

# System Identification

## CE-2: Frequency domain methods

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### 1 Frequency domain Identification (Periodic signal)

We apply a signal that contains several frequency components, such as a PRBS signal. Then we divide element-wise the Fourier transform of the output signal by the Fourier transform of the input signal.

$$G(e^{j\omega}) = \frac{Y(e^{j\omega})}{U(e^{j\omega})}$$

To reduce the noise, we average over 16 periods before the division, leaving us with periods of length 127.

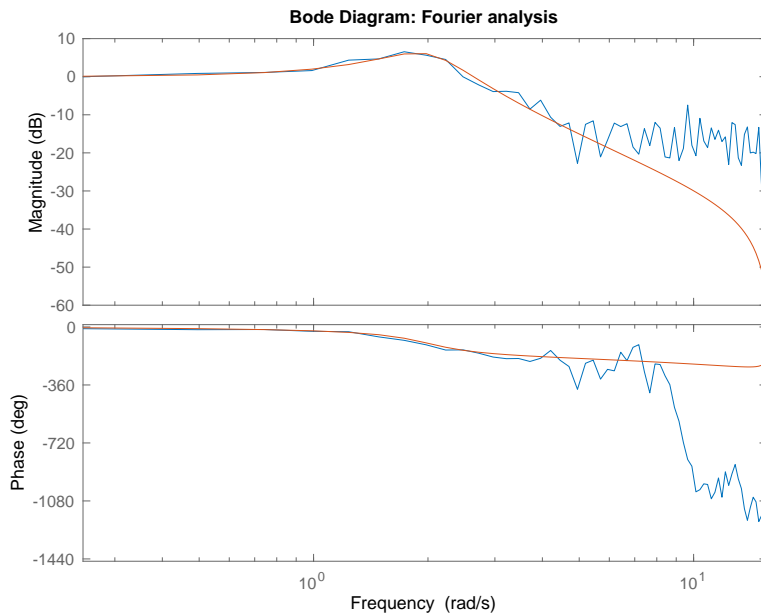


Figure 1: Frequency response using Fourier analysis

The Fourier analysis results in a relatively good reconstruction for lower frequencies while getting relatively noisy at high frequencies.

Listing 1: Fourier analysis method

```
1 % input signal
2 saturation = 0.5;
3 noiseVariance = 0.1;
4
5 N_PERIODS = 16;
6 PERIOD_LEN = 2^7-1;
```

```

7 u = 0.5*prbs(7,N_PERIODS);
8 Te = 0.2; % sample time
9 N = length(u);
10 sim_time = N*Te;
11
12 % simulation
13 simin = struct();
14 simin.signals = struct('values', u);
15 simin.time = linspace(0,N*Te, N);
16 sim('ce1_1_sim')
17
18 %% Fourier transform
19 omega_s = 2*pi/Te;
20 avg = zeros(PERIOD_LEN,1);
21 for i = 1:PERIOD_LEN:N
22     sig = simout(i:i+PERIOD_LEN-1);
23     avg = avg + fft(sig);
24 end
25 freq = [];
26 for i = 0:PERIOD_LEN-1
27     freq = [freq; i*omega_s/127];
28 end
29
30 Y = avg / N_PERIODS;
31 U = fft(u(1:PERIOD_LEN));
32 %% Reconstruction
33
34 Gr = Y ./ U;
35
36 NYQUIST_INDEX = round(PERIOD_LEN/2);
37 freq = freq(1:NYQUIST_INDEX);
38 Gr = Gr(1:NYQUIST_INDEX);
39
40 model = frd(Gr, freq, Te);
41
42 % true system
43 G = tf([4],[1 1 4]);
44 Z = c2d(G, Te, 'zoh');
45
46 % plot
47 figure
48 hold on
49 bode(model)
50 bode(Z,freq)
51 title('Bode_Diagram:_Fourier_analysis')
52 hold off

```

## 2 Frequency domain Identification (Random signal)

We apply a PRBS signal of length 1024 to the simulation using a time step  $Te = 0.2$ .

When the random input signal  $u(k)$  is uncorrelated with the disturbance signal  $d(k)$  then:

$$R_{yu}(h) = g(h) * R_{uu}(h)$$

Taking the FT:

$$\Phi_{yu}(\omega) = G(e^{j\omega})\Phi_{uu}(\omega)$$

Thus we can reconstruct the frequency response by dividing the FTs of cross correlation  $R_{yu}$  and autocorrelation  $R_{uu}$ .

$$G(e^{j\omega}) = \frac{\Phi_{yu}(\omega)}{\Phi_{uu}(\omega)}$$

Figure 2 shows the spectral analysis method applied to the simulation output with a random (PRBS) input. We used the biased cross- and autocorrelation function estimates.

We observe that the estimation is relatively good until the peak at  $1.9\text{rad/s}$  after that it becomes noisy and the phase diverges.

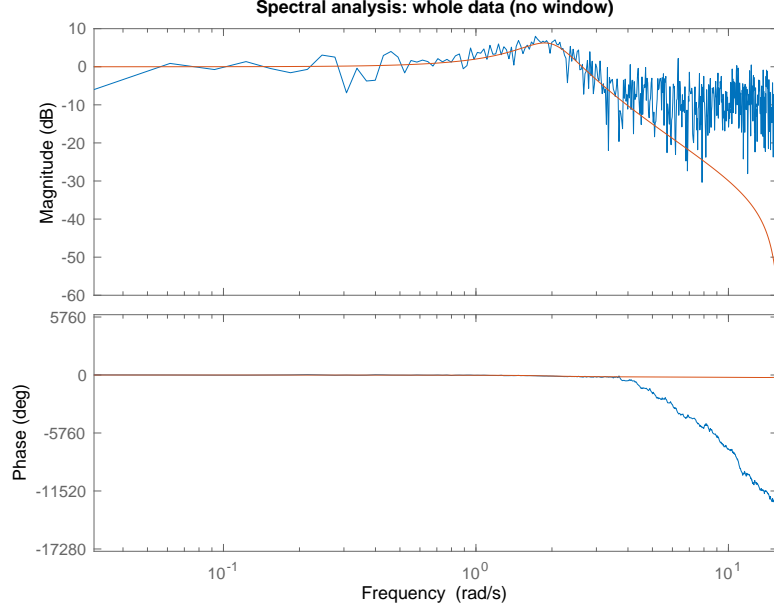


Figure 2: Spectral analysis method.

## Windowing

To reduce the truncation error we use windowing, which is a weighting function in the time domain. The default window is a  $\text{rect}(t)$  function which becomes a  $\text{sinc}(\omega)$  in the Fourier domain. The side lobes introduce errors from other frequencies. We use a Hann window which has a bigger main lobe width (MLW) of  $4\pi/N$  and a second lobe amplitude (SLA) of only 2.7%. The Hann window is defined as follows:

$$f_{\text{Hann}}(t) = \begin{cases} 0.5(1 + \cos(\frac{\pi t}{N})) & \text{for } t \in [-N, N] \\ 0 & \text{elsewhere} \end{cases}$$

Figure 3 shows the reconstruction using a Hann window of length 40. We observe that there is significantly less noise and the phase is more stable. Though the reconstruction has a lower peak at around  $1.9\text{rad/s}$ .

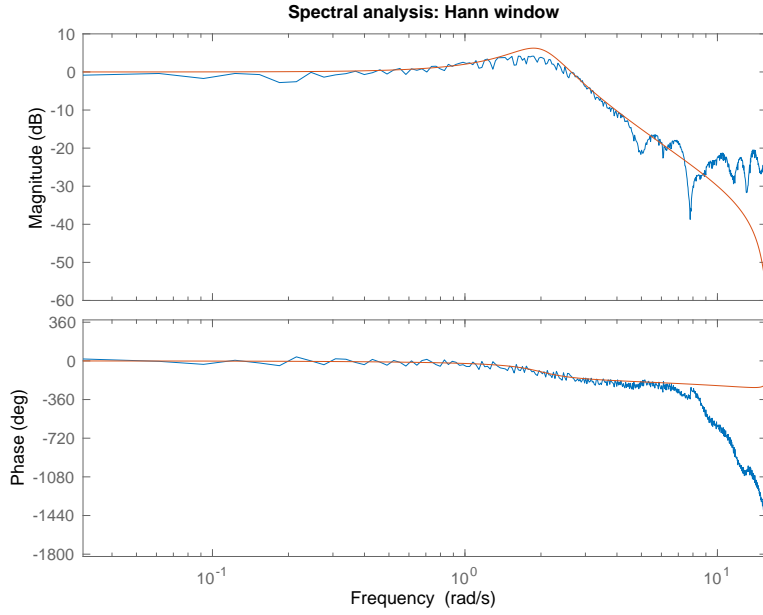


Figure 3: Spectral analysis method with a Hann window.

Listing 2 shows the spectral analysis implementation in form of a Matlab function, allowing for optional windowing and selection of a biased or unbiased estimator of  $R_{yu}$  and  $R_{uu}$ .

Listing 2: spectral analysis

```

1 function model = spectral_analysis(y,u,Te,SCALEOPT>window)
2
3 N = length(u);
4
5 if nargin < 4
6     SCALEOPT = 'biased';
7 end
8 if nargin < 5
9     window = ones(N,1);
10 end
11
12 % correlation
13 Ryu = xcorr(y,u, SCALEOPT);
14 Ruu = xcorr(u,u, SCALEOPT);
15
16 Ryu = Ryu(N:end);
17 Ruu = Ruu(N:end);
18
19 % Windowing
20 padding = zeros(N - length(window), 1);
21 window = [window; padding];
22 Ryu = Ryu.*window;
23
24 % Reconstruction
25 Gr = fft(Ryu)./fft(Ruu);
26
27 omega_s = 2*pi/Te;
28 freq = 0:omega_s/N:(N-1)/N*omega_s;
29
30 NYQUIST_INDEX = round(N/2);
31 Gr = Gr(1:NYQUIST_INDEX);
32 freq = freq(1:NYQUIST_INDEX);
33
34 model = frd(Gr, freq, Te);

```

## Averaging

We can reduce the noise by splitting the data into multiple chunks and averaging over the FT of the cross- and autocorrelation estimates before dividing them.

Figure 4 shows the frequency response reconstruction using averaging over 8 parts. In the left no window was applied and in the right we used a Hann window of length 40. We observe a significant reduction of noise and more stable phase in respect to simple spectral analysis method. When using a window the noise is slightly more reduced but we loose again amplitude at the peak at  $1.9\text{rad/s}$ .

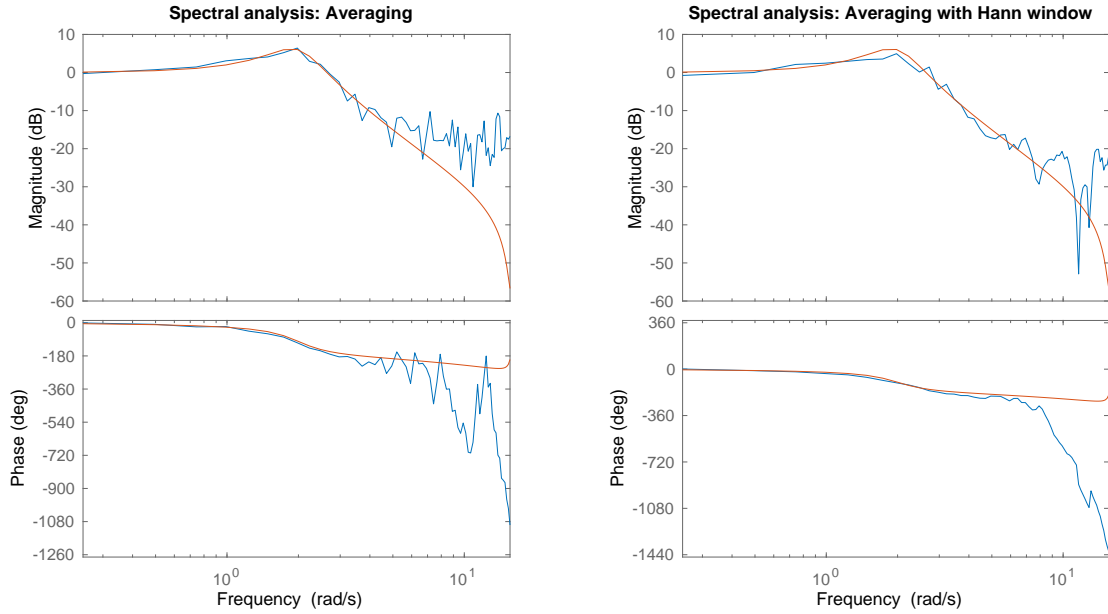


Figure 4: Spectral analysis method using averaging with and without windowing.

Listing 3 shows the spectral analysis implementation with averaging in form of a Matlab function.

Listing 3: spectral analysis avg

```

1 function model = spectral_analysis_avg(y,u,Te,N_AVG,SCALEOPT>window)
2
3 N = floor(length(u)/N_AVG);
4
5 if nargin < 5
6     SCALEOPT = 'biased';
7 end
8 if nargin < 6
9     window = ones(N,1);
10 end
11 padding = zeros(N - length(window), 1);
12 window = [window; padding];
13
14 fft_Ryu = zeros(N,1);
15 fft_Ruu = zeros(N,1);
16 for i = 0:N_AVG-1
17     % split into chunks
18     yc = y(i*N + 1:(i+1)*N);
19     uc = u(i*N + 1:(i+1)*N);
20
21     % correlation
22     Ryu = xcorr(yc,uc, SCALEOPT);
23     Ruu = xcorr(uc,uc, SCALEOPT);
24
25     Ryu = Ryu(N:end);

```

```

26     Ruu = Ruu(N:end);
27
28     % windowing
29     Ryu = Ryu .* window;
30
31     % averaging
32     fft_Ryu = fft_Ryu+fft(Ryu);
33     fft_Ruu = fft_Ruu+fft(Ruu);
34 end
35
36 % Reconstruction
37 Gr = fft_Ryu./fft_Ruu;
38
39 omega_s = 2*pi/Te;
40 freq = 0:omega_s/N:(N-1)/N*omega_s;
41
42 NYQUIST_INDEX = round(N/2);
43 Gr = Gr(1:NYQUIST_INDEX);
44 freq = freq(1:NYQUIST_INDEX);
45
46 model = frd(Gr, freq, Te);

```

## Unbiased estimator of cross- and autocorrelation function

Figure 5 compares results using biased and unbiased estimations of the cross-correlation and autocorrelation functions used in the spectral analysis method. We observe that the unbiased estimator is more noisy and corresponds less to the true model.

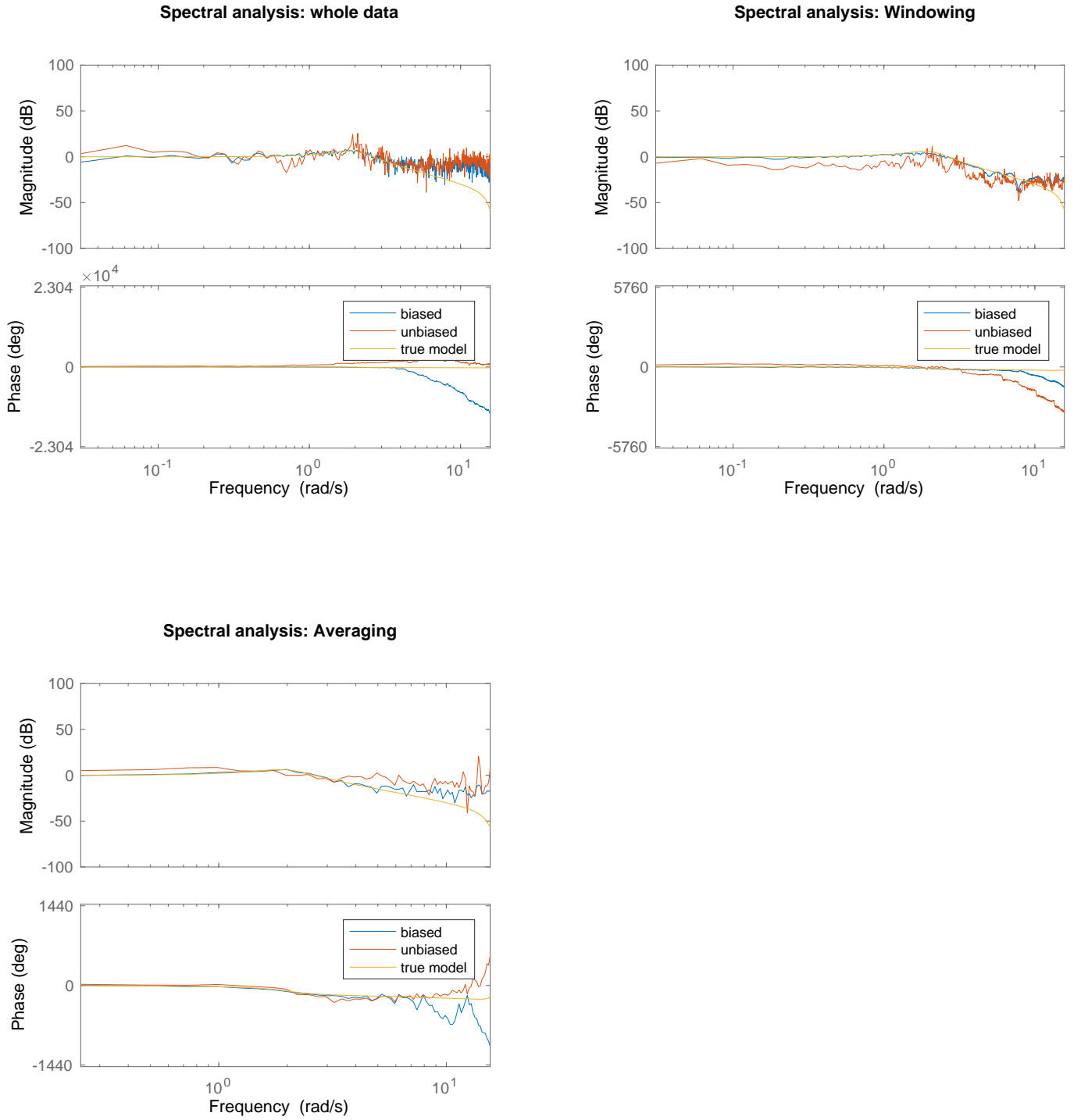


Figure 5: Comparing spectral analysis method based on biased and unbiased estimations of the correlation functions.

### 3 Simulation and plot generation code

Listing 4: Spectral analysis method

```

1  % simulation parameters
2  saturation = 0.5;
3  noiseVariance = 0.1;
4
5  % input signal
6  u = 0.5*prbs(10,1);
7  PERIOD_LEN = length(u);
8  Te = 0.2; % sample time
9  N = length(u);
10 sim_time = N*Te;
11
12 % simulation
13 simin = struct();
14 simin.signals = struct('values', u);
15 simin.time = linspace(0,N*Te, N);
16 sim('ce1_1_sim')
17 y = simout;
18
19 % true system
20 G = tf([4],[1 1 4]);
21 Z = c2d(G, Te, 'zoh');
22
23
24 %% Spectral analysis method
25 model = spectral_analysis(y,u,Te,'biased');
26
27 % Windowing
28 hann = @(M) 0.5+0.5*cos(pi*[0:M-1]/(M-1));
29 hamming = @(M) 0.54+0.46*cos(pi*[0:M-1]/(M-1));
30
31 window = hann(40);
32 model_hann = spectral_analysis(y,u,Te,'biased',window);
33
34 % Bode plot
35 figure
36 hold on
37 bode(model)
38 bode(Z,model.Frequency)
39 title('Spectral_analysis:whole_data(no_window)')
40 hold off
41
42 figure
43 hold on
44 bode(model_hann)
45 bode(Z,model_hann.Frequency)
46 title('Spectral_analysis:Hann_window')
47 hold off
48
49 %% Averaging
50 N_AVG = 8;
51
52 % averaging without window
53 model = spectral_analysis_avg(y,u,Te,N_AVG,'biased');
54
55 % averaging with Hann window
56 window = hann(40);
57 model_hann = spectral_analysis_avg(y,u,Te,N_AVG,'biased',window);
58
59 figure
60 subplot(1,2,1)
61 hold on
62 bode(model)
63 bode(Z,model.Frequency)
64 title('Spectral_analysis:Averaging')
65 hold off

```



```

66 subplot(1,2,2)
67 hold on
68 bode(model_hann)
69 bode(Z,model.Frequency)
70 title('Spectral_analysis: Averaging with Hann window')
71 hold off
72
73
74 %% unbiased plots
75 figure
76 subplot(2,2,1)
77 hold on
78 model_biased = spectral_analysis(y,u,Te,'biased');
79 model_unbiased = spectral_analysis(y,u,Te,'unbiased');
80 bode(model_biased)
81 bode(model_unbiased)
82 bode(Z,model_biased.Frequency)
83 title('Spectral_analysis: whole data')
84 legend('biased','unbiased','true_model')
85 hold off
86
87 window = hann(40);
88 subplot(2,2,2)
89 hold on
90 model_biased = spectral_analysis(y,u,Te,'biased',window);
91 model_unbiased = spectral_analysis(y,u,Te,'unbiased',window);
92 bode(model_biased)
93 bode(model_unbiased)
94 bode(Z,model_biased.Frequency)
95 title('Spectral_analysis: Windowing')
96 legend('biased','unbiased','true_model')
97 hold off
98
99 subplot(2,2,3)
100 hold on
101 model_biased = spectral_analysis_avg(y,u,Te,N_AVG,'biased');
102 model_unbiased = spectral_analysis_avg(y,u,Te,N_AVG,'unbiased');
103 bode(model_biased)
104 bode(model_unbiased)
105 bode(Z,model_biased.Frequency)
106 title('Spectral_analysis: Averaging')
107 legend('biased','unbiased','true_model')
108 hold off

```