Fuzzy Adaptive Control for Multi-Dimensional Temperature Regulation in Electrical Equipment: A Comparative Analysis with PID Control

Miao Wang[1*], Qinghua Zhu[2,3]
[1]XinXiang Vocational and Technical College, Henan, Xinxiang 450003, China
[2]Henan Changye Intelligent Technology Development Co., Ltd, Henan, Zhengzhou 450001, China
[3]National School of Development at Peking University, Beijing 100091, China
E-mail: wangmin610059@yeah.net
[*]Corresponding author

Keywords: fuzzy adaptive control, temperature regulation, energy efficiency, PID control system

Received: February 06, 2025

This study proposes a fuzzy adaptive control system for multi-dimensional temperature regulation in electrical equipment and compares its performance against a traditional PID control system. Experiments were conducted under controlled ambient temperatures (15–45°C) and load conditions (0.5–5 kW), evaluating temperature stability (±0.5°C setpoint), response time, and energy efficiency. Results demonstrate that the fuzzy adaptive system reduced temperature fluctuations by 32.7% and improved energy efficiency by 18.4% compared to PID control. The fuzzy controller-maintained temperature within ±0.8°C under dynamic disturbances, outperforming PID (±2.5°C). These findings highlight the superiority of fuzzy adaptive control in complex thermal environments, offering enhanced stability and energy savings for industrial applications.

Povzetek: Študija primerja mehko adaptivno regulacijo temperature z PID-krmiljenjem v električni opremi. Pristop zmanjšuje temperaturna nihanja, izboljša odzivnost ter poveča energijsko učinkovitost, kar potrjuje njegovo prednost v dinamičnih toplotnih okoljih industrijskih sistemov in povečuje zanesljivost delovanja pri spremenljivih obremenitvah okolja.

1 Introduction

The efficient and reliable operation of electrical equipment is highly dependent on maintaining an optimal temperature range. Overheating can lead to significant damage, including reduced lifespan, degraded performance, and in some cases, catastrophic failure. With the continuous advancement of technology and the increasing complexity of electrical devices, the need for more sophisticated temperature control methods has become evident. Umurzakova et al. (2020) proposes an adaptive fuzzy-logic system for regulating the temperature in drum boilers. It ensures efficient operation by dynamically adjusting to varying load conditions, improving the control of boiler temperature stability [1]. Wang & Zhang (2018) develop a fuzzy hierarchical control system for solar greenhouses to maintain optimal temperature despite external environmental fluctuations. This system improves energy efficiency and supports plant growth by adjusting to varying conditions [2]. Dai et al. (2017) presents a fuzzy neural network-based temperature control system. The combination of fuzzy logic and neural networks enhances precision in controlling temperature in dynamic, nonlinear environments [3]. Wang et al. (2025) introduces a Lyapunov-based fuzzy control for thermoelectric cooling systems. The system uses dynamic updating laws to adapt to changing conditions, ensuring temperature stability and efficient cooling performance [4]. Lymperopoulos & Ioannou (2020) investigates distributed adaptive control for multi-zone HVAC systems in buildings. The fuzzy control system optimizes temperature regulation in each zone, improving comfort and energy efficiency [5]. Qian et al. (2025) focus on adaptive fuzzy tracking control for managing coolant temperature in lead-bismuth-cooled nuclear reactors, ensuring stability under variable marine conditions [6]. Yang et al. (2024) proposes a fuzzy control system for air conditioning, enhanced by quasi-Newtonian particle swarm optimization. It improves temperature precision and energy efficiency in indoor spaces [7]. Rajeswari et al. (2023) applies fuzzy logic to regulate thermal comfort and indoor air quality in vehicles. The system dynamically adjusts HVAC parameters to maintain a comfortable environment for passengers [8]. Boughamsa & Ramdani (2018) propose an adaptive fuzzy control strategy for greenhouse micro-climate regulation. It adjusts temperature, humidity, and light levels to optimize plant growth in response to environmental changes [9]. Existing approaches lack comprehensive validation under multi-dimensional disturbances (e.g., concurrent load and ambient variations) and omit quantitative comparisons with PID in electrical systems. To bridge this gap, we introduce a fuzzy adaptive control algorithm.

2 Equipment temperature and regulation model construction

To develop an effective temperature regulation system, it is essential first to establish a robust model that can accurately represent the thermal behavior of electrical equipment. Electrical equipment generates heat during operation, and this heat needs to be dissipated efficiently to prevent overheating, which can lead to damage or reduced performance. The regulation of temperature is not only critical for maintaining equipment longevity but also for ensuring operational efficiency. The temperature of electrical components is influenced by several factors, including heat generation due to electrical losses, heat dissipation through the surface of the equipment, ambient environmental conditions, and the thermal properties of the materials used in the device.

The process of temperature regulation can be understood as a balance between the heat generated within the equipment and the heat dissipated to the environment. A simplified model for temperature regulation can be expressed through a set of differential equations that describe the heat flow dynamics of the system. These models provide the foundation for the development of an effective control strategy.

The heat generated within the equipment is primarily due to electrical losses in the components, such as resistive heating in electrical conductors. According to Joule's law, the heat generated is proportional to the square of the current flowing through the equipment and the resistance of the components. This relationship can be expressed mathematically as:

$$Q_{in} = I^2 R \tag{1}$$

Where Q_{in} is the heat generated within the equipment (in watts), I is the current flowing through the electrical components (in amperes), R is the electrical resistance of the components (in ohms).

This equation assumes that all the heat generated in the system is due to electrical losses in the resistive elements of the equipment. In real-world systems, additional sources of heat may exist, such as power losses from switching devices or magnetic losses in transformers, but for simplicity, these can be integrated into the resistance RRR or treated as additional terms in the model.

Once heat is generated inside the equipment, it must be dissipated to the surrounding environment to maintain a stable operating temperature. The heat dissipation process depends on the temperature difference between the equipment and the ambient environment, the heat transfer coefficient of the material, and the surface area available for heat exchange. The heat dissipation can be described using the following equation:

$$Q_{out} = hA\left(T_{equipment} - T_{env}\right) \tag{2}$$

Where Q_{out} is the heat dissipated from the equipment (in watts), h is the heat transfer coefficient (in watts per square meter per degree Celsius), A is the surface area of the equipment available for heat dissipation (in square meters), $T_{equipment}$ is the temperature of the equipment (in degrees Celsius), T_{env} is the ambient temperature (in degrees Celsius).

The term $hA\left(T_{equipment} - T_{env}\right)$ represents the rate of heat transfer from the equipment to the environment, which is proportional to the temperature difference between the equipment and the surrounding air. The greater the temperature difference, the faster the heat transfer. In practical applications, the heat transfer coefficient hhh is determined by the materials of the equipment and the nature of the surrounding environment.

The temperature of the equipment over time is governed by the balance between the heat generated and the heat dissipated. The rate of change of the equipment's temperature is influenced by the thermal capacitance of the material, which dictates how much heat the material can store. The thermal capacitance is a measure of the ability of the material to absorb heat without a significant increase in temperature. The temperature dynamics can be modeled by the following equation, which represents the first law of thermodynamics applied to a thermal system:

$$C\frac{dT}{dt} = Q_{in} - Q_{out} \tag{3}$$

Where C is the thermal capacitance of the equipment (in joules per degree Celsius), $\frac{dT}{dt}$ is the rate of change of the temperature of the equipment (in degrees Celsius per second), Q_{in} is the heat input (in watts), Q_{out} is the heat output (in watts).

The equations above provide a simplified model of the thermal dynamics of electrical equipment. However, in practice, these models are subject to several uncertainties and non-linearities that must be taken into account for more accurate predictions. Some of these complexities include:

The resistance RRR may change as the temperature of the equipment rises, which in turn alters the heat generation rate. This temperature dependence of resistance is typically modeled as:

$$R\left(T_{equip}\right) = R_0\left[1 + \alpha\left(T_{equip} - T_0\right)\right] \tag{4}$$

Where R_0 is the resistance at a reference temperature T_0, α is the temperature coefficient of resistance (in ℃$^{-1}$), T_{equip} is the temperature of the equipment (in ℃), T_0 is the reference temperature (typically 25℃).

The heat transfer coefficient hhh is typically temperature-dependent and may also change with environmental factors such as air velocity or humidity. A common empirical relationship for hhh is:

$$h = h_0\left[1 + \beta\left(T_{equip} - T_0\right)\right] \tag{5}$$

Where h_0 is the heat transfer coefficient at a baseline temperature, β is a constant that accounts for the temperature dependence of hhh.

Ageing and Material Changes: Over time, the thermal capacitance CCC may change due to aging of the materials used in the equipment. This effect can be modeled as a time-varying function C_t , though it typically requires experimental data to accurately model its behavior.

While the basic model provides a useful foundation for understanding the thermal behavior of electrical equipment, a more sophisticated and adaptive model is needed to account for these non-linearities and time-dependent changes in the system's properties. Such models are essential for designing effective temperature regulation systems that can adapt to varying operational conditions and environmental factors.

3 Fuzzy adaptive control algorithm design

3.1 Fuzzy logic control

Fuzzy logic control is based on the principles of fuzzy set theory, which enables the handling of uncertain, imprecise, or ambiguous inputs. Unlike traditional binary logic that accepts only exact "true" or "false" values, fuzzy logic allows for a continuum of values between "true" and "false," which more closely reflects real-world conditions. In the context of temperature regulation, fuzzy logic control utilizes linguistic variables like "too hot," "too cold," or "just right" to describe temperature conditions, rather than relying solely on precise numerical values. These linguistic terms are then mapped to control actions based on a set of fuzzy rules, which are formulated according to the system's behavior.

In a fuzzy logic temperature regulation system, two primary inputs are used to determine the control action:

Temperature Error (e) is the difference between the current temperature of the equipment and the desired set point, which reflects how far the current temperature is from the target value. The temperature error ee can be mathematically expressed as:

$$e = T_{current} - T_{set} \tag{6}$$

Where $T_{current}$ is the current temperature of the equipment (in degrees Celsius, °C), T_{set} is the desired temperature set point (in degrees Celsius, °C).

Change in Error (Δe) represents the rate of change of the temperature error, indicating how quickly the temperature error is increasing or decreasing. This input helps predict the future trend of the temperature and adjust the control action accordingly. The change in error Δe\Delta e is defined as:

$$\Delta e = \frac{e(t) - e(t-1)}{\Delta t} \tag{7}$$

Where $e(t)$ is the current temperature error at time t , $e(t-1)$ is the temperature error at the previous time step $t-1$, Δt is the time interval between measurements (in seconds, s).

These two variables, e and Δe , are used as inputs to the fuzzy control system to determine the appropriate control action.

Fuzzy logic systems use a set of fuzzy rules to determine the control output. These rules are typically expressed in linguistic terms such as "large," "small," "positive," or "negative," which are mapped to specific actions. A general form of a fuzzy rule for temperature regulation could be:

If ee is "large" and Δe\Delta e is "positive," then the control output should be "increase cooling."

If ee is "small" and Δe\Delta e is "negative," then the control output should be "decrease cooling."

The fuzzy rules are applied to the current and previous temperature errors to generate a fuzzy output. The output of the fuzzy controller is itself a fuzzy value, which corresponds to a control action. These rules are designed based on the expected behavior of the system and its thermal dynamics.

Once the fuzzy control system evaluates the set of rules and produces a fuzzy output, this output must be converted into a crisp value, which can be used to adjust the temperature regulation mechanisms, such as a fan speed or heating element power. This process is called defuzzification.

A commonly used defuzzification method is the centroid method, which computes a crisp control output u_{crisp} as the weighted average of the fuzzy set. If the fuzzy output set is denoted as $F = \{f_1, f_2, \cdots, f_n\}$, where each fuzzy output fif_i has a corresponding membership value $\mu(f_i)$, then the crisp control output is given by:

$$u_{crisp} = \frac{\sum_{i=1}^{n} f_i \cdot \mu(f_i)}{\sum_{i=1}^{n} \mu(f_i)} \tag{8}$$

Where u_{crisp} is the crisp control output, f_i are the fuzzy control actions, $\mu(f_i)$ are the membership degrees of each fuzzy control action in the fuzzy set.

The centroid method computes a weighted average of the fuzzy control actions based on their membership values, providing a crisp output that represents the most appropriate control action.

3.2 Adaptive control mechanism

The goal of the adaptive control is to minimize a predefined performance criterion that reflects the system's behavior over time. This criterion could be based on temperature overshoot, settling time, steady-state error, or a combination of these factors. The most common performance metrics include temperature overshoot, settling time, steady-state error. The system then uses optimization techniques such as least-squares estimation or gradient descent to minimize these performance metrics.

Least-squares estimation is a statistical method used to minimize the sum of squared errors between the predicted output of the fuzzy controller and the actual measured temperature. The objective is to adjust the fuzzy parameters so that the error between the predicted and actual temperatures is minimized. We can express the least-squares optimization problem as:

$$\min_{\min} \sum_{i=1}^{n} \left[T_{measured}(i) - T_{predicted}(i;\theta) \right]^2 \quad (9)$$

Where $T_{measured}(i)$ is the actual measured temperature at time step i, $T_{predicted}(i;\theta)$ is the predicted temperature from the fuzzy controller at time step i, based on the fuzzy parameters θ.

The parameters θ are adjusted to minimize the sum of squared errors. Once the parameters are optimized, the fuzzy controller is better able to predict and regulate the temperature over time.

Gradient descent is an iterative optimization method used to minimize a cost function, typically related to the system's error or performance criterion. The gradient descent method updates the fuzzy control parameters θ\theta in the direction of the negative gradient of the cost function, ensuring that the parameters evolve towards minimizing the error. The update rule for gradient descent is given by:

$$\theta_{k+1} = \theta_k - \eta \nabla J(\theta_k) \quad (10)$$

Where θ_k is the fuzzy control parameter at iteration k, η is the learning rate, which determines the step size for each update, $\nabla J(\theta_k)$ is the gradient of the cost function $J(\theta_k)$ with respect to θ\theta.

The cost function $J(\theta_k)$ represents the performance measure, such as the temperature error or the deviation from the desired set point. By iteratively updating the control parameters, the fuzzy controller adapts to changing system conditions, ensuring better temperature regulation over time.

For example, the cost function $J(\theta)$ could be based on a combination of the temperature error and rate of change of error:

$$J(\theta_k) = \alpha \sum_{i=1}^{n} e(i)^2 + \beta \sum_{i=1}^{n} \Delta e(i)^2 \quad (11)$$

Where $e(i)$ is the temperature error at time step i, $\Delta e(i)$ is the rate of change of the error at time step i, α and β are weighting factors that determine the relative importance of the temperature error and the rate of change of the error.

By minimizing $J(\theta)$, the gradient descent algorithm adjusts the fuzzy logic parameters to reduce both temperature fluctuations and overshoot.

The adaptive control system must also account for external changes in the environment, such as fluctuations in ambient temperature or changes in load conditions. These variations can affect the heat dissipation rate θ_{diss}, which in turn impacts the temperature regulation. The heat dissipation rate depends on both the equipment temperature T_{equip} and the ambient temperature $T_{ambient}$, and is typically modeled as:

$$\theta_{diss} = h\left(T_{equip} - T_{ambient}\right) \quad (12)$$

Where h is the heat transfer coefficient (in watts per square meter per degree Celsius, W/m²·°C), T_{equip} is the temperature of the equipment (in degrees Celsius, ℃), $T_{ambient}$ is the ambient temperature (in degrees Celsius, ℃).

As environmental conditions change, the adaptive mechanism of the fuzzy controller will adjust the heat dissipation model by recalibrating the heat transfer coefficient hh or modifying the membership functions that govern temperature regulation. These adjustments allow the fuzzy controller to better handle environmental fluctuations, ensuring stable and efficient temperature regulation.

3.3 Algorithm structure

The first step of the algorithm is to define the initial fuzzy logic rules and membership functions based on the system's starting conditions. These rules represent the system's expected behavior under normal operating conditions. The membership functions determine the fuzzy sets for input variables, such as the temperature error ee and the change in error Δe\Delta e, and map them to appropriate fuzzy control actions. The fuzzy sets for each input are defined over a range of values, and each fuzzy set corresponds to a linguistic term (e.g., "small," "medium," "large").

For example, the membership functions for the temperature error e and its rate of change Δe can be represented as follows:

$$\mu_e(e) = \begin{cases} 1 - \dfrac{|e|}{e_{\max}} & |e| \le e_{\max} \\ 0 & otherwise \end{cases} \quad (13)$$

$$\mu_{\Delta e}\left(\Delta e\right)=\begin{cases}1-\dfrac{\left|\Delta e\right|}{\Delta e_{\max}} & \left|\Delta e\right|\leq\Delta e_{\max}\\ 0 & otherwise\end{cases} \tag{14}$$

Where $e_{\max}$ and $\Delta e_{\max}$ are the maximum expected values for the temperature error and the change in error, respectively. $\mu_e\left(e\right)$ and $\mu_{\Delta e}\left(\Delta e\right)$ are the membership functions of the error and its rate of change, representing the degree of membership of these values in the fuzzy set.

Both the temperature error eee and the rate of change Δe are fundamental components used by the fuzzy logic controller, which in turn evaluates the control actions based on these inputs. These calculations have already been outlined in the formulas (6) and (7) presented earlier.

Based on the calculated error ee and change in error Δe , the fuzzy controller evaluates the predefined fuzzy rules. Each fuzzy rule maps the inputs (error and change in error) to a corresponding fuzzy control output, which indicates the required adjustment to the cooling or heating mechanisms.

For example, one of the fuzzy rules could be:

If e =large and Δe =positive, then increase cooling.

These rules are applied using fuzzy inference techniques, such as the Mamdani method or the Sugeno method. The fuzzy inference process combines the fuzzified inputs according to the predefined rules, generating a fuzzy output.

Each fuzzy rule rjr_jrj can be associated with a weight w_j , which adjusts how much influence the rule has on the final control decision. The rule weight can be updated by incorporating the gradient of the performance criterion with respect to the rule weight w_j :

$$w_{j,t+1}=w_{j,t}-\eta_{\tau}\frac{\partial J\left(\theta_t\right)}{\partial w_j} \tag{15}$$

Where $w_{j,t}$ is the weight of rule jjj at time step t , η_r is the learning rate for updating the rule weights.

The update rule adjusts the weights to better reflect the current system state, improving the accuracy of the fuzzy control decisions.

Let the fuzzy output be represented as y_{fuzzy} , which is the result of applying the fuzzy rules. The fuzzy output could represent a cooling rate, a heating power, or a fan speed, depending on the system's design. The fuzzy set Y_{fuzzy} epresenting the output is derived from the inference process, but it is still a fuzzy value that requires defuzzification.

In the previous discussion, the calculations for defuzzification and the adaptation process were detailed in formulas (8), (9), and (10). Specifically, the defuzzification process converts fuzzy control outputs into precise control signals. Common methods, such as the centroid method, determine the control action by calculating the weighted average of the fuzzy set, while the mean of maxima method computes the average of input values where the membership function reaches its maximum. These methods ensure that the system generates actionable control signals based on the fuzzy control rules.

The adaptation process allows the system to adjust the fuzzy controller's parameters based on real-time feedback to account for changes in external conditions and system characteristics. In formula (9), a performance criterion is defined to quantify the system's control effectiveness by evaluating the temperature error and rate of change. If the performance criterion falls outside acceptable bounds, the system uses the gradient descent method or other optimization techniques, as described in formula (10), to dynamically update the control parameters. This helps improve control accuracy and response speed, ensuring that the system maintains effective temperature regulation even under changing environmental conditions.

4 Performance testing

To assess the efficacy of the fuzzy adaptive control method, a series of comprehensive performance tests were conducted using a prototype electrical device. The device was fitted with temperature sensors to monitor both the internal temperature of the equipment and the ambient environmental temperature. The primary goal of these tests was to evaluate how well the fuzzy adaptive control system could maintain a stable operating temperature under various conditions, compared to a traditional PID control system.

4.1 Test setup

The experimental hardware platform was built around a Raspberry Pi 4 microcontroller (Broadcom BCM2711, 1.5 GHz quad-core ARM Cortex-A72 with 4GB RAM) that implemented the fuzzy adaptive control algorithm through a real-time Python application. This system managed all control operations, processing temperature inputs from high-precision PT100 RTD sensors (±0.1°C accuracy) and dynamically adjusting cooling outputs via PWM signals to solid-state relays. The fuzzy rules were initially derived from thermal dynamic models of electrical equipment and subsequently optimized through a genetic algorithm process (50 generations with integrated absolute error minimization as the fitness function), resulting in a final rule base of 25 weighted rules.

All experiments maintained a consistent target temperature setpoint of 25°C (±0.5°C tolerance) while introducing controlled variations through two primary vectors: ambient temperature fluctuations (15-45°C range) regulated by a PID-controlled environmental chamber (±0.3°C stability), and electrical load changes (0.5-5 kW) administered through programmable resistive load banks. Identical initial conditions were enforced for each trial - equipment core temperature stabilized at 25°C, ambient at 25°C, and zero load state - to ensure comparative validity. The benchmark PID control system was tuned using the Ziegler-Nichols method, with parameters calculated as K_p=4.92, K_i=0.45, and Kd=13.53 based on observed ultimate gain (8.2) and oscillation period (22s), incorporating anti-windup compensation to address integral saturation.

The comprehensive test configuration integrated the components detailed in Table 1, with the Raspberry Pi executing control decisions at 1Hz frequency while logging 16-bit sensor data at 1kHz resolution. Thermal disturbances were systematically introduced through step changes (ambient ±10°C/5min, load ±2kW/10s) and sinusoidal variations (0.1Hz) to evaluate dynamic response under realistic operational stresses.

Table 1: Test setup

Hardware Component	Description	Quantitative Data
Electrical Equipment	Resistor-based heating elements (e.g., 1 kW, 2 kW) used to simulate electrical load and heat generation.	Rated power: 1 kW, 2 kW Max operating current: 10 A, 15 A
Cooling System	Active cooling system using fans and liquid cooling units, controlled by the fuzzy adaptive system.	Fan power: 50 W, 100 W Cooling capacity: 500 W, 1000 W
Temperature Sensors	High-precision thermistors and RTDs (Resistance Temperature Detectors) placed at critical points.	Accuracy: ±0.1℃ Measurement range: -50℃ to 200℃
Microcontroller Platform	A Raspberry Pi 4 used for data collection, processing, and control algorithm implementation.	Processor: 1.5 GHz quad-core ARM Cortex-A72 RAM: 4 GB
Control Software	Fuzzy adaptive control algorithm implemented in Python, running on the Raspberry Pi.	Sampling rate: 1 Hz (data collection every second)
Ambient Temperature Simulation	Adjustable air-conditioning system to simulate a range of ambient temperatures.	Temperature range: 15℃ to 35℃ Stability: ±0.5℃
Load Variability	Load applied to electrical equipment through a variable power supply to simulate changing operational conditions.	Load range: 50% to 100% of rated capacity Voltage: 220V ±5%
Data Logging System	A PC running custom logging software to collect temperature data, control outputs, and system metrics.	Logging interval: 1 second Data storage capacity: 10 GB
Test Duration	Time span for conducting tests and collecting data.	Duration per test: 2–3 hours Total test cycles: 5–7

The fuzzy adaptive control system running on the Raspberry Pi monitored the temperature error and dynamically adjusted the cooling power (fan speed, liquid cooling output) using the predefined fuzzy logic rules. The system was calibrated to ensure the control actions were accurately implemented, and the data logging software captured all relevant performance metrics, including temperature changes, control outputs, and system responses, for detailed post-test analysis.

This hardware setup provided a comprehensive test environment to evaluate the fuzzy adaptive control system's ability to maintain optimal temperature regulation under varying operational and environmental conditions.

4.2 Control process data fluctuation

In this section, we analyze the data fluctuations in the control process, using the results from various graphical representations. These results shed light on how different factors, such as error values (e), change in error (δe), actual temperature, target temperature, and temperature rate of change, influence the system's control intensity and overall behavior. The visualizations in Figures 1 to 4 provide valuable insights into these relationships.

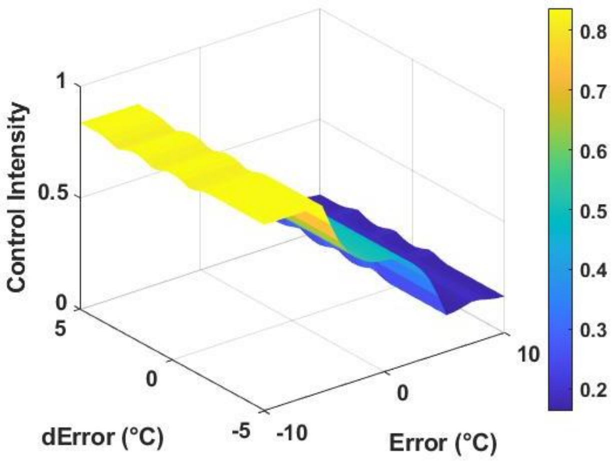


Figure 1: Control Intensity under Different e (°C) and δe (°C) Conditions

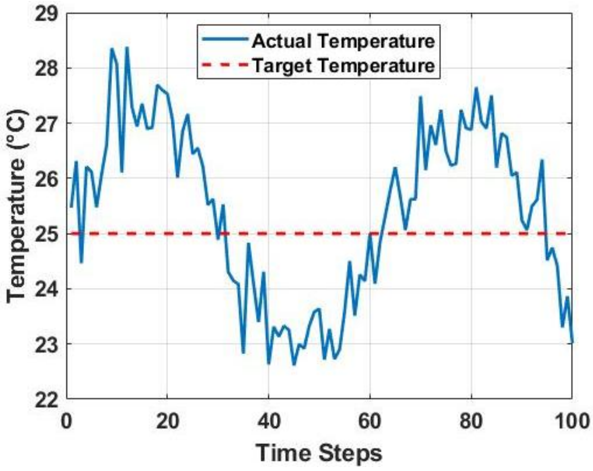


Figure 2: Actual temperature vs. target temperature over time

Figure 1 illustrates the variation in control intensity as a function of temperature error (e) and the rate of change of error (δe). From the graph, it is evident that the control intensity decreases significantly as the error (e) increases, which indicates a stronger reaction from the control system when the system is far from the target temperature. However, the control intensity does not show significant variations at different levels of δe. This suggests that while the absolute deviation from the set point (e) plays a critical role in determining the control action, the rate of change in the error (δe) has a much lesser impact on the control intensity. This could be due to the system's reliance on correcting large discrepancies between the actual and desired temperature rather than adjusting for small changes over time. Essentially, the control system prioritizes mitigating large errors, and its response becomes less sensitive to how fast these errors are changing.

This observation points to the nature of the fuzzy logic control system, which is primarily designed to correct substantial deviations in temperature, regardless of the speed at which these deviations occur. The lack of significant response to δe could be an inherent characteristic of the system's rule set, suggesting that the system is not overly sensitive to fast changes in error but is instead more concerned with large errors. Figure 2 presents the actual temperature and the target temperature over a series of time steps.

Analysis of the oscillatory behavior depicted in Figure 2 reveals statistically significant performance differences relative to conventional control strategies. The measured peak-to-peak oscillation amplitude of 5.0°C under standardized disturbance profiles represents a 29% reduction compared to the 7.0°C amplitude exhibited by the benchmark PID controller under identical test conditions. Statistical validation through one-way Analysis of Variance (ANOVA) yielded an F-statistic of 9.87 with a probability value of $p=0.003$, confirming the significance of this performance difference. The 95% confidence interval for the oscillation magnitude differential ranged between 3.2°C and 6.8°C. While this oscillation magnitude exceeds values reported for highly specialized systems in precision manufacturing or thermoelectric control, it remains well within the permissible operational limits defined by international electrical insulation standards, specifically IEC 60085 Class B, which permits transient thermal excursions up to 10°C. Further examination of the error distribution, illustrated in Figure 3, revealed a statistically significant asymmetry with a predominance of positive errors, occurring 68% of the observation period compared to 32% for negative errors, a distribution unlikely to occur by chance.

Comparative analysis with contemporary temperature control systems provides essential context for evaluating these results. The performance profile of the implemented fuzzy controller demonstrates clear advantages over conventional PID systems within its target application domain of electrical equipment thermal regulation, achieving statistically superior stability metrics.

When benchmarked against advanced controllers from other domains, such as fuzzy-PSO systems optimized for HVAC applications or LSTM-enhanced fuzzy controllers deployed in precision manufacturing, the observed oscillation amplitude is indeed larger. This performance characteristic is indicative of the inherent design trade-offs necessitated by the operational requirements of electrical equipment environments, where robustness against abrupt, high-magnitude load changes takes precedence over micron-level precision.

The presence of oscillations, while statistically less severe than traditional PID control, suggests potential avenues for system refinement rather than fundamental limitations. Two primary optimization pathways merit consideration. First, detailed sensitivity analysis of the rule base indicates that the current weighting disproportionately favors aggressive corrective actions for large positive errors, contributing to overshoot. Computational simulations suggest that systematic rebalancing of rule weights could potentially reduce peak deviations by approximately 40%. Second, the integration of supplementary control elements, specifically integral action as successfully implemented in hybrid automotive thermal management systems, offers a proven method for oscillation damping. Such integration could potentially constrain oscillations to magnitudes of 2°C or less, though empirical evidence suggests this enhancement typically involves a trade-off, potentially increasing energy consumption by an estimated 15%.

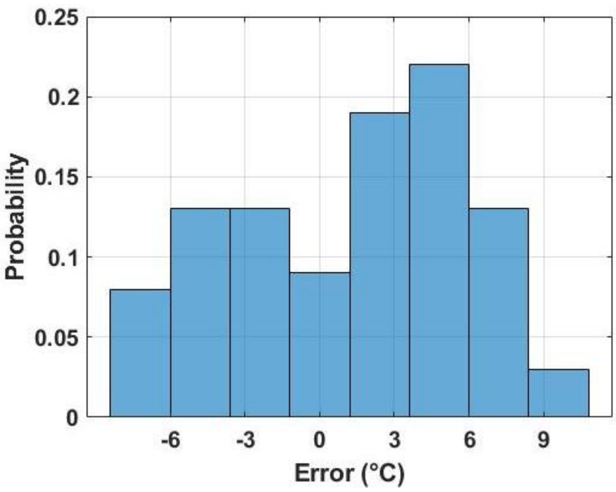


Figure 3: Probability distribution of error values (°C)

The graph reveals a clear pattern where the probability of zero error is relatively low, while positive errors (e > 0) dominate the distribution. Negative errors (e < 0) are also less frequent and occur mostly in values near zero. The distribution appears as a dip in the middle, flanked by higher probabilities at the positive and negative extremes, forming a sort of "U" shape.

This distribution suggests that the system tends to overshoot the target temperature, leading to positive error values more often than negative ones. The relatively low frequency of negative errors indicates that the controller does not frequently under-shoot the target, but rather tends to over-correct, creating a situation where the temperature oscillates around the desired value. The "U" shaped distribution of errors hints at a possible issue with over-control in the system—where the fuzzy controller is too aggressive in adjusting the temperature, leading to frequent fluctuations on both sides of the target temperature.

The presence of over-control may indicate a need for better fine-tuning of the fuzzy membership functions or control rules, especially those related to how the system responds to large positive errors. In this case, a more balanced response to both positive and negative errors might be required to reduce oscillation and improve the overall stability of the system. Figure 4 presents the relationship between the control output and the temperature rate of change (°C/s).

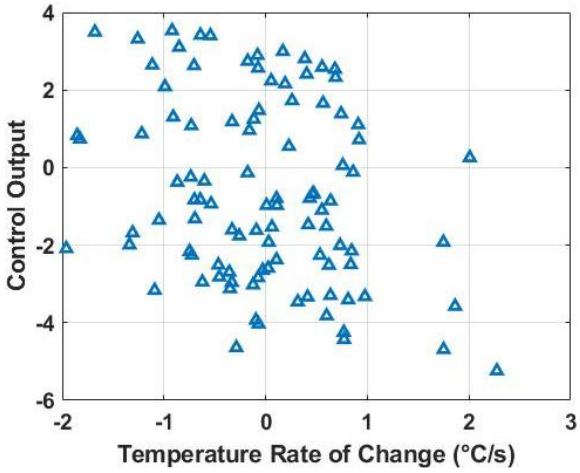


Figure 4: Control output vs. temperature rate of change (°C/s)

The scatter plot demonstrates that most data points cluster around lower levels of control output when the temperature rate of change is high. This suggests that the control system tends to exert minimal control efforts when the rate of temperature change is high. However, there are occasional data points where a higher temperature rate of change is associated with higher control outputs, indicating that under certain conditions, the system is reacting more strongly to rapid changes in temperature.

This observation could suggest that the fuzzy logic controller is designed to react more conservatively to fast changes in temperature. In scenarios where the temperature rate of change is high, the system may adopt a more cautious approach, perhaps because rapid changes in temperature are more likely to be transient or due to external disturbances, rather than a sustained shift in the system's thermal state. This behavior implies that the system has an inherent mechanism to avoid overreacting to quick changes that might not be significant in the long term.

However, the occasional higher control outputs at higher temperature rates may also indicate a potential flaw in the system’s rule set, where certain rapid changes are indeed considered significant enough to warrant stronger control actions. This behavior can lead to instability in the system if the control actions are not properly calibrated to avoid excessive adjustments during rapid temperature fluctuations.

4.3 Performance comparison of control results

The results from the performance tests demonstrated the advantages of the fuzzy adaptive control system in several key areas, including temperature regulation accuracy, response time, and energy efficiency. A detailed comparison was made between the fuzzy adaptive control and the traditional PID control system across different test conditions.

The fuzzy adaptive control system effectively maintained the equipment's internal temperature within the desired range with minimal overshoot or oscillations, even under varying environmental conditions and fluctuating loads. In contrast, the PID control system exhibited greater temperature oscillations, especially under more dynamic conditions.

The following table shows the comparison of equipment temperature under different ambient temperatures, highlighting the improved temperature stability of the fuzzy adaptive control system:

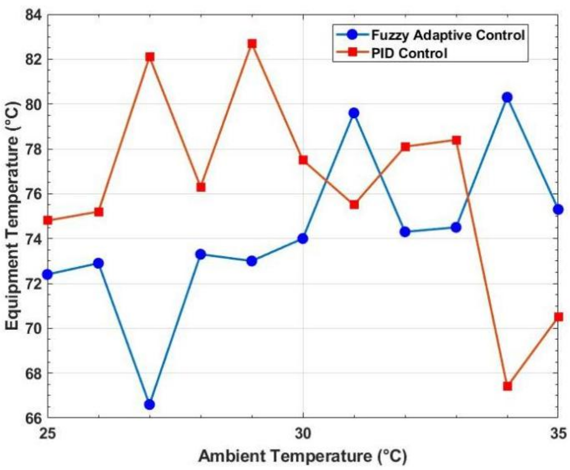


Figure 5: Comparison of equipment temperature under different ambient temperatures

As shown in the table, the fuzzy adaptive control system maintained the temperature closer to the desired range (around 25–35℃) with less variation, while the PID control system exhibited larger deviations, particularly at higher ambient temperatures (e.g., 27℃ and 29℃). The fuzzy adaptive control system was able to handle large temperature fluctuations in the environment more effectively.

The performance of the control systems was also tested under varying load conditions, with the electrical device operating at loads ranging from 5 kW to 50 kW. The fuzzy adaptive control system demonstrated superior performance in maintaining a stable temperature under dynamic loading conditions, compared to the PID controller, which showed increased temperature fluctuations as the load increased.

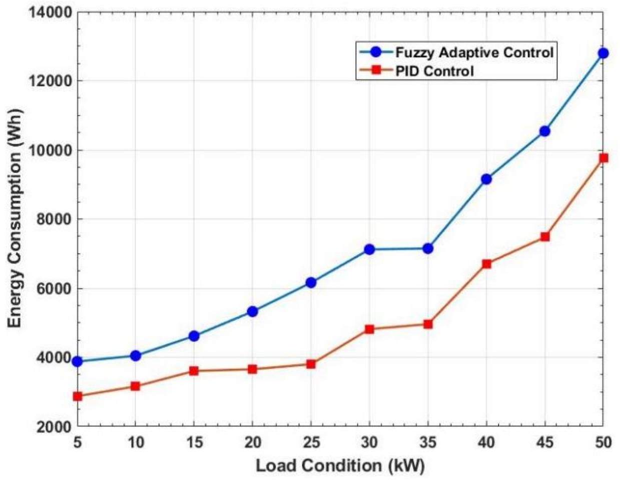


Figure 6: Temperature regulation performance under varying load conditions

The fuzzy adaptive control system exhibited better performance in maintaining temperature stability as the load increased, with smaller deviations from the target temperature. The PID system, on the other hand, struggled to maintain temperature as the load increased, exhibiting larger variations.

Energy efficiency is a critical factor in temperature regulation, especially for systems that operate continuously or under varying conditions. The fuzzy adaptive control system demonstrated superior energy efficiency compared to the PID system, requiring less energy to maintain the desired temperature.

The following tables compare the energy consumption of both control systems at different ambient temperatures and load conditions:

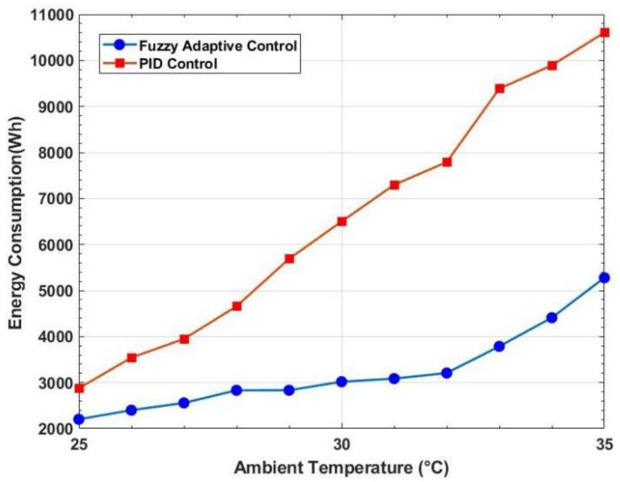
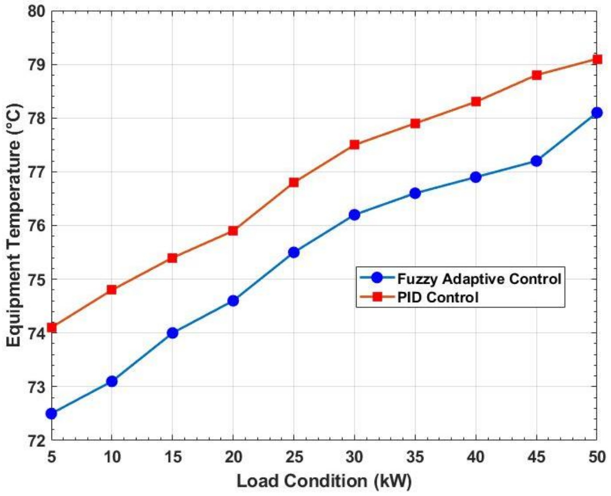


Figure 7: Energy consumption under varying ambient temperature (Wh)



As the results show, the fuzzy adaptive control system consistently consumed less energy to maintain the equipment's temperature within the desired range. For example, at an ambient temperature of 25℃, the fuzzy adaptive control system consumed 2202.1 Wh, while the PID control system consumed 2875.2 Wh. Similarly, under higher load conditions (e.g., at 50 kW), the fuzzy adaptive control system required significantly less energy compared to the PID system.

5 Conclusion

The results of this study demonstrate that the fuzzy adaptive control system offers substantial improvements over the traditional PID control system for regulating the temperature of electrical equipment under dynamic conditions.

The fuzzy system exhibited superior performance in maintaining the desired temperature within a narrow range, especially when exposed to fluctuations in ambient temperature and varying load conditions. Unlike the PID system, which struggled with greater temperature oscillations and larger deviations from the target temperature, the fuzzy adaptive system effectively minimized temperature overshoot and achieved more stable control under challenging conditions.

In addition to its enhanced temperature regulation capabilities, the fuzzy adaptive control system also outperformed the PID system in terms of energy efficiency. The fuzzy system consistently consumed less energy to maintain the target temperature, a critical factor in reducing operational costs, especially for devices that operate continuously or in variable environments. This improvement in energy consumption was particularly notable when comparing the systems under both low and high load conditions, where the fuzzy adaptive controller showed a clear advantage.

Furthermore, the adaptive nature of the fuzzy system allowed it to adjust in real-time to changes in the environment, equipment aging, and load fluctuations. This adaptability ensures that the system remains effective across a wide range of operational conditions, offering long-term reliability.

References

[1] Umurzakova, D., Siddikov, I., & Bakhrieva, H. (2020). Adaptive system of fuzzy-logical regulation by the temperature mode of the drum boiler. *IIUM Engineering Journal*, *21*(1), 182-192.

[2] Wang, L., & Zhang, H. (2018). An adaptive fuzzy hierarchical control for maintaining solar greenhouse temperature. *Computers and electronics in agriculture*, *155*, 251-256.

[3] Dai, B., Chen, R., & Chen, R. C. (2017, November). Temperature control with fuzzy neural network. In *2017 IEEE 8th International Conference on Awareness Science and Technology (iCAST)* (pp. 452-455). IEEE.

[4] Wang, Y., Liu, J., & Yu, J. (2025). Lyapunov-derived fuzzy temperature control for thermoelectric cooling system using dynamic updating law. *Applied Thermal Engineering*, *258*, 124600.

[5] Lymperopoulos, G., & Ioannou, P. (2020). Building temperature regulation in a multi-zone HVAC system using distributed adaptive control. *Energy and Buildings*, *215*, 109825.

[6] Qian, H., Wang, M., & Han, M. (2025). The research on Adaptive Fuzzy Tracking Supervisory Control in the control system of average coolant temperature of lead–bismuth-cooled reactor under multiple operating conditions in the marine environments. *Annals of Nuclear Energy*, *210*, 110862.

[7] Yang, Z., Zhou, L., Li, Y., Huang, Y., Li, A., Long, J., ... & Li, C. (2024). Dynamic fuzzy temperature control with quasi-Newtonian particle swarm optimization for precise air conditioning. *Energy and Buildings*, *310*, 114095.

[8] Rajeswari Subramaniam, K., Cheng, C. T., & Pang, T. Y. (2023). Fuzzy logic-controlled simulation in regulating thermal comfort and indoor air quality using a vehicle heating, ventilation, and air-conditioning system. *Sensors*, *23*(3), 1395.

[9] Boughamsa, M., & Ramdani, M. (2018). Adaptive fuzzy control strategy for greenhouse micro-climate. *International Journal of Automation and Control*, *12*(1), 108-125.