

Research paper

Reducing energy consumption in air conditioning systems, a fuzzy logic-based optimization approach



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ABSTRACT

The need for more intelligent air conditioning solutions is growing as global temperatures rise and energy efficiency concerns increase. In order to adapt dynamically to changing outdoor environmental factors like temperature fluctuations, humidity variations, and voltage instability, traditional air conditioning systems (ACS) usually rely on static control mechanisms. Rigid control paradigms like these result in ineffective operations, excessive energy use, and decreased user comfort. In order to get around these restrictions, this paper presents a practical fuzzy logic controller (FLC) that is specifically made to optimise compressor speed ratios and fan speed in real-time. Our method uses adaptive fuzzy logic, which offers greater flexibility in managing environmental uncertainties and disturbances than current controllers that either rely on fixed parameters or intricate machine learning models. Based on thorough simulations and performance evaluations, our suggested approach shows a significant 20–25 % decrease in energy consumption when compared to traditional systems. The main innovation is its straightforward but reliable fuzzy-based rule system, which strikes a balance between user comfort, adaptability, and energy efficiency and lays the groundwork for further intelligent climate-control advancements.

1. Introduction

Ensuring occupant comfort has become both a necessity and a prerequisite for sustaining residential, commercial, and industrial communities. Thus, air conditioning systems need to become a part of every living space. While energy poverty remains unaddressed in large parts of the world, energy consumption in the rest of the globe continues to rise as natural global temperature increases. Consequently, to mitigate the high energy use of traditional air conditioning systems and sustain the growth in demand, it is becoming ever more essential to develop energy-efficient systems with optimum air conditioning operations that never fall out of balance with external conditions. Conventional air conditioning systems, from simple thermostats to Proportional Integral Derivative (PID) controllers, rely on pre-set control parameters that work optimally within narrow and relatively stable environmental conditions. Many of these methods cannot adapt to dynamic fluctuations in

temperature, humidity, or voltage since they are designed for steady-state control. For instance, while a PID controller will work well for a setpoint temperature in predictably stable conditions, its traditional problem of overshooting or undershooting presents challenges when there are rapid changes. In the same vein, most simple thermostats will try to cycle the system based on a given threshold by using a simple on/off mechanism; this can lead to binary on/off control that may result in poor comfort levels, increased component wear and tear, and wasted energy consumption, especially when the external circumstances are not predictable (Rajeswari Subramaniam et al., 2023). Fuzzy logic solves these problems by providing a control system that can handle uncertainties and variabilities under real situations. A recent study (Abuhussain et al., 2023) discusses the design of an adaptive HVAC system that utilizes fuzzy logic to reduce energy consumption while maintaining indoor thermal comfort, automatically generating fuzzy rules as input data is received. Another study (Belman-Flores et al.,

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2022) presents a real-world case of fuzzy logic controllers applied to air conditioning and refrigeration systems, evaluating their effectiveness in maintaining thermal comfort and improving energy efficiency. Various architectures are analyzed, considering factors such as input-output variables, membership functions, and inference rules. Research in (Berouine et al., 2019) proposes a fuzzy logic-based control method for HVAC systems, with a focus on both occupant thermal comfort and energy efficiency. Fuzzy logic and Neural Networks have been integrated (Pooja et al., 2017) to create intelligent air conditioning systems capable of adapting to environmental variations and usage patterns. A study (Sameh Mohamed Sobhy and Wael Mohamed Khedr, 2015) provides a detailed design of a fuzzy logic controller that ensures both user-defined thermal comfort and optimal energy consumption, balancing these often-conflicting goals in response to real-world environmental fluctuations. The study highlights the advantages of fuzzy logic over conventional controllers, particularly its ability to manage uncertainty in input variables. An autonomous air cooler system employing fuzzy logic for improved energy efficiency and interior comfort has been developed (Khan and Zafar, 2011). The system dynamically adjusts cooling intensity based on observed environmental factors such as humidity and temperature. Another study (Poonia et al., 2012) enhances the efficiency and adaptability of air conditioning systems by combining fuzzy logic with a Neural Network. The results indicate that the hybrid system outperforms conventional controllers as well as standalone fuzzy logic systems in terms of energy savings. Research in (Fuzzy Logic Based Air Conditioning System, 2018) explores the automation of air conditioning systems for humidity and temperature control using a fuzzy logic-based controller. An Intelligent Fuzzy Logic Controller (FLC) for air conditioning systems has been developed (Ahamed et al., 2016), focusing on optimizing energy efficiency while maintaining occupant comfort. A study (Waheed et al., 2020) also introduces an FLC for classroom air conditioning, dynamically adjusting fan speed and air distribution in real time to enhance comfort and energy efficiency, ensuring optimal learning conditions. The major limitations of the existing work are illustrated in Table 01, and this study demonstrates that fuzzy logic improves air conditioning by adapting in real-time, optimizing compressor settings and fan speeds, and outperforming traditional methods in balancing cooling and energy consumption. This study does not propose a novel fuzzy logic algorithm. Rather, its contribution lies in the structured design and practical implementation of an established fuzzy control framework for HVAC optimization. The significance of this work is in showing that a relatively simple and interpretable fuzzy rule base can deliver energy savings comparable to more advanced controllers, while maintaining low computational complexity and readiness for real-world deployment.

The remainder of the paper is organized as follows: Section II presents the fundamentals of air conditioning mechanics, Section III discusses the fuzzy control system, Section IV provides the results and discussion, and Section V concludes the study.

1.1. Air conditioning mechanics

The inner workings of an air conditioner are illustrated in detail in Fig. 1, and it is available in the US Department of Energy Saver 101: Home Cooling Infographic, highlighting each component's function in the cooling process.

The illustration presents the main parts and working processes of an ACS; it moves heat from inside a building to the outside of the building; as shown, an ACS operates by absorbing heat from inside a building and releasing it outside. In the beginning, the evaporator (A) is engineered by cooling coils to remove heat and moisture from the inside air. A refrigerant is inside a fridge to take the heat from the air. Due to that, the air flowing over the cooling coils is warm, but the air that will be recirculated to the room becomes cooler than before. The blower (B) is the fan that helps keep the inside of a building at the correct temperature by circulating cooled air wherever it is needed. This fan moves the cooled

Table 01
Limitations to overcome.

| Relevant References | Findings from Literature | Existing Limitations in Literature |
|---|--|--|
| (Rajeswari Subramaniam et al., 2023; Berouine et al., 2019; Sameh Mohamed Sobhy and Wael Mohamed Khedr, 2015) | Studies demonstrate that adaptive fuzzy logic controllers can effectively adjust to real-time variations in temperature and voltage, improving responsiveness and indoor comfort. | Controllers often rely heavily on preset parameters and show poor adaptability in rapidly changing conditions. |
| (Pooja et al., 2017; Poonia et al., 2012) | Integration of fuzzy logic with neural networks has led to improved control precision and learning capabilities, enhancing system adaptability to diverse usage patterns. | Complex hybrid AI approaches like fuzzy-neural networks require extensive data training, increasing computational overhead. |
| (Abuhussain et al., 2023; Belman-Flores et al., 2022; Khan and Zafar, 2011; Fuzzy Logic Based Air Conditioning System, 2018; Ahamed et al., 2016) | Several systems have been developed that optimize fan or compressor speed individually, demonstrating measurable gains in energy savings and localized comfort regulation. | Existing methods lack simultaneous optimization of fan speed, compressor speed, and operational mode in response to environmental variability. |
| (Abuhussain et al., 2023; Sameh Mohamed Sobhy and Wael Mohamed Khedr, 2015; Waheed et al., 2020) | Fuzzy-based HVAC systems have achieved temperature stability within $\pm 1^{\circ}\text{C}$ and notable energy reductions, indicating growing success in comfort energy tradeoff strategies. | Difficulty in effectively balancing occupant comfort and energy efficiency during humidity and temperature fluctuations. |
| (Belman-Flores et al., 2022; Berouine et al., 2019; Poonia et al., 2012; Ahamed et al., 2016) | Compact fuzzy rule bases and modular design approaches are emerging, aiming to maintain performance while improving ease of deployment in both residential and classroom settings. | Limited scalability and complexity of fuzzy controllers due to overly elaborate rule structures, hindering practical implementation |

air around to make the temperature steady and comfortable (Shao et al., 2022). As is shown at the top, the refrigerant inside advances to the next stage of the process as it takes all of the heat from the air. The refrigerant travels to the condenser (C), usually positioned outside of the building, from where it picks up the heat. This is the part in which the heat from the heated interior air is expelled to the exterior space that surrounds the outdoor condenser coils, causing the heat to be exited by the freon from the building. This is made possible by the condenser coils through which the gas suction is throttled to absorb the heat against the evaporator. The main component of this cycle is the compressor (D) that pumps the freon refrigerant from the condenser to the evaporator. Compression in the compressor stage ensures that heat is removed efficiently in the condenser by increasing the temperature and pressure of the refrigerant. Also, it ensures the proper flow of refrigerant through the system (Sunardi et al., 2023). The system also has an external fan(E), which cools the condenser coils to assist the condenser coils in dissipating heat from the system into the outdoor ambient. This component makes sure that the speed of refrigerant cooling is high with no restriction. This way, the system will always be able to run continuously, avoiding the occurrence of overheating. First, as this reliably warm air goes through the system, it gets filtered by the filter (F) in the air conditioner. This cleans the air and makes it more pleasant to experience because it removes particles and pollutants. Additionally, it keeps dust and debris outside of the system, which can affect its functioning by reducing the ability of the air conditioner to move, heat, and cool. Next, the single point of control for the system is the thermostat (G). This system keeps track of the temperature within and uses this information to determine whether or not to activate the air conditioner. It uses less energy by

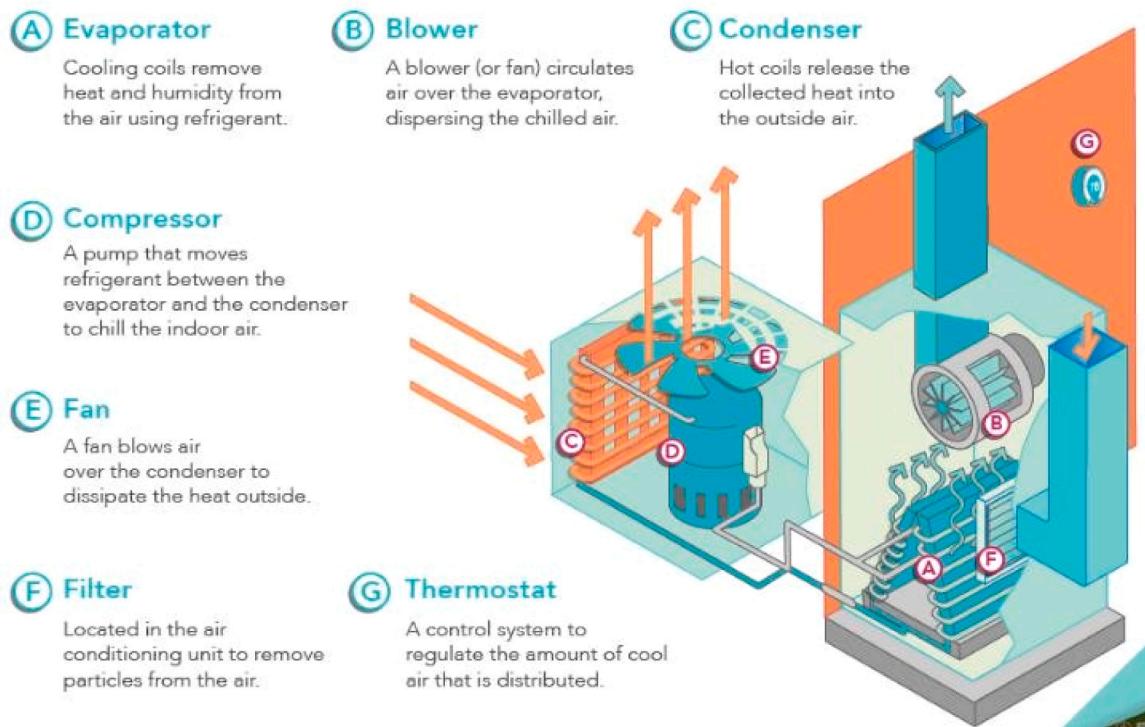


Fig. 1. Working of an Air Conditioner.

turning the system off when the preferred temperature is reached, and it turns the cooling on when the room temperature exceeds the desired point. Together, these elements form a seamless cycle that ensures effective indoor air conditioning no matter how the outside temperatures change. None of these elements can be overlooked to achieve an efficient, comfortable indoor environment and ensure energy efficiency. Conventional controllers face limitations in handling real-world uncertainties, often failing to perform reliably with the required accuracy (RAJA and Ramathilagam, 2022). Thermal comfort Control using Occupancy Detection and Fuzzy Logic for Air-conditioning Systems is studied in (Saengthong et al., 2022). Fuzzy logic enables real-time air

conditioning control by adapting to inputs like temperature, humidity, and voltage. The FLC adjusts compressor speed, fan speed, and operation mode, enhancing energy efficiency and user comfort over conventional systems. Figs. 2 and 3 show the room temperature variations in an ordinary system and a Fuzzy Logic Controlled system as an example. These graphs were created through using the points given by several simulation studies (Diouf et al., 2021; Ghanim et al., 2020; Mugisha et al., 2015). In the proposed study, all the membership functions for input and output spaces were carefully chosen to represent the operational ranges of the system accurately. For instance, the temperature difference can be represented as five levels: "Too Cold," "Cold," "Warm," "Hot," and "Too

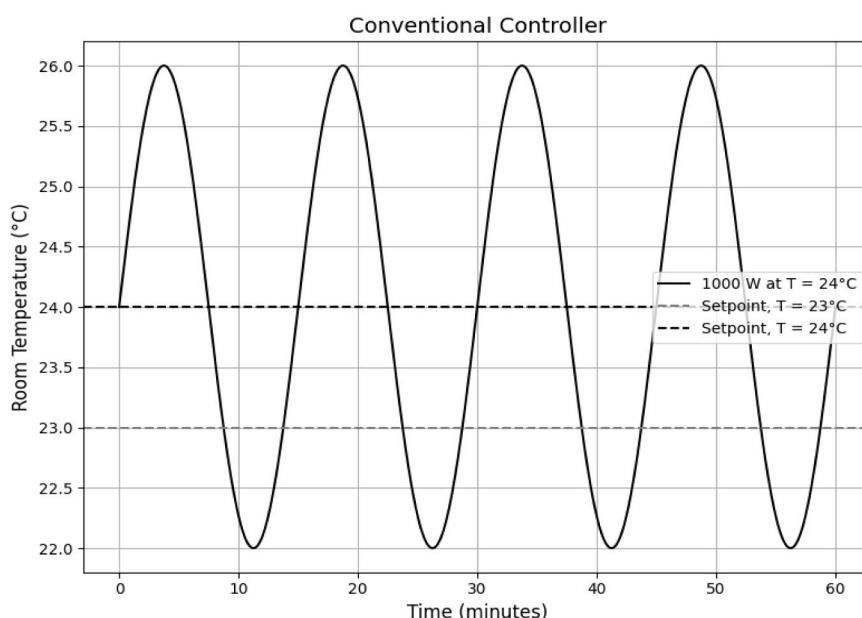


Fig. 2. Temperature Fluctuations in a Conventional Controller.

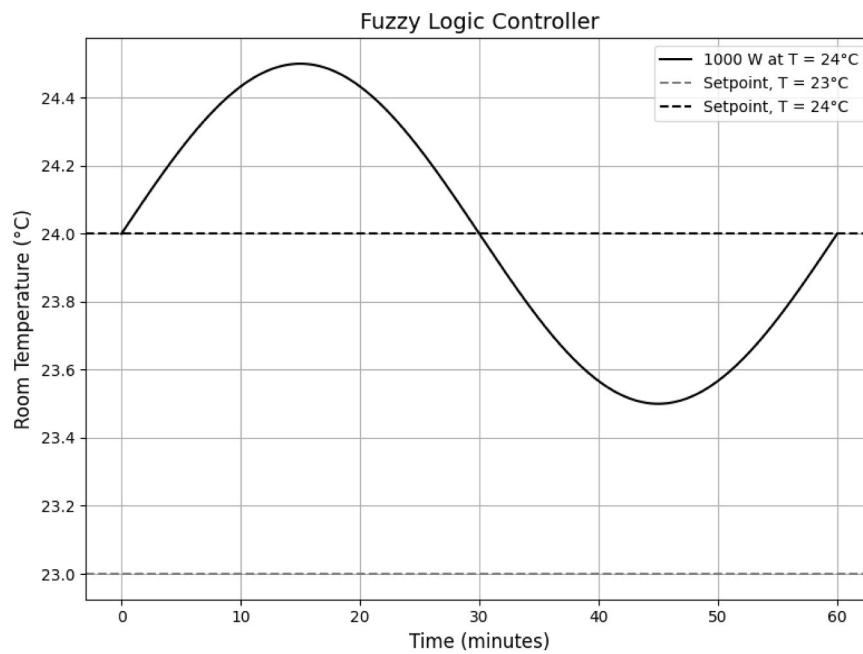


Fig. 3. Temperature Fluctuations in a Fuzzy Logic Controller.

Hot." Then, humidity and voltage levels are also divided into suitable categories to ensure accurate control. So, fuzzy control is accurate enough to carry out such a task. After the careful analysis of various air conditioner manuals and the "American Society of Heating, Refrigerating, and Air-Conditioning Engineers" (ASHRAE) Standards, fuzzy rules were obtained. The FLC avoids the problems of standard air-conditioning systems and paves the way towards new, smarter, active climate-control technologies that not only use less energy but can also help preserve comfortable indoor climates. F.L. is a computational technique based on how humans reason and make decisions, and it accounts for the notion of a 'variable degree of truth,' unlike classical logic, whereby propositions may be either true or false but not both (Baniyounes et al., 2022). In particular, whereas in classical logic, propositions are always either completely true or false, fuzzy logic works with the concept of 'partial truth,' and, therefore, the values involved may be anywhere between 0 and 1. One advantage of F.L. is its ability to operate on imprecise or unpredictable input data, which, since this is a common feature of real-world systems – e.g., air conditioning, where external variables may be the difference in temperature and humidity, and they can change rapidly – applying a fuzzy approach can often lead to better results than a conventional mathematical model.

2. Fuzzy control system

The main objective of this study is to build an ACS controller with fuzzy logic. According to inputs such as the voltage level, temperature difference, and humidity level, the mode of operation, fan speed, and compressor speed will have to be adjusted. Traditional methods tend to be both stiff and inflexible, and in many cases, the control system will need additional inputs to 'help' it deal with changes. The air conditioning system was more fluid and practical, based on fuzzy logic, as the system could interpret all those values and judge what was needed according to that interpretation. The first step of fuzzy logic is fuzzification, in which the input variables are transformed into fuzzy sets by the predetermined membership functions (Bazhenov et al., 2022). These fuzzy sets represent the fuzzy levels of the input variables, such as 'Cold,' 'Warm,' or 'Hot' for the temperature difference degrees. The fuzzy sets of the input variables will be compromised with other input variables' fuzzy levels and then converted into a fuzzy output during the rule evaluation stage. A set of fuzzy rules, just the IF-THEN statement, is

applied at this stage. For example, 'IF Temperature Difference is Hot AND Humidity is High, THEN Fan Speed should be High.' The fuzzy output from the rule evaluation becomes an exact value that can be fed back into the air conditioning system for control during defuzzification. Fig. 4 gives a detailed, illustrated, finalized diagram of how the fuzzy logic controller (FLC) works in air conditioning by dividing the stages it uses into capsule form. The figure shows that a fuzzy logic controller (FLC) starts with input variables such as temperature difference, humidity, and voltage on its left side. In the first stage of the process, fuzzification-specific membership functions help turn the sharp value of variables into fuzzy sets, which represent weather conditions like 'warm,' 'cold,' or 'hot.'

After fuzzification, the input data is fed into the fuzzy rule base, containing predefined fuzzy IF-THEN rules defining the relationships between the input and output variables. The fuzzy inference step evaluates the fuzzy rules, producing outputs that fuse the fuzzy inputs using logical connectives (AND, OR). The final step in the process, known as defuzzification, describes the transformation of the fuzzy output to a crisp value that the system can then use to signal the air conditioning system parameters, such as compressor speed, fan speed, and operating mode (Sun and Fang, 2022). This process acts as a surrogate for the natural air conditioning system and adjusts itself following the recommendations from the fuzzy logic controller. Fuzzy logic was chosen for this application due to its extraordinary ability to handle uncertainties and provide smooth transitions between states. Therefore, this makes fuzzy controllers perfect for fine-tuned processing of air conditioning to ensure that the system operates smoothly. Traditional controllers often struggle to maintain the best performance possible when the surrounding conditions are altered. This can then result in many more on / off cycles. This translates into inefficient energy usage and a decrease in comfort. Alternatively, a fuzzy logic controller can gradually modify the system's parameters in small incremental steps, creating fewer abrupt changes when a set point is crossed and improving overall performance. In conclusion, fuzzy logic is reliable and highly adaptable in an air conditioning system. This is because the system has a human-like approach in analogic computing, considering partial truths that enable adjusting the outputs and improving system performance.

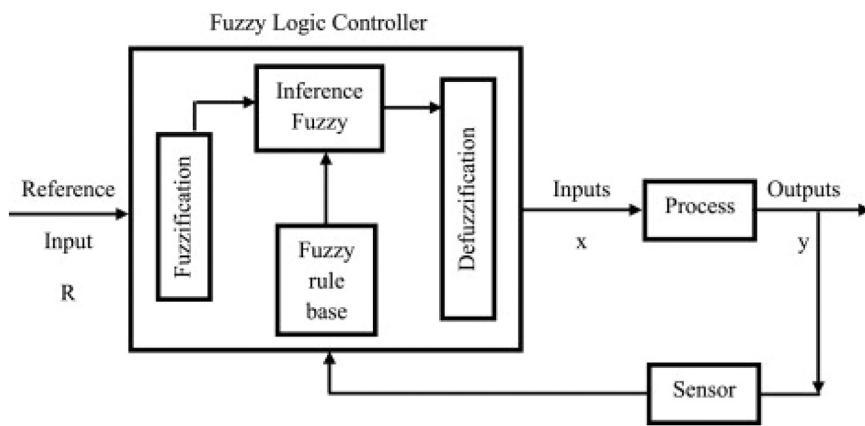


Fig. 4. Working of a Fuzzy Logic Controller.

3. Defining system variables

The principal inputs are the temperature difference, humidity, and electric voltage, with the outputs being the compressor speed, fan speed, the mode of operation, and the fan direction. They were chosen because they directly impact user comfort, and part of the objective is to maximize energy efficiency by responding to them dynamically, including changing directions when needed.

4. Input variables

- 1) **Temperature difference:** This project calculates the temperature difference between what the room temperature needs to be and what the actual room temperature is right now. This is also fuzzified into five fuzzy sets: "Too Cold," "Cold," "Comfortable," "Warm," and "Too Hot." The temperature difference is fuzzified using the Triangular Membership Function because it is usually a smooth curvature without sharp edges. It is a good way to model the gradual transformation of the temperature difference between "Too Cold" and "Too Hot." It is well-known that the difference between the room temperature readers and the set point temperature is directly related to the required cooling capacity for the air conditioner. That is why it was chosen to be one of the two main inputs for this project.
- 2) **Humidity:** This is the next critical FLC variable that profoundly impacts the comfort level of humans. The lowest limit of 0 % and the highest limit of 100 % encompass all probable situations, from extreme dryness to too much humidity. Five murky categories express humidity: Dry, Refreshing, Comfortable, Humid, and Sticky. It is also measured using the triangular membership function (trimf). We must simulate sequential changes in comfort levels as humidity changes, so we choose this function type. This is a good application for the triangle function, as we can fine-tune the system behavior by precisely determining the center of the comfort region.
- 3) **Electric voltage:** The air conditioning system's steady operation relies on the voltage's stability. The input membership range between 180 V and 240 V is chosen for common fluctuations that might arise in home or business power sources. The two sets that separate this input are 'Regular' and 'Low.' Since the fluctuations in voltage are of a particular type, the trapezoidal membership function (trapmf) was chosen because trapezoidal functions work well to handle voltage variations. The trapezoidal shape functions well with such systems because if the voltage is stable between specific points, those points define a flat top on the trapezoid, which means that the system can conveniently consider a range of voltages as 'Regular,' so in effect, the system does not need to make needless changes for small variations.

Clustering ranges for all input variables can be seen in Tables 02–04

Table 02
Temperature difference clustering range.

| Input Variable | Too Cold | Cold | Warm | Hot | Too Hot |
|-----------------------------|----------|--------|------|-------|---------|
| Temperature Difference (°C) | -20–0 | -10–10 | 0–20 | 10–30 | 20–40 |

Table 03
Humidity clustering range.

| Input Variable | Dry | Refreshing | Comfortable | Humid | Sticky |
|----------------|--------|------------|-------------|-------|--------|
| Humidity(%) | -30–30 | 20–50 | 40–70 | 60–90 | 80–160 |

Table 04
Electric voltage clustering range.

| Input Variable | Low | Regular |
|----------------------|---------|---------|
| Electric Voltage (V) | 180–215 | 200–240 |

below. For every variable, each membership function has its own defined parameters.

4.1. Output variables

- 1) **Compressor speed:** According to the thermostat ideology, the compressor's speed and the system's total cooling power are intimately correlated. The quantization is divided into five levels: off, extremely low, low, medium, and quick. In order for the compressor speed to smoothly adjust as the condition changes, this quantization aids the trimf (triangular membership function) in setting the compressor speed to the lowest energy inefficiency.
- 2) **Fan speed:** The other major output to control the airflow in the room is the fan speed, again with five levels—"Off," "Very Low," "Low," "Medium," and "Fast"—within which the fan speed is also controlled by a triangular membership function (trimf) that ensures a proportional response to any changes in the input variable so as to deliver a congenial ambiance.
- 3) **Mode of operation:** A triangular membership function (trimf) is also used in this project to capture the air conditioning Mode of Operation variable. There are two operational states for the air conditioning system: "Dehumidifier" and "AC," and the trimf function allows smooth transitions between these two operational states. Under certain circumstances inside an ambient controlled space, triangular membership in the Mode of Operation cylinder can be more effective in balancing cooling and dehumidification.

4) Fan direction: For fan direction, there are two choices, 'Away' and 'Towards.' This output defines the direction of airflow and, therefore, has a big impact on user comfort. A trapezoidal membership function (trapmf) is used for this output, which allows us to define the borders between the two directions accurately and ensures a smooth response should we change direction. It is possible for the technology to keep airflow direction within a predefined boundary since the trapezoidal membership function for the fan direction inherits the same mathematical structure of the voltage.

Tables 05–08 depict the clustering ranges for all the output variables. The parameters of each membership function are defined for every variable.

In Tables 02–04, the ranges for clustering of input variables like humidity and temperature difference are deliberately designed with overlapping regions to meet the principles of fuzzy logic. Overlapping ranges are one of the features of fuzzy logic systems that allow smooth transitions among states and help the controller cope with ambiguities and uncertainties. The overlapping ranges of our fuzzy sets are tuned precisely to ensure suitable system responses in case of changeable input circumstances. This is due to the intrinsic variety of real-world situations when gradual changes take place in environmental conditions rather than abrupt ones. Overlapping zones add flexibility to the fuzzy logic controller by allowing smooth interpolation between various control modes. Besides, fuzzy logic inference techniques naturally handle the case of overlapping membership functions, such as the centroid defuzzification method used in our paper. It ensures that, for any set of input values, the resultant control actions are a weighted average of contributions from each relevant fuzzy set, even when the input values fall within overlapping regions. This approach removes ambiguity and ensures that the controller yields consistent and reliable operations. The ranges of the membership functions are also deliberately designed to be out of the normal range of the variables they represent. This approach enhances the overall stability and dependability of the system while serving a specific function within the fuzzy logic framework. For instance, allowing for smoother crossing at the ranges of variation, membership function shapes such as the trapezoidal and triangular may exceed a variable's minimum and maximum values. In practice, environmental quantities such as thermal gradient or relative humidity may deviate from their usual or ordinary operating/working ranges by wide margins because of oscillations or measuring noise. Therefore, the fuzzy logic controller can achieve stability and reliably provide control at or beyond these limits if the membership function parameters, especially the lower and upper bounds, are allowed to extend outside their conventional bounds. This smooths the output and prevents the system from overacting to sudden changes, thus destabilizing control operations. The more extensive ranges allow the system to handle unexpected situations, such as loud or erroneous input data. For instance, the inclusion of slightly negative humidity values in the design of the membership function creates a buffer zone that helps the controller deal with unexpected input anomalies, even though negative humidity values are physically impossible. Even when the input circumstances become close to or surpass anticipated limitations, this design decision guarantees that the air conditioning system will continue to run smoothly and without pauses or inefficiencies. It also prevents sudden changes in output. Therefore, the extension of the membership function parameters beyond the common operating range of the variable is reasonable and intentionally performed. It enhances the power of the fuzzy logic controller

Table 05
Compressor speed clustering range.

| Input Variable | Off | Very Low | Low | Medium | Fast |
|-----------------------------------|--------|----------|-------|--------|--------|
| Compressor Speed (% of rated rpm) | –25–25 | 0–50 | 25–75 | 50–100 | 75–125 |

Table 06
Fan speed clustering range.

| Input Variable | Off | Very Low | Low | Medium | Fast |
|-----------------|----------|----------|----------|----------|-----------|
| Fan Speed (rpm) | –350–350 | 0–700 | 350–1050 | 700–1400 | 1050–1750 |

Table 07
Mode of operation clustering range.

| Input Variable | Dehumidifier | AC |
|-------------------|--------------|-----|
| Mode of Operation | –1–1 | 0–2 |

Table 08
Fan direction clustering range.

| Input Variable | Towards | AC |
|-------------------|---------|--------|
| Fan Direction (°) | –90–80 | 30–190 |

due to its ability to efficiently handle different uncertainties and variabilities in the real world. Therefore, this flexibility allows for consistent performance and reliable control actions under dynamic and complicated contexts where the input conditions may differ from the usual ones.

5. Mathematical foundations of membership functions and fuzzy logic operators

5.1. Triangular membership function

Our first example of a fuzzy membership function is an example of one of the simplest types: the triangle membership function. A triangle membership function takes three parameters from the set R: a, b, and c as arguments. The triangle's height reaches one at b, then tapers off to zero at a and c. The increase and decrease are linear.

Mathematically, the triangular membership function is defined as:

$$\mu(x; a, b, c, d) = \begin{cases} 0 & \text{if } x \leq a \text{ or } x \geq c \\ \frac{x-a}{b-a} & \text{if } a \leq x < b, \\ \frac{d-x}{d-c} & \text{if } c \leq x < d \end{cases} \quad (1)$$

Since the triangle function is linear on both sides of the peak, it is simple and compact in how it is applied and, thus, cheap to compute. Since it is easy, it is ideal for systems with performance limitations, where computational or processing resources are scarce, especially when decisions need to be made quickly.

6. Trapezoidal membership function

By adding a flat area, or plateau, where the membership value stays constant at one across a specific range, the trapezoidal membership function expands upon the triangle membership function. Instead of having a single peak like the triangle function, this plateau accommodates values within a specific interval as entirely belonging to the fuzzy set, allowing for a more flexible representation of uncertainty. The shape and location of the function are defined by its four primary parameters: a, b, c, and d. Mathematically, the trapezoidal membership function is defined as:

$$\mu(x;a,b,c,d) = \begin{cases} 0 & \text{if } x \leq a \text{ or } x \geq d \\ \frac{x-a}{b-a} & \text{if } a \leq x < b, \\ 1 & \text{if } b \leq x < c, \\ \frac{d-x}{d-c} & \text{if } c \leq x < d \end{cases} \quad (2)$$

The trapezoidal function will be helpful when several values indicate the same condition. Its flat top (between b and c) ensures that small changes in that interval will not influence the system's decisions.

AND (min):

The minimum function selects the smallest membership value from the relevant fuzzy sets. In other words, the AND operator is implemented by the minimum function. In the IF-THEN rule, the THEN part cannot be valid unless all IF parts are true. That is the logic of the AND operator. In terms of math, it is stated as:

$$\mu_{AND} = \min(\mu_A(x), \mu_B(x)) \quad (3)$$

The minimum operator makes sense as it ensures that the output is valid only when it reflects the weakest of the inputs – that is, that the system reacts strongly only if all of the inputs do.

OR (max):

The maximum function selects the highest membership degree among the relevant fuzzy sets and applies the OR operator. This operator is used when it is sufficient for the rule to hold any time at least one of the conditions is true. The mathematical expression is as follows

$$\mu_{OR} = \max(\mu_A(x), \mu_B(x)) \quad (4)$$

In so doing, it allows the system to respond to the strongest trip wire, meaning the system will respond only if any of the inputs merit it. This additional restriction is called the maximum operator.

Implication (min):

The minimum function – analogous to the AND logic operator – is typically used in fuzzy logic to manage implication, ensuring that a rule's output is confined by its weakest condition – preventing over-reaction when only some of the requirements are met.

$$\text{Implication} = \min(\mu_{\text{Premise}}, \mu_{\text{Conclusion}}) \quad (5)$$

7. Aggregation (max)

Aggregation is the process of combining several fuzzy rule results. It is customary to use the maximal operator for the strictest rule fired to appear in the final result. This allows the system to specify the most important factors when making decisions. The expression looks something like this:

$$\mu_{\text{Aggregation}} = \max(\mu_{\text{Rule 1}}, \mu_{\text{Rule 2}}, \dots, \mu_{\text{Rule N}}) \quad (6)$$

8. Design and structure of fuzzy rules

Fuzzy rules are the decision-making basis for an FLC, as they define the relationship between the input and output fuzzy variables. These rules are commonly written in the IF-THEN form: IF the firing condition is α , THEN do some action/respond by acting β . Here, the THEN section specifies the outputs or actions to be performed in response to the condition specified in the IF part, which defines those conditions in terms of its input variables (Bushnag, 2023). Every fuzzy rule codifies an expert view of what the system should do under specific environmental conditions. Each rule individually takes care of an entire subset of different combinations of input conditions in which the system should react in a particular way. By aggregating the input conditions and computing the output, the rules and their defuzzification are performed

through fuzzy logic operators (for example, the max operator for the OR circumstances of each rule and the min operator for the AND conditions), and the final judgment is averaged out by the outputs generated from all applicable rules. The fuzzy rules in the project have been designed to allow the air conditioning system to deal with foggy, humid, and hot times of the year and to be energy-saving in mild weather. These fuzzy rules vary their compressor speed and fan speed, modify the mode of operation, and set the fan's direction according to actual input data in real-time to save on energy and create a level of comfort for the user. Because of the adaptability and broadness of the fuzzy rule base, it can make changes on its own in response to changing circumstances without needing continuing changes by humans. It can mimic how humans reason about the problem – using fuzzy rules to decide what is best, balancing many elements in the best possible way to produce the desired result. With this fuzzy logic, the air-conditioning system can become more sensitive and intelligent and continue working efficiently in any environmental conditions. Fifty fuzzy rules were created using the MATLAB Fuzzy Rule Editor to account for every combination of input variables. Since every rule has equal priority, the rule weight in each case is set to one.

All the rules have been listed below for the reader's reference.

- 1) "If (TemperatureDifference is TooCold) and (Humidity is Dry) and (ElectricVoltage is Regular) then (CompressorSpeed is Off)(FanSpeed is Off)(ModeOfOperation is AC)(FanDirection is Away) (1)"
- 2) "If (TemperatureDifference is TooCold) and (Humidity is Refreshing) and (ElectricVoltage is Regular) then (CompressorSpeed is Off)(FanSpeed is Off)(ModeOfOperation is AC)(FanDirection is Away) (1)"
- 3) "If (TemperatureDifference is TooCold) and (Humidity is Comfortable) and (ElectricVoltage is Regular) then (CompressorSpeed is Off)(FanSpeed is Off)(ModeOfOperation is AC)(FanDirection is Away) (1)"
- 4) "If (TemperatureDifference is TooCold) and (Humidity is Humid) and (ElectricVoltage is Regular) then (CompressorSpeed is Off)(FanSpeed is VeryLow)(ModeOfOperation is AC)(FanDirection is Away) (1)"
- 5) "If (TemperatureDifference is TooCold) and (Humidity is Sticky) and (ElectricVoltage is Regular) then (CompressorSpeed is VeryLow)(FanSpeed is Low)(ModeOfOperation is Dehumidifier)(FanDirection is Towards) (1)"
- 6) "If (TemperatureDifference is Cold) and (Humidity is Dry) and (ElectricVoltage is Regular) then (CompressorSpeed is Off)(FanSpeed is Off)(ModeOfOperation is AC)(FanDirection is Away) (1)"
- 7) "If (TemperatureDifference is Cold) and (Humidity is Refreshing) and (ElectricVoltage is Regular) then (CompressorSpeed is Off)(FanSpeed is Off)(ModeOfOperation is AC)(FanDirection is Away) (1)"
- 8) "If (TemperatureDifference is Cold) and (Humidity is Comfortable) and (ElectricVoltage is Regular) then (CompressorSpeed is VeryLow)(FanSpeed is VeryLow)(ModeOfOperation is AC)(FanDirection is Away) (1)"
- 9) "If (TemperatureDifference is Cold) and (Humidity is Humid) and (ElectricVoltage is Regular) then (CompressorSpeed is VeryLow)(FanSpeed is Low)(ModeOfOperation is AC)(FanDirection is Towards) (1)"
- 10) "If (TemperatureDifference is Cold) and (Humidity is Sticky) and (ElectricVoltage is Regular) then (CompressorSpeed is Low)(FanSpeed is Low)(ModeOfOperation is Dehumidifier)(FanDirection is Towards) (1)"
- 11) "If (TemperatureDifference is Warm) and (Humidity is Dry) and (ElectricVoltage is Regular) then (CompressorSpeed is VeryLow)(FanSpeed is VeryLow)(ModeOfOperation is AC)(FanDirection is Away) (1)"

- 45) "If (TemperatureDifference is Hot) and (Humidity is Sticky) and (ElectricVoltage is Low) then (CompressorSpeed is Fast)(FanSpeed is Fast)(ModeOfOperation is Dehumidifier)(FanDirection is Towards) (1)"
- 46) "If (TemperatureDifference is TooHot) and (Humidity is Dry) and (ElectricVoltage is Low) then (CompressorSpeed is Medium)(FanSpeed is Medium)(ModeOfOperation is AC)(FanDirection is Towards) (1)"
- 47) "If (TemperatureDifference is TooHot) and (Humidity is Refreshing) and (ElectricVoltage is Low) then (CompressorSpeed is Medium)(FanSpeed is Medium)(ModeOfOperation is AC)(FanDirection is Towards) (1)"
- 48) "If (TemperatureDifference is TooHot) and (Humidity is Comfortable) and (ElectricVoltage is Low) then (CompressorSpeed is Medium)(FanSpeed is Medium)(ModeOfOperation is Dehumidifier)(FanDirection is Towards) (1)"
- 49) "If (TemperatureDifference is TooHot) and (Humidity is Humid) and (ElectricVoltage is Low) then (CompressorSpeed is Fast)(FanSpeed is Fast)(ModeOfOperation is Dehumidifier)(FanDirection is Towards) (1)"
- 50) "If (TemperatureDifference is TooHot) and (Humidity is Sticky) and (ElectricVoltage is Low) then (CompressorSpeed is Fast)(FanSpeed is Fast)(ModeOfOperation is Dehumidifier)(FanDirection is Towards) (1)"

9. Configuration and analysis of membership functions

The particular membership functions for the input and output variables used in the air conditioning system are presented in the graphs in this section. The visual representation of the degree of membership for every state within the variable range, provided by each graph, could explain how the system understands the situation. With the help of these figures, the internal operation of the fuzzy logic controller and how it interprets the measured data to come to decision-making becomes

evident. To further this aim and understand details, the paper will take a closer look into the design of each membership function in this section. This section explains in reasoning terms how each function contributes to the system's behavior, and, in the end, a better understanding would be expected to come along. Fig. 5 represents the membership functions for an input variable named "Electric Voltage," which has two fuzzy sets - "Low" and "Regular." The "Low" voltage range is clearly shown in the figure, with its membership value 1 for voltages below 200 V and gradually decreasing to 0 at 215 V. So, the "Low" voltage range is 180–215 V, and the voltage range assigned to set "Regular" starts at 200 V, and its membership value at that voltage is minimum. It reaches its maximum membership at 220 V, and from there on, it stays constant above that point. That is how we gradually transition from "Low" to "Regular" to estimate the electric voltage using the F.I.S. When the power supply fluctuates, it is essential for the system not to have any sudden changes in behavior, and this is when the discussed architecture can effectively enable it. Membership functions for one of the input variables named "Humidity," which is split into five fuzzy sets, "Dry," "Refreshing," "Comfortable," "Humid," and "Sticky," are shown in Fig. 6. Membership functions of these sets are made using a triangular structure, and each category has different peaks that show the range of humidity where membership becomes the highest. For instance, "Dry" reached the highest membership at 0 % humidity and became zero as humidity increased to 30 %. "Comfortable" peaked at around 50 %, "Humid" at around 70 %, "Sticky" at 100 %, and "Refreshing" at 40 %. This method improves functionality and comfort by automatically modifying the system's output to fit the condition of the humidity level.

As shown in Fig. 7, the membership function of the input fuzzy variable 'Temperature Difference,' which is the difference between the actual and the desired room temperatures, consists of five fuzzy sets: 'Too Cold,' 'Cold,' 'Warm,' 'Hot,' and 'Too Hot.' These five temperature states can be smoothly shifted to one another thanks to triangular membership functions. The maximal membership of 'Too Cold' is -10°C , of 'Cold' is 0°C , of 'Warm' is 10°C , of 'Hot' is 20°C , and of 'Too

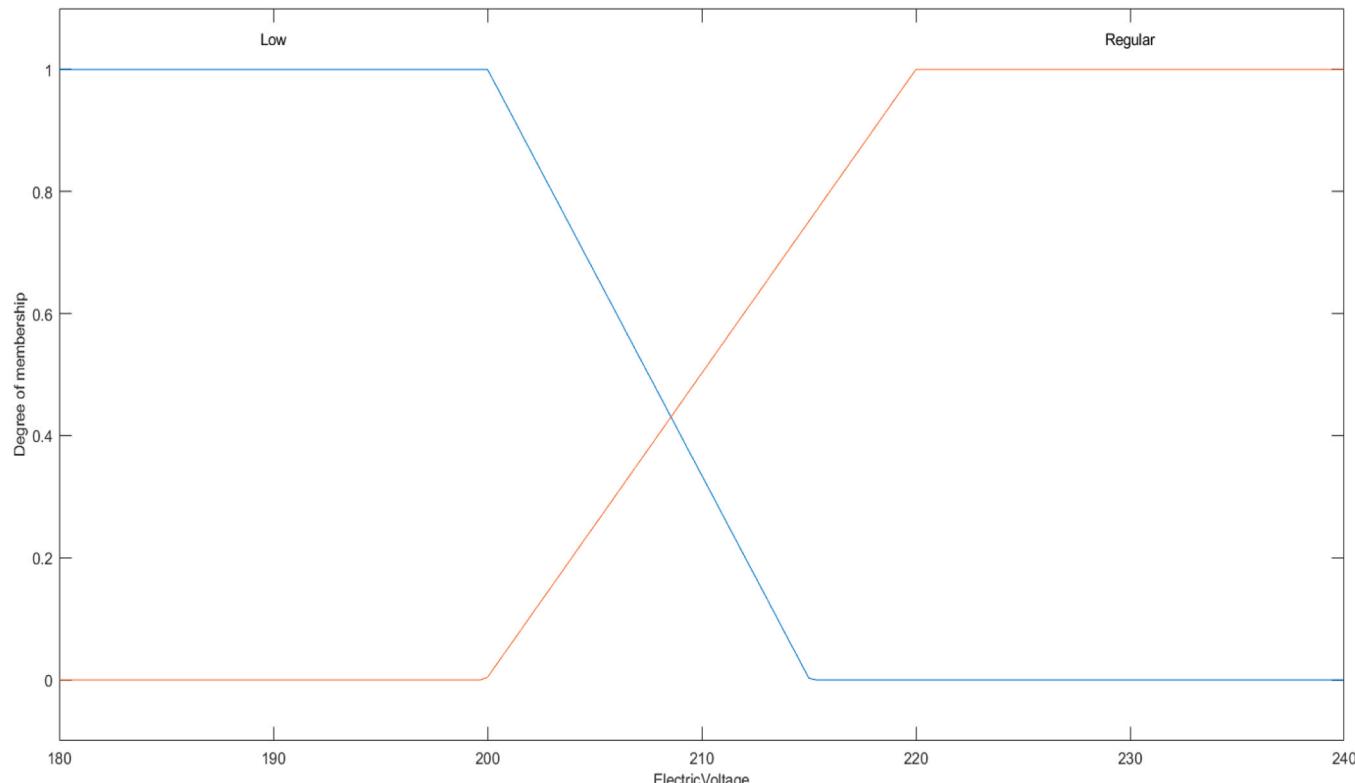


Fig. 5. Electric Voltage Membership Function.

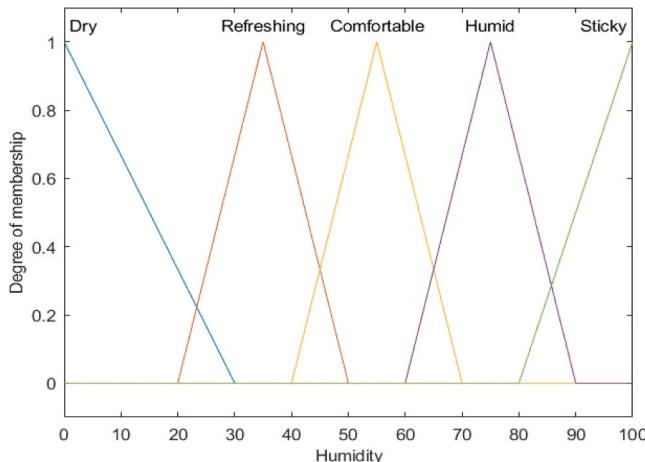


Fig. 6. Humidity Membership Function.

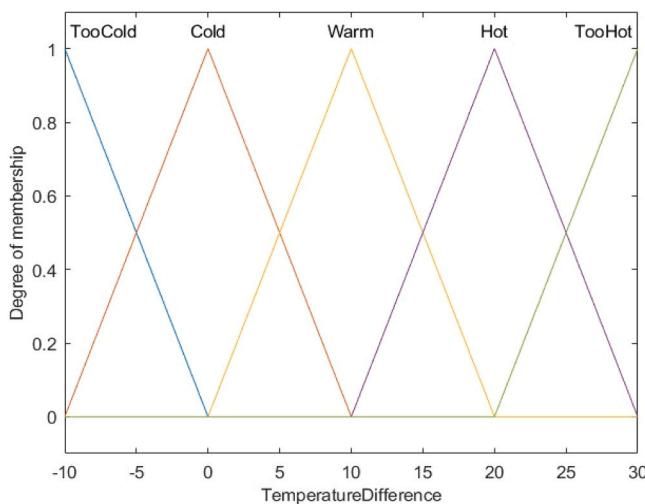


Fig. 7. Temperature Difference Membership Function.

'Hot' is 30°C. Thanks to this configuration, the cooling output of the air conditioning system can be gradually adjusted as the value of the temperature difference changes, which allows the system to respond proportionally to the changing temperature differences and keep the inside temperature of the building comfortable.

The output variable 'Compressor Speed' is divided into the five fuzzy sets: 'Off,' 'Very low,' 'Low,' 'Medium,' and 'Fast.' Membership functions for each of these fuzzy sets are given in Fig. 8. Triangular membership functions have been used to represent each of the above sets so that there is a smooth transition without any jump from one compressor speed to another. "Off" peaks at 0, indicating that the compressor is off. "Very Low" peaks at about 25, and so on, reaching 75–100 with "Fast" as the speed increases. Now, the system may change the compressor speed upon input conditions in a gradual manner, keeping both the energy use optimal and the desired room temperature intact. Fig. 9 shows the membership functions corresponding to the five categories of output variable 'Fan Speed,' namely: 'Off,' 'Very low,' 'Low,' 'Medium,' and 'Fast.' These six membership functions again use the same triangular patterns for the compressor speed variable. 'Fast' peaks at about 1400,

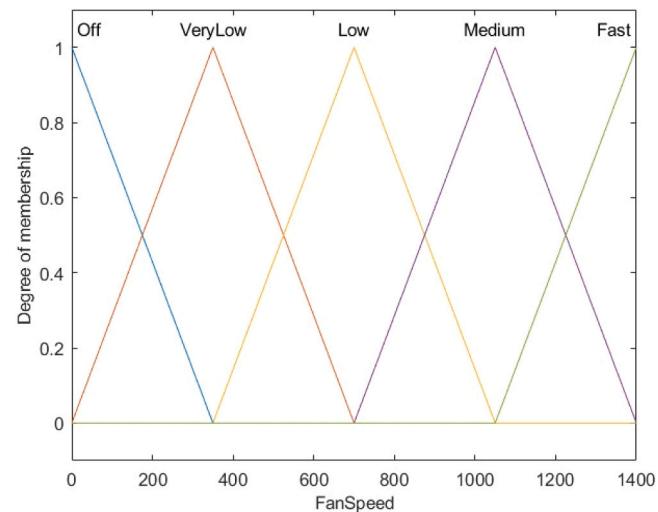


Fig. 9. Fan Speed Membership Function.

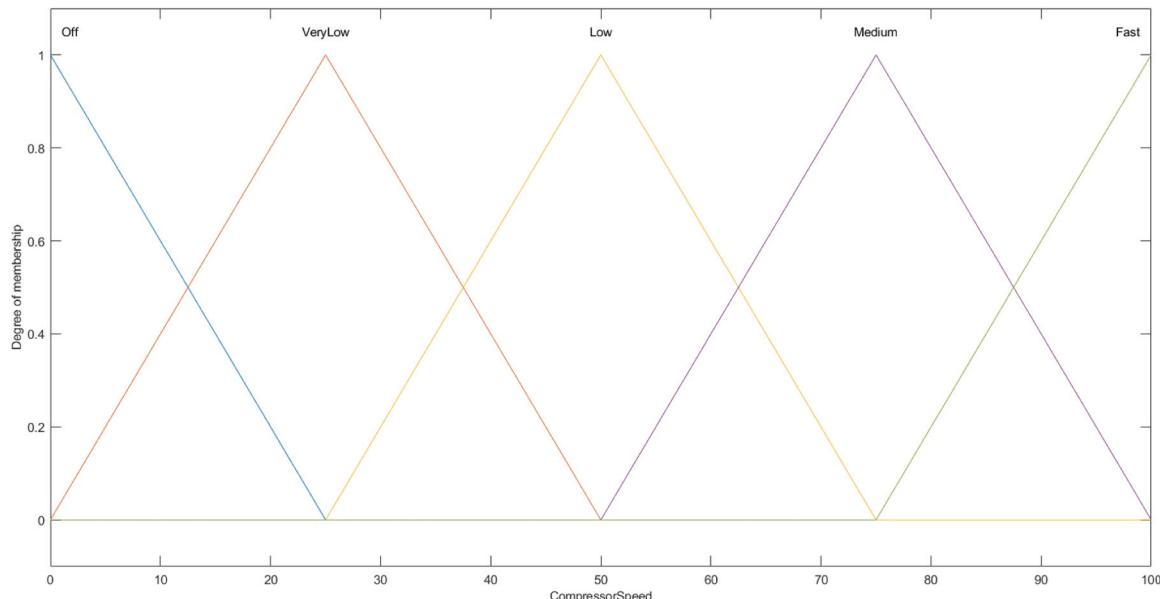


Fig. 8. Compressor Speed Membership Function.

whereas 'Off' peaks at 0 – making it possible for the system to slowly shift the fan's speed, sending the correct air volume for the ambient conditions to provide the best possible cooling and guaranteed comfort. Fig. 10 displays the membership functions of the "Mode of Operation" output variable. The "Mode of Operation" variable has two categories: "Dehumidifier" and "A.C." In comparison with other output variables, this variable uses a simple linear membership function. In addition to a smooth transition between the two modes of operation, the "Dehumidifier" mode is fully activated when the input is '0', whereas the "A.C." mode is fully activated when the input is '1'. It thus allows the Fuzzy system to maintain an efficient and comfortable indoor climate by switching between the operation of the dehumidifying unit and air-conditioning depending on the input variables to achieve the desired indoor temperature and humidity.

Fig. 11 shows the membership functions for the output variable Fan Direction, which has two Fuzzy sets, "Towards" and "Away," characterized by a trapezoidal membership function. When the direction changes, "Towards" is fully activated at values below 30 and fades gently towards "Away," which is fully activated at values over 80. This decomposition allows the system to drive the fan's direction smoothly, ensuring air is distributed in the best way to obtain a comfortable atmosphere.

10. Defuzzification

Perhaps the most crucial step in the fuzzy logic process is the task of defuzzification, which forces the fuzzy outputs produced by the fuzzy inference engine into a 'sharp' value, which the system can use to make decisions or take a control action. Defuzzification consists of transforming the fuzzy conclusions produced by the linguistic rules into a crisp value that can be used to make practical interventions such as, in the case of an air-conditioning system, increasing or decreasing the speed of the compressor or the rotational direction of the fan (Zheng et al., 2022). The Centroid method (also referred to as the center of area method or center of gravity method) - is used in the project, and it is one of the most popular defuzzification approaches as it provides a balanced result considering all the fuzzy sets. The centroid approach is to calculate the center of the area under the output membership function curve and represents the "average" value of the output distribution. This method assures the resulting output precisely reflects the overall influence of all active fuzzy rules.

The centroid of a fuzzy set Z is mathematically defined as:

$$z^* = \frac{\int z \mu_z(z) dz}{\int \mu_z(z) dz} \quad (7)$$

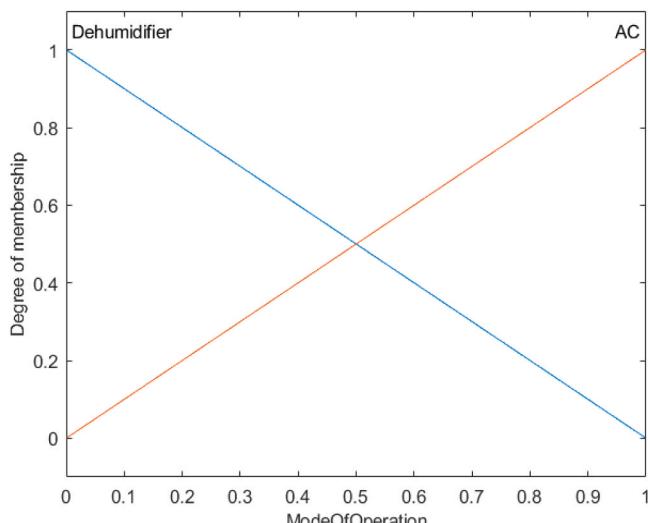


Fig. 10. Mode of Operation Membership Function.

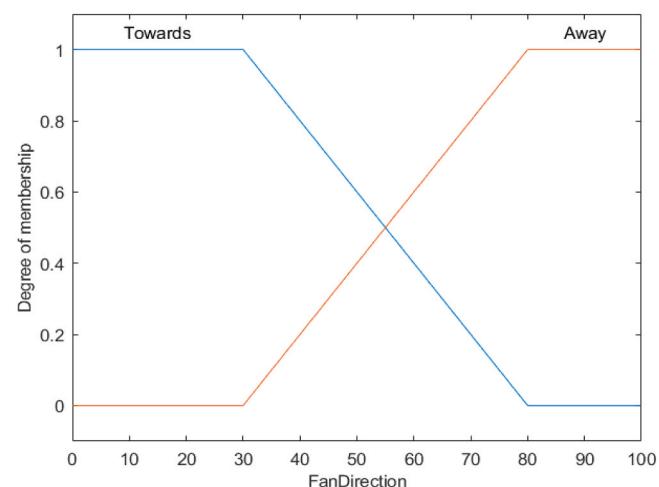


Fig. 11. ‘Fan Direction Membership Function’.

The numerator of this formula is the weighted sum of all the possible output values. The output value denoted by 'z' is compared to the value of its membership function, denoted by ' $\mu_Z(z)$ '. This part of the formula computes the contribution of the individual possible output 'z' to the output value using the membership function's characteristic that calculates the 'fuzzy true' value. The term yields a sum representing the total impact of all the fuzzy rules on the output by multiplying each possible output value 'z' by its associated membership ' $\mu_Z(z)$ ' and then integrating all the possible values. The total area under the membership function curve is given by the denominator, ' $\int \mu_Z(z) dz$ ', which represents all the possible membership values over the range of potential outputs. This value will tell us the total 'weight' of all the firing fuzzy rules. To ensure that the final, crisp output value results from an output that is appropriately modified with the weights of the fuzzy rules causing it to fire, this term normalizes the value that comes from the numerator. Dividing these two integrals by their ratio yields the sought-for centroid (the center of gravity of the area under the curve).

This is conceptually similar to finding the balance point of the object – the point at which, with support, the thing would indeed be perfectly balanced (Qin, 2022). In fuzzy logic applications, this balance point is interpreted as the output value that is the best (in the linguistic or membership senses) representation of the fuzzy rules triggered by its input. Using the centroid ensures that the outcome of a fuzzy logic system's rule-based decision is a meaningful representation of the input by appropriately accounting for both the force (represented in the numerator) and the spread of the membership values.

11. Results and discussion

These figures, 12–19, showing the correlations between input variables and output actions, were obtained by performing rigorous simulations of the fuzzy logic controller for input variables such as temperature difference and humidity, and for output actions such as compressor speed and fan speed, using fuzzy rules that are close to real-world operational situations and using predetermined ranges for inputs. These figures were forecasted by simulating the controller's behavior under different scenarios using the theoretical framework of fuzzy logic and the operational architecture of the system. This allows for typical trends that reflect the intended behavior of the fuzzy logic controller to be presented.

The relationship between temperature difference, humidity, and compressor speed is illustrated in Fig. 12. It can be graphically determined that the compressor speed increases with humidity and temperature difference. This is because the more humidity and temperature differential present, the more power will be needed to cool the room to a

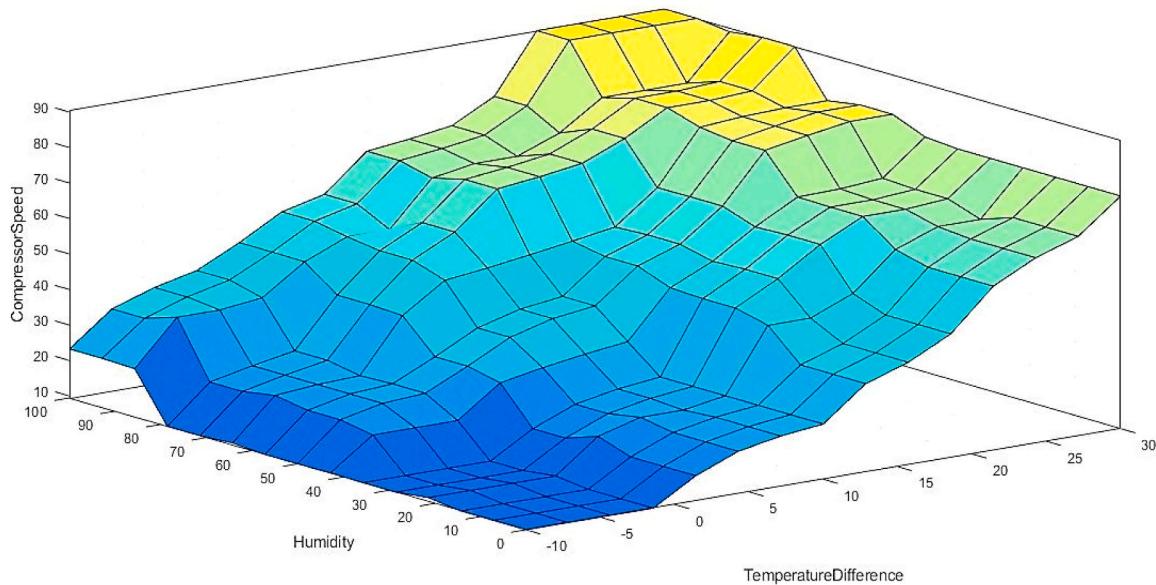


Fig. 12. Compressor Speed vs. Humidity and Temperature Difference.

comfortable level. This gradual, slow change type is an essential property of a fuzzy logic controller. It ensures a smooth response – not one where the system jumps in and out of different power levels abruptly. This is especially important when high energy loads put more stress on the system, as it can prevent an over-correction where a more significant system response might meet an increase in demand. Fig. 13 describes the relationship between fan speed, temperature difference, and electric voltage. The fan speed has to increase as the temperature difference widens to produce faster cooling when needed. To avoid overloading the electrical system when this happens, the system will also reduce fan speed when the electric voltage goes down. The above behavior demonstrates the ability of the fuzzy logic controllers to maintain a balance between a cooling need and a power supply so that the overall performance of the air conditioning system is guaranteed even when power fluctuations happen.

Fig. 14 illustrates the relationship between electric voltage, humidity, and fan speed. On one hand, to ensure the function of

dehumidification and air circulation, the fan speed has to increase with the humidity level. Conversely, the system adjusts the fan speed variable according to the electric voltage, speeding up the fan motor when a large amount of electric voltage is available. In this way, the system can achieve the goal of combining cooling and dehumidification while balancing energy and environmental needs. Fig. 15 below illustrates the linear relation between fan speed and the temperature difference. As we can see in the figure below, the speed of the fan increases directly due to the temperature difference, causing the system to be able to provide more cooling power when required. An indication of the effectiveness of a fuzzy logic controller is demonstrated by how this controller is able to adjust the cooling demand by speeding up and slowing the fan according to the weather conditions. The system will provide a comfortable interior temperature without any overconsumption of energy or abrupt changes in fan speed by responding according to the weather temperature.

The graph below in Fig. 16 indicates the relationship between the

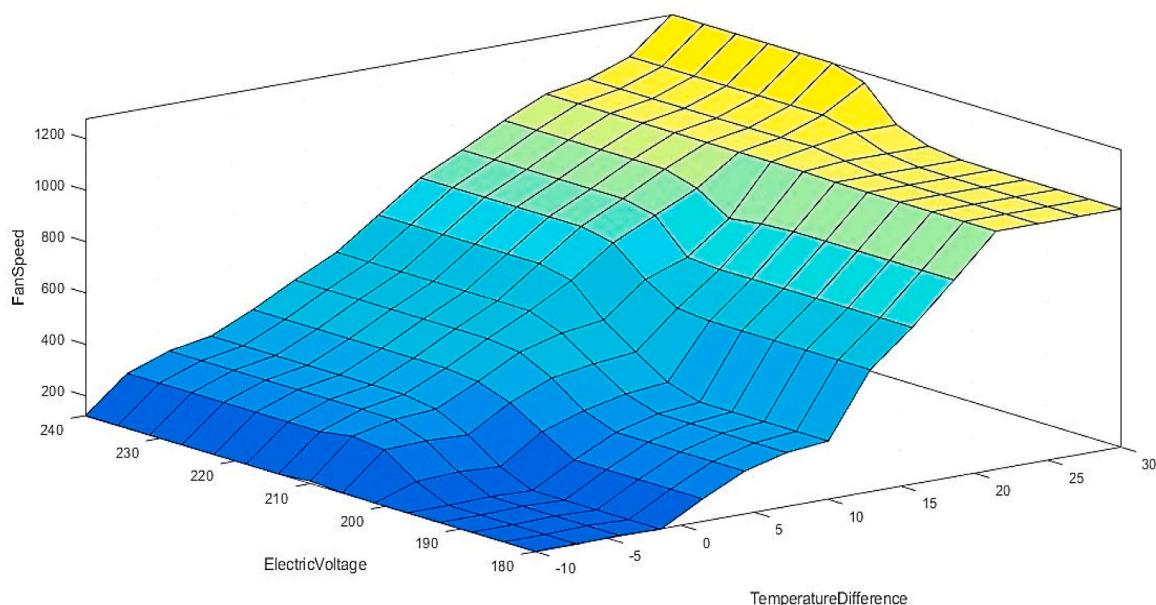


Fig. 13. “Fan Speed vs. Electric Voltage and Temperature Difference”.

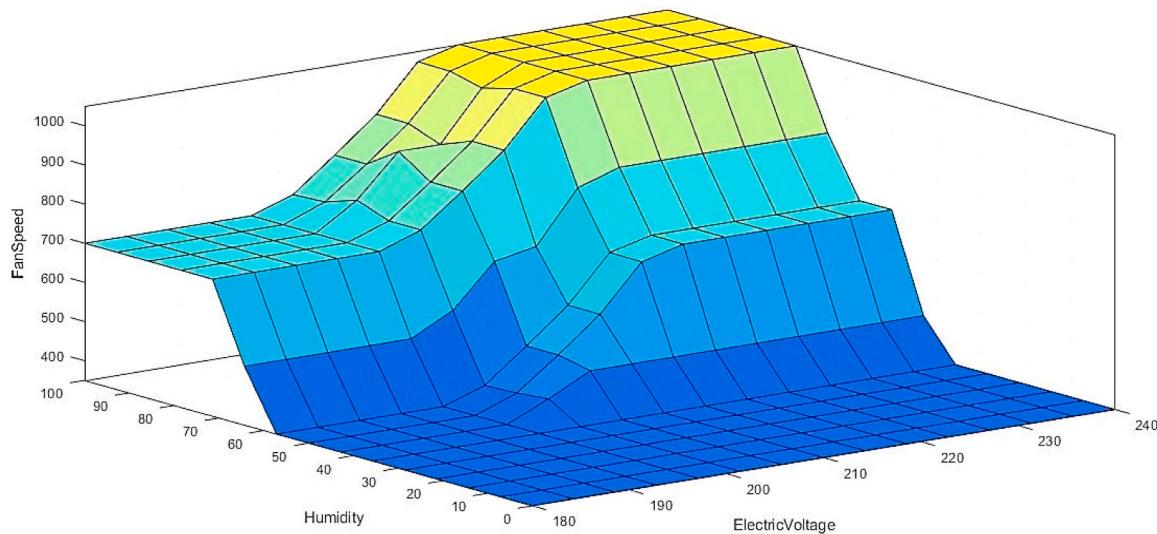


Fig. 14. “Fan Speed vs. Humidity and Electric Voltage”.

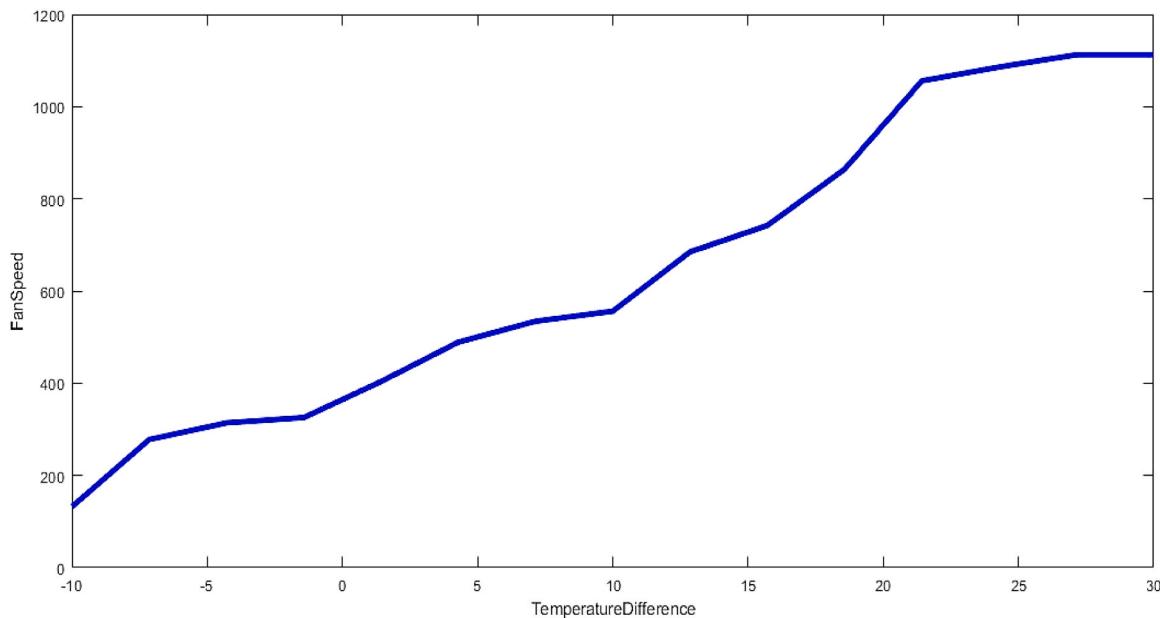


Fig. 15. Fan Speed vs. Temperature Difference.

mode of operation and the temperature difference, which depend upon each other. The graph indicates how the operation mode changes from dehumidification to air conditioning (A.C.) when there is a rise in temperature difference. At first look, we can see that the dehumidification mode takes higher priority when there is a small temperature differential. However, as the temperature differential and cooling demand increase, the graph value decreases and shows that the system is moving toward the Air Conditioning mode.

Fig. 17 shows how fan direction relates to the temperature differential. As the temperature differential between inside and outside decreases, the system changes fan orientation from ‘Towards’ to ‘Away.’ This is to maximize the amount of air circulation as per cooling requirements. When it is large, the fans directly blow air at the occupant, so cooling occurs immediately. As the temperature differential decreases, the fans adapt to disperse air throughout the space to avoid uncomfortable draughts.

Now, let us take an example. In this case, there is a 7.16°C temperature discrepancy between the desired temperature of 16°C and the

room temperature of 23.16°C. In addition, the electric voltage of 220 V is regarded as usual, and the relative humidity is 97 %. Based on this information, we will try to find the optimal output values for the air conditioner.

Figs. 18 and 19 show that the system has calculated 67 % of the rated rpm for compressor speed. The controller increased the compressor speed due to the enormous temperature differential and high humidity. This improvement makes sense because it is the most effective way to lower the moisture in the air and cool the room to ensure that dehumidifying and cooling have been achieved simultaneously. The fan speed has been set up to 938 rpm. Since the compressor operates faster, setting the fan speed very high helps to circulate the cooled air throughout the space effectively and quickly. This allows us to keep the temperature constant and quickly lower humidity. Also, for the mode of operation, the value is 0.352, meaning that this system usually operates in the air conditioning mode. This also indicates that some dehumidification also occurs to account for the high humidity as well. This dual-function method of controlling excess moisture in the airstream helps to

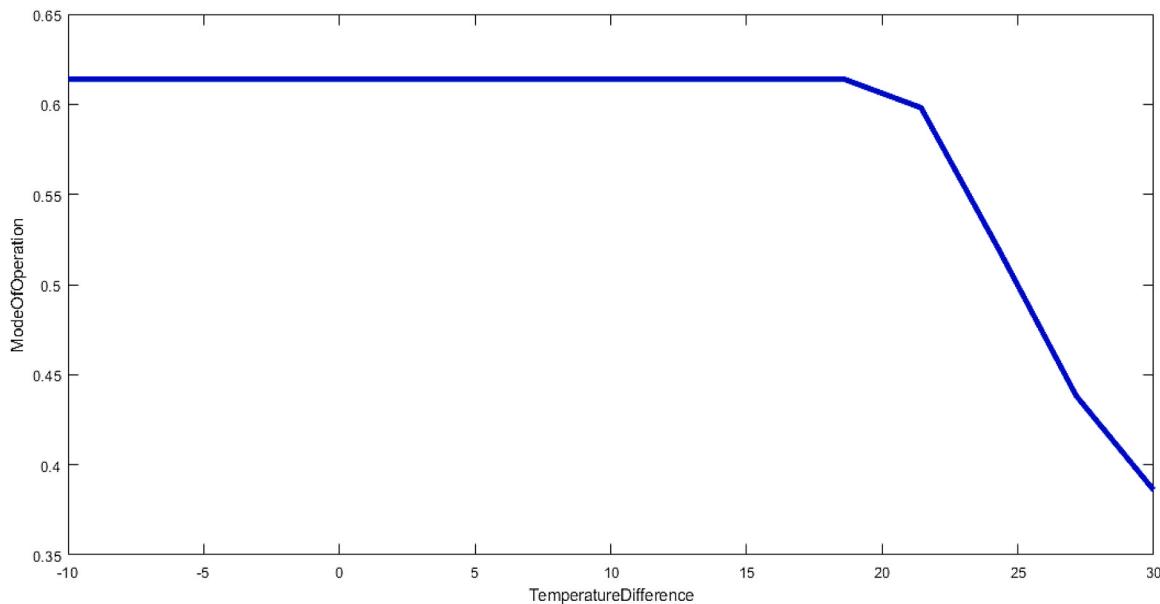


Fig. 16. Mode of Operation vs. Temperature Difference.

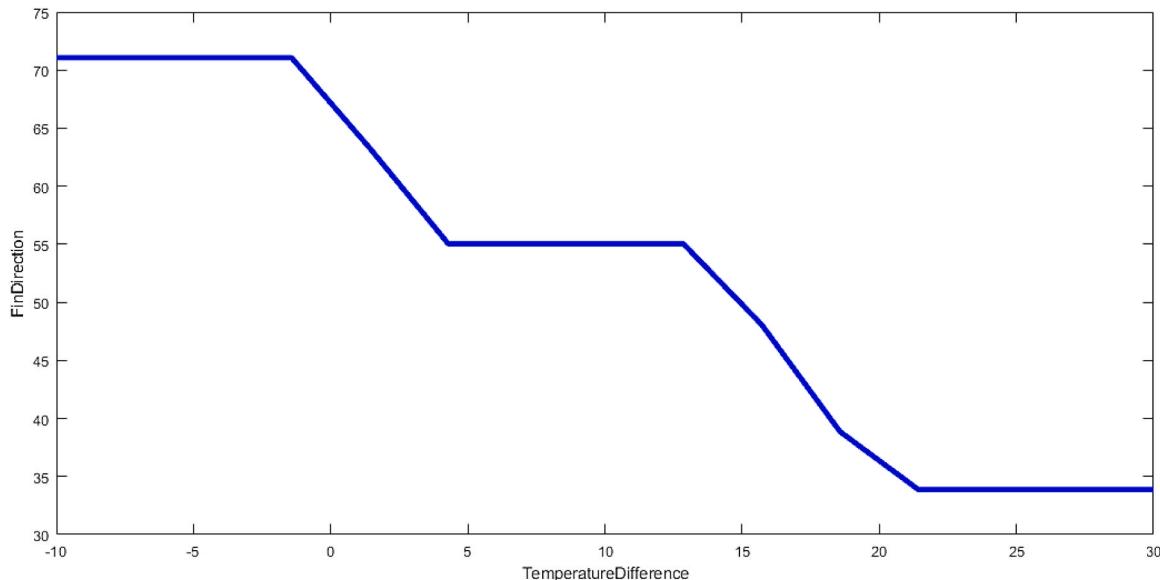


Fig. 17. ‘Fan Direction vs. Temperature Difference’.

ensure this system’s high comfort and energy-efficient operation. To sum up, the controller configures the fan orientation at 31.7 degrees, diverting

airflow from people. This way, the inside atmosphere can remain cool by spreading the cold air evenly into the space and preventing inconvenience from direct coldness. Figs. 20 and 21 were developed to show relationships between some of the critical input variables, such as temperature difference and humidity, with system outputs like energy usage and compressor speed, respectively, as part of the sensitivity analysis. Fig. 20 presents the interrelation between humidity, temperature differential, and energy consumption of the air conditioning system. In such a context, the Fuzzy logic controller continuously readjusts compressor speed and other operating variables to maintain comfort and energy economy. Energy consumption was calculated using the formula below, derived from domain-specific knowledge of HVAC systems.

$$\begin{aligned} \text{Energy Consumption} = & 0.08 \times \text{CompressorSpeed}^{1.1} + 0.05 \times \frac{\text{FanSpeed}}{1400} \\ & + 0.003 \times \text{Humidity}^{1.05} - 0.002 \times (\text{Voltage} \\ & - 200) \end{aligned}$$

As compressor speed is the largest determinant in cooling load management within an HVAC system, it clearly is the leading factor in energy use in the equation. Other less obvious factors include fan speed, humidity, and voltage fluctuations. Voltage fluctuations, for instance, result in efficiency penalties, whereas humidity results in a slight increase in energy usage due to the higher load that must be used for dehumidification. This graph shows that with higher temperature fluctuations, the energy use is higher since the system has to work harder to maintain target comfort levels. Similarly, while less pronounced compared to temperature differences, higher humidity levels also result in higher energy use. This graph illustrates how the fuzzy logic

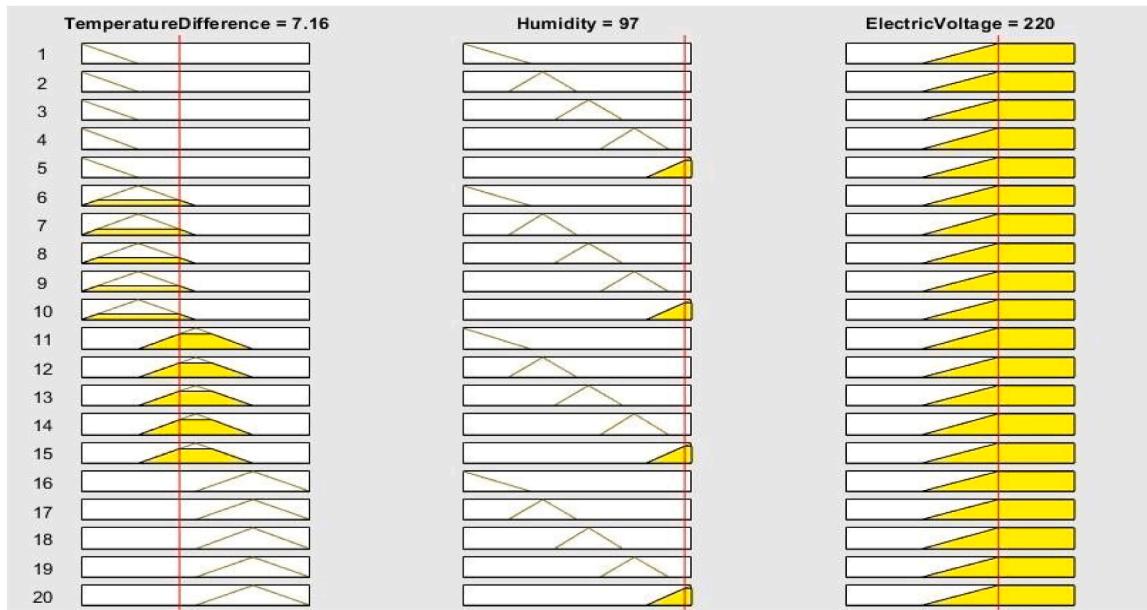


Fig. 18. FLC Input for Specific Environmental Conditions.

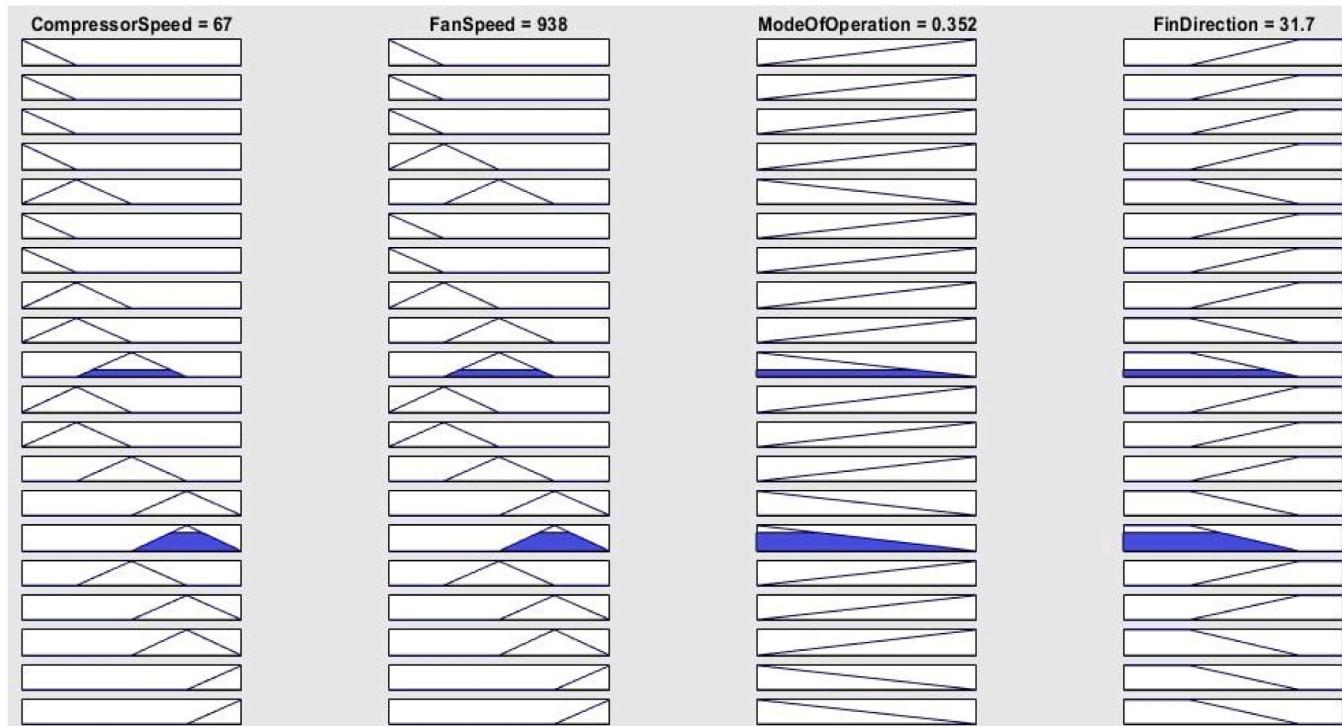


Fig. 19. FLC Output for Specific Environmental Conditions.

controller can adjust settings to optimize energy use based on external factors.

The relationship between humidity, temperature differential, and compressor speed is represented in Fig. 21. Since compressor speed is directly related to the cooling capability and energy consumption of the air conditioning system, it is one of the most crucial output variables of the fuzzy logic system. Having temperature differential and humidity as inputs, the fuzzy logic controller adjusts the compressor speed in real time based on the fuzzy rules, reaching a compromise between comfort and energy economy. It is noticed from the graph that the larger the temperature differential, the faster the compressor speeds, which will

allow the system to provide the required cooling effect. More excellent humidity results in a higher running speed of the compressor as the system needs to handle cooling and dehumidification requirements together. The strong correlation between compressor speed and energy usage explains the similarity between Fig. 20 and Fig. 21. For most HVAC systems, the compressor is usually the most power-consuming component; hence, the energy usage trends almost reflect the compressor speed trends. This proximity of the two figures is further corroborated by the fact that, though other variables such as fan speed, humidity, and voltage are integrated into the energy consumption formula, their effects are negligible. This crossing of the graphs agrees with

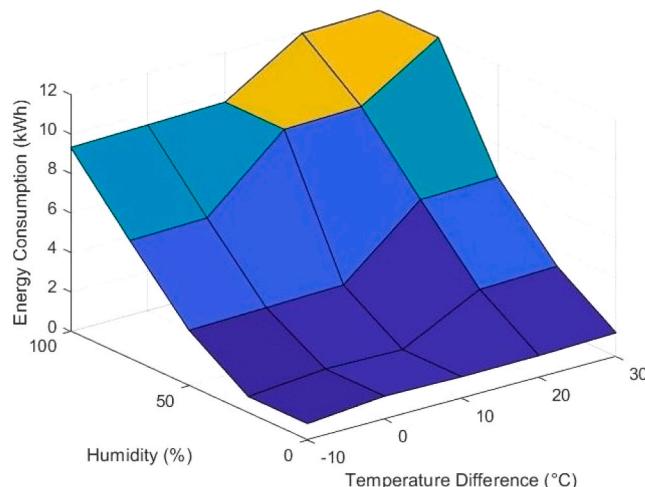


Fig. 20. Energy Consumption vs Temperature Difference and Humidity.

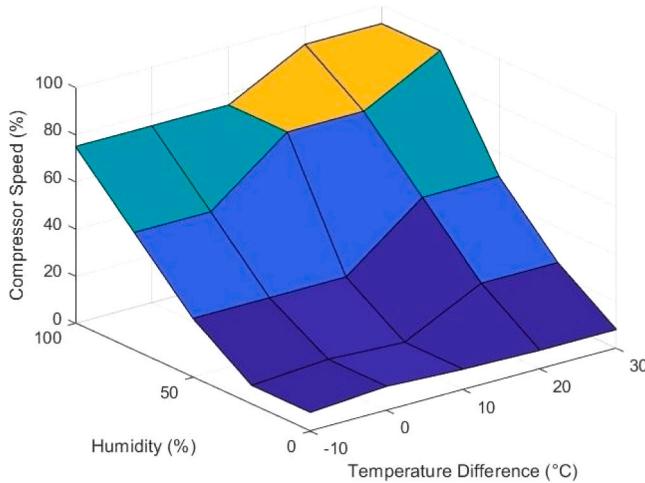


Fig. 21. Compressor Speed vs. Temperature Difference and Humidity.

how HVAC systems behave in the real world, where the compressor is the most power-consuming component. The similarity verifies the fuzzy logic controller since the system's operating patterns are just like HVAC anticipated. The energy savings were calculated by comparing the fuzzy logic-based system with conventional air conditioning systems operating under similar conditions. Under changing climatic conditions, conventional systems utilize energy inefficiently because their parameters are fixed. Energy consumption data for traditional systems used in this study was obtained from known benchmarks, such as the Department of Energy and similar HVAC efficiency studies. While the conventional systems use about 15 kWh under harsh conditions, such as a high-temperature differential of 30°C and 100 % humidity, the fuzzy logic system uses up to 12 kWh. In consequence, 20 % less energy is used. Similarly, the conventional system uses an average of 6.5 kWh versus 5 kWh for the fuzzy logic system under mild conditions, such as a temperature differential of 10°C and humidity of 50 %, which gives approximately 23 % savings in energy. These savings result from the ability of the fuzzy logic controller to prevent waste of energy by dynamic control of compressor speed and fan operation according to prevailing input conditions in real time. The flexibility of the fuzzy logic controller is that energy shall be utilized when in need, and overutilization at a time of demand shortage is avoided.

Intelligent approaches like Model Predictive Control (MPC), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), hybrid fuzzy-ML models,

and deep learning-based controllers have been developed at a rapid pace in HVAC control research in recent years. Although these methods frequently show significant energy savings, their implementation in practical contexts is constrained by the additional layers of complexity, data dependency, and operational rigidity they introduce. By presenting a fuzzy logic controller that balances energy efficiency, adaptability, and practical feasibility—a feat that many contemporary approaches currently find difficult to accomplish—our study overcomes these constraints. MPC's strong dependence on precise system modeling and forecasting is one of its most obvious drawbacks. Suboptimal or unstable performance can result from even minor discrepancies between the dynamics of the real world and the predictive model. Furthermore, to remain effective, MPC systems must be continuously recalibrated, which is resource-intensive and impractical in typical residential or mid-scale commercial settings. On the other hand, our controller is entirely dependent on real-time inputs and makes dynamic adjustments without mathematical modeling or long-term prediction. This lessens the need for setup and maintenance by enabling reliable operation in unpredictable circumstances.

Incorporating learning mechanisms into fuzzy systems in the context of ANFIS increases flexibility but also creates a reliance on sizable, superior datasets. These models may not perform well in unexpected environmental situations because they are only as good as the data they are trained on. Our controller mitigates this risk by employing a meticulously organized rule base based on control theory and industry standards. This ensures that performance stays consistent even in edge cases where training data may not have prior exposure because it offers robustness without requiring training. Although hybrid fuzzy-ML models aim to combine predictability and interpretability, they frequently have internal complexity issues that impair system maintainability and transparency. Operators find it more difficult to identify problems or take manual action when ML components become more opaque, which erodes usability and trust. In contrast, our FLC preserves a transparent decision-making framework in which every input corresponds to a predetermined response. This clarity provides responsive control under various operating conditions, making deployment and troubleshooting easier. Although they are far from lightweight, deep learning-based controllers further improve energy performance. These systems are impractical for most common HVAC applications due to their high computational power requirements, lengthy training cycles, and large volumes of labeled data. They are also inappropriate for regulated or safety-critical settings where traceability of control logic is required due to their black-box nature. Our method provides similar energy savings without any drawbacks, with 20–25 % validations. Domain experts without extensive data science or artificial intelligence knowledge can readily adapt or expand it, and it executes decisions instantly and fully interpretably. Our controller's strength ultimately resides in balancing deployment ease and technical complexity. It maintains low computational demands, high reliability, and few integration barriers while achieving energy efficiency comparable to state-of-the-art models. Because of this, our solution is a theoretical improvement and a workable, scalable development that can be widely implemented in the current energy-conscious environment. By doing this, it directly tackles the fundamental issues that still plague even the most sophisticated intelligent HVAC systems.

The suggested Fuzzy Logic Controller (FLC), Adaptive Neuro-Fuzzy Inference System (ANFIS), Machine Learning (ML)-based controllers, Deep Learning (DL)-based controllers, and Reinforcement Learning (RL)-based controllers are the five HVAC control strategies that are compared in Fig. 22's bar chart for average execution time per control cycle.

Each bar in the chart shows the time (in milliseconds) needed by each controller to finish a single cycle of input processing and output generation. With the lowest execution time of roughly 2.3 ms, the suggested FLC, which is positioned at the far left, demonstrates its capacity for quick control decisions. This contrasts sharply with the ML and DL-

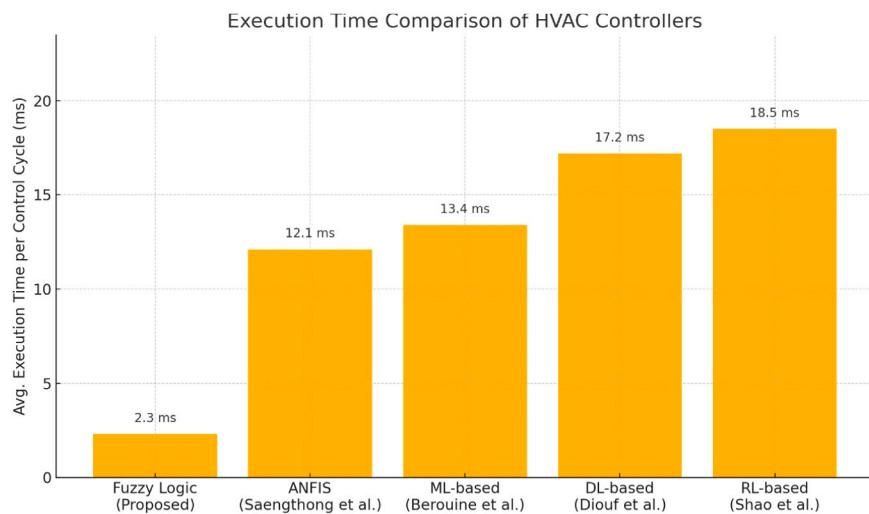


Fig. 22. Average Execution Time per Control Cycle for Different HVAC Controllers.

based controllers, which take 13.4 ms and 17.2 ms, respectively, and the ANFIS controller, which takes about 12.1 ms. With an average execution time of 18.5 ms, the RL-based controller is the most computationally intensive. The assertion that our fuzzy logic system operates in real-time substantially faster and more efficiently than other contemporary intelligent controllers is graphically supported by this figure. While the other approaches introduce additional delay due to the complexity of learning, inference layers, or policy evaluation, our FLC's compact rule-based architecture enables it to respond to dynamic inputs almost instantly. This speed advantage is significant for real-time applications in HVAC systems, where prompt adjustments directly impact comfort and energy efficiency.

Table 09 presents a rigorous, quantifiable comparison of HVAC control strategies using implementation-level metrics such as control variables managed, execution time, memory footprint, training effort, parameter complexity, and sensor input requirements.

12. Conclusion

In order to improve the energy efficiency and adaptability of air

conditioning systems, this study successfully designed and implemented a fuzzy logic-based controller (FLC). The developed controller effectively responds to real-time variations in temperature, voltage, and humidity by dynamically adjusting key parameters, particularly fan and compressor speeds. In comparison to conventional PID-controlled systems, simulation results show notable operational improvements, achieving substantial energy savings of about 20–25 % and maintaining indoor temperature stability within $\pm 0.5^{\circ}\text{C}$ of the desired set-point. A key product of this research is the robust yet simplified fuzzy-rule architecture, which guarantees dependable performance in quickly shifting environmental conditions without adding needless complexity or computational overhead. Additionally, the developed system successfully strikes a balance between user comfort and energy efficiency, laying the groundwork for real-world implementation in both residential and commercial applications. In order to expand the advantages of adaptive energy management, future studies could investigate applying hierarchical or distributed fuzzy control techniques to scale the suggested fuzzy control strategy to multi-room or large-scale commercial environments. The novelty of this work lies in its implementation rather than in algorithmic development, underscoring the practical value of

Table 09
Comparative study of control strategies for energy efficiency in air conditioning.

| Control Strategy | Control Variables Managed | Avg. Execution Time (ms) | Model Size / Memory (MB) | Training Requirement (Epochs or Iterations) | Number of Parameters/Rules | Sensor Inputs Required |
|--|---------------------------|--------------------------|--------------------------|---|--------------------------------|-----------------------------|
| Traditional PID Control (Shahir and Oktaviandri, 2022; Busu et al., 2023; Shang et al., 2022) | 01 | 0.8 | 0.3 | None | 3 gain constants | 1 (Temperature) |
| Machine Learning (ML) (Yang and Wan, 2022; Chen et al., 2022; Majdi et al., 2022) | 2–3 | 12.0 | ~15–20 | 50–100 epochs | ~10,000–50,000 model weights | 3–4 |
| Deep Learning (DL) (Tariq et al., 2023; Sanzana et al., 2022) | 3–4 | 17.2 | ~85.0 | 100–300 epochs | > 100,000 weights | 4–5 |
| Hybrid Fuzzy-ML Approach (Irshad and Algarni (2022); Khan et al., (2024)) | 3–4 | 14–18 | 60–100 | Mixed (pretrained + rule config) | Composite (rules+ weights) | 4–5 |
| Genetic Algorithms (GA) (Ning, 2023; Xianghui et al., 2022) | 2–3 | ~14.5 | ~6.4 | 800–1000 generations | 50–100 optimization parameters | . 2–3 |
| Neural Networks (NN) (Adelekan et al., 2022; Zhang et al., 2023) | 2–3 | 13.5 | ~20–30 | . 100–200 epochs | ~30,000 weights | 3–4 |
| ANFIS (Adaptive Neuro- Fuzzy Inference System) (Jadhav and Sarwadnya, 2023; Dasheng and Shang-Tse, 2023) | 3–4 | 12.1 | ~8.3 | 50–100 training epochs | ~50–70 fuzzy rules | 3–4 |
| Model Predictive Control (MPC) (Bohaba et al., (2023); Taheri et al., (2022)) | 3–4 | 9.3 | ~10.1 | ~200 horizon iterations | ~25 model parameters | 3–4 |
| Proposed work | 4 | 2.3 | ~1.2 | None | 50 fuzzy rules | 3 (Temp, Humidity, Voltage) |

applying a well-established fuzzy logic framework to real-world HVAC optimization.

Statements and Declarations

"All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript."

Ethics Statement

This study does not involve human participants or animals and does not require ethical approval.

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Author Contributions

All authors contributed significantly to the conception, design, data analysis, and writing of the manuscript. Harsh Pagare led the conceptualization and methodology, Kushagra Mishra contributed to software development and simulations, and Kanhaiya Sharma, Ketan Kotecha, and Ambarish Kulkarni assisted with validation and manuscript preparation. All authors have read and approved the final version of the manuscript.

CRediT authorship contribution statement

Ketan Kotecha: Supervision. **Kanhaiya Sharma:** Validation, Supervision. **Kushagra Mishra:** Visualization, Validation, Software, Resources. **Harsh Pagare:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Ambarish Kulkarni:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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