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Intelligent Harmony: Harnessing Deep Reinforcement Learning for Smart Home Energy Management

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A B S T R A C T

This review examines the intricate developments and challenges in smart home energy management systems, with a particular focus on the integration of cutting-edge technologies and innovative methodologies aimed at addressing the rapidly evolving landscape of energy use. Despite significant strides in the field, there remain critical gaps that require further attention. Chief among these are ensuring data privacy and security, which have become increasingly important with the proliferation of interconnected devices, managing the complexity of heterogeneous data from diverse sources, and overcoming persistent interoperability issues that hinder seamless communication among various smart devices. To address these challenges, this review outlines several promising directions for future research. These include the implementation of robust encryption techniques to protect sensitive information, the development of scalable storage solutions to handle the ever-growing volume of data, and the deployment of advanced analytics algorithms capable of real-time processing and decision-making. Additionally, the review emphasizes the need to explore the socio-economic implications of smart energy management systems, particularly in light of global crises such as the COVID-19 pandemic, which have underscored the importance of resilient and sustainable energy infrastructures. By providing a comprehensive overview of both the current state of smart home energy management and the areas that require further exploration, this review aims to foster advancements that will lead to the creation of more efficient, secure, and adaptable systems. Ultimately, addressing these challenges will contribute to the development of sustainable solutions that align with broader societal goals, enhancing the resilience of energy infrastructures while promoting environmental stewardship.

Keywords: *Deep Reinforcement Learning; Smart home; Energy management; Artificial intelligence*

1. Introduction

Energy management in smart homes is one of the important topics in the field of energy and the environment, which can be improved and optimized using intelligent methods and artificial intelligence. One of the methods that can be used for this purpose is deep reinforcement learning (DRL). In this method, an intelligent agent is trained to make optimal decisions based on the current state of the environment and our goal of reducing energy consumption. In other words, the intelligent agent makes decisions according to different environmental conditions that lead to improved energy efficiency and reduced energy consumption costs in the home. To achieve this, a model must first be trained using a deep neural network and a DRL algorithm that can recognize the current state of the environment and enable optimal operations to reduce energy consumption. Subsequently, by employing various methods such as load management, temperature and humidity control, lighting control, and other intelligent methods, energy consumption in the home can be reduced, leading to savings in energy-related costs.

The purpose of energy management in a smart home is to optimize energy consumption in the home by using different smart systems. This optimization can lead to reducing energy costs, reducing energy consumption and preserving the environment. The basis of DRL is a machine learning method that works on deep neural networks and is used to solve problems such as optimization control and resource management in energy control in smart homes. DRL algorithms can be used as an efficient method for control and Energy consumption management to be used in smart homes. By using the DRL method, different smart home systems can be connected to each other and energy consumption can be optimized. For example, by using a DRL system, lighting and heating systems can be connected to each other and intelligently control energy consumption. Also, using this method, energy consumption optimization algorithms can be improved and energy consumption minimized.

Smart houses provide their residents a pleasant, completely regulated, and secure way of living. Furthermore, smart houses have the capability to save energy and reduce expenses by potentially generating revenue via the sale of environmentally friendly renewable energy to the power grid. Conversely, the anticipated reduction in overall residential energy consumption motivates governments to back potential smart-home technology. Several nations have implemented several regulations, legislations, and subsidy initiatives to promote the adoption of smart houses. These measures include incentivizing the improvement of heating systems, providing assistance for constructing energy storage, and implementing smart meter installations. The European Standard EN 15232 (de Normalisation, 2012) and the Energy Performance of Building Directive 2010/31/EU (Zangheri et al., 2021), along with Directive 2009/72/EC and the Energy Road Map 2050 (Skea, 2012), promote the use of smart-home technology to reduce electricity consumption in residential areas. A smart house is equipped with automation systems that regulate various appliances, such as lighting and heating, in response to varying climatic circumstances, hence allowing for environmental management. Currently, modern control schemes include several functionalities in addition to traditional switching operations. They have the capability to see and track the conditions inside the house as well as the actions of its residents. Additionally, they have the capability to autonomously execute pre-programmed activities and control equipment in predetermined patterns, either independently or in accordance with the user's specifications. In addition to the convenience they provide, smart homes ensure the effective use of power, resulting in a decrease in peak load, a reduction in energy costs, and a minimization of greenhouse gas emissions (Al-Ali et al., 2011).

Smart houses may be analyzed from several perspectives. The individual evaluation of communication systems (Kuzlu et al., 2015), social implications (Wilson et al., 2015), thermal properties (Schieweck et al., 2018), technology, and trends of smart houses (Nacer et al., 2017) is conducted. Furthermore, this paper examines the surveillance and simulation of intelligent household devices using intelligent meters in order to achieve precise load prediction, as mentioned in references (Yuan et al., 2020). In recent times, the authorities responsible for the electricity grid have made changes to the household electrical tariffs with the aim of promoting appropriate demand-side control by homeowners. In contrast to other analyses, this research presents an examination of smart houses from the perspective of electrical and economic factors. The article also examines smart-home energy-management systems (SHEMS) in two distinct modes: offline load scheduling and real-time control. The potential effects of atypical power use patterns in smart homes on future smart grids are also outlined.

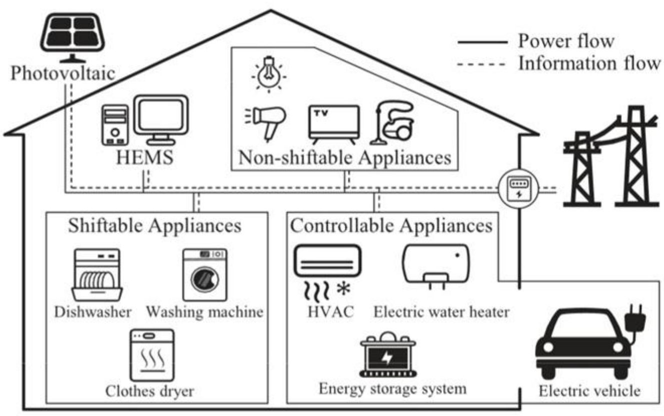
The phrase 'smart home' has been widely used for almost two decades to refer to dwellings equipped with regulated energy systems. This automated system offers a more convenient lifestyle for homeowners compared to traditional non-automated houses, particularly benefiting elderly or handicapped individuals. In recent times, the term 'smart home' has been expanded to include a broader range of technological applications consolidated in a single location. Sowah et al. (2018) describe smart houses as residences that provide their inhabitants a pleasant, secure, and energy-efficient living space at the lowest feasible expenses, independent of the residents' circumstances. A smart house, as defined by the Smart Homes Association, is the incorporation of technology and services via home networking to enhance the quality of life (Robles & Kim, 2010). Makhadmeh et al. (2019) provide a definition of smart homes as residential residences that have integrated smart technology to enhance the comfort of users (residents) by improving safety and healthcare and optimizing electricity usage. Smart-home appliances may be controlled and monitored remotely by users using the home energy-management system (HEMS), which utilizes telecommunication technology to offer a remote monitoring system (Makhadmeh et al., 2019). Smart homes are residential buildings that utilize various communication schemes and optimization algorithms to forecast, analyze, optimize, and regulate their energy consumption patterns based on predetermined user preferences. The goal is to maximize economic benefits while maintaining a comfortable lifestyle within predefined conditions (El-Azab, 2021). The use of distributed clean energy produced by intelligent households offers several advantages for potential intelligent power networks. Therefore, it is essential to do thorough research on the impact of smart houses on future power grids. In the foreseeable future, smart houses will have a significant role as power providers in contemporary grids, rather than only being electricity consumers (El-Azab, 2021).

Considering that the use of smart homes is increasing, the use of DRL method can be used to improve energy consumption optimization algorithms and minimize energy consumption. As the use of smart homes continues to rise, employing DRL methods in energy management within these homes can serve as an efficient solution for improving efficiency and achieving energy savings. Given the widespread application of smart homes in the construction industry and among households, research in this area can lead to enhanced efficiency and cost reduction. Therefore, examining the topics mentioned in the previous response can provide a comprehensive and thorough introduction for further studies in this field.

Additionally, smart homes, by leveraging modern technologies, offer capabilities for intelligent control and management of home resources, including lighting, heating and cooling, CCTV, electronic doors, and more. Energy management in smart homes is of significant importance because, in light of rising energy costs, reducing energy consumption in homes is highly effective both economically and environmentally. For instance, by using smart home systems, artificial lighting can be employed instead of natural light for indoor spaces, thereby significantly reducing electricity consumption. Moreover, advanced technologies such as geothermal heating, intelligent air conditioning systems, and other equipment can be utilized for heating and cooling the home, which further contributes to energy savings as shown in Figure 1.

Figure 1

Architecture of a smart home.



Thus, energy management in a smart home can be economically beneficial for reducing energy costs and enhancing user comfort. Environmentally, it can help preserve natural resources. In a smart home, energy consumption can be controlled using sensors and smart devices. For instance, with the use of motion and light sensors, the home's lighting system can be adjusted to turn off when there is no movement inside and natural light is available, thereby reducing energy consumption. Additionally, smart heating and cooling systems can intelligently regulate the home's temperature, significantly reducing energy usage. With these systems, the temperature can be individually set for each room, reducing energy consumption in less frequently used areas.

Moreover, smart home systems can intelligently manage energy consumption for household electronic devices. For example, electronic equipment can be turned on and off smartly, resulting in substantial energy savings. Overall, using smart home systems can lead to a significant reduction in energy consumption, lowering energy costs and contributing to the conservation of natural resources. Furthermore, smart home systems can help reduce energy consumption during peak pricing periods. For instance, automatic control of heating and cooling systems can minimize energy use when electricity prices are high. Smart home systems can also assist users in better understanding their energy consumption. Users can precisely monitor their energy usage at any time, enabling them to find more efficient methods for managing energy consumption. Ultimately, smart home systems can provide users with better information for making decisions about their energy use. For example, energy consumption data can be accurately compiled over time, offering valuable insights into energy consumption patterns and aiding in the improvement of energy management.

This review aims to provide a comprehensive overview of the application of DRL in smart home energy management, highlighting its potential to revolutionize how energy is optimized in residential settings. By examining recent advancements and current methodologies, this paper contributes to the understanding of how DRL can enhance energy efficiency, reduce costs, and integrate renewable energy sources within smart homes. The review will analyze both model-free and model-based DRL approaches, single-agent and multi-agent systems, and hierarchical reinforcement learning strategies. Additionally, it will discuss key benefits and challenges, present notable case studies, and suggest future research directions to advance the integration of DRL in smart home energy management systems.

2. Literature review

The application of DRL in smart home energy management has garnered significant attention in recent years, with numerous studies exploring its potential to optimize energy consumption, enhance efficiency, and integrate renewable energy sources. Durai et al. (2021) presented an ontology-based model (SQLIO) aimed at preventing and detecting SQL Injection Attacks (SQLIA) in web applications. The authors implemented ontology creation and prediction rule-based vulnerabilities to enhance security in a cloud environment. Their approach addressed SQLIA vulnerabilities to a significant extent, demonstrating its effectiveness in safeguarding web applications. Gupta et al. (2022) presented a comparative review of various side-channel attacks and their countermeasures, highlighting the successful breaches of robust cryptographic operations through side-channel analysis. It discussed the inadvertent leakage of information exploited by these attacks and proposed a new approach to enhance network security. The primary objective was to summarize progress in side-channel attack research and identify future challenges. He and He (2021) explored the fundamental concepts and applications of cloud computing, emphasizing the security concerns intrinsic to its open and distributed nature. They proposed a security-enhancing algorithm using data mining and decision tree techniques, noted for its low computational demand and independence from the number of clients, facilitating practical implementation. Mishra and Chakraborty (2020) explored the transformation of urban centers into smart cities through the integration of ICT, IoT, and AI technologies, focusing on enhancing urban efficiency and reducing costs. They proposed a novel architecture that combined these technologies with distributed cloud computing, aiming for autonomous city management and environmental sustainability. The study highlighted the economic benefits, implementation challenges, and the potential for smart cities to maintain ecological balance using solar energy. Almaiah et al. (2023) introduced a novel data-fusion method paired with an emotional-intelligence-inspired enhanced dynamic Bayesian network (EDBN) for secure healthcare data transmission. They demonstrated superior performance over existing methods like DCNN, FRCNN, and CNN in terms of accuracy, precision, recall, and F1 scores. The proposed approach effectively improved patient care and data security. Wang et al. (2024) explored the use of machine learning, specifically generative adversarial network technology, to detect credit card fraud online. They identified and analyzed characteristics and sources of fraudulent activities, enabling real-time and accurate fraud detection. The research significantly advanced methods for preventing cyber fraud and enhancing network security. Praveen et al. (2023) discussed the challenges and opportunities associated with using cloud computing in the healthcare sector, particularly emphasizing the need to secure sensitive medical data. The research highlighted the DACAR platform as a solution, which used a rule-based information sharing policy and a scalable cloud infrastructure to enhance data security, accuracy, and efficiency. The platform also aimed to address issues of large-scale deployment and service integration in healthcare systems.

There are numerous reviews and survey articles on home energy management systems. Table 1 presents a concise overview of the primary review publications pertaining to HEMS from 2015 to March 2022. These research articles can be broadly classified into architecture based on various features of HEMS. (Zhou et al., 2016), energy management system functionalities (Gholinejad et al., 2021), (Hosseini et al., 2017), infrastructures (Zhou et al., 2016),modeling approaches and categories (Beaudin & Zareipour, 2015), and types of optimal scheduling strategies (Beaudin & Zareipour, 2015), (Zhou et al., 2016), also applications of HEMS in SG (Smart Grid) and DR (Demand Response) (Carreiro et al., 2017) and interdisciplinary reviews on HEMS (McIlvennie et al., 2020). However, according to the classification results, it can be observed that apart from (Zhou et al., 2016), published in 2016, which reviewed all aspects of HEMS comprehensively, other review articles only cover some or even one aspect of HEMS. For instance, reference (Hosseini et al., 2017) focuses on non-intrusive load monitoring, which is a part of the monitoring functions of HEMS, while (Sierla et al., 2022) proposes a three-layer classification of machine learning applications in HEMS. This result not only suggests that the examination of HEMS in recent years has been enhanced due to more thorough investigation, but also demonstrates that the whole discourse on HEMS requires restructuring and enhancement.

Table 1

The various descriptions of smart homes in the literature

Description	Year	Reference
This study reviews the challenges, methods and implications for HEMSS modeling frameworks.	2015	(Beaudin & Zareipour, 2015)
This study provides an overview of the architecture, functions, infrastructure, scheduling strategies and adoption of RERS HEMS.	2016	(Zhou et al., 2016)
This study examined the key functions and energy saving effects of 276 articles published from 1976 to 2014 and 305 EMS related to Building Energy Management Systems (BEMS).	2016	(Lee & Cheng, 2016)
This study examines the concept and cases of BEMSS and the power line communication technology deployed in them.	2016	(Whiffen et al., 2016)
By reviewing its early applications, this paper introduces the problems encountered in achieving a real NILM and proposes a new method, the advanced NILM.	2017	(Hosseini et al., 2017)
This paper provides an in-depth review of charging infrastructure, charging technologies, international standards, applications and energy management systems (EMS) for electric vehicles (EVs).	2017	(Ahmad et al., 2017)
This study reviews back-metric EMS categories, load classification, enabling technologies and standards, and a case study of system implementation.	2017	(El-Azab, 2021)
This paper presents the key features, challenges and integrative models of energy management systems.	2017	(Carreiro et al., 2017)
This study summarizes the architecture and communication infrastructure of the EMS microgrid, analyzes different categories of optimization methods, and presents real-world implementations.	2018	(Zia et al., 2018)
This paper provides an overview beyond the impacts, factors and functions of smart HEMS in increasing energy benefits.	2020	(McIlvennie et al., 2020)
This study reviewed different forms of energy generation technologies, analyzed the quality of the literature, and introduced future recommendations on smart HEMSS.	2021	(Aliero et al., 2021)

This paper summarizes and discusses management strategies and future challenges in the field of BEMSS.	2021	(Mariano-Hernández et al., 2021)
This paper reviews EMSS islanded microgrids in terms of six main optimization aspects, along with future trends.	2021	(Raya-Armenta et al., 2021)
In this research, a scientometric research method is used to provide a 3-layer classification of machine learning applications for HEMS and BEMS functions.	2022	(Sierla et al., 2022)

In conclusion, this systematic review provides a comprehensive synthesis of recent literature exploring various aspects of energy management systems in smart homes. Through an analysis of studies spanning from 2015 to 2022, diverse methodologies, challenges, and future trends in home energy management are elucidated. The reviewed literature highlights the evolution of research from modeling frameworks to advanced optimization strategies, including the integration of renewable energy sources, electric vehicle charging infrastructure, and machine learning applications. Moreover, it underscores the importance of addressing key challenges such as real-time monitoring, communication infrastructure, and interoperability to realize the full potential of smart home energy management systems. Overall, this review contributes valuable insights for researchers, practitioners, and policymakers aiming to advance the efficiency, sustainability, and resilience of residential energy systems. This systematic review is novel in its comprehensive analysis of the diverse DRL methodologies applied to smart home energy management, offering a detailed synthesis of recent advancements, practical applications, and future research directions in this rapidly evolving field.

3. Methodology

As can be seen from Figure 2, the word "smart home" has been extensively searched in the worlds. In recent years, smart homes have witnessed a transformative evolution, driven by advancements in technology and shifting consumer preferences. One prominent trend is the integration of a diverse array of Internet of Things (IoT) devices, which has transformed homes into interconnected ecosystems capable of automation, monitoring, and control. From smart thermostats and lighting systems to security cameras and voice-activated assistants, these interconnected devices offer homeowners unprecedented convenience and control over various aspects of their homes, even from remote locations. Moreover, the increasing emphasis on sustainability and energy conservation has propelled the adoption of energy-efficient appliances and home energy management systems (HEMS) within smart homes. These systems enable homeowners to monitor and optimize their energy usage, leading to cost savings and reduced environmental impact while enhancing overall comfort and convenience.

Another notable trend in smart homes is the growing focus on personalization and customization, driven by advancements in artificial intelligence (AI) and machine learning. AI-powered systems analyze user behavior and preferences to automate routines, adjust settings, and anticipate user needs, thereby enhancing comfort and convenience. Additionally, the integration of health and wellness monitoring devices into smart homes is gaining momentum, allowing individuals to track vital signs, fitness metrics, and sleep patterns from the comfort of their homes. Wearable devices, smart scales, and health tracking apps provide valuable insights into overall well-being, empowering individuals to take proactive steps towards better health management. Overall, these trends underscore the ongoing evolution of smart homes towards greater connectivity, intelligence, and functionality, offering homeowners unprecedented levels of convenience, efficiency, and control over their living environments.

Figure 2

Google Trends report regarding the use of smart homes (GoogleTrends, 2024)

The methodology adopted for this systematic review involved a comprehensive search and selection process to identify relevant literature on energy management systems in smart homes. Initially, a thorough search of academic databases, including IEEE Xplore, ScienceDirect, and Google Scholar, was conducted using specific keywords related to smart home energy management and DRL. The search criteria included studies published between 2015 and 2024 to capture recent advancements in the field. Following the search, the identified studies were screened based on their relevance to the topic, with a focus on methodologies, applications, and implications of DRL in smart home energy management. The selected references were then organized and synthesized to provide a coherent overview of the current state-of-the-art in the field, highlighting key findings, methodologies, and future research directions. This systematic approach ensured the inclusion of diverse perspectives and insights into the review, contributing to its comprehensiveness and relevance to the research domain.

4. Role of DRL in Energy Management Using Neural Networks

DRL is a branch of artificial intelligence that focuses on learning decision-making in dynamic and interactive environments. In this method, an agent learns to receive the maximum reward by performing various actions to achieve its goal. This approach utilizes the concept of trial and error and strives to improve performance by evaluating expectations in the environment. In energy management, DRL can serve as a powerful tool for optimizing energy consumption and reducing associated costs. For example, this method can be applied to optimize electricity consumption in industrial systems, buildings, and transportation, which is one of the applications of DRL in energy control and management.

In the field of heating, ventilation, and air conditioning (HVAC) systems, DRL can be used to optimize energy consumption considering the conditions of HVAC systems, environmental systems, and user preferences. For instance, various intelligent system methods can be proposed to reduce energy consumption in different environments using this approach. DRL can also be used to optimize energy consumption in power grids. In this field, this method can be employed for electricity demand forecasting, generator power regulation, and load distribution optimization. Therefore, DRL can serve as a powerful tool in power grids, where it can be utilized for electricity demand forecasting, generator power regulation, and load distribution optimization. Consequently, DRL can be regarded as a powerful tool for optimizing energy consumption and reducing associated costs in various industries.

DRL can be used to optimize energy consumption in thermal systems. In this field, this method can be used to control the temperature of the building, adjust heating and ventilation systems, and optimize energy consumption. Optimizing energy consumption in water distribution networks. DRL can be used to optimize energy consumption in water distribution networks. By using this method, water distribution systems can intelligently optimize energy consumption and reduce related costs, so DRL can be a powerful tool in optimizing energy consumption and reducing related costs. It is used in various industries. This method, using advanced artificial intelligence techniques, can improve efficiency and optimize energy consumption in interactive dynamic systems.

DRL generally includes three main components, agent environment and reward. In this method, the agent, which can be a robot, a computer program, or any other object, is located in an environment and by performing various actions, it seeks the highest possible reward. This reward can be an operational number such as a score or correct percentage that helps the agent regarding its efficiency and performance in the environment. In energy management, DRL can be used to optimize energy consumption in various industries and systems, for example in production systems. In electricity, DRL can be used to optimize the performance of turbines, adjust the power of generators, and improve the efficiency of transmission and distribution systems. Also, in the automotive industry, DRL can be used to optimize fuel consumption in electric and hybrid vehicles. By using this method, electric and hybrid vehicles can intelligently optimize fuel consumption and reduce related costs in the construction industry. DRL can optimize energy consumption and reduce related costs in heating systems. air conditioning and lighting can be used. By using this method, different systems can be intelligently controlled and as a result, energy consumption can be optimized and costs reduced. Considering the wide range of applications of DRL in energy management, this method can It can be used as a powerful tool in optimizing energy consumption and reducing related costs in various industries. Also, DRL can be used in the optimization of solar and wind energy production systems. Using this method, energy production can be intelligently controlled and energy consumption can be optimized.

In general, DRL, as an innovative and efficient method in energy management, can be utilized as a powerful tool to optimize energy consumption and reduce associated costs across various industries. This method, leveraging the advanced capabilities of artificial intelligence, can intelligently control dynamic interactive systems, resulting in optimized energy consumption and cost reductions. DRL, as one of the advanced methods of artificial intelligence, can offer numerous benefits in energy management. This method can improve the efficiency of various systems, including power generation and distribution systems, urban equipment, transportation systems, and more. One of the significant applications of DRL in energy management is the control of power generation and distribution systems. For instance, by using this method, techniques from DRL can be employed to predict future electricity demand. By adjusting the output of power generation systems accordingly, energy consumption can be optimized, thereby reducing the costs associated with power production and distribution. DRL can be used to optimize transportation systems. This method can intelligently control traffic, optimizing vehicle fuel consumption, which in turn can lead to improved air quality and reduced air pollution in cities. By using this method, air conditioning systems can be intelligently controlled to optimize energy consumption.

DRL can be used as an innovative and efficient solution in energy management and optimization of energy consumption across various systems. This method enables intelligent control of dynamic interactive systems. For instance, it can be utilized to smartly control traffic, thereby optimizing vehicle fuel consumption. This approach can also lead to improved air quality in cities and reduced air pollution. As one of the advanced methods in artificial intelligence, DRL offers numerous benefits in energy management. It can be used to improve the efficiency of various systems, including power generation and distribution systems in different industries, urban equipment, transportation systems, and more. One significant application of DRL in energy management is the control of power generation and distribution systems. For example, this method can be employed to predict future electricity demand using DRL techniques, optimizing energy consumption by adjusting the output of power generation systems, and consequently reducing the costs associated with power generation and distribution.

Deep neural networks can be employed to control and manage smart home systems. For instance, using a deep neural network, the energy consumption of lighting, heating, and cooling systems can be optimized. In this approach, the deep neural network uses data collected from the smart home systems to intelligently and automatically control and optimize the energy consumption of these systems. Deep neural networks can also be employed for forecasting future energy consumption. Utilizing this method, energy consumption can be accurately predicted, and by adjusting the outputs of smart home systems, energy usage can be optimized. Moreover, deep neural networks can be used to detect patterns in energy consumption. By employing this technique, precise consumption patterns within a home can be identified, and with adjustments to smart home systems, energy usage can be optimized. Overall, deep neural networks can serve as an intelligent method for energy management in smart homes, optimizing energy consumption.

Deep neural networks can extensively be used to improve efficiency and optimize energy consumption in smart home systems. This method, using data collected from smart home systems, can intelligently and automatically control and optimize the energy consumption of these systems. For example, in lighting systems, deep neural networks can precisely control the energy consumption of lamps. In this approach, the neural network, using data collected from the lighting system, can intelligently and automatically manage lamp energy consumption based on environmental temperature needs, required light levels, and usage frequency. Similarly, in heating and cooling systems, deep neural networks can be used to optimize energy consumption. Using this method, the required heating and cooling levels can be predicted at any given time, and smart home systems can be adjusted accordingly.

Furthermore, deep neural networks can be used to identify patterns of energy consumption in smart homes. By accurately identifying these consumption patterns, this approach can optimize energy usage by adjusting smart home systems based on these patterns. Overall, deep neural networks serve as an intelligent and automated method in energy management for smart homes. By using this approach, smart home systems can be intelligently controlled, thereby optimizing energy consumption, reducing costs, and ultimately leading to environmental benefits by reducing pollutants and conserving natural resources. Another application of deep neural networks in smart homes includes the prediction and identification of faults in smart home systems. By accurately predicting faults in these systems, this approach can prevent potential costs through timely repair and replacement of components. In conclusion, the use of deep neural networks in energy management in smart homes can enhance the quality of life of the residents, increase the comfort and security of homes, reduce energy costs, and help preserve natural resources.

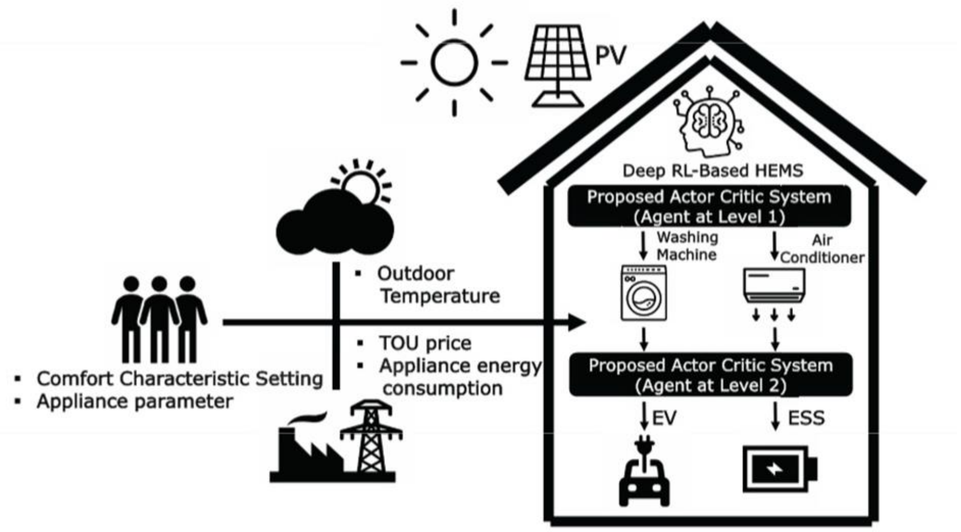
5. DRL method in energy management in smart home

DRL for Smart Home Energy Management Systems: An Intelligent and Automated Approach for Optimizing Home Energy Consumption DRL presents a sophisticated, automated method for controlling and optimizing energy consumption within smart homes. This approach leverages advanced DRL algorithms to perform energy management tasks effectively. In a smart home, the energy management system gathers data on energy usage from various integrated sensors and other data collection systems. Based on this information, DRL algorithms autonomously optimize energy consumption by intelligently controlling different home systems. For instance, in smart home lighting systems, DRL algorithms can autonomously regulate the energy consumption of lights. These optimizations are based on data collected from the lighting system, adjusting the energy usage of lights according to environmental temperature, required illumination levels, and usage frequency. Similarly, for heating and cooling systems, DRL algorithms can optimize energy consumption by predicting and adjusting to the required heating or cooling levels at any given moment. This method allows for the adjustment of smart home systems to enhance energy efficiency effectively.

Moreover, by utilizing DRL algorithms, it is possible to identify patterns in energy consumption within smart homes and enhance energy optimization by adjusting smart home systems accordingly. Overall, the use of DRL in designing smart home energy management systems provides optimization of energy usage, reduction in energy costs, and increased efficiency of smart home systems. Additionally, optimizing energy consumption in smart homes contributes to environmental sustainability and economic benefits. With continuous advancements in DRL, it is expected that this approach will be increasingly incorporated into the design of energy management systems for smart homes. A smart home energy management system utilizing DRL can autonomously and intelligently manage energy consumption based on user needs and usage patterns. This system, equipped with extensive data from various systems, can autonomously and intelligently adjust smart home systems to optimize energy consumption, thereby reducing energy costs. For example, in the management of smart home lighting, a DRL algorithm can automatically adjust home lighting levels based on data collected from sensors, reducing energy consumption. This algorithm can intelligently adjust the required amount of light based on environmental conditions and user needs, utilizing sensor data to automate and smartly manage the lighting conditions as can be seen from Figure 3.

Figure 3

A conceptual house architecture based on deep reinforcement learning (DRL).



A DRL algorithm in a smart home heating and cooling management system can automatically adjust the heating and cooling levels of a home using data collected from sensors, thereby reducing energy consumption. This algorithm can optimize energy usage by predicting the required heating and cooling levels at any given moment, consequently reducing energy costs. Generally, the energy management system in a smart home, by utilizing DRL, can automatically and intelligently reduce energy consumption, thus benefiting both the environment and the country's economy. With the ongoing advancements in DRL, this approach is expected to become increasingly prevalent in designing energy management systems for smart homes in the future, replacing traditional methods due to its reliable performance and high efficiency. One of the advantages of using DRL algorithms in smart home energy management is that these algorithms can intelligently and automatically reduce energy consumption based on environmental conditions and user needs. For example, if a light remains on in an empty room, the smart home energy management system using a DRL algorithm can automatically turn off the light, reducing energy consumption. Moreover, by employing DRL algorithms, it is possible to identify and optimize energy consumption patterns in smart homes by adjusting smart home systems. For instance, a DRL algorithm can detect electricity usage patterns throughout the day and week, and by adjusting smart home systems, it can optimize energy consumption. The use of DRL algorithms in smart home energy management systems can lead to reduced energy costs and enhanced efficiency of smart home systems. By reducing energy consumption, the costs associated with electricity bills decrease, and by improving the efficiency of smart home systems, users can more comfortably and effectively utilize their smart home features.

Overall, the energy management system in a smart home, through the use of DRL, contributes to improving users' quality of life, reducing energy costs, and enhancing environmental sustainability. Given the rapid advancements in DRL, this method is expected to be employed in future designs of energy management systems for smart homes and to become a reliable and efficient alternative to traditional energy management methods, automatically and intelligently reducing energy consumption, thus saving costs and mitigating adverse environmental impacts.

By using the energy management system in the smart home, users can use the facilities of their smart home more easily and better, and as a result, the efficiency of the smart home systems increases. The utilization of DRL can reduce potential errors and enhance the efficiency of energy management systems in smart homes. Broadly, smart home energy management systems improved with DRL contribute to bettering the quality of life for users, reducing energy costs, and enhancing environmental sustainability. The development of these systems, driven by continuous advancements in the field of DRL, promises reliable performance and high efficiency, making them viable replacements for traditional methods in energy management within smart homes. Moreover, the application of these systems in commercial and industrial buildings can also help reduce energy costs and improve the efficiency of their energy management systems. Another application of DRL in smart homes is the control of heating and cooling systems. By employing DRL algorithms, it is possible to identify patterns of energy consumption throughout the day and week, and accordingly adjust heating and cooling systems to optimize energy use. This can lead to reduced energy costs and improved quality of life for users. Overall, the use of DRL in smart homes can contribute to improving the quality of life for users, reducing energy costs, and enhancing the environment. Given the rapid advancements in DRL, it is expected that in the future, this method will be employed in the design of smart home systems and energy management systems in commercial and industrial buildings, potentially replacing traditional approaches in these areas.

6. Challenges and unknown and ambiguous aspects of deep reinforcement learning method

6.1. Lack of access to accurate data

To use the deep reinforcement learning method, we need accurate and complete data of the current state of the environment and energy consumption at home. But in some cases, these data may be ambiguous or incomplete, for example, if the sensors used do not perform their functions correctly, or if the data related to the user's behavior at home is not available.

6.2. Complexities of the environment

Smart homes may be complex and have different dimensions, including a large number of different devices and equipment, different conditions of temperature, humidity, and lighting, as well as intermittent changes in the behavior of users at home. This complexity makes it necessary to design an accurate model for energy management in Smart homes have challenges.

6.3. Uncertainty in environmental conditions

Environmental conditions in smart homes can continuously change; for example, changes may occur due to shifting weather conditions or as inhabitants adopt new behaviors. This uncertainty in environmental conditions can cause models designed for energy management in smart homes to err and yield results lacking sufficient accuracy. Utilizing deep reinforcement learning for energy management in smart homes comes with challenges such as the lack of access to precise data, the complexity of the environment, and uncertainty in environmental conditions. Addressing these challenges may necessitate the design and implementation of specific methods, such as the use of neural networks with high stability, techniques for fitting incomplete and vague data, and methods for detecting and predicting changes in environmental conditions and user behavior in the home. Additionally, new technologies such as recurrent neural networks and multitask learning can be employed to adequately resolve these challenges.

6.4. Variables

The deep reinforcement learning method can help better management and energy efficiency in smart homes with intelligence and effort in implementation and optimization. The variables related to the issue of energy management in smart houses using the deep reinforcement learning method are as follows:

6.5. The current state of the environment

This variable includes information related to temperature, humidity, lighting and other environmental characteristics in the home, which are used in making decisions to optimize energy consumption.

6.6. The amount of energy consumption

This variable contains information about the amount of energy consumption by various devices and equipment in the home, which is used in making decisions to optimize energy consumption.

6.7. Intelligent agent performance

This variable includes information related to the performance of the intelligent agent in making decisions to optimize energy consumption at home.

6.8. Costs related to energy

This variable contains information about the costs related to energy consumption at home, which is used in making decisions to optimize energy consumption.

6.9. User behavior

This variable includes information about the behavior of users at home, which may influence decisions about optimizing energy consumption at home, for example, people may turn on electronic devices and forget to turn them off.

6.10. Environmental changes

This variable includes information related to environmental changes such as changes in temperature, humidity and lighting during the day of the week or season, which should be used in making decisions to optimize environmental changes such as changes in temperature, humidity and lighting during the day of the week or season, which should be used in Decisions to optimize energy consumption at home should be considered.

In general, the variables related to energy management in smart homes using the deep reinforcement learning method include the variables that include the current situation, the environment, the amount of energy consumption, the performance of the smart agent, energy costs, user behavior, and environmental changes. These variables are in decision making. They are used to optimize energy consumption in smart homes. For example, by using these variables, the intelligent agent can decide when and with what settings to turn on and off electronic devices to optimize energy consumption in the home. Gained. Also, according to environmental changes and user behavior, the intelligent agent can decide what changes to make in the settings of electronic devices to optimize energy consumption at home.

6.11. Overview of research background

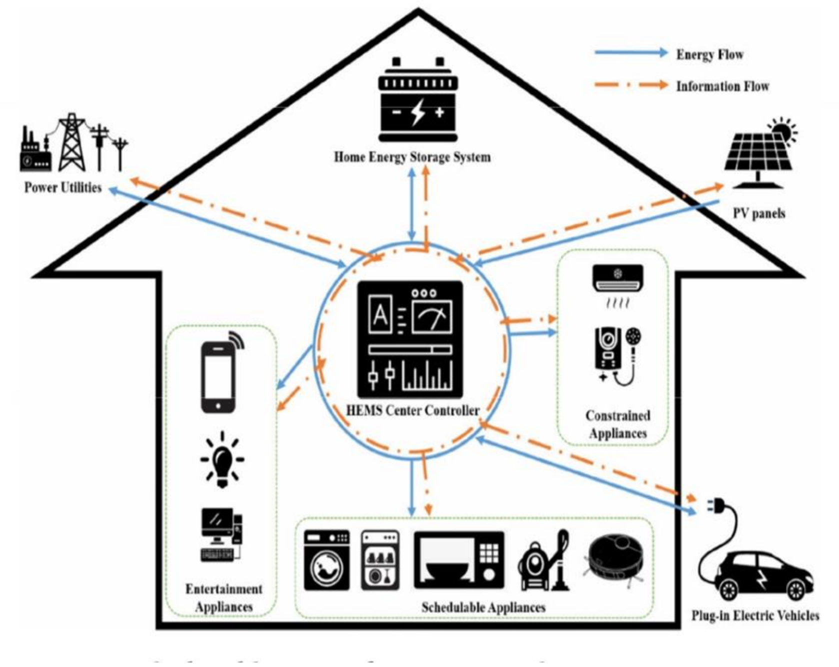
Society faces numerous challenges such as energy shortages and environmental pollution resulting from the use of fossil fuels (Dreidy et al., 2017). Addressing energy challenges requires the provision of dependable and secure energy sources that are not reliant on fossil fuels, which is a primary objective for the majority of governments. (Olatomiwa et al., 2016). Consequently, renewable energy sources, including solar, wind, and biomass energy, are increasingly used on a large scale to provide reliable energy and reduce greenhouse gas emissions (Hu et al., 2018). However, in contrast to conventional energy sources, the unpredictable and sporadic characteristics of renewable energy sources can result in unforeseeable surges in energy generation, which can affect the stability of the power system. (Ahmed et al., 2017). In order to address these limitations, there is a growing advancement in technologies like enhanced metering infrastructure and high-speed bidirectional communications. This progress is facilitating a shift from a centralized conventional power grid to a distributed smart grid.. Therefore, in order to adapt to fluctuations in power prices and other financial incentives and provide flexibility and reliability in the decentralized smart grid, demand response, which refers to alterations in electricity usage by end-users, has also experienced a growing range of variations. (Yan et al., 2018).

In addition, due to the swift advancement of control and communication technologies, a wide range of home electronic, entertainment, information, and communication gadgets have progressively become indispensable components of everyday life. Every day, people's lives are progressively getting more pleasant and intelligent, leading to an overall improvement in living standards.. Nevertheless, the contemporary way of living also presents certain disadvantages. For example, the extensive utilization of intelligent household equipment results in a substantial rise in residential energy usage. (Beaudin & Zareipour, 2015). Furdemore, a lack of awareness regarding energy conservation and occasional negligence in considering the working conditions of electrical equipment by certain inhabitants can lead to situations where low energy consumption or low energy efficiency continues to be a problem in society. Traditional methods of monitoring and controlling are not enough to fulfill the objective of conserving energy in intelligent residences. Hence, efficient strategizing and management of diverse household devices to minimize energy usage in intelligent residences have emerged as a crucial focus. Home energy management systems are utilized to efficiently control and optimize the production and consumption of energy in residential settings. This technology involves the strategic scheduling of home appliances. (Beaudin & Zareipour, 2015). Home energy management systems can reduce energy costs by planning the use or reduction of appliance use, and additionally, energy produced by distributed energy sources can be stored and managed with home energy storage systems (Lokeshgupta & Sivasubramani, 2019), thus improving the overall conditions of energy production and consumption in a home. This is typically achieved using an optimal scheduling algorithm to calculate the appropriate time for rotating and not using tools, considering factors such as external information (e.g., updated grid prices or weather forecasts) and internal information (e.g., consumer preferences or historical appliance usage data) (Leitao et al., 2020).

Compared to manual operations, HEMS have the benefit of automatically assessing power pricing, household demand, the unpredictability of external environmental factors, and tailoring energy consumption programs to effectively manage the usage of household appliances. In more recent years, HEMS have gained significant popularity among end-users, energy corporations, and society as a whole, providing effective control and management of power. HEMS, or Home Energy Management Systems, can save energy for the community and reduce power costs for homeowners by optimizing energy usage based on electricity pricing and individual behaviorsIn addition, Home Energy Management Systems (HEMS) enable utility providers to analyze customers' future energy requirements in order to optimize power use and improve the dependability of power systems. A modern home energy management system, when used by end-users, refers to a modular system that can interact with household appliances and utilities. This system seamlessly integrates all power generation, consumption, and storage equipment within a home, using various smart technologies to enhance energy efficiency. Figure 4 illustrates the overall structure of a home energy management system, which consists of five primary components:

Figure 4

Typical architecture of a HEMS example



In the literature, the central controller is introduced with various technical terms such as smart controller (Zafar et al., 2020), smart center (Zhou et al., 2016) or central platform (Leitao et al., 2020), which is the main component of a HEMS. To manage and optimize the energy consumption of home appliances, there are usually five main functions of system management, including monitoring, recording, management, control and warning (Zhou et al., 2016). Smart home appliances, as the concluding component of HEMS (Home Energy Management System), are devices that possess the ability to monitor, communicate, and be controlled by a central controller. The predetermined goals of Home Energy Management Systems (HEMS) can only be realized when the home appliances are programmed and functioning correctly at the designated times. In order to effectively and efficiently manage energy consumption, it is necessary to model and calculate smart home appliances, as there are different types and quantities of these appliances in each household, resulting in varying levels of electricity consumption and device usage among families (Leitao et al., 2020). In this review, household appliances are divided into regular appliances, smart appliances, and EVs according to whether the device needs a smart plug and can be used as emergency power supply equipment (Zhou et al., 2016). Conventional appliances are defined as typical electrical devices that lack communication and automatic control capabilities. To establish a successful connection between these devices and HEMS, it is necessary for these devices to have additional communication and control equipment, such as smart plugs. These smart plugs should be capable of identifying the connected device and accurately recording its energy usage pattern. Smart appliances in this part are distinct from regular home appliances as they are equipped with intelligent control and communication modules. However, it is important to note that they do not have the capability to offer emergency power supply for other devices. Smart appliances can link to HEMS (Home Energy Management Systems) without the need for extra smart plugs. This reflects the ongoing progress in smart home technology and serves as the foundation for comprehensive domestic energy management (Zhou et al., 2016). The EVs referenced in the HEMS literature encompass both fully electric vehicles powered by rechargeable batteries and hybrid vehicles that utilize electricity as part of their driving energy. An electric vehicle (EV) is a unique form of intelligent device that stands out because of its energy storage system capability. Typically, electric vehicles (EVs) used in home energy management systems (HEMS) have the ability to supply backup power for various household appliances. Recently, electric vehicles have attracted much attention due to their important role in reducing global pollution, improving energy efficiency, promoting grid system stability, and playing an important role in future DR applications (Zafar et al., 2020). In addition to the classification mentioned earlier, Figure 3 presents other classification methods for home appliances that are suitable for modeling and optimization. For example, household appliances can be classified into uncontrollable loads, limitable loads, uninterruptible loads, interruptible loads and regulated loads based on DR behavior (Beaudin & Zareipour, 2015). Principles such as physical properties and job types were described and discussed in (El-Azab, 2021). Batista et al. (2013) classified residential appliances according to their types of tasks to obtain the best possible task activation plan. The devices in this work were classified based on their consumption patterns into time-removable devices, thermostatically controlled devices, and replaceable electrical devices.

7. Challenges and unknown and ambiguous aspects of deep reinforcement learning method

The results emphasize the significance of incorporating sophisticated technology and approaches to tackle the intricacies of managing energy in smart homes. Although there have been notable progressions, there are still a number of obstacles that need to be addressed. These include the need to guarantee the privacy and security of data, efficiently handle diverse types of data, and resolve compatibility problems between different devices. Future research should focus on implementing robust encryption techniques, scalable storage solutions, and advanced analytics algorithms to overcome these challenges. Additionally, transparent data usage policies and user consent mechanisms are essential to foster trust in AI-powered smart homes. Furthermore, the socio-economic implications of energy management schemes, particularly during events like the COVID-19 pandemic, warrant continued investigation to develop resilient and sustainable solutions. Overall, this study provides a comprehensive framework for enhancing smart home energy management systems, paving the way for further innovation and improvement in the field. Also, Table 2 indicates the challenges of artificial intelligence in energy management of smart homes.

Table 2

The challenges of artificial intelligence in energy management of smart homes

Solutions	Challenges	Method	Author
NSGA-II balances cost and comfort objectives. Dynamic factors included in scheduling. SVR provides accurate day-ahead generation predictions. K-means clustering evaluates comfort levels. Numerical simulations validate the method with real data. 51.4% reduction in energy costs demonstrates method efficiency.	Finding optimal trade-offs between minimizing costs and maintaining comfort. Integrating dynamic electricity prices, appliance priorities, cycles, and battery usage. Predicting next-day distributed energy generation accurately. Ensuring the method's efficacy using actual smart home data.	The problem was framed as a multi-objective scheduling problem. Techniques Used: NSGA-II for demand-side management, SVR for forecasting, and K-means for user comfort assessment.	(Rocha et al., 2021)
Employing advanced data fusion algorithms and implementing encryption/access control mechanisms.	Integrating diverse data sources and ensuring privacy/security of collected data.	The study applied a data fusion technique to optimize energy consumption in smart homes.	(Alzoubi, 2022)
Implement cloud computing-based solutions to handle large-scale data processing and analysis efficiently.	Integrating diverse data sources and ensuring accuracy in predicting energy demand fluctuations.	Employ statistical models to analyze energy consumption patterns in smart homes and buildings.	(Mir et al., 2021)
Implementing advanced algorithms and smart grid technologies can streamline energy sharing, optimize resource allocation, and mitigate operational challenges.	Integrating diverse energy resources and coordinating their distribution among multiple households presents logistical complexities.	The study employs cooperative game theory to facilitate the sharing and coordination of excess energy among prosumers in a home-smart community.	(Khayyat & Sami, 2024)
Integration of diverse technologies and algorithms to develop a cohesive system for intelligent energy management while considering occupant preferences and schedules.	Integration of diverse technologies and algorithms to develop a cohesive system for intelligent energy management while considering occupant preferences and schedules.	Utilization of adaptable learning system principles in conjunction with wireless sensors and artificial intelligence for enhanced energy management in smart homes.	(Qela & Mouftah, 2012)
Implementing robust encryption techniques and strict access controls. Employing scalable storage solutions like cloud-based databases and distributed file systems. Utilizing advanced analytics algorithms and edge computing for faster analysis. Standardizing communication protocols and promoting device certification programs.	Ensuring data privacy and security amid potential breaches. Managing large volumes of heterogeneous data efficiently. Processing real-time data streams and extracting meaningful patterns. Ensuring interoperability and compatibility among diverse devices.	Data collection through sensors embedded in various household devices. Storage of collected data in centralized or distributed databases. Analysis of collected data for deriving insights and enabling automation. Data acquisition through IoT protocols like Zigbee, Z-Wave, or Wi-Fi.	(Lashkari et al., 2019)
Implementing robust encryption protocols, anonymization techniques, and transparent data usage policies to address privacy	Overcoming privacy concerns regarding the collection and utilization	The study evaluates algorithmic approaches for enhancing smart homes' utility, focusing on AI integration.	(Kazmi et al., 2017)

concerns and ensure user trust in AI-powered smart homes.	of personal data, ensuring user consent and data security.		
Analysis and comparison of energy scheduling controller techniques. Utilization of renewable-based SHEMS for efficacy and sustainability. Employing multi-objective meta-heuristic optimization algorithms with artificial intelligence. Providing a fundamental platform for further research and improvement of energy management and demand response schemes during the pandemic.	Transition from centralized to distributed energy management systems. Dynamic electricity demand during the pandemic. Incorporation of renewable energy in Smart Home Energy Management Systems (SHEMS). Socio-economic implications of COVID-19 on SHEMS.	Review of energy management schemes for smart homes and renewable energy integration during COVID-19.	(Ayub et al., 2022)
Implementing robust security protocols, enhancing privacy measures, ensuring scalability and interoperability, and developing adaptive systems for managing thermal comfort.	Lack of quality attributes such as security, privacy, scalability, interoperability, and difficulty in managing thermal comfort satisfaction of residents.	Conducted analysis of Smart Home Energy Management Systems (SHEMs) using data from various sources and stakeholders.	(Aliero et al., 2021)
Integration of classification algorithms to enhance accuracy in human activity recognition, minimizing errors in load optimization strategies.	Accurately detecting human activity amidst potential errors from motion sensors.	Utilizing a combination of Hidden Markov Model and Naive Bayes classifier to model human behavior and predict energy usage.	(Gariba & Pipaliya, 2016)

According to Table 2, this study explored various methodologies and technologies for optimizing energy management in smart homes. It addressed challenges such as multi-objective scheduling, data fusion, statistical modeling, cooperative energy sharing, and adaptive learning systems. Each approach aimed to improve energy efficiency, reduce costs, and enhance user comfort while considering factors like privacy, scalability, and interoperability. The results showcased promising advancements in smart home energy management. Implementation of NSGA-II for demand-side management led to a significant reduction in energy costs by 51.4%, demonstrating the efficacy of the method in balancing cost and comfort objectives. Data fusion techniques combined with encryption and access control mechanisms ensured the integration of diverse data sources while safeguarding privacy and security. Statistical models accurately predicted energy demand fluctuations, facilitating efficient resource allocation. Cooperative game theory facilitated energy sharing among prosumers, optimizing resource distribution and mitigating operational complexities. The utilization of adaptable learning systems, coupled with wireless sensors and AI, enhanced energy management while considering occupant preferences and schedules.

8. Conclusion

In conclusion, this review has shed light on the importance of integrating advanced technologies and methodologies to address the complexities inherent in smart home energy management. While significant advancements have been made in recent years, several critical gaps persist, posing challenges to the widespread adoption and effectiveness of smart home energy management systems. Firstly, ensuring data privacy and security remains a paramount concern, particularly given the sensitive nature of the data collected and processed in smart home environments. Robust encryption techniques and strict access controls are necessary to safeguard against potential breaches and unauthorized access. Secondly, managing heterogeneous data efficiently presents a significant challenge, requiring scalable storage solutions and advanced analytics algorithms capable of processing large volumes of data from diverse sources in real-time. Additionally, addressing interoperability issues among devices is essential to ensure seamless integration and communication within smart home ecosystems. Standardizing communication protocols and promoting device certification programs can help alleviate these interoperability challenges. Moreover, while advancements in AI and machine learning hold promise for enhancing smart home energy management, there is a need for further research to develop more sophisticated algorithms and techniques tailored to the unique requirements of smart home environments. Additionally, the socio-economic implications of energy management schemes, particularly in the context of events like the COVID-19 pandemic, warrant further investigation to develop resilient and sustainable solutions that can withstand disruptions and fluctuations in energy demand. Overall, while this review provides valuable insights into the current state-of-the-art in smart home energy management, there is still much work to be done to address the identified gaps and challenges. Future research endeavors should focus on implementing robust encryption techniques, scalable storage solutions, and advanced analytics algorithms, while also considering the socio-economic implications and ensuring transparency and trust in AI-powered smart home systems.

Moving forward, future research in smart home energy management should prioritize the development of innovative solutions that address the identified gaps and challenges. This includes the exploration of advanced encryption techniques and access control mechanisms to ensure data privacy and security, as well as the implementation of scalable storage solutions and real-time analytics algorithms to manage heterogeneous data efficiently. Additionally, efforts should be directed towards promoting interoperability among devices through standardized communication protocols and device certification programs. Moreover, research should focus on advancing AI and machine learning techniques tailored to smart home environments, while also considering the socio-economic implications and resilience of energy management schemes in the face of unforeseen events like the COVID-19 pandemic. Ultimately, by addressing these future suggestions, researchers can contribute to the development of more robust, efficient, and sustainable smart home energy management systems that meet the evolving needs of homeowners and society at large.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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