Cost- and Energy-Efficient Control Systems for Buildings

Cost- and Energy-Efficient Control Systems for Buildings

Kostnads- och energieffektiva styrsystem i byggnader

Davide Rolando, KTH Energy Technology
Marco Molinari, KTH Energy Technology
Jonas Anund, KTH Energy Technology

Contributors:
Alberto Lazzarotto, KTH Energy Technology
Mahsa Farjadnia, KTH Energy Technology

Energimyndighetens projektnummer: P2018-90132

E2B2

Förord

E2B2s vision är en resurs- och energieffektiv byggd miljö.

Bebyggelsesektorn svarar för cirka en tredjedel av Sveriges totala energianvändning och en effektivare energianvändning är en viktig del av utvecklingen av energisystemet. Hållbarhet, effektivitet och robusthet i bebyggelsen behöver stärkas och utvecklas. Lösningarna behöver samspela för att fungera och utnyttjas. Forskning, utveckling, innovation och kommersialisering spelar en avgörande roll.

I E2B2 arbetar forskare och andra aktörer tillsammans för att utveckla samhällets byggande och boende och effektivisera energianvändningen. Syftet med E2B2 är att ta fram ny kunskap, teknik, tjänster och metoder som bidrar till en hållbar energi- och resursanvändning i bebyggelsen.

E2B2 är ett forsknings- och innovationsprogram från Energimyndigheten där IQ Samhällsbyggnad är koordinator. Programmet startade 2013 och en andra programperiod pågår mellan 2018 och 2024. Projektet som beskrivs i den här rapporten har genomförts i programmet med hjälp av statligt stöd från Energimyndigheten.

Sammanfattning

Informations- och kommunikationsteknik (IKT) såsom innovativa övervaknings- och styrsystem har stor potential att förbättra energieffektiviteten i den byggda miljön på ett kostnadseffektivt sätt. Praxis idag är ofta uppbyggnad av stora databaser utan en direkt koppling till eller vision om potentialen som möjliggörs. Testbäddar och riktlinjer kring design av system är nödvändiga för att få en effektiv användning av IKT-lösningar i byggnader. Detta projekt har utnyttjat högupplöst data som samlats in i KTH Live-in Labs forskningstestbäddar. Datan har samlats in genom ett avancerat, modulärt och flexibelt övervakningssystem som möjliggör realtidsdata kring allt från inomhusmiljö och resursflöden till systeminformation från exempelvis bergvärmesystem, solceller, ventilation och energilagring.

Projektet har identifierat begränsningar i byggnadsövervaknings- och kontrollsystem (dataförluster, saknade användbara sensorer) vilka hindrar utvecklingen mot smarta byggnader. Högupplöst data användes för att bedöma byggnadens energiprestanda, inomhusmiljökvalitet och för att ta hänsyn till hur användarnas beteende påverkar byggnadernas drift och prestanda. Projektet implementerade ett nytt mått utvecklat på EU-nivå - Smart Readiness Indicator - för att kvantifiera testbäddarnas smarthet. Dessutom utvecklades och implementerades digitala verktyg för att ge användare möjlighet till realtidsfeedback. Slutligen gav projektet ekonomiska överväganden om de föreslagna övervakningssystemen.

Nyckelord:

Smarta byggnader, energieffektivitet, bra inomhusklimat, hållbara byggnader, användarbeteende i byggnader, living lab, demonstrationsbyggnads testbäddar

Summary

Information and Communication Technologies (ICT) such as innovative monitoring and control solutions have a great potential to enhance the energy efficiency in the built environment in a cost effective way. Common practice typically involves the creation of large databases without an aware vision of their potential exploitation. For an effective employment of ICT solutions in buildings, demonstration through research building testbeds and design guidelines are imperative. This project has exploited high resolution data gathered in KTH Live-in Lab research test-beds through an advanced, modular and flexible monitoring set-up capable to acquire real-time data on indoor environmental quality and the involved energy flows including ground source heat pumps, photovoltaic panels, and ventilation.

The project has identified limitations of building monitoring and control systems (data loss, missing useful sensors) towards smart buildings. High resolution data was used to assess the buildings energy performance, indoor environmental quality and to account for the impact of user behaviour on the operation and performance of buildings. The project deployed a new metric developed within the EU framework - the Smart Readiness Indicator - to quantify the smart readiness level in the testbeds. In addition, digital tools to empower users with real-time feedback to the control loop were developed. Finally, the project provided economic considerations on the proposed monitoring solutions.

Keywords:

Smart buildings, energy efficiency, good indoor environmental climate, sustainable buildings, user behaviour in buildings, living lab, demonstration building testbeds

INNEHÅLL

1 Executive summary

1.1 Problem statement

Information and Communication Technologies (ICT) such as innovative monitoring and control solutions have a great potential to enhance the energy efficiency in the built environment in a cost-effective way. Common practice typically involves the creation of large databases without an aware vision of their potential exploitation. For an effective employment of ICT solutions in buildings, demonstration through research building testbeds and design guidelines are imperative.

The project has identified limitations of building monitoring and control systems (data loss, missing useful sensors) towards smart buildings. High resolution data was used to assess the buildings energy performance, indoor environmental quality and to account for the impact of user behaviour on the operation and performance of buildings. The project deployed a new metric developed within the EU framework - the Smart Readiness Indicator - to quantify the smart readiness level in the testbeds. In addition, digital tools to empower users with real-time feedback to the control loop were developed. Finally, the project provided economic considerations on the proposed monitoring solutions.

1.2 Goals

The goal of the project was to provide an assessment of the state of the art and common practice of monitoring and control systems in the building sector, with a primary focus on the identification of design issues, missed opportunities from current systems that result in inefficient energy use and sub-optimal comfort conditions. The project then proposed a range of solutions for cost-optimal design and implementation of building monitoring and control systems for different types of new and existing buildings, including residential and office facilities.

1.3 Scope

The project investigates technical and economic drivers and bottlenecks towards the development and adoption of smart buildings. Within the project, data collected from the advanced monitoring systems available at KTH Live-In Lab is analyzed and discussed to highlight the advantages, limitations and burdens of common practice adopted in the building sector regarding digital solutions and data infrastructures.

The project was carried out over a period of 3 years and developed mainly at KTH Live-In Lab in collaboration with project partners with proven expertise in the building sector. Within the collaboration with Botrygg, Akademiska Hus and the technical partners Einar Mattsson, Schneider Electric and Bengt Dahlgren, the project involves also additional buildings for replication and knowledge transfer purposes.

The project aimed at identifying and propose cost-effective solutions and digital tools that increase buildings energy efficiency and sustainability.

The project provided an assessment of the inefficient energy use of common faulty systems and guidelines for cost-optimal design and implementation of building monitoring and control systems.

1.4 Implementation and results

The project development included several activities involving three testbeds of KTH Live-in Lab and other facilities in collaboration with project partners. The research activities carried out during the project include data-analysis, economic assessment, development of new solutions and demonstration.

1.4.1 Long term monitoring analysis

The monitoring data from two KTH Live-In Lab testbeds (Testbed EM and Testbed AH) has been analyzed, focusing on the evaluation of energy use and indoor conditions. The analysis revealed a general low usage of data for building operation, a lack of supervision of the monitoring system and a lack of suitable alarm system.

The Testbed EM (Section 3.2) is a set of three residential buildings including 305 student apartments located at the KTH main campus. The data analysis presented in the report covers the energy use in the apartments for space heating and electricity, the domestic hot water use, the local production from the PV systems installed in each of the three buildings, the ground source heat pump system and the ventilation system. Part of the analysis is dedicated to the assessment of the indoor environmental quality, based on the available measurements of temperature, CO_2, DHW and electricity.

The results related to the building system show that some key sensors are not available, preventing a thorough evaluation of the overall system performance (e.g., temperature sensors on the return ducts of the ventilation system, Section 3.2.4.4). The analysis of the ground source heat pump systems shows a potential improvement in the control of the circulation pump and a potential issue due to the unbalanced operation of the three heat pumps installed (Section 3.2.4.2). The results on the evaluation of indoor conditions (Section 3.2.5) show that indoor climate is on average too warm during the heating season – with a significant room to reduce energy use. The use of fresh water, domestic hot water, electricity varies significantly depending on users (i.e., building occupants), even in similar apartments, and data suggests that different users have different preferred comfort ranges.

The Testbed AH is a university building constructed in 2016 used for lecturing; it consists of seven floor areas, 363 study places, six exercise rooms, and 11 group rooms and break out areas for a total of over 3500 m^2. The building system is well documented and the monitoring system is easily accessible monitoring system, but key sensors are missing for an overall indoor air quality evaluation; for example, CO_2 measurements are available only in lecture room.

The results on the data analysis of Testbed AH are available at Section 3.3. Worth noticing, Section 3.3.3 presents the results of a campaign for the validation of the monitoring system where the discrepancy of the indoor temperature measurements is highlighted, suggesting the need of verification and supervision of building monitoring systems.

1.4.2 Evaluation of smartness in buildings

Section 3.5 of the report presents the result of the SRI (Smart Readiness Indicator) assessment, as an aggregated percentage score that indicates how close is the building is to a maximal smart readiness.

The aggregated SRI score resulted in 44% for the Testbed KTH and 29% for the Testbed Einar Mattsson. These results are considered average for candidate smart buildings but it should be also underlined that some important system functionalities like advanced storage systems are being implemented at the time of the analysis. Importantly, this assessment is carried out following the simplified methodology, which includes a more limited set of services.

Both testbeds score relatively low in the monitoring part; this is surprising given the experimental and demonstrative nature of the testbeds. The limiting factor in this domain is mainly in the incapability of either system to display information on energy flows and carriers to the users. For instance, in the Testbed KTH the BMS interface displays real time information about only about indoor environment parameters; however, in the Testbed KTH a web-app can overcome this limitation with a relatively limited implementation effort.

The monitoring system is not used at its full potential, in particular with respect to benchmarking and performance forecasting to users and building operators. Several services in this domain can be improved in a cost-efficient way, due to the limited investment in the infrastructure required.

The higher scores of the Testbed KTH in all domains suggest a relative independence from the building envelope; this factor is significant when upgrading the smartness of existing buildings.

1.4.3 Economic analysis

Smart buildings can lead to lowered operation costs due to a more efficient energy use. In smart buildings, interaction between users and systems can help shifting loads from peak hours to hours with low energy price. Features like energy storage and grid connectivity help reducing operation costs as well as increase user satisfaction. The question then is if this also is reflected in the valuation of smart buildings. Operating cost as well as maintenance costs are expected to be lower in smart buildings compared to conventional buildings, as a result of lower and more efficient use of energy and other resources.

The project covered an economic analysis (Section 3.6) considering two case studies: the Testbed EM and the Uppsala Backe demonstration site.

Uppsala Backe is a demonstration site available to the project through Botrygg, one of the project partners. In Uppsala Backe, two similar buildings (same geometry, building envelope and building HVAC systems) were selected and equipped with different levels of smartness. Two packages for monitoring were proposed and installed: the first building (Hus 2) featured a standard monitoring system while the second one (Hus 4) was equipped with a more advanced setup. Both systems are sufficient to monitor indoor climate and energy use in each apartment, but the advanced package also included more advanced features window opening sensors and local energy metering.

The economic analysis shows that the extra investment (including design and installation) for monitoring systems is between 2.5% and 6.7% of the overall construction cost. Also, economic drivers for the installation of more advanced monitoring systems are in general perceived unclear and no real incentives are available to adopt functionalities (e.g., visualization tools to users) that can cost-efficiently improve the smart readiness of the buildings.

1.4.4 Development of new tools

During the project, the prototype of a custom monitoring platform has been designed, developed and tested. The platform essentially consists of three main components: a web app, a sensing device and a backend infrastructure. In Section 3.7, the main characteristics of the platform are briefly described.

The web app allows the users to provide feedbacks about their perceived comfort and is designed to be user friendly, informative and to provide a non-invasive user experience. The main page of the web app consists in a minimal interface with only a few buttons corresponding to comfort perceptions (e.g., "too cold", "too dry", "poor air quality"). Users can provide a short comment together with the feedback selected.

The hardware of the platform is a monitoring device based on the ESP8266 microcontroller mounted to an electronic board that includes sensors for monitoring temperature, relative humidity, CO_2, equivalent CO_2 (eCO_2), Total Volatile Organic Compound (TVOC) and light intensity. The temperature measurement is redundant and performed by two separate sensors. The measurement of CO_2 is also redundant, but obtained through distinct approaches. A dedicated low-cost CO_2 sensor performs one measurement of CO_2, while a second value (eCO_2) is derived by the measurement of TVOC.

A data infrastructure based on Amazon Web Services (AWS) has been set up to collect store and manage both the user feedbacks and the measurements.

With the support of KTH Innovation, a market analysis was carried out in order to evaluate possible business development out of the idea and technical stack developed within the project. The monitoring platform’s business idea is perceived relevant by the customer groups that have been interviewed.

The monitoring platform developed within the project has been deployed in several proof-of-concept campaigns during the project and a short summary of relevant outcomes are summarized in Section 3.8.2.

1.4.5 KTH Live Development of Digital Twin

During the project, a digital twin of the Testbed KTH has been developed and calibrated, following the definition of “digital twin” of the CIRP Encyclopedia of Production Engineering: “a digital twin is a digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases”.

A description of the digital twin development and calibration is provided in Section 3.1.

The calibration methodology consisted in a screening analysis to select a subset of parameters to optimize and subsequently an optimization process. The implemented calibration minimizes the error

between the model and the monitored data with a multi-objective cost function based on the discrepancy between indoor temperature and the energy demand.

The calibration process has proved to be straightforward and after calibration the overall error has been reduced from 13% to 6%, while guaranteeing that both errors on energy and indoor temperature trends are minimal.

1.5 Highlights

The project focused on numerous interconnected aspects of smart buildings (technological, sociological, and economic).

The foundation of smart buildings relies on the availability of trustworthy data. In order to address common problems in the existing building stock with very limited monitoring capability, this project has focused on the monitoring and control systems of the Live-In Lab testbeds and has used two demonstration sites representative of the standard of new buildings.

The research brought attention to shortcomings of the monitoring systems, mostly caused by data loss and lack of sensors. A greater understanding of the performance of the buildings in some circumstances may have been made possible by the inclusion of more sensors, allowing the reasons of anomalies or increased energy demand to be found.

Improved focus on clearer, more thorough documentation of technical systems and data infrastructures should be promoted as standard practice. There are clear signs that the usage of the data gathered in the examined buildings is extremely limited. Although it is believed that data in buildings is important, it takes time and expertise to conduct in-depth studies of raw data, and the uncertainty surrounding the findings of these analyses tends to deter some main stakeholders.

The SRI approach, which was first put forth as a framework at the EU level, served as an effective instrument in the project to statistically evaluate the smartness of buildings and modernize their systems in order to meet the objectives of the EU energy policy.

According to the cost-benefit analysis, the additional investment costs for commercially available standard and advanced monitoring systems are negligible, and economies of scale can result in further cost savings. Nevertheless, many stakeholders lack sufficient incentives to invest on advanced monitoring systems.

In the building industry, the importance of the impact of users and faults is not fully acknowledged. Cases of user behavior that had a significant impact on the building's functionality were demonstrated inside the project.

Demonstrations and showcases are effective ways to increase the adoption of cost-effective smart solutions in buildings. The control and operation of buildings should be centered on the users, which necessitates tighter cooperation between research and practice.

To have an impact on the building industry, platforms are required that promote best practices for open, scalable demonstrations of the advantages of digitization. The adoption of digitalization toward more sustainable and intelligent buildings should be encouraged. Innovation platforms like the KTH Live-In Lab, to which this project has made a substantial contribution, should be supported.

2 Inledning och bakgrund

2.1 Bakgrund

Information and Communications Technologies (ICTs) can substantially improve the energy performance of buildings. The European Commission has recognized the potential role of ICT in several high level policy documents and by supporting the development and the deployment of energy efficient solutions for buildings.

An ICT infrastructure consists essentially of three main blocks:

1. Monitoring devices
2. Communication infrastructure
3. Data, control and management infrastructure

Monitoring devices include sensors for monitoring physical parameters (e.g. indoor and outdoor temperature, relative humidity, light intensity, user occupancy, CO_2 concentration, concentration of pollutants) and sensors for monitoring consumption (e.g. energy, water, gas). The data generated by the monitoring devices is typically stored in databases or data repositories, analyzed and processed for control and management purposes. Control and management systems in buildings are often referred to as BMS (Building Management Systems). The communication infrastructure allows the data flow between the monitoring devices, the management system and the system actuators.

The design of an ICT infrastructure consists on the selection, integration and maintenance of these three main blocks.

- ICT solutions are very helpful to [1]:
- Verify whether the building and the systems installed perform as designed.
- Monitor that the performance and energy efficiency are stable during the lifetime of the building and do not decrease.
- Achieve more energy savings combining the operation of the different systems in the building.
- Provide feedback to change user's behavior and install new energy efficient technologies or fine tune those already installed.
- Help to increase users' comfort.

BMSs typically include four main functionalities: monitoring, control, optimization and report. However, not all these functionalities are required or always available in a BMS. While monitoring and reporting are common features for BMS, even in small projects for housing, BMS covering the four functions are more commonly implemented in large projects for tertiary service buildings with extensive mechanical, electrical, and pumping systems [1].

ICT solutions are suitable not only for new or recent buildings but also for old buildings

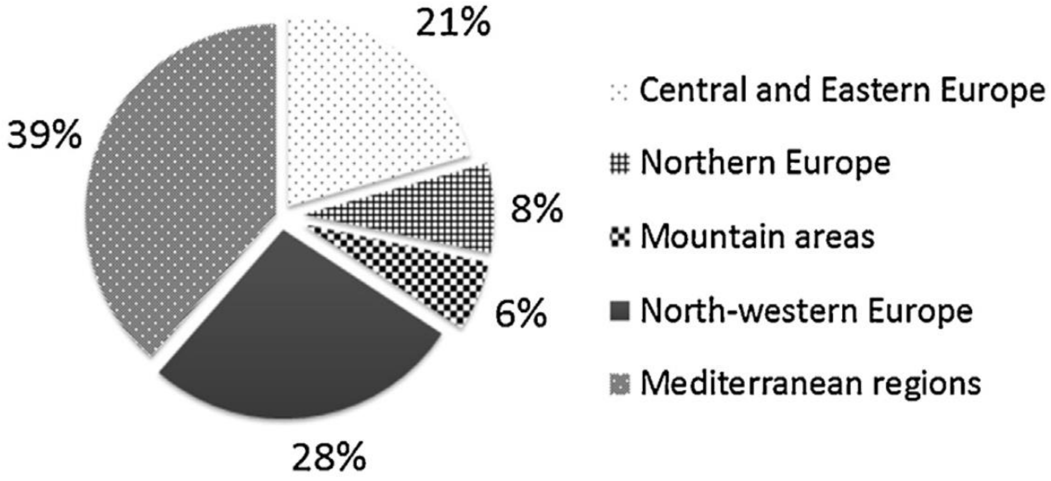


Figure 1 Buildings' location (from 18 European projects reviewed in [1]).

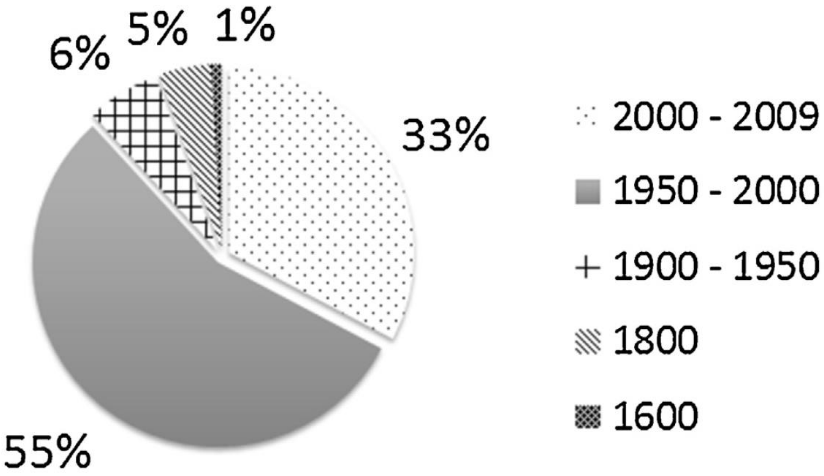


Figure 2 Buildings distribution by year of construction (from 18 European projects reviewed in [1]).

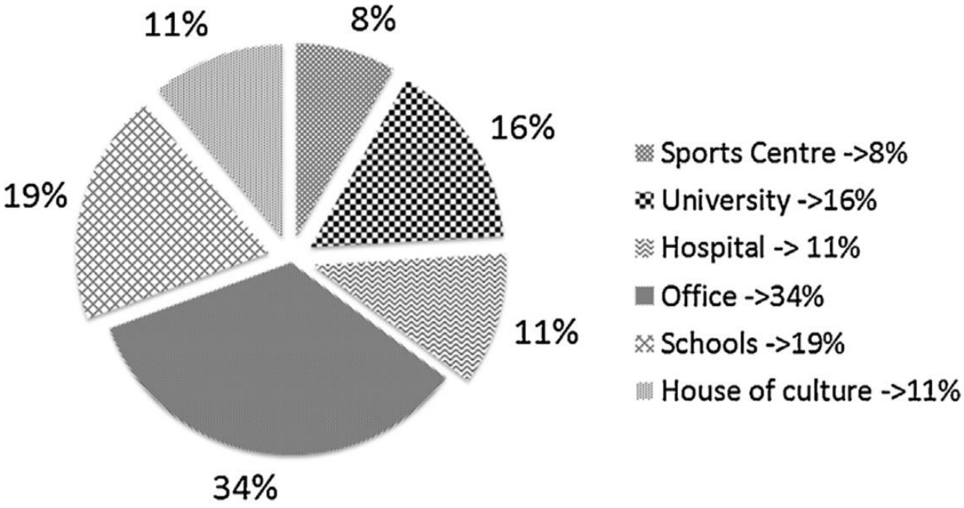


Figure 3 Public buildings distribution by typology (from 18 European projects reviewed in [1]).

A study published in 2016 [1] reviewed the results from 18 European projects involving 105 demonstrations sites where ICT measures have been implemented. The demonstration sites involved 88 cities, located in 23 European countries.

As shown in Figure 1, Figure 2 and Figure 3, social housing and public buildings projects have implemented and developed their pilots across Europe covering the main European climatic regions and countries. The ICT solutions implemented by the projects are suitable not only for new or recent buildings but also and especially for old buildings both in social housing and public buildings (Figure 2). The public buildings projects have implemented ICT solutions in different typologies of buildings in order to prove that their use can help building users to reduce the energy consumption adapting these solutions to the peculiarities of the various activities that take place within public buildings (Figure 3).

The success of ICT solutions is often connected to the awareness, preparation, engagement and motivation of end users.

Results from projects reviewed in [1] covering residential and non-residential buildings (including social housing and public buildings) have built common methodologies to calculate energy savings via ICT and the results are showing significant reductions in energy consumption and CO_2 emissions of about 20%. Nevertheless, it is important to notice that the best results have been achieved where ICT systems should be properly explained to the end users. Furthermore, the better relationships with the tenants, the better the results are, and relevant energy savings are achieved when ICT solutions promote behavioral changes.

Best energy savings are obtained when ICT solutions promotes behavioral changes.

However, several studies highlighted how the replication and scaling of the ICT solutions can lead to discrepancies in the results, mostly attributed to user behavior. In real practice, energy saving can be smaller than predicted, especially when the influence of user behaviors is overlooked.

Energy savings can be smaller than predicted in real practice when the influence of user behaviors is overlooked.

2.1.1 User behavior

Several studies show the central role that occupant behavior has in influencing the energy consumption and contributing to uncertainty in building energy use prediction and simulation [2], [3]. Occupant behavior affects building energy consumption significantly and is a leading source of uncertainty in predicting building energy use [4]–[7].

Simulation results can deviate significantly from the actual energy consumption of a building. Figure 4 shows a comparison between the simulated (predicted) energy consumption modeled during the design phase and the measured energy consumption for 62 Leadership in Energy and Environmental Design (LEED) certified buildings in the United States. For some buildings, models are relatively good predictors of the actual building performance. Nevertheless, there is a normalized root-mean-squared error of 18% [8].

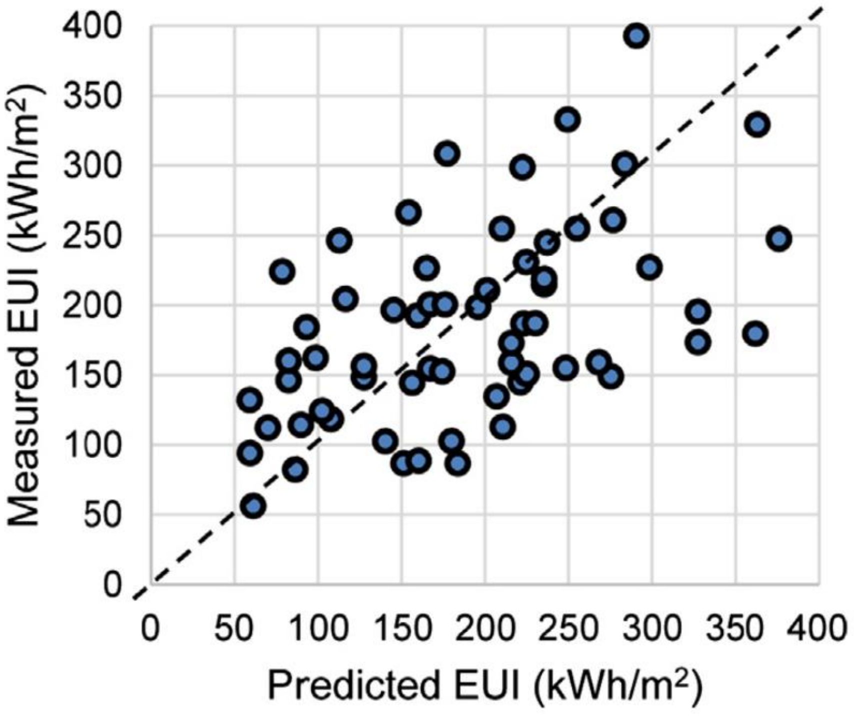


Figure 4 Comparison of measured and predicted energy use for 62 LEED new construction buildings [8].

Yan et al [3] in a state-of-the-art review found a normalized root-mean square error of 18% between predicted and measured energy use in LEED buildings and showed that energy wasteful behaviors could lead to 2 times larger consumption of electricity for air conditioning in apartments with the same physical characteristics.

Studies involving uncertainty in occupant behavior in building energy models, using various occupancy schedules and environmental preferences found that the energy consumption differed 150% or more if the occupant related inputs were maximized and minimized (even for typical occupant behavior patterns) [9]. The way occupants used the heating system made a significant difference on heating energy consumption and the occupants' presence and interaction with various building components significantly affect the energy consumption predictions made by energy simulation, even if the weather conditions, the building envelope, and the equipment are well-defined [10].

The correlation between occupancy and energy use is complex and at the same time not always evident or easy to interpret. Some experimental results presented weak correlation between occupant and energy consumption [11]. Similar findings were presented by another experimental analysis of the energy consumption of a non-domestic building where energy demand profiles were not strongly connected to the occupancy patterns; in that case it was later found that the building was controlled with a building management system where building users have minimal access to the controls [12]. This is one of the many examples of how more adaptable Building Management Systems (BMS) benefit not only electricity consumption, but also space heating and cooling demand.

Considering and understanding occupant behavior are key factors in the evaluation of technologies used in building design and retrofit.

Case studies have demonstrated that occupant behavior influences the adaptability and implementation of building technologies. A description of occupant behavior will result in robust building designs [13] and some studies reported that the energy savings potential, by increasing building insulation, depends heavily on occupants' use of terminal heating systems [14].

Advanced building design and operation requires the understanding of the interactions between occupant behavior and building technologies.

Behavior patterns and technical solutions are interconnected and the effective interaction between occupants and building systems to achieve their comfort and health needs may be more important than the mere technology efficiency indicators.

User presence and behavior patterns not only vary between each other, but also tend to evolve in time [3], [15], [16] and occupants' behavior often also differ due to the individual preferences and environmental perception. Individual user preferences regarding work or living environments span from lighting to temperature and humidity [17]–[19].

Individual's preferred work plane illuminance can range from 230 to 1000 lux [17], thermostat set point could very well vary from below 19ºC to above 25ºC, depending on personal preferences [19] and that identical thermal conditions can lead to both window opening and closing in different offices [20].

The primary factor motivating occupants to open windows in the winter is the indoor air quality

Some studies indicated that the primary factor motivating occupants to open windows in the winter is the indoor air quality while noise from outside is among the primary factors leading a window closing action [21]. Window opening actions can also be driven by indoor humidity and weather conditions, like win, rain and solar radiation [5], [20], [22].

For all this reasons, considering the occupants' behavior in the building design is very challenging. The static schedules often used in building simulation tools are a simplification that does not properly model the complex influence of occupant behavior on building energy consumption and the indoor environment [7], [23], [24]. For example, without modeling occupant use of window blinds, simulation results may indicate that maximizing the window area will lead to maximized daylight utilization. The use of static schedules to represent occupant behavior in building simulation tools fails to reflect this dynamic interaction between the users and a building's design.

Development of occupant models typically require large amounts of data

Several occupancy models have been developed based on long-term observational studies, trying to synthetically describe window operations, shading, lighting [25]–[35], air conditioning operations and clothing [36]–[38]. All these models typically require large amount of data and cannot grasp many aspects of buildings, users and the environment (e.g. building typology, users' culture and climates).

2.1.2 Monitoring Indoor Air Quality (IAQ)

"Indoor air quality" has no universal or standard definition

What is indoor air quality? "Indoor air quality" has no universal or standard definition. In general, IAQ is related to pollutants (e.g., biological, chemical, and physical) within indoor environments that can affect the health of occupants. IAQ is considered a subset of indoor environmental quality (IEQ); the latter includes factors such as lighting, ergonomics, acoustics, and temperature in addition to pollutants [39]. Despite the lack of a universally accepted definition, IAQ is typically associated with the level of air pollutants and the most frequently addressed pollutants are volatile organic compounds (VOCs), formaldehyde, and carbon dioxide (CO_2).

Studies based on long-term indoor monitoring revealed pollutants concentrations that exceeded the recommended values

Several studies focused on the evaluation of Indoor Air Quality (IAQ) in schools, hospitals and offices, by analyzing the data collected through permanent ICT infrastructure or dedicated monitoring devices. The general outcomes from all the studies highlight the importance of continuous monitoring of the indoor environment.

Results of a study involving 25 classrooms [40] suggest that environments (in this case classrooms) with high potentials for natural ventilation do not necessarily provide adequate IAQ; however, occupants' good practice of adaptive behaviors is also required.

Another study published in 2020 [41] analyzed the long-term monitoring data of three non-domestic buildings in UK: a school, a hospital and an office building focusing on measurements of temperature, humidity, CO_2, total volatile organic compounds (TVOC) and air pollutants like $PM_{2.5}$, NO_2. The three case study buildings all represent modern buildings designed to comply with the energy efficiency requirements prevalent at the time of construction. Each had been occupied for at least 3 years at the start of this study, avoiding issues related to initial commissioning and occupants settling in and aiming to ensure the buildings are being occupied and run under typical operating conditions. Figure 5 and Figure 6 show the aggregated results of continuous monitoring of CO_2 and TVOC. For each building, 3 zones have been monitored. In two cases, the continuous monitoring unveiled that excess of CO_2 levels were due to faulty room-based CO_2 sensors, which restricted the activation of automated ventilation. In addition, many actuators for automated ventilation had been installed wrong, limiting their capability to provide the required ventilation. Moreover, during the heating season the ventilation actuators were overruled in order to meet operational energy targets.

"The use of automated louvers was restricted during the heating season in order to meet operational energy targets"

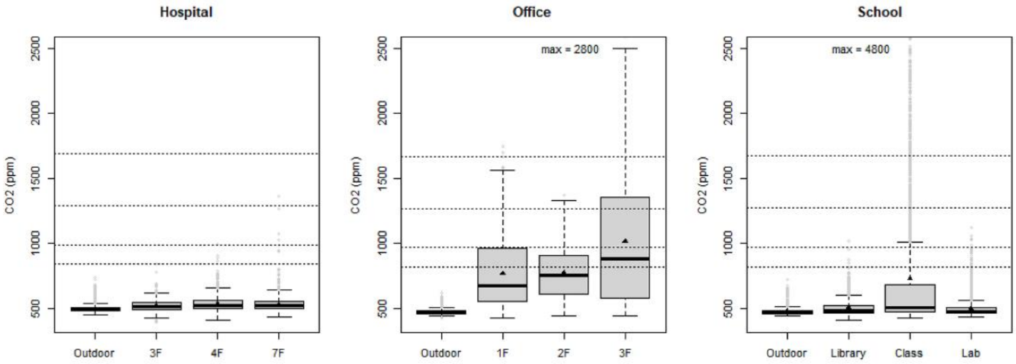


Figure 5 Results of CO_2 monitoring in three case study buildings of [41]. (Hourly data). Thresholds for indoor CO_2 concentrations above ambient by +350, +500, +800 and +1200 ppm.

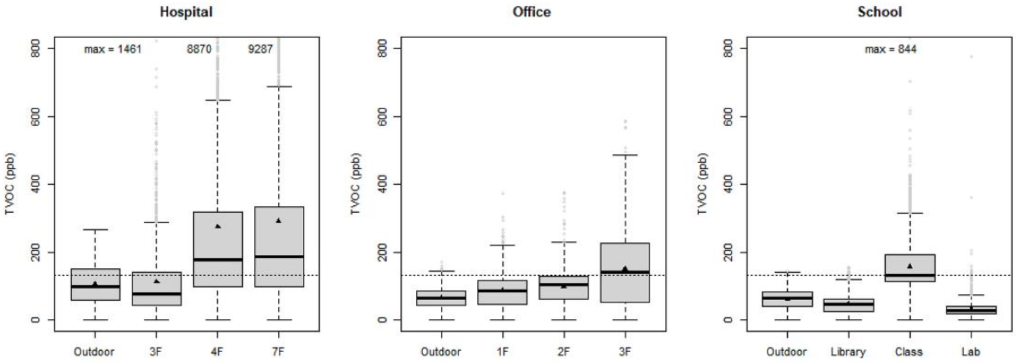


Figure 6 Results of TVOC monitoring in three case study buildings of [41]. Threshold for TVOCs at 131ppb.

Low-cost continuous air quality sensing yields to valuable information upon IAQ and building operation

The study revealed that all formaldehyde measurements in the office building exceeded the recommended values. From a methodological standpoint, low-cost, continuous air quality sensing, has been shown to yield valuable dynamic information upon the relationship between IAQ and both building operation and external environmental conditions. Developments in sensing technologies, along with suitable quality assurance processes, mean there is potential for wider adoption of long-term continuous monitoring [41].

Do 'green' buildings have better indoor environments?

A few studies highlighted the increasing need of long-term monitoring data arguing that research certified "green" buildings focused energy-saving performance and less on keeping an appropriate IAQ for the occupants [42]. The interpretation of the results requires some argumentation. In general, green buildings give superior indoor environment performance compared with similar conventional buildings.

However, results are not always clear and clear metrics are missing. Results show that the highest satisfaction ratings include "satisfaction with a view to the outside, aesthetic appearance, less disturbance from HVAC noise, workplace image, nighttime sleep quality, mood, physical symptoms, and a reduced number of airborne particulates" [43], together with thermal conditions and environmental satisfaction.

Green buildings have the potential to promote more favorable indoor air quality and perceived IAQ is typically better in green buildings than in conventional buildings. However, "green" does not necessarily guarantee good indoor air quality. Current certification procedures are lacking solid guidelines and metrics for IAQ evaluation. Local green building codes, especially in the developing world, often do not systematically recognize IEQ or health as crucial issue [44]. Certification schemes may provide inadequate incentive in the credit system for improving indoor air quality.

Current certification procedures are lacking solid guidelines and metrics for IAQ evaluation

As an example taken from a study in Taiwan [42], out of the 925 green buildings certified in Taiwan by 2012, only 28% (259 certifications) targeted the IEQ criterion (see Figure 7). While the IEQ appeared to be a primary concern for local building occupants, it was less frequently an attribute that the builders and building owners would prioritize when certifying a building. In the certification of green buildings in Taiwan, the IEQ was evaluated by the performance of the building in the acoustics, lighting, ventilation, and materials used in interior construction, with the aim being to facilitate an indoor environment that was healthful and comfortable to the occupants. However, thermal comfort was not considered an essential area of IEQ evaluation [42].

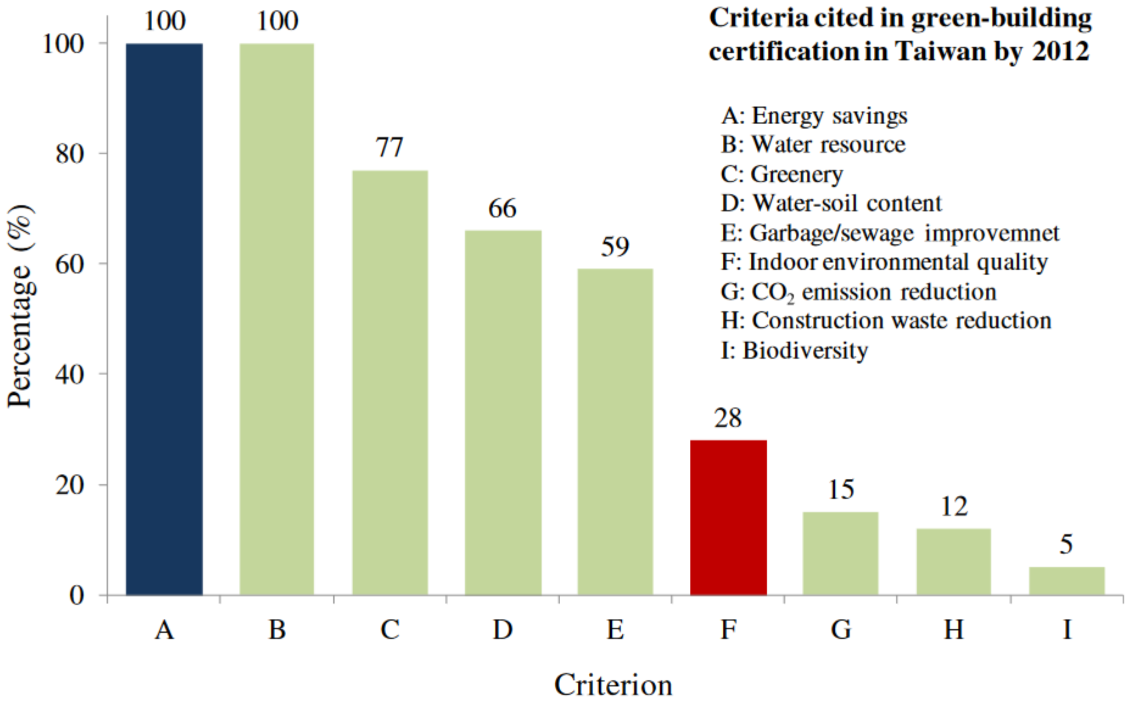


Figure 7 Frequency of individual criteria cited in certification of and satisfied by buildings for a green building label in Taiwan [42].

Interestingly, certain green practices and green products could actually impair indoor air quality. The focus on ventilation as a primary method for IAQ control overlooks opportunities for source control and exposure reduction [39].

Figure 8 shows the results from a study that compared the perceived indoor comfort in conventional buildings and in certified green buildings. [44]. The satisfaction regarding indoor temperature and humidity is notably lower in the green buildings (GB) compared to the conventional buildings (CB).

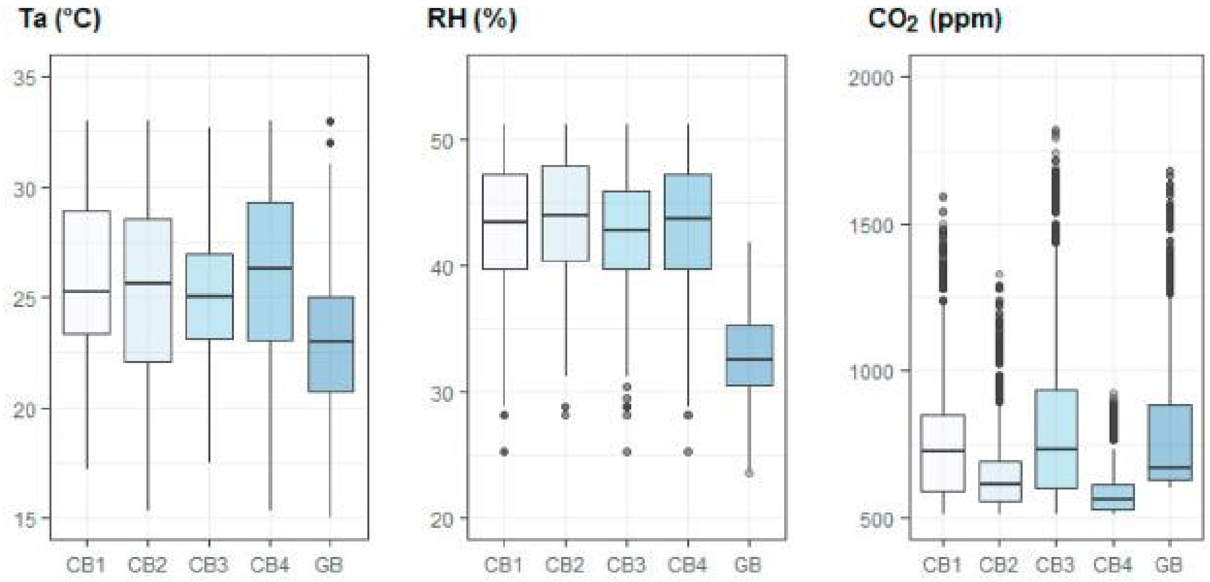


Figure 8 Boxplot the distribution of the Ta, RH, and CO_2 varied across monitored buildings during the same monitored period (CB indicates conventional buildings and GB indicates green building) [44].

The study suggested that green building designers, developers and policymakers pay greater attention to the occupants' related aspects. While reducing energy consumption and consequent emissions are undoubtedly important, designers of green buildings should think beyond these features, towards improving employee health, visual and acoustic comfort. This suggests the need for developing a follow-up management plan, that can be a part of the green building certification scheme [44].

2.1.3 Perceived comfort

The individual perception of comfort is one of the element that draws the complex relationship between the buildings and their users [45].

The quantitative evaluation of the perceived comfort has been the subject of several studies and typically involves questionnaires to the users, together with the collection of data through indoor sensors.

Questionnaires need to be carefully designed in order to [44]:

1) identify potential bias to determine if occupants tend to respond to the surveys more frequently during unfavorable conditions;
2) evaluate the relationship between thermal comfort and temperature, RH measurements;
3) evaluate the relationship between IAQ comfort and measured carbon dioxide concentration;
4) evaluate the interaction between thermal comfort and carbon dioxide concentration, as well as IAQ comfort and temperature measurements.

Assumptions about occupant comfort and its relationship to IEQ may depend on building types

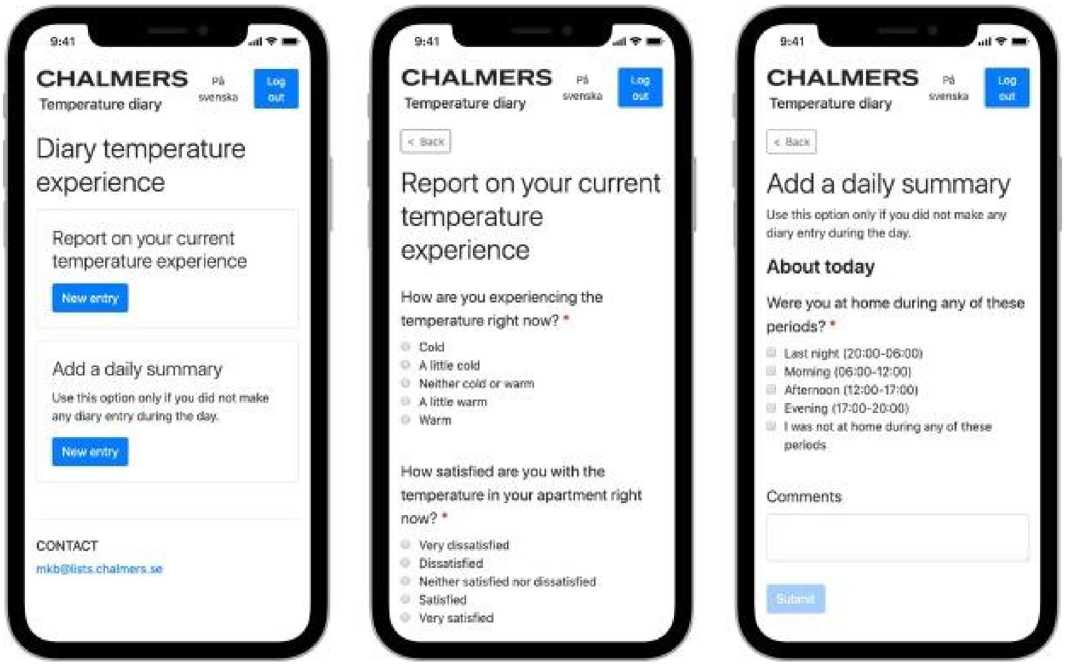
Results of the case study presented in [44], which focused on a sport facility, also suggested that some assumptions about occupant comfort and its relationship to IEQ may not be applicable for different building types. For example, more males reported feeling cool or very cool than females, and the median temperature corresponding to neutral or thermally comfortable votes was higher for male respondents.

The study "My apartment is cold! Household perceptions of indoor climate and demand-side management in Sweden" [46] evaluated the perception of indoor temperature conditions and demand-side management from the perspective of households living in multi-residential buildings in the south of Sweden. The participants were divided in groups and exposed to load shifts over a two-week trial conducted during early winter. The reports highlighted that *although no statistically significant difference was found in thermal sensation or thermal satisfaction, significantly fewer participants could imagine allowing more variation in temperature at home to save energy after the trial than before.*

Users that perceive to be able to control the indoor temperature are more willing to accept larger temperature variations.

The results indicated a demand for more control over the indoor temperature as well as a positive correlation between perceived control and willingness to accept larger temperature variations.

The participant could report the perceived comfort both via mobile app (Figure 9) or via paper. Figure 10 and Figure 11 show examples of aggregated results of the study collected by participants in condition of discomfort.



Diary temperature experience

Report on your current temperature experience

Add a daily summary

Use this option only if you did not make any diary entry during the day.

CONTACT

mkb@lists.chalmers.se

Report on your current temperature experience

How are you experiencing the temperature right now? *

○ Cold
○ A little cold
○ Neither cold or warm
○ A little warm
○ Warm

How satisfied are you with the temperature in your apartment right now? *

○ Very dissatisfied
○ Dissatisfied
○ Neither satisfied nor dissatisfied
○ Satisfied
○ Very satisfied

Add a daily summary

Use this option only if you did not make any diary entry during the day.

About today

Were you at home during any of these periods? *

☐ Last night (20:00-06:00)
☐ Morning (06:00-12:00)
☐ Afternoon (12:00-17:00)
☐ Evening (17:00-20:00)
☐ I was not at home during any of these periods

Comments

Figure 9 Mobile app for the participants of study [46].

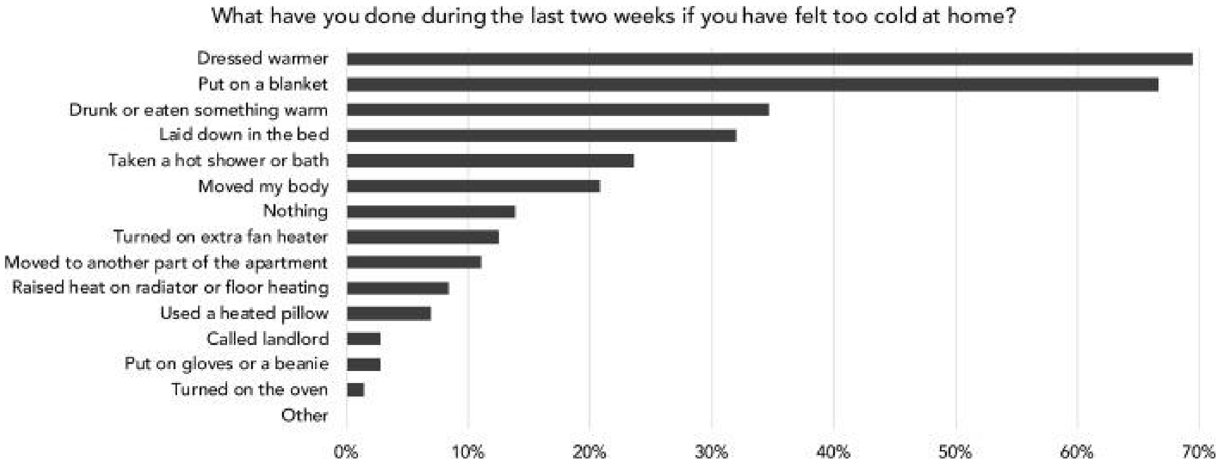


Figure 10 Actions carried out when feeling too cold at home [46].

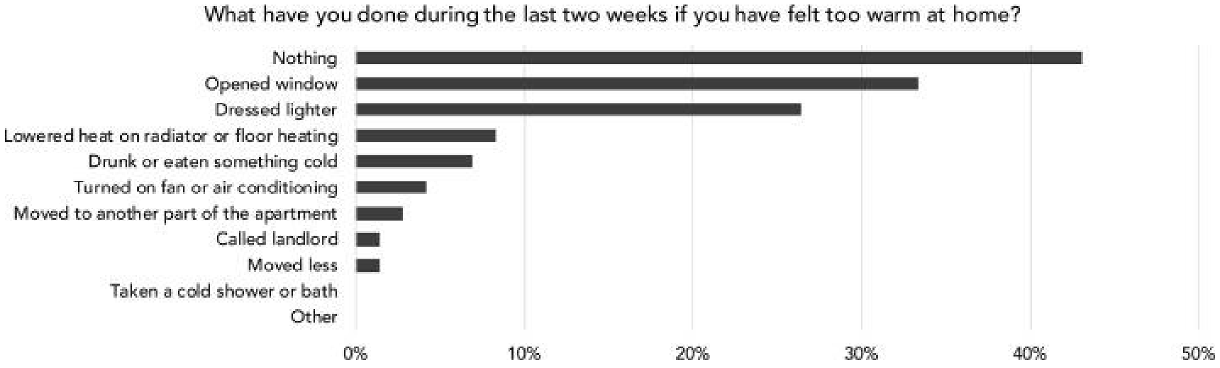


Figure 11 Actions carried out when feeling too warm at home [46].

A study from 2006 [47] presented the results of over 34000 survey responses to air quality and thermal comfort questions in 215 buildings in US, Canada, and Finland. The results show that only in 11% of the buildings the occupants expressed overall satisfaction (more than 80% of the users) with their thermal comfort. Figure 12 shows an example of the results obtained.

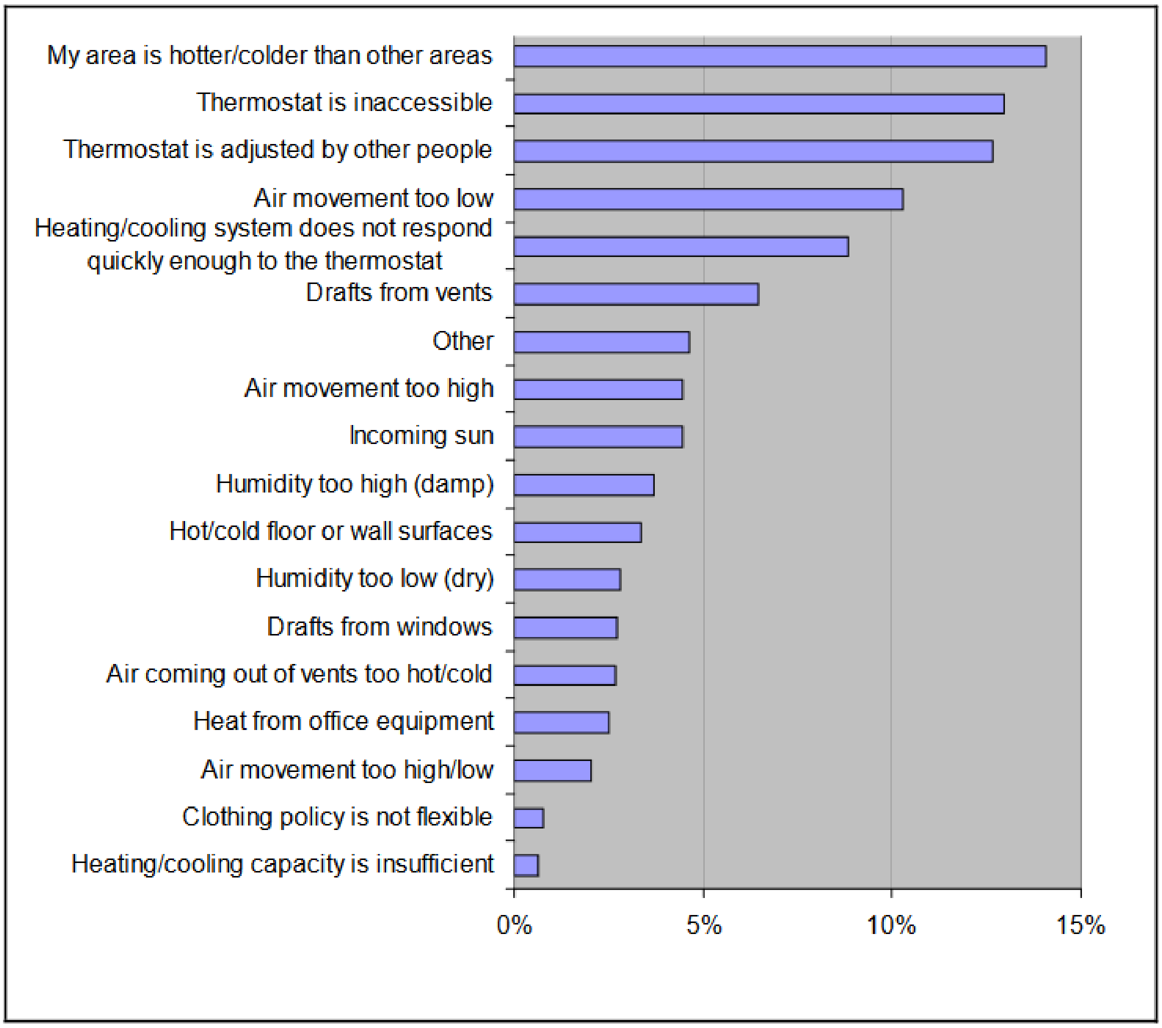


Figure 12 Sources of dissatisfaction with workspace temperature ranked by frequency of occurrence [47].

This study, once again, shows that personal control over environmental conditions (e.g., thermostat or operable window) has a significant positive impact on occupant satisfaction, suggesting possible improvements to how buildings are designed, built, and operated to increase occupant comfort and productivity.

2.2 Syfte och mål

The goal of the project was to provide an assessment of the state of the art and common practice of monitoring and control systems in the building sector, with a primary focus on the identification of design issues, missed opportunities from current systems that result in inefficient energy use and sub-optimal comfort conditions. The project proposed a range of solutions for cost-optimal design and implementation of building monitoring and control systems for different types of new and existing buildings, including residential and office facilities.

The specific goals of the project have been:

- To assess the quality of data from advanced monitoring systems;
- To identify the most common faulty settings in the heating and ventilation systems;
- To showcase the impact of the mutual interaction between faulty settings and user behavior on energy use;
- To improve the exploitation of existing databases;
- To evaluate advanced and self-tuning control strategies;
- To propose and showcase methodologies and metrics to assess the quality of data and the smart readiness of the buildings;
- To showcase the cost-effectiveness of ICT solutions to increase efficient energy use in buildings and improve comfort.

As a result, new opportunities will be enabled to allow new and existing buildings to unlock the potential for energy saving given by digitalization and data-driven services.

2.3 Omfattning och avgränsningar

The project investigated technical and economic drivers and bottlenecks towards the development and adoption of smart buildings. Within the project, data collected from the advanced monitoring systems available at KTH Live-In Lab have been analyzed and discussed to highlight the advantages, limitations and burdens of common practice adopted in the building sector regarding digital solutions and data infrastructures.

The project has been carried out over a period of 3 years and developed mainly at KTH Live-In Lab in collaboration with project partners with proven expertise in the building sector. Within the collaboration with Botrygg, Akademiska Hus and the technical partners Einar Mattsson, Schneider Electric and Bengt Dahlgren, the project involved also additional buildings for replication and knowledge transfer purposes.

The project aimed at identifying and propose cost-effective solutions and digital tools that increase buildings energy efficiency and sustainability.

The project provided an assessment of the inefficient energy use of common faulty systems and guidelines for cost-optimal design and implementation of building monitoring and control systems.

3 Genomförande och resultat

The project development included several activities involving three testbeds of KTH Live-in Lab and other facilities in collaboration with project partners. The research activities carried out during the project include data-analysis, economic assessment, development of new solutions and demonstration. In this section, the implementation and results of the project are summarized.

3.1 KTH Live-In Lab Testbed KTH: monitoring and control infrastructure (WP2, WP3)

The KTH Live-In Lab is a platform for innovation in the building sector that includes three main testbeds and additional demonstrators for buildings [48]. The platforms currently includes three types of demonstrators: a core lab, two extended labs, and external labs (Figure 13). The core lab features the most advanced monitoring platform and allows researchers to interact with users and tailor more easily solutions for research projects. The extended labs feature advanced but commercially available solutions for monitoring and control of the building, while external labs are project-specific and can include standard buildings that share data with the Live-In Lab [49].

The Testbed KTH (core lab) and the Testbed EM (extended lab) are student accommodation while Testbed AH (extended lab) is a lecture building. The Testbed KTH is within the building enclosure of the Testbed EM, but it has an independent heating emission and monitoring system. The experimental setup is described in the following paragraph; more detailed information can be found in [49].

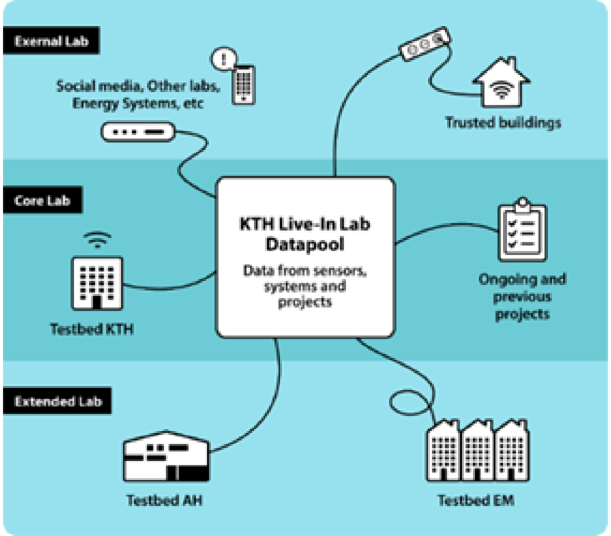


Figure 13 Conceptual layout of KTH Live-In Lab data sources.

The Testbed KTH is the most advanced testbed facility in the Live-In Lab and, compared to the other live-In Lab testbeds, features a more extended sensor network, a higher degree of interaction with the testbed occupants and the possibility of extensive layout redesign. Its overall heated surface is 300 m^2, distributed over approximately 120 m^2 of living space. The layout of the Testbed KTH is flexible and is redesigned every year to accommodate for specific research purposes. The original configuration (Testbed 1.0) consisted in four apartments; each apartment was divided into a living room, a kitchen and a bathroom. The current configuration, called Testbed 3.0, comprises four individual rooms, two bathrooms, a kitchen and a common area. Heating to the apartments is provided by ground-source heat pumps and distributed through the ventilation system. Electricity is generated locally in the Testbed EM with PV panels installed on the flat roof; additionally, an electricity storage system is also available.

Figure 14: Computer-generated view of the Testbed KTH.

Advanced sensing capabilities have been deployed to monitor indoor environment parameters, like temperature, humidity VOC and CO_2, to meter the energy used in the apartments for space heating, domestic hot water production, tap water, as well as the energy delivered from the borehole heat exchangers, the heat recovery and the PV panels. Redundant temperature sensors placed in the walls allow a better assessment of the comfort. Furthermore, real-time measurements of ventilation airflows and temperatures enable detailed mapping of space heating use. Additional sensors detect windows opening and occupancy used to optimize resource usage without compromising user experience. The adoption of light sensors makes it possible to study internal illuminance, maximize the use of daylight and improve the light comfort. Sensors are extensively used to improve energy efficiency and indoor comfort, study user behavior and to improve control and fault detection strategies. Indoor environmental quality is continuously monitored via multiple temperature, relative humidity, CO_2 and VOC sensors in each room. Space heating energy is distributed through the ventilation system and both ventilation and energy are continuously monitored at the apartment level; in addition, electricity consumption is also logged per apartment.

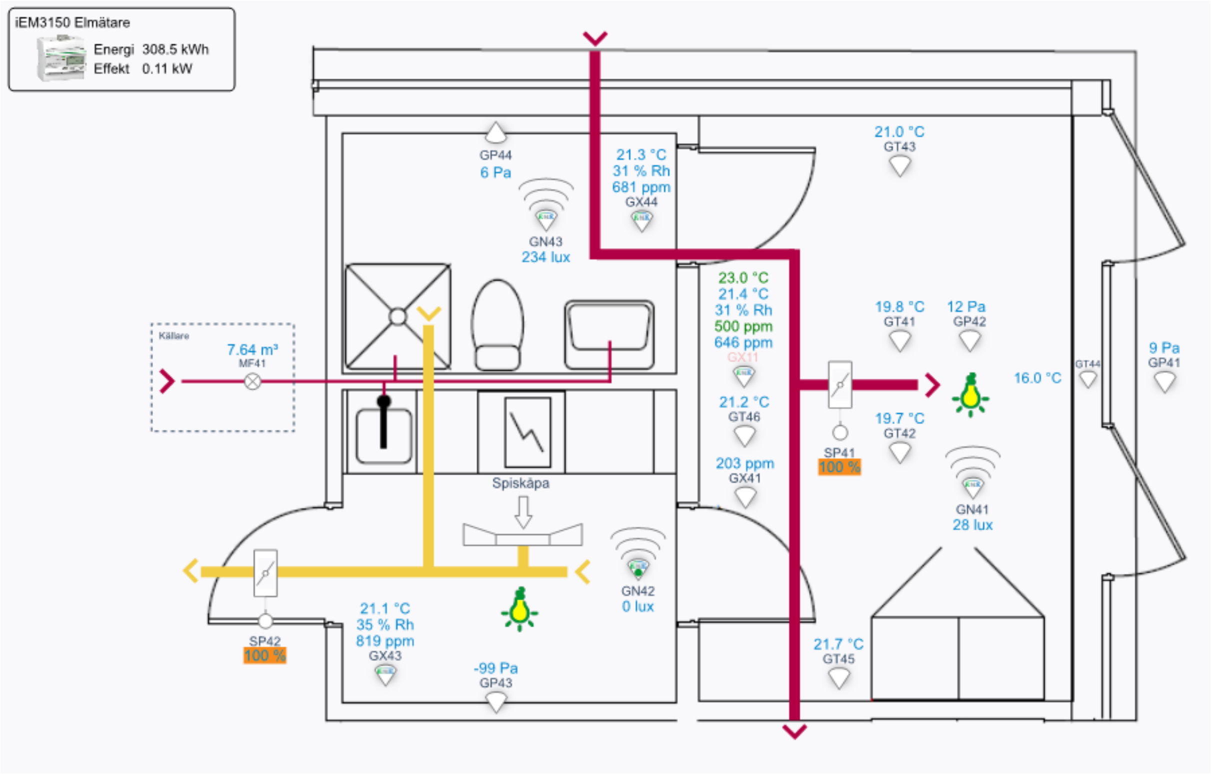


Figure 15: User interface displaying indoor sensor placement and real time values for the building occupants in the Testbed KTH.

3.1.1 Digital twin of the Live-In Lab Testbed KTH: development and calibration

Publication: M. Molinari, D. Rolando. Digital twin of the Live-In Lab Testbed KTH: development and calibration, BuildSim 2020

A research study developed during the project proposed a calibration methodology for the thermal model (energy and comfort) of the Live-In Lab, developed in IDA-ICE, to be deployed as a digital twin. The methodology developed first screens the parameters with most impact on energy use and then calibrates the model minimizing the error in both indoor comfort and energy use with a weighting parameter β. Calibration results have been validated against the measured data. The results of this study are instrumental to the improvement of control systems and foster the modeling of occupant behavior on building energy use.

According to the CIRP Encyclopedia of Production Engineering [50] the definition of a digital twin can be given as:

> *"A digital twin is a digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases."*

A review study [51], identified 13 characteristics common to digital twins; according to [51] all digital twins share, among other characteristics, a physical entity (e.g., a building), the virtual entity or twin (e.g., the building model of the building), a physical and virtual environment (e.g. the weather and the weather monitored data), a physical-to-virtual connection and twinning, i.e., the act of synchronizing virtual and physical states. An interesting example of implementation of a digital twin for buildings can be found in [52]; they present a coupled simulation for the thermal design of a space heating and cooling integrated in a lightweight roof structure to support design improvements.

In building design and operation, digital twins can serve as an invaluable tool to test the effectiveness of advanced control architectures in reducing energy use and providing improved comfort, to test cost-efficient fault detection schemes, to generate realistic data for benchmarking of algorithms and to investigate potential privacy risks related to the increasing sensing and monitoring capabilities.

The Testbed KTH is configured as a smart building; a key element to foster research is the creation of its energy digital twin. The first step in the creation of the digital twin is the implementation and the calibration of an energy model: the study published during the project dealt with the process of calibration and introduced a methodology considered particularly suitable to the specific requirements of a digital twin.

The capability to accurately predict energy use and temperature is crucial. Prediction discrepancies in building simulation models typically arise from uncertainties in input data relative to the building enclosure, like for instance geometry, air-tightness and wall insulation, to the HVAC system, control setting, e.g. temperature set-points, and to the building usage, i.e. internal gains from people, light and equipment. The issue of reliable data retrieval for simulations may be even more problematic for older buildings, where such information may not be available at all – thus relying on an assessment based on expert knowledge. In addition, the monitoring of certain environmental conditions, like solar radiation, can be impracticable, expensive or not commonly available; similarly, certain variables like occupancy estimation in time may not be accurate. All these uncertainties are likely to result in a relevant mismatch between the building and the building model it represents. Building models calibration against measured data has proven an effective way to improve the prediction accuracy of the models.

The calibration of a building energy model can be used as a first step towards the evaluation of energy savings measures: examples can be found in Ascione et al., [53], where a calibration is performed for the whole building model – a university building- on the available monthly energy data (gas and electricity) after a preliminary investigation on the prevalent indoor conditions, with errors after calibration below recommended thresholds.

The building energy model and the measurements refer to the Live-In Lab Testbed KTH (Figure 16). A building model, to be used as a digital twin, has been created in the IDA-ICE 4.8 simulation environment [54]. The IDA-ICE release 4 has been validated according to EN 15255-2007 and performs within given error boundaries (0,5 K for operative temperature and 5 % for maximum and average cooling power) in all but one test cases; validation scores according to EN 15265 are A in most of the heating cases [55]. To enhance the model accuracy, the simulation model features a zone per each room of the apartments; all apartments share the same layout with a living room, a kitchen/entrance and a bathroom.

Figure 16: Computer generated view of the Testbed KTH building [source: property developer Einar Mattsson] and the building model generated in IDA-ICE.

The calibration methodology consisted in a screening analysis to select a subset of parameters to optimize and subsequently an optimization process. The implemented calibration minimizes the error between the model and the monitored data with a multi-objective cost function based on the discrepancy between indoor temperature and the energy demand. In the calibration process the user can set a parameter β to weigh the relative importance of the temperature and energy error.

The calibration process has proved to be straightforward and after calibration the overall error has been reduced from 13% to 6%, while guaranteeing that both errors on energy and indoor temperature trends are minimal. For optimized configurations, the proposed procedure has managed to yield a calibration error below the recommended thresholds in the literature.

Although the monitored dataset is currently limited in extension, the observed dynamics in the model follow closely the monitored temperature and energy trends, which is a key feature for the adoption of the model as digital twin.

The sensor platform of the Testbed KTH, which includes the continuous monitoring of indoor comfort conditions, occupancy and internal gains from detailed electricity readings, has proved an invaluable tool to provide the necessary data for calibration and in the evaluation of the impact of user activities.

3.1.2 Data-driven predictive control for smart buildings

Publication: M. Farjadnia, A. Alanwar, M. U. B. Niazi, M. Molinari, and K. H. Johansson, “Robust Data-Driven Predictive Control of Unknown Nonlinear Systems using Reachability Analysis.” 2022

Buildings are responsible for approximately 40% of the European Union (EU) energy consumption [56]. In EU nations, more than half of this energy is used for comfort control in buildings through Heating, Ventilation, and Air Conditioning (HVAC) systems [57]. In this context, improving the buildings' energy efficiency while properly maintaining users' comfort levels has received considerable attention.

Model Predictive Control (MPC) is an effective advanced control technique in control of buildings for its ability to integrate economic, energy-related, and indoor environmental aspects as well as technical and operational constraints. In general, MPC at each time step computes the control inputs over a given prediction horizon employing the model of the system such that the predicted cost function (i.e., energy or electricity price) is minimized while comfort constraints (i.e., CO_2 and indoor temperature levels) are fulfilled. MPC has been shown to improve the buildings' energy efficiency in both simulations and experimental studies [58]–[60]. For example, Sturzenegger et al. [58] applied MPC to the HVAC systems of a Swiss office building, and they achieved a 17% improvement in energy savings employing MPC compared with Rule-Based Control (RBC). However, a sufficiently descriptive model of the system is required for the MPC method to optimize the closed-loop system performance and guarantee constraint satisfaction [61]. In practice, accurate modeling and identification of buildings are very costly in terms of time and resources [62].

Recently, data-driven control has gained considerable attention as data is becoming more readily available in science and technology. The key idea in data-driven methods is to design control systems directly from data without explicitly identifying a model a priori. This is particularly useful when the system is too complex and deriving a reliable model is challenging and prone to errors. Numerous successful applications of data-driven control in various fields demonstrate how well-suited these techniques are for operating physical systems while achieving high performance [63], [64]. In data-driven predictive control applications for buildings, Smarra et al. [65] presented a method that relies on random forests as a modeling technique and leverages historical data for receding horizon control. The authors show the effectiveness of this method in several building case studies. Recently, Chinde et al. [66] applied the data-enabled predictive control (DeePC) algorithm to the building's HVAC systems. In this approach, past noise-free input-output data are used to predict the future behaviour of the nonlinear system and to compute optimal control inputs. The authors illustrated that the closed-loop simulation results using DeePC approach were comparable with the results employing MPC. However, the authors demonstrated that the performance of DeePC is sensitive to the regularization terms added to deal with nonlinearities. It is important to emphasize that all the works cited above either assume noise-free data or do not provide robust safety guarantees under system constraints.

In the context of this project, we present a robust data-driven predictive control approach to control unknown nonlinear systems under bounded process and measurement noise (see [67] for details).

The proposed approach uses noisy data to derive an implicit data-driven model of the system in real-time and obtains an optimal control input guaranteeing robust constraint satisfaction. We employ a zonotopic set representation in this approach to present an implicit data-driven system representation.

To this end, two online phases are considered: the learning and control phases. The goal of the learning phase is to compute an implicit data-driven representation of the unknown nonlinear system using zonotopes at each time step. In this phase, the unknown nonlinear system is approximated by a data-driven linear model using the past input-output data of the finite horizon. Then, the model mismatch is bounded by a zonotope using the data. In the control phase, we propose a robust, data-driven approach called *nonlinear zonotopic predictive control* (NZPC). NZPC utilizes the learning phase and zonotope recursion at each time step to predict the reachable output set over a finite horizon. The optimal control problem solved by NZPC in this phase yields an optimal control input that minimizes the given cost function and satisfies the specified constraints. In this method, the input-output data set is updated over time as the close-loop system evolves, i.e., old data is discarded each time new data is collected and added to the data set to enhance the implicit system representation and, accordingly, to improve the controller performance. A detailed discussion of NZPC is provided as an attachment to this report.

In a future work, these results will be further exploited to design a data-driven predictive scheme for smart buildings to optimize energy use for space heating while maintaining thermal comfort levels of the occupants without requiring a prior system identification step. NZPC not only provides simpler control implementation by eliminating the need to model the physical system, but also provides safety guarantees under various technical and operational constraints.

3.1.3 Highlights and lessons learned

- Data driven control approaches can become key to reduce the implementation cost for advanced controls in buildings, enhancing their scalability;
- Co-simulation approaches based on calibrated models provide a reliable tool for evaluation of advanced control strategies and demonstration.

3.2 KTH Live-In Lab Testbed EM: long term monitoring analysis (WP2, WP3)

Publication: D. Rolando, W. Mazzotti Pallard, M. Molinari. Long-term evaluation of comfort, indoor air quality and energy performance in buildings: the case of the KTH Live-In Lab testbeds, MDPI Energies 2022

Figure 17 3D view and typical floor configuration of Testbed EM.

In the project, the monitoring data of KTH Live-In Lab Testbed EM has been analyzed to assess the capacity of a commercial, state-of-the-art monitoring system to understand whether the building is operating under acceptable in-door conditions. The study also focused on the use of resources, namely energy for space heating, use of domestic hot water and electricity consumption and the impact of anomalies due to building occupants behavior. Ultimately, the study elaborated considerations on: the amount of data generated in buildings and the amount that is effectively used; the building energy gap assessment; the variability of controllable resources such as domestic hot water and electricity; the identification of occupant behavior on indoor environment conditions and building energy use.

3.2.1 Testbed EM: buildings and apartments

The Testbed Einar Mattsson ("Testbed EM" in the following) is a set of three residential buildings including 305 student apartments located at the main campus of the Royal Institute of Technology (KTH) in Stockholm. The average size of the apartments is approximately 20 m^2, and each includes a living room, a small kitchen and a bathroom. The three buildings have a total heated area of about 10590 m^2.

A set of three 60kW geothermal heat pumps provides heat to the Testbed EM; the heat pumps use 11 boreholes as a heat source. The geothermal installation design has some unconventional features in order to function also as an infrastructure for research. The boreholes have lengths ranging between 225 and 350 meters, with a total length of 3085 meters. Fiber optic cables are installed in 5 boreholes to allow the monitoring of the temperature along the borehole length through a Distributed

Temperature Sensing (DTS) equipment. An additional borehole with a length of 100 meters is available only for testing and research purposes and is not coupled to the three geothermal heat pumps [68].

The buildings feature an efficient thermal envelope and the Termodeck system, an example of Thermally Activated Building Systems (TABS) for heat emission. Ventilation air circulates through the building slabs before entering the rooms, preheating or precooling the slabs; this feature allows a more stable and homogeneous temperature distribution in the indoor spaces, adding to the comfort.

The heating system of the buildings includes a heat recovery system for ventilation and for the wastewater, and 3 waste heat exchangers. In addition, renewable energy is generated locally with 667 PV panels installed on the whole roof surface, for a total of 1150 m^2. Figure 17 shows a 3D view and the blueprints of typical floor in each building of Testbed EM.

3.2.2 Testbed EM: Heat Pump, Ventilation and Monitoring Systems

The buildings are located in a cold climate and are thus heating dominated. Figure 18 shows a simplified schematic of all the sub-systems included in this study. Space heating and Domestic Hot Water (DHW) are provided via Ground Source Heat Pumps (GSHPs). Heat is supplied to the apartments through 5 centralized Air Handling Units (AHUs). Cooling is not actively provided, although free-cooling may occur via the ground. The system does not have an auxiliary heating system although heat recovery on wastewater is implemented and used to pre-heat DHW. In order to smooth out peak demand from the DHW system, 8 m^3 of water tank storage are installed. Incoming fresh air to the AHUs can also be pre-heated from (or cooled by) the boreholes.

Figure 19 shows a simplified schematic of the heat pump system. There are eight series-connected water tanks on the DHW side and two water tanks on the space heating side. The volume of each water tank is 1 m^3. The DHW is circulated around the building and the cold water is pre-heated with wastewater whenever possible. The circulation pumps on the source side are controlled according to a constant pressure drop setting.

Figure 21 shows a schematic of each of the 5 AHUs available in the system and Figure 20 shows a simplified scheme of the heating distribution between one AHU and the apartments. One of the buildings (Building 2) is equipped with two AHUs while Building 1 and Building 3 are equipped with one AHU each. Also, each AHU is connected to a different number of vertical air distribution ducts (called "levels"). Each distribution level is equipped with a heating coil (named "Heating Level k" in Figure 20). As summarized in Table 1, the AHUs of Building 2 serve respectively 4 and 3 levels and the AHUs of Building 1 and Building 3 serve 8 and 9 levels, respectively. The central heating coil named "Heating Level 0" in Figure 21 is available only in the AHUs of Building 2. The AHU installed in Building 3 serves only 4 apartments that are used for research studies and are formally identified as an independent testbed, called Testbed KTH.

Figure 21 shows also a direct connection available between the boreholes and the AHUs to allow, in principle, the pre-heating or cooling of the incoming air in the AHUs.

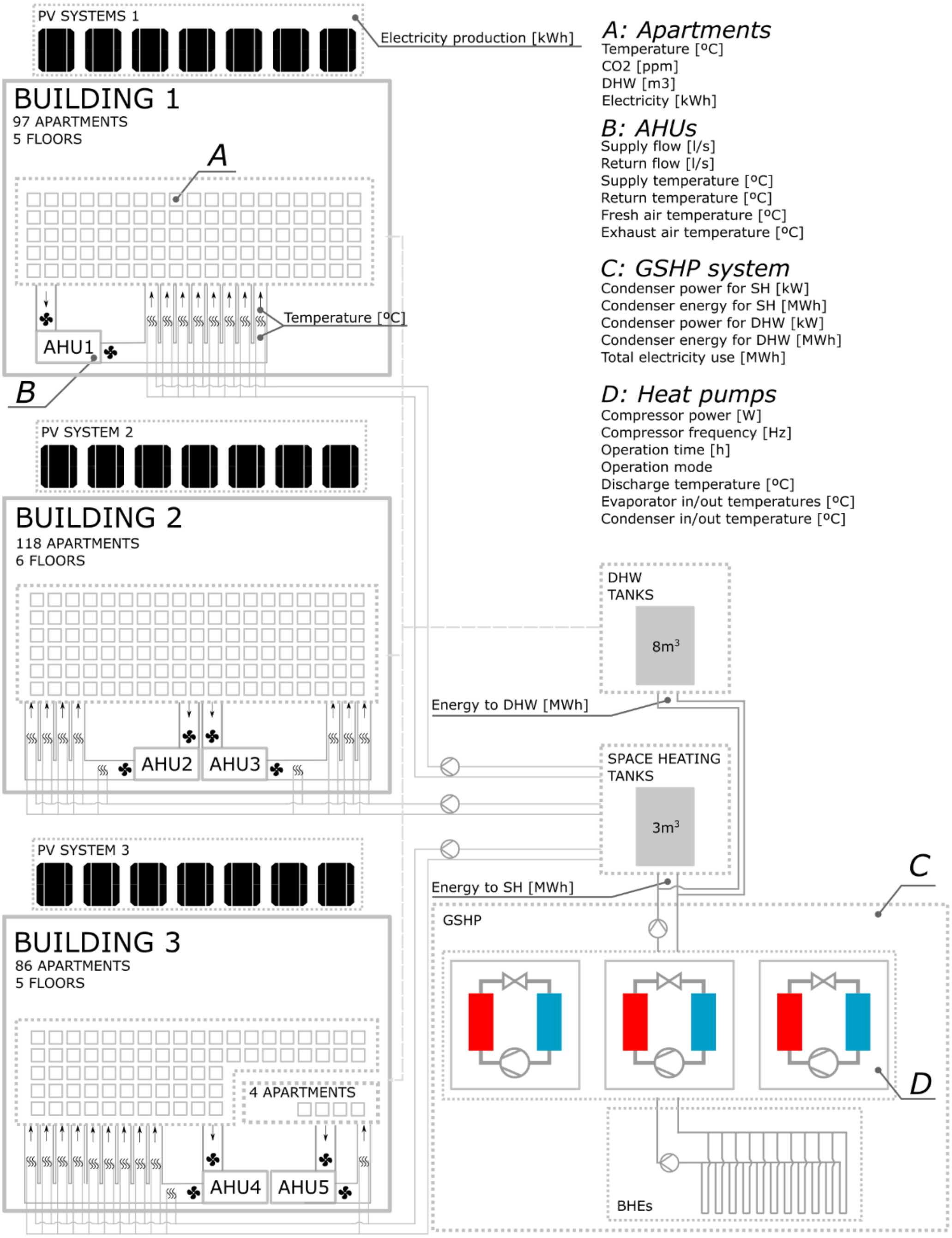


Figure 18 Testbed EM: simplified schematic of the sub-systems examined in this study with indication of the data points considered. An expanded list of the data points is presented in Table 2.

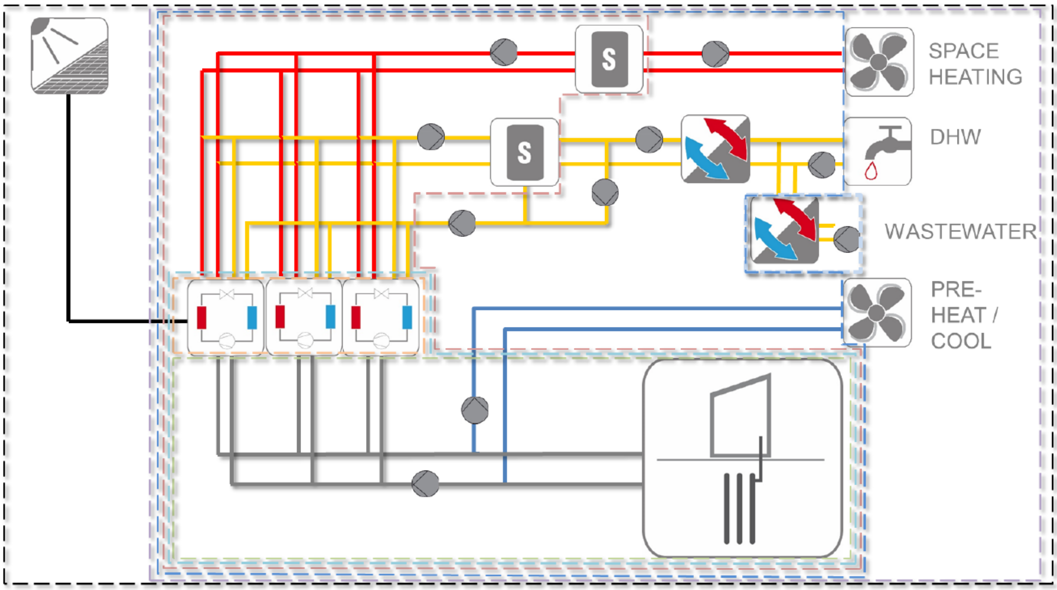


Figure 19 Testbed EM: simplified schematic of the heat pump system. Pictograms by TU Braunschweig IGS, used with permission.

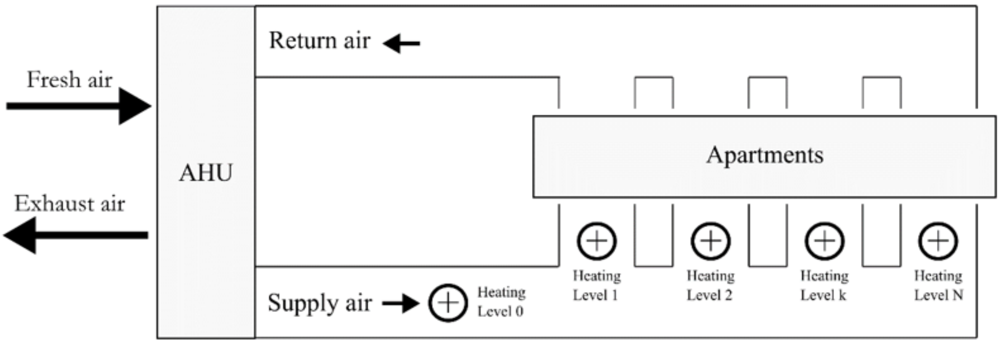


Figure 20 Simplified schematic of heating distribution system of one AHU.

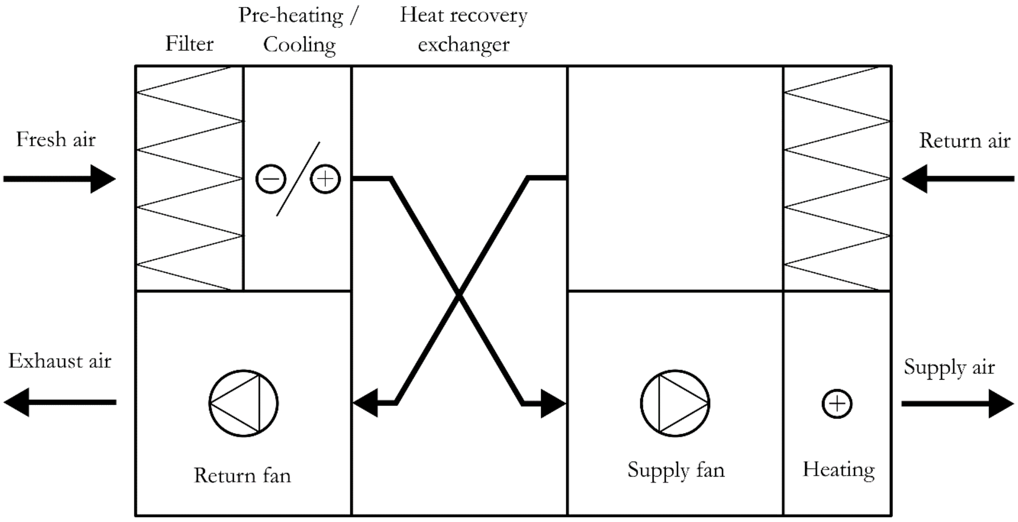


Figure 21 Simplified schematic of the AHUs installed at Testbed EM [69].

Table 1 Distributions levels of each AHU per building.

	AHU 1	**AHU 2**	**AHU 3**	**AHU 4**	**AHU 5**
Building	1	2	2	3	3
Distribution levels	8	4 (+ level 0)	3 (+ level 0)	9	1

3.2.3 Testbed EM: monitoring system

The Testbed EM is equipped with an extensive network of sensors that covers the buildings at apartment, heat pump system and ventilation system levels. At the apartment level, the indoor thermal comfort and air quality are controlled separately in each apartment via dedicated temperature and CO_2 sensors regulating supply and return airflows. In addition, domestic hot water and electricity are measured in all apartments. A total of more than 7000 data points (including sensors, alarms and set points) are continuously logged into a database with a sample rate of 1 minute. The data analysis carried out in this paper covers the 12 months of data between July 2020 and June 2021. Table 2 shows a selected list of the data points used for the data analysis presented in this paper.

Table 2 Main data points used for the data analysis.

Subsystem	**Data point (labels)**
AHU	Air intake temperature (fresh air); Supply temperature (common); Supply temperatures (distribution levels); Return temperature (common); Supply air flow rate; Return air flow rate; Supply air fan power; Return air fan power
Heat pump (individual unit)	Compressor power; Compressor frequency; Operation time; Operation mode (control signal: 0=SH; 1=DHW); Hot gas discharge temperature; Inlet evaporator (fluid side); Outlet evaporator (fluid side); Inlet condenser (fluid side); Outlet condenser (fluid side)
Heat pumps (three units aggregated)	Condenser power for space heating; Condenser power for domestic hot water; Condenser energy for space heating; Condenser energy for domestic hot water; Total electricity use (including heat pump units and borehole circulation pumps)
Apartments	Indoor temperature; CO_2 concentration; Electricity use; DHW use
Buildings	Outdoor temperature; Electricity use of the fresh water pressurizer; Bought electricity (3 buildings); PV electricity production (3 PV systems)
Other	Service room electricity use; Laundry room electricity use

3.2.4 Data analysis: building system

3.2.4.1 Building energy use and energy production

3.2.4.1.1 Energy signature

The monitoring system of Testbed EM includes dedicated data points to account for the bought electricity for the entire facility. Figure 22 shows the daily bought electricity versus the hourly average of the outdoor temperature. As qualitatively expected from buildings with no active cooling system, the peaks of daily energy use occur in winter days.

Quantitatively, the Figure shows a daily baseline use of energy of about 500 kWh/day and a peak of about 2800 kWh/day around -5°C. The aggregated metrics provided in Table 3 highlight that over summer and winter the total energy use is about 66 MWh and 195 MWh, respectively. The table includes also the linear regression coefficients calculated considering the daily values grouped by season. The inspection of the coefficients indicates that a drop of 5ºC of the outdoor temperature corresponds to an increase of the energy use of about 350 kWh/day. It is also interesting to notice from Figure 22 that the daily energy use during spring days appears to be lower than during fall days for a given outdoor temperature. This is consistent with the effect of the solar radiation as shown in a previous research project thought simulations [70]. Although the minimum energy use during spring (782 kWh/day) is in fact about 25% lower than during fall (1036 kWh/day), the average value (1474 kWh/day) is only 6% lower (1575 kWh/day). The regression coefficients show that despite the trend

during the spring being between the trends in winter and fall, the intercept values are shifted down of about 300 kWh/day (2025 kWh/day versus 2291 and 2311 kWh/day).

Table 3 Summary table based on daily energy use of Testbed EM.

	Sum	**Min**	**Max**	**Average**	**Median**	**St.Dev**	**Trend**	**Intercept**
	MWh	kWh/day	kWh/day	kWh/day	kWh/day	kWh/day	kWh/day/K	kWh/day
Summer	66	494	1330	719	684	170	-18.5	1105
Fall	143	1035	2208	1575	1606	294	-61.5	2291
Winter	195	1597	2853	2171	2090	348	-69.2	2311
Spring	135	782	2304	1474	1450	344	-66.4	2025
Overall	540	494	2853	1480	1525	595	-70.1	2234

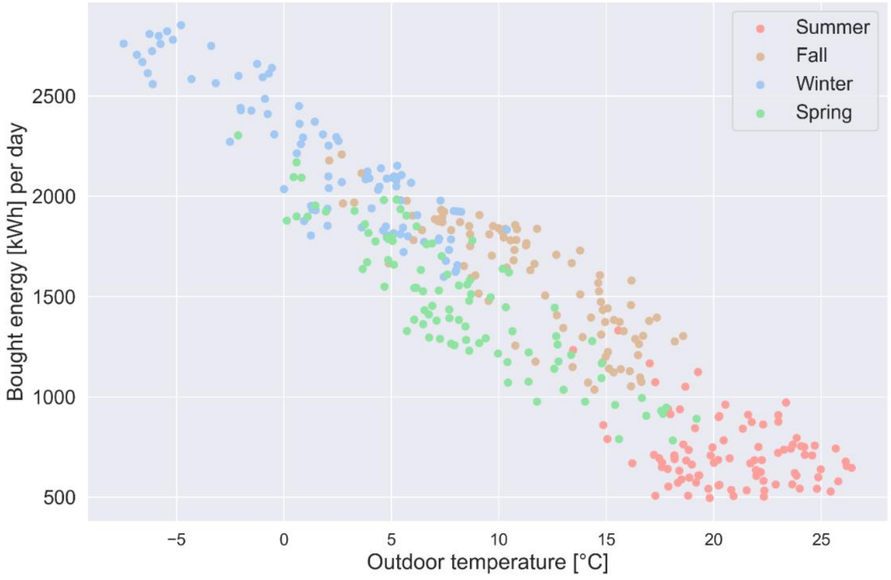


Figure 22 Energy signature: daily bought electricity versus average of outdoor temperature.

3.2.4.1.2 Electricity use of apartments

Figure 23 displays the monthly electricity use of all the 305 apartments in Testbed EM grouped per building. As expected, the electricity use in the months of June, July and August are lower than in other months, given that the users (students) are more likely to be away. Overall, the electricity use for each building is about 85, 103 and 92 MWh and the total over 12 months is about 280 MWh. It should be noted that Building 2 has one more floor compared to Building 1 and Building 3. Figure 24 shows the daily electricity use in the apartments versus the average outdoor temperature. The Figure reveals a clear correlation with the outdoor temperature, especially considering the spring, winter and fall data.

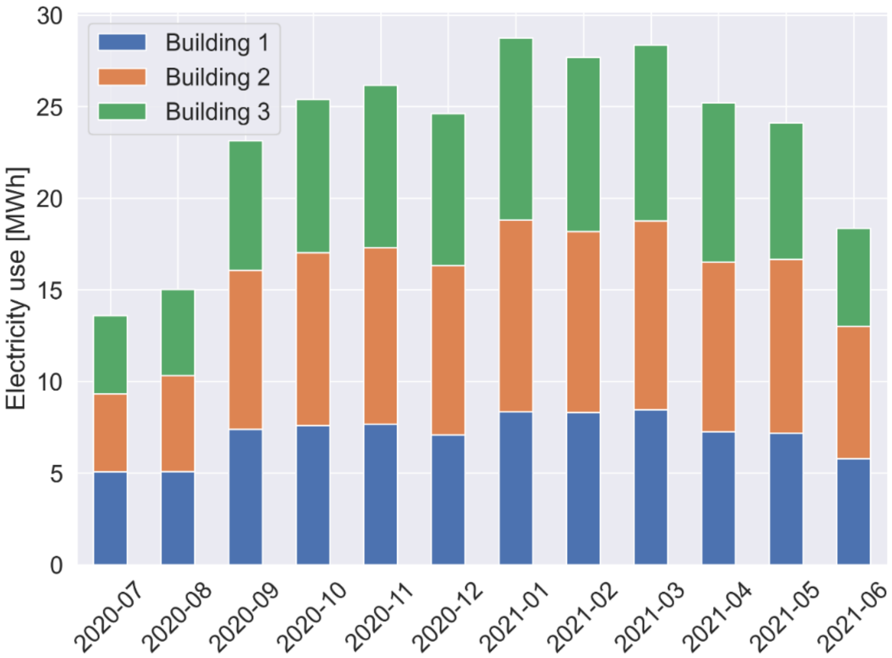


Figure 23 Monthly electricity use in the apartments for the three buildings of Testbed EM.

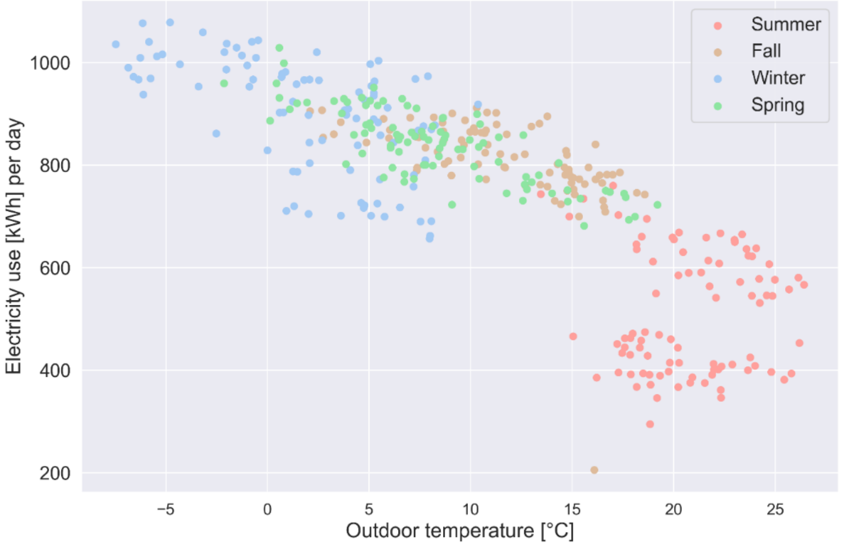


Figure 24 Daily electricity use in the apartments versus average outdoor temperature.

3.2.4.1.3 Electricity production from PV systems

The three PV systems installed include 667 PV, covering a total roof area of 1150 m^2. Figure 25 shows the monthly electricity production of the three PV systems. The total electricity produced over 12 months is about 188 MWh and the specific energy production is about 163 kWh/m^2.

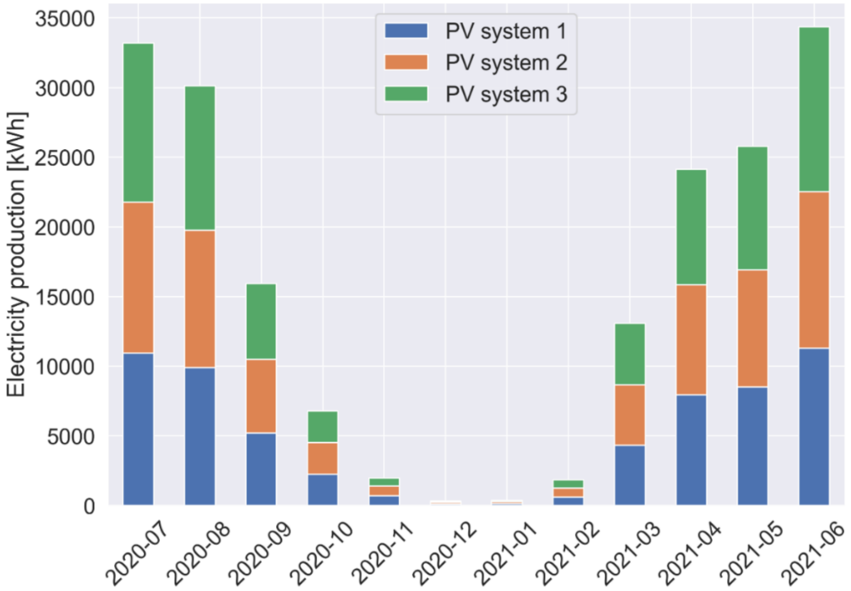


Figure 25 Monthly electricity production from PV systems.

3.2.4.1.4 Domestic hot water (DHW)

Figure 26 shows the monthly DHW use from all 305 apartments. The total volume of DHW used over 12 months is about 6760 m^3, equivalent to an average of about 22 m^3 per year for each apartment, corresponding to about 60 liters per day.

As expected, and as already observed for the electricity use, during the months of June, July and August the users (students) are more likely to be away. A drop of the monthly consumption can also clearly be observed in December. The section dedicated to user behavior contains a more detailed analysis of the DHW use.

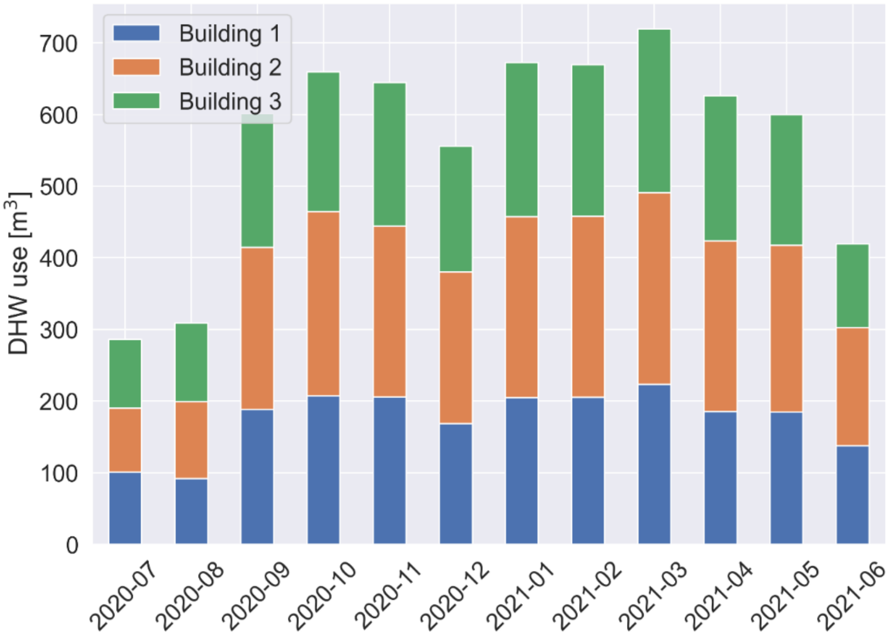


Figure 26 Monthly DHW use of all the apartments of Testbed EM.

3.2.4.2 Heat Pumps

3.2.4.2.1 Heat pumps: delivered energy

The heat pumps operate in two main operation modes: space heating (SH) and domestic hot water (DHW). Figure 27 shows the monthly energy production of the three heat pumps over the analyzed period. The energy production in SH mode is higher during the winter months, with the peak in February, while the monthly energy delivered for DHW production is more uniform. The energy delivered in SH and DHW mode over 12 months is 279 MWh (38% of the total) and 449 MWh (62% of the total), respectively, and the total energy is 728 MWh.

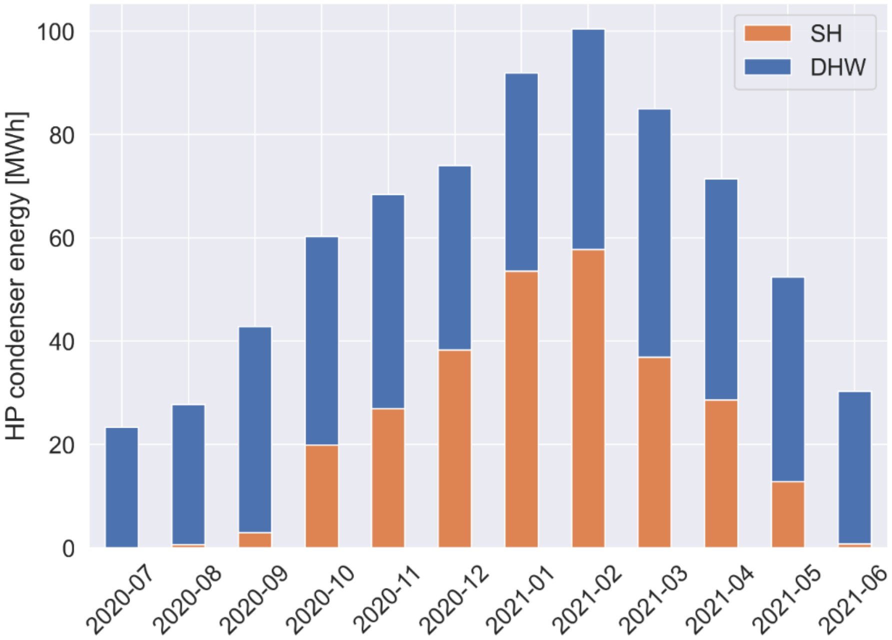


Figure 27 Heat pumps: monthly energy use in space heating (SH) and domestic hot water (DHW) mode.

3.2.4.2.2 Heat pumps: electricity use and operation time

Dedicated data points allow to monitor the heat pump units in terms of electric power of the compressors, electricity use, operation mode and operation time. Table 4, Figure 28 and Figure 29 show the monthly aggregated values.

HP3 operated about 35% more than HP2 and about 23% more than HP1

In terms of operation time, HP3 operated about 35% more than HP2 and about 23% more than HP1. Although the details of the control and operation strategies are not available, the inspection of the operation modes reveals also that the three heat pumps operate following non-uniform patterns. For instance, HP1 was used almost exclusively in DHW mode during the 6 months of 2020 and almost exclusively in SH mode during the six months of 2021. Overall, HP3 operated in DHW 60% more than HP1 and about 76% less in SH mode. It is unclear whether the observed operation patterns follow a dedicated design choice or represent the side effects of the implemented control algorithm. However, the unbalanced operation time and modes between the three units can potentially lead to maintenance issues and should be actively monitored.

Table 4 Heat pumps: monthly electricity use and operation time in SH and DHW modes.

	HP1				HP2				HP3			
	SH		DHW		SH		DHW		SH		DHW	
	MWh	h	MWh	h	MWh	h	MWh	h	MWh	h	MWh	h
2020-07	0.0	4.3	2.4	162.4	0.0	1.3	2.4	174.5	0.0	1.8	2.4	161.7
2020-08	0.0	0.1	2.6	166.0	0.1	7.8	2.5	160.1	0.0	4.1	2.6	212.0
2020-09	0.0	1.4	4.4	229.2	0.3	44.8	3.7	205.2	0.2	31.6	3.9	199.7
2020-10	0.0	3.3	6.8	426.1	2.2	248.3	2.8	165.3	1.9	191.7	4.0	219.2
2020-11	0.1	60.5	7.6	443.1	2.5	253.2	3.5	212.8	2.4	240.9	3.8	225.9
2020-12	0.1	43.3	3.7	204.2	3.6	334.7	5.0	292.1	3.8	350.0	4.8	276.9
2021-01	2.0	152.4	5.3	266.6	4.8	378.2	5.3	289.1	6.6	462.9	3.9	203.6
2021-02	10.3	665.7	0.1	5.0	5.0	349.6	2.7	153.4	0.3	51.0	12.1	565.0
2021-03	7.9	722.2	0.0	0.0	0.3	69.5	3.9	224.1	0.0	40.2	12.9	665.5
2021-04	5.8	664.1	0.0	0.0	0.0	28.5	1.6	102.4	0.0	46.4	12.5	634.3
2021-05	2.3	353.8	0.0	0.0	0.0	15.0	0.7	47.5	0.0	39.5	11.4	591.0
2021-06	0.0	9.2	0.0	0.0	0.0	0.8	0.0	3.7	0.0	58.2	7.8	470.3
Total	29	2680	33	1903	19	1732	34	2030	15	1518	82	4425

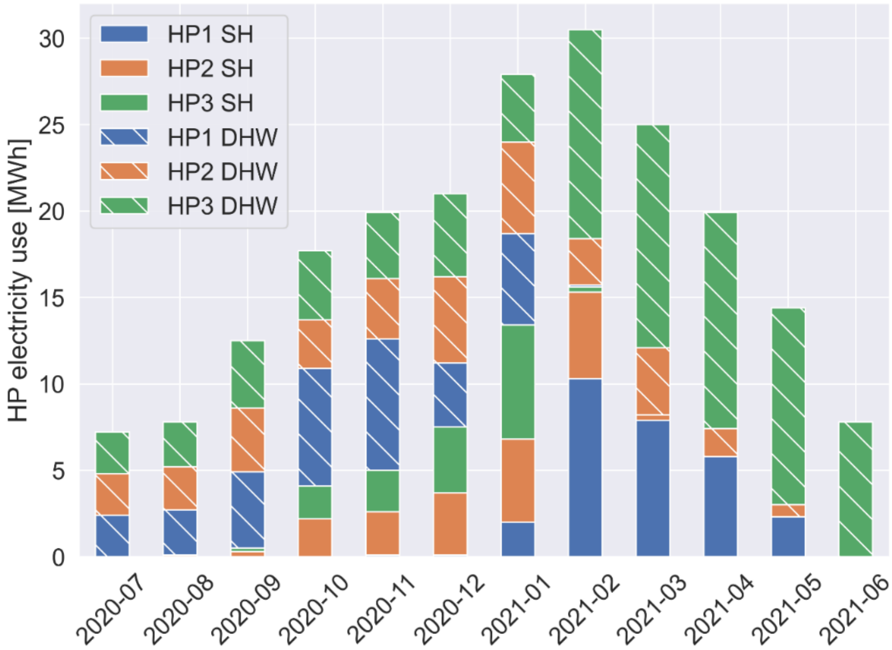


Figure 28 Heat pumps: monthly electricity use in space heating (SH) and domestic hot water (DHW) mode.

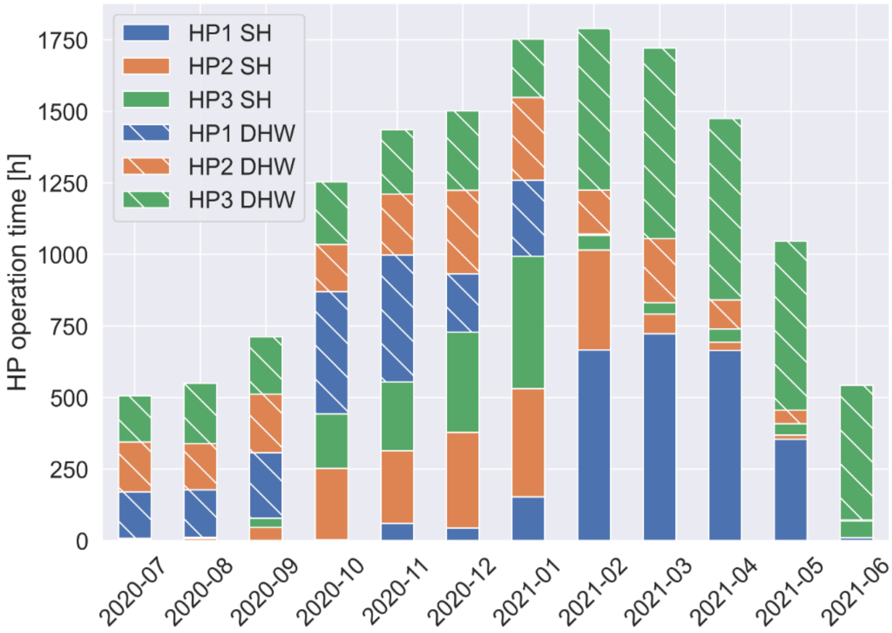


Figure 29 Heat pumps: operation time in space heating (SH) and domestic hot water (DHW) mode.

3.2.4.2.3 Heat pump system: performance

The monitoring system includes three data points continuously logging the "calculated Coefficient Of Performance" (COP) for each heat pump unit. Unfortunately, the details on how the calculation is performed are not documented and therefore the data from these data points is not included in this analysis.

In order to provide an overview of the heat pump system performance, this analysis includes the results of the calculation of average COP, evaluated considering the overall energy provided at the condenser level and the electricity use of the compressors. The results aggregated by month are provided in Table 5. Overall, the average COP over 12 months of operation is about 3.4. In order to evaluate the performance of the GSHP system it is important to include the electricity use of the circulation pumps in the evaluation of the COP. As shown in the Table, the monthly average of the COP evaluated considering the circulation pumps is between 2.1 and 2.8, with an overall average of about 2.6.

Table 5 includes also the monthly percentage of the operation mode ratio, defined as the hours during which the heat pumps operated in DHW mode over the total operation time. A mode ratio of 100% would indicate that the heat pumps operated only in DHW mode. Although the maximum value of the mode ratio corresponds to the minimum value of the COP, the COP values for low mode ratio are not always consistent. Further investigations including temperatures and secondary fluid flows on both the evaporator and condenser sides could clarify these inconsistencies but have not been carried out in this study.

Table 5 Heat pump system: average COP.

Month	**COP avg**	**COP* avg**	**Mode ratio** [%]**
2020-07	3.2	2.1	98
2020-08	3.5	2.5	97
2020-09	3.4	2.7	89
2020-10	3.3	2.7	64
2020-11	3.3	2.7	61
2020-12	3.3	2.6	51
2021-01	3.2	2.6	43
2021-02	3.2	2.7	40
2021-03	3.3	2.8	51
2021-04	3.5	2.8	49
2021-05	3.5	2.6	61
2021-06	3.6	2.4	87

* Including GSHP circulation pumps

** Mode ratio: operation time in DHW mode vs total operation time

3.2.4.3 Energy flows

The Sankey diagram in Figure 30 shows the electricity flows of the system and relative to the period between July 2020 and June 2021.

As shown in the Figure, the total energy use from the facility is 687 MWh per year. Considering the total heated area of 10590 m^2 the value corresponds to an annual energy use of 65 kWh/m^2. The energy value labelled as "service" accounts for the electricity use of the servers, the control system and a water pressurizer pump. The slot named "fans" includes the electricity used by the ventilation system.

In low-energy buildings with GSHP system, the electricity use of the circulation pumps is comparable to the heat pump electricity required for space heating

The electricity use of the geothermal heat pump system is 276 MWh, corresponding to an annual energy use of about 26 kWh/m^2. Considering the electricity for space heating (SH) and domestic hot water production (DHW), the DHW part is 70% of the total. Worth noticing, the electricity use of the circulation pumps is almost the same (even slightly higher for the analyzed period) as the heat pump electricity required for heating the apartments. This helps to remark that the circulation pumps are a relevant and fundamental part of a GSHP system and they need to be included in the evaluation of the system performance. Also, this aspect will play a more and more relevant role as the overall performance of the building enclosure improves. It is also worth to notice that the energy used by the ventilation system (about 69 MWh) is comparable in value to the geothermal circulation pumps and energy for space heating.

The Figure maps the energy flows of the buildings considering only the electricity used for space heating, domestic hot water and ventilation. The electricity use of the apartments and the laundry is excluded from the calculations. The total bought electricity is 174 MWh per year, which is 7% lower than the energy produced by the PV systems. In this scheme, the total energy use by testbed EM is about 362 MWh per year, corresponding to an annual energy use of 34 kWh/m^2. Importantly, the energy flows displayed in the Figure represent the net energy flows over 12 months and do not specify the portion of produced electricity that is actually self-consumed and the part that is sold back to the grid. The exact quota of electricity that is self-consumed over the 12 months analyzed is currently not available. Overall, 76% of the total energy is used by the geothermal system. The energy for domestic hot water production is 41% of the total, while the ventilation system, the circulation pumps and the energy for space heating account each for about 18% of the total.

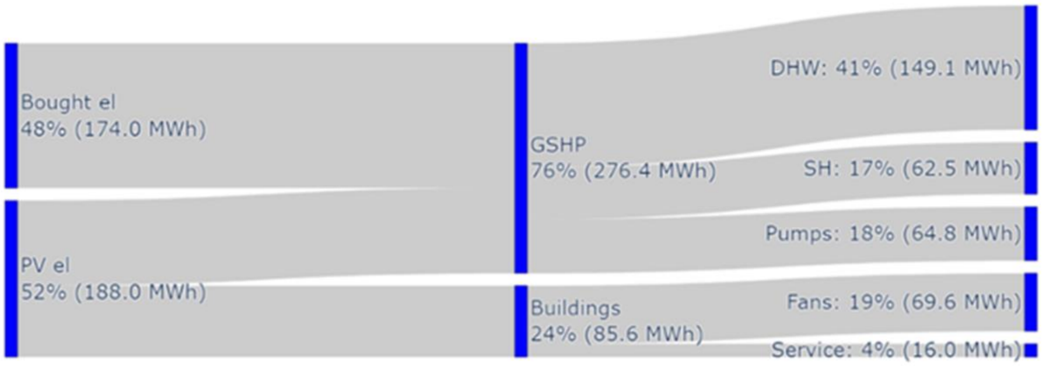


Figure 30 Net energy flows in Testbed EM over 12 months, excluding user direct electricity use. The quota of electricity that is actually self-consumed is not specified in this study.

3.2.4.4 Air handling units (AHUs)

The analysis of the four AHUs available in the system included the calculation of the energy delivered to the apartments using the data logged in the monitoring system. Figure 31 shows the simplified schematic of the supply air flow including an overview of the data points used in the calculations. For each AHU, the heating rate $\dot{Q}_{AHU}$ is calculated as shown in Eq. 5.

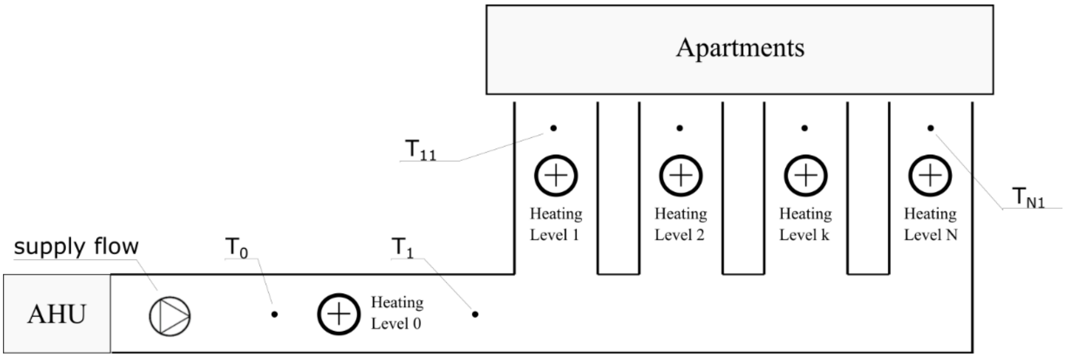


Figure 31 Simplified schematic of the data points used for the calculation of the energy delivered by the AHUs to the apartments.

$$\dot{Q}_{AHU} = \dot{m} \cdot c \cdot \left[(T_1 - T_0) + \sum_{k=1}^{N} \frac{1}{N} \cdot (T_{k1} - T_1) \right] \qquad (5)$$

Where c is the air specific heat (assumed to be constant at 1.003 kJ/kg/K), $\dot{m}$ is the air mass flow rate and T_{k1} is the temperature measured after the heating coil of "Level k". Worth noticing, the evaluation of the volume flow rate was adjusted considering the air density as a function of the air temperature. As specified before, the number of levels available on the supply side of the 4 AHUs installed in Testbed EM is different for each AHU (see Figure 20). Also, the heating coil "Level 0" is available only in AHU2 and AHU3. At each heating level the flow is controlled through duct valves. Although the opening of the valves is monitored by means of dedicated data points, the logged data was considered unreliable in this study and therefore not used in the calculation. Instead, the supply air flow is assumed to be equally distributed between in each of the N heating levels.

Overall, the energy delivered through the ventilation system over 12 months is 112 MWh for Building 2 (AHU2 and AHU3) and about 92 MWh for Building 1 and Building 3.

It is important to notice that relevant "free heating" contributions can be identified in May, June, July, August and September. As shown in Figure 32, in those months the heat delivered through the ventilation system to the apartments appears to be higher than the part of the heat that the heat pumps generated in space heating mode (SH). Although this contradictory and unexpected result has been investigated the possible explanations are not conclusive. One possible reason of the identified inconsistencies may be related to a poor insulation of the ventilation ducts. The practical consequence of this issue is the delivery of heat to the apartments when there is no heat demand. For this reason it is important to notice that a periodic (if not continuous) supervision of the monitored data is critical for the identification of faults or performance degradation in the system. To this regards, automated solutions could also be adopted but are not currently implemented in this system.

Considering the winter months of December, January, February, the difference between the energy generated by the heat pumps in SH mode and the heat delivered by ventilation is about 3 MWh per month. This result can be considered as a preliminary estimation of energy loss of the heating distribution system.

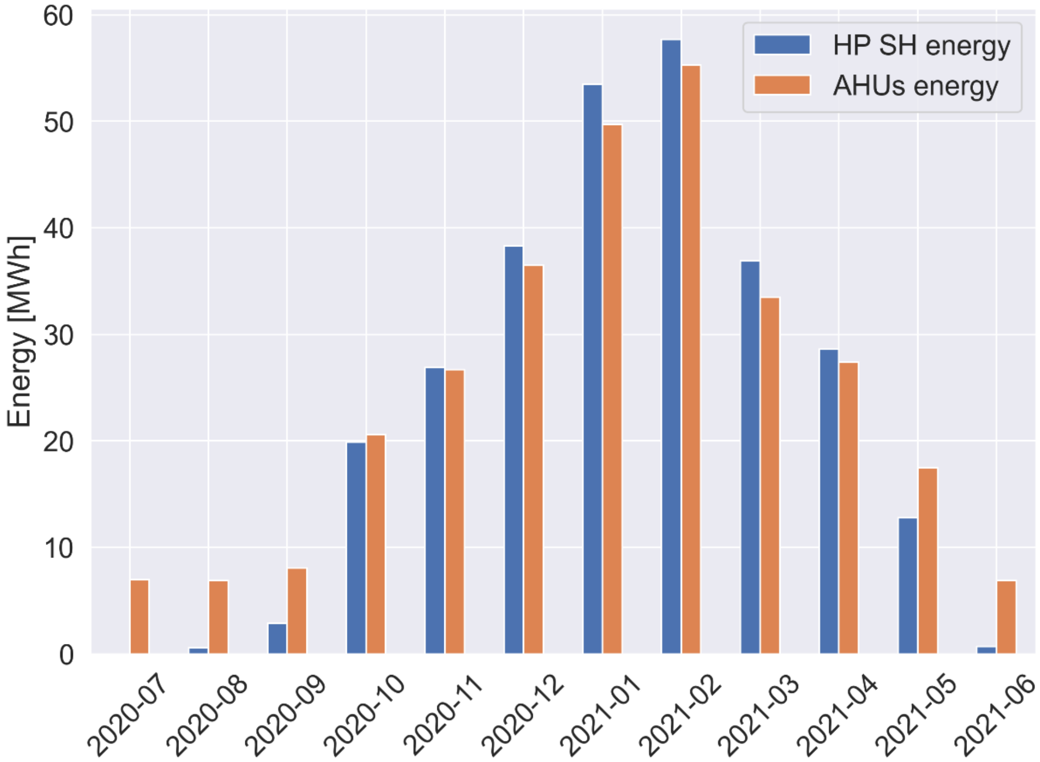


Figure 32 Space heating energy: comparison between calculations heat pump condenser and at the AHU levels.

3.2.5 Data analysis: indoor environment

3.2.5.1 Indoor Environmental Quality assessment

The indoor temperature and CO_2 concentration of all the apartments have been analyzed in order to evaluate the comfort indoor condition. It must be noticed that other measurements fundamental for a thorough assessment of the comfort, like the relative humidity, are unfortunately not currently available in Testbed EM.

3.2.5.1.1 Indoor temperature: overview

Qualitatively, over the 12 months of data included in this study the values of indoor temperature in the apartments presents a large variability and a relatively high average. Figure 33 shows the box plot of the indoor temperature distributions per month and the temperature distribution considering all the hourly values available from the three buildings. During the period between October and April the median temperature in the apartments is always above 24 degrees, highlighting a significant potential for reducing the energy demand. During the warmer months – July, August 2020 and June 2021 – the median temperature in the apartments is above 26 degrees, suggesting an overheating issues in the apartments. The problem of overheating in warmer months is clearly visible in Figure 33 and Figure 34, which displays the distribution of the temperatures in the apartments in the three buildings.

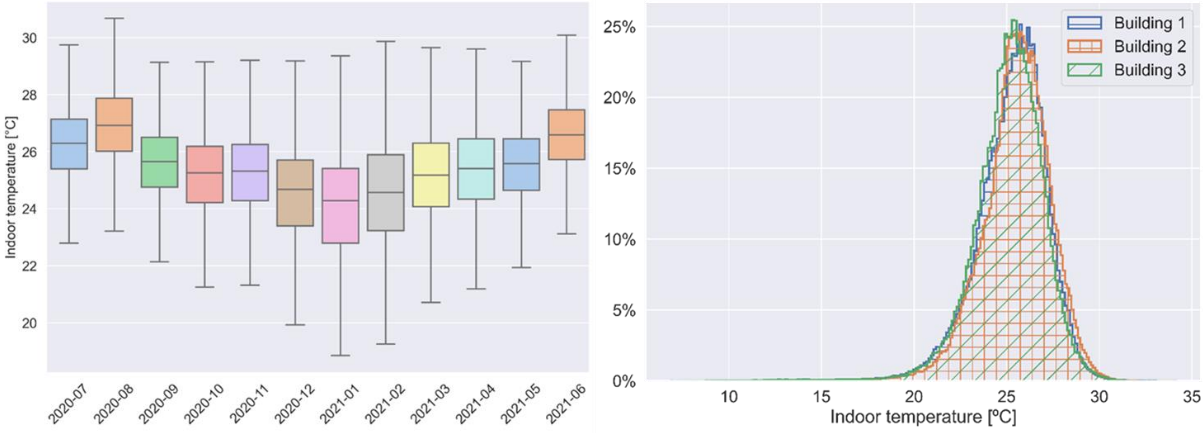


Figure 33 Monthly indoor temperature and probability density from all apartments.

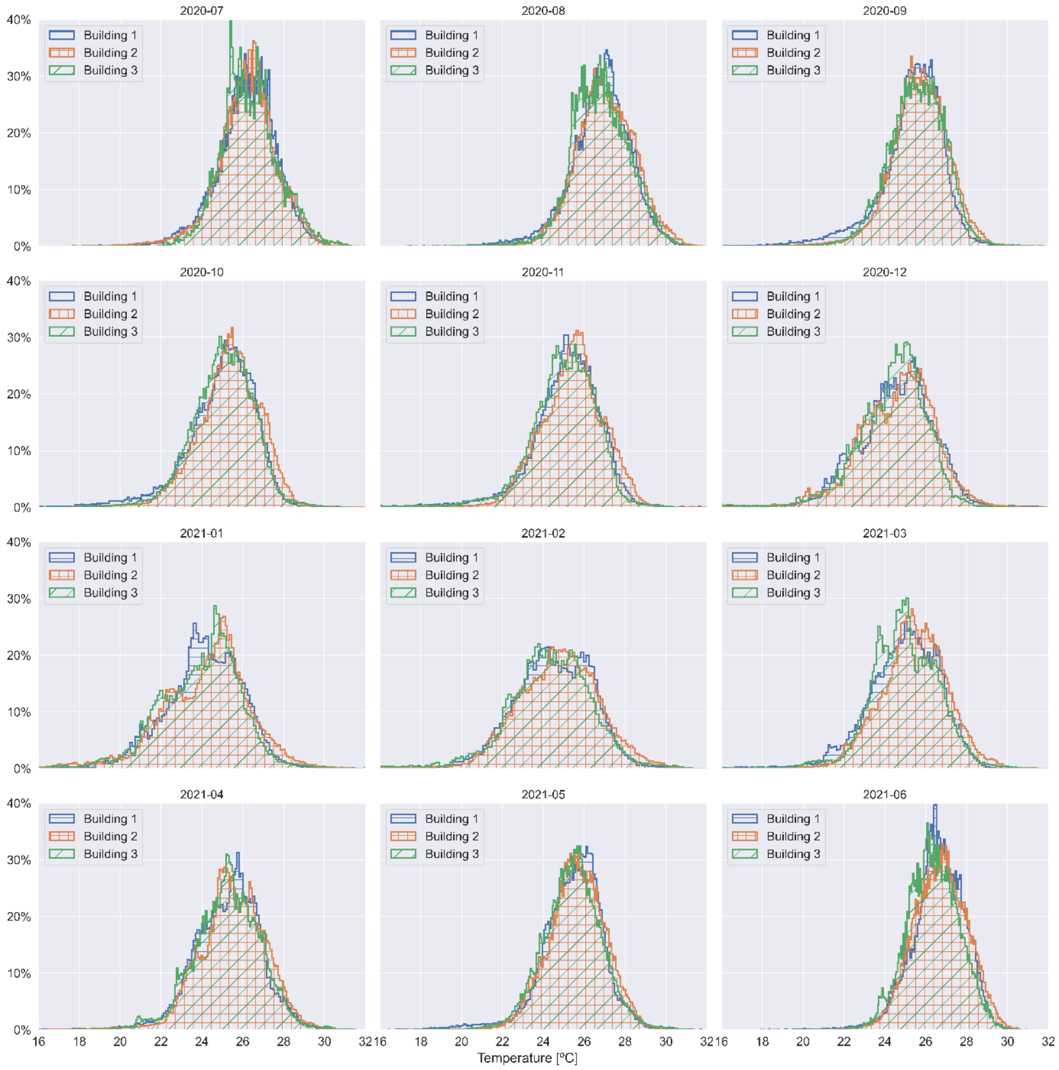


Figure 34 Probability density of hourly indoor temperature from all the apartments grouped by month.

The hourly indoor temperature of all apartments has been parsed in order to identify recurrent conditions and possible patterns. For the sake of brevity, the results of the analysis are here reported with the support of a limited number of examples. Figure 35 provides an overview of the indoor temperatures in a subset of apartments selected and grouped based on arbitrary temperature ranges varying from below 18ºC to above 27ºC. The Figure include the heat map chart built considering the hourly values over the 12 months of data available. The apartments included in the Figure are intentionally grouped and sorted to focus on a number of relevant considerations.

The results can be simplified into three main patterns. A first group of apartments (e.g., 21120 - 31008) presents temperatures within qualitative comfortable ranges (21-24°C) in the coldest months and only with moderate overheating during the warmest months. A second group of apartments shows consistent overheating during the coldest months and extreme overheating during the warmest months. Finally, a third group of apartments shows low temperatures in the coldest months and overheating in summertime.

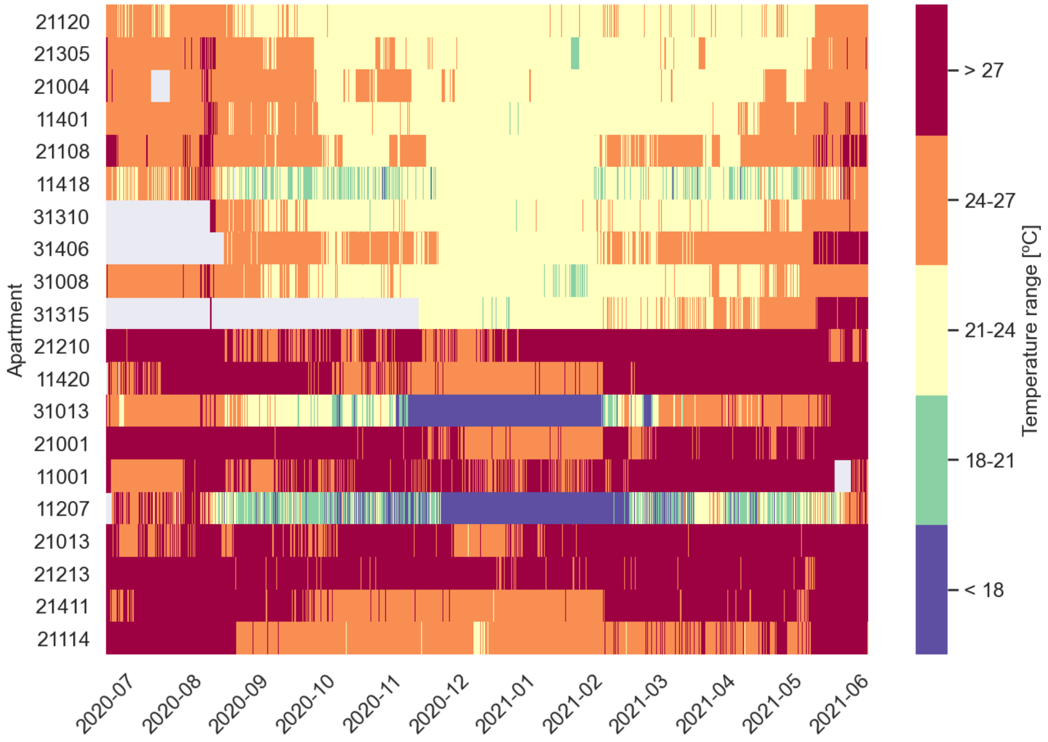


Figure 35 Hourly values of indoor temperature from 20 selected apartments.

3.2.5.1.2 Overview on Indoor air quality: CO_2 concentration

The considerations on the air quality in the apartments in the buildings are based on the CO_2 concentration measurements. Figure 36 summarizes the monthly distribution of the CO_2 concentration in the apartments. The median monthly values are between 400 and 600ppm and the distribution maximums are below 1000ppm, with highest values in January and February 2021. Although the outliers are not included in the Figure, the bar whiskers show minimum values below 200ppm that suggest the presence of measurements errors. The Figure includes the probability density of the CO_2 concentration in the 3 buildings over 12 months, confirming that, approximately, the values are typically in the range 400-600ppm. Figure 38 shows the details of the CO_2 values distribution for each month.

Similarly to Figure 35 for the indoor temperature values, Figure 37 provides an overview of the CO_2 concentration in a subset of apartments selected and grouped based on arbitrary ranges. In particular, from top to bottom, a first group includes apartments where the hourly CO_2 concentration values are always in the range 300-750ppm. A second group of apartments shows hourly peaks of CO_2; within this group, it should be noted that the persistent high values of CO_2 in a number of apartments (e.g., 11216, 11118 and 11109) suggest possible malfunctions of the sensors that could not be verified in this work. Finally, a third group of apartments presenting clear signs of sensor malfunctions are also included in the Figure. Worth noticing, in this Figure all hourly values below 300 and above 5000 fall into the "error" range.

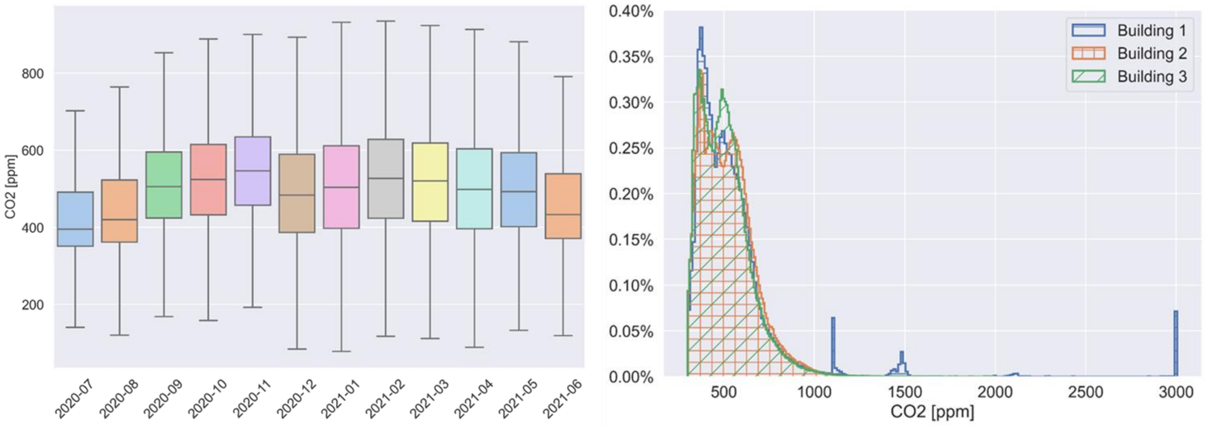


Figure 36 Monthly CO_2 concentration from all apartments and probability density.

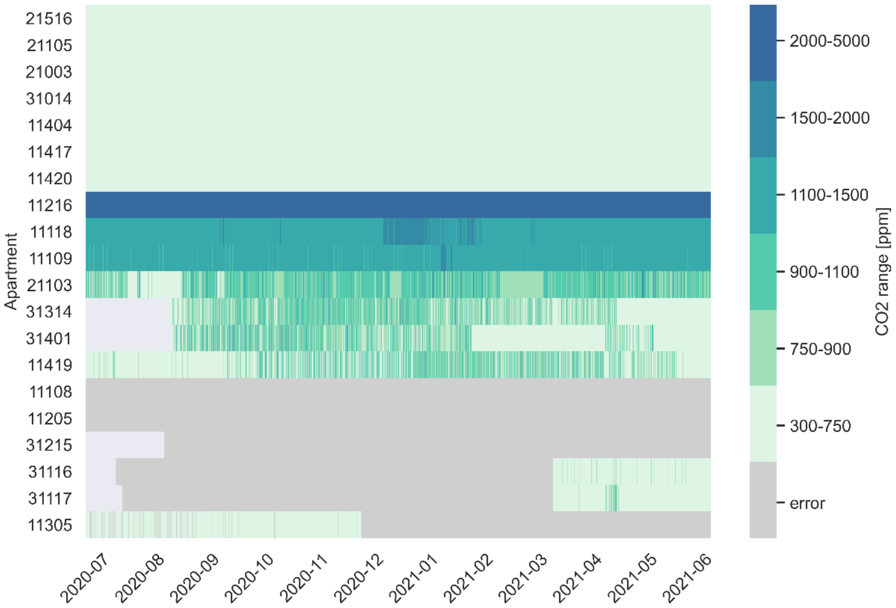


Figure 37 Hourly values of CO_2 index from selected apartments.

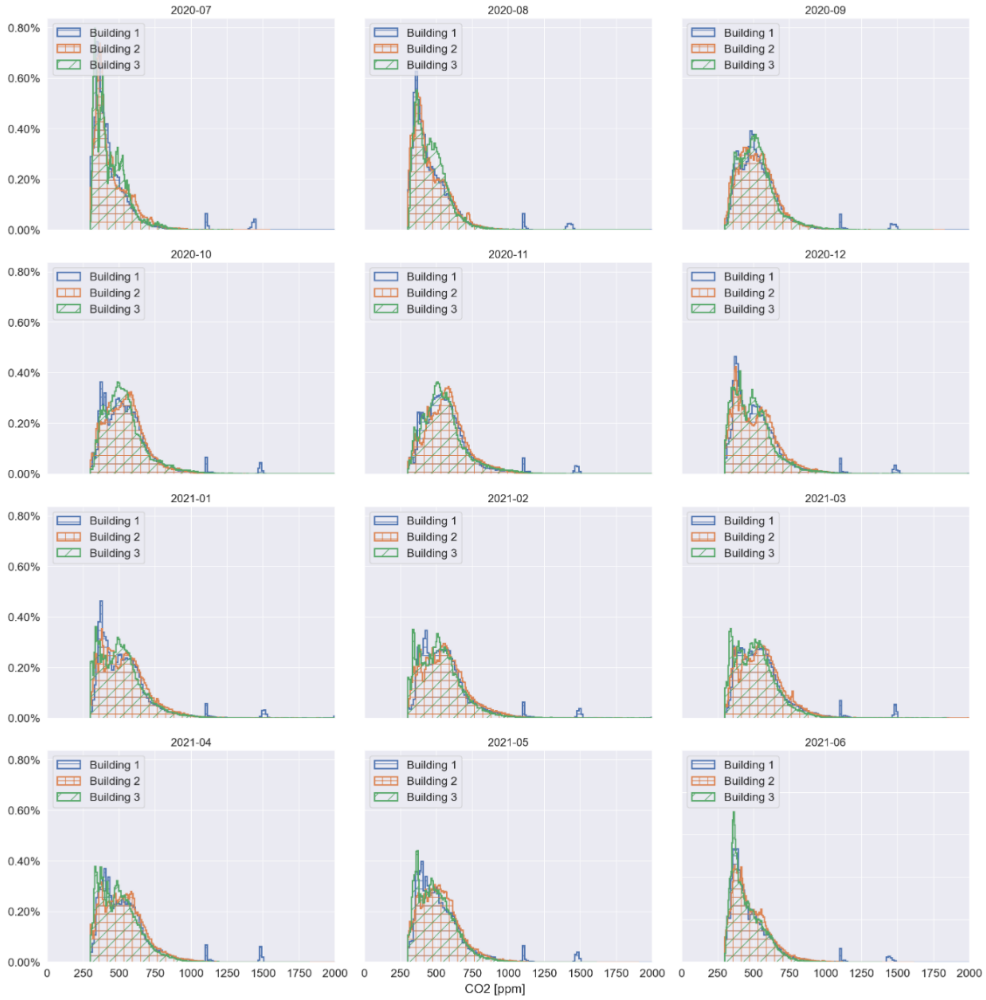


Figure 38 Probability density of hourly values of CO_2 concentration from all the apartments grouped by month.

3.2.5.2 User behavior

Occupants' behavioral patterns are known to affect the energy performance of buildings. Based on the results of the analysis overview, a few examples have been selected to further investigate the details and possible reasons of anomalies.

The evidence collected in this paragraph illustrates primarily examples of the detectable impact of building occupants on the indoor environment and includes an overview of the resources directly controllable by building occupants (DHW and dwelling electricity).

The analysis of the data of the indoor temperature and the CO_2 concentration presented in the previous sections has been combined with a detailed parsing of the electricity and DHW use; they are only briefly summarized in Figure 39 and Figure 40, to explain unexpected or extreme values and identifying possible user patterns. A few case studies are presented in the following.

3.2.5.2.1 Controllable resources: consumption of dwelling electricity and domestic hot water

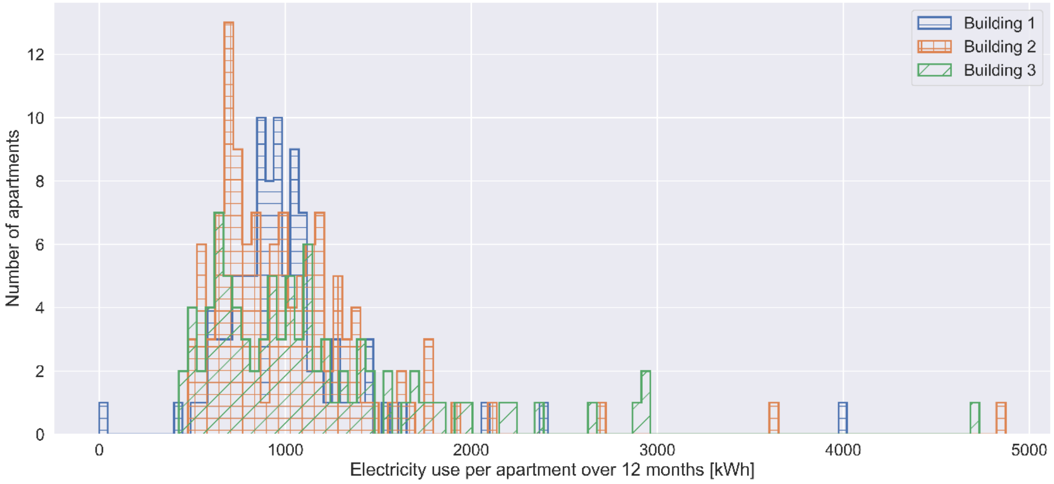


Figure 39 Electricity consumption in the apartments. Overall electricity consumption metered in each apartment is grouped per building.

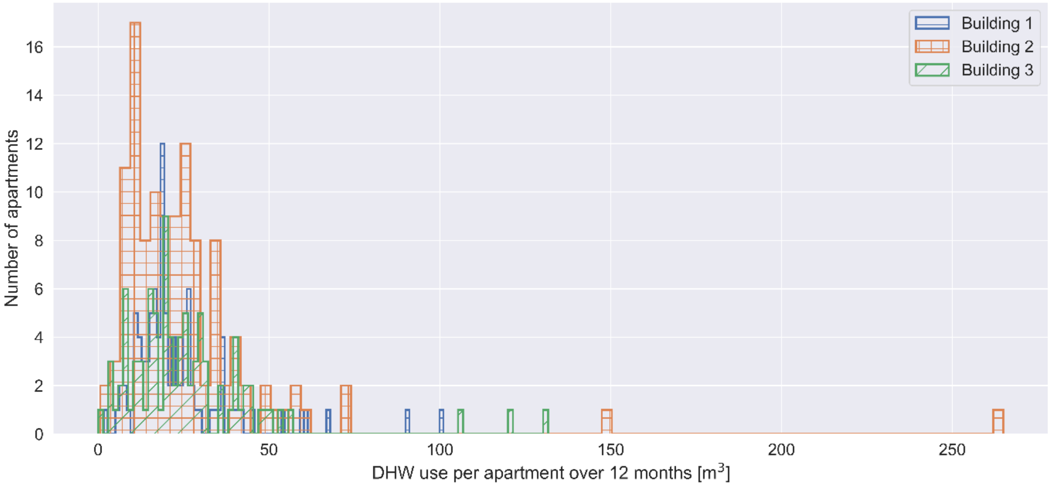


Figure 40 Domestic hot water consumption per building.

3.2.5.2.2 Case Study 1

A first example is shown in Figure 41, where the time series indoor temperature, the CO_2 concentration the DHW use and the electricity use from one apartment (number 11214) are plotted over 12 months. More in details, the indoor temperature is first shown together with the average indoor temperature of the apartments in the same floor (floor 1) and the average indoor temperature from all the apartments of the same building (Building 1). The apartment indoor temperature is included in a second subplot together with the outdoor temperature.

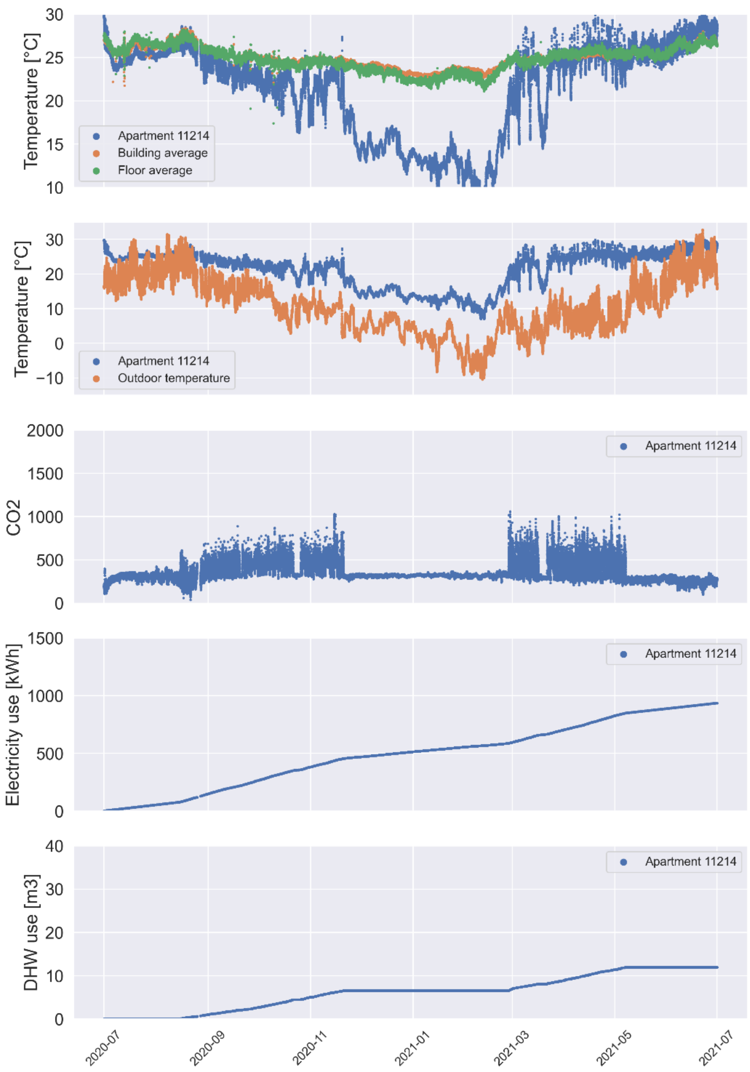


Figure 41 Indoor temperature, CO_2 concentration, electricity use and DHW use of apartment 11214.

Apartment 11214 was selected for a deeper analysis due to the unexpected low temperature recorded for a relatively long period. The inspection of the Figure reveals in fact that for more than three months (from the end of November 2020 until March 2021) the indoor temperature recorded was about 15ºC or lower. Also, in the same period, the indoor temperature pattern follows quite well the outdoor temperature values. The middle subplot of Figure 41 shows the CO_2 concentration in the apartment, clearly showing that in the three months where the indoor temperature was unexpectedly low, the CO_2 concentration was almost perfectly constant at a value of about 380ppm. Although a clear confirmation is not available, these observations clearly suggest that the low indoor temperature is likely due to the fact that the tenant left the apartment for about three months leaving the window open, or not completely close. Additional confirmations of this hypothesis are given by the cumulated DHW use and electricity use. The DHW use is in fact zero over the three months of absence of the tenant and the electricity use exhibit a clear change of trend.

This selected example brings to a few considerations. The type and amount of sensors installed in the apartments allow both a quite useful overview on the indoor air quality and clear identifications of some anomalies. Inferring the long absence of the tenant while the windows in the apartment were left not completely closed was in fact possible just by inspecting the temperature and CO_2 profiles. The data from electricity and DHW meters were useful to confirm the explanation of the anomaly. Although the energy waste directly related to the anomaly here described was not quantified in this study, it is clear that such user behaviors have an impact to the building energy use. Nevertheless, data available is currently not continuously used for the identification of such anomalies and there is currently no control or alarms available in the buildings to track or prevent this type of situations.

3.2.5.2.3 Case Study 2

A second example proposed in this study involves the comparison of measurements from two apartments located in the same building and on the same floor. The two apartments have been selected with the intention to identify different behavioral patterns in similar conditions. Figure 42 shows, from top to bottom, electricity use, indoor temperature, CO_2 concentration and DHW use of apartments 31103 and 31106, located on the first floor of Building 3 and having an area of 23.5 and 29.9 m^2, respectively. Both apartments are located on the same side of the corridor facing south-east. More in detail, apartment 31103 is located on the corner of the building and has one window on the north-east wall and one windows on the south-east wall, while apartment 31106 has two windows facing south-east. The inspection of the subplots of Figure 42 clearly reveals different indoor temperature patterns and different trends of electricity and DHW use. In particular, in the periods July-September 2020 and May-June 2021, the indoor temperature measurements show approximately the same evolution and from the CO_2 measurements both apartments appear to be in use. On the contrary, in the period between October 2020 and April 2021 the indoor temperature in the two apartments suggests completely different patterns. In apartment 31103 the temperature varies between 19ºC and 25ºC while the temperature in apartment 31106 varies approximately between 25ºC and 29ºC, with peaks over 30ºC. The differences in the indoor temperatures during the cold period reveal fundamentally different user preferences, behaviors and patterns. Worth noticing, the largest temperature drops and lowest values in apartment 31103 seem to occur in periods where CO_2 measurements suggest no occupancy. In terms of electricity and DHW use, values and trend of apartment 31103 is within the average, while apartment 31106 falls well outside expected ranges. As it can be noticed in the Figure, the electricity use of apartment 31106 shows a steeper trend compared to apartment 31103, especially in the cold period where the differences of indoor temperatures are larger. Over 12 months, the electricity use in apartment 31106 is about 4 times higher than in apartment 31103. All these observations indicate the extensive use of electric heaters in apartment 31106. Also in terms of DHW use, the consumption in apartment 31106 is about 4 times higher than in apartment 31103.

All the considerations proposed for the Case Study 1 are valid for the example described in the Case Study 2. Additionally, this second example shows how measurements from indoor sensors can reveal extreme differences of user preferences, awareness and behaviors in apartments that are in theory very similar and under the same conditions.

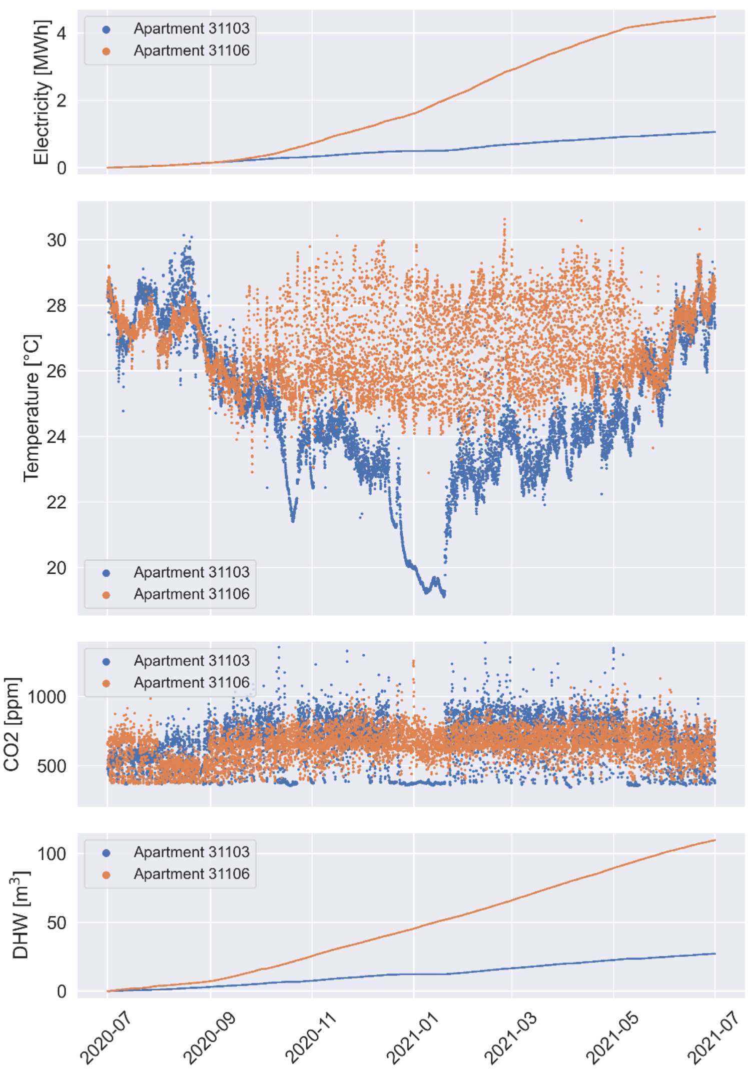


Figure 42 Indoor temperature, CO_2 concentration, electricity use and DHW use of apartments 31103 and 31106.

3.2.5.2.4 Case Study 3

In some cases, users seem to open the window more often than others. Figure 43 shows a case where the occupant supposedly opened the windows to lower the indoor CO_2 levels, accepting quite low indoor temperatures. During February-March 2021 the indoor temperature dropped below 20ºC while the apartment was occupied, as it is clear from the DHW trend and the CO_2 values. During long periods of absence that can be identified again by DHW and CO_2 measurements, the indoor temperature is stable and in line with the average, suggesting that the windows have been left closed. This case is somehow the counterpart of case study 1, where the drop of indoor temperature occurred when the user was away and highlights how user preferences can define different patterns in the indoor environment.

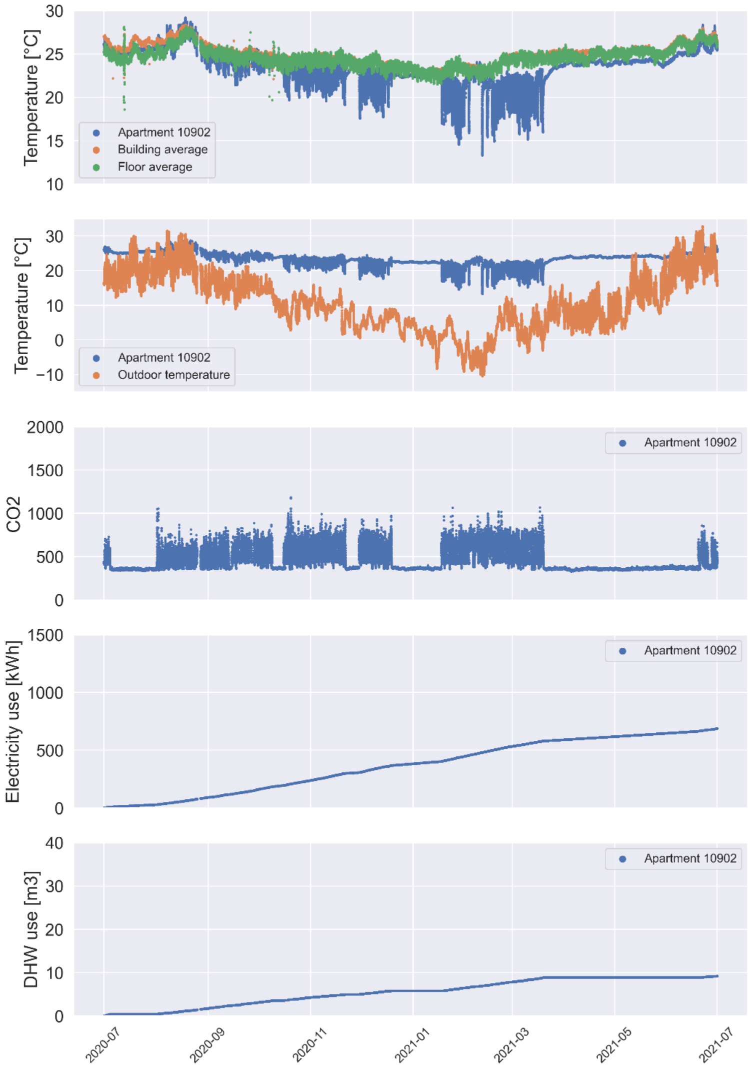


Figure 43 Case study: user opening windows to lower CO_2 levels and accepting relatively low indoor temperatures. During long periods of absence the windows are closed.

3.2.5.2.5 Case Study 4

Figure 44 shows another example where the occupant seems to make use of the window to lower the CO_2 peaks and accepts the indoor temperature to drop below 20ºC. However this case seems less extreme that the previous case study.

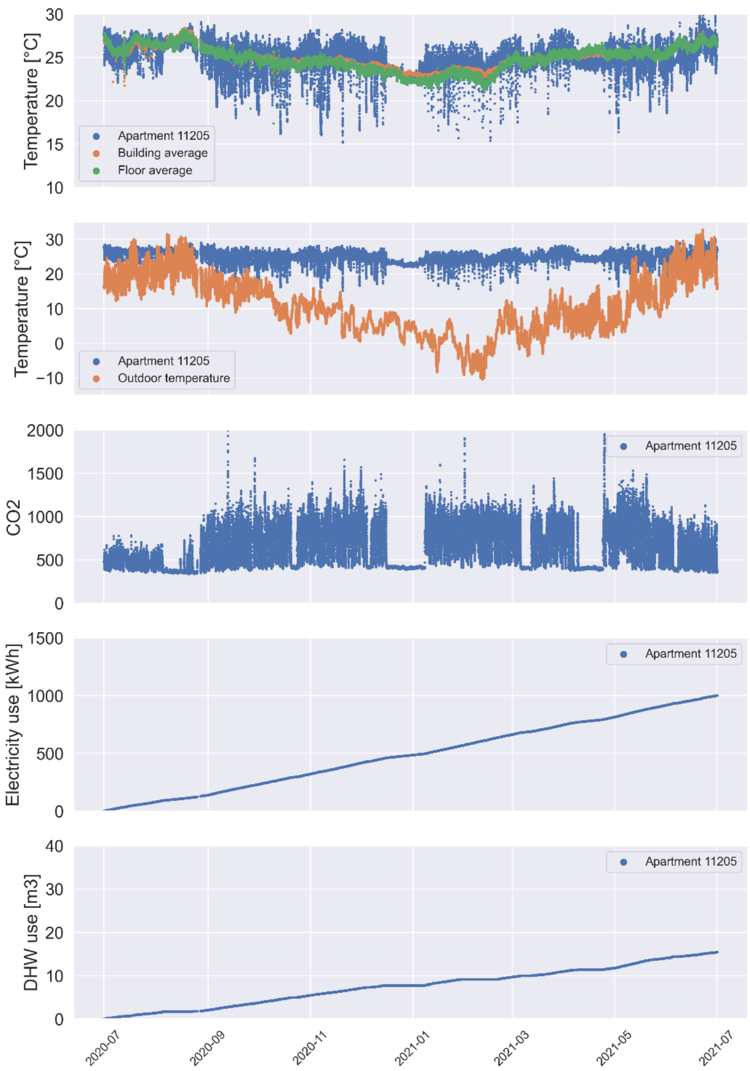


Figure 44 Case study: user opening windows to lower CO_2 levels.

3.2.5.2.6 Case Study 5

In a few (not common) cases, apartments are apparently empty for a long period of time. Figure 45 shows a case where no users occupied the apartment from December 2020 until (at least) the end of the analyzed period. In this case the indoor temperature measurements suggest that the windows have been left closed. Worth noticing, the base electricity consumption of the apartment with no user was around 30kWh per month.

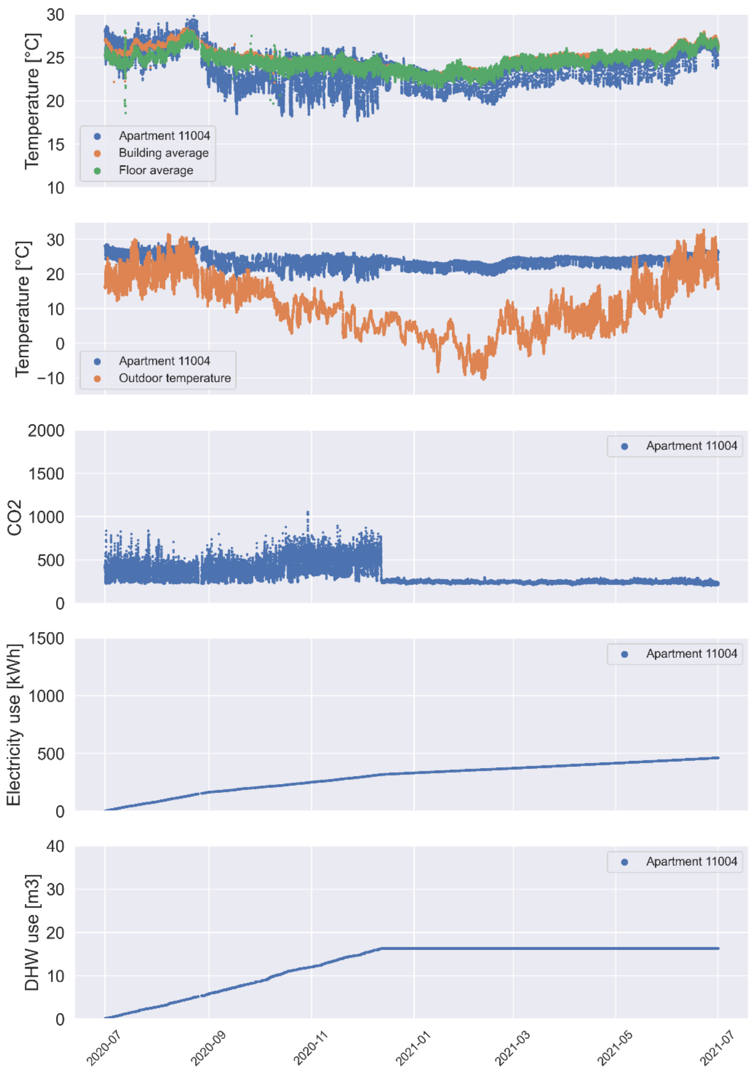


Figure 45 Case study: long period of absence.

3.2.5.2.7 Case Study 6

Figure 46 shows a case of an apartment that was continuously occupied for a long period. The first 50 days of measurements of CO_2, DHW and electricity are not available.

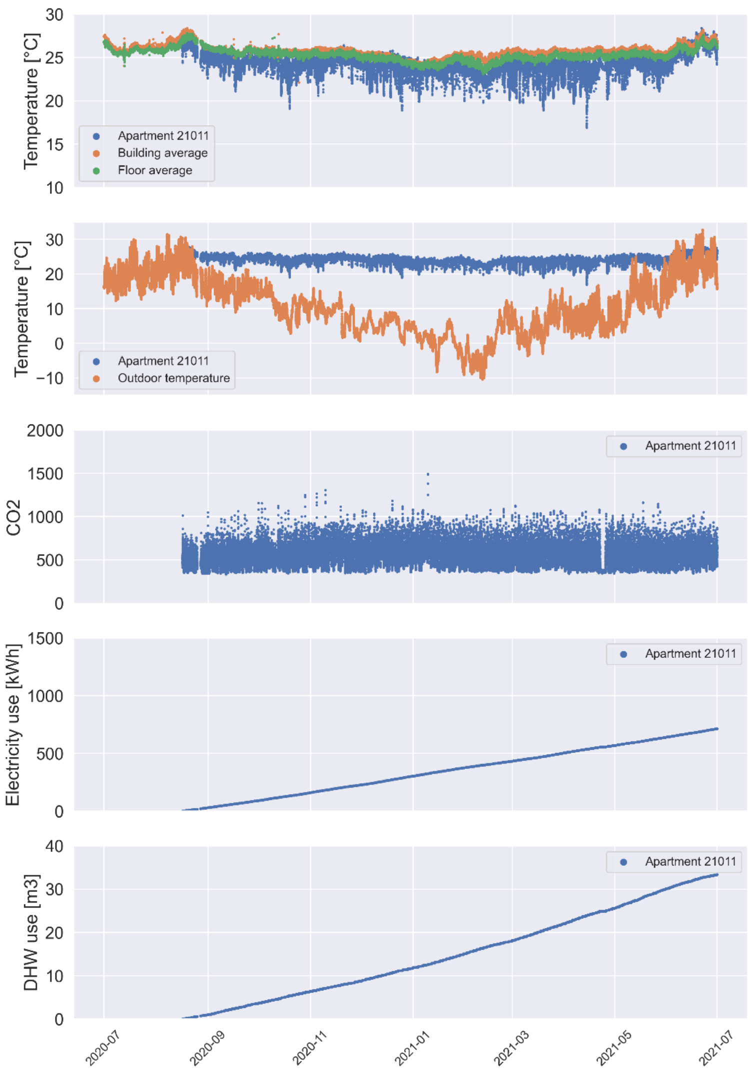


Figure 46 Case study: apartment occupied for a long continuous period with low CO_2 level.

3.2.5.2.8 Case Study 7

In some cases it is clear how user preferences have a direct impact on the energy consumption. Figure 47 shows the measurements from an apartment where the indoor temperature (already relatively high in the apartments) is almost constantly above the average, with temperatures close to 30ºC in winter. The CO_2 measurements indicate that the apartment was clearly occupied and the high levels of CO_2 may also indicate that either more than one user was in fact living in the apartment, or that local anomalies occurred in the ventilation system. The first hypothesis is partially supported by the fact that electricity and DHW use are also above the average in this case.

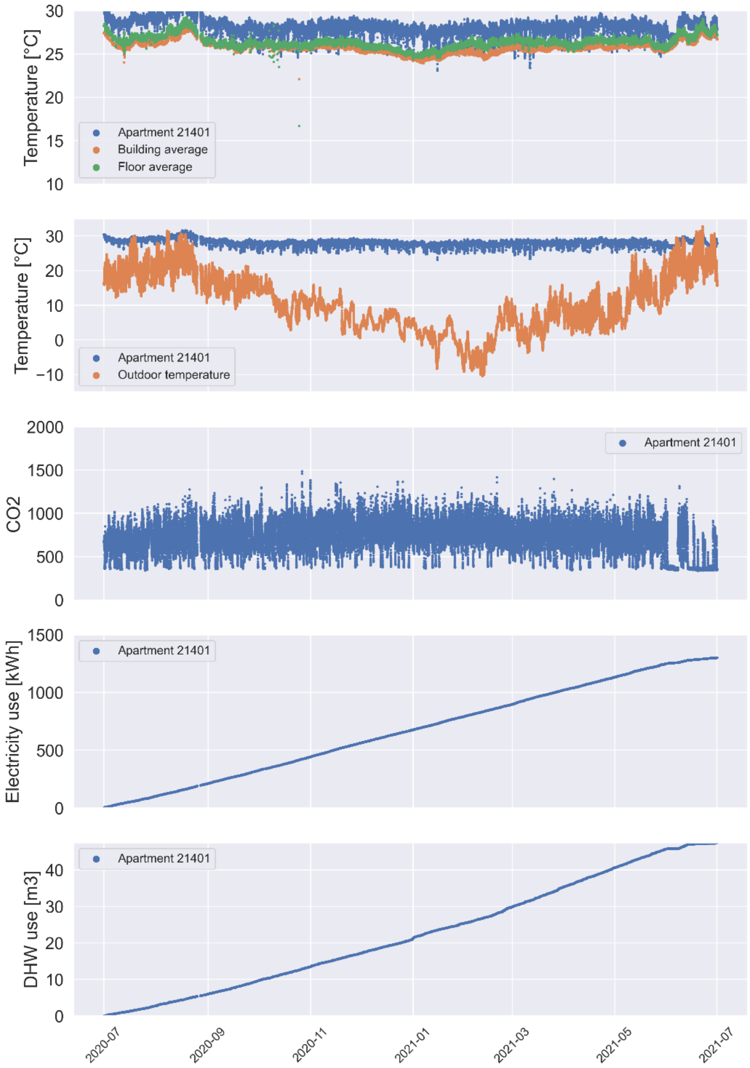


Figure 47 Case study: indoor temperature above the average.

3.2.6 *Highlights and lessons learned*

- More complete and unambiguous documentation is needed on sensor data from technical systems;
- Indoor climate is on average too warm during the heating season – showing significant room to reduce energy consumption;
- Users (i.e., building occupants) in similar apartments show dramatically different use of fresh water, domestic hot water, electricity;
- Users' actions (e.g., operation of windows) cause discomfort and increased energy use;
- Data suggests that different users have different comfort ranges (case 3);

- Current monitoring systems should be upgraded to evaluate of the impact of the users on energy systems and to find causality relations between indoor parameters (e.g., room temperature) and behavior;
- Missing sensors for overall system performance evaluation (e.g., temperature sensors in the ducts for losses and impact of users);
- PV panels cover 50% of the overall electricity consumption;
- Electricity consumption from geothermal heat pumps for space heating is comparable with circulation pumps, showing room for improved operation.

3.3 KTH Live-In Lab Testbed AH: long term monitoring analysis (WP2, WP3)

Publication: M. Molinari, D. Rolando, A. Lazzarotto. Energy and indoor environmental quality monitoring of a lecture building: preliminary results from the KTH Live-In Lab Testbed AH, MITAB 2022.

Figure 48 Testbed AH in the KTH main campus in Stockholm[1].

The Testbed AH is a university building constructed in 2016 used for lecturing; it consists of seven floor areas, 363 study places, six exercise rooms, and 11 group rooms and break out areas for a total of over 3500 m^2.

The building is equipped with a monitoring system that continuously logs the information from an extensive network of sensors. Monitored spaces in the building cover larger areas that are occupied on a regular basis. Smaller areas like group rooms are not monitored; similarly, passages, WCs, and technical rooms are not equipped with indoor sensors. The monitored spaces are breakout rooms,

---

[1] Source: https://campi.kth.se/nyheter/kreativt-larande-i-efterlangtat-hus-1.760862

study areas and lecture rooms, covering approximately 1000 m^2 of indoor space, accounting for two thirds of the total space available for occupants.

The monitoring data of the Testbed Akademiska Hus includes temperature, relative humidity, CO$_2$ together with electricity use, and energy use for heating, cooling, and ventilation. The measurements are acquired every minute and have been analyzed for a time span of four years, from 2018 and 2021. The entire dataset from the Testbed AH analyzed in the project covers over 4 years of measurements, from late 2017 to 2022.

Classrooms, large open spaces, and a few selected rooms are equipped with sensors placed on one of the room walls (located at a height of around one meter from the floor), logging both temperature and relative humidity. Additionally, the temperature is measured also in the return of the ventilation system of every room, where is logged along with the set-point temperature. CO$_2$ is measured only in the classrooms and sensors are placed in the return of the ventilation return.

Thermal power is measured by means of energy meters. There are dedicated sensors and meters for different loops in the circuit, and it is therefore possible to separate the energy for radiators, air curtains, heating provided to the air handling unit, cooling provided to the air handling unit and cooling provided to local servers. The Air Handling Unit heat recovery is calculated via energy balance given measurements for the airflow and inlet and outlet temperatures from the heat recovery heat exchanger.

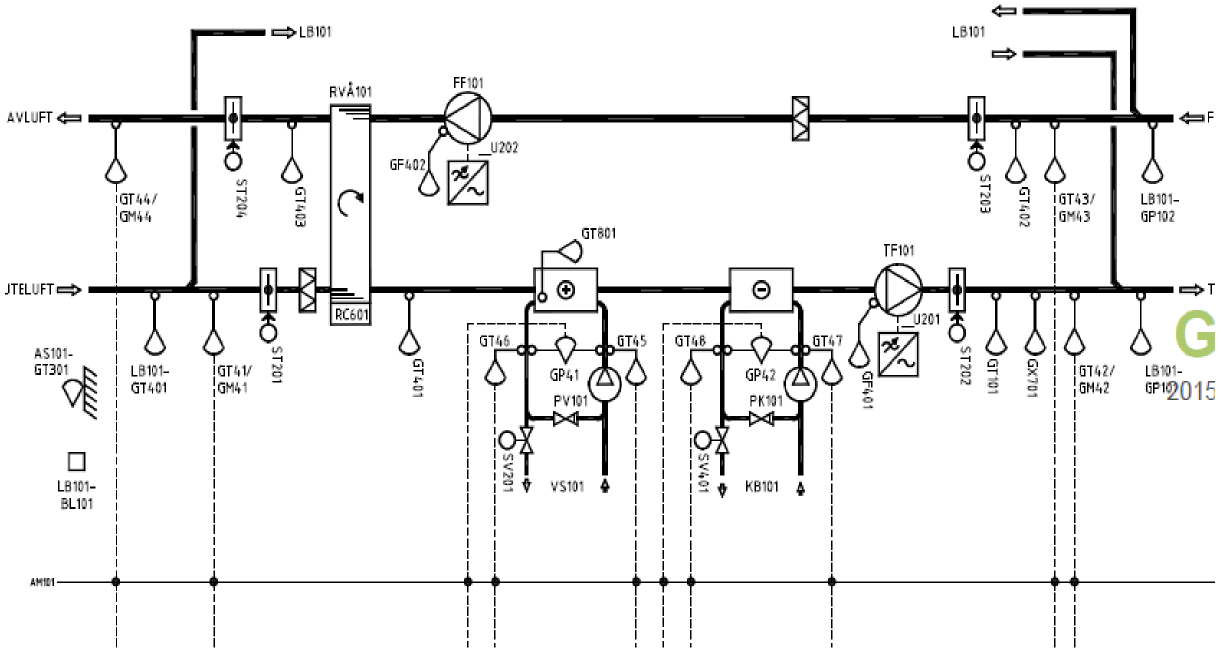


Figure 49 Schematics of the air handling units installed in Testbed AH.

3.3.1 Building energy system

In the Testbed AH space heating is mainly provided by radiators and space cooling is provided by the ventilation system. The system includes two AHUs with the layout schematically shown in Figure 49. The heating coil is used to heat up incoming air from the heat recovery system to temperatures to the target set-points. Heating and cooling are provided by the district heating and cooling network.

Figure 50 shows the energy use per year for the building divided by categories. Notably, the heat recovery is capable to recover most of the thermal energy needed to the building; the demand is mostly heating but the cooling portion is significant.

The building shows the highest energy use in 2018 and the lowest energy use by a large margin in 2020. This low value in 2020 is affected by the pandemic since the building use was largely reduced during this period. This fact can be observed by visualizing the CO_2 time series since CO_2 can be utilized as a proxy for occupancy. Figure 51 shows data of CO_2 for the classrooms during the four years analyzed. Although the data are incomplete in the period of interest, it is possible to see that the CO_2 values in spring 2020 are much lower when compared to the same period in the previous year confirming that the building was not used normally at the time due to the enforcement of online education.

Although the pandemic was the major contributor to the reduced energy use in 2020, another factor that seems to play in favor of this trend is the outdoor temperature conditions. Figure 52 shows the distributions of outdoor temperatures per season and per year. The data available shows that 2020 was milder both in winter and summer compared to the other years. There is some uncertainty in this statement due to a loss of data in winter and autumn 2020.

The reduced energy use in 2019 compared to 2018 could be explained by the milder outdoor conditions. In particular, a significant in reduction in the energy need for cooling during summertime is noticeable.

Regarding 2021, the outdoor temperature shows the lowest values during winter when compared to the other years analyzed. This indicates a rather rigid winter that could explain for instance an increase in the need of heating for air curtains. The energy use is nevertheless lower when compared to 2018 and 2019 as the building utilization was still partial due to hybrid online-onsite education policies.

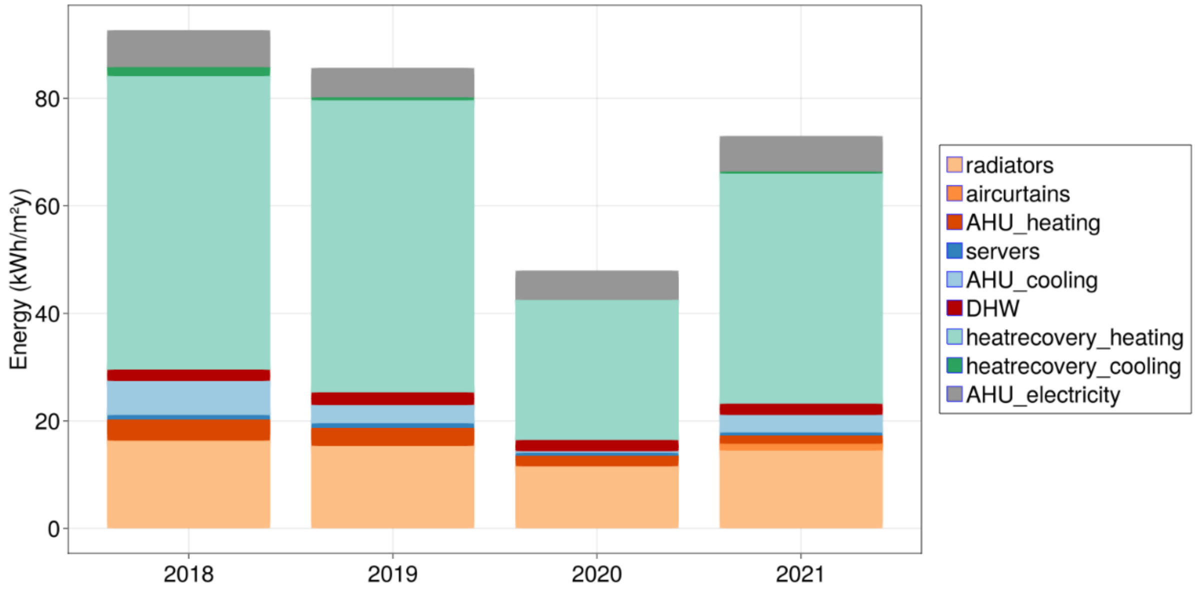


Figure 50 Specific energy demand per year in the Testbed AH.

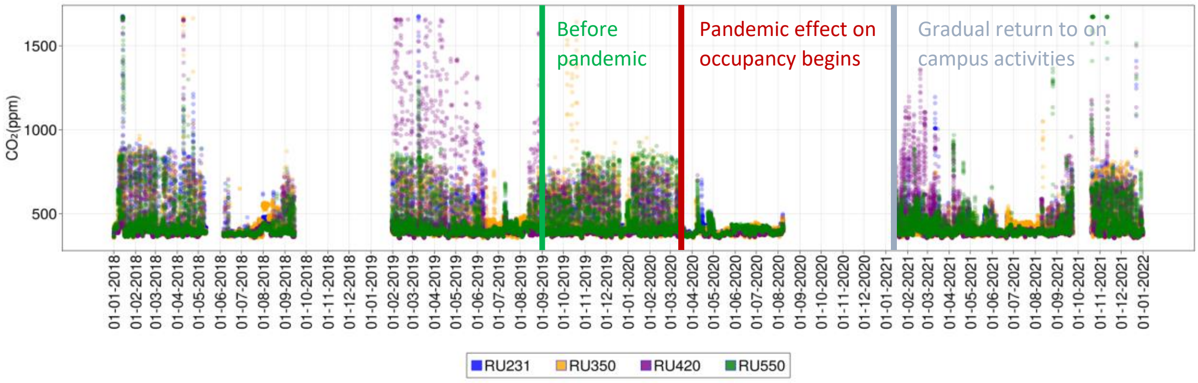


Figure 51 Time series of CO_2 for the four classrooms analyzed.

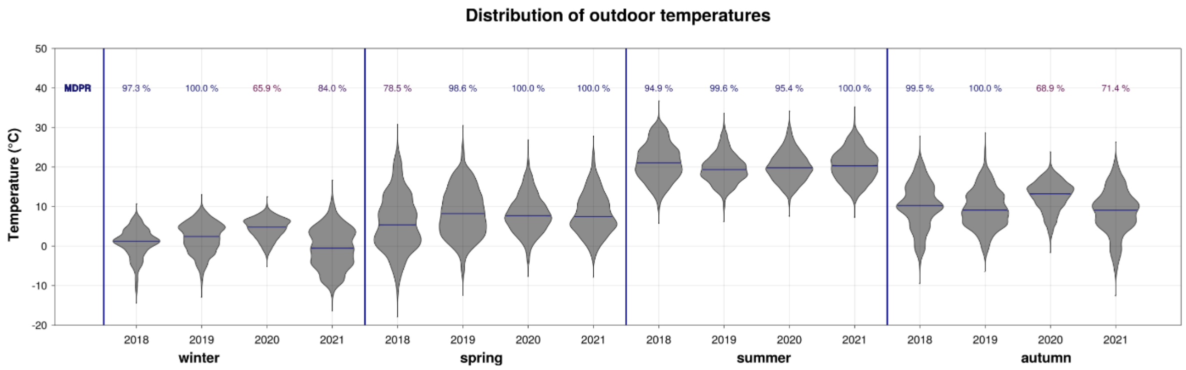


Figure 52 Violin plots comparing the distribution of outdoor temperature per season.

3.3.2 *Indoor air quality*

3.3.2.1 CO_2

Figure 53 and Figure 54 show the distribution of CO_2 during weekdays and daytime, and during nighttime respectively. The distribution during nighttime is mostly around value slightly below 500 ppm, which appears to be the baseline CO_2 measurements in the room. There are some anomalies also in this timeframe such as extreme spikes with values over 1500 ppm, more “spread” distributions that seems to indicate that these classrooms have been used at times also during evenings.

During daytime, the distributions are in general below 1000 ppm. There are however spikes in the distributions above 1000 ppm. In particular, room 420 during winter and spring 2019 had particularly high values of CO_2 crossing consistently the 1000 ppm threshold with peaks of nearly 2000 ppm.

As already pointed out above, the CO_2 data are incomplete at times. In the plots the MDPR values relative to each of the violin plots are reported. The MDPR represents the available number of measurements over the expected number of measurements and shows whether the distribution displayed is relative to a complete, partially incomplete or very incomplete dataset (for more details, see chapter 3.4.2).

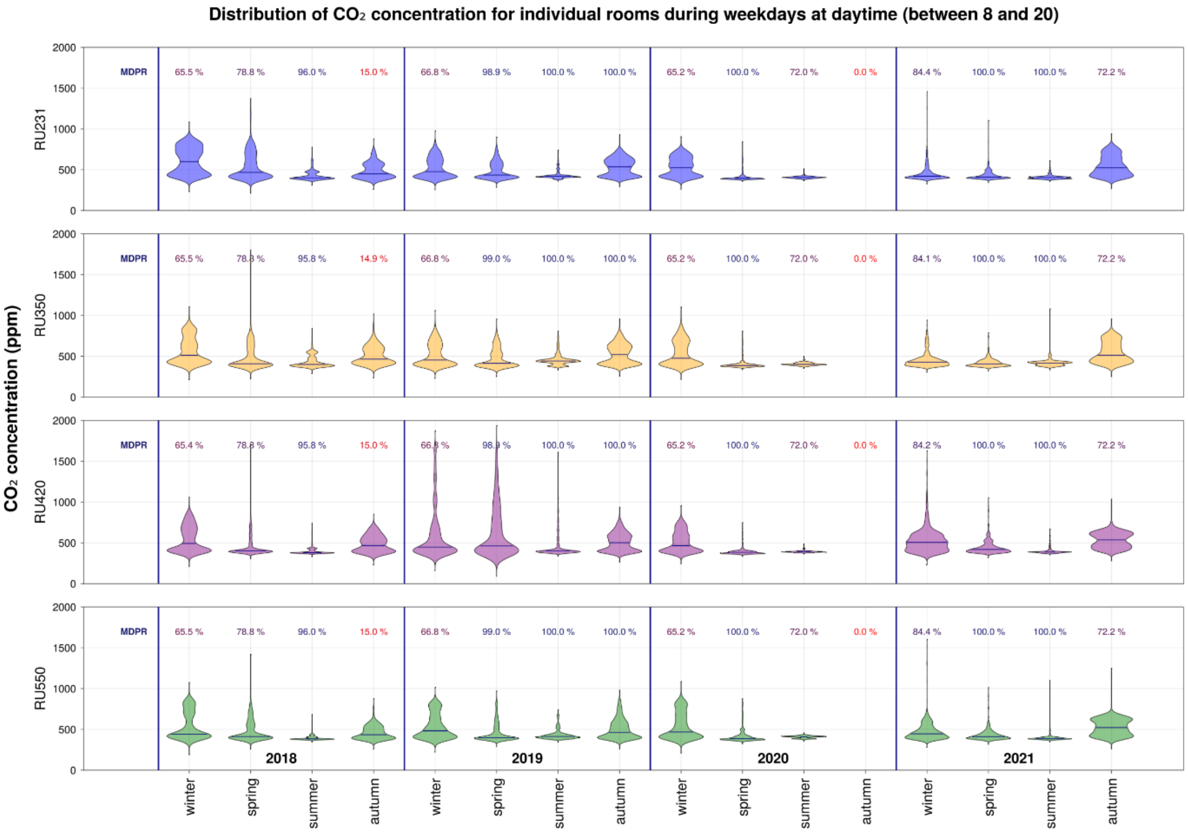


Figure 53 CO_2 concentration in the classroom during daytime and weekdays when the rooms are mostly used.

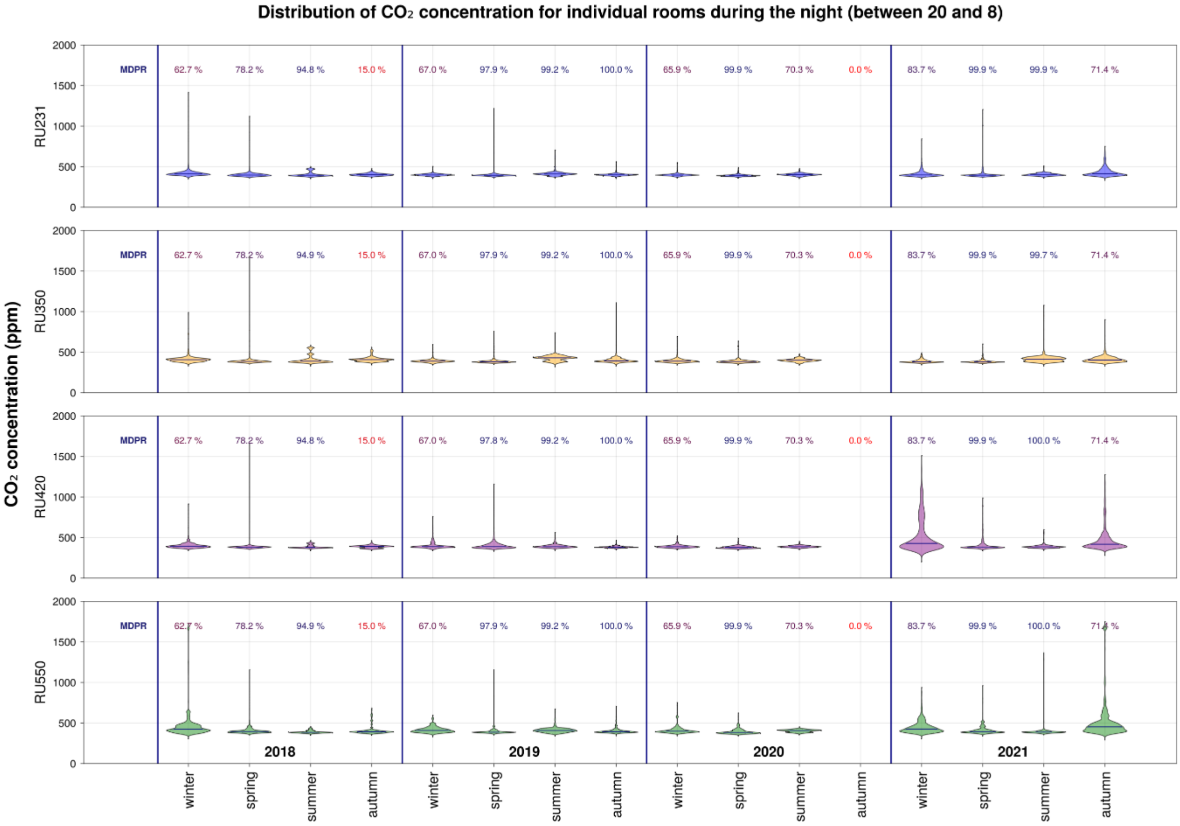


Figure 54 CO_2 concentration in the classroom during nighttime when the rooms are seldom used.

3.3.2.2 Indoor Temperature

Figure 55 shows the indoor temperature in the classrooms during weekday and daytime. The temperature in this section is the temperature measured via the sensors placed on the internal walls. In the plots, two dashed lines provide a lower reference bound of 19˚C and an upper bound of 27˚C. The plot shows that there are some anomalies and that temperature drops below the 19˚C limit.

The mean temperature measured can be significantly different when comparing different rooms.

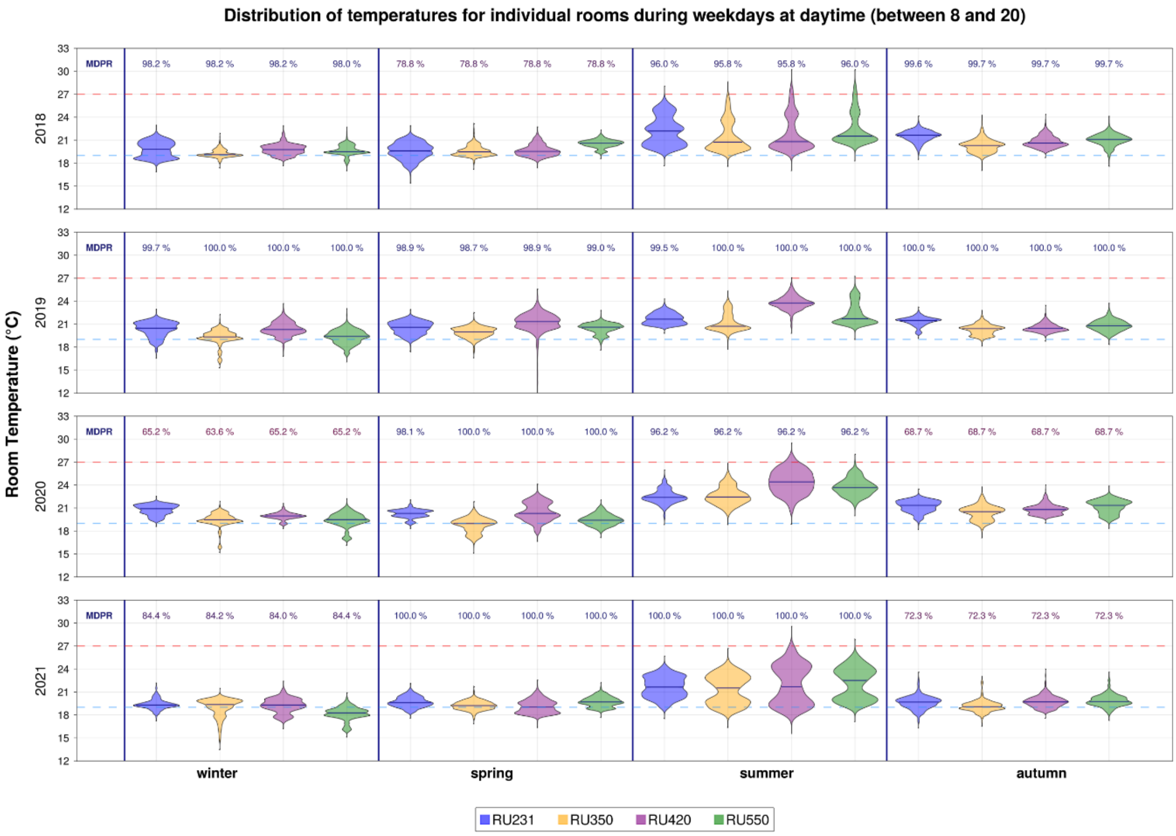


Figure 55 Comparison of temperature distributions in classrooms.

Figure 56 Classrooms temperature and relative humidity.

3.3.2.3 Data anomalies

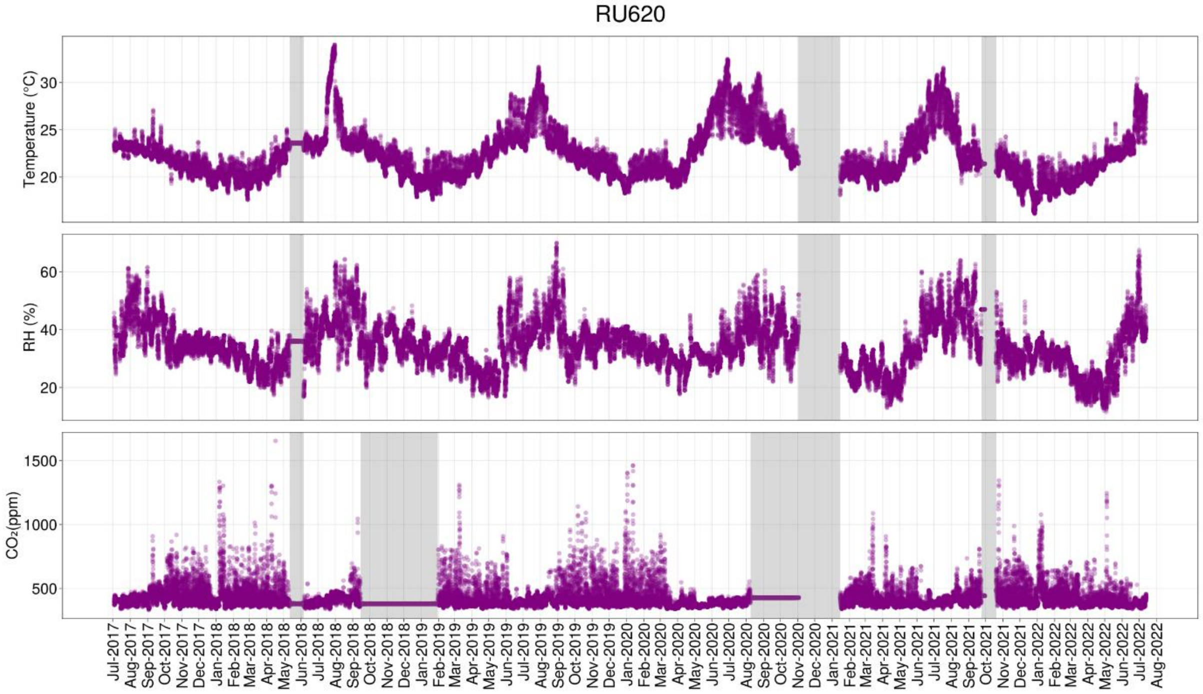


Figure 57 Testbed AH: identification of data gaps and repeated measurements.

The analysis of distributions of data shows the presence of significantly low temperature measurements. The time series data were explored to identify when these anomalies occurred. Two examples are reported below.

3.3.2.3.1 Case 1

This anomaly takes place during spring 2019. During daytime of the 2019-03-22 indoor temperatures are comparable in all rooms. However, the temperature in room 420 decreases during the evening and fluctuates between 5 and 10 ˚C below the other room’s temperatures; the temperature increases to comparable levels on Monday during the day. This situation is compatible with windows open during the weekend.

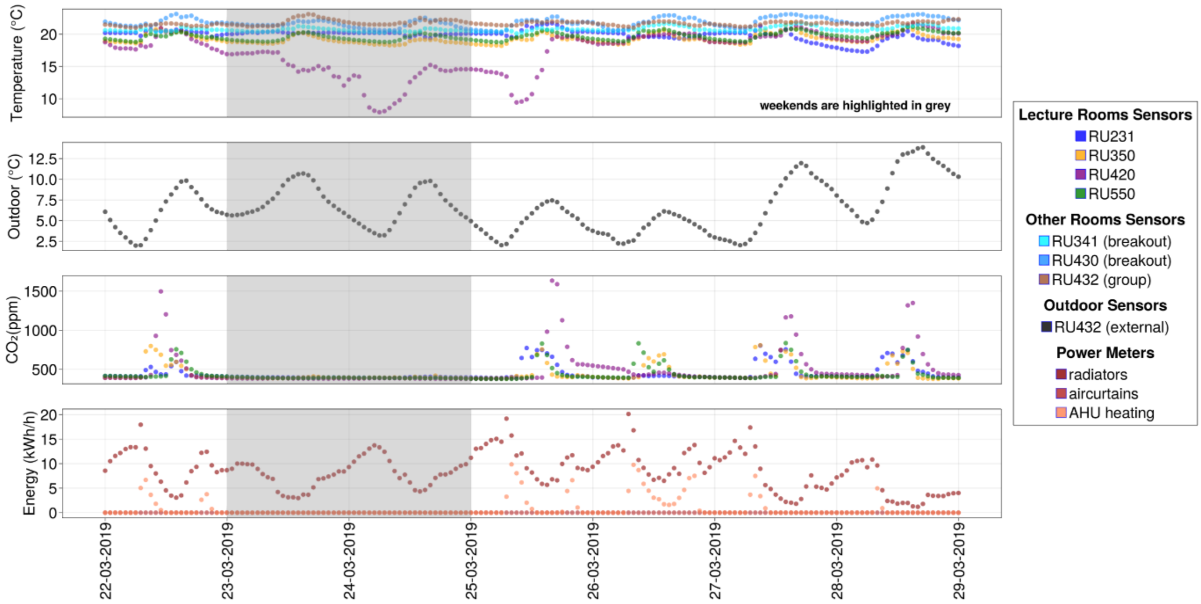


Figure 58 Plot of indoor and outdoor temperatures, CO_2 concentration and metered energy in the monitored rooms. The combination of the temperature readings allows the identification of the potential window opening in the room (RU420). The gray area indicates the days in the week-end.

3.3.2.3.2 Case 2

This case study focused on two months, between 2021-12-01 and 2022-02-01. The indoor temperature was below acceptable thresholds in two rooms for an extended period. The anomaly was fixed in one room, but not in the other one. The anomaly included:

- Low indoor temperatures in rooms 350 and 550;
- Significantly different trends between the various rooms;
- The temperature in room 350 was fixed at the beginning of 2022.

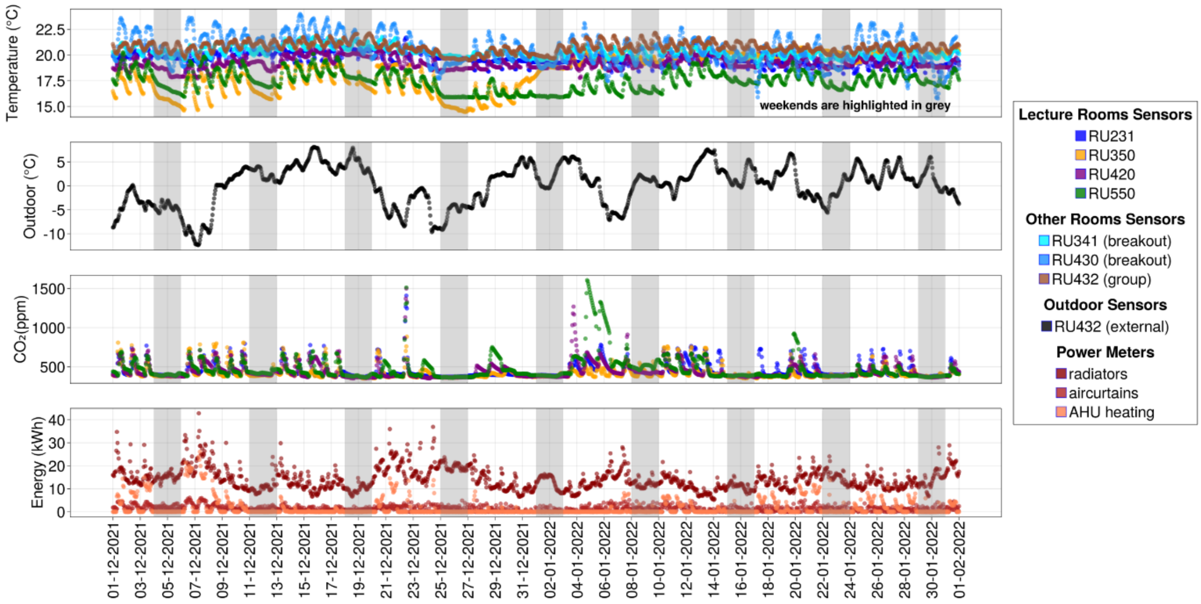


Figure 59 Anomalies in two rooms.

3.3.3 Data validation

Figure 60 Device Chauvin-Arnoux CA1510 installed in the classrooms of Testbed AH during a data validation campaign.

The measurements from the sensors installed in the classrooms of Testbed AH have been verified during the project through a short validation campaign.

A reference device (Chauvin-Arnoux CA1510) has been installed in the classroom of Testbed AH for periods covering between 24h and a few days of measurements. The results of the campaign are shown in Figure 61, Figure 62, Figure 63 and Figure 64.

The Figures show the measurements of indoor temperature, relative humidity and CO_2 collected by the monitoring system of the testbed along the measurement collected by the CA1510 device (identified in the Figures as "ref"). The blue bands in the charts highlight the periods when each of the room were scheduled to be occupied, according to the KTH internal booking system.

From the Figures, it can be noticed that the sensors installed in the Testbed AH consistently underestimate the CO_2 and indoor temperature but overestimate the relative humidity. Considering the accuracy of the device CA1510 and further cross-validations performed using additional lab equipment, the discrepancy of the indoor temperature measurements is the most concerning and requires attention. Overall, the indoor temperature discrepancy is often over 1ºC and exceeds at times 2ºC. This highlights once more the need of verification and supervision of building monitoring systems.

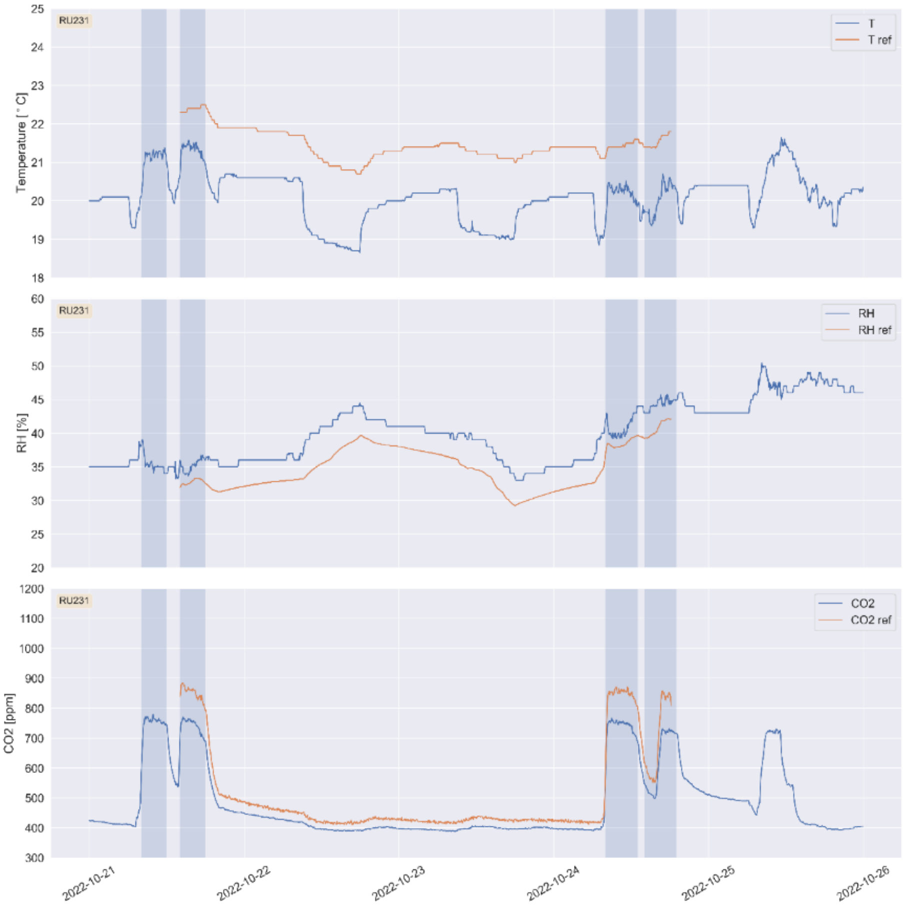


Figure 61 Room U21 (RU231) measurements vs reference device. The highlighted areas indicate the periods when the room was scheduled as occupied.

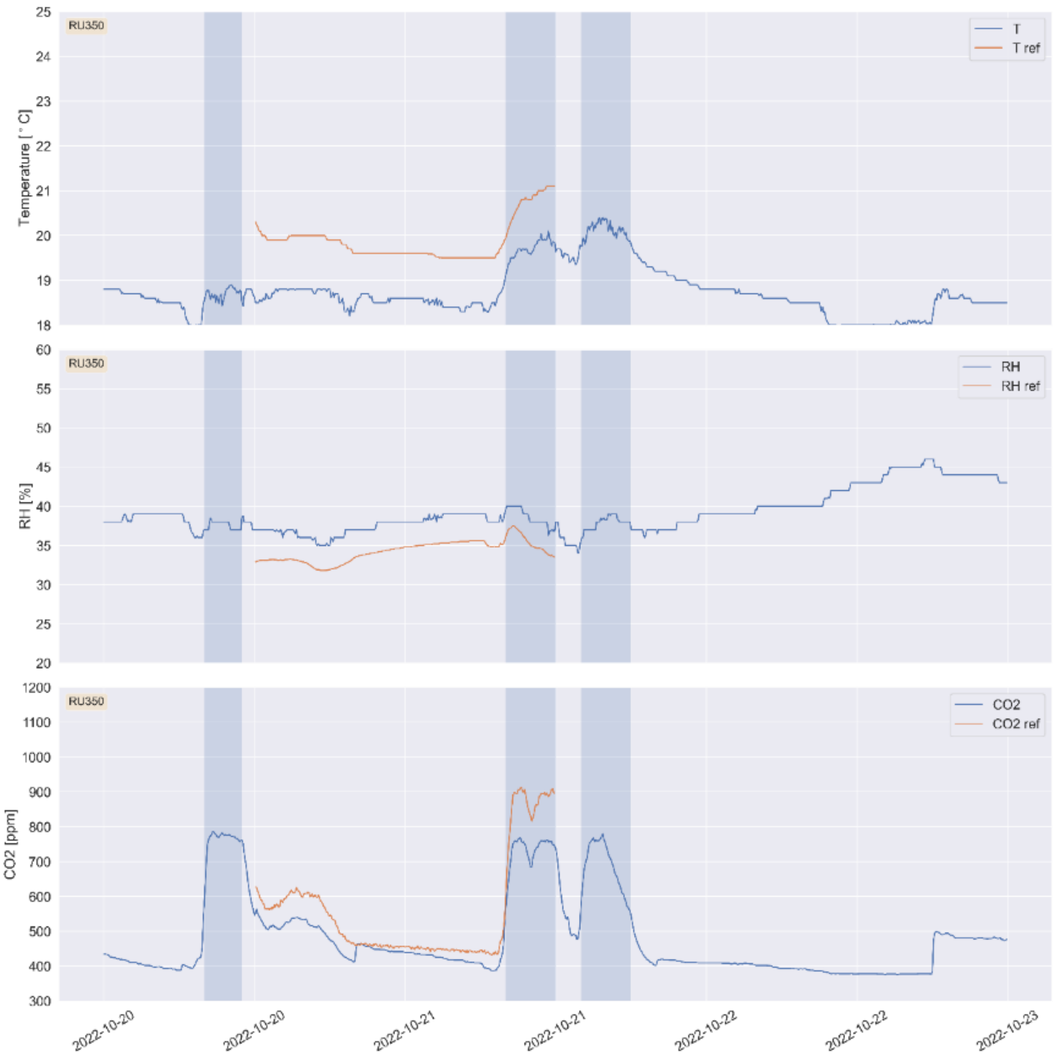


Figure 62 Room U31 (RU350) measurements vs reference device. The highlighted areas indicate the periods when the room was scheduled as occupied.

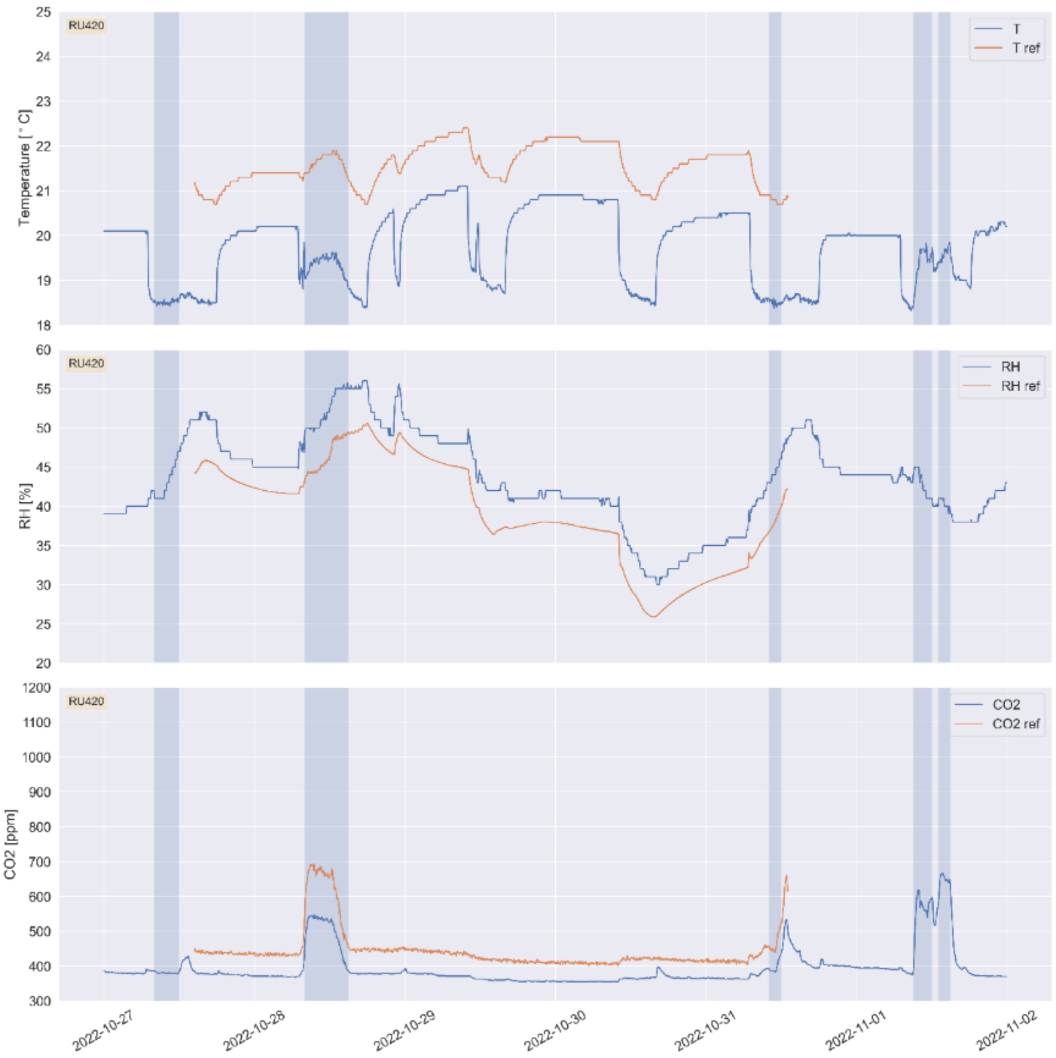


Figure 63 Room U41 (RU420) measurements vs reference device. The highlighted areas indicate the periods when the room was scheduled as occupied.

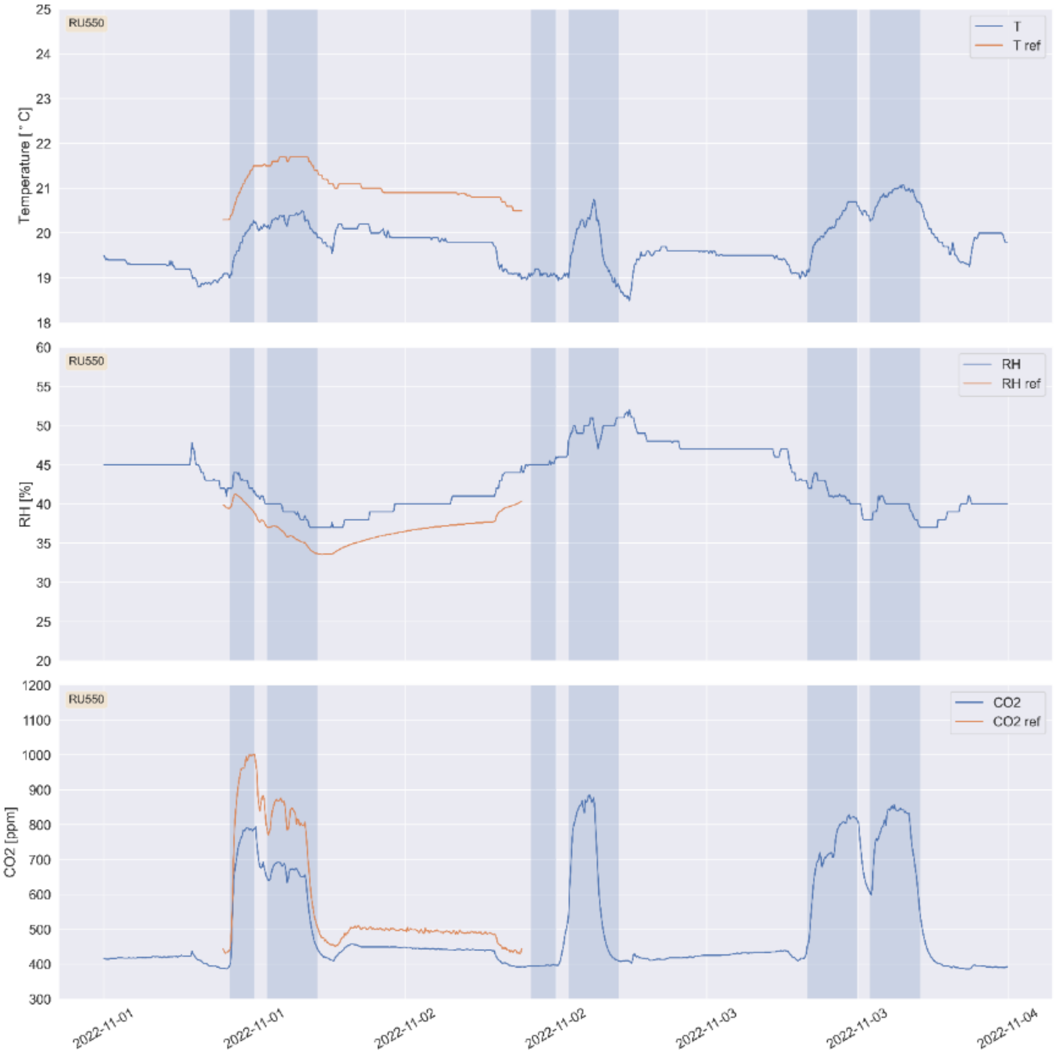


Figure 64 Room U51 (RU550) measurements vs reference device. The highlighted areas indicate the periods when the room was scheduled as occupied.

3.3.4 *Highlights and lessons learned*

- Low usage of data for building operation;
- Lack of supervision of the monitoring system;
- Lack of suitable alarm system;
- Very good documentation of the monitoring system;
- Good and easily accessible monitoring system, but key sensors are missing for an overall indoor air quality evaluation; CO_2 measurements are available only in lecture rooms;
- The action (in particular, operation of the windows) of building occupants interferes with optimal operation of the building;

- Room temperatures are on average too cold in the cooling season, indicating a significant potential for energy saving.

3.4 Monitoring systems: considerations on data quality (WP2, WP3)

The data analysis presented in the previous chapters required extensive works on identification, parsing, mapping and cleaning of the available data. A set of indicators has been evaluated with the goal of giving an overview on the quantity and quality of the available data.

3.4.1 Data identification and mapping

The monitoring system of Testbed EM logs indoor temperature, CO_2 concentration, electricity use and domestic hot water use in all 305 apartments. The system is designed to provide measurements from all the apartments every minute.

An indicator, called Missed Data Points Ratio (MDPR), was defined as the available number of measurements over the expected number of measurements based on the sample rate of 1 min to quantify the data availability over the 12-month period of analysis (Eq. 6). An MDPR of 100% indicates that all measurements are available as expected. In the presented period, the MDPR of Testbed EM is 91.3%.

$$\mathrm{MDPR} = \frac{\text{available number of measurements}}{\text{expected number of measurements}} \tag{6}$$

Overall, the data points of six apartments have no data from either indoor temperature or CO_2 sensors, one apartment has no data from electricity meters while all the DHW data points provide data relative to all the apartments.

Figure 65 shows the MDPR calculated considering the indoor temperature, CO_2, electricity and DHW use from all the apartments of the 3 buildings of Testbed EM. In the Figure, the horizontal blank spots indicate periods where data from specific apartments have been lost. Worth noticing, the vertical blank lines across all apartments identify short periods when the entire monitoring system experienced major malfunctions.

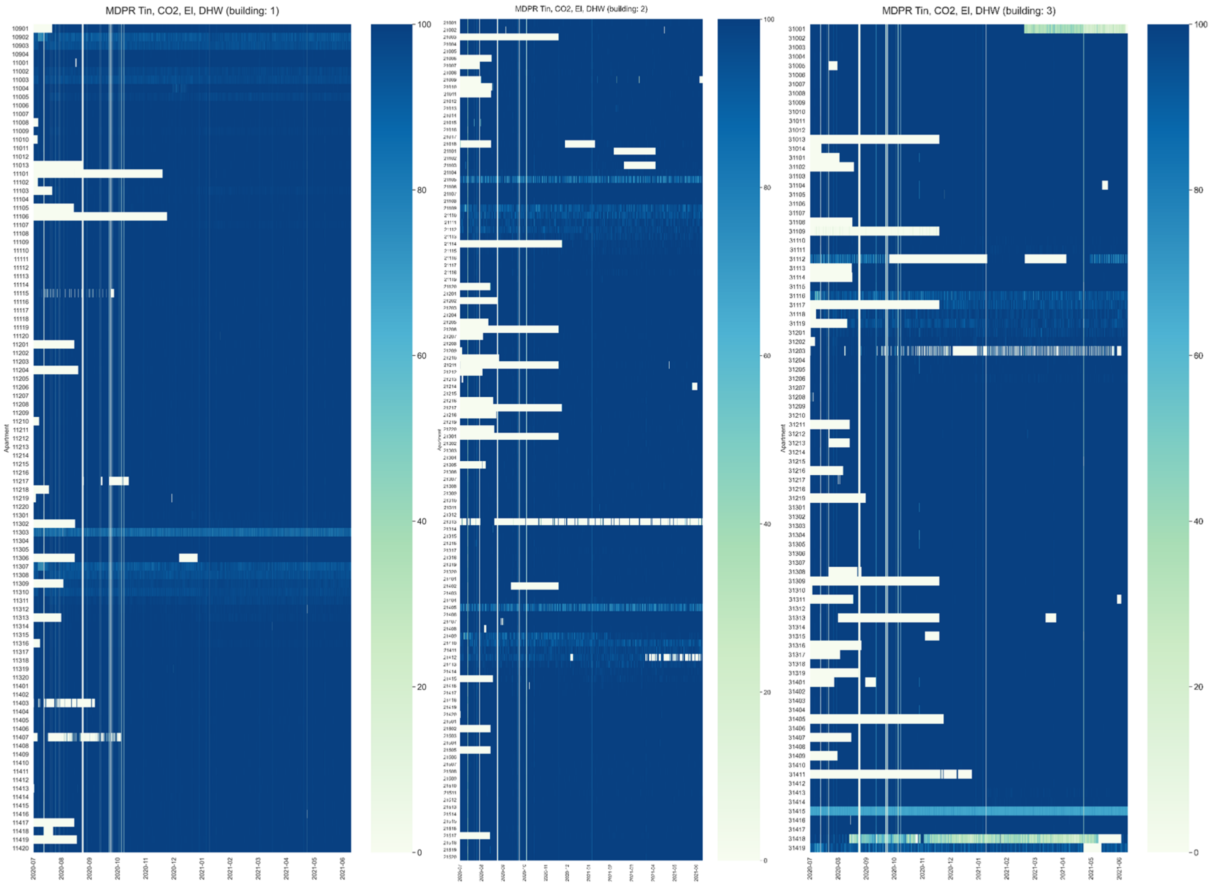


Figure 65 MDPR based on sensors installed in all apartments of Testbed EM.

3.4.1.1 Testbed AH

In Figure 66 the first plot displays the hourly MDPR calculated for a subset of sensors from Testbed AH, including temperature, relative humidity and CO_2 sensors during 2020. The plot shows that for the majority of the period analyzed the data is acquired at the design frequency. The plot shows also that there are large gaps. One significant gap in June 2020 and a very large gap that extends between November 2020 and the end of the year.

Data quality was further analyzed via exploratory analysis, and it was found a special kind of issue. It was identified that every so often a sensor would report the same value over and over for an extended period. Some of these intervals are extended (e.g., more than 15 days up to several months), and could easily be spotted by visual inspection. Figure 67 shows temperature, relative humidity and CO_2 measurements for the classroom 420. In the plots, periods with no data and periods where the data are constant are highlighted. In this Figure a minimum window length of 12 hours was utilized to reject constant data. The interval length (e.g., 12 hours) is arbitrary but needs to be established as the lack of observed variation might be due to changes that are lower compared to the resolution of the measurement instrument. In essence, this criterion enables the elimination of data that are considered likely to be faulty. In the second plot of Figure 66, the data filtration described above -using a 12 hours window- was applied. The results show that the CO_2 sensors have a very long period with constant data from August to November and that different sensors show different patterns in the MDPR.

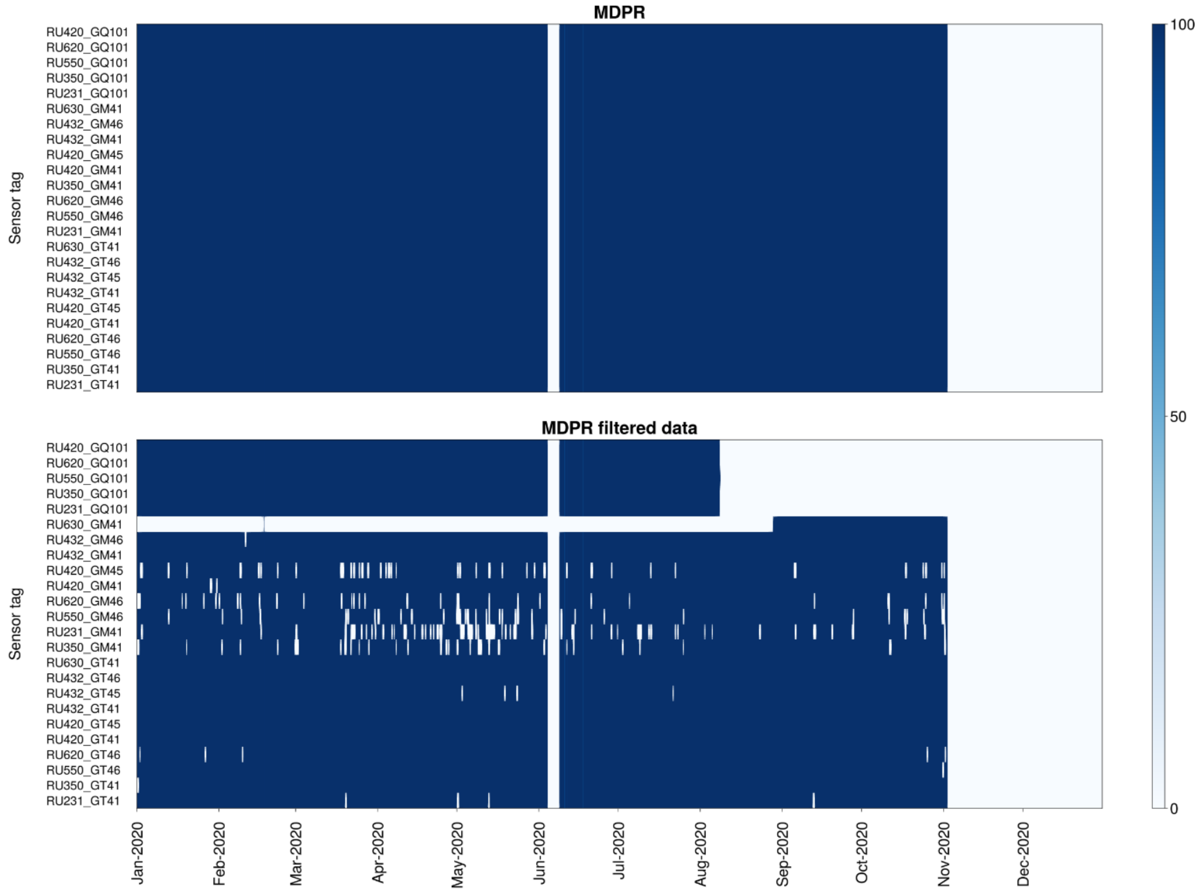


Figure 66 Hourly MDPR during a period of one year for a subset of the sensors available in the building.

Figure 67 Temperature Relative humidity and CO_2 for the classroom 420. In the plot intervals with no values and intervals with constant values are highlighted. The minimum window size utilized for intervals with constant value was 12 hours.

3.4.2 Data quality

A second indicator has been used to identify the measurements of indoor temperature and CO_2 concentration outside expected and reasonable ranges. For the indoor temperature, the filtered data includes the measurements between 10 and 40 °C, while for the CO_2 concentration, the filtered data includes the measurements between 300 and 5000 ppm. The lower limit for the CO_2 level is based on a conservative approximation of the expected average outdoor concentration [23], while the upper limit is a conservative approximation based on the CO_2 distribution in the 305 apartments. The Ratio of Data to Errors (RDE) is defined as the number of filtered measurements over the total number of expected measurements (Eq. 7)

$$\mathrm{RDE} = \frac{\text{filtered number of measurements}}{\text{expected number of measurements}} \tag{7}$$

Figure 68 shows the cumulative RDE calculated for indoor temperature and CO_2 concentration measurements from all 305 apartments. The figure indicates that the data points of CO_2 concentration contain more data outside the expected range compared to the indoor temperature. The inspection of the charts suggests that there is a 40% probability to have missing data or data out-of-range in the available measurements. However, it should be noted that the probability is lower than 20% if we consider 80% of measurements available and within an expected range.

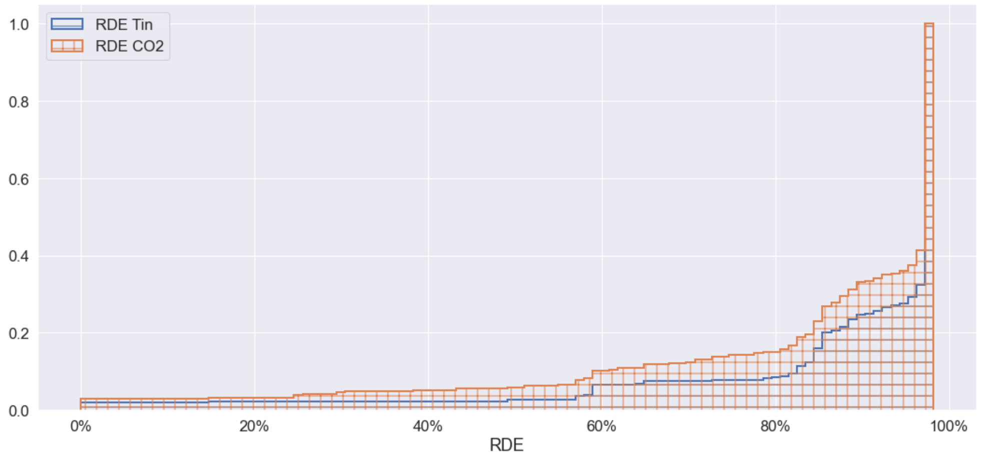


Figure 68 Cumulative RDE for indoor temperature (T_{in}) and CO_2.

3.4.3 Highlights and lessons learned

- Data loss in all monitoring systems is not negligible;
- Current systems have limitations and problems but allow us to map overall system performance;
- Properly configured alarms are fundamental to guarantee availability and integrity of collected data;
- Missing key standard sensors for an overall IEQ evaluation; for instance:
    - Relative humidity in Testbed EM,
    - CO_2 in many rooms of Testbed AH;
- Missing sensors for overall system performance evaluation:
    - Air temperature sensors (Testbed EM) in the ducts for losses and impact of users.

3.5 Smart Readiness Indicator (WP2, WP3)

The smartness level has been assessed for the two residential testbeds, Testbed KTH and Testbed EM, in the KTH Live-In Lab using the Smart Readiness Indicator (SRI), an indicator recently proposed at the EU level. The SRI has been defined in literature [71] as a catalogue of smart ready services to be inspected. The result of the SRI assessment is an aggregated percentage score that indicates how close is the building is to a maximal smart readiness. The SRI evaluator should inspect in a site visit each service and classify it based on a functionality level, i.e. the degree of smartness.

The assessment procedure can be carried out at three levels of detail:

A. a simplified method, that includes a checklist approach with a limited and simplified service list of 39 smart ready services;

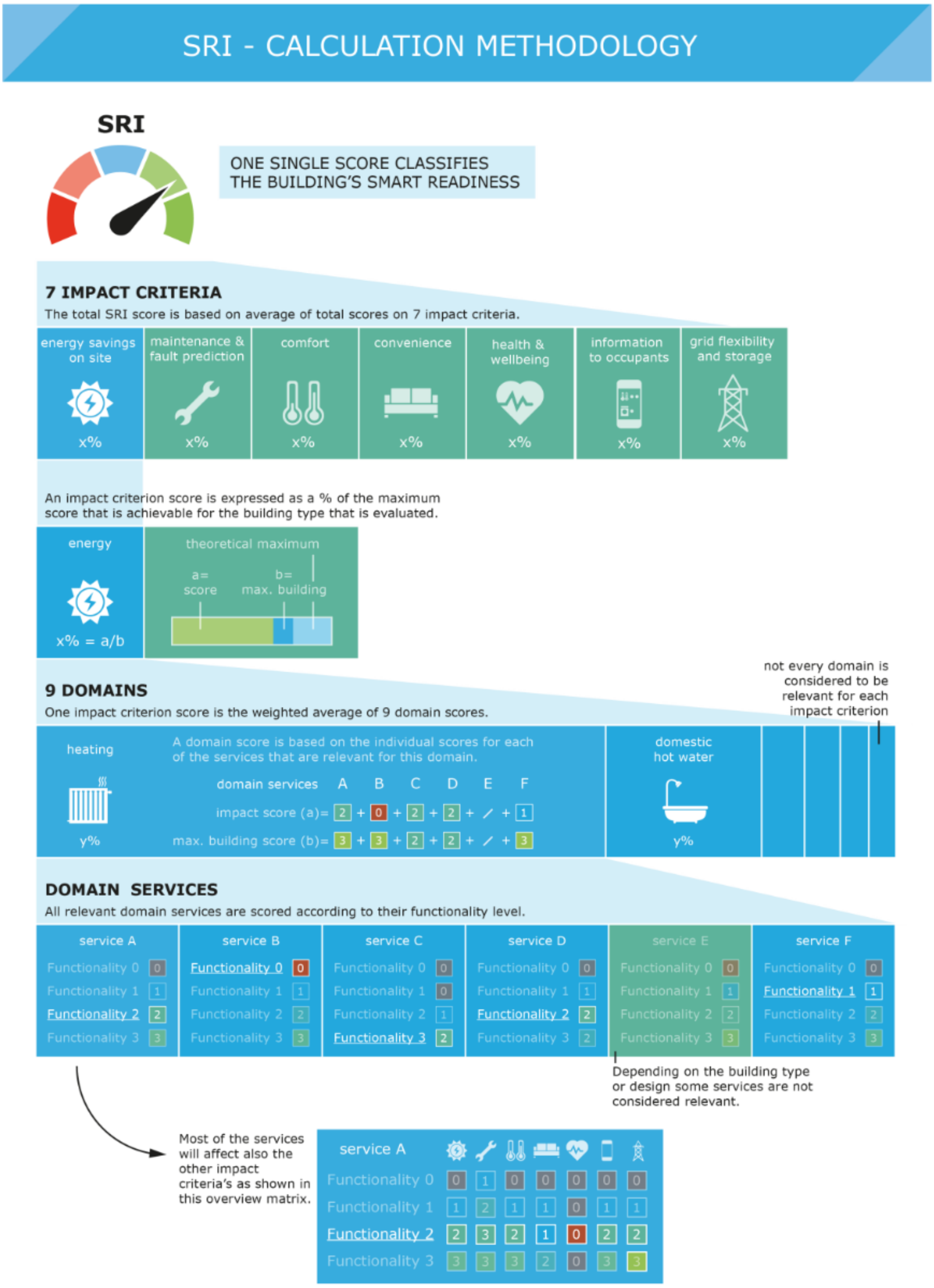
B. an expert SRI assessment, with a checklist approach that covers the full catalogue of the smart services, with 52 smart ready services;
C. an in-use smart building performance, with measured or metered data; this method is considered a potential evolution [72].

So far, the majority of the assessments have been carried out using the methodologies A and B, with no assessment using the methodology C.

The SRI methodology builds on a catalogue of smart ready services, grouped in nine service domains (heating, cooling, domestic hot water, ventilation, lighting, dynamic building envelope, electricity, electric vehicle charging, monitoring and control). The smart services in each domain influence the performance of seven impact criteria (energy savings, maintenance and fault prediction, comfort, convenience, information to occupants, health and wellbeing, energy flexibility and storage). The impact criteria in turn affect the three key functionalities: 1. Maintain energy performance and operation, 2. Respond to the needs of the occupant and 3. Flexibility of a building overall electricity demand.

The conceptual workflow of the SRI evaluation procedure is illustrated in Figure 69 - further details can be found in the Final report on the technical support to the development of a smart readiness indicator for buildings [72]. Each smart ready service is assessed; the score is related to the smart readiness functionality of each service and can have up to five functionality levels with higher functionality levels implying higher smartness.

An Excel-based tool supports the evaluation process, with predefined functionalities for each smart service. The functionality level for each service results in an impact score, i.e. how much each service at the evaluated functionality level affects the impact criteria; impact scores are also tabulated in the Excel-based tool. Individual impact scores are aggregated in a domain impact score, calculated as the ratio between sum of the individual impact scores and the theoretical maximum individual impact scores. For each impact criterion, e.g. comfort, the total impact score is calculated as a weighted sum of all the domain impact scores, with the weighted sum depending on the relative importance for the considered impact.



SRI - CALCULATION METHODOLOGY

ONE SINGLE SCORE CLASSIFIES THE BUILDING'S SMART READINESS

7 IMPACT CRITERIA

The total SRI score is based on average of total scores on 7 impact criteria.

An impact criterion score is expressed as a % of the maximum score that is achievable for the building type that is evaluated.

9 DOMAINS

One impact criterion score is the weighted average of 9 domain scores.

A domain score is based on the individual scores for each of the services that are relevant for this domain.

not every domain is considered to be relevant for each impact criterion

DOMAIN SERVICES

All relevant domain services are scored according to their functionality level.

Depending on the building type or design some services are not considered relevant.

Most of the services will affect also the other impact criteria's as shown in this overview matrix.

Figure 69 Illustration of the workflow of the SRI methodology, [72].

3.5.1 SRI assessment

Table 6 shows the results from the assessment of the Testbed KTH and the Testbed EM for the functionality levels in the domain scores following the methodology A. Neither testbed features a cooling system, dynamic envelope (e.g., automatic blinds) nor electric vehicle charging facilities; therefore, they are not considered in the analysis. The Testbed KTH scores better in all considered domains.

The Testbed KTH scores high in the Controlled ventilation and heating system domains, and similarly does the Testbed EM, due to similarities in the design concepts. Both testbeds use a demand-response ventilation system controlled by temperature and CO_2 sensors, which allows to score high both in the Heating and Ventilation domains. Surprisingly, both testbeds scores average in the monitoring and control domain. The BMSs in both testbeds collect extensive metered data on the building systems and building indoor spaces; however, there is a lack of built-in interfaces that allowing real-time information on these systems to users and managers.

Figure 70 shows the results from the assessment for the Impact scores. Both testbeds ranks similarly in the different Impact scores, with the Testbed KTH scoring higher in all Impact scores. It is important to stress that the Testbed KTH is an experimental facility that, even if it has been designed as a standard building, had extra capital investment available for smartness; in addition, the small scale of the Testbed helps.

Both testbeds score highest in the Energy saving and maintenance Impact (59% for Testbed KTH and 44% for Testbed EM), due to the individual room control and communication with the BMS controllability, the advanced controllability of the generation systems and the data functionalities of the heat generation system. Both Testbed KTH and Testbed EM perform relatively good in the Comfort (40% for Testbed KTH and 28% for Testbed EM) and Maintenance and Fault prediction (36% for Testbed KTH and 27% for Testbed EM), benefitting from individual room control and advanced heat generation control.

In both cases, the weakest Impacts are Flexibility for the grid and storage (20% for Testbed KTH and 15% for Testbed EM) and Information to Occupants (26% for Testbed KTH and 9% for Testbed EM). The Testbed KTH benefits partially from a default user interface that allows building occupants to access real-time information on the status of the indoor spaces. However, the lack of a user-interface for both building managers and users represents a missed opportunity and its implementation is recommended.

Table 6 Results from the SRI assessment – method A. Cooling system, Dynamic envelope and Electric Vehicle Charging results are not applicable since the systems are not present in the buildings.

Domain	Smart ready service	Functionality level	
		Testbed KTH	**Testbed EM**
Heating	Heat emission control	3	3
	Heat generator control (heat pumps)	2	2
	Storage and shifting of thermal energy	1	0
	Report information regarding heating system performance	2	0
Domestic hot water	Control of DHW storage charging (with direct electric heating or integrated electric heat pump)	0	0
	Control of DHW storage charging	1	0
	Report information regarding domestic hot water performance	3	0
Cooling	Cooling emission control	-	-
	Generator control for cooling	-	-
	Flexibility and grid interaction	-	-
	Report information regarding cooling system performance	-	-
Controlled ventilation	Supply air flow control at the room level	4	4
	Reporting information regarding IAQ	2	1
Lighting	Occupancy control for indoor lighting	1	0
Dynamic building envelope	Window solar shading control	-	-
	Reporting information regarding performance	-	-
Electricity	Storage of (locally generated) electricity	1	1
	Reporting information regarding electricity consumption	1	0
	Reporting information regarding local electricity generation	3	2
	Reporting information regarding energy storage	2	2
Electric vehicle charging	Charging capacity	-	-
	EV Charging Grid balancing	-	-
	EV charging information and connectivity	-	-
Monitoring and control	Single platform that allows automated control & coordination between TBS + optimization of energy flow based on occupancy , weather and grid signals	2	1
	Smart Grid Integration	0	0
	Central reporting of TBS performance and energy use	0	0

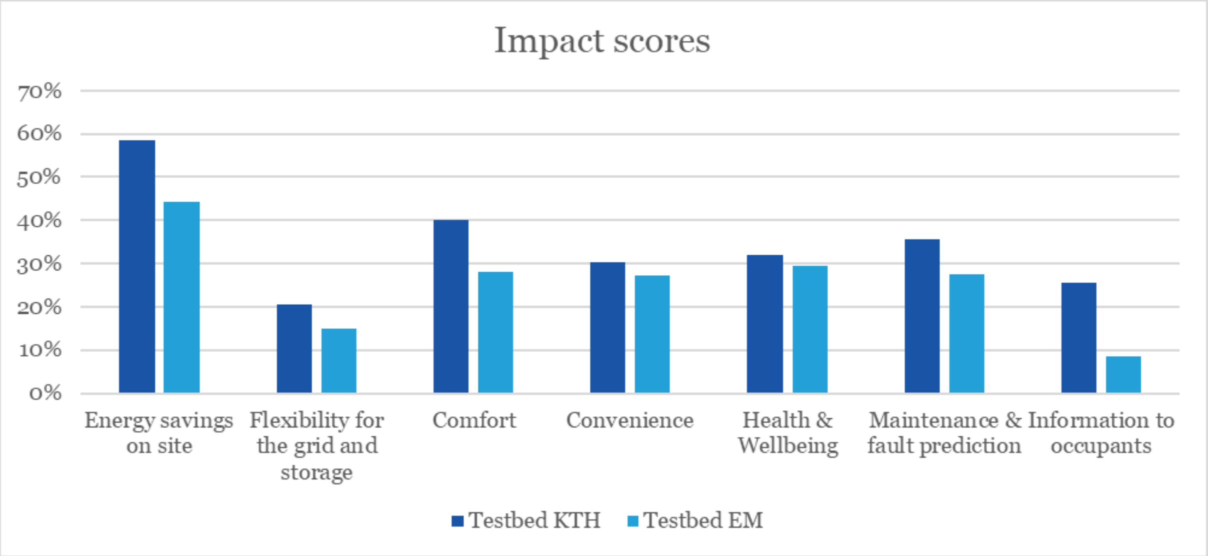


Figure 70 Impact scores from the SRI analysis – method A. The domain scores have been derived using the suggested weighting factors for Northern climates for the residential sector.

3.5.2 *Discussion*

The aggregated SRI score resulted in 44% for the Testbed KTH and 29% for the Testbed Einar Mattsson. These results are considered average for candidate smart buildings but it should be also underlined that some important system functionalities like advanced storage systems are being implemented at the time of the analysis. Importantly, this assessment is carried out following the simplified methodology, which includes a more limited set of services.

Both testbeds score relatively low in the monitoring part; this is surprising given the experimental and demonstrative nature of the testbeds. The limiting factor in this domain is mainly in the incapability of either system to display information on energy flows and carriers to the users. For instance, in the Testbed KTH the BMS interface displays real time information about only about indoor environment parameters; however, in the Testbed KTH a web-app can overcome this limitation with a relatively limited implementation effort.

The monitoring system is not used at its full potential, in particular with respect to benchmarking and performance forecasting to users and building operators. Several services in this domain can be improved in a cost-efficient way, due to the limited investment in the infrastructure required.

A peculiar perspective of this work is in the similarities of the two buildings. Although the physical structure of the building is the same – the Testbed KTH is part of the Testbed EM, the level of the smart building features that they offer differ consistently. The Testbed KTH, in fact, has a completely independent monitoring system and an independent heating and ventilation system, although it can be connected to the energy generation system of the Testbed EM.

The higher scores of the Testbed KTH in all domains suggest a relative independence from the building envelope; this factor is significant when upgrading the smartness of existing buildings.

Regarding costs, it is important to underline that even if the Testbed KTH is an infrastructure conceived for research, its additional features are cost-efficient and commercially available. In other words, the increased scores for the SRI of the Testbed KTH depend more on requested features demanded by designers rather than investment costs.

Table 7 provides an overview of relevant case studies in the literature: the testbed KTH ranks average while the Testbed EM is on the lower range.

Table 7 Comparison of the SRI score for the Testbed KTH and the Testbed EM with relevant case studies.

Building name	**Location**	**Year built**	**Type**	**Score**	**Ref.**
Black Monolith	Bolzano (IT)	2017	Office	66-53***	[73]
Frederick University building	Nicosia (GR)	2007	-	52	[74]
Testbed KTH	**Stockholm (SW)**	**2017**	**Residential**	**44%**	**-**
Faculty of Civil Engineering	Prague	1970s – Re. 2010s	Office	35	[75]
Rýmařov family house	Rýmařov		Residential	37	[75]
Itecons 1	Coimbra (P)	2008	-	20*-16**	[76]
Testbed EM	**Stockholm (SW)**	**2017**	**Residential**	**29%**	**-**
Itecons 2	Coimbra (P)	2015	-	29* -22**	[76]
Praha apartment blocks	Prague	1980s – Re. 2000s	Residential	28	[75]
Všenory family house	Všenory	Ren. 2010s	Residential	14	[75]

3.5.3 Highlights and lessons learned

- The SRI methodology has proven a straightforward methodology to rank the smart functionalities of the building;
- The testbeds analyzed with the SRI approach have a good degree of smartness but a significant potential for cost-efficiently improving the systems exists;
- The SRI analysis has enabled the identification of cost-efficient solutions – mainly related to displaying the information to users - to upgrade the building management system and increase the smart readiness index;
- The SRI analysis may be used to guide the design of the building management systems.

3.6 Economic analysis (WP5)

Smart buildings can lead to lowered operation costs due to more efficient use of energy. In smart buildings, the interaction between users and systems can help to shift loads from peak hours to hours with low energy price. Features like energy storage and grid connectivity help to reduce operation costs as well as increase user satisfaction. The question then is if this also is reflected in the valuation of smart buildings.

Without going into details on the valuation of buildings, a simplified description is that the value of a property is equal to the gross rent minus operating cost (net operating income) divided by a yield. Rent is determined by supply and demand, and demand reflects the willingness to pay for space. The willingness to pay on the other hand is linked to factors such as the productivity the specific space can generate, flexibility, energy or resource efficiency and health aspects. In addition to these values, there is also some form of goodwill value, and in case of smart buildings this factor is potentially higher than conventional buildings.

Operating cost as well as maintenance costs are expected to be lower in smart buildings compared to conventional buildings, as a result of lower and more efficient use of energy and other resources.

Real estate value for smart buildings tends to be higher compared to conventional buildings, due to higher rents and lower operating and maintenance costs. In addition, property value is also affected by the net capitalization factor. Also here, without going into details the interesting part is the so-called risk premium, which is the investor perceived risk related to smart buildings in comparison to conventional buildings. Investors finding smart buildings more risky will require a higher direct yield. However, based on the arguments above, and the current situation on the market with increased energy price and interest rates, the demand for smart buildings is likely to increase, leading to a lower risk for investors. In other words, smart buildings would then be less risky to invest in compared to conventional buildings. Conventional buildings that cannot deliver asked for services and user as well as owner demands can face a situation of increased risk premium.

3.6.1 Costs for BMS: the case study of the Testbed EM

Advanced monitoring and control systems imply additional investment costs. However, it is not straightforward to define what extra mean. Given the discussions on property value above, it is now becoming standard and financially sound to invest in smartness, and the extra costs for these additional systems are rather costs related to higher property value. The following paragraph illustrates the costs related to the difference between a conventional setup and the extra features that enable smart readiness in the Testbed EM, a set of the three buildings representative of modern block of flats.

The total cost for planning and producing the Testbed EM was 347 MSEK, equivalent to approximately 35MEuro, with the buildings being delivered in 2018. The systems enabling smart readiness in the Testbed EM account for 6.3% of the total investments and correspond to 72 000 SEK/apartment. The largest cost is installation of solar PVs, 1.77% for a total of 1150 m^2 generating a yearly figure of 230 000kWh electricity. The second largest cost is the installation of ground source heat pumps, with an additional investment of 1.63% in comparison to the connection to existing district heating network. The additional cost for a more advanced automation system, the system for data acquisition and storage and the optimization of HVAC required an extra investment of 0.12%, 0.69%, and 0.52% respectively, while wastewater heat exchangers accounted for only 0.35%. Given the size and the modularity of the three buildings, the overall extra cost for monitoring, control, data acquisition and storage sums up to a mere 0.81% on the total construction budget and corresponds to 9180 SEK/apartment.

3.6.2 Costs for BMS: the case study of Uppsala Backe

In Uppsala Backe, two similar buildings (same geometry, building envelope and building HVAC systems) were selected and equipped with different levels of smartness. Two packages for monitoring were proposed and installed: the first building (Hus 2) featured a standard monitoring system while the second one (Hus 4) was equipped with a more advanced setup. Both systems are sufficient to monitor indoor climate and energy use in each apartment, but the advanced package also included more advanced features window opening sensors and local energy metering.

The two buildings have a Gross Building Area (GBA) of 801 m^2, and a construction cost of around 35 000 SEK/ m^2. The standard type monitoring system costed 2.5% of total project costs or 890SEK/ m^2 GBA, and the more advanced 3.7% or 1310 SEK/m^2.

3.6.3 Discussion

The cost for monitoring system is lower in Testbed EM compared to Uppsala Backe if looking at percentage of total cost. However, the specific total construction price (SEK/m^2) is higher in Testbed EM (54 800 SEK/m^2 compared to 35 000 SEK/m^2), and the total area is larger (6329 m^2 GBA compared to 801m^2 GBA). The advanced monitoring system in Uppsala Backe accounts for 3.7% of total construction costs, which is 1310 SEK/ m^2 GBA. However, if only accounting for the difference between standard monitoring system and the advanced one, the figure is 1.2% or 420 SEK/m^2 in Uppsala Backe. Testbed EM has a total percentage of 0.81% or 442 SEK/m^2 for monitoring systems.

Window opening sensors are cost-efficient sensors to detect unwanted openings of the windows (for instance extended openings during the heating season); similar information can be inferred from indoor air temperature and CO_2-sensor data. However, the second setup (temperature and CO_2) is slower than window opening sensors and hence less efficient from a technical standpoint, but reduces the costs related to extra sensors, installation, data management and future maintenance.

In order to financially support investment on smart automation systems there needs to be an increased asset value related to decreased operation costs or higher rent levels/price. Future research should investigate long-term performance for the specific buildings, focusing on the added value for extra systems in Uppsala Backe, to investigate lowered operation costs and/or increased subjective vale generation related to the added systems.

3.6.4 Highlights and lessons learned

- Extra investment (including design and installation) for monitoring systems is between 2.5% and 6.7% of the overall construction cost;
- Economic drivers for the installation of more advanced monitoring systems are perceived unclear;
- No real incentives to adopt functionalities (e.g., visualization tools to users) that can cost-efficiently improve the smart readiness of the buildings.

3.7 Monitoring platform (WP2, WP4)

Publication: D. Rolando, M. Molinari. Development of a comfort platform for user feedback: the experience of the KTH Live-In Lab, ICAE International Conference on Applied Energy, 2020

During the project, a customizable low-cost monitoring platform has been designed, developed and tested. The platform essentially consists of three main components: a web app, a sensing device and a backend infrastructure. In this section, the main characteristics of the platform are briefly described.

3.7.1 Software – Comfort App

A web application, called here Comfort App, has been developed to allow building users to provide feedbacks about their perceived comfort. The app is designed to be user friendly, informative and to provide a non-invasive user experience. Figure 71 shows examples of the panels implemented in the web application. The homepage of the web app consists in a minimal interface with a set of buttons corresponding to comfort perceptions (e.g. "Too cold", "Too dry", "Poor air quality"). By tapping one of the buttons, a second panel invites the user to provide a short comment on the choice. Providing the comment is not mandatory. All the feedbacks are stored into a database. Secondary panels show metrics of the feedbacks provided and aggregated metrics to compare (anonymously) the feedbacks from other users in the same building or in the same measurement campaign. The app provides also additional features for researchers and building managers, including the possibility to leave notifications to individual users or to group of users.

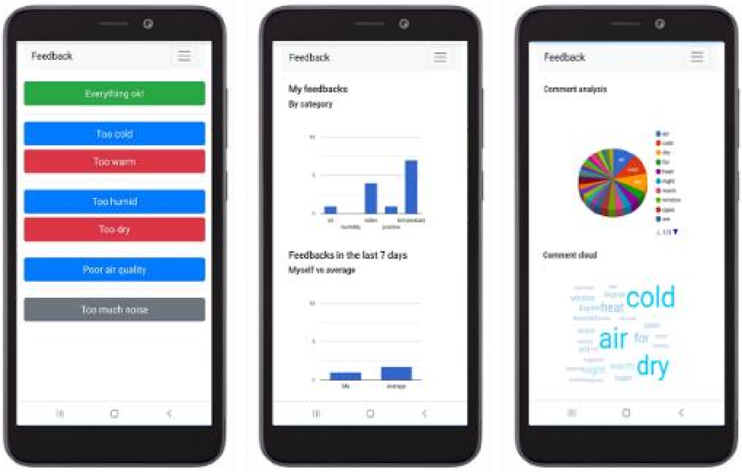


Figure 71 Example of functionalities available in the Comfort App.

3.7.2 Hardware – Comfort Box

The hardware component of the monitoring platform utilizes the ESP12 as core prototyping module. The ESP12 module is a wireless module based on the low cost and low power System on a Chip (SOC) microcontroller ESP8266.

In the prototype, named here Comfort Box, the ESP12 module is mounted to an electronic board that includes several low-cost sensors. The Comfort Box prototype (shown in Figure 72) includes sensors for monitoring temperature, relative humidity, CO_2, equivalent CO_2 (eCO_2), Total Volatile Organic Compound (TVOC) and light intensity. The temperature measurement is redundant and performed by two separate sensors. The measurement of CO_2 is also redundant, but obtained through distinct approaches. A dedicated low-cost CO_2 sensor performs one measurement of CO_2, while a second value (eCO_2) is derived by the measurement of TVOC.

The Comfort Box prototype is powered with 5V DC current provided by an external power supply. Common 5V 1A power supplies are suitable for powering the device. A battery driven device is under development.

Figure 72 Comfort Box prototype: first version (left) and current one (right).

3.7.3 *Sensor calibration*

Each sensor of each Comfort Box is calibrated before installation and the calibration parameters are stored in the database. Due to this design choice, each device always communicates the raw measurements to the server.

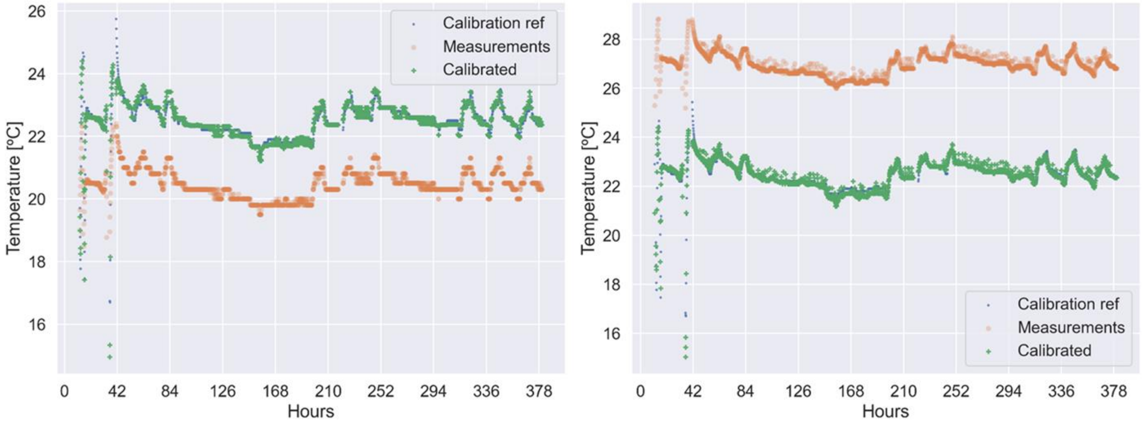


Figure 73 Example of calibration of temperature sensors for one device.

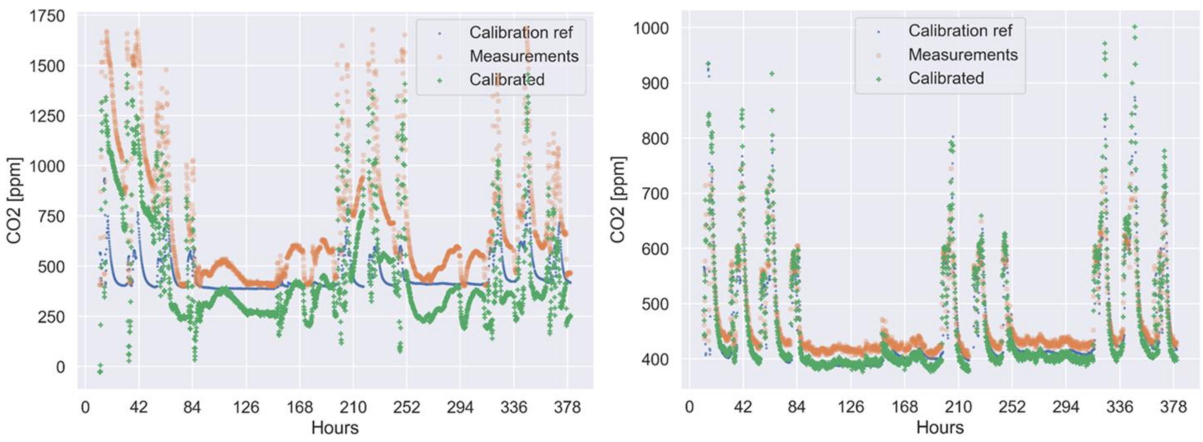


Figure 74 Calibration example of CO_2 sensors for one: eCO_2 sensor (left) and traditional CO_2 sensor (right).

It is important to stress that calibration is a crucial step for devices equipped with low-cost components. The factory calibration of low cost sensors is often not reliable and some examples are shown in the following Figures. Figure 73 shows the results of the calibration for the temperature sensors installed on one Comfort Box. As can be observed the offset of the raw measurements compared to the calibration reference was about 2 and 4ºC in this proposed example. Figure 74 shows the calibration results for the two CO_2 sensors installed, one providing the equivalent-CO_2 measurements (eCO_2) and one low-cost sensor based on traditional CO_2 measurements. The eCO_2 readings are in general less stable and accurate than the measurements provided by traditional CO_2 sensors.

3.7.4 Communication and data management

Compared to other examples available in literature based on similar hardware [77]–[79], the proposed Comfort Box stores no measurements locally but directly transfers all the measurements to a remote server. This design choice has the clear disadvantage of not providing a local backup of the measurements, but, on the other hand, brings numerous advantages in terms of prototype costs, data management and scalability of the solution.

First, the local storage of the measurements requires two main additional components mounted onboard: the physical storage and a Real Time Clock (RTC). While these requirements are somehow obvious, their implications are often overlooked. Low cost prototyping boards (e.g. Arduino) can be configured to store data to an SD card through dedicated modules that are widely available. Not least, recording measurements requires the tracking of the measurement time in order to be meaningful. Dedicated RTC modules for Arduino are available and can be connected to the prototyping boards. It is worth to notice that each additional module has an impact on the cost, design, manufacturing and operation of the entire prototype. Worth noting, examples of unpredictable malfunctioning of low cost RTC modules are available also in research literature [78]. One of the most common problem of RTC is time drifting, adding up over measurement campaigns of only few days.

The local storage of the measurements requires also the data to be physically collected and the reset or maintenance of the storage itself. Also, leaving the data on the device opens to privacy issues quite difficult to control.

All the problems related to the local storage and the RTC modules can only be detected by regular and physical inspection of the device. This implies clear disadvantages for relatively long measurement campaigns with multiple devices.

The wireless communication of the measurement, in principle, solves all the above-mentioned issues and it was a clear design choice for the proposed platform. The remote server automatically assigns the time of the measurement upon receiving the data. The remote server can also detect in real time any anomaly on the communication or the data related to any device.

An API has been developed for the communication and data management. The API handles the authentication and authorization of each Comfort App user and each Comfort Box device. The information coming from the Comfort Box and the Comfort App are secured via public key cryptography techniques. The API also handles the connection between the data transferred through the Comfort App and Comfort Boxes and the relational database where the data model of the Comfort App is implemented.

An admin web interface helps the management of the Comfort Platform. Users, devices, buildings, building rooms and campaigns can be created and configured. Also, measurement campaigns can be monitored in real time and operation parameters of individual Comfort Box can be set. As an example, the measurement interval of each Comfort Box can be individually assigned remotely and modified at any time as needed.

An important aspect of any measurement is the calibration the sensors. Within the Comfort Platform, the calibration parameters for each sensor of each Comfort Box are stored on server side. The calibrated values are calculated upon data request and only raw values are stored.

Finally, Figure 75 shows the simplified layout of the Comfort Platform. The current implementation of the platform allows buildings with limited or not available sensor capability to have the monitoring of the indoor environment and interactive feedback features through a low cost and flexible solution.

3.7.5 Results overview and potential

Figure 76 and Figure 77 show examples of the results obtained through the Comfort App. One of the purposes of the App is to be informative for the users and Figure 76 shows examples of the feedback metrics that are available. Along the summary of the feedbacks from the user, the App provides also aggregated metrics about the user feedbacks compared to the feedbacks sent by the users of the same building. These metrics have the purpose of engaging the users through gamification techniques [80] and the insights of the results will be presented in future works when more data will be available. Figure 77 shows an example of feedbacks metrics available to the building managers. For a given selected period, visual representations of the user perceived comfort are elaborated in real time.

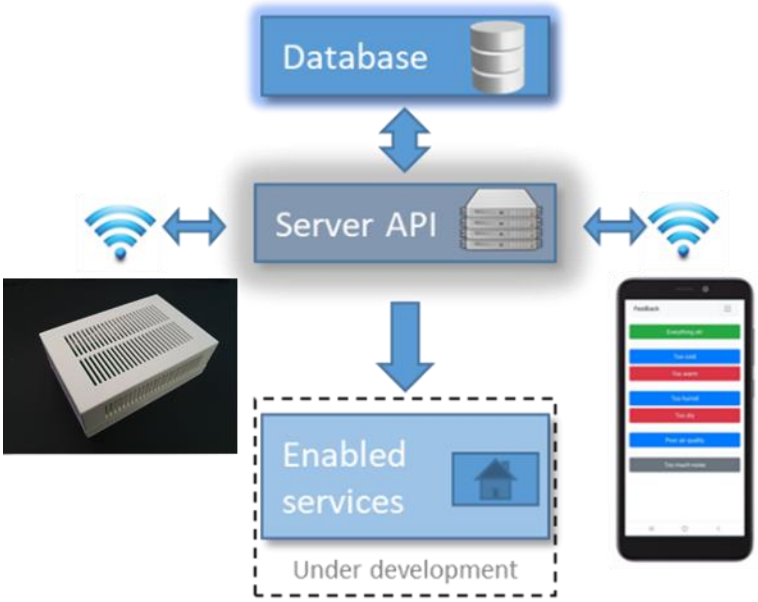


Figure 75 Comfort Platform: simplified layout.

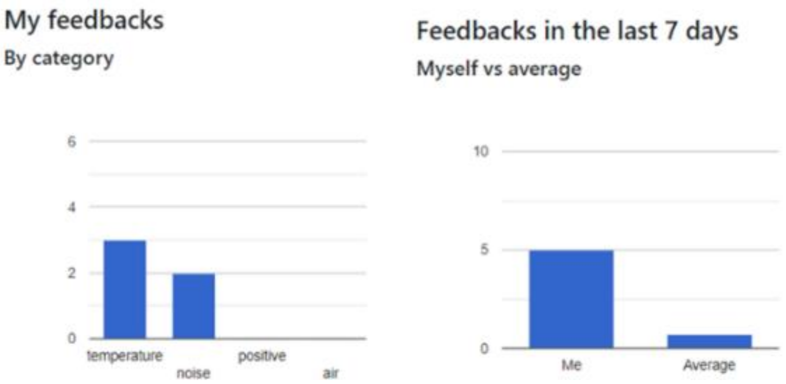


Figure 76 Example of results: comparative feedback from the users.

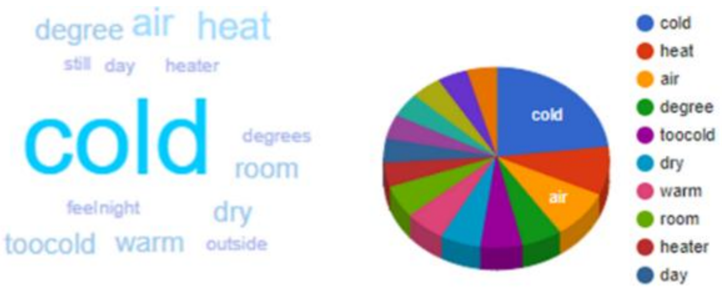


Figure 77 Example of results: word cloud automatically generated by the feedback provided by the students living in the Testbed KTH apartments.

The proposed first version of the Comfort Platform represents a low-cost solution to provide monitoring and communication capabilities to buildings with sensor network limited or not available.

Monitoring the indoor comfort conditions and allowing the user to easily communicate the perceived comfort enables the mapping and identification of critical issues in building energy systems that potentially enables improvement in the building system settings, energy saving behaviors and awareness.

The proposed solution is low-cost, flexible, scalable and contributes to create a bridge between the built environment and new and modern buildings where much relatively costly ICT solutions are included at design stage.

3.7.6 Highlights and lessons learned

- Feedback tools like Comfort platform are crucial to:
    - empower users,
    - provide building operators with information to understand how the building works,
    - fine tune controls with adaptive approaches according to users needs and preferences;
- More data and large-scale applications are needed.

3.7.7 KTH Innovation

During the development of the monitoring platform a collaboration with KTH Innovation[2] was established to improve the platform concept, to explore the possibility for further development and upscaling, and to create a concrete impact out of the platform development.

---

[2] https://www.kth.se/en/om/innovation

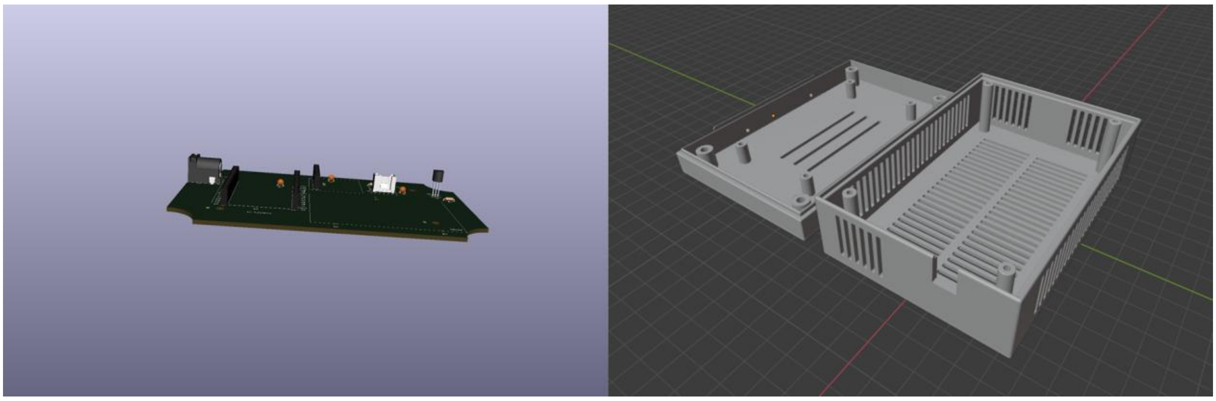


Figure 78 3D models of the Comfort Box electronic board and enclosure.

3.7.7.1 *Market analysis*

With the support of KTH Innovation, a market analysis was carried out reaching the companies listed in Figure 79 in order to evaluate possible business development out of the idea and technical stack developed within the project.

As a result, the Monitoring Platform's business idea is perceived relevant by the customer groups that have been interviewed. The broader market is seeing presence by competitors, but valuable segments are still relatively unexplored. Small real estate owners and developers represent attractive segments to pursue today due to clear benefits from adoption, attractive market size and low penetration.

Figure 79 Companies reached during the market analysis for the Monitoring Platform developed in this project.

3.8 Demonstrations, implementation and prototype sites (WP4)

3.8.1 *Uppsala Backe*

Figure 80 3D render of the Uppsala Backe construction by Botrygg.

Uppsala Backe is a neighbourhood of Uppsala designed and constructed by Botrygg, one of the partners of the project. The collaboration between KTH and Botrygg started during the design phase of Uppsala Backe with the idea of transfering the knowledge from the present research project and from the KTH Live-In LAB testbeds into a real residential construction.

Two buildings of the Uppsala Backe construction project shown in Figure 81 were selected during the design phase to be part of the present research project, with the idea of adopting and demonstrating two different levels of monitoring and automation. In particular, the building *Hus 2* was designed and equipped with traditional ICT infrastructure with basic level of automation, while the design of *Hus 4* included improved ICT infrastructure with additional sensors, actuators and more advanced level of automation. In addition to the measurement of indoor temperature, CO_2 and relative humidity, the monitoring and control system of *Hus 4* is equipped with an advanced solution that includes energy meters and actuators for radiators, ventilation dumpers, magnetic sensors for doors and windows, occupancy sensors and a more advanced control system. As discussed in Section 3.6.2, the cost difference between the advanced system installed in *Hus 4* and the basic solution adopted for *Hus 2* was only about 1% compared to the total construction costs of the buildings.

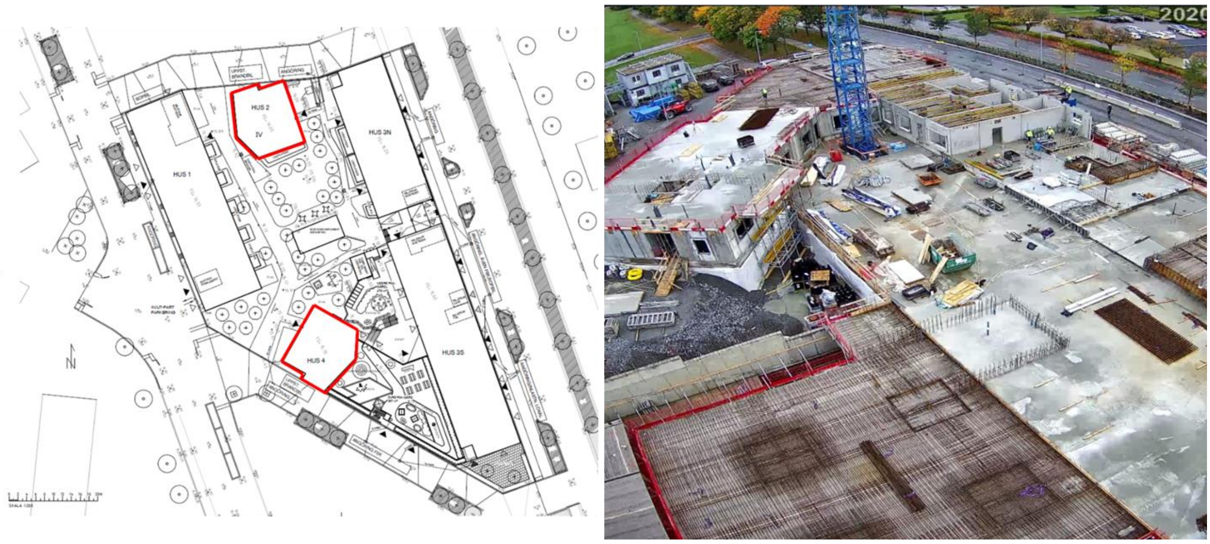


Figure 81 Blueprint of the project area and picture from the initial phase of construction.

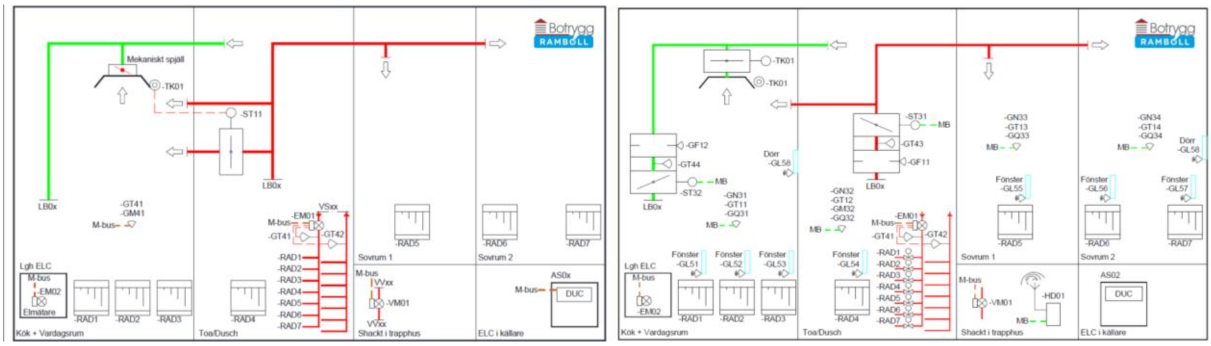


Figure 82 Schematic of the monitoring and automation systems of Hus 2 (left) and Hus 4 (right) in Uppsala Backe construction project.

3.8.2 Monitoring platform

The monitoring platform developed in the project and described in Section 3.7 has been deployed in several proof-of-concept campaigns during the project and a short summary of relevant outcomes are here proposed.

3.8.2.1 Testbed KTH

As described in Section 3.1, Testbed KTH is equipped with an advanced monitoring system that includes temperature, CO_2, relative humidity and VOC sensors, among others. Nevertheless, the interaction and communication to the users is limited to traditional approaches. For these reasons, the users of Testbed KTH have been invited to make use of the Comfort App (see Section 3.7.1) at the beginning of 2021. Figure 83 shows the weekly feedbacks received during the initial period of the campaign, where most of the feedbacks reported that the air was too dry. By the measurements shown in Figure 84 it can be observed that the relative humidity during the campaign was indeed low, with values often close to 20%. Finally, Figure 85 shows the word cloud created out of the comments that the users left along with their feedbacks. Interestingly, Testbed KTH is equipped with wall displays that show in real time the main measurements collected in the apartments, including the relative humidity. While reporting their feedbacks, most of the times the users indicated that the air was dry and commented the value they read on the display. For these reasons, "percent" is among the most frequent words of this campaign

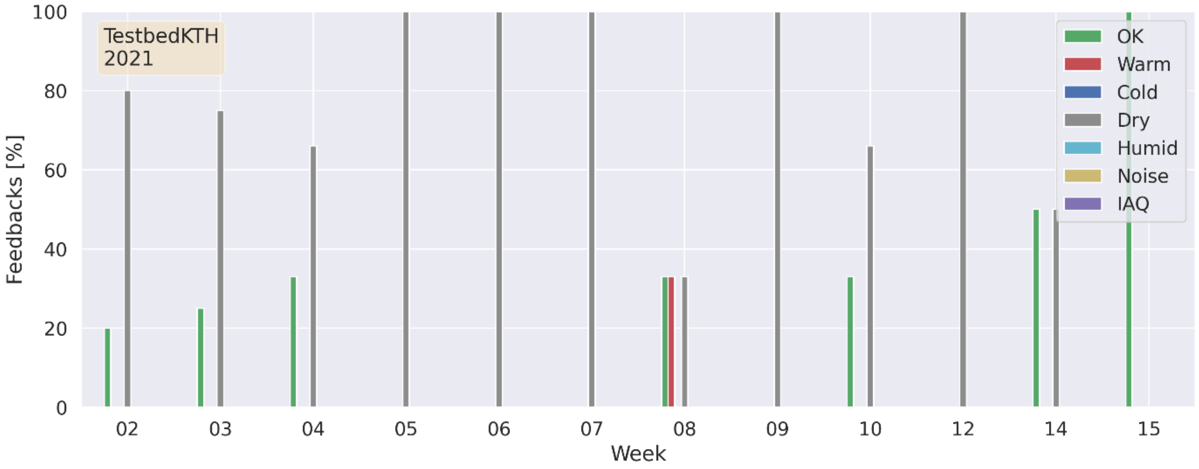


Figure 83 Weekly feedbacks collected during the monitoring platform campaign at Testbed KTH.

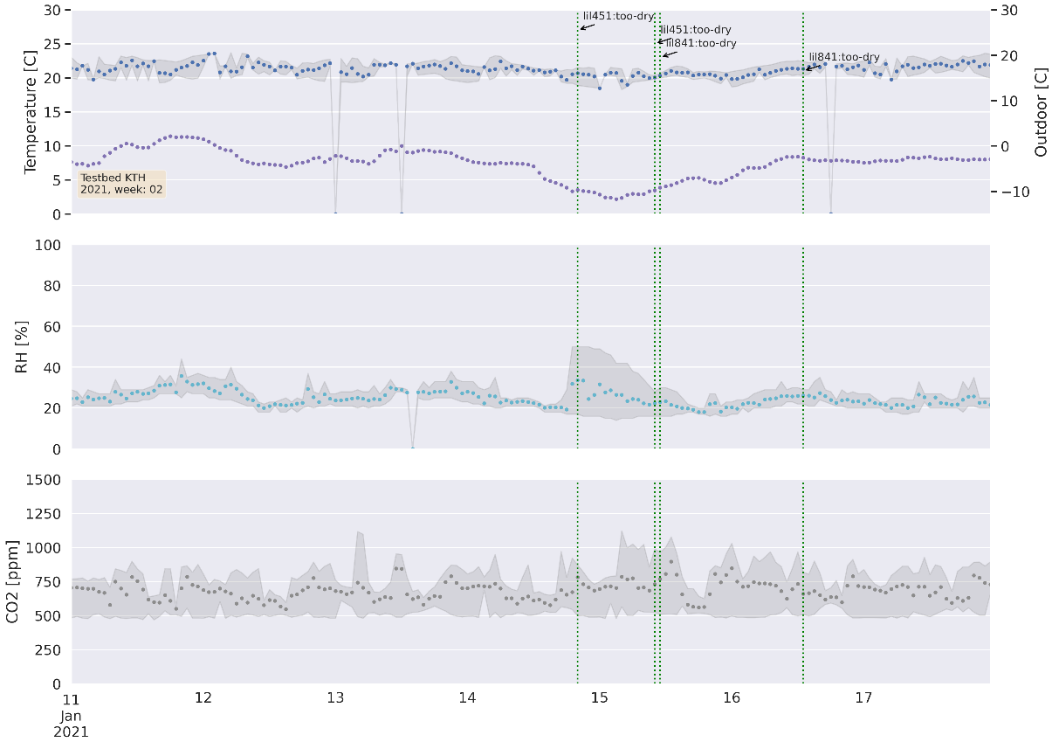


Figure 84 Example of temperature, relative humidity and CO$_2$ collected at Testbed KTH, together with the feedbacks received though the Comfort App.

Figure 85 Word cloud created out of the comments left by the users during the monitoring platform campaign at Testbed KTH.

3.8.2.2 KTH Campus: Draconis

A measurement campaign was also carried out in some of the apartments of the complex of three buildings called "Draconis", located at KTH Campus and operated by Akademiska Hus, Figure 86. The apartments of the buildings are not equipped with any monitoring sensor and both the Comfort App and the Comfort Box (see Section 3.7.2) have been deployed for this campaign.

Figure 86 One three buildings of the Draconis, KTH Campus.

Figure 87 shows that the feedbacks left during the campaign were mixed, with slight predominance of complaints over cold temperatures. This is essentially confirmed by the word cloud shown in Figure 88 where it can be noted that users experienced in general good comfort conditions, a few reports including that the indoor temperature was low and reported a few reports occasions a sensation of bad air quality due to the use of sprays or other product.

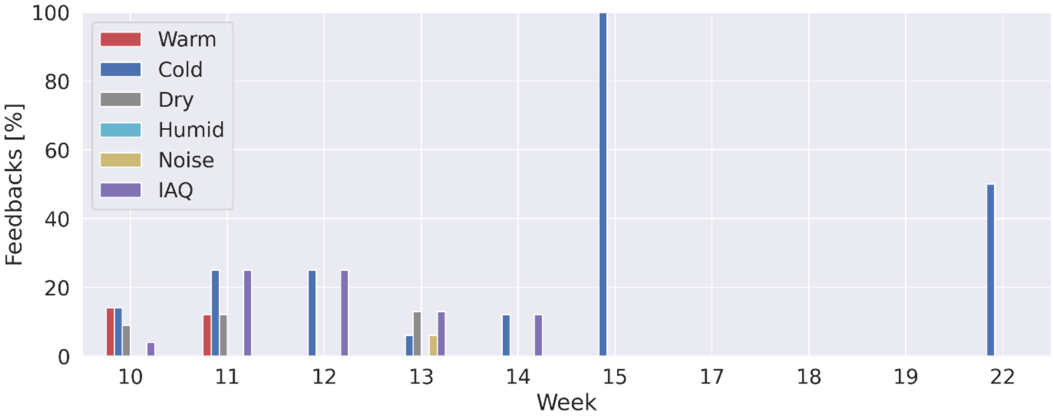


Figure 87 Weekly feedbacks collected during the monitoring platform campaign in Draconis.

Figure 88 Word cloud created out of the comments left by the users during the monitoring platform campaign at Draconis.

3.8.2.3 Vattenfallgymnasiet

Vattenfallgymnasiet, Figure 89, was involved in the deployment of the monitoring platform to collect measurements from classrooms, currently not equipped with any sensor. The interest by Vattenfallgymnasiet was also driven by having the monitoring platform as an educational resource for the students.

Figure 89 One of the buildings of the Vattenfallgymnasiet at Forsmark.

At the end of the project a number of Comfort Boxes have been installed in the main classrooms of the campus. The monitoring campaign is still ongoing; the results are still not available and will be included in future reports or research studies.

4 Diskussion

Smart buildings can be defined as “home-like environments that possess ambient intelligence and automatic control which allows them to respond to the behavior of residents and provide them with various facilities” [81]. One of the underlying messages that can be derived from this definition is that sensors and data are necessary but not sufficient to turn a building into a smart building.

The goals of the project include the assessment of the data quality from advanced monitoring systems. During the project, three advanced monitoring systems have been evaluated and multiple years of data has been extensively analyzed. The evaluations of the Testbed EM (residential building) and Testbed AH (university building) lead to the identification of important limitations and missed opportunities related to data infrastructure design, data management and data utilization.

The Testbed EM is representative of a block of flats built with modern design with commercially available systems. The monitoring systems can be considered sufficiently reliable for the purpose they are designed. The most recurrent issues with the data are empty data points, missing measurements and measurements that have no physically reasonable values (e.g. indoor CO_2 close to zero). Other recurrent issues in the monitoring system include data points with limited availability of meta-data. Nevertheless, these data faults however do not hinder an extensive and meaningful mapping of the indoor dynamics in the considered analysis timeframe. The current monitoring system lacks automated solutions for detecting anomalies, potential energy inefficiency and maintenance issues. However, technical solutions ranging from simple algorithms to machine learning modelling are widely available and should be carefully pondered already in the design phase. Moreover, the lack of a methodologically coherent vision in the sensor network design and installation result in missing sensors and ultimately in missing information. Examples of missing sensors are: relative humidity and window magnetic sensors in the apartments, temperature sensors in the return collectors of the AHUs. Those represent missing opportunities to assess, for instance, the indoor thermal comfort and the losses in the heat distribution systems.

Overall, the amount of data collected and recorded through the monitoring systems of both testbed EM and Testbed AH is considerable but there is evidence, even from discussions with building managers, that only a minor share of the data collected is used.

In Testbed EM, one of the main factors limiting the exploitation of data is poor documentation (e.g. sensor data sheets, database structure), which represents a major obstacle to an agile understanding of the structure and content of the data; for instance, some data points are ambiguously or poorly labelled. A data infrastructure following a more solid and structured design approach (e.g. semantic tagging) would prevent most of these issues and facilitate the adoption of more systematic and automated approaches to data analysis. Another criticality is that data was initially not fully accessible. Data was partly stored in a databased dedicated to accounting and invoicing purposes and partly in a file system where the data of AHUs, GSHP and PV systems were stored offline with no access possibilities. Only during the project (i.e., thanks to the project), a more convenient workflow was established and new possibilities are now enabled, including future data sharing with researchers, teachers and other stakeholders. On the contrary, the very good documentation available for the monitoring system of Testbed AH allowed a very rapid understanding of the system and a productive data analysis workflow.

By the experience matured in the project, it is clear that one of the main limitations to the adoption, full exploitation and future development of smart buildings is the very limited use of the data collected. Valuable information that can be derived by the large amount of data continuously collected is currently dissipated by the almost complete lack of data use and supervision.

In Testbed EM, the analysis of the data from the heat pump units revealed undocumented operation and control patterns that could potentially lead to maintenance issues in the long term. Regarding the indoor environment, although the buildings feature modern heating and control systems with smart building features, the indoor temperatures are above 24ºC throughout the year. This has clear implications on thermal comfort in summer with temperature extremes temperatures and avoidable energy consumption in winter period. The analysis of CO_2 highlights how personal response can create increased energy use and local thermal discomfort by window operation. Windows left open for a significant time lead in fact in some apartments to low temperatures, and has been motivated as response to high set-point temperatures for indoor spaces. In other cases, the analysis of the data indicates that windows have been left open continuously for months during which the tenant left the apartment**.**

The numerous activities and initiatives carried out in this project bring results that help building owners, building operators and other stakeholders to improve design and operation of building monitoring and control system. In the project, in addition to examples of how to use and interpret the available data, a number of case studies have been highlighted to showcase how the evaluation of measurement data in buildings can help to spot faulty conditions that affects system performance, system degradation and user comfort. The results clearly suggest that a number of anomalies can be identified by looking at the data or by implementing relatively simple and automated data-driven procedures. The results also show that data-driven control approaches can become key to reduce the implementation cost for advanced controls in buildings, enhancing scalability. In addition, more sophisticated co-simulation approaches based on calibrated models, as the one developed within the project, provide a reliable tool for evaluation of advanced control strategies and demonstration.

One of the goals of the project was also to help bridging the gap between buildings already equipped with advanced monitoring and control systems and buildings with no sensors available. The rapid development of new and advanced technologies is often beneficial for new constructions while existing buildings (not necessarily old) are typically left behind, due to technical and economic reasons. Through the collaboration with one of the project partners, Botrygg, the project demonstrated that the extra investments for an advanced monitoring and control system, compared to a basic solution, is limited compared to the overall construction cost.

In addition, in this project a prototype of a monitoring platform was conceived, designed and developed, in order to provide a cost-effective and non-invasive solution for existing building with no sensing capability. The proposed prototype allows monitoring of indoor environments through a simple device equipped with calibrated low-cost sensors. The monitoring device does not require any invasive installation procedure and was tested in proof-of-concept monitoring campaigns. The monitoring platform includes also the prototype of a web-app that allows the users to provide feedbacks about their perceived comfort. The platform data infrastructure includes a cloud-based

solution enabled for the development of future services. The proposed monitoring platform gives building operators valuable information about the status of the indoor environment that otherwise would be not available, allowing the identification of control issues (e.g. indoor temperatures too high or too low) or localized issues (e.g. problems in one apartment or on one floor). In synergy with KTH Innovation, a market analysis was carried out to understand the business potential of the proposed platform, attracting the attention of stakeholders interested in participating on further development of the platform in future research projects.

The review and analysis of existing advanced monitoring systems and data repositories carried out in this project confirmed that monitoring data is often collected without exploiting the full potential for innovative solutions, while relatively new buildings are often not equipped with any monitoring systems other than basic solutions.

The results and experience developed during the project attracted different stakeholders eager to implement and adopt innovative solutions that can improve the efficiency of their systems and the user satisfaction, but too often are lacking good references, recommendations and demonstrators. This project contributed to increase the awareness towards practical, reliable and replicable solutions that will foster the adoption of smart building features for new and existing buildings.

4.1 Future work

Future work inspired by this project include the promotion of additional demonstration sites where the knowledge and experience maturated will be transferred. The results and outcomes proposed in this project constitutes a solid basis for future projects. The data analysis carried out in the KTH Live-In Lab testbeds opened the way for the design of automated solutions for anomaly detection and will be further developed. The adoption of the Smart Readiness Indicator will be promoted, to evaluate the possibilities of SRI analysis to guide the design of the building management systems. The development, testing and adoption of digital-twin solutions will follow on two main fronts: the development and showcase of digital-twin demonstrators and the elaboration of innovative business models to accelerate the digitalization in the building sector. The development of the monitoring platform prototype will also continue in collaboration with the stakeholders that confirmed their interest for cost effective solutions that allow the collection of indoor measurements and the interaction with the users in order to improve system performance, identify faulty conditions and ensure user indoor comfort. In addition, a number of monitoring campaigns using the current version of the platform are already planned and will be carried out in the near future.

5 Slutsatser

The project has dealt with several intertwined aspects (technological, societal, economic) towards smart buildings. This project has focused on the monitoring and control systems of the Live-In Lab testbeds, which are representative of the standard of new buildings, and has used a building complex (Draconis) to deal with typical issues in the existing building stock with very limited monitoring capability. Availability of reliable data is the cornerstone of smart buildings,

The project highlighted limitations in the monitoring systems, mainly attributable to data losses and missing sensors. In some cases, additional sensors may have enabled a better understanding of the performance of the building, enabling the identification of the causes of the anomalies or the additional energy expenditure. Common practice should include better attention for unambiguous and more detailed documentations of technical systems and data infrastructures.

There are clear indications that the use of data collected in the analyzed buildings is limited. Data in buildings is seen a valuable but there is a lack for a clear path for its exploitation. Performing detailed analyses from raw data requires time and competence, and the uncertainty regarding achievable results from these analyses seems to deter some main stakeholders.

The SRI methodology, proposed as an early framework at the EU level, proved to be a useful tool in the project to assess quantitatively the smartness of buildings and upgrade their systems towards the EU energy policy goals. The use of the SRI methodology in the building design phase should also be tested to guide towards a consistent design of the monitoring and control system.

The cost-benefit analysis shows that the additional investment cost for commercial standard and advanced monitoring systems are marginal – and further reductions of cost can be achieved with economy of scale. However, the project suggests that many stakeholders do not have sufficient incentives to invest in advanced monitoring systems. For instance, the SRI score in the Live-In Lab testbeds may be cost-efficiently improved adding web interfaces to display information to building occupants and operators, but as far as users are not by design empowered it is unlikely that these extra costs will be sustained in the design phase. Incentives (or alternatively regulations) driving towards the adoption of digitalization may help.

The relevance of the impact of users and faults is not sufficiently understood in the building sector. Within the project, cases of user action with dramatic impact on the operation of the building were illustrated. Demonstrations are powerful means to trigger a change. Users should be considered central in the control and operation of buildings and this calls for a closer collaboration between research and practice. Experimental campaigns based on the IOT Comfort platform are an example of such good practices.

The methodologies proposed in the project can be automated straightforwardly for rapid uptake in the building sector. This paves the way for the future implementation of the still locked potential in tools like digital twins in buildings.

Platforms to enable open and scalable demonstrations and showcase best practices of the benefits of digitalization are needed to make an impact on the building sector. Innovation platforms like the KTH

Live-In Lab, to which this project has significantly contributed, should be encouraged to foster the adoption of digitalization towards more sustainable and smart buildings.

6 Publikationslista

6.1 Research journal publications (WP6)

- Rolando D., Molinari M., Mazzotti Pallard W., Long-Term Evaluation of Comfort, Indoor Air Quality and Energy Performance in Buildings: The Case of the KTH Live-In Lab Testbeds, Energies. 2022; 15(14)
- M. Molinari, J. A. Vogel, D. Rolando, P. Lundquist. Using living labs to tackle innovation bottlenecks: the KTH Live-In Lab case study, Applied Energy, 338, 120877. https://doi.org/10.1016/j.apenergy.2023.120877.

6.2 Conference contributions (WP6)

- M. Molinari, D. Rolando, A. Lazzarotto. Energy and indoor environmental quality monitoring of a lecture building: preliminary results from the KTH Live-In Lab Testbed AH, MIT A+B 2022, MIT, Cambridge, USA.
- Mahsa Farjadnia, Amr Alanwar, Muhammad Umar B. Niazi, Marco Molinari, Karl Henrik Johansson, Robust Data-Driven Predictive Control of Unknown Nonlinear Systems using Reachability Analysis. European Control Conference, ECC2023 (accepted for publication).
- Bäcklund, K., Molinari, M., Lundqvist, P., Karlsson, P. Showcasing the First Steps Towards a Digital Twin for Campus Environments, BuildSim Nordic 2022:10th BuildSim Nordic conference and the 2nd International Nordic conference for IBPSA, 2022, Copenhagen, Denmark.
- Molinari M., Anund Vogel, J., Rolando D., Using Living Labs to tackle innovation bottlenecks: the KTH Live-In Lab case study, MIT A+B 2021, MIT, Cambridge, USA.
- Rolando D., Molinari M., Development of a comfort platform for user feedback: the experience of the KTH Live-In Lab, ICAE 2020, International Conference on Applied Energy, December 2020, Thailand, Paper 385.
- Molinari M., Rolando D., Digital twin of the Live-In Lab Testbed KTH: development and calibration, IBPSA-Nordic International Conference, BuildSim Nordic 2020, October 2020, Oslo.

6.3 Popular science contributions (WP6)

- ”Kostnads- och energieffektiva styrsystem i byggnader”, Kyla och Värme, October 2019.

7 Referenser

[1] A. Jáñez Morán, P. Profaizer, M. Herrando Zapater, M. Andérez Valdavida, and I. Zabalza Bribián, “Information and Communications Technologies (ICTs) for energy efficiency in buildings: Review and analysis of results from EU pilot projects,” *Energy and Buildings*, vol. 127, pp. 128–137, Sep. 2016, doi: 10.1016/j.enbuild.2016.05.064.

[2] T. Hong, S. D’Oca, S. C. Taylor-Lange, W. J. N. Turner, Y. Chen, and S. P. Corgnati, “An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema,” *Building and Environment*, vol. 94, pp. 196–205, Dec. 2015, doi: 10.1016/j.buildenv.2015.08.006.

[3] D. Yan *et al.*, “Occupant behavior modeling for building performance simulation: Current state and future challenges,” *Energy and Buildings*, vol. 107, pp. 264–278, Nov. 2015, doi: 10.1016/j.enbuild.2015.08.032.

[4] W. Zhang, S. Tan, Y. Lei, and S. Wang, “Life cycle assessment of a single-family residential building in Canada: A case study,” *Build. Simul.*, vol. 7, no. 4, pp. 429–438, Aug. 2014, doi: 10.1007/s12273-013-0159-y.

[5] A. Mahdavi and F. Tahmasebi, “People in building performance simulation,” in *Building Performance Simulation for Design and Operation*, 2nd ed., Routledge, 2019.

[6] S. Attia, A. De Herde, E. Gratia, and J. L. M. Hensen, “Achieving informed decision-making for net zero energy buildings design using building performance simulation tools,” *Build. Simul.*, vol. 6, no. 1, pp. 3–21, Mar. 2013, doi: 10.1007/s12273-013-0105-z.

[7] P. Hoes, J. L. M. Hensen, M. G. L. C. Loomans, B. de Vries, and D. Bourgeois, “User behavior in whole building simulation,” *Energy and Buildings*, vol. 41, no. 3, pp. 295–302, Mar. 2009, doi: 10.1016/j.enbuild.2008.09.008.

[8] C. Turner, M. Frankel, and U. G. B. Council, “Energy performance of LEED for new construction buildings,” *New Buildings Institute*, vol. 4, no. 4, pp. 1–42, 2008.

[9] C. M. Clevenger and J. Haymaker, “The impact of the building occupant on energy modeling simulations,” in *Joint International Conference on Computing and Decision Making in Civil and Building Engineering, Montreal, Canada*, 2006, pp. 1–10.

[10] O. Guerra Santin, L. Itard, and H. Visscher, “The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock,” *Energy and Buildings*, vol. 41, no. 11, pp. 1223–1232, Nov. 2009, doi: 10.1016/j.enbuild.2009.07.002.

[11] K.-U. Ahn and C.-S. Park, “Correlation between occupants and energy consumption,” *Energy and Buildings*, vol. 116, no. Complete, pp. 420–433, 2016, doi: 10.1016/j.enbuild.2016.01.010.

[12] M. S. Gul and S. Patidar, “Understanding the energy consumption and occupancy of a multi-purpose academic building,” *Energy and Buildings*, vol. 87, pp. 155–165, Jan. 2015, doi: 10.1016/j.enbuild.2014.11.027.

[13] V. Fabi, T. Buso, R. K. Andersen, S. P. Corgnati, and B. W. Olesen, “Robustness of building design with respect to energy related occupant behaviour: 13th Conference of International Building Performance Simulation Association,” *Proceedings of BS2013*, pp. 1999–2006, 2013.

[14] V. Belessiotis and E. Mathioulakis, “Analytical approach of thermosyphon solar domestic hot water system performance,” *Solar Energy*, vol. 72, no. 4, pp. 307–315, Apr. 2002, doi: 10.1016/S0038-092X(02)00011-7.

[15] B. Lee, M. Trcka, and J. L. M. Hensen, “Building energy simulation and optimization: A case study of industrial halls with varying process loads and occupancy patterns,” *Build. Simul.*, vol. 7, no. 3, pp. 229–236, Jun. 2014, doi: 10.1007/s12273-013-0154-3.

[16] V. Fabi, R. V. Andersen, S. P. Corgnati, and B. W. Olesen, “A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings,” *Build. Simul.*, vol. 6, no. 4, pp. 415–427, Dec. 2013, doi: 10.1007/s12273-013-0119-6.

[17] C. Reinhart and K. Voss, “Monitoring manual control of electric lighting and blinds,” *Lighting Research & Technology*, vol. 35, no. 3, pp. 243–258, Sep. 2003, doi: 10.1191/1365782803li064oa.

[18] A. D. Galasiu and J. A. Veitch, “Occupant preferences and satisfaction with the luminous environment and control systems in daylit offices: a literature review,” *Energy and Buildings*, vol. 38, no. 7, pp. 728–742, Jul. 2006, doi: 10.1016/j.enbuild.2006.03.001.

[19] A. Al-Mumin, O. Khattab, and G. Sridhar, “Occupants’ behavior and activity patterns influencing the energy consumption in the Kuwaiti residences,” *Energy and Buildings*, vol. 35, no. 6, pp. 549–559, Jul. 2003, doi: 10.1016/S0378-7788(02)00167-6.

[20] F. Haldi and D. Robinson, “On the behaviour and adaptation of office occupants,” *Building and Environment*, vol. 43, no. 12, pp. 2163–2177, Dec. 2008, doi: 10.1016/j.buildenv.2008.01.003.

[21] P. R. Warren and L. M. Parkins, “Window-opening behaviour in office buildings,” *Building Services Engineering Research and Technology*, vol. 5, no. 3, pp. 89–101, Aug. 1984, doi: 10.1177/014362448400500301.

[22] A. Roetzel, A. Tsangrassoulis, U. Dietrich, and S. Busching, “A review of occupant control on natural ventilation,” *Renewable and Sustainable Energy Reviews*, vol. 14, no. 3, pp. 1001–1013, Apr. 2010, doi: 10.1016/j.rser.2009.11.005.

[23] S. D’Oca, V. Fabi, S. P. Corgnati, and R. K. Andersen, “Effect of thermostat and window opening occupant behavior models on energy use in homes,” *Build. Simul.*, vol. 7, no. 6, pp. 683–694, Dec. 2014, doi: 10.1007/s12273-014-0191-6.

[24] B. Dong and K. P. Lam, “A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting,” *Build. Simul.*, vol. 7, no. 1, pp. 89–106, Feb. 2014, doi: 10.1007/s12273-013-0142-7.

[25] F. Haldi and D. Robinson, “Interactions with window openings by office occupants,” *Building and Environment*, vol. 44, no. 12, pp. 2378–2395, Dec. 2009, doi: 10.1016/j.buildenv.2009.03.025.

[26] G. Y. Yun and K. Steemers, “Time-dependent occupant behaviour models of window control in summer,” *Building and Environment*, vol. 43, no. 9, pp. 1471–1482, Sep. 2008, doi: 10.1016/j.buildenv.2007.08.001.

[27] Y. S. Lee and A. M. Malkawi, “Simulating multiple occupant behaviors in buildings: An agent-based modeling approach,” *Energy and Buildings*, vol. 69, pp. 407–416, Feb. 2014, doi: 10.1016/j.enbuild.2013.11.020.

[28] R. Andersen, V. Fabi, J. Toftum, S. P. Corgnati, and B. W. Olesen, “Window opening behaviour modelled from measurements in Danish dwellings,” *Building and Environment*, vol. 69, pp. 101–113, Nov. 2013, doi: 10.1016/j.buildenv.2013.07.005.

[29] G. Y. Yun, P. Tuohy, and K. Steemers, “Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models,” *Energy and Buildings*, vol. 41, no. 5, pp. 489–499, May 2009, doi: 10.1016/j.enbuild.2008.11.013.

[30] G. R. Newsham, “Manual control of window blinds and electric lighting: implications for comfort and energy consumption,” *Indoor Environment*, vol. 3, no. 3, pp. 135–144, 1994.

[31] C. F. Reinhart, “Lightswitch-2002: a model for manual and automated control of electric lighting and blinds,” *Solar Energy*, vol. 77, no. 1, pp. 15–28, Jan. 2004, doi: 10.1016/j.solener.2004.04.003.

[32] F. Haldi and D. Robinson, “Adaptive actions on shading devices in response to local visual stimuli,” *Journal of Building Performance Simulation*, vol. 3, no. 2, pp. 135–153, Jun. 2010, doi: 10.1080/19401490903580759.

[33] V. Inkarojrit, *Balancing comfort: occupants' control of window blinds in private offices*. University of California, Berkeley, 2005.

[34] D. R. G. Hunt, "The use of artificial lighting in relation to daylight levels and occupancy," *Building and Environment*, vol. 14, no. 1, pp. 21–33, Jan. 1979, doi: 10.1016/0360-1323(79)90025-8.

[35] D. Lindelöf and N. Morel, "A field investigation of the intermediate light switching by users," *Energy and Buildings*, vol. 38, no. 7, pp. 790–801, Jul. 2006, doi: 10.1016/j.enbuild.2006.03.003.

[36] R. Yasue, H. Habara, A. Nakamichi, and Y. Shimoda, "Modeling the occupant behavior relating to window and air conditioner operation based on survey results," in *Proceedings of the 13th Conference of International Building Performance Simulation Association, Cambery, France*, 2013.

[37] X. Ren, D. Yan, and C. Wang, "Air-conditioning usage conditional probability model for residential buildings," *Building and Environment*, vol. 81, pp. 172–182, Nov. 2014, doi: 10.1016/j.buildenv.2014.06.022.

[38] S. Schiavon and K. H. Lee, "Dynamic predictive clothing insulation models based on outdoor air and indoor operative temperatures," *Building and Environment*, vol. 59, pp. 250–260, Jan. 2013, doi: 10.1016/j.buildenv.2012.08.024.

[39] A. Steinemann, P. Wargocki, and B. Rismanchi, "Ten questions concerning green buildings and indoor air quality," *Building and Environment*, vol. 112, pp. 351–358, Feb. 2017, doi: 10.1016/j.buildenv.2016.11.010.

[40] S. S. Korsavi, A. Montazami, and D. Mumovic, "Indoor air quality (IAQ) in naturally-ventilated primary schools in the UK: Occupant-related factors," *Building and Environment*, vol. 180, p. 106992, Aug. 2020, doi: 10.1016/j.buildenv.2020.106992.

[41] S. Stamp, E. Burman, C. Shrubsole, L. Chatzidiakou, D. Mumovic, and M. Davies, "Long-term, continuous air quality monitoring in a cross-sectional study of three UK non-domestic buildings," *Building and Environment*, vol. 180, p. 107071, Aug. 2020, doi: 10.1016/j.buildenv.2020.107071.

[42] H.-H. Liang, C.-P. Chen, R.-L. Hwang, W.-M. Shih, S.-C. Lo, and H.-Y. Liao, "Satisfaction of occupants toward indoor environment quality of certified green office buildings in Taiwan," *Building and Environment*, vol. 72, pp. 232–242, Feb. 2014, doi: 10.1016/j.buildenv.2013.11.007.

[43] G. R. Newsham *et al.*, "Do 'green' buildings have better indoor environments? New evidence," *Building Research & Information*, vol. 41, no. 4, pp. 415–434, Aug. 2013, doi: 10.1080/09613218.2013.789951.

[44] R. Elnaklah, I. Walker, and S. Natarajan, "Moving to a green building: Indoor environment quality, thermal comfort and health," *Building and Environment*, vol. 191, p. 107592, Mar. 2021, doi: 10.1016/j.buildenv.2021.107592.

[45] R. Liu, E. Fung, and Y. Abida, "5 - Evaluation of perceived comfort and functional performance of activewear," in *Latest Material and Technological Developments for Activewear*, J. Yip, Ed. Woodhead Publishing, 2020, pp. 89–118. doi: 10.1016/B978-0-12-819492-8.00005-3.

[46] S. Hagejärd, G. Dokter, U. Rahe, and P. Femenías, "My apartment is cold! Household perceptions of indoor climate and demand-side management in Sweden," *Energy Research & Social Science*, vol. 73, p. 101948, Mar. 2021, doi: 10.1016/j.erss.2021.101948.

[47] C. Huizenga, S. Abbaszadeh, L. Zagreus, and E. A. Arens, "Air quality and thermal comfort in office buildings: Results of a large indoor environmental quality survey," 2006, Accessed: Jun. 07, 2021. [Online]. Available: https://escholarship.org/uc/item/7897g2f8;jsessionidCEA1E13173D8003D5F74BD638E71785C

[48] "KTH Live-In Lab," *KTH Live-In Lab*. https://www.liveinlab.kth.se/en/start-1.1064463 (accessed Apr. 23, 2021).

[49] "Using Living Labs to tackle innovation bottlenecks: the KTH Live-In Lab case study | Energy Proceedings." https://www.energy-proceedings.org/using-living-labs-to-tackle-innovation-bottlenecks-the-kth-live-in-lab-case-study/ (accessed Sep. 14, 2022).

[50] R. Stark and T. Damerau, “Digital Twin,” in *CIRP Encyclopedia of Production Engineering*, S. Chatti and T. Tolio, Eds. Berlin, Heidelberg: Springer, 2019, pp. 1–8. doi: 10.1007/978-3-642-35950-7_16870-1.

[51] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks, “Characterising the Digital Twin: A systematic literature review,” *CIRP Journal of Manufacturing Science and Technology*, vol. 29, pp. 36–52, May 2020, doi: 10.1016/j.cirpj.2020.02.002.

[52] G. P. Lydon, S. Caranovic, I. Hischier, and A. Schlueter, “Coupled simulation of thermally active building systems to support a digital twin,” *Energy and Buildings*, vol. 202, p. 109298, Nov. 2019, doi: 10.1016/j.enbuild.2019.07.015.

[53] F. Ascione, M. Borrelli, R. F. De Masi, F. de’ Rossi, and G. P. Vanoli, “Energy refurbishment of a University building in cold Italian backcountry. Part 1: Audit and calibration of the numerical model,” *Energy Procedia*, vol. 159, pp. 2–9, Feb. 2019, doi: 10.1016/j.egypro.2018.12.009.

[54] “IDA ICE - Simulation Software | EQUA.” https://www.equa.se/en/ida-ice (accessed Apr. 27, 2020).

[55] Equa Simulation AB and Equa Simulation Finland Oy, “Validation of IDA Indoor Climate and Energy 4.0 with respect to CEN Standards EN 15255-2007 and EN 15265-2007,” Nov. 2010. Accessed: Jul. 09, 2020. [Online]. Available: http://www.equaonline.com/iceuser/validation/CEN_VALIDATION_EN_15255_AND_15265.pdf

[56] “Energy performance of buildings directive.” https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficient-buildings/energy-performance-buildings-directive_en (accessed Nov. 23, 2022).

[57] J. Laustsen, “Energy Efficiency Requirements in Building Codes, Energy Efficiency Policies for New Buildings. IEA Information Paper,” Mar. 2008, Accessed: Nov. 23, 2022. [Online]. Available: https://www.osti.gov/etdeweb/biblio/971038

[58] D. Sturzenegger, D. Gyalistras, M. Morari, and R. S. Smith, “Model Predictive Climate Control of a Swiss Office Building: Implementation, Results, and Cost–Benefit Analysis,” *IEEE Transactions on Control Systems Technology*, vol. 24, no. 1, pp. 1–12, Jan. 2016, doi: 10.1109/TCST.2015.2415411.

[59] J. Drgoňa *et al.*, “All you need to know about model predictive control for buildings,” *Annual Reviews in Control*, vol. 50, pp. 190–232, 2020, doi: 10.1016/j.arcontrol.2020.09.001.

[60] J. Hou, H. Li, N. Nord, and G. Huang, “Model predictive control under weather forecast uncertainty for HVAC systems in university buildings,” *Energy and Buildings*, vol. 257, p. 111793, Feb. 2022, doi: 10.1016/j.enbuild.2021.111793.

[61] L. Hewing, K. P. Wabersich, M. Menner, and M. N. Zeilinger, “Learning-Based Model Predictive Control: Toward Safe Learning in Control,” *Annu. Rev. Control Robot. Auton. Syst.*, vol. 3, no. 1, pp. 269–296, May 2020, doi: 10.1146/annurev-control-090419-075625.

[62] P. E. Valenzuela, A. Ebadat, N. Everitt, and A. Parisio, “Closed-Loop Identification for Model Predictive Control of HVAC Systems: From Input Design to Controller Synthesis,” *IEEE Transactions on Control Systems Technology*, vol. 28, no. 5, pp. 1681–1695, Sep. 2020, doi: 10.1109/TCST.2019.2917675.

[63] P. G. Carlet, A. Favato, S. Bolognani, and F. Dörfler, “Data-Driven Continuous-Set Predictive Current Control for Synchronous Motor Drives,” *IEEE Transactions on Power Electronics*, vol. 37, no. 6, pp. 6637–6646, Jun. 2022, doi: 10.1109/TPEL.2022.3142244.

[64] S. D. Cairano, D. Bernardini, A. Bemporad, and I. V. Kolmanovsky, “Stochastic MPC With Learning for Driver-Predictive Vehicle Control and its Application to HEV Energy Management,” *IEEE Transactions on Control Systems Technology*, vol. 22, no. 3, pp. 1018–1031, May 2014, doi: 10.1109/TCST.2013.2272179.

[65] F. Smarra, A. Jain, T. de Rubeis, D. Ambrosini, A. D’Innocenzo, and R. Mangharam, “Data-driven model predictive control using random forests for building energy optimization and climate control,” *Applied Energy*, vol. 226, pp. 1252–1272, Sep. 2018, doi: 10.1016/j.apenergy.2018.02.126.

[66] V. Chinde, Y. Lin, and M. J. Ellis, "Data-Enabled Predictive Control for Building HVAC Systems," *Journal of Dynamic Systems, Measurement, and Control*, vol. 144, no. 8, p. 081001, Aug. 2022, doi: 10.1115/1.4054314.

[67] M. Farjadnia, A. Alanwar, M. U. B. Niazi, M. Molinari, and K. H. Johansson, "Robust Data-Driven Predictive Control of Unknown Nonlinear Systems using Reachability Analysis." arXiv, Nov. 10, 2022. doi: 10.48550/arXiv.2211.05867.

[68] W. Mazzotti Pallard, "Case study report for Forskningen, Stockholm, Sweden - Three plus energy buildings (by design) with GSHPs, variable-length boreholes, ventilation recovery and pre-heating, wastewater recovery & PV panels," IEA HPT Annex 52, Stockholm, Sweden, Case study project report, 2021. [Online]. Available: https://doi.org/10.23697/dfs2-v474

[69] W. Mazzotti Pallard, *Case study report for Forskningen, Stockholm, Sweden : Three plus energy buildings (by design) with GSHPs, variable-length boreholes, ventilation recovery and pre-heating, wastewater recovery &amp; PV panels*. 2021. Accessed: May 24, 2022. [Online]. Available: https://doi.org/10.23697/dfs2-v474

[70] D. Rolando and H. Madani, "Smart Control Strategies for Heat Pump Systems," *EffSys Expand Research Program, Swedish Energy Agency*, p. 89, 2018.

[71] J. Kurnitski and J. Hogeling, "Smart Readiness Indicator (SRI) for buildings not so smart as expected," p. 4.

[72] Directorate-General for Energy (European Commission) *et al.*, *Final report on the technical support to the development of a smart readiness indicator for buildings: summary*. LU: Publications Office of the European Union, 2020. Accessed: Dec. 09, 2022. [Online]. Available: https://data.europa.eu/doi/10.2833/600706

[73] I. Vigna, R. Pernetti, G. Pernigotto, and A. Gasparella, "Analysis of the Building Smart Readiness Indicator Calculation: A Comparative Case-Study with Two Panels of Experts," *Energies*, vol. 13, no. 11, p. 2796, Jun. 2020, doi: 10.3390/en13112796.

[74] P. A. Fokaides, C. Panteli, and A. Panayidou, "How Are the Smart Readiness Indicators Expected to Affect the Energy Performance of Buildings: First Evidence and Perspectives," *Sustainability*, vol. 12, no. 22, p. 9496, Nov. 2020, doi: 10.3390/su12229496.

[75] O. Horák and K. Kabele, "Testing of Pilot Buildings by the SRI Method," *Heating Ventilation Sanitation*, no. 6, pp. 331–334, 2019.

[76] B. Ramezani, Manuel. G. da Silva, and N. Simões, "Application of smart readiness indicator for Mediterranean buildings in retrofitting actions," *Energy and Buildings*, vol. 249, p. 111173, Oct. 2021, doi: 10.1016/j.enbuild.2021.111173.

[77] M. Scarpa, R. Ravagnin, L. Schibuola, and C. Tambani, "Development and testing of a platform aimed at pervasive monitoring of indoor environment and building energy," *Energy Procedia*, vol. 126, pp. 282–288, Sep. 2017, doi: 10.1016/j.egypro.2017.08.155.

[78] A. S. Ali, Z. Zanzinger, D. Debose, and B. Stephens, "Open Source Building Science Sensors (OSBSS): A low-cost Arduino-based platform for long-term indoor environmental data collection," *Building and Environment*, vol. 100, pp. 114–126, May 2016, doi: 10.1016/j.buildenv.2016.02.010.

[79] K. Menzel, D. Pesch, B. O'Flynn, M. Keane, and C. O'Mathuna, "Towards a wireless sensor platform for energy efficient building operation," *Tsinghua Science and Technology*, vol. 13, no. S1, pp. 381–386, Oct. 2008, doi: 10.1016/S1007-0214(08)70178-0.

[80] J. Iria *et al.*, "A gamification platform to foster energy efficiency in office buildings," *Energy and Buildings*, vol. 222, p. 110101, Sep. 2020, doi: 10.1016/j.enbuild.2020.110101.

[81] L. C. De Silva, C. Morikawa, and I. M. Petra, "State of the art of smart homes," *Engineering Applications of Artificial Intelligence*, vol. 25, no. 7, pp. 1313–1321, Oct. 2012, doi: 10.1016/j.engappai.2012.05.002.

Bilagor

- Testbed KTH data analysis report, Mahsa Farjadnia, 2022
  "Chapter-2-attachment-Testbed_KTH_data_analysis_report.pdf "

Runt 35 procent av all energi i Sverige används i bebyggelsen. I forskningsprogrammet E2B2 arbetar forskare och samhällsaktörer tillsammans för att ta fram kunskap och metoder för att effektivisera energianvändningen och utveckla byggandet och boendet i samhället. I den här rapporten kan du läsa om ett av projekten som ingår i programmet.

E2B2 är Energimyndighetens program där IQ Samhällsbyggnad är koordinator.
Läs mer på www.E2B2.se.