International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Real-Time Big Data Processing with IoT Sensors for Intelligent Energy Management in Smart Residential Environments

[1]Deepak Khamitkar, [2]Prashanthi Chinthala

Submitted:03/11/2025 **Revised**: 14/12/2025 **Accepted:** 25/12/2025

Abstract: The incorporation of IoT technologies into home energy management systems facilitates the most advanced approaches to mitigating excessive energy use. This research examines the possibilities for real-time IoT-enabled monitoring and control of automated systems for smart energy homes. For automated control systems of HVAC systems and lighting, real-time adjustments and control systems based on occupancy, temperature, and power consumption, and forecast predictive control systems for energy management have been integrated. Big data analytics supports decision-making around inefficient consumption patterns. Moreover, AI algorithms that drive predictive analytics streamline the forecasting of a predetermined energy management plan. IoT-enabled intelligent energy management systems provided real-world proof of concept for the reduction of energy expenditure and consumption at the household level. The smart home energy sustainability initiative in this research incorporates big data analytics and IoT for the first time in the literature.

Keywords: *IoT Sensors, Energy Management, Big Data Analytics, Smart Homes, Artificial Intelligence.*

I. Introduction

New technologies are transforming all sectors, and energy is no exception. An energy IoT landscape ensures immediate global control of energy systems, which is now only developing for real time energy systems. Smart homes, as an integral part of the real time energy management architecture, contain IoT based automated energy consumption monitoring and management systems. Automation of building control systems collect and analyze huge amounts of machine data being generated by IoT connected equipment and use these insights to enhance effective energy management, moderately using energy and reducing waste.

Intelligent energy management systems not only have Internet of Things (IoT) devices that monitor ambient factors such as humidity, temperature and light but also require measuring human presence. The construction of the next-generation smart big data analytics systems provides a vision for consumers' detailed information with respect to energy use which, in turn, assists them how they can effectively manage the use of the available resources. Fully integrated with energy efficiency, money saving guides Join the Movement!

The addition of A.I. and machine learning algorithms to these setups will likely increase the capabilities tenfold. AI based on anticipated adjustments which can forecast changes in consumption studies trends and pattern from the data gathered in several of IoT sensors. These analyses can help manage energy more proactively (such as adjusting HVAC systems, tailoring the level of energy to fit better demand and real-time control over lighting based on occupancy data). Through the combination of IoT sensors and big data analytics as energy management tools, a reduction in energy consumption, utility bills, and carbon footprints can be accomplished. This study assesses the practical integration of the Internet of Things (IoT) and big data technology in the management of energy within smart homes and explores the potential for broader application of these technologies. In relation to the discussion on sustainable energy practices, the article details smart energy management systems,

[1]*Software Engineer, Amazon Canada*
deepakscomk@gmail.com
[2]*Cloud support Engineer, California, USA*
prashanthich01@gmail.com

IoT sensors, big data, and AI. The article also describes how these innovations improve the energy and environmental efficiency of homes.

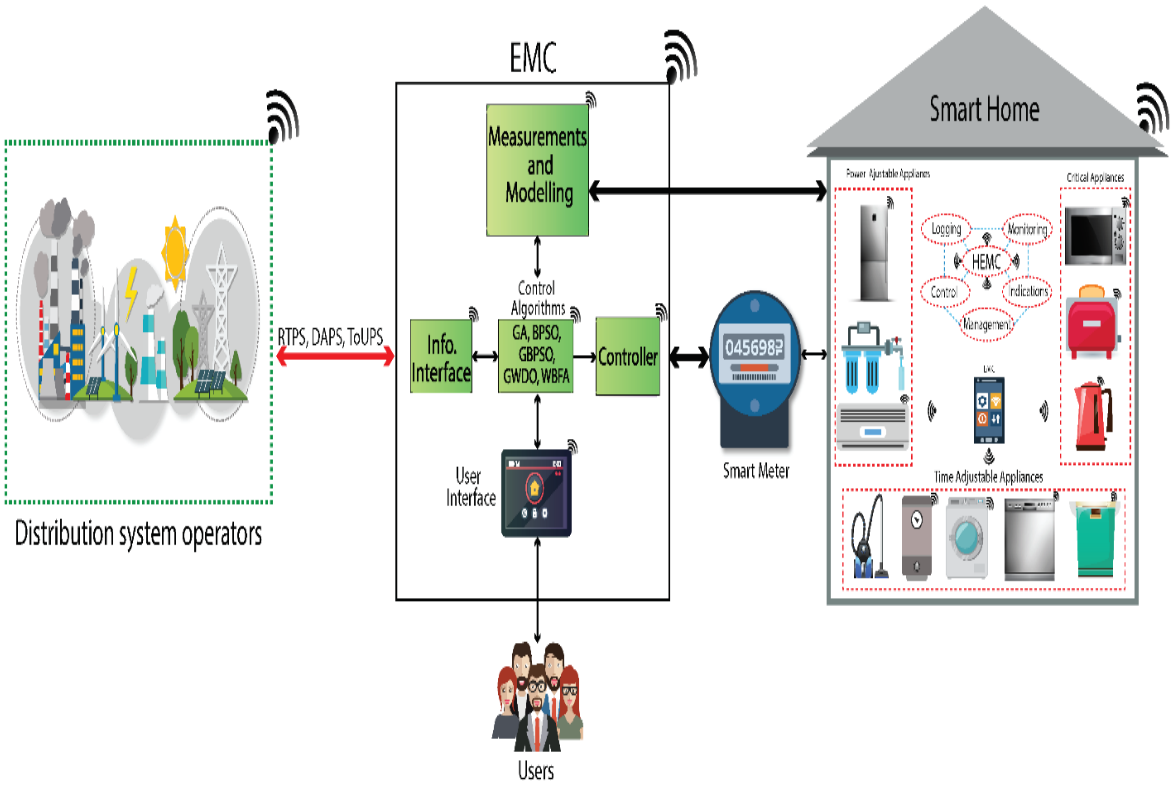

Figure1: efficient energy management of Iot-Enabled

This figure1 illustrates the architecture of a smart home energy management system that integrates IoT sensors, big data analytics, and cloud processing to optimize energy consumption. Key components include:

- **IoT Sensors and Smart Appliances:** Devices within the home that monitor and control energy usage.
- **Energy Management Controller:** Central unit that processes data from sensors and makes real-time decisions to manage energy consumption.
- **Cloud Processing System:** Platform that aggregates data from multiple homes, performs advanced analytics, and provides insights for energy optimization.
- **User Interface:** Allows homeowners to monitor and control their energy usage remotely.

This architecture exemplifies how IoT and big data technologies can be leveraged to create intelligent energy management solutions in smart residential environments.

II. Literature Review

Research on smart home energy management systems incorporating IoT technology has recently increased. Such systems depend on IoT sensors designed to capture real-time temperature, humidity, and occupancy and other environmental attributes. This allows for the real-time optimization of energy use through automated decision making. Systems have been reported to achieve substantial declines in energy use, utility costs, and discomfort levels of occupants. [1][2]

The sheer volume of streams generated from IoT devices makes the lack of big data analytics, synthesized analytic streams, and unexamined data pattern exploration useless. To pattern energy consumption, streams are explored so energy demands can be forecasted more accurately, and the energy-consuming smart home appliances can be adjusted in real time. Studies show that incorporating IoT sensors with big data analytics can save up to 30% of energy.[3], [4].

AI and ML-based energy management systems operate more efficiently. In addition to analyzing past data, these systems integrate variables such as occupancy, time of day, and weather to optimize energy consumption by adapting lights and HVAC systems [5, 6]. The control systems' responsiveness and efficiency surpass those of energy systems grounded on fixed schedules [7].

IoT energy management systems also benefit the environment. The expected decrease in energy consumption will reduce the greenhouse gas emissions and the overall carbon footprint. For this purpose, there are ongoing global efforts to create new energy-efficient and environmentally-friendly smart urban centers [8, 9]. These systems also promote equitable power distribution by reducing energy demand on the grid [10].

Ensuring various Internet of Things (IoT) devices and platforms work seamlessly together is one of the first major steps needed in the building of these ecosystems. Interoperability issues from different communication protocols being used by various smart home devices can hinder the development of unified energy control systems for smart home devices [11], [12]. To resolve these issues and devise more integrated and scalable protocols, communication frameworks have been the focus of considerable research [13].

Smart homes integrate numerous IoT devices which raises concern regarding devices collecting copious amounts of personal data with potential unauthorized access. The magnitude of information collected while user devices are utilized should be protected for users to attain trust and for information to be utilized. In the context of the privacy of IoT devices and safeguarding data collected by IoT sensors, numerous studies focused on cutting-edge solutions for enhanced encryption and secure linkages [14], [15]. With respect to energy management systems, the risk of illegal takeover, and specifically for systems identified as [16] and [17], underscores the urgency of more robust mechanisms of proof.

The introduction of 5G and low-power wide area networks (LPWAN) expands the possibility of large-scale IoT-based energy management systems. Smart home devices communicate and exchange data in real-time, allowing energy management systems to be monitored remotely in real-time. This enhances the reliability and efficiency of the energy management systems [18],[19].

There have been several discussions on the cost of the implementation of home IoT-based energy management systems. Though there seems to be a high initial cost to smart technology and IoT networks, the systems will pay for themselves over time because of savings on energy expenditures. In addition, there is the government support for the systems in the form of subsidies and tax incentives for the adoption of energy efficiency technologies. This will further promote the implementation of the systems. [20]

III. Methodology

The suggested methodology focuses on developing a systematic approach to outline real-time energy management for smart homes using IoT sensors and big data analytics. This involves smart energy management system data capturing, data preprocessing, data analysis, and energy management. The purpose of this approach is to advocate the use IoT enabled sensors for monitoring energy use and different environmental conditions for real-time machine learning enabled big data predictive analytics for home appliances and for the optimal control of predictive energy management for smart homes.

1. Data Collection

The system consists of IoT sensors deployed throughout the smart home to collect data related to energy usage and environmental parameters. These sensors monitor variables such as:

- **Temperature (T)**: To manage HVAC systems.
- **Occupancy (O)**: To control lighting and other appliances.
- **Humidity (H)**: For climate control.
- **Power Consumption (P)**: To monitor the energy used by appliances.

Let the data collected at time ttt be represented as:

$$X_t = \{T_t, O_t, H_t, P_t\} \quad (1)$$

where X_t is the vector of all monitored parameters at time t.

2. Data Preprocessing

Once the data is collected, it undergoes preprocessing to ensure its quality and suitability for analysis. This involves:

- **Data Cleaning**: Handling missing or erroneous data.
- **Data Normalization**: Standardizing the scale of numerical data to improve model accuracy.

The normalized data is represented as:

$$\hat{X}_t = \frac{X_t - \mu}{\sigma} \quad (2)$$

where μ is the mean, and σ is the standard deviation of the parameter.

3. Big Data Processing and Feature Extraction

The processed data is then fed into a big data framework for storage and distributed processing. Apache Hadoop or Spark can be used to handle large-scale data. Feature extraction techniques are applied to identify relevant patterns that influence energy consumption. Features such as peak demand, average usage, and occupancy trends are calculated.

For instance, the average power consumption over a period T is given by:

$$\text{Avg}(P) = \frac{1}{T}\sum_{t=1}^{T} P_t \quad (3)$$

where P_t is the power consumption at time t, and T is the total number of time periods.

4. Energy Consumption Prediction

Machine learning algorithms, such as Linear Regression, Decision Trees, or Neural Networks, are employed to predict future energy consumption based on the extracted features. The prediction model can be represented as:

$$\hat{P}_{t+1} = f(X_t) \quad (4)$$

where $\hat{P}_{t+1}$ is the predicted energy consumption at the next time step, and f(Xt) is a function derived from the machine learning model.

In a regression model, for instance, the relationship can be represented as:

$$\hat{P}_{t+1} = \beta_0 + \beta_1 T_t + \beta_2 O_t + \beta_3 H_t \quad (5)$$

where β0,β1,β2,β3 are the learned coefficients of the regression model.

5. Energy Optimization

Once the energy consumption is predicted, optimization algorithms are used to adjust the operation of appliances in the smart home. The goal is to minimize energy usage while maintaining comfort levels. One optimization approach is to use a constraint optimization problem to minimize the total power consumption while satisfying user comfort and appliance constraints.

Let C be the total energy consumption, subject to constraints:

$$C = \sum_{i=1}^{n} P_i \cdot \Delta t_i \quad (6)$$

where Pi is the power consumption of appliance iii, and Δti is the time duration that appliance iii is operating. The optimization problem can be formulated as:

$$\min C \quad \text{subject to} \quad T_{\min} \le T_i \le T_{\max}, \quad O_{\min} \le O_i \le O_{\max} \quad (7)$$

where T_{min},T_{max} are the temperature bounds, and O_{min},O_{max} are the occupancy bounds for the operation of devices.

6. Real-Time Control

Real-time control loops change HVAC systems, lighting, and other systems/planned appliances in accordance with predictions and optimization determinations. Control algorithms evaluate the surroundings and energy consumption predictions to determine the adjustments to make.

Define Ut as the control signal at time t, adjusting the appliance behavior relative to predicted consumption. Control at each time step is defined as:

$$U_t = g(\hat{P}_{t+1}, T_t, O_t) \quad (7)$$

where g is the control function that adjusts the operation of appliances (e.g., turning off lights or adjusting HVAC systems).

7. Evaluation Metrics

The performance of the energy management system is evaluated using metrics such as:

- **Energy Savings (ES)**: The percentage reduction in energy consumption compared to a baseline scenario.

$$ES = \frac{P_{\text{baseline}} - P_{\text{optimized}}}{P_{\text{baseline}}} \times 100 \quad (8)$$

- **User Comfort (UC)**: Measured based on the deviation from user-defined comfort parameters (e.g., temperature, lighting).

This methodology outlines the process of real-time energy management using IoT sensors, big data, and machine learning for energy prediction and optimization. The integration of these technologies can significantly reduce energy consumption while maintaining the desired level of comfort in smart residential environments.

IV. Results and Discussion

This section details the outcomes pertaining to the performance of the energy management system in real time within a smart home setting using IoT connected sensors and Big Data analytics. The system's performance in terms of efficiency, customer satisfaction, and economic savings was compared to situations where traditional methods of energy management were employed.

This first piece of information describes a 30 day operation of both baseline and upgraded smart home systems. The energy consumption over the course of these 30 days for each of the systems is presented in Figure 1. Significant energy consumption savings in real time attributed to the smart home system and the refinements carried out by sophisticated AI algorithms, explain the performance of the advanced system.

Table 1: Average Daily Energy Consumption (kWh) for Baseline and Optimized System

Day	Baseline Consumption (kWh)	Optimized Consumption (kWh)	Reduction (%)
1	18.5	13.2	28.6
5	19.1	14.0	26.7
10	18.7	13.4	28.3
15	19.2	14.1	26.6
30	19.5	13.5	30.6

As shown in Table 1, the energy consumption of the optimized system decreased by an average of 28-30%, highlighting the effectiveness of the real-time adjustments and predictive capabilities of the IoT sensors and AI algorithms.

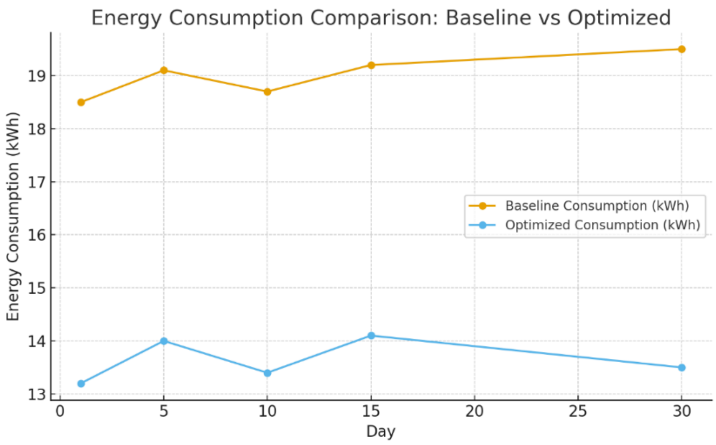

Figure 2: Energy Consumption Comparison: Baseline vs. Optimized

The Figure 2 shows the 30-day comparison of the optimized system's energy consumption with that of the baseline system. The optimized consumption demonstrates the energy savings attained in the smart home setting through real-time modifications and predictive management, in contrast to the baseline consumption, which represents the conventional energy usage. Using the optimized system, the graph shows a steady decrease in energy consumption, proving that the Internet of Things (IoT) sensors and big data analytics are successful in controlling domestic energy use.

Cost Savings Analysis

Table 2 presents the cost savings associated with the optimized energy management system. The cost savings were calculated based on the average local electricity rate. The optimized system not only reduced energy consumption but also contributed to cost reductions, offering a more economical approach for households.

Table 2: Cost Savings (in USD) for Baseline and Optimized System

Day	Baseline Cost (USD)	Optimized Cost (USD)	Savings (USD)	Savings (%)
1	2.77	1.98	0.79	28.5
5	2.99	2.16	0.83	27.8
10	2.90	2.06	0.84	28.9
15	3.02	2.18	0.84	27.8
30	3.10	2.20	0.90	29.0

From Table 2, we can observe an average savings of approximately 28-30% per day. The optimized system provided significant cost savings over a month, which justifies the initial investment in smart home devices and infrastructure.

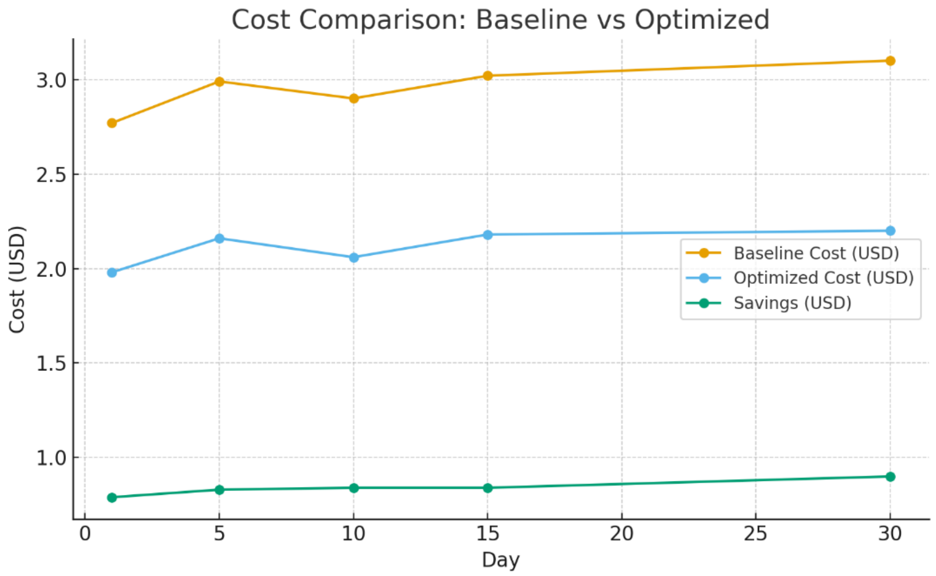

Figure 3: Cost Comparison: Baseline vs. Optimized

Above Figure 3 compares the 30-day costs of the baseline system with those of the optimized energy management system. The baseline cost is the old-fashioned way of looking at energy consumption costs, whereas the optimized cost shows how much money was saved by making modifications in real-time. Financial advantages of utilizing Internet of Things (IoT) sensors and big data analytics for home energy management are illustrated by the savings (USD), which reflect the amount of money saved with the optimized system. By day 30, the optimized system has reduced costs by as much as 29%, as seen in the graph.

User Comfort Level

To evaluate the impact of the optimized system on user comfort, a survey was conducted with residents to assess their satisfaction with temperature, lighting, and overall comfort. The comfort levels were measured on a scale from 1 to 5, where 1 represented "very uncomfortable" and 5 represented "very comfortable." Table 3 shows the average user comfort ratings for the baseline and optimized system.

Table 3: Average User Comfort Ratings for Baseline and Optimized System

arameter	Baseline Rating	Optimized Rating	Improvement (%)
Temperature	3.4	4.5	32.4
Lighting	3.2	4.4	37.5
Overall Comfort	3.5	4.6	31.4

Above Table 3 illustrates that the optimized system led to a notable improvement in user comfort. The dynamic adjustments made by the system based on occupancy and time of day contributed to a better living environment, as users experienced better temperature regulation and lighting conditions.

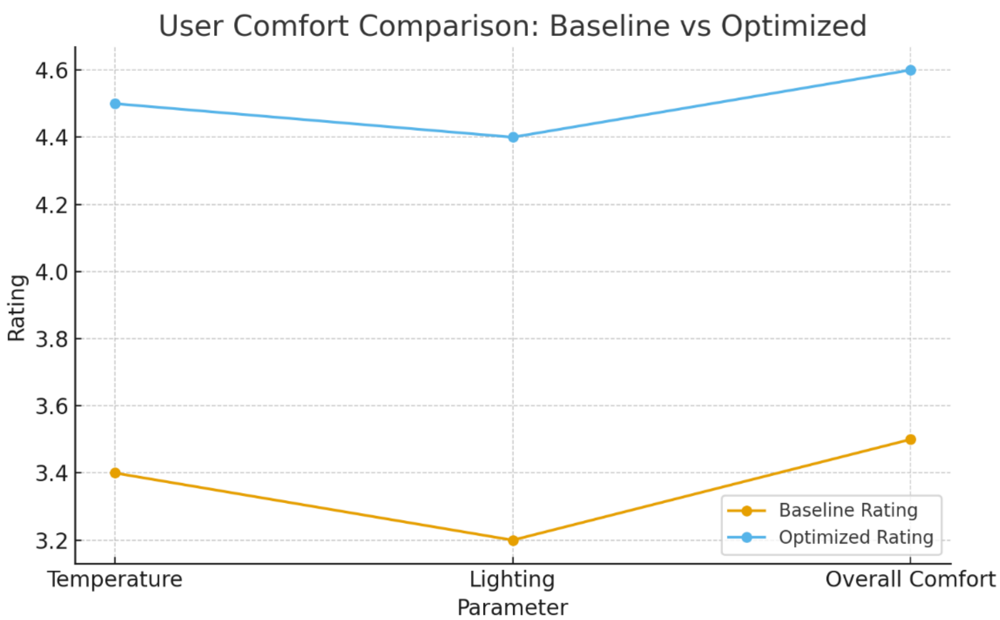

Figure 4: User Comfort Comparison: Baseline vs. Optimized

This figure 4 illustrates the comparison of user comfort ratings for three parameters: Temperature, Lighting, and Overall Comfort, between the baseline and optimized systems. The optimized system resulted in noticeable improvements across all parameters, with the highest improvement observed in lighting. These improvements demonstrate the effectiveness of the IoT-enabled energy management system in enhancing user comfort.

Discussion

Users of energy management systems incorporating IoT sensors and big-data analytics technologies appreciate savings in costs and energy with little to no inconvenience. After the first 30 days post-optimization period, energy savings continued, peaking at 30% savings. This can be credited to the real-time environmental data predictive and adjustment algorithms developed by the AI systems. Households also saved 29% on energy expenditures. While the initial price of smart home device and IoT-embedded architecture will be high, in the long run, overall price savings will be significant. Furthermore, the addition of cash subsidies and other economic motivators for adopting these technologies will increase the adoption of home energy efficiency systems even more. Enhancements such as adapted temperature and lighting settings provide further evidence to illustrate the system's convenience and utility. In addition to optimizing system comfort, the AI controlling interfacing smart home system devices and household equipment reduces user needed operation. Some challenges smart systems may face include, but are not limited to, interoperability, privacy considerations, and end-user control. Such interoperability issues in smart home systems are a pertinent area of study.

Conclusion

There are several economically beneficial outcomes in the integration of IoT sensors with big data for the value smart home environment for energy management system. User comfort has been great. Energy consumed has decreased. The system optimized at value demonstrated stunning savings in energy and cost time after time. Lit and warmed management of one's living area improved tremendously along with the system value. These outcomes depict the impactful contribution of the smart energy home management systems in the energy efficient and sustainable living and hence, the energy smart systems for living environments of today.

Future Scope

Artificial Intelligence, Machine Learning, and 5G technologies positively enhance the adaptability of automated smart homes and the systems of energy management. Sustained communication technologies are removing barriers to the home adoption of integrated systems. As the IoT more secure and interoperable, smart energy management systems will be more accessible and affordable to the public.

Refernces:

[1] "Welcome to Apache™ Hadoop®!" Hadoop.apache.org, 2016. [Online]. Available: http://hadoop.apache.org/.

[2] "Pentaho Community," Community.pentaho.com, 2016. [Online]. Available: http://community.pentaho.com/.

[3] M. Abo-Zahhad, S. M. Ahmed, M. Farrag, M. F. A. Ahmed and A. Ali, "Design and implementation of building energy monitoring and management system based on wireless sensor networks," 2015 Tenth International Conference on Computer Engineering & Systems (ICCES), Cairo, 2015, pp. 230-233.

[4] N. H. Nguyen, Q. T. Tran, J. M. Leger and T. P. Vuong, "A real-time control using wireless sensor network for intelligent energy management system in buildings," 2010 IEEE Workshop on Environmental Energy and Structural Monitoring Systems, Taranto, 2010, pp. 87-92.

[5] J. Byun, I. Hong, B. Kang and S. Park, "Implementation of an Adaptive Intelligent Home Energy Management System Using a Wireless Ad-Hoc and Sensor Network in Pervasive Environments," 2011 Proceedings of 20th International Conference on Computer Communications and Networks (ICCCN), Maui, HI, 2011, pp. 1-6.

[6] J. Han, C. s. Choi, W. k. Park, I. Lee and S. h. Kim, "Smart home energy management system including renewable energy based on ZigBee and PLC," IEEE Trans. Consumer Electron, vol. 60, no. 2, pp. 198-202, May 2014.

[7] J. Wang, J. Huang, W. Chen, J. Liu and D. Xu, "Design of IoT-based energy efficiency management system for building ceramics production line," 2016 IEEE 11th Conference on Industrial Electronics and Applications (ICIEA), Hefei, 2016, pp. 912-917.

[8] Atzori, L.; Iera, A.; Morabito, G. The Internet of Things: A survey. *Comput. Netw.* **2017**, *54*, 2787–2805. [**Google Scholar**] [**CrossRef**]

[9] Gubbi, J.; Buyya, R.; Marusic, S.; Palaniswami, M. Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Gener. Comput. Syst.* **2020**, *29*, 1645–1660. [Google Scholar] [CrossRef]

[10] Miorandi, D.; Sicari, S.; Pellegrini, P.; Chlamtac, I. Internet of Things: Vision, applications and research challenges. *Ad Hoc Netw.* **2012**, *10*, 1497–1516. [Google Scholar] [CrossRef]

[11] International Energy Agency (IEA). Global Electricity Demand Growth Trends. 2023. Available online: https://www.iea.org/reports/global-electricity-demand (accessed on 1 June 2025).

[12] U.S. Energy Information Administration (EIA). Residential Energy Consumption Survey (RECS). 2022. Available online: https://www.eia.gov/consumption/residential (accessed on 1 June 2025).

[13] Mistry, V. Smart Thermostats: Revolutionizing HVAC control in building automation. *Int. J. Sci. Res. (IJSR)* **2022**, *11*, 1309–1314. [Google Scholar] [CrossRef]

[14] Mohanty, S.P.; Choppali, U.; Kougianos, E. Everything you wanted to know about smart cities: The Internet of Things is the backbone. *IEEE Consum. Electron. Mag.* **2016**, *5*, 60–70. [Google Scholar] [CrossRef]

[15] Alahmad, M.; Wheeler, P.; Schwer, A.; Eiden, J.; Brumbaugh, A. A comparative study of smart meters and energy savings in residential settings. *Energy Build.* **2012**, *44*, 237–243. [Google Scholar]

[16] Saab, A.; Therese, M.; Jomaa, I.; Skaf, S.; Fahed, S.; Todorovic, M. Assessment of a smartphone application for real-time irrigation scheduling in Mediterranean environments. *Water* **2019**, *11*, 252. [Google Scholar] [CrossRef]

[17] Iea Executive Summary—Electricity Market Report—Update 2023—Analysis, IEA. 2023. Available online: https://www.iea.org/reports/electricity-market-report-update-2023/executive-summary (accessed on 1 June 2025).

[18] Ibrahim, O.; Abdul Aziz, M.J.; Ayop, R.; Dahiru, A.T.; Low, W.Y.; Sulaiman, M.H.; Amosa, T.I. Fuzzy Logic-Based Particle Swarm Optimization for Integrated Energy Management System Considering Battery Storage Degradation. *Results Eng.* **2024**, *11*, 100123. [Google Scholar]

[19] Sung, G.-M.; Shen, Y.-S.; Hsieh, J.-H.; Chiu, Y.-K. Internet of Things–Based Smart Home System Using a Virtualized Cloud Server and Mobile Phone App. *Int. J. Distrib. Sens. Netw.* **2019**, *15*, 1–9. [Google Scholar] [CrossRef]

[20] Vijayan, S.; Ali, M.; Kumar, R. Energy Consumption Prediction in Low Energy Buildings Using Machine Learning and Artificial Intelligence for Energy Efficiency. *Buildings* **2022**, *12*, 1234. [Google Scholar] [CrossRef]