Review
https://doi.org/10.26599/JIC.2025.9180083

Advances in digital twin technology in industry: A review of applications, challenges, and standardization

Li Ai[1,(✉)], Paul Ziehl[1,2]

[1] *Department of Civil and Environmental Engineering, University of South Carolina, Columbia, SC 29208, USA*
[2] *Department of Mechanical Engineering, University of South Carolina, Columbia, SC 29208, USA*

Received: 2024-08-08 Revised: 2024-09-23 Accepted: 2024-09-27

✉ Address correspondence to Li Ai, ail@email.sc.edu

Abstract

This paper provides a comprehensive literature review on the application of digital twins (DTs) and the development of artificial intelligence (AI), big data and building information management (BIM). Driven by the Internet of Things (IoT), big data analytics and artificial intelligence, DT technology has become a transformative force in Industry 4.0. It enables real-time simulation, analysis, and optimization of industrial systems throughout their lifecycle, leading to significant improvements in operational efficiency and decision-making processes. This review explores the various applications, challenges, and prospects of DTs in the aerospace, manufacturing, construction, and power industries. The key challenges discussed include data management, model complexity, cybersecurity, and standardization. This review highlights the importance of addressing these challenges to realize the full potential of DT technology in various industries while emphasizing the need for high-quality data, accurate modeling, robust security measures, and standardized evaluation criteria. As DT technology continues to evolve, it will play a key role in advancing smart, resilient and efficient industrial systems.

Keywords: Digital twins, building information management, Internet of Things, aerospace, manufacturing, construction, power transmission

1. Introduction

The human industry is becoming increasingly large-scale, systematic and complex, such as large equipment manufacturing, aerospace and construction. Industrial technology has shown a trend of high integration and complexity in pursuit of higher efficiency. Accordingly, increasingly complex industrial equipment faces a relatively high probability of failure, and the evaluation of its performance and expected lifetime will become increasingly complex [1]. Therefore, how to efficiently realize the design, manufacturing, testing, operation, maintenance, fault diagnosis, condition assessment, and life prediction of complex industrial equipment in this context has become a challenge for modern industrial technology [2]. With the emergence of technologies such as the Internet of Things (IoT), cloud computing, and integrated multidomain and multiscale modeling, a new solution, digital twin (DT) technology, has emerged to address the above industrial technology challenges [3-5].

DT technology originated from the concept of "digital equivalence to physical products" proposed by Michael Greaves [6]. In 2006, Hribernik et al. [7]. proposed the concept of "product avatars", which is similar to the concept of DTs. The concept of product avatars aims to create an information management architecture that supports bidirectional information flow from a product-centric perspective. NASA introduced the term DT in 2010 [8]. After more than a decade of development, the concept of DT technology has become increasingly clear, that is, the establishment of a DT mirror image through an information technology platform to simulate physical entities, processes, or systems. The formation of DT technology is inextricably linked to the development of the IoT [9]. The IoT uses its terminal components to collect data for feedback and forms a digital simulation on an informatization platform through wireless transmission, cloud computing, artificial intelligence (AI), machine learning, big data analysis, and other means [10]. Since data collection and feedback are performed in real time, the digital simulation generated on the informatization platform will constantly change according to the actual situation and present the real situation of the simulated object [11-13].

DT technology has rapidly advanced due to the development of key technologies such as multidomain and multiscale integrated modeling, state evaluation, blending data-driven and physical models, data acquisition and transmission, and cloud computing and edge computing [14]. Its essence lies in the integration and comprehensive application of various composite technologies to address issues emerging in the industrial equipment domain [15]. Multiphysics and multiscale modeling are important for high-fidelity modeling of DTs and simplify the contradiction between the virtual model and the complex behavior of physical objects [16]. Data-driven modeling, especially machine learning, provides an alternative approach by learning the relationship between inputs and outputs, enabling models to estimate system behavior without explicit physical principles [17].

For DTs, real-time data acquisition and transmission of the status of the target object are important. Real-time data acquisition primarily demands a broad range covering all aspects of the target object, such as temperature, pressure, and vibration, all of which must be precisely captured through sensors [18]. A stable, reliable, and fast data transmission system ensures that data collected by distributed sensors can reach the information platform in real time and be used for digital model construction and updates [19]. Cloud and edge computing platforms are essential for ensuring that each complex functional step can be accomplished, improving computational performance and flexibility [20].

DTs have diverse applications, from aerospace to manufacturing. In aerospace engineering, DT technology is used to improve the efficiency and safety of aircraft design, testing, and operation [21-24]. It enables real-time monitoring and maintenance planning, enhancing decision-making processes [25-27]. In manufacturing, DTs optimize production processes, enhance quality control, and enable predictive maintenance, leading to increased operational efficiency and reduced costs [28-31]. The integration of AI, big data, and building information management (BIM) with DTs has further expanded their potential [32-35]. AI and big data analytics enhance the ability to process and analyze large volumes of data generated during the lifecycle of a building, optimizing design, construction, and operational strategies [36-38]. BIM enables the creation of accurate virtual models of buildings, facilitating collaboration among stakeholders and ensuring efficient project management [39, 40]. DT technology in power transmission systems enables real-time monitoring, analysis, and optimization, improving reliability and efficiency. It supports predictive maintenance, reduces downtime and enhances system performance [41].

The development of DT technology faces key challenges such as data management, model complexity, cybersecurity, and standardization [42], which are critical to address for widespread adoption and success across industries [43]. This paper provides a comprehensive review of the applications, challenges, and future prospects of DTs, particularly in traditional industries such as aerospace, manufacturing, construction, and power transmission. These sectors, owing to their reliance on complex systems, are well suited to benefit from the integration of DT technologies. The innovation and contribution of this paper lies in its focus on traditional industries where DTs have achieved significant maturity. By concentrating on these domains, the paper highlights the role of DT in improving operational efficiency and integrating with emerging technologies such as the IoT, AI, and big data. Additionally, the paper offers valuable insights into overcoming the challenges of data management, model complexity, cybersecurity, and standardization, providing practical recommendations for real-world industrial applications.

2. Key Technologies for DT

The ability of DT technology to realize the digital simulation of physical entities, processes, or systems is indispensably linked to the development of key technologies such as multidomain and multiscale integrated modeling, state evaluation blending data-driven and physical models, data acquisition and transmission, and cloud computing and edge computing [44]. Its essence lies in the integration and comprehensive application of various composite technologies to address issues emerging in the industrial equipment domain.

2.1 Multiphysics and multiscale modeling

Modeling is the core part of DT and requires a thorough understanding of the physical properties and their interactions. Therefore, multiphysical field and multiscale modeling are important for high-fidelity modeling of DTs [45]. A key issue that should be addressed in DT modeling is to simplify the contradiction between the virtual model and the complex behavior of physical objects. One compromise is to use a modular approach to achieve flexible modeling. Negri et al. [46] suggested incorporating black-box modules in the main simulation model. A functional mock-up interface (FMI) standard is used for the black-box modules, creating functional mock-up units (FMUs), as shown in Figure 1. The various behavioral models of the DT are activated only when needed and interact with the main simulation model through a standard interface. To achieve balance, engineers should determine which components are critical to system functionality and determine the modeling level of each component before creating a DT model of a complex system. As a result, high-fidelity DT models can be created on the basis of different modeling levels.

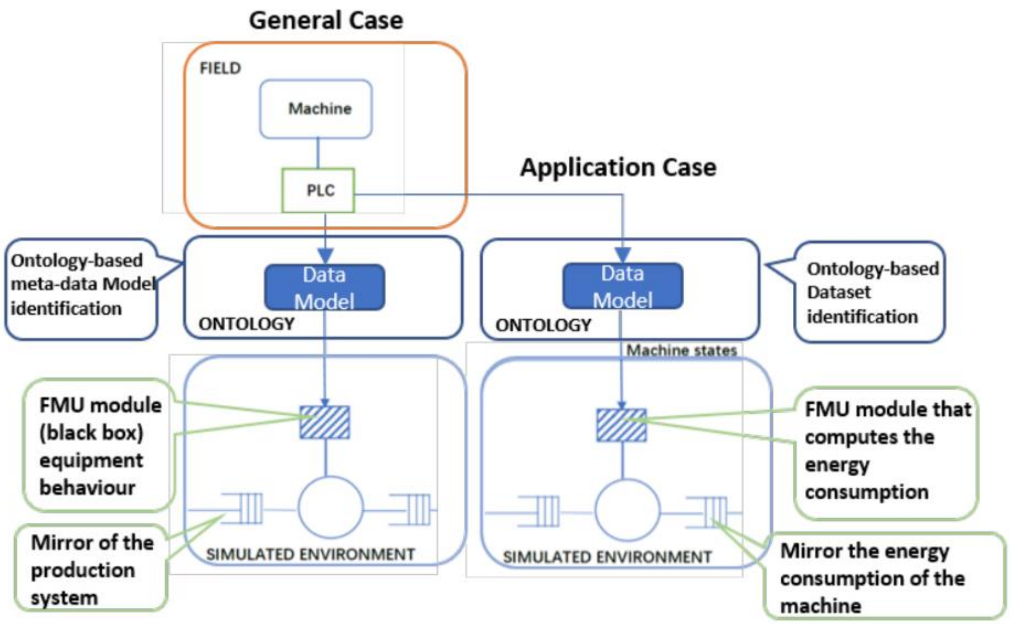

Figure 1: FMU in the application case [46]

2.2 Data-driven Modeling

Although significant progress has been made in the fields of multiphysics and multiscale modeling, developing accurate and reliable numerical physical models for objects with complex mechanical structures is still a major challenge. Relying only on analytical physical models of target objects to assess the state of complex objects cannot yield accurate results. Therefore, data-driven approaches, especially machine learning, can be utilized [47-50]. Machine learning models provide an alternative approach by learning the relationship between inputs and outputs, enabling these models to estimate system behavior without explicit physical principles [51-53]. For example, neural networks can predict possible future failures by learning data from machines under normal operation and failure conditions (Figure 2) [48]. Moreover, real-time simulation ensures that the DT reflects the real-time state of the physical object or system, including real-time data integration and dynamic simulation, to update the model under new data inputs and simulate its future behavior. Model validation and calibration are critical steps to ensure that the DT is accurate and reliable. Comparing the model's predictions with actual observations allows for assessing its accuracy and, if necessary, adjusting the model's parameters to enhance its predictive capabilities.

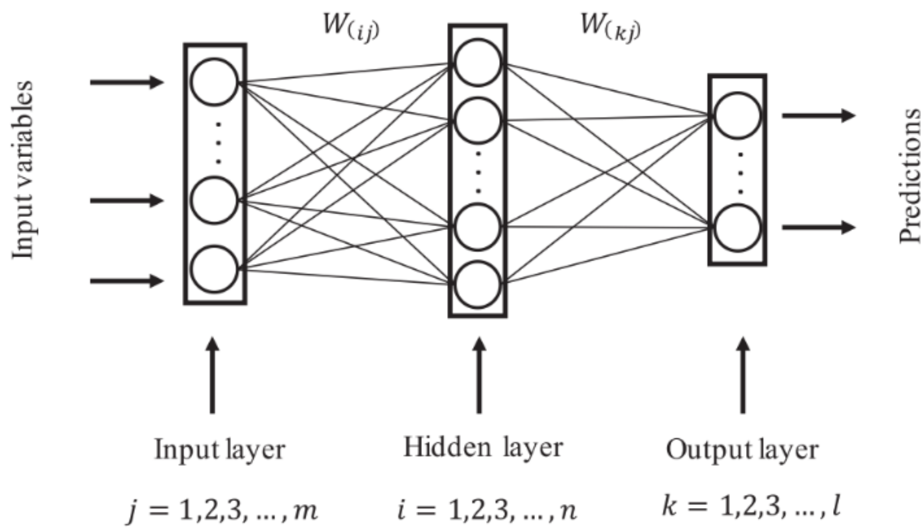

Figure 2: Artificial neural network [48]

2.3 Data acquisition and transmission

For DTs, real-time data acquisition and transmission of the status of the target object are important [54]. Real-time data acquisition and transmission demand two main aspects. First, the acquisition range must be broad, covering all aspects of the target object, such as temperature, pressure, and vibration, all of which must be precisely captured through sensors. Second, a stable, reliable, and fast data transmission system is needed to ensure that the data collected by distributed sensors can reach the information platform in real time, which is used for digital model construction and updates. With the rapid progression of technology, swift advancements in sensor capabilities and the implementation of new transmission technologies have laid a solid foundation for the development of DT technology [55]. For example, with highly integrated microelectromechanical system (MEMS) sensors and narrowband IoT (NB-IoT) technology (Figure 3) in the communication field, these novel data sensors and transmission technologies can achieve high integration and low-cost large-scale applications [56].

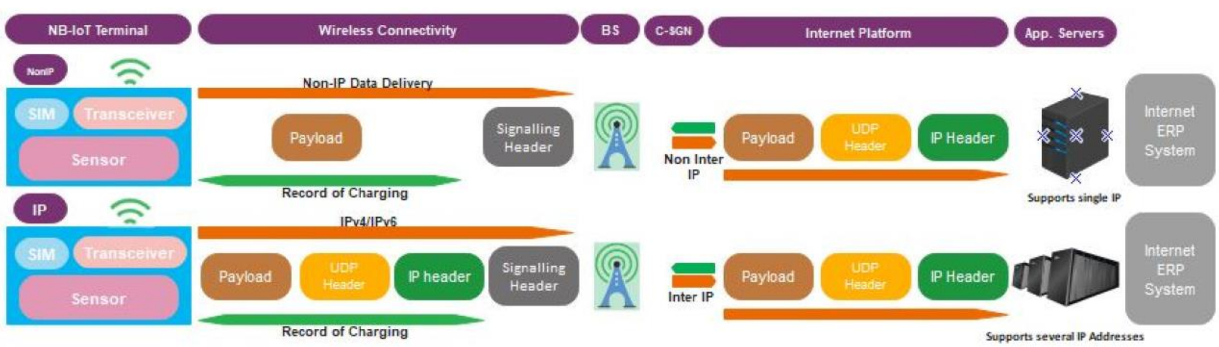

Figure 3: Artificial neural network [56]

2.4 Cloud and edge computing

DTs apply technologies such as sensor data collection, the IoT, and multiphysical field multiscale modeling; therefore, DTs rely on high-performance computing platforms to ensure that each complex functional step can be accomplished. To improve computational performance, DT technology is guaranteed from two main aspects. First, it widely applies cloud computing technology that is based on distributed computing, relies on cloud server resources, and flexibly mobilizes computing resources according to the size of the computing demand [57]. Second, it relies on the development of edge computing, which is a platform that integrates networks, computing, storage, and applications and is able to carry out computing services in close proximity to the side of things or data sources. Moreover, edge computing can also be combined with cloud computing, which can access the historical data of edge computing [58].

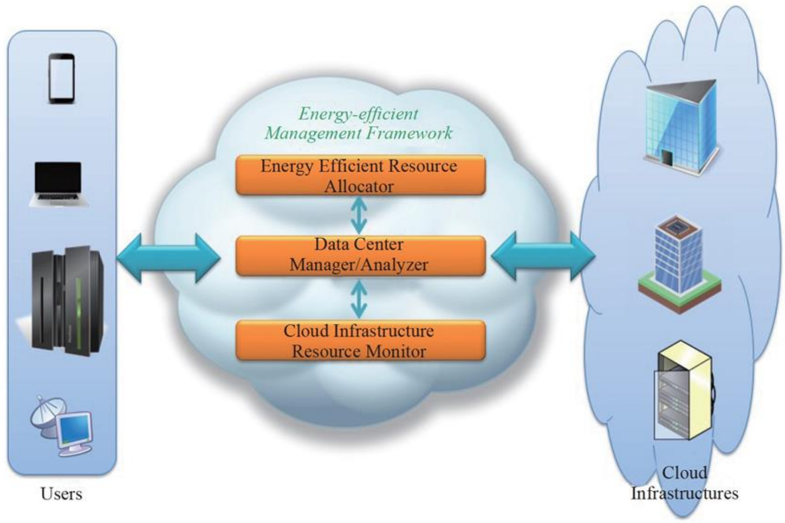

Figure 4: Cloud computing architecture [57]

3. DTs in Aerospace and Manufacturing

3.1 Aerospace Engineering

In the field of aerospace engineering, DT technology is widely used as an innovative approach to improve the efficiency and safety of the design, testing and operation of aircraft. By creating a virtual replica of an aircraft, engineers are able to simulate various flight and environmental conditions within a risk-free virtual environment, thereby optimizing design, predicting, and preventing potential issues and improving maintenance strategies. Throughout the lifecycle of an aircraft, the DT can receive and analyze data collected from its sensor network in real time, providing instantaneous insights into system performance and health, thereby supporting more intelligent decision-making. For example, during flight, DTs can be used to monitor the structural integrity and performance of various systems of aircraft, predict potential failures, and assist in determining the root cause when failures occur. On the ground, maintenance teams can utilize DTs to plan and simulate maintenance operations, ensuring that the actions taken are maximized for safety and efficiency. Moreover, DTs also support more efficient training and preparedness, as pilots and ground personnel can practice and test various scenarios within a simulated virtual environment without the need for expensive and complex physical simulators.

For over a decade, DTs have been evolving in the aerospace industry. NASA pioneered the definition of DT within the realm of aerospace in 2010 and constructed a development roadmap for them [59], which underscored their strategic importance to U.S. space sciences and the Air Force. By 2035, NASA aimed to develop DTs for spacecraft that can adapt and manage comprehensive mission arrays. Simultaneously, the U.S. Air Force has achieved an array of inventive discoveries through feasibility studies of DTs. DTs have evident applications in feasibility analysis, fleet administration, and diagnostics and forecasting during flight [60]. Additionally, in the 2010s, DT-driven intelligent manufacturing emerged as a trending trajectory for Industry 4.0 [61]. Prominent aerospace original equipment manufacturers (OEMs), including Boeing, Airbus, and GE, initiated their respective DT initiatives. These globally dominant aerospace OEMs anticipate DT to dynamically refine design and manufacturing processes, enhancing product quality and dependability while curtailing costs and optimizing time efficiency.

The application of DTs in aerospace continues to be a prominent topic within the academic community, with numerous scholars innovating across various facets. Meyer et al. [62] explored the implementation and advancement of DTs in various sectors, emphasizing their ability to reflect and predict the status of assets, particularly in the aerospace context. An internal project within the German Aerospace Center (DLR) is established, which collaborates with several institutes across IT and aviation engineering to explore methodologies and technologies for DT. Three use cases are defined to demonstrate DT capabilities and uncover new development opportunities, with a particular focus on using DTs as a research tool in the research of aircraft use cases. The project addresses numerous IT-related issues and moves toward a common vision for DT technology, with the next steps involving the implementation and demonstration of prototypes across the defined use cases. The authors present an overview of the project's results and developments, aiming to digitally map aircraft and their components.

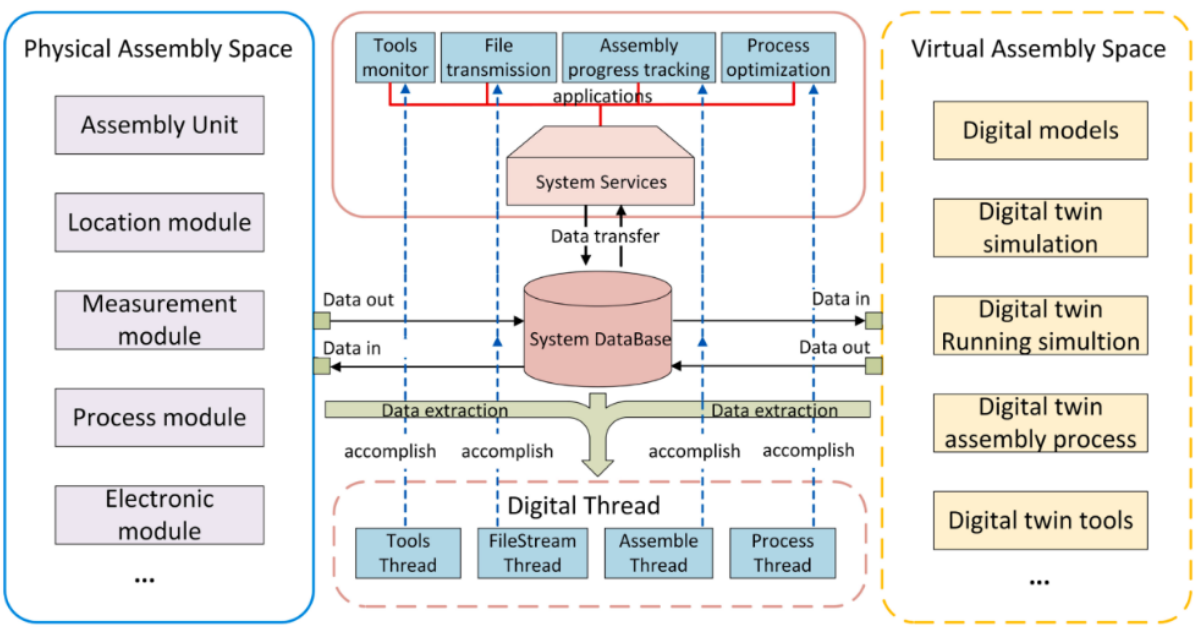

Figure 5: Framework of the digital thread-based DT model [63]

Zhang et al. [63] proposed a digital thread-based modeling DT framework (Figure 5) to manage industrial production sites, particularly focusing on the intricate assembly environment of the aircraft assembly process, through the mapping of physical entities to virtual spaces. Addressing the limitations of existing DT modeling methods, which lack provisions for data flow and intrinsic intermodule interaction, this framework amalgamates the strengths of both DTs and digital threads. Enhanced data management within the framework seeks to augment the controllability and traceability of the manufacturing process and product quality. The implementation of the framework is demonstrated via a case study of the aircraft assembly process, revealing its potential to increase efficiency through comparative analysis.

3.2 Manufacturing

DTs are expanding in manufacturing and can benefit manufacturing operations at different levels. Notably, with process-based DT, companies can achieve production visibility and planning to improve operational agility, increase throughput, and optimize process efficiency across the supply chain [64]. Specific use cases include production monitoring, asset monitoring and machine diagnostics, visual job description support, predictive maintenance, shop floor performance improvement, process optimization, etc. [65]. The application of DTs in the manufacturing industry is divided into three main categories: product DTs, production DTs, and equipment DTs throughout the entire product lifecycle management (PLM).

3.2.1 Product design DT

In the product design phase, generic DTs are utilized for the creation of three-dimensional digital models of the product, accurately recording various physical parameters of the product and presenting them in a visual manner [66]. Through simulation and emulation, the performance and behavior of the product under various external conditions are validated, ensuring that product adaptability is verified during the design phase. Compared with traditional manufacturing methods, which require the production of a batch of physical prototypes to validate product adaptability and performance, the product cycle is significantly shortened, and design verification costs are substantially reduced.

3.2.2 Production DT

During the manufacturing phase of a product, the main objective of production DT is to ensure that products can be produced efficiently, with high quality and at a low cost. The primary entities designed, simulated, and verified are the production systems, which encompass manufacturing processes, manufacturing equipment, manufacturing workshops, and management control systems [45]. DTs can expedite product introduction times, enhance the quality of product designs, reduce production costs, and accelerate product delivery. Virtual production lines established through digital means, which highly integrate the DT of the product itself with production equipment and processes, among other forms of DT, enhance collaborative efficiency.

3.2.3 Equipment DTs

In the manufacturing process, certain equipment or devices are essential, and any malfunction or damage to this equipment often leads to significant losses to the production line. Equipment DTs, through the establishment of DT models of equipment, monitor the real-time operational status of equipment. By utilizing historical data, real-time data, and operational data of the equipment and combining it with big data analysis and mining techniques, equipment operation can be optimized, predictive maintenance and care can be conducted, unplanned downtime risks for key production equipment can be minimized, and the lifespan of key equipment can be extended.

The employment of DTs in manufacturing has captured significant academic interest, with notable innovations emerging in recent years. Bolender et al. [67] explored in depth the ability of DTs to represent, control, predict, and optimize the behavior of cyber-physical production systems (CPPSs) in diverse and complex environments. They recognize the challenges posed by CPPSs, such as differences in behavior due to different deployments, configurations, and environmental factors, and highlight the need for expert human operators to be skilled in modifying CPPS configurations. The authors aim to enhance the adaptability of DTs in such scenarios, leading them to propose a modeling framework for adaptive manufacturing that supports the modeling of domain-specific cases and specifies rules for case similarity and case-based reasoning in modular DTs. They assert that by leveraging explicitly modeled domain expertise, the automatic configuration of DTs can optimize manufacturing time, minimize waste, and significantly contribute to more sustainable manufacturing practices.

Friederich et al. [68] introduced a novel approach to adopting DTs in smart factories, acknowledging the pivotal role they play in enhancing productivity and reducing costs and energy consumption, especially amid the challenges of swiftly changing customer demands and shorter product life cycles (Figure 6). In light of the limitations of traditional modeling and simulation methods in such dynamic contexts, they propose a unique, generic data-driven framework that automatically generates simulation models, forming the foundation for DTs in intelligent manufacturing environments. By utilizing advancements in machine learning and process mining techniques, their innovative framework minimizes, defines, or possibly eliminates the necessity for expert knowledge in extracting corresponding simulation models, a concept they exemplify through a detailed case study.

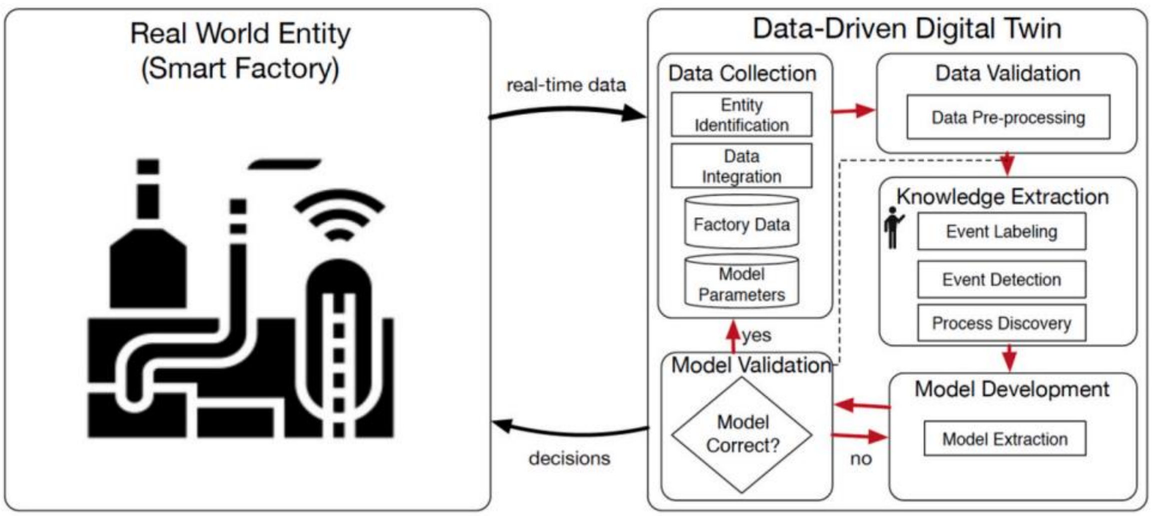

Figure 6: Generic data-driven framework for automated generation of simulation models as the basis for DT for smart factories [68]

4. DT in the Construction Industry

4.1 Development of AI, Big Data and Building Information Management

AI, big data, and BIM are intertwined technologies that collectively enhance the planning, design, construction, and management of buildings and infrastructure. AI has the ability to process and analyze data in a way that can predict outcomes, automate processes, and optimize solutions in the realm of building management. It can be applied in various aspects of BIM, such as automating design processes, enhancing project scheduling, predicting maintenance requirements, and optimizing energy consumption, thereby adding a layer of intelligence and automation to building management.

Big data refer to the enormous volumes of data generated during the lifecycle of a building, which can be structured or unstructured. It includes analyzing large datasets to uncover patterns, correlations, trends, and insights that are important for making informed decisions. In the context of BIM, big data analytics can be used to analyze data from various stages of the building lifecycle to optimize design strategies, improve operational efficiency, and enhance the overall performance of buildings.

BIM is a sophisticated approach to managing the entire lifecycle of a building, from its initial design and construction to its eventual demolition, via comprehensive, digital 3D models. It is not just a type of software or technology but rather an integrative process that facilitates the sharing of valuable information among architects, engineers, construction professionals, and other stakeholders throughout the building's lifecycle. BIM enables the creation of accurate virtual models of buildings, which can be used for planning, design, construction, and operational purposes, ensuring that all parties involved have a unified understanding and can make informed decisions regarding the construction and management of the building. BIM encompasses the entire process of creating and managing information about a building during its entire lifecycle. When infused with AI and Big Data, BIM transforms into a more potent tool. AI algorithms can analyze the Big Data derived from BIM models and operational data to unearth insights that were previously difficult or impossible to ascertain. These insights can then be used to enhance the design, construction, and operational management of buildings, ensuring that they are not only constructed and managed more efficiently but also that they perform optimally throughout their lifecycle.

Together, AI, big data, and BIM form a robust framework that enhances the capabilities of architects, engineers, and construction professionals. This integrated approach ensures that buildings are designed, constructed, and managed in a way that is not only efficient and cost-effective but also sustainable and future-proof, thereby aligning with the objectives of smart, adaptive, and sustainable urban development.

Researchers are currently deepening their research in AI, big data and BIM. For example, Lokshina et al. [69] addressed the relatively slow adoption of digital transformation in the architecture, engineering, and construction (AEC) industry, highlighting BIM as a pivotal technology that could usher the industry in the digital era by enhancing collaboration and communication among stakeholders through information and communication technologies (ICTs). They explore the integration of IOT designs and services into the BIM process, identifying potential security concerns arising from the implementation of the IoT in a modular environment with numerous interdependencies. To mitigate these concerns, this paper proposes a system design that uses blockchain technology to secure and control frameworks that integrate IoT and BIM technologies, exemplifying its application through a smart museum while asserting the generic and versatile applicability of the design in various building categories, such as university renovation projects.

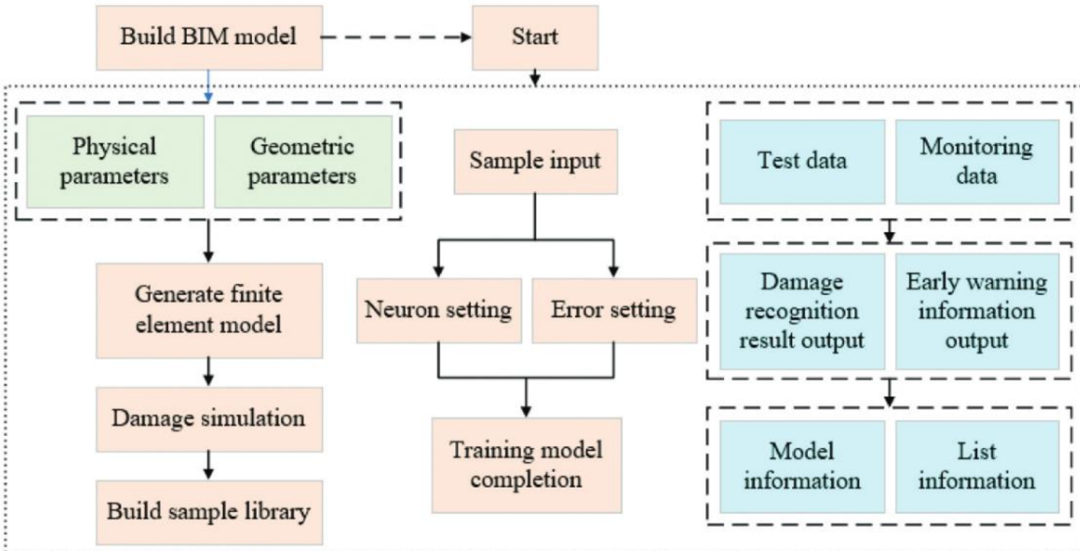

Figure 7: AI-based BIM for intelligent structural damage recognition [70]

Yang et al. [70] studied the intersection of BIM and AI in the construction industry, particularly focusing on addressing existing challenges in intelligent construction technology in China, especially concerning structural damage monitoring during bridge construction (Figure 7). Recognizing limitations in classical neural network algorithms predominantly used in prior research, this study introduces innovative improvement measures, substantiates their efficacy through practical arithmetic examples, and integrates the improved neural network recognition algorithm into the BIM framework to adequately recognize and assess bridge structural damage. This integration not only enhances the intelligence level of the BIM system but also offers insights for progressing intelligent construction technology, which is especially pertinent to bridge construction monitoring.

4.2 DTs in BIM

Integrating DT within BIM represents an innovation that melds physical buildings and structures with their digital counterparts to facilitate enhanced decision-making and management across the entire lifecycle of a building. In the sphere of BIM, DTs enable the creation of a precise virtual model of a building, allowing engineers and architects to conduct visual simulations and analyses during the design and construction phases, thereby assisting in optimizing designs and pinpointing potential issues. A DT can synchronize the real-time data of a building, including structural, environmental, and operational data, to perform continuous monitoring and analysis throughout its entire lifecycle, subsequently increasing operational efficiency and maintenance management. The incorporation of DTs into BIM can augment collaboration among all stakeholders (such as architects, engineers, contractors, and operators) by sharing real-time, accurate building data, ensuring that decisions at each stage are based on precise and timely information. Moreover, DTs not only play a role during the design and construction phases of a building but also provide vital input during the operational phase through predictive maintenance and optimizing building performance, thereby reducing operational costs and enhancing the overall efficacy of the building.

Research on DT applications in BIM in a more digital and intelligent direction. Delbrügger et al. [71] provide an in-depth analysis of the growing role of BIM in asset management during the operation and maintenance phases in the architecture, engineering, and construction industries. They discuss the latest research trends and the influence of industry standards on BIM. While acknowledging BIM's significant contributions, the authors highlight its limitations in terms of information depth and analytical power, especially in the operation and maintenance stages. To address these gaps, they propose a new approach that integrates DT, which leverages AI, machine learning, and data analytics to create dynamic models that can continuously learn from and update them on the basis of various data sources.

With the rapid development of AI, computer vision technology has been widely used in image recognition, facial recognition, intelligent monitoring, and other fields. Some researchers have used computer vision technology for the combination of DTs and BIM. Zhou et al. [72] introduced a pioneering computer vision DT scheme that employs BIM and uses camera videos as input, navigating through challenges related to dimensions, coordinate systems, and object inconsistencies between BIM and camera videos. The proposed DT framework uses a unique method that combines object detection with 3-D object estimation networks to determine object positions and orientations. It includes theorems and lemmas for calculating 3-D coordinates in the building coordinate system (BCS) on the basis of detected 2-D positions. Additionally, the approach features cold-start and run-time object matching schemes to resolve discrepancies between camera footage and BIM. The performance of the proposed approach is substantiated through real-world experiments, which demonstrate precise location error metrics, and notably, it first explores a DT scheme atop BIM via computer vision, potentially sparking further intelligent studies in smart buildings that jointly utilize computer vision and BIM.

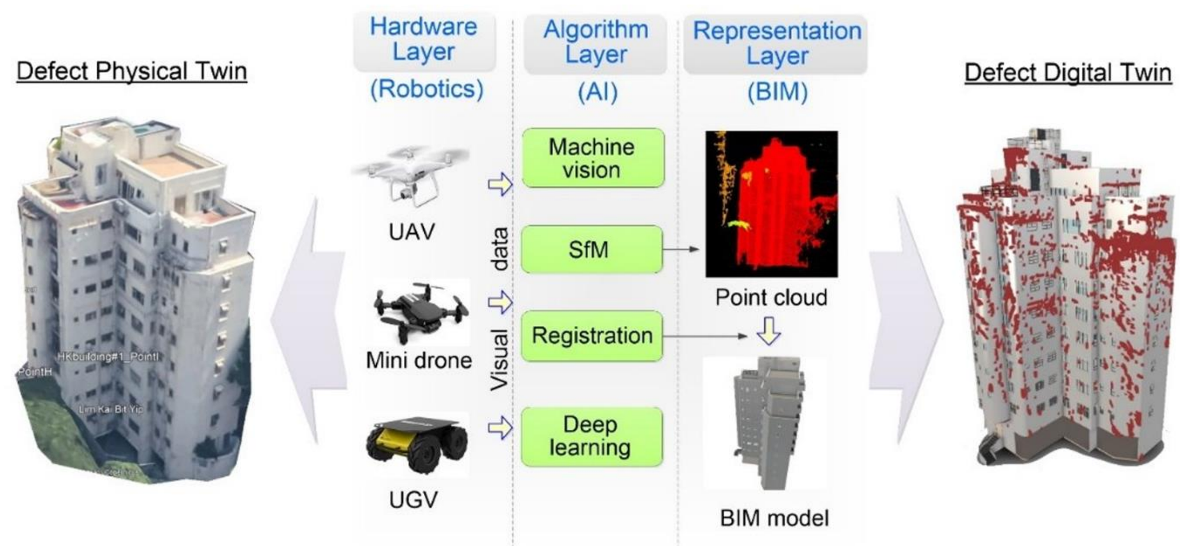

Figure 8: A technical framework that integrates robotics, AI and BIM for defect DTs [73]

Chen et al. [73] developed a technical framework aimed at facilitating defect DTs by synergistically integrating robotics, AI, and BIM, addressing the global issue of aging buildings and infrastructure and the imperative of adept management and renovation (Figure 8). This framework creates a system that connects physical defects with their digital representations in a virtual environment, improving defect information modeling by enabling the quick and efficient capture of precise, current as-damaged data. A case study involving a 10-story residential building in Hong Kong demonstrated the framework's effectiveness in matching defects on the basis of location, geometry, and size. This approach also has potential for broader applications, such as matching facility defects on a street block or even at the city level, which could aid urban renewal initiatives.

4.3 DTs in Infrastructure Assessment

In the global context of aging infrastructure, regular monitoring, assessment, and maintenance are important [74-78]. The DT method has been utilized in infrastructure assessment for many years. The synergistic combination of DTs and sensor monitoring techniques provides multifaceted applications. This integrated approach takes advantage of real-time data collection and computational modeling to provide a comprehensive view of structural integrity. For example, vibration sensors can continuously monitor vibration and motion within an infrastructural component. These real-time monitoring data can be fed into the DT model to replicate the physical characteristics and behavior of the infrastructural component in a virtual environment. Mercedes et al. [79] presented a comprehensive approach to generating seismic fragility curves for a precast reinforced concrete bridge equipped with a vibration-based structural health monitoring (SHM) system located near an active seismic fault in the Dominican Republic. Given that the bridge serves as a critical lifeline to several local communities and is built to outdated construction standards ill suited for seismic resilience, the SHM system is essential for assessing its structural integrity and seismic performance. The authors effectively combine data from the SHM system with computational models to produce fragility curves, offering quantitative measurements of expected damage and probabilistic estimates for exceeding various states of failure as functions of seismic intensity. The authors employ a DT model of the bridge, developed via finite element analysis and data from the SHM system, as a predictive tool for minimizing modeling uncertainties and enhancing the accuracy of the fragility curves. The proposed DT was applied to conduct nonlinear incremental dynamic analysis (IDA) by utilizing ground motions tailored to the seismic fault and site specifics. The analysis revealed that, considering the highest expected acceleration with a 2% chance of surpassing within 50 years, there is a 62% likelihood of the structure sustaining significant damage.

Ye et al. [80] conducted an exploratory study over two years, aiming to create a DT of bridges for structural health monitoring by leveraging interdisciplinary collaboration between civil engineers and statisticians. Their research focused on four key areas: real-time data management via physics-based approaches, data-driven approaches, and the integration of these methods to develop a comprehensive DT framework for railway bridges in Staffordshire, UK. Fidler et al. [81] augmented an existing fiber-optic strain-based bridge structural health monitoring system with additional sensors measuring deck rotation and axle positions to enhance infrastructure asset management. They designed and implemented a system that integrates real-time data into a DT with back ends for analysis and overcame challenges such as synchronizing timestamps from multiple sensors during a time-limited overnight installation. Lin et al. [82] presented a novel DT-based methodology for assessing the seismic collapse performance of large-span cable-stayed bridges under the influence of strong earthquakes. This study investigated a scaled physical model of a large-span cable-stayed bridge with accelerometer sensors and employed linear and nonlinear model updating techniques to create a DT model on the basis of a finite element (FE) model from the original design documents. Subsequently, seismic fragility analysis was performed via the incremental dynamic analysis (IDA) method to generate collapse fragility curves for three different FE models.

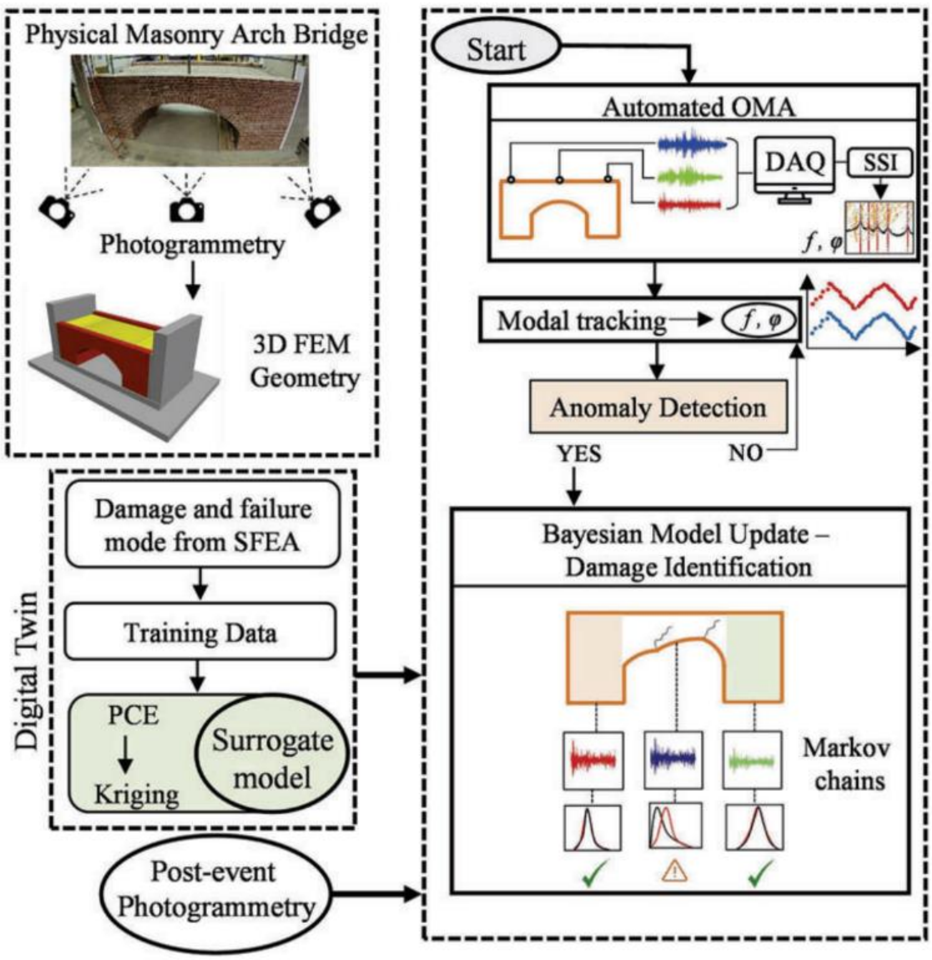

Figure 9: Workflow of masonry arch bridge DT development [83]

Muhit et al. [83] explored the issue of managing aged masonry arch bridges through DTs in Europe. Many bridges in Europe are more than a century old and are subject to operational constraints or closures due to increased traffic loads. The authors introduce a comprehensive framework for creating DTs of these bridges to facilitate more informed decision-making for their repair and maintenance. The authors describe the process of obtaining dynamic characteristics, including the natural frequency and modal shape, through ambient vibration tests via accelerometers. A Bayesian method is applied for identifying structural modal properties within specific time windows. By integrating 3D geometry derived from photogrammetry with these modal properties, the authors develop a high-fidelity numerical model that can be continuously calibrated with real-world data (Figure 9). This framework offers a promising approach for managing aged masonry arch bridges and uses advanced real-time monitoring and data-driven methods to enhance the assessment of damage accumulation over time. Using fiber optic sensors can be another way to collect real-time data and update DT models. For example**,** Febrianto et al. [84] investigated DTs incorporating fiber optic strain sensors. Using a case study of a 27.34-meter-long steel railroad bridge in Staffordshire, UK, fitted with fiber Bragg grating sensors at several locations, the authors used the statistical finite element method (statFEM) to combine real-world data with a physically based model, considering uncertainties in the sensor readings, applied loads, and model errors. The method provides convincing results that effectively predict the "real" system response in the form of strain distributions on the two main I-girders of the bridge during train passage. The study revealed that varying the number of sensors (40, 20, and 10) and their sampling rates did not significantly affect the precision of the strain predictions of the statFEM, as indicated by negligible differences in the 95% confidence intervals. This shows that the statFEM can reduce the cost of sensor networks while maintaining data interpretability, even if the dataset is reduced or incomplete. This suggests that the statFEM can generate reasonable strain distribution predictions at points lacking direct sensor measurements, thus expanding its application to long-term structural health monitoring.

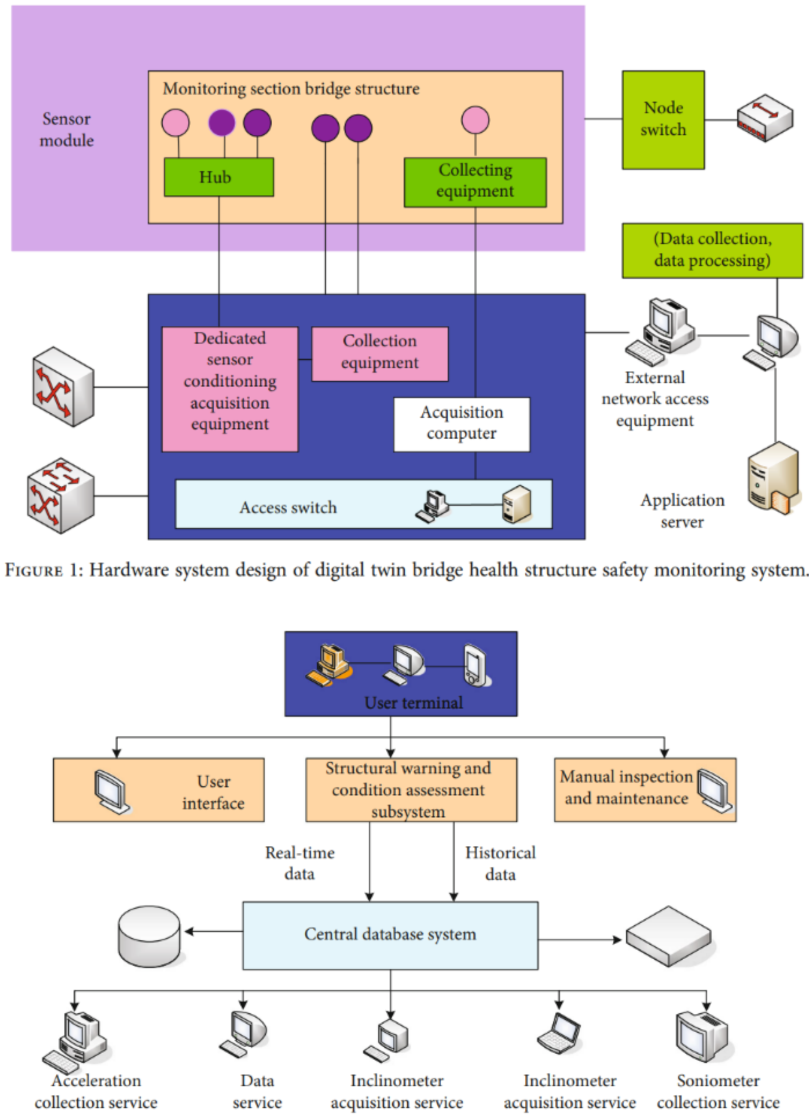

Figure 10: Software modules of the DT bridge health and structural safety monitoring system [85]

Lei et al. [85] presented a DT system for the health monitoring of bridges that uses a high-speed demodulation system grounded in dual long-period fiber gratings. This study stands out for its fiber grating-based damage self-diagnosis system, which facilitates strain distribution and impact load monitoring. Employing advanced information recognition methods, the system adeptly localizes impact loads. The authors address the inherent challenges of dealing with complex, high-volume data by implementing essential data cleaning techniques, including the transformation of data into dimensionless form and the handling of missing values. Furthermore, they analyze and construct a DT KNN model specifically designed for the monitoring and management of bridge transition construction. The system architecture is comprehensive, featuring multiple privilege login modes, a display of BIM models, geographic information, and meteorological data. Additionally, the platform allows for the modification and analysis of data and even includes email warning functions. Figure 10 displays the software modules of the DT bridge health and structural safety monitoring system. Liu et al. [86] developed a real-time, updatable DT model that is based on BIM. Using machine learning algorithms to intelligently interpret strain distributions, they introduced an automated method for identifying, locating, quantifying, and visualizing cracks that addresses the inefficiencies and inaccuracies of manually interpreting distributed fiber optic sensor data, as shown in Figure 11. The model serves as a real-time visualization interface for monitoring cracks, with data continuously provided by distributed fiber optic sensors. The authors validated their method by conducting laboratory tests on concrete beams, achieving highly accurate crack monitoring.

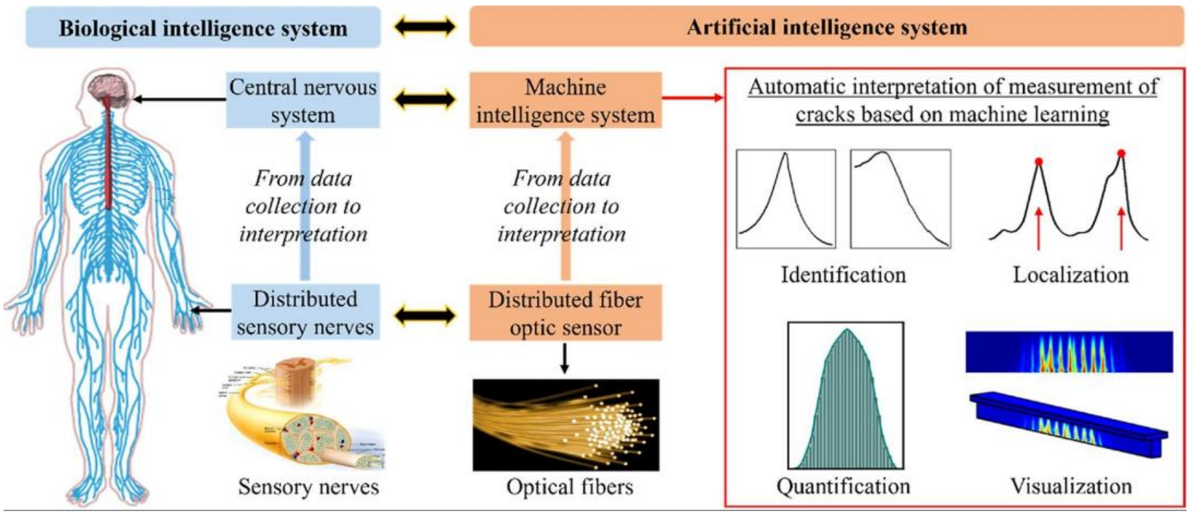

Figure 11: Crack visualization method using fiber optic sensors and DTs [86]

In addition to sensing technologies, drone inspection can be combined with DT modeling, as it provides accurate and comprehensive information on the health condition of the infrastructure surface. Yoon et al. [87] developed a DT model incorporating drone monitoring in response to the urgent need for periodic inspections of aging bridges. Typically, drone inspections map only external damage and do not address seismic performance. The authors propose a comprehensive two-phase method that integrates drone-based inspections into a DT framework followed by a seismic fragility analysis. This model is updated with bridge conditions sourced from drone inspections, translating observed damage into a quantifiable damage index that reflects reductions in structural stiffness. Using this recalibrated DT, the seismic fragility analyses are run with varying earthquake scenarios. Their method, which was tested on an in-service prestressed concrete box bridge, demonstrated a notable difference in the seismic fragility curves of a deteriorated bridge compared with an intact bridge. Benzon et al. [88] introduced a method for constructing an operational DT for expansive infrastructures that uses drone-captured images. Central to this study is the DT's ability to virtually mirror the real-world structure and evolve in tandem with the structure's physical alterations throughout its life span. Validating their approach on a wind turbine transition piece, the authors adeptly harnessed over 500 RGB drone images and multiple LiDAR scans to craft a detailed three-dimensional geometric rendition. This digital construct was then juxtaposed with the original design to identify and quantify manufacturing inconsistencies and tolerances. Leveraging artificial intelligence, the methodology proficiently identified and categorized paint defects from the images, subsequently mapping them onto the 3D model. This offers the opportunity for real-time updates to the DT on the basis of periodic inspections. The paper thoughtfully delineates the core technologies underpinning this DT concept. Importantly, while the focus here is on wind turbines, the authors emphasize the method's broader applicability across industries such as aerospace, marine, transportation, and other substantial infrastructure domains.

5. DTs in the power industry

In contemporary power transmission systems, the incorporation of DT technology is gradually emerging as a pivotal innovative practice, fundamentally esteemed for enabling the simulation, analysis, and optimization of the actual transmission system in real time without necessitating direct intervention in the physical system. The integration of a spectrum of advanced technologies, including IOTs, big data, AI, and DTs, achieves real-time or near-real-time monitoring, analysis, and control of transmission systems. This technology provides a highly accurate and flexible virtual platform for the design, operation, and maintenance of transmission systems. On this platform, engineers and decision-makers can simulate various operational scenarios, validate different control strategies, predict future system behaviors, analyze potential risks and issues, and formulate corresponding optimization strategies and solutions [89]. For example, during the design phase of transmission lines, engineers can simulate different design schemes and operating parameters in a virtual environment via DT technology to ascertain their performance and efficacy in practical applications. In the operational phase, real-time data monitoring and analysis, realized through the DT, can assist operators in comprehending the operational status of the transmission system instantaneously, identifying, and preempting potential failures and risks, and optimizing operational strategies to increase system reliability and economic benefits [90]. In the maintenance phase, the application of DT technology can aid maintenance personnel in accurately gauging the aging and wear status of the transmission system and predicting potential failures and risks, thereby actualizing predictive maintenance, increasing the precision and efficiency of maintenance, and reducing maintenance costs and risks. Furthermore, DT technology can also assist decision-makers in executing more precise energy dispatching and management to navigate the complex and volatile electricity demand and market environment [91]. In conclusion, the application of DT technology in transmission systems not only facilitates the elevation of the intelligence level of system design, operation, and maintenance but also provides robust assurance for the stable, safe, and efficient operation of power systems. This method merits more extensive and profound research and application in future power transmission systems.

In summary, the DT system operates by using its synchronization capabilities to set initial parameters and enable dynamic data interaction, effectively replicating the behavior and environment of physical entities on an information-based platform. The system allows for projections and predictions that are impractical in the real world, utilizing its autonomous features. With its interactive function, the system can adjust and monitor the operational states of physical entities in real time. Additionally, the DT's sharing feature supports joint simulations of multiple components. Building a digital transmission system with DT technology is a gradual process beginning with localized, small-scale applications. Currently, this technology is mainly used in transmission and distribution systems for inspection, maintenance, and power system operation optimization.

5.1 Inspection and Maintenance

Inspection and maintenance in the context of power transmission and distribution systems are critical to ensuring reliability, efficiency, and safety in the delivery of electricity from generation points to end-users. Robust inspection protocols include systematic examination of various components and subsystems, including transformers, transmission lines, and substations, to identify potential vulnerabilities, such as wear and tear, or anomalies that might impede optimal functionality. Moreover, maintenance practices, which may be either preventive or corrective, encompass a range of activities aimed at preserving the condition of the equipment and infrastructure or restoring it to a state in which it can perform its required function. Both aspects are crucial in mitigating the risks of system failure, minimizing unplanned downtimes, and thereby guaranteeing a stable and continuous power supply while also prolonging the lifespan of the assets within the system. Furthermore, advances in technology enable the incorporation of smart solutions, such as the use of DTs, to enhance traditional inspection and maintenance processes by providing precise, real-time data and facilitating predictive maintenance strategies.

Many researchers have begun to focus on this point and have made numerous innovations. Gause et al. [92] explored the digital transformation of essential engineering maintenance processes, with an emphasis on inspecting medium-voltage overhead distribution networks. They employed DT technology for 3D modeling and analysis, utilizing photogrammetry and aerial scanning data (Figure 12). The proposed approach, which supports remote operation and relies on data-driven solutions for objective and cost-effective outcomes, was applied to the Latvian medium-voltage overhead distribution network with support from the Latvian distribution system operator “Sadales tīkls” JSC. This paper outlines practical applications of these data-driven methods for various infrastructure management processes, such as scheduled and unplanned inspections, and vegetation management processes, providing a pathway toward enhanced automation and economic efficiency in maintenance and inspection tasks. Liu et al. [93] addressed the shortcomings of traditional methods for evaluating the status of power transmission and transformation equipment, such as delays and poor data quality, by developing a DT system for this equipment. By integrating and refining sensor data according to the operational characteristics of the equipment and applying big data analysis and data mining techniques, they achieved differentiated status evaluation, precise fault diagnosis, and status prediction. This paper also explored the use of DT technology in online status evaluation for transformers, discussing aspects such as data management, model development, and the future potential of DTs for monitoring key power transmission and transformation equipment. Zhou et al. [94] emphasized the importance of accurately assessing the status of power transformers, which are important components in power grids, to improve management and ensure safe, stable operations. However, they noted that it is difficult to accurately describe asset attributes via a single monitoring system. Given the growing interest in DT technology across various sectors and its limited application in power systems, this paper introduces a method for transformer state assessment via DTs. This method requires the characteristics of multiple heterogeneous systems to be combined to construct a comprehensive asset attribute index, and sample data from various sources are obtained and labeled. The labeled data are then used to guide decision-making in state evaluation, with the DT model's sample data compared to those of physical systems to improve the accuracy of state assessments in the actual system.

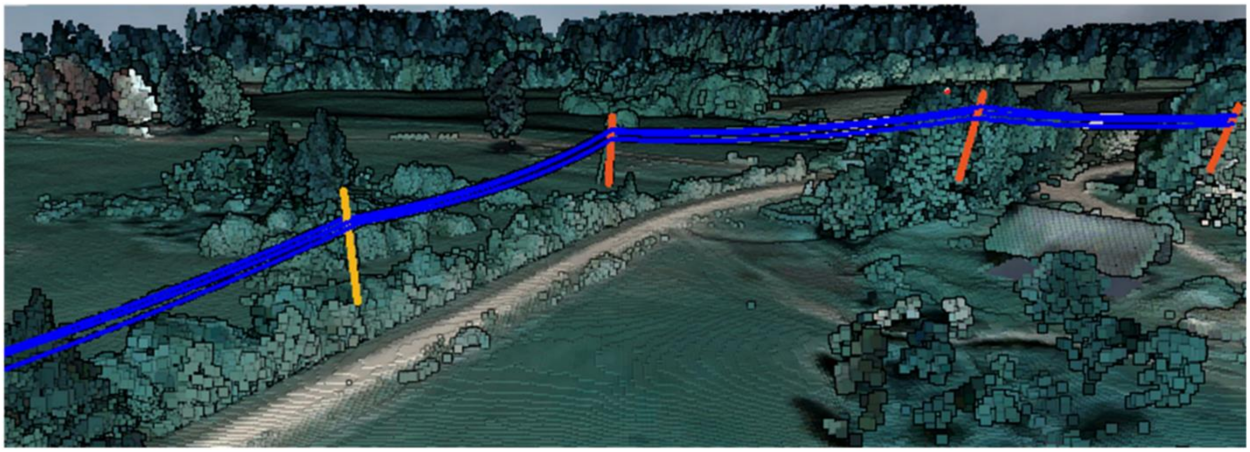

Figure 12: Fragment of an aerial laser scanning power line [92]

5.2 Optimizing the Operation of Power Systems

DT technology plays a pivotal role in optimizing the operation of power systems, establishing a high-fidelity virtual model of physical electrical power systems, which not only enables engineers to simulate and test various operational scenarios and strategies without impacting the actual system but also provides a real-time, dynamic platform for monitoring, analyzing, and optimizing system operation. On this virtual platform, the actual system's operational data are synchronized in real time with the DT, allowing operators to comprehend the system’s operational status and performance instantaneously, thereby enhancing the system's reliability and efficiency. Moreover, DT technology also lends support for the long-term planning and optimization of electrical power system operations; for example, by simulating various operational and investment strategies, operators can analyze and determine the most economical and reliable system upgrade and expansion plans.

Several case studies have been conducted in this field. For example, Tomin et al. [95] explored the burgeoning realm of DT technology in the context of urban electric grids, articulating its potential in bolstering the flexibility, consumption optimization, and reduction of energy losses in urban electrical networks by enabling the simulation and testing of various operational scenarios without impacting actual systems. In 2019, the Irkutsk Scientific Center of the Siberian Branch of the Russian Academy of Sciences initiated a project to install smart power meters for more detailed monitoring of power consumption in a district of Irkutsk. The collected data were intended to create a DT of the district's electrical network. They also proposed a DT concept based on reinforcement machine learning, which allows the creation of an accurate digital model of the electrical network, as depicted in Figure 13. This model enables bidirectional automatic data exchange for modeling, optimization, and control, synchronizing all network information and updating on the basis of system changes and feedback on control actions. Andryushkevich et al. [96] proposed a method for developing DTs of power systems, using the energy supply of a localized R&D facility as an example. They introduce a six-layer architecture for the DT and describe its prototype software, which includes an ontological model, a digital single-line diagram, electronic documentation, master data, load measurement data, and mathematical simulations. The authors address challenges in ontological modeling of the prosumer infrastructure, including customer load and small-scale generation, using OWL for a machine-readable DT representation. They also optimized the configuration of a hybrid power supply system with renewable energy sources on the basis of the developed DT. Arraño-Vargas et al. [97] presented a modular framework for power system DTs (PSDTs) designed to advance future power grids by enhancing network monitoring, operation, and planning across the industry. They noted that current DT frameworks are limited to specific power system components, applications, or users. Their proposed framework is flexible, robust, and cost-effective, with a modular design that allows expansion beyond individual components, facilitating the integration of multiple services and users without disrupting existing modules. Each module can be independently developed, modified, or replaced, enabling more advanced, specialized, and multidomain applications for power system operations and planning. The authors illustrate the initial development of a PSDT via a real-time compatible model of the Australian National Electricity Market, which serves as a foundation for various modules within the DT. They demonstrated potential applications, such as renewable energy integration and "what-if" scenarios, via the electromagnetic transient (EMT) model, highlighting the anticipated future uses of PSDTs.

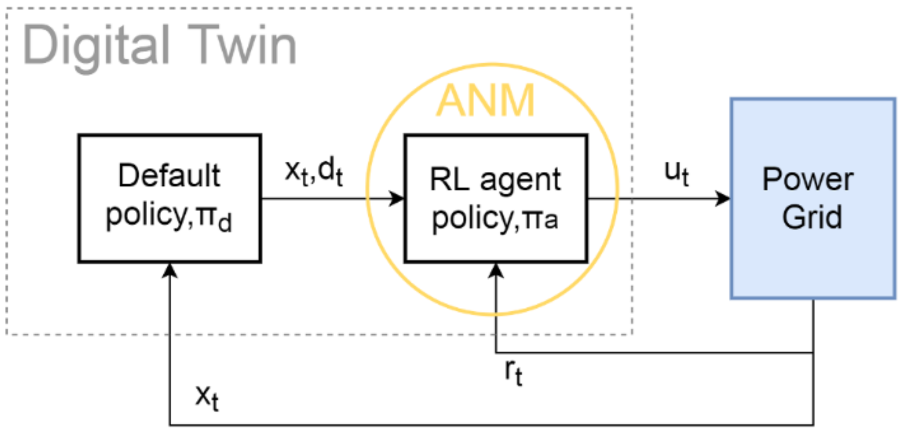

Figure 13: Architecture of the DT for a power grid through RL [96]

6. Challenges and Future of DT

Currently, DT technology, which is supported by a variety of emerging technologies, has great development prospects and value realization capabilities, is being focused on, studied, and practically applied in many industry fields, including military and civilian fields, and has achieved a series of studies and practical results. However, the development of DT technology is currently facing many challenges [98]. The following are the current challenges and research hotspots in the application of DTs in various industries.

6.1 Management of Data

Data management is a foundational element of DTs, serving as the critical link between physical systems and their virtual counterparts. Three key aspects enhance the quality and sophistication of DTs from a data perspective: data perception, data communication, and data analysis.

In terms of data perception, advanced sensor technologies are essential for capturing accurate and real-time data from physical environments. Tao et al. [99] emphasized the importance of integrating high-precision sensors and deploying sensor networks to improve data collection capabilities. They discussed strategies such as using Internet of Things (IoT) devices and implementing redundant sensing to increase reliability and reduce data gaps. Similarly, Fuller et al. [98] highlighted challenges in data acquisition, noting that existing sensing equipment often fails to meet the stringent requirements of DT systems. This shortfall can lead to inaccuracies in the virtual models, affecting their ability to replicate physical behaviors accurately. With respect to data communication, efficient and reliable transmission of data between the physical system and the DT is important. Leng et al. [65] discussed issues such as excessive latency and data noise that can hinder real-time synchronization. They proposed solutions such as implementing high-speed communication networks such as 5G technology and enhancing data transmission protocols to reduce latency and improve data integrity. These measures aim to achieve low-latency, high-accuracy data exchanges, which are essential for responsive DT operations. In the realm of data analysis, Qi et al. [100] explored how integrating big data technologies and artificial intelligence (AI) can continuously optimize analytical algorithms. By leveraging machine learning and predictive analytics, DTs can process vast amounts of data to identify patterns, predict future states, and make informed decisions. This integration enhances the ability of DTs to adapt to changing conditions and improves overall system performance.

6.2 Model development

Model development is a critical but challenging component in the development of DTs across various industries. The physical systems contain a large number of devices, people, and assets, where the large amount of data and complex data dimensions pose great challenges for twin modeling. For example, the modeling of equipment in various industries requires solving the complex problem of building full-scale multiphysics field coupled models [101], just as the modeling of industrial equipment suffers from a large amount of data, structural complexity, and special operating conditions [102]. Throughout the DT model construction process, it becomes critical to combine existing expert empirical knowledge with data-driven modeling techniques to improve model accuracy. In addition, ensuring the symbiosis of virtual and physical systems in DTs is imperative so that the model and physical systems are always synchronized in complex, changing, and unstable operating environments. Tao et al. [4] noted that most existing modeling technologies and tools focus on model construction, with insufficient options for subsequent aspects. There is a lack of a system or standard of technologies and tools to guide the use of technologies and tools in various modeling aspects. The technologies and tools used in the same modeling aspect are not strongly related, and the technologies or tools used in different modeling aspects are also fragmented and lack continuity.

Furthermore, maintaining synchronization between DTs and their physical counterparts is essential for accurate real-time representation. Cimino et al. [30] examined the challenges posed by complex and unstable operational environments, which can lead to discrepancies between the physical system and its DT. They emphasized the need for continuous data updates and adaptive algorithms to ensure that the DT remains an accurate reflection of the physical system over time.

6.3 Cybersecurity of DTs

DT will be the core part of future digitization in various sectors and possibly of the subsequently developed DT systems, so information and physical security issues will be a considerable challenge in the future. Cyberattacks against DTs could lead to a range of problems, such as data leakage, system failure, and poor decision-making, which in turn could lead to more serious societal problems [103]. Information-physical security issues can arise from both internal and external sources, such as external malicious cyber-attacks and internal system operational failures. Establishing accurate security monitoring mechanisms, building strong protection mechanisms against external malicious attacks, and developing effective fault tolerance mechanisms to ensure normal operation in the event of information physical security problems are all issues that must be considered.

Sadeghi et al. [104] detailed how cyberattacks on IoT systems could lead to societal repercussions, such as disruptions in critical infrastructure and services. They stressed the necessity of implementing robust security frameworks that include threat detection, response strategies, and regular security assessments. Masi et al. [105] introduced a specific architectural view, called the cyber security view, in system representation. Thus, a cybersecurity DT is derived as part of the security design practices for industrial automation and control systems used in critical infrastructures. This DT allows cyberattacks to be simulated and countermeasures to be developed. Mustofa et al. [106] discovered that distributed denial-of-service (DDoS) attacks have a greater impact on the IT systems of DT-based organizations than do malware attacks do, particularly in terms of attack propagation, operational performance, reliability, and resilience. These findings have practical applications, allowing DT-based organizations to pinpoint high-risk cyber threats, assess and forecast IT performance during actual cyber incidents, and formulate proactive measures to increase network security.

6.4 Establishment of Standards for DTs

There is also the challenge of establishing suitable, accurate, and quantifiable evaluation systems for the degree of twinning for current and future DT projects across various industries to develop standards. It is necessary to combine the characteristics of DTs with comprehensive and quantifiable project evaluation systems proposed by standardization organizations, industry associations, or other authoritative organizations. In addition to the above evaluation standards, in the future application of DTs, it is necessary to establish universal implementation standards, including hardware, communication technologies and protocols, AI technologies, and universal visualization platforms, in conjunction with the universal standards for DTs [107]. In addition to the physical information security issues described in the previous section, DTs may have several security operational issues that necessitate the establishment of maintenance standards to standardize operations and ensure hardware and software security and data security.

Kritzinger et al. [64] emphasized the need for comprehensive evaluation criteria developed by standardization bodies and industry associations. Such criteria should include performance metrics, data quality standards, and benchmarking tools to objectively assess the effectiveness of DT systems. Schleich et al. [108] highlighted the importance of establishing universal implementation standards related to hardware, communication protocols, AI algorithms, and visualization platforms. Standardized hardware components and interfaces ensure compatibility and ease of integration across different systems. Adopting common communication protocols facilitates seamless data exchange, while standardizing AI algorithms enhances the transparency and reproducibility of analytical processes.

7. Summary and conclusions

DT technology has demonstrated significant potential in transforming various industries by enabling real-time simulation, analysis, and optimization of complex systems. The integration of DTs with AI, big data, and BIM has opened new avenues for innovation and efficiency across sectors such as aerospace, manufacturing, construction, and power transmission systems. This review highlights the diverse applications and benefits of DTs, as well as the challenges that need to be addressed for their widespread adoption. Key challenges include data management, model development, cybersecurity, and the establishment of standardized evaluation criteria. Addressing these challenges is important for realizing the full potential of DT technology and ensuring its successful implementation in Industry 4.0. Future research and development efforts should focus on enhancing data quality, improving model accuracy, ensuring robust cybersecurity measures, and developing universal standards to facilitate the broader application of DTs. As these challenges are overcome, DT technology is poised to play an important role in the evolution of smart, resilient, and efficient industrial systems.

This paper provides a comprehensive review of the application of DTs in traditional industries such as aerospace, manufacturing, construction, and power transmission. However, it is important to acknowledge certain limitations. This paper focuses primarily on the application of DTs in certain traditional industries and does not cover emerging fields such as healthcare and new energy. Additionally, owing to the rapid pace of technological development, the paper may not capture the latest advancements in some areas. As DTs continue to evolve, future research should consider expanding the scope to include more industries and newer innovations.

Acknowledgments

This research was partially supported by CEATI International, Inc., under project #T233700--33145. The views and opinions of the authors expressed herein do not necessarily state or reflect the opinions of the funding agencies.

References

[1] Y. Lu, "Industry 4.0: A survey on technologies, applications and open research issues," *Journal of industrial information integration,* vol. 6, pp. 1-10, 2017.

[2] X. Fang, H. Wang, G. Liu, X. Tian, G. Ding, and H. Zhang, "Industry application of digital twin: From concept to implementation," *The International Journal of Advanced Manufacturing Technology,* vol. 121, pp. 4289-4312, 2022.

[3] Y. Wu, K. Zhang, and Y. Zhang, "Digital twin networks: A survey," *IEEE Internet of Things Journal,* vol. 8, pp. 13789-13804, 2021.

[4] F. Tao, B. Xiao, Q. Qi, J. Cheng, and P. Ji, "Digital twin modeling," *Journal of Manufacturing Systems,* vol. 64, pp. 372-389, 2022.

[5] T. Y. Melesse, V. Di Pasquale, and S. Riemma, "Digital twin models in industrial operations: A systematic literature review," *Procedia Manufacturing,* vol. 42, pp. 267-272, 2020.

[6] M. Grieves, "Digital twin: manufacturing excellence through virtual factory replication," *White paper,* vol. 1, pp. 1-7, 2014.

[7] K. A. Hribernik, L. Rabe, K.-D. Thoben, and J. Schumacher, "The product avatar as a product-instance-centric information management concept," *International Journal of Product Lifecycle Management,* vol. 1, pp. 367-379, 2006.

[8] B. Piascik, J. Vickers, D. Lowry, S. Scotti, J. Stewart, and A. Calomino, "Materials, structures, mechanical systems, and manufacturing roadmap," *NASA TA,* pp. 12-2, 2012.

[9] R. Minerva, G. M. Lee, and N. Crespi, "Digital twin in the IoT context: A survey on technical features, scenarios, and architectural models," *Proceedings of the IEEE,* vol. 108, pp. 1785-1824, 2020.

[10] S. Kumar, P. Tiwari, and M. Zymbler, "Internet of Things is a revolutionary approach for future technology enhancement: a review," *Journal of Big data,* vol. 6, pp. 1-21, 2019.

[11] M. J. Kaur, V. P. Mishra, and P. Maheshwari, "The convergence of digital twin, IoT, and machine learning: transforming data into action," *Digital twin technologies and smart cities,* pp. 3-17, 2020.

[12] M. Jacoby and T. Usländer, "Digital twin and internet of things—Current standards landscape," *Applied Sciences,* vol. 10, p. 6519, 2020.

[13] Z. Jiang, Y. Guo, and Z. Wang, "Digital twin to improve the virtual-real integration of industrial IoT," *Journal of Industrial Information Integration,* vol. 22, p. 100196, 2021.

[14] H. Huang and X. Xu, "Edge computing enhanced digital twins for smart manufacturing," in *International Manufacturing Science and Engineering Conference*, 2021, p. V002T07A020.

[15] K. Y. H. Lim, P. Zheng, and C.-H. Chen, "A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives," *Journal of Intelligent Manufacturing,* vol. 31, pp. 1313-1337, 2020.

[16] S. Mihai, M. Yaqoob, D. V. Hung, W. Davis, P. Towakel, M. Raza*, et al.*, "Digital twins: A survey on enabling technologies, challenges, trends and future prospects," *IEEE Communications Surveys & Tutorials,* vol. 24, pp. 2255-2291, 2022.

[17] F. Jaensch, A. Csiszar, C. Scheifele, and A. Verl, "Digital twins of manufacturing systems as a base for machine learning," in *2018 25th International conference on mechatronics and machine vision in practice (M2VIP)*, 2018, pp. 1-6.

[18] T. H. Luan, R. Liu, L. Gao, R. Li, and H. Zhou, "The paradigm of digital twin communications," *arXiv preprint arXiv:2105.07182,* 2021.

[19] M. Groshev, C. Guimarães, A. De La Oliva, and R. Gazda, "Dissecting the impact of information and communication technologies on digital twins as a service," *IEEE Access,* vol. 9, pp. 102862-102876, 2021.

[20] C. Xu, Z. Tang, H. Yu, P. Zeng, and L. Kong, "Digital twin-driven collaborative scheduling for heterogeneous task and edge-end resource via multiagent deep reinforcement learning," *IEEE Journal on Selected Areas in Communications,* 2023.

[21] R. K. Phanden, P. Sharma, and A. Dubey, "A review on simulation in digital twin for aerospace, manufacturing and robotics," *Materials today: proceedings,* vol. 38, pp. 174-178, 2021.

[22] L. Li, S. Aslam, A. Wileman, and S. Perinpanayagam, "Digital twin in aerospace industry: A gentle introduction," *IEEE Access,* vol. 10, pp. 9543-9562, 2021.

[23] S. Liu, J. Bao, Y. Lu, J. Li, S. Lu, and X. Sun, "Digital twin modeling method based on biomimicry for machining aerospace components," *Journal of manufacturing systems,* vol. 58, pp. 180-195, 2021.

[24] M. Xiong and H. Wang, "Digital twin applications in aviation industry: A review," *The International Journal of Advanced Manufacturing Technology,* vol. 121, pp. 5677-5692, 2022.

[25] A. M. Madni, C. C. Madni, and S. D. Lucero, "Leveraging digital twin technology in model-based systems engineering," *Systems,* vol. 7, p. 7, 2019.

[26] J. Jin, J. Hu, C. Li, Z. Shi, P. Lei, and W. Tian, "A Digital Twin system of reconfigurable tooling for monitoring and evaluating in aerospace assembly," *Journal of Manufacturing Systems,* vol. 68, pp. 56-71, 2023.

[27] C. Li, S. Mahadevan, Y. Ling, S. Choze, and L. Wang, "Dynamic Bayesian network for aircraft wing health monitoring digital twin," *Aiaa Journal,* vol. 55, pp. 930-941, 2017.

[28] A.-R. Al-Ali, R. Gupta, T. Zaman Batool, T. Landolsi, F. Aloul, and A. Al Nabulsi, "Digital twin conceptual model within the context of internet of things," *Future internet,* vol. 12, p. 163, 2020.
[29] B. He and K.-J. Bai, "Digital twin-based sustainable intelligent manufacturing: a review," *Advances in Manufacturing,* vol. 9, pp. 1-21, 2021.
[30] C. Cimino, E. Negri, and L. Fumagalli, "Review of digital twin applications in manufacturing," *Computers in industry,* vol. 113, p. 103130, 2019.
[31] I. Onaji, D. Tiwari, P. Soulatiantork, B. Song, and A. Tiwari, "Digital twin in manufacturing: conceptual framework and case studies," *International journal of computer integrated manufacturing,* vol. 35, pp. 831-858, 2022.
[32] M. Jafari, A. Kavousi-Fard, T. Chen, and M. Karimi, "A review on digital twin technology in smart grid, transportation system and smart city: Challenges and future," *IEEE Access,* vol. 11, pp. 17471-17484, 2023.
[33] Q. Lu, X. Xie, J. Heaton, A. K. Parlikad, and J. Schooling, "From BIM toward digital twin: strategy and future development for smart asset management," *Service Oriented, Holonic and Multiagent Manufacturing Systems for Industry of the Future: Proceedings of SOHOMA 2019 9,* pp. 392-404, 2020.
[34] Y. Pan and L. Zhang, "A BIM-data mining integrated digital twin framework for advanced project management," *Automation in Construction,* vol. 124, p. 103564, 2021.
[35] T. D. Nguyen and S. Adhikari, "The role of bim in integrating digital twin in building construction: A literature review," *Sustainability,* vol. 15, p. 10462, 2023.
[36] Z. Zhang, X. Zhang, G. Zhu, Y. Wang, and P. Hui, "Efficient Task Offloading Algorithm for Digital Twin in Edge/Cloud Computing Environment," *arXiv preprint arXiv:2307.05888,* 2023.
[37] V. Badenko, N. Bolshakov, E. Tishchenko, A. Fedotov, A. Celani, and V. Yadykin, "Integration of digital twin and BIM technologies within factories of the future," *Magazine of Civil Engineering,* p. 10114, 2021.
[38] Y. Jiang, "Intelligent building construction management based on BIM digital twin," *Computational Intelligence and Neuroscience,* vol. 2021, p. 4979249, 2021.
[39] J. Li, J. Wang, Q. Chen, Y. Li, and A. Y. Zomaya, "Digital twin-enabled service satisfaction enhancement in edge computing," in *IEEE INFOCOM 2023-IEEE Conference on Computer Communications*, 2023, pp. 1-10.
[40] R. Sacks, I. Brilakis, E. Pikas, H. S. Xie, and M. Girolami, "Construction with digital twin information systems," *Data-Centric Engineering,* vol. 1, p. e14, 2020.
[41] Z. Wang, R. Gupta, K. Han, H. Wang, A. Ganlath, N. Ammar*,* et al., "Mobility digital twin: Concept, architecture, case study, and future challenges," *IEEE Internet of Things Journal,* vol. 9, pp. 17452-17467, 2022.
[42] M. Lombardi, A. Cammarota, and J. Refoyo, "DEVELOPMENT APPLICATIONS AND BENEFITS OF THE NETWORK DIGITAL TWIN," in *25th International Conference on Electricity Distribution*, 2019.
[43] S. Centomo, A. Avogaro, M. Panato, C. Tadiello, and F. Fummi, "A Design Methodology of Multilevel Digital Twins," in *2021 22nd IEEE International Conference on Industrial Technology (ICIT)*, 2021, pp. 961-966.
[44] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei*,* et al., "Enabling technologies and tools for digital twin," *Journal of Manufacturing Systems,* vol. 58, pp. 3-21, 2021.

[45] E. Negri, L. Fumagalli, and M. Macchi, "A review of the roles of digital twin in CPS-based production systems," *Procedia manufacturing,* vol. 11, pp. 939-948, 2017.

[46] E. Negri, L. Fumagalli, C. Cimino, and M. Macchi, "FMU-supported simulation for CPS digital twin," *Procedia manufacturing,* vol. 28, pp. 201-206, 2019.

[47] A. Wunderlich, K. Booth, and E. Santi, "Hybrid analytical and data-driven modeling techniques for digital twin applications," in *2021 IEEE Electric Ship Technologies Symposium (ESTS)*, 2021, pp. 1-7.

[48] L. Ai, V. Soltangharaei, M. Bayat, B. Greer, and P. Ziehl, "Source localization on large-scale canisters for used nuclear fuel storage using optimal number of acoustic emission sensors," *Nuclear Engineering and Design,* vol. 375, p. 111097, 2021.

[49] L. Ai, V. Soltangharaei, M. Bayat, M. Van Tooren, and P. Ziehl, "Detection of impact on aircraft composite structure using machine learning techniques," *Measurement Science and Technology,* vol. 32, p. 084013, 2021.

[50] L. Ai, S. Flowers, T. Mesaric, B. Henderson, S. Houck, and P. Ziehl, "Acoustic Emission-Based Detection of Impacts on Thermoplastic Aircraft Control Surfaces: A Preliminary Study," *Applied Sciences,* vol. 13, p. 6573, 2023.

[51] L. Ai, K. Laxman, E. Elbatanouny, M. Bayat, M. van Tooren, and P. Ziehl, "Acoustic emission monitoring and automated characterization of low-velocity impacts on composite components," *Mechanical Systems and Signal Processing,* vol. 218, p. 111586, 2024.

[52] L. Ai, V. Soltangharaei, R. Anay, M. J. van Tooren, and P. Ziehl, "Data-Driven Source Localization of Impact on Aircraft Control Surfaces," in *2020 IEEE Aerospace Conference*, 2020, pp. 1-10.

[53] K. Laxman, A. Ross, L. Ai, A. Henderson, E. Elbatanouny, M. Bayat*,* et al., "Determination of vehicle loads on bridges by acoustic emission and an improved ensemble artificial neural network," *Construction and Building Materials,* vol. 364, p. 129844, 2023.

[54] T. H.-J. Uhlemann, C. Schock, C. Lehmann, S. Freiberger, and R. Steinhilper, "The digital twin: demonstrating the potential of real time data acquisition in production systems," *Procedia Manufacturing,* vol. 9, pp. 113-120, 2017.

[55] Y. He, J. Guo, and X. Zheng, "From surveillance to digital twin: Challenges and recent advances of signal processing for industrial internet of things," *IEEE Signal Processing Magazine,* vol. 35, pp. 120-129, 2018.

[56] M. Dangana, S. Ansari, S. M. Asad, S. Hussain, and M. A. Imran, "Toward the Digital Twin (DT) of Narrow-Band Internet of Things (NBIoT) Wireless Communication in Industrial Indoor Environment," *Sensors,* vol. 22, p. 9039, 2022.

[57] C. L. Stergiou and K. E. Psannis, "Digital twin intelligent system for industrial IoT-based big data management and analysis in cloud," *Virtual Reality & Intelligent Hardware,* vol. 4, pp. 279-291, 2022.

[58] P. Durana, V. Krastev, and K. Buckner, "Digital twin modeling, multisensor fusion technology, and data mining algorithms in cloud and edge computing-based Smart city environments," *Geopolitics, History, and International Relations,* vol. 14, pp. 91-106, 2022.

[59] M. Shafto, M. Conroy, R. Doyle, E. Glaessgen, C. Kemp, J. LeMoigne*,* et al., "Modeling, simulation, information technology & processing roadmap," *National Aeronautics and Space Administration,* vol. 32, pp. 1-38, 2012.

[60] E. Glaessgen and D. Stargel, "The digital twin paradigm for future NASA and US Air Force vehicles," in *53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and*

materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA, 2012, p. 1818.

[61] Y. Lu, C. Liu, I. Kevin, K. Wang, H. Huang, and X. Xu, "Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues," *Robotics and computer-integrated manufacturing,* vol. 61, p. 101837, 2020.

[62] H. Meyer, J. Zimdahl, A. Kamtsiuris, R. Meissner, F. Raddatz, S. Haufe*,* et al., "Development of a digital twin for aviation research," 2020.

[63] Q. Zhang, S. Zheng, C. Yu, Q. Wang, and Y. Ke, "Digital thread-based modeling of digital twin framework for the aircraft assembly system," *Journal of Manufacturing Systems,* vol. 65, pp. 406-420, 2022.

[64] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital Twin in manufacturing: A categorical literature review and classification," *Ifac-PapersOnline,* vol. 51, pp. 1016-1022, 2018.

[65] J. Leng, D. Wang, W. Shen, X. Li, Q. Liu, and X. Chen, "Digital twins-based smart manufacturing system design in Industry 4.0: A review," *Journal of manufacturing systems,* vol. 60, pp. 119-137, 2021.

[66] C. Lo, C. Chen, and R. Y. Zhong, "A review of digital twin in product design and development," *Advanced Engineering Informatics,* vol. 48, p. 101297, 2021.

[67] T. Bolender, G. Bürvenich, M. Dalibor, B. Rumpe, and A. Wortmann, "Self-adaptive manufacturing with digital twins," in *2021 International symposium on software engineering for adaptive and self-managing systems (SEAMS)*, 2021, pp. 156-166.

[68] J. Friederich, D. P. Francis, S. Lazarova-Molnar, and N. Mohamed, "A framework for data-driven digital twins of smart manufacturing systems," *Computers in Industry,* vol. 136, p. 103586, 2022.

[69] I. V. Lokshina, M. Greguš, and W. L. Thomas, "Application of integrated building information modeling, IoT and blockchain technologies in system design of a smart building," *Procedia computer science,* vol. 160, pp. 497-502, 2019.

[70] H. Yang and M. Xia, "Advancing Bridge Construction Monitoring: AI-Based Building Information Modeling for Intelligent Structural Damage Recognition," *Applied Artificial Intelligence,* vol. 37, p. 2224995, 2023.

[71] T. Delbrügger, L. T. Lenz, D. Losch, and J. Roßmann, "A navigation framework for digital twins of factories based on building information modeling," in *2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 2017, pp. 1-4.

[72] X. Zhou, K. Sun, J. Wang, J. Zhao, C. Feng, Y. Yang*,* et al., "Computer vision enabled building digital twin using building information model," *IEEE Transactions on Industrial Informatics,* vol. 19, pp. 2684-2692, 2022.

[73] J. Chen, W. Lu, F. Ghansah, and Z. Peng, "Defect digital twinning: A technical framework to integrate robotics, AI and BIM for facility management and renovation," in *IOP Conference Series: Earth and Environmental Science*, 2022, p. 022041.

[74] L. Ai, M. Bayat, and P. Ziehl, "Localizing Damage on Stainless Steel Structures Using Acoustic Emission Signals and Weighted Ensemble Regression-based Convolutional Neural Network," *Measurement,* p. 112659, 2023.

[75] L. Ai, V. Soltangharaei, and P. Ziehl, "Developing a heterogeneous ensemble learning framework to evaluate Alkali-silica reaction damage in concrete using acoustic emission signals," *Mechanical Systems and Signal Processing,* vol. 172, p. 108981, 2022.

[76] L. Ai, V. Soltangharaei, and P. Ziehl, "Evaluation of ASR in Concrete Using Acoustic Emission and Deep Learning," *Nuclear Engineering and Design,* 2021.

[77] L. Ai, B. Zhang, and P. Ziehl, "A transfer learning approach for acoustic emission zonal localization on steel plate-like structure using numerical simulation and unsupervised domain adaptation," *Mechanical Systems and Signal Processing,* vol. 192, p. 110216, 2023.

[78] K. Laxman, N. Tabassum, L. Ai, C. Cole, and P. Ziehl, "Automated crack detection and crack depth prediction for reinforced concrete structures using deep learning," *Construction and Building Materials,* vol. 370, p. 130709, 2023.

[79] N. Rojas-Mercedes, K. Erazo, and L. Di Sarno, "Seismic fragility curves for a concrete bridge using structural health monitoring and digital twins," *Earthq. Struct,* vol. 22, pp. 503-515, 2022.

[80] C. Ye, L. Butler, C. Bartek, M. Iangurazov, Q. Lu, A. Gregory*,* et al., "A digital twin of bridges for structural health monitoring," in *12th International Workshop on Structural Health Monitoring 2019*, 2019.

[81] P. Fidler, F. Huseynov, M. Bravo Haro, V. Vilde, J. Schooling, and C. Middleton, "Augmenting an existing railway bridge monitoring system with additional sensors to create a bridge weigh-in-motion system and digital twin," 2022.

[82] K. Lin, Y.-L. Xu, X. Lu, Z. Guan, and J. Li, "Digital twin-based collapse fragility assessment of a long-span cable-stayed bridge under strong earthquakes," *Automation in Construction,* vol. 123, p. 103547, 2021.

[83] I. Muhit, D. Kawabe, D. Loverdos, B. Liu, Y. Yukihiro, C.-W. Kim*,* et al., "A framework for digital twinning of masonry arch bridges," in *Life-Cycle of Structures and Infrastructure Systems*, ed: CRC Press, 2023, pp. 817-824.

[84] E. Febrianto, L. Butler, M. Girolami, and F. Cirak, "Digital twinning of self-sensing structures using the statistical finite element method," *Data-Centric Engineering,* vol. 3, p. e31, 2022.

[85] Z. Lei, L. Zhu, Y. Fang, C. Niu, and Y. Zhao, "Fiber Bragg grating smart material and structural health monitoring system based on digital twin drive," *Journal of Nanomaterials,* vol. 2022, p. 4356974, 2022.

[86] Y. Liu and Y. Bao, "Automatic interpretation of strain distributions measured from distributed fiber optic sensors for crack monitoring," *Measurement,* vol. 211, p. 112629, 2023.

[87] S. Yoon, S. Lee, S. Kye, I.-H. Kim, H.-J. Jung, and B. F. Spencer Jr, "Seismic fragility analysis of deteriorated bridge structures employing a UAV inspection-based updated digital twin," *Structural and Multidisciplinary Optimization,* vol. 65, p. 346, 2022.

[88] H.-H. Benzon, X. Chen, L. Belcher, O. Castro, K. Branner, and J. Smit, "An operational image-based digital twin for large-scale structures," *Applied Sciences,* vol. 12, p. 3216, 2022.

[89] Z. Zhaoyun and L. Linjun, "Application status and prospects of digital twin technology in distribution grid," *Energy Reports,* vol. 8, pp. 14170-14182, 2022.

[90] M. M. H. Sifat, S. M. Choudhury, S. K. Das, M. H. Ahamed, S. Muyeen, M. M. Hasan*,* et al., "Toward electric digital twin grid: Technology and framework review," *Energy and AI,* p. 100213, 2022.

[91] D. Mourtzis, J. Angelopoulos, and N. Panopoulos, "Development of a PSS for smart grid energy distribution optimization based on digital twin," *Procedia CIRP,* vol. 107, pp. 1138-1143, 2022.

[92] D. Gauce, A. Lektauers, I. Solovjova, R. Grants, D. Kolosovs, and A. Litvinenko, "Application of digital twin in medium-voltage overhead distribution network inspection," *Remote Sensing,* vol. 15, p. 489, 2023.

[93] J. Liu, S. Wang, X. Lu, and T. Li, "Research on online status evaluation technology for main equipment of power transmission and transformation based on digital twin," in *2021 IEEE 5th Conference on Energy internet and Energy System Integration (EI2)*, 2021, pp. 3368-3373.

[94] P. Zhou, J. Li, T. Gao, H. Yuan, Y. Yang, Z. Chen*, et al.*, "Research on mining of transmission grid assets of heterogeneous system based on digital twin," in *2020 IEEE 4th Conference on Energy internet and Energy System Integration (EI2)*, 2020, pp. 3051-3056.

[95] N. Tomin, V. Kurbatsky, V. Borisov, and S. Musalev, "Development of digital twin for load center on the example of distribution network of an urban district," in *E3S Web of Conferences*, 2020, p. 02029.

[96] S. K. Andryushkevich, S. P. Kovalyov, and E. Nefedov, "Composition and application of power system digital twins based on ontological modeling," in *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)*, 2019, pp. 1536-1542.

[97] F. Arraño-Vargas and G. Konstantinou, "Modular design and real-time simulators toward power system digital twins implementation," *IEEE Transactions on Industrial Informatics,* vol. 19, pp. 52-61, 2022.

[98] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital twin: Enabling technologies, challenges and open research," *IEEE access,* vol. 8, pp. 108952-108971, 2020.

[99] F. Tao, H. Zhang, A. Liu, and A. Y. Nee, "Digital twin in industry: State-of-the-art," *IEEE Transactions on industrial informatics,* vol. 15, pp. 2405-2415, 2018.

[100] Q. Qi and F. Tao, "Digital twin and big data toward smart manufacturing and industry 4.0: 360 degree comparison," *Ieee Access,* vol. 6, pp. 3585-3593, 2018.

[101] F. Yang, T. Wu, R. Liao, J. Jiang, T. Chen, and B. Gao, "Application and implementation method of digital twin in electric equipment," *High Voltage Engineering,* vol. 47, pp. 1505-1521, 2021.

[102] B. Qi, P. Zhang, S. Zhang, L. Zhao, H. Wang, M. Huang*, et al.*, "Application status and development prospects of digital twin technology in condition assessment of power transmission and transformation equipment," *High Voltage Engineering,* vol. 47, pp. 1522-1538, 2021.

[103] A. Salvi, P. Spagnoletti, and N. S. Noori, "Cyber-resilience of Critical Cyber Infrastructures: Integrating digital twins in the electric power ecosystem," *Computers & Security,* vol. 112, p. 102507, 2022.

[104] A.-R. Sadeghi, C. Wachsmann, and M. Waidner, "Security and privacy challenges in industrial internet of things," in *Proceedings of the 52nd annual design automation conference*, 2015, pp. 1-6.

[105] M. Masi, G. P. Sellitto, H. Aranha, and T. Pavleska, "Securing critical infrastructures with a cybersecurity digital twin," *Software and Systems Modeling,* vol. 22, pp. 689-707, 2023.

[106] R. Mustofa, M. Rafiquzzaman, and N. U. I. Hossain, "Analyzing the impact of cyber-attacks on the performance of digital twin-based industrial organizations," *Journal of Industrial Information Integration,* vol. 41, p. 100633, 2024.

[107] E. VanDerHorn and S. Mahadevan, "Digital Twin: Generalization, characterization and implementation," *Decision support systems,* vol. 145, p. 113524, 2021.

[108] B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack, "Shaping the digital twin for design and production engineering," *CIRP annals,* vol. 66, pp. 141-144, 2017.