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Enhancing Building Energy Management: Adaptive Edge Computing for Optimized Efficiency and Inhabitant Comfort †

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Abstract: Nowadays, in contemporary building and energy management systems (BEMSs), the predominant approach involves rule-based methodologies, typically employing supervised or unsupervised learning, to deliver energy-saving recommendations to building occupants. However, these BEMSs often suffer from a critical limitation—they are primarily trained on building energy data alone, disregarding crucial elements such as occupant comfort and preferences. This inherent lack of adaptability to occupants significantly hampers the effectiveness of energy-saving solutions. Moreover, the prevalent cloud-based nature of these systems introduces elevated cybersecurity risks and substantial data transmission overheads. In response to these challenges, this article introduces a cutting-edge edge computing architecture grounded in virtual organizations, federated learning, and deep reinforcement learning algorithms, tailored to optimize energy consumption within buildings/homes and facilitate demand response. By integrating energy efficiency measures within virtual organizations, which dynamically learn from real-time inhabitant data while prioritizing comfort, our approach effectively optimizes inhabitant consumption patterns, ushering in a new era of energy efficiency in the built environment.

Keywords: building and energy management systems (BEMSs); edge computing; energy efficiency (EE); federated learning (FL); deep reinforcement learning (deep RL); internet of things (IoT); virtual organizations

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1. Introduction

The demand for commercial and suburban development is growing at a much faster rate than efforts to increase the sustainability of buildings. According to the latest report, the "2022 Global Status Report for Buildings and Construction" from the United Nations Environment Programme (UNEP) [1], published on 9 November 2022, and data extracted from the "Buildings Energy System" report by the International Energy Agency (IEA) [2] in 2021, it was indicated that 28% of the total global energy consumption came from residential and non-residential buildings (excluding the building construction industry, concrete, aluminum, and steel). Furthermore, it has been found that these buildings accounted for 28% of energy-related CO_2 emissions (including both direct and indirect emissions from residential and non-residential buildings) on a global scale. These statistics underscore the critical need for low-carbon, energy-efficient buildings to become the standard in towns and cities worldwide. This would also significantly contribute to preventing further global warming, as outlined in United Nations (UN) Sustainable Development Goal 13, Climate Action [3], which aims to limit the temperature increase to below 2 °C by 2030.

The concept of smart homes aims to not only create environmentally friendly buildings but also promote savings for both inhabitants and distribution network operators (DNOs). Smart buildings are enabled by technologies within the paradigms of the internet of things (IoT), as well as machine learning (ML) and deep learning (DL). IoT-based energy management systems (EMSs) combine sensors, communication protocols, and advanced learning algorithms for the collection of energy and data from homes or industries, enabling information-driven efficient energy use in buildings/homes [4–8]. Similarly, it is necessary to manage other scarce resources in buildings, houses, and industries. Generally, urban and industrial environments use similar technologies for the intelligent management of these resources, as is the case in intelligent water management [9]. Also, important services associated with human activity in buildings and homes are being planned using these technologies, as in the case of waste management [10,11] and garbage collection [12].

There have been numerous ML and DL proposals for energy efficiency in buildings in the recent literature [13–17]. These measures are designed to optimize demand response (DR) through energy consumption and generation forecasts (including distributed energy resources—DER) under different operational circumstances. However, their internal analyses cannot be interpreted; they have a black-box system that identifies the relationship between various inputs and outputs by means of a number of supervised and unsupervised learning algorithms. However, these approaches usually have two major drawbacks:

- The energy efficiency (EE) measures recommended by these ML and DL models solely consider energy-related variables. They are not focused on the inhabitants' ability to adopt these solutions in their daily life, i.e., they do not consider the inhabitants' comfort or the reputation of the recommended energy-saving measures among inhabitants.
- Generally, classical ML models, especially those based on DL, cannot be interpreted, impeding the recommendation of EE measures.

Further advancements in smart buildings have been enabled by the emergence of cloud computing, which makes it possible to control connected devices remotely [18,19]. Unfortunately, the increasing number of IoT devices, network bandwidth, and security weaknesses have become a bottleneck, limiting the performance of these systems. Edge computing is able to support cloud computing solutions, solving the problem of scalability and increasing cybersecurity [20]. It is a new, promising computing paradigm that involves the creation of a network infrastructure in the user's vicinity, which is plentiful in IoT resources (i.e., storage, computing, and bandwidth). Moreover, it minimizes latency by processing real-time, security-crucial data in a one-hop manner [21]. Greater security is provided to sensitive data by processing it at the edge of the network, further security can be added by integrating distributed ledger technology (DLT) [22–24].

In this article, the social computing approach is adapted to provide solutions to the problems discussed above. An architecture based on virtual organizations has been built to propose EE recommendations that encompass the inhabitants' preferences. The system makes these suggestions to users on the basis of analyzing similar consumption behavior profiles. Moreover, the black-box problem is addressed through the integration of federated learning (FL) to training machine learning models, each one of them making use of its own dataset, and deep reinforcement learning (deep RL), which combines reinforcement learning (RL) and deep learning techniques. Deep RL is often classified as a narrow AI technique [25]. This groundbreaking approach brings energy efficiency (EE) measures within virtual organizations that dynamically learn from real-time inhabitant data. As a result, consumption patterns within buildings are no longer rigidly predetermined, but rather adapt and evolve according to the unique needs and preferences of the occupants.

Such adaptability is poised to make BEMSs truly effective, optimizing energy usage while ensuring inhabitant comfort remains paramount.

This paper investigates the design and development of a new DLT platform that acts as an oracle (blockchain oracle) [26,27], gathering information from data sources (i.e., IoT) and guaranteeing its trustworthiness. To achieve this, a set of smart contracts have been designed to publish and/or consume data, and users automatically execute those contracts when uploading information about their buildings or consumption (downloading a report or receiving suggestions from the decision support system (DSS)). The architecture of DLT ensures that the data are owned by the user who subscribes to the contract. Moreover, the implementation of side registers in the data sources helps to reduce the workload in the central ledger (it stores a hash to identify the data store where the real-time information is gathered). In addition, to guaranteeing data privacy and security, the edge nodes (gateways) include crypto-elements that allow them to cipher the IoT data coming from sensors in buildings, even before sending the data to the DLT platform. Also, we have adhered to the best practices and standards related to smart grid technology, particularly referencing IEC TR 63097:2017, which provides a comprehensive framework for smart grid standardization. This standard outlines the roadmap for various processes relevant to our research, such as data collection, analysis, and energy optimization.

In addition to the contributions highlighted above, it is important to note that our research addresses a critical need in a rapidly growing and urbanizing world. The increase in demand for commercial and suburban settlements has placed significant pressure on the sustainability of buildings and their impact on CO_2 emissions. Our focus on creating smart and sustainable buildings, supported by cutting-edge technologies and innovative machine learning approaches, not only aligns with the United Nations' sustainable development goals but also offers concrete solutions to address this growing demand efficiently and environmentally responsibly. Ultimately, our work has the potential to transform the way resources are managed and used in buildings and homes, contributing to a more sustainable and environmentally conscious future in cities worldwide.

This research article is organized as follows: Section 2 presents an overview of the state of the art in building and energy management systems (BEMSs). Section 3 describes the methodology followed in the development of the proposal. Section 4 outlines the architecture of the system. Section 5 presents the conducted case study. Finally, the results and discussion are presented in Section 6; conclusions and future lines of research are discussed in Section 7.

2. State of the Art

The importance of the global building energy management systems and smart building markets may be understood through two corresponding reports recently published by Maximize Market Research. As per the report entitled *"Building Energy Management Systems (BEMS) Market: Global Industry Analysis and Forecast (2023–2029)"* [28], published in July 2023, the BEMSs market was worth USD 8.84 bn in 2022 and total revenue is expected to grow at a rate of 12.4% compound annual growth rate (CAGR) from 2023 to 2029, reaching almost USD 20.04 bn in 2029. On the other hand, in accordance with the report *"Smart Building Market: Global Industry Analysis and Forecast (2023–2029)"* [29], also published in July 2023, the smart building market was valued at USD 80.92 bn in 2022, and the global smart building market size is estimated to grow at a CAGR of 10.89%, thus is expected to reach the value of USD 166.85 bn by 2029.

Smart home and smart building technologies are a current trend in the development of modern society. These technologies are intended to provide intelligent living environments for daily convenience and comfort [30]. A smart building can be defined as a building containing a communications network, linking sensors, smart domestic appliances, and devices that can be remotely monitored and controlled to provide services that respond to the behavior of residents. The main objective of a smart building is to maximize the residents' comfort, whilst enabling them to live in an economic, healthy, and environmentally friendly manner. This goal may be achieved by deploying fully automated control of appliances in order to produce high levels of comfort and security, facilitate energy management, reduce environmental emissions, and optimize energy consumption. Smart buildings have five essential characteristics: automation (ability to perform automatic functions), multi-functionality (ability to perform various duties), adaptability (ability to learn and predict residents' behaviors), interactivity (ability to interact with different stakeholders such as building owner, network operator, etc.), and efficiency (ability to save time, energy, and costs) [31,32].

Another closely related concept is that of a smart city. A smart city would be made up, for the most part, of smart buildings such as those described above. Current cities are experiencing constant growth, as indicated in [33]. Since 2007, the size of the urban population has exceeded that of the rural population, and, according to forecasts, it is expected that by 2050, 68.4% of the population will live in urban environments, as stated in the last report published by the Department of Economic and Social Affairs of the United Nations, under the title *"World Urbanization Prospects The 2018 Revision"* (Table I.3, page 11) [34]. This growth means that urban management is becoming increasingly complex. This fact, together with the need to optimize natural and energy resources, has led to the exploration of new technological buildings, giving rise to numerous studies, pilot tests, and even projects in production. Among notable studies in the field of smart buildings, Ghayvat et al. [35] predicted the well-being of inhabitants. This was achieved through the creation of IoT nodes integrated in a distributed environment for the collection of real-time data from the inhabitant's home. Another relevant study [36] proposed the use of techniques for monitoring energy consumption and tracking electricity market movements for residential energy management, where the home itself acts as a price-taking agent in the local market. Another example is GreenVMAS Gonzalez-Briones2018, a system which uses the residual energy generated by power plants to heat greenhouses. There are also studies dedicated to recognizing the main parameters that should be monitored in the energy management of buildings, as is the case in [37], which explored the energy consumption patterns associated with human occupation using internet of things techniques. Determining these parameters and standardizing them can be decisive for the success of a project in this field. Using this knowledge as a basis, it is possible to build more robust projects with a more reliable scientific basis. A different approach was proposed in [38], where the aim was not to use IoT and sensorization techniques, but to improve energy efficiency directly by changing the behavior of users through education. To this end, the authors studied people's behavior, warning them and correcting the behaviors that caused higher energy consumption. Leaving aside the numerous studies found in the field of smart buildings, we have carried out an analysis of the most promising technologies or disciplines for this sector, among which is the internet of things, better known as IoT. IoT is an emerging discipline in fields such as smart cities, smart homes, physical security, e-health, logistics, etc. [39]. Architectures that enable the IoT to be integrated into smart buildings have been discussed in [39]. In IoT, there are different variants of distributed architecture; some studies, such as the one mentioned above or the study in [40], define a generic and distributed architecture of the IoT applied to the concept of smart cities and smart buildings. IoT generates large amounts of data in all areas where it is applied, allowing smart buildings to become sources of data. Due to the variety and number of different IoT devices that can be applied, there are studies, such as the one presented in [41], dedicated to the transformation of heterogeneous data collected by an IoT network in a smart building into a homogeneous dataset. Linked to the term IoT is a newer term known as the internet of energy or IoE. In [42], this concept was defined as a concrete implementation of the IoT applied to distributed energy systems that seek energy efficiency and aim to protect the environment and avoid unnecessary energy waste.

In the field of artificial intelligence, there are different studies and developments that are beginning to apply this type of technique to energy saving. Among these studies is [43], which compiled works from numerous reliable sources such as Scielo, Dialnet, or Elsevier to determine the different applications of artificial intelligence in energy saving, defending the viability of these techniques. We have also found reviews such as the one in [44], which showed the importance of energy saving and the need to use intelligent models aimed at reducing electricity consumption. Some examples of these applications are found in [45], where the use of a predictive control model in an energy management system is proposed, developing a comfort temperature predictor for heating, ventilating, and air conditioning (HVAC) systems.

The development of smart buildings requires the deployment of disruptive technologies, among which are big data engineering and analytics, artificial intelligence and machine learning, cloud and edge computing, distributed sensing and actuation technologies such as the IoT, etc. The state of the art of specific technologies in connection with the objectives of this work, is presented in the following subsections.

2.1. Edge Computing

The IoT refers to an advanced connection to various devices and systems by means of communication protocols and forming wireless or wired networks, making these components accessible to the user anytime and anywhere. An effective IoT solution should have an architecture capable of coordinating and managing all the resources involved in an IoT environment. A typical IoT system consists of five major components, namely: (1) devices or sensors (terminal), (2) networks (communication infrastructure), (3) cloud (data repository and data processing infrastructure), (4) analytics (computational and data mining algorithm), and (5) actuators or user interfaces (services). The architecture of an IoT system is typically divided into layers; three different architectures had been presented in previous works, as shown in [46]. The most common architecture used in research on smart buildings (SBs) is the three-layer architecture, which consists of the (1) perception layer, (2) network layer, and (3) application layer [47,48].

The IoT requires a robust and resilient architecture for fast data processing as well as storage. Several researchers have suggested that it is necessary to integrate edge computing (EC) with the IoT in SBs. There are two main aims with this: integration (to combine new, intelligent, and interoperable services in SBs) and interoperability (to enable the distribution of smart services among all of the subsystems of a building). The EC serves as the intermediary between the end users/devices and the cloud; it provides processing and storage functionalities to a large number of IoT end-devices. The proximity of edge devices minimizes computational load in the cloud, enhancing real-time responses and reducing network latency to overcome the limitations associated with the cloud computing models [21].

Various edge-computing-based solutions for SBs have been proposed in the literature [49]. Liu et al. [4] designed an edge-computing-based EMS for smart cities using IoT and deep reinforcement learning. The key objectives in this paper included minimizing latency and cost and efficiently managing resources. In [50], the feasibility of using edge computing for state estimation (SE) is presented for distributed monitoring and control tasks in smart grids. The authors integrated two distributed SE solutions (based on probabilistic graphical models and distributed optimization) in a 5G communication scenario using mobile edge computing (MEC). The usability of renewable energy in smart grids using edge computing was proposed in [51] by means of a reference model that integrates the fog computing concept in the smart grid (SG). In [52], a cloud-fog computing architecture was proposed for energy demand scheduling, which improves the daily consumption distribution, reducing the total energy cost for SBs. A model based on cloud–fog, providing different types of computing services for SG resource management for load balancing between the requests of an SG user and service providers, is presented in [53]. A comparison of techniques that might be suitable for the purposes of this work is provided in [54].

The above literature review clearly indicates the potential of edge computing in the development of SBs and in enhancing the SG. However, each work considers a limited set of objectives and considers a specific scenario. Moreover, most of the works are theoretical proposals, and there exists no complete edge-computing-based SB solution covering the whole picture. Therefore, there is a need for an edge-computing-based architecture to comprehensively address all the aspects of SBs from multiple perspectives.

2.2. Federated Learning

As stated in [55], the term federated learning, also known as collaborative learning, was first coined by Google [56–58]. FL is a decentralized ML that trains an algorithm across multiple devices by keeping the data samples local without exchanging them with the centralized server. When using traditional ML, the model is trained with the data received from the different devices that have been uploaded to a centralized server. There, the ML algorithm uses the data to train itself and finally predicts results for new data. However, having users' data continually sent to the server can lead to a so-called "privacy nightmare", where all or part of the data could be leaked or compromised. To deal with those hypothetical privacy problems, federated learning could be one of the best options available. FL generates more robust models without sharing data, leading to privacy-preserved solutions with higher security and access privileges to data [59].

Aledhari et al. [59] also provide a comprehensive study of FL with an emphasis on enabling software and hardware platforms, protocols, real-life applications, and use cases. In [60], the unique characteristics and challenges of federated learning provide a broad overview of current approaches and outline several directions of future work that are relevant to a wide range of research communities. The authors of [61] systematically introduce the existing works of federated learning from five aspects: data partitioning, privacy mechanism, machine learning model, communication architecture, and systems heterogeneity. Moreover, Kairouz et al. [62] discussed recent advances and presented a comprehensive and updated collection of open problems and challenges in FL.

Two of the most recent developments in FL are worth mentioning. The first one presents a novel approach to federated learning, robust federated aggregation (RFA), that endows its aggregation process with greater robustness to potential poisoning of local data or model parameters of participating devices [63]. RFA is agnostic to the level of corruption and aggregates model updates without revealing each device's individual contribution. The second development was presented in [64] and proposes a practical and robust approach to personalization in FL that adjusts to heterogeneous and non-IID (independent and identically distributed) data by balancing the exploration and exploitation of several global models.

For the purposes of this work, FL has many advantages over traditional ML, including the following:

- The preservation of data privacy.
- It is hyper-personalized since it learns from each user's inputs.
- It allows for low cloud infrastructure overheads as the model training, one of the operations with the highest computational cost, is carried out in a distributed manner on several external devices.

2.3. Virtual Organizations

In a complex environment, such as the one proposed in this article, it is difficult to determine when and how to recommend measures to promote changes in consumption or in consumer behavior effectively. To address this problem from an innovative point of view, we can look for inspiration in human societies. In human societies, we can find organizational structures that are created and evolve by means of emergent or complex deliberative behaviors. Agent technology may imitate human societies through the constitution of dynamic virtual organizations of agents. These systems are capable of making decisions in an autonomous and flexible way, cooperating with other systems inside an organization [65,66]. Different studies have provided different perspectives on how organizations should be structured in order to adapt themselves easily and efficiently to changes in their environment, adapting old roles to new circumstances or creating new ones [67–69].

Agent-based virtual organizations are particularly well suited as support for the development of BEMSs [70–74]. They enable the description of structural compositions and functional behavior and the inclusion of normative regulations for controlling agent behavior, for the dynamic entry/exit of components, and for the dynamic formation of agent groups [75]. Virtual organizations provide distributed solutions for the resolution of problems, but at the same time, they also provide a high degree of autonomy and independence. The development of virtual organizations of agents is still a recent field in the multi-agent system paradigm, it is necessary to develop new methods to model agent-based virtual organizations and innovative techniques and provide advanced organizational abilities to virtual organizations.

An analysis of the possibilities and benefits derived from implementing artificial societies shows that virtual organizations are a suitable technology for the complex and highly dynamic operation of BEMSs [76,77].

2.4. Social Computing

Recent tendencies have led to the social computing paradigm under which social systems are designed to facilitate the construction of sociotechnical tools where humans and machines collaborate to resolve social problems [78,79]. These tools have a high level of complexity and must have artificial intelligence to be able to manage artificial societies. Nevertheless, they have the capacities needed to ensure effective collaboration between humans and machines, according to the classification of social computing within the human–machine relationship presented in [79]. The social computing paradigm creates social entities managed by both technology and social processes known as social machines. These entities allow systems to give recommendations to users, such as the social machine developed by Amazon [80], which collaborates with humans to perform tasks. Other examples include the CAPTCHA (completely automated public Turing test to tell computers and humans apart) system for user authentication [81,82], or Twitter's system for predicting social dynamics from behavior data [83].

There is a number of studies that address the problem of behavioral change for energy efficiency by using serious games through social networks [84–86]. However, human–machine interactions are not addressed in depth in these solutions, leaving aside, for example, contextual information that may be useful in the field of our focus. Moreover, these proposals do not offer working infrastructures that would allow for the integration of different technologies, various communication protocols, or diverse ways of promoting social relations. Moreover, they often lack the intelligence to manage the system according to the needs of the game.

In this article, a framework is proposed based on social computing and context awareness, which automates energy efficient actions and encourages a change in the behavior of consumers towards more energy efficient habits in their buildings/homes.

2.5. Deep Learning

An ambitious objective pursued in artificial intelligence (AI) is to develop fully autonomous artificial agents capable of interacting with their environments, learning optimal behavior, and improving their responses over time. Developing such systems is a challenge; it involves several research fields and may have diverse applications, ranging from robots capable of responding to their context to software capable of supporting the human decision-making processes [87]. In the last decade, the application of machine learning techniques in data analysis has been revolutionary [88]. Advances in deep learning techniques [89], the present-day possibilities of collecting and accessing large amounts of data, the processing capacity of computing systems (dedicated processors such as GPUs, cards designed for the computation of artificial intelligence algorithms), as well as the design of new architectures [90] (e.g., edge computing designs combined with a vision processing unit (VPU) or a tensor processing unit (TPU) hardware [91]), have all led to breakthroughs in this area.

This continuous evolution has been crystallized in the new paradigms of AI related to the learning capacities of machines, such as deep learning solutions [92] and reinforced learning (RL) techniques. Thanks to deep neural networks [93], new milestones have been achieved both in the prediction [94] and classification of data [95] (e.g., generative adversarial networks (GANs) [96]) as well as in the processing of long series of data (e.g., recurrent networks [97] and long short-term memory (LSTM) [98]). These cutting-edge solutions [99] (including auto-encoders, deep belief networks, deep forest, capsules, deep Boltzmann machines, and hybrid algorithms merging some of these solutions) have high success rates in pattern recognition [100], artificial vision [101], natural language processing (NLP) [102], data relations, etc. The superposition of different layers for the analysis of big datasets allows such algorithms to cluster [103] and recognize (low level) features in (high level) data (audio, text, images, etc.), overcoming the limitations of previous approaches (e.g., perceptron) and adding abstraction layers to enable these smart systems to handle hierarchical concepts.

Additionally, DL solutions are able to learn from unprocessed data and to improve their response after the training phase. These techniques are very useful when the data samples are incomplete or biased, implementing reinforced learning solutions [104] (e.g., deep Q-network (DQN) or deep Q-learning [105], double DQN, dueling DQN, multi-step DQN, and other algorithms based on policy gradient [106], such as reinforce, advantage actor–critic, natural policy gradient, etc.) are able to evolve the predictive capacity [107] of the system and the accuracy of the responses, even when the system has not been extensively trained or when it is working in a production environment. This new prism allows us to scale AI solutions to high-dimensional problems and provide solutions to complex scenarios.

AI-based smart systems have been demanded in complex environments where new approaches are needed to achieve optimal performance. For these purposes, it has been observed that different evolutionary computation techniques [108] (genetic algorithms [109], swarm intelligence [110], discrete differential evolution algorithms [111], neuroevolutionary learning techniques [112]) obtain good results and improve the multi-criteria optimization problems that take place in such extreme contexts [113], by providing a holistic approach, taking into consideration not only parameters but also topologies and rules.

On the other hand, we may find deep reinforcement learning techniques combining reinforcement learning and deep learning. RL aims to develop and train an ML model through trial and error so that it can reach the correct conclusion and make the right decisions. However, deep RL incorporates DL into the solution, allowing agents to make decisions from unstructured input data [114]. Several papers have recently been published that apply deep RL to smart buildings. A review of deep reinforcement learning for smart building energy management was presented in [115]. A more recent paper presents a systematic review of deep reinforcement-learning-based energy management for different types of buildings [116]. In addition, an energy-efficient heating control system with deep reinforcement learning has been presented for smart buildings [117].

2.6. Research Gaps

In conclusion, the state of the art section has provided a comprehensive overview of various technologies and concepts related to building energy management systems (BEMSs) and smart buildings. It highlights the importance of these technologies in the context of the global building energy management and smart building markets, which are experiencing significant growth. Smart buildings aim to provide intelligent living environments that maximize comfort, energy efficiency, and environmental sustainability.

This section also discusses related concepts such as smart cities, which are closely connected to smart buildings and are expected to grow significantly due to urbanization trends. The review of notable studies and developments in the field demonstrates the diversity of approaches to achieving energy efficiency and user comfort in smart buildings, from IoT integration to behavioral change strategies.

The section further explores specific technologies, including edge computing, federated learning, virtual organizations, social computing, deep learning, threat intelligence, and distributed ledger technologies. These technologies offer opportunities and challenges for enhancing the performance and security of smart buildings.

Overall, the state of the art section lays the foundation for the subsequent discussion of these technologies in connection with the objectives of the work. It identifies key research gaps, including the need for effective integration of emerging technologies, addressing privacy and security challenges, scalability for resource-constrained devices, and promoting user behavior change. These gaps present opportunities for future research and development in the field of smart buildings and energy management systems.

3. Methodology

3.1. Functional Requirements

This subsection presents the functional requirements of the proposed AI-BEMS system. The study entails identifying the data sources that have been used to determine the behavioral patterns, defining use-case scenarios, analyzing customer feedback from a prior project, and stakeholders' needs from a distribution system operators (DSOs) perspective. The methodology used in this study is grounded in action research, fostering collaboration between researchers and practitioners. It involves iterative stages: problem identification, planning, intervention, data collection, reflection, and action. We began by identifying a specific issue and collaboratively planned interventions. These interventions were implemented while collecting relevant data. Data analysis led to a reflective phase, enabling us to evaluate outcomes. Informed decisions guided subsequent actions. This iterative approach resolved the problem and generated actionable insights for future practices, emphasizing real-world relevance and meaningful change.

Data Sources

Five key components have been identified in the IoT layer that cover most of the building's needs, namely, the total building smart meter energy consumption, the heating ventilation and air conditioning (HVAC) system, the lighting system, the electric vehicle (EV), and the water heater (Figure 1). Together, these can cover the largest part of the building's energy consumption. Different synchronous and asynchronous data and metadata can be generated from these devices with different types and velocities. In addition, dealing with energy management in buildings requires knowledge of local weather conditions. Given that weather APIs serve this purpose with high accuracy, the system has been connected to a paid weather API which provides all the needed inputs.

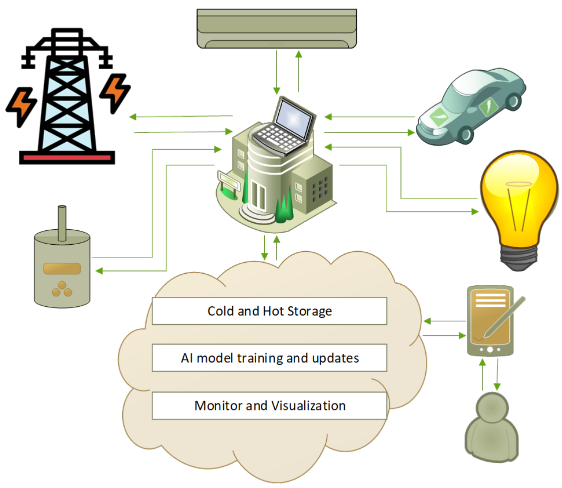

Figure 1. Holistic overview of the system's components.

Also, user preferences and other contextual data play a critical role in the evaluation of the system performance and the analysis of behavioral patterns of the population. Furthermore, under the umbrella of demand side management (DSM), a connection to the distribution system operators (DSOs) is required. This connection provides data related to the electricity tariffs and power and energy reduction/increase demands. Table 1 summarizes a list of device inputs to the energy management system.

Table 1. Input data into the system.

Name of the Variable	Type of Variable	Possible Values	Example	Static	Source
VACATION MODE	Boolean	True/False	Off	No	User comfort preferences setup
Thermal Range (°C)	array	Array between 16 and 32	22,23,24,25,26,27	No	User comfort preferences setup
Exported Energy (Wh)	int	Integer between 0 and 99,999	1609	No	Smart meter
Generated Energy (Wh)	int	Integer between 0 and 99,999	234	No	Smart meter
Purchased Energy (Wh)	int	Integer between 0 and 99,999	2345	No	Smart meter
Self Consumption (Wh)	int	Integer between 0 and 99,999	2342	No	Smart meter
Total Consumption (Wh)	int	Integer between 0 and 99,999	6235	No	Smart meter
Voltage (V)	int	Integer between 0 and 99,999	230	No	Smart meter
Current (A)	int	Integer between 0 and 99,999	10	No	Smart meter
Reactive Energy (VARh)	int	Integer between 0 and 99,999	2345	No	Smart meter
Battery Status (%)	int	Integer between 0 and 100	80	No	EV
Charging Rate (A)	int	Integer between 0 and 32	23	No	EV
Session Status	String	8 character string	Charging	No	EV
Max Available Power (kW)	int	Integer between 6 and 99	32	Yes	EV
End Session Time	float	date-time	44,804.58333	No	EV
Water Heater Status	String	8 character string	Heating	No	Water heater
Water Heater Consumption (Wh)	int	Integer between 0 and 99,999	2300	No	Water heater
Zone Temperature (°C)	int	Integer between 0 and 99	25	No	HVAC
Zone Humidity (%)	int	Integer between 0 and 100	45	No	HVAC
Fan Speed (m/s)	int	Integer between 0 and 99,999	300	No	HVAC
HVAC Mode	String	10 character string	Cool	No	HVAC
Zone Setpoint (°C)	int	Integer between 0 and 99	22	No	HVAC

There are many methods for gathering and evaluating the required experimental datasets. Since most of the project's data are in the shape of time series that are either treated in real-time to make a decision or stored in the database for later processing, time series analysis is one of the analysis mechanisms that has been used throughout the project. Time series analysis is the examination of a series of data items, usually separated by constant periods of time. The goal of time series analysis is to obtain useful statistics and other characteristics from the data. In addition, the analysis of such diverse and big data requires the use of data mining techniques to uncover hidden patterns and optimize the control of the devices. Also, given the complexity of the problem and the high interconnection of different components, sensitivity analysis at different levels should be part of the assessment of how the target variables are impacted by the input variations, scenarios, and assumptions. In addition, behavior analysis forms a cornerstone in the success of the energy management system, as human perception of comfort and satisfaction play a key role in defining the success of the system's actions. Therefore, user preferences and their feedback have been included in the system through direct feedback via the web app and indirectly by analysis of their manual control interventions. Continuous interaction with DSO operators has also been part of the system development and improvements to satisfy their functional and technical requirements. Quantitative and qualitative analyses have also been carried out throughout the product design, development, and testing.

3.2. Non-Functional Requirements

This subsection is dedicated to the definition of the technical specifications of the 3-tier architecture along with the hardware requirements of the edge. Also, it sheds light on the possible energy efficiency (EE) measures that can be used in the context of the desired system.

3.2.1. Specifications of the 3-Tier Architecture

Due to the high complexity and interconnection of the system's components, stringent requirements should be satisfied to achieve the optimal performance of the product. Therefore, multiple specifications at the different layers have been defined and are measured through specific indices that help in the assessment of the overall system. Figure 2 shows the proposed virtual organizations adapted to the 3-tier edge-computing architecture.

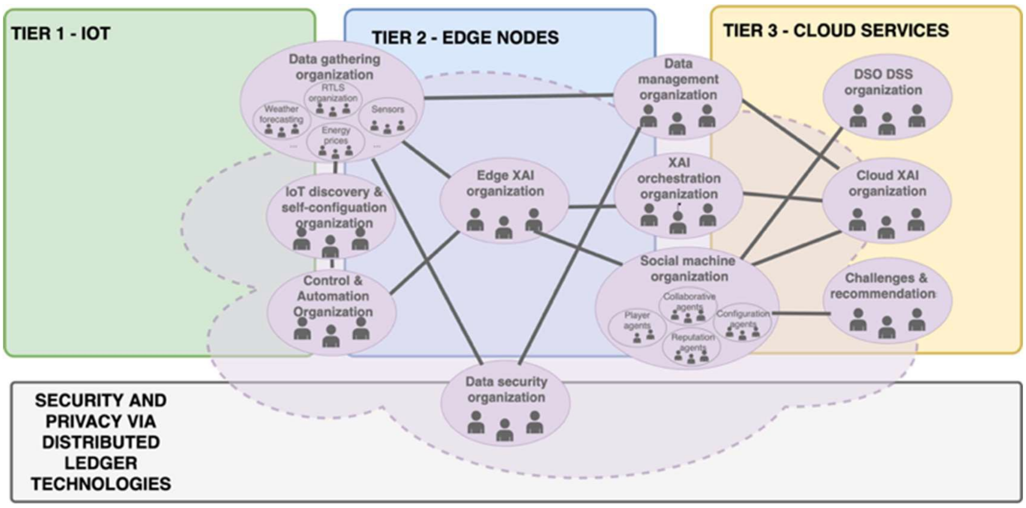

Figure 2. Proposed virtual organizations for a BEMS adapted to the 3-tier edge-computing architecture.

The architectural specifications for edge-building and edge-cloud systems encompass several key aspects that ensure the robustness, flexibility, security, and management capabilities of edge-building and edge-cloud systems, enabling efficient operation and scalability:

- Edge-building architecture emphasizes modularity, allowing components to be added or removed without disrupting the system's flow. Maintenance should be seamless, enabling debugging and issue resolution without affecting other devices or functionalities. Adaptability is crucial for connecting to various devices and protocols, while reliability ensures resilience in the face of failures. Scalability is measured by the system's capacity to handle devices and simultaneous calls. Security is paramount for communication protocols, and orchestration manages call priorities and synchronization. Communication should support both synchronous and asynchronous commands with robust recovery mechanisms. The network architecture must ensure reliable and timely device–edge communication. Lastly, seamless integration is vital for establishing connections with both known and unknown devices.
- On the other hand, the edge–cloud architecture also emphasizes modularity and maintenance, with a focus on communication protocols and acceptable latency. Reliability remains critical, and scalability pertains to the number of buildings supported. Security extends to edge–cloud communication, while storage architecture considers hot and cold storage needs.
- Data management is crucial for handling online and offline data, optimizing data flow between devices, edge, and cloud, integrating data from external sources, and managing data lifecycles based on usage patterns. Demand management with third-party API integration meets the requirements.
- Dashboards provide user and device management interfaces, enabling analytics insights and real-time monitoring. Mobile/web apps offer user interaction and preference management through APIs.
- Logging involves historical user preference logging, device failure tracking, and command logging for smart devices, while alerts notify of device connection failures and power threshold exceedances.

3.2.2. Hardware Requirements of the Edge

The hardware requirements of the edge node have been gathered based on the future applications of this device for the analysis of collected data and the use of federated learning techniques. High requirements are proposed in order for the edge node to be able to perform its task comfortably and with reduced processing times. The edge node must meet several essential criteria to ensure optimal performance and functionality. It necessitates a 64-bit processor with at least 2 cores, 4 GB of LPDDR4 RAM, and a GPU equipped with CUDA cores for efficient processing of intelligent tasks. Additionally, it should support a 64-bit operating system, preferably Ubuntu, and be compatible with Python 3.7 or higher, along with critical libraries such as Pandas, Numpy, Scikit-Learn, or TensorFlow. Wireless connectivity is a must, either through native WiFi capabilities or a WiFi expansion module, while also featuring general-purpose GPIO pins and support for I2C, I2S, SPI, and UART protocols. Wired gigabit ethernet connectivity ensures reliability, and the device should boast AI performance exceeding 0.5 TFLOP while maintaining power consumption below 20 W to promote energy savings in home environments. It is desirable that the edge node has the capability to work with protocols such as Sigfox, Zigbee, ZWave, or LoRa. This may require the use of intermediary hardware.

3.2.3. AI Requirements

Edge computing is a distributed computing paradigm where the data storage and computation are brought closer to the edge device. However, edge AI is the combination of AI and edge computing that has the ability to apply machine learning algorithms to data generated by IoT devices at a local level. As opposed to cloud-based AI, edge computing hardware devices process the data/information and make decisions independently without an internet connection.

Quality of experience (QoE) in edge computing depends on various vital criteria. Performance measures, such as training loss and inference accuracy, stand as crucial benchmarks for assessing the effectiveness of AI models. Cost considerations encompass computation, communication, and energy consumption, with a strong focus on cost reduction, aligning with the mission of edge computing to minimize latency. Privacy and security are intertwined, emphasizing localized data processing to restrict data transmission to external locations. Efficiency, attained through techniques such as model compression and algorithm asynchronization, plays a pivotal role in optimizing performance. Reliability, ensuring uninterrupted operation over prescribed periods, relies on robust security measures and speed.

Challenges within this context extend to deep reinforcement learning (DRL), where resource-constrained edge environments necessitate limitations on mathematical models and optimization problems. Algorithm deployment grapples with the computational complexity of DRL methods and deciding which edge device should handle the deployment of intricate DRL algorithms. Balancing optimality and efficiency remains a core challenge, requiring resource trade-offs in resource-constrained edges. Data availability underscores the need for accessible and usable training data, with incentives for data provisioning. Model selection confronts challenges in selecting appropriate DRL models, defining learning thresholds, and choosing suitable training frameworks. A coordination mechanism remains essential to harmonize disparities in computing power and communication resources among heterogeneous edge devices.

In the realm of deep reinforcement learning (DRL), the main concept revolves around developing AI systems with transparent and understandable decision-making processes. Practical approaches include providing explanations for model decisions to enhance user comprehension. Desired properties encompass supporting user understanding, explaining the underlying DRL models and reasoning, and fostering safety, reliability, and trustworthiness in user interactions. This ensures that DRL systems are both dependable and comprehensible to users, ultimately enhancing their effectiveness in complex decision-making scenarios at the edge.

3.2.4. Energy Efficiency Measures

In the context of energy management, the applicable energy efficiency measures are limited to the actions that can be performed through the controllable components of the different subsystems. In the realm of building optimization, various strategies and measures can be employed to enhance efficiency across different categories. Under the category of ventilation, optimizing HVAC system outdoor airflow rates in compliance with ASHRAE standards or local codes is recommended, with a focus on reducing minimum flow settings for variable-air-volume (VAV) terminals. Additionally, minimizing exhaust and makeup rates when feasible and using operable windows for natural ventilation during mild weather are the proposed approaches. Another practice is eliminating outdoor air ventilation during unoccupied building morning warm-ups to conserve energy.

Concerning HVAC distribution systems, controlling the VAV system's variable frequency drive (VFD) speed based on static pressure needs, resetting the VAV system's supply air temperature set points, and dynamically controlling the heating and cooling duct temperatures to meet load requirements are highlighted. Additionally, creating air movement with fans for a cooling effect and minimizing cooling/heating of unoccupied areas are recommended.

Building automation and control systems play a pivotal role. The creation of separate control zones based on solar exposure and occupancy, coupled with night setbacks and HVAC equipment shutdown during unoccupied periods, can lead to significant energy savings. Employing occupancy sensors and system controls to reduce cooling/heating in unoccupied spaces is also advocated.

Furthermore, retrofitting multiple-zone VAV systems with direct digital control (DDC) controllers and eliminating duplicative zone controls are suggested for efficiency improvements. Adjusting hot water and cold water temperatures based on an outdoor air temperature reset schedule, aligning housekeeping schedules with HVAC use, and installing programmable zone thermostats with appropriate deadbands are recommended practices. Implementing an energy management system (EMS) tailored to optimize HVAC operations based on environmental conditions, changing uses, and timing is encouraged.

4. Proposed Architecture

This section presents the architectural proposal for the system. It starts with the division of architectural layers and the types of nodes deployed in them. Subsequently, these are broken down into the components to be developed, and a technological proposal for their implementation is presented.

4.1. Layer Architecture

As part of the architecture, three layers have been defined, with their respective nodes, each of which houses certain responsibilities in the system. For more detail, the layers are represented in Figure 3. However, each node and its responsibilities are enumerated as follows:

- IoT layer: The main characteristic of the components located in this layer is that they are deployed in the field. This layer is responsible for ingestion and communication at a low level, obtaining data from the different sources of information in the environment, mainly sensors. These make up the physical intake devices, which also belong to this layer. It is worth noting that the nodes in this layer are called "IoT nodes", and that they are physical devices. Specifically, physical intake devices include sensors and sensor aggregation probes. Also in this category are the devices necessary for the communication of the IoT nodes with the edge node, such as a router, gateway, and another network device.
- Edge layer: This layer is the data management system for the data ingested from the IoT layer, and it is responsible for preprocessing the data and applying artificial intelligence analysis to them. This makes it possible to later send the data to the cloud layer to ensure data persistence. The edge layer is housed in one or several computing nodes, deployed in several buildings' rooms, close to the physical devices for data ingestion (probes with a set of integrated sensors). It is important to remark that the nodes described within this layer are called "edge nodes", and in this category are the nodes deployed in the field in charge of centralizing the data intake. They correspond to the edge layer and contain the functionality needed to ingest the data sent by the IoT nodes; they preprocess the data, analyze it (using federated learning), and send it for storage in the cloud nodes.
- Cloud layer: This layer houses the functionalities related to data persistence, coordination of artificial intelligence analysis, and management of content that can be viewed by the user. As its name indicates, this layer is in a cloud environment. It is worth noting that the nodes described within this layer are called "cloud nodes". In this category, they are the nodes deployed in the cloud to perform the persistence, coordination of analysis, and visualization of the IoT data sent by the edge nodes.

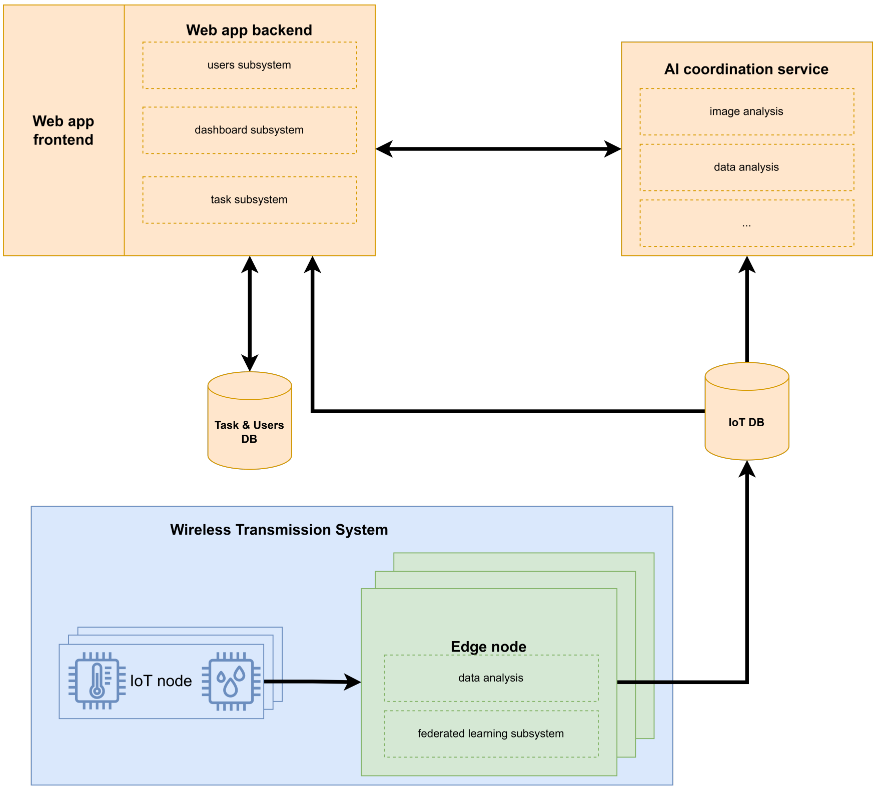

Figure 3. Architectural proposal of components.

4.2. Multi-Agent Architecture

For a more detailed definition, the architecture has been defined in the field of multi-agent systems, as can be seen in Figure 4. The list of agents that make up this system can be traced to the services presented in previous sections and are also outlined below.

- Virtual device organization: This can be composed of several replicated virtual organizations. Represented in blue, it can be formed by the following agents:
  - Edge ingestion agent: An agent in physical devices that is in charge of taking data and sending it to its associated virtual edge organization.
- Virtual edge organization: This can be composed of several replicated virtual organizations. Represented in green, it can be made up of the following agents:
  - Edge analysis agent: Performs simple analyses with a low computational load on its virtual edge organization.
  - Edge coordination agent: Coordinates communications and analysis in the virtual edge organization. It also coordinates data delivery to the virtual cloud organization.
- Virtual cloud organization: Represented in orange, it can be conformed by the following agents:
  - Communication coordination agent: Coordinates the communications in the virtual cloud organization.
  - Cloud ingestion agent: Coordinates the preprocessing of the data ingestion coming from the virtual edge organization, then sends the preprocessed data to the cloud persistence agent.
  - Cloud persistence agent: In charge of storage management in the virtual cloud organization.
  - Cloud analysis agent: In charge of the management of the analyses performed in the virtual cloud organization.

– Cloud coordination agent: In charge of the coordination of tasks, events, and information flows triggered by the user (events coming from the view served by the cloud visualization agent) and the system (events created by this agent in a cyclic way to perform system tasks), within the cloud virtual organization.
– Cloud visualization agent: Provides the user with a graphical interface to interact with the system.

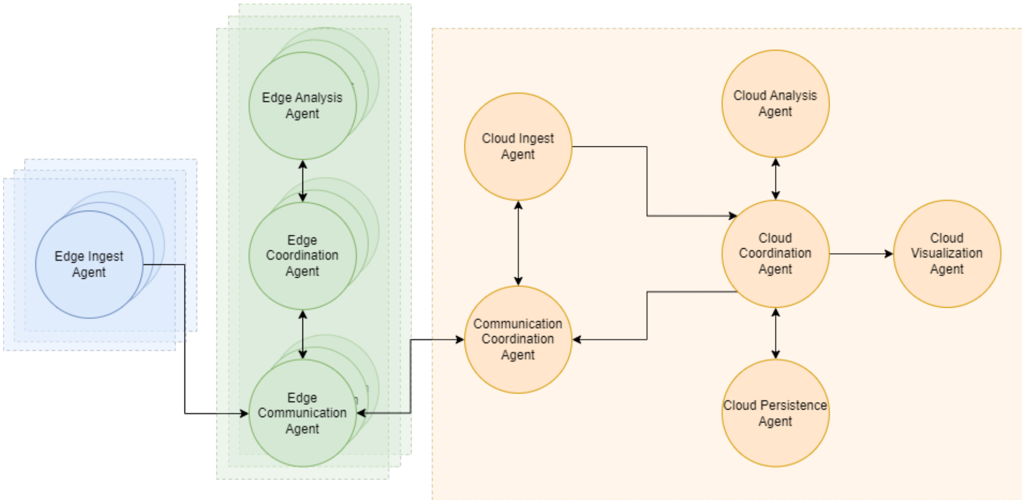

Figure 4. Definition of architecture through the paradigm of multi-agent systems.

4.3. User Roles

The requirements analysis of the BEMS three-tier edge-computing architecture and communications project has identified different types of users in the system. These users will be different depending on whether they can visualize certain types of data or not. Two different user roles have been identified on which to base the operation of the system. Figure 5 shows the user role's in the system.

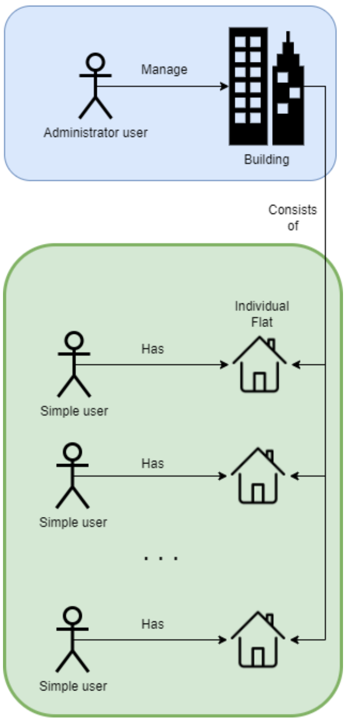

Figure 5. Definition of user roles in the platform.

As seen in Figure 5, there are two different user roles: the administrator user and the simple user. In the scale of privileges, the administrator user is at a higher level, and each simple user has an administrator user on whom it depends. The administrator user is able to view the data of all the simple users that depend on the administrator figure. The user roles are described in a little more detail below.

- Administrator user: This is the advanced user of the system, with access privileges to the data. It represents the person in charge of a building (community president, property manager, or authorized person). This user is able to view the data concerning all the dwellings in the building they manage and the results of the sensors installed in them, as well as the conclusions of the intelligent consumption optimization algorithms.
- Simple user: This is the simple user of the system. It represents the owners or tenants of a house. Owners keep their homes monitored in order to receive information on consumption and suggestions for optimization. A simple user can only access the data of their own home.

4.4. Analysis Architecture

The proposed agent architecture is presented as a service architecture. Given that the layers and their respective types of nodes have been defined, in this section, the architecture's components are defined. For this purpose, several components have been defined, and can be described as follows:

- IoT physical nodes: Consists of sensor nodes (composed of data aggregation probes and physical sensors that perform physical measurements), responsible for collecting data from the environment. Subsequently, the nodes send said data periodically through the IoT wireless transmission system to the event management system.
- IoT wireless transmission system: A network system responsible for providing wide-area coverage to physical IoT nodes in order to communicate with the event management system. It should be noted that this system has several proposed technologies as the basis for its implementation, which is chosen on the basis of the types of sensors, gateways, and other available physical devices.
- Event management system: This is a component that works in the event-driven paradigm, collecting data from the producing subsystems and sending them to the consumer systems subscribed to it.
- Data analysis and federated learning subsystem: Receives all the data from the event management system and applies preprocessing and analysis to it at the edge. This analysis is part of the federated learning paradigm since it is the method that best adapts, in this case, to physical deployment. Subsequently, the subsystem sends the data and results to the cloud ecosystem to allow for their usage by the different cloud services.
- Artificial intelligence coordination service: This service is responsible for carrying out the heaviest statistical and artificial intelligence multiple analyses, which cannot be carried out in the edge environment. It is also responsible for coordinating the federated learning system, i.e., knowledge exchange between the edge nodes.
- Task management service: Carries out task management in the background.
- Ingest management service: Performs data ingestion and stores data in the persistence system.
- Notification alert service: Sends notifications to users and edge devices.
- Web application: Provides the user with a graphical interface which enables them to work with IoT data, analysis, etc. It is responsible for providing the functionality of the system to the user and allowing them to interact.

5. Use Case

The pilot, carried out by the University of Salamanca, was located in the laboratories of the BISITE research group, which has advanced facilities in the new R&D&i building belonging to the University of Salamanca. This building, shown in Figure 6, is newly constructed and is equipped with the latest technologies.

The BISITE laboratories are oriented towards research and innovation at the software level through the development of software prototypes in diverse fields such as artificial intelligence, information retrieval, predictive systems, distributed systems, machine learning, and computer vision. Among the developments that can be carried out at this facility, the study of intelligent networks, ambient intelligence, and subject monitoring stands out.

This laboratory meets the equipment and layout needs for carrying out a pilot, as well as the required electrical and electronic equipment, given that it is a research facility. The activities that have been carried out as part of the AI-BEMS project have taken place at these facilities, using the laboratory and its equipment to contribute to the development of the pilot and the deployment of the different hardware and software elements proposed in the project.

More specifically, the study has been conducted in one of the research laboratories (office 1), which has a surface area of 80 square meters and includes a main room, two meeting rooms, and its own data center, an average consumption of 9922 kilowatt hours (kWh), and an occupancy of 15 people; see Figure 6. Also, as this is in Spain, it operates on a standard voltage of 230 V at a frequency of 50 Hz, aligning with most of Europe.

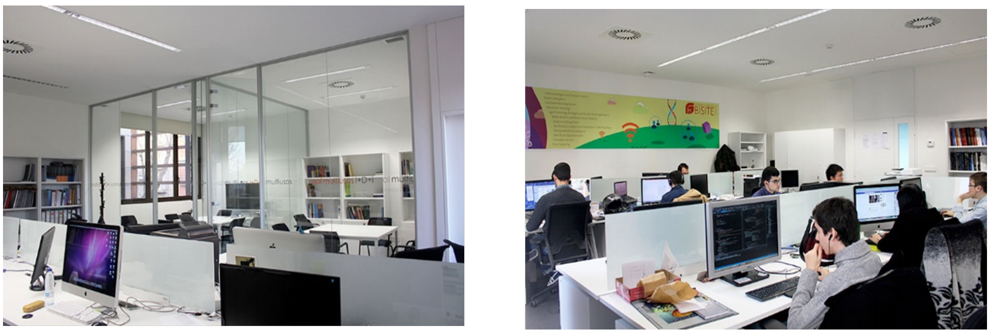

Figure 6. Pilot testing facility at the University of Salamanca.

Thanks to the characteristics of the research group, it has been possible to develop and deploy all the applications sought in the project, integrate the different monitoring and communication technologies that are incorporated into the system, perform testing and validation of the generated prototypes, as well as complete the development of the software for the intelligent platform that incorporates intelligent functionalities to support decision making.

Regarding the equipment that was available for the AI-BEMS project and contributed to its successful completion, the following tools were available:

- Heat pump–air conditioner:
  - Model: PKA-RP60KAL.
  - Brand: Mitsubishi Electric.
- Other pieces of equipment that have been used:
  - Data concentrator board based on Nvidia brand.
  - Communication modules: WiFi, Bluetooth, Zigbee, etc.
  - Sensors, controllers, and actuators of different types.
  - Equipment, development environments, software, servers, and infrastructure for the deployment of solutions both locally and in the cloud.

It can be inferred that both the human resources and the material resources are adequate for the development of the project and in line with the ambitious scope defined for it.

5.1. Hardware Components

The design of the different components in the edge solution covers the main loads in a typical house/building, namely, the heating, ventilation, and air conditioning, the electric vehicle, the tank-based electric water heater, and other heavy plug loads. Table 2 below illustrates the different devices that were involved and the respective monitoring and controlling devices.

Table 2. List of hardware and edge devices and components.

Component	Product	Description
Edge Device	Jetson Nano (Nvidia)	A compact, potent, and powerful kit designed to run powerful AI and machine learning algorithms with minimal power consumption.
Smart Meter	Wibeee Box (Wibeee)	A smart energy monitoring device with many features enabling wireless communication with the edge device. It also supports standalone operations via the manufacturer API.
HVAC	Aidoo Pro (Airzone)	An innovative smart thermostat that enables the control of a wide variety of HVAC systems, including the split units and centralized systems.
EV	EO Charging/EO Hub (EO)	A smart EV charger that has multiple features allowing for the efficient control of the charging sessions.
Plug Loads	Aeotec Smart Switch (Aeotec)	A smart plug that allows the control automation of significant plug loads. Also facilitates the control of the standard water heaters.
Cloud Platform	AWS (Amazon)	The cloud provider that hosts the cloud side of the solution.

5.2. Edge Computing Pilot Objectives

The objective of this pilot is to test the feasibility of developing intelligent solutions for the optimization of energy consumption by means of systems deployed in delocalized environments.

The conclusions of this pilot can be applied to systems for both commercial buildings and homes, the latter being a less explored and larger market. Therefore, the cost of hardware devices and the privacy of customer data are aspects that the study should also cover.

Goals

- General goals:
  - Benchmark of the different architecture designs: hybrid cloud–edge architecture options.
  - Validate connectivity between devices and edge computing devices: latency, frequency, protocols.
  - Validate the proper access to external public and private data sources and centralized resources.
  - Identify system vulnerabilities in terms of the security of customer data in outdoor systems and communications with the outside.
  - Identify data protection options.

- Data analytics goals:
  - Receive pre-trained data from cloud systems.
  - Data storage capacity on the edge device.
  - Data exchange between central systems and edge; data privacy.
  - Analyze the processing capacity at the edge for data and processes such as training and execution of machine learning processes.
    * The volume of data that can be processed.
    * The execution times in training/execution.
    * Limitations in terms of optimization models or algorithms.
  - Cost analysis of the solution in implementation and maintenance.
  - Benchmark architecture, cost, and functionality.

5.3. Architecture Implementation

Finally, in accordance with the multi-agent and component architectures described in the previous sections, system implementation in the scope of a multi-agent system is illustrated in Figure 7. It corresponds to the previous architecture, defining a possible stack of technologies to be used for this purpose. The technologies used for the implementation of the system are defined as follows:

- IoT wireless transmission system: Implemented through a WiFi network, which provides a large area of connectivity at the cost of reduced bandwidth, making it ideal for the use case that had been considered in this research. However, it may be necessary to use other technologies, such as LoRa, depending on the constraints of the physical environment of deployment and those of implementation.
- Event management system: A free software system that implements the MQTT protocol (two), designed and built specifically for multi-sensor data ingestion use cases in IoT environments. Specifically, the selected system is Eclipse Mosquitto, under the Eclipse license.
- Nvidia Jetson: This is the edge node implementation. It is proposed to use an Nvidia Jetson board to be able to carry out artificial intelligence analyses under the federated learning paradigm developed in Python. Among other advantages, this language allows for agile development, helping to adapt the data to the needs of the components that belong to the IoT and cloud layers, since this component is the interface between these two.
- Artificial intelligence coordination service: This consists of an API rest, which contains integrated heavy artificial intelligence models that cannot be carried out at the edge due to the computing demand they offer. It also holds the responsibility of coordinating the process of exchanging knowledge regarding federated learning between the edge nodes. Since these are developed in Python, this API is also to be developed in Python together with Flask, the most widely used framework for developing API rest in Python today.
- Task service, ingest service, and alert notification service: These are implemented in Python alongside Flask, the most widely used framework for API rest development in Python today, due to the flexibility they offer.
- Web application: A web application developed in JavaScript in the context of the MEVN stack. This component has two main sections: the backend, which is to be developed on the Node.js framework, and Express due to the use of the MEVN stack. In the case of the frontend, the Vue.js framework is to be developed due to the use of the MEVN stack.
- Databases: It has been decided to use PostgreSQL, because it is the most used SQL database today due to its extensibility, replication capacity, and agile development ability.
- A complete smart platform based on virtual organizations, designed as a three-tier architecture capable of ingesting data from multiple sources and providing tailored responses for an efficient energy consumption pattern.

- An IoT network and edge gateways capable of meeting the data ingestion requirements of the platform to be deployed in the pilot stage and of encrypting data at the hardware level.
- A data security and privacy protocol integrating cutting-edge cryptography solutions and a DLT-based approach.
- A social machine capable of managing the information processed by the platform, classifying, and monitoring the information, identifying different scenarios, and providing tailored responses (DSS).
- A new deep reinforcement learning approach (deep symbolic learning) using hybrid neuro-symbolic artificial intelligence algorithms for better integration of machine reasoning and learning capacities.
- New predictive and optimization models based on hybrid symbolic learning.
- Datasets gathered from the buildings involved in the demonstration phase, which enable the retrieval of information about consumption in buildings (anonymized/aggregated and fully compliant with all ethical and privacy recommendations/legal frameworks).
- Models (e.g., energy consumption, suggestions vs. pattern modification, energy demand) considering social and human behavioral aspects (data correlation).

The local platform allows users to consult the most up-to-date information collected by the sensors and the historical information collected by the sensors in their homes. The standard home automation protocols that allow for communication with the sensors have been implemented. The local or edge system is responsible for sending all the necessary data to the cloud on a regular basis. The system allows the user to consult, update, remove, and register all existing actuators in the local environment, which can be controlled by the edge system. Moreover, the system makes it possible to visualize the relevant data, allowing the user to have a global vision of the actions and recommendations of the home.

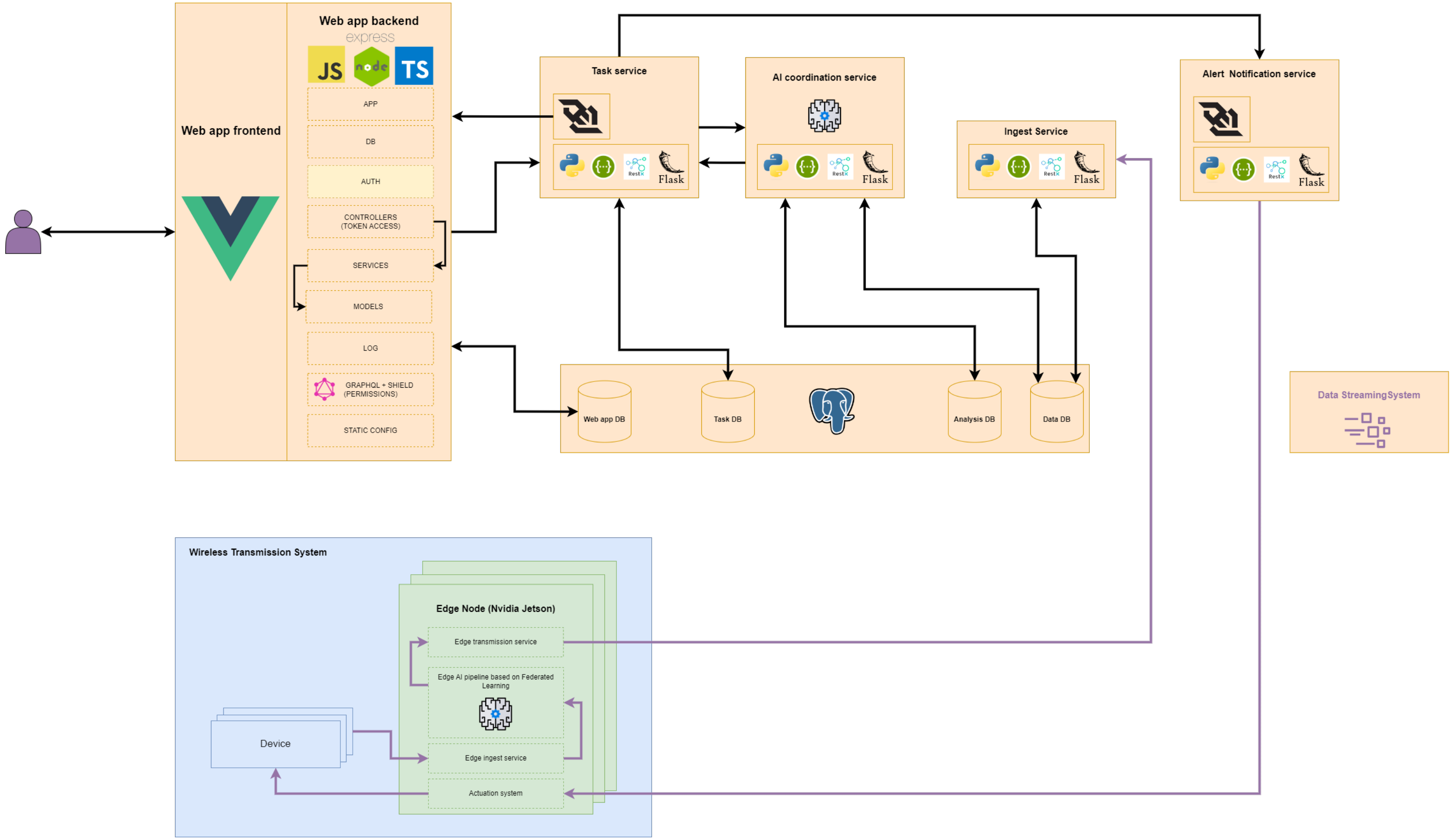

Figure 7. Final architecture implementation.

6. Results and Discussion

In this section, we present the tangible outcomes—the developed dashboards tailored for each of our devices, coupled with the surrounding facilities. These results represent our research, aimed at augmenting user experience and knowledge.

We dissect the visual interfaces and functionalities of these dashboards, showcasing their inherent capacity to provide real-time insights, thereby fostering informed decision making and establishing a profound connection between users and their respective devices. These dashboards transcend mere data representation; they offer heightened intelligence and operational efficiency.

Regarding the smart meter, we have designed a series of graphical representations to empower users with insightful information. In Figure 8, on the left we show the energy value ring chart which provides real-time energy exchanges as percentages, making it easier to comprehend energy consumption, generation, export, and purchase. To the right of the image, monthly and annual changes in energy values are depicted through a bar chart. These visuals enhance real-time understanding, enabling users to make informed decisions regarding their electricity consumption and costs.

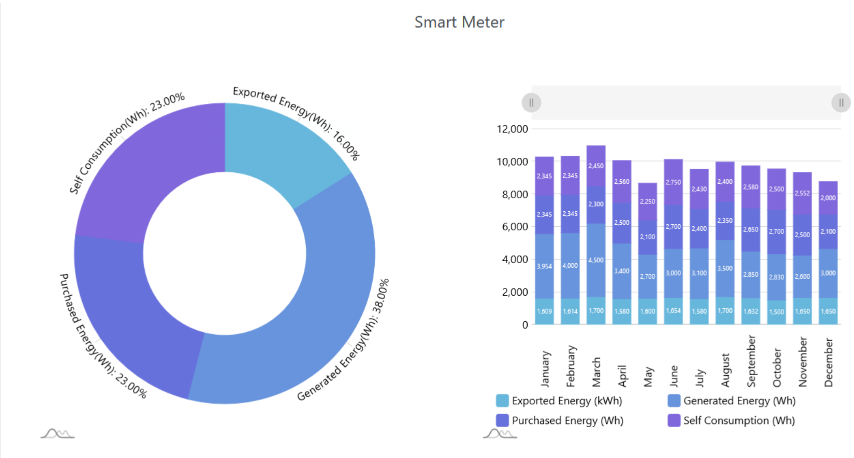

Figure 8. Smart meter panel with information about energy consumption, generation, export, and purchase.

Continuing with the EV charger, a graphical representation has been designed to showcase the battery capacity using an icon and the corresponding percentage, as shown in Figure 9. This approach offers a straightforward and easily comprehensible solution. Additionally, it provides the battery status and the estimated remaining time, among other relevant values.

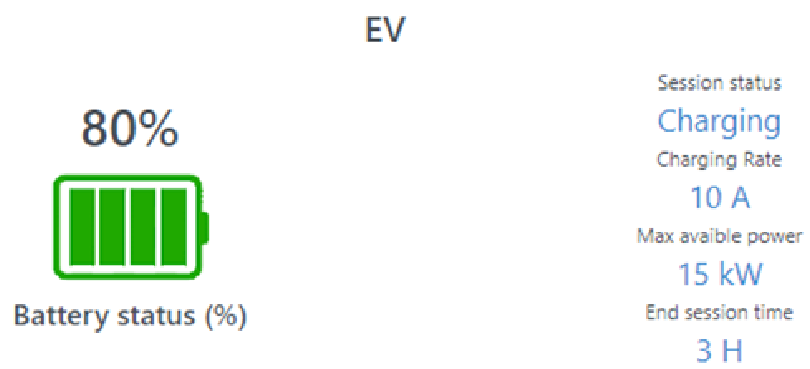

Figure 9. EV panel to showcase the battery status.

In the water heater graphs (Figure 10), users are given the option to turn the heater on or off. Furthermore, a dialog box displays daily consumption and the total cost, calculated based on the kilowatt hour tariff and the energy consumed thus far. Also, we can see that the consumption for the water heater is depicted in either euros or watts, as selected from the drop-down menu. Notably, the bar chart representing consumption in euros changes color as a value approaches a certain threshold.

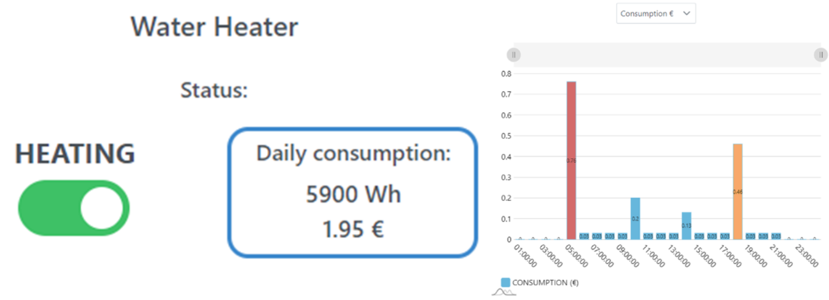

Figure 10. Water heater panel information.

The HVAC system ensures the comfort of occupants and maintains indoor air quality by regulating temperature and controlling humidity and air quality. One of the noteworthy features of modern HVAC systems is their ability to provide detailed information and allow for the direct control of various environmental variables. An example of this is the control panel found in most advanced HVAC systems. This panel (Figure 11) offers real-time information to users about ambient temperature, humidity levels, and airflow velocity. This information is essential for occupants to have a precise understanding of the conditions in their environment.

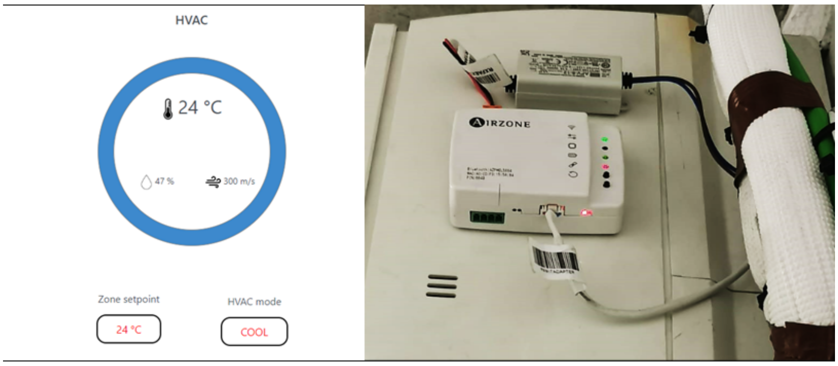

Figure 11. HVAC panel information.

In addition to providing valuable information, the control panel also allows users to adjust and customize HVAC system settings according to their individual preferences. For instance, it is possible to easily and quickly modify the indoor temperature to adapt to specific user needs or changing outdoor weather conditions. Likewise, users can seamlessly switch between different system modes, such as heating during winter and cooling during summer, in an efficient manner.

Lastly, the weather API plays an essential role by collecting detailed and up-to-date meteorological information. This dataset encompasses several crucial parameters that significantly influence planning and decision making in both everyday settings and commercial and industrial activities. The provided data include, among others, the precipitation percentage, visibility, outdoor temperature, and wind speed.

It is noteworthy that the weather API not only provides these data points individually but also visually presents them through graphs displaying a week-long historical record, as shown in Figure 12. This graphical representation facilitates the comprehension and analysis of weather trends over time, proving invaluable in strategic decision making based on meteorological information.

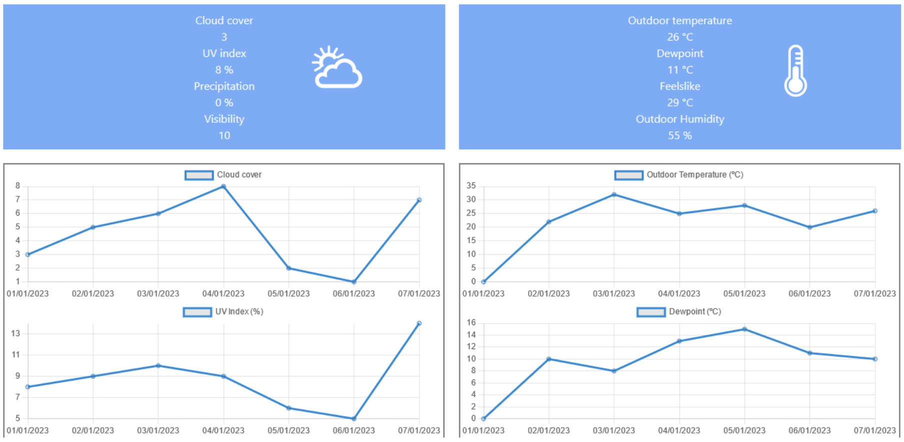

Figure 12. Weather panel real-time and historic data information.

The implications of our findings and their significance are considered, and we also outline potential avenues for future research. Historically, building and energy management systems (BEMSs) have predominantly relied on rule-based methodologies, including supervised or unsupervised learning, to provide energy-saving recommendations. These conventional systems, however, have been hampered by their exclusive focus on energy data, often neglecting critical variables such as occupant comfort and preferences. This limitation has constrained the effectiveness of energy-saving solutions in practical, real-world scenarios.

Our research aims to rectify these limitations by introducing a novel edge computing architecture grounded in virtual organizations, federated learning, and deep reinforcement learning algorithms. This innovative framework provides a more holistic approach to energy optimization within buildings and homes. It not only prioritizes energy efficiency but also accounts for the dynamic nature of occupant behavior and preferences. The selection of an appropriate cable size is of paramount importance to ensure safe and efficient power distribution. For example, consider a suburban area comprising 50 houses, each with a monthly electricity consumption of 800 kWh. In this scenario, a main aluminum distribution line is utilized, and we opt for a 70 mm^2 cross-section—a common choice for medium voltage systems.

Our research findings have substantial implications for the field of energy management in buildings. By integrating energy efficiency measures within virtual organizations that adapt in real time based on inhabitant data, we have successfully optimized consumption patterns while concurrently ensuring occupant comfort. This transformative approach represents a paradigm shift from conventional BEMS solutions, underscoring the significance of incorporating human-centric factors into energy management systems.

Furthermore, our proposition to implement edge computing serves as a viable solution to address the shortcomings of cloud-based systems, such as cybersecurity vulnerabilities and data transmission complexities. This transition to edge computing not only fortifies data security but also diminishes latency, facilitating real-time decision making and, thus, enriching the landscape of energy management practices.

7. Conclusions

In this study, we have presented a sophisticated smart platform engineered to optimize energy consumption within both individual buildings and entire districts, effectively ushering in a paradigm shift in the domain of energy management. Our platform operates by seamlessly integrating energy-saving recommendations geared towards inducing behavioral changes in end-users while concurrently streamlining the load on the power grid. Our exploration began with a comprehensive review of the state-of-the-art literature pertaining to building and energy management systems (BEMSs). This extensive investigation served as the foundation upon which our innovative platform was developed. The architectural framework we have meticulously designed serves as a powerful tool in the realm of energy efficiency, fostering a fundamental shift in the consumption patterns of users. This transformation is poised to yield sustained reductions in energy consumption over time, significantly contributing to a greener and more sustainable future. Notably, our platform is engineered to cater not to a single user but to a group of aggregated users, enabling the extraction of comprehensive smart building energy consumption profiles. This scalability extends seamlessly to the district level, where it offers the potential for substantial load shifting within the power grid. This has far-reaching implications, such as resource allocation optimization, mitigation of overloads, and a reduction in maintenance costs, thereby ensuring the efficient and balanced utilization of critical infrastructure.

Looking ahead, several avenues for future research emerge from our work. First and foremost, further exploration into the integration of deep reinforcement learning and federated learning algorithms in energy management systems. The potential for these technologies to adapt and optimize energy consumption in real time while respecting privacy constraints should be further explored. To bring our innovative system to fruition in real-world applications, the next crucial step involves its practical implementation in residential and commercial buildings. This endeavor will serve as a testament to the feasibility and effectiveness of our intelligent platform in diverse settings. Through pilot projects and case studies, we aim to validate its capabilities and adaptability, measuring its impact on energy efficiency and user satisfaction. These real-world deployments will not only underscore the system's practicality but also provide invaluable insights for further refinement. In achieving this, we move closer to a future where our technology is seamlessly integrated into homes and businesses, fostering a sustainable and energy-efficient built environment. Furthermore, it is imperative to delve into the scalability and practicality of implementing virtual organizations across diverse building and home environments. Understanding the adaptability of this approach to multifaceted contexts and its potential for widespread adoption remains pivotal for ensuring its long-term viability and continued transformative impact.

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