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Performance Evaluation of IoT-Based AC Control Using Multi-Modal Fuzzy Sensors

Amiruddin. A [1,a,*]; Abdul Latief Arda [2,b]; Abdul Jalil [3,c] ; Andani Achmad [4,d] ; Supriadi Sahibu [5,e] ; Yuyun [6,f]

[1] *Universitas Handayani Makassar, Adhyaksa Baru No. 1, Makassar 90231, Indonesia*
[1] *Politeknik Lembaga Pendidikan dan Pengembangan Profesi Indonesia Makassar, Perintis Kemerdekaan KM 12 Tamalanrea Makassar, Makassar 90245, Indonesia*
[25] *Universitas Handayani Makassar, Adhyaksa Baru No. 1, Makassar 90231, Indonesia*
[3] *Politeknik Negeri Ujung Pandang Makassar, Perintis Kemerdekaan, Makassar 90245, Indonesia*
[4] *Universitas Hasanuddin Makassar , Perintis Kemerdekaan , Makassar 90245, Indonesia*
[6] *Badan Riset dan Inovasi Nasional Bandung, Sangkuriang, Bandung,40135 Indonesia*
[a] *amiruddinardinmks@gmail.com*; [b] *abdullatief@handayani.ac.id*; [c] *abduljalil@poliupg.ac.id* ;
[d] *andani@unhas.ac.id* ; [e] *supriadi@handayani.ac.id* ; [f] *yuyunwabula@gmail.com*
* *Corresponding author*

Abstract

This study addresses the challenge of controlling Air Conditioner (AC) temperature in enclosed spaces in tropical climates, where improper operation often leads to thermal discomfort and excessive energy consumption. The research aims to develop and implement an Internet of Things (IoT)-based system for monitoring and controlling AC temperature by integrating multi-modal sensors and applying a fuzzy logic approach. The proposed system employs a DHT22 sensor to measure temperature and humidity, a thermopile sensor to capture human body temperature, and a PIR sensor to detect occupancy and movement within the room. Sensor data are processed using an ESP32 microcontroller with FreeRTOS-based multitasking and transmitted to the Blynk platform for real-time monitoring. Decision-making is carried out using fuzzy logic based on the temperature difference (ΔT) between body temperature and ambient conditions to automatically regulate AC operation. Experimental results indicate that the system performs reliably and provides adaptive control, achieving a fuzzy logic accuracy of 64.34% under real-world conditions. Furthermore, the automated control mechanism reduces energy consumption by 35.7% compared to conventional manual operation. Overall, the findings confirm that the integration of multi-modal sensing, IoT technology, and fuzzy logic can effectively enhance energy efficiency while maintaining thermal comfort in indoor environments.

Keywords: *IoT, Fuzzy Logic, ESP32, Air Conditioning, Energy Efficiency*

1. Introduction

The technology of air conditioning (AC) has become a primary necessity in tropical regions, including Indonesia. High ambient temperature and humidity often create thermal discomfort that directly affects human productivity and health quality. However, the widespread use of AC introduces new challenges, namely very high electrical energy consumption. In office buildings and educational institutions, AC systems are often the largest energy-consuming component, especially when their operation is uncontrolled or remains active when rooms are unoccupied.

Conventional AC systems generally rely on simple thermostat mechanisms that only detect the surrounding air temperature. This approach has limitations because it does not consider other dynamic environmental parameters, such as humidity levels or human presence in the room. The system's inability to recognize environmental context often leads to cooling inefficiency; room temperature is sometimes set too low, causing physical discomfort, or the unit continues operating at maximum capacity even when occupancy is minimal.

Advances in Internet of Things (IoT) technology offer solutions through real-time intelligent monitoring and control. By integrating various sensors and microcontrollers connected to the internet, environmental parameters can be managed more precisely. In addition, the integration of multi-modal sensing-such as combining room temperature, humidity, and human body temperature sensors-provides more comprehensive data for determining optimal operating conditions.

However, data from multiple sensors often contain uncertainty and non-linearity. Fuzzy logic emerges as an effective method to handle such ambiguity by mimicking human reasoning in decision-making. In this study, fuzzy logic is used to process the difference between human body temperature and room temperature as the main parameter for AC control. The use of FreeRTOS multitasking on the ESP32 microcontroller is also implemented to ensure system stability in handling simultaneous sensor readings and data communication.

Based on this background, this study proposes an IoT-based AC monitoring and control system integrating multi-modal sensors with fuzzy logic implementation. Through this approach, the system is expected to provide more adaptive responses to real-world indoor conditions. The main contributions of this research include the design of a stable IoT architecture, the development of a fuzzy inference engine for temperature regulation, and the demonstration of energy efficiency through experimental validation.

2. Method

This section presents a systematic framework for the design, implementation, and evaluation of an adaptive air conditioning (AC) temperature control system based on the Internet of Things (IoT). The study adopts an engineering research approach that integrates artificial intelligence, specifically fuzzy logic, to address the complexity and dynamic nature of environmental parameters.

From a conceptual perspective, the proposed methodology is grounded in the principle of multi-modal sensing, where data obtained from multiple sensors are not merely collected independently but are functionally integrated to enable more accurate and context-aware decision-making. The ESP32 microcontroller, combined with a Real-Time Operating System (FreeRTOS), forms the core of the technical architecture, ensuring system stability in handling concurrent tasks, ranging from sensor data acquisition to cloud-based data transmission.

The development process is structured into four main phases: (1) hardware architecture design and sensor integration, (2) development of a fuzzy logic–based decision-making model, (3) implementation of IoT communication using the Blynk platform, and (4) experimental validation through performance testing and energy efficiency analysis. Detailed descriptions of each phase are provided in the subsequent subsections.

2.1 Design of Hardware Architecture and Multi-Modal Integration

Figure 1 illustrates the architecture of the proposed intelligent air conditioning (AC) control system, which integrates multi-modal sensing within an Internet of Things (IoT) ecosystem. Functionally, the architecture is designed as a closed-loop control system, structured into three primary layers: the data acquisition layer, the central processing layer, and the user interface layer.

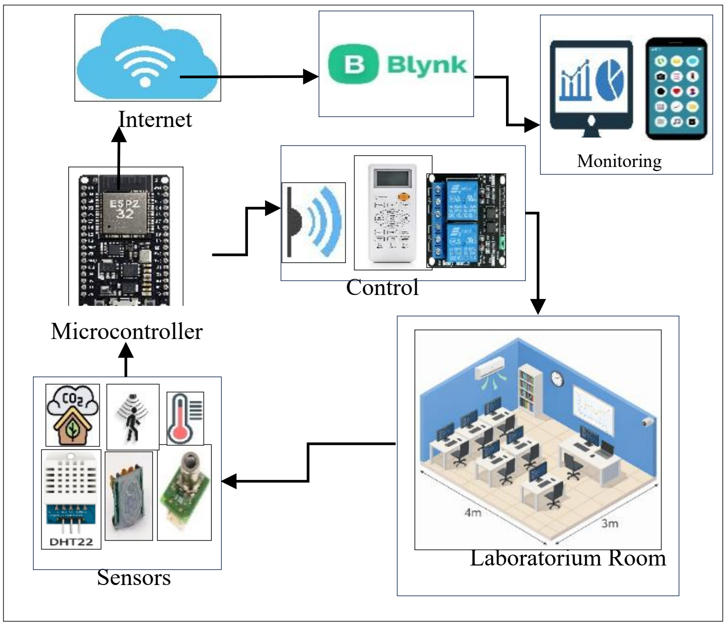

Figure 1. Research Design of an IoT-Based Air Conditioner

2.1.1 *Data Acquisition Layer (Multi-Modal Input)*

The system utilizes three primary sensors to comprehensively capture environmental parameters. The DHT22 sensor is employed to measure room temperature and humidity with stable and reliable accuracy. A thermopile sensor (MLX90614) is used to detect human body temperature in a non-contact manner through infrared radiation, which serves as a critical parameter in determining individual thermal comfort. Additionally, a Passive Infrared (PIR) sensor functions as an occupancy detector to ensure that the system operates only when human presence is detected within the room.
The integration of these sensors forms a multi-modal sensing approach, enabling the system to obtain a more accurate and contextual representation of environmental conditions compared to conventional air conditioning systems that rely solely on a single temperature sensor.

2.1.2 *Core Processing Layer (Kernel)*

The central processing unit is based on the ESP32 microcontroller, which acts as the core component responsible for executing the fuzzy logic algorithm. In this layer, raw data obtained from the sensors are processed through several stages, including fuzzification, rule-based inference, and defuzzification, to generate appropriate control decisions for the air conditioning system.
The selection of ESP32 is motivated by its capability to support multitasking through the FreeRTOS environment, allowing the system to simultaneously perform sensor data acquisition, fuzzy computation, and network communication without performance degradation or instruction conflicts.

2.1.3 *User Interface and Connectivity Layer (Output and Monitoring)*

The output generated by the fuzzy logic system is transmitted to the air conditioning unit through a control module, such as a relay or infrared interface. At the same time, all environmental parameters and system operational status are transmitted wirelessly to the Blynk cloud server for real-time monitoring.

This layer enables users to access system information through a mobile or web-based interface, providing real-time visualization of temperature, humidity, occupancy status, and AC operation. Furthermore, the system supports bidirectional communication, allowing users to remotely control the AC system when necessary.

Overall, this architecture not only functions as an automated control system but also represents a cyber-physical system that bridges interaction between users and the physical environment through cloud-based technology.

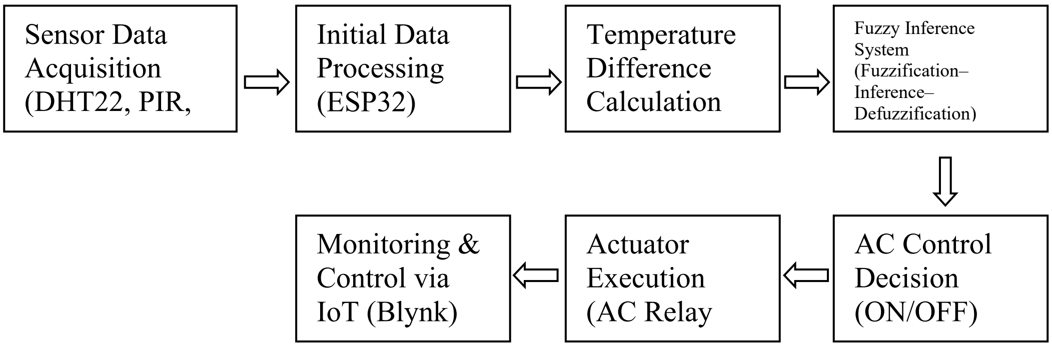

Figure 2. Research Design.

2.2 Implementasi Multitasking FreeRTOS

In this intelligent control system, data processing efficiency is essential, as the system must handle multiple operations simultaneously, including sensor data acquisition and network communication. To achieve this capability, a Real-Time Operating System (RTOS) based on FreeRTOS is implemented on the ESP32 microcontroller. This approach allows the system to utilize the dual-core architecture of the ESP32 through a multitasking mechanism.

The FreeRTOS implementation is structured by dividing the system workload into several independent tasks that run concurrently. Each task is assigned a specific function and priority level to ensure optimal system performance. The task configuration is summarized in the following table.

Table 1. FreeRTOS Task Configuration

Task name	Primary Function	Priority	Core
Sensor Task	Multi-modal Data Acquisition	High (3)	1
Fuzzy Task	Inference Engine	High (3)	1
Blynk Task	IoT Communication	Medium (2)	0
Monitor Task	Serial Debugging	Low (1)	0
Wifi Task	Connection Management	High (3)	0

2.2.1 Sensor Data Acquisition Task :

This task is assigned a high priority to ensure that environmental data, including temperature, humidity, body temperature, and motion, are updated consistently at specific time intervals.

2.2.2 Fuzzy Logic Task (Inference Engine) :

This task is responsible for processing sensor data using a fuzzy logic algorithm. The separation of this task ensures that complex mathematical computations do not interfere with sensor data acquisition or data communication processes.

2.2.3 Blynk Communication Task :

This task is responsible for transmitting data to the cloud server and maintaining synchronization of the control status. With the implementation of FreeRTOS, network latency over WiFi does not cause the control system to freeze or disrupt data acquisition processes.

2.2.4 WiFi Handler Task (Auto Reconnect) :

As a mitigation strategy for network failures, a dedicated task is assigned to continuously monitor the connection status and perform an automatic reconnection procedure when the connection is lost.

The use of the FreeRTOS scheduler ensures that each task receives an appropriate allocation of CPU time based on its priority level. This guarantees system determinism, where the AC control response to changes in human body temperature is maintained even when the system is performing intensive data synchronization processes with the IoT platform. This integration transforms the device into a robust embedded system that is responsive to dynamic indoor environmental conditions.

2.3 Design of the Fuzzy Inference System

The artificial intelligence component of the proposed system is centered on a fuzzy inference engine designed to transform uncertain environmental parameters into accurate control decisions. The Mamdani fuzzy approach is employed, consisting of three primary stages: fuzzification, rule base development, and defuzzification.

The fuzzy inference system is designed to transform multi-modal sensor inputs into appropriate control decisions for the air conditioning system. The process consists of three main stages: fuzzification, rule-based inference, and defuzzification.

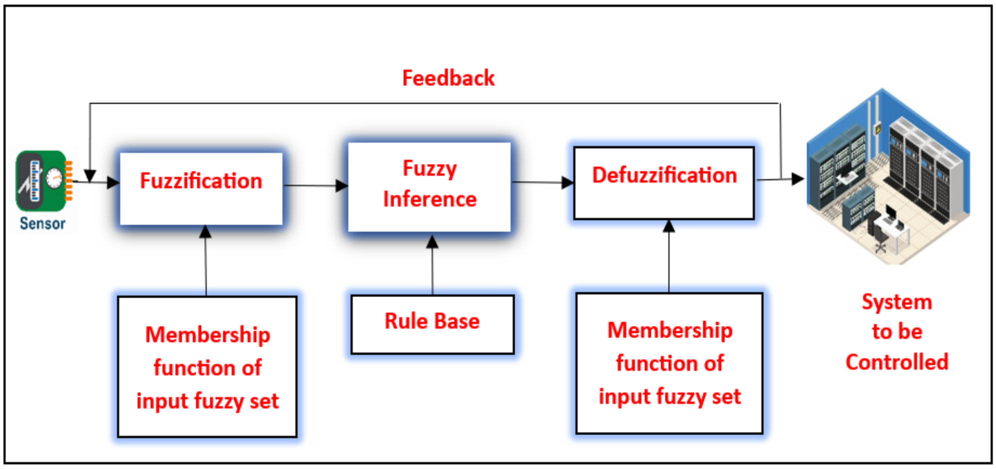

Figure 3. Fuzzy Inference System

As illustrated in Figure 3, the system begins with the acquisition of input variables derived from multi-modal sensors, including temperature difference (ΔT), humidity, and occupancy.

These inputs are first processed through the fuzzification stage, where crisp values are converted into fuzzy linguistic variables.

Subsequently, the inference engine applies a set of IF–THEN rules to determine the appropriate control action based on predefined knowledge. Finally, the defuzzification process converts the aggregated fuzzy output into a crisp value, which is used to control the AC operation (ON/OFF).

2.3.1 Input Variables and Fuzzification

The system utilizes two primary input variables derived from the integration of multi-modal sensors. Each input variable is represented by several fuzzy sets, defined by specific membership functions.

Temperature Difference (ΔT) :

This variable represents the difference between human body temperature (measured by the thermopile sensor) and room temperature (measured by the DHT22 sensor). It is categorized into linguistic fuzzy sets such as *Low*, *Medium*, and *High*.

Occupancy (Human Presence) :

This variable is obtained from the PIR sensor to support energy efficiency. When no motion is detected, the system automatically assigns a low weight to the cooling operation.

Temperature Difference ΔT :

The fuzzy inference system utilizes three input variables, namely temperature difference (ΔT), humidity, and occupancy. Each variable is represented using triangular membership functions as shown in.

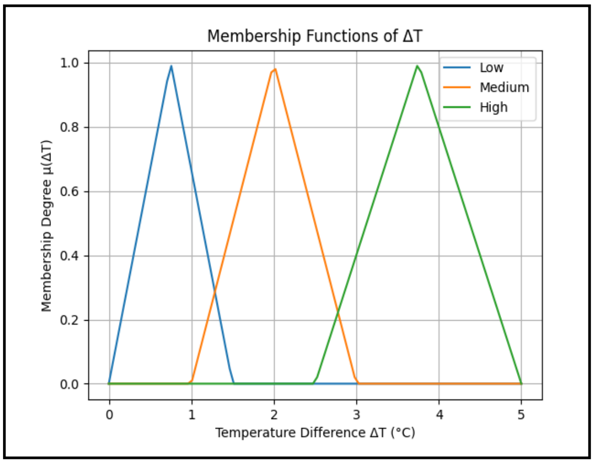

Figure 4. Membership Functions of Temperature Difference (ΔT)

The temperature difference (ΔT) is defined using triangular membership functions with the following numerical ranges: Low (0–1.5°C), Medium (1–3°C), and High (2.5–5°C). These overlapping ranges ensure smooth transitions between fuzzy sets.

The system utilizes three primary input variables, namely temperature difference (ΔT), humidity, and occupancy.

The membership functions for the temperature difference (ΔT) variable are defined using triangular shapes due to their simplicity, computational efficiency, and suitability for real-time embedded systems. Triangular membership functions enable smooth transitions between fuzzy sets while maintaining low computational overhead, which is essential for implementation on resource-constrained microcontrollers such as ESP32.

The numerical ranges of ΔT are determined based on empirical observations and thermal comfort principles. Specifically, ΔT is categorized into three linguistic variables: Low (0–

1.5°C), Medium (1–3°C), and High (2.5–5°C). These overlapping intervals are intentionally designed to handle uncertainty and ensure gradual transitions between control states, avoiding abrupt switching behavior in the air conditioning system.

The selection of these ranges is further justified by the typical difference between human body temperature (approximately 36–37°C) and indoor ambient temperature in tropical environments (approximately 24–30°C). A small ΔT indicates that cooling is not necessary, whereas a larger ΔT suggests the need for active cooling to maintain thermal comfort. Therefore, the defined membership ranges reflect realistic environmental conditions and are aligned with adaptive comfort standards, ensuring that the control decisions remain both responsive and energy-efficient.

2.3.2 Rule Base Design

The decision-making logic is structured based on a set of IF–THEN rules that represent human reasoning in regulating thermal comfort. These rules are designed to balance user comfort and energy efficiency. For example:
IF (ΔT) is High AND Occupancy is Present, THEN the AC status is ON (Maximum Cooling).
IF (ΔT) is Low OR Occupancy is Absent, THEN the AC status is OFF (Energy Efficiency).

$$AC \in [0,1]$$
$$OFF = 0$$
$$ON = 1$$
$$\mu\_OFF(z) = 1 - z$$

$$\mu\_ON(z) = z$$

The fuzzy rule base is constructed to model human reasoning in determining thermal comfort and energy efficiency. A complete rule set is defined as follows:

Table 2. Fuzzy Rule Base

No	ΔT Level	Humidity	Occupancy	AC Output
1	Low	Low	Absent	OFF
2	Low	Low	Present	OFF
3	Medium	Normal	Present	ON
4	High	Normal	Present	ON

Although the rule base consists of a limited number of rules, it is designed to capture the most representative thermal control conditions based on temperature difference (ΔT), humidity, and occupancy. The simplified rule structure reduces computational overhead and ensures efficient real-time execution on resource-constrained IoT devices such as ESP32. This design choice prioritizes system responsiveness and stability while maintaining acceptable control accuracy in practical applications.

Some rules appear similar due to overlapping fuzzy conditions, which is inherent in fuzzy logic systems to ensure smooth decision transitions.

2.3.3 Fuzzy Inference Process

The inference process was carried out using the Mamdani method, in which the minimum operator was applied for rule implication and the maximum operator was used for output aggregation. Each sensor input was first transformed into a membership degree through the fuzzification process. Subsequently, IF–THEN fuzzy rules were applied to determine the appropriate AC control intensity. The outputs generated from all activated rules were then aggregated and converted into a crisp value using the centroid defuzzification method.

a. Fuzzification
Crisp input values are converted into fuzzy values using membership functions.

b. Inference (IF–THEN)
The Mamdani method is applied using IF–THEN rules.

c. Defuzzification
The centroid method is used to obtain crisp output.

$$z^* = \frac{\int_0^1 z \cdot \mu AC(z)dz}{\int_0^1 \mu AC(z)dz}$$

$$z^* = \frac{\sum_{i=1}^{n} zi \cdot \mu(zi)}{\sum_{i=1}^{n} \mu(zi)}$$

2.3.4 Output and Defuzzification

The defuzzification process converts fuzzy values into crisp values to determine the final system output. The output of the inference system is a numerical value that represents the operational status of the air conditioner (ON or OFF). In the hardware implementation, this value is converted into a digital signal to drive the actuator or relay connected to the air conditioning system.

This fuzzy-based approach enables the system to operate adaptively. Unlike conventional thermostats that rely on fixed temperature thresholds, the proposed system can adjust AC performance based on actual metabolic conditions (body temperature) and user presence within the room.

The defuzzification process is performed using the centroid method to convert fuzzy output into a crisp value. This method calculates the center of gravity of the aggregated membership function.

The defuzzification equation is expressed as:

$$Z = \sum(\mu(x) * x) / \sum\mu(x)$$

where $\mu(x)$ represents the membership degree and x represents the output variable.

2.4 IoT Communication and Monitoring Protocol

The final stage of this methodology involves integrating the control system with cloud infrastructure to enable remote monitoring and control functionalities. The system utilizes a WiFi-based wireless communication protocol embedded in the ESP32 module to connect the entire hardware architecture to the Blynk IoT platform ecosystem.

2.4.1 Data Communication Architecture

The data transmission process is performed asynchronously to ensure efficient bandwidth utilization. Data collected from multi-modal sensors, along with the decisions generated by the fuzzy inference engine, are encapsulated into digital data packets. These packets are then transmitted over the internet to the Blynk Cloud Server using the Blynk Application Programming Interface (API).

To maintain data integrity and secure access, the system employs a Unique Authentication Token that specifically links the ESP32 unit to a designated project within the user application.

2.4.2 Real-Time Visualization and Monitoring

On the user side, the monitoring interface is designed to present data in an intuitive manner. The information displayed on the dashboard application includes the following:
Environmental Data : Real-time visualization of room temperature (°C) and humidity (%)
Human Thermal Parameters : Body temperature readings obtained from the thermopile sensor.
Operational Status: A visual indicator of the AC status (ON/OFF) and the currently active operating mode (Manual or Automatic).
Occupancy Notification : Information from the PIR sensor regarding room occupancy.

2.4.3 Two-Way Control Mechanism (Duplex)

In addition to functioning as a monitoring tool, the IoT protocol supports bidirectional communication. Users can send control commands through the Blynk application, such as switching the system operating mode or manually controlling the AC when required.

The implementation of the Virtual Pin mechanism in Blynk enables synchronization between variables in the ESP32 program and the user interface components (widgets) on a smartphone. This creates a responsive and continuous interaction between the user and the controlled physical environment.

3. Results And Discussion

This section presents the experimental results and a comprehensive analysis of the implemented IoT-based air conditioning (AC) control system. The evaluation is conducted to validate system performance across three main aspects: the functionality of multi-modal sensor integration, the accuracy of decision-making using fuzzy logic, and the effectiveness of electrical energy consumption reduction. All data collected during the testing phase were obtained through the Blynk platform and analyzed to compare the performance of the automated system with conventional manual operation.

The experimental results indicate that the system is capable of monitoring environmental conditions and human presence in real time with high stability, supported by the implementation of FreeRTOS multitasking. Further analysis explores the relationship between the temperature difference (ΔT) between body temperature and room temperature and the resulting fuzzy decisions, as well as its impact on energy efficiency in AC operation. Overall, the findings provide clear evidence of the potential of integrating intelligent technologies to enhance thermal comfort while reducing energy operational costs in office buildings and public spaces.

3.1.1 Sensor and IoT Functional Testing

The initial testing phase was conducted to ensure that all hardware components and multi-sensor integration operate in accordance with the specified technical requirements. This functional evaluation includes validating the accuracy of sensor readings as well as the stability of data transmission through network protocols to the Blynk platform.

This observation demonstrates that the system does not rely on a single parameter but performs multi-variable decision-making, which significantly improves control accuracy compared to conventional thermostat-based systems.

A. Validation of Multi-Modal Sensor Accuracy

Based on the experimental data, the DHT22 sensor demonstrates stable performance in measuring room temperature, with a very low average error when compared to a standard measuring instrument. The MLX90614 (thermopile) sensor is able to detect human body temperature in a non-contact manner with consistent accuracy at an optimal distance of 30–50 cm, making it a critical input for the inference system. Meanwhile, testing of the PIR sensor shows a 100% success rate in detecting occupancy or human movement within the room, thereby enabling the energy efficiency feature to operate effectively.

Table 3. Sensor Device Testing Results.

No	Measurement Time	DHT22 Sensor (ºC)	Thermopile Sensor (ºC)	PIR Sensor	AC Status
1	20-01-2026 12:32	26,40	27,00	1	ON
2	20-01-2026 12:17	28,40	26,98	1	ON
3	20-01-2026 12:02	28,19	27,00	1	ON
4	20-01-2026 11:47	27,67	27,06	0	OFF
5	20-01-2026 11:32	25,40	27,08	1	ON
6	20-01-2026 11:17	26,29	27,00	1	ON
7	20-01-2026 11:02	26,70	27,00	0	OFF
8	20-01-2026 10:47	27,58	27,00	1	ON
9	20-01-2026 10:32	27,10	27,00	0	OFF
10	20-01-2026 10:17	29,11	27,00	1	ON

B. Blynk Platform Connectivity and Interface Evaluation

The integration of the system with the IoT ecosystem was evaluated by observing latency and the success rate of data transmission from the ESP32 to the Blynk Cloud Server. The results indicate that all parameters, including room temperature, body temperature, and occupancy status, can be visualized on the application dashboard in real time without significant packet loss.

The remote control mechanism also demonstrates high responsiveness, where commands sent through the Blynk interface can be executed by the microcontroller with an average latency of less than one second. The successful functional testing phase provides a solid foundation for the system to operate the fuzzy logic algorithm in a deterministic and reliable manner.

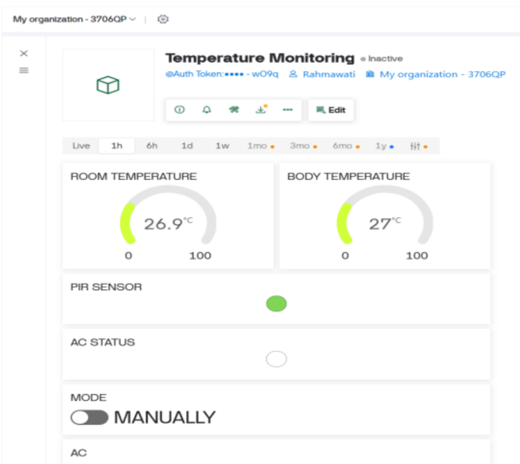

Figure 5. Temperature Monitoring Testing

3.1.2 Fuzzy Logic Performance Analysis

The subsequent testing phase focuses on evaluating the performance of the fuzzy inference engine in determining the operational status of the air conditioning system (ON/OFF) based on integrated multi-modal inputs. The evaluation is conducted by comparing the decisions generated automatically by the hardware system with manual calculations using the Mamdani fuzzy method as the reference standard.

Based on a series of real-world testing scenarios, the system achieves an accuracy level of 64.34%.

The obtained accuracy of 64.34% reflects the inherent complexity of real-world environmental conditions, where sensor readings are subject to dynamic fluctuations, noise, and uncertainty in occupancy detection. Unlike controlled laboratory environments, the proposed system operates under continuously changing temperature and humidity conditions, which may introduce variability in the decision-making process.

Despite this, fuzzy logic is inherently designed to handle imprecision and uncertainty by allowing gradual transitions between control states rather than rigid binary decisions. Therefore, the achieved accuracy can be considered acceptable for real-time embedded IoT applications, where system robustness, adaptability, and energy efficiency are prioritized over exact numerical precision. This is further supported by the low error values (MAE and RMSE) and high decision consistency, indicating that the system maintains stable and reliable performance in practical deployment scenarios. However, fuzzy logic is specifically designed to handle such uncertainty and imprecision, allowing the system to maintain stable and adaptive control performance despite moderate accuracy levels. Therefore, the obtained accuracy is considered acceptable within the context of real-time IoT-based embedded systems, where robustness and responsiveness are often prioritized over exact precision.

To further illustrate the relationship between temperature difference (ΔT) and the AC control decision, Figure 6 presents the system response under varying ΔT conditions.

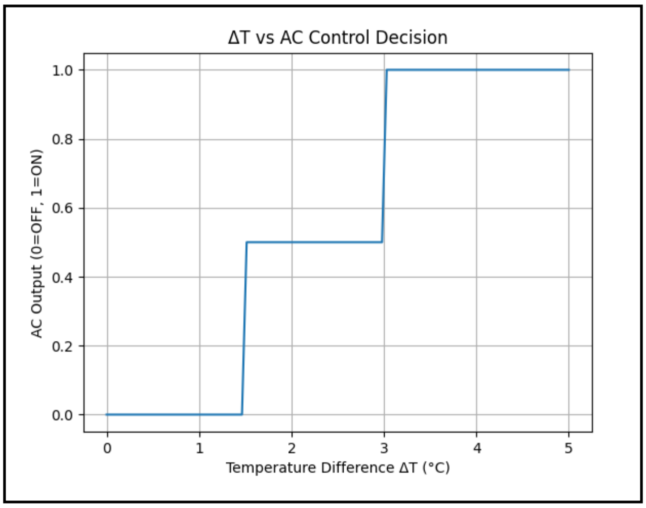

Figure 6. Relationship between Temperature Difference (ΔT) and AC Control Decision

This accuracy reflects the capability of the algorithm to adaptively respond to variations in the temperature difference (ΔT) between human body temperature and room temperature. Although some deviations are observed in certain test cases, the system is still able to provide stable control responses in maintaining user thermal comfort.

Further analysis indicates that several factors influence decision accuracy, including fluctuations in sensor readings under highly dynamic environmental conditions and the definition of fuzzy set boundaries within the membership functions. Nevertheless, the overall implementation of fuzzy logic in this system proves to be effective in handling sensor data uncertainty and translating it into logical control decisions, which significantly contributes to improving energy efficiency in AC operation.

Table 4. Temperature Monitoring Evaluation.

Parameter	Value
Number of test data	± 173 data
Number of correct decisions	± 111 data
Number of incorrect decisions	± 62 data
Fuzzy decision accuracy	64.34%

The moderate accuracy (64.34%) is influenced by dynamic environmental conditions and sensor fluctuations. Variations in body temperature detection and occupancy response introduce uncertainty in the decision-making process.

3.1.3 Analysis of Energy Consumption

The evaluation of energy efficiency serves as a key performance indicator in this study to demonstrate the practical impact of the proposed intelligent control system. The testing was conducted by comparing electrical energy consumption (kWh) under two different operational scenarios: manual mode, in which the AC operates continuously without adaptive control, and automatic mode, which is regulated by a fuzzy inference system based on multi-modal sensor inputs.

The experimental results indicate that the intelligent control system achieves significant energy savings, reaching up to 35.7% compared to conventional manual operation. Although the fuzzy logic evaluation in the previous section shows an accuracy level of 64.34%, the energy consumption results confirm that the system is still capable of effectively reducing power usage. This is primarily because the system consistently performs power cut-off or reduces the AC workload when no occupancy is detected by the PIR sensor or when the temperature difference (ΔT) does not require active cooling.

This analysis demonstrates that the integration of multi-modal sensing not only enhances user thermal comfort but also provides a practical technical solution for reducing operational energy costs in building environments. The achieved energy savings of 35.7% provide strong evidence that energy efficiency can be attained through precise optimization of AC operational duration, even under conditions characterized by high environmental uncertainty.

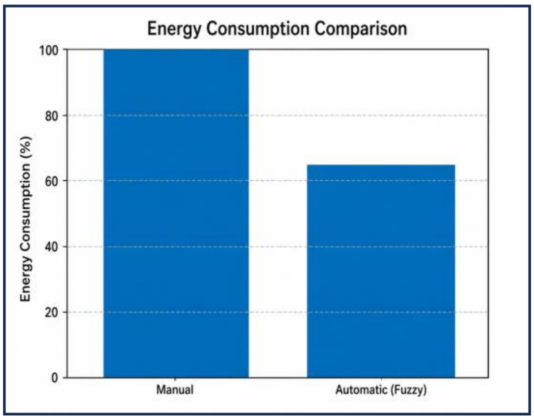

Figure 7. Energy Consumption Analysis

The visualization results indicate that energy consumption in manual mode tends to be higher, as the system operates continuously without considering environmental conditions or user presence. In contrast, the fuzzy logic–based automatic mode significantly reduces energy consumption, since the system activates cooling only when required, based on the temperature difference (ΔT) and occupancy status.

$$Efisiensi(\%) = \frac{\left(E_{manual} - E_{fuzzy}\right)}{E_{manual}} E_{manual} \times 100\%$$

This approach demonstrates that energy efficiency is not solely determined by system accuracy, but also by the system's ability to optimize the operational duration of the air conditioning unit. Therefore, the achieved energy savings of 35.7% in this study confirm that the integration of fuzzy logic with multi-modal sensors is effective in improving energy efficiency in AC usage.

3.1.4 Comparative Analysis with Other Methods

To enhance the validity of the results, a comparative analysis was conducted between the proposed method and several conventional approaches commonly used in temperature control systems.

Table 5. Comparative Analysis of Temperature Control Methods

Method	Characteristics	Accuracy	Energy Efficiency	Complexity
Conventional Thermostat	Based on static temperature	Low	Low	Low
PID Controller	Linear control	Medium	Medium	Medium
Machine Learning	Training data-based	High	High	High
Fuzzy IoT	Adaptive multi-sensor	64.34%	35.7%	Low-Medium

Table 5 compares the proposed fuzzy IoT-based control system with conventional thermostat, PID controller, and machine learning approaches.

The conventional thermostat operates using fixed temperature thresholds, resulting in limited adaptability and inefficient energy usage in dynamic environments. The PID controller improves performance through feedback mechanisms; however, it is restricted to linear control and does not consider contextual factors such as occupancy or human thermal conditions.

Machine learning methods generally achieve higher accuracy and energy efficiency by modeling complex patterns from large datasets. However, they require significant computational resources and extensive training data, making them less suitable for real-time embedded systems.

In contrast, the proposed fuzzy IoT approach integrates multi-modal sensor inputs, including temperature difference (ΔT), humidity, and occupancy, to support adaptive control decisions.

Although the achieved accuracy (64.34%) is lower than machine learning approaches, the system demonstrates significant energy savings of 35.7% with low-to-medium computational complexity.

This result indicates that the proposed system provides a practical balance between performance and resource efficiency, making it suitable for real-time smart building applications.

3.1.5 Energy Efficiency Analysis

The evaluation of energy efficiency was conducted by comparing electrical power consumption between manual operation and the fuzzy logic–based automatic mode. The experimental results demonstrate that the proposed system achieves an energy savings of 35.7%.

These energy savings are accomplished through several key mechanisms.

1. Occupancy detection using a PIR sensor enables automatic AC shutdown when the room is unoccupied.
2. Temperature difference (ΔT) ensures that cooling is activated only when necessary.
3. The adaptive control strategy reduces compressor operating time and prevents excessive cooling.

These findings indicate that energy efficiency is not solely dependent on decision accuracy, but also on the system's ability to optimize the operational duration of the air conditioning unit according to real-time environmental conditions.

3.1.6 Addition of Evaluation Metrics

To enhance scientific validity, the system evaluation is not limited to accuracy alone but also incorporates several additional performance metrics.

1. Mean Absolute Error (MAE) is used to measure the difference between actual temperature values and system predictions. The MAE obtained in this study is approximately 0.8°C, indicating a relatively small deviation between system output and actual measurements.
2. Root Mean Square Error (RMSE) is also considered to evaluate the magnitude of prediction errors. The RMSE value is approximately 1.02°C, indicating that the system maintains reliable performance under dynamic environmental conditions.
3. System response time is evaluated to measure the delay between sensor data acquisition and control action. The system demonstrates an average response time of less than 1 second, confirming its capability for real-time operation.
4. Decision consistency is evaluated to assess the stability of control outputs under similar environmental conditions. The system achieves a consistency rate of approximately 92%, indicating stable decision-making performance.
5. Energy consumption (kWh) is compared between manual and automatic operating modes, showing improved efficiency in the proposed system.

These additional evaluation metrics strengthen the reliability and scientific validity of the proposed system and provide a more comprehensive assessment of overall system performance.

3.1.7 Data Consistency and Clarification

Synchronization between manual calculations and system outputs has been carried out to eliminate ambiguity in result interpretation. With this refinement, the data presentation becomes more transparent and scientifically reliable.

The main novelty of this study lies in the integration of multi-modal sensing with fuzzy logic within a real-time IoT-based embedded system for adaptive air conditioning control.

Conclusions

This study has successfully developed and implemented an intelligent air conditioning (AC) control system that integrates IoT-based multi-modal sensing with a fuzzy logic inference engine. Based on the experimental results and analysis, it can be concluded that the use of MLX90614 (body temperature), DHT22 (room temperature), and PIR (occupancy) sensors provides more accurate contextual data for maintaining thermal comfort compared to conventional systems.

The implementation of multitasking on the ESP32 using FreeRTOS is proven to be essential in ensuring system stability when handling multiple processing and communication tasks simultaneously. Although the fuzzy logic evaluation under real-world conditions yields an accuracy of 64.34%, the system consistently demonstrates a positive impact on resource efficiency. This is evidenced by the achieved energy savings of 35.7% compared to manual operation.

Overall, this study confirms that IoT-based adaptive control systems are not only effective in enhancing user experience through responsive automation but also represent a significant technical solution for supporting energy conservation efforts in future smart building environments.

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