

1: 20 points

Model Order Reduction Problems

(a) Let

$$G(s) = \sum_{i=1}^5 \frac{\alpha^{2i}}{s + \alpha^{2i}}.$$

Find a balanced realization for each of the following α using Matlab: $\alpha = 2, 4, 20, 50$. Discuss the behavior of the Hankel singular values as $\alpha \rightarrow \infty$.

(b) Note that a time delay can be approximated as

$$e^{-\tau s} \approx \left(\frac{1 - \frac{\tau}{2n}s}{1 + \frac{\tau}{2n}s} \right)^n$$

for a sufficiently large n . Let a process model $\frac{e^{-s}}{1+Ts}$ be approximated by

$$G(s) = \left(\frac{1 - 0.05s}{1 + 0.05s} \right)^{10} \frac{1}{1 + sT}.$$

For each $T = 0, 0.01, 0.1, 1, 10$, find the smallest order model using balanced truncation such that the approximation error is no greater than 0.1. Use Matlab to solve.

2: 30 points

LMI Problems

(a) Consider the system

$$A = \begin{bmatrix} -5 & 1 & 2 \\ 1 & -9 & 1 \\ -1 & -10 & -3 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

Compute the H_2 norm of the system using LMIs in Matlab.

(c) Consider the system

$$A = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & -2 & 10 \\ 0 & 1 & -2 \end{bmatrix} \quad B = \begin{bmatrix} 1 & 0 \\ -2 & 2 \\ 0 & 1 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Determine whether this system is stabilizable and detectable using LMIs in Matlab.

(d) Consider the system of form

$$\begin{aligned} \dot{x} &= Ax + B_1 u + B_2 w \\ z &= Cx + Du \end{aligned}$$

with

$$A = \begin{bmatrix} -5 & 1 & 0 \\ 0 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad B_1 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} \quad B_2 = \begin{bmatrix} 0.05 \\ 0 \\ 0.03 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 1 \end{bmatrix} \quad D = \begin{bmatrix} 1 & 3 \\ 1 & 0 \end{bmatrix}.$$

Design a state feedback control law $u = Kx$ that solves the H_2 optimal control problem using LMIs in Matlab.

4: 30 points

Design Problem: LMI Synthesis

Consider the distillation column with plant model

$$G(s) = \frac{1}{75s + 1} \begin{bmatrix} 87.8 & -86.4 \\ 108.2 & -109.6 \end{bmatrix}.$$

Assuming multiplicative input uncertainty of the form $W_I(s) = \frac{10s+10}{s+100} I_{2 \times 2}$ and performance weight $W_P(s) = \frac{0.5s+10}{s+0.1} I_{2 \times 2}$, design a 1.) an H_∞ optimal controller, 2.) a μ -synthesis controller, and 3.) a mixed H_2 / H_∞ controller that minimizes the H_2 norm such that robust stability is maintained. Plot the uncertain sensitivity functions that are obtained for all three design approaches. Which approach works “best”?

1a

```

s = tf("s");
alpha = 2;
G = 0;
for i = 1:5
    G = G + (alpha^(2*i))/(s+alpha^(2*i));
end
[sysb,g] = balreal(G)

```

sysb =

```

A =
      x1      x2      x3      x4      x5
x1 -219.5  262.5 -178.9 -92.16  36.04
x2  262.5 -381.4  315.6  180.4 -73.27
x3 -178.9  315.6 -352.6 -257.6  117.3
x4 -92.16  180.4 -257.6 -268.6  160.5
x5  36.04 -73.27  117.3  160.5 -142

```

```

B =
      u1
x1 -26.27
x2  22.12
x3 -12.13
x4 -5.73
x5  2.18

```

```

C =
      x1      x2      x3      x4      x5
y1 -26.27  22.12 -12.13 -5.73  2.18

```

```

D =
      u1
y1  0

```

Continuous-time state-space model.

```

g = 5x1
    1.5721
    0.6413
    0.2087
    0.0611
    0.0167

```

```

alpha = 4;
G = 0;
for i = 1:5
    G = G + (alpha^(2*i))/(s+alpha^(2*i));
end
[sysb,g] = balreal(G)

```

sysb =

```

A =
      x1      x2      x3      x4      x5
x1 -1.271e+05 -1.955e+05  1.917e+05  1.411e+05 -7.235e+04
x2 -1.955e+05 -3.109e+05  3.183e+05  2.436e+05 -1.281e+05
x3  1.917e+05  3.183e+05 -3.465e+05 -2.82e+05  1.55e+05
x4  1.411e+05  2.436e+05 -2.82e+05 -2.462e+05  1.432e+05
x5 -7.235e+04 -1.281e+05  1.55e+05  1.432e+05 -8.766e+04

```

```

B =
      u1
x1  502.1
x2  654.4
x3 -538.5
x4 -347.6
x5  165.4

```

```

C =
      x1      x2      x3      x4      x5
y1  502.1  654.4 -538.5 -347.6  165.4

```

```

D =
      u1
y1  0

```

Continuous-time state-space model.

```

g = 5x1
    0.9917
    0.6885
    0.4185
    0.2453
    0.1560

```

```

alpha = 20;
G = 0;
for i = 1:5
    G = G + (alpha^(2*i))/(s+alpha^(2*i));
end
[sysb,g] = balreal(G)

sysb =

A =
      x1      x2      x3      x4      x5
x1 -8.977e+11  1.536e+12 -1.744e+12  1.485e+12  8.471e+11
x2  1.536e+12 -2.63e+12  2.992e+12 -2.553e+12 -1.458e+12
x3 -1.744e+12  2.992e+12 -3.411e+12  2.918e+12  1.67e+12
x4  1.485e+12 -2.553e+12  2.918e+12 -2.502e+12 -1.435e+12
x5  8.471e+11 -1.458e+12  1.67e+12 -1.435e+12 -8.237e+11

B =
      u1
x1 -1.029e+06
x2  1.699e+06
x3 -1.841e+06
x4  1.499e+06
x5  8.283e+05

C =
      x1      x2      x3      x4      x5
y1 -1.029e+06  1.699e+06 -1.841e+06  1.499e+06  8.283e+05

D =
      u1
y1  0

Continuous-time state-space model.
g = 5x1
    0.5894
    0.5485
    0.4967
    0.4490
    0.4165

```

```

alpha = 50;
G = 0;
for i = 1:5
    G = G + (alpha^(2*i))/(s+alpha^(2*i));
end
[sysb,g] = balreal(G)

sysb =

A =
      x1      x2      x3      x4      x5
x1 -8.29e+15  1.43e+16 -1.642e+16  1.414e+16  8.128e+15
x2  1.43e+16 -2.467e+16  2.833e+16 -2.44e+16 -1.403e+16
x3 -1.642e+16  2.833e+16 -3.255e+16  2.805e+16  1.614e+16
x4  1.414e+16 -2.44e+16  2.805e+16 -2.418e+16 -1.391e+16
x5  8.128e+15 -1.403e+16  1.614e+16 -1.391e+16 -8.008e+15

B =
      u1
x1  9.419e+07
x2 -1.601e+08
x3  1.803e+08
x4 -1.523e+08
x5 -8.638e+07

C =
      x1      x2      x3      x4      x5
y1  9.419e+07 -1.601e+08  1.803e+08 -1.523e+08 -8.638e+07

D =
      u1
y1  0

Continuous-time state-space model.
g = 5x1
    0.5351
    0.5198
    0.4995
    0.4798
    0.4658

```

The Hankel singular values will approach to 0.5 when alpha tends to infinity.

16

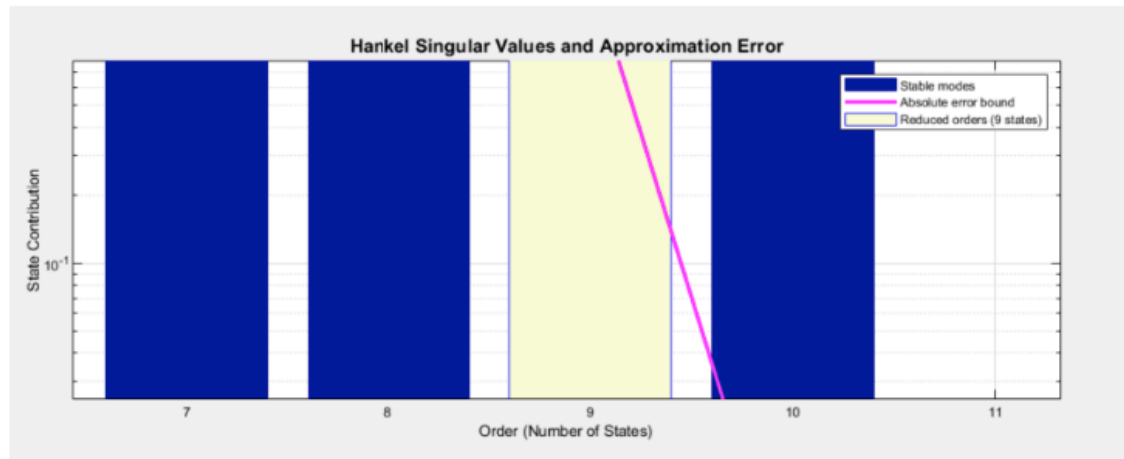
```

s = tf("s");
T = 0;
G_td = ((1-0.05*s)/(1+0.05*s))^(10) * (1/(1+s*T));
Gr = balancmr(G_td, 'MaxError', 0.1);
size(Gr)

```

State-space model with 1 outputs, 1 inputs, and 10 states.

```
%modelReducer(G_td)
```



Smallest order model for $T = 0$ is 10.

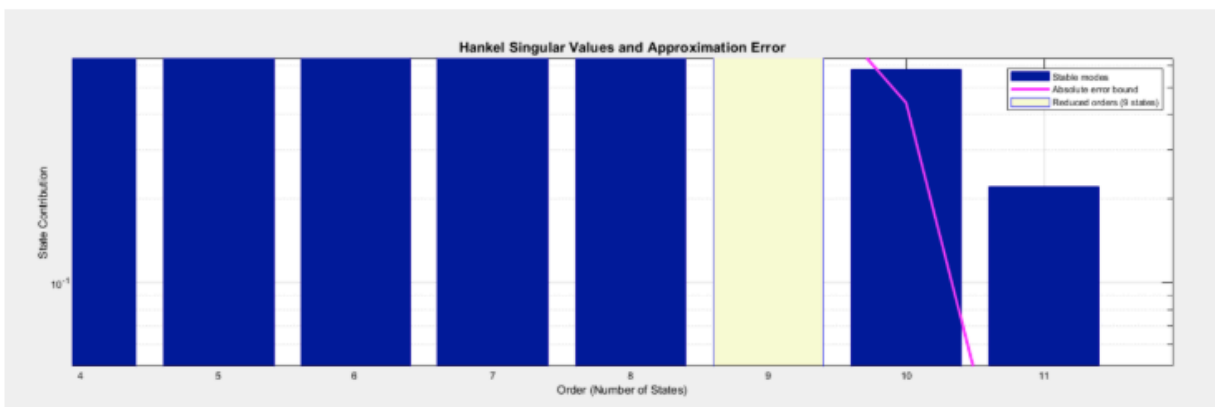
```

s = tf("s");
T = 0.01;
G_td = ((1-0.05*s)/(1+0.05*s))^(10) * (1/(1+s*T));
Gr = balancmr(G_td, 'MaxError', 0.1);
size(Gr)

```

State-space model with 1 outputs, 1 inputs, and 11 states.

```
%modelReducer(G_td)
```

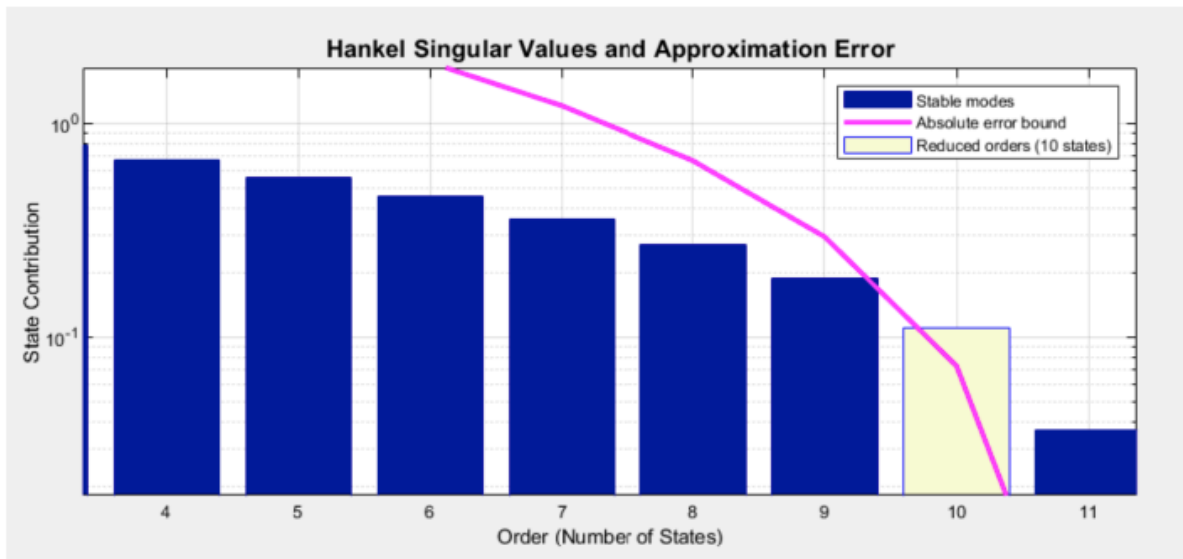


Smallest order model for $T = 0.01$ is 11.

```
s = tf("s");
T = 0.1;
G_td = ((1-0.05*s)/(1+0.05*s))^(10) * (1/(1+s*T));
Gr = balancmr(G_td, 'MaxError', 0.1);
size(Gr)
```

State-space model with 1 outputs, 1 inputs, and 10 states.

```
%modelReducer(G_td)
```

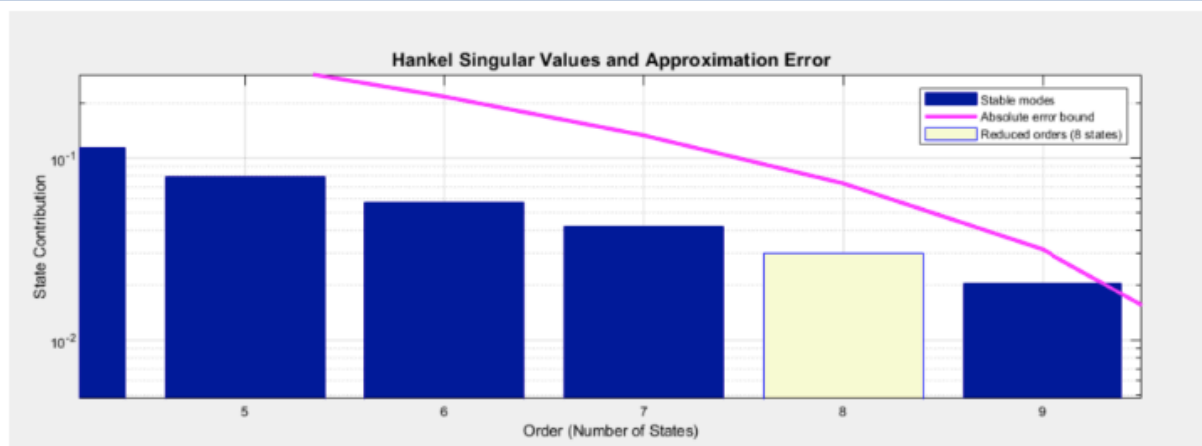


Smallest order model for $T = 0.1$ is 10.

```
s = tf("s");
T = 1;
G_td = ((1-0.05*s)/(1+0.05*s))^(10) * (1/(1+s*T));
Gr = balancmr(G_td, 'MaxError', 0.1);
size(Gr)
```

State-space model with 1 outputs, 1 inputs, and 8 states.

```
%modelReducer(G_td)
```

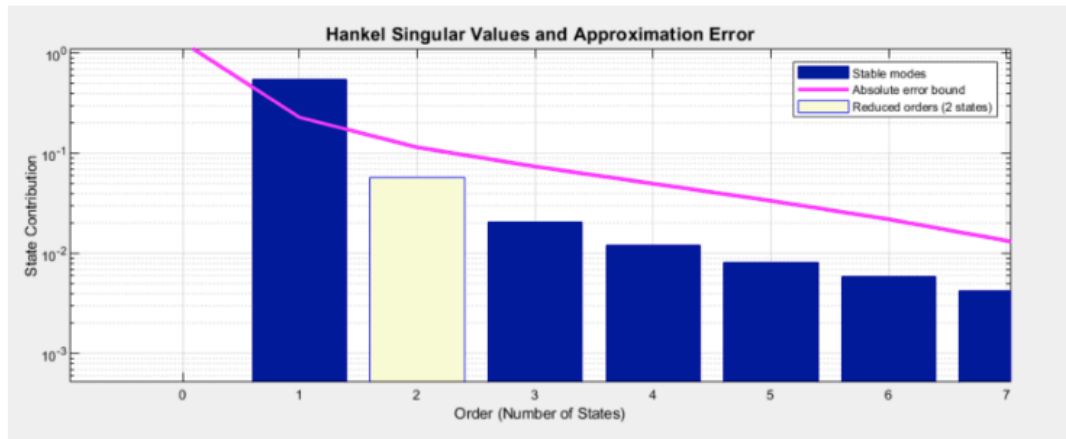


Smallest order model for $T = 1$ is 8.

```
s = tf("s");
T = 10;
G_td = ((1-0.05*s)/(1+0.05*s))^(10) * (1/(1+s*T));
Gr = balancmr(G_td, 'MaxError', 0.1);
size(Gr)
```

State-space model with 1 outputs, 1 inputs, and 3 states.

```
%modelReducer(G_td)
```



Smallest order model for T = 10 is 3.

2a

```
A = [-5 1 2; 1 -9 1; -1 -10 -3];
B = [0 1 0]';
C = [1 0 0; 0 0 1];
D = [0;0];
G = ss(A,B,C,D);
h2norm = h2norm_lmi_yalmip(G)
```

```
4          0.115743
***      new lower bound:    0.103352
5          0.113392
***      new lower bound:    0.107265
6          0.112832
***      new lower bound:    0.109341
7          0.112359
***      new lower bound:    0.110516
8          0.112016
***      new lower bound:    0.111166
9          0.111908
***      new lower bound:    0.111773
10         0.111908
***      new lower bound:    0.111860
```

```
Result: feasible solution of required accuracy
best objective value:    0.111908
guaranteed absolute accuracy: 4.84e-05
f-radius saturation: 0.000% of R = 1.00e+09
h2norm = 0.3345
```

2b

```
A = [0.5 0 0; 0 -2 10; 0 1 -2];
B = [1 0;-2 2;0 1];
C = [1 0 0;0 0 1];
D = [0 0;0 0];
stabilizable = lmiisstabilizable_yalmip(ss(A,B,C,D))
```

Solver for LMI feasibility problems $L(x) < R(x)$
 This solver minimizes t subject to $L(x) < R(x) + t \cdot I$
 The best value of t should be negative for feasibility

Iteration : Best value of t so far

1	0.024819
2	-0.019360

Result: best value of t : -0.019360
 f-radius saturation: 0.000% of $R = 1.00e+09$

 You are using LMILAB. Please don't use LMILAB with YALMIP
<https://yalmip.github.io/solver/lmilab/>

Install a better SDP solver
<https://yalmip.github.io/allsolvers/>

To get rid of this message, edit callmilab.m
 (but don't expect support when things do not work,
 YALMIP + LMILAB => No support)

 stabilizable = 1

```
function stabilizable = lmiisstabilizable_yalmip(sys)
    [A,B,C,D] = ssdata(sys);
    gamma=sdpvar(1); % symbolic decision variables
    P = sdpvar(size(A,1));
    % define the constraints.
    % NOTE: YALMIP does not actually handle strict inequalities. We need to
    % SLIGHTLY modify the problem to get a proper solution
    eps = 1e-10;
    F = [P >= eps*eye(size(P)), A*P+P*A'<=gamma*B*B', gamma>=eps];
    % Solve the minimization problem. For feasibility, we do not need to
    % provide an objective function.
    optimize(F);
    %Check to see if constraints were violated; a negative number implies
    %that a constraint was not satisfied.
    isStable = check(F);
    if(min(isStable) < 0)
        stabilizable = 0;
    else
        stabilizable = 1;
    end
end
```



```
detectable = lmiisdetectable_yalmip(ss(A,B,C,D))
```

```
Solver for LMI feasibility problems  $L(x) < R(x)$   
This solver minimizes  $t$  subject to  $L(x) < R(x) + t \cdot I$   
The best value of  $t$  should be negative for feasibility
```

```
Iteration : Best value of  $t$  so far
```

```
1 -0.607322
```

```
Result: best value of  $t$ : -0.607322  
f-radius saturation: 0.000% of  $R = 1.00e+09$ 
```

```
#####  
You are using LMILAB. Please don't use LMILAB with YALMIP  
https://yalmip.github.io/solver/lmilab/
```

```
Install a better SDP solver  
https://yalmip.github.io/allsolvers/
```

```
To get rid of this message, edit calllmilab.m  
(but don't expect support when things do not work,  
YALMIP + LMILAB => No support)
```

```
#####  
detectable = 1
```

```
function detectable = lmiisdetectable_yalmip(sys)  
[A,B,C,D] = ssdata(sys);  
w = sdpvar(size(B,2),size(A,1),'full'); % symbolic decision variables  
P = sdpvar(size(A,1));  
% define the constraints.  
% NOTE: YALMIP does not actually handle strict inequalities. We need to  
% SLIGHTLY modify the problem to get a proper solution  
eps = 1e-10;  
F = [P >= eps*eye(size(P)), A'*P+P*A+w'*C+C'*w<=eps];  
% Solve the minimization problem. For feasibility, we do not need to  
% provide an objective function.  
optimize(F);  
%Check to see if constraints were violated; a negative number implies  
%that a constraint was not satisfied.  
isStable = check(F);  
if(min(isStable) < 0)  
detectable = 0;  
else  
detectable = 1;  
end  
end
```

2C

```
A = [-5 1 0;0 1 1;1 1 1];  
B1 = [0 0;0 1;1 0];  
B2 = [0.05 0 0.03]';  
C = [1 0 0;0 2 1];  
D = [1 3;1 0];  
[K, ~] = h2sf(A, B1, B2, C, D);
```

```
23 6.149579e-03  
24 6.149579e-03  
25 6.149579e-03  
26 6.149579e-03  
27 6.149579e-03  
28 6.149579e-03  
*** new lower bound: 6.148980e-03
```

```
Result: feasible solution of required accuracy  
best objective value: 6.149579e-03  
guaranteed absolute accuracy: 5.99e-07  
f-radius saturation: 3.392% of  $R = 1.00e+09$ 
```

```
#####  
You are using LMILAB. Please don't use LMILAB with YALMIP  
https://yalmip.github.io/solver/lmilab/
```

```
Install a better SDP solver  
https://yalmip.github.io/allsolvers/
```

K

```
K = 2x3  
-0.3606 -4.8947 -4.3199  
-0.2517 0.8280 0.8501
```

```

function [K,gamma] = h2sf(A, B1, B2, C, D)
    z = sdpvar(size(C*A, 1));
    w = sdpvar(size(B1,2),size(A,1),'full'); % symbolic decision variables
    X = sdpvar(size(A,1));
    gamma = sdpvar(1);
    % define the constraints.
    % NOTE: YALMIP does not actually handle strict inequalities. We need to
    % SLIGHTLY modify the problem to get a proper solution
    eps = 1e-10;
    con1 = A*X+B1*w+(A*X+B1*w)'+B2*B2';
    con2 = [-z C*X+D*w; (C*X+D*w)' -X];
    F = [con1 <= eps, con2<=eps, trace(z)<=gamma];
    % Solve the minimization problem. For feasibility, we do not need to
    % provide an objective function.
    optimize(F,gamma);
    gamma = sqrt(value(gamma));
    K = value(w) * inv(value(X));
end

```

3. H_∞ Controller

```

s = tf('s');
G = (1/(75*s+1))*[87.8 -86.4;108.2 -109.6];
WI = (10*s+10)/(s+100)*eye(2);
Wp = (0.5*s+10)/(s+0.1);
Wp = (Wp/(s/1000+1))*eye(2);

systemnames = 'G WI Wp';
inputvar = '[du{2};r{2};u{2}]';
outputvar = '[WI;Wp;r-G]'; %For h2hinfsyn, we need the uncertainties (H_inf outputs) at the top
input_to_G = '[u+du]';
input_to_Wp = '[r-G]';
input_to_WI = '[u]';
cleanupsysic = 'yes'; %This drops all the useless variables from workspace
P = sysic;

```

1) H_∞ Controller synthesis

```

[Kinf,CL,GAM] = hinfsyn(P,2,2);%This is for a sanity check
Kinf

```

μ controller

```

delta1 = ultidyn('delta1',[1,1]);
delta2 = ultidyn('delta2',[1,1]);
Ghat = G*(eye(2)+[delta1 0;0 delta2]*WI); %input multiplicative structured uncertainty
systemnames = 'Ghat Wp';
inputvar = '[r{2};u{2}]';
outputvar = '[Wp;Ghat;r-Ghat]'; %For h2hinfsyn, we need the uncertainties (H_inf outputs) at the top
input_to_Ghat = '[u]';
input_to_Wp = '[r-Ghat]';
cleanupsysic = 'yes'; %This drops all the useless variables from workspace
Pmu = sysic;
[Kmu,CLP,mu_mu] = musyn(Pmu,2,2);

```

D-K ITERATION SUMMARY:

Iter	Robust performance			Fit order	
	K Step	Peak MU	D Fit	D	
1	10.84	10.84	10.94	20	
2	7.997	7.997	8	12	
3	6.091	6.091	6.104	12	
4	5.231	5.231	5.24	12	
5	4.839	4.839	4.844	12	
6	4.632	4.632	4.647	12	
7	4.51	4.511	4.531	12	
8	4.434	4.434	4.457	16	
9	4.38	4.38	4.404	16	
10	4.34	4.342	4.365	16	

Best achieved robust performance: 4.34

Kmu

3) H_2/H_∞ Controller synthesis

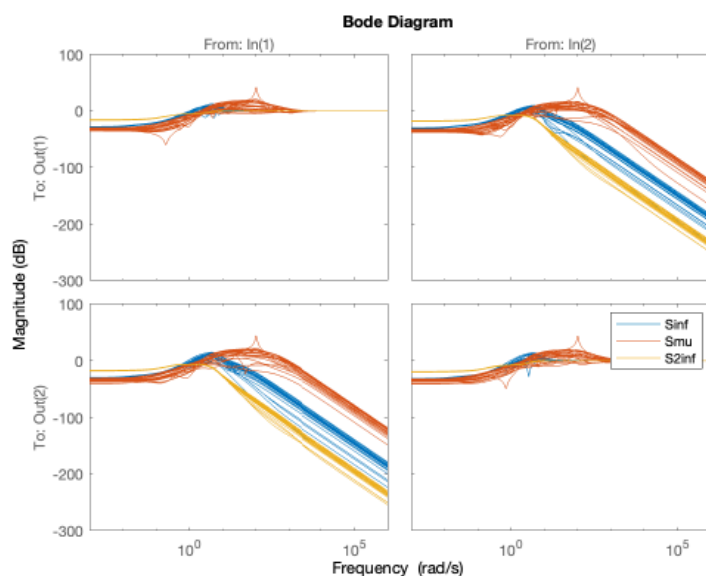
```
[K2inf,CL,normz,info] = h2hinfsyn(prescale(ss(P)),2,2,2,[0,1],'HINFMAX',1);
K2inf
```

K2inf =

```
A =
      x1      x2      x3      x4      x5      x6      x7      x8      x9      x10     x11     x12     x13
x1    -18.96     5.836   -0.1167   0.1204   0.06514  0.02329  -0.001168  0.0003553  0.007327  -0.02632  -0.03396  0.01921  -0.003615
x2     5.788    -31.96   -0.1372  -0.03984  -0.001209  -0.01292  0.008306  0.0003096  -0.001547  -0.08594  -0.1186  -0.008592  -0.01128
x3    -0.003888  -0.002563  -999.2   0.1845  -0.06666  0.147   4.137   17.89   -2.488   1.15   1.324   7.169   -20.17
x4    -0.002278  0.00856  0.1565  -999.5   0.263  0.2531  2.053   9.802   3.427   0.6797  0.8329  -21.08  -6.523
x5    -0.0004478  0.003581  0.1777  0.7246  -999.9  0.7169  -6.467   5.78   1.545  0.4386  0.5075  -9.195  -6.478
x6    -0.002125  0.004189  0.006813  0.1346  0.1087  -1000  7.537   3.029  0.9831  -0.01855  0.02242  -6.214  2.914
x7    -0.006217  0.04827  -4.353  -1.21  0.1349  -8.684  0.01522  0.1914  -5.406e-05  1.656  4.268  0.05683  0.2596
x8    0.008371  0.0006927  18.65  9.315  3.095  5.91  -0.2195  -0.8237  0.01335  -13.09  -14.63  -0.3384  -1.121
x9    0.1394  -0.03858  -3.498  -5.135  19.56  11.55  -0.0712  -0.003861  -0.1315  0.8124  0.9825  0.1786  0.09186
x10   -0.002259  0.002047  0.7845  0.5185  0.07538  0.4438  -0.684  -12.38  0.6782  -995.7  5.192  -15.11  -59.31
x11   -0.003207  0.003284  0.7525  0.5708  0.0931  0.4706  -6.312  -12.75  0.1295  4.25  -995  -18.11  -53.07
x12    0.03772  -0.0135  7.149  -18.38  -8.269  -5.951  -0.1313  -0.3156  0.09638  -14.77  -19.08  -1.144  -1.923
x13    0.008183  0.01351  -11.6  -3.395  1.908  -6.989  -0.3426  -1.312  0.03539  -56.62  -66.9  -2.106  -7.276
x14    0.003576  0.09279  10.94  3.831  2.168  -0.3125  0.1239  0.3134  -0.006368  20.41  23.4  0.7584  2.704
x15    0.005773  0.07200  11.75  4.060  2.53  0.1187  0.04563  0.04597  0.005025  2.345  12.08  0.2153  1.163
```

Uncertain Sensitivity Plot

```
bodemag(inv(eye(2)+Ghat*Kinf),inv(eye(2)+Ghat*Kmu),inv(eye(2)+Ghat*K2inf));
legend("Sinf","Smu","S2inf");
```



Mu-synthesis controller has best performance