Journal of Electronics and Electrical Engineering
https://ojs.wiserpub.com/index.php/JEEE

Review

# Intelligent Machine Learning Techniques for Energy Consumption Forecasting in Smart Buildings—A Review

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**Received:** 25 March 2026; **Revised:** 17 June 2026; **Accepted:** 25 June 2026; **Published:** 24 August 2026

**Abstract:** Accurate forecasting of energy consumption in smart buildings is an important part of environmentally sustainable energy management and smart grid operations. Numerous studies have employed singular Machine Learning (ML) techniques to estimate a building's energy requirements; however, most reviews examine only a limited number of algorithms, forecasting horizons, or datasets. They do not consider how smart homes operate as a whole, how ensemble learning functions, or how to evaluate models. This paper provides a structured and systematic analysis of machine learning-based energy consumption forecasting methodologies within the extensive framework of smart home systems. This review differs from earlier surveys in that it examines (i) the architectural features of smart homes that affect data generation and forecasting accuracy, (ii) a wide range of supervised and ensemble regression methods, such as Random Forest (RF), Gradient Boosting (GB), Extreme Gradient Boosting (XGBoost), Ridge, Lasso, voting regressors, and stacking regressors, and (iii) various evaluation and interpretability frameworks used to assess predictive reliability. The study meticulously assesses algorithms based on their precision, scalability, interpretability, computational cost, robustness to noise, and suitability for nonlinear energy patterns. This review also stresses the utility of hybrid and ensemble machine learning methods for improving prediction accuracy and system stability in changing home environments. The paper uses quantitative metrics, visualization tools, and Explainable Artificial Intelligence (XAI) methods from the literature to compare performance and examine forecasting outcomes. This work provides a comprehensive foundation for developing accurate, scalable, and comprehensible energy forecasting models for next-generation smart homes by integrating smart building system architecture, machine learning methodologies, ensemble techniques, and evaluation frameworks into a unified analytical perspective. The findings indicate unresolved issues and propose avenues for further investigation into hybrid modeling and real-time intelligent energy management systems.

***Keywords***: smart buildings, energy consumption forecasting, Machine Learning (ML), hybrid models, Explainable Artificial Intelligence (XAI), smart energy management

## 1. Introduction

Buildings are among the world's largest energy-consuming sectors and make a substantial contribution to energy-related greenhouse-gas emissions and environmental impacts [1]. According to worldwide energy reports, residential and commercial buildings account for a substantial proportion of the world's final energy consumption, which make the enhancement of building energy efficiency a critical component of the sustainable development strategy and climate


DOI: https://doi.org/10.37256/jeee.5220269945

change mitigation efforts [2], [3]. The rapid development of urban areas and the increasing need for indoor comfort has made reducing energy consumption, while keeping comfort at an acceptable level, one of the major challenges for policy makers, utility suppliers and building operators [4].

Recent advances in sensing technologies, Internet of Things (IoT), smart meters and Building Management Systems (BMS) have transformed conventional buildings into data-rich and highly networked settings [5]-[7]. Modern smart buildings regularly generate large amounts of operational data related to energy consumption, occupancy patterns, indoor ambient conditions, equipment status, and climatic elements [5]. These data streams provide unprecedented opportunities for energy management and data-driven decision making. Energy consumption forecasting is one of the most important and most researched areas among the many applications enabled by smart building technologies [8], [9].

Accurate forecast of energy consumption in buildings is essential for a variety of applications in energy management such as demand response programs, Heating, Ventilation and Air Conditioning (HVAC) control optimization, peak-load management, integration of renewable energy sources, energy trading and smart grid operation [10], [11]. Accurate projections enable building operators to estimate future energy needs, optimize scheduling strategies, reduce operational costs, and enhance overall energy efficiency. Moreover, the accuracy of the predictions is highly dependent on the effectiveness of current control systems and the development of sustainable and resilient energy infrastructures [12], [13].

According to the prediction horizon, building energy forecasting is often divided into short-term forecasting [14]-[16], medium-term forecasting [17], and long-term forecasting [18]. The primary uses of short-term projections are for real-time control, demand side management and operational optimization. Medium-term predictions are useful for maintenance planning and energy scheduling, while long-term forecasts are vital for infrastructure development, retrofit assessments, and strategic energy planning. However, the realistic forecast of building energy consumption is still a difficult topic since the energy demand is influenced by a series of dynamic and non-linear factors such as weather conditions, occupancy behavior, building characteristics, operational schedules, and management techniques [19].

To address these challenges, the academic community has gradually turned to machine learning and artificial intelligence algorithms that can discover complicated relationships directly from historical data. Traditional machine learning methods such as Support Vector Regression (SVR) [9], [20], Random Forest (RF) [2], [21], Gradient Boosting and Extreme Gradient Boosting (XGBoost) [21], [22] were employed in early studies and demonstrated good predictive performance with low computational complexity. These approaches remain attractive for many practical purposes because of their robustness, interpretability and effectiveness when the training data is limited.

The increasing availability of building data has motivated the adoption of deep learning technologies. Artificial neural networks [23], convolutional neural networks [16], [24], long short-term memory networks [19], [24], [25], and gated recurrent unit networks [24] have shown strong abilities in modeling complicated non-linear relationships and temporal dependencies in energy consumption data. This capacity to learn patterns directly from historical observations has led to their wide adoption in smart building energy forecasting research. More recently, transformer-based designs have emerged as a viable alternative to recurrent techniques by using self-attention mechanisms which can better capture long-range temporal relationships and interactions in sequential data [4], [26], [27]. Informer, Temporal Fusion Transformer (TFT) and PatchTST [14] are among of the models that have shown state-of-the-art forecasting performance in many energy prediction applications.

In addition to single forecasting models, the literature is increasingly shifting toward hybrid and ensemble approaches that integrate multiple learning paradigms into unified frameworks. Hybrid techniques such as convolutional feature extraction + recurrent temporal modeling, signal decomposition, attention mechanism, and optimization algorithms have shown superior prediction accuracy in several building scenarios [15], [25]. Such as Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM), Convolutional Neural Network–Gated Recurrent Unit (CNN-GRU), Empirical Mode Decomposition–Long Short-Term Memory (EMD-LSTM), decomposition enhanced Transformer models and optimization assisted XGBoost frameworks [16], [24], [28]. In addition, ensemble learning approaches have been exploited to improve resilience of forecasting by aggregating predictions from several complementing models [29], [30].

Meanwhile, the science of forecasting has evolved beyond mere predictive accuracy. New paradigms such as transfer learning [14], [27], federated learning [31]-[34] and Explainable Artificial Intelligence (XAI) [15], [35], [36] have addressed some practical shortcomings of previous forecasting systems. Transfer learning enhances the model's adaptability in data-scarce environments, federated learning facilitates collaborative forecasting while maintaining data privacy, and XAI techniques bolster openness and trustworthiness by presenting interpretable explanations of model predictions. These improvements are part of a broader move towards intelligent forecasting systems that are accurate, scalable, transportable, privacy-preserving and interpretable.

Although a wide range of research exists on building energy forecasting, the field remains rather fragmented [2], [3], [21]. Many studies focus on one forecasting method, one deep learning architecture, or one application situation. Moreover, the rapid development of Transformer-based forecasting, hybrid intelligent systems, federated learning, and explainable AI has significantly expanded the scope of this field in recent years. There is now a growing need for a comprehensive and up-to-date assessment that systematically combines these achievements and evaluates critically their strengths, limitations and promise for the future.

Therefore, this paper provides a comprehensive review of clever machine learning techniques for prediction of energy demand in smart buildings. This review provides a comprehensive examination of conventional machine learning algorithms, deep learning architectures, hybrid and ensemble forecasting frameworks, and emerging intelligent paradigms. Moreover, the illustrative forecasting studies are comparatively evaluated on the basis of forecasting objectives, datasets, performance measures and practical usage. Finally, we discuss the essential difficulties and future research areas in the aspects of transferability, privacy preservation, explainability, uncertainty quantification, foundation models and digital-twin-enabled forecasting systems.

The present review makes four contributions. First, a thorough evaluation of classical machine learning, deep learning, hybrid and new intelligent forecasting techniques for smart building energy prediction is given. Second, it provides a careful comparative assessment of representative forecasting studies, with emphasis on their performance characteristics, strengths and constraints. Thirdly it talks about recent developments in the discipline, particularly in the area of transfer learning, federated learning and explainable artificial intelligence. Finally, we explore the key issues and future research directions that need to be addressed for the development of trustworthy, scalable, interpretable, and autonomous forecasting systems for next-generation smart buildings.

The remainder of this paper is organized as follows. Section 2 provides the study techniques for identification, filtering and analysis of the literature. Section 3 is devoted to smart buildings and smart home systems, their architecture, essential components and their role in smart energy management. Section 4 presents the methodology of energy consumption forecasting, forecasting horizons, influencing factors, input variables and performance evaluation measures. Section 5 describes the clever machine learning algorithms for energy forecasting. It covers the traditional machine learning algorithms, deep learning architectures, hybrid and ensemble models, and new developing paradigms such as transfer learning, federated learning and explainable artificial intelligence. Section 6 includes a comparative analysis of representative forecasting studies showing differences in forecasting goals, data sets, model features and reported performance. In Section 7, we focus on key concerns and future research areas on intelligent energy forecasting for smart buildings. Finally, in Section 8, the research is concluded with a summary of the key findings and future perspectives for the development of intelligent, scalable and trustworthy forecasting systems.

## 2. Research methodology

This review employs a systematic literature analysis technique to provide a comprehensive overview of intelligent machine learning algorithms for predicting energy consumption in smart buildings. The objective of this review is to provide a comprehensive and full examination of the state-of-the-art advances in data-driven energy consumption estimates of smart buildings. The purpose of the study is to identify and evaluate the most important approaches emerged in the last years, in particular those based on machine learning and deep learning. The article also discusses the growing popularity of hybrid frameworks that combine several modelling techniques to enhance forecasting accuracy and robustness. Emerging intelligent forecasting models for scalability, adaptability, interpretability and privacy challenges are also examined in detail. Through this study, this review aims to give the readers with a comprehensive understanding of the current research trends, methodological advancements and future directions of smart building energy forecasting. The literature search was performed in important scientific databases such as IEEE Xplore, ScienceDirect, SpringerLink and Google Scholar. This timeframe was selected as the period from January 2010 to June 2026 because the machine learning and artificial intelligence approaches have started to gain more attention in research on building energy forecasting. The major search query used in the literature retrieval approach was:

("smart building" OR "intelligent building") AND ("energy consumption prediction" OR "load prediction") AND "machine learning"

The scope of the review is the original and research articles in English related to the forecast of building energy consumption based on data-driven intelligent approaches. The literature reviewed included diverse forecasting approaches such as classical machine learning models, deep learning architectures, ensemble methods, hybrid prediction frameworks, transfer learning strategies, federated learning approaches, and explainable artificial intelligence techniques. For a consistent evaluation of the predicting performance only studies reporting quantitative assessment indicators were evaluated. Commonly used metrics were Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Coefficient of Variation of Root Mean Square Error (CV-RMSE), and coefficient of determination. The implementation of these standardized parameters allows a more trustworthy evaluation of the accuracy and effectiveness of alternative forecasting approaches, across different datasets and application scenarios.

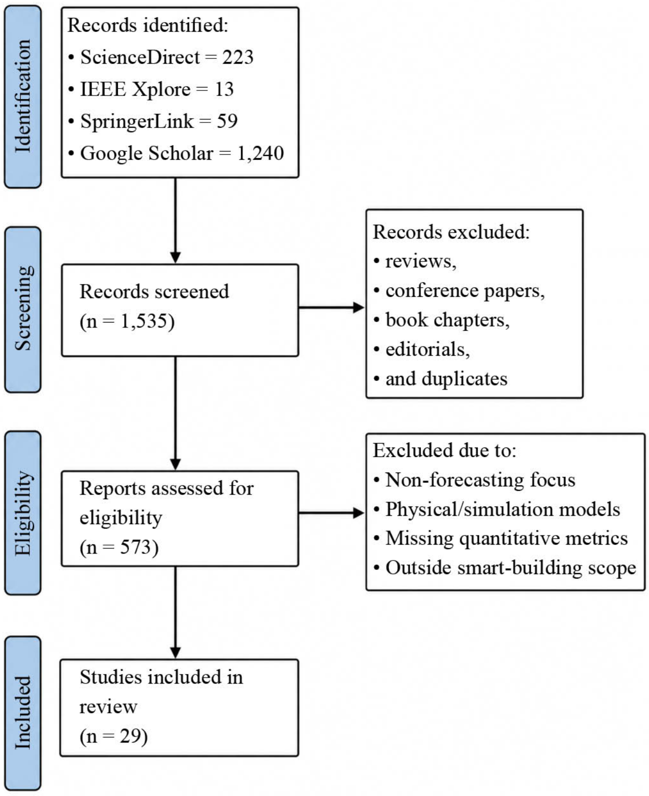


**Figure 1.** Workflow of the literature search and article selection process

In order to be compatible with the objectives of this study, some categories of publications were excluded. Exclusion criteria were review papers, survey articles, systematic reviews, novels, book chapters, editorials and letters. Furthermore, studies pertaining to renewable energy generation forecasting, electricity price forecasting, large-scale power system load forecast or energy management application without a forecasting component were excluded. The emphasis was on research of forecasting-oriented, thus the studies that focused on HVAC control, optimization of thermal comfort, operational scheduling, demand response control or energy optimization schemes without clear forecasting targets were omitted. For the same reason, techniques of modelling based on first principles equations, thermal simulation software or engineering models, both physical and simulation-based, were also rejected. This review considers only the data-driven forecasting methods.

Figure 1 shows the overall approach of literature detection, filtering, evaluation and ultimate selection of research.

## 3. Smart home system

Smart home systems have evolved from simple automation solutions to sophisticated, linked environments that optimize occupant comfort, improve security and increase energy efficiency. This evolution has been driven by the advances in the Internet of Things (IoT) that allow the seamless integration of sensor, communication, computing and control technologies in residential settings. Through this integration, smart homes can continuously monitor operating conditions and dynamically manage household resources. Occupants are able to interact and operate a variety of technologies such as the lighting system, heating, ventilation and air-conditioning equipment, domestic appliances and security systems using smartphones, web-based platforms or voice-enabled assistants. Moreover, the massive data generated by these connected devices has opened up new prospects for the application of machine learning techniques for forecasting energy consumption, demand management, and intelligent decision making processes [37].

As shown in Figure 2, a typical smart home energy management architecture is composed of several interrelated subsystems, including a central control unit, smart appliances, sensing and monitoring devices, energy generation and storage resources, human-machine interaction interfaces, and communication networks. Together, these components form the Home Energy Management System (HEMS), which serves as the central infrastructure for data collection, system coordination, and forecast-based energy optimization. The Home Energy Management System integrates the predictive analytics with the real-time monitoring and control capability. It encourages the effective use of energy and enables the construction of smart and sustainable domestic energy management schemes.

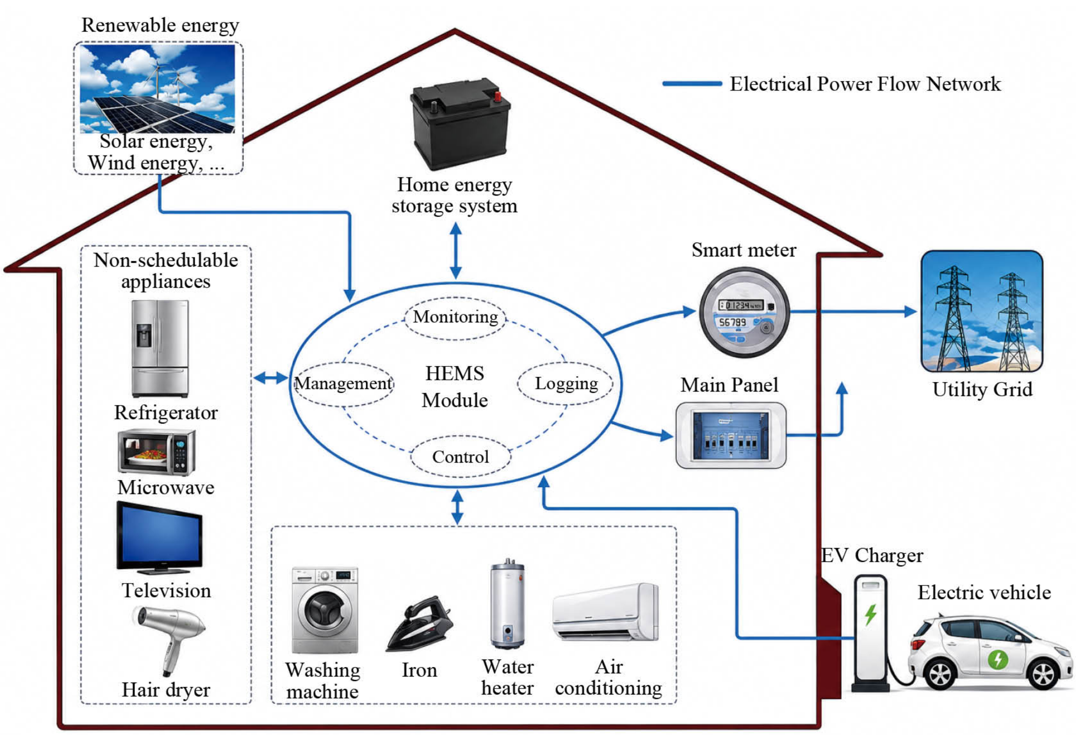


**Figure 2.** Overall architecture of a HEMS [10]

### 3.1 *Central controller*

The central controller, often known as the smart controller or central platform, is the core of the HEMS design [10]. Recent HEMS architectures integrate smart-grid connectivity and advanced metering infrastructure with monitoring, forecasting, optimization, and automated control functions [38], HEMS platforms have progressed to complex systems integrating forecasting, optimization and automatic control functionalities.

The controller constantly collects information from sensors, smart meters and linked devices to monitor energy usage trends and ambient conditions. HEMS can use machine learning based forecasting models to assess historical and real-time data and forecast future energy demand, thereby enabling intelligent scheduling decisions [39]. The controller dynamically controls the functioning of the appliances with respect to the occupancy conditions, weather fluctuations and electricity pricing schemes based on the projected consumption profiles.

The controller allows real-time control operations and anomaly detection besides energy management tasks. Machine learning methods improve fault diagnostic skills by detecting irregular consumption behaviors and predicting potential equipment failures before they become major occurrences [40]. The central controller transforms smart homes into intelligent, adaptive environments that can optimize occupant comfort with energy economy.

### 3.2 *Smart home appliances*

Household energy demand is strongly influenced by space heating and cooling, water heating, refrigeration, lighting, and other electrical appliances [41]. When supplied by fossil-fuel-based electricity or through the direct combustion of fossil fuels, these end uses contribute to energy-related greenhouse-gas emissions [1]. Thus, their inclusion in HEMS frameworks is vital to enable effective demand side energy management.

In general, smart appliances can be categorized according to their operational flexibility and functions in energy management. HVAC systems and water heaters are important controllable loads and also high-consumption equipment. Medium-load appliances such as washing machines can sometimes be switched to off-peak periods. Scheduling mechanisms can be used to automatically control low power devices such as lighting systems. Incorporating sensing capabilities and machine learning algorithms allows appliances to learn user preferences and adapt their operation to occupants' behavioral patterns [42].

The increasing share of Electric Vehicles (EVs) offers new possibilities for domestic energy management. EV batteries can serve as distributed energy storage resources with Vehicle-to-Grid (V2G) technology providing the services of peak shaving and load balancing. So, load prioritization and appliance scheduling algorithms [43] supported by accurate demand forecasting, have a vital role in optimizing the energy consumption in smart homes.

### 3.3 *Detection and measurement devices*

Accurate sensing and data collection are the backbone of intelligent energy forecasting in smart home scenarios. Modern smart homes are fitted with a variety of sensors which constantly monitor information about ambient conditions and occupant behaviors and system operating states to enable effective monitoring and control. Temperature, humidity, occupancy, illumination levels, gas concentration, vibration and power consumption measurements give crucial information for understanding the elements influencing home energy demand, and for constructing credible forecasting models.

Different sensor technologies in a Home Energy Management System provide complementary roles in facilitating energy-efficient operation and decision-making. Environmental sensors are mostly used for monitoring the indoor environment and occupants' comfort. Motion and occupancy sensors enable the deployment of occupancy-aware energy management systems. Gas-leak sensors, smoke sensors, and flame detectors are safety-oriented sensors that are important for detecting potentially dangerous situations at an early stage. Condition-monitoring sensors are also being used extensively to monitor equipment performance and support predictive-maintenance techniques. Table 1 summarizes common sensor technologies and their respective functions in home energy management systems [44], [45].

The fusion of heterogeneous sensor streams generates high-resolution time-series datasets, which are the key inputs for machine learning models. Thus, the sensing precision directly effects the prediction accuracy, operational reliability, and effectiveness of real-time control decisions.

**Table 1.** Commonly used sensor devices in home energy management systems

| Sensor Type | Function | Application Examples |
|---|---|---|
| Passive Infrared Sensor | Detects motion via infrared radiation changes. | Intrusion alerts, elderly care systems. |
| Temperature Sensor | Measures ambient temperature. | Room temperature control, fire warning systems. |
| Humidity Sensor | Measures moisture levels in the air. | Atmosphere monitoring, automated climate control. |
| Gas Sensor | Detects harmful gases like propane or carbon monoxide. | Gas leakage detection, fire prevention. |
| Smoke Sensor | Detects the presence of smoke or fire. | Fire alarm system, early warning systems. |
| Ultrasonic Sensor | Measures distance to objects by sound waves. | Automatic doors, water level monitoring. |
| Flame Sensor | Detects the presence of flame in a room. | Fire detection, security systems. |
| Light Detection Sensor | Measures light intensity in an area. | Lighting automation, daylight monitoring. |
| Pressure Sensor | Detects atmospheric pressure or applied force. | health monitoring (e.g., blood pressure). |
| Accelerometer | Measures acceleration forces and movements. | Intrusion detection, elderly health monitoring. |
| Door Sensor | Detects whether a door is open or closed. | Home security, elderly care systems. |
| Gyroscope | Measures orientation and angular velocity. | Gesture control, orientation detection. |
| Pulse Sensor | Measures human heart rate. | Health monitoring in smart homes, elderly care |
| Fluid Detection Sensor | Detects the presence of water or other fluids. | Water leakage detection. |
| Camera | Captures video and images for processing and security. | Surveillance, gesture recognition, monitoring. |
| Force-Sensing Resistor | Detects force and pressure changes. | Activity monitoring, pressure-sensitive security. |
| Flex Sensor | Measures bending or deflection of objects. | Gesture-controlled systems, elderly |

## 3.4 *Energy production and storage systems*

The rapid penetration of distributed energy resources has radically changed the role of home consumers, transforming them into active participants in both energy generation and consumption. The shift to the prosumer paradigm has become a major element of contemporary smart energy systems. The photovoltaic power forecasting for a short term period has been integrated into the home energy management systems for controlling the distributed energy sources in the house on a predictive basis [46]. Moreover, current studies on cost have revealed a decline in the cost of renewable energy production [47]. In this regard, short-term load forecasting of residences has become extremely important [48].

The variability and weather dependence of renewable energy output, however, pose major challenges in maintaining a balance between electricity supply and demand. Thus, energy storage systems are an integral part of smart home energy systems. These systems increase the dependability, stability and efficiency of energy consumption by absorbing excess energy while generation is high and supplying it when demand exceeds production.

Today, the most widespread storage technology for residential applications is lithium-ion batteries due to their high energy density, extended cycle life and good performance features. Lead acid batteries still find place in cost sensitive applications due to comparatively low initial expenditure. At the same time, developing storage technologies like as flow batteries, saltwater batteries, and zinc-ion batteries are receiving growing scientific and industrial attention for possible benefits in safety, sustainability, and long-term operational performance. Table 2 presents an illustrative comparison of selected battery technologies relevant to domestic renewable-energy systems [49].

Distributed generating with storage resources provides energy resiliency, decreases dependence on the utility grid during peak periods, and allows for scheduling methods based on forecasts. Accurate load prediction is crucial to coordinate renewable generation, battery operation and demand response programs.

**Table 2.** Comparison of energy storage technologies for smart homes

| Renewable Energy Source | Battery Type Used | Notes |
|---|---|---|
| Solar Power | Lithium-ion (Li-ion), Lead-acid, Saltwater, Zinc-ion | Lithium-ion batteries are the most efficient and common choice. Lead-acid is cost-effective but less efficient. Saltwater and Zinc-ion are environmentally friendly alternatives. |
| Wind Power | Lithium-ion (Li-ion), Lead-acid, Flow batteries | Lithium-ion batteries are widely used for their high energy density. Lead-acid is cheaper but less efficient. Flow batteries are better suited for larger scale systems. |
| Hydropower (Micro Hydro) | Lithium-ion (Li-ion), Lead-acid, Flow batteries | Lithium-ion batteries are preferred for their long lifespan and efficiency. Flow batteries are more suitable for larger-scale installations. |
| Geothermal Energy | Lithium-ion (Li-ion), Lead-acid | Lithium-ion is the most commonly used due to its efficiency. Lead-acid is less expensive but has a shorter lifespan. |
| Biomass Energy | Lithium-ion (Li-ion), Lead-acid, Flow batteries | Lithium-ion batteries are commonly used for energy storage. Flow batteries offer scalability for larger biomass systems. Lead-acid is a budget-friendly option. |

## 3.5 *Human-Machine Interface (HMI)*

The Human-Machine Interface (HMI) serves as the communication layer between occupants and the HEMS intelligence. HMIs turn complicated energy data into easy-to-understand and visual formats that can enhance user awareness and encourage user participation in energy-saving efforts.

Modern interfaces now provide real-time usage monitoring, graphical feedback, appliance scheduling features and individualized energy conservation tips [19]. Also, users can set energy goals and monitor performance of the system through mobile apps and web portals. The transition of HMI technologies from traditional desktop applications to responsive, voice-enabled interfaces has greatly enhanced accessibility and user experience [7].

More than visualisation, HMIs provide the opportunity for forecast-based decision-making by allowing the residents to comprehend the expected consumption trends and to be actively involved in domestic energy optimisation.

## 3.6 *Communication infrastructure*

Reliable communication networks provide the basis for the reliable operation of smart home technologies. Sensors, controllers, appliances, and end-user interfaces continuously exchange data, enabling real-time forecasting, optimization, and automated control actions [50].

In HEMS, communication is usually carried out by local device-to-controller communication and external communication with cloud platforms or smart grids. Popular local communication technologies include ZigBee [51], [52], LoRa/LoRaWAN [53], Wi-Fi [6], RF technologies [54], Z-Wave [55], and 6LoWPAN [56]. IoT-enabled smart-meter and sensor streams may be directly utilized as predictive inputs of building energy-consumption models [57] for forecasting-oriented HEMS. Another low-power alternative for sustainable buildings is the wireless sensing based on EnOcean [58]. At the modeling layer, smart-building studies at the home level indicate the significance of high-resolution domestic energy data for accurate short-term forecasts [59]. Other wireless and networked communication methods utilized in smart-home and smart-grid settings include Bluetooth, LAN, and cellular IoT [60]-[62].

These communication methods have different trade-offs in terms of transmission range, deployment cost, latency, dependability and energy efficiency (Table 3) [36]. The communication infrastructures are important in the practical realization of machine learning-enabled forecasting and intelligent energy management in smart homes, since these features directly influence data availability and response.

**Table 3.** Comparison of smart home communication technologies

| Communication Technology | Description | Advantages | Challenges |
|---|---|---|---|
| Ethernet (Wired) | High-speed wired network for device communication. | Reliable with high data rates. | High installation and deployment costs. |
| BACnet (Wired) | Designed for building automation and control networks. | Consistent data rate and stability. | Complex installation requirements. |
| Modbus (Wired) | Common in industrial applications for control systems. | High reliability. | Requires physical wiring, higher costs. |
| Wi-Fi (Wireless) | Standard for connecting devices in smart homes. | No need for wiring, widespread compatibility. | Signal interference in densely packed areas. |
| Zigbee (Wireless) | Low-power wireless protocol for energy-efficient devices. | Easy setup, low installation cost, reliable. | Limited range and prone to interference. |
| Bluetooth (Wireless) | Short-range wireless communication for device control. | Low cost, energy-efficient for small data transfers. | Limited to short-distance communication. |
| LoRa (Wireless) | Long-range, low-power communication ideal for wide coverage. | Wide coverage with low power consumption. | Limited data transfer rates. |
| 6LoWPAN (Wireless) | Integrates IPv6 with low-power wireless networks. | Enables low-power Internet connectivity. | Limited data bandwidth. |
| EnOcean (Wireless) | Energy-harvesting wireless technology. | Low maintenance, energy-efficient. | Limited range, potential signal issues in dense setups. |

# 4. Energy consumption forecasting framework

The rising deployment of distributed energy resources and the progressive move from conventional energy consumers to prosumer-oriented energy systems have significantly transformed the smart building forecasting environment. Today's homes are no longer passive consumers of electricity, but instead are becoming active participants in the grid, with distributed assets, including rooftop solar PV, battery energy storage, electric vehicles and other intelligent energy resources that can interact dynamically with the grid. Although these technologies provide tremendous opportunity to improve the energy efficiency and sustainability, they also create more variability, uncertainty, and complexity in the building energy consumption patterns. Accurate forecasting is therefore a vital need for the support of demand response programs, energy storage operation optimization, grid interaction enhancement and overall energy management strategies. Therefore, the contemporary day forecasting methods need to account not just for the traditional consumption behaviour, but also the issues connected with the dispersed generation, bi-directional power flow and the new prosumer-based energy ecosystems.

Energy consumption forecasting in smart buildings is not limited to the development of predictive models but should be considered as a holistic end-to-end process including data collection, pre-processing, model development, performance evaluation and operational deployment. In the existing literature, this method is often referred to as an integrated forecasting framework in which sensing technologies, analytical models, validation procedures and control mechanisms are linked to support building energy management objectives. The implementation of such a framework is particularly important in the smart building environment, because energy demand is influenced by a large variety of inter-related factors, such as weather conditions, occupants' behavior, equipment operation schedules, building characteristics, and control actions. Also, these elements are generally dynamic and vary over time, making it more difficult to maintain forecasting accuracy and model reliability [63], [64].

## 4.1 *Forecasting objectives*

The choice of an acceptable forecast horizon is influenced by the aims of forecasting, availability of input data and the use of the forecasting results. In smart building environments, the forecasting horizons are generally divided into short-term, medium-term, and long-term with different operational and strategic aims. Short-term forecasting is mostly used for real-time energy management tasks, such as heating, ventilation and air-conditioning control, demand response implementation and operational scheduling. Medium-term forecasting is useful for planning activities like energy procurement, maintenance scheduling, tariff optimization, while long-term forecasting is used generally for strategic decision-making processes like building retrofitting, system capacity planning and long-term energy budgeting [35], [64].

Short-term forecasting is commonly understood as a forecasting horizon of a few minutes up to one day ahead and represents the most common forecasting category used in smart building applications. The reason it is so popular is that it is directly relevant to operational optimization and real-time control. It has been shown in previous works that predicting accuracy in a short-term horizon largely depends on historical energy consumption, temporal aspects (time of day, day of week) and weather-related variables. Accurate short-term projections allow building operators to lower peak demand, improve occupant comfort and take proactive control actions ahead of large variances in energy usage [11], [65], [66].

Medium term forecasting is often for a few days to a few weeks ahead and is particularly useful for operational planning and resource management. At this forecasting horizon, the forecasts can help decision-makers improve maintenance schedules, staff allocation, operational planning and energy purchasing strategies. Forecasted weather conditions, occupancy trends, and calendar-related information play a more important role in medium-term prediction models than in short-term forecasting models, as the impact of real-time sensor measurements reduces as the length of the forecasting horizon increases. One of the fundamental problems of medium-term forecasting is the gradual build-up of uncertainty in external influencing factors, which usually leads in a loss of prediction accuracy [17].

Long-term forecasts are for a period of a few months to a few years and are mostly used to help policy formation, planning of infrastructure, investment planning and sustainability evaluations. Long-term forecasting deals with larger consumption patterns, such as seasonal changes, long-term trends and annual energy demand profiles, while short-term forecasting is concerned with particular operational behaviour. It has been shown in previous review studies that reliable long-term forecasting often needs more than historical energy measurements to be included, e.g. building characteristics, climatic conditions, urban context, socioeconomic factors and occupant-related variables [18].

## 4.2 *General forecasting pipeline*

A typical forecasting pipeline for smart buildings can be structured in six stages: data collecting, preprocessing, feature engineering, model construction, validation and deployment (Figure 3).

This arrangement matches the multi-layered perspective typically taken in building energy management schemes, where data gathering, analytics, and decision support are regarded as interrelated modules rather than independent stages [13].

The first stage is data acquisition, which involves collecting power, heating, cooling, and auxiliary load data from building systems and external sources [11], [63]. Energy statistics are typically coupled with weather, occupancy, and operating data, since building energy use varies on both indoor and outside conditions. The quality of this stage has a substantial impact on the overall forecasting process, since missing or low-frequency measurements might reduce the model accuracy.

Data preparation is the process of converting raw measurements into a useful format. This step usually includes missing value handling, noise filtering, resampling, alignment of multi-source time series and outlier detection [26], [67], [68]. Preprocessing is particularly critical in smart building applications as the sensor data and management system logs tend to be heterogeneous in sample frequency, timestamp format and completeness.

Feature engineering involves the conversion of raw data into predictive variables, such as lagged consumption, rolling averages, occupancy indications, day type, holiday flags, and weather-related features [26], [37], [45], [69]. Exogenous factors, particularly weather variables, were found to enhance building load forecasting in previous research as they take into account nonlinear environmental impacts on demand. For long horizon models, engineered calendar and seasonal elements are often as essential as the previous load.

Model development involves the selection and training of forecasting models. Traditional statistical methods, classical machine learning and deep learning have all been utilized, but new research reveal that deep learning often outperforms the others when the data are sufficiently rich and sequential patterns are strong [2], [3], [12]. Review work shows that there is no single best model. The optimum model choice depends on the prediction horizon, data availability, interpretability requirements and deployment restrictions.

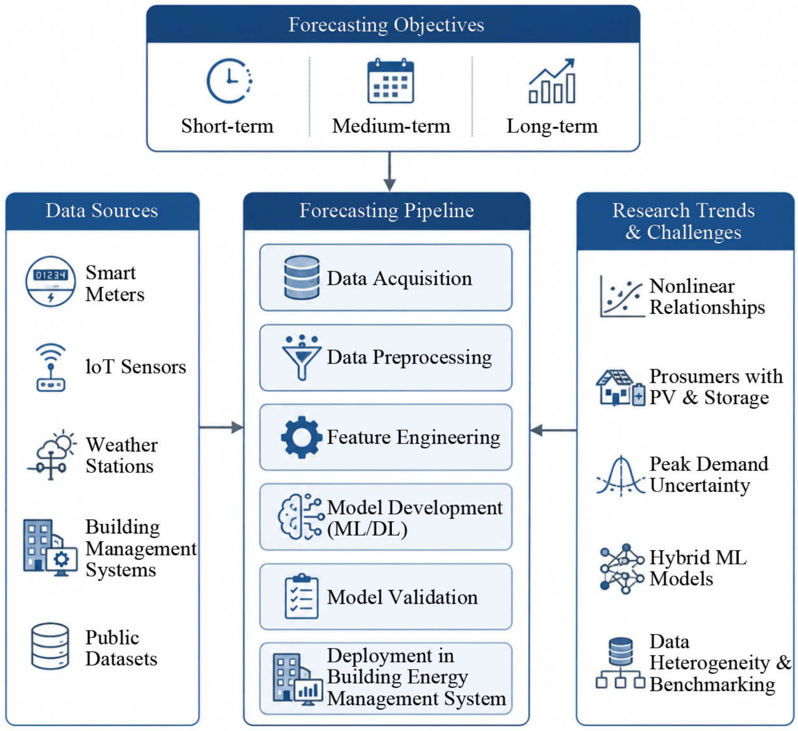


**Figure 3.** General framework for intelligent energy consumption forecasting in smart buildings

The model validation tests the generalization of model to new data [3], [31]. In forecasting, a common technique is to partition the data into training, validation and test sets and evaluate the model on future time periods using error-based metrics. This phase is very important, since building energy data are time dependent and random splitting can exaggerate the performance if temporal leakage happens.

Deployment of the forecasting model renders it an operational tool in a building energy management system [8]. In a deployed setting predictions can be used for HVAC scheduling, anomaly detection, demand response and closed loop optimization. In the literature, deployment is increasingly viewed as part of the forecasting lifecycle, rather than a final technical detail, since the practical value of the model depends on integration with control and monitoring systems.

## 4.3 *Data sources for forecasting*

The accuracy and reliability of the energy consumption forecasting models largely depend on the quality, diversity and relevance of the input data utilized during the model development. Forecasting frameworks for smart building environments usually aggregate several data sources to capture the internal building dynamics as well as the external influences impacting energy demand. The most often employed input categories include historical energy data, weather-related variables, building attributes, operational information, occupancy and behavioral factors, and other external impacts as shown in Figure 4. The integration of these varied data sources allows the forecasting models to better characterize the complex connections governing energy consumption trends in smart buildings.

Data from smart meters are among the most essential information sources for energy forecasting applications. These devices facilitate high-resolution, time-stamped measurements of electricity and utility consumption, allowing researchers and practitioners to study the consumption patterns at various temporal scales [3], [70]. Smart meters directly measure real energy use, which is typically the main goal variable in forecasting research. Historical smart meter consumption statistics are commonly integrated with lagged observations, time-related indicators and calendar-based variables to increase the accuracy of forecasts and the resilience of models [63].

The widespread use of Internet of Things sensors, which monitor indoor environmental factors on an ongoing basis, provides useful information about the physical and operating status of a building. Typical measures include temperature, humidity, carbon dioxide content, occupancy and illumination [5]. These variables are crucial because they reflect environmental and behavioral factors which have a large effect on energy use. Internet of Things data in intelligent building environments enable forecasting models to include real-time variations and enable adaptive control schemes reacting dynamically to changing conditions.

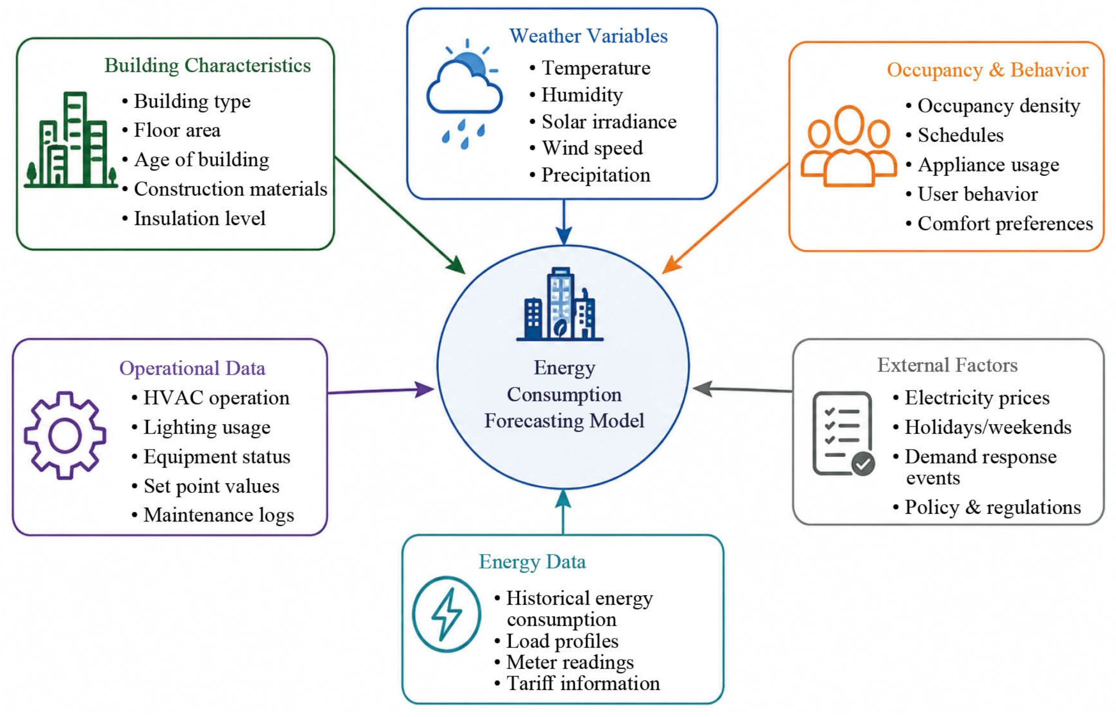


**Figure 4.** Major data sources and input variables for predicting energy consumption in smart buildings

Weather data is among the most used types of exogenous variables in building energy forecasts. Weather stations typically provide outside temperature, solar irradiance, humidity, wind speed, precipitation, and cloud cover [11], [63]. Many studies have shown that the weather-related variables considerably enhance the forecasting effectiveness, especially for the heating, ventilation, and air-conditioning loads that are extremely sensitive to environmental conditions. As a result, weather information is often included in forecasting models to account for changes in energy consumption due to weather patterns.

Building Management Systems give precise information on the operation of building equipment and control operations. Examples include equipment status, control setpoints, timetables, alarm recordings and system control signals [31]. These data sources are particularly useful since they provide information on changes in energy use that cannot be explained by previous load measurements alone. Building Management System data in advanced smart building applications allows the coupling of forecasting models to automated control and optimization mechanisms, therefore contributing to more effective energy management techniques.

Also, public available datasets are important in the building energy forecasting research. Open access databases enable benchmarking, comparative evaluations and repeatability of research findings across diverse climatic regions and building kinds [3], [63]. They provide a common ground for analyzing forecasting methods and let researchers compare model performance on an equal footing. However, to reach higher levels of predicting accuracy and practical applicability, many publically available datasets need to be enhanced with other information, such as weather variables, occupancy data, and building attributes.

### 4.4 *Research trends and forecasting challenges*

Despite the advances made in smart building energy forecasting, there are still constraints that limit the accuracy, scalability and practical deployment of forecasting models. These challenges are fueled by several intertwined factors, such as data quality issues, high-dimensional input spaces, dynamic and nonlinear consumption patterns, computational complexity, generalization to different building environments, data privacy issues, and interpretability of advanced forecasting models, as depicted in Figure 5. These problems are still crucial for the advancement of reliable and intelligent energy management systems.

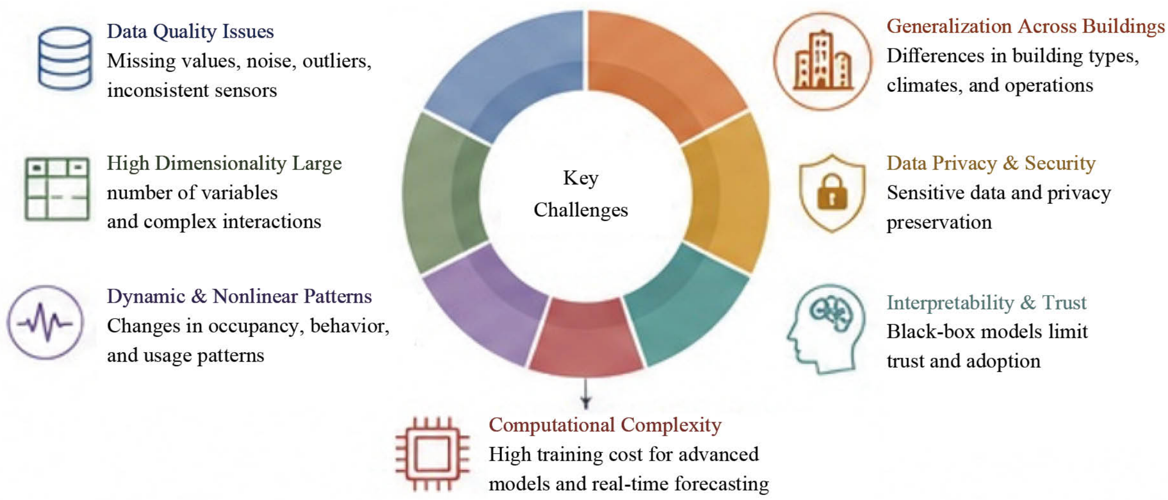


**Figure 5.** Key challenges and research issues in smart building energy consumption forecasting

One of the main challenges is related to the difficulty of estimating the energy consumption behavior in modern smart buildings. Current statistical forecasting methods fail to reflect the nonlinear interdependencies and high-dimensional interconnections among meteorological conditions, occupancy behavior, equipment operation schedules and dispersed energy supplies. Therefore, data-driven techniques based on machine learning and deep learning have attracted much more interest since they have the ability to handle heterogeneous data sources and understand complicated temporal and spatial correlations directly from historical observations [2], [3].

Another noteworthy trend is the shift from conventional energy users to prosumers, who consume and produce power with the help of distributed renewable energy technologies such as rooftop photovoltaic systems and small-scale wind energy systems. While this change is contributing to improved sustainability and energy independence, it is also adding more unpredictability and variability to building load profiles. This has led to an increasing importance of precise forecasting for the management of energy storage, the installation of demand response and grid stability. In particular, the accurate prediction of peak demand remains a key concern. Errors in load forecasting in peak demand periods can adversely influence system reliability and lead to increased operational costs [71], [72].

To overcome these problems, more recent research has been directed towards hybrid forecasting frameworks with a mixture of analytical methodologies, including signal decomposition methods and intelligent prediction models. These approaches are directed at improving forecasting resilience, enhancing prediction accuracy, and better handling the dynamic character of smart building energy systems [73]. However, there are still a number of poorly explored issues such as the lack of mainstream benchmarking practices, the heterogeneity of available datasets, the limited model transferability across buildings, and the integration of forecasting models into broader energy management architectures [63], [74]. These issues highlight the necessity for developing broad comparison frameworks that can systematically evaluate intelligent forecasting approaches and point out future research possibilities, which is one of the main objectives of this review.

## 5. Intelligent machine learning techniques for energy forecasting

Intelligent sensing technologies, enhanced metering infrastructure and Internet of Things-enabled intelligent buildings have led to high-resolution energy data proliferation on an unprecedented scale. This has resulted in the application of intelligent forecasting algorithms capable of extracting important patterns from complicated and diverse data sets. Traditional statistical methods are not able to effectively capture nonlinear relationships among a large number of influencing variables (weather conditions, occupancy behavior, building characteristics, equipment operation schedules, distributed energy resources etc), while intelligent forecasting methods are. Thus, these methods are now basic components of modern energy management systems for smart buildings.

As illustrated in Figure 6, the intelligent energy forecasting approaches may be generally divided into four major groups, traditional machine learning methods, deep learning architectures, hybrid forecasting methods, and novel intelligent paradigms. The classification highlights the evolution of forecasting research, from very simple predictive models to increasingly complex approaches seeking to improve accuracy, resilience, scalability and interpretability of forecasting.

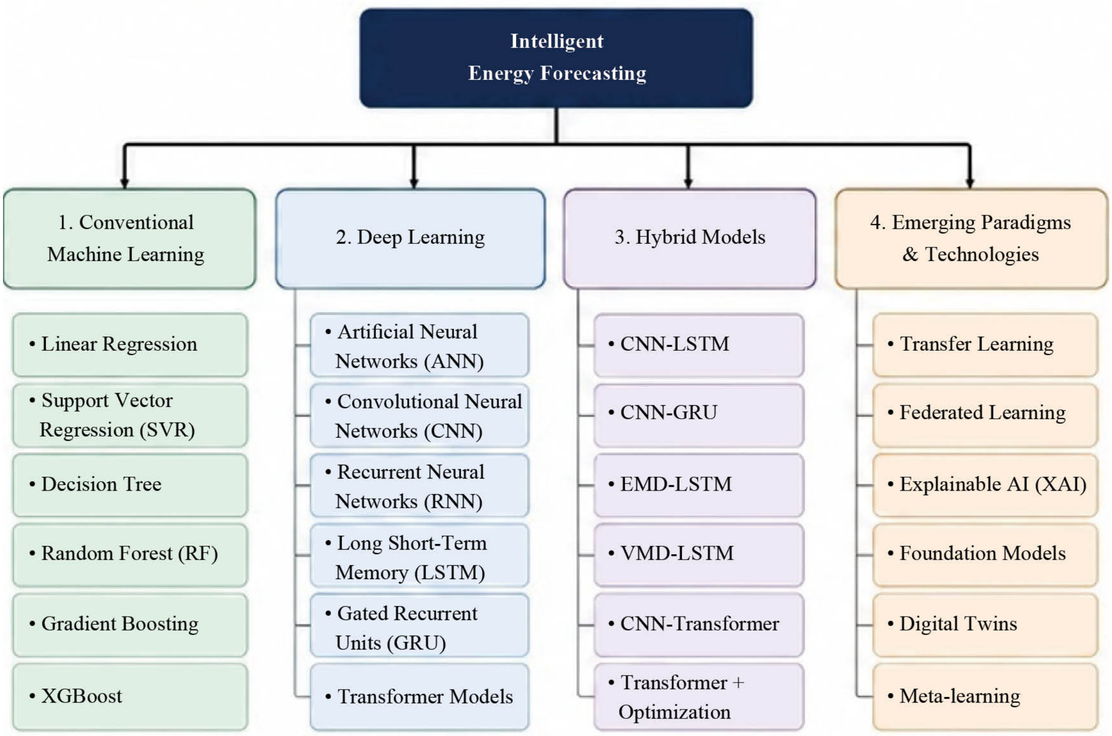


**Figure 6.** Classification of intelligent prediction methods for smart building energy consumption prediction

Data-driven energy forecasting approaches are based on traditional machine learning algorithms that are still widely used due to their inexpensive computational cost and good prediction performances on structured datasets. Most prominent methods are linear regression, support vector regression, decision trees, random forests, gradient boosting and extreme gradient boosting. These algorithms have been proved to be beneficial in modeling the energy consumption trends and to find connections between the energy demand and the variables affecting the energy demand.

The availability of large scale data sets has permitted the adoption of deep learning algorithms that automatically build hierarchical feature representations from raw data. Representative designs include of artificial neural networks, convolutional neural networks, recurrent neural networks, long short-term memory networks, gated recurrent unit networks and transformer-based models. These approaches have proved to be rather successful in capturing the complex temporal dependencies and nonlinear interactions that govern the dynamics of building energy use.

Researchers have been building hybrid forecasting frameworks increasingly to achieve better forecasting performance by exploiting the benefits of many approaches. Some of the common examples are convolutional neural networks with long short term memory networks, convolutional neural networks with gated recurrent unit networks, empirical mode decomposition with long short term memory networks, variational mode decomposition with long short term memory networks and transformer based architectures with optimization algorithms. This hybrid technique tries to improve the robustness of the forecasting by treating the problems of feature extraction, noise reduction and temporal modeling in the same way.

More lately, several emergent paradigms have received much research interest for their capacity to bypass the issues with traditional forecasting models. These include techniques like transfer learning, federated learning, explainable AI, foundation models, digital twins and meta-learning. Overall, these methods address the issues of improved model transferability, data privacy, interpretability, scalability and flexibility in a variety of architectural contexts. Therefore, they are relevant research subjects for next generation intelligent energy forecasting systems.

Forecasting approaches can be characterized according to the learning paradigm from the learning perspective. Supervised learning methods are based on labelled historical records to learn the relationships between input factors and future energy demand and hence dominate the energy forecasting literature. However, unsupervised learning algorithms are more often utilized for extracting underlying structures in unlabeled data sets and have been more frequently applied in applications such as building segmentation, occupancy analysis, anomaly detection and energy benchmarking. The research on energy prediction for smart buildings is still dominated by supervised learning algorithms, as energy forecasting is largely about estimating future use from historical measurements.

## 5.1 *Conventional machine learning methods*

Traditional machine learning approaches were the mainstay of building energy prediction before the advent of deep learning. These methods usually need handcrafted characteristics and domain knowledge but usually have strong predictive performance with relatively modest computing costs.

### 5.1.1 *Linear Regression (LR)*

Linear Regression (LR) is one of the oldest techniques used for building energy prediction because of its simplicity and interpretability. LR models assume a linear relationship between energy demand and explanatory variables and estimate energy consumption as a weighted combination of input features.

Even though linear models can only capture linear dependencies, they have been successfully utilized for baseline forecasting and benchmarking. Amasyali and El-Gohary [37] remarked that linear models are still appealing when interpretability and computational efficiency are important. However, their prediction accuracy drops significantly in complex smart building environments with nonlinear relationships between meteorological factors, occupancy behaviors and equipment operations.

### 5.1.2 *Support Vector Regression (SVR)*

One of the most used machine learning methods for building energy consumption prediction is the Support Vector Regression (SVR). SVR is based on the principles of Statistical Learning Theory and tries to find the ideal regression function with the minimum prediction error and maximum generalization performance. Different from traditional regression approaches, the SVR can efficiently model the nonlinear relationships through the use of kernel functions, which is particularly appropriate for complex building energy systems, where the consumption behavior is influenced by many interacting factors, such as weather conditions, occupancy behavior, and operational schedule.

The usefulness of SVR has been established in early experiments for short-term building energy forecasting. Dong et al. [75] showed that SVR provided better prediction accuracy than traditional statistical models in predicting hourly building energy demand using weather and occupancy related factors. Similarly, Fan et al. [69] also demonstrated that SVR is better than the classic regression methods because it can model the nonlinear dependencies in energy consumption data.

Recent progress further confirms the usefulness of SVR in smart building application. Nutakki et al. [20] proposed an intelligent energy consumption forecasting framework for smart buildings and observed that SVR provided good forecasting accuracy when integrated with improved feature selection and data pretreatment approaches. The results showed that SVR could successfully deal with the nonlinear patterns of energy use and produce credible short-term forecasts under different operating situations. Furthermore, the research also pointed out that the SVR model showed good generalization ability even when environmental and occupancy parameters varied, further validating the applicability of the proposed approach in real-world smart building energy management systems.

A further key advantage of SVR is its robustness for small and even modestly sized datasets, which is a prevalent aspect of many building energy studies. Moreover, the training sample size required by SVR is usually smaller than deep learning methods, but it can also achieve comparable forecast performance. However, the prediction accuracy of SVR highly depends on the suitable selection of kernel functions and hyperparameters, such as penalty parameter, kernel width and insensitive loss function. Additionally, computational complexity is significantly increased as the quantity of the dataset increases, which may limit its scalability for large-scale IoT-enabled smart building systems.

Overall, SVR has been an effective and robust forecasting technique particularly when the amount of the dataset is reasonable, the nonlinear interactions are critical and the interpretability of the model and computing efficiency are crucial concerns.

#### 5.1.3 *Decision Trees (DT) and Random Forest (RF)*

Decision Tree (DT) models split the feature space into a hierarchy of decision rules that aid in prediction while keeping the model interpretable [25]. However, individual trees are often suffering from instability and overfitting. Breiman [76] addressed these restrictions by proposing Random Forest (RF), which combines several decision trees built on bootstrapped data. The ensemble mechanism increases robustness and decreases prediction variance.

RF also obtained comparable accuracy with little parameter tuning, and was evaluated with multiple machine learning methods for building energy forecasting by Ahmad et al. [77]. RF models are particularly useful for heterogeneous variables and missing values, which are prevalent in smart building data. However, performance degradations may be caused by long-term temporal dependencies dominating consumption dynamics.

#### 5.1.4 *Gradient Boosting (GB) and Extreme Gradient Boosting (XGBoost)*

Recently, the boosting based machine learning algorithms have received great attention in building energy forecasting due to their capacity to simulate complicated nonlinear relationships with excellent prediction accuracy. Gradient Boosting Machines (GBMs) are built by the sequential development of weak learners (often decision trees), where each learner attempts to correct the residual errors of the previous models. This iterative learning approach allows the boosting algorithms to learn more complex energy usage patterns than many classic regression techniques.

Extreme Gradient Boosting (XGBoost) is one of the most successful boosting algorithms in energy forecasting applications [25]. XGBoost is an implementation of gradient boosted decision trees optimized for speed and performance. XGBoost is an enhanced version of gradient boosting with regularization, parallelization, tree pruning and handling of sparse data built in, for greater performance and faster calculation. Chen and Guestrin [78] showed that these modifications greatly improve scalability and generalization performance over previous boosting methods.

Its applicability for energy forecasting jobs has been recently confirmed by several studies. Mustaffa and Sulaiman [22] proposed hybrid models for building cooling and heating loads prediction by integrating XGBoost and metaheuristic optimization techniques. The results indicated that the optimized XGBoost-based models were able to forecast with high accuracy. The Genetic Algorithm–XGBoost (GA-XGBoost) model achieved the lowest forecasting error compared to the other models studied. The study showed that XGBoost can effectively capture nonlinear energy consumption aspects, and is versatile enough to deal with complex building load profiles.

XGBoost also has the advantage of being robust to different feature datasets, for example, weather variables, occupancy, operational schedules, and building features. Furthermore, feature importance analysis may be readily obtained from the trained models, which enhances interpretability and supports energy management decision-making [36].

However, despite all its advantages, XGBoost is still susceptible to the choice of hyperparameters such as tree depth, learning rate and number of boosting rounds. Furthermore, a high model complexity could increase the risk of overfitting if suitable regularization and validation techniques are not applied. However, XGBoost has now proved to be one of the most effective traditional machine learning approaches in energy forecasting of smart buildings as a result of its remarkable balance between prediction accuracy, computation efficiency and interpretability.

## 5.2 *Deep learning methods*

The increasing deployment of IoT-enabled sensing infrastructures has greatly enhanced the availability of large scale time-series data, thereby easing the move from traditional Machine Learning (ML) approaches to deep learning techniques. Deep learning models can automatically learn hierarchical feature representations from raw data, which reduces the dependency on created features, unlike standard approaches.

### 5.2.1 *Artificial Neural Networks (ANNs)*

Artificial Neural Networks (ANNs) are among the earliest intelligent approaches for energy prediction and serve as the backbone of modern deep learning methodologies. ANNs are based on the human brain structure and consist of interconnected processing units (neurons) grouped in layers, i.e., input, hidden and output layer. These networks are trained iteratively and learn sophisticated correlations from past data without any explicit mathematical formulation. Their capacity to approximate nonlinear functions makes them particularly well adapted to capture the highly dynamic and nonlinear behavior of building energy consumption.

Early studies employed feedforward neural networks to capture nonlinear interactions between climatic elements, occupancy schedules, building features, and operational parameters. Kalogirou [79] also gave one of the earliest contributions in this field, extensively demonstrating the applicability of ANN models in a number of building energy applications, such as energy consumption prediction, HVAC system analysis, thermal comfort assessment and renewable energy integration. The study emphasized that ANN based models may learn complex input-output relationships that are difficult to be modelled using conventional statistical techniques thereby proving the neural network as a practical alternative for building energy modelling and forecasting.

ANN techniques have been further validated by subsequent investigations on real-world forecasting applications. Escrivá-Escrivá et al. [23] proposed an ANN based approach to forecast short term electric energy usage in buildings. The methodology is based on the separate modelling of the several end-use processes and summing together to get the total demand of the building. Their research showed that well chosen training samples and physically meaningful input variables could result in smaller forecasting errors when using properly designed neural network architectures to predict quarter-hourly electricity use. ANN models have proved their potential in supporting demand-side management and energy optimization solutions for commercial buildings

ANN-based forecasting has become very popular because of several advantages such as flexibility in dealing with nonlinear relationships, robustness against noisy data, and the capability to include various input features such as meteorological conditions, occupancy information, historical loads, and operational parameters. So, ANNs outperform traditional regression-based algorithms when sufficient training data are available. Moreover, multiple research have indicated ANN models as one of the most popular data-driven strategies for building energy prediction due to its strong predictive ability for different types of buildings and forecast horizons.

Nevertheless, the usual shallow ANN topologies present some constraints despite these advantages. The performance of the method is quite sensitive to the choice of network architecture, training procedures and quality of the data. More importantly, feedforward ANNs process data one-by-one, and hence are limited in their ability to grasp long-term temporal connections inherent in time series of building energy demand. This limitation led to the development of more advanced deep learning models like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) which are designed to identify sequential and temporal patterns in energy consumption data.

### 5.2.2 *Convolutional Neural Networks (CNNs)*

Convolutional Neural Networks (CNNs) were originally designed for computer vision tasks and have been widely employed in building energy forecasts due to their excellent feature extraction capacity. Unlike typical machine learning algorithms that rely on hand-crafted features, CNNs learn hierarchical representations directly from raw input data through a series of convolutional and pooling operations. This capability enables CNN models to learn local temporal patterns, periodic trends and nonlinear correlations hidden in high-dimensional building energy information.

CNNs are very good at extracting relevant features from the multivariate time series data provided by smart meters, IoT sensors, weather stations and building management systems in applications related to energy forecasting. CNN architectures based on convolutional filters are able to capture short-term consumption changes and local relationships that are hard to capture with traditional forecasting approaches. So, models based on CNNs are generally better than other models in projected accuracy, and need less major feature engineering.

In various studies, CNN-based models have proved useful for building-energy prediction. Somu et al. [80] developed a CNN-LSTM framework that extracts local patterns and temporal dependencies from building energy-consumption data and reported improved forecasting performance over conventional baselines. Moreover, comprehensive assessments of data-driven forecasting methodologies have identified CNNs as promising deep-learning techniques for building-energy applications because of their ability to automatically acquire meaningful representations from complex and diverse data [24].

But the use of standalone CNN models has disadvantages in the long-term forecasting challenge. Convolutional layers are effective in learning local patterns but are not particularly designed to learn long-range temporal correlations that are commonly present in building energy use time series [16]. More recent work has consequently focused on hybrid CNN-based architectures that take advantage of the capabilities of CNNs to extract spatial data and the ability of recurrent and attention-based models to learn temporal information.

To sum up, CNNs are still an important aspect of modern energy forecasting systems. However, their greatest influence in modern smart building applications is increasingly achieved by hybrid architectures, where convolutional feature extraction is combined with sophisticated temporal modeling algorithms to improve prediction performance and generalization capabilities.

### 5.2.3 *Recurrent Neural Networks (RNNs), LSTM, and GRU*

However, feedforward neural networks are not well suited for capturing high-level temporal dependencies, seasonal patterns, and sequential correlations in building energy usage data. To tackle these challenges, Recurrent Neural Networks (RNNs) are proposed to handle sequential input by employing internal memory states to transport information over time steps. This makes RNNs naturally suited for time series forecasting situations where the future energy consumption relies on past observations and external influencing factors such as weather conditions, occupancy schedules and operational aspects.

Although theoretically useful, traditional RNNs are limited in their capacity to learn long-term temporal relationships [16], [81] due to vanishing and ballooning gradient problems during training. When the input sequence length rises, the network loses more and more knowledge of earlier observations, and the forecast accuracy of intricate energy consumption time series degrades. The application of vanilla RNNs for energy forecast in smart building application has so been limited.

To overcome these limitations, LSTM networks were introduced that featured memory cells and gating mechanisms that controlled the flow of information across time. The forget, input and output gates allow LSTM networks to decide which information should be stored or discarded so that they may well mimic short-term fluctuations and long-term consumption patterns [24]. These qualities have made LSTM one of the most common deep learning algorithms to generate energy predictions.

In numerous research, LSTM based models have been proved to be useful in evaluating building energy usage [15], [25], [82]. Recent studies have showed that LSTM architectures routinely outperform traditional machine learning algorithms in capturing nonlinear temporal dependencies in multivariate energy data [21]. The LSTM has been the dominant technique for smart building forecasting systems thanks to its ability to blend historical load profiles with weather variables, occupancy information and operational characteristics. Moreover, recent studies on commercial and residential buildings [15], [24], [25] demonstrate that the hybrid LSTM-based models may substantially enhance the prediction accuracy by learning the complicated temporal dynamics and multi-scale consumption patterns.

The LSTM networks have a great predictive performance but the rather sophisticated design results in a large number of trainable parameters which increases the processing requirements and training time. A simpler recurrent design, GRUs are depicted as combining the capabilities of the multiple LSTM gates into update and reset processes. This simple architecture reduces model complexity yet still retains the ability to learn long-term temporal link.

A number of comparative studies have demonstrated that GRU models deliver prediction accuracy similar to LSTMs but with fewer parameters and training timeframes [24]. These qualities make GRU particularly appealing for real-time prediction applications, edge-computing environments and smart building control systems with limited computational resources. Thus GRU based models have grown more and more popular in the energy forecasting applications where the processing efficiency is a major element.

Recurrent architectures have generally contributed much to the status of energy forecasting by making it possible to describe temporal correlations appropriately in building energy consumption data. The RNNs originated the discipline of sequential learning, but they have been outperformed by the LSTM and GRU networks, which have become the de facto recurrent networks for learning long-term temporal patterns. However, recurrent systems process the input in a sequential way which can limit computational efficiency and an ability to define very long-range dependencies. These limitations have led to the development of attention based architectures specifically Transformer models discussed in the next section.

### 5.2.4 *Transformer-based models*

Recently, transformer designs have been proposed as one of the most promising deep learning models for energy predictions. The transformer, originally developed for natural language processing, replaces the recurrent structure with a self-attention mechanism that enables the direct representation of relations among all elements of an input sequence. Unlike sequential models like recurrent neural networks, Transformers are parallelizable and thus more computationally efficient at learning from long historical time series and capturing long-range dependency.

The fundamental advantage of Transformer models for energy forecasting is the capacity to learn complicated temporal dependencies without the necessity of recurrent memory structures. The models use multi-head self-attention to automatically determine the most relevant past observations that affect future energy use. This is especially beneficial in smart building applications where energy consumption is impacted by a number of interacting factors such as weather conditions, occupant behaviour, operating schedules and seasonal patterns [26].

The original Transformer architecture has been followed by a number of specialized variations for time-series forecasting. The most influential are Informer, Autoformer and Temporal Fusion Transformer (TFT) are meant to improve the forecast efficiency for big sequential data sets [14]. To reduce the computational complexity, Informer uses ProbSparse self-attention. Autoformer proposes decomposition strategies to extract the trend and seasonal component from time-series data. These advances have allowed Transformer based models to outperform some standard recurrent architectures in long-horizon forecasting.

Recently, it has been demonstrated that transformer based approaches are successful to generate energy predictions. Yu et al. [83] developed a Transformer-based forecasting framework for the day-ahead cooling demand prediction of huge airport buildings, outperforming other common forecasting models in terms of predictive accuracy. The proposed architecture of the Temporal Fusion Transformer was able to grasp complex cooling load dynamics while offering increased model interpretability with attention approaches. Large scale building energy studies also demonstrated substantial performance advantages with the use of attention-based designs to foresee extremely variable energy demand patterns.

Transformers have quickly evolved and new sophisticated architectures have been proposed for building energy applications. Metaformer, a Transformer based architecture paired with personalized federated learning for multi-building energy forecasting, was proposed by Wang et al. [31]. Their techniques enhance the forecasting accuracy by 10% to 40% over the state-of-the-art baseline models, with lower memory requirements and data privacy preservation on distributed building datasets. The results show the scalability of Transformer topologies for huge smart-city energy management systems.

Recently, large-scale pre-trained Transformer models have been examined for energy forecasting. Spencer et al. [27] conducted a comparative study of transfer learning algorithms for the Transformer, Informer and PatchTST designs on multiple building datasets. Results indicate that transfer learning based on transformer significantly improves forecasting performance for data-scarcity scenarios, with the PatchTST always beating the vanilla transformer and Informer models. The results demonstrate that pre-training and transfer learning are more relevant for future smart building applications when historical data is not easily accessible.

Some problems also exist in the Transformer architectures, albeit they are more accurate in prediction. They need big training datasets, significant computing resources and careful tuning of hyperparameters to perform well. Furthermore, concentration approaches often increase the memory usage notably for very long input sequences. New versions such as Informer, Autoformer, PatchTST and Metaformer have mostly overcome these limits. But the computational performance still plays an important role for real time deployment in resource restricted smart building systems.

In summary, Transformer-based models have the state-of-the-art in building energy forecasting. They are a valid alternative to recurrent architectures, as they can capture long-range temporal dependencies, readily handle large-scale datasets and allow transfer learning. Recently, however, research have begun to increasingly implement Transformer methods in tandem with other deep learning models. The next section presents such hybrid forecasting frameworks.

### 5.3 *Hybrid and ensemble approaches*

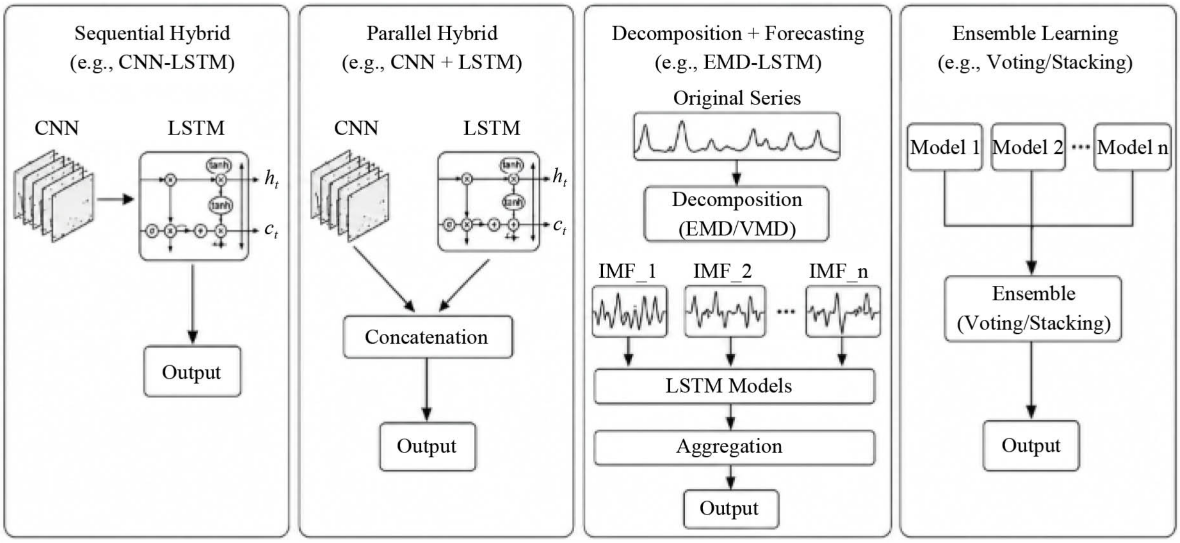


**Figure 7.** Hybrid and ensemble learning frameworks for prediction of energy consumption

Individual machine learning and deep learning models have been quite successful in building energy forecasting, but their performance is typically not consistent for different building types, forecasting horizons, and operating situations. Building energy consumption data are characterized by complicated nonlinear interactions, temporal dependencies, seasonal changes, and noise, which might restrict the performance of a single forecasting model. As a result, the blending of more than one predictive strategy inside hybrid and ensemble forecasting frameworks has garnered increased interest owing to the benefits of the individual methods. These approaches are sequential hybrid architectures, parallel hybrid models, decomposition-based forecasting frameworks and ensemble learning methods as depicted in Figure 7. Hybrid and ensemble techniques typically improve the accuracy, robustness and generalization performance of smart building applications by combining complementing modeling skills.

### 5.3.1 *Hybrid deep learning models*

Hybrid forecasting architectures integrate more than one learning paradigm into a single framework to leverage the inherent strengths of each one and mitigate their individual weaknesses. The increasing demand for highly accurate prediction systems and the availability of large-scale sensor data have made hybrid model development one of the most active research fields in smart building energy forecasting.

The CNN-LSTM architecture is one of the initial and most used hybrid frameworks. The convolutional layers automatically identify typical local characteristics and hidden consumption patterns from the historical energy data and the LSTM layers learn the long-term temporal correlations in these models. The feature extraction and sequential learning capabilities combined allow the CNN-LSTM models to well capture the spatial and temporal features of building energy use. Ibude et al. [24] explored hybrid deep neural network architectures for smart building multi-timescale energy forecasting. They reported that the CNN-LSTMs achieved better predictive performance than the standalone CNN and recurrent models at minute level, hourly and daily forecasting timeframes. The results demonstrated the complementary capacities of convolutional feature extraction and recurrent temporal modeling in complex smart building systems.

In the next study this notion was developed further by building CNN-GRU and CNN-BiLSTM architectures. Compared with LSTM-based frameworks, the GRU-based hybrid models usually require fewer trainable parameters, while achieving competitive prediction accuracy. The bi-directional recurrent layers enhance the forecasting capacity by using the input from the forward and backward temporal directions. These architectures have shown promising results in applications characterized by highly dynamic occupancy patterns and erratic energy consumption tendencies.

Besides the integration of neural architectures, another important research trend is the fusion of signal-decomposition techniques and deep-learning models. Building energy-consumption time series typically contain multiple frequency components associated with weather fluctuations, occupant variations, equipment operation, and seasonal effects. In forecasting, preprocessing tools such as Wavelet Transform (WT) [84], Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) are increasingly used to decompose complex signals into simpler subcomponents [85].

Recently, it is demonstrated that the decomposition-based hybrid frameworks improve the forecasting accuracy greatly by alleviating the non-stationarity and noise. Huang et al. [85] proposed an EMD-LSTM-Markov based framework for cooling load prediction of buildings and obtained significant performance improvements compared to typical LSTM models. The proposed system dissected the original signal into intrinsic mode functions before recurrent learning, so was more successful in capturing the underlying consumption pattern and improved the stability of long term forecasting. It was found that VMD-LSTM and CEEMDAN improved forecasting systems provide similar benefits in buildings with very volatile energy demand patterns.

The rapid growth of attention processes and Transformer topologies has further accelerated the development of next-generation hybrid forecasting systems. While Transformer models have been quite successful in capturing long-range dependency, new work suggests that combining the Transformer with other complementary feature extraction or decomposition procedures can lead to substantial improvement in the prediction performance. Therefore, hybrid frameworks and decomposition-enhanced Transformer models based on CNN–Transformer, BiLSTM–Transformer, and Informer can be alternatives to standard recurrent architectures [14].

Yu et al. [83] developed a Transformer-based framework for day-ahead cooling demand forecast for airport buildings, and they showed that it achieved significant improvement over existing deep learning algorithms. Recently, Wang et al. [31] proposed a Metaformer-based forecasting system with tailored federated learning for multi-building energy prediction. The results show that the accuracy of prediction may be significantly improved with less memory consumption and the privacy of data can be guaranteed in remote building systems. The results show that Transformer-enhanced hybrid systems are becoming increasingly important for smart building applications at scale.

Another fast-growing research area is the integration of optimization methods with machine learning and deep learning models. The model performance significantly relies on the choice of hyperparameters, network configuration and the feature selection techniques. To solve these challenges, academics have used evolutionary and metaheuristic optimization approaches (GA, Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA)) in forecasting frameworks.

A major example is the GA-XGBoost model proposed by Mustaffa and Sulaiman [22] which combined the Extreme Gradient Boosting with genetic optimization methodologies for building energy demand forecasts. The improved framework resulted in less prediction errors than the typical XGBoost implementations, confirming the efficiency of metaheuristic assisted learning techniques. Similar improvements have been achieved with PSO-LSTM and GWO-BiLSTM models showing the potential of optimization enhanced forecasting systems for complicated smart building datasets.

In general, the evolution of hybrid forecasting models shows a tendency from single architectural solutions to integrated frameworks that may simultaneously exploit the capabilities of feature extraction, temporal learning, signal decomposition, attention mechanisms and optimization methods. Current evidence shows that these multi-component architectures reliably provide higher accuracy in forecasting and better generalization performance than standalone machine learning or deep learning models, especially in complex smart building environments with nonlinear and non-stationary energy consumption patterns.

#### 5.3.2 *Ensemble learning approaches*

Ensemble learning is an important forecasting technique. It combines the predictions of many different models in order to boost robustness, stability and generalization performance. Unlike hybrid designs that integrate many learning mechanisms into a single framework, ensemble methods merge the outputs of different forecasting models, employing a number of techniques such as bagging, boosting, stacking and weighted averaging [30].

The underlying motivation for the ensemble projections is that different building operating conditions would presumably disclose different strengths and weaknesses of the particular models. Ensemble techniques combine many predictors to reduce biases and variations inherent to individual models and hence improve the trustworthiness of the forecast as a whole.

Recent researches have proved the effectiveness of ensemble framework for building energy prediction. As Ahmad et al. [77] said, ensemble approaches always outperformed the individual machine learning models in terms of stable forecasting performance for different building datasets and forecasting horizons. Their analysis demonstrated that the heterogeneous predictors combinations generally improve robustness in case of different weather conditions and occupancy patterns.

Recent research has shown an increasing interest in ensemble frameworks that integrate the predictions of machine learning and deep learning into a single forecasting system. Stacking or weighted aggregation processes are used to pair algorithms such as Random Forest, XGBoost, LSTM and GRU to take advantage of their complementing learning capabilities for such architectures [28]. Recently, Sim et al. [29] introduced a deep learning-based ensemble forecasting framework for the power consumption prediction, and established that the integration of many predictive models significantly reduced the forecasting errors compared with individual predictors. It was shown that ensemble structures were particularly good at representing complex nonlinear relationships and temporal patterns in energy consumption data and improved the resilience of the forecasts under different operating conditions. These results further support the growing attraction of ensemble learning methods for smart energy management systems.

However, ensemble methods are often associated with higher computational costs, more complex implementation and less interpretability. Moreover, the performance gain from ensemble learning is heavily dependent on the diversity and quality of the underlying models. Ensemble forecasting is still an effective way to improve the robustness of prediction. It is a key feature of modern smart building energy management systems.

## 5.4 *Emerging trends in intelligent forecasting*

The recent advances in artificial intelligence have led to new paradigms that aim to overcome several long-standing challenges in building energy forecasting, including limited data availability, poor model transferability, privacy concerns, and the lack of transparency of complex deep learning architectures. Thus, more and more the present research is focused on forecasting frameworks that are accurate, scalable, transferable, privacy-preserving and interpretable.

### 5.4.1 *Transfer learning and knowledge transfer*

Deep learning methods for building energy consumption prediction are often dependent on the enormous amount of historical data. However, many buildings, especially those recently commissioned or with insufficient monitoring infrastructure, lack the data necessary to effectively train complicated forecasting models. This problem has motivated an increasing interest in transfer learning systems that enable knowledge learned in data rich settings to be transferred to similar forecasting tasks.

Pan and Yang [86] formally defined transfer learning as a machine learning paradigm that aims to transfer the knowledge obtained in a source domain to improve the learning performance in a target domain. Transfer learning is utilized in building energy forecasting to reduce the training load, speed up the convergence of the model and improve the prediction accuracy, especially when there are few historical observations [21].

One of the first studies to show this in building-specific contexts is that of Le et al. [87], who developed a transfer learning framework to estimate residential building energy consumption with pre-trained deep neural networks. Their experimental results found that the transfer of model parameters from buildings with high quantity of data might significantly improve the prediction performance for target buildings with minimal training samples. Moreover, the proposed approach was able to reduce the training time while maintaining the competitive prediction accuracy, which demonstrates the practical importance of the transfer learning for real-world smart building applications.

Recent advances have brought transfer learning from classical neural network architectures to large-scale time series forecasting frameworks. Spencer et al. [27] explored transfer learning methodologies for the models of the Transformer, Informer, and PatchTST on several building datasets, demonstrating a substantial improvement in forecasting performance for data-scarce situations. It is demonstrated that pre-trained Transformer-based architectures exhibit high generalization ability and good flexibility to varied building settings with low fine-tuning requirements.

The rising success of transfer learning has also prompted interests in foundation models for time-series forecasting. They are trained on big and diverse datasets as in the case of large language models such as in natural language processing and then fine-tuned for specific forecasting applications. It is envisaged that these approaches will enhance the scalability of the model, reduce dependence on building-specific data and enable the implementation of intelligent forecasting systems in different smart building scenarios.

To sum up, transfer learning has proven to be a feasible approach to overcome one of the most stubborn problems in building energy forecasting, which is the absence of high-quality training data. This allows to increase the flexibility of the model and the reuse of information throughout buildings and forecasting jobs, thereby encouraging a wider use of intelligent energy management systems.

### 5.4.2 *Federated learning and privacy-preserving forecasting*

Data privacy and cybersecurity issues are key challenges for the development of generalized forecasting models for smart buildings. Building operators are generally reluctant to provide particular information on occupancy, operations schedules and records of energy consumption due to confidentiality and security considerations.

Federated Learning (FL) is a promising approach to this problem. Rather than a normal centralized learning system, federated learning allows the buildings to jointly train the forecasting models without exchanging raw data. Instead of exchanging actual data between entities, only model parameters or gradients are sent. This ensures data privacy, while enabling collaborative learning [34].

Recently, federated forecasting has been highlighted as an increasingly important direction in smart building systems. Wang et al. [31] proposed a personalized federated learning system for the energy consumption forecasting of several buildings. The proposed approach produced up to 40% improvement in prediction accuracy compared to previous approaches while preserving user privacy. Their results show that a federated strategy may easily deal with data heterogeneity across buildings and enable scalable forecasting systems for smart cities.

Federated learning has recently been connected to explainable artificial intelligence and blockchain-enabled infrastructures to build secure and trustworthy energy management systems [32]. These frameworks provide privacy-preserving forecasting and also provide transparency and traceability that can increase the confidence of stakeholders in intelligent building management platforms. However, there still exist practical challenges such as communication cost, Non-Independent and Non-Identically Distributed (non-IID) data, synchronization and model convergence concerns across distributed clients.

### 5.4.3 *Explainable Artificial Intelligence (XAI)*

Deep learning and Transformer-based forecasting models can achieve superior prediction performance; However, the implementation of these models in operational smart building scenarios is sometimes limited by their black-box nature. The importance of communicating to building managers and decision makers the factors affecting the forecasting outcome is increasing, especially in cases where the forecasts have an impact on the strategies for energy management, demand response operations and building control decisions.

One proposed solution to this difficulty is known as Explainable Artificial Intelligence (XAI). XAI offers improved model transparency and interpretability with minimal loss of prediction performance. XAI techniques help users to comprehend how input variables influence the prediction results, thereby improving the trust, responsibility and confidence in decision making. Traditional performance-driven techniques focus only on prediction accuracy [15], whereas explainable forecasting frameworks strive to blend predictive strength with human interpretability.

The most popular XAI methods are Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP). LIME locally explains the behavior of complex models around particular predictions [88]. SHAP estimates the effect of each input feature based on the cooperative game theory [89]. SHAP is one of the most often utilized explainability methodologies in the energy forecasting literature, due to its theoretical consistency and ability to give local and global interpretation [36].

More lately, there is a tendency towards embedding explainability mechanisms within the forecasting frameworks themselves, instead of solely using post-hoc interpretation methodologies [35]. For example, Lahyani et al. [15] presented an interpretable hybrid deep learning framework that incorporated an attention mechanism into the short-term load forecasting model, demonstrating that the attention-based interpretability can lead to improved forecasting accuracy and provide interpretable insights into the temporal dependencies influencing energy demand. The proposed methodology boosts the transparency and maintains the prediction power of the state-of-the-art deep learning architectures by weighting the historical observations differently and by selecting the crucial time periods of the forecasting outcomes.

In various recent review studies, importance of explainability in intelligent building systems has been highlighted. Haghighat et al. [36] reviewed the literature of explainable ML methods for smart building applications such as energy forecasting, HVAC optimization, defects detection and indoor environment management. The investigation demonstrated a strong surge of adoption of SHAP-based interpretation frameworks and attention-based explainability techniques in energy applications. The review showed that prior energy use, outside weather, occupancy behavior and time-related variables were consistently found to be the most relevant predictors of future building energy demand.

Explainability is also lately starting to interact with other developing paradigms such as federated learning, privacy-preserving artificial intelligence and trustworthy artificial intelligence systems. Federated smart energy management systems with embedded XAI modules have been proposed to provide predictive transparency, privacy protection and stakeholders' confidence at the same time [32]. Such progress will accelerate the application of intelligent forecasting systems in the real world smart building environments.

Much has been achieved. Much remains to be achieved. Explainability approaches tend to be computationally expensive. diverse interpretation methods may result in diverse interpretations of the same forecasting model. Furthermore, there is no standardized way to assess the quality and reliability of explanations for energy forecasting applications [36]. Future research will thus be oriented towards the establishment of standard explainability measures, the integration of intrinsically interpretable forecasting systems and the creation of trustworthy AI frameworks that will concurrently fulfill the goals of accuracy, transparency, fairness and privacy.

In brief, explainable artificial intelligence is fast becoming an integral part of intelligent forecasting systems rather than an additional analytical tool. As forecasting infrastructures get more complicated, understanding, validating and trusting model predictions will be as vital as predictive accuracy itself. Hence, XAI is anticipated to be a key element in the next generation of smart building energy forecasting and management systems.

## 6. Comparative analysis of intelligent forecasting studies

Many machine learning and deep learning techniques have been proposed for building energy consumption forecasting, but direct comparisons among published studies are still difficult due to significant differences in datasets, building types, forecasting horizons, input features, evaluation metrics and experiment settings. Therefore, a systematic comparison study is needed to find the relative merits and demerits of the existing methodologies, and to show the current research trends in intelligent forecasting for smart buildings.

### 6.1 *Evaluation metrics and benchmarking practices*

An important stage in assessing the usefulness of forecasting models for smart building energy prediction is evaluating their performance. However, variations in the evaluation criteria used in different studies often make direct comparisons impossible. The most popular performance indicators are Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Bias Error (MBE), coefficient of determination ($R^2$) and Coefficient of Variation of Root Mean Square Error (CV-RMSE). Taken together, these indicators afford useful insights into forecasting accuracy, model reliability and the nature of prediction errors.

Mean Absolute Error (MAE) represents the average of the absolute errors:

$$\text{MAE} = \frac{1}{N}\sum |y_i - \widehat{y_i}| \tag{1}$$

where $y_i$ and $\widehat{y_i}$ denote the actual and predicted values, respectively.

The Root Mean Square Error (RMSE) is given as:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum (y_i - \widehat{y_i})^2} \tag{2}$$

RMSE places greater emphasis on large forecasting errors and is therefore particularly sensitive to outliers.

The Mean Absolute Percentage Error (MAPE) is given by:

$$\text{MAPE}(\%) = \frac{100}{N}\sum \left|\frac{(y_i - \widehat{y_i})}{y_i}\right|. \tag{3}$$

MAPE provides an intuitive percentage-based measure of forecasting accuracy; however, it may become unstable when actual values approach zero.

The coefficient of determination ($R^2$) evaluates the proportion of variance explained by the forecasting model:

$$R^2 = 1 - \left[ \frac{\sum (y_i - \widehat{y}_i)^2}{\sum (y_i - \overline{y})^2} \right] \tag{4}$$

where $\overline{y}$ represents the mean of observed values.

For building energy applications, ASHRAE Guideline 14 frequently recommends the coefficient of variation of RMSE:

$$\text{CV(RMSE)}\ (\%) = \left(\frac{RMSE}{\overline{y}}\right) \times 100. \tag{5}$$

This makes it possible to compare performance across datasets with varied scales of consumption.

Their widespread acceptance has not eliminated differences in the selection of metrics, techniques for preprocessing data, tactics for train–test splits, and forecasting horizons, which continue to impede meaningful comparisons between studies. Hence, the formulation of common benchmarking techniques and public datasets is still an important research challenge.

## 6.2 *Comparative evaluation of forecasting models*

Table 4 presents a comparative overview of selected studies from the final eligible publications, illustrating the diversity of forecasting tasks, datasets, prediction horizons, evaluation criteria, and intelligent forecasting algorithms in the literature. The surveyed works reveal the fast progress of energy forecasting methods and main themes in the advancement of data-driven methods for smart building applications.

Table 4 and Figure 8 depict the evolution of intelligent forecasting from traditional machine learning algorithms to more complicated deep learning, hybrid, transformer-based and privacy-preserving frameworks. Most of the previous studies have adopted techniques such as support vector regression, random forest, artificial neural network and gradient boosting techniques to obtain sufficient performance in forecasting non-linear energy consumption trends. However, over the last few years, other sophisticated architectures such as convolutional neural networks, long short-term memory networks, gated recurrent unit networks, graph-based models and transformer architectures have been gradually adopted to capture complicated temporal connections and dynamic building behaviours.

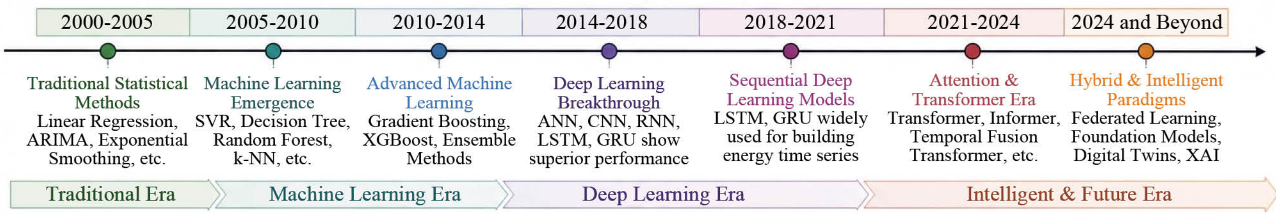


**Figure 8.** Development of intelligent forecasting methods for smart building energy use prediction (2000-2024 and beyond)

The results also reveal that hybrid and ensemble forecasting frameworks beat individual models in predictive performance. Hybrid approaches comprising feature extraction techniques, signal decomposition methods, recurrent neural networks, optimization algorithms and ensemble learning strategies are always associated with advances in prediction accuracy and robustness. In particular, several hybrid deep learning and transformer-based frameworks showed promising reductions in predicting errors while keeping a high predictive dependability throughout varied forecasting horizons.

**Table 4.** Representative studies on intelligent energy consumption forecasting in smart buildings, including machine learning, deep learning, hybrid, and emerging forecasting approaches

| Ref. | Year | Forecasting Task | Method Category | Model / Framework | Building Type/Dataset | Horizon | Metrics | Key Quantitative Findings |
|---|---|---|---|---|---|---|---|---|
| [20] | 2024 | Building Energy Forecasting | ML | SVR | Smart building dataset | Short-term | RMSE, MAE | SVR effectively captured nonlinear consumption patterns, achieving an accuracy of 97.3%. |
| [22] | 2025 | Building Energy Forecasting | Ensemble ML | XGBoost | Commercial buildings | Short-term | RMSE, MAPE | XGBoost outperformed conventional tree-based models. |
| [16] | 2023 | Residential Load Forecasting | Hybrid DeepLearning (DL) | CNN-GRU CNN-LSTM | Residential smart building | Short-term (Hourly) | MAE, RMSE, $R^2$ | Forecasting accuracy reached 97%. |
| [24] | 2024 | Multi-timescale Energy Forecasting | Ensemble DL | CNN–LSTM–BiLSTM–GRU | Smart buildings | Minute, Hourly, Daily | Mean Squared Error (MSE) | Best minute-level MSE = 0.109. |
| [14] | 2025 | Building Energy Forecasting | Transformer | Temporal Fusion Transformer (TFT) | Cross-domain building datasets | Short-term | RMSE, MAE, $R^2$ | RMSE reduced by up to 20%; $R^2$ improved by 41%. |
| [83] | 2024 | Cooling Load Forecasting | Transformer Hybrid | k-means + TFT | Airport cooling system | Day-ahead | MAE, MAPE, CV-RMSE, $R^2$ | MAE reduced by 384 kW; MAPE by 3%; CV-RMSE by 5%; $R^2$ improved by 0.058. |
| [85] | 2024 | Building Cooling Load Forecasting | Hybrid DL | EMD–LSTM–Markov | Office building (Guangzhou) | Short-term | RMSE, MAPE | RMSE = 4.53; MAPE = 0.84%; RMSE reduced by 40–94%. |
| [30] | 2024 | Segregated Load Forecasting | Ensemble ML | Voting Regression | Pecan Street Dataport | Short-term | MAE, MSE | Best MAE = 0.05708. |
| [28] | 2026 | Electricity Consumption Profiling | Hybrid DL | CNN–LSTM + Clustering | Precon House & CU-BEMS | Daily | Accuracy | Classification accuracy = 87.59% and 86.40%. |
| [29] | 2025 | Residential Energy Forecasting | Ensemble ML | Clustering + CatBoost + LightGBM | Korean apartments | Monthly | Prediction error metrics | Ensemble models significantly outperformed non-clustered ML models ($p < 0.05$). |
| [87] | 2020 | Multiple Energy Forecasting | Transfer Learning | Transfer Learning–LSTM | Two smart buildings (South Korea) | Short-term | MAE, RMSE | Reduced computational overhead while improving forecasting performance. |
| [34] | 2025 | Smart Office Energy Forecasting | Federated Learning (FL) | FedProx-CNN | IoT smart office dataset | Hourly | MAE | Lowest MAE = 0.755. |
| [32] | 2025 | Smart Building Energy Forecasting | Federated Learning + Explainable AI | FL-driven XAI Model | Smart Buildings within Smart Grid Environment | Hourly | RMSE, MAE, MSE, $R^2$ | Superior performance compared previously published approaches. |

**Table 4.** (cont.)

| Ref. | Year | Forecasting Task | Method Category | Model / Framework | Building Type/Dataset | Horizon | Metrics | Key Quantitative Findings |
|---|---|---|---|---|---|---|---|---|
| [9] | 2025 | Indoor Energy Awareness Forecasting | Spatio-temporal DL | Graph Convolutional Network-Gated Recurrent Unit | IoT-enabled smart buildings | Short-term | $R^2$ | Best $R^2$ = 0.9976. |
| [33] | 2026 | Building Energy Forecasting | Federated DL | Edge–Fog FL Framework | Smart building environments | Short-term | MSE, MAE, $R^2$ | LSTM achieved MAE = 3.07 and $R^2$ = 0.9233. |
| [19] | 2025 | Heating/Cooling Energy Forecasting | DL | LSTM, GRU, XGBoost | Smart building systems | Hourly/Daily | $R^2$ | Best $R^2$ = 97.2%. |
| [90] | 2025 | Smart Building Energy Forecasting | Hybrid DL | EEMD–ED-LSTM–ECA | Residential smart building | Hourly | MAE, RMSE, $R^2$ | 24-h forecast: RMSE = 0.164 kW, $R^2$ = 0.944. |
| [91] | 2026 | Appliance-Level Energy Forecasting | Hybrid ML | Extreme Gradient Boosting Regressor / Light Gradient Boosting Regressor + Non-Monopolize Search + Black-Winged Kite Algorithm | Multi-sensor smart systems | Short-term | RMSE, $R^2$ | RMSE reduced by 54.3%; $R^2$ = 0.9865. |
| [92] | 2025 | Smart Home Energy Forecasting | Hybrid ML | RF- Dynamic Differential Annealed Optimization | Smart homes | Short-term | RMSE | Best RMSE = 0.172. |
| [93] | 2025 | Building Energy Forecasting | FL + Anomaly Detection | Elliptic envelope and Isolation Forest -FL | Energy consumption datasets | Short-term | Symmetric Mean Absolute Percentage Error (SMAPE), MAE | SMAPE improved by 13%; MAE improved by 17% compared with FedAvg. |

Another interesting trend that emerges from recent studies is the rising use of transfer learning, federated learning and explainable artificial intelligence. The new paradigms strive to tackle the problems of model transferability, data privacy, scalability and interpretability, which become more and more important in the context of modern smart building systems. For large scale smart building implementations, federated learning frameworks are highly wanted where collaborative model creation may be performed without compromising the privacy of the data.

Overall, the results shown in Table 4 and the historical trend given in Figure 8 demonstrate that the state of the art is gradually shifting from isolated forecasting models to interconnected intelligent forecasting ecosystems. In the future we expect more attention on hybrid architectures, attention-based.

### 6.3 *Influence of forecasting horizon*

One of the most critical elements influencing model selection and forecasting performance in smart building energy prediction is the forecasting horizon. The prediction interval is energy forecasting problems are typically classified into short-term, medium-term and long-term forecasting tasks, which are differentiated by their goals, data needs, and modeling challenges.

Short-term forecasting is the most studied forecasting horizon in the literature, which usually extends few minutes to few days ahead. The most popular applications that have led to the widespread adoption of the technique are demand response, heating, ventilation and air-conditioning control, peak demand management and real-time operational scheduling. Short-term forecasting has seen good performance from deep learning architectures like long short-term memory networks, gated recurrent unit networks, convolutional neural network-long short-term memory hybrids, and transformer-based models. These models are capable of capturing complex temporal dependencies and fast-changing consumption patterns effectively.

Forecasts over the medium term horizon typically range from a couple of days to a few months and are extensively used for energy planning, maintenance scheduling, and operational optimization. At this forecasting horizon, ensemble learning techniques and hybrid forecasting frameworks are typically utilized, since they provide a good compromise between prediction accuracy, robustness and generalization capabilities under varied operating parameters.

While long-term forecasting of a few months to a few years remains relatively under-explored, it is useful for strategic decision making, infrastructure planning, retrofit evaluation and energy policy design. The much lower predictive power for longer forecasting horizons is due to increasing uncertainty about future weather conditions, occupancy behaviour, technology advancements and regulation changes. Recently, transformer-based architectures and transfer learning approaches have gained more and more attention to deal with these issues, showing promise in improving the long-horizon forecasting performance and model adaptability.

The studied literature indicates that the forecasting horizon should be regarded as a fundamental consideration in the choice of forecasting algorithms, because models that perform excellently for short-term predictions do not necessarily perform similarly for long-term applications [3].

### 6.4 *Synthesis of key findings*

A comparative assessment of intelligent forecasting experiments reveals a number of noteworthy observations.

First, the results strongly support the “No Free Lunch” theorem, which states that no single forecasting technique systematically outperforms all others across different datasets, building types, and forecasting horizons. The choice of model should be driven by application needs and not by the performance claimed for individual case studies.

Secondly, the forecasting performance is highly dependent on availability and quality of data. Traditional machine learning models are typically good in small data environments, whereas deep learning methods require large datasets to utilize their representation learning power.

Third, we observe a clear trend in the literature towards hybrid and attention enhanced architectures for stand-alone forecasting models. Recent studies progressively merge convolutional networks, recurrent structures, Transformer models, signal decomposition techniques, and optimization algorithms in unified forecasting frameworks. These hybrid methodologies constitute the state of the art of building energy forecasting.

Fourth, new paradigms such as transfer learning, federated learning and explainable artificial intelligence are beginning to change the goals of forecasting research from prediction accuracy to other aspects. The needs for forecasting systems are increasingly and more focused on scalability, transferability, privacy protection, transparency, and deployability in real world smart building situations.

Finally, the lack of shared datasets and benchmarking tools continues to be a major obstacle for objective model comparisons. Future research should incorporate reproducible evaluation protocols, open-access benchmark datasets, and comprehensive evaluations of the performance in terms of forecasting accuracy, computational efficiency, interpretability, robustness and real-world deployment aspects.

## 7. Challenges and future research directions

Despite great progress in intelligent forecasting approaches, many problems still exist that hinder the widespread deployment of forecasting systems in real-world smart building contexts. These issues must be addressed to produce forecasting systems that are accurate, scalable, trustworthy, and practically useful.

### 7.1 *Data availability and quality*

High-quality historical data are essential for the success of machine learning and deep learning models. However, many buildings do not have extensive monitoring systems and generate partial, noisy or inconsistent data. Common problems in building energy databases are still missing numbers, sensor failures, communication interruptions and measurement inaccuracies.

Although a few of these concerns can be handled by contemporary pre-processing methods, data quality is still one of the dominant challenges for good forecasting. Future research has to focus on robust data cleaning, anomaly detection, data fusion and synthetic data creation methods that can improve model performance under poor data settings.

### 7.2 *Generalization and transferability*

Many forecasting models are developed and validated on data gathered from one building or a few case studies. As a result, models that work well in one context tend to perform poorly when deployed in buildings with different operational aspects, occupancy patterns, climatic situations or energy systems.

Model generalization is still a big concern for the academic community. Promising solutions are provided by transfer learning, domain adaptation, and foundation-model-based forecasting frameworks that enable knowledge transfer between various buildings and geographical regions. Future forecasting systems should be able to adjust to changing circumstances with minimal retraining.

### 7.3 *Long-term forecasting and uncertainty quantification*

Most prior studies have focused on short-term forecasting due to its direct relevance to operational energy management and demand-response applications. On the other side, long-term forecasting is generally under-researched, but it is vital for retrofit planning, infrastructure development, policy assessment and sustainability analysis.

Furthermore, many forecasting methods provide point forecasts and do not give a clear quantification of the uncertainty. Due to the stochastic nature of weather conditions, occupancy patterns and user behaviour there is an increasing demand for uncertainty aware forecasting systems. Therefore, probabilistic forecasting, Bayesian deep learning, quantile regression and uncertainty quantification methodologies are expected to be more interesting in future studies.

### 7.4 *Explainability and trustworthy artificial intelligence*

The increasing complexity of forecasting systems has significantly improved the predictive performance but has also diminished the transparency of the models. In real-world applications of building management, stakeholders need to be provided explanations of what factors influence the anticipated results before they can use AI-based decision support systems.

Recent advances in XAI address this problem somewhat with strategies like SHAP, LIME, attention based interpretation mechanism. However, explainability is still a very active research area, particularly for Transformer-based and foundation-model systems. "Future forecasting systems need to balance predicted accuracy with transparency, justice, responsibility and user trust".

### 7.5 *Privacy-preserving and distributed learning*

Data privacy and cybersecurity have become major concerns with the increased deployment of smart meters, IoT devices, and building automation systems. However, building operators are often not keen on providing particular data on energy consumption and occupancy, which limits the opportunities for collaborative model development.

Federated Learning has been offered as a potential paradigm for privacy-preserving forecasting where several buildings can train shared models without exchanging raw data. However, communication efficiency, model convergence, diversity of data distribution and security vulnerability are still ongoing issues. Future work should focus on scalable federated forecasting frameworks to support large-scale smart city ecosystems.

### 7.6 *Integration of foundation models and digital twins*

Recent advances in artificial intelligence suggest that foundation models could have the same transformative effect on time-series forecasting as they have had on natural language understanding. Large pre-trained forecasting systems can learn generic temporal representations from different energy datasets, and adapt to specific buildings using lightweight fine-tuning methods.

At the same time, the application of digital twin technologies creates new opportunities for intelligent forecasting and energy management. Digital twins are virtual copies of physical structures which interact with forecasting models in real time to continually simulate, optimize and support decision-making. One such path is the combination of foundation models, digital twins and intelligent control systems for next generation smart building energy management platform.

### 7.7 *Toward autonomous energy management systems*

The ultimate goal of intelligent forecasting is not only to predict future energy demand but also to enable autonomous and adaptive energy management. It is expected that future systems will integrate forecasting, optimization, control, explainability and decision making.

Machine learning, deep learning, reinforcement learning, digital twins, federated learning and explainable AI could one day come together to provide self-learning building ecosystems that can constantly optimize energy performance while responding to changing environmental and operational situations.

## 8. Conclusion

Accurate prediction of building energy demand is crucial for realizing intelligent, energy-saving, and sustainable smart buildings. The availability of sensor technologies, smart meters and IoT infrastructures have been more and more increasing, promoting the usage of advanced artificial intelligence algorithms for forecasting applications. Thus, in the previous decade, various machine learning, deep learning, hybrid and innovative forecasting algorithms have been suggested.

This paper presented a comprehensive overview on the development of intelligent forecasting methods for the prediction of smart building energy consumption. Traditional machine learning methods such as SVR, Random Forest, Gradient Boosting, and XGBoost remain attractive due to their robustness, interpretability, and relatively low computational requirements. However, the feature engineering requirements and the limited capability to describe complex temporal dependencies often constrain the forecasting performance.

Deep learning architectures have substantially improved the accuracy of forecasting by learning nonlinear representations and automating feature extraction. ANN, LSTM networks, GRU and Transformer based designs have shown a high efficiency in several prediction scenarios. Recently, Transformer based models have shown remarkable potential in capturing long-range temporal linkages and handling big scale multivariate datasets.

The review also highlighted the growing importance of hybrid forecasting systems. Hybrid models often achieve state-of-the-art predictive accuracy by merging complementary techniques, such as feature extraction, signal decomposition, sequence learning, attention mechanisms, and optimization algorithms. Results indicate an apparent transition from individual forecasting approaches towards integrated intelligent frameworks to deal with the increasingly sophisticated energy consumption patterns.

New research areas such as transfer learning, federated learning and XAI were also addressed. The paradigms not only improve the projected accuracy, but also solve the problems of data sparsity, privacy protection, model transparency and practical implementation. The rising utilization mirrors the general trend in forecasting research towards trustworthy, scalable and human-centric intelligent systems.

The comparative analysis in this work demonstrates that no single forecasting approach outperforms all others across diverse building types, datasets, and forecasting horizons. The performance of forecasting depends a lot on the data qualities, the application needs and the operational variables. Thus the model selection should be driven by the specific aims of the deployment, not a single performance measure.

We expect future work to focus on foundation model-based forecasting, uncertainty-aware prediction, privacy-preserving collaborative learning, explainable forecasting systems, and digital twin integration. The convergence of these technologies is expected to lead to the development of autonomous energy management systems that can learn, adapt and optimize building performance in real-time.

Intelligent forecasting has typically evolved from a pure prediction problem to a vital enabling element for next-generation smart buildings. Future advances in artificial intelligence are expected to improve the accuracy, interpretability, scalability and operational value of forecasts, helping to develop more sustainable and energy efficient built environments.

## Author contributions

The following individuals were involved in the development of this project: A.N.G., A.K. and Y.F. designed the study; A.N.G., A.K. and Y.F. built the methodology; A.N.G. carried out the investigation and literature review; A.N.G., A.K. and Y.F. conducted the formal analysis; A.K. and Y.F. validated the findings; A.N.G. prepared the original draft; A.N.G., A.K. and Y.F. reviewed and edited the manuscript; A.N.G. oversaw the visualization; A.K. and Y.F. oversaw the research; A.K. and Y.F. coordinated the project administration. All authors have read and approved the final version of the text.. Funding: This research received no external funding.

## Funding

This research received no external funding.

## Data availability statement

This study did not generate or analyze any new data. All information relevant to the study is available in the cited publications; therefore, data sharing is not applicable.

## Acknowledgments

The authors have no acknowledgments to declare.

## Conflict of interest

The authors declare no conflicts of interest.

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