DIGITAL TWINS FOR SMART DECISION MAKING IN ASSET MANAGEMENT

Chady Elias & Raja R.A. Issa

Rinker School of Construction Management, University of Florida, USA

ABSTRACT: *This study discusses the classification of Digital Twins (DTs) and their use in the Architecture, Engineering, Construction, and Operations (AECO) industry, the differences between building information modeling (BIM) and DT are emphasized and platforms for implementing DTs are compared. DTs are quickly gaining traction in the AECO industry because they create the ability to interact virtually with all physical smart devices in the built environment. The need for replicas goes all the way back to the 1960s, when NASA created physical replicas of spaceships and connected them to simulators to develop workshop solutions on the ground. DTs are simply building blocks of the metaverse that act as a real-time digital copy of a physical object. Based on data from the physical asset or system, the physical twin (PT), a DT unlocks value in supporting smart decision-making by combining artificial intelligence (AI) with the internet of things (IoT).*

KEYWORDS: *Digital Twins; Internet of Things; Artificial Intelligence; Asset Management.*

1. INTRODUCTION

Digital Twins (DTs) are quickly gaining traction in the AECO industry are quickly becoming synonymous with smart cities because they create the ability to interact virtually with all physical smart devices. DTs allow us to integrate in a physical environment data and information on what is happening in that environment thus converting that physical environment into a virtual one, that can be used in real time, or in aggregate, to facilitate the analyses of physical spaces.

In the AECO industry, the focus on DTs has increased due to the proliferation of digitalization and integration processes. For example, there has been a marked growth in the development of Building Information Modeling (BIM), but while BIM has instigated the digitalization and integration of design and construction information, its utility for smart decision-making in the postconstruction stage is limited as the data and information captured in BIM outputs are static. Consequently, the need for technology that enables dynamic optimization of BIM data and operational data has grown. DTs have shown early promise in the AECO industry to elevate BIM from static to actionable and dynamic virtual models.

2. BACKGROUND

The path from building information modeling (BIM) to DTs involves the integration of multiple data sources (see Fig. 1).

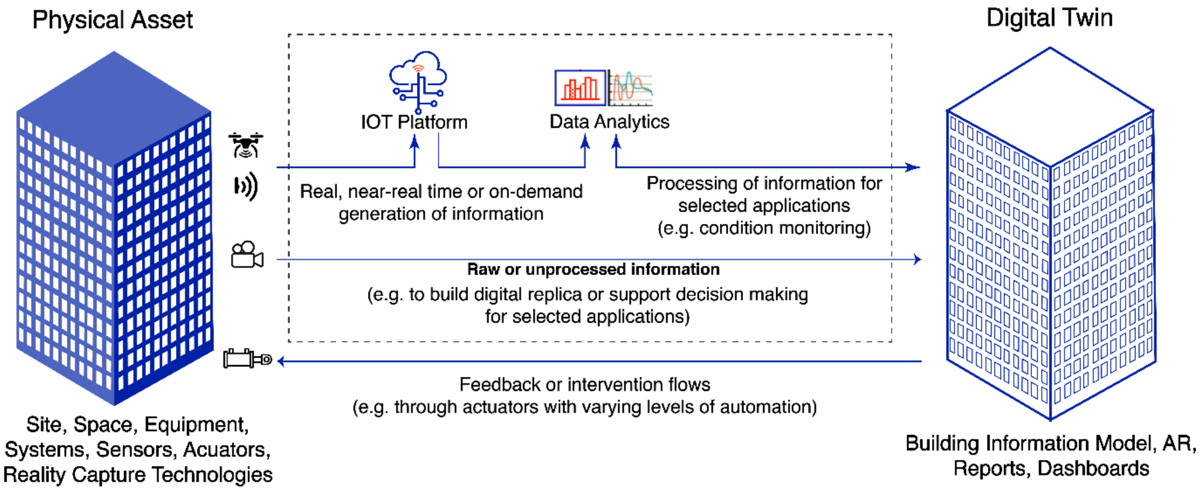

Fig. 1: Essential components to create a DT of a building (Adapted from Khajavi et al. 2019)

Referee List (DOI: 10.36253/fup_referee_list)
FUP Best Practice in Scholarly Publishing (DOI 10.36253/fup_best_practice)

Chady Elias, Raja Issa, *Digital Twins for Smart Decision Making in Asset Management*, pp. 1255-1260, © 2023 Author(s), CC BY NC 4.0, DOI 10.36253/979-12-215-0289-3.123

2.1 Building Information Modeling (BIM)

BIM as a digital technology continues to stimulate new workflows in the AECO industry. The capabilities of BIM to generate three-dimensional visualizations, and data rich models have resulted in its extension to facility lifecycle activities including facility management, operations and maintenance (O&M), commissioning and close-out, energy management, and space management, all key aspects of FM (Becerik-Gerber et al. 2012). Major progress has been made in the efficient transfer of design and construction data to FM systems, e.g., Computerized Maintenance Management Systems (CMMS), by using open standards, e.g., Construction Operation Building information exchange (COBie). Identification and specification of the required data during the facility design stage and requiring appropriate BIM deliverables is essential to developing models which are beneficial to facility managers. The data allows facility managers to analyze operational data while allowing owners a complete view of their assets (Asare et al. 2021).

Selecting the proper BIM level of development (LOD) is crucial in successfully developing a DT. The LODs for sharing building information models with project participants, as prescribed in the American Institute of Architects (AIA) E202 contract (AIA 2022), range from LOD 100 to LOD 500 (see Table 1). BIM, specifically the LOD 500 model, is the foundation of the Existence DT. The next step in the integration of BIM, FM and O&M lies in the development of DTs.

Table 1. AIA E202 LODs (AIA 2022)

§	Levels of Development (LOD)
4.2	**100:** The Model Element may be graphically represented in the Model with a symbol or other generic representation. but does not satisfy the requirements for LOD 200. Information related to the Model Element (e.g., cost per square foot. tonnage of HVAC, etc.) can be delivered from other Model Elements.
4.3	**200:** The Model Element is generically and graphically represented within the Model with approximate quantity, size, shape, location, and orientation.
4.4	**300:** The Model Element, as designed, is graphically represented within the Model such that its quantity, size, shape, location, and orientation can be measured.
4.4.1	**350:** The Model Element, as designed, is graphically represented within the Model such that its quantity, size, shape, location, orientation, and interfaces with adjacent or dependent Model Elements can be measured.
4.5	**400:** The Model Element is graphically represented within the Model with detail sufficient for fabrication, assembly, and installation.
4.6	**500:** The Model Element is a graphic representation of an existing or as-constructed condition developed through a combination of observation, field verification, or interpolation. The level of accuracy shall be noted or attached to the Model Element.

2.2 Internet of Things (IoT)

The internet of things (IoT) presents us with opportunities for transforming work and everyday life. The IoT is at the intersection of the physical and digital worlds, with all kinds of devices harnessing the power of interconnectivity to provide seamless experiences for businesses and consumers alike. To reach its full potential, IoT has to shift from continuing to provide incremental value amid siloed clusters to unlock its vast potential value as a fully interconnected IoT ecosystem. This will require an integrated IoT network within and across all industries. The main obstacle to be confronted is the cybersecurity risk which detrimentally impacts the trust needed to integrate IoT applications and networks. For smart cities, as with other applications, the expected solution lies in the merging of IoT and cybersecurity to form a new, integrated system (Greer et al. 2019).

2.3 Digital Twins (DTs)

A DT is comprised of three principal parts: a physical system in real space, the physical twin (PT); a virtual system in cyberspace, the DT; and the connection between real and cyber space for transferring data and information using cyber-physical systems and the internet of things (CPS/IoT). A DT creates an accurate digital model of the physical system in cyberspace that can accurately replicate and simulate the behavior of the PT. According to Tao et al. (2018), a DT can also provide a digital footprint of products by integrating geometry, structure, behavior, rules and functional properties. Salvador Palau et al. (2019) noted that DTs can also be considered as intelligent agents with prediction, communication, and data preprocessing capabilities.

Kritzinger et al. (2018) distinguished the various digital forms and categorized them as digital model, digital shadow and DT based on the automated dataflow between them (see Fig. 2). The Digital Model is a digital representation of an existing or planned physical object that does not use automated data exchange between the physical object and the digital object. Changes in the state of the physical object have no direct impact on the digital object and vice versa. The Digital Shadow is derived from the Digital Model and represents one-way data flow between the state of an existing physical object and a digital object. A change in state of the physical object leads to a change of state in the digital object, but not vice versa. The DT is characterized by automated bi-directional data flow between the physical and digital objects, which possess intelligence and decision-making capabilities that enable the automated feedback loop to the physical entity. A change in state of the physical object directly results in a change in state of the digital object and vice versa.

The combination of the PT and its corresponding DT is the fundamental building block of fully connected and flexible systems that are able to learn and adapt to new demands. Some of the DT roles include remote monitoring, predictive analytics, simulating future behavior, and optimization. To fulfil these roles, DTs rely on certain capabilities that exist across all of them. These required DT capabilities are summarized as follows (Redelinghuys et al. 2020):

- Acquire PT state - The DT must be able to acquire data from a variety of sensor types (e.g., temperature, pressure and vibration sensors and counters or PLC registers) from the PT. The PT sensor data collected is refined and enriched (e.g., through combination and adding context) into information sets that describe the state of the PT.

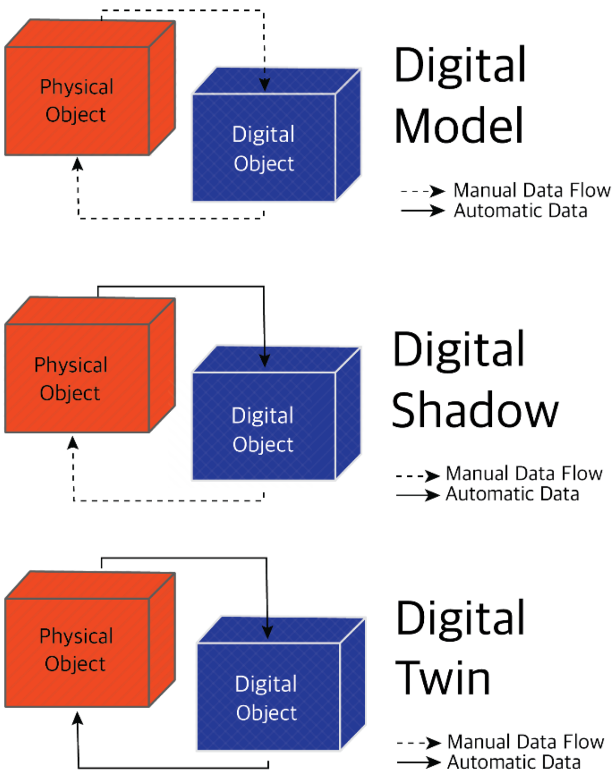

Fig. 2: Evolution from Digital Forms to Digital Twins (Adapted from Kritzinger et al. 2018).

- Maintain Information Repository - The state information obtained from the PT sensors is stored for easy access through the internet. This repository typically relies on Cloud-based storage, since large volumes of data may be stored for long periods of time.

- Simulate operation - The simulation of the PT's operation, i.e., predicting its future behavior from a given starting state and selected set of conditions, is required for some of the envisioned roles of the DT including the evaluation of new processes and different operation schedules.

- Emulate operation - Using emulation to imitate and visually represent or reproduce the action or function of the PT in real-time using feedback from embedded sensors.

Changes in the physical process will impact the digital world through the feedback of real-time embedded sensors and actuators. Using this data feedback, digital models can be used to interpret the behavior of machines or systems, and predict future state from real-time and historical data, as well as experience and knowledge. The core elements of a DT are the models and data. CPS, and the technologies required for developing CPS, are considered as a necessary foundation for implementing DTs.

Major challenges to adopting DTs include global connectivity, data integration and interoperability, data standardization, security and integrity, real-time performance and reliability, as well as barriers to its implementation and legacy system transformation (Attaran and Celik 2023). These challenges play a fundamental role in the development of DTs, as the connections between the PT and its corresponding DT typically rely on internet enabled connectivity.

3. CLASSIFICATIONS AND LEVELS OF MATURITY

There is not one single definition for what a DT is or the capabilities it provides. There are numerous types of DTs and levels of functionality based on the needs or the organization or project and the maturity of the data available. The development of a DT is a continuum, with the model evolving with the addition of new data and capabilities, the following classifications were developed by KPMG (2022) to indicate the level of functionality of the DT based on the types and level of data and capabilities that the system provides (see Figure 3):

- Existence twin: Furnishes principal project information, e.g., details on asset location and properties, enabling a single source of truth for asset data across the project. Traditional CAD and BIM systems are examples of an existence twin. This DT definition differs from that of the Kritzinger et al. (2018) classification of the evolution from digital forms to DTs.

- Status twin: Provides information on the status and condition of assets as detected by embedded IoT sensors. This can provide important insights into construction quality and progress, as well as asset health status over its lifecycle, and enables prediction of future performance based on the data collected.

- Operational twin: Allows for a real-time view of the project and the operational asset. This can provide critical insights into real-time performance and risks, both during construction and operations, and it enables more informed decision-making.

- Simulation twin: Enables teams to assess the impact of different design, construction, and operational decisions, allowing optimization of improvements in cost, performance, and risk. A simulation twin enables better and more thorough planning and can help minimize the risk of costly design and construction errors and faulty operational control changes.

- Cognitive twin: Uses AI and real-time data collection to analyze data, make decisions and optimize operational performance. This enables refinements made in real-time based on live data to adapt to existing conditions.

These classifications imply that an organization does not need to develop a highly advanced and complex model to see value from investing in DT technologies. For example, existence and status DTs can provide important project management insights on the physical configuration, properties, budget and cost, and as-built condition of a project and its component assets.

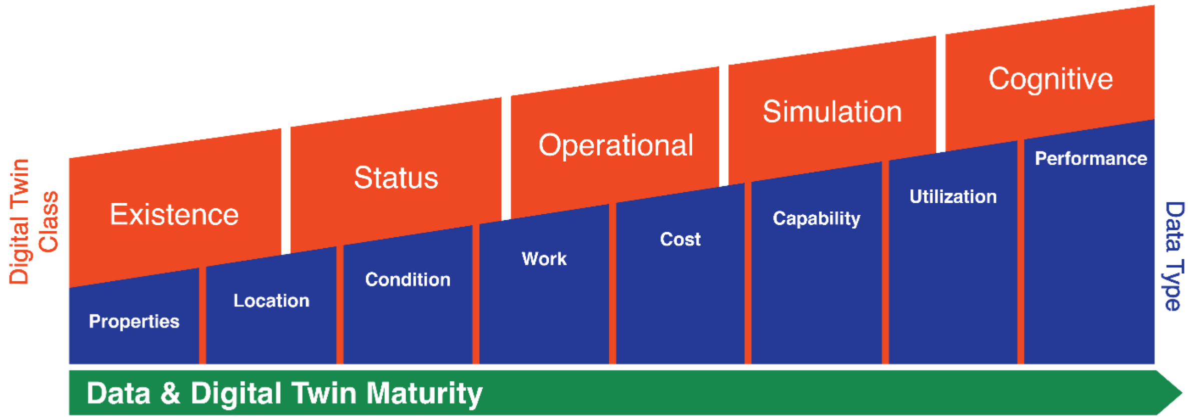

Figure 4. Data and DT Maturity (Adapted from KPMG 2022)

4. DIFFERENCES BETWEEN BIM AND DT

The building information model focuses on replicating the physical asset throughout the asset's lifecycle, while the DT replicates and enables a connection with the physical asset during operations. In BIM, there is total split between the digital and the physical asset, while, for DTs this split is distorted due to asset instrumentation and data synchronization between the physical and the digital asset. BIM is used in the three main phases of the built asset's lifecycle, design, build, and operations (Brilakis et al. 2019), while the DT is focused primarily on operations. These models have varying degrees of detail for their specific use-cases, i.e., built asset design, design-construction coordination, optimal asset delivery, and facility management. For DTs, there are no standard specifications for model detail or fidelity available. BIM has limited support for asset monitoring and control and for asset performance simulations during operations, while the DT does not consider discipline coordination for built asset delivery (Delgado and Oyedele 2021).

5. PLATFORMS FOR IMPLEMENTING DTs

There are three categories of data platforms for implementing DTs (Adamenko et al. 2020):

1. IoT Platforms: They provide data connectivity between the real and virtual world. Typically equipped with resources that establish connection between networked devices and the applications that process and/or visualize the data. Examples include Azure Digital Twins and IoT, Amazon Web Services IoT TwinMaker, Siemens MindSphere and Eclipse. DT design with such tools is more data-based. They provide a user interface (UI) for data modeling.

2. Gaming Engines: These platforms facilitate the development of executable video game-like applications. Their high-end visualization capabilities can be combined with IoT Platforms to achieve user-friendly DT applications. Examples include Unreal Engine, and Unity 3D. They require extensive programming to model DT data.

3. Commercial modeling and Simulation Platforms: These tools typically support design and implementation of system-based DTs. Examples include ANSYS, Autodesk Tandem, NVIDIA Omniverse, Microsoft Azure and Unreal Engine. They each provide a user interface (UI) for data modeling, e.g., Digital Twin Definition Language (DTDL) based on JSON-LD for Azure models, and the Universal Scene Description (USD) language for the Omniverse platform.

6. CONCLUSION

DTs provide a new outlook for smart decision-making in the AECO industry. From an operations and maintenance perspective, DTs can provide a dynamic view of facility status, enable operational control, support scenario planning and testing, and afford overall operational intelligence. To achieve high-performing DTs for smart decision-making, it is important to develop high-quality BIM outputs and supplement them with high-fidelity data. This requires a clear understanding of the different types of DTs, the tools for developing them, as well as knowing how and where to apply DTs. A macro-level roadmap to transforming BIM to DTs has been presented. As adoption of DTs increases, it is important to address the issues of standardization of DT design and implementation. This includes testing implementation tools and methods towards identifying the creation of DTs that can truly make decision-making in the AECO industry smarter.

REFERENCES

Adamenko, D., Kunnen, S., & Nagarajah, A. (2020a). Comparative Analysis of Platforms for Designing a Digital Twin. *In: Ivanov, V., Trojanowska, J., Pavlenko, I., Zajac, & J., Peraković, D. (eds.), Advances in Design, Simulation and Manufacturing III. DSMIE 2020.* Lecture Notes in Mechanical Engineering. Springer, Cham. https://doi.org/10.1007/978-3-030-50794-7_1.

American Institute of Architects (AIA) (2022). AIA Document E202™-2022: BIM Exhibit for Sharing Models with Project Participants.

Asare, K.A.B., Issa, R.R.A., Rui. L. & Anumba, C. (2021). "BIM for Facilities Management: Potential Legal Issues and Opportunities," Journal of Legal Affairs and Dispute Resolution in Engineering and Construction, 2021, 13(4), https://doi.org/10.1061/(ASCE)LA.1943-4170.0000502..

Attaran, A. & Celik, B. G. (2023). Digital Twin: Benefits, use cases, challenges, and opportunities, Decision Analytics Journal, 6, 100165, https://doi.org/10.1016/j.dajour.2023.100165.

Becerik-Gerber, B., F. Jazizadeh, N. Li, & G. Calis. 2012. "Application Areas and Data Requirements for BIM-Enabled Facilities Management." Journal of Construction Engineering and Management 138 (3): 431–42. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000433.

Brilakis, I., Pan, Y., Borrmann, A., Mayer, H.-G., Rhein, F., Vos, C., Pettinato, E., & Wagner, S. (2019). "Built Environment Digital Twining". International Workshop on Built Environment Digital Twinning presented by TUM Institute for Advanced Study and Siemens AG. https://doi.org/10.17863/CAM.65445.

Delgado, J. M. D. and Oyedele, L. (2021). Digital Twins for the built environment: Learning from conceptual and process models in manufacturing. Advanced Engineering Informatics, 49, 101332. https://doi.org/10.1016/j.aei.2021.101332.

Greer, C., Burns, M., Wollman, D., and Griffor, E. (2019). Cyber-physical systems and Internet of Things. National Institute of Standards and Technology (NIST) Special Publication 1900-202. https://doi.org/10.6028/NIST.SP1900-202.

Khajavi, S.H.; Motlagh, N.H.; Jaribion, A.; Werner, L.C.; Holmstrom, J. (2019). Digital Twin: Vision, Benefits, Boundaries, and Creation for Buildings. IEEE Access, 7, 147406-147419.

KPMG (2022). Insight report: Innovation & R&D in construction.

Kritzinger, W., Karner, M., Traar, G., Henjes, J., and Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine, 51(11), 1016-1022. https://doi.org/10.1016/j.ifacol.2018.08.474.

Redelinghuys, A.J.H., Basson, A.H. & Kruger, K. (2020). A six-layer architecture for the digital twin: a manufacturing case study implementation. Journal of Intelligent Manufacturing, 31, 1383-1402. https://doi.org/10.1007/s10845-019-01516-6.

Salvador Palau, A., Dhada, M. H., & Parlikad, A. K. (2019). Multiagent system architectures for collaborative prognostics. Journal of Intelligent Manufacturing, 30(8), 2999–3013.https://doi.org/10.1007/s10845-019-01478-9.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., and Sui, F. (2018). Digital twin-driven product design, manufacturing and service with big data. International Journal of Advanced Manufacturing Technology, 94(9-12), 3563–3576. https://doi.org/10.1007/s00170-017-0233-1.