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Literature review of digital twin technologies for civil infrastructure

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ABSTRACT

Currently, there are numerous drawbacks associated with infrastructure health monitoring and management, such as inefficiency, subpar real-time functionality, demanding data requirements, and high cost. Digital twin (DT), a hybrid of a computational simulation and an actual physical system, has been proposed to overcome these challenges and become increasingly popular for modeling civil infrastructure systems. This literature review summarized different methods to build digital twins in civil infrastructure. In addition, this review also introduced the current progress of digital twins in different infrastructure sectors, including smart cities and urban spaces, transport systems, and energy systems, along with detailed examples of their various applications. Finally, the current challenges in digital twin technologies for civil infrastructure are also highlighted.

1. Introduction

Nowadays, infrastructure health monitoring and management relies on site inspections and dedicated software and hardware to collect, store, and process data. Nevertheless, monitoring infrastructures is a multidisciplinary task with too many variables to consider, causing 0.4–2% of the construction cost to be spent on maintaining the civil infrastructure's service life (Mahmoodian et al., 2022). Traditionally, the practical methods for the maintenance, repair, and reconstruction of civil engineering systems are mostly based on scheduled time (Zonta et al., 2007). The problems can only be detected during the inspection which may increase the risk of structural failure (Bado et al., 2022). To overcome the drawbacks of the traditional approaches, more recently, the Building Information Modelling (BIM) systems are leveraged to provide a view of a modeled asset or system (Callcut et al., 2021). BIM is a process that involves creating a digital model of a building or structure to plan, design, construct, and maintain it. However, BIM has limitations in dealing with a building's life-cycle procurement processes and lacks virtual interactions with the real assets, which means BIM does not provide real-time feedback on asset performance or operational decisions (Lu et al., 2020).

In general, for infrastructure inspections, identifying defects, and determining maintenance strategies, there is no universal data model that can eliminate inconsistencies and inefficiency. Moreover, infrastructure maintenance decisions need to be based on an ever-increasing amount of collected data, which cannot be managed with the existing practices (Mahmoodian et al., 2022). To overcome these challenges and limitations of traditional approaches, digital twins have been proposed and become increasingly popular for civil infrastructure systems (Callcut et al., 2021).

Digital twin is the combination of a computational model and a real-world system, designed to monitor, control, and optimize assets' functionality. A digital twin embraces data exchange in both directions between physical and digital objects. Through data and feedback, a digital twin can develop capacities for autonomy and to learn from and reason about its environment. Due to the nature of the digital twin and its applicability to multiple industries and domains, its definition and main characteristics may vary (Callcut et al., 2021). Based on different applications, the method of establishing digital twins and processing data is also different. There are three main methods that help digital twins deal with demanding data which are Big Data Analytics, Machine Learning and Cloud and Edge Computing (Callcut et al., 2021). Big data analytics is a widely used approach to analyze enormous datasets collected from various sources, including sensors, and organizing this information in a meaningful manner (IBM, 2020). Machine learning is a type of artificial intelligence that allows a system to learn from a dataset, It is comparable to big data analytics in that it employs algorithms that iteratively learn from data to produce valuable analysis and insights (Hurwitz and Kirsch, 2018). Using pattern recognition, Machine learning can predict potential risks and devise novel solutions to enhance the system's performance (Michalis et al., 2019). Cloud computing refers to the provision of computational and storage services to local devices through a data center connected via the internet. The advantages of cloud computing become apparent when data reaches the

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data center and becomes available for analysis (Pu et al., 2015). Edge computing can be considered an intermediary between local devices and cloud computing (Zhou et al., 2019). It is a computing paradigm where processing occurs in close proximity to the data source, creating a decentralized hierarchy of data processing (Lin et al., 2019). The goal of edge computing techniques is to improve the computational efficiency of the established twin and alleviate the burden on the cloud (Huang and Xu, 2021; Zhang et al., 2021).

Real-time monitoring can be done using digital twins, which can help in detecting any defects or problems in the early stages (Mahmoodian et al., 2022). A digital twin is designed as a virtual model to accurately reflect a physical object. The object studied is equipped with multi-modal sensors in critical areas of functionality. These sensors produce data about different aspects of the physical object's performance, such as energy output, temperature, and weather conditions. After that, the data will be placed in a processing system and applied for a digital copy. Besides, the digital twin also empowers the maintenance strategies (Dinter et al., 2022), indicating the ways to preserve the systems. Digital twins can predict potential problems in a product or system by analyzing data and suggesting solutions before any breakdown occurs (Jones et al., 2020). This predictive maintenance helps in minimizing downtime, increasing reliability, and improving efficiency. Furthermore, Digital twins provide a complete life cycle management of the product or system, from design, development, manufacturing, and maintenance to decommissioning (Macchi et al., 2018). It helps in optimizing the life cycle and improving the overall quality of the product or system. The traits of digital twins discussed above enable them to accommodate innovative facilities (Liu et al., 2021), ranging from intelligent infrastructure (Broo et al., 2022) to buildings (Shahzad et al., 2022).

The remaining sections of this paper are arranged as follows. Section 2 introduces four different methods to build digital twins in civil infrastructures. For applications of the digital twin, in section 3, we highlighted different types of digital twins in different infrastructure sectors and the current development status. Applications and examples of digital twins in smart cities and urban spaces, transport systems, and energy systems are discussed in detail in sections 3.1, 3.2, and 3.3, respectively. Section 4 summarized major challenges in current digital twin applications on civil infrastructures.

2. Methods to build digital twins in civil infrastructures

2.1. Finite element-based method

In the application of digital twins in civil infrastructures, Finite Element-based Method (FEM) is one of the most popular numerical techniques to build the twin and then obtain field mechanical or electrical quantities in the virtual domain (Teng et al., 2023). Commercial FEM software such as ABAQUS is leveraged to build the numerical model as its virtual twin. The virtual twin parameters are obtained from the physical entities. After model validation, the virtual twin which is essentially a FEM model will generate a massive amount of dataset which will then communicate with the real measured data from the physical asset. The framework of this application is shown in Fig. 1. In addition to building purely the mechanical models of real assets as the virtual twin, the FEM model can also be used to establish electro-mechanical coupled models which can not only output mechanical properties such as displacement or mechanical load, but also directly generate the electric output of the sensors embedded in the structure such as electric charges or voltages. Researchers have built a multi-physics numerical model of structures and piezoelectric transducers in ABAQUS to emulate the guided wave propagation in composite structures (Liu et al., 2023). This model can be treated as the virtual twin of a structure with embedded sensors for the real-time structural damage identification of the real assets. However, the drawback of current FEM models to build the virtual twin is that it requires significant computational resources, and their size and time step constraints render them unsuitable for real-time simulation environments (Liu et al., 2009; Tavana and Dinavahi, 2016).

Numerical models resembling real bridges were automatically modeled using DT technology, and the pre-trained convolutional neural network (CNN) was trained on these models. Then, the vibration tests were conducted on the real bridge. The pre-trained CNN was fine-tuned using a portion of the real measured data through Transfer Learning, with the remaining data used for performance evaluation.

2.2. Data-driven based approach

Simulation models that are derived and parameterized based on data are known as data-driven simulation models (Lattner et al., 2010). One example that uses the data-driven digital twin in a smart factory function is depicted in Fig. 2. Compared to traditional methods, data-driven models have a higher level of accuracy in reflecting the actual systems (Wang et al., 2021). Data provides the opportunity to employ Machine Learning (ML) and Artificial Intelligence (AI) methods to simulate phenomena that are difficult to replicate using traditional theoretical analysis or standard simulation modelling. Additionally, simulation can be combined with ML and AI techniques to gain a deeper insight into the functioning of certain systems (Alexopoulos et al., 2020; Cavalcante et al., 2019). However, this approach still necessitates human involvement to facilitate automation (Friederich et al., 2022).

The smart factory continuously generates data through IoT devices and sensors, serving as the starting point for data-driven modeling. The data is then validated through cleaning, pre-processing, and integration. Event labeling is performed semi-automatically to make events more explicit and aid model development. The model is then validated.

2.3. 3D model reconstruction using laser scanning method

The use of Three-dimensional (3D) laser scanning has emerged as a non-contact measuring tool to quickly gather surface topography data points. Laser scanning systems can be classified into aerial, mobile, and terrestrial depending on the location of the laser sensor during data acquisition. With their sub-millimeter precision, rapid speed, and low cost, terrestrial laser scanners (TLS) shows high potential for inspection operations compared to traditional methods (Hosamo and Hosamo, 2022). A structured approach is suggested to collect accurate survey data using a terrestrial laser scanner integrated with a total station and creating a BIM model as the foundation for digital management (Mill et al., 2013). Additionally, an overview of an automated as-built BIM model construction utilizing laser scanner data is introduced in (Pătrăucean et al., 2015). This technology enables the detection and classification of damage to facades, identification of constructed

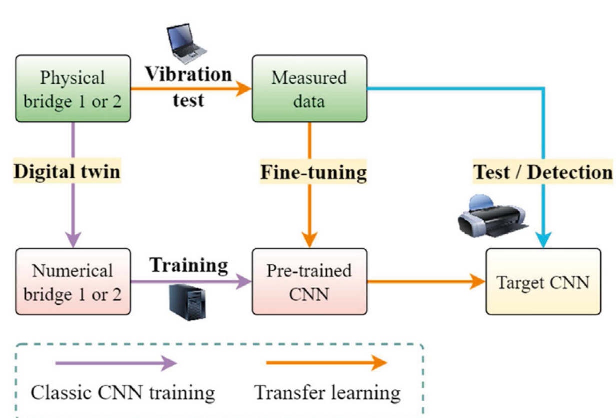

Fig. 1. The framework of using FEM method to build digital twin in a bridge application (Teng et al., 2023).

deviations from the design, and realization of clash detection between structures.

2.4. 3D model reconstruction using the Unmanned Aerial Vehicle (UAV) based method

The Unmanned Aerial Vehicle (UAV) leveraging the rapid development in camera sensing techniques (Zhou et al., 2023) which can capture high-resolution digital images serves as another emerging approach to build the virtual twin (Mohammadi et al., 2021) (Wang et al., 2022a). The flight plan for the UAV is predefined including the number of take-offs, sides of the civil infrastructure to capture, paths of the UAV, and angles of the photos to be taken. After obtaining the images taken by the UAV, multiple image post-processing techniques will be applied to convert these 2D images into 3D digital point clouds. Therefore, these 3D representations of the virtual twin of the civil infrastructure such as the bridge are constructed. Structural information will be obtained, and quality assessment will be performed based on the reconstructed virtual 3D representation. Although rapid, precise, and voluminous collection of remote data provided by UAV photogrammetry makes it a popular option for digital modeling of civil infrastructures, there is still a lack of a unified standard to evaluate the accuracy of the quality, integrity and the geometric accuracy of the point clouds for this 3D model. In addition, for blind spots of the civil infrastructure where the UAV is not capable to capture the images, manpower has to be involved to manually take images for these unreachable areas by UAVs.

3. Digital twin progress in different infrastructure sectors

Having a digital replica of a physical thing can significantly improve one or more of the following processes—Design, Simulation, Planning, Building, Operating, Maintaining, Optimizing, and Disposal (Kritzinger et al., 2018; Montero and Finger, 2021). For the design phase, it's possible to be able to virtually create a solution and accurately render it operationally before a single physical action is taken. Then we can simulate that solution under different types of factual scenarios (Roy et al., 2020). Based on the data provided, the design can then be modified. In the build phase, a digital twin can be used to provide the construction specifications or what we call parametric estimates to different providers (Eckhart and Ekelhart, 2018). In this way. A digital twin can be significant and streamline the procurement process. In addition, and importantly during the build, sensors are applied to the physical object to collect and transmit data back to its virtual replica (Bondoc et al., 2022). At this point, with enough sensors, the virtual twin provides all relevant data about the state of the physical twin. During operations, abundant data has been collected and fed back to its digital twin over a digital thread (Singh et al., 2021). Thinking of this as a data pipeline that enables analytics of various states and stages backed by artificial intelligence (Hänel et al., 2021). The digital twin can identify and even predict maintenance issues before they happen (Juarez et al., 2021). It has become the data-informed model of a physical system. This compelling feature reduces cost since it's typically cheaper proactively conduct maintenance. Therefore, depending on the type of objective, digital twins in different infrastructure sectors have been developed. And, the usage of the digital twin in different sectors has been on the rise in recent years. A review of research literature with the explicit usage of the term "digital twin" has revealed research in usage in the following areas shown in Table 1.

In this subsection, we reviewed the types of digital twins in three main infrastructure sectors and introduce the progress and examples in these sectors.

3.1. Smart cities and urban spaces

Digital transformation is an essential choice of urban governance. A more comprehensive assessment will be able to be made by governments once they can perceive and predict the unmeasurable indicators in the past physical world (Deng et al., 2021). It also outlines the blueprint of a digital twin city: "All entities in digital twins will exist simultaneously in parallel with historical records that can be traced, a present state that can be checked, and a future state that can be predicted". As technology advances are people-focused and improve citizens' lives rather than achieving economic efficiency, digital twins are used at the city level to improve the quality of life, mobility, and services (Botín-Sanabria et al., 2022; Zanella et al., 2014; Zhao et al., 2022b). Modern smart cities use real-time sensor data to improve the efficiency, sustainability, and security of urban spaces while reducing costs and resource consumption (Lee et al., 2020). Through the urban digital twin (Dembski et al., 2020), we can achieve a better knowledge of possible solutions to urban challenges involving public decision-making to reach agreements.

For urban traffic networks composed of roads, bridges are arteries that unblock traffic congestion and provide the impetus for rapid development (Krawtschuk et al., 2012). Therefore, as an important part of the intelligent urban infrastructure system, bridges are accelerating toward digital and intelligent management under the application of digital twins (Ye et al., 2019). For example, digital twin technology has been investigated in structural damage detection of various urban structures including bridges. Several studies have explored the use of digital twins to improve capabilities in structural damage detection. The authors in (Ritto and Rochinha, 2021) built the digital twin for structural damage detection through the integration of a physics-based model and machine learning techniques. The machine learning classifier, acting as a digital twin, is trained using data from a stochastic computational model

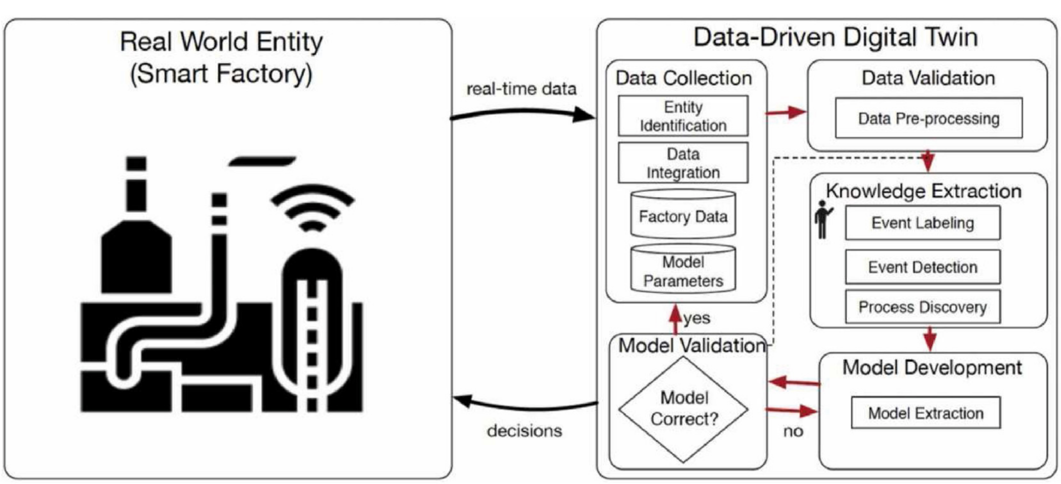

Fig. 2. Framework for the proposed data-driven smart factory (Friederich et al., 2022).

Table 1
Digital twin technology applied in different research.

Section	Application
Smart Cities and Urban Spaces	Using UAV and transformer-based neural network to detect and quantify concrete cracks (Ding et al., 2023)
	Forecasting building performance from UAV graphic surveys (Levine and Spencer Jr, 2022)
	Improved structural damage detection based on the convolutional neural network (Teng et al., 2023)
	Post-earthquake structural condition assessment using UAV and digital twin (Wang et al., 2022a).
	Finding and quantifying truss damage using deep neural networks and finite element models (Shu et al., 2023b)
	Finding sources of social inequity and solutions to improve the social resilience of urban communities by investigating various parameters of city infrastructure (Fan, 2022)
	Using point cloud data and deep learning to assess precast concrete components' dimensional quality (Shu et al., 2023a)
	A CNN-based deep learning approach is used to automatically detect and evaluate cracks in concrete structures at the pixel level (Shu et al., 2023a)
	Developing seismic fragility curves for concrete bridges using structural health monitoring (SHM) and digital twins (Rojas-Mercedes et al., 2022)
	Using Digital Twin to manage lifecycle fatigue for steel bridges (Jiang et al., 2021)
Transportation	Design, construction, and maintenance of railway stations using BIM and Revit software (Kaewunruen and Xu, 2018)
	Using digital twin to assess life cycle assessment (LCA) for Precast Advanced Track (PCAT) slab systems (Borjigin et al., 2022)
	Railway maintenance and resilience optimization using DT technology (Kaewunruen et al., 2022)
	Digital twin-based model for maintaining switch machines (Yang et al., 2021)
	A system for optimizing scheduling when a delay occurs on a railway using automatic feedback (Liu et al., 2022)
	A system that utilizes minimal sensors to estimate the real-time responses of a pipe to seismic and arbitrary loads (Bo et al., 2020)
	MBS-based wheel and rail life prediction (H-Nia et al., 2022)
	Monitoring subsea pipeline systems with integrated sensors (Chen et al., 2022)
Energy system	A DT-based framework to determine the best energy-saving technologies and strategies in existing buildings (Seo and Yun, 2022)
	Analyzing and optimizing energy consumption and achieving sustainable development goals in energy management (Francisco et al., 2020)
	A coupled simulation for designing a thermal system integrated with a lightweight roof structure (Lydon et al., 2019)
	Using a digital twin to make energy system design decisions (Granacher et al., 2022)
	Using digital twins to store thermal energy in building (Lv et al., 2023)
Industry	Industrial parallel intelligent control system (e.g., used in electrical station boiler and steam turbine system) (Li et al., 2021)

based on physics. It can then be connected to the physical twin to support real-time decisions. A framework (Dang et al., 2021) is also presented for structural health monitoring in cloud computing and deep learning, which enables efficient real-time monitoring and maintenance tasks. However, structure damage detection based on the convolutional neural network still faces some unprecedented challenges. It is well known that CNN needs lots of training samples but it's difficult to get enough samples for different damage scenarios. Also, the current vibration-based damage detection techniques are unable to produce desirable detection outcomes owing to the influence of environmental elements, measurement inaccuracies, and suboptimal handling of extensive bridge monitoring information. To solve these problems, numerous damage samples through numerical models using digital twin technology were generated (Teng et al., 2023). The Bayesian optimization algorithm is utilized by the authors to achieve time-efficient and non-redundant data collection through the selection of the optimal combination of sampling points. These models' simulation outcomes can then be utilized to train a CNN, which is subsequently utilized to identify damage in real-world structures. This approach not only enhances CNN's convergence speed but also greatly improves detection accuracy. The schematics of this digital twin for bridge models are shown in Fig. 3.

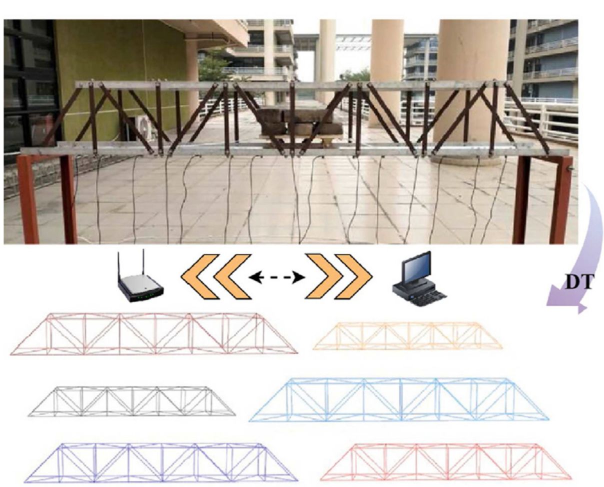

Fig. 3. The structural digital twin application of the bridge (Teng et al., 2023).

Moreover, facing the multi-scale, multi-scenario, and multi-dimensional application of digital twins in bridges, this technology is based on designing and building 3D models of physical entities suitable for digital twin applications. To enable the rapid development of digital twins, a complex bridge twin can be divided into several simple models and then assembled into the complex model through information fusion, multi-scale association and multi-scenarios iterations (Jia et al., 2022). During the assembly process, errors will gradually accumulate, which means that the twins have very high demands on precision. Among the advanced technologies used to provide qualitative digital models, Unmanned Aerial Vehicle photogrammetry and Terrestrial Laser Scanning are the most common methods used to output high-precision point cloud data for model reconstruction (Mohammadi et al., 2021). Therefore, an object fitting method that can digitally twin bridges is proposed to depict the true geometry of the bridge and automate from point cloud data to a 3D model (Lu and Brilakis, 2019). Another factor that needs to be considered in the modeling is random traffic loads. How to reflect the impact of vehicle loads on the response function in the model is a challenge, especially when there are multiple vehicles(Zhao et al., 2022a). Based on high-assurance twins, real-time monitoring data of bridges can be continuously exchanged and updated between physical entities and twins, which enables stakeholders to jointly utilize data throughout the life cycle, including design and construction, operation and maintenance (Shim et al., 2019). For example, the nonlinear fatigue damage model based on the continuum damage mechanics can be introduced into the twin, which helps engineers to predict the development of the defect that cannot consider welding residual stress for the S–N curves based on fatigue evaluation and life prediction method (Yu et al., 2022). Moreover, digital twin can also perform multimedia knowledge-based bridge health monitoring and predicts the best time point for maintenance based on a small amount of data collected from the bridge, which further reduces maintenance costs and extend the life of bridges (Kang et al., 2021). Another application of digital twins is to assess the impact of extreme natural disasters on the strength of bridges, such as the collapse brittleness assessment based on digital twins of long-span cable-stayed bridges under strong earthquakes (Lin et al., 2021). Finally, for the bridge group in a region, each bridge can be virtualized through digital twins and connected through the measured traffic load, so as to realize

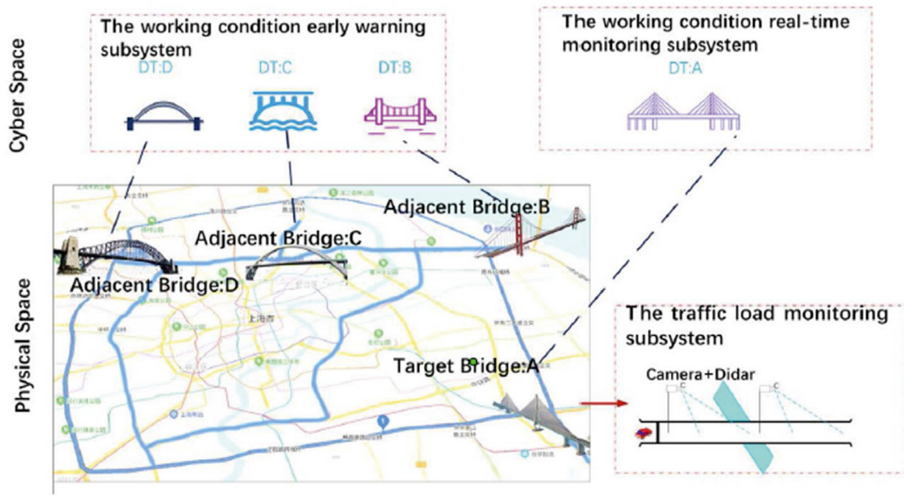

Fig. 4. Composition of bridge digital twin system of bridge network (Dan et al., 2022).

the working status awareness and safety warning of all bridges in the regional traffic network(Dan et al., 2022). The Composition of bridge digital twin system of bridge network is shown in Fig. 4.

Fig. 4 displays the precise location of the target and adjacent bridges in the group. Longitudinal monitoring of the target bridge is conducted using high-definition cameras and Lidar arrays.

Digital twin techniques also help in the assessment of structural conditions of buildings after earthquakes (Hoskere et al., 2022). A graphics-based digital twin framework (Wang et al., 2022a) has been proposed and demonstrated on a reinforced concrete building under post-earthquake conditions. This framework combined physics-based graphics model with digital twin, which consists of finite element (FE) model and a photorealistic computer graphics (CG) model of the physical asset. In their study, the computer graphics model will represent both health and damaged conditions of the physical building, where the damaged cases were obtained under different levels of seismic load. In order to localize these damages, a variety of UAV inspection trajectories were used. These trajectories guided the reconstruction of a point cloud using the CG model which generated rendered images. The point cloud shown in Fig. 5 then served as the basis for damage evaluation in the building depending on the point-cloud density.

Fig. 5(a) displays the point cloud constructed from 972 images rendered from the undamaged CG model under optimal lighting conditions, with 954 of these images successfully registered. Fig. 5(b) demonstrates the utilization of Cloud Compare to evaluate point cloud density in a quantitative manner.

3.2. Digital twins in transport systems

Digital twin technology is rapidly gaining popularity in the transport sector as a means of creating virtual replicas of physical systems, enabling real-time monitoring, analysis, and prediction of performance. One major application of digital twin techniques in transport systems is predictive maintenance. The precision of safety prediction can be improved to 90.43% (Lv et al., 2021) by using the digital twin model. It is predicted that digital twins will be used throughout the construction and maintenance processes of highways by 2032–2035 (Highways, 2020). Another significant application of digital twins in transport systems is real-time performance monitoring. Nowadays, cities with high populations and vehicle-to-population ratios are facing the problem of how to efficiently manage transport flows (Rudskoy et al., 2021). The digital twin can be applied with Intelligent Transport System which is based on AI algorithms. The system enables continuous and immediate collection of information regarding the traffic situation. This data is processed by AI algorithms to provide a foundation for future forecasts regarding the development of the traffic situation. The emergence of this system can

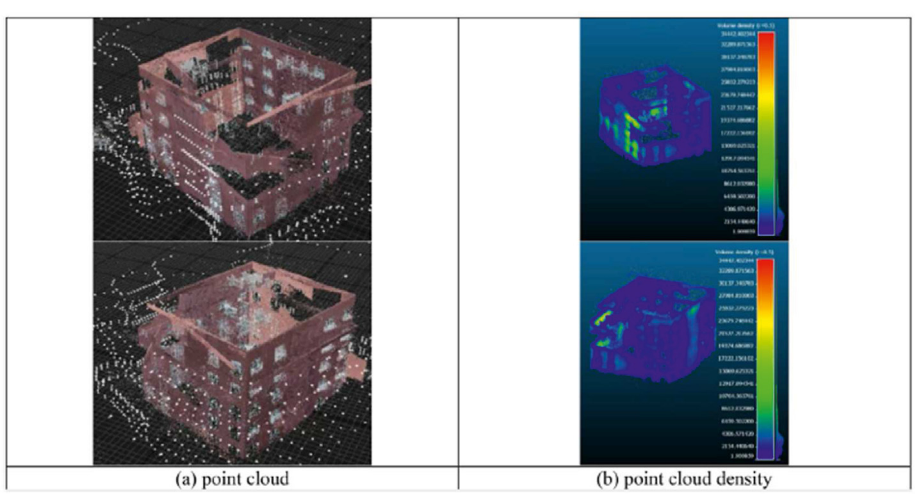

Fig. 5. Point cloud reconstruction for damage evaluation in a building structure (Wang et al., 2022a).

not only increase the road network throughput but also improve road safety.

The digital twin system of the underground pipeline network (UPN) is a significant component of smart cities' transport infrastructure, as the UPN itself plays a crucial role as an underground infrastructure and structure (Li et al., 2023). The advent of digital twin technology offers an effective means to achieve remote monitoring and control, predict downtime, and mitigate risks associated with subsea oil and gas pipeline systems (Chen et al., 2022). A digital twin of a pipeline is established based on the pressure signal generated by a pipeline leak, and pipeline leak detection is researched (Wang et al., 2023). Real-time data is mapped to simulate a virtual space model, while the twin platform transmits the data to the pipeline leak identification model to construct a feature vector and determine the pipeline's operational conditions. The experimental results demonstrate that this method has a high identification accuracy for each leakage point and is a viable approach for detecting pipeline leaks, thereby establishing a solid foundation for future gas pipeline leak identification using digital twin technology.

As an emerging technology, the digital twin has very promising prospects and development potential in fault diagnosis and prognosis for railway applications. Compared with traditional fault diagnosis methods, the digital twin has demonstrated its prevailing capabilities for smart fault diagnosis through real-time visualization and status monitoring, enabling intelligent prognostics (Wu et al., 2022). A digital-twin-based approach was proposed for the fault diagnosis of high-speed train bogies (Wu et al., 2022). The goal of this approach was to enhance the safe operations of high-speed trains by reducing the failure rate of the bogie and the cost of its maintenance. A seven-dimension-based framework was leveraged to build the digital twin of the bogie. A deep CNN was then used for fault diagnosis of the bogie. The framework for their digital twin system is shown in Fig. 6 below.

Service performance information is input into the digital space and the digital twin model is fragmented by timing signals. The vibration model is mapped to signal processing to extract time and frequency domain features, which are used for fault diagnosis through the analytical-driven and data-driven models. The analytical-driven model extracts primary features by inputting vibration timing data, and feature data from primary features is used for fault diagnosis through processing.

In addition, the feasibility of digital twin technology for railway maintenance and resilience optimization also has been demonstrated. By using Building Information Modelling (BIM) integration through a life cycle analysis, an innovative digital twin is developed to improve the sustainability and resilience of the railway bridge (Kaewunruen et al., 2022). Based on the ability of immediate real-time updating and access across different data layers, the digital twin performs as a visual and information platform that allows all project parties to collaborate, visualize and share data throughout the whole life cycle of a project. As shown in Fig. 7, the maintenance timeline schedule of the Minnamurra Railway Bridge is incorporated in BIM-based digital twin by enabling effective asset management tools using Revit and Navisworks. Besides, digital twins can also evaluate and determine cost estimation and estimation of Greenhouse Gas (GHG) emission, which enhance asset management, operation and maintenance to a more sustainable level for railway infrastructures.

3.3. Digital twins in energy systems

Energy management is one of the most critical areas of interest in the development of smart civil infrastructures. Digital twins allow the energy industry to model physical assets to improve its efficiency, reduce costs, and even forecast potential problems. There are promising digital twins (Andriopoulos et al., 2023) that can facilitate the flexibility of service provision from industrial energy systems. One of the practical applications of digital twins in energy systems is predictive maintenance to improve energy efficiency in buildings. Predictive maintenance of energy systems is based on analyzing the system data, looking for patterns, and predicting the best maintenance strategy to achieve energy efficiency. Several studies have explored the use of digital twin techniques to predict the maintenance of energy systems. An artificial neural network (ANN) was introduced as a digital twin to model several existing hotels in Mexico (Mengual Torres et al., 2022). The data on the consumption of electrical and thermal energy was collected from each hotel to train the artificial neural networks. Then the model will evaluate different scenarios for partially replacing energy-consuming devices in the hotels while optimizing a combination of three indicators: energy-use index, equivalent–CO_2–emission index, and energy-cost index. This ANN-based digital twin model can provide the complete range of potential technology substitutions based on specific examples, all while requiring

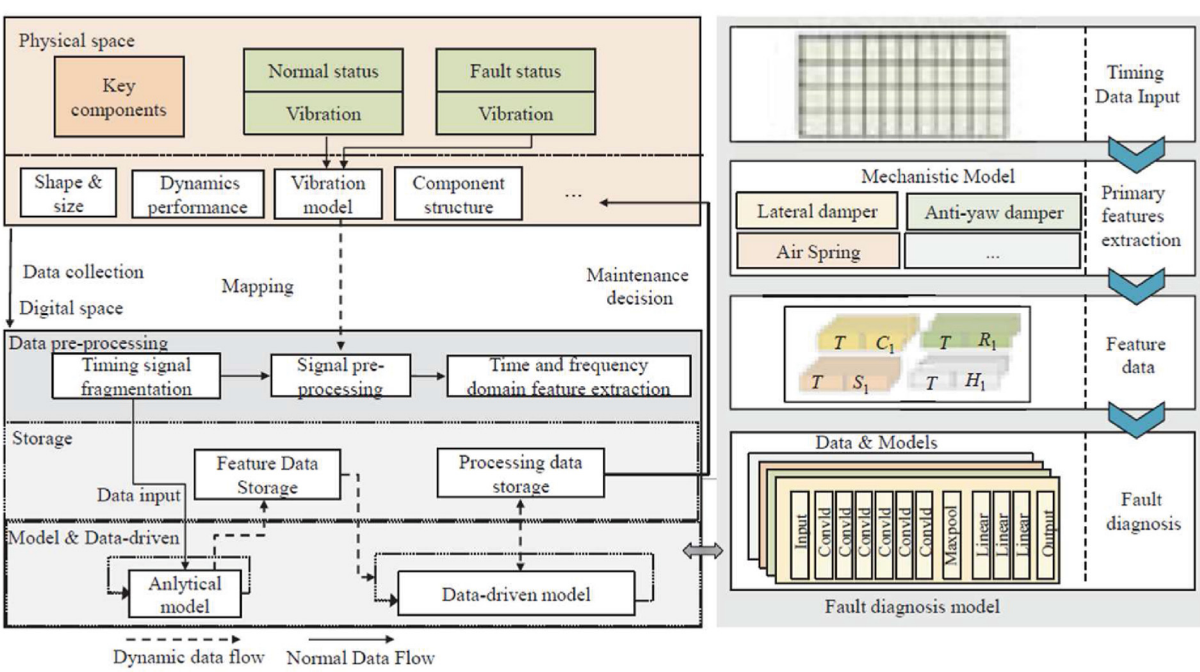

Fig. 6. Framework for the digital twin system of the bogie in high-speed train (Wu et al., 2022).

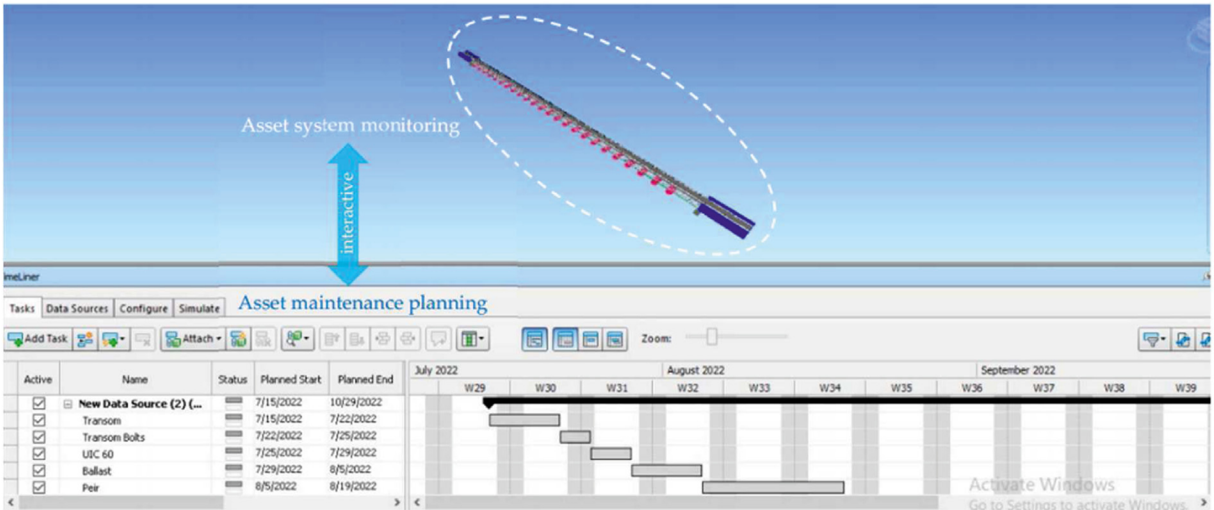

Fig. 7. BIM-based digital twin optimizes the timeline maintenance schedule (Kaewunruen et al., 2022).

significantly less computation time. The results can be provided to managers to guide their decision-making processes regarding the replacement of energy-consuming devices in existing hotels (Bortolini et al., 2022). Another application of the digital twin technique in energy systems is building energy management. Leveraging digital twins, urban buildings can use real-time data and models to analyze and optimize energy consumption and achieve sustainable development goals in energy management (Francisco et al., 2020). A digital twin-based assessment framework shown in Fig. 8 was proposed for lighting energy-saving strategies in educational buildings (Seo and Yun, 2022). The framework involves constructing a digital twin model that simulates the lighting system operations in real-world buildings, to identify the most effective energy-saving technologies and tactics for implementation in such buildings. Integrating digital twins into a decision support system can assist engineers and managers in determining the optimal planning and management approach.

The proposed framework incorporates the building's design plan, stochastic lighting operating schedule based on occupant behavior, and building usage schedule into a digital twin model. This model is utilized to analyze the impact of each energy-saving strategy.

A building energy model (BEM) for an existing building using laser scanning technology was also proposed in (Zhao et al., 2021). BEM can be described as a combination of BIM modeling and energy consumption simulation (Arumägi and Kalamees, 2020; Mellado et al., 2020; Wang et al., 2022a). The BIM model is generated by scanning the existing building data and importing the point cloud data into Revit. And the process of building energy consumption simulation is shown in Fig. 9. The authors' objective was to evaluate the feasibility of retrofitting schemes based on the concept of nearly zero-energy buildings (nZEBs) and to improve energy efficiency in buildings by clean energy strategies. Artificial intelligence technologies were also combined to analyze, predict and control the use and management of building energy in a more precise manner in digital twining to achieve more efficient, reliable, and energy-efficient building operations (Agostinelli et al., 2021).

The BIM model created in Revit is used to partition thermal zones and set parameters. The Revit model is then exported to the gbXML format to simulate whether the existing building's nZEB retrofitting scheme meets specifications.

The energy system is a crucial infrastructure that has a strong relationship with urban production and daily life, and it holds a significant role in constructing a smart city (Thornbush and Golubchikov, 2021). Currently, the optimization of the energy system is based on specific steady-state models, which cannot describe the conversion and energy consumption characteristics of multiple energy types accurately in the actual system. This is because these parameters are closely linked to the system operating environment, working conditions, and other factors. A solution to this problem is introduced in (Huang et al., 2022) in the form of the CloudIEPS, an energy internet planning platform based on a digital twin model. Once the CloudIEPS digital twin model is created, the integrated optimization module can incorporate the optimization algorithm kernel to design a proper system. By providing customized energy supply and managing the demand-supply interaction, energy efficiency and service quality can be boosted comprehensively.

Digital Twin can also be used in a biomass energy system. Atikokan Generating Station proposed an Atikokan digital twin to enhance the biomass-fired tower boiler's efficiency (Spinti et al., 2022). The Atikokan Digital Twin uses surrogate models to incorporate data from high-fidelity boiler simulations, along with historical process data and a range of Bayesian machine learning tools, to analyze a complex and multivariate system. It helps optimize the energy usage of the biomass plant by providing insight into energy production, reducing downtime, and identifying areas of energy waste. The system uses real-time data analysis, predictive analytics, and machine learning models to make automatic adjustments to the plant's operations. This results in more efficient energy production and cost savings (Spinti et al., 2023).

4. Current challenges in the applications of digital twin for civil infrastructure

Currently, there are also challenges in digital twin applications of civil infrastructure. Due to the complexity and diversity of civil infrastructure, there are inevitable deviations between digital twins and physical entities, which leads to the accumulation of errors. To keep the fidelity of the twins, a reasonable parameter update strategy must be developed to ensure high consistency between twins and physical entity, which needs to balance the update frequency, calculation amount and real-time delay. Kim obtains the geometric and geospatial information of infrastructure by using deep learning algorithms to process real-time participatory sensing data and robustly updates the up-to-date condition of infrastructure into the digital twin city model (Kim and Ham, 2022). Alibrandi integrates the methods and tools of statistics and risk analysis with machine learning and introduces a novel concept of digital twin called risk-informed digital twin (RDT) to respond to the challenges of multiple sources of uncertainty during the lifecycle (Alibrandi, 2022). Another challenge is to achieve bidirectional interaction between twins and physical entities. In general, it is relatively easy for physical entities to pass state parameters to twins, such as the update process of twins. While the more critical aspect is how to use the output data of twins to guide the

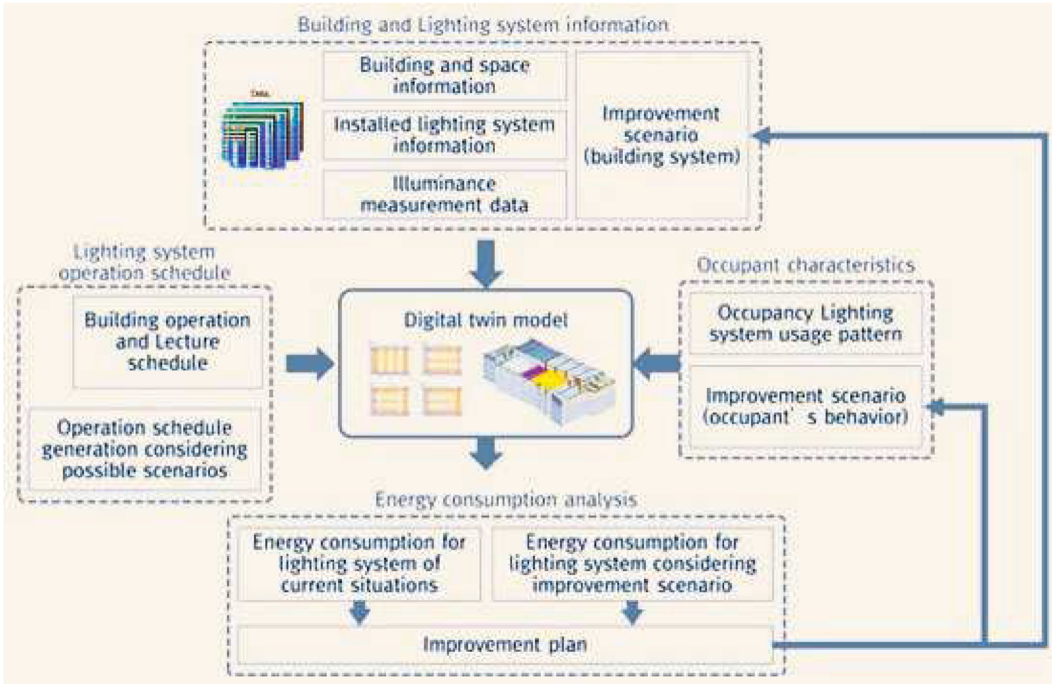

Fig. 8. A digital twin-based assessment framework for evaluating the lighting energy-saving strategies in educational buildings (Seo and Yun, 2022).

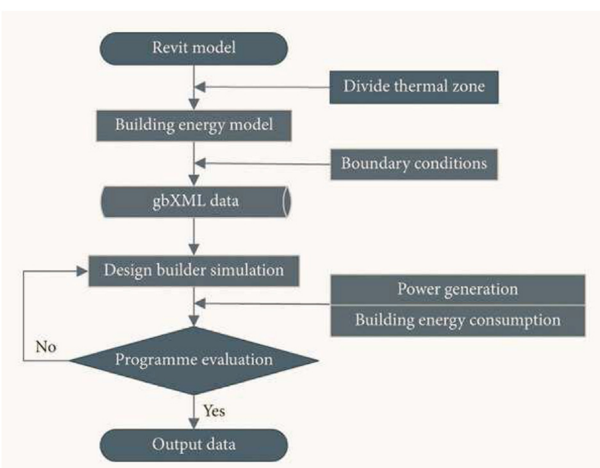

Fig. 9. The process of simulating building energy consumption (Zhao et al., 2021).

operation of physical entities in turn. Based on virtual reality technology, Wang constructs a virtual reality interaction model and realizes the Interaction between the physical construction site entity model and the digital twin virtual body model with a delay of less than 3ms (Wang et al., 2022b). Dang designs a cloud-based digital twin framework for real-time SHM applications, which uses a cloud platform to facilitate two-way feedback and uses DL algorithms to iteratively improve both the digital and physical structures as one closed system (Dang et al., 2021). All in all, two-way interaction is not only the main characteristic of digital twin technology but also the way it generates value.

5. Conclusion

Over the years, infrastructure health monitoring and management has become increasingly important in assessing the damages of these critical structures and estimating their remaining service life for maintenance purposes. However, current methods which leverage continuous monitoring of the civil infrastructure data in real time face the challenges of demanding data requirements, limited real-time functionality, ineffectiveness and high price. To overcome these current limitations, digital twin, which is a computational model that emulates a civil infrastructure and surrounding environment, has been applied and demonstrated great potential in the application of real-world civil infrastructure problems. In this review paper, we have summed up different methodologies to build the digital twin in the area of civil infrastructures. The digital twin examples in various civil infrastructure sections have been introduced including bridges, high-speed railways, subsea pipelines and so on. Finally, the challenges associated with the current digital twin techniques in civil infrastructures are highlighted. How to build a high fidelity and in the meantime computationally efficient digital twin is a major challenge. Future work also needs to be focused on enhancing the real interaction/ communication between the digital twin and real asset.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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