CHAPTER 6

Digital Twins and Their Roles in Building Deep Renovation Life Cycle

Yuandong Pan, Zhiqi Hu, and Ioannis Brilakis

Abstract Digital twins have started to diffuse within architecture, engineering, construction, and operations (AECO), based on their emerging and anticipated benefits to the various stakeholders involved in the building life cycle. However, their applications are still at an early stage, and much effort is still needed to exploit their full potential. This chapter explains some key notions to help understand digital twins in AECO. It exposes the various definitions of digital twins and illustrates the basic steps and relevant methods for creating a digital twin. The chapter also provides an overview of the state-of-the-art deep learning methods for digital twins and discusses some real-life use cases. Finally, the chapter discusses the benefits and challenges associated with the adoption of digital twins.

Y. Pan
Technical University of Munich, Munich, Germany

Z. Hu (✉) • I. Brilakis
Construction Information Technology Laboratory (CIT Lab), University of Cambridge, Cambridge, UK
e-mail: zh334@cam.ac.uk

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6.1 Introduction

The construction sector remains one of the least digitised sectors. Digitalisation and automation can prove particularly valuable in overcoming a number of traditional challenges in architecture, engineering, construction, and operations (AECO). First, over half of the labour time is spent waiting for materials, equipment, and instructions on how to conduct the work during the construction stage, resulting in low productivity and shrinking profit margins. Second, many construction companies have suffered from underperforming projects, which leads to cost and schedule overruns and asset's quality issues. Third, many assets are designed for functional activities. Less consideration is given to their environmental impact leading to high carbon emissions and resource wastage. Fourth, due to skill shortage, it is difficult to recruit enough construction professionals, such as supervisors, estimators, and engineers, which exacerbates the issue related to delays, asset qualities, and safety.

Digital twin (DT) is an emerging technological paradigm for achieving smart buildings, infrastructure, and cities (Tao et al., 2019). DT applications can facilitate project management in the AECO sector by increasing productivity and efficiency. From manual drawings to computer-aided design, object-oriented design, and computational design, computer power is shaping the process of assets' construction and maintenance by encoding decision-makings through machine learning and other advanced technologies. This chapter aims to provide an overview of digital twins and their applications in the context of building renovation and discuss their main advantages, benefits, challenges, and barriers to adoption. The next section presents the definition of digital twins. The following section presents the main steps for creating a digital twin. This is followed by the presentation of a series of use cases and some concluding remarks on potential future developments.

6.2 What Is a Digital Twin

According to Tao et al. (2019), a DT consists of three main elements: a physical product, a virtual representation of the physical product, and the connection that links these two parts together and enables data exchange and information sharing. The physical product refers to the actual asset built in the real (physical) world, which can also be defined as physical twin (PT). It can be a residential or a commercial building, a hospital, a school, a bridge, and so on. The virtual representation refers to the digital replica of the physical asset, which can exist throughout its life cycle. This data can be accumulated over time and updated at different stages of a physical asset's lifetime. The connection that links these two parts can be considered as an information exchanger to store, link, and update all product and process information over time. A DT can serve as an information repository for storing and sharing an asset's properties throughout its life cycle (El Saddik, 2018).

According to Sacks et al. (2020), a DT is dynamic and thus can be enriched through different stages of an asset's life cycle. Figure 6.1 depicts a typical life cycle of an asset PT and its DT from the design stage, through the construction stage, to the operation stage.

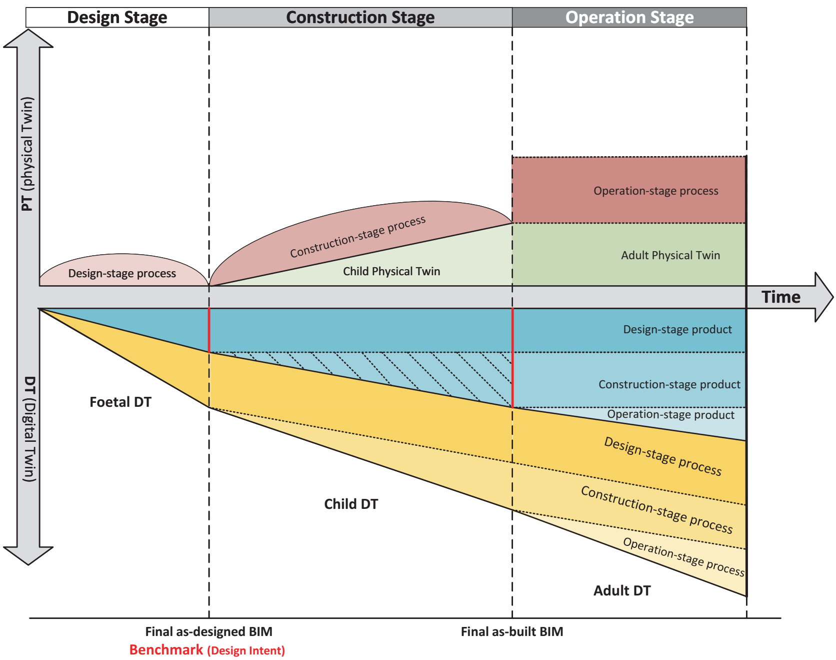

Fig. 6.1 A typical life cycle of an asset PT and its DT from the design, construction, to the operation stage

At the design stage, the asset's designers start working on the conceptual plan. The asset's foetal DT contains both product and process information, where the former refers to different as-designed building information models (BIMs).[1] Many of these models can be proposed at the beginning, but only the final client-approved design file at the end of the design stage can be marked as "Design Intent", which means it will serve as a benchmark for evaluating the construction outcomes and can be considered as a guidance for the purpose of maintenance.

At the construction stage, the child PT contains off-site prefabricated assemblies and on-site constructed components. Therefore, the child DT consists of as-built product information and as-performed process information to mirror the asset's physical status at different steps during the construction stage. It should be noted that the product information and the process information accumulate over time into the child DT until the completion of construction. Each change will be updated in the asset's child DT to reflect the as-is status and thus can facilitate progress monitoring and quality control.

Lastly, at the operation stage, the adult PT remains unchangeable status because of the completion of the construction. The asset's adult DT can support the analyses of performance, such as energy consumption and component maintenance. The collected data will be added to the as-maintained product to enrich the asset's adult DT. To conclude, an asset's DT should contain all information that represents the related physical information throughout its life cycle. Both the physical product and process will be assigned to the DT as a virtual copy throughout the asset's life cycle. Moreover, the logic of PT and DT can be extended to any type of physical entity, from small-scale manufactured objects to large-scale city-level objects. The product and process information contained in the DT should be determined by its purpose. Thus, a DT can be standardised and extensible to address current project management problems in the AECO sector.

6.3 Creating Digital Twins

As mentioned in the previous section, a DT contains product information and process information. A geometric DT (GDT) is fundamental as it is used to create links with process information during the asset's life cycle. Creating a GDT of an existing asset typically involves the following two

[1] Chapter 3 in this book provides a more detailed discussion on BIM.

steps: (1) capturing raw visual and spatial data in the form of RGB images and laser-scanned point clouds and (2) detecting geometric objects and relationships between objects. Step 1 of this process is significantly more automated than step 2, as shown by Agapaki and Brilakis (2021). Unfortunately, the effort and corresponding cost required to complete step 2 for most assets still represent a barrier to adoption as it may completely offset the value created by the geometric DT.

For data capturing (step 1), two major technologies are currently used to capture the geometry of an asset: laser scanning (terrestrial and mobile) and photogrammetry. The data generated should reflect the physical surfaces of objects in the real world. Due to the discrete nature of the capturing techniques, the data provided by scanners is also discrete. Laser scanners generate point clouds that are sets of points in a 3D space. Each point is defined by three coordinates and additional information depending on the device used, which could be intensity, normality, and colour information, among others.

As for step 2, detecting geometric objects and their geometric relationships is still a time-consuming manual task. Lu et al. (2019), for example, scanned ten different road bridges and estimated that approximately 28 hours of work are required, on average, for the as-is modelling in contrast to 2.82 hours for data capturing. A number of leading 3D CAD companies (Autodesk, Bentley, ClearEdge3D, etc.) have developed software products that provide a variety of 3D modelling features which enable modelling from point cloud data. Agapaki et al. (2018) suggest that 64% of man-hour savings can be achieved by using state-of-the-art software supporting a semi-automated modelling process. However, 2382 man-hours are still needed to model, for example, a small petrochemical plant with 240,687 objects and 53,834 pipes.

In order to reduce the human effort in creating a GDT, researchers have proposed a number of alternative approaches mostly focused on structural elements. Sanchez and Zakhor (2012) proposed a method that applies principal component analysis (PCA) and random sample consensus (RANSAC) to find relatively large-scale architectural structures, such as ceilings and floors. Monszpart et al. (2015) extracted planar structures in a point cloud that follows regularity constraints. They applied this approach in different scenarios, such as urban scenes, as well as the exterior and interior of buildings. Oesau et al. (2014) used horizontal slicing and then volumetric-cell labelling method. The volumetric cells are formulated as energy minimisation and solved by the graph-cut method. Xiao and

Furukawa (2014) proposed a method called "inverse constructive solid geometry (CSG)" which detects planar surfaces and subsequently fits the cuboid primitives to the point cloud. Ochmann et al. (2016) proposed a method that explicitly represents buildings as interconnected volumetric wall elements. They determined the optimal room and wall layout by graph-cut-based multi-label energy minimisation. A method named void-growing method by Pan et al. (2021) aims to extract void room spaces in the point cloud firstly and subsequently extract 3D models of different objects.

Other approaches leverage prior knowledge to reconstruct walls and rooms. Stambler and Huber (2015), for example, proposed the concept of enclosure reasoning that defines rooms as cycles of walls enclosing free interior space. Region growing is then applied to segment the point clouds, and simulated annealing is used to optimise rooms and walls. Tran et al. (2019) proposed a method called shape grammar to model indoor environments. They created 3D parametric models by placing cuboids into point clouds and classifying them into elements and spaces. The wall candidates are obtained from pairs of adjacent peaks in the histogram of point coordinates. Hu et al. (2022) provide a more in-depth review of this literature.

Deep learning (DL) is also widely applied to extract semantic information from spatial and visual data. VoxNet is proposed by Maturana and Scherer (2015) to detect classes of objects from point cloud data. It aims to predict a class label for the input. Volumetric grids representing the spatial occupancy are calculated first and then applied to 3D CNNs. Qi et al. (2017a) instead proposed the first neural network architecture, PointNet, designed for 3D deep learning in the point cloud. PointNet takes the point cloud as input and predicts labels for the entire input (point cloud classification) or labels for each point (point cloud segmentation). An improved version of the PointNet architecture called PointNet++ has then been presented by Qi et al. (2017b) and claims to provide better performance by considering spatial information of points in the point sets. These DL methods have been adopted in the AECO sector to facilitate GDT construction (Agapaki & Brilakis, 2020; Perez-Perez et al., 2021).

In summary, current approaches are still not fully automated, which means they still require human effort in the process of reconstruction. Their performance, especially when applied to a point cloud with high occlusions, would decrease due to the geometric occlusion of furniture. On the other hand, DL is an efficient and powerful tool that can be used to extract semantic information from the point cloud, but the lack of labelled data sets in the AECO domain causes difficulties with regard to training which in turn affects models' performance. In addition to this, the overall prediction performance differs significantly across categories, which makes it really hard to create a detailed GDT representing the current state of an asset when only considering the output of the DL methods.

6.4 Digital Twin Use Cases

There are several use cases of DT in the construction sector, including construction progress monitoring, facilities management and operation, asset condition monitoring, sustainable development, and more. DT can provide reliable and useful information during a building's life cycle to AECO stakeholders.

DT can be applied to any physical asset at any given time. For historical assets which have been completed many years or decades ago and do not yet have any digital records, DT can help to start and keep a record of their performance for better maintenance and renovation. For facilities under construction, a dynamic DT can support real-time progress monitoring, quality control, diagnostics, and prognostics. In addition, DT can also be used in the future for capital investment projects before the design and construction of the facility, as it provides an efficient way to simulate the performance of a building and aid the decision-making process.

The way the physical and the digital twins are synchronised in real use cases depends on the purpose of the DT, which also determines the content of DTs (i.e., the elements and processes to be digitised, the level of detail required, how frequent the model is supposed to be updated, etc.). As the concept of digital twins is broad, it is impractical to propose a precise and detailed definition of a digital twin that covers everything without considering its purpose. Some potential applications of DTs relevant to deep building renovations are presented hereafter.

Example 1: Condition Monitoring

A DT can be used to monitor the current condition of a building. By capturing geometric information through different sensors, the current condition of the asset can be visualised and represented by the DT. The geometry of facilities can be monitored by comparing the current condition with previous asset conditions over time, which allows a DT to give maintenance suggestions to the asset holders and managers (Hu et al., 2023).

Apart from monitoring the geometry change of a discrete asset, DT can also be used to monitor more complex large-scale systems, for example, the sewer system of a city. In this context, predictive maintenance operations can be utilised to identify potential blockages. Similarly, the current state of flow in pipes can be recorded and compared with the historical values to predict or locate disruptions in the system. Predictive maintenance recommendations or alerts can be sent to facility managers for more informed and timely decision-making.

Example 2: Facility Management
There is a very broad spectrum of facility operation, which includes but is not limited to operation management of mechanical, electrical, and plumbing (MEP) components in a facility (Z. Hu et al., 2016; Cheng et al., 2020), internal environment monitoring (Cao et al., 2015), and working productivity (Meerman et al., 2014). With the increasing adoption of the Internet of Things (IoT) and artificial intelligence (AI) which are key components supporting DTs, facility management is becoming more and more intelligent. Similarly, augmented reality (AR) and virtual reality (VR) can be used in conjunction with DT to visualise the built environment and improve efficiency (Baek et al., 2019; Chen et al., 2020; Chen et al., 2021; Zhang et al., 2020).

The concept of the digital twin is capable of embedding all these use cases in facility management according to the concept illustrated in Fig. 6.2. Relevant objects and values are captured and represented in a detailed digital model through capturing devices like laser scanners and cameras. By applying various IoT sensors such as thermometers, hygrometers, and carbon dioxide sensors, different values (like temperature, humidity, and carbon dioxide level) that represent internal environment conditions can be recorded and then updated in the digital model regularly. AI-relevant technologies can be used to help the process of creating the initial model as well as updating the model throughout a facility's life cycle. Facility managers can check the visually assistive information provided by AR and VR devices, which is able to lighten their workload and benefit working efficiency. From small-scale facilities, like offices, to large-scale urban environments, different sensors can be used to find how people exactly use these facilities and map occupant behaviour. With a better understanding of this data, the environmental conditions can be optimised, ultimately improving human wellness and living satisfaction.

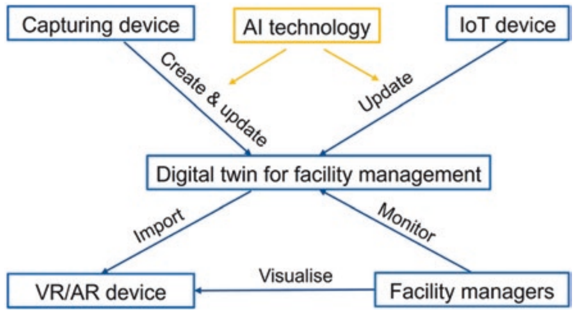

Fig. 6.2 Digital twin for facility management

Example 3: Environment Simulation
Digital twins can be used in the renovation phase of a project to simulate various scenarios without modifying the real asset. These scenarios can involve changing the natural light design, artificial lighting, heating simulation, and so forth. By only modifying facilities in the DT, the impact of these changes can be understood without implementing the modifications in the real world. VR/AR devices can make use of the DT to visualise the proposed designs and show the impact of changes and modifications (e.g., lighting). This improves the decision-making of renovation and enhances the communication between designers and clients. For instance, different lighting atmospheres can be visualised, helping designers to aesthetically assess the design and present the outcomes of the setup to their clients (Natephra et al., 2017).

6.5 Challenges to Digital Twin Adoption

Despite the fact that a DT is considered to offer benefits to all stakeholders of the built environment, some challenges hinder its adoption in real projects. Firstly, the effort involved in creating a digital twin is demanding, which undermines its feasibility and benefits. Many researchers are working on automating the process of digital twinning in the built environment in order to reduce human effort. The effort in the existing literature has been concentrated on reconstructing relatively large structural elements like ceilings, floors, and walls. MEP elements (such as fire alarms, emergency switches, etc.) should also be included in a DT, as these are essential elements for facility managers. In the repair and maintenance (R & M) activities of an asset, MEP costs usually constitute the largest share of the total cost (Adán et al., 2018). Therefore, a DT would be more valuable if it were to contain those elements. In addition, facility management also involves floor plans, space utilisation, asset location, and technical plants (D'Urso, 2011), which requires more accurate capture and modelling. Text information such as room numbers and serial numbers (IDs) of objects that can identify the corresponding asset instance is also beneficial, especially when managing large-scale facilities. These IDs represent the exact object instances in a facility and can be used to make the links between physical assets and DT much clearer. Currently, such activities are mainly performed manually in real projects. Some studies (e.g., Pan et al., 2022) in this area have started to emerge.

6.6 Conclusion and Future Direction

This chapter provides an overview of the background, definitions, generation, and applications of DT in the built environment generally and building renovation specifically. The state-of-the-art methods to create and update the geometry of digital twins were described. The potential applications of DTs, along with their advantages and current challenges, have been discussed with examples. The overarching conclusion is that DTs provide benefits and offer applications across the whole life cycle of built assets. Much research is still required to support the generation and the update of DTs, which is necessary to support the identified applications and unlock their respective benefits.

In the built environment, how to generate and update DTs precisely and efficiently to bring the benefits into real applications throughout the whole life cycle of a facility is still under research.

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