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Analysis of Artificial Neural Network Based Direct inverse controller with conventional PI (Designed at Lower Dilution Rate) controller for Bioreactor

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Abstract: In this paper presents about control of Bioreactor useing Artificial Neural Network based direct inverse controller. Bioreactor has become an active area of research in recent years. Neural network based direct controller designed for the control of bioreactor. In the first step the neural network model of bioreactor is obtained by levenburg- marquard training the data for the training the network generated using mathematical model of bioreactor.

Keywords: direct inverse Neural network control, bioreactor, dilution rate,productivity.

1. 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.

2. 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.

3. 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.

4. CONTROL OF BIOREACTORS USING NEURAL NETWORK:

The inherent non-linearity of the fermentation process often renders control difficult. Neural network has become popular tool for modeling and control of dynamic process, demonstrating the ability of handling non-linearity. Many neural network controllers are of the rule-based type where the controller's output response is described by a series of control rules.

The unique features of this neural network control technique include:

- A wide operation range for handling a non-linear process.
- Robustness for dealing with random disturbance and possible system parameter Drafting.
- Relatively simple implementation.

In the present work, neural network control is designed and evaluated for the continuous bioreactor with one input and one output to overcome the control problems associated with linear P1 controller due to the input multiplicity.

5. Model Equations for Bioreactor

.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.

Finally, the model equations can be written as;

X = -DX + μX (1)

S = D (S_f - S) – μX/Y (2)

P = -DP + (αμ +β) X (3)

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:

$$\mu = \frac{\mu_m (1 - P/P_m) S}{K_m + S + S_2/K_1} \quad (4)$$

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

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

X = – DX + μX

S = D (S_f–S) – μX/Y

P = –DP+ (αμ+ β) X

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

In practice, the model parameters in equations (1)-(4) are chosen to fit experimental data (Munack and Thoma, 1986; Enfors et a!., 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 tm tend to be especially sensitive to changes in the operating conditions.. For instance, the product is totally growth-associated if a α ≠ 0, β = 0, totally non growth-associated if a = 0, β≠ 0, and a combination of the two if α ≠ 0, β≠0. Simple Monod kinetics (Johnson, 1987) can be obtained by setting Pm = K1 =α ‘c. In many fermentations such as penicillin production, cell growth is inhibited by high substrate concentrations so that 0 < K1 < cc. If the growth rate approaches zero at high product concentrations then 0 <Pm < α.

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 (5)

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6. DESIGN OF A DIRECT INVERSE NEURAL NETWORK CONTROL

Conceptually, the most fundamental neural network based controllers are probably those using the "inverse" of the process as the controller. The simplest concept is called direct inverse control.

The principle of this is that if the process can be described by:

$$y(t+1) = g\big(y(t),\ldots\ldots, y(t-n+1), u(t), \ldots, u(t-m)\big) \qquad (6)$$

where the system output y(t+1) depends on the preceding n-output and m-input values, the system inverse model can be generally presented in the following form

$$u(t) = g^{-1}\big(y(t+1), y(t),\ldots, y(t-n+1), u(t-1), u(t-m)\big) \qquad (7)$$

Here y(t+1) is an unknown value, and hence can be substituted by the output quantity desired value r(t+1). The simplest way to arrive at a system inverse neural model is it to train the neural network to approximate the system inverse model. There are several references available which use this idea, e.g., Psaltis et al. (1988), Hunt & Sbarbaro (1991), and Hunt et al. (1992).

7. Simulation Results and Discussion of Proposed Direct inverse neural network controller with Conventional PI (designed at lower input Dilution rate) Controller

The performance of proposed direct inverse neural network controller and conventional PI controller to the Continuous Bioreactor with input multiplicities at lower and higher dilution rates is evaluated using the closed loop block diagrams as shown in Figs 1 & 2. During the identification and control tasks the NNSYSID (M. Nørgaard, 1996) and NNCTRL (K. J. Hunt, D. Sbarbaro, R. Zbikowski and PGawthrop, 2000) **toolboxes** for **MATLAB** were used. The parameters of conventional PI controller used in the simulation studies are, Kc=0.1, τ_I =8.82 hr (Chidambaram M and G.P. Reddy (1995))

The simulation studies for servo and regulatory problem have been presented below at lower dilution rates.

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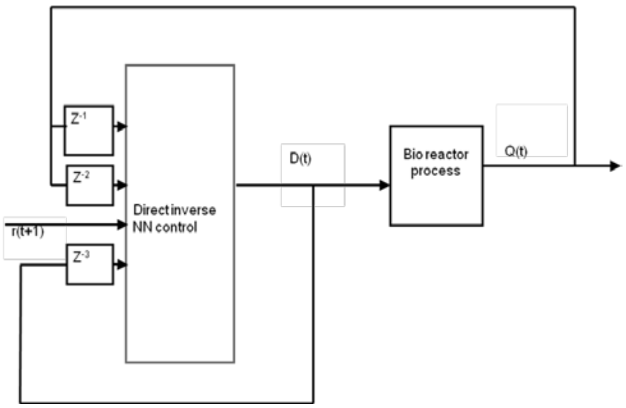

Fig .1. Closed loop block diagram of Direct Inverse Neural Network Control

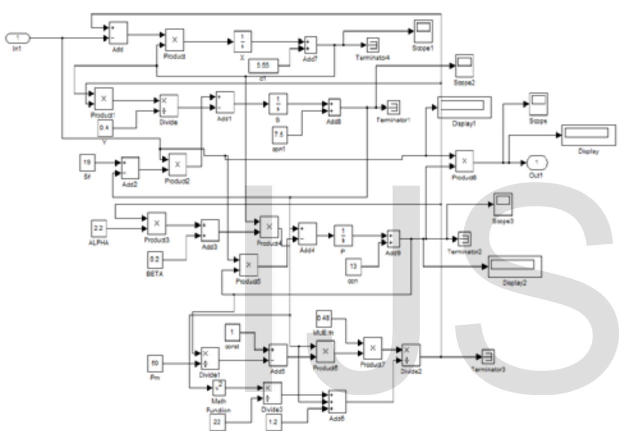

Fig 2.Dynamic simulink block of Bioreactor

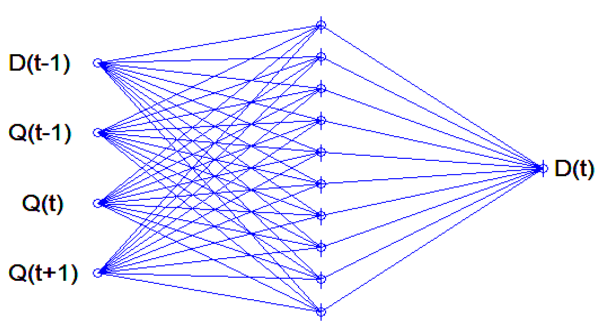

Fig 3. Structure of Bioreactor inverse neural network model at Lower input.

During the identification and control tasks the NNSYSID (M. Nørgaard, 1996). and NNCTRL (K. J. Hunt, D. Sbarbaro, R. Zbikowski and P. J. Gawthrop, 1992) **toolboxes** for **MATLAB** are used.

7.1 Lower dilution rate (D =0.09368hr^{-1})

7.1.1 Servo problem:

The servo response has been studied by giving a step change in set point of productivity with direct inverse neural network and PI controller.

At lower dilution rate the servo problem has been analyzed by giving step change in set point of productivity from 3.0 to 3.1 and the corresponding responses are shown fig.4.Direct inverse control shows stable response at about 10hrs. Whereas PI reaches after 100 hrs .Its corresponding control action in terms of dilution rate is shown in fig. 5.

Fig 6 shows the step change in the set point of productivity from 3.0 to 2.9.In this response the NNDIC reaches the set point at around 20 hrs without any offset whereas PI is reaching the set point at 300 hrs.The corresponding manipulated variable in terms

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of dilution rate versus time behavior is shown fig 7

7.1.2 Regulatory problem:

The regulatory response in productivity of Direct inverse neural network controller and PI controller for dilution rate input of disturbance in feed substrate concentration have been studied and they are stated below:

The regulatory response in productivity of Direct inverse neural network and conventional PI is shown in fig 8 for a step change in feed substrate concentration from 20 to 24(+20%).. Proposed neural network control has less deviation of 3% whereas conventional PI controller has a larger deviation of about 8%. Direct inverse neural network controller has low settling time than the PI controller. The corresponding control actions for manipulated variable in terms of dilution rate versus time behavior are shown in fig 9.

The regulatory response in productivity of Direct inverse neural network controller and PI controller for dilution rate input of disturbance in feed substrate concentration have been studied and they are stated below:

The regulatory response in productivity of Direct inverse neural network and conventional PI is shown in fig 10. for a step change in feed substrate concentration from 20 to 16(-20%). Proposed neural network control has less deviation of 4% whereas conventional PI controller has a larger deviation of about 8%. Direct inverse neural network controller has low settling time than the PI controller. The corresponding control actions for manipulated variable in terms of dilution rate versus time behavior are shown in fig 11.

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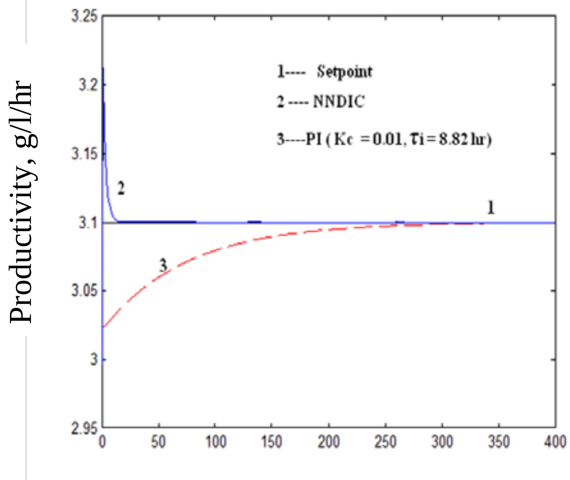
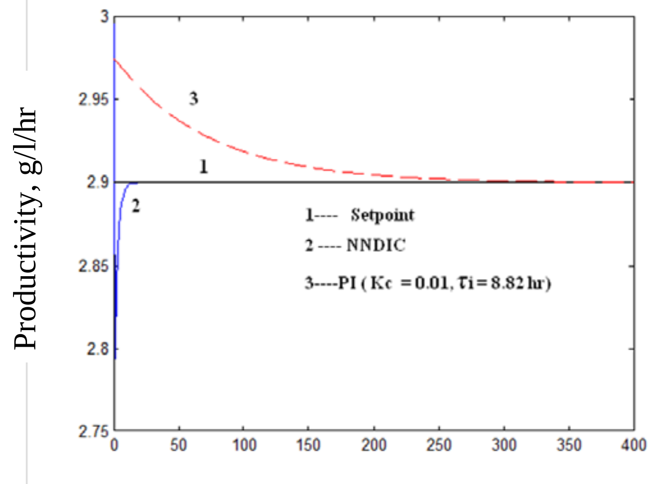
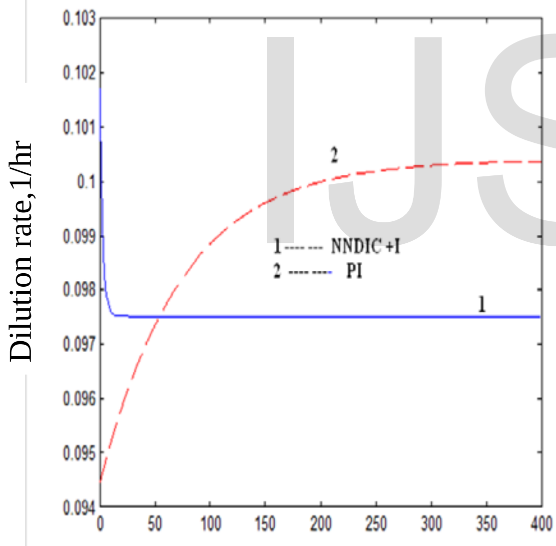


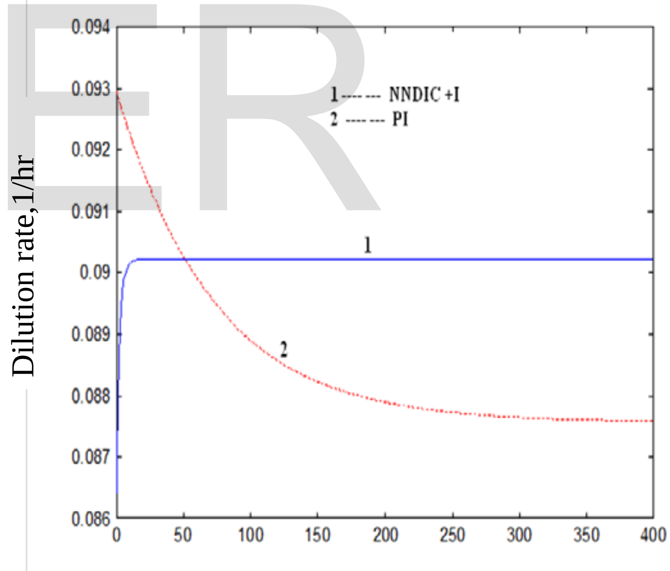
Time, hr
Fig 4. Closed loop response of productivity for step change in set point from 3.0 to 3.1 (+10%) at lower input



Time, hr
Fig 6. Closed loop response of productivity for step change in set point from 3.0 to 2.9 (-10%) at lower input



Time, hr
Fig 5. Control actions in Dilution rate Vs time as shown in fig 4



Time, hr
Fig 7 Control action in Dilution rate Vs time as shown in fig 6

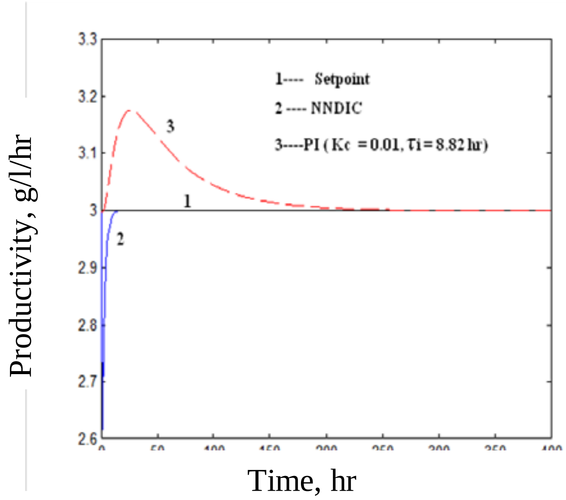


Fig 8 Productivity Versus time for change in Sf from 20 to 24 g/l at lower input

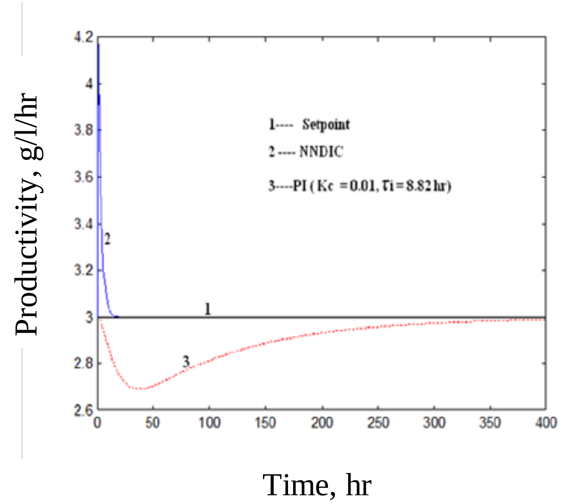


Fig 10 Productivity Versus time for change in Sf from 20 to 16 g/l at lower input

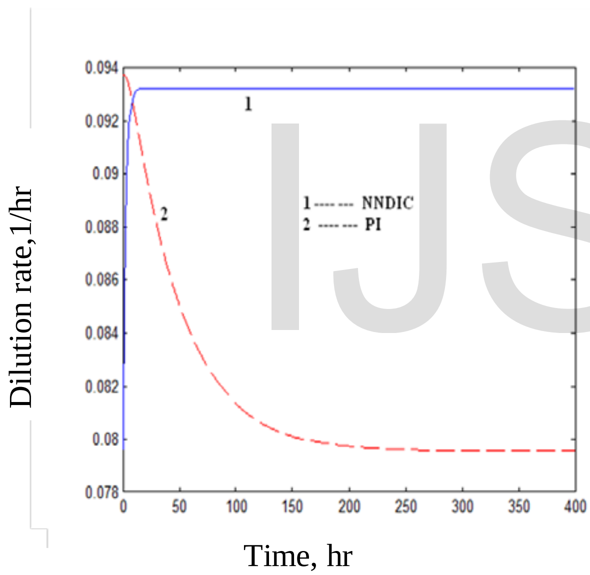


Fig 9 Control action in Dilution rate Vs time as shown in fig 8

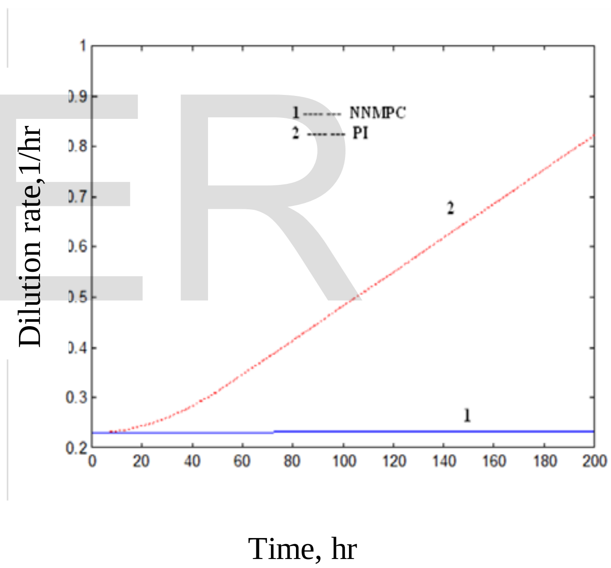


Fig 11 Control action in Dilution rate Vs time as shown in fig 10

CONCLUSIONS

In the present work, the performance of conventional PI controller and Neural Network based direct inverse controller is studied for the set point change and feed 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 to 3.1 g/l/h is stable with offset and for another set point change of 3 to 2.9 g/l/h is stable with offset response due to input multiplicities. Whereas proposed neural network based direct inverse controller is giving stable and faster response in all above cases.

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