Research Seminar

Subspace Identification of Hammerstein and Wiener Models

Speaker

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Outline

- Introduction: Motivation, New results
- A (very) brief review on Subspace State-Space System IDentification Methods
- Block-oriented Nonlinear Models
- Subspace Identification of Hammerstein Models
- Subspace Identification of Wiener Models
- Simulation Examples
- Conclusions
Motivation for Nonlinear (Subspace) Identification

- Most physical processes have a nonlinear behaviour, except in a limited range where they can be considered linear.
- The performance of controllers designed from a linear approximation is strongly influenced by a change in the operating point of the system.
- Nonlinear models are able to describe more accurately the global behaviour of the system, independently of the operating point.
- Many dynamical systems can be represented by the interconnection of static nonlinearities and LTI systems. These models are called block-oriented nonlinear models.
• Subspace Methods have been very successful for the identification of LTI models in many practical applications.

• Although there is a well developed theory for Subspace Identification methods for LTI systems, this is not the case for nonlinear systems. Some recent contributions in this area are: (Verhaegen & Westwick, 1996) in Subspace Identification of Hammerstein and Wiener models, and (Chen & Maciejowski, 2000) and (Favoreel et al., 1999) in Subspace Identification of bilinear systems.
The new results (Gomez & Baeyens, 2005)

• New subspace algorithms for the simultaneous identification of the linear and nonlinear parts of multivariable Hammerstein and Wiener models are presented.

• The proposed algorithms consist basically of two steps:
  
  **Step 1:** a standard (linear) subspace algorithm applied to an equivalent linear system whose inputs (outputs) are filtered (by the basis functions describing the static nonlinearities) versions of the original inputs (outputs).

  **Step 2:** a 2-norm minimization problem which is solved via an SVD.

• Provided the conditions for the consistency of the linear subspace algorithm used in Step 1 are satisfied, consistency of the estimates can be guaranteed.
References


Subspace State-Space System IDentification

4SID Methods

Properties

- They combine tools of System Theory, Numerical Linear Algebra and Geometry (projections).

- They have their origin in Realization Theory as developed in the 60/70s (Ho & Kalman, 1966).

- They provide reliable state-space models of multivariable LTI systems directly from input-output data.

- They don’t require iterative optimization procedures → no problems with local minima, convergence and initialization.
They don’t require a particular (canonical) state-space realization → numerical conditioning improves.

They require a modest computational load in comparison to traditional identification methods like PEM.

The algorithms can be (they have been) efficiently implemented in software like Matlab.

Main computational tools are QR and SVD.

All subspace methods compute at some stage the subspace spanned by the columns of the extended observability matrix.

The various algorithms (e.g., N4SID, MOESP, CVA) differ in the way the extended observability matrix is estimated and also in the way it is used to compute the system matrices.
The system model

\[ x_{k+1} = Ax_k + Bu_k + Ke_k \]
\[ y_k = Cx_k + Du_k + e_k \]

State-space model in innovation form

The identification problem

To estimate the system matrices \((A, B, C, D)\) and \(K\), and the model order \(n\), from an \((N+\alpha-1)\)-point data set of input and output measurements

\[ \{u_k, y_k\}_{k=1}^{N+\alpha-1} \]
Realization-based 4SID Methods

For a LTI system, a **minimal** state-space realization \((A, B, C, D)\) completely defines the input-output properties of the system through

\[
y_k = \sum_{\ell=0}^{\infty} h_\ell u_{k-\ell}
\]

**convolution sum**

where the impulse response coefficients \(h_\ell\) are related to the system matrices by

\[
h_\ell = \begin{cases} 
D, & \ell = 0 \\
CA^{\ell-1}B, & \ell > 0 
\end{cases}
\]
An estimate of the extended observability matrix can be computed by a full rank factorization of the impulse response Hankel matrix. This factorization is provided by the SVD of matrix $H_{ij}$. 

$$H_{ij} = \Gamma_i C_j$$
\[ H_{ij} = [U_1 \quad U_2] \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} [V_1^T \quad V_2^T] \approx U_1 \Sigma_1 V_1^T = \left( U_1 \Sigma_1^{1/2} \right) \left( \Sigma_1^{1/2} V_1^T \right) \]

In the absence of noise, \( H_{ij} \) will be a rank \( n \) matrix, and \( \Sigma_1 \) will contain the \( n \) non-zero singular values \( \rightarrow \text{model order is computed.} \) In the presence of noise, \( H_{ij} \) will have full rank and a rank reduction stage will be required for the model order determination.

**Problems:** it is necessary to measure or to estimate (for example, via correlation analysis) the impulse response of the system \( \rightarrow \text{not good} \)
Direct 4SID Methods

\[
Y_\alpha = \Gamma_\alpha X + H_\alpha U_\alpha + N_\alpha
\]

fundamental equation \hspace{1cm} (1)

\[
Y_\alpha = \begin{bmatrix}
y_1 & y_2 & \cdots & y_N \\
y_2 & y_3 & \cdots & y_{N+1} \\
\vdots & \vdots & \ddots & \vdots \\
y_{\alpha-1} & y_{\alpha} & \cdots & y_{N+\alpha-1}
\end{bmatrix}
\]

Output block Hankel matrix

(In a similar way are defined the Input block Hankel matrix \(U_\alpha\) and the Noise block Hankel matrix \(N_\alpha\).)

\[
\Gamma_\alpha = \begin{bmatrix}
C \\
CA \\
\vdots \\
CA^{\alpha-1}
\end{bmatrix}
\]

Extended \((\alpha > n)\)

Observability Matrix

\[
X = [x_1, x_2, \cdots, x_N]
\]

State Sequence Matrix
\[
H_\alpha = \begin{bmatrix}
D & 0 & 0 & \ldots & 0 \\
CB & D & 0 & \ldots & 0 \\
CAB & CB & D & \ldots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
CA^{\alpha-2}B & CA^{\alpha-3}B & CA^{\alpha-4}B & \ldots & D
\end{bmatrix}
\]

Lower triangular block
Toeplitz matrix of impulse responses (unknown).

The main idea of Direct 4SID methods

In the absence of noise \((N_\alpha = 0)\), eq. (1) becomes

\[
Y_\alpha = \Gamma_\alpha X + H_\alpha U_\alpha
\]

(2)

and the part of the output which does not emanate from the state can be removed by multiplying (from the right) both sides of eq. (2) by the orthogonal projection onto the null space of \(U_\alpha\), i.e. by
\[ \Pi_{\perp U_{\alpha}^T} \Delta = I - U_{\alpha}^T (U_{\alpha} U_{\alpha}^T)^{-1} U_{\alpha} = U_{\alpha} \]  

orthogonal projection

such that  
\[ U_{\alpha} U_{\alpha}^\perp = I \]

This yields

\[ Y_{\alpha} U_{\alpha}^\perp = \Gamma_{\alpha} X U_{\alpha}^\perp \]  

(3)

**Note** that the matrix on the left depends exclusively on the input-output data. Then, a **full rank factorization** of this matrix will provide an estimate \( \hat{\Gamma}_{\alpha} \) of the extended observability matrix. Estimates of the corresponding system matrices can be obtained by resorting to the **shift invariance property** of the extended observability matrix, and by solving a system of linear equations in the least squares sense.
The factorization is provided by the SVD of the matrix on the left side

\[
Y_\alpha \mathbf{U}_\alpha^\perp = \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix}
\approx U_1 \Sigma_1 V_1^T = \left( U_1 \Sigma_1^{1/2} \right) \left( \Sigma_1^{1/2} V_1^T \right)
\]

(4)

**Rank Reduction**

*(model order estimation)*

(In the absence of noise \( \Sigma_2 = 0 \))

**Weighting Matrices**

Row and column weighting matrices can be introduced in (4) before performing the SVD of the matrix in the left hand side. Any choice of positive-definite weighting matrices \( W_r \) and \( W_c \) will result in consistent estimates of the extended observability matrix.
\[ W_r Y_\alpha U_\alpha \perp W_c = \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} \approx U_1 \Sigma_1 V_1^T = \left( U_1 \Sigma_1^{\frac{1}{2}} \right) \left( \Sigma_1^{\frac{1}{2}} V_1^T \right) \]

**change of coordinates in state-space**

Existing algorithms employ the following choices for matrices \( W_r \) and \( W_c \),

- **MOESP** (Verhaegen, 1994): \( W_r = I, \ W_c = \left( \frac{1}{N} \Phi \Pi U_\alpha^T \Phi^T \right)^{-1} \Phi \Pi U_\alpha^T \)

- **CVA** (Larimore, 1990): \( W_r = \left( \frac{1}{N} Y_\alpha \Pi U_\alpha^T Y_\alpha^T \right)^{-\frac{1}{2}}, \ W_c = \left( \frac{1}{N} \Phi \Pi U_\alpha^T \Phi^T \right)^{-\frac{1}{2}} \)

- **N4SID** (Van Overschee and de Moor, 1994):
  \[ W_r = I, \ W_c = \left( \frac{1}{N} \Phi \Pi U_\alpha^T \Phi^T \right)^{-1} \Phi \]
Computation of the system matrices

Given an estimate $\hat{\Gamma}_\alpha$ of the extended observability matrix, estimates of the system matrices can be computed as:

- $\hat{C}$: first row block of $\hat{\Gamma}_\alpha$
- $\hat{A}$: solving in the least squares sense

\[
\Gamma_\alpha = \Gamma_\alpha \hat{A}
\]

- $\hat{B}$ and $\hat{D}$: solving a system of linear equations

shift-invariance property
Presence of noise

In the presence of noise

\[ Y_\alpha = \Gamma_\alpha X + H_\alpha U_\alpha + N_\alpha \]

and

\[ Y_\alpha U_\alpha^\perp = \Gamma_\alpha X + N_\alpha U_\alpha^\perp \]

The noise term can be removed by correlating it away with a suitable matrix. This can be interpreted as an oblique projection.
Block-oriented Nonlinear Models

Fig. 1: Hammerstein Model (NL)

Fig. 2: Wiener Model (LN)

Fig. 3: Hammerstein-Wiener Model (NLN)

Fig. 4: Hammerstein-Wiener Model (LNL)
Hammerstein Model Identification

Problem Formulation

\[ y_k = N(u_k) = \sum_{i=1}^{r} \alpha_i g_i(u_k) \]  

LTI subsystem

\[
\begin{align*}
  x_{k+1} &= Ax_k + Bv_k + \omega_k \\
  y_k &= Cx_k + Dv_k + \nu_k
\end{align*}
\]

Nonlinear subsystem

\[ g_i(\bullet): \mathbb{R}^p \rightarrow \mathbb{R}^p, \quad (i = 1, \ldots, r) \]

known basis functions

\[ \alpha_i \in \mathbb{R}^{p \times p}, \quad (i = 1, \ldots, r) \]

unknown matrix parameters

Fig. 5: Hammerstein model

\[ u_k \rightarrow N(.) \rightarrow A \quad B \rightarrow C \quad D \rightarrow y_k \]

y_k ∈ \mathbb{R}^m, \quad x_k ∈ \mathbb{R}^n, \quad v_k ∈ \mathbb{R}^p

\[ \omega_k ∈ \mathbb{R}^n, \quad \nu_k ∈ \mathbb{R}^m \]

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**Identification problem:** to estimate the unknown parameter matrices

\[ \alpha_i \in \mathbb{R}^{p \times p}, (i = 1, \ldots, r) \]

and \( A, B, C, \) and \( D \) characterizing the nonlinear and the linear parts, respectively, and the model order \( n \), from an \( N \)-point data set \( \{u_k, y_k\}_{k=1}^N \) of observed input-output measurements.

**Subspace Identification Algorithm**

\[
\begin{align*}
\begin{cases}
x_{k+1} &= Ax_k + \sum_{i=1}^{r} B \alpha_i g_i(u_k) + \omega_k \\
y_k &= Cx_k + \sum_{i=1}^{r} D \alpha_i g_i(u_k) + \nu_k
\end{cases}
\end{align*}
\]

**Normalization** \( \|\alpha_i\|_2 = 1 \)

**Identifiability problem**
Defining \[ \tilde{B} = [B \alpha_1, \ldots, B \alpha_r], \quad \tilde{D} = [D \alpha_1, \ldots, D \alpha_r], \quad U_k = [g_1^T(u_k), \ldots, g_r^T(u_k)]^T \]

\[
\begin{cases}
    x_{k+1} = Ax_k + \tilde{B}U_k + \omega_k \\
y_k = Cx_k + \tilde{D}U_k + \nu_k
\end{cases}
\]

**Linear Subspace Algorithms**
(N4SID, MOESP, CVA)

**Estimates** \( \hat{A}, \hat{B}, \hat{C}, \hat{D}, \) model order \( n \)

Fig. 6: Equivalent LTI system with input \( U_k \)
Defining \( \alpha = [\alpha_1, \ldots, \alpha_r]^T \), then \( \widetilde{B} = B\alpha^T \), and \( \widetilde{D} = D\alpha^T \), so that

\[
\Theta_{BD} \overset{\Delta}{=} \begin{bmatrix} \widetilde{B} \\ \widetilde{D} \end{bmatrix} = \begin{bmatrix} B \\ D \end{bmatrix} \alpha^T
\]

The problem then is how to compute estimates of matrices \( B, D, \) and \( \alpha \) from the estimate of the matrices \( \widetilde{B}, \) and \( \widetilde{D} \) (i.e., from an estimate of \( \Theta_{BD} \)).

It is clear that the closest, in the 2-norm sense, estimates \( \hat{B}, \hat{D}, \) and \( \hat{\alpha} \) are such that

\[
(\hat{B}, \hat{D}, \hat{\alpha}) = \arg\min_{B, D, \alpha} \left\{ \left\| \hat{\Theta}_{BD} - \begin{bmatrix} B \\ D \end{bmatrix} \alpha^T \right\|_2^2 \right\}
\]

The solution to this optimization problem is provided by the SVD of \( \hat{\Theta}_{BD} \).
Let $\hat{\Theta}_{BD} \in \mathbb{R}^{(n+m) \times rp}$ have rank $s>p$, and let its economy size SVD be partitioned as

$$
\hat{\Theta}_{BD} = U\Sigma V^T = \sum_{i=1}^{s} \sigma_i u_i v_i^T = \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix}
$$

with $U_1 \in \mathbb{R}^{(n+m) \times p}$, $V_1 \in \mathbb{R}^{rp \times p}$, and $\Sigma_1 = \text{diag} (\sigma_1, \sigma_2, \ldots, \sigma_p)$.

Then

$$
\begin{bmatrix} \hat{B} \\ \hat{D} \end{bmatrix}, \hat{\alpha} = \underset{B,D,\alpha}{\text{argmin}} \left\| \hat{\Theta}_{BD} - \begin{bmatrix} B \\ D \end{bmatrix} \alpha^T \right\|_2^2 = (U_1 \Sigma_1, V_1),
$$

and the approximation error is given by

$$
\left\| \hat{\Theta}_{BD} - \begin{bmatrix} \hat{B} \\ \hat{D} \end{bmatrix} \alpha^T \right\|_2^2 = \sigma_{p+1}^2.
$$

**Normalization in $\alpha$ provided by the SVD**
The subspace algorithm can be summarized as follows.

**Step 1:** Compute estimates of the system matrices \((A, \hat{B}, C, \hat{D})\), and the model order \(n\), using any available (linear) subspace algorithm, such as N4SID, MOESP, CVA.

**Step 2:** Based on the estimates \(\hat{B}\) and \(\hat{D}\) compute an estimate \(\hat{\Theta}_{BD}\) of matrix \(\Theta_{BD}\).

**Step 3:** Compute the SVD of \(\hat{\Theta}_{BD}\) and its partition as in (4).

**Step 4:** Compute the estimates of the parameter matrices \(B, D,\) and \(\alpha\) as

\[
\begin{bmatrix}
\hat{B} \\
\hat{D}
\end{bmatrix} = U_1 \Sigma_1
\]

\[
\hat{\alpha} = V_1
\]
Under some assumptions on **persistency of excitation** of the inputs, which depend on the particular subspace method used in **Step 1** of the algorithm, the estimates $\left(\hat{A}, \hat{B}, \hat{C}, \hat{D}\right)$ are **consistent** in the sense that they converge to the true values when the number of data points $N \rightarrow \infty$. The consistency of $\hat{B}$ and $\hat{D}$, implies that of $B$, $D$, and $\alpha$. 

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Wiener Model Identification

**Problem Formulation**

**LTI subsystem**

\[
\begin{align*}
x_{k+1} &= Ax_k + Bu_k + \omega_k \quad (5) \\
v_k &= Cx_k + Du_k + \nu_k \quad (6)
\end{align*}
\]

\[u_k \in \mathbb{R}^p, \quad x_k \in \mathbb{R}^n, \quad \nu_k \in \mathbb{R}^m\]

\[\omega_k \in \mathbb{R}^n, \quad \nu_k \in \mathbb{R}^m\]

**Nonlinear subsystem**

\[v_k = N^{-1}(y_k) = \sum_{i=1}^{r} \alpha_i g_i(y_k) \quad (7)\]

\[g_i(\bullet): \mathbb{R}^m \to \mathbb{R}^m, (i = 1, \cdots, r)\]

\[\alpha_i \in \mathbb{R}^{m \times m}, \quad (i = 1, \cdots, r)\]

known basis functions

unknown matrix parameters

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Identification problem: to estimate the unknown parameter matrices
\[ \alpha_i \in \mathbb{R}^{m \times m}, \quad (i = 1, \ldots, r), \] and \( A, B, C, \) and \( D \) characterizing the nonlinear and the linear parts, respectively, and the model order \( n \), from an \( N \)-point data set \( \{u_k, y_k\}_{k=1}^N \) of observed input-output measurements.

Subspace Identification Algorithm

\[ \begin{align*}
\alpha &\in [\alpha_1, \ldots, \alpha_r], \quad Y_k = \left[ g_1^T (y_k), \ldots, g_r^T (y_k) \right]^T \\
\alpha^+ &\overset{\text{Normalization}}{=} \frac{\alpha}{\|\alpha\|_2} = 1
\end{align*} \]

Identifiability problem

\[ \begin{align*}
\alpha^+ C &\overset{\text{Identifiability}}{=} \tilde{C}, \quad \alpha^+ D \overset{\text{Identifiability}}{=} \tilde{D}
\end{align*} \]
\[ \begin{cases} x_{k+1} = Ax_k + Bu_k + \omega_k \\ Y_k = \tilde{C}x_k + \tilde{D}u_k + \tilde{\nu}_k \end{cases} \]

**Linear Subspace Algorithms**

(N4SID, MOESP, CVA)

**Estimates** \( \hat{A}, \hat{B}, \hat{C}, \hat{D}, \) model order \( n \)

Fig. 8: Equivalent LTI model with output \( Y_k \)
The **problem** is how to compute estimates of matrices $C, D,$ and $\alpha^+$ from the estimates of the matrices $\tilde{C},$ and $\tilde{D}$

Similarly to what was done for the Hammerstein model the closest, in the 2-norm sense, estimates $\hat{C}, \hat{D},$ and $\hat{\alpha}^+$ are such that

$$
(\hat{C}, \hat{D}, \hat{\alpha}^+) = \arg\min_{C, D, \alpha^+} \left\{ \left\| \begin{bmatrix} \hat{C} & \hat{D} \end{bmatrix} - \alpha^+[C \ D] \right\|_2^2 \right\}
$$

The **solution** to this optimization problem is provided by the SVD of the matrix $\begin{bmatrix} \hat{C} & \hat{D} \end{bmatrix}$
Result 3

Let $\begin{bmatrix} \hat{C} & \hat{D} \end{bmatrix} \in \mathbb{R}^{mr \times (n+p)}$ have rank $s>m$, and let its economy size SVD be partitioned as

$$
\begin{bmatrix} \hat{C} & \hat{D} \end{bmatrix} = U \Sigma V^T = \sum_{i=1}^{s} \sigma_i u_i v_i^T = [U_1 \quad U_2] \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix}
$$

(8)

with $U_1 \in \mathbb{R}^{mr \times m}$, $V_1 \in \mathbb{R}^{(n+p) \times m}$, and $\Sigma_1 = \text{diag} (\sigma_1, \sigma_2, \ldots, \sigma_m)$. Then

$$
(\hat{\alpha}^+, [\hat{C} \quad \hat{D}]) = \arg \min_{C,D,\alpha^+} \left\| \begin{bmatrix} \hat{C} & \hat{D} \end{bmatrix} - \alpha^+ [C \quad D] \right\|_2^2 = (U_1, \Sigma_1 V_1^T),
$$

and the approximation error is given by

$$
\left\| \begin{bmatrix} \hat{C} & \hat{D} \end{bmatrix} - \hat{\alpha}^+ [\hat{C} \quad \hat{D}] \right\|_2^2 = \sigma_{m+1}^2.
$$

Normalization in $\alpha^+$ provided by the SVD.
Identification Algorithm

The subspace algorithm can be summarized as follows.

**Step 1:** Compute estimates of the system matrices \((A, B, \tilde{C}, \tilde{D})\), and the model order \(n\), using any available (linear) subspace algorithm, such as N4SID, MOESP, CVA.

**Step 2:** Compute the SVD of \(\begin{bmatrix} \hat{C} & \hat{D} \end{bmatrix}\) and its partition as in (8).

**Step 3:** Compute the estimates of the parameter matrices \(C, D,\) and \(\alpha^+\) as

\[
\begin{bmatrix} \hat{C} & \hat{D} \end{bmatrix} = \Sigma_1 V_1^T
\]

\(\hat{\alpha} = U_1^+\)

respectively.
Simulation Examples

Example 1: Hammerstein Model ID ("academic")

The True System

\[ G(z) = \frac{z^2 + 0.7z - 1.5}{z^3 + 0.9z^2 + 0.15z + 0.002} \]

linear subsystem

\[ N(u_k) = 0.8589 \, u_k + 0.0149 \, u_k^2 - 0.5113 \, u_k^3 - 0.0263 \, u_k^4 \]

nonlinear subsystem

The input and noise

\[ u_k = \sin(0.0005\pi k) + 0.5 \sin(0.0015\pi k) + \]
\[ + 0.3 \sin(0.0025\pi k) + 0.1 \sin(0.0035\pi k) + \gamma_k \]

input

\[ \Phi_v(\omega) = \frac{0.64 \times 10^{-8}}{1.2 - 0.4 \cos(\omega)} \]

Spectrum of the zero mean coloured noise

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The Estimated Nonlinear Subsystem

\[ \hat{N}(u_k) = 0.8589 u_k + 0.0142 u_k^2 - 0.5113 u_k^3 - 0.0260 u_k^4 \]

Estimated nonlinear subsystem

Fig. 9: True (blue) and Estimated (green) nonlinear characteristic.

The Estimated Linear Subsystem

\[ \hat{G}(z) = \frac{0.9986 z^2 + 0.6997 z - 1.4984}{z^3 + 0.9002 z^2 + 0.1495 z + 0.0014} \]

Estimated linear subsystem
Fig. 10: True (green) and Estimated (blue) Output.
Example 2: Hammerstein Model ID (Binary Distillation Column)

**Input:** reflux ratio \( u \)

**Outputs:**
- overhead flow rate \( y_1 \)
- overhead methanol concentration \( y_2 \)
- bottom flow rate \( y_3 \)
- bottom methanol concentration \( y_4 \)

Fig. 11: Schematic representation of the distillation column

(Weischedel & McAvoy, 1980)
Fig. 12: Left Plot: Estimation (first 1000 points), and validation (remaining 1000 points) Input Data. Right Plot: Estimation (first 1000 points) and Validation (remaining 1000 points) Output Data.
Fig. 13: True (blue) and Estimated (red) Outputs (validation data)
The Estimated Linear Subsystem

Third order model with eigenvalues at

\[\{0.4916, 0.9557, 0.9726\}\]

The Estimated Nonlinear Subsystem

Third order polynomial

Fig. 14: Estimated Nonlinear Characteristic
Example 3: Wiener Model ID (pH Neutralization Process)

- **base**: NaOH  
- **acid**: HNO₃  
- **buffer**: NaHCO₃

- **Manipulated variable**: base flow rate \((u₁)\)
- **Disturbances**: buffer flow rate \((u₂)\) and acid flow rate \((u₃)\)
- **Output**: pH of the effluent solution \((y)\)

Fig. 15: Schematic representation of the pH Neutralization Process  
(Henson & Seborg, 92, 94, 97)
Simulation Model based on first principles (introducing two reaction invariants for each inlet stream)

\[ \dot{x} = f(x) + g(x)u_1 + p(x)u_2 \]

\[ h(x, y) = 0 \]

where

\[ x = [x_1, x_2]^T = [W_a, W_b]^T \]

\[ f(x) = \left[ \frac{u_3}{V} (W_{a3} - x_1), \frac{u_3}{V} (W_{b3} - x_2) \right]^T \]

\[ g(x) = \left[ \frac{1}{V} (W_{a1} - x_1), \frac{1}{V} (W_{b1} - x_2) \right]^T \]

\[ p(x) = \left[ \frac{1}{V} (W_{a2} - x_1), \frac{1}{V} (W_{b2} - x_2) \right]^T \]

\[ h(x, y) = x_1 + 10^{y-14} - 10^{-y} + x_2 \frac{1 + 2 \times 10^{y-pK_2}}{1 + 10^{pK_1-y} + 10^{y-pK_2}} \]
Fig. 16: Estimation (first 1000 points) and validation (remaining 600 points) input-output data.
The Estimated Linear Subsystem

Third order model

\[
\hat{G}(z) = \frac{0.0062z^2 - 0.0122z + 0.006}{z^3 - 2.9466z^2 + 2.8940z - 0.9474}
\]

The Estimated Nonlinear Subsystem

Third order polynomial

\[
\hat{N}^{-1}(y_k) = 0.0319 y_k^3 + 0.0358 y_k^2 + 0.9989 y_k
\]

Fig. 17: Estimated Nonlinear Characteristic.
Fig. 18: True (blue) and estimated (red) Output (Estimation/Validation data).
Conclusions

• New subspace methods for the simultaneous identification of the linear and nonlinear parts of multivariable Hammerstein and Wiener models have been presented.

• The proposed methods make use of a standard (linear) subspace method followed by a 2-norm minimization problem which is solved via an SVD.

• The proposed methods generalize all the families of linear subspace methods to this class of nonlinear models.

• The method provides consistent estimates under the same conditions on persistency of excitation required by the (linear) subspace method used as the first step of the algorithm.

• The estimated models are in a format which is suitable for their use in standard (linear) Model Predictive Control schemes.
Subspace Identification of Hammerstein and Wiener Models

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Research Seminar