Internet of Things (IoT) in buildings: a learning factory

Enrique **Cano-Suñén** [1], Ignacio **Martínez Ruiz** [2*], Ángel **Fernández Cuello** [2], Belén **Zalba** [3] **and** Roberto **Casas** [2]

[1] Smart Cities Lab. Engineering Research Institute of Aragon (I3A). University of Zaragoza (UZ)
[2] Human Openware (HOWLab). Engineering Research Institute of Aragon (I3A). University of Zaragoza (UZ)
[3] GITSE. Engineering Research Institute of Aragon (I3A). University of Zaragoza (UZ)
* Correspondence: *imr@unizar.es*

Highlights

- To understand the built environment as a complex system IoT ecosystems are key to fill the gap between theoretical simulations and real measurements.
- IoT is a cost-effective learning factory to make data-driven decisions and open for third-party to contribute community research.
- IoT offers lessons about building complexity, costs, savings, climate change, social vulnerability, sustainability, reducing building energy consumption, and improving IAQ

Abstract: Advances towards smart ecosystems showcase Internet of Things (IoT) as a transversal strategy to improve energy efficiency in buildings, enhance their comfort and environmental conditions, and increase knowledge about building behavior, its relationships with users and the interconnections among themselves and the environmental and ecological context. EU estimates that 75% of the building stock is inefficient and more than 40 years old. Although many buildings have some type of system for regulating the indoor temperature, only a small subset provides integrated Heating, Ventilation, and Air Conditioning (HVAC) systems. Within that subset, only a small percentage includes smart sensors, and only a slight portion of that percentage integrates those sensors into IoT ecosystems. This work pursues two objectives. The first is to understand the built environment as a set of interconnected systems constituting a complex framework in which IoT ecosystems are key enabling technologies for improving energy efficiency and Indoor Air Quality (IAQ) by filling the gap between theoretical simulations and real measurements. The second is to understand IoT ecosystems as cost-effective solutions for acquiring data through connected sensors, analyzing information in real-time, and building knowledge to make data-driven decisions. The dataset is publicly available for third-party use to assist the scientific community in its research studies. This paper details the functional scheme of the IoT ecosystem following a 3-level methodology for: (1) identifying buildings (with regard to their use patterns, thermal variation, geographical orientation, etc.) to analyze their performance; (2) selecting representative spaces (according to their location, orientation, use, size, occupancy, etc.) to monitor their behavior; and (3) deploying and configuring an infrastructure with +200 geolocated wireless sensors in +100 representative spaces, collecting a dataset of +10000 measurements every hour. The results obtained through real installations with IoT as learning factory, include several learned lessons about building complexity, energy consumption, costs, savings, IAQ and health improvement. A proof-of-concept of building performance prediction based on neural networks (applied to CO_2 and temperature) is proposed. This first learning shows that IAQ measurements meet recommended levels around 90% of the time and that an IoT-managed HVAC system can achieve energy consumption savings of between 10 and 15%. In summary, in a real context involving economic restrictions, complexity, high energy costs, social vulnerability, and climate change, IoT-based strategies, as proposed in this work, offer a modular and interoperable approach moving towards smart communities (buildings, cities, regions, etc.) by improving energy efficiency and environmental quality (indoor and outdoor) at low cost, with quick implementation, and low impact on users. Great challenges remain for growth and interconnection in IoT use, especially challenges posed by climate change and sustainability.

Keyworks: Internet of Things (IoT); Indoor Air Quality (IAQ); Energy efficiency; Smart buildings; Learning factory

1. Introduction

According to a special report by the European Court of Auditors [1], buildings are responsible for 40% of energy consumption and 36% of greenhouse gas emissions in Europe. According to Eurostat [2], buildings have contributed approximately 25–28% to energy consumption in Europe since 1995. Energy consumption in households is the main reason for the observed greenhouse gas emissions of the sector [3]. Buildings and households, given their energy savings potential, have priority consideration in the European Union (EU) 2030 agenda to meet the EU's Sustainable Development Goals (SDGs), with a commitment to reduce energy consumption by more than 30% by 2030 [4]. According to the United States (US) Environmental Protection Agency (EPA) [5] and the EU [6], people spend 80–90% of their time indoors, where air quality is 2 to 5 times worse than outdoors. High Indoor Air Quality (IAQ) is thus of utmost importance.

Addressing these key challenges is not mandatory but rather the subject of policy recommendations. In this context, the main relevant European norm is the Energy Performance Buildings Directive (EPBD) 2018/844/EU [7]. EPBD promotes energy efficiency in buildings through several initiatives related to Internet of Things (IoT) technologies and Heating, Ventilation and Air Conditioning (HVAC) systems, among other key topics. According to EPBD, the energy performance of buildings should be calculated on the basis of a methodology, which can be differentiated at national and regional levels. In addition to thermal characteristics, it considers other relevant factors, such as: heating and air conditioning installations, ventilation strategies, application of energy from renewable sources, building automation and control systems, smart solutions, passive heating and cooling elements, adequate natural light and air quality, and design of the building, among others. The methodology should be based on hourly or sub-hourly time steps, ensure the representation of actual operating conditions, and enable the use of metered energy to verify correctness and facilitate comparability. From these premises, proposed solutions should be transversal strategies and consider the following key aspects of building environments:

- Few buildings have complete HVAC systems; most have air conditioning only, heating only, heating and air conditioning distribution or systems that provide combined ventilation, heating, and cooling.
- Few buildings include IoT: although it is becoming more common to incorporate sensors that are used by Supervisory Control And Data Acquisition (SCADA) systems to control HVAC systems, integrating such systems into IoT ecosystems, as proposed in this paper, remains a challenge.
- The European building stock is largely obsolete, so interventions to improve energy efficiency must also ensure air quality to maintain a healthy and comfortable indoor environment with minimal energy use and environmental impact.
- The built environment is huge, so transversal strategies need to be low in cost and economically sustainable.

All these considerations call for consideration of which strategies are the most effective in improving building performance, especially energy efficiency and IAQ. This question is beginning addressed in research on the design and construction of new buildings called *smart buildings* when integrated with IoT technology. However, as mentioned previously, the current reality of the built environment is that only a minority of buildings include IoT. It is necessary to assess how IoT-based strategies can be cost-effective and sustainable. Incorporating IoT technologies enables continuous collection of data to know how buildings behave and making data-driven decisions to improve IAQ and reduce its energy consumption and carbon footprint [8]. IoT allows the collection of vast amounts of data that, if properly transmitted and processed (by cloud or in-house facilities), can be converted into meaningful information [9]. This information, conveniently visualized and analyzed, generates knowledge, induces feedback on the acquisition and processing of data, and, most importantly, allows intelligent decisions based on valuable data [10].

Thus, IoT monitoring offers configurable solutions in a customized way for specific cases and contexts. Furthermore, each building is unique in its shape, construction solution, location, climate, and usage, making IoT monitoring a transversal solution, offering both configurable options and the ability to adapt to each specific case and context. IoT is one of the technological paradigms destined to exponentially increase with a high impact on the daily behavior of potential users [11]. However, since this research area is an emerging field, the available literature is still limited. In [12], assuming this scope is a relatively new development, a comprehensive review was detailed by analyzing the potential of connecting Building Information Modelling (BIM) and smart buildings with IoT-based data sources. In [13], several examples of IoT implementation (within the last five years) in residential and commercial buildings were reviewed. And in [14], a system was developed in an IoT lab system to monitor the activities in the lab. The added value of this paper is to highlight IoT ecosystems as key elements in turning a building into a learning factory. And university buildings are especially suitable as experimental testbeds for current and future generations because of their heterogeneity, use variety (classrooms, offices, laboratories, study rooms, canteens, etc.), seasonality, high variability in occupancy and density, high energy demands, diversity of management systems, and other multiple factors. In this complex context, learning implies performance: learning by doing. Thus, this work proposes a methodology (from a real intervention in built environment through a designed, implemented, and deployed IoT ecosystem) as a learning factory in a continuous cycle for direct application in academic works, researching projects and institutional initiatives, extendable to professional environments, tertiary buildings and smart cities, focused on energy efficiency, IAQ and (building and human) behavior patterns.

With regard to energy efficiency, in the current context in which climate change and environmental degradation pose serious global challenges [15] [16], energy efficiency is essential to decarbonization and limiting, as set in the Paris Agreement in 2015, the increase in the global temperature to 1.5°C [17]. Some studies have examined the usefulness of continuous monitoring systems in improving the energy efficiency of buildings [18–20]. However, most such studies rely on BIM software models, unlike the methodology proposed in this paper, which is based on real building measurements. Other studies propose recognizing innovations in the energy efficiency and sustainability of existing buildings (as a Building Renovation Passport, BRP) but do not implement technological solutions to quantify their potential outcomes. This paper demonstrates how quantitative results can be obtained by the deployment and implementation of an entire IoT ecosystem. Batista et al. [21] used an equipment control system to investigate the performance of the air conditioning system of a small auditorium in Brazil, achieving a 20% of energy consumption reduction and improving thermal comfort; but those outcomes are not correlated with IAQ parameters such as CO_2 and occupancy. More recently, the occupancy of an office building was monitored with the objective of developing occupancy models and determining their impact on the energy performance of the building [22]; but the monitored spaces were not categorized according to their key characteristics, such as location, orientation, use, size, occupancy, etc. With regard to thermal comfort, Li et al. [23] performed correlation analyses based on continuous thermal comfort measurements from four office buildings in Australia, supporting the use of continuous monitoring technologies for long-term thermal comfort evaluation. Furthermore, several key actions to improve building operation management have been shown to reduce energy demand, such as rating tools and disclosure [24], energy audits [25], energy management systems [18], smart controls, and building passports [19]. The literature shows that buildings can be understood as complex systems and that there is a lack of published research on quantitative analysis, such as this work, about interaction of building energy performance parameters interacting with factors such as weather, use patterns, occupancy variation, etc.

With regard to IAQ, the World Health Organization (WHO) estimates that more than 100 diseases are associated with the effects of unhealthy indoor environments. In this context, the United Nations (UN) has established various SDGs for 2030 [20], paying special attention to air quality [26]. According to the US EPA, IAQ refers to the air quality within and around buildings and structures, especially as it relates to the health and comfort of building occupants [5]. Good IAQ contributes to well-being, comfort, health, and productivity in people. Some recommendations to improve IAQ include the following [27]: to choose building materials and furnishings with low pollutant emission rates (new buildings or renovations), to reduce sources of pollutant emissions (stoves, cleaning products), purify the air (by particle filtration, removal of pollutant gases, and microbiological control), and ventilate building interiors (which dilutes any type of pollutant through mixing with outside air). Although IAQ is not exclusively related to the CO_2 concentration [28], some articles relate occupancy to CO_2 concentration and propose required air ventilation rates to keep the concentration below a set level [29–35]. The European Commission has analyzed the regulations on IAQ in countries and the existing varieties of ventilation systems, concluding that there is still significant progress to be made in IAQ measurement and quantitative analysis [36]. All these studies remark on the need for continuous monitoring systems through IoT ecosystems that provide real measurements of building behavior to improve IAQ in buildings.

Moreover, given the relationship between energy efficiency and IAQ with people's behavior, as well as the building itself [37, 38], it is necessary to complement simulation studies with real quantitative measurements. In the last 20–30 years, notable advances have been made in building energy simulation, but much less progress has been made in terms of measuring, analyzing, and learning about the real operation and performance of the buildings. Numerous studies [39–41] show that there is a large difference between theoretical values and real data on building environments, which has been called Building Performance Gap (BPG), especially in heterogeneous university buildings with high complexity and variable occupation. These differences are due to the numerous simplifying assumptions required to model and simulate the real behavior of buildings. Algorithms have been designed to reduce the BPG [42]. All this reveals that it is necessary to not only simulate buildings but also perform continuous IoT monitoring and data analysis to understand how they behave under real operating conditions.

In recent years, the integration of IoT technologies in buildings has emerged as a promising approach to enhance energy efficiency and indoor comfort [63][64]. However, buildings often face challenges in optimizing their HVAC systems as data can be dynamic and highly variable [65][66]. Nevertheless, IoT data analytics offers a better opportunity to analyze such data and provide valuable insights for building management. Leveraging data-driven models such as Machine Learning (ML) and Deep Learning (DL) becomes essential for analyzing nonlinear relationships between buildings and occupants [67][68][69]. With numerous variables influencing indoor comfort and energy savings, predictive control methods like Model Predictive Control (MPC) can contribute significantly to energy conservation efforts [70][71][72].

Furthermore, in this technological context, in which buildings can be understood as complex dynamic processes, advances in MPC show promise for analyzing how variables such as occupancy, weather, climate, orientation, infiltration (air permeability), thermal inertia, and HVAC systems interact to improve energy efficiency and IAQ [43]. And, to continue developing MPC, it is key to have quality and structured data and therefore IoT ecosystems. In recent years, Recurrent Neural Network (RNN) modeling used to predict CO_2 and temperature has experienced significant growth. In [44], it was shown that a linear regression model is not able to predict indoor environment indicators with high accuracy, concluding that more complex models based on neural networks are needed. In [45], an RNN was used to predict CO_2 levels using 10 weeks of measurements with 75% of the data used to train the network and the remaining 25% used to test it. In [46], a modelling and optimization approach was proposed to minimize energy consumption by developing models to predict indoor environmental parameters (humidity, temperature, CO_2) and energy consumption in real time using neural networks and achieving very high reliability.

This paper aims two objectives. An objective is to understand the built environment as a complex system in which IoT ecosystems are key to enabling technologies to move towards transversal strategies to improve energy efficiency and IAQ. Thus, this work proposes IoT as learning factory (from the Latin *factorium, "place of doers, makers"*) where the data set is open and public for third-party use to contribute to the scientific community in its research efforts (available from *https://sensorizar.unizar.es*). Other objective is to understand IoT ecosystems as cost-effective solutions that acquire data (from real measurements through connected sensors), analyze real-time information (to improve operations: maintenance, scheduling, etc.), and build knowledge (to make data-driven decisions).

With these aims, in the current context of the built environment (Building and IoT: reality and challenges section analyzes the main factors involved in the building reality) with economic restrictions, complexity, higher energy costs, social vulnerability and climate change, this work proposes IoT-driven strategies as a novel and necessary contribution due to its open, modular, interoperable, transversal and cost-effective approach, as it is properly justified with the obtained outcomes in *Results and Discussion* section. The Material and Methods section details the functional scheme of the IoT ecosystem applied to built environment (as complex systems) focused on energy efficiency and IAQ. The Results and Discussion section shows several results of experiments at building scale, focused on CO_2 and energy consumption monitoring through real installations, to promote IoT as key to understanding building complexity and proposing a proof-of-concept of prediction of CO_2 and temperature based on a neural network. Finally, the Conclusions section details the scientific contributions of the work from a critical point of view and proposes further research studies.

2. Building and IoT: reality and challenges

The EU says in its "Renovation wave for Europe" strategy that a trend of renewal for Europe allows "greening our buildings, creating jobs, and improving our lives." Its goal is to double the annual energy renewal rates in the next ten years. In 2014–2020, the EU allocated approximately €14 billion to improving the energy efficiency of buildings [47]. In addition, member states<s: age, infrastructure, electrification, climatic and urban context, energy demand, diversity of stakeholders, and complexity.

Age. The EU estimates that 75% of the European building stock is inefficient and more than 40 years old on average [48]. Buildings around the world (mostly in Europe), when they are appropriately designed, constructed, renovated, and maintained, are long-lasting structures capable of provide providing their occupants with suitable indoor conditions, protection from extremes of hot and cold temperatures, and low energy costs. As detailed in Table 1 (from *Eurostat* [49]) , the average ages of buildings in Europe are distributed as follows: greater than 75 years (22.3%), 45–75 years (44.1%), 25–45 years (22.1%), and less than 25 years (9.8%). In Spain, there are approximately 10 million buildings (9,730,999 dwellings and 83,786 with other uses), with an average age of 37 years [49]. In addition, the percentage of new buildings (0.34%) is minimal compared to the total number of buildings: at that rate, more than 300 years would be required to replace the entire building stock.

Infrastructures. Although many buildings have some kind of system for regulating their indoor temperature, only a small subset provides an entire HVAC system; within that subset, only a low percentage includes smart sensors, and only a minimum of that percentage integrates those sensors into IoT ecosystems. And these facts especially impact non-residential buildings (e.g., public institutions, government, services, etc.), mostly located in old monumental buildings that lack HVAC systems. From the HVAC systems engineering point of view, historic buildings that have not been affected by recent maintenance work, whether ordinary, extraordinary, or preventive, are generally equipped with obsolete equipment. In many buildings, the thermal envelope is inefficient. Existing heating and air conditioning systems can be replaced but can be evidence of the past and, as such, have historical interest; therefore, they should be carefully recovered, valued, and, if possible, made useable.

Table 1. Distribution of dwellings (% of all dwellings) by period of construction, (national averages and capital city regions). *Source*: Eurostat [49]

		Period of construction							
		Before 1976		**1946-1980**		**1981-2000**		**2001-onwards**	
Country	Capital city region	National Average	Capital Region	National Average	Capital Region	National Average	Capital Region	National Average	Capital Region
EU-28		22,3	–	44,1	–	22,1	–	9,8	–
Belgium	Arr.Bruxelles/Arr.van Brussel-Hoofdsta	37,1	51,7	38,2	37,0	16,5	7,1	8,2	4,1
Bulgaria	Sofia (stolitsa)	10,5	5,6	55,4	45,8	25,5	3,2	8,6	15,4
Czech Republic	Hlavní město Praha	19,0	29,4	37,1	30,4	20,5	20,7	7,7	7,4
Denmark	Byen København	34,1	68,1	44,6	21,8	14,0	5,7	7,2	4,4
Germany	Berlin	24,3	42,3	46,5	36,3	23,1	19,2	6,1	2,1
Estonia(¹)	Põhja-Eesti	17,0	12,0	47,1	47,3	22,8	23,2	9,4	15,2
Ireland	Dublin	13,0	13,9	22,9	30,8	20,7	20,2	22,0	18,0
Greece	Attik	7,6	2,4	47,8	55,1	29,1	27,1	15,5	15,3
Spain Madrid	Madrid	11,1	8,0	43,0	50,3	24,7	24,2	18,5	14,9
France	Paris	28,7	59,7	37,0	26,0	23,9	11,7	10,4	2,5
Grad Zagreb	Croatia	13,6	13,7	42,5	43,3	23,6	22,3	11,0	17,0
Italy	Roma	20,7	12,3	51,4	60,1	19,8	20,4	7,9	7,1
Cyprus	Kýpros	3,0	–	24,6	–	36,1	–	34,1	–
Latvia	Riga	22,7	23,5	46,6	48,4	24,3	21,7	5,1	6,1
Lithuania	Vilniaus apskritis	13,6	12,7	49,6	43,3	28,9	30,2	6,2	12,6
Luxembourg	Luxembourg	21,8	–	31,5	–	21,6	–	14,0	–
Hungary	Budapest	20,3	33,2	48,3	38,0	21,7	17,3	9,7	11,6
Malta	Malta	13,0	13,5	23,2	24,3	23,4	24,1	8,7	9,1
Netherlands	Groot-Amsterdam	18,9	32,7	41,9	29,7	26,4	25,0	9,5	10,1
Austria (²)	Wien	25,5	42,4	40,1	35,4	22,7	14,6	11,7	7,6
Poland	Miasto Warszawa	19,1	10,3	43,0	49,1	22,7	16,1	11,4	17,8
Portugal	Grande Lisboal	10,7	9,8	37,1	46,0	36,0	31,4	16,3	12,8
Romania	Bucureşti	11,2	7,7	59,1	60,3	19,0	23,3	8,0	5,5
Slovenia	Osrednjeslovenska	21,3	16,6	45,0	47,9	25,0	23,7	8,7	11,8
Slovakia	Bratislavský kraj	8,2	8,7	52,6	48,0	21,5	23,5	5,8	11,3
Finland	Helsinki-Uusimaa	9,6	12,1	48,7	44,3	29,7	29,8	10,7	12,8
Sweden	Stockholms lan	24,3	23,8	47,7	44,1	12,3	12,4	4,6	6,8
United Kingdom (³)	Inner London (⁴)	37,8	57,7	39,7	26,6	15,6	10,4	6,9	5,3
Iceland	Hofuôborgarsvæði	11,5	10,3	44,5	42,9	25,1	27,1	18,9	19,6
Liechtenstein	Liechtensteir	9,7	–	38,0	–	33,1	–	16,0	–
Norway	Oslo	16,8	31,0	41,3	38,7	23,2	20,0	12,7	10,0
Switzerland	Bern	26,6	32,3	41,1	41,2	21,5	18,3	10,8	8,2

(¹) Also comprises dwellings in uncompleted buildings, in those case where a residential building under construction
(²) Before 1945 instead of before 1946. 1945-1980 instead of 1946-1980
(³) Low reliability
(⁴) Average of Inner London - West (NUTS UKI11) and of Inner London - East (UKI12)

IoT technologies. Among all the technical characteristics of IoT technologies, in the context of this study, it is important to highlight three key features. The cost is minimal compared to the economic costs of any action at building scale. IoT wireless technologies offer very high capabilities with a very low number of sensors, with lifetimes of years (even for photovoltaic batteries), without the need for wiring (neither for power nor for communications), and without impact in the infrastructures (by putting sensors on walls, windows or ceilings). IoT ecosystems require highly qualified technical staff, continuous management (for calibration and monitoring), managers with digitalization training, and analysts with data-driven vision to obtain operational conclusions. On the other hand, IoT technologies are already mature: once deployed, they require very little maintenance and return real-time data, that represent building performance well.

Electrification. The climate emergency and dependence on fossil fuels have promoted policies to replace boilers in buildings with heat pumps. Following EPBD, the European Commission proposes that all newly buildings do not produce emissions from 2028 onward, as well as the elimination of fossil fuels from 2035 onward, with replacement by heat pump systems based on electricity or hydrogen (blended with natural gas or waste), although some reports rule this out as being feasible on a large scale [50,51]. Thus, continuous monitoring provided by IoT ecosystems appears to be the best option for HVAC systems (based on electrical energy) to adjust their regulation to the environment, consumption, behavior, and renewable energies. In addition, building systems whose operation is electrical are easier to regulate (than systems based on combustion) and allow adjustments with respect to energy demand both at the building scale and at the city scale. The increasing adoption of HVAC systems and the rising demand for thermal comfort, coupled with the imperative to reduce emissions, has positioned it as a primary driver of global electricity demand growth [62].

Climatic and urban context. The current climatic and energy context involves sequenced boundary conditions: (1) extreme temperatures will involve extreme climate events (2) that will increase the demand for air conditioning and heating equipment (3) that will produce an increase in energy demand (4) in an aged built environment where majority of which is energy inefficient (5) without a monitoring or management system. Furthermore, urban trends suggest that, in 2030, 50.9% of Europeans will live in cities, 26.9% in towns and semi-dense areas, and only 20.6% in rural areas [52]. The combination of an aging population and highly urbanized ecosystems means that the population is becoming more vulnerable to heat and that demand for cooling in buildings is rising quickly. All of these concerns require intervention in buildings to examine key elements of sustainable cooling policies and their potential impacts on vulnerable groups by reducing health risks, inequalities, and summer energy poverty. In the EU in 2022, compared with 1979, the need for heating a given building was approximately 20% lower, and the need to cool a given building was almost four times higher [53]. In the summer of 2022, with successive long heatwaves and high energy prices, heat stress created a sense of urgency about acquiring air conditioning devices. However, there is a gap between knowledge about overheating in buildings and the percentage of EU citizens unable to keep their homes comfortably cool during the summer. This growth in demand for thermal comfort and healthy environments with good IAQ creates a growth in energy demand, despite the current situation of economic restrictions, high energy costs, emissions consequences, and climatic, social, and environmental impacts [54]. Thus, IoT ecosystems, as proposed in this paper, provide transversal strategies for addressing this complex context and choosing customized solutions for each specific situation.

Energy demand and IAQ. The growth in the need for thermal comfort and better IAQ implies increased energy demand. Environmental change is estimated to be responsible for an increase of 212% in energy use for cooling residential buildings between 2010 and 2019 [55]. The majority of European buildings lack air conditioning and ventilation systems, and only recently have buildings been designed in accordance with energy criteria [48]. Therefore, various actions are necessary, such as: renovation of building envelopes, installation of photovoltaic panels, improvement of HVAC systems, promotion of passive strategies, efficient air conditioning systems, installation of ventilation systems, urban revegetation policies (to avoid *heat island* effects and extreme temperatures), access to renewable energy, and living in greener environments with lower traffic densities, among others. However, all these strategies carry high economic costs, are difficult to provide to vulnerable groups, and imply social inequities and energy poverty. Thus, IoT-based strategies, as proposed in this paper, means a cost-effective contribution, technically feasible, and socially accessible, especially for public buildings and urban areas occupied by vulnerable groups.

Diversity of stakeholders. Buildings are interconnected at various scales and levels (see Table 2): space (local), building (community), neighborhood (intra-local), city (local), region (intra-national), country (national), and zone (international). Thus, the widespread implementation of IoT transversal strategies at all scales is key to understanding building behavior in relation to human behavior by obtaining accurate information to make data-driven decisions at different levels:

- For users, IoT enhances HVAC systems with low cost, time and impact.
- For architects, IoT improves knowledge about the real behavior of buildings and users (overcoming the gap between theoretical values and real data) for use in evidence-based architectural design.
- For engineers, IoT facilitates the study of the most suitable energy system for each building according to its location, orientation, design, typology of spaces, uses, etc.
- For urbanists, extrapolated to the urban scale and combined with Geographical Information System (GIS), IoT provides general strategies by zones.
- For geographers, overcoming the urban scale, IoT learns social behaviors, patterns, trends, etc.
- For epidemiologists and doctors, IoT makes it possible to correlate the spread of certain diseases with IAQ and environmental parameters and trends.
- For local, national, and international institutions, IoT provides data on behavior patterns for use in developing and implementing strategies for rehabilitation, energy management, etc., for energy, electricity, CO_2, etc.

Table 2. Scaling the built environment and its types of users to understand IoT as learning factory. *Source*: own; from several studies, such as [1], [2], and [7], among others.

Scale (level)	Stakeholders	Services for users	IoT functionalities
Space (personal)	User	Knowledge of environmental parameters (IAQ, temperature, humidity, occupancy) of specific spaces based on their activities, habits, and preferences.	Automation based on user behavior patterns. Adjustment of HVAC systems to certain environmental parameters, energy prices, renewable energy production, etc.
Building (community)	Architect	Design based on buildings behavior patterns according to each specific feature.	Smart design based on real data obtained from IoT monitoring and integration of passive and active building systems.
	Engineer	Design of the most appropriate energy solution based on the behavior parameters of building and users and available energy sources. Choice of the best combination between on-site renewable energy generation systems, air condition needs, and type of HVAC solution.	Real-time adaptation to multiple and diverse situations that can occur within a building.
Neighborhood (intra-local)	Urbanist	Appropriate solutions for each specific situation, to propose the best energy strategy and/or energy rehabilitation of new/existing neighborhoods.	Continuous monitoring of neighborhoods to obtain data and behavior patterns with which to characterize local policies and automatic systems customized to the neighborhood scale.
City (local)	Local institutions	Urban policies and plans to implement adequate and customized solutions for each city.	Smart infrastructures. Smart environments. Smart governance. Smart cities.
Region (intra-national)	Epidemiologist Doctor	Correlation of IAQ and environmental parameters with the spread of certain diseases.	Simulation and evaluation of different data-driven public health policies.
Country (national)	National institutions	Data from behavior patterns to develop global strategies for energy rehabilitation, electric production, and CO_2 management.	Simulation of scenarios and evaluation of the national strategies about the built environment with social implications.
Zone (inter-national)	International institutions	Data to implement global strategies for energy consumption based on energy availability, social equality, and climate change.	Simulation of scenarios and evaluation of the international strategies about the built environment with social implications.

Complexity. The growing availability of information, technological advances, global interconnectivity, population growth, and environmental, biological, and socioeconomic challenges generate more interdependent systems that are difficult to understand in their entirety. The acquisition and measurement of data provide empirical and quantitative information to understand and characterize key aspects of the reality under study. Monitoring and analyzing data allows the identification of patterns, relationships, dynamics, and new emergent features that reveal the most significant interdependencies, diversity, and structure within a system. Thus, IoT-driven solutions allow evaluation of system adaptability and understanding of how different variables interact with each other and impact the overall system behavior.

3. Materials and Methods

Following the theory of knowledge by which "*everything flows, is in permanent evolution … nothing is static, everything is dynamic: every entity or object is a complex process,*" a building can be defined as a set of dynamic, interconnected processes to provide a human habitat. Furthermore, the large number of systems, services, functionalities, parameters, metrics, etc., of a building lead to complexity in understanding it as a whole and foreseeing how it will behave and evolve. From these two approaches, a building can be defined as a complex system, as illustrated by central element in Figure 1.

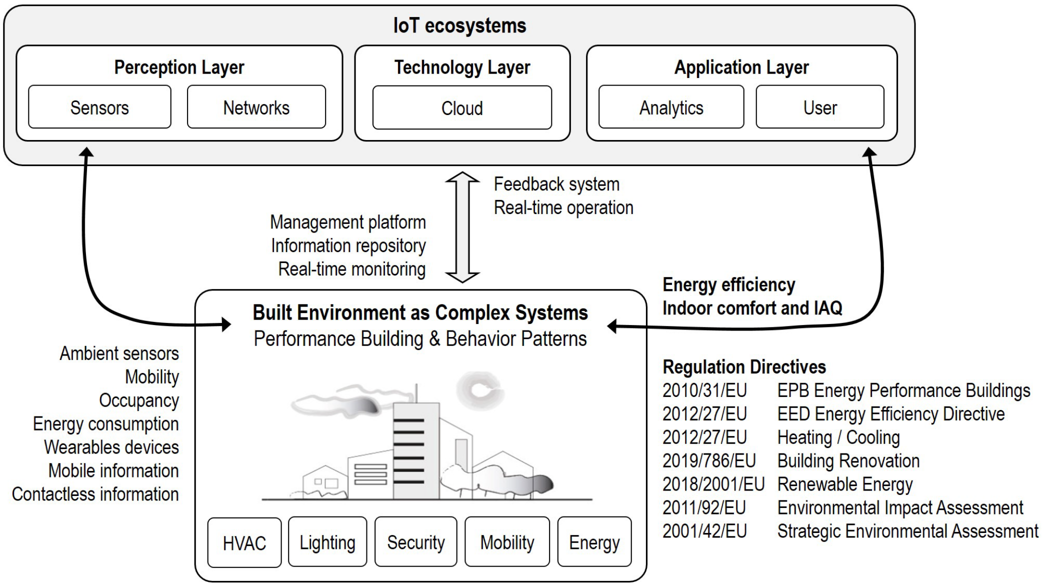


Figure 1. IoT ecosystems in buildings as complex systems. *Source*: own; from several studies, such as [1], [2], and [7], among others.

Buildings do not exist in isolation but rather are interconnected at various scales and levels (neighborhood, city, region, etc.), forming communities. Information flows and knowledge is shared at these interconnected levels. Therefore IoT-based initiatives are mandatory to develop transversal strategies, as emphasized in EPBD [7]: "… *promotion of smart technologies and infrastructure for sustainable mobility in buildings,*" and "… *integration of smart charging services enable[s] the energy system integration of buildings.*" In this context, it is essential to understand the relationships between buildings and their communities (urban and rural, cities and villages, etc.) conforming to the built environment (see Figure 1) that also constitute complex systems understood as interconnections of buildings used by many people, also who are themselves interconnected with each other and with the environmental context. As remarked in EPBD [7]: "*In order to digitalize the building sector, the Union's connectivity targets and ambitions for the deployment of high-capacity communication networks are important for smart homes and well-connected communities.*"

These concepts of building performance and behavior patterns (see Figure 1) lead to understanding IoT as enabling technologies to quantitatively parameterize Key Performance Indicators (KPIs) of the built environment. As EPBD emphasizes, as of 2026 (article 13), the Smart Readiness Indicator (SRI) [56] is an essential parameter for making building owners and occupants aware of the value hidden in building automation and digital supervision of building technical systems by providing energy savings thanks to new smart features that IoT enables [57]. In summary, moving towards the paradigm of *hybrid twins* means integrating IoT ecosystems into *smart communities* (buildings, cities, etc.) to acquire data (through real measurements), comparing them, and turning them into information to generate knowledge for use in making data-driven decisions.

The functional scheme of an IoT ecosystem consists of 5 modules grouped in 3 layers (see the upper area of Figure 1): perception (including sensors and networks), technology (cloud), and application (analytics and user). Each of these 5 modules are following detailed is described below:

- **Sensors.** There is a huge variety of sensors available to measure parameters of interest in buildings, such as (see the left area of Figure 1): ambient (CO_2, temperature, humidity), mobility, occupancy, energy consumption, wearable devices, mobile information, contactless information (such as Radio Frequency Identification (RFID) tags), etc. As the focus of this study was on energy efficiency and IAQ, sensors for measuring energy consumption (kWh), CO_2 level (ppm), temperature (°C), humidity (%) and occupancy (pax) were included. The strategies for the selection of sensors followed several alternatives to prioritize the most appropriate suitability implementation with minimal cost. Wired alternatives were discarded because their installation would be problematic, and combinations of wired sensors and wireless gateways were also discarded because their connectivity would be problematic. Wireless sensors that work with both commercial solutions and open IoT cloud networks were considered. The latter option was chosen for its good scalability, high adaptability, and moderate cost. Monitoring spaces were representatively selected and labelled according to their key characteristics, such as: location (floor, building, campus), orientation (north, south, east, west), use (classroom, study room, office, laboratory, library, canteen, etc.), size (large, medium, small), occupancy (high, medium, low), etc.
- **Networks**. Sensors collect data. These collected data are sent to the following communication levels by various interconnected devices through their associated connectivity technologies. There are two main strategies: rely on classical cabled infrastructure centralized in SCADA systems or to use wireless protocols routed to the cloud using specific gateways, such as Wireless Fidelity (WiFi), 4G and Low Power Wide Area Network (LPWAN) technological family such as SigFox, Narrow Band IoT (NB-IoT) and Low Range Wide Area Network (LoRaWAN). Figure 2 shows a performance comparative to determine the most appropriate technology in order to propose homogeneous infrastructures. This comparison shows, among other issues, the importance of battery life and ease of battery replacement. As consequence of minimum maintenance cost and highest energy optimization and coverage range, LoRaWAN technology was selected for this work from the rest of LPWAN technological family. LoRaWAN specification [58] is a networking protocol, designed to wirelessly connect battery operated sensors with bi-directional communication and localization services, that targets other key IoT requirements such as end-to-end security, high interoperability and low monthly costs due to provider network fees.

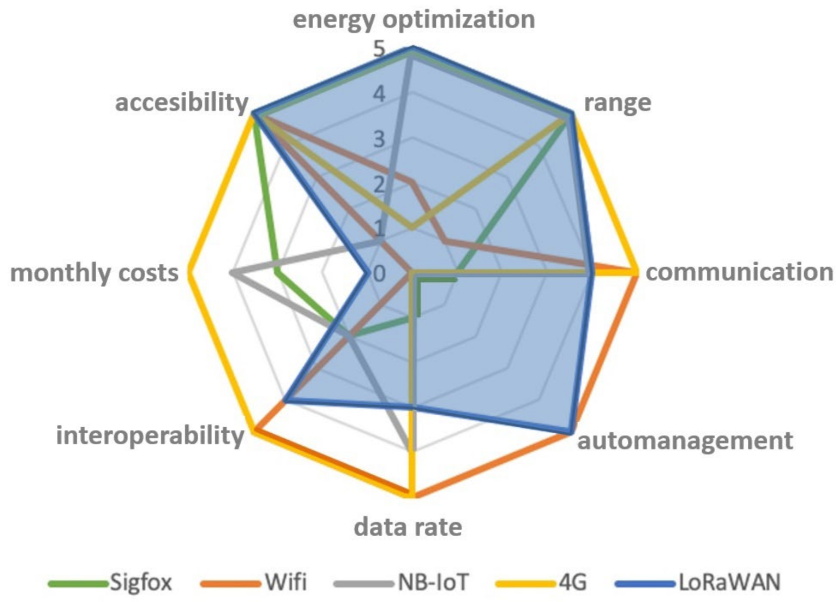


Figure 2. Comparison between LoRaWAN and LPWAN technological family. *Source*: own; from several studies, such as [58], among others.

- **Cloud**. Cloud computing services use a network layer (to connect remote devices or industrial TCP-IP protocols such as MODBUS-TCP or OPCUA through SCADA systems) with centralized resources (data centers). Currently, there are different types of clouds (public, private, hybrid) and new service models called *X as a Service* (XaaS), where X can be Software (SaaS), Platform (PaaS), Infrastructure (IaaS), among others. With the popularization of cloud services, the number of devices has exponentially increased. Given that critical and large-scale processes require increasingly fast and effective computational power, a new concept emerges: edge computing. Thus, edge computing refers to how computational processes are performed on or near the peripheral devices (edge). Finally, a third concept arises: fog computing, to refer a decentralized structure in which resources, including data and applications, are located in a logical place between the cloud and the data source. Due to the wide variety of sensors and scenarios in smart buildings, this research has utilized both edge services (for energy measurements considered as big data) and cloud services (for IAQ measurements considered as small data). The IoT ecosystem developed in this work integrates three main functionalities (see middle area in Figure 1): a management platform (to homogenize and control acquired data), an information repository (following the design principles of scalability, flexibility and big data processing), and real-time monitoring (with geopositioned information). Furthermore, these functionalities interconnect with two key services (above detailed): analytics technics (*artificial intelligence*, *machine learning*, *deep learning* and *neuronal networks*) and applications and services for user experience to offer variability for visualization and interaction through mobile apps, web interfaces, data dashboard with KPIs and other added-value services.
- **Analytics**. From the information processed and stored in the cloud, many analytics technologies exist for extraction of key factors, real time data exchange, remote monitoring, etc. This is crucial as it provides ubiquitous access, either through platforms or online applications, to real-time levels of CO_2, temperature, occupancy, and energy consumption in a specific place, thereby facilitating the monitoring and control of KPIs as well as the subsequent analysis of both user behavior and building performance. In addition, the connection of sensors to the IoT infrastructure of a building enables integration with other systems, such as: (see lower area in Figure 1): HVAC,

lighting, security (alarm, fire, etc.), mobility, energy management, etc. This provides facilities for coordination and global optimization of building systems and improves their structure by enhancing their efficiency, safety, wellness and comfort. IoT systems allow obtaining the necessary data to obtain information using Computer Science techniques. This information is crucial to increase the knowledge about a system, enabling real-time operation and making predictions about its behavior. Having a robust, open, and flexible IoT system is essential for Computer Science to process and analyze the collected data, which in turn allows making informed decisions and optimizing the system.

- **User**. From all the data collected by the sensors and the information computed by the analytics, IoT systems visualize knowledge. Report generation or dashboard visualization helps to better understanding of environment behavior and supports the informed decision-making about the aforementioned building systems (HVAC, lighting, security, mobility, energy management, etc.). In this work, the combined analysis (from CO_2, temperature, humidity, occupancy and energy consumption) enable the development of management models of energy efficiency and IAQ. With them, smart automation and control systems, both for ventilation and air conditioning systems, can be regulated based on occupancy levels, usage planning, and external environmental conditions. It even allows the development of models that incorporate parameters such as the economic cost of energy, on-site renewable energy production, human behavior, or the environmental impact of the building. Moreover, IoT systems can send real-time alerts or notifications when KPIs reach predefined threshold, and take actions to correct situations, ensure a healthy environment, etc.

All this implies that buildings can be characterized as complex systems (see middle area in Figure 1), where feedback from contextual knowledge includes energy efficiency performance, indoor comfort, IAQ, environmental impact, facility management and location-based services, among others. As this work is focused in energy efficiency and IAQ, their implications in this context are following detailed. On the one hand, the energy demand in a building can be estimated through the energy regulations when it was built. However, several key factors (design, orientation, ubication, use) can produce large consumption variations studies [39]. Even in newly buildings, there are significant differences between calculated energy and measured consumption, reinforcing the idea of filling the gap between theoretical values and real data studies [40,41][42]. Thus, data provide by IoT ecosystems are essential to make knowledge-driven decisions.

On the other hand, to improve IAQ, two main parameters come into play: introducing exterior air and filtering it. Introducing exterior air can be achieved without supplying energy to the system through natural ventilation. However, mechanical ventilation can provide controlled and filtered flows at the cost of energy consumption. Hybrid systems offer the advantages of both approaches, but it is essential to discern when and how to combine them. In all three cases, measurements provided by IoT ecosystems are crucial to understand how HVAC systems interact with users and the building, enabling to make knowledge-driven decisions. Therefore, a continuous and real-time monitoring of building performance (as energy consumption, HVAC and SCADA services, ambient sensors, etc.), comparing with external data (as historical weather data and forecast), and integrating with other key variables (as renewable energy levels of the photovoltaic panels) lead IoT ecosystems as a great learning factory to understand how a building really works under their operating conditions.

As detailed in the Results and Discussion section, an entire university campus (with 3 buildings of 14,000 m^2 for 1,000 students and 250 staff, 21,000 m^2 for 1,500 students and 350 staff, and 27,000 m^2 for 2,000 students and 450 staff) has been used as IoT learning factory. As Figure 3 shows, it is essential to understand the current status of the built environment, which typically can be classified into one of the following three general types of buildings (not only university buildings) according to ventilation and energy efficiency:

- Buildings without mechanical ventilation, and insulation deficiencies in both thermal transmittance of the building envelope and air permeability.
- Buildings with hybrid systems, that incorporate ventilation and air conditioning systems, either mechanical or hybrid, without CO_2 sensors but with temperature controls in several indoor spaces and large uncontrolled airflows (through open windows, open doors, inefficient materials, etc.).
- Efficient energy buildings: a minority of buildings with HVAC systems, high thermal insulation, high-performance windows, heat recovery ventilation equipment, and very-low-permeability materials.

In many cases, none of these buildings types have previously deployed IoT ecosystems. Thus, improvements in the key factors in building performance involve transversal efficiency and IAQ strategies, such as the following:

- Replacement of the building envelope to reduce energy transfer and air permeability.
- Replacement of the current HVAC systems with more efficient solutions by designing a ventilation network with dual flow and sectorization to incorporate heat recovery systems.
- Integration of a smart management and control system through IoT ecosystems.

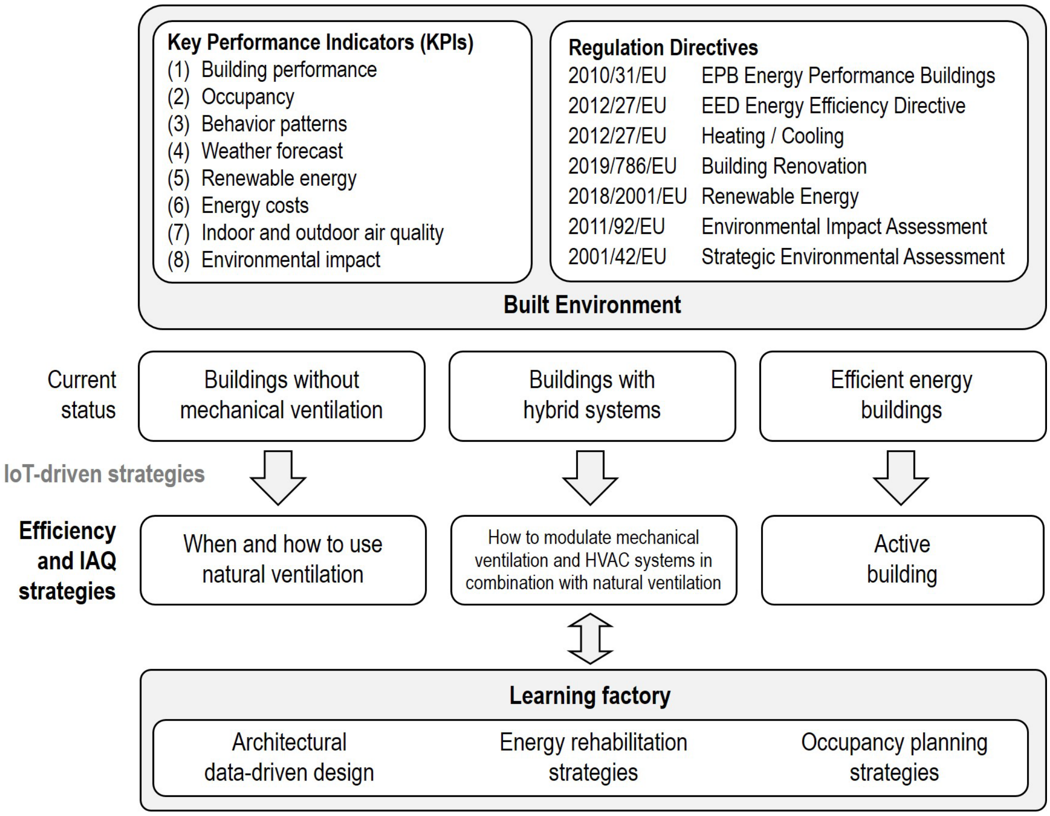


Figure 3. IoT as key enabling ecosystem to understand the building complexity. *Source*: own; from several studies, such as [1], [2], and [7], among others.

It is well known that, for the first scenario, it is essential to reduce the energy transfer that occurs in the building envelope and decrease air permeability, as well as to improve the performance of HVAC systems. In the second case, a possible improvement involves installing new distribution systems and suitable terminals for each space. Both of these strategies have significant impacts on users, as well as high economic costs. In the third scenario, it is necessary to introduce smart systems capable of making real-time adaptive decisions. In all three cases, the IoT strategy proves to be effective and compatible and could be the appropriate solution in terms of cost-effectiveness, technically feasibility and socially accessibility; especially for public buildings and urban areas occupied by vulnerable groups. As shown in Figure 3, the added-value of IoT-based strategies is:

- In buildings without mechanical ventilation, IoT helps to improve IAQ by detecting potentially dangerous concentrations of CO_2 (through alarms or visual indicators) and adjusting when and how to use natural ventilation, in combination with available HVAC systems, according to both indoor and outdoor conditions. It allows for manual minimization of energy losses while minimizing health risks.
- In buildings with hybrid systems, IoT enables smart control of the systems, whether centralized or specific to each space. Thus, IoT provides users knowledge about how to modulate mechanical ventilation and HVAC systems in combination with natural ventilation, according to both indoor and outdoor conditions, and regarding with the environmental context.
- In efficient energy buildings, IoT enables precise and smart adjustment of HVAC systems, moving towards the paradigm of *active building*. An *active building* is capable of using Artificial Intelligence (AI) to make real-time adaptive decisions. This term highlights the building's ability to smartly adapt to changing conditions and demands, leading to improve energy efficiency, comfort, and IAQ. IoT informs users when to select natural ventilation, essential to connect people with the environment.

In all cases, the integration of IoT ecosystems into built environment leads to learn, model, and visualize when the building systems (management, operating, production, distribution, etc.) are most efficient, according to its KPIs such as (see right upper area in Figure 3): (1) building performance, (2) occupancy, (3) behavior patterns, (4) weather forecast, (5) renewable energy, (6) energy costs, (7) indoor and outdoor air quality, and (8) environmental impact.

All these concepts show that IoT ecosystems are key to understand the building behavior in relation to human behavior. In addition to better adjust HVAC or SCADA systems, IoT compares the overall building performance and also connects it with the natural environment. And it is essential because there are not two habitats alike in the world. Two identical buildings can have different behaviors depending on how users interact with them; and vice versa: identical uses in different buildings can yield different results. In this complexity of interconnections and interrelations, IoT arise as the transversal discipline that should better meet the challenge to understand buildings as complex systems by using their behavior and knowledge as learning factory to make data-driven decisions.

As shown in lower part of Figure 3 and discussed in the Results and Discussion section, IoT as a learning factory contributes to improving overall knowledge about architectural data-driven design, energy rehabilitation actions, and occupancy planning strategies.

4. Results and Discussion

Following all the premises detailed in previous sections, an IoT ecosystem (named *sensoriZAR*) was designed, developed, and implemented on the *Campus Río Ebro* of the University of Zaragoza (Spain) [59]. *sensoriZAR* was designed to store a large volume of heterogeneous data (acquired at high speed), homogenize it into information, and provide added-value knowledge. Its functional architecture follows the principles detailed in Figure 1 by integrating 5 modules in 3 layers: data acquisition (from sensors) and network interconnection (perception layer); information storage and processing (technologies layer), and knowledge analytics and visualization (application layer). Thus, *sensoriZAR* harmonizes various mechanisms for importing, exporting, downloading, monitoring, and integrating data through Application Programming Interfaces (APIs) for third-party use, including research studies) and making data-driven decisions. *sensoriZAR* was built as a homogeneous and ultra-low-energy-consumption IoT ecosystem with free hardware and software to be a cost-effective and sustainable IoT-based tool for improving energy efficiency and IAQ in buildings.

The methodology of *sensoriZAR* IoT ecosystem for systematizing the acquisition, store and processing, and analysis and visualization of real-time measurements, follows a 3-level process:

1. **Identify buildings to analyze their performance requirements**. University buildings shows different orientations (north, south, east, and west), predetermined use patterns (regarding timetables), non-predetermined behaviors (regarding people performance), and high thermal variation (low temperatures in winter and high temperatures in summer), among many other sources of variation. Three buildings on the *Campus Río Ebro* were selected for study: *Ada Byron* (Building I), *Torres Quevedo* (Building II), and *Agustín de Betancourt* (Building III). These buildings were selected because of their diversity of uses, the heterogeneity of their spaces, and the possibility of sectorizing their HVAC systems, among other key factors that allow the systems to be extrapolated to the rest of the university campus.
2. **Select representative spaces to monitor**. As detailed in the Materials and Methods section, the monitoring spaces were selected and labelled according to their key characteristics, such as their location (floor, building, campus), orientation (north, south, east, west), use (classroom, study room, office, laboratory, library, canteen, etc.), size (large, medium, small), occupancy (high, medium, low), etc. As a representative example, Figure 4 shows all the ambient sensors deployed in Building I of *Campus Río Ebro*.
3. **Deploy the sensor infrastructure and configure the IoT ecosystem**. *sensoriZAR* was deployed with more than 200 geolocated wireless ambient sensors in more than 100 representative spaces in the 3 buildings of *Campus Río Ebro* (Building I, II and III). This deployment collects a dataset of more than 10000 real-time measurements every hour of CO_2, temperature, humidity, and occupancy. Furthermore, the IoT ecosystem also integrated energy and electricity consumption data from the SCADA systems for the entire *Campus Río Ebro*.

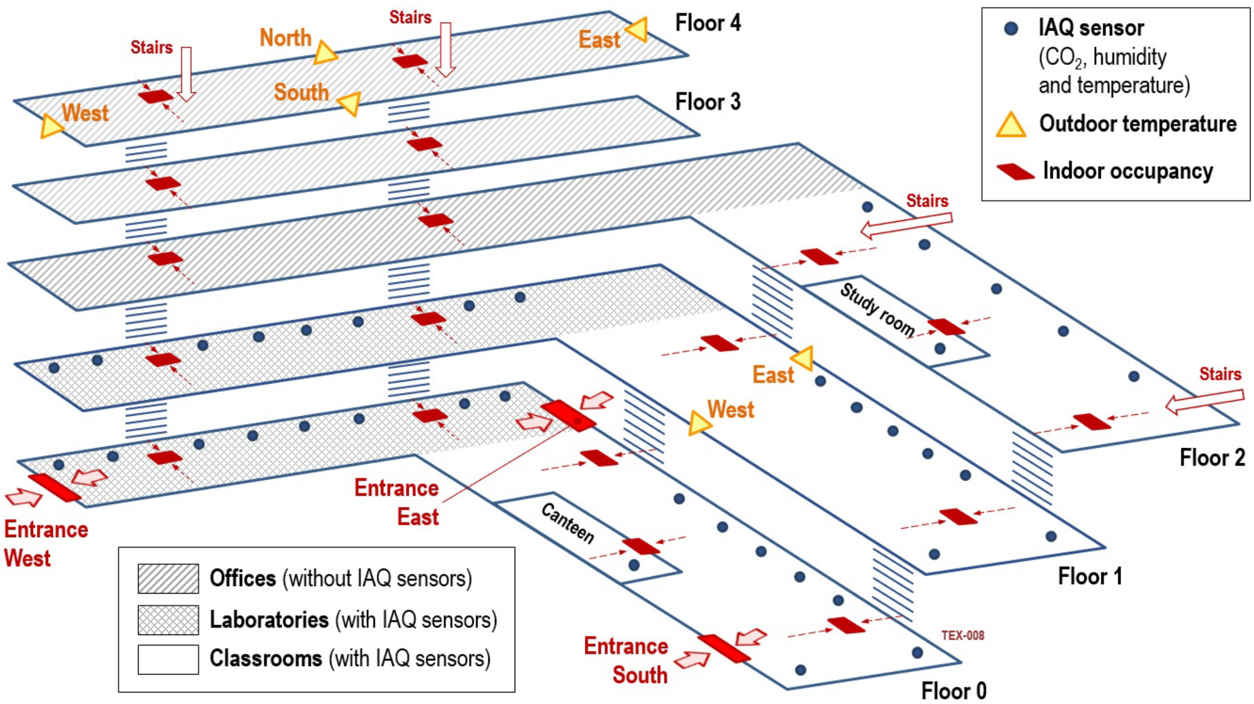


Figure 4. Ambient sensors deployed by *sensoriZAR* in Building I of Campus Río Ebro. *Source*: own; data available from *https://sensorizar.unizar.es*.

From this methodology, as this work focuses on energy efficiency and IAQ, the following results show several experiments through real installations where IoT allows understanding the building complexity and proposing a proof-of-concept of prediction of CO_2 and temperature based on neural networks.

First, focused on energy efficiency analysis, Figures 5 and 6 illustrate several lessons learned about energy consumption, costs, and savings. As a representative example, Figure 5 shows the average temperature evolution each day of the week in a building of *Campus Río Ebro* (Building I). The measurements (graphic in orange color) are the result of averaging the daily temperature measurements of every monitoring space in Building I during the fall semester (Figure 6 details December 2022 and January 2023). As in Spain, following Order PCM/466/2022 [60] for buildings of the General State Administration and institutional public sector entities, public buildings with associated HVAC energy consumption must keep the indoor temperature (when heating) between 17 and 21°C, these thresholds have been marked in Figure 5 with a pink line (for 17°C) and a yellow line (for 21°C). Every week is delimited between vertical blue lines, and every day can be identified by its maximum (peak) temperature value: a zoom is detailed (framed in green color) where every peak is underlined as Monday, Tuesday, etc., including the weekend (shaded in yellow color). Thus, Figure 5 highlights two interesting features:

- Every week there is an increase in the average daily temperature (as a *sawtooth*), which helps to explain the thermal inertia of the building behavior. It is very interesting to know this behavior because, by measuring the daily maximums and minimums according to each day of the week and comparing the graph with the 21°C threshold, it is possible to estimate the savings potential. According to the measurements obtained, the implementation of an IoT-managed HVAC system should imply savings between 10 and 15% of total energy consumption by switching off the heating pumps when monitoring spaces reach thermal comfort (around 21°C).
- On weekends and holidays, such as Christmas (areas shaded in yellow color), average temperatures drop below the 17°C threshold. Thus, the start of each week on Monday implies a significant energy consumption to increase temperatures to the thermal comfort zone (between 19 and 21°C according to [60]). It is very interesting to quantify this energy consumption to analyze diverse strategies that would avoid an excessive decrease in building temperature, and thus it would not be necessary to overcome a very high slope at the beginning of each week.

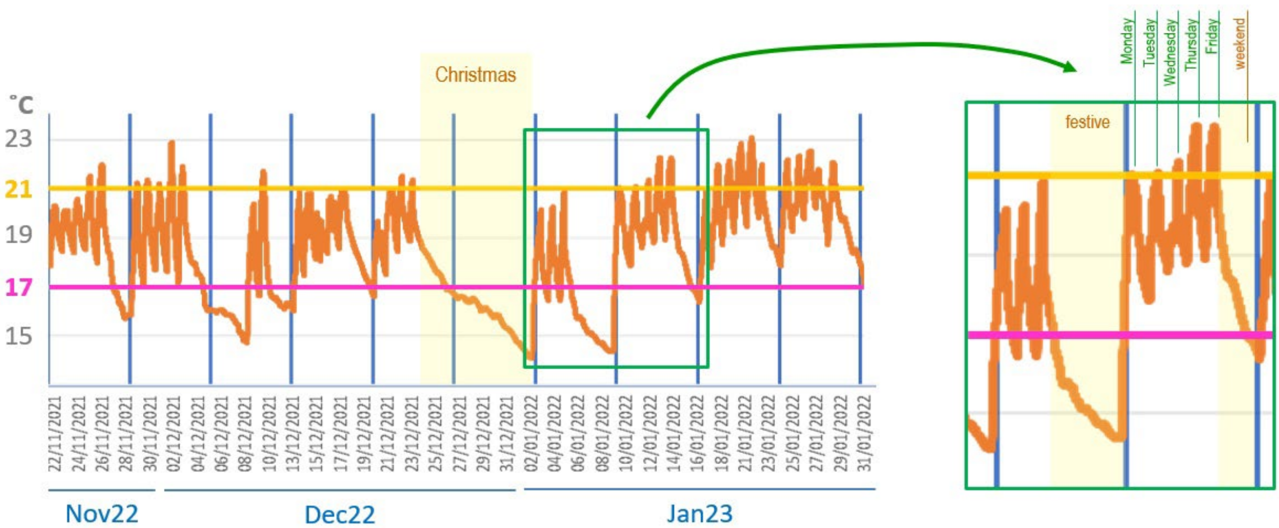


Figure 5. Average temperature evolution each day of the week. *Source*: own; data available from *https://sensorizar.unizar.es*.

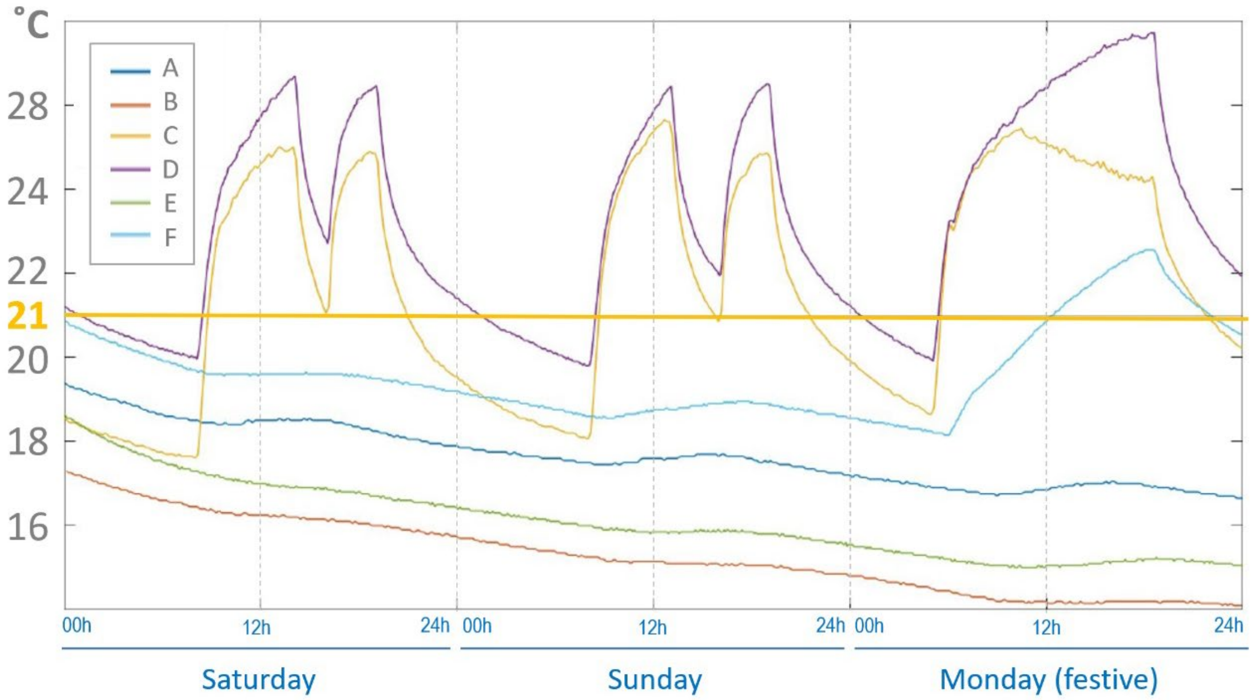


Figure 6. Detail of instant temperatures in several representative classrooms during a weekend. *Source*: own; data available from *https://sensorizar.unizar.es*.

To deeply analyze some of these trends, Figure 6 shows (as a zoom) the detail of the daily temperatures of various monitored spaces in this building, specifically, 6 classrooms on the second floor with the same characteristics: capacity for 70 people (medium size) with medium occupancy and north orientation. The measurements (graphics in different colors for every classroom from A to F) are the instant temperature during three days (Saturday, Sunday, and a holiday Monday). Figure 6 shows that several some classrooms (D, C, and F) follow anomalous trends since their temperatures reach very high values when the heating system should be disconnected. Thanks to the IoT ecosystem reporting this building performance, the Energy Management System was queried, and it was found that the thermostats in those classrooms (C in orange and D in purple) were not working correctly. Thus, the HVAC system was active all weekend. In addition, classroom F (in blue) was not marked in the Energy Management System as a holiday, so the HVAC system started on Monday as if it were a conventional week.

All these quantitative results demonstrate the value of using IoT ecosystems for real-time monitoring building KPIs to detect anomalies, correct malfunctions, and even anticipate potential breakdowns through predictive techniques, as it is studied in the third contribution of this section.

Second, focused on IAQ analysis, Figures 7 and 8 show several lessons learned about the improvement of healthy environments. Figure 7 shows the average CO_2 levels (in percentages; see the left axis) of every building in *Campus Río Ebro* (Buildings I, II, and III). These average CO_2 levels are the result of averaging the daily CO_2 measurements of every monitoring space in each building during the fall semester (from September 2022 to January 2023). The average values show in all cases how CO_2 levels meet the recommended levels (CO_2 < 1000 ppm (in light green) under usual conditions, with CO_2 < 800 ppm (in dark green) to minimize the COVID-19 risk) around 90% of the time: 88.22% in Building I, 92.26% in Building II, and 93.36% in Building III.

Figure 8 shows, as a zoom, the detail of a representative space of each of these buildings to analyze similarities and differences according to each type of space: (a) in Building I, a classroom with a capacity for 120 people (large) with high occupancy and a northern orientation; (b) in Building II, a computer room with a capacity for 44 people (small) with high occupancy and a western orientation; and (c) in Building III, a canteen with capacity for 260 people (very large) with a medium occupancy and an eastern orientation.

In a controlled masterclass environment where only the teacher is speaking most of the time, Figure 8(a) shows how $CO_2 < 1000$ ppm more than 95% of the time. In a more variable environment and a space with a smaller capacity, in which people interact with computers, talk to each other, the teacher interacts with each practice group, etc., Figure 8(b) shows how CO_2 increases ($CO_2 > 1000$ ppm around 20%) and also the maximum CO_2 measurements increase (red dots in right axis are higher than 2000 ppm). In For an environment such as a canteen, with high roaming (the flow of people constantly changing), open spaces, and high ceilings that imply air and CO_2 renewal, Figure 8(c) shows $CO_2 <$ 1000 ppm of almost 100%.

All these results show interesting trends in the CO_2 behavior in buildings depending on the typologies of spaces, their size, orientation, location, and use, among other features. Furthermore, the contribution of IoT ecosystems as learning factories allow these trends to be extrapolated to all types of buildings: administration, institutional, education, services, etc.

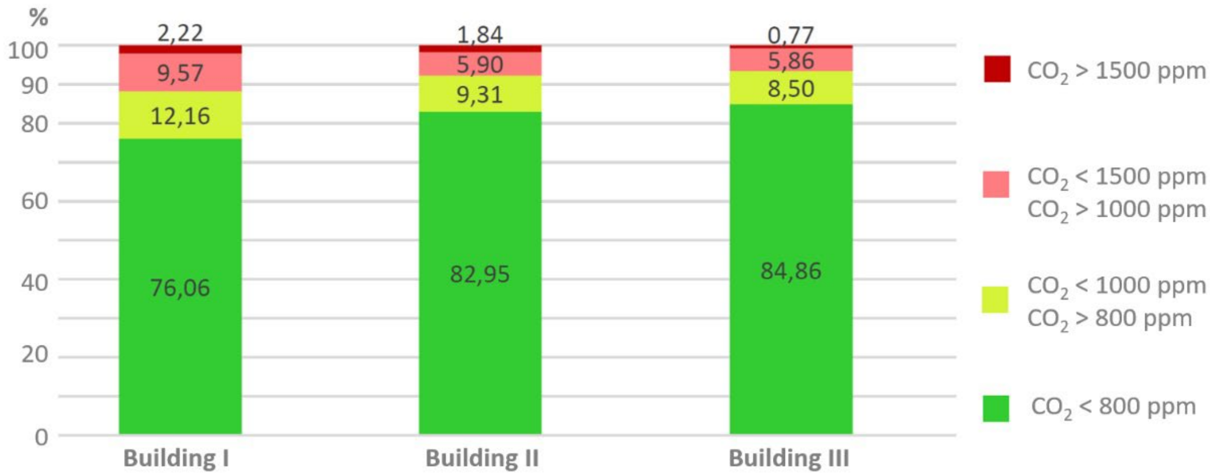
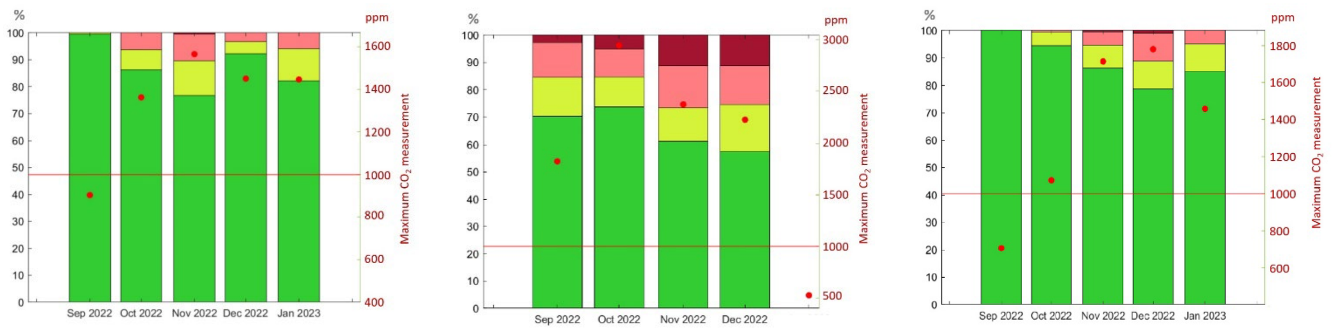


Figure 7. Average CO_2 levels in the university campus in fall semester. *Source*: own; data available from *https://sensorizar.unizar.es*.



(a) classroom in Building I

(b) computer room in Building II

(c) canteen in Building III

Figure 8. Average CO_2 (left) and maximum CO_2 (rights) in representative spaces. *Source*: own; data available from *https://sensorizar.unizar.es*.

Thus, as a third contribution to learning to estimate CO_2 levels more accurately and enhance the numerical model by applying Computer Science techniques, a prediction model based on a Back Propagation Neural Network (BPNN) was researched. Indeed, the BPNN enables quick and accurate identification of nonlinear relationships between various input variables and output objectives, thus enhancing the prediction of complex systems. A prediction model for the study room can be used with a double purpose: to inform the user about the trend in the value of CO_2 and temperature; and to be implemented in a smart control system for the HVAC system, which, in the case of a predicted temperature increase (due to human load, solar, etc.), for example, switches off the heating supply before the setpoint temperature is reached, with consequent energy savings, or it renews the air, with consequent air quality improvement.

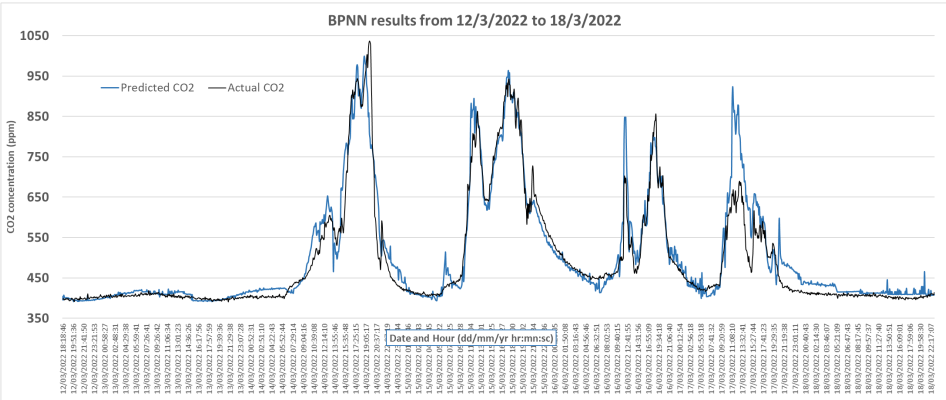
The experiment involved the study room, which is a large space located on the ground floor, facing south, and equipped with large glass windows. It has a surface area of 761 m², an air volume of 2666 m³, and a maximum capacity of 464 people. The occupation is high and variable. The actual occupation was measured with a sensor that determines the exact number of people present at any given moment. More than 1500 measurement records of each type for the opening hours of March 2022 were analyzed. The BPNN was trained for a prediction horizon of one hour. The neural network application used was Neural Net Fitting (Matlab r2022a), along with a Bayesian regularization algorithm of 10 hidden neurons (the hidden layer size), as indicated by default in [61]. 70% of the input data was used to train the network, and of the remaining 30%, 15% was used for validation (validating the network and stopping training before overfitting occurs), and 15 % was used to test the network independently.

The data collected by the sensors, such as CO_2 (ppm), temperature (°C), humidity (%), occupancy (pax), and accumulated occupancy (pax) values, were used as inputs to predict the CO_2 values and indoor temperature. Table 3 shows the input data (columns 2–6), where accumulated occupancy is the addition of the occupancy of the last 55 minutes (with measurements every 11 minutes per period). Columns 7–8 show the predictions for CO_2 and temperature for 5 subsequent time periods. As an example, 8 training records are shown in Table 3. Predictions (shaded in rows 1–3, columns 7–8) are adjusted accurately to measurements made one hour later (shaded in rows 13–15, columns 2–3).

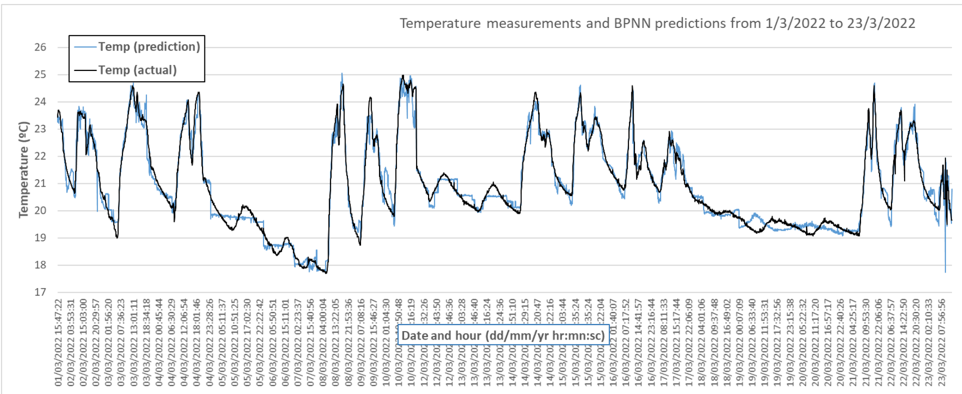
Table 3. Network input, target and predicted data. *Source*: own; data available from *https://sensorizar.unizar.es*.

Time (gmt+2)	CO2 (ppm)	Temperature (°C)	Humidity (%)	Occupancy (pax)	Accumulated occupancy (pax)	CO2 prediction (ppm)	CO2 relative error (%)	Temperature prediction (°C)	Temperature relative error (%)
18:25:02	776	23.00	45	104	614	**819**	**2.46**	**22.73**	**0.39**
18:30:03	735	22.86	44	101	620	800	2.03	23.01	1.86
18:35:04	719	22.78	44	99	620	785	1.23	23.00	1.93
18:40:03	711	22.76	44	101	621	786	2.98	22.95	1.86
18:45:03	718	22.78	44	98	614	781	0.39	22.98	1.97
18:50:02	738	22.78	44	94	597	771	0.71	23.01	2.28
18:55:04	756	22.81	44	83	576	759	0.05	23.17	3.09
19:00:03	757	22.74	44	76	551	739	0.97	23.16	3.23
19:05:03	752	22.72	44	80	532	738	-0.08	22.93	2.39
19:10:03	756	22.72	44	80	511	739	1.12	22.80	2.11
19:15:03	783	22.64	44	74	487	714	-1.53	22.86	1.87
19:20:03	**797**	**22.64**	44	74	467	713	-1.74	22.77	2.07
19:25:03	784	22.58	45	82	466	709	0.19	22.29	0.26
19:30:04	775	22.56	45	85	475	714	5.01	22.25	0.27

Figure 9 shows the results obtained by applying the neural network to the data measured during the month of March, obtaining a regression value of R^2 = 0.996 and a Mean Squared Error (MSE) of 535 for CO_2 and 0.219 for temperature. This high degree of correlation confirms the usefulness of the BPNN as a promising strategy for making this type of prediction if the sample size is sufficiently large. The precision of the prediction (±23.13 ppm) is less than that of the CO_2 sensors, which is ±40 ppm. Similar results can be found for temperature, where a precision of ±0.46°C is like to ±0.45°C of sensor precision. The predicted values (indicated by the blue line) fits fit the measured values (indicated by the black line) remarkably well. The neural network obtained is already available for use in the IoT ecosystem as a prediction tool for levels CO_2 and temperature. To further increase the level of accuracy additional experimental data could be obtained throughout the entire year. Furthermore, variables such as humidity, HVAC system operation, indoor activity, windows opening, wind incidence, and other external climatic characteristics should be included, to increase the correlation between sensor data and predictions or the time horizon of the prediction. Given the demonstrated usefulness of the BPNN, additional experiments should be carried out to extend the methodology to other kind of spaces.



(a) CO_2



(a) Temperature

Figure 9. Neural network results for CO_2 and temperature predictions. *Source*: own; data available from *https://sensorizar.unizar.es*

5. Conclusions

The proposed methodology, understanding that the implementation of an IoT ecosystem turns buildings (especially university buildings) into a learning factory, show several lessons learned through real installations about how IoT ecosystems can behave as cost-effective solutions to understand the built environment as a complex system. Moreover, deployment of IoT-driven solutions contributes as transversal strategies to improve energy efficiency and IAQ and help to predict building performance. Implementation of IoT ecosystems facilitates the customized analytical study of specific situations.

As it is well known, the major industrial companies are working on digital twins models. In that context of proprietary solutions (that usually offers closed and expensive solutions), this work proposes a transversal IoT ecosystem developed from the premises of opening (software and hardware), modularity and interoperability. Furthermore, this work provides mechanisms for importing, exporting, downloading, monitoring, and integrating data through APIs for third-party use to assist scientific community and also industrial sector in its innovations and research studies

As mentioned in the Introduction section, IoT ecosystems are key to understanding the complexity of the built environment by filling the gap between theoretical simulations and real measurements. This change in environment (between simulated and real behavior) is attributable to the key reasons for building performance: the variety of uses, characteristics of construction, orientation, location, climatic conditions, and environmental context, among other factors. Thus, IoT ecosystems are key to transversal strategies for reducing energy consumption, increasing energy efficiency, improving IAQ, enhancing healthy environments and predicting performance, for the following reasons:

- IoT helps us to understand user and building behavior patterns and adjust energy production to real demand and vice versa and understand how buildings process energy, enabling changes in the behavior patterns of their managers and users.
- By combining real data on energy use, CO_2, temperature, and occupancy, IoT helps us to understand buildings as complex systems in specific climatic locations and perform modeling, simulations, and predictions towards the paradigm of *hybrid twins*. Thus, IoT monitoring provides the knowledge to characterize the built environment (since the information to create a digital model is not always available), overcoming the difficulty of access to data, such as: construction materials, architectonic decisions, thermal bridges, uncontrolled infiltrations, window efficiency, HVAC performance, among other factors.
- IoT permits detailed analysis of specific cases, uses, and spaces to identify the best energy retrofit strategies. For each building case, IoT helps to quantify which energy improvement strategy will be most effective in reducing energy consumption and greenhouse gas emissions.
- IoT facilitates the detection of anomalies, energy leaks, airflow, unused spaces, open windows, etc., as well as inefficiencies in HVAC systems and maintenance failures, among other potential malfunctions.
- IoT enables smart management in operation together with the building systems: HVAC, SCADA, lighting, security, mobility, climate regulation, home automation, access control, etc.
- IoT ecosystems, when interconnected on a larger scale (city, region, country, etc.), provide data for use in sociodemographic studies and analysis of how buildings are used, enabling knowledge-driven decisions for rehabilitation strategies. Mobility and communities are closely interconnected, providing insights into how users invest time and energy.

IoT also shows limitations. It needs to be integrated together with the building systems and their data deeply analyzed using Computer Science techniques to keep moving forward *hybrid twins* by combining active and passive systems on buildings that are activated (automatically and/or manually) with the IoT-generated knowledge. These are future lines of this work. On the one hand, to include much more variables (indoor activity, outdoor weather, windows opening, wind incidence, etc.) and to integrate the building systems (climate regulation, lighting, mobility, security, etc.) to better understand the complexity. On the other hand, to deep this understanding by applying Computer Science methodologies to enhance decision-making for the management and optimization of the built environment.

In summary, in real contexts of economic restrictions, complexity, high energy costs, social vulnerability, and climate change, IoT-based strategies, such as those proposed in this work, highlight as open, modular, interoperable, and cost-effective approaches to moving towards smart communities by improving energy efficiency and indoor and outdoor environmental quality with low cost, quick implementation, and low impact on users. These IoT-based strategies address great challenges for growth, interconnection, climate change, and overall sustainability. Through real-time monitoring of building performance, IoT ecosystems can be seen as a way to democratizing information while saving energy and costs, especially for public buildings and urban areas with vulnerable groups, while maintaining the comfort, well-being, and quality of life of the people who daily live the building.

Funding: The work was supported by the *Zaragoza Vivienda* UZ Chair (CAT-C019/2020_3-UZ) and the UZ Scientific Policy Vice-rectorate (SGI-171481 EQUZ2022-TEC-11) and it has been awarded for Multidisciplinary Innovation - SAMCA UZ Chair (2000/0074).

Acknowledgments: The authors thanks for several data and their contributions to this work to Ángel Pueyo (UZ vice-rector for Planning, Sustainability and Infrastructure); Head management team of UZ Engineering and Architecture School (EINA); José Miguel Jover and Salvador Nevot (UZ *smart campus* initiative, *smartcampus.unizar.es*); David Cambra (UZ Green Office, *oficinaverde.unizar.es*); Alberto Mur, Jorge Vizárraga, Álvaro Marco and Teresa Blanco (HOWLab, *howlab.unizar.es*); Enrique Torres (GaZ, *gaz.i3a.es*), Raquel Trillo (DisCo, *webdiis.unizar.es/DISCO*); Sergio Ilarri (COSMOS, *cos2mos.unizar.es*); Silvia Guillén-Lambea (GITSE, *i3a.unizar.es/gitse*); and Belinda López-Mesa, José María Castejón, Ángel Bayod, Antonio Montañés, and Miguel García Monge; all this people as members of Engineering Research Institute of Aragón (I3A) Smart Cities Lab (*smartcities.unizar.es*).

References

1. European Court of Auditors, Energy efficiency in buildings: greater focus on cost-effectiveness still needed, Luxembourg, 2020. https://op.europa.eu/webpub/eca/special-reports/energy-efficiency-11-2020/en/index.html (accessed May 28, 2023).
2. Eurostat. Statistics Explained, Final energy consumption by sector, EU, 2021, Eurostat. (2023). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Final_energy_consumption_by_sector,_EU,_2021,_(%25_of_total,_based_on_terajoules).PNG (accessed June 14, 2023).
3. COMMISSION STAFF WORKING DOCUMENT, Climate Mainstreaming Architecture in the 2021-2027 Multiannual Financial Framework, Brussels, 2022. https://commission.europa.eu/system/files/2022-06/swd_2022_225_climate_mainstreaming_architecture_2021-2027.pdf (accessed June 14, 2023).
4. General Secretariat of the Council, Building a sustainable Europe by 2030 – Progress thus far and next steps - Council conclusions (10 December 2019) , Brussels, 2019. https://www.consilium.europa.eu/media/41693/sest14835-en19.pdf (accessed June 14, 2023).
5. United States Environment Protection Agency (EPA), Why Indoor Air Quality is Important to Schools, (2022). https://www.epa.gov/iaq-schools/why-indoor-air-quality-important-schools (accessed June 14, 2023).
6. Joint Research Centre, Indoor air pollution: new EU research reveals higher risks than previously thought, Brussels, 2003. https://ec.europa.eu/commission/presscorner/detail/en/IP_03_1278 (accessed June 14, 2023).
7. THE EUROPEAN PARLIAMENT AND OF THE COUNCIL, Consolidated text: Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings (recast), 2021.
8. D. Evans, The Internet of Things. How the Next Evolution of the Internet is Changing Everything , 2011. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.cisco.com/c/dam/en_us/about/ac79/docs/innov/IoT_IBSG_0411FINAL.pdf (accessed June 14, 2023).
9. R. van der Meulen, Gartner Says 6.4 Billion Connected "Things" Will Be in Use in 2016, Up 30 Percent From 2015, Gartner. (2015). https://www.gartner.com/en/newsroom/press-releases/2015-11-10-gartner-says-6-billion-connected-things-will-be-in-use-in-2016-up-30-percent-from-2015 (accessed June 14, 2023).
10. Q. Ashraf, M. Yusoff, A. Azman, N. Nor, N. Fuzi, M. Saharedan, N. Omar, Energy monitoring prototype for Internet of Things: Preliminary results, 2015. https://doi.org/10.1109/WF-IoT.2015.7389157.
11. L. Atzori, A. Iera, G. Morabito, The Internet of Things: A survey, Computer Networks. 54 (2010) 2787–2805. https://doi.org/10.1016/j.comnet.2010.05.010.
12. S. Tang, D.R. Shelden, C.M. Eastman, P. Pishdad-Bozorgi, X. Gao, A review of building information modeling (BIM) and the internet of things (IoT) devices integration: Present status and future trends, Autom Constr. 101 (2019) 127–139. https://doi.org/10.1016/j.autcon.2019.01.020.
13. K. Lawal, H.N. Rafsanjani, Trends, benefits, risks, and challenges of IoT implementation in residential and commercial buildings, Energy and Built Environment. 3 (2022) 251–266. https://doi.org/10.1016/j.enbenv.2021.01.009.
14. M. Poongothai, P.M. Subramanian, A. Rajeswari, Design and implementation of IoT based smart laboratory, in: 2018 5th International Conference on Industrial Engineering and Applications (ICIEA), IEEE, 2018: pp. 169–173. https://doi.org/10.1109/IEA.2018.8387090.

15. T.I.P. on C.C. IPCC, Mitigation of Climate Change Climate Change 2022 Working Group III contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, 2022. https://www.ipcc.ch/site/assets/uploads/2018/05/uncertainty-guidance-note.pdf. (accessed July 17, 2022).
16. United Nations, Climate Change, United Nations. Global Issues. (n.d.). https://www.un.org/en/global-issues/climate-change (accessed June 14, 2023).
17. European Commission, Paris Agreement, European Commission. Climate Action. (2016). https://climate.ec.europa.eu/eu-action/international-action-climate-change/climate-negotiations/paris-agreement_en (accessed June 14, 2023).
18. A.H. Oti, E. Kurul, F. Cheung, J.H.M. Tah, A framework for the utilization of Building Management System data in building information models for building design and operation, Autom Constr. 72 (2016) 195–210. https://doi.org/10.1016/j.autcon.2016.08.043.
19. M.M. Sesana, G. Salvalai, A review on Building Renovation Passport: Potentialities and barriers on current initiatives, Energy Build. 173 (2018) 195–205. https://doi.org/10.1016/j.enbuild.2018.05.027.
20. United Nations, United Nations Sustainable Development Goals, (n.d.). https://www.un.org/sustainabledevelopment/ (accessed June 14, 2023).
21. A.P. Batista, M.E.A. Freitas, F.G. Jota, Evaluation and improvement of the energy performance of a building's equipment and subsystems through continuous monitoring, Energy Build. 75 (2014) 368–381. https://doi.org/10.1016/j.enbuild.2014.02.029.
22. C. Piselli, A.L. Pisello, Occupant behavior long-term continuous monitoring integrated to prediction models: Impact on office building energy performance, Energy. 176 (2019) 667–681. https://doi.org/10.1016/j.energy.2019.04.005.
23. P. Li, T. Parkinson, S. Schiavon, T.M. Froese, R. de Dear, A. Rysanek, S. Staub-French, Improved long-term thermal comfort indices for continuous monitoring, Energy Build. 224 (2020) 110270. https://doi.org/10.1016/j.enbuild.2020.110270.
24. P.A. Fokaides, C. Panteli, A. Panayidou, How Are the Smart Readiness Indicators Expected to Affect the Energy Performance of Buildings: First Evidence and Perspectives, Sustainability. 12 (2020) 9496. https://doi.org/10.3390/su12229496.
25. C.A. Balaras, K.G. Droutsa, E.G. Dascalaki, S. Kontoyiannidis, A. Moro, E. Bazzan, Urban Sustainability Audits and Ratings of the Built Environment, Energies (Basel). 12 (2019) 4243. https://doi.org/10.3390/en12224243.
26. General Secretariat of the Council, Building a sustainable Europe by 2030 – Progress thus far and next steps - Council conclusions, Brussels, 2019. https://www.consilium.europa.eu/media/41693/se-st14835-en19.pdf (accessed May 28, 2023).
27. ASHRAE, ASHRAE Position Document on Indoor Carbon Dioxide, Georgia, 2022. https://www.ashrae.org/file%20library/about/position%20documents/pd_indoorcarbondioxide_2022.pdf (accessed June 14, 2023).
28. A. Persily, Development and application of an indoor carbon dioxide metric, Indoor Air. 32 (2022). https://doi.org/10.1111/ina.13059.
29. S. Batterman, Review and Extension of CO2-Based Methods to Determine Ventilation Rates with Application to School Classrooms, Int J Environ Res Public Health. 14 (2017) 145. https://doi.org/10.3390/ijerph14020145.
30. A. Franco, F. Leccese, Measurement of CO2 concentration for occupancy estimation in educational buildings with energy efficiency purposes, Journal of Building Engineering. 32 (2020) 101714. https://doi.org/10.1016/j.jobe.2020.101714.
31. A. Franco, E. Schito, Definition of Optimal Ventilation Rates for Balancing Comfort and Energy Use in Indoor Spaces Using CO2 Concentration Data, Buildings. 10 (2020) 135. https://doi.org/10.3390/buildings10080135.
32. A. Kabirikopaei, J. Lau, Uncertainty analysis of various CO2-Based tracer-gas methods for estimating seasonal ventilation rates in classrooms with different mechanical systems, Build Environ. 179 (2020) 107003. https://doi.org/10.1016/j.buildenv.2020.107003.
33. A. Kabirikopaei, J. Lau, Uncertainty analysis of various CO2-Based tracer-gas methods for estimating seasonal ventilation rates in classrooms with different mechanical systems, Build Environ. 179 (2020) 107003. https://doi.org/10.1016/j.buildenv.2020.107003.
34. M. Justo Alonso, S. Wolf, R.B. Jørgensen, H. Madsen, H.M. Mathisen, A methodology for the selection of pollutants for ensuring good indoor air quality using the de-trended cross-correlation function, Build Environ. 209 (2022) 108668. https://doi.org/10.1016/j.buildenv.2021.108668.
35. L. Morawska, J. Allen, W. Bahnfleth, P.M. Bluyssen, A. Boerstra, G. Buonanno, J. Cao, S.J. Dancer, A. Floto, F. Franchimon, T. Greenhalgh, C. Haworth, J. Hogeling, C. Isaxon, J.L. Jimenez, J. Kurnitski, Y. Li, M. Loomans, G. Marks, L.C. Marr, L. Mazzarella, A.K. Melikov, S. Miller, D.K. Milton, W. Nazaroff, P. V. Nielsen, C. Noakes, J. Peccia, K. Prather, X. Querol, C. Sekhar, O. Seppänen, S. Tanabe, J.W. Tang, R. Tellier, K.W. Tham, P. Wargocki, A. Wierzbicka, M. Yao, A paradigm shift to combat indoor respiratory infection, Science (1979). 372 (2021) 689–691. https://doi.org/10.1126/science.abg2025.
36. C. européenne, D. générale de l'énergie, F. Durier, M. De Strycker, G. Guyot, M. Sherman, V. Leprince, M. Urbani, B. De Blaere, A. Mélois, P. Selle-Marquis, A. Janssens, Y. Decorte, P. Wouters, Technical study on the possible introduction of inspection of stand-alone ventilation systems in buildings : final report, Publications Office, 2020. https://doi.org/doi/10.2833/621790.
37. Y. Sun, T.-Y. Wu, G. Zhao, M. Guizani, Efficient Rule Engine for Smart Building Systems, IEEE Transactions on Computers. 64 (2015) 1658–1669. https://doi.org/10.1109/TC.2014.2345385.

38. M.S. Çıdık, S. Phillips, Buildings as complex systems: the impact of organisational culture on building safety, Construction Management and Economics. 39 (2021) 972–987. https://doi.org/10.1080/01446193.2021.1966816.
39. I. Uriarte, A. Erkoreka, A. Legorburu, K. Martin-Escudero, C. Giraldo-Soto, M. Odriozola-Maritorena, Decoupling the heat loss coefficient of an in-use office building into its transmission and infiltration heat loss coefficients, Journal of Building Engineering. 43 (2021) 102591. https://doi.org/10.1016/j.jobe.2021.102591.
40. M. Herrando, D. Cambra, M. Navarro, L. de la Cruz, G. Millán, I. Zabalza, Energy Performance Certification of Faculty Buildings in Spain: The gap between estimated and real energy consumption, Energy Convers Manag. 125 (2016) 141–153. https://doi.org/10.1016/j.enconman.2016.04.037.
41. P.X.W. Zou, X. Xu, J. Sanjayan, J. Wang, Review of 10 years research on building energy performance gap: Life-cycle and stakeholder perspectives, Energy Build. 178 (2018) 165–181. https://doi.org/10.1016/j.enbuild.2018.08.040.
42. A. Figueiredo, J. Kämpf, R. Vicente, R. Oliveira, T. Silva, Comparison between monitored and simulated data using evolutionary algorithms: Reducing the performance gap in dynamic building simulation, Journal of Building Engineering. 17 (2018) 96–106. https://doi.org/10.1016/j.jobe.2018.02.003.
43. S. Taheri, P. Hosseini, A. Razban, Model predictive control of heating, ventilation, and air conditioning (HVAC) systems: A state-of-the-art review, Journal of Building Engineering. 60 (2022) 105067. https://doi.org/10.1016/j.jobe.2022.105067.
44. X. Tian, Y. Cheng, Z. Lin, Modelling indoor environment indicators using artificial neural network in the stratified environments, Build Environ. 208 (2022) 108581. https://doi.org/10.1016/j.buildenv.2021.108581.
45. L.C. Tagliabue, F. Re Cecconi, S. Rinaldi, A.L.C. Ciribini, Data driven indoor air quality prediction in educational facilities based on IoT network, Energy Build. 236 (2021) 110782. https://doi.org/10.1016/j.enbuild.2021.110782.
46. Z. Afroz, G.M. Shafiullah, T. Urmee, M.A. Shoeb, G. Higgins, Predictive modelling and optimization of HVAC systems using neural network and particle swarm optimization algorithm, Build Environ. 209 (2022) 108681. https://doi.org/10.1016/j.buildenv.2021.108681.
47. European Commission, Renovation wave. Renovating the EU building stock will improve energy efficiency while driving the clean energy transition, European Commission. (2020). https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficient-buildings/renovation-wave_en (accessed June 14, 2023).
48. Eurpean Commission, In focus: Energy efficiency in buildings, Eurpean Commission. (2020). https://commission.europa.eu/news/focus-energy-efficiency-buildings-2020-02-17_en (accessed June 14, 2023).
49. Eurotstat Statistics Explained, Dwellings by period of construction, national averages and capital regions, 2011, Eurotstat. (2011). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Dwellings_by_period_of_construction,_national_averages_and_capital_regions,_2011_(%25_share_of_all_dwellings)_PITEU17.png (accessed June 14, 2023).
50. A.D. Korberg, J.Z. Thellufsen, I.R. Skov, M. Chang, S. Paardekooper, H. Lund, B.V. Mathiesen, On the feasibility of direct hydrogen utilisation in a fossil-free Europe, Int J Hydrogen Energy. 48 (2023) 2877–2891. https://doi.org/https://doi.org/10.1016/j.ijhydene.2022.10.170.
51. J. Rosenow, Is heating homes with hydrogen all but a pipe dream? An evidence review, Joule. 6 (2022) 2225–2228. https://doi.org/https://doi.org/10.1016/j.joule.2022.08.015.
52. E. Commission, J.R. Centre, Atlas of the human planet 2020 : open geoinformation for research, policy, and action, Publications Office, 2021. https://doi.org/doi/10.2760/16432.
53. Eurostat Statistic Explained, Heating and cooling degree days - statistics, Eurostat. (2023). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Heating_and_cooling_degree_days_-_statistics (accessed June 14, 2023).
54. S. Quefelec, Cooling buildings sustainably in Europe: exploring the links between climate change mitigation and adaptation, and their social impacts, European Environment Agency. (2022). https://www.eea.europa.eu/publications/cooling-buildings-sustainably-in-europe (accessed June 2, 2023).
55. International Energy Agency, The Future of Cooling Opportunities for energyefficient air conditioning, 2018.
56. European Commission, Smart Readiness Indicator (SRI) for Buildings, (2018). https://smartreadinessindicator.eu/ (accessed June 28, 2023).
57. European Commission, Outcomes of the first technical study about SRI, (2018). https://smartreadinessindicator.eu/1st-technical-study-outcome (accessed June 28, 2023).
58. LoRa Alliance, What is LoRaWAN Specification, LoRa Alliance. (2023). https://lora-alliance.org/about-lorawan/ (accessed June 28, 2023).
59. I. Martínez, B. Zalba, R. Trillo-Lado, T. Blanco, D. Cambra, R. Casas, Internet of Things (IoT) as Sustainable Development Goals (SDG) Enabling Technology towards Smart Readiness Indicators (SRI) for University Buildings, Sustainability. 13 (2021) 7647. https://doi.org/10.3390/su13147647.
60. Ministerio de la Presidencia, Real Decreto 1826/2009, de 27 de noviembre, por el que se modifica el Reglamento de instalaciones térmicas en los edificios, aprobado por Real Decreto 1027/2007, de 20 de julio, Documento BOE-A-2009-19915, Spain, 2009.
61. MATLAB & Simulink - MathWorks, Fit Data with a Shallow Neural Network, (2023). https://es.mathworks.com/help/deeplearning/gs/fit-data-with-a-neural-network.html (accessed June 28, 2023).