

Batch Fermentation /w pH Inhibition. Model parameter estimation from dynamic data.
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Model parameters

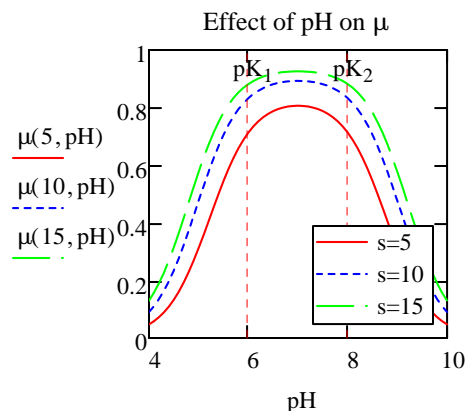
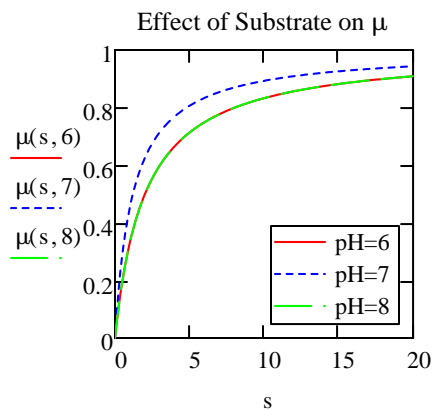
$$\mu_m := 1 \text{ hr}^{-1} \quad K_s := 1 \text{ g/L} \quad pK_1 := 6 \quad K_1 := 10^{-pK_1}$$

$$Y_x := 0.5 \text{ g biomass/g substrate} \quad pK_2 := 8 \quad K_2 := 10^{-pK_2}$$

$$\mu(s, H) = \frac{\mu_m \cdot s}{K_s \cdot \left(1 + \frac{H}{K_1} + \frac{K_2}{H}\right) + s}$$

$$\mu(s, \text{pH}) := \frac{\mu_m \cdot s}{K_s \cdot \left(1 + 10^{-\text{pH} + pK_1} + 10^{-pK_2 + \text{pH}}\right) + s}$$

Product formation $\alpha := 10^{-5} \text{ mole H/g biomass}$ $\beta := 10^{-7} \text{ mole H/(hr-g biomass)}$
 $s := 0, 0.1 \dots 20$ $\text{pH} := 4, 4.1 \dots 10$



This organism is actually quite pH tolerant. It grows over a very wide pH range.

Simulate batch fermentation. Initial condition $x_0 := 0.1\text{g/L}$ $s_0 := 10 \text{ g/L}$ $H_0 := 10^{-9} \text{ mole/L}$

ODEs

$$\text{pH}_0 := -\log(H_0) = 9$$

$$\text{dxdt}(x, s, H) := \mu(s, -\log(H)) \cdot x \quad \dots \text{biomass}$$

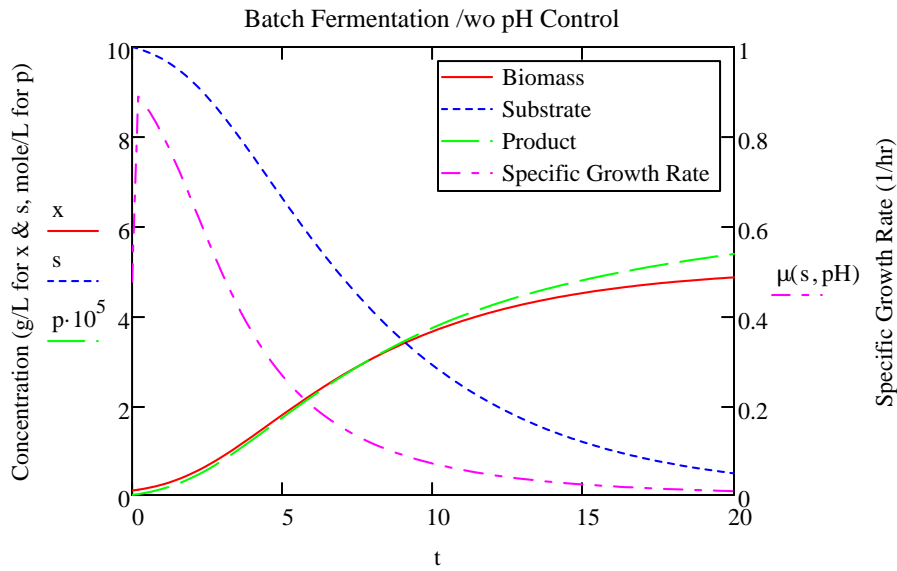
$$\text{dsdt}(x, s, H) := -\frac{1}{Y_x} \cdot \mu(s, -\log(H)) \cdot x \quad \dots \text{substrate}$$

$$\text{dHdt}(x, s, H) := \alpha \cdot \mu(s, -\log(H)) \cdot x + \beta \cdot x \quad \dots \text{product (which is directly related to H)}$$

$$\text{dydt}(t, y) := \begin{pmatrix} \text{dxdt}(y_0, y_1, y_2) \\ \text{dsdt}(y_0, y_1, y_2) \\ \text{dHdt}(y_0, y_1, y_2) \end{pmatrix} \quad \text{I.C.} \quad y_{\text{init}} := \begin{pmatrix} x_0 \\ s_0 \\ H_0 \end{pmatrix}$$

Length of time to complete fermentation $t_f := 20$ $n := 100$

$$ty := \text{rkfixed}(y_{\text{init}}, 0, t_f, n, \text{dydt}) \quad t := ty^{\langle 0 \rangle} \quad x := ty^{\langle 1 \rangle} \quad s := ty^{\langle 2 \rangle} \quad H := ty^{\langle 3 \rangle} \quad \text{pH} := -\log(H) \quad p := H$$



ODEs with pH controlled at pH=7 Time (hr)

$$dxdt(x, s, p) := \mu(s, 7) \cdot x \quad \dots \text{biomass}$$

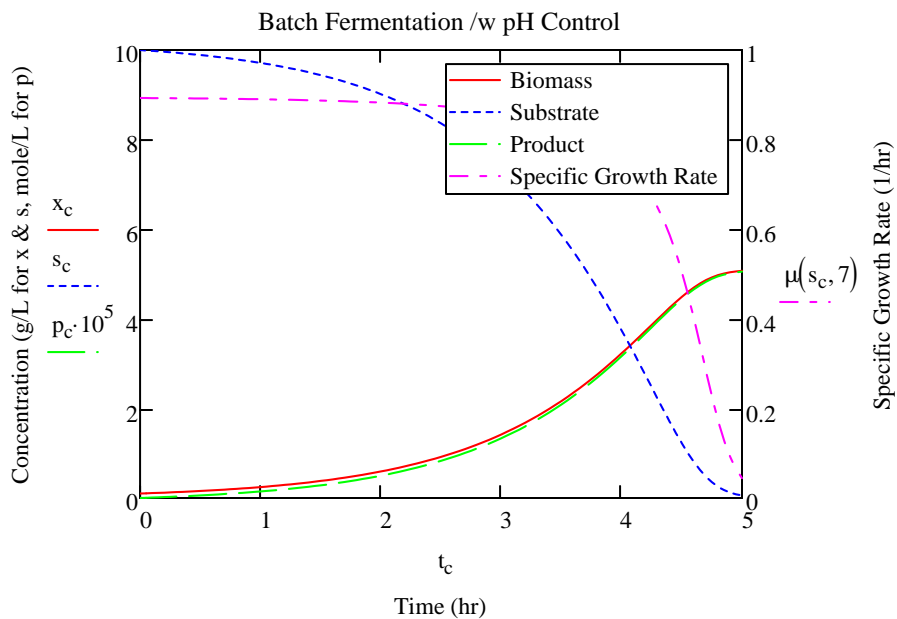
$$dsdt(x, s, p) := -\frac{1}{Y_x} \cdot \mu(s, 7) \cdot x \quad \dots \text{substrate}$$

$$dpdt(x, s, p) := \alpha \cdot \mu(s, 7) \cdot x + \beta \cdot x \quad \dots \text{product}$$

$$dydt(t, y) := \begin{pmatrix} dxdt(y_0, y_1, y_2) \\ dsdt(y_0, y_1, y_2) \\ dpdt(y_0, y_1, y_2) \end{pmatrix} \quad \text{I.C.} \quad y_{init} := \begin{pmatrix} x_0 \\ s_0 \\ H_0 \end{pmatrix}$$

Length of time to complete fermentation $t_{fc} := 5$

$$ty_c := rkfixed(y_{init}, 0, t_{fc}, n, dydt) \quad t_c := ty_c \langle 0 \rangle \quad x_c := ty_c \langle 1 \rangle \quad s_c := ty_c \langle 2 \rangle \quad p_c := ty_c \langle 3 \rangle$$



Note that biomass and product concentrations closely match, because product formation is dominated by the growth-related term $\alpha \cdot \mu \cdot x$.

Without pH control, fermentation lasted $t_f = 20 \text{ hr}$ Product productivity $\frac{H_n - H_0}{t_f} = 2.69 \times 10^{-6} \text{ mole/(L}\cdot\text{h)}$

With pH control, fermentation lasted $t_{fc} = 5 \text{ hr}$ Product productivity $\frac{p_n - H_0}{t_{fc}} = 1.076 \times 10^{-5} \text{ mole/(L}\cdot\text{h)}$

Product productivity with pH control is ~5X higher than that without pH control.

Estimate Model Parameter from Dynamic Data. Estimate 4 model parameters simultaneously.

$$p := (\mu_m \ K_s)^T$$

$$\text{ty}(p) := \begin{cases} (\mu_m \ K_s) \leftarrow p^T \\ \mu(s, \text{pH}) \leftarrow \frac{\mu_m \cdot s}{K_s \cdot \left(1 + 10^{-\text{pH} + \text{p}K_1} + 10^{-\text{p}K_2 + \text{pH}}\right) + s} \\ \text{dxdt}(x, s, H) \leftarrow \mu(s, -\log(H)) \cdot x \\ \text{dsdt}(x, s, H) \leftarrow -\frac{1}{Y_x} \cdot \mu(s, -\log(H)) \cdot x \\ \text{dHdt}(x, s, H) \leftarrow \alpha \cdot \mu(s, -\log(H)) \cdot x + \beta \cdot x \\ \text{dydt}(t, y) \leftarrow \begin{pmatrix} \text{dxdt}(y_0, y_1, y_2) \\ \text{dsdt}(y_0, y_1, y_2) \\ \text{dHdt}(y_0, y_1, y_2) \end{pmatrix} \\ \text{ty} \leftarrow \text{rkfixed}(y_{\text{init}}, 0, t_f, n, \text{dydt}) \end{cases}$$

True: $\text{ty}_m := \text{ty}(p) \quad t := \text{ty}_m^{(0)} \quad x_m := \text{ty}_m^{(1)} \quad s_m := \text{ty}_m^{(2)} \quad H_m := \text{ty}_m^{(3)} \quad \text{pH}_m := -\log(H_m)$

$$\text{sse}(p) := \begin{cases} \text{ty} \leftarrow \text{ty}(p) \\ (x \ s \ H) \leftarrow (\text{ty}^{(1)} \ \text{ty}^{(2)} \ \text{ty}^{(3)}) \\ \text{pH} \leftarrow -\log(H) \\ \text{sse} \leftarrow (x - x_m) \cdot (x - x_m) + (s - s_m) \cdot (s - s_m) + (\text{pH} - \text{pH}_m) \cdot (\text{pH} - \text{pH}_m) \end{cases}$$

True value: $p^T = (1 \ 1)$

Initial guess: $p := (10 \ 10)^T \quad \text{sse}(p) = 308.744$

Estimated value: $p := \text{Minimize}(\text{sse}, p) = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad \text{sse}(p) = 1.933 \times 10^{-11} \quad \dots \text{ Good!}$

Estimate 4 model parameters simultaneously.

$$p := (\mu_m \quad K_s \quad pK_1 \quad pK_2)^T$$

$$\begin{aligned}
 \text{ty}(p) := & \left(\mu_m \quad K_s \quad pK_1 \quad pK_2 \right) \leftarrow p^T \\
 \mu(s, \text{pH}) \leftarrow & \frac{\mu_m \cdot s}{K_s \cdot \left(1 + 10^{-\text{pH} + pK_1} + 10^{-pK_2 + \text{pH}} \right) + s} \\
 \text{dxdt}(x, s, H) \leftarrow & \mu(s, -\log(H)) \cdot x \\
 \text{dsdt}(x, s, H) \leftarrow & -\frac{1}{Y_x} \cdot \mu(s, -\log(H)) \cdot x \\
 \text{dHdt}(x, s, H) \leftarrow & \alpha \cdot \mu(s, -\log(H)) \cdot x + \beta \cdot x \\
 \text{dydt}(t, y) \leftarrow & \begin{pmatrix} \text{dxdt}(y_0, y_1, y_2) \\ \text{dsdt}(y_0, y_1, y_2) \\ \text{dHdt}(y_0, y_1, y_2) \end{pmatrix} \\
 \text{ty} \leftarrow & \text{rkfixed}(y_{\text{init}}, 0, t_f, n, \text{dydt})
 \end{aligned}$$

True: $ty_m := \text{ty}(p) \quad t := ty_m^{(0)} \quad x_m := ty_m^{(1)} \quad s_m := ty_m^{(2)} \quad H_m := ty_m^{(3)} \quad \text{pH}_m := -\log(H_m)$

$$\begin{aligned}
 \text{sse}(p) := & \left| \begin{array}{l} \text{ty} \leftarrow \text{ty}(p) \\ (x \quad s \quad H) \leftarrow (ty^{(1)} \quad ty^{(2)} \quad ty^{(3)}) \\ \text{pH} \leftarrow -\log(H) \\ \text{sse} \leftarrow (x - x_m) \cdot (x - x_m) + (s - s_m) \cdot (s - s_m) + (\text{pH} - \text{pH}_m) \cdot (\text{pH} - \text{pH}_m) \end{array} \right.
 \end{aligned}$$

True value: $p^T = (1 \quad 1 \quad 6 \quad 8)$

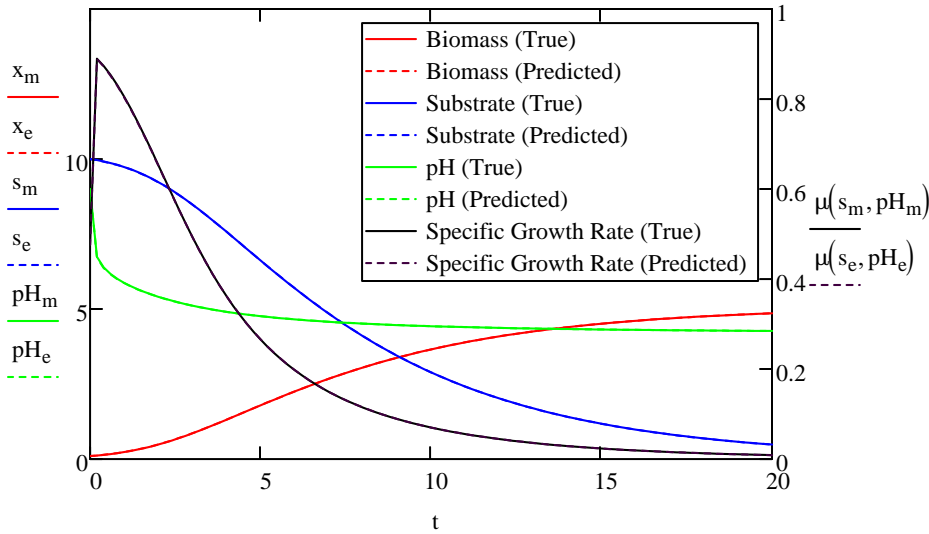
Initial guess: $p := (2 \quad 2 \quad 5 \quad 10)^T \quad \text{sse}(p) = 1.563 \times 10^3$

Estimated value: $p := \text{Minimize}(\text{sse}, p) = \begin{pmatrix} 1.097 \\ 2.159 \\ 5.697 \\ 9.968 \end{pmatrix} \quad \text{sse}(p) = 2.791 \times 10^{-3}$

← K_s, pK_1, pK_2 estimates are off.

Estimated values of x, s, pH are good.

Predicted: $ty_e := \text{ty}(p) \quad t := ty_e^{(0)} \quad x_e := ty_e^{(1)} \quad s_e := ty_e^{(2)} \quad H_e := ty_e^{(3)} \quad \text{pH}_e := -\log(H_e)$



Estimate 5 model parameters simultaneously.

$$p := (\mu_m \ K_s \ pK_1 \ pK_2 \ Y_x)^T$$

$$ty(p) := \begin{cases} (\mu_m \ K_s \ pK_1 \ pK_2 \ Y_x) \leftarrow p^T \\ \mu(s, pH) \leftarrow \frac{\mu_m \cdot s}{K_s \cdot (1 + 10^{-pH+pK_1} + 10^{-pK_2+pH}) + s} \\ dxdt(x, s, H) \leftarrow \mu(s, -\log(H)) \cdot x \\ dsdt(x, s, H) \leftarrow -\frac{1}{Y_x} \cdot \mu(s, -\log(H)) \cdot x \\ dHdt(x, s, H) \leftarrow \alpha \cdot \mu(s, -\log(H)) \cdot x + \beta \cdot x \\ dydt(t, y) \leftarrow \begin{pmatrix} dxdt(y_0, y_1, y_2) \\ dsdt(y_0, y_1, y_2) \\ dHdt(y_0, y_1, y_2) \end{pmatrix} \\ ty \leftarrow rkfixed(y_{init}, 0, t_f, n, dydt) \end{cases}$$

True: $ty_m := ty(p) \quad t := ty_m^{(0)} \quad x_m := ty_m^{(1)} \quad s_m := ty_m^{(2)} \quad H_m := ty_m^{(3)} \quad pH_m := -\log(H_m)$

$$sse(p) := \begin{cases} ty \leftarrow ty(p) \\ (x \ s \ H) \leftarrow (ty^{(1)} \ ty^{(2)} \ ty^{(3)}) \\ pH \leftarrow -\log(H) \\ sse \leftarrow (x - x_m) \cdot (x - x_m) + (s - s_m) \cdot (s - s_m) + (pH - pH_m) \cdot (pH - pH_m) \end{cases}$$

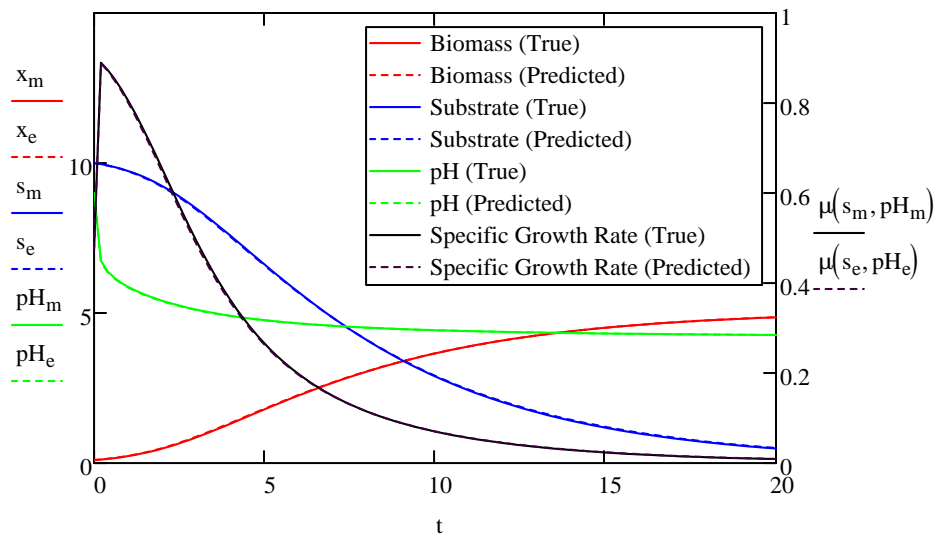
True value: $p^T = (1 \ 1 \ 6 \ 8 \ 0.5)$

Initial guess: $p := (2 \ 2 \ 5 \ 10 \ 1)^T$ $sse(p) = 4.133 \times 10^3$

Estimated value: $p := \text{Minimize}(sse, p) = \begin{pmatrix} 1.111 \\ 2.024 \\ 5.74 \\ 9.947 \\ 0.501 \end{pmatrix}$ $sse(p) = 0.077$

← K_s, pK_1, pK_2 estimates are off.
 Estimated values of x, s, pH are good.

Predicted: $ty_e := ty(p)$ $t := ty_e^{(0)}$ $x_e := ty_e^{(1)}$ $s_e := ty_e^{(2)}$ $H_e := ty_e^{(3)}$ $pH_e := -\log(H_e)$



Estimate all 7 model parameters simultaneously. Since α & β are not $O(1)$, the sse minimization step will terminate prematurely and return the same set of parameters as the initial guess. Here we adjust the magnitude to bring all parameters to $O(1)$.

$$p := \left(\mu_m \quad K_s \quad pK_1 \quad pK_2 \quad Y_x \quad \alpha \cdot 10^5 \quad \beta \cdot 10^7 \right)^T$$

$$ty(p) := \begin{cases} \left(\mu_m \quad K_s \quad pK_1 \quad pK_2 \quad Y_x \quad \alpha \quad \beta \right) \leftarrow p^T \\ \alpha \leftarrow \alpha \cdot 10^{-5} \\ \beta \leftarrow \beta \cdot 10^{-7} \\ \mu(s, pH) \leftarrow \frac{\mu_m \cdot s}{K_s \cdot \left(1 + 10^{-pH+pK_1} + 10^{-pK_2+pH} \right) + s} \\ dxdt(x, s, H) \leftarrow \mu(s, -\log(H)) \cdot x \\ dsdt(x, s, H) \leftarrow -\frac{1}{Y_x} \cdot \mu(s, -\log(H)) \cdot x \\ dHdt(x, s, H) \leftarrow \alpha \cdot \mu(s, -\log(H)) \cdot x + \beta \cdot x \\ dydt(t, y) \leftarrow \begin{pmatrix} dxdt(y_0, y_1, y_2) \\ dsdt(y_0, y_1, y_2) \\ dHdt(y_0, y_1, y_2) \end{pmatrix} \\ ty \leftarrow rkfixed(y_{init}, 0, t_f, n, dydt) \end{cases}$$

True: $ty_m := ty(p) \quad t := ty_m^{(0)} \quad x_m := ty_m^{(1)} \quad s_m := ty_m^{(2)} \quad H_m := ty_m^{(3)} \quad pH_m := -\log(H_m)$

$$sse(p) := \begin{cases} ty \leftarrow ty(p) \\ (x \quad s \quad H) \leftarrow (ty^{(1)} \quad ty^{(2)} \quad ty^{(3)}) \\ pH \leftarrow -\log(H) \\ sse \leftarrow (x - x_m) \cdot (x - x_m) + (s - s_m) \cdot (s - s_m) + (pH - pH_m) \cdot (pH - pH_m) \end{cases}$$

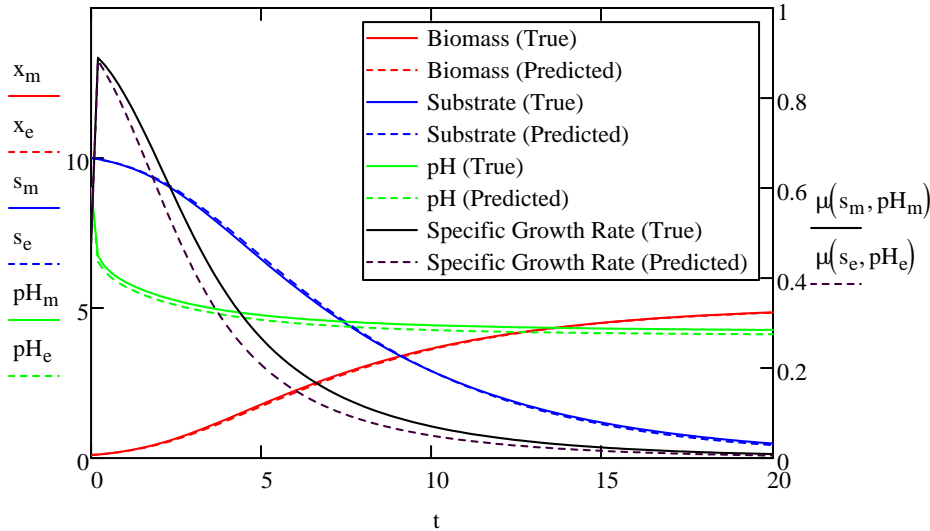
True value: $p^T = (1 \quad 1 \quad 6 \quad 8 \quad 0.5 \quad 1 \quad 1)$

Initial guess: $p := (2 \quad 2 \quad 5 \quad 10 \quad 1 \quad 2 \quad 0.5)^T \quad sse(p) = 3.276 \times 10^3$

Estimated value: $p := \text{Minimize}(sse, p) = \begin{pmatrix} 1.049 \\ 2.167 \\ 5.495 \\ 9.958 \\ 0.496 \\ 1.512 \\ 0.496 \end{pmatrix} \quad sse(p) = 2.86$

← $K_s, pK_1, pK_2, \alpha, \text{ \& } \beta$ estimates are off.
The estimated values of x, s, pH are ok.

Predicted: $ty_e := ty(p)$ $t := ty_e^{(0)}$ $x_e := ty_e^{(1)}$ $s_e := ty_e^{(2)}$ $H_e := ty_e^{(3)}$ $pH_e := -\log(H_e)$



In general, μ_m and Y_x are estimated well. The estimated pK_1 value is adjusted from the initial guess toward the true value, but the estimated pK_2 value does not change much from the initial guess, because the pH dynamic data do not stay around the pK_2 range. Likewise, the K_s value is not estimated well, because the dynamic data for s do not hover around the K_s range for long. The value of α & β estimates are off with α been adjusted toward the true value more than β , because the growth-related term $\alpha \cdot \mu \cdot x$ overshadows the maintenance-related term $\beta \cdot x$ in dp/dt . If we let fermentation run longer such that the term the term $\beta \cdot x$ becomes more significant than the term $\alpha \cdot \mu \cdot x$, we will be able to estimate β better. The predicted values of x , s , pH are all quite good. **In summary, to achieve better estimates of all the model parameters, we need to have data from more runs that cover the range of the model variables being estimated.**