

## LECTURES 23-29: Microbial Growth and Bioreactors

**Problem 1:** Consider the model of a constant –volume, non-ideally mixed chemostate with sterile feed, consisting of following equations, with initial condition being given by  $S=X=0$  at  $t=0$ :

$$\frac{dX}{dt} = \frac{X_m - X}{t_{mix}} + \mu X, \quad (1) \quad \frac{X_m - X}{t_{mix}} = -\frac{X_m}{\tau}, \quad (2)$$

$$\frac{dS}{dt} = \frac{S_m - S}{t_{mix}} - \mu X, \quad (3) \quad \frac{S_m - S}{t_{mix}} = \frac{S_0 - S_m}{\tau}, \quad (4)$$

where  $X$  and  $S$  are the average cell and substrate concentrations in the chemostate, respectively, while  $X_m$  and  $S_m$  are the mixing-cup cell and substrate concentrations in the chemostate respectively,  $S_0$  is the inlet substrate concentration,  $t_{mix}$  and  $\tau$  are the mixing time and residence time respectively, and  $\mu$  is the specific growth rate of cells, given by

$$\mu = \frac{\mu_{\max} S}{K_S + S + S^2 / K_I} \quad (5).$$

Obtain the steady states of the above model given by equations (1-5) and examine the stability of each steady-state.

Solution: From equation (2)

$$\frac{X_m - X}{t_{mix}} = -\frac{X_m}{\tau} = -DX_m \quad (10.1)$$

where D- dilution rate

$$X_m = \frac{X\tau}{\tau + t_{mix}} \quad (10.2)$$

Using eqn.(10.2) in eqn.(1), we get

$$\frac{dX}{dt} = \mu X - \frac{X}{\tau + t_{mix}} \quad (10.3)$$

$$\frac{dX}{dt} = \left[ \mu - \frac{D}{\left(1 + \frac{t_{mix}}{\tau}\right)} \right] X \quad (10.4)$$

Also

$$\frac{S_m - S}{t_{mix}} = \frac{S_0 - S_m}{\tau}$$

or

$$S_m = \frac{(S_0 t_{mix} + S\tau)}{\tau + t_{mix}} \quad (10.5)$$

Put eqn. (10.5) into given eqn.(3), so we get

$$\frac{dS}{dt} = \frac{D(S_0 - S)}{\left(1 + \frac{t_{mix}}{\tau}\right)} - \mu X \quad (10.6)$$

and

$$\mu = \frac{\mu_{max} S + \mu_2}{\left(K_s + S + \frac{S^2}{K_I}\right)} \quad (10.7)$$

Now at S.S

$$(A) \quad \frac{dX}{dt} = 0$$

Therefore from (10.4)

$$\left[ \mu - \frac{D}{\left(1 + \frac{t_{mix}}{\tau}\right)} \right] X = 0$$

**Case 1:** if  $X_{ss} \neq 0$  (Non-wash out case)

$$D = \mu \left( 1 + \frac{t_{mix}}{\tau} \right)$$

Lets say

$$\alpha = \left( 1 + \frac{t_{mix}}{\tau} \right) \quad (\alpha > 1)$$

therefore

$$D = \alpha \mu$$

$$D = \alpha (\mu_{max} S_{ss} + \mu_2) \quad (10.8)$$

from eqn.(10.7) and eqn.(10.8)

$$\frac{D}{K_I} S_{ss}^2 + S_{ss} (D - \alpha \mu_{max}) + (DK_s - \alpha \mu_2) = 0 \quad (10.9)$$

$$S_{ss} = \frac{S(\alpha\mu_{\max} - D) \pm \sqrt{(\alpha\mu_{\max} - D)^2 - \frac{4D}{K_I}(DK_s - \alpha\mu^2)}}{\frac{2D}{K_I}} \quad (10.10)$$

(provided determinant >0)

and from eqn.(10.6) (at S.S)

$$\frac{D}{\alpha}(S_0 - S_{ss}) = \mu X \quad (10.11)$$

or

$$X = (S_0 - S_{ss}) \quad [:: D = \alpha\mu]$$

**Case 2:** Wash out state

$$\text{if } \frac{D}{\alpha} > \mu$$

$$X_{ss} = 0$$

$$S_{ss} = S_0$$

**Stability Analysis:**

**Case 1:**  $D = \alpha\mu$

Jacobian matrix can be formed as

$$A = \begin{pmatrix} \frac{\partial f_1}{\partial X} & \frac{\partial f_1}{\partial S} \\ \frac{\partial f_2}{\partial X} & \frac{\partial f_2}{\partial S} \end{pmatrix}$$

$$\frac{\partial f_1}{\partial X} = \left( \mu - \frac{D}{\alpha} \right) = 0 ;$$

$$\frac{\partial f_1}{\partial S} = X \frac{\partial \mu}{\partial S}$$

$$\frac{\partial f_2}{\partial X} = -\mu ;$$

$$\frac{\partial f_2}{\partial S} = -\frac{D}{\alpha} - X \frac{\partial \mu}{\partial S}$$

Now

$$\frac{\partial \mu}{\partial S} = \frac{\mu_{\max} \left( K_s - \frac{S_2}{K_I} \right) - \mu_s \left( 1 + \frac{2S}{K_I} \right)}{\left( K_s + S + \frac{S^2}{K_I} \right)^2} \quad (10.12)$$

$$\therefore A = \begin{pmatrix} 0 & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$$

$$|A - \lambda I| = 0 \quad \begin{vmatrix} -\lambda & a_{12} \\ a_{21} & a_{22} - \lambda \end{vmatrix} = 0$$

$$\lambda^2 - a_{22}\lambda - a_{12}a_{21} = 0$$

Now by Routh-Hurwitz criteria

$$\begin{vmatrix} \beta_1 & \beta_3 \\ 1 & \beta_2 \end{vmatrix} > 0 \quad \beta_1 > 0$$

$$\beta_1 = -a_{22} = \frac{D}{\alpha} + X \frac{\partial \mu}{\partial S}$$

For stability  $\beta_1 > 0$

i.e.  $\frac{\partial \mu}{\partial S} > 0$

Hence from eqn.(10.14)

$$\mu_{\max} \left( K_s - \frac{S^2}{K_I} \right) - \mu_2 \left( 1 + \frac{2S}{K_I} \right) > 0$$

$$\text{Let } \frac{\mu_{\max}}{\mu_2} = \mu'_{\max}$$

$$\therefore \mu'_{\max} \left( K_s - \frac{S^2}{K_I} \right) - \left( 1 + \frac{2S}{K_I} \right) > 0$$

Hence one of the root is

$$\text{root 1} = \frac{\frac{-2}{K_I} + \sqrt{\frac{4}{K_I^2} - \frac{4\mu'_{\max}}{K_I} (1 - \mu'_{\max} K_s)}}{\frac{2\mu'_{\max}}{K_I}}$$

**So for stability**

$$0 < S < \text{root 1}$$

$$S_{ss} < \frac{\frac{-1}{K_I} + \sqrt{1 + \mu'_{\max} K_I (\mu'_{\max} K_s - 1)}}{\mu'_{\max}}$$

(10.13)

Equation (10.13) is the condition for stability.

If  $S_{ss}$  satisfies above condition,  $\beta_2 > 0$  also satisfied and the system steady state would be stable.

### Case 2: Wash-out state

Here  $D > \alpha\mu$  &  $X_{ss} = 0$  &  $S_{ss} = 0$

$$\therefore A = \begin{pmatrix} \mu - \frac{D}{\alpha} & 0 \\ -\mu & \frac{-D}{\alpha} \end{pmatrix}$$

$$|A - \lambda I| = 0 \quad \begin{vmatrix} \left(\mu - \frac{D}{\alpha}\right) - \lambda & 0 \\ -\mu & -D - \lambda \end{vmatrix} = 0$$



## Problem 2:

The following prey-predator model is used to describe the predation by an amoeba on a bacterium. Obtain analytically the steady states of the model and examine their stability using linear stability analysis. All symbols in the model have their usual meanings.

$$\frac{ds}{dt} = D(s_0 - s) - \frac{\mu_s(s)}{Y_s} n_1, \quad (1)$$

$$\frac{dn_1}{dt} = -Dn_1 + \mu_s(s) n_1 - \frac{\mu_p(n_1)}{Y_p} n_2, \quad (2)$$

$$\frac{dn_2}{dt} = -Dn_2 + \mu_p(n_1) n_2. \quad (3)$$

For equation (1), (2) and (3), steady states are

$$D(s_0 - s_s) - \frac{\mu_s(s)}{Y_s} n_{1s} = 0, \quad (12.1)$$

$$-Dn_{1s} + \mu_s(s)n_{1s} - \frac{\mu_p(n_{1s})}{Y_p} n_{2s} = 0, \quad (12.2)$$

$$-n_{2s} (D - \mu_p(n_{1s})) = 0 \quad (12.3)$$

from (12.3)  $n_{2s} = 0$  or  $D = \mu_p(n_{1s})$

for  $n_{2s} = 0$ , from (12.2)

$$-n_{1s} (D - \mu_s(s)) = 0$$

$$n_{1s} = 0$$

Therefore from eqn.(12.1)

$$S_s = S_0$$

or  $D = \mu_s (s_s)$

$$D = \frac{\mu_{s\max} S_s}{K_s + S_s} \Rightarrow S_s = \frac{DK_s}{(\mu_{\max} - D)} \quad (12.4)$$

(for  $\mu_{\max} > D$ )

Now from (12.1) & (12.4)

$$D \left( S_0 - \frac{DK_s}{(\mu_{s\max} - D)} \right) = \frac{D}{\gamma_s} n_{1s}$$

Therefore

$$n_{1s} = \gamma_s \left( s_0 - \frac{DK_s}{(\mu_{s\max} - D)} \right)$$

For  $D = \mu_p(n_{1s})$

$$D = \frac{\mu_{p\max} n_{1s}}{K_p + n_{1s}} \Rightarrow n_{1s} = \frac{K_p D}{(\mu_{p\max} - D)}$$

$$\left( \text{for } \mu_{p\max} > D \right)$$

Putting in eqn.(12.1) we get

$$D(s_0 - s_s) - \frac{\mu_{s \max} s_s}{\gamma_s (K_s + s_s)} \frac{K_p D}{(\mu_{p \max} - D)} = 0$$

Solving for  $s_s$

$$s_s = \frac{-B + \sqrt{B^2 + 4s_0 K_s}}{2} \quad (12.5)$$

where

$$B = \left[ \frac{\mu_{s \max} n_{1s}}{D \gamma_s} - K_s + s_0 \right]$$

Also from eqn. (12.2)

$$-Dn_{1s} + \gamma_s D(s_0 - s) - \frac{D}{\gamma_p} n_{2s} = 0$$

$$\therefore n_{2s} = \gamma_p \left[ -n_{1s} + \gamma_s (s_0 - s_s) \right] \quad (12.6)$$

So steady states are as follows:

Steady State 1:

$$s_s = s_0$$

$$n_{1s} = 0$$

$$n_{2s} = 0$$

Steady State 2:

$$S_s = \frac{K_s D}{(\mu_{s \max} - D)}$$

$$n_{1s} = \gamma_s \left( S_0 - \frac{DK_s}{(\mu_{s \max} - D)} \right)$$

$$n_{2s} = 0$$

and

Steady State 3:

$$S_s = \frac{-B + \sqrt{B^2 + 4s_0 K_s}}{2}$$

$$n_{1s} = \frac{K_p D}{(\mu_{p \max} - D)}$$

$$n_{2s} = \gamma_p \left[ \frac{-K_p D}{(\mu_{p \max} - D)} + \gamma_s \left[ s_0 - \left( \frac{-B + \sqrt{B^2 - 4s_0 K_s}}{2} \right) \right] \right]$$

Where

$$B = \left[ \frac{\mu_{s \max}}{D \gamma_s} \frac{K_p D}{(\mu_{p \max} - D)} - K_s + s_0 \right]$$

## Linear Stability Analysis:

Jacobian matrix can be formed as

$$J = \begin{pmatrix} -D - \frac{n_1}{\gamma_s} \frac{\partial \mu_s(s)}{\partial s} & \frac{-\mu_s}{Y_s} & 0 \\ n_1 \frac{\partial \mu_s(s)}{\partial s} & \left( -D + \mu_s(s) - \frac{n_2}{\gamma_p} \frac{\partial \mu_p(n_1)}{\partial n_1} \right) & \frac{-\mu_p(n_1)}{\gamma_p} \\ 0 & n_2 \frac{\partial \mu_p(n_1)}{\partial n_1} & -D + \mu_p(n_1) \end{pmatrix} \quad (12.7)$$

$$\frac{\partial \mu_s}{\partial s} = \frac{\mu_{s \max} K_s}{(K_s + s)^2}$$

$$\frac{\partial \mu_p}{\partial n_1} = \frac{\mu_{p \max} K_p}{(K_p + n_1)^2}$$

Thus for Steady State 1, (0,0,0), we have

$$A = \begin{pmatrix} -D & 0 & 0 \\ 0 & -D & 0 \\ 0 & 0 & -D \end{pmatrix}$$

$$|A - \lambda I| = 0$$

$$|A - \lambda I| = 0$$

$$\lambda_i = a_{33} \quad \text{and} \quad \left[ \lambda_i^2 - \lambda_i a_{11} - a_{21} a_{12} \right] = 0$$

Now  $a_{33} < 0$  and

$$-a_{11} > 0 \quad \text{so} \quad a_{11} < 0$$

$$-a_{21} a_{12} > 0$$

Now

$$a_{11} = - \left( D + \frac{n_{1s}}{\gamma_s} \frac{\partial \mu_s}{\partial s} \right)$$

$$(D + \lambda)^3 = 0 \quad \Rightarrow \quad \lambda_i = -D$$

So as  $D$  is always  $>0$ , so  $\lambda_i < 0$

So Stable Steady State.

Now, for steady state 2, we have

$$A = \begin{pmatrix} a_{11} & \frac{D}{\gamma_s} & 0 \\ a_{21} & 0 & \frac{-\mu_p(n_1)}{\gamma_p} \\ 0 & 0 & -D + \mu_p(n_1) \end{pmatrix}$$

Now  $\left( D + \frac{n_{1s}}{\gamma_s} \frac{\partial \mu_s}{\partial s} \right)$  is always +ve

so  $a_{11} < 0$  is satisfied

$$\begin{aligned} a_{33} &= -D + \mu_p (n_1) \\ &= -D \frac{\mu_{p \max} \left[ \gamma_s \left( s_0 - \frac{DK_s}{(\mu_{s \max} - D)} \right) \right]}{K_p + \gamma_s \left( s_0 - \frac{DK_s}{(\mu_{s \max} - D)} \right)} \end{aligned}$$

$$\Rightarrow -D(K_p + n_{1s}) + \mu_{p \max} n_{1s} < 0$$

$$\therefore \frac{-DK_p}{(\mu_{p \max} - D)} < n_{1s}$$

For  $D > \mu_{p\max}$

$$\frac{-DK_p}{(\mu_{p\max} - D)} > n_{1s}$$

So for  $D > \mu_{p\max}$  and  $D < \mu_{p\max}$ , this condition should be satisfied.

For Stability

$$\frac{K_p}{(D - \mu_{p\max})} > \frac{K_s}{(\mu_{s\max} - D)}$$

Now  $-a_{21} \cdot a_{12} > 0$

$$a_{21} = n_{1s} \frac{\partial \mu_s}{\partial s} > 0$$

$$a_{12} = -\frac{\mu_s(s)}{\gamma_s} < 0$$

So condition  $-a_{21} \cdot a_{12} > 0$  is always satisfied

so steady state exist only if  $D < \mu_{s \max}$  and stable for  $D < \mu_{p \max}$  .

and conditionally stable for  $D > \mu_{p \max}$  only if

$$\frac{K_p}{(D - \mu_{p \max})} > \frac{K_s}{(\mu_{s \max} - D)}$$