Nonlinear Adaptive Control of Fermentation Process in Stirred Tank Bioreactor

Hak Kyeong Kim, Tan Tien Nguyen, Nam Soo Jeong, and Sang Bong Kim

Abstract: This paper proposes a nonlinear adaptive controller based on back-stepping method for tracking reference substrate concentration by manipulating dilution rate in a continuous baker's yeast cultivating process in stirred tank bioreactor. Control law is obtained from Lyapunov control function to ensure asymptotical stability of the system. The Haldane model for the specific growth rate depending on only substrate concentration is used in this paper. Due to the uncertainty of specific growth rate, it has been modified as a function including the unknown parameter with known bounded values. The substrate concentration in the bioreactor and feed line are measured. The deviation from the reference is observed when the external disturbance such as the change of the feed is introduced to the system. The effectiveness of the proposed controller is shown through simulation results in continuous system.

Keywords: a non-linear adaptive controller, back-stepping method, bioreactor, tracking

I. Introduction

Fermentation is an important process for cultivating microorganisms. Fermentation can be run as a batch, fed-batch and continuous process. In a continuous system, the substrate is supplied to the bioreactor and extracted from the bioreactor. Fermentation process is so complex, time varying and highly nonlinear. Due to pH, dissolved oxygen, temperature, antifoam addition, biomass accumulation, production formation and nutrient depletion during fermentation process, the dynamic behavior is significantly changed. So it is difficult to make a model and control for fermentation process exactly. Specially, the exact estimate of the specific growth rate is so uncertain because it depends on parameters such as biomass concentration, substrate concentration, production formulation and temperature, etc. This uncertainty makes adaptive control theory enable to be applied to fermentation process.

L. Chen, et al., 1991, proposed general adaptive nonlinear method for the ethanol regulation in yeast production process by manipulating dilution rate in fed-batch biological bioreactors when ethanol concentration, dissolved oxygen concentration, CO_2 concentration and gas outflow rate are measured online with fixed known influent substrate concentration, and unknown specific growth rate.

M. Maher, et al., 1993 developed adaptive filtering and estimation algorithms using extended Kalman filter, the Dochain-Bastin method and Zeng-Dahou method in a nonlinear fermentation process.

G. Roux, et al., 1994, proposed adaptive nonlinear method by using an operation of projection for controlling alcoholic fermentation process in continuous stirred tank bioreactor. The good regulation profiles and tracking the temporal evaluation of certain biological parameters were presented by their proposed method.

R. Schneider, et al, 1994, proposed adaptive model-based prediction control to control the state variables of the process around a defined trajectory for the fed-batch fermentation process. Sliding-mode method for controlling fermentation process has been applied for tracking reference substrate concentration by using dilution rate as control variable [1-3].

Miroslav Krstic, 1995, applied adaptive back-stepping method for the control of biochemical process with assumption of constant dilution rate and defined specific growth rate function. This function includes two unknown parameters. Yet there is no way of deriving such function from the known models of specific growth rate.

It is important that the substrate concentration in bioreactor keeps constant in continuous fermentation process. Therefore, in this paper, we proposed a nonlinear adaptive controller for the tracking to reference substrate concentration of output substrate concentration by manipulating dilution rate in a continuous baker's yeast cultivating process in stirred tank bioreactor. Control law is obtained from Lyapunov control function to ensure global asymptotical stability of the system by using adaptive nonlinear back-stepping method. The specific growth rate is modified based on Haldane model depending only on substrate concentration in the bioreactor and feed line is assumed to be measured. Because of the uncertainty of specific growth rate, the specific growth rate can be modified as a function including the unknown parameter with known bounded values. The deviation from the reference is observed when the external disturbance such as the change of the feed is introduced to the system. The effectiveness of the proposed controller is shown through simulation results in continuous system.

II. Process Model

Stirred tank bioreactor studied in this paper is shown in Fig 1. The process considered is a continuous stirred tank in which the growth of microorganism is controlled. The bioreactor is continuously fed with the influent substrate. It is assumed that the rate of outflow is equal to the rate of inflow. The volume of culture remains culture without washout. It is considered that the feeding substrate is diluted in the water stream and the dilution rate is used as the process input. The substrate concentration is regarded as output.

The system dynamic equations on the substrate and the

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biomass are given as the following nonlinear form[2].

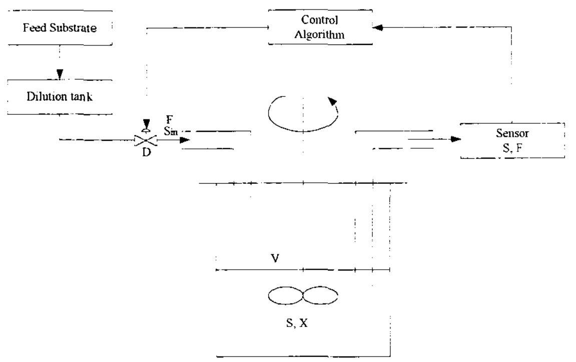

Fig. 1. Stirred tank bioreactor system

$$\dot{S} = -k\mu(S)X + D(S_{in} - S) \tag{1}$$

$$\dot{X} = \mu(S)X - DX \tag{2}$$

$$y = S \tag{3}$$

where

- X : biomass concentration in the reactor
- S : output substrate concentration in the reactor
- D : dilution rate
- μ : the specific growth rate
- k : the known yield coefficient
- S_{in} : influent substrate concentration
- y : system output

The specific growth rate is known to be a complex function of plant states and several biological parameters. More than 60 expressions have been suggested such as Monod', Contois', Haldane's model, etc. The choice of an approximate model for $\mu(S)$ is far from being an easy task. In our case, it is modeled from the Haldane model as the following

$$\mu_H = \frac{k_i \mu_m S}{k_s k_i + k_i S + S^2} \tag{4}$$

where

- μ_m : the maximum specific growth rate
- k_s : a saturation constant
- k_i : an inhibition constant.

Control objective and constraints: The control objective is to regulate substrate concentration S in bioreactor as level of reference substrate concentration S_{ref} by manipulating dilution rate D based on measurement data of S and X. Control constraints are $0 < D < \mu < \mu_m$, $X > 0$ and $0 < S \le S_{in}$ for any $t \ge 0$.

III. Controller Design

Define $x_1 \equiv S - S_{ref}$ and $x_2 \equiv X$. Because of the uncertainty of specific growth rate, the specific growth rate $\mu(S)$ of Eqs. (1) and (2) can be modified from Hadane's model of Eq.(4) as the function of Eq. (5) including the unknown parameter θ with bounded values. That is, to make adaptive control theory using back stepping method, we define Eqs. (5), (6) and (7).

$$\mu \equiv \mu(S) \equiv k_u + \theta\,(\mu_H - k_u) \tag{5}$$

$$\mu x_2 \equiv k_u x_2 + \theta\,\varphi(x_1, x_2, S_{ref}) \tag{6}$$

$$\begin{aligned}\varphi &= \varphi(x_1, x_2, S_{ref}) \\ &= \frac{k_i \mu_m (x_1 + S_{ref}) x_2}{k_s k_i + k_i(x_1 + S_{ref}) + (x_1 + S_{ref})^2} - k_u x_2 \\ &= (\mu_H - k_u) x_2\end{aligned} \tag{7}$$

where

- k_u : unit conversion parameter
- $\theta \in [\theta_{min}, \theta_{max}]$: adaptation parameter

With Eqs. (6) and (7), the system dynamic equation can be written as:

$$\dot{x}_1 = -k k_u x_2 - k\theta\varphi + (S_{in} - x_1 - S_{ref})D - \dot{S}_{ref} \tag{8}$$

$$\dot{x}_2 = k_u x_2 + \theta\varphi - D x_2 \tag{9}$$

Now, we design controller using adaptive back-stepping method as the following.

Step 1. Define the first tracking error

$$z_1 = x_1 \tag{10}$$

whose derivative can be expressed as

$$\begin{aligned}\dot{z}_1 &= \dot{x}_1 \\ &= -k k_u x_2 - k\theta\varphi + (S_{in} - x_1 - S_{ref})D - \dot{S}_{ref}\end{aligned} \tag{11}$$

Choose x_2 as virtual input. By putting Eq. (11) to be $-c_1 z_1$, $c_1 > 0$ and x_2 can be expressed as

$$x_2 = \frac{c_1 z_1 - k\theta\varphi + (S_{in} - x_1 - S_{ref})D - \dot{S}_{ref}}{k k_u} \tag{12}$$

If Eq. (12) is replaced by parameter estimate $\hat{\theta}$ of unknown bounded parameter θ, the estimate α_1 of x_2 can be written as

$$\begin{aligned}\alpha_1 &= \alpha_1(x_1, \varphi, \hat{\theta}, D, \dot{S}_{ref}) \\ &= \frac{c_1 z_1 - k\hat{\theta}\varphi + (S_{in} - x_1 - S_{ref})D - \dot{S}_{ref}}{k k_u}\end{aligned} \tag{13}$$

Introduce the second error variable as

$$z_2 = x_2 - \alpha_1 = -\frac{\tilde{\theta}\varphi}{k_u} \tag{14}$$

where α_1 is the stabilizing function for x_2 and where $\tilde{\theta} = \theta - \hat{\theta}$ is the error of parameter estimation.

$$\begin{aligned}\dot{z}_1 &= -k k_u x_2 - k\theta\varphi + (S_{in} - x_1 - S_{ref})D - \dot{S}_{ref} \\ &= -c_1 z_1 - k k_u z_2 - k\tilde{\theta}\varphi\end{aligned} \tag{15}$$

Choosing Lyapunov function as the following

$$V_1 = V_1(z_1,\tilde{\theta}) = \frac{1}{2}z_1^2 + \frac{1}{2\gamma}\tilde{\theta}^2 \ge 0 \tag{16}$$

where $\gamma > 0$ is adaptation gain.

With Eqs. (13) and (14), the first derivative of V_1 along the solution of Eq. (15) is as follows.

$$\dot{V}_1 = z_1\dot{z}_1 - \frac{1}{\gamma}\tilde{\theta}\dot{\hat{\theta}}$$
$$= -c_1z_1^2 - kk_u z_1 z_2 + \tilde{\theta}\left(-k\varphi z_1 - \frac{1}{\gamma}\dot{\hat{\theta}}\right) \tag{17}$$

Step 2. According to the computation in Step 1, in case that $\dot{\hat{\theta}} = -\gamma k\phi z_1$, $\dot{V}_1$ is non-positive in z_1 when $z_2 = 0$. Therefore, the Lyapunov function V_1 must be modified into the new Lyapunov function V_2 including the error variable z_2, as follows

$$V_2 = V_2(z_1,z_2,\tilde{\theta}) = \frac{1}{2}z_2^2 + V_1 \ge 0 \tag{18}$$

The derivative of $z_2 = x_2 - \alpha_1$ is

$$\dot{z}_2 = \dot{x}_2 - \dot{\alpha}_1$$
$$= \left(1+\frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_2}\right)(k_u x_2 + \theta\varphi - Dx_2) - \left(\frac{c_1-D}{kk_u} - \frac{\hat{\theta}}{k_u}\times\frac{\partial\varphi}{\partial x_1}\right)\left(-c_1z_1 - kk_u z_2 - k\tilde{\theta}\varphi\right) + \frac{\varphi}{k_u}\dot{\hat{\theta}} - \frac{\partial\alpha_1}{\partial D}\dot{D}$$
$$+ \frac{1}{kk_u}\ddot{S}_{ref} \tag{19}$$

where

$$\frac{\partial\alpha_1}{\partial D} = \frac{S_{in} - x_1 - S_{ref}}{kk_u} \tag{20}$$

$$\frac{\partial\varphi}{\partial x_1} = \frac{k_i\mu_m[k_ik_s - (x_1+S_{ref})^2]x_2}{[k_sk_i + k_i(x_1+S_{ref}) + (x_1+S_{ref})^2]^2} \tag{21}$$

$$\frac{\partial\varphi}{\partial x_2} = \frac{k_i\varphi_m(x_1+S_{ref})}{k_sk_i + k_i(x_1+S_{ref}) + (x_1+S_{ref})^2} - k_u \tag{22}$$

The derivative of V_2 is

$$\dot{V}_2 = -c_1z_1^2 + \tilde{\theta}\left\{-k\varphi z_1 - \frac{1}{\gamma}\dot{\hat{\theta}} + \left[\left(1+\frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_2}\right)\varphi + \left(\frac{c_1-D}{kk_u} - \frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_1}\right)k\varphi\right]z_2\right\} + z_2\left[-kk_u z_1 + \left(1+\frac{\hat{\theta}}{k_u}\times\frac{\partial\varphi}{\partial x_2}\right)(k_u x_2 + \hat{\theta}\varphi - Dx_2) - \left(\frac{c_1-D}{kk_u} - \frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_1}\right)\times\right.$$
$$\left.(-c_1z_1 - kk_u z_2) + \frac{\varphi}{k_u}\dot{\hat{\theta}} - \frac{\partial\alpha_1}{\partial D}\dot{D} + \frac{1}{kk_u}\ddot{S}_{ref}\right] \tag{23}$$

where the following update law for parameter estimate eliminates $\tilde{\theta}$ -term in Eq. (23).

$$\dot{\hat{\theta}} = \gamma\left[-k\varphi z_1 + \left\{\left(1+\frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_2}\right)\varphi + \left(\frac{c_1-D}{kk_u} - \frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_1}\right)k\varphi\right\}z_2\right] \tag{24}$$

The dynamic feedback controller for system stabilization is obtained by letting the last bracket in Eq. (23) be equal to $-c_2z_2$, $c_2 > 0$. After some rearrangement, we have the control dynamics as

$$\dot{D} = \frac{1}{\frac{\partial\alpha_1}{\partial D}}\left[-\left(1+\frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_2}\right)x_2 - \frac{1}{kk_u}(kk_u z_2 + c_1z_1)\right]D$$
$$+\frac{1}{\frac{\partial\alpha_1}{\partial D}}\left[c_2z_2 - kk_u z_1 + \left(1+\frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_2}\right)(k_u x_2 + \hat{\theta}\varphi)\right.$$
$$\left.+\left(\frac{c_1}{kk_u} - \frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_1}\right)(c_1z_1 + kk_u z_2) + \frac{\varphi}{k_u}\dot{\hat{\theta}} + \frac{1}{kk_u}\ddot{S}_{ref}\right] \tag{25}$$

Eq. (25) is a form of $\dot{D} = AD + B$. Control input D can be obtained by just numerical integration of Eq .(25) using Eqs. (20)-(22) and Eq. (24). That is, D is the solution of Eq. (25). However, in simulation, all equations must be transformed into discrete equations. So Eq. (25) can also be transformed into discrete equation $D(m) = A(m-1)D(m-1) + B(m-1)$. After that, the solution $D(m)$ of the discrete equation can be obtained. Discrete time $t = mT$. T is a sampling time and m is an integer.

With Eqs. (24) and (25), $\dot{V}_2$ is non-positive as follows

$$\dot{V}_2 = -c_1z_1^2 - c_2z_2^2 \le 0 \tag{26}$$

The closed loop system equations of the process become the following.

$$\dot{z}_1 = -c_1z_1 - kk_u z_2 - k\varphi\tilde{\theta} \tag{27}$$

$$\dot{z}_2 = -c_2z_2 + kk_u z_1 + \left[\left(1+\frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_2}\right)\varphi + \left(\left(\frac{c_1-D}{kk_u}\right) - \frac{\hat{\theta}}{k_u}\frac{\partial\varphi}{\partial x_1}\right)k\varphi\right]\tilde{\theta} \tag{28}$$

This block diagram of the proposed method is shown in Fig 2.

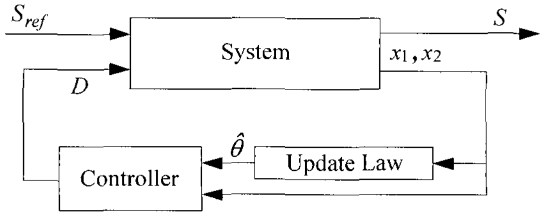

Fig. 2. Block diagram of the proposed method

If $\tilde{\theta} = 0$, Eq. (27)-(28) become linear asymptotically stable system as follows.

$$\dot{z}_1 = -c_1 z_1 - kk_u z_2 \tag{29}$$

$$\dot{z}_2 = -c_2 z_2 + kk_u z_1 \tag{30}$$

By Lasalle's invariance theorem and Lasalle-Yoshizawa theorem[4,5,10], the global asymptotic stability is guaranteed at $z_1 = 0$ and $z_2 = 0$ under the conditions of Eqs. (24) and (25). It is shown that all of trajectories of the closed loop adaptive system are converged to the set where $\dot{V}_2 = -c_1 z_1^2 - c_2 z_2^2 = 0$ implying that $\lim_{t\to\infty} z_1(t) = 0$ and $\lim_{t\to\infty} z_2(t) = 0$. That is, because $z_1 = x_1 = S - S_{ref}$ and $z_2 = x_2 - \alpha_1 = X - \alpha_1$, they imply that $S \to S_{ref}$ and $X \to \alpha_1$ as $t \to \infty$. Since $z_1 = x_1$, x_1 is also bounded and converges to zero. From $x_2 = z_2 + \alpha_1$, $\lim_{t\to\infty} x_2 = \alpha_1$ because z_2 goes to zero as $t \to \infty$. That is, x_2 will not converge to zero but to α_1 as $t \to \infty$. $\theta \to \hat{\theta}$ from Eqs. (12) and (13) because $x_2 \to \alpha$ as $t \to \infty$. So $\tilde{\theta} \to 0$ as $t \to \infty$. So $\hat{\theta}$ is bounded because θ is bounded. They mean that the boundedness of z_1, z_2 and $\tilde{\theta}$ is guaranteed. The boundedness of x_2 depends on α_1 because $z_2 = 0$ as $t \to \infty$. It is also shown that x_2 goes to α_1 of Eq. (31) from the fact that $\dot{x}_1 = -kk_u x_2 - k\theta\varphi + (S_{in} - S_{ref})D - \dot{S}_{ref}$ of Eq. (8) goes to zero because not only x_1 and $\dot{x}_1$ converge to zero but also $\hat{\theta} \to \theta$ as $t \to \infty$.

$$\alpha_1 = \alpha_1(0, \varphi, \hat{\theta}, D, \dot{S}_{ref}) = \frac{-k\hat{\theta}\varphi + (S_{in} - S_{ref})D - \dot{S}_{ref}}{kk_u} \tag{31}$$

$$\varphi = \varphi(0, 0, \alpha_1, S_{ref}) = \frac{k_i \mu_m S_{ref} \alpha_1}{k_s k_i + k_i S_{ref} + S_{ref}^2} - k_u \alpha_1 \tag{32}$$

Control input D can be obtained from Eq. (25) to be bounded and satisfy control constraint conditions mentioned as before by choosing c_1 and c_2 properly. The boundedness of α_1 depends on φ from Eq. (31) if S_{in} and S_{ref} are bounded. Finally, φ of Eq. (32) and x_2 can be bounded by choosing c_1, c_2 and α_1 properly.

IV. Simulation results

To verify the effectiveness of the proposed controller, simulations have been done with the changes of reference substrate concentration and influent substrate concentration. The numerical values used for these simulations follow the work of Simutis et al.[3] and are given in Table 1.

Table 1. The numerical values for simulation

Parameters	Units	Values
Saturation constant k_s	g/l	0.1
Maximum specific growth rate μ_m	$1/h$	0.3
Yield coefficient k		2
Inhibition constant k_i	g/l	50
Influent substrate concentration S_{in}	g/l	20

The unit conversion value is chosen to be k_u=0.275$l/(gh)$, constants in controller are $c_1 = 5$ and $c_2 = 1$, and the adaptation gain is $\gamma = 0.0115$. The initial values used for simulation are $\theta = 1$, $S(0)$=1g/l, $X(0)$=0.5g/l and $\hat{\theta}(0) = 1.2$.

The first simulation has been done to show the tracking performance of the proposed controller. Reference substrate concetration S_{ref} is assumed to be changed as a step type as shown in Fig.3 when the influent substrate concentration is constant. The simulation results are shown in Figs. 3-7. The output substrate concentration S tracks reference substrate concentration well as shown in Fig. 3. The variation of the biomass concentration X increases smoothly as shown in Fig. 4. The error estimating parameters $\tilde{\theta}$ converges to zero as shown in Fig. 5. The proposed control input, dilution rate D, and its derivative, dD/dt are shown in Figs. 6 and 7. As shown in Figs. 6 and 7, it is shown that the dilution rate varies in an acceptable range of control constraints mentioned previously.

The second simulation has been done with the change of the influent substrate concentration S_{in} when the reference substrate concentration is unchanged. This simulation has been done to know the controlled system performance under disturbance. The change of S_{in} is also to be a step type as 20, 18, and 24 g/l during each 10 hours. The simulation results are shown in Figs. 8-12. Although there are bigger fluctuations at the time with the change of S_{in} than at the time with the change of S_{ref}, the simulation result with the change of the influent substrate concentration S_{in} shows similar results with the changes of reference substrate concentration and also show the good tracking performance to reference well.

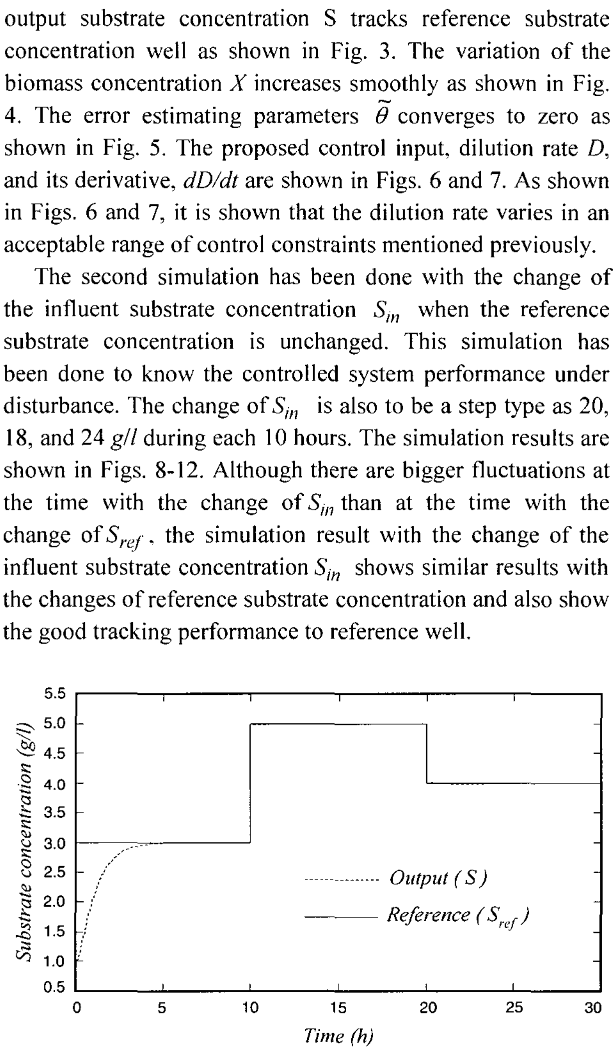

Fig. 3. Output substrate concentration S during the step change of reference substrate concentration S_{ref}

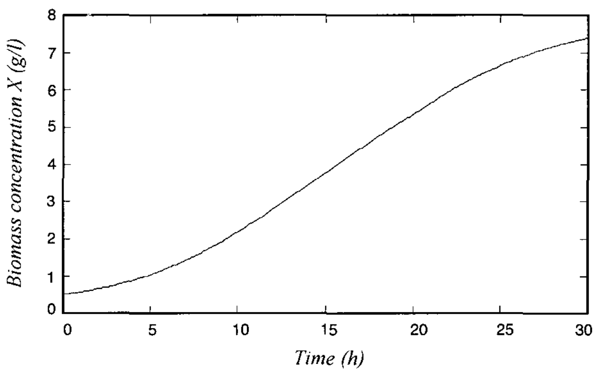

Fig. 4. Biomass concentration X during the step change of reference substrate concentration S_{ref}

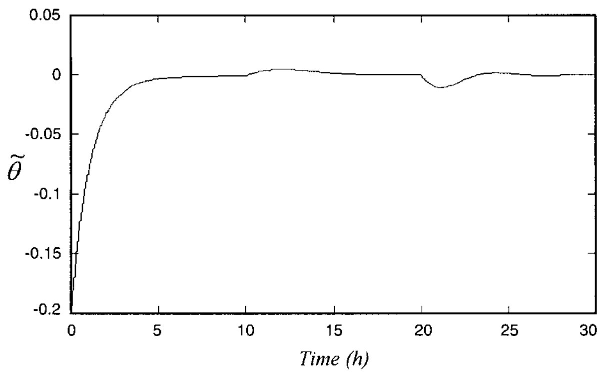

Fig. 5. $\tilde{\theta}$ during the step change of reference substrate concentration S_{ref}

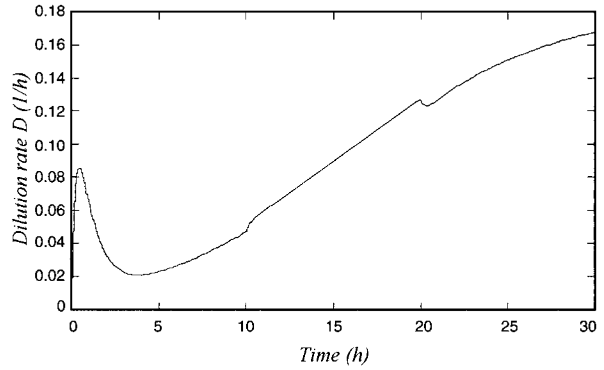

Fig. 6. Dilution rate D (control input) during the step change of reference substrate concentration S_{ref}

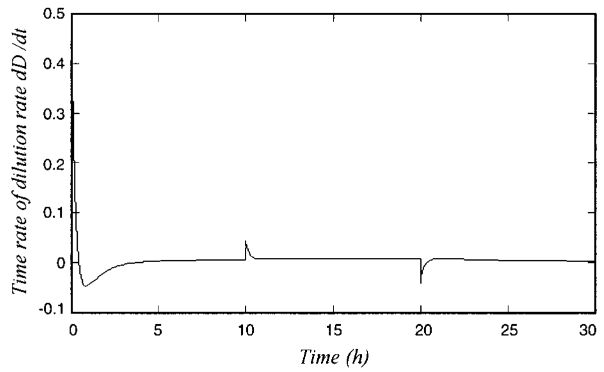

Fig. 7. Time rate of dilution rate dD/dt during the step change of reference substrate concentration S_{ref}

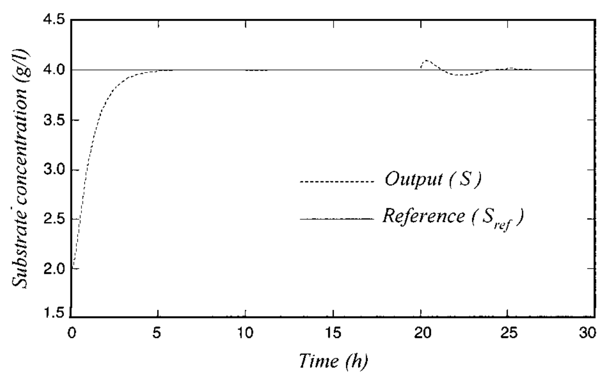

Fig. 8. Output substrate concentration S during the step change of the influent substrate concentration S_{in}

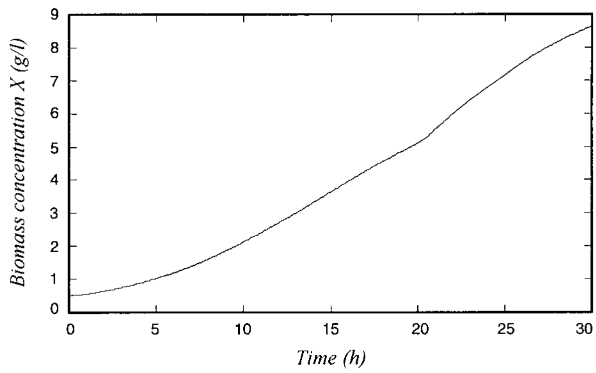

Fig. 9. Biomass concentration X during the step change of the influent substrate concentration S_{in}

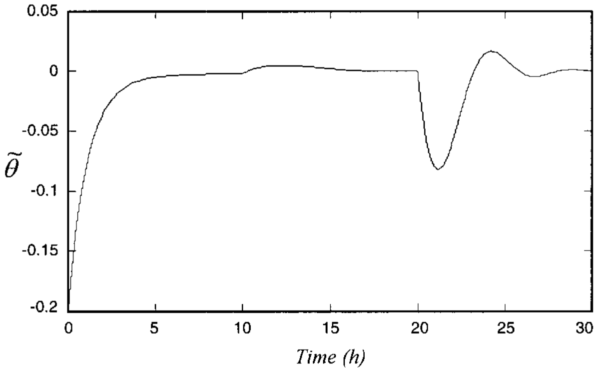

Fig. 10. $\tilde{\theta}$ during the step change of the influent substrate concentration

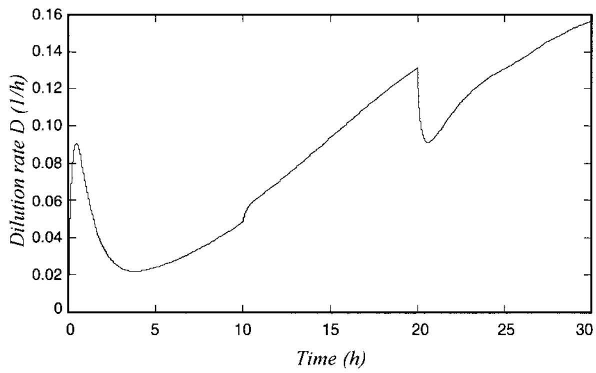

Fig. 11. Dilution rate D (control input) during the step change of the influent substrate concentration S_{in}

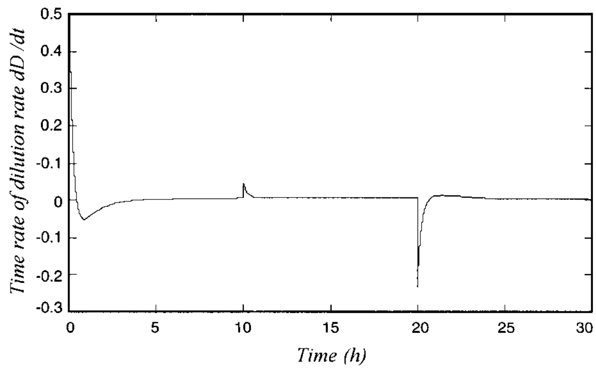

Fig. 12. Time rate of Dilution rate dD/dt during the step change of the influent substrate concentration S_{in}

VI. Conclusion

A nonlinear adaptive controller based on back-stepping method has been introduced for a continuous baker's yeast cultivating process in stirred tank bioreactor. Because of the uncertainty of specific growth rate, the specific growth rate has been modified as a function including the unknown parameter with known bounded values. The simulation results show that the proposed controller can be used for tracking reference substrate concentration with good performance even in the changes of both reference substrate and influent substrate. The proposed controller rejects the effect of the step change of the influent substrate concentration. Smooth biomass concentration is obtained even in both the change of reference substrate concentration and the variation of influent feed substrate concentration for continuous fermentation processes. The dilution rate increases with almost constant slope except when reference substrate concentration and influent substrate concentration are changed to track the reference substrate concentration.

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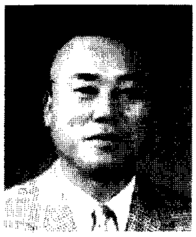

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