Energy & Buildings 353 (2026) 116874

Contents lists available at ScienceDirect

Energy & Buildings

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

Clustering analysis for indoor temperature and energy pattern identification through long-term monitoring data in a university classroom

Graziano Salvalai [a,*], Roberto Villa [a], Manuela Grecchi [a], Gabriele Bernardini [b], Marco D'Orazio [b]

[a] Department of Architecture, Built Environment and Construction Engineering, Politecnico di Milano – Via Giuseppe Ponzio 31, 20133 Milan, Italy
[b] Department of Civil and Building Engineering and Architecture (DICEA), Università Politecnica delle Marche – Via Brecce Bianche 12, 60131 Ancona, Italy

ARTICLE INFO

Keywords:
Indoor Environmental Quality (IEQ)
Energy efficiency
Energy management
Experimental analysis
University building

ABSTRACT

Approximately 10% of Italy's building stock is owned by local public authorities, which are generally characterized by a low level of digitalization. The lack of a common repository and data leads to poor energy efficiency, management, and Indoor Environmental Quality (IEQ). The present research, based on a post-occupancy evaluation using real-time data collection essential for verifying building performance and operation, has a twofold objective: the first is the assessment over time of the IEQ and energy efficiency under real operation conditions; the second is the characterization, through clustering methods, of indoor air temperatures and energy needs. The assessment has been performed in a representative classroom of Politecnico di Milano University using a sensor network for IEQ and energy monitoring. The data collection shows that, during the winter season, the temperature falls outside comfort class II for 50% of the occupied hours. In summer, overheating is detected for 35% of the occupied hours. The clustering analysis successfully identified daily operational patterns for both key variables, air temperature and energy. Four clusters corresponding to the winter, summer, and intermediate seasons were identified from indoor temperature data, yielding a Silhouette Score of 0.488. Concurrently, three clusters corresponding to heating, cooling, and ventilation-only modes were identified with a Silhouette Score of 0.8015. The present work confirms that continuous monitoring and clustering analysis represent a valuable methodology for pattern identification within large operational datasets, enabling the quantification of typical operational modes, thereby establishing a foundation for advanced diagnostics and appropriate control strategies.

1. Introduction

Nowadays, besides the energy performance of buildings, thermal comfort and Indoor Environment Quality (IEQ) have gathered greater attention among researchers, architects, building managers, and occupants. As recently highlighted by the new Energy Performance of Buildings Directive (EPBD) [1], improved living standards and increased concerns for human health and well-being have underscored the importance of ensuring indoor comfort in buildings, with a particular emphasis on indoor air quality and thermal comfort [2]. IEQ represents a fundamental aspect of buildings [3], and it is well known that healthy buildings can positively impact the well-being and users' comfort [4,5]. This is particularly relevant in school buildings where young people spend most of their time learning and engaging in academic activities [6]. CO_2 concentration is the most frequently measured parameter as it is often used as an indicator of air quality level [7]. However, IEQ is a multi-domain concept, and it includes not only thermal comfort, but it involves air quality, lighting, and acoustics parameters [8]. Low IEQ results in Sick Building Syndrome (SBS), with a high impact on health, productivity, learning capabilities, perception, and performance [9]. The IEQ should be regarded as complementary to building energy efficiency analysis, as it can significantly influence energy consumption. Thermal comfort is an important factor for the IEQ, and it is also one of the primary drivers of energy consumption in buildings [10]. In mechanically ventilated buildings, the HVAC systems are designed to keep high IEQ levels, mainly according to international and national standards and recommendations [11]. These standards include ISO 7730 (2006) [12], EN 15251 (2007) [13], ASHRAE 55, and ASHRAE 62.1 [14]. Educational buildings, such as schools, constitute a significant category, as students spend a substantial portion of their time within

* Corresponding author.
E-mail address: graziano.salvalai@polimi.it (G. Salvalai).

https://doi.org/10.1016/j.enbuild.2025.116874
Received 26 June 2025; Received in revised form 26 August 2025; Accepted 12 December 2025
Available online 15 December 2025

these environments [15]. In school building design, efforts are being made to ensure the construction of quality learning environments. Students' comfort and performance should be a central priority in school design, aligning with a user-centered approach; however, this must be balanced with a detailed analysis of the building's energy consumption and cost-effectiveness. [16]. The 61 national public universities in Italy comprise 1,878 buildings nationwide, covering an area of 9.4 million m2 and serving approximately 1,909,360 students. Of this building stock, approximately 43 % is situated in cold zones with over 3000 Heating Degree Days (HDD), and more than 60 % was constructed before 1990 [17]. The EU supports member states in the digitalization of data on school buildings to enhance occupant comfort and well-being and to reduce energy consumption [18]. At the national level, many European countries implement economic measures to improve the intelligence of school buildings [19]. While many studies assess Indoor Environmental Quality (IEQ) using questionnaires, integrating monitored data enables a more comprehensive evaluation [20]. IEQ assessment in schools, particularly concerning children, has received considerable attention [21,15]; however, research focusing on higher education buildings, such as universities, remains limited and often overlooked[22]. Moreover, due to the strong interdependence between building energy efficiency and IEQ, these two dimensions must be analyzed in an integrated and comprehensive manner [6]. Despite the availability of numerous IEQ standards, the relationship between IEQ and building energy efficiency remains insufficiently defined [23]. Occupant well-being, thermal comfort, energy efficiency, and productivity are primary concerns for facility managers, necessitating continuous data analysis [24]. The continuous monitoring of IEQ and energy-related parameters is fundamental for maintaining comfortable and healthy IEQ while minimizing energy consumption [25]. Conventional data analysis is generally hard to apply in large data-set analysis [26], and clustering algorithms can help with data interpretation [27]. While previous clustering studies have primarily focused on load analysis, energy analysis, and fault detection [28,29,30], relatively few have explored its application in the context of IEQ assessment. This paper, therefore, develops a data-driven approach for the combined assessment of IEQ and energy efficiency. The proposed methodology provides i) an assessment of post-occupancy IEQ and associated energy requirements under continuous real-world operation, using monitored data, and ii) a characterization of indoor air temperature and Air Handling Unit (AHU) energy consumption through clustering-based pattern detection.. This work contributes to defining methods and tools for continuous monitoring analysis by integrating clustering techniques, thereby enhancing their applicability for data-driven facility management. Specifically, continuous monitoring allows for i) the collection of real-time alerts, ii) the enhancement of occupant well-being, iii) an increase in operational energy efficiency [31], and iv) reduced system downtime [32]. Clustering analysis, in turn, facilitates i) pattern discovery, ii) the simplification of large datasets [33], iii) support for anomaly detection [34], and iv) progress towards maintenance optimization [35]. Consequently, these outcomes enable facility managers to gain an overview of the building's current IEQ status and energy needs, while allowing technical staff to understand operational patterns and identify deviations from expected behavior that may indicate failures or critical conditions. The approach is implemented in a university classroom, selected as a representative case study due to its complexity, dynamic occupancy, and varied operational conditions, and is designed to be scalable and transferable to other comparable building typologies and uses. The classroom has been equipped with several sensors in order to collect multiple IEQ parameters such as air temperature [°C], illuminance level [Lux], relative humidity [RH], carbon dioxide [ppm], particular matter (PM_1, $PM_{2.5}$, PM_4, PM_{10}) [$\mu g/m^3$] and volatile organic compounds (VOCs) [ppb]. In parallel, the dedicated Air Handling Unit is equipped with a set of sensors for detecting the fan's electrical energy absorption and the heating/cooling thermal energy. The monitoring campaign was performed between April 2024 and February 2025 and data were collected and processed through Python algorithms for visualization and clustering, using validated approaches for pattern detection [36]. Based on the considerations outlined above, the paper is structured as follows. Section 2 introduces the overall methodology applied in the research focusing on IEQ and energy efficiency, the description of the case study and the sensors set-up and installation. Section 3 discusses the results from the monitoring campaign with the focus on the combined assessment of IEQ and energy consumption levels. Section 4 presents the clustering analysis and the pattern identification. Finally, Section 5 discusses the main findings and future works. The research activities have been developed within the DIGITMAN project [37] that aims at developing a predictive approach, based on occupancy data integrated into a common digital framework, to improve real building operations, supporting public authorities in developing effective management strategies. [37].

2. Methodology of work

To ensure a comprehensive evaluation of HVAC system performance within an occupied indoor environment, a structured experimental and analytical framework was developed. The whole experimental campaign was designed with a twofold objective: first, to evaluate indoor environmental quality (IEQ) and energy use under real operational conditions; and second, to identify and characterize typical patterns of indoor air temperature and energy consumption using data-driven clustering techniques. The inclusion of thermal comfort and air quality parameters aligns with the first objective, providing a holistic assessment of the indoor environment and supporting the relevance of the selected case study. The clustering analysis was applied specifically to temperature and energy consumption data due to their direct relevance to thermal comfort and HVAC performance and related maintenance. Fig. 1 illustrates the adopted methodology, which is organized into four key phases and includes references to the corresponding methodological and results sections. The method is designed to be both scalable and replicable, allowing for application across different case studies and building types. The initial phases are data acquisition and pre-processing, first, a dedicated monitoring system was designed and installed in a specific classroom at Politecnico di Milano University (Section 2.1) to continuously measure IEQ, external environmental conditions, and AHU operation (electrical and thermal energy). Data acquisition and preliminary analysis were then performed, focusing on the winter and summer periods. Subsequently, collected data were pre-processed to verify their quality and consistency (Section 2.2). These steps provide the basis for the real-time analysis tools presented in Section 3 and the subsequent clustering procedures. The third phase comprises data processing (Section 2.4), followed by the fourth phase, data clustering (Section 2.5). These processes yield the average daily profiles that are evaluated and interpreted in Section 4.

To select appropriate metrics for the numerous IEQ parameters measured, a wide range of regulations was considered. Table 1 summarizes the key thresholds derived from relevant standards and guidelines. In addition to thermo-hygrometric conditions, air quality was evaluated based on guidelines from the World Health Organization [38,39]. This approach provides a comprehensive assessment of the environmental conditions within educational building. Subjective evaluations of thermal comfort and air quality through questionnaires were outside the scope of this study, which primarily focused on objective, sensor-based data. Given the comprehensive nature of comfort monitoring through sensors, additional comfort surveys were deemed unnecessary for this analysis.

2.1. Case study description

The experimental campaign has been carried out in one classroom of Politecnico di Milano University in the Lecco Campus, located 45 km north of Milan, Italy. The campus, shown in Fig. 2a), consists of 5

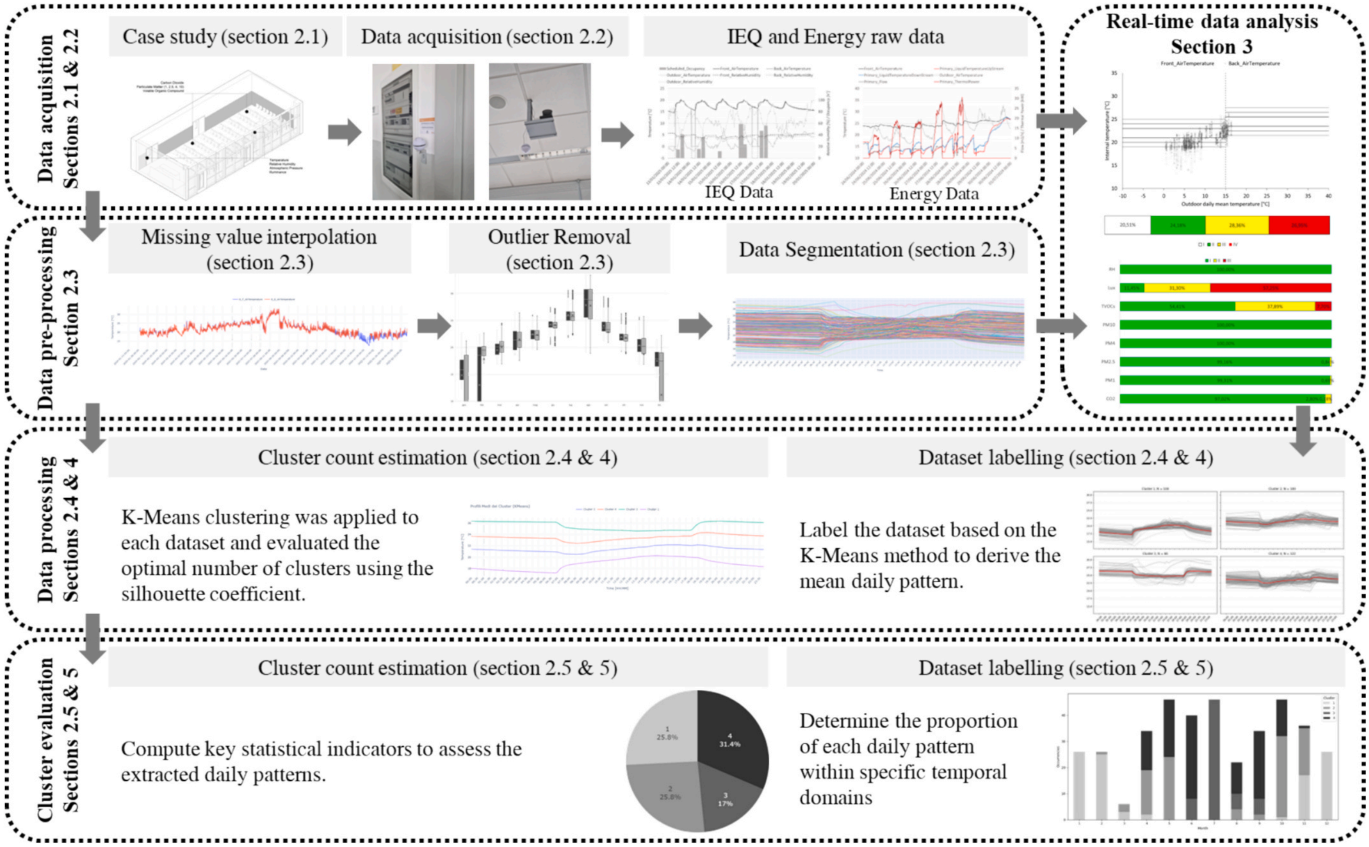


Fig. 1. Graphical representation of the methodology.

Table 1
Threshold values for indoor environmental comfort.

Parameter	Good	Acceptable	Bad	Reference
Ta [°C] (Winter)	22 ± 1	20 – 21 23 – 24	< 20 > 24	[39–41]
Ta [°C] (Summer)	24.5 ± 1	22.5 – 23.5 25.5 – 26.5	< 22.5 > 26.5	[39–41]
RH [%]	30 – 70	20 – 30 70 – 80	< 20 > 80	[38]
CO_2 [ppm]	< 950	950 – 1200	> 1750	[39]
PM_1 [μg/m^3]	< 12	12 – 35	> 35	[38]
$PM_{2.5}$ [μg/m^3]	< 12	12 – 35	> 35	[38]
PM_4 [μg/m^3]	< 40	40 – 50	> 50	[38]
PM_{10} [μg/m^3]	<40	40 – 50	> 50	[38]
VOCs [ppb]	< 220	220 – 660	> 660	[38]
Luminance [Lux]	500 – 750	300 – 500 750 – 1000	< 300 > 1000	[42,43]

buildings dedicated to teaching, research, and lab activities with a total floor area of 47,000 m^2. A total of 29 classrooms are distributed in two main buildings capable of accommodating 2850 students. Lecco (45° 51′ N, 9° 23′ E) is characterized by a humid temperate climate, classified as Cfb according to the Koppen-Geiger classification system [44].

The classroom under analysis is located at the first floor of Building n° 9 of the Campus, highlighted in light blue in Fig. 2b). The classroom floor area, height, and volume are respectively 170.71 m^2, 3.80 m, and 648.70 m^3. The room can host a maximum of 100 students (Fig. 3a) and it is characterized by a full south-west glazed façade. Indoor temperature, relative humidity, and CO_2 concentration levels are guaranteed by a dedicated HVAC system (Fig. 3b). This configuration is typical of many newly constructed or retrofitted educational university buildings in similar climatic contexts and geographical areas. From this perspective, the approach adopted in this study is considered representative of this

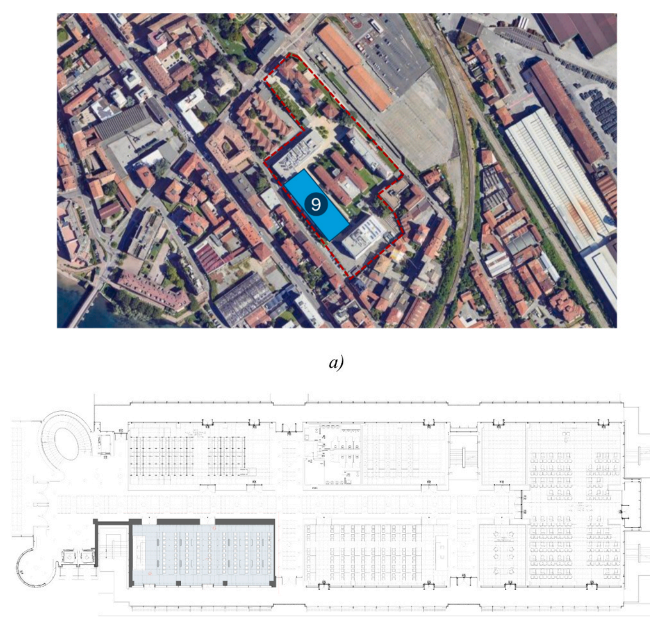


Fig. 2. A) aerial view of the university campus, b) building diagram of the first floor, in light blue the location of the monitored classroom. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

a) b)

Fig. 3. A) view of the monitored classroom; b) view of the ahu serving the classroom located in the rooftop.

category of buildings, particularly in terms of thermal behavior, environmental control strategies, and occupancy patterns. Moreover, the simplicity of the monitoring setup and the use of standard data analysis methods based on international guidelines make the results easily transferable to comparable building typologies. Actual classroom occupancy was derived by combining on-site survey counts with student enrollment data for the scheduled courses. In detail Table 2 presents the weekly schedules for the fall (September–December) and spring (March–June) semesters. This approach yielded a reliable occupancy profile for our analysis without relying on occupancy sensors, which would have introduced additional complexities related to GDPR compliance.

A dedicated Building Management System (BMS) controls the AHU, regulating damper openings and heating/cooling coil valves to maintain proper indoor temperature, relative humidity, and CO_2 setpoints. The Constant Air Volume (CAV) unit supplies a continuous airflow of 7200 m^3/h, equivalent to 6 Air Changes per Hour (ACH). The technical specifications of the AHU are provided in Table 3.

The selected classroom, aside from variations caused by specific class schedules, exhibits typical operational characteristics of a university campus, making it a representative reference case for the development and validation of the proposed methodology. The primary objective of the DIGITMAN project is to develop a predictive approach, based on occupancy data integrated within a common digital framework, to optimize building stock management by supporting the efficient allocation of technical and economic resources during actual building operation. This comprehensive approach addresses three main areas: maintenance, operation, and safety, within large university building stocks. Given the significant importance of maintenance in terms of both cost and user impact, we have chosen to apply the methodology to a fully HVAC-equipped case study. This enables a more thorough understanding of building performance and operational challenges, thereby enhancing the practical relevance and applicability of the findings.

Table 3
Air Handling Unit characteristics.

Parameter	Value
Supply airflow	7,200 m^3/h
Return airflow	6,600 m^3/h
Maximum return airflow	6,600 m^3/h
Minimum return airflow	3,900 m^3/h
Maximum supply airflow	7,200 m^3/h
Minimum supply airflow	3,900 m^3/h
COP Plate Energy Recovery	60 %
Supply static pressure	280 Pa
Supply fan power	5.5 kW
Return static pressure	150 Pa
Return fan power	2.2 kW
Primary cooling/heating coil power	60 kW
Cooling water in/out	8/13 °C
Secondary heating coil power	10 kW
Heating water in/out	35/30 °C

2.2. *Data acquisition*

The indoor monitoring network incorporated several devices equipped with sensors to measure various environmental parameters, including air temperature (°C), relative humidity (%), atmospheric pressure (hPa), illuminance (lux), carbon dioxide (ppm), particulate matter (μg/m^3), and volatile organic compounds (ppb). A dedicated system monitored the AHU to collect data on fan electrical power consumption and the heating and cooling energy required for air conditioning during summer and winter. Outdoor weather conditions were monitored by a set of sensors located near the building. Sensor specifications, including measurement range and accuracy, are listed in Table 4.

In detail, four sensors were installed in the classroom to monitor IEQ distribution, with two positioned at the front and two at the back (Fig. 4). The sensors were intentionally positioned at different heights to

Table 2
Measured mean occupancy in classroom B1.5 during the fall and spring semester, based on scheduled attendance and validated through direct observational surveys.

	Day	9:00/ 10:00	10:00/ 11:00	11:00/ 12:00	12:00/ 13:00	13:00/ 14:00	14:00/ 15:00	15:00/ 16:00	16:00/ 17:00	17:00/ 18:00
September – December	Monday	/	/	/	/	/	24	24	24	24
	Tuesday	16	16	16	16	/	21	21	21	21
	Wednesday	12	12	12	12	/	/	/	/	/
	Thursday	24	24	24	24	/	24	24	24	24
	Friday	12	12	12	12	/	15	15	15	15
March – June	Monday	15	15	15	15	/	17	17	17	17
	Tuesday	/	/	/	/	/	15	15	15	15
	Wednesday	/	/	/	/	/	/	/	/	/
	Thursday	35	35	35	35	35	/	/	/	/
	Friday	35	35	35	35	/	41	41	41	41

Table 4
Sensors' characteristics.

Sensor	Parameter	Measuring range and accuracy
LSI Lastem – Sphensor PRMPB0402	Air temperature (°C)	±0,1 °C; Max ± 0,3 °C (at 20 °C to 60 °C) ±0,2 °C; Max ± 0,3 °C (at −40 °C to 20 °C; 60 °C to 80 °C)
	Atmospheric pressure (Pa)	600 hPa to 1100 hPa 0,18 hPa (at 25 °C) ±0,6 hPa (@ −40 °C to 85 °C)
	Relative humidity (%)	±1,5 %; Max ± 2 % (at 25 °C; 0 % to 80 %) ±2 %; Max ± 3 % (at 25 °C; 80 % to 100 %)
	Illuminance sensor	±5% MV ± 5 lx
LSI Lastem – Sphensor PRMPA0423	Carbon dioxide concentration (ppb)	0 to 5000 ppm <± (50 ppm + 3 % of measured value)
	Volatile organic Compounds (ppb)	0 to 60000 ppb Ethanol: 15 % of the measured value H2: 10 % of the measured value
	Particulate Matter (μg/m^3)	0 to 1000 μg/m^3 PM_1 e $PM_{2.5}$: 0 to 100 μg/m^3 ± 10 μg/m^3 100 to 1000 μg/m^3 ± 10 % of measured value PM_4 e PM_{10}: 0 to 100 μg/m^3 ± 25 μg/m^3 100 to 1000 μg/m^3 ± 25 % of measured value
RIELS Instruments – RIF600S	Temperature (°C)	± 0,8 °C (@ 100 °C)
smart-MAIC – D103-22	Current (A)	<1 % (50 mA to 100 A)
LSI Lastem – Weather station	Temperature (°C)	− 40 °C to 80 °C 0.1 °C (@ 0 °C)
	Relative humidity (%)	0 % to 100 % ±1% (@5% to 95 %)
	Globe Temperature (°C)	− 20 °C to 80 °C ±0,1 °C (@ − 20 °C to 50 °C) ±0,15 °C (@ 50 °C to 70 °C)
	Global Radiation (W/m^2)	0 W/m^2 to 1500 W/m^2 285 nm to 3000 nm
	Wind Speed (m/s)	0 m/s to 25 m/s: ± 0,25 m/s or 3 % >25 m/s: 2 % ± 0.1 m/s or ± 1 %
	Wind Direction (°)	0° to 360° ± 1 %

capture also potential vertical temperature stratification, which can typically occur in HVAC heated room. The CO_2 sensors were installed near the ceiling at a height of 3.00 m. One temperature sensor at the front of the classroom was positioned at 1.20 m, while one sensor at the back was positioned at 2.50 m high. From the spatial point of view the sensors were positioned on opposite sides of the classroom to capture potential thermal gradients: one sensor was placed near the fully glazed external wall, and the other near the opaque party wall, at different heights. This placement was intended to reflect the most thermally dynamic zones of the space, capturing the influence of solar gains, external temperature fluctuations, and potential infiltration. While this setup may not fully represent every microclimate within the room, it was considered appropriate for the scope of this study, which focuses on identifying trends in thermal comfort/IEQ using objective, sensor-based data.

Three-phase power meters were installed on the AHU electrical panel to monitor and determine the operating schedule and measure energy consumption. A schematic of the AHU, indicating its main components and measurement points, is provided in Fig. 5.To quantify the energy transferred from the primary and secondary coils to the supply air, sensors and loggers were mounted directly on the ventilation unit (Fig. 6). These devices measured the inlet and outlet coil temperatures and the water mass flow rate, which were used to calculate energy transfer during winter and summer operations.

The data collection granularity is set at 60-second intervals, with indoor sensors transmitting measurements to a border router located in the classroom's false ceiling. The weather station measures external environmental parameters and transmits data to a local server at ten-minute intervals. AHU electrical power is measured by amperometric clamps, with data transmitted to a web platform at one-minute intervals. Water temperature and mass flow rate are recorded by two dataloggers and transmitted to a web server.

2.3. Data pre-processing

The data pre-processing represents the initial step in the clustering workflow, given that raw data frequently contains missing or inconsistent values. This process involves four steps: i) timestamp alignment, ii) missing value interpolation, iii) outliers' removal, and iv) data segmentation. Given that measurements originated from multiple sensors with staggered start times and acknowledging that the majority of data transmission occurred wirelessly, dataset alignment was achieved by constructing a unified temporal index. Missing values, which resulted primarily from wireless transmission interruptions, were addressed using linear interpolation. Outliers were identified using the Interquartile Range (IQR) method [45], where values falling outside the bounds of 1.5 times the IQR above the third quartile (Q3) and below the first quartile (Q1) were replaced via linear interpolation [46]. Finally, the data were segmented by resampling the continuous time-series data into Daily Profiles (DPs), each comprising 144 measurements.

2.4. Data processing for cluster evaluation

To ensure the clustering process was not biased by non-operational periods, days when the university was closed were excluded from the dataset. Subsequently, all features were scaled to a range of 0 to 1 using the MinMaxScaler method. Given the minimal temporal distortion and time-shifting resulting from the pre-processing, the Ensemble Weighted Distance (EWD), developed by Sha et al. [47], was deemed as a suitable distance metric for this scope. The K-Means algorithm [48] was employed for clustering, which partitions data by assigning each point to the cluster with the nearest centroid, iteratively minimizing the within-cluster sum of squares. This algorithm was selected after a comparative evaluation against other methods, such as K-Medoids and density-based approaches (e.g., DBSCAN), which proved less effective in providing balanced and interpretable partitioning for this specific dataset. The algorithm was executed for a range of clusters (k) from 2 to 20, with a maximum of 300 iterations per run, consistent with scikit-learn library defaults. To quantitatively evaluate performance, the Silhouette score [49] was calculated for each k-value, and the optimal number of clusters was identified as the configuration that maximized this score. While clustering provides a valuable method for grouping similar DPs, the raw cluster assignments alone lack direct interpretability for building operators and do not readily translate into actionable insights. As noted in prior works [50,36] translating cluster outputs into meaningful knowledge requires a post-processing phase and interpretation. Therefore, a post-clustering analysis was performed, which involved two key steps. First, descriptive statistics (e.g., mean, minimum, maximum) were calculated to characterize the central tendency and variability of the profiles within each cluster. Second, the temporal distribution of each cluster was analyzed by examining its frequency of occurrence by month and season, which served to link the identified patterns to specific operational periods (e.g., heating or cooling seasons, occupancy schedules) and climatic conditions.

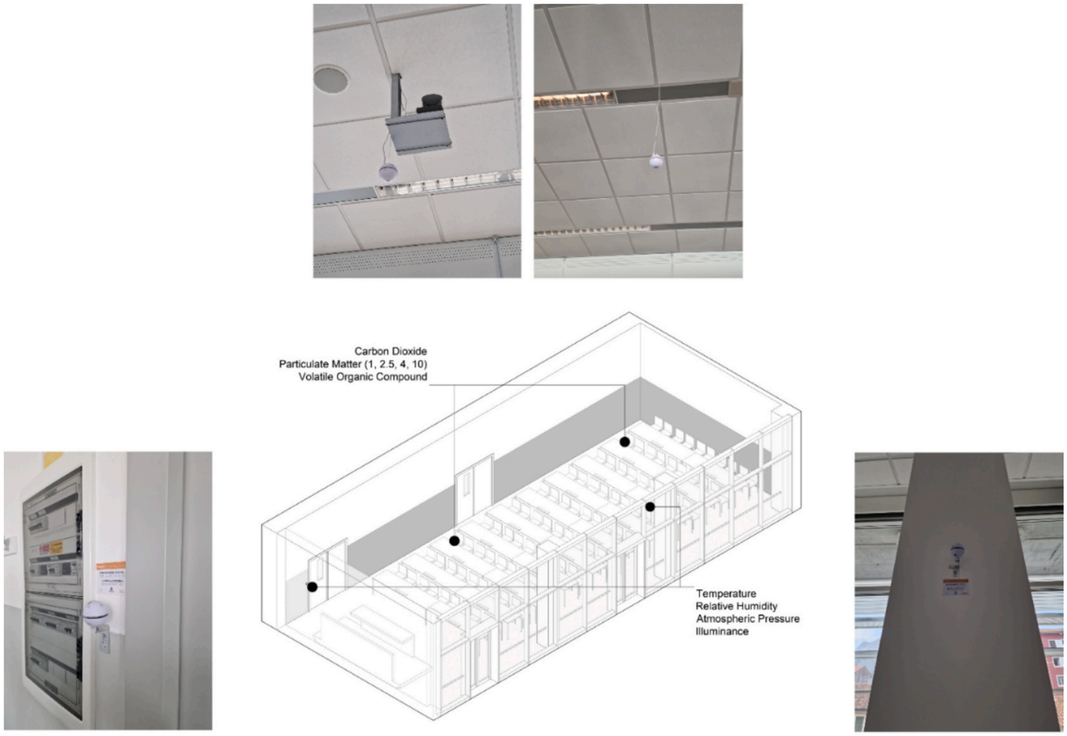


Fig. 4. Axonometric view and sensors' positioning of the monitored classroom.

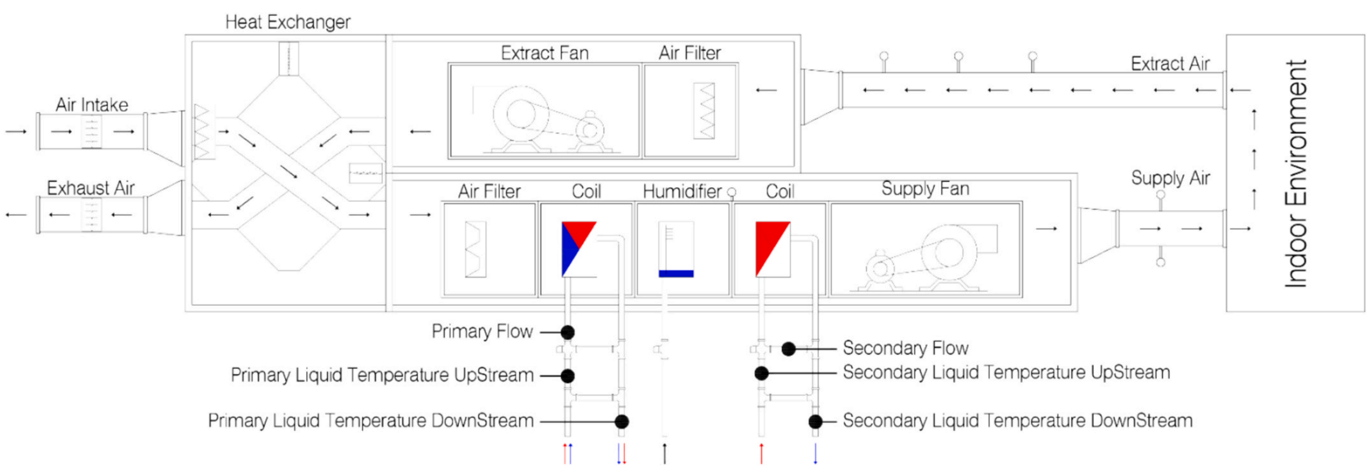


Fig. 5. Air Handling Unit schematic representation with sensor's position.

3. Monitoring results and data interpretation

3.1. Local weather conditions monitoring

Meteorological parameters were recorded by a local weather station equipped with sensors for measuring temperature, humidity, black-bulb temperature, wind speed, wind direction, and direct solar radiation. A threshold of 15 °C for the outdoor Daily Mean Temperature (DMT) [39] was used to classify days into winter and summer periods. The analysis indicated that all days from November to March, 84 % of days in October, and 74 % of days in April were classified as winter days. Days from June to September were classified as summer days.

During the winter season, the mean DMT was approximately 9 °C, and the mean global solar radiation on a horizontal plane was 644.9 W/m^2. During the summer season, these values increased to approximately 21 °C and 1015.0 W/m^2, respectively. The temperature and global solar radiation throughout the monitored period are presented in Fig. 7. The graph effectively highlights the correlation between solar radiation and outdoor temperature, especially during the warmer months where higher radiation corresponds with elevated temperatures.

3.2. IEQ data analysis

This section provides an overview of the IEQ conditions, focusing on temperature, relative humidity, and other air quality-related parameters detailed in section 2.1. The comfort evaluation in this analysis is based on the PMV model defined by EN ISO 7730, ensuring standardized assessment criteria [51,52].Throughout the winter period, the indoor ambient temperature fluctuates daily between 18.6 °C and 21.3 °C, whereas the indoor relative humidity maintains a consistent level of approximately 40 %. (Fig. 8a).

Analyzing the comfort conditions during working hours, Fig. 8c

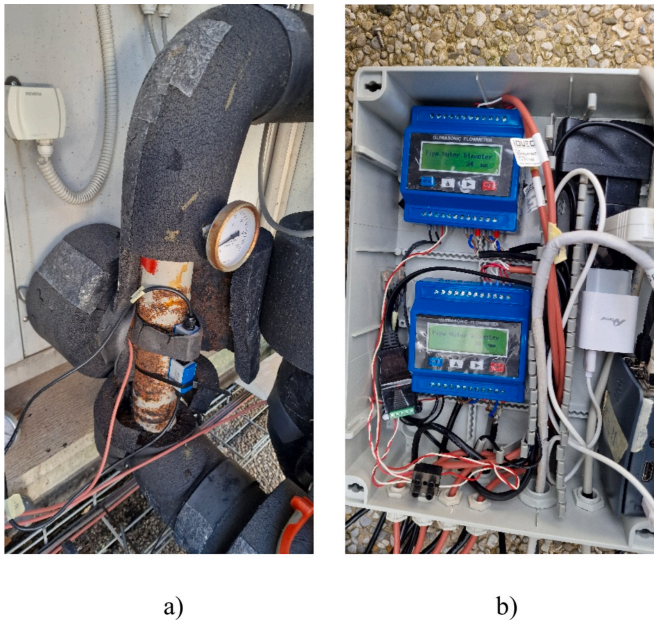


Fig. 6. A) position of the ultrasonic flowmeter on the water pipe of the primary heating/cooling coil; b) data loggers for ahu measurements collection.

presents the distribution of comfort conditions during working hours, showing that 20.51 % of the time corresponds to Comfort Class I, 24.18 % to Class II, and 28.36 % to Class III. Notably, the combined percentage of time within Class I and II comfort levels amounts to 44.69 %. This relatively low value is primarily due to a specific university energy-saving policy whereby the temperature set point during winter is maintained at 20 °C during occupied hours. Additionally, the heating system is turned off during the night, allowing indoor temperatures to drop to around 15 °C, and the programmed start time for the heating system is 6:00 PM. As a result, the recorded temperature data include periods, particularly during the morning warm-up phase, when temperatures fall below the defined comfort thresholds, despite the absence of occupants during those hours. The winter comfort result can inform the development of targeted interventions, including the implementation of more adaptive heating control strategies and improvements in the thermal performance of the existing aluminum-frame, double-glazed windows.

The summer period is characterized by an average indoor temperature that varies between 22.4 °C and 25.9 °C, with a mean relative humidity that ranges from 60.8 % to 69 % (Fig. 8b). The comfort analysis during the summer season shows 62.19 % of the hours within Class II and approximately 12.46 % of the hours inside Class III. For 25.32 % of the hours, the indoor temperature exceeds class III, indicating that users experience overheating (Fig. 8d). This highlights the potential benefit of implementing more detailed shading control strategies to mitigate solar gains and enhance thermal comfort.

Regarding the Indoor Air Quality (IAQ) analysis, the data measured during the winter season, specifically during the days between January 27th and February 2nd, shows average PM10 levels of 3 $\mu g/m^3$ (Fig. 9a). Generally, PM concentration appears to fluctuate throughout the monitoring period, with some peaks aligning with periods of higher occupancy, suggesting a possible influence of occupant presence on particulate matter levels. However, there are also periods where PM10 levels rise independently of occupancy, indicating potential contributions from other sources such as outdoor air infiltration or indoor activities unrelated to occupants.

The VOC levels are, on average, around 350 ppb, with values fluctuating between 200 ppb and 750 ppb (Fig. 9b). VOC levels exhibit noticeable spikes that generally coincide with periods of higher scheduled occupancy, suggesting a link between occupant presence and increased indoor VOC concentrations. The concentration levels can be influenced by various sources including building materials, cleaning products, and furnishings, which might explain the differences in concentration profiles between the front and back sensor locations. The Front_VOC sensor tends to register higher peaks compared to the Back_VOC sensor, possibly due to localized sources. The CO_2 concentration is on average around 560 ppm, with a minimum of 480 ppm and a maximum of 650 ppm (Fig. 9c). The graph illustrates a clear correlation between occupancy and indoor CO_2 concentrations. Peaks in CO_2 levels closely follow periods of increased occupancy, as shown by both

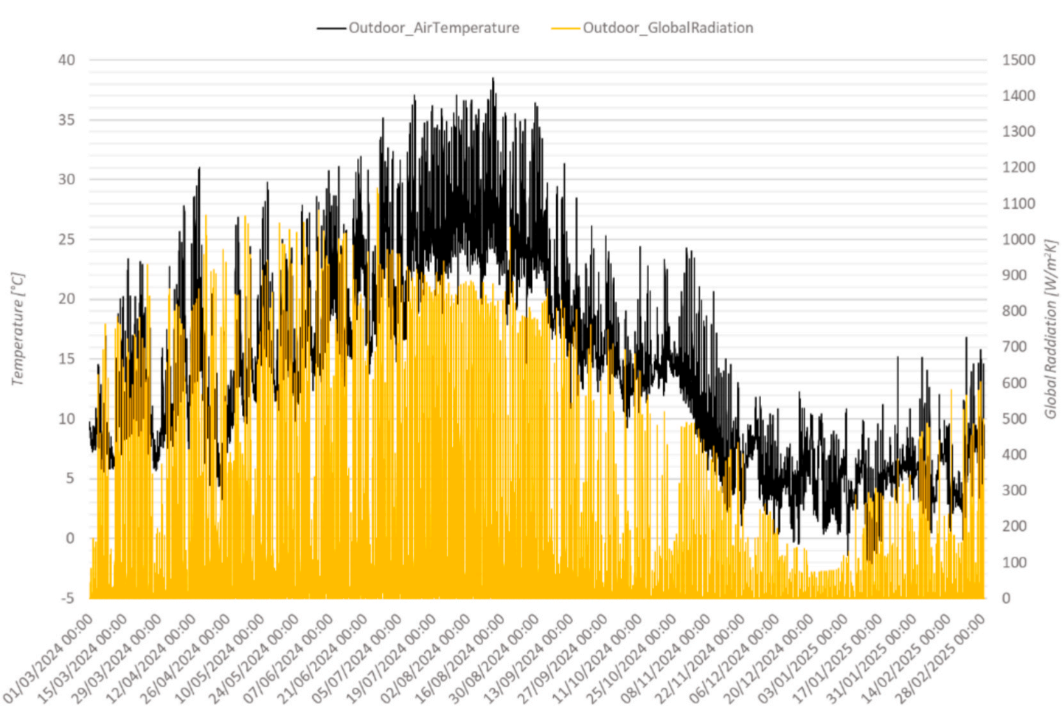


Fig. 7. Outdoor temperature, relative humidity, and solar horizontal radiation, measured by the microclimate weather station located into the university campus.

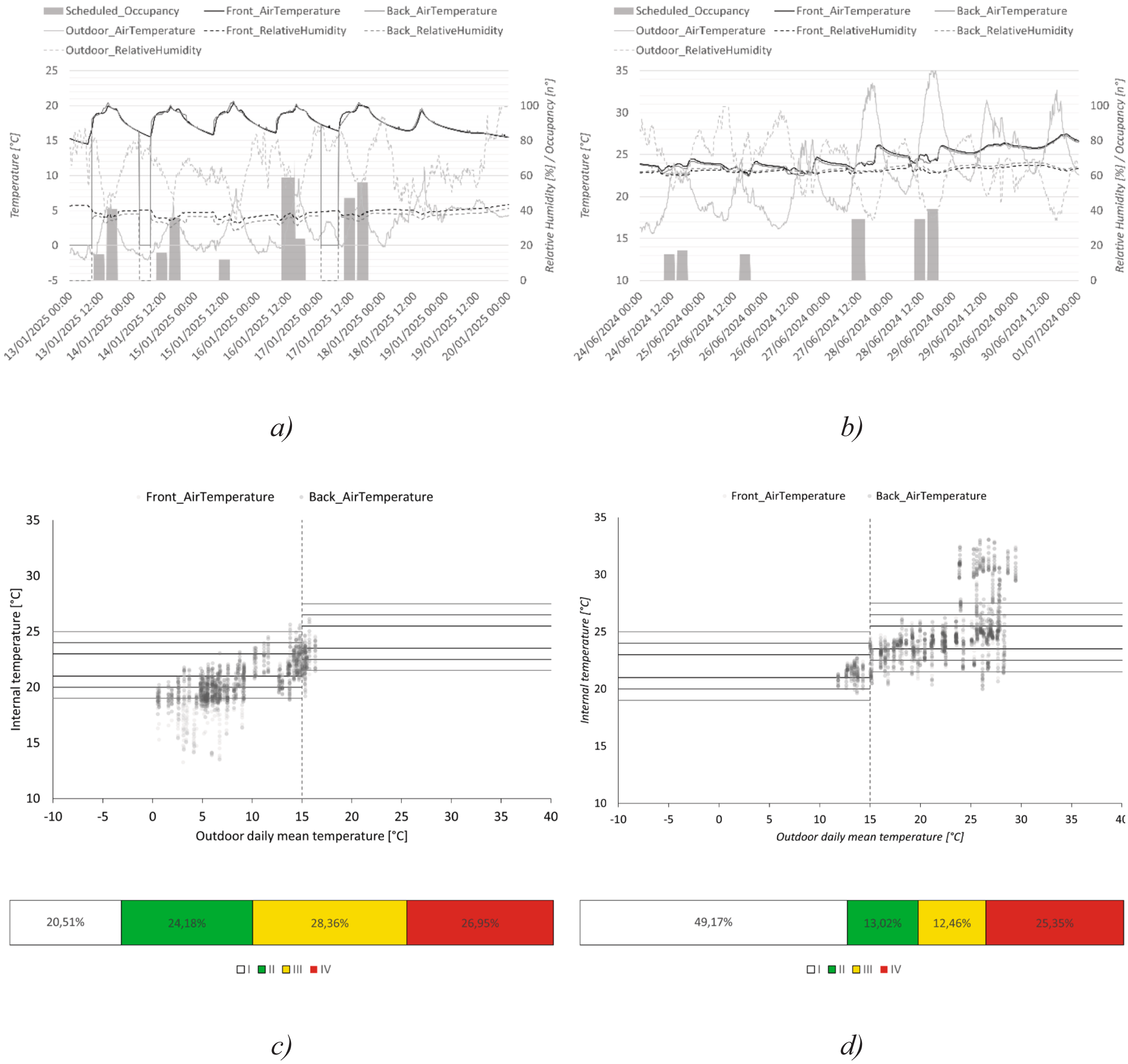


Fig. 8. A) external and internal temperature and humidity distribution during typical winter week– January 13th – January 20th; b) External and internal temperature and humidity distribution during typical summer week – June 24th – July 1st; c) External and internal temperature (scatter chart) and comfort class distribution (bar chart) during opening hours in winter period; d) External and internal temperature (scatter chart) and comfort class distribution (bar chart) during opening hours in summer period.

scheduled occupancy (grey bars) and estimated occupancy (solid and dashed lines). When occupancy rises, CO_2 concentrations increase, reflecting the accumulation of exhaled CO_2 in the space. Conversely, during low or zero occupancy periods, CO_2 levels drop significantly, indicating effective ventilation or air exchange. This relationship confirms that CO_2 concentration serves as a reliable proxy for occupancy estimation and indoor air quality monitoring. Additionally, the similarity between the estimated occupancy lines and scheduled occupancy suggests the estimation method effectively captures the actual presence of occupants, as supported by the CO_2 trends.

Fig. 9d summarizes the IEQ parameters measured from October 2024 to March 2025. The Illuminance level is generally above the optimal level for 11.45 % of the time and in Class II for 31.30 % of the time; as previously stated, the illuminance values are not completely representative since the lighting system can be dimmed based on the needs. The VOC level falls within Class I for 54.41 % of the time, Class II for 37.89 % of the time, and outside the comfort range for 7.70 % of the time. The PM concentration (PM_1, $PM_{2.5}$, PM_{10}, and PM_4) levels consistently remain within the regulatory limits.

The IAQ has been investigated in the summer using the data collected during the days between June 24th and July 1st. The average PM_{10} concentration was equal to 2 μg/m^3 with a peak of 5 μg/m^3 (Fig. 10a). The VOC analysis shows observed values ranging from 100 ppb to 1000 ppb with an average around 500 ppb (Fig. 10b). The average CO_2 level recorded is equal to 500 ppm, with a lower value of 400 ppm and peaks of 700 ppm (Fig. 10c). A comprehensive summary of IEQ parameters measured between March and September 2024 is presented in Fig. 10d. Relative Humidity is consistently within the optimal comfort range. The illuminance exceeds optimal levels for more than 20 % of the time and falls within the Class II levels for more than 38 % of the time. VOC levels are categorized in Class I and II, respectively, for 60.31 % and 22.67 % of the time, with only 17.02 % of the time out of the comfort range. As for the winter season, the PM concentration falls within the comfort range for the totality of the time. Accordingly, the CO_2 concentration is 95.89 % in Class I.

The data analysis was conducted in accordance with established international standards to ensure rigor and comparability. This approach allowed us to establish a clear, quantifiable understanding of

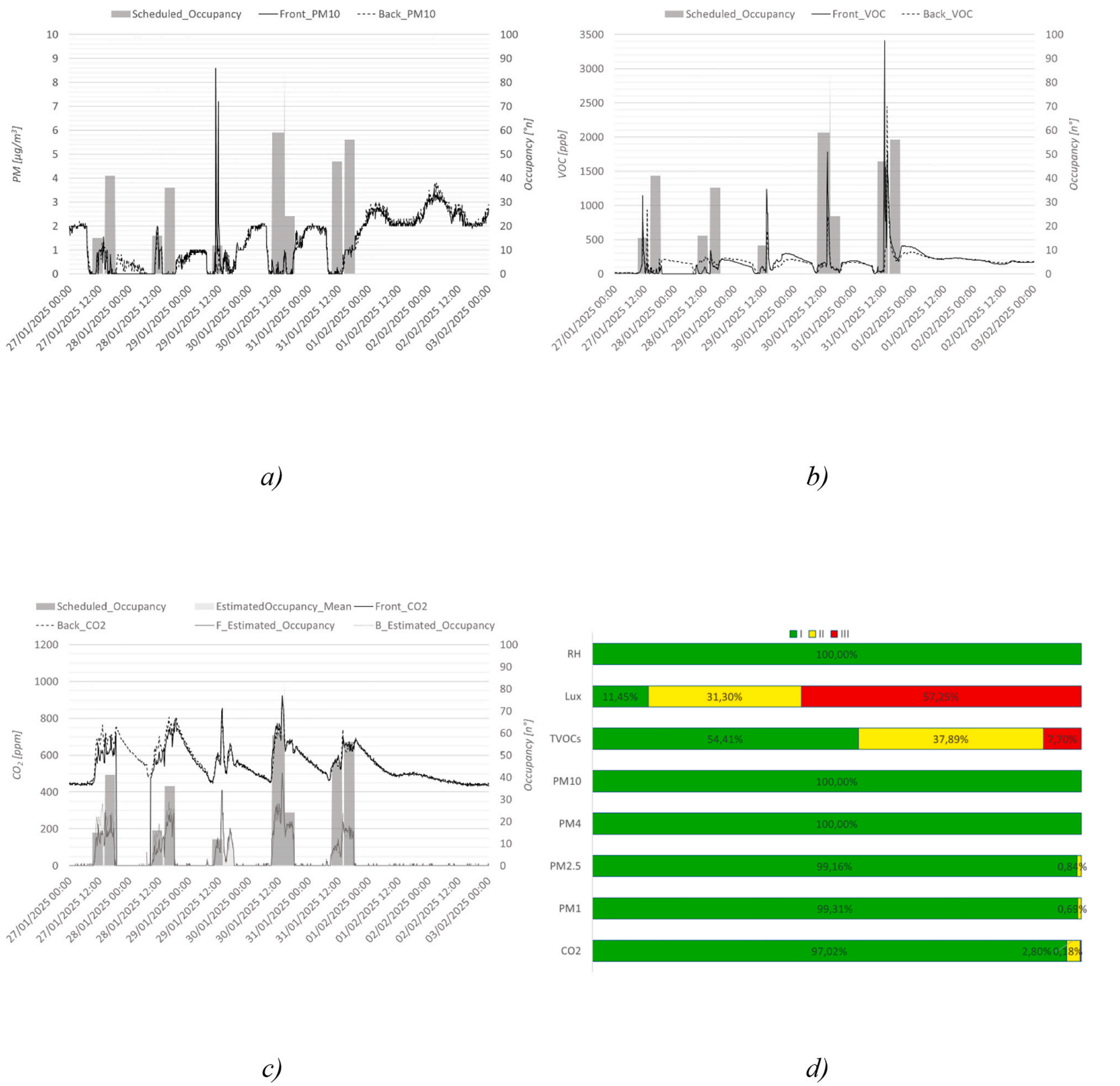


Fig. 9. A) pm_{10} distribution during the week January 27th – February 2nd, 2025; b) TVOC distribution during the week January 27th – February 2nd, 2025; c) CO_2 distribution during the week January 27th – February 2nd, 2025; d) IEQ parameters levels during opening hours in winter period.

indoor environmental conditions, providing a solid foundation for future research that may incorporate subjective comfort assessments and occupant feedback. For this main reason occupant surveys were considered out of scope for this particular study due to time and resource constraints, as well as the study's primary focus on objective, sensor-based data. However future work will incorporate post-occupancy surveys or user feedback to enrich the evaluation of perceived comfort and satisfaction.

3.3. AHU operational data analysis

This section presents an analysis of the AHU operational performance across both summer and winter seasons. The experimental measurement shows that the water temperature level of the primary coil in winter operation varies between 43 °C and 36 °C, respectively, for the inlet and outlet water stream (Fig. 11a), while for the secondary coil, the water temperature ranges between 40 °C and 35 °C (Fig. 11b). During the summer period, the average supply water temperature was 12 °C, with peak values reaching 14 °C, while the mean return water temperature was 16 °C, peaking at 19 °C (Fig. 11c). For the secondary coil, the inlet and outlet water temperatures were 27 °C and 33 °C, respectively, for the supply and return streams (Fig. 11d).

Throughout the whole monitoring campaign, the average electrical fan power absorption was constant and equal to 5.82 kW, reflecting the operation of a Constant Air Volume (CAV) system. The electrical fan power intensity monitoring shows clearly the schedule of operation of the AHU (Figs. 12a and b), which extends from 7 a.m. to 6p.m., providing ventilation to the spaces one hour before the expected occupancy and stopping operating at 6:30p.m. The daily electrical energy fan consumption was equal to 64.30 kWh.

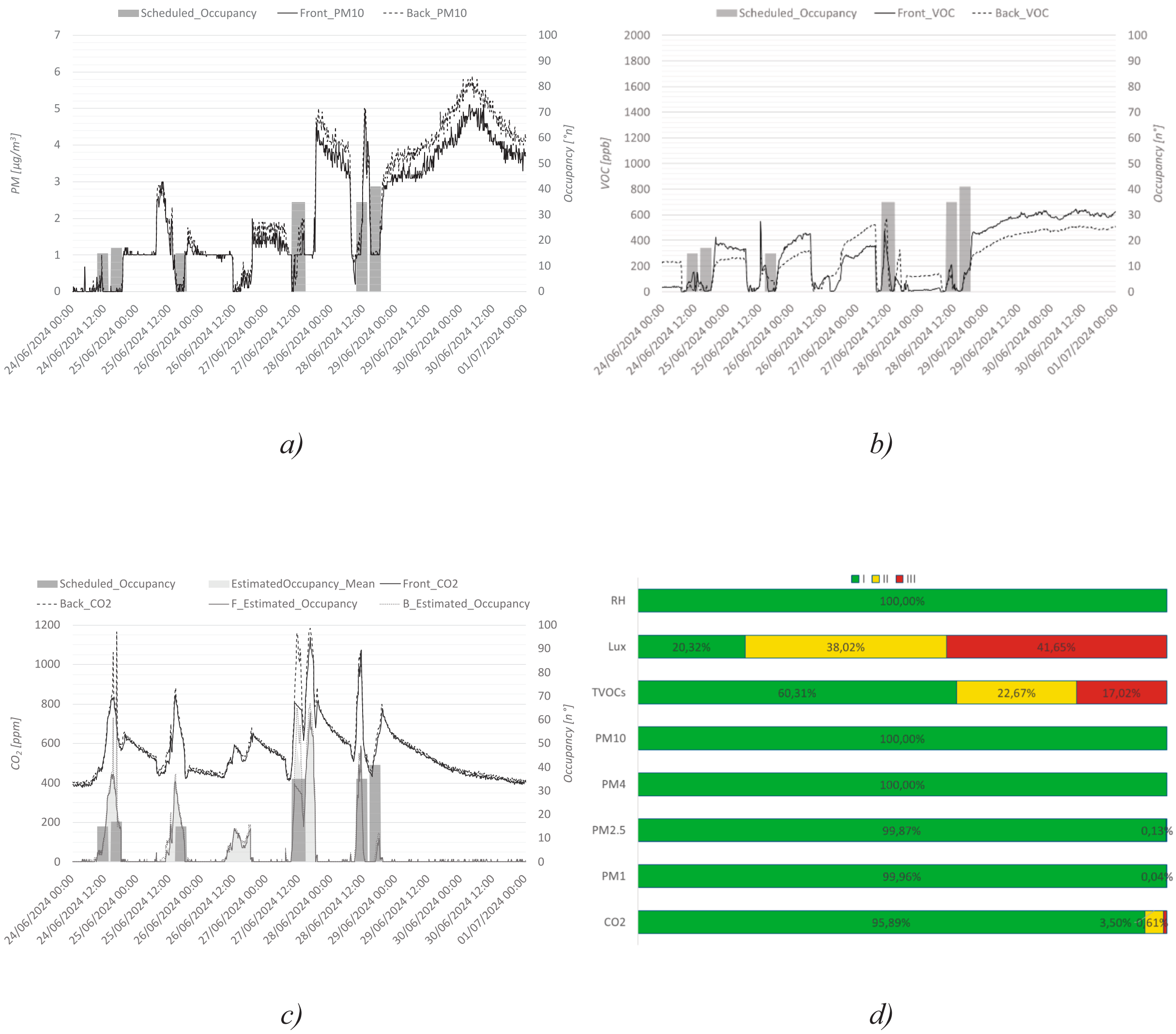


Fig. 10. A) pm10 distribution during the week june 24th – July 1st, 2024; b) TVOC distribution during the week June 24th – July 1st, 2024; c) CO_2 distribution during the week June 24th – July 1st, 2024; d) IEQ parameters levels during opening hours in summer period.

4. Clustering results and daily patterns

4.1. Indoor temperature clustering analysis

This section details the application of clustering methodologies to extract inherent IEQ patterns from an extensive dataset, to support subsequent building performance evaluation and diagnosis. The comprehensive dataset subjected to this analysis comprised 388 complete DPs, with each day represented by 144 discrete measurements, yielding a total of 55,872 data points. These profiles were derived from monitoring periods spanning from 4th April 2024 to 3rd March 2025, for the front sensor, and from 26th March 2024 to 14th February 2025, for the back sensor. The final dataset of 388 complete DPs was obtained from an initial pool of 786 monitoring days by excluding university closing days and systematically discarding profiles with more than 12 consecutive missing measurements. Following this filtering, a further 200 outlier data points (approximately 0.36 %) were identified and removed using the IQR method. Using the K-Means algorithm, four was identified as the optimal number of clusters, yielding the highest Silhouette Score of 0.4867. This score reflects the low variability between daily profiles when the HVAC system is active; however, the resulting clusters still correspond to distinct and interpretable operational modes. Cluster balance was also assessed to ensure the algorithm identified meaningful groupings and avoided the formation of spurious single-day clusters or one dominant cluster with several minor ones. The overall results of this clustering process, including the relative proportion of days in each cluster and their monthly distribution, are presented in Fig. 13a and Fig. 13c, respectively. The specific temperature DPs characterizing each cluster are shown in Fig. 13b. Cluster 1 is characterized by a temperature profile that decreases until 7:00 a.m., followed by a rapid temperature rise upon the activation of the HVAC system. It exhibits a clear temperature dip in the early morning hours (around 05:00 to 08:00) followed by a steady increase during the day, peaking in the afternoon before declining again. Besides the HVAC operation influence, this pattern suggests the impact of solar gains, as well as reduced occupancy and HVAC activity during nighttime and early morning, resulting in cooler temperatures. The fluctuation of the average cluster temperature profile is approximately 2.5 °C, with the lowest value of 17.5 °C occurring at 6:00 a.m. This pattern is associated with the winter period when the AHU operates in heating mode.

Cluster 2 represents the temperature profile during the middle seasons, spring and autumn. It shows relatively stable temperatures overnight and a gradual temperature increase starting later in the morning, peaking slightly in the afternoon before decreasing. This profile remains relatively constant throughout the day with a temperature variation within 1.5 °C, varying between 20.5 °C and 22 °C. In this cluster, the

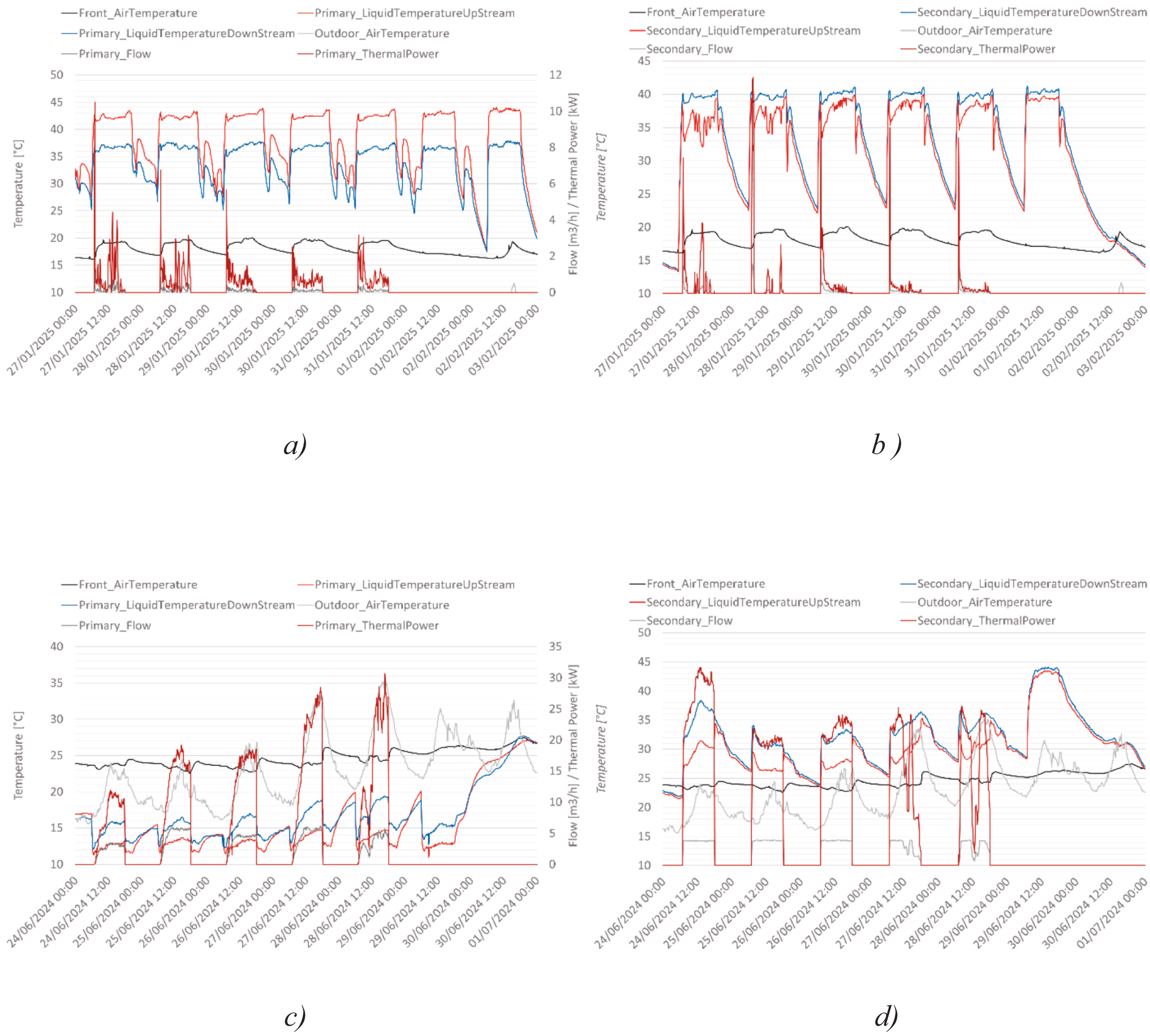


Fig. 11. Parameters measured in the primary coil (a) and secondary coil (b) of the AHU in winter conditions during the week of January 27th – February 2nd, 2025; parameters measured in the primary coil (c) and secondary coil (d) of the AHU in winter condition during the week June 24th – 30th 2024.

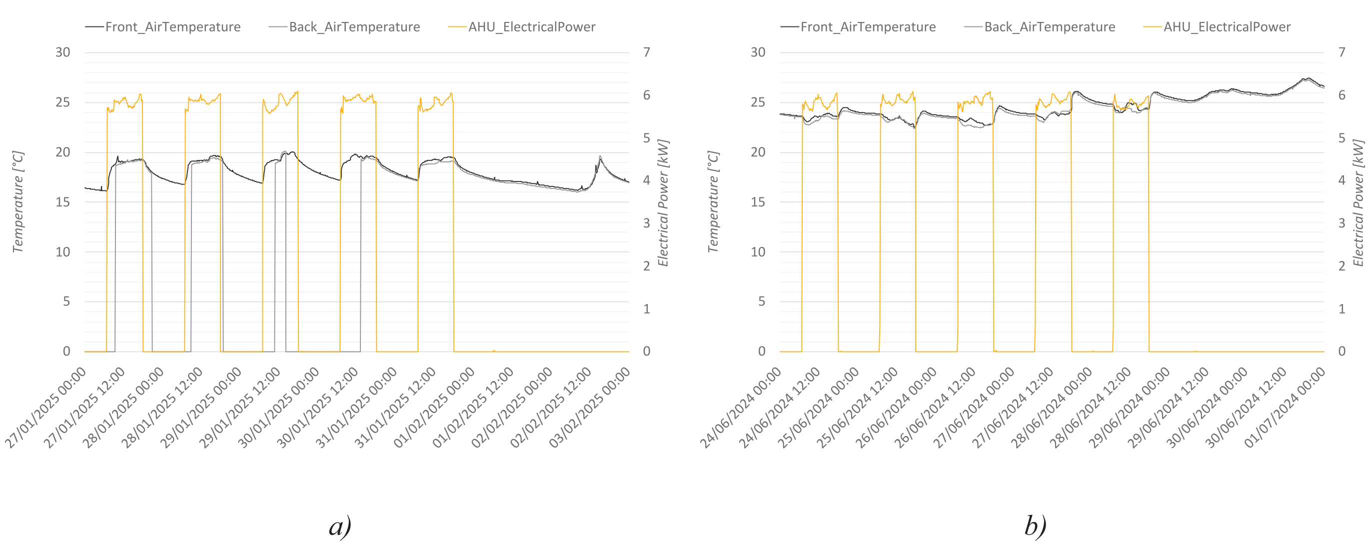
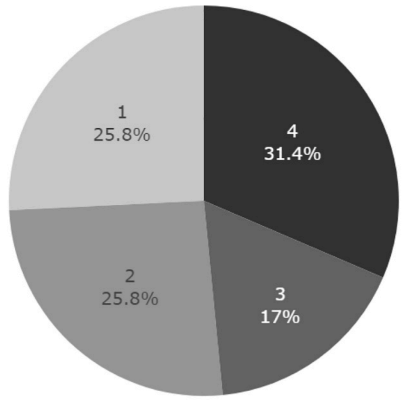
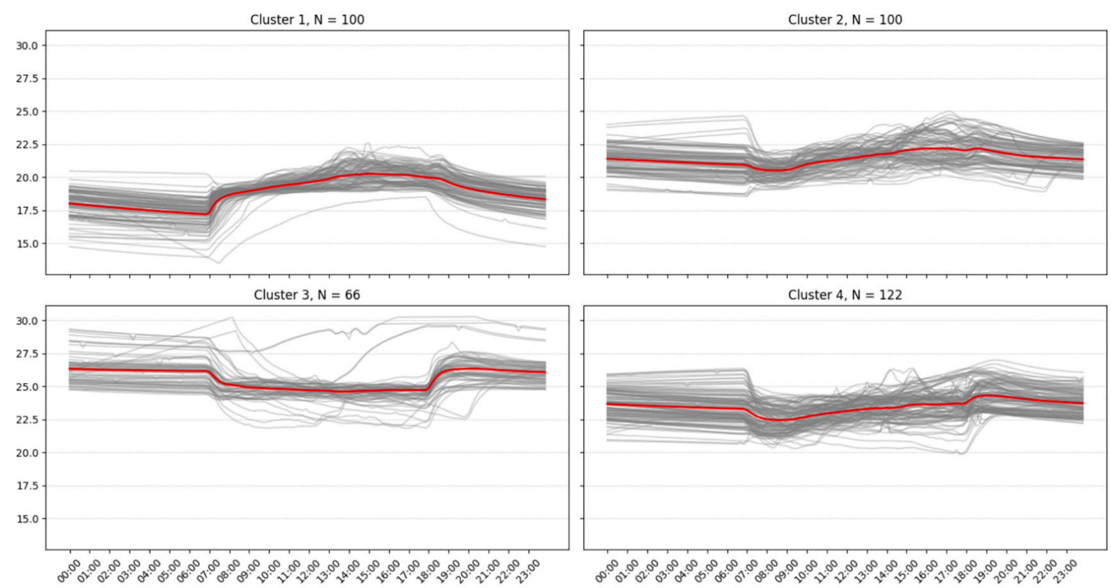


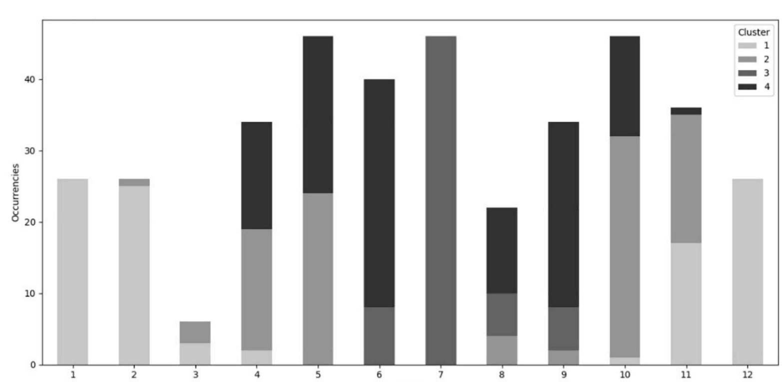
Fig. 12. AHU electrical energy consumption and room air temperature between January 27th – and February 2nd, 2025; a) and during June 24th and July 1st, 2024b).



a)



b)



c)

Fig. 13. A) temperature cluster proportion, b) temperature dps of k-means cluster associated with own segmented data. the grey lines represent the data objects that were assigned to that cluster and the red lines represent the temperature profile for that cluster, c) temperature cluster monthly distribution.

ventilation system provided only mechanical ventilation and did not modulate the air temperature supply, except throughout the heat recovery unit.

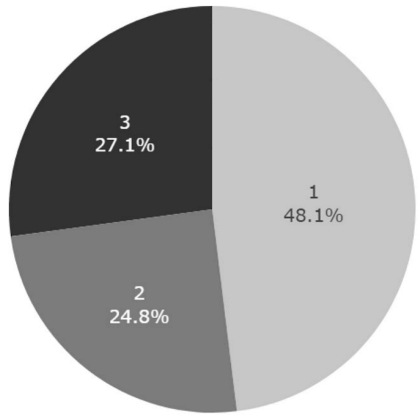
Cluster 3 represents summer operation, from June to September. It displays generally higher temperatures throughout the day with less variability overnight. The temperature drop during the day is due to the HVAC cooling system operation and the shading mechanisms that mitigate solar gains during peak sunlight hours. This cluster exhibits a temperature range of approximately 1.5 °C, with a notable feature being a rapid temperature increase within thirty minutes after AHU shutdown, attributable to high solar and internal loads. Cluster 4 presents a pattern similar to Cluster 2 but with a slightly earlier temperature dip in the morning and a more pronounced midday drop. This could indicate precooling through mechanical ventilation. The temperature increase during the day is due to increase solar radiation and occupancy. In this cluster, the temperature variation remains within a range of 2 °C. A notable temperature increase occurs upon deactivation of the AHU at 6:00 PM, attributable to solar radiation impacting the west-facing glazing.

4.2. AHU monitoring clustering analysis

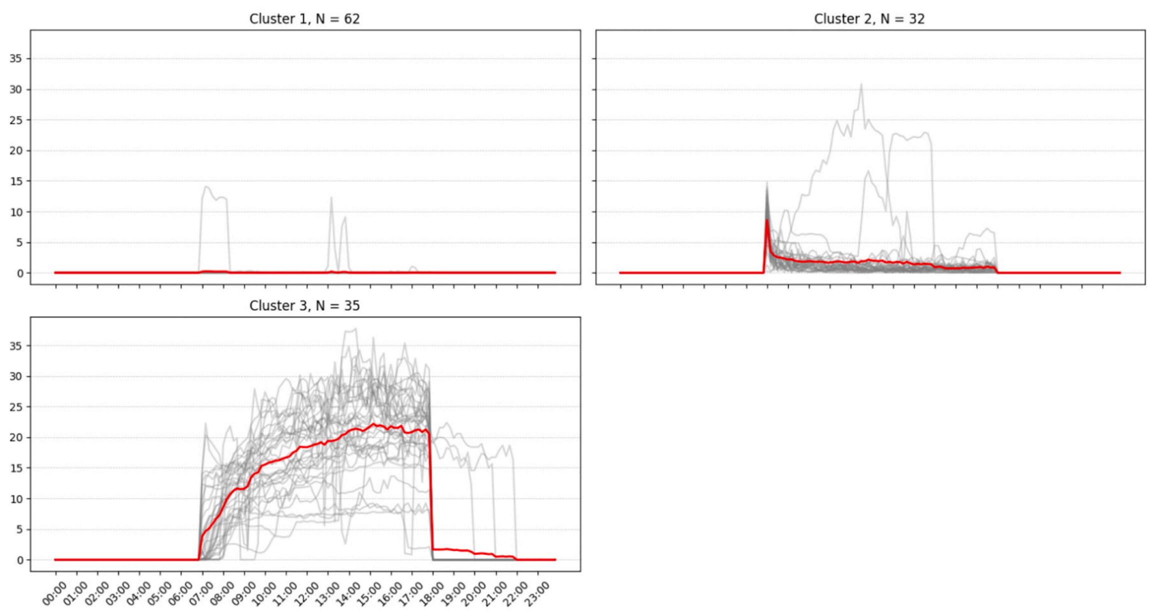
The results of the clustering analysis applied to AHU thermal power are summarized in Fig. 14. The analysis was based on 129 complete days, each comprising 144 measurements, resulting in a total of 18,576 measurements. These profiles were collected during the monitoring periods spanning from 24th June 2024 to 3rd March 2025. Closing days and incomplete DPs were excluded from the final dataset. The optimal number of clusters, determined using the K-Means algorithm, was 3, achieving a Silhouette Score of 0.8015. A cluster balance analysis was also conducted, which confirmed that while Cluster 1 accounted for 48 % of the days (Fig. 14a), the other two clusters share the remaining of the dataset with 24.8 % and 27.1 %, respectively. The monthly distribution of these clusters is shown in Fig. 14c. The thermal power DPs for each cluster are illustrated in Fig. 14b. Cluster 1 is characterized by a minimal thermal energy consumption, indicating that the AHU provides only ventilation. This pattern is representative of the typical intermediate seasons when the external air temperature was close to the required supply air temperature. Cluster 2 suggests a short, intense event or activity occurring in the morning, such as a brief system startup after which conditions return to a baseline inactive state. In detail it is evident a typical power peak of 8 kW during start-up and a mean power of approximately 3 kW throughout the day. Cluster 3 reflects the typical summer day, where activity ramps up in the morning, remains elevated during business hours, and ceases in the evening. The shape of this curve suggests a strong correlation with HVAC operation, occupant presence and solar gains. The profile exhibits an upward trend, reaching a peak of 22 kW between 2:00p.m. and 3:00 p.m.

5. Discussions and final remarks

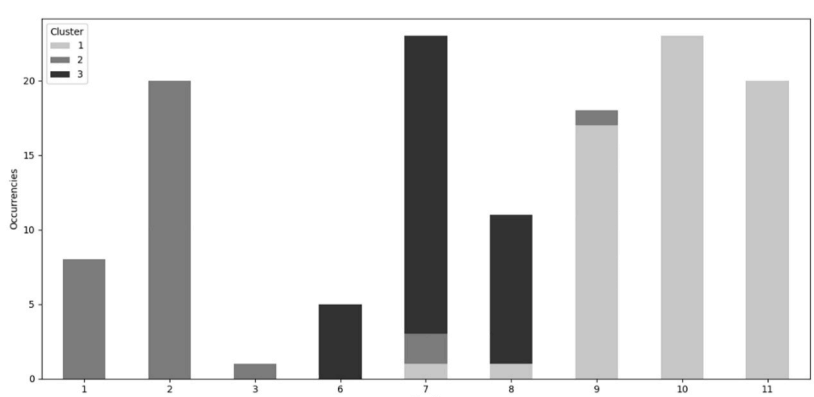
This study presents a comprehensive assessment of IEQ and energy efficiency in higher educational buildings, utilizing long-term monitoring data collected in a university classroom at Politecnico di Milano university, Italy. The experimental campaign quantified indoor thermal comfort conditions and air quality parameters, while also examining the energy-related performance of the dedicated CAV AHU through clustering analysis. The research was conducted with a twofold objective: the first was the evaluation of the IEQ and energy use under real operational conditions; the second was the identification and characterization of typical patterns for indoor air temperature and energy use through data-driven clustering methods. The monitoring was carried out between June 2024 and March 2025. The results demonstrate that a CAV AHU operating on a fixed schedule fails to consistently maintain optimal comfort conditions. Long-term measurements revealed that indoor temperatures fell outside comfort class II for 50 % of occupied hours in winter, while overheating occurred during 35 % of occupied hours in summer. This highlights a clear mismatch between the fixed operation of the HVAC system and the varying comfort needs of the occupant. Therefore, targeted measures, such as optimizing control strategies, implementing adaptive setpoints, or upgrading HVAC components, are necessary to better align and maintain system energy efficiency with occupant comfort requirements. Additionally, all actions should be systematically recorded in a digital logbook to ensure traceability, facilitate performance monitoring, and support continuous improvement [53,54]. While the AHU maintained acceptable levels for most air pollutants, such as PM and TVOC, it was unable to respond dynamically to high occupancy levels, leading to frequent spikes in CO_2 concentration. This highlights the importance of real-time monitoring data for assessing indoor comfort conditions and their relationship with AHU setpoints and operational schedules. In winter, the AHU setpoint should be modulated according to the expected internal gains (e.g., occupancy), increasing the temperature setpoint during low-occupancy periods and reducing it during peak occupancy. Similarly, in summer, the cooling setpoint should be adapted to both occupancy levels and external temperature to prevent overheating. Despite adequate pollutant control in average conditions, peak occupancy scenarios require a better balance between fresh and exhaust air to maintain acceptable IAQ levels. To address these operational inefficiencies, a K-Means clustering approach was employed to detect typical usage patterns. The cluster analysis on indoor temperature data identified four distinct operational modes—winter heating, summer cooling, and two intermediate seasons with differing thermal characteristics. A parallel analysis of AHU thermal power data revealed three clusters, corresponding to heating, cooling, and ventilation-only operations. The quality of these clusters was quantitatively assessed using Silhouette scores, yielding 0.4879 for the indoor temperature patterns and 0.8015 for the AHU thermal power profiles. These values indicate satisfactory and strong cluster separation, respectively. The resulting patterns represent operational signatures or behavioral benchmarks of the monitored classroom and its associated AHU, derived directly from empirical data. These data-driven benchmarks provide valuable insights for improving building control strategies. Specifically, the average profile of each cluster can be used to fine-tune seasonal baseline schedules and control setpoints in the Building Management System (BMS). Moreover, the continuous monitoring of deviations between real-time conditions and expected cluster-based profiles allows the implementation of automated Fault Detection and Diagnosis (FDD) methodologies, in alignment with approaches already proposed in the literature [30]. Such strategies enable a shift from reactive to proactive building management by facilitating rapid identification of anomalies, equipment malfunctions, or performance degradation. The adopted methodological approach—combining detailed monitoring and unsupervised clustering of both IAQ and energy-related data—establishes a robust and scalable framework for evaluating building performance under actual operational conditions. The results emphasize the crucial role of clustering techniques in identifying representative behavioral models in large datasets, offering a foundation for the development of adaptive control strategies. These strategies could enable real-time adjustment of ventilation and temperature settings based on occupancy and outdoor climate, thereby enhancing both thermal comfort and energy efficiency. Future research will aim to generalize this methodology across multiple case studies with different system configurations. Planned extensions include the integration of real-time occupancy measurements and the implementation of predictive control systems. These advancements are expected to support energy-efficient, occupant-centric renovation strategies, ultimately contributing to improved comfort, reduced operational costs, and sustainable facility management in educational buildings. The outcomes of this study contribute directly to long-term renovation planning aimed at maintaining high IEQ levels with optimized energy use. An occupant-focused, data-informed, and energy-efficient operational approach could



a)



b)



c)

Fig. 14. Cluster distribution in terms of a) Thermal power cluster share, b) Thermal power DPs of K-Means cluster associated with own segmented data. The grey lines represent the data objects that were assigned to that cluster and the red lines represent the energy profile for that cluster c) Thermal power cluster monthly distribution. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

significantly improve the learning environment and overall well-being of students [55,56].

CRediT authorship contribution statement

Graziano Salvalai: Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition. **Roberto Villa:** Writing – original draft, Visualization, Investigation, Data curation. **Manuela Grecchi:** Writing – review & editing, Investigation. **Gabriele Bernardini:** Writing – review & editing, Methodology. **Marco D'Orazio:** Writing – review & editing, Project administration, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Funded by the European Union-Next Generation EU, Mission 4 Component 1 CUP: D53D23003630006.

Data availability

The data that has been used is confidential.

References

[1] European Commission Directive (EU) 2024/1275 of the European Parliament and of the Council of 24 April 2024 on the Energy Performance of Buildings (Recast).
[2] H. Shin, M. Kang, S.H. Mun, Y. Kwak, J.H. Huh, A Study on Changes in Occupants' Thermal Sensation Owing to CO_2 Concentration Using PMV and TSV, Build. Environ. 187 (2021) 107413, https://doi.org/10.1016/J.BUILDENV.2020.107413.
[3] A. Verma, V. Gupta, K. Nihar, A. Jana, R.K. Jain, C. Deb, Tropical Climates and the Interplay between IEQ and Energy Consumption in Buildings: A Review, Build. Environ. 242 (2023) 110551, https://doi.org/10.1016/j.buildenv.2023.110551.
[4] B. Simanic, B. Nordquist, H. Bagge, D. Johansson, Indoor Air Temperatures, CO2 Concentrations and Ventilation Rates: Long-Term Measurements in Newly Built Low-Energy Schools in Sweden, Journalof Building Engineering 25 (2019) 100827, https://doi.org/10.1016/j.jobe.2019.100827.
[5] M.S.J. Talukdar, T.H. Talukdar, M.K. Singh, M.A. Baten, M.S. Hossen, Status of Thermal Comfort in Naturally Ventilated University Classrooms of Bangladesh in Hot and Humid Summer Season, Journal of Building Engineering 32 (2020) 101700, https://doi.org/10.1016/j.jobe.2020.101700.
[6] S.A. Ghita, T. Catalina, Energy Efficiency versus Indoor Environmental Quality in Different Romanian Countryside Schools, Energy Build. 92 (2015) 140–154, https://doi.org/10.1016/j.enbuild.2015.01.049.
[7] K. Kuga, J. Zhu, P. Wargocki, K. Ito, The Effects of Air Temperature and Background CO2 Concentration on Human Metabolic CO2 Emissions, Build. Environ. 276 (2025) 112857, https://doi.org/10.1016/J.BUILDENV.2025.112857.
[8] Y. Zhao, D. Li, Multi-Domain Indoor Environmental Quality in Buildings: A Review of Their Interaction and Combined Effects on Occupant Satisfaction, Build. Environ. 228 (2023) 109844, https://doi.org/10.1016/J.BUILDENV.2022.109844.
[9] Y. Geng, W. Ji, B. Lin, Y. Zhu, The Impact of Thermal Environment on Occupant IEQ Perception and Productivity, Build. Environ. 121 (2017) 158–167, https://doi.org/10.1016/j.buildenv.2017.05.022.
[10] S.P. Corgnati, R. Ansaldi, M. Filippi, Thermal Comfort in Italian Classrooms under Free Running Conditions during Mid Seasons: Assessment through Objective and Subjective Approaches, Build. Environ. 44 (2009) 785–792, https://doi.org/10.1016/j.buildenv.2008.05.023.
[11] Y. Wang, G. Shen, A. Mehmani, Indoor Environmental Wellness Index (IEW-Index): Towards Intelligent Building Systems Automation and Optimization, Build. Environ. 247 (2024) 111039, https://doi.org/10.1016/J.BUILDENV.2023.111039.
[12] ISO Standard (2005).
[13] BS EN 15251 BS EN 15251. *Indoor environmental input parameters for design and assessment of energy performance of buildings* **2007**.
[14] D. Khovalyg, O.B. Kazanci, H. Halvorsen, I. Gundlach, W.P. Bahnfleth, J. Toftum, B.W. Olesen, Critical Review of Standards for Indoor Thermal Environment and Air Quality, Energy Build. 213 (2020) 109819, https://doi.org/10.1016/J.ENBUILD.2020.109819.
[15] S.S. Korsavi, A. Montazami, D. Mumovic, The Impact of Indoor Environment Quality (IEQ) on School Children's Overall Comfort in the UK; a Regression Approach, Build. Environ. 185 (2020) 107309, https://doi.org/10.1016/j.buildenv.2020.107309.
[16] J. Kim, T. Hong, J. Jeong, M. Lee, M. Lee, K. Jeong, C. Koo, J. Jeong, Establishment of an Optimal Occupant Behavior Considering the Energy Consumption and Indoor Environmental Quality by Region, Appl. Energy 204 (2017) 1431–1443, https://doi.org/10.1016/J.APENERGY.2017.05.017.
[17] Open Data Immobili PA - MEF Dipartimento Dell'Economia Available online: https://www.de.mef.gov.it/it/attivita_istituzionali/patrimonio_pubblico/censimento_immobili_pubblici/open_data_immobili/index.html (accessed on 10 March 2025).
[18] Special Report 11 (2023) (2023) 78.
[19] M. García-Monge, B. Zalba, R. Casas, E. Cano, S. Guillén-Lambea, B. López-Mesa, I. Martínez, Is IoT Monitoring Key to Improve Building Energy Efficiency? Case Study of a Smart Campus in Spain, Energy Build. 285 (2023) 112882, https://doi.org/10.1016/J.ENBUILD.2023.112882.
[20] L. Pistore, F. Cappelletti, P. Romagnoni, A. Zonta, Assessment of the IEQ in Two High Schools by Means of Monitoring, Surveys and Dynamic Simulation. Energy Procedia 82 (2015) 519–525, https://doi.org/10.1016/J.EGYPRO.2015.11.864.
[21] C.M. Rodríguez, M.C. Coronado, J.M. Medina, Thermal Comfort in Educational Buildings: The Classroom-Comfort-Data Method Applied to Schools in Bogotá, Colombia. Build Environ 194 (2021) 107682 https://doi.org/10.1016/j.buildenv.2021.107682.
[22] M.C. Lee, K.W. Mui, L.T. Wong, W.Y. Chan, E.W.M. Lee, C.T. Cheung, Student Learning Performance and Indoor Environmental Quality (IEQ) in Air-Conditioned University Teaching Rooms, Build Environ 49 (2012) 238–244, https://doi.org/10.1016/J.BUILDENV.2011.10.001.
[23] I. Asadi, N. Mahyuddin, P. Shafigh, A Review on Indoor Environmental Quality (IEQ) and Energy Consumption in Building Based on Occupant Behavior, Facilities 35 (2017) 684–695, https://doi.org/10.1108/F-06-2016-0062.
[24] T. Parkinson, A. Parkinson, R. de Dear, Continuous IEQ Monitoring System: Context and Development, Build. Environ. 149 (2019) 15–25, https://doi.org/10.1016/J.BUILDENV.2018.12.010.
[25] G. Vergerio, C. Becchio, Pursuing Occupants' Health and Well-Being in Building Management: Definition of New Metrics Based on Indoor Air Parameters, Build. Environ. 223 (2022) 109447, https://doi.org/10.1016/J.BUILDENV.2022.109447.
[26] C. Bolchini, A. Geronazzo, E. Quintarelli, Smart Buildings: A Monitoring and Data Analysis Methodological Framework, Build. Environ. 121 (2017) 93–105, https://doi.org/10.1016/J.BUILDENV.2017.05.014.
[27] Y. Liu, X. Li, C. Sun, Q. Dong, Q. Yin, B. Yan, An Indoor Thermal Comfort Model for Group Thermal Comfort Prediction Based on K-Means++ Algorithm, Energy Build. 327 (2025) 115000, https://doi.org/10.1016/J.ENBUILD.2024.115000.
[28] A. Rajabi, M. Eskandari, M.J. Ghadi, L. Li, J. Zhang, P. Siano, A Comparative Study of Clustering Techniques for Electrical Load Pattern Segmentation, Renew. Sustain. Energy Rev. 120 (2020) 109628, https://doi.org/10.1016/J.RSER.2019.109628.
[29] H.B. Gunay, Z. Shi, Cluster Analysis-Based Anomaly Detection in Building Automation Systems, Energy Build. 228 (2020) 110445, https://doi.org/10.1016/J.ENBUILD.2020.110445.
[30] R. Yan, Z. Ma, G. Kokogiannakis, Y. Zhao, A Sensor Fault Detection Strategy for Air Handling Units Using Cluster Analysis, Autom. Constr. 70 (2016) 77–88, https://doi.org/10.1016/J.AUTCON.2016.06.005.
[31] F. Troncoso-Pastoriza, M. Martínez-Comesaña, A. Ogando-Martínez, J. López-Gómez, P. Eguía-Oller, L. Febrero-Garrido, IoT-Based Platform for Automated IEQ Spatio-Temporal Analysis in Buildings Using Machine Learning Techniques, Autom. Constr. 139 (2022) 104261, https://doi.org/10.1016/J.AUTCON.2022.104261.
[32] B. Dong, K. Liu, C. Lei, R. Song, Remote Monitoring and Diagnosis for Building Maintenance Units Based on Internet of Things System, Appl. Sci. 15 (2025) doi: 10.3390/app15094829.
[33] Y. Wu, X. Zhou, M. Qian, Y. Jin, H. Sun, D. Yan, Novel Approach to Typical Air-Conditioning Behavior Pattern Extraction Based on Large-Scale VRF System Online Monitoring Data, Journal of Building Engineering 69 (2023) 106243, https://doi.org/10.1016/J.JOBE.2023.106243.
[34] Q. Lu, X. Xie, A.K. Parlikad, J.M. Schooling, Digital Twin-Enabled Anomaly Detection for Built Asset Monitoring in Operation and Maintenance, Autom. Constr. 118 (2020) 103277, https://doi.org/10.1016/J.AUTCON.2020.103277.
[35] M. D'Orazio, E. Di Giuseppe, G. Bernardini, Occupant Density Impact on Building Maintenance: Data-Driven Approach for University Buildings, Autom. Constr. 141 (2022) 104451, https://doi.org/10.1016/J.AUTCON.2022.104451.
[36] B.W. Hobson, H.B. Gunay, A. Ashouri, G.R. Newsham, Clustering and Motif Identification for Occupancy-Centric Control of an Air Handling Unit, Energy Build. 223 (2020) 110179, https://doi.org/10.1016/J.ENBUILD.2020.110179.
[37] DIGITMAN – AI POWERED PLATFORM TO IMPROVE THE MAINTENANCE OF BUILDINGS Available online: https://www.digitman-project.net/ (accessed on 10 March 2025).
[38] Organization 58 (2021).
[39] UNI EN 16798-1:2019 - UNI Ente Italiano Di Normazione Available online: https://store.uni.com/uni-en-16798-1-2019 (accessed on 24 March 2025).
[40] UNI EN 16798-3:2018 - UNI Ente Italiano Di Normazione Available online: https://store.uni.com/uni-en-16798-3-2018 (accessed on 24 March 2025).
[41] EN 15251:2007 - UNI Ente Italiano Di Normazione Available online: https://store.uni.com/en-15251-2007 (accessed on 24 March 2025).
[42] Lighting Guide 05: Lighting for Education (2011) | CIBSE Available online: https://www.cibse.org/knowledge-research/knowledge-portal/lighting-guide-05-lighting-for-education-2011 (accessed on 24 March 2025).
[43] *Light and Lighting. Lighting of Work Places. Part 1 Indoor Work Places*; British Standards Institution, 2021; ISBN 9780539027518.

[44] M.C. Peel, B.L. Finlayson, T.A. McMahon, Updated World Map of the Köppen-Geiger Climate Classification, Hydrol. Earth Syst. Sci. (2007), https://doi.org/10.5194/hess-11-1633-2007.
[45] I. Range, The Concise Encyclopedia of Statistics (2008) 266–267, https://doi.org/10.1007/978-0-387-32833-1_200.
[46] D. Nečas, Basic Data Processing, Quantitative Data Processing in Scanning Probe Microscopy: SPM Applications for Nanometrology: Second Edition (2018) 65–96, https://doi.org/10.1016/B978-0-12-813347-7.00004-2.
[47] X. Sha, Z. Ma, S. Sethuvenkatraman, W. Li, A New Clustering Method with an Ensemble of Weighted Distance Metrics to Discover Daily Patterns of Indoor Air Quality, Journal of Building Engineering 76 (2023) 107289, https://doi.org/10.1016/J.JOBE.2023.107289.
[48] S.P. Lloyd, Least Squares Quantization in PCM, IEEE Trans. Inf. Theory 28 (1982) 129–137, https://doi.org/10.1109/TIT.1982.1056489.
[49] P.J. Rousseeuw, Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis, J. Comput. Appl. Math. 20 (1987) 53–65, https://doi.org/10.1016/0377-0427(87)90125-7.
[50] Y. Geng, W. Ji, Y. Xie, B. Lin, W. Zhuang, A Sub-Sequence Clustering Method for Identifying Daily Indoor Environmental Patterns from Massive Time-Series Data, Autom. Constr. 139 (2022) 104303, https://doi.org/10.1016/J.AUTCON.2022.104303.
[51] P. Engelmann, D. Kalz, G. Salvalai, Cooling Concepts for Non-Residential Buildings: A Comparison of Cooling Concepts in Different Climate Zones, Energy Build. 82 (2014) 447–456, https://doi.org/10.1016/J.ENBUILD.2014.07.011.
[52] G. Salvalai, J. Pfafferott, M.M. Sesana, Assessing Energy and Thermal Comfort of Different Low-Energy Cooling Concepts for Non-Residential Buildings, Energy Convers Manag 76 (2013) 332–341, https://doi.org/10.1016/J.ENCONMAN.2013.07.064.
[53] M. Gómez-Gil, M.M. Sesana, G. Salvalai, A. Espinosa-Fernández, B. López-Mesa, The Digital Building Logbook as a Gateway Linked to Existing National Data Sources: The Cases of Spain and Italy, Journal of Building Engineering 63 (2023) 105461, https://doi.org/10.1016/J.JOBE.2022.105461.
[54] M.M. Sesana, G. Salvalai, A Review on Building Renovation Passport: Potentialities and Barriers on Current Initiatives, Energy Build. 173 (2018) 195–205, https://doi.org/10.1016/J.ENBUILD.2018.05.027.
[55] G. Kazar, U. Yiğit, K.E. Boyabatlı, Predicting Maintenance Cost Overruns in Public School Buildings Using a Rough Topological Approach, Autom. Constr. 168 (2024) 105810, https://doi.org/10.1016/J.AUTCON.2024.105810.
[56] D.G.J. Opoku, S. Perera, R. Osei-Kyei, M. Rashidi, Digital Twin Application in the Construction Industry: A Literature Review, Journal of Building Engineering 40 (2021).