FREQUENCY-DOMAIN SYSTEM IDENTIFICATION FOR HIGH-PRECISION CONTROL DESIGN

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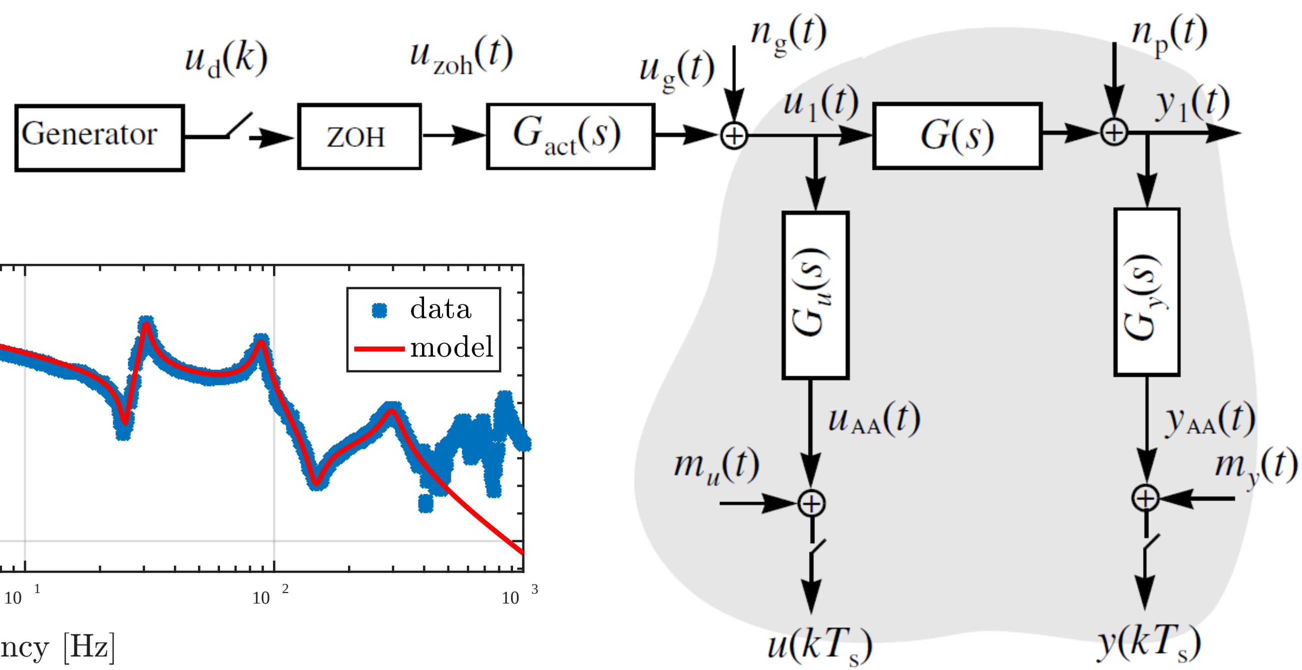
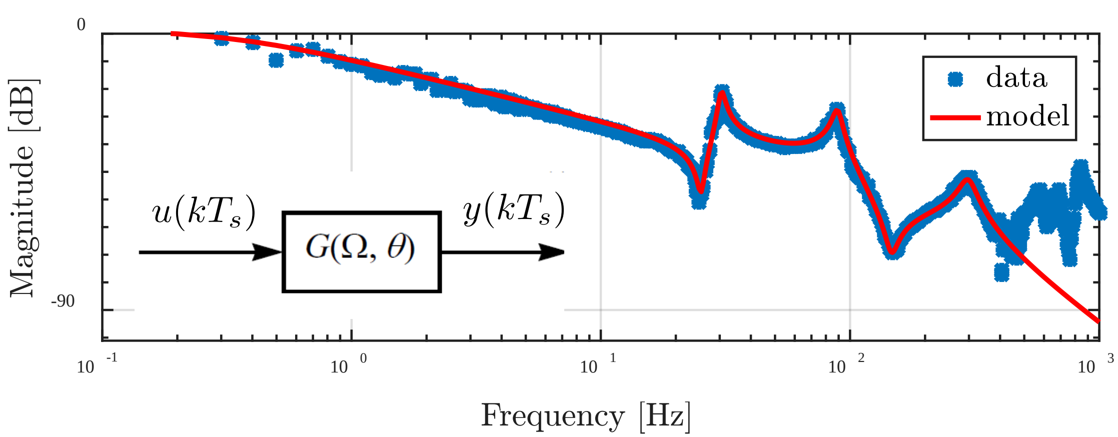




Main References

→ [1] K. Astrom, *Introduction to Stochastic Control Theory.* Academic Press: New York, 1970.

[2] G. Box and G. Jenkins, *Time Series Analysis: Forecasting and control.* Holden-Day: Oakland, 1970.

[3] G. Goodwin and R. Payne, *Dynamic System Identification. Experiment Design and Data Analysis.* Academic Press: New York, 1977.

[4] M. Zarrop, *Optimal experiment design for dynamic system identification.* Series of Lectures Notes in Control and Information Sciences, Springer-Verlag, Berlin, 1979.

[5] K. Godfrey, *Perturbation Signals for System Identification.* Prentice-Hall, London, 1993.

[6] L. Ljung, *System Identification: Toolbox User's Guide.* The MathWorks, Natick, 1995.

→ TDI

[7] 足立修一, MATLABによる制御のためのシステム同定. 東京電機大学出版局, 1996.

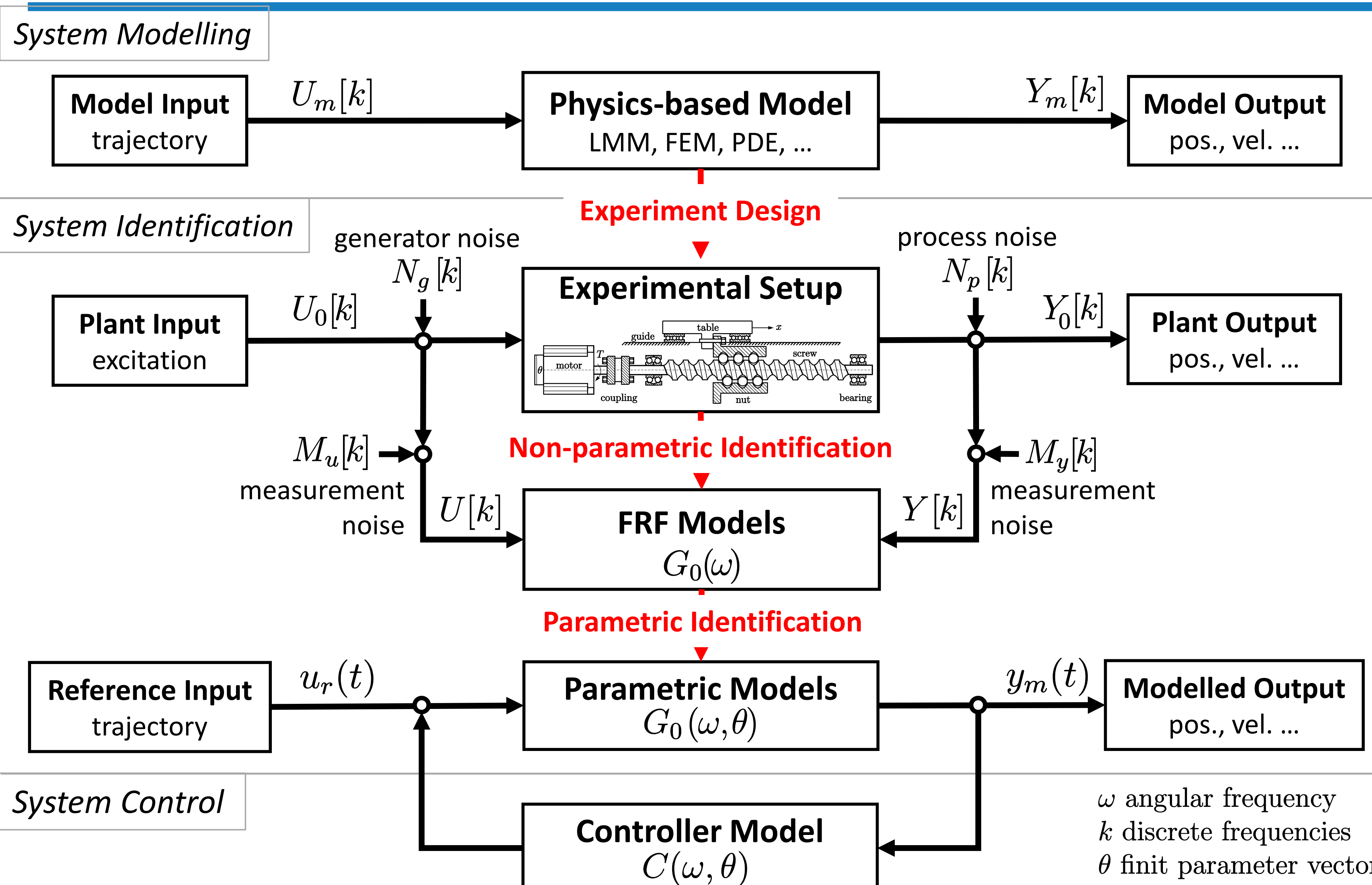
[8] L. Ljung, *System Identification: theory for the user.* MIT Press, Cambridge, MA, 1999.

[9] R. Pintelon and J. Schoukens, *Identification of linear systems: a practical guideline to accurate modeling.* Pergamon Oxford, 2001.

→ FDI

[10] R. Pintelon and J. Schoukens, *System Identification: a frequency domain approach.* IEEE Press: Piscataway, New Jersey (second edition), 2012.

System Identification for Control



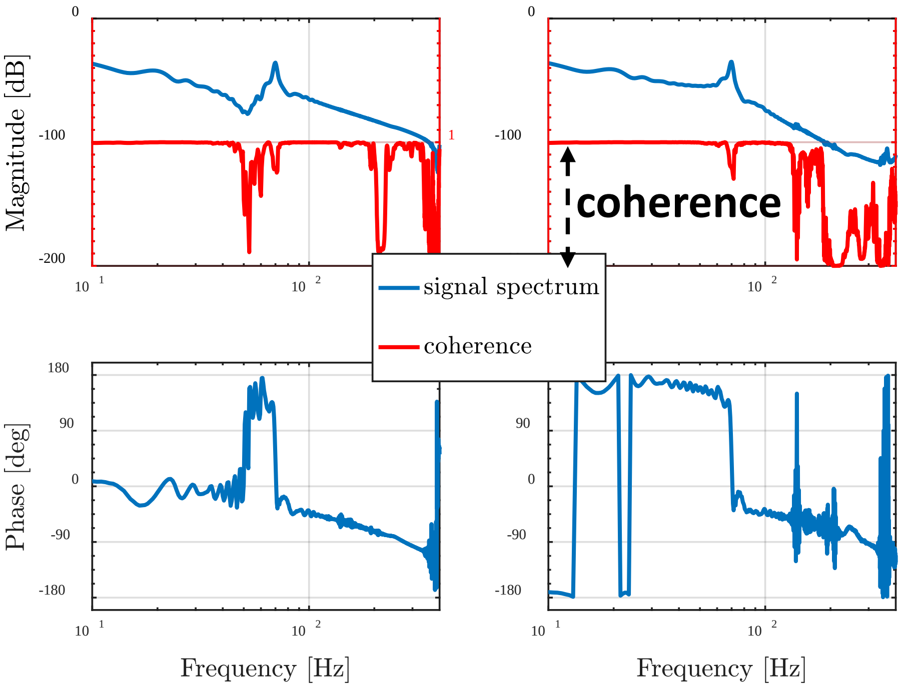
Overview of Non-Parametric Methods

- **Methods**

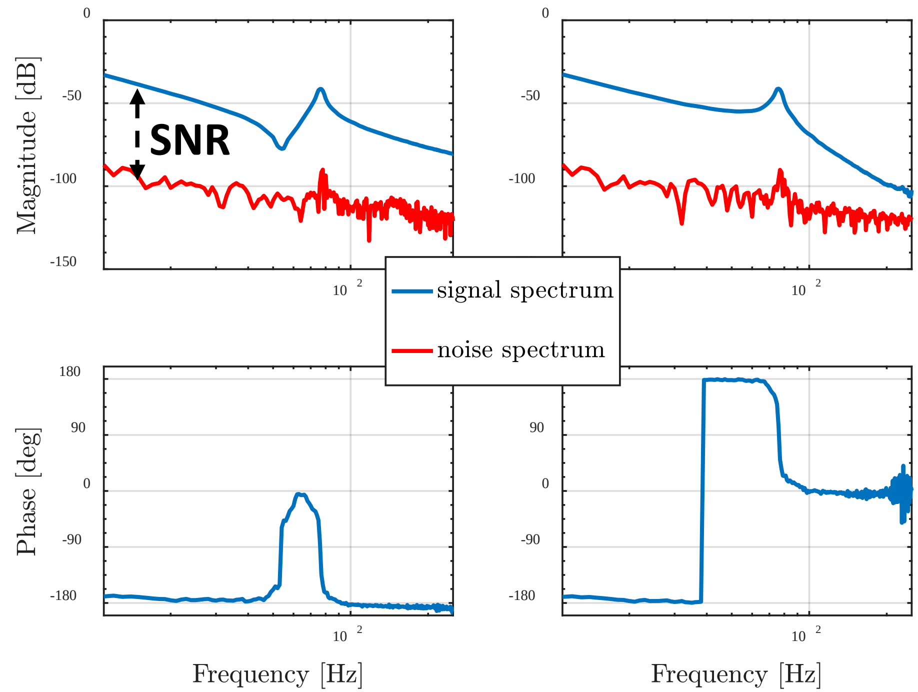
Servo Analyzer
Random excitation
Output-only noise

Proposed Analyzer
Periodic excitation
Input-output noise

- **Results**



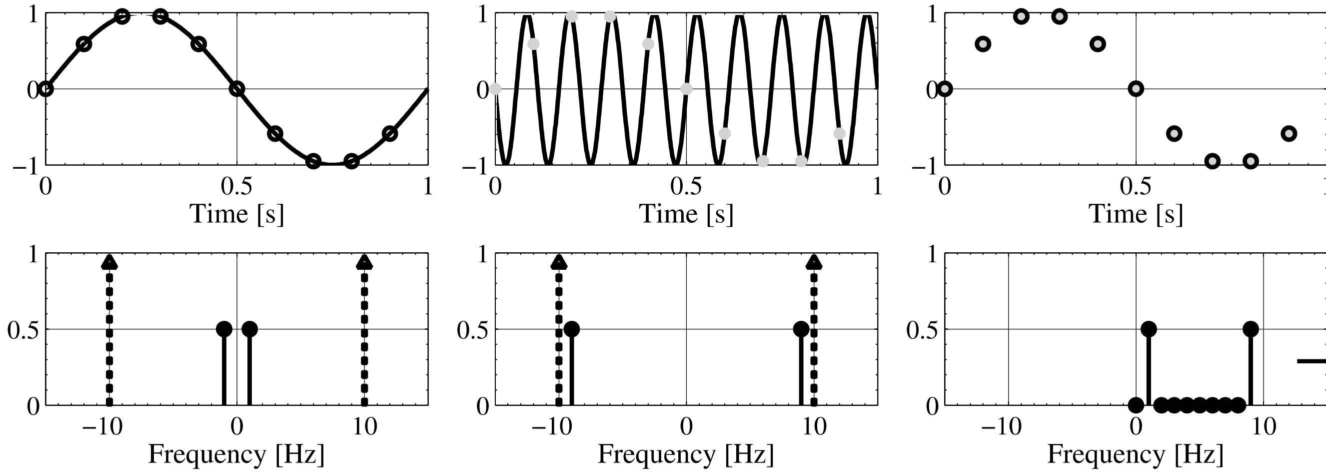
2-5min experiment



10s experiment

Discrete Fourier Transform – *Problems*

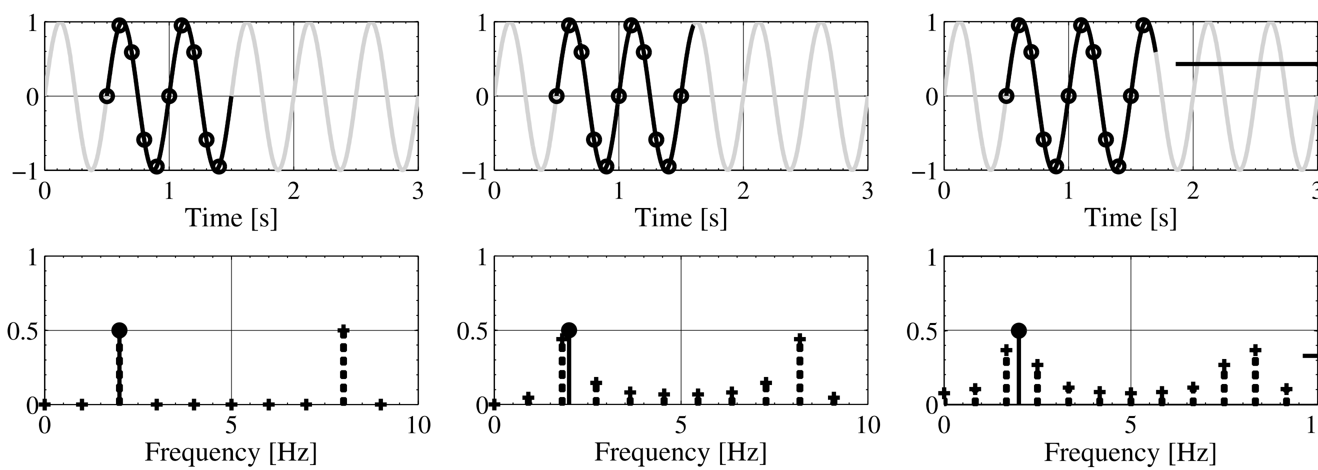
- **Aliasing errors:** high frequency components mirrored at lower frequencies around Nyquist



(a) Slow Sine: 1 Hz (b) Fast Sine: 9 Hz (c) Sampled Sine: 10 Hz

→ **aliasing**

- **Leakage errors:** signal spectrum smeared out due to finite measurement length



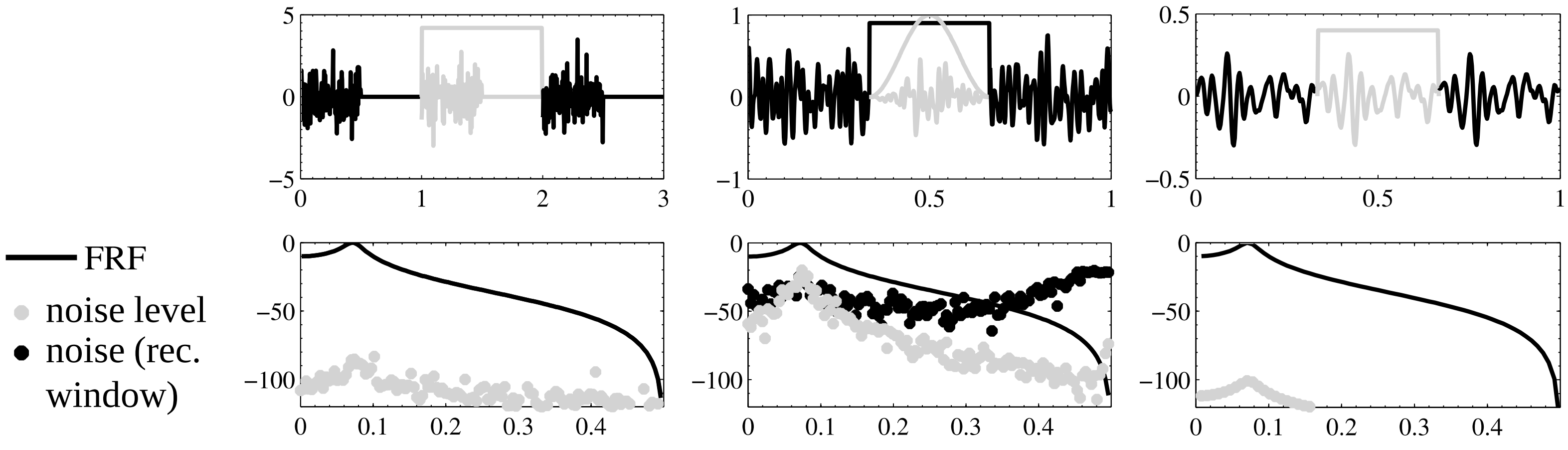
→ rectangular window

→ **leakage**

(a) Window: 10 samples (b) Window: 11 samples (c) Window: 12 samples

Discrete Fourier Transform – *Remedies*

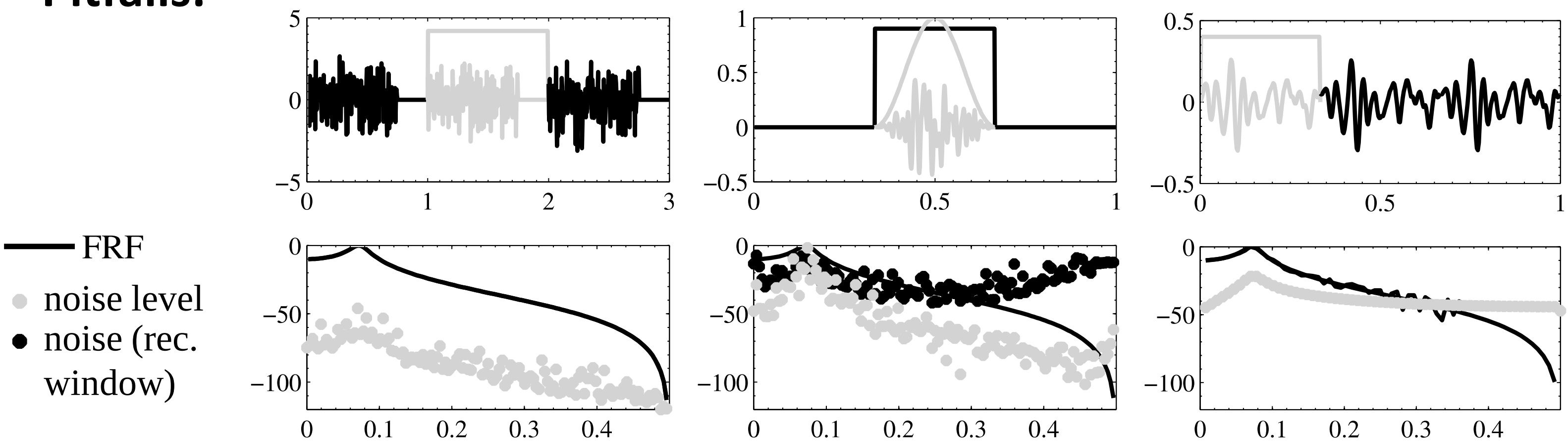
- **Anti-Aliasing:** set high sampling frequencies, don't excite near-Nyquist, anti-aliasing filters
- **Anti-Leakage:** 2 solutions & 1 trade-off



(a) Burst Excitation (b) Random Excitation (c) Periodic Excitation

- **Pitfalls:**

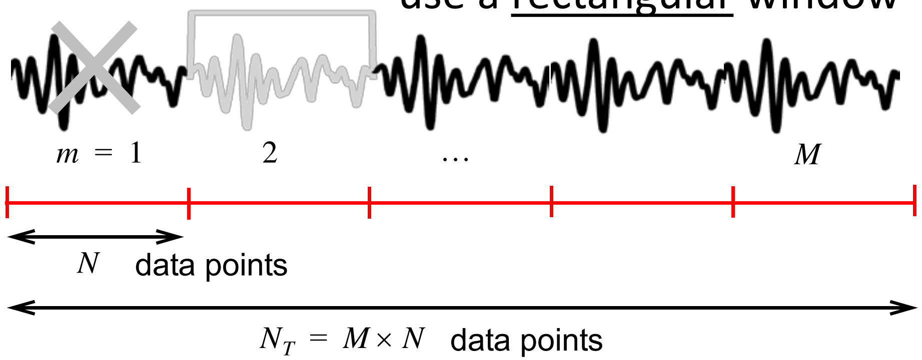
long windows **averages necessary** **remove transients**

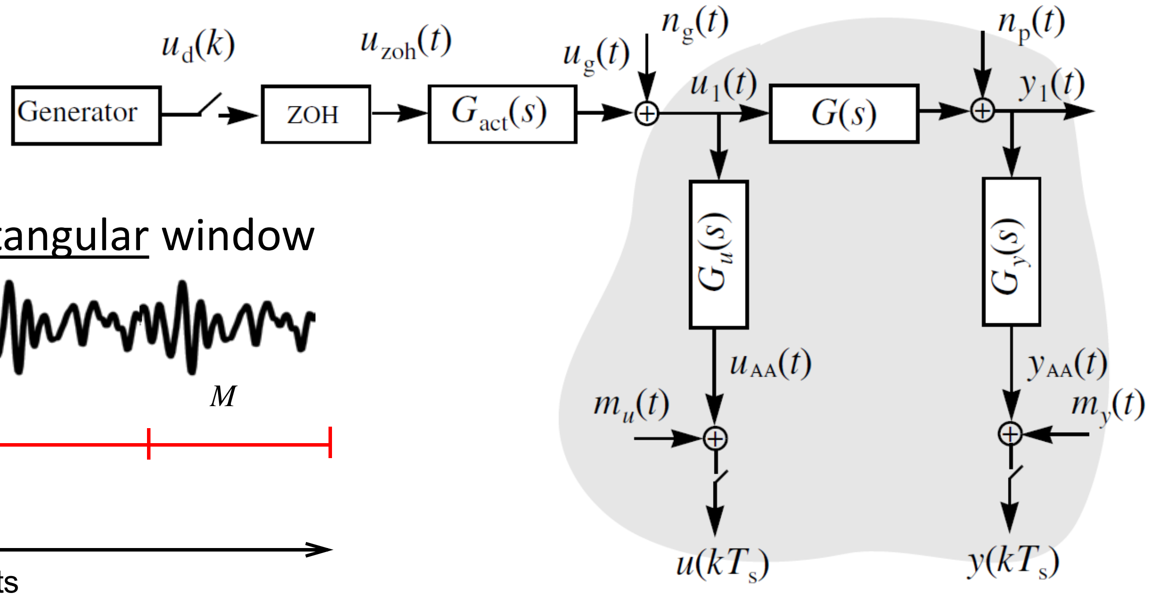


(a) Burst Excitation (b) Random Excitation (c) Periodic Excitation

Periodic Excitation – *Acquisition*

- **Procedure**
  measure M consecutive periods of steady state response





- **Data Obtained**

Sample means
$$\hat{Y}(k) = \frac{1}{M}\sum_{m=1}^{M} Y^{\langle m\rangle}(k), \quad \hat{U}(k) = \frac{1}{M}\sum_{m=1}^{M} U^{\langle m\rangle}(k)$$

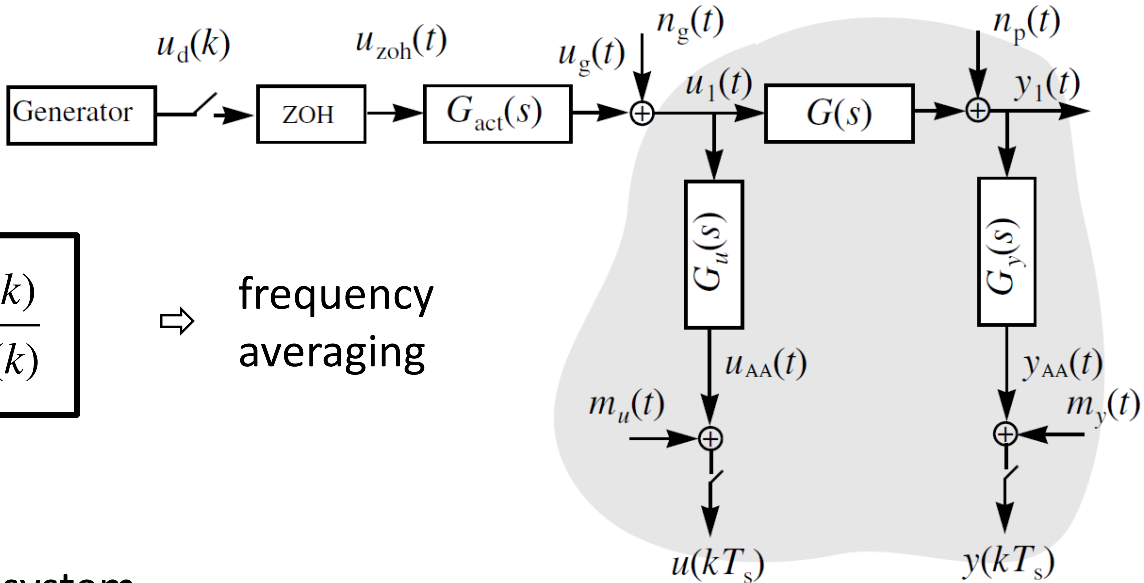
Sample (co-)variances
$$\hat{\sigma}_Y^2(k) = \frac{1}{M(M-1)}\sum_{m=1}^{M}\left|Y^{\langle m\rangle}(k) - \hat{Y}(k)\right|^2, \quad \hat{\sigma}_U^2(k) = \frac{1}{M(M-1)}\sum_{m=1}^{M}\left|U^{\langle m\rangle}(k) - \hat{U}(k)\right|^2$$

$$\hat{\sigma}_{YU}^2(k) = \frac{1}{M(M-1)}\sum_{m=1}^{M}\left(Y^{\langle m\rangle}(k) - \hat{Y}(k)\right)\left(U^{\langle m\rangle}(k) - \hat{U}(k)\right)$$

Note : decrease FRF estimate uncertainty = M larger for given N_T
increasing FRF frequency resolution = N larger for given N_T

Periodic Excitation – *Processing*

- **Frequency Response**
  Maximum likelihood approach assuming noise on both records



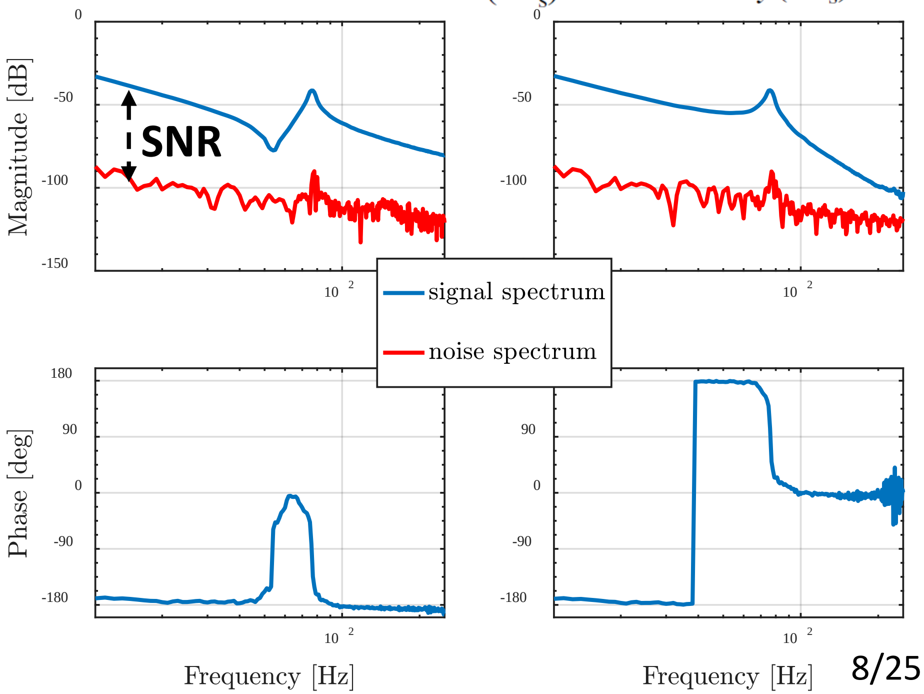
$$\hat{G}_{ML}(j\omega_k) = \frac{\hat{Y}(k)}{\hat{U}(k)} = \frac{M^{-1}\sum_{m=1}^{M} Y^{\langle m \rangle}(k)}{M^{-1}\sum_{m=1}^{M} U^{\langle m \rangle}(k)}$$

⇨ frequency averaging

- **Variance**
  Sample variance of non-parametric system model also called Cramer-Rao lower bound

$$\hat{\sigma}_G^2(k) = |\hat{G}_{ML}(j\omega_k)|^2 \cdot \left[\frac{\hat{\sigma}_Y^2(k)}{|\hat{Y}(k)|^2} + \frac{\hat{\sigma}_U^2(k)}{|\hat{U}(k)|^2} - 2\mathrm{Re}\left(\frac{\hat{\sigma}_{YU}^2(k)}{\hat{Y}(k)\overline{\hat{U}(k)}}\right)\right]$$

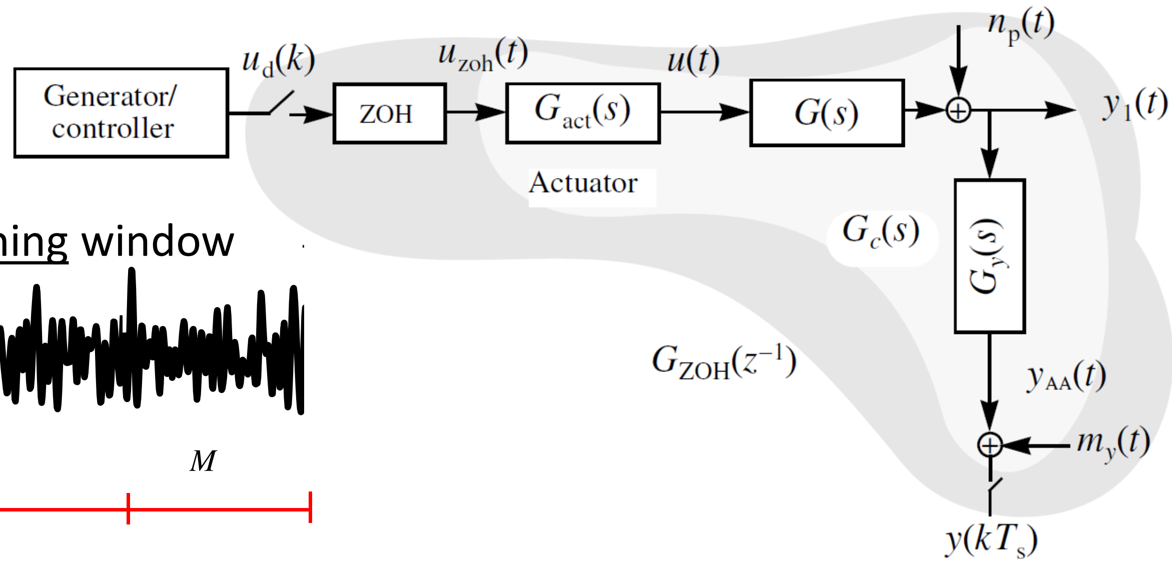
⇨ non-parametric noise model

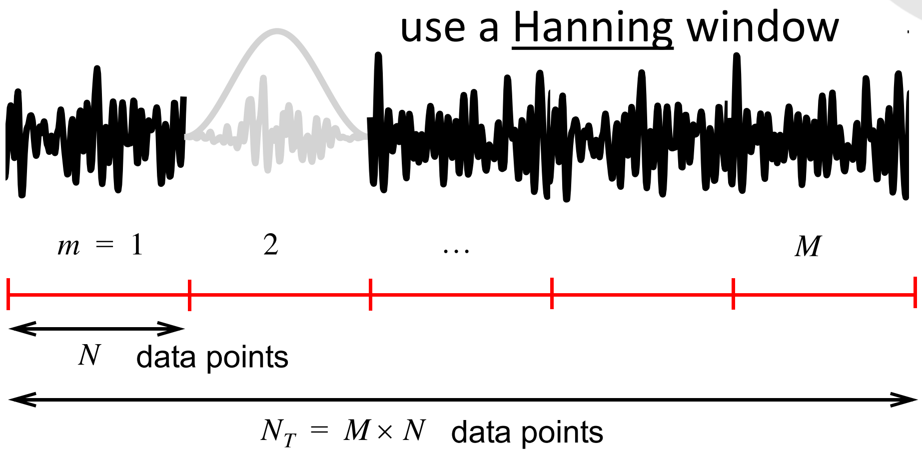


Random Excitation – *Acquisition*

- **Procedure**

  Divide the input-output records in M segments





- **Data Extraction**

Sample auto- and cross-power spectra

$$\hat{S}_{Y_w}(k) = M^{-1}\sum_{m=1}^{M}|Y_w^{\langle m\rangle}|^2, \quad \hat{S}_{U_w}(k) = M^{-1}\sum_{m=1}^{M}|U_w^{\langle m\rangle}|^2$$

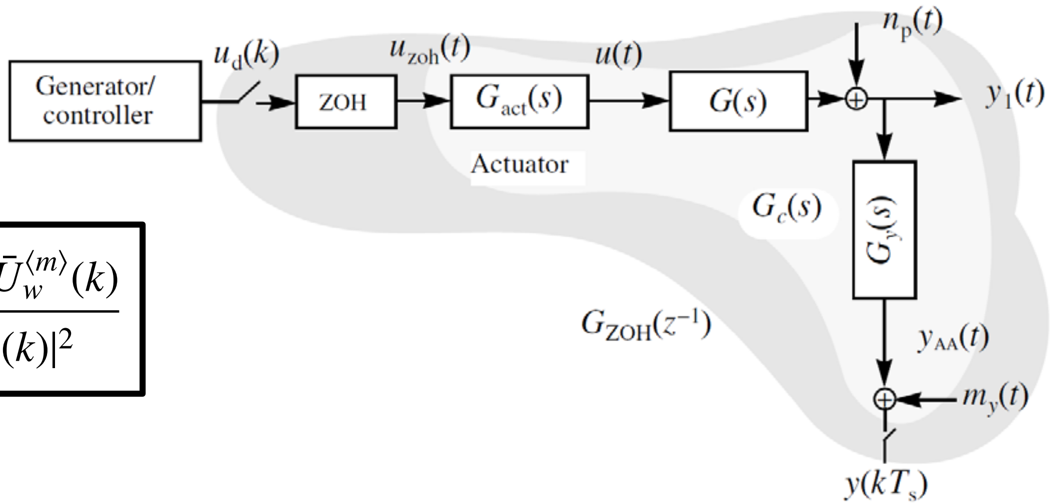
$$\hat{S}_{Y_wU_w}(k) = M^{-1}\sum_{m=1}^{M}Y_w^{\langle m\rangle}(k)\overline{U_w^{\langle m\rangle}}(k)$$

Sample variance

$$\hat{\sigma}^2_{\hat{G}}(k) = |\hat{G}(j\omega_k)|^2\frac{1-\gamma^2(\omega_k)}{\gamma^2(\omega_k)}, \quad \text{with} \quad \gamma^2(\omega_k) = \frac{|\hat{S}_{Y_wU_w}(j\omega_k)|^2}{\hat{S}_{U_w}(j\omega)\hat{S}_{Y_w}(j\omega_k)}$$

Random Excitation – *Processing*

- **Frequency Response**
  Least squares approach assuming input signal is exactly known

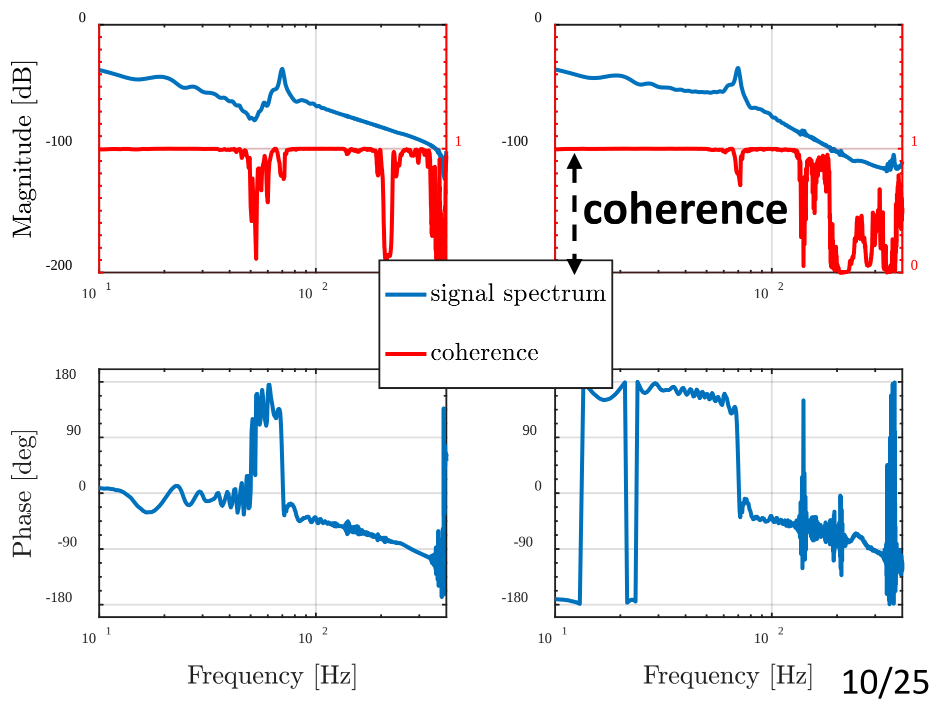


$$\hat{G}_1(j\omega_k) = \frac{\hat{S}_{Y_w U_w}(k)}{\hat{S}_{U_w}(k)} = \frac{M^{-1}\sum_{m=1}^{M} Y_w^{\langle m\rangle}(k)\bar{U}_w^{\langle m\rangle}(k)}{M^{-1}\sum_{m=1}^{M}|U_w^{\langle m\rangle}(k)|^2}$$

- **Coherence**
  Quantifies the quality of data by measuring the input to output linear relationship

$$\gamma^2(\omega_k) = \frac{|\hat{S}_{Y_w U_w}(j\omega_k)|^2}{\hat{S}_{U_w}(j\omega)\hat{S}_{Y_w}(j\omega_k)}$$

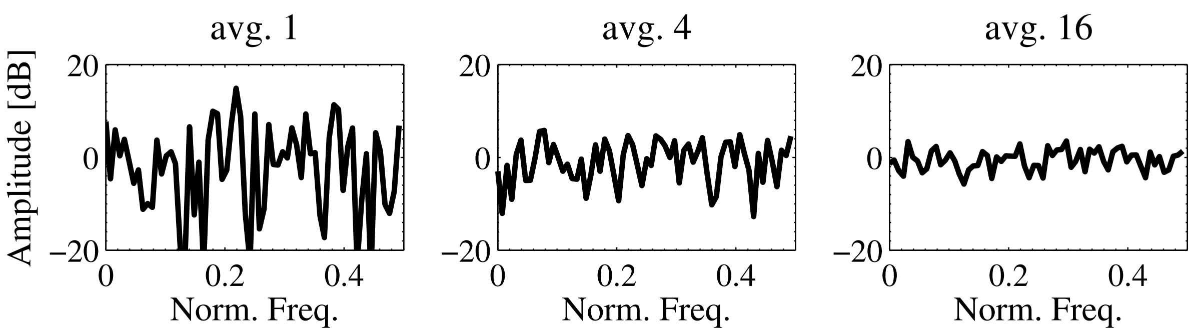
$$0 \le \gamma^2(\omega_k) \le 1$$



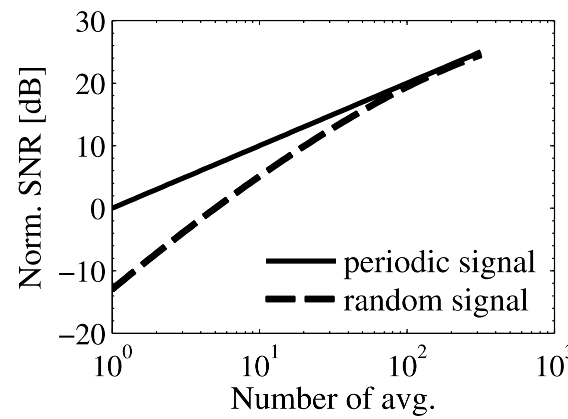
Note : coherences indicates presence of
- extraneous noise
- non-linear distortions
- leakage errors
- non-measured input or disturbance

Problems with Random Excitations

- **Longer experiment time**
  white noise input amplitude spectrum contains random large drops

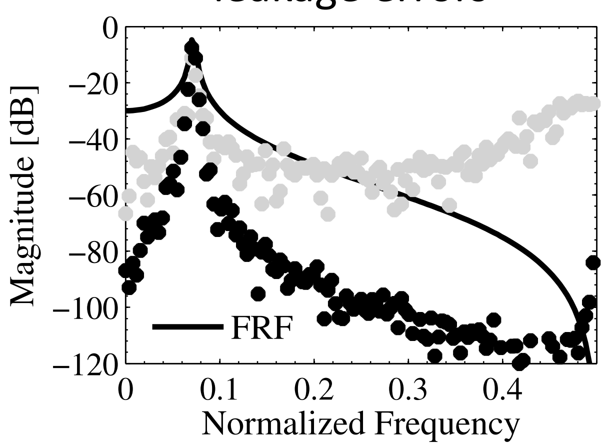


Input power spectrum of white noise sequences averaged over M-blocks

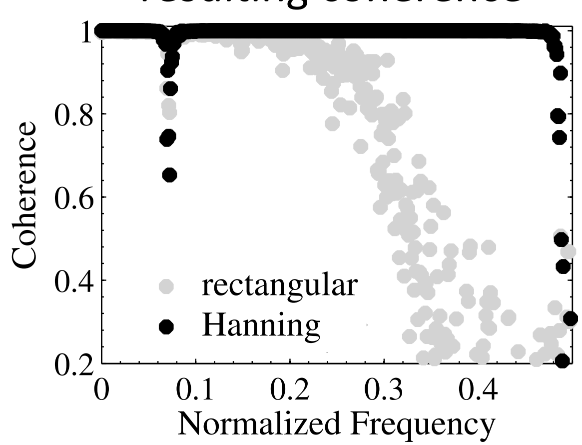


- **Lower FRF resolution**
  windowing reduces leakage, but <u>not</u> in strong varying FRF frequencies, e.g. (anti-)resonances

leakage errors



resulting coherence



Experiment Design

- **Constrained optimization**

$$\underset{u(\cdot)}{\text{minimize}} \quad \max_{k=1\ldots F}\left(\sigma_G^2(k)\right)$$ → i.e. minimize piek variance

subject to ($\forall t \in [0, t_f]$):

amplitude constraint: $\max|u(t)| \le u_{max}$ → e.g. max stage stroke

input power constraint: $\int_{t_0}^{t_f} |u(t)|^2 \, dt \le P_{max}$ → e.g. max actuator power

acquisition constraints: $t_f \le t_{max}, \quad f_s \le f_{s,max}$ → e.g. embedded system

- **Non-parametric design criteria**
  minimal and flat SNR i.e. define two characteristics:

Crest factor $$Cr(u) = \frac{u_{peak}}{u_{rmse}} = \frac{\max_{t \in N} |u(t)|}{u_{rms}\sqrt{P_{int}/P_{tot}}}$$ → i.e. signal compactness

Time factor * $$Tf(u) = \max_{k \in F} 0.5 Cr^2(u) \frac{U_{rmse}^2}{|U(k)|^2}$$ → i.e. efficiency of signal

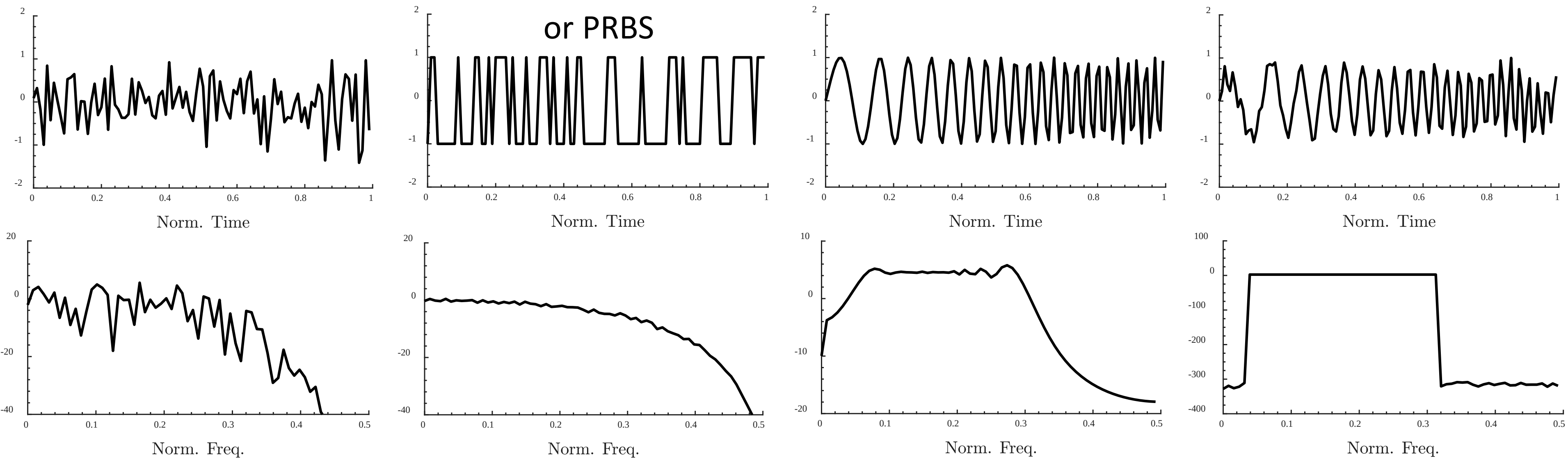
(*) required measurement time per frequency line to reach desired SNR

3.2 EXCITATION

Excitation Signals Comparison

Random | **Periodic**

Random noise | Binary sequence or PRBS | Sweptsine | Multisine



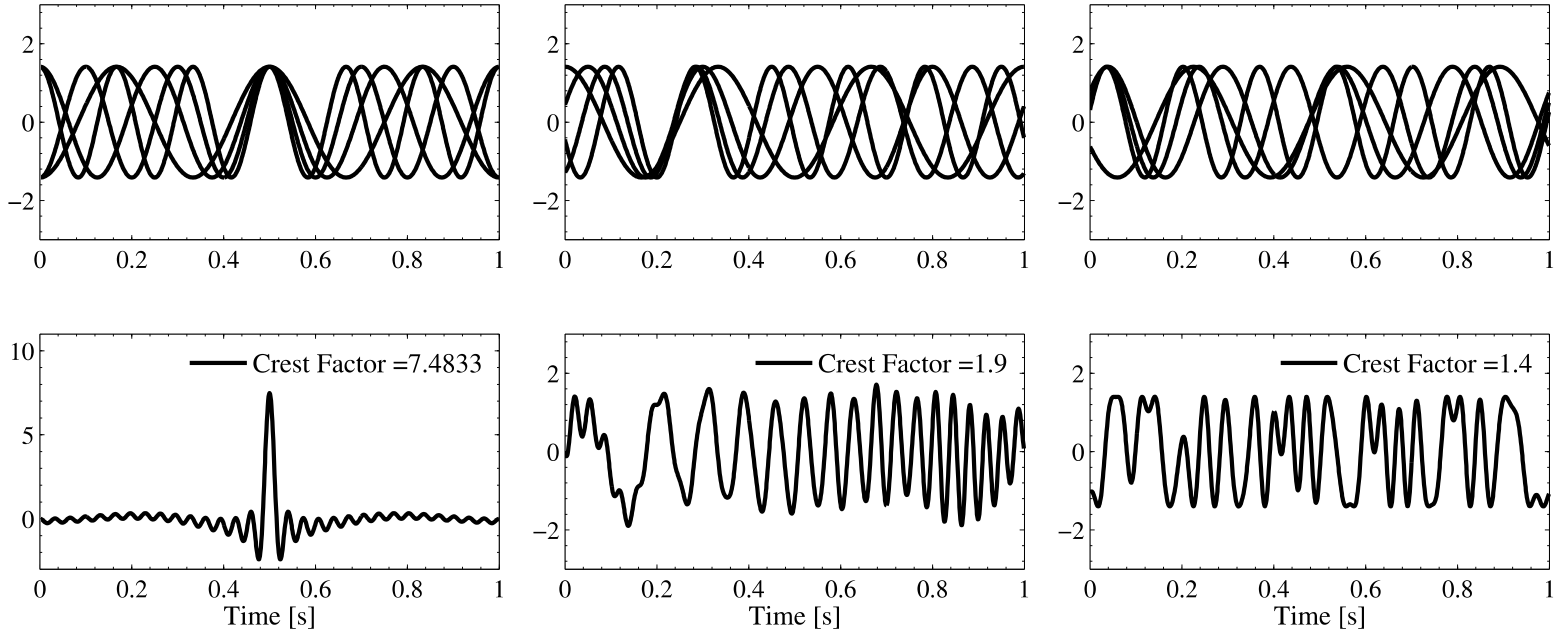
Type	Signal	Crest Factor	Time Factor	Leakage	Arbitrary Amplitude Spectrum
Periodic	Swept Sine	1.45	1.5 - 4	no	no
	Stepped Sine	1.41	1(*)	no	yes
	Multisine	1.41 - 1.7	1	no	yes
Random	PRBS	1	1.5 - 4.5	no	no
	Random Noise	3	4.5	yes	no

(*) without considering transients between steps

Multisine Optimization

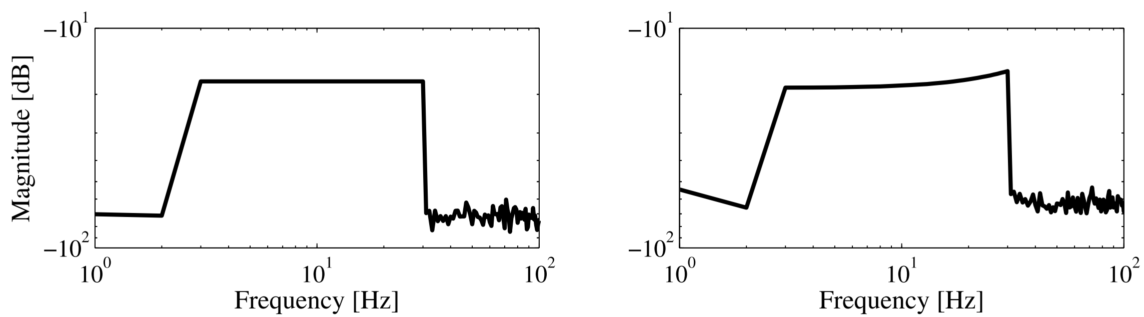
- **Crest Factor optimization** – Phase calculation

problem | analytical solution | numerical solution



(a) Fixed phase (b) Schroeder phase (c) Optimized phase

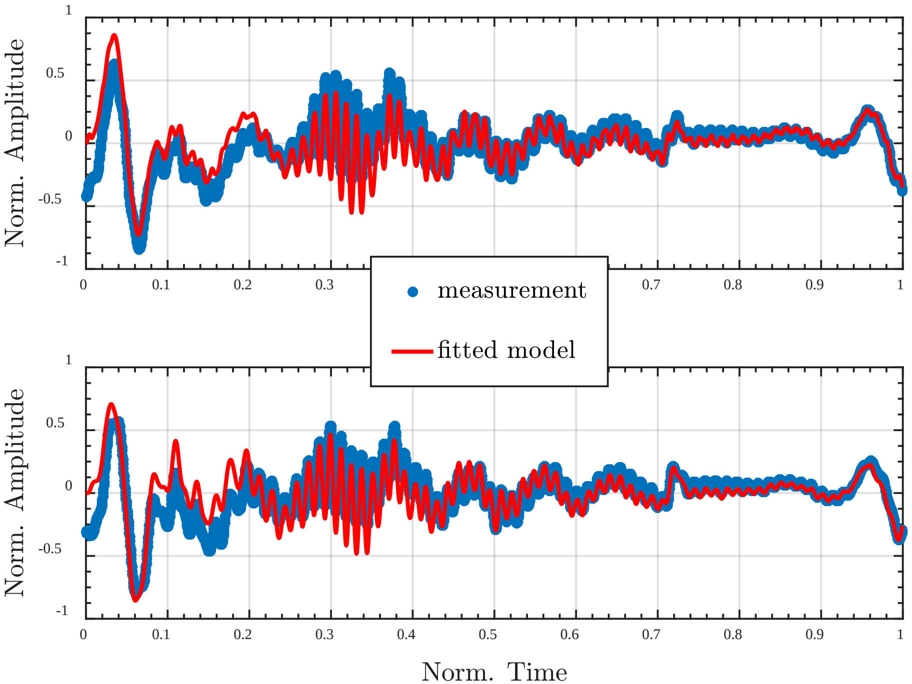
- **Time Factor optimization** – Amplitude spectrum shaping for flat SNR

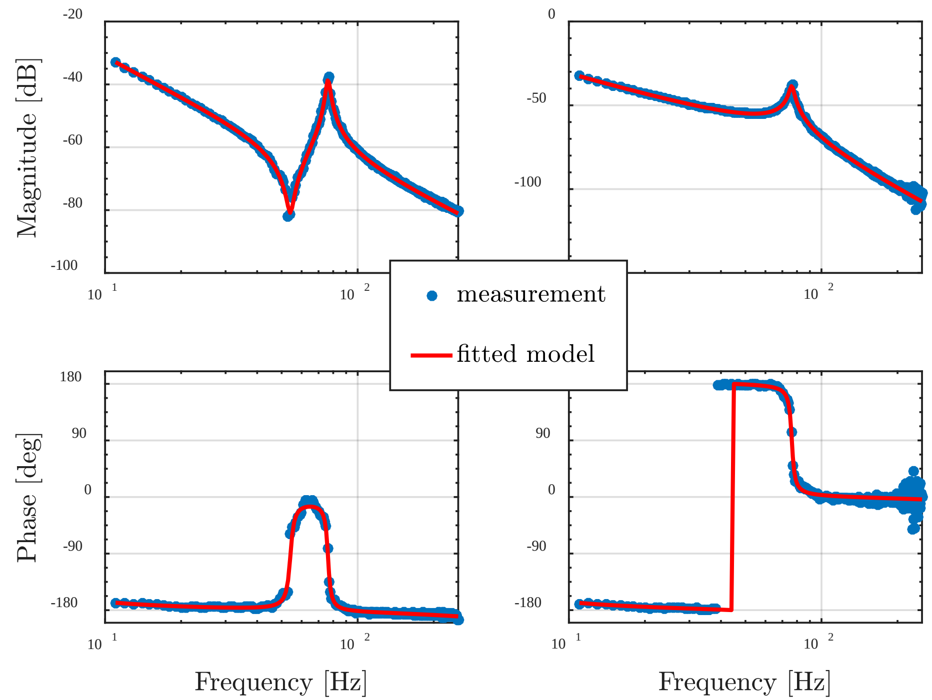


(*) example: see beyond the current loop low-pass filter

Parametric Methods Overview

TDI with random excitation	**FDI with periodic excitation**
Discrete-time modeling	Continuous-time modeling
Minimum-Phase zero's only	Non-Minimum-Phase zero's possible
Parametric noise model	Non-parametric noise model





5.24s – SISO optimization

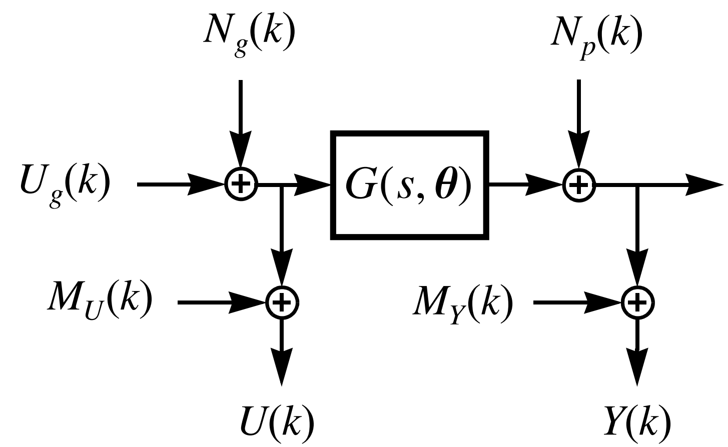
Conventional

0.32s – SIMO optimization

Proposed

4.2 PARAMETRIC
Frequency Domain Identification (FDI)

- **Parametrization:** Error-In-Variables structure



$N_g(k)$ generator noise

$N_p(k)$ process noise

$M_U(k)$ input measurement noise

$M_Y(k)$ output measurement noise

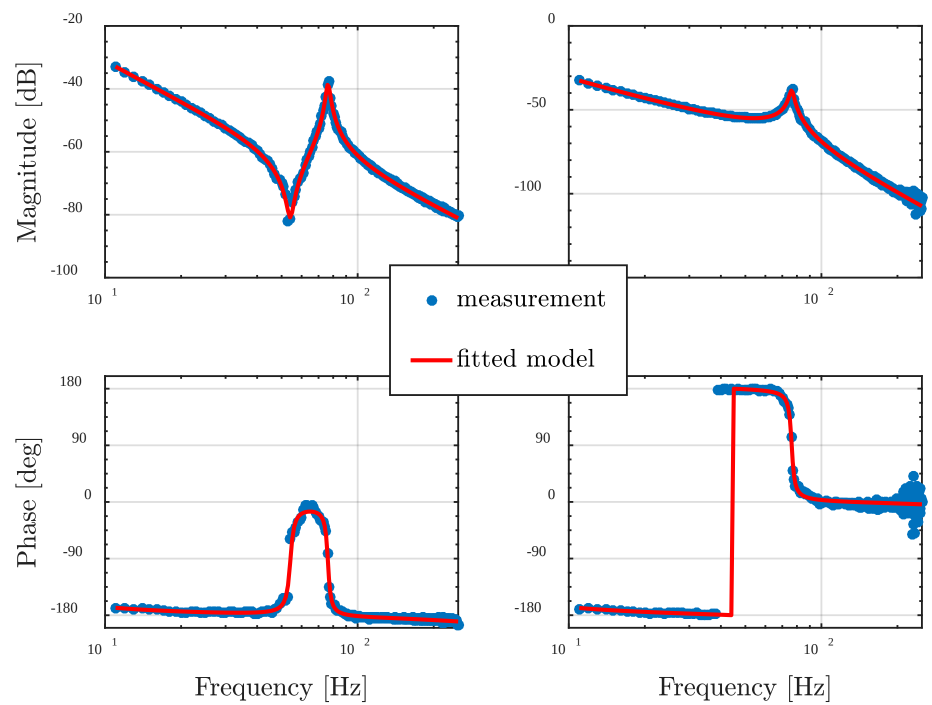
$$G(s,\boldsymbol{\theta}) = \frac{N(s,\boldsymbol{\theta})}{D(s,\boldsymbol{\theta})} = \frac{\sum_{r=0}^{n_b} b_{n_b-r} s^r}{\sum_{r=0}^{n_a} a_{n_a-r} s^r}$$

with $\boldsymbol{\theta} = \begin{bmatrix} a_0 & \dots & a_{n_a} & b_0 & \dots & b_{n_b} \end{bmatrix}^T$

- **Optimization:** non-linear least squares

$$\min_{\boldsymbol{\theta}^{\langle i \rangle}} \sum_{k=1}^{F} \left| W(s_k) \left(\hat{G}(s_k) - G(s_k,\boldsymbol{\theta}) \right) \right|^2$$

$$\min_{\boldsymbol{\theta}^{\langle i \rangle}} \sum_{k=1}^{F} \left| \frac{W(s_k)}{D(s_k,\boldsymbol{\theta})} \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}) \\ N(s_k,\boldsymbol{\theta}) \end{bmatrix} \right|^2$$



FD Identification Algorithm

- **Problem Formulation:** Non-linear Least Squares

$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \left| \frac{W(s_k)}{D(s_k,\boldsymbol{\theta})} \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}) \\ N(s_k,\boldsymbol{\theta}) \end{bmatrix} \right|^2$$

- **Problem Reformulation**

<u>Approach 1</u>: Analytical Linear Least Squares

$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \left| W(s_k) \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}) \\ N(s_k,\boldsymbol{\theta}) \end{bmatrix} \right|^2$$

→ biased, but useful for starting-values

<u>Approach 2</u>: Iteratively Linear Least Squares

a) Sanathan-Koerner:

$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \left| \frac{W(s_k)}{D(s_k,\boldsymbol{\theta}^{\langle i-1\rangle})} \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}^{\langle i\rangle}) \\ N(s_k,\boldsymbol{\theta}^{\langle i\rangle}) \end{bmatrix} \right|^2$$

b) Gauss-Newton: $J_{GN}^{\langle i\rangle} = \frac{\partial V_{NL}^{\langle i\rangle}}{\partial \theta} = 0$

$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \left| \frac{W(s_k)}{D(s_k,\boldsymbol{\theta}^{\langle i-1\rangle})} \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}^{\langle i-1\rangle}) \\ N(s_k,\boldsymbol{\theta}^{\langle i-1\rangle}) - \frac{N(s_k,\boldsymbol{\theta}^{\langle i-1\rangle})D(s_k,\boldsymbol{\theta}^{\langle i\rangle})}{D(s_k,\boldsymbol{\theta}^{\langle i-1\rangle})} + N(s_k,\boldsymbol{\theta}^{\langle i\rangle}) \end{bmatrix} \right|^2$$

c) Instrumental Variable:

$$\sum_{k=1}^{F} \left[\frac{-\partial \hat{P}(s_k,\boldsymbol{\theta}^{\langle i-1\rangle})}{\partial \boldsymbol{\theta}^T} \right]^* W^*(s_k) \frac{W(s_k)}{D(s_k,\boldsymbol{\theta}^{\langle i-1\rangle})} \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}^{\langle i\rangle}) \\ N(s_k,\boldsymbol{\theta}^{\langle i\rangle}) \end{bmatrix} = 0$$

FD Identification Weighting

- **General Formulation**

$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \left| \frac{W(s_k)}{D(s_k,\boldsymbol{\theta})} \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}) \\ N(s_k,\boldsymbol{\theta}) \end{bmatrix} \right|^2$$

Deterministic Approach

$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \left| \frac{w_k}{D(s_k,\boldsymbol{\theta})} \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}) \\ N(s_k,\boldsymbol{\theta}) \end{bmatrix} \right|^2$$

$$\text{with} \quad w_k \simeq \gamma^2(\omega_k)$$

no a-priori information used

Weighted Least Squares (Markov) Estimator

$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \frac{|\varepsilon(s_k,\ \boldsymbol{\theta},\ Z(k))|^2}{w_k^{-1}}$$

Stochastic Approach

$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \left| \frac{\hat{C}^{-1}(s_k)}{D(s_k,\boldsymbol{\theta})} \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}) \\ N(s_k,\boldsymbol{\theta}) \end{bmatrix} \right|^2$$

$$\text{with} \quad \hat{C}(s_k) = \begin{bmatrix} \hat{\sigma}_U^2(s_k) & \hat{\sigma}_{YU}^2(s_k) \\ \overline{\hat{\sigma}}_{YU}^2(s_k) & \hat{\sigma}_Y^2(s_k) \end{bmatrix}$$

Sample (co-)variances used

Maximum Likelihood Estimator

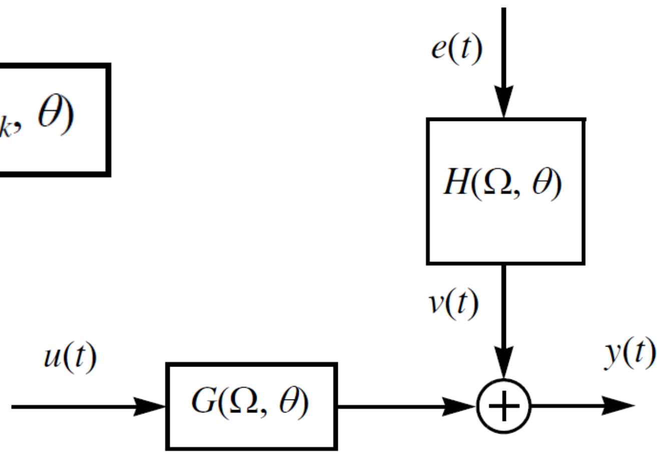
$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \frac{|\varepsilon(s_k,\ \boldsymbol{\theta},\ Z(k))|^2}{\sigma_\varepsilon^2(s_k,\ \boldsymbol{\theta})}$$

$$\min_{\boldsymbol{\theta}^{\langle i\rangle}} \sum_{k=1}^{F} \frac{\left| \begin{bmatrix} \hat{Y}(s_k) & -\hat{U}(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}) \\ N(s_k,\boldsymbol{\theta}) \end{bmatrix} \right|^2}{\sigma_Y^2(s_k)|D(s_k,\boldsymbol{\theta})|^2 + \sigma_U^2(s_k)|N(s_k,\boldsymbol{\theta})|^2 - 2\mathrm{Re}\left(\sigma_{YU}^2(s_k) D(s_k,\boldsymbol{\theta}) \overline{N}(s_k,\boldsymbol{\theta})\right)}$$

Time-Domain Identification (TDI)

- **Parametrization:** parametric noise structure

$$Y(k) = G(\Omega_k, \theta)U(k) + T_G(\Omega_k, \theta) + H(\Omega_k, \theta)E(k) + T_H(\Omega_k, \theta)$$



	Plant	Noise
model	$G(\Omega, \theta) = \dfrac{B(\Omega, \theta)}{A(\Omega, \theta)}$	$H(\Omega_k, \theta) = \dfrac{C(\Omega, \theta)}{D(\Omega, \theta)}$
transient	$T_G(\Omega, \theta) = \dfrac{I_G(\Omega, \theta)}{A(\Omega, \theta)}$,	$T_H(\Omega, \theta) = \dfrac{I_H(\Omega, \theta)}{D(\Omega, \theta)}$

- **Model structures:**

AR = autoregressive

MA = moving average

X = exogenous input

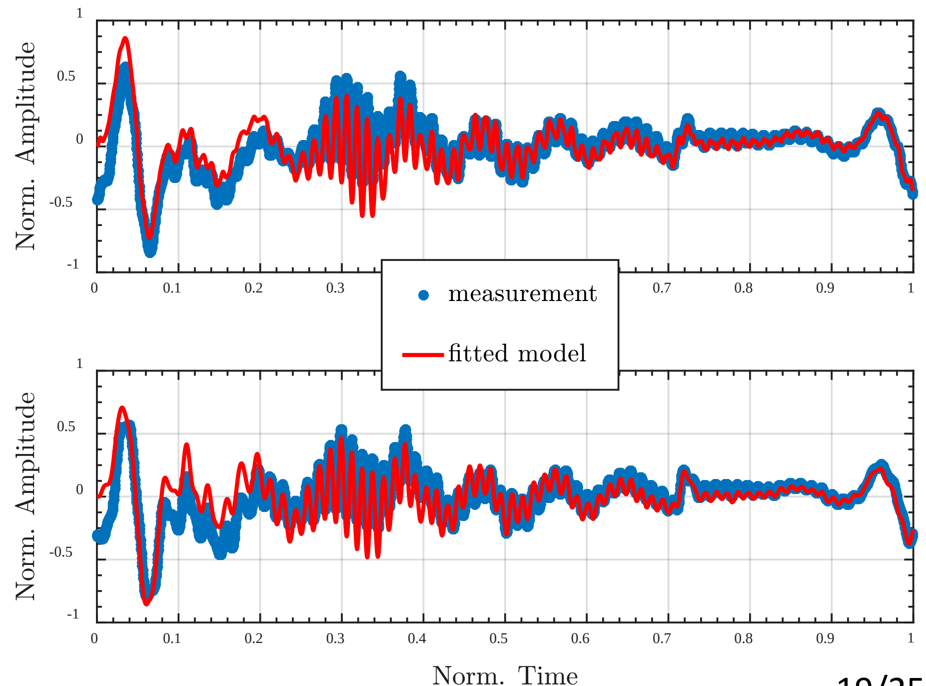
BJ = Box-Jenkins

ARX: $C = 1$, $D = A$, $T_H = 0$

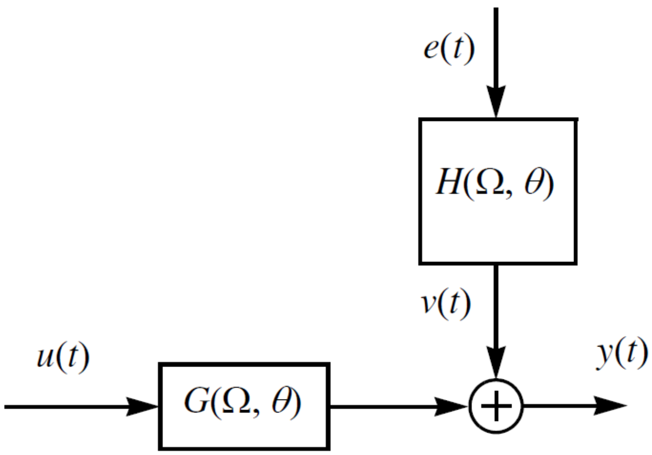
ARMAX: $D = A$, $T_H = 0$, $n_{i_g} \geq \max(n_a, n_b, n_c) - 1$

ARMA: $G = 0$, $T_G = 0$

BJ: $D \neq A$



- **Estimation Framework**



One-step-ahead prediction

$$v(t) = H(q)e(t) = e(t) + (H(q) - 1)\, e(t)$$
$$= e(t) + \left(1 - H^{-1}(q)\right) v(t)$$

One-step-ahead predictor output

$$\hat{y}(t|t-1) = G(q)u(t) + \hat{v}(t|t-1)$$
$$= H^{-1}(q)G(q)u(t) + \left(1 - H^{-1}(q)\right) y(t)$$

Prediction error

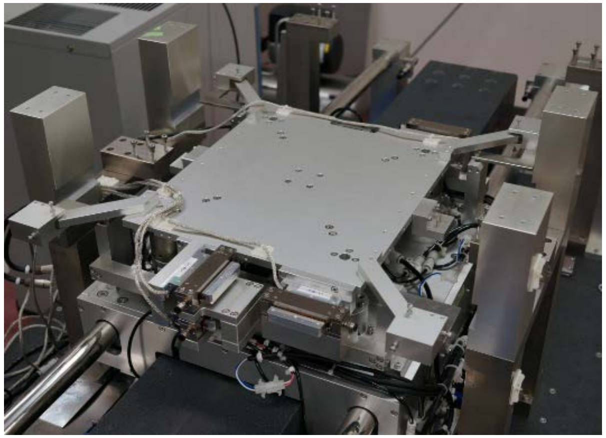
$$\varepsilon(t) = y(t) - \hat{y}(t|t-1)$$
$$= H^{-1}(q)\ (y(t) - G(q)u(t))$$

Prediction error cost function

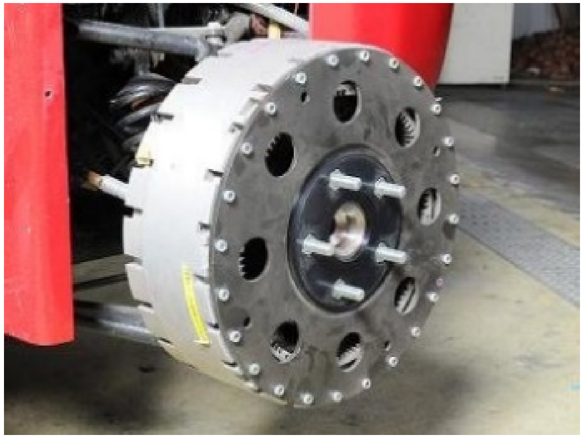
$$\boxed{V_{PE}(\boldsymbol{\theta}, z) = \sum_{t=0}^{N-1} \varepsilon^2(t, \boldsymbol{\theta}) = \sum_{t=0}^{N-1} \left(H^{-1}(q, \boldsymbol{\theta})\,(y(t) - G(q, \boldsymbol{\theta})u(t))\right)^2}$$

HFLab Application Range

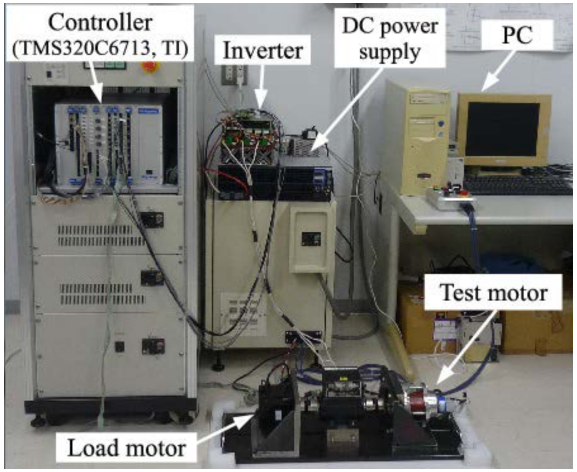
Machine-tool stages



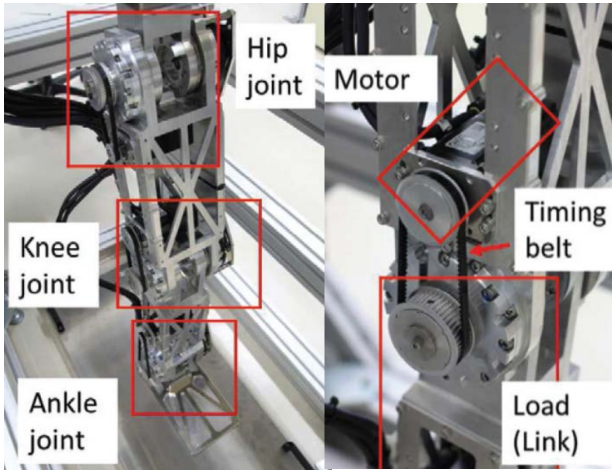
High-precision stages



In-Wheel-Motors



Motors & converters



Robotics

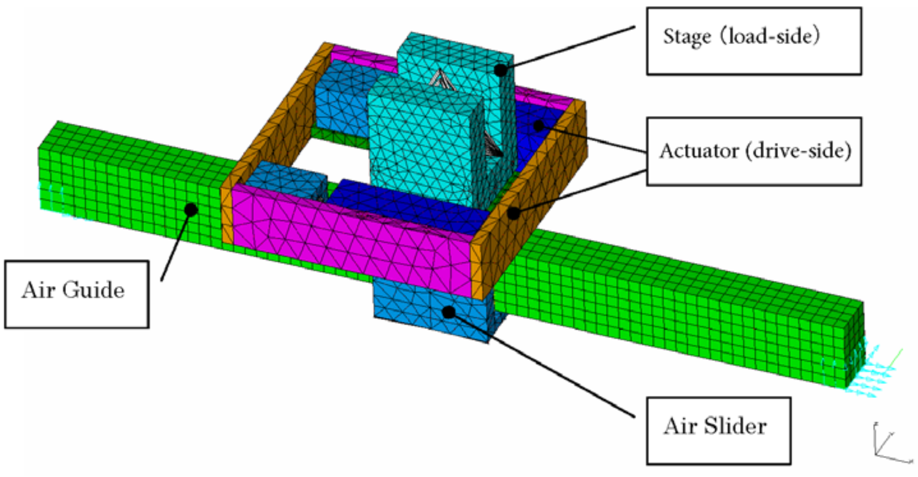
http://hflab.k.u-tokyo.ac.jp/

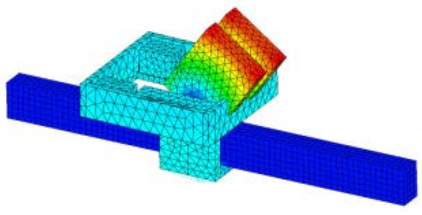
other challenges …

Open Source Matlab Toolbox: www.github.com/thomasbeauduin/FdiTools

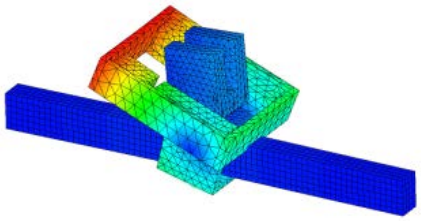
High-precision Stage – *Finite Element Model*

- **Finite-Element-Analysis**

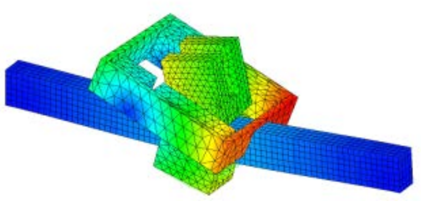




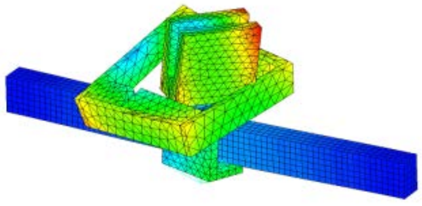
(a) Pitching at 43 Hz



(b) Pitching at 200 Hz

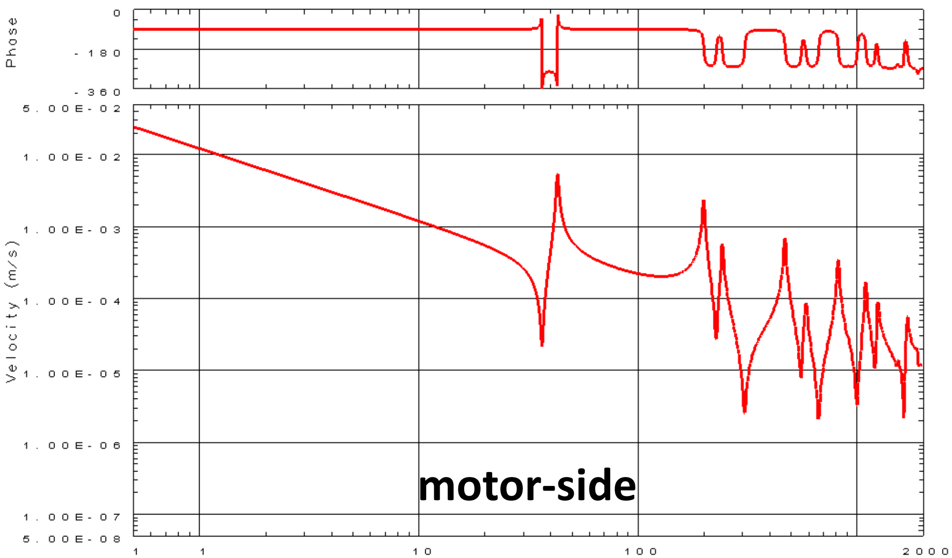


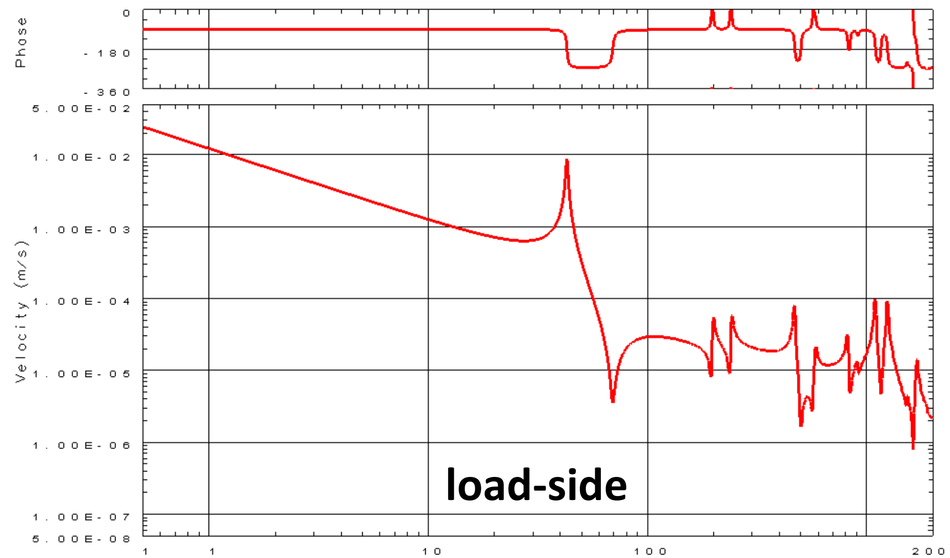
(c) Pitching at 243 Hz



(d) Twist at 400 Hz

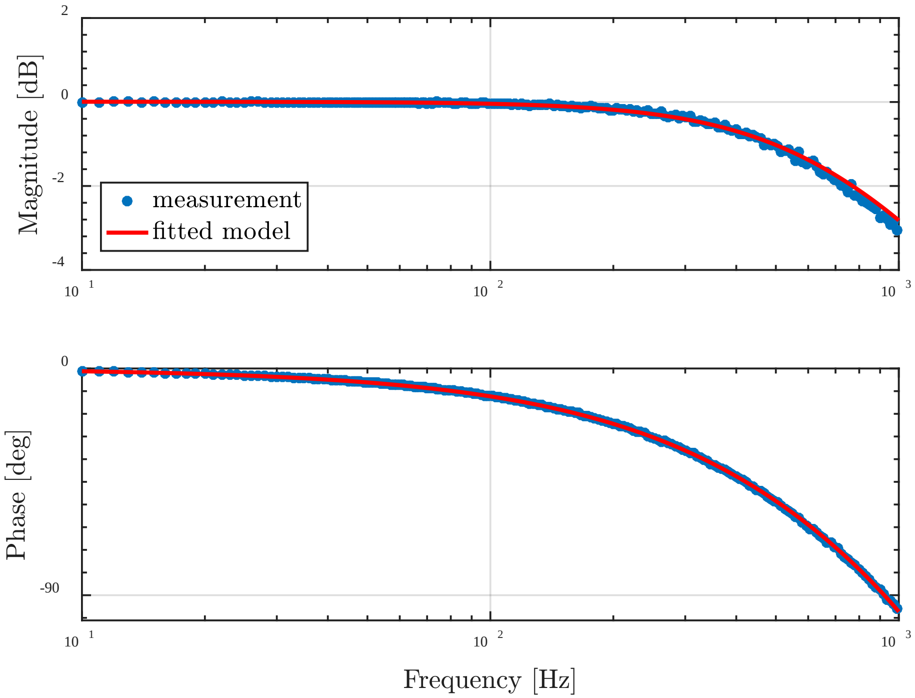
- **Bode-diagrams**





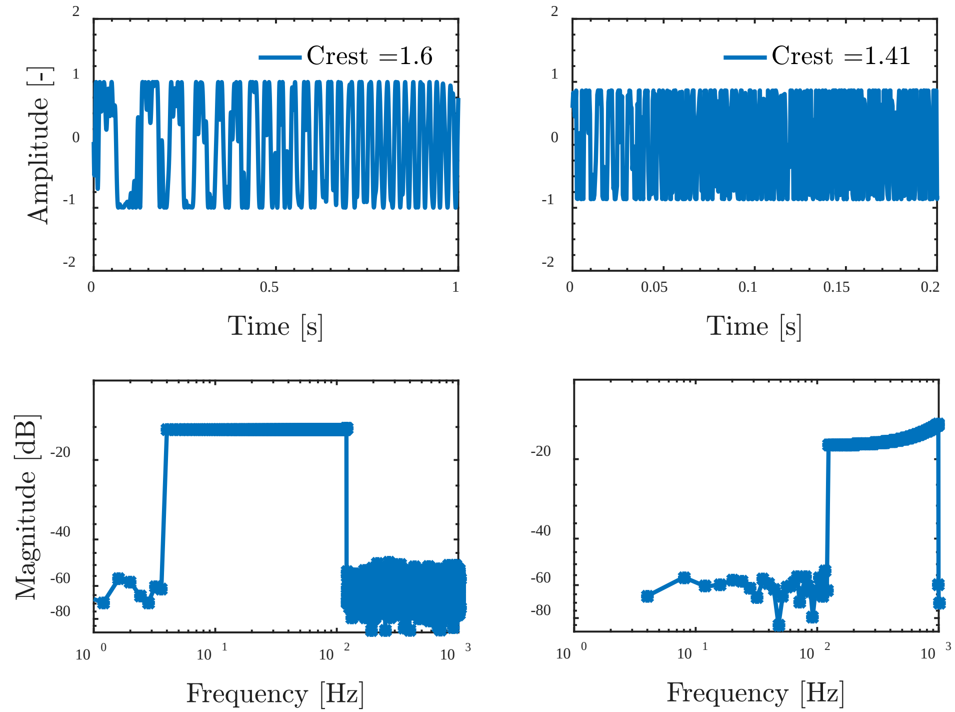
Excitation Design – *Multisine*

- **Inner-loop design**



1kHz – current control bandwidth
Weighted Least Square Estimation
Proposed Analyzer

- **Inverse Multisine design**



a) **Quasi-Logarithmic grid**
wide spectrum – limited frequency lines

b) **Linear-Segmented grid**
limited spectrum – high precision data

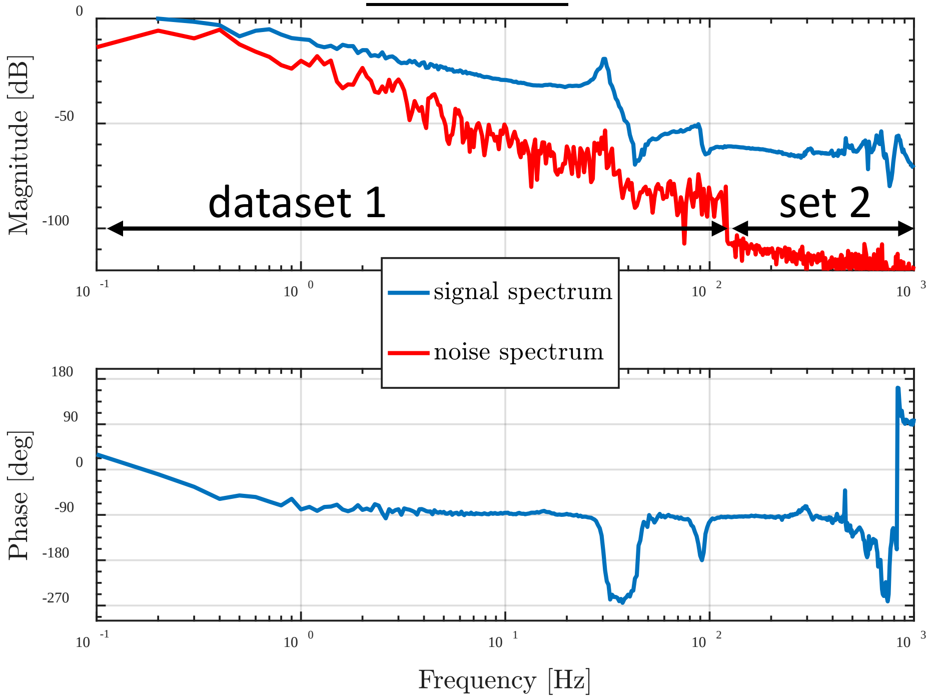
Non-parametric identification – *SIMO*

- **Maximum likelihood estimator (MLE)**

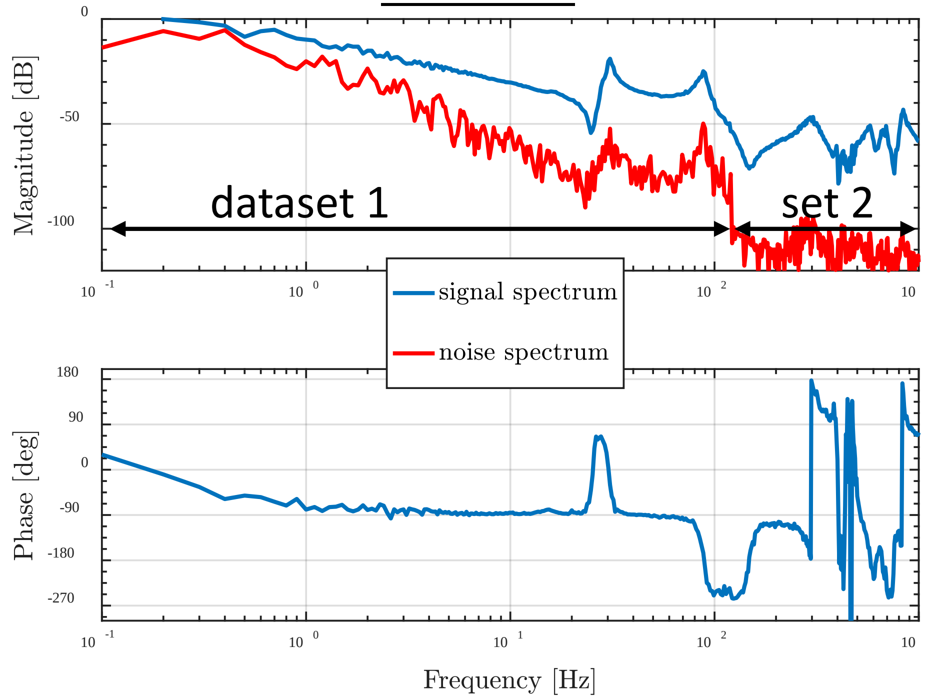
$$\hat{G}_{ML}(j\omega_k) = \frac{\hat{Y}(k)}{\hat{U}(k)} = \frac{M^{-1}\sum_{m=1}^{M} Y^{\langle m\rangle}(k)}{M^{-1}\sum_{m=1}^{M} U^{\langle m\rangle}(k)}$$

$$\hat{\sigma}_G^2(k) = |\hat{G}_{ML}(j\omega_k)|^2 \cdot \left[\frac{\hat{\sigma}_Y^2(k)}{|\hat{Y}(k)|^2} + \frac{\hat{\sigma}_U^2(k)}{|\hat{U}(k)|^2} - 2\mathrm{Re}\left(\frac{\hat{\sigma}_{YU}^2(k)}{\hat{Y}(k)\overline{\hat{U}(k)}}\right)\right]$$

Drive – side



Load – side



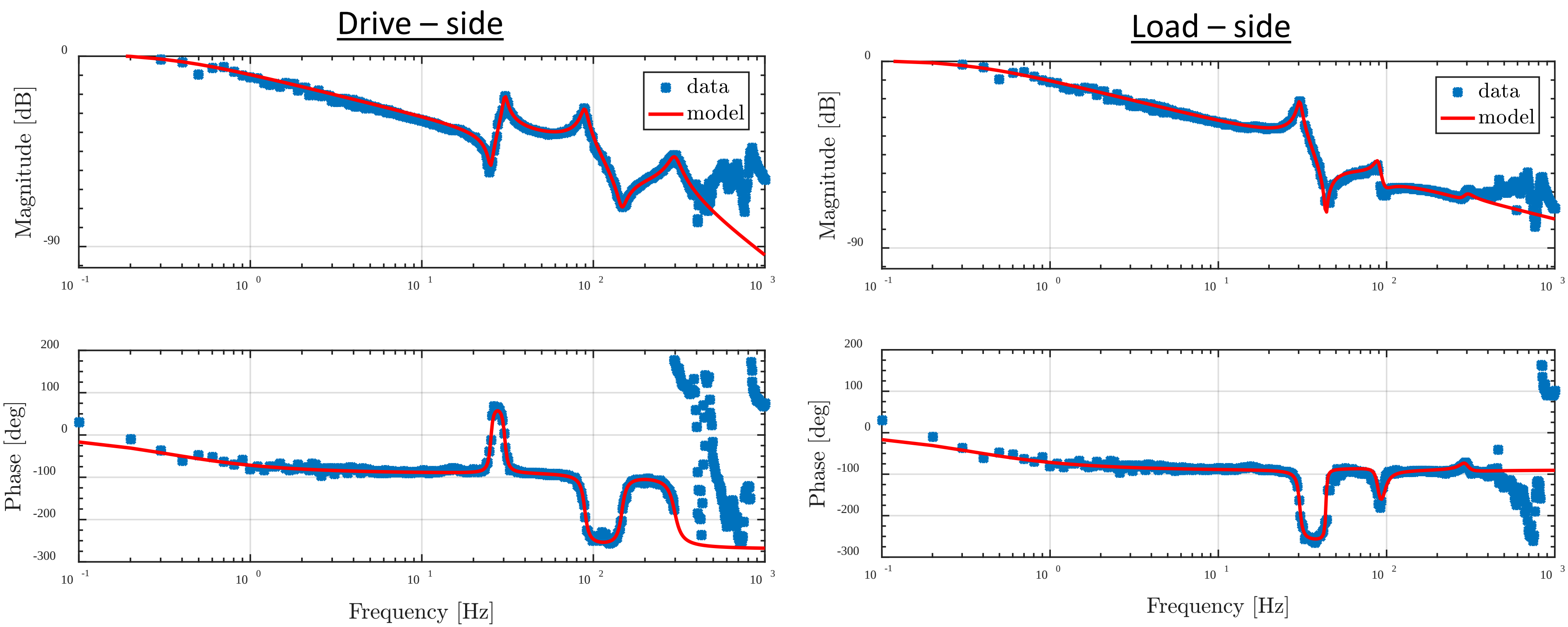
2 x 10s – segmented experiments

Proposed Analyzer

Parametric Identification – *SIMO*

- **Maximum likelihood estimator (MLE)**

$$\min_{\boldsymbol{\theta}^{(i)}} \sum_{k=1}^{F} \frac{\left| \begin{bmatrix} Y_m(s_k) & -U_m(s_k) \end{bmatrix} \begin{bmatrix} D(s_k,\boldsymbol{\theta}) \\ N(s_k,\boldsymbol{\theta}) \end{bmatrix} \right|^2}{\sigma_Y^2(s_k)|D(s_k,\boldsymbol{\theta})|^2 + \sigma_U^2(s_k)|N(s_k,\boldsymbol{\theta})|^2 - 2\mathrm{Re}\left(\sigma_{YU}^2(s_k)D(s_k,\boldsymbol{\theta})\overline{N}(s_k,\boldsymbol{\theta})\right)}$$



5.24s – SIMO optimization

FREQUENCY-DOMAIN SYSTEM IDENTIFICATION FOR HIGH-PRECISION CONTROL DESIGN

Thomas Beauduin, Hiroshi Fujimoto (The University of Tokyo)

ご清聴ありがとうございました

Thank you for your kind attention

Frequency Domain Identification for Control

- **STEP 1: Excitation Design**

- **STEP 2: Non-Parametric Identification**

- **STEP 3: Parametric Identification**