A Comparative Experimental Evaluation of iPI and iPI-Fuzzy Controllers for a Thermal Process with a Long Dead Time

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Abstract: This paper introduces a control approach integrating intelligent proportional-integral (iPI) control with fuzzy logic, specifically designed for temperature management using the Temperature Control Laboratory (TCLab) platform. The proposed controller leverages a model-free methodology that transcends traditional PID constraints by incorporating real-time parameter estimation and adaptive algorithms. The system is adaptable to handle dynamic temperature variations and external disturbances by combining intelligent control techniques with fuzzy logic. Experimental validation in the TCLAB reveals significant improvements in temperature tracking precision and system robustness across diverse operational conditions.

1 INTRODUCTION

Thermal processes are fundamental to the success of chemical engineering and drive innovation across fields such as reaction engineering, biomedicine, energy production, materials science, and green chemistry (Plawsky, 2020). Although chemical engineering was historically centered on the petrochemical and heavy chemical industries, its scope has expanded to include biomedicine, environmental sustainability, advanced materials, and the mitigation of climate change (Jain and Goodson, 2011). Achievements such as the development of antibiotics, vaccines, and immunological advancements are heavily based on precise thermal regulation to ensure reaction efficiency and product stability, significantly improving global health and longevity. Similarly, the fabrication of semiconductor materials (May and Spanos, 2006), a key to the microelectronics revolution, requires meticulous temperature control to achieve the precision required for modern computing and the digital era. In these diverse applications, temperature control is a critical challenge to ensure the stability, safety and performance of chemical processes in laboratory experiments, advanced manufacturing, and industrial systems (Vásquez et al., 2023; Obando et al., 2023).

Effective control systems are essential for thermal processes in chemical engineering, addressing two primary objectives: regulation and tracking. Regulation involves maintaining process temperatures at specific set points to ensure stable and consistent operation, which is critical to meeting industrial requirements such as cost efficiency, production targets, safety standards, and product quality. Precise temperature control is indispensable for chemical reactions and material synthesis, where deviations can compromise efficiency or safety. However, tracking entails guiding the process temperature from one operating state to another, often to accommodate changes in economic conditions, product requirements, operational constraints, environmental regulations, or safety protocols. Reliable tracking ensures smooth transitions while minimizing disruptions and maintaining compliance with quality and operational objectives. Together, these functions enable thermal process control systems to meet dynamic industrial demands effectively and safely (Smith and Corripio, 2005; Liptak et al., 2018).

Thermal process control strategies vary according to the complexity and needs of the system, considering process dynamics, delays, and goals. Com-

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mon approaches include PID Control, which balances fast response, eliminates steady-state error, and anticipates future errors, though it requires tuning for best performance; Cascade Control, which uses two loops to enhance accuracy and disturbance rejection, often in heat exchangers and reactors; Feedforward Control, which predicts disturbances and adjusts proactively, typically used in systems with measurable disturbances; Model Predictive Control (MPC), which utilizes process models to predict and optimize future behavior, ideal for complex systems with constraints; Smith Predictor, designed for systems with significant time delays to improve stability and response; Adaptive Control, which adjusts parameters based on real-time changes, maintaining performance under varying conditions; Fuzzy Logic Control, which handles nonlinearities and uncertainties by mimicking human decision-making (Smith and Corripio, 2005; Kocaarslan et al., 2006; Liptak et al., 2018; Schwenzer et al., 2021; Mejia et al., 2022).

Previous approaches depend on precise models and parameters. Analytical models offer insights but are complicated by nonlinearities, increasing computational demands (Sardella et al., 2019). Building comprehensive models is challenging due to the complexity of the system and the accuracy of the parameters (Gude et al., 2024), making phenomenological models difficult to implement in industrial settings (Gude, 2023). Empirical models such as First-Order Plus Dead Time (FOPDT) are effective alternatives for control design, accurately representing the core dynamics of many industrial processes (Gude et al., 2024; Obando et al., 2023; Liptak et al., 2018).

Model-free control (MFC) emerges as an auspicious approach in this context, offering remarkable adaptability by eliminating the need for complex mathematical modeling (Fliess and Join, 2013). Instead, it relies on dynamic, data-driven parameter estimation, and continuous system adaptation. This methodology proves especially valuable in systems characterized by inherent nonlinearities and unpredictable variations, such as temperature control environments. MFC is characterized by its remarkable adaptability, making it an ideal choice for complex or poorly understood systems, as adequately as those subjected to frequent disturbances and constant variations (Fliess and Join, 2013; Precup et al., 2017). An innovative control strategy derived from MFC principles is the intelligent PID approach (iPID), as discussed in (Fliess and Join, 2013; Precup et al., 2017). This method marks important progress in control theory by overcoming the traditional PID drawbacks through adaptive parameter alterations and nonlinear gain methods.

The Arduino-based Temperature Control Lab (TCLab) was developed to study process dynamics and control. This lab provides an online experience with basic programming modules in Matlab, Python, or Java for students. Participants gain access to sensor data and devices for feedback control. Preliminary evidence indicates that TCLab enhances learning; however, further research is required to evaluate its effect on students' understanding of system dynamics and process control (de Moura Oliveira et al., 2022). Additional uses of control systems on the TCLab device are examined in (Mejia et al., 2022; Patel, 2023).

In this study, iPI controllers were employed for thermal processes that exhibit long delays, exploring two alternatives: traditional iPI as introduced by Fliess (Fliess and Join, 2013) and a fuzzy iPI control applied to TCLab. The concept involves incorporating fuzzy logic into the iPI to determine whether such integration could enhance the system's robustness and responsiveness in temperature control (Zhang and Liu, 2006). A comparative analysis of both controllers was conducted for set-point changes and disturbance rejection.

The paper is divided as follows: In Section 2, some fundamentals are described, Section 3 shows the methodology of design, Section 4 presents the results in the TCLab, and finally the conclusions are drawn in Section 5.

2 TIME DELAY BASICS

This section outlines the theoretical foundation and motivation behind the proposed control methodology, emphasizing its relevance in tackling the challenges inherent to temperature control with long delays.

2.1 Challenges

Time delays in industrial processes can arise from various sources, and understanding these delays is critical for optimizing and controlling systems effectively (Smith and Corripio, 2005; Espin et al., 2022). Such delays can significantly affect the performance of closed-loop control systems, especially when dead time is considerable. Increased dead time results in several issues, including reduced crossover frequencies and critical gains, which make the controller more sensitive to noise. Additionally, corrective actions by the controller are delayed, leading to slower transient responses and an increased risk of system instability (Mejia et al., 2022; Sardella et al., 2019).

The primary difficulty with time delays is that they prevent the timely detection of disturbances and delay the corresponding corrective actions, leading to mismatched responses and potential loss of stability. From a classical control perspective, time delays introduce negative phase shifts, reducing the critical frequency and phase margin. This, in turn, limits the permissible control gain and response speed. A common mitigation strategy is to decrease the gain and increase the integration constant; however, while this can reduce the effects of delays, it often compromises system performance by producing sluggish responses and poor disturbance rejection. Such performance degradation is typically unacceptable in industrial settings. These limitations highlight the need for advanced control strategies specifically designed to address the challenges posed by systems with significant time delays. Fuzzy controllers are particularly suited for systems with dominant time delays due to their heuristic rule-based adaptability to nonlinear dynamics and parametric variations. Recent studies (Tanaka et al., 2023; Wang et al., 2022) demonstrate their effectiveness in industrial thermal processes, where real-time estimation and adaptive tuning mitigate delay-induced instability.

3 INTELLIGENT PID CONTROLLER APPROACHES

This section employs the Fliess recommended method to develop an iPI fuzzy controller. The layout of this section is as follows. In section 3.1, we detail the controller design following Fliess's approach. Section 3.2 delves into fuzzy methodology and section 3.3 focuses on the preliminary tuning via the particle swarm optimization (PSO) algorithm.

3.1 iPI Controller Proposal by Fliess

One promising approach to designing model-free controllers is the intelligent PID (iPI) methodology. Replaces the conventional process model with an ultralocal model and incorporates an estimator to update it dynamically. Inspired by traditional PID controllers, this method leads to several variations, including iP, iPI, iPI, and iPI controllers. The ultralocal model for an SISO system is represented as:

$$\dot{y}(t) = F(t) + \alpha u(t). \tag{1}$$

where $F(t)$ captures the unmodeled dynamics and disturbances, $\alpha \in \mathbb{R}$ is a positive design parameter chosen to align the magnitudes of $\dot{y}(t)$ and $\alpha m(t)$, and $m(t)$ is the control input.

The control objective is defined through the tracking error:

$$e(t) = R(t) - y(t). \tag{2}$$

Here, $R(t)$ denotes the desired reference temperature, while $y(t)$ corresponds to the measured system output temperature. This error metric provides the foundation for designing the control law, ensuring that the system output converges to the reference value with minimal deviation, even in the presence of disturbances or model uncertainties.

For the iPI controller, the control law takes the form:

$$u_1(t) = \frac{1}{\alpha}\left[-\hat{F}(t) + \dot{R}(t) + K_P e(t) + K_I \int_0^t e(\tau)d\tau\right]. \tag{3}$$

where K_p and K_i are the proportional and integral gains, respectively, and are tuned to ensure accurate tracking of $R(t)$. Substituting the model equation into the control law results in the closed-loop error dynamics:

$$\dot{e}(t) + K_P e(t) + K_I \int_0^t e(\tau)d\tau = 0. \tag{4}$$

which indicates that disturbances and unmodeled components encapsulated in $F(t)$ are effectively canceled.

The gains for a PI-Fuzzy is necessary to first create the control law that the derivative part entails. In this case, we proposed to add the derivative part keeping a first ultra local model.

$$u_2(t) = \frac{1}{\alpha}[-\hat{F}(t) + \dot{R}(t) + K_P e(t) + K_D \dot{e}]. \tag{5}$$

To estimate $\dot{y}(t)$, various methods can be employed, such as numerical differentiation or filtering. A first-order low-pass filter is commonly used, defined as

$$H_{LP}(s) = \frac{K_{LP}s}{T_{LP}s + 1}, \tag{6}$$

where K_{LP} and T_{LP} are the gain of the filter and the time constant, chosen to balance the noise reduction and delay. Using this filter, the disturbance estimation is given by:

$$F(t) = \dot{y}(t) - \alpha u(t). \tag{7}$$

where $\dot{y}(t)$ represents the estimated derivative of the output of the system.

3.2 iPI Fuzzy Controller Proposal

A fuzzy PI controller is designed based on the structure of the previously described fuzzy PD controller. To implement the fuzzy PI configuration, the output of the fuzzy PD controller is integrated, as illustrated in Fig. 1.

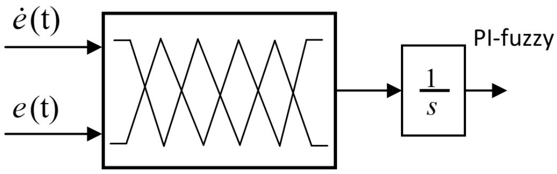

Figure 1: Control PI-fuzzy Scheme.

Table 1 displays the PD-fuzzy rules utilized in the TcLab. In this context, the terms *NB* and *PB* represent ”negative big” and ”positive big,” respectively. These labels belong to a set of rules that establish connections between the input and output variables using fuzzy values. Specifically, *NB* refers to a highly negative value, while *PB* corresponds to a strongly positive value within the framework of the fuzzy logic system.

Table 1: Fuzzy Table.

$\dot{e}/e$	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NM	NM	NS	ZE	PS
NS	NB	NM	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PB
PM	NS	ZE	PS	PM	PB	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

The three-dimensional surface depicted in 2 illustrates how these rules are employed to generate a continuous output from the fuzzy system. The surface's shape and colors reveal how the output values change based on different input combinations, offering a visual representation of the way the fuzzy rules convert inputs into a corresponding output.

3.3 Initial Tuning Parameters Based on Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a renowned metaheuristic algorithm influenced by the behavior of a flock of birds searching for food. Each bird communicates its findings with the group, helping to locate the most advantageous prey collectively (Wang et al., 2018). This process involves every bird seeking its own best solution within a multidimensional space, and the most effective solution identified by the entire swarm becomes the optimal result in the PSO.

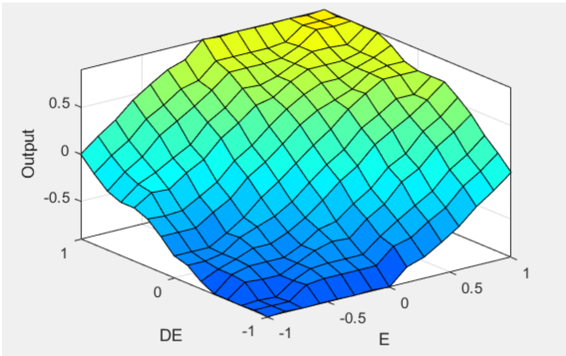

Figure 2: Fuzzy Surface.

A minimization objective function dependent on the error is proposed, known as the Integral Squared Error (*ISE*), This function allows the reference to reach fast, as described in (Campos et al., 2018), resulting in the cost function presented in (8).

$$C_f = ISE \tag{8}$$

The optimization focused on adjusting the initial PID controller parameters and α, while the derivative values H_{LP1} and H_{LP2} were kept constant at 1.

4 RESULTS AND DISCUSSIONS

This section presents the performance assessment of the proposed controllers by examining a scenario that involves an experimental setup using the TCLab device. The results include setpoint and disturbance changes.

4.1 Thermal Process - TCLab

The TCLab device, shown in Fig. 3 is an Arduino Kit that consists of two heaters and two temperature sensors that emulate a real-life process in which different control techniques can be implemented. The heaters are controlled through Pulse Width Modulation (PWM) as detailed in (Mejia et al., 2022)

According to previous works (Mejia et al., 2022), for example, the FOPDT model of the TCLab device exhibits a dead time t_0 significantly shorter, almost one-tenth, compared to the time constant τ. Consequently, to evaluate controller schemes for long delay systems, a software-induced time delay of 175 [s] was incorporated into the TCLab to make a dominant time delay system, as depicted in Fig. 4. This configuration was utilized throughout the remainder of the article.

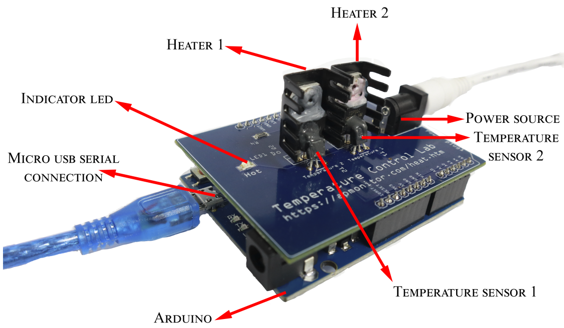

Figure 3: TCLab diagram.

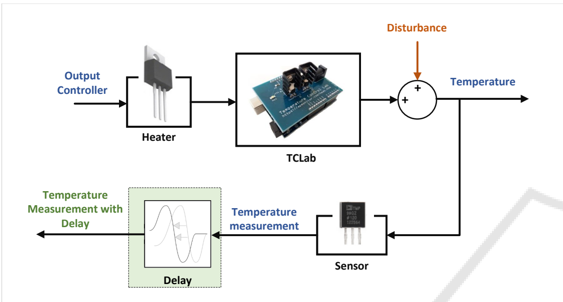

Figure 4: Temperature process block diagram.

4.2 iPI Controller Approaches

As observed in Fig.5, the general control architecture is designed to address the application of the controllers to the Temperature Control Lab (TCLAB) with dominant time delay.

The schematic directly includes this delay, emphasizing its importance in developing the control strategy and its impact on system performance. Additionally, the schematic includes essential components to improve the controller's efficiency. Low-pass filters ($H_{LP1}(s)$ and $H_{LP2}(s)$) mitigate noise and high-frequency disturbances, while the gain term $\frac{1}{\alpha}$ ensures a stable control response.

The two controllers are implemented to address the complexities of TCLAB's behavior with the dominant time delay. In this case, the two alternatives are considered, with the second one combining the intelligent PID (iPI) control framework with the adaptability of fuzzy logic. This hybrid control strategy processes the error ($e(t)$) and its derivative ($\dot{e}(t)$) as input, mapping them into seven fuzzy subsets. A Takagi-Sugeno inference mechanism, coupled with a centroid defuzzification method, generates a succinct control signal that effectively handles the nonlinearities and uncertainties inherent in the system. The integral action, introduced by integrating the output of the iPI-Fuzzy controller, ensures steady-state error elimination while preserving the flexibility and robustness of the fuzzy logic framework.

4.3 Reference Tracking and Disturbance

Fig.6, which illustrates the output of the transmitter (TO), captures the thermal response of the TCLAB system under the control actions of the iPI and iPI-Fuzzy strategies. Both controllers effectively track the initial reference, showing their capability to regulate the system's output within acceptable bounds. However, the iPI-Fuzzy controller demonstrates superior accuracy in reference tracking, maintaining behavior closer to the desired setpoint with minimal steady-state error.

During dynamic transitions, including disturbance around 3500 s, the iPI-Fuzzy outperforms the iPI by exhibiting reduced overshoot and a smoother recovery to the target value. This superior adaptability underscores the advantages of the fuzzy logic-based approach in handling the TCLAB's dominant delay, as well as its inherent nonlinearities and uncertainties. Furthermore, the iPI-Fuzzy controller design ensures enhanced stability, achieving robust performance even under challenging conditions, optimizing the thermal response, and minimizing deviations from the reference signal.

Fig. 7, depicting the Controller Output (CO) over time, highlights the system's response to reference tracking under both the iPI and the iPI-Fuzzy control strategies. Both controllers exhibit a rapid rise to achieve the desired set point, demonstrating their ability to handle initial dynamic changes effectively. However, the iPI-Fuzzy demonstrates superior performance, as evidenced by its smoother trajectory and reduced overshoot during the transient phase. Around 3500 seconds, when a disturbance is introduced, the iPI-Fuzzy controller outperforms the iPI by recovering more quickly and maintaining a steadier output with significantly lower oscillations. This behavior underscores the enhanced adaptability and robustness of iPI-Fuzzy in managing dynamic system variations. Furthermore, the inclusion of low-pass filters in the controller design effectively mitigates high-frequency noise, ensuring the stability and reliability of the control signals throughout the process. These attributes make the iPI-Fuzzy a more efficient and precise option for disturbance rejection and reference tracking.

In reference tracking tests, the iPI-Fuzzy controller exhibited superior performance compared to the conventional iPI controller. This was reflected in a more accurate response, with fewer overshoots and

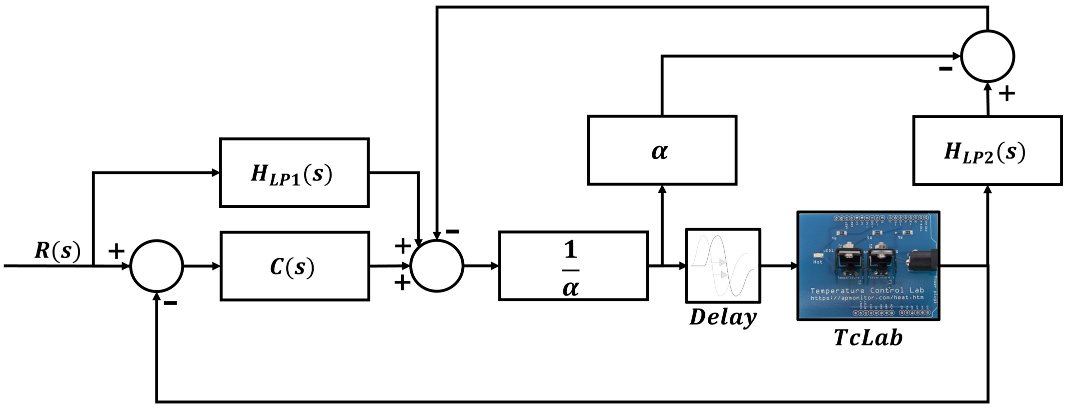

Figure 5: Schematic of Model-Free with Dominant Delay in the TCLab

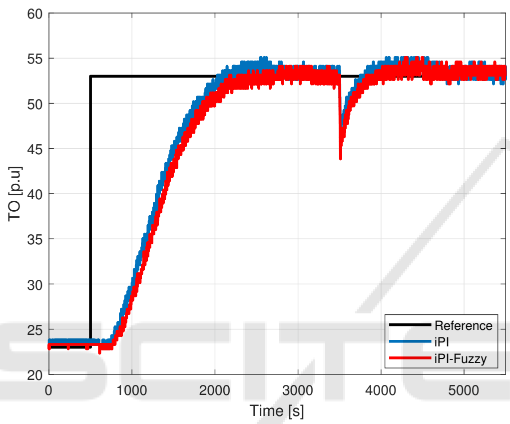

Figure 6: Transmitter Output for iPI vs. iPI-Fuzzy.

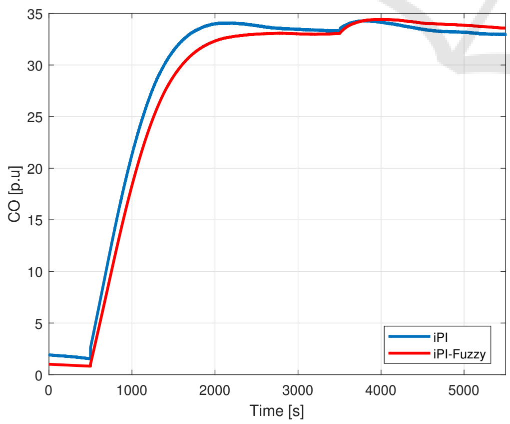

Figure 7: Controller Output for iPI vs. iPI-Fuzzy.

shorter settling times. These improvements can be attributed to the fuzzy logic's ability to handle nonlinearity and adapt to system variations in real-time.

The behavior of the iPI-Fuzzy allowed the system to efficiently reach the target temperature values while optimizing energy consumption, highlighting its ability to adapt to the variable dynamics of the TCLab. In contrast, the iPI controller showed less accurate tracking and longer settling times due to its more static design. In disturbance rejection tests, the iPI-Fuzzy controller proved to be more robust than the conventional iPI controller. When external disturbances were introduced into the system, such as changes in ambient temperature, the iPI-Fuzzy quickly compensated for these disturbances, restoring the temperature to the target value in less time.

In contrast, the iPI controller experienced a slower recovery period to reestablish system stability, showing significant fluctuations away from the target temperature. This highlights the benefits of integrating fuzzy logic as it enables adaptive modifications when unexpected shifts occur in the system's operating conditions.

Table 2: Performance evaluation for reference tracking and disturbance test.

	ISE	ISCO	MP [%]	t_s [s]
iPI	6.0×10^5	4.8×10^6	3.8	3000.0
iPI-Fuzzy	5.4×10^5	5.0×10^6	0.0	3500.0

Here is the paraphrased text in English:

Table 2 provides a detailed comparative analysis of the iPI and iPI-Fuzzy controllers, focusing on their performance in two key aspects: reference tracking and disturbance rejection. These functionalities are crucial for ensuring system stability and accuracy, particularly in thermal processes where delays, disturbances, and nonlinear behaviors are common.

The iPI-Fuzzy controller outperforms the conventional iPI controller in reference tracking, as evidenced by its significantly lower Integral Squared Error (ISE). This metric quantifies the accumulated error over time, especially during transient states. A lower ISE indicates that the controller has effectively minimized the deviation between the system's actual output and the desired reference signal, ensuring a closer adherence to the intended trajectory. This improved tracking capability is essential in industrial applications such as semiconductor manufacturing or chemical processing, where even small variations in temperature or other variables can lead to inefficiencies, safety risks, or product quality issues.

However, this increased accuracy comes at the expense of higher control effort, as indicated by the Integral Squared Control Output (ISCO). This measure reflects the total energy or effort required by the controller to maintain the desired output. While the iPI-Fuzzy controller excels at minimizing tracking error, it demands greater control effort, which could result in higher energy consumption or accelerated wear on system components. In contrast, the iPI controller, though less effective in reducing tracking error, demonstrates better performance in terms of ISCO. By balancing error reduction with energy efficiency, the iPI controller is a more suitable option for applications where minimizing energy consumption and operational costs is a priority.

Regarding overshoot (Maximum Peak, MP), the iPI-Fuzzy controller presents a clear advantage. Overshoot refers to how much the system output exceeds the desired reference value before stabilizing at the steady-state level. In applications where overshoot is undesirable—such as in precise thermal control, where excessive heating could cause damage or compromise product quality—minimizing this effect is critical. The iPI-Fuzzy controller achieves this by ensuring a smooth and controlled approach to the setpoint, making it particularly valuable in industries where maintaining precise parameter control is essential for safety and performance.

Conversely, the traditional iPI controller exhibits a slight but noticeable overshoot, which could pose challenges in sensitive applications. While this overshoot may not significantly impact performance in many cases, it could introduce unwanted fluctuations in systems that demand high precision or operate under strict safety regulations.

Regarding settling time (t_s), the iPI controller provides a faster response. Settling time represents the period required for the system to reach and remain within a specified range around the setpoint after a disturbance or reference change. A shorter settling time indicates that the system stabilizes more quickly, which is advantageous in applications requiring rapid adaptation to changing conditions or strict time constraints.

However, this faster stabilization comes at the cost of reduced smoothness in system response. The iPI-Fuzzy controller, while exhibiting a slightly longer settling time, prioritizes smoother transitions. This approach is beneficial in processes where stability and gradual response are more important than speed. In industries with long-duration thermal processes or applications where abrupt changes must be avoided to preserve material integrity or process stability, the smoother response of the iPI-Fuzzy controller is often the preferred choice.

5 CONCLUSIONS

This study has conducted a comprehensive comparison between the iPI and iPI-Fuzzy controllers in the context of the TCLab system. The results demonstrate that the iPI-Fuzzy controller offers a more robust and adaptable solution for controlling nonlinear systems with time delays. This controller excels in maintaining accurate reference tracking and disturbance rejection, particularly in dynamic environments where traditional controllers like iPI face limitations. The iPI-Fuzzy controller's ability to eliminate overshoot and adapt more effectively to disturbances underscores its suitability for real-time thermal process control.

While the iPI controller shows advantages in terms of quicker settling time and energy efficiency, the iPI-Fuzzy controller provides smoother system transitions and better stability, making it a superior choice in applications where robustness and precision are prioritized over speed. This study validates the potential of fuzzy logic to enhance the performance of thermal process control, particularly in the presence of nonlinearities and delays.

For future work, further enhancements to the control framework are suggested. Integrating machine learning techniques for real-time parameter tuning could improve the adaptability of the controller, allowing for automatic adjustments based on changing system dynamics. Moreover, extending the methodology to larger and more complex thermal systems, as well as to multi-input, multi-output (MIMO) applications, presents an exciting avenue for future research and development. This could broaden the applicability of the proposed controllers to more industrial-scale systems and further optimize their performance.

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REFERENCES

Campos, J., Jaramillo, S., Morales, L., Camacho, O., Chávez, D., and Pozo, D. (2018). Pso tuning for fuzzy pd+ i controller applied to a mobile robot trajectory control. In *2018 International Conference on Information Systems and Computer Science (INCISCOS)*, pages 62–68. IEEE.

de Moura Oliveira, P., Soares, F., and Cardoso, A. (2022). Pocket-sized portable labs: Control engineering practice made easy in covid-19 pandemic times. *Ifac-papersonline*, 55(17):150–155.

Espin, J., Castrillon, F., Leiva, H., and Camacho, O. (2022). A modified smith predictor based–sliding mode control approach for integrating processes with dead time. *Alexandria Engineering Journal*, 61(12):10119–10137.

Fliess, M. and Join, C. (2013). Model-free control. *International journal of control, vol. 86, no. 12, pp. 2228–2252*.

Gude, J. J. (2023). *Contributions to fractional-order modelling and control of dynamic systems: A theoretical and practical approach*. PhD thesis, Universidad de Deusto.

Gude, J. J., García Bringas, P., Herrera, M., Rincón, L., Di Teodoro, A., and Camacho, O. (2024). Fractional-order model identification based on the process reaction curve: A unified framework for chemical processes. *Results in Engineering*, 21:101757.

Jain, A. and Goodson, K. E. (2011). Thermal microdevices for biological and biomedical applications. *Journal of Thermal Biology*, 36(4):209–218.

Kocaarslan, I., Çam, E., and Tiryaki, H. (2006). A fuzzy logic controller application for thermal power plants. *Energy conversion and management*, 47(4):442–458.

Liptak, B. G., Piovoso, M. J., Shinskey, F. G., Eren, H., Totherow, G. K., Jamison, J. E., Morgan, D., Hertanu, H. I., Marszal, E. M., Berge, J., et al. (2018). *Instrument engineers' handbook, volume two: Process control and optimization*. CRC press.

May, G. S. and Spanos, C. J. (2006). *Fundamentals of semiconductor manufacturing and process control*. John Wiley & Sons.

Mejia, C., Salazar, E., and Camacho, O. (2022). A comparative experimental evaluation of various smith predictor approaches for a thermal process with large dead time. *Alexandria Engineering Journal*, 61(12):9377–9394.

Obando, C., Rojas, R., Ulloa, F., and Camacho, O. (2023). Dual-mode based sliding mode control approach for nonlinear chemical processes. *ACS omega*, 8(10):9511–9525.

Patel, K. M. (2023). A practical reinforcement learning implementation approach for continuous process control. *Computers & Chemical Engineering*, 174:108232.

Plawsky, J. L. (2020). *Transport phenomena fundamentals*. CRC press.

Precup, R.-E., Radac, M.-B., Roman, R.-C., and Petriu, E. M. (2017). Model-free sliding mode control of nonlinear systems: Algorithms and experiments. *Information Sciences*, 381:176–192.

Sardella, M. F., Serrano, M. E., Camacho, O., and Scaglia, G. J. (2019). Design and application of a linear algebra based controller from a reduced-order model for regulation and tracking of chemical processes under uncertainties. *Industrial & Engineering Chemistry Research*, 58(33):15222–15231.

Schwenzer, M., Ay, M., Bergs, T., and Abel, D. (2021). Review on model predictive control: An engineering perspective. *The International Journal of Advanced Manufacturing Technology*, 117(5):1327–1349.

Smith, C. A. and Corripio, A. B. (2005). *Principles and practices of automatic process control*. John wiley & sons.

Tanaka, K., Wang, L., and Camacho, O. (2023). Fuzzy control for time-delay systems. *IEEE Transactions on Fuzzy Systems*, 31(4):1122–1135.

Vásquez, M., Yanascual, J., Herrera, M., Prado, A., and Camacho, O. (2023). A hybrid sliding mode control based on a nonlinear pid surface for nonlinear chemical processes. *Engineering Science and Technology, an International Journal*, 40:101361.

Wang, D., Tan, D., and Liu, L. (2018). Particle swarm optimization algorithm: an overview. *Soft computing*, 22(2):387–408.

Wang, L., Gude, J. J., and Patel, K. M. (2022). Fractional pid for industrial thermal processes. *Journal of Process Control*, 110:45–58.

Zhang, H. and Liu, D. (2006). Fuzzy modeling and fuzzy control. *Springer Science & Business Media*.