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Analysis and Comparation Between Classic and Fuzzy Controllers for a Level System

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Abstract: This paper aims to analyze and compare the differents kinds of fuzzy Logic and Classic Controllers, PI, PD, and PID to level control. Using a real second order didactic plant with a smooth nonlinearity, so we could evidence, in practice, the real potential of FLC to nonlinear systems. In situations there is required high performance without forcing the actuator.

Keywords: Fuzzy Controller, Intelligent Control, Non Linear System Control.

1. INTRODUCTION

The use of computional devices is becoming even more frequent in the industry nowadays. Whether through microcontrollers, Programmable Logic Controllers (CLP) or a computer. In general, on this devices, computational routines are embedded that make the control a plant or process.

That control can be subdivided in various kinds, that includes Classic Control and Intelligent Control (IC). The last one aims to substitute classic controllers or even a manual controllers. The area of IC gained prominence in industry as well as in academics, where we can see a lot of articles which shows Artificial Intelligence (AI) techniques for control are replacing some classic controllers in the industry. As can be seen in the article Zhao and Collins Jr (2003) which use fuzzy PI to control an industrial Weigh Belt Feeder.

AI also stands out for provide control of real process which, sometimes, cannot be well controlled by a classic linear control. Usually for that kinds of plants, may be too hard to find a linear equation or a linearized model to make a good tune of a PID controller. So, the classic techniques of control may not be the best choice to control this plants.

AI's field of study include fuzzy logic, Artificial Neural Network, Genetic Algorithms, hybrids controllers that combines characteristics of several AI techniques. Among they, fuzzy logic stands because its allow an excellent representation of imprecise human knowledge to a language that machines can understand and because it is able to deal with the nonlinearities. The fuzzy logic resulted from the need to handle imprecise quantities and nonlinear system which includes almost all of the known real processes.

The robotics are an area where Fuzzy Logic Controllers(FLC) are widely used, as can be seen on papers of Huser et al. (1995) and Lilly (2007). The first one uses a FLC to control the navigation of a robot. The second uses a controller of the same type to control the navegation of a vehicle to avoid obstacles.

But, FLC is not restrict to robotics, the use of this kind of logic can be seen in da Silva (2007). On his article, he uses a fuzzy to identify torque load in induction engines. FLC can also be used to control the triggering of a three phase induction engine, as seen in Bordon (2004).

Another important application to the industry is the control of level of tanks and reservoirs. In majority of cases, precision and efficiency are critical to the success of production. That can be seen in papers that uses FLCs to control levels, which is characterized as a non-linear process, see the articles of Chang and Chang (2006) and Wu and Tan (2004).

So, as the usage of fuzzy grows, this paper was developed with the propose to analyze and compare three types of classical controllers and FLC. The selected controllers were: PI, PD, and PID to perform this comparison.

2. THEORICAL FUNDAMENTATION

2.1 Fuzzy Logic Controllers

The basic idea in fuzzy control is to model the actions from specialist knowledge, rather than, necessarily, modeling the process itself, according to Gomide and Gudwin (1994). This knowledge is passed to the fuzzy controller through its knowledge base, with rules like:

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IF <condition> THEN <action>
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A skilled operator can be interviewed to help formulate the set of fuzzy rules, he will associate input with output, in his own language. Thus, fuzzy systems can produce estimates of a system non-linear complex without recourse to mathematical models. In this scope, the fuzzy methodology is an estimation model input and output free of mathematical models, see Shaw and Simões (2007). For this reason the use of FLCs is very interesting in situations in which the system to be controlled by this strong non-linearities or when the information on the system are subject to uncertainties.

The types of FLCs studied in this work are:

2.2 Proportional-Integrate(PI) FLC

The expression for this controller can be saw at (1).

$$\frac{du(t)}{dt} = k_p \cdot \frac{de(t)}{dt} + k_i \cdot e(t) \tag{1}$$

Where, $du(t)$ is the variation of the control signal, $e(t)$ is the error (the difference between the reference signal and the output of the process), $de(t)$ is the variation in the error and k_p and k_i are constants tuned by the designer of the controller. It is important to note that the output of this controller must be integrated before it can be used to control the process, since it is the variation of the control action.

2.3 Proportional-Derivative(PD) FLC

The expression for this controller can be saw at (2).

$$u(t) = k_p \cdot e(t) + k_d \cdot \frac{de(t)}{dt} \tag{2}$$

Where, $u(t)$ is the control signal, $e(t)$ is the error (the difference between the reference signal and the output of the process), $de(t)$ is the variation in the error and k_p and k_d are constant tuned by the designer of the controller.

2.4 Proportional-Integrative-Derivative (PID) FLC

The expression for this controller can be saw at (3).

$$\frac{du(t)}{dt} = k_p \cdot \frac{de(t)}{dt} + k_i \cdot e(t) + k_d \cdot \frac{d^2e(t)}{dt^2} \tag{3}$$

Where, $du(t)$ is the variation of the control signal, $e(t)$ is the error (the difference between the reference signal and the output of the process), $de(t)$ is the variation in the error $d^2e(t)$ is the variation of the error's variation and k_p, k_i and k_d are constant tuned by the designer of the controller.

It is important to note that the output of this controller should also be integrated before it can be used to control the process, since it is the variation of the control action.

2.5 Quantitative Measure of Controller Performance

The Performance indices serve to establish the main criteria for evaluating performance for industrial controllers to make comparisons between different types of controllers, this quantitative performance comparison is chosen so that it is placed emphasis on specifications considered important system.

There are several performance indices, the most commonly used are based on the integral of error, a few examples: Integrated Squared Error(ISE), Integrated Absolute Error(IAE), Integrated Time Squared Error(ITSE) and Integrated Time absolute Error(ITAE).

There are also indices more complete that take into considerations more parameters such as is the case of Goodhart's indices(IG).

For this paper the IAE, ITAE and IG were chosen, as will be described below, see Dorf and Bishop (2001) Where the IEA and ITEA equations are obtained from then discretization of the analytical equation:

Integrated Absolute Error (IAE): Which is giving by the equation 4.

$$IAE = \frac{1}{N}\sum_{k=1}^{N}|e(k)| \tag{4}$$

Integrated Time Absolute Erro (ITAE): Which is giving by the equation 5.

$$ITAE = \frac{1}{N}\sum_{k=1}^{N}t|e(k)|. \tag{5}$$

Goodhart Index (IG): Which is given by the expression 6

$$IG = \alpha_1 \cdot \epsilon_1 + \alpha_2 \cdot \epsilon_2 + \alpha_3 \cdot \epsilon_3 \tag{6}$$

Where α_1, α_2 and α_3 are the weights that are given to ϵ_1, ϵ_2, and ϵ_3, respectively, and are expressed by:

$$\epsilon_1 = \frac{1}{N}\sum_{k=1}^{N}u(k) \tag{7}$$

$$\epsilon_2 = \frac{1}{N}\sum_{k=1}^{N}(u(k) - \epsilon_1)^2 \tag{8}$$

$$\epsilon_3 = \frac{1}{N}\sum_{k=1}^{N}(r(k) - y(k))^2 \tag{9}$$

Where $u(k)$ is the control signal, $r(k)$ is the reference $y(k)$ is the response, and N is the number of samples.

It can be observed that ϵ_1 is proportional to the control signal, ϵ_2 depends on the variation of the control signal and ϵ_3 depends on the mean square error.

3. DESIGN AND CONTROLLERS TESTS

The software was developed to perform the calculation of the FLC. To develop this program, modularization was used to facilities the implementation.

In total, three modules were developed to build the whole software. Every module has a specific function. The first module is named "Fuzzy Editor" which is responsible by edit the fuzzy created. The second one is "Supervising System", this is the module responsible to send and receive the data from the plant which is wanted to control.

The third module is named "Fuzzy Machine" which is responsible to calculate the values of fuzzy created. It receives the values from the second module and calculates the control action which must be taken.

The application has already all the interlock system, so the user does not have to worry, for example, exceed their operating limits, ensuring some integrity the plant. The application also provides the adequacy of inputs and outputs for each type of FLC.

The software was developed in C++ using Nokia's interface of programming, Qt Creator, for more information on the application developed see Martins et al. (2014).

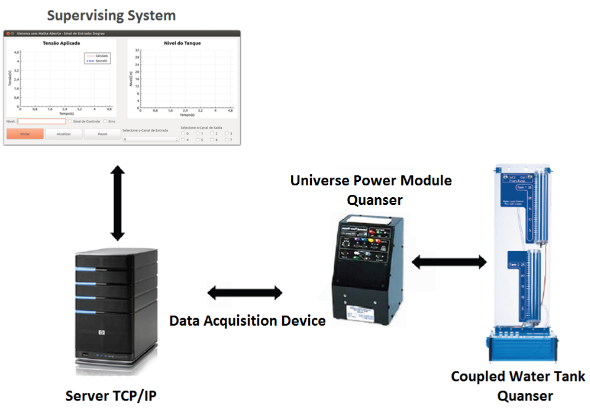

Fig. 1. Comunication Between Supervisory application and Level

The plant consists of a pump, two tanks coupled vertical and a reservoir below them. The two tanks contains a hole in its base which allows the flow of water, the upper tank receiving water pumped from the reservoir, thus the upper tank feeds the bottom tank through the hole in the base and the lower tank closes a cycle with water returning to the reservoir by its bore.

To this paper, all the FLCs was manual implemented based in the Sugeno model that uses probabilistics methods to evaluate the t-norm and t-conorm. The Sugeno fuzzy technique is used to obtain the fuzzy controller. The fuzzy PI, PD, and PID controller is developed using the system error. To the PI and PD have two-term the first is error and the second is the derivative of the error and to PID is used another term, the derivative of derivative of the error. The Sugeno's output is a linear function.

Based on this, we implemented a FLC to a tank's level to differents setpoints. The knowledge base which relates the input membership functions with Sugeno output fuctions that can be seen at table 4, to fuzzy-PI, table 5, to fuzzy-PD, and tables 6, 7 and 8 to fuzzy-PID.

3.1 Classic Controllers

The PID classic controllers was projected to the operation point of 15(fiveten) cm that is the linearization point, and also was project to achieve a fast rising point, but 180 seconds is not enough to correct the steady state error.

3.2 Fuzzy Controllers

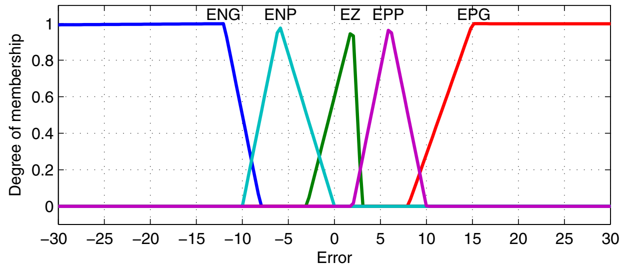

Fig. 2. Membership Functions for input error to Fuzzy-PI

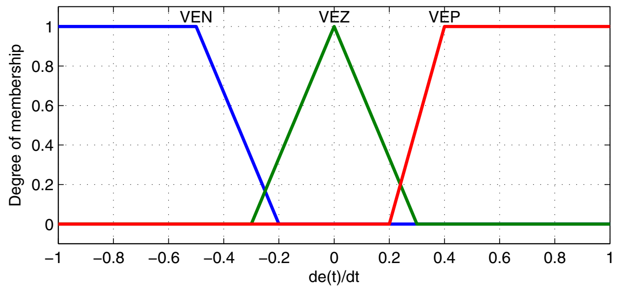

Fig. 3. Membership Functions for input *de(t)* - Fuzzy-PI and Fuzzy-PD

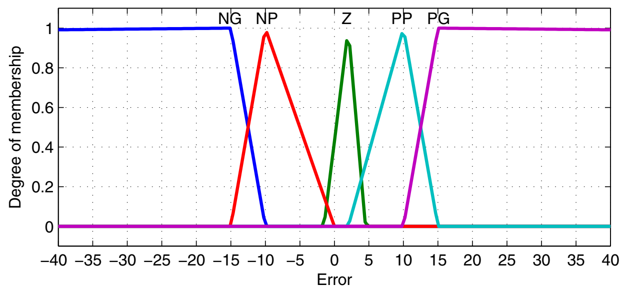

Fig. 4. Membership Functions for input error to Fuzzy-PD

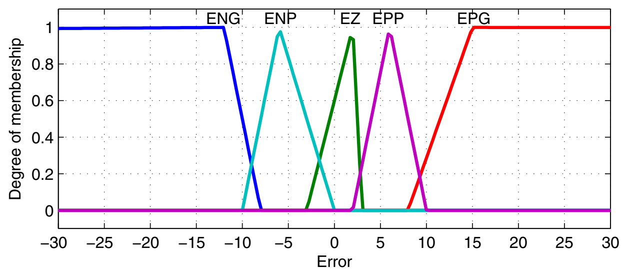

Fig. 5. Membership Functions for input error to Fuzzy-PID

Table 1. Classic PID Parameters

	PI	PD	PID
K_p	4	3	3
K_i	0.025		0.0028
K_d		0.0025	0.005

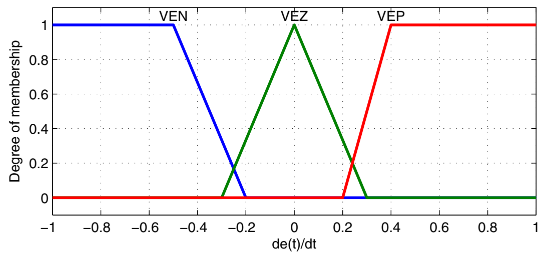

Fig. 6. Membership Functions for input $de(t)$ to Fuzzy-PID

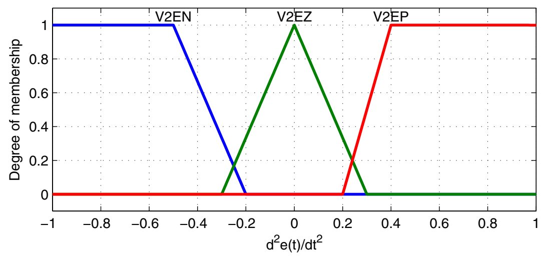

Fig. 7. Membership Functions for input $d^2e(t)$ to Fuzzy-PID

The membership functions's parameters are shown at table 2. The functions are not symmetric, because the force of the gravity, to negative error, helps to faster drain the water.

Table 2. Membership Functions

	M.Fs.	PI	PD	PID
Error	NH	[-3000 -12 -8]	[-3000 -15 -10]	[-3000 -12 -8]
	NL	[-10 -6 0]	[-15 -10 0]	[-10 -6 0]
	Z	[-3 2 3]	[-1.5 2 4.5]	[-3 2 3]
	PL	[2 6 10]	[2 10 15]	[2 6 10]
	PH	[8 15 30000]	[10 15 3000]	[8 15 30000]
$\frac{du(t)}{dt}$	DN	[-10000 -0.5 -0.2]	[-300 -0.5 0]	[-10000 -0.5 -0.2]
	DZ	[-0.3 0 0.3]	[-0.3 0 0.3]	[-0.3 0 0.3]
	DP	[0.2 0.4 10000]	[0 0.5 300]	[0.2 0.4 10000]
$\frac{d^2u(t)}{dt^2}$	DDN			[-10000 -0.5 -0.2]
	DDZ			[-0.3 0 0.3]
	DDP			[0.2 0.4 10000]

Table 3. Sugeno Functions

M.Fs	PI	PD	PID
B	[0.015 0.4 0]	[1.25 0.0005 0.75]	[0.015 0.4 0.000005 0]
S+	[0.018 0.2 0]	[0.25 0.0001 0]	[0.018 0.2 0.00002 0]
M+	[0.012 0.15 0]	[0.75 0.0002 0]	[0.012 0.15 0.00001 0]
Z	[0.001 0.3 0]		[0.001 0.2 0.00001 0]
M-	[0.04 0.2 0]		[0.038 0.2 0.00001 0]
S-	[0.01 0.2 0]		[0.01 0.2 0.00002 0]

3.3 Controllers PI

Table 4. FAM to the Fuzzy-PI Controller

Derror/Error	NH	NL	Z	PL	PH
Negative	H	M-	L+	M+	H
Zero	M-	L-	Z	L+	M+
Positive	H	M-	L-	M+	H

Table 5. FAM to the Fuzzy-PD controller

Derror/Error	NH	NL	Z	PL	PH
Negative	L	M	H	M	L
Zero	L	M	H	M	L
Positive	L	M	H	M	L

Table 6. FAM to the Fuzzy-PID controller with DDerror = N

Derror/Error	NH	NL	Z	PL	PH
Negative	H	M-	L+	M+	H
Zero	M-	L-	Z	L+	M+
Positive	H	M-	L-	M+	H

Table 7. FAM to the Fuzzy-PID controller with DDerror = Z

Derror/Error	NH	NL	Z	PL	PH
Negative	H	M-	L+	M+	H
Zero	M-	L-	Z	L+	M+
Positive	H	M-	L-	M+	H

Table 8. FAM to the Fuzzy-PID controller with DDerror = P

Derror/Error	NH	NL	Z	PL	PH
Negative	H	M-	L+	M+	H
Zero	M-	L-	Z	L+	M+
Positive	H	M-	L-	M+	H

3.4 Controllers PID

4. RESULTS

4.1 Controllers PI

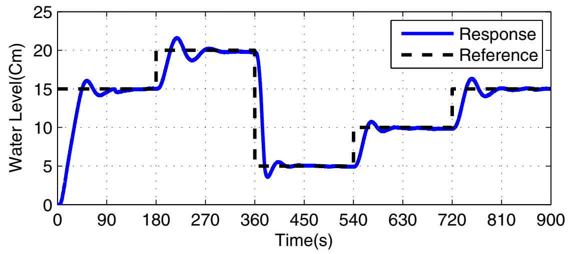

Fig. 8. System Response to Fuzzy-PI Controller

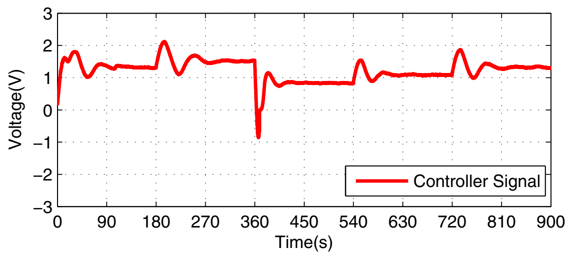

Fig. 9. Fuzzy-PI controller's signal

Table 9. Performance indices to PI Controllers

Indices	Fuzzy	Classic
IAE	10069.4332	6716.9334
ITAE	2753418.496	2102077.6082
IG	2.5706	4.6518

As can be seen in the table the value of IEA of fuzzy is greater than the PI classic, this happen because the

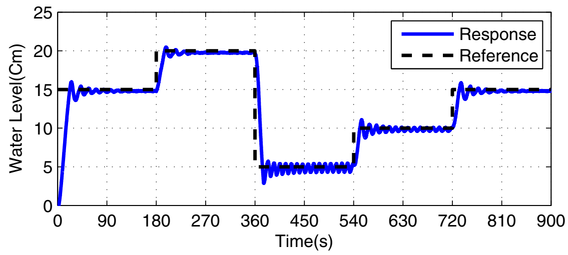

Fig. 10. Classic PI system response

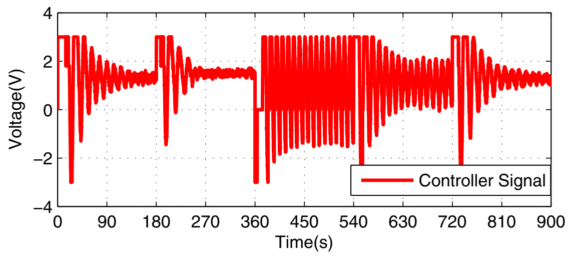

Fig. 11. Classic PI controller's signal

PI fuzzy controller is softer so that its action is slower which implies directly in IEA, as can also be observed in all rise time, where the classic had a better response, but when the controller classic moves away from the point of operation, 15cm, has an output unsatisfactory and a overshoot higher, but the same is not observed in fuzzy, due to its characteristic of nonlinearity.

When we analyze the IG the fuzzy has a better answer. As the IG considerates the variation of the control signal as can be seen in figure 11 the control signal PI classic had an aggressive behavior, which affected its assessment, normally a sign thus is unwanted since this type of behavior reduces the useful life of the actuator. In a general way the fuzzy had a better performance, even with a IEA higher, but had a response was desirable for the various setpoints.

4.2 Controllers PD

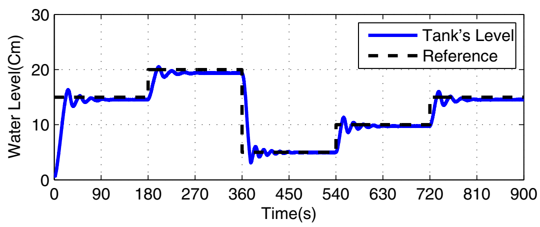

Fig. 12. System Response to Fuzzy-PD Controller

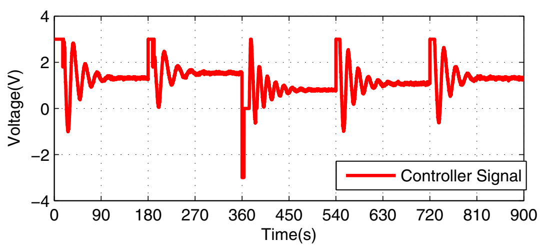

Fig. 13. Fuzzy-PD controller's signal

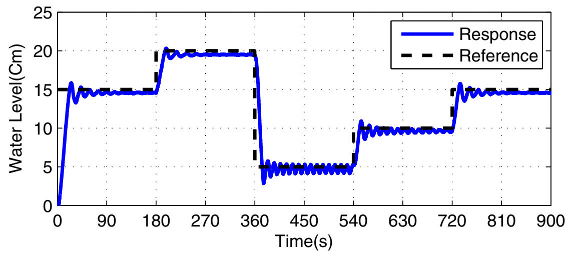

Fig. 14. System Response to Classic PD Controller

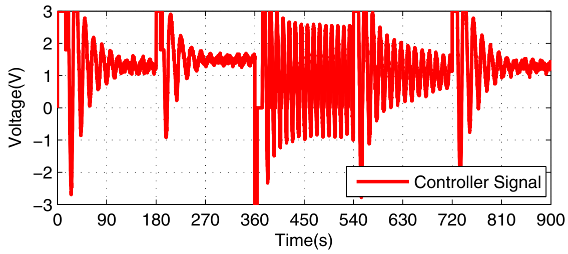

Fig. 15. Classic PD Controller's signal

Table 10. Performance indices to PD Controllers

Indices	Fuzzy	Classic
IAE	7745.6878	8050.7655
ITAE	2505851.1635	2695707.2424
IG	3.0803	4.2097

As can be observed in graphics of the levels, the behavior of the PD fuzzy and the PD classic is very similar, but in certain setpoints the behavior of the classic is undesirable, this setpoints are away from the point of operation where the PD classic loses performance in which the curve of control signal shows an effort unnecessary of actuator.

To analyze the control signal it is possible to observe that the PD fuzzy is softer compared to the classic. When observing the table PD fuzzy has a IEA smaller in relation to PD classic as well as the ITAE, the happen because the response of the classic is undesired away from point of operation and the fuzzy behaves well.

The fuzzy has a good assessment in IG. Note that the behavior of the fuzzy for setpoint equal to 5 cm has steady state error, this occurs due to non-linearity of fuzzy. In a general way the fuzzy obtained the best performance, it is the Performance Indices and table.

4.3 Controllers PID

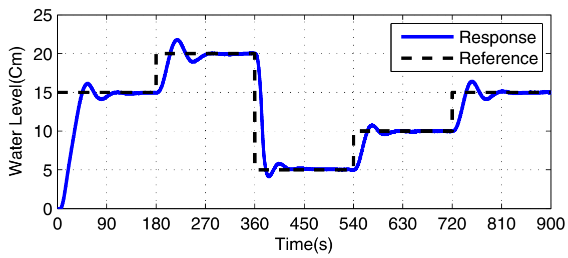

Fig. 16. System Response to Fuzzy-PID Controller

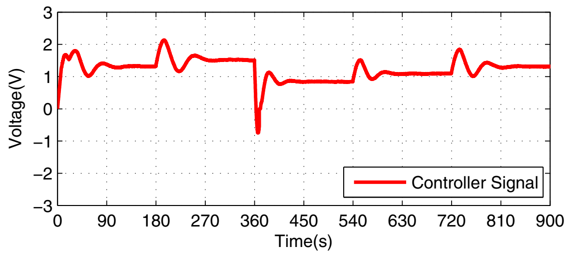

Fig. 17. Fuzzy-PID controller's signal

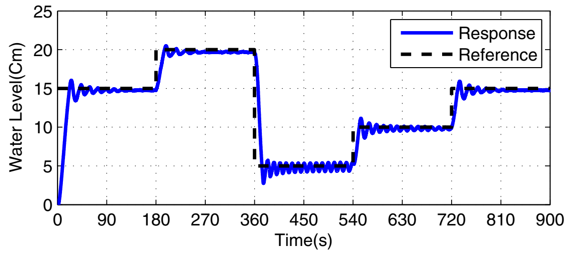

Fig. 18. Classic PID controller response

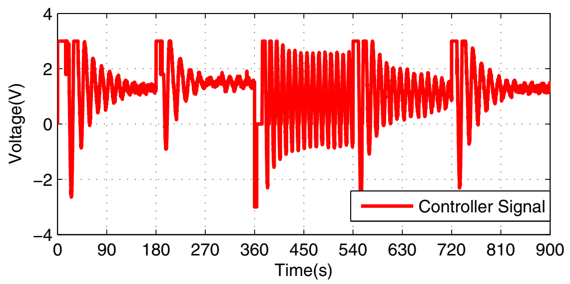

Fig. 19. Classic PID controller's signal

Table 11. Performance indices to PID Controllers

Indices	Fuzzy	Classic
IAE	10066.6561	6967.5883
ITAE	2668034.6865	2194671.8211
IG	2.5662	4.1393

Analyzing the table 11 along with the graphics, we can see that the PID classic controller has a IEA less than the fuzzy-PID controller, this is due PID classic has more abrupt changes in the control signal, forcing the pump, while the fuzzy-PID showed a control signal more damped than the classic, without abrupt changes in control signal.

It is noticed by the graphics by adding the derivative action to the controller, we achieved a faster correction of the error of transitional regime than PI controllers. Note that the IG to the fuzzy-PID got a better result because when trying to fix the steady state error faster, the classic PID controller signal has a aggressive behavior,causing larges variations int he control signal,switching the pump what is extremely bad for actuators in order that the switching voltage can shoten the life of the pump. The ITEA, dues the fuzzy-PID is slower than classic-PID, the values to the classic one is better than the fuzzy one.

5. CONCLUSION

Through the results it is possible to observe that the fuzzy can had a good performance in relation to classic controllers, but has a greater number of parameters to tune in relation to the classic. This makes it difficult to obtain, in a manual way, a tuning that can be considered optimal with respect to any performance indices, motivating the use of numerical optimization techniques for automatic tuning of fuzzy controllers or even hybrid techniques like neurofuzzy.

The characteristic non-linear the Fuzzy provide a great capacity to adapt non-linearities of plant which implies that a good performance in the whole range of operation. This feature becomes even more-prominent in plants with non-linearities more accentuated. This cannot be noticed in classic controllers due to its linear behavior.

Although the plant used in this study is simple and with smooth non linearities, the results demonstrate the potential of fuzzy controllers for practical applications.

ACKNOWLEDGEMENTS

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