Digital twin for indoor condition monitoring in living labs: University library case study

Automation in Construction 157 (2024) 105188

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Digital twin for indoor condition monitoring in living labs: University library case study

De-Graft Joe Opoku [a,*], Srinath Perera [a], Robert Osei-Kyei [a], Maria Rashidi [b], Keivan Bamdad [a], Tosin Famakinwa [c]

[a] Centre for Smart Modern Construction (c4SMC), School of Engineering, Design and Built Environment, Western Sydney University, Locked Bag 1797, Penrith, NSW 2751, Australia
[b] Centre for Infrastructure Engineering (CIE), School of Engineering, Design and Built Environment, Western Sydney University, Locked Bag 1797, Penrith, NSW 2751, Australia
[c] Teaching and Research Technical Services (TRTS), Built Environment and Engineering Cluster, Western Sydney University, Locked Bag 1797, Penrith, NSW 2751, Australia

ARTICLE INFO

Keywords:
Building information modelling (BIM)
Digital twin (DT)
IoT platforms
Living lab
Semiotic representation

ABSTRACT

Digital twin, a technology bridging the physical and digital domains, has found extensive application in digitally advanced industries. However, its adoption in the construction sector remains limited, hindered by challenges related to construction, integration with real-time data capture, and visualisation platforms. This paper presents a construction industry digital twin that combines Building Information Modelling-based data visualisation with an Internet of Things-driven live data capture platform, outlining a methodology for its development. The digital twin was implemented in a university library embodying the 'Living Lab' concept to account for the nuances associated with live environments. It integrates sensors with Building Information Modelling to offer a semiotic representation of the library's internal conditions in digital twin, empowering facility managers to proactively optimize thermal, lighting, and air quality.

1. Introduction

Conventional facilities management relies on Building Automation Systems (BAS) for monitoring and controlling buildings and other facilities. The coordination of activities depends on human efforts with limited automation through the Internet of Things (IoT) devices [17,28]. To be able to achieve efficient and reliable management of facilities, there is a need to embrace emerging digital technologies. This need has given prominence to Building Information Modelling (BIM), which provides access to rich semantic information regarding the graphical and non-graphical data of the building [23,48]. Notwithstanding, BIM works with static data and therefore has limitations regarding access to real-time data for building operations [45]. Further, Lu et al. [35] mentioned that currently, BIM lacks the capability to completely enhance the management of buildings and other facilities. This requires the integration of IoT sensor devices to aid in harnessing real-time data to provide content-rich BIM models. Further, the data need to be stored and securely shared to assist facility managers to make informed decisions in critical situations regarding the operation and maintenance of buildings and other facilities. One significant technology that has the capability to comprehensively meet and address some of these needs is the concept of digital twin (DT). These key needs include access to dynamic and real-time data, the current and future status of the facility/building, up-to-date requirements for effective building operation and maintenance, energy consumption optimisation, performance management, maintenance management, structural health monitoring, and continuous provision of updated representation of the current state of the building/facility to enhance decision-making among others. DT integrates other emerging technologies like machine learning, artificial intelligence (AI) and data analytics to help in making much more informed decisions regarding the operation as well as maintenance of buildings and other facilities [46,58].

Previous studies within the construction domain have established the abilities of DT to enhance the management of buildings and other built

* Corresponding author.
E-mail addresses: d.opoku@westernsydney.edu.au (D.-G.J. Opoku), srinath.perera@westernsydney.edu.au (S. Perera), r.osei-kyei@westernsydney.edu.au (R. Osei-Kyei), m.rashidi@westernsydney.edu.au (M. Rashidi), k.bamdad@westernsydney.edu.au (K. Bamdad), t.famakinwa@westernsydney.edu.au (T. Famakinwa).

https://doi.org/10.1016/j.autcon.2023.105188
Received 19 May 2023; Received in revised form 2 November 2023; Accepted 5 November 2023
Available online 9 November 2023

environment facilities. For instance, Lu et al. [34] developed a DT at the building and city levels and presented a demonstrator of a building DT located on the West Cambridge site. The authors established the relevance of DT to facility management. Wang et al. [57] presented a BIM-based IoT-driven DT for inspecting environmental conditions during COVID time. The authors indicated that DT has the potential to enhance indoor health as well as well well-being in COVID situations. In addition, Lin and Cheung [32] developed a BIM-based/ wireless sensor networks (WSNs) DT for monitoring the environment of an underground parking garage in smart cities. The authors also established that the DT system offers a platform that is efficient and enhances safety in the monitoring of the environmental conditions in garages. Although some works have been carried out in the construction industry regarding the adoption of DT, the technology has seen minimal adoption and utilisation in the industry [45]. This reluctance in embracing DT technology is because of the difficulties surrounding the development of DTs. These challenges include the requirement for the integration of a visualisation platform with a data capture platform, precisely, a live stream data capture platform [49,57]. There are also too many available technologies and this makes it extremely difficult to select the appropriate technology at any given time [32]. Also, the selection of an appropriate digital platform for capturing data dynamically and in real-time presents substantial challenges [32]. Finally, there is also a lack of education, skills and standardization regarding the development of DT [46]. This study, therefore, aims to provide an indication of how to select an appropriate digital platform that captures data dynamically and in real-time, select an appropriate visualisation platform and integrate the live data with the visualisation platform to build a DT.

Further, it is noted from the available literature that little attention has been focused on educational buildings regarding the utilisation of DT [46]. Educational buildings exhibit constant interactions with their occupants and have greater population density compared to commercial and residential buildings [16]. One significant building within the educational sector that is worth discussing, in terms of usage by its occupants is the library building. A study in the University of Illinois Chicago library revealed that 90% of the students in the University used the library [50]. Thus, a much higher percentage of time and interactions are experienced in library buildings. It is worth mentioning that the DT of a library building is not different from that of other buildings. However, there are significant differences between the requirements and features of a library building and other buildings. This study focuses on the interactions in the library to improve occupants' comfort and energy consumption. A BIM-based and IoT-driven DT of a library building is developed using a system architecture that is implemented through the development of a demonstrator for the John Phillips Library building at Western Sydney University in Australia. This demonstrator is to experiment with the 'Living Lab' concept across universities. The developed system supports a synchronous analysis of the indoor environmental conditions data and digital description of the 'Living Lab' (geometries and locations) for enhanced automation in environmental conditions monitoring for occupants' comfort and energy consumption optimisation. The contributions of this study lie in the fact it provides an exemplar for similar works to be undertaken in creating a DT. The application domain is also unique since it is one of the pioneering studies in educational buildings focusing on occupants' comfort and energy consumption improvements. Further, the study experiments on the 'Living Lab' concept across universities and provides DT developers with an opportunity to determine best practices in DT development in the construction industry. Finally, the study provided some lessons learnt in DT development, which will be beneficial to researchers and industry stakeholders.

The rest of the paper is organized as follows: Section 2 presents the literature review. Section 3 discusses the system architecture for DT development. The case study selected for this study and experiment detail is discussed in section 4. Section 5 elaborates on the development of the DT of the library building. Finally, the paper is concluded with implications for practice as well as future research directions in section 6.

2. Review of DT for smart facility management in educational buildings

Smart facility management (SFM) refers to the integration of various technologies, processes, and systems to enhance the management of a particular facility. The fundamental requirements for SFM pitch on the access to real-time data that is integrated into a computing platform for intelligent analytics and decision-making. With the advent of Industry 4.0, several cutting-edge technologies including BIM have been introduced in facility management. BIM is a heavily technology-driven methodology utilised for improving the performance and efficiency of assets during their design, construction, operation, and maintenance phases [36]. The National BIM Guide separated the definition of BIM into two namely BIM as a product and BIM as a process [42]. As a product, BIM denotes a 3D parametric object and functional data. Whilst as a process, BIM refers to workflow-based modelling to achieve a critical collaborative information model. The National Institute of Building Science (NIBS) also defined BIM as a "digital representation of the physical and functional characteristics of a facility and a shared knowledge resource for information about a facility forming a reliable basis for decisions during its lifecycle from inception onwards" ([43], p.7). Notwithstanding these definitions, Eastman et al. [19] indicated that the main idea to enhance the understanding of BIM is the concept of parametric objects and how it differs from conventional 2D objects. Within the context of this study, BIM is viewed as a digital representation of the physical and functional characteristics of a facility and shared knowledge resources for information about the facility for improved decision-making and management.

Although BIM-enabled facility management presents an object-oriented, parametric as well as machine-readable 3D database, the focus has mainly been on maintenance management and building operations. However, one key activity of facility managers has to do with ensuring the comfort of the facility's occupants [14] and that is difficult to manage with BIM. Also, the lack of realistic as-built together with outdated and insufficient building information hinders the utilisation of BIM for facility management in existing buildings [9]. This unavailability of adequate building information, therefore, results in inefficient management of the building, excessive increase in cost and time as well as uncertain building management outcomes.

The available literature has, therefore, acknowledged the need to advance the capabilities of BIM to ensure SFM. For instance, Kim et al. [30] found out that the information in BIM is not adequately transferred from the construction phase to the operational phase to ensure adequate facility management. Although, there is a need to present high-quality data to facility managers for efficient and effective management. Further, the lack of adequate data in the as-built BIM models limits its potential in the operation and management of the facility [37]. In another study by Shalabi and Turkan [51], it was reported that the data gathered from facility management systems such as building management systems (BMS) are limited in capabilities regarding visualisation and interoperability. A very significant technology that has the potential to address most of these issues in facility management is the concept of DT. DT possesses the ability to coordinate several models across the lifecycle of the system [7]. It can then be used to simulate the character, conditions and status of the physical asset for various decision-making regarding the management, operation and comfort of the facility's occupants. To articulate this study, a DT refers to a dynamic digital representation of a physical asset, processes as well as systems using IoT devices and occupants' feedback information [11,25]. As mentioned by Xu et al. [58] and Opoku et al. [45], the technologies that are currently supporting the application of DT in the construction industry are WSNs, BIM, data analytics and machine learning.

Further, within the construction industry, Lin and Cheung [32] reported that an application of DT could be derived from the combination of BIM and WSNs. The authors stated that the combined BIM and WSNs present an active real-time model with useful information for the operation and management of buildings. BIM offers parameterised and digitalised information regarding the building in a 3D illustrative model to assist in planning, designing, construction and management through visualisation capabilities [3]. Whilst WSNs present a network of sensor nodes that is capable of monitoring, communicating, judging and reacting to external conditions [15].

There have been some studies focusing on the integration of BIM and WSNs technologies as applications of DT in the construction industry. For instance, Wang et al. [57] presented a BIM-based IoT-driven DT for inspecting environmental conditions during the COVID-19 pandemic. Tsai et al. [55] proposed a novel approach for corrosion prediction under insulation using sensing technology and mathematical modelling of corrosion in a BIM-based system. Lin and Cheung [32] developed an innovative monitoring as well as a control system for environmental management in an underground garage using BIM and WSNs technologies. Dave et al. [18] presented a platform for integrating the built environment data with IoT sensors in a campus-wide deployment to provide energy usage, user comfort and occupancy information. Jiang et al. [27] presented a DT-enabled smart modular integrated construction with a robotic demonstration for re-engineered on-site assembly. Rao et al. [47] presented an extensive and up-to-date review of the available literature on real-time monitoring of construction projects. The integration of BIM and sensors have been applied severally in the automation of facilities to enhance the intelligence of buildings [32].

Notwithstanding the efforts geared towards the integration of WSNs and BIM technologies, only a few studies have been directed towards the educational sector. It must be noted that the educational sector has a highly dynamic environment and presents excellent avenues for active utilisation by researchers in developing emerging technologies. This study, therefore, focuses on the above-mentioned context for enhancing decision-making in managing buildings.

3. System architecture for DT development

This research offers a system architecture for developing the digital twin of the library building. Several system architectures for developing DT have been proposed in the literature. These system architectures have been based on either three, four, or five architectural layers or components. For instance, Tsai et al. [55] developed a system architecture for predicting corrosion under insulation using three distinct layers comprising a user interface, logic, and data layers. Lin and Cheung [32] presented a system architecture for developing an advanced monitoring and control system for monitoring an underground parking garage. The authors created a four-layered system architecture comprising a sensor layer, database layer, application layer, and presentation layer. Lu et al. [34] developed also a system architecture for DT specifically designed at both the building and city levels. The authors presented a five-layered system architecture that comprised data acquisition, transmission, digital modelling, data/model integration, and service layers. Finally, Schweigkofler et al. [49] offered a four-layered system architecture for energy management to include data acquisition, data integration, data visualisation, and data analysis layers. Notwithstanding the diverse presentations of the system architecture for DT development by different researchers, the key components should be a layer for data acquisition, data communication and storage, data modelling and integration, and finally, data analysis, and visualisation. It was realised that presenting the system architecture in five layers was merely separating the modelling and integration components, which could be combined to present a more concise and focused understanding of the architecture. Also, utilising a three-layered system architecture would not present a better understanding of the architecture since some of the components would have to be integrated thereby, providing limited detail in the architecture.

Based on simplicity, communication efficiency and types of sensor devices used, a four-layered system architecture for developing the BIM-based and IoT-driven DT system for improving the indoor environmental conditions in the "Living Lab" was developed. Although three, four, or five-layered system architectures for DT development have been reported by other works, this current study used a four-layered architecture similar to that of Lin and Cheung [32] and Schweigkofler et al. [49] since that is more logically representing and better fits the components to be presented in this study. As shown in Fig. 1, the architecture is composed of four essential components: data acquisition, data communication and storage, data and model integration, and data analysis and visualisation components. These components are discussed in the subsequent subsections to present an overview of the architecture utilised in developing the DT of the library building.

3.1. Data acquisition component

In developing the DT of the library building, the foundation of the system is the data acquisition component. The design and selection of the data acquisition mechanism are very essential and challenging. This is due to the large volume and complexity of the data. Further, it becomes more challenging in terms of the data type, format, source, and content. In addition, there are several techniques when considering data collection. These include contactless techniques, for instance, distributed IoT sensor systems, radio-frequency identification (RFID), wireless communication, and mobile access (WiFi environment). For instance, Tsai et al. [55] utilised RFID readers to read tags on-site and communicate with a data hub in a local wireless internet environment. The hub then integrated all values of the readers and streams these values to the system via Hypertext Transfer Protocol (HTTP) request. Another study by Lin and Cheung [32] used a WSNs system to collect data and transmit it to a router for data storage. Lu et al. [34] also utilised data stored in Building Management System (BMS) and Monnit wireless sensors for developing a DT. Wang et al. [57] used Arduino-based wireless sensing devices to automatically read signal inputs to convert them to digital outputs.

In selecting the data acquisition devices, initial consideration was given to using the Raspberry Pi microcomputer. Although connecting Raspberry Pi with sensors and deploying a code that uses TCP/IP protocol was viewed as one of the most cost-efficient methods, the complexity of implementing such an architecture was going to be very much higher. There is also the need to accurately calibrate the sensors to collect the data using Raspberry Pi devices. Furthermore, developing the frontend and backend software as well as troubleshooting the issues involved in collecting the data on different software layers was going to be time-consuming. In addition, a fleet of Raspberry Pi devices requires a separate software layer for their management.

Further, there is also an issue with implementing Raspberry Pi devices on university campuses specifically relating to internet connectivity. To connect to the internet on university campuses, users are required to input their student/staff credentials. Alternatively, the university could create separate login credentials for all IoT devices. However, this comes with a security risk where the credentials are subject to compromise with the devices. Due to the constraints associated with using Raspberry Pi devices, there was the need to resort to an alternative approach to address the data acquisition in the library building. The LoRa end devices (sensors) were therefore selected for data acquisition (see Fig. 1). LoRa, a modulation technology that allows the transmission of data over long-range (i.e. up to 20 km) within an outdoor environment presented an opportunity for connectivity over longer distances [1]. The long-distance connectivity together with the low energy consumption of LoRa made it extremely useful for LP-WAN technologies applications in IoT [12]. Data was sent from the end devices of LoRa to a gateway via a single wireless hop. Further, the gateway was then connected to the network server using a non-LoRaWAN network, thereby providing a bidirectional communication

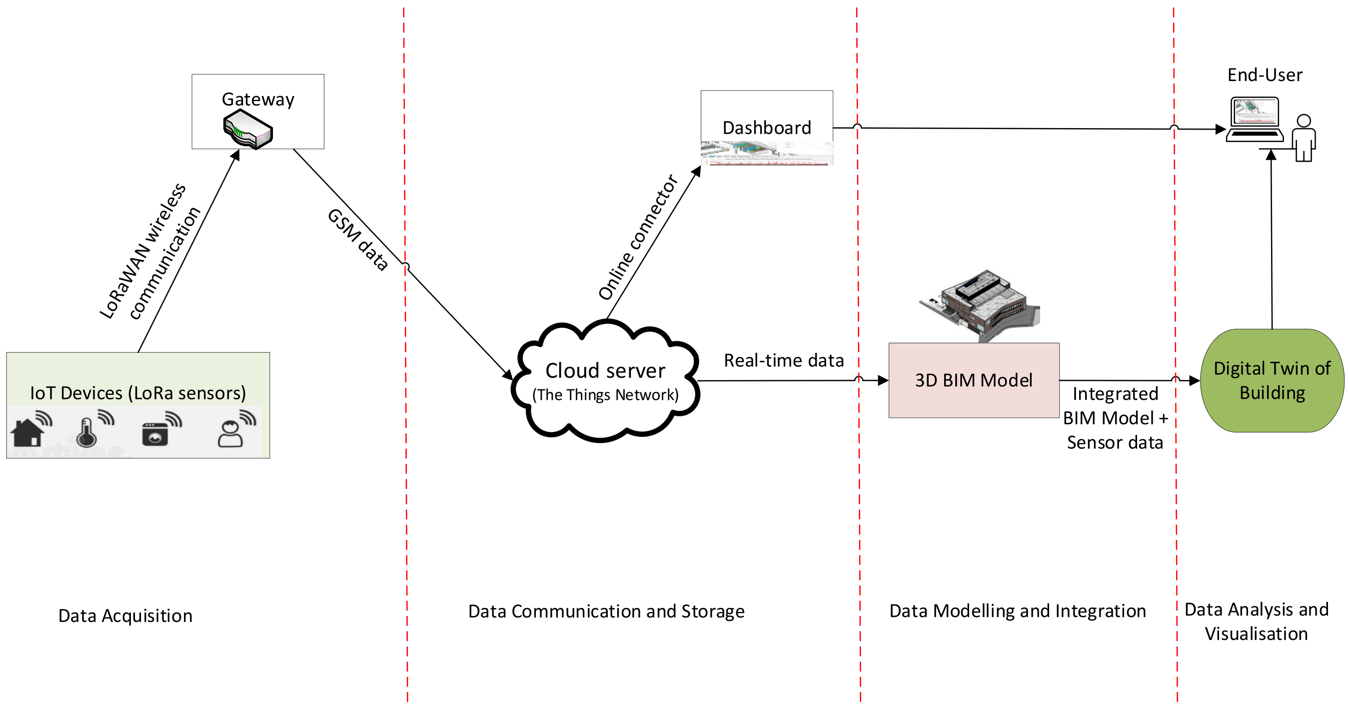

Fig. 1. System architecture for DT development.

protocol [52]. LoRa sensors and LoRaWAN communication can overcome the issues arising from using Raspberry Pi end devices [59]. More specifically, LoRa sensors do not need much calibration relative to the sensors connected to the Raspberry Pi. GSM router works as a gateway for LoRa sensors that communicates with the Things Network over LoRaWAN, thereby implementing a system that becomes independent of the university campus' internet connectivity (see Fig. 1).

3.2. Data communication and storage

The data communication and storage component aims at sending the data to the gateway and network server. Several data communication technologies could be utilised in this component which includes short-range coverage access network technologies including WiFi, near-field communication (NFC), Zigbee, and *Z*-Wave [21]. Also, the wider coverage access network technologies include low-power wide-area networks (LP-WAN), long-term evolution (LTE), 3G, 4G, and 5G [44]. Notwithstanding the upsurge in technology developments, the most utilised wireless local-area network (WLAN) technology is WiFi. Though WiFi is the normally used WLAN technology, there are several security issues when developing a DT of a building [31]. Nathali Silva et al. [41] however mentioned that LP-WAN and light fidelity (Li-Fi) network technologies are good alternatives for wide-range coverage when considering transmission speed and energy efficiency of networks in developing digital twin of buildings. Wang et al. [57] mentioned that, in terms of using Arduino microcontroller boards for data transmission, direct connections via wired cables are excessively expensive and ineffective. This connectivity would therefore require the programming of the microcontrollers to link up with a WiFi network. Subsequently, the WiFi network would then transmit the data to a distributed Internet Protocol (IP) address [57]. This process is quite laborious and tedious. Thus, the current study resorted to using a gateway that uses GSM for data communication.

Additionally, the gateway uses GSM for creating its network specifically for the LoRa end devices (sensors). The LoRa sensors and the gateway were located in two different buildings. Since LoRa sensors can transmit over long distances, the data collection was continuous and uninterrupted. This study used MultiTech Conduit AP, which is the Accept Point for LoRa Technology [33]. The Conduit AP access point allows the extension of LoRa connectivity and provides coverage in hard-to-reach areas [40]. The gateway was set up as Packet Forwarder, receiving Lora packets from end devices and forwarding them to a cloud network server, "The Things Network" (TTN) using an IP/UDP link (see Fig. 1). The gateway also reduces upstream communication and operational cost while providing Ethernet IP backhaul or optional 4G-LTE IP backhaul [40]. The use of GSM ensures that the network is independent of the university's network connectivity. In addition, the MultiTech Conduit AP is easy to install and deploy in terms of setting up data communication and storage. The deployment of the LoRaWAN network, gateway, and sensors on the university premises presents a unique challenge regarding power availability and the complexity of installation tasks. MultiTech Conduit AP addresses these challenges by providing various models with several power options that include powering over Ethernet [40]. Furthermore, TTN provides a set of tools and a global network that allows users to build an IoT application at a low cost while providing maximum security and scalability [54]. In addition, "The Things Stack" provides easy tools to use and set up with the LoRa end devices (sensors). It is a LoRaWAN Network Server that securely manages applications, end devices, and gateways [54]. Additionally, the Things Stacks minimizes the time it would have taken to build a backend software from scratch instead of collecting the data. Furthermore, TTN manages the data collection and the fleet of end devices and transmits the data to the TagoIO platform, which stores the time-series data in a database [53]. The platform can then be used to create dashboards to observe real-time data.

3.3. Data and model integration component

BIM applications allow the user to visualise the sensor data via a 3D BIM model and create user-defined extensions that aid the achievement of specific functions and objectives [55]. The data and model integration component aims at integrating real-time data with the 3D BIM model. For instance, Lu et al. [34] and Schweigkofler et al. [49] developed 3D BIM models using Autodesk Revit software (.rvt) and utilised Autodesk Forge Application Programming Interface (API) for visualisation. Particularly, the authors utilised a web-based program design using Java script and C# programming language. However, Schweigkofler et al. [49] utilised Visual Studio Code for the integration. Moreover, Lin and Cheung [32] used Autodesk Revit software for developing the 3D BIM model and adopted a Navisworks API for the visualisation of the data. The authors then integrated the model and sensor data using C# applications. Another study by Tsai et al. [55] utilised a web-based 3D BIM model and used Autodesk Forge API for data visualisation. Wang et al. [57] developed a 3D BIM model in Autodesk Revit software and used Autodesk Dynamo Studio and Python scripting for the integration of the model and sensor data.

This study, therefore, used the TTN database, 3D BIM model, WSNs, and C# applications for their integration. Thus, the component has a dynamic 3D BIM model for integrating the location-specific conditions of the six selected group study rooms in the library. The measured temperature, humidity, light, carbon dioxide (Co2), and total volatile organic compounds (TVOC) values together with their corresponding X-Y curve diagrams are shown in real-time on a specific window. When a specific date and time are selected, the conditions of the selected room are displayed in both the data blocks and X-Y curve diagrams. To do this, a 3D BIM model was created using version 2020 of the Autodesk Revit software. The sensor devices were represented by creating a unique family. This unique family represented the real position of the sensors in the university library. The sensors installed in the library were developed as types under the sensor family with variable type and instance properties. A parameter was created for the sensor family and categorized under Identity Data. The Identity Data is a section in the Type Properties window that has the family type's identification parameters. Thus, it contains the parameters for the name, location as well as the sensor's activation state. Another parameter was also created to cater for the indoor environmental parameters being measured. A unique alphanumeric ID was used to define each of the virtual sensors that were created in the 3D model. These unique alphanumeric IDs correspond to the specific locations and positions of the various sensor devices in the physical library building. The ID is generated automatically and has the group study room's number to uniquely and accurately identify the various sensor devices. Subsequently, the created 3D BIM was uploaded to the Autodesk Revit software to display the model content in 3D viewer. The sensor data was then read using the created Revit plug-in from the TagoIO server via the API. Further, the data ID was linked with the corresponding rooms in the Revit model and the volume of each room was configured. Following that, each of the rooms was divided according to the number of data types (i.e. divide each room into six equal parts to visualise the six measured data types or parameters from the sensors). Finally, the created individual volumes were colorized to represent the data retrieved from the sensors.

Further, to achieve the data and model integration, a dynamic data integration process was created between the 3D BIM model (.rvt) and IoT sensor devices. This was done by mapping and connecting the sensor data from the TagoIO database to the sensor family in the model created in Autodesk Revit software. The software possesses an API service that allows the development of scalable and customised solutions to solve problems relating to the design and engineering of assets. The sensor data was extracted from a commercial platform (i.e. TagoIO database) using Restful API via HTTP requests in JSON format. In addition, Autodesk Revit API was used to create a plug-in that was written in C# programming language (i.e.,.NET framework). The C# programming language was chosen based on its object-oriented as well as component-oriented nature. Autodesk Revit C# SDK (i.e. from Autodesk developer centre) was used to create a panel layout contained in the plug-in. Further, a controller was then created using Autodesk Revit API to access the BIM data loaded in Revit. Following that, another controller was created using TagoIO API to access the sensor data. TagoIO provides an API that enables the usage of C# with web request for accessing the sensor data.

3.4. Data analysis and visualisation component

The data analysis and visualisation component is the implementation phase of the DT's system architecture. This phase allows the interaction between the user and the data and model integration of the DT. The user can analyse and visualise the conditions of the physical asset in this phase. Lin and Cheung [32] referred to this component as the presentation layer, which visualises the dynamic model with the conditions data. The authors further mentioned that the component provides a user interface developed for managing the facility efficiently. Lu et al. [34] also referred to this component as the service layer, which interprets the data and enables interactions between the DT system and its users. The authors developed dashboards that could inform decision-making on services, such as the detection of anomalies in pumps, optimisation and prioritisation of maintenance activities, ambient environmental monitoring, and environmentally friendly urban energy planning. Wang et al. [57] in this phase presented dashboards to monitor the environmental conditions during the outbreak of the COVID-19 pandemic. Schweigkofler et al. [49] utilised the Autodesk Forge platform for visualising the monitored environmental conditions.

In this study, the designed DT's system architecture was targeted at building and facilities management professionals to assist them in decision-making. In order to ensure that operation performances are not compromised, it is important to ensure that the optimised decisions are verified and manually confirmed in practice before implementation. This is a key requirement in the initial implementation phase of the DT [34]. The proof of concept of the DT was implemented using a university library building. The outputs of the combined 3D BIM model and the environmental conditions data are visualised in the professional BIM platform (i.e. Autodesk Revit). The platform enables the user to interact with the application and access spatial information in real-time on a dashboard. In order to visualise the data in a line chart, each line/ parameter with its assigned colour (see Fig. 5 and Fig. 9) was a type of data. The X-axis presented the time when the data collected and the Y-axis presented the value of the data. Thus, the presented graphs showed the real-time changes of the data on a specified date and time. In addition, the real-time data was reflected in the 3D volumes in the model using the volume transparency. This was to show the concentration of the data in each room once a specific room was selected. Subsequently, the indoor environmental conditions data retrieved from the IoT sensor equipment were analysed and compared with the recommended standards for an office space like the library. The developed system provides an option for retrieving monitored outputs in CSV file format for performing further analysis.

4. Case study for the development of the DT system

This section presents the methodology for developing the DT system of the “Living Lab”. The study offers a flexible and scalable workflow for enabling the integration of IoT-BIM in a DT. This study developed and validated the new system using an experiment intended to collect, process and visualise real-time data for improved decision-making in facility management. The details of the methodology are presented in the following sub-sections.

4.1. Overview of the building selected for the case study

An existing University library building located on the Kingswood campus of Western Sydney University (WSU), Australia was chosen as the case study for this research. The library building was selected based on its constant interaction with its occupants. Furthermore, the case study was chosen in keeping with experimenting on the ‘Living Lab’ concept factoring in all nuances associated with live environments. The building is a five-storey building, has a total floor area of 6700m^2 and a north-south orientation. The library building includes several spaces for the day-to-day running of the facility and includes; study spaces (open study areas, student group study rooms, quiet study areas, silent study areas, and access rooms), printing areas, collection areas, and office spaces. There are several critical stakeholders of the library, which include library managers, librarians, students, and the University's Office of Estate and Commercial (OEC), which is responsible for the operation and maintenance requirements for the entire university. In addition, the stakeholders also include the University Facility Management Team, which is responsible for the day-to-day operation and maintenance of specific buildings (in this case, the library building) on campus.

Additionally, this study has narrowed its focus to the group study rooms on level 01 due to the extensive floor area, research limitations, and practicality. Furthermore, the choice of the group study rooms was a result of their constant interactions with the occupants of the library. There are six (6) group study rooms, which have a total floor area of 86m^2, and each room measures approximately 4 m $\times$ 3.5 m. The maximum capacity of each of the six group study rooms is between 6 and 8 persons at any given time. Fig. 2 shows the selected library building utilised as the case study for this research.

4.2. Model development and sensor deployment

4.2.1. BIM model development

The 3D model of the university library was designed within the BIM environment using the existing documentation available to the researchers. Autodesk Revit 2020 software (.rvt file) was used as the modelling tool. The general overview of the model is presented in Fig. 3.

The accuracy of the geometric representation of the library building and the positions of the sensors depends on the level of information needed. In this study, the geometrical information for most of the elements is mainly represented on a generic level whilst some elements like walls, doors, windows and sensors are represented in detail. The BIM environment has the advantage of being able to integrate different information types in a single model. For instance, the sensors possess information regarding real-time data on the indoor environmental parameters in the DT. Fig. 4 presents an example of the chosen group study rooms on level 01 utilised for the study.

4.2.2. Semiotic representation of the indoor conditions of the building

The visualisation of information and design of the user interface are essential components for enhanced building and facility management. The way and how information is represented and visualised presents a forelead in managing various conditions [22]. In the development of a DT of a building, the representation of the physical building's indoor environmental conditions is essential to present a clear picture for both the building or facility manager and the occupants of the building or facility. A clear distinction of how the conditions are represented together with the process of representation ultimately affects the management of the building's internal conditions. The meaning of signs and symbols is significantly dependent on the expectations of the sender of the information as well as the recipient of those signs and symbols [13]. A collective expectation is therefore highly important in enhancing the understanding of the various parties to the communication [10]. Semiotics, a concept that provides meaning and significance to a particular phenomenon using signs and symbols is utilised in developing the DT of the library building. The concept is employed in providing meaning to the indoor conditions and assisting in the visualisation of both the real-time and historical data on the measured parameters [20,38]. Semiotic representations therefore enhance the ability to efficiently and effectively visualise, understand and manage the indoor conditions of the building. In this study, colour-coded data blocks are used to visualise, communicate and understand the conditions in the various rooms under consideration.

Practically, the top shield of the BIM model structure would have to be modified, clipped or truncated to ensure that, the interior conditions and assets can be shown when operating the model. Furthermore, room components associated with the locations being monitored were created for the purpose of displaying the indoor environmental conditions and parameters. For example, a component added for temperature variations was altered to show the temperature difference in real-time through an indication of a colour-coded data block. The method is adopted to show the temperature, humidity, light (illumination), Co2, TVOC and motion (activity level) statuses in the six group study rooms (See Fig. 5).

4.2.3. IoT sensor devices

Several factors including the communication protocol, accuracy and aesthetics due to the delicate nature of the location for the sensor deployment were considered in selecting the sensors for the study. The planned location for the deployment was the university's library. Thus, wired sensors were ruled out because of the exorbitant cost of making them look good aesthetically. The study therefore considered Bluetooth-based sensors using Raspberry Pi or Arduino. Notwithstanding, these sensors were also ruled out due to their limited distance of operation. Additionally, the study considered WiFi-based sensors, however, they were also ruled out because of the Information Technology (IT) network security protocols of the university. The study therefore explored LoRa sensors that utilise GSM routers as gateways that communicate with the Things Network over LoRaWAN protocol. This eliminates the need to connect to the university network and allows for an independent collection of data. LoRaWAN is cost-effective both in terms of hardware

Fig. 2. John Phillips Library on the Kingswood campus at WSU.

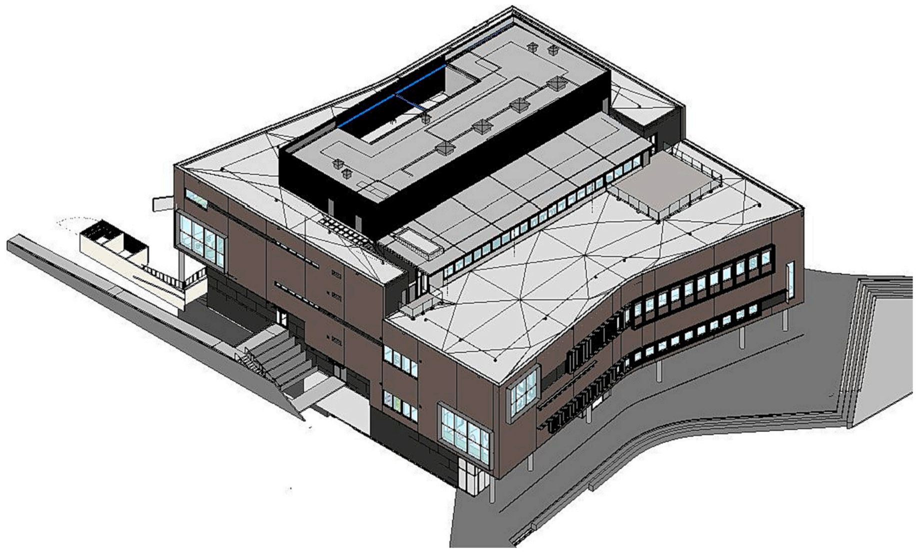

Fig. 3. Overview of the BIM model of the university library.

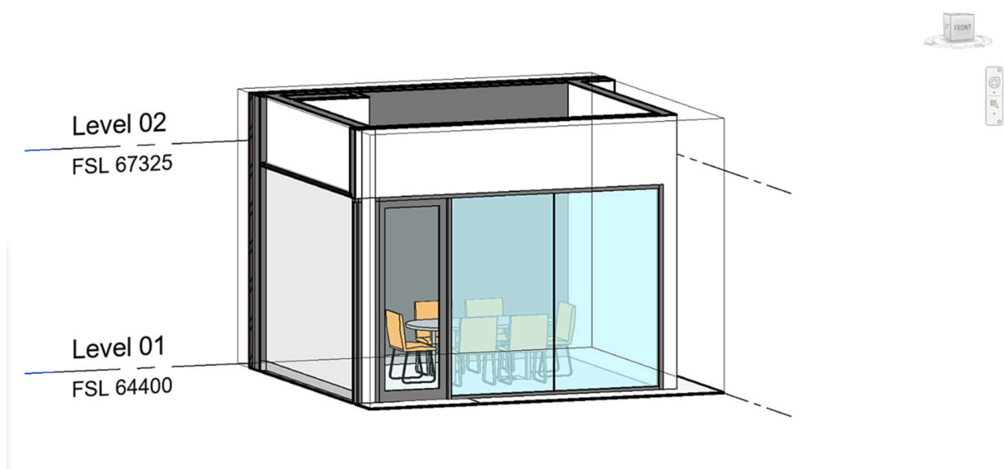

Fig. 4. An example of the group study room utilised in the study.

and operational expenses. The technology's long-range capabilities meant fewer gateways were needed to cover a large area, thereby, reducing infrastructure costs. It is worth mentioning that, this study used only one gateway (i.e. MultiTech Conduit® AP). The study opted for LoRa sensors (i.e. Milesight IoT sensors AM107 and AM307) that had multiple sensing capabilities in a single sensor providing the needed aesthetics. The configuration of the Milesight IoT sensors AM107 and AM307 via NFC also provided the easiness of maintenance and calibration. Finally, the low power consumption of the Milesight IoT sensors AM107 and AM307 ensured the ease of maintenance for a considerable period of data collection. These cost and technical characteristics of the Milesight IoT sensors AM107 and AM307 met the requirements and thus, were selected for the study. The details of the sensors are presented below:

- AM107 is a compact and integrated indoor ambience monitoring sensor for indoor environmental parameters (i.e. temperature, humidity, light, Co2, TVOC) and motion. The accuracy of the temperature sensor is ± 0.3 °C and has a measurement range from -20 °C to +70 °C and a resolution of 0.1 °C. In addition, the humidity sensor has an accuracy of $\pm 3\%$, a measurement range of 0–100% RH, and a resolution of 0.5% RH. In terms of the light sensor, the measurement range and accuracy are 60,000 lx (visible + IR, IR) and ± 30%, respectively. In addition, the Co2 sensor has an accuracy of ±30 ppm or ± 3% of reading, measurements ranging from 400 to 5000 ppm, and a resolution of 1 ppm. Finally, the accuracy, measurement range and resolution of the TVOC sensor are ±15%, 0-6000 ppb and 1 ppb, respectively.
- AM307 is also a compact and integrated indoor ambience monitoring sensor for indoor environmental parameters (i.e. temperature, humidity, light, Co2, TVOC) and motion. However, in addition to the aforementioned environmental parameters, the AM307 sensor also measures the fine particulate matter (PM2.5) that exists in the air. The diameter of the tiny particles normally measures lesser than 2.5 μm and are able to travel deeper into the respiratory system of humans. The PM2.5 sensor has an accuracy of ± 10 μg/m^3 with measurement range and resolution of 0-1000 μg/m^3 and 1 μg/m^3, respectively. Regarding the temperature sensor, the accuracy is ±1 °C, and the measurement range is -40 °C to 85 °C. The accuracy, measurement range and resolution of the humidity sensor are ±3%, 0–100% RH and 0.5% RH, respectively. The Co2 sensor has an accuracy of ±30 ppm or ± 3% of reading, measurements ranging from 400 to 5000 ppm and a resolution of 1 ppm. Regarding the TVOC sensor, the accuracy is ±15% while the measurement range is 0–500

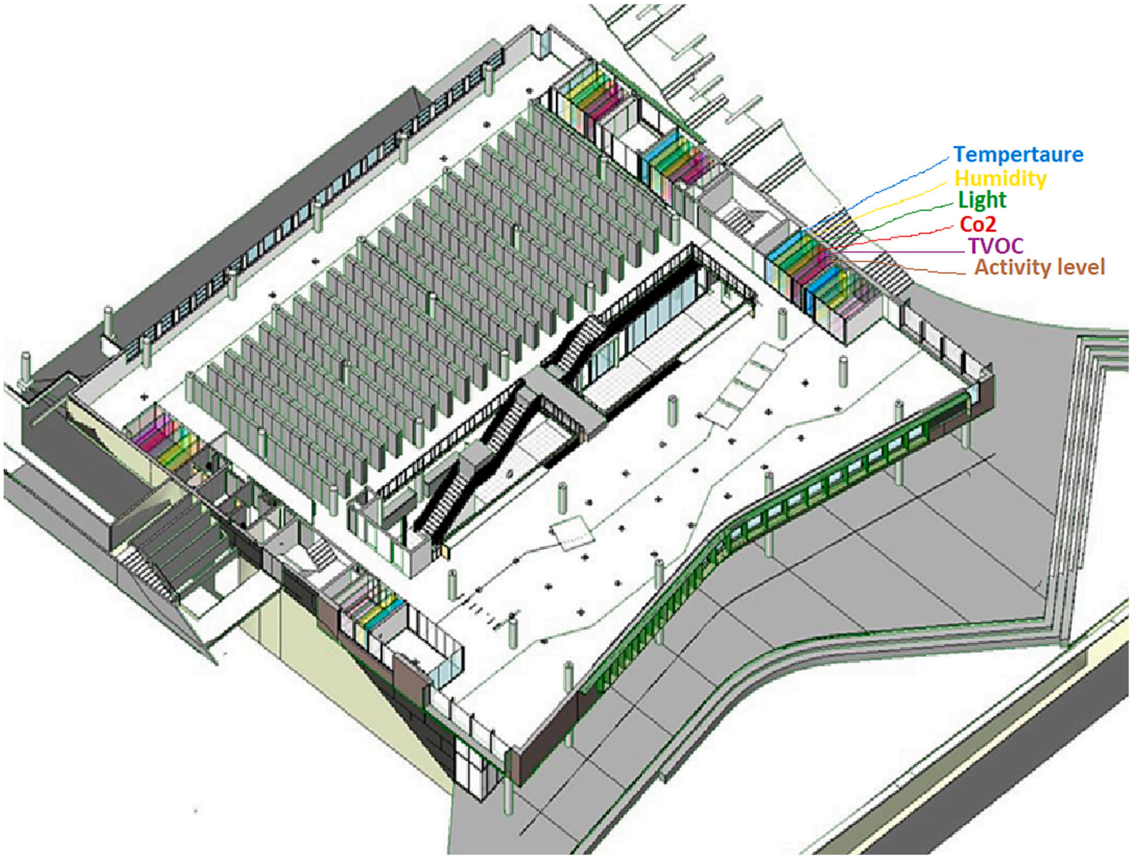

Fig. 5. Semiotic representation of internal environmental conditions in the BIM model.

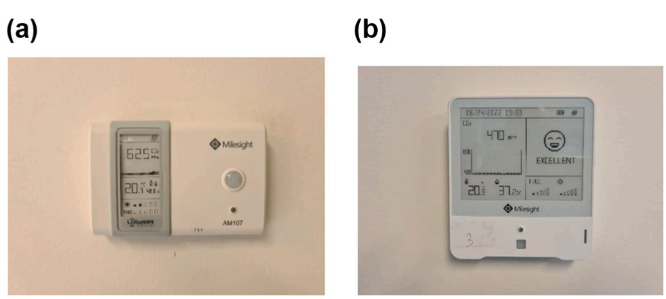

Fig. 6. (a) Milesight AM107 sensor device Fig. 6. (b) Milesight AM307 sensor device.

(IAQ index). The indoor air quality (IAQ) index quantifies the overall quality of the air within a building/ indoor space. IAQ index provides information about the concentration of various contaminants and pollutants in the air and thus, affects occupant comfort and health [39]. TVOC concentration is one of the factors used to quantify the IAQ index [24,39]. Meyer [39] indicated that TVOC is the summation of various classifications of organic compounds including Very Volatile Organic Compound (VVOC), an example is formaldehyde; Volatile Organic Compound (VOC), an example is benzene; and Semi Volatile Organic Compound (SVOC), an example is diisononyl phthalate. A high level of TVOC affects personal comfort, perception of cleanliness and health of building occupants [8,24,39].

In addition to the identified features of the selected IoT sensor devices, both sensors could monitor the activity levels in the selected group study rooms. This was very important since occupancy densities in the room are vital to the operation of the library, especially in the post-COVID-19 era. This requires the installation of motion detectors in the selected rooms to detect their occupancies. The AM107 has a passive infrared (PIR) sensor that detects infrared signals in movements. The detection area is 94^0 horizontal and 82^0 vertical, the detection distance is 5 m and the output range is 0–65,535. Regarding the AM307, the detection area, detection range and status are 80^0 horizontal and 55^0 vertical, and vacant/occupied, respectively. It is worth noting that no specific project accuracy requirements were documented at the start of the study. The temperature and humidity values of the AM107 and AM307 sensors were calibrated against known values in a controlled environment before deployment. The measured temperature on the sensors in comparison to the controlled room temperature for a period of 24 h was within the range of $\pm 1\%$. The sensors operated within the manufacturer's technical specifications and accuracy. Furthermore, the sensors' performance was continually tested and validated at different intervals by comparing the screen display data to the data on the display dashboard. The overall project accuracy was dependent on the sensor accuracy which was validated by the researchers and the accuracy of the data transmitted over the LoRaWAN protocol. All sensors operated within the manufacturer's range of accuracy during this project. Furthermore, the manufacturer provided different methods for calibrating the Co2 values of the AM107 and AM307 sensors. The study opted for the manual calibration/background calibration that defines the outdoor environment Co2 value as 400 ppm. Thus, each sensor was taken to the outdoor area where the Co2 value was adjusted to 400 ppm before deployment. The location of the IoT sensor devices in the monitored rooms is illustrated in red dots in Fig. 7.

5. Digital twin of the library building

An approach for optimising the indoor environmental conditions in the library building is presented in the following sub-sections. It is worth

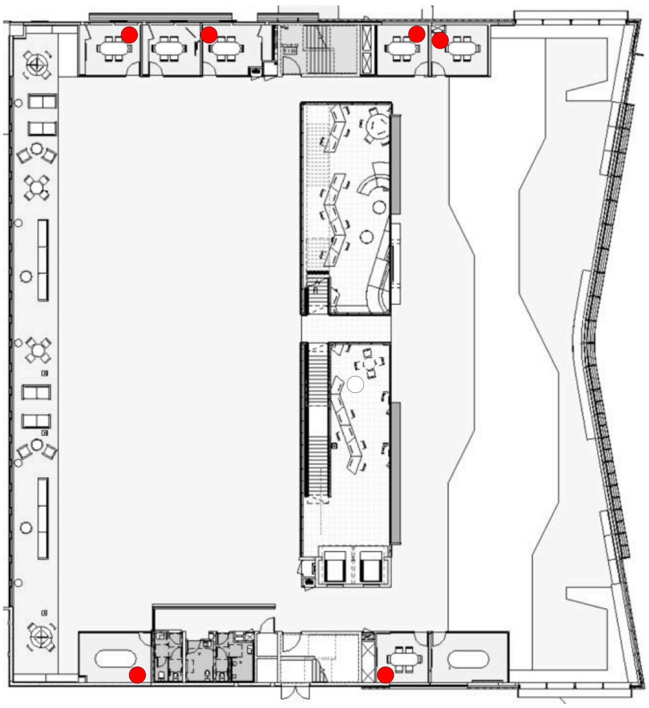

Fig. 7. IoT sensors deployment in the target rooms.

noting that, these conditions significantly affect the utilisation of energy in the building. The occupants-building interactions present quantitative variables that have the possibility of influencing the overall energy usage and consumption, and comfort in the building [56]. The conditions have the potential to significantly affect the occupants' productivity in the building [26].

5.1. Digital twin implementation process model

Fig. 8 presents the processes followed in developing the DT of the library building. The processes consist of seven steps and include the development of a 3D BIM model for simulation, visualisation of the 3D BIM model on a cloud-based platform, real-time data visualisation on a cloud-based platform, real-time data for prediction, development of best practice guidelines for decision-making, real-time data support from digital twin, and control feedback to physical building for energy and indoor environmental conditions optimisation. As indicated in section 4, the 3D BIM model of the library building was developed using Autodesk Revit 2020 software (.rvt file) in the first stage. The model is then simulated to assess the energy consumption of the target group study rooms under consideration. These rooms were the identified rooms where sensors devices were installed to assess the indoor environmental conditions. Stages 2 and 3 are to visualise the 3D BIM model and real-time data from the sensor devices on a cloud-based platform. The outputs of the combined 3D BIM model and sensor data are visualised on a dashboard. The model can easily be explored by selecting the specific GSR with a designated sensor ID and specifying the quantity of data to visualise. The monitored indoor environmental parameter (temperature,

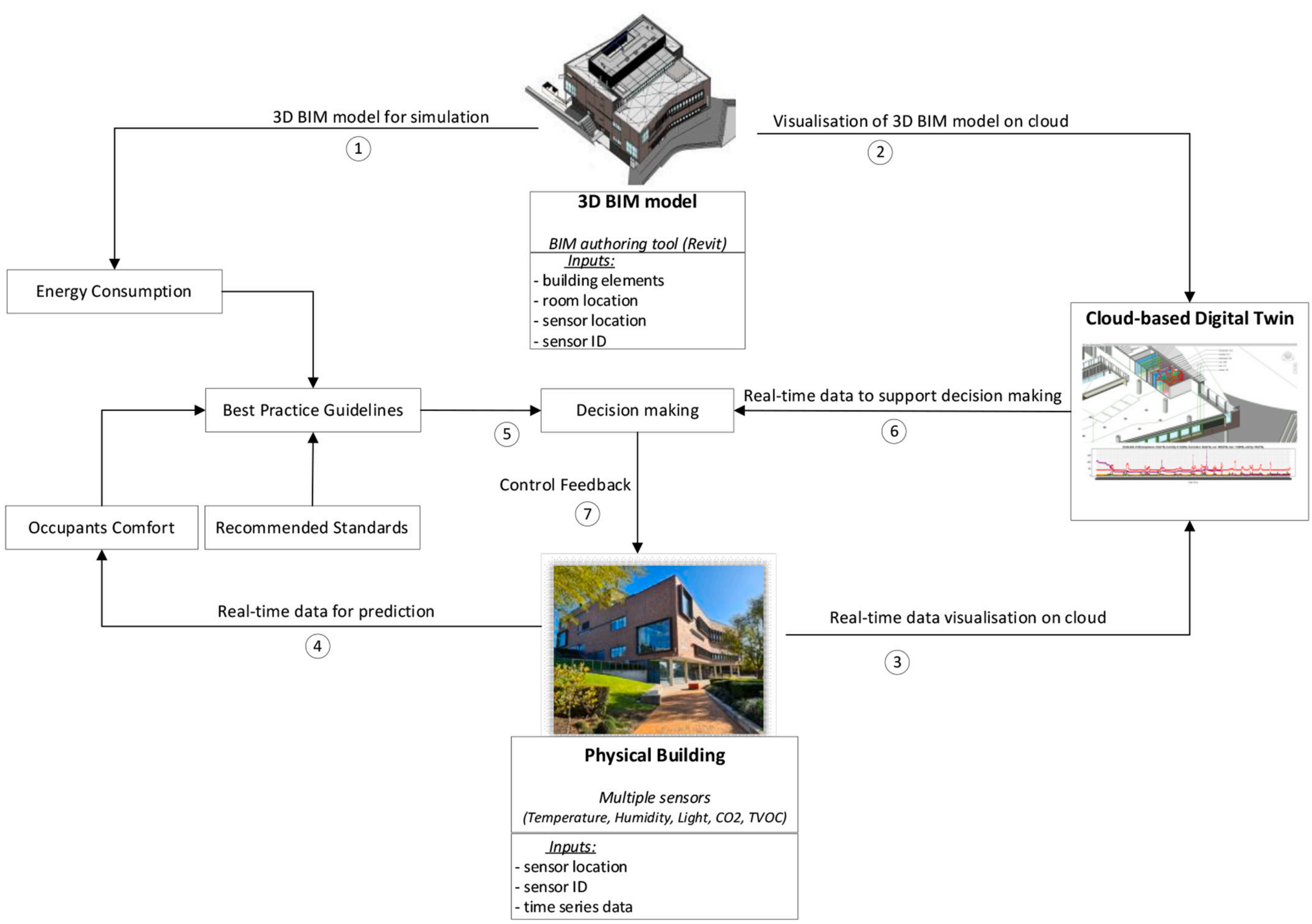

Fig. 8. Process model for digital twin implementation.

humidity, light, Co2, TVOC) and activity level of occupants are represented using colour-coded data blocks in the digital twin. The colour-coded data blocks present outputs of the data analysis in the digital twin.

Further, both maximum and minimum range values are used to determine the visualised colour of the various monitored parameters. This is indicated as the transparency in the digital twin. The following colours are assigned to the various parameters; temperature – blue, humidity- yellow, light (illumination) – green, Co2 – red, TVOC – purple, and activity level – brown. In order to make the data meaningful to the user, the recommended standards for the library building have been added to compare with measured values and colour-coded data blocks. The dashboard enables the user to display both real-time data and any historical data depending on the specific date and time selected. This is possible once a specific GSR and sensor ID have been selected. A CSV file is also available for download once a specific timeframe is specified. This capability has been explored to analyse the time-series data from May to August 2022. This period spans the autumn and spring semesters of the academic calendar. The system has been active since May 2022. The findings from March 22, 2023, at 2:58 pm for the selected target room are presented in Fig. 9. Stage 4 entails comparing the occupants' views regarding their comfort in the library building with the recommended standards to aid in the development of the best practice guidelines. These guidelines are aimed at optimising energy consumption and indoor environmental conditions of the library building. In stages 5 and 6, the developed guidelines together with the real-time and historical data are used to assist the facilities manager in making informed decisions regarding the building. Finally, control feedback is provided to the BMS to take suitable corrective actions in the physical library building.

5.2. *Evaluation and discussion of the results from the indoor environmental monitoring*

Fig. 9 shows the measurement of the indoor environmental conditions in the target rooms. The overall temperature in the target rooms ranges from 19.6 °C to 24.8 °C. The highest temperature value is experienced in the target room located in the western part of the building. This is due to the fact that the western target rooms are glazed and oriented towards the east where the sun rises. In this situation, it is expected that the air temperature would be slightly higher. Notwithstanding, due to the collection in the library, the temperature is normally lower than that which would be comfortable for humans. In comparison to the recommended standards in Table 1, the temperature threshold for a comfortable working environment in an office setting should be between 21 °C to 24 °C [4]. This infers that the library becomes so cold that it opposes a comfortable work environment which would advertently affect the productivity of the occupants [2,29]. The relative humidity is also steadily distributed in the monitored rooms. The highest of the humidity readings was 62.5% whilst the lowest was 27.5%. Similarly, from Table 1, it can be seen that ASHRAE [4] recommends 40–60% RH for a comfortable office work environment. This means the conditions in the target rooms especially the lowest humidity significantly contribute to the heat index of the occupants. It must be noted that the reason for the even distribution of both temperature and humidity is that the monitored target rooms had limited exposure to daylight. In terms of illumination, the maximum and lowest readings were 268 lx and 1 lx, respectively. The lighting levels indicate the rooms are very clear and occupants can comfortably engage in their reading activities when compared to the recommended standards [6]. It must be noted that in order to better appreciate the DT system's functionality, a clearer view of the system is presented in Fig. 10.

Additionally, the study also monitored the Co2 concentration in the target rooms with the highest reading being 1183 ppm and the lowest

Table 1
Recommended standards for monitored environmental parameters.

Indoor Environmental Parameter	Threshold	References
Temperature	21 - 24 °C	ASHRAE 55
Relative humidity	40–60%	ASHRAE 55
Lighting	320 lx (horizontal)	NABERS
	160 lx (vertical)	AS1680
Co2	1000 ppm	ASHRAE 62
	500 ppm	Wargocki 2016
TVOC	500 μg/m^3	LEED V4/ NABERS

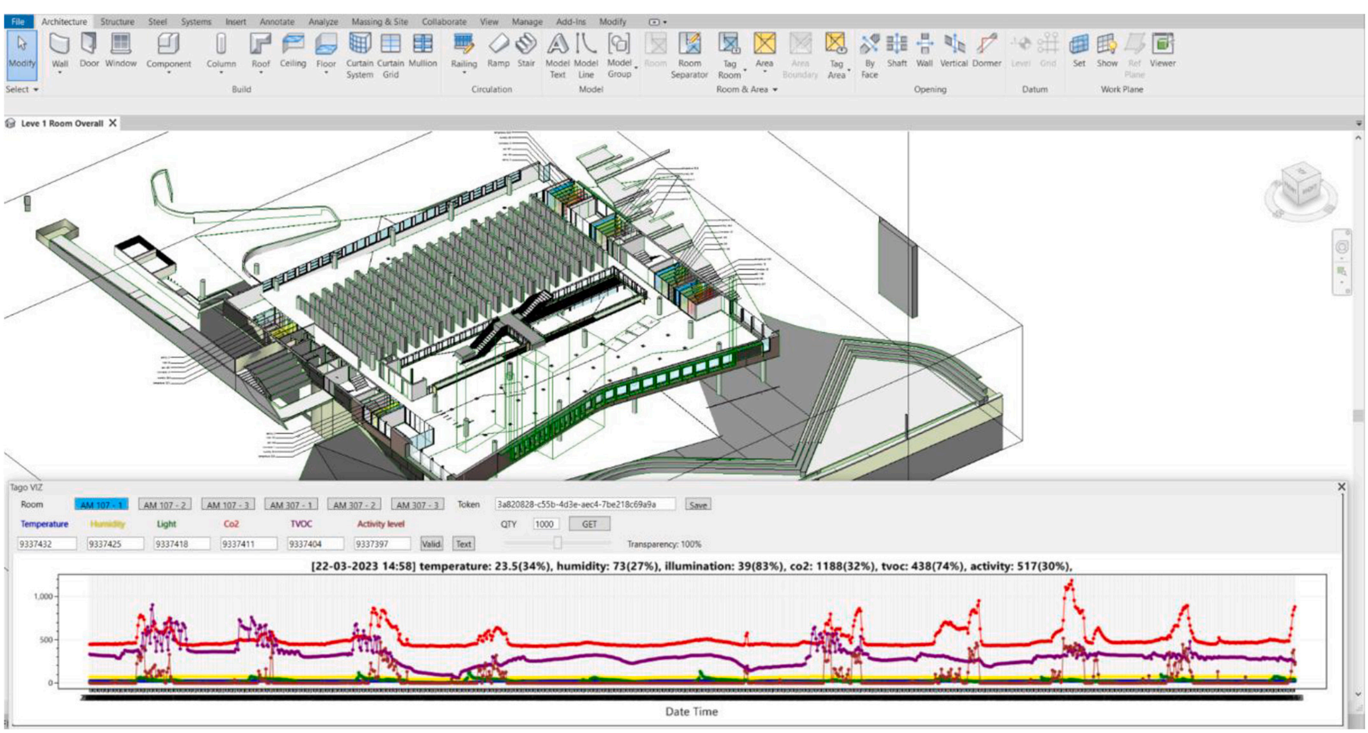

Fig. 9. Screenshot of indoor environmental conditions monitoring in DT.

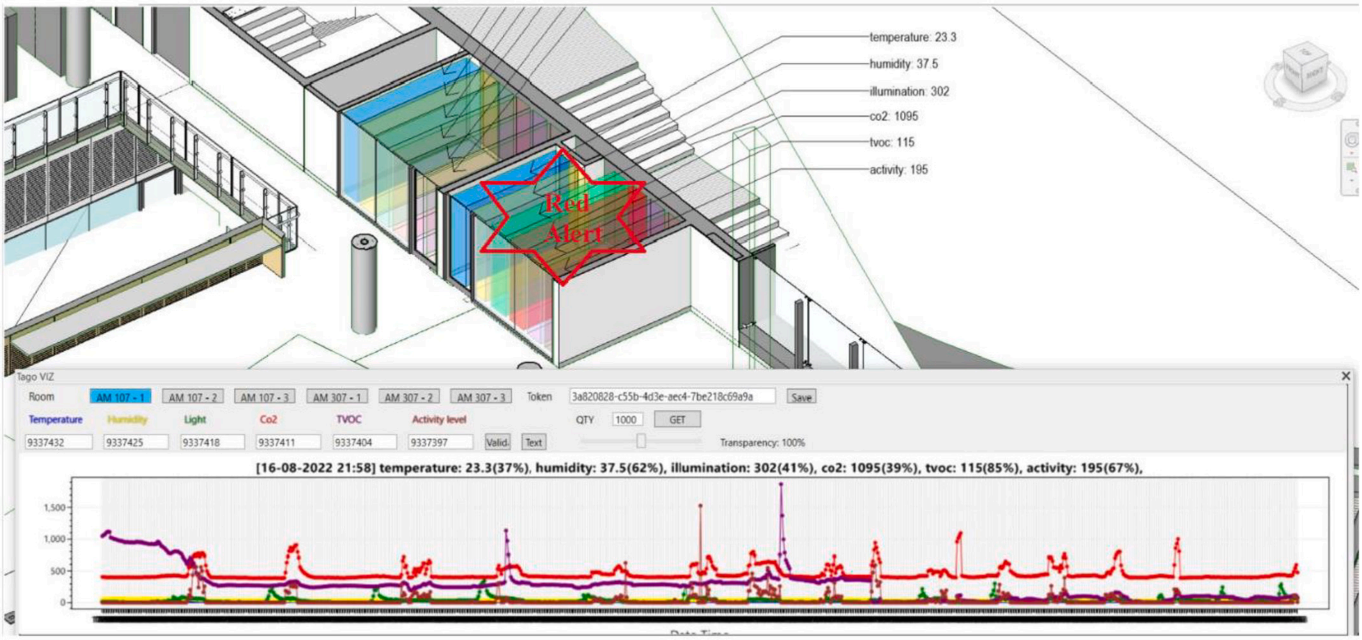

Fig. 10. Environmental condition anomaly detection in DT.

reading being 402 ppm. Compared to the recommended standard of 1000 ppm [5] in Table 1, the highest reading is above the standard and raises health concerns. As expected in the post-COVID-19 era, air quality is an essential requirement due to the respiratory issues associated with the pandemic. TVOC was also measured and the highest reading was 1083 ppb whilst the lowest reading was 4 ppb. These readings present a very unhealthy issue considering the air quality index, especially for occupants with respiratory diseases. Further, the results from the period under evaluation with an identified anomaly is presented in Fig. 10.

The results in Fig. 10 reveal that temperature, humidity, illumination, Co2 and TVOC are 23.3 °C, 37.5% RH, 302 lx, 1095 ppm, and 115 $\mu g/m^3$ respectively. Comparing the findings in digital twin to the recommended standards for the library building, temperature and lighting levels were adequate for occupants' comfortable working space. However, humidity level was slightly below the recommended standard range of 40–60% whilst Co2 was slightly above the recommended level of 1000 ppm. In addition, TVOC was also below the recommended threshold of 500 $\mu g/m^3$. This presents an opportunity for the facilities manager to further check the real-time and historical humidity and Co2 data to analyse faults in BMS. This can assist the facilities manager to make appropriate critical decisions if the need arises within this COVID-19 era. Notwithstanding, in a fully functional DT system, the sensors send signals to the BMS if any violation occurs and the actuators are then adjusted to fix the violation. This process is automated by the BMS and in most cases; the facility manager would not need to interfere with the process of the corrective actions. Apart from the visual representation of the conditions, the DT system also enhances prediction and decision making through the testing of different scenarios.

The occupancy of the target rooms was also determined using PIR sensors to determine the number of occupants in each room at any given period. The sensors were located close to the doors at appropriate distances to avoid intrusion and unnecessary counts due to the glazed nature of the target rooms. To test the reliability and effectiveness of the PIR sensor, the researchers walked into the target rooms in sequence and the sensor detected their activity levels or movements. However, the glazed nature of some of the target rooms made it difficult to ascertain the actual number of occupants in those rooms at any given time. A manual random inspection of the rooms at regular intervals was therefore recommended to determine the occupancy of those rooms. It was also possible to determine the room occupancy at any given time by establishing a correlation between the Co2 levels and physical occupancy checks. Notwithstanding, a different sensor that only read motions in the rooms could be installed but would add up to the cost of implementation. This information can assist the facility manager in promptly identifying the congested rooms with adverse Co2 levels and investigating any COVID-19-related health risks. Further, this data can enhance the decision-making of the facility manager in scheduling space clean-ups after the usage of the target rooms. This data can also help the facility manager to determine whether or not the maximum permissible number of occupants has been reached to minimise the spread of COVID-19.

5.3. *Lessons learnt from the DT development*

The main lessons learnt from the development of the DT system, which are worth mentioning, include the following:

- Data type, format, source, and content are key considerations when selecting an appropriate data acquisition protocol due to the massive volume of data to be collected.
- Selection of appropriate IoT sensor devices requires critical thinking since internet connectivity depending on available restrictions poses a challenge to DT development.
- Choosing and creating reliable network connectivity for efficient and effective real-time data flow between the physical model and virtual counterpart is vital for DT development.
- Choosing appropriate digital modelling tools, and creating digital models including the data schema is essential.
- Ensuring continuous and consistent synchronization together with quality control of the data being gathered is vital.
- Critical thinking regarding the selection of sensors to minimise energy consumption by the sensors since some do not run on batteries.
- Considering a possible integration of the DT system with other systems to ensure a holistic smart systems approach.

6. Conclusions

DTs have witnessed extensive advocacy and desire for their implementation across various industries including construction. The technology is being promoted by industry practitioners and researchers to be used in tackling some of the challenges of the construction industry. Within the construction industry, BIM and WSNs technologies are currently aiding the implementation of DTs. While BIM enables visual 3D communication, WSNs technology provides real-time data communication through IoT applications in DTs. To take advantage of the potential of DT, this paper aimed at providing an indication of how to select an appropriate digital platform that captures data dynamically and in real-time, select an appropriate visualisation platform and integrate the live data with the visualisation platform to build a DT. This study utilises an applied case study for which a prototype has been developed and tested for demonstrating the development of a DT in the construction industry. The system integrates real-time data collected through multiple sensors with a 3D BIM-based model that automatically combines the monitored data. The current state of the building is then reflected in the BIM model.

Further, the system provides an efficient platform and an impression of the building's indoor environmental conditions to the facility manager for prompt decision-making and data-driven predictive actions. It also enhances and promotes the commitment to taking improvement actions for building occupants' comfort. In addition, the colour-coded data blocks demonstrate the degree of risks associated with the various monitored environmental condition parameters. The system has proven that DT technology could be embraced to enhance the health and well-being of building occupants, especially during this post-COVID-19 era and ensure efficient energy management.

In terms of contribution to knowledge, this study provides a methodology for similar works to be carried out in creating a DT. This study's application domain is in educational buildings focusing on improving buildings' indoor environmental conditions monitoring for occupants' comfort and energy consumption optimisation. The study also experiments on the 'Living Lab' concept across universities. Further, this study provides DT developers with an opportunity to determine the best practices for developing DT in the construction industry. The paper has presented some lessons learnt in DT development, which will be beneficial to researchers and industry stakeholders wishing to develop DT.

However, the paper has some limitations that are worth mentioning. The first limitation has to do with the number of selected target rooms and sensors utilised in the study. Since cost is a major component in the implementation of DTs, only six group study rooms and six sensors were used in the study. The number of rooms could have been increased and other sensors could have been introduced to add to the data for much more informed decision-making. Secondly, only indoor environmental conditions monitoring has been reported in this study without the energy simulation and best practice guidelines as indicated in the process model. These would be addressed in future studies. Thirdly, the study's dependence on commercial software for DT system development could constrain the replicability and adaptability of the developed DT system.

In upcoming studies, the authors will explore data analytics techniques and integrate them into the developed DT system to provide feedback to the building management system (BMS) and actuators to take corrective actions in the physical building. It is also envisaged that future studies would provide facility managers with an opportunity to access the monitored data via mobile devices (i.e. cell phones).

Declaration of Competing Interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgement

We acknowledge Western Sydney University (WSU) for funding this study through the Western Sydney University Postgraduate Research Scholarship and the Environmental Sustainability Unit of the Office of Estate and Commercial (OEC). This study forms part of a research project being conducted at the Centre for Smart Modern Construction (c4SMC) at WSU. We are extremely grateful to the Editors and Reviewers whose constructive and invaluable comments and suggestions helped improve the quality of this paper significantly.

References

[1] M.A.M. Almuhaya, W.A. Jabbar, N. Sulaiman, S. Abdulmalek, A survey on LoRaWAN technology: recent trends, opportunities, simulation tools and future directions, Electronics 11 (1) (2022) 164. https://www.mdpi.com/2079-9292/11/1/164.

[2] M.S. Andargie, E. Azar, An applied framework to evaluate the impact of indoor office environmental factors on occupants' comfort and working conditions, Sustain. Cities Soc. 46 (2019), 101447, https://doi.org/10.1016/j.scs.2019.101447.

[3] M.K. Ansah, X. Chen, H. Yang, L. Lu, P.T. Lam, A review and outlook for integrated BIM application in green building assessment, Sustain. Cities Soc. 48 (2019), 101576, https://doi.org/10.1016/j.scs.2019.101576.

[4] ASHRAE, ANSI/ASHRAE Standard 55–2017. Thermal Environmental Conditions for Human Occupancy, American Society of Heating, Refrigeration and Air-Conditioning Engineers Inc., Atlanta, USA, 2017. Accessed: 05 May 2022, URL: https://www.ashrae.org/technical-resources/bookstore/standard-55-thermal-environmental-conditions-for-human-occupancy.

[5] ASHRAE, ANSI/ASHRAE Standard 62.1-2019. Ventilation for Acceptable Indoor Air Quality, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc, Atlanta, USA, 2019. Accessed: 20 January 2023, URL: https://www.ashrae.org/about/news/2019/ashrae-releases-updated-versions-of-standard-62-1-and-62-2.

[6] Australian Standard, AS1680.1-1990. Recommended Maintenace Illuminances for Various Tasks, Activities or Interiors, Standards Australia, Homebush, NSW, ISBN: 0726263273.

[7] M. Bajaj, B. Cole, D. Zwemer, Architecture to geometry-integrating system models with mechanical design, in: Proceedings of the American Institute of Aeronautics and Astronautics SPACE, long Beach, CA, USA, 13-16 September 2016, 2016, p. 5470, https://doi.org/10.2514/6.2016-5470.

[8] S. Batterman, C.-u. Peng, TVOC and CO2 concentrations as indicators in indoor air quality studies, Am. Ind. Hyg. Assoc. J. 56 (1) (1995) 55–65, https://doi.org/10.1080/15428119591017321.

[9] B. Becerik-Gerber, F. Jazizadeh, N. Li, G. Calis, Application areas and data requirements for BIM-enabled facilities management, J. Constr. Eng. Manag. 138 (3) (2012) 431–442, https://doi.org/10.1061/(asce)co.1943-7862.0000433. <https://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000433>.

[10] F. Beck, A. Borrmann, T.H. Kolbe, The need for a differentiation between heterogeneous information integration approaches in the field of "bim-gis integration": a literature review, ISPRS Ann. Photogram. Remote Sens. Spatial Inform. Sci. 6 (2020) 21–28, https://doi.org/10.5194/isprs-annals-VI-4-W1-2020-21-2020.

[11] A. Bolton, M. Enzer, J. Schooling, The Gemini Principles: Guiding Values for the National Digital Twin and Information Management Framework, Centre for Digital Built Britain and Digital Framework Task Group, Cambridge, UK, 2018, https://doi.org/10.17863/CAM.32260.

[12] T. Bouguera, J.-F. Diouris, J.-J. Chaillout, R. Jaouadi, G. Andrieux, Energy consumption model for sensor nodes based on LoRa and LoRaWAN, Sensors 18 (7) (2018) 2104, https://doi.org/10.3390/s18072104.

[13] J. Brodeur, Geosemantic Interoperability and the Geospatial Semantic Web, Springer Handbook of Geographic Information, 2012, pp. 291–310, https://doi.org/10.1007/978-3-540-72680-7_15.

[14] W. Chen, K. Chen, J.C. Cheng, Q. Wang, V.J. Gan, BIM-based framework for automatic scheduling of facility maintenance work orders, Autom. Constr. 91 (2018) 15–30, https://doi.org/10.1016/j.autcon.2018.03.007.

[15] W.F. Cheung, T.H. Lin, Y.C. Lin, A real-time construction safety monitoring system for hazardous gas integrating wireless sensor network and building information modeling technologies, Sensors (Switzerland) 18, no.2 (2018), https://doi.org/10.3390/s18020436.

[16] V. Chithra, S.S. Nagendra, Indoor air quality investigations in a naturally ventilated school building located close to an urban roadway in Chennai, India, Build. Environ. 54 (2012) 159–167, https://doi.org/10.1016/j.buildenv.2012.01.016.

[17] A. Čolaković, M. Hadžialić, Internet of Things (IoT): a review of enabling technologies, challenges, and open research issues, Comput. Netw. 144 (2018) 17–39, https://doi.org/10.1016/j.comnet.2018.07.017.

[18] B. Dave, A. Buda, A. Nurminen, K. Främling, A framework for integrating BIM and IoT through open standards, Autom. Constr. 95 (2018) 35–45, https://doi.org/10.1016/j.autcon.2018.07.022. https://doi.org/10.1016/j.autcon.2018.07.022.

[19] C. Eastman, P. Teicholz, R. Sacks, K. Liston, BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers, and

Contractors, John Wiley & Sons, Inc, Hoboken, New Jersey, USA, 2008. ISBN: 1119287537, 9781119287537.
[20] V.L. Gamsakhurdia, Semiotic construction of the self in multicultural societies: a theory of proculturation, Routledge (2020), https://doi.org/10.4324/9780429201240.
[21] X. Ge, S. Tu, G. Mao, C.-X. Wang, T. Han, 5G ultra-dense cellular networks, Inst. Elect. Electron. Eng. Wireless Commun. 23 (1) (2016) 72–79, https://doi.org/10.1109/MWC.2016.7422408.
[22] J.A. Goguen, D.F. Harrell, 7 information visualisation and semiotic morphisms, in: Studies in Multidisciplinarity vol. 2, Elsevier, 2005, pp. 83–97. http://www.cs.ucsd.edu/users/goguen/papers/sm/vzln.html.
[23] R. He, M. Li, V.J.L. Gan, J. Ma, BIM-enabled computerized design and digital fabrication of industrialized buildings: a case study, J. Clean. Prod. 278 (2021), https://doi.org/10.1016/j.jclepro.2020.123505. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85089736108&doi=10.1016%2fj.jclepro.2020.123505&partnerID=40&md5=476e56667edc4eff6f84cb0e5c609497>.
[24] P. Hui, L.T. Wong, K.W. Mui, Feasibility study of an express assessment protocol for the indoor air quality of air-conditioned offices, Indoor Built Environ. 15 (4) (2006) 373–378, https://doi.org/10.1177/1420326X06067866.
[25] P. Inyim, J. Rivera, Y. Zhu, Integration of building information modeling and economic and environmental impact analysis to support sustainable building design, J. Manag. Eng. 31 (1) (2015) A4014002, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000308.
[26] F. Jazizadeh, A. Ghahramani, B. Becerik-Gerber, T. Kichkaylo, M. Orosz, Human-building interaction framework for personalized thermal comfort-driven systems in office buildings, J. Comput. Civ. Eng. 28 (1) (2014) 2–16, https://doi.org/10.1061/(asce)cp.1943-5487.0000300. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000300.
[27] Y. Jiang, M. Li, D. Guo, W. Wu, R.Y. Zhong, G.Q. Huang, Digital twin-enabled smart modular integrated construction system for on-site assembly, Comput. Ind. 136 (2022), https://doi.org/10.1016/j.compind.2021.103594. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85121923542&doi=10.1016%2fj.compind.2021.103594&partnerID=40&md5=56b48df4f157aab9d82877caf4466dde.
[28] Y. Jiang, S. Yin, O. Kaynak, Data-driven monitoring and safety control of industrial cyber-physical systems: basics and beyond, Inst. Elect. Electron. Eng. Access 6 (2018) 47374–47384, https://doi.org/10.1109/ACCESS.2018.2866403.
[29] A. Kaushik, M. Arif, P. Tumula, O.J. Ebohon, Effect of thermal comfort on occupant productivity in office buildings: response surface analysis, Build. Environ. 180 (2020), 107021, https://doi.org/10.1016/j.buildenv.2020.107021.
[30] K. Kim, H. Kim, W. Kim, C. Kim, J. Kim, J. Yu, Integration of ifc objects and facility management work information using semantic web, Autom. Constr. 87 (2018) 173–187, https://doi.org/10.1016/j.autcon.2017.12.019.
[31] W. Lehr, L.W. McKnight, Wireless internet access: 3G vs. WiFi? Telecommun. Policy 27 (5–6) (2003) 351–370, https://doi.org/10.1016/S0308-5961(03)00004-1.
[32] Y.C.P. Lin, W.F. Cheung, Developing WSN/BIM-based environmental monitoring management system for parking garages in smart cities, J. Manag. Eng. 36 (3) (2020), https://doi.org/10.1061/(ASCE)ME.1943-5479.0000760. Scopus.
[33] Y. Liu, K.A. Hassan, M. Karlsson, Z. Pang, S. Gong, A data-centric internet of things framework based on azure cloud, Inst. Elect. Electron. Eng. Access 7 (2019) 53839–53858, https://doi.org/10.1109/ACCESS.2019.2913224.
[34] Q. Lu, A.K. Parlikad, P. Woodall, G. Don Ranasinghe, X. Xie, Z. Liang, et al., Developing a digital twin at building and city levels: case study of West Cambridge Campus, J. Manag. Eng. 36 (3) (2020), https://doi.org/10.1061/(ASCE)ME.1943-5479.0000763.
[35] Q. Lu, X. Xie, A.K. Parlikad, J.M. Schooling, Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance, Autom. Constr. 118 (2020). Scopus, DOI 10.1016/j.autcon.2020.103277.
[36] Y. Lu, Z. Wu, R. Chang, Y. Li, Building information modeling (BIM) for green buildings: a critical review and future directions, Autom. Constr. 83 (2017) 134–148, https://doi.org/10.1016/j.autcon.2017.08.024.
[37] A. Mannino, M.C. Dejaco, F. Re Cecconi, Building information modelling and internet of things integration for facility management-literature review and future needs, Appl. Sci. (Switzerland) 11 (7) (2021), https://doi.org/10.3390/app11073062.
[38] P. Matus, Discursive representation: semiotics, theory, and method, Semiotica 2018 (225) (2018) 103–127, https://doi.org/10.1515/sem-2017-0019.
[39] C. Meyer, Overview of TVOC and indoor air quality, in: Renesas Electronics Corporation: Tokyo, Japan, 2018. Accessed: 15 February 2023, URL: https://www.mouser.com/pdfdocs/IDT_ ZMOD4410-Overview-TVOC-IAQWHP20180524.pdf.
[40] MultiTech, MultiTech Conduit AP, Access Point for Lora technology (MTCAP series), viewed 22 April 2022. https://www.multitech.com/brands/multiconnect-conduit-ap, 2022.
[41] B. Nathali Silva, M. Khan, K. Han, Big data analytics embedded smart city architecture for performance enhancement through real-time data processing and decision-making, Wirel. Commun. Mob. Comput. 2017 (2017), https://doi.org/10.1155/2017/9429676.
[42] NATSPEC, *NATSPEC National BIM guide*, Construction Information System Limited, Sydney, Australia, Accessed: 21 November 2022. http://codebim.com/wp-content/uploads/2013/06/NATSPEC_National_BIM_Guide_v1.0_Sep_2011.pdf, 2016.
[43] NIBS, p.7, *National BIM Standard Version 1 - Part 1: Overview, Principles, and Methodologies [online]*, National Institute of Building Science, London, viewed 20 January 2020, 2007 http://www.wbdg.org.
[44] N. Ohmura, E. Takase, S. Ogino, Y. Okano, S. Arai, Material property of on-metal magnetic sheet attached on NFC/HF-RFID antenna and research of its proper pattern and size on, Inst. Elect. Electron. Eng. 2 (2013) 1158–1161 (ISBN: 978-756414279-7).
[45] D.G.J. Opoku, S. Perera, R. Osei-Kyei, M. Rashidi, Digital twin application in the construction industry: a literature review, J. Build. Eng. 40 (2021), 102726, https://doi.org/10.1016/j.jobe.2021.102726.
[46] D.G.J. Opoku, S. Perera, R. Osei-Kyei, M. Rashidi, K. Bamdad, T. Famakinwa, Barriers to the adoption of digital twin in the construction industry: a literature review, Informatics 10 (1) (2023) 14, https://doi.org/10.3390/informatics10010014.
[47] A.S. Rao, M. Radanovic, Y. Liu, S. Hu, Y. Fang, K. Khoshelham, et al., Real-time monitoring of construction sites: sensors, methods, and applications, Autom. Constr. 136 (2022), 104099, https://doi.org/10.1016/j.autcon.2021.104099.
[48] G.N. Sava, S. Pluteanu, V. Tanasiev, R. Patrascu, H. Necula, Integration of BIM solutions and IoT in smart houses, Inst. Elect. Electron. Eng. (2018), https://doi.org/10.1109/eeeic.2018.8494628. https://doi.org/10.1109/EEEIC.2018.8494628.
[49] A. Schweigkofler, O. Braholli, S. Akro, D. Siegele, P. Penna, C. Marcher, L. Tagliabue, D. Matt, Digital Twin as energy management tool through IoT and BIM data integration, in: Proceedings of the CLIMA 2022 Conference, 22–25 May, Rotterdam, The Netherlands, 2022, https://doi.org/10.34641/clima.2022.46.
[50] J.M. Scoulas, E. Carrillo, L. Naru, Assessing user experience: incorporating student voice in libraries' pandemic response, J. Libr. Adm. 61 (6) (2021) 686–703, https://doi.org/10.1080/01930826.2021.1947058.
[51] F. Shalabi, Y. Turkan, IFC BIM-based facility management approach to optimize data collection for corrective maintenance, J. Perform. Constr. Facil. 31 (1) (2017) 04016081, https://doi.org/10.1061/(ASCE)CF.1943-5509.0000941.
[52] N. Sornin, M. Luis, T. Eirich, T. Kramp, O. Hersent, LoRa specification 1.0 LoRa alliance standard specification, 2015. Accessed: 15 October 2022, http://www.lora-alliance.org/.
[53] TagoIO, Easily create your own IoT solutions, viewed 15 April 2022. https://tago.io/, 2022.
[54] The Things Network, Lorawan, 2022 viewed 11 April 2022, https://www.thethingsnetwork.org/docs/lorawan/.
[55] Y.-H. Tsai, J. Wang, W.-T. Chien, C.-Y. Wei, X. Wang, S.-H. Hsieh, A BIM-based approach for predicting corrosion under insulation, Autom. Constr. 107 (2019), 102923, https://doi.org/10.1016/j.autcon.2019.102923.
[56] C. Wang, J. Zhu, Developments in the understanding of gas–solid contact efficiency in the circulating fluidized bed riser reactor: a review, Chin. J. Chem. Eng. 24 (1) (2016) 53–62, https://doi.org/10.1016/j.cjche.2015.07.004.
[57] T. Wang, V.J. Gan, D. Hu, H. Liu, Digital twin-enabled built environment sensing and monitoring through semantic enrichment of BIM with SensorML, Autom. Constr. 144 (2022), 104625, https://doi.org/10.1016/j.autcon.2022.104625.
[58] Y. Xu, Y. Sun, X. Liu, Y. Zheng, A digital-twin-assisted fault diagnosis using deep transfer learning, Inst. Elect. Electron. Eng. Access 7 (2019) 19990–19999, https://doi.org/10.1109/ACCESS.2018.2890566.
[59] D. Zorbas, K. Abdelfadeel, P. Kotzanikolaou, D. Pesch, TS-LoRa: time-slotted LoRaWAN for the industrial internet of things, Comput. Commun. 153 (2020) 1–10, https://doi.org/10.1016/j.comcom.2020.01.056.