

Set-Membership Identification of Wiener models with noninvertible nonlinearity

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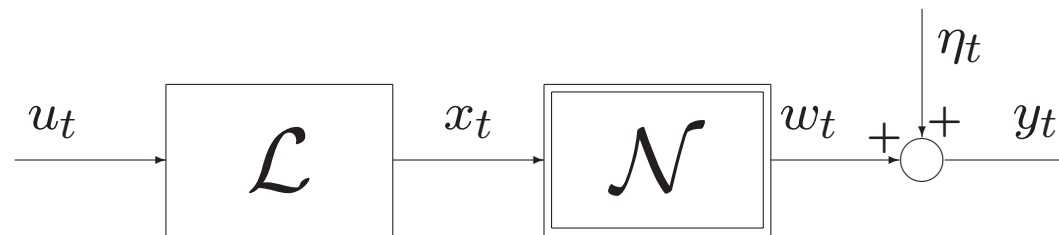
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Identificazione di sistemi nonlineari
Bertinoro, 9-11 Luglio 2007*

Wiener models

Wiener models consist of a linear dynamic system followed by a static nonlinearity



where:

\mathcal{N} : **static** (i.e. memoryless) **nonlinearity**

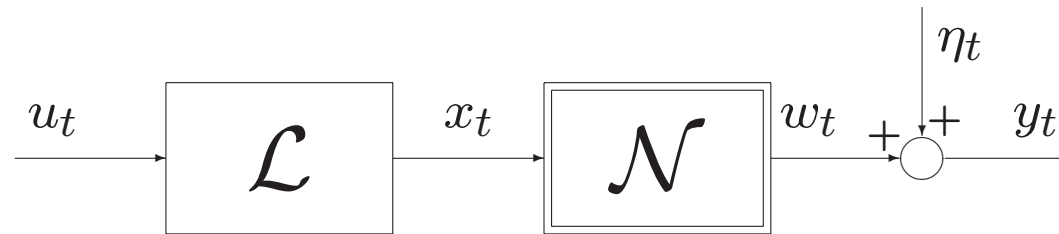
\mathcal{L} : linear subsystem

x_t : inner signal **not measurable**

Identification of Wiener models

- Motivations:
 - Main attractive feature: ability to embed process structure knowledge (e.g. nonlinearity in the measurement equipment).
 - Applications: nonlinear filtering, acoustic echo cancellation, identification of biological systems, modelling of electrical stimulated muscles, modeling of distillation columns ... many more

Problem formulation



$$w_t = \sum_{k=1}^n \gamma_k x_t^k$$

$$A(q^{-1}) = 1 + a_1 q^{-1} + \dots + a_{na} q^{-na}$$

$$B(q^{-1}) = b_0 + b_1 q^{-1} + \dots + b_{nb} q^{-nb}$$

$$q^{-1} x_t = x_{t-1}$$

$$y_t = w_t + \eta_t$$

Problem formulation

- **Aim:** compute **bounds** on the parameters $\gamma^T = [\gamma_1 \ \gamma_2 \ \dots \ \gamma_n]$, $\theta^T = [a_1 \ \dots \ a_{na} \ b_0 \ \dots \ b_{nb}]$.
- **Prior assumption on the system:**
 1. **stability**;
 2. n , na and nb are **known**;
 3. the **steady-state gain** is **not zero**;
 4. a rough **upper bound** on the **settling time** of the system is known;
- **Prior assumption on the measurement uncertainty:**
 1. $\{\eta_t\}$ is UBB: $\|\{\eta_t\}\|_\infty \leq \Delta\eta_t$;
 2. $\Delta\eta_t$ is **known**;

Proposed solution: preliminary

Three-stage solution:

- **First stage:** computation of **bounds** on the **nonlinear block** parameters γ .
- **Second stage:** computation of **bounds** on the **inner (unmeasurable) signal** x_t .
- **Third stage:** computation of **bounds** on the **linear block** parameters.

Proposed solution: preliminary

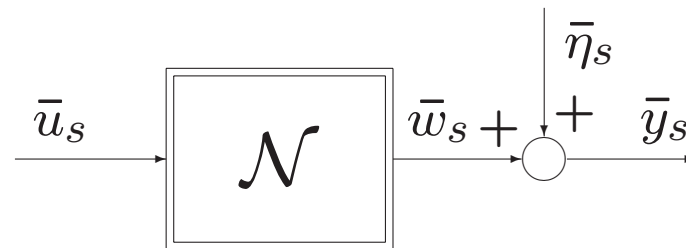
Remark 1: The parameterization is not unique

$$\Rightarrow \text{assume } g_{dc} = \frac{\sum_{j=0}^{nb} b_j}{1 + \sum_{i=1}^{na} a_i} = 1$$

Remark 2: Stimulate the system with a set of **step inputs** with **different amplitudes**



Steady-state operating conditions:



1st Stage: assessment of tight bounds on γ

- Get $M \geq n$ *steady-state measurements*:

$$\bar{y}_s = \sum_{k=1}^n \gamma_k \bar{u}_s^k + \bar{\eta}_s, \quad s = 1, \dots, M$$

- The *feasible parameter set* of the nonlinear block, is defined as:

$$\mathcal{D}_\gamma = \left\{ \gamma \in \mathbb{R}^n : \bar{y}_s = \sum_{k=1}^n \gamma_k \bar{u}_s^k + \bar{\eta}_s, |\bar{\eta}_s| \leq \Delta \bar{\eta}_s; s = 1, \dots, M \right\}$$

- \mathcal{D}_γ is a *convex polytope*:
 - (a) Provides *tight bounds* on parameters γ
 - (b) Can be computed through standard algorithm from the SM literature

1st Stage: orthotope-outer bounding set \mathcal{B}_γ containing \mathcal{D}_γ

The shape of \mathcal{D}_γ may result quite complex for large M and n

⇒ Compute a **tight orthotope outer-bound**:

$$\mathcal{B}_\gamma = \{ \gamma \in R^n : \gamma_j = \gamma_j^c + \delta\gamma_j, \\ | \delta\gamma_j | \leq \Delta\gamma_j/2, j = 1, \dots, n \}$$

$$\gamma_j^c = \frac{\gamma_j^{\min} + \gamma_j^{\max}}{2}$$

$$\Delta\gamma_j = | \gamma_j^{\max} - \gamma_j^{\min} |$$

$$\gamma_j^{\min} = \min_{\gamma \in \mathcal{D}_\gamma} \gamma_j \quad \gamma_j^{\max} = \max_{\gamma \in \mathcal{D}_\gamma} \gamma_j$$

Computational aspects: \mathcal{B}_γ is obtained solving $2n$ LP problems with n variables and $2M$ constraints.

2nd Stage: bounds on the inner signal x_t

Simplified case: exactly known γ

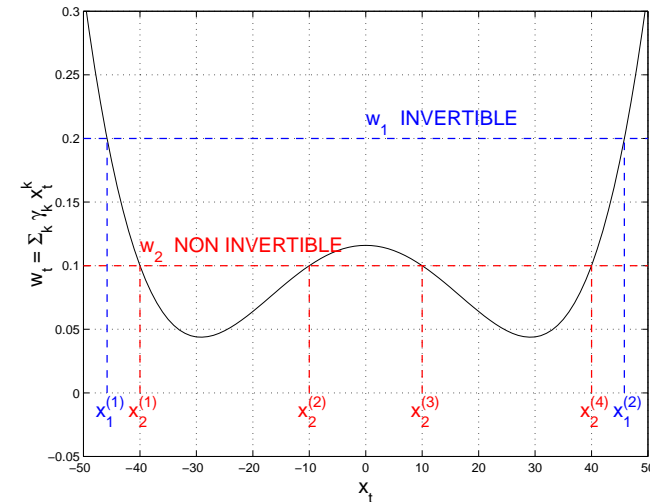
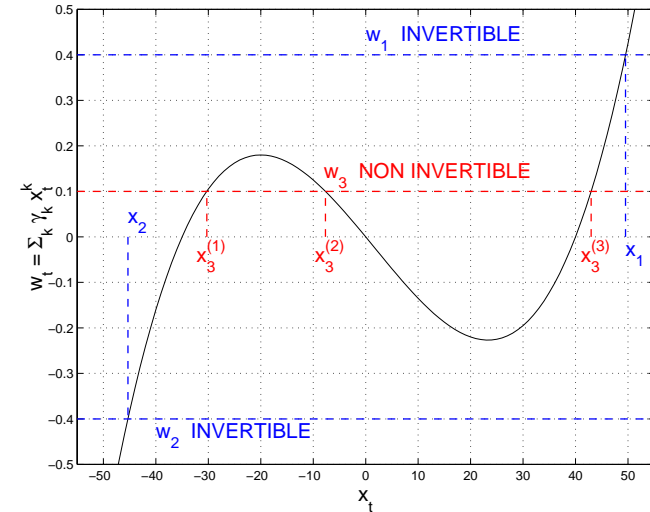
- **Task:** for given $\{w_t\}$ compute $\{x_t\}$, solving:

$$w_t - \sum_{k=1}^n \gamma_k x_t^k = p_t(x_t, w_t) = 0$$

- **Problem:** polynomials are **noninvertible**
- **Key idea:** design $\{u_t\}$ to drive $\{x_t\} \subset \Lambda^*$ such that:

$$\begin{cases} p_t(x_t, w_t) = 0 \\ x_t \in \Lambda^* \end{cases} \quad (1)$$

has a unique solution for each t



2nd Stage: bounds on the inner signal x_t

Definition 1

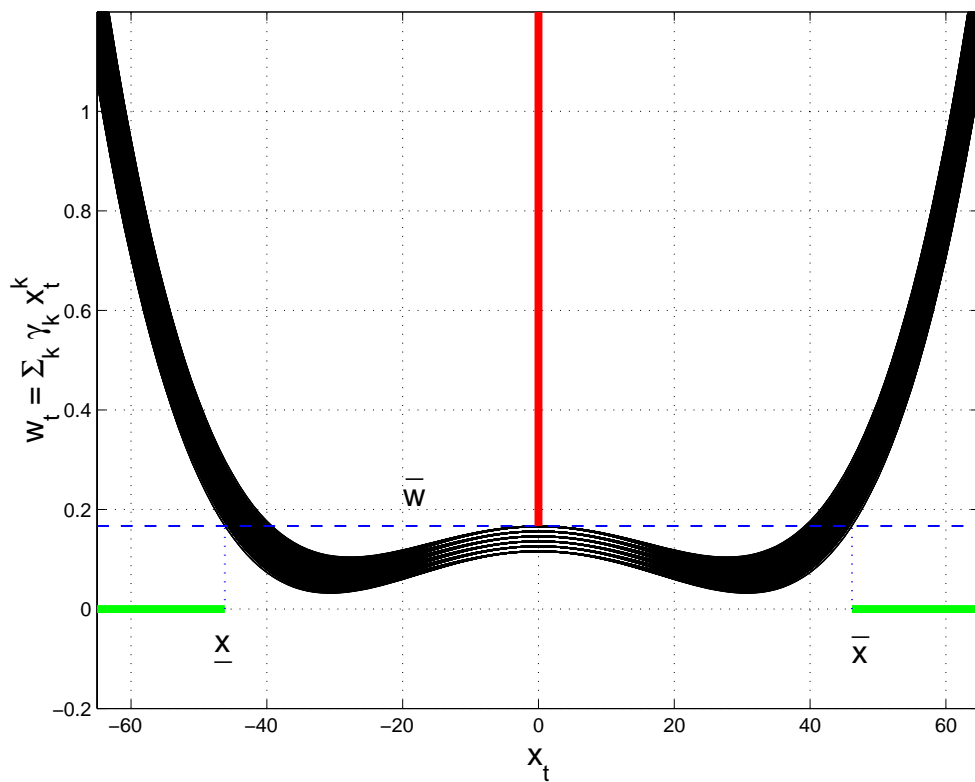
The set $W \subset R$ is an **Output Invertibility Interval** if for $w_t \in W$ each $p_t(x_t, w_t, \gamma) \in \Pi_t$ shows either only **one real root** (n odd) or two real roots when (n even).

Definition 2

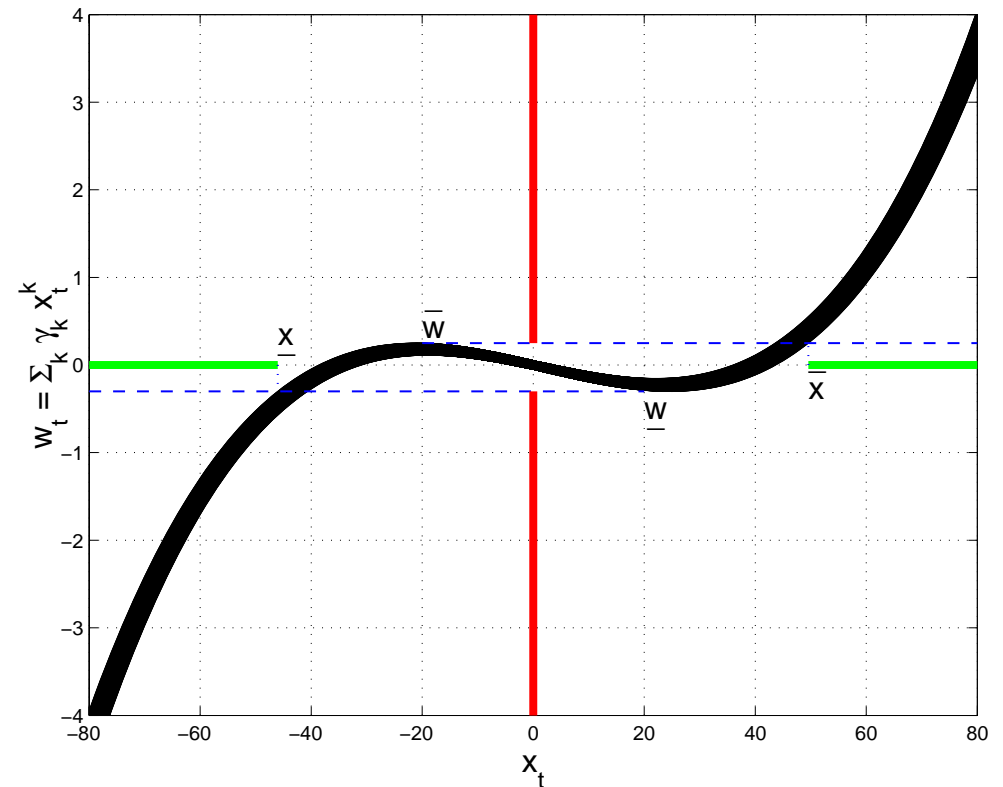
The set $X \subset R$ is a **Feasible Inner-signal Interval** if the set of output values $\mathcal{O} = \{w_t \in R : w_t = \mathcal{N}(x_t, \gamma), \mathcal{N}(x_t, \gamma) \in \mathcal{V}_t, x_t \in X\}$ is an **Output Invertibility Interval**

2nd Stage: bounds on the inner signal x_t

Case n even



Case n odd



2nd Stage: bounds on the inner signal x_t

Proposition 1 (Output Invertibility Intervals)

$\mathcal{N}(x_t, \gamma)$ with $\gamma \in \mathcal{D}_\gamma$, shows the following **Output Invertibility Intervals** (case n odd):

$$\overline{W} =]\bar{w}, +\infty[\quad \text{and} \quad \underline{W} =]-\infty, \underline{w}[$$

where

$$\bar{w} = \max_{x_t \in \Upsilon_t} \max_{\gamma \in \mathcal{D}_\gamma} \sum_{k=1}^n \gamma_k x_t^k, \quad \underline{w} = \min_{x_t \in \Upsilon_t} \min_{\gamma \in \mathcal{D}_\gamma} \sum_{k=1}^n \gamma_k x_t^k$$

$$\Upsilon_t = \left\{ x_t \in R : \frac{d}{dx_t} \sum_{k=1}^n \gamma_k x_t^k = 0, \text{ for some } \gamma \in \mathcal{D}_\gamma \right\}$$

2nd Stage: bounds on the inner signal x_t

Proposition 2 (Feasible Inner-signal Intervals)

The Wiener system with uncertain $\mathcal{N}(x_t, \gamma)$, shows the following Feasible Inner-signal Intervals (case n odd and $\gamma_n > 0$):

$$\bar{X} =]\bar{x}, +\infty[\quad \text{and} \quad \underline{X} =]-\infty, \underline{x}[$$

where

$$\begin{aligned} \bar{x} &= \max \left\{ x_t \in R : \bar{w} - \sum_{k=1}^n \gamma_k x_t^k = 0, \text{ for some } \gamma \in \mathcal{D}_\gamma \right\} \\ \underline{x} &= \min \left\{ x_t \in R : \underline{w} - \sum_{k=1}^n \gamma_k x_t^k = 0, \text{ for some } \gamma \in \mathcal{D}_\gamma \right\}. \end{aligned} \quad (2)$$

2nd Stage: Input Sequence Design

$u_t = u_{DC} + u_{td}$ such that $x_t = x_{DC} + x_{td} \in \text{Feasible Inner-signal Interval}$
 $g_{dc} = 1 \Rightarrow u_{DC} = x_{DC}$

Proposition 3 (Input sequence design)

- For a given $u_{DC} \geq \bar{x}$, each sample of the sequence $\{x_t\}$ belongs to \bar{X} if:

$$\|\{u_{td}\}\|_{\infty} \leq \frac{|u_{DC} - \bar{x}|}{h_{up}}$$

- For given $u_{DC} \leq \underline{x}$, each sample of the sequence $\{x_t\}$ belongs to \underline{X} if:

$$\|\{u_{td}\}\|_{\infty} \leq \frac{|u_{DC} - \underline{x}|}{h_{up}}$$

where: $\|h\|_1 \leq h_{up}$; h : impulse response the linear block; $\|h\|_1$: ℓ_1 norm of the linear block;
 $\|\cdot\|_{\infty}$: ℓ_{∞} norm of a sequence.

2nd Stage: Input Sequence Design

Proposition 4 (Input signal design)

All the samples of $\{w_t\}$ belong to W^* if the samples of $\{y_t\}$ satisfy the following inequalities (case n odd):

$$y_t > \bar{y} \quad \forall t \quad \text{or} \quad y_t < \underline{y} \quad \forall t, \quad \text{when } n \text{ is odd} \quad (3)$$

where

$$\bar{y} = \bar{w} + \Delta\eta_t, \quad \underline{y} = \underline{w} - \Delta\eta_t$$



No bound h_{up} is *a priori* known



Tune amplitude of $\{u_{td}\}$ until $\{y_t\}$ satisfies (3)

2nd Stage: bounds on $\{x_t\}$

Proposition 5 (Inner-signal bounds)

Given:

- $\mathcal{N}(x_t, \gamma)$ with $\gamma \in \mathcal{D}_\gamma$
- $\{u_t\}$ which drives $\{x_t\}$ into X^*
- the measured output sequence $\{y_t\}$



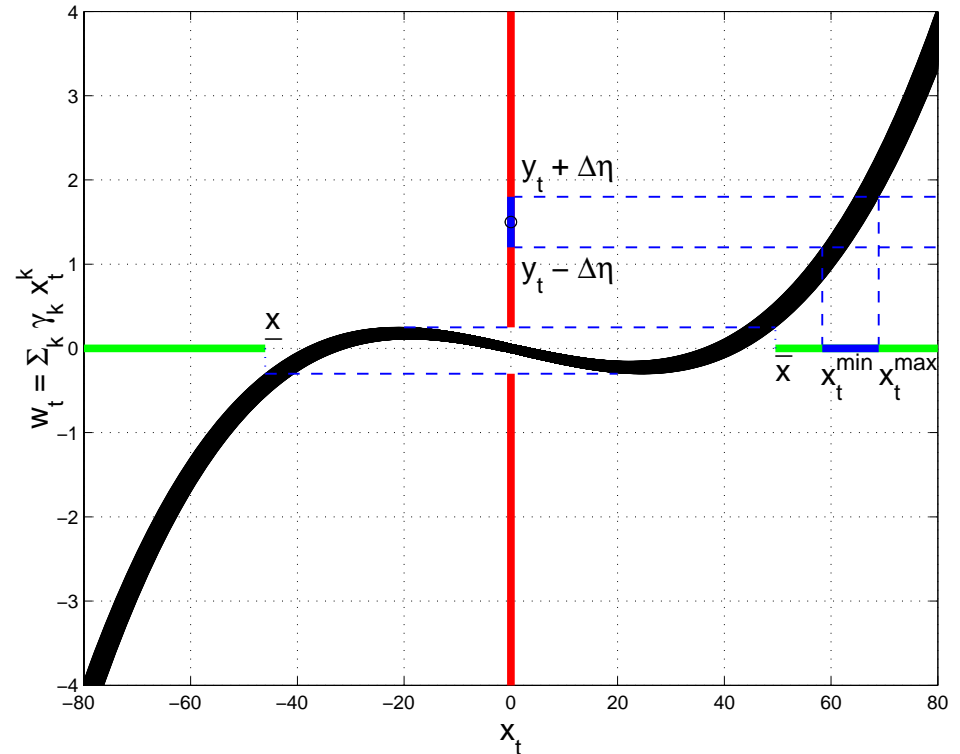
Each sample x_t of $\{x_t\}$ is bounded as follows:

$$x_t^{\min} \leq x_t \leq x_t^{\max} \quad (4)$$

where (case $\gamma_n > 0$ and $X^* = \bar{X}$):

$$x_t^{\min} = \min \left\{ x_t \in R : y_t - \Delta\eta_t - \sum_{k=1}^n \gamma_k x_t^k = 0, \text{ for some } \gamma \in \mathcal{D}_\gamma \right\}$$

$$x_t^{\max} = \max \left\{ x_t \in X^* : y_t + \Delta\eta_t - \sum_{k=1}^n \gamma_k x_t^k = 0, \text{ for some } \gamma \in \mathcal{D}_\gamma \right\}$$



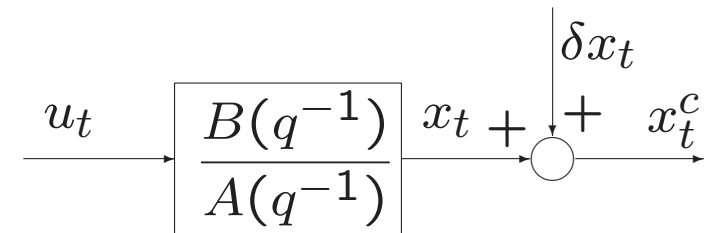
3rd stage: bounds on θ

Given the designed input sequence $\{u_t\}$, the uncertain inner sequence $\{x_t\}$ we define:

$$x_t^c = \frac{x_t^{\min} + x_t^{\max}}{2}$$

$$|\delta x_t| \leq \Delta x_t$$

$$\Delta x_t = \frac{x_t^{\max} - x_t^{\min}}{2}$$



Output Error problem with UBB errors (special case of EIV problem)

(V. Cerone - "Feasible parameter set of linear models with bounded errors in all variables", *Automatica* '93)

2nd Stage: Computational aspects

Computation of Υ_t :

find the roots of the uncertain polynomial:

$$p_t'(x_t, \gamma) = \frac{d}{dx_t} \sum_{k=1}^n \gamma_k x_t^k = - \sum_{k=1}^n k \gamma_k x_t^{k-1}$$

Proposed approach: gridding on $x_t \rightarrow$ one LP problem for each x_t .

Computation of \bar{w} and \underline{w} :

solve the following two nonlinear programming problems:

$$\bar{w} = \max_{x_t \in \Upsilon_t} \max_{\gamma \in \mathcal{D}_\gamma} \sum_{k=1}^n \gamma_k x_t^k \quad \text{and} \quad \underline{w} = \min_{x_t \in \Upsilon_t} \min_{\gamma \in \mathcal{D}_\gamma} \sum_{k=1}^n \gamma_k x_t^k$$

Proposed approach: gridding on the set $\Upsilon_t \rightarrow$ one LP problem for each x_t .

2nd Stage: Computational aspects

Computation of \bar{x} and \underline{x} :

solve the following problems (n odd, $\gamma_n > 0$):

$$\bar{x} = \max\{x_t \in R : p_t(x_t, \gamma, \bar{w}) = 0, \text{ for some } \gamma \in \mathcal{D}_\gamma\} \quad (5)$$

and

$$\underline{x} = \min\{x_t \in R : p_t(x_t, \gamma, \underline{w}) = 0, \text{ for some } \gamma \in \mathcal{D}_\gamma\} \quad (6)$$

Computation of x_t^{max} and x_t^{min} :

solve the following problems:

$$x_t^{max} = \max\{x_t \in \bar{X} : p_t(x_t, \gamma, y_t + \Delta\eta_t) = 0, \text{ for some } \gamma \in \mathcal{D}_\gamma\} \quad (7)$$

$$x_t^{min} = \min\{x_t \in R : p_t(x_t, \gamma, y_t - \Delta\eta_t) = 0, \text{ for some } \gamma \in \mathcal{D}_\gamma\} \quad (8)$$

2nd Stage: Computational aspects

Algorithm 1 (Computation of \bar{x})

1. **Set** $\alpha = \alpha_0$ and $\epsilon =$ prescribed tolerance.
2. **Compute**
 $r = \max\{x_t \in R : p_t^{nom}(x_t, \gamma^c, \bar{w}) = 0\}$.
3. **Set** $x_m = r$.
4. **Set** $x_M = x_m + \alpha$.
5. **IF** $\exists \gamma^\diamond \in \mathcal{D}_\gamma : p_t(x_M, \gamma^\diamond, \bar{w}) = 0$ **then**
 $x_m = x_M$;
else
IF $|x_M - x_m| < \epsilon$ **then**
 $\bar{x}_* = x_M$;
return \bar{x}_* ;
stop algorithm.
else
 $\alpha = \alpha/2$;
end if
end if.
8. Repeat from 4.

Main properties:

1. Algorithm 1 is **convergent**.
2. Algorithm 1 **provides an upper bound \bar{x}_* of \bar{x} with $|\bar{x}_* - \bar{x}| \leq \epsilon$.**
3. **Step 5 is a LP problem.**

Remark: Algorithm 1 can be also used to compute \underline{x} , x_t^{max} and x_t^{min}

Example:

Parameters of the simulated system:

$$\begin{aligned}\gamma_1 &= -5, \gamma_2 = -4, \gamma_3 = 1; \\ A(q^{-1}) &= (1 - 1.1q^{-1} + 0.28q^{-2}); \\ B(q^{-1}) &= (0.1q^{-1} + 0.08q^{-2})\end{aligned}$$

Signal to noise ratio:

$$SNR = 10 \log \left\{ \frac{\sum_{t=1}^N w_t^2}{\sum_{t=1}^N \eta_t^2} \right\}$$

Measurement output errors:

Bounded absolute output errors have been considered:

$$\begin{aligned}|\eta_t| &\leq \Delta\eta_t; \quad \eta_t \text{ belongs to the uniform distribution } U[-\Delta\eta_t, +\Delta\eta_t] \\ |\bar{\eta}_s| &\leq \Delta\bar{\eta}_s; \quad \bar{\eta}_s \text{ belongs to the uniform distribution } U[-\Delta\bar{\eta}_s, +\Delta\bar{\eta}_s]\end{aligned}$$

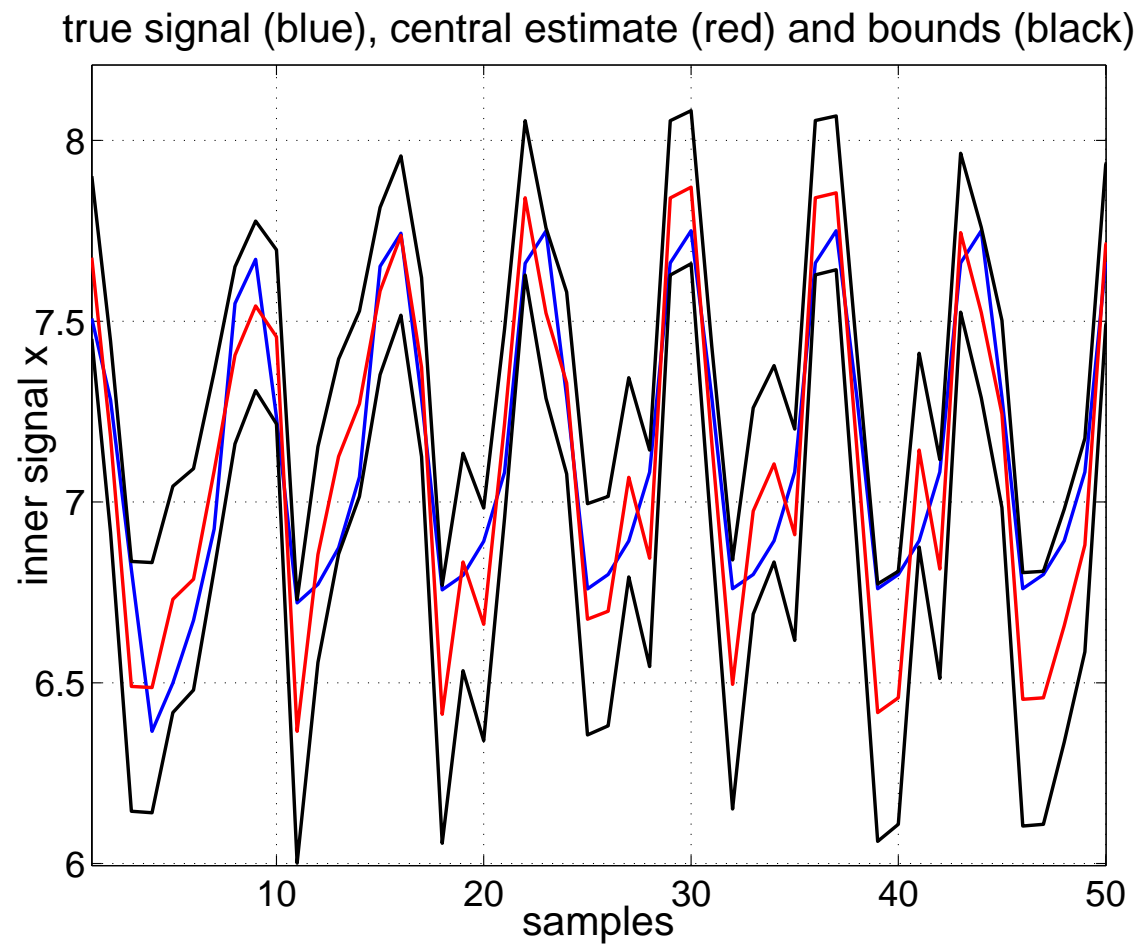
$$\Delta\eta_t = \Delta\bar{\eta}_s \doteq \Delta\eta$$

Nonlinear block parameter: central estimates and parameters uncertainty bounds

Number of steady-state samples: $M = 50$

| \overline{SNR} (dB) | γ_j | True Value | γ_j^c | $\Delta\gamma_j$ |
|--------------------------|------------|------------|--------------|------------------|
| 58.2 | γ_1 | -5.000 | -4.999 | 2.1e-3 |
| | γ_2 | -4.000 | -4.000 | 1.8e-4 |
| | γ_3 | 1.000 | 1.000 | 4.8e-5 |
| 38.2 | γ_1 | -5.000 | -5.027 | 3.6e-2 |
| | γ_2 | -4.000 | -3.995 | 8.1e-3 |
| | γ_3 | 1.000 | 1.001 | 1.6e-3 |
| 18.4 | γ_1 | -5.000 | -5.101 | 1.1e-1 |
| | γ_2 | -4.000 | -4.000 | 1.0e-2 |
| | γ_3 | 1.000 | 1.004 | 5.1e-3 |

Inner signal estimate



Linear block parameters: central estimates and parameters uncertainty bounds

Number of transient samples: $N = 100$

| SNR (dB) | θ_j | True Value | θ_j^c | $\Delta\theta_j$ |
|----------|------------|------------|--------------|------------------|
| 58.2 | θ_1 | -1.100 | -1.100 | 5.3e-3 |
| | θ_2 | 0.280 | 0.280 | 5.1e-3 |
| | θ_3 | 0.100 | 0.100 | 6.1e-4 |
| | θ_4 | 0.080 | 0.080 | 5.6e-4 |
| 38.0 | θ_1 | -1.100 | -1.106 | 7.9e-2 |
| | θ_2 | 0.280 | 0.288 | 7.4e-2 |
| | θ_3 | 0.100 | 0.100 | 8.0e-3 |
| | θ_4 | 0.080 | 0.081 | 9.0e-3 |
| 18.2 | θ_1 | -1.100 | -1.211 | 3.9e-1 |
| | θ_2 | 0.280 | 0.403 | 3.6e-1 |
| | θ_3 | 0.100 | 0.099 | 4.2e-2 |
| | θ_4 | 0.080 | 0.101 | 4.7e-2 |

Number of transient samples: $N = 1000$

| SNR (dB) | θ_j | True Value | θ_j^c | $\Delta\theta_j$ |
|----------|------------|------------|--------------|------------------|
| 58.2 | θ_1 | -1.100 | -1.100 | 1.9e-3 |
| | θ_2 | 0.280 | 0.280 | 1.8e-3 |
| | θ_3 | 0.100 | 0.100 | 1.9e-4 |
| | θ_4 | 0.080 | 0.080 | 2.2e-4 |
| 38.4 | θ_1 | -1.100 | -1.102 | 5.8e-2 |
| | θ_2 | 0.280 | 0.282 | 5.4e-2 |
| | θ_3 | 0.100 | 0.100 | 6.1e-3 |
| | θ_4 | 0.080 | 0.079 | 5.9e-3 |
| 18.2 | θ_1 | -1.100 | -1.113 | 1.5e-1 |
| | θ_2 | 0.280 | 0.293 | 1.4e-1 |
| | θ_3 | 0.100 | 0.101 | 1.6e-2 |
| | θ_4 | 0.080 | 0.078 | 1.7e-2 |

Conclusions and references

- The proposed three-stage parameter bounding procedure provides:
 - **tight bounds** on the parameters of the **nonlinear block** using steady-state input-output data;
 - **overbounds** on the parameters of the **linear part**, through the computation of bounds on the unmeasurable inner signal x_t ;
- The numerical example has showed the effectiveness of the proposed procedure.
- The approach is computationally tractable (**in the above example the experiment with $M = 50$ and $N = 1000$ required about 3 minutes (AMD 3200 processor)**).

Reference paper:

V. Cerone, D. Regruto, "Parameter bounds evaluation of Wiener models with noninvertible polynomial nonlinearities," *Automatica*, vol. 42, pp. 1775–1781, 2002.
