# Compressed Markov parameter estimation in PBSID 

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## Abstract-

## I. INTRODUCTION

blablabla

## II. The compressed Markov paramter estimation

First we define the stacked vector $Y$ :

$$
Y=\left[\begin{array}{lll}
y_{p+1}, & \cdots, & y_{N}
\end{array}\right],
$$

In a similar way we can obtain the stacked vectors $U, X$. Further, we define the stacked matrix $Z$ :

$$
Z=\left[\begin{array}{lll}
\bar{z}_{1}, & \cdots, & \bar{z}_{N-p+1}
\end{array}\right] .
$$

Using the VARX model structure and if the matrix $\Psi=$ $\left[\begin{array}{ll}Z^{T} & U^{T}\end{array}\right]^{T}$ has full row rank, the Markov parameter set $\Xi$ can be estimated by solving the following linear problem:

$$
\begin{equation*}
\min _{\Xi}\|Y-\Xi \Psi\|_{F}^{2} \tag{1}
\end{equation*}
$$

However, for a large window it is possible that the matrix $\Psi=\left[\begin{array}{ll}Z^{T} & U^{T}\end{array}\right]^{T}$ is singular. If that is the case, apply the Partial Least-Squares (PLS) method as follows:

$$
\Psi=\left[\begin{array}{ll}
U & U_{\perp}
\end{array}\right]\left[\begin{array}{cc}
\Sigma & 0  \tag{2}\\
0 & 0
\end{array}\right]\left[\begin{array}{c}
V \\
V_{\perp}
\end{array}\right]
$$

Define $\breve{\Xi}=\Xi U$, and $\breve{\Psi}=U^{T} \Psi=\Sigma V$, then the compressed Markov parameter set $\Xi$ can be estimated by solving the following linear problem:

$$
\begin{equation*}
\min _{\Xi}\|Y-\Xi ⿹ \Xi \Psi \Psi\|_{F}^{2} \tag{3}
\end{equation*}
$$

## III. ObTAINING THE EXTENDED OBSERVABILITY TIMES

 CONTROLLABILITY MATRIXThe approximation of the matrix $\widetilde{\Gamma \mathcal{K}}$, which can be fully constructed by the Markov parameter set $\Xi$ and is given by ${ }^{1}$ :

$$
\widetilde{\Gamma \mathcal{K}} Z=\left[\begin{array}{c}
\Xi(:, 1: p m)  \tag{4}\\
{\left[O^{\ell \times m},\right.} \\
{\left[O_{(:, 1:(p-1) m)}^{\ell \times 2 m},\right.} \\
\left.\Xi_{(:, 1:(p-2) m)}\right] \\
\vdots \\
{\left[O^{\ell \times(f-1) m},\right.} \\
\Xi(:, 1:(p-f+1) m)]
\end{array}\right] Z .
$$

This research is supported under the WE@SEA program of SenterNovem, an agency of the Dutch Ministry of Economic Affairs to promote sustainable development and innovation.

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${ }^{1}$ For simplicity Matlab notation is used.
with compressed Markov parameters

$$
\left.\left.\widetilde{\Gamma \mathcal{K}} Z=\left[\begin{array}{c}
\breve{\Xi} U^{T}(:, 1: p m)  \tag{5}\\
{\left[O^{\ell \times m},\right.} \\
\Xi U^{T}(:, 1:(p-1) m) \\
{\left[O^{\ell \times 2 m},\right.} \\
\Xi U^{T}(:, 1:(p-2) m)
\end{array}\right] \quad \text { } \begin{array}{c} 
\\
{\left[O^{\ell \times(f-1) m},\right.} \\
\Xi U^{T}(:, 1:(p-f+1) m)
\end{array}\right]\right] Z
$$

Now define:

$$
Z=\left[\begin{array}{c}
Z_{(1)} \\
Z_{(2)} \\
\vdots \\
Z_{(p)}
\end{array}\right], \quad U=\left[\begin{array}{c}
U_{(1)} \\
U_{(2)} \\
\vdots \\
U_{(p)}
\end{array}\right]
$$

it becomes

$$
\widetilde{\Gamma \mathcal{K}} Z=\left[\begin{array}{c}
\Xi\left(\sum_{i=1}^{p} U_{(i)}^{T} Z_{(i)}\right)  \tag{6}\\
\breve{\Xi}\left(\sum_{i=1}^{p-1} U_{(i)}^{T} Z_{(i+1)}\right) \\
\Xi\left(\sum_{i=1}^{p-2} U_{(i)}^{T} Z_{(i+2)}\right) \\
\vdots \\
\breve{\Xi} U_{(1)}^{T} Z_{(p)}
\end{array}\right]
$$

