Digital Twin: Vision, Benefits, Boundaries, and Creation for Buildings

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ABSTRACT The concept of a digital twin has been used in some industries where an accurate digital model of the equipment can be used for predictive maintenance. The use of a digital twin for performance is critical, and for capital-intensive equipment such as jet engines it proved to be successful in terms of cost savings and reliability improvements. In this paper, we aim to study the expansion of the digital twin in including building life cycle management and explore the benefits and shortcomings of such implementation. In four rounds of experimentation, more than 25,000 sensor reading instances were collected, analyzed, and utilized to create and test a limited digital twin of an office building facade element. This is performed to point out the method of implementation, highlight the benefits gained from digital twin, and to uncover some of the technical shortcomings of the current Internet of Things systems for this purpose.

INDEX TERMS Building information modeling, digital twin, life cycle management, Internet of Things, wireless sensor network.

I. INTRODUCTION

The emergence of the Internet of Things (IoT) which is partly the result of Moore's law that allowed powerful semiconductor chips to be produced at very low prices [1] can impact every aspect of our economy [2], [3]. Developments such as cars that are connected and autonomous [4] to flying robots [5] and smart houses [6] are all examples of either IoT being integrated into legacy systems or IoT enabling the creation of entirely new concepts. Smart buildings are emerging as the next frontier in the development cycle of architectural structures [7]. Embedding programmable services into the residential buildings is currently underway, including services such as heating and cooling as well as the integration of household appliances. This collaboration is taking place between the largest household appliance manufacturers and internet companies such as Amazon, Google, and Microsoft.

A concept that is explored extensively in the literature and has been implemented in real-world construction projects around the world is building information modeling (BIM) [8]–[10].

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BIM is a platform for keeping an accurate and interoperable record of building information to enhance planning, construction, and maintenance over the life cycle of a facility [10], [11]. In particular, BIM has been developed for embedding the building's 3D computer aided design (CAD) model with additional data related to building specification, time schedule, cost estimation, and maintenance management (i.e., 4D, 5D, and 6D) [12]–[14] to reduce cost by preventing mistakes in the design and construction phase [15]. Currently, BIM is used in architecture, construction, engineering and facility management (AEC/FM) functions for design visualization and consistency, clash detection, lean construction, cost and time estimation, and enhanced stakeholders' interoperability [10]. Efforts [16, p. 19] to ensure BIM benefits from real-time data inputs (e.g. from sensors and IoT devices) are underway [17]; these efforts, in turn would benefit the buildings that already have implemented BIM or are willing to undertake the effort and cost of creating BIM documentation. More than 80% of buildings in Europe are constructed prior to 1990, and therefore do not have BIM [10], [18]–[21]. For existing buildings without BIM documentation, there exist major obstacles to produce it (i.e., high effort requirement for creating and updating the BIM model and difficulties
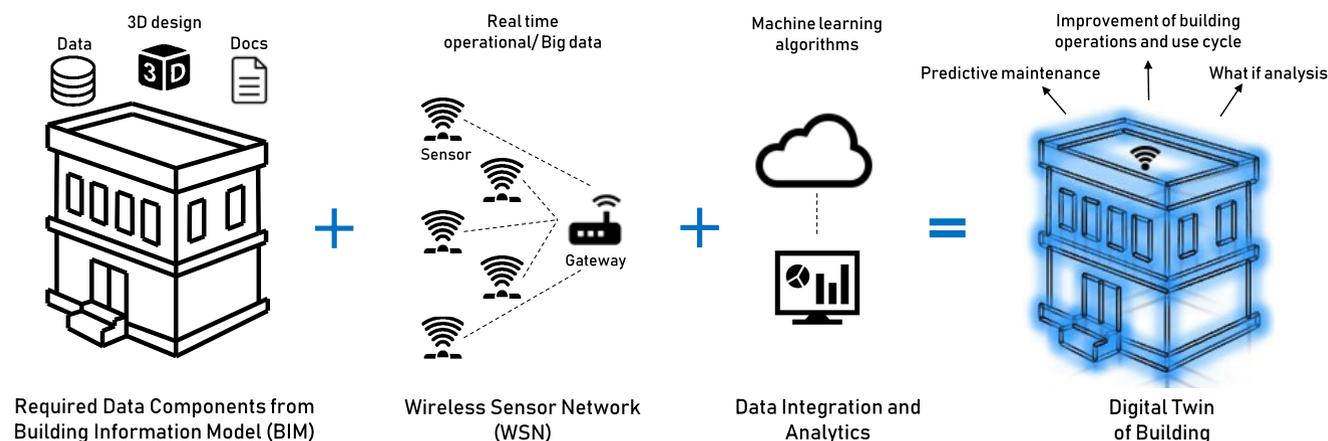
FIGURE 1. Essential components to create a digital twin of building and difference with BIM.

related to the solving the issues of uncertain data and relationships in the BIM [10]). Existing buildings can therefore benefit from the implementation of a digital twin, which is a known concept in the field of manufacturing [22], for the enhancement of building operation and maintenance and for the implementation of a closed-loop design [23].

Wireless sensor network (WSN) integration and data analytics are two of the components required for the creation of a digital twin [24]. Digital twin visualization for a building can rely on 3D CAD model extracted from BIM or a custom 3D model of the building. The digital twin of a building can utilize various sensor networks to create a real-time view of the asset (see Fig. 1). This dynamic view allows for real-time analytics, informed decision-making, building efficiency, and comfort enhancement.

The first major difference between a building's BIM and digital twin is that the former was designed to improve the efficiency of design and construction and is still used in these phases of the building life cycle [25], whereas the latter is designed to monitor a physical asset and improve its operational efficiency and to enable predictive maintenance [26]. The second major difference is that BIM was not designed to work with real-time data and is still used in the industry for design, construction, and maintenance tasks and interoperability, which do not necessarily require real-time capability [27]; meanwhile, digital twin is the digital counterpart of a physical asset and works contrary to the current BIM platform. Digital twin works specifically with real-time data fed by the sensor systems to record and analyze the real-time structural and environmental parameters of a physical asset for the purpose of performing highly accurate digital twin simulation and data analytics [26]. The third difference between the two concepts is related to the type of data required for the construction of each model. While BIM is suitable for the integration of cost estimation and time schedule data to enhance the efficiency of a construction project [8], [28], digital twin is designed to integrate real-time sensor readings to analyze and improve

the building's interaction with the environment and with users [29].

In this paper, we aim to explore issues related to the creation of a building's digital twin and propose a method for its implementation for a building facade. Moreover, the paper discusses some of the applications of the digital twin of a building facade.

This paper is organized in the following manner. After the research introduction, the study presents the literature review, which explores the research conducted on digital twin, building information modeling, comparison of BIM and digital twin of building, and smart buildings. In the third section, the research methodology and the case study setup are explained in detail. Following this, the results are presented in the sections that concern technical obstacles, validation of data, sensor configuration, and digital twin creation. The next section is the discussion of benefits of the digital twin of buildings, and the study ends with the conclusions.

II. LITERATURE REVIEW
A. DIGITAL TWIN
At present, one of the standard methods for enhancing system design, testing, and maintenance is through modeling and simulation. Modeling and simulation play a decisive role in supporting design tasks and validating system properties. However, the first simulation-based solutions are known for optimized operations and failure prediction [34]. The digital twin emerged from the integration of sensor networks and the digitalization of machinery and production systems in the manufacturing industry [35]. The main difference between simulation in the design phase and a digital twin is that the latter requires a physical asset and a sensor network, while the former does not [24]. Accordingly, the study in [35] presented an expanded definition: "digital twins will facilitate the means to monitor, understand, and optimize the functions of all physical entities, living as well as nonliving, by enabling the seamless transmission of data between the physical and virtual world."

TABLE 1. A detailed comparison of BIM and digital twin of building.

Differentiator / Concept	Application focus	Users	Supporting technology	Software	Stage of life cycle	Concept origin
BIM	Design visualization and consistency, Clash detection, Lean construction, Time and cost estimation, Stakeholders' interoperability [10]	AEC, Facility manager [16], [30]	Detailed 3D model, Common data environment (CDE), Industry Foundation Class (IFC), Construction Operations Building Information Exchange (COBie) [16]	Revit, MicroStation, ArchiCAD, Open source BIMserver, Grevit [16]	Design, Construction, Use (maintenance), Demolition [31]	Charles Eastman [16]
Digital Twin of Building	Predictive maintenance [26], Tenant comfort enhancement, Resource consumption efficiency, What-if analysis, Closed-loop design [23]	Architect, Facility manager	3D model, WSN, Data analytics, Machine learning [32]	Predix, Dasher 360, Ecodomus	Use (operation) [33]	NASA's Apollo program [22]

The research in [36] described the simulation aspect of digital twins as the collection of relevant digital artifacts that involves engineering and operation data, in addition to behavior description using various simulation models. Digital twins utilize these specific simulation models based on their capability for solving problems, deriving relevant solutions for real-life systems, and describing behavior. In general, the study in [36] defined the vision of the digital twin as "a comprehensive physical and functional description of a component, product or system together with all available operational data."

The digital twin is a concept that can be exerted to many fields and technologies [37], and therefore it seems the concept could disrupt industries beyond manufacturing. In addition, the digital twin was one of the top ten strategic technology trends of 2018, and based on research future predictions, the digital twin market will reach 15 billion dollars by 2023 [35], [38]. The research in [39] defined the digital twin of a building as the "interaction between the real-world building's indoor environment and a digital yet realistic virtual representation model of building environment, which provides the opportunity on real-time monitoring and data acquisition." In their delineation, an indoor environment indicates information on the air temperature, airflow, relative humidity, and lighting condition, while a digital virtual one indicates computational fluid dynamics and luminance level. Moreover, based on study presented in [39], some of the considerable benefits of creating digital twin of a building are as follows: 1) gathering, generating and visualizing the environment of the building, 2) analyzing data irregularities, and 3) optimizing building services.

B. BUILDING INFORMATION MODELING

According to the US National Building Information Model Standard Project Committee [30], BIM is "a digital representation of physical and functional characteristics of a facility. A BIM is a shared knowledge resource for information about a facility, forming a reliable basis for decisions during its life cycle; defined as existing from earliest conception to demolition." Meanwhile, [31] defines BIM as "an overarching term to describe a variety of activities in object-oriented Computer Aided Design (CAD), which supports the representation of building elements in terms of their 3D geometric and non-geometric (functional) attributes and relationships."

BIM is different from 3D CAD modeling [30], [31], [40]. The main emphasis of BIM is on embedded information (e.g., specification, material type, installation method, time, cost) in the design model and on the interoperability of this comprehensive information-rich model for enhanced collaboration in the AEC/FM community.

In an ideal case scenario, BIM can also be used to simulate operations management on a construction site during construction and can thus support and optimize the development of the construction schedule [41].

BIM has been changing over the history of its existence. According to the BIM maturity model presented in [16, p. 15-16], Level 0 BIM in the 1990s took advantage of early CAD modeling software, hence, information was scattered, and data sharing was mostly on paper drawings. During the 2000s, Level 1 BIM became popular; companies started to use 3D CAD modeling, and common data environment (CDE) was used for digital data sharing. However, Level 1 BIM did not allow project team members to share the models with one another. Level 2 BIM gained traction during the 2010s when collaboration and sharing of digital files and models entered the next evolution level through the use of common file formats and the introduction of Industry Foundation Class (IFC) and Construction Operations Building Information Exchange (COBie). Most companies are currently at Level 1 or Level 2 however; nonetheless, Level 3 BIM is being developed with an emphasis on stakeholders' collaboration (i.e., through the use of same design model). The design model of Level 3 BIM is stored in a centralized cloud-based repository to ensure collaboration throughout the building life cycle.

BIM is still mostly used for resource efficiency enhancement during facility design and construction [10], [42] and knowledge exchange [11]. The purpose is to facilitate the tasks of building architects, engineers, and facility managers and avoid costly design mistakes [11]–[14].

C. COMPARISON OF BIM AND DIGITAL TWIN OF BUILDING

BIM and digital twin of building can be compared in detail based on the following aspects; application focus, users, supporting technology, software, stages of life cycle, and origin (see Table 1). BIM is mainly used to prevent errors during the design of a building, facilitate communication between

stakeholders, improve construction efficiency, and monitor the construction project's time and cost [10]. Meanwhile, the digital twin of a building can be used for predictive maintenance [26], resource efficiency improvement, enhancement of tenants' comfort, what-if analysis for optimization of the building design, and enabling closed-loop design [23] to transfer learnings from a building to the future ones. The users of BIM are architects, engineers, and constructors who utilize it during the design and construction phase [9], [16]. BIM is also used by facility managers [30] for maintenance planning throughout the building life cycle. Notably, BIM can be used during the demolition [31] as it contains relevant information. Digital twin is utilized by facility managers in the use phase of the building life cycle to enhance its operation. Digital twin also provides architects valuable inputs for the design of future buildings based on the detected flaws and improvement areas unveiled during the use phase of a building.

Technologies that support BIM at its current form are detailed 3D CAD modeling, CDE to create a single source of information for the collaboration of project teams, and standard data formats for sharing and exchanging BIM data between different software applications such as IFC and COBie [16]. Supporting technologies for digital twin are 3D CAD modeling, WSNs, machine learning algorithms [32], and data analytics. The major software applications used for BIM are Autodesk Revit, ArchiCAD by Graphisoft, MicroStation by Bentley Systems, and the open source BIMserver by TNO [16]. Meanwhile, some of the software applications used to create a digital twin are Predix from General Electric, Dasher 360 from Autodesk, and Ecodomus. Notably, the origin of the two concepts are also different. BIM was conceptualized by Charles Eastman in the mid-1970s [16] and was implemented for the first time in the RUCAPS CAD system for the London Heathrow Airport Terminal 3 design and construction [43], [44]. Digital twin conceptualization originates from the Apollo program at NASA [22], where a physical twin of the crew module was kept on the ground to simulate conditions and resolve possible issues that the spacecraft may face in space. However, the actual implementation of digital twin occurred only recently when General Electric developed the Predix software platform for the collection and analysis of the data from sensors installed in GE90 jet engines for blades degradation monitoring and predictive maintenance [45]–[47].

Regarding flexibility, although some buildings are still constructed using pre-BIM traditional practices, they can benefit from digital twin by being retrofitted with sensors and by taking advantage of cloud-based analytics tools.

D. INTERNET OF THINGS AND SMART BUILDINGS
The IoT is significantly expanding, and it is predicted to reach a staggering 20 billion internet-connected things by 2020 [48]. The study in [49] defined IoT as "an open and comprehensive network of intelligent objects that have the capacity to auto-organize, share information, data, and resources, reacting and acting in the face of situations and changes in the environment." In discussing modern advancement in innovative internet technologies and WSN, IoT has emerged as a ubiquitous global computing network where the collected data from more affordable and available sensors and actuators can be utilized for data analysis-based control of the resources or physical environments [48], [50], [51]. With the enhancement of computing and communication capabilities for the physical objects (i.e., the things in IoT), these objects can provide high-quality services for the users through their wired or wireless communications [9]. The concept of a smart city can be pragmatic in light of this breakthrough. One of the main service domains in a smart city is a smart building [50]. According to the research in [52], three primary characteristics that identify a smart building are its components, functions, and outcomes. Components consist of multiple interconnected pieces of technical building equipment and appliances, sensing and control infrastructure, and emerging technologies. All of these components behave according to their functions, which define the intelligence and effectiveness of the building and which eventually result in certain outcomes, such as health, comfort, productivity, and energy efficiency [53]; all these would benefit the environment, society, and the economy.

E. GAP IN THE LITERATURE
Although the concept of IoT has been studied extensively in the context of future connected equipment and the possibilities that come from it [54]–[57], the use of IoT-enabled sensor networks to build a digital twin of a smart building was not extensively studied. The study in [39] presented a brief overview of a conceptual framework for a transition from a physical room to a digital twin, but the study fell short in providing an in-depth technical analysis of the framework for the transition, and they also did not present any empirical experimentation to support their concept. The study in [58] provided a background on the concept of the digital twin of a building and briefly pinpointed the potential applications, but it did not provide any real-world proof or data. In another article, [59] presented a case of digital twin utilization by Kone company to improve the elevator service in buildings while reducing maintenance cost. Fraunhofer Building Innovation Alliance is studying the digital twin of buildings, and in a published short note, it highlighted the digital twin of a building's potential benefits throughout the building life cycle [60]. The study in [61] utilized the concept of digital twin of a building to calculate the rate of return on investment in upgrading existing buildings to net-zero energy buildings (NZEB). Their research was based on a BIM model that was simulated in Revit software for energy saving calculations. However, they stopped short of implementing the digital twin of a building and collecting real-time empirical data. In this research, we contribute to filling the knowledge gap by investigating the creation of a sensor network for the digital twin of a building and by studying the current technical shortcomings of establishing a digital twin. The application and the benefits
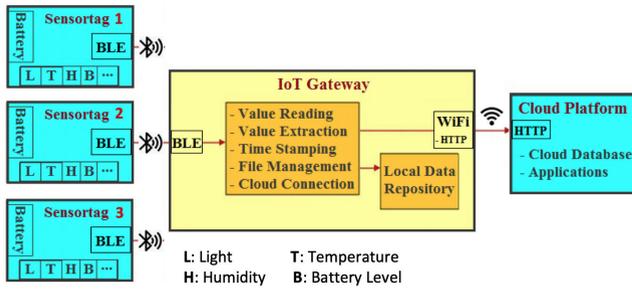
FIGURE 2. Data flow diagram of the designed sensor network.

of the digital twin of a building are also discussed in this paper.

III. METHODOLOGY

The methodology used in this research is experimentation using a testbed. To collect data, we created a WSN that was installed on the building facade of an office building at the Aalto University in Finland. The aim was to collect light, ambient temperature, and relative humidity measurements data of the environment.

A. EXPERIMENT TESTBED SETUP

Texas Instruments (TI) Sensortag CC2650 was selected due to its characteristics, such as the availability of various sensors on each tag, Bluetooth Low Energy (BLE) communication technology, coin-cell power source, and low cost. Another important aspect that led to this selection was the existence of a large community of developers around this sensor hardware platform. In addition, we used a Raspberry Pi 3B+ as the sensor network gateway. We utilized Raspbian as the operating system on the network gateway, and we used an open source collector code by the IBM company in Python programming language for communication and for recording the data that were generated by TI Sensortags. This code was modified to lengthen the period between sensor data recordings up to 240 seconds, and further developments allowed for offline and cloud-based recording of the sensors' data. For the offline part, which was used for the development of this paper, the data recordings were stored in *.csv* files on the gateway's local memory. Fig. 2 shows the data flow diagram for our sensor network.

B. DATA COLLECTION STEPS

The process of data collection followed a four-step process, as illustrated in Fig. 3. Step 1 is initial testing, debugging, and WSN setup verification. Step 2 pertains to expanding the WSN. Step 3 relates to sensors' reading validation, while Step 4 describes the creation and visualization of a limited facade digital twin. All of these steps are explained individually in the following subsections.

1) INITIAL TESTING, DEBUGGING, AND WSN SETUP VERIFICATION

During the initial testing, we evaluated the performance of WSN inside the building using three Sensortags. We then
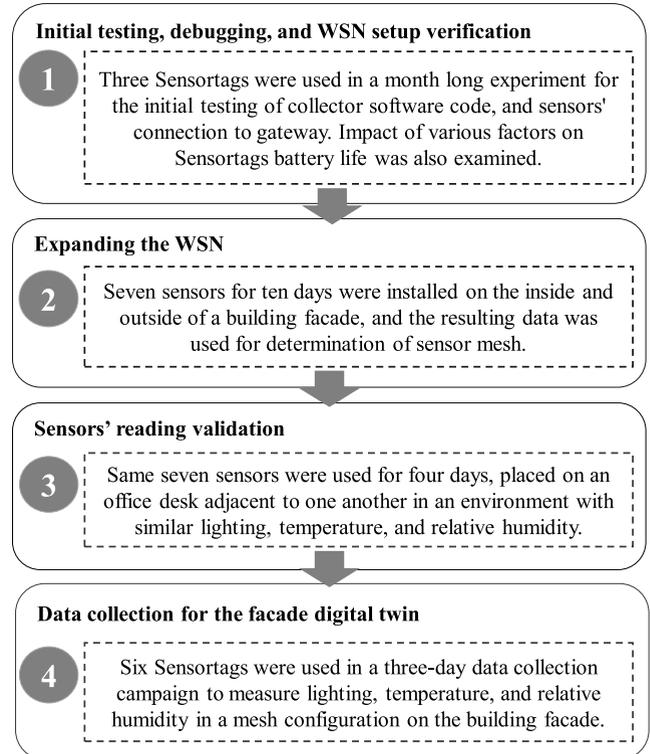

FIGURE 3. Four phases of data collection.

initiated several data collection tests over a period of one month while the sensors were installed on the inside and outside of the building facade. During this time, we examined the impact of distance and data recording time interval on the battery life of the Sensortags. Moreover, the continuous connectivity between the gateway and the Sensortags was investigated. We encountered a number of serious issues with the stability of the communication between the Sensortags and the gateway. After analyzing the data collected from the initial tests, we formulated solutions for the communication issues encountered during the tests to expand the sensor network.

2) EXPANDING THE WSN

We expanded the sensor network from three sensors to seven. Fig. 4 shows the arrangement of the seven sensors. A data set was collected for a period of 10 days, during which the sensors were on the building facade, both inside (i.e., on the windows) and outside. Three sensors were installed inside the room, specifically on the windows facing outward, and four sensors were installed on the facade, facing outward of the same wall as the inside sensors. This data set was utilized to determine the optimal mesh of the WSN on the building facade. Throughout the data collection campaign, in order to prevent confusion regarding the assignment of sensor readings to the sensor that it belongs to, a constant one-to-one matching is used where the name of the sensor data file on the gateway corresponds to a similar physical designation, which is based on each sensor's constant MAC address (see Table 2).

(a) Location of sensors on the inside and outside of the workplace.

(b) Arrangement of the seven Sensortags on the building facade.

FIGURE 4. Sensor configurations at the office building.

TABLE 2. Sample of the table used for the sensors' physical and virtual designations in relation to MAC addresses.

| Physical Numbering	MAC Address	File Title (.csv)
$S1$	$98:07:2d:40:f1:04$	Sensor1

3) SENSORS' READING VALIDATION

A different data set was collected to examine the validity of the sensors' readings and to determine each sensor's error range for each environmental parameter of light, ambient temperature, and relative humidity. This data set was collected while sensors were placed adjacent to one another on the surface of an office desk where light, ambient temperature, and relative humidity were the same for all the sensors. The data collection interval was set to 90 seconds for all sensors. Section V uses this data set to calculate the sensors' error range. We used Minitab and Microsoft Excel software to analyze the sensors' data sets and produce the time series graphs.

4) DATA COLLECTION FOR THE FACADE DIGITAL TWIN

In the last round of data collection, six sensors were installed on the facade of a building at the Aalto University campus, and a data set of environmental lighting, ambient temperature, and relative humidity was collected. This data set was used for the creation and visualization of the digital twin of the building facade.

C. RAW SENSOR DATA PROCESSING

The data collected from the sensors contained noise due to multiple factors. These factors caused the sensors to disconnect or to not be able to send the correct data to the gateway. One of the reasons was the low battery level, which caused the energy-intensive sensors to send wrong readings (noise) to
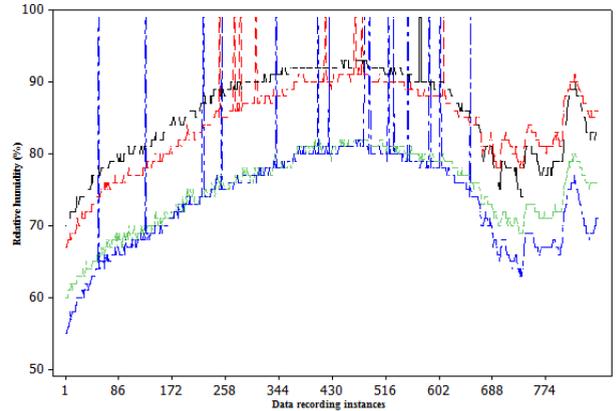
(a) Time series graph of raw relative humidity data (in percentage) recorded by four sensors on the building facade.
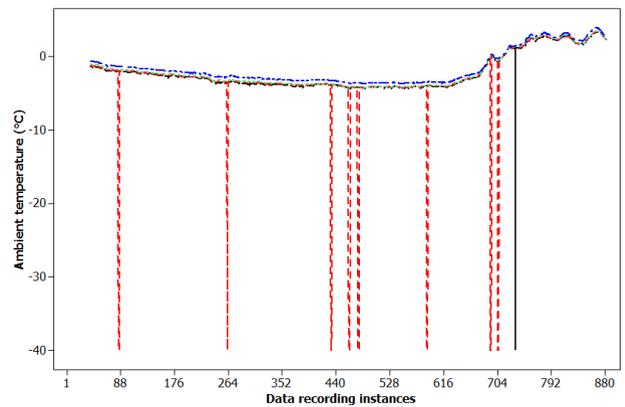
(b) Time series graph of raw ambient temperature data recorded by four sensors on the building facade.

FIGURE 5. Time series plot for temperature, and humidity measurements before noise cleansing.

the gateway. The ambient temperature and relative humidity sensors on TI Sensortags are energy-intensive and they can stop sending accurate readings when the battery levels are low even before the TI Sensortag itself runs out of power and turns off. The other source of noise was produced when the sensors were disconnected from the gateway for any reason. One of the main disconnectivity causes was the obstacles between the sensor and the gateway. For instance, the dual layer glass of the building windows significantly attenuated the Bluetooth signal strength and disrupted the connectivity. Fig. 5(a) and Fig. 5(b) illustrate the noise in one of the sensor data recordings before data cleansing. In order to remove the noise from temperature (e.g., -40.0 readings) and relative humidity (e.g.: 0.0 and 99.0 readings), we initially reviewed the data and then cleansed it. It should be noted that light readings of the sensors did not have noise and could thus be utilized without cleansing.

IV. TECHNICAL OBSTACLES

In this section, we present the important technical shortcomings and challenges that we faced while creating our limited building's facade digital twin. We also present the solutions

that were utilized to address them. In the developed testbed, the gateway used Bluetooth to communicate with the TI Sensortags. Therefore, the Bluetooth channel was continuously receiving the data sent from the Sensortags. Our experiments showed that when the gateway was continuously connected to the cloud through Wi-Fi, it caused disruptions to the Bluetooth channel and resulted in a disconnection between the sensors and the gateway. To resolve this technical issue, we disabled the Bluetooth link of the gateway, and we used a USB Bluetooth dongle to enable the Bluetooth communications. In this fashion, we resolved the disconnectivity issue of the gateway while keeping it connected to the internet through Wi-Fi.

In another experiment, we measured the light values for indoor and outdoor environments. Our tests showed that locating the sensor behind the window glass attenuates the Bluetooth signal strength considerably while putting a strain on the sensor's battery. This often caused the disconnectivity between the sensor and the gateway. The solution to this issue was found to be the placement of the gateway on the same side of the window that the sensors are located.

The other concern that needed to be addressed was the number of sensors. We considered a scenario where there was a need for more than 10 Sensortags to be used for data collection. Thus, to decrease the traffic caused by the Sensortags data transmission, we tried using two parallel gateways. The result of this test showed that using parallel gateways without software modifications would cause communication disruptions. A software solution can resolve this hardware issue by dedicating specific sensors to a specific gateway and disabling blind pairing with Bluetooth devices on the gateway. A solution to sensor disconnectivity for cases where the number of sensors is higher than seven can involve lengthening the data upload intervals for the sensors; we suggest setting this interval to be over three minutes, as our experimentation showed that this would provide a highly reliable connection between the sensors and the gateway.

In the following round of hands-on testing, which was performed to find a better economically justified sensor option, a test was conducted utilizing a different Sensortag that was built by another manufacturer with our gateway. Bluetooth 4.0 BLE Sensor Tag/iBeacon Station NRF51822 was the tested Sensortag. The results showed that although NRF51822 Sensortag has an ambient light sensor as well as temperature and relative humidity sensors, these might not be suitable for this project because of two reasons. Firstly, there was a lack of support availability by the supplier company and user community while, user-friendly software resources for the NRF51822 Sensortags were also scarce. These are important negative points in comparison to the TI Sensortags. The second reason was related to the power management on NRF51822 Sensortags, which does not allow for smart power management. In such a setting, a sensor would run out of battery significantly earlier than the TI Sensortags, which offer smart power management. Therefore, the application of NRF51822 Sensortags would be very costly from the

management perspective, although their initial purchasing price is one-third that of TI Sensortags.

We conducted tests where the battery level readings of the Sensortags were activated in the code. In this way, the operator can gain visibility into the inner workings of the sensor from an energy consumption perspective and implement a better battery replacement policy. Furthermore, to fully understand the impact of sensor data transfer frequency on their battery life, we tested different time intervals to find an optimal data transfer latency between every two measurements. We performed data collection with intervals of 20, 30, 60, 90, 120, and 240 seconds using three Sensortags. This test was performed to understand the optimal setting for the data collection while considering the Sensortags' battery consumption and the number and types of parameters measured. Our conclusion is that setting a short time interval decreases the battery life of the Sensortags and causes connectivity issues between the Sensortags and the gateway. Thus, using a short time interval is not an optimal method for data measurement. Moreover, the short time interval also increases the amount of collected data, which would be similar in the measured values since little change occurs in a short time, and consequently the complexity of data analysis is increased. However, using a longer time interval is also not an accurate solution for certain environmental factors with rapid fluctuations such as light; while factors such as temperature and relative humidity that change gradually can benefit from longer data recording intervals. Our conclusion is that when setting the time interval, three major points should be considered: 1) the number of deployed Sensortags, 2) the number of measured environmental factors, and 3) the type of measured environmental factors. Considering these points, in our setting we set the recording time interval to 90 seconds.

In this research, we used BLE technology for the communication between sensors and gateway due to its affordability, availability, and low energy consumption [62] that allow battery-powered sensors. In contrast to Zigbee, BLE communication technology is widely and out of the box available in consumer electronic devices [63] such as laptops, smartphones, and in our case, Raspberry Pi 3B+. BLE consumes less energy than Zigbee [62]. The data rate for BLE (i.e., 1 Mbit/s for short bursts) is four times greater than Zigbee (i.e., 250 Kbit/s) [64], [65]. Moreover, in performing the experiments for this research, we did not require data transmission over long distances; thus, BLE was a suitable choice. Nonetheless, based on the comparison presented in Table 3 for a real-world digital twin creation project for a building, Zigbee is more suitable.

Zigbee by design offers meshing capability [66] and thus, requires a lower number of gateways compared to the BLE technology. Zigbee-enabled sensors relay the information through the mesh network. In other words, the data travels from a single sensor device across a group of routers (i.e., Zigbee nodes) until the transmission reaches the IoT gateway. In the case of data transmission failure at any router, data

TABLE 3. Comparison of Zigbee and BLE.

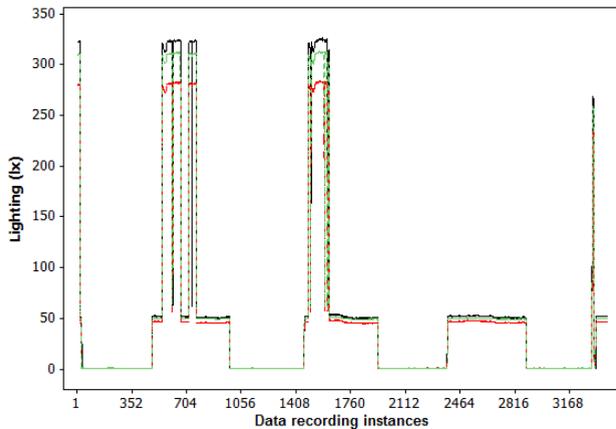| Technology Parameter	BLE	Zigbee (802.15.4)
Range [64], [66], [69]	Up to 50m	Up to 100m
Power consumption [62]	Very low	Low
Data rate [64], [65]	1Mbit/s	250 Kbit/s
Max. data payload [64], [65]	37 Bytes	102 Bytes
No. of connections [71]	Limited	Large
Network topology [66]	Star	Star/Mesh/Tree

TABLE 4. Error range for different sensortags.

Sensor / Parameter	Light	Temperature	Humidity
sensor 1 (S1)	+1%	−0.3%	+9%
sensor 2 (S2)	−2%	+0.35%	+12%
sensor 3 (S3)	−3%	−0.06%	+13%
sensor 4 (S4)	+4%	−0.6%	+17%
sensor 5 (S5)	0%	0%	0%
sensor 6 (S6)	−4%	+0.1%	−4%
sensor 7 (S7)	−10%	−0.4%	−9%

FIGURE 6. Time series plot for light measurements of sensors 4 (black), 5 (green), and 7 (red).

the sensors in order to create the digital twin, we needed to eliminate the error range of the sensors. After calculating the percentage of error for each sensor, an error correction coefficient was introduced for each sensor. This assists in removing false variations from sensor readings. Table 4 presents the error range for seven Sensortags. This table is used for determining the error percentage of various sensors compared to sensor 5 (S5), which has been selected as the reference Sensortag. Among all Sensortags used in our experimentation, S5 was selected as the golden sample since the readings of this sensor (i.e., light, ambient temperature, and relative humidity) were closest to the readings of recently calibrated industrial sensors at the Aalto University's Metrology Research Institute.

is automatically transferred to another router; thus, Zigbee offers a highly reliable network with almost zero information loss [67]. The mesh networking feature of the technology significantly extends the communication range [68]. The maximum range of Zigbee is up to 100 meters [64], [66], [69] in node-to-node communication. These features of Zigbee, hence, makes it a suitable candidate [70] for a WSN for the digital twin of a building.

On the contrary, BLE works in a star network topology [66] with limited connected nodes, where the gateway is at the center. In other words, each BLE-enabled sensor requires to be directly connected to a gateway. BLE communication is vulnerable to interruptions and data loss under certain conditions [72]. Thus, BLE communication is not preferable for real-world implementation of large WSNs that cover large areas.

V. VALIDATION OF DATA
Using the data set collected to evaluate the validity of sensors' readings, we realized that measurable differences exist between the readings of various sensors, and these differences can lead to inaccurate interpretation of experimental data. A time series plot for the light measurements by three Sensortags in a similar lighting condition is presented in Fig. 6, which shows the differences in the readings of the sensors and the increased deviation while the lighting is increased.

The same pattern was identified for all the sensor recordings related to the ambient temperature and the relative humidity. Therefore, before analyzing the data collected from

## VI. DETERMINING THE SENSOR CONFIGURATION
It is important to optimize the number of sensors required for a building from a cost perspective as well as the usability of the system. To be more specific, the cost factors related to the implementation of a sensor network on the building facade for the purpose of creating a digital twin are as follows: 1) sensor network design; 2) the procurement of sensors, gateways, and other related hardware and software; 3) installation costs related to sensors and back-end systems; 4) the monitoring and data collection as well as the analysis and fusion of results into the smart building systems; and 5) system maintenance related to the sensors' battery replacement (in case of battery-powered systems), sensor replacement in case of damage and loss, connectivity maintenance for both wired and wireless connections, as well as gateway and software maintenance and updates.

After we selected and cleansed the data set and determined the error range, we started the analysis of the data that was collected from the sensors on the building facade to determine a suitable configuration for the Sensortags. Figs. 7(a), 7(b), and 7(c) illustrate the light, temperature, and humidity recordings by four Sensortags. These four Sensortags are part of the seven Sensortags configuration illustrated in Fig. 4. Three of the sensors are installed on a straight horizontal line, one meter apart. The fourth sensor is installed at 0.6 meters above the middle sensor.
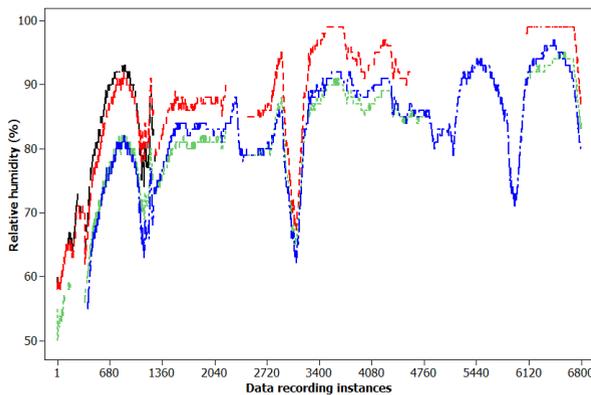
For the sensor configuration optimization, the following Algorithm 1 is applied. Given that the sensor mesh includes m rows and n columns, s_{ij} refers to spatial grid for sensor in the row i and column j and α_{ij} is the measurement of sensor s_{ij}. This algorithm performs in two steps: The hor-
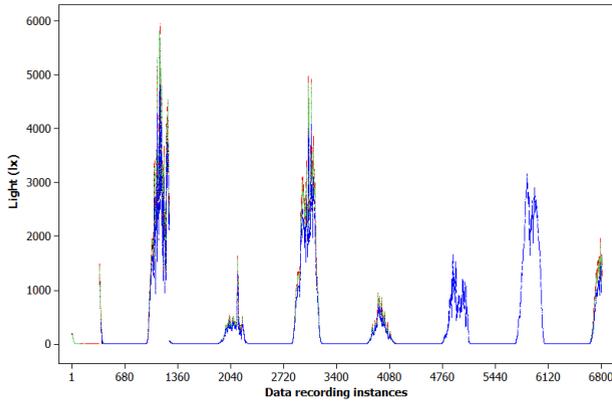
(a) Light measurements.
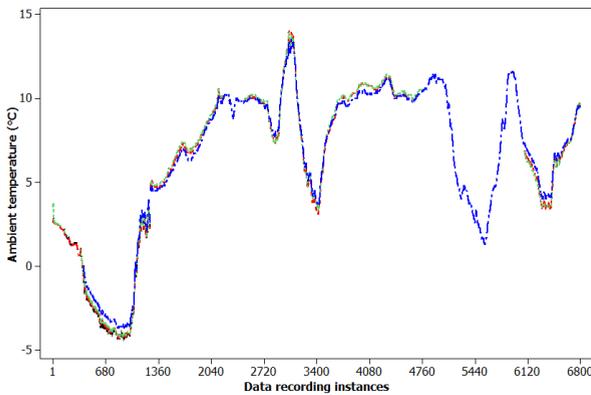
(b) Temperature measurements.

(c) Humidity measurements.

FIGURE 7. Time series plots for light, temperature, and humidity measurements by sensors 3 (black), 4 (red), 5 (green), and 7 (blue) that were installed on the building facade over an eight-day time span.

izontal optimization of sensors' configuration, followed by the vertical optimization of sensors' configuration. In the horizontal optimization, the difference between two immediately adjacent sensors' measurements is compared with the difference of the error range of the same sensors, while taking into account the intended accuracy. Intended accuracy (IA) in this algorithm refers to the decision maker or facility manager's required sensor network accuracy. As long as the difference between the measurements of adjacent sensors is

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Algorithm 1 Sensor Mesh Optimization

Initialization:

1: s_{ij}: Sensor in row i and column j
2: α_{ij}: Measurement of sensor s_{ij}
3: S : Matrix of α_{ij} for all i and j
4: **Set** m : The number of sensors' rows
5: **Set** n : The number of sensors' column
6: **Set** e_{ij} : Error range of sensor s_{ij}
7: **Set** IA : Intended accuracy set by decision maker
8: **Set** $A = B = C = \emptyset$
   Horizontal optimization
9: **for** $i = 1$ to m **do**
10:    **Set** $j = 1$, $j' = 2$
11:    **while** ($j' < m + 1$) **do**
12:       **if** ($\alpha_{ij} - \alpha_{ij'} \leqslant |e_{ij} - e_{ij'}| + IA$) **then**
13:          $A \longleftarrow A \cup s_{ij'}$
14:          $j' \longleftarrow j' + 1$
15:       **else**
16:          $j \longleftarrow j'$
17:          $j' \longleftarrow j' + 1$
18:       **end if**
19:    **end while**
20: **end for**
   Vertical optimization
21: **for** $j = 1$ to n **do**
22:    **Set** $i = 1$, $i' = 2$
23:    **while** ($i' < n + 1$) **do**
24:       **if** ($\alpha_{ij} - \alpha_{i'j} \leqslant |e_{ij} - e_{i'j}| + IA$) **then**
25:          $B \longleftarrow B \cup s_{i'j}$
26:          $i' \longleftarrow i' + 1$
27:       **else**
28:          $i \longleftarrow i'$
29:          $i' \longleftarrow i' + 1$
30:       **end if**
31:    **end while**
32: **end for**
   Set of all redundant sensors
33: $C \longleftarrow A \cap B$
34: **Return** C

---

lower than the difference of their error range plus the IA, the algorithm replaces the adjacent sensor measurements with the next immediate horizontally adjacent sensor measurements and performs the same calculation until the difference between the measurements of two sensors compared exceeds the difference of the error range of the same sensors plus the IA. Subsequently, the algorithm stores all the redundant sensors in set A. By completing the first full row, the algorithm continues the horizontal optimization by performing the same steps for the immediate next row. The same steps are consequently performed for the vertical optimization of sensor configuration, and the algorithm stores all the yielding redundant sensors in set B. Finally, the overall optimized sensor mesh is determined by removing the sensors in set C, which is the intersection of A and B.
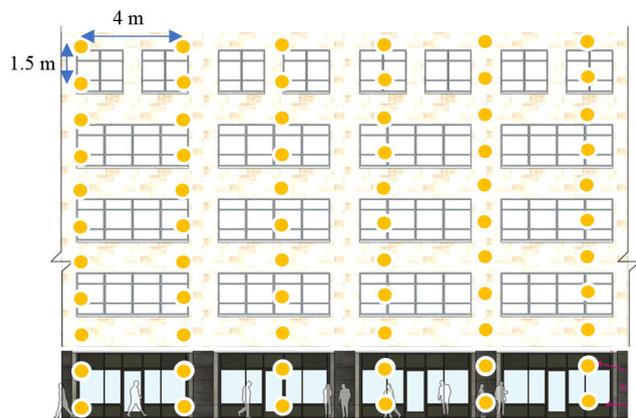
FIGURE 8. Suggested sensors' mesh on a simple building facade that was used in Section VII for the creation of a limited digital twin of the building facade.

The data collected by all seven sensors contained information on lighting (lx), temperature ($C°$), and relative humidity (%), and the sensors were installed in a configuration that covered 3.4 meters horizontally and 0.6 meters vertically. The preliminary analysis of this data illustrated that the deviation among the recording of the sensors is largely due to the sensors' defined error range. Therefore, we conclude that a digital twin of the building facade can be created with an acceptable accuracy using a configuration where the sensors covering the building facade are installed in a mesh with a horizontal distance of greater than 3.4 meters from one another and a vertical distance of greater than 0.6 meters.

Fig. 8 presents the proposed sensor mesh for creating digital twin of a building in this research. This sensor configuration is used for minimizing the cost of the sensor network, while maintaining the IA of the WSN readings at a high level. In this sensor mesh, the horizontal distance between the sensors is 4 meters, and the vertical distance between the sensors is 1.5 meters. The proposed sensor mesh in Fig. 8 is utilized in a limited experiment with six Sensortags to create the digital twin of the building facade. Section VII explains the method used and the results of our digital twin creation and visualization experiment.

In this research, the digital twin of building facade was created based on a WSN with a mesh topology. The reason behind the selection of mesh topology over star and tree topologies is that the mesh topology is a common and preferable configuration for real-world smart building WSNs [73]; thus, mesh is used to retain the applicability of the research results for real-world building's digital twin creation while using other communication technologies such as Zigbee or LoRa.

VII. DIGITAL TWIN CREATION AND VISUALIZATION
The location of sensors on the building facade for the creation of the digital twin is shown in Fig. 9. The sensors are located at the center of each rectangular area, and in this configuration each sensor covers 6 m^2 of the building facade. The collected

data by the light sensors of Sensortags were processed before being utilized by software to visualize the real-time state of facade brightness; this visualization was done by assigning a specific color to the *lux* values in a color spectrum. The color spectrum was defined by selecting the yellow color range and by assigning a light shade of yellow to the bright lights with a light intensity of 2400 *lux* and higher, while a dark shade of yellow was assigned to an 800-lux light intensity and lower. The light intensities between 800 and 2400 *lux* are automatically assigned different shades of yellow between the two selected colors according to their light intensity values. In this research, we selected this high color contrast for a relatively small light intensity range in order to facilitate the illustration; however, in real-world implementation the range can be wider. This method of creating a building facade digital twin through the real-time visualization of sensor readings can be performed using other sensor types (e.g., ambient temperature, relative humidity or sensors measuring other environmental attributes); this can be done by only assigning a suitable data variation range and the selection of a distinct color spectrum. For instance, a temperature digital twin of the building facade can be created by assigning a color spectrum, starting with dark blue and ending with dark red to a temperature range of $-30°C$ to $+40°C$.

Fig. 9 illustrates the creation, visualization, and testing of the building facade digital twin that was implemented in this research. The presence of an obstacle such as a person or a car can be detected visually by the digital twin in real-time. In Fig. 9(e), the person's distance to the wall is 0.5 meters, while the vehicle and the tree are 6.2 meters and 5.3 meters away from it, respectively. In this illustration, the reading of the light sensor that is adjacent to the person shows a significant value drop compared to the other sensors' readings (i.e., 875 *lux* compared to above 2000 *lux*). As Fig. 9(f) illustrates, this sudden change of lighting is visualized by the building facade digital twin.

VIII. DISCUSSION OF BENEFITS OF THE DIGITAL TWIN OF BUILDINGS
Several benefits can be found in using the digital twin of a building, and one of them is the building energy efficiency [61] with regard to the heating and light distribution when and where required. A digital twin can provide data regarding the building's maintenance needs. Moreover, a digital twin can be used by the architects to improve the performance of future buildings. We discuss these applications in detail in this section.

An air conditioning system can source its air from a cooler part of a building outdoors rather than expend energy to cool and recirculate the same air. This requires real-time monitoring of air pollution and air temperature and relative humidity of the whole building facade. The digital twin of a building with sensors measuring air quality, temperature, and relative humidity can provide the required data for such a hybrid air conditioning system for the indoor spaces [74], [75].
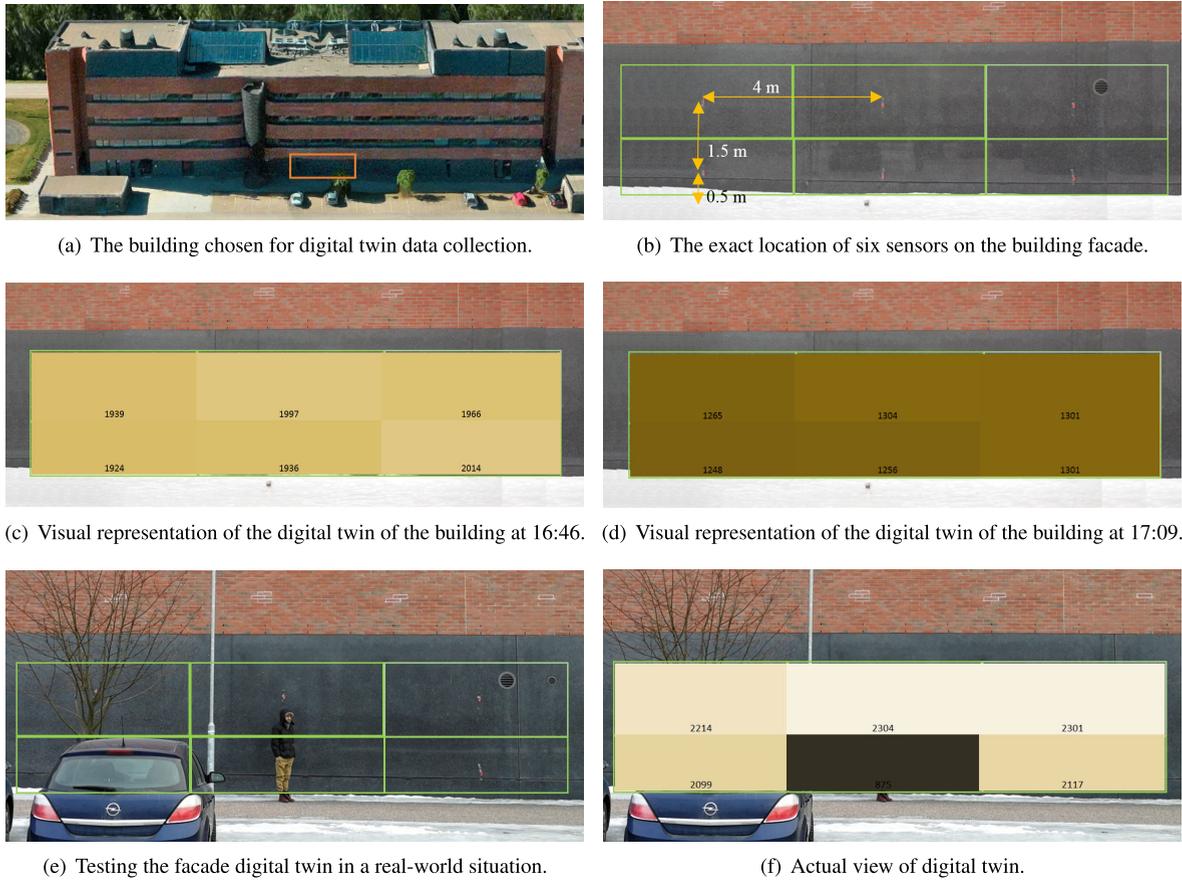
(a) The building chosen for digital twin data collection.

(b) The exact location of six sensors on the building facade.

(c) Visual representation of the digital twin of the building at 16:46.

(d) Visual representation of the digital twin of the building at 17:09.

(e) Testing the facade digital twin in a real-world situation.

(f) Actual view of digital twin.

FIGURE 9. Facade digital twin created based on real-time sensor data of lighting.

In addition, an indoor measurement of the ambient light that is received from the outdoors allows for a fine adjustment of the lighting level inside the building [53]. As a result, the amount of energy consumed by the lighting system during the daytime can be drastically decreased. For instance, if operators are aware of the level of light reduction from the window glass, it would be possible for them to utilize smart curtains for controlling the level of light on a real-time basis inside building spaces. Accordingly, the temperature variations sourced from the sunlight received inside the building can be purposefully utilized for heating and cooling by the air conditioning systems.

Moreover, designing a sensor network for the building facade and obtaining a digital twin enables the building designers and architects to improve the efficiency of the building during modifications, renovation, [76] and also when designing the future buildings. For example, the architects utilizing the information on the directions of sunlight and wind obtained at the building facade can design a building that uses these natural resources to improve the lighting and airflow inside the building. In this way, they can potentially design a system that enables energy savings in lighting, ventilation, and cooling while offering visual and thermal comfort for the building tenants.

Another potential application of buildings' digital twin is in the creation of accurate city digital twin. By integrating the

components of buildings' digital twin that are not proprietary, a more comprehensive and holistic model can be created which enables city planners to access an unprecedented level of accuracy for city planning, project implementations and operations [77].

IX. CONCLUSION

In this research, we presented a method for establishing a sensor network to create a building real-time digital model, also known as a digital twin. The paper accomplished this through the collection and analysis of the specific environmental factors in the exact surroundings of the building. Although the extent of this study did not go further than utilizing a limited sensor network and three environmental parameters for sensing (i.e., light, temperature and relative humidity), the step-by-step framework introduced in this research can be utilized to create a more comprehensive digital twin of a building facade as well as a building interior. This can be done using different types of sensors and communication protocols. Some of the technical obstacles in creating the digital twin of a building were also explained in detail, and the implementable solutions were proposed. This research concluded by suggesting a framework to determine the sensor arrangement on a building facade to enable a digital twin and by discussing the benefits of the digital twin of a building. Among the applications of a digital twin, we focused on

lowering maintenance cost, increasing tenants' comfort, and lowering the overall management and operational cost of a building.

This research was conducted on a building facade, this means the future research can examine the implementation of the digital twin for a building interior. Moreover, another area of exploration for future studies can be the expansion of sensor network presented in this research to include more sensors with a higher variety to allow for additional applications for the digital twin of a building. For instance, the integration of other sensing devices (e.g., visual or stereoscopic sensors on a building facade) can have applications in real-time security and in people movement monitoring while enhancing the accuracy and resilience of the data feed. In addition to this, a study of system affordability versus its benefits is also worthwhile.

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