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Performance comparison between PI digital and fuzzy controllers in a level control system

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Abstract. Liquid level systems are important in many industrial and academic applications, so measurement and control systems need to be as accurate as possible for this process. However, a level system has a nonlinear dynamic which increases the difficult of modelling and design controller by classical methods. In order to address these issues, this paper discusses the modeling of a nonlinear level plant and the implementation of strategies for PI control and fuzzy control. The control algorithms are embedded in an 8 bits microcontroller, which provides the plant sample data via serial communication. Response specifications are stipulated so that the performance of the controllers is evaluated and compared. The results show a better performance for the fuzzy controller which could avoid larges overshoots with low computation costs and none anti-wind up strategies.

Keywords: Fuzzy controller, PI controller, Level System.

1 Introduction

Most industrial processes are controlled by conventional PID-type controllers (VERBRUGGEN; ZIMMERMANN; BABUŠKA, 2013) and their variations, depending on the ease of tuning (ÅSTRÖM; HÄGGLUND, 1995; OGATA, 2009). However, these controllers are generally designed from linear process models with time-invariant parameters. When these conditions are violated, i.e the process has nonlinearity or important parametric variations during operation or over time, the controller may be unable to give the control system the desired performance (BOBÁL et al., 2006).

A classic example of a nonlinear system is the liquid level system (CAMPOS; TEIXEIRA, 2006; OGATA, 2009; PALM, 2014). It is characterized as a system with a variant parameter with the level, and, under certain conditions, presents nonlinearity due to the change of laminar fluid flow to turbulent (OGATA, 2009). Thus, if the designer adopts a controller design methodology based on the application of linear techniques, it is necessary to characterize linear mathematical models under different operating conditions, usually obtained from experimental tests to identify their parameters, followed by validation with a computer simulation.

On the work presented by Hu, Li e Huang (2010) a combination between a PID control and a inverse system was used to control the level of a double-hold water tank. In Chang (2012) a method to optimally tuning a PI controller based on artificial bee colony optimization was applied to a physical liquid-level system with two inputs and two outputs. On Janarthanan, Thirukkuralkani e Vijayachitra (2014) a Fractional Order Proportional Integral Derivative controller was designed for a conical tank level system. On Shehu e Wahab (2016) several PI strategies were applied and compared to a MPC control for a coupled-Tank level system. A PI controller tuned by a Bee Swarm Optimization metaheuristic was applied to a level system and compared to the classical method Rivera Internal Method Control in Panoeiro et al. (2018). On Rahmawati et al. (2018) a PI controller tuned with St. Clair method was proposed to a level system.

Although many processes present the difficulties mentioned, it is not uncommon to find relatively complex processes being satisfactorily controlled by humans, called experts, without formal understanding of a model or the physical details involved (PASSINO; YURKOVICH; REINFRANK, 1998; OVIEDO; VANDEWALLE; WERTZ, 2006; ENGELBRECHT, 2007). This ability presented by humans inspired the use of computational intelligence, notably the fuzzy control technique. This, in turn, emulates the way the human being understands reality. Here, subjective perceptions such as human heuristics, intuition, and experience are converted into simple mathematical representations and logical rules that make up the control algorithm. In this way, a fuzzy controller can become a logical model of the way the operator thinks when manipulating the system.

On Zhao (2010) a fuzzy ruled system was designed to tuning a PID controller to control a simulated two-container water tank liquid level plant. In Ahmed, Petrov e Ichtev (2010) a model predictive fuzzy control was study and applied to a tank level system. Chen et al. (2010) proposed a self-adaptive fuzzy-PID to control a boiler drum water level. On the work of Bhandare e Kulkarni (2015) a comparison of a PID and Fuzzy Logic Controller for a liquid level system was made. The work of Lamkhade, Parvat e Kadu (2015) proposed a method to design and implement a fuzzy controller to a level control system. Bo, Chuang e Meng (2016) designed a fuzzy controller using PLC in order to regulate a liquid level system. On Popescu (2018) a comparative study of the PID and fuzzy logic controllers performance for a level control system was made by means of a Delta V distributed system.

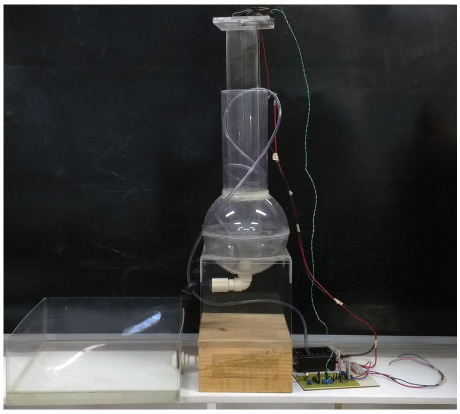
This paper presents an experimental comparison of the static and dynamic responses of level control systems in a specially designed acrylic tank to highlight nonlinear behavior. PI-type controllers, designed from the application of linear control design techniques, and controller developed from the application of computational intelligence techniques, more specifically fuzzy logic, are used.

2 Methodology

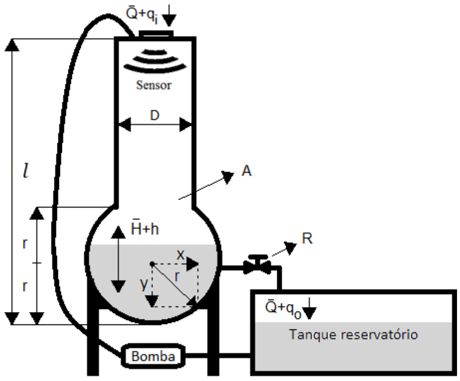
This section covers the configuration and mathematical modeling of the level plan, in this case, state equation model and transfer function model, and brief comments on the design methodology of the PI and fuzzy controllers.

2.1 The Level Plant Configuration

The level plant structure, object of this paper, was specially developed in acrylic to provide the evaluation of controllers under two different conditions. As can be seen from Figure 1, the structure is composed of a spherical base of radius 11.75 cm, on which there is a cylindrical tube with 27 cm high and 11.78 cm diameter.



(a) Physical structure image



(b) System diagram

Figure 1: Level system structure.

The liquid, in this case water, is pumped by a motor-pump assembly with a maximum flow rate of 66.3 cm^3/s, a maximum current of 3 A and a nominal DC voltage of 12 V. Variable voltages can be applied from the CI LMD18200, which is configured to operate as a unidirectional Buck type DC/DC converter. The 10-bit resolution Pulse Width Modulation (PWM) signal is applied to the IC from the output of the digital controller implemented in an ATMEGA328P microcontroller. This microcontroller also sends information to a supervision application developed on the Labview® platform through the serial port.

The level sensor is mounted on top of the tank structure and is of the HC-SR04 ultrasound type. It provides the controller with digital information of duration proportional to the distance between the sensor and the liquid surface. Due to the multiple sound signal reflections that occur when the liquid surface (tank level) is in the sphere region, it was decided to confine the signals emitted by the ultrasound in a 60 cm long acrylic tube with hexagonal cross section. 80 cm^2, which runs internally throughout the tank.

The level system also has a 20 liter acrylic auxiliary tank for water supply and reception, as well as crystal hose, PVC fittings and manual valve installed at the base of the ball. The vessel is filled from the top at atmospheric pressure.

2.2 Mathematical Modeling

Referring to the linearized model of liquid level systems discussed in (OGATA, 2009), which is considered laminar flow, and with the help of Figure 1b, wich have its parameter defined in Table 1, the mass balance equation is given by

$$q_i - q_o = A\frac{dh}{dt}, \tag{1}$$

where $q_o = h/R$. From these equations two discrete models are obtained: state equations and transfer function. The first one is used to simulate the plant with its nonlinear characteristics and the second one is used to design controllers from the application of linear design techniques.

2.2.1 State equations

The model presented in Equation 2 below

$$h[k+1] = \left(1 - \frac{T}{RA}\right) h[k] + \frac{T}{A} q_i[k] \tag{2}$$

the representation by discrete equations of state. It has facilities for incorporating the variation of vessel fluid capacitance (A) and valve fluid resistance (R) in its recursive solution. It is important to remember that the valve resistance varies with the valve opening and, with a definite opening, increases with increasing level. Thus, after experimentation, Equation 3 is adopted to relate the fluidic resistance of the valve as a function of level to 1/4 valve opening

$$R = 0.0348h + 0.1746. \tag{3}$$

Fluid capacitance varies according to Equations 4 and 5, respectively for the spherical and cylindrical regions:

$$A = \pi(2lr - l^2) \tag{4}$$

and

$$A = \frac{\pi D^2}{4} \tag{5}$$

For model validation, tank filling experiments with the valve fully closed and tank emptying are performed. In the case of filling, two conditions were imposed: one with maintaining the auxiliary tank level constant, which ensures constant suction pressure of the pump, and another without this concern. The experiments result as well as the computer simulation can be seen in Figure 2a for the filling experiment and in Figure 2b for the emptying one.

It is observed that tank filling test 1 has an expected divergence as the pressure is not kept constant at the pump suction line, but the results of tests 2 and 3 are very close to the simulation. The same can be said about tank emptying tests. The authors consider the state equation model adequate to represent the level plant.

The model presented in Equation 6 below

$$\frac{H(z)}{Q_i(z)} = \frac{RT}{RA + T - RAz^{-1}} \tag{6}$$

represents the transfer function of the plant. In this, the parameters R and A are considered invariant around some point of operation.

As the level plan presents regions where the dynamic behaviors are different, two models are elaborated. In both, the sample rate is T = 0.1s and the experimentally obtained fluid resistance is $R = 0.46$ s/cm^2.

The first model, called G_1, is designed as if the entire vessel are cylindrical with cross-section equal to that of the actual cylinder. Thus, the capacitance is $A_1 = 108.98$ cm^2 and the model is given by Equation 7

Table 1: Physical Level Plant Parameters.

Par.	Description	Par.	Description
Q	flow rate on steady state (cm$^3/s$)	R	valve fluid resistance (s/cm^2)
q_i	small deviation on input flow rate (cm$^3/s$)	D	cylinder cross section diameter (cm)
q_o	small deviation on output flow rate (cm$^3/s$)	r	sphere radius (cm)
H	level height on steady state (cm)	l	total tank height (cm)
h	small deviation on level height (cm)	x	sphere cross section radius (cm)
A	tank capacitance (cm^2)	y	sphere level (cm)

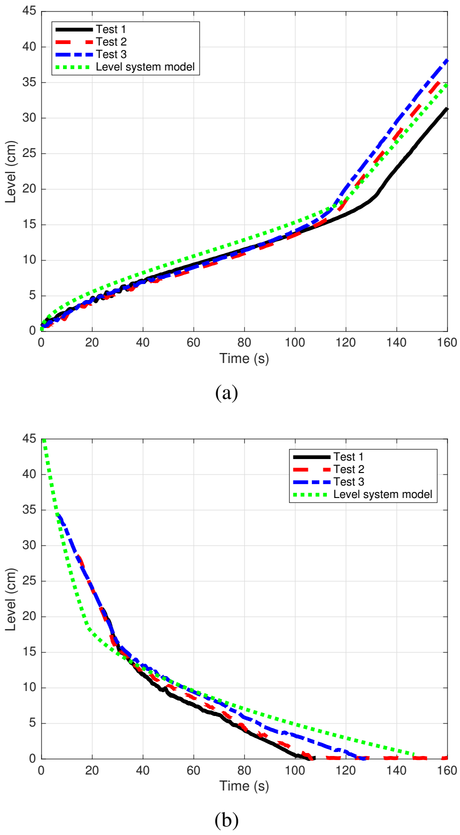


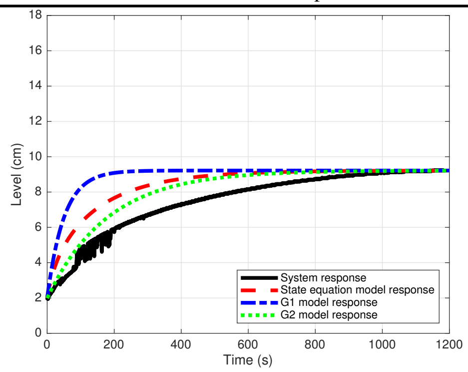
Figure 2: (a) Tank filling tests, (b) tank emptying tests.

$$G_1(z) = \frac{H(z)}{Q_i(z)} = \frac{0.046}{50.23 - 50.13z^{-1}}. \quad (7)$$

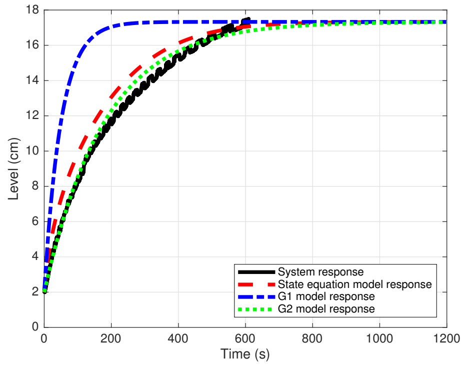
The second model, called G_2, is designed as if the entire vessel were cylindrical in cross-section equal to that of the central part of the sphere. Thus, the capacitance is $A_2 = 390.57$ cm^2 and the model is given by Equation 8

$$G_2(z) = \frac{H(z)}{Q_i(z)} = \frac{0.046}{179.8 - 179.7z^{-1}}. \quad (8)$$

Then, two open-loop tests are performed in the real system and, with the aid of a simulation software, their dynamic responses are compared to the responses of the three obtained models. Both tests consist of applying a unit step input signal to the system. For the first experiment, it is determined that the desired operating point is the central part of the sphere, since it is considered that this point represents the worst case in the spherical region due to its larger diameter. For the second experiment is sought the point where the system reaches the permanent state at the top of the sphere, or beginning of the cylinder, because from this level the obtained system can be considered linear. The results can be seen in Figure 3.



(a)



(b)

Figure 3: Comparison of models with real system . (a) Response in the sphere and (b) in the cylinder.

In Figure 3a, the steady state level occurs approximately in the middle of the sphere. The noise measured at the beginning of the test possibly reflects the effect of ripples on the water surface, which occur more intensely in the lower part of the tank. As expected, the dynamic responses of the state equation model and G_2 are close. Both, however, differ from the actual answer.

In Figure 3b, the permanent state level occurs at the top of the sphere near the cylindrical region. The responses of the real system, the state equation model, and the G_2 are quite similar.

The authors believe that the G_2 model is suitable for the development of the controller design, given the similarity of its response to the real system and to the equation of state model. Regardless of the divergence of the response from the G_1 model to the actual system response, it will also be used for controller design. The idea is to evaluate the robustness of the project methodology.

2.3 Controllers design

In this subsection we briefly present the design methodologies of two PI type controllers and the fuzzy controller. Control systems are intended to meet the following design specifications: overshoot less than 10% and accommodation time less than 210 seconds.

2.3.1 PI controllers

Linear models in transfer functions called G_1 and G_2 are used for the design of two digital PI controllers. The controller G_{c_1} designed for G_1 is expected to perform better in the cylindrical region and the controller G_{c_2} designed for G_2 is expected to have better response in the spherical region. The structure used for the PI controller is proposed by Chen (2006), in which the transfer function is given by

$$U(z) = \left[k_p + \frac{k_i}{(1 - z^{-1})}\right] E(z), \tag{9}$$

where k_p is the proportional gain and k_i is the integrator.

In order to properly design the controllers it is necessary to determine the model for the pump which is given by the relation *Pump flow* (cm^3/s) $\times$ *Motor voltage* (V) and given by $P_f = 6.3645V - 10.0662$, the static gain of the DC/DC converter which is $G_{DC/DC} = 12/1023$ and the sensor gain which is unitary.

The controllers are tuning by pole allocation and its transfer functions are given by

$$G_{c_1} = 110.32\frac{z - 0.995}{z - 1} \tag{10}$$

and

$$G_{c_2} = 263.14\frac{z - 0.998}{z - 1} \tag{11}$$

2.3.2 Fuzzy controller

The inputs chosen for the fuzzy controller are the “error”, ie the difference between the setpoint value and the feedback value from the level sensor, and the “error variation”. The pertinence functions of the inputs are represented in Figure 4a and 4b.

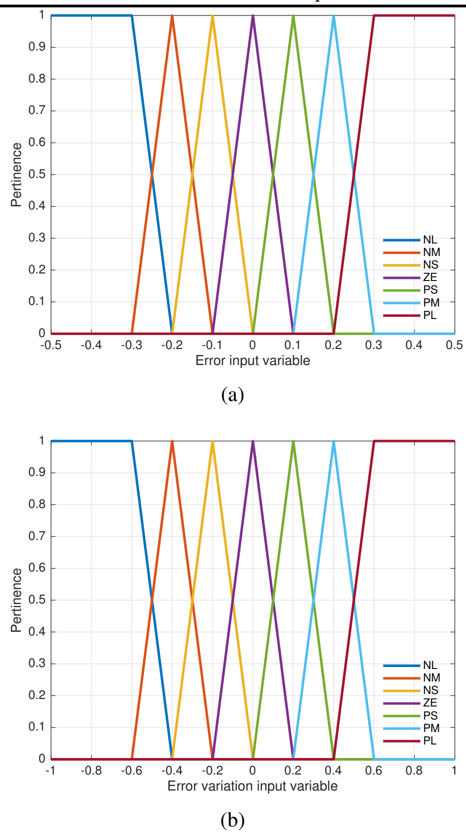


Figure 4: Pertinence functions. (a) Error input and (b) Error variation input.

In the fuzzification step the fuzzy machine inputs, in this case the controller, are converted into fuzzy values associated with membership functions represented by the following linguistic variables: NL - large negative, NM - medium negative, NS - small negative, ZE - zero, PS - small positive, PM - medium positive and PL - large positive. The ranges of values, in which fuzzy sets are mathematically modeled in their discourse universes, were established from the understanding of system behavior, followed by subsequent adjustments.

In the inference process the fuzzy inputs are subject to the rules, which determine the fuzzy output. For the error entries and error variance 49 rules are elaborated that use IF-THEN statements relating their pertinence functions and generating the pertinence function of the output. The language variables chosen for the controller output are: ZE - zero, VSO - very small output, SO - small output, MO - medium output, AMO - above medium output, LO - large output and VLO - very large output. These rules are organized in Table 2.

Table 2: Physical Level Plant Parameters.

Δe \ e	NL	NM	NS	ZE	PS	PM	PL
NL	ZE	ZE	ZE	ZE	VSO	SO	MO
NM	ZE	ZE	ZE	VSO	SO	MO	AMO
NS	ZE	ZE	VSO	SO	MO	AMO	LO
ZE	ZE	VSO	SO	MO	AMO	LO	VLO
PS	VSO	SO	MO	AMO	LO	VLO	VLO
PM	SO	MO	AMO	LO	VLO	VLO	VLO
PL	MO	AMO	LO	VLO	VLO	VLO	VLO

The value ranges for the control output pertinence functions were defined based on simulated tuning attempts and are presented in Figure 5.

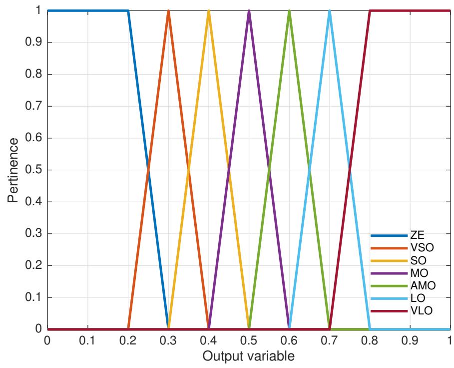


Figure 5: Pertinence function for the output.

The result of the fuzzy output for each rule is determined from Mamdani's implication (VERBRUGGEN; ZIMMERMANN; BABUŠKA, 2013; ENGELBRECHT, 2007) as follows.

$$\mu_c = min(\mu_e(u), \mu_{\Delta e(u)}). \quad (12)$$

In the defuzzification step the heights method is used. Thus, the crisp output of the controller y_c is the result of the weighting of the fuzzy outputs of the activated rules, as presented in Equation 13.

$$y_c = \sum_{i=0}^{n}(\mu_i y_i) / \sum_{i=0}^{n} \mu_i \quad (13)$$

where the weighting factors y_i correspond to the peak values of each membership function activated in the output speech universe.

The output y_cs normalized to a value range between 0 and 1. It is then multiplied by an experimentally defined adjustment factor to determine the integer value stored in the PWM register (10 bits), which defines the voltage applied to the motor pump by the DC/DC converter.

Computer simulations are performed with the purpose of tuning the controller. It is found that only the 21 hatched rules in Table 2 are used in the control process. As a consequence, there is a drastic reduction in the computational cost of the controller and the adaptation in the pertinence sets of the Δe discourse universe, as can be seen in Figure 6d.

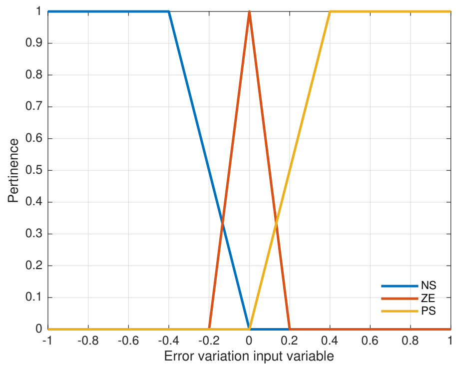
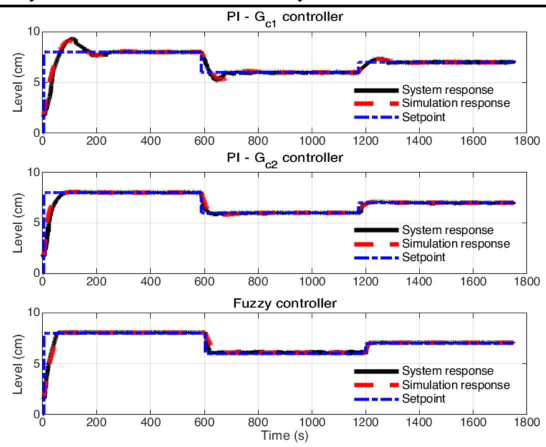
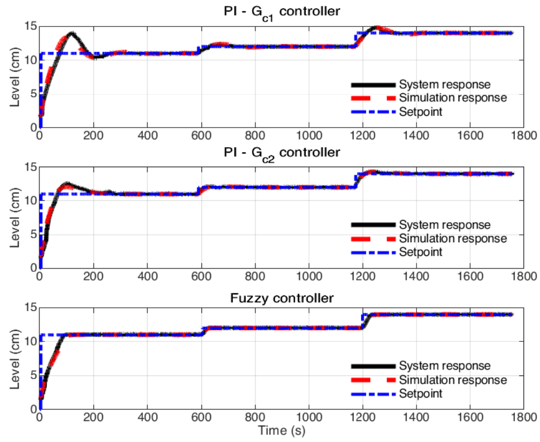


Figure 6: Pruned pertinence function for Error variation.



(a)



(b)

Figure 7: System response for (a) Test 1 and (b) Test 2.

3 Results and discussions

The performance evaluation of the proposed control systems is based on four experiments. The first test is made in the lower part of the sphere, the second one in its central part and the third one in the upper part. The fourth test is focused on the cylinder. The hand valve has a fixed opening of approximately 1/4 turn. The graphs generated in each test are shown in Figure 7 and 8. The values obtained in each test are shown in Table 3.

Analyzing the graphs, we find that the response of the control systems are very close to the computer simulations.

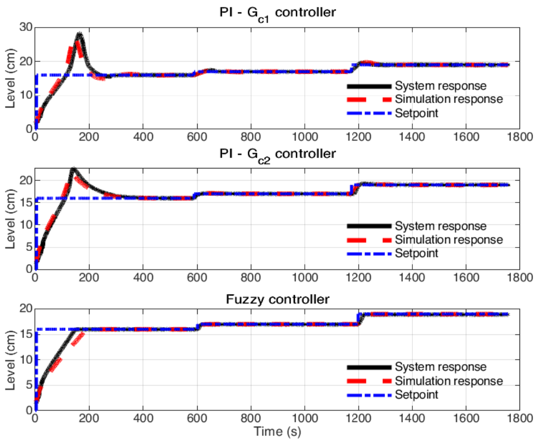
The experimental responses presented in the graphs of Figure 7a are quite noisy. This is due to turbulence in the water surface due to potting. In other experiments, potting is performed with the submerged discharge nozzle.

In general, it is observed that when large step setpoint variations are applied, systems controlled by PI controllers have large overshoots. This inappropriate behavior can be circumvented by applying anti-windup techniques or even promoting ramp setpoint variation.

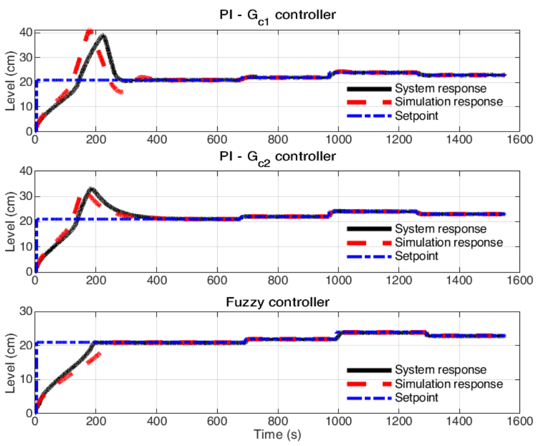
The accommodation times of the system controlled by PI controllers tend to be longer than those controlled by fuzzy controllers.

Table 3: Numerical test results for controllers in step-response. In it, h is the desired and achieved level (cm) in each steady state, O is the maximum overshoot and t_s is the settling time.

Test	h (cm)	G_{c_1}		G_{c_2}		Fuzzy		Test	h (cm)	G_{c_1}		G_{c_2}		Fuzzy	
		O(%)	t_s(s)	O(%)	t_s(s)	O(%)	t_s(s)			O(%)	t_s(s)	O(%)	t_s(s)	O(%)	t_s(s)
1	8	16.3	248	1.62	167	1	54	3	16	76.1	303	41.9	458	0.12	174
	6	13,6	86	5.5	120	0.33	20		17	2.58	87	0.64	131	0.23	19
	7	5.14	117	1.71	141	0.9	18		19	3.78	203	1.52	77	0.52	20
2	11	27.2	254	14.2	278	0	88	4	21	86.6	336	58	496	0.47	189
	12	3.33	122	1.25	90	0	25		22	1.31	60	3.63	15	0.45	7
	14	5.71	222	2.42	121	0	34		24	1.79	75	0.66	68	0.62	14
									23	0.95	61	0.3	31	0.43	2



(a)



(b)

Figure 8: System response for (a) Test 3 and (b) Test 4.

The design requirements are all met when the fuzzy controller acts on the level system. There is virtually no overshoot and accommodation times are low. The controller is less sensitive to noise due to turbulence on the liquid surface.

4 Conclusions

Controlling nonlinear plants with conventional PI controllers brings several difficulties and challenges, especially regarding system modeling. Its implementation is not always satisfactory in meeting the design specifications, since the controller design is based on a local linear model and is controlled at different operating points. It has been observed that when the controller is subjected to large magnitude setpoint inputs, too large overhangs occur. This effect could be reduced in the G_{c_2} controller by increasing the proportional gain by about 46% of the projected gain. Gain increases beyond the above would cause controller saturation.

In the case of the fuzzy controller, there is no need for a mathematical modeling of the plant. However, the tuning work of the controller is exhausting. However, when this step is exceeded, its performance at several operating points becomes superior to PI controllers, having considerably shorter accommodation times and a virtually constant overshoot range of about 0.4% at all regions.

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