

# Set-membership identification of LTI discrete-time models

Diego Regruto and Sophie M. Fosson



**Politecnico  
di Torino**

Department of Control and  
Computer Engineering



May 2024

# Main ingredients

- We consider a discrete-time system described in following parameterized *regression form*

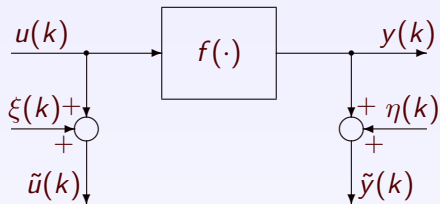
$$y(k) = f(y(k-1), y(k-2), \dots, y(k-n), u(k), u(k-1), \dots, u(k-m), \theta) \quad (1)$$

where  $m \leq n$

- A-priori information on the system
  - ▶  $n$  and  $m$  are known
  - ▶  $f \in \mathcal{F}$  where  $\mathcal{F}$  is the class of model selected on the basis of our *physical insights*
- A-priori information on the noise
  - ▶ the noise structure (i.e. the way the uncertainty affects the input-output data) is known
  - ▶ the noise is assumed to belong to a known bounded set  $\mathcal{B}$

# Noise structures

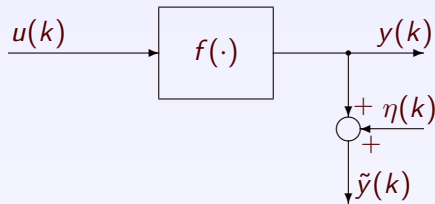
## EIV set-up



- *Errors-in-variables* (EIV) problems refer to the most general case where both the input and the output collected samples are affected by noise
- $\xi = [\xi(1), \dots, \xi(H)] \in \mathcal{B}_\xi$
- $\eta = [\eta(1), \dots, \eta(H)] \in \mathcal{B}_\eta$
- $\mathcal{B}_\xi$  and  $\mathcal{B}_\eta$  are bounded set described by *polynomial constraints*
- Most common case:  $\mathcal{B}_\eta = \{\eta : |\eta(k)| \leq \Delta_\eta\}$ ,  $\mathcal{B}_\xi = \{\xi : |\xi(k)| \leq \Delta_\xi\}$

# Noise structures

## Output-error (OE) set-up



- *Output error* (OE) problems refer to the case where only the output collected samples are affected by noise, while the input is assumed to be exactly known
- $\eta = [\eta(1), \dots, \eta(H)] \in \mathcal{B}_\eta$
- $\mathcal{B}_\eta$  is a bounded set described by *polynomial constraints*
- Most common case:  $\mathcal{B}_\eta = \{\eta : |\eta(k)| \leq \Delta_\eta\}$

# Feasible parameter set (FPS)

- In the framework of set-membership (SM) identification, all the parameter values consistent with the a-priori information on the model, the a-priori information on the noise, and the collected input-output data, are considered as feasible solution of the system identification problem
- The set of all such values is called the *feasible parameter set* (FPS)  $\mathcal{D}_\theta$
- The FPS for the general EIV problem is implicitly defined as follows

$$\begin{aligned}\mathcal{D}_\theta = & \{ \theta \in \mathbb{R}^p : y(k) = f(y(k-1), \dots, y(k-n)), u(k), \dots, u(k-m)), \\ & k = n+1, \dots, H, \\ & y(k) = \tilde{y}(k) - \eta(k), \quad u(k) = \tilde{u}(k) - \xi(k), \quad k = 1, \dots, H \\ & | \xi(k) | \leq \Delta \xi(k), \quad | \eta(k) | \leq \Delta \eta(k), \quad k = 1, \dots, H \},\end{aligned}\tag{2}$$

# Feasible parameter set (FPS)

## LTI EIV discrete-time systems

- The FPS for the case of LTI discrete-time systems with EIV noise structure is given by

$$\begin{aligned}\mathcal{D}_\theta &= \left\{ \theta \in \mathbb{R}^p : (y(k) - \eta(k)) + \sum_{i=1}^n a_i (y(k-i) - \eta(k-i)) = \right. \\ &= \sum_{j=0}^m b_j (u(k-j) - \xi(k-j)), \quad t = n+1, \dots, H, \\ &\left. | \xi(k) | \leq \Delta \xi(k), \quad | \eta(k) | \leq \Delta \eta(k), \quad k = 1, \dots, H \right\},\end{aligned}\tag{3}$$

- The FPS enjoys the following interesting features:
  - ▶ The *true* value of the parameter vector  $\theta$  is guaranteed to belong to  $\mathcal{D}_\theta$
  - ▶  $\mathcal{D}_\theta$  implicitly quantify the uncertainty affecting our mathematical model

# Parameter Uncertainty Intervals

- The FPS  $\mathcal{D}_\theta$  allows us to compute the minimum and the maximum possible values of each single component  $\theta_k$  of the parameter vector  $\theta$
- Such bounds implicitly provide the so called *parameter uncertainty intervals* (PUI) for  $\theta_k$  formally defined as

$$PUI_k = [\underline{\theta}_k; \bar{\theta}_k] \quad (4)$$

where

$$\underline{\theta}_k = \min_{\theta \in \mathcal{D}_\theta} \theta_k, \quad \bar{\theta}_k = \max_{\theta \in \mathcal{D}_\theta} \theta_k. \quad (5)$$

- Computation of  $PUI_k$  requires to compute the **global optimal solution** of optimization problems in equation (5).

# Extended feasible parameter set (EFPS)

## LTI EIV discrete-time systems

- The FPS defined in equation (3) depends on some additional unknowns (all the samples of the noise sequences)
- The constraints defining  $\mathcal{D}_\theta$  cannot be rearranged in such a way to eliminate dependencies on such additional variables
- To solve problems (5) we need to extend the space of decision variables in by defining the *Extended feasible parameter set* (EFPS)

$$\begin{aligned}\mathcal{D}_{\theta,\eta,\xi} = & \left\{ \theta \in \mathbb{R}^p, \eta \in \mathbb{R}^H, \xi \in \mathbb{R}^H : (y(k) - \eta(k)) + \sum_{i=1}^n a_i (y(k-i) - \eta(k-i)) = \right. \\ & \left. = \sum_{j=0}^m b_j (u(k-j) - \xi(k-j)), \quad t = n+1, \dots, H, \right. \\ & \left. | \xi(k) | \leq \Delta \xi(k), \quad | \eta(k) | \leq \Delta \eta(k), \quad k = 1, \dots, H \right\},\end{aligned}\tag{6}$$



# Extended feasible parameter set (EFPS)

## LTI EIV discrete-time systems

- $\mathcal{D}_{\theta,\eta,\xi}$  is the set of all the parameter values and noise samples values that are consistent with the a-priori on assumption on the system, the noise structure and the noise bounds
- $\mathcal{D}_{\theta}$  is the projection on the parameter space  $\mathbb{R}^p$  of  $\mathcal{D}_{\theta,\eta,\xi}$
- Computation of *PUIs* can be performed on the extended space of parameter and noise samples as follows

$$\underline{\theta}_k = \min_{\theta,\eta,\xi \in \mathcal{D}_{\theta,\eta,\xi}} \theta_k, \quad \bar{\theta}_k = \max_{\theta,\eta,\xi \in \mathcal{D}_{\theta,\eta,\xi}} \theta_k. \quad (7)$$

- $\mathcal{D}_{\theta,\eta,\xi}$  is a non-convex set defined by polynomial (bilinear) constraints

# Convex relaxations for PUIs computation

## LTI EIV discrete-time systems

- Computation of parameter bounds (PUIs) require the solution to the global optimum of non-convex polynomial optimization problems
- By applying *Moments theory* (Lasserre) or *Sum-of-squares (SOS) theory* (Chesi, Parrillo) it is possible to build a sequence of convex semidefinite (SDP) optimization whose size/complexity depends on a parameter called *order of relaxation*  $\delta$
- For any given  $\delta$  the following inequalities hold

$$\underline{\theta}_k^\delta \leq \underline{\theta}_k, \quad \bar{\theta}_k^\delta \geq \bar{\theta}_k \quad (8)$$

- Furthermore

$$\lim_{\delta \rightarrow \infty} \underline{\theta}_k^\delta = \underline{\theta}_k, \quad \lim_{\delta \rightarrow \infty} \bar{\theta}_k^\delta = \bar{\theta}_k \quad (9)$$