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AI-Driven Climate Based Control and Energy Analytics for Smart Buildings

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Abstract

With the ever-increasing demands on energy usage in modern buildings, there has emerged the need for intelligent and efficient energy management systems that will be able to optimize resource use without compromising occupant comfort. This study introduces a novel framework for climate-based control and energy analytics in smart buildings using Internet of Things sensors and AI-based predictive analytics for adaptive energy management. Real-time environmental data collection and intelligent decision support were used to optimize lighting, ventilation, and climate control systems' operations in dynamic environments. In this regard, the proposed framework applied a hybrid control approach that integrated automatic control based on sensor readings and predictive analytics to minimize unnecessary operation of appliances, hence promoting energy efficiency. Performance evaluation using traditional Full Load Mode and AI-Based Mode revealed that the proposed solution was more efficient in energy utilization compared to the existing systems. It was able to conserve about 30% of energy consumption, reducing power usage from 4311 mW to 2874 mW. Additionally, the proposed predictive analytics model showed an estimated operational efficiency of 85.51%.

Keywords: Smart Buildings, Internet of Things (IoT), Energy Management Systems, Energy Analytics, Long Short-Term Memory (LSTM), Message Queuing Telemetry Transport (MQTT), Energy Efficiency Optimization.

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1. Introduction

Buildings consumes a great deal of energy across the world, especially due to the heating, ventilation, and air-conditioning system, lighting and indoor environment control systems. Most existing automated systems for buildings run on preset schedules and static thresholds that lead to wasteful energy consumption and ineffective operations of appliances. As a result, there is an increased need for efficient buildings hence leading to increased innovation of intelligent smart buildings systems.

Advances in Internet of Things (IoT) technology, embedded system and AI have led to monitoring and intelligent energy consumption in smart buildings. An IoT sensor network monitors the various operating and environment parameter information which include the temperature, moisture, illumination, occupancy, air pollution, and power consumption. The gathered sensor data can be analyzed via AI to allow adaptive control of the various systems and devices including the HVAC, lighting, and other electrical appliances [1]. Unlike the existing rule-based systems, AI-based systems will provide predictive analysis to allow prediction of energy consumption and appliance scheduling.

In several machine learning algorithms, LSTM Neural Network is very appropriate in the creation of energy prediction model, since it can learn dependencies from sequences. Implementation of predictive analytic models that are based on LSTM neural network in combination with IoT sensor and cloud communications allows effective and intelligent energy management, maintaining comfort of occupants and indoor environment quality [2].

The current research introduces a climate-based control and energy analytics approach to smart building utilizing IoT sensors, MQTT–Firebase cloud communication, and LSTM-based predictive modeling. The introduced approach involves ESP32-based embedded controller for adaptive control of appliances according to occupancy, environmental conditions, and predicted energy consumption needs [3]. The results of testing performed in Full Load Mode and AI-Based mode confirm substantial energy savings and reliability of the introduced framework.

2. Proposed Methodology

This research describes an intelligent Internet of Things-based approach for climate-controlled automation and energy analysis in smart buildings. It involves constant monitoring of the environment, occupancy, and energy consumption, while simultaneously optimizing the operation of the appliances through an automatic process that increases energy efficiency and improves user satisfaction [4]. The design combines distributed sensing, embedded control, cloud communications, and AI-driven analytics in one comprehensive energy management platform. The hardware design for the proposed system is presented in Figure 1.

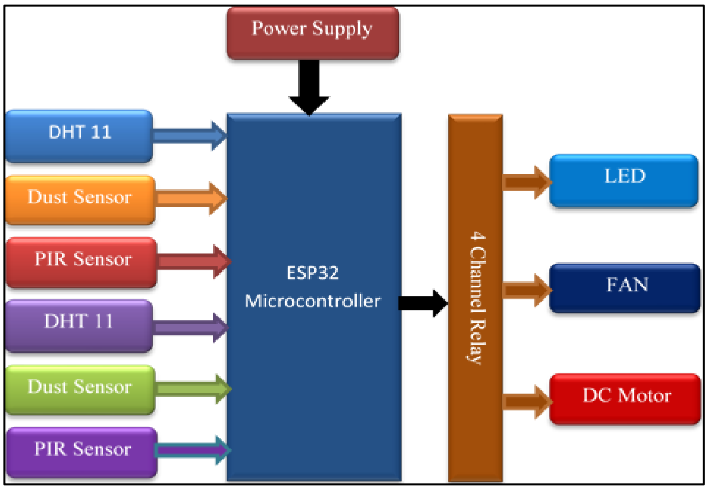

Figure 1. Architecture of the Proposed AI-Driven Smart Building System

The complete system workflow (as shown in figure 2) comprises of three main layers. First is the sensing layer that includes collection of information from multiple environmental and operational variables by employing heterogeneous Internet of Things (IoT) sensors. These sensors include collecting temperature and humidity readings through DHT11, detecting ambient light by employing LDR sensor, detecting presence through PIR sensor, measuring air quality by using dust sensors, identifying rainfall through rain sensor, and electrical power measurement using current sensors such as INA219 or ZMPT101B. The use of heterogeneous types of sensors provides all-encompassing situational understanding inside the indoor environment [5].

The embedded control layer is centered around the ESP32 microcontroller, which acts as the primary processing and communication unit of the proposed system. The ESP32 continuously collects sensor data, executes local control logic, and communicates with cloud services through wireless networking. The controller supports both threshold-based automation and AI-assisted decision-making to ensure reliable and adaptive operation. Based on environmental conditions and occupancy status, the controller dynamically activates or deactivates connected appliances through a 4-channel relay module [6]. The controlled devices include lighting systems, ventilation units, fans, HVAC equipment, and air purification systems. Additional alert mechanisms, such as buzzers and LED indicators, are incorporated to notify users during abnormal operating conditions including poor air quality, excessive power consumption, or adverse weather conditions.

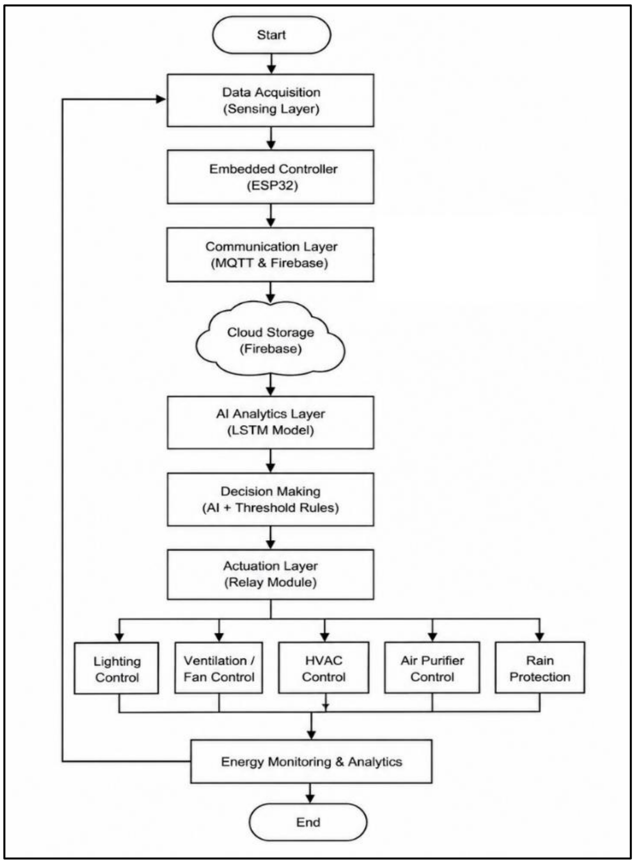

Figure 2. Overall Workflow of the Proposed System

For the purpose of intelligent energy management, the proposed approach makes use of predictive analysis based on LSTM neural networks. The LSTM network is used because of its ability to identify temporal relationships in the sequential input sensor data and predict the near future trends in energy consumption [2]. Multivariate time series data of temperature, humidity, occupancy, illumination, air quality, and past energy consumption is analyzed and used to train the prediction model. The model is used to make future predictions regarding energy demands and efficiency, which can then be used for optimal scheduling of appliances while saving energy in unnecessary cases. The decision-making process does not fully rely on AI predictions but also uses other parameters including comfort and safety constraints.

An integrated system using MQTT protocols along with Firebase cloud-based services is adopted to support live tracking and control features. The use of MQTT protocol helps achieve efficient publish-subscribe communication by establishing an effective link between the ESP32 controller and cloud-based services; this makes the MQTT protocol an appropriate choice for IoT data transmission [3]. Data from sensors and device status information are regularly transmitted to the cloud, where Firebase facilitates secure database management, visualization, and trend analysis. Moreover, the cloud service platform allows for remote supervision, through which individuals can observe and manipulate IoT activities at any time.

The hybrid control system adopted in the proposed framework comprises threshold-based automation and AI-optimized control. Threshold control guarantees an instant reaction to important environmental changes. For example, lights will automatically turn on when occupancy occurs under low light levels, heating, ventilating, and air conditioning (HVAC) systems start operating when temperatures go above preset comfort values, while air cleaning systems start working when particles exceed acceptable air pollution levels [7]. At the same time, the AI algorithm analyzes historical and current data from sensors for optimization of appliances operation modes and energy conservation. Thresholds for triggering appliances operations are listed in Table 1 below.

Table 1. Threshold Conditions for Sensor-Based Appliance Automation

Condition	Sensor	Threshold	Action	Relay/Output
Low light / Occupancy detected	LDR + PIR	LDR < 50 OR PIR = HIGH	Turn ON room lighting	Relay 1 (LED Lights)
Adequate light / No occupancy	LDR + PIR	LDR ≥ 50 AND PIR = LOW	Turn OFF room lighting	Relay 1 OFF
Poor air quality	Dust Sensor	Dust density > 1000 μg/m³	Turn ON air purifier & buzzer alert	Relay 2 + Buzzer
Restored air quality	Dust Sensor	Dust density ≤ 1000 μg/m³	Turn OFF air purifier & buzzer	Relay 2 OFF + Buzzer OFF
High temperature	DHT11	Temp > 40°C	Turn ON fan or AC	Relay 3
Normal temperature	DHT11	Temp ≤ 40°C	Turn OFF fan or AC	Relay 3 OFF
Rain detected	Rain Sensor	Rain value < 50	Turn ON outdoor protective systems	Relay 4

3. Experimental Setup

The design of the smart building architecture was put into practical testing in an indoor setting through experimentation to assess its efficiency, accuracy in prediction, and ability to optimize energy consumption. The experimental framework includes embedded systems, cloud communication, and machine learning-based analytical tools for climate regulation and energy optimization.

3.1 Hardware Configuration

The hardware configuration comprises an ESP32 microcontroller integrated with different types of sensors and actuators to monitor environmental conditions and automate household appliances. The ESP32 functions as the core processor that will collect data from sensors, process it locally, control relays, and communicate wirelessly. The hardware components adopted in the system design are listed in Table 2.

Table 2. Hardware Configuration of the Proposed Smart Building System

Hardware Component	Function
ESP32 Microcontroller	Central processing and wireless communication
DHT11 Sensor	Temperature and humidity monitoring
LDR Sensor	Ambient light detection
PIR Sensor	Occupancy and motion sensing
Dust Sensor	Indoor air quality monitoring
Rain Sensor	Rainfall detection
INA219 / ZMPT101B	Power consumption monitoring
4-Channel Relay Module	Appliance switching and automation
LED Indicators	System status indication
Buzzer	Alert generation during abnormal conditions
Fan / DC Motor	Ventilation and HVAC simulation
Power Supply Unit	Power delivery to the system

3.2 Software and Communication Environment

The software architecture comprises elements of embedded systems programming, IoT connectivity, cloud computing, and machine learning technologies. The ESP32 firmware was programmed in the Arduino environment to enable sensor interaction, threshold-based operation, and MQTT communication. Analytical tasks were carried out via cloud-based Python solutions. The software architecture utilized in the experiment is shown in Table 3 below.

Table 3. Software and Communication Platforms Used in the Experimental Setup

Software / Platform	Purpose
Arduino IDE	ESP32 programming and sensor integration
Python	Data processing and predictive analytics
Anaconda Navigator	Machine learning environment
Visual Studio Code	Model development and testing
MQTT Protocol	Real-time IoT communication
Firebase	Cloud storage and remote monitoring
LSTM Neural Network	Energy prediction and analytics

3.3 LSTM Training and Validation Strategy

The LSTM neural network model was trained based on multivariate time series datasets gathered from the IoT-based smart building system prototype. Temperature, humidity, light intensity, occupancy, air quality, rainfall, and power consumption datasets were gathered from sensors integrated into the smart building system. The sensor datasets were collected every 30 seconds and uploaded to the Firebase cloud database using MQTT protocol. Around 12,000 data entries were recorded for 10 days in both Full Load Mode and AI-based modes. A sample dataset is provided in Table 4.

Table 4. Sample Multivariate IoT Sensor Dataset Used for LSTM Training

S. No	Temp (°C)	Humidity (%)	Light	Occupancy	Dust (µg/m³)	Rain	Power (mW)
1	31.2	62	45	1	820	78	2980
2	31.5	63	42	1	845	80	3012
3	32.1	61	38	1	910	82	3155
4	33.4	60	55	0	960	85	2870
5	34.2	58	60	0	1015	48	3265

The preprocessing process involved the normalization of the obtained data and conversion to sequential input windows. For splitting, a temporal split ratio of 80:20 was adopted, whereby 9,600 data points were reserved for training while 2,400 data points were set aside for testing and validation purposes. The trained LSTM model was responsible for forecasting energy consumption, which was incorporated into the adaptive controller for intelligent energy management.

3.4 Experimental Evaluation Scenarios

In order to analyze the efficiency of the proposed framework, several automation scenarios were analyzed in actual operational conditions. Such scenarios involve adaptive lighting system, air quality management system, temperature-controlled ventilation system, rain-activated system, and AI-based monitoring of energy. The automation scenarios tested and their results are shown in Table 5.

Table 5. Experimental Automation Scenarios and Operational Outcomes

Case Study	Input Condition	Automated Action	Outcome
Lighting Control	Low illumination and occupancy detected	Automatic lighting activation	Reduced lighting energy consumption
Air Quality Monitoring	Dust concentration exceeds threshold	Air purifier and buzzer activated	Improved indoor air quality
Temperature Control	Temperature exceeds threshold	Fan/HVAC activation	Improved thermal comfort
Rain Detection	Rainfall detected	Outdoor protection activated	Enhanced operational safety
Energy Monitoring	Real-time current sensing	AI-based energy analysis	~30% energy savings

4. Results and Discussion

The suggested AI-based intelligent building control system was tested under two different working scenarios, viz., Full Load Mode and AI-Based Mode, to examine the efficiency of adaptive control and energy prediction strategies. The performance test was conducted based on real-time sensor data collected from the implemented IoT system architecture. The assessment was centered on power consumption, appliance behavior, environmental impact, and prediction capabilities of the LSTM network [8]. In Full Load Mode, all connected appliances were always operational regardless of occupancy and environmental conditions.

Table 6. Comparative Performance Analysis of Full Load and AI-Based Operating Modes

Parameter	Full Load Mode	AI-Based Mode
Power Consumption (mW)	4311	2874
Appliance Operation	Continuous Operation	Sensor-Based Adaptive Control
Measured Efficiency	66.95%	67.85%
Predicted Efficiency	74.85%	85.51%

From above Table 6,

$$\text{Full Load Mode Power Consumption} = 4311\ \text{mW}$$

$$\text{Al-Based Mode Power Consumption} = 2874\ \text{mW}$$

The percentage energy savings can be calculated as:

$$\text{Energy Savings (\%)} = \frac{\text{Full Load Power} - \text{AI-Based Power}}{\text{Full Load Power}} \times 100$$

Substituting the values:

$$\text{Energy Savings} = \frac{4311 - 2874}{4311} \times 100$$
$$= \frac{1437}{4311} \times 100$$
$$\approx 33.33\%$$

These savings have mainly been accomplished by means of adaptive scheduling of appliances. Lighting control made use of both light intensity readings from the LDR sensor and the presence or absence of people sensed by the PIR sensor in order to avoid unnecessary use of lights when there was sufficient natural light or the presence of occupants. Likewise, activation of the HVAC system occurred only if the indoor temperature surpassed the pre-defined threshold level of 40°C. Dust detection involved continuous monitoring of dust density levels, while the air purification system was triggered only if the dust level exceeded 1000 µg/m³. Outdoor system protection against rain was automated using rain sensors, which would trigger action if rainfall exceeded the threshold value [9]. The implemented automation scenarios are illustrated in Figures 3-6.

Figure 3. Experimental Setup for Adaptive Lighting Control

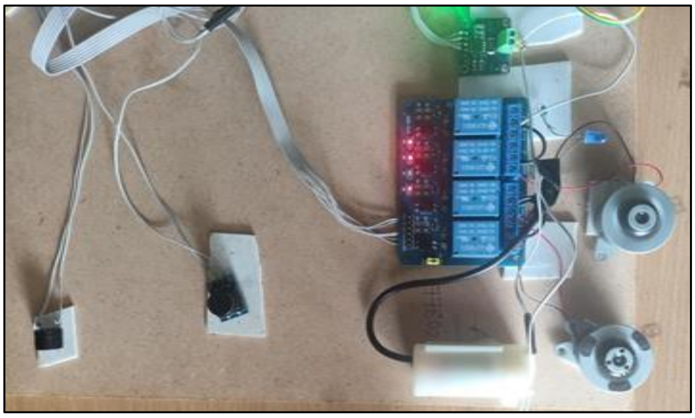

Figure 4. Experimental Setup for Air Quality Monitoring and Control

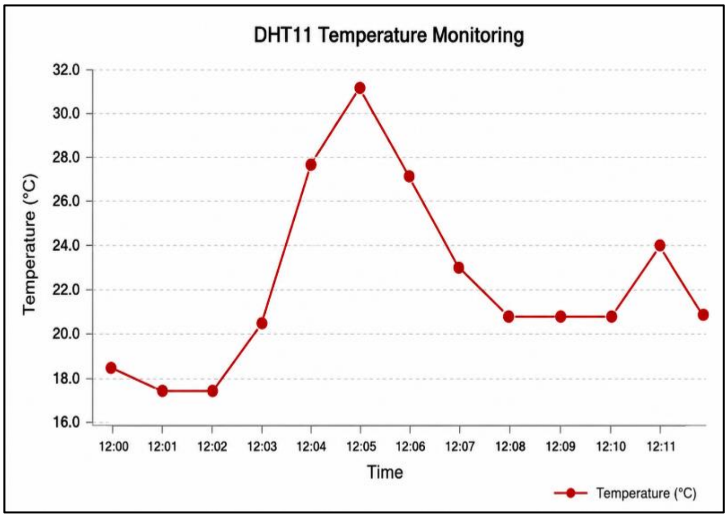

Figure 5. Temperature-Based Ventilation and HVAC Control Operation

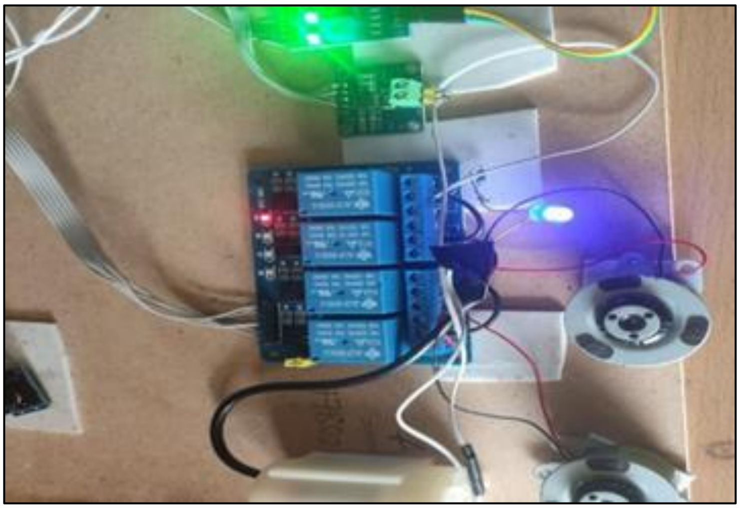

Figure 6. Rain-Triggered Automation and Protective Control Mechanism

The training process involved time series data from multiple sensors related to temperature, humidity, lighting intensity, occupancy presence, air quality levels, and past consumption values. Short-term predictions for energy consumption were made using the LSTM-based model, which were incorporated into the adaptive control system. Efficiency levels predicted by the model achieved a value of 85.51% during AI-Based Mode, while measured efficiency levels obtained were 67.85%. Such a disparity in prediction is an indication that more areas of optimization were found through the prediction model, but constrained by safety and comfort parameters.

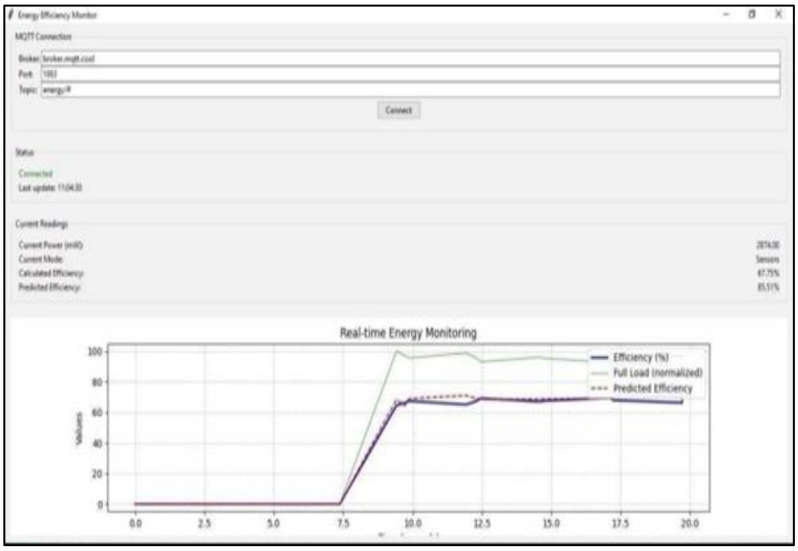

Figure 7. Energy Efficiency Characteristics Under Full Load Mode

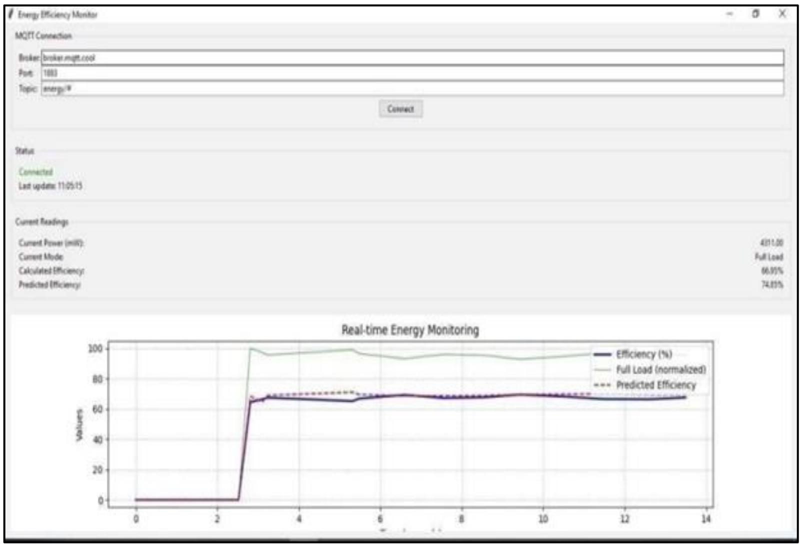

Figure 8. Energy Efficiency Characteristics Under AI-Based Mode

Efficiency attributes under both modes of operations are illustrated in Figures 7 and 8. From the findings, it is evident that the proposed artificial intelligence-enabled control system was successful in eliminating wastage in appliance operation without affecting the stability of the environment. In comparison with the Full Load mode, the adaptive model exhibited better synchronization among sensor data collection, prediction, and appliance control, leading to reduced energy consumption and increased efficiency [10].

The experimental results have proven the effectiveness of using IoT sensors along with the communication system of MQTT-Firebase and the prediction system based on LSTM in the real-time energy management of smart buildings. The combination between threshold-based automation and prediction system in the hybrid system is effective in managing the dynamic environment.

5. Conclusion

The study proposed a solution for climate control and energy management in smart buildings using IoT technology. In the proposed solution, an IoT-based sensor network was integrated with artificial intelligence-based decision support systems. With a combination of threshold-based automation and LSTM-based prediction modeling, the framework provided efficient and effective optimization of the control of lights, HVAC, and air quality management under different environmental conditions. Experiments proved that the proposed system significantly saved electricity consumption, with about 30% energy saving from full-load operations. Moreover, the proposed system increased efficiency and reliability by optimizing energy management decisions in real-time. These findings clearly indicate that the integration of IoT sensing devices and artificial intelligence-based analytics could improve energy efficiency and sustainability in modern smart buildings. The future research direction will be towards incorporating renewable energy sources into the system, enhancing the prediction model by employing advanced deep learning techniques, and scaling up the proposed framework for smart buildings/cities applications.

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