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A Survey on IoT and Artificial Intelligence-Based Smart Home Energy Management Systems: Techniques, Challenges and Future Directions

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Abstract: The increasing penetration of Internet of Things (IoT) devices, renewable energy resources, smart meters, and connected appliances has created new opportunities for intelligent energy management in residential environments. Conventional energy management approaches are often limited by manual monitoring, inaccurate demand estimation, limited interoperability, and the inability to respond dynamically to changing consumption patterns. This paper presents a technical survey of recent research in IoT- and Artificial Intelligence (AI)-based smart home and smart grid energy management. Twenty representative studies covering energy monitoring, load forecasting, non-intrusive load monitoring, demand response, appliance scheduling, anomaly detection, optimization, edge AI, and user behavior modeling are analyzed. The reviewed studies demonstrate that machine learning, deep learning, optimization algorithms, IoT communication technologies, and edge computing can substantially improve energy awareness, forecasting, cost reduction, and automated control. However, significant challenges remain in dataset availability, cross-household generalization, computational complexity, cybersecurity, privacy, interoperability, and large-scale deployment. The survey develops a taxonomy of existing approaches, compares their methodologies and reported results, identifies research gaps, and discusses future directions toward adaptive, secure, low-cost, explainable, and autonomous home energy management systems.

Index Terms: Internet of Things, smart home, energy management, artificial intelligence, load forecasting, demand response

I. INTRODUCTION

A. Background and Motivation

The rapid growth of electricity consumption, distributed renewable energy resources, connected appliances, and digital communication technologies has accelerated the transition from conventional electricity networks toward intelligent energy systems. Smart grids use sensing, communication, computation, and control technologies to improve the interaction between energy suppliers and consumers. At the household level, Home Energy Management Systems (HEMS) provide mechanisms for monitoring energy consumption, forecasting demand, scheduling appliances, and supporting energy-efficient behavior.

The increasing availability of IoT-enabled sensors and smart meters has made it possible to collect high-resolution electricity consumption data. Such data can subsequently be processed using machine learning and optimization techniques. The reviewed literature demonstrates this transition from basic monitoring systems toward intelligent predictive and autonomous energy management.

For example, an IoT-based energy management architecture can collect measurements from individual devices and transfer them to a centralized analytics platform. An early smart-home energy management approach employed IoT data-acquisition modules and centralized Big Data analytics to monitor household devices and HVAC systems [1]. More recent approaches increasingly move intelligence toward edge devices and integrate AI-based prediction and optimization.

Energy forecasting is one of the major components of intelligent HEMS. Accurate forecasting enables households and utilities to anticipate future demand and perform proactive scheduling. Recent research has investigated Transformer

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networks, LSTM models, gradient boosting, quantile regression, and other machine learning algorithms for this purpose [3], [11], [18].

B. Need for This Survey

Although numerous studies have investigated individual components of smart energy management, the research landscape is fragmented across monitoring, forecasting, optimization, demand response, energy disaggregation, edge computing, and human behavior.

There is therefore a need for a consolidated technical survey that examines these technologies from a common smart-home energy management perspective. This survey focuses on the interaction between IoT infrastructure and AI-based intelligence and identifies the trade-offs between prediction accuracy, computational complexity, cost, scalability, and practical deployment.

The reviewed literature also indicates that high reported performance does not necessarily imply good real-world generalization. Several studies are evaluated on a single household, a limited number of sites, simulated datasets, or small-scale prototypes. These limitations motivate further research toward scalable and robust systems.

C. Contributions of This Paper

The main contributions of this survey are:

1) A taxonomy of IoT- and AI-based smart-home energy management technologies is developed.
2) Twenty recent and representative research works are systematically analyzed according to methodology, application, datasets, results, advantages, and limitations.
3) Monitoring, forecasting, scheduling, optimization, NILM, anomaly detection, edge AI, and user behavior approaches are compared.
4) Key research challenges involving scalability, cybersecurity, privacy, interoperability, computation, and dataset diversity are identified.
5) Future research directions for adaptive and autonomous smart-home energy management are proposed.

D. Paper Organization

The remainder of this paper is organized as follows. Section II describes the survey methodology. Section III presents the taxonomy of smart-home energy management technologies. Section IV reviews the selected literature. Section V provides comparative analysis. Section VI discusses challenges and future directions. Section VII concludes the paper.

II. METHODOLOGY OF SURVEY

A. Data Sources

The literature considered in this survey was obtained primarily from peer-reviewed and technical publications supplied for the study. The source collection contains publications from IEEE, Springer, Elsevier, and other engineering journals and conference proceedings.

The review emphasizes research published between 2020 and 2026, while one earlier foundational work from 2017 is retained because of its relevance to IoT-based smart-home energy management.

B. Search Keywords

The following keyword groups were used to characterize the literature:

- “smart home energy management”
- “IoT energy monitoring”
- “artificial intelligence energy management”
- “household energy forecasting”
- “load forecasting LSTM”
- “energy disaggregation NILM”
- “demand response smart home”
- “edge AI energy forecasting”
- “appliance scheduling”
- “smart meter IoT”

C. Inclusion Criteria

A study was considered relevant when it satisfied one or more of the following criteria:

1) Addresses residential, household, or smart-grid energy management.
2) Uses IoT, machine learning, artificial intelligence, optimization, edge computing, or related technologies.
3) Provides a technical implementation, experiment, simulation, dataset, or quantitative evaluation.
4) Reports measurable performance or clearly describes system functionality.

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D. Exclusion Criteria

Studies were excluded when they were unrelated to household or smart-grid energy management, lacked sufficient technical description, or focused exclusively on unrelated industrial applications.

A total of twenty principal papers were selected for detailed analysis. The papers span energy monitoring, prediction, optimization, scheduling, anomaly detection, energy disaggregation, and user-centered energy conservation.

III. TAXONOMY OF SMART HOME ENERGY MANAGEMENT

The reviewed literature can be classified into six major categories:

1) IoT-based energy monitoring and metering.
2) AI-based energy forecasting.
3) Energy disaggregation and appliance identification.
4) Demand response and appliance scheduling.
5) Optimization and intelligent energy management.
6) Edge computing, anomaly detection, and user behavior.

A. IoT-Based Energy Monitoring

IoT monitoring systems establish the sensing and communication foundation of HEMS. Typical systems employ current and voltage sensors, microcontrollers, wireless communication, cloud services, and mobile dashboards.

ESP32-based monitoring has been demonstrated as a low-cost solution for real-time measurement of voltage, current, active power, and cumulative energy consumption [10]. Similarly, Arduino-based smart energy meters integrate sensors, Blynk, Wi-Fi, relay control, and fire detection [8].

B. AI-Based Energy Forecasting

Forecasting systems use historical energy measurements to estimate future consumption. Conventional machine learning, deep learning, ensemble learning, Transformers, and probabilistic models are represented in the reviewed literature.

Transformer-based forecasting combined with Stationary Wavelet Transform decomposition has been investigated for household electricity prediction [3]. Quantile-LSTM and clustering have been proposed for probabilistic short-term load forecasting [11]. More recently, multiple algorithms including gradient boosting and NGBoost have been compared across different temporal resolutions [18].

C. Energy Disaggregation

Non-Intrusive Load Monitoring (NILM) attempts to estimate individual appliance consumption from aggregate household measurements. This approach reduces the requirement for individual sensors on every appliance. A hybrid HDBSCAN-FHMM method first identifies appliance operating states using clustering and then performs energy disaggregation using a modified Factorial Hidden Markov Model [14].

IoT and AI-Based Smart Home Energy Management	
IoT Monitoring and Smart Metering	AI-Based Energy Forecasting
Energy Disaggregation and NILM	Demand Response and Scheduling
Optimization and Intelligent Control	Edge AI, Anomaly Detection and User Behavior

Fig. 1. Taxonomy of IoT- and AI-based smart-home energy management approaches identified from the reviewed literature.

D. Demand Response and Scheduling

Demand response shifts flexible electricity consumption according to price signals, grid requirements, or renewable-energy availability.

The IESR approach provides real-time appliance scheduling recommendations based on energy consumption, user-defined criteria, and electricity price signals [5]. IoT-based demand response architectures further integrate photovoltaic generation, energy storage, advanced metering, and Time-of-Use pricing [15].



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E. Optimization and Intelligent Control

Optimization techniques are used to minimize energy cost, peak-to-average ratio, or other objectives while satisfying household constraints.

The Long-Term Memory Artificial Rabbit Optimization (LMARO) algorithm was proposed for residential energy optimization and reported cost reductions of up to 22% for individual households and larger improvements in multi-household simulations [16].

F. Edge AI and Intelligent Monitoring

Edge computing reduces latency and dependence on remote cloud servers by performing inference close to the sensing device. ESP32-S3-based TinyML forecasting demonstrates that useful energy prediction can be performed on resource-constrained hardware [17].

Anomaly detection is another important component. Machine-learning methods have been investigated for identifying point, contextual, and collective anomalies in heterogeneous IoT sensor streams [6].

IV. LITERATURE REVIEW

A. IoT-Based Monitoring and Metering

Al-Ali et al. presented a smart-home energy management system based on IoT data-acquisition modules, a mesh network, centralized processing, and Big Data analytics. HVAC systems were used as a case study. The architecture demonstrated how off-the-shelf analytics tools could be integrated into residential energy management [1].

Castro et al. developed IntelliPlugs, an IoT-based smart plug supporting Wi-Fi and GSM communication. The system was designed for real-time monitoring and control and incorporated electrical and environmental sensors. Its principal strength is dual connectivity, while its limitation is the absence of advanced AI-based analytics [2].

El-Khozondar et al. proposed an ESP32-based energy monitoring system using Blynk and WhatsApp notifications. The system measures voltage, current, active power, and cumulative consumption. The work emphasizes low-cost implementation and real-time user feedback [10].

Jambhulkar et al. proposed an IoT-based smart energy meter using Arduino, current sensing, Blynk, voice control, temperature and humidity sensing, and flame detection. The system enables remote monitoring and control of domestic appliances [8].

Cuenca-Enrique et al. addressed monitoring challenges in rural Solar Home Systems using a hybrid LoRa and mobile-network architecture. Eight systems were retrofitted in a pilot deployment in Panama. The work demonstrates the importance of low-power and low-connectivity-aware communication architectures [13].

B. AI-Based Energy Forecasting

Saoud et al. introduced a hybrid household energy forecasting approach combining Stationary Wavelet Transform and Transformer networks. The wavelet transform decomposes consumption signals while the Transformer learns patterns in the resulting subbands. The reported experiments demonstrated superior performance compared with existing prediction methods [3].

Masood et al. proposed a clustering-based probabilistic forecasting framework using quantile LSTM and log-cosh quantile loss. The method was evaluated for 15-minute and one-hour day-ahead forecasting. The proposed approach improved prediction interval coverage compared with several benchmark quantile models [11].

Devanathan et al. conducted a multi-algorithm analysis of household energy consumption across hourly, daily, weekly, monthly, and quarterly horizons. Eight machine-learning algorithms were evaluated. The study reported that the best model varies according to the forecasting horizon, demonstrating the importance of temporal resolution in model selection [18].

Moura et al. investigated on-device monthly energy forecasting using an ESP32-S3. The experiments used three-day windows and compared different harmonic input regimes. The study reported approximately $R^2 = 0.93$ in the single-phase case, with sub-millisecond latency and sub-millijoule inference energy [17].

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C. Energy Disaggregation and NILM

Tokam et al. proposed an HDBSCAN-FHMM architecture for NILM. HDBSCAN identifies appliance operating states before a modified FHMM performs disaggregation. The approach was evaluated on the AMPds dataset and improved F1 score, MAE, and Match Rate relative to reference methods [14].

The eLAMI dataset work by Tari et al. addresses a different but complementary problem: the shortage of rich household energy datasets. The authors developed a real-measurement-based simulated dataset containing more than 400 electrical parameters for 36 appliances. Validation was performed against real measurements [4].

D. Demand Response and Scheduling

Fakhar et al. developed IESR, an instant energy scheduling recommendation method that detects appliances operating during peak-price periods and generates recommendations according to user-defined criteria. Experiments using public datasets and multiple price signals reported cost savings of up to 84% [5].

Habibu et al. proposed an IoT-enabled energy management controller integrating photovoltaic generation, energy storage, advanced metering infrastructure, and appliance scheduling under Time-of-Use pricing. The architecture seeks autonomous demand response and improved renewable-energy utilization [15].

E. Optimization-Based Energy Management

Youssef et al. proposed LMARO, an enhanced Artificial Rabbit Optimization algorithm for residential energy management. A multiple-knapsack model was used to constrain energy consumption during peak periods. Simulation results reported cost reductions and reductions in the peak-to-average ratio for multiple-household scenarios [16].

George and Selvakumar reviewed smart-home energy management in India from a socio-economic and policy perspective. Their study analyzed energy consumption among 200 low-tension consumers and reported that lighting-load re-engineering could save up to 4.68 MWh annually. The study also highlights barriers involving pricing, adoption, privacy, and policy [9].

F. Anomaly Detection and Intelligent Security

Majib et al. investigated anomaly detection in smart buildings using DIY IoT devices. Point, contextual, and collective anomalies were studied using machine-learning techniques. The work also highlights the difficulty of combining sensors operating at different sampling rates [6].

Bhardwaj and Joshi proposed a unified AI framework for MATTER-enabled smart homes. The system combines ensemble prediction, LSTM/One-Class SVM/autoencoder anomaly detection, and reinforcement learning for resource allocation. The study reported 92% prediction accuracy, 0.97 precision and 0.95 recall for anomaly detection, and an Energy Efficiency Ratio of 0.82 [12].

G. User Behavior and Human-Centered Management

Mataloto et al. investigated long-term energy savings through user behavior modeling. Their system employed interactive dashboards, 3D visualization, mobile connectivity, and utility integration. A one-year deployment reported an average energy reduction of 19%, while a survey involving 208 participants evaluated user acceptance and usefulness [7].

The literature suggests that technically accurate energy management is not sufficient by itself. User engagement, explainability, privacy, and perceived usefulness can determine whether energy saving behaviors persist over time.

H. Additional IoT and Smart-Grid Architectures

Rubymeena et al. proposed an IoT-based smart-grid energy management system with AI-assisted emergency shutdown. The system supports remote monitoring and automated responses during electrical hazards. Its main limitation is that the implementation remains at the prototype stage [19].

The reviewed studies collectively demonstrate an evolution from simple monitoring systems toward integrated architectures combining sensing, prediction, optimization, and autonomous control.

V. COMPARATIVE ANALYSIS

Table I summarizes the twenty principal studies. The comparison considers the main technology, application, evaluation method, and principal reported outcome.

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TABLE I
COMPARISON OF THE TWENTY REVIEWED STUDIES

No.	Study	Year	Main Technique	Dataset / Evaluation	Major Result / Limitation
1	Devanathan et al.	2026	Multi-algorithm AI forecasting	Household energy data	Up to 99.99% reported accuracy; single-household limitation
2	Al-Ali et al.	2017	IoT mesh + Big Data analytics	HVAC prototype	Scalable EMS concept; server and congestion limitations
3	Bhardwaj and Joshi	2025	Ensemble ML + LSTM + OCSVM + RL	Smart-home scenarios and emulated attacks	92% prediction accuracy; edge-resource limitations
4	Cuenca-Enrique et al.	2025	LoRa + mobile communication	8 rural Solar Home Systems	Low-power remote monitoring; small pilot
5	Anuraj et al.	2026	Web of Things + edge computing	Raspberry Pi rehabilitation case study	Interoperability and real-time edge operation; preliminary validation
6	El-Khozondar et al.	2024	ESP32 + Blynk + Wi-Fi	Experimental monitoring	Low-cost real-time monitoring; platform limitations
7	Masood et al.	2024	Clustering + Quantile LSTM	Household load datasets	Improved prediction interval coverage; short-term scope
8	Saoud et al.	2022	SWT + Transformer	Household power consumption	Superior forecasting performance; regular sampling requirement
9	Tokam et al.	2025	HDBSCAN + modified FHMM	AMPds dataset	Improved F1, MAE and Match Rate; computational cost
10	Fakhar et al.	2022	Instant scheduling recommendation	Two public datasets	Up to 84% cost saving; predefined user criteria
11	Castro et al.	2020	Arduino smart plug + WiFi/GSM	Prototype	Dual connectivity and monitoring; limited AI
12	Jambhulkar et al.	2023	Arduino + Blynk + voice control	Prototype	Remote monitoring and safety detection; basic analytics
13	Mataloto et al.	2023	User behavior modeling	1-year deployment + 208 participants	19% energy reduction; adoption concerns
14	Moura et al.	2026	TinyML on ESP32-S3	Two 30-day sites	$R^2 \approx 0.93$; domain-shift limitation
15	Tari et al.	2022	Real-measurement-based simulation	36 appliances, 400+ parameters	Rich open dataset; simulation fidelity limitation
16	Rubymeena et al.	2026	IoT + AI emergency control	Prototype system	Automated hazard response; prototype limitation
17	Youssef et al.	2025	LMARO optimization	CEC functions + HEM model	22% single-household cost reduction; simulation-based
18	Majib et al.	2022	ML anomaly detection	DIY IoT sensor data	Point/contextual/collective anomaly detection; heterogeneous sampling issues
19	Habibu et al.	2025	IoT demand response + optimization	Synthetic data	Improved economic efficiency; limited real-world validation
20	George and Selvakumar	2024	Review + Indian case study	200 low-tension consumers	4.68 MWh/year potential lighting saving; policy-oriented

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A. Accuracy and Forecasting Performance

Forecasting-oriented studies generally report high predictive performance, but direct comparison is difficult because different datasets, prediction horizons, evaluation metrics, and experimental conditions are used. Devanathan et al. reported different best-performing algorithms for hourly, daily, weekly, monthly, and quarterly horizons [18]. Masood et al. focused on probabilistic forecasts and prediction interval coverage rather than a single deterministic accuracy value [11].

The Transformer-SWT approach demonstrates the usefulness of signal decomposition before deep learning, whereas TinyML work emphasizes the additional constraints of memory, latency, and energy consumption [3], [17].

B. Cost and Complexity

IoT monitoring systems based on Arduino and ESP32 provide attractive low-cost implementation options. However, systems using advanced AI models may require substantially greater computational resources. Edge AI provides an alternative by executing optimized models directly on microcontrollers.

Optimization methods such as LMARO can improve energy cost and peak demand but often depend on simulation and may become computationally expensive as the number of appliances increases [16].

C. Dataset Limitations

Dataset quality is one of the most important limitations across the reviewed literature. Some studies use single-household datasets, small pilots, synthetic data, or short observation periods. The eLAMI dataset addresses the lack of rich electrical parameters by providing more than 400 parameters across 36 appliances [4].

Nevertheless, simulated data cannot completely reproduce the variability, noise, appliance aging, and behavioral changes found in real households.

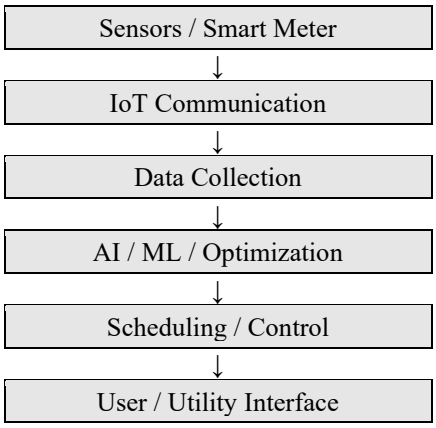


Fig. 2. Generic architecture of an intelligent IoT-based home energy management system.

TABLE II
CROSS-STUDY COMPARISON BY SYSTEM CHARACTERISTIC

Characteristic	IoT	AI/ML	Edge	Real Deployment
Monitoring	High	Low	Medium	Medium
Forecasting	Medium	High	Increasing	Medium
NILM	Medium	High	Low	Low
Scheduling	High	Medium	Medium	Medium
Optimization	Medium	High	Low–Medium	Low
Anomaly Detection	High	High	Increasing	Medium
User Modeling	High	Medium	Medium	High

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VI. CHALLENGES AND FUTURE DIRECTIONS

A. Dataset Diversity and Generalization

A major research gap is the lack of large, geographically diverse, multi-season household datasets. Models trained using one household or one site may not generalize to other homes.

Future direction: Future studies should construct privacy-preserving multi-household datasets covering different climates, appliance types, lifestyles, seasons, and electricity tariff structures.

B. Computational Complexity

Deep learning and metaheuristic optimization algorithms can require considerable computational resources. This becomes problematic for low-cost IoT devices.

Future direction: Model compression, quantization, knowledge distillation, pruning, TinyML, and hardware-aware neural architecture design can enable intelligent inference on microcontrollers.

C. Privacy and Cybersecurity

Smart homes continuously collect detailed information about household behavior. Electricity consumption can indirectly reveal occupancy patterns and lifestyle characteristics.

Future direction: Federated learning, differential privacy, secure aggregation, encrypted communication, and zero-trust IoT architectures should be investigated.

D. Interoperability

The rapid growth of heterogeneous IoT devices creates interoperability problems. Devices may use different protocols, data formats, and vendor-specific platforms.

Future direction: Standardized frameworks such as MATTER and Web of Things can provide common device descriptions and communication interfaces. AI systems should also be designed to operate across heterogeneous hardware.

E. Real-Time Adaptive Control

Many studies perform prediction or optimization independently. A practical HEMS requires a closed-loop system that senses current conditions, predicts future demand, makes decisions, and observes the resulting outcome.

Future direction: Reinforcement learning and online learning can provide adaptive decision-making under changing occupancy, appliance usage, renewable generation, and electricity prices.

F. Explainability and User Acceptance

Users may hesitate to accept automated energy decisions when the system cannot explain why an appliance was scheduled or switched off. User engagement is therefore an important factor in long-term energy savings.

Future direction: Explainable AI techniques such as SHAP and LIME, together with user-centered dashboard design, can improve trust and acceptance. The MATTER-enabled study specifically identifies explainability as a future enhancement [12].

VII. RESEARCH OPPORTUNITIES FOR AN INTEGRATED HEMS

The reviewed literature suggests that future smart-home energy management systems should integrate five layers. First, a sensing layer should collect voltage, current, power, environmental, and appliance-level information. Second, an IoT communication layer should provide reliable and interoperable connectivity. Third, an intelligence layer should combine forecasting, anomaly detection, and appliance identification. Fourth, an optimization layer should determine cost- and energy-efficient actions. Finally, a control and user layer should execute decisions while allowing user intervention.

Such an architecture would combine the strengths of the reviewed research. For example, low-cost ESP32 sensing can provide the hardware platform, Transformer or LSTM models can support forecasting, NILM can identify appliance-level consumption, reinforcement learning can support adaptive scheduling, and edge computing can reduce response latency.

The major research opportunity is therefore not simply improving one individual algorithm but designing an integrated system capable of operating reliably under realistic household conditions.

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VIII. CONCLUSION

This survey reviewed twenty studies covering IoT monitoring, smart metering, artificial intelligence, energy forecasting, non-intrusive load monitoring, demand response, scheduling, optimization, anomaly detection, edge computing, and user behavior modeling for smart-home energy management. The literature shows that the field is progressing from basic energy monitoring toward predictive and increasingly autonomous energy management.

Machine learning and deep learning provide strong capabilities for forecasting and anomaly detection, while optimization and demand response methods support cost and peak-load reduction. At the same time, low-cost IoT and edge platforms make intelligent energy management increasingly practical. However, limited datasets, computational constraints, cybersecurity risks, interoperability problems, and limited real-world validation remain significant barriers.

Future HEMS research should therefore emphasize integrated, privacy-preserving, explainable, interoperable, and adaptive architectures. Combining IoT sensing, edge AI, predictive analytics, reinforcement learning, and optimization offers a promising direction toward autonomous and energy-efficient smart homes.

REFERENCES

[1] A. R. Al-Ali, I. A. Zualkernan, M. Rashid, R. Gupta, and M. AliKarar, “A smart home energy management system using IoT and big data analytics approach,” 2017.
[2] R. C. C. Castro, M. A. R. Lunaria, E. dR. Magsakay, M. C. Leyesa, N. E. G. Silao, J. G. Jaudian, and E. J. Morsiquillo, “IntelliPlugs: IoT-based smart plug for energy monitoring and control through WiFi and GSM,” 2020.
[3] L. S. Saoud, H. Al-Marzouqi, and R. Hussein, “Household energy consumption prediction using the stationary wavelet transform and transformers,” IEEE Access, 2022, doi: 10.1109/ACCESS.2022.3140818.
[4] L. Tari, G. Berrettoni, C. Bourelly, G. Cerro, D. Capriglione, and L. Ferrigno, “eLAMI—An innovative simulated dataset of electrical loads for advanced smart energy applications,” IEEE Access, 2022, doi: 10.1109/ACCESS.2022.3201960.
[5] M. Z. Fakhar, E. Yalcin, and A. Bilge, “IESR: Instant energy scheduling recommendations for cost saving in smart homes,” IEEE Access, 2022, doi: 10.1109/ACCESS.2022.3174073.
[6] Y. Majib, M. Barhamgi, B. M. Heravi, S. Kariyawasam, and C. Perera, “Detecting anomalies within smart buildings using do-it-yourself Internet of Things,” Journal of Ambient Intelligence and Humanized Computing, vol. 14, pp. 4727–4743, 2023, doi: 10.1007/s12652-022-04376-w.
[7] B. Mataloto, J. C. Ferreira, and R. P. Resende, “Long term energy savings through user behavior modeling in smart homes,” IEEE Access, 2023, doi: 10.1109/ACCESS.2023.3272888.
[8] A. T. Jambhulkar, A. M. Bhoyar, C. M. Shivankar, P. S. Balwad, and P. Nandankar, “IoT-based smart energy meter for monitoring home appliances,” International Journal of Innovations in Engineering and Science, vol. 8, no. 7, pp. 1–5, 2023.
[9] T. George and A. I. Selvakumar, “Smart home energy management systems in India: A socio-economic commitment towards a green future,” Discover Sustainability, vol. 5, 101, 2024, doi: 10.1007/s43621-024-00295-2.
[10] H. J. El-Khozondar, S. Y. Mtair, K. O. Qoffa, O. I. Qasem, A. H. Munyarawi, Y. F. Nassar, E. H. E. Bayoumi, and A. A. E. B. A. El Halim, “A smart energy monitoring system using ESP32 microcontroller,” ePrime—Advances in Electrical Engineering, Electronics and Energy, vol. 9, 100666, 2024.
[11] Z. Masood, R. Gantassi, and Y. Choi, “Enhancing short-term electric load forecasting for households using quantile LSTM and clustering-based probabilistic approach,” IEEE Access, 2024, doi: 10.1109/ACCESS.2024.3406439.
[12] N. Bhardwaj and P. Joshi, “Adaptive energy management for MATTER-enabled smart homes,” IEEE Access, 2025, doi: 10.1109/ACCESS.2025.3584381.
[13] C. Cuenca-Enrique, L. Del-Río-Carazo, E. Acquila-Natale, and S. Iglesias-Pradas, “Addressing connectivity challenges in solar home systems: A monitoring solution for rural electrification,” IEEE Access, 2025, doi: 10.1109/ACCESS.2025.3585231.
[14] L. W. Tokam, S. K. Apeke, and S. S. Ouro-Djobo, “Hybrid HDBSCAN-FHMM approach for energy disaggregation in non-intrusive load monitoring (NILM) systems,” IEEE Access, 2025, doi: 10.1109/ACCESS.2025.3570930.
[15] H. M. A., S. Sivakumar, G. R. Kanagachidambaresan, and E. S. Mwanandiye, “An effective IoT-based demand response for energy-efficient smart homes,” Energy Informatics, vol. 8, 125, 2025.
[16] H. Youssef, S. Kamel, and M. H. Hassan, “Smart home energy management with long-term memory artificial rabbit algorithm for cost and load optimization,” 2025.
[17] G. A. Moura, A. W. A. Soares, D. R. Belfort, and S. Y. C. Catunda, “On-device edge AI for monthly energy forecasting on ESP32-S3 using 3-day windows: Hardware-constrained feasibility with harmonics and offline interharmonic benchmarking,” 2026.

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DOI: 10.17148/IJARCCE.2026.1510138

[18] D. B., J. V. K., P. K. L., P. Manelllore, L. S. A., K. S., and S. A., "AI-based energy consumption forecasting in smart homes using multi-algorithm analysis across temporal resolutions," Results in Engineering, 2026.
[19] A. Rubymeena, N. Jagadeshwari, K. Priyanka, G. Gobika, and V. Sivanantham, "IoT based smart grid energy management system with artificial intelligence," International Journal of Engineering Research and Technology, 2026.
[20] B. Anuraj, J.-M. Aerts, and J.-P. Calbimonte, "An edge-enabled Web of Things framework for home rehabilitation monitoring of older adults," IEEE Access, 2026, doi: 10.1109/ACCESS.2026.3671678.
[21] C. W. Gellings, The Smart Grid: Enabling Energy Efficiency and Demand Response. Boca Raton, FL, USA: CRC Press, 2009.
[22] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—The new and improved power grid: A survey," IEEE Communications Surveys & Tutorials, vol. 14, no. 4, pp. 944–980, 2012.
[23] D. S. Parker, "The economics of smart home energy management," Energy Policy, 2015.
[24] J. Z. Kolter and M. J. Johnson, "REDD: A public data set for energy disaggregation research," in Proc. SustKDD Workshop, 2011.
[25] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu, and Y. Zhang, "Short-term residential load forecasting based on LSTM recurrent neural network," IEEE Transactions on Smart Grid, vol. 10, no. 1, pp. 841–851, 2019.

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