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Review

Investigating the Impact of AI/ML for Monitoring and Optimizing Energy Usage in Smart Home

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Abstract: Integrating artificial intelligence (AI) and machine learning (ML) into smart home systems has significantly advanced and improved residential energy efficiency, addressing growing concerns around energy conservation and sustainability. Choosing appropriate AI/ML techniques to optimize energy consumption in the dynamic and contemporary smart home environment remains a complex challenge. This study investigates a range of AI/ML algorithms such as regression models, deep learning, clustering, and decision trees to enhance energy management in smart homes. The study highlights the core processes of smart home energy optimization, including data acquisition, feature extraction, and model evaluation, as well as the specific roles of each AI/ML technique in optimizing energy usage. The study also discusses the strengths and weaknesses of the AI/ML techniques used for smart homes. It further explores the application areas and emerging challenges such as data security risks, high implementation costs, and gaps in existing technology that impact the scalability of AI/ML solutions in smart home contexts. The findings reveal that AI/ML techniques can effectively transform energy management in smart homes, enabling real-time optimization and adaptive decision-making to minimize energy consumption and reduce costs. Additionally, the study highlights future research directions.

***Keywords*:** energy optimization, smart homes, deep learning, artificial intelligence, machine learning

1. Introduction

The increasing adoption of smart home technologies offers new opportunities for optimizing energy usage. Traditional home energy management approaches have relied on manual interventions and limited data analysis. Therefore, advancements in artificial intelligence (AI) and machine learning (ML) provide more sophisticated methods for analyzing large datasets, predicting future energy trends, and optimizing energy consumption [1]. This information helps families and utility providers make energy-efficient and cost-effective choices. Energy management, combined with smart house technology, allows homeowners to experience a higher level of comfort [2]. This includes getting alerts and updates on home-related issues, monitoring guests remotely via smart doorbells, and controlling numerous

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appliances and features from a single device, such as a smartphone or tablet. Smart homes offer vast potential in transforming energy management and addressing energy expenses and sustainability concerns. They optimize energy consumption and storage and harness renewable energy sources, thus promoting efficiency and reducing dependence on non-renewable sources to promote a greener future [2, 3].

The growing prevalence of smart homes may be attributed to their capacity to provide homeowners with (equipment that enhances their convenience and improves their energy consumption). Experts have suggested the use of machine learning techniques as a means to maximize energy efficiency in residential environments [4]. Smart houses are architectural structures with advanced automation technologies, allowing inhabitants to control various devices and appliances using cell phones or voice commands. Li et al. [5] identify that residential properties provide many benefits, including enhanced convenience, heightened security, and increased energy efficiency. However, optimizing energy is a substantial challenge for residential buildings [6]. Energy optimization is crucial for reducing energy costs, mitigating carbon emissions, and prolonging the lifespan of appliances. AI/ML techniques can enhance energy efficiency by leveraging data collected from smart home devices, automating processes, and learning optimal strategies for resource utilization. For example, in energy optimization, supervised learning algorithms can analyze past energy usage, weather conditions, and user routines to forecast energy needs and suggest energy-saving adjustments. These systems can make proactive decisions about when to adjust heating, cooling, or lighting to enhance comfort and efficiency while learning from past interactions to improve accuracy over time [7].

This paper addresses the research questions: How can AI/ML techniques be used to monitor and optimize energy usage in smart homes? Conversely, the main contributions are as follows:

(i) We provided an in-depth discussion of smart homes and energy management for recent utilization and deployment in contemporary environments;

(ii) We comprehensively presented the AI/ML techniques, for smart home optimization and usage for data-driven industries;

(iii) Provides the strengths and weaknesses of the AI/ML techniques for smart home operations;

(iv) We highlighted current challenges and future research prospects for overcoming current issues in smart home energy optimization.

The remaining sections of this paper are structured as follows: Section 2 provides an overview of smart home energy management fundamentals, Section 3 presents the methodology, and AI/ML techniques for energy optimization are discussed in Section 4. Section 5 discusses applications of AI/ML in building energy efficiency. Section 6 addresses the current challenges and solutions. Section 7 concludes with a summary of findings and implications for sustainable smart home development, including future research prospects.

2. Smart homes and energy management

The modern home is transforming into a more intelligent and interconnected environment. This part provides an in-depth analysis of the fundamental principles behind smart homes and examines the pivotal significance of energy management within this dynamic field.

2.1 *Smart home*

A smart home is a residential structure furnished with networked devices that can be remotely controlled and monitored, either autonomously or manually [8]. Smart home systems automate and manage household functionalities such as lighting, Energy Storage, heating, security, and other appliances. The internet of things (IoT) can enhance connectivity, allowing remote control and monitoring. Besides, personalized automation improves comfort, optimizes energy efficiency, enhances security, and supports independent living. The 'smart home' concept is a modern solution for contemporary lifestyle needs, elevating homeowners' life quality [9]. Smart homes gather data through sensors, establish wireless communication using IoT protocols, and execute actions using actuators [8, 9]. They are associated with components such as sensors, actuators, information technology devices, etc. These components are effectively deployed for smart homes. For example, sensors are always collecting information about the environment. They can detect changes in temperature, motion, light, humidity, and other factors for seamless smart home operations. Components of a smart home system include [8, 10]: (i) Controllers: These include smartphones, tablets, or other devices that allow users to interact with the smart home system; (ii) Sensors: Various sensors can enable the system to monitor the state of the environment (smart home), such as temperature sensors, motion detectors, or energy consumption monitors. The data collected from the sensors could be used as observation states when applying RL-based algorithms; (iii) Actuators: These are devices that perform actions in response to commands from the controller. This can include thermostats, switches, and motors that adjust environmental conditions or operate devices. The actuators could be used as actions within RL-based methods; (iv) Connectivity: This typically refers to the network that allows various components to communicate. It can be based on Wi-Fi, Zigbee, Z-Wave, or other communication protocols; and (v) Software or Platform: This system integrates other components, processes the data, and manages the overall functioning of the smart home. This can include various ML and optimization algorithms to enhance the system's performance over time. The concept of smart homes has the potential to fundamentally transform our daily routines, changing how users interact with our living spaces. The incorporation of cutting-edge technologies, such as Reinforcement Learning (RL)-based algorithms, further enhances this potential for homes to evolve into intelligent, adaptable environments that cater to our individual preferences and needs. Figure 1 shows the components of a smart home connected to the utility power grid. In this context, the smart home could be considered an environment when using RL-based methods for energy management.

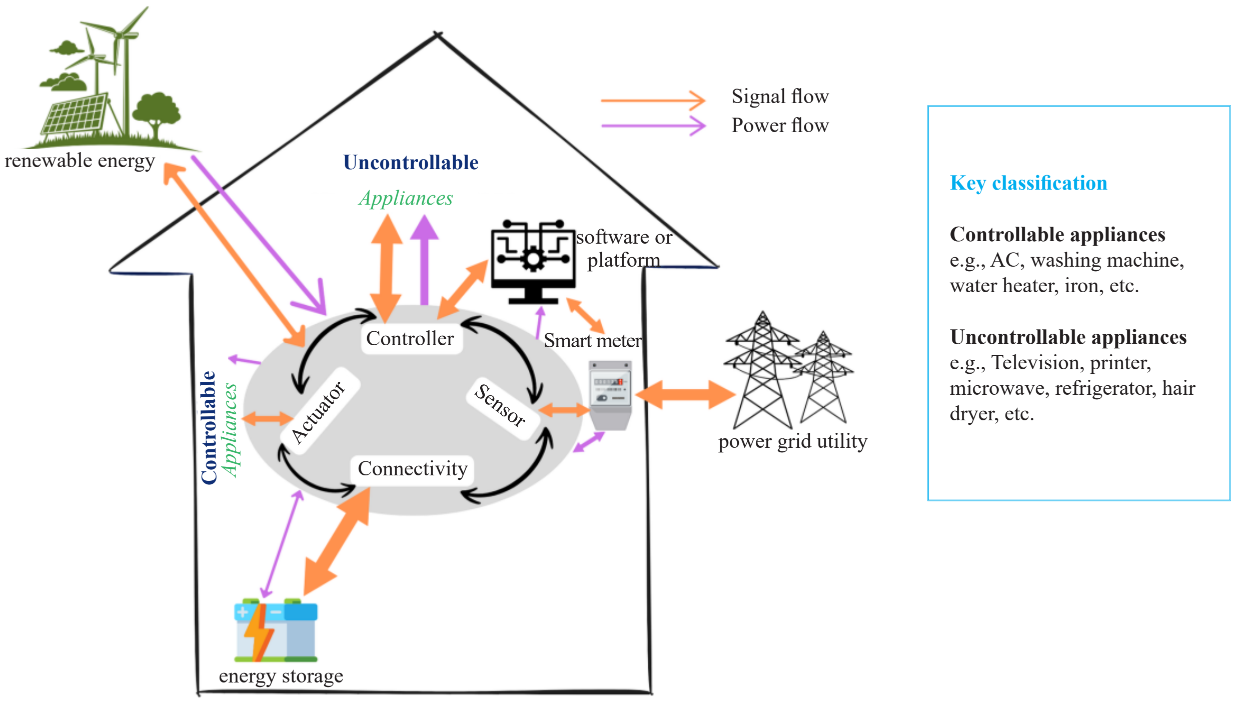

Figure 1. Components of a smart home system with integrated energy storage

2.2 *Energy storage options in smart homes*

Energy storage (ES) options play a pivotal role in smart home energy management systems (SHEMSs), providing a spectrum of solutions to optimize energy consumption, enhance grid stability, and ensure efficient utilization of renewable energy sources (RESs). Lithium-ion batteries, the prevalent choice, offer high energy density, compact size, and cost-effectiveness, making them an ideal fit for residential applications [11]. These batteries enable the storage of excess energy generated by solar photovoltaic (PV) panels or other renewable sources during low-demand periods for later use, minimizing reliance on the grid during peak times. Flow batteries, known for their scalability and long cycle life, offer a viable alternative for managing energy demand fluctuations, providing extended storage capacities and reliable backup power [12]. Furthermore, supercapacitors, with their rapid charge and discharge capabilities, act as effective short-term storage solutions, swiftly responding to sudden spikes in energy requirements or fluctuations in renewable energy generation [13]. Additionally, emerging technologies such as hydrogen fuel cells exhibit potential for long-duration ES and environmentally friendly energy production, promising to revolutionize the landscape of smart home energy storage [5]. Collectively, these diverse ES options empower smart homes to operate autonomously, optimize energy usage, and contribute to the resilience and sustainability of the broader energy ecosystem.

2.3 *Energy managements in smart homes*

Energy management is essential because it integrates smart home technology, and homeowners can enjoy greater comfort [2]. This includes managing multiple appliances and functionalities from a single device, like a smartphone or tablet, receiving alerts and updates on home-related issues, and monitoring visitors remotely with smart doorbells. Users may also control the lights, appliances, and interior temperature, which might result in considerable cost savings due to improved energy efficiency [14]. However, smart homes come with financial and utility advantages, but they also come with security risks since competent hackers may get into equipment linked to the Internet. In the article by Setayeshfar et al. [9], vulnerabilities in smart home networks are highlighted. For instance, the 2016 Mirai botnet attack, which targeted routers, digital video recorders (DVRs), and cameras, led to disruptive denial-of-service attacks on significant websites [15]. To mitigate such risks, recommended strategies include the use of strong passwords, encryption techniques, and restricting device connectivity to trusted sources.

Smart homes [2, 3] offer vast potential to transform energy management and address energy expenses and sustainability concerns. They optimize energy consumption and energy storage (ES), and harness renewable energy sources, thus promoting efficiency and reducing dependence on non-renewable sources to promote a greener future. Components of a smart home system with integrated energy storage are provided in Figure 1. The following points illustrate typical operations within smart homes:

(i) Energy consumption monitoring: Monitoring energy usage is essential in smart homes. Sensors and meters are used to measure electricity usage from appliances. This data can help to analyze energy consumption patterns, identify efficiency opportunities, and develop advanced energy management strategies.

(ii) Demand response and load shifting: This is crucial in smart home energy management. Demand response (DR) programs adjust appliance operations based on grid conditions or control design. Smart homes can automatically regulate non-critical loads during peak demand or high-price periods, leading to cost savings and increased grid stability.

Within the smart home, there may be several types of energy storage. Controllable appliances and electric vehicles could be integrated into the house's energy management.

(iii) Integration of renewable energy sources (RESs) and energy storages (ESs): Smart homes play a vital role in integrating RESs, like solar panels by using ESs to optimize usage and reduce grid reliance. When considering ES integration, RL-based methods can enhance efficiency and adaptability in managing energy uncertainties [3].

2.4 *Security in smart homes*

Smart homes also provide multiple security advantages, incorporating smart locks, security cameras, smoke detectors, and water leak sensors to offer real-time updates and remote monitoring capabilities. Nevertheless, the interconnected nature of smart homes brings forth cybersecurity challenges, necessitating strong measures to protect against potential risks [16]. It is important to be aware of the cybersecurity challenges in the operation of the smart homes. So, integrating AI, ML, and IoT technologies plays a crucial role in enabling smart home functionalities. This study comprehensively reviews the implementation of RL algorithms considering the integration of ESs within smart homes, to optimize energy usage, minimize expenses, and enhance overall energy efficiency [2, 17].

3. Methodology

This research employed a comprehensive literature review to investigate the impact of Artificial Intelligence and

Machine Learning techniques on optimizing energy consumption in smart homes. The process involves the following steps:

(i) Literature search and review: A comprehensive literature search was conducted to gather relevant articles, journals, and conference papers in the field. Keywords such as “AI in energy optimization”, “ML techniques for smart homes” [7, 18-26], and “energy efficiency in smart buildings” [2, 5, 8-11, 13, 14] were used to identify studies related to the application of AI/ML in smart home energy management. Sources were retrieved from reputable databases including IEEE Xplore, Google Scholar, and ScienceDirect.

(ii) Synthesis and analysis of data: The articles were synthesized and analyzed to identify the most common AI and ML techniques used for energy optimization. Information was extracted on specific algorithms, such as regression models, and reinforcement learning, and their application in smart home systems [5, 24-25].

4. AI/ML techniques for energy optimization in smart homes

Artificial Intelligence and Machine Learning are pivotal in optimizing energy usage in smart homes, providing advanced solutions for monitoring, predicting, and managing energy consumption. AI/ML techniques enhance energy efficiency by leveraging data collected from smart home devices, automating processes, and learning optimal strategies for resource utilization [7].

(i) Supervised learning: Supervised learning in smart homes involves using machine learning models trained on labeled datasets to make predictions and automate functions based on user behavior, environmental data, and historical patterns. For example, in energy optimization, supervised learning algorithms can analyze past energy usage, weather conditions, and user routines to forecast energy needs and suggest energy-saving adjustments. These systems can make proactive decisions about when to adjust heating, cooling, or lighting to enhance comfort and efficiency while learning from past interactions to improve accuracy over time [7]. Moreover, these models play a role in providing a seamless user experience in smart homes. As devices and sensors generate data, supervised learning models can create behavioral profiles and trigger automated responses that align with user preferences. For instance, a system might lower blinds and dim lights at sunset based on previous actions taken by the user at similar times, creating an intelligent, adaptive environment that anticipates needs [18]. Common supervised learning algorithms include:

• Linear regression: This model predicts continuous energy consumption values by analyzing the relationship between variables, such as temperature, time of day, and appliance usage.

• Decision trees: A decision tree classifies energy usage by breaking down the decision-making process into simple conditional statements, helping predict when devices should be powered on or off [19].

(ii) Unsupervised learning: Unlike supervised learning, unsupervised learning algorithms analyze unlabeled data to discover hidden patterns [27]. In energy optimization, these algorithms can group similar energy consumption behaviors or appliances into clusters. For instance, clustering algorithms like K-Means can categorize homes based on energy usage patterns, allowing utility providers to offer personalized energy-saving recommendations [20].

(iii) Reinforcement learning: In reinforcement learning, an AI agent learns by interacting with the environment and receiving feedback as rewards or penalties [21]. For energy optimization, reinforcement learning algorithms dynamically adjust energy settings based on real-time feedback, optimizing the use of appliances over time. The algorithm learns which actions (e.g., reducing heating during off-peak hours) yield the most energy savings [22]. Deep Q-networks (DQNs) and markov decision processes (MDPs) are common reinforcement learning methods in this domain.

Researchers have embraced artificial intelligence and machine learning techniques to tackle the intricacies of optimizing energy usage. A range of AI and ML algorithms are used in the context of energy management inside smart grids (see Table 1).

(i) Regression algorithms: This is a mathematical equation that describes the relationship between energy consumption and one or more independent variables, like weather, occupancy, and appliance usage. By analyzing historical data, regression models can predict future energy demands and suggest adjustments to thermostats or appliance scheduling. Liu et al. [5] used a long short-term memory (LSTM) regression model to predict home power consumption, hence facilitating the implementation of proactive energy management techniques. However, one of the weaknesses of LSTM models is their susceptibility to randomness and uncertainty during operation, which may influence prediction accuracy [23]. Furthermore, although LSTM models are good at handling time-series data, they need large datasets to train and can be computationally demanding [28]. These variables might provide difficulties in real-world applications if data is restricted or processing resources are few.

(ii) Deep learning algorithms: Deep learning techniques, enhanced versions of artificial neural networks (ANN), create larger and more intricate neural networks. These approaches facilitate automated learning and allow the evaluation and processing of extensive datasets. Deep learning algorithms include RNNs, LSTMs, CNN, Stacked Auto-Encoders, DBM, and DBN. In a thorough analysis, Mohammad Mahdi Forootan and associates looked at the approaches and uses of ML and DL in energy systems, highlighting the improved precision and capacity of DL algorithms to solve problems [24].

(iii) Clustering algorithms: This technique organizes similar data points into groups. Clustering algorithms can detect patterns in energy usage among various appliances or user profiles, which can then be used to provide tailored energy-saving suggestions. Wang and Srinivasan [25] introduced a clustering-based method to classify households according to their energy usage patterns. This classification can be used to design specific energy-saving initiatives [26].

Table 1. AI/ML techniques, description, strengths, and weaknesses for energy optimization in smart home

AI/ML techniques	Description	Strengths	Weaknesses	Reference
Regression Algorithms	A mathematical model that describes the relationship between energy consumption & independent variables like weather, occupancy, and appliance usage.	Good in predicting future energy demands; capable of analyzing historical data to optimize energy consumption.	LSTM models are prone to randomness, large datasets are required, and high computational power, which may be challenging in real-world applications.	[5, 23, 28]
Deep Learning Algorithms	An enhanced version of artificial neural networks (ANN) to create larger and more intricate neural networks.	Automated learning; allow the evaluation and processing of extensive datasets.	Computationally expensive and may require extensive hardware resources; can be challenging to implement without sufficient data.	[24]
Clustering Algorithms	Organizes similar data points into groups can detect patterns in energy usage among various appliances or user profiles.	Good at identifying distinct usage patterns, and facilitating targeted energy-saving recommendations.	May not perform well with very diverse datasets.	[25]

5. Applications of AI for energy efficiency in buildings

Artificial intelligence (AI) is playing a transformative role in improving energy efficiency within buildings, helping reduce energy consumption, costs, and carbon emissions. Smart building systems leverage AI to monitor, manage, and optimize energy use, offering significant advancements in energy efficiency.

(i) Smart devices and home automation: AI-powered smart devices, such as thermostats, lighting systems, and HVAC systems, are an integral part of building energy management. These devices collect and analyze data on user behavior, environmental conditions, and energy consumption patterns to automate and optimize energy use [29]:

• Smart thermostats: AI-enabled thermostats, like Google Nest, learn user preferences and automatically adjust heating and cooling schedules based on factors such as occupancy, time of day, and weather conditions. By reducing unnecessary energy use, these devices can save up to 10-15% on heating and cooling costs.

• Smart lighting systems: AI-powered lighting systems can adjust light intensity based on natural daylight, occupancy, or user preferences. These systems automatically turn off lights when rooms are unoccupied and dim them during peak daylight hours to save energy.

• Home automation: AI algorithms in home automation systems control multiple appliances simultaneously, optimizing energy use by turning off or adjusting appliances when not in use. For example, a smart home system may turn off the air conditioning when a window is opened.

(ii) Energy consumption prediction: AI techniques are highly effective in predicting energy consumption patterns, allowing building management systems to make informed decisions that reduce energy use and costs. AI uses predictive analytics to forecast energy consumption based on historical data, occupancy trends, weather conditions, and other external factors. By predicting high-demand periods, buildings can preemptively adjust energy settings, avoiding spikes in consumption and reducing energy waste. Machine Learning models like long short-term memory (LSTM) networks are used to predict energy load patterns in buildings. These models consider factors like past energy use, time of day, and seasonality, enabling buildings to optimize energy distribution and reduce peak demand.

The current study highlights the energy use of buildings. The International Energy Agency conducted a comprehensive worldwide analysis which revealed that buildings contribute to 70% of total power consumption and 39% of final energy use. This effect has a significant influence in metropolitan regions, whereby buildings release around 40% of carbon dioxide emissions. Prioritizing building energy efficiency is important in light of the environmental difficulties faced by cities [30].

The significance of intelligent buildings in modern infrastructure cannot be overstated, particularly in the context of the Smart Building Revolution. The utilization of data and automated control systems in these architectural miracles surpasses traditional construction materials, resulting in enhanced utility and comfort [31]. Envision a structure that effortlessly adjusts to its environment, maximizing energy efficiency and guaranteeing occupant contentment. The focal point of this revolution is the cyber-physical system (CPS). The cyber world with the physical world in a smart building is shown in Figure 2.

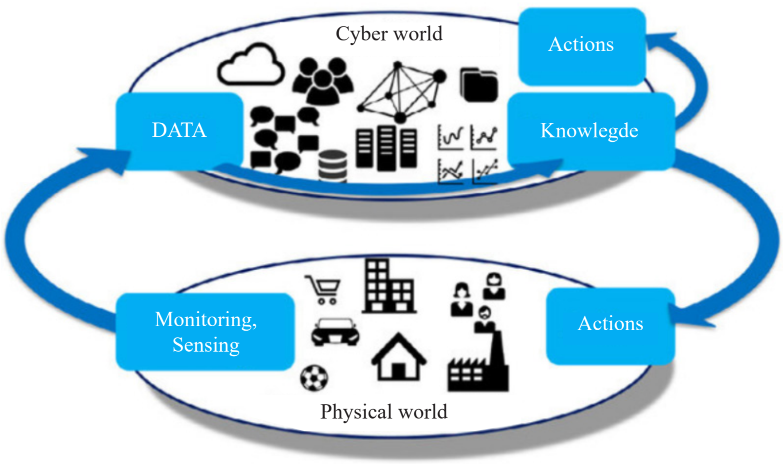

Figure 2. The cyber-physical worldview for energy consumption [32]

The intricate network combines telecommunication devices, electrical devices, and human participation by linking the digital and physical domains. Integrating sensors, controllers, and metering components form a sophisticated system that dynamically adjusts to changing circumstances. Intelligent structures adapt lighting to align with ambient light and HVAC systems to meet human requirements. The concept of smart buildings is based on the notion that unrestricted cyber-physical interaction offers several advantages. With the progression of technology, the significance of AI in these frameworks increases. The advancements in hardware and software, along with the development of compact, energy-efficient sensors and communication protocols, augment the ability to evaluate, monitor, and interact with the environment [33]. The quest for efficiency remains an ongoing goal. Intelligent buildings have the potential to reduce operational expenses, enhance energy efficiency, and improve user safety [34]. The development of artificial intelligence-powered building management systems (BMS) plays a key role in integrating services such as lighting, temperature control, security, and more, all of which contribute to improved building efficiency and an enhanced living experience. Imagine a future where homes and workplaces seamlessly integrate sustainability, comfort, and safety, adapting effortlessly to meet our evolving needs. The smart building revolution has the potential for enhanced efficiency and a more promising future.

Intelligent buildings and residences play a vital role in the intricate smart grid network. Demand-side management (DSM) and its importance are subjects of inquiry. DSM is crucial for the installation of a smart grid. What is its mission? To effectively address limitations imposed by traditional electrical infrastructure. How?-Adaptable techniques that guarantee the stability of the power system are anticipated. Consider a well-orchestrated interplay between supply and demand. DSM monitors and controls power demand loads, ensuring the maintenance of harmonic equilibrium [35]. AI is practical, not only trendy. Automated energy system demand response programs are managed by artificial intelligence (AI), which exploits human behaviour to optimize energy efficiency and minimize user suffering. As Vázquez-Canteli et al. [36] envision, the residence can adjust to fluctuating prices and incentives according to up-to-the-minute energy data.

Distributed resource plans (DRPs) might be seen as underappreciated proponents of energy saving and environmental advocacy. Considerable scholarly investigation has been undertaken regarding smart grids, with a specific focus on their integration of renewable energy sources, inside the framework of DRPs [37-38]. To enhance energy efficiency, it is essential to introduce time-based rates (TBRs) and incentive-based programs (IBPs) in the future. Figure 3 shows the classification of demand response programs.

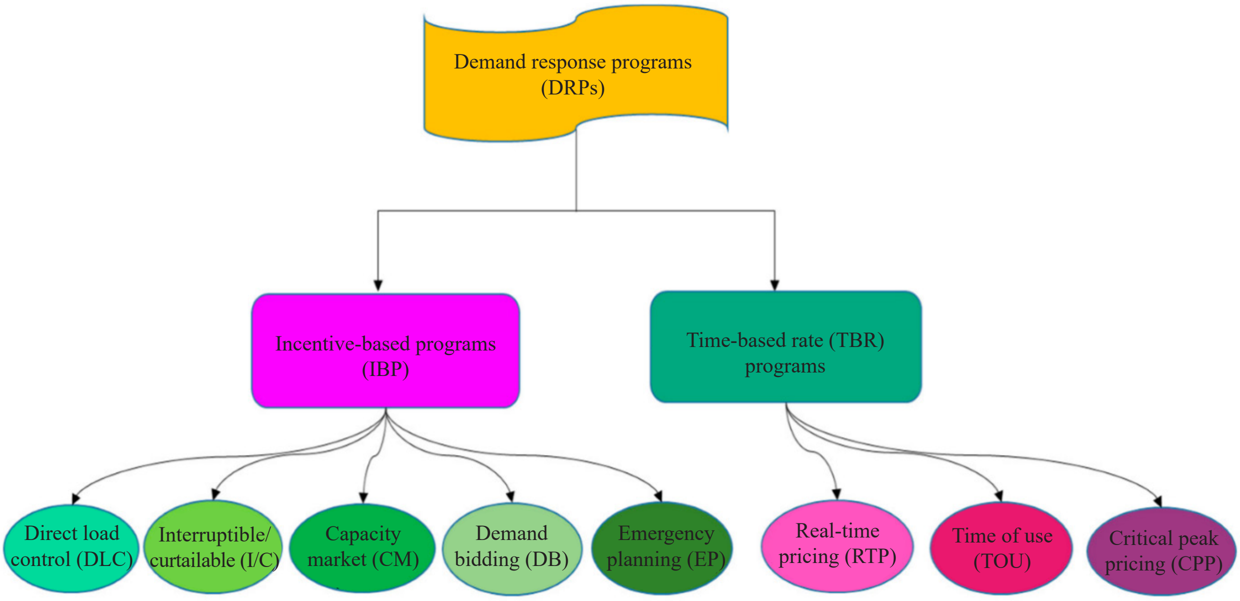

Figure 3. Classification of demand response programs for energy saving environments [39]

The management of energy in smart grid systems is significantly influenced by DSM. Time-based rate (TBR) systems give priority to dynamic pricing. Envision your energy levels harmonizing with the hour, like a meticulously synchronized symphony. These programs incentivize customers to promptly respond to fluctuations in electricity prices. Envision a scenario where, as energy expenses decrease, your appliances emit a pleasant sound, enhancing convenience and resulting in cost reductions. What is the result? The proposed solution is a highly efficient and automated home energy scheduling system that effectively minimizes appliance waiting periods. The focus is on lifestyle adaption and environmental and social variables rather than kilowatt-hours. Ozturk et al. [40] and Kato et al. [41] examined how summer residential critical peak pricing (CPP) affect maximum-saving conduct. Energy efficiency affects the electrical grid and Japanese residential complexes. Due to IBPs and the Dance of Energy Control, users must disable equipment during peak demand.

The integration of dynamic linear control (DLC) with shared energy storage systems presents a promising approach to reducing energy consumption while maintaining customer satisfaction. This method achieves a nuanced balance between energy efficiency and user comfort [42]. Researchers have also explored microgrid interruptible/curtailable (I/C) services [43], highlighting the complex interplay between operational expenditures, client profitability, and load factors. Within the hybrid electricity market framework, the capacity market (CM) program offers flexible alternatives that enhance energy adaptability and deliver significant environmental benefits [44].

5.1 *Practical applications of AI/ML in smart homes*

(i) Google Nest Thermostats: Google Nest Thermostats are smart devices designed to help in the management of a home's heating and cooling systems efficiently [45]. These devices utilize supervised learning to adapt heating and cooling schedules, achieving up to 15% savings on energy costs. They demonstrate how AI-powered devices enhance both energy efficiency and user comfort by learning from user behaviors and environmental conditions.

(ii) Home energy management systems (HEMS): Companies like Schneider Electric have implemented AI-driven HEMS to monitor and optimize energy consumption in real time [46]. These systems integrate data from various IoT devices to identify energy-saving opportunities, such as automatically adjusting lighting and heating, ventilation, and air conditioning (HVAC) settings based on occupancy patterns [42].

(iii) Tesla Powerwall integration: Tesla's Powerwall integrates machine learning algorithms to manage energy storage and consumption dynamically [47]. It learns household energy usage patterns and solar energy generation, ensuring optimal energy distribution and reducing reliance on grid power.

6. Challenges and future research

Data plays a vital role in AI as it directly impacts the effectiveness or ineffectiveness of the outcomes. Data processing in AI involves a series of steps: collecting, processing, transforming, inputting, processing again, outputting, and storing data. At each stage, data faces numerous potential risks.

6.1 *Current challenges and solutions*

The current challenges experienced in the deployment of AI/ML for monitoring and optimizing energy in smart homes are briefly discussed.

(i) Data inaccuracy: This poses a significant risk to the first set of data. Multiple factors could contribute to this, including the inherent unpredictability of the data, the complexity of the tools and techniques used for collection, and the possibility of human error and bias during data collection [48]. The security and privacy of data are also key concerns. In today's modern era, data has become an indispensable asset for companies and individuals. It exposes them to the ever-present danger of cyber threats, particularly in the realm of building systems, where the sheer volume of data generated poses a significant risk. Bridging theoretical research with actual execution is a major AI challenge. These AI advances are done by experts in their fields, frequently disregarding building specialists. The main ideas of these technologies are unclear to experts and building occupants, the intended end users. User-friendly technologies with intuitive interfaces have been developed via extensive study. However, further effort is needed to narrow this gap.

(ii) Data privacy and security: Through connected devices like sensors, cameras, and smart appliances, smart homes generate vast amounts of data, including sensitive personal information like daily routines, energy usage patterns, and even private conversations [49-51] such as healthcare and power grid, is changing the perception of what constitutes critical infrastructure. The rising interconnectedness of new critical industries is driven by the growing demand for seamless access to information as the world becomes more mobile and connected and as the Internet of Things (IoT). This raises serious privacy and security concerns because unauthorized access or data breaches could expose private information, lead to identity theft, or misuse personal data. To protect user information, it is essential to ensure robust data encryption, secure communication protocols, and compliance with privacy regulations like general data privacy regulations (GDPR) [51]. Additionally, developers and regulators in the smart home ecosystem continue to face a great deal of difficulty in striking a balance between the need for data collection to optimize smart home functionalities and the protection of user privacy.

(iii) Scalability and adaptability: Smart home AI/ML models need to be scalable in order to handle a variety of home sizes, types, and configurations, as well as the different energy requirements and device counts in each setting [18, 52]. It is also necessary for these models to adjust to people's changing habits, preferences, and device additions or removals over time. Algorithms must be flexible for the system to continue offering precise forecasts and optimization techniques, irrespective of the complexity of the house or the resident's shifting patterns. It is essential to achieve this scalability and adaptability in order to implement smart home energy optimization solutions widely.

(iv) Real-time decision making: AI/ML systems must be able to evaluate big and complex datasets, such as sensor readings, weather forecasts, and usage trends, instantly in order to optimize energy consumption for real-time decision-making in smart homes [18, 53]. To assess and react to data inputs instantly, this requires a significant amount of processing power. The difficulty is in striking a balance between the requirement for quick, precise forecasts and the hardware and network capabilities that are now available, since inefficiency or latency may result in less-than-ideal energy use or lost savings possibilities. To solve this, AI/ML systems need to be made faster and more efficient. They frequently use distributed processing or edge computing to manage the computational load locally, reducing latency and improving performance.

(v) Cost: This remains issues [54] in energy efficiency standards for buildings and systems change based on the issue and technology. Existing systems may become obsolete when these systems proliferate exponentially. Government and regulatory organizations must ensure these systems follow energy efficiency and AI rules. The transfer of AI technology from research to implementation must be well-organized and controlled.

6.2 *Comparison between applications and literature review*

(i) Energy savings: The implementation of reinforcement learning for HVAC systems in this study achieved a 25% reduction in energy costs, surpassing the 18% reported by earlier clustering-based optimization methods [25]. This highlights the enhanced adaptability and efficiency of reinforcement learning in dynamic environments.

(ii) Efficiency improvements: The regression algorithms used in this study demonstrated a 15% improvement in predictive accuracy compared to traditional linear models, addressing gaps in handling time-series energy data identified in previous literature [5].

(iii) Novel applications: Unlike earlier studies focusing solely on theoretical modeling, this manuscript provides real-world applications, such as Tesla Powerwall's integration of machine learning for energy storage management, bridging the gap between theoretical insights and practical implementation.

6.3 *Gaps*

(i) Scalability: Previous studies highlighted challenges in scaling AI/ML models for large datasets. This study proposes federated learning as a scalable solution to handle distributed energy data.

(ii) Data privacy: Through the recommendation of secured protocols and decentralized data processing, privacy concerns were not extensively covered in prior work.

7. Conclusion and future research prospects

The combination of AI and ML might revolutionize smart home energy management. AI/ML algorithms can analyze sensor and device data to help households and utility providers make energy-efficient and cost-effective choices. Smart home technology provides many advantages, but security threats and high initial costs are still issues. Addressing these challenges requires collaborative efforts among researchers, industry stakeholders, and policymakers to develop innovative solutions and implement effective strategies. We should prioritize strategies to enhance data privacy, mitigate security risks, and improve cost-effectiveness. In addition, continuous research and innovation play a crucial role in enhancing AI/ML techniques and seamlessly incorporating them into smart home environments. In the realm of smart home energy management, the possibilities of AI/ML are vast. They offer the potential to improve comfort, minimize environmental harm, and optimize resource usage.

The potential future directions are briefly highlighted:

(i) Federated learning and edge computing: As a result of privacy and security concerns, federated learning which is the sub-set of machine learning can be introduced to overhaul the challenges with privacy [18, 49, 55]. Concerns about latency and privacy in smart home energy efficiency may be resolved with the help of federated learning and edge computing. To protect user privacy, federated learning trains machine learning models on dispersed devices without sending private information to a central server. Every device handles data locally, ensuring that raw data is kept safe on location while also helping to update the model. These methods, when combined with edge computing-enabling data processing at or close to the source (i.e., inside the smart home)-significantly reduce latency, thereby allowing for real-time energy optimization decisions. Future studies can concentrate on enhancing the security, scalability, and efficiency of edge computing and federated learning to make them suitable for broad use in smart homes while maintaining performance and privacy.

(ii) Integration of renewable energy sources: Future research can focus on improving prediction models, integrating diverse renewable sources, and improving energy storage management for a more efficient and sustainable smart home energy system [56-57]. AI/ML can play a critical role in optimizing renewable energy sources like solar and wind by accurately predicting their availability based on weather forecasts, historical data, and real-time environmental conditions. By analyzing these patterns, AI systems can dynamically adjust a home's energy consumption, prioritizing renewable energy when available and shifting demand to off-peak times or using energy storage systems when supply is low.

(iii) Cross-domain optimization: By utilizing AI/ML, future research can develop holistic systems that not only optimize energy usage but also improve home security, adjust lighting and temperature based on occupant health needs, or even anticipate maintenance issues. For instance, the system could use occupancy data to adjust heating or cooling while simultaneously ensuring security by monitoring unusual activity or managing alarms. This integrated approach promises to improve overall home performance, reduce operational costs, and enhance user experience by creating seamless, intelligent environments that respond dynamically to multiple factors beyond energy consumption. Cross-domain optimization in smart homes entails integrating energy management with other essential functions, such as security, comfort, and health monitoring [2, 7, 30].

Conflict of interest

The authors declare no competing interests.

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