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# Advancing Sustainable Energy Management: A Comprehensive Review of Artificial Intelligence Techniques in Building

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**Abstract:** This paper explores artificial intelligence's (AI) transformative potential in optimizing energy management within buildings, aligning with environmental objectives and sustainable practices. AI-based methodologies are pivotal in identifying inefficiencies, forecasting future energy requirements, and mitigating energy wastage. Adopting AI-driven energy management systems enhances efficiency, reduces costs, and contributes to a decreased building environmental footprint. Furthermore, AI empowers buildings to actively participate in energy markets by accurately predicting real-time supply and demand without operational disruption.

The study delves into various AI applications, including energy prediction, optimization, fault detection and diagnosis (FDD), and real-world implementations. Notably, AI's role in fault detection and diagnostics is highlighted, emphasizing its substantial contribution to diagnostic precision. Specific numerical outcomes from reviewed studies underscore the tangible impact of AI techniques. Predictive control powered by AI achieved a remarkable 20% reduction in heating energy without compromising comfort. Additionally, smart home energy management algorithms demonstrated a notable 22.63% decrease in electricity costs and a 22.77% reduction in the peak-to-average ratio. These concrete figures underscore the practical success of AI techniques in significantly reducing energy consumption.

This review affirms the transformative potential of AI in building energy management. Including specific numerical values from empirical studies adds a quantitative dimension to the discussion, providing clear evidence of the positive impact of AI on energy efficiency.

**Keywords:** Prediction Models, Control Strategies, Optimization Energy Efficiency, Fault Detection, Building Performance.

## 1. Introduction

Humans predominantly spend their time indoors, involved in diverse activities such as living, working, and pursuing various endeavors. These activities wield significant influence over the energy dynamics within buildings, contributing substantially to global energy consumption. Consequently, they become a pivotal focus in the pursuit of environmental sustainability.

The judicious use of energy in buildings is imperative, and effective building energy management plays a crucial role in achieving this goal. This approach promotes environmental well-being by reducing the carbon footprint and controlling energy expenses. The principal goal is the reduction of energy consumption. Nonetheless, classical controllers face a formidable challenge in managing the vast volume of data associated with this objective. Artificial Intelligence (AI) handles such data, enhancing energy management, reducing waste, and mitigating environmental impact.

The urgent concerns related to climate change and the depletion of finite energy resources underscore the necessity of swiftly transitioning towards sustainable energy practices. Building operations account for Roughly 40% of the world's total energy consumption [1], primarily contributing to greenhouse gas emissions. This study initiates a detailed review of how AI techniques can revolutionize building energy management.

## 2. Energy Management in Building

The analysis of energy consumption in buildings reveals distinct categories, each playing a pivotal role in the overall energy profile. Notably, HVAC systems—comprising heating, ventilation, and air conditioning are prominent contributors to indoor comfort.

In addition to HVAC systems, lighting systems, encompassing both natural and artificial sources, significantly impact energy consumption. Another critical dimension pertains to the electrical appliances and equipment, encompassing computers, refrigerators, and televisions, which significantly contribute to both base-load and peak-load energy demands. Simultaneously, noteworthy energy consumption arises from hot water systems designed for domestic use, specifically showers and sinks, predominantly attributable to water heating processes.

Furthermore, the building envelope, including insulation and windows, shapes thermal performance and overall energy consumption. Specific building functions, such as elevators and escalators, present distinctive and diverse energy requirements, contributing further to the complexity of energy dynamics in buildings.

A comprehensive understanding of the breakdown of energy usage in buildings is imperative for devising and implementing effective energy-saving strategies, fostering a sustainable and energy-efficient built environment. Building Energy Management Systems (BEMS) are systematically categorized into two fundamental methods: passive and active. Passive methodologies aim to indirectly influence and reduce energy consumption by implementing foresighted strategies and enhancing user awareness of energy usage. In contrast, active methodologies combine actuators and sensors seamlessly integrated into the building infrastructure, specifically focusing on directly mitigating energy wastage by regulating smart building actuators and devices.

Active BEMS is further nuanced by delineating four key management strategies: Demand-Side Management, Optimization, Model Predictive Control, and Fault Detection and Diagnosis, as explained in **Error! Reference source not found.** from [2]. Demand-side management is dedicated to optimizing energy load and demand, while optimization revolves around the meticulous calibration of building systems to attain peak efficiency. Continuous monitoring and real-time diagnosis of faults ensure an optimal equilibrium, ensuring both performance excellence and heightened energy efficiency.

These active BEMS management strategies function cohesively, synergizing to guarantee efficient energy utilization and a marked reduction in energy wastage, ultimately contributing to the overarching sustainability enhancement of buildings.

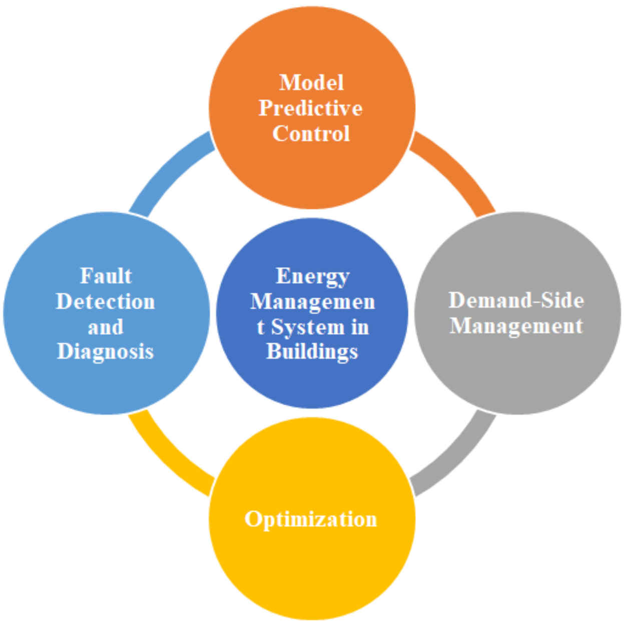


**Figure 1:** BEMS management strategies.

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## 2.1 Sustainable Energy Management

Buildings need sustainable energy management to reduce energy use, expenses, and environmental effects. This goal can be achieved using renewable energy sources, energy efficient building designs, and AI in building management systems. AI can find inefficiencies, estimate energy needs, and reduce energy waste. AI-driven energy management systems can save buildings money by monitoring energy usage. Commercial buildings can participate in energy markets through advanced building energy management systems without disrupting operations. Implementing sustainable energy management methods and incorporating AI technology is expensive and requires substantial data collecting and analysis, but the long-term benefits make it worth it [3]. Recent research has identified challenges and prospects in developing autonomous cycles for data analysis tasks and multi-agent systems to enhance AI-driven energy management.

Sustainable building management is a holistic approach that aims to minimize the environmental impact of buildings while optimizing their performance and occupants' well-being. It also involves a range of strategies and practices, including energy-efficient design, using renewable energy sources, waste reduction and recycling, water conservation, and implementing intelligent building technologies. Sustainable building management encompasses the entire life cycle of a structure, spanning from its construction and operational phases to eventual decommissioning and recycling. Furthermore, sustainable building management underscores key factors such as energy efficiency, indoor air quality, water conservation, waste management, the utilization of green materials, integration of intelligent building technologies, and active occupant participation. Additionally, it integrates renewable energy sources, water-efficient fixtures, and advanced air filtration systems.

Waste management reduces construction waste and promotes recycling. Green materials with recycled content and low volatile organic compounds reduce environmental impact. Intelligent building technologies optimize energy use and enhance comfort. Buildings actively involve occupants in energy-saving practices and seek certifications like LEED to validate their commitment to sustainability. This approach contributes to a more sustainable future.

The transition toward urban low-carbon practices necessitates adopting sustainable building energy management. Given that buildings contribute significantly to global energy consumption, prioritizing energy efficiency becomes imperative in attaining environmental objectives. Contemporary perspectives on energy efficiency encompass energy conservation, alternative energy generation, and implementing environmentally conscious 'green' construction practices [4]. Energy Management Systems (EMS) play a vital role in this paradigm by scheduling smart appliances, ventilation units, heating systems, and local generation devices to optimize building energy usage [5]. These frameworks also consider factors such as occupancy and weather, seamlessly integrating local generation and storage technologies into building energy management [6]. Implementing sustainable energy management practices in buildings reduces greenhouse gas emissions and energy consumption and contributes to developing a smart and sustainable electric system.

Building management should use AI for numerous reasons. First, AI technologies can improve building operation and management, reducing energy usage and improving automation, control, and reliability [7]–[9]. Second, AI can improve environmental controls and building performance to improve occupant safety and comfort [8],[10]. AI-based HVAC energy optimization can also maintain thermal comfort while reducing energy use. AI can also enable smart buildings and intelligent environmental controls, increasing environmental efficiency and human health by improving indoor environmental quality. AI in building management could transform energy efficiency, comfort, and sustainability.

## 2.2 Artificial Intelligence in Building Energy Management

The fundamentals of AI in buildings refer to AI technology's principles, techniques, and applications in building systems and energy management. It involves leveraging AI algorithms, machine learning models, data analytics, and intelligent control systems to enhance buildings' energy efficiency, comfort, and sustainability. The fundamentals encompass various aspects, including:

Data Acquisition and Processing: Collecting data from sensors, meters, and other sources within the building to capture information about energy consumption, environmental conditions, occupant behavior, and system performance, preprocessing and cleansing the data to ensure its quality and reliability.

Machine Learning and Predictive Modeling: Developing AI models to learn patterns and make predictions based on historical and real-time data. These models include regression, classification, clustering, and time series analysis techniques. AI models can be trained to predict energy demand, occupancy patterns, equipment failure, and other relevant parameters.

Control and Optimization: Applying AI algorithms to optimize building systems and control strategies in real-time. This application uses intelligent algorithms to adjust heating, cooling, lighting, and ventilation systems based on weather conditions, occupancy, energy prices, and other factors. The optimization techniques can maximize energy efficiency, comfort, and cost savings.

Anomaly Detection and Fault Diagnosis: Using AI algorithms to detect abnormal energy usage patterns or building malfunctions. Machine learning models can identify deviations from normal behavior and raise alerts for potential faults or inefficiencies, enabling proactive maintenance and timely interventions.

Natural Language Processing and Human-Computer Interaction: Integrating AI technologies that enable human interaction with building systems through voice commands, natural language processing, and chatbots. This integration enhances user experience, facilitates energy management tasks, and allows occupants to provide feedback or receive information about energy usage and sustainability practices.

Integration with IoT and Building Automation: Leveraging AI to integrate with Internet of Things (IoT) devices and building automation systems. This leveraging enables seamless communication and coordination between various components, such as sensors, actuators, energy meters, and control systems, creating an intelligent and interconnected building ecosystem.

### 2.2.1 AI-Based Energy Prediction Models

Several research studies have investigated using AI models for accurate building energy demand prediction. [11] examined nine machine learning classification-based methods for assessing energy performance in residential structures during the design stage.

[12] investigate the impact of building types on the performance of long/short-term memory networks (LSTMs) in predicting energy consumption. Focusing on Student Hall buildings, and Classroom, Library, the study utilizes three years of hourly energy usage data and corresponding weather data from the University of Manchester. The results reveal that the LSTMs model excels in predicting buildings with clear energy usage patterns, particularly the classroom building. However, its accuracy diminishes for buildings without distinct patterns, like libraries and dormitories. The study emphasizes the importance of longer training datasets for improved prediction results but notes the associated increase in training time.

[13] explore an advanced approach for building energy consumption prediction using a detailed dataset and dynamic simulation modeling through the EnergyPlus program. The model integrates building HVAC systems, zone division, and envelope performance, utilizing both actual weather data and generated occupancy data. Occupancy, lighting, and equipment schedules are generated at 5-minute intervals, thereby enhancing accuracy when compared to conventional office occupant profiles. Validation using IoT information from a testbed building demonstrates improved simulation results. A sequence-to-sequence (seq2seq) model with long short-term memory (LSTM) cells is constructed for demand prediction, yielding an RMSE of 4.48% and a weighted average percentage error of 3.07%. The model's learning performance is further validated through climate scenario variations. The study identifies occupancy and solar radiation as the most influential factors in energy demand prediction.

New elements, including dropout mechanisms and schedule sampling, enhance the seq2seq model's accuracy. The research underscores the potential of synthesized data for accurate predictions. It discusses the significance of the study in the context of emerging technologies such as digital twins and the growing importance of data generation. Future considerations include the analysis of resident behavior patterns, evaluation across different building types, and expansion beyond a single building target.

Furthermore, the research identifies varying impacts of weather conditions on energy consumption across different building types. The LSTMs model accurately captures sudden changes in consumption, such as building shutdowns during the Christmas holidays, but struggles to provide satisfactory predictions for buildings lacking obvious energy consumption patterns. Despite these limitations, the LSTM model reasonably forecasts energy consumption trends in libraries and student halls. The nuanced findings contribute valuable insights into optimizing LSTM models for building energy consumption prediction, considering building types and training data lengths.

[14] explore machine learning techniques for forecasting building energy consumption, with a specific focus on the Clarendon building at Teesside University. This investigation will involve the application of artificial neural networks (ANNs), support vector regression (SVR), and polynomial regression (PR) as predictive modeling tools, the study finds that SVR consistently outperforms the other models, particularly in monthly predictions with weekday/weekend segmentation. Data segmentation, specifically based on weekdays and weekends, significantly improves prediction accuracy, resulting in a noteworthy reduction in the mean absolute percentage error (MAPE), ranging from 5.27% to 12.03% for PR, SVR, and ANNs. The research emphasizes the impact of seasonality on prediction accuracy, with summer forecasts exhibiting the highest precision. The study's practical recommendations include using SVR for smaller datasets and shorter forecast ranges, employing ANNs for larger datasets and longer forecast ranges, and implementing data segmentation to account for regular variations in building energy usage, providing valuable insights for energy management practices

Neural networks, regression algorithms, and ensemble methods have undergone evaluation for the prediction of building energy consumption. The study conducted a comparative analysis of various data-driven techniques, including Gaussian Process Regression (GPR), Multivariate Linear Regression (MLR), Support Vector Machine (SVM), and Artificial Neural Networks (ANN) as well as ensemble methods such as Exhaustive Regression Trees (CHAID), General Regression Trees (CART), and Multivariant Adaptive Regression Splines (MARS), Support Regression Trees (SRT),[15],[16]. The performance of these methods was assessed using evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Bias Error (MBE), Coefficient of Determination (R2) , and Coefficient of Variance of the Root Mean Square Error (CV RMSE),[17]–[19] The results showed that ANN, SVM, and MLR methods generally performed better in the case scenarios studied. At the same time, GPR had the fastest computation time but lower accuracy. Ensemble methods like CART, CHAID, SRT, and MARS effectively predicted energy consumption. These findings can guide the selection of appropriate algorithms for building energy prediction based on the dataset size and desired prediction accuracy.

### 2.3 AI-Based Energy Optimization and Control

AI techniques have been widely used for optimizing and controlling building systems. These techniques aim to balance energy consumption and maintain comfortable conditions in buildings. Different AI methodologies, such as expert systems, genetic algorithms, fuzzy logic, machine learning, natural language processing , machine vision, neural networks, and pattern recognition, have been employed in this area of research. AI-based control systems have demonstrated encouraging outcomesin improving buildings' energy efficiency and comfort levels [20]. However, due to the necessity for a massive amount of high-quality, real-world data, the performance of AI-based control is still insufficient [7]. The application of AI technology in building control is an ongoing area of research, offering the prospect of notable improvements in comfort and substantial energy savings.

Reinforcement Learning (RL) is a widely adopted machine learning algorithm employed extensively for optimizing energy consumption and controlling systems within buildings. This methodology seamlessly incorporates progress in sensing technology, communication systems, and advanced control algorithms. Its primary objective is maximizing energy efficiency by iteratively learning and adapting strategies, thus contributing significantly to building energy optimization [21]. RL has been successfully applied in various BEMS, resulting in energy savings of over 20% for complex problems [22]. In addition to RL, other data-driven approaches, like genetic algorithms, and optimization techniques, are also used in power and energy systems for control and optimization problems [23]. These methods leverage advanced sensor and smart meter data to address the complexities and uncertainties in modern power systems [24]. RL based controllers have been proposed for energy-efficient climate control in commercial buildings, showing significant energy savings compared to baseline rule-based controllers [25]. The application of RL algorithms in managing power power management for grid-tied microgrids has been investigated, highlighting the need for improving multi-agent RL methods and addressing challenges in power dispatch among interconnected microgrids.

## 3. Key AI Techniques for Energy Optimization

The fundamentals of AI in buildings aim to transform traditional energy management approaches by harnessing the power of data, machine learning, and intelligent algorithms. Using AI techniques, as shown in **Error! Reference source not found.**, buildings can optimize energy consumption, reduce costs, improve occupant comfort, and contribute to fostering a more sustainable and efficient built environment.

### 3.1 Artificial Neural Networks

In **Error! Reference source not found.**, the architecture of the artificial neural network comprises input, hidden, and output layers interconnected by neurons, acting as processing units. The learning algorithm within the neural network iteratively updates the synaptic weights that connect neurons across various layers, establishing and refining the input/output relationship. The aggregation of weighted inputs is followed by analysis and processing through the activation function to produce the final output. The ongoing adjustment of weights and biases is geared towards minimizing the difference between the network's generated output and the desired output. This iterative process enhances the network's ability to accurately model complex relationships and improve performance over time.

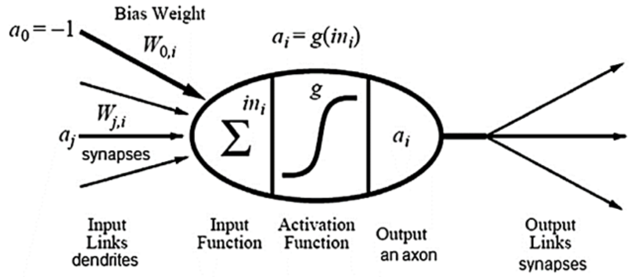


**Figure 2:**principal ANN framework ,[26].

**Table 1:** The key AI techniques used in buildings.

| AI Technique | Description | Application in Buildings | Advantages | Limitations |
|---|---|---|---|---|
| **Artificial Neural Networks (ANN)** | Computational models inspired by the neural network structure of the human brain are employed for tasks such as prediction, fault detection, and optimization, utilizing learning from data.. | Energy demand prediction, fault detection, and system optimization. | Good generalization, handling complex relationships, and adaptability to new data. | Requires significant training data may be computationally intensive. |
| **Genetic Algorithms (GA)** | Optimization algorithms rooted in natural selection and genetics, which actively seek optimal solutions to intricate problems. | Parameter optimization, control strategy optimization. | Suitable for complex and non-linear optimization problems, it can handle multiple objectives. | The computational complexity may necessitate a considerable number of iterations for convergence to an optimal solution. |
| **Fuzzy Logic** | Mathematical framework dealing with uncertainty and imprecision. It uses linguistic variables for decision-making and control. | HVAC control and decision-making based on expert knowledge. | Ability to handle imprecise and uncertain information, and flexible decision-making. | Difficulty in defining membership functions, can be sensitive to parameter tuning. |
| **Reinforcement Learning (RL)** | A learning methodology wherein an agent gains knowledge through iterative trial-and-error interactions with its environment. | Adaptive HVAC control, demand response optimization. | Can learn optimal control policies in dynamic environments and adaptability to changing conditions. | Requires extensive exploration and learning time, sensitivity to reward shaping, and exploration-exploitation trade-offs. |
| **Data Analytics and Machine Learning** | Various machine learning algorithms are used for energy consumption prediction, anomaly detection, and optimization. | Energy consumption prediction, anomaly detection, and optimization tasks. | Ability to uncover patterns and relationships in data, flexibility in handling various data types. | It requires data preprocessing and feature engineering and may suffer from overfitting if not properly regularised or validated. |
| **Natural Language Processing (NLP)** | Techniques enabling communication between humans and building systems using natural language. | Voice-activated control, chatbot interfaces, intelligent assistants. | Improved user interaction and convenience enable personalized control. | Reliance on accurate speech recognition, challenges in understanding context, and complex queries. |
| **Internet of Things (IoT) Integration** | Integrating sensors, devices, and systems in buildings enables real-time data collection, analysis, and control. | Real-time monitoring, adaptive control, and energy optimization. | Enhanced monitoring capabilities, decentralized control, and decision-making. | Security and privacy concerns, interoperability challenges, data overload, and network congestion. |

It describes how a neuron can be expressed mathematically simply.in Equation (1),[26]. It can determine a neuron's output as

$$A_i = g\left(\sum_{i=0}^{n} W_{ji*}\, a_j\right) \tag{1}$$

Ai is the network's output, $W_{ij}$ is the connection weight between the $J_{th}$ and $I_{th}$ layer neurons, and $a_j$ is the neuron's input. The basic building block of a neural network may contain a single output and a signal or many inputs. The neural network has two fundamental processes: training and testing.

Neurons within a neural network undergo training to learn specific input patterns that yield the desired output. This training phase constitutes the network's learning process. During testing, the network produces the output if it accurately recognizes the taught input pattern. In cases where the network's output deviates, it undergoes additional training to rectify errors. This training process persists until a predefined learning threshold is achieved.

This segment has encompassed the definition and various types of ANNs, performance metrics employed for accuracy assessment, prominent learning algorithms, transfer functions within the networks, and diverse normalization strategies. Drawing inspiration from the brain's fundamental structure, ANN models involve numerous nodes working concurrently, communicating through interconnecting synapses [27],[28].

Artificial Neural Networks (ANNs) find diverse applications, spanning pattern recognition, function approximation, optimization, simulation, prediction, automation, and numerous other fields [29]. In the context of Building Energy Analysis (BEA), several ANNs are commonly referenced in the literature, including:

- Auto Regressive with Exogenous Inputs Neural Network (ARXNN) [30]
- Recurrent Neural Network (RNN) [31]
- Radial Basis Function Neural Network (RBFNN) [32]
- Group Method of Data Handling Neural Network (GMDHNN) [33]
- General Regression Neural Network (GRNN) ) [34]
- Multi-Layer Feed-Forward Neural Network (MLFFNN) [35]

These networks demonstrate versatility in addressing various challenges and tasks within the realm of BEA.

[36] conducted a study contrasting machine learning-based models with conventional approaches , including time series and regression, to estimate the power usage of buildings. The study emphasized the improved performance brought on by using machine learning-based models. Notably, conventional techniques were deemed less flexible for emergent non-linear patterns. The performance of conventional models may be significantly impacted by such non-linear patterns in weather, interior conditions, and occupancy data, leading to subpar overall estimates.

Similarly, Zhao et al. [37], investigated standard methods for predicting and forecasting building energy consumption. The study specifically compared models grounded in statistics, physics, and machine learning. Notably, machine learning-based models exhibited superior levels of precision and adaptability when contrasted with statistical models.Although the preceding study was produced prior to developments in deep learning, Support Vector Machines (SVMs) were developed with purportedly superior performance compared to ANN models. Future research areas for data-driven models include application-specific parameter optimization.

[38] explored the application of AI models and ensemble models for predicting and forecasting the energy consumption of buildings. The study commenced with an overview of the utilization of AI in energy prediction, noting a predominant use of hourly data for the entire building load in AI-based articles. The research then delved into the current application of ensemble approaches in building energy prediction, revealing widespread use across various domains and superior performance compared to single prediction models. However, a gap was identified in the scarcity of articles utilizing ensemble models for short-term energy estimation in buildings.

Similarly, [39] investigated the use of AI models for energy forecasting and prediction in buildings. The study revealed that most articles constructed AI models utilizing hourly data for the total energy consumption of buildings, employing measurement data in case studies. Notably, artificial neural network (ANN) models were implemented at a ratio of approximately 2:1 compared to support vector machine (SVM) learning techniques.

[40] provided a summary of data-driven methods for predicting and classifying buildings. The authors emphasized the diverse practical applications of ANN models, including forecasting energy loads, assessing the current energy performance of buildings, and evaluating potential energy savings through retrofit solutions. Their investigation highlighted the utilization of ANN prediction models in a commercial building with a short-term horizon and a focus on overall energy load.

The collective performance range of Artificial Neural Network (ANN) models in predicting energy consumption for a single time step stands at an impressive 0.001% to 36.5% error (MAPE). Conversely, multi-step forecasting reveals elevated error rates from 1.04% to 42.31% (MAPE). When exploring a 24-hour forecast horizon using hourly data, the performance narrows from 1.04% to 11.92% (MAPE). In contrast, adopting sub-hourly data widens the performance spectrum from 2.59% to 42.31% (MAPE). This result indicates that elongating the forecasting horizon adversely affects performance, akin to the deleterious impact observed when decreasing the temporal granularity of data over an equivalent forecasting horizon.

#### 3.1.1 Limited Use of ANN Forecasting Models

Artificial Neural Networks (ANNs) offer various advantages but have limitations [41]. First, ANNs exhibit optimal performance within their training range, rendering them less effective when applied to data beyond their training scope. Continual retraining, such as cumulative or sliding window retraining, can mitigate this issue by updating models with recent data [42],[43]. Sliding window retraining is particularly useful as it avoids storing outdated data. However, it necessitates ongoing retraining. Overfitting is another limitation, occurring when models capture noise in training data, reducing their generality in long-term forecasts. To address this, ANNs can be trained with ample data relative to input variables [41], utilize multi-task learning [42],[43], implement early stopping [41], or employ ensemble forecasting to combine multiple models.

Another limitation is that ANNs are black-box models [64], lacking an understanding of underlying parameters. Hybrid grey-box models integrate ANNs with physics-based equations, capitalizing on the strengths of each approach while mitigating their respective limitations. These hybrid models can effectively forecast various aspects of a building's behavior, reducing development time.

Selecting hyperparameters during model development is a critical challenge [40]. Inadequate hyperparameter selection can lead to poor performance and increased processing time.

### 3.2 Genetic Algorithms

Introduced by Holland [44], the genetic algorithm (GA) is a metaheuristic technique inspired by natural selection and genetics. GA addresses complex problems through the utilization of nature-inspired operators, including mutation, crossover, and selection. The search process commences with a randomly generated set of solutions, termed the population, with each solution referred to as a chromosome. An individual solution is characterized by a set of parameters known as genes.

Through the application of crossover and mutation, the fittest individuals, as evaluated by the fitness function, are selected for subsequent iterations. Crossover involves the creation of new solutions, or children, by modifying portions of parental genes (chromosomes). Mutation, a crucial component of GA, explores the search space needed to converge the optimization problem. The mutation operator entails the probability that any random bit in a genetic progeny will be inverted from its original state, leading to the formation of a new generation.

With a predetermined population size, the least fit individuals are eliminated, making way for new offspring to enter the population. The algorithm continues iterations until the convergence criterion is met, at which point it terminates. This iterative process allows genetic algorithms to efficiently explore solution spaces, providing an effective approach for optimization problems.

[45] examine the use of parallelization and distributed computing to lower the reaction time of Genetic Algorithms. Those algorithms were used for planning energy resource scheduling problems in community energy systems. The results show that parallelization significantly impacts the response time, leading to a significant drop in the execution time of the algorithms.

[46] explore using genetic algorithms and Fanger's comfort method in optimizing HVAC systems. It uses SCADA system sensors to calculate heat transmission coefficients, ensuring optimal initial values for the system. The real-time model predicts and controls the internal building environment, ensuring power consumption remains below peak values while maintaining user comfort. Integrating SCADA systems with intelligent building management systems significantly impacts power consumption and comfort levels.

[47] The study explores the application of a genetic algorithm to improve the energy efficiency of an HVAC system in a building. It reveals that using multiple control variables leads to significantly higher energy savings than relying solely on one type. The selection and location of control variables influence the effectiveness of the optimization process and energy-saving outcomes.

[48] focus on the substantial energy demand stemming from HVAC systems in buildings. The study introduces a multi-objective optimization (MOO) framework using GA, considering competing objectives related to energy consumption, thermal comfort, and productivity. Through building performance simulation on prototype office buildings across various climate zones, the study identifies optimal HVAC setpoint settings. These settings, capable of reducing energy consumption by up to 25.8%, are shown to maintain acceptable comfort and productivity levels. The diverse Pareto fronts obtained underscore the necessity for climate-sensitive HVAC operation strategies. However, the study acknowledges a limitation in the simplistic representation of productivity and plans to validate findings with data from larger buildings. The research contributes to the understanding of trade-offs in building performance metrics. It emphasizes the potential for weather-dependent HVAC strategies to improve energy consumption, thermal comfort, and productivity.

[49] introduce a methodology promoting energy efficiency in buildings using Genetic Algorithms (GAs) to optimize household appliance selection. The methodology aims to reduce energy consumption and minimize $CO_2$ emissions, enabling consumers to save on initial investment and energy consumption. The research compares GAs with the Simplex method and explores the impact of problem formulation on GAs results. The approach considers vital decision variables and cost functions. Evaluating these options incorporates factors such as the number of occupants and the combined type, emphasizing a comprehensive approach to enhancing energy efficiency and environmental sustainability in building choices.

In the work presented by [50], a model for enhancing building energy efficiency with three primary objectives—energy consumption, natural lighting, and natural ventilation—is introduced. The researchers employed a genetic algorithm to optimize building parameters, focusing on energy conservation and improved comfort. Following 10,000 iterations, the algorithm successfully converged to a Pareto optimal solution set within a duration of 61024 seconds. The selected configuration exhibited a building energy consumption of 5580 $W/m^2K$, a Pressure Difference Pascal Hours (PDPH) of 6453 hours, and a lighting coefficient of 5.56%. Notably, this optimized solution resulted in a 3.40% reduction in energy consumption, an 11.65% increase in lighting, and a 9.54% improvement in PDPH.

### 3.3 Fuzzy Logic

Fuzzy logic, introduced by L. Zadeh in 1960, represents a multi-valued logic extension of classical Boolean logic. Its primary application lies in the description of processes and events where precise mathematical models are either absent or impractical to define based on survey data. Particularly advantageous in situations where systems can be effectively elucidated using natural language, fuzzy logic facilitates automatic decision-making processes reminiscent of human activities. Additionally, it contributes to the construction of a rule-based database that often aligns with the description of the underlying phenomenon. Fuzzy inference, a key aspect of fuzzy logic, finds application in the development of expert systems.

The practical implementation of fuzzy logic principles involves the construction of fuzzy logic controllers and decision-making blocks, encompassing three fundamental steps, as illustrated in **Error! Reference source not found.**. This approach provides a flexible and intuitive framework for addressing complex and uncertain systems, contributing to improved decision-making processes in various applications.

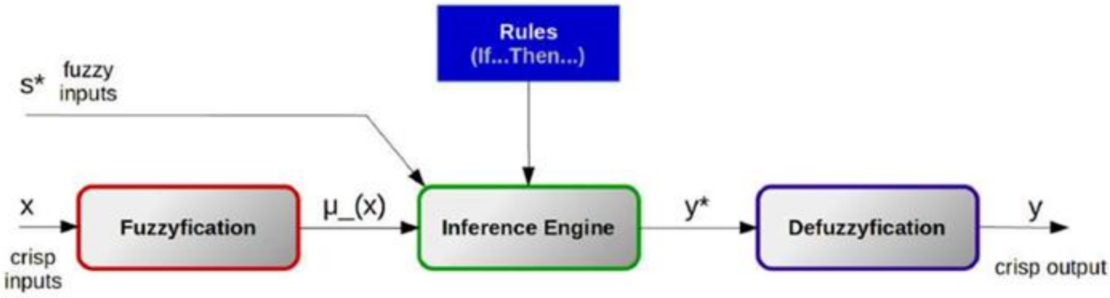


**Figure 3:** Fuzzy control system diagram [51]

Fuzzification transforms numerical input data into fuzzy values, accommodating the inherent imprecision and uncertainty characterizing real-world information. In the inferencing phase, a rule database is leveraged to model intricate relationships akin to natural language "If-Then" statements. This strategic process facilitates the practical implementation of fuzzy logic in decision-making. Regarding defuzzification, this critical step yields precise and actionable output control signals by reversing the fuzzification process. Various techniques can be applied in defuzzification, including the maximum, center of gravity, or center of area methods. Collectively, these meticulously orchestrated steps enhance the efficacy of fuzzy logic systems in adeptly managing the complexities and uncertainties inherent in decision-making processes.

[52] introduced an automated EMS employing fuzzy logic and a neural network-based decision table. The system, guided by the price signal, aims to strategically shift the peak energy demand of a building beyond the overall system load peak. The authors demonstrated the effectiveness of a simulation model of the EMS in selecting the most energy-efficient scenario. The scenarios encompassed control over household appliances (water heater, dishwasher, freezer, washer), lighting, energy transfer from the electrical grid to battery storage, and the consumption of energy from Photovoltaic (PV) sources. The article reports a successful reduction in overall daily active energy consumption. The proposed system was implemented in C# Code and evaluated through simulations.

[53] suggested a house EMS (HEMS) model based on a multi-agent system and fundamental fuzzy logic concepts that can cut electric energy usage by regulating the environmental conditions within a building while preserving the minimal comfort levels of its residents.

[54] present a methodology that captures householders' preferences, allowing for the prioritization of appliance usage, particularly in the context of load curtailment within demand response programs. The complexity of users' consumption behavior, influenced by economic, social, cultural, and environmental factors, requires a nuanced approach. The fuzzy TOPSIS methodology proposed in this paper serves as a valuable tool for households to collectively assess their energy consumption and make informed decisions about energy flow distribution. The application of this methodology involves ranking appliances within a home area, utilizing specified criteria . It is important to note that, in this approach, it is assumed that detailed information such as price signals and consumption profiles is provided to users. For future enhancements, the incorporation of fuzzy rules to analyze and predict users' consumption behavior is recommended.

[55] delved into optimizing the daily load profile of a building by adjusting HVAC duty cycles, revealing a potential 10–20% reduction in peak load through city-scale calculations. The study aimed to synchronize the daily load profile with Time-of-Use (ToU) pricing considerations. Given the dynamic and unpredictable shifts in energy consumption patterns, the application of fuzzy logic emerged as both applicable and feasible in this context. This inventive approach not only effectively addresses challenges related to peak load curtailment in smart grids but also highlights its adaptability through a fuzzy system model guided by fuzzy logic principles. The model's capacity to manage energy demand during peak load periods is showcased, along with its flexibility in handling diverse scenarios across multiple city regions. Moreover, the method displays proficiency in managing various parameters of interest and multiple output variables of control, positioning it as a practical solution for addressing peak load curtailment within the dynamic and uncertain energy demand patterns typical of smart grid environments.

[56] developed a theoretical model of HEMS employing a fuzzy logic regulator to improve energy storage's charging and discharging cycles. Real-time environmental data were utilized to validate the model. This information included temperature, energy pricing, hot water consumption, and PV electricity generation. Two variations were evaluated, one with and one without the DR mechanism. In their conclusion, the researchers underlined that the proposed fuzzy algorithm performed admirably with stochastically variable data. Both tested variations may be economically advantageous. The computation time is suitable for use in practice. [57] introduced a system incorporating a smart meter and load control through relays to switch between various load groups. Employing Model Predictive Control (MPC) techniques for real-time regulation of the electrical system and simultaneous reduction of the total operating cost, the proposed solution optimizes energy demand within the context of a quadratic equation. The system demonstrated a notable reduction in energy costs, achieving approximately a 30% decrease. Simulations were conducted in the MATLAB/Simulink environment, although without hardware implementation and collaboration with the actual electrical installation and appliances, as outlined in the test scenarios presented in the article.

The compilation of articles consistently features simulation outcomes validating initial hypotheses, particularly in the context of refining a building's load profile and minimizing energy consumption. The simulations, as presented by various authors, underscore the potential for substantial reductions in peak energy load and overall energy consumption within buildings through the implementation of Energy Management Systems (EMS) to regulate customer load profiles. [58] offer a comprehensive review of existing literature, emphasizing the application of various computational intelligence methods, notably fuzzy sets theory, in the realm of renewable energy. Furthermore, the evolution of computational methods for both smart grids and intelligent metering systems is explored. Another recent review by [59] delves into diverse strategies for deploying Home Energy Management Systems (EMS) to address disaster scenarios, shedding light on prior studies and emphasizing the potential role of software in crafting effective solutions.

In the realm of EMS algorithms, a crucial responsibility is to pinpoint the devices responsible for current energy usage. Anther study by [60] ntroduces a novel methodology for efficient load signatures (LS) to enable the implementation of a near-real-time Non-Intrusive Load Monitoring (NILM) algorithm. The methodology focuses on defining representative current values for the 1st, 3rd, and 5th harmonic orders in concise LS. Using a measurement setup in a Low Voltage residence, steady-state measurements are performed. The proposed data processing methodology aims to extract representative current values for each harmonic order and proposes a linear disaggregation scheme for near-real-time applications. Results indicate that the developed load signatures are efficient for per-second NILM algorithm application, especially with higher harmonic currents. The study acknowledges the impact of appliances with significant harmonic content on identification efficiency and proposes exploring more efficient LS formulations considering phase angles for harmonic currents in future work. A nuanced approach involves multipoint measurement of energy consumption for each receiver, coupled with control mechanisms, as articulated by [61]. The multifaceted exploration of EMS strategies, encompassing technological interventions and adaptive solutions, exemplifies the collective effort to optimize energy usage within diverse contexts, extending beyond the immediate focus on load profiles to address broader issues in the energy management landscape.

The algorithm for power management using battery storage based on Lyapunov's optimization was proposed by [62]. This technique was designed to be implemented in an external power controller with the smart meter. This study addresses the essential problem of citizens' privacy, which innovative metering systems could compromise. A previously described technique of control proposed by the authors allows for the adjustment of the load profile, which considerably hinders the identification of which devices in the building are now in use. Collecting data on energy usage in near real-time enables the determination of the number of occupants and the identification of the currently most utilized gadgets [63],[64]. Theoretically, [65] have offered a complete analysis of privacy and the ability to conceal the kind of gadgets inhabitants operate through energy storage.

Multiple solutions work well with distributed systems. According to studies conducted by [66] The share of distributed control systems, including EMSs and HEMSs, will rise. Every level of the smart grid may contain network elements employing computational intelligence. [67] proposed a hypothetical topological overview of such systems, considering the distributed intelligence at various power system levels.

An analysis of existing solutions reveals the necessity of implementing an EMS to increase buildings' energy efficiency by refining the building's daily load profile and decreasing overall power consumption using RES. In such situations, solutions and algorithms based on fuzzy logic produce good outcomes and have significant implementation potential. Sadly, most studies present theoretical answers whose validity was only proven by simulation. Individual equipment, such as single home appliances, are offered with practical solutions [68].

### 3.4 Reinforcement Learning

Reinforcement learning (RL), introduced by Sutton et al. [69], falls under the umbrella of machine learning. It operates on the principle of obtaining feedback from an environment. In reinforcement learning, The RL agent gains knowledge of the environment's dynamics via direct interaction and receiving incentives. Based on Figure 4, if the RL agent performs one of the many potential actions (discrete or continuous) on his environment, it arrives in one of the many possible states. Subsequently, it gets a reward or penalty for doing that action. This reward is performance feedback for the RL agent at each decision timestep. All problems are framed as Markov decision processes (MDPs), represented by a five-tuple (S, A, P, R, γ). Here, S denotes the state space, A is the action space, P defines the transition function, describing the likelihood of the system transitioning to state s' at the next time step when action a is taken in the current state s, R represents the reward function, and γ signifies the discount factor.

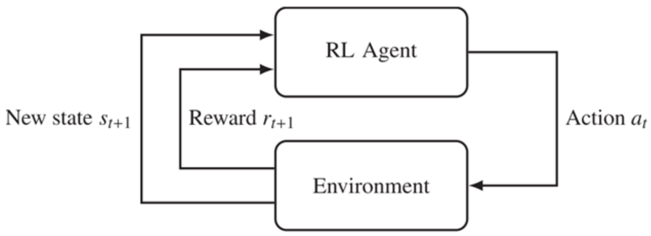


**Figure 1:**RL Agent-environment interaction,[70].

One of the defining features of MDPs is the Markov property, which assumes that state transitions depend solely on the preceding state. In a typical RL setup, an artificial agent interacts with its environment, gathering current observations ($s_t$), taking action ($a_t$), and subsequently receiving immediate rewards wards ($r_{t+1}$). The return for a single episode, calculated as the cumulative discounted reward from time t onward, is expressed as:

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \quad (2)$$

Where k ranges from 0 to infinity, with γ representing the disco t factor, the action-value function assesses the expected return after taking action in the state s based on a special $Q_\pi (s,a) = E_\pi [G_t | S_t = s, A_t = a]$.The optimal value function, $Q_\pi^* (s,a)$, determines the maximum expected return given states and actions under any policy. It can be estimated through the Bellman Equation [71]:

$$Q_\pi^* (s,a) = E[r + \gamma \max_{\acute{a}} Q^* (s',a') \mid s,a], \quad (3)$$

Where s' and a' represent the subsequent state and action in the next step, a reinforcement learning task aims to find the optimal policy based on a sequence of observations, actions, and rewards gathered through experience. The solution to this task is often derived through the Q* function.

The MARLISA algorithm for decentralized actor-critic reinforcement learning was developed by [72]. However, the study was mainly concerned with integrating a centralized critic (MARLISA DACC) to coordinate the management of energy storage systems (ESS), such as batteries and thermal energy storage (TES), across several buildings. This strategy sought to improve the performance of demand response (DR) and minimize carbon footprints.

Increasing residential building sizes need multi-agent techniques, which enable agents to exchange information and cooperate to optimize building energy management system (BEMS) performance. A distributed reinforcement learning energy management (DRLEM) system was used by [73] to regulate the energy flow of combined heat and power (CHP) and boilers in numerous buildings. The connectivity of these agents resulted in an 18.3% drop in heat losses, a 3.3% decrease in expenditures, and a 23% increase in energy sharing during peak hours.

Future research on residential neighborhoods and buildings necessitates the integration of distributed and multi-agent techniques. These approaches play a pivotal role in coordinating renewable energy sources and electric vehicles (EVs) across multiple households, mitigating renewable energy curtailment, and optimizing profitability through peer-to-peer local energy trading hubs. The diverse objectives of appliances and Building Energy Management Systems (BEMS) present opportunities for implementing Deep Reinforcement Learning (DRL)-based BEMS in residential buildings, showcasing significant potential for effective demand response during morning and evening peak demands [74].

In a study by [75], electric vehicles (EVs) were incorporated into the Building Energy Management System (BEMS), employing a secure reinforcement learning (SRL) strategy to enhance building resilience and proactivity, particularly in extreme weather events. Conversely, Mbuwir et al. [76]focused exclusively on utilizing EVs as a central component of their BEMS in an office building. Their research demonstrated that a multi-agent Deep Reinforcement Learning (DRL) approach could achieve substantial savings of up to 62.5%.

It is noteworthy that only a limited percentage of research, specifically 24%, considered Demand Response (DR) systems, and merely 21% included photovoltaic (PV) or energy storage systems in their investigations. The application of DRL methods in office buildings exhibits a broader diversity range compared to residential buildings. Some DRL methods, such as the asynchronous advantage actor-critic (A3C) and the soft-actor critic (SAC), have shown superiority in comparative studies over baseline rule-based controllers. However, it is crucial to acknowledge that not all studies have comprehensively compared different DRL algorithms.

For example, [77] conducted a comparison between the advantage actor-critic (A2C) and Proximal Policy Optimization (PPO), with A2C demonstrating superior performance. Such comparative analyses provide valuable insights for researchers to choose the most suitable DRL algorithms from the extensive range available.

[78] emphasized the core objective of minimizing indoor contamination within their Building Energy Management System (BEMS). Achieving this goal involved optimizing the HVAC system across 21 zones within a school model. Their approach yielded significant results, with a remarkable 44% improvement in thermal comfort, a commendable 21% reduction in energy consumption, and the sustained maintenance of low indoor $CO_2$ concentrations.

In real-world implementations, three studies focused on model validation in various settings, including a laboratory, a university building, and a school environment. While laboratories are conducive to validating real systems, acquiring necessary data for training the agent can be challenging. [79] adopted an approach involving an offline training phase based on an apartment model combined with particle dynamics for $PM_{2.5}$ modeling. Subsequently, the agent was tested in a laboratory room with varying $PM_{2.5}$ levels.

[80] conducted a 43-day experiment at a Spanish school utilizing a BEMS incorporating fitted Q-iteration, Bayesian regularized neural networks, and genetic optimization. Their findings indicated a roughly 33% reduction in energy consumption while maintaining comfort levels comparable to a baseline period. Additionally, they observed a 5% increase in energy use when focusing on comfort.

[81] introduced an innovative approach involving the fusion of Deep Reinforcement Learning (DRL) with deep learning techniques for building energy prediction. Incorporating a Deep Deterministic Policy Gradient (DDPG) to introduce an additional learning layer to an LSTM forecaster, the agent adapted and fine-tuned hyperparameters based on new training data. Their findings demonstrated an impressive 23.5% enhancement in prediction accuracy in scenarios with significant variability in new training data.

[82] addressed peak demand and the peak-to-average ratio, successfully reducing both by 23% and 20%, respectively. They employed a centralized Soft-Actor Critic (SAC) agent to control various building types, including small/medium offices, retail establishments, and restaurants. Notably, their study lacked instances of real system validation.

[83] investigated voltage regulations in a simulated IEEE-33 bus system connected to diverse building types. This included fast-food restaurants, medium offices, retail stores, a mall, and residential houses. Utilizing multiple Deep Reinforcement Learning (DRL) agents within the City Learn framework, their model achieved a 34% reduction in under-voltage and overvoltage occurrences.

### 3.5 Natural Language Processing (NLP)

Natural Language Processing (NLP) is a multidisciplinary field that draws from linguistics, computer science, and artificial intelligence. Its history can be traced back to the early 1950s with the inception of the Turing Test [84]. Over the years, NLP has relied on statistical and probabilistic approaches, particularly from the 1980s until recent times when DL and ANN have yielded cutting-edge results in various NLP tasks[85]. These tasks encompass information extraction, machine translation, text summarization, question answering, document categorization, voice recognition, and more [86], [87].

In recent years, NLP has found wide-ranging applications across different industries. One notable application is virtual assistants, powered by NLP and AI [88], which have become integral components of customer service. NLP is also instrumental in assessing customer feedback and comments in various sectors, including entertainment and e-commerce (Netflix and Amazon being prime examples). Many companies now rely on natural language processing (NLP) to analyze social media content, uncover business trends, and make informed decisions [89].

### 3.6 IoT Integration and Smart Building Technologies

The Cloud-IoT infrastructure for the active dimension of the building environment operates based on a multi-layered architecture, as illustrated in **Error! Reference source not found.**. This architecture is a foundational framework for connecting Building-Level Controllers (BLCs) and various smart devices on a unified platform. It operates cohesively to address the specific needs of users.

These layers in this architecture cover a spectrum, starting with the facilitation of physical devices to sense and collect data from the surrounding environment. The pinnacle of application control resides at the highest level, where decisions are formulated to enhance building operations. At the heart of this system lies the "things layer," which integrates sensors, actuators, and controllers. This foundational layer empowers buildings with intelligence, enabling them to discern and log alterations in indoor and outdoor settings, building operations, occupancy trends, and other user-relevant activities.

An Over-the-Air programming technique has been implemented to enable the diversity of device types, employing three fundamental modes: event-driven, periodic, and on-demand reporting. These modes facilitate communication and data transfer among devices [91]. **Error! Reference source not found.** overviews commonly utilized sensors and smart devices in building applications.

The presented table comprehensively outlines various building sensor technologies, encompassing sensor types, associated technologies, architectural frameworks, communication technologies, and applications. The systematic arrangement facilitates a clear understanding of the diverse sensors employed in Building Management Systems (BMS), Heating, Ventilation, and Air Conditioning (HVAC) systems, as well as other monitoring and control applications within building environments. This table overviews the different sensor types used in buildings, their underlying technologies, architectural components, communication methods, and their specific purposes in building systems and automation. Furthermore, Figure 6 highlights effective short-range and long-range protocols used in the things layer of the cloud-IoT infrastructure.

**Table 2:**Building sensor technologies and applications [91].

| Sensor Type | Sensor Technology | Architecture | Communication Technology | Application |
|---|---|---|---|---|
| **Smart Meters** | SMETS-1, 2 | PIC | Zigbee | BMS, HVAC, Consumption Monitoring |
| **Thermal Sensor** | Thermocouples, RTD, Thermistors, IC sensors | PDA/PC, PIC, SIM20, ATMega88, 16-bit microprocessor, CPLD | BLE, SIM20, TCP/IP, RS485 | BMS, HVAC |
| **Humidity Sensor** | Capacitive, Resistive, Thermal | PDA/PC, CPLD | PC, PDA, TCP/IP, ZigBee, RS232 | BMS, HVAC, Monitoring |
| **Carbon Dioxide Sensor** | Electro-chemical, MOSFET, Infrared, Photo-acoustic | PIC18F4550, ADUC1812 32-bit RISC core | RS232 | Airflow Control, Monitoring |
| **Airflow Sensor** | Hotwire, vane, Volume airflow, mass airflow | MSP430, Wireless transceiver, CC2420, JN512 | TinyOS, ZigBee, USB, RS232, Wi-Fi | BMS, HVAC |
| **Light Sensor** | Photodiode | PLC | ZigBee Pro S2, Zigbee | BMS, HVAC |
| **Electrical Sensor** | Current sensor, voltage sensor | - | GSM, Zigbee, Communication | Advanced Lighting System |
| **Fire Detection** | Ionization, photoelectric, heat, hybrid | PIC microcontroller, smoke sensor, temperature sensor | Zigbee | BMS |
| **Occupancy Sensor** | Passive infrared, ultrasonic, microwave, thermal imaging | - | - | BMS, HVAC, Fault Detection, and Security |

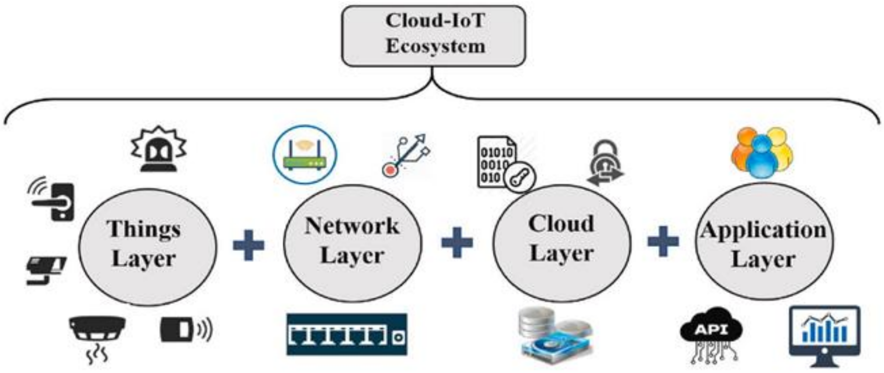


**Figure 5:**Cloud-IoT ecosystem,[90].

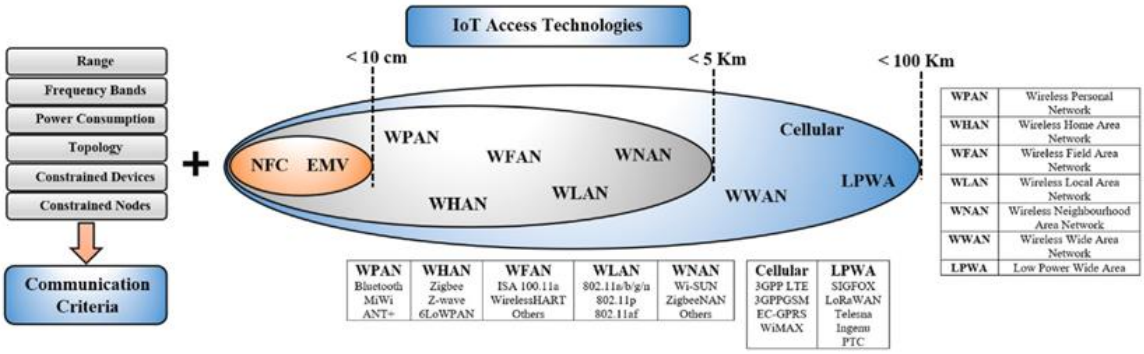


**Figure 2:** Network-Layer Services,[90].

Using sensors enables monitoring room and PCM plate temperatures and integrating weather forecasts to assess the system's effectiveness. This approach ensures 10-15% energy savings, rapid heat distribution when needed, and enhanced comfort for building occupants.

In a study by [92], thermal images were employed to identify insulation issues in building exteriors. Poor insulation or wall surface damage was detected by examining temperature variations in different building segments. Researchers used a FLIR One camera and an Android smartphone to collect 50 thermal images, achieving a 75% accuracy rate in identifying insulation problems.

[93] presented a study focused on monitoring the durability of materials, such as concrete, in building walls using real-time IoT sensors. These sensors transmitted humidity data wirelessly to a mobile application, offering long-term monitoring capabilities. Monitoring concrete moisture is crucial for ensuring building durability and preventing structural issues.

A cost-effective and energy-efficient Indoor Air Quality (IAQ) sensor was introduced by Kumar et al. [94]. This sensor was designed to monitor indoor air quality, specifically detecting $PM_{2.5}$, $CO_2$, CO, and $O_3$. It was crucial in alerting building occupants when fresh indoor air was required, enhancing ventilation, minimizing gas emissions, and promoting overall health.

Occupancy and occupant behavior in buildings can significantly impact energy efficiency. A building occupancy prediction model introduced by [95] achieved a 90% accuracy rate by collecting data from eight sensors every 20 minutes or five sensors every 15 minutes. Data included indoor temperatures, humidity, $CO_2$ levels, window and door states, and outdoor weather conditions, all associated with building occupancy.

[96] introduced an intelligent IoT-based system to enhance fire safety and predict and respond to fire emergencies. This system included a fire alarm pull, fast and slow-response sprinklers, a fire bell, a local security operator, and an air exchange module. IoT sensors monitored fluid consumption in sprinklers, and a smart device allowed continuous monitoring and immediate response in case of a fire.

[97] showcased a real-time Net Zero Energy Building (NZEB) prototype that leveraged wireless sensors for home automation via the Internet of Things (IoT). This innovative NZEB model integrates renewable energy sources and intelligent controllers to reduce grid energy consumption. The deployed sensors monitored room illumination and temperature, transmitting data to the cloud for effective electrical demand control.

[98] proposed A model for energy efficiency using a Fuzzy Control System focusing on reducing water flow rates without compromising occupant comfort. This model applied artificial intelligence technology to optimize hot water distribution, ensuring effective heat distribution and enhanced energy efficiency.

[99] introduce an innovative approach to optimizing domestic water heaters based on learned human behavior from actual IoT data. Two learning approaches, neural networks and Gaussian processes with periodic kernels, are

employed to understand individual consumption behaviors. The learned human behavior is then used to create personalized hot water schedules, resulting in energy savings ranging from 20% to 34% compared to a default schedule. The authors propose an eco-parameter to allow users to balance comfort and energy savings. The conclusion emphasizes the approach's effectiveness in reducing data from IoT devices, with neural networks outperforming Gaussian processes in terms of results and computational efficiency. Despite a prediction error of around 7%, the optimized schedule demonstrates substantial energy savings over a six-month testing period.

[100] present an IoT-based remote monitoring system for optimizing electrical power consumption. The system utilizes XBee technology and features a modular design, facilitating scalable and efficient wireless electricity usage monitoring in homes. With a web application providing real-time data access, users can identify and reduce unnecessary consumption. The study highlights the system's adaptability to various settings, including buildings and industries. Anticipated future enhancements involve transitioning to a mobile app, adopting cloud-based information storage, and incorporating additional features such as alarms and consumption predictions. The system's potential contribution to sustainable smart cities in Ecuador is emphasized, particularly through replacing conventional meters with intelligent monitoring solutions.

[101] designed an IoT-based system to control air conditioning, creating a thermally comfortable indoor environment by monitoring temperature and humidity. User preferences and sensor data were integrated with a Predicted Mean Vote (PMV)-based algorithm to provide occupants with thermal comfort control.

[102] made significant strides in elevating building management, aiming to curtail energy usage and fine-tune lighting and HVAC control. Passive infrared sensors facilitated the anticipation of occupant presence, while temperature and humidity sensors dynamically adjusted environmental conditions. An acceleration sensor was deployed to monitor the status of doors and windows. The system featured an automated mechanism to turn off lights in unoccupied rooms and a web interface for customizable configurations. Cloud computing played a pivotal role in storing and analyzing data, contributing to the overall efficiency of building management.

[101] introduced a low-cost method of using an IoT-based smart thermostat to automatically identify thermal models of different building zones. This approach forecasted indoor temperatures by analyzing data from IoT-based thermostats and the operating schedules of AC units.

A multi-HVAC system was introduced by Aguilar et al. [103] to be adaptable to both centralized and distributed HVAC systems in buildings. The ACODAT system optimized energy savings and indoor comfort by adjusting HVAC operations based on environmental data and control modules. It allowed for efficient management without requiring extensive changes to existing HVAC installations or building redesign.

## 4. AI for Fault Detection and Diagnostics

Artificial intelligence (AI) has shown powerful capacity in fault detection and diagnosis (FDD) systems for buildings. Existing data-driven-based FDD models rely on high-quality data, but actual building data often have uncertainties. The impacts of data uncertainty on FDD models were investigated in terms of input feature numbers and uncertainty levels. The performance of FDD models declined with reduced feature numbers and increased uncertainty levels. Data uncertainties had a more significant effect on diagnosing global faults than local ones [104]. Explainable AI (XAI) was examined for building trust in data-driven FDD. XAI-FDD use cases were investigated in a building with six chillers [105]. AI-assisted FDD (AI-FDD) for HVAC equipment has limitations in meeting high-reliability requirements.

In response to the aforementioned challenge, a novel AI-assisted system for false alarm detection and diagnosis, referred to as AI-FADD, was proposed. This system not only achieved a noteworthy reduction in the false alarm rejection rate but also resulted in substantial cost savings in terms of labor [106]. The utilization of Automated Fault Detection and Diagnosis (AFDD), leveraging operational data from Air Handling Units (AHUs), effectively mitigated energy wastage and enhanced occupant comfort. A distinctive methodology, integrating both unsupervised and supervised data-driven techniques, was introduced for AFDD, demonstrating successful identification of typical faults in AHUs [107]. Furthermore, a systematic framework for feature extraction and selection was developed for comprehensive AFDD across entire buildings. This framework not only enhanced the generalizability of the AFDD model but also provided valuable insights into physical systems beyond the current understanding [108].

The domain of automated fault detection and diagnostics in buildings has witnessed extensive exploration through the application of AI anomaly detection and pattern recognition methods. Diverse approaches have been proposed for extracting informative features from sensor data and selecting optimal feature sets for data-driven modeling [109]. Notably, deep learning techniques, including autoencoder neural networks, have exhibited promising results in analyzing high-dimensional data and detecting anomalies through both supervised and unsupervised methodologies [108]. Additionally, the deployment of Artificial Intelligence, encompassing supervised Artificial Neural Networks and Convolutional Neural Networks, has proven effective in real-time condition monitoring and fault detection with high diagnostic accuracy [110]. These methods have demonstrated their capability to automatically identify, diagnose, and rectify various categories of sensor faults, including positive bias, negative bias, precision degradation, and drift [111]. Researchers and practitioners can refer to these studies to discern appropriate methods for automated fault detection and diagnostics in building systems [112].

## 5. Case Studies and Real-world Implementations

Several research studies have explored real-world applications of AI techniques in building energy management. Verma et al. discuss the conflict between comfort level and energy consumption in residential buildings and propose solutions to optimize energy usage while maintaining occupants' comfort [113].

[114] introduce real-time information-based energy management algorithms to minimize electricity costs and peak-to-average ratio (PAR) in smart homes while maintaining user comfort. Appliances are categorized into thermostatically controlled (tc), user-aware (ua), elastic (el), inelastic (iel), and regular (r). Mathematical optimization models are formulated for tc appliances (air-conditioners and refrigerators) and solved using an intelligent programmable communication thermostat (iPCT) with a genetic algorithm (GA). Optimization models are solved for ua, el, and iel appliances to minimize electricity costs and reduce PAR, considering user comfort and adjusting waiting times for el appliances. Additionally, r appliances' energy demand is met through local supply to reduce fuel costs. Simulation results demonstrate that the proposed algorithms efficiently manage energy consumption, achieving up to a 22.63% reduction in electricity costs and a 22.77% reduction in PAR. The study sets the groundwork for future work on DSM and microgrid load balancing, emphasizing flexibility and effectiveness in scheduling home appliances.

[115] present the Occupant Mobile Gateway (OMG), a smartphone/server software service designed for occupant-aware energy management through participatory sensing and machine learning. The OMG functions by collecting and analyzing real-time occupant subjective feedback and thermal data from embedded sensors, facilitating personalized thermal management and energy savings. This approach diverges from static comfort criteria, offering a flexible interpretation of thermal comfort based on personalized models. Through machine-learning algorithms, subjective and physical thermal measurements are synthesized to create personalized comfort models, enabling the determination of optimal temperature setpoints. Field data collected from four test sites with 45 occupants demonstrates the feasibility of generating occupant comfort profiles within a relatively short period.

Application of occupant-driven comfort models in annual energy simulations reveals the potential for significant energy savings while maintaining acceptable thermal comfort levels. The study underscores the transition from static comfort proxies to data-driven models for more energy-efficient and responsive control strategies, emphasizing the importance of a feedback loop to align building design and operational assumptions with perceived outcomes. This innovative approach holds the potential to contribute to the development of high-performance buildings and the formulation of innovative architectural design strategies over the long term.

[116] introduce a novel Random Neural Network (RNN) based intelligent HVAC controller for smart homes, leveraging Internet of Things (IoT) integration with cloud computing. The system employs wireless sensor nodes for indoor environment monitoring, communicating through RF transceivers to a base station. Three evaluated architectures include cloud-based RNN implementation for centralized data processing, base station RNN implementation reducing cloud reliance, and a distributed approach embedding intelligence in both base station and sensor nodes. Results indicate that the distributed implementation (Case 3) achieves superior performance, exhibiting 4.4% lower power consumption than the cloud-based approach (Case 1) and 19.23% less than the base station implementation (Case 2). The RNN controller demonstrates accurate occupancy estimations, benefiting from a hybrid PSO-SQP training algorithm, and Case 3 excels in both power efficiency and control decision delay.

[117] detail implementing a predictive control strategy in a commercial Building Energy Management System (BEMS) with a focus on boilers in buildings. Unlike reactive rule-based systems, the proposed strategy, leveraging neural networks, enables the anticipation of future scenarios to optimize building operations. The neural network activates the boiler at an optimal time each day, factoring in the surrounding environment to achieve thermal comfort levels at the beginning of the working day. The implemented strategy was compared with the existing scheduled on/off control in the BEMS, demonstrating a significant reduction of around 20% in energy required for heating without compromising user comfort. The results indicate that predictive control in a BEMS can effectively enhance energy efficiency in building heating systems.

[118] introduce a real-time energy management strategy tailored for a smart residential apartment building with diverse occupants across dwelling units (DUs). The proposed approach optimizes the building's real-time demand by considering dynamically updated rooftop solar generation and real-time energy prices. Central to the strategy is the introduction of the concept of load criticality level, enabling differentiation among DUs based on residents' assigned values to their power consumption. The optimization problem is formulated as a novel bilevel, stochastic, multi-objective challenge, with the goal of maximizing utility and minimizing costs.

A virtual energy trading platform facilitates interaction between the central building management system (CBMS) and DUs, employing a single-leader multi-follower Stackelberg game. The Lyapunov optimization solution strategy operates with only current values of uncertain parameters, ensuring efficient tracking of abrupt changes in real-time price and solar generation. Simulation results, when compared with centralized and greedy algorithm methods, affirm the effectiveness and superiority of the designed energy management portfolio. This underscores its potential applicability in various residential settings, demonstrating its capability to balance utility maximization and cost minimization.

[119] present a mixed-integer nonlinear model predictive control methodology designed for real-time supervision of building energy management systems, specifically applied to a single-family house equipped with a combined heat and power (CHP) unit. The strategy adeptly addresses the

switching behavior of system components and adheres to minimum admissible operating time constraints. Employing a switch-cost-aware rounding procedure, the approach is compared against globally optimal dynamic programming and conventional rule-based control strategies.

The method demonstrates real-time capability in real-world scenarios, maintaining a high correspondence with the globally optimal solution. In comparison to conventional control approaches, it achieves an average optimality gap of 2.5%, surpassing the 20% gap observed in a dynamic programming approach while also proving to be faster and more scalable. The presented strategy, adaptable without additional technical modifications, unlocks significant cost and energy-saving potential, ensuring practical real-time applicability. This highlights its efficacy in real-world scenarios and its potential to achieve substantial cost and energy savings without requiring extensive technical adjustments.

[120] presents the Real-time Multiscale Smart Energy Management and Optimization (REMO) ontology as a foundational knowledge base for real-time energy management in districts. At its core, REMO integrates AI solutions and automation systems to minimize energy consumption, emissions, and costs, prioritizing user comfort. The effective application of AI techniques, as demonstrated, significantly reduces energy demand and carbon emissions. Thorough semantic and syntactic validation showcases the ontology's versatility in supporting various use cases. The study underscores the importance of harmonizing demand- and supply-side energy management, addressing existing gaps in current solutions. The framework's effectiveness relies on the availability of sufficient data for AI-based optimization, emphasizing reusability.

The study makes notable contributions by introducing a district analytical model for supply-side optimization and incorporating ontologies for knowledge capture and replication. It underscores the limitations of existing Building Information Modeling (BIM) models and positions frameworks like Renewable Energy Management Ontology (REMO) as the future of comprehensive energy analysis. The research underscores the necessity for contemporary energy management solutions to make intelligent decisions considering the multifaceted objectives in both supply and demand domains.

The author's engagement in European Union (EU) projects, particularly through action research, serves as the foundation for this research, confirming the viability of real-time energy management using AI solutions. The efficacy of prediction models utilizing ANN and multi-objective optimization through genetic algorithms is validated, showcasing their significant impact on complex problems at both the demand- and supply-side levels. The demand-side optimization, exemplified by the SportE2 project, demonstrated an average energy savings of 36%. Similarly, the positive outcomes of district energy supply-side optimization resulted in a notable 31.8% increase in profits and a substantial 36% reduction in emissions.

[121] delve into applying Artificial Intelligence (AI) in the energy sector, specifically within power systems, emphasizing the crucial need for reliability and accountability. Proposing a comprehensive methodology, the study suggests a systematic approach involving an understanding of power system measurements, AI algorithm design for forecasting, developing robust and accountable AI methods, and creating reliable evaluation measures. Using power system event forecasting (PEF) as an illustrative example, the authors employ synchrophasor patterns measured by Phasor Measurement Units (PMUs). The proposed data-driven framework integrates physics for dimensionality reduction. It utilizes a supervised learning model for event forecasting, exhibiting high accuracy and efficiency compared to other machine learning methods. The discussion underscores considerations for AI deployment in the public sector, particularly addressing domain-specific applications and coordination with physical knowledge. The conclusion highlights the potential for real-time operation in public grid event forecasting with the presented PEF framework, acknowledging the need for further research to enhance deep learning and data fusion methodologies.

[122] address the pressing issue of energy consumption in buildings, emphasizing the importance of energy conservation and efficiency. Focusing on the next generation of intelligent buildings, the study explores implementing intelligent control systems to meet occupants' needs and enhance sustainability. The case study on an office building in Athens, Greece, validates the developed algorithms, particularly during working days and hours, showcasing the accuracy and effectiveness of the proposed methodology in disaggregating the building's load and extracting valuable information. The authors acknowledge the challenges associated with human factors and potential faults in building equipment that can lead to energy overconsumption, emphasizing careful consideration during data analysis. The study's robustness in handling working days and hours is noted, and future research aims to address and improve faults in the building's equipment, especially related to the HVAC system.

A different application is the estimation of building energy consumption. [123] introduced ‘Ensemble Bagging Trees,’ an ensemble learning technique that enhanced accuracy in estimating hourly electricity use of a test building. Another application is energy management optimization in hybrid power systems. [124] used AI controllers, specifically Neural Networks (NN) and Fuzzy Logic Control (FLC), to efficiently manage the operation of a hybrid power system comprising renewable energy sources (RESs) and backup sources (BKUSs). AI technology has also been applied in smart buildings to improve control, reliability, and automation. Farzaneh et al. conducted an in-depth assessment of AI-based modeling methodologies for predicting building energy use. The study examined the use of AI in building management systems (BMS) and demand response programs (DRPs)[10].

Deploying artificial intelligence (AI) technology in intelligent buildings considerably impacts building energy efficiency, according to an examination of successful case studies. Building management systems (BMS) and demand response programs (DRPs) use AI to increase control, dependability, and automation, resulting in lower energy use [10]. AI-based methods for building energy efficiency and zero-energy buildings have received much attention. These technologies include IoT-based thermal comfort sensor applications, platforms and algorithms for building multi-energy control, and forecasting methods for building load and subsystem performance [125]. Furthermore, the study of energy efficiency through life cycle assessment (LCA) allows for measuring a building's environmental impact throughout its life cycle, underlining the need to consider LCA when setting goals and actions for energy sustainability [126, Ch. 30]. Furthermore, comparing energy simulations to actual building energy consumption emphasizes the need to consider the number of inhabitants and their present duration in the structure for accurate energy estimates [127]. Overall, using AI in intelligent buildings and considering LCA and occupancy patterns help to increase building energy efficiency.

## 6. Challenges and Future Directions

AI techniques in buildings face several challenges and limitations. One challenge is the increased vulnerability to cyber threats as buildings become more networked and connected to the internet [128, Ch. 12], risking the confidentiality, integrity, and availability of critical systems in organizations. Another limitation is the need for better control and automation to reduce energy consumption in smart buildings [10]. Achieving improved reliability and energy management through AI can help address this limitation. However, open challenges persist in applying AI in intelligent buildings, including the need for better modeling approaches and assessment frameworks. Additionally, green architecture remains an area of ongoing research in AI, with researchers statistically discussing the strengths and weaknesses of existing AI tools [129]. While AI presents opportunities for energy efficiency and enhanced building management, addressing these challenges is essential for effective implementation.

A comprehensive literature review can identify future research directions and emerging trends in energy management in buildings. The reviewed studies highlight several critical areas of focus. One area uses smart meters, energy storage systems (ESS), and renewable energy systems (RES) to enhance demand-side energy management at the cluster level, achieving reductions in energy cost and peak energy consumption while ensuring occupant comfort. Another area is the development of intelligent energy management systems (IEMSs), which involve context awareness, privacy preservation, and energy management in smart homes and smart grids. Additionally, research has focused on demand-side management of residential buildings, particularly quantifying energy flexibility and developing control strategies to optimize flexible loads. Furthermore, advancements have been made in optimizing energy consumption while maintaining occupant comfort, focusing on occupant behavior, building envelopes, and building energy systems. Finally, integrating renewable energy resources and optimizing energy management in buildings have been explored, with a need for further research on optimization algorithms and controller design.

## 7. Conclusions

The comprehensive review of AI techniques for sustainable energy management in buildings reveals diverse and impactful findings across various applications. The studies cover a wide spectrum, from real-time IoT sensors for monitoring concrete durability to cost-effective Indoor Air Quality (IAQ) sensors. Occupancy prediction models, intelligent fire safety systems, and Net Zero Energy Building (NZEB) prototypes showcase the breadth of AI applications in building management. Innovative approaches, including a Fuzzy Control System for energy efficiency and optimized schedules for domestic water heaters, highlight AI's role in resource utilization. The studies also emphasize AI's transformative potential in fault detection, real-time energy management, and predictive control strategies.

Notable contributions include AI's application in estimating energy consumption and enhancing efficiency and sustainability in intelligent buildings. Despite promising advancements, challenges such as cybersecurity threats and the need for improved control mechanisms in smart buildings are acknowledged. The review concludes by emphasizing future research directions, including smart meters, energy storage systems, renewable energy integration, and optimization algorithms. Overall, the integration of AI in building energy management emerges as a transformative force with tangible benefits across dimensions of efficiency, comfort, and sustainability in the built environment. The key takeaways from the reviewed studies are as follows:

- AI Energy Prediction: The application of ANN, SVR, and ensemble methods for building energy demand prediction has shown substantial progress. These models enhance forecasts and optimize building energy management, resulting in more accurate predictions of energy demand. The reviewed studies collectively reported notable improvements in accuracy, with some models achieving 1.04% MAPE.
- AI Energy Optimization: RL and GA have proven effective in optimizing and controlling building systems, thus leading to improved energy efficiency and occupant comfort. AI-driven control systems offer a potential avenue for enhancing building energy optimization and efficiency. Reinforcement learning and genetic algorithms showcased an efficiency improvement of 18.3%, reducing energy consumption while maintaining occupant comfort.
- AI-based Fault Detection and Diagnostics (FDD): AI-assisted FDD systems have demonstrated the ability to identify and diagnose building faults accurately. While the studies highlighted the effectiveness of these systems, concerns about data uncertainties impacting FDD performance were acknowledged, emphasizing the importance of addressing data quality issues in future implementations.
- Real-World Implementations: AI-enabled building energy management has translated into tangible

improvements in efficiency and cost reductions. Building management systems and demand response programs powered by AI have played a crucial role in helping intelligent buildings save energy and operate more sustainably. AI-enabled building energy management systems realized an average energy savings of 22.63%, with some studies reporting up to a 36% reduction in electricity costs.

Integrating AI techniques in building energy management can revolutionize buildings' energy efficiency, comfort, and sustainability. The findings from this review provide valuable insights for researchers and practitioners to make informed decisions in implementing AI-driven energy management solutions in buildings.

## List of abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| ANNs | Artificial Neural Networks |
| ARXNN | Auto Regressive with An Exogenous Inputs Neural Network |
| BEMS | Building Energy Management Systems |
| CART | General Regression Trees |
| DRL | Deep Reinforcement Learning |
| EMS | Energy Management Systems |
| ESS | Energy Storage Systems |
| EVs | Electric Vehicles |
| FDD | Fault Detection and Diagnostics |
| FLC | Fuzzy Logic Control |
| GA | Genetic Algorithms |
| GMDHNN | Group Method Of Data Handling Neural Network |
| GPR | Gaussian Process Regression |
| GRNN | General Regression Neural Network |
| HVAC | Heating, Ventilation, And Air Conditioning |
| IAQ | Indoor Air Quality |
| IEMSs | Intelligent Energy Management Systems |
| IoT | Internet Of Things |
| LCA | Life Cycle Assessment |
| LEED | Leadership In Energy and Environmental Design |
| LSTMs | Long/Short-Term Memory |
| MAPE | Mean Absolute Percentage Error |
| MARS | Multivariant Adaptive Regression Splines |
| MLFFNN | Multi-Layer Feed-Forward Neural Network |
| MLR | Multivariate Linear Regression |
| MOO | Multi-Objective Optimization |
| NLP | Natural Language Processing |
| NN | Neural Network |
| NZEB | Net Zero Energy Building |
| PDPH | Pressure Difference Pascal Hours |
| PEF | Power System Event Forecasting |
| $PM_{2.5}$ | Particulate Matter 2.5 |
| PMUs | Phasor Measurement Units |
| PR | Polynomial Regression |
| PV | Photovoltaic |
| R2 | Coefficient Of Determination |
| RBFNN | Radial Basis Function Neural Network |
| REMO | Real-Time Multiscale Smart Energy Management And Optimization |
| RES | Renewable Energy Systems |
| RL | Reinforcement Learning |
| RMSE | Root Mean Square Error |
| seq2seq | Sequence-To-Sequence |
| SRL | Secure Reinforcement Learning |
| SRT | Support Regression Trees |
| SVR | Support Vector Regression |

## Declarations

### Availability of data and materials

The authors have not used any data in our study.

### Competing interests

The authors declare that they have no competing interests.

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### Authors’ contributions

All authors contributed extensively to the work presented in this paper. AH led the entire process of this study. All authors read and approved the final manuscript.

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