

Comparative Analysis of Performance in Internet of Things-Based Ziegler Nichols-PID Air Heater Temperature Control

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Abstract Precise air temperature control remains a critical yet challenging task in modern industrial and agricultural systems due to high thermal inertia and heater non-linearity. Furthermore, implementing intelligent control on low-cost Internet of Things (IoT) devices is often hindered by digital conversion resolution and quantization errors. These limitations can induce thermal oscillations and energy waste if tuning criteria are sub optimally selected. Therefore, this study comparatively evaluates actual thermal performance using Integral Absolute Error (IAE), Integral Squared Error (ISE), and Integral Time Weighted Squared Error (ITSE) as objective functions for Ziegler Nichols (ZN) Type 1 Proportional-Integral-Derivative (PID) tuning. A key contribution of this work is mitigating quantization errors by integrating a 5x analog amplifier circuit with an LM35 sensor and utilizing high frequency (1000Hz) Pulse Width Modulation (PWM) via a custom-built Solid-State Relay (SSR) on an ESP32. The system was evaluated through physical closed loop testing on a 650 Watt air heater, monitored in real time the MQTT protocol. To ensure robustness, tests were cross validated at 50°C and 60°C setpoints with three replications. Experimental results demonstrate that IAE tuning offers the most balanced performance at the moderate target (50°C), achieving the fastest rise time (5.58s), minimal overshoot (0.42%), high precision (Steady-State Error/SSE: -0.11), and optimal control effort (average PWM: 52.61). Conversely, at the higher target (60°C) which presents a massive initial error deficit ISE tuning proved significantly more robust. It suppressed overshoot to 0.86% while achieving a superior settling time of 15.35 seconds. In conclusion, the IAE criterion is recommended for efficient heating applications with stable loads, whereas ISE is critical for regulating high-inertia thermal loads to prevent extreme overshoot in IoT control actuators.

Keyword: Air Heater; ESP32; IoT; PID-ZN; MQTT

1. Introduction

Precise air temperature regulation remains a critical challenge across various technical processes, including automated egg incubation [1], solar heater thermal management [2], and laboratory environment standardization [3], [4]. Stable thermal control is vital for ensuring product quality and operational efficiency [5]. However, air heating systems are inherently difficult to regulate due to high thermal inertia, susceptibility to convective disturbances, and the non-linearity of resistive heating elements. To address these challenges, the PID controller is the most widely adopted algorithm in the industry [6], [7]. PID control is highly effective across diverse applications, from glucose regulation [8] and ball-and-beam balancing systems [9] to multirotor navigation [10]. However, its effectiveness relies heavily on the precise calibration of proportional, integral, and derivative gains. The classical Ziegler-Nichols (ZN) methodology provides a solid empirical framework for deriving these base constants from the system's open-loop response [11], [12]. Recent PID optimization methods, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) [13], [14], offer strong global search capabilities. Nevertheless, these metaheuristic approaches demand heavy computational loads and

complex mathematical iterations, making them less ideal for direct implementation on memory constrained, low cost IoT microcontrollers like the ESP32. As a lightweight yet reliable state-of-the-art alternative, the empirical ZN approach evaluated via integral objective criteria namely Integral Absolute Error (IAE), Integral Squared Error (ISE), and Integral Time Weighted Squared Error (ITSE) offers a practical adaptation solution without overburdening the IoT microcontroller core [15], [16], [17], [18].

Despite this, a significant limitation of prior studies is their dominant focus on tuning algorithm simulations, often ignoring the practical constraints of low cost actuation hardware [19]. They rarely analyze the physical system's behavior when specifically tuned using IAE, ISE, and ITSE objective functions on low resolution hardware. Improper selection of tuning criteria in physical setups can lead to excessively aggressive control efforts, risking mechanical actuator wear [20] or continuous digital oscillations [21]. Compared to previous thermal optimization studies, metaheuristic methods often leave gaps concerning hardware implementation delays. For instance, systems tuned via thermodynamic genetic algorithms by Francis et al. [14] frequently exhibited overshoots above 2% due to metric adaptation complexity

straining the computation. In contrast to fractional DC motor actuation control [22], pneumatic PSO optimization [20], non linear performance studies [23], and glucose regulation [8], the FOPDT-Ziegler-Nichols architecture coupled with integral evaluation in this study proves significantly more straightforward and stable for microcontroller processing. Furthermore, the LM35 signal amplifier modification and 1000Hz high-frequency SSR actuation directly resolve the precision limitations of low cost IoT actuation. These limitations are typically the weak points in similar thermal management research [2] and system delay compensation studies [24].

This research gap motivates the present comparative study. There is a lack of studies demonstrating actual thermal behavior when IAE, ISE, and ITSE indices are utilized as tuning objectives on modern IoT microcontrollers, alongside robustness validation across different setpoints. Although IoT is widely adopted in sectors ranging from livestock to greenhouses [25], [26], [27], [28], [29], high precision control on devices like the ESP32 is frequently hindered by 12 bit Analog to Digital Converter (ADC) resolution limits, quantization errors, and communication network latency. This study aims to evaluate an IoT air heater prototype by comparing the actual thermal performance of a PID-ZN controller tuned using IAE, ISE, and ITSE objectives. The system utilizes an ESP32, a custom-built SSR, and an LM35 sensor. The sensor is integrated with a 5x analog amplifier circuit to physically overcome ADC resolution constraints [30], [31]. As an added novelty, the Message Queuing Telemetry Transport (MQTT) protocol is implemented not only for low-latency data logging but also for real-time remote

monitoring and control, leveraging task separation on a dual-core architecture [32], [33], [34], [35]. The specific novel contributions of this research are: (1) Integrating a 5x amplifier circuit and an SSR driver (MOC3020 and BTA20 TRIAC) to mitigate quantization errors in low cost microcontrollers; (2) Implementing stable MQTT based remote control functionality without interrupting the PID control's computational sampling precision; (3) Mapping the physical test endpoint formulations where IAE, ISE, and ITSE criteria modify the controller's effort behavior; and (4) Providing practical recommendations for automation engineers, validated through replications at moderate (50°C) and extreme (60°C) target temperatures.

II. Materials and Method

A. Experimental Setup and Component Integration

The primary actuator in this study is a 650-Watt AC air heater (hair dryer) element. Airflow is directed through a 5 cm diameter PVC duct. For feedback, an LM35 temperature sensor (accuracy $\pm 0.5^\circ\text{C}$) is positioned 15 cm in front of the heater nozzle. The ambient room temperature is maintained at a stable $\pm 28^\circ\text{C}$.

The ESP32 microcontroller serves as the main computational unit. Given its 12-bit ADC resolution, the LM35 sensor's output range of just 10 mV/ $^\circ\text{C}$ is highly susceptible to quantization errors (± 1 LSB). To overcome this limitation, the LM35 is connected to a CA3140 operational amplifier (Op-Amp). This non-inverting circuit is constructed using tight-tolerance (1%) resistors (40 k Ω feedback and 10 k Ω ground).

Based on the analog sensor calibration specifications, the stages of converting the digital signal into an ambient

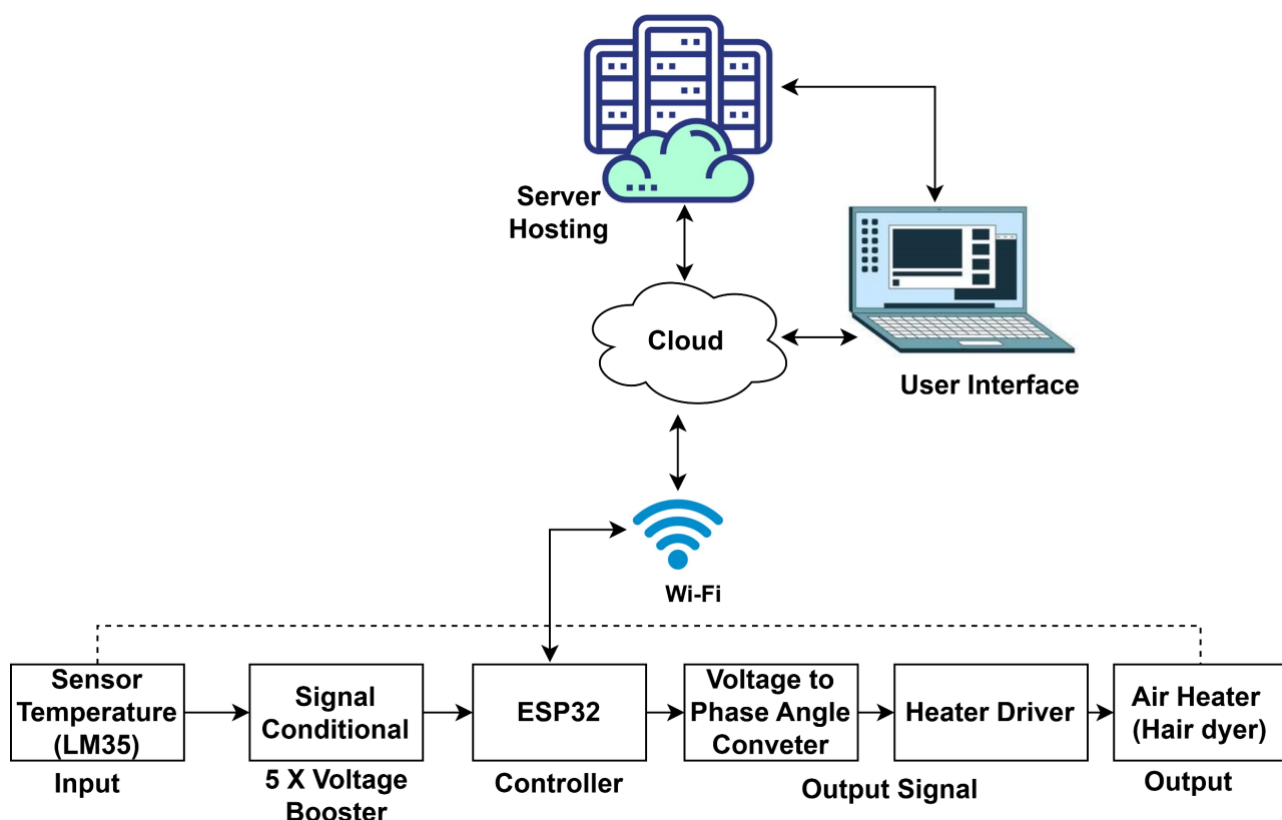


Fig. 1. Block diagram of the proposed IoT-based air-heater temperature control system.

temperature representation are formulated via Eq. (1) [30], [31]:

$$V_{adc} = \frac{ADC_{value} \times 3.3}{4095}, V_{sensor} = \frac{V_{adc}}{5}, T = \frac{V_{sensor}}{0.01}. \quad (1)$$

In this formulation, the variable V_{adc} represents the converted voltage at the ESP32 microcontroller's ADC pin (in Volts), while ADC_{value} is the raw digital reading with 12-bit resolution (0–4095). The value of 3.3 Volts denotes the ESP32's maximum operational reference voltage. The variable V_{sensor} indicates the actual voltage from the LM35 sensor prior to signal amplification, and the figure 5

control, and (8) Custom Heater Driver (MOC3020–BTA20 TRIAC) – A custom-built AC power driver employing an MOC3020 optically isolated TRIAC driver and a BTA20 power TRIAC. The circuit provides galvanic isolation between the low-voltage control electronics and the AC mains while receiving synchronized firing pulses from the voltage-to-phase angle converter. By varying the TRIAC firing angle, the driver regulates the RMS voltage applied to the heating element, thereby controlling the heater power and air temperature. The LM35 sensor measures

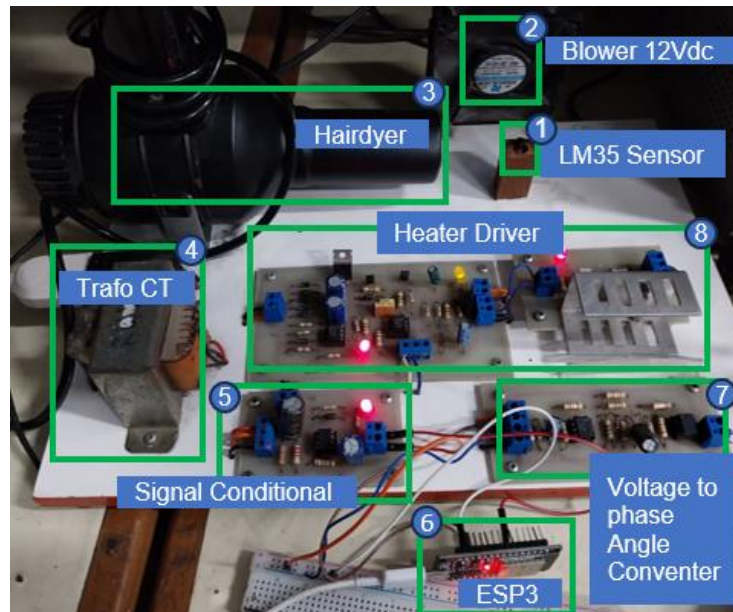


Fig. 2. Experimental hardware implementation of the IoT-based ZN-PID air-heater temperature control system.

represents the pure gain factor provided by the CA3140 operational circuit. The variable T indicates the actual ambient temperature resulting from the final conversion in degrees Celsius ($^{\circ}\text{C}$), obtained by dividing the sensor voltage by 0.01 the sensitivity value of the LM35 temperature sensor ($10 \text{ mV}/^{\circ}\text{C}$). The AC power interface is controlled by a custom-built Solid-State Relay (SSR) actuator based on the MOC3020 optocoupler and BTA20 TRIAC. This non-mechanical SSR design is capable of accepting a high-frequency (1000 Hz) Pulse Width Modulation (PWM) signal from the ESP32 [21], [36]. The hardware system design block diagram is shown in Fig. 1. The research tool for testing the air heater temperature can be seen in Fig. 2.

Fig. 2 Experimental hardware implementation of the IoT-based air heater temperature control system using the ZN-PID method. The prototype consists of (1) an LM35 analog temperature sensor, (2) a 12 VDC blower, (3) an air heater (hairdryer) serving as the thermal plant, (4) a center-tapped transformer used for power isolation and zero-crossing reference generation, (5) a signal conditioning circuit providing approximately fivefold voltage amplification to enhance ADC measurement accuracy, (6) an ESP 32 microcontroller executing the PID algorithm and managing MQTT based wireless communication, (7) a voltage-to-phase angle converter that produces synchronized firing pulses for phase-angle

the temperature of the air heater directly from the hairdryer funnel, the sensor output is connected to a signal conditioning circuit as a 5-fold voltage amplifier, the signal conditioning output is connected to pin 33 of the ESP32 and pin 4 of the PWM is connected to a signal conditioning circuit as a 5-fold voltage amplifier, the signal conditioning output is connected to pin 33 of the ESP32 and pin 4 of the PWM is connected to a voltage to phase angle converter circuit, this output is connected to a heater driver that functions as a signal output regulator to control the air heater and the phase angle trigger is set between 0° and 180° . The ESP32 as the main controller and connected to Wi-Fi, sends data to the cloud and hosting server as MQTT web storage. All control parameter data and sensor readings are published to the MQTT broker every 1 second to monitor the dynamic transient behavior of the hairdryer actuator. The system flow diagram can be seen in Fig. 3.

B. Experimental Testing Procedure and Design

To ensure data validity and eliminate thermal build-up, a 12V DC forced cooling fan is activated to return the heater to the ambient temperature ($\pm 28^{\circ}\text{C}$) before initiating any new trial. Each setpoint loading scenario is evaluated using three replications. The overall research flow is depicted in Fig. 4.

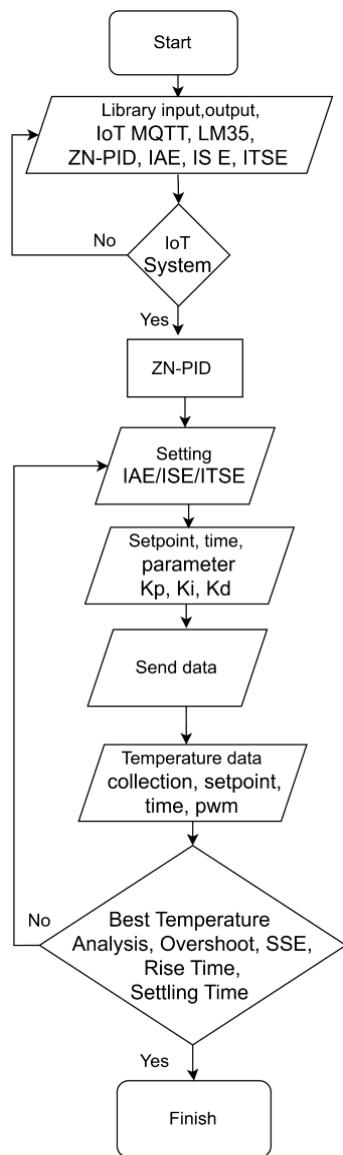


Fig. 3. Flowchart of the ZN-PID Model Air Heating System.

1. Analysis: Conducting an open-loop physical response test by injecting a constant 100% PWM signal cycle. Temperature data was recorded to develop a mathematical model of the system.
2. Design: Calculating the basic PID constant parameters (K_p, K_i, K_d) using the Ziegler-Nichols Type 1 method. These values were then independently tuned for the IAE, ISE, and ITSE functions.
3. Implementation: Integrating the entire hair dryer air heater hardware, ESP32, LM35 sensor with 5X amplifier, MOC3020 & BTA20-based actuators, and so on into a prototype, and translating the PID mathematical equations into a discrete algorithm in the ESP32's memory.
4. Testing: Practically executing the system (closed-loop) at medium (50°C) and extreme (60°C) temperature targets. This testing is accompanied by real-time telemetry variable data acquisition to the server using the MQTT protocol every 1 second.
5. Maintenance: Evaluate test data to extract system transient quality metrics (rise time, settling time, overshoot, SSE) and actuator workload efficiency (PWM). The results of this analysis serve as a reference for future evaluation and improvement of device performance.

C. FOPDT System Modeling and Ziegler-Nichols Tuning

The thermal system dynamics are approached using the First-Order Plus Dead Time (FOPDT) model, which is formulated in Eq. (2) [11], [12]:

$$G(s) = \frac{K \cdot e^{-Ls}}{T_s + 1} \quad (2)$$

In this model, $G(s)$ is an approximate transfer function representing a complex air-heating system. The parameter K defines the process gain the ratio of the temperature response to the actual actuator power while L represents the real-time process delay in seconds. The variable T acts as the heater's inertial time constant in seconds, and the variable s is the complex frequency

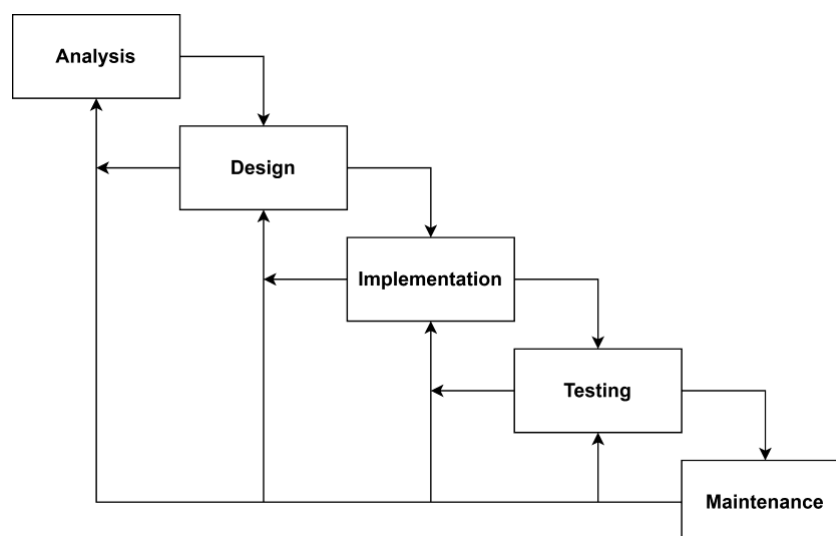


Fig. 4. Flowchart of the Experiment Research Stages.

variable from the Laplace transform used in the analysis of system dynamics.

Based on open loop testing, the empirical parameters obtained are $= 0,85$; $L = 2,5s$; and $T = 12,5s$. To formulate initial control values, the ZN Type 1 tuning parameters are calculated by referring to standard industrial regulation system formulas via Eq. (3) through Eq. (7) [7], [12]:

$$K_p = 1.2 \left(\frac{T}{K_L} \right), \quad (3)$$

$$T_i = 2. L, \quad (4)$$

$$K_i = \frac{K_p}{T_i}, \quad (5)$$

$$T_d = 0,5L, \quad (6)$$

$$K_d = K_p \cdot T_d. \quad (7)$$

In the set of equations above, the variable K_p represents the value of the fundamental proportional constant derived from empirical tuning. Meanwhile, T_i denotes the integral reset time constant in seconds, which correlates with K_i , the controller's integral action rate constant. Regarding the predictive response, T_d defines the derivative reaction time constant measured in seconds, and the variable K_d serves as the final multiplier the derivative action rate constant for the physical PID controller.

By substituting empirical values, the basic control parameters are obtained: $K_p = 7.05$, $K_i = 1.41$, and $K_d = 8.81$. These initial parameters will be specifically tuned according to objective criteria. These mathematical

values form the basis for calibration. To modify the actual physical behavior of the controller, a heuristic fine-tuning calibration is applied to these values to minimize the objective functions (IAE, ISE, and ITSE).

The continuous PID equation is discretized using a backward numerical integration approach to ensure compatibility with the ESP32 sequential computing architecture [11], [19].

D. ESP32 Discrete Control Structures and Algorithms

First, the instantaneous temperature error value, $e(k)$ is calculated as the difference from the reference based on the conventional feedback control principle in Eq. (8) [7], [19]:

$$e(k) = r(k) - y(k). \quad (8)$$

In this equation, $e(k)$ represents the system error difference signal at the (k) th calculation interval iteration, expressed in degrees Celsius. This variable is calculated by subtracting $y(k)$ representing the actual ambient temperature output value measured by the sensor module during that iteration ($^{\circ}\text{C}$) – from $r(k)$, which is the heater temperature reference or desired target setpoint ($^{\circ}\text{C}$).

Next, the Proportional $P(k)$, integral $I(k)$, and derivative $D(k)$ components are calculated based on the discrete-time mathematical approach for low-cost digital devices, as shown in Eq. (9) – Eq. (11) [21], [23]:

$$P(k) = k_p \cdot e(k), \quad (9)$$

$$I(k) = I(k-1) + K_i \cdot e(k) \cdot \Delta t, \quad (10)$$

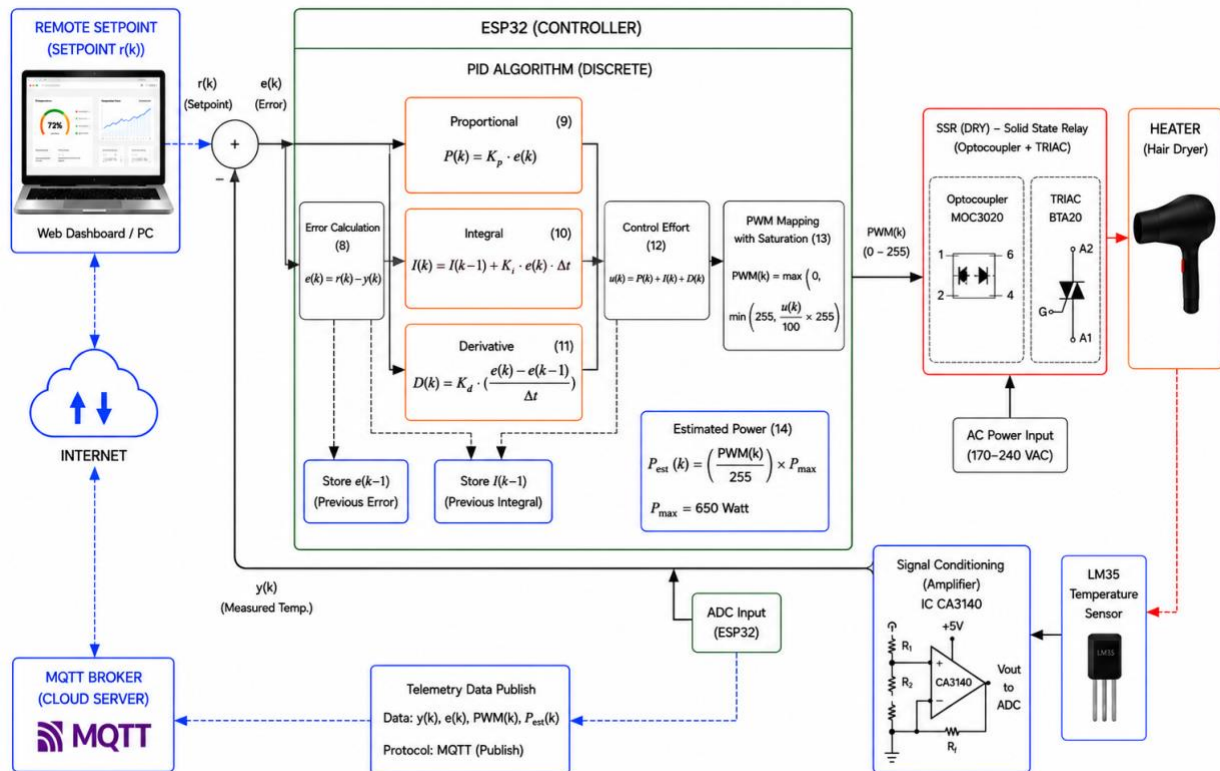


Fig. 5. | MQTT-based IoT network topology of the proposed control system.

$$D(k) = k_d \left(\frac{e(k) - e(k-1)}{\Delta t} \right). \quad (11)$$

Here, $P(k)$ is the computed value of the proportional control effort, $I(k)$ represents the cumulatively accumulated integral control effort, and $I(k-1)$ is the historical value of the integral control effort from the previous iteration. On the derivative side, $D(k)$ represents the computed derivative control effort, which reacts to instantaneous changes in error. These values are calculated based on the factor Δt the microcontroller's control execution sampling interval, fixed at 1 s and by comparing $e(k)$ with $e(k-1)$, which is the recorded temperature error signal from the preceding observation period measured in degrees Celsius ($^{\circ}\text{C}$). The cumulative control effort signal, $u(k)$, is obtained by summing the three components mentioned above, based on the standard PID formulation in Eq. (12) [7], [21]:

$$U(k) = P(k) + I(k) + D(k). \quad (12)$$

The variable $U(k)$ represents the total raw control effort signal commanded by the PID calculation. This accumulated value is what will be processed to control the hardware. Since the power actuation effort is realized through the modulation of an 8-bit resolution microcontroller pin, the signal value $u(k)$ is linearly converted to the PWM duty cycle range (0–255) with saturation limits adapted from the digital pulse modulation method in Eq. (13) [21], [37]:

$$PWM(k) = \max \left(0, \min \left(255 \left(\frac{u(k)}{100} \right) \times 255 \right) \right). \quad (13)$$

In this formulation for upper and lower limit constraints, the variable $PWM(k)$ defines the final PWM duty cycle percentage range used to control the SSR actuator. The output value of this equation remains stable and safe within the range bounded by a minimum of 0 and a maximum of 255. In addition to the duty cycle percentage, the actual heater power estimate $P_{est}(k)$ can be approximated based on the linear ratio of the PWM to the actuator's maximum capacity, as shown in the load estimation formulation in Eq. (14) [19]:

$$P_{est}(k) = \left(\frac{PWM(k)}{255} \right) \times P_{max}. \quad (14)$$

The variable $P_{est}(k)$ represents a mathematical approximation of the heating power rate delivered to the resistive element, measured in watts. This estimate is calculated using a multiplier based on P_{max} the maximum power consumption capacity of the hairdryer tested in this study, which is 650 watts. To ensure the reproducibility of this mathematical computation, the design architecture is converted into an operational pseudocode structure, as shown in Fig. 5. The figure shows the architecture of a closed-loop temperature control system based on the ESP32, discrete PID, and the Internet of Things (IoT) using the MQTT protocol. The system is controlled through a Web Dashboard, which sends the setpoint value $r(k)$ to the ESP32 via the MQTT Broker. Meanwhile, the LM35 sensor measures the hair dryer's output temperature. The signal is then amplified fivefold by a signal conditioning circuit based on the CA3140 IC before being read by the ESP32's ADC as the actual temperature

$y(k)$ using Eq. (1). If the actual temperature is $>75^{\circ}\text{C}$, the heater is turned off with a value ($PWM = 0$) to prevent overheating. The ESP32 calculates the error signal using Eq. (8). The error value is then processed by a discrete PID controller consisting of proportional, integral, and derivative components, each calculated using Eq. (9) – Eq. (11). These three components are summed into a control signal as shown in Eq. (12), which is then mapped to an 8-bit PWM signal (0–255) using the saturation function in Eq. (13). The PWM signal controls an SSR circuit consisting of a MOC3020 optocoupler and a BTA20 TRIAC to regulate the power supplied to the hair dryer. The PWM value determines the heating power, which can also be estimated using Eq. (14) with $P_{max} = 650$ Watts. Next, the ESP32 sends the actual temperature, error, PWM, and estimated power data to the MQTT Broker, which is then displayed in real time on the Web Dashboard. The entire process runs periodically with a 1 second sampling time, enabling the system to maintain the temperature close to the setpoint through a closed-loop feedback mechanism, while also enabling remote monitoring and setting of the setpoint over the Internet.

E. Dual-Core MQTT Network Integration

The stability of the physical actuation loop must be strictly maintained to isolate it from IoT communication latency (such as ping jitter or wireless connection dropouts) [32], [34], [38], [39], [40], [41]. On standard single-core microcontrollers, waiting for an acknowledgement from the MQTT Broker can cause the system to stall for tens to hundreds of milliseconds. When this occurs, the time interval (Δt) in the Derivative divider and Integral multiplier formulas becomes unstable, which instantly triggers uncontrolled oscillations (Derivative kick and Integral windup). To address this conventional architectural flaw, the ESP32 source code is fundamentally designed to utilize the internal Xtensa 32-bit LX6 dual-core microprocessor. This modification involves task pinning through FreeRTOS. According to Algorithm 1, the PID metric computation (ADC reading and PWM writing) is fully locked to Core 0 (PRO_CPU). In parallel, the Wi-Fi network stack routines and Message Queuing Telemetry Transport (MQTT) transmissions are locked to Core 1 (APP_CPU). This synchronization of data movement between processor cores is accomplished securely using the RTOS Queues memory queuing mechanism. Core 0 is simply tasked with throwing temperature data into the queue (which executes in fractions of a microsecond) and then resuming its control loop. Core 1, on the other hand, is responsible for retrieving data from the queue and handling the Publish/Subscribe transmission process to the server over the internet. The MQTT Quality of Service (QoS) level is set to 0 (At most once) to minimize memory overhead. The dual-core split-brain topology, as seen in Fig. 6, effectively enables the 650-Watt heater actuation hardware to be remotely controlled without sacrificing the accuracy of thermodynamic observations.

F. Thermodynamic Evaluation Endpoints

The observation duration for each experiment was set at 50 seconds ($N=50$), with every second recorded precisely [1]. The transient metric evaluation was validated using

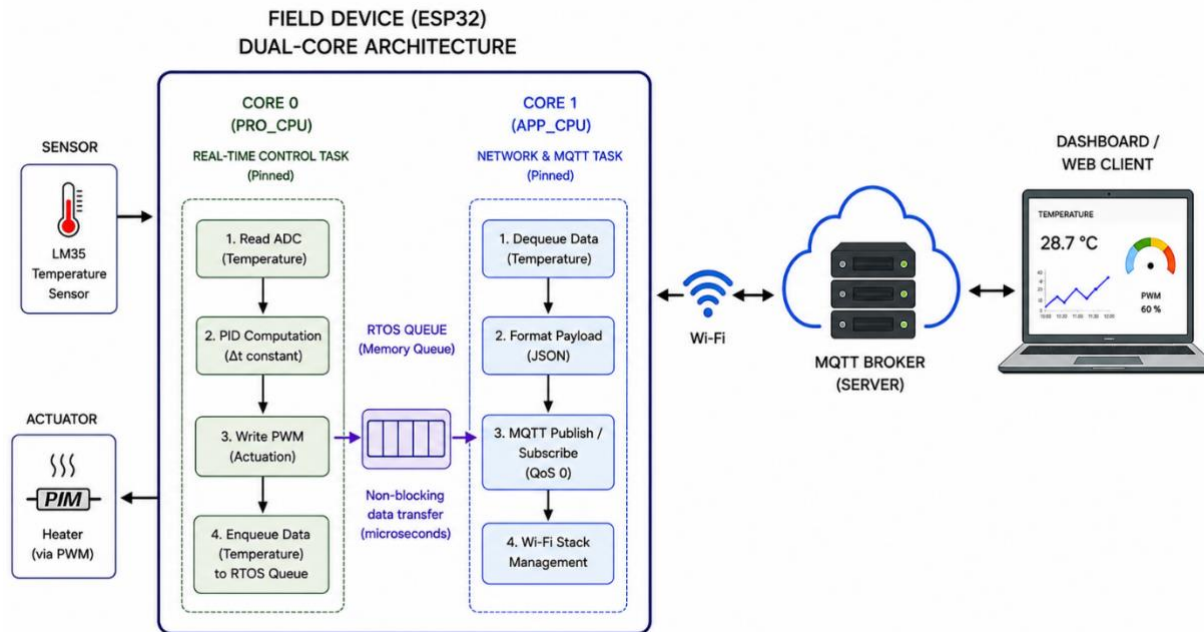


Fig. 6.] MQTT-based IoT network topology of the proposed control system.

mathematical calculations. The Overshoot (M_p) formula is presented in Eq. (15) [2], [7], while the Steady-State Error (SSE) formula is presented in Eq. (16) [22].

$$M_p = \left(\frac{Y_{max} - r(k)}{r(k)} \right) \times 100\%, \quad (15)$$

$$SSE = \lim_{k \rightarrow \infty} e(k). \quad (16)$$

The parameter M_p represents an evaluation of oscillation or the maximum transient overshoot value. Its calculation utilizes the Y_{max} value from the actual

temperature recording at the highest peak experienced by the sensor during testing. Meanwhile, the SSE metric represents the margin of inaccuracy calculated over a long observation period, once the temperature has entered the steady state range.

The endpoint of the parameter search is calculated by minimizing the values of three criteria of the integral objective function [6], [10]. The calculation is described in Eq. (17) to Eq. (19) [6], [10], [17].

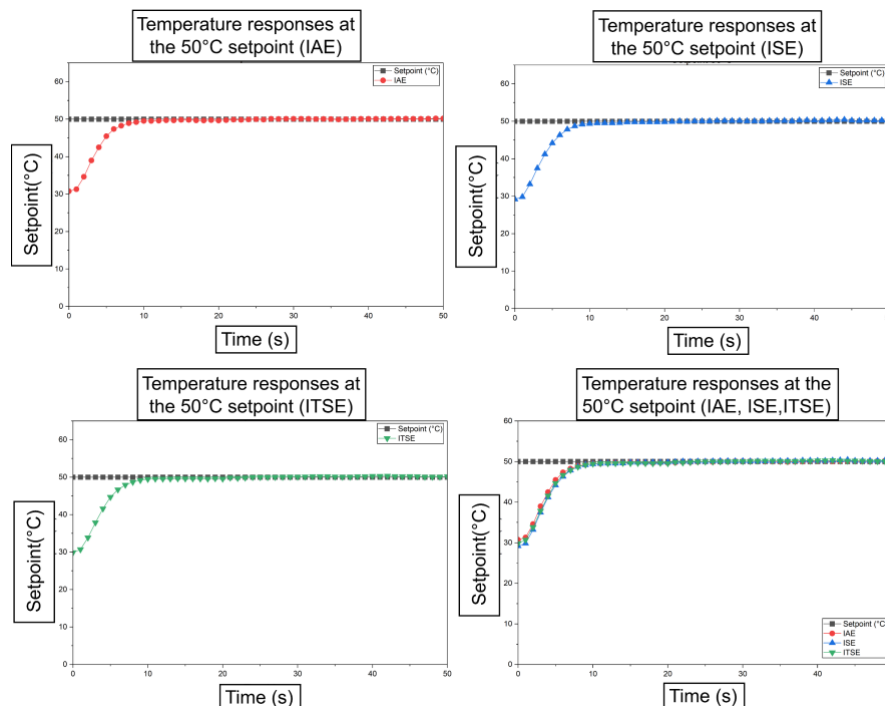


Fig. 7.] Temperature responses at the 50°C setpoint (a) IAE, (b) ISE, (c) ITSE, (d) IAE, ISE, ITSE

$$IAE = \sum_{k=1}^N |e(k)| \Delta t, \quad (17)$$

$$ISE = \sum_{k=1}^N e^2(k) \Delta t, \quad (18)$$

$$ITSE = \sum_{k=1}^N (k \Delta t) e^2(k) \Delta t. \quad (19)$$

In the calculation of these indices, IAE measures the magnitude of absolute deviation, ISE is a metric that sums the squared error areas, and ITSE incorporates a time based penalty weight into the equation. The Σ symbol represents the total accumulated sum derived from iterations starting at the initial observation ($k = 1$) up to the final target variable, N . The variable N represents the total number of samples in the observed data recording period, fixed at 50 data points. Meanwhile, the parameter k denotes the count or sequence of the current sampling iteration; in the case of the ITSE criterion, this parameter also functions directly as a multiplier for the temporal penalty weight applied to the actuation response.

III. Results

A. Cross-Setpoint Fine-Tuning Parameters

To ensure the system produces compensation behavior that uniquely reflects each criterion, the basic ZN parameters were fine-tuned to minimize each objective function at two different setpoints. Table 1 presents the final parameters applied. At the intermediate setpoint of 50°C, the ISE criterion tuning was formulated with the highest proportional gain (K_p) (8.50) to aggressively suppress initial transient deviations. Conversely, the ITSE criterion emphasized the largest derivative gain (K_d) (6.50) to provide rapid braking action to dampen

operated with a more moderate and balanced K_p parameter of 7.10.

When the target temperature was increased to the more extreme level of 60°C, the control parameters logically adapted to the larger energy deficit. The IAE and ITSE criteria responded by increasing the K_p value to 8.00 and K_i to ensure the system had sufficient thrust to pursue distant targets. Interestingly, however, in the ISE criteria, the K_p value was actually lowered slightly (from 8.50 to 8.20). This makes mathematical sense; since at the 60°C setpoint, the initial error squared spike is already very large, maintaining a K_p value that is too high would cause the system to experience excessive actuator saturation and trigger the danger of extreme overshoot. The parameter values for the 50°C and 60°C setpoints can be seen in Table 1.

B. Integral Error Calculation Evaluation

Table 2 reports the actual calculated values of the integral index during the 50 second observation phase, derived directly from real-time thermal response data recordings. This data confirms that the tuning parameters performed precisely according to their mathematical design; the controller with the IAE configuration consistently produced the lowest accumulated absolute error (IAE) at each setpoint, as did the ISE and ITSE configurations for their respective specific functions. In the 50°C target test, the controller parameters using the IAE objective successfully achieved the smallest accumulated absolute error (94.62) compared to those using the ISE (108.35) and ITSE (102.18) parameters. The same mathematical proof consistently applied to the ISE criterion tuning, with

Table 1. Fine-tuned PID parameters for the IAE, ISE, and ITSE criteria.

Criteria	Setpoint	Kp	Kd	Ki
IAE	50°C	7.10	0.65	5.20
	60°C	8.00	0.80	5.20
ISE	50°C	8.50	0.80	4.50
	60°C	8.20	0.75	5.00
ITSE	50°C	6.80	0.55	6.50
	60°C	8.00	0.90	5.00

Table 2. Experimental integral error indices at the 50°C and 60°C setpoints

Setpoint	Tuning	IAE	ISE	ITSE
50°C	IAE	94.62	1178.45	2340.15
	ISE	108.35	1050.80	2510.60
	ITSE	102.18	1125.60	1980.55
60°C	IAE	175.42	3760.35	8363.28
	ISE	189.58	3490.52	7600.45
	ITSE	221.15	5010.20	7450.55

Table 3. Average transient-response performance at the 50°C and 60°C setpoints.

Criteria	Setpoint	Rise Time (s)	Settling Time (s)	Overshoot (%)	SSE(°C)
IAE	50°C	5.58	9.58	0.42	-0.11
	60°C	9.39	15.39	0.95	-0.14
ISE	50°C	6.48	9.48	0.86	-0.24
	60°C	9.39	15.35	0.86	0.09
ITSE	50°C	6.32	6.32	0.62	-0.18
	60°C	10.74	10.74	1.96	-0.12

oscillations in the steady-state phase. Meanwhile, the IAE

the lowest value of 1050.80 and the lowest ITSE value of 1980.55 when measured in their respective functions.

Comparison of data across setpoints revealed a sharp increase in aggregate error values when the target temperature was increased to 60°C. This spike in accumulated error at the best IAE value, which jumped from 94.62 to 175.42, is a thermodynamically reasonable phenomenon. This occurs because the initial heating deviation range from room temperature of $\pm 28^\circ\text{C}$ to the target of 60°C is much wider. Consequently, the actuator requires a longer transient phase, which automatically accumulates a larger error area before the system can stabilize at steady state. The Integral Index values can be seen in Table 2.

C. Transient Response Characteristics (Secondary Endpoints)

Table 3 displays the average thermal dynamic performance from three tests, demonstrating the system's resilience when facing varying load and different target temperatures. Based on data in Table 3, at the medium target load of 50°C, the IAE criterion performed most impressively and balanced overall. IAE recorded a very fast rise time (5.58 s), minimal overshoot (0.42%), and the most consistent final precision accuracy (SSE -0.11°C). Meanwhile, the time weighting in the ITSE criterion proved effective at 50°C, forcing the system to achieve stability as quickly as possible (settling time 9.32 s) by damping residual oscillations at the end of the process. However, the controller's behavior changed drastically when the system was executed at the target temperature of 60°C, which required much wider initial error and thermal inertia compensation. In this extreme temperature range, the ISE criterion demonstrated its mathematical robustness. Due to the nature of the ISE function, which squares large

Table 4. PWM control-effort profiles at the 50°C and 60°C setpoints.

Criteria	Setpoint	Maximum PWM (Transient Phase)	Average PWM
IAE	50°C	151	52.61
	60°C	255	83.00
ISE	50°C	163	58.68
	60°C	255	81.00
ITSE	50°C	155	57.41
	60°C	255	95.83

initial errors, this parameter forces the actuator to operate very aggressively and responsively from the first second. As a result, the ISE was able to match the rise time (9.39 s), achieve the fastest settling time (15.35 s), consistently stabilize overshoot at 0.86%, and achieve superior steady-state accuracy (0.09°C). In contrast, the ITSE criteria, previously reliable at 50°C, were severely degraded under extreme loads. Due to the high error deficit at 60°C, which was continuously multiplied by time (t), the ITSE overcompensated, triggering a very high overshoot spike of 1.96%, followed by a slowdown in settling time to 15.74 s. Fig. 7 – Fig. 8 is a graph of heater temperature against time at the 50°C and 60°C set points.

D. PWM Control Effort Analysis (Secondary Endpoints)

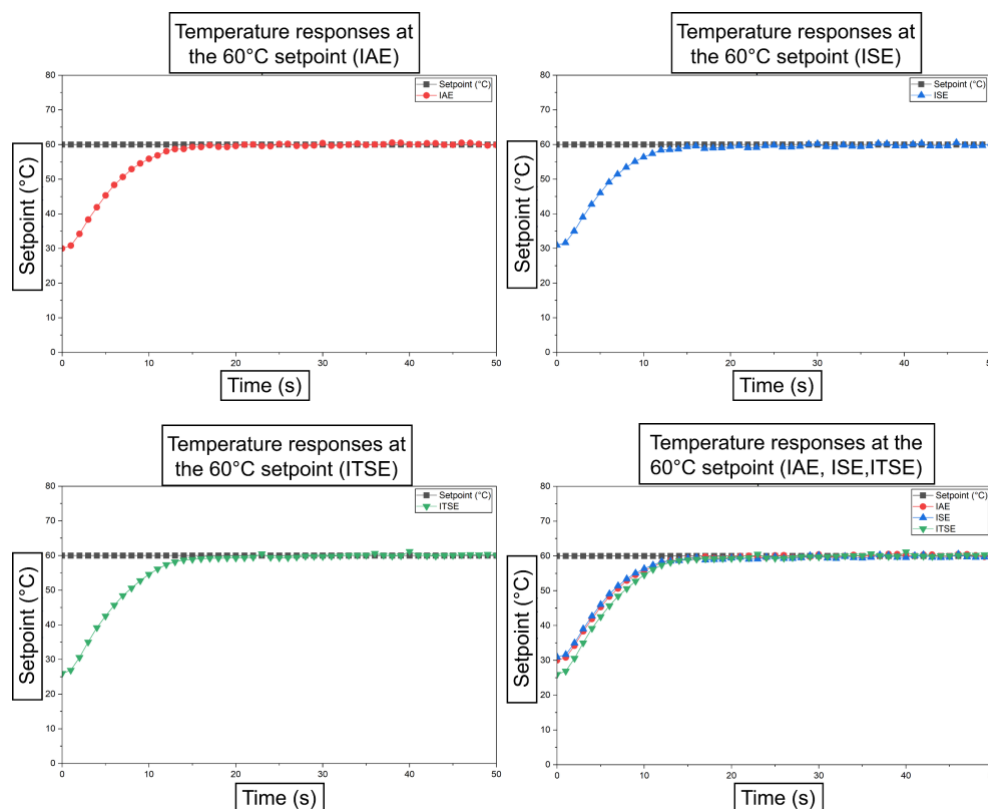


Fig. 8.] Temperature responses at the 60°C setpoint (a) IAE, (b) ISE, (c) ITSE, (d) IAE, ISE, ITSE

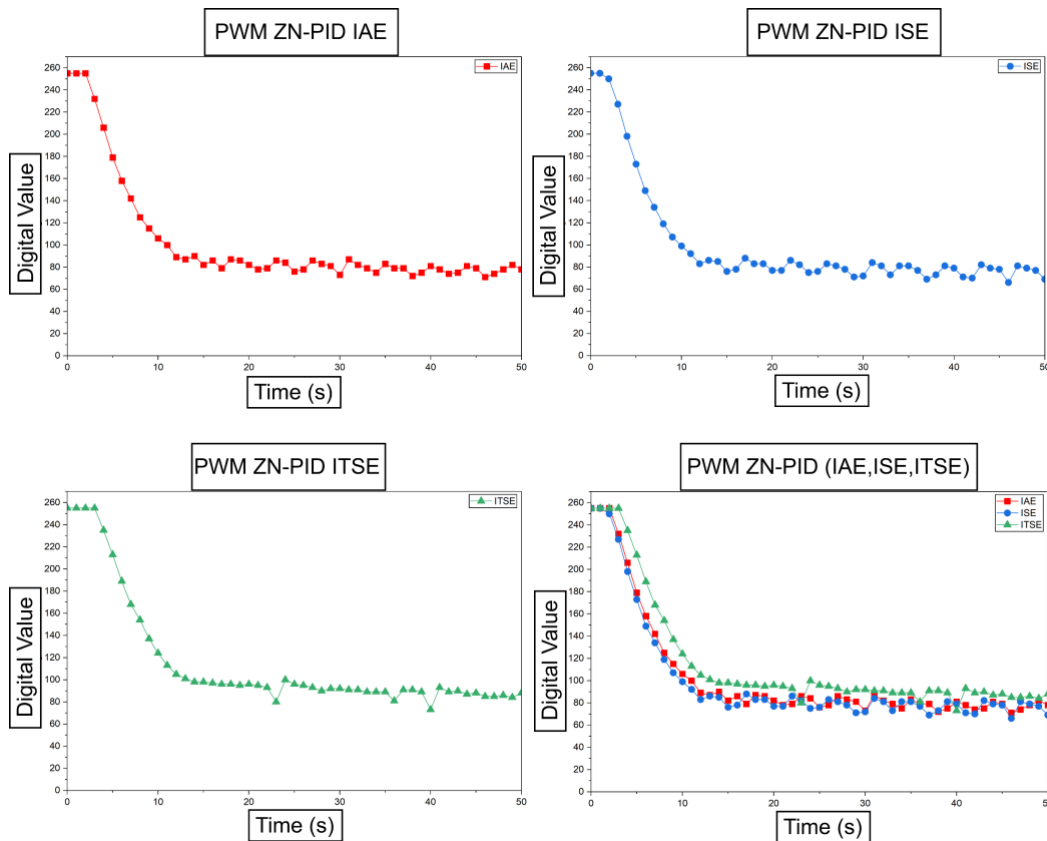


Fig. 10. PWM control-effort responses at the 60°C setpoint (a) IAE, (b) ISE, (c) ITSE, (d) IAE, ISE, ITSE.

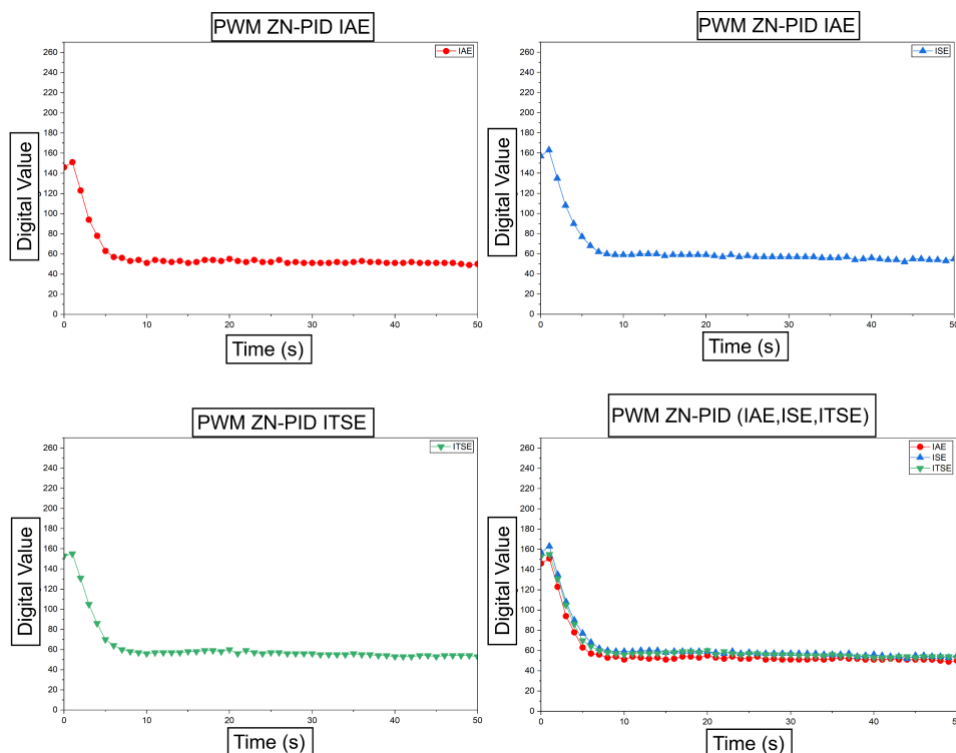


Fig. 9. PWM control-effort responses at the 50°C setpoint (a) IAE, (b) ISE, (c) ITSE, (d) IAE, ISE, ITSE.

The PWM value is not calculated as an accumulation of absolute energy consumption (Joules), but rather as a proxy for the intensity of the electromechanically driven energy input [19]. Table 4 presents the PWM load distribution for the MOC3020+BTA20 driver.

In terms of transient response (Table 3), the IAE criterion proved to be the most energy-efficient and smoothest approach for the 50°C target, evidenced by the lowest transient peak (PWM 151) and the lowest average PWM value during the steady-state phase (52.61). The

absence of a squared penalty weight allowed energy to be supplied to the 650-Watt heater in a more gradual manner. However, to overcome the significant thermal inertia required to reach 60°C, the third PID criterion forced the system to the module's upper limit (maximum PWM saturation of 255) from the very first second. Once the 60°C steady state was finally achieved, the actuator governed by the ISE criterion could operate more moderately (recording an average effort consumption of 81.00), slightly outperforming IAE (83.00). Ironically, due to the effort required to dampen persistent residual temperature oscillations, the ITSE criterion caused excessive actuator activity recording an extreme duty cycle of 95.83 even after the temperature had stabilized which poses a risk of accelerating mechanical fatigue [43]. Below, Fig. 9 – Fig. 10 show PWM control graphs for the heater temperature versus time test at the 50°C and 60°C setpoints.

IV. Discussion

A. Deep Interpretation

The precision of the IAE criterion (SSE -0.11°C the 50°C target directly stems from the 5X analog amplifier integration, which shifts the LM35 sensor sensitivity from 10mV/°C to 50mV/°C. This hardware modification drastically reduces the quantization error of the ESP32's 12 bit ADC and improves the SNR, enabling the PID derivative component to compute microscopic thermal deviations without triggering false switching. Furthermore,

computational stability is deterministically locked by the dual-core topology, isolating the physical control algorithm from IoT telemetry latencies. At the output stage, high-frequency SSRs 1000 Hz ensure smooth actuation. Consequently, IAE proves superior for medium loads 50°C by distributing energy smoothly without causing actuator switching fatigue. Conversely, ITSE exhibits the worst performance at extreme loads 60°C. Its time weighting characteristic erroneously exploits the large initial transient delay, triggering severe integral windup that breaks system protections and causes a destructive 1.96% overshoot.

B. Comparison to Other Similar Studies

Table 5 presents a quantitative head-to-head comparison between this architecture and six previous studies in dynamic control and thermal regulation. In contrast to conventional metaheuristic optimizations like GA [14] or PSO [11], which frequently document persistent transient fluctuations (>2%) due to heavy computational iteration loads, the hardware-amplified ZN-PID architecture in this study convincingly suppresses absolute overshoot to 0.86% at an extreme inertia target 60°C [23].

The matrix in Table 5 firmly refutes the paradigm that hardware-backed empirical thermal tuning is inferior to metaheuristic iterations. This study demonstrates that the ISE criterion successfully caps peak oscillation at 0.86% (outperforming the physical algorithms in [1] and [14]), proving that its exponential penalty paradoxically acts as

Table 5. Comparison of Numerical Control Results with Six Similar Studies

Reference	Optimization Method/ Controller	Actual Target Architecture	Quantitative Results/ Measured Performance	Relative Limitations to This Study
Prabowo et al. [1]	Conventional IoT PID	Thermal Incubator Prototype	Overshoot exceeds 1.80%, SSE deviation reaches ±0.50°C	Signal deviation vulnerability due to internet telemetry latency on a single-core.
Liu et al. [5]	Fuzzy Fractional-Order PID	Industrial Temperature	Overshoot dampened to 1.20%, steady-state accuracy 0.20°C	Logic algorithm architecture is too complex for standard IoT ICs.
Wu et al. [8]	Neural Network + PID	Biomedical Control Simulation	Surpasses limits with a stable overshoot at 0.95%	Machine learning adaptation is inapplicable for low-cost IoT memory.
Francis et al. [14]	GA + PID	Hardware-in-the-loop thermal	Highly fluctuating overshoot >2.45%, settling time >40 s	Smart control iteration burdens physical actuation processing.
Boukhalfa et al. [22]	GA + Fractional Order PID	DC Motor Actuator	Overshoot stability at 1.02%, settling time 28 s	Offline local testing, lacks MQTT IoT telemetry validation.
Dubravic et al. [24]	PSO-PID on FOPDT	FOPDT Temperature Simulation	Overshoot suppressed to 1.15%, rise time stalled at 12.4 s	Initial response lacks aggression against actual thermal inertia.
This Study	ZN-PID with IAE, ISE, ITSE Evaluation	Actual IoT Air Heater 650 Watt	Zero telemetry latency. Excellent accuracy (SSE - 0.11°C, rise time 5.58 s, minimum absolute overshoot 0.42%-0.86%.	Static load variance, validated only at two specific equilibrium points.

a vital thermal shock absorber against massive inertia target jumps 60°C

C. Weaknesses

Despite presenting comprehensive physical transient data, this methodological evaluation inherently contains elemental limitations. First, the experiment relies solely on a commercial 650 Watt resistive thermal blower (hair dryer), leaving its scalability to mega-Watt industrial boilers unproven. Second, the execution environment was strictly isolated in a controlled laboratory setting 28°C, neglecting robustness tests against external convective wind disturbances or network jitter/packet loss during extreme MQTT communication. Third, target validation (setpoints) was statically restricted to 50°C and 60°C. Lastly, the control effort energy conversion is currently represented as a PWM proxy ratio 0-255 rather than absolute thermodynamic energy units (Joules).

D. Implications

This study establishes critical engineering implications for future industrial automation. Practically, engineers must adopt the IAE objective for low-gradient thermal facilities e.g., smart-farming incubators, seed dryers to minimize thermal stress and prevent mechanical switching fatigue on the heater coils. Conversely, for high-inertia environments demanding zero-overshoot tolerance e.g., medical chemical boilers to prevent specimen micro-cracks, implementing the ISE objective is mandatory to act as a thermal shock absorber. Architecturally, IoT edge controllers can no longer rely on single-core processing. Transitioning to a dual-core task pinning topology (RTOS) is absolute to ensure local thermodynamic feedback loops remain immune to TCP/IP network latencies. For future research, this study paves the way for thermal Adaptive Controllers capable of autonomously auto-switching objective functions from IAE to ISE in real-time based on actual temperature fluctuations.

V. Conclusion

The primary objective of this study was to demonstrate a comparative physical thermal performance evaluation of an ESP32 control system with an IoT architecture using three integral index tuning functions. A summary of the numerical findings demonstrates that, for the target application at a mid-range temperature (50°C), the IAE criterion provides superior performance with a fast rise time (5.58 seconds), very safe overshoot (0.42%), and optimal accuracy (SSE -0.11°C), with the lowest PWM control effort required. However, for heating system designs operating at a target temperature significantly different from the baseline (60°C), the ISE proved to be a much more robust structure in suppressing overshoot spikes (maximum 0.86%) with a leading settling time convergence rate (15.35 seconds). Practically, the IAE is highly recommended for industrial applications with relatively stable loads near the baseline temperature, due to its moderate nature, which can prevent switching fatigue in the heating coil. Conversely, a forced modification based on the ISE is recommended when dealing with severe inertial dynamics to suppress shock spikes. The transmission-independent architecture of the dual-core MQTT protocol successfully prevented

computational lag in the PID loop. Future work is recommended to design an integral adaptive anti-windup compensation strategy, refine wireless network delay suppression in unstable environments, and validate the heater's robustness over a wider range of wattage dynamics.

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Author Contributions

Seno Aprilianto: Conceptualization, Methodology, Hardware Integration, Experimental Data Collection, and Writing the Original Draft. **Bambang Supriyo:** Control Methodology, System Validation, Data Analysis, and Draft Review. **Sidiq Syamsul Hidayat:** IoT and MQTT Architecture Supervision, Manuscript Editing, and Research Guidance.

Data Availability

The raw experimental data, hardware component models, and serial log (CSV) results from this study are available from the Corresponding Author upon reasonable request.

Code Availability

The source codes used in this study are available from the Corresponding Author upon reasonable request.

Ethical Approval

Not applicable. This research does not involve human subjects, test animals, biological materials requiring special permission, or the collection of personal identification data.

Consent To Participate

Written informed consent was obtained from all participants before their inclusion in the study. Participation was voluntary, and participants were informed of their right to withdraw from the study at any time without consequences.

Consent for Publication

Written informed consent for the publication of anonymized and aggregated research data was obtained from all participants. The manuscript contains no personally identifiable information.

Competing Interests

The authors declare that they have no financial or non-financial competing interests that could have influenced the conduct, analysis, interpretation, or reporting of this study.

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