

Dutch Institute of Systems and Control

**Course: System Identification
Spring 2018**

Assignment number 4 (concerning Lectures 7 and 8)

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Xavier Bombois
Directeur de Recherche CNRS
Ecole Centrale de Lyon, France
e-mail: xavier.bombois@ec-lyon.fr

Paul Van den Hof
Department of Electrical Engineering
Eindhoven University of Technology
email: p.m.j.vandenhof@tue.nl

Problem 1

Let us consider the following unknown true system¹:

$$\mathcal{S} : \quad y(t) = G(z, \theta_0)u(t) + e(t) \quad (1)$$

where $e(t)$ is a white noise of variance σ_e^2 and $G(z, \theta_0)$ is parametrized as follows:

$$G(z, \theta_0) = \theta_0 \Lambda(z) \quad (2)$$

with $\theta_0 \in \mathbf{R}$ is an unknown parameter (θ_0 is a scalar) and $\Lambda(z)$ a known transfer function. The modulus $|\Lambda(e^{j\omega})|$ of $\Lambda(z)$ is represented in Figure 1. Let us also notice that the noise transfer function $H_0(z)$ in (1) is here given by $H_0(z) = 1$.

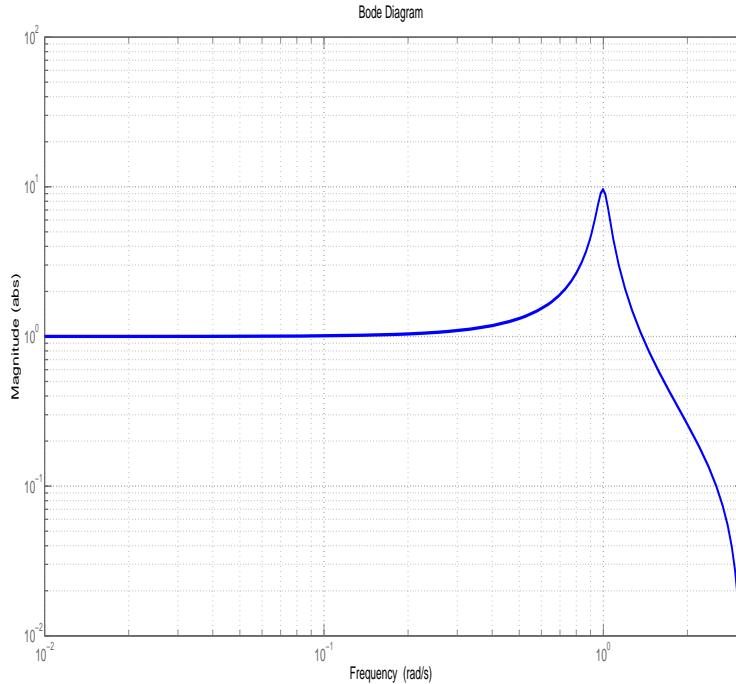


Figure 1: The modulus $|\Lambda(e^{j\omega})|$ of $\Lambda(z)$ as a function of the frequency ω

We choose the following full-order model structure \mathcal{M} for \mathcal{S} :

$$\mathcal{M} = \{G(z, \theta) = \theta \Lambda(z) \mid \theta \in \mathbf{R}\}$$

Note that, since $H_0(z) = 1$, the noise model $H(z, \theta)$ is also chosen equal to 1.

¹The sampling time T_s is here supposed equal to $T_s = 1$ second.

We apply an input signal $u(t)$ of power spectrum $\Phi_u(\omega)$ to the true system (1) for a duration N and the corresponding output $y(t)$ is collected. This yields the data set $Z^N = \{y(t) | t = 1...N\}$. Based on Z^N , we can identify an estimate $\hat{\theta}_N$ of θ_0 using the prediction error criterion i.e.

$$\hat{\theta}_N = \arg \min_{\theta} \frac{1}{N} \sum_{t=1}^N \epsilon^2(t, \theta)$$

where $\epsilon(t, \theta) = y(t) - G(z, \theta)u(t)$. The variance σ_{θ}^2 of $\hat{\theta}_N$ is (asymptotically) given by:

$$\sigma_{\theta}^2 = \frac{\sigma_e^2}{N} (\bar{E}\psi(t, \theta_0)\psi^T(t, \theta_0))^{-1} = \frac{\sigma_e^2}{N} (\bar{E}\psi^2(t, \theta_0))^{-1} \quad (3)$$

with $\psi(t, \theta) = -\frac{\partial \varepsilon(t, \theta)}{\partial \theta}$. Notice that σ_{θ}^2 corresponds to the quantity $cov(\hat{\theta}_N) = \frac{P_{\theta}}{N}$ in the slides of lecture 7 and that σ_{θ}^2 is here a scalar and not a matrix.

- a.** Show that the variance σ_{θ}^2 of $\hat{\theta}_N$ given in (3) can also be expressed as:

$$\sigma_{\theta}^2 = \frac{\sigma_e^2}{N} \left(\frac{1}{2\pi} \int_{-\pi}^{\pi} |\Lambda(e^{j\omega})|^2 \Phi_u(\omega) d\omega \right)^{-1} \quad (4)$$

We will now address the problem of optimally designing the spectrum $\Phi_u(\omega)$ of the input signal $u(t)$ in order to guarantee that the variance σ_{θ}^2 of $\hat{\theta}_N$ remains smaller than a given threshold γ . For this purpose, we consider the following optimization problem:

$$\begin{aligned} & \min_{\Phi_u(\omega)} \quad \frac{1}{2\pi} \int_{-\pi}^{\pi} \Phi_u(\omega) d\omega \\ & \text{subject to } \Phi_u(\omega) \geq 0 \quad \forall \omega \quad \text{and to} \end{aligned} \quad (5)$$

$$\sigma_{\theta}^2 \leq \gamma$$

Suppose first that we restrict attention to white noise input signals $u(t)$ having an arbitrary variance σ_u^2 . In this case, the power spectrum $\Phi_u(\omega)$ is given by $\Phi_u(\omega) = \sigma_u^2 \forall \omega$ and the decision variable of (5) is σ_u^2 .

- b.** Denote by $\sigma_{u,opt}^2$ the value of σ_u^2 corresponding to the solution of (5) in this case. Give an expression of $\sigma_{u,opt}^2$ as a function of N , σ_e^2 , $\Lambda(z)$ and γ .

Suppose now that we restrict attention to input signals having the following form:

$$u(t) = A \sin(\omega_0 t) \quad (6)$$

with an arbitrary amplitude A and a given frequency ω_0 . In this case, the power spectrum $\Phi_u(\omega)$ is given by $\Phi_u(\omega) = \frac{\pi}{2} A^2 (\delta(\omega - \omega_0) + \delta(\omega + \omega_0))$ and the decision variable of (5) is A .

- c. Denote by A_{opt} the value of A corresponding to the solution of (5) in this case. Give an expression of A_{opt} as a function of N , σ_e^2 , $\Lambda(z)$, ω_0 and γ .

Suppose finally that we restrict attention to input signals having the form (6) with an arbitrary amplitude A and an **arbitrary** frequency ω_0 . In this case, the decision variable of (5) are both A and ω_0 .

- d. Denote by A_{opt} and $\omega_{0,opt}$ the value of A and ω_0 corresponding to the solution of (5) in this case. Give a numerical value for $\omega_{0,opt}$ as well as an expression for A_{opt} as a function of N , σ_e^2 and γ . Use for this purpose the answer to item (c.) and Figure 1.

Problem 2

Consider the first order system

$$y(t) = G_0(q)u(t) + H_0(q)e(t)$$

with

$$G_0(q) = \frac{b_0 q^{-1}}{1 + a_0 q^{-1}} \quad H_0(q) = \frac{1}{1 + a_0 q^{-1}}$$

with a_0 , b_0 given real-valued coefficients, and $\{e(t)\}$ a white noise process of zero mean and variance σ_e^2 .

The input signal satisfies

$$u(t) = r(t) - cy(t)$$

with $c \in \mathbb{R}$ and $\{r(t)\}$ a quasi-stationary signal that is uncorrelated with $\{e(t)\}$.

Consider the situation that we want to identify this system with the direct identification method, using measurements of $\{u(t), y(t)\}$.

- What are the minimum excitation conditions on $\{r(t)\}$ in order to be able to arrive at a consistent estimate of $(G_0(q), H_0(q))$?
- Re-design the controller in such a way that it remains to have the property of having a finite impulse response (FIR), but additionally provides an experimental situation in which the direct method can yield a consistent estimate of the system (G_0, H_0) even when $\{r(t)\} = 0$, so on the basis of excitation of the loop through $\{e(t)\}$.