Digital Twins in AEC Infrastructure and Building Management Systems

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Abstract

The current practice of Architecture, Engineering, and Construction (AEC) management systems relies on time-consuming, manual methods for data collection, analyzing, and decision-making. This affects the productivity of the industry in all phases: design, construction, operation, and maintenance of their assets. Adoption of innovative technologies is the key solution for the AEC industry to overcome the challenges they face and follow other reinvented industries. Although recent advancements have been proposed for more productive data acquisition and decision support by leveraging digital tools, Building Information Modeling (BIM), Internet of Things (IoT), and Artificial Intelligence (AI), the fragmented approach of adoption and the absence of a connected workflow is a barrier. Digital Twin (DT) is a digital presentation of a physical entity that replicates the status and behavior of its physical counterpart. It can help to improve overall system effectiveness and reliable data-informed decisions. However, the concept of DT and its key features is still not well-understood in the AEC industry. Therefore, this paper aims to review and investigate the twinning requirements and characteristics of DT and discuss its structure and potential solutions in terms of AEC infrastructure and buildings assets operations and maintenance systems. The DT concept, main characteristics, and critical considerations for the AEC sector are highlighted and classification for DT levels is introduced and discussed.

Keywords: AEC; Digital twin; Smart infrastructure and building systems; Intelligent operation management; Predictive maintenance

1. Introduction

Annual construction industry contribution was estimated as 13% of the world gross domestic product (GDP) (Barbosa et al., 2017), and is expected to reach $14 trillion by 2030 (Perspectives & Economics, 2015). In 2018, this sector contributed to 10% of the Australian economy with around $110 billion and employed more than 1 million people. Despite the significance of its contribution, the growth of its global labor productivity has averaged only 1% per year over the past twenty years, which is extremely low compared with 2.8% and 3.6% growth rates for the total world economy and manufacturing sector, respectively. International programs were established to identify key objectives for the development of this industry. It was found that it needs to achieve more integrated processes with new information and production technologies, aiming to enable the construction industry to follow the manufacturing sector (Milford, 2009).

The construction industry has started to adopt Building Information Modeling (BIM) and digital tools in the current industrial revolution. However, the implementation of technologies is still in its infancy, as the industry is characterized by slow adoption of new technologies partly due to the fragmented nature of the industry, segmentation, and resistance to change (Beetz, et al., 2020). These factors influenced the adoption of cutting-edge technologies, such as Digital Twin (DT) for integrated digital systems. (Callcut et al., 2021) observed that the adoption of DT in AEC industry tends to be fragmented and dispersed. Consequently, the industry continues to rely on traditional tools and techniques in collecting, analyzing and driving the decision process. This resulted in the absence of a centric dataset and the lack of smart capabilities and systems efficiencies across all phases of a construction project.

Moreover, since the start of the current industrial revolution, advancements in technology have enhanced productivity in various industries. This digital transformation includes data sensors, machines, big data modeling, cloud computing, and Information Technology (IT) systems, which led to the use of predictive approaches and improved decision-making, improved data exchange, and applications by leveraging Artificial intelligence (AI) algorithms and smart techniques. Currently, there is a focus on introducing Digital Twins (DT) for enabled data-driven decisions and more integrated applications in various industries (van Dinter et al., 2022). DT is a digital representation of a physical product that mimics real-world behavior by leveraging data from the physical element, process, or system to its virtual counterpart. The virtual models are supported by simulation tools, cloud-based connections, sensors and databases that are introduced to enable remote management and interaction with physical assets (Tao & Zhang, 2017).

The understanding of DT in the AEC industry is currently fragmented (Callcut et al., 2021). The adoption of DTs is still in its evolutionary stage due to inconsistencies in definitions and characterizations (Jones et al., 2020). This lack of knowledge will affect the overall digitization of the industry as the transition movement aimed to integrate subsystems that can work as part of one inter-connected system to improve productivity and performance.

Moreover, intelligent systems comprise digital subsystems that communicate through a digital data; therefore, the currently developed subsystems will remain fragmented and lack an integrated systematic workflow unless the integration frameworks and capabilities of these systems have been well understood in the AEC assets context. There is also a lack of prototypes and studies, and possible solutions that digital twins may provide (Jones et al., 2020; Broo & Schooling, 2021). Therefore, this work aims to investigate the current state of the DT concept and adoption in the AEC industry and provide insight into future research and a developmental requirement to implement true DT in this sector and maximize the benefits.

2. Digital Twin: Definition and Characteristics

DTs' core characteristics were identified as follows; life-cycle phases data of the asset, synchronization rate of data, types of connections between spaces (bi-directional or one-way flow), and sensor data. In addition, advanced analytical techniques were developed for enabling twinning capabilities such as predicting, forecasting, alerts, or fault detection through data-driven models and physics-based simulations.

In terms of connections, the core definition established by Grieves focuses on the linkage nature between two spaces being bidirectional and having multiple virtual spaces for a single real one (Grieves, 2014). However, the latter proposed data flow types were based on the level of automation between the physical and the virtual parts of an asset (Kritzinger et al., 2018), where three types of DTs are classified as a digital model, digital shadow, and digital twin. The twin is when data transfer is bi-directional, digital shadow has one-way data transfer and the digital model is where no automatic transfer of data exists. Figure 1 shows the three types mentioned.

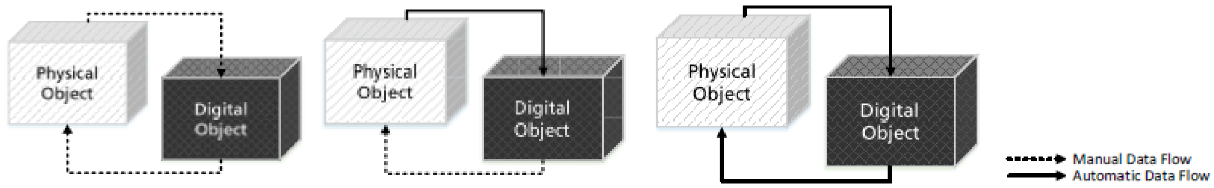

Fig. 1: (a) Digital model, **(b)** Digital shadow, and **(c)** Digital twin, based on data flow type (Kritzinger et al., 2018)

In terms of lifecycle inclusion in DT, (Söderberg et al., 2017) considered the life cycle of manufacturing phases as a core point in their definitions. (Zhang et al., 2017) added product life cycle and simulation of integrated data and defined the prediction component to be the main part of DT. Others included mechanical analysis, advanced analytical algorithms, and simulation models (Dassisti et al., 2017; Tao, et al., 2019). (Schleich et al., 2017) considered the need for a two-way connection between a physical and virtual entity, whereas (Trauer's et al., 2020) definition focuses on the need to exchange data information involving sensors, data, and models.

(Semeraro et al., 2021) described the DT in terms of a system capable of synchronizing data, modeling the behavior of the physical space, and communicating services by the virtual space, with the ability to simulate the product life cycle. Visualization and simulation, along with continuous data updates are features also found to be a main part of the DT. As stated in ISO (2019), ongoing updates in the virtual part reflect the changes in the physical counterpart to represent status. (Defraeye et al., 2021) included all the essential elements, geometrical components, and properties of the material; they also included continuously updated sensor data and realistic simulation for the relevant processes throughout the product lifecycle. The core features of DT found in literature definitions and descriptions are summarized in Figure 2 below.

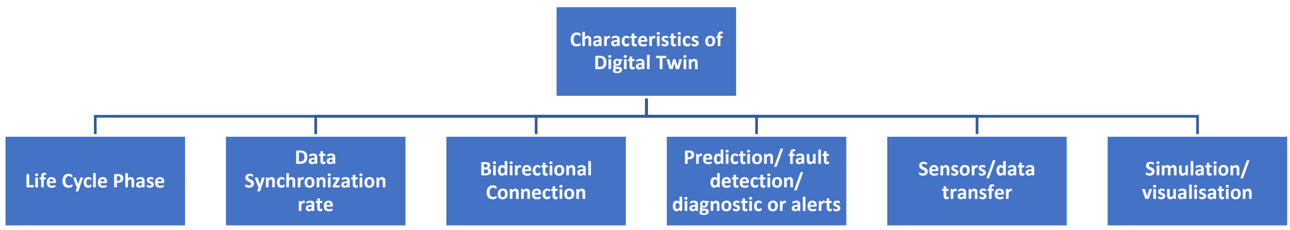

Fig. 2: Characteristics of Digital twin

DT can be developed for any real-world asset, for example, buildings and civil infrastructure assets (Bado, 2022). It can be developed at the unit level, system level, and system-of-systems level. At the system level, the DT can be developed for the process (Bao et al., 2019). DT in the manufacturing process aimed to improve resource allocation, process controls and production plans to validate the production process before or during it. Therefore, process twinning can be possible in AEC processes, such as the use of a DT for construction methods, processes, and operations for monitoring and control.

In terms of the synchronization rate for DT, most definitions stated the need for real-time data transfer. However, continuous data transfer might not be necessary in some cases or not possible either in the construction sector. The frequency of data transfer and updating the DT model status depends on the frequency of the decision-making cycle or when a significant change in the physical asset occurs, i.e. periodic asset inspection data. (Callcut et al., 2021) compared the need for real-time data in two different scenarios and reported that data rates could be varied based on need. For example, twinning traffic on roads networks for navigation maps use, as digital maps collect traffic data from the location data of users' GPS in real-time, along with local traffic information (rules, directions, priorities etc.) and automatically learn from historical and live traffic data to provide directions, optimize driving routes, and predict arrival time along with dynamic visualizing. Note that, the decisions during this operation including driving speed, traveling time, selecting routes, and optimizing options are performed continuously for the user and system.

On the other hand, the solid, or static physical assets such as structural assets might not need to have bidirectional connections, as in this case, the feedback from virtual to physical can be physical action orders such as scheduling maintenance or manual responses. (Stark & Damerau. 2019) noted that plans or reactions based on virtual feedback and decision-making can affect physical space and change its status. It can be considered as a feedback flow of data transferred indirectly by the users or decision-makers and divided into virtual flow to a decision maker and the decision to the physical part, where the decision-maker can be a user, operator, asset owner, etc. According to that, the digital shadow structure can be presented in a more realistic flow as shown in Figure 3.

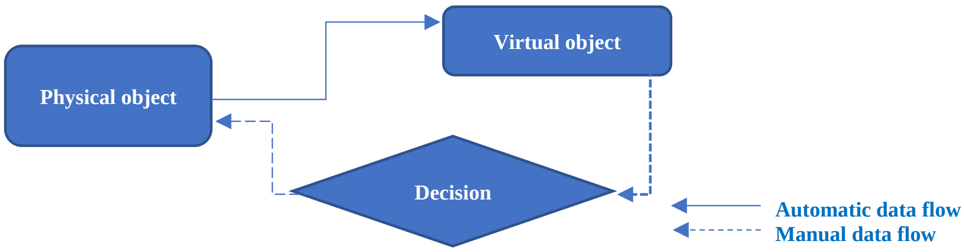

Fig. 3: Digital shadow data flow structure

The life cycle of the product is a necessity included in most definitions of DT (Schroeder et al., 2016; Söderberg et al., 2017; Zhang et al., 2017), and it was the main core of the DT concept introduced by (Grieves, 2014). Asset life cycle models and data serve as crucial sources of information regarding the various life phases of physical assets. These models aim to facilitate effective communication of operational activities and responses related to the assets, thereby enabling better decision-making processes (Zhanget al., 2019). The data related to asset life cycle phases encompass essential information for each stage of the asset, including planning, design, construction, operation, and maintenance. Integrating all relevant asset data in a holistic model providing a comprehensive view of the purpose and function of the DT utilization. (Defraeye et al., 2021) emphasized that the comprehensive model should incorporate all essential elements, including geometrical components and material properties.

DT features such as monitoring, diagnosing, and predicting the state and behavior of the twinned entity, indicated the prediction capability, and fault detection for observing a discrepancy and abnormality in the behavior and performance of a system (Amruthnath & Gupta, 2018), by using rules, analytical models, and machine learning, such as use failure data for predicting machine failure. The simulation is also an essential part, as it can generate failure to be used in predicting defects (Aivaliotis et al., 2019). Simulation can be implemented for predictive modeling, visualization components (Gunal, 2019), and optimizing future operations (van der Horn & Mahadevan, 2021). As a result, a digital twin for AEC use can be defined as a virtual copy (graphical and non-graphical information) of a certain asset, process, or system of connected assets that comprise the purpose-related lifecycle data, reasonable data exchange and synchronization, analytical and simulation models, and intelligent techniques, to model real-world conditions and responses of the physical entity.

3. Current State of Digital Twin in AEC

In the construction industry, the potential reported applications of DT include supporting decision-making in energy management, procurement, the feasibility of a project, and sustainability (Opoku et al., 2021), as well as improving future actions and extending the lifetime of the built infrastructure and improving sustainability. Many different works leveraged an integration of BIM models in the AEC industry with external data sources and processes such as cloud computing, scanning sensors and IoT. Integrations purposed for the design phase, operation and maintenance, construction progress and quality processes. In terms of the design phase, (Jiang et al., 2021) discussed the mechanism of the fatigue management system using Digital Twins and noted that fatigue data including historical fatigue after the bridge retirement, can be supported by the integration of information for the more insightful design and management of new bridges. For road pavement design, digital twin included structured geometric and attribute data of a constructed road using secondary raw materials (SRMs), including real-time material characteristics using sensors to support data centralization and graphical presentation of road performance indicators (Meža et al., 2021).

For the maintenance phase, DT was used to predict the highway tunnel pavement performance where sensors were used for asset performance, data collection along with other life cycle-related data (maintenance records, traffic flow, etc.), in addition to advanced analytical modeling; multisource spatial-temporal data and dynamic visualization, which allowed for enhanced maintenance method (Yu et al., 2020). Visualization of anomalies to assess the conditions of assets is a major step in decision-making and maintenance planning such as defects, cracks, etc. For that purpose, an interactive system to display pavement cracks in 3D visualization was developed (Cao et al., 2022), where cracks detection and segmentation were implemented via 3D edge detection and deep learning algorithms, and data was collected using a camera and laser scanning sensors.

At a system level, (Dan et al., 2022) developed a DT system for a group of bridges, where traffic load is measured by a camera sensor, machine vision, Weigh-In-Motion (WIM) System, and cloud-based finite element models integrated to analyze mechanical responses for real-time fatigue analysis and monitoring. Another work presented the progressive settlement based on road traffic, using LIDAR (Light Detection and Ranging) sensor data, UAV-based camera sensors for traffic counting, and environmental air quality sensors, where scanned assets were converted into standard CAD packages (Steyn & Broekman, 2021). In terms of health monitoring, BIM and GIS integration process was used for a cable-stayed bridge in Africa, the structure as-built was modeled using a point cloud, and geographic information of the external environment represented and visualized as 3D GIS objects for flatness and distortion monitoring. In that work, an IoT network was used to stream data such as temperature, tilt, and deformation (Sofia et al., 2020).

Few works used a bi-directional flow of data in their systems, aiming at activating alerts in the physical space and issuing action orders. For instance, advanced monitoring and control for underground garage environment management using BIM and Wireless Sensor Networks (WSN) to capture environment conditions presented visually for an effective monitoring system with abnormality data detection and alerts execution (Lin & Cheung, 2020). As a conceptual framework for web-based building management, (Deng et al., 2021) discussed a framework, in which the authors described BIM integrated with simulations, IoT, and AI for real-time indoor environment and occupant's comfort with predictions and responding controls automatically. (Valinejadshoubi et al., 2021) used BIM model, IoT, database system integrated via Dynamo (Visual Programming Environment), and cloud-based services to enable cloud-based monitoring systems to detect the thermal comfort levels of office occupants based on predefined targeted thresholds for monitoring alerts.

Building energy-related works were found to be the most studied area, because of the need for an intelligent platform for real-time management. (Peng et al., 2020) developed a hospital building operations system by integrating BIM models, multisource data, and algorithms to monitor and identify abnormal consumption patterns to enable effective administrative management with automated feedback from the digital platform to the real space. (Rafsanjani & Ghahramani, 2020) proposed a system using IoT sensors to evaluate the behavior of energy consumption by individuals. They were able to identify and classify occupants' consumption trends for energy savings reaction.

In road construction, a recent study developed a framework for an intelligent real-time roller compaction system to assess the quality and manage road layers compaction process (Han et al., 2022), where IoT is adopted to connect physical and virtual space for actual operations in road construction, and the quality of the process assessed and visualized. As a smart city planning use, DT for green spaces and skylines planning was developed by (White et al., 2021). The authors aimed at creating a publicly open digital twin that enabled data feedback exchange from users to interact on planned changes. A summary of DT applications in AEC is presented in Table 1.

Table 1: Digital Twin Applications in AEC

Author	Description	Bidirectional	Synchronization (real time)	Sensors	Visualization/Simulation	Prediction, fault detection
(Rafsanjani & Ghahramani, 2020)	Energy consumption		x	x		x
(White et al., 2021)	DT for smart city		x	x	x	
(Lin and Cheung, 2020)	Underground Garage	x	x	x	x	x
(Lu, et al., 2020)	Energy demand			x		x
(Peng, et al., 2020)	Hospital building operations	x	x	x	x	x
(Meža et al., 2021)	Pavement secondary material		x	x	x	
(Yu et al., 2020)	Highway Tunnel Pavement			x	x	x
(Xie et al., 2020)	Anomaly detection		x	x	x	x
(Steyn & Broekman, 2021)	Settlement of bridge			x	x	
(Dan et al., 2022)	Bridge fatigue monitoring		x	x	x	x
(Sofia et al., 2020)	Monitor health of the bridge		x	x	x	
(Shim et al., 2019)	Pre-stressed concrete bridge			x	x	x
(Deng et al., 2021)	Building management	x	x	x	x	x
(Cao, 2022)	Cracks visualizing system			x	x	x
(Han et al., 2022)	Intelligent compaction system		x	x	x	x
(Valinejadshoubi et al., 2021)	Thermal monitoring		x	x	x	x

4. Discussion

To identify the status of DT applications in AEC, a classification of the main DT features and relevant AEC studies was conducted. In addition, understanding DT applications and capabilities from different sectors were used to interpret the AEC-related works into levels of twinning. Identified levels can be discussed as follows, the first level is where BIM is integrated with IoT and visualized live data for monitoring, predefined triggers, alerts etc. The second level incorporates integration with artificial intelligence (AI) techniques, analytical models, or computational models for predictions and simulation to support the decision-making process. The predictive feature is a key feature at this level that can enable predicting defects or the future status of the asset.

The third level shall include more advanced integration and involves the prediction of the state of the asset combined with automated decision guidance, process, or optimized actions. These actions can be descriptive plans based on predefined policies and informative embedded data, or actual actions for real-time control as a feedback capability to manage the operations of the asset. However, control actions can only be adopted when this automation is possible in the physical part i.e., mechanical, electrical process or computerized object, as this can be implemented through a bi-directional connection between two spaces for the developed DT.

Most of the studies' prototypes are based on local BIM platforms, using visual programming in most cases, a few (Valinejadshoubi, et al., 2021; White, Zink, et al., 2021) have shared the developed prototype to cloud-based access. However, recently, cloud services such as Amazon and Google Cloud developed cloud-supported tools for analyzing and visualizing data with the integration possibilities of AI and IoT. Nevertheless, cloud-based frameworks can expand to a more collaborative involvement of stakeholders in the management platform for better decisions and monitoring.

Monitoring the interior environment, operation, and maintenance management was also found as the key focus of AEC DT adoption (Lu et al., 2020; Rafsanjani & Ghahramani, 2020). On the other hand, applications for bridge health monitoring are found common in infrastructure assets applications (Shim et al., 2019; Sofia et al., 2020; Dan, Ying et al., 2022). However, most of these studies were classified in levels 1 & 2, which helped in supporting decision making in an efficient and real-time manner in some cases. Other proposed frameworks involved predictive ability using analytical modeling, or artificial intelligence algorithms to predict status or health measures, (Yu et al., 2020; Deng et al., 2021).

These works are considered a promising start toward a higher level of twinning, as they can perform predictive monitoring for the future state, which might lead to enhanced maintenance planning and actions by optimizing the traditional maintenance approach. DTs have more capabilities to be leveraged in this industry. DTs (level 3) utilizations are needed for automation in actions, optimization, and guidance for maintenance operations. Many utilization methods found effective in optimizing maintenance, such as integrating knowledge-based systems using ANN (Li, Yin et al., 2022), and Reinforcement learning (RL) in optimizing maintenance (Yao et al., 2020). This will overcome the current challenges of corrective and preventative approaches used in building and infrastructure assets.

5. Conclusion

This paper investigated the DT concept, definition, and characteristics as implemented in other advanced sectors and provided a fundamental understanding of the characteristics of the required

Digital Twin for the AEC industry. DT characteristics and types are identified and discussed along with critical features applicable to AEC. The current literature works were reviewed and evaluated. Three levels of DT based on enabled capabilities were introduced and described in this study. The results can help to develop a true Digital Twin in terms of automated building operation and predictive infrastructure maintenance in AEC, by integrating IoT, advanced modeling and simulation methods, predictions, decision support systems and automation. This study has limitations that could be addressed by future research. First, the study focused on conceptual aspects of DT implementation in AEC with limited focus on technical aspects. Second, only the most relevant publications in DT lifecycle phases were considered in this review.

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