PD and PID Fuzzy Logic Controllers. Application to Neutralization Processes

María C. Palancar, Lourdes Martín, José M. Aragón, Javier Villa

Department of Chemical Engineering, University Complutense of Madrid, ES-28040 Madrid, Spain

Abstract

The performance of two Fuzzy Logic Controllers (FLCs), Proportional-Derivative Controller (PD-FLC) and Proportional-Integral-Derivative controller (PID-FLC) for the pH control was studied in a neutralization process. The process used to test the controller performance is the continuous neutralization of acetic and propionic acids in a water stream with an aqueous solution of sodium hydroxide. The best results were obtained with the PID-FLC. For acidic stream flow rate and concentration perturbations lower than 50 %, the pH of the outlet stream shows overshoots lower than 1 pH units.

Keywords: Process control, neutralization, fuzzy logic, pH-control

1. Introduction

The pH control plays an important role in several industrial processes. Neutralization is subjected to many difficulties (non linearity, high sensitivity to small perturbations, etc). These special characteristics lead to the great number of strategies about pH control that have been reported in the literature. So, several alternatives to classical PID controllers for pH control have been considered, including different types of linear and nonlinear models (Palancar *et al.* 1996) and artificial neural networks (ANN) (Palancar *et al.* 1998).
The FLC has been applied to control diverse processes during the last years, Chen *et al.* (1993) and Edgar and Poslethwaite (2000). There are some papers in the bibliography that study the pH control by applying the Fuzzy Logic (FL). For example, Menzl *et al.* (1996) have developed a self optimizing FLC to control the pH in a bioreactor and in a waste water neutralization process. The running and lag time of two pumps to acid or base feed are the manipulated variables. The FLC calculates the modification of both times (running and lag) from the actual pH values and the titration zone where it is. Some works study the tuning of Proportional-Integral (PI) FLC. So, Regunath and Kadirkamanathan (2001) have developed a controller that aims to maintain the pH at a reference trajectory in the presence of severe changes in

the influent composition and/or flow rate. The controller is a Proportional –Integral (PI) with a dimensional Sugeno type Fuzzy Inference System (FIS) and a Basic Evolutionary Program (BEP) that are used for tuning the controller. Babuska *et al.* (2002) have used the FL to obtain an adaptive parameter that is used to tune the proportional and integral gains. Other authors such as Fuente *et al.* (2006) use the FL to generate Proportional-Derivative (PD) control action. These authors make the controller adaptive feeding to FLC one variable that is representative of the titration curve zone that corresponds to the actual pH. The developed controller is applied to the pH control of the neutralization process to maintain the pH at values below 6.

The aim of this work is to compare the performance of two FLCs, PD-FLC and PID-FLC for the pH control in a neutralization process. The objective of this controller is to maintain the pH at a value of 7 in the presence of changes in either the influent composition or the flow rate. The paper is organized as follows: firstly, the neutralization process and the process model are described. Then, a description of the controller model is explained. Finally, the results obtained are analyzed.

Neutralization Process and Process Model

The process used to test the controller performance is the continuous neutralization of an aqueous stream of a mixture of acetic and propionic acids with an aqueous solution of sodium hydroxide. The neutralization vessel is a Continuous Stirred Tank Reactor (CSTR) of 1750 cm^3 and the mean residence time of the liquid was between 300 and 1800 s.

The equilibrium reactions taking place in an aqueous mixture of acetic acid, propionic acid and sodium hydroxide are shown in Eq. 1.

$$\begin{aligned} &CH_3CO_2H \leftrightarrow CH_3COO^- + H^+ \\ &CH_3CH_2CO_2H \leftrightarrow CH_3CH_2COO^- + H^+ \\ &NaOH \rightarrow Na^+ + OH^- \\ &H_2O \leftrightarrow H^+ + OH^- \end{aligned} \qquad (1)$$

The whole process was simulated by a numerical model of invariants, eq. 2, already described in a previous paper (Palancar *et al.* 1996) and has been obtained by solving the charge and material balances expressed in the function of the process invariants.

$$\begin{aligned} &-\left[H^+\right]^4 - \left(\gamma + K_{a_1} + K_{a_2}\right)\left[H^+\right]^3 + \left(K_w + \beta K_{a_2} + \alpha K_{a_1} - \gamma\left(K_{a_2} + K_{a_1}\right)\right)\left[H^+\right]^2 + \\ &+\left((\alpha+\beta)K_{a_1} K_{a_2} - \gamma K_{a_2} K_{a_1} + K_w\left(K_{a_2} + K_{a_1}\right)\right)\left[H^+\right] + K_w K_{a_1} K_{a_2} = 0 \end{aligned} \qquad (2)$$

where K_{a_1}, K_{a_2} and K_w are dissociation constants of the acetic and propionic acids and water, respectively and α, β and γ are the invariants, eqs.3-5.

$$\alpha = \left[CH_3COO^-\right] + \left[CH_3COOH\right] \qquad (3)$$

$$\beta = \left[CH_3CH_2COO^-\right] + \left[CH_3CH_2COOH\right] \qquad (4)$$

$$\gamma = \left\lfloor Na^{+} \right\rfloor \qquad (5)$$

Controller model

The control system is a feedback loop in which the measured variable is the pH inside the neutralization vessel, the manipulated variable is the flow rate of the alkaline stream and the control action is based on PD or PID FLCs, Fig. 1. The PD-FLC considers the error, *e(k)* eq. 6, and the error derivative, *DEE (k)* eq. 7, as the two input variables of the controller. The PID-FLC considers the pH error, pH error derivative and pH cumulative error, *INE(k)* eq. 8, as the three input variables of the controller. For both controllers, the output variable is the valve stem position, x_v, which regulates the flow rate of the neutralizing agent stream.

$$e(k) = pH_{set} - pH(k) \qquad (6)$$

$$DEE(k) = \frac{e(k) - e(k-1)}{\Delta T} \qquad (7)$$

$$INE(k) = INE(k-1) + \left(e(k) + e(k-1)\right)\frac{\Delta T}{2} \qquad (8)$$

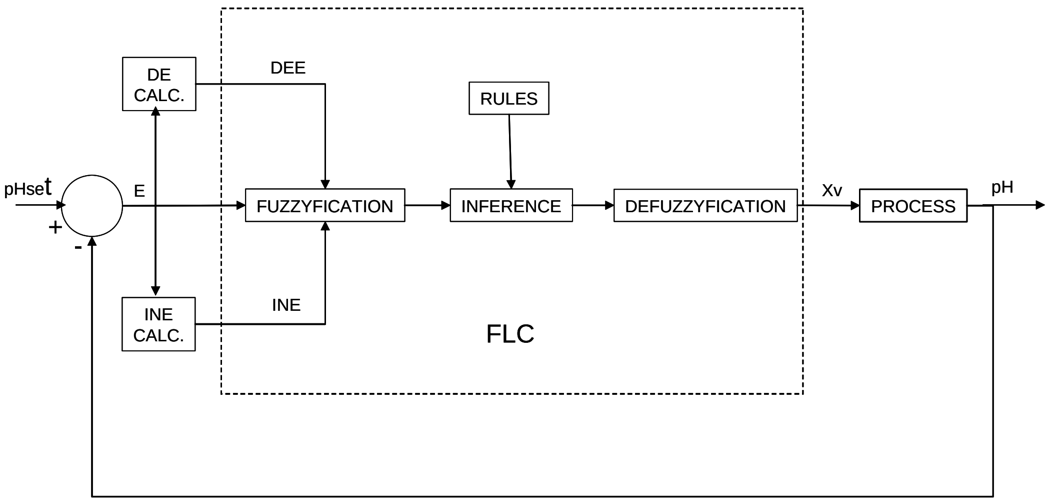

Figure 1. - Control system.

A FLC design follows in three calculation steps: Fuzzyfication, fuzzy inference and defuzzyfication, Fig. 1.

In the fuzzyfication step, fuzzy variables are obtained from the FLC input variables (*e(k)* and *DEE(k)* for the PD-FLC and *e(k)*, *DEE(k)* and *INE(k)* for the PID-FLC) and output, x_v, variable for both PD and PID controller. The fuzzyfication step requires defining the membership functions or fuzzy set into the range of variation of each FLC input variables and to associate each of its value with one degree of membership into each membership functions defined previously. In this work, the membership functions defined are triangular functions that are frequently used in FLCs design. The number and shape of membership functions were selected in basis of the system response against different perturbations of the input variables. The PD-FLC has 5, 3 and 7 membership functions for the *e(k)*, *DEE(k)* and $x_v(k)$, respectively. The PID-FLC has 7, 3, 3 and 7 membership functions for the *e(k)*, *DEE(k)*, *INE(k)* and $x_v(k)$, respectively

With membership functions defined for FLC inputs and outputs, rule base of *IF-THEN* type conditional rules are formulate, Fig 2. Then, with fuzzy logic inference, the rule base and corresponding membership functions are used to analyze controller inputs and determine controller outputs.

	IF	AND	AND	THEN
Rule	e(k)	DEE(k)	INE(k)	xv
1	ANE	NE	NE	MMA
2	ANE	NE	ZE	MMA
3	ANE	NE	PO	MA
4	ANE	ZE	NE	MA
5	ANE	ZE	ZE	MA
6	ANE	ZE	PO	A+
7	ANE	PO	NE	A+
8	ANE	PO	ZE	A+
9	ANE	PO	PO	A
10	MNE	NE	NE	MA
11	MNE	NE	ZE	MA
12	MNE	NE	PO	A+
13	MNE	ZE	NE	A
14	MNE	ZE	ZE	A
15	MNE	ZE	PO	A
16	MNE	PO	NE	C
17	MNE	PO	ZE	MC
18	MNE	PO	PO	A
19	PNE	NE	NE	ZE
20	PNE	NE	ZE	A+
21	PNE	NE	PO	A+
22	PNE	ZE	NE	A
23	PNE	ZE	ZE	A
24	PNE	ZE	PO	A
25	PNE	PO	NE	MC+
26	PNE	PO	ZE	MC+
27	PNE	PO	PO	A
28	ZE	NE	NE	C
29	ZE	NE	ZE	ZE
30	ZE	NE	PO	ZE
31	ZE	ZE	NE	C
32	ZE	ZE	ZE	ZE

	IF	AND	AND	THEN
Rule	e(k)	DEE(k)	INE(k)	xv
33	ZE	ZE	PO	ZE
34	ZE	PO	NE	ZE
35	ZE	PO	ZE	MC+
36	ZE	PO	PO	ZE
37	PPO	NE	NE	ZE
38	PPO	NE	ZE	ZE
39	PPO	NE	PO	ZE
40	PPO	ZE	NE	ZE
41	PPO	ZE	ZE	C
42	PPO	ZE	PO	C
43	PPO	PO	NE	C
44	PPO	PO	ZE	MC+
45	PPO	PO	PO	MC+
46	MPO	NE	NE	MC+
47	MPO	NE	ZE	MC+
48	MPO	NE	PO	MC+
49	MPO	ZE	NE	MC+
50	MPO	ZE	ZE	MC+
51	MPO	ZE	PO	MC
52	MPO	PO	NE	MC
53	MPO	PO	ZE	MC
54	MPO	PO	PO	MC
55	APO	NE	NE	MC
56	APO	NE	ZE	MC
57	APO	NE	PO	MC
58	APO	ZE	NE	MMC
59	APO	ZE	ZE	MMC
60	APO	ZE	PO	MMC
61	APO	PO	NE	MMC
62	APO	PO	ZE	MMC
63	APO	PO	PO	MMC

Figure 2. – Rule base of the PID controller. NE: Negative. ZE: zero. PO: Positive. ANE: High negative. MNE: Medium negative. PNE: Low negative. PPO: low positive. MPO: Medium negative. APO: High positive. MMC: Maximum closed. MC: High closed. C^+: Medium closed. A: low opening. A^+: Medium opening.

The conclusion of each rule base is the membership functions of the output variable. If the rule base is of intersection (*AND*), the degree of membership obtained for each rule is done by eq. 9.

$$\mu(x_v) = \mu(e) \wedge \mu(DEE) \wedge \mu(INE) \qquad (9)$$

where $\mu(x_v)$, $\mu(e)$, $\mu(DEE)$ and $\mu(INE)$ are the degree of membership in each rule for x_v, e, DEE and INE, respectively.

The defuzzyfication step aims to obtain a physical value of x_v from the linguistic value done for eq. 9. In this work, the Centre-of-Area (CoA) method, eq. 10, is used to make the deffuzzyfication.

$$x_v(k)=\frac{\sum \mu(x_v)\int x_v\ \mu(x_v)dx_v}{\sum \mu(x_v)\int \mu(x_v)dx_v} \qquad (10)$$

Results

This study has been made by applying the numerical simulation of the controlled neutralization process. The simulation has been made by using LabView©.
The steady state operation conditions used in the simulation are shown in table 1.

Table 1 - Steady state operation conditions

Variable	Steady state value
Acidic flow rate	$2.36\ 10^{-3}$ L/s
Acetic concentration	0.2 mol/L
Propionic concentration	0.1 mol/L
Sodium hydroxide	0.2 mol/L

The robustness and adaptability of the controller were studied under three different circumstances: 1) start up; 2) acid flow rate perturbations and 3) acid concentration perturbations. The set point in all simulations was 7.
In the start up, the system in initial steady state is at pH = 2; when the control loop is closed, the set point is reached in 50 s and the response has not overshoot and offset.
The controller performance against perturbations of the concentrations or flow rate of acids was tested by using steps rate ranged from ± 10% to ± 90% of the initial steady state value. The response curves are always underdamped, independently of the FLC used (PD or PID). Also, in all cases, when the step perturbation drives to a decreasing pH, the response of the system is better, since lower overshoots occur. This fact has been pointed out for other types of controllers, ANN or Model Reference Controller (MRC) (Palancar *et al.* 1996 and 1998).
When the PD-FLC is used, the response setting time ranges between 0.28 and 0.9 min; these values are lower than the ones obtained with ANN based controllers (Palancar *et al.* 1998). The overshoot of the pH response to perturbations that drives to a pH decreasing is lower than 0.5 pH units. When the perturbations drive to a pH increasing, the overshoots are greater than 3 pH units.
Examples of the results obtained when the PID-FLC is used are shown in Figs. 3 and 4. In both figures the zone 1 corresponds to the start up and the zone 2 shows the response to acidic concentration perturbations, Fig. 3, and acidic flow rate perturbations, Fig. 4. When the PID-FLC is used, the response overshoots obtained are lower than the ones obtained with the PD-FLC. The response overshoots are less than 1 pH- unit for step perturbations less than 50%. The response setting times are similar with both controllers

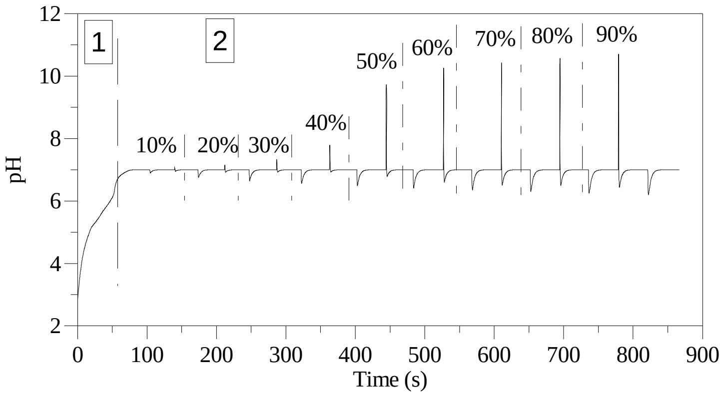

Figure 3. – Variation of pH *vs* time during the system start up and after acidic concentration perturbations. Zone 1: Start up. Zone 2: Acidic concentration perturbations. The % is referred to the steady state value before perturbation.

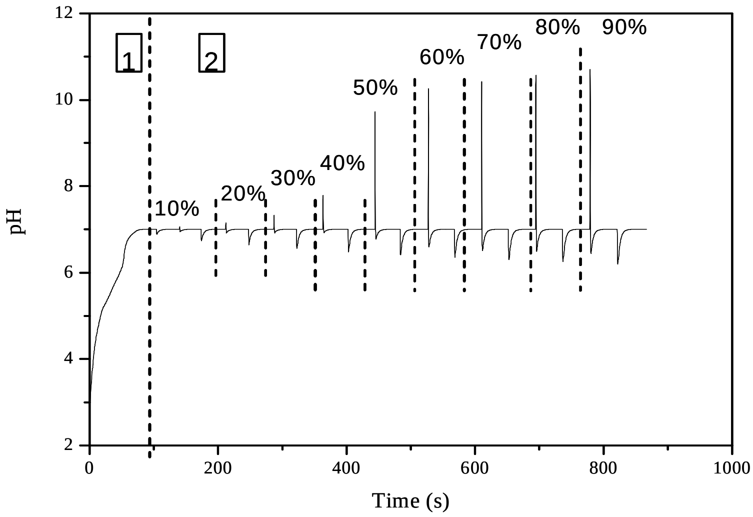

Figure 4. – Variation of pH *vs* time during the system start up and after acidic flow rate perturbations. Zone 1: Start up. Zone 2: Acidic flow rate perturbations. The % is referred to the steady state value before perturbation.

Conclusions

The applicability of a controller based on fuzzy logic was tested in a process of neutralization of acetic and propionic acids with sodium hydroxide.
To design the controller it is necessary to know previously the response of the system against potential perturbations during its operation. This information should be the basis for selecting the FLC input variables, membership functions and the fuzzy rules.
Good results have been obtained, for the system studied, by using three input variables: error, error derivative and accumulated integral of the error.
The number of fuzzy sets is function of the variable considered. The error and valve stem position require greater number of fuzzy sets than the rest of the input variables.

Here, the best results have been obtained when the number of fuzzy sets was seven for the error and stem valve and three for the error derivative and accumulated integral of the error. The “minimum” operator and the CoA method are adequate for the fuzzy inference and defuzzyfication, respectively.
Considering the accumulate integral of error as one FLC input variable, the FLC behaviour improves: The offset is eliminated and the response overshoots are lower than the ones when the accumulate integral of error is not considered.
The FLC were tested for controlling the start up of a CSTR and to counteract the perturbations of the flow rate and concentration of the acidic stream. The start up is completed in about 55 s. The system response for step perturbations in the flow rate or in the concentration of the acidic stream is underdamped with small overshoot. The FLC corrects perturbations of up to 50 % the flow rate of the acidic stream and concentration of acids in the acidic stream with errors smaller than 1 pH-unit.

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