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Digital Twin for Smart Buildings: Enabling Technologies, Lifecycle Applications, and Emerging Frontiers

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Abstract. Digital Twin (DT) is an advanced evolution of Building Information Modeling (BIM) that allows interactive data management throughout the life cycle of smart buildings. This systematic review aims to argue that the evolution from static BIM to interactive DTs can be described in five evolutionary stages due to the breakthroughs in data protocols, rendering, and interaction modalities. Furthermore, by leveraging IoT, real-time analytics, and AI, DTs can improve the simulation, monitoring, and optimization of the building's life cycle in the design, construction, and operation stages. This systematic review investigates the technological evolution from static BIM to interactive digital twins and discusses the supporting technologies, including open data protocols, real-time rendering, and immersive interaction modalities. This study also addresses the five main application areas, including collaborative design, construction supervision, and predictive maintenance, and discusses the existing challenges related to data interoperability, model accuracy, and cybersecurity. In the future, breakthroughs in AI, extended reality (XR), scalable platforms, and urban-scale digital twins will drive the development of this field. Looking forward, the review identifies that the combination of AI, extended reality (XR), and scalable platforms will drive the development of this field. Despite existing challenges, this systematic review argues that DTs will become a key enabler of digitalization in the AEC industry to achieve unprecedented levels of efficiency, sustainability, and intelligence.

Keywords: Digital Twin; BIM; Smart Building; IoT; Lifecycle Application.

1. Introduction

Digital twin (DT) technology, in which dynamic virtual doubles of real objects are set up in the AEC industry. From static 3D models to cyber-physical systems encompassing IoT, AI, and the cloud, DTs evolve to synchronize the virtual and the physical in real time for monitoring, simulation, prediction, and decision making during a building's entire lifecycle. This feature makes DTs a key to realizing substantial efficiency gains and sustainability objectives in the built environment.

The focus on sustainable development makes the application of digital twins (DTs) in smart buildings significant. With buildings responsible for nearly 40% of global energy use and one-third of greenhouse gas emissions, enhancing operational efficiency and reducing the environmental footprint is imperative. Smart-building DTs integrate BIM for static data and IoT for dynamic operations, offering significant potential for energy savings. However, semantic-level interoperability remains a major barrier to implementing advanced functions like autonomous control and predictive analytics. Although multi-layer and ontology-based frameworks have been proposed, they often lack robust validation in large-scale, real-world scenarios, and current applications are mostly restricted to visualization and basic monitoring. In the civil engineering domain, DT applications are expanding across design, construction, and operation [1,2]. At the design stage, DTs enable simulation-based optimization of building performance. During construction, they support real-time monitoring of processes, safety, and quality management [3]. In the operation phase, DTs contribute to energy management, facility maintenance, and structural health monitoring. Nevertheless, most of these implementations remain fragmented and lack unified frameworks, still grappling with fundamental challenges such as seamless data integration, maintaining high model fidelity without prohibitive computational cost, and ensuring scalability. This is particularly evident when compared with the more mature practices in aerospace and manufacturing. Existing reviews have underscored the need to resolve contradictions between model granularity and computational complexity, enhance multi-source data fusion, and establish collaborative mechanisms for the co-evolution of physical and digital systems.

To address these gaps and synthesize the fragmented knowledge, the present systematic review aims to synthesize the current state of DT development in civil engineering and smart buildings. Specifically, it examines conceptual models, implementation frameworks, and application scenarios reported in both international and Chinese literature. By mapping research progress, identifying gaps, and highlighting future directions such as AI-enabled DTs and standardized data frameworks, this study provides a structured foundation for advancing digital twin technology in the AEC industry.

2. The Technological Evolution: From Static BIM to Dynamic Digital Twins

Building Information Modeling (BIM) has served as the cornerstone of digital design and construction, and it is widely adopted across the architecture, engineering, and construction (AEC) industry. Traditional Building Information Modeling (BIM) only focuses on the static representation of geometric and semantic information of buildings. It is limited in the perception of real-time data and dynamic response, which cannot meet the requirements of smart building lifecycle management.

Against this background, the digital twin (DT) has been proposed as an extension of BIM. It enables the transition from static representation to a dynamic digital twin of buildings. With the support of Internet of Things (IoT), cloud computing, and real-time data integration, digital twin maps the operational state of buildings into virtual space. It establishes a closed-loop system between virtual and physical buildings and enables real-time interaction, simulation, and prediction. The evolutionary process from static BIM to integrated DTs can be categorized into five developmental stages. Each stage is characterized by different technological focuses and confronted with unique limitations, which are summarized in Table 1 before being discussed in detail in the following section.

2.1. A Stage-Based Framework for BIM-to-DT Evolution

The evolutionary process from static BIM to integrated DTs can be categorized into five developmental stages. Each stage is characterized by different technological focuses and is confronted with unique limitations.

Table 1. Stages of Technological Evolution from BIM to Digital Twin

Stage	Status/Maturity	Key Characteristics	Limitations
BIM Deepening	2019 - Present	Emphasizes 3D modeling and information integration, facilitating multidisciplinary collaborative design and clash detection.	Data silos persist; poor interoperability between different systems restricts information flow and sharing.
CIM (City Information Modeling)	Developing in parallel with BIM	Integrates GIS and IoT technologies to achieve city-scale data integration and visualization.	Lacks intelligent decision-making support and has weak multi-source data fusion capabilities, hindering real-time analysis of complex urban issues.
Twin Modeling	Current application phase	Establishes dynamic connections between physical entities and virtual models using IoT sensors and WebGL cloud rendering.	Analytical capacity remains limited, often restricted to monitoring and visualization, with insufficient capabilities for deep reasoning and optimization.
AI-Enabled Closed Loop	Emerging development phase	Incorporates big data, knowledge graphs, and AI algorithms to achieve energy optimization and predictive decision-making.	Practical implementations often remain conceptual without full-scale validation; the shift from passive monitoring to active intelligent control is not yet fully realized.
Low-Code Twin Operation	Future Vision	Aims to realize AI agent-hosted, low-code operational environments to reduce development and deployment thresholds.	A future vision focusing on ease of use, automation, and scalability; its technical pathway and industry adoption require further validation.

2.1.1. BIM dependency (2019–Present)

Aimed at maximizing the value of digital design models beyond mere documentation, the BIM deepening phase emphasizes 3D modeling and information integration, facilitating multidisciplinary collaborative design and clash detection. However, this stage is still plagued by data silos, where poor interoperability between different systems restricts information flow and sharing [4,5].

2.1.2. City information modeling (CIM).

To scale beyond individual buildings and address urban-scale challenges, CIM integrates GIS and IoT technologies to achieve city-scale data integration and visualization. Its limitations lie in the lack of intelligent decision-making support and weak multi-source data fusion capabilities, making it difficult to perform real-time analysis and response to complex urban issues.

2.1.3. Twin modeling.

To bridge the static digital model with the dynamic physical world, twin modeling utilizes IoT sensors and WebGL cloud rendering to establish dynamic connections between physical entities and virtual models. However, its current analytical capacity remains limited, often restricted to monitoring and visualization, with insufficient capabilities for deep reasoning and optimization [6].

2.1.4. AI-enabled closed loop.

To transition from passive monitoring and description to active, intelligent optimization, this stage incorporates big data, knowledge graphs, and AI algorithms to achieve energy optimization and predictive decision-making [7]. It marks a shift from passive monitoring to active, intelligent control, though practical implementations often remain conceptual without full-scale validation.

2.1.5. Low-code twin operation (up to 2025).

Seeking to democratize access and accelerate adoption by lowering the technical barriers to implementation, the future stage aims to realize AI agent-hosted, low-code operational environments, reducing the threshold for development and deployment. It emphasizes ease of use, automation, and scalability in digital twin applications.

2.2. Key Technical Support

Concurrent breakthroughs in several key enabling technologies have enabled the progression through these stages.

2.2.1. Evolution of data protocols: from closed files to open streaming services.

Early BIM relied on closed file formats (e.g., IFC, COBie) for data exchange, which hindered real-time synchronization. The adoption of lightweight, open streaming protocols such as MQTT, HTTP/HTTPS, and WebSocket has enabled real-time data transmission, supporting dynamic updates and semantic-level interoperability between heterogeneous systems.

2.2.2. Rendering technology: from offline to real-time web rendering.

Traditional offline rendering methods were time-consuming and unsuitable for interactive applications. The development of Web-based real-time rendering technologies, such as WebGL and cloud rendering, has enabled lightweight, platform-agnostic visualization, greatly enhancing the accessibility and user experience of digital twin platforms.

2.2.3. Interaction modalities.

Early interaction was limited to mouse and keyboard inputs within localized software environments. The integration of extended reality (XR), including virtual reality (VR), augmented reality (AR), and mixed reality (MR), combined with natural user interfaces (e.g., gesture and voice control), has enabled more immersive and intuitive interaction between users and digital twin models, thereby lowering the barrier to interaction and enabling more stakeholders to engage with the DT.

This evolution reflects a broader shift within the AEC industry toward cyber-physical systems, driving the convergence of BIM, IoT, AI, and cloud computing to support smarter, more responsive, and sustainable building environments. This evolutionary pathway, from static information models to dynamic, intelligent twins, encapsulates the ongoing digital transformation within the AEC sector.

3. Core Application Areas of Digital Twins in Smart Buildings

The value of Digital Twins is best demonstrated in the three life phases of a building: design, construction, and operation. This section summarizes how the use of DT technology affects the three phases of a building's life through the introduction of new capabilities. Digital Twin (DT) technology goes beyond the static digital twin (BIM) and uses data-driven and dynamic technology for the whole life of the building. DTs establish a two-way connection between the physical things and their digital twins and use them for the simulation, online monitoring, prediction, and optimization in the three phases of design, construction, and operation. Detailed review of the relevant work shows that both the research and application are gradually advancing toward all three phases [8,9].

3.1. Design Stage

At design time, DT applications include planning, concept design, detailed design, review design, and simulation [10]. DT technology aggregates detailed project information into a single model and supports communication between architects, structural engineers, and other MEP experts. This improves collaboration and minimizes misunderstandings due to limited or inconsistent data. That is, DT modifications due to a lack of data can be avoided. For instance, Lu et al. developed a semi-automated method to derive accurate geometric DTs from images and CAD drawings [11]. With this method, accurate 3D models can be rapidly generated. This approach shows how DT technology can accelerate 3D models created from legacy data and reduce initial model cost.

In addition, DTs usually cooperate with Virtual Reality (VR) and allow designers to locate potential problems and avoid design defects at an early stage. The virtual validation stage helps to avoid costly remedial actions and excessive drawing revisions during the construction phase. Enhanced simulation capabilities also accelerate design iterations and optimize final schemes. A notable example is provided by Matthias Flora et al., who developed a DT for underground infrastructure projects [12]. Their work exemplifies the use of DTs to synthesize complex, multi-source data (geological, machinery) for generating constructible designs, moving beyond passive visualization to active design generation. By incorporating geological data, site conditions, and construction machinery into the virtual model, they generated designs tailored for mechanized construction—substantially improving precision and efficiency.

Current research indicates a clear shift from theoretical exploration toward practical applications and integration, underscoring the growing maturity of DT use in the design stage.

3.2. Construction Stage

The construction stage, characterized by dynamicity and uncertainty, benefits from DT's ability to create a real-time digital counterpart of the jobsite. Research on DT applications during the construction stage primarily focuses on process supervision, quality and safety control, and the management of personnel, materials, and machinery [13].

3.2.1. Process supervision.

DTs enable intelligent and visualized monitoring. Liu Zhanhe et al. installed sensors on a double-layer inner-ring wheel-type cable truss during tensioning operations [14]. Real-time data were integrated into a DT platform and compared with theoretical simulations via similarity analysis, facilitating real-time decision-making and safety risk alerts. This method improved efficiency, reduced rework and errors, and enhanced information utilization compared to conventional approaches. Similarly, D. Gerhard et al. applied DT principles to monitor the production of high-performance precast concrete components, significantly improving the efficiency of modular construction [15].

3.2.2. Quality and safety control.

Emerging studies highlight the potential of DTs in construction safety and quality management. Xie Xianqi et al. proposed a new generation of intelligent DT-based quality and safety management systems, integrating product design, intelligent perception of project conditions, data-driven control, and dynamic monitoring [16]. Ha Tran et al. employed LiDAR-based DTs to automatically compare as-built 3D models of prefabricated facades with design models, ensuring geometric accuracy, completeness, and correctness [17].

3.2.3. Human, material and machinery management.

DTs overcome the static limitations of BIM by integrating real-time, dynamic site data, synchronizing physical and virtual systems. Xie Linlin et al. combined BIM, IoT, big data, and AI to develop an intelligent scheduling platform for prefabricated projects, enabling real-time interaction between physical and virtual environments to manage disruptions better and enhance scheduling autonomy [18]. Wang Xi et al. designed a VR-based DT system for human–robot collaboration, where humans focused on high-level planning and robots handled perception and execution tasks. Lee Dongmin et al. tested a traceable DT framework using IoT sensors for real-time BIM updates and blockchain to authenticate data transactions, ensuring reliable and transparent information sharing among stakeholders [19]. Collectively, these studies show that DT-driven management of human, material, and machinery resources leads to more responsive and autonomous project control.

Despite these advances, literature indicates that most current DT applications in construction remain at a primary level, often limited to model display and data visualization, rather than establishing a fully digital, integrated, and intelligent jobsite management framework [15]. Many applications are still experimental and lack validation in large-scale projects. Future research should prioritize the integration of multiple digital technologies and the development of comprehensive DT-based construction management platforms [10].

3.3. Operation and Maintenance (O&M) Stage

DT applications in the operation and maintenance (O&M) stage are extensive, covering equipment and facility management, maintenance, monitoring, energy optimization, and structural health monitoring [20]. By leveraging real-time data, DTs enable facility managers to make data-driven decisions, optimize building performance, maximize energy efficiency, and implement predictive maintenance strategies. For example, Lin et al. integrated BIM with Wireless Sensor Networks (WSN) by deploying sensors in an underground parking garage to monitor CO levels, temperature, and humidity [21]. The real-time data was visualized in the BIM model, establishing a preliminary DT for efficient environmental monitoring. Lu et al. proposed a novel data structure to automatically extract diagnostic information from a building's DT, thereby developing an automated asset management system for HVAC systems [22]. Xie Xiang et al. combined Augmented Reality (AR) with DT to design methods for automatic anomaly detection and fault isolation, supporting managers in addressing issues that affect occupant thermal comfort [20]. Shim Chang-Su et al. applied DT concepts to integrate a 3D model-based maintenance system with an image-processing-based digital inspection tool, establishing a reliable framework for the maintenance of prestressed concrete bridges [23]. These examples illustrate the diverse potential of DTs in O&M, from environmental monitoring to automated diagnostics and immersive maintenance support.

Despite these advances, challenges remain. One key issue is that O&M data is often acquired through reverse engineering with cloud technologies, rather than being seamlessly inherited from the construction phase, which restricts the DT's full potential [10]. Moreover, most practical applications are concentrated on large-scale infrastructure projects, where data completeness is insufficient to establish a robust physical–virtual connection. Future research should emphasize ensuring data continuity across lifecycle stages and strengthening the linkage between physical assets and their digital twins.

4. Challenges and Future Trends

Despite the significant potential and promising applications of Digital Twins (DTs) in smart buildings, their widespread adoption and maturation face several formidable challenges. These challenges, however, are actively being addressed by technological evolution, which is shaping clear future trends. Simultaneously, emerging technologies and evolving paradigms are shaping clear future trends for their development.

4.1. Current Challenges

4.1.1. Data interoperability and integration.

The foremost challenge lies in the seamless integration of heterogeneous data from disparate sources. BIM models (often based on IFC standards), IoT sensor data (using protocols like MQTT, LoRaWAN), and legacy systems (BMS, SCADA) operate on different semantics and protocols. This lack of standardized, semantic-level interoperability creates data silos, hinders the creation of a unified, high-fidelity digital twin, and complicates data exchange throughout the building lifecycle. This fundamentally undermines the core promise of a unified, holistic digital twin.

4.1.2. Model fidelity and computational complexity.

A tension exists between the desired high granularity and accuracy of the digital twin model and the associated computational cost and complexity. Highly detailed models require significant processing power for real-time simulation and analytics, posing challenges for scalability and practical implementation, especially for complex building portfolios. Thus, the digital twin often remains a static snapshot rather than a living, evolving entity.

4.1.3. Data continuity and lifecycle management.

There is a critical disconnect between data generated during design, construction, and operation. Often, the as-built DT is not effectively handed over for operational use, and operational data is not fed back to inform future design. This broken lifecycle data loop prevents the DT from realizing its full potential for continuous learning and optimization [10].

4.1.4. Privacy and cybersecurity.

DTs rely on continuous streams of sensitive data, including occupant behavior, energy consumption patterns, and building operational metrics. This raises significant concerns about data privacy, ownership, and vulnerability to cyber-attacks. Securing the entire DT ecosystem, from edge devices to the cloud platform, is paramount to ensuring trust and safety [18].

4.1.5. High implementation cost and ROI uncertainty.

The initial investment required for sensor deployment, platform development, data integration, and expertise can be prohibitive, particularly for existing buildings. The return on investment (ROI), while promising in the long term, can be difficult to quantify clearly in the short term, deterring stakeholders.

4.2. Future Trends

4.2.1. AI-Powered autonomous decision-making.

To overcome the limitations of current descriptive analytics and unlock predictive capabilities, the integration of Artificial Intelligence (AI) and Machine Learning (ML) will evolve DTs from descriptive and diagnostic tools to prescriptive and predictive systems. Future DTs will leverage AI algorithms not only for anomaly detection but for autonomous optimization of building systems (e.g., HVAC, lighting), predictive maintenance scheduling, and even real-time emergency response, moving towards self-healing and self-optimizing buildings.

4.2.2. Integration with extended reality (XR).

Aiming to bridge the digital-physical interaction gap and lower the expertise barrier for using complex DT data, the fusion of DT with Augmented Reality (AR) and Virtual Reality (VR) will revolutionize interaction paradigms. Facility managers will use AR glasses for immersive, overlay-guided maintenance, while designers and stakeholders will employ VR for immersive design reviews and operational training within the virtual twin before physical implementation.

4.2.3. Scalable platforms and standardized frameworks.

Directly tackling the interoperability and cost challenges, the future will see the rise of open, interoperable, and cloud-based DT platforms. These platforms will offer scalable services and advocate for standardized data models and APIs (e.g., evolving IFC standards to include IoT data), lowering the barrier to entry and facilitating easier integration of new technologies and data sources [10].

4.2.4. From single buildings to urban scale: supporting smart cities.

Moving beyond the scope of single buildings to address systemic efficiency challenges, DT technology will scale beyond individual buildings to encompass districts and entire cities (City Digital Twins). Building-level twins will become crucial nodes in a larger urban network, enabling city-wide simulations for energy grid optimization, traffic management, emergency evacuation planning, and holistic urban sustainability analysis [9].

4.2.5. Blockchain for data integrity and trust.

To establish trust and ensure data integrity in collaborative environments, Blockchain technology is anticipated to be integrated with DTs to create secure, transparent, and immutable records of all transactions and changes within the twin. This can enhance data provenance, ensure auditability for compliance, and secure collaborative workflows among multiple stakeholders.

5. Conclusion

Drawing upon a systematic analysis of the literature, this review has charted the evolution and application of Digital Twin (DT) technology within the smart building domain. This review synthesizes the current state of Digital Twin (DT) technology in smart building development, highlighting its shift from static BIM models to dynamic cyber-physical systems integrated with IoT, AI, and real-time analytics. Research demonstrates DTs' value across the building lifecycle: enabling collaborative design and simulation, enhancing real-time monitoring and control during construction, and supporting predictive maintenance and energy optimization in operation. However, the path to maturity is impeded by persistent challenges. These include, but are not limited to, issues of data interoperability, model fidelity-complexity trade-offs, lifecycle data discontinuity, and cybersecurity risks. The resolution of these challenges is intrinsically linked to the emerging trends identified, such as leveraging AI for autonomous decision-making, integrating AR/VR for immersive interaction, developing standardized open platforms to lower barriers to entry, and scaling DTs for smart city integration.

In sum, while DT applications in the AEC industry are still maturing, their potential to improve efficiency, sustainability, and intelligence in smart buildings is undeniable, positioning DTs not merely as a technological tool but as a fundamental enabler of a more resilient, sustainable, and intelligent built environment. This review has contributed to the field by synthesizing the current state-of-the-art, framing the evolution from BIM to DT as a staged process, and mapping the core applications across the building lifecycle. By doing so, it provides a structured foundation and clear roadmap for researchers and practitioners alike to advance digital twin technology.

References

[1] Eneyew, Dagimawi D., Miriam AM Capretz, and Girma T. Bitsuamlak. Toward smart-building digital twins: BIM and IoT data integration. IEEE Access, 2022, 10: 130487 - 130506.

[2] Sepasgozar, Samad ME, et al. BIM and digital twin for development convergence technologies as the future of digital construction. Buildings, 2023, 13 (2): 441.

[3] Baghalzadeh Shishehgarkhaneh, Milad, et al. Internet of Things (IoT), Building Information Modeling (BIM), and Digital Twin (DT) in the construction industry: A review, bibliometric, and network analysis. Buildings, 2022, 12 (10): 1503.

[4] Tang, Shu, et al. A review of building information modeling (BIM) and the internet of things (IoT) devices integration: Present status and future trends. Automation in construction, 2019, 101: 127 - 139.

[5] Omrany, Hossein, et al. The uptake of City Information Modeling (CIM): A comprehensive review of current implementations, challenges and future outlook. Smart and Sustainable Built Environment, 2023, 12 (5): 1090 - 1116.

[6] Boje, Calin, et al. Towards a semantic Construction Digital Twin: Directions for future research. Automation in construction, 2020, 114: 103179.

[7] Ranawaka, Ama, et al. Leveraging the Synergy of Digital Twins and Artificial Intelligence for Sustainable Power Grids: A Scopus Review. Energies, 2024, 17 (21): 5342

[8] Jiang, Feng, et al. Digital twin and its implementations in the civil engineering sector. Automation in Construction, 2021, 130: 103838.

[9] Opoku, De-Graft Joe, et al. Digital twin application in the construction industry: A literature review. Journal of Building Engineering, 2021, 40: 102726.

[10] Liu Gang, Ma Zhiliang, Zeng Bo, Tan Xiao, Song Yinyuan. A Review on the Application of Digital Twin Technology in Construction Engineering. Journal of Information Technology in Civil Engineering and Architecture, 2023, 15 (6), 1 - 8.

[11] Lu, Qiuchen, et al. Semi-automatic geometric digital twinning for existing buildings based on images and CAD drawings. Automation in Construction, 2020, 115: 103183.

[12] Flora, Matthias, Georg Fröch, and Werner Gächter. Optimierung des Baumanagements im Untertagebau mittels digitaler Infrastruktur-Informationsmodelle. Bautechnik, 2020, 97 (11): 780 - 788.

[13] Zhang, Ye, et al. Digital twin in computational design and robotic construction of wooden architecture. Advances in Civil Engineering, 2021, (1): 8898997.

[14] Liu Zhanhe, Shi Guoliang, Sun Jiajia. Digital Twin Technology and Its Application in Intelligent Construction. Industrial Construction, 2021, 51 (3), 184 - 192.

[15] Gerhard, Detlef, Matthias Neges, and Mario Wolf. Transfer of digital twin concepts to the production of precast concrete parts in the construction industry. ZWF Zeitschrift fuer Wirtschaftlichen Fabrikbetrieb 115 (2020): 58 - 61.

[16] Xie Xianqi, Deng Liming, Xiao Mingzhao, et al. Research on the Development of a New Generation of Construction Quality and Safety Management. Strategic Study of CAE, 2021, 23 (4), 71 - 78.

[17] Tran, Ha, et al. A digital twin approach for geometric quality assessment of as-built prefabricated façades. Journal of Building Engineering, 2021, 41: 102377.

[18] Xie Linlin, Chen Yajiao. Research on an Intelligent Scheduling Management Platform for Prefabricated Construction Projects Based on BIM and Digital Twin Technology. Construction Economics, 2020, 41 (9), 44 - 48.

[19] Lee, Dongmin, et al. Integrated digital twin and blockchain framework to support accountable information sharing in construction projects. Automation in construction, 2021, 127: 103688.

[20] Khajavi, Siavash H., et al. Digital twin: vision, benefits, boundaries, and creation for buildings. IEEE Access, 2019, 7: 147406 - 147419.

[21] Lin, Yu-Cheng, and Weng-Fong Cheung. Internet of Things (IoT) and internet-enabled physical devices for Construction 4.0. Construction 4.0. Routledge, 2020, 350 - 369.

[22] Lu, Qiuchen, et al. Activity theory-based analysis of BIM implementation in building O&M and first response. Automation in Construction, 2018, 85: 317 - 332.

[23] Shim, Chang-Su, et al. Development of a bridge maintenance system for prestressed concrete bridges using 3D digital twin model. Structure and Infrastructure Engineering, 2019, 15 (10): 1319 - 1332.