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Tuning of Adaptive PID Controllers Based on Fuzzy Rules for Friction Welding Process

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ABSTRACT: *This article presents an adaptive PID controller, tuned based on Rules Fuzzy and compared with the second method of tuning Ziegler-Nichols (ZN) applied to a plant in a friction welding process industrial. The performance of PID controllers, with respect to the behavior to follow the reference value (unit step), is evaluated through computational experiments, based on mathematical models described by transfer functions.*
KEYWORDS: *Adaptive PID controller, Fuzzy rules, Ziegler-Nichols Tuning Method, Computational Experiments.*

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I. INTRODUCTION

The control design is a complex problem that requires considerations of many problems, such as reducing the disturbance load, tracking the set point, robustness in relation to process variations/model uncertainty and effects of measurement noise [1]. Controllers with Proportional, Integral and Derivative (PID) actions are used extensively in the process industry. Such as: system electronics, aircraft and missile autopilots, ships, mining equipment and industrial robots [2]. Its popularity is due to its simple structure and robustness in many applications, as well as the familiarity of engineers and operators with PID algorithms, as these are easy to implement and meet the many needs of industrial control systems [3] and [4].

To solve this problem, several techniques have been developed for tuning PID controllers [5], [6] and [7]. If the required performance is not rigorous, conventional methods of tuning PID controllers are sufficient in many industrial control systems [8]. However, due to the development of commercial competition, systems are becoming more complex structures to be controlled and with more stringent performance requirements, where more efficient tuning methods are needed [9].

The increasing complexity of modern industrial processes has made it difficult to design control systems, and the application of control procedures with fixed gains is often inadequate [10] and [11]. The development of adaptive control in the last decades has made an effort to establish control techniques capable of solving difficulties such as uncertainties, disturbances, modeling and parametric variations [8].

This article presents an innovative method of tuning adaptive PID controllers based on fuzzy rules to be implemented in microcontrollers and programmable logic controllers (PLC). Contributing to the technological development of industrial processes of real plants [11].

The article is organized as follows: Section 2 presents the plan and a brief description of it. In Section 3, the computational experiments for the second Ziegler-Nichols method and for the PID-Fuzzy method are presented and evaluated. Finally, Section 4 presents the conclusion of the work.

II. FRICTION WELDING PROCESS

This Section presents the process of the friction welding plant to evaluate the tuning method of PID controllers based on fuzzy rules, with the gain vector $K^{\{pid\}}$ (K_p, K_i and K_d) determined by Ziegler-Nichols second method.

III. DESCRIPTION OF THE FRICTION WELDING PROCESS

In [12] we present the plan of the friction welding process that is used to evaluate the tuning method proposed in this article. In the temperature control of an industrial friction welding process friction stir welding (FSW). A tool non-consumable rotary, consisting of a conical probe and a shoulder, is immersed in the weld metal and crosses along the welding line, as shown in Figure (1). The frictional heat is generated between the tool and the weld metal, causing the metal to soften, normally without reaching the melting point, and allowing the tool to cross the weld line. The three most common input parameters are: tool rotation rate; welding speed along the welding line and axial force [12].

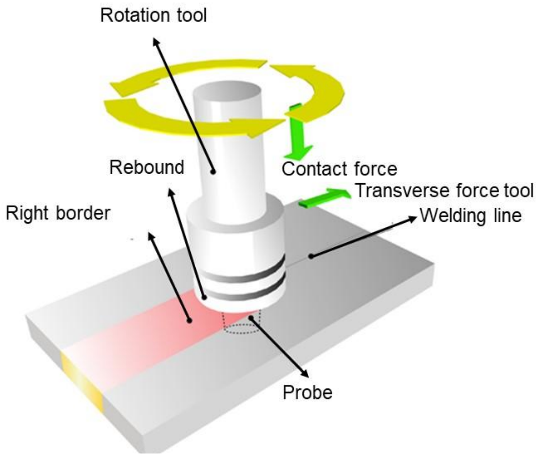

Figure 1: Illustration of the friction welding process

Temperature control can be an important part of the FSW process if it has non-uniform thermal boundary conditions or if it is used on a material with a lower allowed temperature range, the so-called process window. If the welding temperature is too high for a long period of time, there is a risk of fracturing the probe. Likewise, extremely low temperatures can result in discontinuities in the weld. A study presented by [13] showed that the rotation rate is the most appropriate control signal for controlling the weld temperature.

For the plant, three transfer functions (TFs) are given, which are called $G_1(s)$, $G_2(s)$ and $G_3(s)$.

TF $G_1(s)$ is given by

$$G_1(s) = \frac{1}{0.001s^2 + 0.1s + 2} \qquad (1)$$

TF $G_2(s)$ is given by

$$G_2(s) = \frac{1}{0.01s^3 + 0.21s^2 + 1.2s + 1} \qquad (2)$$

TF $G_3(s)$ is given by

$$G_3(s) = \frac{1}{s^3 + 3s^2 + 3s + 1} \qquad (3)$$

COMPUTATIONAL EXPERIMENTS

The experiments simulated in the MATLAB software are presented. The values of the parameters K_p, K_i and K_d are determined by the second method of Ziegler-Nichols and adjusted by fuzzy rules.

The root location method is used in this article to determine K_{cr} and P_{cr}. In the Figures 2-4 the place of roots for TFs is illustrated $G_1(s)$, $G_2(s)$ and $G_3(s)$ represented by the Eqs. (1)-(3). n the above figures, the values of K_{cr} are used, which are used to determine the parameters of the earnings K_p and the values of ω_{cr} to determine the parameters of the critical periods P_{cr}, which are used to determine T_i and T_d used in the calculations of K_i and K_d. These values are associated with Table 1 and are presented in Table 2.

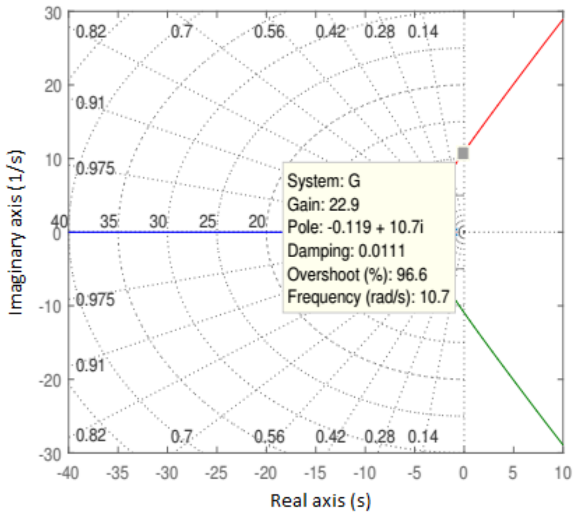

Figure 2: Root location associated with Eq. (1).

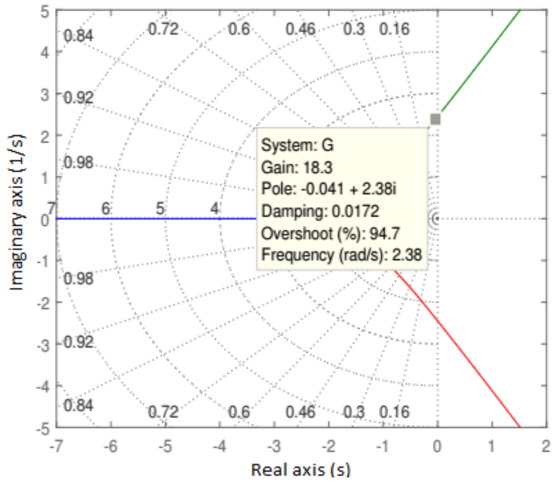

Figure 3: Root location associated with Eq. (2).

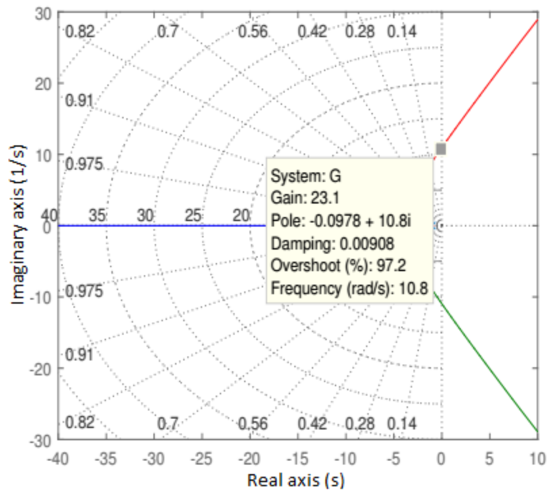

Figure 4: Root location associated with Eq. (3).

The tuning methods of PID controllers used in this article are: 1) The second Ziegler-Nichols method and affects fine tuning in the PID controller gains vector parameters; 2) A PID controller tuning method combining the second Ziegler-Nichols method based on fuzzy rules, called the PID-Fuzzy controller.

3.1 Método Ziegler-Nichols

The second Ziegler-Nichols method defines $T_i = \infty$ and $T_d = 0$. Using only the proportional control action. Increasing K_p from *0* to the critical gain value K_{cr}, in which the output exhibits a sustained oscillation from the beginning to the end of the sampling interval. Then, the K_{cr}, and the critical period P_{cr}, are calculated experimentally. The parameters suggested by ZN, are illustrated in Table 1.

Table 1: Ziegler-Nichols tuning rule based on critical gain and critical period (second method).

Controller type	K_p	T_i	T_d
P	$0.50\ K_{cr}$	∞	0
PI	$0.45\ K_{cr}$	$1/1.2\ P_{cr}$	0
PID	$0.60\ K_{cr}$	$0.5\ P_{cr}$	$0.125\ P_{cr}$

If the system has a mathematical model known as TT, you can use the root location method to find the gain K_{cr}, and the frequency of sustained oscillations ω_{cr}. Where the critical period is given by

$$P_{cr} = \frac{2\pi}{\omega_{cr}} \qquad (4)$$

The transfer function of the PID controller used in this article, is given by

$$G_c(s) = K_p\left(1 + \frac{1}{T_i s} + T_d s\right) \qquad (5)$$

3.2 Calculation of gain vector parameters K^{pid}

To find the values of K_{cr}, and ω_{cr}, we used the root location method, crossing the branches of the root location with the $j\omega$ axis, as shown in Figure 2-4 and associated with Table 1. These values are illustrated in Table 2.

Table 2: Critical gains and sustained oscillations.

Transfer function	K_{cr}	ω_{cr}
$G_1(s)$	22.9	10.7
$G_2(s)$	18.3	2.38
$G_3(s)$	22.1	10.8

The K^{pid} gains vector parameters (K_p, K_p and K_d) determined by the second method of Ziegler-Nichols based on the critical gain associated with Table 2 and in the critical period associated with Eq. (4), are presented in the following table.

Table 3: K^{pid} parameters, determined by Ziegler-Nichols based on critical gain and critical period.

Transfer function	K_p	K_i	K_d
$G_1(s)$	13.44	3.99	0.30
$G_2(s)$	15.54	4.36	0.30
$G_3(s)$	13.86	3.99	0.29

3.3 Tuning of PID controllers based on fuzzy rules

In order to contribute to meeting new market demands and technological development, an innovative method based on mathematical models for online and optimal tuning of PID controllers in industrial systems is presented.

Methods for tuning PID controllers, based on CI, are associated by selecting the gains from the K^{pid} gain vector of the models described by TFs that define the mapping of the error inputs of the feedback to the output spaces .

The gains vector K^{pid} drives the transformations between the input spaces and the output spaces. In turn, the output spaces are mapped to the spaces of the figures of merits in the domain of time and frequency to assess the operating costs of the controllers' performance.

Adaptive PID control models provide K^{pid} gain vectors that make commitments between design specifications and meet control energy costs through mergers between bio-inspired approaches and machine learning [15].

In this work, the parameters of the gain vector K^{pid} are adjusted by fuzzy rules during the operational process according to the parametric variations of the plant, in order to ensure that the control system is kept stabilized regardless of changes in your requirements. The PID-Fuzzy controller model proposed in this article was presented by [16]. This model was customized for the operational processes of the plant evaluated in this article. The PID-Fuzzy control model uses a system based on fuzzy rules to tune the PID controller, scheduling the parameters of the K^{pid} earnings vector online.

The fuzzy system assumes the values K'_p, K'_i and K'_d determined by the second method of Ziegler-Niechols. Where, the error $e(t)$ and the derivative of the error $\dot{e}(t)$ are the inputs of the fuzzy system and the outputs K_p, K_i and K_d. Where the gain K'_i is determined by means of a linear transformation using values of α, presented in Table 2, which are determined experimentally [17]. Defines C_i and D_i big or small and are characterized by the membership functions (MFs), where the classification of these functions, μ, and the variable $x = (K'_p \ or \ K'_i)$ has the following relationship $u_{Small}(x) = -\frac{1}{4}\ln x \ or \ x_{Small}(\mu) = 1 - e^{-4\mu}$ for Small and $u_{Big}(x) = -\frac{1}{4}\ln x \ or \ x_{Big}(\mu) = 1 - e^{-4\mu}$, for Grande. For example:

$"SE\ e(k)\ is\ Z0\ and\ \Delta e(k)\ is\ NB,\ ENTÃO$

$K'_p\ is\ small, K'_d\ is\ Big\ and\ \alpha = 5".$

The true value of the i^th μ_i rule is obtained by the product of the MF values in the preceding part of the rule, which is given by

$$\mu_i = \mu_{A_i}[e(k)] \times \mu_{B_i}[\Delta e(k)], \tag{6}$$

where μ_{A_i} is the MF value of the set fuzzy A_i given a value of \$ $e(k)$, and μ_{B_i} \$ is the value of the MF of the set fuzzy B_i given a value of $\Delta e(k)$.

When using FPs \ citep {zhao1993fuzzy}, the following condition is met

$$\sum_{i=1}^{m} \mu_i = 1 . \tag{7}$$

So, defuzzification produces the following

$$K'_p = \sum_{i=1}^{m} \mu_i K'_{p,i}, \tag{8}$$

$$K'_p = \sum_{i=1}^{m} \mu_i K'_{d,i}, \tag{9}$$

$$\alpha = \sum_{i=1}^{m} \mu_i \alpha_i . \tag{10}$$

Here $K'_{p,i}$ is the value of K'_p corresponding to the degree μ_i for the \$ ith rule $K'_{d,i}$ is obtained in the same way and α is the parameter used to calculate K'_d \citep {zhao1993fuzzy}.

The parameters K'_p, K'_p and K'_i are determined from a set of rules fuzzy. The fuzzy logic model consists of a fuzzy inference system of the Mamdani with two entries that are the error $e(t)$ and the derivative of the error $\dot{e}(t)$ and three exits: K'_p, K'_i and K'_d. These are the PID controller online parameters.

The Mamdani inference model proposes a M binary fuzzy relationship between x and u to mathematically model the rule base. This method is based on the *max-min* inference composition rule. Its procedure is as follows:

1) In each R_i rule the conditional "If x is A_j, then u is B_j is modeled by applying the minimum;

2) The application Λ (minimum) is adopted for the logical concept "e" and the maximum for "or".

Thus, the fuzzy relationship M is the fuzzy subset of $X \times U$ whose membership function is given by

$$\begin{aligned}\varphi_M(x,u) &= \max_{1\le i\le r}(\varphi_{R_i}(x,u)) \\ &= \max_{1\le i\le r}[(\varphi_{A_j}(x)\Lambda\varphi B_J(u)]\end{aligned} \quad (11)$$

Where r the number of rules that make up the rule base, and A_j and B_j are the fuzzy subsets of the J rule.

The escalation of gains K^{pid} is performed by the fuzzy system. The K_P and K_D earnings follow the rules in Table 2, while K_i follows the rules in Table 3. Where *B* is large and *S* is small, with MFs being big and small respectively, *NB* is big negative, NM is medium negative, NS is small negative, ZO is zero, PS is small positive, PM is medium positive and PB is big positive.

The escalation of earnings K^{pid} is performed by the fuzzy system. The K_p and K_d earnings follow the rules in Table 2, while K_i follows the rules in Table 3. Where B is big and S is small, with MFs being large and small respectively, NB is big negative, NM is medium negative, NS is small negative, ZO is zero, PS is small positive, PM is medium positive and PB is great positive.

Table 4: Tuning rules of the fuzzy system for the outputs K_p and K_d

$e(t)$ \ $\dot{e}(t)$	NB	NM	NS	ZO	PS	PM	PB
NB	B/S	B/S	B/S	B/S	B/S	B/S	B/S
NM	S/B	B/B	B/S	B/S	B/S	B/B	S/B
NS	S/B	S/B	B/B	B/S	B/B	S/B	S/B
ZO	S/B	S/B	S/B	S/B	B/S	S/B	S/B
PS	S/B	S/B	B/B	B/S	B/B	S/B	S/B
PM	S/B	B/B	S/B	B/B	B/S	B/B	S/B
PB	B/S	B/S	B/S	B/S	B/S	B/S	B/S

Table 5: System tuning rules fuzzy for outputs K_i

$e(t)$ \ $\dot{e}(t)$	NB	NM	NS	ZO	PS	PM	PB
NB	2	2	2	2	2	2	2
NM	3	3	2	2	2	3	3
NS	4	3	3	2	3	3	4
ZO	5	4	3	3	3	4	5
PS	4	4	4	2	3	3	4
PM	3	3	2	2	2	3	3
PB	2	2	2	2	2	2	2

The PID-Fuzzy controller has 7 linguistic terms and 49 rules, where system errors and PID controller earnings are related to Tables 1 and 2. The adopted MF was of the Mamdani type, implemented with the minimum operator and the defuzzification method adopted was the center of gravity method, which guarantees a smooth and continuous control surface. The fuzzy system entries are the error and the derivative of the error. As illustrated in Figure 5.

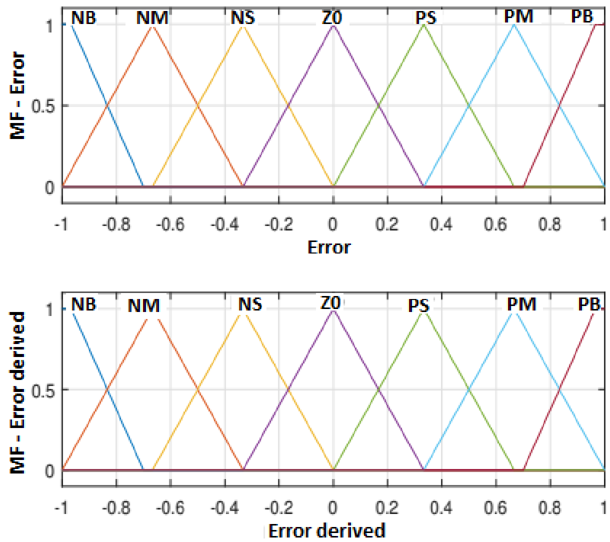

Figure 5: Input membership function.

Figure 6 illustrates the outputs of the fuzzy system, which are the parameters K_p, K_d and K_i. For the K_p and K_d exits, the MF was Gaussian type and for the K_i output the MF was singleton, since the K_i adjustment values are the constants α, as shown in Table 5.

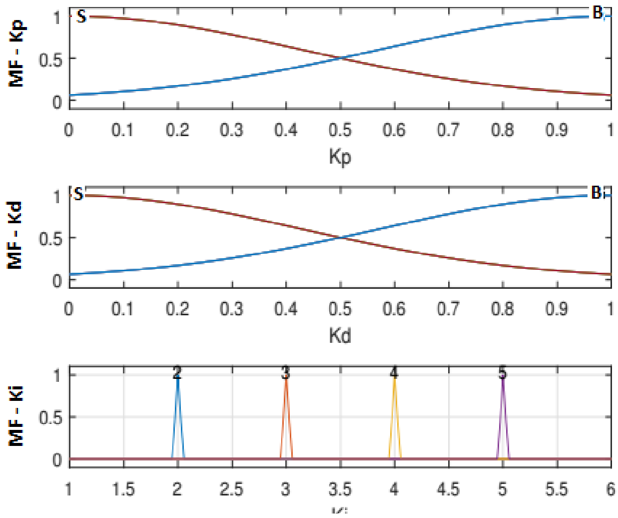

Figure 6: Output membership function.

In Figure 7, the fuzzy surface of the behavior of variables is illustrated: error, derived from the error and the values of the constant α .

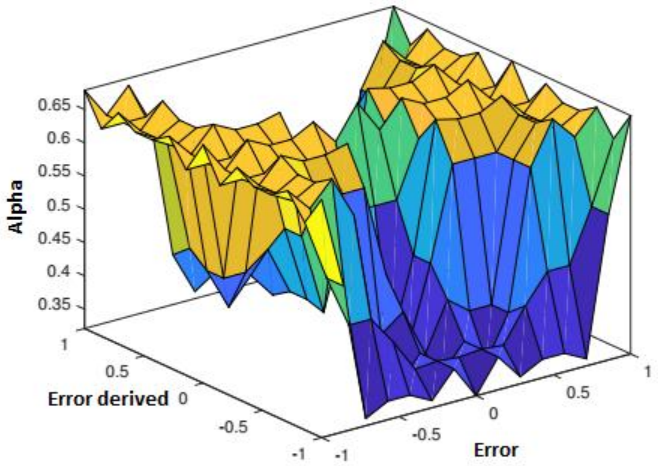

Figure 7: View of the fuzzy surface.

IV. EXPERIMENTAL RESULTS

The experimental results show that the tuning method of PID controllers adjusted by fuzzy rules, obtains the best performance with respect to reaching the control objectives, keeping in regime, without variations around the stationary error.

In the Figures of 8-10, the performance of the PID-ZN and PID-Fuzzy controllers is presented for the TFs given in Eqs. (1), (2}) and (3). Where it can be seen that both the PID-ZN controller and the PID-Fuzzy controller achieve the control objective. However, the PID-Fuzzy controller, obtains better performance, meeting the project specifications. The PID-ZN controller applied to the FTs of the Eqs. (1) and (2), oscillated a lot at the beginning, reaching a \ textit {overshoot} around 40%, exceeding the value specified in projects and for the FT given in Eq. (3) the behavior is super damped, but it took longer to enter a stationary error regime.

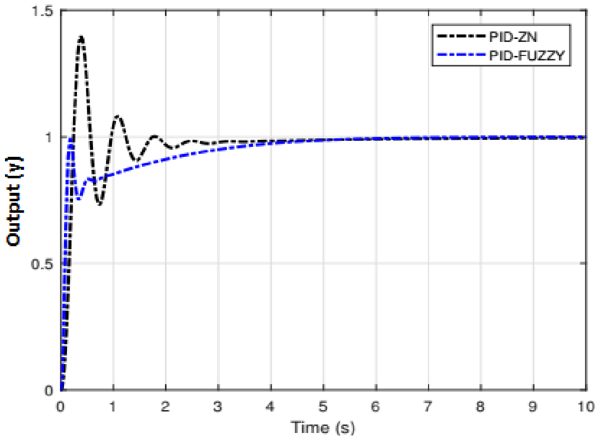

Figure 8: PID-Fuzzy associated with Eq. (1).

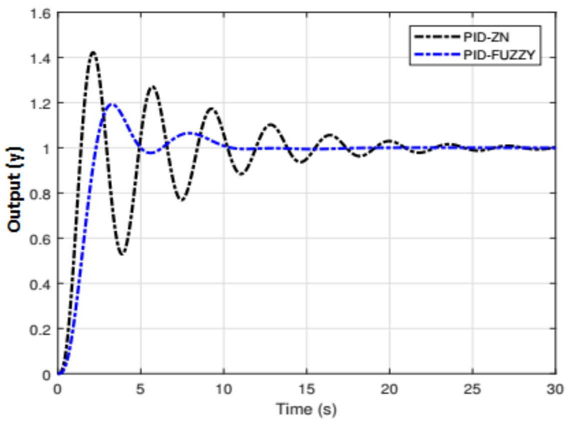

Figure 9: PID-Fuzzy associated with Eq. (2).

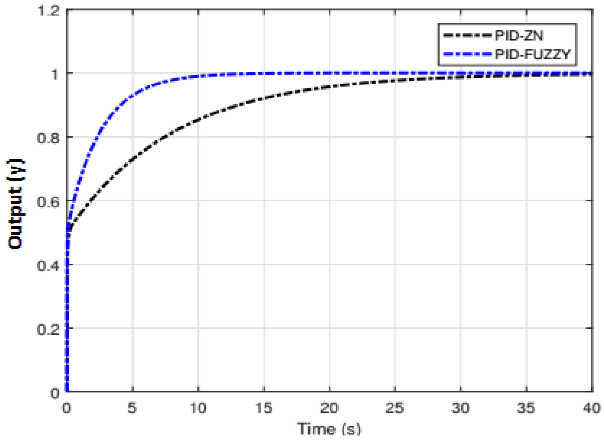

Figure 10: PID-Fuzzy associated with Eq. (3).

V. CONCLUSION

Tuning a PID controller is not a trivial process, it requires expert technique. Conventional methods do not serve plants with a high degree of control complexity in their totality. Most of the time, PID controllers applied in industrial processes do not have a derivative action. therefore, it can often compromise the efficiency of the PID controller. Therefore, the tuning of the three action parameters (P, I and D), requires more sophisticated methods. Therefore, the PID-Fuzzy controller can be an alternative to solve this problem. Because the fuzzy system fine-tunes each parameter of the K^{pid} gain vector in order to find the optimal parameters of the PID actions simultaneously, ensuring greater efficiency of the controller.

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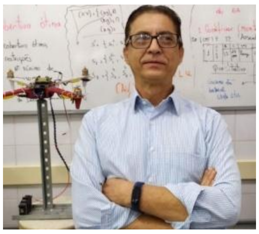

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