DESIGN OF A FUZZY CONTROLLER FOR A HEATING FURNACE SYSTEM

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(Received: 19 April 2025; Accepted: 23 May 2025; Published online: 25 June 2025)

***ABSTRACT*:** In thermal process control, conventional methods like PID often struggle to cope with nonlinearities, time delays, and external disturbances. This study presents the design and implementation of a Mamdani-type fuzzy logic controller for temperature regulation in furnace systems. Unlike traditional controllers, fuzzy logic offers flexibility, robustness, and does not require an accurate mathematical model. The proposed controller uses two input variables—temperature error and its rate of change—and one output variable to adjust the TRIAC firing angle, controlling the system's power input. Through MATLAB simulation and hardware implementation with LM35 sensors and TRIAC modules, the fuzzy system demonstrates rapid response, no overshoot, and stable operation across varying setpoints (50°C, 70°C, 90°C). Comparative results highlight the superior performance of fuzzy control over conventional PID, especially in systems with nonlinear behavior and dynamic characteristics. The findings confirm that fuzzy logic is a practical and efficient solution for real-time temperature control applications, offering high adaptability without manual parameter tuning.

KEY WORDS: fuzzy control; temperature regulation; Mamdani inference; nonlinear systems; TRIAC; LM35 sensor; real-time control; fuzzy logic controller.

1. INTRODUCTION

In industrial environments where thermal processes are involved—such as ceramic kilns, annealing furnaces, and drying chambers—accurate temperature regulation is essential to ensure product consistency, operational safety, and energy efficiency. While Proportional–Integral–Derivative (PID) controllers have long been the de facto choice due to their simplicity and broad applicability, they often fall short in handling systems with significant nonlinearity, time delays, and disturbances [1, 2]. It has motivated a wide body of research aimed at enhancing conventional PID strategies or developing intelligent control techniques better suited for complex thermal dynamics [3, 4].

Among these efforts, several recent studies have introduced promising ideas in intelligent and nonlinear control for thermal processes. However, a critical examination reveals that most still suffer from fundamental limitations—either in adaptability, practical implementation, or scalability [3]. This section reviews seven representative studies, each illustrating different directions of control strategy development, while highlighting the gaps that remain unresolved.

Nguyen Truong Sanh and Nguyen Chi Ngon (2017) proposed an approach that combines a single-neuron PID controller with an RBF neural network-based system identifier for a stirred-tank heating model. The method showed resilience against external disturbances in simulation. However, its reliance on online training introduces considerable computational overhead and poses risks of instability, especially under dynamic or high-speed thermal conditions [5].

Similarly, Phung Tien Duy and colleagues (2020) developed a self-tuning PID mechanism using iterative feedback with relay elements. Their method simplifies the PID tuning process and reduces manual effort. However, it still assumes a largely linear model structure. It depends on classical Ziegler–Nichols-based heuristics, which are not well-suited for thermal systems exhibiting strong nonlinear behavior or changing parameters [6].

Taking a different approach, Trieu Quoc Huy (2023) investigated a fuzzy–PID hybrid controller tailored for an agricultural drying furnace. While the combination leverages the intuitive flexibility of fuzzy logic, the fuzzy rule base is crafted manually, primarily through trial-and-error. It not only restricts scalability but also undermines robustness in the face of new or varying system configurations[7].

More advanced techniques, such as Model Predictive Control (MPC), were explored by Tran Thai Anh Au and Truong Thi Bich Thanh (2016). MPC offers a structured way to incorporate system constraints and future predictions into the control loop. However, its effectiveness relies heavily on the availability of accurate plant models. In systems with unmodeled nonlinearities or real-time constraints, MPC becomes computationally intensive and less practical for deployment on embedded hardware [8].

Another direction is gain scheduling, as demonstrated by Surus et al. (2023), who applied this technique to enhance a PID controller used in semiconductor crystal growth. By adjusting PID gains according to operating conditions, the authors achieved faster rise times and reduced overshoot. Nevertheless, gain scheduling cannot respond adaptively to unexpected system behavior or environmental changes, limiting its robustness in real-time applications [9].

To improve fuzzy PID performance, Meng Jintao and co-authors (2023) incorporated a genetic algorithm (GA) to optimize fuzzy rules and PID parameters for a vacuum annealing furnace. Although this method showed notable gains in control accuracy and energy efficiency, the design remains semi-heuristic and static. The fuzzy rules are still manually curated, which hinders online adaptability and complicates deployment in systems with variable thermal zones or operating conditions [10].

Gani et al. (2019) also focused on PID tuning using a GA, demonstrating reduced overshoot and better response times in an electric furnace system. Despite these improvements, their solution retains the classic PID structure, offering no mechanism to incorporate linguistic reasoning or handle qualitative uncertainty, both of which are essential in complex thermal environments [11].

Taken together, these studies illustrate significant strides in control system design but also reveal an overreliance on PID-based frameworks, whether enhanced by heuristics, hybridization, or optimization. What is still lacking is a shift toward fully intelligent control systems that operate independently of precise plant models or fixed-rule structures [12, 13, 14]. This limitation is not only apparent in industrial settings but also reflected in autonomous thermal management systems in microenvironments and Internet of Things (IoT)-based embedded platforms, where thermal unpredictability is prevalent and requires non-model-based solutions [15].

Motivated by these gaps, this paper introduces a purely fuzzy logic controller based on the Mamdani inference model [16], designed specifically for thermal systems. Unlike hybrid approaches that still depend on underlying PID dynamics or optimization loops, our method employs direct linguistic modeling, enabling it to reason in a human-like fashion without requiring prior knowledge of the plant model. The proposed system is simple to implement, interpretable, and inherently robust to noise and nonlinearity [17,18]. Through both simulation and hardware experimentation, we demonstrate its superior adaptability and performance compared to traditional and hybrid intelligent controllers [19,20].

2. CONTROL ALGORITHM

The program uses a fuzzy logic control system of the Mamdani type to regulate temperature through the LM35 sensor and TRIAC. The system has two input variables: the temperature error E (the difference between the set temperature and the measured temperature) and the rate of change of the error dE. Each input variable is defined by several fuzzy sets representing different levels, such as strong negative, near zero, positive, and very positive for the error, and small, medium, and large for the error's rate of change. The system output is the control value for the TRIAC firing time, also represented by fuzzy sets corresponding to different power levels. During operation, the system performs fuzzification (converting input values into degrees of membership in fuzzy sets), applies predefined fuzzy rules that relate the input variables to the output, and finally performs defuzzification to convert the fuzzy result into a specific control value. These fuzzy rules combine conditions on the error and its rate of change to determine the appropriate power level, thereby precisely adjusting the temperature as desired.

3. SIMULATION

3.1. Designing a Fuzzy System on MATLAB

The membership function plot for the error variable **e** uses five triangular functions labeled *am*, *z*, *d*, *zd*, and *rd*, representing different levels of temperature error from strongly negative to strongly positive. The range is set from –10 to 40, with functions more densely clustered near zero to increase sensitivity when the system is close to the desired temperature. The distribution is biased toward positive values, reflecting the typical behavior of heating systems where positive errors (temperature too low) are more frequent and critical. This asymmetric design improves control accuracy and responsiveness in real-world thermal regulation scenarios.

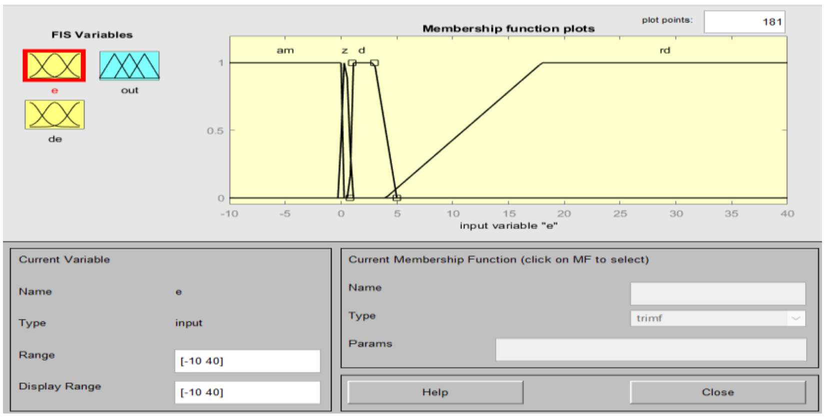


Fig. 1. Input variable error E

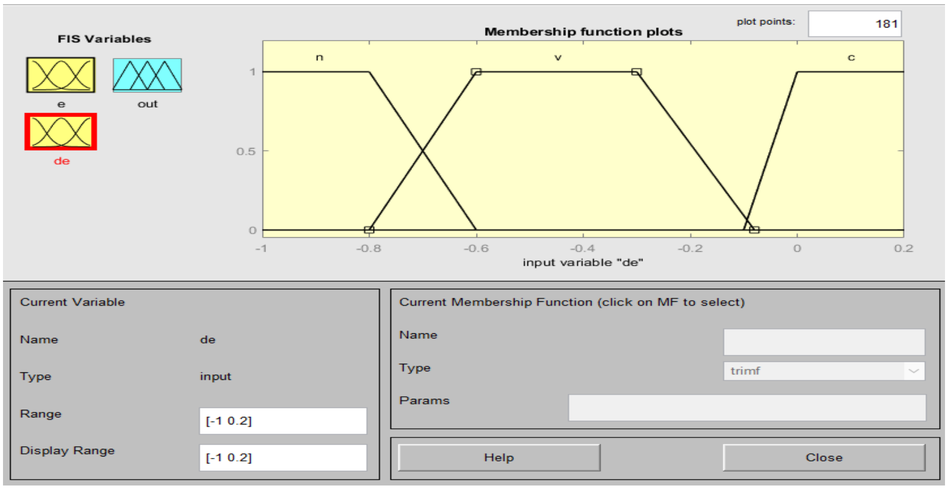


Fig. 2. Input variable error rate dE

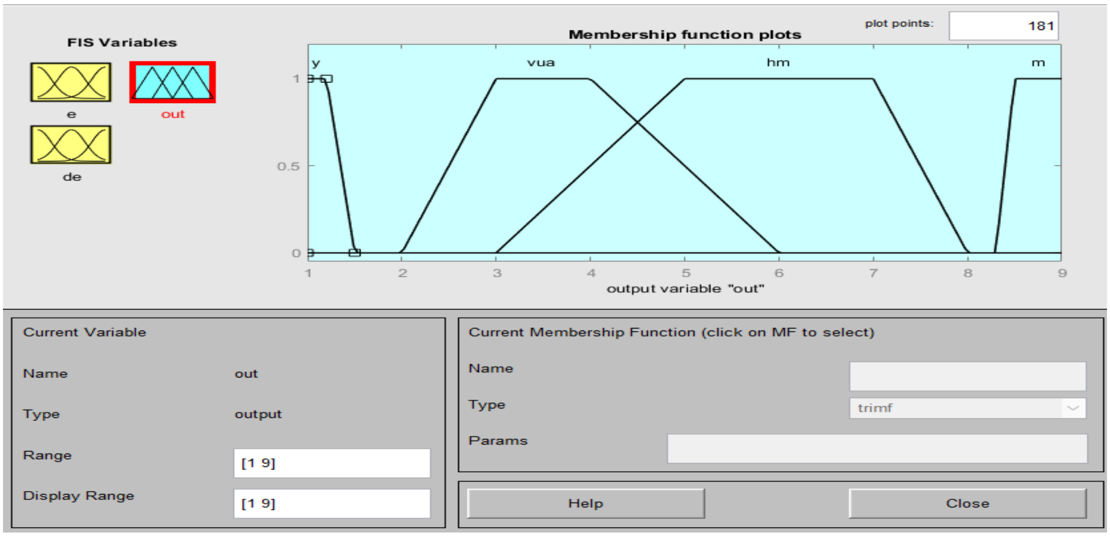


Fig. 3. Output variable: TRIAC firing time

The membership function plot for the derivative of error dE is defined over the range of -1 to 0.2 and uses three triangular functions: *n*, *v*, and *c*. This variable reflects the rate of change of the temperature error, helping the controller predict system behavior. The membership functions are asymmetrically distributed, with a wider spread on the negative side to give more attention to decreasing error trends, which are common in heating systems as temperature approaches the setpoint. This design improves the controller's ability to react smoothly and prevent overshooting.

The output variable out, which represents the TRIAC firing time, is defined over the range [1–9] and is divided into four triangular membership functions: *y*, *v*, *hm*, and *m*. This configuration allows the fuzzy controller to adjust the power supplied to the heating element based on the evaluated error and its rate of change. The output values increase from left to right, corresponding to longer TRIAC conduction times and thus greater heat output. This setup enables smooth, gradual control of the heater, reducing temperature overshoot and improving system stability.

Table 1: Fuzzy rule table

E\DE	**N**	**V**	**C**
A	Y	Y	Y
Z	V	HM	HM
D	HM	M	M
RD	M	M	M

The fuzzy rule table is designed to reflect an intuitive and gradual control strategy that adjusts the TRIAC firing time based on both the current error (E) and the rate of change of error (DE). When the temperature is much higher than the setpoint, corresponding to large negative errors, the system consistently applies the lowest output level to reduce heating power and prevent overshoot. As the error approaches zero, indicating the system is nearing the desired temperature, the controller responds with moderate output levels that balance between maintaining stability and ensuring sufficient heating. In these conditions, if the rate of change of error suggests that the temperature is rising too quickly, the output is reduced accordingly. Conversely, when the error becomes positive, meaning the actual temperature is below the setpoint, the system begins to increase the output. The greater the error, the stronger the output becomes, especially when the temperature is increasing slowly or not at all. It ensures that the system reacts aggressively to significant deviations while remaining conservative near the target value. The structure of the rule base allows the fuzzy controller to handle dynamic changes smoothly, avoiding abrupt transitions and ensuring a more stable temperature control process.

3.2. Simulation Model

The simulation model represents a furnace temperature control system using a fuzzy controller within the Simulink environment. The reference temperature is set at 50°C and is compared with the actual temperature measured from the furnace to calculate the error. The error and its derivative are fed into the fuzzy controller, which performs fuzzy inference to generate an appropriate control signal. This output signal is then sent to the furnace model, where the heating process is simulated. The actual furnace temperature is fed back into the system to complete the control loop. A Scope block is used to visually monitor the temperature response over time, allowing for an evaluation of the fuzzy controller's effectiveness in maintaining stability and tracking the desired temperature setpoint.

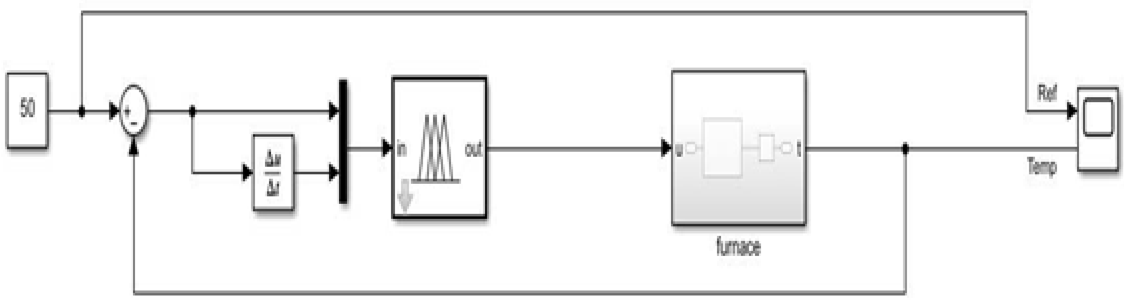


Fig. 4. Simulation Model

3.3. Simulation Results

Comment: The system's response demonstrates excellent temperature regulation capability. The temperature rises steadily and rapidly, reaching the desired value in a short period with virtually no overshoot. After the transient phase, the system quickly stabilizes and maintains the temperature close to the reference value with nearly zero steady-state error. It indicates that the controller is capable of accurately and effectively tracking the reference signal, ensuring stable long-term performance.

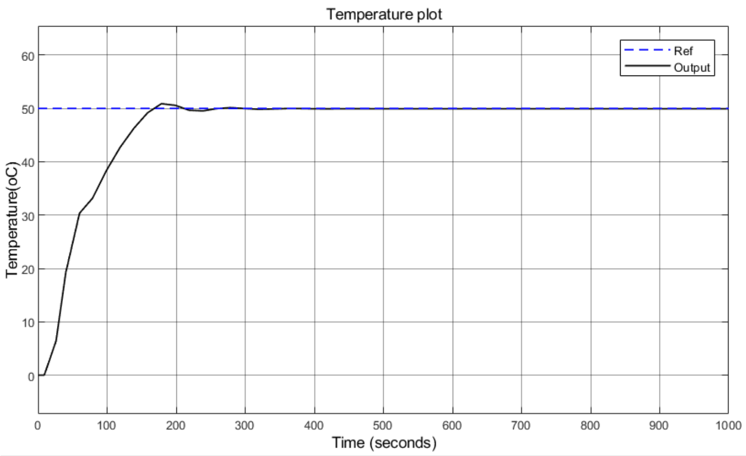


Fig. 5. Simulation results

4. MODEL EXPERIMENTATION

4.1. Hardware

The system consists of four main components: a computer interface, a control block, a power circuit, and a sensor block. The computer is used to monitor and adjust parameters through a graphical interface. The control block processes input data and generates appropriate control signals based on a fuzzy logic algorithm. These signals are then sent to the power circuit, which drives the heating element accordingly. The sensor block continuously measures the temperature and sends feedback to the control block to complete the closed-loop system.

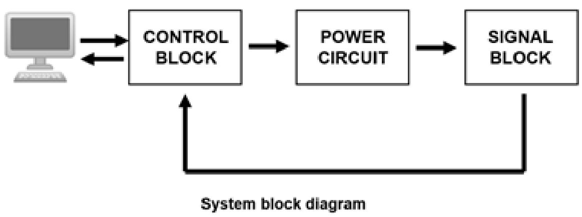
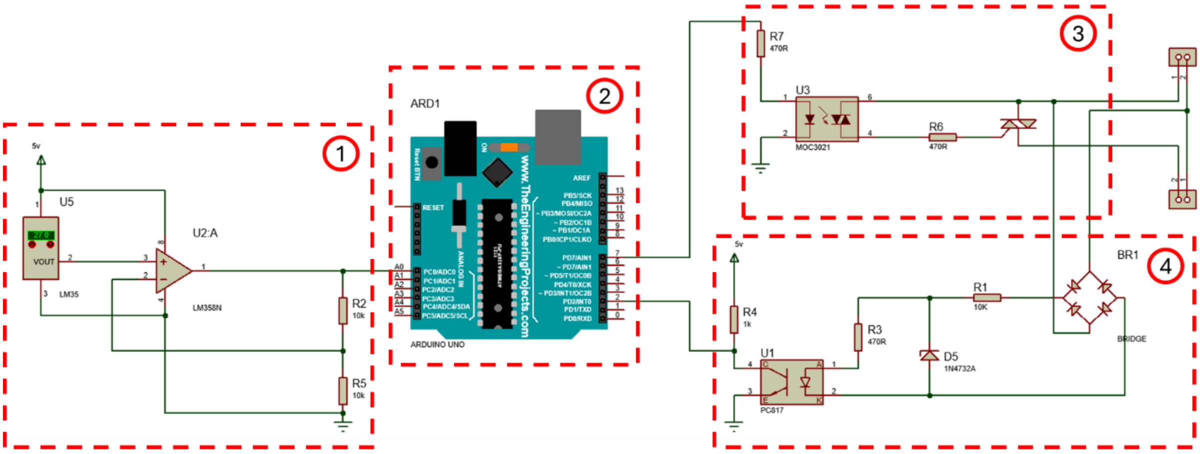


Fig. 6. Block diagram of the temperature control system



1. Amplifier circuit and LM35 sensor
2. Arduino Uno microcontroller
3. Power driver circuit
4. Zero – crossing detection circuit

Fig. 7. The circuit diagram

This system integrates sensing, control, and power modulation circuits to maintain a stable temperature in real time.

The temperature is measured using an LM35 precision sensor, which generates a voltage linearly proportional to the temperature (10 mV/°C). To enhance signal readability, especially for small changes in temperature, the sensor output is amplified using an LM358P operational amplifier configured as a non-inverting amplifier with a gain of 2. The amplified voltage is then fed into one of the Arduino's analog input pins.

Within the Arduino Uno, a fuzzy logic controller is implemented to process the input temperature and determine the appropriate heating power level. This control strategy is well-suited for systems with nonlinear dynamics and uncertain parameters, such as thermal processes.

In order to regulate the AC power delivered to the heating element (a lamp), the system employs phase-angle control. A zero-crossing detection circuit based on the PC817 opto-isolator detects the moments when the AC voltage crosses zero. These signals are sent to the Arduino, allowing it to precisely calculate and delay the firing angle for triggering the triac.

The power modulation is performed using the MOC3020 opto-isolator, which is designed for triggering triacs without zero-crossing detection built-in. It makes it ideal for phase-angle control applications, where firing must occur at any desired delay after the zero-crossing point. The MOC3020 ensures electrical isolation between the low-voltage control side and the high-voltage AC power line. The output of the MOC3020 drives a triac, which modulates the effective power supplied to the lamp.

Together, these components form a closed-loop temperature control system that is both responsive and electrically safe. The combination of fuzzy logic control with real-time power modulation ensures smooth and intelligent temperature regulation suitable for educational demonstrations and small-scale industrial systems.

4.2. Experimental Results

Survey of systems using fuzzy logic

Comment: The system response indicates good control performance with a short rise time and no significant overshoot. The temperature quickly rises from approximately 33°C to nearly 50°C within about 30 seconds, and then stabilizes around the desired setpoint. Minor oscillations appear after settling, but with small amplitude, demonstrating high stability. The steady-state error is nearly zero, proving the controller's ability to accurately and effectively track the reference temperature.

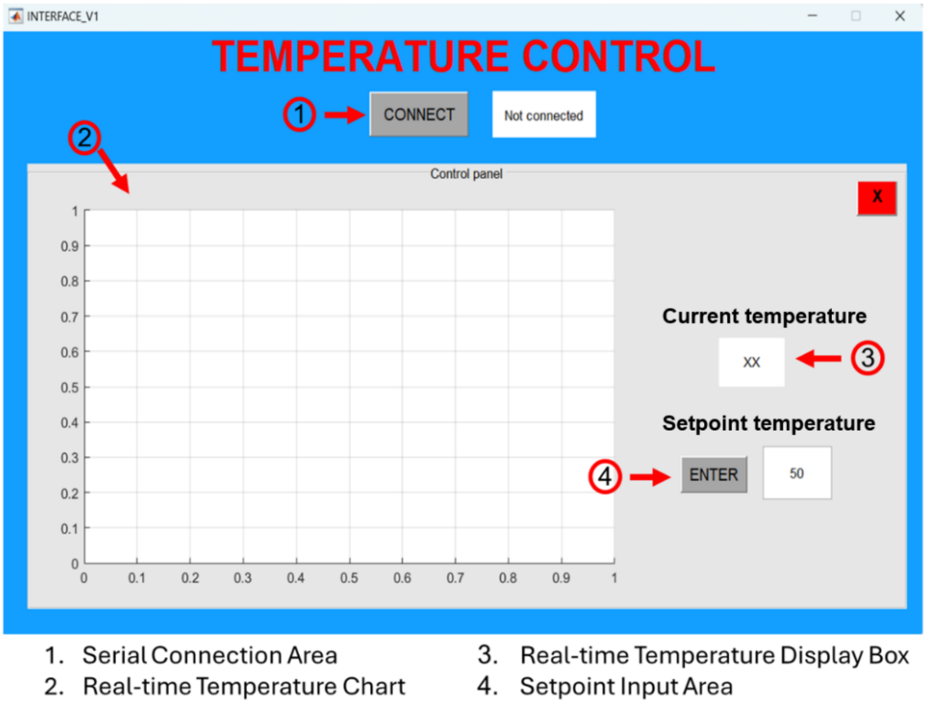


Fig. 8. User Interface Layout

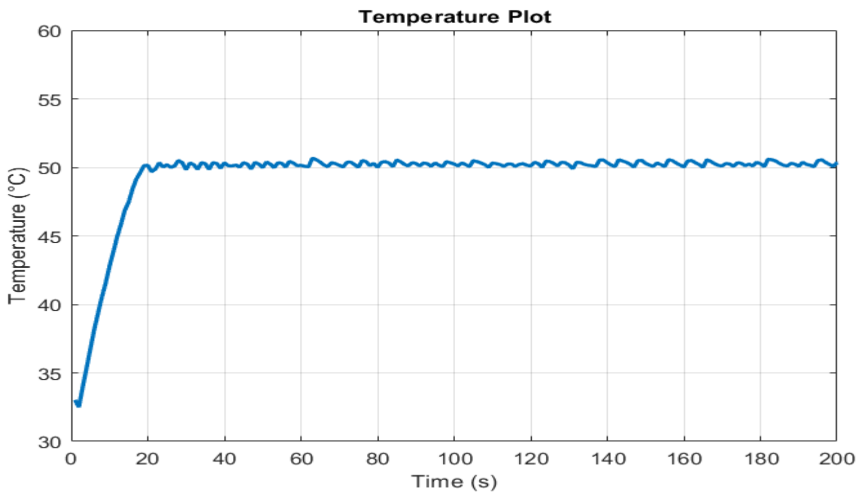


Fig. 9. Output response using fuzzy logic with a setpoint of 50°C

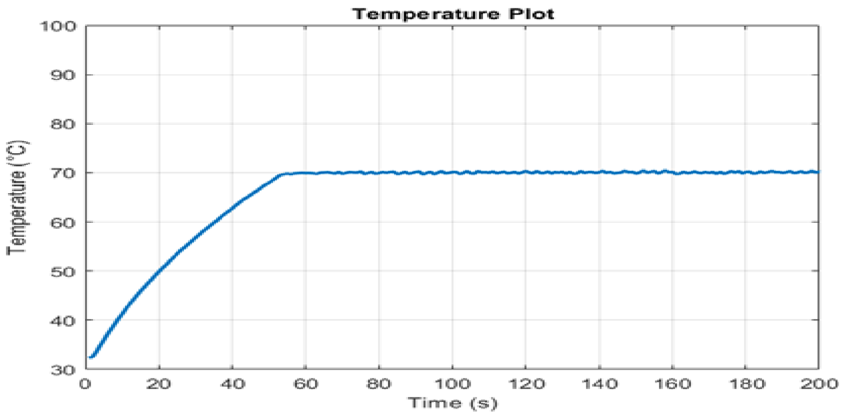


Fig. 10. Output response using fuzzy logic with a setpoint of 70°C

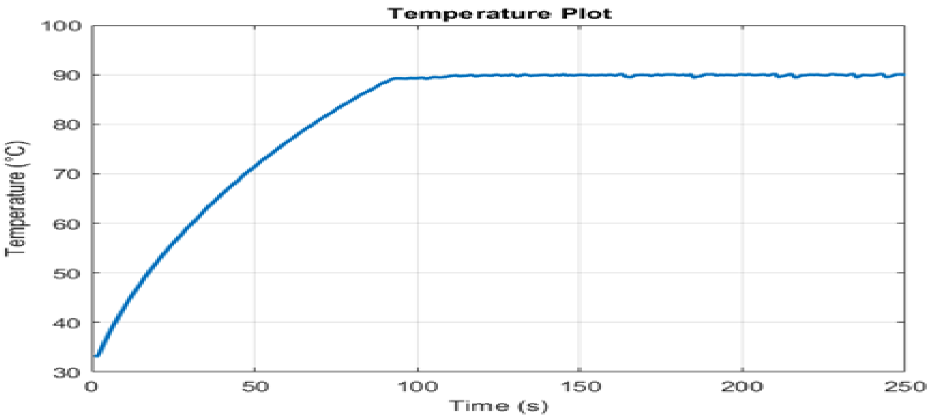


Fig. 11. Output response using fuzzy logic with a setpoint of 90°C

Comment: The system response shows stable and effective temperature control. The temperature rises steadily from approximately 35°C and reaches the target value of around 70°C within about 82 seconds, with no noticeable overshoot. After settling, the system maintains a consistent temperature with only minor fluctuations. The steady-state error is negligible, indicating high accuracy in tracking the setpoint.

Comment: The system exhibits a stable temperature control response, with a smooth and steady rise from approximately 35°C to the target value of around 90°C within about 138 seconds. There is no overshoot, and the temperature remains stable afterward with minimal oscillation, indicating high system stability. The steady-state error is nearly zero, demonstrating the controller's reliable and accurate setpoint tracking capability.

Table 2: Table of System Quality Using Fuzzy Logic

	50	**70**	**90**
POT (%)	0	0	0
e_{xl} (ºC)	0	0	0
t_{xl} (s)	30	82	138

5. CONCLUTION

Based on the experimental results, it can be observed that the fuzzy logic controller provides fast, stable, and accurate temperature control. The system easily reaches the setpoint without overshoot, and performs especially well at higher temperature levels. Moreover, fuzzy logic demonstrates strong adaptability to changes in the setpoint without requiring manual tuning of control parameters. This adaptability enables the system to maintain stable performance under real-world conditions, where system characteristics may vary over time.

In comparison, traditional PID controllers, although capable of ensuring final accuracy, often struggle with nonlinear or changing dynamics, resulting in longer settling times and significant overshoot. Therefore, fuzzy logic stands out as a more effective and adaptive control solution in temperature regulation tasks.

ACKNOWLEDGEMENT

We, authors, want to give thanks to Mr. Thanh-Phuong Nguyen (ID: 21151152 - HCMUTE) and Hai-Thanh Nguyen (lecturer of Nguyen Huu Canh Technical and Economics Intermediate School, Vietnam) for their financial support for this contribution.

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