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# Parametric scaling-based tuning of direct fuzzy controller with hardware-in-the-loop validation on an industrial platform

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**ABSTRACT**

Although conventional proportional-integral-derivative (PID) controllers dominate the industrial sector, their inherent limitations in handling complex nonlinear processes often necessitate more flexible control alternatives. This study proposes a novel parametric scaling method designed to systematically fine-tune fuzzy controllers specifically for nonlinear processes. Unlike traditional trial-and-error approaches, this methodology utilizes a structured scaling framework to adjust controller parameters, thereby significantly simplifying the tuning process while ensuring robust and reliable control performance. The effectiveness and industrial applicability of the proposed controller were validated using a high-fidelity hardware-in-the-loop (HIL) simulation scheme. In this experimental setup, a nonlinear level plant is simulated in real-time, while the fuzzy controller executes directly on an industrial programmable logic controller (PLC). The performance of the proposed system was rigorously evaluated and compared using standard error metrics, with a particular focus on reference tracking accuracy and disturbance rejection capabilities under various operating conditions. This proposed approach successfully aims to improve industrial applicability by effectively reducing tuning complexity and enhancing overall system performance.

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## 1. INTRODUCTION

While proportional-integral-derivative (PID) controllers dominate industry, their limitations in nonlinear systems motivate fuzzy-based alternatives. Fuzzy logic controllers (FLCs) are highly effective in managing nonlinear systems, offering adaptable control surfaces and processing multiple variables through fuzzy sets and membership functions [1]-[6]. However, the extensive array of tunable parameters, including discourse universes, fuzzy set definitions, and scaling factors, makes heuristic adjustment inefficient [7]. This situation highlights the critical need for systematic tuning methodologies, such as those that adapt FLCs to operate with conventional PID input-output signals [8], [9].

Given the inherent nonlinearities in hydraulic level systems, stemming from characteristics like flow rate, turbulence, and tank geometry [10], [11], nonlinear control techniques have been employed. These approaches often involve modifying membership functions to tailor control surfaces for varying system behaviors, leading to reduced overshoot and smoother responses [12], [13].

Advanced control methodologies, including adaptive [14], [15], predictive [16], [17], and sliding mode control [18], [19], offer robust solutions for dynamic systems by addressing stability, performance optimization, and disturbance rejection. Parallel to this, hardware-in-the-loop (HIL) platforms have become

essential in industrial applications. HIL facilitates accurate, secure, and cost-effective process simulations, significantly shortening development cycles and enabling practical testing for systems, such as level control plants, where real-world experimentation is often constrained by operational limitations [20]-[23].

Practical model-based fine-tuning methodologies have been barely worked for non-linear level processes control. This paper proposes a methodology for a direct FLC using fine-tuning regions, which allow modification of the controller's scaling factors to achieve nonlinear behavior. These regions are generated by evaluating temporal performance criteria, such as settling time (Ts) and overshoot percentage (%Mp). In general terms, the proposed method utilized first-order plus dead time (FOPDT) models, varying the ratio ($T_m/\tau$) to emulate nonlinear behaviors between the plant's input and output.

The proposed method was validated using an HIL scheme emulating the behavior of a level plant located in the instrumentation laboratory of Escuela Colombiana de Carreras Industriales (ECCI) University in Colombia. The model was taken from [24] and executed in laboratory virtual instrument engineering workbench (LabVIEW), while the FLC ran on a Siemens S7-1200 programmable logic controller (PLC). The final results show that the proposed method, based on the fine-tuning regions obtained, improves the integral of time-weighted absolute error (ITAE) and integral of absolute error (IAE) temporal performance indices by approximately 50% compared to the conventional PID tuning using the internal model control (IMC) method.

## 2. METHOD

### 2.1. Direct fuzzy controller

The fuzzy proportional derivative plus integral (FPD+I) architecture, as reported in [8], was implemented on an industrial platform using function blocks and structured control language (SCL) language within totally integrated automation (TIA) Portal. As depicted in Figure 1, this architecture integrates a fuzzy proportional derivative (FPD) system with added integral action. The controller receives error ($e$) and its derivative ($\Delta e$) as inputs, which are then weighted by scaling factors gain/scaling factor for change in error (GCE), gain/scaling factor for error (GE), and gain/scaling factor for integral error (GIE). The final controller output is adjusted by gain/scaling factor for controller output (GCU), with the integral action computed independently due to the rule base's dependence on steady-state error.

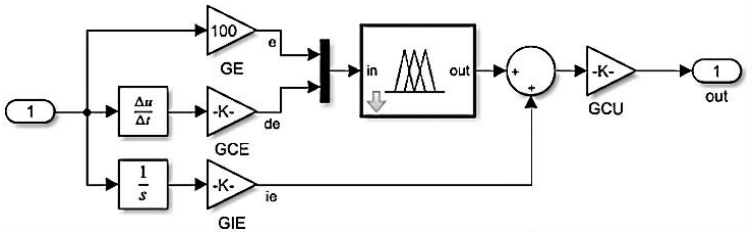



Figure 1. Architecture FPD+I

#### 2.1.1. Fuzzyfication

The fuzzification process [8] converts the controller's inputs (error e and its derivative Δe, denoted as '$In$') into fuzzy sets. As illustrated in Figure 2(a), triangular membership functions, defined by (1) to (3) over a universe of discourse of [-100, 100], assign linguistic labels (negative ($N$), zero ($Z$), positive ($P$)) and their respective degrees of membership.

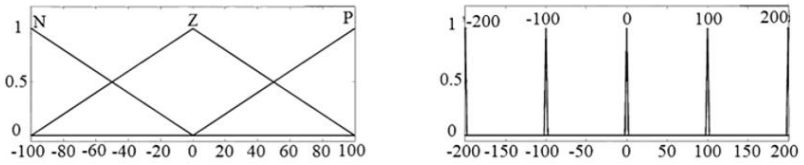
$$MF(N) = \left(\frac{-In}{100}\right) \forall\, In \in [-100,\, 0] \quad (1)$$

$$MF(P) = \left(\frac{In}{100}\right) \forall\, In \in [0,\, 100] \quad (2)$$

$$MF(Z) = \left(\frac{100-|In|}{100}\right) \forall\, In \in [-100,\, 100] \quad (3)$$

#### 2.1.2. Inference

Using singleton output fuzzy sets (Figure 2(b)) and the product aggregation method, the inference engine [8] processes the degrees of membership. This generates weighted rule outputs based on the 9-rule base (Table 1), which are then summed up to obtain the output.




(a) (b)

Figure 2. Fuzzy sets: (a) FLC membership functions and (b) Output fuzzy sets

Table 1. Base of 9 rules

| $U$ | | $\Delta e$ | | |
|---|---|---|---|---|
| | | $N$ | $Z$ | $P$ |
| $e$ | $N$ | -200 | -100 | 0 |
| | $Z$ | -100 | 0 | 100 |
| | $P$ | 0 | 100 | 200 |

### 2.1.3. Deffuzification

The defuzzification stage [8] determines the crisp control action, using the weighted average method. This involves summing the products of the rule outputs and their corresponding weights, which is then divided by the inference output.

### 2.1.4. Architecture

The FPD+I architecture is implemented [8], with scaling factors using (4), (5), (6), and (7), where "$Kp$" is the proportional gain, "$Td$" is the derivative time, and "$Ti$" is the integral time from conventional PID tuning. Normalized error and its derivative are multiplied by 'GE' and 'GCE', respectively. Normalization is mandatory to mitigate input saturation within the control system's operational domain. These blocks are parametrized based on the maximum amplitude of the set point step signal (NORMAL IN) according to $x_{norm} = 2\frac{x-x_{min}}{x_{max}-x_{min}} - 1$. To obtain the final control action, the FLC output is un-normalized (NORMAL OUT) according to $x_{un-norm} = 4x$, aiming a discourse universe from -200 to 200, next the integral of the error is added and multiplied by 'GIE'. Finally, the total is multiplied by 'GCU'. The implemented architecture is shown in Figure 3.

$$GE = 100 \tag{4}$$

$$GCU = Kp/GE \tag{5}$$

$$GCE = Td * GE \tag{6}$$

$$GIE = GE/Ti \tag{7}$$

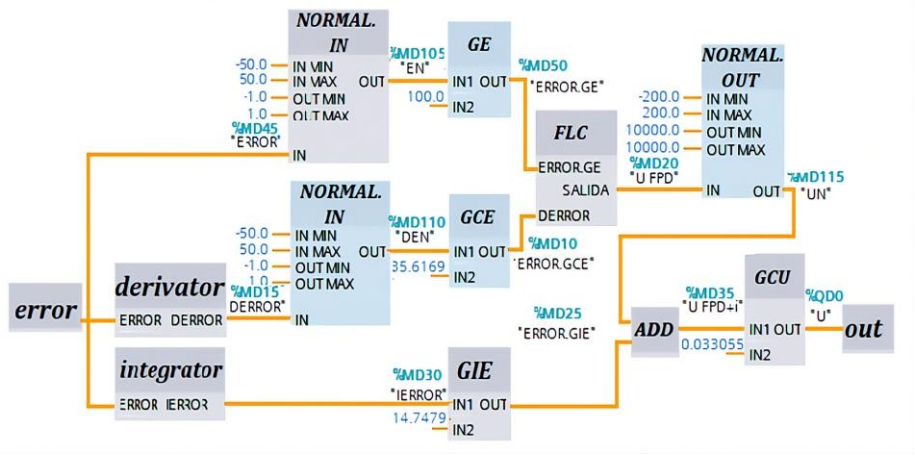



Figure 3. FPD+I architecture in FBD language in TIA portal

## 2.2. Proposed methodology

### 2.2.1. Controller design

The FPD+I architecture was implemented in a simulation environment using MATLAB and Simulink. Starting from the fuzzy equivalent of a continuous conventional PID controller with ideal architecture and derivative filter on the error. To perform parametric analysis for different closed-loop plant dynamics, several FOPDT models, as in (8), were implemented. Table 2 shows the parameters considered, for which the plant's nonlinearity was emulated by changing the system's ($T_m/\tau$) ratios.

$$Gs(s) = \frac{K_m}{\tau s+1} e^{-T_m s} \quad (8)$$

Table 2. Generic FOPDT models

| Model | $K_m$ | $\tau$ | $T_m$ | $T_m/\tau$ |
|---|---|---|---|---|
| Gs1 | 0.1 | 1.5 | 0.1 | 0.1 |
| Gs2 | 0.12 | 2.0 | 0.4 | 0.2 |
| Gs3 | 0.159 | 2.2 | 0.8 | 0.3 |
| Gs4 | 0.255 | 3.0 | 2.2 | 0.7 |
| Gs5 | 0.255 | 4.0 | 4.0 | 1.0 |
| Gs6 | 0.255 | 6.0 | 6.0 | 1.5 |
| Gs7 | 0.255 | 8.0 | 8.0 | 2.0 |

### 2.2.2. Parametric variation

Since scaling factors GCE, GIE and GCU allow changes in FLC control surface, parametric analysis was performed through a multiplier of initial scaling factors. In this analysis, scaling factors were varied systematically: GIE and GCU adjusted by $\alpha$ multipliers, overshoot constrained below 5%. '$\alpha$GCE' and '$\alpha$GIE' factors varied up to 2 times their value with 0.2 size steps. '$\alpha$GCU' up to 5 times in intervals of '0.25'. During parametric variation, it was also observed that changes in time response caused by '$\alpha$GCE' are not significant, hence its variation was discarded.

### 2.2.3. Minimal regions

From the parametric variation, surfaces for %Mp and Ts were generated, referred to in this work as "Minimal Regions". In Figure 4 (left), the point $\alpha$GCU = $\alpha$GIE = 1 is the fuzzy tuning equivalent for the conventional PID controller, which will be the initial tuning reference. For each $T_m/\tau$ ratio a %Mp and Ts region has been generated, and only regions which meet allowed time response parameters will be retained. For instance, in Figure 4 (right), the minimal region of Ts in low dynamics (Ts1) for a system with ratio ($T_m/\tau$) = 0.3 is shown, where values that do not meet the proposed criteria are discarded. The yellow region represents settling times that exceed those of the conventional controller, and the blue region represents times less than or equal to the criterion.

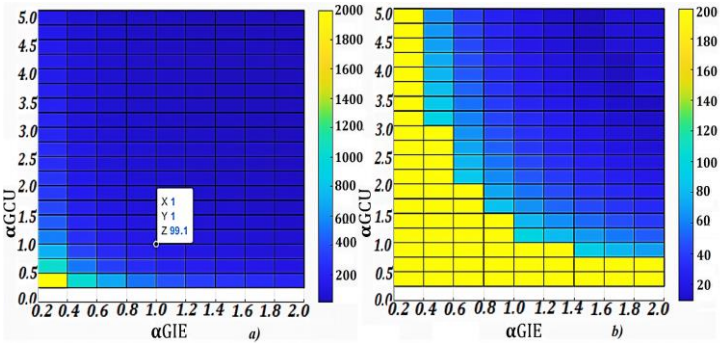



Figure 4. Minimal regions Ts1 with a ratio ($T_m/\tau$) of 0.3

### 2.2.4. Fine-tuning regions

Once the minimal regions were obtained, a masking process was performed to visualize the regions where the design criteria converge, referred to in this work as "fine-tuning regions". These regions contain the factors $\alpha$GCU and $\alpha$GIE that satisfy design criteria for plants with ratios ($T_m/\tau$) from 0.1 to 1.5.

However, the method's current range of validity is inherently constrained by the fuzzy inference scheme and the mapping technique used for PID equivalence [8]. These design choices, while ensuring seamless integration into industrial PLC architectures, impose specific operational boundaries. Alternatively, exploring different equivalence methods or transitioning toward a fuzzy gain scheduling approach could potentially broaden this range, allowing for more dynamic parameter adaptation across a wider set of operating conditions.

In Figure 5, the result of the masking process is shown to visualize the regions that meet the design criteria: %Mp1 (row 1), Ts1 (row 2), and Ts2 (row 3). To obtain a fine-tuning that improves all three parameters, it is necessary to use all three regions to find a common point. In Figure 5 (row 1), the yellow regions represent scaling factors that produce %Mp greater than the conventional controller, while the cyan regions represent values that produce a response with %Mp less than the conventional controller. In Figure 5 (rows 2) and (row 3), the dark blue regions do not meet the criterion, while the cyan regions produce desirable settling times.

Based on the analysis, the following fine-tuning methodology for the direct FLC is proposed:

- Process reaction curve for low and high operation dynamics (FOPDT).
- Tuning of the Conventional PID controller.
- Conversion to FLC using scaling factors [8].
- Fine-tuning of the FLC.
- Selection of the points in the fine-tuning regions, depending on the system type ($T_m/\tau$) and the design criteria.
- Modification of GIE and GCU multiplying them by their respective $\alpha$ factors obtained in the regions.
- Temporal performance index to validate the results.

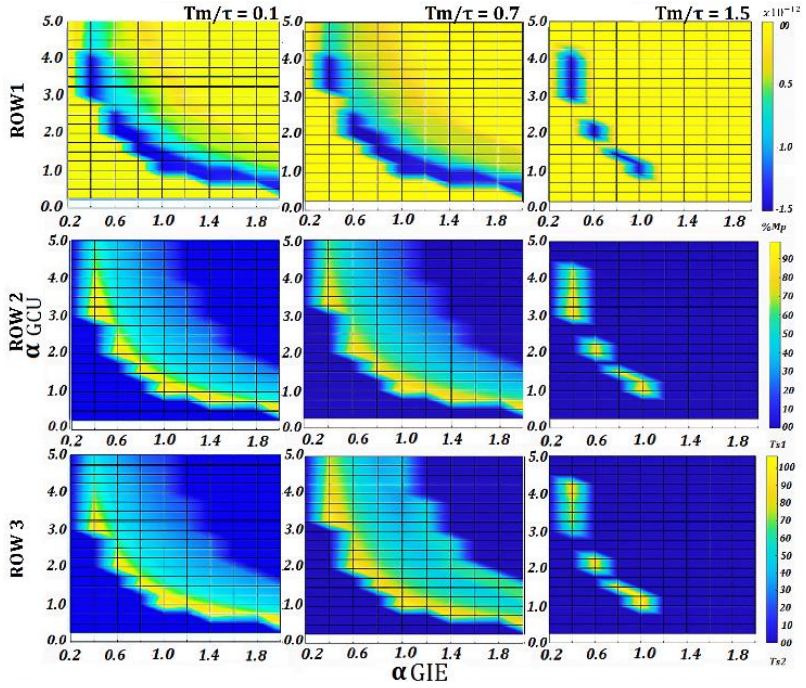



Figure 5. Fine-tuning regions for %Mp and Ts with ratio ($T_m/\tau$) = 0.1 – 0.7 – 1.5

### 2.2.5. Validation

The final validation of the proposed methodology is centered on the evaluation of system performance across representative operating scenarios. To quantify the effectiveness of the fine-tuning regions, the controller's response is assessed using widely established performance metrics, specifically the IAE and ITAE. These indices are utilized to evaluate the controller's capacity for precise reference tracking and robust disturbance rejection. Furthermore, the validation process incorporates temporal performance criteria, including percentage overshoot (%Mp) and Ts. These metrics are essential for characterizing the system's dynamic response; however, their target values are context-dependent and are adjusted according to the specific requirements and operational constraints of the plant under investigation.

## 3. RESULTS AND DISCUSSION

### 3.1. Case study

Using the instrumentation module located in the laboratory of ECCI University, Figure 6(a), the three components of the hydraulic level system (tank, actuator and sensor) were selected. These components, in conjunction with the plant´s dynamics, contribute to the system's nonlinearity. For example, the tank's dynamics vary according to its height and shape. The actuator has a dynamic characteristic related to its response, while the sensor introduces a considerable dead time and a nonlinear dynamic due to its characteristic curve. These were modeled in national instruments (NI) LabVIEW using difference equations, a sampling time of 100 ms, and communication via open platform communications (OPC) protocol to the FLC.

The general diagram of the HIL scheme is shown in Figure 6(b), and it is comprised of the following components [21]:

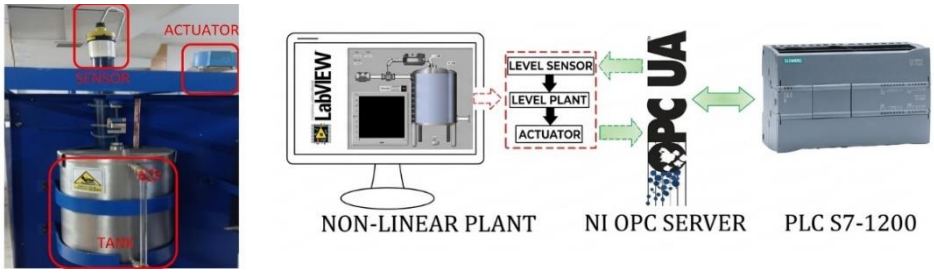
- The hardware controller: Siemens S7-1200 PLC, which runs the controller to be tested.
- The simulation software: LabVIEW, responsible for simulating the hydraulic plant in a virtual environment.
- The input/output (I/O) interface: this is the set of both physical and network connections that link the whole HIL scheme.

Physical tests were not carried out because of technical constraints, specifically those related to the update of sensors and actuators.

#### 3.1.1. Tank

A cylindrical tank is considered, represented by (9), with its static and dynamic characteristics organized in Table 3.

$$h = \int \left( \frac{Qin - a\sqrt{2gh}}{A} \right) dh \tag{9}$$




(a) (b)

Figure 6. Physical implementation: (a) instrumentation module at ECCI University and (b) HIL communication structure

Table 3. Units for level model

| Symbol | Description | Value |
|---|---|---|
| Qin | Inlet flow | 0.005 $m^3/s$ |
| $r$ tank | Tank radious | 0.15 m |
| $r$ pipeline | Pipeline radious | 0.0254 m |
| $h$ tank | Tank height | 0.5 m |
| $A$ | Tank area | 0.070685 $m^2$ |
| $a$ | Pipeline area | 0.002026 $m^2$ |
| $g$ | Gravity | 9.8 $m/s^2$ |
| $h$ | Level | m - cm |

#### 3.1.2. Actuator

A DANFOSS EV260B solenoid valve is modeled using the first-order (10), where the input signal is the percentage opening (%Co) and the output is the flow rate (Q2), with (τv) as the time constant and (Kv) as the static gain of the valve.

$$Q2(s) \frac{Kv,\%Co(s)}{\tau_v s + 1} \tag{10}$$

### 3.1.3. Sensor

Data reading is performed by a DL-34 ultrasonic sensor, modeled as a generalized instrument. Its dynamic behavior follows an FOPDT (11), while its static characteristic is described by an ideal line (12) and a 3rd-order polynomial (13). These are obtained from the sensor's characteristic curve [25] and empirical equations. Here, "$I$" is the output signal in the range (4 to 20) mA, and "$h$" is the input signal in cm.

$$Gs(s) = \frac{1}{s+1} e^{-1s} \tag{11}$$

$$I = 0.32h + 4 \tag{12}$$

$$I = -7x10^{-5}h^3 + 0.0046h^2 + 0.265h + 4 \tag{13}$$

### 3.1.4. Extended plant

To characterize and obtain a more realistic behavior, the dynamics of each element of the hydraulic level system were combined. Additionally, a graphical interface of the process was implemented, and communication variables were added to close the control loop in the HIL scheme and subsequently validate the proposed methodology. This implementation is shown in Figure 7.

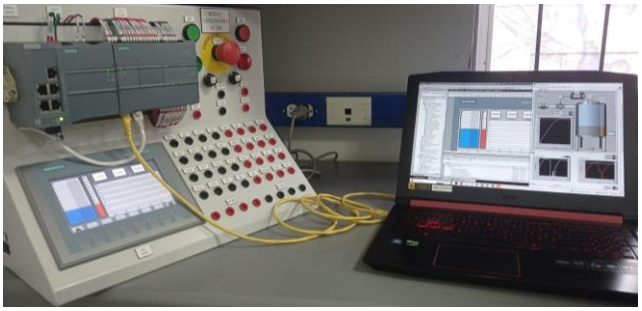


Figure 7. HIL simulation platform PLC + model

### 3.1.5. Conventional tuning

To establish a baseline for comparison, three FOPDT models, by smith method [26], were derived from step response characterization at 40%, 80%, and 100% operating points (Table 4). Among Rovira, Smith, and IMC PID tuning methods [27], the IMC approach yielded the best temporal performance based on IAE and ITAE metrics (Table 5). Its fuzzy counterpart was subsequently configured (Table 6) and validated through a reference tracking test in the HIL scheme (Figure 6(b)) to confirm equivalence. In Figure 8, the response of the controllers in the HIL scheme to a reference tracking test is shown to verify their equivalence.

Table 4. FOPTD model

| Operation point (%) | $K_m$ | $\tau$ | $T_m$ |
|---|---|---|---|
| 40 | 0.1595 | 0.844 | 2.291 |
| 80 | 0.2130 | 2.258 | 7.848 |
| 100 | 0.2550 | 2.230 | 8.850 |

Table 5. Index performance of tuning methods

| Set point (cm) | ITAE rovira | | ITAE smith | | IMC | |
|---|---|---|---|---|---|---|
| | ITAE | IAE | ITAE | IAE | ITAE | IAE |
| 6 | 10890 | 21.78 | 9030 | 18.03 | 9454 | 18.91 |
| 12.5 | 15670 | 31.35 | 13110 | 26.21 | 14320 | 28.65 |
| 50 | 41650 | 83.30 | 44490 | 88.98 | 41350 | 82.69 |
| Avg. | 22737 | 45.48 | 22210 | 44.42 | 21708 | 43.42 |

Table 6. Tuning scale factors IMC and fuzzy

| IMC | | | Fuzzy equivalent | | |
|---|---|---|---|---|---|
| $Kp$ | $Ti$ | $Td$ | GCU | GIE | GCE |
| 0.6611 | 2.712 | 0.356 | 0.006622 | 36.8698 | 35.616 |

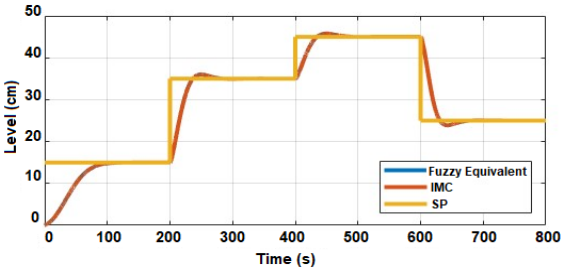



Figure 8. Comparative response between IMC and FLC

Based on the conventional tuning, fine-tuning of the FLC was performed methodology for the level system. In Figure 9, the fine-tuning regions are used to improve the performance of the conventional controller, which is located at the co-ordinates $\alpha$ = (1, 1). The selected point for tuning in the three regions is $\alpha$ = (0.4, 5) which was determined through visual inspection followed by iterative simulations to ensure compliance with design requirements. While this manual selection is effective, an alternative approach could involve applying optimization algorithms or Pareto front analysis to systematically identify an optimal operating point. The $\alpha$ from the axes were extracted and multiplied by their respective scaling factors, resulting in: GCE = 35.6169, GIE × 0.4 = 14.7479, GCU × 5.0 = 0.03311, GE = 100. Finally, temporal performance index tests were conducted to evaluate its behavior. Figure 10 shows the behavior of the two tunings in the reference tracking test, obtaining better response times, less overshoot and improved temporal performance indices after the applied fine-tuning, as shown in Table 7.

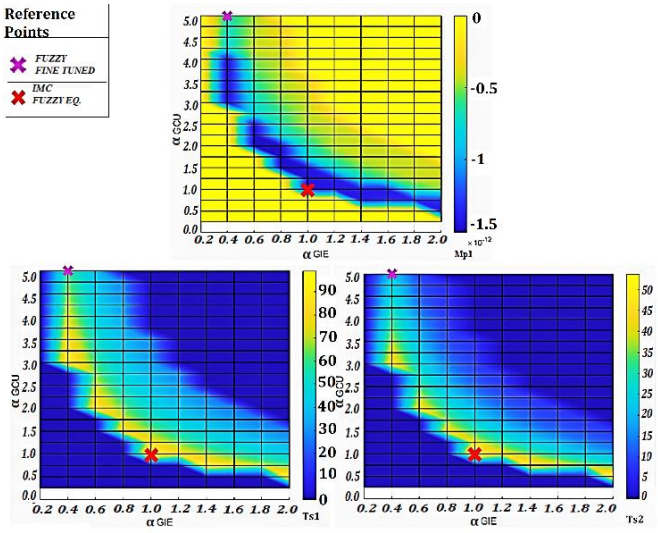



Figure 9. Fine-tuning regions for the ratio ($T_m/\tau$) of 0.3 to 0.2

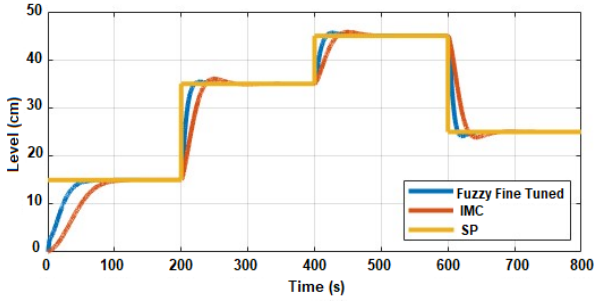



Figure 10. Comparative response in reference tracking

Table 7. Performance measurements against reference changes

| Controller | SP | Tr (s) | Mp (%) | Ts (s) | IAE | ITAE |
|---|---|---|---|---|---|---|
| IMC and fuzzy equivalent | 15 | 129.7 | 0.07 | 95.5 | 537.056 | 132,406 |
| | 35 | 36.4 | 2.98 | 61.5 | | |
| | 45 | 34.5 | 1.74 | 28.9 | | |
| | 25 | 30.9 | -4.53 | 69.8 | | |
| Fuzzy fine tuned | 15 | 87.2 | 0.07 | 56.0 | 265.287 | 62,498 |
| | 35 | 20.0 | 1.20 | 16.7 | | |
| | 45 | 17.7 | 1.39 | 13.9 | | |
| | 25 | 14.8 | -3.48 | 29.2 | | |

Additionally, disturbance rejection tests were conducted in Figure 11 by applying a 20% addition to the control action at time $t$ = 200 s. These were measured using temporal performance indices in Table 7, showing a significant improvement over the conventional method. Table 8 shows the performance indexes comparison, where fine-tuning regions methodology improves the behavior up to 50%. These results are a suitable alternative against modern tuning techniques, for instance in [28] achieved 45% improvement using a genetic-algorithm-based method.

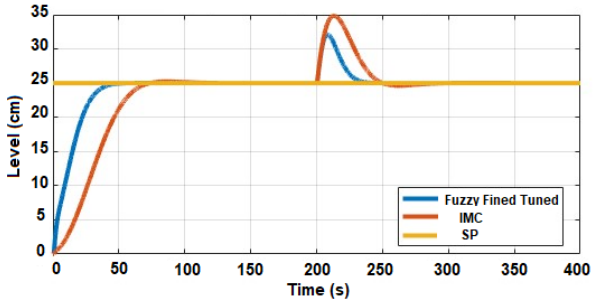



Figure 11. Comparative response in disturbance rejection

Table 8. Performance measurements against disturbance

| Controller | IAE | ITAE |
|---|---|---|
| IMC and fuzzy equivalent | 398.678 | 27056 |
| Fuzzy fine tuned | 188.119 | 10452 |

## 4. CONCLUSION

The proposed methodology based on fine-tuning regions to systematically adjust scaling factors, significantly enhances control performance for nonlinear processes. This study demonstrates a robust alternative to conventional PID control. Experimental results obtained through the HIL scheme reveal a 50% improvement in ITAE and IAE performance indices, validating the controller's effectiveness in both reference tracking and disturbance rejection tasks. A key contribution of this work is the visual interpretability of the tuning surfaces, which offers control engineers an intuitive and reliable tool for parameter selection. Furthermore, the successful implementation on industrial PLC hardware using SCL confirms the methodology's scalability and suitability for real-world applications. While the current validation is focused on specific hydraulic dynamics, the proposed framework provides a foundation for extending fine-tuning to broader process dynamics and diverse industrial platforms, thereby advancing the practical deployment of intelligent control systems. Future work will focus on expanding the methodology's scope. First, implementing a fuzzy supervisor could address current limitations regarding the method's range of validity. Second, while this study prioritizes direct industrial implementation as a PID alternative, future research could include benchmarking against advanced nonlinear control strategies, provided that computational costs are managed. Finally, although this work builds upon a well-established and industrially validated control scheme, a formal robustness analysis remains a recommended avenue for further investigation.

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## AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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| Jhon Edisson Rodríguez-Castellanos | ✓ | ✓ | | ✓ | ✓ | ✓ | | | ✓ | | | ✓ | | |
| Jorge Eduardo Cote-Ballesteros | ✓ | | | | ✓ | | | | | ✓ | | | | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [initials: AFC].

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