a long lifespan. This study presents a general framework with different digital twin enabling technologies for the turbomachinery life cycle, including the design phase, experimental phase, manufacturing and assembly phase, operation and maintenance phase, and recycle phase. The existing digital twin and turbomachinery are briefly reviewed. New digital twin technologies are discussed, including modelling, simulation, sensors, Industrial Internet of Things, big data, and AI technologies. Finally, the major challenges and opportunities of DT for turbomachinery are discussed.

Keywords: sustainability; digital twin; life cycle; turbomachinery; simulation

1. Introduction

With the in-depth integration of a new generation of information technology, academia and industry have carried out significant research and development on emerging technology fields such as Industry 4.0 [1], big data [2], Internet of Things (IoT) [3], cloud computing [4], artificial intelligence [5], and blockchain [6]. As an enabling technology and a means to develop the concept of intelligent equipment, digital twin (DT) technology can provide an engineering process for solving the problem of cyber-physical integration of intelligent equipment and systems [7]. Currently, turbomachinery plays a significant role in the economy, especially in large-scale industrial systems. Turbomachinery is also a high emission equipment in the energy field including thermal power plants, gas turbine power plants, hydropower stations, and nuclear power stations. For sustainability-oriented development of turbomachinery, many projects, such as the aviation programmes ACARE 2020 and Flightpath 2050 [8], have attempted to reduce fuel consumption using Life Cycle Engineering (LCE) methodology [9]. Therefore, using LCE with DT is a crucial method to solve turbomachinery energy and sustainable development problems, and will be reviewed in this study.

The concept of DT was first proposed by Grieves [10] at the University of Michigan in 2003. Grieves stated that product life cycle management (PLM) is intended to be the informational equivalent of being in physical possession and examining an item; this was considered the prototype of the DT concept. In the following years, Grieves updated his theory and named the concept a “mirrored spaced model” and an “information mirroring model” [11,12]. In 2010, the National Aeronautics and Space Administration (NASA) [13] introduced the concept of DT in the space technology roadmap, intending to use DT to implement comprehensive diagnosis and prediction functions for flight systems to ensure continuous and safe operation during their service life. The Air Force Research Laboratory (AFRL) [14] introduced a conceptual model, in 2011, that used DT technology to predict the...
life of aircraft structures and gradually extended it to the airframe condition assessment study. They also combined historical flight monitoring data to virtual flight to assess the maximum allowable load while ensuring airworthiness and safety, thereby reducing the life cycle maintenance and increasing aircraft availability.

Meanwhile, the US Department of Defense designed a digital thread (a physical-based model instance), which became the basis for cross-domain data exchange. In 2012, Glaessgen and Stargel [15] first defined DT as an integrated Multiphysics, multiscale, probabilistic simulation. This simulation used physical models, sensor updates, and fleet history, to mirror its corresponding flying twin's life. With the recent improvement of sensing, software and hardware technology, combined with computing performance improvements, the DT concept has been further developed, especially in the real-time operation monitoring of products and equipment.

From a life cycle perspective, turbomachinery includes design, production, maintenance, repair and operation (MRO) and recycling, as shown in Figure 1 [9]. DT technology can provide support and guidance for the design and development, manufacturing [16], operation and maintenance, monitoring and fault diagnosis [17], and later the recycling of turbomachinery. In the traditional design mode for manufacturing and assembly, various requirements and constraints of the manufacturing process, including processing capacity, economic accuracy, and process capability, are integrated into the modelling process. Effective modelling and analysis methods are employed to ensure an efficient and economic design result for manufacturing. DT also supports the test and verification of product performance and product function and optimizes and improves product design through product history data and maintenance data. One of its goals is to meet the product life cycle design as an evolution and extension of the manufacturing and assembly design.

![Figure 1. Individual phases of the LCE concept of turbomachinery [9].](image)

At present, the real-world system design and maintenance strategy can be summarized as a safety margin design with periodic maintenance. In other words, the system type is designed according to previous experience, and a large safety factor is used to cover uncertainty [18]. When the system is in service, a periodic maintenance mode was adopted, and corresponding maintenance measures are taken to ensure the long-term stability of the system operation. Periodic maintenance of complex systems often results in a lack of accurate knowledge of the system’s current status and can result in too-little maintenance, or worse, untimely maintenance, which can lead to premature failure of the system, the
result being high maintenance costs and poor reliability. The emergence of the concept of DT provides a new way to solve the above problems. DT aims to create a digital model to collect all the data from the physical system. Through real-time monitoring of system status and dynamic updating of the digital model, DT improves the system diagnosis, evaluation, and prediction ability [19]. Meanwhile, real-world system operation and maintenance can be optimized online to improve structural design redundancy, avoid over frequent periodic maintenance, and ensure safety.

The traditional development of turbomachinery is unable to meet the increasing equipment performance and working range requirements. Digital and intelligent development with informatization is the trend in the future development of turbomachinery. Introducing DT to turbomachinery will lead to disruptive innovation of intelligent turbomachinery manufacturing and service.

From a life cycle perspective, Kendrik et al. [20] conducted a status survey of DT techniques, as well as the engineering PLM and business innovation. However, few reports exist on DT technologies for turbomachinery from a life cycle perspective. In addition, the necessary technology and promotion of DT is still at the initial stages for turbomachinery. Finally, there is a need to further study turbomachinery using DT for sustainable development, although many theories and practical application systems have previously been developed [21,22].

The remainder of the paper is organized as follows: Section 2 provides a literature review of the DT in the life cycle engineering of turbomachinery; Section 3 reviews a few key technologies applied in turbomachinery; Section 4 addresses some research challenges and opportunities in turbomachinery; and Section 5 provides some concluding remarks.

2. Literature Review

This section outlines the DT for the turbomachinery life cycle, including applications and common system structures for all stages of the life cycle.

2.1. Overview on Life Cycle of Turbomachinery with Digital Twin

Since the concept of DT was proposed, many scholars have conducted research on the application of turbomachinery. A life cycle closed loop for turbomachinery consists of five phases, followed by a design phase, an experimental phase, a manufacturing and assembly phase, an operation and maintenance phase, and a recycled phase. The various phases of the life cycle of the existing DT engineering of turbomachinery are summarized in Table 1.

From Table 1, it can be concluded that most research focuses on turbines [24–37] and aeroengines [14,45–52]. In terms of the application of turbines, research on wind turbines [30–37] accounts for a large proportion. In the aerospace field, some scholars have made efforts on aeroengines [45,47], while others have studied aircraft [14,49–52].

From the perspective of the life cycle, the most numerous phases are monitoring [30–32,34–37,47] and manufacturing [27,39–41,45,51]. In addition, there is currently a certain amount of research in the prediction [14,25,26,44,46] and design [27,38,42] phases, and many scholars are also concerned about the operation and maintenance [29,43,51] phase.

In the listed literature, 7 papers have been conducted on turbomachinery components, accounting for about 23%, while 18 for asset level, 2 for system level, and 4 for network level, accounting for 58%, 6%, and 13% respectively. Thus, in recent years, most of the research has been related to turbomachinery assets. There are some studies that have established a complete system or platform [26,30,35–38,43,52]; however, more research has only proposed a framework or model of the DT [14,24,25,27–29,31–34,39–42,44–51], and turning them into practical applications remains to be studied.
Table 1. Summary of existing digital twin engineering of turbomachinery.

| Ref                  | Country       | Type         | Phase                  | Tech                      | Sustainability | Key Feature                                                                 |
|----------------------|---------------|--------------|------------------------|---------------------------|----------------|-----------------------------------------------------------------------------|
| Yu et al. (2020) [23]| China         | Steam turbine| Monitoring             | Hybrid modelling          | No             | A hybrid modelling method based on operation data and first-principle mechanism |
| LeBlane and Ferreira (2020) [24]| The Netherlands| H-VAWT turbine| Analysis               | —                         | No             | Methodologies used in the development of the model for an H style vertical axis wind turbine |
| Moroz et al. (2019) [25]| USA           | Gas turbine  | Predicting performance| Physics-based methods/modules | Yes            | A flexible, fast and high-fidelity approach of GTU part-load and off-design performance prediction |
| Tiainen et al. (2019) [26]| Austria      | Rotor system | Predicting dynamic behavior | Virtual sensor based on a recurrent neural network | No             | A complete proof-of-concept DT system with wireless sensing with flexible measurement patterns, data transfer, storage, and visualization in an interactive 3D view |
| Dawes et al. (2019) [27]| UK            | Gas turbine  | Design and manufacturing| Simulation                | Yes            | The heart should be an integrated, physics-based simulation workflow          |
| Wang et al. (2018) [28]| China         | Rotating machinery | Fault diagnosis | Model                     | Yes            | A DT reference model for rotating machinery fault diagnosis                  |
| Sivalingam et al. (2018) [29]| Singapore   | Wind turbine | Operation and maintenance | RUL prediction | No             | A complete framework is established                                         |
| Babadi et al. (2018) [30]| Iran         | Wind turbine | Monitoring and analysis | IoT                       | No             | A comprehensive IoT-based methodology including sensors, IT networks, local and wide-area communication media, database, and data analytics platforms |
| Botz et al. (2020) [31]| Germany      | Wind turbine | Monitoring             | RUL prediction            | No             | Used measurement data and models to determine material stress at high stress locations for fatigue calculations and remaining service life (RUL) estimation |
| Ref | Country  | Type                  | Phase                  | Tech                     | Sustainability | Key Feature                                                                 |
|-----|----------|-----------------------|------------------------|--------------------------|----------------|-----------------------------------------------------------------------------|
|     |          | Application of Turbine|                        |                          |                | A DT concept with a focus on estimating wind speed, thrust, torque, tower-top position, and loads in the tower using supervisory control and data acquisition (SCADA) measurements |
| Branlard et al. (2020) [32] | USA | Wind turbine | Monitoring | Signals estimation | No | A DT highlighting key processes including system identification, data-augmented modelling, and verification and validation |
| Wagg et al. (2020) [33] | UK | Wind turbine | Asset management | Mathematical framework | No | A numerical model of an onshore wind turbine was created with FAST software developed by the US National Renewable Energy Laboratory (NREL) |
| Pimenta et al. (2020) [34] | Portugal | Onshore wind turbine | Monitoring | Numerical simulation | Yes | The SHM using OMA and CMS for FOWTs is implemented, including the floater-tower-blade coupling effects |
| Kim et al. (2019) [35] | USA | Offshore wind turbine | Health monitoring | Operational modal analysis (OMA) | Yes | Smart glasses enable the user to access the AR and interact with the DT to monitor and analyze single WECs and entire wind farms |
| Pargmann et al. (2018) [36] | Germany | Wind turbine | Monitoring | AR | No | Combined a mechanical model and a set of measurements to estimate signals that are not available in the measurements, such as wind speed, thrust, tower position, and tower loads |
| Branlard et al. (2020) [37] | USA | Wind turbine | Monitoring and estimation | Kalman filtering technique | No | A comprehensive modelling strategy for developing a multi-domain live simulation platform of large generators for wind and hydropower plants |

**Application of Rotating Machinery and Components**

| Amir (2019) [38] | Germany | Generators | Design | Modelling strategy | Yes | A comprehensive modelling strategy for developing a multi-domain live simulation platform of large generators for wind and hydropower plants |
| Ref                          | Country | Type                  | Phase          | Tech                        | Sustainability | Key Feature                                                                 |
|------------------------------|---------|-----------------------|----------------|-----------------------------|----------------|-----------------------------------------------------------------------------|
| Bolotov et al. (2019) [39]   | Russia  | Turbine rotor         | Manufacturing  | Software system             | Yes            | Assess the operating modes of the turbine rotor and determine the dependence of imbalance on the rotor speed |
| Zhou et al. (2020) [40]      | China   | Centrifugal impeller  | Manufacturing  | Iterative optimization      | No             | A tool-path generation method for centrifugal impeller (CI) five-axis flank milling |
| Zhang and Zhu (2019) [41]    | China   | Aero-engine fan blade | Manufacturing  | Digital thread              | Yes            | An innovative application framework of DT-PMS                               |
| Omidi et al. (2019) [42]     | China   | Centrifugal Compressor| Design         | Genetic algorithms (GA)     | No             | A hybrid optimization model based on genetic algorithms and a 3D simulation of compressors to examine the certain parameters such as blade angle at leading and trailing edges and the starting point of splitter blades |
| Oyekan et al. (2020) [43]    | UK      | Fan blade             | Maintenance    | Vision sensor               | —              | Track and remove the coating material of a fan blade in a closed-loop approach |
| Sahoo et al. (2017) [44]     | India   | Wind turbine blades   | Prediction     | Conception                  | No             | Extended for the actual dimensions of the wind turbine web structures       |

**Table 1. Cont.**

Application of Aero-Engine

| Ref                          | Country | Type             | Phase     | Tech                              | Sustainability | Key Feature                                                                 |
|------------------------------|---------|------------------|-----------|-----------------------------------|----------------|-----------------------------------------------------------------------------|
| Xu et al. (2020) [45]         | China   | Aircraft engine  | Manufacturing and assembly | DoE and data analysis service system | Yes            | DT-driven optimization method with a DTAF and several DT modules          |
| Renganathan et al. (2020) [46]| USA     | Airfoil          | Prediction | Bayesian inference                | No             | A method to fuse noisy, incomplete, and biased aerodynamic field information from wind-tunnel measurements and high-fidelity mathematical model predictions |
| Zaccaria et al. (2018) [47]   | Sweden  | Aero-engine      | Monitoring and diagnosis | Framework             | Yes            | A multi-level approach from anomaly detection to failure quantification     |
| Ref                  | Country      | Type        | Phase              | Tech                              | Sustainability | Key Feature                                                                 |
|---------------------|--------------|-------------|--------------------|-----------------------------------|----------------|--------------------------------------------------------------------------------|
| Tuegel et al. (2011) [14] | USA          | Aircraft    | Life prediction    | Modelling                         | Yes            | Reengineering of the aircraft structural life prediction process to fully exploit advances in very high-performance digital computing |
| Ye et al. (2020) [48]    | China        | Spacecraft  | Health management  | Dynamic Bayesian network framework | Yes            | Crack growth model can be updated to have a lower uncertainty through a framework tracking the life of spacecraft structures |
| Seshadri et al. (2017) [49] | USA          | Aircraft    | Health management  | Guided wave responses              | No             | A damage characterization method using a wave propagation response estimated at multiple sensor locations and an optimization procedure combined with wave propagation analysis to predict damage location |
| Li et al. (2017) [50]    | USA          | Aircraft    | Health monitoring  | Dynamic Bayesian network           | Yes            | A versatile probabilistic model for diagnosis and prognosis to realize the DT vision |
| Zheng et al. (2018) [51]  | Canada       | Aircraft    | Maintenance, repair, and overhaul | —                                 | No             | Reviews the overall framework to develop a DT coupled with the industrial Internet of Things technology to advance aerospace platforms autonomy |
| Guo et al. (2018) [52]   | China        | Aircraft    | Manufacturing and assembly | Modelling                         | Yes            | A practical assembly site which is consisted by coordination element, coordination relationship, and control method for coordination accuracy |

Notes: “Yes” or “No” under Sustainability: The object has sustainability or not; “—”: Related information is not available from the source.
2.2. Digital Twin-Based Turbomachinery Applications

Turbomachinery based on a DT includes the following applications:

1. Power industry equipment and systems [53]. DT can digitize all stages of the life cycle for power generation equipment [54] used in the power industry [55], such as wind turbine manufacturing, assembly, operation and maintenance, power network data transmission, and user services.

2. Aero-engine DT has been used to solve aircraft-related problems in the aerospace industry [56] from the beginning of DT applications. DT is employed during test and manufacture of aeroengines, which significantly reduces the cost of the design and manufacturing stage.

3. Rotating machinery parts DT can also be applied to the whole or part of rotating machinery, e.g., a DT for a single blade [44] used to obtain vibration or structural parameters more accurately and conveniently.

2.3. Digital Twin Technologies for Turbomachinery

Many DT technologies play an essential role in the life cycle of turbomachinery design, manufacturing, operation, and maintenance. In the product design stage, the model-based definition (MBD) technology realizes the efficient expression of product data [57], and the lightweight model technology optimizes the model’s storage structure. The simulation and optimization technology makes the product DT model closer to the physical product’s functions and characteristics [58]. In the manufacturing and assembly stage, DT uses multi-level interconnection such as industrial Internet, IoT, and sensors, and collaborates with information technologies such as artificial intelligence, machine learning, data mining, and high-performance computing. These technologies play an essential role in multi-source structure data collection, data integration display, product production supervision, quality management, intelligent analysis, and decision-making [59] in complex dynamic spaces. In the operation and maintenance phase, DT comprehensively utilizes sensor technology, traceability technology, simulation technology, and IoT technology to support status tracking and monitoring, early fault warning, life prediction [60], and positioning analysis. The conceptual diagram of a wind turbine realizing DT is shown in Figure 2.
2.4. A Proposed General Framework for Turbomachinery from a Life Cycle Perspective

The development of turbomachines involves complex system engineering, development requirements, system composition, product technology, manufacturing processes, test and maintenance, project management, working environment, and other issues. As a possible way to realize the interactive integration of the physical world and the digital world, DT is gradually applied to all aspects of the product life cycle, including product design, industrial production, and manufacturing services. Use of DT for improving turbomachinery R&D quality, manufacturing, production efficiency, and predictive maintenance of equipment is of great significance.

The DT application framework for the turbomachinery closed-loop life cycle is depicted in Figure 3. It is important to note that the DTs have different forms at different stages of the whole life cycle. Specifically, in the design and test stage where there is no physical entity, the requirements for the DT of turbomachinery is the user’s requirements. By inputting the quantitative user requirements into the DT and modifying its model, turbomachinery design’s reliability can be predicted. In the manufacturing/assembly and operation/service stages, the physical turbomachinery corresponds to the DT turbomachinery. The physical turbomachinery measurement parameters are transmitted to the DT in real-time to realize the high fusion of virtual and real entities.

In the scrapping/recycling stage, DT can be extended to the next cycle’s development process, forming a closed-loop life cycle, even though the physical entity does not exist. The application process of each stage is introduced as follows.

Figure 3. A general LCE framework for turbomachinery with digital twin.
(1) Design phase

Product design is an essential part in the product life cycle and the first step in applying DT technology to smart manufacturing. The traditional design method has many problems, such as high cost [61], inaccurate demand, difficult design cooperation, and the prototype’s trial production cycle [62]. Furthermore, it cannot provide timely feedback or verify performance, which seriously affects an enterprises’ product innovation and market development. Therefore, DT technology is gradually being introduced. This enables designers to compare the virtual products’ performance in different environments and to minimize inconsistency in the product’s actual behavior versus the expected behavior. At the same time, DT can avoid lengthy testing by evaluating virtual products, thus accelerating the design cycle.

Benjamin et al. [63] proposed the first theoretical and conceptual framework for DT, which could provide methods for product life cycle applications. Based on the DT for the same type of turbomachine, according to the quantitative user requirements, it can be quickly constructed in the design phase [64]. The new turbomachinery’s whole simulation model is modified to form the DT of the new turbomachinery. Digital prototypes and design requirements form a pair of virtual and real twins at the product design stage. Through a variety of simulation software, the structural strength and performance of the design model of the whole machine, subsystem, and parts are analyzed, including the product shape, function, characteristics, machinability, assembly, and maintainability. The analysis results are compared with the function and performance indicators of the design requirements to verify the rationality of the design scheme. Then, the design scheme comparison and optimization iteration is carried out with a short design cycle.

Zhang et al. [65] proposed a deep learning-enabled framework for intelligent process planning of a digital twin manufacturing cell (DTMC). Tao et al. [66] proposed a product design framework based on DT technology. The framework focuses on connecting physical products with virtual products and is mainly suitable for the iterative optimization design of existing products. Most of the selected design methods that constitute DTPD (i.e., DT-driven product design) have proven to be more useful for redesigning existing products. Baldassarre et al. [67] presented a virtual prototyping method for wind turbine blade design. Numerical modelling data and experimental data on turbine blade geometry and structural/dynamical behavior were combined to obtain an economical DT model which could help reduce the uncertainty in the turbine life cycle. Liu et al. [68] presented a quad-play CMCO (i.e., configuration design—motion planning—control development—optimization decoupling) design architecture for flow-type design smart manufacturing system in the Industry 4.0 context. Shao and Helu [69] synthesized different viewpoints of DT design models. They also studied the DT’s standardized framework, enabling context-dependent implementations and promoting DT components’ reusability.

(2) Experimental phase

In the real test of the turbomachinery system, physical and virtual tests are real and virtual twins. The physical test is relatively intuitive with specific results, but the test cost is relatively high, and the preparation period is lengthy. Due to the limitation of the number of sensors and the installation location, the test information obtained is limited. However, the virtual test can verify various application conditions, avoid over-test or under-test problems, obtain more comprehensive measurement information, and make up for the shortcomings and limitations of the physical test technology. Physical tests and virtual tests verify each other, improving virtual tests iteratively and effectively reducing the number and cost of physical tests. The evolution and perfection of product DT is carried out through continuous interaction with the product entity. In the later manufacturing phase, the physical reality world transfers the measured production data (such as test data, progress data, logistics data) to the virtual products and displays them in real-time. The monitoring of production measured data and a production process based on the product model (including comparisons of design value/measured value and actual
material characteristics/design material characteristics) is realized. The ratio of planned and actual completion progress was equal. In addition, the prediction and analysis of quality, manufacturing resources, and production progress are realized with the physical production data through the intelligent prediction and analysis of logistics and progress. Simultaneously, the intelligent decision-making module formulates corresponding solutions, according to the prediction and analysis results, and feeds these back to the physical products to realize the dynamic control and optimization of the physical products and achieve virtual integration and virtual control. Therefore, realizing real-time accurate and effective information extraction, and reliable transmission of multi-source heterogeneous data in the complex and dynamic entity space is a prerequisite for the realization of a DT. In recent years, the rapid development of the IoT, sensor networks and recognition technology has provided a set of practical solutions. In addition, the rapid development of artificial intelligence, machine learning, data mining, high-performance computing, and other technologies provide essential technical support. Leblanc and Ferreira [24] conducted a series of tests on the pitch turbine to ensure that the DT finite element model is consistent with reality. And the test results’ analysis has been improved by having a well-calibrated DT model of the turbine.

Traditional turbomachines mainly depend on physical tests. To test the actual performance and characteristics of turbomachinery, a test bench that can simulate the actual working environment needs to be established. A turbomachine virtual test system and a comprehensive test environment could be made based on the DT turbomachine formed in the design stage. Based on quantified comprehensive test environment parameters, the model can be continuously updated, and the test plan and test parameters can be optimized.

(3) Manufacturing and assembly phases

The manufacturing of turbomachinery involves complex system engineering. DT technology can connect the physical equipment with virtual equipment in the information world. The virtual equipment can reflect the physical equipment production situation in real-time and reflect the actual production process. The DT can perform control functions to increase the production system’s flexibility, improve production efficiency and product quality, as well as reduce energy and material consumption. Before the turbomachine is manufactured and assembled, the manufacturing and assembly process can be optimized based on its DT models. The manufacturing and assembly process information is collected in real-time through sensors, based on big data technology, which drives the continuous update of the turbomachine DT to achieve a high degree of approximation between the virtual and the real. Some researchers have designed a turbomachinery smart assembly process [70] and realized a part of the turbomachinery assembly’s DT model [40,71]. With the support of the IoT technology, real-time monitoring, correction, and control of the manufacturing process of turbomachine parts ensures the processing quality of parts and the forming of a personalized turbomachinery DT for the follow-up operation and maintenance.

In the manufacturing phase, the physical workshop and the virtual workshop are virtual and real twins. At present, DT can perform a real-time dynamic simulation and analysis of crucial parameters such as parts processing [72], layout design, production process, assembly process of the production line, and transfer the actual operating status of the physical workshop to the virtual workshop system. Combining the two enables production line planning and design, rational allocation of resources on the production line, optimization of production structure and business processes, and provide decision-making suggestions for workshop operations and dynamic adjustments [73].

In the turbomachinery structure, the same parts’ physical properties have individual differences and dispersion within the tolerance range. The material-matching stage does not consider the parts’ physical attributes and matching status, resulting in inconsistent and unstable matching among the physical parts. Therefore, repeated assembly tests, replacement parts, and additional processing to meet the assembly quality control requirements occurs with low assembly efficiency. In consideration of this, in the assembly phase, DT
can realize the interaction and integration of the physical assembly and virtual model. According to the structure and assembly process of the parts, the DT model can be used to establish the matching relationship between the parts, thereby bridging the gap between product assembly design and manufacturing.

Tao et al. [74] proposed a new method for product design, manufacturing, and service driven by DT. In addition, the detailed application methods and frameworks of DT-driven product design, manufacturing, and service are reviewed. Kritzinger [75] argued that production planning and control is the main data-sink that links everything together in the production system, thus processing production planning and control is a research focus of manufacturing DT. Bao et al. [76] provided the methods for constructing the product DT and process DT. DT is constructed by a unified model in the product design, manufacturing and MRO phases to facilitate information exchange and sharing between different phases.

(4) Operation and maintenance phases

At present, the turbomachinery industry is shifting from reactive maintenance to proactive maintenance. The goal is to reduce maintenance costs, operational downtime and capital investment by extending the service life of components [51]. When the physical entity is delivered, a highly consistent DT of the turbomachine is delivered to the user simultaneously. In the operation and maintenance phase, DT continuously revises the corresponding simulation model with real-time turbomachine operating and environmental parameters. The DT model can predict physical entity performance in real-time, perform fault diagnosis [50] and alarm [49], and use virtual reality (VR)/augmented reality (AR) and other virtual reality technologies. It can also realize immersive interaction between support experts and maintenance personnel and conduct maintenance plan formulation and virtual maintenance training. For example, for the operation and maintenance of wind turbines, condition-based maintenance is preferred over preventive maintenance based on time. Sivalingam et al. [29] proposed a methodology for offshore fixed and floating platforms. In the methodology, a framework for physics-based Remaining Useful Life (RUL) prediction was developed. Fixed and floating offshore 5 MW NREL (National Renewable Energy Laboratory) wind turbines were compared to quantify the impact of medium and short-term thermal cyclic loads changes on the power converter. A process of the constructed DT technology platform is shown in Figure 4.

Figure 4. Schematic diagram of the digital twin structure of offshore wind farm operation and maintenance [29].

In the operation stage, the physical entity and virtual entity of the turbomachinery for wind power generation are a pair of virtual and real twins. Turbomachinery researchers monitor and analyze the entity’s real-time operation status through sensor data, and frequently predict the health status and remaining service life of products [77]. Predictive
maintenance for fault diagnosis is supported through historical maintenance records and relevant user data, thus supporting and maintaining complex equipment systems, and is the primary module of the health management system (HMS). The current HMS mainly depends on the system’s mathematical model and sensor data. Developing more intelligent algorithms to analyze and guarantee the target system, HMS can provide system monitoring and life prediction of its crucial components and health management functions. The development of system fault diagnosis and prediction of HMS has become broader with more high-precision sensing technology, multi-domain and multi-model fusion technology, life cycle management technology, and high-performance computing technology. These modern technologies support HMS’s development towards more accurate calculations and more intelligent analysis. Thus, HMS is evolving in the direction of DT. DT integrates various advanced technologies to support and monitor complex equipment’s entire life cycle process, including equipment design, production, maintenance, and other sub-processes [78]. DT realizes rapid real-time condition monitoring and evaluation in the process of complex equipment operation, supports the collaborative management and maintenance, and task realization of complex equipment clusters under the specified environment. Thus, DT reduces the system maintenance cost and the dependence on research and technical personnel. Moreover, DT will be pushed back to the life cycle starting point, system design, to guide the complex system’s improvement and identify where system design can be optimized and provided more prior knowledge from the DT.

(5) Recycled phasees

After the physical entity is recycled or scrapped, the corresponding DT serves as the storage and management library of digital information throughout the turbomachine’s life cycle. This library can be permanently preserved and used in the development process, similar to turbomachine, to build a closed-loop flow. Ye et al. [48] proposed a DT framework to track the life of spacecraft structures. The proposed framework has functions such as diagnosis, model updating, performance evaluation and data storage. The improved model can more accurately predict future crack growth and reusable life. The digital design and application mode of the turbomachine’s life cycle can significantly accelerate the development process and improve the reliability of future designs. As the last link in the life cycle, the recycling phase plays a vital role, which provides conditions for the sustainable development of turbomachinery.

3. Digital Twin’s Key Technologies and Applications towards Turbomachinery

To realize a DT system for turbomachinery, various key technical support [79], such as sensor technology, modelling, and big data technology are needed, as shown in Figure 5.

![Figure 5. Key technologies and the relationships of digital twin.](image-url)
3.1. Modelling and Simulation

Most of the current modelling and simulation methods are used to develop mature models in specific fields and then use integration and data fusion methods to fuse independent models from different fields into a comprehensive system-level model. However, this fusion method is not deep enough and lacks a reasonable explanation, limiting the usefulness of deep fusion of models from different fields. The difficulty of multi-domain fusion modelling is that the fusion of multiple characteristics will lead to a large degree of freedom of the system equation. The data collected by sensors needs to be highly consistent with the actual system data to ensure the dynamic updating of the model based on high-precision sensor measurement, which requires more advanced research in simulation for DT [80].

DT has been developed from the initial two-dimensional design to three-dimensional modelling and from three-dimensional wireframe modelling to three-dimensional solid modelling and feature modelling. Generally, the 3D model of a product includes geometric information and assembly relationships and manufacturing information such as product manufacturing information, PMI (manufacturing information, including dimensions, tolerances, geometric tolerances, roughness, and material specifications) and other manufacturing information to realize MBD. A fusion of physical space and digital space model is shown in Figure 6.

![Figure 6. The fusion of physical space and digital space model [41].](image)

Lightweight 3D models with geometric information can only be extracted from the complete 3D feature models with process features to support 3D product models’ quick browsing. Based on 3D modelling and display technology, VR technology has achieved rapid development. VR is widely used in the virtual experience of complex objects such as automobiles, airplanes, factories, including the immersive virtual reality system cave, 3D rendering technology for product display and marketing, and driving simulation technology. In recent years, AR technology has been developed. AR can integrate physical models and digital models in a visual environment to realize sensor data visualization. Thus, AR can carry out 3D visualization of product operation, assembly and disassem-
Virtual simulation technology has developed from the initial finite element analysis to the simulation of convection field, thermal field, electromagnetic field, and other physical fields such as multi-domain physical modelling. One of the objects of the simulation is physical phenomena, such as vibration, collision, noise and explosion. And the system of the whole product simulation as well as the simulation of various processing technologies such as injection molding, casting, welding and bending, can help the product achieve multidisciplinary simulation and optimization of the overall performance. There are also human factors, equipment, and simulation. If the simulation object is distinguished, the virtual simulation technology can be divided into product performance simulation, manufacturing process simulation, and digital factory simulation [81]. In the design and experiment phase of turbomachinery, the application of the modelling and simulation technologies will help accelerate the construction of complete DT model of turbomachinery.

In the process of digital design technology, virtual simulation technology development and integrated application, digital mock-up (DMU) [82], digital prototyping [83], virtual prototype [84], and functional virtual are used to produce a prototype. Other technologies are mainly used to realize the motion simulation, assembly simulation, and performance simulation of complex products. Through the virtual test of the digital prototype, physical prototypes and physical tests can be reduced, as well as the cost of product development and trial production. Thus, related research and development efficiency can be improved.

3.2. Sensors and Industrial Internet of Things

With the development of sensor technology and wireless communication technology, the application of the IoT has become increasingly widespread since the 21st century [61]. The Industrial Internet of Things (IIoT) has also been widely used by industry to support the monitoring and maintenance of high value equipment. The data type and acquisition frequency of IIoT are much higher than typical IoT applications. The mathematical model and analysis method of applications are more complicated than in typical IoT applications. The reliability of turbomachinery DT simulation is highly dependent on the data collected from the actual running device [64]; therefore, a large amount of data is collected by sensors, and software components are also an essential part of it [85]. There are few status parameters monitored in turbomachinery operation with limited measurement positions, such as flow, speed, pressure, and heat flux density. Therefore, more online monitoring technologies should be introduced to collect the status parameters of systems such as wind farms [86], crucial parts of devices such as steam turbines at high frequency, stress distribution, deformation, air velocity, temperature [87], and crack formation.

The combination of the two technologies can be applied to the real-time reporting of wind turbine damage. Based on this, some studies are developing acoustic sensors to monitor the health of wind turbines. The sensor uses the IoT to report in real time, which can improve the efficiency of blade monitoring.

3.3. Big-Data and AI Technologies

DT itself has a vast database for integrity maintenance and data processing. DT needs this database to maintain geometric integrity, make model discretization, and maintain them during the lifetime of turbomachinery. Simultaneously, the discretized model will be automatically updated with the turbomachinery damage and repair data [88]. Additionally, the generated data from the design, test, or physical operation of the device is also vast. These data must have fast and accurate traceability [89], allowing a user-friendly way to present forecast information to users, support designers or decision-makers to judge [90].

Tao et al. [74] reviewed the concept and application of big data and DT in different phases, including design, production, manufacturing and predictive maintenance. The similarities and differences between big data and DT are compared from the perspective of
general data. Because of the complementarity of big data and DT, smart manufacturing can be promoted if the two are integrated.

The monitoring of turbomachinery needs a huge amount of data. Taking the operation monitoring of a steam turbine as an example, the data required to realize the DT of a steam turbine includes the temperature, pressure, and vibration parameters of the cylinder and blades at all stages, which involves big data technology, especially data transmission and data storage. AI technology is also crucial to the construction of a DT model in the operation and maintenance phase of turbomachinery. Continuously training the model through the obtained data, the DT of turbomachinery can independently help technicians get the state of the turbomachinery quickly, and then judge the time and method of maintenance.

4. Major Challenges and Opportunities

At present, the application of DT in the turbomachinery industry still faces some challenges [91]. First, DT is a comprehensive technology system involving many fields, which is difficult to implement. The framework of DT technology and the definition of the model structure of DT is not mature. The method of carrying out knowledge reasoning and discovery based on the DT to achieve the ultimate intelligence goal remains to be studied. Second, the key technologies of DT are still in development, such as the big data of fault diagnosis [92], dynamic modelling of complex systems under uncertainty, online real-time analysis, mathematical calculation methods, lightweight and distributed sensor monitoring technology. In addition, it is still necessary to improve the development and operation integration platform of the autonomous DT at the level of DT tools.

4.1. Smart Design of Turbomachinery

Currently, the digital design of turbomachinery is still in its infancy [93]. For example, the aerospace industry’s advantages are more reflected in the level of integrated innovation, and the level of essential design ability is still not high. The digital design in many traditional industries is at a low level. The necessary mathematical and simulation models needed to support the DT system’s construction, especially the digital simulation ability of crucial core components or processes, has become a significant bottleneck restricting DT technology development. For highly complex electromechanical smooth integration products, DT can construct the product model in the R&D stage and accelerate product R&D through the application of engineering simulation technology. Thus, DT helps enterprises bring innovative technology to the market with less cost and faster speed. Using DT technology, we can use simulation software for structure, heat, electromagnetism, fluid, and control to carry out single physical field simulation and multi-field coupling simulation, optimize, confirm, and verify the product design, and build an accurate, comprehensive simulation model to analyze the performance of physical products and realize continuous innovation. The production cycle can be significantly shortened through the combination of generative design technology, additive manufacturing technology, and hardware in the loop simulation technology.

4.2. Machining Components of Turbomachinery with Digital Twin

The intelligent machining technology using DT combined with modern sensing, 5G communication, other new generations of information technology, and realizing real-time data conversion and transmission through the standard data interface. Establishing a DT model through online monitoring data can realize the digitization and real-time virtual visualization of the processing process. The dynamic integration of intelligent machining control systems and processing equipment can realize the deep integration of the physical and information worlds of the manufacturing process and realize the high-performance manufacturing of each specimen. Compared with the traditional Numerical Control machining, intelligent machining technology takes DT as the core, takes the processing of big data and its mining method as the support, and adopts the undisturbed embedded multi-source perception and graphics processor (GPU). The DT models of
essential component processing are established by combining high-performance technology with a digital integration approach of artificial experience knowledge. These models are expected to promote the high integration of human knowledge and machine knowledge in necessary component processing and the explosive growth of machine knowledge to realize the major improvement in the manufacturing quality of complex vital components [94].

Several technical problems need to be solved to realize intelligent machining technology driven by DT and construct the complex component manufacturing process’s VR integration system: (1) Construction of an intelligent processing technology system; taking the high-performance manufacturing of complex parts as traction, research the theory of all-element fusion between real-time physical space and DT virtual space, and establish a digital twin-based intelligent processing technology architecture, which covers simulation, IoT, data, control, and other technologies. (2) Non-interference sensing and processing of multi-source data; the machining process is highly nonlinear and difficult to predict accurately. Based on new technologies such as smart sensing and 5G, a multi-source machining process is established and a DT process model is established. The established DT model of the process can study digital twin behavior simulation, reliability verification, and visual analysis of operating status, forming a mechanism of human-machine knowledge fusion and machine knowledge accumulation. (3) Data-driven process regulation and autonomous evolution through the collection, analysis, and judgement of on-site processing data, the mapping relationship between process state data and processing quality is established to realize the control and independent optimization of the process. Establish a data-driven mechanism for independent diagnosis and evolution of the machining process to realize the accumulation of machine knowledge during the machining process.

4.3. Sustainability and Predictive Maintenance of Turbomachinery with DT

As one of the significant indicators for achieving environmental sustainability, reducing carbon dioxide emissions is one of the research topics worldwide. Electricity usage, city gas consumption [95], and vehicle usage, etc., are the main emission sources of carbon dioxide, and using DT technology to reduce their emissions will help achieve sustainable development. The emissions are closely related to turbomachinery. The consideration of sustainability has become an integral part of activities in the turbomachinery industry, where efficient maintenance schemes play an important role in improving sustainability as they significantly reduce downtime, energy and material waste. Currently, time-based PM strategies are widely used in the turbomachinery industry, where maintenance is carried out periodically according to prior or historical knowledge of the process or equipment. However, these strategies are conservative and insecure because the true failure development cannot be monitored in real-time. Frequent maintenance activities also increase the cost as more energy, materials, and uptime are wasted by the maintenance activities, negatively impacting the environment, such as increasing carbon dioxide emissions. Taking the power industry as an example, the implementation of DT for power generation equipment in the operation and maintenance phase can effectively control the start and stop time of the machine, thereby achieving carbon dioxide emission reduction by reducing fuel and waste. Therefore, predictive maintenance of turbomachinery will be a problem-solving method. In this method, we make an intelligent interconnection and simulation analysis through the sensor data collected in real-time during equipment operation, which is transferred to its DT model. Thus, the health status and fault symptoms of the equipment can be diagnosed to make fault predictions. If the operating condition of the product changes, the adjustment measures can be used. To verify the DT model on the simulation cloud platform, the actual product’s operating parameters can be adjusted if there is no problem.

For the sustainability of turbomachinery with DT, an effective and efficient LCE for systematically planning, regulating, and controlling the features of a turbomachinery, especially for predictive maintenance, can be considered. Particularly for turbomachinery with a high volume of investment and a long lifespan, life cycle-oriented consideration is
of particular importance. Thus, the turbomachinery industry will meet the requirements of higher efficiency and lower costs while simultaneously enhancing sustainability.

5. Conclusions

In this study, a review of turbomachinery with DT techniques from a life cycle perspective was performed. This review covered sustainability-oriented turbomachinery development activities, including the design phase, experimental phase, manufacturing and assembly phase, operation and maintenance phase, and recycled phase. Recently, DTs have attracted widespread attention from academia and industry. As a new technology, DT can improve the life cycle of turbomachinery from different aspects. However, the application still requires breakthroughs in key technologies such as complex system modelling and simulation, sensing and IoT, big data and AI, dynamic data-driven analysis, and decision-making.

A comprehensive review of about 35 related projects revealed that most systems and applications developed so far are for turbomachinery and DT techniques. Specific efforts have been made for the application of turbines, rotating machinery and components, and aeroengines. For key technologies of DT for turbomachinery, modelling and simulation, sensors, IIoT, big data, and AI technologies was discussed. This review also identified several research challenges and opportunities, including the smart design of turbomachinery, machining components of turbomachinery with DT, sustainability, and predictive maintenance of turbomachinery with DT. Future studies will focus on how to design and implement a sustainable DT system for turbomachinery.

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