Journal of Operation and Automation in Power Engineering

Vol. XX, No. XX, XXXX, Pages: XXXX (Proofed)

http://joape.uma.ac.ir

Review Paper

Current Efficacy and Innovations in Smart Home Energy Management: A Review of IoT, AI, and Renewable Integration for Optimal Efficiency

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Abstract— *Smart home energy management (SHEM) strategies effectively overcome the limitations of traditional methods by automating tasks through smart meters, appliances, and home automation systems, thus reducing manual effort and enhancing efficiency. Using Internet of Things (IoT) and artificial intelligence (AI) technologies, SHEM systems provide real-time optimization and precise adjustments, leading to quick identification and reduction of energy waste. They facilitate the integration and optimization of renewable energy sources like solar panels, improving sustainability and reducing reliance on grid electricity. Additionally, SHEM systems are scalable, accommodating the needs of larger or more complex homes while offering significant energy savings and enhanced convenience. Recent advancements include integrating advanced metering infrastructure, smart sensors, and home energy storage systems with supervisory control and data acquisition (SCADA) to manage energy generation, transmission, and distribution effectively. Despite the potential benefits, challenges remain, such as system complexity and the need for optimal control strategies. Thus, continued research and development are crucial for refining smart solutions and algorithms, ultimately enhancing energy efficiency, cost savings, and user comfort. The evolving role of smart homes and grids underscores the importance of collaboration among researchers, industry stakeholders, and policymakers to achieve a more sustainable, efficient, and secure future. This review explores SHEM systems, highlighting recent studies using advanced technologies like smart meters, IoT, AI, and other tools to improve energy efficiency, reduce costs, and integrate renewable energy, while addressing challenges.*

Keywords—Smart home energy management, smart grids, energy, internet of things, artificial neural network.

NOMENCLATURE

Abbreviations

AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Networks
BESS	Battery Energy Storage Systems
CNNs	Convolutional Neural Networks
CPS	Cyber-Physical Systems
DLNA	Digital Living Network Alliance
DR	Demand Response
DRL	Deep Reinforcement Learning
ESPs	Energy Service Providers
HAN	Home Area Networks
HEM	Home Energy Management
HVAC	Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
IT	Information Technology
M2M	Machine-to-Machine
MAS	Multi-Agent Systems
ML	Machine Learning
MPC	Model Predictive Control
NILM	Non-Intrusive Load Monitoring
OT	Operational Technology
PV	Photovoltaic
RES	Renewable Energy Sources
RL	Reinforcement Learning
SCADA	Supervisory Control and Data Acquisition
SHEM	Smart Home Energy Management
SHS	Smart Home Systems
SPs	Smart Plugs
SUN	Smart Utility Network
SVM	Support Vector Machines
UPnP	Universal Plug and Play
VE	Virtual Environments
XAI	Explainable Artificial Intelligence

Received: 17 Feb. 2025
Revised: 30 Aug. 2025
Accepted: 10 Sept. 2025
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DOI: 10.22098/joape.2025.16813.2305

1. INTRODUCTION

Home energy management (HEM) refers to a suite of technologies, systems, and strategies designed to monitor, control, and optimize the consumption of energy within residential homes [1, 2]. The primary objectives of HEM are to improve energy efficiency, reduce energy costs, and promote sustainable energy usage practices [2].

Traditional home energy management strategies involve improving insulation, adjusting thermostats, using energy-efficient appliances, and employing natural ventilation [3–5]. Nonetheless, these methods require continuous manual effort, lack real-time data, and cannot effectively integrate renewable energy sources, resulting in lower efficiency and limited scalability compared to modern, automated systems [5–8].

Notably, smart home energy management (SHEM) strategies effectively address the limitations of traditional methods by automating tasks with smart meters, appliances, and home automation systems, reducing manual effort. Using Internet of Things (IoT) and artificial intelligence (AI) technologies, SHEM systems provide real-time optimization and precise adjustments, enhancing efficiency. Real-time feedback from energy monitoring systems helps identify and reduce waste quickly [9, 10]. Indeed, these systems can integrate and optimize renewable energy sources like solar panels, improving sustainability and reducing reliance on grid electricity. Additionally, they are scalable, meeting the needs of larger or more complex homes while providing significant energy savings, improved efficiency, and increased convenience and comfort despite initial costs and interoperability challenges [11].

In recent years, various approaches to SHEM have been explored, including advanced metering infrastructure (AMI) [12, 13], smart sensor technologies [14, 15], smart home appliances [16], home area networks (HAN) [17, 18], and home energy storage systems (HESS) [19, 20]. Notably, SHEM involves supervisory control and data acquisition (SCADA) integrated with energy management systems to manage the generation, transmission, and distribution within smart grids. This integration is crucial for effective demand-side management, enabling real-time monitoring and control of home appliances based on user preferences through intelligent ambient systems, aiming to reduce electricity costs and improve energy efficiency [21].

Despite growing interest in SHEM, existing reviews often focus on specific components or overlook practical integration challenges. Few address behavioral, architectural, and thermal comfort aspects alongside technology. This review bridges that gap by critically synthesizing recent literature, emphasizing application-driven strategies, thermal comfort, consumer electronics management, and intelligent, weather-responsive control. Its novelty lies in a multi-layered perspective: summarizing advanced technologies, contextualizing them in real residential settings, classifying energy domains, highlighting practical implementation with real-time data, and integrating user-centric, environment-adaptive control and behavioral models to support intelligent, sustainable, and human-aware smart homes. This review will elucidate how SHEM systems overcome the limitations of traditional methods using smart meters, IoT, AI, and smart grids, focusing on their impact on energy efficiency, cost savings, and renewable integration, while addressing scalability and cost challenges.

2. ACHIEVING INTEROPERABILITY AND ENERGY EFFICIENCY IN SMART HOMES

The smart home represents a significant advancement in residential technology, where various subsystems are interconnected to enhance energy efficiency, reduce operating costs, and improve safety, comfort, and multimedia services. This interconnected environment relies on a distributed system where numerous entities collaborate to manage the interactions between subsystems such as home automation, digital entertainment, assistive computing, healthcare, surveillance, and energy management.

In recent years, the primary focus has been on integrating these technologies and facilitating communication between subsystems through device connectivity and HAN [22–24]. Many smart home automation solutions have emerged, each with unique communication protocols and architectures. These solutions fall into two main categories: open systems, which have public specifications and standardized protocols like Konnex, Lonworks, and Zigbee [25–28], and proprietary systems, which are developed by specific companies or consortia with restricted technical details, such as SCS by Bticino and Legrand, By-Me by Vimar, and C-BUS by Schneider Electric [29–31]. Establishing standards and common rules within these systems is essential for ensuring device interoperability and integrating products from various manufacturers.

Achieving interoperability in smart home systems (SHS) and virtual environments (VE) is both essential and challenging. It requires seamless integration of diverse home subsystems and products from multiple manufacturers, while also coordinating the roles of internal users (e.g., residents) and external stakeholders (e.g., manufacturers, service providers, and energy utilities). The primary challenges include managing the vast amount of data generated, the complexity of integrating diverse devices, and the varying roles of the partners involved. Despite the concept of interconnected smart appliances and home networks being well-established, true interoperability remains difficult to achieve due to regulatory constraints, safety concerns, and the lack of a universally interoperable system architecture [32, 33].

To address these challenges, researchers have developed a comprehensive methodology for SHEM. This methodology involves classifying devices into homogeneous categories, identifying significant information categories, defining an information management model, and establishing syntactic rules for service provision. In a smart home, devices are organized into several distinct categories based on their functionality and role within the household. These categories include household appliances, meters, environmental controls, domestic hot water and heating, ventilation, and air conditioning (HVAC) systems, and consumer electronics. Everyday appliances—such as refrigerators, ovens, and washing machines—are now commonly equipped with microcontrollers and communication modules that link them to the home network. This connectivity enables automated operation and smooth interaction with other smart home systems. For instance, a smart refrigerator can monitor food inventory and suggest recipes, while a smart washing machine can optimize water and detergent usage [34, 35].

Meters are another crucial category, encompassing devices that measure and report real-time data on electricity, gas, and water consumption [36]. These smart meters are essential for efficient energy management as they enable remote monitoring and control, helping homeowners track usage and detect any irregularities, such as gas leaks or water leaks. Environmental controls include devices that manage the home's climate and safety, such as lighting systems, door and window sensors, and alarm systems. These devices control various environmental aspects, from turning lights on and off to adjusting window blinds based on the time of day or occupancy [37–39].

Domestic hot water and HVAC systems represent another key category, covering devices that manage heating, ventilation, and air conditioning, as well as hot water systems. These systems often include sensors to monitor temperature and humidity, optimizing climate control and ensuring comfort [40]. For example, a smart thermostat can adjust the temperature based on the time of day and occupancy patterns, leading to energy savings and enhanced comfort [41]. Consumer electronics, such as smart TVs, game consoles, and kitchen appliances like coffee makers, form the final category. These devices are characterized by low and constant energy consumption and often have simple on/off functions [42]. Smart TVs that integrate with other home systems to provide a seamless entertainment experience are a common example [43, 44].

State parameters refer to the current status of devices, such as whether a light is on or a door is locked, enabling real-time monitoring and remote control. External data encompasses information from outside the home environment, such as building characteristics, occupant profiles, and climatic conditions. This data helps tailor device performance to the specific context of the home. Derived data, obtained through analysis and statistics, provides insights such as average usage times and expenditure patterns, which can be used to develop enhanced services and functionalities [45, 46].

The information management model in a smart home correlates these categories with device functionalities, input and output data, and the roles of various VE actors. It integrates both external and derived data, defining system actions such as reading information and executing commands [47, 48]. For example, the model specifies how data should be visualized across different interfaces to ensure clarity and usability for both homeowners and VE actors. This approach ensures that devices can communicate effectively and perform their functions in harmony, leading to a well-coordinated smart home system [49, 50].

To enable efficient energy-control services and ensure interoperability, the model includes syntactic rules and algorithms. These rules define how information should be processed and how actions should be executed. For instance, algorithms may analyze data to predict peak energy usage times and adjust HVAC settings accordingly [51, 52]. The interoperability rules ensure that devices and systems from different manufacturers can work together seamlessly, despite differences in hardware and software. This structured approach to device and information management is crucial for creating a smart home that is both efficient and responsive to the needs of its users [53, 54]. Implementing a smart home system requires using power line standards (e.g., X10, HomePlug) for basic connectivity, along with wired and wireless communication protocols (e.g., TCP, Ethernet, USB, ZigBee, Wi-Fi, Bluetooth) to ensure network interoperability. A local gateway connects the home network to the internet, consolidating data and enabling seamless communication between devices [55–58].

3. Understanding smart grids, their efficacy and challenges

Smart grids represent a significant advancement over traditional electricity distribution networks, leveraging both physical and logical technological components to improve efficiency and resilience. The global adoption of smart grids is growing due to the numerous benefits they offer, including enhanced safety, efficiency, and sustainability in electricity distribution [59, 60]. One of the primary advantages of smart grids is their ability to provide a safer and more resilient electricity distribution network. This is achieved through advanced technologies that enable self-healing protection mechanisms, allowing the grid to automatically detect and isolate faults, minimizing downtime and service interruptions [61]. Additionally, smart grids feature advanced monitoring capabilities and load management, which facilitate real-time observation and adjustment of electricity distribution based on demand and generation conditions [62].

Cost reduction is another significant benefit of smart grids. This means that by dynamically balancing production and demand, smart grids can reduce operational costs associated with maintaining excess peak production capacity [63]. This not only lowers expenses but also supports a cleaner and more decentralized production of electricity. The bidirectional flow of electricity in smart grids allows for better integration of renewable energy sources, further enhancing the grid's efficiency and sustainability [63, 64].

The implementation of a smart grid involves establishing a complex communications network capable of monitoring and controlling the grid's operations. This network generates a vast amount of data that must be processed and analyzed to optimize grid performance [65]. Advances in computing power and AI are crucial in managing this data, enabling features such as efficient planning, outage management, fraud detection, and power distribution optimization [66]. AI techniques help in reasoning and decision-making processes, improving the overall functionality and reliability of the smart grid [67].

However, the extensive data collection and analysis inherent in smart grids introduce new security challenges. At the architectural level, securing communication between devices and applications is critical. This includes managing credentials and ensuring dynamic authorization to control data access effectively. Smart devices within the grid must also be protected with secure elements to prevent unauthorized access and tampering. The challenge lies in developing low-cost, scalable security solutions that are suitable for the diverse components of a smart grid [68].

From a software perspective, managing the security of applications that control and monitor the grid is essential. The integrity of data storage and distribution, as well as the trustworthiness of devices, sensors, and actuators, must be ensured to prevent malicious interference and maintain the grid's reliability. The smart grid ecosystem encompasses various stages of the energy value chain. The process begins with energy production, where power plants provide data on electricity generation. This information then flows through the transmission and distribution network, with meters tracking the movement of energy. Distribution units report their performance, and consumers interact with the grid through smart homes, which manage energy consumption and production. Outsourcing companies and other business units also engage with the grid, handling and transmitting data [69–71].

Given the extensive network of actors involved in the energy value chain, smart grids are susceptible to security threats. Recent studies suggest the use of blockchain technology to address these vulnerabilities. Blockchain can help mitigate centralization issues, support crowdsourced energy systems, eliminate single points of failure, and prevent fraud. Although these technologies offer promising theoretical and experimental solutions, their practical application in smart grids is still under development [72–76].

In conclusion, while smart grids offer numerous benefits, they also present significant challenges, particularly in terms of security and data management. Addressing these challenges requires ongoing research and the development of robust security architectures and technologies to ensure the smart grid's effectiveness and reliability.

3.1. The evolution of cyber-security in cyber-physical systems and smart grids

SHEM are increasingly integrated with cyber-physical systems (CPS) and smart grids, leveraging interconnected IoT devices, cloud services, and real-time data communication. As a result, the cybersecurity challenges faced by SHEMS are intertwined with those affecting broader CPS and grid infrastructures. Understanding the evolution of cybersecurity in these domains provides essential context to grasp the current and emerging security threats, vulnerabilities, and mitigation strategies applicable to smart homes. This section reviews key developments in cybersecurity for CPS and smart grids to highlight lessons and approaches that are highly relevant for securing SHEMS.

In the early days of cybersecurity, the focus was primarily on protecting information technology (IT) systems, particularly as local networks began to interconnect with the internet. However, with the rise of machine-to-machine (M2M) communication and the adoption of smart grids (SG), the landscape of cybersecurity has become more complex and intertwined [77]. This evolution has given rise to the concept of CPS, which encompass a broad range of technologies including SCADA systems, industrial automation and control systems (ICAS), embedded command and control systems, and the IoT [78–80].

CPS integrate physical processes with computational elements, which requires a comprehensive approach to security that spans both physical and cyber realms. Traditional cybersecurity measures, which focus on IT and operational technology (OT) separately, are no longer sufficient. Instead, a federated approach is necessary to address the unique challenges posed by CPS. This approach involves evaluating the impact of cyber incidents on grid operations, assessing vulnerabilities in SCADA protocols, and identifying potential attack scenarios within this integrated environment [81, 82].

Critical infrastructure, such as electrical, gas, and water grids, is essential for national security and daily life. Documents like "Smart

Grid Cyber Security Potential Threats, Vulnerabilities and Risks" from California State University Sacramento, NIST's "Guidelines for Smart Grid Cyber Security," and European standards proposed by the European Smart Grids Task Force highlight significant concerns about the security of these infrastructures [83, 84].

Smart grid applications generally follow a client-server architecture, where security measures focus on securing point-to-point communication between gateways and application servers. As M2M services platforms become more prevalent, the communication model shifts from a simple client-server model to a more complex point-to-multipoint peer-to-peer model. This evolution increases the demand for dynamic and robust security measures. A critical aspect of this new security paradigm is the management of credentials used to secure M2M applications. Historically, credential management focused on securing communication between devices and application servers. With the shift to peer-to-peer communication, it has become essential to secure interactions among devices and multiple authorized applications. Fine-grain authorization, which precisely controls which applications can interact with which devices, is essential for maintaining security [85, 86].

Credential management also involves protecting the storage and use of credentials to prevent unauthorized access and device cloning. Secure elements, which are specialized hardware designed to protect stored credentials, offer a proven solution. Traditionally, secure element management has been handled by entities that issue the secure elements. Recently, a new model has emerged where secure elements are used in a multitenant fashion, allowing multiple service providers to store and manage their credentials securely on a single platform. This model is particularly relevant for smart grids, where it supports the emerging business models for grid operation and enhances security [87].

Modern approaches also explore blockchain-based decentralized and secure keyless signature schemes, which could offer further improvements in security for smart grids and IoT devices. While this multitenant model is promising, it faces challenges in terms of cost and complexity, especially when compared to mobile applications. The variety of use cases and configurations in smart grids requires cost-effective and straightforward secure element solutions to enable widespread deployment.

3.2. Integration of AI and Machine Learning (ML) in smart grid-enabled SHEM

The integration of AI and machine learning (ML) into smart grid-enabled SHEM system represents a transformative step toward creating adaptive, efficient, and intelligent residential energy solutions [88, 89]. Unlike conventional rule-based methods, AI and ML techniques enable autonomous decision-making by learning from historical and real-time data, allowing SHEMS to optimize energy consumption dynamically in response to changing environmental conditions, electricity prices, and user behaviors [90].

Various AI and ML techniques have been adopted in the context of SHEM. Supervised learning models such as artificial neural networks (ANN) [91, 92], support vector machines (SVM) [93], and decision trees have been widely used for applications including short-term load forecasting, user behavior prediction, and energy demand classification [90, 94]. These models offer substantial improvements in prediction accuracy compared to traditional statistical approaches. For instance, ANNs have achieved 5–10% higher accuracy in predicting household energy usage than linear regression models. Another investigation into lighting consumption in a commercial setting reported the ANN model achieved only 0.56% error versus 8% for polynomial regression (a close relative of linear regression), equating to about a 7.5% absolute improvement [95, 96]. In contrast, unsupervised learning methods like K-means clustering, principal component analysis, and autoencoders are particularly effective in scenarios where labeled data is limited. These models have been successfully used for user profiling, appliance load disaggregation, and anomaly detection, uncovering hidden patterns in energy usage and helping customize energy-saving recommendations. In some studies, clustering techniques have enabled an 8–12% reduction in peak demand through more personalized demand response strategies [97–99].

Reinforcement learning (RL), particularly in its deep reinforcement learning (DRL) form, is another powerful technique employed in SHEMS. In this framework, an agent interacts with the environment, learning optimal control policies to maximize rewards such as cost savings or thermal comfort [100, 101]. DRL-based HVAC systems, for example, have shown 20–30% energy savings over traditional PID controllers while maintaining desired comfort levels. Beyond individual homes, game theory and multi-agent systems (MAS) help manage local energy sources, allow neighbors to trade energy with each other, and coordinate electricity use in small communities or microgrids. These models provide decentralized control frameworks, often employing Nash equilibrium or cooperative game strategies to ensure fairness and efficiency among multiple users, with reported reductions of up to 18% in energy bills [102–105].

Model predictive control (MPC) is another technique frequently integrated into SHEM system due to its ability to handle multi-objective optimization problems under dynamic constraints. MPC models make control decisions based on future predictions, optimizing appliance scheduling, renewable energy integration, and energy storage utilization. Compared to rule-based systems, MPC has demonstrated up to 25% improvement in energy cost efficiency in homes equipped with solar panels and battery systems [106–110].

These AI and ML techniques are applied across a broad spectrum of SHEM system functions, including load forecasting, real-time appliance scheduling, fault detection, demand response optimization, and occupant behavior modeling. Techniques like LSTM networks, XGBoost, and genetic algorithms have been employed to predict and shape energy consumption patterns, while deep autoencoders and isolation forests assist in early fault detection and predictive maintenance. For non-intrusive load monitoring (NILM), convolutional neural networks (CNNs) and deep autoencoders disaggregate energy consumption by appliance, providing fine-grained control and feedback without extensive hardware deployment [88–90, 111–113].

Despite their demonstrated benefits, AI and ML models in SHEM system face several challenges. A major limitation is their reliance on large, high-quality datasets, which are not always available due to privacy restrictions, device heterogeneity, or limited user engagement. Additionally, the complexity of advanced models such as deep neural networks and DRL makes them computationally intensive and difficult to interpret, which can hinder their deployment in low-power smart home devices. Moreover, integrating AI-based decisions with heterogeneous devices, communication protocols, and standards across smart homes raises issues of interoperability. User acceptance also remains a concern, particularly when autonomous systems override manual control or when concerns about data privacy and surveillance arise. Furthermore, models developed for a specific home may not scale effectively across homes with different architectures, usage behaviors, or environmental contexts [88–90, 111–114].

To address the remaining limitations and enhance the adoption of AI and ML in SHEM system, future research must focus on developing privacy-preserving learning methods such as federated learning, which enables model training across multiple homes without sharing sensitive data. The adoption of explainable AI (XAI) frameworks is also essential to improve transparency and user trust in automated systems. Edge AI approaches, which allow real-time processing at the device level without relying on cloud infrastructure, offer promising solutions to reduce latency and ensure local autonomy. Furthermore, cross-domain transfer learning techniques can help generalize models to diverse residential contexts, and the integration of behavioral economics with AI could encourage energy-saving habits through subtle behavioral nudges. Several recent studies provide insights into different approaches and innovations in this field, demonstrating how they contribute to more effective energy management and integration with the smart grid.

Overall, the incorporation of AI and ML into smart grid-enabled SHEM system holds immense potential to reshape residential energy landscapes. Indeed, by enabling intelligent, autonomous, and adaptive control, these technologies pave the way toward more sustainable, cost-effective, and user-centric energy management. While challenges remain, ongoing advancements in model efficiency, interpretability, and user integration are steadily transforming SHEM system into an indispensable component of the future smart grid ecosystem.

4. SHEM System architecture

In the landscape of smart home energy management, several notable architectures illustrate different approaches to integrating technology for optimizing energy consumption and enhancing efficiency. In general, the SHEM architecture, as illustrated in Fig. 1, consists of several key components including a HAN, smart plugs (SPs), occupancy sensors, a centralized SHEM, mobile devices, and Energy Service Providers (ESPs). The HAN employs various wireless technologies such as Wi-Fi, PLC, ZigBee, and Smart Utility Network (SUN) to facilitate communication among devices. SPs are matched to individual appliances to collect and report energy consumption data. Occupancy sensors detect people in a room and adjust the lights automatically. Users can monitor and control appliances via mobile devices, while ESPs provide services like DR and real-time pricing. The SHEM can operate in manual or automatic modes to manage energy in response to these signals [127].

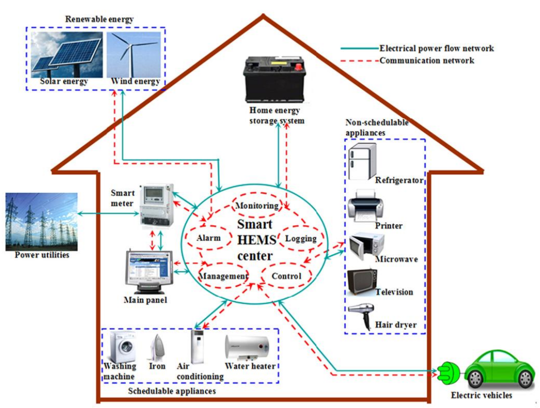

Fig. 1. Overall architecture of a representative SHEM system [127, 128].

Zhai *et al.* proposed a fundamental SHEM system architecture where the core component is the SHEM system unit connected to all home appliances through smart plugs. These smart plugs are essential as they monitor and control the energy usage of the connected devices. The SHEM system unit also communicates with a gateway to receive Demand Response (DR) commands from the utility. This architecture, depicted in Fig. 2, is designed for basic energy management without integrating renewable energy sources (RESs) or energy storage systems. The focus here is on direct control and monitoring of energy consumption through smart plugs and the ability to respond to utility commands [129]. Although this design is simple and easy to implement, it cannot take advantage of onsite energy generation or storage, which limits its ability to respond to fluctuations in demand or maintain power during outages. Additionally, using smart plugs for every appliance increases both complexity and cost, potentially making the system harder to scale for larger or more diverse homes. The absence of predictive or adaptive control algorithms restricts the system's ability to optimize energy usage proactively, and its effectiveness is closely tied to the availability and responsiveness of utility DR signals. Thus, although suitable for foundational energy management and load control, this model may fall short in addressing the dynamic and distributed energy challenges of modern smart homes.

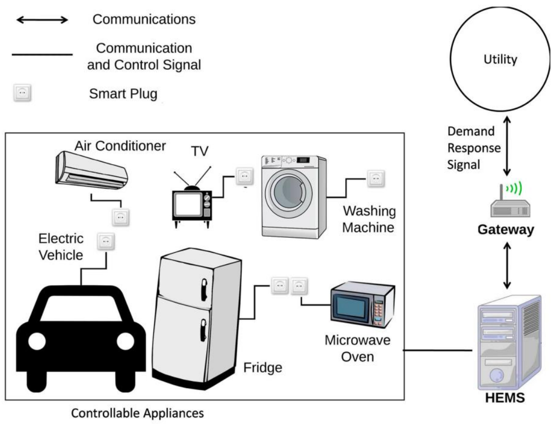

Fig. 2. Architecture of SHEM system in Zhai *et al.* [129].

Pawar and Vittal [130] expand on this model by incorporating RESs and storage systems, as shown in Fig. 3. Their architecture is similar to that of Zhai *et al.* but adds RESs, such as solar panels, and energy storage systems, like batteries, into the SHEM system . This integration allows for a more comprehensive energy management strategy, leveraging renewable energy to reduce dependence on the grid and using storage systems to balance supply and demand effectively. This enhanced setup supports better energy efficiency and resilience compared to the simpler model of Zhai *et al.* [130]. The energy storage components play a critical role in balancing the intermittent nature of renewables by storing excess generation during peak production periods and releasing it during high demand or low generation intervals. As a result, this full integration improves system resilience and energy efficiency by balancing supply and demand, reducing energy costs, and enabling the home to operate independently during grid disturbances or outages. Compared to the more basic model of Zhai *et al.*, Pawar and Vittal's design offers a more robust and sustainable energy management solution aligned with modern smart grid objectives.

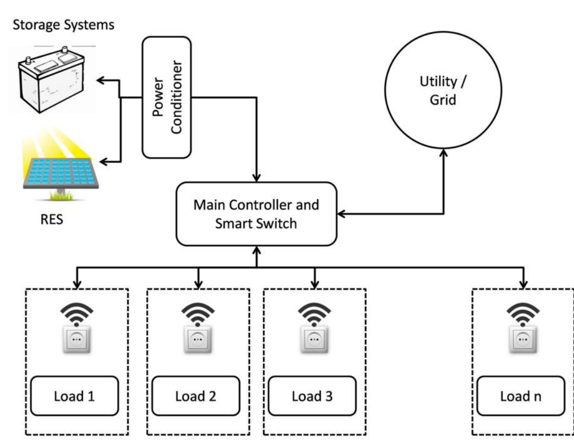

Fig. 3. Structure of SHEM system in Pawar and Vittal [130].

In Killian *et al.*, the architecture becomes more complex with

Table 1. Recent advances in smart home energy management and smart grid integration: key approaches and findings.

Study / Authors	Approach / Technology	Objective / Focus	Key findings / Contributions	Dataset / Application	Performance gain / Results	Ref
Fan *et al.*	Online event-triggering algorithm with Lyapunov optimization	Minimize electricity costs, maintain user comfort	Schedules controllable loads based on current info; reduces calculations; lowers electricity bills without comfort loss	Controllable household loads	Lowers electricity bills without comfort loss	[115]
Fan *et al.*	Coalitional game theory & online energy management (Lyapunov)	Manage air conditioning in smart communities	Reduces electricity costs, improves load-serving profitability; balances energy use and thermal comfort	Air conditioning units in smart communities	Reduces electricity costs, improves load-serving profitability	[116]
Ikpehai *et al.*	Low-power Power Line Communication (6LoPLC) over IPv6	Home energy management communication	High reliability and cost-effective; suitable for smart grids; less ideal for high-throughput scenarios	Home area network communication	Less ideal for high-throughput scenarios	[117]
Ahmed *et al.*	Lightning search algorithm combined with Artificial Neural Network (ANN)	Optimize home energy scheduling	Shifts peak load to off-peak, reduces energy consumption and emissions, improves efficiency and savings	Household energy scheduling	Improves efficiency and savings	[118]
Nguyen *et al.*	Dynamic electricity pricing	Study consumer behavior & energy consumption	13.8% reduction in electricity use on Nushima Island; shows pricing can encourage sustainable energy use	Residential consumption data	13.8% reduction in electricity use	[119]
Moon *et al.*	ANN prediction model for building heating control	Optimize temperature adjustment timing	Efficiently manages heating, reaches setpoints, maintains comfort	Building heating control	Reaches setpoints and maintains comfort	[120]
Pitì *et al.*	Review of smart meters and pricing models in Europe	Energy demand-supply balancing	Transition from flat-rate to Time-of-Use & Real-Time Pricing improves consumption tracking and smart grid integration	European residential data	Improves consumption tracking and smart grid integration	[121]
Niaz *et al.*	Multi-user full-duplex Visible Light Communication (VLC) system	Smart home data transmission	Supports multiple devices/users, energy-efficient, lower maintenance costs despite high initial investment	Smart home data transmission	Energy-efficient, lower maintenance costs	[122]
Chen *et al.*	Real-time load coordination strategy with stationary energy storage	Minimize electricity costs in homes with renewables	5% grid cost reduction; defers 50% flexible loads with limited disruption	Homes with renewables	5% grid cost reduction, limited disruption	[123]
Nakıp *et al.*	Recurrent Trend Predictive Neural Network-based Forecast Embedded Scheduling (rTPNN-FES)	Forecast renewable generation & schedule appliances	Outperforms state-of-the-art forecasting; near-optimal scheduling faster than traditional methods	Renewable generation forecasting & appliance scheduling	Near-optimal scheduling faster than traditional methods	[124]
Li *et al.*	Federated Learning (FL) combined with Trust Region Policy Optimization (TRPO)	Reduce emissions and costs in smart grids	Effective policy learning on heterogeneous data; maintains privacy	Smart grid heterogeneous data	Reduces emissions and costs	[125]
Alamin *et al.*	Economic model-based Predictive Control (MPC) with day-ahead pricing	Optimize HVAC energy use with thermal comfort	Balances energy use and comfort; reduces expenditures while maximizing satisfaction	HVAC energy use	Reduces expenditures while maximizing satisfaction	[126]

the introduction of capacitors into the SHEM system environment, illustrated in Fig. 4. Capacitors are added to manage power quality by stabilizing voltage levels and improving the overall efficiency of power distribution. This model incorporates both renewable energy sources (RESs) and storage systems, while also managing power flow using capacitors, representing an advanced approach to maintaining stability and efficiency in smart homes [131]. Thus, by actively controlling reactive power, capacitors help reduce losses and prevent voltage sags or spikes, which is crucial for protecting sensitive electronic devices and ensuring consistent energy delivery within increasingly complex smart home electrical networks.

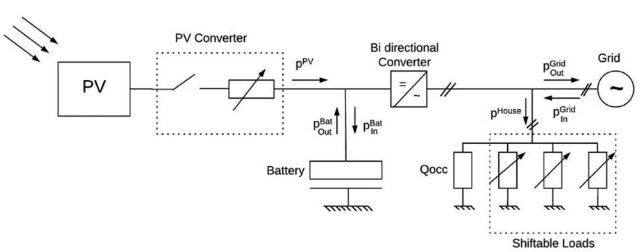

Fig. 4. Structure of SHEM system in Killian *et al.* [131].

Jin *et al.* introduced a sophisticated MPC system, depicted in Fig. 5. The MPC is a central control strategy that interacts with both utility providers and various home appliances. Each appliance is equipped with its own controller or meter, enabling detailed monitoring and management. The system includes a photovoltaic (PV) array and a battery system, enhancing the home's ability to generate and store renewable energy. Additionally, a measurement and learning block analyzes historical energy usage data to identify patterns and optimize energy management. The MPC also gathers weather data and user preferences to adapt its control strategies and implement DR events as necessary [132].

However, the complexity of the MPC model requires substantial computational resources and accurate forecasting data, which may limit its real-time applicability in resource-constrained environments. Additionally, the dependency on reliable weather data and user input introduces potential uncertainties that could affect control performance. Despite these challenges, the MPC system represents a significant step toward intelligent, adaptive SHEM system capable of enhancing energy efficiency and user comfort.

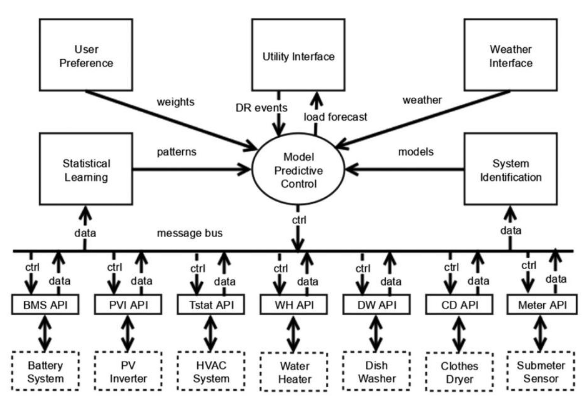

Fig. 5. Structure of SHEM system in Jin *et al.* [132].

Zunnurain and Maruf proposed an architecture, illustrated in Fig. 6, that connects to the utility grid via a smart meter but notably excludes RESs. Instead, the system integrates an energy storage unit to enhance flexibility in managing energy consumption. A key feature of this model is the classification of household appliances into critical and non-critical loads, which enables the SHEM system to prioritize energy allocation accordingly—ensuring that essential devices such as refrigerators and medical equipment receive uninterrupted power, while deferrable loads like laundry machines are scheduled for off-peak periods. The centralized SHEM system controller employs a load-shifting algorithm to optimize energy usage by dynamically rescheduling non-critical appliances, aiming to reduce peak demand and electricity costs. However, the model's optimization approach is based solely on fixed operational criteria and does not incorporate user preferences or comfort levels, which may limit its practicality and acceptance in real-world applications where occupant behavior and satisfaction are crucial factors [133].

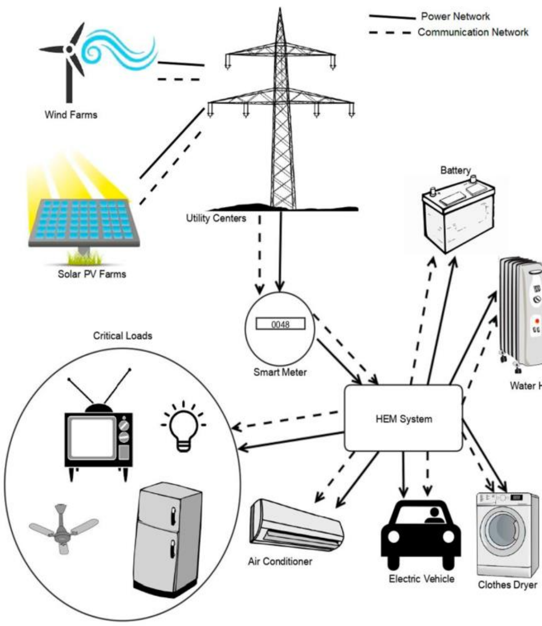

Fig. 6. Architecture of SHEM system in Zunnurain and Maruf [133].

Yener *et al.* described a broader grid integration system, depicted in Fig. 7, where smart homes are part of a larger grid system. The main grid center includes a database and control server that interact with individual client home servers. These client home servers manage RESs and loads within the smart homes and are controlled via mobile devices by the homeowners. This architecture facilitates coordination between the grid and individual homes, allowing for the effective implementation of DR events and monitoring of energy usage. It assumes the presence of RESs and emphasizes the importance of grid-wide integration for effective energy management [134]. However, this centralized design may face scalability challenges as the number of connected homes increases, potentially leading to communication bottlenecks and increased latency. Moreover, the reliance on continuous connectivity and centralized control raises concerns about system robustness and cybersecurity vulnerabilities. While enabling comprehensive grid coordination, the model assumes widespread adoption of RESs, which may limit applicability in regions with low renewable penetration.

Luo *et al.* offered a comprehensive SHEM system architecture that takes into account a wide array of inputs for optimal energy management, as shown in Fig. 8. Their system incorporates a Natural Aggregation Algorithm for finding optimal solutions, a solar database for forecasting solar power generation, and a home database for historical usage and peak power information. Additionally, it considers operational constraints, real-time pricing,

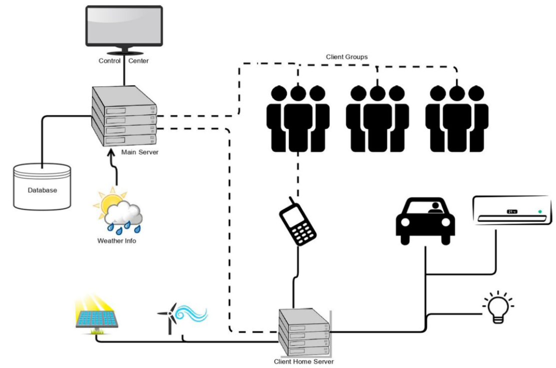

Fig. 7. Structure of SHEM system as part of grid in Yener *et al.* [134].

and the specifics of controllable appliances. The system also manages energy storage by controlling the charging and discharging of Battery Energy Storage Systems (BESS). This detailed approach aims to maximize energy efficiency by integrating various data sources and optimizing energy usage dynamically [135].

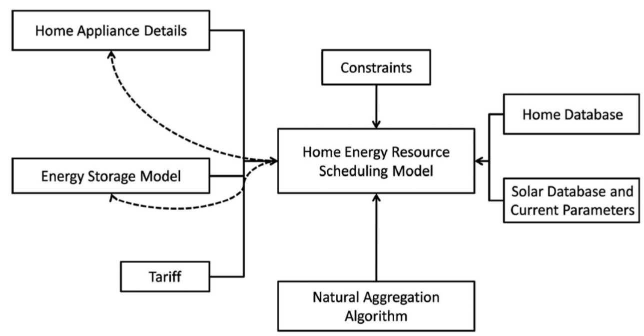

Fig. 8. Structure of SHEM system in Luo *et al.* [135].

Lokeshgupta and Sivasubramani introduced a unique architecture that incorporates a dump load alongside RESs, as shown in Fig. 9. The dump load is used to manage excess wind power by redirecting surplus energy away from the primary system when generation exceeds consumption. This approach helps maintain system stability and efficiency by dealing with variability in renewable energy production [136]. This strategy is particularly important for addressing the intermittent and variable nature of wind energy, preventing overloading and potential damage to system components. Thus, by absorbing the excess power, the dump load helps maintain voltage and frequency stability within the smart home energy management system, thereby enhancing overall system reliability and operational efficiency. This method also facilitates smoother integration of renewables by mitigating the impact of fluctuations in energy production on the grid and household loads.

While the incorporation of a dump load in Lokeshgupta and Sivasubramani's architecture effectively manages the intermittency and surplus of wind-generated power, it introduces certain limitations. The reliance on dump loads can lead to wasted energy when excess generation cannot be stored or utilized elsewhere, reducing overall system efficiency. Additionally, this approach may require careful sizing and control strategies to avoid unnecessary energy dissipation and to maintain optimal system operation. Despite these challenges, the method enhances stability and reliability, making it a practical solution for managing renewable variability in SHEM system.

Overall, these architectures represent a spectrum of smart home energy management solutions, ranging from basic monitoring

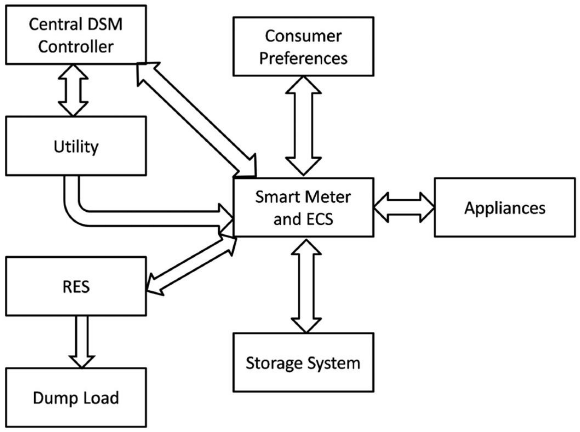

Fig. 9. Structure of SHEM system in Lokeshgupta and Sivasubramani [136].

and control systems to advanced setups integrating renewable energy, storage, and predictive control strategies. Each architecture offers unique features and benefits, catering to different levels of complexity and user needs in optimizing home energy usage. To justify the adoption of new technologies such as smart homes, it is crucial to identify applications and scenarios where these systems can deliver significant improvements. The next section examines various use case categories that demonstrate considerable potential for energy savings, particularly within the residential sector.

4.1. Thermal comfort

The report highlights that space heating constitutes approximately 57% of total energy demand in residential homes across the European Union. This significant portion underscores the potential for substantial energy savings through intelligent management of heating systems and home appliances [137].

A) Weather-responsive heating control

One effective strategy for reducing energy consumption is to synchronize heating with weather forecasts. For instance, on a sunny winter day, opening shutters in parts of the house that are exposed to sunlight can utilize solar radiation to warm the indoor environment. This passive solar heating can reduce the reliance on mechanical heating systems. The effectiveness of this approach depends on the building's orientation and the transmissivity of window glazing. The key is to implement such strategies only in areas where sunlight can actually penetrate and contribute to heating [138, 139].

B) Utilizing thermal inertia

Another crucial factor in energy-efficient heating is understanding and leveraging the building's thermal inertia. Thermal inertia is a building's ability to store and retain heat. For instance, a room next to other heated spaces warms up faster than a room exposed to the outside, thanks to the thermal mass of nearby rooms and the insulation of the walls [141]. Knowledge about the thickness and material of walls and floors can help in optimizing heating schedules. Understanding these thermal properties allows a heating control system to schedule heating cycles to pre-warm spaces before they are occupied, reducing energy waste [140].

C) Impact of external factors

External factors such as wind and temperature also play a significant role in space heating. Wind increases the rate of air exchange through gaps in the building envelope, which can lead to higher heat loss. This can be quantified using the blower door test, which measures the air leakage rate of a building [143]. Additionally, the difference between inside and outside temperatures affects how quickly heat is lost. These factors must be considered in thermal calculations to improve the accuracy of heating strategies [142].

D) Cooling strategies

In the summer, managing cooling efficiently involves using weather data and building design to reduce reliance on artificial cooling systems [144]. For instance, when a cool night is expected, night purging can naturally cool a building by letting in outside air. The building's thermal mass then helps keep it comfortable during the day. To save energy, unoccupied rooms can be cooled more, while occupied rooms stay at a comfortable temperature. Additionally, if the weather is calm, natural ventilation by opening windows can further aid in cooling the building [144–146].

E) Managing overheating and ventilation

Preventing overheating in the summer can also be achieved through intelligent control of shutters and blinds. The building, by closing them in unoccupied rooms, can reduce solar heat gain and keep temperatures in check. Similarly, during extreme weather conditions, it is crucial to manage ventilation carefully. For instance, during high winds or intense heat, relying on natural ventilation might not be ideal, and mechanical systems may be preferable. Conversely, in cooler conditions, opening windows in unoccupied spaces can facilitate rapid air exchange [149, 150].

Additionally, integrating weather forecasts with building management systems enables proactive adjustments to heating, cooling, and ventilation strategies, optimizing energy use while maintaining occupant comfort. Advanced sensors can monitor indoor temperature, humidity, and occupancy in real time, allowing dynamic control of shutters, blinds, and ventilation to respond effectively to changing environmental conditions. Such adaptive measures not only improve energy efficiency but also enhance indoor air quality and overall living comfort [147, 148].

F) Balancing air quality and humidity

Maintaining air quality and humidity is another important aspect of energy-efficient space conditioning. While it is possible to rely entirely on artificial systems for air quality control, a balanced approach that includes natural ventilation can be more energy-efficient [150]. For example, during moderate weather conditions, opening windows can improve air quality without significant energy costs. However, during extreme weather or when solar radiation is intense, natural ventilation might lead to discomfort or energy inefficiencies. Similarly, for humidification, using natural methods when conditions permit can save energy compared to mechanical humidifiers, which require energy-intensive cooling and reheating processes [150–152].

4.2. Visual comfort

The subjective feeling of comfort in living spaces extends beyond just thermal comfort; visual satisfaction is equally important. An effective approach to enhancing visual comfort while also reducing energy consumption involves intelligent lighting management. One key aspect of this is intelligent blind control, which optimizes natural light use and minimizes the need for artificial lighting. Indeed, a system, by aligning blinds with the position of the sun, can enhance the lighting conditions inside a room. This adjustment ensures that rooms receive an adequate amount of natural light, thereby improving visual comfort and reducing reliance on artificial sources [153, 154].

Intelligent blind control systems use sensors, such as luxmeters, to measure the intensity of light within a room. Based on these measurements, the system can automatically adjust the position of the blinds to maintain a desired level of luminosity. For example, if the sunlight is too strong, the blinds might be tilted to diffuse the light and reduce glare. Conversely, if the room lacks sufficient natural light, the blinds can be opened further to let in more sunlight. If these adjustments are not enough to meet the required light levels, the system can also manage additional artificial lighting to compensate for any deficiencies. This dual approach of

Table 2. Strategies for thermal comfort and energy efficiency.

Strategy	Mechanism	Key benefit	Ref.
Weather responsive heating	Use weather forecasts + passive solar (open/close shutters on sunny days)	Reduces mechanical heating loads	[138, 139]
Leveraging thermal inertia	Exploit building materials' heat storage (wall/floor mass, adjacent conditioned rooms)	Pre-conditioning spaces, minimizing energy waste	[140, 141]
External factors adjustment	Account for wind-driven air leakage (blower door test) and ΔT heat loss	Improves accuracy of heating control	[142, 143]
Cooling via night purging	Night-time ventilation + thermal mass discharge	Lowers daytime cooling demand	[144–146]
Smart overheating and ventilation control	Adaptive blind/shutter closure in empty rooms; switch between natural/mechanical ventilation based on weather/occupancy	Maintains comfort, prevents overheating	[147–150]
Air quality and humidity balance	Blend natural ventilation with mechanical systems; use humidity-sensitive controls	Optimizes IAQ and RH with minimal energy	[150–152]

combining natural and artificial light helps in achieving optimal lighting conditions while conserving energy [153–157].

User preferences and autonomy are crucial considerations in the design of intelligent lighting systems. Users typically prefer to have control over their environment and may resist being entirely dependent on automated systems. To address this, intelligent blind control should ideally be programmed to perform adjustments when a room is unoccupied. This approach respects user autonomy by avoiding unnecessary changes when occupants are present, thus allowing them to maintain personal control over their lighting preferences. The system can also offer users the option to manually override automated settings, ensuring a balance between automation and personal preference.

Weather conditions significantly impact lighting needs, and incorporating this data into the control system can further enhance visual comfort. For instance, on overcast days, when natural light is limited, the system might need to increase the use of artificial lighting. On sunny days, the system can adjust the blinds to manage glare and reflections effectively [157–159]. Notably, by integrating weather forecasts into the system, adjustments can be made proactively to maintain consistent lighting levels. This foresight helps in optimizing both comfort and energy efficiency, as it minimizes the need for manual adjustments and ensures that the lighting system adapts to changing external conditions.

4.3. Energy-efficient operation of white goods

In recent years, the concept of smart homes and buildings has expanded beyond the traditional focus on thermal and visual comfort to encompass a broader range of functionalities. Modern smart home systems now emphasize the integration of a diverse array of devices, particularly consumer electronics and household appliances, into automation networks. This shift is driven by the need to enhance energy efficiency and optimize the operation of these devices, which collectively represent a significant portion of a household's total energy consumption.

Key to this integration are standards like Universal Plug and Play (UPnP) [160] and Digital Living Network Alliance (DLNA) [23]. These standards facilitate the seamless connection and communication between various devices in a smart home environment. As a result, the smart home system can effectively manage and control a wide range of appliances, which include everything from kitchen appliances to entertainment systems.

Household appliances—such as washing machines, dishwashers, refrigerators, and electric water heaters—contribute significantly to overall energy consumption. They contribute to the household's energy balance in several ways. For instance, a washing machine requires both electrical energy and hot water, while a refrigerator runs continuously to maintain its cooling function. Understanding these diverse energy needs is crucial for effective energy management. From an energy perspective, appliances can generally be categorized into two types: those that operate continuously and those that are active periodically. Continuous-running devices, like refrigerators, consume energy consistently throughout their operation. Optimizing these devices involves reducing the energy used during their regular operation. For example, a smart system could adjust the refrigerator's cooling power based on its content. When the refrigerator is nearly full, it requires more energy to maintain the desired temperature compared to when it is less occupied. The system, by automatically detecting the amount of food inside, can adjust the cooling power accordingly to minimize energy use.

In contrast, periodically active devices, such as dishwashers, are used at intervals. Optimization for these devices involves not only controlling their operation but also scheduling their use based on factors like energy availability and user convenience. For example, a smart home system can customize a dishwasher's cycle, changing the water temperature and duration to match the type and number of dishes. Moreover, the system can determine the optimal time to start the dishwasher by considering external factors like weather forecasts. If sunshine is expected, the system can delay the dishwasher's start time to utilize solar energy from a rooftop photovoltaic system. This approach leverages local energy sources to reduce reliance on grid power and improve overall energy efficiency.

Furthermore, the integration of household appliances into a smart home system allows for advanced interactions with smart grids and demand-side management applications. This interaction involves managing and distributing energy loads based on real-time data and forecasts. For instance, the smart home system can run appliances when energy demand is low or when renewable energy is available. This not only helps in optimizing the use of local energy producers but also contributes to balancing energy consumption across the grid.

4.4. Energy-efficient operation of brown goods

Consumer electronics, which encompass a wide range of everyday devices powered by electricity, are integral to modern home entertainment systems. Consequently, their role in smart home setups is significant, particularly concerning comfort and convenience. Technically, these devices typically offer two primary energy-saving modes. The first is the stand-by mode, a common but often criticized feature due to its questionable sustainability, as it can still consume between 2% to over 50% of the energy used during regular operation. The second mode involves completely turning off the device and ideally disconnecting it from the electrical circuit, which ensures zero energy consumption [23, 161]. Unlike household appliances, consumer electronics cannot have their operation postponed to times when surplus energy is available. Therefore, turning off unused devices does not need a smart home system, but people often forget to do it manually, either for convenience or because there are many devices. Here, the context-awareness feature of smart homes proves advantageous. Smart homes, by utilizing information about room occupancy and usage patterns, can automatically turn off devices in empty rooms, thus enhancing energy efficiency without compromising user comfort [162].

A more sophisticated approach within smart homes involves a layered energy management strategy for consumer electronics. Initially, devices are placed in stand-by mode for a specified period before being completely powered off. For example, if a user leaves the room during a TV commercial break, the system will not immediately shut down the television. Instead, it will wait for a predetermined time, monitoring for further user activity, such as preparing for bed, before deciding to turn off the TV.

Furthermore, the system must handle exceptions proficiently. For instance, a VCR should only be turned off if it is not in the middle of recording. The smart home system can also ensure the VCR is powered on just before a scheduled recording. This intelligent management of consumer electronics within smart homes demonstrates the benefits of integrating advanced automation, enhancing both energy efficiency and user convenience.

5. IoT in SHEM Systems

The Internet of Things, or IoT, plays a central role in modern SHEM systems by connecting everyday devices, appliances, sensors, and energy resources into a single intelligent network [163, 164]. This network allows the home not just to monitor energy use, but to actively analyze and optimize it in real time, transforming traditional passive energy consumption into a dynamic, adaptive system [165]. For instance, sensors embedded in smart meters, thermostats, lighting systems, appliances, and even electric vehicles continuously collect detailed data on electricity usage, indoor temperature, occupancy patterns, air quality, and battery charge levels [166, 167]. These sensors act as the “eyes and ears” of the smart home, detecting changes and sending this information through local communication networks—such as Wi-Fi, ZigBee, Thread, or Power Line Communication—to a central hub or gateway. The hub serves as the “brain” of the system, processing incoming data, coordinating devices, and making intelligent decisions. It can respond immediately, such as adjusting the thermostat, dimming or turning off lights, or optimizing appliance schedules based on predicted energy demand. In addition, some devices can communicate directly with each other, enabling decentralized decision-making—for example, a smart washing machine might delay its operation until solar panels generate sufficient electricity [168–171].

Data sent to cloud servers allows for more advanced functions, including long-term energy tracking, predictive modeling, and anomaly detection—such as identifying unusually high energy use from a malfunctioning appliance [172, 173]. Cloud-based analytics can also integrate weather forecasts, time-of-use electricity pricing, and user behavior patterns to optimize energy use and reduce costs [174]. Moreover, many SHEM systems now incorporate machine learning algorithms that learn from residents’ habits and automatically suggest or implement energy-saving actions, like pre-cooling the house when electricity is cheaper or gradually reducing heating in unused rooms. Indeed, by combining real-time monitoring, automation, predictive insights, and adaptive learning, IoT transforms a smart home into an energy-efficient, self-regulating ecosystem that reduces costs, lowers carbon footprints, and enhances comfort [175, 176].

IoT-enabled SHEM systems help save energy and reduce costs in several ways. By analyzing patterns of energy use, they can automatically control heating, cooling, lighting, and appliances based on when people are home, what they are doing, and the cost of electricity at different times of day [177–179]. For instance, a washing machine or dishwasher could run when electricity is cheapest, or the heating system could lower the temperature in empty rooms [180]. Studies and pilot programs have shown that such automation can reduce household energy use by 10–30%, saving money and reducing environmental impact. Beyond efficiency, IoT systems can detect irregular energy patterns that may indicate a malfunctioning appliance, allowing maintenance before a problem becomes serious. This not only saves money on repairs but also prolongs the life of household devices [178, 181, 182].

Another important feature of IoT in SHEM is its ability to support and optimize the integration of renewable energy sources. Devices such as solar panels, home batteries, and electric vehicles can all be coordinated by the system to make the most efficient use of available energy. For example, when solar panels generate excess electricity during the day, the system can automatically store this energy in home batteries or use it to charge an electric vehicle, reducing reliance on the electrical grid and lowering energy costs [177, 183, 184]. In addition, advanced IoT-enabled SHEM systems can predict energy generation based on weather forecasts and consumption patterns, ensuring that renewable energy is used optimally throughout the day. Some homes equipped with bidirectional smart meters can even feed surplus electricity back into the grid, contributing to grid stability and supporting broader energy management efforts. Participation in demand response programs is another key advantage, where the system adjusts energy use in real time—such as delaying appliance operation or reducing heating and cooling—to match grid supply and prevent blackouts. Indeed, by intelligently managing renewable energy, IoT-enabled SHEM systems not only improve efficiency and reduce costs but also help households contribute to a more sustainable and resilient energy network [177, 185].

For these systems to work smoothly, devices must be able to communicate using common standards. IoT supports multiple communication protocols and data formats, which allows different devices—from various manufacturers—to work together. Central hubs often translate between these protocols, creating a seamless network that is easy to expand. Advanced control algorithms can then optimize energy use based on forecasts of electricity prices, weather conditions, and household habits. For example, predictive algorithms can determine the best time to run appliances or charge batteries, while reinforcement learning models can gradually improve energy management strategies over time. Even when the system makes decisions automatically, it always prioritizes safety and comfort, keeping room temperatures within a comfortable range and preventing damage to appliances [186–189].

A key strength of IoT-based SHEM is its ability to keep homeowners actively engaged and informed about their energy consumption. User-friendly dashboards, mobile apps, and even voice-controlled interfaces allow residents to monitor in real time how much energy each device is using, how much it costs, and what its environmental impact is, such as carbon emissions associated with electricity use. This transparency empowers users to make informed decisions, adjust their habits, and set energy-saving goals. Moreover, users can override automatic system settings, customize preferences for heating, cooling, lighting, and appliance schedules, or receive alerts if a device is malfunctioning or consuming more energy than expected [177, 190, 191]. At the same time, robust cybersecurity and privacy measures are integrated into these systems to protect sensitive data. Information is encrypted during transmission, devices are authenticated before connecting to the network, and homeowners retain full control over what data is shared with cloud services. This ensures that the benefits of energy efficiency, convenience, and sustainability do not come at the expense of security or personal privacy, creating a reliable and trustworthy smart home ecosystem [192–194].

In summary, IoT transforms a regular home into a smart, energy-conscious environment. By connecting devices, collecting and analyzing data, and automating control, IoT-enabled SHEM systems reduce energy consumption, save money, support renewable energy, and help maintain a stable and efficient grid. At the same time, they keep the homeowner informed and in control, making energy management not just effective but also understandable and practical for everyday life.

6. Global Adoption Trends of Communication Protocols and SHEM Architectures

The global adoption of SHEM system varies according to regional technological infrastructure, regulations, and consumer preferences, with communication protocols playing a central role in enabling seamless interaction between devices, sensors, and controllers. Wired standards such as Power Line Communication (PLC), Ethernet, and HomePNA are commonly used in regions with established building infrastructures, offering reliable connectivity and high data throughput without the need for additional cabling [195–197]. Wireless protocols—including Wi-Fi, ZigBee, Bluetooth, Thread, and the emerging Matter standard—are increasingly preferred for their flexibility, low-power operation, and ease of deployment [198, 199].

Wi-Fi is widespread due to its ubiquity, high data rates, and integration with most consumer devices such as smartphones, laptops, and smart appliances. It is ideal for applications that require fast data transfer, video streaming, or real-time communication, although its higher power consumption may limit suitability for battery-operated IoT devices. ZigBee and Thread, on the other hand, are optimized for mesh networking, allowing devices to relay information through one another, which increases range and network reliability without relying solely on a central router. These protocols are highly energy-efficient, making them well-suited for low-power sensors, smart lighting, and home automation systems. They can support large-scale networks with hundreds of nodes, ensuring scalability while maintaining low energy consumption [200, 201]. Matter, developed by the Connectivity Standards Alliance, provides a common application layer that ensures interoperability across devices from different manufacturers. It works over existing technologies like Wi-Fi, Thread, and Ethernet, reducing fragmentation, simplifying setup, enhancing security, and improving the user experience by allowing seamless integration of smart home products regardless of brand [202–204].

SHEMS architectures are generally classified as centralized, distributed, or hybrid. Centralized systems rely on a single controller to manage all devices, offering simplicity and easier monitoring but limited scalability. Distributed systems employ multiple controllers to manage device groups independently, enhancing resilience, fault tolerance, and scalability. Hybrid systems combine centralized monitoring with local control, balancing efficiency, flexibility, and responsiveness, making them suitable for homes with diverse energy resources or integration with renewable sources [205–208].

Regional adoption trends reflect these technological and architectural choices. Europe leads in SHEMS deployment due to strict energy regulations, government incentives, and high renewable energy penetration, commonly using ZigBee and Z-Wave protocols, with increasing adoption of Matter to improve interoperability [209, 210]. North America emphasizes smart grid integration, leveraging Wi-Fi, ZigBee, Thread, and Matter to ensure device compatibility, while distributed and hybrid architectures are increasingly favored in urban and multi-unit housing [204, 211]. In the Asia-Pacific region, adoption varies widely: countries like Japan and South Korea focus on energy optimization and renewable integration, using PLC, Thread, and hybrid architectures to balance centralized and local control [212, 213].

Future trends indicate that SHEMS adoption will continue to expand globally as communication technologies advance, renewable energy integration increases, and standardized protocols like Matter gain traction. Emphasis is shifting toward interoperable, scalable, and user-centric systems that can interact with smart grids, dynamically optimize energy consumption, and support sustainable, low-carbon residential environments worldwide. Effective implementation of these systems requires careful consideration of regional infrastructure, energy policies, and user behavior to ensure that SHEMS are both technically viable and socially acceptable.

7. Challenges, Limitations, and Future Research

The evolution of smart homes is moving rapidly beyond basic automation and convenience, toward creating sustainable, energy-efficient, and highly interconnected residential ecosystems. This transformation is driven by the integration of diverse subsystems—ranging from home automation and digital entertainment to healthcare monitoring and advanced energy management—forming complex cyber-physical systems that improve occupant comfort, reduce energy consumption, and enhance environmental sustainability.

A major challenge lies in achieving seamless interoperability among heterogeneous devices and systems, which often use varied communication protocols, hardware capabilities, and proprietary standards. Overcoming this requires bridging open and closed platforms to enable unified data exchange, semantic interoperability, and coordinated control across appliances, sensors, distributed energy resources, storage units, and electric vehicles. Developing advanced control algorithms capable of real-time orchestration, predictive optimization, and adaptive management is essential to minimize energy use dynamically while ensuring occupant comfort, grid stability, and equipment longevity.

As the digital era progresses, the paradigm of smart homes is advancing well beyond basic automation and user convenience toward the realization of sustainable, energy-efficient, and highly interconnected residential environments. This shift is propelled by the integration of diverse subsystems encompassing home automation, digital entertainment, healthcare monitoring, and sophisticated energy management frameworks, culminating in complex cyber-physical ecosystems that holistically enhance occupant comfort, energy efficiency, and environmental sustainability.

A central technical challenge remains achieving seamless interoperability among heterogeneous devices and subsystems, often characterized by disparate communication protocols, hardware capabilities, and proprietary standards. Addressing this requires bridging open and closed platforms to facilitate unified data exchange, semantic interoperability, and coordinated control across appliances, sensors, distributed energy resources, energy storage units, and electric vehicles. Developing advanced control algorithms capable of real-time device orchestration, predictive optimization, and adaptive energy management is critical for dynamically minimizing energy consumption while maintaining stringent constraints on occupant comfort, grid stability, and equipment longevity.

Emergent technologies such as smart grids, cyber-physical systems, and edge/fog computing architectures provide promising avenues to bolster system responsiveness, scalability, and resilience. Edge computing, for example, reduces latency and bandwidth requirements by processing data locally, enabling near-real-time decision making critical for demand response and fault detection. Integrating smart homes with advanced energy grids enables active participation in demand response schemes, facilitates peer-to-peer energy trading, optimizes the use of renewable energy sources (e.g., rooftop photovoltaics, wind turbines), and enhances grid stability via bidirectional energy flows and ancillary services. Such integration fosters the prosumer model, decentralizing energy generation and consumption, and contributes to the evolution of flexible, self-healing, and resilient energy networks.

However, the proliferation of interconnected devices generates massive, heterogeneous datasets characterized by high volume, velocity, and variety, necessitating robust data processing pipelines underpinned by ML, DL, and AI. These technologies enable advanced functionalities such as anomaly detection, predictive maintenance, load forecasting, user behavior modeling, and personalized energy management. Concurrently, the expanded attack surface and sensitive nature of energy consumption and personal data raise significant concerns regarding data privacy, cybersecurity, and secure communication, necessitating the adoption of robust encryption methods, distributed authentication protocols, intrusion detection systems, and privacy-preserving data aggregation techniques.

Complementary to technical solutions, regulatory frameworks and interoperability standards are imperative to harmonize device integration, ensure system safety, and cultivate user trust. The fragmentation of standards across manufacturers and regions presents barriers to large-scale deployment, underscoring the need for unified protocols such as IEEE 2030.5, OpenADR, and standardized IoT communication stacks. These demands concerted interdisciplinary collaboration among researchers, industry stakeholders, utilities, and policymakers to establish rigorous certification protocols, standardized interfaces, and best practice guidelines that encourage innovation while safeguarding users and critical infrastructure.

Looking forward, cutting-edge research should explore blockchain and distributed ledger technologies for decentralized, immutable, and transparent data management, potentially revolutionizing trust and security models in smart homes. The deployment of next-generation communication technologies such as 5G and emerging 6G networks will underpin ultra-reliable, low-latency connectivity essential for real-time control, distributed coordination, and support for massive device density. Moreover, advancements in energy storage technologies—including high-capacity home-scale batteries, vehicle-to-grid integration, and second-life battery applications—will significantly amplify the capability of smart homes to perform dynamic load balancing, optimize renewable energy utilization, provide frequency regulation, and participate in ancillary service markets.

8. CONCLUSION

This review highlights advancements in SHEM systems, showing their evolution from traditional manual methods to intelligent, automated, and interconnected solutions. Conventional approaches—such as insulation improvements and manual thermostat adjustments—are limited by a lack of real-time data, poor scalability, and minimal integration with RES. In contrast, SHEM systems leverage IoT devices, smart meters, and AI to optimize energy dynamically, improving efficiency, reducing costs, and enhancing occupant comfort. Architectural improvements integrate RES, energy storage, and power quality management, with solar panels and batteries supporting load balancing, capacitors stabilizing voltage, and dump loads managing excess intermittent energy. AI and ML are central, with supervised models like ANNs outperforming linear forecasting, unsupervised techniques enabling load disaggregation and anomaly detection, deep reinforcement learning achieving HVAC energy savings, MPC optimizing appliance scheduling, and game theory with multi-agent systems supporting decentralized control and peer-to-peer trading. Challenges remain in interoperability, secure data management, and user acceptance, while occupant comfort benefits from weather-responsive heating, thermal inertia, adaptive ventilation, and intelligent lighting. Integration of household appliances and electronics allows fine-grained energy management, and emerging technologies—blockchain, edge computing, and 5G/6G—offer further improvements. Overall, combining AI, RES, and adaptive strategies significantly enhances efficiency, reduces costs, improves comfort, and supports grid stability despite ongoing challenges.

ACKNOWLEDGEMENT

The authors acknowledge the use of artificial intelligence tools (e.g., ChatGPT by OpenAI) for language editing and clarity improvement during the preparation of this manuscript. The authors are fully responsible for the scientific content, analysis, and conclusions.

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