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FUZZY GAIN SCHEDULING: COMPARISON OF THE CONTROL STRATEGY

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Abstract

The use of better control strategies has a great interest in all kinds of industries in recent years since it allows better use of resources and therefore becomes an important factor in reducing costs associated with reprocessing and unnecessary spending of raw materials. This research evaluates the performance of a control strategy, in which the tuning parameters of a classic controller are supplied by a fuzzy logic algorithm (Fuzzy Gain Scheduling). the behaviour of the strategy is tested in a mixer-reactor system and is compared with that achieved through the implementation of a classic controller, a dynamic matrix system, and fuzzy logic control. In the results, it can be seen that the Fuzzy Gain Scheduling strategy presents a good behaviour, improving around 25% compared with the other alternatives, this added to the advantage of being able to include previous experience on the process, in the actions that are taken by the strategy to keep desired operating ranges.

Keywords: Dynamic matrix control, Fuzzy logic control, Model predictive control, Process control, Stirred tank-reactor.

1. Introduction

In process control the most widely used system at the industrial level is the proportional, integral, and derivative (PID) controller loop, this very important alternative represents around 90% of the market [1]. however, its performance against some highly non-linear processes can be affected because it is based on a linear representation of the systems. To face this problem, advanced control strategies have been developed to allow dealing with non-linearities and obtain better results. The use of fuzzy logic to monitor PID controllers is one of these alternatives, which is designed to improve the performance of the classic PID and address nonlinearities.

Several studies on PID controllers improved by algorithms have been developed previously, the most relevant started around 1990 with [2-5], they use tuning techniques using diffuse logic implemented in different systems to keep the parameters in the desired ranges. That is how in [4] a fuzzy inference engine is used to supply the tuning parameters of a controller which was implemented to maintain the level in a container of a power generation plant achieving better performance than the PID system.

In Ling and Edgar [6] they used the in-line tuning technique using diffuse logic implemented in a water-gas shift reactor to keep the temperature in the desired ranges, commenting that greater stability and response speed is achieved in the proposed strategy than in classical PID control.

In Müller et al. [7] a similar strategy is used to perform the control in a wastewater treatment process, the strategy could detect the presence of unsafe conditions and based on that diagnosis, a set of fuzzy logic rules allowed actions to be taken to return the process to a safe operating state, improvements of up to 47% are obtained in the relevant variables.

Abilov et al. [8] showed the performance of a MIMO multivariable control loop using fuzzy logic implemented over an oil refining industry process, comment that the implemented control performs better than classic control and stabilization time is lower by up to 20% than in a simple loop with PID. Sarma [9] analysed the performance of a diffuse control strategy implemented in an exothermic reactor with high non-linearities in two of its output variables, the results say that diffuse control performs better for this application in both servo and regulatory control and oscillations up to 15% lower than those achieved with classic PID control are obtained.

Research on the use of fuzzy logic to improve classical control continued and appear [10-14] in which controllers are optimized, the results show that minor deviations are obtained in all cases when a supervised control is implemented. In the last decade [15-27] they used Fuzzy Gain Scheduling for processes with high nonlinearities showing favourable results with decreases of up to 10% of the error. More recently [28-38] use the on-line supervisor system as an option to improve the goals of different processes with promising results in all cases.

Although there are several types of research in the field of fuzzy logic and its application has been done in many systems, it is important to compare its results with recent control strategies, the following sections show the implementation of fuzzy fain scheduling in a reactor-mixer and its comparison with the dynamic matrix (DMC) and fuzzy logic control (FLC).

2. Dynamic System Modelling

The process used in the study exists as a part of many industrial methods to obtain a substance from a combination of different condition parameters, the reason to use it here is that due to its behaviour, under certain conditions it is possible to obtain changes in process gain during normal operation. It occurs in two stages, the first in a stirred tank where enters a flow f_i (f_1) with a temperature T_1, which has a C_{A1} concentration of substance A, also enters a recirculation flow f_r with temperature T_7 and C_{A7} concentration of the substance A and C_{B7}, C_{C7} of products B and C that comes from the reactor downstream and that constitutes the process second stage.

The stirred tank is heated by the action of the steam flow w_S from a coil located inside, from which comes an f_0 purge flow and an f_2 process flow which have a temperature T_2 and concentrations C_{A2}, C_{B2}, C_{C2} of A, B and C respectively.

The stirred tank and the reactor are joined by a piping system, the f_4 flow enters the reactor with properties different from point 2 due to transport delay, inside the reactor take place the reaction $A \rightarrow 2B+C$ and exits the f_5 flow with temperature T_5 and concentrations C_{A5}, C_{B5}, C_{C5}.

The recirculation flow is supplied by a pump connected to the reactor outlet by a piping system. Figure 1 shows a system schematic.

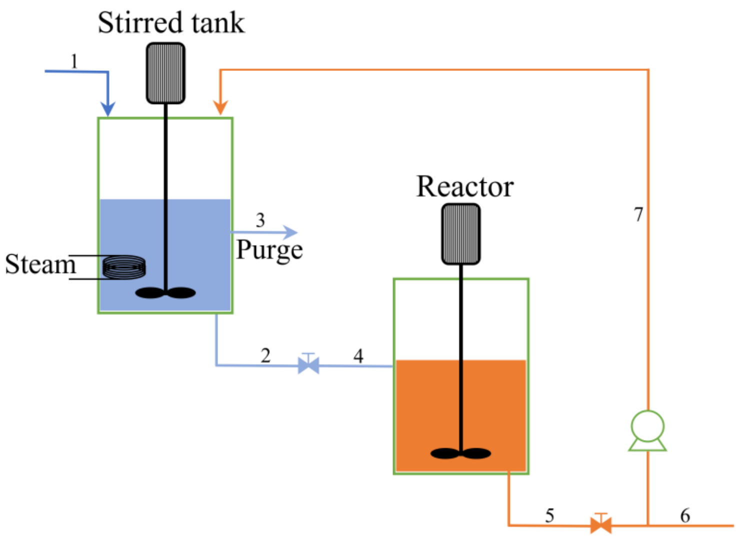

Fig. 1. Stirred tank-reactor system.

2.1. Dynamic model

For dynamic modelling, equations corresponding to fundamental principles of thermodynamics and heat transfer are used, and are shown in the system below together with representations for transport delay:

Stirred tank mass balance:

$$f_1(t)\rho_1(t)+f_r(t)\rho_5(t)-f_0(t)\rho_2(t)-f_2(t)\rho_2(t)=A_t\frac{d}{dt}\left[h_1(t)\rho_2(t)\right] \quad (1)$$

Reactor mass balance

$$f_2(t)\rho_4(t)-f_5(t)\rho_5(t)=A_R\frac{d}{dt}\left[h_2(t)\rho_5(t)\right] \tag{2}$$

Molar balance of A in stirred tank

$$f_1(t)C_{A1}(t)+f_r(t)C_{A5}(t)-f_0(t)C_{A2}(t)-f_2(t)C_{A2}(t)=A_R\frac{d}{dt}\left[h_1(t)C_{A2}(t)\right] \tag{3}$$

Molar balance of B in stirred tank

$$f_r(t)C_{B5}(t)-f_0(t)C_{B2}(t)-f_2(t)C_{B2}(t)=A_R\frac{d}{dt}\left[h_1(t)C_{B2}(t)\right] \tag{4}$$

Molar balance of C in stirred tank

$$f_r(t)C_{C5}(t)-f_0(t)C_{C2}(t)-f_2(t)C_{C2}(t)=A_R\frac{d}{dt}\left[h_1(t)C_{C2}(t)\right] \tag{5}$$

Molar balance of A in Reactor

$$f_2(t)C_{A4}(t)-f_5(t)C_{A5}(t)-0{,}5A_Rr_B(t)h_2(t)=A_R\frac{d}{dt}\left[h_2(t)C_{A5}(t)\right] \tag{6}$$

Molar balance of B in Reactor

$$f_2(t)C_{B4}(t)-f_5(t)C_{B5}(t)+A_Rr_B(t)h_2(t)=A_R\frac{d}{dt}\left[h_2(t)C_{B5}(t)\right] \tag{7}$$

Molar balance of C in Reactor

$$f_2(t)C_{C4}(t)-f_5(t)C_{C5}(t)+0{,}5A_Rr_B(t)h_2(t)=A_R\frac{d}{dt}\left[h_2(t)C_{C5}(t)\right] \tag{8}$$

Energy Balances Mixer:

$$\begin{aligned}&f_1(t)\rho_1(t)c_pT_1(t)+f_r(t)\rho_5(t)c_pT_5(t)-f_0(t)\rho_2(t)c_pT_2(t)\\&-f_2(t)\rho_2(t)c_pT_2(t)+UA_s\left[T_s(t)-T_2(t)\right]=A_tc_v\frac{d}{dt}\left[h_1(t)\rho_2(t)T_2(t)\right]\end{aligned} \tag{9}$$

Energy balance in the steam coil

$$w_s(t)\lambda-UA_s\left[T_s(t)-T_2(t)\right]=C_M\frac{d}{dt}\left[T_s(t)\right] \tag{10}$$

Reactor Energy Balance

$$\begin{aligned}&f_2(t)\rho_4(t)c_pT_4(t)-f_5(t)\rho_5(t)c_pT_5(t)+A_Rh_2(t)r_B(t)\Delta H_B\\&=A_Rc_v\frac{d}{dt}\left[h_2(t)\rho_5(t)T_5(t)\right]\end{aligned} \tag{11}$$

Stirred tank inlet density

$$\rho_1(t)=\rho_0+\alpha_1C_{A1}(t) \tag{12}$$

Stirred tank outlet density

$$\rho_2(t)=\rho_0+\alpha_1C_{A2}(t)+\alpha_2C_{B2}(t)+\alpha_3C_{C2}(t) \tag{13}$$

Reactor output density

$$\rho_5(t)=\rho_0+\alpha_1C_{A5}(t)+\alpha_2C_{B5}(t)+\alpha_3C_{C5}(t) \tag{14}$$

Reaction rate

$$r_B=K_0C_AC_{B5}(t)e^{-\frac{E}{RT}} \tag{15}$$

In the dynamic model α is a known constant, ρ is density, f is the actual flow, h is the level of fluid, A_R is the bottom area in the reactor, C_{Ax} is the concentration of substance A in position x, C_{Bx} is the concentration of substance B in position x, C_{Cx} is the concentration of substance C in position x, T_x is the temperature in position x, C_p and C_v are specific heat at constant pressure and volume, λ is water heat of vaporization and ΔH is reaction energy.

The system of equations (1) to (15) together with the transport delay, are suitable to represent the dynamics of the process studied, the transfer function obtained after modelling the entire system using computational tools is shown in the next section Eq. (16).

3. Results and Discussion

The results of control strategies are shown in this section, the study was carried using numerical methods in MATLAB Simulink and the appropriate modelling of system equation proposed in Section 2.1, Eq. (1) - Eq. (15).

3.1. Classic PID control

The Concentration of A in the reactor outlet flow is the controlled variable for the implemented strategy. To establish the parameters of the controller, a test is performed to identify the process by changing the steam flow (w_s) from its steady state to 5% above this value. The results allowed to adjust a first order plus deadtime model using the FIT 3 method proposed by Smith and Corripio [39], the model variables are shown in Table 1 and the associated transfer function in Eq. (16).

$$G(s)=\frac{-0,3e^{-9.2s}}{30,4s+1} \tag{16}$$

Using this model, the Dhalin synthesis tuning method for PID controllers is applied and the values for gain, integral time, and derivative time shown in Table 2 are obtained.

Table 1. First-order plus deadtime model.

	Fit 3
K	-0,3
τ	30,4
t_0	9,2

Table 2. PID controller parameters.

	PID
t_I	30,4
τ_D	4,6
K_c	-5,8

By establishing the PID feedback control strategy, the behavior of the changes in each control point and disturbances is obtained, as shown in Fig. 2.

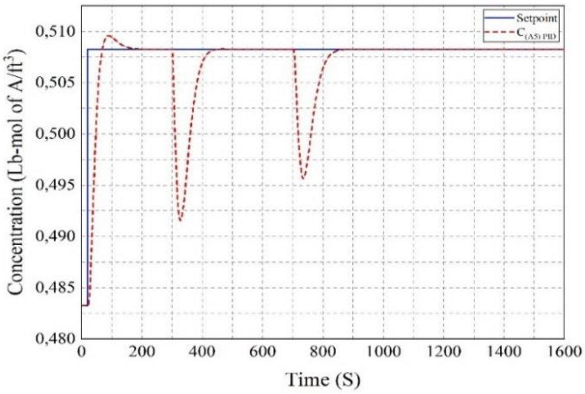

Fig. 2. Behaviour against Setpoint disturbances (10s), 5% of T_1 (300 s) and in C_{A1} (700 s) (PID).

3.2. Dynamic matrix control

To implement the dynamic matrix control (DMC) strategy, the first thing is to set the control horizon which is normally an integer between 1 and 6 [40], in the particular case the system takes a control horizon (HC) of 5 to decrease the controller aggressiveness, also the process response curve is determined against changes in the controller, then the sampling time and sample size are chosen, the size of the controller output vector to be predicted is then obtained, construct the system representation matrix against changes in the controller signal, finally, the DMC algorithm is implemented using the least-squares method and the suppression factor (λ) is calculated using the formulation developed by Iglesias et al. [41] which appears in Eq. (17). Figure 3 shows the performance of the DMC system.

$$\lambda = 1{,}6Kp\left(\frac{t_0}{\tau}\right)^{0,4} = 0{,}3 \tag{17}$$

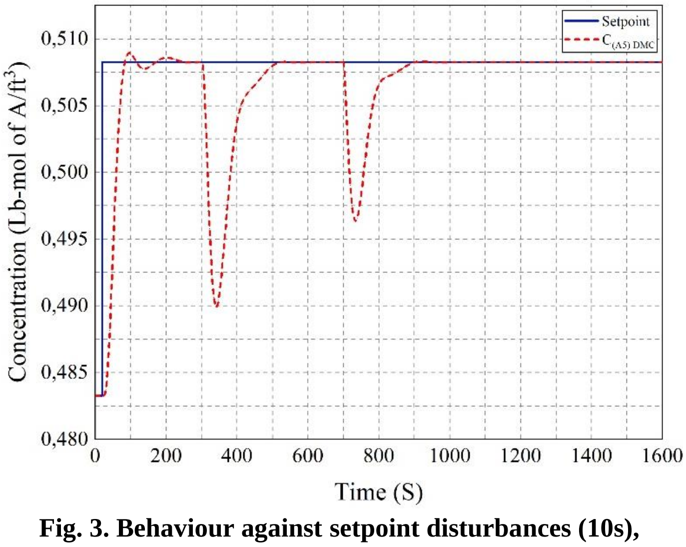

Fig. 3. Behaviour against setpoint disturbances (10s), 5% of T_1 (300 s) and in C_{A1} (700 s) (DMC).

3.3. Fuzzy logic control

To develop a correct control strategy using fuzzy logic (FLC) it is necessary to establish the error behaviour in terms of its absolute value as well as its change rate, the following linguistic variables were used in this research: (NB) Negative big, (NS) Negative small, (Z) Zero, (PS) Positive Small and (PB) Positive big, which were accompanied by rules based on the knowledge of the analysed system to obtain the desired results. Figure 4 shows the performance of the FLC control strategy for changes at the checkpoint and against disturbances.

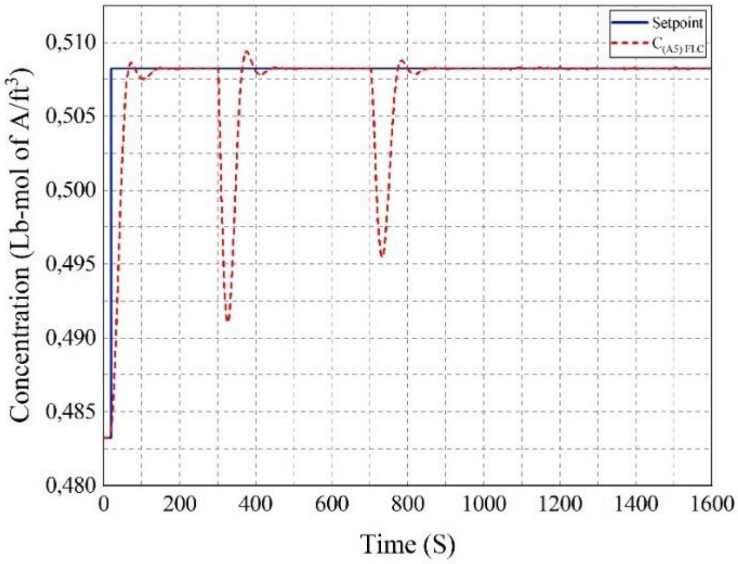

Fig. 4. Behaviour against Setpoint disturbances (10s), 5% of T_1 (300 s) and in C_{A1} (700 s) (FLC).

3.4. PID fuzzy gain scheduling

To implement a control strategy using gain scheduling (PFGS), it is required to establish membership rules and functions, which allow the calculation of the PID controller adjustment parameters in real-time and for any operating condition. Figure 5 presents the strategy block diagram and Tables 3, 4, and 5 show the rules used, based on the methodology proposed by Zhao et al. [2].

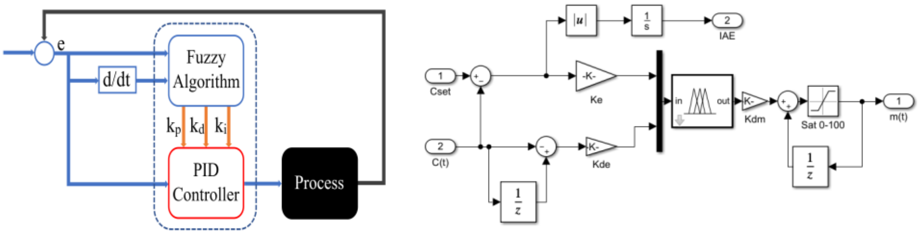

Fig. 5. PFGS block diagram.

The fuzzy algorithm is used to adjust the control parameters of the system, obtaining values B and S which change from 0.0 to 1.0.

This uses the error $e(k)$ and the change in error $\Delta e(k)$ for the whole system. NB, NM, NS, ZO, PS, PM, and PB correspond to a value between -1.0 and 1.0 (NB: -0.9; NM: -0.6; NS: -0.3; ZO: 0.0; PS:0.3; PM:0.6; PB:0.9), which are presented in Tables 3, 4 and 5.

Table 3. *Kp* rules.

		Δe (error change)						
		NB	**NM**	**NS**	**ZO**	**PS**	**PM**	**PB**
e(error)	**NB**	B	B	B	B	B	B	B
	NM	S	B	B	B	B	B	S
	NS	S	S	B	B	B	S	S
	ZO	S	S	S	B	S	S	S
	PS	S	S	B	B	B	S	S
	PM	S	B	B	B	B	B	S
	PB	B	B	B	B	B	B	B

Table 4. *Kd* rules.

		Δe (error change)						
		NB	**NM**	**NS**	**ZO**	**PS**	**PM**	**PB**
e(error)	**NB**	S	S	S	S	S	S	S
	NM	B	B	S	S	S	B	B
	NS	B	B	B	S	B	B	B
	ZO	B	B	B	B	B	B	B
	PS	B	B	B	S	B	B	B
	PM	B	B	S	S	S	B	B
	PB	S	S	S	S	S	S	S

Table 5. α rules.

		Δe (error change)						
		NB	**NM**	**NS**	**ZO**	**PS**	**PM**	**PB**
e(error)	**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	3	3	2	3	3	4
	PM	3	3	2	2	2	3	3
	PB	2	2	2	2	2	2	2

The method used in [2] is based on the system frequency response, so it is necessary to know the ultimate gain (K_{cu}) and the last period (T_u) for the calculations of $K_{c,max}$, K_{cmin}, $K_{d,max}$, and $K_{d,min}$ which are parameters required by Gain scheduling. Figure 6 shows the results obtained for the PFGS control.

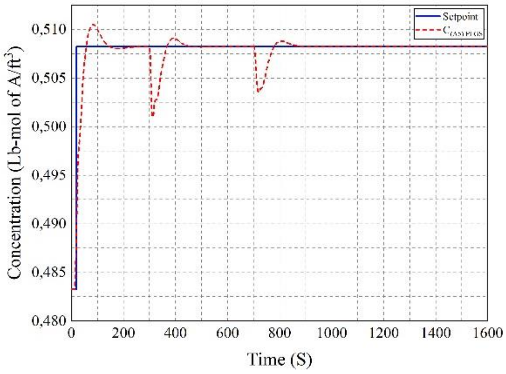

Fig. 6. Behaviour against Setpoint disturbances (10s), 5% of T_1 (300 s) and in C_{A1} (700 s) (FPGS).

3.5. Control strategies analysis

In all cases, the controller performance is evaluated by applying a change of +/- 10% in setpoint and +/- 10% in temperature (T_1) and concentration (C_{A1}) of inlet flow (f_1). Table 6 shows the results of the Integral Absolute Error (IAE) which is a control measure very precise and gives exact comparisons between different control strategies. Figure 7 shows the behaviour of all strategies for a modification of the operating point, a lower IAE value can be seen for the case in which Fuzzy Gain Scheduling is used, showing that this strategy is an efficient alternative for the control of systems and present a better performance than other control strategies in around 25% in all analysed scenarios.

Table 6. Integral absolute error results.

Strategy	IAE Concentration
PID	113,0
FLC	98,5
DMC	109,4
PFGS	77,8

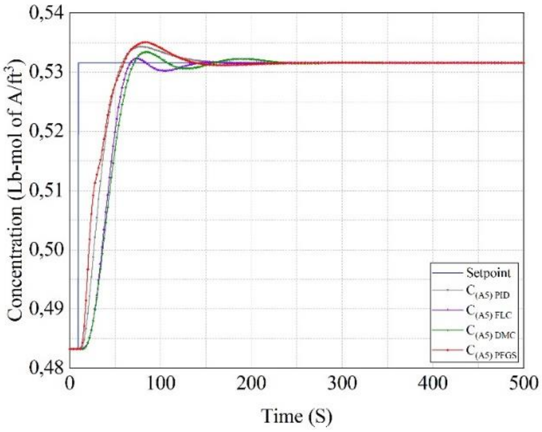

Fig. 7. Behaviour against Setpoint disturbances (10s), 5% of T_1 (300 s) and in C_{A1} (700 s) (FPGS).

4. Conclusions

In this paper, a mathematical model of a combined process with reactions is used to capture the dynamic behaviour of a nonlinear system. PID controllers can be easily tuned when compared to advanced control strategies like dynamic matrix control, fuzzy logic, and Gain scheduling; however, they have limitations for the process that has a considerable change of its dynamics with a change in the operating condition.

The FPGS strategy proposed is an alternative because even though requires previous knowledge of the system behaviour to implement accurate inference rules, it can easily adjust the response against a significant change in process dynamic. As a result of this, and based on integral absolute error, the strategy based on Fuzzy Gain Scheduling presents a better behaviour than classic PID control, dynamic matrix control, and fuzzy logic control, improving up to 25% performance, which allows saying that there are lower deviations from the setpoint when using this alternative.

On the other hand, the implementation of this advanced strategy is an attractive option because it allows to develop the control of several loops with the implementation of a single system, and it is also possible to deal with processes dynamics with large nonlinearities and disturbances such as changes in process gain during operation.

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