

Control of Input Multiplicity Process (Bioreactor) using Fuzzy logic Techniques

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Abstract

In the present work, a Fuzzy logic controller is analyzed to a continuous bioreactor which exhibits input multiplicities in dilution rate on productivity. i.e., two values of dilution rate will give the same value of productivity. The Performance of proposed Fuzzy logic controller and conventional PI controller has been evaluated near optimum productivity. As the Fuzzy controller provides always the two values of Dilution rate for control action and by selecting the value nearer to the operating point, it is found to give stable and faster responses than conventional PI controller. The PI controller results in wash out condition or switch over from initial lower input dilution rate to higher input dilution rate or vice versa. Thus, Fuzzy control is found to overcome the control problems of PI controller due to the input multiplicities near optimal productivity. It is interesting to note that the present fuzzy logic controller is giving superior performance like previously proposed nonlinear controller by authors (Reddy, G.P. and Chidambaram, M (1995)) to overcome the control problems due to input multiplicities and however fuzzy logic controller is less computationally involved than nonlinear controller.

Keywords: Fuzzy logic control, Bioreactor, Input Multiplicities, Near optimal productivity.

I. INTRODUCTION

A control system is defined as a system in which deliberate guidance or manipulation is used to achieve a prescribed value of a variable. In the last two decades, a new direction to control has gained considerable attention. This new approach to control is called 'Intelligent control'. The term 'conventional control' refers to theories and methods that are employed to control dynamic systems whose behavior is primarily described by differential and difference equations. The term 'intelligent control' addresses to more general control problems. It may refer to systems, which cannot be adequately described by a differential equations framework. There are three basic approaches to intelligent control knowledge-based experts systems, fuzzy logic and neural networks.

II. CONTINUOUS BIOREACTORS:

In most of the continuous fermentation processes, one of the output variables is chosen as the controlled

variable (biomass concentration or product concentration) and its estimated optimal open loop profile of a constant set point is tracked. A continuous stirred tank fermenter (CSTF) is an ideal reactor, which is based on the assumption that the reactor contents are well mixed.

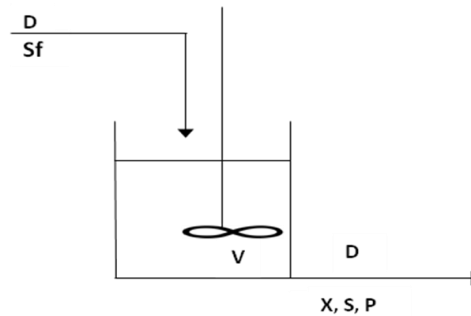


Fig 1. Continuous Bioreactor

III. PROBLEMS WITH THE CONVENTIONAL CONTROLLER

The control of non-linear process like fermentation by conventional controller does not give satisfactory results. This is due to the change in process gain and time constant with operating conditions. In certain processes, more than one value of a manipulated variable (u) produces the same value of an output variable. Such situation is called as input multiplicities. The value of the steady-state gain of the process changes as the manipulated variable changes and after certain value of u the sign of the gain value also changes. The controller tuned at one operating condition may even destabilize the system at another operating point. Di Biasio et al., (1994) have reported that the global stability of the reactor depends on the existence and stability of the other steady conditions. The performance on the closed system is compared with that of a linear P1 proposed by Henson and Seborg. Any constraint on the manipulated variable (which is often unavoidable in practice) can result in a total of 5 steady states (three stable and two saddle points) even though a sufficient control action is present.

IV. MATHEMATICAL MODELLING OF A CONTINUOUS BIOREACTOR

A schematic of a continuous bioreactor is shown in figure.1-We assume that the bioreactor has constant volume, its contents are well mixed, and the feed is sterile. The dilution rate D and the feed substrate concentration S_f are available as manipulated inputs. The effluent cell-mass or biomass concentration X , substrate concentration S and product concentration P are the process state variables. In ethanol production, for example, X , Y , and P represent yeast, glucose, and ethanol concentrations, respectively.

A. MODEL DERIVATION

The dynamic model is developed by writing material balances on the biomass (cells), the substrate (feed source for cells) and the product. Biomass grows by feeding on the substrate results in generation of product.

Biomass Material Balance

We write biomass material balance as:

Rate of accumulation = i/p – o/p + generation
 $d(VX)/dt = FX_f - FX + Vr_1$ (1)

Substrate Material Balance:

The substrate material balance is written as:

Rate of accumulation = i/p – o/p – consumption
 $d(VS)/dt = F S_f - FS - Vr_2$ (2)

Product Material Balance:

Finally, the product material balance is written as:

Rate of accumulation = i/p – o/p + generation
 $D(VP)/dt = 0 - FP + Vr_3$ (3)

The reaction rate (mass of the cells generation/Volume/time) is normally written in the following form:

$r_1 = \mu X$ (4)
 As yield $Y = r_1/r_2$, $r_2 = r_1/Y$
 And hence $r_2 = \mu X/Y$ (5)

Similarly $r_3 = (\alpha\mu + \beta) X$ (6)

Defining F/V as D , the dilution rate, and assuming biomass feed concentration as Zero, we find:

$dX/dt = -D X + \mu X$
 $dS/dt = D S_f - Ds - \mu X/Y$
 $dP/dt = -D P + (\alpha\mu + \beta) X$

Finally, the model equations can be written as;

$X = -DX + \mu X$ (7)

$S = D (S_f - S) - \mu X/Y$ (8)

$P = -DP + (\alpha\mu + \beta) X$ (9)

This unstructured model can describe a variety of fermentations. Because Y and P are assumed to be independent of the operating conditions, above model is called a constant yield model. The specific growth rate model is allowed to exhibit both substrate and product inhibition:

$$\mu = \frac{\mu_m (1 - P/P_m) S}{K_m + S + S_2 / K_1}$$
 (10)

This model contains four model parameters: the maximum specific growth rate m , the product saturation constant P_m , the substrate saturation constant K_m , and the substrate inhibition constant K_1 .

Model equation of the system on which the study is based:

$$X = -DX + \mu X$$

$$S = D (S_f - S) - \mu X/Y$$

$$P = -DP + (\alpha\mu + \beta) X$$

$$\mu = \frac{\mu_m (1 - P/P_m) S}{K_m + S + S_2 / K_1}$$

In practice, the model parameters in equations (7)-(10) are chosen to fit experimental data (Munack and Thoma, 1986; Enfors et al., 1990). If the bioreactor deviates significantly from the operating conditions where the data was collected, the model parameters previously determined may no longer be valid. The cell-mass yield Y and the maximum specific growth rate μ_m tend to be especially sensitive to changes in the operating conditions. From a process control perspective, these two model parameters can be viewed as unmeasured disturbances because they may exhibit significant time-varying behavior. Many types of fermentations can be modeled by choosing the model parameters appropriately. For instance, the product is totally growth-associated if a $\alpha \neq 0$, $\beta = 0$, totally non growth-associated if $\alpha = 0$, $\beta \neq 0$, and a combination of the two if $\alpha \neq 0$, $\beta \neq 0$. Simple Monod kinetics (Johnson, 1987) can be obtained by setting $P_m = K_1 = \alpha \cdot c$. In many fermentations such as penicillin production, cell growth is inhibited by high substrate concentrations so that $0 < K_1 < c$. If the growth rate approaches zero at high product concentrations then $0 < P_m < \alpha$.

Nominal model parameters and operating conditions used throughout the study are listed below:

Variable	Nominal value
Y	0.4 g/g
A	2.2 g/g
B	0.2 h ⁻¹
μ_m	0.48 h ⁻¹
P_m	50 g/l
K_m	1.2 g/l

K_1	22 g/l
S_f	20 g/l

If the biomass and substrate are of negligible value when compared to that of the product, the productivity Q can be defined as the amount of product cells produced per unit time:

$$Q = DP \quad (11)$$

V. DESIGN OF FUZZY LOGIC CONTROLLER FOR CONTINUOUS BIOREACTOR WITH INPUT MULTIPLICITY

A. Design of a fuzzy logic controller

In the fuzzification step, the productivity and productivity rate are selected as input variables to the fuzzy controller. Universes of discourse of these input variables are divided into three fuzzy sets and they are linguistically called as HIGH, LOW and OK as shown in the Figs.3 & 4. The Gaussian membership functions with the appropriate ranges have been used for these fuzzy sets. The lower and higher values of the dilution rate (D) have been selected as Fuzzy output variables.

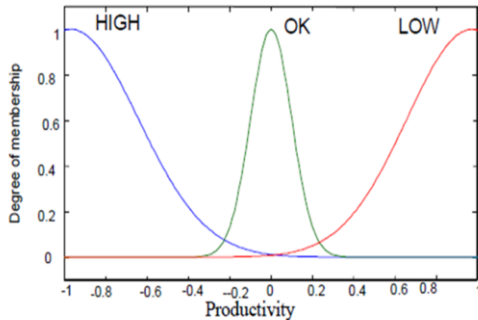


Fig 2 Fuzzy sets of Productivity

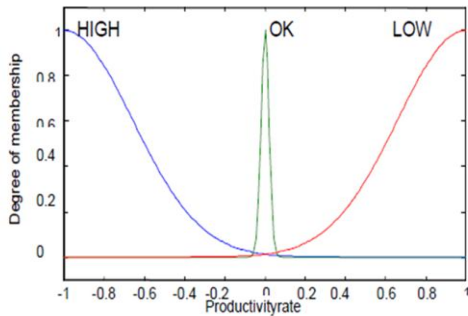


Fig 3 Fuzzy sets of Productivity

Similar to the input variables the universe of discourse of the output variables is divided into three fuzzy sets with linguistic names INCREASE, DECREASE, and NORMAL as shown in the Figs.4 & 5. In the rule base, the rules have been considered to generate the control

action at lower and higher values of dilution rate (D). The rule base takes into account the opposite behavior at both the input values. i.e. process gain is positive at lower input value and it is negative at higher input value

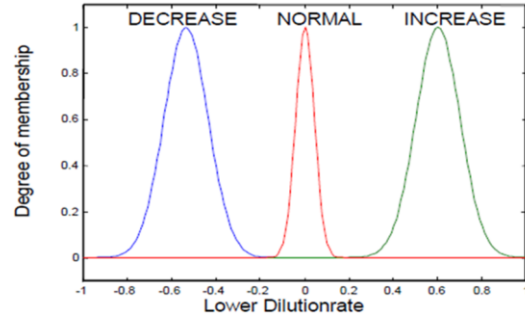


Fig 4. Fuzzy sets of lower dilution rate

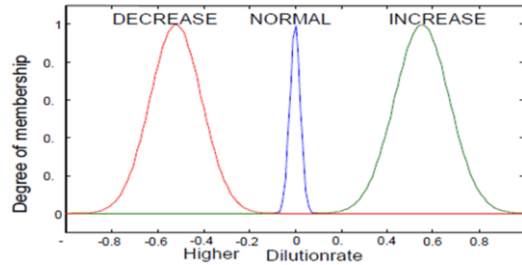


Fig 5. Fuzzy sets of higher dilution rate

- (1) If (productivity is HIGH) then (lower_Dilutionrate is DECREASE)(higher_Dilutionrate is INCREASE)
- (2) If (productivity is LOW) then (lower_Dilutionrate is INCREASE)(higher_Dilutionrate is DECREASE)
- (3) If (productivity is OK) then (lower_Dilutionrate is NORMAL)(higher_Dilutionrate is NORMAL)
- (4) If (productivity is OK) and (productivity rate is HIGH) then (lower_Dilutionrate is DECREASE)(higher_Dilutionrate is INCREASE)
- (5) If (productivity is OK) and (productivity rate is LOW) then (lower_Dilutionrate is INCREASE)(higher_Dilutionrate is DECREASE)
- (6) If (productivity is OK) and (productivity rate is OK) then (lower_Dilutionrate is NORMAL)(higher_Dilutionrate is NORMAL)

The centroid method has been used to obtain the crisp value in the dilution rate. The fuzzy controller always provides two crisp values i.e. one is at lower value ($D = 0.13 \text{ h}^{-1}$) and the other is at higher value ($D = 0.22 \text{ h}^{-1}$) in dilution rates for control action and the value, which is nearer to the operating value between these two, is to be selected for the implementation.

VI. RESULTS AND DISCUSSION

The performance of proposed fuzzy logic controller and conventional PI controller to the Continuous bioreactor with input multiplicities in dilution rate is evaluated using the closed loop block diagrams as shown in Figs 6 & 7. These block diagram are developed using MATLAB version 6.1 and its associated SIMULINK and FUZZY LOGIC tool boxes. The scaling factors (gains): Gain=3, Gain1=0.02 Gain2=0.0046, Gain3=0.00032 for the fuzzy logic controller have obtained by trial and error method from simulation studies. The parameters of conventional PI controller used in the simulation studies are, $K_c=0.01$, $\tau_i = 8.82$ h (Chidambaram, M and Reddy, G.P. (1995)).

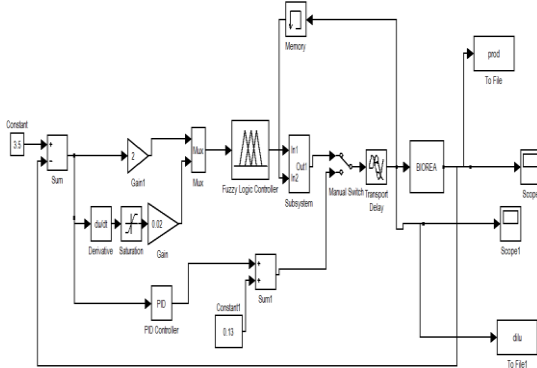


Fig 6. Block diagram for fuzzy logic controller & Conventional PI controller

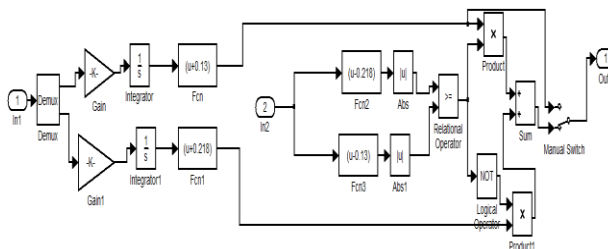


Fig 7 Block diagram for Subsystem of Fuzzy logic controller shown in Fig 6

A. At lower input Dilution rate ($D=0.13 \text{ hr}^{-1}$)

B. Servo problem:

The closed loop responses at two operating points for set point change of $\pm 10\%$, have been obtained and are presented in Figures from 8 to 9. In these Figures, the response of PI is compared with fuzzy controller. For $+10\%$ changes in set point, here the PI reaches the set point within 100 hrs of time, whereas the fuzzy controller reaches the set point in 40 hrs of time. These results show that fuzzy controller performance has been faster with response time lower than that of PI controller. Similar kind of faster responses are obtained for -10% . are presented in figures 10 and 11

.The performances of Fuzzy control remain superior at all three operating points.

C. Regulatory responses

Regulatory response in productivity of fuzzy logic and conventional PI is shown in Fig. 12 for a step change in substrate feed concentration (S_f) from 20 to 24 g/l. This result shows that the faster than that of the linear PI. Present controller has maximum deviation of less than 2% whereas PI controller has a larger deviation of about 6%. Fuzzy logic controller has lower settling time than the PI controller. The corresponding control actions in terms of dilution rate are smooth and they are shown in Fig 13.

Regulatory response in productivity of fuzzy logic and conventional PI is shown in Fig. 14 for a step change in substrate feed concentration (S_f) from 20 to 18 g/l. This result shows that the faster than that of the linear PI. Present controller has maximum deviation of less than 1% whereas PI controller has a larger deviation of about 8%. Fuzzy logic controller has lower settling time than the PI controller. The corresponding control actions are smooth, they are shown in Fig 15

D. Higher input Dilution rate ($D=0.218 \text{ hr}^{-1}$)

a). Servo problem

At higher input dilution rate the servo problem has been evaluated by giving step change in set point of productivity Q from 3.5 to 3.6 (positive side) and the corresponding responses are shown in fig 16 fuzzy logic controller shows stable and offset free response and it reaches the set point at about 200hrs where as PI shows unstable response. The corresponding control actions in terms of Dilution rate is shown in fig. 17.

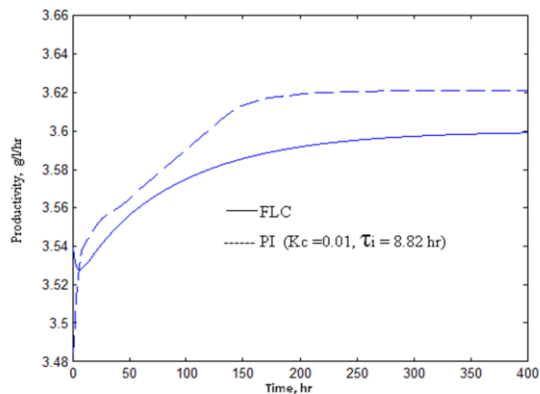


Fig 8 Closed loop response of productivity for step change in set point from 3.5 to 3.6 (+10%) at lower input

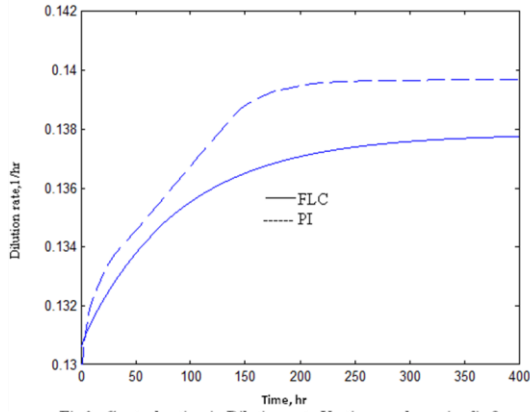


Fig 9 Control action in Dilution rate Vs time as shown in fig 8

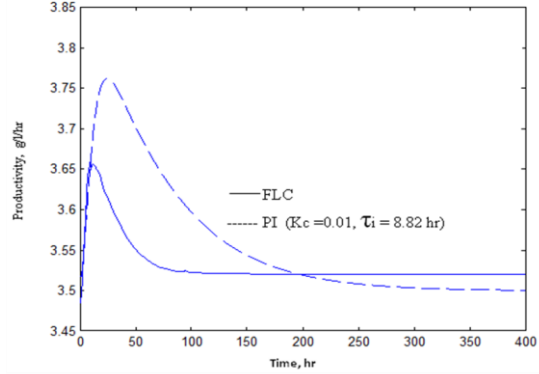


Fig 12 Closed loop response of productivity for a change in Sf from 20 to 24(+20%) at lower input

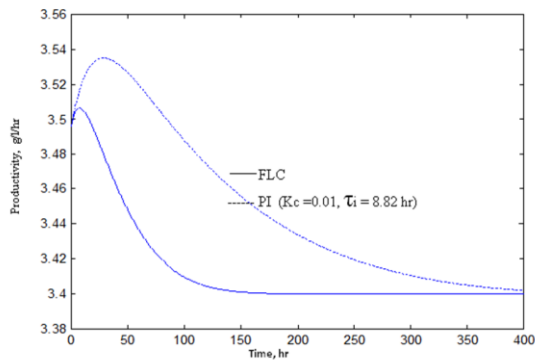


Fig 10 Closed loop response of productivity for step change in set point from 3.5 to 3.4 (-10%) at lower input

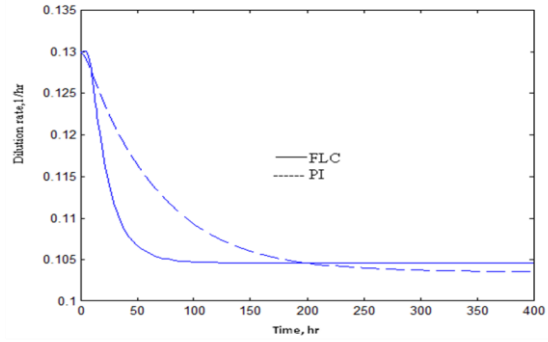


Fig 13 Control action in Dilution rate Vs time as shown in fig 12

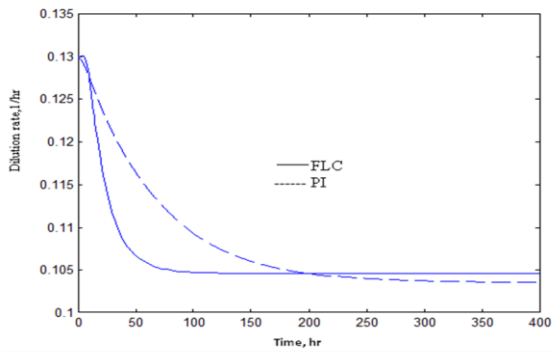


Fig 11 Control action in Dilution rate Vs time as shown in fig 10

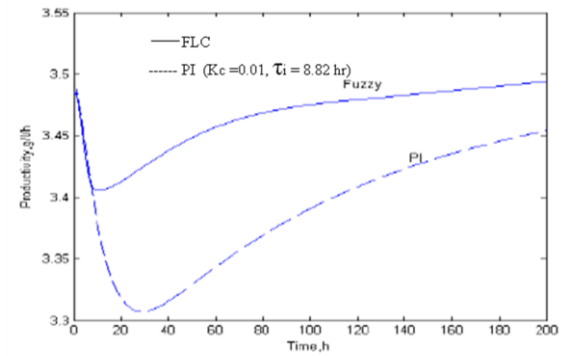


Fig 14 Closed loop response of productivity for a change in Sf from 20 to 18 (-10%) at lower input

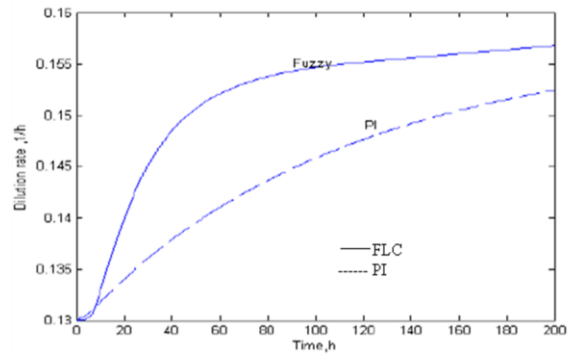


Fig 15 Control action in Dilution rate Vs time as shown in fig 14

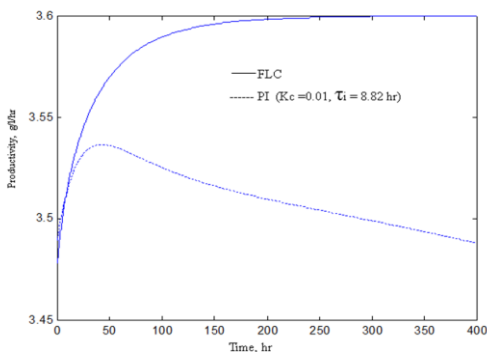


Fig 16 Closed loop response of productivity for step change in set point from 3.5 to 3.6 (+10%) at higher input

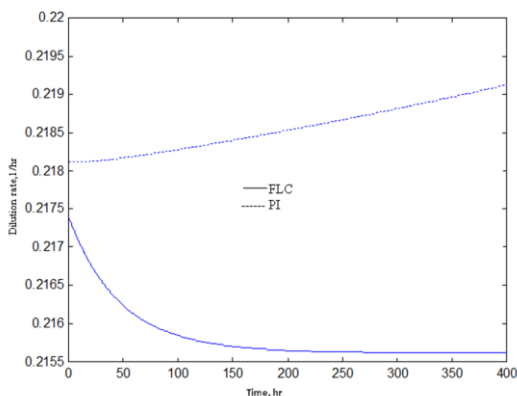


Fig 17 Control action in Dilution rate Vs time as shown in fig 16

CONCLUSIONS

In the present work, the performance of conventional PI controller and Fuzzy logic controller controller is studied for the set point changes at lower input dilution rates. Based on the above studies the following conclusions are made.

At lower input dilution rate, response of PI controller for set point change from 3.5 to 3.6 g/l/h is stable with offset and for another set point change of 3.5 to 3.4 g/l/h is stable with offset response due to input multiplicities. Whereas proposed fuzzy logic controller is giving stable and faster responses.

The conventional PI controller designed at lower dilution rate is given unstable response at higher dilution rates, where as fuzzy logic controller gives stable , offset free and faster response for servo and regulatory problems.

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