A Systematic Review of Smart Home Energy Management Systems: Methodologies, Challenges, and Future Directions

Abstract

This systematic review synthesizes the current state of research on smart home energy management systems (HEMS), focusing on optimization algorithms, IoT and communication technologies, renewable energy integration, demand response strategies, security challenges, and emerging approaches. The analysis reveals a diverse landscape of methodologies, with heuristic algorithms like WDOA and GHSA demonstrating efficiency in cost reduction, while mathematical methods such as MILP offer precision at the expense of computational complexity. IoT-based architectures, including fog computing and WI-SUN protocols, enhance real-time processing but face scalability and interoperability challenges. Renewable energy integration remains a critical focus, with studies emphasizing the need for robust storage solutions and adaptive optimization techniques. Demand response strategies, bolstered by AI and behavioral data, show promise in improving energy efficiency, though external factors like pricing structures and consumer behavior pose limitations. Security and privacy concerns, particularly false data injection attacks and lightweight cryptographic protocols, highlight the need for resilient frameworks. Emerging approaches, such as reinforcement learning and deep neural networks, suggest future directions for adaptive, data-driven HEMS. The review identifies key gaps, including the lack of real-world validation, scalability issues, and the need for hybrid models that combine the strengths of existing methodologies.

Keywords

Smart Home Energy Management Systems (HEMS), Optimization Algorithms, IoT and Communication Technologies, Renewable Energy Integration, Demand Response, Security and Privacy

Glossary & Abbreviations

HEMS: Home Energy Management System

IoT: Internet of Things

NIALM: Non-Intrusive Appliance Load Monitoring

PV: Photovoltaic

TOUP: Time-of-Use Pricing

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1 Introduction

Smart home energy management systems (HEMS) have emerged as a critical component of modern energy infrastructure, driven by the need for efficient energy consumption, cost reduction, and the integration of renewable energy sources. As residential energy demands continue to rise, HEMS play a pivotal role in optimizing energy usage, managing peak loads, and enhancing grid stability. This systematic review aims to synthesize the current state of research on HEMS, focusing on the methodologies, challenges, and future directions in the field.

The review is structured to address six key themes: optimization algorithms and methodologies, IoT and communication technologies, renewable energy integration and storage, demand response and load management, security and privacy challenges, and emerging approaches. Each theme is explored through a comparative analysis of existing studies, highlighting areas of consensus, discrepancies in results, and research gaps. By integrating findings across these themes, this review provides a comprehensive overview of the field, emphasizing the practical implications and deployment considerations for HEMS.

The optimization of HEMS involves a trade-off between computational efficiency and accuracy, with heuristic algorithms offering adaptability and mathematical methods providing precision. IoT and communication technologies, while enhancing real-time processing, face challenges in scalability and interoperability. The integration of renewable energy sources and storage systems is critical for balancing cost and efficiency, though real-world validation remains limited. Demand response strategies, bolstered by AI and behavioral data, show promise in improving energy efficiency, though external factors like pricing structures and consumer behavior pose limitations. Security and privacy concerns, particularly false data injection attacks and lightweight cryptographic protocols, highlight the need for resilient frameworks. Emerging approaches, such as reinforcement learning and deep neural networks, suggest future directions for adaptive, data-driven HEMS.

This review identifies key gaps in the literature, including the lack of real-world validation, scalability issues, and the need for hybrid models that combine the strengths of existing methodologies. By addressing these gaps, future research can enhance the practical viability and effectiveness of HEMS, contributing to a more sustainable and efficient energy future.

2 Optimization Algorithms and Methodologies

The optimization algorithms and methodologies employed in smart home energy management systems (HEMS) exhibit significant diversity, each with distinct advantages and limitations. A notable comparison arises between heuristic and mathematical techniques, as highlighted by Molla [1]. Mathematical methods, such as Mixed Integer Linear Programming (MILP) and Linear Programming, are praised for their precision but are often computationally intensive for complex problems. In contrast, heuristic techniques, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Gray Wolf Optimization, offer greater efficiency and flexibility, particularly in integrating renewable energy sources. This trade-off is further exemplified in the work of Javadi [2], which employs MILP within a risk-constrained optimization model to minimize electricity bills and manage prosumer discomfort. The study demonstrates the effectiveness of MILP in handling fixed, controllable, and interruptible loads, though it acknowledges the computational complexity inherent in such models.

Heuristic algorithms, however, have shown promise in addressing some of these computational challenges. For instance, Alsokhiry [3] introduces a wind-driven optimization algorithm (WDOA) that outperforms differential evolution (DE) in minimizing power costs and peak load demands. The WDOA-based HEMS framework achieves a peak load of 3.23 kW during off-peak hours, compared to DE's 3.88 kW, and reduces the overall energy price to 0.12 USD/day with a peak-to-average ratio (PAR) of 4.7. Despite these advantages, the study notes limitations in predicting individual behavior and non-linear power usage profiles, which are common challenges in heuristic approaches. Similarly, Hussain [4] proposes a genetic harmony search algorithm (GHSA) that combines the strengths of genetic algorithms and harmony search. The GHSA demonstrates superior performance in reducing electricity costs, PAR, and maximizing user comfort compared to WDO, HSA, and GA. This suggests that hybrid heuristic methods may offer more robust solutions for complex HEMS optimization problems.

Another innovative approach is presented by Zhao [5], which utilizes state-space approximate dynamic programming (SS-ADP) to achieve near-optimal solutions with significantly reduced computational time. The SS-ADP method, combined with LSTM-RNN for real-time forecasting, achieves solutions within 0.8% of optimal dynamic programming (DP) solutions while reducing computational time by at least 20%. This approach addresses the critical need for real-time decision-making in HEMS, though it acknowledges the necessity for finer discretization in certain state-spaces to improve accuracy. The integration of machine learning techniques, such as LSTM-RNN, further enhances the adaptability of these systems to dynamic energy environments.

Despite the progress in optimization methodologies, discrepancies in results and limitations persist. For example, while heuristic algorithms like WDOA and GHSA excel in efficiency and adaptability, they often struggle with the unpredictability of user behavior and non-linear power usage patterns. Mathematical methods, on the other hand, provide high accuracy but may not be scalable for real-time applications. The comparative analysis by Molla [1] underscores the need for further research to bridge these gaps, particularly in addressing non-linearity and deregulated market constraints. Additionally, the integration of renewable energy sources, such as photovoltaic (PV) systems, remains a challenge that requires more sophisticated optimization techniques to balance cost, efficiency, and user comfort effectively.

3 IoT and Communication Technologies

The integration of IoT and communication technologies in Home Energy Management Systems (HEMS) has been explored through various architectures and protocols, each presenting distinct advantages and limitations. A notable approach is the IoT-based Homergy system, which integrates both smart and non-smart appliances via an IoT device (Homergy Box) and a cloud-based database, achieving significant energy savings in high-consuming households (13 kWh improvement) while highlighting the cost implications of scaling such systems [6]. This practical deployment underscores the feasibility of IoT in diverse energy consumption scenarios but raises concerns about the economic viability of widespread adoption due to hardware costs.

In contrast, fog-computing-based architectures leveraging Zigbee communication have demonstrated high accuracy in appliance identification and demand response. The study by Dhaou et al. [7] employs TinyML algorithms (decision tree and SVM) to achieve 99% accuracy in smart plug identification and a 30% reduction in power costs through time-of-use-based demand response. However, the system's reliance on Zigbee introduces communication latency challenges in larger residential areas, and sensor calibration requirements may limit scalability. The use of fog computing addresses real-time processing needs but necessitates robust edge infrastructure, which may not be universally accessible.

Interoperability among heterogeneous devices remains a critical challenge, as addressed by Motta et al. [8], who propose a Wireless Smart Ubiquitous Network (WI-SUN) architecture to standardize communication between devices from different manufacturers. This system employs machine learning for load disaggregation and supports real-time energy control, outperforming similar systems in functionality. While the lightweight middleware and edge computing capabilities enhance flexibility, the need for further real-world testing suggests potential gaps in adaptability across diverse environments. The reliance on WI-SUN for both Home Area Network (HAN) and Field Area Network (FAN) communication highlights the importance of standardized protocols but also introduces dependencies on specific network infrastructures.

Machine-to-Machine (M2M) communication has been explored as a cost-minimizing solution for HEMS, with Niyato et al. [9] framing the optimal traffic concentration problem as a dynamic programming challenge. Their findings indicate that optimal cluster sizes of 3-4 nodes minimize costs for packet generation rates of 1.2 packets per minute, though assumptions of fixed concentrator costs and linear QoS degradation may oversimplify real-world complexities. This approach emphasizes the role of network topology in cost efficiency but may not fully account for dynamic environmental factors.

Historically, ZigBee sensor networks have been foundational in HEMS, as demonstrated by Han et al. [10], who introduced the Disjoint Multi-Path Routing (DMPR) protocol to enhance network performance. While this system effectively integrates sensing and actuation, its reliance on IEEE802.15.4 and ZigBee may limit compatibility with newer, more scalable protocols. The DMPR protocol improves robustness but does not address the broader interoperability challenges faced by modern HEMS.

Collectively, these studies highlight a tension between standardization and flexibility in communication protocols. While Zigbee and WI-SUN offer robust solutions for specific use cases, their limitations in scalability and interoperability suggest a need for hybrid or adaptive architectures. The economic and infrastructural constraints of IoT deployments, as noted in [6] and [7], further complicate widespread adoption. Future research should prioritize cost-effective, interoperable communication frameworks that balance real-time processing with long-term scalability.

4 Renewable Energy Integration and Storage

The integration of renewable energy sources and storage systems in smart home energy management systems (HEMS) has been explored through various methodologies, each with distinct strengths and limitations. A common theme across studies is the emphasis on optimizing energy usage and cost reduction while accommodating the intermittency of renewable sources.

[3] focuses on the integration of a rooftop photovoltaic (PV) system within a HEMS framework, employing a wind-driven optimization algorithm (WDOA) to minimize power costs and peak load demands. The study demonstrates the effectiveness of WDOA in reducing total energy costs to 0.12 USD/day with a peak-to-average ratio (PAR) of 4.7, outperforming differential evolution (DE) algorithms. However, the unpredictability of individual behavior and non-linear power usage profiles are noted as limitations, highlighting the challenge of real-world deployment. Similarly, [11] presents a comprehensive HEMS model that integrates distributed generation systems, energy storage devices, and electric vehicle charging. The framework leverages advanced metering infrastructure (AMI) and emphasizes the role of artificial intelligence in optimizing energy scheduling. While the study provides a broad overview of HEMS components, it lacks empirical validation of its proposed model, which limits its practical applicability.

[12] introduces a coordinated control scheme for a low-voltage energy router-based HEMS, designed to maximize the use of renewable energy sources (RESs) while maintaining grid stability. The proposed fuzzy logic control-based power management strategy demonstrates strong performance in simulations, effectively suppressing the impact of RES output fluctuations. However, the study's reliance on MATLAB/Simulink simulations without real-world testing raises questions about its scalability and robustness in practical scenarios. In contrast, [13] proposes a three-time-frame energy management scheme for PV-powered grid-connected smart homes, utilizing mixed-integer linear programming (MILP) optimization. The study evaluates three management concepts—load shifting, vehicle-to-home, and reducing air conditioning—under a block-rate pricing scheme. Results indicate significant reductions in electricity bills, ranging from 61% to 19%, depending on the management technique. The inclusion of battery lifetime constraints and user comfort limits adds practical value, though the study's focus on a specific regional tariff (Egyptian) may limit its generalizability.

[14] explores the integration of photovoltaic power generation and energy storage, proposing home appliances as distributed reactive sources to support grid voltage regulation. The study discusses topological and control amendments to enable appliances to provide reactive power support (RPS), fitting within a broader HEMS architecture. While the concept is innovative, the lack of empirical data on its implementation in real-world settings leaves unanswered questions about its feasibility and effectiveness in diverse grid conditions.

Across these studies, a consensus emerges on the importance of optimization algorithms and storage systems in enhancing the efficiency of HEMS. However, discrepancies arise in the choice of methodologies—ranging from metaheuristic algorithms (WDOA) to linear programming (MILP) and fuzzy logic control. The effectiveness of these approaches varies, with WDOA and MILP demonstrating tangible cost reductions, while fuzzy logic control excels in maintaining grid stability. A critical gap in the literature is the limited real-world validation of these models, which often rely on simulations or regional case studies. Future research should prioritize empirical testing and cross-regional applicability to bridge the gap between theoretical frameworks and practical deployment.

5 Demand Response and Load Management

Demand response (DR) strategies and load management techniques are critical components of smart home energy management systems (HEMS), as they directly influence energy efficiency and cost savings. Various methodologies have been proposed to optimize energy consumption, each with distinct advantages and limitations.

One prominent approach involves the use of optimization algorithms to schedule power consumption devices. For instance, Ma et al. [11] present a HEMS model that integrates distributed generation systems, energy storage devices, and electric vehicle charging. Their framework leverages advanced metering infrastructure (AMI) to optimize the scheduling of home energy sources, demonstrating the potential for cost reduction through dynamic tariff adaptation. Similarly, Baig et al. [15] employ the single knapsack problem to solve load scheduling, showcasing a hardware implementation using Zigbee transceivers and microcontrollers. While both studies highlight the effectiveness of optimization techniques, Ma et al.'s approach is more comprehensive, incorporating renewable energy sources and storage, whereas Baig et al.'s method focuses on a narrower set of appliances.

Another key aspect of demand response is the integration of behavioral and contextual data. Mubdir et al. [16] introduce a Smart Home Energy Management System (SHEMS) that detects residents' activity states using a Hidden Markov Model (HMM). By optimizing appliance operation based on real-time occupancy data, their system achieves an 18% reduction in energy consumption. This methodology contrasts with traditional scheduling approaches by emphasizing adaptive control based on user behavior, though it relies heavily on the accuracy of motion sensors and assumes fixed transition times between states.

The socio-economic dimension of demand response is also critical, particularly in regions with varying energy policies. George et al. [17] analyze the impact of billing schemes on consumer energy savings in India, revealing that inclining block rate billing can discourage efficiency. Their study proposes a new billing scheme and optimization methods for load scheduling, underscoring the need for policy alignment with technological advancements. However, the lack of smart metering infrastructure in their case study limits the scalability of their findings.

Artificial intelligence (AI) has emerged as a powerful tool for enhancing demand response strategies. Shareef et al. [18] review the application of AI techniques, such as artificial neural networks and fuzzy logic, in load scheduling controllers. These methods offer adaptive and intelligent solutions for managing energy consumption, though their effectiveness depends on the quality of input data and the complexity of the home environment. The integration of AI with traditional optimization algorithms, as suggested by Ma et al. [11], could further improve the responsiveness and efficiency of HEMS.

Despite these advancements, several challenges persist. The reliance on accurate sensor data, as seen in Mubdir et al.'s work [16], introduces potential vulnerabilities in real-world deployment. Additionally, the effectiveness of demand response strategies is often constrained by external factors, such as energy pricing structures and consumer behavior, as highlighted by George et al. [17]. Future research should focus on developing robust, adaptive systems that can accommodate these uncertainties while maximizing energy efficiency and cost savings.

6 Security and Privacy in HEMS

Security and privacy in Home Energy Management Systems (HEMS) present critical challenges that must be addressed to ensure the reliability and safety of smart home energy management. The integration of IoT devices and communication technologies in HEMS introduces vulnerabilities that can be exploited through various cyber-attacks, necessitating robust mitigation strategies.

One of the primary concerns in HEMS security is the establishment of secure communication channels. Li [19] proposes a lightweight key establishment protocol designed specifically for the computational constraints of wireless sensor nodes in smart home applications. This protocol aims to address the inadequacy of traditional security measures, which are often too resource-intensive for IoT devices. The focus on lightweight cryptographic methods highlights a critical gap in the adaptation of conventional security protocols to the unique requirements of HEMS.

Cyber-attacks such as false data injection attacks (FDIAs) pose significant threats to the integrity of HEMS. Sethi [20] investigates the impact of FDIAs on demand scheduling and energy cost minimization, proposing a cyber-attack resilient scheduling model. The study incorporates machine learning techniques to model FDIAs and integrates battery degradation costs into the optimization framework. The results demonstrate the robustness of the proposed model against FDIAs, emphasizing the need for resilient scheduling schemes that account for both energy efficiency and security.

The broader impact of cyber-attacks on HEMS is further explored by Sajeev [21], which focuses on attacks targeting price manipulation within an aggregator system. The study highlights the safety-critical nature of such attacks due to their direct connection with electricity management. Mitigation strategies, including detection methods, are discussed, with simulations demonstrating the feasibility of these approaches. The emphasis on price attacks underscores the economic and operational risks associated with cyber threats in HEMS.

Security measures for component integration are also critical in ensuring the overall resilience of HEMS. Chen [22] presents a Smart HEMS prototype based on fog-cloud computing, utilizing a two-stage Non-Intrusive Appliance Load Monitoring (NIALM) approach. The prototype leverages an artificial neural network to monitor electrical appliances non-intrusively, with a focus on secure data processing and communication. The integration of fog computing addresses the need for localized data processing, reducing latency and enhancing security by minimizing the exposure of sensitive data to centralized cloud systems.

Similarly, Gonzalez_Gil [23] proposes a modular and interoperable SHEMS architecture that integrates semantic web technologies and standard interfaces for secure data communication. The architecture is validated through implementation in a real smart home test-bed, demonstrating its ability to support interoperability and security. The study highlights the importance of standardized interfaces and semantic technologies in enhancing the security and integration capabilities of HEMS.

In summary, the security and privacy challenges in HEMS are multifaceted, requiring a combination of lightweight cryptographic protocols, resilient scheduling models, and secure component integration strategies. While advancements have been made in addressing specific vulnerabilities, such as FDIAs and price manipulation attacks, further research is needed to develop comprehensive security frameworks that can adapt to the evolving threat landscape in smart home energy management.

7 Emerging and Miscellaneous Approaches

Emerging approaches in smart home energy management systems (HEMS) are increasingly leveraging advanced computational techniques and novel architectures to address the complexities of energy optimization. One such approach is the integration of non-intrusive appliance load monitoring (NIALM) with fog (edge) computing, as demonstrated by Chen et al. [22]. Their study presents a Smart HEMS prototype that utilizes an artificial neural network-based NIALM approach to monitor electrical appliances without intrusive plug-load meters. The system's feasibility is enhanced by its deployment over fog-cloud computing, which addresses the computational demands of IoT devices at the network edge. This approach highlights the potential of edge computing to reduce latency and bandwidth usage, though its scalability and real-world applicability beyond controlled environments remain to be thoroughly evaluated.

In contrast, Lee et al. [24] propose a data-driven methodology employing reinforcement learning, specifically Q-learning, to optimize energy consumption in a smart home equipped with solar photovoltaic (PV) systems and energy storage. The integration of an artificial neural network for indoor temperature prediction enhances the Q-learning algorithm's ability to balance energy costs and user comfort. The reported 14% reduction in electricity bills suggests the efficacy of reinforcement learning in adaptive energy management. However, the reliance on simulated environments and the lack of real-world validation may limit the generalizability of these findings. Additionally, the computational complexity of reinforcement learning models could pose challenges for deployment in resource-constrained IoT devices.

Deep neural networks (DNNs) have also been explored for energy consumption prediction, as seen in the work of Devi et al. [25]. Their system, which achieved accuracy rates of 89-97%, outperforms traditional algorithms like the stochastic gradient search (SGS) and harmony search (HAS). The use of IoT devices for real-time data collection further underscores the practical deployment potential of DNNs in HEMS. Nevertheless, the high implementation costs and cybersecurity vulnerabilities identified in this study are critical limitations that necessitate further research into cost-effective and secure solutions.

Fuzzy expert systems represent another emerging approach, as illustrated by Zhang et al. [26] in their FES-EESHM framework. This system employs fuzzy logic to manage microgrids with renewable energy sources, storage systems, and controllable loads. The fuzzy expert system's ability to handle multiple input variables, such as insolation and wind speed, demonstrates its potential for complex decision-making in energy management. However, the reliance on expert-defined rules may introduce subjectivity, and the system's performance in dynamic, real-world scenarios requires further validation.

Raza et al. [27] provide a comprehensive analysis of forecasting models and scheduling optimization approaches, emphasizing the importance of precise load forecasting and scheduling in HEMS. Their review highlights the need for adaptive models that can accommodate varying energy demands and renewable energy integration. While their work does not propose a specific algorithm, it underscores the gaps in current research, particularly in the development of robust, real-time forecasting and scheduling techniques that can operate efficiently in heterogeneous smart home environments.

Collectively, these studies illustrate a shift towards more adaptive, data-driven, and computationally intelligent approaches in HEMS. However, the transition from simulation-based validation to real-world deployment remains a significant challenge. Issues such as computational resource constraints, cybersecurity risks, and the scalability of these emerging technologies must be addressed to ensure their practical viability. Future research should focus on hybrid models that combine the strengths of reinforcement learning, deep neural networks, and fuzzy logic to create more resilient and efficient energy management systems.

8 Conclusion

This systematic review has synthesized the current state of research on smart home energy management systems (HEMS), highlighting the diverse methodologies, challenges, and future directions in the field. The analysis reveals a landscape characterized by a trade-off between computational efficiency and accuracy in optimization algorithms, with heuristic techniques offering adaptability and mathematical methods providing precision. IoT and communication technologies, while enhancing real-time processing, face challenges in scalability and interoperability. The integration of renewable energy sources and storage systems is critical for balancing cost and efficiency, though real-world validation remains limited. Demand response strategies, bolstered by AI and behavioral data, show promise in improving energy efficiency, though external factors like pricing structures and consumer behavior pose limitations. Security and privacy concerns, particularly false data injection attacks and lightweight cryptographic protocols, highlight the need for resilient frameworks. Emerging approaches, such as reinforcement learning and deep neural networks, suggest future directions for adaptive, data-driven HEMS.

Key gaps identified in the literature include the lack of real-world validation, scalability issues, and the need for hybrid models that combine the strengths of existing methodologies. Future research should prioritize empirical testing and cross-regional applicability to bridge the gap between theoretical frameworks and practical deployment. Additionally, the development of cost-effective, interoperable communication frameworks and comprehensive security measures will be essential for the widespread adoption of HEMS. By addressing these challenges, future research can enhance the practical viability and effectiveness of HEMS, contributing to a more sustainable and efficient energy future.

As summarized in the comparison table, the reviewed studies highlight diverse approaches to optimizing HEMS, with a strong emphasis on the integration of renewable energy sources, demand response strategies, and advanced optimization algorithms. The patterns identified in the table suggest a need for further research to address the limitations and gaps in current methodologies, particularly in the areas of real-world validation, scalability, and security. By building on the findings of this review, future research can contribute to the development of more robust, adaptive, and efficient HEMS that meet the evolving needs of modern energy management.

9 Comparison of Home Energy Management Systems (HEMS) Research

Table 1: Comparison of Home Energy Management Systems (HEMS) Research

Ref	Objective/Research Question	Methodology/Approach	Key Findings/Results
[6]	Design and implement an IoT-based HEMS integrating smart and non-smart appliances.	Developed Homergy with IoT device, cloud database, and mobile app; tested in three scenarios.	Achieved weekly energy savings of 0.5 kWh (low-consuming house) and 13 kWh improvement over smart-devices-only systems.
[3]	Develop a HEMS framework using TOUP and WDOA to minimize power costs and peak load demands.	Employed WDOA for optimization and compared with differential evolution using a 5 kW rooftop PV system.	WDOA reduced peak load to 3.23 kW and achieved an energy price of 0.12 USD/day with PAR of 4.7.
[7]	Design an IoT-enabled smart meter and plug for HEMS using fog computing and TinyML.	Used Raspberry Pi, Arduino, Zigbee, and TinyML algorithms for appliance identification and demand response.	Achieved 99% accuracy for smart plug and 97% for smart meter, reducing power costs by 30%.
[8]	Propose a smart HEMS architecture enabling interoperability among devices from different manufacturers.	Used WI-SUN HAN/FAN, machine learning for load disaggregation, and a web/mobile platform for control.	Supported real-time control and transparent addition of new devices with lightweight middleware.
[23]	Propose a modular, interoperable, and secure SHEMS architecture integrating with existing HASs.	Theoretical design validated in a real smart home test-bed using semantic web technologies.	Demonstrated interoperability, security, and integration with existing systems in a real smart home test-bed.
[9]	Investigate M2M communication in smart grid for HEMS to minimize cost.	Presented M2M-based network architecture and applied dynamic programming for optimal cluster formation.	Optimal cluster size of 3-4 nodes minimized HEMS cost for a packet generation rate of 1.2 packets/minute.
[11]	Optimize home energy mix using HEMS with distributed generation and energy storage.	Proposed a framework based on AMI with local information management terminal for data storage and scheduling.	Established an optimized simulation model for scheduling new HEMS with PV systems and energy storage.
[1]	Review optimization techniques for HEMS focusing on mathematical and heuristic methods.	Literature review comparing mathematical (e.g., MILP) and heuristic (e.g., PSO, GA) techniques.	Mathematical techniques offer high accuracy but are time-consuming; heuristics provide efficiency and renewable integration.
[12]	Develop coordinated control for energy router-based HEMS to integrate renewable energy sources.	Used MATLAB/Simulink to model a fuzzy logic control-based power management strategy.	Demonstrated effective use of RES generations while maintaining operational stability and grid collaboration.
[16]	Design a SHEMS reducing energy consumption by detecting residents' activity states.	Used HMM for state estimation and WiFi/GSM for communication; tested via simulation.	Achieved 18% reduction in energy consumption with response time within 1-2 seconds.
[5]	Develop a fast and optimal SHEMS using SS-ADP and real-time control strategies.	Hierarchical SS-ADP with clustering and LSTM-RNN for PV and load forecasting.	SS-ADP solutions were within 0.8% of optimal DP solutions with 20% reduction in computational time.

Ref	Objective/Research Question	Methodology/Approach	Key Findings/Results
[4]	Propose an efficient HEMS controller using genetic harmony search algorithm (GHSA).	Applied GHSA for single and multiple homes with RTEP and CPP tariffs; compared with WDO, HSA, and GA.	GHSA outperformed existing algorithms in reducing electricity cost, PAR, and maximizing user comfort.
[13]	Propose a three-time-frame energy management scheme for PV-powered grid-connected smart homes.	Used mixed-integer linear programming for load shifting, vehicle-to-home, and reducing air conditioning.	Reduced electrical power bill by 61% to 19% of the default case bill under slab tariff.
[17]	Analyze socio-economic commitment towards green future through HEMS adoption in India.	Case study and energy survey of 200 consumers in Kerala, India, with optimization methods review.	Reengineering lighting loads saved up to 4.68 MWh annually; proposed new billing scheme.
[22]	Develop a smart HEMS prototype using fog-cloud computing and NIALM.	Used Tridium's Niagara Frameworkő with artificial neural network-based NIALM approach.	Established a feasible and usable SHEMS prototype with two-stage NIALM for non-intrusive monitoring.
[24]	Leverage reinforcement learning for optimal energy consumption in smart homes with PV and storage.	Applied model-free Q-learning and artificial neural network for indoor temperature prediction.	Reduced electricity bill by 14% while maintaining preferred comfort level.
[25]	Design a smart HEMS using IoT and machine learning to optimize energy consumption.	Used IoT devices and deep neural network (DNN) for real-time monitoring and dynamic pricing optimization.	DNN achieved 89-97% accuracy and 89-98% precision, outperforming existing algorithms.
[26]	Develop a fuzzy expert system for efficient energy smart home management systems.	Used fuzzy expert framework with input variables like insolation, electricity price, and wind speed.	Enhanced energy and storage utilization for renewable energy and maximized microgrid's financial gain.
[14]	Feasibility study of home appliances for grid reactive power support in HEMS.	Proposed amendments in topology and control for home appliances to provide reactive power support.	Home appliances can serve as distributed reactive sources for voltage regulation and stability.
[10]	Develop a SHEMS based on IEEE802.15.4 and ZigBee for green home energy network.	Developed DMPR routing protocol for ZigBee sensor networks and implemented in real environment.	Improved performance of ZigBee sensor networks and provided intelligent services for users.
[19]	Propose a lightweight key establishment protocol for secure HEMS.	Developed a lightweight security protocol for wireless sensor nodes in HEMS.	Addressed initial session key establishment between wireless nodes and control center.
[27]	Analyze forecasting models and scheduling strategies for optimal HEMS performance.	Reviewed forecasting models and scheduling optimization approaches in HEMS.	Identified future technical advancements and research gaps in load forecasting and scheduling.

Ref	Objective/Research Question	Methodology/Approach	Key Findings/Results
[15]	Present an energy management system for efficient load management using single knapsack problem.	Used graphical user interface and load scheduling with single knapsack problem; implemented with HMI.	Demonstrated runtime data logging and control of appliances using LABVIEW and MATLAB simulations.
[18]	Review HEMS incorporating demand response tools and load scheduling controllers.	Comprehensive review of DR programs, smart technologies, and heuristic optimization techniques.	Highlighted the application of artificial intelligence and heuristic techniques for optimal scheduling.
[2]	Propose a self-scheduling framework for HEMS using risk-constrained optimization.	Used MILP model and CVaR for reducing electricity bill and managing prosumer discomfort index.	Validated performance in mitigating electricity bill while maintaining desired discomfort index.
[20]	Formulate a cyber attack resilient scheduling model for SHEMS.	Modeled FDIA using machine learning and incorporated battery degradation cost in scheduling.	Developed a robust formulation against FDI attacks and optimized energy cost with battery degradation.
[21]	Investigate the impact of cyber-attacks on HEMS and propose mitigation strategies.	Focused on price attacks in HEMS under aggregator system; proposed detection and mitigation methods.	Presented results from simulations and detection methods for cyber-attack mitigation.

10 Discussion

The reviewed studies highlight diverse approaches to optimizing home energy management systems (HEMS), with a strong emphasis on integration of renewable energy sources, demand response strategies, and advanced optimization algorithms. Studies such as [3] and [4] demonstrate the effectiveness of heuristic algorithms like WDOA and GHSA in minimizing energy costs and peak-to-average ratios (PAR), while [5] introduces state-space approximate dynamic programming (SS-ADP) for real-time decision-making, achieving near-optimal solutions with reduced computational time. These methodologies underscore the shift towards more adaptive and efficient optimization techniques, though limitations such as the unpredictability of user behavior and the need for finer discretization in state-spaces remain unresolved. Additionally, the integration of renewable energy sources, as seen in [12] and [13], showcases the potential for HEMS to enhance grid stability and reduce reliance on traditional energy sources, with [13] achieving significant bill reductions through load shifting and vehicle-to-home strategies.

The role of IoT and communication technologies is another critical theme, with studies like [6] and [7] leveraging IoT devices and fog computing to improve energy efficiency and appliance identification accuracy. The use of TinyML and fog computing in [7] highlights the potential for edge computing to reduce latency and enhance real-time decision-making, though challenges such as communication latency in large residential areas persist. Security and privacy concerns are addressed in studies like [19] and [20], which propose lightweight key establishment protocols and cyber-attack resilient scheduling models, respectively. These contributions are essential for ensuring the robustness of HEMS against cyber threats, though further research is needed to address evolving attack vectors and the integration of advanced encryption techniques. Future work should focus on developing more scalable and secure HEMS architectures that can seamlessly integrate with emerging smart grid technologies and adapt to dynamic energy markets.

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