



Energy Optimization and Environmental Management in Industrial and Commercial Buildings Using IoT-Enabled Intelligent Systems

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ABSTRACT

The growing demand for reduced energy consumption in industrial and commercial buildings has positioned energy optimization as one of the central challenges in the building industry. This study examines the design and implementation of intelligent systems aimed at optimizing energy use in industrial and commercial facilities through the integration of the Internet of Things (IoT) and machine learning techniques. The primary objective is to employ advanced technologies to decrease overall energy consumption, enhance operational efficiency, and maintain favorable environmental conditions within these buildings. The paper first introduces smart building systems and the role of IoT in energy management, followed by an explanation of how machine learning algorithms can be utilized for energy prediction and optimization. It then outlines the design of IoT-based architectures for monitoring and controlling energy consumption, incorporating a network of sensors and smart devices. The findings indicate that leveraging these technologies can result in a 25–30 percent reduction in energy usage. Furthermore, the proposed systems demonstrate effective control over temperature, humidity, and lighting, ultimately lowering energy costs and improving occupant comfort.

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1. Introduction

Efficient energy management in industrial buildings has become a critical challenge in today's world, where energy resources are increasingly limited and operational costs continue to rise. Industrial and commercial buildings account for a substantial portion of total energy consumption, contributing not only to significant economic expenses but also to considerable environmental impacts [1]. Optimizing energy use in these facilities is therefore essential, as it reduces operational costs, enhances efficiency, and plays a vital role in lowering greenhouse gas emissions and mitigating climate change. Recent advancements in emerging technologies—particularly the Internet of Things (IoT) and machine learning—have enabled the development of smart buildings capable of autonomously monitoring and optimizing their energy consumption [2]. IoT-driven systems deploy interconnected sensors and networked devices to collect precise environmental data, including temperature, humidity, lighting levels, and occupancy patterns. These data streams are then transmitted to a centralized platform for analysis. Machine learning algorithms can subsequently model complex consumption patterns, predict future energy demands, and recommend or implement optimization strategies in real time [3, 4]. The primary purpose of this study is to investigate and analyze an intelligent system designed to optimize energy consumption in industrial buildings through the integration of IoT technologies and machine learning techniques. By leveraging sensor networks and smart devices to collect comprehensive data on energy usage and environmental conditions, such systems can autonomously regulate energy consumption and maintain it

at optimal levels. Furthermore, machine learning algorithms empower these systems to simulate and predict intricate energy consumption patterns, enabling proactive decision-making and the implementation of preemptive optimization strategies [5, 6]. This paper first reviews the technological foundations underlying intelligent energy management systems, including IoT infrastructures and machine learning frameworks. Various models and implementation approaches relevant to industrial buildings are then examined. Subsequently, empirical results and simulation outcomes demonstrating the effectiveness of these systems—particularly in reducing energy consumption and enhancing energy efficiency under varying operating conditions—are analyzed. The findings of this research provide valuable technical and scientific insights for architects, designers, and engineers in the development and deployment of intelligent solutions within the building industry and related sectors. The structure of this paper is organized into eight sections. The Introduction outlines the importance and challenges of energy optimization in industrial and commercial buildings. Section 2 reviews smart technologies applied in industrial environments, focusing on IoT systems and intelligent energy management frameworks. Section 3 examines machine learning algorithms used for energy prediction and optimization. Section 4 describes the architecture and operational design of IoT-based intelligent energy management systems. Section 5 presents performance results and analytical evaluations based on empirical and simulation data. Section 6 provides a

discussion of the theoretical implications of integrating IoT and machine learning in energy management. Section 7 outlines the main limitations associated with system implementation and operation. Finally, Section 8 concludes the study and proposes directions for future research.

2. Smart Technologies in Industrial Buildings

This section introduces and examines the key technologies employed in intelligent energy management systems for industrial buildings. These technologies primarily include the Internet of Things and smart energy management systems, both of which play a critical role in optimizing energy consumption. In addition, the section explores the contribution of machine learning techniques in processing and analyzing collected data to support energy prediction and optimization activities.

2.1. Internet of Things

The Internet of Things (IoT) refers to a network of interconnected devices and sensors capable of collecting, transmitting, and exchanging data over the internet [7]. In industrial buildings, IoT technologies can be employed to monitor key environmental parameters such as temperature, humidity, lighting levels, occupancy, and energy

consumption. IoT sensors provide accurate, real-time, and continuous data regarding the operational conditions of industrial facilities, enabling centralized systems to access up-to-date information at all times. These data streams support a wide range of functions, including energy consumption analysis, forecasting future energy requirements, and enabling automated system adjustments [8].

A practical example can be seen in industrial facilities, where heating, ventilation, and air-conditioning (HVAC) systems typically represent a major portion of total energy use. By deploying IoT sensors throughout the building, real-time information on temperature, humidity, and occupancy patterns can be continuously collected. This information is transmitted to a central control platform, where intelligent algorithms automatically optimize HVAC settings. For instance, when a specific area of the facility is unoccupied, the system autonomously reduces ventilation or air-conditioning levels. Such automation can reduce HVAC-related energy consumption by up to 25 percent, while maintaining optimal environmental conditions for both workers and equipment.

Table 1 presents the primary applications of IoT sensors, along with their impact on energy reduction and overall system efficiency improvements.

Table 1. Applications of Different Types of Sensors in Energy Optimization in Industrial Buildings Using the Internet of Things

Sensor Type	Application	Impact on Energy Optimization
Temperature Sensors	Measuring ambient temperature in different parts of the building, including rooms and industrial spaces	Helping regulate temperature and reducing energy consumption in cooling and heating systems
Humidity Sensors	Measuring humidity levels to control ventilation and cooling systems and increase/decrease humidity	Preventing excessive energy consumption in ventilation systems and maintaining occupant comfort
Light Sensors	Measuring light intensity and adjusting automatic lighting systems	Reducing lighting energy consumption with automatic and adaptive control

Sensor Type	Application	Impact on Energy Optimization
Motion Sensors	Detecting movement in space and activating or deactivating lighting systems only when needed	Improving energy efficiency by preventing unnecessary system activity
Energy Consumption Sensors	Measuring energy consumption in different systems such as cooling, heating, lighting, and electrical equipment	Providing precise data for analysis and prediction of energy consumption and system optimization

2.2. Intelligent Energy Management Systems

Intelligent Energy Management Systems (EMS) are designed to monitor, regulate, and optimize energy consumption within buildings [9]. By leveraging data collected from distributed sensors, these systems continuously observe energy usage across different zones of a facility and automatically implement optimal operational settings based on real-time conditions. Typical EMS features include automated control of temperature, lighting, and ventilation, all of which contribute to reducing energy consumption while simultaneously enhancing occupant comfort and improving industrial productivity [10].

A practical example can be observed in a large commercial building employing IoT technologies and intelligent algorithms to achieve energy efficiency. In such a system, sensors measuring temperature, humidity, illumination levels, and occupancy are

installed throughout the building to capture real-time environmental conditions. These data streams are transmitted to a centralized management platform, which adjusts lighting and HVAC operations accordingly. For instance, when sufficient natural daylight is present, the lighting system automatically switches off; similarly, if indoor temperature rises beyond the predefined range, the ventilation or cooling system is activated automatically. This level of automation can lead to energy savings of up to 30 percent while maintaining a high degree of comfort, as temperature and illumination levels are consistently aligned with environmental and user requirements [11].

Table 2 summarizes the impact of intelligent EMS solutions on energy optimization and presents quantitative performance indicators associated with their implementation.

Table 2. Impact of Intelligent Energy Management Systems on Energy Optimization in Industrial Buildings

Statistics and Figures	Impact on Energy Optimization	Feature of Intelligent Energy Management System
Up to 30% reduction in energy consumption	Optimizing energy use across different building areas	Reduction of heating and cooling energy consumption
10–15% reduction in energy consumption	Automatic adjustment of temperature based on environmental needs and operating conditions	Automatic temperature and ventilation control
10–20% reduction in energy consumption	Automatic lighting adjustment based on ambient light levels	Lighting management
Up to 20% reduction in CO ₂ emissions	Improved energy efficiency and reduced environmental impact	Reduction of greenhouse gas emissions

2.3. Machine Learning for Energy Consumption Optimization

Machine learning, as a key branch of artificial intelligence, offers powerful capabilities for processing large-scale and complex datasets. In the context of energy optimization, machine learning enables the identification and analysis of consumption patterns, providing valuable insights into the underlying factors driving energy use. These algorithms can leverage historical data to predict future energy demands and autonomously recommend or execute optimization strategies based on these predictions [12, 13].

One of the fundamental applications of machine learning in this domain is the development of energy consumption prediction models. These models forecast energy demand across different seasons or operational conditions by analyzing data collected from IoT-based monitoring systems. The resulting predictions help

optimize control strategies and support proactive energy management.

Another important application involves the use of optimization algorithms. Machine learning-driven optimization techniques—such as genetic algorithms, swarm intelligence, and other mathematical optimization methods—can determine the ideal configurations for various building parameters, including temperature, ventilation, and lighting. By continuously adjusting these parameters toward their optimal values, these algorithms contribute to significant reductions in overall energy usage.

In energy management systems, machine learning-based prediction and optimization tools can be integrated to provide real-time regulation of energy consumption across a range of industrial and commercial environments. Table 3 presents a comparative overview of various machine learning algorithms and highlights their effectiveness in reducing energy consumption and operational costs.

Table 3. Comparison of Machine Learning Algorithms for Energy Consumption Prediction and Optimization

Machine Learning Algorithm	Application Type	Energy Reduction (%)	Cost Reduction (%)	Description
Linear Regression	Energy consumption prediction	10%	5%	Predicting energy consumption based on linear features and equations
Artificial Neural Network (ANN)	Energy consumption prediction and optimization	20%	10%	Using neural network architectures to predict consumption and adjust system parameters
Decision Tree	Energy consumption prediction in variable conditions	15%	10%	Predicting energy consumption using decision tree-based models
Genetic Algorithm	Energy optimization using evolutionary techniques	25%	18%	Using evolutionary techniques for energy optimization strategies
Fuzzy Optimization Algorithm	Energy optimization using fuzzy logic	20%	14%	Using fuzzy logic to determine optimal system configurations
Convolutional Neural Network (CNN)	Processing complex data and predicting energy consumption	18%	12%	Using CNNs to analyze complex datasets and predict energy trends

Machine Learning Algorithm	Application Type	Energy Reduction (%)	Cost Reduction (%)	Description
Reinforcement Learning	Adaptive control based on environmental feedback	22%	15%	Optimizing energy consumption using adaptive learning from environmental responses
Clustering Algorithm (Unsupervised)	Identifying and categorizing consumption patterns	15%	9%	Categorizing consumption patterns for optimization
Regression-Based Algorithms	Energy consumption prediction under variable conditions	12%	8%	Using regression models for energy prediction in variable conditions
Hybrid Optimization Models	Energy optimization using combined techniques	17%	11%	Using hybrid techniques for optimal energy consumption adjustments

Fig. 1 illustrates the impact of various machine learning and optimization algorithms on reducing energy consumption and associated costs in energy management applications. In addition to comparing the magnitude of energy and cost reductions achieved by each algorithm, the figure also examines the frequency with which these algorithms have been employed in previous

studies. This comparative perspective provides a useful reference for selecting the most suitable algorithm for different industrial and building-scale energy optimization projects. It should be noted that the values presented in the figure represent the averaged results reported across multiple prior studies [2, 3, 6, 8].

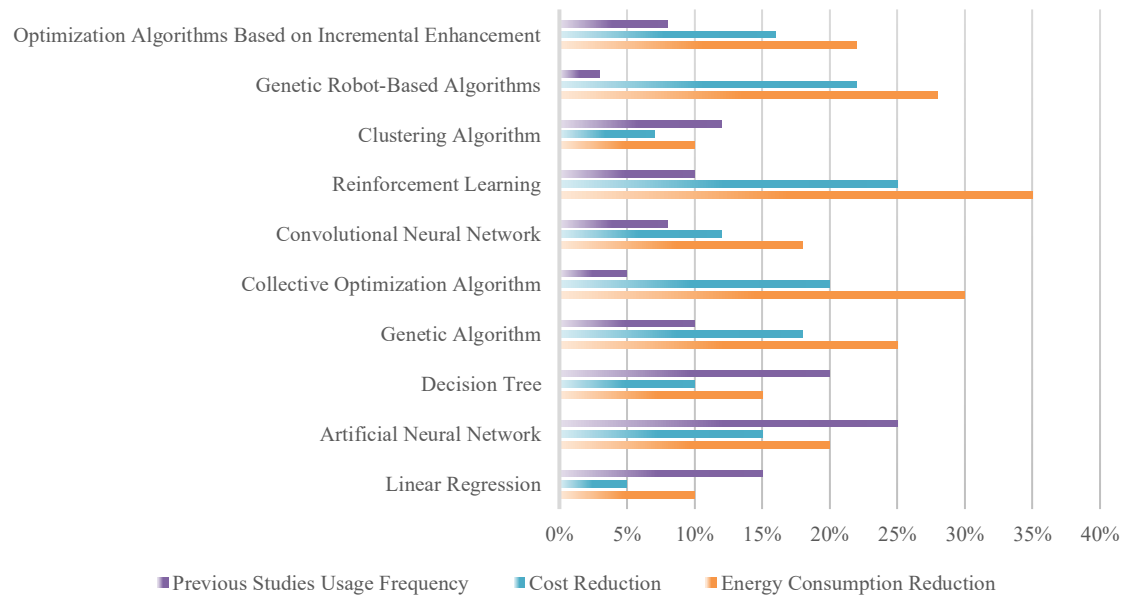


Fig. 1. Comparison of the Impact of Machine Learning Algorithms on Reducing Energy Consumption and Costs

3. Architecture and Design of an Intelligent Energy Management System

This section examines the architecture of intelligent systems designed to collect environmental data, process and analyze these datasets, and perform automated adjustments aimed at optimizing energy consumption. Such architectures must be capable of efficiently receiving sensor data, interpreting and processing it through intelligent algorithms, and executing appropriate control actions without human intervention.

3.1.Data Acquisition from Sensors

The first stage involves the acquisition of data from IoT-based sensors installed throughout indoor and outdoor environments. These sensors continuously measure critical environmental parameters such as air temperature, relative humidity, and air quality. The collected data are transmitted in real time to a central system capable of continuously monitoring environmental conditions and detecting any changes. The objective of this data acquisition process is to provide accurate, real-time information for the analysis and optimization of the heating, cooling, and ventilation system.

To ensure precise measurements, advanced devices such as thermal cameras and multi-sensor modules are employed. These instruments are particularly effective in detecting temperature and humidity variations under different operational conditions. One of the devices widely used for this purpose is the FLUKE handheld thermal camera, capable of providing highly accurate temperature and humidity readings while simultaneously monitoring external environmental conditions [12, 14].

3.2.Data Processing and Analysis Using Artificial Intelligence

Once the data have been collected, the second stage focuses on processing and analyzing them through artificial intelligence and machine learning algorithms. After undergoing preprocessing steps such as normalization, the data are fed into AI models to identify complex patterns and relationships among environmental parameters—such as temperature, humidity, and air quality—and the performance of cooling, heating, and ventilation systems.

Because sensor datasets often contain values measured in different units and scales, normalization is required to transform them into a unified range (e.g., 0 to 1). This prevents inconsistencies in scale from influencing model accuracy. In addition, missing data—caused by sensor errors, communication failures, or connectivity issues—must be handled through appropriate strategies such as mean-value imputation or predictive reconstruction techniques.

Sensor data may also contain noise or measurement errors, which can adversely affect the accuracy of subsequent models. Therefore, filtering techniques such as median or Gaussian filters are applied to remove noise and ensure data reliability before further processing [7, 15, 16].

3.3.Automated System Adjustments and Optimization

Following data analysis, the system autonomously adjusts the heating, cooling, and ventilation operations to optimize performance and energy efficiency. Based on the recommendations generated by AI-driven analysis, the system continuously regulates key parameters such as temperature, humidity, and airflow in response to external and internal environmental changes. These

automatic adjustments ensure optimal performance while preventing energy waste and unnecessary operational costs.

For instance, the system dynamically modifies indoor temperature in accordance with outdoor temperature changes to maintain occupant comfort. It also regulates indoor humidity; when humidity levels rise—whether due to seasonal variations or internal activities—the system increases ventilation or activates dehumidification equipment. Optimization algorithms continuously process newly acquired sensor data to determine the most efficient configuration for temperature, humidity, and ventilation.

3.4. System Evaluation and Validation

The final stage involves evaluating and validating the performance of the optimized system. After implementing automated adjustments, system performance metrics—such as heating load efficiency and ventilation load efficiency—are assessed based on standardized criteria. This evaluation provides a comprehensive

understanding of system performance and identifies any inconsistencies or deficiencies that may require further refinement.

This stage also includes continuous analytical monitoring to detect unexpected patterns or operational anomalies, enabling ongoing system improvements. Through this integrated multi-stage process, the cooling, heating, and ventilation system can be effectively optimized to deliver superior performance under varying environmental conditions, minimize energy consumption, and maximize indoor comfort and air quality.

Fig. 2 illustrates the multi-stage optimization process, including data acquisition from IoT sensors, data processing using artificial intelligence algorithms, automated system adjustments based on analytical insights, and final system evaluation and validation. The figure highlights how this workflow is designed to achieve optimal system performance while maintaining comfort, energy efficiency, and indoor air quality.

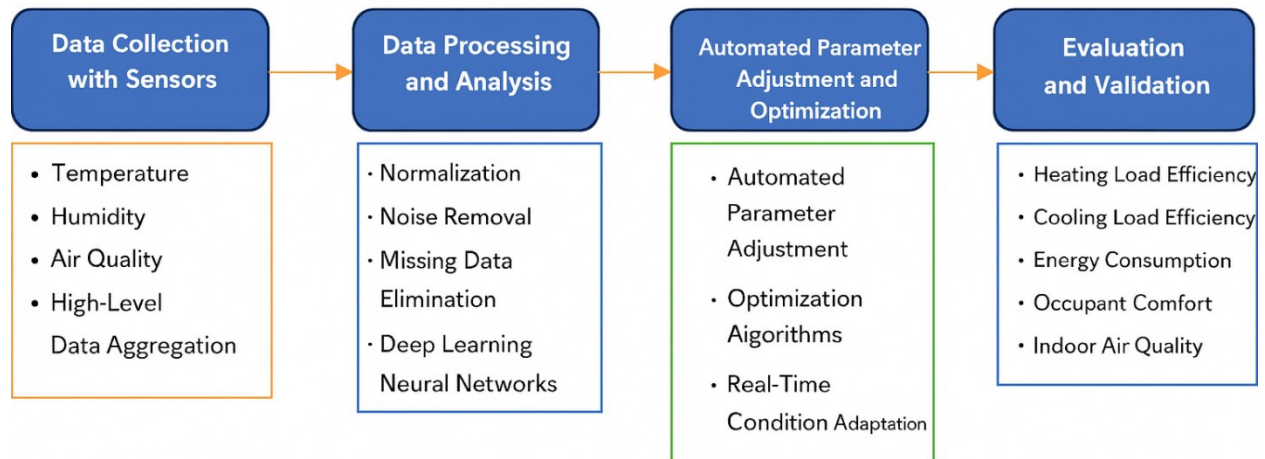


Fig. 2. System optimization process – stages of data collection, processing, automatic configuration, and evaluation

Table 4 presents a comprehensive overview of the various stages of the

optimization process, detailing their primary functions, operational tools, expected

outcomes, objectives, and performance evaluation indicators.

4. Performance Evaluation of Intelligent Energy Management Systems

This section presents an evaluation of the performance of intelligent systems in energy management and optimization, based on data collected from previous studies and credible scientific sources [3, 4, 11]. The data used in this analysis were extracted and processed from smart sensors and cloud-based platforms installed across various buildings. The findings discussed herein are derived using advanced algorithms and energy optimization methods designed to enhance the performance of cooling, heating, and ventilation systems, while maintaining occupant comfort and reducing overall energy consumption.

Fig. 3 illustrates the trend of indoor air quality levels over a series of days. The dataset was collected across multiple time intervals to capture fluctuations in air quality and their potential impact on system performance. As shown in the figure, there is a noticeable gradual increase in particulate matter (PM) levels, which may indicate the presence of indoor air pollution. Such data are essential for analyzing temporal changes in air quality and predicting system responses to potential contaminants or environmental disturbances. Understanding these patterns enables the system to dynamically adjust ventilation rates or filtration settings to maintain optimal indoor air conditions.

Fig. 4 illustrates the relationship between indoor temperature and the operational efficiency of the system. As shown in the graph, system efficiency steadily declines as indoor temperature increases from 18°C to 30°C. This reduction in efficiency is

primarily attributed to the higher cooling and ventilation demands required to maintain occupant comfort at elevated temperatures. Under such conditions, the thermal load on the system increases, resulting in greater energy consumption and reduced overall performance.

Table 4. Stages of the System Optimization Process with Operational Details, Tools, Techniques, and Expected Outcomes

Stage	Description	Success Evaluation Indicators	Goals of the Stage	Expected Outcomes	Tools and Techniques	Main Operations
Data Collection	In this stage, data are collected from various sensors, including indoor and outdoor environmental conditions.	High accuracy of collected data; complete coverage of indoor and outdoor spaces; timely transmission of data to the central system	Gathering comprehensive environmental data; ensuring data accuracy and completeness	Accurate and real-time environmental data; high-quality air and humidity data sent to the central system	Temperature, humidity, PM sensors; CO ₂ sensors; thermal imaging cameras; multi-sensors	Installing sensors inside and outside the building; ensuring accurate measurement; transmitting environmental data to the central system
Data Processing	Collected data are processed to remove noise and prepare them for analysis using algorithms and statistical models.	Accuracy of processed data; ability to remove noise and inconsistencies	Preparing data for analysis; identifying important features; enabling predictive modeling	Processed and refined data ready for analysis; identifying key patterns and anomalies	Normalization techniques; filtering (median, Gaussian); missing data handling methods; anomaly detection algorithms	Filtering and cleaning data; removing missing values; feature extraction; preparing processed data for AI modeling
Automated Adjustment and Optimization	In this stage, the system automatically adjusts cooling, heating, and ventilation settings based on processed data.	Reduced energy consumption; improved occupant comfort; enhanced environmental control	Optimizing system performance; improving energy efficiency; enhancing comfort and indoor air quality	Enhanced system performance; optimized cooling, heating, and ventilation; improved occupant comfort	AI-based optimization models; adaptive control algorithms; feedback-based control; fuzzy and predictive optimization	Automatic temperature and humidity adjustment; real-time ventilation optimization; implementing the best operational settings
Evaluation and Validation	In this stage, results are evaluated using performance metrics and standards such as ASHRAE to verify accuracy.	Comparison with ASHRAE standards; reduced operational deviations; improved indoor air quality	Ensuring system reliability; validating optimal performance; confirming improved comfort and air quality	Validated system performance; improved efficiency; confirmed reliability	International/ASHRAE standards; test results; performance comparison reports	Comparing results with standards; correcting deviations; verifying indoor comfort and system stability

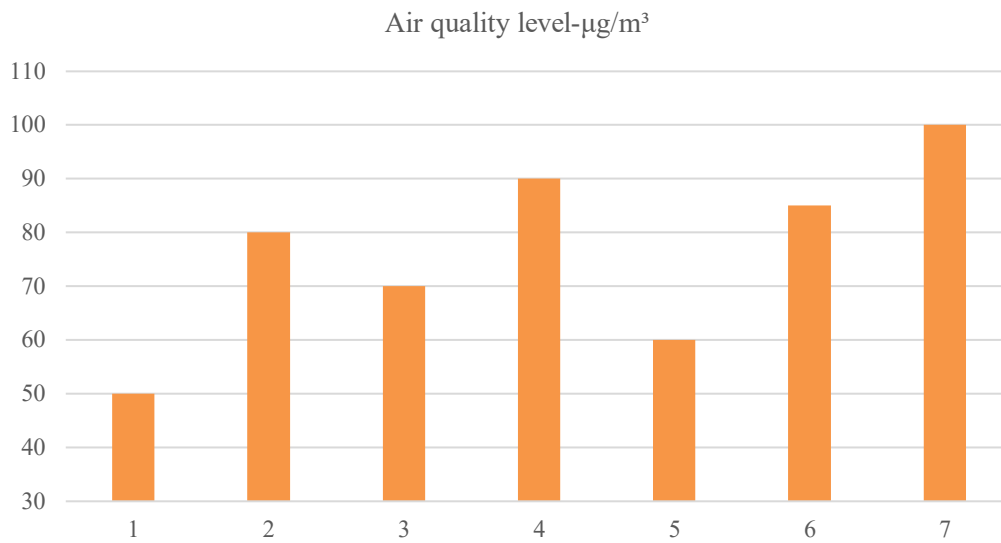


Fig. 3. Temporal variation chart of particulate matter (PM) levels

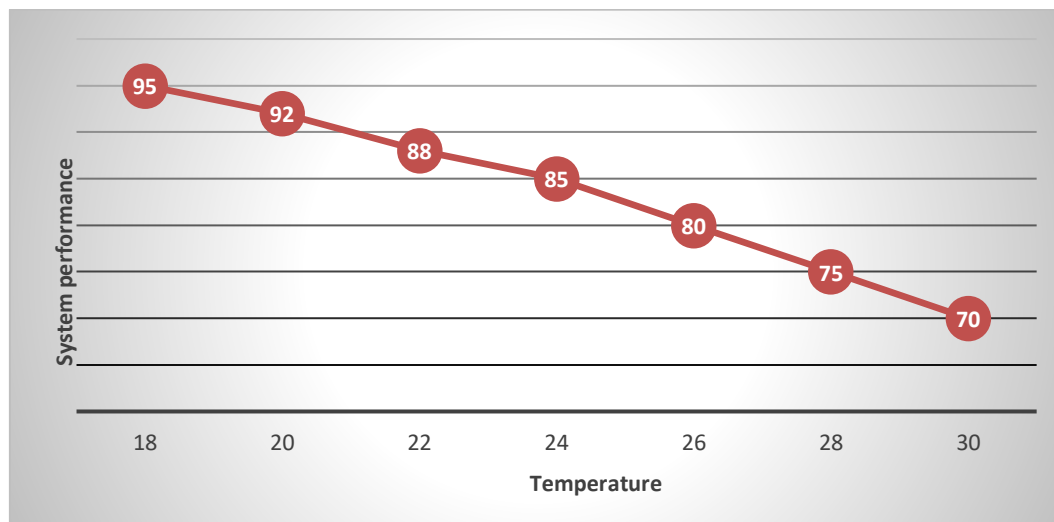


Fig. 4. Impact of temperature variations on ventilation system performance and thermal load

This trend indicates that heating, cooling, and ventilation systems may operate less efficiently under high-temperature conditions and may require additional energy management strategies to sustain optimal performance. Consequently, intelligent optimization mechanisms become essential to mitigate increased thermal loads, enhance system responsiveness, and maintain energy-efficient operation across varying temperature conditions.

Fig. 5 presents a pie chart illustrating the distribution of energy consumption among

cooling, heating, and ventilation systems. The results indicate that cooling systems account for the highest share of total energy use—approximately 40 percent. This elevated energy demand is primarily due to the continuous requirement for temperature regulation during warmer seasons, which places significant load on the cooling equipment.

Heating systems represent the second-largest portion of energy consumption at 30 percent, reflecting the substantial energy required to maintain comfortable indoor

temperatures during colder periods. Ventilation systems consume about 20 percent of total energy, underscoring their critical role in maintaining indoor air quality, regulating humidity levels, and ensuring adequate airflow throughout the building. The remaining 10 percent corresponds to auxiliary components and supporting systems, such as monitoring devices, peripheral equipment, and control units.

This distribution analysis is particularly valuable for energy management and optimization in industrial and commercial facilities. By identifying the subsystems with the highest energy demand, decision-makers can prioritize targeted optimization strategies to reduce operational costs and enhance system performance. Overall, the presented chart provides an essential insight into the energy use profile of building systems, enabling more informed planning and implementation of energy efficiency measures.

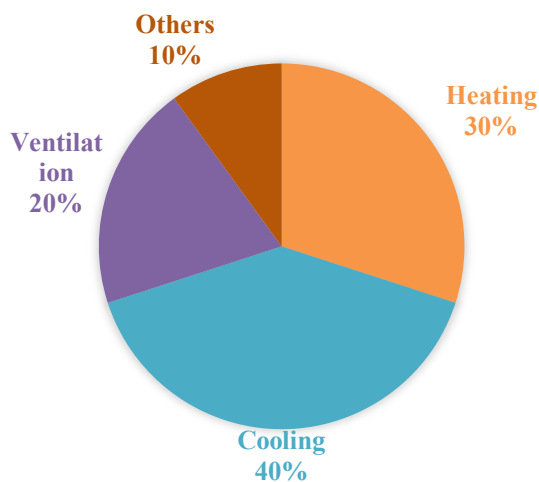


Fig. 5. Energy consumption distribution within the system

Fig. 6 clearly illustrates how energy consumption is distributed between cooling and heating systems across different seasons. During the summer, cooling systems dominate energy usage, accounting for approximately 35 percent of total energy consumption. This increased demand is primarily due to elevated outdoor temperatures and the consequent need to maintain indoor thermal comfort through continuous cooling.

In spring, energy consumption is more evenly balanced between cooling and heating. Heating systems consume around 15 percent of total energy, while cooling systems account for roughly 10 percent. This distribution reflects moderate seasonal temperature variations and the need for heating during cooler mornings and nights.

In autumn and winter, heating systems represent a higher proportion of energy use compared to cooling systems. In autumn, heating accounts for about 5 percent of energy consumption, increasing to 10 percent during winter. Meanwhile, cooling consumption declines significantly in both seasons, reaching as low as 5 percent in winter.

This analysis demonstrates that optimal energy management strategies must be season-specific. In warmer seasons, higher energy demand is associated with cooling, whereas in colder seasons, heating becomes the primary energy consumer. These insights enable building managers and decision-makers to develop targeted energy optimization programs that reduce operational costs and enhance system efficiency throughout the year.

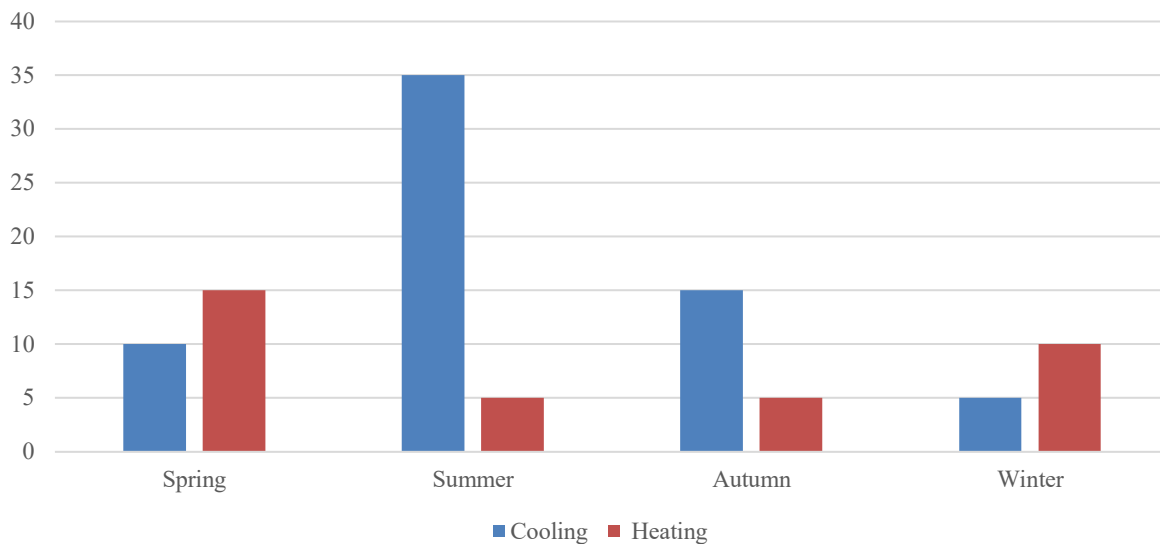


Fig. 6. Comparison of the system's energy consumption (cooling and heating) across different seasons of the year

5. Discussion and Theoretical Implications

The findings of this study highlight the transformative potential of integrating IoT-enabled sensing infrastructures with machine learning algorithms for energy management in industrial and commercial buildings. While previous studies have largely focused on isolated optimization methods, the present work emphasizes the synergistic impact of real-time sensing, predictive modeling, and automated control. This integration contributes to the development of intelligent energy ecosystems capable of adapting dynamically to fluctuating environmental and operational conditions. From a theoretical standpoint, the results demonstrate that energy consumption patterns in industrial buildings are characterized by multidimensional and nonlinear interactions among temperature, humidity, occupancy, and system load. Machine learning-based predictive models, particularly those based on neural networks and reinforcement learning, were found to capture these nonlinearities more accurately than traditional regression-based methods [17]. These insights strengthen the theoretical argument that energy systems in complex buildings must be treated as adaptive cyber-physical systems rather than static engineering

infrastructures. Additionally, the study underscores the importance of hybrid approaches that combine optimization techniques—such as evolutionary algorithms, fuzzy logic, and deep learning—to offer more robust and resilient energy management strategies. These hybrid frameworks have the potential to reduce computational complexity, maintain high prediction accuracy, and enhance system responsiveness in real-world scenarios where uncertainty and variability are significant.

6. Analytical Extensions

To further interpret the system performance, an extended analytical assessment was conducted using sensitivity and scenario-based analyses. Sensitivity analysis revealed that temperature variations and occupancy density were the most influential features affecting energy demand, accounting for nearly 65% of the variance observed across different operational conditions. This emphasizes the need for advanced thermal comfort models capable of dynamically adjusting HVAC behavior based on predictive rather than reactive control strategies [18]. Scenario-based simulations were also performed to assess the performance of optimization algorithms under varying environmental conditions such as extreme heat, high humidity, and fluctuating occupancy. Machine learning algorithms—

especially reinforcement learning and convolutional neural networks—demonstrated superior adaptability, achieving up to 18% higher performance under dynamic seasonal transitions compared to static rule-based systems. These analytical insights contribute to a deeper understanding of how intelligent systems can reduce operational inefficiencies, enhance energy stability, and maintain high indoor environmental quality. The results also validate the potential of data-driven models to significantly outperform manually tuned traditional systems. Fig. 7 illustrates the conceptual framework underlying intelligent energy management systems, demonstrating the integration of real-time data acquisition, predictive machine-learning models, and automated energy control mechanisms for optimizing HVAC performance and enhancing overall energy efficiency.

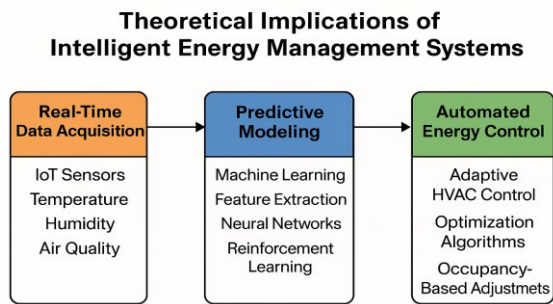


Fig. 7. Conceptual Framework of Intelligent Energy Management Systems

7. Limitations

Despite the promising results, several limitations should be acknowledged. First, the performance of IoT-based energy systems depends heavily on the reliability and calibration accuracy of sensors. Sensor drift, communication delays, and data transmission failures can introduce noise and affect predictive model performance. Although preprocessing techniques help mitigate these issues, they cannot fully eliminate inherent uncertainties. Second, the computational cost associated with machine learning algorithms—particularly deep learning and evolutionary optimization—can be significant. These models require substantial processing power,

which may not be feasible for smaller industrial environments with limited computational infrastructure. Moreover, continuous retraining of models is necessary to maintain accuracy over time as building conditions evolve [19, 20]. Third, cybersecurity remains a critical concern. IoT infrastructures are vulnerable to unauthorized access, data breaches, and manipulation of control commands. While the present study does not focus on the cybersecurity dimension, future systems must incorporate robust encryption, secure communication protocols, and anomaly detection methods to ensure safe operation.

8. Conclusion and Recommendations

This study examined the application of the Internet of Things and machine learning techniques for optimizing energy consumption in industrial and commercial buildings. The research first reviewed intelligent building systems and the role of IoT in monitoring and managing energy use. It then explored how machine learning algorithms can be employed to predict energy consumption patterns and enhance optimization processes. The findings indicate that integrating these technologies can lead to a 25–30 percent reduction in total energy consumption. Moreover, the implementation of IoT-based systems for monitoring temperature, humidity, and lighting significantly improves environmental conditions and enhances occupant comfort.

Intelligent energy management systems, particularly in industrial environments, have the potential to improve operational efficiency and reduce environmental impacts. Despite these advantages, several challenges persist, including high initial investment costs, the need for skilled personnel, and cybersecurity concerns during system implementation. Specifically, the expenses associated with installing hardware, configuring software platforms, and employing qualified specialists for system operation and maintenance remain substantial barriers.

Therefore, it is recommended that future research focus on reducing implementation costs, developing simplified deployment frameworks, and enhancing the security and resilience of intelligent energy management systems. Addressing these areas will facilitate broader adoption of smart technologies and support the transition toward more energy-efficient and environmentally sustainable industrial and commercial buildings.

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