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Building Information Modeling and Building Performance Simulation-Based Decision Support Systems for Improved Built Heritage Operation

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Abstract: Adapting outdated building stocks' operations to meet current environmental and economic demands poses significant challenges that, to be faced, require a shift toward digitalization in the architecture, engineering, construction, and operation sectors. Digital tools capable of acquiring, structuring, sharing, processing, and visualizing built assets' data in the form of knowledge need to be conceptualized and developed to inform asset managers in decision-making and strategic planning. This paper explores how building information modeling and building performance simulation technologies can be integrated into digital decision support systems (DSS) to make building data accessible and usable by non-digital expert operators through user-friendly services. The method followed to develop the digital DSS is illustrated and then demonstrated with a simulation-based application conducted on the heritage case study of the Faculty of Engineering in Bologna, Italy. The analysis allows insights into the building's energy performance at the space and hour scale and explores its relationship with the planned occupancy through a data visualization approach. In addition, the conceptualization of the DSS within a digital twin vision lays the foundations for future extensions to other technologies and data, including, for example, live sensor measurements, occupant feedback, and forecasting algorithms.

Keywords: built heritage; performance-based management; building information modeling; building performance simulation; digital twins

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1. Introduction

The architecture, engineering, construction, and operation (AECO) sector accounts for a large amount of global energy use and environmental impact [1–3]. Buildings are responsible for approximately 75% of primary energy consumption in cities [4] and contribute to 40% of annual environmental impact in terms of greenhouse gas emissions [5]. The World Green Building Council has set an ambitious goal for global buildings and infrastructure to reduce carbon emissions by 40% before 2030 and to achieve complete carbon neutrality in buildings by 2050 [6].

The built environment sits, therefore, at the crossroads of many policies and international initiatives like the European Green Deal [7], sustaining the ambitious objectives of the Renovation Wave [8] and aligning with the bold aims of the New European Bauhaus [9]. Within this context, the Built4People Agenda 2021–2027 identified the main challenges as the absence of comprehensive innovation that adopts a systemic approach and that considers the entire lifecycle of buildings, the need to minimize the significant carbon and environmental impact of the construction and built environment, and the limited adoption of innovative solutions with limited potential for long-term transformative change [10].

Moving towards a sustainable and energy-sensible built environment involves two key aspects. Firstly, it requires the development of long-term strategic plans to renovate existing building stocks. Secondly, it necessitates optimizing building operations in the short term, focusing on reducing energy consumption, minimizing environmental impacts, and lowering operational costs, all while ensuring comfortable conditions for occupants. Addressing the latter aspect is crucial, as energy consumption and costs during the operational phase can account for up to 75% of those incurred during the construction phase [11].

The challenges related to the built environment are particularly pronounced when considering the built cultural heritage (BCH) [12], which includes buildings with an important historical, artistic, cultural, and aesthetic significance, usually listed by local regulations, to allow their protection and sustainable conservation. In the case of BCH, traditional energy renovation and upgrade approaches often prove incompatible with heritage buildings' characteristics. These constructions were originally designed to accommodate past lifestyles and uses, and preserving their adaptability to the current needs is vital for their resilience. Since the conservation regulations in place to safeguard BCH restrict extensive and intrusive interventions, finding reversible and minimally disruptive solutions becomes essential for successfully adapting them, while also considering the associated costs of such measures.

The ongoing digitalization of the AECO sector demonstrates innovative strategies for the improvement of monitoring, management, and operation of BCH, linking energy savings with lower maintenance costs and better preservation [13]. Advanced digital methods and tools, capable of generating valuable knowledge in the form of information, are emerging for providing decision support to building administrators [14]. However, synthesizing existing buildings' knowledge seems very challenging today due to the articulation of the exposed demanding framework. Among the various topics, the knowledge issue is critically important concerning energy management [15,16]. A better understanding of the energy behavior of heritage buildings is typically necessary in comparison with non-listed ones since typical energy retrofit interventions, such as wall insulation, are often limited for them [17].

The complexity of such a framework demands a holistic approach to integrate both economic–financial asset management and technical–functional management within the context of performance-based strategies, aiming to achieve two key goals. First, improving the buildings and their physical performance characteristics; second, optimizing the balance between functional requirements and energy demands and environmental impacts. It means that, on the one hand, built heritage needs to be maintained and improved in terms of performance to ensure its effective use [18,19]. On the other hand, administrations must meet additional functional needs for optimizing logistics and planning occupancy and maintenance while minimizing operational costs and considering the relationship with the urban context and its services. According to this key, a paradigmatic divergence emerges between the increasingly complex instances of dynamism that characterize the current demanding framework and the static nature of the physical apparatus where it is hosted. In order to grasp such complexity and readily adapt outdated building stocks to the mutability of the current demanding framework, it is necessary to combine the "static knowledge" of the containers—the buildings—with the "dynamic knowledge" of the contents—users, and activities inside them.

Nevertheless, various gaps hinder building management practices from fully grasping such knowledge, often resulting in inefficient construction use and waste of technical and financial resources [20]. These gaps are usually related to scarce building managers' expertise in the information science field (knowledge gap) [21], poor coordination of the multiple players traditionally involved in building management (coordination gap) [22], serious financial limitations (finance gap) [23], information unavailability or untraceability (information gap) [24,25], and insufficient data visualization tools (visualization gap) [26].

In order to address such challenges, the digital twin (DT) paradigm is emerging to enable new ways of sharing existing buildings' knowledge towards cost–benefit optimization during their use [27–30]. Based both on real-time measurement and building performance simulations (BPS), DTs can improve the understating of building performance by evaluating important key performance indicators (KPIs) regarding day-to-day use (space management and facilities), consumption (energy and resources), and impact (cost, environment, and users' well-being), which support asset managers in their decision-making and strategic planning.

Paper Scope and Structure

This paper presents and demonstrates the method followed for delivering a BPS-based decision support system (DSS) designed to provide the asset managers of a significant educational heritage building at the Faculty of Engineering of Bologna [31,32] with valuable information about its energy performance.

The primary application of the digital decision support system focuses on energy-aware occupancy scheduling for buildings that exhibit intermittent space usage, such as university buildings, schools, recreational spaces, co-working areas, museums, as well as large office environments that have recently undergone the working-from-home implementation wave [33,34].

The DSS services provided can be utilized even by non-digital experts through user-friendly dashboards, allowing administrations to capture the benefits of digitization in the short term without disrupting the organizational structure of their technical offices. Geometrical, construction, functional, and operational information regarding the building is collected, processed, and encapsulated in the services to facilitate the consultation of digital models and, thus, improve data understanding. More specifically, in the presented experimentation, information related to the planned occupancy of the building (number of occupants, functions, and space use) provided by the asset management system (AMS) is combined with data about the building performance (heating energy and electricity need), calculated by an energy simulation performed through the Energy Plus calculation engine [35].

Using the developed tools, a study is conducted to analyze the energy consumption of significant rooms operating under different occupancy conditions in a case study building and compare their behavior during a significant winter operational day. This application identifies energy, environmental, and cost KPIs, creating an information system supporting energy-oriented occupancy-planning processes.

The paper is organized as follows: Section 2 provides a background on the research. Section 3 presents the materials and methods used to implement the DSS conceptually and practically. Section 4 showcases the results of applying the DSS to the selected case study building, as mentioned earlier. Section 5 expands on the results within the broader context of building performance-based management and demand-driven controls. Lastly, Section 6 concludes the paper by highlighting its limitations and suggesting areas for future research and development.

2. Background

2.1. Large Public Building Stock Management

Over the past century, a vast building stock was built in Europe to respond to the dramatic urban population increase resulting from internal migratory movements toward industrialized cities. Today, this heritage could appear unsuitable and, in some ways excessive, compared to the contemporary needs, in terms of quantity, quality, and location. The major problem of controlling the quantity of the national building stock while increasing its quality now emerges. While it is possible to think of replacement actions in cases where a noticeable physical and functional deterioration of buildings is so strong as to affect urban settlement quality, most of the built heritage needs to be preserved and upgraded: indeed, almost 75% of the building stock is inefficient according to the current regulatory framework, and about 85–95% of today's existing buildings will still be standing in 2050 [36]. In these cases, it is necessary, in fact, to recover or improve the quality gradually lost over time to respond also to contemporary needs, whose complexity is progressively increasing.

For instance, this issue represents one of the main critical issues that public administrations record when managing large assets since they are responsible for managing significant portions of the national building stock. In Italy, local governments own approximately 80% of the 1 million public real estate cadastral units, of which 60% were built before 1980 (Figure 1), covering an area of 325 million square meters—about 10% of the entire Italian building stock [37].

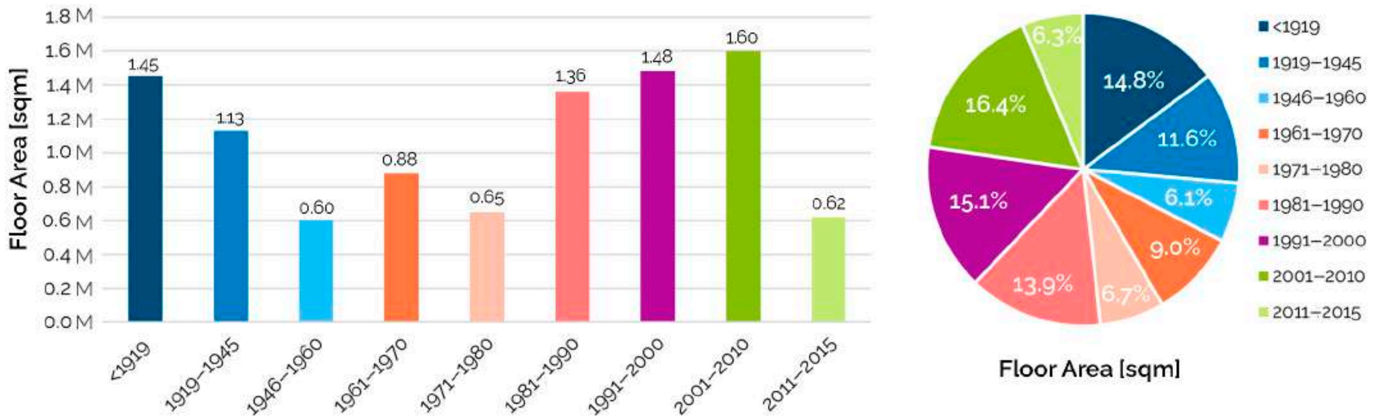


Figure 1. Public building stock managed by Italian local public authorities according to a report provided by the Ministero dell'Economia e delle Finanze in 2016. Authors' graphical elaboration [37].

The amount of money spent annually to manage these buildings is very large due to their obsolescence, functional complexity, and dimensions, and can reach up to 75% of the overall lifecycle cost [11]. These buildings face daily performance requirements and regulatory upgrades concerning safety, operation, and maintenance [38]. Furthermore, conservation and renovation are even more challenging for listed buildings due to their subjection to the protection constraints dictated by the Cultural Heritage and Landscape Code [39]. The extraordinary cost and the time necessary to reach a whole deep renovation of this building stock requires strategies and tools capable of correctly planning the allocation of public administration's technical and economic resources to reduce operation and maintenance (O&M) costs [38]. This goal can be achieved if an adequate understanding of the heritage performance is reached beforehand.

For administrations, a twofold issue arises. On the one hand, it is necessary to conserve and improve the containers, i.e., the buildings, their physical characteristics, and their state of conservation. On the other hand, they need to ensure functional, environmental, and economic compatibility of their contents, respecting the current requirement framework in terms of logistics and technological modernization.

2.2. Gaps and Challenges in Building Management

Current building management practices demonstrate several areas for improvement that hinder the goal of sustainable building operation. According to a recent literature review by Abuimara et al. [20], building management gaps can be grouped into knowledge, coordination, finance, information, and visualization issues.

Concerning the knowledge gap, building management professionals often need more information science expertise. Without comprehensively understanding these issues, technical difficulties emerge in predicting the economic, environmental, and financial impacts of management actions. Among the various causes, the lack of standardized training bodies and educational programs has a principal role [21].

Second, many coordination problems exist in current management practices. Building management teams are often temporary and outsourced, needing more spatial and temporal connectivity. Shared information language is rare among actors, limiting trust and causing misunderstandings [22,40]. Conflicting relationships and biases among actors can arise, resulting in delays, inefficiency, and economic waste, making it difficult to predict the immediate benefits of digitization for public building owners [23].

Regarding finance, public building managers often have limited budgets and decision-making power in strategic investment planning, and opportunities for savings need to be systematically framed within strategic visions or highlighted by sufficient tools.

From the information point of view, low traceability and inadequate sensing infrastructure are frequent in outdated buildings. When collected, data are fragmented into different data silos belonging to various actors and not cross-integrated [41]. In addition, although occupancy data critically influence a building's operation, it is often disregarded due to the technical difficulties in modeling it, as well as privacy issues [25]. The BCH field presents additional problems, as it can be difficult to find and share information about unique historical architectures, which is usually fragmented across numerous paper archives [42].

Finally, there are several challenges in visualizing information related to large asset management, including the need for more user-friendly, scalable, and customizable tools to visualize data in the context of the entire portfolio or city [26,43].

All these challenges can limit the ability to effectively understand and improve management activities, making it difficult for stakeholders with low technical digital skills to use human-building interfaces.

2.3. Digital Transition for the Built Environment

The digital transition allows various sectors, including construction and building management, to move towards sustainable development.

Despite the several barriers that exist to digitizing the AECO industry, the international scientific and professional community has introduced new digital paradigms in the construction industry in recent decades, such as BIM [44], heritage BIM (HBIM) [45], smart and cognitive buildings [46,47], DTs [48], Internet of Things (IoT) [49], and artificial intelligence (AI) [50]. In response to the frenetic pace imposed by digitization, various national and international institutions have proposed standards, protocols, specifications, and regulations. In Italy, the modification of the procurement code d.lg. 50/2016, UNI 11337-4: 2017 [51], and UNI EN ISO 19650: 2019 [52] were released. In addition, the software industry has also contributed to the development of new digital practices. BIM authoring tools have been introduced and updated, and their interoperability with BPS software has been implemented to develop advanced shared digital environments [53]. The idea of open tools, data, and models is now widely accepted [54,55]. In addition, smart contracts and blockchains are being introduced to make all information exchanges between the parties involved transparent and reliable [56].

Nevertheless, all these advances are likely to produce "bewilderment" among actors within the dense forest of the digital transition. As a result, the goals, outcomes, and benefits of adopting new processes could become unclear. For instance, DTs' potential benefits are clear for building operators; nevertheless, there is still a lack of clarity surrounding their definition and uses [28]. The literature underlines that developing higher-level conceptual constructs is necessary to promote the sector's digital innovation. This means that two different knowledge levels must be investigated. The former must define new ontological models to enable the organic development of new digital practices, activate standardized and shared information protocols, and encourage the involvement of all operators in the computerized technical management of built assets [57]. The latter must provide valuable tools and methods for enhancing existing buildings' use by demonstrating practical application within significant case studies [58,59].

2.4. Energy-Related Operational Issues in University Campuses

In this broad context, the research focuses on energy-related issues that emerge in higher education buildings during their operation. The topic is becoming relevant since, over the past few years, higher education institutions globally have set target goals for energy savings and emission reductions, leading to the implementation of numerous measures to reduce energy usage [60–62]. These measures include adopting advanced techniques such as renewable energy sources, renovating older buildings, and promoting awareness of energy conservation practices.

In these buildings, energy needs are strictly related to occupancy conditions [33]. The energy usage and intensity of buildings on a higher education campus are influenced by several factors, including the climate, building systems, construction type, and occupancy conditions [63]. Occupancy variables, such as the presence of students and staff members and their activities, can play a significant role in determining energy consumption levels, although their consideration is often overlooked [34]. In this context, adopting a DT environment could enable an understanding of complex relationships between the asset and its contents, from the scale of individual buildings to the urban scale of the portfolio [64].

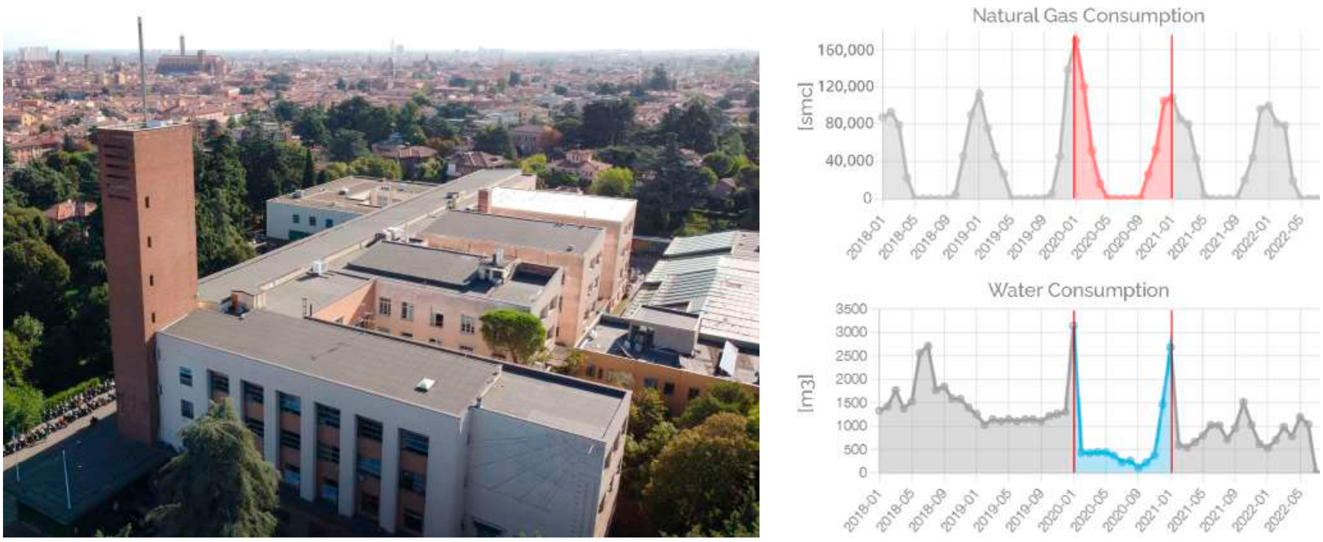
3. Materials and Methods

This section presents the methodology used for the development of the DSS. It begins by providing an overview of the selected case study. Then, the conceptualization of the DT system is reported, followed by a detailed explanation of its methodological implementation. In the next section, instead, the results of a study that utilized the developed tools in the case study building are presented.

3.1. Case Study

The university campus owned by the University of Bologna is taken as a test bed. It holds around one million square meters of public real estate assets in the Emilia–Romagna region, with a population of approximately 70,000 people and various functions.

In particular, an emblematic case study is identified in the building of the Faculty of Engineering at the University of Bologna (Figure 2a). Built between 1932 and 1935, it is one of the first 20th-century buildings to be listed in the city and is considered a local rationalist heritage gem due to its use of industrial systems and materials, innovative finishes, and lack of decorations [31,32]. With its 19,200 sqm of net floor area and four levels, its maximum capacity amount to 5000 users (including researchers, employees, and students), with approximately 2500 students using the building during academic timetable hours 5 days a week, 11 months a year.



(**a**) (**b**)

Figure 2. The Faculty of Engineering of Bologna: (**a**) aerial photography (2022); (**b**) natural gas and domestic hot water consumption for the operation of the building from 2018 to 2022.

Like many modern buildings constructed between the 1920s and 1960s, this building is affected by inherent characteristics that limit its potential for improvement. Specifically, due to its old HVAC systems and construction type, it lacks energy flexibility, as demonstrated by higher-than-normal heating consumption during the COVID-19 pandemic, despite the building being unoccupied for several months. During that period, a noticeable decrease in building occupancy was observed, resulting in many spaces remaining unoccupied for several months, as demonstrated by the evident reduction of domestic hot water consumption in Figure 2b. However, there was no corresponding decrease in natural gas consumption for heating, which remained similar to pre-COVID years, indicating a critical mismatch between energy demand and usage.

3.2. Decision Support System Conceptualization

3.2.1. Digital Twin Model

According to the literature, a DT can be defined as an information environment capable of abstracting, structuring, processing, and visualizing relevant information about an object, process, environment, or system that exists in the real physical world [65].

In the AECO sector, building DTs hold great potential to describe, inspect, monitor, maintain, and manage built assets throughout their lifecycle [48]. In the future, building DTs are expected to reason, learn, optimize, predict, make decisions, and, eventually, autonomously transform their real twins by employing data and intelligent computational models.

The developed DSS adopted refers to the DT model conceptualization proposed by Tao et al. [66], who define a five-dimensional and service-oriented DT model (Figure 3). This model, developed in the Smart Manufacturing (SM) domain [67], expands on the three-entity model proposed by Grieves [68]. The five DT entities are:

1. Physical asset, the asset entity in the physical space;
2. Virtual asset, the asset entity in the virtual space;
3. Connections, the data and information connections (or flows) that bind the physical and virtual entities;
4. DT data, which consists of the fusion and integration of all data related to the physical and virtual entities and their elaboration into more accurate and complete information;
5. Services, facilitate the visualization and use of the information collected or processed by the DT, which is standardized and "encapsulated" according to the needs of different actors and functions [69].

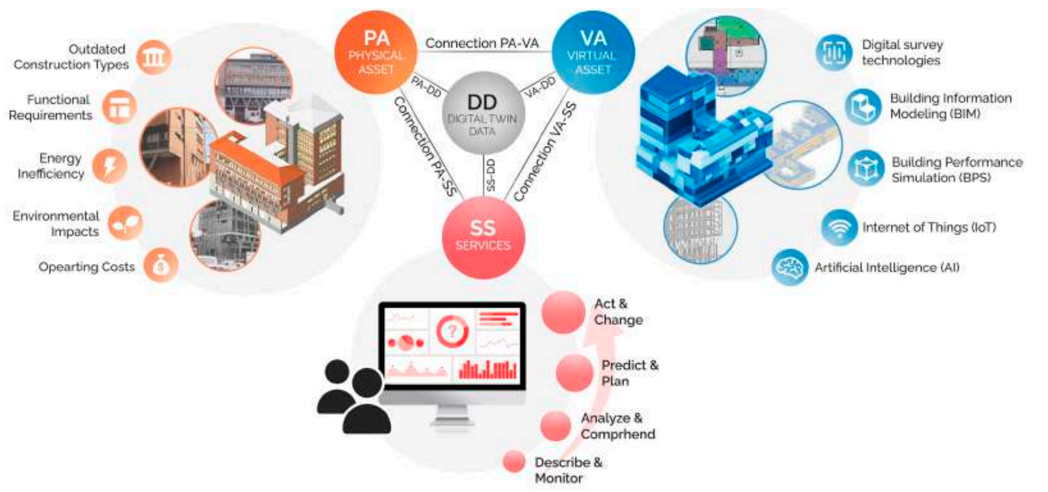


Figure 3. Five-dimension digital twin model and its purposes. (VA: virtual asset, PA: physical asset, DD: digital twin data, SS: services).

3.2.2. Information Management Framework

A conceptual framework is proposed to support the delivery of the DSS and allow efficient information tracking and management during the development process (Figure 4). It outlines the information covering the description, documentation, and analysis of the physical asset in the digital asset as it increases its technology readiness level (TRL). Formulated as an extension of the Lifecycle Information Transformation and Exchange (LITE) framework proposed by Succar and Poirier [57], the framework consists of many concepts:

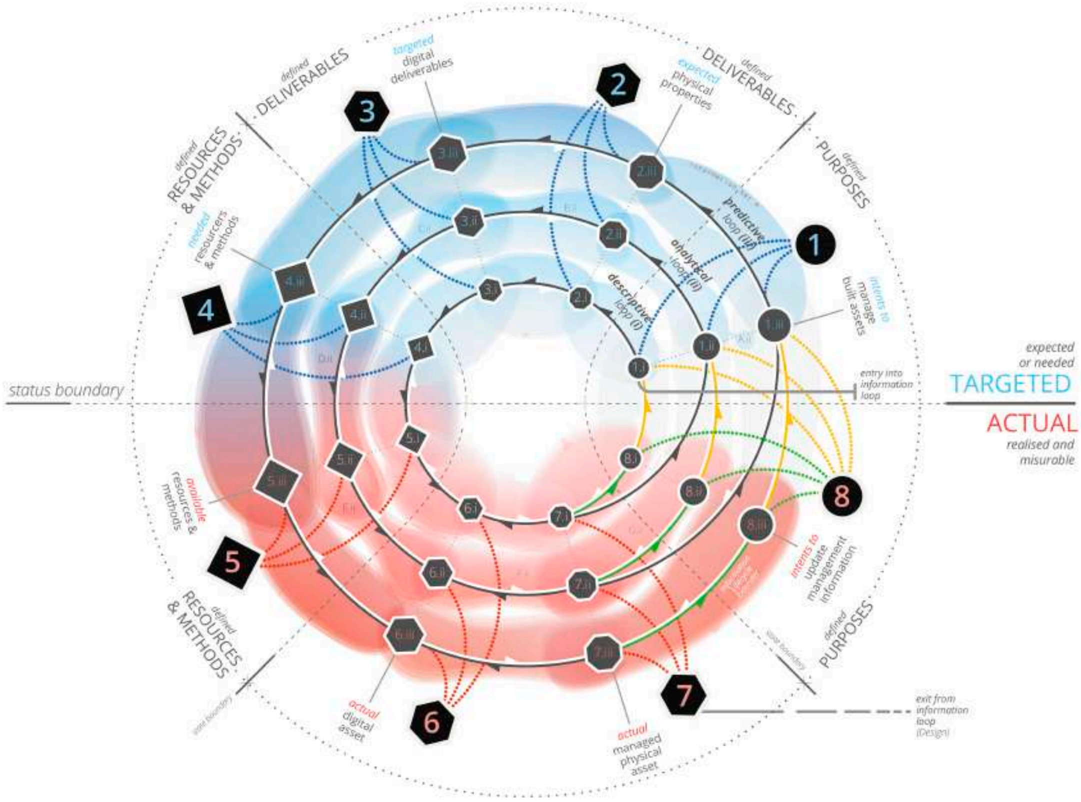


Figure 4. Information lifecycle management framework.

- Information statuses describe information while continuously exchanging, processing, and transforming during its lifecycle from a programmatic state (targeted state) to an applicative state (actual state).
- Information states capture the information transformation and describe it from being a simple purpose to a digital deliverable and a resource.
- Information loops identify the maturity of information through four consequential levels describing the capability of the DT system. These include a Descriptive Loop (i), a BIM-based level to document and describe information related to the current state of the physical asset; an Analytical loop (ii), a BPS-based level to analyze and process information related to the current or future state of the physical asset by using deterministic models; a Predictive loop (iii): an IoT-based level to analyze and process information related to the current or future state of the physical asset through data monitoring or predictive models (ML) based on sensor data coming from the physical asset; a Proactive loop, to integrate all the information acquired or processed in the previous levels within a centralized data environment and allow filtered visualization and interaction of information through DT Services to benchmark the building operational issues or predict new ones.
- Information milestones represent, for each loop, the steps that information traverses throughout its lifecycle.
- Information flows refer to the movement of information between information milestones (forward flows for actions and reverse flow for checks) or within information milestones (inward flows for data acquisition and outward flows for data sharing).

- Information links refer to the migration of information throughout information loops, allowing interoperability between different models, documents, data, resources, methods, and actors involved in other information loops.

The development of the DSS involves eight steps, defined as Information Milestones, which pass from the conceptualization of the DT to its actual use. These are:

1. Determining the intent to manage the physical asset (PA);
2. Identifying the physical properties to collect from the PA as well as the properties to investigate through the DSS;
3. Targeting the digital deliverables to produce for storing the collected data and create the DSS;
4. Comprehending what the resources and methods needed to set up the DSS are;
5. Setting up an actual method and using the available resources to implement the DSS;
6. Realizing the actual digital deliverables and integrating them into the digital asset (DA);
7. Letting asset managers adopt and use the DA;
8. Thinking about possible improvements or new uses of the DA.

As shown in the next section, the information milestones define the steps followed in the practical implementation of the research.

3.3. Implementation

This section presents the steps followed to deliver the DSS, guided by the above-discussed framework. DSS services are created to allow asset managers to interact with data stored in complex models through user-friendly dashboards. These services allow for searching, querying, filtering, and visualizing information related to building performance by linking and processing data provided by building information models (BIM) and building energy models (BEM). At this research stage, the analytical information loop has been reached, which means a BPS-based application capable of analyzing and processing information related to the current or future state of the physical asset using calibrated deterministic simulation models.

3.3.1. Purposes

The first implementation step consists of defining the intent to digitally manage the physical asset and the motivation behind developing the DSS. It means compiling the explicit reasons behind the required functions and the value sought from procuring the new DA for operating the PA.

In this case, as mentioned, the primary intent of the DSS is to enable performance-based operation of existing buildings by creating an information environment capable of sharing knowledge about their energy performance and relating it to information about planned occupancy conditions. The aim is to help to ensure managers are more aware of the energy behavior of the buildings they manage when planning occupancy. For instance, with reference to the selected case study, whose analysis is shown in the next section, this can be achieved by understanding the energy needs associated with specific occupancy patterns and activities in order to prioritize the use of the most energy-efficient areas inside the building during appropriate hours and seasons.

Since sensors or IoT devices are not yet installed in the discussed case study, which is a frequent condition in most heritage buildings, the platform uses time-series data simulated by BPS models and data commonly shared by the energy services providers, such as monthly natural gas and electricity bills. The developed DSS, therefore, can be seen as a transitional tool towards realizing the concept of a smart heritage [70], bridging the gap between the current state and the smarter future one.

3.3.2. Deliverables

Information Requirements

In the second implementation phase, information requirements are defined. These include the specifications of information needed to set up the DSS and clarify functions expected to be delivered by it to achieve the defined purposes. This stage involves two key steps. Firstly, it requires defining an ontological data model that effectively organizes the data. Secondly, it entails listing the expected properties of the PA that need to be collected or analyzed.

The knowledge data model establishes semantic and hierarchical rules between building elements for organizing data and encapsulating it in services. Employing a proper data structure makes it possible to seamlessly associate the expected properties to be collected with specific building elements, treating them as attributes. Moreover, this coherent attachment ensures a well-organized representation of the data.

Figure 5 depicts an overview of the data model used in the research. It is based on five types of entities connected by specific relationships:

- Elements (el), which represent the spatial (buildings, storeys, zones, and spaces) and construction components of buildings (walls, floors, roofs, and openings);
- Property sets (ps), which assign properties to the elements grouped by theme and type;
- Naming conventions (nc), which standardize the language of different models;
- Points (pt) are discrete units of information about an observation at a given time, as in the Brick's ontology [71];
- Key performance indicator sets (ks) are collections of metrics and measures that are used to evaluate the performance of building spatial elements.

A modular approach is used to create a flexible network structure for packaging and exchanging information.

After defining the knowledge data model, information templates are formalized. They consist of pre-organized tabular models describing element properties in the form of property sets, naming conventions, or points. These properties may be related to specific uses, disciplines, purposes, and operators. Moreover, they can include details about the data provider, the sources from which the data was acquired, its unique identification, its type and description, and the data itself. For example, when the DSS is used for energy management purposes, a physical element such as a thermal zone can be described with basic descriptive properties (e.g., identifier, name, size, and function) or more elaborated properties (e.g., heating demand, cooling demand, and lighting demand) that can be exchanged between the building manager and the energy modeler. Appendix A provides a detailed listing of information templates associated with the elements involved in the analysis proposed in Section 4.

Digital Models

The "deliverables" stage also involves targeting the digital deliverables to realize storing and structuring the PA's data and transforming it into valuable information shareable via the DSS.

For this application, three main digital deliverables are established: a building information model (BIM), a building energy model (BEM), and a schedule database (SD).

The building information model (BIM) consists of building elements, their basic geometry, and their static properties at a LoD200 level of development. In this level, spaces are modeled with enclosing elements like walls, elevations, floors, and roofs whose geometry is represented using generic objects. Moreover, the BIM is used to assign the semantic relationships between the elements necessary to map them according to the proposed ontology, which is based on the Industry Foundation Classes (IFC) and Green Building XML (gbXML) schema, as reported in Figures 5 and 6. BIM is also used as the basis for energy analysis; it encloses spaces, zones, and envelope elements whose function and characteristics are relevant to perform energy simulations.

The BEM consists of a physics-based model, realized in energy analysis software, to simulate the building energy behavior. By taking as input local weather data and a description of a building (including geometry, materials, occupancy, and HVAC systems), the BEM allows for calculating thermal loads, system response to those loads, resulting energy use, and related metrics like occupant comfort and energy costs through physics equations. It can allow for conducting dynamic analyses for a full year of calculations on an hourly basis, allowing evaluation system interactions between occupancy and energy hour by hour and zone by zone.

The SD contains information about occupancy, lighting, heating, cooling, and ventilation schedules, such as the number of people expected to occupy each space at a given time of the year and the HVAC operation times. Regarding educational buildings, occupancy information strictly related to the academic timetable can be provided by the university's Asset Management Services (AMS).

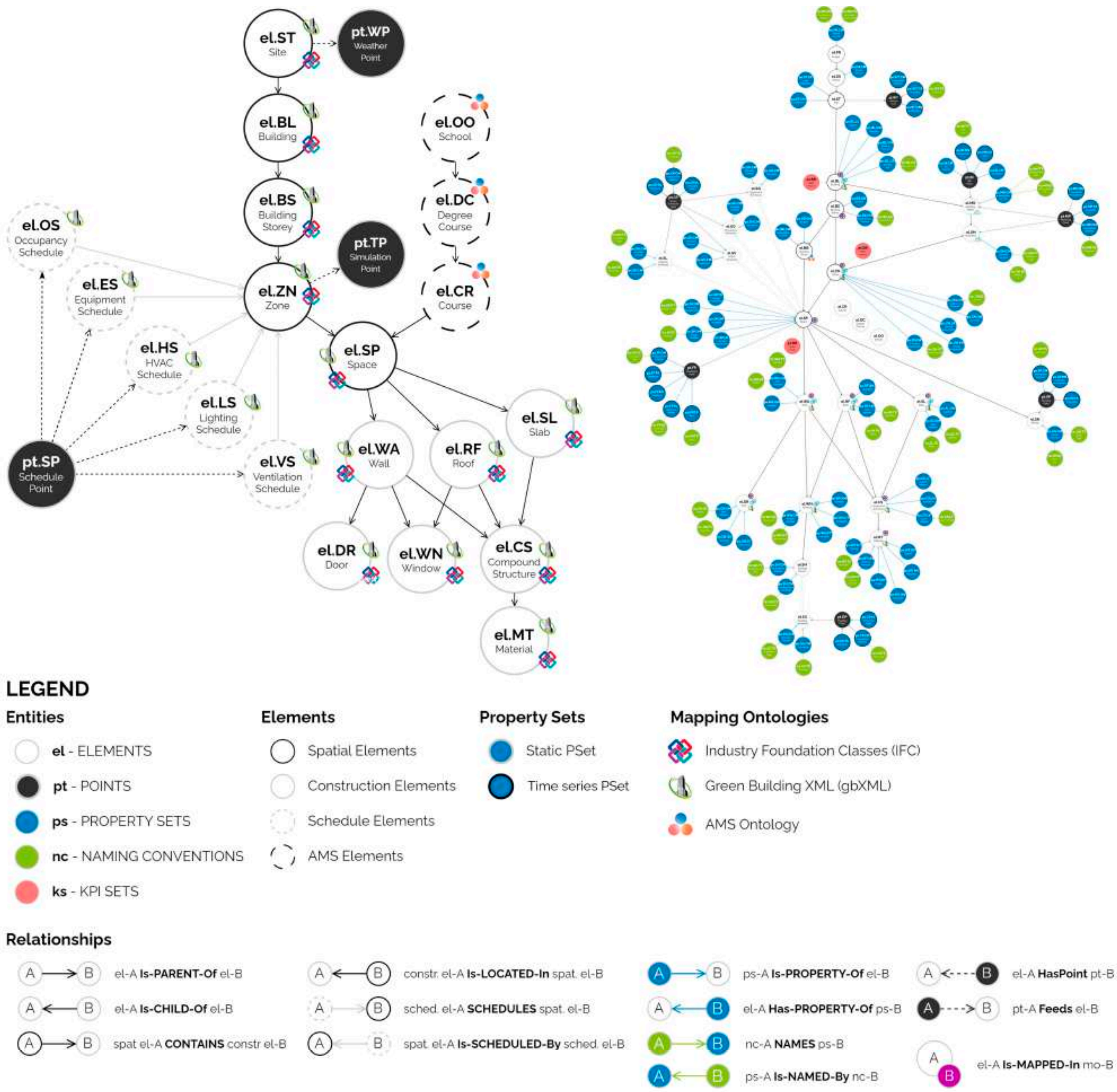


Figure 5. Ontology data model designed to implement the digital twin prototype in a network graph visualization.

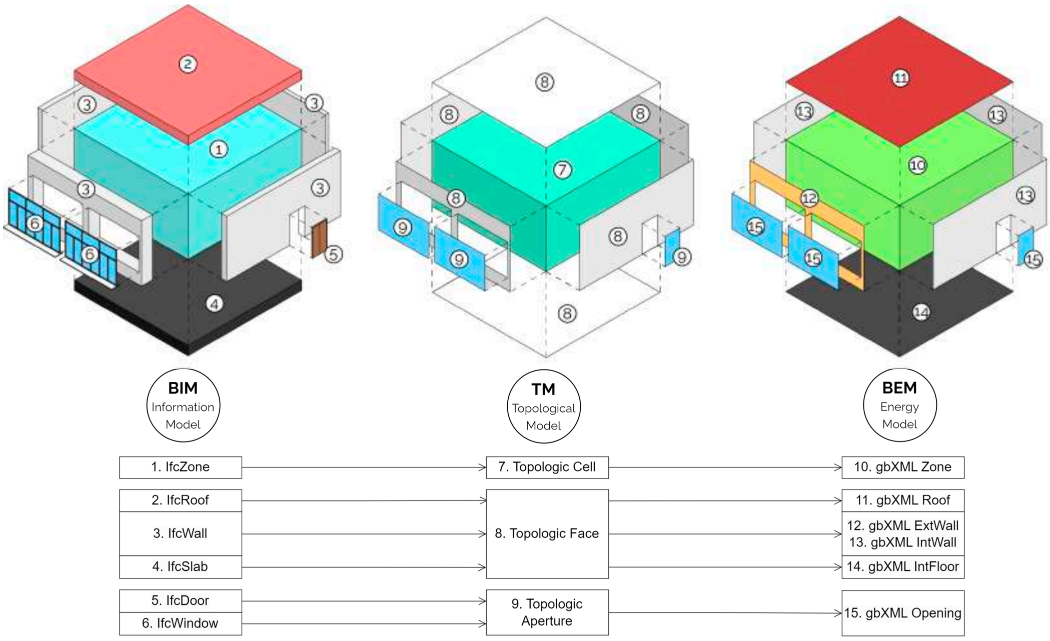


Figure 6. IFC, Topologic, and gbXML ontology alignment in the BIM to BEM workflow.

3.3.3. Resources and Methods

Once the digital deliverables are defined, the resources and methods are identified for delivering them. Resources refer to the human and machine actors and the physical, technical, financial, and other resources to be invested in transforming the targeted deliverables into actual ones. Methods refer to all the methodologies and tools for achieving DT purposes.

In particular, data collection, processing, and integration methods are defined at this stage. The first involves techniques for acquiring extensive knowledge about the asset's current condition. The seconds include workflows to deliver reliable digital models, such as BIM generation workflows, BPS analysis workflows, and strategies for achieving interoperability between BIM and BEM. The last provides techniques for linking the data available across multiple decentralized models, such as the BIM, the BEM, and the AMS' database. This integration is usually not straightforward because these models and systems rely on different modeling approaches, languages, and protocols, which are usually incompatible by definition.

Data Collection

In this application, the data collection strategy involves several preliminary in situ investigations; the consultation of historical and archival sources in public and private archives to know the construction features of buildings; the analysis of bibliographical work on the building; terrestrial laser scanner (TLS) surveys, the acquisition of drawings by the asset managers for getting the geometrical properties of building elements; discussions with administrators for understanding the actual uses of the different zones of the building, as well as to acquire energy bills and information related energy costs; the consultation of the AMS to know the occupation times.

Data Modeling

Data modeling and processing procedures and tools are also set.

Autodesk Revit is chosen as the BIM authoring software, while Topologic, a software library proposed by Jabi et al. [72], is used for performing BIM to BEM interoperability. The proposed approach consists of creating a topological model (TM) as means for data exchange between the BIM and the BEM (Figure 7). Visual programming (VP) algorithms in Grasshopper are used for achieving this task by using application programming interfaces

(APIs) to interoperate both with Autodesk Revit—via the Rhino.Inside add-on [73]—and with Energy Plus BPS engine—through the Ladybug Tools library [74].

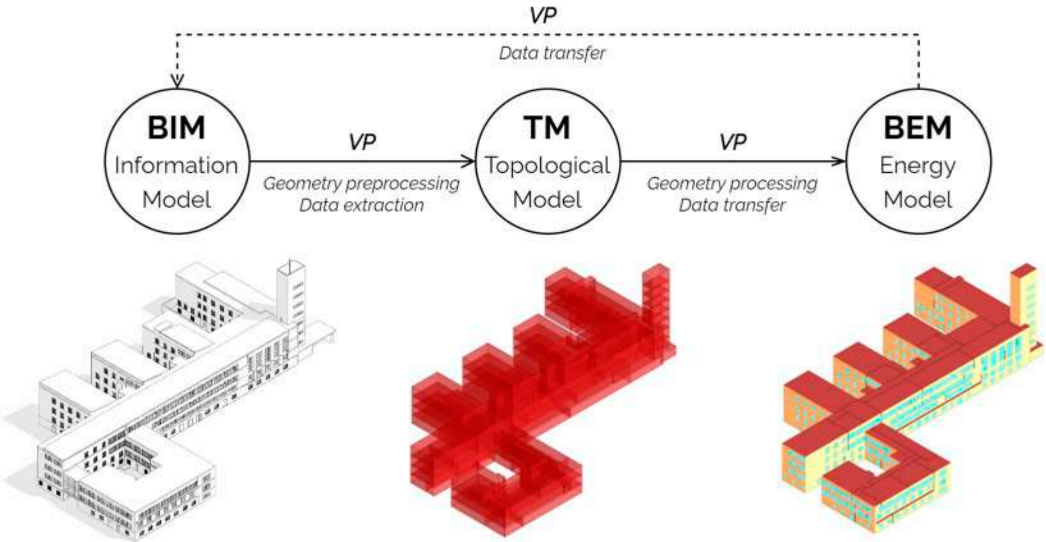


Figure 7. BIM to BEM conceptual workflow.

On the one hand, such tools allow complex geometrical operations to help BIM volume-based geometries match with BEM surface-based geometries; on the other hand, every change or modification on the BIM model is automatically registered in the topological and BEM model without loss of information or need to update the other models manually. Moreover, by working through VP algorithms, information can easily be imported and exported to tabular formats, as preferred. For instance, starting from the data provided by the University's AMS application [75], the classroom occupancy schedules, in .CSV format, are linked to the TM and the BEM through Grasshopper (GH), allowing us to estimate people's internal gains. Climatic data are also input in the BEM following a similar approach but using the EnergyPlus Weather File (EPW) format. At the same time, the results of the energy analyses are exported in .CSV file according to the predefined information templates so that they can be easily transferred to a centralized data repository. In the case of geometrical or information changes to the BIM model, such as variations in occupancy type, all the models can be automatically updated while maintaining the same data structure. This is achieved by rerunning the Grasshopper (GH) script after editing the BIM.

The initial phase of the BIM to BEM workflow involves creating the BIM, which serves as the foundation for the TM and BEM. The BIM combines geometric data of building components with information about space uses, thermal envelope characteristics, and zone energy loads. It incorporates spatial elements such as ifcBuilding, ifcBuildingStorey, ifcSpace, and ifcZone, along with construction elements like ifcWall, ifcRoof, ifcSlab, ifcWindow, and ifcDoor.

In the workflow, BIM space elements are selected from Autodesk Revit using the Rhino.Inside.Revit plug-in. The spaces with similar characteristics (in terms of functions, occupancy patterns, exposure conditions, and HVAC systems) are grouped into thermal zones. Then, a geometry voxelization algorithm is applied to simplify the high-resolution and volume-based geometries of the BIM in order to make them lighter and compatible with the TM and BEM. The zones are abstracted as Topologic Cells, and the properties of the BIM zone elements are transferred to these using the "Topology.SetDictionary" function. Next, the opaque envelope elements, represented as layered objects in the BIM, are linked to Topologic Faces, planar surfaces that bind the TM cells. As the cells act as the fundamental spatial units of the TM, the properties of the faces can be interpreted as attributes of the cells. By associating the TM faces with the corresponding BIM objects, the thermal properties of the construction, such as walls, roofs, and slabs, can be transferred from the BIM elements to the TM faces and subsequently to the TM cells. In the subsequent step, the glazed envelope elements are represented in the TM as Topologic Apertures, which are the openings within the faces that define the cells. Window, curtain wall, and door elements are selected in Grasshopper from the BIM using a similar approach as for spaces and opaque envelope elements. Their 2D profile is extracted and projected onto the corresponding TM faces. Finally, in the last stage, the TM cells, enriched with valuable information from the BIM, are aggregated into a single entity called the Topologic CellComplex. This CellComplex represents the entire building as the aggregation of the zones.

After this stage, the BEM is constructed based on the TM using the Honeybee plug-in from Ladybug Tools. The TM cells are transformed into gbXML Zone elements, while the cell faces and apertures are transformed into gbXML construction elements according to the ontology alignment in Figure 6. Once the ontologies are federated, the BEM model creation is brought off to assign all the BIM's information to the BEM reported in Appendices A and B.

The EnergyPlus Weather File (EPW) format is used to input climatic data. It consists of a header with location information and 8760 data lines representing each hour of the year, including weather parameters like temperature, humidity, radiation, illuminance, wind speed, and sky cover. Thanks to unique IDs, the HVAC and occupancy schedules are created in a CSV file and linked to the BIM, TM, and BEM models. The occupancy schedules are obtained from the academic timetable. In particular, the number of students attending each course is determined by leveraging the AMS information, including details about each lesson, such as time, classroom, and course. This allows for estimating the expected number of classroom occupants throughout the academic year, directly affecting the building's energy behavior.

To prepare for the energy simulation in EnergyPlus, simulation options are configured using components from Ladybug Tools. After the simulation is executed, the resulting energy data is saved in a CSV output file. Energy model calibration is then conducted by comparing the average actual annual energy consumption over the past three years, as indicated in the energy bills, with the calculated values from the energy simulation for the entire building. These results are subsequently parsed and linked to BIM zones using a unique identifier, enabling further analysis and integration with the building model.

Data Linking, Processing, and Visualization

From the data integration perspective, to deliver a DSS accessible from the web, a web application has been developed.

This app uses JavaScript for both the back- and front-end development. Python is also used in the back-end for interacting with the Energy Plus engine. One of its key functionalities is linking data from different models, displaying the 3D geometry of IFC spatial elements in a web browser, and visualizing related performance data by coloring them in gradient colors. Additionally, the application allows for visualizing time-series data related to spaces by selecting them intuitively, which is a poorly developed function in commercial energy modeling software and university digital services [26]. The data is then presented on dashboards with a user-friendly interface that enables building managers to view and interact with the building data even if they lack digital expertise.

For the purposes of this study, the DSS is developed for combining BIM, BPS, and SD data according to the data conversion and storage infrastructure shown in Figure 8.

First, the BIM model, created in Autodesk Revit (RVT), is exported in IFC and read into JavaScript Object Notation (JSON) thanks to the IFC.js toolkit [76]. Then, the RVT is used to generate the BEM through VP algorithms in Grasshopper, as exposed. An Energy Plus Input Data File (IDF) is created, a dynamic energy simulation is run, and time series results are stored in CSV. Also, occupancy data from the AMS are collected in CSV. BEM and SD produce 8760 data points for each zone of the building since the simulation is run for every hour between 1 January 2022 to 31 December 2022 to calculate zone energy use (cooling load, heating load, electric light and equipment loads), gains and losses (people gains, solar gains). These CSVs are converted to JSON files and stored in the linked data repository (Figure 9). Specific data pipelines carry out data transformations by linking data gathered through the various models and then processing, refining, and providing access to it based on the specific information needs of data consumers and applications. Finally, valuable data is visualized on interactive dashboards thanks to the use of a web application.

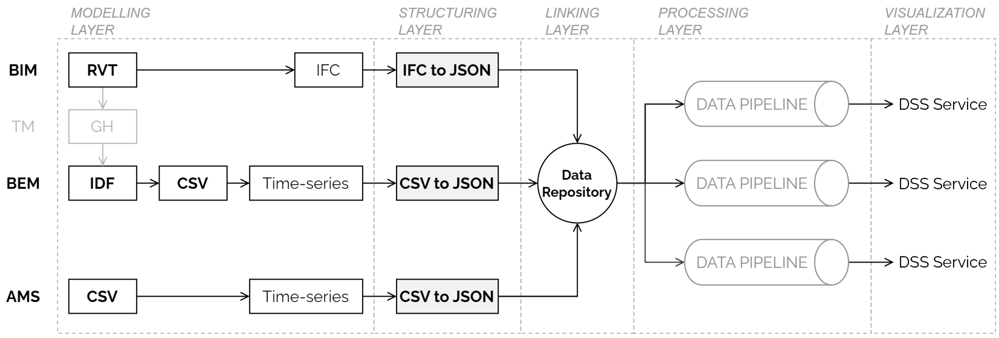


Figure 8. Data flow for delivering DT services.

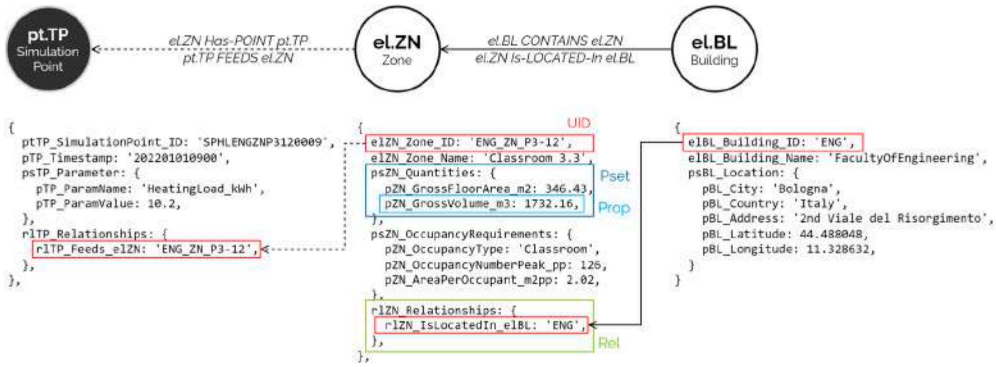


Figure 9. Example of JSON object definition for simulation points (pt.TP), zone elements (el.ZN), and building (el.BL).

The adoption of open BIM technology enables establishing an informational standardization layer, allowing the implementation of various applications without necessitating alterations to the data structure. By utilizing a linked data (LD) approach, a data lake architecture, and extract–transform–load (ETL) processes, the developed models can be easily augmented with static and dynamic data from other databases, IoT devices, software, or occupants, ensuring interoperability, scalability, and customization of the solution to meet specific user information requirements.

An example of BIM, BEM, and SD data is provided in Table 1.

Table 1. Example of BIM, BEM, and SD data extraction.

Zone UID (BIM)	Zone Name (BIM)	Net Area (BIM) (m^2)	Timestamp (Y–M–D H:M)	Occupancy Rate (SD) (%)	Heating Demand (BEM) (kWh)
ENG_ZN_P3-12	Classroom 3.3	346.43	21 January 2022 09:00 21 January 2022 10:00	0.85 0.90	10.20 4.59
ENG_ZN_P3-15	Classroom 3.6	252.97	21 January 2022 09:00 21 January 2022 10:00	0.00 0.75	4.13 2.04

3.3.4. Service Interaction

Once the DSS is completed, it is utilized as a decision support system (DSS) to simulate various scenarios. These simulations allow for exploring how energy loads may vary across different building zones at an hourly scale. The variations can be observed in response to different occupancy conditions and times, as well as the implementation of smart technologies aimed at enhancing controls (such as thermostats and occupancy detectors for lighting).

All elements included in the dashboards are interactive and allow sorting, filtering, and aggregating data by building, zone, hour, and function. Upon selecting a specific area in the 3D model and setting a date and time, the application recognizes the element's unique identifier (UID) and the chosen date and time. It then employs a query function to access data from the repository and display it related to that space in gradient colors. The information window presents space-related metrics, including net area, volume, occupancy type, and energy-related KPIs. Furthermore, the dashboard features line charts that exhibit time-series data. Users can examine KPIs for individual spaces or entire buildings and aggregate them over different timeframes. In this way, the DSS offers a snapshot of crucial building areas during various periods, which can differ significantly due to seasonal fluctuations in occupancy and energy requirements (e.g., academic schedules, heating and cooling demands).

The visualization of such data in an interactive and filterable environment could be of great help to building administrators, for example, to analyze and monitor the energy performance parameters of the entire building portfolio and to understand what the major critical issues are to be solved to optimize energy management, limiting impacts, consumption, and costs. This functionality can also enable managers to prioritize maintenance and renovation efforts, particularly in extensive and outdated building stocks that necessitate regular updates and enhancements.

An example of the service's graphical user interface (GUI) is illustrated in Figure 10. The indicators demonstrate that on 13 February 2022, the heating demand for the chosen classroom was nearly nonexistent between 1:00 p.m. and 7:00 p.m. when the room was fully occupied, and internal gains from occupants were substantial. This data contrasts with the HVAC system's operation, which is consistently scheduled to be active during these hours. The misalignment between energy demand and HVAC usage indicates potential energy waste and subsequent financial loss. Utilizing this information, building managers can adjust the HVAC system's schedule to optimize energy management within the building.

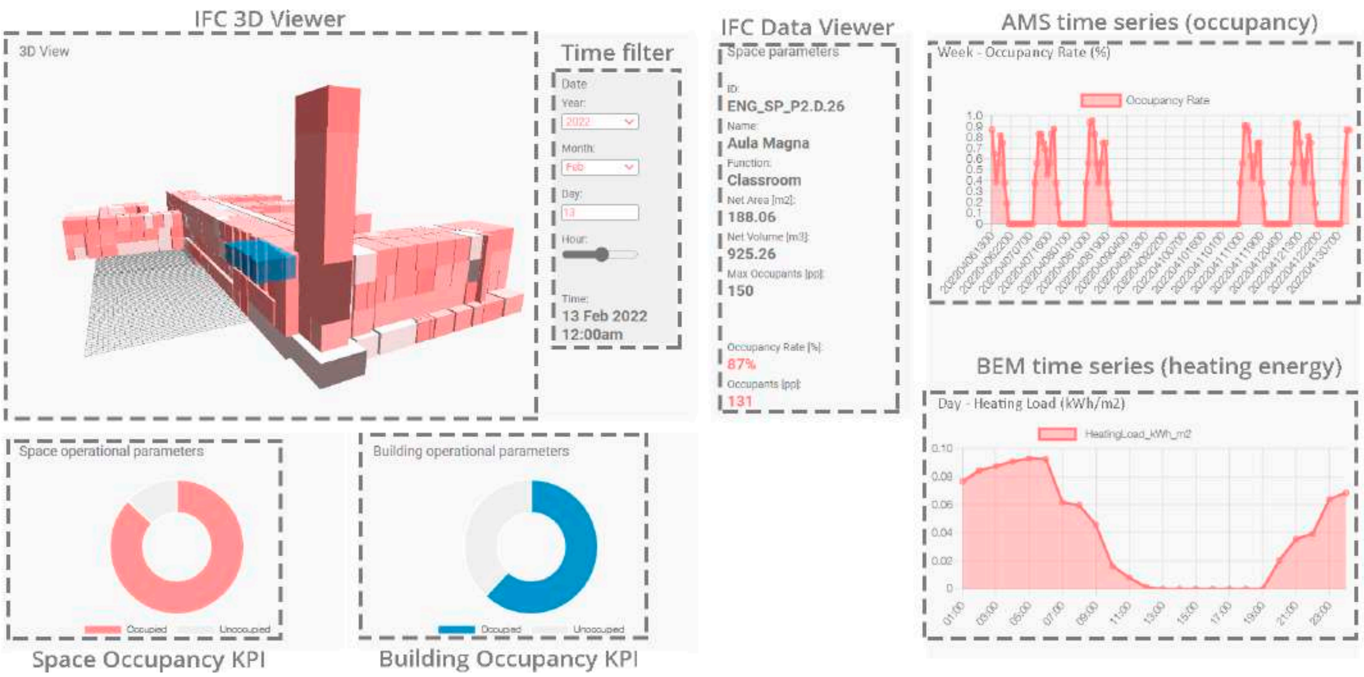


Figure 10. Dashboard prototype for visualizing energy- and occupancy-related data on IFC files.

4. Results

4.1. Energy Modeling Hypotheses

The building energy model, calibrated with actual energy bills, was subsequently employed for a comprehensive evaluation using the developed tools. This model considers the building zones' dimensions, construction, and occupancy characteristics, as well as the respective electricity and natural gas demands categorized by end uses. This section presents the main findings to compare the energy performance among the classrooms in the case study building on a significant winter operational day.

Table 2 displays the fundamental input parameters used for the analysis, while Table 3 shows the most important weather data for the selected day. The study utilized the EPW file of Bologna-Borgo Panigale, Italy, which contains hourly weather data for the specified location (Longitude: 11.30, Latitude: 44.53), situated in the Köppen–Geiger climate zone Cfa (humid subtropical climate with no dry season) at 49 m above sea level. Table 4 presents a summary of the EPW data.

Table 2. Input parameters for the energy analysis.

Analysis Day	Natural Gas Cost	Electricity Cost	Emissions for Electricity Mixes	Emissions for Heat Production from Natural Gas
23 February 2022 [1]	0.054 EUR/kWh [2]	0.159 EUR/kWh [2]	0.49 $kgCO_2eq/kWh$ [3]	0.25 $kgCO_2eq/kWh$ [3]

[1] The day is representative of a winter condition in Bologna (Italy) with mild cold and a typical day of classes, as the academic calendar schedules exams until mid-February. [2] Energy costs are derived from the average energy bills of 2020, 2021, and 2022. The conversion from standard cubic meters (smc), as in the bills, to kilowatt-hours (kWh) for natural gas is achieved by applying a conversion factor of 10.69, considering the calorific value of the gas. [3] Emission factors are based on the greenhouse gas emissions from the energy database of the International Energy Agency (IEA) that include global annual GHG emissions of each state from energy and related indicators, including CO_2, CH_4, N_2O emissions from fuel combustion, and fugitive emissions.

Table 3. Main weather data for 23 February from EPW.

Min Temperature	Mean Temperature	Max Temperature	Min Humidity	Max Humidity
5.9 °C	7.6 °C	10.2 °C	44%	94%

Table 4. Summary of weather data from EPW.

Average Yearly Temperature	Hottest Yearly Temperature	Coldest Yearly Temperature	Annual Cumulative Horizontal Solar Radiation	Percentage of Diffuse Horizontal Solar Radiation
13.0 °C	31.7 °C	−3.1 °C	1142.24 Wh/m^2	53.7%

The academic calendar of the selected case study is divided into two main periods: exams and class periods. In 2022, the exam period spanned from 10 January to 20 February and then from 13 June to 18 September. On the other hand, the class period encompassed the periods from 21 February to 12 June and from 19 September to 23 December. To illustrate a representative scenario, 23 February 2022 was chosen as it represented the coldest day during the class period in the selected context. On this day, the building was occupied to a significant extent, in contrast to the exam period when there were fewer individuals present.

In the analysis, it is assumed that each zone is equipped with thermostats. The heating setpoints are considered to be 20 °C from 7:00 a.m. to 8:00 p.m. and 16 °C during the night. The lighting is assumed to be always on from 8:00 a.m. to 8:00 p.m., while the occupancy conditions reflect the planned number of occupants based on the AMS apps. Mechanical ventilation has not been taken into account, as the building is naturally ventilated. Cooling has also not been considered since the analysis refers to winter conditions. The natural ventilation rate is assumed to be 0.3 h^{-1}, based on the findings of the study of Semprini et al., who conducted an energy audit for the same case study building [77].

Due to the challenges of obtaining comprehensive information about the HVAC system, it is not extensively incorporated into the BEM. As a result, the main key performance indicator (KPI) related to the energy behavior of each zone is an approximation based on considering the energy demanded by each zone instead of the energy supplied to it by the HVAC system. This approximation is justified by the uniformity of the HVAC system throughout the entire building. Therefore, to evaluate the expected costs and emissions associated with zone operation, the energy demand (in kWh) is multiplied by the factors mentioned in Table 2.

Table 5 presents the summarized data of the energy model.

Table 5. Energy model overview.

Gross Conditioned Area	Gross Unconditioned Area	Gross Conditioned Volume	Mean U-Value Opaque Envelope	Glazed/Opaque Envelope Surface Ratio
18,738 m^2	523 m^2	81,382 m^3	1.10 W/m^2K	29%

Furthermore, the KPIs in Table 6 are used to compare the energy demand and associated costs among various building zones. These KPIs are categorized into dimensional KPIs, energy KPIs, cost KPIs, and environmental KPIs. Additionally, solar and people's internal gains are taken into account to provide further insight into grasping the energy behavior of each classroom.

Table 6. Comparative key performance indicators (KPIs) used in the analysis to assess thermal zone behavior.

Dimensional KPIs	Energy KPIs	Cost KPIs	Emissions KPIs
Net area (sqm) Occupancy number at peak (people count)	Energy demanded for heating (kWh) Energy demanded for lighting (kWh) Energy demanded for equipment (kWh) Natural Gas demanded for heating (kWh) Electricity demanded for lighting and equipment (kWh)	Costs for heating (EUR) Costs for lighting (EUR) Costs for equipment (EUR) Total costs (EUR)	Equivalent emissions for heating ($kgCO_2eq$) Equivalent emissions for lighting ($kgCO_2eq$) Equivalent emissions for equipment ($kgCO_2eq$)

4.2. Zone Clustering

To facilitate a meaningful comparison of the energy performance among the zones, they were clustered in groups. Specifically, the zones were grouped into five clusters based on their area and peak occupancy number. Only rooms designated for classroom functions were considered for this analysis. The K-means algorithm was utilized for this purpose. In brief, it consists of a machine-learning technique that partitions data points into clusters based on their similarity.

As shown in Figure 11, Cluster A comprises classrooms with an area of less than 80 sqm and accommodating up to 50 people, representing the smaller-sized classrooms in the building. Cluster E consists of classrooms with an area larger than 190 sqm and accommodating up to 175 occupants, representing larger classrooms. Cluster B includes classrooms with an occupancy range of 80 to 120 people and an area between 100 and 150 sqm. Cluster C contains classrooms with an occupancy range between 125 and 150 people and an area between 100 and 120 sqm. Lastly, Cluster D represents classrooms with an occupancy range of 140 to 150 people and an area between 160 and 180 square meters. Each cluster is assigned a distinct color, as depicted in the figure, and will be consistently identified with that color throughout the analysis.

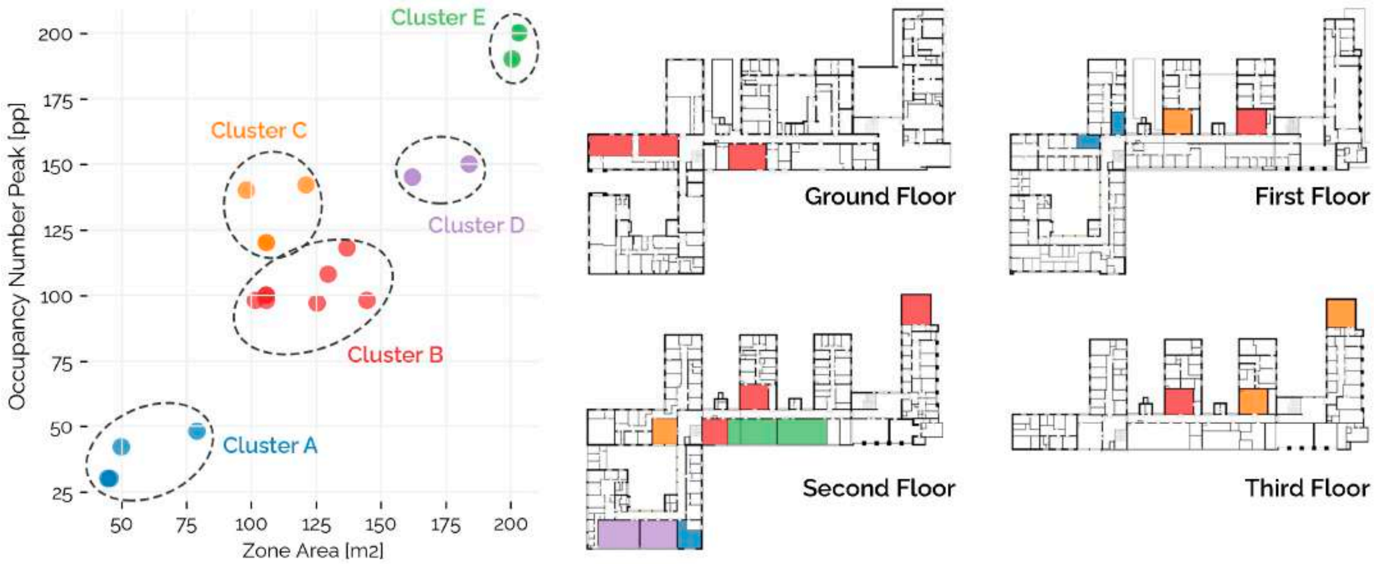


Figure 11. K-means clustering of the classrooms by area and peak occupancy number.

4.3. Energy Simulation Results

4.3.1. Energy Demand

For the specific day considered, the classrooms alone are projected to have the following energy and environmental impacts:

- The total heating demand is estimated to be 3405.77 kWh;
- The electricity demand for lighting and equipment is estimated to be 321.36 kWh;
- The overall management costs are calculated to be EUR 183.9 for heating and EUR 51.11 for lighting and equipment;
- The total equivalent emissions for the day are estimated at 1668.83 kgCO_2eq for heating and 76.56 kgCO_2eq for lighting and equipment.

The classrooms considered have a total area of 2355 sqm, accounting for 13% of the entire building area, and a maximum capacity of 2174 students, as defined in the building's fire plan, constituting approximately 43% of the total hypothetical occupants.

Figure 12 presents several results for the selected day, organized by zones. It is evident that there is a notable correlation between occupancy and heating demand, as the demand becomes almost negligible when the classrooms are fully occupied.

4.3.2. Space Ranking

In order to calculate the costs and emissions, the energy demand is multiplied by the appropriate factors, taking into account natural gas for heating and electricity for all other end uses (lighting and equipment). The same approach is applied for both costs and emissions calculations. This allows us to rank classrooms based on cost and emission metrics, as shown in Figure 13. Cluster by cluster, this ranking provides insights into the relative performance of classrooms in terms of their associated costs and environmental emissions.

4.3.3. Space Comparison

Figure 14 enhances the synthesis of results by providing a comprehensive overview through a parallel coordinate graph. The parallel graph utilizes a series of parallel axes, each representing a different variable or attribute. For each classroom, a data line connects the points on each attribute axis, representing the values of the variables for individual observations. It attempts to offer a synthetic visual representation that enables the exploration, comparison, and interpretation of the complex datasets deriving from the Energy Plus simulation.

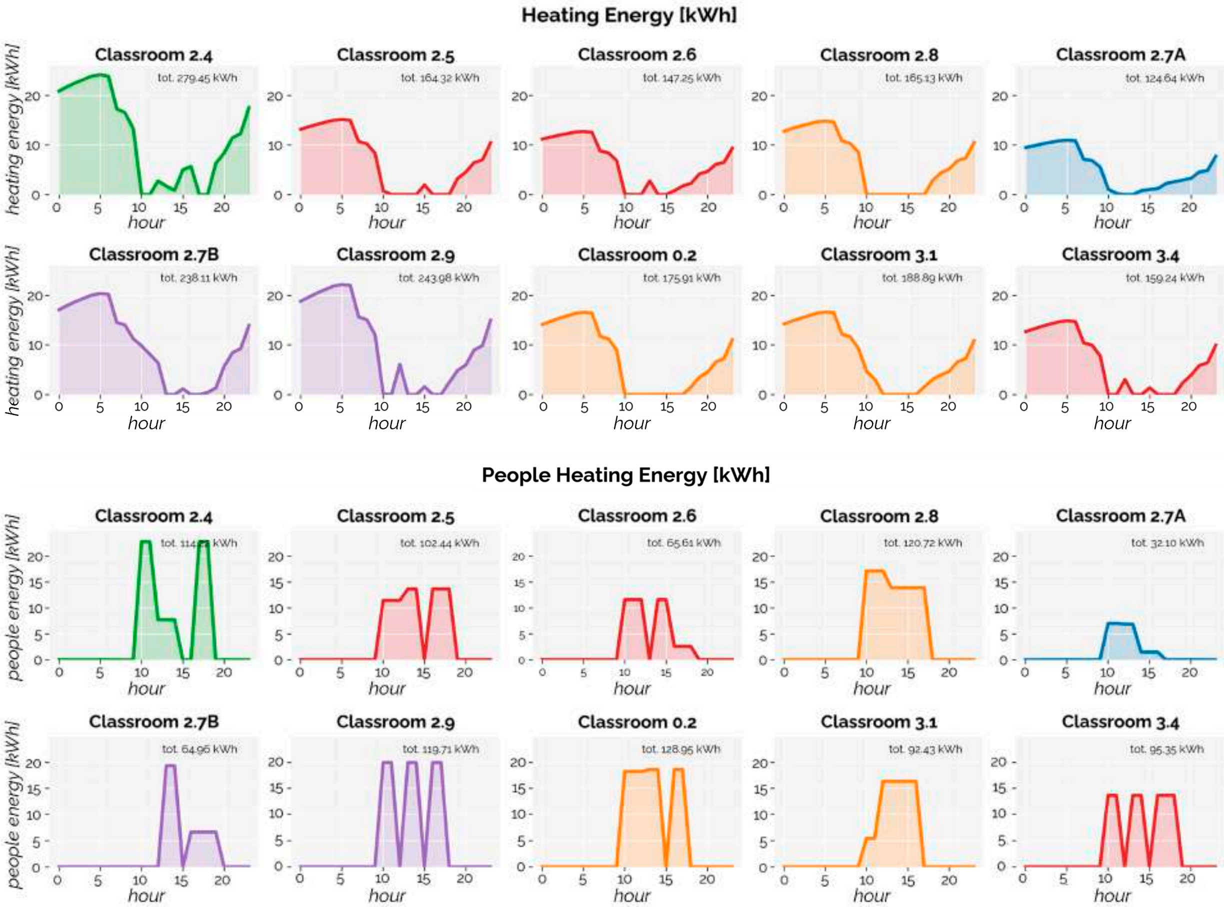


Figure 12. Visualization of hourly heating demand for some classrooms on the specified date and time. Data are colored according to the clusters identified in Figure 11.

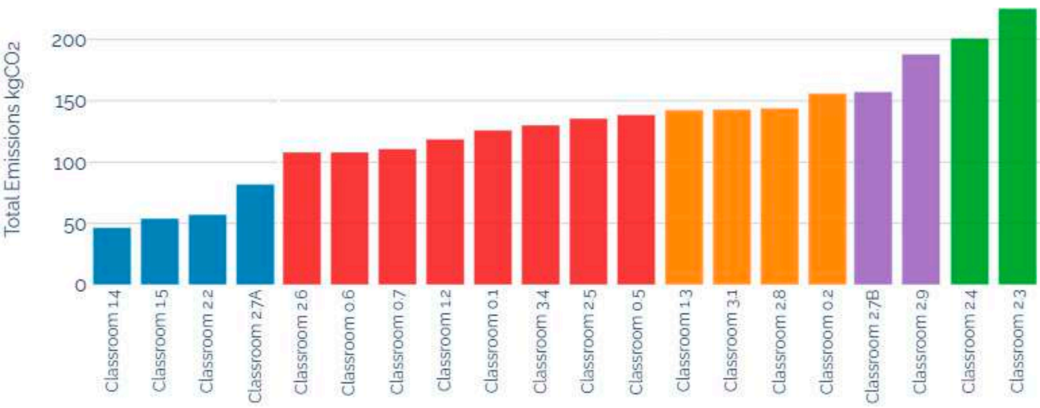


Figure 13. Total emissions for each classroom during the analysis day. Data are colored according to the clusters identified in Figure 11.

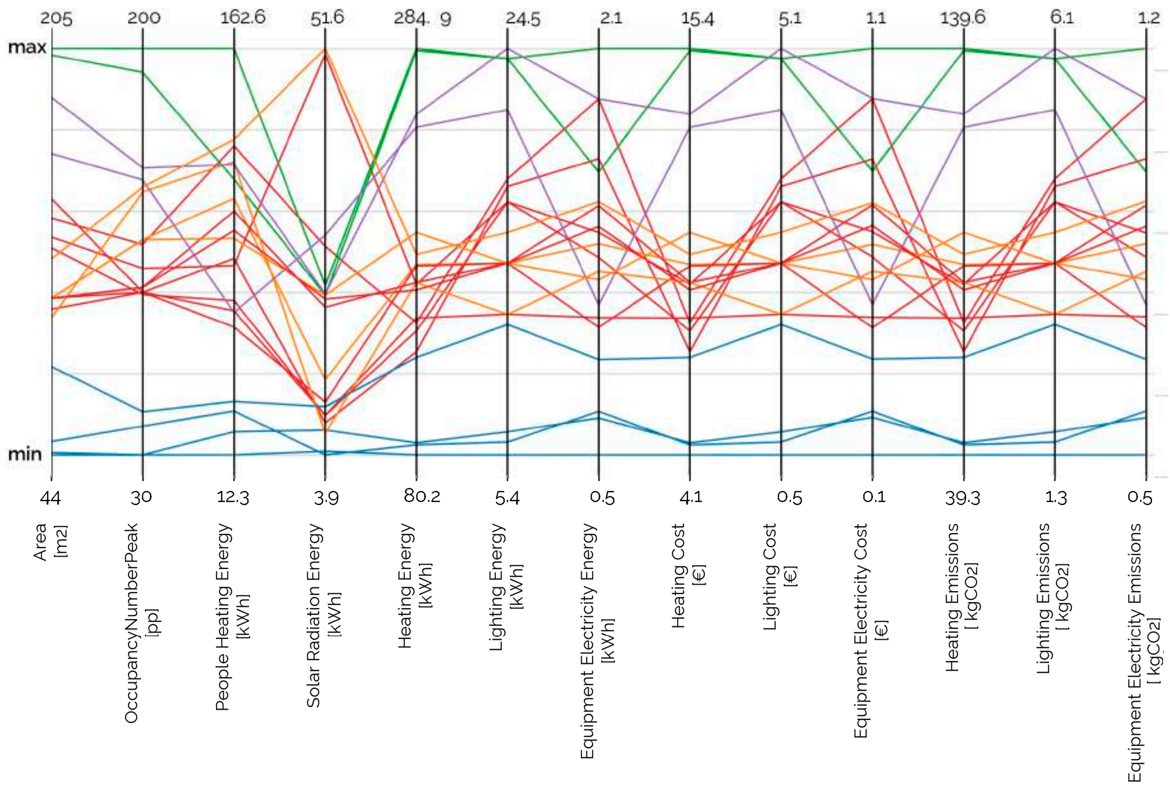


Figure 14. Parallel coordinate graph showcasing a comparison of the classrooms through the KPIs identified in Table 5. Lineplots are colored according to the clusters identified in Figure 11.

5. Discussion

5.1. BIM to BEM Interoperability

Numerous research studies have reported on the issue of interoperability between BIM and BEM. These studies consistently indicate several unresolved challenges associated with developing BIM-based building energy modeling [78]. For example, the complexity of geometry in digital environmental simulations can lead to computational bottlenecks [79]. BIM-based simulation models often result in high polygon counts, making simulations more time-consuming and less controlled. BPS tools usually require models with regular squared mesh for tasks like daylight analysis, computational fluid dynamics, or safety pathfinding simulations. Furthermore, BIM and BEM systems might employ different geometry kernels and data dictionaries, impacting their performance and compatibility with various software tools [80]. This discrepancy in underlying data structures can hinder smooth data exchange and integration between the two systems, further complicating the interoperability challenge.

The data exchange between BIM and BEM systems typically occurs through two file formats: IFC and gbXML. Each format offers distinct advantages in this context. IFC is widely recognized as the standard format for information exchange in BIM. It comprehensively represents building elements and their properties, allowing for detailed modeling and collaboration across different software platforms. On the other hand, gbXML is specifically designed for energy simulation purposes. Rather than object-based modeling, it is based on rectangular-shaped surfaces and attributes. gbXML can store a wide range of building information required for energy simulations, making it suitable for BEM applications. However, integrating IFC with gbXML is not straightforward due to the differences in modeling approaches, languages, and protocols employed by these systems. Compatibility issues can arise, and additional effort may be required to bridge the gap and enable seamless data exchange between the two formats.

Improving interoperability between BIM and BEM remains challenging, despite advancements made through file formats such as IFC and gbXML. The current approach involves creating a separate, unlinked digital model (the BEM) based on the BIM, rather than achieving bidirectional data exchange and storing energy data within a unified model. This data integration process is not optimal in terms of data flow.

To address this issue, this research proposes an alternative method, relying on both IFC and gbXML, for BIM-BEM bidirectional integration based on the creation of a Topological Model (TM) as a means of data exchange between the two models thanks to VP algorithms. The TM simplifies the representation of buildings by breaking them down into cells (spaces) that are bounded by faces (walls, floors, and roofs) and connected by openings (windows and doors), helping the BIM be compatible with the BEM modeling environment. The use of VP offers several advantages. Firstly, it enables the integration of complex geometric operations to align BIM's volume-based geometries with BEM's surface-based geometries. Secondly, any changes made to the BIM model are automatically reflected in both the TM and BEM models and vice versa, eliminating the need for manual updates. This eliminates the need for file exporting, reducing the risk of losing information and avoiding time-consuming coordination issues. Furthermore, VP allows access to energy-related data from external sources (such as occupant schedules, energy bills, and monitoring data), which can be used in simulations for comprehensive and accurate analyses. As cons, this method requires advanced digital skills and proper data flow management to ensure standardized procedures.

5.2. Energy Consumption Prediction Methods

In recent decades, scientists and engineers have dedicated significant efforts to developing approaches for predicting energy consumption. These approaches can be broadly categorized into three types: building physical energy models (referred to as "white box" models), data-driven models (referred to as "black box" models), and hybrid models (referred to as "grey box" models) [81].

The first category of building energy models, known as the "white box" model, relies on detailed building parameters and heat balance equations. This approach involves modeling the physical characteristics of a building, such as its construction materials, insulation, ventilation systems, and thermal properties, and the contextual factors, such as solar radiation, weather conditions, and occupancy patterns. The modeling and calibration process of "white box" software poses significant challenges for building energy stakeholders due to the extensive input parameters required, leading to time-consuming development on a physical software platform and high simulation economic costs. However, when well calibrated, the physical models' prediction accuracy can be higher than the statistical models [82], as well as their interpretability.

Given the limitations of white box models and the rapid advancements in big data technologies like sub-metering and smart buildings, data-driven models have emerged as a viable alternative in the last decade. Black box models offer a simpler approach by capturing the linear and nonlinear relationships between input and output variables. The main research efforts in the last period focused on investigating deep learning techniques and optimizing two key aspects: the significance of features to train models and the choice of algorithms. However, training these models and achieving accurate predictions under different conditions typically require vast amounts of historical data and a lengthy training period [81]. Moreover, while black box models have the advantage of needing less building information for their development, their prediction accuracy fluctuates, particularly when applied to different building scenarios. To address these challenges, a solution known as the "grey box" approach has been suggested by the literature. This method incorporates a simplified physical model and readily available data to simulate building energy demand, effectively combining the benefits of white and black box approaches.

White box models were employed in the presented application because of the absence of measurement data and their higher level of standardization in already developed software ontologies (compared to the black box and grey box models currently available in the literature). By adopting this approach, the connection between input and output for analysis becomes more comprehensible, particularly in terms of educating building managers about building behavior. However, some approximations were made due to the complexity of inputting the many input parameters required by Energy Plus for calculation, as discussed in the previous section.

5.3. Limitations and Future Developments

Numerous limitations and potential future developments of the developed DSS can be highlighted.

First, conducting a detailed analysis and refining the evaluation of various scenarios concerning different occupancy conditions is crucial. This analysis will provide insights into how operations can be improved effectively through occupancy. Moreover, assessing the potential impact of implementing diverse demand-control technologies within the building, such as thermostats, occupancy sensors, and lighting sensors, is essential. As demonstrated by Mosteiro-Romeiro et al. [33], integrating these technologies harmoniously with occupancy planning strategies can make it possible to ensure that the building's supply aligns with the demand, thereby encouraging flexible attendance modes and reducing energy use and related costs and emissions.

In the proposed analysis, only the classrooms have been evaluated. However, the analysis could be further extended to include other areas, such as offices, in order to assess the long-term effects of the increased prevalence of remote working and studying due to the COVID-19 pandemic or variations in the academic calendar [34]. This will enable better planning and optimization of resources to accommodate the evolving needs and trends in workspace utilization.

The extension of the exposed information system to more categories of building management (e.g., water consumption, indoor air quality, and waste management) and the scale of the entire building portfolio may aid administrators in assessing the scale interactions subsisting between buildings within the portfolio, the city, and the environment. In addition, if similar systems are framed in administration performance goals, they may enable the development of comprehensive decision-support tools for improving knowledge about actual conditions of use of buildings, making related information immediately and easily accessible, and the planning of management and renovation roadmap capable of considering the priorities of intervention within the administered estate quantitatively.

Lastly, only BPS data are currently used in the DSS. The lack of real sensor data from buildings, as opposed to just simulated data from building performance simulations, can bring the "performance gap" in evaluations, introducing significant discrepancies between simulated and real energy use [83]. To overcome this limitation, using smart energy meters and sensors for real-time monitoring of energy parameters could provide more reliable estimations. Following a similar approach, data from sensors and IoT devices will be inserted into the DSS to predict building performance more reliably.

6. Conclusions

Managing outdated public heritage buildings in Europe has become increasingly significant in recent years. These buildings, which include those operated by public administrations, require ongoing upgrades and improvements related to safety, operation, and maintenance to meet current needs. However, building management practices are not always equipped to address the complexity of these issues effectively. Several gaps in public building management of building stocks make it difficult to conserve the physical characteristics of buildings while ensuring functional, environmental, and economic compatibility with the current demanding framework, producing high costs for owners and environmental impact.

Digital technologies like Digital Twin (DT) are emerging to solve this issue and allow informed building management practices. However, there is still a lack of clarity surrounding their definition and uses. On the one hand, higher-level conceptual constructs are necessary to promote an organic DT development activating standardized and shared information modeling protocols; on the other hand, applicative examples are required to demonstrate the advantages of adopting such technologies, which require high digital skills and, so, high initial investments of resources for public administrations to face their digital transition.

The paper introduced a top-level framework for delivering built assets' information lifecycle management and its application for creating a DT prototype. From the initial intent to digitally manage an existing asset until the end of its lifecycle, the framework defines information transformations during its continuous updates. It is articulated according to eight information milestones: intents to improve the physical asset, expected properties, targeted deliverables, needed resources and methods, available resources and methods, actual digital asset development, digital asset adoption, and intents to improve the digital asset. In the study, this framework guided the development of a DT web application for sharing information related to energy and occupancy issues of a selected case study from the alma mater's building stock. The application prototype allowed the visualization of expected building performance data through KPI-based dashboards by linking different data models, such as building information models (BIM) and building energy models (BEM), forming a decision support system usable by building managers.

The research aimed to go beyond individual case studies and provide a comprehensive framework to modularly integrate and utilize various types of information, regardless of their nature. Despite some limitations discussed in the text, the presented analysis showcased an evaluative and testing nature of a developed DSS, highlighting how BIM and BPS can contribute to addressing some digitization challenges in the AECO sector if framed within a systemic perspective. By systematizing BIM and BEM data into an information environment, easily accessible to building operations staff, the information stored in the models can be inspected to understand building performance better and support decision-making processes.

The paper, therefore, offered an interpretation of the challenge of integrating BPS and BIM within a DT framework. It acknowledged that this effort represents a small step towards defining such systems and attributes its potential usefulness in scenarios where data quality and quantity are lacking, such as in outdated existing buildings. Within this perspective, even if not using live data, the research has leveraged the concept of DT to support the vision of data integration, considered one of the fundamental layers in defining and implementing DT systems. In future developments, sensor data measured from the real physical asset will be integrated to perform an effective coupling between the physical asset and the digital asset, improving data reliability and fidelity, as well as the DT sensitivity to catch the behavior of the building with higher accuracy.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Cell properties transferred from the building information model (BIM) to the topolgical model (TM).

Property Set	Properties
Cell.Common	Zone ID (str), Zone Name (str)
Cell.Relationships	ChildOf: Building (rel), ChildOf: Building Storey (rel), ParentOf: Faces (rel), ParentOf: Apertures (rel)
Cell.Quantities	Gross Volume (m^3), Net Volume (m^3), Gross Area (m^2), Net Area (m^2), Gross Height (m), Net Height (m)
Cell.LightingAndEquipment	ArtificialLighting (bool), IlluminanceSetpoint (lux), LightingPowerDensity (W/m^2), EquipmentPowerDensity (W/m^2), LightingSchedule (rel), EquipmentSchedule (rel)
Cell.OccupancyRequirements	IsOccupied (bool), AreaPerOccupant (mq/pp), OccupancyNumber (pp), OccupancType (str), OccupancySchedule (rel)
Cell.ThermalRequirements	IsHeated (bool), IsCooled (bool), IsVentilated (bool), TemperatureSummerMax (°C), TemperatureSummerMin (°C), TemperatureWinterMax (°C), TemperatureWinterMin (°C), HumidityMax (%), HumidityMin (%), NaturalVentilationRate ($m^3/(s \cdot m^2)$), MechVentilationRate ($m^3/(s \cdot m^2)$), CoolingSchedule (rel), HeatingSchedule (rel), VentilationSchedule (rel)

Table A2. Face properties transferred from the BIM to the TM.

Property Set	Properties
Face.Common	Face ID (str), Face Name (str), Face Type (str)
Face.Relationships	ChildOf: Building (rel), ChildOf: Building Storey (rel), ChildOf: Cell(rel), ParentOf: Apertures (rel)
Face.Quantities	Length (m), Width (m), Height (m), GrossSideArea (m^2), NetSideArea (m^2), GrossVolume (m^3), NetVolume (m^2), GrossWeight (kg), NetWeight (kg)
Face.Materials	MaterialLayer1: (Name (rel), Thickness (m), Conductivity (W/mK), Density (kg/m^3), SpecificHeat (K/kgK); MaterialLayer2: (Name (rel), Thickness (m), Conductivity (W/mK), Density (kg/m^3), SpecificHeat (K/kgK); MaterialLayerN: (Name (rel), Thickness (m), Conductivity (W/mK), Density (kg/m^3), SpecificHeat (K/kgK)
Face.ThermalProperties	U-Value (W/m^2K), R-Value (m^2K/W), VolumetricHeatCapacity (J/km^3)
Face.Common	Face ID (str), Face Name (str), Face Type (str)

Table A3. Aperture properties transferred from the BIM to the TM.

Property Set	Properties
Aperture.Common	Face ID (str), Face Name (str), Face Type (str)
Aperture.Relationships	ChildOf: Building (rel), ChildOf: Building Storey (rel), ChildOf: Cell (rel)
Aperture.Quantities	Width (m), Height (m), Area (m^2), Perimeter (m)
Aperture.ThermalProperties	U-Value (W/m^2K), SolarHeatGainCoefficient (float), VisibileTrasmittance (float)

Appendix B

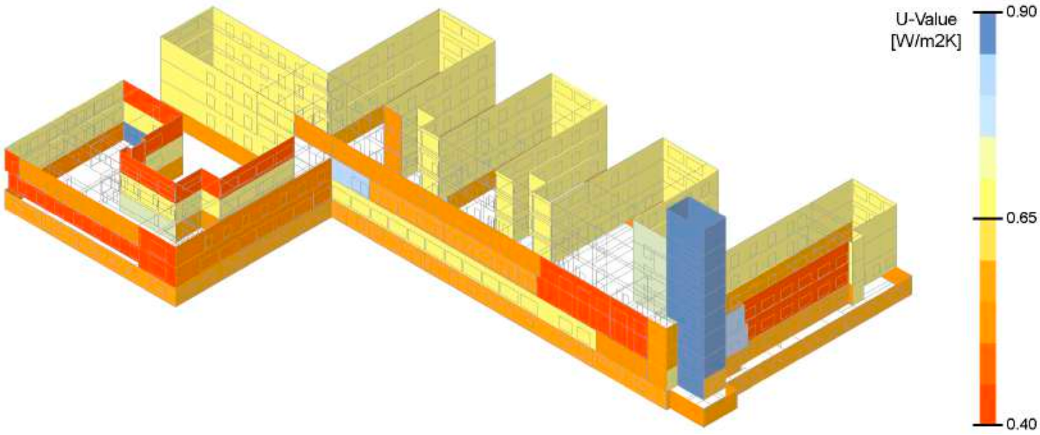

Figure A1. U-values of opaque construction elements input in the BEM model.

Table A4. U-values of opaque construction elements input in the BEM model.

Construction Type	Element	Materials (External to Internal Layers)	U-Value (W/m^{2}K)
AreatedBrickWall_36cm	Wall	Plaster_2cm, Areated brick_32cm, GypsiumPlaster_2cm	0.72
BrickWall_50cm_2	Wall	Plaster_2cm, SolidBrick_14cm, Air_16cm, SolidBrick_14cm, GypsiumPlaster_2cm	0.68
MixedBrickConcreteWall_120cm	Wall	Plaster_2cm, SolidBrick_14cm, SolidBrick_14cm, ReinforcedConcrete_45cm, Air_36cm, SolidBrick_14cm, GypsiumPlaster_2cm	0.55
MixedBrickConcreteWall_160cm	Wall	Plaster_2cm, SolidBrick_14cm, SolidBrick_14cm, SolidBrick_14cm, Air_16cm, ReinforcedConcrete_95cm, GypsiumPlaster_2cm	0.41
SolidBrickWall_45cm	Wall	SolidBrick_14cm, SolidBrick_14cm, SolidBrick_14cm	0.45
SolidBrickWall_47cm	Wall	SolidBrick_14cm, SolidBrick_14cm, SolidBrick_28cm, GypsiumPlaster_2cm	0.54
SolidBrickWall_50cm	Wall	Plaster_3cm, SolidBrick_14cm, SolidBrick_14cm, SolidBrick_28cm, GypsiumPlaster_2cm	0.51
SolidBrickWall_30cm	Wall	SolidBrick_14cm, SolidBrick_14cm, GypsiumPlaster_2cm	0.85
SolidBrickWall_34cm	Wall	Plaster_2cm, SolidBrick_14cm, SolidBrick_14cm, GypsiumPlaster_2cm	0.76
SolidBrickWall_37cm	Wall	Plaster_3cm, SolidBrick_14cm, SolidBrick_14cm, GypsiumPlaster_2cm	0.72
SolidBrickWall_49cm	Wall	Plaster_2cm, SolidBrick_14cm, Air_, SolidBrick_14cm, GypsiumPlaster_2cm	0.68
SolidBrickWall_62cm	Wall	Plaster_2cm, SolidBrick_28cm_30cm, Air_14cm, SolidBrick_14cm, GypsiumPlaster_1cm	0.49
SolidBrickWall_64cm	Wall	Plaster_2cm, Air_17cm, SolidBrick_14cm, Air_16cm, SolidBrick_14cm, GypsiumPlaster_1cm	0.64
SolidBrickWall_64cm	Wall	Plaster_2cm, SolidBrick_14cm, SolidBrick_14cm, SolidBrick_14cm, SolidBrick_14cm, GypsiumPlaster_2cm	0.40
SolidBrickWall_72cm	Wall	SolidBrick_28cm, Air_28cm, SolidBrick_14cm, GypsiumPlaster_2cm	0.50

Table A4. *Cont.*

Construction Type	Element	Materials (External to Internal Layers)	U-Value (W/m^{2}K)
SolidBrickWall_77cm	Wall	SolidBrick_14cm, SolidBrick_28cm, Air_30cm, SolidBrick_14cm, GypsiumPlaster_2cm	0.46
SolidBrickWall_79cm	Wall	Plaster_2cm, SolidBrick_14cm, SolidBrick_14cm, Air_31cm, SolidBrick_14cm, GypsiumPlaster_1cm	0.46
SolidBrickWall_82cm	Wall	SolidBrick_28cm, Air_38cm, SolidBrick_14cm, GypsiumPlaster_2cm	0.47
HollowConcreteFloor_60cm	Floor	CeramicTiles_2cm, LightConcrete_8cm, HollowSlab_48cm, GypsiumPlaster_2cm	1.16
HollowConcreteFloor_52cm	Floor	CeramicTiles_2cm, LightConcrete_8cm, HollowSlab_40cm, GypsiumPlaster_2cm	1.35
HollowConcreteRoof_52cm	Roof	Gravel_10cm, WaterProofMembane_1cm, HollowSlab_40cm, GypsiumPlaster_2cm	1.41
GroundFloor_50cm	Floor	CeramicTiles_2cm, LightConcrete_8cm, ConcreteSlab_20cm, Gravel_20cm	3.03

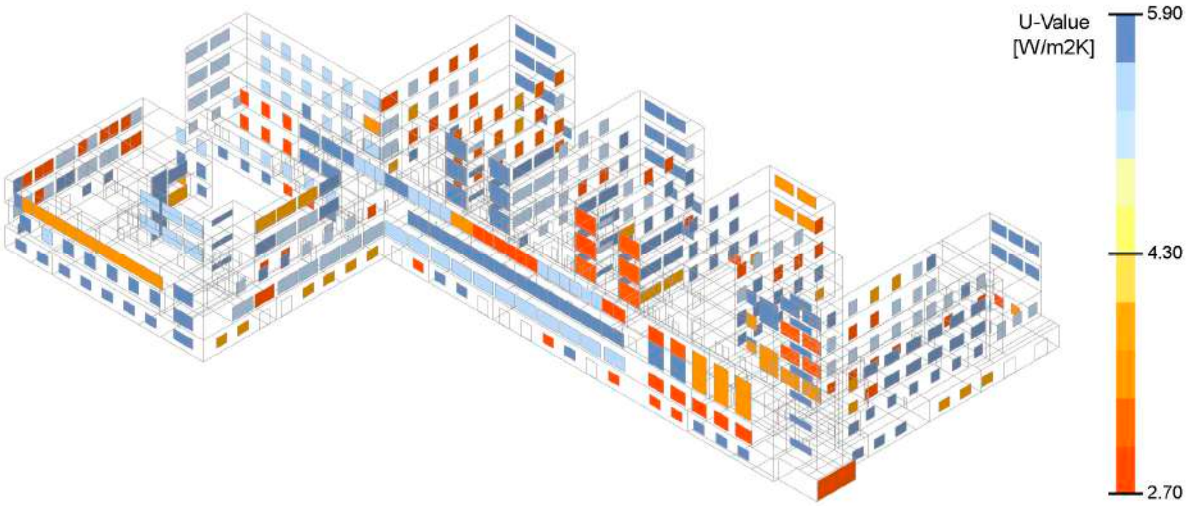

Figure A2. U-values of glazed construction elements input in the BEM model.

Table A5. U-values of glazed construction elements input in the BEM model.

Opening Type	Frame Material	Glass Type	U-Value (W/m^{2}K)
SteelFrame_SingleGlass_Old	Steel	Single Layer	5.5–5.8
AluminiumFrame_DoubleGlass_Old	Alluminium	Double Layer	3.0–3.4
WoodFrame_SingleGlass_Old	Wood	Single Layer	4.5–4.9
WoodFrame_DoublGlass_Recent	Wood	Double Layer	2.7–2.9

Appendix C

Table A6. Descriptive properties of the spaces selected for the analysis.

Space Name	Building Storey	Cluster ID	Area (m^2)	Occupancy Number Peak (pp)	Area/Occupant (mq/pp)
Classroom 0.1	Second Floor	B	129.6	108	1.20
Classroom 0.2	Third Floor	C	121.1	142	0.85
Classroom 0.5	Ground Floor	B	136.9	118	1.16
Classroom 0.6	Ground Floor	B	125.4	97	1.29
Classroom 0.7	Ground Floor	B	144.6	98	1.48
Classroom 1.2	First Floor	B	105.8	98	1.08
Classroom 1.3	First Floor	C	105.8	120	0.88
Classroom 1.4	First Floor	A	44.7	30	1.49
Classroom 1.5	First Floor	A	45.6	30	1.52
Classroom 2.2	Second Floor	A	49.9	42	1.19
Classroom 2.3	Second Floor	E	203.1	200	1.02
Classroom 2.4	Second Floor	E	200.5	190	1.06
Classroom 2.5	Second Floor	B	105.8	100	1.06
Classroom 2.6	Second Floor	B	101.5	98	1.04
Classroom 2.7A	Second Floor	A	79.1	48	1.65
Classroom 2.7B	Second Floor	D	162.1	145	1.12
Classroom 2.8	Second Floor	C	98.1	140	0.70
Classroom 2.9	Second Floor	D	184	150	1.23
Classroom 3.1	Third Floor	C	105.8	120	0.88
Classroom 3.4	Third Floor	B	105.7	100	1.06

Table A7. Energy results of the spaces selected for the analysis for the mentioned operational winter day. Energy demand.

Space Name	Equipment Energy (kWh)	Lighting Energy (kWh)	Heating Energy (kWh)	People Heating Energy (kWh)	Solar Radiation Energy (kWh)
Classroom 0.1	0.82	17.28	166.11	82.33	50.93
Classroom 0.2	0.91	15.84	181.2	128.94	51.62
Classroom 0.5	1.22	18.36	146.77	126.60	28.43
Classroom 0.6	0.74	17.28	142.64	69.41	8.61
Classroom 0.7	1.04	18.00	132.17	84.94	7.73
Classroom 1.2	0.53	14.40	175.37	59.60	10.17
Classroom 1.3	0.78	14.40	176.14	107.21	12.82
Classroom 1.4	0.15	5.40	80.19	12.31	4.41
Classroom 1.5	0.26	6.48	86.24	20.85	6.88
Classroom 2.2	0.28	6.00	85.23	28.56	3.98
Classroom 2.3	1.37	24.00	284.92	162.64	23.85
Classroom 2.4	1.00	24.00	283.86	114.21	22.71
Classroom 2.5	0.90	14.40	166.99	102.43	21.28
Classroom 2.6	0.56	12.00	149.11	65.61	8.62
Classroom 2.7A	0.44	11.52	129.30	32.09	9.63
Classroom 2.7B	0.60	21.60	245.20	64.95	29.73
Classroom 2.8	0.70	12.00	166.95	120.72	6.50
Classroom 2.9	1.22	24.48	251.85	119.70	22.86
Classroom 3.1	0.68	14.40	192.22	92.42	22.70
Classroom 3.4	0.84	14.40	163.21	95.35	22.25

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