A Stable Artificial Neural Network Based NARMA-L2 Control of a Bioreactor with Input Multiplicities

Ginuga Prabhaker Reddy, Poondla Radha Krishna and Chanda Swetha

***Abstract*—In this paper, the Neural network based NARMA-L2 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 Neural network based NARMA-L2 controller and conventional PI controller have been evaluated through simulation studies. As the NARMA-L2 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 better 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, NARMA-L2 controller is found to overcome the control problems of PI controller due to the input multiplicities.**

***Index Terms*— NARMA-L2 controller, Bioreactor, Input Multiplicities, Stable control**

I. INTRODUCTION

The term Input multiplicity means, more than one value of input variable producing the same value of output. It is a kind of nonlinearity in the process. Input multiplicity occurs due to the competing effects in the processes. Dynamic and steady state behavior of the process with input multiplicity will remain distinct at different input values for the same output. Processes with multiple reactions, multi reactors or recycle structures are shown to exhibit input multiplicities [1,2]. Conventional linear PI controller will have control problems like instability, oscillatory and less economical due to input multiplicities in the process [3]. Model based nonlinear controllers are found to be appropriate for the processes with input multiplicities and however they are computationally involved [4,5].

The inherent nonlinearity of the bioreactor often renders control difficult [6,7]. 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 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. 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. Among these intelligent controllers, Neural networks control has become popular tool [8] for control of dynamic process, demonstrating the ability of handling non linearity.

In this work, the design and evaluation of Neural network based NARMA-L2 controller is presented to overcome the control problems associated with conventional PI controller due to input multiplicities.

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II. DESCRIPTION AND MODEL OF A BIOREACTOR PROCESS

We consider here an isothermal continuous bio reactor, which can be described by the following unstructured model equations [9]. It may be suitably considered for simulation studies and for the evaluation of the proposed Neural Networks based controller:

Cell Balance:

$$dX/dt = - DX + \mu X \tag{1}$$

Substrate Balance:

$$dS/dt = D(Sf - S) - \mu X/Y \tag{2}$$

Product Balance:

$$dP/dt = -DP + (\alpha\mu + \beta)X \tag{3}$$

$$\text{At } t = 0,\ X=Xs,\ S=Ss,\ P=Ps \tag{4}$$

Here, X= cell or biomass concentration,(g/l), S = substrate concentration, (g/l), P=product concentration,

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(g/l), Sf = Feed substrate concentration, (g/l) and D = Dilution rate (1/h).

The specific growth rate model (μ) is assumed to exhibit both substrate and product inhibition:

$$\mu=\mu_m\{[1-(P/P_m)]S\}/(K_m+S+S^2/K_i) \quad (5)$$

Where, μ_m, Pm, Km, and Ki are respectively the maximum specific growth rate, product saturation constant, substrate saturation constant and substrate inhibition constant. The nominal values of the parameters and the operating conditions used in the present study are given as [5]: α=2.2 g/g, β=0.2 g/g, μ_m =0.48 h^{-1}, P_m= 50 g/l, K_m=1.2 g/l, Ki=22 g/l , S_f=20 g/l, Y=0.4 g/g

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:

$$Q=DP \quad (6)$$

The steady state values of X,S,P and hence Q are calculated for the operating conditions. Fig. 1 shows the steady-state response of Q versus D. For a given value of Q there are two values of D due to input multiplicities.

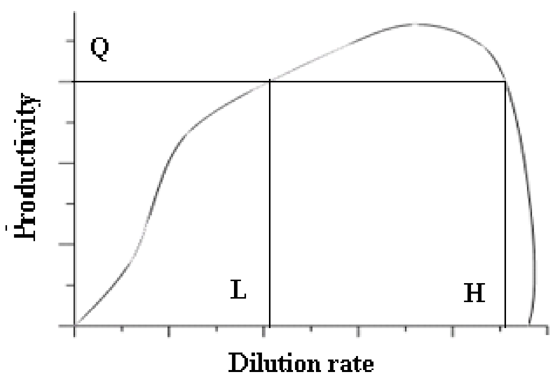

Fig.1 Productivity (Q) verses dilution rate (D) at the steady-state condition. L- Lower dilution rate and H=Higher dilution rate

The value of Q is 3.0 (g/l h) is selected and it is obtained with either D = 0.23781/h or D=0.09386 1/h. At the lower value of D, the steady-state gain is positive and at the larger value of D the gain is negative.

III. DESIGN OF A NEURAL NETWORK BASED NARMA – L2 CONTROLLER OF A BIOREACTOR

Generally, nonlinear process is given by the following discrete model,

$$\hat{y}(k+d)=f[y(k),y(k-1),\dots,y(k-n+1),u(k-1),\dots,u(k-m+1)]+g[y(k),y(k-1),\dots,y(k-n+1),u(k-1),\dots,u(k-m+1)].u(k) \quad (7)$$

This model is in companion form, where the next controller input, $u(k)$ is not contained inside the nonlinearity. The advantage of this form is that it can solve for the control input that causes the system output to follow the set point, $y(k+d) = y_r(k+d)$. The resulting controller would have the form,

$$u(k)=\frac{y_r(k+d)-f[y(k),y(k-1),\dots,y(k-n+1),u(k-1),\dots,u(k-n+1)]}{g[y(k),y(k-1),\dots,y(k-n+1),u(k-1),\dots,u(k-n+1)]} \quad (8)$$

Using this equation, directly it can solve control problems, because it may determine the control input, $u(k)$ based on the output at the same time, $y(k)$. From Eq.(8) the NARMA-L2 controller for Bioreactor, the dilution rate is given as,

$$D(k+1)=\frac{Q_r(k+d)-f[Q(k),\dots,Q(k-n+1),D(k),\dots,D(k-n+1)]}{g[Q(k),\dots,Q(k-n+1),D(k),\dots,D(k-n+1)]} \quad (9)$$

IV.SIMULATION RESULTS AND DISCUSSION

The performance of proposed neural network based NARMA-L2 controller and conventional PID controller to the continuous bioreactor in dilution rate is evaluated using SIMULINK model shown below in Fig.2.

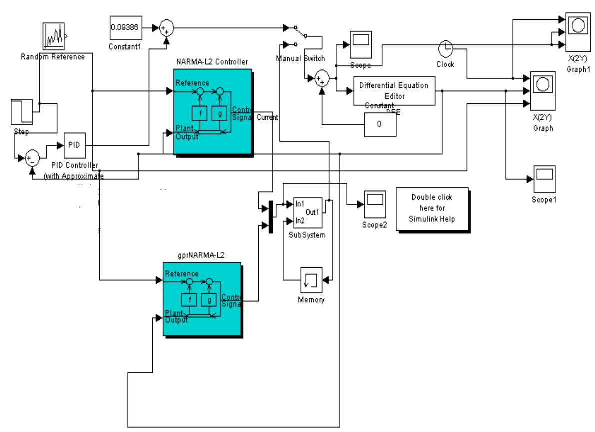

Fig. 2 Simulink model of NN-NARMA-L2 and PID control of Bioreactor.

The response of PID controller for set point change of 3 to 2.5 g/l/h is shown in Fig.3. It shows fast and smooth response. The corresponding PID control action is presented in Fig.4 shows a smooth action.

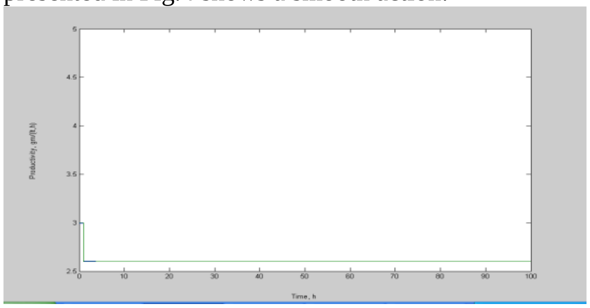

Fig. 3 Response of PID controller in Productivity versus time for Set point change from 3 to 2.5 g/l/h at lower input dilution rate.

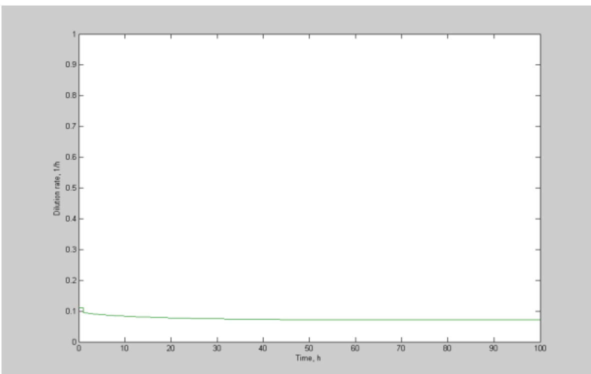

Fig. 4 Control action of PID in dilution rate for the response shown in Fig.3.

However, The PID response for a set point change of 3 to 4 g/l/h is given in Fig.5 shows immediate reaching the set point of 4 g/l/h and after some time, response goes unstable condition and results in washout condition. This is due to shifting of input from lower value of dilution rate to higher input value as shown in Fig.6. As it shifts to higher input dilution rate, PID controller becomes unstable, because the controller gain is positive and process gain remains negative at higher dilution rate.

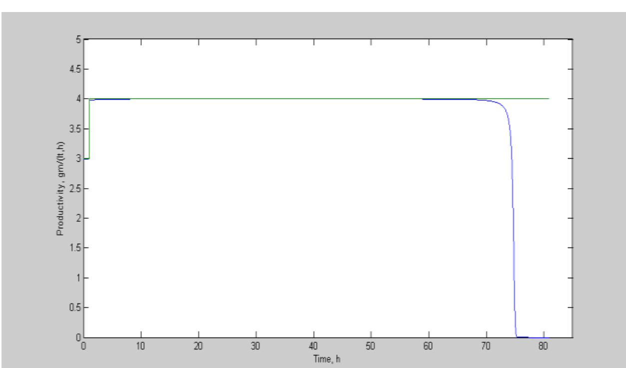

Fig. 5 Response of PID controller in productivity versus time for setpoint change from 3 to 4 g/l/h at lower input dilution rate

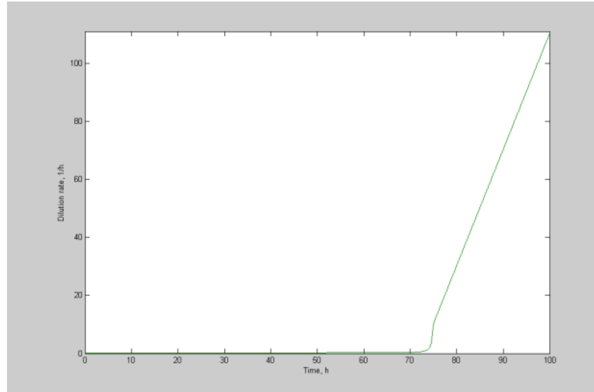

Fig.6. PID Control action in dilution rate for the response shown in Fig.5.

Now, The response of NN based NARMA-L2 controller for a set point change of 3 to 2.5 g/l/h is presented in Fig.7. It shows faster and smooth response. And, Fig.8 gives control action in dilution rate.

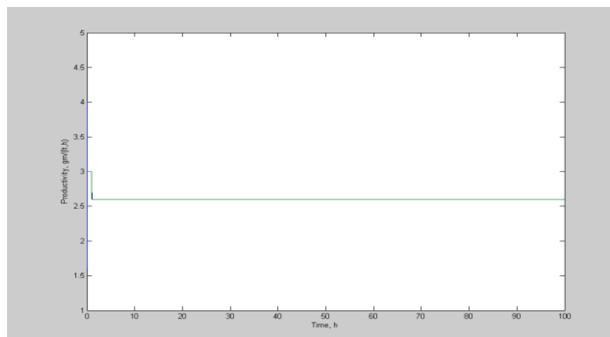

Fig 7: Response of NARMA –L2 Controller in Productivity versus time for Set point change from 3 to 2.5 g/lh at lower input Dilution rate.

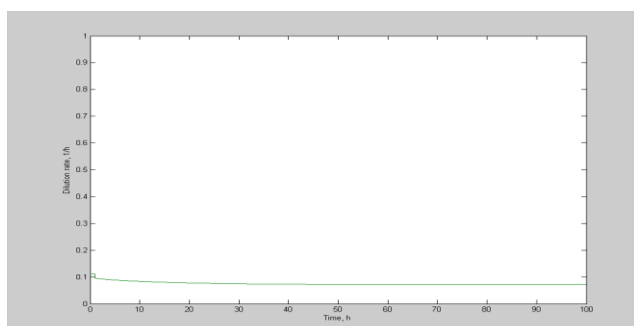

Fig. 8 NARMA -L2 Control action in dilution rate for the response shown in Fig.7

And, for set point change of 3 to 4 g/l/h the response of proposed NN based NARMA-L2 controller is shown in Fig.9. Unlike in conventional PID controller, the response of present NARMA-L2 controller is stable and reaches the set point with some offset. The offset has resulted due to process and controller mismatch. The present Neural Network control action is obtained as smooth and it is given in Fig.10.

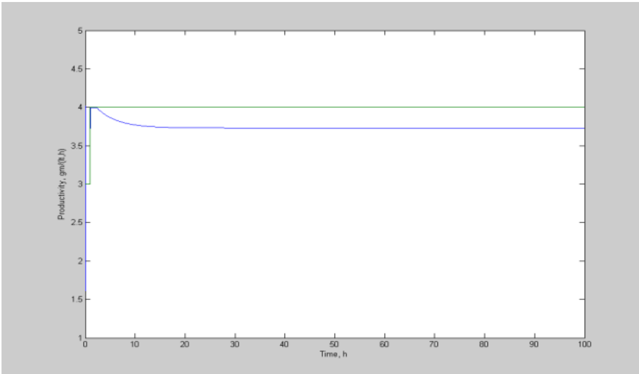

Fig. 9 Response of NARMA –L2 Controller in Productivityversus time for Set point change from 3 to 4 g/lh at lower input Dilution rate.

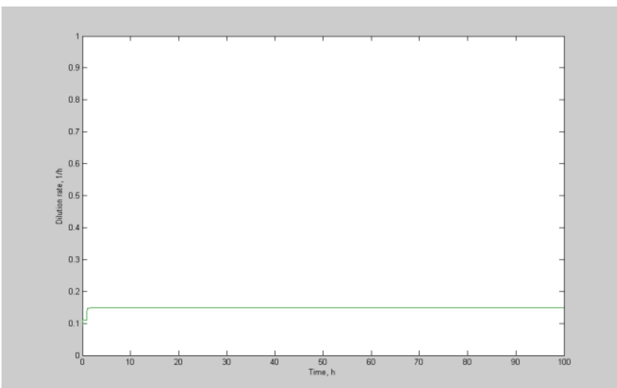

Fig.10 NARMA-L2 Control action in dilution rate for the response shown in Fig.9.

Next, the performance of conventional PID and proposed NN based NARMA-L2 controller is evaluated at higher input diluton rate.

The response of PID controller for set point change from 3 to 4 g/lh is shown in Fig.11. This servo response has resulted in unstable condition due to opposite sign of the process gain at higher input dilution rate. The control action of PID controller is given in Fig.12. The present NN based NARMA-L2 controller response for set point change from 3 to 4 is stable as given in Fig.13. The NARMA-L2 control action is given in Fig.14.

At higher input dilution rate, The response of NARMA-L2 controller for set point change of 3 to 2.5 g/l/h is shown in Fig.15 and shows a faster response. The control action of NARMA-L2 controller is given in Fig.16.

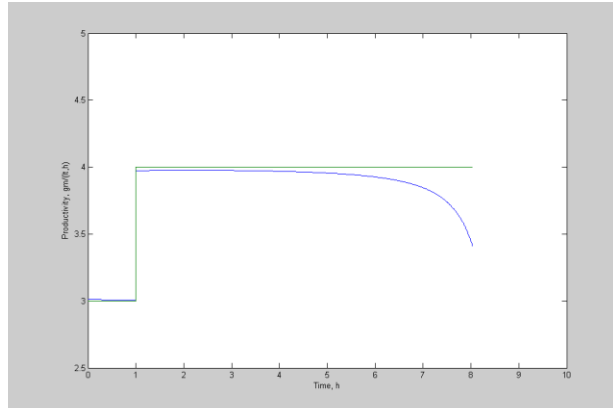

Fig. 11 Response of PID controller in productivity versus time for setpoint change from 3 to 4 g/l/h at higher input dilution rate

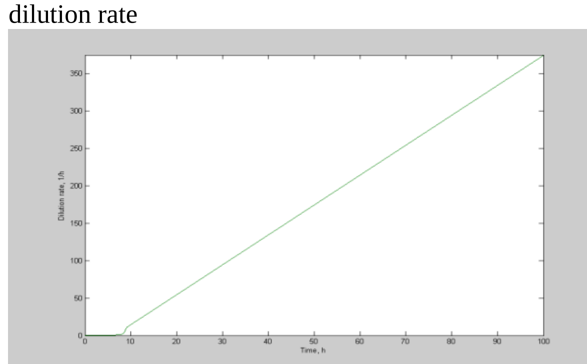

Fig. 12 PID Control action in dilution rate for the response shown in Fig.11.

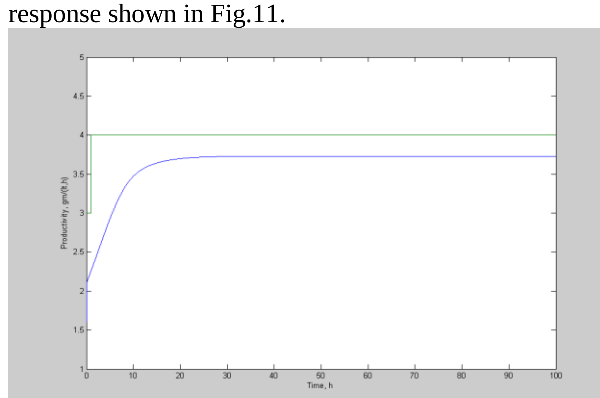

Fig. 13 Response of NARMA –L2 Controller in Productivity versus time for Setpoint change from 3 to 4g/lh at higher input Dilution rate.

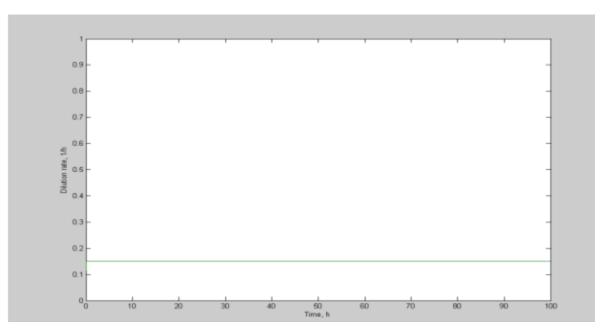

Fig.14. NARMA L2 Control action in dilution rate for the response shown in Fig.13

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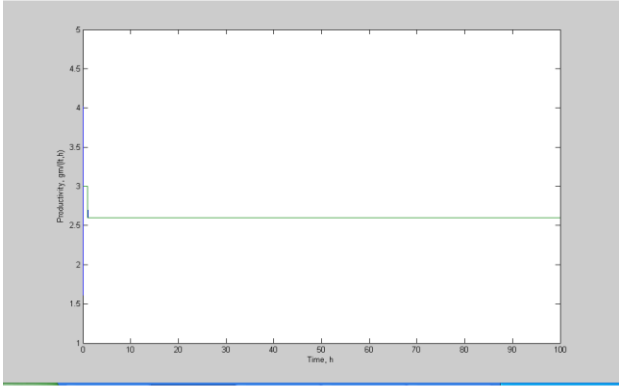

Fig.15 Response of NARMA –L2 Controller in Productivity versus time for Setpoint change from 3 to 4 g/lh at higher input Dilution rate.

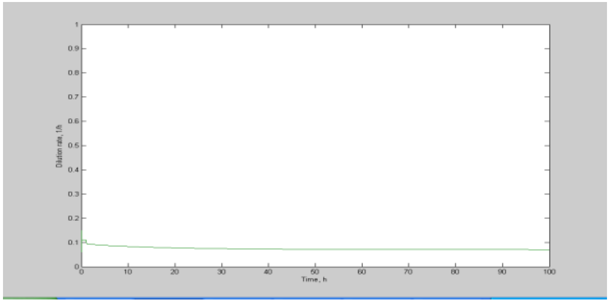

Fig.16 NARMA-L2 Control action in dilution rate for the response shown in Fig.15

V. CONCLUSIONS

In the present work, the performance of conventional PID controller and Neural Network based controller is studied for the set point changes at lower and higher input dilution rates. Based on the above studies the following conclusions are made.

At lower input dilution rate, response of PID controller for set point change from 3 to 2.5 g/l/h is stable and for another set point change of 3 to 4 g/l/h is unstable response due to input multiplicities. Whereas proposed neural network based NARMA-L2 controller is giving stable response for the both set point changes. Similarly, at higher input dilution rate, the conventional PID is found to be unstable and the NARMA-L2 controller is stable. Thus, the proposed NN based NARMA-L2 is found to overcome the control problems due to input multiplicities.

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