Digital Twins of Smart Buildings: Technical Solutions and Challenges

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***Abstract*—Digital Twins (DTs) have emerged as a critical technology for enhancing the management and optimization of buildings, enabling real-time monitoring, predictive maintenance, and energy efficiency through the integration of Internet of Things (IoT) sensors and advanced data analytics. In the context of smart buildings, in particular, DTs are essential in bringing the best architectural practices for real-time processing of sensor data, building information models, and supporting efficient operation, energy management, and occupant comfort. This paper critically examines recent advancements in applications of sensor-driven DTs for smart buildings, and highlights the main aspects of their technical solutions, including types of sensors, use-case problems, visualization approaches, as well as continuously present challenges in these applications.**

***Index Terms*—Digital twins, smart buildings, visualization.**

I. Introduction

Digital Twins (DTs) are digital replicas of physical systems that synchronize with real-world data via smart sensor devices, mathematical models, and real-time data analysis to predict and optimize their behavior [1]. By combining data integration, visualization, and analysis, they enable real-time monitoring and insights [2]. Smart buildings are physical infrastructures equipped with interconnected systems and sensors to enhance operational efficiency [3], environmental performance, and occupant comfort. They are designed to provide an efficient environment for easy operation and management of residential and commercial areas [4]. They are used to improve building energy efficiency, allowing managers to receive real-time data on various energy metrics of their buildings and act on them. Ongoing research explores how DTs can further enhance such capabilities by taking advantage of a stronger level of building representation along with control capabilities. As the complexity and volume of building data grow, visualization also becomes an essential component of DTs [5]. From dashboards displaying energy consumption to 3D models reflecting real-time room usage, visualization techniques play a central role in helping stakeholders understand, interact with, and make decisions based on the building's digital counterpart.

The main goal of this study is to investigate existing use cases of sensor-driven *digital twins for smart buildings (SBDTs)*, and create an overview of the range of practically-available applications of SBDTs. We consider a diverse range of residential and recreational buildings that were modeled or used in a DT, with some examples being: an industrial plant room [6], an airport [7], an operating room of a healthcare facility [8], a cultural heritage building [9] and university buildings [10]. The physical and functional characteristics of the building are usually represented digitally in BIM data.

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To achieve the main goal, we address the following sub-questions: (i) what sensors types are commonly used? (ii) what specific problem or use cases are addressed? (iii) what models, tools, or applications are used to solve these problems? (iv) what visualization approaches are employed? (v) what challenges are commonly faced in the process? While not providing an exhaustive overview of all available work on SBDTs, due to the fast-moving field and the variety of used terms, we nevertheless present a number of representative studies, to illustrate each considered aspect.

II. Related Work

Recent advances in sensor technology, data analytics, and AI-driven modeling have sustained growing interest in the development of SBDTs for improved sensor data analytics.

Eneyew et al. [11] addressed interoperability problems, where data from Building Information Modeling (BIM) and the Internet of Things (IoT) are rarely easily integrated, exchanged, or utilized across different platforms and applications. An ontology based on RDF triples was created for quick analysis and monitoring of the incoming sensor data.

Rane et al. [12] reviewed a crossover between Artificial Intelligence (AI) and IoT in Architecture, Engineering, and Construction (AEC) area, finding a variety of used sensors. Environmental monitoring sensors measure air quality, noise levels, temperature, etc. for safety and well-being on the job site. Structural health monitoring sensors allow for the early detection of structural anomalies, such as vibrations and deformations in the material. Asset tracking could monitor inventory, prevent theft, and optimize resource allocation. The computer vision and light detection and range (LiDAR) sensors are usable as visual input to AI models.

Latifah et al. [13] conducted a review of energy efficiency models for smart buildings, highlighting the importance of simulations based on outdoor and indoor façade temperature supported by Machine Learning (ML) models. They highlighted the role of sensing systems that measure energy efficiency, living cost, human comfort, and occupant productivity.

The application of BIM in the building lifecycle was emphasized, from the pre-construction design, verification phase, and post-construction facility management, demonstrating the importance of digital building representations. Um-e-Habiba et al. [14] noted that occupant comfort needs to be carefully balanced with energy efficiency, which is done through a process called Occupant-Centric Control (OCC). OCC systems adjust HVAC systems based on the preferences and behaviors of the individual occupants. However, this is rather complex due to the large variety in occupant preferences, and they suggested control solutions that utilize real-time feedback mechanisms, such as real-time energy usage simulation and optimization that can also be used for the early detection of faults. Notable issues were complexity trade-offs and interoperability on the side of buildings, as AI control-based strategies were generally not robust or scalable across different buildings.

Deng et al. [15] focused on the evolution of intelligent building representations in the AEC industry through BIMs and DTs. They showed that DT-based real-time energy monitoring led to increased energy efficiency through improved decisions about the control of lighting and HVAC systems, predicting energy consumption, and optimizing building performance. Using weather data improved accuracy of energy simulations. Building Automation Systems (BAS) are created and integrated with BIM to automate HVAC systems to improve efficiency in a flexible approach that can still work during peak hours. The challenges encountered were interoperability, a lack of real-time simulations and predictions for more accurate decisions, and more automated feedback and control.

III. Smart Building Digital Twins

This section describes the main aspects of SBDTs in four areas of interest: types of sensors, types of problems, the solutions used, and the visualization approaches.

A. Types of Sensors

Sensors support important contextual building information. Table I shows the various sensors used, grouped into categories. *Environmental monitoring* covers sensors that measure general data about the building, such as temperature or humidity. *HVAC systems* regulate indoor temperature, humidity, and air quality in the building, sensors are used on HVAC systems, focusing on its working operation, such as its vibrations to water flow. Some research used more specialized *air quality and safety* sensors that have domain-specific usage. Motion sensors or low-resolution cameras have been used to measure *occupancy* and maintain occupant privacy. Fire-related safety sensors have also been used by specialized temperature sensors in vulnerable areas. *Structural health* was estimated by measuring the vibrations of certain parts of the building.

B. Problems addressed and use-cases

Sensor data from buildings and IoT devices are aggregated to support specific use cases. The categorized applications are summarized in Table II. *Preventive maintenance*, such as fault detection, is used on building systems, e.g. HVAC, to reduce costs and downtime. *Energy optimization* reduces energy usage, whilst maintaining occupant comfort. *Air quality and safety* addressed domain-specific problems such as in a healthcare facility that aimed to maintain a sterile environment and safe working conditions. Fire safety addressed a different domain-specific problem aimed at decreasing vulnerabilities to fire-related incidents. Climate change adaptation was used to adapt the systems of a building to long-term external changes. Finally, *structural monitoring* and preservation covered research that aimed at preserving the integrity of the building.

TABLE I
SENSOR CATEGORIES

Sensor Category	Specific Sensors	Representative Studies
Environmental Monitoring	Temperature, Humidity, Airflow	[6], [16], [7], [8], [9], [17], [10], [18], [19]
HVAC and Energy Systems	Power, Pressure, Flow (cooling systems), Energy consumption	[6], [16], [10], [20]
Air Quality and Safety	Particulate contamination, Nitrous oxide, carbon dioxide, air quality (general), Pollution	[8], [9], [7], [21]
Occupancy sensing and feedback	Motion sensors, privacy-preserving sensors (low-res cameras, heat maps), occupant feedback	[7], [22], [10]
Building health	Temperature (fire-related), Heat generation sensors, structural health	[22], [7], [23]

C. Solutions used

To address the aforementioned problems, various technical solutions were applied, as shown in Table III.

Anomaly and change detection algorithms were successfully used for problems such as predictive maintenance. Algorithms such as Bayesian online change point detection could detect anomalies and changes in vibrations of an HVAC system [6].

Industry Foundation Classes (IFC) are a widely used open standard for *data exchange* in AEC industries to tackle *interoperability problems* and improve compatibility and standardization [7]. This is especially useful for SBDTs, where heterogeneous sensor data often require transformation to integrate with BIM. For this purpose, Hosamo et al. [10] used ontologies as a formal representation of domain knowledge that defines a set of entities and their relationships.

Kritzinger et al. [24] discussed the ability of DTs to influence the object they are modeling, thus focusing on the *control and optimization* aspect. Genkin et al. [17] introduced an autonomic control loop, a cyclical framework that continuously applied changes to the system to optimize energy usage. Zahid et al. [18] created DynamicPMV, a variant of the predicted mean vote that calculates the optimal temperature using the feedback of the occupants for each enclosed space at a time, while improving energy efficiency. On the other hand, some solutions provide frameworks or algorithms without the full-featured control loop. Liu et al. [22] created an overview of a

TABLE II
PROBLEM CATEGORIES

Problem Category	Specific Problems	Representative Studies
Preventive maintenance	Fault detection and diagnosis in building systems, predicting maintenance repairs, condition prediction	[16], [22], [17], [10], [20]
Energy Optimization	More efficient energy usage whilst maintaining occupant comfort, adapting building systems to climate change	[7], [22], [17], [10], [18], [19]
Air Quality and Safety	Room air quality, sterile environment maintenance, anesthetic gas control, fire safety monitoring	[8], [21], [22]
Structural Monitoring & Preservation	Real-time monitoring, predictive preservation, 3D modeling/simulation	[9], [23]

TABLE III
SOLUTION CATEGORIES

Solution Category	Specific Solutions/Applications	Representative Studies
Anomaly and Change Detection Algorithms	Bayesian online change point detection, Bag of Words feature extraction, Symbolic Aggregate Approximation, Kullback-Leibler Divergence	[6], [16], [10]
Data integration and modeling	Ontology, Industry Foundation Classes schema	[10], [6], [16], [7], [23]
Control and Optimization	Autonomic Control Loops, Predicted mean vote, ML to feed control decisions	[17], [18], [22]
Machine Learning Models	SVM, Random Forest, ANNs, Bayesian networks, XGBoost, Remaining Useful Life, Predictive ML for maintenance	[7], [9], [22], [10], [20], [21], [19]
Data Visualization & Monitoring	Power BI dashboards with threshold-based alerts, KPIs for various metrics, Autodesk Revit for visualization	[8], [9], [6], [7], [23]
Signal Processing and data cleaning	Digital Signal Processing to denoise sensor data	[23]

variety of solutions that can be utilized for human-in-the-loop-centric controls but do not control the environment themselves.

ML models, trained on historical sensor data, were used for energy efficiency, predictive maintenance, air quality and safety, and structural health maintenance. Hosamo et al. [10] used the remaining useful life of HVAC units to dynamically schedule maintenance. These models were able to predict and prevent potential issues, leading to improved outcomes in the system's lifespan. Elarwady et al. [19] used Prophet time series model to predict thermal comfort based on standardized thermal comfort models, created using international standards such as ASHRAE Standard 55 and ISO 7730, tuned based on expected levels of clothing insulation.

Another strong feature of integrating BIM data with sensor data is the ability to have a detailed *visual overview* of the building. This is usually done with Power BI or Autodesk Revit, with Power BI allowing more focus to be placed on displaying data aggregations and KPIs for various metrics, while Autodesk Revit was used to create and display a real-time 3D visual of the building. Visualization approaches are investigated in detail in Section III-D.

Hu et al. [23] utilized *signal processing* to denoise sensor data in sensitive settings such as measuring structural building health metrics using laser distance sensor data. Two kinds of transforms, the wavelet transform and the fast Fourier transform, were found to be effective at the denoising task.

D. Visualization approaches

Visualization plays a crucial role in making complex building data interpretable and actionable for technical and non-technical users. It can directly influence decision-making efficiency, system transparency, and user engagement. Moreover, visualizations serve as a bridge between different stakeholders: facility managers, technical staff, and end-users each interpret and use building data differently. This diversity imposes high demands on visual tools to be not only functionally complete, but also tailored to the needs and mental models of their target users. The visualization process involves gathering and aggregating data from diverse sources and converting the raw attributes and conditions of physical environments into accessible and understandable representations. Table IV lists the commonly visualized SBDT data types, their acquisition methods, and studies involved. *Environmental data*, such as temperature, humidity, and wind conditions, is the most common data type for visualizations, supporting indoor environment analysis and device management. *Spatial and structural data*, including room width, height, and spatial locations, can be extracted from CAD planning drawings or BIM models. It is often utilized to support navigation and room-level analysis. *Equipment specification data*, involving the physical information of facilities and sensors, is visualized to improve the process management and system diagnostics. *Occupancy and people flow data* is often inferred from motion sensors or scheduling systems, are visualized to facilitate the control of movements and the optimization of space.

To present these data types, visualization techniques transform raw information into meaningful and interpretable representations. At application layer, techniques can be classified by their visualization forms and interaction types respectively. Table V shows the forms of visualization used to represent building-related data, along with relevant studies. *2D Visualization* typically represents data using line charts, dashboards, or heat maps. *3D visualization* presents building structures and spatial layouts, often realized through modeling tools such as Three.js and Blender. *Map-based visualization* can provide additional urban context information to support high-level spatial analysis. *Immersive visualization*, including Augmented, Virtual and Mixed Reality, enable users to explore and navigate in virtual environments and interact with building components or sensor feedback in a highly engaging manner. These techniques are increasingly used to enhance spatial understanding, training, and system navigation in SBDTs.

Visualization techniques can be categorized into three in-

TABLE IV
DATA TYPES FOR VISUALIZATION

Data Category	Typical Data Instances	Data Source	Representative Studies
Environmental Sensor and Energy Data	Temperature, humidity, wind velocity, wind direction, water consumption, electricity usage	Building sensors, IoT devices, building systems, HVAC systems	[25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38]
Spatial and Structural Data	Room width, height, spatial location	CAD files, BIM models	[25], [27], [39], [40], [30], [31], [36], [37], [38], [41]
Equipment Specification Data	Distribution cabinet, HD camera, intelligent sensors	Equipment specifications and technical documents	[25], [39], [40], [36], [38], [41]
Occupancy and Human Movement Data	Occupancy rates, classroom and meeting room usage	Inferred from vibration sensors, motion detection, scheduling logs	[29], [37], [42]

TABLE V
VISUALIZATION FORMS

Visualization Form	Example Tools	Representative Studies
2D Visualization	HTML for line chart, dashboard, heat map	[26], [27], [28], [30], [32], [35], [37]
3D Visualization	OsmbuildingJS, Blender	[25], [26], [39], [40], [30], [34], [36], [38]
Map-based Visualization	OpenStreetMap	[43], [44], [28], [31]
Immersive Visualization (AR/VR/MR)	Microsoft HoloLens	[31], [34], [38], [41]

teraction levels: static, interactive, and real-time. *Static visualization* [33] provides fixed, non-interactive representations of data, and thus it is less commonly used due to its limited functionality. *Interactive visualization* [28] allows the engagement of user with data through actions such as clicking, zooming, or selecting. With continuously updating live data from sensors or building systems, *real-time visualization* allows users to observe changes with minimal latency and supports continuous monitoring and responsive analysis [40].

Visualization in SBDTs is applied across a range of application areas. E.g., in smart campus scenarios it supports space utilization and occupancy monitoring across lecture halls, meeting rooms, and public spaces. Interactive dashboards and map-based crowd layouts are not only effective for optimizing scheduling and identifying underused or overcrowded areas but also prove useful in managing public health scenarios, such as controlling infection spread. In the context of facilities and asset monitoring, visualization provides real-time insight into the operational status of building systems and equipment. This helps to detect malfunctions and schedule preventive maintenance, reducing operational downtime and ensuring service continuity. Visualization of energy data allows users to track, evaluate, and optimize energy usage. Within DT frameworks, it further incorporates predictive features by combining environmental sensor inputs with historical usage patterns to forecast energy demand and support informed decision-making. Visualization can also serve as an interactive communication tool between the system and its users to improve usability, situational awareness, and user engagement. Lastly, visualization can enhance model-building accuracy during the initial construction, by enabling comparison between BIM data, as-built conditions, and live feedback.

IV. CHALLENGES

Smart buildings face a wide range of challenges, many of them recurring across the industry.

Integration continues to be a challenge. This is often addressed through the creation of an integration model, e.g. by creating an ontology or by utilizing IFC schemas. Abdelalim et al. [7] noted that creating the integration of BIM, IoT, and DT required significant programming expertise and trial-and-error. Harode et al. [8] in their integration process linked each sensor data to a unique object ID, which would require a lot of work if needed to be done for hundreds of other buildings.

Another common challenge is *quality issues of real-time data*, such as data loss, network latency, storage bottlenecks, errors in an automated integration process. Hu et al. [23] focused on improving the sensor update frequency to 5 times per second, which they believed is necessary for accurate real-time monitoring and decision-making. There were also challenges related to the complexity and maintenance of the models used. Abdelalim et al. [7] found that as real-time data evolves, AI models require retraining to maintain accuracy, a phenomenon known as concept drift. This extra specification requires more complicated infrastructure and challenge systems as conditions change. Some solutions used non-connected models, worked only with historical data, or were unable to utilize real-time data in general, instead providing a framework and testing on historical data, which shows the difficulty in creating true DTs.

Many investigated systems do not have a *fully-automatic control mechanism* that can directly change the environment of the building based on the real-time context data, instead relying on manual intervention. Such solutions are closer to Digital Shadows, rather than DTs. This limits the scalability and adoption and requires continuous involvement of domain experts rather than enabling automated decision-making processes. An architectural roadmap on how to bridge the gap toward fully autonomous control is needed. However, the reasons preventing the full adoption of automation extend beyond the technical realm. Ramsauer et al. [45] point out the complexity of the task of ensuring human comfort. In case of dissatisfaction, facility managers have to manually adjust badly designed automated behavior, which can become an unwieldy time-consuming task.

Occupant comfort is a common challenge, due to a large number of factors that affect the degree of comfort, such as age and physical condition of the occupants. Hosamo et al. [10] noted the difficulties in measuring many of these factors. Liu et al. [22] analyzed that taking into account the diversity of occupant behaviors makes it difficult to create control solutions that can match the needs of all occupants, while also reducing energy usage. They suggested that occupants may have limited awareness of their energy consumption and how their behavior impacts it. Occupant comfort is difficult to measure, whilst also maintaining privacy of the occupants. Liu et al. [22] recommended addressing privacy concerns through the use of fuzzy information such as low-resolution cameras and heat maps, or adding noise to the data.

Scalability of systems to larger or more complex buildings introduces further complications [34], [46]. Manual configuration for each sensor-object mapping or data node becomes infeasible at scale [47]. Some current systems lack orchestration platforms that support distributed control across interconnected components. E.g., a common communication protocol MQTT is not designed for massive publisher-subscriber models, thereby limiting extensibility [25].

Making complex data accessible and understandable to users is a fundamental visualization challenge [27], [41]. The key is to achieve the right balance between comprehensive information and visual simplicity [48], prioritizing clarity over complexity, and ensuring that users can quickly interpret and act on the information presented without being overwhelmed by unnecessary details or confusing layouts. E.g., getting occupants to use less energy through self-motivation could be achieved by using dashboards that give a detailed overview of usage and recommendations. The environmental data sources, such as temperature, humidity, CO_2 levels, and energy consumption, are closely linked to comfort, sustainability, and efficiency goals, and are often visualized in SBDTs. Spatial and structural data also appear frequently, often in the form of room layout, floor plans, or 3D building models. These elements serve as an important spatial reference, helping users intuitively understand where data is coming from and what it relates to in the physical environment.

The existing solutions often present limited *evaluation of user experience and interaction quality*. SBDT solutions should systematically assess whether the visualizations are effective, usable, or adaptable to different user groups. SBDTs should provide design guidance tailored to different user roles or application goals, and involve users more actively in the design and evaluation of visualization systems, especially through co-design workshops or usability testing. In addition, privacy concerns are often underexplored, especially for occupancy or camera-based systems that could expose sensitive information. Other gaps include the lack of discussion on UI/UX design principles, deployment in multi-building or campus-scale systems, and transparent documentation of the limitations of the proposed visual solutions.

As SBDTs increasingly rely on interconnected cloud services and real-time control, ensuring *system security* is critical [27], [29], [35], [41]. Cloud deployments improves scalability and availability, but introduce risks of unauthorized access, data misuse and manipulation, or system disruptions, which pose severe risks in DT environments.

V. Conclusion

This paper explores the implementation of digital twins in smart buildings, focusing on documenting diverse aspects of the technical solutions, analysing existing SBDT use-cases, used sensors and visualisation techniques, and presents the most common challenges in SBDTs.

Sensors commonly used in smart buildings include devices for environmental monitoring, energy and HVAC systems, air quality, occupancy sensing and feedback, and building health sensors. The main use-cases address preventive maintenance, energy optimization, air quality and safety, and structural monitoring and preservation. ML models are the most common method of solving challenges. Other technical solutions include statistical models for anomaly and change detection, integration and modeling models, advanced control systems, data visualization and real-time monitoring, and signal processing. Commonly visualised data are environmental and energy conditions, spatial and structural data, equipment specifications, and occupancy and human movement information. Visual modalities include 2D dashboards and charts, 3D models, and map-based dashboards, though immersive visualization (VR/AR/MR) is increasingly gaining attention for its potential in real-time navigation and user interaction. In terms of interaction levels, real-time visualization is the most dominant, as it supports dynamic monitoring.

Implementations of SBDTs face challenges in terms of data integration, data quality issues, control mechanisms, scalability, and security. Human involvement presents additional challenges in considering occupant comfort, accessibility and understandability of data, and the quality of user experience.

Sensor-based SBDTs are increasingly employed in building operations, and have the potential to transform the way that buildings are designed, operated, and maintained in the future.

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