International Journal of Informatics and Computation (IJICOM)
Vol.7, No.2, 2025
ISSN: 2685-8711, E-ISSN: 2714-5263 DOI: 10.35842/ijicom

Leveraging Energy Efficiency of Smart Room using Blink System

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Abstract

This research presents the prototype of an IoT-based automatic room temperature control system to improve energy efficiency within an office. The designed smart room system uses a NodeMCU ESP8266 microcontroller, a DHT22 sensor for monitoring temperature and humidity, a proximity sensor to detect occupancy, and an infrared blaster to control the AC. An LCD displays real-time data, and integration with the Blynk app allows remote monitoring. The system automatically adjusts the AC temperature based on room occupancy and turns off the AC after 45 minutes of inactivity. According to the experimental results, energy consumption before implementation was 88.1 kWh per week, dropping to 38.5 kWh after, achieving a 56.3% energy saving without reducing user comfort. These results show that the system is effective and cost-efficient for smart building applications.

Keywords:
Energy efficiency, ESP8266, proximity sensor, infrared LED, DHT22, Blynk.

1. Introduction

Smart rooms increasingly rely on occupant-centric building control (OCC) strategies to reduce HVAC-related energy consumption by adapting to real-time occupancy and comfort preferences. Traditional Building Energy Management Systems (BEMS) often follow static schedules or fixed temperature settings that don't account for dynamic human behavior or changing room conditions. This lack of adaptability results in energy inefficiency and occupant discomfort. In large, shared spaces such as offices or classrooms, this inefficiency can accumulate significantly over time, highlighting the need for intelligent control systems that can respond more effectively to actual usage patterns [1].

Efforts to improve energy efficiency have turned toward artificial intelligence (AI) and machine learning (ML)-based approaches. Techniques such as predictive modeling, reinforcement learning, and unsupervised learning allow systems to anticipate occupancy and adjust environmental parameters proactively. However, the performance of these systems is highly dependent on the availability of accurate, labeled datasets and often struggles in non-stationary environments where human behavior shifts unpredictably. Moreover, integrating these complex models into real-time control loops can result in computational bottlenecks, making them less viable for deployment in constrained environments like microcontroller-based systems [2].

Another critical issue with current smart room energy management systems is the inability to detect and respond to anomalies in energy consumption effectively. Traditional systems primarily rely on predefined thresholds, which are inadequate for detecting subtle

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or multivariate anomalies caused by sensor drift, device faults, or environmental changes. Recent advancements using Graph Attention Networks (GATs) have shown improved performance in identifying anomalies across multiple correlated sensor streams, allowing for a more holistic and accurate understanding of system health. However, such advanced analytics remain largely disconnected from the control mechanisms in place, reducing their practical impact on energy savings [3].

Sensor sparsity is another limitation commonly encountered in smart environments. Most implementations rely on low-resolution sensor deployments, such as a single PIR (Passive Infrared) sensor per room, which leads to high false-negative and false-positive rates in occupancy detection. These inaccuracies can result in unnecessary activation or deactivation of systems, undermining the efficiency gains expected from smart automation. Studies have shown that these errors are particularly frequent in areas with intermittent human presence, where the sensor fails to register subtle movements, leading to poor control decisions [4].

The granularity of control also plays a crucial role in determining the effectiveness of smart energy systems. Many existing solutions operate at the building or floor level, providing only coarse adjustments that ignore individual comfort preferences or microclimate variations within a room. Without room-level or even desk-level control, energy-saving strategies cannot deliver personalized comfort, leading to user dissatisfaction and frequent manual overrides that negate automation benefits. Moreover, clustering techniques used for profiling energy usage are often not integrated with real-time actuation systems, limiting their utility to post-hoc analysis rather than real-time optimization [5].

Finally, as smart room systems become increasingly dependent on IoT infrastructure, privacy and cybersecurity concerns grow more prominent. These systems collect sensitive data on occupancy patterns, device usage, and even behavioral habits, which can be exploited if not properly secured. Many current implementations fail to incorporate encryption, authentication, or anonymization techniques, making them vulnerable to attacks. Research into privacy-aware architectures has shown that while solutions exist, they are often too resource-intensive or complex to implement on low-power embedded systems used in many smart environments [6].

2. Related Works

Agarwal et al. conducted a field study comparing presence-based control approaches for heating, ventilation, and air conditioning (HVAC) loads in real buildings. Their findings revealed that systems relying on real-time occupancy sensors could reduce energy consumption by up to 20% compared to fixed-schedule controls. However, they also observed that such reactive systems often compromise thermal comfort due to delayed or inaccurate occupancy detection. This emphasizes the necessity of improving responsiveness and accuracy in occupant-aware control systems [1].

Merabet et al. [2] reviewed artificial intelligence techniques for achieving thermal comfort and energy efficiency in smart indoor environments. Their study highlighted that reinforcement learning and consumption prediction models could enhance efficiency by approximately 15%, contingent on the availability of high-quality historical data. However, they also noted that the practical deployment of these models remains challenging, especially in dynamic environments where user behavior fluctuates significantly [2].

Zhang et al. introduced an anomaly detection method for building energy consumption using a graph convolutional network with an attention mechanism. Their experimental results, based on real-world datasets, demonstrated superior performance in identifying abnormal energy usage patterns when compared to traditional methods. Despite these advantages, the study noted a lack of integration between anomaly detection and automated control mechanisms within smart building infrastructures [3].

Howard et al. proposed a label-free machine learning approach using time series analysis to detect energy inefficiencies in commercial buildings. Their model achieved an accuracy of 92% by utilizing environmental sensor data such as temperature and equipment activity without relying on occupancy sensors. This highlights the potential of post-consumption analytics in identifying inefficiencies, particularly in environments where real-time presence data may not be feasible to collect [6].

Llaria et al. investigated privacy and security concerns in IoT-based smart building environments. Their findings revealed that many implementations, particularly in small-scale or institutional deployments, lacked adequate encryption and data anonymization protocols. As a result, occupancy and behavioral data remained vulnerable to exploitation. The study advocated for privacy-by-design principles to be embedded in all smart room architectures, especially those involving occupancy-based energy control [6].

Zhao et al. developed a multivariate time series anomaly detection method using graph attention networks (GAT) to enhance interpretability and accuracy in energy consumption monitoring. The proposed model successfully captured inter-sensor dependencies and outperformed traditional models such as DAGMM and LSTM-NDT by improving the F1-score by approximately 4%. Their work presents a promising direction for anomaly detection in complex building environments, where multiple energy variables interact dynamically [7].

Sun et al. proposed an electricity anomaly detection framework based on a CNN–BiLSTM–Attention hybrid architecture. The model achieved an accuracy exceeding 91% in identifying abnormal electricity usage patterns. While the study focused on electrical distribution networks, the underlying techniques are adaptable to real-time HVAC control in smart rooms. The ability to anticipate and prevent abnormal energy consumption can significantly contribute to overall efficiency in intelligent environments [8].

3. Proposed Method

3.1 Sensor Requirements

In the system architecture design stage, appropriate hardware components are identified to enable accurate monitoring and control of smart room environments. A proximity sensor, such as a PIR or an ultrasonic sensor to detect the presence and number of occupants within the room. This occupancy information is crucial for adjusting the HVAC operation dynamically, reducing energy consumption during periods of low or no occupancy. Research by Demrozi et al. demonstrated that low-cost proximity sensing using BLE and IR-based counters can achieve occupancy detection accuracies exceeding 97%, making them suitable for real-time HVAC management in smart environments [9]. Meanwhile, a DHT22 (AM2302) sensor is integrated to measure both temperature and relative humidity with ±0.5°C and ±2–5% accuracy, respectively, which is essential for maintaining user comfort while enabling precise climate control [10]. An infrared (IR) LED module is used to replicate air conditioner remote control signals, allowing the system to interact with conventional AC units without requiring hardware modification in embedded IoT prototypes [11].

The NodeMCU ESP8266 microcontroller serves as the central unit orchestrating all sensor data collection, control logic execution, and actuation. With built-in Wi-Fi support and low power consumption, it supports both real-time monitoring and cloud-based data access. The control logic involves analyzing input from proximity and temperature sensors to determine optimal AC operation, which is then communicated to the AC unit via IR signals. LCDs are utilized to provide local feedback, while a Blynk-based mobile interface allows remote users to monitor and control environmental conditions. Prior studies have successfully implemented NodeMCU-based systems integrated with Blynk and DHT22 sensors, highlighting their feasibility and reliability for residential and educational energy automation projects [10][12]. Such configurations facilitate remote access, real-time responsiveness, and user-centric energy savings in the development of an intelligent and sustainable Blink System for smart rooms.

3.2 System Design

In this study, we design the Blink System's operational logic initiates with a proximity sensor (such as an ultrasonic or IR beam counter) that continuously monitors the presence and number of occupants entering or exiting the room. This count is essential for incrementally adjusting the air conditioner's setpoint: the system automatically sets the AC to 26 °C for one to two occupants, 24 °C for three to four occupants, and 22 °C for five or more occupants. This dynamic, occupancy-informed temperature strategy aligns with findings by Kim et al., who demonstrated that LSTM-based occupancy prediction allows predictive HVAC control to reduce energy use by up to 50% while maintaining thermal comfort, because the system can preemptively adjust the environment before occupancy changes become inconvenient [13]. Furthermore, Schneider Electric reported real-world deployments achieving energy savings of approximately 22% in commercial meeting rooms using occupancy-based delays and setbacks, which indicates the practical effectiveness of fine-grained control logic driven by occupant presence [14].

To further optimize energy use, Blink System implements a 45-minute inactivity timeout: if no presence is detected during this interval, the system automatically turns off the air conditioner. This approach mirrors reactive control strategies that minimize HVAC runtime during extended unoccupied periods, a method shown to yield 11–34% energy savings in residential and institutional settings [15]. The core processing is performed by the NodeMCU ESP8266 module, combining proximity data and temperature readings to execute decision logic and generate infrared signals emulating remote control commands. Similar embedded-control architectures that integrate NodeMCU with DHT sensors and infrared actuators in experimental smart room platforms, highlighting reliable real-time control and remote telemetry via Blynk or similar cloud-based dashboards [16]. Fig. 1 depicts the system design of the smart room.

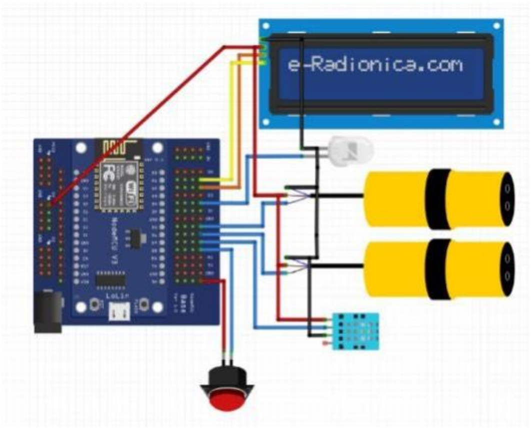

Fig. 1: System Design of Smart Room

In this study, the system hardware comprises NodeMCU, various sensors, and an LCD module, all integrated onto a custom-designed printed circuit board (PCB) and programmed using the Arduino IDE environment. Infrared communication with the air conditioner is facilitated through the IRremoteESP8266 library, enabling the transmission of control signals, while real-time monitoring of environmental parameters and occupancy is supported via the Blynk mobile application. System performance was evaluated through deployment in the Sukma Komputer technician room under multiple test scenarios involving varying numbers of occupants and environmental conditions. To quantify the effectiveness of the system in reducing energy consumption, electrical usage was measured using a wattmeter before and after implementation, allowing for a comparative analysis of energy efficiency outcomes.

3.3 Scenario Formulation

To support the proposed method for an IoT-based automatic room temperature control system, several mathematical formulas are required to represent occupancy-based temperature control, energy consumption, and efficiency gain as follows:

1. Occupancy-Based Temperature Control Rule

The system logic is based on the number of people Nin the room. A piecewise function can define the temperature setpoint T_s:

$$T_s = \begin{cases} 26^\circ C, & 1 \le N \le 2 \\ 24^\circ C, & 3 \le N \le 4 \\ 22^\circ C, & N \ge 5 \end{cases} \tag{1}$$

2. Energy Consumption Calculation

To evaluate power efficiency, calculate energy consumption (E) using:

$$E = P \times t \tag{2}$$

Where:

- E is energy in kilowatt-hours (kWh)
- P is the average power consumption in kilowatts (kW)
- P is the operational time in hours (h)

This is used for both pre- and post-system installation conditions.

3. Energy Saving Percentage

To determine the percentage of energy saved after implementing the system:

$$\text{Energy Saving}(\%) = \left(\frac{E_{\text{before}} - E_{\text{after}}}{E_{\text{before}}}\right) \times 100 \tag{3}$$

Where:

- E_{before} = energy used before the system
- E_{after} = energy used after the system

4. Occupancy Detection Condition

Let $S(t)$ be the binary signal from the proximity sensor at time t, and define the occupancy count Nas:

$$N(t) = \sum_{i=0}^{t} [S_{\text{in}}(i) - S_{\text{out}}(i)] \tag{4}$$

Where:

- $S_{\text{in}}(i)$ = sensor pulse for a person entering
- $S_{\text{out}}(i)$ = sensor pulse for a person exiting

5. Inactivity Timeout for AC Off

The system deactivates the AC if no presence is detected within a set time T_{timeout}

$$\text{If } \Delta t_{\text{last\_presence}} \ge T_{\text{timeout}} \Rightarrow \text{AC} = \text{OFF} \tag{5}$$

Where:

- $\Delta t_{\text{last\_presence}}$ = elapsed time since last motion detected
- T_{timeout} = 45 minutes (default threshold)

The proposed IoT-based automatic room temperature control system incorporates a series of mathematical models to regulate energy usage and occupant comfort efficiently. The primary logic relies on an occupancy-based control function, which adjusts air conditioner (AC) settings according to the number of detected users. This piecewise control strategy assigns specific temperature values such as 26°C for 1–2 people, 24°C for 3–4 people, and 22°C for five or more individuals to maintain thermal comfort without unnecessary energy use. The system also uses a basic count function to estimate real-time occupancy by tracking entry and exit events, ensuring that temperature adjustments reflect actual room activity. Additionally, a timeout condition automatically disables the AC if no presence is detected for a defined period (e.g., 45 minutes), further preventing energy waste in unoccupied spaces.

To quantify the energy efficiency, the system applies the energy consumption formula $E = P \times t$, where P is the power drawn by the AC in kilowatts and t is the operational time in hours. This allows comparison of energy use before and after automation. The energy saving percentage is calculated using $\text{Saving} = \frac{E_{\text{before}} - E_{\text{after}}}{E_{\text{before}}} \times 100\%$ which showed a significant reduction of 56.3% in weekly energy usage, from 88.1 kWh to 38.5 kWh. These mathematical formulations are essential in validating the performance and effectiveness of the smart system and demonstrate its potential as an energy-saving solution suitable for office or educational environments.

4. Experimental Setup

1. Smart Room Location

In this study, we conducted the smart home testing in the technician room at Sukma Komputer, utilizing a Gree brand air conditioner as the controlled device. They installed the system beneath the AC unit and near the power source to ensure efficient integration and minimal wiring complexity. To accurately detect user presence, they positioned the proximity sensor at the entrance of the room, allowing real-time monitoring of occupancy. They aligned the infrared LED directly with the AC's receiver panel to ensure reliable and uninterrupted signal transmission during operation. Fig. 2 depicts the smart room sensor installation.

Fig. 2: Smart room site with sensor installation

4.2 System Setup

This proposed system integrates several key hardware components designed to operate collaboratively for efficient environmental monitoring and control. At the core, the NodeMCU ESP8266 microcontroller functions as the central unit responsible for data processing, sensor coordination, and communication. A proximity sensor is employed to detect and count room occupants, enabling adaptive control based on user presence. The DHT22 sensor measures ambient temperature and humidity, supplying real-time environmental data. An infrared (IR) blaster transmits configuration signals to the air conditioner, allowing automated adjustment of temperature settings. A 16x2 I2C LCD module visually displays critical information such as room temperature and the number of users. Additionally, a push button offers manual control to activate or deactivate the system as needed, and a dedicated power supply unit ensures consistent energy delivery to all components. The connectivity and interaction among these components are illustrated in Fig. 3.

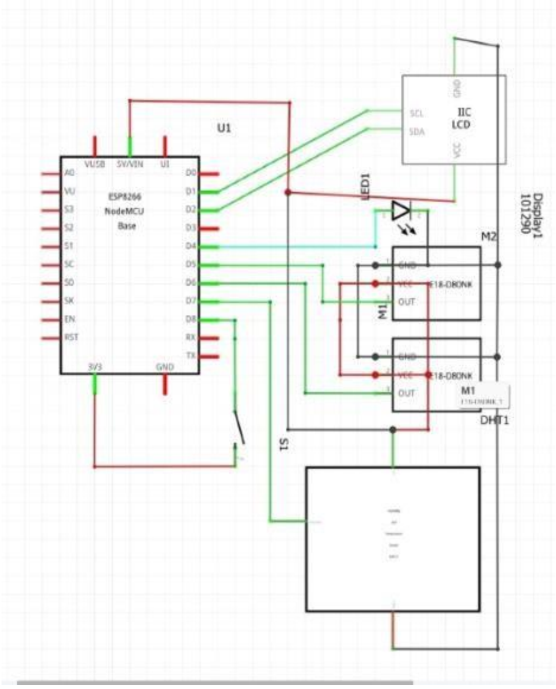

Fig. 3. System connection circuit

4.3 Testing Scenarios

The system was evaluated under multiple test scenarios to assess its responsiveness and functional reliability in real-world conditions. In the first scenario, the entry of a single occupant triggered the system to adjust the air conditioner to 26°C, aligning with energy-saving parameters for low occupancy. The second scenario involved three individuals entering the room, prompting the system to lower the temperature to 24°C to maintain thermal comfort. In the third scenario, the room remained unoccupied for 45 minutes, leading the system to automatically turn off the air conditioner to conserve energy. Finally, in the fourth scenario, the system detected a returning occupant and reactivated the air conditioner accordingly, confirming its capability to autonomously resume operations based on real-time occupancy input. These tests demonstrate the system's adaptive control logic and potential for improving energy efficiency through intelligent environmental regulation.

5. Results and Analysis

5.1 Functional Analysis

The system successfully detects the number of people in the room using a proximity sensor and automatically adjusts the AC temperature using an infrared blaster. From the test results, each scenario of changing the number of people provides a fast system response, with an average response time of about 1 second. The temperature setting runs according to logic:

- 1-2 people → temperature set to 26°C
- 3-4 people → temperature set to 24°C
- ≥5 people → temperature set to 22°C
- No activity detected for 45 minutes → AC is automatically turned off

The number of people and temperature were also successfully displayed on the LCD and Blynk app, providing easy real-time monitoring from a mobile device.

In addition to energy efficiency, the response time was also tested to measure the system's response to changes in the number of users accurately and quickly. There were no delays that interfered with comfort, and the system still provided the option of manual control via the ON/OFF button. Table 1 displays the test results of the response time of the smart room.

Table 1. System Response Test Results

Number of People	Set Temperature (°C)	Response Time
1	26°C	±1 second
3	24°C	±1 second
5	22°C	±1 second

5.2 Energy Effectiveness Testing

According to the experimental results, one of the most significant results was the energy efficiency. The use of a wattmeter showed that before the automated system was implemented, the AC electricity consumption reached 88.1 kWh/week. After the implementation of the system, the consumption dropped drastically to 38.5 kWh/week, resulting in a saving of 56.3%. These results show that the developed IoT-based automation system can minimize energy waste without reducing the comfort of room users. Table 2. Comparison of Energy Consumption Before and After application of the Smart Room system.

Table 2. Comparison of Energy Consumption Before and After the Smart Room Application

Condition	Energy Consumption (kWh/week)
Before automatic	88,1
After automatic	38,5
Savings	56,3%

The proposed system demonstrates several notable advantages in terms of functionality and energy efficiency. One of the most significant benefits is its ability to reduce energy consumption by 56.3%, primarily through occupancy-based automation of air conditioner usage. This adaptive control not only lowers operational costs but also contributes to sustainable energy practices. Additionally, the system enables real-time monitoring via the Blynk application, allowing users to observe temperature and room activity remotely from a smartphone. The hardware configuration is versatile and can be easily adapted for use with a wide range of air conditioners that operate with infrared remote controls, enhancing its applicability in various settings.

However, the system also presents some limitations. Its functionality is confined to air conditioners equipped with infrared receivers, restricting compatibility with certain newer models or smart AC systems that utilize alternative communication protocols. The proximity sensor's effectiveness relies on users passing through a specific detection point; therefore, if individuals enter without being detected, the automation logic may not activate correctly. Furthermore, the system's reliance on a Wi-Fi connection for real-time monitoring via Blynk introduces potential vulnerabilities, such as loss of functionality during network outages or in areas with poor connectivity. These constraints highlight areas for future enhancement, such as integrating alternative communication interfaces or more robust presence detection methods.

6. Conclusion

The research successfully developed and implemented an Internet of Things (IoT)-based automatic room temperature control system aimed at enhancing the energy efficiency of air conditioner (AC) usage. The system is built upon a NodeMCU ESP8266 microcontroller, serving as the central processing unit, and is integrated with a proximity sensor to detect occupancy, a DHT22 sensor to monitor ambient temperature and humidity, and an infrared (IR) blaster to transmit automatic control commands to the AC unit. The experimental results demonstrated the system’s effectiveness in dynamically adjusting temperature settings based on occupancy levels, with thresholds set to 26°C, 24°C, and 22°C depending on the number of people present.

Furthermore, the system is capable of switching off the air conditioner autonomously after 45 minutes of detected inactivity. This automation led to a significant reduction in weekly energy consumption by 56.3%, decreasing from 88.1 kWh to 38.5 kWh. Additionally, real-time environmental data, including temperature and user count, were displayed via a 16x2 LCD and monitored remotely through the Blynk mobile application. These outcomes suggest that the proposed system is not only technically viable but also practical and scalable, offering an eco-friendly energy-saving solution suitable for office and educational facility deployment.

To enhance the system’s performance and applicability, several improvements are recommended. First, incorporating additional motion sensors such as Passive Infrared (PIR) detectors can improve the accuracy of user presence detection, particularly in scenarios where individuals may not pass directly through the proximity sensor’s range. Second, expanding the system’s compatibility with modern air conditioners that use non-infrared communication protocols, including inverter-type AC units, to broaden its usability. Third, integrating renewable energy sources such as photovoltaic (solar) panels can further increase the system's sustainability and reduce dependency on conventional power. Finally, embedding artificial intelligence (AI)-based adaptive control algorithms would enable more intelligent and context-aware temperature regulation, thereby enhancing user comfort while maintaining optimal energy efficiency. These suggested enhancements pave the way for future developments toward smarter, greener building automation systems.

Acknowledgment

The authors would like to thank Sukma Komputer for providing permission and facilities to conduct system testing directly in the technician's room. Gratitude is also expressed to the supervisors, namely I Gede Juliana Eka Putra, S.T., M.T., and I Nyoman Purnama, S.T., M.T., for their guidance, direction, and scientific support that is very meaningful in this research process. Appreciation is also given to the entire testing team and Informatics Engineering laboratory staff who have helped in the process of testing tools and verifying field data. Finally, the author would like to thank his family and colleagues who always provide moral support and motivation in completing this research. Hopefully, the results of this research can make a positive contribution to the development of IoT-based technology for energy efficiency and environmental sustainability.

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