

# A Survey For Real-Time Energy Monitoring and Management Using IoT and Machine Learning

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**Abstract**—The growing demand for energy, coupled with rising costs and sustainability concerns, has motivated extensive research into efficient energy monitoring and management systems. This review consolidates findings from sixteen prominent studies spanning IoT-enabled smart homes, real-time monitoring, non-intrusive load monitoring (NILM), energy forecasting, and microgrid management. These works demonstrate diverse approaches, including machine learning, artificial intelligence, middleware design, graph signal processing, and low-cost IoT protocols. A comparative analysis highlights advancements in real-time anomaly detection, appliance-level disaggregation, and hierarchical energy management systems. The review also identifies current challenges such as interoperability, data scarcity, system scalability, and user adaptability, while outlining promising research directions toward affordable, reliable, and sustainable energy solutions.

**Index Terms**—Energy Management, Internet of Things (IoT), Machine Learning, Time-Series Forecasting, Anomaly Detection, Smart Grid, LSTM, Smart Home

## I. INTRODUCTION

The global rise in energy consumption, combined with increasing electricity costs and the urgent need for sustainability, has intensified the demand for intelligent energy management systems. Conventional monitoring approaches, such as smart meters, typically provide only aggregate consumption data without offering insights at the room or appliance level. This lack of granularity prevents users from detecting abnormal usage patterns, identifying faulty appliances, or making informed decisions regarding energy conservation.

To address these challenges, researchers have explored a wide spectrum of technologies, including the Internet of Things (IoT), artificial intelligence (AI), machine learning

(ML), and advanced communication protocols. IoT enables real-time data acquisition from non-intrusive sensors and smart appliances, while AI and ML facilitate accurate load disaggregation, anomaly detection, and demand forecasting. In parallel, middleware solutions and energy management controllers have been developed to overcome interoperability and control challenges in complex environments such as smart homes, microgrids, and urban infrastructures.

The research surveyed in this review paper spans sixteen notable contributions, covering IoT-based smart home systems [1]–[4], energy forecasting and load disaggregation techniques [5]–[8], computational intelligence for microgrid energy management [9], [10], advanced NILM methods [11], [12], user-centric automation systems [13], [14], and holistic reviews of energy management strategies [15], [16]. Together, these studies provide a comprehensive perspective on how technological innovations are transforming energy monitoring from simple measurement tools into intelligent systems capable of adaptive, predictive, and sustainable management.

This review synthesizes the findings of these works under key thematic categories, evaluates their strengths and limitations, and highlights future directions for building scalable, affordable, and user-friendly energy management ecosystems.

## II. IOT ARCHITECTURES FOR SMART HOMES AND BUILDINGS

The Internet of Things (IoT) plays a central role in modern energy monitoring and management systems by connecting appliances, sensors, and control units into a unified intelligent framework. These architectures enable

real-time monitoring, predictive analytics, and automated control, making them an essential foundation for smart homes and buildings.

Al-Ali et al. [1] developed a multi-layer IoT-based Energy Management System (EMS) that incorporates big data analytics to provide predictive insights and optimize energy usage. Their approach highlights how IoT can go beyond passive monitoring to support proactive decision-making. Similarly, Villegas-Ch. et al. [2] integrated AI techniques into IoT monitoring systems, achieving up to 98.7% accuracy in anomaly detection, which underscores the potential of AI-enabled IoT solutions to improve system reliability and efficiency.

Cruz et al. [3] emphasized the need for middleware frameworks that ensure interoperability, scalability, and security in IoT environments. As different devices often use heterogeneous communication protocols, middleware becomes essential for enabling seamless data exchange across platforms. In large-scale deployments, such as smart buildings or campuses, this modular middleware ensures that the system remains adaptable as new devices are added.

Minoli et al. [4] contributed by addressing the security and standardization challenges in IoT-based smart buildings. Their work points out that as IoT adoption grows, risks such as unauthorized access, privacy breaches, and inconsistent standards could hinder scalability. Incorporating robust security mechanisms and adopting standardized communication protocols are therefore critical to the success of IoT-driven EMS.

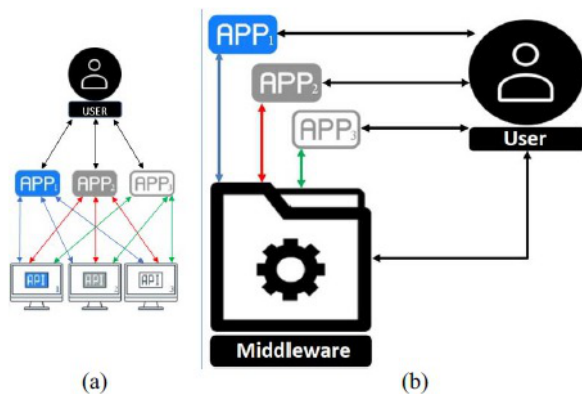


Fig. 1. Illustration of the communication (a) without middleware and (b) with middleware.

These studies collectively highlight the layered architecture of IoT solutions, typically consisting of sensors, communication protocols, middleware, and application interfaces, offering a scalable and adaptable foundation for smart energy systems.

### III. LOAD FORECASTING AND ENERGY DISAGGREGATION

Load forecasting and energy disaggregation have become critical for optimizing energy consumption and ensuring efficient power distribution in both residential and microgrid settings. Traditional aggregate load data is insufficient for identifying individual appliance usage patterns. Hence, researchers have focused on non-intrusive

load monitoring (NILM) and demand forecasting as enabling technologies.

Yu et al. [5] introduced a sparse coding approach, which uses signal decomposition to predict household energy consumption with improved accuracy. Unlike traditional statistical models, sparse coding can effectively distinguish overlapping load signatures, which is one of the major challenges in NILM. Zhao et al. [6] enhanced event-based NILM using graph signal processing, improving robustness in noisy environments and making it possible to detect events even when multiple devices operate simultaneously.

Afzalan et al. [7] proposed a self-configuring event detection framework, leveraging motif-based clustering to adapt to new appliances without manual intervention. This represents a step toward fully autonomous NILM systems. In parallel, Alcalá et al. [8] achieved 98.6% accuracy in activity recognition using a single-point sensing system, demonstrating that NILM can also be applied for human activity detection in smart homes.

Overall, these studies show that NILM and forecasting methods not only improve energy management but also open doors to applications such as appliance-specific billing, fault detection, and user behavior analysis. However, they also highlight the need for scalable, low-cost implementations that can operate in real time.

### IV. COMPUTATIONAL INTELLIGENCE FOR MICROGRID ENERGY MANAGEMENT

Microgrids, which integrate distributed energy resources such as solar panels and wind turbines, require advanced control systems to balance supply and demand effectively. Computational intelligence techniques including machine learning, fuzzy logic, and optimization algorithms are increasingly being applied for this purpose.

Bilal et al. [9] conducted a comprehensive review of AI-driven energy management systems for microgrids, categorizing strategies into centralized, decentralized, and hierarchical approaches. Centralized methods offer global optimization but suffer from high communication overhead. In contrast, decentralized systems are more robust but may lead to suboptimal energy allocation. Hierarchical approaches, which combine both, have emerged as the most practical for real-world deployment.

Sreevidhya et al. [10] demonstrated the application of ML in NILM at the microgrid level by comparing classifiers. Their study found that K-Nearest Neighbor (KNN) achieved 100% classification accuracy, outperforming decision trees. This underlines the potential of ML in achieving precise load identification, which is crucial for microgrid stability.

The implication is clear: computational intelligence enables predictive control, fault tolerance, and renewable energy integration in microgrids. However, the reliance on high-quality datasets and the computational complexity of these models remain challenges for large-scale adoption.

### V. ADVANCES IN NILM THROUGH MACHINE LEARNING

Recent advances in NILM are characterized by a shift from traditional supervised learning approaches to more data-efficient techniques, such as semi-supervised and

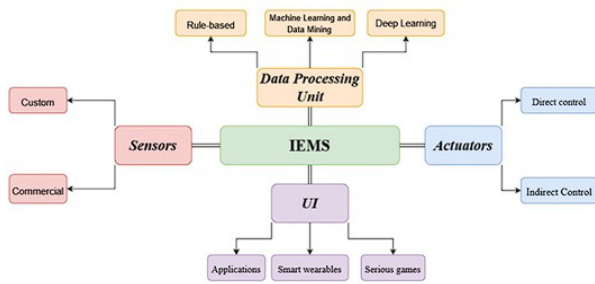


Fig. 2. Classification figure of the components of an IEMS

unsupervised learning. This transition is driven by the scarcity of labeled datasets and the diversity of appliance signatures.

Zhao et al. [11] introduced a self-supervised CNN framework, using V-I trajectory images for feature extraction. Their model achieved F-scores of around 0.97, setting a benchmark for NILM accuracy. This approach reduces the need for extensive labeled data, making NILM more scalable. Liu et al. [12] further contributed by employing unsupervised fuzzy clustering, which delivered over 90% accuracy while eliminating the dependency on labeled training datasets.

These studies highlight how deep learning and unsupervised methods are transforming NILM from a research problem into a deployable solution. However, the trade-off between accuracy and computational cost persists, as deep learning models demand powerful hardware, which may not be suitable for edge devices in cost-sensitive applications.

## VI. DATASETS AND EVALUATION METRICS

The performance of NILM and energy management systems depends heavily on the availability of reliable datasets and the use of appropriate evaluation metrics. Across the surveyed works, several benchmark datasets are commonly used.

The REDD (Reference Energy Disaggregation Dataset) and UK-DALE (Domestic Appliance-Level Electricity Dataset) are among the most widely used datasets for NILM research [6], [11], [12]. REDD provides high-frequency power consumption data collected from multiple households in the U.S., while UK-DALE offers long-term, appliance-level monitoring from homes in the U.K. Both datasets are instrumental in testing NILM algorithms, though they have limitations such as limited geographic diversity and appliance variability.

Other datasets, such as the AMPDs (Almanac of Minutely Power Dataset), provide long-duration consumption data for a single household in Canada, focusing on detailed, minute-level monitoring. While useful for longitudinal studies, their lack of multi-household diversity reduces generalizability. Some studies also use custom datasets tailored to specific contexts, but the absence of standardized public datasets limits comparability across research [7], [8].

Evaluation metrics are equally important. Most NILM studies employ accuracy, precision, recall, and F-score to quantify classification performance [11]. Energy-specific

metrics, such as energy estimation error and normalized disaggregation error, are used to measure how accurately total consumption is broken down into appliance-level loads [5], [12]. In forecasting, metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are standard benchmarks for predictive performance [5].

TABLE I  
COMMONLY USED DATASETS IN NILM AND EMS RESEARCH.  
EVALUATION METRICS INCLUDE ACCURACY, PRECISION, RECALL,  
F-SCORE, MAE, RMSE, AND MAPE.

Dataset	Scale	Notes
REDD	15 kHz, 3–4 mo / 6 homes	Benchmark; limited households
UK-DALE	1 Hz + 16 kHz, 4 yr / 5 homes	Long-term; small sample size
AMPDs	1 min, 2 yr / 1 home	Detailed; single household
Custom	Varies	Case-specific; not generalizable

Despite these contributions, challenges persist. Existing datasets do not adequately represent diverse geographic regions, appliance types, and cultural usage patterns. Moreover, the lack of standardized evaluation protocols makes it difficult to compare algorithms fairly. Future work should prioritize creating large-scale, open datasets and adopting unified evaluation benchmarks, enabling more robust, reproducible, and globally applicable EMS solutions.

## VII. USER-CENTRIC AUTOMATION AND COMMUNICATION PROTOCOLS

For energy management systems to succeed, user engagement and accessibility are as important as technical accuracy. Several studies have focused on developing systems that are low-cost, user-friendly, and reliable.

Dwivedi et al. [13] created a GSM-enabled Android application for home automation, targeting users such as the elderly and differently abled. The system provided a practical, affordable solution for remote appliance control, demonstrating that energy management technologies can also serve social inclusion goals. Islam and Mahmud [14] addressed communication bottlenecks in microgrids by designing a peer-to-peer IoT protocol. Their protocol reduced latency and improved reliability compared to centralized systems, paving the way for decentralized energy trading.

Together, these studies emphasize that the success of smart energy systems depends not only on technical efficiency but also on ease of use, inclusivity, and resilient communication infrastructure. Future work should further explore integrating voice assistants, mobile applications, and decentralized IoT protocols to make energy systems more user-centered.

## VIII. ENERGY MANAGEMENT CONTROLLERS AND INTELLIGENT EMS

Energy Management Controllers (EMCs) form the backbone of smart energy systems, orchestrating the flow of power across devices, households, and microgrids. Controllers are typically classified into centralized, decentralized, and hierarchical systems.

Bakre et al. [15] reviewed these strategies, noting that centralized systems, while simple to manage, often face issues of single-point failure and scalability. Decentralized controllers improve resilience but lack coordination across the network. Hierarchical approaches, combining the strengths of both, emerged as the most effective for large-scale systems.

Mischos et al. [16] further categorized Intelligent EMS into direct control strategies (automation-based systems that directly regulate appliances) and indirect control strategies (systems that influence user behavior via feedback and incentives). Their review found that direct control works best in commercial environments where automation is acceptable, whereas indirect control strategies are more effective in residential contexts, encouraging users to actively participate in energy saving.

These insights underline that the choice of controller must be context-specific, balancing automation with user involvement, and scalability with cost-efficiency. Hybrid models that integrate AI-driven optimization with user-centric control mechanisms represent the most promising path forward.

## IX. COMPARISON OF METHODS

The research surveyed in this review proposes diverse methods for energy monitoring and management, ranging from IoT-based architectures and machine learning models to communication protocols and intelligent control strategies. Each approach addresses specific challenges such as real-time monitoring, appliance-level energy disaggregation, prediction accuracy, scalability, and user accessibility. A comparative analysis of these methods highlights their strengths, limitations, and suitability for different application scenarios.

One of the most widely adopted approaches in energy management systems is the IoT-based architecture for real-time monitoring. Studies such as Al-Ali et al. [1] and Minoli et al. [4] propose multi-layer IoT frameworks that integrate sensors, communication networks, cloud platforms, and user interfaces. These systems enable continuous data acquisition and remote monitoring of electricity consumption. The primary advantage of IoT-based systems lies in their ability to provide real-time insights and automate energy control. However, these architectures often face challenges related to interoperability, security, and scalability when integrating heterogeneous devices from multiple vendors.

Another category of methods focuses on Artificial Intelligence and Machine Learning techniques for anomaly detection and intelligent decision-making. Villegas-Ch. et al. [2] demonstrated that AI-based monitoring systems can achieve high accuracy in detecting abnormal energy usage patterns. Compared with rule-based systems, ML-based models are capable of learning complex patterns from historical energy data and adapting to dynamic consumption behaviors. However, these approaches require large volumes of training data and computational resources, which may limit their deployment on low-power edge devices.

A significant portion of the literature also concentrates on Non-Intrusive Load Monitoring techniques. NILM

methods aim to disaggregate total household energy consumption into individual appliance-level usage without installing dedicated sensors for each device. Yu et al. [5] proposed a sparse coding approach for load forecasting that improves prediction accuracy by decomposing energy signals into representative components. Similarly, Zhao et al. [6] introduced a graph signal processing method that enhances event-based NILM by effectively identifying appliance switching events even in noisy environments.

Further advancements in NILM include event-based and self-configuring systems. Afzal et al. [7] developed a motif-based clustering approach that automatically detects patterns in energy signals and adapts to new appliances without manual configuration. This approach improves scalability compared to traditional supervised learning methods. Alcalá et al. [8] demonstrated that event-based disaggregation techniques can achieve high accuracy using single-point sensors, making them cost-effective for residential applications.

Machine learning classifiers are also widely used for energy monitoring tasks. Sreevidhya et al. [10] compared multiple classification algorithms for NILM and reported that the K-Nearest Neighbor (KNN) algorithm achieved higher classification accuracy compared to decision trees. While KNN provides excellent accuracy for appliance identification, it may suffer from increased computational complexity when handling large datasets. Decision trees, on the other hand, offer faster computation and easier interpretability but may not achieve the same level of classification precision.

Recent studies have also explored deep learning approaches to improve the performance of NILM systems. Zhao et al. [11] introduced a self-supervised convolutional neural network (CNN) that uses voltage-current trajectory images for appliance recognition. This method reduces dependency on labeled datasets while maintaining high detection accuracy. Liu et al. [12] proposed an unsupervised fuzzy clustering approach that eliminates the need for labeled data entirely, making it suitable for large-scale deployments where manual labeling is impractical. However, deep learning models generally require powerful hardware and higher energy consumption for training.

Beyond monitoring and disaggregation techniques, energy management controllers play a critical role in optimizing energy usage across larger systems such as microgrids. Bilal et al. [9] reviewed computational intelligence approaches including optimization algorithms, neural networks, and fuzzy logic controllers. These methods enable dynamic energy balancing and renewable energy integration. Bakre et al. [15] further categorized energy management controllers into centralized, decentralized, and hierarchical systems. While centralized systems offer better global optimization, they suffer from scalability issues and single points of failure. Decentralized systems provide improved reliability but may lack coordination across the network. Hierarchical approaches combine the benefits of both and are increasingly considered the most practical solution for complex energy systems.

Communication protocols and user-centric solutions also represent an important category of energy management methods. Dwivedi et al. [13] proposed a GSM-

enabled home automation system controlled via an Android application, which provides a low-cost solution for remote appliance management. In contrast, Islam and Mahmud [14] developed a peer-to-peer IoT communication protocol designed specifically for smart microgrids. Their decentralized communication model reduces latency and improves system reliability compared to centralized cloud-based architectures.

Overall, the comparison of these methods reveals that no single technique is sufficient to address all aspects of energy monitoring and management. IoT architectures provide the infrastructure for data collection and communication, while machine learning and NILM algorithms enable intelligent data analysis and appliance-level insights. Energy management controllers optimize system-level performance, and communication protocols ensure efficient interaction between devices and users. Therefore, the most effective energy management solutions are typically hybrid systems that combine IoT sensing, machine learning analytics, and intelligent control mechanisms

## X. LIMITATIONS

Despite notable progress, several limitations persist across the reviewed works.

TABLE II  
SUMMARY OF KEY LIMITATIONS IN ENERGY MANAGEMENT SYSTEMS

Limitation	Description
Interoperability and Standardization	Fragmented and proprietary IoT protocols hinder seamless device integration and scaling.
Data Availability	Scarcity of labeled datasets limits the performance of supervised ML methods in NILM and forecasting.
Accuracy–Cost Trade-off	High accuracy AI models require computational resources often unavailable on low-cost or edge devices.
User Acceptance	Systems relying solely on automation may face resistance; those needing frequent user input risk disengagement.

First, interoperability and standardization remain significant hurdles. Many IoT solutions operate on proprietary or fragmented protocols, making integration across devices and vendors challenging. Without a unified standard, scaling such systems beyond individual households or small communities is difficult.

Second, data availability poses a barrier to machine learning-based NILM methods. While supervised approaches show excellent accuracy, they require large volumes of labeled data, which are often scarce. Even unsupervised and self-supervised methods, though promising, still face challenges in generalizing across diverse appliances and usage patterns.

Finally, the trade-off between accuracy and cost continues to limit widespread adoption. High-performing AI models often demand computational resources unsuitable for low-cost or edge devices. Conversely, simpler solutions, while affordable, may sacrifice accuracy or scalability. Moreover, user acceptance is not guaranteed—systems that rely solely on automation may face resistance, while those requiring frequent user input risk disengagement over time.

## XI. CONCLUSION

This review has examined a wide range of approaches to intelligent energy management systems, covering IoT-based architectures, load forecasting, NILM advancements, microgrid energy management, user-centric solutions, and controller strategies. The surveyed works demonstrate that energy monitoring has evolved from simple data collection to sophisticated systems capable of providing real-time feedback, predictive analytics, and adaptive control. With IoT integration, users gain granular insights into consumption patterns, while machine learning techniques, particularly in NILM, enable accurate appliance-level disaggregation.

At the system level, computational intelligence and advanced control strategies have shown significant potential for improving microgrid stability, renewable energy integration, and demand-side management. Meanwhile, user-centric solutions highlight the importance of accessibility, inclusivity, and communication protocols in ensuring widespread adoption. Together, these approaches represent a paradigm shift toward sustainable, efficient, and user-driven energy systems.

Nevertheless, limitations remain. The lack of interoperability, dataset diversity, and standardized evaluation metrics continues to constrain scalability and comparability of solutions. High computational demands and cybersecurity risks further add to the complexity of large-scale deployments. Addressing these gaps will be essential for future progress.

Looking ahead, research should focus on lightweight AI and edge computing, the creation of standardized IoT protocols, and the development of large-scale, diverse NILM datasets. Equally important are privacy-preserving methods and user-centric innovations that encourage long-term engagement. By combining these directions, future EMS can become not only technically advanced but also socially inclusive and globally scalable.

In conclusion, intelligent energy management systems hold immense potential in the transition toward a sustainable energy future. By bridging technical innovation with practical deployment, these systems can contribute to reducing energy costs, supporting renewable adoption, and achieving global sustainability targets.

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