

SSY280 Model predictive control
Assignment 2
Steady state targets and disturbance modeling
Group 20

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1 Introduction

This report is about obtaining zero off-set when applying MPC control to a MIMO plant, and using this knowledge to control a chemical reactor model. An offset-free controller is one that drives controlled outputs to their desired targets at steady state. In the linear model predictive control (MPC) framework, offset-free control is usually achieved by adding step disturbances to the process model.

2 Steady-state targets

In this section, we consider the following system with two inputs and two outputs:

$$A = \begin{bmatrix} 0.5 & 0 & 0 & 0 \\ 0 & 0.6 & 0 & 0 \\ 0 & 0 & 0.5 & 0 \\ 0 & 0 & 0 & 0.6 \end{bmatrix}, B = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.4 \\ 0.25 & 0 \\ 0 & 0.6 \end{bmatrix}, C = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix}$$

And the task is to find the setpoint targets (x_s, u_s, z_s) .

2.1 Task a) Both manipulated input are used for control

In this case the system inputs, m is equal to the number of outputs, $p = m$ and the output setpoint is defined, $z_{sp} = [1 \ -1]^T$. The given C matrix has dimension (2×4) and thus the output vector y has dimension (2×1) . Since the given setpoint vector with controlled outputs z_{sp} has dimension (2×1) to $z_{sp} = y_{sp}$ and $C = C_z$ for this case. To find the steady state targets the system in 1 is solved.

$$\underbrace{\begin{bmatrix} I - A & -B \\ C_z & 0 \end{bmatrix}}_{A_{eq}} \begin{bmatrix} x_s \\ u_s \end{bmatrix} = \underbrace{\begin{bmatrix} 0 \\ z_{sp} \end{bmatrix}}_{b_{eq}} \quad (1)$$

Solve the system of linear equations in MATLAB either using $A_{eq} \setminus b_{eq}$ or the function 'linsolve' to find the steady state targets.

The steady state target is:

$$x_s = \begin{bmatrix} 2.5 \\ -1.5 \\ 1.25 \\ -2.25 \end{bmatrix} \quad u_s = \begin{bmatrix} 2.5 \\ -1.5 \end{bmatrix} \quad z_s = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

In order to check if the output setpoint is possible to attain, $HCx_s = C_z x_s = z_{sp} = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$ must be fulfilled. Since $C = C_z$ the 'selection matrix' $H = I_4$ and then it is fulfilled, when assuming the controlled outputs are a selection of the measured outputs.

2.2 Task b) Only the first manipulated input is available for control

In this case only the first manipulated input is available for control, so the number of outputs p are more than the number of inputs m , ($p > m$). Then there are more

equations than unknown and is an overdetermined problem witch in general has no solutions, since there is not a full row rank. If there is any solution, it means that some equations are linear combinations of others. Which isn't the case for this task so the output setpoint in (a) is not attainable, and we can not get the target setpoint in this case.

It is possible though to get a solution using least square for this problem. Then the solution that has the smallest error is attained by minimizing the difference between Cx_s and setpoint y_{sp} . This is done below by solving the following optimization problem using $Q_s = I$ and $R_s = 0$:

$$\min_{x_s, u_s} (|Cx_s - y_{sp}|_{Q_s}^2), \quad Q_s \succeq 0 \quad (2)$$

$$\text{s.t.} \quad \underbrace{\begin{bmatrix} I - A & -B \end{bmatrix}}_{A_{eq}} \underbrace{\begin{bmatrix} x_s \\ u_s \end{bmatrix}}_z = \underbrace{0}_{b_{eq}} \quad (3)$$

Rewrite the optimization problem on form:

$$\min_z \quad \frac{1}{2} z^T H_M z + f^T z \quad (4)$$

$$\text{s.t.} \quad A_{eq} z = b_{eq} \quad (5)$$

With $z = [x_{s1} \quad x_{s2} \quad x_{s3} \quad x_{s4} \quad u_{s1}]^T$

$$\Rightarrow \min_{x_s, u_s} (|Cx_s - y_{sp}|_{Q_s}^2) \quad (6)$$

$$= \min_{x_s, u_s} ((Cx_s - y_{sp})^T Q_s (Cx_s - y_{sp})) \quad (7)$$

$$= \min_{x_s, u_s} (x_s^T \underbrace{C^T Q C}_{2\bar{H}_x} x_s - \underbrace{2y_{sp}^T Q C}_{f_x^T} x_s + \underbrace{y_{sp}^T Q y_{sp}}_{constant}) \quad (8)$$

Then the we get the Hessian matrix H:

$$H_M = \begin{bmatrix} 2 & 2 & 0 & 0 & 0 \\ 2 & 2 & 0 & 0 & 0 \\ 0 & 0 & 2 & 2 & 0 \\ 0 & 0 & 2 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}, f = \begin{bmatrix} -2 \\ -2 \\ 2 \\ 2 \\ 0 \end{bmatrix}$$

$$A_{eq} = \begin{bmatrix} 0.5 & 0 & 0 & 0 & -0.5 \\ 0 & 0.4 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0 & -0.25 \\ 0 & 0 & 0 & 0.4 & 0 \end{bmatrix}, b_{eq} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Then using the MATLAB function 'quadprog' the target setpoints that is optimal for this case is obtained:

$$x_s = \begin{bmatrix} 0.4 \\ 0 \\ 0.2 \\ 0 \end{bmatrix}, \quad u_s = 0.4, \quad z_s = \begin{bmatrix} 0.4 \\ 0.2 \end{bmatrix}$$

2.3 Task c) Only the first output has a set point

In this case both manipulated inputs are available for control, but only the first output has a setpoint, so the number of inputs, m are more than the number of outputs, p ($p < m$).

To find the best steady state targets, we need to solve the following optimization problem using $(Q_s = 0, R_s = I)$, $u_{sp} = [0 \ 0]^T$:

$$\min_{x_s, u_s} (|u_s - u_{sp}|_{R_s}^2) \quad (9)$$

$$\text{s.t.} \quad \begin{bmatrix} I - A & -B \\ C_z & 0 \end{bmatrix} \begin{bmatrix} x_s \\ u_s \end{bmatrix} = \begin{bmatrix} 0 \\ z_{sp} \end{bmatrix} \quad (10)$$

Rewrite the optimization problem on form :

$$\min_z \frac{1}{2} z^T H_M z + f^T z \quad (11)$$

$$\text{s.t.} \quad A_{eq} z = b_{eq} \quad (12)$$

With $z = [x_{s1} \ x_{s2} \ x_{s3} \ x_{s4} \ u_{s1} \ u_{s2}]^T$

$$\min_{x_s, u_s} (|u_s - u_{sp}|_{R_s}^2) \quad (13)$$

$$= \min_{x_s, u_s} ((u_s - u_{sp})^T R_s (u_s - u_{sp})) \quad (14)$$

$$= \min_{x_s, u_s} (u_s^T \underbrace{R_s}_{2\bar{H}_u} u_s - \underbrace{2u_{sp}^T R_s}_{f_u^T} u_s + \underbrace{u_{sp}^T R_s u_{sp}}_{constant}) \quad (15)$$

Then the Hessian matrix should be:

$$H_M = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 \end{bmatrix}, f = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$A_{eq} = \begin{bmatrix} 0.5 & 0 & 0 & 0 & -0.5 & 0 \\ 0 & 0.4 & 0 & 0 & 0 & -0.4 \\ 0 & 0 & 0.5 & 0 & -0.25 & 0 \\ 0 & 0 & 0 & 0.4 & 0 & -0.6 \\ 1 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}, b_{eq} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

The target setpoints are:

$$x_s = \begin{bmatrix} 0.5 \\ 0.5 \\ 0.25 \\ 0.75 \end{bmatrix}, \quad u_s = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}, \quad z_s = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Comments: Here the number of inputs are more than the number of outputs, so there are fewer equations than unknown, so this is an undetermined problem. An undetermined linear system has either no solution or infinitely many solutions. In our case there are infinitely many solutions and we solve it by using the MATLAB function 'quadprog' to find the optimal one which is given above.

3 Chemical reactor control

3.1 Introduction

In this part we apply MPC to this chemical reactor model, including a disturbance model to achieve off-set control of the controlled outputs, namely the concentration, c and the tank level, h . The controlled system has the following state space matrices given:

$$A = \begin{bmatrix} 0.2681 & -0.00338 & -0.00728 \\ 9.7032 & 0.3279 & -25.44 \\ 0 & 0 & 1 \end{bmatrix} \quad B = \begin{bmatrix} -0.00537 & 0.1655 \\ 1.297 & 97.91 \\ 0 & -6.637 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The following are some preparations before:

3.1.1 Augmented model including disturbances

$$\begin{bmatrix} x \\ d \end{bmatrix}^+ = \underbrace{\begin{bmatrix} A & B_d \\ 0 & I \end{bmatrix}}_{A_e} \begin{bmatrix} x \\ d \end{bmatrix} + \underbrace{\begin{bmatrix} B \\ 0 \end{bmatrix}}_{B_e} u$$

$$y = \underbrace{\begin{bmatrix} C & C_d \end{bmatrix}}_{C_e} \begin{bmatrix} x \\ d \end{bmatrix}$$

3.1.2 A designed Stated estimator for process and disturbance states

To be able to estimate states and disturbances the equation 16 is calculates for every iteration in the loop. To find the gain Le the function `kalman` was used in MATLAB. Input to the function is tuning parameters `Qk` and `Rk` representing the variance of the process noise and measurement noise, `NN` as the covariance of the different noises, `delayed` so the function found estimation using the time step before and `sysd = ss(Ae,Be_new,Ce,[],Ts)`; where `Be_new = [Be, G]` where $G = I_{n+nd}$ representing the process noise as n and nd is the number of states and disturbances. `[kest,Le,P] = kalman(sysd,Qk,Rk,NN,'delayed')`;

$$\begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix}^+ = \underbrace{\begin{bmatrix} A & B_d \\ 0 & I \end{bmatrix}}_{A_e} \begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix} + \underbrace{\begin{bmatrix} B \\ 0 \end{bmatrix}}_{B_e} u + \underbrace{\begin{bmatrix} L_x \\ L_d \end{bmatrix}}_{L_e} \left(y_k - \underbrace{\begin{bmatrix} C & C_d \end{bmatrix}}_{C_e} \begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix} \right) \quad (16)$$

3.1.3 The extended MPC algorithm with a steady state target calculation

$$\begin{bmatrix} I - A & -B \\ HC & 0 \end{bmatrix} \begin{bmatrix} x_s \\ u_s \end{bmatrix} = \begin{bmatrix} B_d \hat{d} \\ z_{sp} - HC \hat{d} \end{bmatrix}$$

Where x_s and u_s is the state and input in steady state, and z_{sp} is the desired output setpoint which is set it to a zero vector in this assignment since off-set control is applied.

3.1.4 The extended MPC algorithm to handle different values for prediction and control horizon

The optimization problem for the MPC algorithm is:

$$\begin{aligned} \min_{x_s, u_s} & ((Cx_{s,N} + C_d\hat{d}_N - y_{sp})^T P_f (Cx_{s,N} + C_d\hat{d}_N - y_{sp}) + \\ & \sum_{i=0}^{M-1} (u_{s,i} - u_{sp}) R_s (u_{s,i} - u_{sp}) + (u_{s,i} - u_{sp}) \underbrace{(N - M - 1) R_s}_{R_N} (u_{s,i} - u_{sp}) + \\ & \sum_{i=0}^{N-1} (Cx_{s,i} + C_d\hat{d}_i - y_{sp}) Q_s (Cx_{s,i} + C_d\hat{d}_i - y_{sp})) \quad (17) \end{aligned}$$

s.t.

$$\begin{bmatrix} I - A & -B \\ HC & 0 \end{bmatrix} \begin{bmatrix} x_s \\ u_s \end{bmatrix} = \begin{bmatrix} B_d \hat{d} \\ z_{sp} - HC \hat{d} \end{bmatrix}$$

Rewrite the optimization problem on form:

$$\min_z \quad \frac{1}{2} z^T H_M z + f^T z \quad (18)$$

$$\text{s.t.} \quad A_{eq} z = b_{eq} \quad (19)$$

With $z = [\delta x^T(k+1) \quad \delta x^T(k+2) \quad \cdots \quad \delta x^T(k+N) \quad \delta u(k) \quad \cdots \quad \delta u(k+M)]^T$.

For this algorithm, the control horizon is $M = 3$, the prediction horizon is $N = 10$ and the final cost penalty is $P_f = Q_s$. The hessian matrix and equality constraints for the optimization problem are:

$$H_M = \begin{bmatrix} Q_s & 0 & \cdots & & 0 \\ 0 & \ddots & & & \\ & & Q_s & \ddots & \vdots \\ \vdots & & & P_f & \\ & & & & R_s \\ & & & & & \ddots & 0 \\ 0 & & \cdots & & 0 & R_N \end{bmatrix}, \quad f = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

$$A_{eq} = \begin{bmatrix} -I & 0 & \cdots & & 0 & \cdots & 0 & B & 0 & 0 \\ A & -I & 0 & \cdots & & 0 & \cdots & 0 & B & 0 \\ 0 & A & -I & 0 & \cdots & & 0 & \cdots & 0 & B \\ \vdots & \ddots & \ddots & & & & & & \vdots & \\ & & \ddots & & & & \vdots & & & \\ 0 & & \cdots & & 0 & A & -I & 0 & 0 & B \end{bmatrix}, \quad b_{eq} = \begin{bmatrix} -A \\ 0 \\ \vdots \\ 0 \end{bmatrix} \delta x$$

3.2 Tasks

We are free to choose how the integrating disturbance affects the states and measured outputs through the choice of B_d and C_d . The only restriction is that the augmented system is detectable. The interesting part here is to find out if we are going to successfully get an offset free controller with these modification, which is also the goals.

The target problem is assumed feasible. Augment the system model with a number of integrating disturbance equal to the number of measurements ($n_d = p$) (not the number of controlled variables) to guarantee offset free control; choose any $B_d \in \mathbb{R}^{n \times p}$ and $C_d \in \mathbb{R}^{p \times p}$ such that:

$$\text{rank} \begin{bmatrix} I - A & -B_d \\ C & C_d \end{bmatrix} = n + p,$$

If the plant output $y(k)$ goes to steady state y_s , the closed-loop system is stable, and constraints are not active at steady state, then there is zero offset in the controlled variables, that is $Hy_s = z_{sp}$.

3.2.1 Task d) Block diagram of the model predictive controller

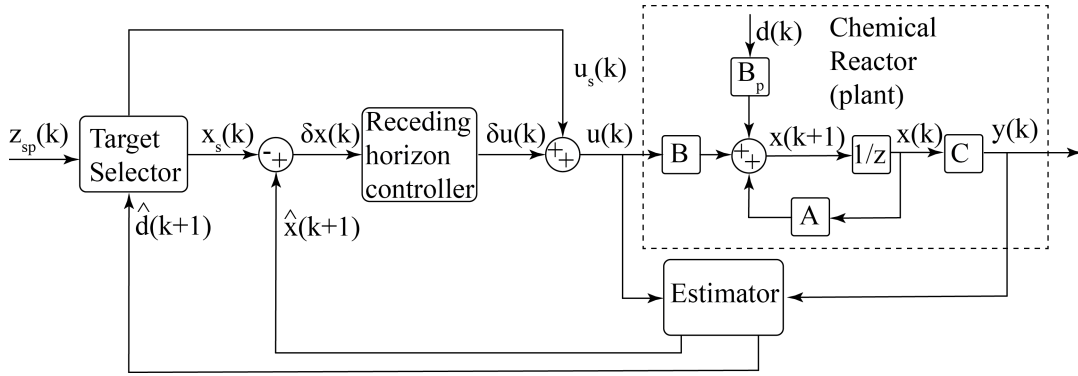


Figure 1: MPC controller consisting of: receding horizon controller, state estimator and target selector

3.2.2 Task e) Model 'a' in Matlab

The augmented system is detectable if and only if the nonaugmented system (A, C) is detectable, and the following condition holds:

$$\text{rank} \begin{bmatrix} I - A & -B_d \\ C & C_d \end{bmatrix} = n + n_d,$$

Where n is the dimension of the states and n_d is the number of integrating disturbance.

For model 'a' this rank condition holds, so the augmented system for 'a' is detectable. Now the integrating disturbances are added to the two controlled variables (c and h) by choosing

$$C_d = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix}, B_d = 0$$

The result is shown in the figure 2,4 and 4 below:

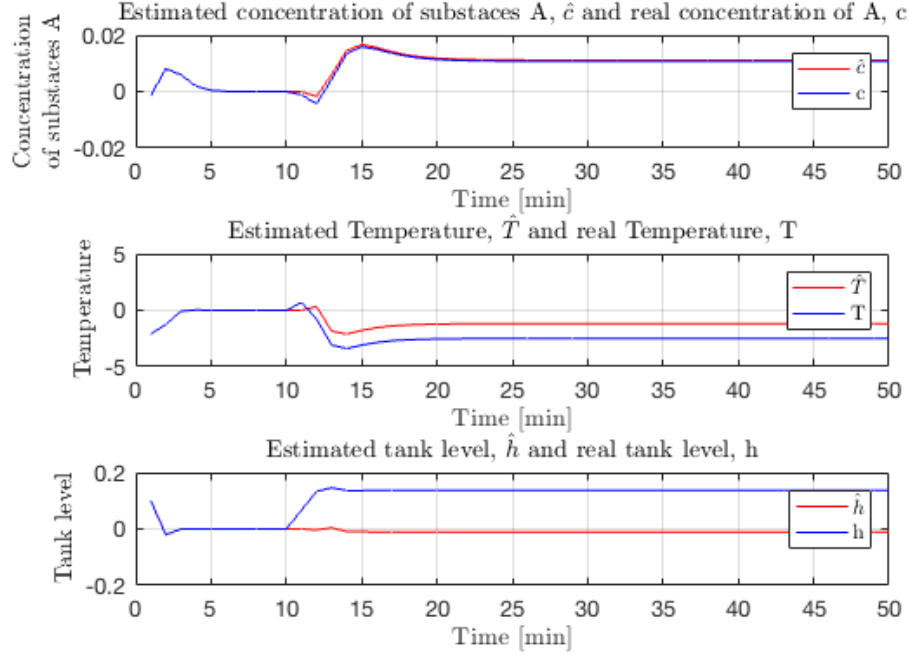


Figure 2: Estimated states and "real" states for model 'a'.

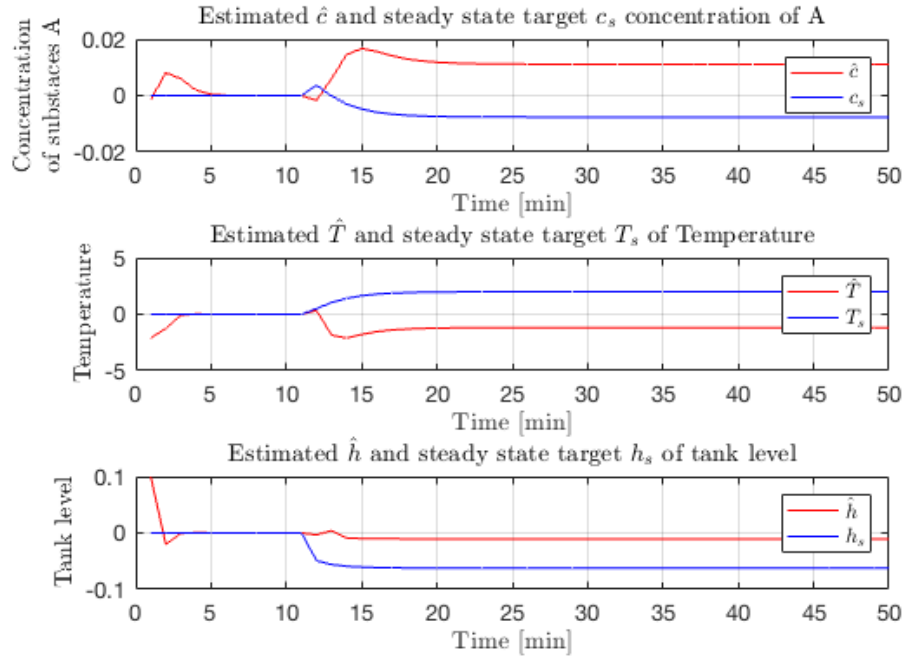


Figure 3: Estimated states and steady state targets for model 'a'.

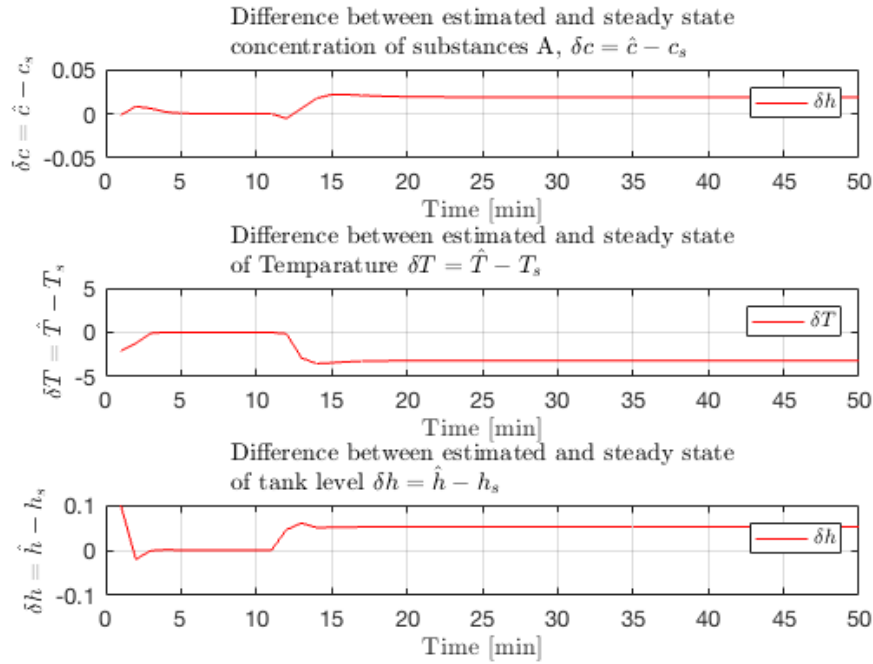


Figure 4: Offset for outputs both controlled and uncontrolled $\delta y = \hat{y} - y_s$, model 'a'.

Here notice that by adding integrating disturbances to the two controlled variables, c and h, both of these controlled variables as well as the third T, all still display nonzero offset from steady state. For the two controlled ones the offset is approximately 10% compared to the uncontrolled temperature.

3.2.3 Task f) Model 'b' in Matlab

A third disturbance is added to the second output giving:

$$C_d = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}, B_d = 0$$

The augmented system is not detectable with this disturbance model. The rank of $\begin{bmatrix} I - A & -B_d \\ C & C_d \end{bmatrix}$ is only 5 instead of 6. The problem here is that the system level is itself an integrator, and we can not distinguish h from the integrating disturbance added to h. Still the algorithm is generating results which is visualized in figure 5,7 and 7.

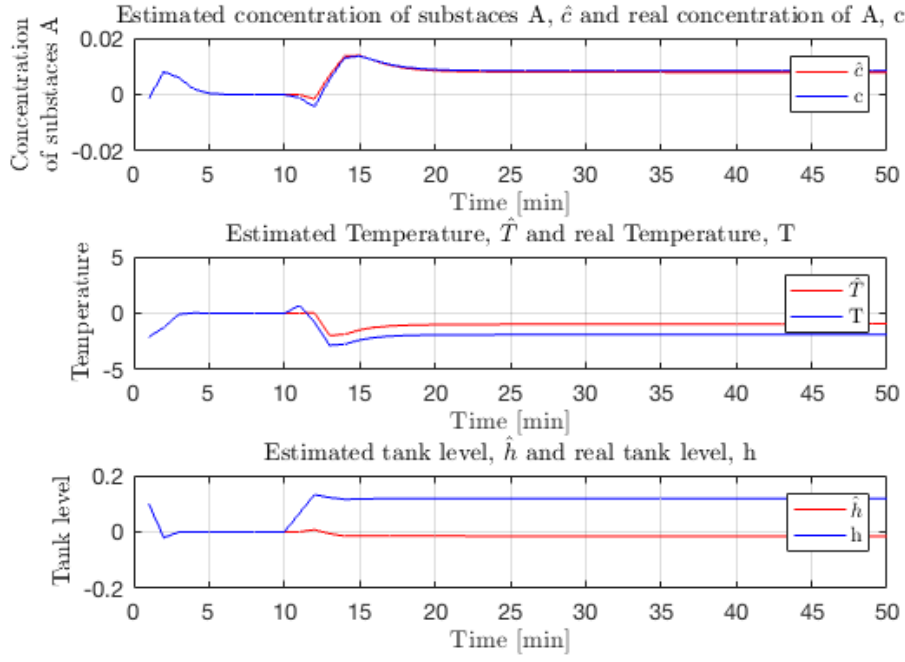


Figure 5: Estimated states and "real" states for model 'b'.

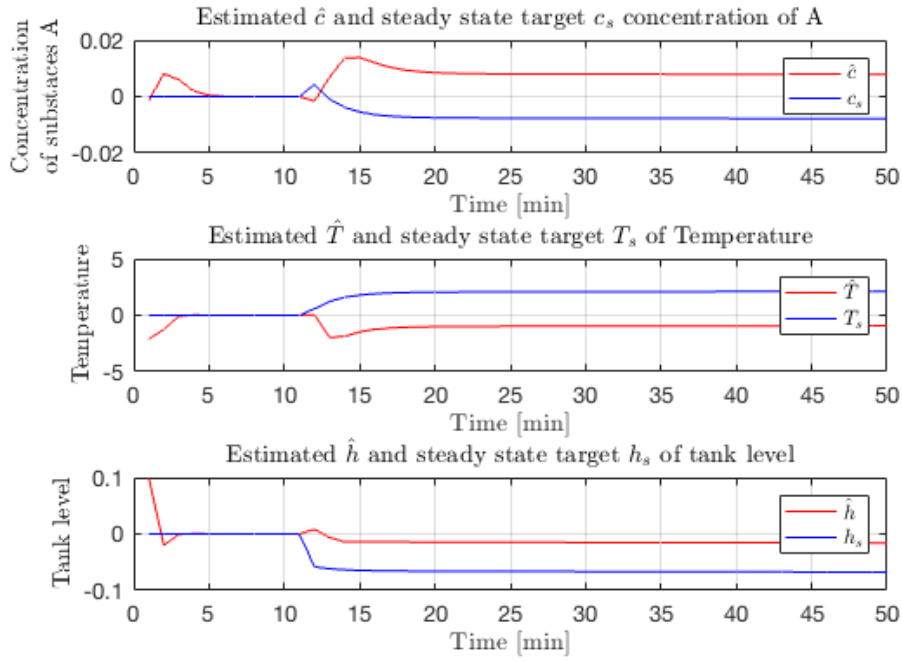


Figure 6: Estimated states and steady state targets for model 'b'.

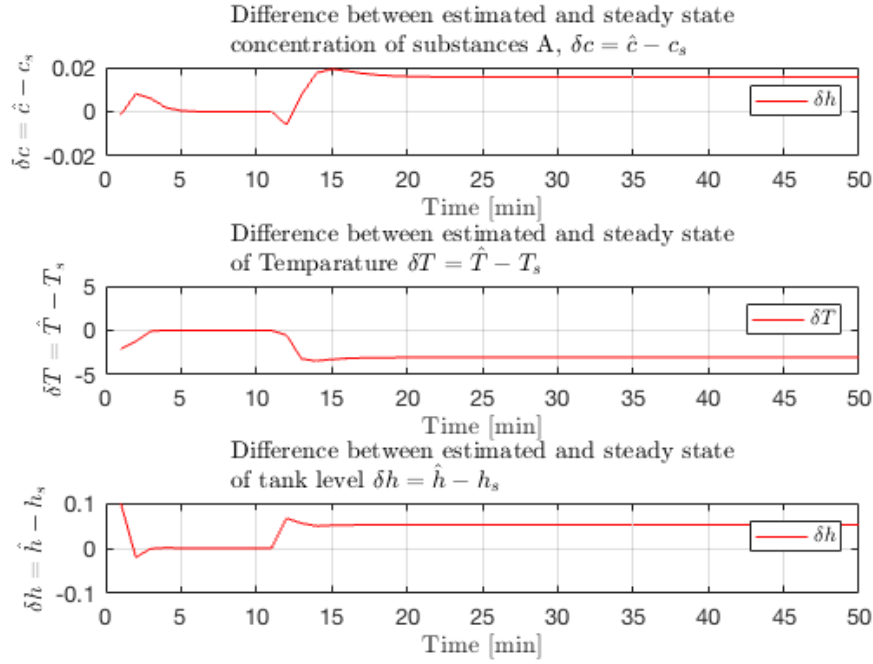


Figure 7: Offset for outputs both controlled and uncontrolled $\delta y = \hat{y} - y^s$, model 'b'.

Here it can be seen that the result is still not offset free and almost identical to the result for task e). To get a stable gain from the kalman function we were forced to increase the variance for the process noise a factor 10^3 .

3.2.4 Task g) Model 'c' in Matlab

For this case we choose to model two integrating disturbances for the two controlled variables, c and h. One integrating third disturbance is added to the second of the manipulated inputs, the outlet flow rate.

$$C_d = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, B_d = \begin{bmatrix} 0 & 0 & 0.1655 \\ 0 & 0 & 97.91 \\ 0 & 0 & -6.637 \end{bmatrix}$$

The augmented system is detectable for this disturbance model. The results for this are shown in figure 8, 10 and 10. We see that we have zero offset in both the two controlled variables, c and h, and the second output T.

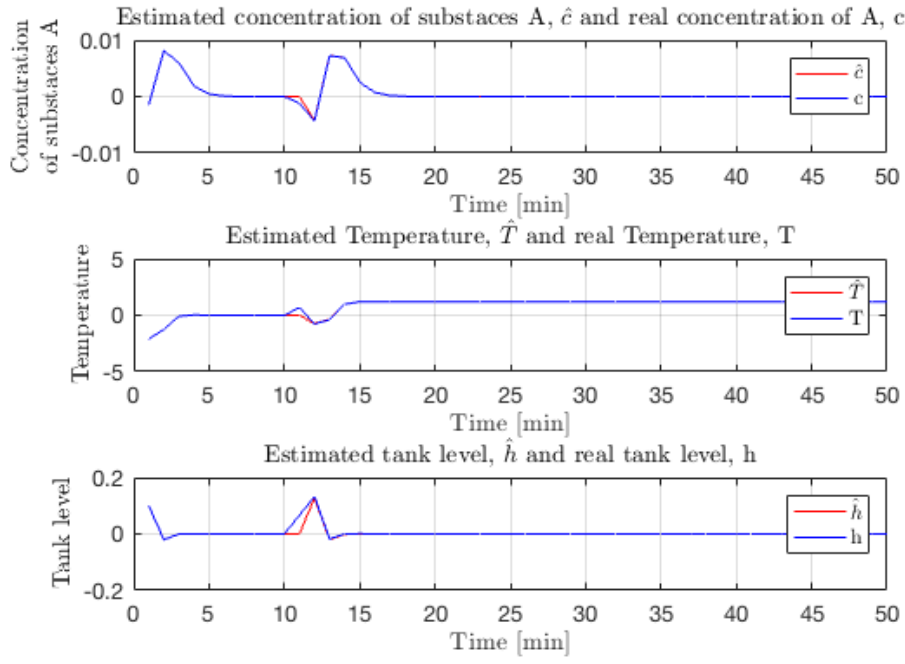


Figure 8: Estimated states and "real" states for model 'c'.

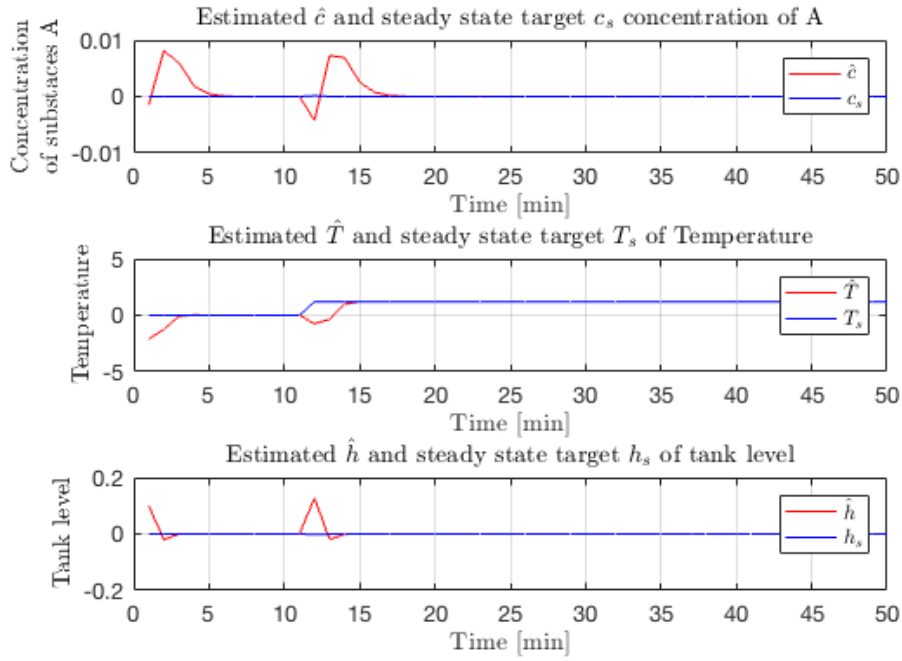


Figure 9: Estimated states and steady state targets for model 'c'.

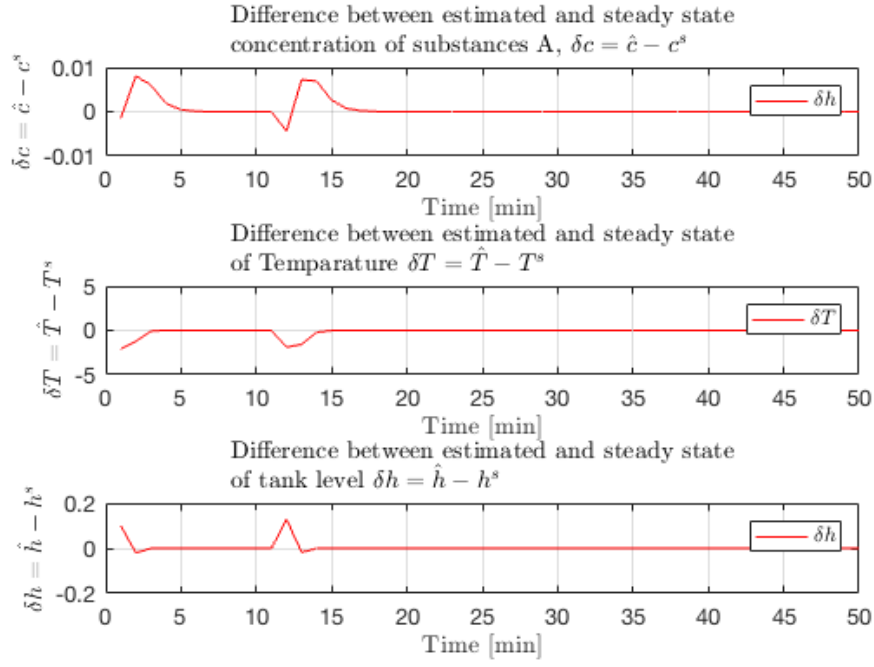


Figure 10: Offset for outputs both controlled and uncontrolled $\delta y = \hat{y} - y^s$, model 'c'.

Notice also that the dynamic behavior of all three outputs is superior to that achieved with the model using two integrating disturbances. The true disturbance, which is a step at the inlet flowrate, is better represented by including the integrator in the outlet flowrate. With a more accurate disturbance model, better overall control is achieved. The controller uses smaller manipulated variable action and also achieves better output variable behavior. An added bonus is that steady offset is removed in the maximum possible number of outputs.

4 Apendix Matlab code

4.1 Code for exercise a-c

```
1 clear all
2 close all
3 clc
4
5 A = diag([0.5 0.6 0.5 0.6]);
6 B = [diag([0.5 0.4]); diag([0.25 0.6])];
7 C = [1 1 0 0; 0 0 1 1];
8 zsp = [1 1]';
9
10 n = size(A,1); % n is the dimension of the state
11 m = size(B,2); % m is the dimension of the control signal
12 p = size(C,1); % p is the dimension of the measured output
13
14 H = eye(p);
15 % H = [1 0 0; 0 0 1]
16
17 Ta = [eye(n) A , B;
18       H*C zeros(size(H,1),m)];
19
20 Tb = [zeros(n,1); zsp];
21
22 z_target = Ta\Tb;
23 z_target_linsolve = linsolve(Ta,Tb);
24 zs=C*z_target(1:n)
25
26 %% part b) p>m
27 clear all
28 close all
29 clc
30
31 A = diag([0.5 0.6 0.5 0.6]);
32 % B = [diag([0.5 0.4]); zeros(2,2)];
33 % B = [0.5 0; 0 0; 0.25 0; 0 0];
34 B = [0.5 0 0.25 0]';
35 C = [1 1 0 0; 0 0 1 1];
36 zsp = [1 1]';
37
38 n = size(A,1); % n is the dimension of the state
39 m = size(B,2); % m is the dimension of the control signal
40 p = size(C,1); % p is the dimension of the measured output
41
42 Qs = eye(p);
43 Q_bar = 2*C'*Qs*C;
44 R_bar = zeros(m,m);
45 Hm = blkdiag(Q_bar, R_bar);
46 f = [ 2*zsp'*Qs*C, zeros(1,m)]';
47
48 H = eye(p);
49
50 Aeq = [eye(n) A , B];
51 rank(Aeq)
52
53 beq = [zeros(n,1)];
54
55 Ain = [];
56 Bin = [];
57 options = optimset('Algorithm','interior point convex','Display','off');
58 z = quadprog(Hm,f,Ain,Bin,Aeq,beq,[],[],[],options)
59 zs=C*z(1:n)
60
61 %% Part c p<m
62
63 clear all
64 close all
65 clc
66
67 A = diag([0.5 0.6 0.5 0.6]);
68 B = [diag([0.5 0.4]); diag([0.25 0.6])];
69 C = [1 1 0 0; 0 0 1 1];
70
71 zsp = [1]';
72 usp = [0 0]';
73
74 n = size(A,1); % n is the dimension of the state
75 m = size(B,2); % m is the dimension of the control signal
76 p = size(C,1); % p is the dimension of the measured output
77
78 H = [1 0];
79
80 Qs = zeros(n,n);
81 Q_bar = Qs;
82 R_bar = eye(m)*2;
83 Hm = blkdiag(Q_bar, R_bar);
84 f = [zeros(1,n), 2*usp'*R_bar]';
85
86 Aeq = [eye(n) A , B;
87       H*C zeros(size(H,1),m)];
88
89 beq = [zeros(n,1);
90       zsp];
```

```

91
92 Ain = [];
93 Bin = [];
94
95 options = optimset('Algorithm','interior point convex','Display','off');
96 z = quadprog(Hm,f,Ain,Bin,Aeq,beq,[],[],[],options);
97
98 zs=C*z(1:n)

```

4.2 Code for exercise e-g

```

1 %=====
2 % SSY280 Model Predictive Control 2012
3 %
4 % Homework Assignment 2:
5 % MPC Control of a Linearized MMO Well Stirred Chemical Reactor
6 % Revised 2013 02 10
7 %=====
8
9 %***** Initialization block *****
10
11 clear;
12 close all
13 tf=50; % number of simulation steps
14
15 %=====
16 % Process model
17 %=====
18
19 % h = 1; % sampling time in minutes
20 Ts = 60; % sampling time in seconds
21
22 % Definition of chemical reactor plant
23 A = [ 0.2681 0.00338 0.00728;
24       9.7032 0.3279 25.44;
25       0 0 1 ];
26 B = [ 0.00537 0.1655;
27       1.297 97.91 ;
28       0 6.637];
29 C = [ 1 0 0;
30       0 1 0;
31       0 0 1];
32 Bp = [ 0.1175;
33        69.74;
34        6.637 ]; % Disturbances matrix
35
36 n = size(A,1); % n is the dimension of the state
37 m = size(B,2); % m is the dimension of the control signal
38 p = size(C,1); % p is the dimension of the measured output
39
40 d=0.01*[zeros(1*tf/5,1);ones(4*tf/5,1)]; % unmeasured disturbance trajectory
41
42 x0 = [0.01;1;0.1]; % initial condition of system's state
43
44
45 %=====
46 % Set up estimated model
47 %=====
48
49 % Three cases to be investigated
50
51 example = 'b';
52 switch example
53     case 'a'
54         nd = 2;
55         Bd = zeros(n,nd);
56         Cd = [1 0;0 0; 0 1];
57         q=1; r=1;
58     case 'b'
59         nd=3;
60         Bd = zeros(n,nd);
61         Cd = [1 0 0;0 0 1;0 1 0];
62         q=1000; r=1;
63     case 'c'
64         nd=3;
65         Bd = [zeros(3,2) Bp];
66         Cd = [1 0 0;0 0 0;0 1 0];
67         q=1; r=1;
68 end
69
70
71
72 % Augment the model with constant disturbances
73
74 Ae = [A Bd; zeros(nd,n) eye(nd)]; %
75 Be = [B ; zeros(nd,m)]; %
76 % Be_2 = [zeros(n,nd);eye(nd)];
77 G = eye(n+nd);
78 Be_new = [Be, G];
79 Ce = [C Cd];
80
81 % Check augmented system stability

```



```

82 if rank([eye(n) A Bd;C Cd]) == n+nd
83     disp('augmented system is stable')
84 else
85     disp('augmented system is not stable')
86 end
87 % Calculate estimated gain
88
89 sysd = ss(Ae,Be_new,Ce,[],Ts);
90 Qk = eye(n+nd)*q; % Variance of process noise
91 Rk = eye(n)*r; % Variance of measurement noise
92 NN = 0; % Covariance of measurement noise and process noise
93 [kest,Le,P] = kalman(sysd,Qk,Rk,NN,'delayed');
94
95 % Check estimator stability poles <= 1
96 estimator_poles = eig(Ae Le*Ce)
97 abs(estimator_poles)
98
99 %=====
100 % Prepare for computing steady state targets
101 %=====
102
103 % Select 1st and 3rd outputs as controlled outputs
104 H = [1 0 0;0 0 1];
105
106 % Matrices for steady state target calculation to be used later
107
108 Ta = [eye(n) A , B;
109       H*C zeros(size(H,1),m)];
110
111
112 % YOUR CODE GOES HERE
113
114 %=====
115 % Set up MPC controller
116 %=====
117
118 N=10; % prediction horizon
119 M=3; % control horizon
120
121 Q = diag([1 0.001 1]); % state penalty
122 Pf = Q; % terminal state penalty
123 R = 0.01*eye(m); % control penalty
124
125 %=====
126 % Build Hessian Matrix
127 %=====
128
129 %YOUR MODIFIED CODE FROM ASSIGNMENT 1 GOES HERE
130 Q_bar=kron(eye(N 1),Q);
131 R_bar=kron(eye(M 1),R);
132 % Hessian matrix
133 HM=(blkdiag(Q_bar,Pf,R_bar,R*(N M 1)));
134 %=====
135 % Equality Constraints
136 %=====
137
138 Nn = kron(eye(N 1), A);
139 nn = zeros(n,n*N n);
140 nN = [nn;Nn];
141 NN = [nN,zeros(n*N,n)];
142 Mn = kron(eye(M),B);
143 MM = zeros(n*(N M),m*(M 1));
144 BM = repmat(B,N M,1);
145 mM = [Mn;MM,BM];
146
147 Aeq = [kron(eye(N),eye(n)) + NN,mM];
148 AA = [ A;zeros(n*N n,n)];
149
150 % YOUR MODIFIED CODE FROM ASSIGNMENT 1 GOES HERE
151
152 %=====
153 % Inequality Constraints
154 %=====
155
156 Ain = [];
157 Bin = [];
158
159 %=====
160 % Choose QP solver
161 %=====
162
163 solver = 'int';
164 switch solver
165     case 'int'
166         options = optimset('Algorithm','interior point convex',...
167                             'Display','off');
168     case 'set'
169         options = optimset('Algorithm','active set','Display','off');
170 end
171
172 %***** End of initialization *****
173
174 %=====
175 % Simulation
176 %=====
177
178 % Initialization
179

```

```

180 % YOUR CODE GOES HERE INITIALIZE ALL VARIABLES NEEDED
181 dhat = zeros(nd,1); % initialize estimated disturbances
182 xdhat = [x0;dhat]; % initialize estimated state vector and disturbances
183 xk = x0; % initial state value for process
184 yk = C*xk; % initial output value for process
185 zsp = zeros(m,1); % Setpoint
186 uk = zsp; % initial input value for process
187
188 % Construct matrixes to save values in
189 xdhat_save = zeros(n+nd,tf);
190 z_target_save = zeros(n+m,tf);
191 uk_save = zeros(m,tf);
192 yk_save = zeros(n,tf);
193 xk_save = zeros(n,tf);
194 delta_x_save = zeros(n,tf);
195 delta_u_save = zeros(m,tf);
196
197 % Simulate closed loop system
198
199 for k = 1:tf
200
201     %=====
202     % Update the estimated state xhat(k|k 1)
203     %=====
204
205     xdhat = Ae*xdhat + Be*uk + Le*(yk - Ce*xdhat);
206
207     %=====
208     % Update the process state x(k) and output y(k)
209     %=====
210
211     xk = A*xk + B*uk + Bp*d(k);
212     yk = C*xk;
213
214     %=====
215     % Calculate steady state targets xs and us
216     %=====
217
218     dhat = xdhat(n+1:end);
219
220     Tb = [Bd*dhat;
221           zsp - H*Cd*dhat];
222
223     z_target = Ta\Tb;
224
225     %=====
226     % Solve the QP (for the deviation variables!)
227     %=====
228     xhat = xdhat(1:n);
229     delta_x = xhat - z_target(1:n);
230     beq = -AA*delta_x;
231     % UPDATE RHS OF EQUALITY CONSTRAINT HERE
232
233     % NOTE THAT HM IS USED FOR THE HESSIAN, NOT TO BE CONFUSED
234     % WITH H THAT IS USED FOR SELECTING CONTROLLED VARIABLES
235     z = quadprog(HM,[], Ain, Bin, Aeq, beq, [], [], [], options);
236
237     % CALCULATE THE NEW CONTROL SIGNAL HERE
238     delta_u = z(n*N+1:n*N+m);
239     uk = delta_u + z_target(n+1:n+m);
240     % NOTE THAT YOU NEED TO GO FROM DEVIATION VARIABLES TO 'REAL' ONES!
241
242     %=====
243     % Store current variables in log
244     %=====
245     xdhat_save(:,k) = xdhat;
246     z_target_save(:,k) = z_target;
247     uk_save(:,k) = uk;
248     yk_save(:,k) = yk;
249     xk_save(:,k) = xk;
250     delta_x_save(:,k) = delta_x;
251     delta_u_save(:,k) = delta_u;
252
253 end % simulation loop
254 %=====
255 % Plot results
256 %=====
257
258 textsize = 13;
259 t = (1:1:tf);
260
261 figure;
262 subplot(3,1,1);
263 plot(t, xdhat_save(1,:), 'r', t, xk_save(1,:), 'b'); % concentration subst A
264 grid on;
265 set(gca, 'fontsize', textsize);
266 legend({'$\hat{c}$', 'c'}, 'Interpreter', 'latex')
267 title({'Estimated concentration of substaces A, $\hat{c}$ and real concentration of A, c'}...
268       , 'Interpreter', 'latex')
269 ylabel({'Concentration', 'of substaces A'}, 'Interpreter', 'latex')
270 xlabel('Time [min]', 'Interpreter', 'latex')
271
272 subplot(3,1,2);
273 plot(t, xdhat_save(2,:), 'r', t, xk_save(2,:), 'b'); % Temperature
274 grid on;
275 set(gca, 'fontsize', textsize);
276 legend({'$\hat{T}$', 'T'}, 'Interpreter', 'latex')
277 title({'Estimated Temperature, $\hat{T}$ and real Temperature, T'}, ...
278       'Interpreter', 'latex')

```

```

278 ylabel({'Temperature'}, 'Interpreter', 'latex')% not given anny units o this
279 xlabel('Time [min]', 'Interpreter', 'latex')
280
281 subplot(3,1,3);
282 plot(t, xdhat.save(3,:), 'r', t, xk.save(3,:), 'b'); % Tank level
283 grid on;
284 set(gca, 'fontsize', textsize)
285 legend({'$\hat{h}$', 'h'}, 'Interpreter', 'latex')
286 title({'Estimated tank level, $\hat{h}$ and real tank level, h'}, ...
287       'Interpreter', 'latex')
288 ylabel({'Tank level'}, 'Interpreter', 'latex')% not given anny units o this
289 xlabel('Time [min]', 'Interpreter', 'latex')
290
291
292 figure;
293 subplot(3,1,1);
294 plot(t, delta_x_save(1,:), 'r'); % concentration subst A
295 grid on;
296 set(gca, 'fontsize', textsize)
297 legend({'$\delta h$'}, 'Interpreter', 'latex');
298 title({'Difference between estimated and steady state', ...
299       'concentration of substances A, $\delta c = \hat{c} c_s$'}, ...
300       'Interpreter', 'latex')
301 ylabel({'$\delta c = \hat{c} c_s$'}, 'Interpreter', 'latex')% not given anny units o this
302 xlabel('Time [min]', 'Interpreter', 'latex')
303
304
305 subplot(3,1,2);
306 plot(t, delta_x_save(2,:), 'r'); % Temperature
307 grid on;
308 set(gca, 'fontsize', textsize)
309 legend({'$\delta T$'}, 'Interpreter', 'latex');
310 title({'Difference between estimated and steady state', ...
311       'of Temperature $\delta T = \hat{T} T_s$'}, 'Interpreter', 'latex')
312 ylabel({'$\delta T = \hat{T} T_s$'}, 'Interpreter', 'latex')% not given anny units o this
313 xlabel('Time [min]', 'Interpreter', 'latex')
314
315 subplot(3,1,3);
316 plot(t, delta_x_save(3,:), 'r'); % Tank level
317 grid on;
318 set(gca, 'fontsize', textsize)
319 legend({'$\delta h$'}, 'Interpreter', 'latex');
320 title({'Difference between estimated and steady state', ...
321       'of tank level $\delta h = \hat{h} h_s$'}, 'Interpreter', 'latex')
322 ylabel({'$\delta h = \hat{h} h_s$'}, 'Interpreter', 'latex')% not given anny units o this
323 xlabel('Time [min]', 'Interpreter', 'latex')
324
325 figure;
326 subplot(3,1,1);
327 plot(t, xdhat.save(1,:), 'r', t, z_target.save(1,:), 'b'); % concentration subst A
328 grid on;
329 set(gca, 'fontsize', textsize)
330 legend({'$\hat{c}$', '$c_s$'}, 'Interpreter', 'latex')
331 title({'Estimated $\hat{c}$ and steady state target $c_s$ concentration of A'}, ...
332       'Interpreter', 'latex')
333 ylabel({'Concentration', 'of substaces A'}, 'Interpreter', 'latex')% not given anny units o this
334 xlabel('Time [min]', 'Interpreter', 'latex')
335
336 subplot(3,1,2);
337 plot(t, xdhat.save(2,:), 'r', t, z_target.save(2,:), 'b'); % Temperature
338 grid on;
339 set(gca, 'fontsize', textsize)
340 legend({'$\hat{T}$', '$T_s$'}, 'Interpreter', 'latex')
341 title({'Estimated $\hat{T}$ and steady state target $T_s$ of Temperature'}, ...
342       'Interpreter', 'latex')
343 ylabel({'Temperature'}, 'Interpreter', 'latex')% not given anny units o this
344 xlabel('Time [min]', 'Interpreter', 'latex')
345
346 subplot(3,1,3);
347 plot(t, xdhat.save(3,:), 'r', t, z_target.save(3,:), 'b'); % Tank level
348 grid on;
349 set(gca, 'fontsize', textsize)
350 legend({'$\hat{h}$', '$h_s$'}, 'Interpreter', 'latex')
351 title({'Estimated $\hat{h}$ and steady state target $h_s$ of tank level'}, ...
352       'Interpreter', 'latex')
353 ylabel({'Tank level'}, 'Interpreter', 'latex')% not given anny units o this
354 xlabel('Time [min]', 'Interpreter', 'latex')

```