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ORIGINAL ARTICLE

Analyzing the implementation of predictive control systems and application of stored data in non-residential buildings

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Abstract In non-residential buildings, building energy management systems (BEMS) and the application of data hold significant promise in reducing energy consumption. Nevertheless, BEMS have different levels of complexity, benefit, and limitation. Despite the advanced technologies and improvements in building operation, there is a clear gap in the actual performance of buildings that has been attributed to the adoption of advanced technologies. Consequently, there is an increasing need for researchers and practitioners to study current practices in order to identify and address the challenges that compromise the core objectives of BEMS. For this reason, this paper aims to validate three research questions: (i) to examine the current state of BEMS and its functionalities; (ii) to analyze the type of control used; (iii) and to determine the availability of historical data compiled by BEMS and its application in non-residential buildings. A survey of 676 buildings and interviews with building professionals were conducted. The findings confirmed that most of the buildings applied BEMS with scheduled control. In addition, a lack of digitized data for analysis and predictions was detected. Indeed, only 0.60% of the investigated buildings implemented predictive control. Finally, using hierarchical clustering analysis, responses were grouped to analyze similarities between them. The study findings help to develop targeted actions for implementing predictive control in non-residential buildings.

Keywords Building energy management system · Energy efficiency · Control system · Data storage · Non-residential buildings

Introduction

European Union (EU) established energy targets to attain climate neutrality by 2050 (European Commission, 2020). These targets can be summarized in three groups: (i) to reduce greenhouse gas emissions; (ii) to increase the ratio of renewable energies; (iii) and to improve energy efficiency (European Commission, 2019a). To ensure the realization of the aforementioned targets, the EU designed a set of transformative policies that EU members are committed to implement. Buildings are essential for accomplishing those targets in terms of optimizing building energy efficiency and energy demand (IEA, 2021a), since they account for 35% of global final energy use and 38% of global energy-related CO_2 emissions in 2019 (Alliance, 2020). Besides, based on the latest IEA report (IEA, 2021b), roughly 75% of buildings in the EU are not energy-efficient, with around 90% expected to still

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be in use in 2050 (IEA, 2021b). Most building energy consumption occurs during the operational stage (Asdrubali & Grazieschi, 2020). Indeed, heating, ventilation, and air conditioning systems (HVAC) are significant contributors in this stage (Zhang, Chong, et al., 2019; Zhang, Xue, et al., 2019). HVAC systems often work inefficiently due to improper control strategies (Afroz et al., 2018; Zhang, Chong, et al., 2019; Zhang, Xue, et al., 2019).

Building energy management systems (BEMS) play an important role in optimizing HVAC systems as it enables buildings to be more intelligent through real-time automatic monitoring and control (Molina-Solana et al., 2017; Xiao & Fan, 2014). Types of controls implemented in BEMS consist of classical developments based on rules (e.g., reactive "if-then-else" controls (Drgoňa et al., 2018, Drgoňa et al., 2020, Killian & Kozek, 2016, Zhang, Chong, et al., 2019)) to more advanced controls (e.g., model predictive controls (MPC) (Al Dakheel et al., 2020; Behrooz et al., 2018; Chen et al., 2020; Drgoňa et al., 2020; Himeur et al., 2021; Ke et al., 2020; Killian & Kozek, 2016; Kuivjõgi et al., 2021; Li et al., 2020; Li & Wen, 2014; Mullen et al., 2015; Rohde et al., 2020)). The achieved savings of control systems range between 20-45%. They correlate directly with the technology implemented to optimize the buildings' energy consumption (Halhoul Merabet et al., 2021; Li et al., 2020). Most existing commercial BEMS are reactive rule-based (Drgoňa et al., 2018; Freund & Schmitz, 2021; Hilliard, 2017; Hong et al., 2020; Macarulla et al., 2017; Yang et al., 2020; Zhang, Chong, et al., 2019). This means they cannot predict future scenarios or adapt to unexpected events. As a consequence, their energy-saving capabilities are limited (Drgoňa et al., 2018; Freund & Schmitz, 2021; Macarulla et al., 2017; Savadkoohi et al., 2023; Zhang et al., 2019). Therefore, recent developments in BEMS are focused on advanced control systems to overcome the low potential of current BEMS (Boodi et al., 2018; Jang et al., 2019; Stoffel et al., 2023; Stoffel et al., 2024). Advanced control systems are central components of intelligent buildings (Chen et al., 2020). The benefits of these systems are significant and have been widely recognized, as evidenced by the current intensive interest of researchers (e.g., data-driven predictive control (Ke et al., 2020), dynamic optimization of control setpoints (Rohde et al., 2020), transfer learning with deep neural networks in smart buildings (Chen et al., 2020), and real-time big data analytics for the energy efficiency improvement (Li et al., 2020; Drgoňa et al., 2018; Drgoňa et al., 2020; Sangi et al., 2019). Nevertheless, the application of advanced control systems has not yet been generalized (Abuimara et al., 2021). These technologies' field validations are still very limited and are in the early stages (Drgoňa et al., 2020; Granderson et al., 2018; Žáčeková et al., 2014). This suggests a critical need to significantly increase the large-scale deployment of new technologies and innovations across the building industry (European Commission, 2019a).

The integration of BEMS with advanced data analysis techniques has become increasingly important for effective energy management and optimization in buildings (Aguilar et al., 2021; Fan et al., 2021; Grillone et al., 2021; Himeur et al., 2022; Naganathan et al., 2016; Yuan et al., 2021). One such data analysis technique is Hierarchical Agglomerative Clustering (HAC), which offers a powerful approach for identifying patterns and grouping similar entities based on their energy managemnet characteristics. By applying HAC to the data collected from BEMS, it is possible to uncover distinct clusters or groups of buildings that exhibit similar BEMS profiles. This clustering approach provides valuable insights into building energy performance, facilitates benchmarking, and enables targeted energy conservation strategies. Moreover, the combination of BEMS and HAC can help in identifying pecularities, detecting anomalies, and ultimately enhancing energy efficiency in building portfolios.

Considering the aforementioned aspects, this paper aims to analyze whether the application of advanced controls has been generalized in non-residential buildings. For this reason, this study was divided into three steps: examining the current state of BEMS and its functionalities, analyzing the type of controls used, and determining the availability of historical data stored by BEMS and its application in non-residential buildings. The remaining parts of the paper were organized as follows. In Section 2, the problem statement and background of the research are discussed. In Section 3, the methodology framework is provided by reviewing the current BEMS through surveys and interviews. In Section 4, the results of the cases were evaluated and discussed. Finally, the paper closes with the trends and the main conclusions of this research.

Problem statement and background

In the building industry, words like building automation system (BAS), building automation and control system (BACS), building management system (BMS), building energy management system (BEMS), energy management and control system (EMCS), home energy management system (HEMS), and intelligent building energy management systems (iBEMS) were used interchangeably to describe software and hardware technologies that enable to manage energy in buildings (Al Dakheel et al., 2020; Boodi et al., 2018; Drgoňa et al., 2018; Jang et al., 2019; Kwak et al., 2015; Li et al., 2020; Macarulla et al., 2017; Mariano-Hernández et al., 2021; Papadopoulos et al., 2019; Papantoniou et al., 2015; Savadkoohi et al., 2023; Serale et al., 2018; Whitney et al., 2020; Xiao & Fan, 2014; Yang et al., 2020; Zong et al., 2019). These terminologies have a wide range of definitions but always suggest automating operations in buildings with different levels of efficiency and intelligence. Building energy management system (BEMS) is the most common term found in the literature and is the word discussed in this paper.

Concerning the control systems implemented in BEMS, these can be summarized in two main groups: traditional or classical control strategies (TCS) and advanced control strategies (ACS) (Gholamzadehmir et al., 2020). On the one hand, TCS includes sequencing control (on/off control) and process control (P, PI, and PID control). On the other hand, ACS involves hard control (gain scheduling, nonlinear, robust, optimal control, and model predictive control), soft control (fuzzy logic and neural network control), and hybrid control (fusion of hard and soft control techniques) (Afram & Janabi-Sharifi, 2014a, 2014b; Afroz et al., 2018; Behrooz et al., 2018; Gholamzadehmir et al., 2020; Homod, 2013; Yao & Shekhar, 2021). In this context, several researchers have been reported that most existing control systems are based on TCS with a schedule (Afram & Janabi-Sharifi, 2017; Drgoňa et al., 2018; Drgoňa et al., 2020; Homod, 2018; Reynolds et al., 2018; Zhang et al., 2019) despite the advanced technologies. Such systems are limited to the energy manager's experience to condition the building operation (Savadkoohi et al., 2023) by turning on/off the HVAC system (Li et al., 2020; Zhang, Xue, et al., 2019). Furthermore, these systems have limited energy-saving capabilities, low performance, and cheap hardware and software solutions. Consequently, they are not optimal or adaptive to the surroundings (Afram & Janabi-Sharifi, 2017; Drgoňa et al., 2020) since data collection and mechanisms to obtain hidden knowledge from BEMS data (e.g., data mining) are not yet available (Papadopoulos et al., 2019; Srivastava et al., 2019). In other words, BEMS with TCS are used for simple data storage without sufficient insight to optimize equipment operations (Abuimara et al., 2021). Previous studies have demonstrated that capturing building historical data (e.g., building monitoring and operational data) and interpreting it in a meaningful way can help engineers and energy managers improve energy-efficiency solutions and drive down costs (Molina-Solana et al., 2017; Reynolds et al., 2018; Srivastava et al., 2019). Thus, implementing real-time analysis and predictive controls can make better use of existing building data (Jang et al., 2019; Srivastava et al., 2019).

Therefore, the enhancement of building operational performance, taking full advantage of operational data through ACS, results in higher energy savings and improved indoor environmental conditions (Behrooz et al., 2018; Xiao & Fan, 2014; Yao & Shekhar, 2021). It optimizes the behaviors of building facilities based on future predictions (Drgoňa et al., 2020; Kwak et al., 2015). In this direction, there is no evidence of the current use of ACS in the real built environment. For this reason, it is of great interest to analyze the application of advanced controls in the building industry, highlighting the influential factors and the gaps related to strategies and techniques implemented in BEMS. This study consist of answering the following research questions:

i. What is the current state of BEMS in non-residential buildings in terms of their use, application priorities, and the adoption of MPC methods?
ii. How are data storage practices in buildings structured, particularly concerning the accessibility and availability of historical data, to support the implementation of MPC in BEMS?
iii. How useful is the stored data in current BEMS for enhancing the effectiveness of MPC systems?

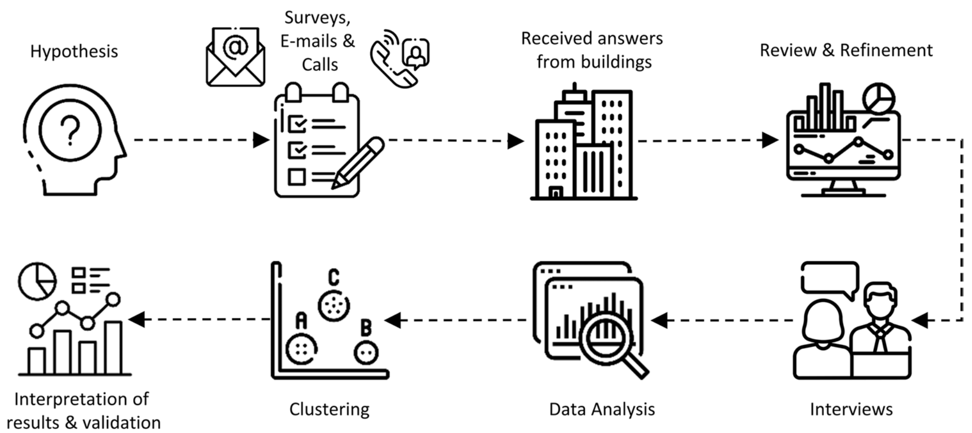


Fig. 1 Flowchart of the research methodology

Methodology

A flowchart of the research methodology is shown in Fig. 1. This methodology was developed based on established approaches used by researchers investigating energy management practices in non-residential buildings and collaborating with professionals in the building industry (e.g., Abuimara et al., 2021; Cristino et al., 2021; Srivastava et al., 2019). A combination of building surveys and interviews were used to study the impact of the research questions on the current application of ACS in non-residential buildings. It should be noted that the scope of this work was only focused on non-residential buildings with the professional role of building energy manager. However, the implications for residential buildings might differ due to different energy usage patterns and management needs. The data collection was centered in Catalonia, a region known for its diverse building stock ranging from historical buildings to modern infrastructure. This diversity improves the representativeness of our sample. Our collaboration with professional associations ensured access to a variety of non-residential buildings, including educational institutions, commercial properties, and public buildings. This variety was important for a comprehensive analysis of BEMS. While the sample is representative of the Catalonia-Spain, there might be regional-specific factors such as climate, local regulatory frameworks, and energy policies that influence the generality of the results that should be considered when extrapolating our findings to other regions in Spain or beyond. The diversity within the Catalonia building stock adds robustness to our findings. However, differences in building management practices, technology adoption rates, and energy consumption patterns in other regions could lead to variations in the applicability of our conclusions.

The survey, provided in Appendix A, was designed with seven generic questions according to the study's main objective and literature review, aimed at addressing the three research questions outlined in section 2. The survey was distributed via email through the university and building maintenance associations to different building professionals who manage building energy. During this process, Spanish professional associations helped to promote the survey and encourage its affiliated professionals to participate (e.g., Association of Maintenance Managers -AGEM-). AGEM in Barcelona operates under the sponsorship of the Catalan Energy Institute, which contribute to promoting as a reference association in the technical management of buildings and maintenance within Catalonia.

The collected survey responses provided valuable insights into the management practices of 676 non-residential buildings. During the data analysis, efforts were made to validate the consistency of the answers and avoid duplications (e.g., multiple responses from the same building). In the second step of the research, in-depth semi-structured interviews were conducted with the building practitioners who had participated in the survey. Afterward, the interviewees were selected randomly from the list of respondents.

In total, 42 semi-structured expert interviews were conducted. These interviews were designed and performed to (1) identify key factors for selecting the type of control used and current undergoing issues on BEMS implementation, (2) determine the current state of data availability, storage, and its usage, and (3) integrate the expert (e.g., building operation practitioner) knowledge and experiences to facilitate the adoption of advanced controls. Therefore, the interviews served to further refine the survey responses and to obtain the soft knowledge that cannot be captured through the survey alone such as identifying barriers to implementing advanced controls, and market trends. Interviewees, who were mainly mid to senior-level building operators and energy managers, were also asked for clarifications regarding their answers. Additionally, the evidence of interviews was used to augment the literature review findings. Finally, the survey and interview data were linked and analyzed to identify patterns and summarize the main conclusions derived from the qualitative data.

Accordingly, HAC with Ward's linkage as the clustering method was applied for specifying the distance between the qualitative data and responses (Tokuda et al., 2022). Specifically, the Gower's distance metric was used with the "cluster" and "gclus" libraries in R (Ezugwu et al., 2022; Fionn & Pierre, 2014). It depicts how survey answers are iteratively combined into groups based on their dissimilarity (distance). Different clustering methods have been tested in the literature for classifying the large datasets into several categories according to typical patterns identified in the clustering analysis (i.e., K-means, Hierarchical, Gaussian Mixture Models, Self-Organizing Maps, Fuzzy C-means clustering, etc.) (Cristino et al., 2021; Grillone et al., 2021; Xiao & Fan, 2014). The choice of clustering method depends on the characteristics of the dataset and the specific objectives of the analysis. In this work, HAC as a complementary analysis was performed to enhance the reliability of the data collected with the application of a survey and the knowledge discovered in the interviews. Overall, HAC is advantageous for survey datasets as it provides a hierarchical structure, allows for flexible interpretation of the number of clusters, supports visualization via dendrogram, and handles different levels of similarity. Unlike some other clustering methods that require the specification of the number of clusters beforehand, HAC does not require this parameter. It can handle datasets where the optimal number of clusters is not known in advance. The dendrogram allows for flexible interpretation, as the number of clusters can be chosen by cutting the dendrogram at different levels. This statistical analysis is computed as the increase in the error sum of squares (ESS) after fusing two clusters into a single cluster. Therefore, the frequency distribution of the total number of 676 observations which were unequally distributed, was explored within categories according to similar characteristics in survey observations answered by the participants.

Results and discussion

Table 1 displays the responses received from various building types, including offices (public administration, industry, and services); educational buildings (kindergartens, primary schools, secondary schools, and universities); health services (primary health centers, elderly care centers, hospitals); commerce and retail; and museums. Table 2 presents additional information about the Spanish professional associations and details about the buildings and respondents. The obtained results were systematically categorized according to the research questions outlined in section 2.

Use of building energy management systems

According to the survey feedback, it was observed that 70.60% of the investigated buildings used BEMS, while 29.40% did not employ BEMS (Fig. 2). Thus, among the received answers, offices had the highest adoption rate of BEMS implementation (93.40%), followed by educational buildings (48.40%) and health services (38.30%). This discrepancy could be attributed to the fact that the private sector mainly manages offices, whereas the public sector manages educational buildings and health services. Consequently, it can be inferred that the private sector has invested more in improving their building's energy performance. However, it is crucial for public institutions to allocate resources towards improving the performance of their buildings. Moreover, accelerating the share of BEMS in both public and private sectors is of the utmost importance since any gaps and delays in its implementation could affect the pathways for achieving the 2030 and 2050 energy objectives (European Commission, 2020).

Table 1 Building domain data source

Segment	Total of answers	% of answers
Offices	348	51.48%
Educational buildings	275	40.68%
Health Services	47	6.95%
Commerce/retail	5	0.74%
Museums	1	0.15%
Total	**676**	**100%**

Based on the feedback provided by building management professionals during the interviews, it was emphasized that BEMS should ensure easy integration with other protocols, while providing extensive control capabilities with minimal constraints. This ongoing concerns regarding adoption of highly scalable and versatile BEMS with a reasonable cost has also been highlighted by Cristino et al. (2021). In addition, the importance of user-friendly configurability, and enabling practitioners and maintenance staff to easily navigate BEMS operations were emphasized during the interviews. Moreover, practitioners expressed a preference for avoiding dependence on a single supplier due to uncertainties and financial challenges, as also noted by Al Dakheel et al., (2020). The findings further revealed that, based on the respondents' experience, building managers tend to work with specific suppliers, limiting the potential for system integration. Our findings also noted that the implementation of BEMS often involves annual or monthly fees for data management including monitoring, control, and supervision. Moreover, only 1-5% of the total maintenance budget was allocated to system monitoring and Technical Control System (TCS). Communication issues among devices were highlighted by interviewees as a significant concern as well, with reports indicating that approximately 40% of sensors experienced connectivity failures, resulting in abnormal or missing data values that can compromise subsequent data analysis. Lack of participation by practitioners in pre-occupancy decisions during the building design stage was also mentioned as an operational challenge. All above mentioned barriers contribute to the performance gap and mismatch between the operational and design phase of the buildings, as well as the individuals involved in energy management procedures such as designers and operators (Abuimara et al., 2021; Whitney et al., 2020). Consequently, it was found that after the installation and commissioning of building control systems, inadequate functioning of the employed control systems in BEMS operations can be observed. This problem was further enhanced when practitioners monitor and supervise multiple buildings with incompatibilities and inter-relations affected by different installed BEMS brand (Van Dronkelaar et al., 2016).

Fig. 2 Current application of BEMS

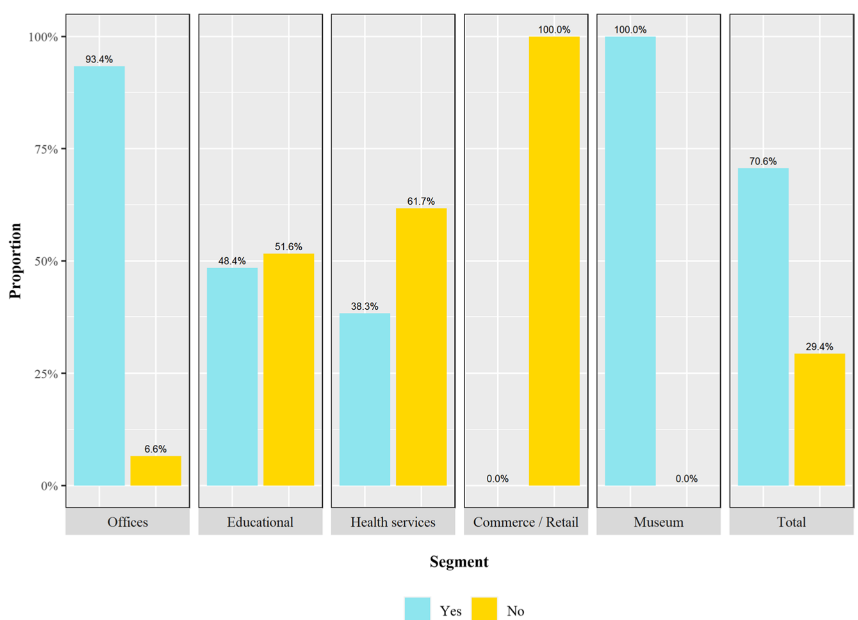


Figure 3 shows the distribution of control methods deployed in the sampled buildings. Despite the recognized inefficiency of scheduled control systems in HVAC operation (Gholamzadehmir et al., 2020; Jang et al., 2019; Macarulla et al., 2017), it was found to be the most applied approach accounting for 95.40% of cases. As can be seen from the distribution of responses, specifically, scheduled control was widely adopted in office buildings (93.10%), educational facilities (98.20%), and health services establishments (97.90%). These findings corroborate the previously identified barriers and limitations to restrain implementation of advanced controls. Nevertheless, our results indicated a considerable potential for enhancing existing scheduled control systems by incorporating intelligent functionalities to optimize HVAC operation. During the interviews, practitioners also reported that the schedule control was adjusted based on environmental conditions particularly in response to low external temperatures. For instance, the operators, based on their own experience, modify the schedule to turn on the HVAC system earlier. Such modifications were typically prompted by occupant complaints or the forecast of cold weather conditions. Additionally, manual control was reported in 4% of the sampled buildings, necessitating non-automated operation by operators to switch the HVAC system on or off.

Although ACS were recognized as the most effective method for optimizing HVAC operation and improving thermal comfort through predictive control strategies (Halhoul Merabet et al., 2021; Yang et al., 2020), in this study, the utilization of ACS was found to be limited, accounting for only 0.60% of the investigated buildings. This finding was aligned with previous studies that have been highlighted the challenges associated with implementing ACS in real-world scenarios (Abuimara et al., 2021). These include but not limited to integration with existing systems, data quality and availability, cost of implementation, technical expertise, privacy and security concerns, regulatory and compliance issues, and scalability and flexibility (Aliero et al., 2022; Liu et al., 2023; Soleimanijavid et al., 2024). This work aslo revealed that building technical capacity was often overlooked, representing a significant limitation in the adoption of low-carbon and digital solutions, including predictive controls (IEA, 2021a). Furthermore, the actual status of control systems highlighted the critical barriers faced in achieving the EU's energy targets, as also noted by other researchers (Abuimara et al., 2021; Fuentes-del-burgo et al., 2021; Himeur et al., 2021; Kuivjõgi et al., 2021; Whitney et al., 2020). Another notable issue identified during interviews was the discrepancy between the perception of maintenance staff and installation, with advanced control systems being

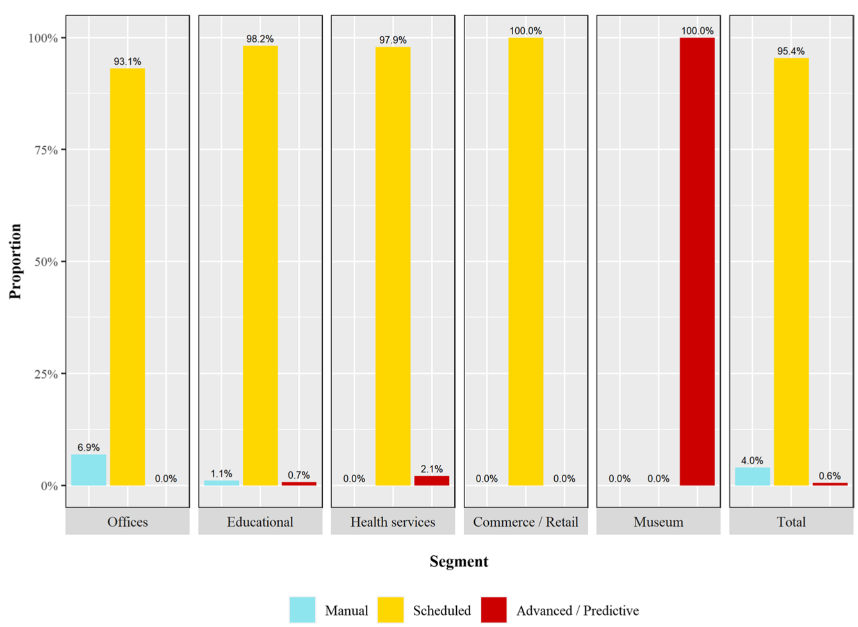


Fig. 3 Current type of control methods

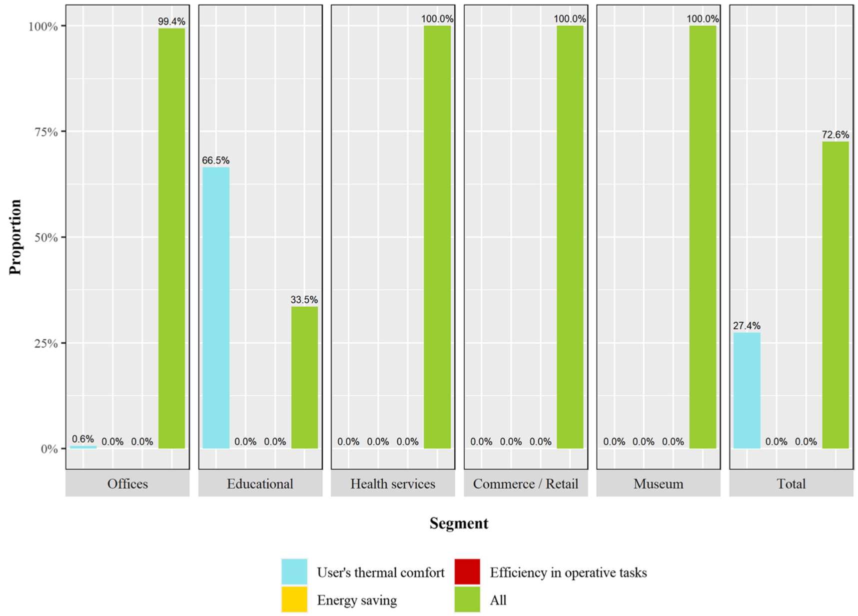


Fig. 4 Priorities of BEMS

often downgraded to simple control systems. Additionally, it was observed that a majority of the practitioners interviewed lacked knowledge and expertise in the field of BEMS and ACS (i.e., background knowledge and expertise, tools they use, feedback mechanism, etc.), as also stated in previous studies (Abuimara et al., 2021; Kuivjõgi et al., 2021).

Upon analyzing the correlation between the adoption of BEMS and the type of control, it was found that some buildings employed scheduled-based control systems without utilizing a BEMS platform. This indicates that they relied on simple technologies such as fixed and manual time programmers, necessitating any adjustments to be made on-site. Remarkably, practitioners acknowledged that some HAVC systems have been operating during unoccupied hours of the building. During the interviews, practitioners also highlighted challenges associated with modifying schedules and set points in BEMS, especially when managing multiple buildings simultaneously. The process of implementing these changes for each building was found to be time-consuming in order to select the optimal temperature set point for several buildings. Consequently, service interruptions could result in inefficiencies. Therefore, if a building manager supervises multiple HVAC systems without centralized control, it can pose difficulties in maintaining thermal comfort. This is because, to maintain thermal comfort in the building, the HVAC system controller must be optimized for the daily modification of working days and unoccupied periods with distinct setpoint schedule. The aforementioned scenarios demonstrated how enhancing BEMS practices is strongly reliant on the type of control system used. This can lead to a plausible explanation for the ongoing challenges in achieving the EU's energy targets within the building industry, despite building energy efficiency improvements being emphasized as the second most frequently cited action within all contributions (Global CCS, 2021).

As shown in Fig. 4, a substantial portion of the sampled buildings, over 50%, assigned equal priority to all factors in BEMS operation, reflecting a positive trend. Specifically, 72.60% of cases reported that users' thermal comfort, energy-saving, and efficiency in operative tasks hold equal weightage. In contrast, 27.40% of cases emphasized that their priority was only the user's thermal comfort. This highlighted the criticality of prioritizing alternative approaches to BEMS, as it is directly linked to building energy performance. The perspectives of building management professionals and building owners of the same building play a critical role in the success of energy-efficiency decision-making. Based on interviews, it was evident that most building owners do not possess adequate control and oversight of BEMS, with control predominantly relying on the bidder or the external entity

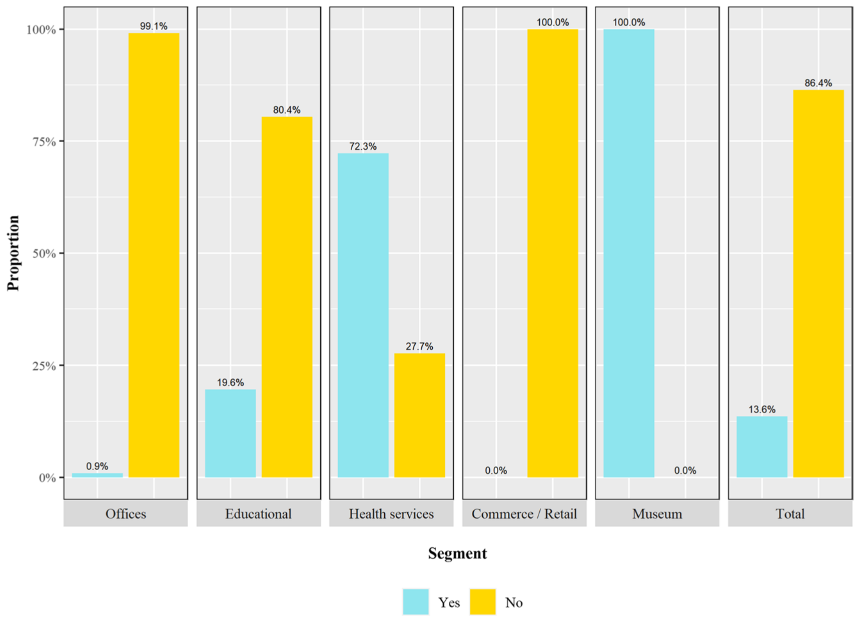


Fig. 5 Digitization of data

responsible for service provision. Consequently, building owners often lack direct responsibility for energy costs (e.g., utility consumption and billing data), which underscores the need for active involvement and initiatives from all stakeholders to promote technology adoption in non-residential buildings.

Availability of data in building energy management systems

This section focuses on the availability of historical data, which is the most useful tool for applying ACS and getting feedback for BEMS decision-making. The current study revealed that the majority of buildings (86.40%) have not implemented data digitization, with only 13.60% of data being digitized for further use (see Fig. 5). Specifically, offices (99.10%) and educational buildings (80.40%) did not apply data digitization, potentially limiting the implementation of predictive controls. By contrast, data analytics and simulation would assist engineers and energy managers in proposing effective energy efficiency solutions, thereby enhancing building energy performance and behavior over time (Srivastava et al., 2019).

In line with the global status report of 2021 (Global CCS, 2021), the utilization of tools for energy performance and management in building operations remained minimal. This was primarily attributed to the lack of access to digitized data, which significantly impacts the adoption of data usage in building energy simulation and data analytics. In a broader view, building digitization and data management can be leveraged to improve efficiency and drive down costs (Ma et al., 2021). Notably, BEMS generates a tremendous amount of data from 7.5 billion connected devices such as smart meters, sensors, and other Internet of Things (IoT) and 0.1 billion connected devices for space conditioning by 2021 (IEA, 2021b). Nonetheless, the lack of convenient tools for analyzing such data as highlighted in this study, will prevent its comprehensive interpretation and utilization.

Following the previous discussion, existing technologies offer the capability to collect and store vast amounts of data from in-situ and external sources such as environmental data, energy consumption, and costs (Molina-Solana et al., 2017). In this regard, BACnet and Modbus protocols were found to be commonly employed for data communication in which accessibility and availability of a significant amount of historical data can be crucial for assessing the actual building performance and occupant behavior (Serale et al., 2018). According to Fig. 6, the results obtained from the surveyed samples were as follows: 67.90% of buildings monitored and stored data with a data acquisition interval of 15 minutes; 7.80% of buildings only monitored data

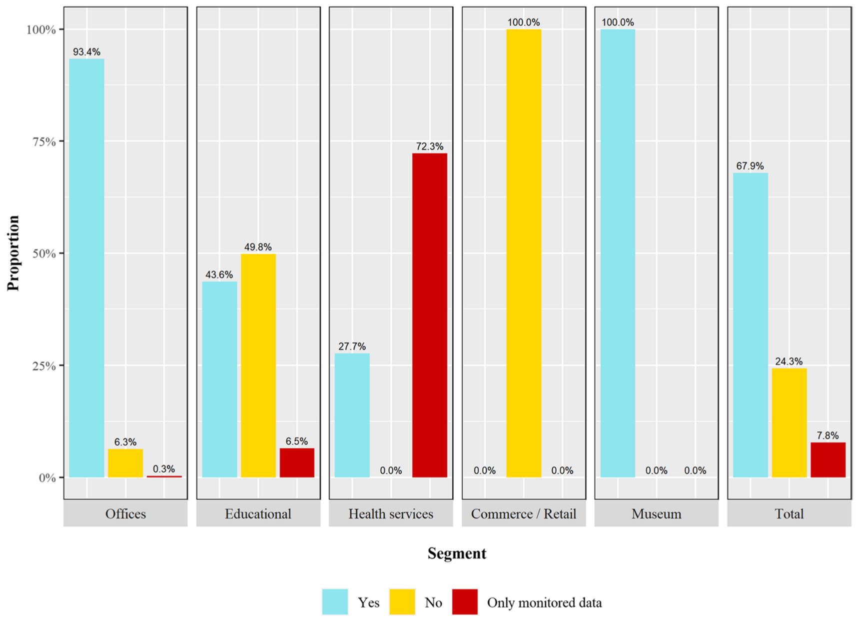


Fig. 6 BEMS historical data availability

with access to an online platform with recent values, and 24.30% of buildings did not employ monitoring and control systems to store data.

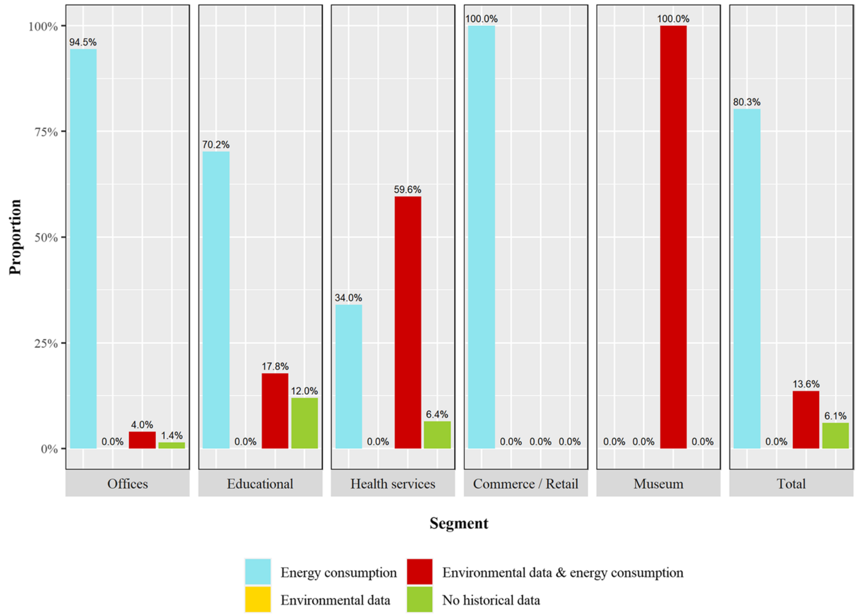
Concerning the features of the historical data presented in Fig. 7, this mainly involved information related to energy consumption (80.30%), with higher availability among offices (94.50%), educational buildings (70.20%), and health services (34.00%). Based on the obtained results, only 13.60% of stored data of all non-residential buildings referred to energy consumption and environmental data. Hence, predictive models could only be implemented in the 13.60% of buildings that collect both indoor and outdoor environmental data (Drgoňa et al., 2020).

Usage of data in building energy management systems

Based on the survey results (see Fig. 8), 62.30% of buildings conducted a comparative analysis using historical data, mainly offices (92.00%) and educational buildings (36.7%). 31.80% of samples used data for facility performance evaluation, including educational buildings (57.8%) and health services (100%). In addition, no data usage was reported by 5.80% of the buildings. Therefore, a meager percentage of cases (0.10%) focused on applying data to implement predictive control and improve optimal decision-making. More precisely, only one building, a museum, was found to employ a predictive control system. This museum was part of a lighthouse demonstrator for an efficient building, applying a predictive control system developed by a startup. This observation is consistent with prior research findings, which highlighted the challenge of data management as one of the major barriers to building digitalization (IEA, 2021a). The obtained findings were entirely consistent with the EU report which highlighted that a large portion of generated data from sources (90%), was not currently analyzed and used (IEA, 2021a). In this case, with increasing available data through the building life cycles, data management and utilization have become a significant challenge (Zhan & Chong, 2021). Interviews revealed that measured data was collected and incorporated into the control system; however, its performance depends on the accuracy and quality of stored data in a real application (Gholamzadehmir et al., 2020).

As the energy efficiency investment in the building industry in Europe has grown from 141.9 billion USD to 193.0 billion USD (2015-2021) (IEA, 2021b), it is evident from the obtained results that the owners and enterprises made high investments, but data was still not used. For this reason, one of the main challenges that could affect the performance of BEMS in existing buildings was found to be the lack of effective data interpretation and utilization for optimizing HVAC control systems. Besides, the interviews

Fig. 7 Type of stored data



pointed out that a lack of a convenient intelligent system for remote operation of buildings was one of the challenges faced by building professionals that potentialy leading to higher operating costs of the HVAC systems (Zhan & Chong, 2021). Another example discovered during interviews was that building information modeling (BIM) or Deemed-to-satisfy provisions (DTS) could present high computation time and complexity as the practitioners found them challenging to make energy-efficient decisions. It can be considered as a significant limitation in improving building performance. Moreover, the obtained results indicated that BEMS were not operating as energy-efficient as they could be in non-residential buildings, which was in accordance with the results presented by Yang et al., (2020).

Survey analysis

HAC with Ward's linkage as the clustering strategy was employed using an arbitrary dissimilarity matrix to analyze the survey responses. By examining the dendrogram presented in Fig. 9, two main cut-off distances between groups (reffered to as cut-tree #1 and cut-tree #2) could be identified. Determining where to cut the dendrogram in HAC involves finding an optimal point that best captures the underlying structure of the data. However, it requires some trial and error, especially, the choice may also depend on domain knowledge and the specific goals of analysis. The first cut-tree (i.e., cut-tree #1) distinguished two different clusters. Cluster C1-A included 348 observations, consisting office buildings that implemented BEMS with scheduled control. These buildings had available energy consumption data, mainly for comparative analysis, but lacked data digitization. In addition, their priorities focused on users' thermal comfort, energy-saving, and efficiency in operative tasks. On the other hand, cluster C1-B consisted of a mix group of 328 observations. At a lower distance level (i.e., cut-tree #2), one more cluster may be detected. Cluster C2-A, represents similar characteristics to cluster C1-A defined in the first cut-tree (i.e., C1-A). Cluster C2-B consisted of 275 observations of educational buildings which were not implemented BEMS using scheduled control. These buildings have no digitized historical data available. However, their priority was the user's thermal comfort. In addition, they applied facility performance evaluation. Cluster C2-C consisted of a mix group of 53 observations, including other types of buildings, covering various categories. Therefore, these two selected cut-trees were considered to provide a clearer identification of the clusters within the dataset.

The application of HAC to our observations enabled the identification of significant variations among different building sectors. Figure 10 shows frequency distributions among three different clusters derived

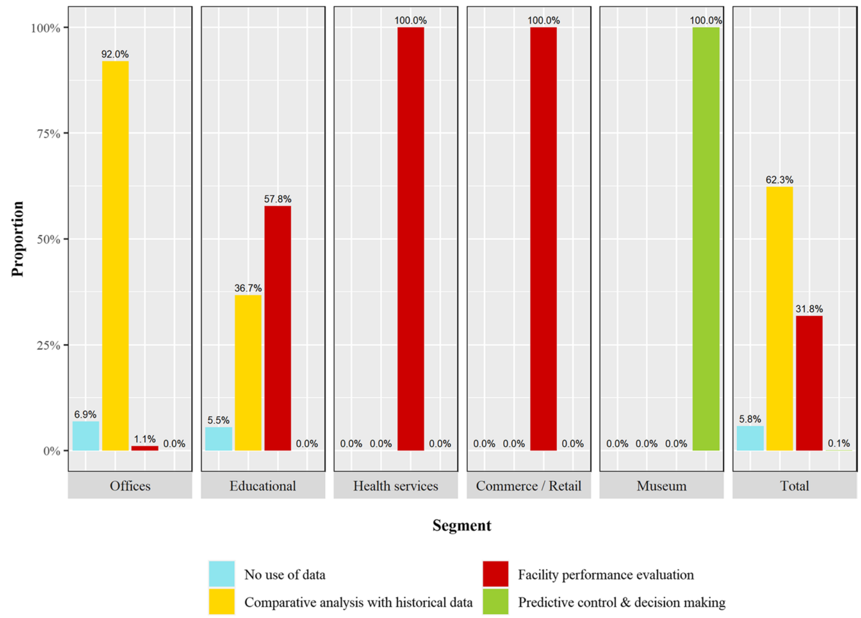


Fig. 8 Use of stored data

from cut-tree #2. A total of 676 observations resulted in two optimal clusters (i.e., clusters A and B) which exhibited relatively similar convergence values and a substantial number of observations. Clusters A and B displayed unique characteristics. It means in each group, there was one unique type of parameter from the eight different categories analyzed. One of the first results of this analysis confirmed that offices and educational buildings, with similar heating and cooling conditions hold a significant share in non-residential sector.

Overall, according to the obtained result, it was evident that office and educational buildings had distinct preferences and characteristics regarding the implementation of control systems. Office buildings predominantly used BEMS with scheduled control, whereas educational buildings relied on scheduled control in the absence of the BEMS. These characteristics became more evident at the category level, where the lack of digitized historical data was detected to implement BEMS and control systems. Moreover, the HAC analysis supported the identification of common tendencies in office and educational buildings. Those buildings played an increasingly important role in reducing the operational costs by the current implementation of control systems. Nevertheless, corrective solutions were different in terms of enhancing the energy efficiency and reducing the cost. Educational buildings, which were mainly managed by the public sector, needed more targeted financing actions with easy-to-understand information on the benefits of implementing BEMS to improve energy performance. This approach could facilitate the work of public authorities. Available technical assistance might be considered a starting mechanism of a forward-looking approach to implement ACS over time. In this way, a practical guide can be provided to the complex public building sector, to systematically address key barriers in small and manageable steps. In the case of offices mainly belonging to the private sector, they had the necessary infrastructure for the implementation of ACS. However, they needed to enhance information tools, particularly continuous building data collection and training for improving practitioners' skills. These measures would make office buildings more resilient and accessible to implement ACS.

Other types of non-residential buildings such as health services, commerce/retail and museums were categorized together in cluster C2-C (Fig. 10). These buildings often had the similar energy use patterns for heating, cooling and operating appliances (Nematchoua et al., 2019). Persuant to our obtained result as shown in Fig. 10, those buildings defined a mixed characteristics regarding the use of BEMS, type of control, data availability, etc. In this case, a generalized consensus approach could not be

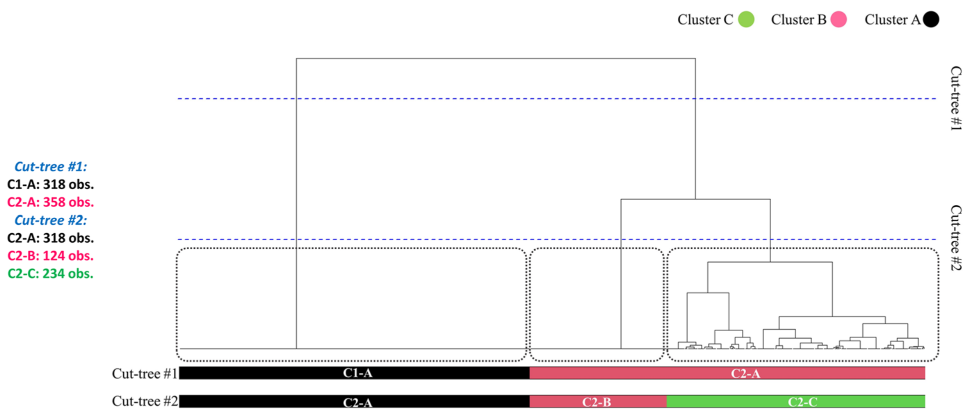


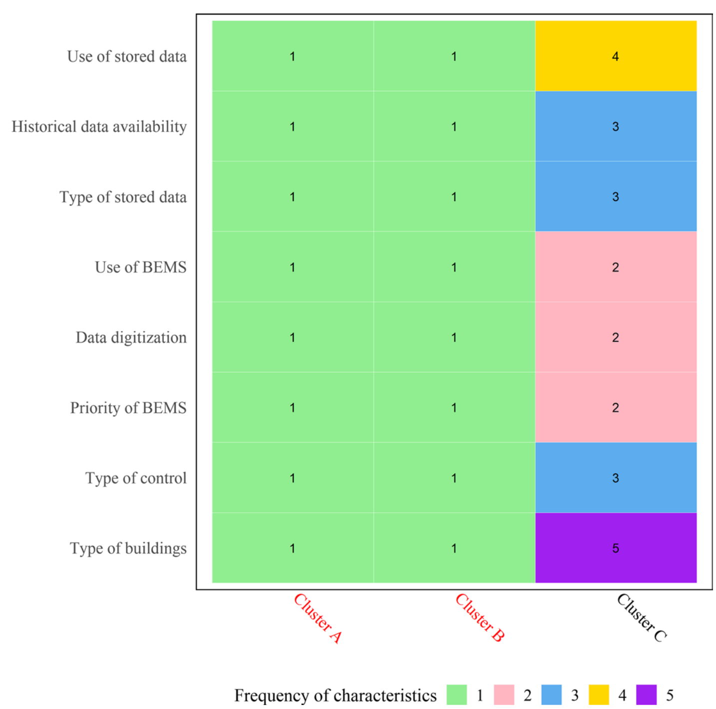
Fig. 9 Dendrogram describing the hierarchical clustering analysis using Ward's method based on the number of observations for each cluster in both cut trees

employed in order to optimize the operating BEMS. Instead, an intersectional approach and critical analysis of the underlying factors influencing their overall performance were necessary. The key strategy, therefore lies not only in investing in the implementation of ACS but also in maintaining the equilibrium between economic factors and the building practitioners' knowledge.

Conclusions

The main scientific contribution of this study was to analyze the implementation of advanced control systems in non-residential buildings. It specifically examined the types of control systems used, data storage practices, and their role in addressing the current challenges that buildings face in

Fig. 10 Frequency of characteristics based on the result of Hierarchical clustering



achieving EU energy performance targets. A total of 676 non-residential buildings were assessed, taking into account the inputs from several building energy managers and practitioners. The frequency distribution of the observations using hierarchical clustering analysis was explored within three categories according to similar characteristics in survey responses. The findings revealed that two optimal clusters, primarily composed of offices and educational buildings, presented a significant proportion of the observations and had the highest shares in non-residential buildings. By analyzing the differences between offices and educational buildings, it can be inferred that the priorities and challenges associated with BEMS implementation are limited on how this technology is being used in the sense of its efficiency and integration.

This study demonstrated that despite the widespread development of smart meters and sensors, predictive controls were rarely implemented in non-residential buildings (0.60%). In addition, specific barriers such as building technical capacity and motivations for engaging in BEMS practices affected the application of such controls in non-residential buildings. The obtained results confirmed the hypothesis that there is a common consensus in which most buildings used BEMS with scheduled on/off based control. This strategy requires high efforts to change the HVAC system schedule since it is based on trial and error experiments, leading to less energy savings. The findings also revealed that the usual demand across all segments was a flexible, integrated, versatile, and scalable control system. Furthermore, practitioners had no preference for BEMS associated with specific brands. In this case, they were willing to implement an effective and robust level of system functions in BEMS. It was found that most investigated buildings monitored and stored data mainly involving information related to energy consumption. Furthermore, practitioners did not store environmental data due to the lack of knowledge about its significance and potential applications. Therefore, this research demonstrated that a considerable amount of historical data was not stored for predictive control and decision-making. If the frameworks were in place to access such data, they could provide valuable information to users in real-time to control HVAC systems efficiently. Thus, it could facilitate the development of strategies to mitigate the barriers to implementing advanced controls in non-residential buildings. By way of example, the barriers to data storage were related to connectivity problems.

This research also suggested that improving building performance and energy efficiency was not yet systematically integrated into the public sector. Therefore, reliable data was not available. To address the knowledge gap identified as a professional/technical barrier, an effective action plan could be an ongoing training of building management professionals. Further, financial barriers should be solved by policymakers to invest more in the public sector with a representative action plan for more financial flexibility and promoting best practices in this type of buildings. More concrete actions should be taken with the public and private sectors to develop lighthouse buildings as exemplars. These initiatives would help to acquire the technical competence to implement advanced controls adapted to different types of non-residential buildings. Thus, this will improve the desire to solve the challenges confronting this industry. In addition, better partnerships between building designers in the installation phase and practitioners in the operation phase were needed, to ensure innovative solutions for positive outcomes in reality.

Finally, this research identified the main group of non-residential buildings with current challenges and several barriers that affect the implementation of advanced control systems. Additionally, it could effectively provide public institutions, researchers, and building professionals with a deeper understanding of what today's BEMS is delivering and how it can be improved upon by prioritizing effective mitigation and adaptation actions. The prospective scope for future work is to expand this experiment to a wider scale in other regions by providing the basis for the adoption of advanced controls to overcome the existing barriers that hold back progress in non-residential buildings. In this manner, it could also potentially continue field validations of commercialized BEMS based on advanced controls that can provide benefits for building operators and managers.

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CRediT authorship contribution statement Marjan Savadkoohi: Writing - original draft, Writing -review & editing, Investigation, Data Analysis, Visualization. Marcel Macarulla : Conceptualization, Methodology, Review & editing, Supervision. Blanca Tejedor: Data collection, Validation, Investigation, Review & editing. Miquel Casals: Supervision, Review & editing.

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Declaration

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Appendix A

The interview questionnaire (Energy management of the building)

1- Does your enterprise use a BEMS (Building Energy Management System)?
   Yes
   No
   Other

If so, specify when the building had an energy management system and the commercial name of the system.

2- What is the type of control system used for the facilities?
   Manual control
   Schedule control
   Advanced or Predictive control

3- What is the top priority in building energy management?
   User's thermal comfort
   Energy savings
   Operational efficiency
   All above
   Other

4- Has any type of data digitization been done for building management or maintenance tasks?
   Yes
   No

5- Is building data monitored and stored in real-time? (e.g., T^{a}, RH%, etc.)
   No data collection
   Signal inputs are monitored.
   Yes, data is monitored and stored.

6- Is historical data available for the building (environmental/consumption)?
   Yes, environmental data.
   Yes, energy consumption.
   Yes, environmental data and energy consumption.
   No

7- What is the use of the information collected from the facilities (e.g., boiler)?
   No use of data
   Comparative analysis with historical data

Table 2 Detailed information about the Spanish professional associations and the respondents

Enterprise	Buildings	Number of Buildings	City	Country	Sector activity	Enterprise Size
UPC- Polytechnic University of Catalonia	Campus Diagonal South I ETSAB EPSEB FME	5	Barcelona	Spain	Education	Big – National (>100 employees)
UPC- Polytechnic University of Catalonia	Campus Diagonal Nord ETSETB ETSECCPB FIB	37	Barcelona	Spain	Education	Big – National (>100 employees)
City hall Sant Just Desvern	City hall	1	Sant Just Desvern	Spain	Public Administration	Big – National (>100 employees)
UPC- Polytechnic University of Catalonia	Campus Terrassa ESEIAAT	12	Terrassa	Spain	Education	Big – National (>100 employees)
UPC- Polytechnic University of Catalonia	Campus Baix Llobregat EETAC EEABB	2	Castelldefels	Spain	Education	Big – National (>100 employees)
UPC- Polytechnic University of Catalonia	Campus Manresa EPSEM	5	Manresa	Spain	Education	Mid-Size (10 - 100 employees)
UPC- Polytechnic University of Catalonia	Campus Diagonal Besós-EEBE	13	Barcelona	Spain	Education	Big – National (>100 employees)
UPC- Polytechnic University of Catalonia	Campus Diagonal South 2-ETSEIB	9	Barcelona	Spain	Education	Big - National (>100 employees)
UPC- Polytechnic University of Catalonia	Infrastructure Service-Vertex Building	1	Barcelona	Spain	Education	Big – National (>100 employees)
University of Lleida-UdL	Infrastructure Service	5	Lleida	Spain	Education	Big – National (>100 employees)
City hall Vilanova i la Geltrú	City hall	1	Vilanova i la Geltrú	Spain	Public Administration	Big – National (>100 employees)
Autonomous University of Barcelona-UAB	Campus UAB	24	Cerdanyola del Vallés	Spain	Education	Big – National (>100 employees)
Roca Village	Commercial center, Outlet (Properties + rented spaces)	5	La Roca del Vallés	Spain	Commerce Retail	Big – International (>100 employees)
Rovira & Virgili University - URV	Campus Tarragona Campus Terres de l'Ebre	5	Tarrgona	Spain	Education	Big – National (>100 employees)
Terrassa Hospital	Hospital	56	Terrassa	Spain	Health Services	Big – National (>100 employees)
Quirón Health service	Teknon Clinic Hospital	1	Barcelona	Spain	Health Services	Big – International (>100 employees)
Pompeu Fabra University - UPF	Campus Barcelona	16	Barcelona	Spain	Education	Big – National (>100 employees)
Girona University-UdG	Campus Montilivi	14	Girona	Spain	Education	Big – National (>100 employees)
ICT Public Innovation Agency-Neàpolis	Public Innovation Agency for ICT	1	Vilanova i la Geltrú	Spain	Industry	Mid-Size (10 - 100 employees)
National Museum of Science and Technology of Catalonia (MNACTEC)	Museum	1	Terrassa	Spain	Heritage Building Culture	Mid-Size (10 - 100 employees)
Government institution of Catalonia- GENCAT	Infrastructure Services of the Catalan Government (schools, CAPs, hospitals, police stations etc.)	318	Catalonia	Spain	Industry - Services	Big – National (>100 employees)

Facility performance evaluation
Predictive control and decision making

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