

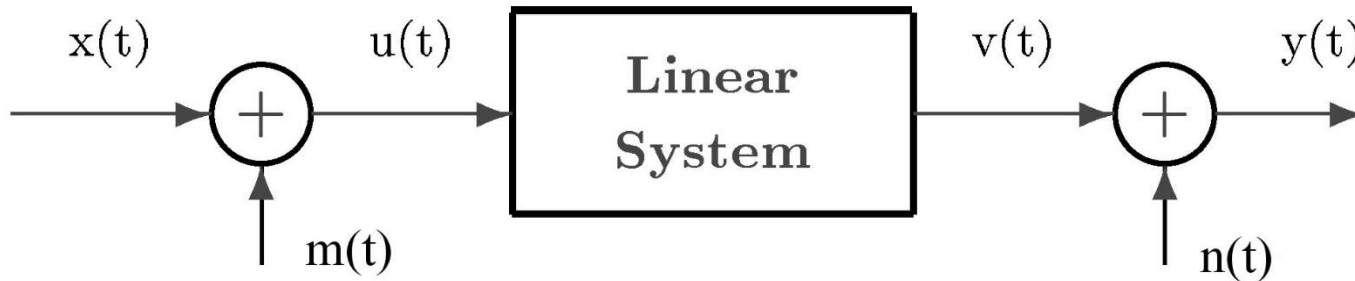
## 9. System identification

Structural Dynamics part of 4DM00

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# System identification

Assume a linear relation between input and output signals.  
How to estimate this relation based on measurements  $x(t)$  and  $y(t)$ ?  
General situation: input noise  $m(t)$  and output noise  $n(t)$ .



First, only output noise ( $m(t) \equiv 0$ ).

$$y(t) = h(t) \otimes x(t) + n(t)$$

# Time-domain approach

Assume:

- No input noise, only output noise:  $y(t) = h(t) \otimes x(t) + n(t)$ .
- Input  $x(t)$  and output noise  $n(t)$  are independent:  $R_{xn}(\tau) = \mathbb{E}[x(t)n(t + \tau)] \equiv 0$ .

Then

$$\begin{aligned} R_{xy}(\tau) &= \mathbb{E}[x(t)y(t + \tau)] = \mathbb{E}\left[x(t) \left[ \left( \int_{-\infty}^{\infty} h(\xi)x(t + \tau - \xi)d\xi \right) + n(t + \tau) \right]\right] \\ &= \int_{-\infty}^{\infty} h(\xi)\mathbb{E}[x(t)x(t + \tau - \xi)]d\xi + \mathbb{E}[x(t)n(t + \tau)] \\ &= \int_{-\infty}^{\infty} h(\xi)R_{xx}(\tau - \xi)d\xi = h(\tau) \otimes R_{xx}(\tau) \end{aligned}$$

In principle possible to estimate  $h(t)$  from  $R_{xx}(\tau)$  and  $R_{xy}(\tau)$ .  
However, convolution makes time domain approach unsuitable.

# Frequency domain approach

The time domain approach resulted in:

$$R_{xy}(t) = h(t) \otimes R_{xx}(t)$$

Problematic due to convolution.

⇒ transform to the frequency domain:

$$S_{xy}(f) = H_{xy}(f)S_{xx}(f)$$

**$H_1$ -estimator** for FRF  $H_{xy}(f)$ :

$$\hat{H}_1(f) = \frac{\hat{S}_{xy}(f)}{\hat{S}_{xx}(f)}.$$

Note:

- The  $H_1$  estimator is unbiased in the absence of input noise.

# Alternative derivation in the frequency domain

Consider again a rectangular window  $w_T(t)$  which is 1 for  $0 \leq t \leq T$  and 0 otherwise. Windowed signals  $y_T(t) = y(t)w_T(t)$ ,  $x_T(t) = x(t)w_T(t)$  and  $n_T(t) = n(t)w_T(t)$ .

Multiply  $y(t) = h(t) \otimes x(t) + n(t)$  by  $w_T(t)$ :

$$y_T(t) = w_T(t)(h(t) \otimes x(t)) + n_T(t) = w_T(t)(h(t) \otimes x_T(t)) + n_T(t)$$

Note: future inputs do not influence past outputs  $h(t) \otimes x(t) = h(t) \otimes x_T(t)$  for  $t \leq T$ .

1. Transform to frequency domain:

$$Y_T(f) = W_T(f) \otimes (H_{xy}(f)X_T(f)) + N_T(f)$$

2. Multiply by  $X_T^*(f)$

$$X_T^*(f)Y_T(f) = X_T^*(f) \left( W_T(f) \otimes (H_{xy}(f)X_T(f)) \right) + X_T^*(f)N_T(f)$$

3. Multiply by  $1/T$  and take the limit for  $T \rightarrow \infty$ .

$$S_{xy}(f) = H_{xy}(f)S_{xx}(f) + S_{xn}(f) = H_{xy}(f)S_{xx}(f)$$

Note that  $S_{xn}(f) = F[R_{xn}(\tau)] = 0$  when  $x(t)$  and  $n(t)$  are independent.

# Influence of output noise on the FRF estimate

$$Y(f) = H_{xy}(f)X(f) + N(f)$$

Therefore,

$$\begin{aligned} Y^*(f)Y(f) \\ = H_{xy}^*(f)H_{xy}(f)X^*(f)X(f) + H_{xy}^*(f)X^*(f)N(f) + H_{xy}(f)N^*(f)X(f) + N^*(f)N(f) \end{aligned}$$

Indeed, it can be shown that

$$S_{yy}(f) = |H_{xy}(f)|^2 S_{xx}(f) + H^*(f)S_{xn}(f) + H(f)S_{nx}(f) + S_{nn}(f).$$

Note that  $S_{xn}(f) = \overline{S_{nx}(f)} \equiv 0$  when  $x(t)$  and  $n(t)$  are independent. Therefore,

$$S_{yy}(f) = |H_{xy}(f)|^2 S_{xx}(f) + S_{nn}(f)$$

# Influence of output noise on the FRF estimate

$$S_{yy}(f) = |H_{xy}(f)|^2 S_{xx}(f) + S_{nn}(f), \quad S_{nn}(f) = S_{yy}(f) - |H_{xy}(f)|^2 S_{xx}(f)$$

But  $H_{xy}(f) = S_{xy}(f)/S_{xx}(f)$ , therefore

$$S_{nn}(f) = S_{yy}(f) - \frac{|S_{xy}(f)|^2}{|S_{xx}(f)|^2} S_{xx}(f) = \left( 1 - \frac{|S_{xy}(f)|^2}{S_{xx}(f)S_{yy}(f)} \right) S_{yy}(f).$$

We now recognize the **coherence function**  $\gamma_{xy}(f)$

$$0 \leq \gamma_{xy}^2(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f)S_{yy}(f)} \leq 1.$$

We conclude:

$$S_{nn}(f) = \left( 1 - \gamma_{xy}^2(f) \right) S_{yy}(f)$$

# Influence of output noise on the FRF estimate

Recall that  $y(t) = v(t) + n(t)$

$v(t)$  is the part of  $y(t)$  that is not influenced by the noise  $n(t)$ .

Because  $Y(f) = V(f) + N(f)$

$$Y^*(f)Y(f) = V^*(f)V(f) + N^*(f)V(f) + V^*(f)N(f) + N^*(f)N(f)$$

Indeed, it is true that

$$S_{yy}(f) = S_{vv}(f) + S_{nv}(f) + S_{vn}(f) + S_{nn}(f).$$

It can be shown that  $v(t)$  and  $n(t)$  are uncorrelated when  $x(t)$  and  $n(t)$  are independent.

$$S_{yy}(f) = S_{vv}(f) + S_{nn}(f)$$



# Influence of output noise on the FRF estimate

$$S_{nn}(f) = \left(1 - \gamma_{xy}^2(f)\right) S_{yy}(f),$$

$$S_{vv}(f) = S_{yy}(f) - S_{nn}(f) = \gamma_{xy}^2(f) S_{yy}(f)$$

The coherence function  $\gamma_{xy}^2(f)$  ( $0 \leq \gamma_{xy}^2(f) \leq 1$ ) thus tells which part of  $S_{yy}(f)$  is caused by the noise  $n(t)$  and which part by  $v(t)$ .

$\gamma_{xy}^2(f) \rightarrow 1$ : strong linear relation between input and output at frequency  $f$

$\gamma_{xy}^2(f) \rightarrow 0$ : no linear relation between input and output at frequency  $f$ ,  
output dominated by noise and/or nonlinear effects

# Variance of the estimators

- The standard deviation of the  $H_1$ -estimator  $\hat{H}_1(f) = \hat{S}_{xy}(f)/\hat{S}_{xx}(f)$  is

$$\sigma_{|\hat{H}_1|} = (\text{var}[\hat{H}_1(f)])^{1/2} \approx \frac{[1 - \hat{\gamma}_{xy}^2(f)]^{\frac{1}{2}}}{|\hat{\gamma}_{xy}(f)|\sqrt{2N}} |\hat{H}_{xy}(f)|$$

- The standard deviation of the coherence estimator  $\hat{\gamma}_{xy}^2(f) = |\hat{S}_{xy}(f)|^2 / (\hat{S}_{xx}(f)\hat{S}_{yy}(f))$  is

$$\sigma_{\hat{\gamma}_{xy}^2} = (\text{var}[\hat{\gamma}_{xy}^2(f)])^{1/2} \approx \frac{\sqrt{2}[1 - \hat{\gamma}_{xy}^2(f)]}{|\hat{\gamma}_{xy}(f)|\sqrt{N}} \hat{\gamma}_{xy}^2(f)$$

- The standard deviation of the estimator  $\hat{S}_{vv}(f) = |\hat{S}_{xy}(f)|^2 / \hat{S}_{xx}(f)$  is

$$\sigma_{\hat{S}_{vv}} = (\text{var}[\hat{S}_{vv}(f)])^{1/2} \approx \frac{[2 - \hat{\gamma}_{xy}^2(f)]^{1/2}}{|\hat{\gamma}_{xy}(f)|\sqrt{N}} \hat{S}_{vv}(f)$$

These standard deviations can be used to define 95%-confidence intervals.

# Example: 2-dof system

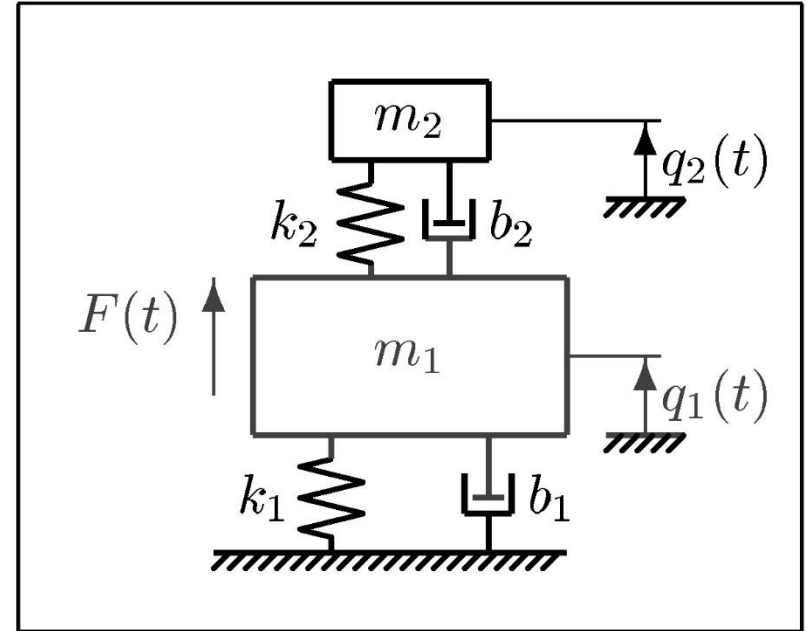
Properties:

$$m_1 = 1 \text{ kg}, m_2 = 0.3 \text{ kg},$$
$$k_1 = 100 \text{ N/m}, k_2 = 50 \text{ N/m},$$
$$b_1 = 1 \text{ Ns/m}, b_2 = 0.4 \text{ Ns/m}.$$

Excitation:  $x(t) = F(t)$

Response:  $y(t) = q_1(t)$

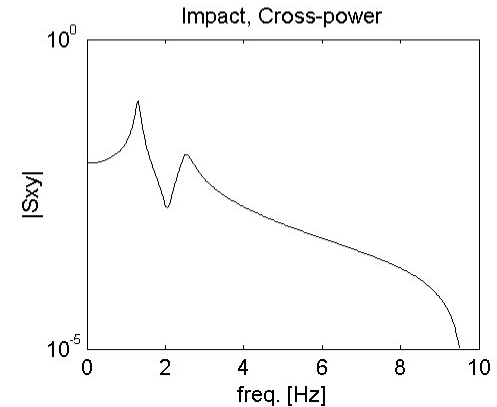
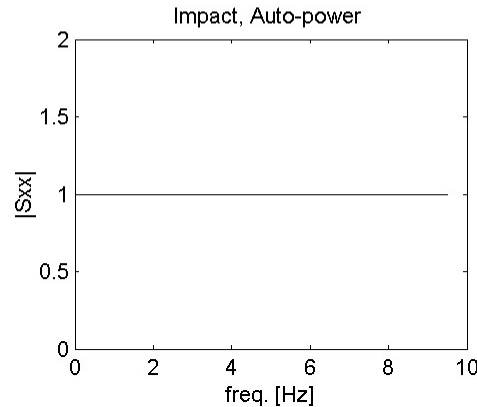
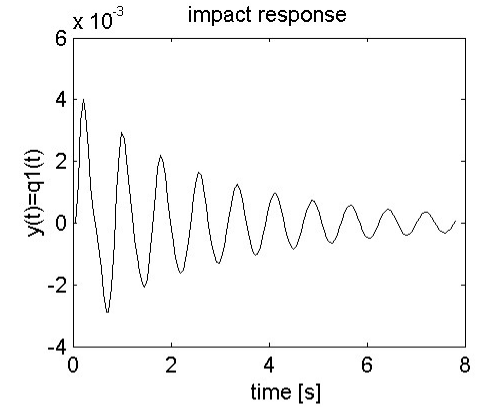
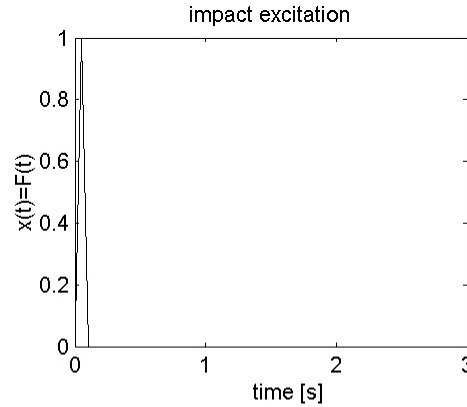
simulated experiment  
no noise, so  $n(t) = 0$ .



# Example: 2-dof system

Case 1:

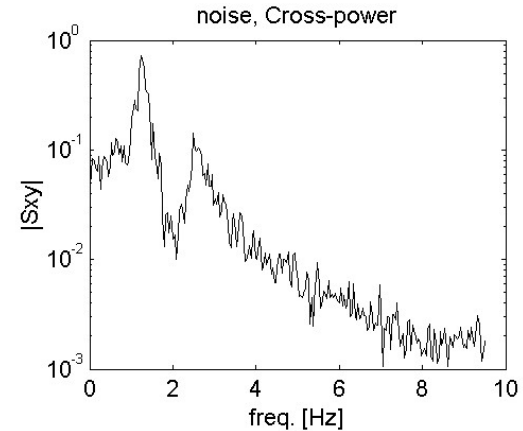
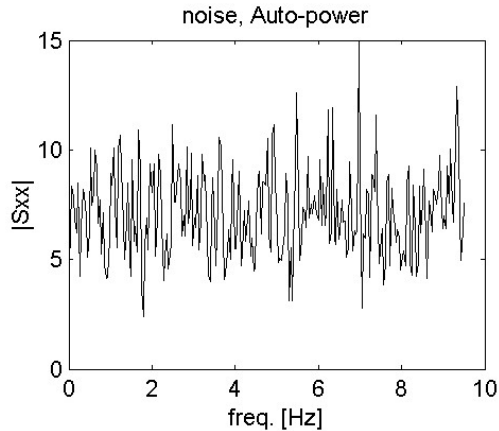
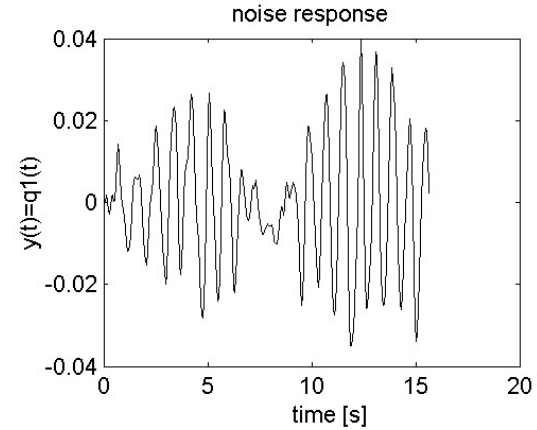
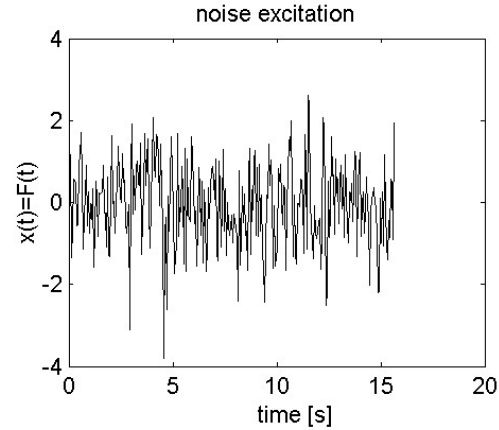
Hammer (impact) excitation  
(2 records of 512 time points)



# Example: 2-dof system

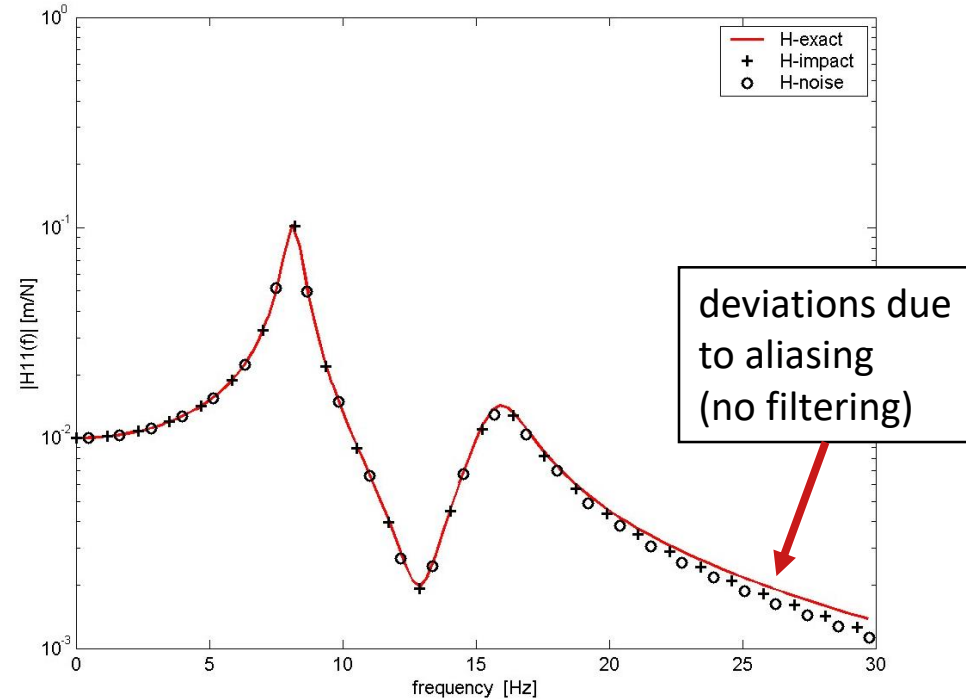
Case 2:

White noise excitation,  
10 records of 512 time points,  
Hanning window



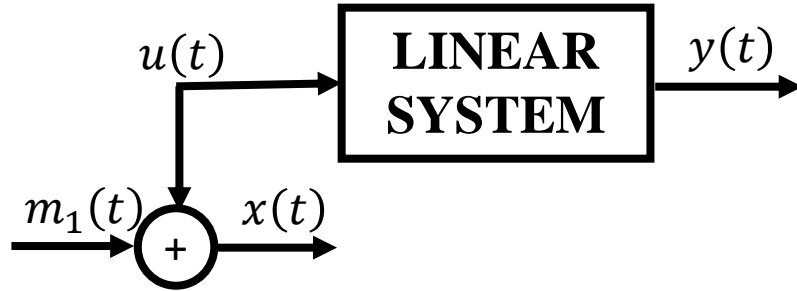
# Example: 2-dof system

- Exact FRF (red)
- Estimated FRF based on **impact** excitation (case 1, +)
- Estimated FRF based on **white noise** excitation (case 2, o)



## 9b. Input noise

## Two types of input noise

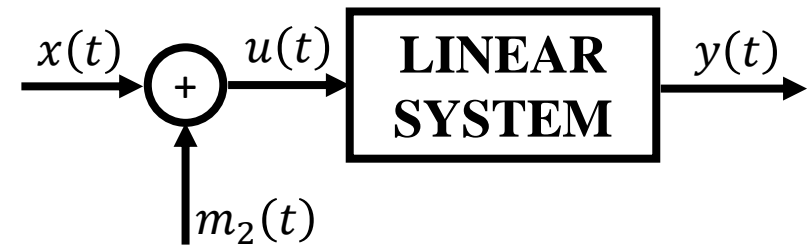


$x(t)$  and  $y(t)$  are measured

$m_1(t)$ : unknown noise source at input,  
does not go through system

$$\begin{aligned} y(t) &= h(t) \otimes u(t) \\ &= h(t) \otimes (x(t) - m_1(t)) \end{aligned}$$

**$m_1(t)$  and  $u(t)$  are statistically independent**  
 **$m_1(t)$  and  $x(t)$  are not statistically independent**



$x(t)$  and  $y(t)$  are measured

$m_2(t)$ : unknown noise source at input,  
does go through system

$$\begin{aligned} y(t) &= h(t) \otimes u(t) \\ &= h(t) \otimes (x(t) + m_2(t)) \end{aligned}$$

**$m_2(t)$  and  $x(t)$  are statistically independent**  
 **$m_2(t)$  and  $u(t)$  are not statistically independent**



# Input noise $m_1(t)$

- $m_1(t)$  and  $u(t)$  are independent
- $m_1(t)$  and  $x(t)$  are not independent
- $y(t) = h(t) \otimes (x(t) - m_1(t))$

In the frequency domain,

$$Y(f) = H_{xy}(f)(X(f) - M_1(f))$$

Two options:

- OPTION 1: Multiply by  $X^*(f)$

$$X^*(f)Y(f) = H_{xy}(f)X^*(f)(X(f) - M_1(f))$$

$$S_{xy}(f) = H_{xy}(f) \left( S_{xx}(f) - S_{xm_1}(f) \right)$$

But  $x(t)$  and  $m_1(t)$  are not independent, so  $S_{xm_1}(f) \neq 0$ !

The  $H_1$ -estimator  $\hat{S}_{xy}(f)/\hat{S}_{xx}(f)$  is biased!

## Input noise $m_1(t)$

- $m_1(t)$  and  $u(t)$  are independent
- $m_1(t)$  and  $x(t)$  are not independent
- $y(t) = h(t) \otimes (x(t) - m_1(t))$

In the frequency domain,

$$Y(f) = H_{xy}(f)(X(f) - M_1(f))$$

Two options:

- OPTION 2: Multiply by  $Y^*(f)$

$$Y^*(f)Y(f) = H_{xy}(f)Y^*(f)(X(f) - M_1(f))$$

$$S_{yy}(f) = H_{xy}(f) \left( S_{yx}(f) - S_{ym_1}(f) \right)$$

$y(t)$  and  $m_1(t)$  are independent

(because  $u(t)$  and  $m_1(t)$  are independent and  $y(t)$  depends linearly on  $u(t)$ )

The  **$H_2$ -estimator**  $\hat{S}_{yy}(f)/\hat{S}_{yx}(f)$  is unbiased!

# Input noise $m_2(t)$

- $m_2(t)$  and  $x(t)$  are independent
- $m_2(t)$  and  $u(t)$  are not independent
- $y(t) = h(t) \otimes (x(t) + m_2(t))$

In the frequency domain,

$$Y(f) = H_{xy}(f)(X(f) + M_2(f))$$

Two options:

- OPTION 1: Multiply by  $X^*(f)$

$$X^*(f)Y(f) = H_{xy}(f)X^*(f)(X(f) + M_2(f))$$

$$S_{xy}(f) = H_{xy}(f)(S_{xx}(f) + S_{xm_2}(f))$$

But  $x(t)$  and  $m_2(t)$  are not independent, so  $S_{xm_2}(f) \neq 0$ !

The  $H_1$ -estimator  $\hat{S}_{xy}(f)/\hat{S}_{xx}(f)$  is unbiased!  
(it can be verified similarly that the  $H_2$ -estimator is biased).

# Two estimators

So we have found two estimators:

$$\hat{H}_1(f) = \frac{\hat{S}_{xy}(f)}{\hat{S}_{xx}(f)}, \quad \hat{H}_2(f) = \frac{\hat{S}_{yy}(f)}{\hat{S}_{yx}(f)}.$$

Note that

$$\frac{\hat{H}_1(f)}{\hat{H}_2(f)} = \frac{\hat{S}_{xy}(f)\hat{S}_{yx}(f)}{\hat{S}_{xx}(f)\hat{S}_{yy}(f)} = \frac{|\hat{S}_{xy}(f)|^2}{\hat{S}_{xx}(f)\hat{S}_{yy}(f)} = \hat{\gamma}_{xy}^2(f)$$

So the estimators will differ iff  $\hat{\gamma}_{xy}^2(f) < 1$ .

⇒ without noise  $\hat{H}_1(f) = \hat{H}_2(f)$ .

## Example: 2-dof system

$$M\ddot{q}(t) + B\dot{q}(t) + Kq(t) = F(t)$$

$$M = \begin{bmatrix} 1 & 0 \\ 0 & 0.2 \end{bmatrix}, \quad B = \begin{bmatrix} 0.055 & -0.0003 \\ -0.0003 & 0.03 \end{bmatrix}, \quad K = \begin{bmatrix} 1.2 & -0.2 \\ -0.2 & 0.2 \end{bmatrix}$$

$$q(t) = \begin{bmatrix} q_1(t) \\ q_2(t) \end{bmatrix}, \quad F(t) = \begin{bmatrix} 0 \\ F_2(t) \end{bmatrix}.$$

Simulated experiment, estimate the collocated FRF of dof 2:  $H_{22}(f) = Q_2/F_2 = Y/X$

Input force  $F_2(t) = x(t)$ : random noise, normal pdf ( $\mu_x = 0, \sigma_x = 1$ )

After numerical integration: response  $q_2(t) = y(t), \sigma_y \approx 10$

Add 2 disturbance noises:  $m_1(t), \sigma_{m_1} = 0.2$  and  $n(t), \sigma_n = 2$

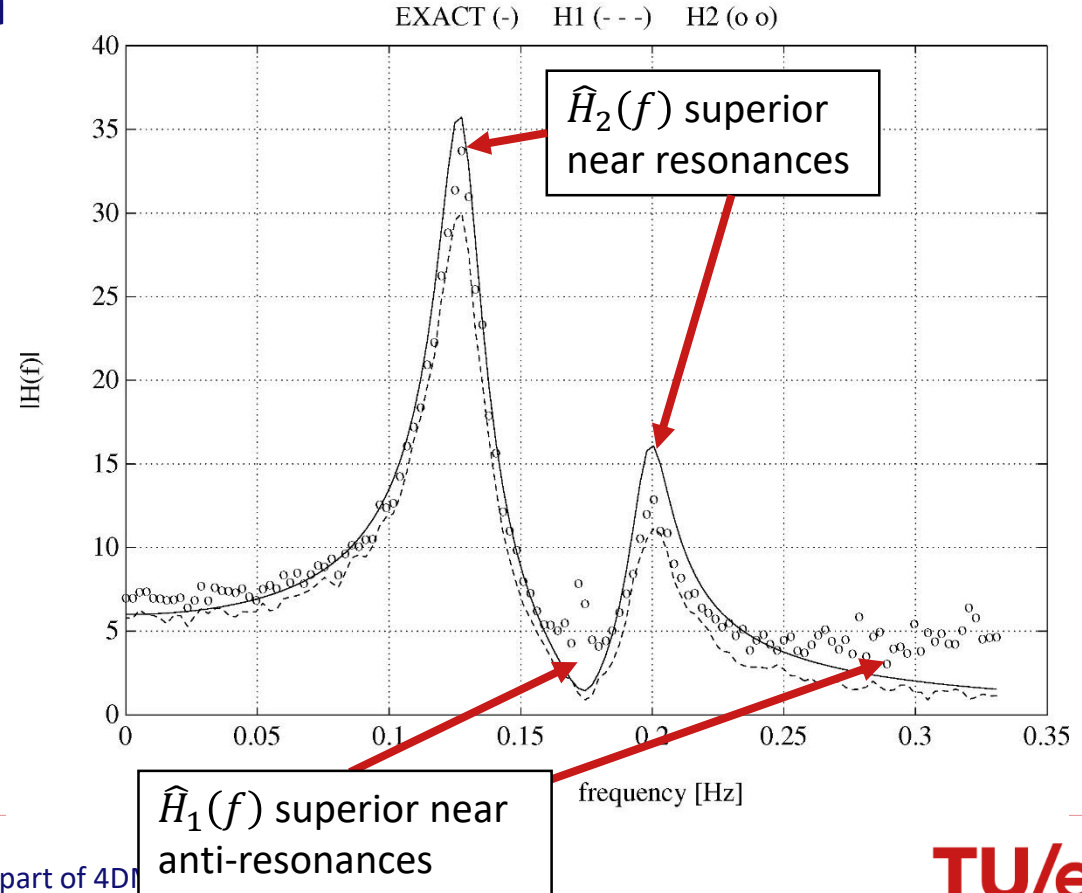
Discrete  $x(t_k), y(t_k)$  are generated,  $\Delta T = 1.2$  s,  $k = 1, 2, \dots, 10000$

# Example: 2-dof system

The estimators

- $\hat{H}_1(f)$  (- - -) and
  - $\hat{H}_2(f)$  (o o)
- are compared to
- the exact solution  $H_{xy}(f)$  (---).

(39 records of 256 time points)



# Estimation near anti-resonances and resonances

- Near anti-resonances:

large input  $u(t)$  gives small response  $v(t)$

$S_{nn}(f_{ar})$  has large influence on  $S_{yy}(f_{ar}) = S_{vv}(f_{ar}) + S_{nn}(f_{ar})$

Noise  $n(t)$  strongly influences the estimator

$$\hat{H}_2(f_{ar}) = \frac{\hat{S}_{yy}(f_{ar})}{\hat{S}_{yx}(f_{ar})}$$

- Near resonances:

small input  $u(t)$  gives large response  $v(t)$

$S_{m_1 m_1}(f_{res})$  has large influence on  $S_{xx}(f_{res}) = S_{uu}(f_{res}) + S_{m_1 m_1}(f_{res})$

Noise  $m_1(t)$  strongly influences the estimator

$$\hat{H}_1(f_{res}) = \frac{\hat{S}_{xy}(f_{res})}{\hat{S}_{xx}(f_{res})}$$

# Summary

Three estimators for  $H_{xy}(f)$ :

- $\hat{H}_0(f) = \frac{\hat{Y}(f)}{\hat{X}(f)}$  Rarely used, difficult to create accurate estimator
- $\hat{H}_1(f) = \frac{\hat{S}_{xy}(f)}{\hat{S}_{xx}(f)}$  to be used when the (input or output) noise is independent of  $x(t)$   
superior near anti-resonances
- $\hat{H}_2(f) = \frac{\hat{S}_{yy}(f)}{\hat{S}_{yx}(f)}$  to be used when the (input) noise is independent of  $u(t)$   
superior near resonances

Without disturbance noise, these 3 estimators are **equivalent!**

## Warning:

For a single record  $N = 1$ ,  $\hat{H}_1(f) = \hat{H}_2(f)$  and  $\gamma_{xy}(f) \equiv 1$ ! Noise cannot be seen for  $N = 1$ !  
Choose the number of records  $N$  large enough to properly identify the influence of noise!