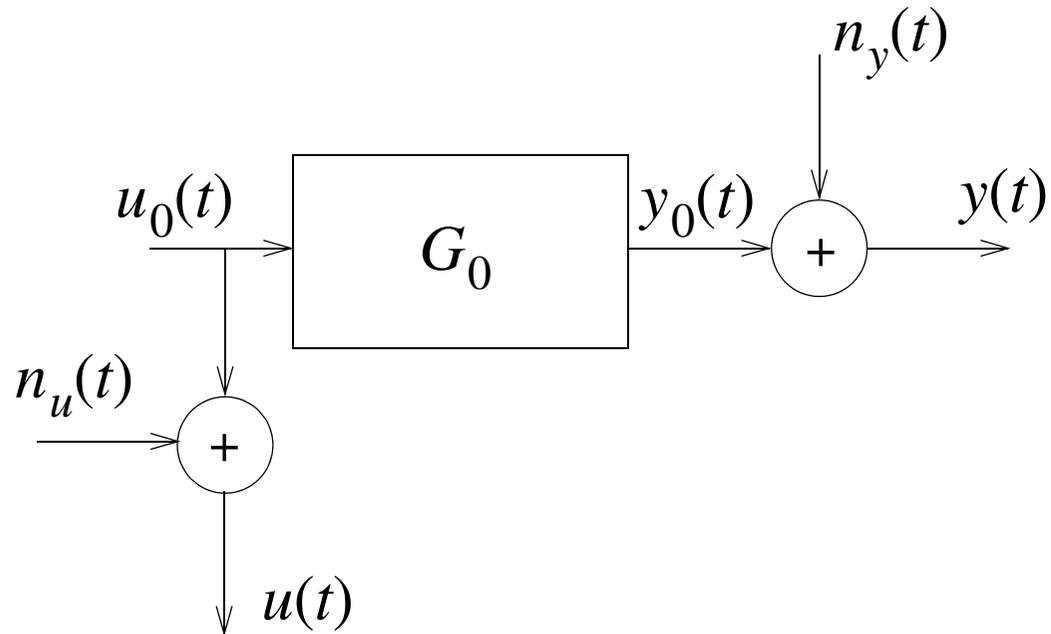


Identifiability analysis for errors-in-variables problems

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Problem statement



$$u(t) = u_0(t) + n_u(t)$$

$$y(t) = y_0(t) + n_y(t)$$

$$t = 1, \dots, T$$

$u_0(t)$, $n_u(t)$, $n_y(t)$: filtered Gaussian noise

Frequency domain representation

Time to frequency domain transform

$$X(\Omega_k) = \frac{1}{\sqrt{N}} \sum_{t=0}^{T-1} x(t) e^{-2\pi kt/T}$$

$$U(\Omega_k) = U_0(\Omega_k) + N_u(\Omega_k)$$

$$Y(\Omega_k) = Y_0(\Omega_k) + N_y(\Omega_k)$$

$$k = 0, 1, \dots, \frac{T}{2}$$

Problem statement (Cnt'd)

All information captured by the 2nd order moments

Asymptotically ($N \rightarrow \infty$), $\begin{bmatrix} U_0(\Omega_k) & N_u(\Omega_k) \\ Y_0(\Omega_k) & N_y(\Omega_k) \end{bmatrix}$ and $\begin{bmatrix} U_0(\Omega_l) & N_u(\Omega_l) \\ Y_0(\Omega_l) & N_y(\Omega_l) \end{bmatrix}$ independent for $k \neq l$

Asymptotically block diagonal matrix:

$$C(\Omega_k) = E \left\{ \begin{bmatrix} U(\Omega_k) & Y(\Omega_k) \end{bmatrix}^H \begin{bmatrix} U(\Omega_k) & Y(\Omega_k) \end{bmatrix} \right\}$$

$$= \begin{bmatrix} S_{u_0 u_0}(\Omega_k) + S_{n_u n_u}(\Omega_k) & G_0(\Omega_k) S_{u_0 u_0}(\Omega_k) + S_{n_u n_y}(\Omega_k) \\ \overline{G_0}(\Omega_k) S_{u_0 u_0}(\Omega_k) + \overline{S_{n_u n_y}}(\Omega_k) & |G_0(\Omega_k)|^2 S_{u_0 u_0}(\Omega_k) + S_{n_y n_y}(\Omega_k) \end{bmatrix}$$

$$k = 0, 1, \dots, \frac{T}{2}$$

Identifiability?

Can G_0 be identified from

$$C(\Omega_k) \quad \{\Omega_k, k = 1, \dots, N \leq T/2\}$$

Identifiability?

- parametric or nonparametric plant model
- parametric or nonparametric noise model
 - + coloured, mutually correlated noise
 - + coloured, mutually uncorrelated noise
 - + white, mutually uncorrelated noise

Basic idea

unknown parameters $><$ # constraints

$G_0(\Omega_k)$ a solution $\rightarrow \lambda_k G_0(\Omega_k)$ a solution?

Example 1

model: nonparametric plant $G(\Omega_k)$ and nonparametric noise $\begin{bmatrix} S_{n_u n_u}(\Omega_k) & 0 \\ 0 & S_{n_y n_y}(\Omega_k) \end{bmatrix}$

Available information

$$S_{u_0 u_0}(\Omega_k) + S_{n_u n_u}(\Omega_k) = \hat{S}_{u_0 u_0}(\Omega_k) + \hat{S}_{n_u n_u}(\Omega_k), \quad (N \text{ real equations})$$

$$G_0(\Omega_k) S_{u_0 u_0}(\Omega_k) = |\hat{G}(\Omega_k)| e^{j\angle \hat{G}(\Omega_k)} \hat{S}_{u_0 u_0}(\Omega_k), \quad (2N \text{ complex equations})$$

$$|G_0(\Omega_k)|^2 S_{u_0 u_0}(\Omega_k) + S_{n_y n_y}(\Omega_k) = |\hat{G}(\Omega_k)|^2 \hat{S}_{u_0 u_0}(\Omega_k) + \hat{S}_{n_y n_y}(\Omega_k) \quad (N \text{ real equations}).$$

Unknown parameters:

$$G(\Omega_k) : 2N \quad S_{u_0 u_0}(\Omega_k) : N \quad S_{n_u n_u}(\Omega_k) : N \quad S_{n_y n_y}(\Omega_k) : N \rightarrow 5N$$

N degrees of freedom: check $G(\Omega_k) \rightarrow \lambda_k G(\Omega_k)$

Example 1 (cont'd)

$$|\hat{G}(\Omega_k)| = \lambda_k |G_0(\Omega_k)|$$

$$\hat{S}_{u_0 u_0}(\Omega_k) = S_{u_0 u_0}(\Omega_k) / \lambda_k$$

$$\hat{S}_{n_u n_u}(\Omega_k) - S_{n_u n_u}(\Omega_k) = S_{u_0 u_0}(\Omega_k) (1 - 1/\lambda_k)$$

$$\hat{S}_{n_y n_y}(\Omega_k) - S_{n_y n_y}(\Omega_k) = |G_0(\Omega_k)|^2 S_{u_0 u_0}(\Omega_k) (1 - \lambda_k)$$

Conclusion

$$\hat{G}(\Omega_k) = \lambda_k G_0(\Omega_k), \text{ with } \lambda_{\min, k} \leq \lambda_k \leq \lambda_{\max, k}$$

$$\lambda_{\min, k} = \frac{S_{u_0 u_0}(\Omega_k)}{S_{n_u n_u}(\Omega_k) + S_{u_0 u_0}(\Omega_k)} \quad \lambda_{\max, k} = \frac{|G_0(\Omega_k)|^2 S_{u_0 u_0}(\Omega_k) + S_{n_y n_y}(\Omega_k)}{|G_0(\Omega_k)|^2 S_{u_0 u_0}(\Omega_k)}$$

Example 2

model: parametric plant $G(\Omega_k, \theta_G)$ and nonparametric noise $\begin{bmatrix} S_{n_u n_u}(\Omega_k) & 0 \\ 0 & S_{n_y n_y}(\Omega_k) \end{bmatrix}$

Available information

$$S_{u_0 u_0}(\Omega_k) + S_{n_u n_u}(\Omega_k) = \hat{S}_{u_0 u_0}(\Omega_k) + \hat{S}_{n_u n_u}(\Omega_k), \quad (N \text{ real equations})$$

$$G_0(\Omega_k) S_{u_0 u_0}(\Omega_k) = |\hat{G}(\Omega_k, \theta_G)| e^{j\angle \hat{G}(\Omega_k, \theta_G)} \hat{S}_{u_0 u_0}(\Omega_k),$$

$$|G_0(\Omega_k)|^2 S_{u_0 u_0}(\Omega_k) + S_{n_y n_y}(\Omega_k) = |\hat{G}(\Omega_k, \theta_G)|^2 \hat{S}_{u_0 u_0}(\Omega_k) + \hat{S}_{n_y n_y}(\Omega_k) \quad (N \text{ real equations}).$$

Example 2 (Cnt'd)

model: parametric plant $G(\Omega_k, \theta_G)$ and nonparametric noise

$$\begin{bmatrix} S_{n_u n_u}(\Omega_k) & 0 \\ 0 & S_{n_y n_y}(\Omega_k) \end{bmatrix}$$

$$G_0(\Omega_k) S_{u_0 u_0}(\Omega_k) = |\hat{G}(\Omega_k, \theta_G)| e^{j \angle \hat{G}(\Omega_k, \theta_G)} \hat{S}_{u_0 u_0}(\Omega_k),$$

$$|G(\Omega_k, \theta_G) S_{u_0 u_0}(\Omega_k)| \rightarrow N$$

$$\text{phase}(G(\Omega_k, \theta_G) S_{u_0 u_0}(\Omega_k)) = \text{phase } G(\Omega_k, \theta_G) \rightarrow n_{\theta_G} - 1$$

Assumption:

Plant model order: known

or

Plant has no quadrant symmetric poles or zeros

constraints:

$$3N + n_{\theta_G} - 1$$

Unknown parameters:

$$G(\Omega_k, \theta) : n_{\theta_G} \quad S_{u_0 u_0}(\Omega_k) : N \quad S_{n_u n_u}(\Omega_k) : N \quad S_{n_y n_y}(\Omega_k) : N \rightarrow 3N + n_{\theta_G}$$

Conclusion: Parametric plant model $G(\Omega_k, \theta)$:

1 degree of freedom left:

$$\hat{G}(\Omega_k, \hat{\theta}_G) = \lambda G_0(\Omega_k),$$

with

$$\max \lambda_{\min, k} \leq \lambda \leq \min \lambda_{\max, k}$$

Example 3

model: parametric plant $G(\theta_G)$

$$\text{parametric noise } \begin{bmatrix} S_{n_u n_u}(\theta_{n_u}) & 0 \\ 0 & S_{n_y n_y}(\theta_{n_y}) \end{bmatrix}$$

non parametric or parametric signal model

Similar to previous situation: 1 degree of freedom left

$$\hat{S}_{u_0 u_0} = S_{u_0 u_0} / \lambda$$

$$\hat{S}_{n_u n_u} = S_{n_u n_u} + S_{u_0 u_0} (1 - 1/\lambda)$$

$$\hat{S}_{n_y n_y} = S_{n_y n_y} + |G|^2 S_{u_0 u_0} (1 - \lambda)$$

Possibility 1

Noise model order: known

Plant model order: known

Signal model: nonparametric

$$\begin{aligned}\hat{S}_{n_u n_u}(\theta_{n_u}) &= S_{n_u n_u}(\theta_{n_u}) + S_{u_0 u_0}(\Omega_k)(1 - 1/\lambda) \\ \hat{S}_{n_y n_y}(\theta_{n_y}) &= S_{n_y n_y}(\theta_{n_y}) + |G_0(\Omega_k)|^2 S_{u_0 u_0}(\Omega_k)(1 - \lambda)\end{aligned}\tag{1}$$

Identifiable if for $\alpha \in \mathbf{R}_0$

i) the order of $S_{n_u n_u}(\theta_{n_u}) + \alpha S_{u_0 u_0}(\Omega_k)$ is larger than that of $S_{n_u n_u}(\theta_{n_u})$

or

ii) the order of $S_{n_y n_y}(\theta_{n_y}) + \alpha |G_0(\Omega_k)|^2 S_{u_0 u_0}(\Omega_k)$ is larger than that of $S_{n_y n_y}(\theta_{n_y})$

Possibility 2

Noise model order: known

Plant model order: not known

Signal model: non parametric

If the plant is known to have no quadrant symmetric poles or zeros -->
orders can be retrieved

Previous situation is valid

Possibility 3

Noise model order: not known

Plant model order: not known

Signal model: parametric

1) If the plant is known to have no quadrant symmetric poles or zeros --> orders can be retrieved

2) Additional assumption

for $\alpha \in \mathbb{R}_0$

i) the order of $S_{n_u n_u}(\theta_{n_u}) + \alpha S_{u_0 u_0}(\Omega_k)$ is larger than that of $S_{n_u n_u}(\theta_{n_u})$

or

ii) the order of $S_{n_y n_y}(\theta_{n_y}) + \alpha |G_0(\Omega_k)|^2 S_{u_0 u_0}(\Omega_k)$ is larger than that of $S_{n_y n_y}(\theta_{n_y})$.

Illustration: Setup

plant model $G_0(z) = \frac{1 + 0.5z^{-1}}{0.8 - 12z^{-1} + 5.6z^{-2}}$

signal model $S_{u_0u_0} = |L(z)|^2$, $L(z) = \frac{1}{1 - \frac{0.5}{\beta}z^{-1}}$, $\beta = 1, 10, 100$

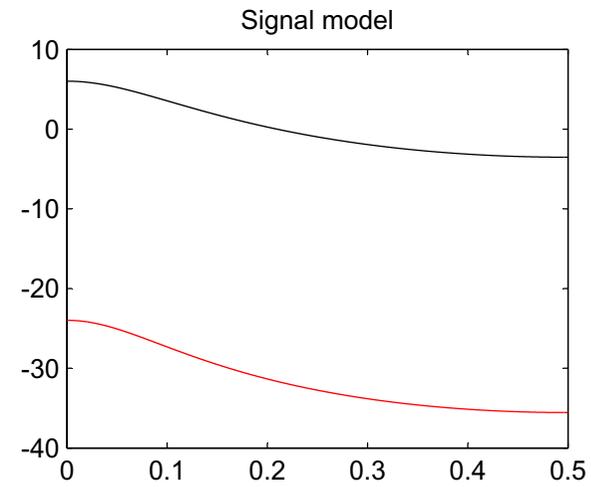
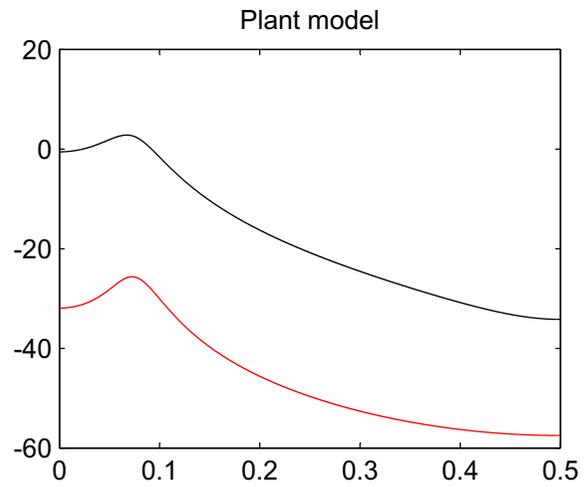
noise model

input: $S_{n_u n_u} = 1$

output: $S_{n_y n_y} = |G_0(z)|^2$

model orders plant, signal, and noise are known

Illustration: results $\beta = 1$



CR-bound

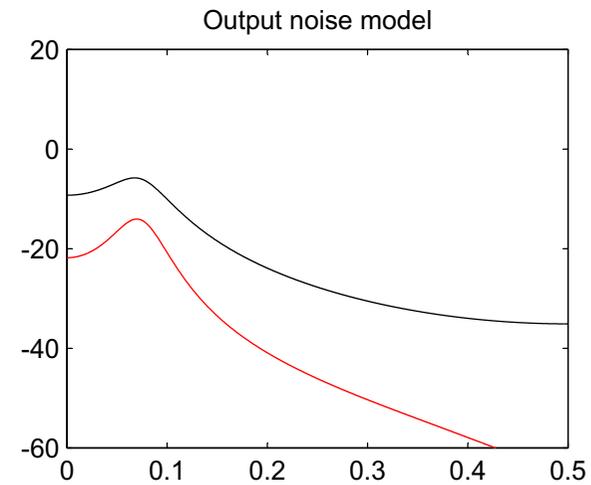
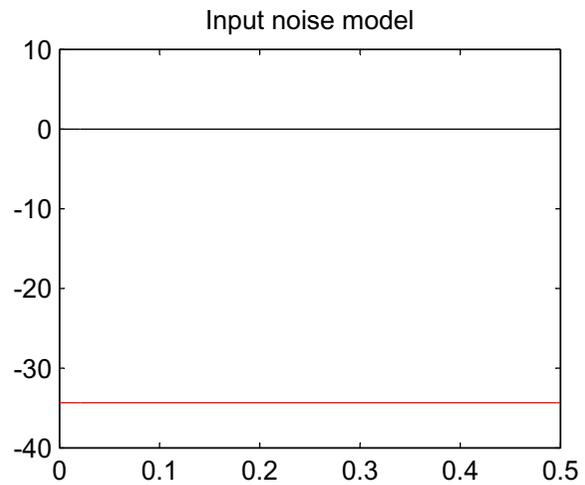
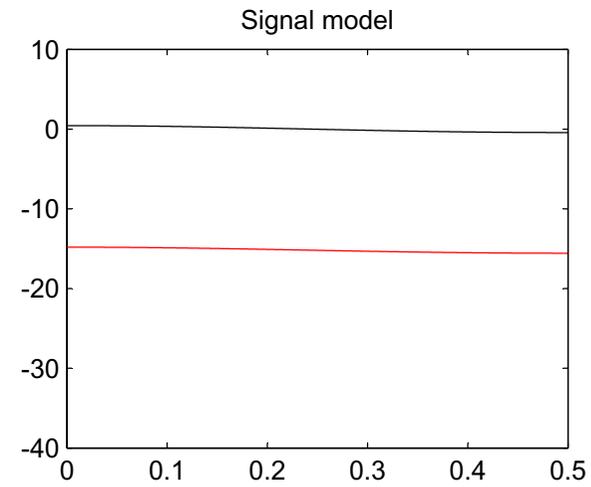
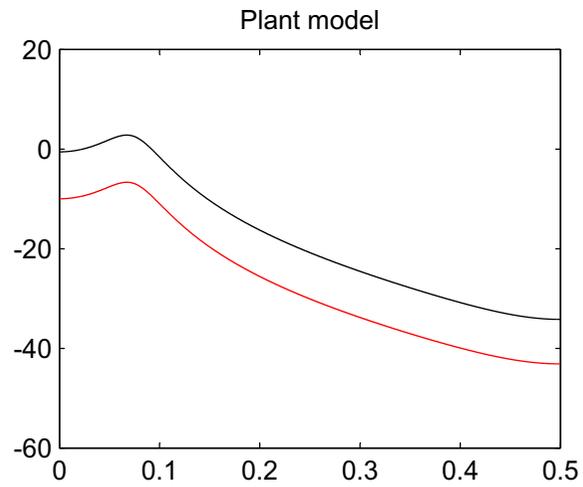


Illustration: results $\beta = 10$



CR-bound

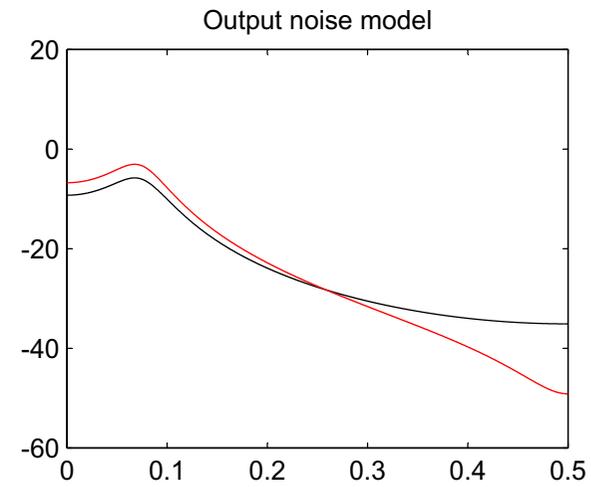
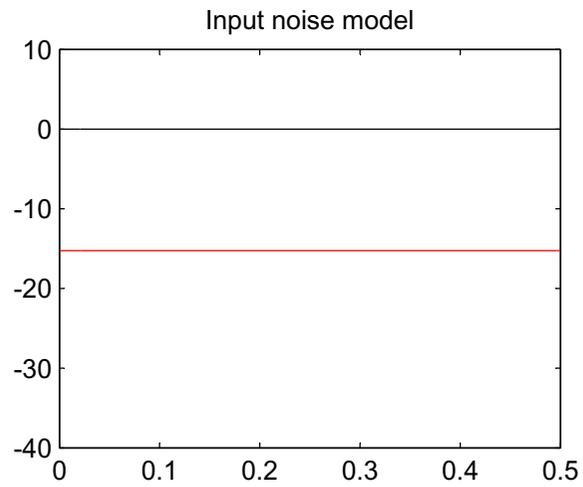
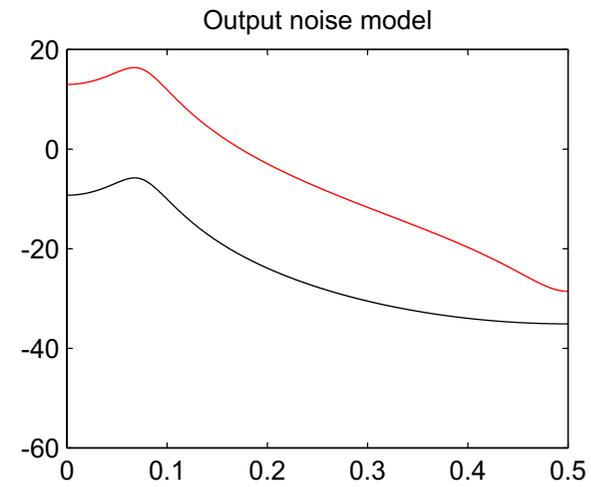
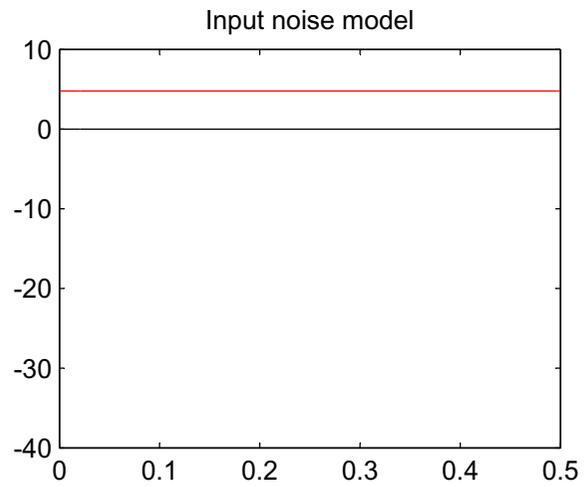
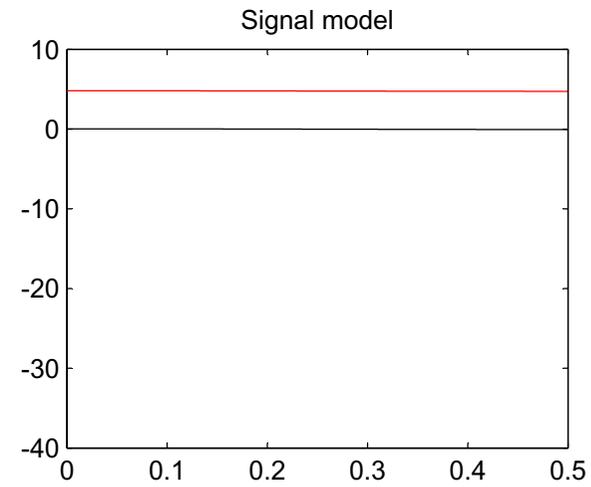
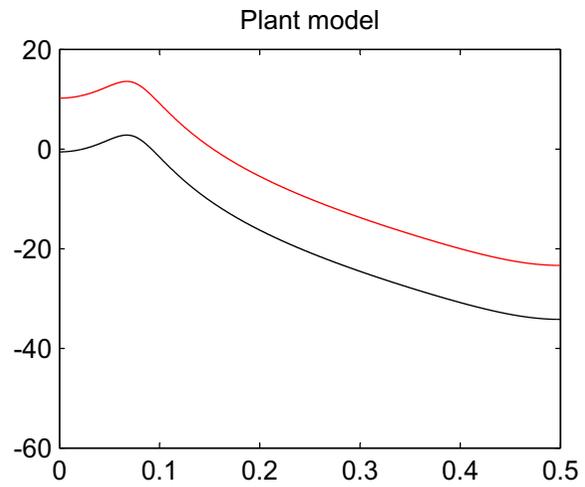
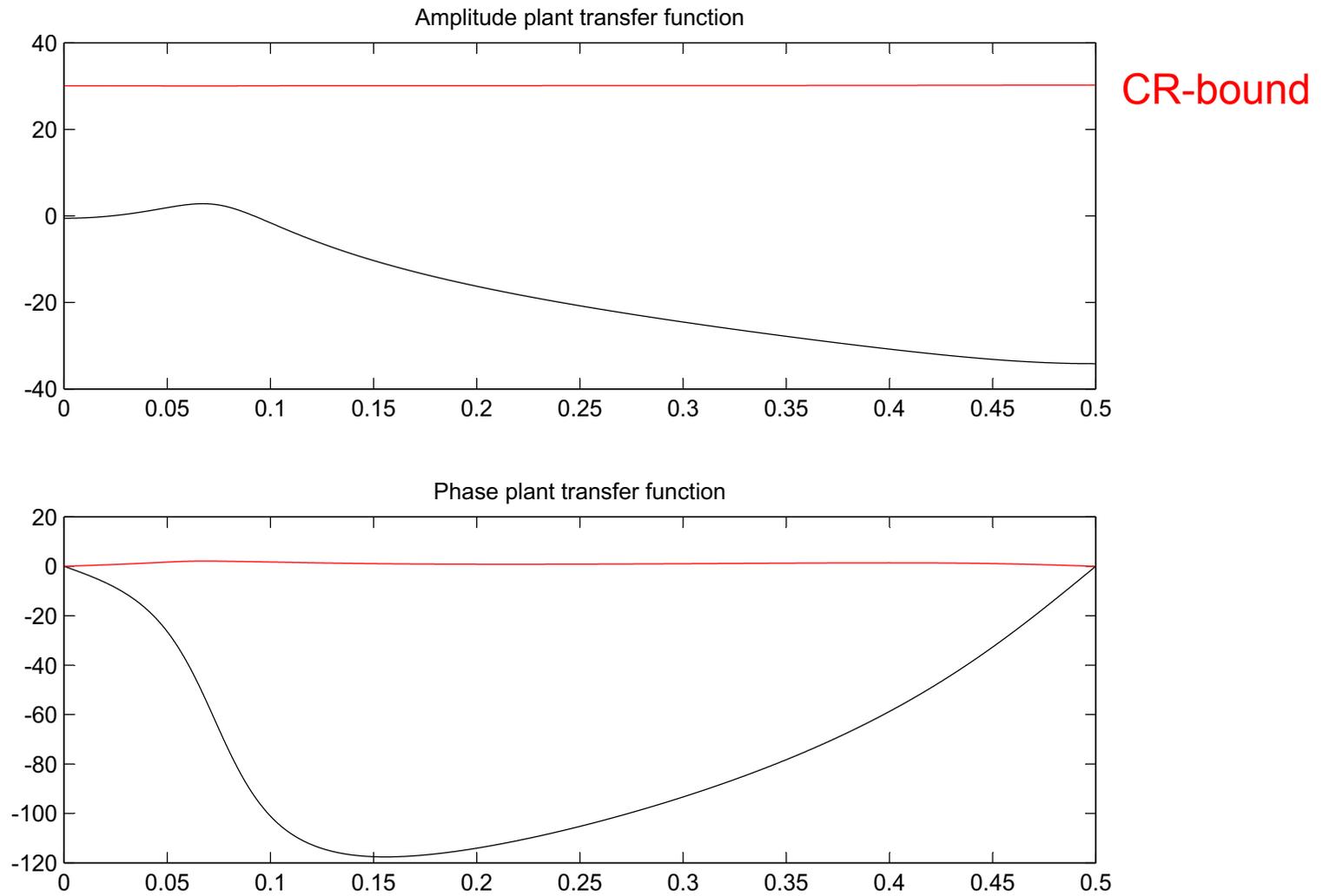


Illustration: results $\beta = 100$

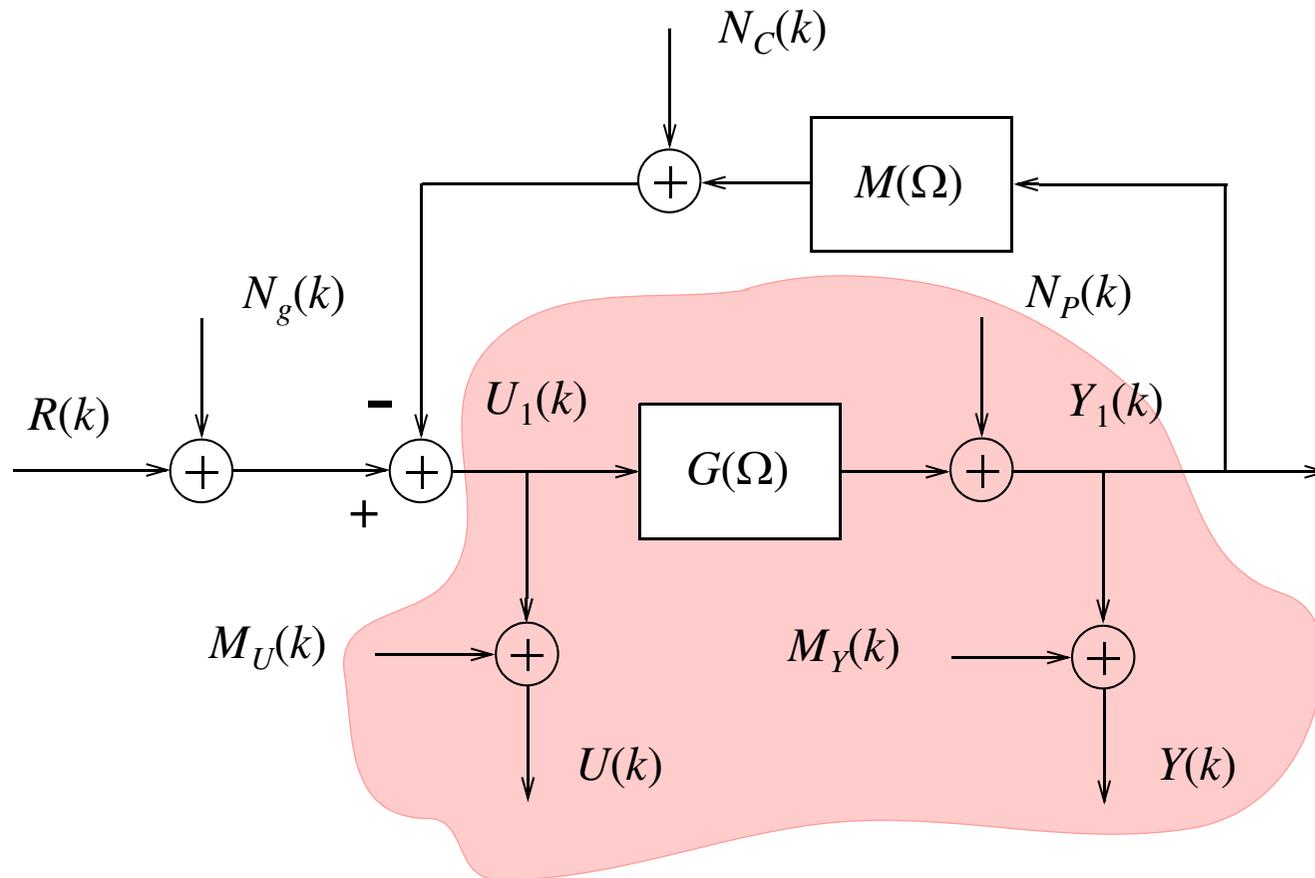


CR-bound

Illustration: results $\beta = 100$



Experimental constraint: periodic excitations



Nonparametric estimates for

$$S_{u_0 u_0}(\Omega_k), S_{y_0 u_0}(\Omega_k), S_{n_u n_u}(\Omega_k), S_{n_y n_y}(\Omega_k), S_{n_u n_y}(\Omega_k)$$

The problem is identifiable using nonparametric noise models.

Conclusions

- periodic signals: full blown feedback problem can be easily solved
- arbitrary signals:
 - simple tools for an identifiability study
 - a huge model selection problem is hidden