Leveraging Cutting-Edge Technologies into Energy Management Smart Buildings: An Era of Revolution

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Abstract

Recently, the emergence of cutting-edge technologies is transforming Smart Buildings (SBs) by enabling advanced energy management solutions that improve sustainability and efficiency. This study explores the integration of the Internet of Things (IoT), Artificial Intelligence (AI), Edge and Fog Computing (EFC) and Federated Learning (FL) in smart buildings, highlighting their pivotal role in optimizing energy consumption. However, this integration encounters several challenges related to architectural design and system components. A novel multilayer architecture is proposed to address energy consumption optimization using these technologies. The discussion focuses on key architectural challenges and reviews recent techniques and approaches developed to overcome them. The paper also presents an overview of the benchmark datasets used for validation, along with various market solutions that support the implementation of the proposed architecture. To assess efficiency, the study includes a performance analysis of energy prediction methods, using selected techniques evaluated under specific criteria. The findings identify open issues and suggest directions for future research in smart building Energy Management Systems (EMSs).

1. Introduction

1.1. Context

Today, energy plays an essential role in our daily lives and represents a key concern for individuals, institutions, and governments. According to the European Commission [1], efficient management and consumption optimization is certainly an attractive means to reduce the impacts related to energy on the environment. By prioritizing efficient energy use in daily practices and infrastructure, we can enjoy improved access to reliable energy, leading to improved safety, affordability, and overall comfort. In addition, as energy efficiency measures contribute to mitigating environmental degradation, they directly contribute to protecting public health and well-being, fostering a sustainable and resilient future for generations to come. To achieve this objective, an efficient Energy Management System (EMS) paradigm emerges as a fruitful way in the context of smart buildings.

1.2. Motivation and Challenges

Recently, the integration of cutting-edge technologies into EMS has led to a revolution in smart buildings. In particular, EMS leverages IoT and Artificial Intelligence (AI) in smart buildings to capture and exchange real-time interaction data with the external environment. On the one hand, the IoT provides a powerful technology that connects remote sensors for heating/cooling or any other necessary utility inside the building to more likely regulate energy usage and improve the occupancy experience in smart buildings. It is estimated that a smart building with integrated IoT accounts for around 30-50% savings compared to traditional buildings [2, 3]. On the other hand, AI offers another layer of sophistication and optimization in smart buildings. AI algorithms can analyze vast amounts of data collected from IoT devices and autonomously adapt to dynamic environmental conditions and occupant preferences to further improve energy efficiency and user experiences [4].

Unfortunately, applying AI techniques mainly faces two major challenges: the first is related to the huge computation needed due to the big data collection, and the second is related to the user privacy, where residents have to

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share sometimes sensitive building data with the authorities. To address such challenges, we propose to integrate two particular approaches in the smart building architecture: edge/fog computing (EFC) and federated learning (FL). The first approach involves decentralizing computing resources closer to the data source, reducing latency, and improving real-time processing capabilities. In the context of smart buildings, EFC translates into the deployment of computing resources at the edge of the network, allowing faster decision-making and response to data generated by IoT devices within the building. This not only optimizes energy management, but also enables faster and more localized control of building systems, contributing to a more responsive and adaptive infrastructure. The second approach, e.g. FL, presents a collaborative and privacy-preserving method for model training across decentralized devices. This allows AI models to be learned on various end-user devices without the need to share sensitive information centrally in smart buildings. Thus, FL is particularly relevant when dealing with occupant behavior patterns and energy consumption preferences within buildings. Using Federated learning, smart building systems can adapt and optimize according to the unique characteristics of each building and its occupants, contributing to more personalized and efficient energy usage.

1.3. Major Contributions

Traditional approaches to energy management often face challenges in adapting to the dynamic and complex nature of modern building environments. To address these challenges, there is growing interest in leveraging cutting-edge technologies in smart buildings. The major contributions of this work are as follows.

1. Proposing a new architecture for smart buildings that integrates cutting-edge technologies, particularly IoT, EFC and FL, for real-time energy consumption prediction and optimization. The new architecture consists of several layers, each one using different technologies, has its own components, and provides various services.
2. The critical importance of IoT technologies in enabling real-time data collection and automation, essential for optimizing energy usage in smart buildings, is highlighted.
3. Investigating the impact of federated learning in preserving data privacy and security in smart buildings, ensuring compliance with regulatory requirements, and addressing stakeholder concerns.
4. Identify key challenges and limitations associated with the integration of cutting-edge technologies into smart building EMS.
5. Providing a comprehensive review of various research and market solutions while classifying them into some categories.
6. Performing, through real building data, a comparative analysis of some existing techniques and demonstrating the efficiency of using such technologies in energy optimization in smart buildings.
7. Providing practical recommendations for future implementations to improve energy efficiency and sustainability.

In contrast to existing work, our proposed architecture stands out due to its holistic integration of IoT, edge/fog computing, and federated learning in a unified multilayer design. Each layer in the architecture is assigned a specific role based on the sensitivity of the data, processing latency, and resource availability. Furthermore, the architecture directly addresses key challenges such as user privacy, latency, and scalability by embedding federated learning models in the edge and fog layers. This design allows local data processing, distributed learning, and intelligent coordination while preserving privacy. This end-to-end framework, validated with real-world benchmarks, provides a comprehensive, privacy-sensitive, and energy-efficient EMS solution that is not yet covered in the current literature.

1.4. Abbreviations

For the sake of clarity, Table 1 presents the list of acronyms used in this paper.

1.5. Structure of the Survey

In order to clearly guide the readers through this study and for the sake of easy-to-follow, Figure 1 shows the layout of this article.

2. Systematic Literature Review Methodology

In pursuit of a comprehensive understanding of the landscape of energy consumption in smart buildings, the Systematic Literature Review (SLR) adheres to a meticulously designed methodology. The research questions and objectives were clearly delineated to guide the review process, focusing on crucial aspects such as the effectiveness of energy efficiency techniques and the trends shaping the field. In establishing inclusion and exclusion criteria, careful

Table 1
Abbreviations used throughout the study.

Abbreviation	Meaning
IoT	Internet of Things
SB	Smart Building
EMS	Energy Management System
ECP	Energy Consumption Prediction
FL	Federated Learning
DL	Deep Learning
EC	Edge Computing
FC	Fog Computing
CC	Cloud Computing
AI	Artificial Intelligence
ML	Machine Learning
SLR	Systematic Literature Review
RQ	Research Question
HVAC	Heating, Ventilation, and Air Conditioning
KNN	K-Nearest Neighbor
LANs	Local Area Networks
RFID	Radio Frequency Identification
QoS	Quality of Service
DR	Demand Response
SVM	Support Vector Machine
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
R^2	R-squared
NS	Not Specified

consideration was taken regarding publication sources, types, and relevance to smart building energy consumption, ensuring a refined selection process. The comprehensive search strategy encompassed diverse databases and employed tailored keywords and controlled vocabulary specific to energy consumption in smart buildings, fostering an exhaustive exploration of the existing literature. The study selection process involved a systematic and transparent approach, focusing on a rigorous selection of titles and abstracts, followed by the application of predefined criteria for full text review. A structured data extraction form facilitated the synthesis of pertinent information, encompassing variables such as research methodologies, energy optimization techniques, and key findings. Quality assessment criteria were applied judiciously, allowing for the discernment of methodological care in the selected studies. The subsequent synthesis of the results aimed to identify patterns, trends, and research gaps in energy consumption within smart buildings, providing a holistic perspective on the current state of the field. The distribution of findings will be approached with clarity and visual aids, improving the accessibility of the review insights. This SLR not only reflects on its limitations and potential biases, but also proposes future research directions based on identified gaps, contributing to the ongoing discourse and evolution of energy consumption management in smart buildings.

2.1. Research Questions

This survey aims to investigate the dynamic domain of energy consumption optimization within smart buildings, addressing key research questions to advance our understanding and contribute to ongoing developments. Our investigation spans key facets, from the efficacy of traditional and modern energy optimization techniques to the integration of advanced technologies such as federated learning and edge/fog computing architectures. We seek to elucidate challenges and opportunities in data privacy, scalability, and energy efficiency in smart building deployments. In addition, our study delves into the complexities of integrating federated learning into energy management systems,

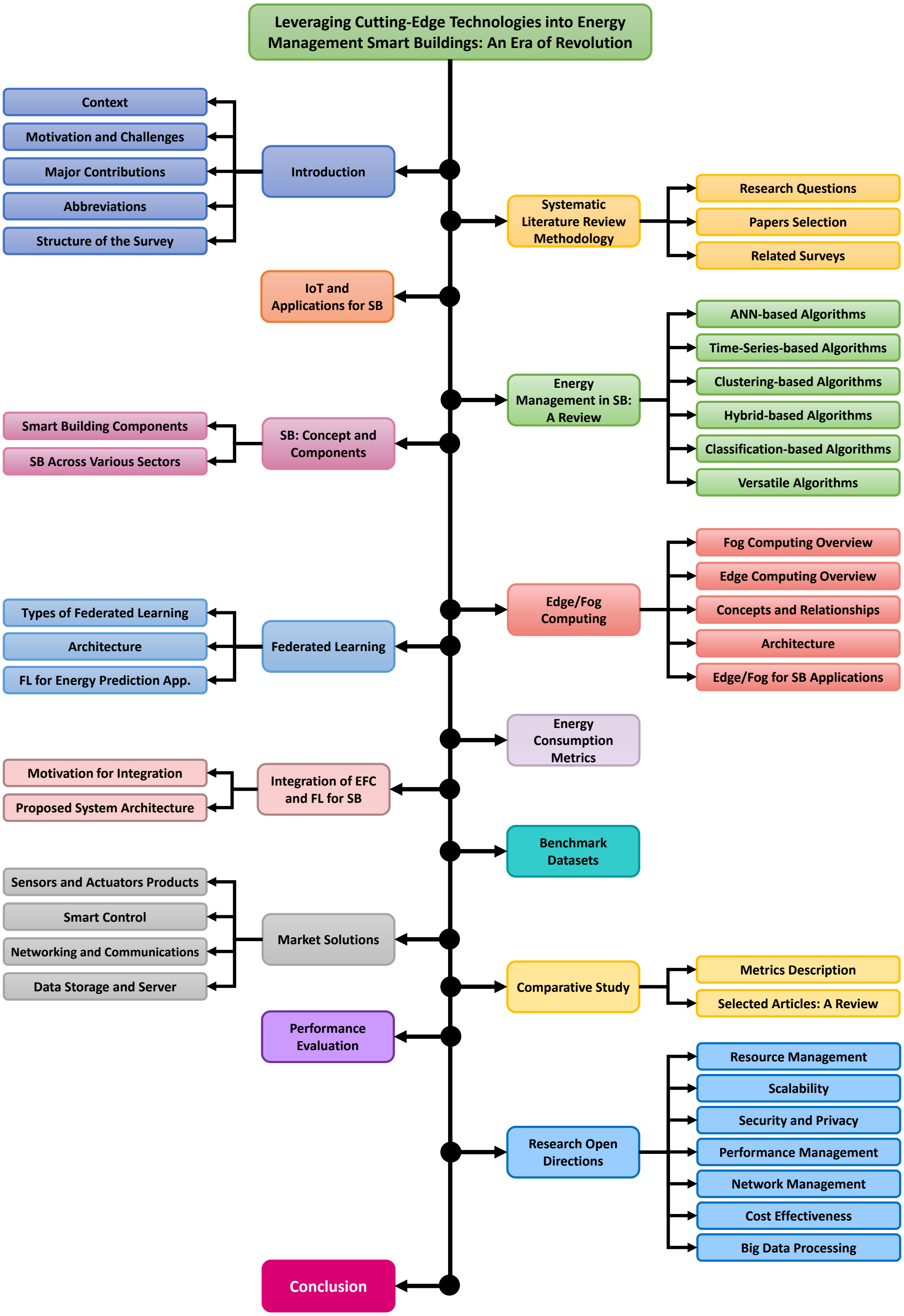

Figure 1: General diagrammatic view of this survey structure.

examining potential vulnerabilities and mitigation strategies. We also explore the importance of real-time data analytics, proactive response mechanisms, and the role of user behavior in enhancing energy optimization in smart buildings. In addition, we analyze the unique challenges associated with implementing federated learning and edge/fog computing for energy optimization. For this purpose, we define different research questions illustrated by the following.

- RQ1: What are the emerging applications of energy consumption optimization in smart buildings in various sectors, such as residential, commercial, healthcare, and industrial, and what are the specific techniques and approaches employed in each domain?
- RQ2: How do different smart building technologies, such as IoT devices, edge/fog computing, and federated learning, contribute to optimizing energy consumption in diverse building environments?
- RQ3: What are the most effective metrics for measuring energy consumption in smart buildings, and how do these metrics facilitate real-time monitoring and management of energy use?
- RQ4: How does the integration of federated learning with edge/fog computing contribute to real-time energy consumption prediction and optimization in smart building environments?
- RQ5: What are the key challenges and limitations associated with the integration of federated learning and edge/fog computing for energy optimization in smart buildings and how can these challenges be addressed?

2.2. Papers Selection

Our database is composed of research papers published between 2017 and 2023 in different reputable journals and conferences. The selection of research papers was based on several key criteria. Priority was given to papers published in reputable and well-established journals and conferences. Additionally, the number of citations was considered as an indicator of the paper's impact within the research community. Most of the selected works were published in the last five years to ensure the inclusion of recent advancements. Furthermore, all papers contained relevant keywords and content directly related to the energy management systems in smart buildings while highlighting cutting-edge technologies such as edge/fog computing, federated learning, AI, etc. Subsequently, the literature search was conducted using various combinations of keywords in the selected databases. These included terms such as: *"smart buildings," "energy management," "edge computing," "fog computing," "federated learning," "energy prediction," "IoT,"* and *"optimization"*. Boolean logic and search filters were applied to narrow down the results and identify the studies that are most relevant to our objectives. Duplicate records and non-peer reviewed articles were excluded to maintain the scientific rigor of the review.

The selection methodology is illustrated through two figures. Figure 2 highlights the selected articles according to the publication year, and Figure 3 highlights the most famous publisher for the selected articles.

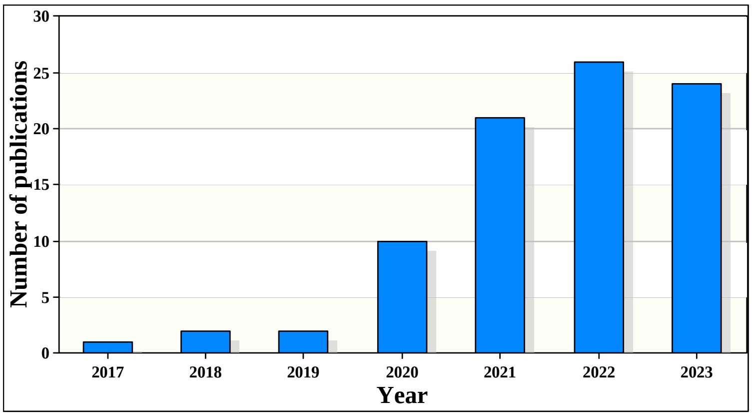

Figure 2: Publications in terms of year.

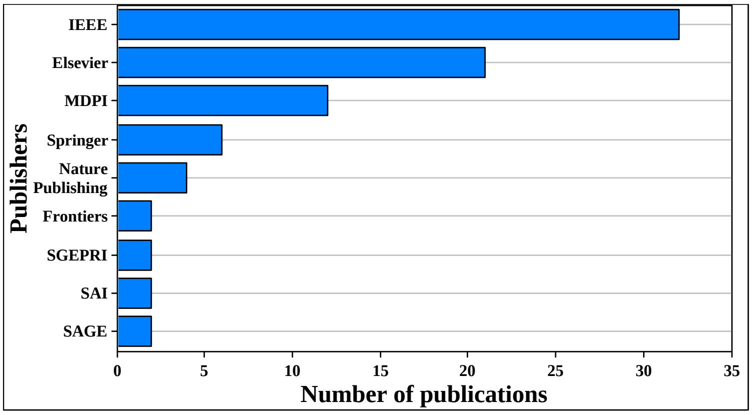

Figure 3: Publications in terms of publishers.

2.3. Related Surveys

In the realm of integrating cutting-edge technologies into SB EMS, the landscape of existing research is still relatively nascent despite notable advancements in recent years. An examination of related surveys and review articles (Table 2) reveals a sparse coverage of this specific intersection. Although there have been commendable efforts to explore the integration of edge and fog computing with federated learning techniques for optimizing energy usage in smart buildings, the existing literature predominantly addresses only fragmented aspects of this complex domain. A comprehensive survey that thoroughly investigates the application of federated learning across the spectrum of edge/fog environments within smart buildings is notably absent. Given this gap in understanding, the present juncture offers an opportune time to critically evaluate existing studies and propose novel directions for further exploration. This imperative for fresh insights and avenues for research will be elaborated on in subsequent sections of this manuscript.

However, despite these contributions, the reviewed surveys exhibit several limitations. Most focus on isolated technologies such as IoT, edge/fog computing, or federated learning, without offering an integrated perspective that reflects their combined deployment in smart building contexts. Furthermore, few of these works provide deep technical evaluation or practical deployment insights, particularly with regard to scalability, real-time processing, or privacy-preserving mechanisms. Another notable gap is the limited use of real-world datasets and the lack of comparative analysis using standardized performance metrics, which reduces the ability to assess applicability in realistic environments.

3. IoT Systems and Applications for Energy Consumption in Smart Buildings

Recent developments in sensor technology, wireless communication, network protocols, microelectronics, cloud computing, and machine learning, among other fields, are fueling the expansion of the Internet of Things (IoT). The widespread adoption of IoT systems is becoming increasingly prevalent, covering various application areas such as smart grids, industrial automation, healthcare, sports/fitness, smart farming, environmental monitoring, smart cities, intelligent transportation systems, logistics, etc. One of the main driving areas of the IoT is in the context of smart buildings and smart homes, where several applications are envisioned, such as energy consumption reduction; energy management of smart grids, battery storage systems, electric mobility, and renewable energy sources; monitoring and control of indoor environment parameters, such as air quality and thermal comfort; and structural health monitoring. In this sense, the IoT system generally comprises, among other components, a network of IoT devices interfacing with sensors and actuators that are remotely configured, monitored, and controlled, manually by users and / or through intelligent automatic algorithms, with the support of cloud computing services [24]. In this section, we provide a brief review of the application of the IoT paradigm in different research areas, with a focus on smart building scenarios.

Utilizing IoT technologies for real-time monitoring and management of electric loads in households offers means to minimize waste and optimize building energy usage, thereby boosting energy efficiency. Sanchez-Sutil et al. exemplify this in [25] with an IoT-ready smart plug designed to measure and regulate energy consumption across diverse building types. These smart plugs are equipped to track voltage, current, power, and energy usage, transmitting data instantly to an IoT cloud via LoRaWAN wireless technology. Through experimental trials in six households, the

Table 2
Comparative overview of related survey papers and the scope of this study.

Ref.	Year	Proposal	IoT	Edge	Fog	FL
[5]	2020	It addresses computing and networking bottlenecks in the large-scale deployment of IoT applications by using FC technology.	✓	✓	✓	X
[6]	2020	It highlights challenges in traditional CC and explores three EC technologies: mobile EC, cloudlets, and FC.	X	✓	✓	X
[7]	2020	It proposes a SLR method for fog-based smart homes.	X	X	✓	X
[8]	2020	It provides a new classification of FL topics and research fields based on a thorough analysis of the main technical challenges and related works.	X	X	X	✓
[9]	2021	It highlights energy management in SBs and homes using FC.	✓	X	✓	X
[10]	2021	It presents a literature review of SB development using IoT and DL.	✓	✓	✓	X
[11]	2021	It introduces the definition, key technologies, and classifications of FL, explores its practical applications, and highlights current challenges and future research directions.	X	X	X	✓
[12]	2021	A comprehensive survey of emerging FL applications in IoT networks is provided, starting with recent advances and leading to their integration.	✓	X	X	✓
[13]	2022	It explores how EC addresses the challenges of efficient, fast, and secure processing of massive edge data in traditional cloud-based systems.	X	✓	X	X
[14]	2022	It presents a comprehensive review of research work on the existing technologies and applications of IoT in buildings.	✓	X	X	X
[15]	2022	It identifies the latest trends and their technological advances in IoT-ECP.	✓	✓	✓	X
[16]	2022	It conducts an extensive review of the EC-CC system and its application to the smart grid.	X	✓	✓	X
[17]	2023	It reviews the convergence of deep learning with cloud, fog, edge, and IoT computing, highlighting challenges and future research goals.	✓	✓	✓	X
[4]	2023	It shows how the combination of AI, Big Data, and IoT are used for smart EMS.	✓	✓	✓	X
[18]	2023	It provides detailed coverage of Edge–Fog–Cloud frameworks and IIoT data.	✓	✓	✓	X
[19]	2023	It develops a comprehensive IoT-based framework for smart city energy management.	✓	X	X	X
[20]	2023	A comprehensive survey on integrating FL with smart city applications to ensure privacy and protect sensitive information.	X	X	X	✓
[21]	2024	A review comparing edge, cloud, and hybrid computing for IoT, emphasizing hybrid models as a balanced solution for low latency, bandwidth, and privacy.	✓	✓	✓	X
[22]	2024	A review of AI-based fog computing optimizations in resource management, scheduling, and load balancing, with key challenges and future directions.	✓	X	✓	X
[23]	2024	A review of FL, covering its framework, benefits, applications, and challenges, with emphasis on privacy and distributed collaboration.	X	X	X	✓
This study	2024	It shows the importance of integrating cutting-edge technologies into EMS of SB, presents a promising avenue for enhancing the efficiency and sustainability of smart building operations, offering novel solutions to longstanding challenges in energy consumption management.	✓	✓	✓	✓

authors showcase the effectiveness, simplicity, reliability, and cost-efficiency of the proposed IoT system. Furthermore, they conduct a thorough analysis and comparison of various smart plug models, encompassing both experimental prototypes and commercially available alternatives. In [26], Balakumar et al. propose an IoT-integrated demand-side management (DSM) scheme for scheduling electrical appliances in smart homes effectively. The scheme aims to reduce consumers' electricity costs and minimize peak loads by encouraging the use of renewable energy sources (RESs) and implementing dynamic pricing. The IoT system utilizes Modbus, a real-time wired networking protocol, while the DSM scheme employs the binary firefly optimization algorithm. Experimental and simulation results indicate that dynamic incentives and pricing can significantly reduce tariffs for smart home users. Hossain et al. in [27] implemented the Internet of Things (IoT) paradigm in the context of a building energy management system, aiming to enhance the environmental performance of buildings and improve learning experiences related to energy and sustainability. The study focused on an educational building within a university campus in London. Various IoT sensor devices were strategically placed across three floors of the building to enable continuous real-time monitoring of ambient air temperature, relative humidity, illuminance, carbon dioxide levels, and sound levels. Additionally, educational workshops were conducted using IoT sensor devices and portable Bluetooth sensors, facilitating real-time data visualization. These workshops aimed to raise students' awareness of the impact of environmental and behavioral changes on energy consumption, with feedback collected through online questionnaires. In [28], Tanasiev et al. investigate the application of Internet of Things (IoT) systems for connecting and managing devices in the monitoring and control of heating, ventilation, and air conditioning (HVAC) systems within a practical case scenario. The proposed solution employs the MQTT (Message Queuing Telemetry Transport) application layer protocol and RESTful APIs as the communication layers for data exchange. At the software level, integration was accomplished using the Node-RED programming tool, facilitating the interconnection of various data flows and applications. The authors highlight the simplicity of integrating diverse devices, reduction in debugging and deployment time, and the flexibility for replicating the system in different application areas as key advantages of their proposed solution. The developed system underwent testing, employing a proportional integral derivative (PID) controller and a local programmable logic controller (PLC). Balikhina et al [29] utilized the Amazon Web Service IoT platform to develop and implement a system architecture for smart electricity meters to monitor and control the energy usage of residential buildings in a more effective way. The system's architecture is made up of three major components: a base station which has the IoT gateway mainly for the communication network, a user interface for allowing users to communicate with the system, and appliance controllers for remotely controlling the appliances. The system collects information from different appliances and sends them through the gateway to the base station for storage and computing. The major limitation of this work however is the lack of smartphone and web applications to allow the users to effectively monitor and control their home appliances remotely. In [30], Calvo et al. propose an Internet of Things (IoT) system centered around affordable open-source hardware and software. The system is built upon a scalable IoT architecture that incorporates edge, fog, and cloud layers. Its primary focus is on monitoring indoor environmental quality (IEQ) parameters in buildings, with key objectives including ensuring appropriate temperature and humidity conditions, implementing measures to reduce energy consumption, and ensuring air quality. A prototype of the IoT system was developed and implemented in a university building using the existing Wi-Fi infrastructure. Additionally, a smart sensor node was specifically designed to measure temperature, humidity, equivalent CO2, and volatile organic compounds (VOC). Marinakis and Doukas [31] used the integrations between buildings and IoT solutions to propose intelligent energy management in residential settings. The system acquires and analyzes the energy data of buildings and displays the analyzed data in real time to the occupants of the buildings. The system then sends notifications and recommendations to the occupants to help them properly manage their energy and save costs. The system uses Semantic Web technologies to combine the data (including occupants' behavior, energy prices, building data, and weather information) collected from multiple sources to monitor and learn the energy behavior of the building to accurately recommend energy-saving solutions to occupants. In designing this system, the authors focused on system flexibility and scalability, thereby the system can be modified to fit the occupants' demands and the building's characteristics. Coates et al. [32] described the challenges in the deployment of IoT systems for smart buildings. They explained how the architectural designs of buildings can be changed over time and how IoT has affected this transformation. Accordingly, they proposed a smart building monitoring system that could be used for monitoring occupancy in the rooms in real time using light sensors, heat sensors, and relays. Within the study, the authors highlighted and discussed the need for both virtual and physical testing of IoT systems to ensure their successful operations. Fernando et al. [33] proposed an IoT-based intelligent energy platform to properly manage and analyze energy data collected from residential buildings, especially large-sized buildings. The platform was designed to acquire both historical and real-time data to perform more accurate data analysis. The platform also supports different applications and functions such as time series storage, data volatility monitoring, and data filtering. Additionally, the platform includes a virtual area detection function to perform energy detection and prediction. A web application was developed for the platform to visualize and regulate the analyzed energy data. In [34], Jooseok Oh presents an empirical study on the implications of educating users on the use of IoT systems to reduce home energy consumption and encourage behavior changes toward energy savings and sustainability.

Over 15 months, homeowners received training regarding smart plug devices for energy consumption monitoring and reduction, after which surveys were performed to assess parameters such as user satisfaction and frequency, and their relation with energy consumption reductions. The IoT products provided to the users were smart plugs and switches currently available on the market, with functions such as power monitoring and control, scheduling and timers, and using 5G, LTE, Wi-Fi, and Bluetooth wireless network technologies. Luo et al. [35] proposed that the combination of big data and IoT can be employed in the energy management systems of office buildings. Accordingly, they developed an IoT four-layered big data platform to predict the day-ahead heating/cooling demands of buildings. The four layers are the sensor layer collects energy-related data, the storage layer to stores the collected data, the analytics support layer for analysis and prediction, and the service layer to connects the prediction model to the building energy system. To collect data, sensors are installed in both the indoor and outdoor environment of a building to collect energy-related data. The prediction models of the platform were designed using the combination of two machine learning techniques: artificial neural network and k-means clustering. The K-means clustering identifies the behavior of daily outdoor weather profiles while the neural network works as the prediction model. Stojkoska and Trivodaliev [36] developed an IoT-based three-tier system to integrate smart homes into microgrids to improve the energy efficiency of homes with renewable distributed energy sources generated by the microgrid. The three tiers are smart home, Nano-grid, and microgrid. In the first tier, the sensor network collects data from the devices in the home and stores them in a smart meter. In the second tier, all smart meters of different residential buildings interact with each other to exchange information. In the third tier, the gateways from all the buildings communicate with the utility division of the homes. A fog computing approach based on prediction filters was employed to process and analyze data to decrease traffic problems resulting from wireless communications. The ability to monitor the integrity of a wide variety of civil structures in a continuous and fine-grained way using low-cost technologies is essential both from an economic and a life-saving standpoint. In [37], Di Nuzzo et al. propose an IoT system applied to structural health monitoring in buildings. The design of its wireless sensor node is based on low-cost MEMS accelerometers and employs the NB-IoT protocol to provide low-power, long-range communication with a server via 4G networks. Through experimental performance evaluation tests, the authors achieved a lifetime of more than ten years with a 17,000 mAh battery and, alternatively, an unlimited lifetime with energy harvested from a small solar panel. Compared to a high-precision measurement instrument, results show a difference of less than 0.08% in the accuracy of estimating the modal vibration frequencies, with a cost reduction of around ten times.

In conclusion, the integration of IoT systems within smart buildings presents a vast array of potential applications, offering significant advantages on multiple fronts. These include enhanced energy efficiency and sustainability, advancements in comfort and safety of the occupant, as well as the facilitation of predictive maintenance strategies. Through real-time monitoring, data analytics, and intelligent automation, IoT technologies are poised to revolutionize building management, paving the way for smarter, more efficient, and more sustainable built environments. As research and implementation efforts continue to evolve, the promise of IoT in shaping the future of smart buildings remains deep, promising a landscape of enhanced functionality, efficiency, and resilience.

4. Energy Management in Smart Buildings: A Summary of Decade Revolution

In the dynamic landscape of smart Energy Management Systems (EMS) over the past decade, there has been a paradigm shift driven by the remarkable progress in the Internet of Things (IoT) technologies. The integration of IoT has revolutionized the way we monitor, control, and optimize energy consumption, ushering in an era of smart and interconnected energy ecosystems. This transformative synergy empowers organizations to achieve unprecedented levels of efficiency, sustainability, and adaptability, reflecting the transformative impact of IoT for smart EMS. This section delves into a comprehensive exploration of the transformative decade that has unfolded, encapsulating the innovative approaches employed in the energy management paradigm. To better understand the scope and direction of these innovations, we conducted a comprehensive review of approximately 100 relevant research articles published during this period. This retrospective analysis organizes them into six distinct categories, each representing a unique facet of minimizing energy consumption in smart environments: artificial neural networks, time series-based algorithms, clustering-based approaches, hybrid-based techniques, classification-based methods, and versatile algorithms. These categories not only serve as a testament to the diversity of applications in smart EMS but also highlight the synergy between cutting-edge machine learning techniques and the ongoing battle against energy consumption in smart buildings. The subsequent discussion will illuminate the nuances and advancements within each category, providing a panoramic view of the revolutionary strides that have shaped the contemporary landscape of energy management systems.

4.1. Artificial Neural Network-based Algorithms

In the realm of smart EMS, the term "ANN" typically refers to Artificial Neural Networks. This computational model, drawing inspiration from the structure and function of biological neural networks such as the human brain, consists of interconnected nodes (or artificial neurons). These nodes are organized into layers, including an input layer, one or more hidden layers, and an output layer. In the forthcoming discussion, we will dive into several articles that utilize ANN and elucidate how this model is integrated into their respective systems within the energy management domain.

First, in [38], the study presents a vision-based approach to optimize energy consumption in smart homes by employing facial recognition through YOLOv5n. Specifically, the YOLOv5n model is deployed on a Jetson Nano platform to detect and authenticate residents based on visual data captured by 2D cameras installed throughout the house. When a known resident is recognized entering or leaving the house, the system automatically controls the energy-consuming devices to optimize usage. Among the tested YOLOv5 variants, YOLOv5n demonstrated the best trade-off between speed and accuracy for the intended smart home deployment. Meanwhile, the authors of [39] introduce a Smart Home Energy Management System (SHEMS) designed for residential demand-side management. The system aims to optimize energy consumption and enhance demand-side management in smart homes. The proposed approach employs a two-stage Non-Intrusive Appliance Load Monitoring (NIALM) technique, with additional integration of Artificial Neural Networks (ANN) for enhanced data analysis. Fog-cloud analytics are utilized to process and analyze data, providing scalability and responsiveness to the system. Moreover, in [40] they introduce a cutting-edge approach to thermal comfort management through the application of Federated Learning. The central focus is on addressing the thermal comfort needs of individuals in diverse environments with precise real-time accurate prediction while maintaining privacy using FedAvg strategy and neural networks (NN). Federated Learning, a decentralized machine learning approach, is employed to train models locally on individual devices, preserving data privacy while collaboratively improving the overall thermal comfort management system. The goal of [41] is to introduce an innovative solution for appliance recognition in residential buildings, utilizing Federated Learning and a Deep Neural Network (DNN) with three convolutional layers. This approach addresses privacy concerns with decentralized data while effectively handling mislabeled datasets. The work of [42] employed an innovative approach, combining Federated Learning and a DNN with ReLU activation, to enhance energy prediction in smart buildings while prioritizing privacy. The incorporation of privacy-preserving mechanisms aligns with the sensitivity of smart building data. In [43] they propose an advanced solution using Federated Learning for detecting energy theft behaviors in smart grids while prioritizing consumers' privacy by predicting the time series data generated from smart meters. The framework incorporates a privacy-preserving mechanism and likely involves a Temporal Convolutional Network (TCN) for accurate detection. And in [44], they employ the Deep Deterministic Policy Gradient (DDPG) algorithm to enhance resource allocation and energy management in smart buildings utilizing cooperative computation offloading in SDN-enabled edge computing-based with device-to-device (D2D) aided end-to-end communication. This algorithm likely plays a crucial role in minimizing energy consumption, total delay of tasks, and optimizing decision-making processes. As we see, ANN is the most famous model, for this in [45], they propose a novel approach to address data silos in building energy consumption prediction. Leveraging federated learning and employing an Artificial Neural Network (ANN) model, the method facilitates collaborative model training across decentralized datasets. The integration of an ANN model underscores its potential in capturing complex patterns for accurate short-term energy consumption predictions. On the other side, the authors of [46] present an adaptive method for residential load forecasting using Federated Learning. The approach incorporates deep learning techniques, likely involving Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), to adaptively model and forecast load patterns to reduce the cost of energy consumption. The use of Federated Learning ensures privacy preservation in a decentralized setting. [47] propose a valuable framework for scaling smart cities, integrating the CRISP-DM model and ANN within the context of Federated Learning for accurate and privacy-preserving building energy performance prediction. Same as [48], they propose an innovative method for identifying consumer characteristics in the electricity sector using Federated Learning. By leveraging this decentralized approach, privacy concerns are addressed during the model training process. The paper likely employs the ANN model, to achieve accurate consumer characterization and then offer them diversified services.

Table 3
Summary of state-of-the-art artificial neural network (ANN)-based algorithms.

Ref.	Year	Methods	Evaluation Metrics	Results
[38]	2023	YOLOv5n	mAP, F1-score, Recall, Precision	0.77, 0.74, 0.70, 0.78
[39]	2021	ANN, two-fold cross-validation	F-measure, MSE	1.0, 0.0013
[40]	2022	NN, FedAvg	MAE, MSE, Accuracy	0.1164, 0.1065, 0.8039
[41]	2022	DNN, canonical Newton's method, FedAvg	Accuracy	≥86%
[42]	2021	DNN, weighted average	RMSLE, Time	1.2, 208.6 sec
[43]	2021	LDP scheme (K-RR), TCN	Accuracy	∼92%
[44]	2023	DDPG	NS	NS
[45]	2022	ANN, grid search, secure aggregation	CV, RMSE	22.2%
[46]	2022	Min-max normalization, CNN-LSTM, FedAVG	MAPE, Accuracy	4.83%, ∼90%
[47]	2023	One-hot encoding, normalization, ANN, Fed-Avg	MAPE	29.431
[48]	2021	PCA, ANN, cross-validation	Accuracy, MCC score	68.53%, 0.2989

Since many of these works combine ANN with Federated Learning (FL), it is important to clarify why FL is introduced and how it differs from traditional deep learning approaches. Unlike conventional models that require centralized data, FL enables devices or buildings to train models locally without exposing raw data. This supports privacy preservation, reduces communication overhead, and improves scalability in distributed environments such as smart buildings. FL is particularly useful when data cannot be shared due to sensitivity or regulation. Compared to other decentralized methods, such as Split Learning (which distributes parts of the model) or Distributed Computing (which offloads processing without privacy guarantees), FL offers a more privacy-conscious and coordinated framework.

Table 3 summarizes the state-of-the-art techniques based on ANN algorithms.

4.2. Time-Series-based Algorithms

Time-series-based algorithms are analytical tools that focus on sequential data points arranged chronologically. These algorithms aim to reveal inherent patterns, trends, or dependencies within the temporal structure of the data. By recognizing and leveraging the sequential nature of information, these methods contribute to making predictions or uncovering insights about future values. They find widespread application in various domains, such as smart grids, healthcare, transportation, and industrial processes, where understanding and predicting trends over time is essential. Using mathematical and statistical techniques, time series-based algorithms play a pivotal role in decision-making processes and forecasting applications. Subsequently, we will provide a summary of articles using this algorithm in the context of energy consumption prediction.

First, the authors of [49] present a Vector Autoregressive (VAR) model for forecasting electricity consumption in a Smart Metering System. The methodology includes dimensionality reduction, utilizing the Pearson coefficient for analyzing weather variable correlations. Emphasizing a decentralized edge/fog-cloud architecture, the model enhances accuracy and efficiency in time-series predictions. This integration showcases the synergy of advanced forecasting techniques and emerging edge computing paradigms, particularly within the context of smart grids. Meanwhile, [50] utilizes a distributed approach for load forecasting, incorporating smart meter data and implementing Federated Learning (FL) with Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) models. This framework allows for collaborative model training across decentralized smart meters, improving load forecasting accuracy. Additionally, the inclusion of techniques like min-max normalization enhances the model's robustness, providing a privacy-preserving and efficient solution for load forecasting in smart grid scenarios. In [51], the authors employ a privacy-preserving approach for residential short-term load forecasting, incorporating techniques such as Min–Max scaling for data normalization, Long Short-Term Memory (LSTM) networks for sequence modeling, and Differential Privacy (DP) to safeguard individual data during the federated learning process. This combination of methods strives to ensure accurate load forecasting while maintaining a robust privacy framework for individual residential energy consumption data. Same as [52] they utilize LSTM (Long Short-Term Memory) networks as the core algorithm for Electrical Load Forecasting. This choice of algorithm reflects a focus on sophisticated sequence modeling to enhance the accuracy of load forecasting, demonstrating the significance of LSTM in capturing intricate temporal relationships within the electrical load data. [53] aims to secure the performance of smart home applications

Table 4
Summary of state-of-the-art time-series forecasting algorithms.

Ref.	Year	Methods	Evaluation Metrics	Results
[49]	NS	Pearson coefficient correlation method, VAR model	NS	NS
[50]	2022	LSTM, Min-max normalization, sliding window, FedAVG, FedSGD	MAPE, RMSE	14.7522, 0.6138
[51]	2022	Min–max scaler, LSTM, DP, SecAgg	MSE, RMSE, MAE, MAPE	0.0003, 0.017, 0.005, 10
[52]	2020	LSTM, FedAvg	NS	NS
[53]	2021	LSTM, Gradient Selection Mechanism, FedAVG	Accuracy	97%
[54]	2022	CNN (Seq2Point), FedAvg	Accuracy, Precision, Recall, F1, MAE, RETE	0.98, 0.64, 0.8, 0.59, 20, 0.01
[55]	2021	LSTM, FederatedAveraging	NS	NS
[56]	2022	LSTM, FedAvg, FedYogi	RMSE	NS
[57]	2023	Seq2Point, VAE, FedAvg, FedAtt	NS	NS
[58]	2023	LSTM, FedAAVG	MAPE	4.891
[59]	2023	LSTM, Q-learning algorithm	NS	NS

and protect user data privacy by forecasting future energy consumption for specific devices in residences for the upcoming hour. This is achieved through the utilization of LSTM for effective sequence modeling and a Gradient Selection Mechanism, enhancing the accuracy of predictions. On the other side, [54] proposes a Federated Learning Model combining a short Sequence to Point (Seq2Point) Mechanism for Smart Home Energy Disaggregation. The objective is to enhance disaggregation accuracy collaboratively while prioritizing user privacy and trustworthiness in the overall system. This novel approach contributes significantly to advancing energy disaggregation techniques within the context of secure and privacy-preserving smart home environments. [55] develops an electricity load forecast model to maintain a healthy and comfortable indoor environment for the occupants' well-being, while simultaneously minimizing building energy use through the implementation of a Long Short-Term Memory (LSTM) algorithm. This will be achieved by forecasting the energy load based on previous observations of the household electrical load and real-time environmental variables. In [56], they focus on residential energy forecasting using federated learning and edge computing to uphold the privacy of energy consumption data. The methodology employs LSTM for time-series forecasting and integrates federated learning algorithms, including FedAvg and FedYogi. On the other side, [57] seeks to integrate Federated Learning (FL) with Non-Intrusive Load Monitoring (NILM) to enhance client privacy, minimize data transmission costs, and maintain comparable performance with centralized models. The methodology involves deploying the Short Seq2Point CNN model for appliance-wise power consumption calculation, employing the Variational Auto-Encoder (VAE) model, and utilizing both Seq2Point and VAE within the FL framework. The research of [58] aims to achieve day-ahead forecasting for residential load through a modified federated learning algorithm, focusing on customer demand management. The proposed methodology involves using LSTM to train local models for clients within the federated learning framework, employing the Adam optimizer. And finally [59] focuses on residential energy consumption forecasting with an emphasis on preventing household privacy leakage and ensuring user privacy. The methodology introduces the Federated Reinforcement Learning (FedRL) model, incorporating LSTM networks to train local data for each household. The Q-learning algorithm is utilized to assign weights to the local models uploaded by individual households, contributing to overall privacy protection while training an effective predictive model.

Table 4 summarizes the state-of-the-art techniques based on time-series algorithms.

4.3. Clustering-based Algorithms

In the context of smart EMS, clustering involves grouping similar entities to optimize energy consumption and enhance decision-making. By categorizing buildings, devices, or processes based on specific features, smart EMS gains insight into usage patterns, enabling tailored strategies. This data-driven approach allows for informed decisions on energy allocation, demand response, and efficiency measures. Clustering promotes adaptability, which is crucial for accommodating changes in demand and integrating new technologies. Predictive modeling benefits from identifying patterns within clusters, aiding in forecasting and proactive measures. Clustering insights continually drive improvements, ensuring a dynamic and sustainable energy management approach. In the following, we will summarize the best articles based on clustering algorithms.

First, the research of [60] introduces a pioneering multi-tier architecture for data analytics in smart metering systems, addressing real-time and delayed-time processing. The methodology involves Smart Meters with varied communication technologies, data aggregation by the Data Concentrator, and storage in a sophisticated database. Utilizing ARIMA, SARIMAX, decision tree, k-means clustering, and Bayesian classifier for predictions enhances the analytical depth. The integration of both wired and wireless communication technologies demonstrates versatility. Then, the authors of [61] utilize coalition game theory to optimize energy allocation within a smart building while maintaining a balance between generation and demand. The Shapley value rule is employed for fair and efficient distribution of surplus energy among buildings. This approach shares parallels with clustering, as coalition game theory involves grouping entities to maximize utility, akin to clustering's grouping based on similarities. And, in [62] evaluates the performance of a smart building monitoring system, focusing on information gathering from diverse sensors. Two architectural designs, a public cloud Kubernetes cluster, and a local datacenter Kubernetes cluster, are compared. Utilizing a Node.js library, the study filters sensor data, detecting abnormal situations based on pre-defined thresholds. The crucial alerting mechanism promptly notifies responsible personnel during emergencies, showcasing a comprehensive approach to enhance efficiency in smart building emergency response. [63] tackles the crucial need for localized and robust building energy performance grading methods. The proposed GREEN grading system employs sophisticated techniques such as logarithmic transformation, hyper-parameter tuning, and K-means clustering. This innovative approach not only cleans and predicts Energy Use Intensity (EUI) but also assigns grades based on energy performance ratios. The comprehensive methodology, including a 5-fold cross-validation, demonstrates a systematic and effective framework for advancing data-driven urban energy efficiency and carbon reduction policies. On the other side, [64] presents an innovative solution for forecasting individual house and aggregate electrical demands, emphasizing data privacy through federated learning and edge computing. The use of FedAvg for aggregation, LSTM for time-series forecasting, and a clustering method with hyperparameter tuning demonstrates a well-rounded methodology. This approach not only ensures accurate predictions but also addresses the critical aspect of data privacy in the context of electrical load forecasting. Meanwhile, [65] delves into private load forecasting using Federated Learning (FL) and LSTM networks, exploring various training approaches, including FL with Euclidean clustering. The study demonstrates a comprehensive methodology, incorporating techniques like min-max normalization and federated averaging. This holistic exploration of short-term load forecasting addresses privacy concerns, with a specific focus on the innovative combination of FL and Euclidean clustering for improved performance. The authors in [66] present a forward-looking strategy for real-time energy consumption forecasting within the next hour. Employing a Federated Learning framework, the methodology integrates LSTM for accurate forecasting at the edge, k-means for customer clustering, and FedAVG for effective model aggregation. The innovative approach not only addresses short-term energy consumption challenges but also ensures localized notification to customers about potential anomalies, showcasing the potential of Federated Learning in enhancing energy efficiency and customer awareness at the edge. In [67], they introduce an innovative framework for fine-grained monitoring and prediction of individual household power consumption. By combining K-means for load clustering, LSTM for accurate forecasting, and Federated Averaging (FedAvg) for distributed model aggregation, the methodology provides a comprehensive approach to enhance short-term load forecasting. The integration of load clustering ensures a nuanced understanding of residential loads, making the proposed framework promising for advancing the accuracy and granularity of load predictions in residential settings. Finally, [68] presents an innovative approach to energy demand prediction using Federated Learning and Clustering. Employing the OPTICS algorithm for client clustering and Bidirectional LSTM modeling, the methodology enables distributed training and model aggregation, fostering collaborative refinement. This strategy holds promise for accurate energy demand predictions and efficient consumption management within a federated learning framework.

Table 5 summarizes the state-of-the-art techniques based on clustering algorithms.

4.4. Hybrid-based Algorithms

Hybrid-based algorithms are a sophisticated approach in machine learning that combines elements from various methodologies to boost overall performance. By integrating techniques such as artificial neural networks, time series analysis, clustering, and classification, these algorithms aim to leverage the strengths of each component. This hybridization often leads to improved adaptability, robustness, and efficiency across diverse data types and tasks. In particular, they excel in energy efficiency applications, offering potent solutions for complex real-world problems

Table 5
Summary of state-of-the-art clustering-based algorithms.

Ref.	Year	Methods	Evaluation Metrics	Results
[60]	2020	ARIMA, SARIMAX, DT, k-means clustering, Bayesian classifier	Final Score	98.17%
[61]	2023	Coalition game method-based Shapley value rule	Execution time, Response time	2.40 sec, 0.1 ms
[62]	2022	Public cloud Kubernetes cluster, local datacenter Kubernetes cluster	NS	NS
[63]	2018	Logarithmic transformation, Hyper-parameter tuning, XGBoost, K-means clustering, 5-fold cross-validation	R^2	0.31
[64]	2022	LSTM, clustering method based on hyperparameter tuning, FedAvg	RMSE	0.117 kWh
[65]	2022	Min-max normalization, LSTM, FedAvg, Euclidean (L2) clustering distance metric	NS	NS
[66]	2021	LSTM, k-means, FedAvg	RMSE, Training time	0.133, 2.87
[67]	2021	K-means, LSTM, FedAvg	RMSE, MAPE, MAE	0.6092, 91.67, 0.4084
[68]	2021	OPTICS algorithm, RNN (Bidirectional LSTM)	NS	NS

where singular approaches may fall short. In the following, we will investigate many articles using this type of machine learning algorithms.

First, the authors of [69] present an innovative approach to optimize electricity consumption in smart homes. The integration of a fog-based IoT framework, Markov chain model, and PF-PEC algorithm provides a comprehensive solution. The utilization of user activity data for energy consumption forecasting, combined with dynamic adjustments based on environmental factors, enhances the efficiency of energy management. In [70], they discuss a cutting-edge hybrid approach promising advancements in intelligent energy management and efficiency, seamlessly blending fog-based architecture, Markov Chain analysis, linear prediction, and fuzzy rule-based decision-making. By harnessing data from low-power Sensor and Actuator Networks, the system not only accurately recognizes user activities but dynamically adapts to the environment based on updated fuzzy rules, ensuring significant energy savings. The emphasis on cross-validation underscores the robust evaluation of regression and classification schemes. The study of [71] proposes an edge computing-based model employing machine learning techniques such as KNN Regressor, Random Forest, Extra Tree Regressor, Gradient Boosting, and MLP Regressor. It shows promise in optimizing smart city energy consumption. Meanwhile, the authors of [72] propose a commendable approach, integrating blockchain and edge computing for secure smart home energy management. The real-time data collection strategy aligns to enhance IoT user privacy and reduce energy consumption. While the use of ARIMA and LSTM showcases a thoughtful analytical approach to forecasting the energy usage of smart homes. The paper [73] impressively achieves its objectives by offering a comprehensive review of major forecasting techniques, including ANN, ARIMA, SVM, Fuzzy time series, and Grey prediction model. The paper serves as a valuable resource for understanding and selecting appropriate hybrid models and forecasting techniques in the domain of building energy consumption. Now, the paper [74] aims to reduce building energy consumption through an autonomous federated learning (FL) approach. By monitoring and implementing automatic on/off systems for lights, fans, doors, windows, and other electrical components, the objective aligns with energy efficiency goals. The proposed methodology employs FL, featuring NCA feature selection and the application of various machine learning models, including ANN, SVM, Bagging, and Linear Regression (LR). This approach reflects a robust strategy for implementing AI in buildings with a focus on energy optimization. The authors of [75] offer an insightful overview of machine learning methods applied to building energy consumption prediction. The proposed hybrid approach involves the utilization of parallel SVM and least squares SVM (LS-SVM) for energy consumption prediction. Additionally, the inclusion of an ANN model based on high-throughput screening (HTS) demonstrates an efficient approach to predicting and optimizing the performance of solar collectors. The paper [76] aims to accurately forecast the future net-energy of a net-metering system while prioritizing customer privacy. The proposed methodology introduces a hybrid deep learning (DL) net-energy forecasting model for net-metering systems. The approach includes the use of the autocorrelation function (ACF) to measure the correlation between time-series data and its lagged version.

Table 6
Summary of state-of-the-art hybrid approaches that combine multiple types of algorithms.

Ref.	Year	Methods	Evaluation Metrics	Results
[69]	2023	Markov chain model, PF-PEC algorithm	MAE, Latency	0.008, 0.5 s
[70]	2020	Markov Chain, linear prediction, fuzzy method, cross-validation	NS	NS
[71]	2021	KNN Regressor, Random Forest, Extra Tree Regressor, Gradient Boosting, MLP Regressor	Train R^2, Test R^2, RMSE	0.993, 0.837, 0.403
[72]	2023	ARIMA, LSTM	R^2, Accuracy	0.0004638, 99.52%
[73]	2017	ANN, ARIMA, SVM, Fuzzy time series, Grey prediction model, MA, ES	NS	NS
[74]	2022	NCA feature selection, ANN, SVM, Bagging, LR	MAPE, R^2	0.5677, 99.84%
[75]	2019	LS-SVM, ANN	NS	NS
[76]	2023	ACF, CNN, LSTM	MSE, RMSE, MAE, nMAE, MAAPE	0.32, 0.57, 0.32, 2.80, 2.72
[77]	2022	Pearson's Correlation, Spearman's Correlation, PCA, Multiple Linear Regression, Autocorrelation Analysis, ARIMA, LSTM	RMSE, MAPE, R^2	0.0101, 15.0250, 0.9939
[78]	2023	MHD-LSTM	RMSE, MAE, R^2, Accuracy	22.0157, 17.3011, 0.9996, 0.9795

Additionally, a CNN module is applied to extract essential features before inputting them into the LSTM module, chosen for its ability to capture correlations in time-series data. Addressing the imperative for energy consumption forecasting in building energy management systems, [77] focuses on minimizing energy usage during periods of high prices to ensure user comfort and promote sustainable consumption practices. The proposed methodology utilizes a feature engineering approach to analyze energy consumption variables in smart buildings. Techniques such as Pearson's and Spearman's correlation analyses, Principal Component Analysis (PCA), Multiple Linear Regression, and Autocorrelation Analysis are employed for thorough feature analysis. Subsequently, the LSTM technique is implemented for energy consumption prediction tasks. Finally, Intending to reduce computing consumption, counter malicious attacks, and understand user needs for improved services, the paper [78] introduces a PoQ-based federated learning method for private electricity consumption forecasting. The proposed methodology employs an MHD-LSTM network model, featuring two layers of bidirectional LSTM (BLSTM) and one layer of unidirectional LSTM. Notably, the PoQ consensus mechanism initializes the global model and securely stores parameters on the blockchain, enhancing the network's resilience and privacy.

Table 6 summarizes the state-of-the-art techniques based on hybrid algorithms.

4.5. Classification-based Algorithms

Classification methods are a category of machine learning algorithms designed for the task of assigning predefined labels or categories to input data based on its features. The primary goal is to develop a model that can learn patterns and relationships within the data to make accurate predictions about the class or category of new, unseen instances. These methods are widely applied in the field of intelligent EMS. In this context, these algorithms play a crucial role in tasks such as load forecasting, fault detection, and optimization, aiding in efficient management and control of energy resources. Classification algorithms encompass various techniques, including logistic regression, decision trees, support vector machines, k-nearest neighbors, and neural networks, each with its strengths, assumptions, and suitability for different types of datasets and tasks. The selection of an appropriate classification method depends on the characteristics of the data and the nature of the problem at hand. In the following, we will give a summary of articles on classification-based algorithms.

First, [79] introduces a commendable Disaster Emergency Response Framework for Smart Buildings, focusing on real-time prediction and evacuation strategies. The integration of IoT, fog computing, and machine learning algorithms showcases a robust approach. The use of diverse sensory nodes ensures complete data collection, while the energy-efficient ANOVA model and SVM for event detection contribute to system efficiency. The authors of [80] present an innovative approach to energy management by integrating a rule-based algorithm for micromoment feature extraction

Table 7
Summary of state-of-the-art classification-based algorithms used in smart buildings.

Ref.	Year	Techniques and Algorithms	Metrics	Results
[79]	2022	ANOVA model, SVM, SVD	Execution time, latency	5 min, 38 sec
[80]	2021	Rule-based algorithm, EBT classifier	Accuracy, F1	99%, 99%
[81]	2020	SVM, pixelating technique	NS	NS
[82]	2023	DT algorithm	Accuracy	≥ 80%
[83]	2018	GBM hyper-parameters tuning (5-fold CV)	Execution time, R^2, CV(RMSE), NMBE	7 min, 88%, 81%, 59%
[84]	2018	SVR	NS	NS
[85]	2021	Actor–critic DRL, FedSGD	Computation time	512 sec

and an Ensemble Bagged Trees (EBT) classifier to detect anomalous energy consumption. The emphasis on an edge-based architecture highlights the importance of real-time processing and efficient monitoring. The objective of advising end users about energy saving recommendations via a mobile application aligns with the growing demand for intelligent solutions on the Internet of Energy. The proposed framework holds promise for improving energy efficiency, encouraging habit change, and reducing electricity costs. And in [81], they address the critical objective of finding a privacy solution to protect occupants from profiling and tracking within smart buildings. The proposed methodology, IoTFC, employs a Support Vector Machine (SVM) for data classification and anomaly detection. In addition, a pixelating technique is utilized to enhance privacy. The framework emphasizes secure data exchange between sensors and cloud layers while ensuring robust solutions for access control, authentication, anomaly detection, and privacy. The paper [82] has the central objective of reducing energy consumption by identifying abnormal energy usage patterns. The aim is to create environmentally friendly smart buildings that adapt to diverse lifestyles. The methodology introduces the DSBDA model, which involves the collection of data streams from IoT sensors. This data is then analyzed using an AI-driven decision tree algorithm. Based on the output of the algorithm, the controller optimizes energy consumption, and an automated system is activated through an agent. In this study [83], the objective is to predict and reduce building energy consumption over 6 and 12 month training periods. The proposed methodology employs a gradient boosting machine (GBM) algorithm with three versions for hyperparameter tuning: GBM with 5-fold cross-validation (CV), GBM day with a day as a block in 5-fold block CV, and GBM week with a week as a block in 5-fold block CV. This approach demonstrates the efficacy of gradient improvement in accurately modeling and reducing energy usage in commercial buildings. A comprehensive approach to identifying abnormal energy consumption patterns through the temporal analysis of smart meter data is presented in [84]. The proposed model, which features preprocessing, feature extraction, support vector regression, profiling, and visualization, demonstrates a holistic solution for effective energy management. By combining machine learning techniques and visualization tools, the article contributes to enhancing anomaly detection and understanding energy consumption behaviors in smart building environments. Finally, [85] aims to optimize the Shared Energy Storage System (SESS) and the Heating, Ventilation, and Air Conditioning (HVAC) systems while protecting privacy in heterogeneous building environments. Using a Federated Deep Reinforcement Learning (DRL) approach, it applies actor–critic DRL for agent training, specifically using the ADAM algorithm for HVAC and SESS agents.

Table 7 summarizes the state-of-the-art techniques based on classification algorithms.

4.6. Versatile Algorithms

Versatile algorithms in the context of smart EMS refer to algorithms that demonstrate adaptability and flexibility to handle a diverse range of challenges within the energy domain. These algorithms are designed to be applicable to various energy sources, scales of operation, and dynamic environmental conditions. They can seamlessly integrate with different types of energy infrastructure, accommodate various energy consumption patterns, and optimize energy usage based on factors such as cost, efficiency, and environmental impact. Versatile algorithms often incorporate features such as scalability, interoperability, and the ability to leverage machine learning techniques for continuous improvement and adaptation to changing conditions in real time. Their versatility makes them valuable tools for addressing the complex and evolving nature of energy management in different contexts and applications. In the following, we will present different papers in this category.

Table 8
Summary of versatile algorithms applied across different energy management tasks.

Ref.	Year	Methods	Metrics Evaluation	Results
[86]	2022	XOR data aggregation method	NS	NS
[87]	2023	Lyapunov's theory	NS	NS
[88]	2021	RabbitMQ	NS	NS
[89]	2022	ALST algorithm	Overall score, Median score	7.85, 8
[90]	2023	DDPG algorithm	NS	NS
[91]	2022	Hybrid meta-heuristic algorithm MGAPSO	NS	NS
[92]	2023	Two metaheuristics IDE and GWO	Response time, Processing time	63.02 ms, 13.39 ms
[93]	2023	PSO, LM	MSE, RMSE, MAE, R^2	0.10, 0.40, 4, 0.9913

First, [86] proposes FARDA, a fog computing-based solution, to address security concerns in IoT data aggregation within smart buildings. Employing the Monero protocol for key generation and an XOR data aggregation method, FARDA ensures anonymity in user bidding, service provision, and reward distribution. The paper contributes significantly to enhancing privacy and security in IoT environments, particularly in the context of smart buildings, by introducing an innovative and effective fog-based anonymous reward data aggregation scheme. The authors of [87] present offloading policies that achieve a balance between energy consumption at fog nodes and the monetary cost associated with cloud usage. The proposed methodology, employing Lyapunov's theory on data related to traffic flows from various applications, offers a systematic approach to optimizing energy-aware offloading strategies. By leveraging Lyapunov's theory, the scheme contributes to efficient decision-making in fog-cloud architectures, providing a valuable solution for managing energy consumption and costs in dynamic computing environments. And in [88], they aim to maximize the potential of smart climatic test facilities. The proposed PPSBF methodology seamlessly integrates real-time data acquisition, transmission, and processing using technologies like IBMStreams and DB2. This case study exemplifies the synergy between edge computing, big data, and cloud architecture, showcasing an effective framework for optimizing smart building functionalities and enabling retrospective analysis of climatic test facility data. The paper [89] introduces an innovative smart building solution inspired by the collective behavior of bee swarms. Honeycomb seamlessly integrates Building Automation Systems (BAS), IoT, and distributed systems. The proposed methodology, featuring sensor/actuators deployment, the application of the Asynchronous Leaderless Spanning Tree (ALST) algorithm within Honeycomb, and the establishment of the Business/Platform layer, exemplifies an open-source approach to intelligent building management. In this study, [90], they aim to optimize task offloading decisions and minimize the energy consumption of IoT devices, along with reducing total task delay. The proposed REED model involves an agent collecting pertinent information from the SDN controller and employing the Deep Deterministic Policy Gradient (DDPG) algorithm to make optimal decisions for tasks. This methodology introduces an effective approach to enhance resource allocation and energy management in smart buildings, particularly within the context of Software-Defined Networking (SDN) and Edge Computing, contributing to improved efficiency and reduced energy consumption in IoT-enabled environments. An EGAPSO algorithm presented in [91] effectively combines Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to optimize service time, cost, and energy consumption. By introducing the MGAPSO algorithm and combining Elitism-based GA (EGA) with PSO in the EGAPSO algorithm, the research offers a robust strategy for efficient service placement in fog computing environments. In [92], the aim is to enhance the Cloud-Fog-Cloud (CFC) architecture's data analysis and management with minimal latency using metaheuristic algorithms. The proposed methodology, HGWDE, combines Improved Differential Evolution (IDE) and Gray Wolf Optimization (GWO) to optimize energy usage efficiently in smart grids. Finally, [93] proposes a hybrid protocol FedLM-PSO approach that utilizes Particle Swarm Optimization (PSO) and Levenberg Marquardt (LM) for training Multilayer Perceptron (MLP) models in a Federated Learning environment, aiming for near-optimal configurations. This strategy presents a concise and promising solution for enhancing energy consumption efficiency in smart buildings.

Table 8 summarizes the state-of-the-art techniques based on versatile algorithms.

5. Smart Building: Concept and Components

Smart Building (SB) systems represent an innovative approach to modernizing building infrastructure for better efficiency, sustainability, and comfort of occupants. They integrate a wide range of subsystems into a unified environment, including energy management, temperature monitoring, security, lighting control, telecommunications, office automation, and maintenance systems. At their core, SBs rely on interconnected components such as sensors, actuators, controllers, and communication networks. These enable data collection, automated control, and coordinated responses across systems. For example, sensors detect temperature, humidity, or occupancy; actuators adjust HVAC and lighting; controllers process data and trigger actions; and networks ensure seamless communication. Together, these components create a dynamic and adaptive environment that improves building performance, energy efficiency, and overall functionality [94]. Figure 4 presents examples of smart appliances and systems. Centralized management of these elements enables efficient energy operation and intelligent coordination of green and conventional energy sources. Typically, an SB uses an Ethernet backbone with a bridge to a Controller Area Network (CAN) [95].

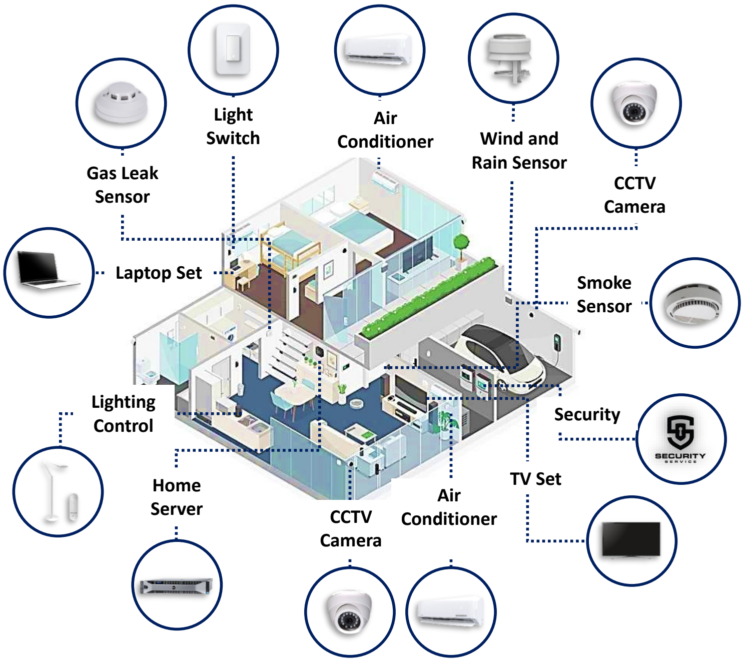

Figure 4: Smart appliances, sensors, and actuators in a smart residential building.

5.1. Smart Building Components

Advances in smart building technology have driven the extensive development of Smart Buildings to generate economic and environmental benefits for building owners through the convergence of IoT and building automation systems. Figure 5 shows the key components of Smart Building systems, these include extensive sensors and actuator systems, networking and communication systems, software platform system, HVAC system, and smart control devices [96].

Current systems employ control devices and smart sensors interconnected with a central system strategically placed throughout the environment. Each system has its own network and communication infrastructure that facilitate communication with the central system. SBs serve as interconnected networks that act as a communication backbone for multiple systems. Among these systems, HVAC equipment is one of the most complex, comprising numerous components arranged to regulate temperature and ventilation. In addition to providing comfort for the occupants, the HVAC system significantly influences energy consumption and plays a crucial role in life safety. Smart buildings leverage technology to monitor and control facility systems, making necessary adjustments as needed. The primary goal of a smart building is to utilize computer systems and software to manage lighting, alarm systems, HVAC, and other building systems through a unified computer interface.

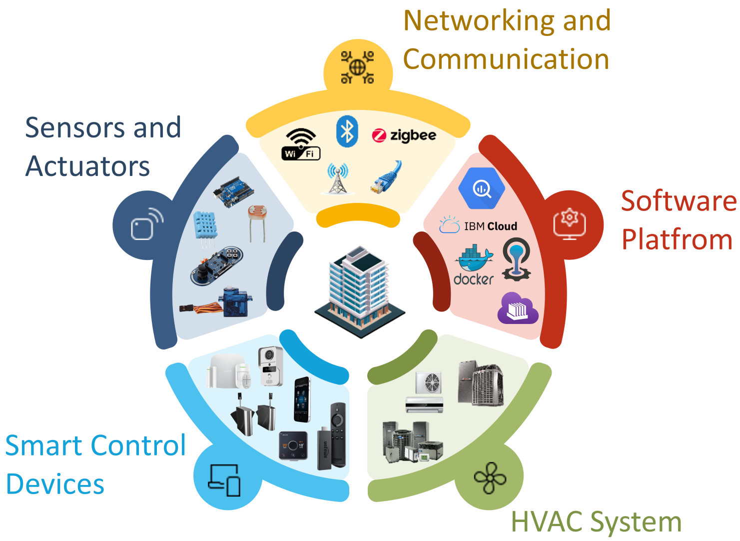

Figure 5: Components of Smart Buildings.

5.1.1. Sensors and Actuators

Sensors and actuators serve as essential mechanical components that are responsible for measuring and regulating environmental parameters within their surroundings. Sensors gather data from the environment, making it accessible to the system. For example, infrared (IR) sensors can detect the presence of humans within a room. However, an actuator translates an electrical control signal into a physical action, enabling automated and remote interaction with the environment. For example, a light actuator can toggle electric lights on/off and adjust their brightness. Rapid advancements in micromechanics, microelectronics, integrated optics, and related technologies have facilitated the emergence of various smart sensors integrated into everyday objects and infrastructure within smart building environments. These sensors, often worn by users or embedded in building systems, are interconnected via network technologies to efficiently collect contextual information about daily activities, with reduced energy consumption and processing resources. Environmental sensors are designed to monitor the conditions in each room or zone within a building, while wearable sensors are used to monitor and control mobile activities and physiological signals [96]. We can distinguish between the following types of sensors and actuators in the literature.

- Environmental sensors: data collected from environmental sensors within a smart building (SB) can provide valuable insights into human behaviors. These sensory data are analyzed to observe daily activities such as bathing, dressing, meal preparation, and medication intake. Environmental sensing relies on various types of sensors, including binary sensors, RFID technology, and video cameras, distributed throughout the home. Motion sensors, like infrared presence sensors, detect occupants' presence, while pressure sensors on objects like beds and chairs track their actions and locations. The contact switches on the doors and cabinets monitor the interactions with these objects. Light, humidity, temperature, and power sensors are also deployed to recognize activities, measuring light intensity, air humidity, temperature, and power usage, respectively, in specific areas of the building.

- Wearable sensors and biosensors: these sensors, whether attached directly or indirectly to the user's body, are compact enough to be affixed to clothing and accessories like wristwatches, glasses, belts, and shoes. They fall into two main categories: inertial sensors and vital sign sensors, also known as biosensors. Inertial sensors, such as accelerometers, gyroscopes, and magnetic sensors, are portable and offer detailed insights into the user's actions and posture without stationary units. They require receivers and cameras for data collection, which makes them suitable for use outside laboratory settings. Vital sign sensors, such as those that measure blood pressure, skin temperature, and heart rate, are essential for health monitoring. Common inertial sensors for activity tracking include accelerometers, which measure acceleration rates, useful for monitoring various activities such as exercise, standing, walking, or climbing stairs. Gyroscopes, on the other hand, measure angular velocity and

Table 9
Overview of smart sensors commonly used in smart buildings.

Sensor	Measurement	Category
Infrared sensor	Presence of an individual within a room	Environmental sensors
Video cameras	Human activities	
RFID	Identification of objects	
Motion sensor	Object, user presence, location	
Contact switch	Identifying users' interactions with the object	
Pressure sensor	Monitoring the user's movements and location	
Light sensor	Intensity of light	
Temperature sensor	Environmental temperature	
Humidity sensor	Detecting the humidity level in a particular location	
Power sensor	Monitoring the usage of electrical devices	
Accelerometer	The acceleration rate along a specific axis	Wearable sensors
Gyroscope	Angular velocity and maintain orientation	
Electroencephalography	Monitoring the electrical activity of the brain	
Electrooculography	Monitoring eye movement or ocular activity	
Electromyography	Monitoring muscular activity	
Electrocardiography	Monitoring heart and blood pressure via pressure sensors	
CO_2 gas sensors	Monitoring breathing or respiratory activity	
Thermal sensors	Monitoring body temperature	
Galvanic skin response	Monitoring skin sweating	
CO_2 sensor	Monitoring indoor air quality based on CO_2 concentration	HVAC sensors
Airflow sensor	Measuring airflow rates within ventilation ducts	
Pressure differential sensor	Monitoring air pressure differences across building zones	
VOC sensor	Detecting harmful airborne substances and pollutants	
Occupancy sensor	Controlling HVAC systems based on room occupancy	

orientation. Vital sign sensors encompass a range of devices, from electrocardiogram (ECG) sensors for heart activity to pressure sensors for blood pressure and CO2 gas sensors for respiration. These sensors play a crucial role in monitoring various vital signs, including heart rate, blood pressure, blood glucose, oxygen saturation, and respiratory rate. In addition, sensors such as electroencephalography (EEG) and electromyography (EMG) monitor brain activity and muscle movement, respectively.

- Heating, Ventilation, and Air Conditioning (HVAC): the HVAC system plays a vital role in providing services within smart buildings (SBs), contributing significantly to efficient energy use and enhancing occupant comfort. Beyond regulating temperature, HVAC control systems aim to maintain comfort by managing humidity levels, air pressure, airflow, and air quality within enclosed spaces. Monitoring CO2, humidity and temperature levels is crucial for improving occupant well-being, as these factors can impact health and comfort. Heating and cooling systems consume a large amount of energy in buildings, so it is necessary to optimize them using smart controllers and sensors to save operational costs. Smart HVAC systems can efficiently detect and control different air quality parameters within the building utilizing distributed sensors and Variable Air Volume (VAV) fans throughout the building to perform optimal ventilation. Most of the current HVAC actuation systems in smart buildings are based on data collected about the occupants using sensors and cameras, which are used specifically for HVAC systems.

Table 9 shows a summary of different types of smart sensors in SBs.

5.1.2. Smart Control Devices

Smart control devices play a crucial role in smart building systems by gathering data from various sensors, analyzing this data, and initiating actions through actuators in response to sensor-detected events. These devices are capable of functioning autonomously without relying on a central server for control. However, they may need to communicate with each other, either directly or through a smart gateway, to coordinate actions or share information

Table 10
Overview of control devices applied in smart building environments.

Device	Description
WeMo	WeMo offers a range of smart home automation products, including smart plugs, light switches, and sensors, which can be controlled remotely via a smartphone app or voice commands.
Nest Thermostat	The Nest Thermostat is a smart thermostat that learns users' heating and cooling preferences over time and adjusts settings automatically to optimize energy efficiency and comfort.
SmartThings	SmartThings offers a smart home hub and a variety of compatible sensors and devices that enable users to monitor and control their home environment remotely.
Sensibo Sky	Sensibo Sky Smart Air Conditioner Controller enables users to control their air conditioning units remotely via a smartphone app, optimizing temperature settings and reducing energy waste.
Philips Hue	Philips Hue offers smart lighting solutions that allow users to control the color, brightness, and scheduling of their lights using a smartphone app or voice commands.
Canary	Canary offers smart home security cameras that monitor users' homes for motion, sound, and other activities, providing real-time alerts and video footage via a smartphone app.
Envoy S Metered	Enphase Envoy-S Metered is a smart energy monitoring system that tracks solar production, energy consumption, and storage in real-time, providing insights to homeowners to optimize energy usage and maximize savings.
Honeywell	Honeywell offers a range of smart thermostats, security systems, and other home automation products that enable users to monitor and control their home environment remotely.

effectively. This decentralized approach improves the flexibility and responsiveness of smart building systems, allowing efficient management and optimization of building operations [96]. Table 10 shows various smart control devices in the SBs.

5.1.3. Networking and Communication

Networking and communication are vital components of smart building systems, particularly in relation to energy consumption management. These technologies facilitate the seamless integration of various devices, sensors, and systems within a building, allowing real-time data collection, analysis, and action to optimize energy usage. Through networking, sensors, meters, and monitoring devices throughout the building can transmit energy consumption data to a central management system for analysis. This integration enables different subsystems, such as lighting, HVAC, and occupancy detection, to communicate and share data, leading to more efficient energy usage. Building managers and operators can remotely monitor and control energy-consuming devices and systems, adjusting settings based on real-time data to optimize energy consumption. In addition, networking enables the transfer of energy consumption data to cloud-based analytics platforms, where advanced algorithms identify patterns and trends to inform energy-saving strategies. In addition, networking facilitates interaction with the electrical grid, allowing smart buildings to participate in demand response programs and adjust energy consumption based on grid signals. Predictive maintenance strategies are also supported, with connected devices transmitting diagnostic data for proactive equipment maintenance and monitoring, ultimately reducing downtime and energy waste. In summary, communication and networking technologies are crucial for efficiently managing energy consumption in smart buildings, leading to optimization, cost reduction, and sustainability. Effective communication ensures seamless operation, responsiveness to changing conditions, and a comfortable environment for the occupants. Interoperability standards and clear communication protocols are key to integrating various devices and systems, enabling data exchange and coordinated actions toward energy efficiency and occupant well-being.

Following this classification, we delve into the details of each type of smart building network technology: communication protocols, wireless, and wired technologies [14]:

- Communication protocols:
  - BACnet (Building Automation and Control Networks): is a widely used protocol specifically designed for building automation and control systems. Facilitates communication between different devices and systems, such as HVAC, lighting, security, and more, allowing them to exchange data and commands effectively.

  - Modbus: is a serial communication protocol commonly used in industrial automation applications. It enables communication between devices such as sensors, meters, and programmable logic controllers (PLCs) over serial connections such as RS-485 or Ethernet.
  - MQTT (Message Queuing Telemetry Transport): is a lightweight and efficient publish-subscribe messaging protocol ideal for IoT applications. Enables devices to publish data to a central broker and subscribe to receive relevant information, facilitating efficient communication in smart building environments.
  - CoAP (Constrained Application Protocol): is a specialized protocol designed for resource-constrained IoT devices, particularly those operating on low-power networks. Provides a lightweight and efficient communication mechanism for devices in smart buildings to exchange data and control commands.

- Wireless technologies:

  - Wi-Fi: it provides high-speed wireless communication using radio waves, allowing devices in smart buildings to connect to local networks and the Internet. Wi-Fi offers flexibility, high bandwidth, and widespread compatibility, making it suitable for various smart building applications.
  - Zigbee: is a low-power, low-data-rate wireless communication protocol commonly used in smart building automation systems. It enables devices to form mesh networks, facilitating communication between sensors, actuators, and other IoT devices over longer distances with minimal power consumption.
  - Bluetooth: It technology enables short-range wireless communication between devices, making it suitable for applications such as indoor positioning, asset tracking, and personal area networks within smart buildings.
  - Mobile networks: such as 4G LTE and 5G provide connectivity for smart building devices in areas without Wi-Fi coverage or as a backup connection. Mobile networks offer a wide coverage and reliability, allowing remote monitoring and control of building systems.
  - Thread: Thread is a low-power IPv6-based mesh networking protocol designed for IoT devices in smart buildings. It offers secure and reliable communication over the IEEE 802.15.4 standard, supports self-healing mesh networks, and enables direct IP connectivity, making it ideal for scalable, secure, and energy-efficient communication between smart sensors and actuators.

- Wired technologies:

  - Power Line Communication (PLC): is a technology that utilizes a building's existing electrical wiring to transmit data signals, eliminating the need for separate communication cables. Commonly used in smart buildings, PLC facilitates communication for devices such as smart plugs, meters, and home automation systems. This method simplifies installation and reduces costs by taking advantage of the infrastructure already in place. PLC operates by modulating the data onto the electrical power waveform, allowing efficient transmission without interfering with normal electrical functions. In general, PLC offers a convenient and cost-effective solution for establishing communication between devices in smart buildings.
  - Ethernet and LAN (Local Area Network): Their connections are fundamental for high-speed and reliable communication within smart buildings. These connections are commonly used to link devices that require high bandwidth and low latency, such as servers, routers, switches, and IP cameras. Ethernet, a prevalent wired LAN technology based on the IEEE 802.3 standard, uses cables such as coaxial, twisted pairs, and fiber optics for data transfer. With data transmission rates ranging between 100 Mb/s and 1000 Mb/s, Ethernet offers a relatively inexpensive option, though it is most suitable for short-distance data transfers. Despite this limitation, Ethernet and LAN connections remain stable and secure, making them ideal for critical applications within smart building environments.
  - Fiber-optic cable: In modern smart buildings, fiber optic cable plays a crucial role in the establishment of reliable and high-speed communication networks. Serving as the backbone of the building's infrastructure, fiber-optic cables connect various systems and devices, enabling seamless integration of smart technologies such as security, HVAC control, and energy management. With its unparalleled bandwidth and immunity

to electromagnetic interference, fiber optic cable ensures efficient data transmission and supports data-intensive applications without latency or degradation in performance. By investing in fiber optic infrastructure, building owners can futureproof their networks and accommodate emerging technologies, while ensuring the security and reliability of critical building systems.

- Privacy and Ethical Considerations: In smart building environments, both wireless and wired communication networks handle potentially sensitive data, such as occupant behavior, device usage, and real-time energy consumption. This raises significant privacy and ethical concerns. Wireless communications, while convenient, are particularly susceptible to eavesdropping, spoofing, and man-in-the-middle attacks due to their broadcast nature. To mitigate these risks, encryption protocols such as WPA3 for Wi-Fi, secure key exchange mechanisms, and authentication procedures must be implemented. Wired communication offers greater security, but is not immune to risks such as physical tampering or unauthorized tapping of cables. Ethical considerations also arise in terms of data ownership, consent, and transparency of usage. It is essential to ensure that the collected data are anonymized where possible, stored, secure, and accessed only by authorized parties. Adherence to data protection regulations and the incorporation of privacy-by-design principles into system architecture are crucial steps toward ethically responsible smart building deployment.

5.1.4. Software Platform

The role of software platforms in smart buildings is paramount, ensuring seamless communication and secure data exchange between various appliances, systems, and cloud-based servers. These platforms serve as the backbone for exchanging, storing, and disseminating information using different communication protocols such as push, pull, and publish/subscribe methods. In addition, the software platform enables remote monitoring and control of energy-consuming devices and systems, allowing building managers to adjust settings, schedule operations, and implement energy-saving strategies from a centralized interface. It also facilitates interaction with external systems, such as utility providers or demand response programs, to participate in energy management initiatives and grid optimization efforts. For example, the Tridium Niagara framework is a robust software platform developed specifically for building automation and control. Niagara framework acts as a unified interface for integrating various building systems and devices, enabling efficient data sharing, monitoring, and control. Building managers can utilize the Niagara Framework to remotely monitor energy consumption, adjust settings, and implement energy saving measures, all from a centralized interface. Moreover, the open architecture of the platform allows for seamless integration with devices from different manufacturers, ensuring compatibility and ease of use for building operators [39].

Recognizing the importance of interoperability, joint commercial enterprises are spearheading the development of open-source software platforms. These platforms aim to simplify data exchange between devices from different manufacturers, alleviating concerns about compatibility issues. This initiative ensures that users can seamlessly integrate electrical and electronic devices from various brands within their homes without worrying about compatibility. In addition, these advanced platforms extend beyond basic communication functions, offering a variety of building services such as entertainment, energy efficiency management, and security technologies, further enhancing the experience of a smart building.

5.2. Examples of Smart Buildings Across Various Sectors

Explore diverse applications of energy consumption optimization in smart buildings in various sectors, including offices, hospitals, residential complexes, educational institutions, industrial facilities, hospitality venues, and sports arenas. Each domain presents distinctive strategies and technologies that aim to improve energy efficiency and sustainability within smart building ecosystems.

- Smart Offices: In smart offices, energy consumption optimization focuses on intelligent lighting systems, HVAC control, and occupancy sensing to regulate temperature and lighting based on occupancy patterns. Smart sensors and automated systems adjust energy usage in real time, maximizing efficiency while ensuring a comfortable working environment for employees.

- Smart Hospitals: Optimization of energy consumption in smart hospitals revolves around maintaining critical infrastructure while minimizing waste. Advanced HVAC systems, energy-efficient lighting, and smart power management systems ensure optimal energy usage without compromising patient care. In addition, real-time monitoring of equipment and facilities helps quickly identify and address energy inefficiencies.

- Smart Residential Buildings: In smart residential buildings, energy consumption optimization is achieved through smart thermostats, energy-efficient appliances, and home automation systems. Residents can remotely control heating, cooling, lighting, and other appliances to minimize energy usage while maximizing comfort and convenience.
- Smart Educational Institutions: Optimization of energy consumption in smart educational institutions focuses on reducing energy waste in classrooms, laboratories, and administrative areas. Smart lighting, occupancy sensors, and automated HVAC systems help regulate energy usage based on occupancy schedules, saving costs, and reducing environmental impact.
- Smart Industrial Buildings: Optimization of energy consumption in smart industrial buildings involves streamlining manufacturing processes, optimizing equipment usage, and implementing energy-efficient technologies. Industrial IoT (IIoT) devices monitor energy-intensive operations, identify inefficiencies, and suggest improvements to minimize energy consumption and enhance productivity.
- Smart Hospitality: In smart hospitality settings, optimizing energy consumption is essential to provide guests with a comfortable and sustainable experience. Smart room controls, energy-efficient appliances, and automated systems adjust energy usage based on occupancy levels and guest preferences, reducing operational costs while maintaining high service standards.
- Smart Sports Arenas and Venues: Optimization of energy consumption in smart sports arenas and venues focuses on improving the spectator experience while minimizing environmental impact. Smart lighting systems, energy-efficient HVAC systems, and renewable energy sources contribute to reducing energy consumption during events while ensuring a comfortable environment for attendees. In addition, real-time monitoring and analytics help identify opportunities for further energy savings and operational improvements.

6. Edge/Fog Computing

The Internet of Things (IoT) is projected to link billions or even trillions of devices by 2025 [97], resulting in an enormous volume of data, estimated to reach 500 zettabytes [98]. Moreover, modern applications such as Demand Response (DR) platforms demand rapid response times. However, energy consumption poses a significant challenge in wireless communication, particularly due to the limited resources of IoT devices that cannot handle local computation and processing. Consequently, conventional centralized architecture, which relies on data centers owned by companies such as Google, Microsoft, and Amazon, does not meet the needs of IoT applications for storage, computation, and networking resources. Additionally, the process of sending generated and processed data to the cloud for analysis introduces delays that can negatively impact both end-user QoS and experience.

6.1. Fog Computing Overview

Fog computing, a decentralized paradigm introduced by Cisco Systems, serves as a pivotal link between IoT devices and the cloud, prioritizing speed and efficiency by decentralizing computation to the network's edge. Unlike traditional cloud computing, which requires data transmission to central data centers, fog computing disperses computational, storage, and networking resources to end devices, thereby mitigating latency and enhancing QoS. This innovative approach revolutionizes various sectors like Smart Buildings and Smart Grids by granting devices autonomy to manage tasks effectively. In addition, fog computing optimizes energy consumption by offloading computational tasks from resource-constrained devices to nearby fog nodes, reducing the need for continuous data transmission to distant cloud servers. This not only improves performance but also decreases the ecological footprint associated with excessive energy use. In essence, fog computing ensures seamless user experiences, fosters data efficiency, and promotes sustainable computing practices in the era of IoT proliferation [99].

Some of the features of fog computing include:

- Awareness regarding the location of edge: Fog computing identifies edge device locations for efficient resource allocation.
- Very low latency: Processing tasks near the edge of the network ensures faster response times.
- Mobility support: Seamless connectivity for mobile devices within the network.

- Real-time services: Immediate data processing for timely decision making.
- Interoperability: Smooth communication among diverse devices and applications.
- Heterogeneous nature: Support integration of various hardware and software platforms.
- Inseparability: Fog computing tightly integrates with edge devices and network infrastructure.

6.2. Edge Computing Overview

In recent years, computing trends have shifted, with services moving from centralized clouds to the edge of networks, a concept is known as edge computing. Unlike fog computing, where local area networks act as gateways, edge computing employs smart devices such as programmable automation controllers (PACs) for computing tasks. Edge computing addresses issues such as high latency and energy consumption in cloud computing by enabling low-latency computation offloading for resource-constrained devices and IoT applications. It also offers benefits such as content caching and storage to effectively manage network traffic. Although edge computing improves user experience and provides prompt services, it also encounters challenges such as latency, bandwidth costs, energy consumption, security, and QoS. This practice involves processing, storing, and analyzing data close to the source of data generation, rather than relying solely on centralized data centers or cloud computing resources. By bringing computation and data storage closer to the devices or "edge" of the network, where data are being generated, edge computing reduces latency, optimizes bandwidth usage, enhances privacy, and improves overall efficiency [99].

The key features of edge computing include:

- Reduced Latency: Edge computing ensures minimal delays by processing data closer to its source, improving real-time performance.
- Bandwidth Optimization: Edge computing minimizes bandwidth usage by processing data locally and transmitting only essential information, reducing network congestion and costs.
- Improved Privacy and Security: Edge computing can improve data privacy by keeping sensitive information local, rather than transmitting it to centralized servers.
- Scalability: Edge computing allows for distributed scalability, as computing resources can be added or removed as needed at various edge locations, providing flexibility and efficiency in resource utilization.
- Resilience: The distributed architecture improves system resilience by reducing the impact of single points of failure. If one edge node fails, the others can continue to operate independently.
- Automation: Edge computing automates tasks on the network edge, streamlining operations, and reducing manual intervention.

6.3. Concepts and Relationships

To address the ambiguity surrounding the distinction between edge computing and fog computing, we start this discussion by describing both edge and fog computing from different perspectives. Some researchers argue that edge and fog computing are essentially the same, differing only in their terminology, while others distinguish them as distinct concepts. According to Goscinski et al. [100], edge computing emphasizes data processing at the network edge, while fog computing extends beyond this to include the edge cloud, bridging between the cloud and the edge. In contrast, Chiang et al. [101] assert that fog computing constitutes an end-to-end architecture, dispersing control, storage, computing, and networking functions closer to end-users along the cloud-to-things continuum, while the edge pertains specifically to the edge network infrastructure. Furthermore, Pan et al. [102] suggest that fog computing serves as a backdrop for the IoT, extending cloud computing and various services to devices such as switches and routers, while edge computing involves the movement of data, services and applications from the core to the network edge, aligning with a core-edge topology. In a nutshell, both edge and fog computing have the same research topics and both aim at the decentralization of data processing from the cloud to the network edge. Using edge and fog computing technologies, smart buildings can achieve more efficient energy optimization through real-time data processing, local decision making, reduced data transmission, and improved system resilience.

6.4. Architecture

The Edge/Fog architecture refers to a decentralized computing approach that distributes computational resources, storage, and networking capabilities closer to the data source or end-users. In this architecture, computing tasks are performed at the edge of the network or within the fog layer, which lies between the cloud and the edge devices. This proximity allows for faster data processing, reduced latency, and improved efficiency in handling data-intensive applications. Edge/Fog architecture is particularly beneficial for applications that require real-time responsiveness, such as IoT and smart buildings. Provides a flexible and scalable framework for deploying and managing distributed computing resources in various environments. Figure 6 illustrates a comprehensive Edge/Fog computing architecture and the intricate interconnections between its components [99].

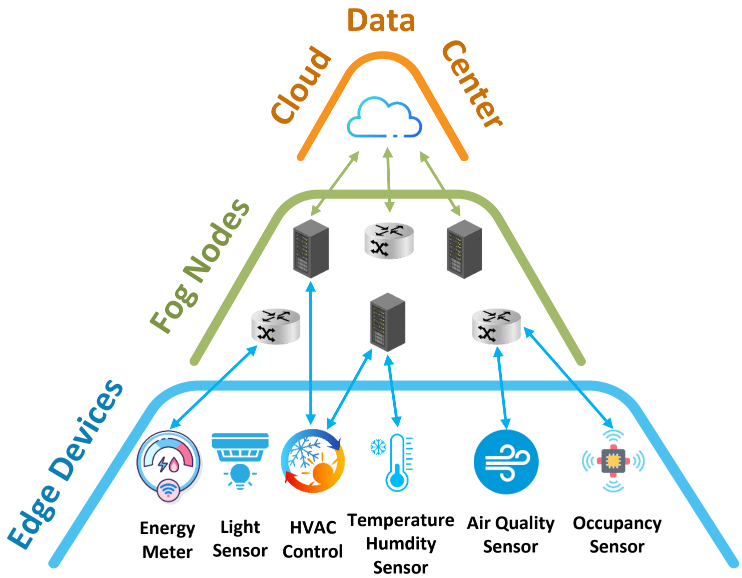

Figure 6: Basic architecture of edge/fog computing.

6.5. Edge/Fog for Smart Buildings Applications

Edge and / or fog computing offers transformative solutions for smart building applications, revolutionizing how energy management and optimization are achieved. These technologies equip smart buildings with real-time data processing and decision-making capabilities at the network edge, enabling rapid responses to changing environmental conditions and occupant needs. By distributing computational tasks across edge devices and fog nodes within the building infrastructure, these systems can analyze vast amounts of data locally, minimizing reliance on centralized servers and reducing latency in critical operations. This localized approach not only improves energy efficiency, but also improves overall building performance and occupant comfort. In addition, edge and fog computing enhances the resilience and reliability of smart building systems, ensuring continuous operation even in the face of network interruptions or cloud outages. Through their integration, smart buildings can unlock new levels of efficiency, sustainability, and responsiveness, ultimately creating more comfortable, cost-effective, and environmentally friendly built environments. Many fog-based and edge-based architectures have been proposed and utilized in many applications in the past few years because of the increasing interest in fog and edge computing.

In their recent work, [103] introduces fog computing as an innovative platform for home energy management, offering users the ability to deploy energy management with control-as-a-service, all while reducing implementation costs and time to market. The authors conducted experiments with two prototypes, namely Home and Micro Grid. However, moving the processing of high-power central processing nodes to smaller devices at the edge of the network requires a comprehensive description and precise details. Compared to others, [104] outlines the application of fog computing to enhance a data center's capacity to manage energy consumption within a building. Moreover, [105] employs the fog computing paradigm in their study, where they introduce a system architecture designed to optimize energy usage based on user location information. Fog computing is utilized to handle service requests according to location. In [106], the authors explore the integration of energy management into an edge/fog computing platform. They investigated the feasibility, scalability, adaptability, and interoperability of executing energy management and associated control algorithms within a Fog computing environment. In addition, they developed a prototype Home Energy Management System (HEMS) that coordinates with a laboratory-scale microgrid for HVAC applications. Kong et al. [107] introduced a framework for edge-cloud coordination, in which service providers maintain comprehensive profiles of popular appliances, conduct model fitting algorithms in the cloud, and train customized models using household data. These personalized models are then deployed in real-time on the edge devices of households, utilizing aggregated load data. Finally, Luo et al. [108] introduced a short-term energy prediction system utilizing an edge computing framework. They collected and preprocessed data, applying regression prediction distributed among sensing nodes, routing nodes, and a central server. Additionally, they employed an online deep neural network model tailored to the characteristics of IoT data for energy prediction. Real-world energy prediction experiments demonstrated the ability of the system to provide high-precision real-time energy prediction effectively.

7. Federated Learning

Federated learning (FL) represents a cutting-edge advancement in the realm of machine learning. Unlike conventional approaches that involve shipping raw data from diverse sources to a central model, FL innovatively shifts the global ML algorithm itself onto individual devices. In this paradigm, the parameters collected from these local devices are relayed to the central ML algorithm for global training and predictive tasks. This decentralization of models to the very devices where data originates distinguishes FL from traditional ML methods. FL emerges as a promising solution, particularly pertinent in the context of smart buildings, where challenges such as protecting privacy, managing massive amounts of data, and tasks such as predicting energy consumption are crucial. By allowing data to remain localized and minimizing the need for data exchange or uploads to central cloud servers, FL not only addresses these challenges but also empowers decision makers to make timely real-time decisions based on insights from distributed sources. One of the core principles of FL is its ability to facilitate the training of shared statistics through decentralized machines or servers. Although data scientists and researchers may use similar models to train data, FL avoids the need to disclose private data to cloud servers or engage in data sharing with other researchers. This unique approach promotes collaboration and knowledge sharing while protecting sensitive information. Moreover, FL often incorporates privacy-preserving techniques such as differential privacy, secure aggregation, and federated averaging, further enhancing data privacy and security throughout the learning process [20].

7.1. Types of Federated Learning

In this section, we introduce different types of Federated Learning frameworks [109]:

- Vertical Federated Learning (VFL): It is applied when various devices possess datasets that feature different attributes but are derived from similar instances. For example, if two organizations manage buildings within a smart city and collect data on energy consumption, temperature, and occupancy levels, but each building has additional sensors measuring different parameters like humidity or lighting usage, VFL enables collaboration to improve energy efficiency without sharing raw data directly.

- Horizontal Federated Learning (HFL): It is used in scenarios where each device contains datasets with consistent feature spaces but distinct sample instances. For example, consider smart buildings managed by different organizations within a city. Each building may gather data on energy consumption, temperature, and occupancy using similar sensors, but the specific data points collected vary due to differences in building structure and usage patterns. With HFL, these organizations can collaborate to optimize energy efficiency by pooling insights from their diverse datasets while preserving data privacy and security.

- Federated Transfer Learning (FTL): It combines federated learning with transfer learning techniques, enabling the transfer of knowledge from a pre-trained global model to local models on individual devices or nodes. This allows each device to adapt the global model to its local data while incorporating new features, similar to traditional machine learning. FTL facilitates collaborative learning across distributed devices or nodes, particularly useful for scenarios like extending vertical federated learning to include additional sample instances not present across all collaborating organizations, all while preserving data privacy and addressing challenges such as data heterogeneity and limited computational resources.

7.2. Architecture

Figure 7 shows a simple representation of federated learning. FL has primarily four main steps [109]: (these steps will be iteratively repeated as desired)

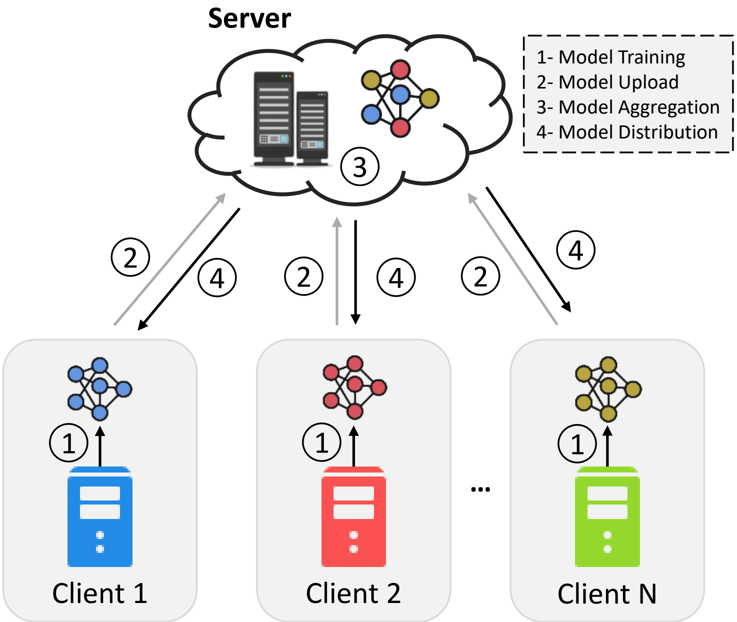

Figure 7: Basic architecture of federated learning.

- Client Selection: The server selects participants from a device pool either randomly or using specific algorithms.
- Parameter Broadcasting: The server shares the global model parameters with the selected clients.
- Local Model Training: Clients will parallelly retrain the models using their local data.
- Model Aggregation: Clients will send back their local model parameters to the server, which aggregates them into the global model.

7.3. Federated Learning for Energy Prediction Applications

FL offers significant potential to optimize energy consumption within Smart Building Applications. Using FL, Smart Building systems can collaborate across distributed devices or nodes to collectively train machine learning models while preserving data privacy and security. This approach enables the aggregation of information from various datasets collected within various building components, such as HVAC systems, lighting, occupancy sensors, and energy meters. Through FL, Smart Building applications can achieve more accurate predictions and proactive energy management strategies tailored to specific building environments, ultimately leading to improved energy efficiency and cost savings. In the following, we will introduce some machine learning examples for energy prediction in smart buildings.

Rodriguez Mier et al. [110] introduced a knowledge model to construct predictive energy consumption models tailored to smart buildings. They developed a multistep prediction model that uses a hybrid genetic fuzzy system, integrating a feature selection technique. The authors use a database that stores two types of signal: synchronous signals that record at a constant rate of 10 s (e.g., temperature, sensors, etc.) and asynchronous signals that record when a value changes (e.g., indoor temperatures, error signals, etc.). In addition, they collect humidity, solar radiation power, and pressure. Alduailij et al. [111] examine various statistical and machine learning (ML) methods to forecast energy consumption in five different types of buildings. Their focus lies particularly in predicting peak demand, with the aim of improving energy efficiency within these buildings. Hadri et al. [112] deploy various methods to forecast appliance energy consumption, incorporating occupancy and context-driven control data from buildings. Sulo et al. [113] examined methods to improve energy efficiency of buildings, employing an LSTM model to forecast energy consumption on campuses of the City University of New York. Furthermore, Pinto et al. [114] introduced three ensemble learning techniques (XGBOOST, random forests, and a modified version of Adaboost) to predict energy consumption one hour in advance, utilizing actual data collected from an office building. The work of Somu et al. [115] described a deep learning framework based on CNN (convolutional neural networks)-LSTM to provide building energy consumption forecasts. CNN-LSTM uses K-means to determine the energy consumption pattern/trend, CNN to extract features about energy consumption, and LSTM to handle long-term dependencies. Umair et al. [116] conducted an in-depth analysis of the challenges and future directions of deploying Federated Learning (FL) in resource-constrained IoT environments, which are common in smart building contexts. Their study highlighted critical limitations such as communication costs, system latency, client heterogeneity, and privacy concerns when using centralized ML models. To overcome these, they explored energy-efficient neural architectures (e.g., Spiking Neural Networks), asynchronous training techniques to address straggler clients, and privacy-preserving mechanisms like Secure Multiparty Computation (SMC) and Differential Privacy (DP). The paper offers valuable recommendations on how to adapt FL frameworks for real-world IoT deployments, making it especially relevant for scalable and secure smart building energy applications. In another relevant study, Umair et al. [117] proposed a Federated Learning framework that combined Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) for network intrusion detection, emphasizing both accuracy and data confidentiality. The system applies a Dynamic Weighted Aggregation Federated Learning (DWAFL) approach, which assigns weights to client contributions based on local model performance. While their focus was on cybersecurity, the methodology demonstrates how FL can effectively model sensitive distributed data without centralizing it, a principle that can also benefit energy prediction scenarios in smart buildings, particularly when dealing with privacy-critical environments and heterogeneous client devices. Finally, Umair et al. [118] proposed a Federated Learning-based intrusion detection framework tailored to detect Botnet attacks such as DoS, DDoS, and infiltration. Their approach incorporates dynamic model aggregation at the client level, effectively addressing privacy and scalability issues inherent to centralized methods. Although the study focuses on cybersecurity challenges, the demonstrated ability of FL to securely handle distributed and sensitive data highlights its broader relevance, particularly in smart building scenarios that require both data privacy and robust real-time analytics.

8. Energy Consumption Metrics

This section provides a comprehensive overview of key metrics used to measure and evaluate energy consumption in smart buildings. These metrics play a crucial role in assessing energy efficiency, identifying areas for improvement, and monitoring environmental impact. From fundamental metrics like total energy consumption and energy intensity to more advanced metrics such as carbon intensity and demand response participation, this section covers a wide range of parameters essential to understand and manage energy use effectively. In addition, the section highlights the importance of each metric and its relevance in guiding energy management strategies toward sustainability and cost-effectiveness in smart building operations. Here are some examples:

- *Energy Consumption (kWh)*: The total amount of energy consumed by the building over a specific period, typically measured in kilowatt hours (kWh). This is a fundamental metric that is used to measure overall energy usage.

- *Energy Intensity (kWh/sq.ft)*: Calculated by dividing the total energy consumption by the total floor area of the building. It provides a normalized measure of energy efficiency, allowing for comparisons between buildings of different sizes.

- *Peak Demand (kW)*: The maximum amount of power (in kilowatts) consumed by the building at any given time. Monitoring peak demand helps optimize energy usage during high-demand periods.

- *Carbon Intensity (kgCO2/kWh)*: The amount of carbon dioxide emitted per unit of energy consumed. It provides information on the environmental impact of energy use and supports sustainability goals.

- *Energy Cost (USD)*: The total cost of energy consumption, considering the unit cost of electricity. Monitoring energy costs helps budget and identify cost-saving opportunities.

- *Energy Use Intensity (EUI)*: A comprehensive metric that considers energy consumption per square foot of the building, often categorized by building type. It provides a benchmark for comparing energy performance in different types of buildings.

- *Renewable Energy Penetration (%)*: The percentage of total energy consumption derived from renewable sources. This metric reflects the building's commitment to sustainable and green energy practices.

- *Demand Response Participation (%)*: The percentage of time or events during which the building participates in demand response programs. This metric reflects the building's responsiveness to grid conditions and willingness to contribute to grid stability.

- *Energy Efficiency Ratio (EER) for HVAC systems*: Specifically applicable to heating, ventilation, and air conditioning (HVAC) systems, the EER is the ratio of cooling capacity (in BTU) to power input (in watts). It assesses the efficiency of HVAC systems in providing cooling.

These metrics, when used collectively, provide a comprehensive understanding of the energy performance of a building. They are valuable tools for building managers, engineers, and policy makers to optimize energy consumption and work towards sustainability goals.

9. Integration of Edge/Fog Computing and Federated Learning for Energy Optimization

In this section, we discuss the integration of Edge/Fog Computing and Federated Learning (FL) for energy optimization in smart buildings. We begin by exploring the intrinsic motivations behind the merging of these cutting-edge technologies and highlighting their synergistic potential in addressing the challenges of energy efficiency and sustainability. Subsequently, we propose a comprehensive architecture that delineates the orchestrated steps involved in harnessing the combined power of Edge/Fog Computing and FL for dynamic energy optimization in smart building environments.

9.1. Motivation for Integration

The integration of edge/fog computing and federated learning holds significant promise for revolutionizing smart building energy optimization. Edge/fog computing brings computation and data storage closer to the edge of the network, reducing latency and bandwidth usage by processing data locally. This proximity to data sources in smart buildings enables real-time analysis and decision making, which is critical for dynamic energy optimization. Additionally, edge/fog computing supports the deployment of lightweight algorithms tailored to resource-constrained edge devices, ensuring efficient energy management without overwhelming computational overhead.

However, federated learning introduces a collaborative approach to model training, allowing multiple edge devices to collectively learn a global model while preserving data privacy. In the context of smart buildings, where sensitive occupant data is involved, federated learning ensures that individual data remain on site, safeguarding privacy while enabling collective learning. By aggregating insights from various edge devices in the building, federated learning facilitates the creation of comprehensive energy optimization models that capture the intricacies of building dynamics and occupant behavior.

The synergy between edge/fog computing and federated learning addresses several challenges inherent in smart building energy optimization. Firstly, the localized processing capabilities of edge/fog computing enable real-time analysis of sensor data streams, allowing for immediate responses to changing environmental conditions and energy demands. This agility is crucial to optimizing energy usage while ensuring occupant comfort and operational efficiency.

Secondly, federated learning enables the collaborative aggregation of insights from distributed edge devices without compromising data privacy. This collaborative model training process fosters the development of robust energy optimization models that generalize well across diverse building environments. In addition, federated learning adapts to the evolving dynamics of the building and the preferences of the occupant over time, ensuring continuous improvement in energy efficiency and sustainability.

In essence, the integration of edge/fog computing and federated learning empowers smart building systems to leverage localized intelligence while benefiting from collective wisdom. Using the strengths of both technologies, smart buildings can achieve higher levels of energy efficiency, sustainability, and occupant comfort, bringing about a new era of intelligent and adaptive building management.

9.2. Proposed System Architecture

In this paper, we proposed a new architecture that integrates Edge/Fog Computing and Federated Learning into Energy Management in Smart Buildings (EFC-FL-EM-SB). Compared to existing architectures in the literature, our architecture introduces several novel enhancements. Most prior work either centralize computation in the cloud or address edge/fog computing and federated learning separately. Our approach integrates them into a cohesive multi-layer architecture, with IoT handling real-time sensing, edge/fog nodes performing localized learning and aggregation, and federated learning ensuring privacy-preserving collaboration across layers. This layered orchestration is specifically designed to meet the challenges of optimizing energy consumption in smart buildings, balancing low latency, data privacy, and adaptive control. These distinctions fill the architectural gaps identified in previous surveys (see Table 2). Basically, Figure 8 shows the EFC-FL-EM-SB architecture that consists of five layers: perception, network, fog, middleware, and application.

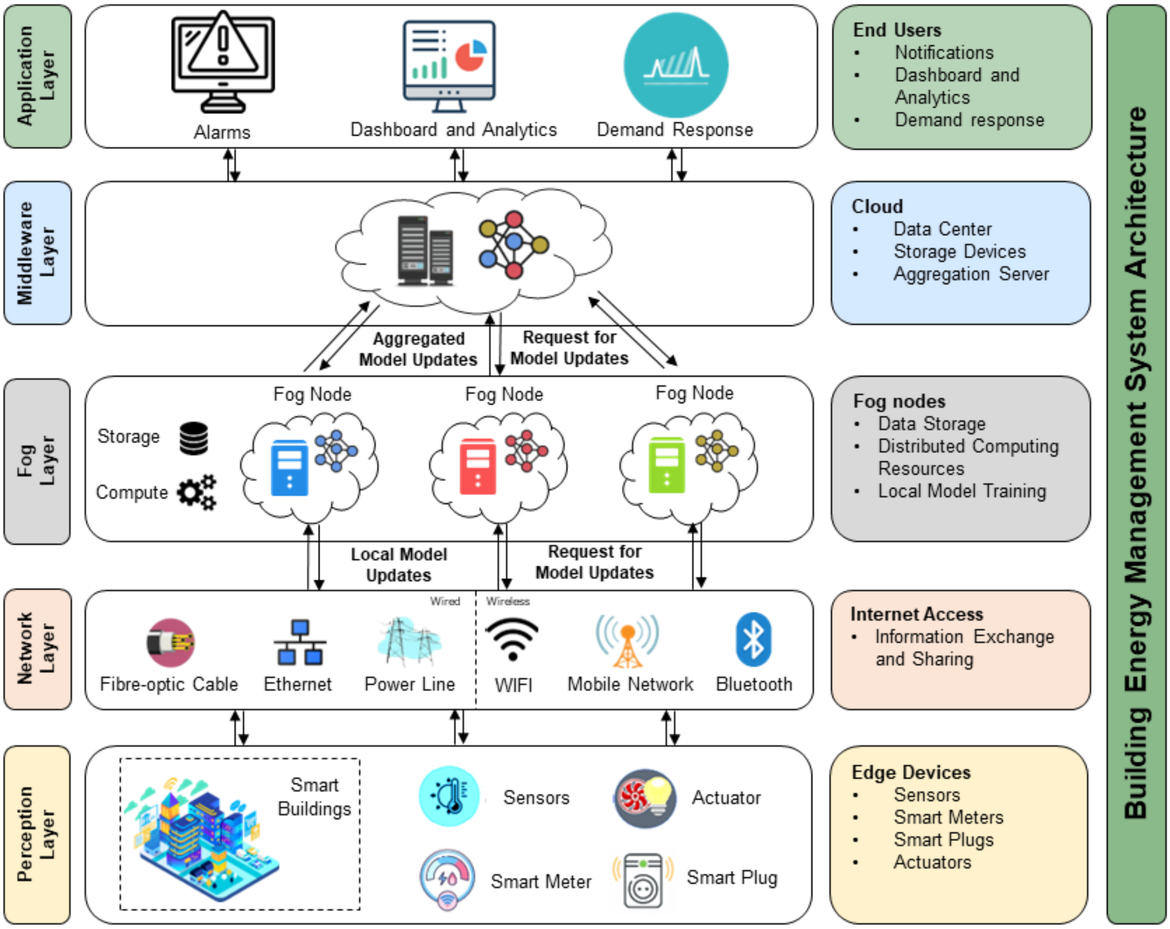

Figure 8: EFC-FL-EM-SB architecture.

9.2.1. Perception Layer

- It consists of edge devices deployed within buildings, such as sensors, smart meters, smart plugs, actuators, and other IoT devices. These devices are responsible for collecting real-time data related to energy consumption, environmental conditions, occupancy patterns, and other relevant metrics.

- Sensors, smart meters, smart plugs, and actuators are essential components within the perception layer of the architecture. Sensors continuously monitor various parameters within the building, such as electricity usage, temperature, humidity, light levels, and occupancy status, providing real-time data insights. Smart meters measure energy consumption at different points in the electrical system of the building, offering granular data on energy usage patterns. In addition, smart plugs and actuators allow for control and automation of electrical devices, allowing for dynamic adjustments to optimize energy efficiency and occupant comfort. Together, these devices form a comprehensive monitoring and control system that facilitates intelligent energy management within the building.

- Data collected on edge devices are time-stamped and processed locally to extract relevant information. This includes preprocessing techniques such as filling missing values (for example, using time-based interpolation), filtering outliers, normalizing feature scales, and aggregating sensor readings over fixed intervals (for example, hourly averages). These steps are crucial to ensure data quality, reduce redundancy, and prepare the information for efficient and reliable transmission to the network layer.

9.2.2. Network Layer

- It facilitates communication and data exchange between edge devices, fog nodes, and cloud infrastructure. It encompasses wired and wireless communication protocols, such as fiber optic cables, Ethernet, Wi-Fi, and Bluetooth, depending on the specific requirements of the building environment.

- Edge devices communicate with each other and with nearby fog nodes to exchange data and synchronize their operations. Data are transmitted securely over the network using encryption and authentication mechanisms to protect against unauthorized access and tampering.

- This layer also handles network management tasks, such as routing, addressing, and quality of service (QoS) enforcement, to ensure reliable and efficient data transmission throughout the energy management system of the building.

9.2.3. Fog Layer

- It comprises a distributed network of fog nodes deployed within the building or its vicinity. Each fog node is equipped with computational resources, such as CPUs, GPUs, or FPGAs, capable of performing local model training and inference tasks.

- This layer may contain switches that interconnect fog nodes and facilitate communication within the local network. In addition, a router connected to the switch may serve as a gateway to connect the fog layer with the middleware layer. Furthermore, the fog layer can include gateways and base stations to bridge communication between edge devices, sensors, and the fog computing infrastructure. These components collectively enable efficient data processing, communication, and integration within the fog computing environment, optimize resource utilization, and minimize latency for edge computing applications.

- The server in the middleware layer shares the global model parameters with the selected nodes. Each fog node independently trains a local model using the data it collects from nearby edge devices within the same geographical area or building zone. Local training typically involves supervised learning algorithms, such as shallow neural networks or regression models, depending on the complexity of the task and the available hardware. Training is carried out in short cycles (local epochs) using a mini-batch gradient descent, adapted to the resource limits of each node. Once trained, these local models are sent back to the server for aggregation and further processing. Training algorithms, such as federated learning, enable collaborative model training while preserving data privacy and security at the edge.

- Fog nodes analyze locally processed data to derive insights and generate actionable recommendations in real time. This layer enables autonomous decision making and control within the building, reduces dependence on centralized cloud services, and minimizes latency for time-sensitive applications.

9.2.4. Middleware Layer

- It serves as an intermediate layer between the fog nodes and the centralized cloud infrastructure, often housed within a data center. It aggregates local models from multiple fog nodes in different building zones or geographical locations.

- Aggregated models are processed and fused to generate a holistic view of the building's energy consumption patterns, operational efficiency, and performance metrics. This layer enables cross-domain analysis and coordination, facilitating global optimization and resource allocation decisions.

- Model aggregation techniques, such as ensemble learning or federated averaging, are used to combine local models and produce a consolidated global model representative of the entire building or facility. Federated averaging (FedAvg) is used as the primary aggregation method, where the global model is updated by computing a weighted average of all the parameters of the local model received. This ensures consistency while preserving the diversity of the model between different building zones. Advanced variants, such as asynchronous FL or momentum-based aggregation, can also be adopted to improve convergence and adaptability. The global model captures collective insights and trends derived from distributed data sources while maintaining scalability and adaptability to dynamic environments.

- Security and privacy are addressed by embedding multiple protective mechanisms throughout the architecture. Communications between edge, fog, and middleware layers are secured using encryption and authentication protocols. To prevent leakage of sensitive occupant data, only model parameters, not raw data, are transmitted. Additionally, differential privacy can be applied to model updates by injecting statistical noise, and secure aggregation protocols ensure that individual contributions cannot be inferred during the averaging process. These measures help prevent attacks such as model inversion or membership inference.

9.2.5. Application Layer

- Interfaces with end-users and external systems to deliver actionable insights, recommendations, and alerts based on the processed data and models. It includes user interfaces, dashboards, APIs, and integration points with building management systems (BMS), energy management systems (EMS), and other relevant software platforms.

- End users, including building occupants, facility managers, energy auditors, and sustainability professionals, interact with the system through intuitive interfaces to monitor energy consumption, set preferences, and receive notifications about anomalies or optimization opportunities.

- Applications running on top of the architecture leverage the aggregated data and predictive models to optimize energy usage, schedule maintenance activities, adjust environmental settings, and implement demand response strategies in alignment with the building's operational goals and sustainability objectives.

10. Benchmark Datasets

The selection of an appropriate dataset is crucial in the field of energy consumption optimization in smart buildings, particularly when leveraging machine learning (ML) and deep learning (DL) techniques. The effectiveness of energy optimization algorithms is heavily based on the quality and relevance of the dataset used for training and evaluation. A comprehensive dataset should accurately capture the diverse patterns of energy use within smart buildings, encompassing both typical consumption behaviors and anomalies that may occur in real-time operations. In the context of smart buildings, where optimizing energy consumption is crucial for sustainability and cost effectiveness, access to high-quality datasets is essential for researchers and practitioners. Benchmark datasets serve as foundational resources for advancing research and development efforts in analyzing energy consumption within smart buildings. Despite improvements in dataset availability, challenges remain in terms of diversity, size, and granularity. Public datasets often have limitations and may raise concerns about data privacy and sensitivity. However, leveraging existing public datasets remains valuable for exploring fundamental research questions, validating methodologies, and fostering collaboration within the research community. Efforts to curate, standardize, and expand the availability of diverse and high quality benchmark datasets are essential to drive innovation in smart building energy management. The most widely used datasets are described in Table 11. To ensure a relevant and fair performance evaluation, the benchmark

Table 11
Popular public datasets for building energy consumption analysis.

Dataset	Description
ASHRAE Global Thermal Comfort Database II	Compiled by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), this database contains thermal comfort data collected from field studies conducted worldwide. It provides valuable insights into occupant comfort preferences and building performance.
Pecan Street	Collected by the Pecan Street Project, this dataset includes high-resolution energy usage data from residential buildings equipped with smart meters, solar panels, and other energy monitoring devices. It is valuable for studying residential energy consumption patterns and behaviors.
UK-DALE (Domestic Appliance-Level Electricity)	An open-access dataset from the UK recording Domestic Appliance-Level Electricity to conduct research on disaggregation algorithms, with data describing not just the aggregate demand per building but also the 'ground truth' demand of individual appliances. It was built at a sample rate of 16 kHz for the whole house and at 1/6 Hz for individual appliances. It was recorded from five houses, one of which was recorded for 655 days.
DRED (Dutch Residential Energy Dataset)	The DRED contains energy consumption data from households in the Netherlands, including information on electricity, gas, and ambient parameters, as well as building characteristics and occupant data. The dataset was compiled by the Dutch government and collected over 6 months from 5th July to 5th December 2015.
CU-BEMS (Cornell University Building Energy Management System)	A dataset contains energy consumption data from various buildings on the Cornell University campus. It includes information such as electricity usage, heating and cooling demand, environmental conditions, and building occupancy. Researchers often use this dataset for studying energy consumption patterns, developing predictive models, and evaluating energy efficiency measures in commercial buildings.
LCL (Low Carbon London)	A collection of smart meter data from residential households in London, UK. It includes detailed electricity consumption readings at frequent intervals (e.g., every 30 minutes) for a large number of households over an extended period. Researchers and data scientists use the LCL dataset to analyze household energy usage behavior, identify energy-saving opportunities, and develop demand response strategies.

datasets were selected based on the following criteria: (i) availability of real energy consumption data from smart buildings, (ii) diversity in types of buildings and geographical regions, (iii) adequate granularity of the data (hourly or finer), and (iv) recognition and frequency of usage in related studies. These datasets provide a reliable basis for evaluating the effectiveness of the proposed architecture and associated techniques.

11. Market Solutions

In this section, we provide a brief description of existing market energy measurement products applicable in smart buildings. Indeed, the selection of such solutions was guided by several criteria: (i) the availability and documentation of the solution, (ii) the relevance to the components of the proposed architecture (e.g., IoT sensors, edge / fog platforms, federated learning frameworks), (iii) adoption in actual smart building projects and (iv) technological compatibility with our system requirements. These factors ensure practical alignment with the proposed architecture and its feasibility in real-world deployments. However, these solutions still suffer from limited adaptability, lack of context awareness, and communication issues between heterogeneous devices and platforms. Most existing solutions are commercial and proprietary platforms that provide integrated hardware-software systems for building energy management, often with limited openness or customization. In contrast, open-source implementations remain relatively rare in large-scale deployments. We classify the market solutions according to the following categories:

11.1. Sensors and Actuators Products

In the realm of smart buildings, a variety of sensors and actuators are used to improve efficiency, comfort, and security. These components are essential for real-time monitoring and control of building environments. In this section, we will explore different products that are pivotal in smart building systems, including environmental sensors

(Temperature, Humidity, Light Sensors, etc.), wearable sensors (CO2 gas sensors, Thermal sensors,etc.), and various types of actuators. Each product is designed to measure, control, and optimize specific aspects of building operations, contributing to the overall intelligence and functionality of smart buildings.

- Environmental Sensors: Figure 9 illustrates various products of environmental sensors available in the market that are described as follows:

Figure 9: Popular environmental sensor platforms in the market.

  - BME280 [119]: is a well-known Bosch combined digital humidity, pressure, and temperature sensor. The BME280 is highly efficient and delivers superior performance in applications that require accurate and reliable environmental monitoring of these parameters.
  - Honeywell HumidIcon™ HIH8000 Series [120]: comprises digital output-type sensors that integrate relative humidity (RH) and temperature measurements into a single package. These sensors offer high accuracy, with ± 2.0 %RH for humidity and ± 0.5 °C for temperature, making them ideal for applications that require precise environmental monitoring and control.
  - Sensirion SHT3x [121]: the series of humidity sensors, including the models SHT30, SHT31, and SHT35, offers advanced humidity detection for smart buildings. These sensors feature multiple interfaces (I²C, analog voltage output), a wide operating voltage range (2.15 to 5.5 V), and are available in various volumes, ensuring reliable and accurate measurements.
  - Texas Instruments HDC1080 [122]: is a digital humidity sensor with an integrated temperature sensor that delivers excellent measurement accuracy with minimal power consumption. It operates over a wide supply range and serves as a cost-effective, low-power alternative to other solutions. Both sensors are factory calibrated, making them ideal for a wide range of common smart building applications.
  - Airthings Wave Plus [123]: monitors your home air quality with an app-enabled indoor air monitor that measures six aspects of air quality, including radon and carbon dioxide (CO2). It provides live readings synced to the Airthings app on your mobile device via Bluetooth. This battery-powered device can be placed on a surface or mounted on a wall, eliminating the need for messy cables.
  - Honeywell HPM Series Particulate Matter Sensors [124]: measures PM2.5 and PM10 levels for air quality monitoring. It uses laser-based technology to detect and count particles by light scattering. Operating in a

range from 0 to 1,000 μg/m3, the sensor illuminates the particles with a laser, measures the reflected light with a detector, and converts it into an electrical signal to determine the concentration of the particles.

- TE Connectivity TSYS01 [125]: is a sensor designed to measure light intensity, primarily used in applications such as daylight harvesting and lighting control systems. It provides crucial data to optimize energy efficiency and enhance user comfort by intelligently adjusting lighting based on ambient light levels. This sensor plays a vital role in modern building automation and environmental monitoring efforts, ensuring that spaces are efficiently illuminated while minimizing energy consumption.
- Vishay Semiconductors TEMT6000X01 [126]: is an ambient light sensor housed in a miniature 1206 surface mount package. This silicon NPN epitaxial planar phototransistor is sensitive to visible light with a peak sensitivity at 570 nm, similar to that of the human eye. It is used for automatic lighting adjustments in applications such as display backlight dimming in LCDs, keypad backlighting in mobile devices, and various industrial lighting controls.
- Panasonic EKMB Series [127]: features passive infrared (PIR) motion sensors with a wide 150 ° field of view and a flat rectangular shape for improved detection on a single axis. They can detect motion directly approaching the sensor and have a low current consumption of 1μA, making them ideal for battery-powered applications. These sensors are RoHS (Restriction of Hazardous Substances) and REACH (Registration, Evaluation, Authorization, and Restriction of Chemicals) compliant and are commonly used in security systems, lighting control, thermostats, video intercoms, doorbells, IP cameras, TVs, and PC monitors.
- Philips Hue Motion Sensor [128]: improves Hue lighting automation by detecting motion and ambient light. It can trigger actions based on movement and light levels, offering customizable settings for different times of day. During the day, it adjusts lighting based on daylight sufficiency, while at night, it activates a dim "night mode". The sensor can also automatically turn off lights after a set period without movement, with adjustable sensitivity to prevent unnecessary light changes. Ideal for smart lighting systems.
- Legrand Wattstopper DW-311 [129]: dual-technology dimming wall switch sensor controls lights based on occupancy using passive infrared (PIR) and ultrasonic sensors. It allows for dimming adjustments and works with 0-10 VDC dimming drivers and ballasts, making it suitable for lighting control and HVAC systems.
- Lutron Radio Powr Savr [130]: wireless occupancy/vacancy sensors provide convenient light control and energy savings through easy installation. These sensors detect occupancy and direct compatible wireless controls to turn off lights and plug loads based on room occupancy, ideal for wireless lighting control.
- Honeywell TruStability® HSC Series [131]: measures air and liquid pressure with high precision, offering analog or digital ratio. Fully calibrated and temperature compensated, it updates pressure readings at 1 kHz for analog output and 2 kHz for digital output. Ideal for HVAC systems and water management.
- TE Connectivity MS5803-14BA [132]: measures barometric pressure and is designed for environmental monitoring and HVAC systems. It features high resolution and supports communication via SPI and I2C bus interfaces.
- Schneider Electric PowerLogic PM5000 Series [133]: meters measure electrical energy consumption and are designed for energy management systems. They offer precise metering capabilities tailored for cost management applications, enabling energy allocation, tenant metering, sub-billing, energy savings identification, equipment efficiency optimization, and power quality assessment within electrical networks.
- Siemens Sentron PAC3200 [134]: measures power quality and energy use, making it ideal for energy monitoring and management applications. It provides detailed insights into electrical parameters such as voltage, current, power, and harmonics, facilitating efficient energy use and troubleshooting in industrial and commercial settings.
- Landis+Gyr E450 [135]: meter measures electricity consumption and is a key component of their advanced metering infrastructure (AMI). It features multi-energy data collection, two-way remote communication, and supports open standards for integration with third-party applications. Designed for smart grid and energy management, the E450 offers enhanced security, flexibility, and cost efficiency for utilities.
- Itron Centron II [136]: meter measures electricity usage for residential applications and utility metering. It is a single-phase solid-state meter known for its digital accuracy, reliability, and serviceability. Featuring

personality modules for various communication and measurement options, including remote disconnect capabilities, Centron II supports automated meter reading (AMR), smart grid, and advanced metering infrastructure (AMI) initiatives, adapting to current and future utility requirements.

- Wearable Sensors: Figure 10 illustrates various products of wearable sensors available in the market that are described as follows:

Figure 10: Popular wearable sensor platforms in the market.

  - CO2Meter Rad-0102 [137]: a wearable CO2 gas sensor is designed for personal use to monitor carbon dioxide levels in the surrounding environment. Its compact design allows it to be worn, making it ideal for tracking CO2 exposure in various settings, especially indoors, where proper ventilation and air quality management are essential for energy efficiency.
  - Sensirion SCD4x [138]: typically used in stationary applications, the Sensirion SCD4x series can be adapted for wearable purposes due to its compact size and low power consumption. It accurately measures CO2 concentrations and is suitable for integration into wearable devices to monitor air quality.
  - K30 CO2 Sensor Module [139]: measures the levels of carbon dioxide (CO2) in the environment and can be integrated into wearable devices to monitor indoor air quality, playing a crucial role in optimizing HVAC systems in smart buildings.
  - Thermosense [140]: monitors body temperature continuously and accurately in contact with the ear or forehead. It can also measure the temperature of environments, such as room temperature. With a design focused on ease of use, it includes a fever indicator and can store up to 9 readings, making it essential to detect changes in occupant comfort levels and inform HVAC system adjustments for energy efficiency in smart buildings.
  - FLIR Lepton [141]: made in the USA and ITAR-free, is a compact and cost-effective long-wave infrared camera module. Adaptable for wearable applications, it allows non-contact temperature measurements, which is useful for monitoring equipment, detecting overheating, and assessing thermal comfort in smart buildings. Lepton offers multiple resolutions, field-of-view options, and absolute temperature output on specific models, with extensive integration support for efficient development.
  - Fitbit Sense [142]: originally a health and fitness tracker, Fitbit Sense monitors physiological data such as heart rate and activity levels. These data can indirectly support energy management strategies in smart buildings by providing insights into occupant behavior and comfort.
  - Empatica E4 [143]: is a wearable device designed for research and clinical applications, measuring heart rate variability, skin conductance, temperature, and motion. It supports data recording, management, and

real-time streaming to the Empatica Realtime app for both Android and iOS devices, making it ideal for monitoring occupant comfort and energy use in smart buildings. E4 also measures PPG for Heart Rate Variability (HRV) studies.

  - BioHarness [144]: is a wearable sensor that monitors vital signs such as heart rate, respiration rate, and posture. It offers live data viewing and logging via Bluetooth and AcqKnowledge software, making it useful for understanding occupant behavior and comfort in smart buildings. It is ideal for applications in exercise physiology, sports conditioning, public health, and psychological studies.

- Actuators: Figure 11 illustrates various actuator products available in the market.

Figure 11: Popular actuator platforms in the market.

  - Belimo CM Series [145]: Actuators are compact, efficient motor-driven actuators for HVAC applications, offering three-position and modulating control with a 2.0 Nm torque. Features include a 0-95° adjustable span, 1.0 m prewired cables, and optional auxiliary switches and feedback potentiometers. Ideal for damper areas up to 0.4 m^2, they are used in ventilation sections for 90 ° movement from zero to fully open.
  - Honeywell ML Series Actuators [146]: especially ML7984, are reliable linear motorized linkages for HVAC systems. They offer up to 19mm travel, mount on V5011/V5013 valves, and work with Series 70/90 controllers. Features include configurable DIP switches, selectable 2-10Vdc/4-20mA inputs, and compatibility with both Vac and Vdc power supplies.
  - Johnson Controls VA-4233 Actuators [147]: deliver robust performance for building automation, designed for cold, hot, and steam applications. They feature automatic spring return for power failure scenarios, no-linkage mounting for quick installation, reversible stroke direction for versatility, and an integral position indicator for visual stem position representation.
  - Siemens GMA Series Actuators [148]: are designed for precise control in smart buildings. These OpenAir direct-coupled spring return electronic actuators modulate and control HVAC dampers in constant or variable air volume systems, providing up to 62 lb-in (7 Nm) torque. They ensure that the dampers return to a fail-safe position during power failures.
  - Schneider Electric SmartX Actuators [149]: provide energy-efficient solutions for modern building management. These direct-coupled actuators are versatile and designed for both damper and valve control applications.
  - Danfoss AME Series Actuators [150]: ensure efficient operation in smart HVAC systems. They provide fast and accurate responses to control signals for optimal indoor climate control, specifically designed to fit AB-QM Pressure-Independent Balancing and Control Valves (PICVs).

- Table 12 summarizes the well-known market energy-efficient sensor and actuator products based on the monitoring of energy consumption in smart buildings.

11.2. Smart Control Devices

Smart control devices refer to intelligent systems or devices that manage and optimize the operation of various building systems based on data received from sensors. These devices include programmable logic controllers (PLCs), distributed control systems (DCS), or even smart home hubs that centrally manage and automate different aspects of

Table 12
Overview of commercial sensors and actuators used in energy monitoring products.

Product	Company	Detection Features
Environmental Sensors		
BME280	Bosch [119]	Temperature, humidity, and pressure
HIH8000 Series	Honeywell [120]	Temperature and humidity
SHT3x	Sensirion [121]	Temperature and humidity
HDC1080	Texas Instruments [122]	Temperature and humidity
Wave Plus	Airthings [123]	Radon, CO_2, VOCs, temperature, humidity, air pressure
HPM Series	Honeywell [124]	Particulate matter (PM2.5 and PM10)
TSYS01	TE Connectivity [125]	Light intensity
TEMT6000X01	Vishay Semiconductors [126]	Ambient light
EKMB Series	Panasonic [127]	Motion
Hue Motion Sensor	Philips [128]	Motion and ambient light
Wattstopper DW-311	Legrand [129]	Occupancy
Radio Powr Savr	Lutron [130]	Occupancy
TruStability HSC Series	Honeywell [131]	Air and liquid pressure
MS5803-14BA	TE Connectivity [132]	Barometric pressure
PowerLogic PM5000 Series	Schneider Electric [133]	Electrical energy consumption
Sentron PAC3200	Siemens [134]	Power quality and energy usage
E450	Landis+Gyr [135]	Electricity consumption
Centron II	Itron [136]	Electricity usage
Wearable Sensors		
CO_2Meter Rad-0102	CO_2Meter [137]	Carbon dioxide (CO_2) levels
Sensirion SCD4x	Sensirion AG [138]	Carbon dioxide (CO_2) concentrations
K30 CO_2	Senseair AB [139]	Carbon dioxide (CO_2) levels
Thermosense	Thermosense [140]	Body and environmental temperature, fever indicator
FLIR Lepton	FLIR Systems [141]	Non-contact temperature, infrared imaging, overheating detection, thermal comfort
Fitbit Sense	Fitbit [142]	Heart rate, activity levels
Empatica E4	Empatica [143]	HRV, skin conductance, temperature, motion
BioHarness	Medtronic [144]	Heart rate, respiration rate, posture
Actuators		
Belimo CM Series	Belimo [145]	Position feedback, torque overload detection, control signal response, span monitoring
ML7984	Honeywell [146]	Compatibility with Vac and Vdc power supplies
VA-4233	Johnson Controls [147]	Automatic spring return for power failure
GMA Series	Siemens [148]	HVAC damper modulation, fail-safe return
SmartX	Schneider Electric [149]	Damper and valve control applications
AME Series	Danfoss [150]	Indoor climate control

the building's operation. They receive input from sensors, process these data to make decisions or adjustments, and then send commands to actuators to achieve desired environmental conditions, energy efficiency, comfort levels, and operational goals.

- Siemens Desigo CC [151]: is an advanced building management platform that integrates HVAC, lighting, security, and energy management systems. It serves as a powerful open solution within the Siemens Xcelerator portfolio, enabling smart buildings to optimize comfort, security, and efficiency while facilitating the transition to self-adapting building environments.

- Johnson Controls Metasys [152]: is a sophisticated building automation system that integrates HVAC, lighting, security, and other building systems onto a unified platform. It improves energy management efficiency by enabling seamless communication and smart decision-making, while improving occupant comfort, safety, and productivity in commercial buildings.

- Schneider Electric EcoStruxure Building Operation [153]: is a flexible software platform that integrates and manages multiple building systems and devices through a unified interface. It enables efficient control and monitoring, providing actionable insights to improve energy management, operational efficiency, and occupant comfort. EcoStruxure aims to optimize building performance, reduce carbon footprint, and promote sustainable environments through data-driven decision-making.

- Honeywell Enterprise Buildings Integrator (EBI) [154]: is a comprehensive platform that centrally controls and monitors building systems such as building management, fire and life safety, and security. It integrates these systems with open architecture and web services, offering tools and analytics for real-time facility data management. The purpose of EBI is to optimize energy use, reduce operational costs, and improve occupant comfort and safety in commercial buildings.

- Trane Tracer™ SC+ [155]: is an advanced building automation system focused on centralized control and monitoring of HVAC systems in commercial buildings. It simplifies operations and enhances comfort and efficiency through integrated system management. Preengineered Tracer® system applications ensure optimal performance under various conditions, making it user-friendly for operators and efficient for building engineers.

- ABB Ability™ System 800xA [156]: is an integrated building automation solution that combines monitoring, control, and optimization of building systems. It improves energy efficiency and operational performance by consolidating process, electrical, safety, and telecom systems into a unified platform. The system includes advanced operator control features, such as Extended Operator Workplace, to improve productivity and operational decision-making in building environments.

- Lutron Quantum [157]: is a sophisticated networked lighting control system that offers integrated lighting and shade control, advanced programming, and energy management capabilities. It supports centralized control of more than 10,000 devices, improving energy efficiency, comfort, and operational effectiveness in building environments.

11.3. Networking and Communication Devices

Networking and communication devices in smart buildings encompass a range of robust and scalable solutions designed to ensure reliable connectivity, security, and management in diverse environments. These devices integrate advanced technologies to support high-performance networking, wireless connectivity, and industrial-grade reliability, essential to optimize operational efficiency and enhance user experience in modern building infrastructures. Figure 12 illustrates various products of networking and communication devices available in the market that are described as follows:

- Cisco Catalyst Series Switches [158]: are high-performance networking devices that provide reliable and secure connectivity for smart building networks. Examples include the Catalyst 9400 Series for enterprise-class midsize and large campus access networks, the Catalyst 9300 Series for lean-branch and campus access networks needing extra scale and security, the Catalyst 9200 Series for small branches and midsize campuses, and the Meraki MS390 Series, which offers cloud-managed switching for simplified management and reduced complexity. These switches ensure a robust and scalable network infrastructure for smart buildings.

- HPE Aruba Wireless Access Points [159]: are designed to provide robust and scalable Wi-Fi connectivity throughout smart buildings. They provide secure and fast wired/wireless access for mobile, remote, and temporary workspaces, ensuring reliable access to corporate applications anywhere and anytime.

- Juniper Networks EX Series Ethernet Switches [160]: offer flexible and scalable connectivity for smart building networks, ensuring high performance and reliability. These cloud-ready switches simplify wired access networks, reducing risk and cost while maintaining quality and innovation. They can be easily installed, configured, and managed through the Juniper Mist Cloud and combined with the Juniper Wi-Fi portfolio for a unified, AI-driven wired and wireless solution that provides secure connectivity at scale.

- Ubiquiti UniFi Security Gateways [161]: are integrated security devices that provide advanced firewall protection and secure networking for smart building environments. These powerful gateways run the UniFi application suite, supporting networking, WiFi, camera security, door access, business VoIP, and more, ensuring complete security and connectivity.

- Ruckus ICX Series Switches [162]: are designed for smart buildings to deliver high-density networking, reliable connectivity, and simplified management. These switches feature low-latency, non-blocking architecture for excellent throughput and work seamlessly with RUCKUS wireless access points, SmartZone™ network controllers, and RUCKUS Cloud™ to provide a high-performance and cost-effective unified wired and wireless access solution.

- Extreme Networks Summit Series Switches [163]: offer high-performance networking capabilities with advanced security features for smart building applications. The X620 family, in particular, consists of compact 10Gb Ethernet switches designed for high-speed edge applications. These switches support intelligent Layer 2 switching and Layer 3 IPv4/IPv6 routing, and simplify network operation with the high availability ExtremeXOS modular operating system, ensuring ease of use and consistency across the network.

- Moxa Industrial Ethernet Switches [164]: are robust industrial-grade switches designed to withstand harsh environments while providing reliable networking for smart building infrastructure. They offer features such as network redundancy, enhanced security, easy management, and competitive price-to-performance ratios, ensuring reliable performance under demanding conditions.

- Siemens RUGGEDCOM Networking Devices [165]: are industrial grade devices that ensure reliable communication and connectivity in smart building applications, even under challenging conditions. Known for their performance in harsh environments, these devices provide secure access and network management, setting the standard for reliable communications in various industrial networks.

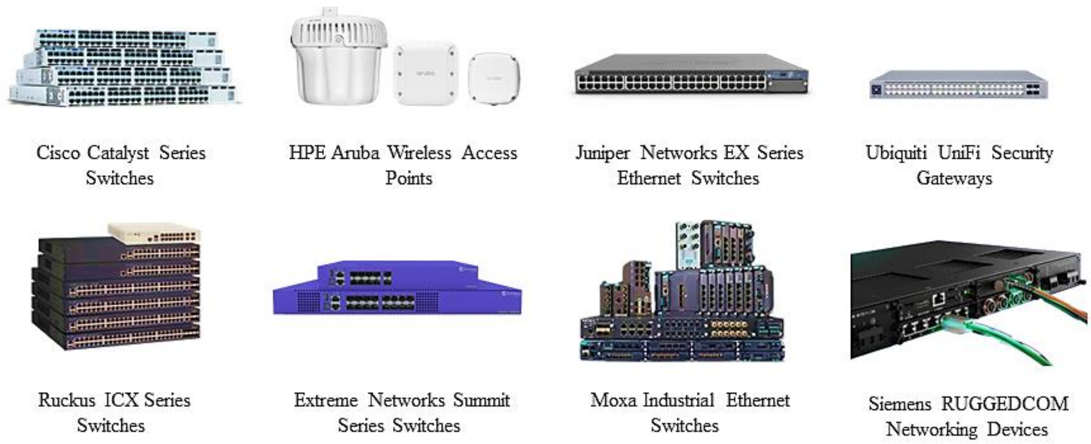

Figure 12: Popular networking and communication platforms in the market.

11.4. Data Storage and Server Devices

Data Storage and Server Devices for smart buildings encompass a range of high-performance servers and storage solutions designed to handle complex data processing, storage, and management tasks. These devices offer scalability, reliability, and advanced features, such as AI-driven data management and secure storage, optimizing efficiency, and supporting critical operations in modern building infrastructures. Figure 13 illustrates various products of data storage and server devices available in the market that are described as follows:

- Dell EMC PowerEdge Servers [166]: are high-performance servers specifically designed for smart buildings, offering scalability and reliability in handling data processing and storage requirements. PowerEdge XE servers,

Figure 13: Popular data storage and server platforms in the market.

in particular, are tailored for complex and compute-intensive edge workloads, featuring robust performance capabilities and ample storage capacity to support critical operations in challenging environments.

- HPE ProLiant Servers [167]: are versatile computing solutions designed for smart building applications, offering robust performance and efficiency in data storage and management. These servers are known for their trusted security features and capabilities that enable data insights and innovations across edge and cloud environments, supporting critical operations with reliability and scalability.
- Cisco UCS Servers [168]: are part of the Unified Computing System, providing integrated computing, networking, and storage resources optimized for smart building environments. These servers streamline data center operations by combining computing, networking, and storage into a single cohesive system, enhancing efficiency, scalability, and management simplicity for modern building infrastructures.
- Lenovo ThinkSystem Servers [169]: are renowned for their reliability and scalability, catering to the needs of data storage and processing in smart building systems. Lenovo offers a diverse range of server solutions, including compact blade servers for space-saving applications, edge servers for localized data processing, and mission-critical servers for uninterrupted operations. These servers are essential for handling large volumes of data and complex applications, ensuring efficient performance and supporting future growth and innovation in business environments.
- NetApp AFF Series All-Flash Storage [170]: arrays offer high performance, low-latency storage solutions for smart building applications. They accelerate and consolidate diverse workloads like VMware, databases, and AI, providing unified data storage with advanced management features and industry-leading ransomware protection. Designed for scalability and seamless hybrid cloud integration, NetApp AFF systems optimize data handling in modern building environments.
- IBM FlashSystem Storage [171]: offers advanced storage solutions that take advantage of IBM's cutting-edge flash technology. These systems provide fast and reliable data storage optimized for smart building analytics and applications. With capabilities like AI-driven data tiering and IBM Storage Virtualize software, FlashSystem simplifies management and enhances real-time data access and processing, supporting efficient operations in modern building infrastructures.
- Synology DiskStation NAS [172]: provides network-attached storage solutions designed for smart building operations. These systems offer scalable storage capacity and efficient data management capabilities, enabling users to build robust shared storage environments. With features like multi-level encryption for enhanced data security, Synology NAS DiskStation ensures reliable and secure storage solutions.

- QNAP Turbo NAS (Network Attached Storage) [173]: devices offer high-speed data transfer and extensive storage capacity options, adapted for data storage and management in smart buildings. Designed for performance and reliability, the QNAP Turbo NAS provides an affordable and easy-to-manage solution. It supports iSCSI (Internet Small Computer Systems Interface) service for virtualized and clustered environments, aiming to reduce the total cost of ownership (TCO) while delivering robust storage capabilities for modern building operations.

12. Energy Consumption Prediction in Smart Buildings: A Comparative Study

In this section, we select a set of articles that focus on prediction of energy consumption within the smart building domain and evaluate them using a variety of performance metrics. The goal is to identify the most effective techniques based on standardized criteria.

To ensure a fair and rigorous comparison, the selected methods were chosen based on the following standards:

- Relevance to the Domain: We include techniques that have been widely adopted in the recent literature that specifically target energy prediction in smart buildings.

- Dataset Compatibility: The methods were required to be applicable to publicly available or real-world benchmark datasets, as detailed in Section 10.

- Standard Evaluation Metrics: All approaches were evaluated using common performance metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), accuracy, and the coefficient of determination ($\boldsymbol{R}^2$), ensuring comparability and objectivity.

- Reproducibility: Priority was given to techniques with accessible implementation details or reproducible evaluation procedures as documented in the literature.

Based on these criteria, we conduct a comparative analysis to determine which techniques demonstrate superior performance and provide insights into the most suitable approaches for energy consumption prediction in smart buildings.

12.1. Metrics Description

In our study, we set the following performance metrics:

12.1.1. Mean Squared Error (MSE)

It is a statistical measure used to assess the accuracy of predictions made by a model. It quantifies the average squared difference between the predicted values and the actual values in a dataset. In the domain of energy consumption prediction, MSE is commonly employed to evaluate the effectiveness of predictive models in estimating energy consumption patterns. A lower MSE indicates better alignment between the predicted and actual values, suggesting a higher accuracy in the model predictions. To calculate MSE, we take the squared difference between each predicted value and its corresponding actual value, sum up these squared differences for all data points, and then divide by the total number of data points. It should be noted that, in the context of energy consumption prediction, the unit of measure for MSE is typically kilowatt hours (kWh).

12.1.2. Root Mean Squared Error (RMSE)

It is a statistical measure commonly used in the domain of energy consumption prediction to evaluate the accuracy of predictive models. It is calculated as the square root of the average of the squared differences between the predicted values and the actual values in a dataset, making it essentially the average squared of the Mean Squared Error (MSE). RMSE provides a single value that quantifies the average deviation between predicted and actual values, with lower RMSE values indicating better alignment between predictions and observations. RMSE is preferred over MSE, as it is in the same unit as the original data, making it more interpretable and facilitating comparisons between different models or datasets. In the context of energy consumption prediction, RMSE is often expressed in units of kilowatt hours (kWh), similar to MSE.

12.1.3. Mean Absolute Error (MAE)

It is a statistical metric commonly used in the domain of energy consumption prediction to quantify the average magnitude of errors between predicted and actual values. It is calculated as the average of the absolute differences between each predicted value and its corresponding actual value in a dataset, with units typically expressed in kilowatt hours (kWh). MAE provides a straightforward measure of prediction accuracy, regardless of the direction of errors, with lower MAE values indicating better alignment between predicted and actual values. This metric is valuable for assessing the performance of predictive models and comparing their accuracy across different scenarios or datasets.

12.1.4. R-squared (R^2)

In the domain of energy consumption prediction, R-squared is a statistical metric used to evaluate the goodness-of-fit of a predictive model. It indicates the proportion of the variance in the energy consumption data that is explained by the independent variables included in the model. The R^2 values range from 0 to 1, with higher values indicating a better fit of the model to the data. A value of 1 indicates that the model perfectly explains the variability in the energy consumption data, while a value of 0 suggests that the model does not explain any of the variance. R-squared is commonly used to assess the effectiveness of predictive models in capturing the variability of energy consumption patterns.

12.1.5. Accuracy

In the domain of energy consumption prediction, accuracy refers to the closeness of the predicted energy consumption values to the actual energy consumption values, typically measured as a percentage (%). It is a measure of how well a predictive model performs in estimating energy usage patterns. Higher accuracy indicates that the model predictions align closely with the actual energy consumption data, while lower accuracy suggests discrepancies between predicted and observed values. Accuracy is a critical metric for evaluating the reliability and effectiveness of predictive models in forming decision-making processes related to energy management, resource allocation, and sustainability initiatives.

12.1.6. Average Latency

In the domain of energy consumption prediction, average latency refers to the average amount of time it takes for a predictive model to generate predictions for energy consumption data, typically measured in seconds (s). It measures the delay between the input of data into the model and the output of predictions. Lower latency values indicate faster prediction times, allowing faster responses to changes in energy consumption patterns. Average latency is an important consideration in real-time energy management systems, where timely predictions are essential to make timely decisions and adjustments to optimize energy use and efficiency.

12.1.7. Execution Time

It refers to the duration it takes for a program to complete all tasks related to data processing, cleaning, model training, and prediction generation, typically measured in seconds (s). It encompasses the time required to load and preprocess raw data, performing any necessary data cleaning or transformation steps, training predictive models, and generating predictions for energy consumption. Lower execution times indicate faster data processing and analysis, allowing more efficient decision making and real-time insights into energy usage patterns. Efficient execution times are crucial to ensure timely responses to changes in energy consumption dynamics and optimizing the overall performance of energy management systems.

12.2. Selected Articles: A Review

The authors of [69] introduce a novel approach to predict energy consumption in smart home environments using a Markov chain-based probabilistic model. The predictions generated by this model are utilized by a newly developed comfort-aware energy-saving algorithm called PF-PEC. This algorithm effectively reduces total energy consumption while maintaining standard human comfort levels. In addition, a fog-based Internet of Things (IoT) architecture is implemented to seamlessly integrate the algorithm into real-world scenarios. The experimental findings demonstrate significant energy conservation in the daily usage of electricity. The experiments were carried out in a multistory home located in Lahore, which covered an area of 1125 square feet and accommodated three occupants.

The authors of [39] present a Smart Home Energy Management System (SHEMS) tailored for residential demand side management, focusing on optimizing energy usage and improving management practices within smart homes. Their method involves a two-step Non-Intrusive Appliance Load Monitoring (NIALM) approach, complemented by the integration of Artificial Neural Networks (ANN) for more comprehensive data analysis. Fog-cloud analytics play a crucial role in processing and analyzing data, ensuring the system's scalability and responsiveness. Data are collected from electrical appliances that were targeted, learned, and recognized through AI, including a laptop, a hair dryer, a steamer, an electric fan, and a vacuum cleaner.

The authors of [50] propose the use of federated learning for load forecasting using smart meter data. This approach allows for the training of a unified model using data from all participating smart meters without necessitating the sharing of local data. LSTM, a variant of RNN, is employed for training the model and forecasting. The study examines two alternative federated learning strategies: FedSGD, which performs a single gradient descent step on the client before consolidating updates on the server, and FedAVG, which executes multiple steps before consolidation. Given the diverse nature of residential consumers, training a single model poses challenges due to variations in load profiles among consumers. The findings indicate that FedAVG outperforms FedSGD in terms of accuracy, while also requiring fewer communication rounds. Real-world data provided by London Hydro through Green Button Connect My Data (CDM). The evaluation was carried out with 19 residential consumers, each one containing hourly energy consumption for three years, resulting in 25,560 readings per household, or 485,640 readings in total.

The authors of [64] introduce a novel approach to predict individual household and aggregate electrical demands, with a focus on preserving data privacy through federated learning and edge computing. The use of FedAvg for aggregation, LSTM for time series forecasting, and a clustering method with hyperparameter tuning showcase a comprehensive methodology. This approach not only guarantees precise predictions, but also tackles the crucial issue of data privacy in the realm of electrical load forecasting. Data were collected from 75 locations within the City of Edmonton. The data were provided by the EPCOR distribution company under the APIC-alliance project and are not available online.

The authors of [58] aim to achieve a day-ahead forecast of residential load employing a customized federated learning algorithm, with a particular emphasis on customer demand management. The proposed approach involves training local models for clients within the federated learning framework using LSTM, along with the utilization of the Adam optimizer. The smart meter data used in this study were electricity load data extracted at 1 h intervals from January 1 to November 30, 2016, for 3,226 households of 40 buildings in Seoul, South Korea.

Finally, the authors of [45] introduce a novel approach aimed at addressing data silos in building energy consumption prediction. Using federated learning and employing an Artificial Neural Network (ANN) model, this method enables training of collaborative model in decentralized datasets. The incorporation of an ANN model highlights its ability to capture intricate patterns, which improves the accuracy of short-term energy consumption predictions. Dataset from the Building Data Genome Project. Operational data are used from 13 similar office buildings located in the cold-climate zone with similar gross floor areas. They are collected from June to October with a sampling interval of one hour.

13. Performance Evaluation

In this section, we analyze the selected papers taking into consideration their architectures, methodologies, advantages, and limitations. The experiments and evaluations were carried out using a high performance server setup. Specifically, we utilized an HPE ProLiant ML150 Gen9 Server equipped with a 64-bit 6-core Intel Xeon CPU running at 1.7 GHz, 64 GB of RAM, and a storage configuration comprising a 240 GB SSD and 8 TB HDD. The system operated on Windows Server 2012 R2. All implementations and simulations were developed using Python, leveraging widely adopted libraries such as TensorFlow for deep learning, Scikit-learn for preprocessing and statistical evaluation, Pandas for time series manipulation, and Matplotlib/Seaborn for visualization. These tools enabled reproducible experimentation and robust comparative analysis.

For this purpose, we chose the Pecan Street dataset, [1] which is a well-known benchmark dataset in the field of prediction of energy consumption in smart buildings. This dataset is widely used to evaluate and compare total energy consumption. It includes minute-interval appliance-level customer electricity use from nearly $1,000$ houses and apartments in Pecan Street's multi-state residential electricity use research, as well as ERCOT market operations. For prediction purposes, we took 2 years worth of continuous electricity usage data of 12 houses, each considered as an individual edge device, comprising $17,428$ raw data from the Pecan Street dataset. The dataset contains 10 features for each record. The features provide information about weather data from underground weather and energy usage data.

[1] https://github.com/xhan0o/Energy-prediction-smart-cities/blob/master/LSTM/Main_Raw.csv

Table 13
Dataset features with units and descriptions.

Feature	Unit / Description
DateTime	Date-time format (timestamp)
TotalUsage	kWh
Month	1–12
Temperature	Fahrenheit (°F)
Humidity	Percentage (%)
Hour of the day	0–23
Minute of the day	0–3599
Day of week	0–6
Weekend/Weekday	1 = Weekend, 0 = Weekday
Holiday	1 = Holiday, 0 = Not a holiday

This dataset is widely recognized in the academic literature for its high quality, completeness, and consistent structure. It provides data on appliance-level electricity usage in addition to weather-related information, collected using smart meters and external weather stations. In our study, we combined the energy usage data with the hourly weather data retrieved from Weather Underground. To ensure data reliability, we performed thorough preprocessing. We first checked for any discontinuities in the time series. Houses with non-continuous or fragmented electricity usage records were excluded from the analysis. For weather data, which typically follows a smooth temporal trend, we applied a simple time-based interpolation method to fill in missing values. For example, missing temperature readings were estimated using the average of adjacent time points (e.g. $T_2 = \frac{T_1+T_3}{2}$), using the natural continuity of environmental variables. In addition, categorical and time-based features such as holiday indicators, weekdays, months, and hours were reconstructed from the original timestamps using Python's Pandas library. For instance, attributes like `Hour`, `Minute`, and `Month` were extracted with commands such as: `df['Hour'] = df['DateTime'].dt.hour`. These preprocessing steps helped ensure that the dataset was clean, consistent, and well prepared for an accurate performance evaluation. Table 13 shows the list of features included in the dataset with their measurement.

In Table 14, we show the results obtained for each metric for all compared papers. The model in [50] achieved the highest accuracy (92.3%) along with the lowest error metrics (MSE = 16.72, RMSE = 4.08, MAE = 3.03), which makes it very suitable for precise energy forecasting. However, it came at the cost of a relatively high execution time (224.2s) and latency (0.99s), which may limit its use in real-time or resource-constrained environments. Similarly, the model in [45] delivered excellent performance with very close accuracy (92.25%) and nearly identical error rates (MSE = 16.77, RMSE = 4.09, MAE = 3.06), but with better efficiency in terms of latency (0.68s) and execution time (145.72s), suggesting it is a strong candidate for balanced deployments. The model in [39] showed good predictive capacity (accuracy = 89.28%) with moderate error values and a very efficient runtime (41.9s), indicating its potential for low-latency applications that still require reliable accuracy. In contrast, while [69] had the fastest execution time (0.56s) and lowest latency (0.11s), it recorded the lowest accuracy (57.12%) and the highest error values, making it more suitable for lightweight environments where speed is more critical than precision. The model in [64] achieved solid accuracy (90.82%) and good error scores, but with a very high execution time (856.03s), making it impractical for time-sensitive scenarios despite its predictive strength. Finally, [58] offered a reasonable trade-off, with decent accuracy (80.35%) and moderate latency (0.88s), making it a viable option for near-real-time systems that can tolerate slight compromises in accuracy. In summary, while [50] offers the best accuracy, [45] provides a better balance between performance and computational efficiency. The selection of the optimal model depends on the specific constraints and requirements of the deployment environment.

As shown in Table 14, the results reveal two facts: 1) none of the techniques is dominant in all performance metrics, and 2) the existing techniques show promising techniques for predicting energy consumption in smart buildings. Thus, in order to identify the best technique, we employed a nonparametric statistical tool known as the Friedman test. This test is designed to compare multiple related groups and serves as an extension of the Wilcoxon signed-rank test, making

Table 14
Performance metrics used in the selected papers for energy prediction evaluation.

Ref.	MSE	RMSE	MAE	R^2	Accuracy (%)	Latency (s)	Execution Time (s)
[69]	92.80	9.63	7.66	0.57	57.12	0.11	0.56
[39]	23.27	4.82	3.67	0.89	89.28	0.54	41.90
[50]	16.72	4.08	3.03	0.92	92.30	0.99	224.20
[64]	19.99	4.47	3.27	0.91	90.82	0.92	856.03
[58]	42.53	6.52	4.84	0.80	80.35	0.88	117.12
[45]	16.77	4.09	3.06	0.92	92.25	0.68	145.72

it applicable when dealing with more than two related groups and in situations where the data may not adhere to a normal distribution. In addition, the Friedman test is particularly valuable in scenarios where the dependent variable is measured on an ordinal scale, and observations are paired or matched across all conditions or levels of the independent variable. The procedure involves independently ranking the data for each group and calculating the Friedman statistic, which is based on the squared differences between the ranks of the corresponding observations across different groups. The null hypothesis assumes that there is no difference between the groups, while the alternative hypothesis posits a significant difference. If the value p associated with the Friedman statistic is below the chosen significance level, the null hypothesis is rejected, indicating a significant difference between the groups. Post hoc tests can be used to pinpoint specific group differences when the overall test yields a significant result. Consequently, Table 14 represents a matrix in which each row indicates the value for each technique, while each column represents a specific metric. First, for each group, we rank the observations from 1 to N, where N is the number of observations in each group. Then, for each observation, we compute the squared difference between its rank in each group and its mean rank across all groups. Furthermore, we calculate the sum of these squared differences for all observations and multiply this sum by a correction factor, which is

$$\frac{k^2}{k(k-1)}$$

where k is the number of groups. The formula for the Friedman statistic is often expressed as follows.

$$\chi^2 = \frac{12}{Nk(k+1)} \sum_{j=1}^{k} R_j^2 - 3N(k+1) \tag{1}$$

Where N is the number of observations in each group, k is the number of groups, and R_j is the sum of ranks for the j-th group.

Finally, the computed Friedman statistic is then compared to the chi-square distribution with $k-1$ degrees of freedom to obtain the value p. This p-value has a value of 0.005 in our analysis, which allows us to compare these different six articles. Following the application of the post hoc Nemenyi test to evaluate the six papers, which allows for pairwise comparisons between the papers, we proceeded to calculate the average rank for each technique. This average rank serves as an aggregate measure of performance in all evaluated metrics. By determining the paper with the highest average rank, we identify the technique that, on average, performed the best across all metrics considered. In our analysis, the technique proposed in [50] is considered the best existing in such a domain and demonstrates the most favorable performance compared to the others in the study.

14. Research Open Directions

The efficient management of energy consumption in smart buildings is a critical objective aimed at reducing environmental impact and enhancing sustainability. However, the effectiveness of Energy Management Systems (EMS) can be significantly impacted by dynamic factors such as changing weather conditions. Research has shown that fluctuations in temperature and climate patterns can lead to substantial changes in heating and cooling demands, which poses challenges to traditional EMS solutions. In light of these challenges, there is a growing emphasis on developing reliable, secure, cost-effective, and scalable EMS solutions that can adapt to evolving environmental conditions and optimize energy use efficiently. This section explores the importance of addressing these key considerations in the design and implementation of EMS for smart buildings, highlighting strategies and technologies to enhance performance and resilience in the face of changing environmental dynamics.

14.1. Resource Management

- Description: Resource management involves the efficient allocation and utilization of computational resources ranging from cloud servers to edge devices located near the user.

- Challenges: Balancing computational tasks between cloud servers and edge devices introduces complexities in resource allocation and coordination. Challenges include determining optimal task distribution strategies, minimizing latency for user-centric applications, and ensuring seamless scalability as user demands fluctuate.

- Considerations: Implementing intelligent task-offloading mechanisms that dynamically distribute processing tasks between the cloud and edge devices based on factors such as computational requirements, network conditions, and user proximity is essential. Using edge computing for latency-sensitive tasks and leveraging cloud resources for computationally intensive workloads can enhance overall system performance and user experience. In addition, employing predictive analytics and machine learning algorithms to anticipate user demands and proactively allocate resources can improve resource utilization efficiency and scalability.

14.2. Scalability

- Description: Scalability refers to the ability of the integrated system to accommodate a growing number of edge devices, fog nodes, and data sources while maintaining performance and efficiency.

- Challenges: As the number of devices and data sources increases in smart building environments, scalability becomes a significant concern. Scaling machine learning algorithms to handle a large volume of data distributed across edge devices and fog nodes without compromising performance and efficiency poses challenges. A non-scalable system cannot handle the expansion and thus, will become unreliable and need a replacement in future

- Considerations: The design of scalable architectures and algorithms that can efficiently distribute computational tasks, manage communication overhead, and ensure synchronization among distributed components is crucial. In addition, implementing mechanisms for dynamic resource allocation and load balancing can help address scalability challenges.

14.3. Security and Privacy

- Description: Security and privacy concerns arise due to the decentralized nature of edge/fog computing and the sensitive nature of data collected from smart building environments.

- Challenges: Protecting data privacy and ensuring secure communication between edge devices, fog nodes, and central servers is paramount. Edge devices may have limited security capabilities, making them vulnerable to cyber threats and attacks. Furthermore, federated learning involves sharing model updates and aggregated information across distributed nodes, raising concerns about data leakage and unauthorized access.

- Considerations: Implement robust encryption techniques, authentication mechanisms, and access control policies to safeguard data privacy and ensure secure communication is essential. In addition, incorporating privacy-preserving techniques such as differential privacy and secure multiparty computation can mitigate privacy risks associated with federated learning.

14.4. Performance Management

- Description: Performance management involves optimizing system performance in terms of computational efficiency, latency, and throughput while minimizing energy consumption and resource utilization.

- Challenges: Ensuring optimal performance of machine learning algorithms on resource-constrained edge devices and fog nodes is challenging. Factors such as limited processing power, memory, and bandwidth can impact the performance of distributed learning tasks. Moreover, coordinating model training and aggregation processes across heterogeneous devices introduces latency and communication overhead.

- Considerations: The use of lightweight machine learning models, efficient communication protocols, and task scheduling algorithms can improve performance management in integrated edge/fog computing and federated learning systems. In addition, leveraging edge caching and preprocessing techniques to reduce data transmission and processing overhead can enhance overall system performance.

14.5. Network Management

- Description: Network management involves overseeing the communication infrastructure that connects various devices within the smart building ecosystem, including edge devices, fog nodes, and central servers.
- Challenges: Managing network architecture in smart buildings presents challenges such as ensuring low latency, high reliability, and seamless connectivity across heterogeneous devices and communication protocols. In addition, accommodating the dynamic nature of smart building environments, where devices may frequently join or leave the network, adds complexity to network management tasks.
- Considerations: Implementing robust network protocols and architectures, such as 5G, Wi-Fi 6, and LoRaWAN, can provide reliable, high-speed connectivity tailored to the diverse requirements of smart building applications. Employing network virtualization techniques enables efficient resource allocation and isolation, improving network performance and security. Furthermore, integrating network management solutions with edge computing platforms can facilitate real-time monitoring, analysis, and optimization of network traffic, enhancing overall system reliability and responsiveness.

14.6. Cost Effectiveness

- Description: Cost-effectiveness in smart buildings involves optimizing the deployment and operation costs associated with integrated edge/fog computing and federated learning systems. This includes expenses related to hardware purchase, infrastructure setup, and ongoing operational expenditures.
- Challenges: The deployment and management of edge devices, fog nodes, and central servers incurs various costs, including hardware acquisition, infrastructure setup, and ongoing operational expenses. Furthermore, federated learning requires substantial computational resources and communication bandwidth for model training and aggregation, leading to increased energy consumption and resource utilization.
- Considerations: Adopting cost-effective hardware platforms, energy-efficient algorithms, and resource provisioning strategies can help mitigate the financial implications of deploying and operating integrated systems. Furthermore, exploring cloud-based solutions to offload computational tasks and leverage serverless computing models can reduce infrastructure costs and improve cost-effectiveness.

14.7. Big Data Processing

- Description: Big data processing involves handling and analyzing large volumes of data generated by edge devices and sensors in smart building environments.
- Challenges: Processing and analyzing big data in real-time presents challenges due to the distributed nature of edge/fog computing and the heterogeneity of data sources. In addition, traditional centralized data processing approaches may not be suitable for handling the velocity, variety, and volume of data generated in smart building environments.
- Considerations: Leveraging distributed data processing frameworks, stream processing techniques, and edge analytics algorithms can enable efficient handling and analysis of big data in integrated edge/fog computing environments. Furthermore, employing data compression, filtering, and aggregation methods at the edge can reduce data transmission and storage overhead, facilitating real-time analytics and decision making.

15. Conclusion

This study has provided a comprehensive overview of energy management systems (EMS) in smart buildings, highlighting their importance in optimizing energy consumption, reducing environmental impact, and improving sustainability. Through an exploration of key components, challenges, and future directions, the study has underscored the critical role of EMS in addressing dynamic factors such as changing weather conditions and evolving environmental dynamics. The integration of edge/fog computing and federated learning had emerged as a promising approach to overcome challenges and improve energy optimization in smart buildings, leveraging synergies between these technologies. However, the adoption of EMS faces various challenges, including resource management, scalability, security and privacy concerns, performance management, network management, cost-effectiveness, and big data processing. Addressing these challenges requires innovative strategies and technologies, such as dynamic resource allocation, resource virtualization, dynamic scaling, QoS management, and resilient architecture design. For real-world deployment, future work should focus on developing lightweight EMS models that can run efficiently on edge devices with limited resources. Integrating containerized or serverless frameworks can enhance scalability and facilitate easier deployment across heterogeneous building infrastructures. From a scalability perspective, distributed orchestration mechanisms should be explored to dynamically manage workloads across edge, fog, and cloud layers. Federated model updates should also be optimized using asynchronous or event-driven communication to reduce bandwidth and latency overheads. Regulatory and privacy constraints must also be addressed by embedding privacy preservation mechanisms, such as secure aggregation, differential privacy, and auditable model training logs, to ensure data security and user trust in real-world settings. Despite these challenges, ongoing research initiatives and advances in EMS offer promising opportunities to improve energy efficiency, reduce operational costs, and promote sustainable practices in smart building environments. As the field continues to evolve, the collaboration between researchers, industry stakeholders, and policy makers will be crucial in driving innovation and fostering the widespread adoption of EMS for a greener and more energy-efficient future.

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CRediT authorship contribution statement

Jessica Al Achy: Conceptualization, Software, Formal analysis, Data Curation, Writing - Original Draft. **Hassan Harb:** Methodology, Validation, Visualization, Writing - Review Editing, Supervision. **Abdallah Makhoul:** Investigation, Resources, Writing - Review Editing, Project administration.

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