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Review

An overview of Optimization and learning algorithms for energy management in smart homes

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ABSTRACT

Smart home electric energy management systems are designed to optimize energy efficiency, reduce waste, and promote sustainability. This paper aims to conduct a literature review on optimization and learning algorithms for energy management in smart homes. The research methodology involves retrieving data from the Scopus database and visualizing the information through VOSviewer. The results of the literature reviewed encompass a wide range of strategies and algorithms aimed at optimizing energy management in smart homes. A key noticeable aspect is the diverse application of advanced optimization techniques and machine learning algorithms to enhance energy efficiency, reduce costs, and promote sustainability. The study contributes by providing an in-depth analysis of optimization algorithms for energy cost reduction, evaluating and categorizing learning algorithms, and identifying best practices for optimizing energy consumption in smart homes.

1. Introduction

Recent research has explored the intersection of optimization algorithms and machine learning, particularly in supervised learning contexts. Studies have investigated how optimization techniques can be learned automatically rather than hand-designed [1,2]. Various optimization methods have been applied to improve the performance of machine learning models, including gradient-based approaches, stochastic methods, and second-order techniques [3]. Researchers have also examined the application of these algorithms in specific domains, such as finance [4]. The evolution of neural network optimization has seen a shift from complex gradient-based algorithms to gradient-free methods and from fixed topologies to cascade architectures [5]. Additionally, work has been done on discovering domain-specific optimization algorithms through supervised learning approaches [6]. These advancements aim to enhance machine learning models' generalization performance and learning speed across various applications [7]. Current research on energy management in smart homes focuses on optimizing energy consumption using various machine learning and optimization techniques. Studies have explored the use of algorithms like Stochastic Gradient Descent [8], Long Short-Term Memory Networks [9], and meta-heuristic techniques such as Genetic Algorithm, Grey Wolf Optimization, and Salp Swarm Optimization [10]. These approaches aim to reduce energy costs and peak-to-average ratios while considering user preferences and environmental factors [11, 12]. Home Energy Management Systems (HEMS) has emerged as a solution for optimal asset and appliance management [13]. Recent advancements include the application of Model Predictive Control and Reinforcement Learning for managing renewable energy in smart grids [14]. Deep Q-learning and double deep Q-learning have also shown promise in optimizing home energy management, outperforming traditional methods like Particle Swarm Optimization [15]. Recent research on energy management in smart homes leverages machine learning and optimization techniques to optimize energy consumption. Key algorithms include Stochastic Gradient Descent, Long Short-Term memory networks, and meta-heuristic methods like Genetic Algorithm and Grey Wolf Optimization. These methods aim to reduce energy costs and peak-to-average ratios while accommodating user preferences and environmental factors. HEMS utilizes Model Predictive Control, Reinforcement Learning, Deep Q-learning, and double deep Q-learning for managing renewable energy, showing significant improvements over traditional methods. However, there is a gap in the literature regarding a comprehensive review of these optimization and learning algorithms. Thus, the aim of this study is to conduct a systematic review of this topic. The contributions of this literature review are:

- Providing an in-depth analysis of optimization algorithms for energy cost reduction in smart homes.
- Evaluating and categorizing learning algorithms in energy management for smart homes.
- Identifying and summarizing best practices for optimizing energy consumption in smart homes.
- Future research proposals and directions will be suggested in this paper.

The paper's organization is as follows: Section 2: Relevant Theory examines the core theories that form the basis of this study. Section 3: Methodology outlines the research design and data gathering techniques. Section 4: Results and Discussion analyzes the findings of the study. Section 5: Overall Results Discussion. Section 6: Conclusions and Future Research Proposals summarizes the main findings and suggests directions for future research.

2. Relevant theory

One of the formulas used is the payback period, which measures the time it takes for the investment to pay for itself through energy savings. Smart homes can reduce the payback period through rapid energy savings. Encourages investment in smart home energy management systems. These formulas are essential for smart home electric energy management, as they help optimize energy consumption, reduce waste, and promote sustainability. By understanding and applying these formulas, smart homes can minimize their environmental impact while maximizing energy efficiency and cost savings [16].

$$PP = \frac{IC}{AES} \tag{1}$$

The payback period (PP) is the time it takes for the investment to pay for itself through energy savings, calculated by dividing the investment cost (IC) by the annual energy savings (AES). The other formula is Return on investment, which is the ratio of energy savings to investment cost. Smart homes can provide a high ROI through energy savings and increased property value, justifying investment in smart home energy management systems [17].

$$ROI = \frac{ES \times CS}{IC} \tag{2}$$

Return on investment (ROI) is the ratio of energy savings (ES) multiplied by cost savings (CS) to the investment cost (IC). Thirty Energy efficiency is the ratio of energy saved to total energy consumed. Smart homes can optimize energy efficiency through automated lighting and temperature control. Reduces energy consumption, lowers bills, and minimizes environmental impact [18].

$$EE = \left(\frac{ES}{TEC}\right) \times 100 \tag{3}$$

Energy efficiency (EE) is calculated by dividing the energy saved (ES) by the total energy consumed (TEC) and multiplying by 100. Lastly, the Load factor is the ratio of average power to peak power. Smart homes can improve load factor through load balancing and scheduling. Reduces energy waste, lowers bills, and optimizes energy usage [19].

$$LF = \frac{P_{avg}}{P_{max}} \tag{4}$$

Where Load Factor (LF) is the ratio of average power (P_{avg}) to peak power (P_{max}).

3. Methodology

3.1 Identification

The study's initial phase involved a comprehensive search for relevant documents within the Scopus database. This process yielded a total of 57 initial records. The search was conducted using a strategic combination of keywords to ensure thorough coverage of the topic. Specifically, the keywords “smart home” AND “electrical” OR “electric” AND “energy management” AND “machine learning”. This approach was designed to capture a wide range of literature pertaining to the use of unmanned aerial vehicles in the context of power line inspection operations. The resulting dataset forms the basis for subsequent analysis and review.

3.2 Screening

The filtering process was initiated to refine the initial set of 57 documents. The first criterion applied was the range of publication years, limited to the period from 2019 to 2023, which resulted in 40 remaining documents. Next, the search was restricted to the subject area of "Engineering," further narrowing the pool to 30 documents. Subsequently, the document type was filtered to include only articles and conference papers, reducing the count to 25. Finally, the language criterion was applied, selecting only English-language documents, which left 22 documents. These 22 documents were then exported for further analysis and qualified for the subsequent screening process (Table 1).

Table 1. Example of inclusion and exclusion criteria

Item name	Inclusion criteria	Exclusion criteria
Database	Scopus	IEEE, google scholar, web of science
Publication Period	2020-2023	The document published in 2019 and before
Document type	Articles and reference paper	Book chapters, books, notes, letters, editorials reviews.
Subject area	Engineering	Energy, mathematics, physical, life, social, health and humanities sciences.
Language area	English	Other languages
File Type	CSV	RIS, Bib Tex, plain text
Documents	22 documents	35 documents
Keywords	Smart home	Other keywords

3.3 Eligibility

Out of the 22 exported papers, a closer examination revealed that 2 of the documents were review papers, which did not fit the criteria for original research required for this study. Additionally, six papers were determined to be irrelevant to the specific focus on smart homes, energy management, and electrical. After excluding these inaccessible, review, and irrelevant documents, a total of 14 papers were identified as meeting the eligibility criteria. These 75 documents were thus deemed suitable for further detailed analysis and formed the core dataset for the subsequent stages of the research process.

3.4 Synthesis and themes classification

The synthesis of the 14 finalist documents involved a detailed review and thematic classification to organize and understand the breadth of research covered. Each document was analyzed to identify key themes, and the classification helped in categorizing the documents into distinct areas of focus, which included different types of algorithmic (machine learning, particle swarm optimization, Q- learning) that may be used to conduct research in smart homes for energy management. Each document was assigned to one of these themes based on its content, allowing for a structured analysis of the collective findings. This thematic classification not only facilitated a comprehensive synthesis of the literature but also highlighted the key areas where energy management and cost-saving are driving innovation in smart homes.

3.5 VOSviewer analyzation

To analyze using VOSviewer, you first download your VOSviewer app on your desktop. Create a bibliographic map using a document from Scopus that you must save as a CVS file; it must include all the documents that are included in your literature review and are relevant to the area of interest. While selecting inclusions, include Co-occurrence, All Keywords, full counting. The threshold must be above 20. If not, reduce the minimum number of occurrences of keywords to 3. The first bibliographic map must be saved as network visualization. To get an overlay visualization map request on the top, there must be a selected written overlay visualization. To get a cluster, select save and save your file. In that saved document, you will have all the keywords classed per cluster, make a table, and from that table, analyze and observe your information per network visualization and overlay visualization.

4. Results and discussions

4.1 Optimization algorithms for energy cost reduction in smart homes

The aim was to minimize energy costs in smart urban homes. Polar bear optimization algorithm, differential evolution, and practice swarm optimization algorithm were used. Two energy cost metrics were used, namely critical peak price and real time price by Zhang and Xie [20]. This research paper is about finding an accurate and efficient method to predict occupancy in smart homes. They used genetic algorithms and particle swarm optimization. During the research, they discovered that the genetic algorithm and particle swarm optimization were more accurate than the long short-term memory network done by Mahjoub et al. [21]. This paper developed a novel algorithm for collaborative execution before and after dependency-based requirements. Tested through simulation, compared with particle swarm. Demonstrated improved performance in percentage cost reduction peak to the average ratio by Vasudevan et al. [22].

4.2 Learning algorithms in energy management for smart homes

Meng and Feng [23] presented a comprehensive approach to energy management in smart homes, combining cutting-edge technologies like extreme machine learning, the internet of things, and real-time monitoring to optimize energy efficiency and reduce costs. This paper presents a comprehensive framework for appliance recognition in smart homes, enabling efficient energy management and customized monitoring. Three machine learning models were included for classification tasks like feed-forward neural network, long short-term memory, and support vector machine, search done by Franco et al. [24]. The paper presents a comprehensive solution for load recognition in a home energy management system, combining efficient event detection and advanced machine learning techniques for accurate appliance identification. A fast and accurate event detector stage using wavelet transform. This approach achieved accuracy above 98% on refit, making it highly efficient and effective [25]. Keerthisinghe et al. [26] proposed a policy function approximation algorithm using machine learning to control photovoltaic storage systems in smart homes. The results show that policy function approximation solutions are close to optimal solutions obtained through dynamic programming, making them efficient and adaptive solutions for smart home energy management. Tundis et al. [27] suggested a model for automatically identifying appliances in smart homes to facilitate dynamic load management and energy efficiency in smart grids. The approach extracted 19 features from device profiles, including energy consumption, time usage, and location, employing machine learning classifiers to identify appliances based on these features.

Applying a model-free Q learning method to schedule for individually controllable home appliances, using an artificial neural network and Q learning algorithm to learn the relationship between the indoor temperature and energy consumption, was conducted. According to research done by Lee and Choi [28], the proposed algorithm outperformed the existing approach by 14%, resulting in lower electricity bills. Tai et al. [29] integrated deep Q network agents to learn and control appliance usage and energy storage. The system aims to reduce energy costs and peak demand considering uncertain user behaviors. The result showed 28.9% in peak value, 20.9% in peak-to-average ratio, and 28.6% in electricity cost.

4.3 Optimizing energy consumption in smart homes

Khan et al. [30] proposed a smart home automation system to control energy consumption. The system works in three phases: phase 1 is feature extraction and classification using 1D-DCNN to identify energy patterns from historical data, phase 2 is load forecasting using LSTM-based extracted features, and phase 3 is scheduling algorithm to optimize appliance operational time. The problem addressed in this article is the need for an efficient method to estimate the individual power usage of electrical appliances in a smart home. They used a two-step method. First, collect and store current data of individual appliances with varying loads. Secondly, estimate individual load current using the stored data. The artificial bee colony algorithm is used for estimating an individual electrical load by Ghosh and Chatterjee [31]. The paper presents an approach to optimize energy consumption and management in smart homes using deep reinforcement learning. The results demonstrated the effectiveness of the proposed approach in reducing total electricity cost, optimizing energy storage system and Electric vehicle state of energy, and meeting consumer preferences [32]. Leonori et al.

[33] identified a suitable energy management systems model for real-time energy management in resource-constrained devices, considering both performance and computational effort. They compared different lightweight energy management system models for microgrids, Nano grids, smart homes, and hybrid electric vehicles and analyzed the computational effort required by each EMS model.

4.4 Trends analysis

4.4.1 Network visualization based on smart home electric energy management

Table 2 represents the clusters under network visualization, which is a great way to visualize and understand the relationships between different keywords and concepts. Cluster 1 is made up of 13 items, cluster 2 is made up of 10 items, and cluster 3 is made up of 8 items; all these clusters are made up of keywords, links, Total link strength, and occurrences. On these clusters, what has been found is that the higher the Total Link Strength, the higher the Occurrences, and the lower the Total Link Strength, the lower the Occurrences; for example, cluster 1 has a high total link strength on "energy utilization" and high occurrence is also on "energy utilization". Low total link strength is on "deep learning" and the low occurrences are also on "deep learning". Cluster 2 has a high total link strength on "automation" and high occurrences also on "automation" and a low total link strength on "algorithm" and low occurrences is also on "algorithm". Cluster 3 has high total link strength in "smart homes" and high occurrences in "smart homes," low total link strength on "electric power transmission networks," and low occurrences in "electric power transmission networks".

Figure 1 is a map for network visualization. The colors show the keywords under some colors are related to each other, and the clusters are represented by the colors: cluster 1 is in red color, cluster 2 is in green color, cluster 3 is in blue color. On cluster 1, the researchers were more focused on energy utilization; on cluster 2 research were more focused on automation; and on cluster 3 research were more focused on smart homes. The line in between indicates the links between keywords. The more lines indicate the strength, and the closer suggests the relationship between the keywords. The ones that are the same colors indicate they fall under the same cluster. The bigger the dot, the higher the strength links.

4.4.2 Overlay visualization based on smart home electric energy management

Table 3 indicates different clusters under overlay visualization; the tables show which had the most trends in the years 2021 to 2023; during the year 2020, the average citation on cluster 1 was on simulation and less on learning systems. The most average citation in cluster 2 was on learning algorithms during 2020 and less on electric load during 2023; in cluster 3, the most average citation was on the smart grid during 2021 and less on energy efficiency during 2022.

Figure 2 shows the overlay visualization based on smart home electric energy management. This shows the keywords that the researchers were most interested in between the years 2020 and 2023, and according to this map, it seems that they were more focused on automation, energy management, learning algorithms, smart homes, and machine learning. Their focus was less on forecasting, energy efficiency, electric load, human and long, short term memory.

Table 2. Keywords with, links, total link strength with occurrence based on smart home electric energy management

Description		Network Visualization (Gap Analysis)		
Keywords	**No.**	**Links**	**Total link Strength**	**Occurrences**
Cluster 1				
article	1	28	53	3
controlled study	1	28	53	3
deep learning	1	26	40	3
domestic appliances	1	29	60	4
electric energy storage	1	27	47	3
energy conservation	1	29	58	4
energy consumption	1	29	65	4
energy utilization	1	30	73	5
human	1	28	53	3
learning systems	1	26	48	5
reinforcement learning	1	24	43	3
scheduling	1	27	44	3
simulation	1	28	61	4
Cluster 2				
algorithm	2	23	34	3
automation	2	30	125	13
digital storage	2	28	47	4
electric loads	2	17	24	3
energy management	2	30	89	8
energy management systems	2	29	53	6
intelligent buildings	2	28	63	7
learning algorithms	2	29	63	6
machine learning	2	29	70	6
neural networks	2	24	36	3
Cluster 3				
electric power transmission networks	3	17	24	3
energy efficiency	3	27	46	4
forecasting	3	23	32	3
internet of things	3	25	37	3
long short-term memory	3	23	32	3
smart grid	3	25	36	3
smart homes	3	30	77	7
smart power grids	3	30	62	6

5. Discussion

The literature reviewed encompasses a wide range of strategies and algorithms aimed at optimizing energy management in smart homes. A key noticeable aspect is the diverse application of advanced optimization techniques and machine learning algorithms to enhance energy efficiency, reduce costs, and promote sustainability. Various studies have implemented algorithms such as polar bear optimization, differential evolution, particle swarm optimization, artificial bee colony, genetic algorithms, and deep reinforcement learning. These approaches address challenges like peak load reduction, accurate appliance load estimation, occupancy prediction, and dynamic load management. Techniques like Q-learning, artificial neural networks, extreme machine learning, and policy function approximation are also explored to create adaptive, real-time energy management systems. The research highlights the effectiveness of these advanced methodologies in achieving significant improvements in energy cost reduction, peak-to-average ratio, and overall energy management efficiency in smart urban homes.

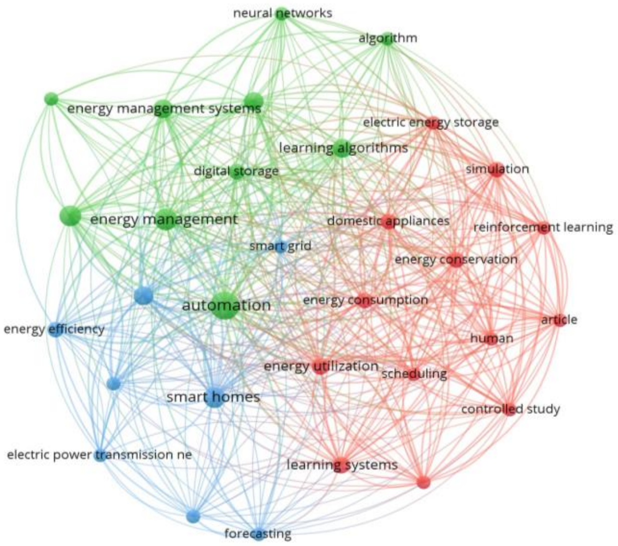

Figure 1. Network visualization based on smart home electric energy management

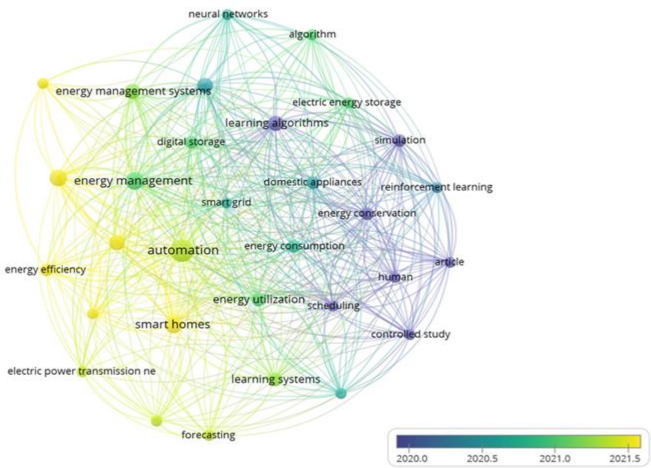

Figure 2. Overlay visualization based on smart home electric energy management

Table 3. Keywords with links, average publication year, and average citation based on smart home electric energy management

Description		Overlay Visualisation (Trend Analysis)	
Keywords	**No.**	**Avg. pub. Year**	**Avg. citations**
Cluster 1			
article	1	2020	58
controlled study	1	2020	58
deep learning	1	2021	37
domestic appliances	1	2021	44
electric energy storage	1	2021	53
energy conservation	1	2020	52
energy consumption	1	2021	43.5
energy utilization	1	2021	37.8
human	1	2020	58
learning systems	1	2021	27.2
reinforcement learning	1	2020	58
scheduling	1	2020	56
simulation	1	2020	59.5
Cluster 2			
algorithm	2	2021	47.6667
automation	2	2021	27.4615
digital storage	2	2021	31.25
electric loads	2	2023	12
energy management	2	2021	26.875
energy management systems	2	2021	34
intelligent buildings	2	2021	19
learning algorithms	2	2020	49.6667
machine learning	2	2021	37.1667
neural networks	2	2021	48
Cluster 3			
electric power transmission networks	3	2021	14.3333
energy efficiency	3	2022	6.5
forecasting	3	2021	10.3333
internet of things	3	2022	11.3333
long short-term memory	3	2021	10.3333
smart grid	3	2021	37.3333
smart homes	3	2022	18.4286
smart power grids	3	2022	20.3333

6. Conclusions

This paper conducted literature review on optimization and learning algorithms for energy management in smart homes. The research methodology involved retrieving data from the Scopus database and visualizing the information through VOSviewer. The results of the literature reviewed encompass a wide range of strategies and algorithms aimed at optimizing energy management in smart homes. A key noticeable aspect was the diverse application of advanced optimization techniques and machine learning algorithms to enhance energy efficiency, reduce costs, and promote sustainability. The study contributed by providing an in-depth analysis of optimization algorithms for energy cost reduction, evaluating and categorizing learning algorithms, and identifying best practices for optimizing energy consumption in smart homes. While the reviewed literature extensively covers various optimization techniques and machine learning algorithms for smart home energy management, several gaps remain for future research. Integration of multiple renewable energy sources beyond photovoltaic systems, such as wind and hydro, needs more comprehensive exploration. Additionally, user behavior and preferences are often overlooked; future studies should focus on user-centric models that adapt to lifestyle patterns and comfort levels. Scalability and real-world implementation of these algorithms require further investigation to address large-scale deployment challenges. Cybersecurity and privacy concerns are critical as connectivity increases, necessitating research on secure algorithms and protocols. Lastly, the lack of interoperability and standardization among different smart home devices calls for studies aimed at developing universal standards and protocols to enhance system integration and efficiency.

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Ethical issue
The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement
The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest
The authors declare no potential conflict of interest.

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