Master thesis

Master Program in Architecture Construction City

From 3D surveying to BIM modelling, supporting real-time building monitoring

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I hereby declare that the contents and organisation of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

Kasra Khajehei Turin, July 06, 2026

Abstract

The Architecture, Engineering, Construction, and Operation (AECO) sector is shifting from static, document-based practices toward data-driven management of the built environment. Building Information Modelling (BIM) is now common in design and construction, while the Internet of Things (IoT) enables the continuous collection of operational data such as temperature, humidity, and air quality during building use. Combining the two is not straightforward: a BIM model alone is largely static, and raw sensor readings mean little without spatial and semantic context. Linking BIM geometry with real-time IoT data is therefore a central requirement for Digital Twins and Digital Shadows, yet most existing solutions remain fragmented or focused on heritage rather than modern functional buildings.

This thesis defines and documents a reproducible workflow for building a Digital Shadow of an operational building, using a conference room of the Energy Center at the Politecnico di Torino as the case study. A Digital Shadow is understood here as a one-way flow of data from the physical asset to a semantically structured digital model that supports monitoring and visualization, and as a first step toward a full Digital Twin with two-way control and actuation. The Energy Center was selected because it already hosts an IoT sensor network and allowed direct access for both the survey and the validation of the workflow.

The methodology is organized in three stages. The first is a 3D metric survey combining terrestrial laser scanning, a topographic control network measured with a total station, and SLAM-based mobile mapping. The second processes the resulting point cloud and reconstructs it through a Scan-to-BIM procedure into an as-built model, whose geometry is verified against the point cloud through a surface-based deviation analysis. The third links real-time environmental data (temperature, humidity, and air quality) to the model, stores the values in dedicated sensor parameters, and visualizes indoor conditions at room scale through a color-coded response.

The results confirm that the workflow is technically feasible and that a semantically structured BIM model can act as more than a static container of geometry, hosting operational data at both the object and the room scale. They also show that integration depends mainly on consistent naming, stable identifiers, and clear data-mapping rules, rather than on the communication technology alone. The implementation was carried out on a single room in a local environment, but the workflow is modular and can be extended to the whole building and developed toward a complete Digital Twin. Its main contribution is therefore methodological: a clear and repeatable path from reality capture to a working Digital Shadow of a real operational building.

Keywords: Digital Shadow, BIM–IoT integration, Scan-to-BIM, 3D metric survey, building monitoring

Self-Declaration of Generative AI Use

Generative AI tools were used during the preparation of this thesis exclusively for editorial support, such as grammar correction, translation, paraphrasing suggestions, and improving readability, and for the production of some of the schematic figures used in the thesis.

Acknowledgment

I would like to express my sincere gratitude to my supervisors for their guidance throughout this thesis. I am grateful to Prof. Elisabetta Colucci and Prof. Lorenzo Teppati Losè for their support in carrying out the survey, which formed the basis of this thesis, and to Prof. Luca Barbierato for proposing the Energy Center as the case study and for enabling access to the building and its sensor infrastructure.

Dedication

To the people of Iran, and to those who have given everything for their homeland.

To my parents and my sister, without whom I would not be here.

And to myself, for seeing it through.

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Chapter 1

Introduction

1.1 Background and Motivation

The Architecture, Engineering, Construction, and Operation (AECO) sector is currently undergoing a profound digital transformation. Historically, the management of the built environment relied on static, document-based approaches that often resulted in severe information loss during the handover from the construction phase to the operational phase (Mannino et al., 2021). Today, Building Information Modelling (BIM) has become a standard across the industry; however, its application is frequently limited to the design and construction stages. Extending the use of BIM into the operations and maintenance lifecycle presents a major opportunity to improve facility management, preventive conservation, and energy efficiency (Biagini et al., 2024; Chatsuwan et al., 2025). The built environment is therefore increasingly managed through data-driven approaches that connect physical assets with digital representations across their entire lifecycle.

Concurrently, the proliferation of the Internet of Things (IoT) has enabled the continuous collection of real-time environmental and operational data within smart buildings (Eneyew et al., 2022). Low-cost sensor networks can actively monitor parameters such as temperature, humidity, and air quality, generating vast amounts of time-series data. However, raw IoT data inherently lacks spatial and semantic context; a numerical sensor reading provides limited value to a facility manager if its exact location, spatial boundaries, and relationship to surrounding building elements are unknown (Tang et al., 2019). Consequently, integrating static BIM geometry with dynamic IoT data streams has emerged as a critical requirement for intelligent, proactive building management (Quinn et al., 2020).

This need for integration is the foundational premise behind Digital Twins (DT) and Digital Shadows within the built environment. Originally developed in the aerospace and manufacturing industries to reproduce and monitor highly complex physical systems, these concepts represent a paradigm shift toward data-driven asset management (Khajavi et al., 2019; Sepasgozar, 2021). A Digital Shadow establishes a one-way data flow from a physical asset to a semantically enriched digital model, enabling real-time monitoring, visualization, and diagnostics (Boje et al., 2020). A Digital Twin builds upon this by establishing a bi-directional loop capable of simulation, automated control, and actuation (Sepasgozar, 2021). For contemporary facility management, establishing a robust, geometrically accurate Digital Shadow is the vital first step before a fully autonomous Digital Twin can be realized.

Recent studies demonstrate the viability of this data-driven direction across multiple scales and building types. At the component level, Khajavi et al. (2019) presented a facade-level digital twin of an office building designed to support predictive maintenance forecasting. At the building scale, Marzouk and Abdelaty (2014) demonstrated how wireless environmental sensors could be connected to a BIM environment to calculate and visualize thermal comfort indicators within subway stations. Similarly, Desogus et al. (2021) developed a monitoring workflow for a university pavilion, combining a building information model with observed building-performance data to support the analysis of energy use and indoor comfort. At a broader scale, Yadav et al. (2024) proposed an Urban Digital Twin of Turin to enable multi-scale visualization and urban management insights.

Together, these examples show that digital representation approaches can range from component-level monitoring to city-scale management. However, despite dozens of successful prototypes, a significant challenge remains: implementations are often highly fragmented, customized for narrow use cases, or focused heavily on historic heritage applications rather than modern, functional institutional buildings. There is a pressing need for consistent, scalable workflows that bridge the gap between accurate 3D metric surveying, semantic BIM structuring, and interoperable IoT data integration. This necessity forms the core motivation of this research, which seeks to document a clear, reproducible pathway from reality capture to a functional Digital Shadow.

1.2 Research Aim and Scope

This thesis aims to define and document a reproducible workflow for developing a Digital Shadow for an operational building, using the Politecnico di Torino Energy Center as the case study. The Digital Shadow is intended as an as-is and semantically structured digital representation that can host and relate operational observations to support monitoring and decision-making throughout building operation (Sepasgozar, 2021; Biagini et al., 2024).

The scope of the work includes: (i) reviewing current research on Digital Twins and Digital Shadows in the built environment and identifying key gaps and limitations; (ii) defining the overall methodological pipeline and expected deliverables required to build a coherent digital representation of the case study; and (iii) outlining a strategy to structure and connect available operational data to building entities in a way that is meaningful for facility-management use cases. The approach adopts a multi-scale logic, where territorial context supports the framing of the building-scale study. The thesis focuses on the physical/real-to-digital direction (data acquisition, post-processing, structuring, and modelling) and does not address closed-loop control, automated actuation, or a full enterprise deployment, which are considered future extensions.

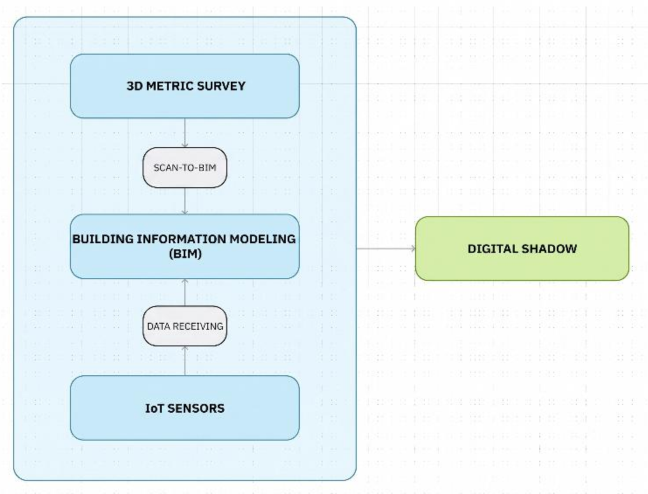


Figure 1 Conceptual Flow Diagram of Thesis Focus Area

1.3 Research Gaps and Contributions

The integration of Building Information Modelling (BIM), the Internet of Things (IoT), and Digital Twin (DT) technologies is opening new possibilities for preventive conservation, predictive maintenance, and more sustainable building management. At the same time, significant challenges remain in terms of standardization, scalability, and interoperability across different application scales.

Due to these lacks, this thesis intends to investigate the contributions of existing research into four thematic areas: (i) Digital Twins and Shadows in the built environment; (ii) BIM–IoT integration method and approach; (iii) Predictive maintenance and facility management; and (iv) Critical gaps and challenges. The conclusion of the discussion is the identification of the research gap that the thesis can fill: the creation of scalable Digital Twin framework of a modern functional building, exemplified by the Energy Center (Figure 2) at Politecnico di Torino.

1.4 Case Study: Politecnico di Torino Energy Center Building

The choice of this building as a case study is inspired by a number of factors. To start with, the Energy Center already has a network of IoT sensors built into it when constructing it, which was supervised by Professor Luca Barbierato, the Department of Control and Computer Engineering (DAUIN), who is also directly engaged in this study. Second, the access we have to this facility is a privilege that allows us to test, confirm, and verify the proposed framework in a real-life situation, which further makes it an excellent case study in regard to the purposes of this thesis.

Figure 2 Politecnico di Torino Energy Center Building (Creator: Michele D'Ottavio). ©Michele D'Ottavio.

1.5 Thesis Structure

This thesis is organized into four main chapters, followed by the references and appendices. Chapter 1 introduces the research background, defines the aim and scope of the study, identifies the main research gaps and contributions, and presents the Politecnico di Torino Energy Center as the case study. Chapter 2 reviews the state of the art on Digital Twins and Digital Shadows in the built environment, BIM–IoT integration approaches, enabling technologies and standards, and predictive maintenance and facility-management applications, concluding with the identification of the main gaps, the formulation of the research questions, and the positioning of the thesis contribution. Chapter 3 presents the methodology adopted in the research, from territorial framing and GIS support to 3D metric survey, topographic control, data processing, Scan-to-BIM modelling, model verification against the point cloud, and BIM–IoT data linkage and visualization. Chapter 4 discusses the main outcomes of the work, answers the research questions, clarifies the scope and limitations of the study, and outlines future developments and final conclusions. The thesis concludes with the references and two appendices: Appendix A, containing the full BIM–IoT integration table used in the literature review, and Appendix B, containing the survey campaign fieldbook, including control-network records, target documentation, and annotated survey notes.

Chapter 2

Literature Review

2.1 Digital Twins in the Built Environment

The concept of Digital Twins (DTs) first emerged in the aerospace and manufacturing industries as a way to reproduce and monitor highly complex physical systems (Khajavi et al., 2019; Sepasgozar, 2021). In recent years, this paradigm has migrated into the AECO domain, where DTs are increasingly understood as digital representations dynamically linked to physical assets through bi-directional, real-time data exchange (Sepasgozar, 2021). Early applications in construction emphasized the potential of DTs for closed-loop control systems and predictive maintenance (Sacks et al., 2020; Khajavi et al., 2019), while more recent contributions highlight the importance of human-machine collaboration, acknowledging that automation alone cannot replace human expertise (Agrawal et al., 2023). Systematic reviews underline both the opportunities such as efficiency gains and lifecycle optimization and the challenges of implementation, including issues of interoperability, standardization, and high initial costs (Yildirim & Giran, 2024; Nalioglu et al., 2023).

In existing-building and as-built applications, the development of DTs in AECO has increasingly relied on 3D metric survey technologies such as Light Detection and Ranging (LiDAR), photogrammetry, and Simultaneous Localization and Mapping (SLAM) (Tuhaise et al., 2023; Yadav et al., 2024; Volk et al., 2014). These techniques generate dense point clouds that support accurate 3D reconstruction and can be converted into semantically enriched BIM models through Scan-to-BIM workflows (Volk et al., 2014; Boje et al., 2020; see Section 3.7.2). In comparison with standard BIM models, which tend to be an idealized abstraction, point cloud-based DTs provide as-built geometric fidelity, which allows the detection of surface deformations, materials, and structural variation, with a sub-centimetric precision. Yadav et al. (2024) demonstrated how aerial LiDAR and photogrammetry can support Urban Digital Twins (UDTs) by acquiring dense spatial datasets and classifying them semantically into buildings, roads, and vegetation. Such multi-source point cloud integration enhances multi-scale analysis and urban management through standards like CityGML. Similarly, HBIM–GIS integration frameworks highlight how laser scanning and photogrammetry are crucial for documenting complex geometries of historic structures and converting raw scans into semantically structured models compliant with IFC or CityGML data standards, thereby enriching Digital Twins with both semantic and spatial accuracy.

Before the use of TLS or SLAM for detailed 3D acquisition, traditional geomatics techniques such as GNSS and Total Station surveys are often used to establish a stable control network and reference system. This topographic backbone supports the georeferencing of the model and improves the consistency of scan registration across different areas and acquisition sessions, plus it allows to control the error propagation on the acquired datasets. At the building scale, terrestrial laser scanning (TLS) has become a standard for generating as-built models. TLS provides consistent, highly accurate geometric documentation, particularly suited to structural monitoring and deformation analysis. However, its logistical demands, line-of-sight constraints, time-consuming scan registration, and comparatively higher acquisition costs than other survey instruments can limit continuous data acquisition. To address these issues, SLAM-based mobile mapping systems have emerged as a complementary method. By using handheld or drone-mounted LiDAR scanners, SLAM allows rapid, flexible data capture in environments where static scanning is impractical. Recent studies indicate that, although SLAM-based mobile mapping systems generally produce point clouds with lower geometric accuracy than static TLS, they can effectively support rapid indoor surveys, construction progress monitoring, and Digital-Twin-oriented real-time monitoring workflows where frequent spatial updates are needed (Salgues et al., 2020; Sgrenzaroli et al., 2022; Hu & Assaad, 2024).

These considerations are also consistent with previous field activities carried out by the Politecnico di Torino Geomatics Laboratory in Valle Stura, on the Bandia plateau between Valle Grana and the heights above Sambuco, within a training mission focused on the documentation and mapping of fortified and underground heritage structures. In that context, which the author joined as part of an internship activity, TLS, drone photogrammetry, and SLAM-based mobile mapping were combined to document irregular geometries, capture difficult or partially inaccessible areas, and generate complementary datasets to support conservation-oriented and HBIM-oriented workflows. The operation formed part of a broader documentation effort aimed at producing reliable spatial data for the conservation, valorization, and sustainable management of the local cultural heritage (Politecnico di Torino, 2025).

Despite their potential, several challenges remain. First, processing and managing the vast volumes of data generated by point clouds requires significant computational resources and advanced algorithms for feature extraction. Second, workflows for semantic enrichment converting raw scans into parametric BIM elements are not yet standardized, leading to variability in quality and interoperability. Third, most applications still rely on static or periodic scans, whereas the integration of continuous sensor streams into point-cloud based DTs is less developed, limiting predictive maintenance applications.

Overall, point-cloud based methods represent a critical bridge between physical reality and digital representation, enhancing the fidelity and applicability of Digital Twins. By linking TLS, photogrammetry, and SLAM workflows, Digital Twins can achieve higher accuracy in documenting the built environment while supporting both heritage conservation and contemporary building management, a direction directly relevant to the Energy Center case study developed in this thesis.

2.1.1 Digital Shadow vs Digital Twin

A Digital Shadow provides a one-way data flow from the physical system to its model for visualization, alarms, and analytics. A Digital Twin establishes a bi-directional loop that adds rules, simulation, and, where appropriate, actuation or feedback to the asset (Sepasgozar, 2021; Boje et al., 2020). In this thesis, the Energy Center implementation is treated as a Digital Shadow, with a clear upgrade path toward a Digital Twin through the future inclusion of rule engines and controlled feedback.

More specifically, a Digital Model is a static or manually updated representation with no live connection to the physical asset, whereas a Digital Shadow introduces a one-way data flow from the real system to the digital environment, enabling monitoring, visualization, and data-driven interpretation. A Digital Twin goes further by establishing a bi-directional relationship in which the digital system not only receives and interprets real-world data, but can also support simulation, decision rules, and feedback actions that influence the physical asset. In this sense, the distinction is not only technical, but also functional: it depends on the level of synchronization, automation, and operational agency embedded in the system (Sepasgozar, 2021; Boje et al., 2020; Sacks et al., 2020). These key differences are summarized and compared in Table 1.

Table 1 Comparison between a Digital Model, a Digital Shadow, and a Digital Twin in terms of data flow, update logic, and operational relationship with the physical asset.

Criterion	Digital Model	Digital Shadow	Digital Twin
Connection to the physical asset	No automatic connection	One-way connection from the physical asset to the digital model	Two-way connection between the physical asset and the digital model
Update mode	Manual or periodic updating	Automatic updating from observed data	Automatic and bidirectional updating
Data flow direction	None or manual import only	Physical-to-digital	Physical-to-digital and digital-to-physical
Ability to influence the physical asset	No	No	Yes, through feedback, control, or actuation logic

Criterion	Digital Model	Digital Shadow	Digital Twin
Main function	Representation and documentation	Monitoring, visualization, and interpretation	Monitoring, simulation, optimization, and operational feedback
Level of operational integration	Low	Medium	High
Typical application stage	Design, documentation, static asset description	Live monitoring and condition awareness	Advanced management, predictive control, and automated decision support

2.2 BIM-IoT Integration Approaches (State of the Art)

The integration of BIM and IoT represents one of the most active areas of research in smart building innovation. Across the reviewed literature (see table 2 and Appendix A, Table A.1), BIM–IoT integration has already been implemented many times, but almost always through bespoke, project-specific pipelines that are difficult to reuse. Even when the goal is similar, each contribution adopts a different combination of tools and data flows (for example, Revit + MS Access and WSN for Cairo metro stations, Revit + Dynamo + low-cost sensors for the Mandolesi pavilion, FM-BIM + Cassandra + Dynamo for BAS data, MQTT + web viewers for real-time monitoring, or IFC + RDF graphs in asset-management platforms), with different APIs, databases, schemas and naming conventions.

This fragmentation is repeatedly highlighted as one of the main gaps in the current "digital twin" landscape: despite dozens of successful prototypes, there is still no widely accepted, standard method for linking BIM models with IoT data in a way that is interoperable, scalable and vendor-neutral (Tang et al. 2019, Mannino et al. 2021, Sacks et al. 2020, Sepasgozar 2021). Tang and co-authors review how BIM models are linked to live data streams from IoT devices, classifying existing work into five main technical paths (APIs with databases, custom schemas, query layers, semantic web and hybrid cloud platforms) and comparing them on flexibility, scalability and implementation effort for Digital Twin-ready workflows (Tang et al., 2019).

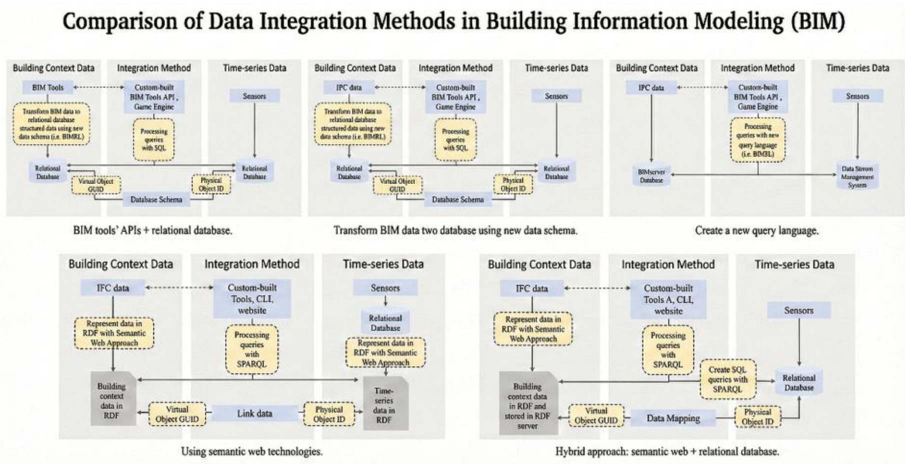


Figure 3 Comparison of BIM–IoT data integration methods. Adapted from Tang et al. (2019, Figs. 1–5), Automation in Construction. © Elsevier.

Marzouk and Abdelaty build a Revit-based BIM of Cairo metro stations, connect it to a database populated by wireless environmental sensors (temperature, humidity and air quality) and use this pipeline to calculate and visualise thermal comfort and service-level indicators directly in the 3D model for each station zone (Marzouk & Abdelaty, 2014). Zhang and Bai attach RFID-based wireless strain sensors to reinforced-concrete elements, stream strain measurements into a backend database and link each sensor ID to structural components in the BIM model, so that structural condition and damage indices can be assessed and visualised by querying the BIM–database pair rather than raw sensor feeds (Zhang & Bai, 2015).

Arslan and colleagues deploy a sensor network on construction sites to measure environmental parameters relevant to safety (such as temperature, humidity, noise and dust levels), store readings in a central database and integrate them with a BIM model that provides 3D visualisation and mobile alerts, creating a real-time H&S monitoring and notification workflow (Arslan et al., 2014).

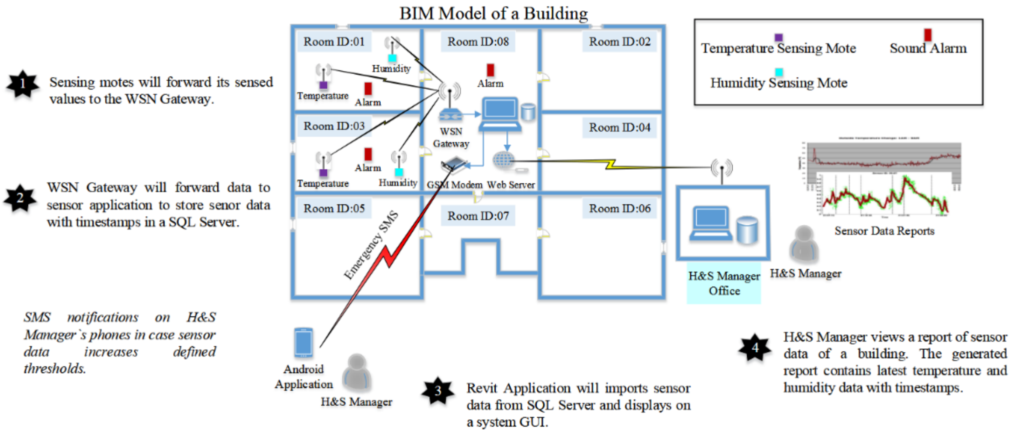


Figure 4 Integration model of real-time environmental monitoring, visualization and notification system for construction H&S management. Reproduced from Arslan et al. (2014, Fig. 3). CC BY 3.0.

Woo and co-authors develop a detailed “virtual campus” BIM for a university, export model data to a game-engine environment and bind it to energy-meter readings and building management system data so that energy performance benchmarks and consumption profiles can be explored interactively at building and room level (Woo et al., 2016).

Solihin and co-authors propose a simplified relational database schema that converts IFC-based BIM models into a spatially enabled SQL database, enabling efficient queries on building elements and spaces and providing a general backend structure for later binding of time-series IoT data to those BIM entities (Solihin et al., 2017). Motamedi and colleagues integrate facilities management data (work orders, sensor readings and failure logs) with BIM by exporting building components and systems into a specialized database, then building a visual analytics environment where users can trace root causes of failures by querying component histories and seeing results directly in the BIM view (Motamedi et al., 2014).

Kang and Choi introduce BIM Perspective Definition (BPD) metadata, where BIM elements are exported into a database enriched with FM-oriented tags and relationships so that heterogeneous FM data (including sensor histories and maintenance records) can be aligned with the BIM structure and retrieved from the perspective of specific management tasks (Kang & Choi, 2015). Mazairac and Beetz design BIMQL, a query language that allows users to select and filter BIM elements using a SQL-like syntax, effectively acting as a logical layer on top of IFC data and enabling later integration of live sensor information by querying both model geometry and associated attributes in a unified way (Mazairac & Beetz, 2013).

Alves and co-authors propose BIMSL, a service layer that exposes BIM data through RESTful services and supports the registration of real-time sensor streams, allowing external applications to bind incoming measurements to BIM objects via unique identifiers and query current or historical conditions without directly manipulating the native BIM file (Alves et al., 2017). Dibley and colleagues develop an ontology framework in which building elements, sensor types and observed phenomena are described as semantic classes, then connect live sensor data to these classes so that complex building states (for example comfort conditions or system faults) can be inferred from reasoning over the linked BIM–sensor knowledge base (Dibley et al., 2012).

Curry and co-authors present a linked-data architecture where BIM, building management system data and IoT sensor streams are all exposed as RDF graphs and connected by shared identifiers and ontologies, enabling cross-domain queries that combine static BIM geometry with time-series measurements and asset management data in a single SPARQL layer (Curry et al., 2013). Hu and colleagues propose a hybrid architecture in which contextual building data from BIM and other sources are stored in RDF, while time-series measurements remain in relational databases; the two are linked by identifiers so that performance rules can query both spaces at once, allowing building performance evaluations directly over combined BIM–sensor data (Hu et al., 2016).

McGlinn and co-authors implement BuildVis, a web-based interface that connects semantic models of public buildings with building energy management systems and sensor data, enabling users to navigate the BIM-derived spatial structure in the browser while viewing, filtering and comparing real-time and historical environmental measurements and control states (McGlinn et al., 2017). Desogus and colleagues create a Revit-based BIM of the Mandolesi pavilion at the University of Cagliari and integrate it with low-cost IoT sensors measuring indoor temperature, illuminance and energy consumption; data are streamed to a common platform where the BIM geometry is used to visualize current conditions and explore historical trends for retrofit decision-making (Desogus et al., 2021).

Cheng and co-authors develop a BIM-integrated smart monitoring system for fire prevention and disaster relief, linking Bluetooth-based fire sensors (temperature and smoke) and building emergency devices to a Fire Safety BIM; data are sent to a backend system and visualized in 3D so operators can see alarm locations, plan evacuation routes and support real-time rescue decisions (Cheng et al., 2017). Quinn and colleagues propose a Building Automation System–BIM integration technique where BAS and IoT sensor tags are mapped to FM-BIM elements using a linked-data structure, allowing live building automation data streams to be accessed and visualized through the BIM using a uniform naming and graph-based query model (Quinn et al., 2020).

Valinejadshoubi and co-authors implement an automated alert system for thermal comfort in a Revit model of an office room, where temperature and humidity sensors send data to a MySQL database and a workflow compares readings to ASHRAE thresholds, updates room colors in BIM and pushes alerts to facility managers when discomfort is detected (Valinejadshoubi et al., 2021).

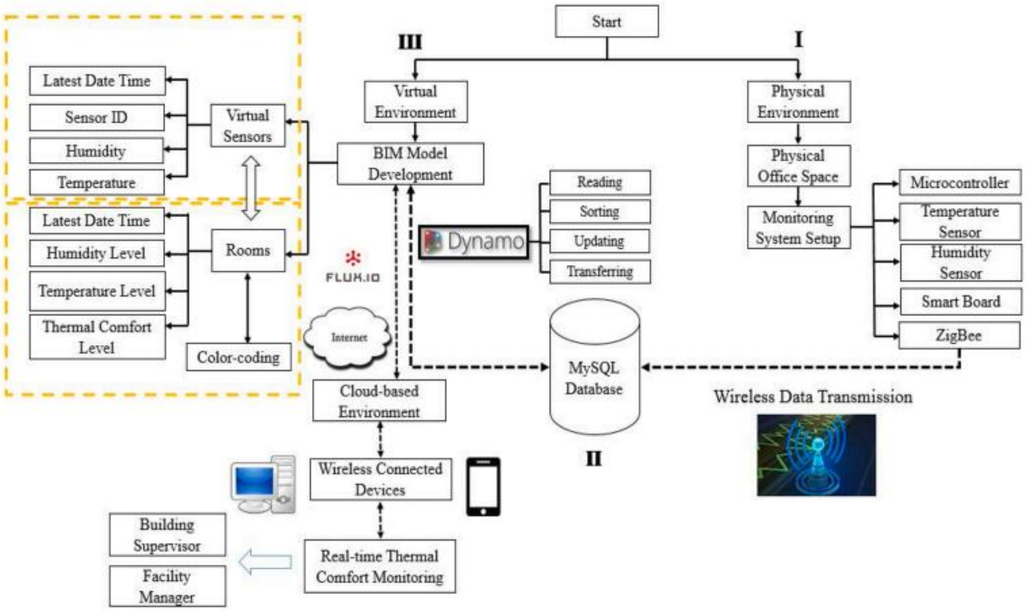


Figure 5 Hierarchy of the study for BIM–IoT-based thermal comfort monitoring. Reproduced from Valinejadshoubi et al. (2021, Fig. 2), Sustainable Cities and Society, 66, 102602.

Kensek investigates several case studies where environmental sensors (light, humidity and CO_2) are connected to a BIM environment using Arduino boards, Grasshopper/Firefly, Dynamo and the Revit API, creating simple digital models that respond in real time to sensor inputs and testing different ways of binding physical sensor IDs to BIM elements (Kensek, 2014).

Wang and co-authors design a building model management system that integrates MQTT over WebSocket with a Three.js-based 3D BIM viewer, where IoT devices publish measurements to an MQTT broker and the web client subscribes and updates BIM-linked objects in real time, enabling browser-based monitoring and early warnings directly on the 3D model (Wang et al., 2025). Scianna and colleagues build a digital twin of a laboratory bridge beam model, connect low-cost IoT displacement sensors to a relational database and then bind the measured deflections to the corresponding beam elements in the BIM model, so that structural behavior and risk conditions can be monitored in real time through the BIM–database connection (Scianna et al., 2022).

Chatsuwan develop a BIM–IoT integration tool for facility management that uses open standards (IFC, JSON), Node-RED flows and cloud services to link indoor environmental quality sensors to IFC-based BIM models, exposing a web dashboard where managers can monitor real-time IEQ data, historical trends and alarms spatialized through the BIM geometry (Chatsuwan et al., 2025).

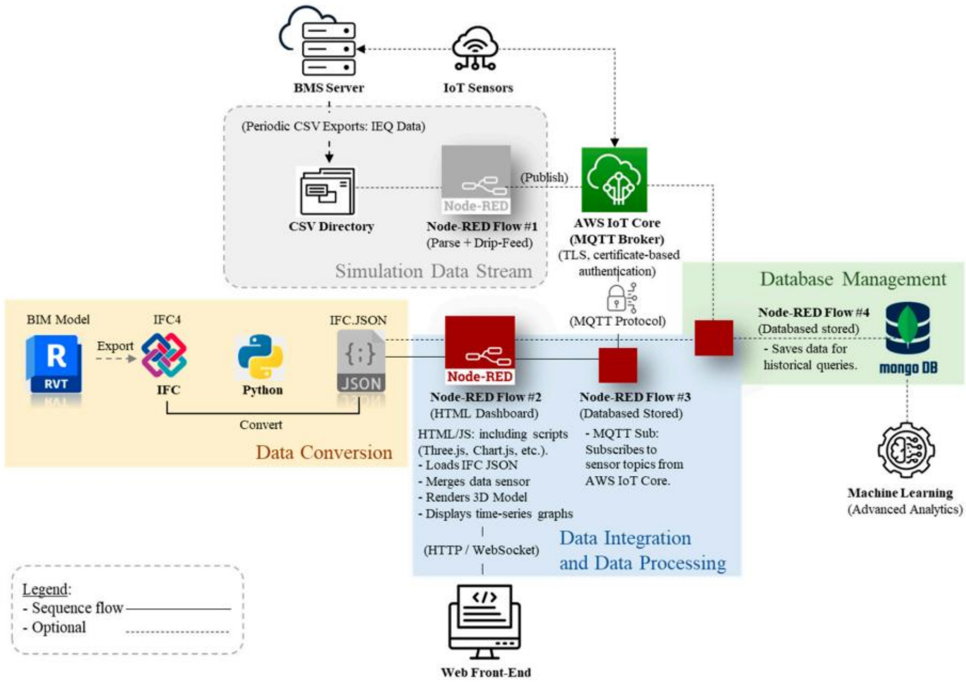


Figure 6 Comprehensive BIM–IoT integration framework. Reproduced from Chatsuwan et al. (2025, Fig. 12), Buildings. CC BY 4.0.

Biagini and colleagues design an asset-management platform for the University of Florence's building stock in which IFC models are converted to RDF using modular ontologies and linked to IoT sensor data, enabling two workflows for BIM-to-Digital-Twin: one based on direct sensor–IFC bindings and one using semantic web technologies to query maintenance, monitoring and spatial data together (Biagini et al., 2024).

Table 2 provides a summary of the integration methods identified in the reviewed sources. Table 1 presents a condensed selection of representative BIM–IoT integration studies; the complete dataset is provided in Appendix A (Table A.1).

Table 2 Summary of BIM-IoT data integration methods in the studied references

Article	**Authors**	**Data type**	**Database format**	**BIM tools**	**Integration method**
A review of BIM and IoT devices integration: Present status and future trends	Shu Tang et al.	Temperature, Humidity, Time-series data	Relational Database (MS Access, MySQL)	Revit, IFC, Navisworks	Identified 5 main methods: API-based, IFC/Schema, Query Languages, Semantic Web, Hybrid

Article	Authors	Data type	Database format	BIM tools	Integration method
Monitoring thermal comfort in subways using building information modelling and wireless sensor networks	Mohamed Marzouk, Ahmed Abdelaty	Temperature, Humidity	MS Access (Relational Database)	Revit (with DB Link API)	WSN→MS Access DB←Revit (DB Link API)→Link Sensors to BIM elements for monitoring
Simplified relational database schema for BIM data (BIMRL Schema)	Li et al.	Building objects, geometry, properties, relationships	Oracle DB with BIMRL Schema (Star/Snowflake)	Revit, IFC (ETL with Xbim parser)	IFC export→ETL→BIMRL schema (fact/dimension tables)→SQL queries for analytics/FM
BIMQL - An open query language for building information models	Jakob Beetz, et al.	BIM objects, geometry, properties	IFC-based BIM models in BIMserver	Open BIMserver, IFC format	BIMQL queries (SELECT/WHERE/SET)→Simplified syntax→Platform-independent on IFC models
Ontology framework for intelligent sensor-based building monitoring (OntoFM)	Pauwels et al.	Building structure, sensor readings (temp, motion)	OWL ontologies, RDF representation	IFC, OWL, Semantic Web technologies	BIM/IFC+Sensors→OWL ontologies→RDF representation→Agent framework for queries
Linking building data in the cloud using linked data	Beecham et al.	Building info, sensor data,	RDF (Linked Data cloud)	IFC, Semantic Web standards	Multi-source data→Convert to RDF via wrappers→Query via SPARQL→Cross-domain insights

Article	**Authors**	**Data type**	**Database format**	**BIM tools**	**Integration method**
		assets, occupancy, weather, business data			
Building automation system - BIM integration using linked data structure	Eadie et al.	HVAC, automation system readings, facility performance data	Cassandra Database (time-series), CSV export	Revit 2019, Dynamo (Visual Programming Language)	BAS data→Cassandra→CSV →Dynamo import→Python filter→Map to Revit FM-BIM via Element.SetParameterByName
Enhancing Facility Management with BIM and IoT Integration in Open Standard Environment	Lee et al.	Environmental sensors, HVAC, building systems	Time-series database, middleware server (HTTP/MQTT)	Revit, Archicad, IFC export	BIM→IFC export→Collect IoT data→Custom mapping (Sensor ID→BIM Space ID)→Integration framework→Unified visualization
FROM BIM TO DIGITAL TWIN - IoT Integration Case Study 1 (Snap4City)	Desogus et al.	Temperature, Humidity, Environmental data	Snap4City IoT platform with RDF, Elastic Search	IFC (BIM Surfer viewer)	Raspberry Pi (Edge)→Node-Red→Snap4City IoT Device→Broker→Node-Red processing→BIM Surfer + live data
FROM BIM TO DIGITAL TWIN - IoT Integration Case Study 2 (LoRaWAN)	Desogus et al.	Environmental data (Temp, Humid	Niagara framework with BACnet, MongoDB NoSQL	IFC models	LoRaWAN sensors→Gateway (BACnet)→Niagara (normalize)→MongoDB →Link to BIM/IFC for DT visualization

Article	Authors	Data type	Database format	BIM tools	Integration method
		ity, etc.)			
Building Model Management System Integrating MQTT Sensing	Song et al.	Temperature, Humidity, Illumination (STM32 sensors)	MQTT (EMQX/NanoMQ broker) with WebSocket, Spring Boot	Revit, SketchUp, Three.js web viewer	STM32→LoRaWAN/Zigbee→Edge MQTT Gateway→MQTT Broker→Web API/WebSocket→Viewer integration
Development of IoT and BIM-based automated alert system for thermal comfort	Choi et al.	Temperature, Humidity (5-minute intervals)	MySQL Relational Database	Revit Architecture 2018, Dynamo	Waspmote sensors (ZigBee)→MySQL (6 tables)←Revit model→Threshold-based alerts + dashboard/reporting

2.3 Technology and Standards for BIM-IoT Integration

The main issue with BIM-IoT integration is a data-interoperability issue: BIM information has objects, spaces, and relationships, whereas the IoT streams are time-stamped, high-frequency, and tend to be heterogeneous. Consequently, the literature narrows down on integration strategies that specify (i) the whereabouts of the data, (ii) how BIM entities are named and (iii) how sensor streams are addressed to the entities to be extracted and visualized.

The most common synthesis, which has been widely cited, has found five repetitive patterns of integration. They are: (1) API-based integrations, where the BIM authoring tools provide programmatic access to element properties; (2) IFC/schema-based approaches, where model data is exported in neutral form and supplemented externally; (3) database-based transformations to convert the BIM to relational representations; (4) query-language approaches that add special mechanisms to access BIM-IoT information; and (5) semantic-web and hybrid approaches that combine multiple representations to enhance flexibility and reuse. The main takeaway is that there is no single pattern that is applicable in all use cases; which method to use will depend on scale and the openness a system needs as well as how well identifiers are stable across software boundaries.

The interoperability standards, particularly open exchange formats are not optional but design constraints. It is stated in the literature that the failure of integration pipelines at scale occurs frequently when identifiers are not conserved, property sets are inconsistent, or sensor naming policies are not controlled. As a result, strong methods do not view exports (e.g., IFC) and mappings (sensor registry and ID maps) as informal byproducts of modelling, but rather as engineered deliverables that are to be validated.

Regarding the Facility Management (FM) aspect, the research indicates that the integration value will only appear when the operations tasks are able to confidently utilize the combined dataset. It must involve regular asset/space semantics in BIM, traceable connection to sensor sources, data management practices that help sustain changes in time. One theme recurring is that BIM-IoT studies frequently show that prototypes work, however that standardization and cross-building transferability is still to come-particularly with modern functional buildings, with systems in the thousands and constantly changing.

These findings are used in this thesis to inform an IFC-first and identifier-first mindset: the integration is structured based on consistent references between (i) semantic BIM entities and (ii) sensor streams, and mapping logic and data governance assumptions are explicitly documented. This stance justifies a Digital Shadow installation that is oriented on monitoring and decision support, and continues to an upgrade to a more comprehensive Digital Twin in which bidirectional control and simulation can be added.

2.4 Predictive Maintenance and Facility Management

A major promise of Digital Twin technology lies in its ability to support predictive maintenance, moving beyond reactive or preventive approaches. The use of BIM as a data infrastructure for fault detection and diagnostics (Dong et al., 2014) was an early milestone, showing how semantic building models could structure fault data for HVAC systems. More recent developments extend this logic through IoT integration. Khajavi et al. (2019) demonstrated predictive maintenance in action by testing a DT prototype for façade systems, showing that sensor-driven monitoring could anticipate degradation before failure. Similarly, Pishdad-Bozorgi et al. (2018) introduced the concept of FM-enabled BIM, emphasizing lifecycle risk management through linked digital models. Mannino et al. (2021) focused specifically on BIM–IoT integration for Facility Management (FM), conducting a literature review that revealed gaps in data collection optimization and long-term information management. Their study emphasized the importance of Industry 4.0 sensors in enriching FM-BIMs, highlighting the transition toward proactive and intelligent facility management. Domain-specific research has also explored predictive monitoring. Cheng et al. (2017) developed a BIM-integrated fire prevention system, while Andrade et al. (2021) proposed SmartCom, a smart home system for energy optimization through NFC and Wi-Fi-based user identification.

These efforts underscore the versatility of predictive monitoring, though most remain confined to either residential or industrial contexts rather than public institutional buildings. Across the reviewed literature, a clear consensus emerges: predictive maintenance frameworks are technically feasible but fragmented, often tailored to narrow use cases. The lack of generalizable, scalable models applicable across diverse building types constitutes a significant gap.

2.5 Challenges, Gaps and Limitations

This section synthesizes the main challenges that emerge directly from the literature review in Chapter 2. While challenges and gaps are often introduced at the end of Chapter 1, they are placed here because they are an explicit outcome of the state-of-the-art analysis and serve as the basis for the research questions and the multi-scale framing adopted in this thesis. Despite rapid progress, the literature reveals persistent challenges:

- **Conceptual ambiguity:** The distinction between digital twin, digital shadow, and BIM extensions remains contested, limiting standardization (Sepasgozar, 2021; Boje et al., 2020).
- **Fragmentation of implementations:** Most systems are prototype-based, focusing on narrow domains (Desogus et al., 2021; Mamaghani & Zolfaghari, 2023) rather than holistic frameworks.
- **Interoperability barriers:** A recurring theme is the difficulty of integrating heterogeneous sensor data into BIM/DT environments due to lack of open standards (Tang et al., 2019; Mannino et al., 2021).
- **Scalability and generalization:** Applications often target smart homes, heritage sites, or isolated infrastructure systems (Cheng et al., 2017; Andrade et al., 2021), with limited evidence on large, functional institutional buildings.
- **Data governance and security**: Issues of privacy, cybersecurity, and data ownership are repeatedly cited as underexplored dimensions in BIM–IoT–DT integration (Nalioğlu et al., 2023).
- **Human-in-the-loop considerations:** Studies such as Agrawal et al. (2023) highlight the lack of attention to how DTs redistribute responsibilities between human operators and automated systems.

2.6 Research Questions and Objectives

Based on the gaps and limitations identified above, this thesis is guided by the following research questions:

RQ1. What workflow stages, information requirements, and technical deliverables are necessary to establish a reliable Digital Shadow for an operational building, from 3D survey to BIM-based monitoring?

RQ2. How can selected BIM entities and monitoring zones be semantically structured so that operational observations can be consistently linked to them for visualization and facility-management-oriented interpretation?

RQ3. What identifier, naming, and data-exchange assumptions are necessary to support interoperable transfer of environmental observations from an external data source into the BIM environment?

To answer these questions, the thesis pursues four objectives: (O1) organize and synthesize the state of the art; (O2) define an end-to-end workflow and its deliverables; (O3) document a semantic structuring and mapping strategy suitable for facility-management applications; and (O4) demonstrate the workflow on the selected case study and discuss transferability and limitations.

Novelty: Positioning this Thesis

The literature review shows that research on Digital Twins, Digital Shadows, BIM, and IoT integration in the built environment is active but still fragmented. Existing studies have demonstrated the feasibility of individual components of these systems, such as real-time monitoring, BIM-based visualization, semantic data integration, and facility-oriented applications. However, these contributions are often developed as isolated prototypes, heritage-oriented applications, laboratory demonstrators, or subsystem-specific case studies rather than as transferable workflows for contemporary operational buildings.

The novelty of this thesis lies in its multidisciplinary, workflow-oriented approach. Rather than addressing only one technical layer, the study connects territorial framing, geomatic survey, point-cloud processing, Scan-to-BIM modelling, model verification, semantic information structuring, and BIM–IoT data linkage within a single methodological chain applied to a real case study. In this sense, the thesis does not propose a new standalone software tool or a complete Digital Twin platform; instead, it contributes a reproducible framework showing how an operational building can be transformed from surveyed physical reality into a semantically structured Digital Shadow environment prepared for environmental-data integration and monitoring-oriented interpretation.

A further element of novelty lies in the type of case study and in the scale of the implemented workflow. Much of the reviewed literature focuses on heritage assets, residential demonstrators, or isolated technical systems, whereas this thesis is developed on the Politecnico di Torino Energy Center as a modern, functioning institutional building. The originality of the work, therefore, lies not in a single isolated technical step, but in the integration of methods and disciplines that are often treated separately: GIS-based contextual framing, integrated 3D metric survey, as-built BIM reconstruction, geometric verification against the point cloud, and the linkage of environmental observations to semantically structured BIM entities within a coherent Digital Shadow workflow.

For these reasons, the contribution of this thesis should be understood as methodological rather than merely descriptive. Its novelty lies in demonstrating that the transition from 3D metric survey to structured BIM and then to data linkage and monitoring-oriented visualization can be organized as a coherent and transferable process for a contemporary building context. In this way, the thesis helps bridge the gap between the conceptual promise of Digital Twins and the practical development of operationally meaningful Digital Shadow workflows for real buildings.

Chapter 3

Methodology

3.1 Overall Workflow

The methodology of this thesis is structured as a three-stage workflow for the development of a Digital Shadow of the Energy Center. First, the as-built condition is documented through an integrated 3D metric survey, producing a georeferenced point-cloud dataset that constitutes the geometric baseline of the building. Second, this unstructured reality-capture dataset is processed and translated through a Scan-to-BIM workflow into a semantically structured BIM model, in which the surveyed geometry is interpreted and organized as coherent building elements, spaces, levels, and information parameters. Third, environmental data are linked to BIM entities through a stable identification and mapping strategy, enabling interoperable visualization and monitoring by combining geometric fidelity, semantic structure, and time-series measurements within a single digital environment. These 3 stages are detailed in Sections 3.5, 3.6, and 3.7, respectively.

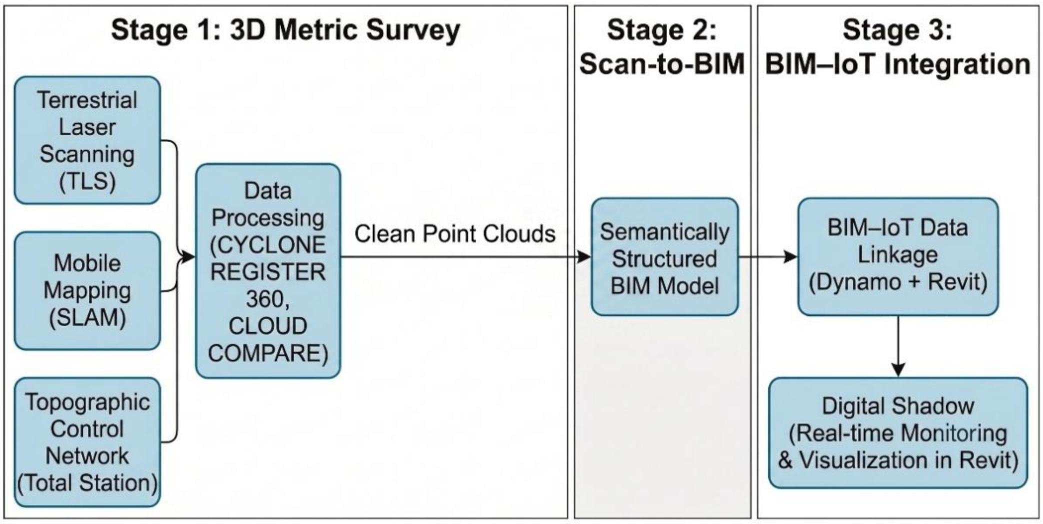


Figure 7 Overall methodology pipeline: from 3D metric survey and unstructured point-cloud acquisition to Scan-to-BIM structuring and Digital Shadow integration.

3.2 Territorial Analysis and GIS Contribution

This thesis adopts a multi-scale perspective then territorial and urban context is analysed to frame the building-scale case study and to support the interpretability of the Digital Shadow workflow. In this research, the Geographic Information System (GIS) is intended as the environment for collecting, organizing, managing, and visualizing georeferenced spatial data related to the study area.

The territorial datasets used for this phase were obtained from the **Geoportale Piemonte**, with particular reference to the **BDTRE** regional database (Regione Piemonte, n.d.). These data were used to reconstruct the spatial context of the study area at city and district scale and to support the preparation of the localization and zoning maps included in this chapter. In order to maintain geometric consistency across all territorial layers, the GIS workflow was developed in the projected coordinate reference system **WGS 84 / UTM zone 32N (EPSG:32632)**, which was adopted as the common spatial reference for data import, visualization, and map production.

From an operational point of view, the GIS project was organized into thematic groups in order to maintain a clear and reproducible structure. The main layer groups included: **(i)** base territorial and cartographic reference data, **(ii)** administrative and zoning layers, **(iii)** urban-context and localization layers for the case-study area, and **(iv)** derived maps produced specifically for the thesis. This structure made it possible to separate raw source data from processed outputs, reduce ambiguity in layer management, and facilitate the production of consistent map layouts for the successive scales of representation.

Within the overall methodology, the GIS contribution therefore serves as a contextual support layer for the following stages of the research. It provides the spatial framework through which the Energy Center is identified and interpreted within Turin, while the core development of the thesis remains focused on building-scale survey, Scan-to-BIM modelling, semantic structuring, and BIM–IoT integration. In this sense, the GIS component strengthens the territorial readability of the case study and ensures that the building-level workflow is not presented as an isolated object, but as part of a wider spatial and institutional context.

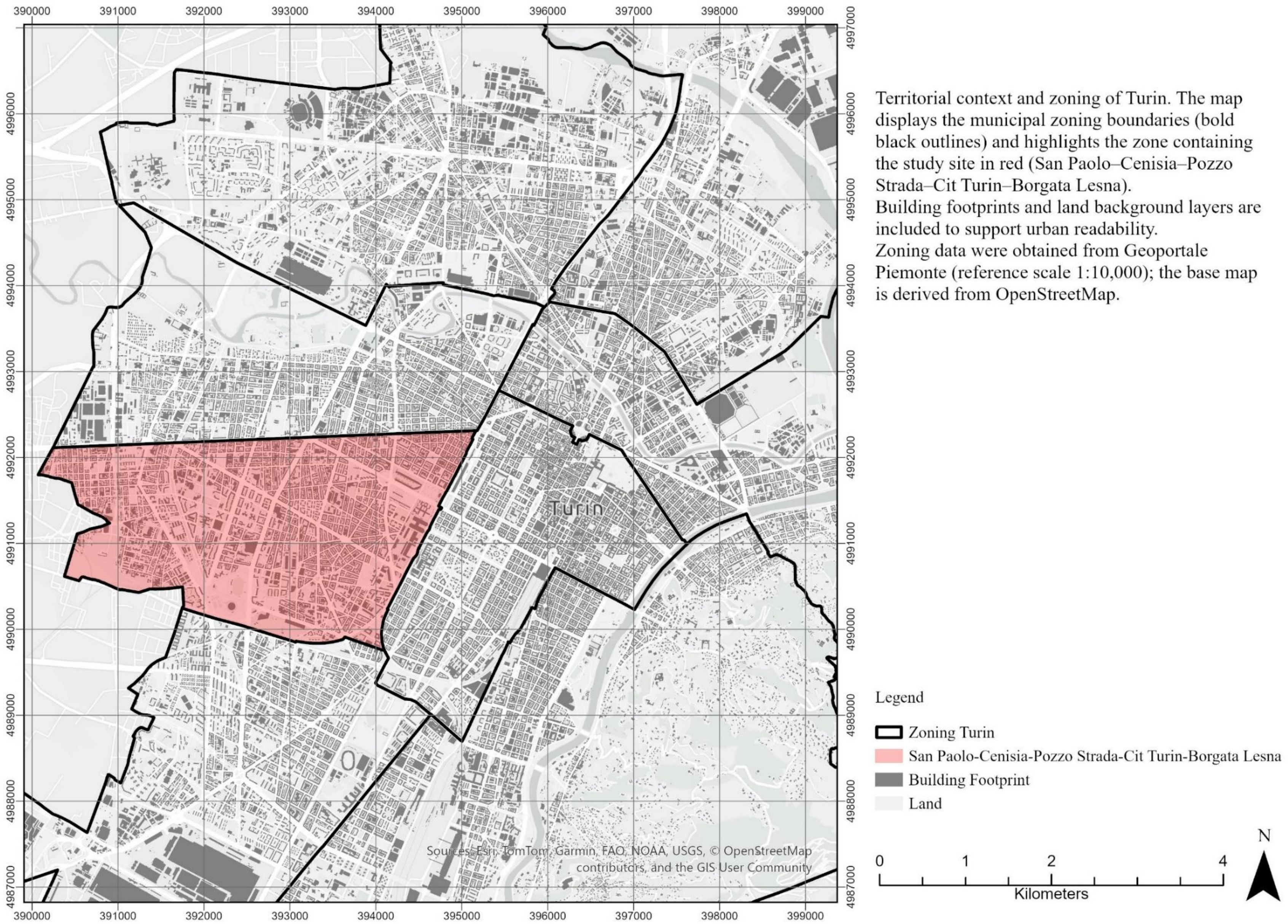


Figure 8 Zoning context of Turin, highlighting the zone containing the study site. Coordinate reference system: WGS 84 / UTM zone 32N (EPSG:32632). Source: author's elaboration on Geoportale Piemonte / BDTRE data.

3.3 Case Study: Energy Center Building

This thesis is applied to the **Politecnico di Torino Energy Center**, a contemporary building located in Turin, in the Piedmont Region of northern Italy. The building is situated at **Via Paolo Borsellino 53, 10138 Torino (TO), Italy**. The Energy Center hosts research and technical activities related to energy systems and building technologies and includes laboratories, technical rooms, service areas, and spaces containing monitored building systems. These characteristics make it a suitable case study for the development and testing of a Digital Shadow workflow in a real operational environment.

The location and urban context of the case study are illustrated in **Figure 9**, produced within the GIS workflow described in Section 3.2. The map was prepared in **ArcGIS (Esri, n.d.)** using territorial base data obtained from the **Geoportale Piemonte**, with particular reference to the **BDTRE** regional database, and was managed in the projected coordinate reference system **WGS 84 / UTM zone 32N (EPSG:32632)**. It was developed at an urban-context scale in order to show the position of the Energy Center within Turin and its relation to the surrounding built fabric and road network.

The selection of the Energy Center as the case study is based on two main reasons. First, the building includes an existing **IoT sensor infrastructure**, which makes it particularly relevant for a BIM–IoT-oriented research workflow. Their existence also supported the development of the BIM–IoT integration workflow later implemented in this thesis through environmental data linkage and BIM-side visualization logic. Second, the research team had **direct access to the building and its technical spaces**, making it possible to carry out the full building-scale workflow, including 3D metric survey, Scan-to-BIM modelling, model verification, and BIM–IoT workflow implementation developed in this thesis.

The Energy Center is particularly relevant because it is a **non-historic, fully operational contemporary building**, whereas much of the Digital Twin and BIM–IoT literature focuses either on heritage assets, experimental setups, or subsystem-specific case studies. For this reason, it provides an appropriate testbed for exploring a transferable Digital Shadow workflow for a modern institutional building, in line with the research gap identified in Chapter 2.

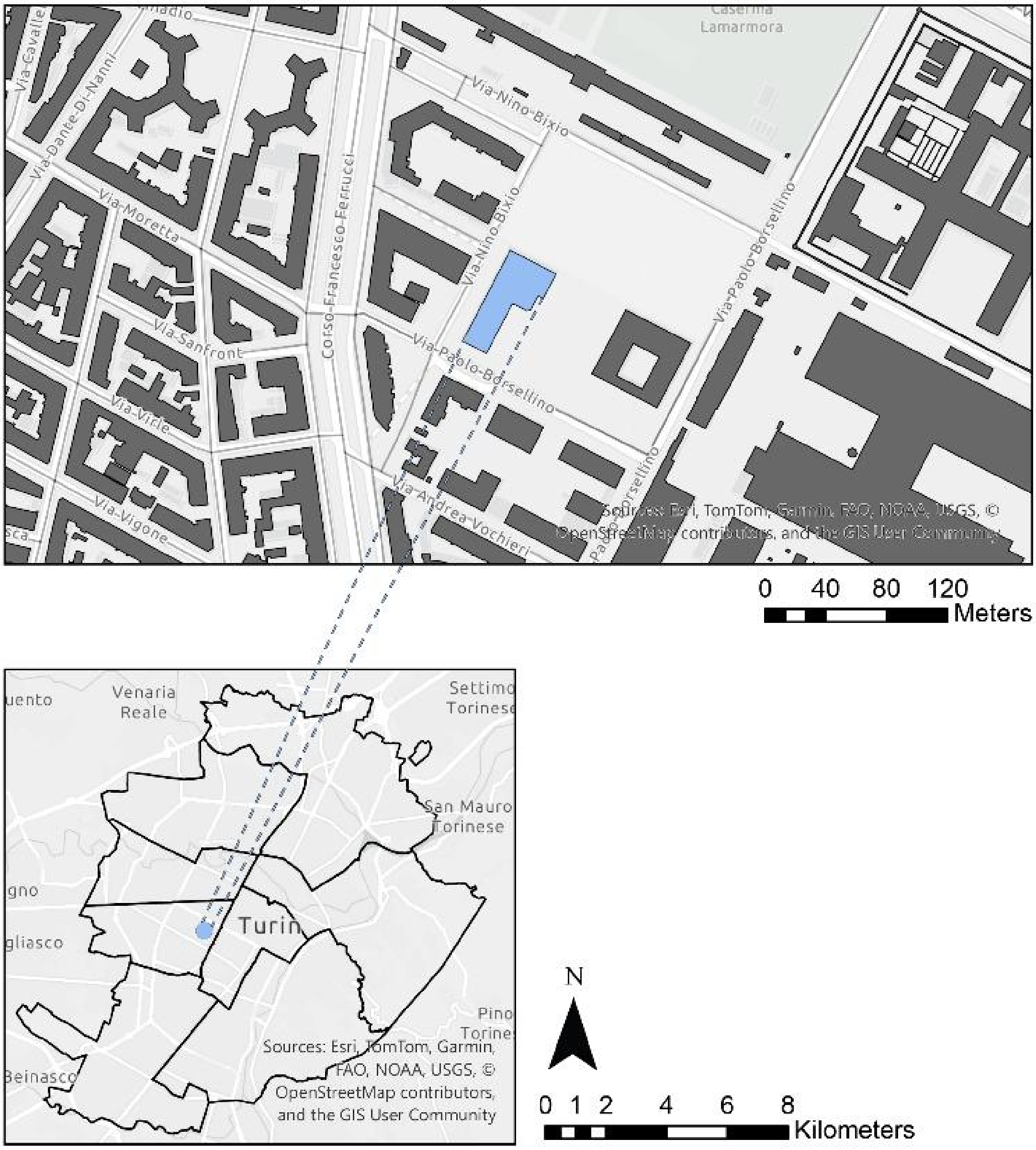


Figure 9 Location and urban context of the Energy Center building in Turin (Piedmont, Italy), produced from Geoportale Piemonte / BDTRE spatial data in ArcGIS and referenced in WGS 84 / UTM zone 32N (EPSG:32632).

3.4 Technologies and Software

As mentioned above, the workflow in the Digital Shadow of this thesis is structured into three steps: (1) 3D metric survey to build the as-built geometry, (2) Scan-to-

BIM to build a semantically structured BIM model, and (3) integration of IoT sensor data by linking measurements in time-series to BIM objects by stable identifiers. The technologies and software are thus reported stage by stage clearly informing what each tool was applied and yielded.

This section summarizes the main software tools and applications used across the three workflow stages. The purpose is to clarify the role of each tool in the pipeline, without repeating the detailed methodological steps that are explained in Sections 3.5–3.7.

Stage 1 – 3D Metric Survey (Acquisition, Registration, and Validation). The 3D metric survey combined topographic control, terrestrial laser scanning, and complementary mobile mapping. A **Leica RTC360** was used as the main TLS instrument for the acquisition of dense point-cloud data. The topographic part of the workflow was developed through **Total Station (TS)** measurements, which were used to establish the control network, measure reference vertices and targets, and provide a stable geometric framework for scan registration and for limiting error propagation across the different acquisition sessions. For TLS registration and alignment control, **Leica Cyclone REGISTER 360** was used as the main software environment (Leica Geosystems, n.d.).

Stage 2 – Point-Cloud Preparation and Scan-to-BIM Authoring. **CloudCompare v2.14.beta** was used to inspect, clean, and prepare the registered point clouds, including noise and outlier removal, subsampling where necessary, and segmentation of the dataset into more manageable subsets for modelling. **Autodesk ReCap Pro** was then used to index and manage the processed point clouds and to generate BIM-compatible point-cloud references for linking into the BIM authoring environment. **Autodesk Revit** was used for the Scan-to-BIM phase and for the semantic structuring of the case-study model, including the reconstruction of the architectural elements and the definition of the parameters later used for data linkage and visualization (Autodesk, n.d.-a, n.d.-b; CloudCompare project, n.d.).

Stage 3 – IoT Data Pipeline and BIM Integration. Python was used to develop the publisher and subscriber scripts that handled the transfer and exposure of environmental observations. A local MQTT broker was used as the intermediate communication layer, while a local HTTP JSON endpoint exposed the latest payload for BIM-side access. Inside the BIM environment, Dynamo for Revit was used to retrieve the JSON payload, parse the Temperature, Humidity, and AirQuality values, update the selected Revit elements, and apply the room-scale colour visualization logic described in Section 3.7.2. In this way, the software stack of the final stage supported the transfer of environmental observations into the BIM model and their visualization in Revit (Autodesk, n.d.-c; Eclipse Foundation, n.d.; Python Software Foundation, n.d.).

3.4.1 Data Formats and Standards

The workflow uses different data formats, each optimized for a specific task. For the as-built stage, survey outputs are managed as registered point clouds in standard exchange formats [e.g., E57 / LAS/LAZ / PTS], and as indexed project formats for BIM referencing [e.g., RCP/RCS]. For BIM authoring, the working model is maintained in the native authoring format [RVT], while open exchange is supported through IFC exports where interoperability with external viewers or downstream pipelines is required (Tang et al., 2019). For the IoT layer, sensor readings are handled as time-stamped records and exchanged as lightweight structured data [CSV/JSON], complemented by a stable identifier strategy (sensor IDs, space/equipment IDs, and mapping tables) that preserves traceability between measurements and BIM entities.

3.5 Data Acquisition and Survey

This section details the operational steps used to generate the geometric baseline for the Digital Shadow. It describes how the survey data were acquired on site, including planning considerations and field deliverables. The survey campaign was documented through a structured fieldbook including annotated photographs, control-point sketches, Total Station setup notes, and target IDs used during acquisition and later processing. The complete fieldbook is provided in Appendix B to ensure traceability and reproducibility of the geometric baseline. The subsequent registration, cleaning, segmentation, and BIM-ready preparation of the point clouds are described in Section 3.6.

3.5.1 3D Metric Survey

The workflow begins with an integrated 3D metric survey of the Energy Center to capture the as-built geometry with sufficient density and accuracy for downstream modelling. Terrestrial laser scanning (TLS) is used as the primary method because it provides high-density point measurements suitable for precise geometric documentation. In parallel, SLAM-based mobile mapping is employed as a complementary approach to accelerate acquisition in circulation and connection areas, where rapid coverage is beneficial and repeated static setups may be inefficient. The combination of TLS (as a high-accuracy reference) and SLAM (as an efficient coverage method) supports a balanced dataset that is both geometrically robust and operationally feasible for a functioning building environment. In parallel with the TLS and SLAM acquisitions, a topographic control network was established to provide a stable reference system for all datasets and to ensure consistent registration between acquisitions performed in different sessions and spaces. This step was critical because the geometric reliability of the subsequent georeferencing, registration, and data integration phases depended on the quality of these preliminary measurements. A network based on external reference vertices and TS-measured targets was therefore used as the geometric backbone of the survey workflow, providing a common spatial framework for the different acquisitions, supporting scan orientation and registration, and helping to contain cumulative error propagation across the surveyed areas. This logic is consistent with integrated geomatic workflows in which a reference topographic network and measured control points are used to support multi-sensor acquisition, registration, and accuracy assessment (Chiabrando et al., 2017; Teppati Losè et al., 2021). In parallel with acquisition, the control framework and measurement logic were documented in a fieldbook to support later registration decisions and quality checks. This documentation includes (i) monographs for external reference vertices around the building perimeter, (ii) Total Station setup records, including instrument and prism heights where relevant, and (iii) an indexed target list with annotated photographs showing the placement and visibility of measured points across exterior and interior locations (Appendix B).

During acquisition, scans are planned to ensure adequate overlap between stations and to reduce occlusions in technical rooms, corridors, and service areas. Field notes are used to document scan positions, critical areas requiring higher detail (e.g., equipment rooms and dense mechanical, electrical, and plumbing (MEP) zones), and access constraints. The expected deliverables of this stage are (i) raw TLS scan sets, (ii) SLAM trajectories and derived point clouds where applicable, and (iii) an initial dataset prepared for registration and consistency checks.

3.5.1.1 Topographic control network and Total Station (TS) acquisition

A Total Station (TS) survey was used to measure the control network vertices and to acquire the coordinates of a set of signalized targets and key architectural points visible from multiple scan positions. This approach follows standard scan-registration logic: each TLS scan is initially produced in a local coordinate system centered on the scanner position, so the reference system changes when the instrument is moved. By measuring common targets and/or scan stations with the Total Station, the individual point clouds can be transformed into a shared coordinate system, strengthening registration reliability and enabling cross-comparison between datasets, in line with integrated geomatic workflows based on reference topographic networks and measured control points (Chiabrando et al., 2017; Teppati Losè et al., 2021).

Prior to the laser scanning campaign, a topographic control network was established to provide a stable and georeferenced reference system for the registration of the TLS and SLAM datasets. The network was designed as a closed loop encircling the Energy Center building, incorporating both exterior control stations and interior tie points to ensure reliable geometric connections between outdoor and indoor scan positions.

The control network was created using a Leica Total Station. The survey began at the main front entrance of the building (point 100) and proceeded around the perimeter, closing the loop near the rear (back) entrance. Four primary exterior control stations, labelled A, B, C and D, were established at key locations around the building envelope. Station D was positioned adjacent to the back entrance, effectively completing the exterior polygonal loop. Additional control points were measured inside the building through doorways and open circulation spaces, linking the exterior network to the interior environments.

In total, 81 control points were measured, numbered sequentially from 100 to 181. The points were distributed to provide sufficient overlap and geometric redundancy between adjacent scan positions. All control points were documented in the fieldbook with sketches (monographs) indicating their position relative to stable architectural features, accompanied by photographs to support future re-occupation and unambiguous identification during the registration process (see Appendix B and Figure 11).

To ensure robust alignment, targets were distributed to guarantee overlap between adjacent acquisitions and to create "homologous" points observable across multiple scans. These TS-measured targets were then used as fixed constraints during registration, reducing cumulative error and providing a consistent spatial structure for subsequent processing. The fieldbook also records representative TS setups and target observations that connect exterior control to interior points, providing the practical traceability layer behind the control-network description (Appendix B).

SLAM-based mobile mapping was adopted specifically to accelerate the capture of circulation spaces and GNSS-denied indoor and basement environments, where static acquisition is slower and operational constraints such as access, time windows, and human movement are more critical. SLAM systems combine LiDAR observations with inertial measurements and simultaneous localization and mapping algorithms to estimate trajectories and generate point clouds in the instrument's working reference system. This makes them particularly suitable for rapid indoor documentation and for complex environments where acquisition speed and flexibility are important. At the same time, their geometric stability is generally lower than that of static TLS over extended paths, so their outputs benefit from external control and from integration within broader multisensor survey workflows in order to limit drift and maintain geometric reliability. For this reason, in the present workflow the SLAM dataset was treated as complementary to TLS and was aligned within the same overall survey-control logic, rather than being considered an independent high-accuracy reference dataset (Sammartano & Spanò, 2018; Sammartano et al., 2021; Salgues et al., 2020; Sgrenzaroli et al., 2022; Hu & Assaad, 2024).

Figure 10 Topographic control network around the Energy Center building, showing the four exterior control stations (Points A–D). Basemap: Esri / OpenStreetMap.

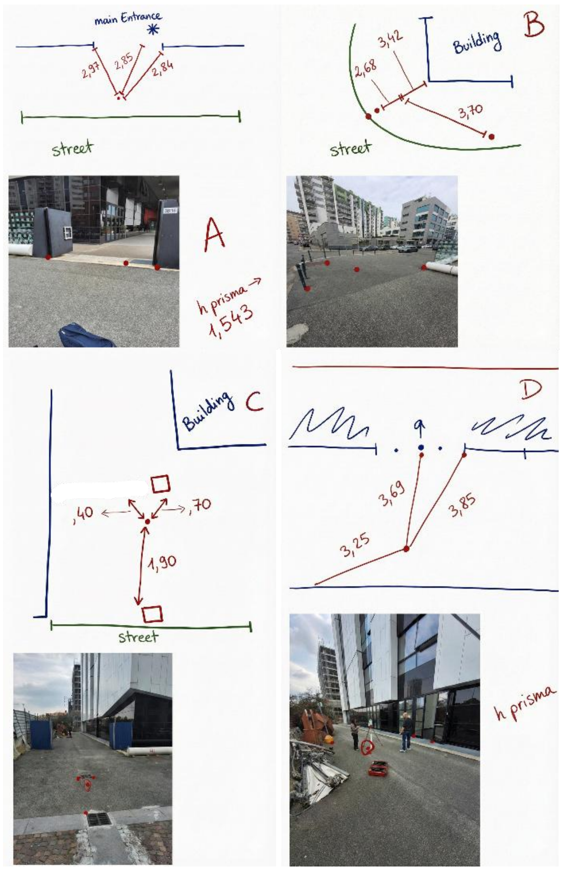


Figure 11 Fieldbook excerpts documenting external control vertices (monographs with sketches .and photographs) used as the topographic backbone for registration

3.5.1.2 Survey report

The survey campaign produced a structured field report to ensure traceability and reproducibility of the acquisition. This report includes: (i) control point/vertex monographs (location, photos, and materialization notes), (ii) TS setup notes (instrument height, prism height, station identifiers, orientation references), (iii) a target list with IDs and placement logic (interior/exterior connection points), and (iv) a photo log documenting acquisition conditions and target visibility. Consistent with good geomatics practice, field data were also reviewed and downloaded at the end of each survey day to check completeness and reduce the risk of missing coverage. The full report is referenced in the Appendix, while representative figures are included in the methodology section.

The full survey campaign fieldbook (control-point monographs, TS setup notes, target list, and annotated photo log used as processing notes) is included in Appendix B. Representative excerpts are reported in Section 3.5.1.1 to illustrate how the control framework and targets were established on site.

3.6 Data Processing, BIM Authoring and Semantic Structuring

After acquisition, the survey data were processed to create a single coherent point-cloud dataset that could be used as a dependable geometric reference for the Scan-to-BIM phase. The first step of this post-acquisition workflow was the calculation and verification of the topographic control network, through which the coordinates of the reference vertices and measured targets were established. This step was necessary to provide the common spatial framework used for the subsequent registration and alignment of the TLS scans and, where applicable, of the complementary SLAM-derived datasets. Once the control framework had been defined, the different acquisitions were brought into a consistent coordinate system through scan-registration procedures and quality checks. Registration reports and coordinate-consistency tests were then used to verify that the combined dataset remained coherent across floors and between separate building zones. The main output of this stage was a registered point-cloud dataset suitable for downstream cleaning, segmentation, and BIM-oriented preparation.

3.6.1 Data Processing

Following registration, point-cloud preparation focuses on improving usability and reducing modelling uncertainty. Typical operations include noise/outlier removal, performance-oriented subsampling, and segmentation into structured subsets (for example, by floors, areas, or systems). This step is particularly important in technical buildings, where dense MEP elements can increase visual clutter and reduce modelling clarity if the point cloud is not structured. The resulting outputs are a set of cleaned and organized point-cloud references that support efficient navigation, clipping, and modelling decisions in the BIM authoring environment. Registration and alignment was performed based on specific scan-registration software: Leica Cyclone Register 360 to control scan alignment, assess registration quality, and export a registered point-cloud dataset that could be utilized downstream to model. Where applicable, TS-measured control points and signalized targets documented during acquisition were used as registration constraints and as verification references to limit drift and improve cross-area consistency (see Section 3.4.1.1 and Appendix B). CloudCompare was used to perform cleaning and preparation operations such as noise/outlier removal, performance-oriented subsampling, and subdivision into floors, areas, and systems, generating structured subsets that reduced modelling uncertainty and improved repeatability.

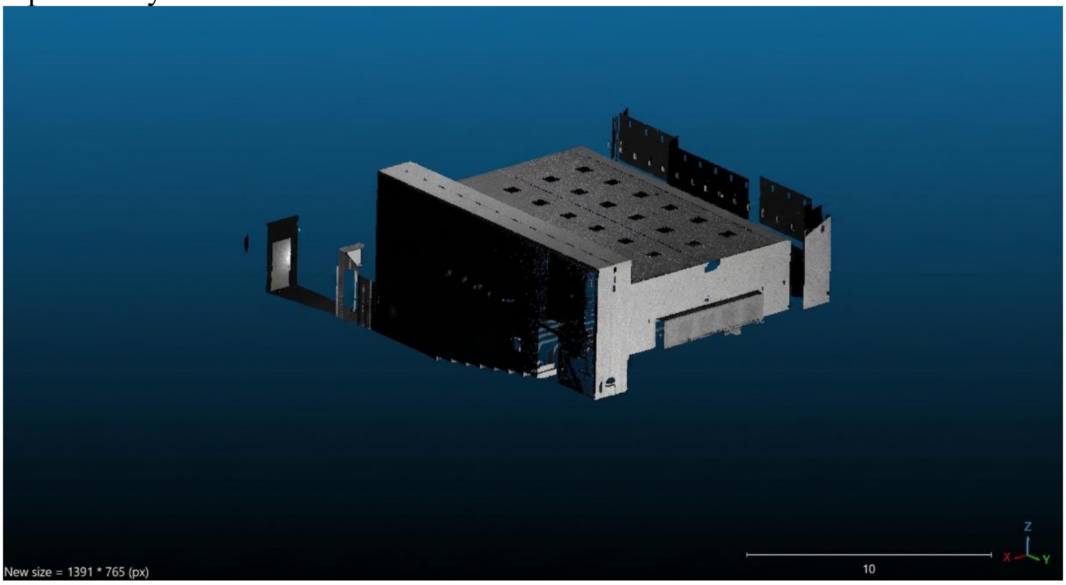


Figure 12 Isolation of the conference-room case-study point cloud in CloudCompare after registration and preprocessing.

3.6.2 Scan-to-BIM

After registration and general point-cloud preparation, the workflow proceeded to the Scan-to-BIM phase, focusing on the conference room selected as the detailed case-study space within the Energy Center. Because the original survey dataset covered a wider portion of the building than was required for the detailed modelling task, the point cloud was first further restricted in CloudCompare in order to isolate the relevant area and reduce unnecessary surrounding geometry. This step made the dataset more manageable for downstream BIM authoring and ensured that the modelling effort remained aligned with the effective spatial scope of the research.

Once the case-study subset had been isolated, the processed point cloud was transferred to Autodesk ReCap to generate an indexed **RCP** file suitable for linking into Autodesk Revit. The RCP file was then imported into Revit and used as the geometric reference for the as-built reconstruction of the conference room and its immediate envelope context. The indexed conference-room point cloud in Autodesk ReCap is shown in Figure 13.

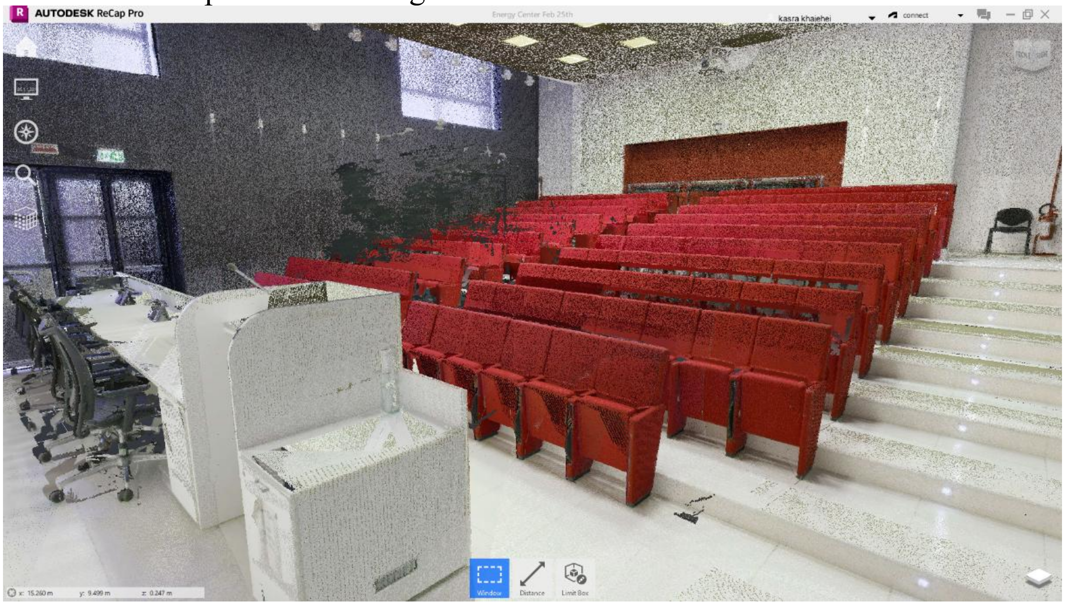


Figure 13 Conference-room point cloud in Autodesk ReCap, used to generate the RCP reference for BIM authoring in Revit.

The modelling phase began with the definition of the principal reference levels derived from the scan data. The definition of the principal reference levels in Revit is illustrated in Figure 14.

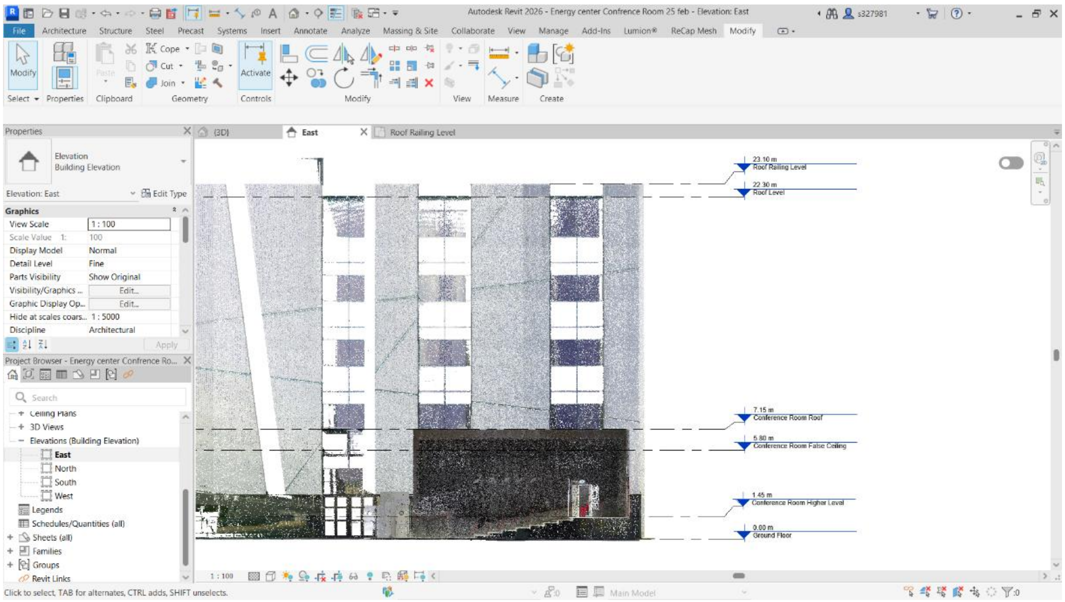


Figure 14 Definition of the principal reference levels in Revit on the basis of the linked point cloud.

On this basis, the as-built BIM model was progressively reconstructed using the point cloud as the main geometric reference. At this stage, the modelling included the principal architectural and fixed interior elements of the conference room, namely floors and stepped seating levels, walls, façade and envelope components, roof, ceiling and false ceiling, doors and openings, lighting fixtures, and the main fixed furniture and seating elements. MEP systems were not modelled in this phase, since the objective was to establish a reliable architectural and spatial BIM basis for subsequent semantic structuring and data integration. The resulting as-built BIM model is shown in Figure 15.

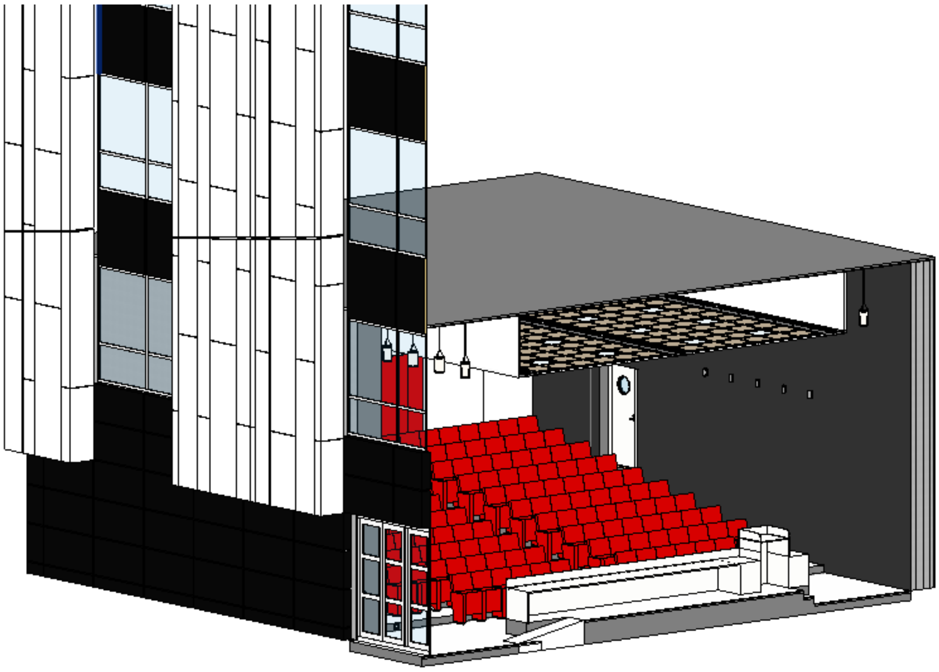


Figure 15 As-built BIM model of the conference room, showing the architectural shell, envelope context, and main fixed interior elements reconstructed from the point cloud.

From a methodological point of view, this phase represents the transition from an unstructured reality-capture dataset to a structured information model. The point cloud provides dense geometric evidence of the existing condition, but it does not by itself constitute an operational model. Through the Scan-to-BIM workflow, this geometric evidence was interpreted, simplified where necessary, and translated into a BIM environment where the surveyed space could be represented through coherent model elements, levels, spatial references, and object-based relationships. According to the current stage of development, the resulting model can be considered approximately equivalent to **LOD 300**, meaning that it provides a geometrically reliable and sufficiently detailed representation for documentation, spatial understanding, and the following stages of the thesis. A representative interior comparison between the linked point cloud and the reconstructed BIM model is reported in Figure 16.

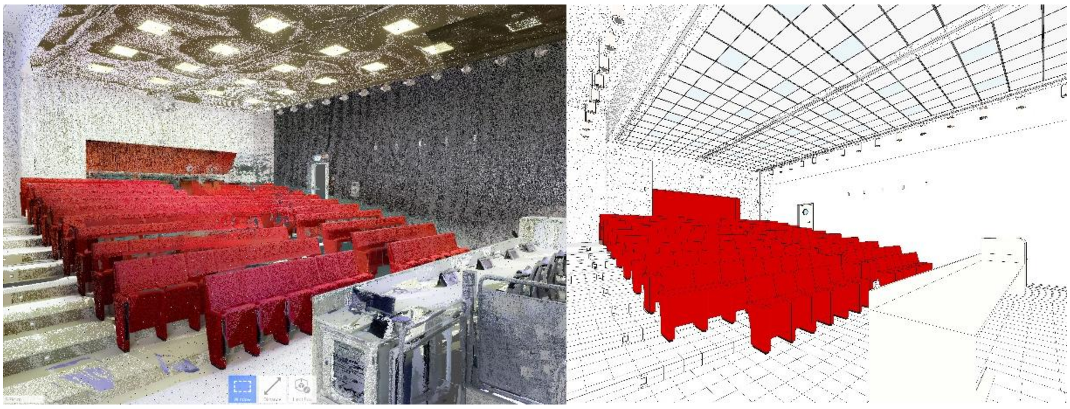


Figure 16 Interior comparison between the linked point cloud and the as-built BIM model of the conference room in Revit.

3.6.3 Model verification against the point cloud

After the Scan-to-BIM phase, the reconstructed BIM model was subjected to a verification step in order to evaluate its geometric correspondence with the surveyed reality. This phase was carried out in **FARO As-Built for Revit**, using the linked point cloud as the geometric reference and the as-built BIM model as the object of comparison. At this stage, the plugin was used as a model-checking tool rather than as an automatic modelling tool, with the objective of assessing the consistency between the reconstructed architectural model and the scan data before proceeding to the next stage of the workflow.

The verification was performed through surface-based comparison workflows in Revit. The analysis focused on the principal architectural surfaces modelled in the conference room, particularly walls, floor areas, stage elements, and stepped seating surfaces, in order to visualize the deviations between the BIM model and the point cloud. To support this operation, dedicated working views and section-box configurations were used to isolate the relevant portions of the room and ensure correct visibility and selection of the analyzed surfaces.

The purpose of this phase was twofold. First, it introduced an explicit quality-control step into the Scan-to-BIM workflow, allowing the model to be assessed not only through visual comparison but also through deviation analysis. Second, it helped identify whether discrepancies between the as-built model and the surveyed geometry were generally limited and distributed across the room or concentrated in specific local areas that might require further refinement.

In the implemented analysis workflow, the BIM model was compared to the point cloud using a **mean grid size of 0.05 m** and a **maximum surface distance of 0.30 m**. The analysis was carried out on **364 selected faces**, generating approximately **529,857 analysis points**. The parameter settings used for the verification are shown in Figure 17.

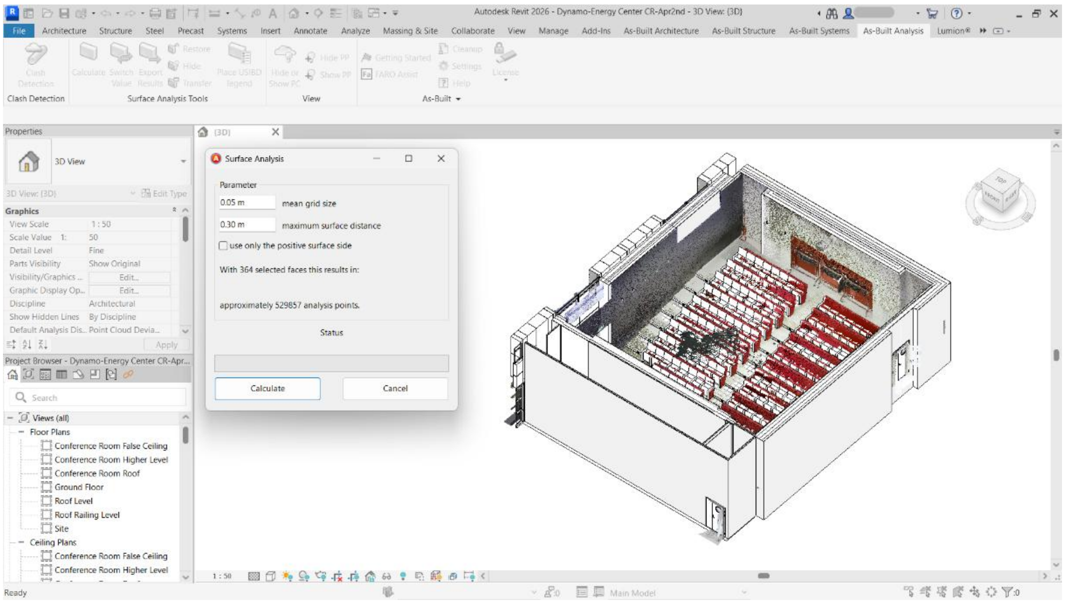
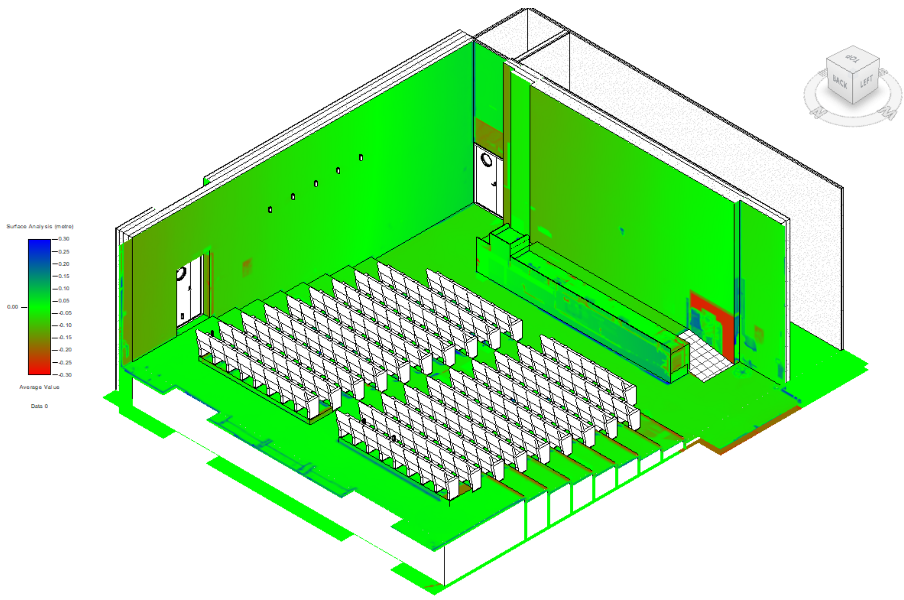


Figure 17 Surface-analysis parameters used in FARO As-Built for Revit for the comparison between the BIM model and the linked point cloud.

The resulting outputs consisted of coloured deviation maps and numerical summaries, which made it possible to identify the degree of correspondence between the reconstructed model and the surveyed surfaces and to detect localized zones with greater deviation. Representative deviation-analysis views are reported in Figure 18.



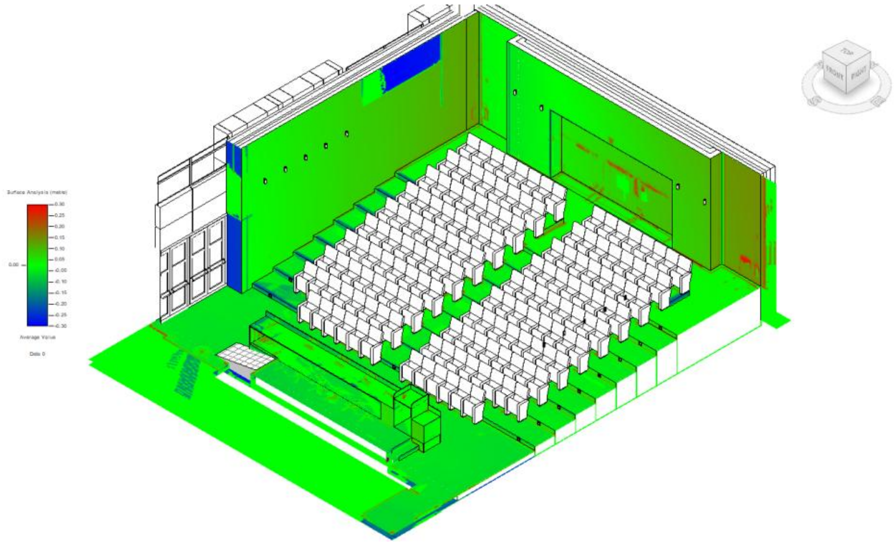


Figure 18 Surface-based deviation analysis between the as-built BIM model and the linked point cloud in FARO As-Built for Revit.

The deviation maps showed that most analyzed surfaces fell within limited deviation ranges, while more evident discrepancies appeared in localized areas, particularly near edges, openings, and some floor or stage zones.

This verification phase is important because the reliability of a Scan-to-BIM model does not depend only on the completion of the modelling task, but also on the degree to which the resulting BIM geometry reflects the measured condition of the real space. By checking the model against the point cloud, the workflow strengthens the credibility of the as-built reconstruction and clarifies the level of confidence that can be associated with the BIM model before moving toward semantic structuring and IoT-data linkage.

3.7 IoT Data Pipeline and Mapping Strategy

To enable the Digital Shadow, the geometric and semantic building representation must be connected to operational data streams. This subsection describes how the Energy Center's existing IoT sensors are prepared for integration with the BIM environment by defining a repeatable linking strategy between sensor measurements (time-series data) and BIM entities (spaces, equipment, or zones). In practice, this requires (i) establishing a sensor inventory with stable identifiers and metadata, (ii) organizing sensor readings as time-stamped records in a structured database, and (iii) generating mapping artefacts that explicitly record the relationship between sensor IDs and BIM object identifiers.

In the BIM environment, the integration is treated as a binding task. BIM entities that represent the measurement context (e.g., rooms, equipment, monitoring zones) are assigned consistent identifiers and parameters that can store sensor references.

Automation routines (for example, through visual programming) support repeatable operations such as importing sensor metadata, writing sensor tags/IDs into BIM parameters, and exporting mapping tables. The key deliverables are: (1) a clear identifier strategy, (2) BIM parameters populated to support linkage, and (3) mapping tables that allow sensor measurements to be retrieved and interpreted in the correct spatial and semantic context.

This integration preparation step establishes the minimum technical backbone required for a Digital Shadow, where the data flow remains one-way from the physical asset to the digital model for visualization and monitoring. It also preserves an upgrade path toward a full Digital Twin by ensuring that the data structures and identifiers are consistent and scalable for later analytics, rule engines, or controlled feedback logic.

3.7.1 BIM–IoT data transfer architecture

After outlining the identifier logic and mapping strategy for linking sensor observations to BIM entities, the workflow proceeded to the implementation of a BIM–IoT data-transfer architecture aimed at testing the effective integration of environmental data into the BIM environment. In the present phase of the research, recorded environmental data were used in order to validate the data-transfer, parameter-updating, and BIM-side visualization workflow within a controlled setup.

The workflow was implemented on the conference room selected as the detailed case-study space within the Energy Center model. Its purpose was to verify, in a controlled and reproducible way, that a Digital Shadow workflow could be established in which environmental observations were received, interpreted, written into BIM parameters, and visualized directly in the Revit model. In this sense, this stage represented the practical implementation of the BIM–IoT mapping logic developed in the thesis.

The test focused on three indoor environmental variables: **Temperature**, **Humidity**, and **AirQuality**. These variables were selected because they are representative of indoor environmental monitoring and are consistent with the types of observations commonly addressed in BIM–IoT integration studies related to room-condition assessment, thermal comfort, and environmental visualization (Kensek, 2014; Desogus et al., 2021). Their combined use also made it possible to move beyond the simple updating of isolated numerical values and to test a room-scale visualization logic (Desogus et al., 2021).

From a system perspective, the implemented workflow was organized into four layers: a data layer, a communication layer, a local data-exposure layer, and a BIM-side processing and visualization layer. This decomposition was useful because it kept the setup modular. In particular, the BIM-side logic was structured independently from the specific source of the environmental observations, provided that the same naming logic and payload structure were preserved. The Dynamo workflow for data retrieval and parameter updating was structured following guidance from Chinthakindi Saketh, who developed a similar BIM–IoT integration approach in his thesis under the supervision of Prof. Luca Barbierato. This emphasis on structured integration and stable mapping logic is consistent with the broader literature on BIM–IoT interoperability, which highlights that successful integration depends not only on communication tools but also on clear data organization, mapping consistency, and reusable connection patterns (Tang et al., 2019; Quinn et al., 2020). The overall sequence of the implemented BIM–IoT visualization workflow is summarized schematically in Figure 19[1].

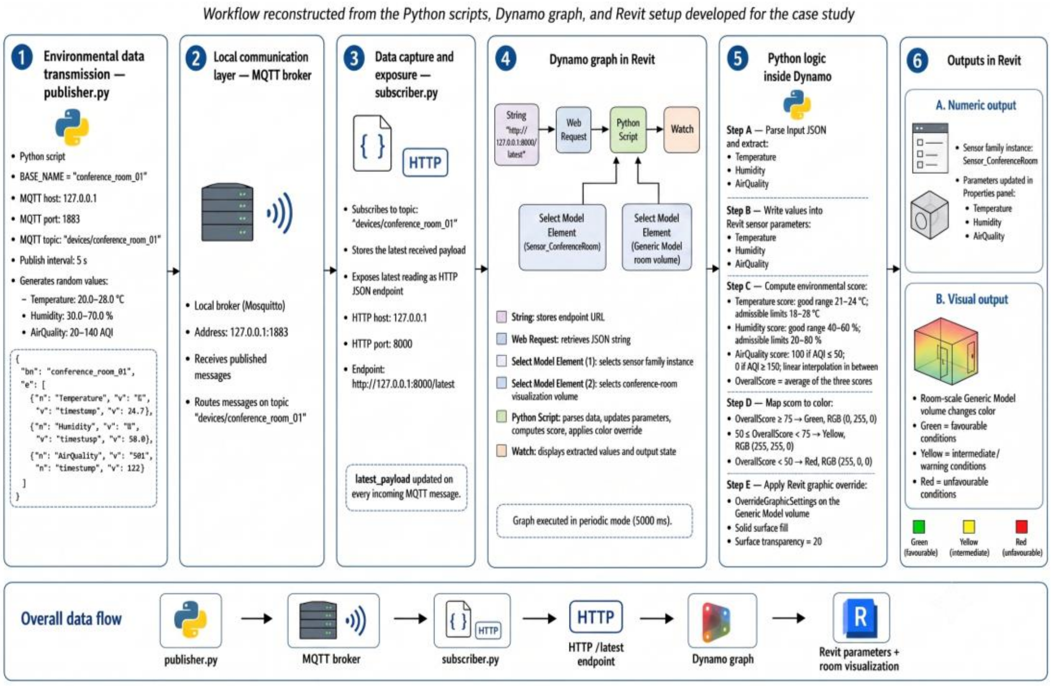


Figure 19 Schematic representation of the BIM–IoT visualization workflow, showing the sequence from environmental data transfer and processing to numeric and visual outputs in Revit.

To support message exchange, a local MQTT-based setup was adopted. A local broker was used as an intermediate communication layer, while two Python scripts managed the generation and reception of the environmental values. The first script acted as a publisher, transmitting time-varying environmental readings for Temperature, Humidity, and AirQuality. The second script acted as a subscriber, listening to the published topic, capturing the latest message, and exposing it through a local HTTP JSON endpoint.

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[1] Figure 18 was graphically generated with the support of a generative AI tool (ChatGPT 5.4) on the basis of the author's workflow specification; the workflow logic, technical content, and final editorial selection were defined and reviewed by the author.

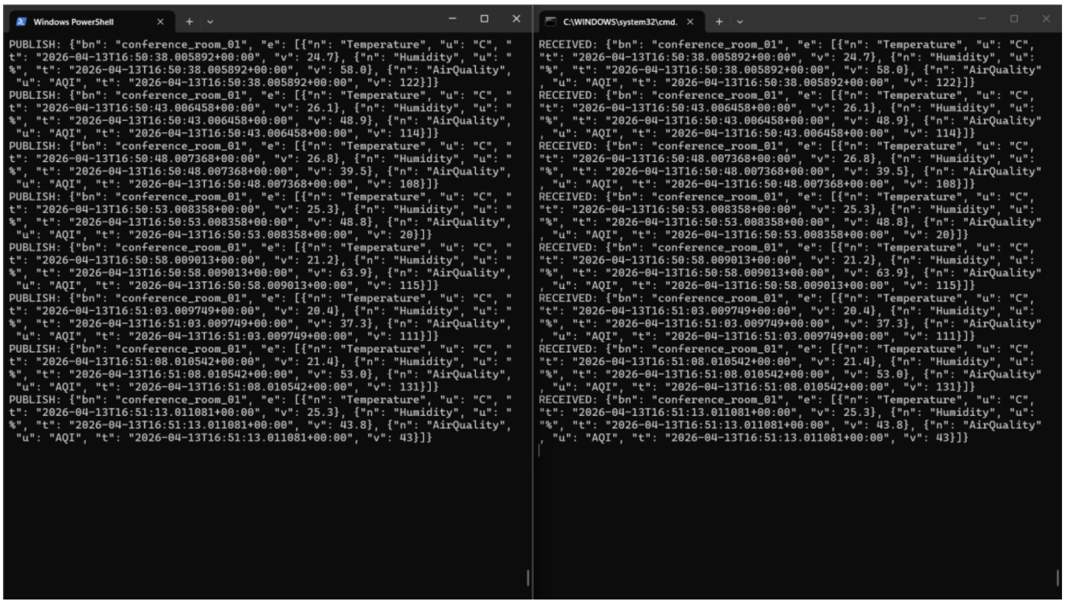

Figure 20 Local publisher/subscriber communication used in the BIM–IoT workflow, showing environmental values being published and received through the data-transfer chain.

This solution made it possible to implement a sensor-data transfer workflow while keeping the environment fully local and technically manageable during testing. Although the specific local implementation was developed for this thesis, the general principle of lightweight middleware and intermediate data layers between environmental observations and BIM is consistent with common BIM–IoT integration approaches identified in the literature (Tang et al., 2019; Desogus et al., 2021).

At the communication level, the payload was structured as a compact JSON message containing a base identifier for the monitored room and a list of timestamped environmental observations. Each observation included the variable name, its unit, the timestamp, and the numerical value. The subscriber continuously updated the most recent message and made it available through a local endpoint, which was then queried from within Dynamo.

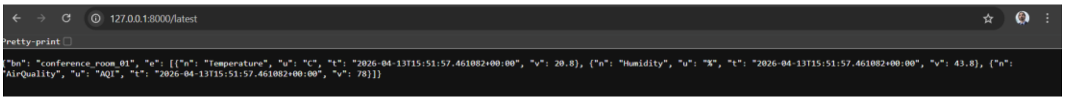

Figure 21 Latest environmental payload exposed through the local HTTP JSON endpoint used as the bridge between the environmental dataset and Dynamo.

In this way, the implemented workflow created a lightweight bridge between the external data source and the BIM model without requiring a direct database connection at this stage. The architecture adopted in this thesis is case-specific in its local implementation, while following an integration logic consistent with common BIM–IoT workflows reported in the literature, where external environmental data are processed through intermediate communication layers before being linked to BIM elements (Tang et al., 2019; Quinn et al., 2020). The implemented architecture maintained a one-way data flow only, from environmental observations toward the BIM model. No actuation, feedback control, or command transmission toward a physical system was introduced. Therefore, consistently with the conceptual framing of the thesis, this phase should be interpreted as a Digital Shadow implementation rather than as a full Digital Twin implementation, since it supports monitoring and interpretation but not bi-directional control or self-management (Sepasgozar, 2021).

3.7.2 BIM-side implementation and room-scale visualization in Revit/Dynamo

On the BIM side, the implemented workflow required the explicit preparation of both a measurement object and a visualization object inside the conference-room model. The measurement object was implemented through a custom Revit family representing the sensor. This family was enriched with three instance parameters: **Temperature**, **Humidity**, and **AirQuality**. These parameters provided a semantic location inside the BIM model where incoming observations could be written numerically and later inspected directly through the Revit properties panel.

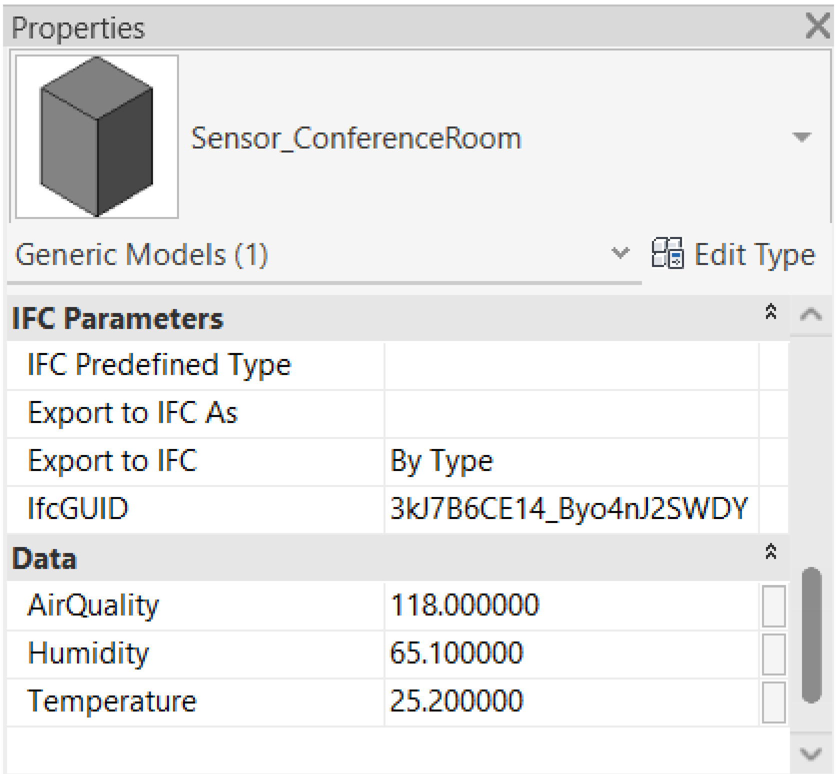

Figure 22 Custom Revit sensor family with Temperature, Humidity, and AirQuality instance parameters updated from the local data stream.

The naming of these parameters was treated carefully, since consistency between the external data labels and the BIM-side parameter names was necessary for the automation logic to work reliably. In practical terms, the variable names arriving from the JSON stream had to correspond to the parameter names searched by the Dynamo/Python routine in Revit. This reflects a broader principle already discussed in the thesis: the success of BIM–IoT integration depends not only on communication technology, but also on the stability and consistency of identifiers and naming conventions across the entire workflow (Tang et al., 2019; Quinn et al., 2020).

In parallel with the sensor family, a second BIM object was created to support room-scale visualization. Instead of visualizing only the sensor family itself, a **Generic Model** volume was modelled so as to occupy the main air volume of the conference room. This object was used as a spatial proxy of the monitored indoor condition. Since environmental variables such as temperature, humidity, and air quality are more meaningfully interpreted at room scale than as isolated point values, this volumetric representation provided a clearer and more legible monitoring-oriented visualization. The chosen element was modelled so that the resulting colour changes could remain visible while preserving the spatial readability of the room.

Within Dynamo, the BIM-side workflow was implemented through a compact graph. A **String** node stored the local HTTP address of the JSON endpoint. A **Web Request** node retrieved the latest available environmental reading from that address. Two **Select Model Element** nodes were then used to identify the target BIM elements in Revit: the sensor family instance and the Generic Model volume used for visualization. The returned JSON payload, together with the selected BIM elements, was passed to a **Python Script** node, where the main processing logic was executed. During testing, a **Watch** node was used to inspect the parsed values and the computed outputs. In this way, the graph remained relatively simple, while still making each step of the workflow explicit and traceable.

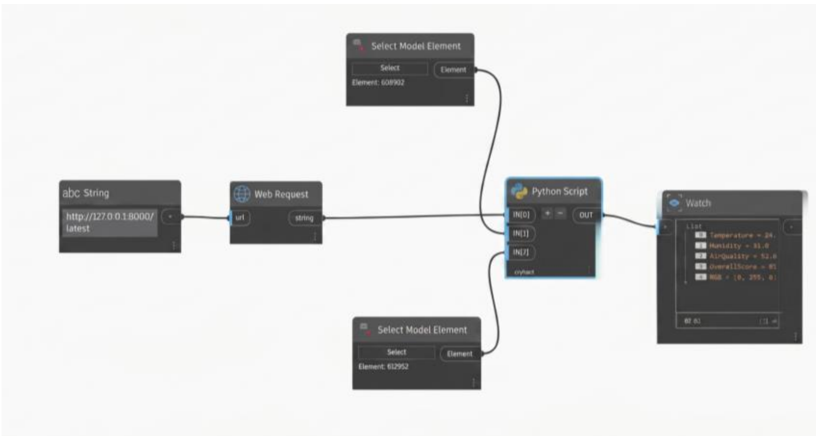

Figure 23 Dynamo graph used to retrieve the latest JSON payload, parse Temperature, Humidity, and AirQuality values, and update the selected BIM elements in Revit.

Inside the Python routine, the JSON message was parsed and the three relevant variables were extracted by name: Temperature, Humidity, and AirQuality. The script then wrote the numerical values of these variables into the corresponding parameters of the sensor family instance. This ensured that the BIM model was not only showing a graphical response but was also storing the incoming observations directly in the properties of a BIM element. The coexistence of numeric object-level storage and room-level visualization is consistent with the wider literature on FM-BIM and BIM–IoT integration, where time-series data are mapped to BIM elements in order to support both direct inspection and spatio-temporal interpretation (Desogus et al., 2021; Quinn et al., 2020).

The same routine also generated a simplified environmental-condition score and the corresponding colour output. Rather than relying on a single-variable threshold, the implemented workflow evaluated the three monitored variables independently and then combined them into a single room-scale indicator. For **Temperature**, the script defined a preferred range between **21.0 °C and 24.0 °C**, with outer admissible limits at **18.0 °C** and **28.0 °C**. Values within the preferred range received the maximum score, while values outside the outer limits received the minimum score; values between these intervals were interpolated linearly. For **Humidity**, the preferred range was set between **40.0% and 60.0%**, with outer limits at **20.0%** and **80.0%**, again using linear interpolation between the preferred and limiting conditions. For **AirQuality**, values **up to 50 AQI** received the maximum score, values **from 150 AQI upward** received the minimum score, and intermediate values were linearly scaled.

After the three partial scores had been calculated, they were averaged into a single **overall environmental-condition score**. This scoring logic was intentionally simplified and introduced primarily for technical validation of the integration and visualization workflow, rather than as a final standardized indoor-comfort assessment model. The final visual state was then assigned according to three classes: **green** for overall scores **greater than or equal to 75**, **yellow** for scores between **50 and 75**, and **red** for scores **below 50**.

A graphic override was then applied to the Generic Model volume in the active Revit view, changing its surface colour according to the evaluated room condition. The implemented RGB values were **(0, 255, 0)** for green, **(255, 255, 0)** for yellow, and **(255, 0, 0)** for red. A surface transparency value was also applied in order to preserve the spatial legibility of the room while keeping the volumetric response visible. As a result, the BIM-side workflow was performing four operations simultaneously: retrieving the latest environmental data from the local endpoint, parsing and interpreting the incoming values, updating the sensor-family parameters numerically, and applying a room-scale visual response to the conference-room volume. The graph was run in periodic mode, so that the BIM model reacted continuously to changing input values and produced the effect of a live monitoring workflow inside Revit. This type of automated data exchange and BIM-side update is consistent with previous demonstrations of dynamic sensor-to-model linkage through Revit, Dynamo, and API-based routines (Kensek, 2014; Desogus et al., 2021).

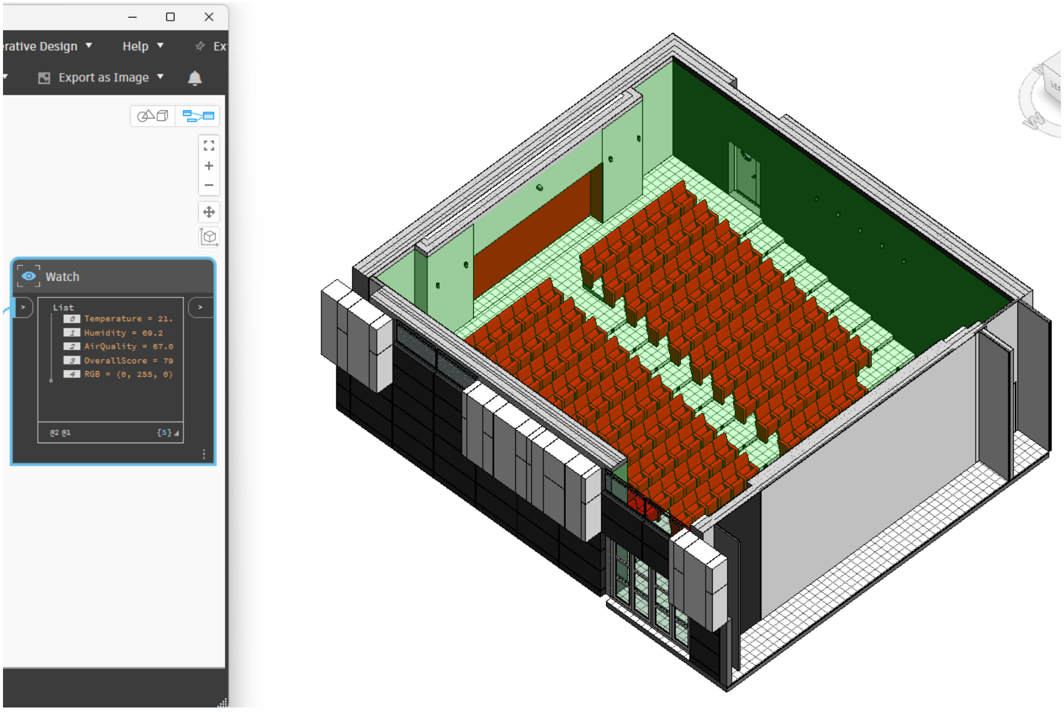

Figure 24 Room-scale colour-response states of the conference-room Generic Model during periodic BIM–IoT workflow execution in Revit, Showing Green colour with Overall Score = 79, good conditions (Temp 21°, Humidity 69.2, AirQuality 67).

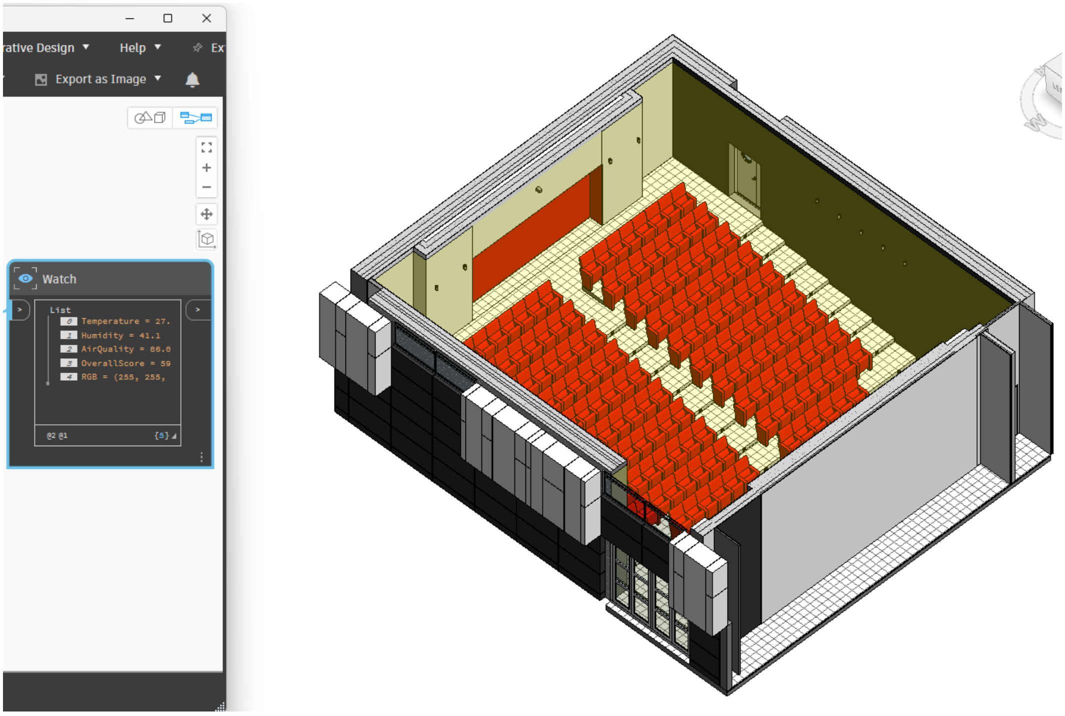

Figure 25 Room-scale colour-response states of the conference-room Generic Model during periodic BIM–IoT workflow execution in Revit, Showing Yellow colour with Overall Score = 59, moderate conditions (Temp 27°, Humidity 41.1, AirQuality 86).

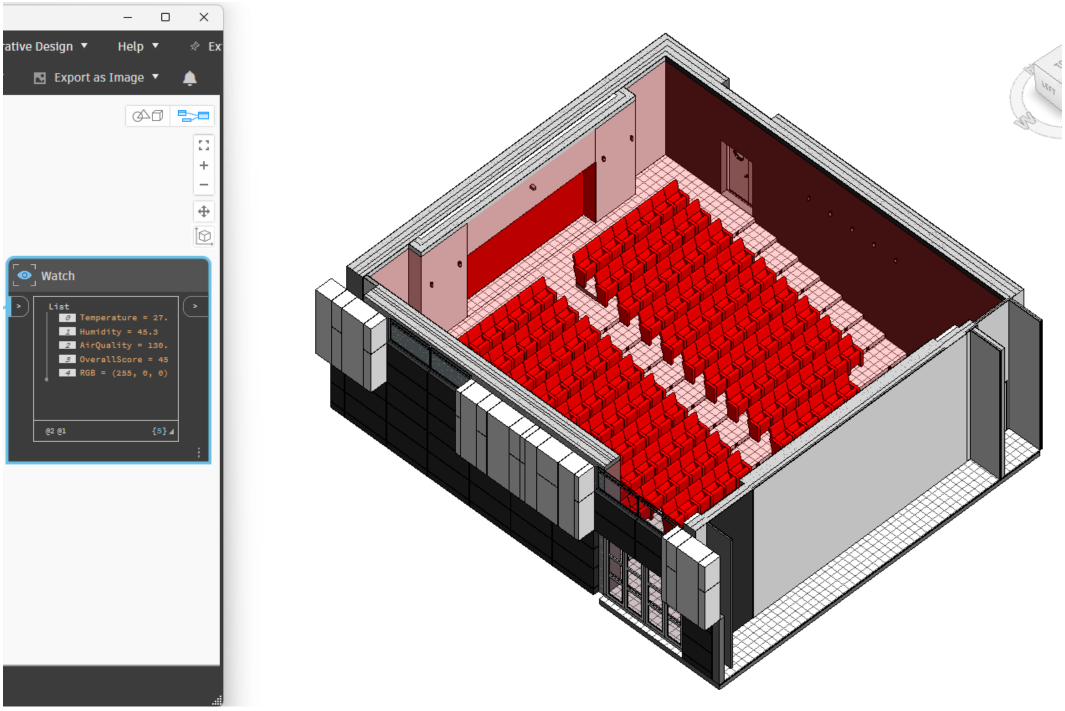

Figure 26 Room-scale colour-response states of the conference-room Generic Model during periodic BIM–IoT workflow execution in Revit, Showing Red with Overall Score = 45, poor conditions (Temp 27°, Humidity 45.3, AirQuality 130).

3.7.3 Validation of the BIM–IoT workflow and observed outcomes

After the full local setup had been completed, the BIM–IoT workflow was tested through repeated execution cycles using environmental data. The publisher script continuously transmitted changing Temperature, Humidity, and AirQuality values; the subscriber captured them and updated the local JSON endpoint; Dynamo periodically queried the endpoint; and Revit responded by updating both the sensor-family parameters and the room-scale Generic Model visualization.

The validation of the workflow was based on three observable outcomes. First, the numerical parameters of the custom sensor family were successfully updated in Revit, demonstrating that the BIM model could receive and store the incoming values directly at object level. Second, the Generic Model volume filling the conference room changed colour dynamically in response to the incoming values and the computed overall environmental score. Third, the full chain remained operational over repeated runs, confirming that the workflow was not a one-time static import but a functioning data-linkage process in which changing input values produced corresponding changes inside the BIM environment.

From a methodological point of view, this result is significant because it demonstrates that the semantically structured BIM model can function as more than a static repository of geometric and descriptive information. The implemented setup reproduces the essential logic of a Digital Shadow installation: environmental observations generated externally are transmitted through a lightweight pipeline, interpreted through a mapping routine, written into BIM attributes, and visualized directly within the BIM model without manual rewriting of values (Tang et al., 2019; Desogus et al., 2021; Quinn et al., 2020).

At the same time, the implemented workflow remains intentionally limited in scope. The colour logic is simplified and was introduced primarily to validate the integration and visualization workflow technically. Nevertheless, for the purposes of the present phase, the adopted logic was sufficient to verify that the BIM-side integration and automated update process were functioning correctly.

Another limitation is that the entire setup was implemented in a fully local environment. The MQTT broker, Python scripts, local HTTP JSON endpoint, Dynamo graph, and Revit session all operated on the same machine during testing. This choice was deliberate, because it reduced setup complexity and allowed the workflow to be validated step by step. At the same time, the modular structure of the workflow means that the same BIM-side logic can be maintained while extending the data source and the operational scale in future phases, provided that the same variable structure and naming conventions are preserved. This type of replaceable integration logic is consistent with the broader aim of creating reusable BIM–IoT workflows rather than isolated one-off connections (Tang et al., 2019).

This stage should therefore be understood as the completed implementation of the BIM–IoT visualization workflow for the conference-room case study. It demonstrates that the methodological transition proposed in this thesis, from geometric acquisition, to semantic BIM structuring, to data linkage and visualization, is technically achievable within a coherent Digital Shadow framework. It also establishes the practical basis for subsequent extensions of the workflow toward wider operational deployment. The distinction between this one-way monitoring-oriented implementation and a full two-way Digital Twin remains important and is consistent with the conceptual differentiation discussed by Sepasgozar (2021).

Chapter 4

Discussion, Conclusions, and Future Developments

4.1 Discussion of the main outcomes

This thesis developed and tested a coherent workflow for the creation of a Digital Shadow of the Politecnico di Torino Energy Center, moving from territorial framing and 3D metric survey to Scan-to-BIM modelling, geometric verification, and BIM–IoT integration. The main outcome of the work is therefore not limited to the production of a digital model of the case-study space, but lies in the definition of a connected methodological chain in which geometric acquisition, semantic structuring, and operational-data linkage were treated as interdependent phases of the same process. In this sense, the thesis demonstrates that the development of a Digital Shadow for an operational building requires not only accurate survey data, but also a structured transition from unorganized geometric evidence to a BIM environment prepared for data interpretation and monitoring.

A first important outcome concerns the survey-to-model transition. The integrated geomatic workflow, based on topographic control, TLS acquisition, complementary SLAM-based capture, registration, and point-cloud preparation, provided the geometric basis for the as-built reconstruction of the conference-room case study. Through the Scan-to-BIM phase, the surveyed space was translated into a semantically structured BIM model that could support not only geometric representation, but also the later organization of monitored information. The model-verification step against the point cloud further strengthened this result by introducing an explicit quality-control phase, clarifying the degree of correspondence between the reconstructed BIM model and the measured condition of the real space. This is significant because it means that the BIM model used in the subsequent stages was not only modelled from survey data, but also checked against them as a dependable geometric reference.

A second important outcome concerns the BIM–IoT phase. The implemented workflow demonstrated that structured environmental observations could be transferred, interpreted, written into BIM parameters, and visualized directly inside the Revit environment. This validated the technical feasibility of a one-way data-linkage workflow in which the BIM model acts not only as a static geometric container but as an environment capable of hosting and displaying changing operational information. The sensor family and the room-scale Generic Model volume together showed that the same incoming data can be represented both numerically and spatially, supporting a more meaningful interpretation of monitored room conditions.

From a broader methodological point of view, the thesis also shows that the key value of the proposed workflow lies in the explicit structuring of identifiers, naming logic, and data-exchange assumptions. The workflow did not function simply because data were generated, but because the relationship between the external payload, the BIM-side parameters, and the selected monitored entities was defined in a clear and repeatable way. This aspect is central to the overall contribution of the thesis, since it connects the literature-review findings on BIM–IoT interoperability with an applied case-study implementation. In other words, the work demonstrates that the transition from survey to monitoring is not only a technological sequence, but also an organizational problem of structuring, mapping, and maintaining semantic consistency across the workflow.

For these reasons, the final result of the thesis should be understood as the successful development of a Digital Shadow workflow rather than a full Digital Twin. The completed workflow establishes a reliable methodological basis that links 3D metric survey, as-built BIM structuring, model verification, and environmental-data visualization in a coherent framework. At the same time, the one-way nature of the implemented data flow clearly positions the achieved result within the Digital Shadow domain. This distinction is important, because it defines both the actual contribution of the present work and the starting point for its possible future extension toward broader building-scale deployment and more advanced data integration.

4.2 Answers to the research questions

Regarding RQ1, the study identified a coherent sequence of stages, information requirements, and technical deliverables necessary to establish a Digital Shadow for an operational building. These include: territorial and case-study framing; integrated 3D metric survey; topographic control and network-based registration support; point-cloud processing and segmentation; Scan-to-BIM modelling; verification of the reconstructed model against the survey data; semantic preparation of BIM entities; and the implementation of a BIM–IoT data-linkage workflow for environmental visualization. The corresponding deliverables were a registered and structured point-cloud dataset, an as-built BIM model of the conference-room case study, a verified geometric basis for later integration, and a functioning workflow capable of receiving, interpreting, and visualizing environmental observations inside the BIM environment. In this sense, the thesis answered RQ1 by demonstrating not only which stages are required, but also how these stages relate to one another within a reproducible end-to-end workflow.

Regarding **RQ2**, the thesis showed that selected BIM entities and monitoring zones can be semantically structured through a combination of object-level and space-level modelling choices. On the one hand, a dedicated sensor-family object was used to host the incoming numerical values through explicit instance parameters. On the other hand, a Generic Model volume representing the monitored air volume of the conference room was used as a room-scale visualization object. This distinction made it possible to separate the numerical storage of the monitored variables from their spatial interpretation inside the BIM model. The result is that operational observations were not treated as isolated values alone, but were linked to semantically readable BIM entities capable of supporting both direct inspection and monitoring-oriented interpretation. RQ2 is therefore answered by showing that consistent linkage depends on the semantic preparation of both measurement objects and monitored zones, rather than on parameter assignment alone.

Regarding RQ3, the thesis demonstrated that interoperable transfer of environmental observations into the BIM environment depends on a stable identifier and naming logic, together with a controlled data-exchange structure. In the implemented workflow, this requirement was addressed through a structured JSON payload, explicit variable names, a stable base identifier for the monitored room, and a direct correspondence between the names used in the external payload and the parameters searched by the BIM-side routine. The workflow also separated the data source, communication layer, local endpoint, and BIM-side processing logic into distinct but connected parts, making the overall structure modular and repeatable. For this reason, the workflow confirms that the success of BIM–IoT linkage does not depend only on communication technology, but also on the clarity of the mapping assumptions that connect external observations to BIM entities. RQ3 is therefore answered by showing that naming consistency, explicit mapping logic, and structured payload design are necessary conditions for reliable data transfer into a semantically structured BIM model.

4.3 Scope and limitations of the study

The results of this thesis should be interpreted within the scope intentionally defined for a master's-level applied research project. First, the detailed implementation of the workflow was developed on the conference-room case study within the Energy Center, rather than on the entire building at the same level of detail. This choice made it possible to maintain the work at a manageable and methodologically coherent scale, while still demonstrating the complete logic of the proposed Digital Shadow workflow on a real operational space. In this sense, the selected room should be understood as a representative demonstrator of the methodology rather than as an isolated exception. Extending the same process to additional rooms or to larger portions of the building would primarily increase the spatial scale of application and the range of possible analyses, without changing the overall methodological structure demonstrated in the thesis.

A second limitation concerns the operational environment in which the BIM–IoT workflow was implemented. The data-transfer and visualization chain was developed in a controlled local configuration, in which the communication layer, data-exposure layer, Dynamo graph, and Revit model operated within the same local environment. This choice reduced implementation complexity and made it possible to validate the data-linkage logic, parameter updating, and room-scale visualization step by step. At the same time, it means that the present work should be understood as a technically validated workflow rather than as a full building-management deployment environment.

A further limitation concerns accessibility of the final visualization environment. In its current form, the workflow is visualized directly in Revit through Dynamo-based automation and view-specific graphic overrides. Although this configuration was appropriate for developing and validating the BIM-side logic, it also means that consultation of the results still depends on access to the BIM authoring environment and on a certain level of software familiarity. For this reason, the present implementation is more suitable as a research and development workflow than as a lightweight consultation interface for broader operational users.

Finally, the scope of the thesis remains aligned with the Digital Shadow concept rather than with a full Digital Twin implementation. The workflow establishes a one-way relation from environmental observations to the BIM model, enabling structured linkage, visualization, and interpretation, but it does not include actuation, automated control, or bi-directional feedback toward the physical asset. The achieved result should therefore be interpreted as a coherent Digital Shadow workflow for monitoring-oriented applications, while more advanced Digital Twin capabilities remain outside the present scope.

4.4 Future developments

The workflow developed in this thesis opens several coherent directions for future development. A first natural extension concerns spatial scale. While the present implementation was focused on the conference-room case study, the same methodological logic could be extended to additional rooms and, progressively, to a wider building-scale configuration. This would make it possible to test the robustness of the identifier strategy, semantic structuring logic, and BIM–IoT linkage across a larger number of monitored entities and operational conditions.

A second important development concerns the data source and update regime. In future phases, the workflow could be connected to continuously updated environmental data streams in order to move from the present controlled implementation toward a more operational monitoring setup. In this context, the stability of identifiers, naming conventions, and payload structure would remain essential, since the scalability of BIM–IoT workflows depend not only on communication technologies but also on the consistency of the integration logic across software and data layers (Tang et al., 2019; Quinn et al., 2020).

A third development concerns the accessibility of the visualization environment. At present, the room-condition response is visualized directly in Revit, which is effective for BIM-side implementation but less convenient for users who do not work with BIM authoring tools. A valuable extension would therefore be the development of a lightweight viewer or web-based visualization interface capable of displaying the monitored space, the linked environmental values, and the changing room-state colours without requiring direct interaction with Revit. This would make the results more accessible to a wider range of stakeholders and would align the workflow more closely with web-based and dashboard-oriented BIM–IoT applications proposed in the literature (McGlinn et al., 2017; Desogus et al., 2021; Wang et al., 2025; Chatsuwan et al., 2025). In addition, exporting the semantically structured BIM model to external 3D platforms and game engines (e.g., Unity or Unreal Engine) represents another promising direction. This approach would allow for more interactive and accessible visualization experiences, supporting enhanced navigation, multi-user access, and the integration of real-time data layers without depending on BIM authoring software.

More advanced future work could also explore the difference between lightweight viewers and richer interactive visualization environments. A viewer is suitable when the objective is direct consultation, clarity, and ease of access, whereas a more advanced interactive platform may become relevant when the goal is to support broader navigation, richer interaction, or multi-user exploration of the monitored building environment. For the present research, however, the most meaningful next step would be to prioritize a simple and accessible visualization layer before moving toward more complex front-end environments.

In concrete terms, a natural outcome of this progression would be the publication of the semantically structured 3D BIM model as a web-based platform, allowing the geometry and its linked environmental data to be explored directly through a standard web browser, without installing BIM authoring or game-engine software. Such a browser-based solution would make the monitored building environment accessible to facility managers and other non-specialist users. More broadly, these developments would contribute to the gradual transition from a BIM-cantered research workflow toward a more operationally deployable Digital Shadow environment, while preserving the methodological basis established in this thesis.

4.5 Final conclusions

This thesis defined and demonstrated a coherent workflow for the development of a Digital Shadow for the Politecnico di Torino Energy Center, integrating territorial framing, 3D metric survey, point-cloud processing, Scan-to-BIM modelling, model verification, semantic structuring, and BIM–IoT data linkage within a single methodological chain. The contribution of the work lies not only in the production of an as-built BIM model of the conference-room case study, but more importantly in the demonstration that these different phases can be organized as an interdependent and reproducible process for a contemporary operational building context.

The thesis showed that the transition from surveyed physical reality to a semantically structured BIM environment is a necessary condition for meaningful monitoring-oriented applications. It also demonstrated that environmental observations can be linked to BIM entities through stable naming logic, structured data exchange, and explicit mapping assumptions, allowing the BIM model to function as more than a static repository of geometric information. In this way, the work confirmed the technical feasibility of a Digital Shadow workflow in which environmental data can be interpreted and visualized directly within the model through both object-level and room-scale representations.

From a broader perspective, the thesis contributes to current research by proposing a multidisciplinary and workflow-oriented approach that connects geomatics, BIM, and data integration within a real case study, rather than treating these domains as isolated technical layers. For this reason, its main value is methodological: it provides a structured basis for future extensions toward wider deployment, more accessible visualization environments, and progressively more advanced building-monitoring applications. In this sense, the work helps bridge the gap between conceptual discussions of Digital Twins and the practical implementation of operationally meaningful Digital Shadow workflows for real buildings.

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Appendix A – Full BIM–IoT Integration Table

Article/Paper Name	Authors	Purpose	Source Type	Data Types Used	Database/Format	BIM Tools	Case Study	Integration Method
A review of BIM and IoT devices integration: Present status and future trends	Shu Tang, Dennis R. Shelden, Charles M. Eastman, Pardis Pishdad-Bozorgi, Xinghua Gao	Comprehensive review of 97 papers analyzing BIM-IoT integration across construction, operations, H&S, logistics, facility management	Journal Article - Automation in Construction (2019)	Temperature, Humidity, Time-series data	Relational Database (MS Access, MySQL)	Revit, IFC, Navisworks	Multiple domains: operations, H&S, logistics, FM	Identified 5 main methods: API-based, IFC/Schema, Query Languages, Semantic Web, Hybrid
Monitoring thermal comfort in subways using building information modeling	Mohamed Marzouk, Ahmed Abdelaty	Real-time temperature and humidity monitoring in subway environments using WSN and BIM	Journal Article	Temperature, Humidity	MS Access (Relational Database)	Revit (with DB Link API)	Subway thermal comfort monitoring	WSN→MS Access DB←Revit (DB Link API) →Link Sensor ID to BIM→Real-time in Revit properties
Rapid structural condition assessment using RFID-based wireless strain sensor	Yunfeng Zhang, Linjia Bai	Structural health monitoring and assessment using RFID sensors linked to BIM	Journal Article - Automation in Construction (2015)	Strain data (micro-strain)	MySQL / MS Access	Revit	Hybrid simulation tests on truss structures	RFID sensors→DB (MySQL/Access) ←BIM export→Link via ID→Data visualization in Revit
Real-time Environmental Monitoring, Visualization and Notification for H&S Management	Muhammad Arslan, Dr. Zainab Riaz, Dr. Adnan Khalid Kiani	Real-time health & safety monitoring with live alerts and visualization	Conference Paper - ICON Feb	Temperature, Humidity, Safety alerts	SQL Server (Relational Database)	Revit (Custom GUI with C# API)	Construction site H&S monitoring	WSN→SQL Server←Revit→Custom GUI (C#)→Two-way flow→SMS notifications

Article/Paper Name	Authors	Purpose	Source Type	Data Types Used	Database/Format	BIM Tools	Case Study	Integration Method
Simplified relational database schema for BIM data (BIMRL Schema)	Wawan Solihin, Charles Eastman, Yong-Cheol Lee, Dong-Hoon Yang	Transform IFC BIM data into efficient relational database schema for powerful SQL queries	Journal Article - Automation in Construction (2017)	Building objects, geometry, properties, relationships	Oracle DB with BIMRL Schema (Star/Snowflake)	Revit, IFC (ETL with Xbim parser)	Space program compliance, spatial analysis	IFC export→ETL→BIMRL schema (fact/dimension tables) →SQL spatial/property queries
Knowledge-assisted BIM-based visual analytics for failure root cause detection	Ali Motamedi, Amin Hammad, Yoosef Asen	Integrated FM data and BIM for root cause analysis using fault trees and analytics	Journal Article (2014)	Asset info, FM data, maintenance records, fault trees, sensor data	Custom Relational Database	Revit, IFC formats	Concordia Genomics RC - temperature diagnosis	BIM+FM data→Unified DB→Fault trees linked to assets→Query+color-coded visualization
BIM perspective definition metadata for FM data (BPD Metadata)	Tae-Wook Kang, Hyun-Sang Choi	Metadata-driven BIM-FM data integration with role-based views for different users	Journal Article (2015)	Facility data, spatial info, user-specific FM data	Centralized Relational DB with BPD XML	Revit, IFC	Facility management with multi-user roles	ETL with BPD metadata→Custom DB→BPD engine creates role-based views→Tailored extraction
BIMQL - An open query language for building information models	Wiet Mazairac, Jakob Beetz	Domain-specific query language for selecting and updating BIM data without deep programming	Research Paper	BIM objects, geometry, properties	IFC-based BIM models in BIMserver	Open BIMserver, IFC format	Platform-independent BIM querying	BIMQL queries (SELECT/WHERE/SET) →Simplified syntax→Platform-independent on IFC models
BIMSL: Generic approach to integration of BIM with real-time sensor data	Miguel Alves, Paulo Carreira, António Aguiar Costa	Domain-specific language for querying both static BIM data and real-time IoT sensor data	Research Paper	BIM model data, real-time sensor data (temp, energy)	IFC, sensor data streams with stream processing	BIMserver, sensor platforms	Building energy and environmental monitoring	BIMSL queries→Esper Engine (continuous data) →Combined BIM+sensor results

Article/Paper Name	Authors	Purpose	Source Type	Data Types Used	Database/Format	BIM Tools	Case Study	Integration Method
Ontology framework for intelligent sensor-based building monitoring (OntoFM)	Michael Dibley, Haijiang Li, Yacine Rezgui, John Miles	Semantic web approach using ontologies to link sensor data with building information	Journal Article - Automation in Construction (2012)	Building structure, sensor readings (temp, motion)	OWL ontologies, RDF representation	IFC, OWL, Semantic Web technologies	Intelligent sensor-based facility monitoring	BIM/IFC+Sensors→OWL ontologies→RDF representation→Agent framework for queries
Linking building data in the cloud using linked data	Edward Curry, James O'Donnell, Edward Corry, Souleiman Hasan, Marcus Keane, Seán O'Riain	Integrate cross-domain building data (BIM, energy, assets, occupancy, weather) using linked data	Journal Article - Advanced Engineering Informatics (2013)	Building info, sensor data, assets, occupancy, weather, business data	RDF (Linked Data cloud)	IFC, Semantic Web standards	Office building energy management across domains	Multi-source data→Convert to RDF via wrappers→Query via SPARQL→Cross-domain insights
Building performance optimization: Hybrid architecture for contextual and time-series data	Shushan Hu, Edward Corry, Edward Curry, William J.N. Turner, James O'Donnell	Hybrid combining relational DB (time-series) with semantic web (contextual) for performance assessment	Journal Article - Automation in Construction (2016)	Building context (geometry, HVAC, sensors), time-series data	Hybrid: RDF (context) + Relational DB (time-series) with DB-RDF	IFC, RDF semantic web, Relational DB	Building performance monitoring and assessment	BIM in RDF+Sensor in DB→DB-RDF schema→SPARQL→SQL→Combined analysis
Usability evaluation of web-based energy management tool (BuildVis)	Kris McGlinn, Baris Yuce, Hendro Wicaksono, Shaun Howell, Yacine Rezgui	Web-based BEMS tool for intelligent FM energy saving suggestions using hybrid KB system	Journal Article - Automation in Construction (2017)	Building context, real-time sensor/setpoint data, simulation	Hybrid: RDF (Fuseki) + SQL (high-speed time-series)	IFC, OWL, RDF, web interface	Facility energy management with AI-driven suggestions	BIM/IFC (RDF)+Real-time sensors (SQL)→Data Mining+Simulation rules→Fuzzy Reasoner→BuildVis

Article/Paper Name	Authors	Purpose	Source Type	Data Types Used	Database/Format	BIM Tools	Case Study	Integration Method
BIM and IoT Sensors Integration Framework for Consumption and Conditions Monitoring	Giuseppe Desogus, Emanuela Quaquero, Giulia Rubiu, Gianluca Gatto, Cristian Perra	Framework integrating real-time sensor data (IoT) with BIM for energy and indoor conditions	Journal/Conference Paper	Temperature, Humidity, Luminance, Noise, Electricity consumption	IoT platform (WiDom cloud), Revit shared parameters	Revit, Dynamo scripts	Existing building monitoring with multiple sensors	Sensors→IoT platform→Dynamo scripts (API)→Map to Revit shared parameters→Real-time BIM viz
BIM integrated smart monitoring for building fire prevention and disaster relief	Min-Yuan Cheng, Kuan-Chang Chiu, Yo-Ming Hsieh, I-Tung Yang, Jui-Sheng Chou, Yu-Wei Wu	Real-time fire detection and emergency evacuation guidance using BIM-IoT with dynamic routing	Journal Article - Automation in Construction (2017)	Smoke, Temperature, Battery status, Location (BLE)	MySQL Database	Revit 2015 (Custom C# modules via API)	Emergency evacuation guidance with real-time fire spread	FireSense sensors (BLE)→MySQL←Revit API (C#)→Dijkstra routing→Mobile app+3D BIM viz
Building automation system - BIM integration using linked data structure	Caroline Quinn, Ali Zargar Shabestani, Tony Misic, Sara Gilani, Marin Litoiuc, J.J. McArthur	Link building automation system data to FM-BIM model for facility operations visualization	Journal/Conference Paper	HVAC, automation system readings, facility performance data	Cassandra Database (time-series), CSV export	Revit 2019, Dynamo (Visual Programming Language)	Building operations data visualization in BIM	BAS data→Cassandra→CSV→Dynamo import→Python filter→Map to Revit FM-BIM via Element.SetParameterByName
Development of IoT and BIM-based automated alert system for thermal comfort	Mojtaba Valinejadshoubi, Osama Moselhi, Ashutosh Bagchi, Ashraf Salem	Automated thermal comfort monitoring with alerts using IoT sensors and BIM visualization	Journal Article - Sustainable Cities and Society (2021)	Temperature, Humidity (5-minute intervals)	MySQL Relational Database	Revit Architecture 2018, Dynamo	Office thermal comfort monitoring with comfort indexing	Waspmote sensors (ZigBee)→MySQL (6 tables) ←Revit with virtual sensors→Dynamo (9 modules) →Color-coded viz
Enhancing Facility Management with BIM and IoT Integration in Open Standard Environment	Mayurachat Chatsuwan, Masayuki Ichinose, Haitham Alkhalaf	Framework for BIM-IoT integration using open standards (IFC) with flexible sensor mapping	Journal/Conference Paper	Environmental sensors, HVAC, building systems	Time-series database, middleware server (HTTP/MQTT)	Revit, Archicad, IFC export	Generic facility management with open standards	BIM→IFC export→Collect IoT data→Custom mapping (Sensor ID→BIM Space ID) →Integration framework→Unified viz

Article/Paper Name	Authors	Purpose	Source Type	Data Types Used	Database/Format	BIM Tools	Case Study	Integration Method
FROM BIM TO DIGITAL TWIN - IoT Integration Case Study 1 (Snap4City)	Carlo Biagini, Andrea Bongini, Luca Marzi	Integration of IoT sensors with BIM in Snap4City platform for real-time asset monitoring	Conference/Journal Paper	Temperature, Humidity, Environmental data	Snap4City IoT platform with RDF, Elastic Search	IFC (BIM Surfer viewer)	Department of Statistics - Real-time sensor dashboard with IFC	Raspberry Pi (Edge)→Node-Red→Snap4City IoT Device→Broker→Node-Red processing→BIM Surfer+live data
FROM BIM TO DIGITAL TWIN - IoT Integration Case Study 2 (LoRaWAN)	Carlo Biagini, Andrea Bongini, Luca Marzi	LoRaWAN sensor network integrated with Niagara framework for building automation	Conference/Journal Paper	Environmental data (Temp, Humidity, etc.)	Niagara framework with BACnet, MongoDB NoSQL	IFC models	Department of Mathematics 'Ulisse Dini' - LoRaWAN network	LoRaWAN sensors→Gateway (BACnet)→Niagara (normalize/aggregate) →Haystack tags→CSV→MongoDB
Integration of Environmental Sensors with BIM - Method 1: Dynamo (Visual Scripting)	K. M. Kensek	Arduino sensor integration with BIM using Dynamo visual programming	Research Paper/Case Study	Light levels (photoresistor)	Text file (.txt) intermediary, direct memory	Revit, Dynamo (visual programming)	Façade dynamic parameter control via light sensors	Arduino→Dynamo nodes→Update Revit family parameters (window shade, louvers, overhang)
Integration of Environmental Sensors with BIM - Method 2: Direct Revit API	K. M. Kensek	Arduino sensor integration with BIM using direct C# API with bidirectional control	Research Paper/Case Study	Light levels, servo control	Text file (.txt) intermediary	Revit, Custom C# DLL (Revit API), Processing	Façade component geometry updates and servo feedback	Arduino→Processing (serial)→.txt file←.dll (Revit API) →Update Revit parameters↔Arduino servo (bidirectional)
Building Model Management System Integrating MQTT Sensing	Ziang Wang, HanXiao, Changsheng Guan, Liming Zhou, Daiguang Fu	Building management system with real-time MQTT sensor integration and bidirectional control	Research Paper	Temperature, Humidity, Illumination (STM32 sensors)	MQTT (EMQX/NanoMQ broker) with WebSocket, Spring Boot	Revit, SketchUp, Three.js web viewer	Building management with real-time IoT controls	STM32→LoRaWAN/Zigbee →Edge MQTT Gateway→MQTT Broker→Spring Boot→WebSocket frontend (Three.js) →3D BIM

Article/Paper Name	Authors	Purpose	Source Type	Data Types Used	Database/Format	BIM Tools	Case Study	Integration Method
Structure Monitoring with BIM and IoT - Bridge Beam Case Study	Andrea Scianna, Giuseppe Fulvio Gaglio, Marcello La Guardia	Structural health monitoring of bridge beams using IoT sensors and BIM visualization	Case Study Paper	Distance measurements, Applied force (HC-SR04 ultrasonic)	MySQL Database	Revit (API programming)	Bridge beam structural monitoring and deflection tracking	Arduino+ESP8266 (WiFi)→MySQL (PHP)←Revit API (auto-collect) →Load into beam parameters→Visual deflection
Virtual Campus Model and Energy Benchmarking	Woo et al.	Energy monitoring and benchmarking of university campus using wireless sensors and game engine	Case Study Paper	Energy consumption data	Excel (temporary) →MS Access (relational), MySQL	Revit, Unity Game Engine	University campus energy performance analysis	Wireless sensors→Excel→MS Access←Revit (DB Link) →MySQL→Unity→Interactive real-time energy dashboard

Appendix B – Survey Campaign Fieldbook (TS control network, target log, photo documentation)

This appendix reports the full fieldbook produced during the survey campaign described in Section 3.5.1. It includes, in sequence: the control-point monographs and coordinate log for the topographic network (Points 100–181), and the photographic documentation of targets and instrument setup used to support registration. Representative excerpts of this material are also presented in Figure 11, within the main text.

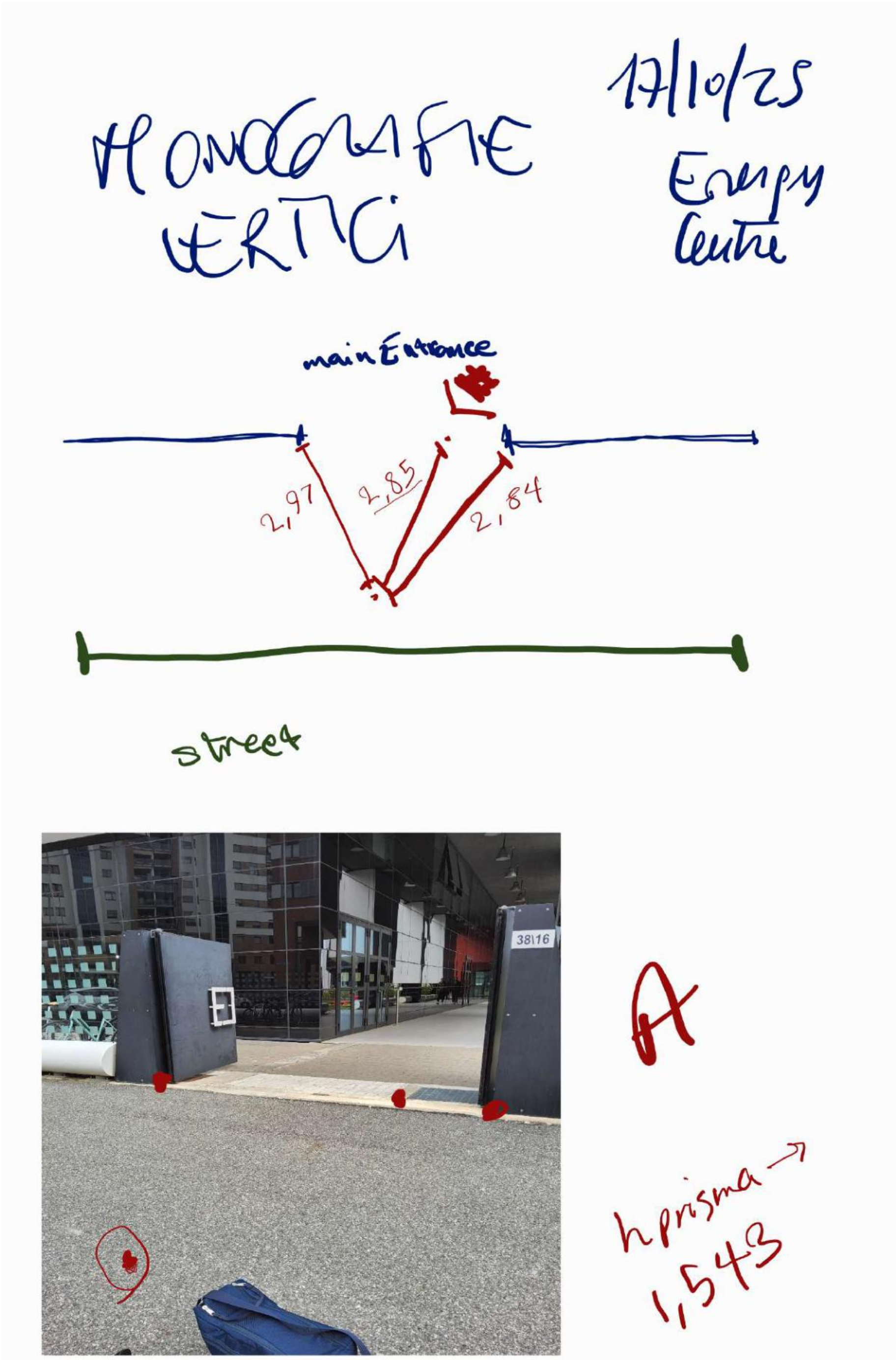

Figure B.1 Monograph of control point A (main entrance), with offset measurements to the entrance corners and the corresponding site photograph.

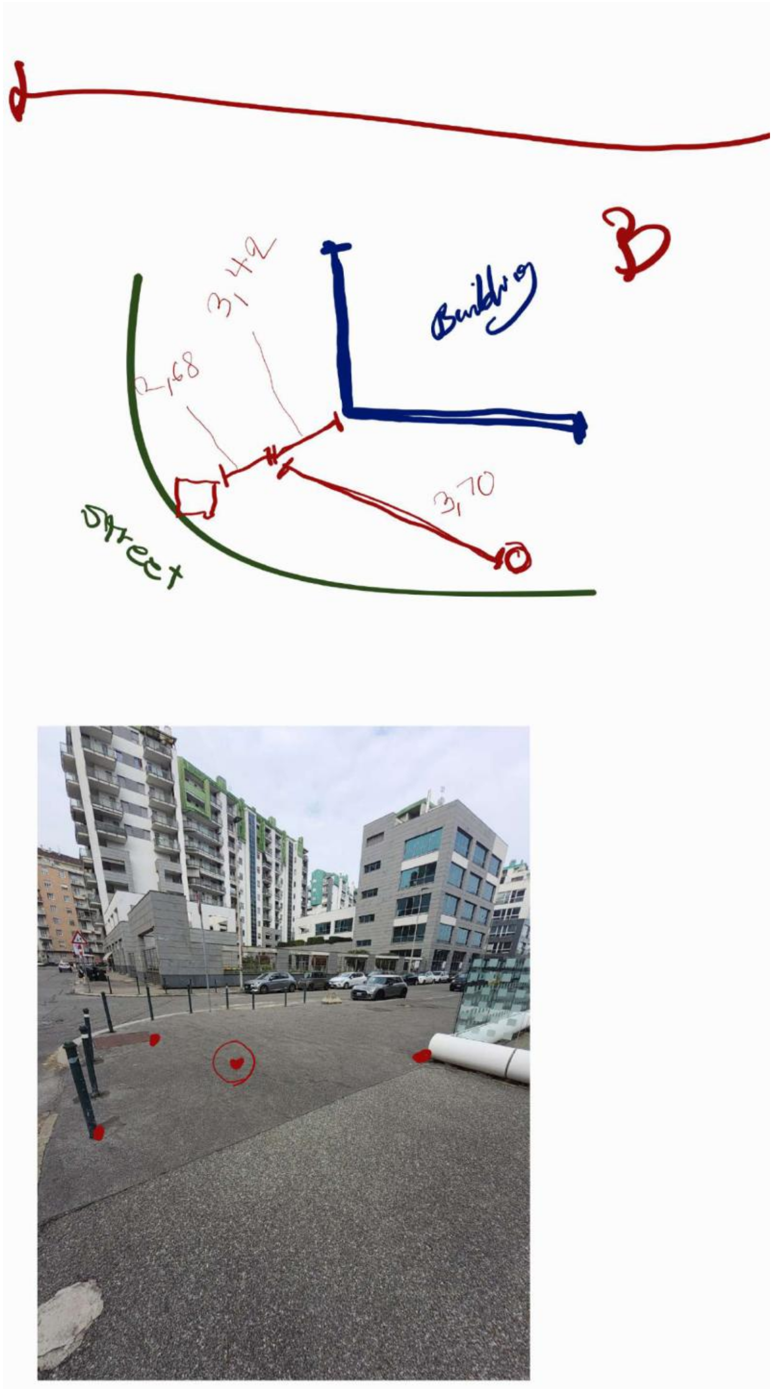

Figure B.2 Monograph of control point B, with offset measurements to the building corner and an adjacent reference feature, and the corresponding site photograph.

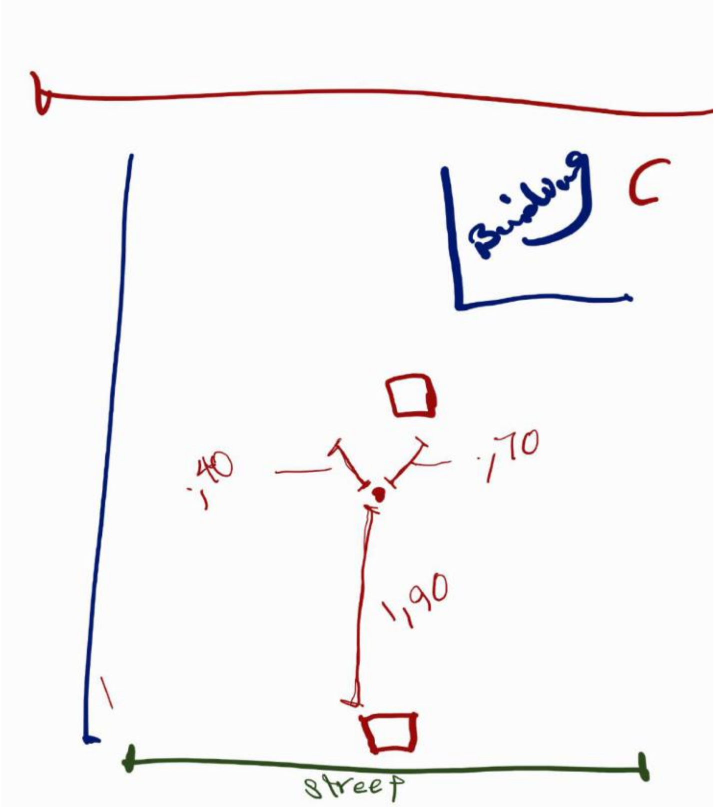

Figure B.3 Monograph of control point C, with offset measurements to nearby reference features and the corresponding site photograph.

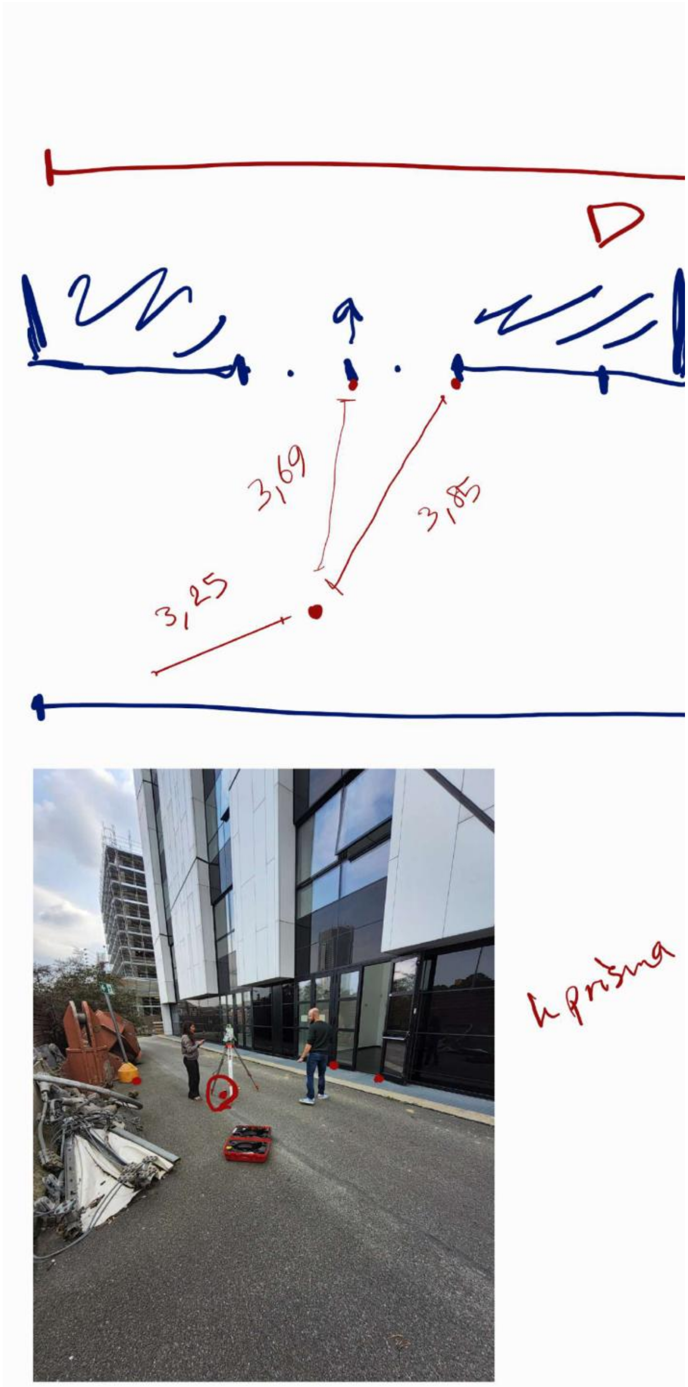

Figure B.4 Monograph of control point D, with offset measurements to nearby reference features and a photograph of the Total Station setup.

Figure B.5 Total Station setup at point D, with instrument height and circle readings, and a photograph of the interior entrance control points.

Figure B.6 Interior control points at the entrance hallway (top) and exterior control points along the building's angled curtain wall (bottom).

Figure B.7 Exterior control points along the glazed base, with the Total Station in the foreground (top), and further control points along the adjacent street elevation (bottom).

Figure B.8 Instrument orientation notes and exterior control points along the building's angled facade.

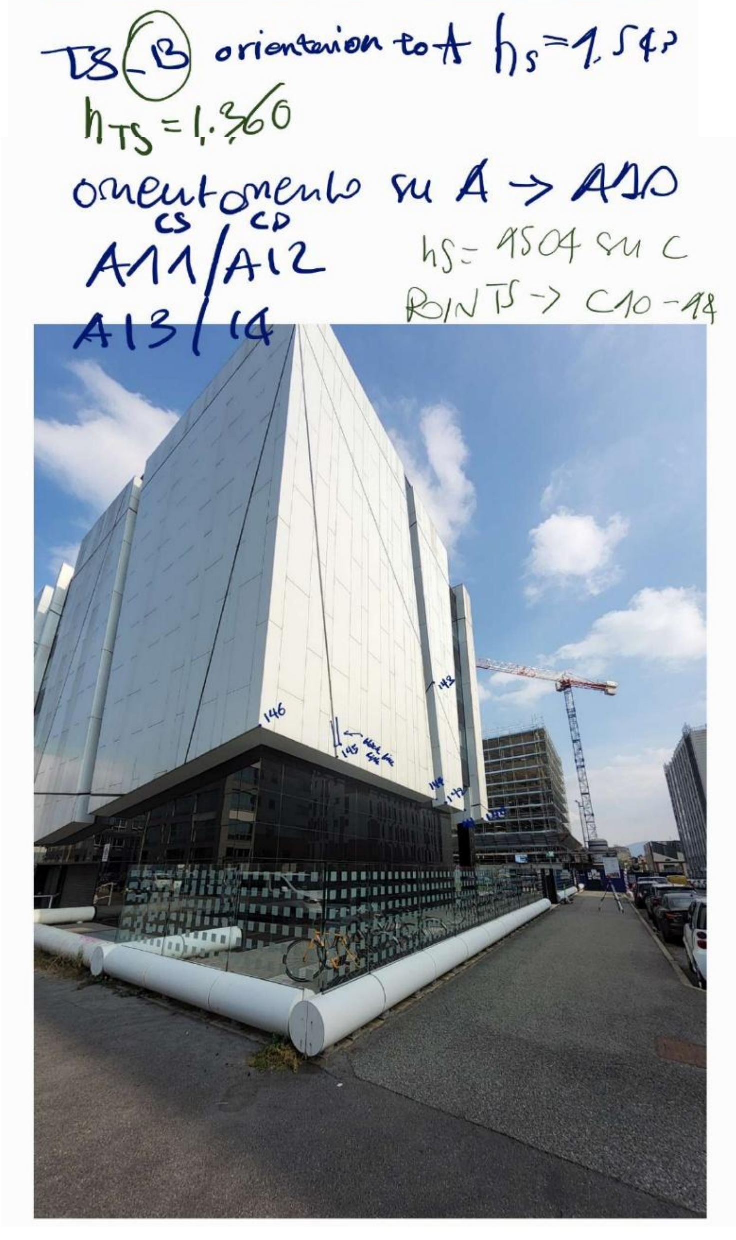

Figure B.9 Total Station setup at point B, oriented to point A, with control points marked along the building's colonnade.