International Conference on System Dynamics and Control -ICSDC
19th -22nd August 2010

DESIGN OF NEURAL CONTROLLERS FOR VARIOUS CONFIGURATIONS OF CONTINUOUS BIOREACTOR

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Abstract. *In the present study, the Neural network (NN) based controller design has been implemented for a non-linear continuous bioreactor process. Multilayer feed forward networks (FFNN) were used as direct inverse neural network (DINN) controllers as well as IMC based NN controllers. The training as well as testing database was created by perturbing the open loop process with pseudo random signals (PRS). For set point tracking; at an operating condition where the cell growth is substrate limited, the DINN controllers were designed for conventional turbidostat and nutristat configurations. DINN controllers performed effectively for set-point tracking. To address the disturbance rejection problems, which are very likely to be faced by the bioreactors, the IMC based neural control architecture was proposed with suitable choice of filter and disturbance transfer function. To assess the controllability of the various bioreactor configurations, like conventional turbidostat and nutristat & concentration turbidostat and nutristat, the offset or degree of disturbance rejection by the proposed IMC based NN controllers were utilized. The 'concentration turbidostat' using the feed substrate concentration as the manipulated variable was found to be the best control configuration among the continuous bioreactor configurations.*

Key words *turbidostat; nutristat; DINN; IMC; controllability; FFNN; Filter*

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I. INTRODUCTION

Neural networks have got various applications including pattern recognition, clustering, function approximation & prediction, optimization, process identification & control. The network stores knowledge in two forms a) the connection between the nodes b) the weight factors of these connections, Neural networks are better suited for processing noisy, incomplete, or inconsistent data and Neural networks mimic human learning processes. In the recent years, there have been significant advances in control system design for non-linear processes. One such method is the non-linear inverse model based control strategy. This method is dependent on the availability of the inverse of the system model. Neural networks (NN) have the potential to approximate any non-linear system including their forward & inverse dynamics. Inverse neural network have been utilized as the controller. For training the neural network, the process input-output data is generated by applying a pseudo random signal to the open loop process and the learning is carried out by considering the future process outputs as the reference set point. IMC (Internal model control) strategy integrates the plant model and its inverse in a feedback control loop. NN based IMC scheme is used; especially for disturbance rejection problem. Application of NN based controllers in chemical processes have gained huge momentum as a result of focused R&D activities taken up by several researchers including Donat et al. (1990); Ydstie (1990); Hernandez and Arkun (1990); Psichogios and Ungar (1991); Dirion et al. (1995); Hussain et al. (2001); Varshney et al. (2009) in recent years.

Bioreactor control has been an active area of research over a decade or so. For optimization of cell mass growth and product formation continuous mode of operation of bioreactors are desirable not the traditional fed batch bioreactors. Several researchers like Edwards et al. (1972), Agrawal and Lim (1984), Menawat & Balachander (1991) have studied the continuous bioreactor problem. A (2×2) bioreactor process having two states namely biomass (x_1 , X g/L) and substrate concentrations (S or x_2 g/L) are controlled by dilution rate (D=F/V (h^{-1})) and feed substrate concentration (S_f or x_{2f} g/L) at the various operating points of the bio-process. The parameters like specific growth rate (μ), yield constant (Y) , & saturation rate constant (k_1, k_m) of the kinetic models are either inadequately determined or vary from time to time regarding the process operation. The aforesaid parameters have been considered as disturbance to the process. The disturbance rejection has given a consideration in selecting suitable control configuration for the continuous bioreactors. The primary aim of a continuous bioreactor is to avoid wash out condition which ceases reaction. This may be done either by controlling cell mass or substrate concentrations. In order to maintain the reaction rate and product quality, both of them may be controlled with dilution rate and feed substrate concentration as manipulated variables, thus two degrees of freedom is available for control. However this is expensive and redundant probably, because microorganisms have intracellular regulatory mechanisms, and there exist strong interaction between the two outputs [11]. One may achieve acceptable control performances of both outputs by controlling only one of them. This give rise to four numbers of (1×1) control configurations possible which are as follows:

- Conventional turbidostat $(D \to X)$: Dilution rate is used to control cell concentration
- Conventional nutristat $(D \to S)$: Dilution rate is used to control substrate concentration
- Concentration turbidostat $(S_f \to X)$: Feed substrate concentration is used to control biomass or cell concentration
- Concentration nutristat $(S_f \to S)$: Feed substrate concentration is used to control substrate concentration

In that case with one of the loops being closed (by choosing any one of the four control configurations) and keeping the second manipulated input constant, the uncontrolled output should be relatively insensitive to disturbances. Some of the aforesaid configurations have better 'built-in' disturbance rejection ability than others; i.e., the sensitivity of the uncontrolled output with respect to disturbances is less.

Considering the immense commercial significance of the continuous bioreactor process the ANN based non-linear controller design have been implemented for various configurations of it. In the present study, the direct inverse neural network controllers (DINN) were designed for conventional turbidostat and nutristat for set point tracking at an operating condition where the cell growth is substrate limited. IMC based NN controllers were designed for conventional turbidostat and nutristat & concentration turbidostat and nutristat with which their disturbance rejection performance were tested; as well as controllability of those configurations were assessed.

2. Modeling

2.1. Model of bioreactor

The study is based on single biomass-single substrate process. The following are the model equation based on first principle.

Material Balance:

Rate of accumulation= inflow-outflow + generation - consumption

For biomass

$$\frac{d(Vx_1)}{dt} = Fx_{1f} - Fx_1 + Vr_1 \quad (1)$$

For substrate

$$\frac{d(Vx_2)}{dt} = Fx_{2f} - Fx_2 + Vr_2 \quad (2)$$

The reaction rate is given by

$$r_1 = \mu x_1 \quad (3)$$

Where x_{1f} & x_{2f} are the biomass concentration and the substrate concentration in feed, respectively. x_1 & x_2 are the biomass and substrate composition, respectively. μ , the specific growth is a function of substrate concentration and given by the substrate inhibition growth rate expression:

$$\mu = \frac{\mu_{max} x_2}{k_m + x_2 + k_1 x_2^2} \quad (4)$$

The relation between the rate of generation of cells and consumption of nutrients is defined by the yield Y

$$Y = \frac{r_1}{r_2}. \quad (5)$$

Introducing the dilution rate ($D = \frac{F}{V}$) and assuming there is no biomass in the feed, i.e., x_{1f}=0.

We get the following model equations

$$\frac{dx_1}{dt} = (\mu - D)x_1 \quad (6)$$

$$\frac{dx_2}{dt} = D(x_{2f} - x_2) - \frac{\mu x_1}{Y} \quad (7)$$

The inputs are dilution rate and feed substrate concentration and the outputs are the concentrations of substrate and biomass (All values in deviation form). The values of steady state dilution rate (D_s), feed substrate concentration (x_{2fs}), and the various parameters are presented in Table 1. The state-space matrices are as follows:

$$A = \begin{vmatrix} \mu - D_s & x_{1s}\mu_s' \\ -\frac{\mu}{Y} & -D_s - \frac{x_{1s}\mu_s'}{Y} \end{vmatrix} \quad (8)$$

$$B = \begin{vmatrix} x_{1s} & 0 \\ x_{2fs} - x_{2s} & D_s \end{vmatrix} \quad (9)$$

$$C = \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} \quad (10)$$

μ_s' represents the derivative of growth rate with respect to substrate concentration at steady state and given by

$$\frac{d\mu_s}{dx_{2s}}; \qquad \mu_s' = \frac{\mu_{max}(k_m - k_1 x_{2s}^2)}{(k_m + x_{2s} + k_1 x_{2s}^2)^2} \quad (11)$$

Table 1 Parameters for rate inhibition kinetics and steady state values of manipulated inputs

Disturbances	Value
μ_{max}	0.53 h^{-1}
k_m	0.12 g/L
K_1	0.4545 L/g
Y	0.4
x_{2fs}	4.0 g/L
D_s	0.3 h^{-1}

The above state space matrices were used to find turbidostat and nutristat transfer functions for set point tracking problems. Solving the steady state equations (6) & (7), we get three different equilibrium points depending on the initial conditions.

- When biomass concentration is zero, it is a washout condition with zero gain, trivial solution.
- When both the concentrations (biomass & substrate) are high it leads to unstable equilibrium

- When there is substrate limiting condition it is a stable equilibrium.

The system model around the second equilibrium point renders unbounded outputs when excited with pseudo random binary signals (PRBS). So the steady state values of third equilibrium; x_{1s} = 1.5302g/L, x_{2s} = 0.1746g/L were considered for the database development required for training the NNs. For disturbance rejection problems, which were implemented using IMC based NN scheme, a state space model was developed to determine a (2×5) disturbance transfer function matrix. The various disturbances considered were $\mu_{max}, Y, k_m, D, \& x_{2f}$ and the disturbance transfer function transfer functions were of same order to that of the process. Following are the state space matrices.

$$A = \begin{vmatrix} \mu - D_s & x_{1s}\mu_s' \\ -\frac{\mu}{Y} & -D_s - \frac{x_{1s}\mu_s'}{Y} \end{vmatrix} \tag{12}$$

$$B = \begin{bmatrix} \frac{\mu}{\mu_m} & \frac{-\mu_m x_{2s}}{(k_m + x_{2s} + k_1 x_{2s}^2)} & 0 & -x_{1s} & 0 \\ -x_{1s}\frac{\mu}{\mu_m} & \frac{-\mu_m x_{2s}}{(k_m + x_{2s} + k_1 x_{2s}^2)}\frac{x_{1s}}{Y} & \mu\frac{x_{1s}}{Y^2} & -(x_{2s} - x_{2fs}) & D_s \end{bmatrix} \tag{13}$$

$$C = \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} \tag{14}$$

$$D = \begin{bmatrix} 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \end{bmatrix} \tag{15}$$

Where load matrix is $u = \begin{pmatrix} \mu_{max} \\ k_m \\ Y \\ D \\ x_{2f} \end{pmatrix}$ (16)

2.2 Neural Network model for direct inverse controller

In the direct method, a NN is trained with observed input-output data from the open loop process to represent its inverse dynamics. Hence the resulting inverse NN model can be used as a controller typically in a feed forward fashion. In an IMC based NN scheme, a NN based process model is placed parallel with the process. The difference between the process and the network output is used for the feedback purpose. This feedback signal is then processed by the inverse NN in the forward path. It is to be noted that the implementation of IMC based NN is limited only to open loop stable processes. The learning phase of the network is an off-line process and the historic data base of the process is used for training and testing the networks. In the present study, the training as well as testing database was created by exciting the open loop process with pseudo random binary signals (PRBS).

In order to develop DINN controller, the training of the proposed multi layer FF NN (4, 3, and 1) was performed using the gradient based Levenberg-Marquardt method. Performance criterion was MSE between the network output and target. The network predicted the outputs of the controller $(D, \& x_{2f})$ which actually are the manipulated variable to the process. The inputs and outputs of NN (4, 3.1 or N1, N2 & N3) regarding the training & control phase were as follows,

Training Phase:

$$N1 = \{y(t), y(t-1), y(t-2), u(t-2)\} \tag{17}$$
$$N3 = u(t-1) \tag{18}$$

Control Phase:

$$N1 = \{y(t+1), y(t), y(t-1), u(t-1)\} \tag{19}$$
$$N3 = u(t) \tag{20}$$

Fig. 1 presents the network architecture in the control mode. Sampling time of 0.8 time unit and 2 time unit were used for training the two kinds of turbidostat $(D \to X)$ servo networks, each of the networks demonstrated minimum offset of 0.001 with simulation intervals of 2 time unit and 4 time unit respectively. For nutristat $(D \to S)$ servo networks, sampling time of 0.8 time unit and 2 time unit were used for training, each of them demonstrated minimum offset of 0.001 with simulation intervals of 4 time unit and 3 time unit, respectively.

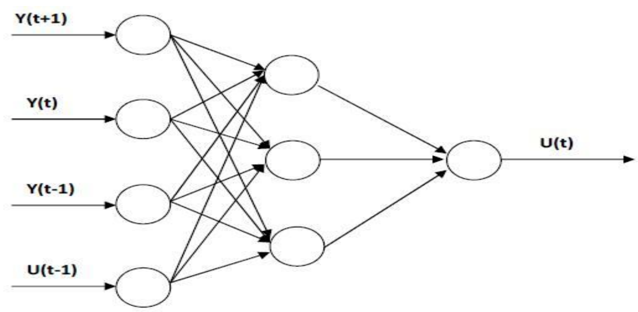


Fig.1 DINN network architecture in control mode.

2.3 NN based internal model control

An IMC structured closed loop was used with a disturbance transfer function of same order to that of process transfer function. The various disturbances considered were $\mu_{max}, Y, k_m, D, \& x_{2f}$. In IMC scheme, the proposed FF network (6, 3, and 1) representing the process model, used the following inputs & outputs,

Training phase

$$N1 = \{y(t-3), y(t-2), u(t-3), u(t-2), u(t-1), u(t)\} \tag{21}$$

$$N3 = y(t-1) \tag{22}$$

Simulation Phase

$$N1 = \{y(t-2), y(t-1), u(t-3), u(t-2), u(t-1), u(t)\} \tag{23}$$
$$N3 = y(t) \tag{24}$$

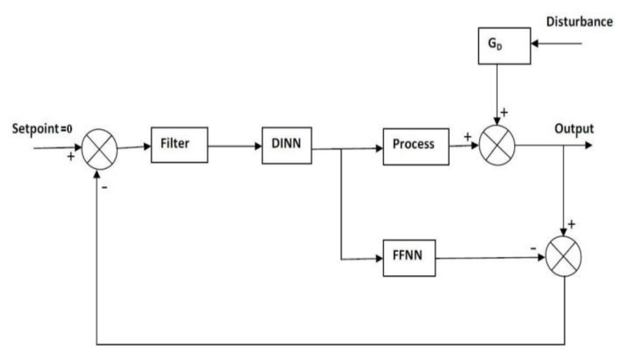


Fig.2 Block diagram of closed loop IMC scheme.

Fig. 2 represents the block diagram of closed loop IMC scheme. The following filter transfer function was used in the closed loop simulation.

$$G_f = \frac{\gamma S+1}{(\lambda s+1)^2} \tag{25}$$

$$\text{Where } \lambda = {}^{\tau_p}/_{5}, \text{ and } \gamma = \frac{(2\lambda\tau_p-\lambda^2)}{\tau_p} \tag{26}$$

3. Results & discussions

The performance of the developed controllers was tested of their set point tracking ability. The closed loop response in biomass concentration for unit step change in dilution rate at t=20 th time instant using the conventional turbidostat servo controller is shown in Fig.3, which reflect a perfect set point tracking. For monitoring substrate concentrations, the closed loop response of the substrate concentration for unit step change in dilution rate at t=24 th time instant using conventional nutristat controller is shown in Fig. 4, which also ensures the perfect set point tracking.

To assess the controllability of each of the continuous bioreactor configurations, the closed loop disturbance rejection performance of them were taken in to consideration. Table 2 represents the offset in disturbance rejection for unit step change in all the load variables (mentioned in eq. (16)) by all 4 continuous bioreactor configurations without any adjustment of bias. For the present equilibrium point where the cell growth is substrate limited, the concentration turbidostat using the feed substrate concentration as the manipulated variable seems the best control configuration. The performance of conventional turbidostat is poor in rejecting the disturbance in the yield Y. Conventional nutristat is unacceptable control configuration especially; when it is the case of disturbance rejection in μ_{max} & k_m. Concentration nutristat is incapable of disturbance rejection in D $(dilution\ rate)$. The disturbance rejection performances of concentration turbidostat are shown in Fig. 5.

Table 2 Disturbance rejection performance by closed loop bioreactor configurations

Configurations/ Disturbances	D—X	D—S	x_{2f}—X	x_{2f}—S
μ_{max}	0.4711	8.3554	0.198	-0.239
k_m	-3.15	10.3195	-1.153	-0.392
Y	1.2874	-5.6397	0.331	0.5639
D	-0.608	-6.0281	-0.396	1.4473
x_{2f}	0.1342	-1.1808	0.1011	0.0035

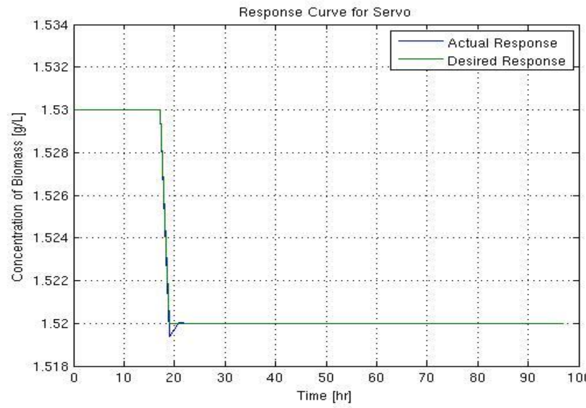


Fig.3 Response in biomass concentration for unit step change in dilution rate using conventional servo turbidostat controller (trained network with 0.8 time unit sampling intervals).

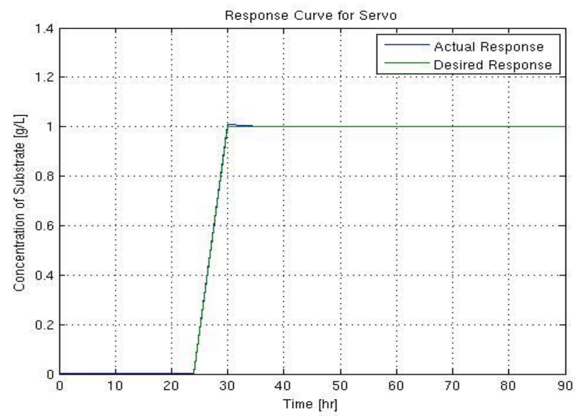
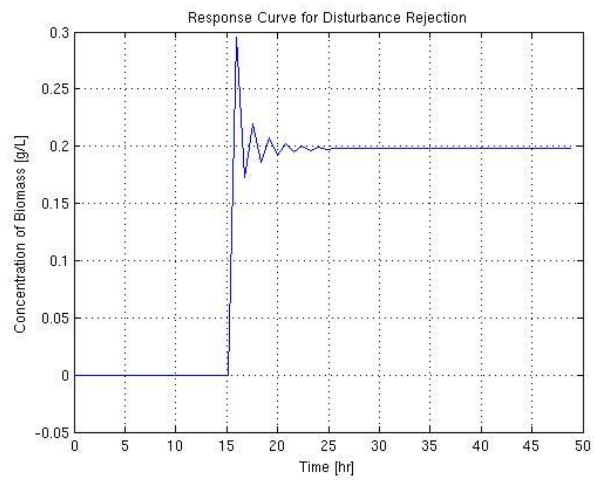
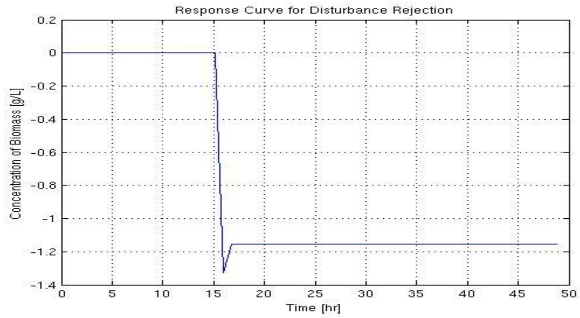


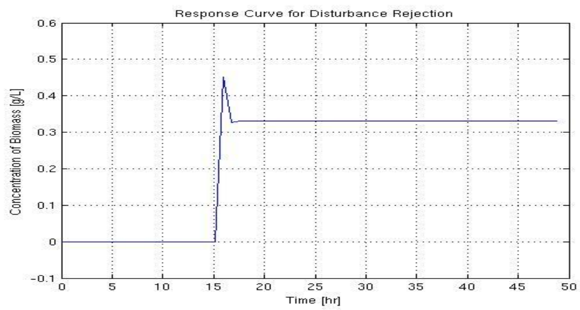
Fig.4 Response in substrate concentration for unit step change in dilution rate using conventional servo nutristat controller (trained network with 2 time unit sampling interval).



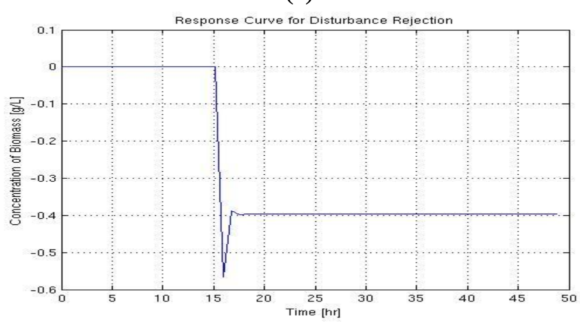
(a)



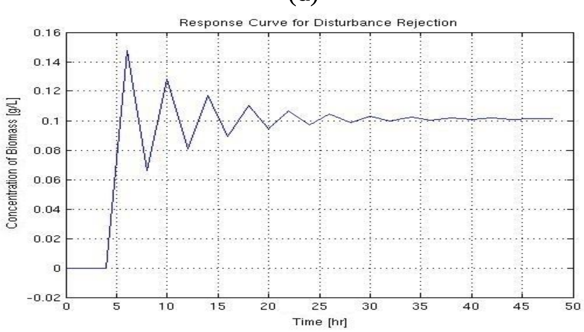
(b)



(c)



(d)



(e)

Fig.5 Disturbance rejection by concentration turbidostat: in (a) in μ_{max} (b) in k_m (c) in Y (d) in D (e) in x_{2f}

4. Conclusion

Present study utilized the neural network as non-linear controller for a continuous bioreactor process. The training as well as testing database was created by exciting the open loop process with pseudo random binary signals (PRBS). Both DINN and IMC based NN controller strategies were implemented successfully. The process chosen was open loop stable. The designed FFNN (4 3 1) SISO controllers effectively could track the changes in biomass as well as substrate concentration. To address the disturbance rejection; caused by either of $\mu_{max}, Y, k_m, D, \& x_{2f}$, IMC based neural control architecture (6 3 1) was proposed with suitable choice of filter and disturbance transfer functions having the same order to that of the process. To assess the controllability of the various configurations, the offset or degree of disturbance rejection of the proposed IMC based NN controllers were utilized. The concentration turbidostat using the feed substrate concentration as the manipulated variable was found to be the best disturbance rejecting SISO control configuration. Hence, making the other uncontrolled state; the substrate concentration being relatively insensitive to disturbances while manipulated variable D is kept constant. One can thus achieve control of both outputs by controlling only one of them.

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6. References

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