

FPGA-Based Fuzzy-PID Hybrid Control for Electric Oven Temperature

Kendali *Hybrid Fuzzy-PID* berbasis FPGA pada Suhu Oven Listrik

¹Yurixa Sakhinatul Putri ^{*}), ¹Ihsan Auditia Akhinov, ¹Hariyanto, ¹Hana Kamila Adiningtyas,
¹Elitaria Bestri Agustina Siregar, ¹Muhammad Alief Putra, and ¹Muhammad Farrel Abdoel Jabbar

¹Department of Electrical Engineering, Politeknik Negeri Jakarta 16425, Depok, Indonesia

^{*}) corresponding email: yurixa.sakhinatul.putri@elektro.pnj.ac.id

Abstract

Resistive electric ovens exhibit high thermal inertia and nonlinear dynamics, making fixed-parameter PID controllers prone to overshoot and slow responses under varying setpoints. This study proposes and implements a Hybrid Fuzzy-PID controller on a Cyclone IV FPGA using a zero-order Takagi-Sugeno fuzzy inference system as a real-time auto-tuner for the K_p and K_i parameters. The controller is evaluated against a conventional PID controller tuned using the Ziegler-Nichols method. The fuzzy inference system uses error and delta error as inputs to adapt the controller parameters according to changes in the thermal response of the oven. All control algorithms are implemented in VHDL on a Cyclone IV FPGA without floating-point operations. Experimental results demonstrate that the proposed Hybrid Fuzzy-PID controller provides improved thermal response compared with the conventional PID controller, achieving faster settling behavior, controlled overshoot, and lower average power consumption under the tested conditions. The FPGA-based implementation also provides more accurate and deterministic actuation than the microcontroller-based implementation. These findings demonstrate that the proposed FPGA-based Hybrid Fuzzy-PID controller can improve real-time temperature regulation and power utilization in resistive electric ovens.

Keywords: Fuzzy-PID, FPGA Cyclone IV, electric oven, Ziegler-Nichols, auto-tuning

Abstrak

Oven listrik berbasis elemen resistif memiliki inersia termal yang tinggi dan dinamika nonlinier, sehingga pengendali PID dengan parameter tetap rentan mengalami overshoot dan respons yang lambat saat terjadi perubahan setpoint. Penelitian ini mengusulkan dan mengimplementasikan pengendali Hybrid Fuzzy-PID pada FPGA Cyclone IV menggunakan sistem inferensi fuzzy Takagi-Sugeno orde nol sebagai auto-tuner parameter K_p dan K_i secara real-time. Kinerja pengendali dibandingkan dengan PID konvensional yang dituning menggunakan metode Ziegler-Nichols. Sistem inferensi fuzzy menggunakan error dan delta error sebagai masukan untuk menyesuaikan parameter kendali berdasarkan perubahan respons termal oven. Seluruh algoritma kendali diimplementasikan dalam VHDL pada FPGA Cyclone IV tanpa operasi floating-point. Hasil pengujian menunjukkan bahwa pengendali Hybrid Fuzzy-PID mampu memberikan respons termal yang lebih baik dibandingkan PID konvensional, dengan waktu menuju kondisi stabil yang lebih cepat, overshoot yang lebih terkendali, serta konsumsi daya rata-rata yang lebih rendah pada kondisi pengujian. Implementasi berbasis FPGA juga menghasilkan aktuasi yang lebih akurat dan deterministik dibandingkan implementasi berbasis mikrokontroler. Hasil penelitian menunjukkan bahwa Hybrid Fuzzy-PID berbasis FPGA mampu meningkatkan kinerja pengaturan suhu dan penggunaan daya pada oven listrik resistif secara real-time.

Kata Kunci: Fuzzy-PID, FPGA Cyclone IV, oven listrik, Ziegler-Nichols, auto-tuning.

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1 Introduction

Accurate temperature control is essential in thermal processes because the ability to reach and maintain a desired operating temperature directly affects process consistency and control performance. Thermal systems are widely encountered in industrial heating applications, where temperature responses are influenced by thermal inertia, heat-transfer characteristics, and residual heat. These characteristics make temperature control challenging because the system temperature may continue to change even after the heating input is reduced or removed, potentially resulting in overshoot and prolonged settling behavior. In this study, a resistive electric oven is used as a real experimental thermal plant for investigating temperature-control strategies under the characteristics of a slow and inertia-dominated physical system. Its thermal behavior provides a practical experimental representation of temperature-control challenges encountered in other thermal processes that involve heat accumulation, slow responses, and residual thermal effects.

Because of these thermal characteristics, an appropriate control strategy is required to regulate the oven temperature effectively. Proportional-Integral-Derivative (PID) control remains widely used because of its simple structure and practical tuning procedures [41]. However, its performance depends strongly on the selected controller gains, and fixed gains may not provide equally satisfactory responses throughout the operating range of a thermal plant. In the preliminary characterization conducted in this study, the Ziegler-Nichols-based PID controller exhibited different overshoot characteristics at different temperature setpoints. This observation indicates that a single set of fixed controller parameters may not provide consistent control performance under varying operating conditions of the oven. Therefore, a control mechanism capable of adapting the controller parameters according to the current operating condition is required.

One approach that has been widely investigated to overcome the limitations of fixed-parameter PID control is the integration of fuzzy logic. Fuzzy logic can represent control knowledge through linguistic rules and adjust controller actions without requiring an exact mathematical model of the controlled plant. In adaptive PID applications, fuzzy inference can be used to modify controller parameters based on the instantaneous control error and its rate of change [2]. This capability makes fuzzy-based adaptation particularly relevant for thermal systems with nonlinear and time-varying characteristics, where changes in operating conditions can affect the performance of fixed controller parameters.

The potential of fuzzy-based adaptation in thermal control has been demonstrated in several previous studies. Jiang and Jiang developed a fuzzy self-tuning PID strategy for temperature-control applications [3]. Huang et al. applied an auto-encoder and fuzzy PI control approach to an electric heating furnace [4], while Meng et al. developed a GA-Fuzzy-PID temperature-control system for a vacuum annealing furnace [5]. Abdrakhmanov et al. implemented an intelligent Fuzzy-PID temperature-control system for an intelligent building environment [6]. Fuzzy adaptive PID strategies have also been investigated for other thermal processes, including lead patenting furnaces [7], induction heating systems [8], industrial temperature systems [2], and proton exchange membrane fuel cell systems [9]. These studies demonstrate the applicability of fuzzy-based adaptation to temperature control across different thermal processes. However, the controller implementation platform also plays an important role, particularly when adaptive control algorithms are required to operate within a real-time control loop.

In addition to controller design, FPGA platforms have been investigated as an alternative implementation platform for real-time control applications. Previous studies have reported FPGA-based implementations of temperature controllers and fuzzy adaptive PID algorithms, including FPGA-based fuzzy-PID temperature control [10], FPGA-based PID implementation for a refrigeration temperature-control system [11], and FPGA-based fuzzy adaptive PID control [12]. FPGA technology has also been widely investigated for industrial control applications and provides a suitable platform for implementing dedicated hardware control architectures [13]. The use of FPGA is therefore relevant when multiple controller functions, such as fuzzy inference, online parameter adjustment, and PID signal generation, need to be integrated within a unified hardware architecture.

Although fuzzy-based adaptive temperature control and FPGA implementation have been investigated separately and in various application contexts, differences remain in terms of the controlled plant, controller architecture, and implementation platform. Previous studies have demonstrated fuzzy-based adaptive control in thermal applications such as electric heating furnaces, induction heating systems, plant factory temperature control, and other thermal processes [4],[7],[8],[14], while FPGA-based temperature controllers and fuzzy adaptive PID algorithms have also been reported [10],[11],[12]. Therefore, the research gap addressed in this study is not the individual application of fuzzy-PID control or FPGA technology. Instead, this study focuses on the experimental integration of a PID baseline derived from the characterization of a real resistive electric oven, an online fuzzy tuning mechanism, and a complete controller implementation on a Cyclone IV FPGA within a single experimental system.

To support this integrated implementation, an appropriate fuzzy inference structure and hardware architecture are required. In this study, a zero-order Takagi-Sugeno fuzzy inference structure is adopted based on the Takagi-Sugeno fuzzy modeling framework [15] and implemented using fixed-point arithmetic to avoid floating-point operations. The Cyclone IV FPGA is used as the target platform to integrate the controller functions within a unified hardware-based architecture for deterministic real-time operation. Through this architecture, the fuzzy inference mechanism, controller parameter adjustment, and PID signal generation can be implemented as part of a single hardware-based control system.

Accordingly, the objective of this study is to design, implement, and experimentally evaluate a Hybrid Fuzzy-PID temperature-control system for a real resistive electric oven using a Cyclone IV FPGA. The study investigates whether an online fuzzy tuning mechanism can improve the control performance of a Ziegler-Nichols-based PID baseline while maintaining a deterministic hardware-based implementation.

The novelty and contribution of this study lie in the integration and experimental validation of the proposed approach. First, a baseline PID controller is derived from the experimental open-loop characterization of the actual resistive electric oven using the Ziegler-Nichols method, providing a plant-specific reference for controller evaluation. Second, a zero-order Takagi-Sugeno fuzzy inference mechanism is integrated as an online tuning layer and implemented using fixed-point VHDL on a Cyclone IV FPGA. Third, the proposed system is experimentally evaluated on a physical oven and compared with the baseline PID controller, while the timing accuracy of the FPGA-generated actuation signal is also examined through direct oscilloscope measurements.

2 Method

This study employed a quantitative experimental research method to design, implement, and evaluate a Hybrid Fuzzy-PID temperature control system for a resistive electric oven. The research was conducted using a controlled experimental approach in which the performance of the proposed Hybrid Fuzzy-PID controller was measured and compared with a conventional PID controller derived using the Ziegler-Nichols method.

The experimental procedure consisted of five main stages. First, the dynamic characteristics of the electric oven plant were identified through an open-loop experiment to obtain the parameters required for determining the baseline PID controller. Second, the fuzzy inference system was designed as an online tuning mechanism for the PID controller. Third, the proposed control algorithms were implemented in VHDL on a Cyclone IV FPGA. Fourth, the integrated control system was experimentally tested on the physical electric oven under controlled operating conditions. Finally, the experimental results were quantitatively evaluated based on temperature-response characteristics, controller performance, actuation precision, and power consumption.

The experimental design involved comparative testing between the conventional Ziegler-Nichols-based PID controller and the proposed Hybrid Fuzzy-PID controller. In addition, two fuzzy membership-function configurations were evaluated to examine their influence on controller performance. The main performance evaluation was conducted at a temperature setpoint of 130°C, while preliminary PID characterization was performed at multiple setpoints to observe variations in the thermal response of the oven.

2.1 Temperature Control System Design

The electric oven temperature control system developed in this study utilizes a hybrid Fuzzy-PID control architecture implemented on a Cyclone IV FPGA. This approach aims to achieve a rapid, stable, and adaptive temperature response under varying operating conditions. The experimental platform is a Maspion 901S electric oven, modified with a high-precision temperature sensor, a power acquisition module, and a digital processing unit serving as the main controller. The system architecture comprises five integrated subsystems: power distribution, data acquisition, main control, user interface, and power execution, as illustrated in the system block diagram.

The power distribution subsystem supplies a 24 VDC operating voltage to all electronic components by converting AC mains voltage, while the unaltered AC voltage is directed to the power execution subsystem for heating. The data acquisition subsystem includes a PT100 RTD sensor for measuring oven chamber temperature, a current transformer (CT) for non-invasive current measurement, and a PZEM-004T module for calculating voltage, current, and active power parameters of the heating element [16]. These data are transmitted to the ESP32 microcontroller, which functions as a data gateway [17] and provides a UART communication interface to the Cyclone IV EP4CE6E22C8 FPGA. The FPGA serves as a parallel computing center, executing the Fuzzy Inference System (FIS) algorithm, PID calculations, and phase control signal generation within a single VHDL entity. The resulting control signals are sent to the LSA-002 AC dimmer module, which adjusts the TRIAC firing angle to regulate power supplied to the two tubular heater elements. Operational parameters, including temperature, voltage, current, and power, are displayed in real time on an OLED screen as part of the user interface subsystem, as shown in Figure 1.

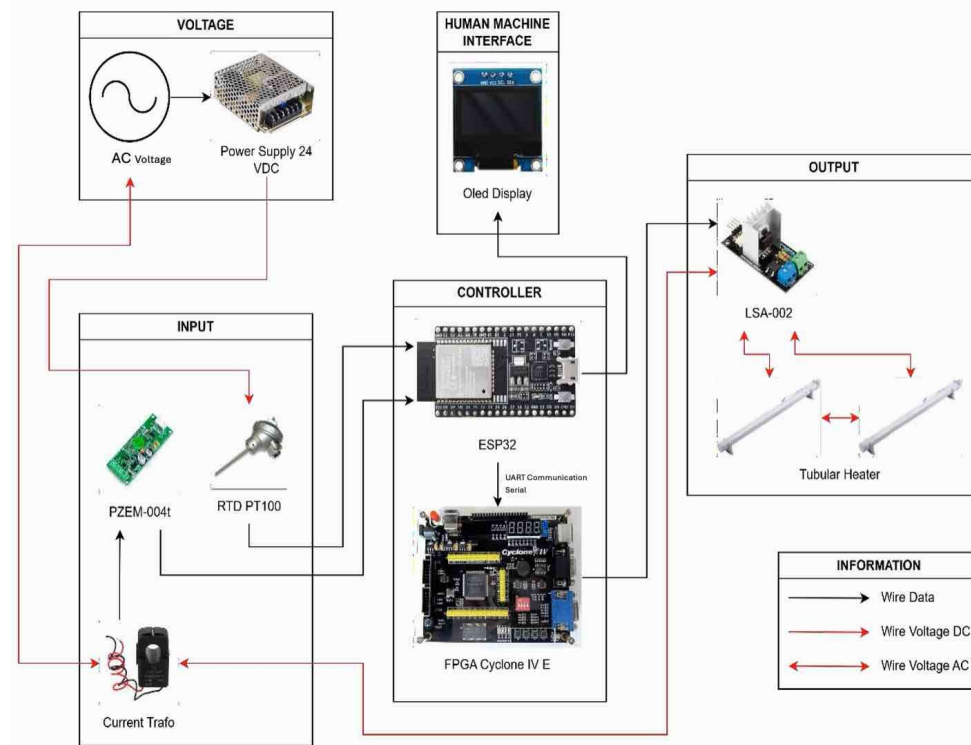


Figure 1. Block diagram of the fuzzy-PID control system.

2.2 Plant Characterization and PID Baseline Determination Using the Ziegler-Nichols Method

Prior to implementing the fuzzy control layer, the dynamic characteristics of the electric oven plant were determined through open-loop testing to establish the initial PID controller parameters. In this test, a constant input signal of full power (100%) was applied to the actuator without feedback from the temperature sensor. The resulting increase in oven chamber temperature over time was recorded to generate a response curve. From this response curve, the process parameters-gain (K), time constant (T), and dead time (L)-were extracted to serve as the basis for the Ziegler-Nichols tuning calculation [1], [18],[19],[20].

The difference between the observed maximum and minimum temperatures (Δ) was calculated using Equation (1). With a maximum temperature of 150,9°C and a minimum temperature of 27,9°C, Δ was determined to be 123°C.

$$\Delta = \text{MAX_Value} - \text{MIN_Value} \quad (1)$$

The gain (K) was calculated as the ratio of Δ to the change in the input signal (δ) using Equation (2), where δ represents the difference between the actuator's final and initial input values (100% - 0% = 100). This calculation yielded a value of K equal to 1,23.

$$K = \Delta / \delta \quad (2)$$

The times required for the temperature to reach 63% and 28% of Δ , denoted as T63% and T28%, respectively, were determined from the response curve data as 472 s and 280 s. The process time constant (T) and dead time (L) were then calculated using Equations (3) and (4).

$$T = 1,5 \times (T63\% - T28\%) \quad (3)$$

$$L = T63\% - T \quad (4)$$

Based on these equations, the time constant T was calculated as 288 s and the dead time L as 184 s. These values were then used in the Ziegler-Nichols tuning formula to obtain the parameters Kp, Ti (integral time

constant), and T_d (derivative time constant) using Equations (5)–(7). The parameters K_i and K_d for the parallel PID implementation were obtained using Equations (8) and (9).

$$K_p = 1,2 \times (T / L) \quad (5)$$

$$T_i = 2L \quad (6)$$

$$T_d = 0,5L \quad (7)$$

$$K_i = K_p / T_i \quad (8)$$

$$K_d = K_p \times T_d \quad (9)$$

These calculations yielded baseline PID parameters of $K_p = 1,88$, $K_i = 0,0051$, and $K_d = 172,8$. These values were used as the starting point for the conventional PID controller prior to performance comparison with the Hybrid Fuzzy-PID controller. Although the oven plant is capable of reaching a physical heating capacity of up to 223°C , the operational range of the closed-loop system was limited to a maximum of 150°C to ensure component safety and maintain the linearity of the PT100 RTD sensor readings.

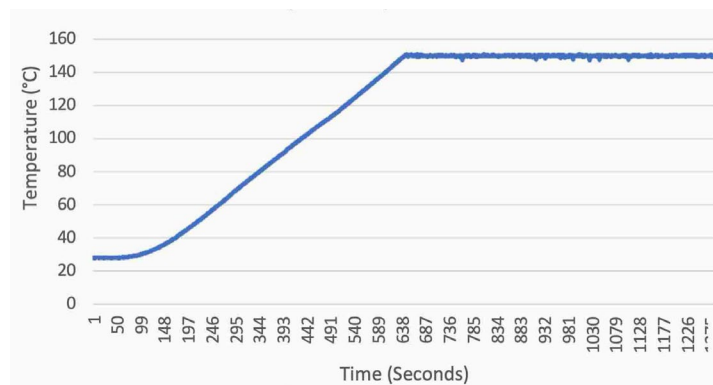


Figure 2. Open-loop test data results graph

2.3 Design of a Fuzzy Inference System as a PID Auto-Tuner

The intelligence layer of the system is realized using a Fuzzy Inference System (FIS) based on the Zero-Order Takagi-Sugeno method [15],[21],[22],[23], which serves as an adaptive PID parameter auto-tuner. This inference system receives two input variables: error (e), defined as the difference between the setpoint temperature and the actual temperature, and delta error (Δe), defined as the rate of temperature change between sampling intervals. Both input variables are processed through three sequential stages: fuzzification, rule base evaluation, and Sugeno defuzzification. These stages generate direct outputs for the K_p and K_i parameters, while the K_d parameter remains fixed, as determined by Ziegler-Nichols tuning, to minimize noise amplification in the derivative action. To reduce computational complexity on the hardware, all data processing employs fixed-point integer scaling, with physical temperature data represented on a $\times 10$ scale.

This study evaluated and compared two membership set configurations [24],[25],[26]. The first configuration, referred to as Membership Function 3, divides each error and delta error variable into three linguistic sets: Negative (N), Zero (Z), and Positive (P). This results in nine fuzzy rules (3×3), which serve as a baseline for comparison. In this configuration, the delta error domain consists of unscaled physical values ranging from $-0,5$ to $0,5^\circ\text{C}$ per 100 ms. The second configuration, Membership Function 5, is the primary configuration used in this study. It divides both input variables into five linguistic sets: Negative Big (NB), Negative Small (NS), Zero (Z), Positive Small (PS), and Positive Big (PB), resulting in 25 fuzzy rules (5×5). The error variable is mapped to a domain of -40°C to 40°C , consistent with Membership Function 3, while the delta error is mapped to a scaled integer domain of -15 to 15 to enhance quantization precision in the VHDL fixed-point register. A key design decision in Membership Function 5 is the intentional shift of the Zero set peak to $e = 3^\circ\text{C}$, rather than $e = 0^\circ\text{C}$. This adjustment compensates for the oven's thermal lag caused by the thermal inertia of the heating elements, ensuring that conditions near steady state are classified as "stable" even when the actual temperature is slightly below the setpoint.

$$K_p^* = \Sigma(w_i \times K_{p,i}) / \Sigma(w_i) \quad (20)$$

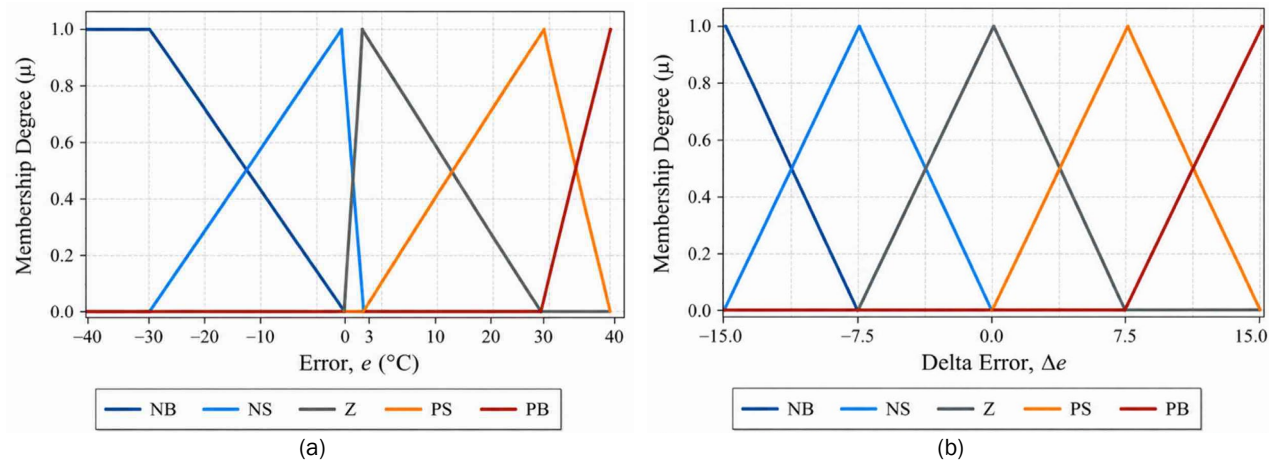


Figure 3. (a) Membership functions for input Error; (b) Membership functions for delta error

Table 1. Fuzzy-PID Rule Base Matrix (Membership Function 5)

Error \ Δ Error	NB	NS	Z	PS	PB
NB	SK	SK	SK	K	K
NS	SK	K	K	S	S
Z	S	K	K	S	B
PS	S	S	B	B	SB
PB	B	B	SB	SB	SB

The output levels in the Fuzzy-PID rule base matrix are defined by five linguistic categories: SK (Very Small), K (Small), S (Medium), B (Large), and SB (Very Large). Each category represents the magnitude of the Kp and Ki gains simultaneously, consistent with the zero-order Sugeno inference principle applied in this system. The SK level corresponds to the minimum gain, which is applied when the error condition indicates severe overheating, eliminating the need for further increases in control action even if the delta error varies. In contrast, the SB level represents the most aggressive gain, applied when the actual temperature is significantly below the setpoint and shows no improvement, requiring a rapid system response. The intermediate levels - K, S, and B - serve as transitional stages, enabling gradual adjustment of the Kp and Ki gain values as the combination of error and delta error changes. This approach ensures that the controller output transitions smoothly, minimizing sudden spikes that could lead to oscillations or overshoot in temperature control.

Table 2. Zero-order sugeno output constants

Linguistic Level	Kp ($\times 1000$)	Ki ($\times 1000$)	Effective Kp	Effective Ki
SK (Very Small)	50	1	0,050	0,001
K (Small)	110	2	0,110	0,002
S (Medium)	170	3	0,170	0,003
B (Large)	235	4	0,235	0,004

2.4 Implementation on a Cyclone IV FPGA

The control algorithms were implemented in VHDL and synthesized using Quartus Prime software for the Cyclone IV EP4CE6E22C8 FPGA, operating at a clock frequency of 50 MHz. The hardware architecture comprises four primary functional blocks executed in parallel within a single VHDL entity [13],[27]: a UART receiver block for acquiring digital temperature data from the ESP32; a Fuzzy Inference System block responsible for the fuzzification stage, evaluation of 25 rules, and Sugeno defuzzification; a PID block that computes the control signal based on dynamically updated Kp, Ki, and Kd parameters; and a phase control block that translates the PID output into a delay time for triggering the actuation signal to the LSA-002 AC dimmer module.

The parallel processing capabilities of FPGA architecture enable each functional block to operate concurrently, eliminating the need for sequential execution as seen in microcontroller architectures. To ensure numerical precision and prevent register overflow, all PID and FIS computations utilize fixed-point arithmetic [10],[11], [12],[28],[29]. Parameter scaling for Kp, Ki, and Kd is performed prior to input into the PID accumulation block. This fixed-point methodology was selected to reduce the complexity associated with floating-point logic elements on an FPGA and to guarantee deterministic execution time, which is critical for real-time temperature control applications.

2.5 Test Setup

The experimental test object was a Maspion 901S electric oven modified with a high-precision temperature sensor, a data acquisition module, and a digital processing unit, as described in Subsection 2.1. The experimental evaluation was conducted under controlled operating conditions using comparative tests between the conventional PID controller and the proposed Hybrid Fuzzy-PID controller. Initial plant characterization was conducted through open-loop testing and Ziegler-Nichols baseline PID tuning at multiple setpoint values to provide an overview of the oven's dynamic characteristics (see Section 1 and Subsection 3.2). All major control system evaluations—including membership function configuration comparisons, direct comparison of the Hybrid Fuzzy-PID and conventional PID, FPGA actuation precision, and power efficiency—were conducted at the 130°C setpoint, which served as the primary operating condition.

Control system performance was evaluated using six standard transient response parameters: delay time, rise time, peak time, percentage overshoot, settling time, and steady-state error. Delay time (T_d) is defined as the time required for the temperature to reach 50% of the total temperature change range (ΔT), with the T50% threshold specified in Equation (11). Rise time (T_r) is defined as the time interval between reaching 10% and 90% of ΔT , as described in Equation (12).

$$T_{50\%} = T_{\text{initial}} + 0,5(SP - T_{\text{initial}}) \quad (11)$$

$$T_r = T_{90\%} - T_{10\%} \quad (12)$$

The overshoot percentage (%OS) quantifies the extent to which the peak temperature (T_{max}) exceeds the setpoint (SP), as defined in Equation (13). The steady-state error (%ess) measures the average deviation of the final value (y_{ss}) from the setpoint under steady-state conditions, as specified in Equation (14). Settling time (T_s) is defined as the duration required for the temperature to enter and remain within a $\pm 5\%$ tolerance band around the setpoint without further deviation.

$$\%OS = \frac{T_{\text{max}} - SP}{SP} \times 100\% \quad (13)$$

$$\%ess = \frac{|SP - y_{\text{ss}}|}{SP} \times 100\% \quad (14)$$

To further assess hardware actuation precision, the firing delay was measured using a digital oscilloscope and converted into the firing phase angle (shooting angle, α) based on the duration of one half-cycle of 50 Hz AC, where 10 ms corresponds to 180° , as described in Equation (15). The deviation of the actuation angle from the ideal target value was quantified using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), with RMSE defined in Equation (16). These metrics were employed to compare execution determinism between the Cyclone IV FPGA and the ESP32 microcontroller.

$$\alpha = (t_{\text{delay}} / 10) \times 180^\circ \quad (35)$$

$$RMSE = \sqrt{\frac{\sum (\alpha_{\text{actual}} - \alpha_{\text{target}})^2}{n}} \quad (16)$$

3 Results and Discussion

3.1 System Implementation on the Cyclone IV FPGA: Comparative Analysis of Actuation Precision

Actuation precision was evaluated by comparing the phase control signals generated by the Cyclone IV EP4CE6E22C8 FPGA and the microcontroller, utilizing direct oscilloscope measurements of firing angle and triac delay time. The results indicate that the FPGA achieved a root mean square error (RMSE) in actuation angle of $0,18^\circ$ and an actuation accuracy of 99,71%. In contrast, the microcontroller exhibited a substantially higher RMSE of $18,32^\circ$ and an actuation accuracy of only 75,90%, as summarized in Table 3.

Table 3. Comparative actuation precision of FPGA and microcontroller

Platform	Time fluctuation range (<i>jitter</i>)	RMSE of actuation angle	Actuation accuracy
Microcontroller	1,16–5,00 ms	$18,32^\circ$	75,90%
Cyclone IV FPGA	3,44–3,46 ms	$0,18^\circ$	99,71%

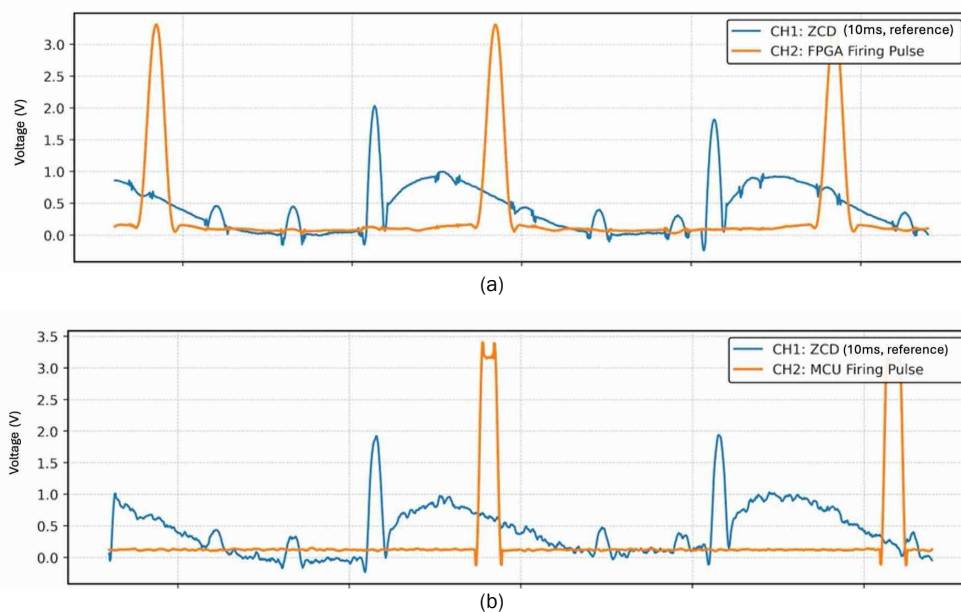


Figure 4. (a) FPGA-Based system response (actual data) between zero-crossing signal and dimmer trigger on the FPGA; (b) Microcontroller-Based system response (actual data) between zero-crossing signal and signal waveforms on the microcontroller

The observed differences in accuracy correspond to variations in delay time (*jitter*) across both platforms. The microcontroller demonstrates a broad jitter range, from 1,16 to 5,00 ms, whereas the FPGA maintains a much narrower and nearly constant range, from 3,44 to 3,46 ms. This outcome confirms that the FPGA architecture, which executes the UART receiver, FIS, PID, and phase control logic blocks in parallel within a single VHDL entity, ensures execution-time determinism that is challenging to achieve with the sequential, interrupt-driven architecture of a microcontroller [13]. Instability in microcontroller delay time directly contributes to inaccuracies in the triac firing angle, ultimately reducing the precision of power delivery to the heating element. These results provide quantitative evidence that selecting an FPGA as the computing platform is justified by robust quantitative analysis, particularly for alternating current power phase control applications requiring high temporal precision.

3.2 Plant Characterization and Ziegler-Nichols Baseline PID Control

Baseline testing of the Ziegler-Nichols PID controller was performed at three setpoint values: 70°C , 100°C , and 130°C . This approach enabled a comprehensive assessment of the electric oven plant's behavior across different operating conditions.

The Ziegler-Nichols PID baseline, as established in Subsection 2.2 ($K_p = 1,88$; $K_i = 0,0051$; $K_d = 172,8$), was evaluated at the 130°C setpoint, which represents the primary operating condition for this study. The controller achieved a settling time of 441 s, an overshoot of 4,38% (peak of $135,7^\circ\text{C}$), and a steady-state error

of 0,522%. These results provide the primary benchmark for subsequent comparison with the Hybrid Fuzzy-PID system. From the perspective of the oven temperature-control target, the results indicate that the fixed PID controller can regulate the temperature toward the desired setpoint; however, the relatively long settling time and variation in response characteristics across different setpoints indicate limitations in maintaining consistent control performance under changing operating conditions.

Initial characterization across a broader setpoint range (70°C and 100°C, as referenced in Subsection 1) revealed that PID overshoot increased substantially as the setpoint decreased, reaching 16,43% at 70°C compared to 4.38% at 130°C. This result indicates that the PID gain is inconsistent across the operating range. This empirical observation provides the primary motivation for implementing a fuzzy auto-tuning mechanism, as outlined in the Introduction. The remainder of this section, including all tests in Subsections 3.3 through 3.5, focuses exclusively on the 130°C setpoint. The key parameters obtained from the open-loop characterization and Ziegler-Nichols tuning are summarized in Table 4.

Table 4. Summary of electric oven plant characterization and baseline PID parameters

Parameter	Value	Description
Input Condition	100%	Full heating power during open-loop testing
Dead time, L	184 s	Delay before significant temperature response
Time constant, T	288 s	Thermal response characteristic of the oven plant
Kp	1,88	Proportional gain obtained using the Ziegler-Nichols method
Ki	0,0051	Integral gain obtained using the Ziegler-Nichols method
Kd	172,8	Derivative gain obtained using the Ziegler-Nichols method

3.3 Implementation of Fuzzy Logic for Auto-Tuning: Comparative Analysis of Membership Function 3 and Membership Function 5

To assess the impact of fuzzy set partition resolution on auto-tuning performance, this study compared a configuration with three membership sets (Membership Function 3, 9 rules) to one with five membership sets (Membership Function 5, 25 rules) at a setpoint of 130°C. The results of this comparison are summarized in Table 5.

Table 5. Performance comparison between Membership Function 3 and Membership Function 5 at a setpoint of 130°C

Configuration	Time to reach setpoint	Overshoot	SSE
Membership Function 3 (9 rule)	366 sec	20,0°C	±3,15°C
Membership Function 5 (25 rule)	393 sec	6,2°C	±2,20°C

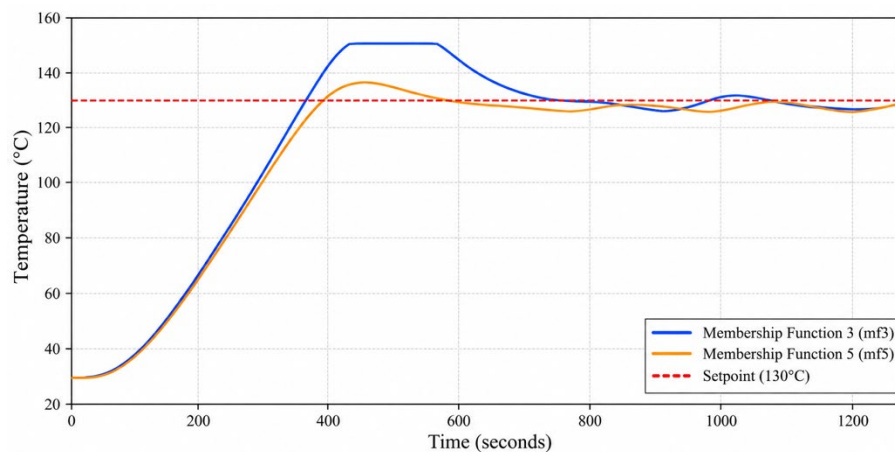


Figure 5. Temperature response curves comparison for membership function 3 and membership function 5 (0-1250 seconds)

Membership Function 3 reached the setpoint faster, with a settling time of 366 s, compared with 393 s for Membership Function 5. However, Membership Function 3 produced a substantially larger overshoot of 20,0 °C, whereas Membership Function 5 limited the overshoot to 6,2 °C and exhibited a smaller steady-state error ($\pm 2,20^\circ\text{C}$ versus $\pm 3,15^\circ\text{C}$). This trade-off indicates that increasing the resolution of the fuzzy partitions provides a smoother adjustment of the control action as the oven temperature approaches the desired setpoint, thereby reducing excessive temperature excursions, although at the expense of a 27 s increase in response time. For the temperature-control target of the oven, limiting excessive overshoot is particularly important because the oven temperature directly determines the thermal conditions experienced by the material inside the heating chamber. Therefore, Membership Function 5 was selected for subsequent evaluation because it provided a more controlled and stable temperature response near the desired operating condition.

3.4 Performance Comparison: Hybrid Fuzzy-PID versus Ziegler-Nichols Baseline PID

The final performance comparison between the Hybrid Fuzzy-PID system with Membership Function 5 configuration and the baseline Ziegler-Nichols PID at a setpoint of 130 °C is presented in Table 6.

Table 6. Comparison of the performance of the Hybrid Fuzzy-PID and Ziegler-Nichols PID at a setpoint of 130 °C

Parameter	PID Ziegler-Nichols (baseline)	Hybrid Fuzzy-PID (Membership Function 5)
Settling time	441 s	393 s
Overshoot	4,38% (135,7 °C)	4,76% (136,2 °C)
Steady-state error	0,522%	1,69%

The Hybrid Fuzzy-PID achieved a settling time of 393 s, which was 48 s faster than the Ziegler-Nichols PID at 441 s. Both controllers exhibited comparable overshoot values of 4,76% for the Hybrid Fuzzy-PID and 4,38% for the conventional PID. However, the Ziegler-Nichols PID demonstrated better steady-state precision, with a steady-state error of 0,522% compared with 1,69% for the Hybrid Fuzzy-PID. For the temperature-control objective of the oven, these results indicate that the proposed controller improved the speed at which the oven approached the desired operating temperature while maintaining overshoot at a level comparable to the baseline PID. However, the larger steady-state error indicates that further refinement of the fuzzy tuning mechanism is required to improve temperature regulation near the setpoint.

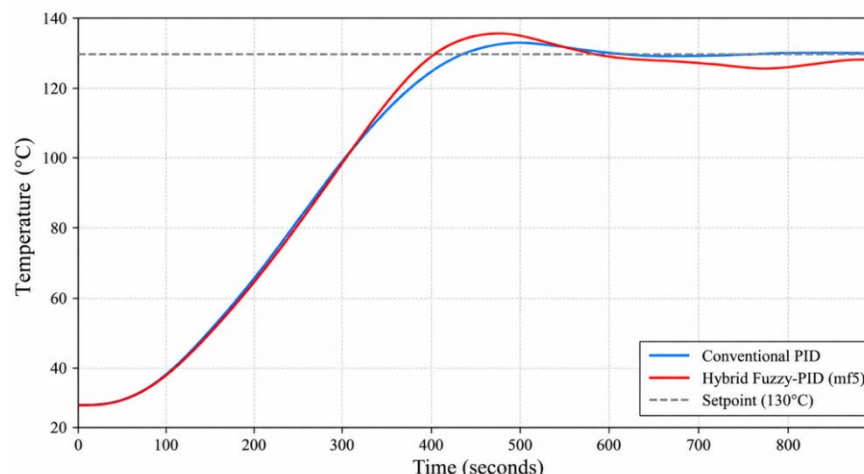


Figure 6. Temperature response curves comparison between baseline-pid and hybrid fuzzy-PID

These results demonstrate a trade-off between response speed and steady-state accuracy. The fuzzy auto-tuning mechanism dynamically adjusts the Kp and Ki parameters according to the magnitude of the control error and its rate of change, enabling stronger control action when the oven temperature is far from the setpoint and thereby accelerating the heating response. However, near steady-state conditions, the current dynamic gain-adjustment strategy is less effective than the fixed Ziegler-Nichols parameters in suppressing small temperature deviations around the setpoint. For the electric oven plant, this behavior indicates that the proposed Hybrid Fuzzy-PID is more effective in improving the transient heating response, whereas further optimization is required to improve temperature regulation during the steady-state phase. This limitation is associated with the current rule-based configuration and Sugeno constants.

3.5 Power Consumption Efficiency and Integration of Scientific Contributions

Power consumption testing showed that the Hybrid Fuzzy-PID consumed an average power of 220,3 W, compared with 276,1 W for the conventional PID, corresponding to a 20,2% reduction in average power consumption, as summarized in Table 7. For the electric oven plant, this result indicates that the proposed adaptive control strategy can reduce the average electrical power required during the evaluated operating condition while maintaining temperature regulation around the desired setpoint.

Table 7. Comparison of average power consumption between Ziegler-Nichols PID and Hybrid Fuzzy-PID

Control system	Average total power	Efficiency relative to baseline
PID Ziegler-Nichols	276,1 W	—
Hybrid Fuzzy-PID (Membership Function 5)	220,3 W	20,2%

During the transient heating phase, the Hybrid Fuzzy-PID exhibited slightly higher power consumption because the controller applied more aggressive control action when the temperature error was large. However, the overall average power consumption was lower because the controller adjusted the heating action more effectively as the oven approached and operated around the desired temperature. For the electric oven plant, this behavior indicates that the proposed control strategy can improve energy utilization without requiring the heating element to continuously operate at the same control intensity throughout the operating period.

The findings of this study align with previous research reporting the superiority of adaptive fuzzy control over conventional PID control in nonlinear thermal systems, particularly regarding response speed and energy efficiency [3], [4], [6], [7], [12], [30]. Distinct from most prior studies, which are simulation-based or tested on systems other than ovens, this work integrates three elements rarely reported together: a baseline PID systematically derived from real plant characterization using the Ziegler-Nichols method; a zero-order Takagi-Sugeno fuzzy auto-tuning mechanism implemented as fixed-point digital logic to maximize FPGA logic efficiency; and quantitative evidence of FPGA determinism superiority over microcontrollers, demonstrated through direct oscilloscope measurements. The integration of these elements in a single FPGA-based resistive electric oven system represents the primary contribution of this study.

Several limitations should be considered when interpreting these results. The rule base and Sugeno constants in the fuzzy inference system were determined heuristically based on manual observations and have not been optimized using computational methods such as genetic algorithms, particle swarm optimization, or ANFIS. Additionally, testing was limited to a single type of electric oven with one temperature measurement point, so generalization to other thermal plants should be approached with caution. Future research should focus on computational optimization of the rule base and Sugeno constants to mitigate the trade-off between overshoot and steady-state precision, as well as expanding testing to a broader range of plants and sensor configurations.

The results of the device's implementation can be seen in Figures 7 and 8, and its specifications are listed in Table 8.

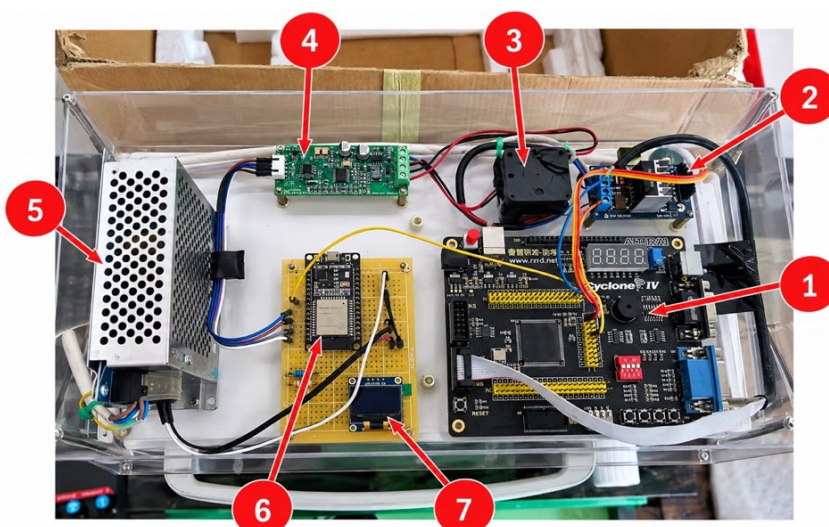


Figure 7. Top view hardware prototype of the testing system

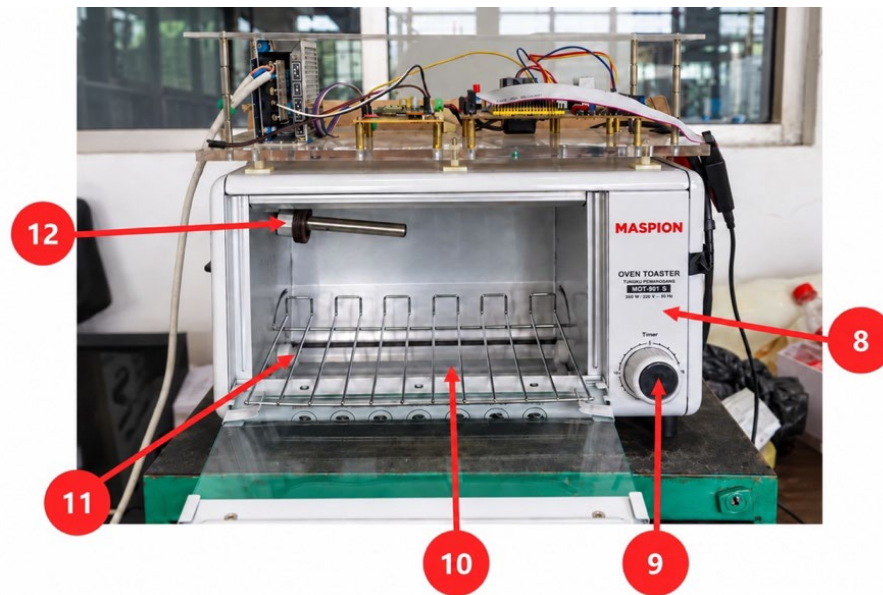


Figure 8. Front view hardware prototype of the testing system

Table 8. List of components and specifications

No	Components	Specifications
1	FPGA board	Altera Cyclone IV EP4CE6E22C8 chip, programmed via Quartus Prime (VHDL)
2	AC dimmer module	LSA-002, phase-angle power modulation, high voltage
3	Trafo/relay module	Step-down transformer (for isolation/AC power switching)
4	Power monitoring module	PZEM-004T, Modbus RTU communication (UART)
5	Power supply	SMPS (Switching Mode Power Supply)
6	Microcontroller	ESP32 DevKit
7	Display	0.96" I2C OLED (128x64), driver
8	Toaster oven	Maspion MOT-901S, resistive toaster oven — power (watts) must be checked on the back label
9	Timer knob	Oven's built-in mechanical knob
10	Resistive heating element	Wire/rod-shaped heating element inside the oven cavity
11	Baking rack	Stainless steel wire
12	PT100 temperature sensor	PT100 RTD with 4–20 mA transmitter

Overall, the experimental results demonstrate that the proposed Hybrid Fuzzy-PID controller can improve the transient response and reduce average power consumption of the resistive electric oven while maintaining a deterministic hardware-based implementation on the Cyclone IV FPGA. The comparison with the conventional Ziegler-Nichols PID also reveals a trade-off between faster temperature response and steady-state precision, indicating that further optimization of the fuzzy tuning mechanism is still required. These findings provide the basis for the conclusions regarding the effectiveness, limitations, and practical implications of the proposed FPGA-based Hybrid Fuzzy-PID temperature-control system.

4 Conclusion

This study designed, implemented, and experimentally evaluated a Hybrid Fuzzy-PID temperature-control system for a resistive electric oven using a Cyclone IV FPGA. The system was developed by combining a baseline PID controller derived from the experimental characterization of the oven with a zero-order Takagi-Sugeno fuzzy tuning mechanism implemented as an online adjustment layer. The controller was integrated into a unified VHDL-based hardware architecture to support deterministic real-time operation.

The experimental results demonstrate that the proposed Hybrid Fuzzy-PID approach provides a more controlled temperature response than the conventional fixed-parameter PID controller. The fuzzy tuning mechanism improved the controller's ability to regulate the oven temperature, particularly by reducing excessive temperature excursions near the desired operating condition. The comparison of different membership-function configurations also showed that the selection of the fuzzy partition structure influences the trade-off between response speed and temperature stability.

The proposed FPGA-based implementation further demonstrated that the complete control process, including fuzzy inference, parameter adjustment, and control signal generation, can be implemented within a unified hardware architecture. This implementation provides deterministic actuation and supports real-time operation without relying on a sequential software-based control structure.

Overall, the findings demonstrate that integrating experimental plant characterization, fuzzy-based parameter adaptation, and FPGA-based hardware implementation provides a practical approach for improving temperature control in thermal systems with slow and inertia-dominated dynamics. Although the proposed controller improves the overall control response, further optimization of the fuzzy rule base and tuning parameters is still required to achieve a better balance between transient performance and steady-state accuracy. Future work may therefore focus on systematic optimization of the fuzzy tuning mechanism and its evaluation under broader operating conditions and thermal disturbances.

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Reference

- [1] K. J. Åström and T. Hägglund, "Revisiting the Ziegler-Nichols step response method for PID control," *J. Process Control*, vol. 14, no. 6, pp. 635–650, 2004. <https://doi.org/10.1016/j.jprocont.2004.01.002>
- [2] L. Liu, D. Xue, and S. Zhang, "General type industrial temperature system control based on fuzzy fractional-order PID controller," *Complex & Intelligent Systems*, vol. 9, pp. 2585–2597, 2023. <https://doi.org/10.1007/s40747-021-00431-9>
- [3] W. Jiang and X. Jiang, "Design of an intelligent temperature control system based on the fuzzy self-tuning PID," *Procedia Eng.*, vol. 43, pp. 307–311, 2012. <https://doi.org/10.1016/j.proeng.2012.08.053>
- [4] H. Huang, Y. Luo, C. Zhao, and H. Suo, "Temperature control method for electric heating furnaces based on auto-encoder and fuzzy PI control," *Sensors*, vol. 25, no. 16, p. 5020, 2025. <https://doi.org/10.3390/s25165020>
- [5] J. Meng, H. Gao, M. Ruan, H. Guo, X. Zhou, and D. Zhang, "Design of vacuum annealing furnace temperature control system based on GA-Fuzzy-PID algorithm," *PLOS ONE*, vol. 18, no. 11, p. e0293823, 2023. <https://doi.org/10.1371/journal.pone.0293823>
- [6] R. Abdrakhmanov, K. Berkimbayev, A. Seitmuratov, A. Ibashova, A. Aliyeva, and G. Nurmukhanbetova, "Intelligent Fuzzy-PID temperature control system for ensuring comfortable microclimate in an intelligent building," *Int. J. Adv. Comput. Sci. Appl.*, vol. 15, no. 3, pp. 299–307, 2024. <https://doi.org/10.14569/IJACSA.2024.0150331>
- [7] J. Huang, F. Huang, J. Liang, J. Chen, and P. Li, "Fuzzy adaptive PID algorithm in temperature control system of lead patenting furnace," *Adv. Civ. Eng.*, vol. 2024, 2024. <https://doi.org/10.1155/2024/4519537>
- [8] Y. Wang, "Research on variable universe fuzzy PID control strategy of pipe lining induction heating system," *Modelling and Simulation in Engineering*, 2020, p. 8852943. <https://doi.org/10.1155/2020/8852943>
- [9] M. Fang, X. Wan, and J. Zou, "Temperature control for a proton exchange membrane fuel cell system using feed-forward fuzzy PID controller," in *Proc. 3rd International Conference on Green Energy, Environment and Sustainable Development (GEESD 2022)*, 2022. <https://doi.org/10.3233/ATDE220315>
- [10] Y. J. Chen, "Design of temperature control system based on FPGA and fuzzy-PID control algorithm," *Appl. Mech. Mater.*, vol. 599–601, pp. 1124–1127, 2014. <https://doi.org/10.4028/www.scientific.net/AMM.599-601.1124>

- [11] R. B. Ali, M. A. Jaballah, E. Aridhi, and A. Mami, "Design and FPGA-implementation of a PID controller for temperature control in a refrigeration system," *Indian J. Sci. Technol.*, vol. 11, no. 16, 2018. <https://doi.org/10.17485/ijst/2018/v11i16/121762>
- [12] X. Zhang, G. Qin, M. Zhang, and Y. Ma, "Design of fuzzy adaptive PID temperature controller based on FPGA," *TELKOMNIKA Indones. J. Electr. Eng.*, vol. 11, no. 10, pp. 6008–6016, 2013. <https://doi.org/10.11591/telkomnika.v11i10.3459>
- [13] E. Monmasson and M. N. Cirstea, "FPGA design methodology for industrial control systems - A review," *IEEE Trans. Ind. Electron.*, vol. 54, no. 4, pp. 1824–1842, 2007. <https://doi.org/10.1109/TIE.2007.898281>
- [14] H. Xie, Y. Yan, and T. Zeng, "Simulations of fuzzy PID temperature control system for plant factory," in *Proc. 2021 International Conference on Wireless Communications, Networking and Applications, Lecture Notes in Electrical Engineering*, pp. 1089–1099, 2022. https://doi.org/10.1007/978-981-19-2456-9_109
- [15] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," *IEEE Trans. Syst. Man. Cybern.*, vol. 15, no. 1, pp. 116–132, 1985. <https://doi.org/10.1109/TSMC.1985.6313399>
- [16] R. W. Syufrijal, M. Rif'an, and R. Anugerah, "IoT based smart energy meter using Modbus protocol as electricity saving effort," in *Proceedings of the Conference on Broad Exposure to Science and Technology 2021 (BEST 2021)*, pp. 184–188, 2022. <https://doi.org/10.2991/aer.k.220131.031>
- [17] A. A. Sneineh and A. A. A. Shabaneh, "Design of a smart hydroponics monitoring system using an ESP32 microcontroller and the Internet of Things," *MethodsX*, vol. 11, p. 102401, 2023. <https://doi.org/10.1016/j.mex.2023.102401>
- [18] M. Huba, S. Chamraz, P. Bistak, and D. Vrancic, "Making the PI and PID controller tuning inspired by Ziegler and Nichols precise and reliable," *Sensors*, vol. 21, no. 18, p. 6157, 2021. <https://doi.org/10.3390/s21186157>
- [19] Y. Mewada, S. Prajapati, and R. Hakani, "System for PID control and autotuning PID using Ziegler-Nichols method," *Influ. Int. J. Sci. Rev.*, vol. 4, no. 1, pp. 249–253, 2022. <https://doi.org/10.54783/influencejournal.v4i1.23>
- [20] F. Haugen and B. Lie, "Relaxed Ziegler-Nichols closed loop tuning of PI controllers," *Model. Identif. Control*, vol. 34, no. 2, pp. 83–97, 2013. <https://doi.org/10.4173/mic.2013.2.4>
- [21] M. Sugeno and G. T. Kang, "Structure identification of fuzzy model," *Fuzzy Sets Syst.*, vol. 28, no. 1, pp. 15–33, 1988. [https://doi.org/10.1016/0165-0114\(88\)90113-3](https://doi.org/10.1016/0165-0114(88)90113-3)
- [22] H. Ying, "General SISO Takagi-Sugeno fuzzy systems with linear rule consequent are universal approximators," *IEEE Trans. Fuzzy Syst.*, vol. 6, no. 4, 1998. <https://doi.org/10.1109/91.728456>
- [23] J. L. Castro, "Fuzzy logic controllers are universal approximators," *IEEE Trans. Syst. Man. Cybern.*, vol. 25, no. 4, pp. 629–635, 1995. <https://doi.org/10.1109/21.370193>
- [24] J. P. Cao, S. K. Jeong, and Y. M. Jung, "Fuzzy logic controller design with unevenly-distributed membership function for high performance chamber cooling system," *J. Cent. South Univ.*, vol. 21, pp. 2684–2692, 2014. <https://doi.org/10.1007/s11771-014-2230-y>
- [25] S. Hanumanthakari, "Comparative analysis of different types of membership functions for fuzzy logic controller in direct torque control of induction motor," in *Intelligent and Cloud Computing : Proceeding of the First International Conference on Intelligent Computing in Control and Communication (ICCC 2020)*, Springer, 2021. https://doi.org/10.1007/978-981-15-8439-8_33
- [26] A. Shitsukane, C. Otieno, J. O. Imende, and L. Mukhongo, "Comparative analysis of membership functions in fuzzy logic controllers for robot path planning optimization," *Int. J. Math. Sci. Comput.*, vol. 11, no. 3, pp. 47–57, 2025. <https://doi.org/10.5815/ijmsc.2025.03.04>
- [27] A. D. Benhamadouche, A. Ballouti, F. Djahli, and A. Sahli, "FPGA based hardware-in-the-loop simulation for digital control of power converters using VHDL-AMS," *Int. J. Adv. Comput. Sci. Appl.*, vol. 9, no. 12, 2018,. <https://doi.org/10.14569/IJACSA.2018.091273>
- [28] E. A. Ramadan, M. El-bardini, and M. A. Fkirin, "Design and FPGA-implementation of an improved adaptive fuzzy logic controller for DC motor speed control," *Ain Shams Eng. J.*, vol. 5, no. 3, pp. 803–816, 2014. <https://doi.org/10.1016/j.asej.2014.04.002>
- [29] M. Y. Hassan and S. F. Abulhail, "FPGA based P/PI/PD/PID-like interval type-2 FLC design for control systems," *Kufa J. Eng.*, vol. 9, no. 3, pp. 165–179, 2018. <https://doi.org/10.30572/2018/kje/090312>
- [30] Z. Zhang and Q. Nan, "Adaptive network-based fuzzy inference system-proportional-integral-derivative controller based on FPGA and its application in radiofrequency ablation temperature control," *Appl. Sci.*, vol. 14, no. 11, p. 4510, 2024. <https://doi.org/10.3390/app14114510>