System Identification

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Part VIII

Instrumental variable methods. Closed-loop identification

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Classification

1. Mental or verbal models
2. Graphs and tables (nonparametric)
3. Mathematical models, with two subtypes:
   - First-principles, analytical models
   - Models from system identification

Like prediction error methods, instrumental variable methods produce *parametric*, polynomial models.

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Overall motivation

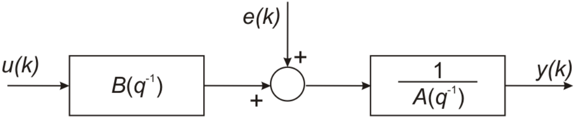
- The ARX method is simple (linear regression), but only supports limited classes of disturbance
- General PEM supports any (reasonable) disturbance, but it is relatively difficult to apply from a numerical point of view

Can we come up with a method that combines both advantages?

Yes! Instrumental variables

Recall ARX model

$$A(q^{-1})y(k) = B(q^{-1})u(k) + e(k)$$
$$(1+a_1q^{-1} + \cdots + a_{na}q^{-na})y(k) =$$
$$(b_1q^{-1} + \cdots + b_{nb}q^{-nb})u(k) + e(k)$$



In explicit form:

$$y(k) + a_1y(k-1) + a_2y(k-2) + \ldots + a_{na}y(k-na)$$
$$= b_1u(k-1) + b_2u(k-2) + \ldots + b_{nb}u(k-nb) + e(k)$$

where the model parameters are: $a_1, a_2, \ldots, a_{n_a}$ and $b_1, b_2, \ldots, b_{nb}$.

Linear regression representation

$$
\begin{aligned}
y(k) = & - a_1 y(k-1) - a_2 y(k-2) - \ldots - a_{na} y(k-na) \\
& b_1 u(k-1) + b_2 u(k-2) + \ldots + b_{nb} u(k-nb) + e(k) \\
= & \begin{bmatrix} -y(k-1) & \cdots & -y(k-na) & u(k-1) & \cdots & u(k-nb) \end{bmatrix} \\
& \cdot \begin{bmatrix} a_1 & \cdots & a_{na} & b_1 & \cdots & b_{nb} \end{bmatrix}^\top + e(k) \\
=: & \varphi^\top(k)\theta + e(k)
\end{aligned}
$$

Regressor vector: $\varphi \in \mathbb{R}^{na+nb}$, previous output and input values.

Parameter vector: $\theta \in \mathbb{R}^{na+nb}$, polynomial coefficients.

Identification problem and solution

Given dataset $u(k), y(k)$, $k = 1, \ldots, N$, find model parameters θ to achieve small errors $\varepsilon(k)$ in:

$$y(k) = \varphi^\top(k)\theta + \varepsilon(k)$$

Formal objective: minimize the mean squared error:

$$V(\theta) = \frac{1}{N}\sum_{k=1}^{N} \varepsilon(k)^2$$

Solution: can be written in several ways, here we use:

$$\widehat{\theta} = \left[\frac{1}{N}\sum_{k=1}^{N} \varphi(k)\varphi^\top(k)\right]^{-1} \left[\frac{1}{N}\sum_{k=1}^{N} \varphi(k)y(k)\right]$$

Parameter errors

Recall that for the guarantees, a true parameter vector θ_0 is assumed to exist:

$$y(k) = \varphi^\top(k)\theta_0 + v(k)$$

Analyze the parameter errors (a vector of n elements):

$$\begin{aligned}
\widehat{\theta} - \theta_0 &= \left[\frac{1}{N}\sum_{k=1}^{N}\varphi(k)\varphi^\top(k)\right]^{-1}\left[\frac{1}{N}\sum_{k=1}^{N}\varphi(k)y(k)\right] \\
&- \left[\frac{1}{N}\sum_{k=1}^{N}\varphi(k)\varphi^\top(k)\right]^{-1}\left[\frac{1}{N}\sum_{k=1}^{N}\varphi(k)\varphi^\top(k)\right]\theta_0 \\
&= \left[\frac{1}{N}\sum_{k=1}^{N}\varphi(k)\varphi^\top(k)\right]^{-1}\left[\frac{1}{N}\sum_{k=1}^{N}\varphi(k)[y(k) - \varphi^\top(k)\theta_0]\right] \\
&= \left[\frac{1}{N}\sum_{k=1}^{N}\varphi(k)\varphi^\top(k)\right]^{-1}\left[\frac{1}{N}\sum_{k=1}^{N}\varphi(k)v(k)\right]
\end{aligned}$$

Further assumptions

We wish the algorithm to be consistent: the parameter errors should become 0 in the limit of infinite data (and they should be well-defined).

As $N \to \infty$:

$$\frac{1}{N}\sum_{k=1}^{N} \varphi(k)\varphi^\top(k) \to \mathrm{E}\left\{\varphi(k)\varphi^\top(k)\right\}$$

$$\frac{1}{N}\sum_{k=1}^{N} \varphi(k)v(k) \to \mathrm{E}\left\{\varphi(k)v(k)\right\}$$

For the error to be (1) well-defined and (2) equal to zero, we need:

1. $\mathrm{E}\left\{\varphi(k)\varphi^\top(k)\right\}$ invertible.
2. $\mathrm{E}\left\{\varphi(k)v(k)\right\}$ zero.

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Motivation: ARX requires white noise

- We have $\mathrm{E}\left\{\varphi(k)v(k)\right\} = 0$ if the elements of $\varphi(k)$ are uncorrelated with $v(k)$ (note that $v(k)$ is assumed zero-mean).
- But $\varphi(k)$ includes $y(k-1), y(k-2), \ldots,$ which depend on $v(k-1), v(k-2), \ldots$!
- So the only option is to have $v(k)$ uncorrelated with $v(k-1), v(k-2), \ldots \quad \Rightarrow \quad v(k)$ must be *white noise*.

Instrumental variables are a solution to remove this limitation to white noise.

Intuition

$$\widehat{\theta} - \theta_0 = \left[\frac{1}{N} \sum_{k=1}^{N} \varphi(k) \varphi^\top(k) \right]^{-1} \left[\frac{1}{N} \sum_{k=1}^{N} \varphi(k) v(k) \right]$$

Idea: What if a different vector than $\varphi(k)$ could be included in the parameter errors?

$$\widehat{\theta} - \theta_0 = \left[\frac{1}{N} \sum_{k=1}^{N} Z(k) \varphi^\top(k) \right]^{-1} \left[\frac{1}{N} \sum_{k=1}^{N} Z(k) v(k) \right]$$

where the elements of $Z(k)$ are uncorrelated with $v(k)$. Then $\mathrm{E}\left\{ Z(k) v(k) \right\} = 0$ and the error can be zero.

Vector $Z(k)$ has n elements, which are called instruments.

Instrumental variable method

In order to have:

$$\widehat{\theta} - \theta_0 = \left[\frac{1}{N}\sum_{k=1}^{N} Z(k)\varphi^\top(k)\right]^{-1} \left[\frac{1}{N}\sum_{k=1}^{N} Z(k)v(k)\right] \tag{8.1}$$

the estimated parameter must be:

$$\widehat{\theta} = \left[\frac{1}{N}\sum_{k=1}^{N} Z(k)\varphi^\top(k)\right]^{-1} \left[\frac{1}{N}\sum_{k=1}^{N} Z(k)y(k)\right] \tag{8.2}$$

This $\widehat{\theta}$ is the solution to the system of n equations:

$$\boxed{\left[\frac{1}{N}\sum_{k=1}^{N} Z(k)[\varphi^\top(k)\theta - y(k)]\right] = 0} \tag{8.3}$$

Constructing and solving this system gives the basic instrumental variable (IV) method.

Exercise: Show that (8.3) implies (8.2), and that (8.2) implies (8.1).

Simple instruments

So far the instruments $Z(k)$ were not discussed. They are usually created based on the inputs (including outputs would lead to correlation with v and so eliminate the advantage of IV).

Simple possibility: just include additional delayed inputs to obtain a vector of the appropriate size, $n = na + nb$:

$$Z(k) = [u(k - nb - 1), \dots u(k - na - nb), u(k - 1), \dots, u(k - nb)]^\top$$

Compare to original vector:

$$\varphi(k) = [-y(k - 1), \dots, -y(k - na), u(k - 1), \dots, u(k - nb)]^\top$$

Generalization

Pass the input through a transfer function:

$$\boxed{C(q^{-1})x(k) = D(q^{-1})u(k)}$$

$$\begin{aligned}(1 + c_1 q^{-1} + \cdots + c_{nb} q^{-nc})x(k) &= \\ (d_1 q^{-1} + \cdots + d_{nd} q^{-nd})u(k)\end{aligned}$$

$$\begin{aligned}x(k) = &- c_1 x(k-1) - c_2 x(k-2) - \ldots - c_{nc} x(k-nc) \\ &+ d_1 u(k-1) + d_2 u(k-2) + \ldots + d_{nd} u(k-nd)\end{aligned}$$

and take *na* past values from the output x:

$$\boxed{Z(k) = [-x(k-1), \ldots, -x(k-na), u(k-1), \ldots, u(k-nb)]^\top}$$

Remark: $C(q^{-1})$, $D(q^{-1})$ have different meanings than in PEM.

Generalized instruments: obtaining the simple case

In order to obtain:

$$Z(k) = [u(k - nb - 1), \ldots u(k - na - nb), u(k - 1), \ldots, u(k - nb)]^\top$$

set $C = 1$, $D = -q^{-nb}$.

Exercise: Verify that the desired $Z(k)$ is indeed obtained.

Generalized instruments: Initial model

Generalized instruments:

$$Z(k) = [-x(k-1), \dots, -x(k-na), u(k-1), u(k-2), \dots, u(k-nb)]^\top$$

Compare to original vector:

$$\varphi(k) = [-y(k-1), \dots, -y(k-na), u(k-1), \dots, u(k-nb)]^\top$$

Idea: Take instrument generator equal to an initial model, $C(q^{-1}) = \widehat{A}(q^{-1})$, $D(q^{-1}) = \widehat{B}(q^{-1})$. This model can be obtained e.g. with ARX estimation.

The instruments are an approximation of y:

$$Z(k) = [-\hat{y}(k-1), \dots - \hat{y}(k-na), u(k-1), \dots, u(k-nb)]^\top$$

that has the crucial advantage of being *uncorrelated* with the noise.

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Comparison

Both PEM and IV can be seen as extensions of ARX:

$$A(q^{-1})y(k) = B(q^{-1})u(k) + e(k)$$

to disturbances $v(k)$ different from white noise $e(k)$.

- PEM explicitly include the disturbance model in the structure, e.g. in ARMAX $v(k) = C(q^{-1})e(k)$ leading to $A(q^{-1})y(k) = B(q^{-1})u(k) + C(q^{-1})e(k)$.
- IV methods do *not* explicitly model the disturbance, but are designed to be resilient to non-white, “colored” disturbance, by using instruments $Z(k)$ uncorrelated with it.

Comparison (continued)

Advantage of IV: Simple model structure, identification consists only of solving a system of linear equations. In contrast, PEM required solving optimization problems with e.g. Newton's method, was susceptible to local minima etc.

Disadvantage of IV: In practice, for finite number N of data, model quality depends heavily on the choice of instruments $Z(k)$. Moreover, the resulting model has a larger risk of being unstable (even for a stable real system).

Methods exist to choose instruments $Z(k)$ that are optimal in a certain sense, but they will not be discussed here.

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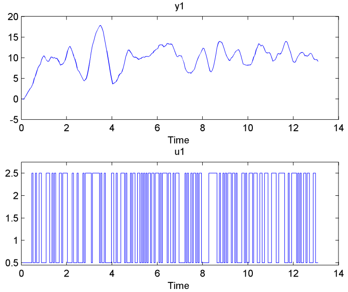
Experimental data

Separate identification and validation data sets:

`plot(id);` and `plot(val);`



From prior knowledge, the system has order 2 and the disturbance is colored (does not obey the ARX model structure).

Remarks: As before, the identification input is a pseudo-random binary signal, and the validation input a sequence of steps.

IV identification with custom instruments

Define the instruments by the generating transfer function, using polynomials $C(q^{-1})$ and $D(q^{-1})$.

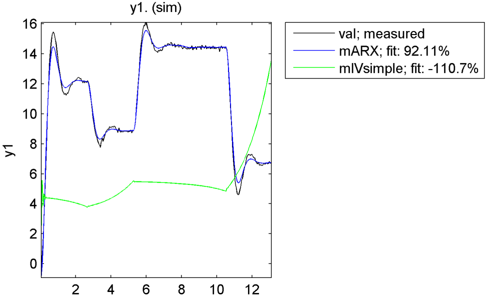
```
model = iv(id, [na, nb, nk], C, D);
```

Arguments:

1. Identification data.
2. Array containing the orders of A and B and the delay nk (like for ARX).
3. Polynomials C and D, as vectors of coefficients in increasing power of q^{-1}.

Result with simple instruments

Take $C(q^{-1}) = 1$, $D(q^{-1}) = -q^{-nb}$, leading to
$Z(k) = [u(k - nb - 1), \dots u(k - na - nb), u(k-1), \dots, u(k - nb)]^\top$.
Compare to ARX.



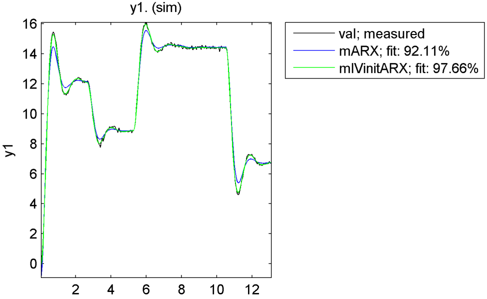
Conclusions:

- Model unstable ⇒ in general, must pay attention because IV models are not guaranteed to be stable! (recall the Comparison)
- Results very bad with this simple choice.

Result with ARX-model instruments

Take $C(q^{-1}) = \hat{A}(q^{-1})$, $D(q^{-1}) = \hat{B}(q^{-1})$ from the ARX experiment, leading to

$Z(k) = [-\hat{y}(k-1), \dots - \hat{y}(k-na), u(k-1), \dots, u(k-nb)]^\top$.

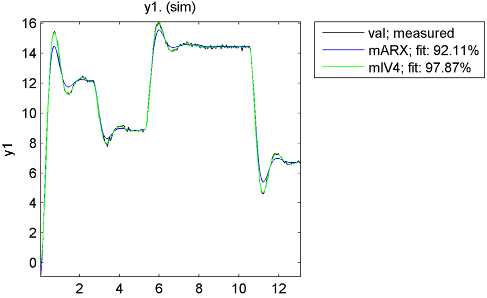


Conclusion: IV obtains better results. This is because the disturbance is colored, and IV can deal effectively with this case (whereas ARX cannot – but it still provides a useful starting point for IV).

Result with automatic instruments

```
model = iv4(id, [na, nb, nk]);
```

Implements an algorithm that generates near-optimal instruments.



Conclusion: Virtually the same performance as ARX instruments.

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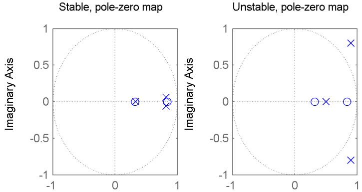
Assumptions

Assumptions (simplified)

1. The disturbance $v(k) = H(q^{-1})e(k)$ where $e(k)$ is zero-mean white noise, and $H(q^{-1})$ is a transfer function satisfying certain conditions.
2. The input signal $u(k)$ has a sufficiently large order of PE and does not depend on the disturbance (the experiment is open-loop).
3. The real system is stable and *uniquely* representable by the model chosen: there exists exactly one θ_0 so that polynomials $A(q^{-1}; \theta_0)$ and $B(q^{-1}; \theta_0)$ are identical to those of the real system.
4. Matrix $\mathrm{E}\left\{Z(k)Z^\top(k)\right\}$ is invertible.

Discussion of assumptions

- Assumption 1 shows the main advantage of IV over PEM: the disturbance can be colored.
- Assumptions 2 and 3 are not very different from those made by PEM. Stability of a discrete-time system requires its poles to be strictly inside the unit circle:



Question: Why is the experiment not allowed to be closed-loop?

- Assumption 4 is required to solve the linear system, and given an input with sufficient order of PE boils down to an appropriate selection of instruments (e.g. not repeating the same delayed input $u(k-i)$ twice).

Guarantee

Theorem 1

As the number of data points $N \to \infty$, the solution $\widehat{\theta}$ of IV estimation converges to the true parameter vector θ_0.

Remark: This is a consistency guarantee, in the limit of infinitely many data points.

Possible extensions

- Multiple-input, multiple-output systems.
- Larger-dimension instruments Z than parameter vectors θ — with other modifications, called extended IV methods.
- Identification of systems operating in closed loop: next

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Motivation

In practice, systems must often be controlled, because when they operate on their own, in open loop:

- They would be unstable
- Safety or economical limits for the signals would not be satisfied

This means that $u(k)$ is computed using feedback from $y(k)$: the system operates in closed loop

Closed-loop identification

However, most of the techniques that we studied assume the system functions in open loop! For instance, IV guarantees require (among other things):

- ...
- The input signal $u(k)$ does not depend on the disturbance (the experiment is open-loop)
- ...

Removing this condition leads to **closed-loop identification**.

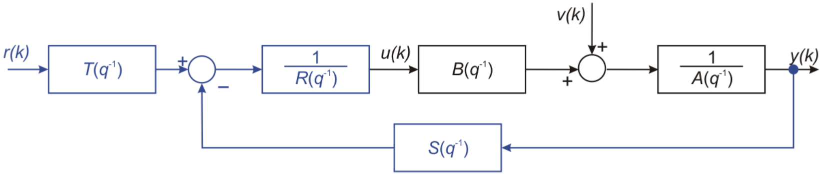
Several techniques can be modified for this setting, notably including prediction error methods.

Here, we will focus on IV methods since they are easy to modify.

Closed-loop IV structure

$$A(q^{-1})y(k) = B(q^{-1})u(k) + v(k)$$
$$R(q^{-1})u(k) = T(q^{-1})r(k) - S(q^{-1})y(k)$$

R, T, S polynomials



Therefore, in general $u(k)$ depends:

- dynamically (via $R(q^{-1})$),
- on the system output with negative feedback through $S(q^{-1})$,
- and through $T(q^{-1})$ on an external input $r(k)$
  – usually a reference signal

Challenge

The open-loop condition will of course fail. Let us dig deeper into it.

The underlying reason for which we needed the loop open was to make the parameter errors:

$$\widehat{\theta} - \theta_0 = \left[\frac{1}{N} \sum_{k=1}^{N} Z(k) \varphi^\top(k) \right]^{-1} \left[\frac{1}{N} \sum_{k=1}^{N} Z(k) v(k) \right]$$

equal to zero, leading to a good model. For this, we require:

- $\mathrm{E}\left\{ Z(k) v(k) \right\}$ zero.
- $\mathrm{E}\left\{ Z(k) \varphi^\top(k) \right\}$ invertible.

With the usual IV choices, computed based on u (which now depends on y and hence on v), the first condition would fail.

Closed-loop IV idea

The vector of IVs $Z(k)$ is not allowed to depend on $u(k)$ anymore.

Idea: **make it a function of $r(k)$**!

Then:

- $\mathrm{E}\left\{Z(k)v(k)\right\}$ will naturally be zero, since we are the ones generating the reference r, independently from the disturbance v
- We can make $\mathrm{E}\left\{Z(k)\varphi^\top(k)\right\}$ invertible by ensuring the IVs are good (e.g. no linear dependence), and that the reference r has a sufficiently high order of PE

Example choices of IVs

Simplest idea – include in Z the appropriate number of delayed reference values:

$$\boxed{Z(k) = [r(k-1), r(k-2), \dots r(k-na-nb)]^\top}$$

Slightly generalized to linear combinations of these values:

$$Z(k) = F \cdot [r(k-1), r(k-2), \dots r(k-na-nb)]^\top$$

where F is invertible. The simple case is recovered by taking F the identity matrix.