

# System Identification – ARX method

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## 1 Theory

Let  $t_0, t_1, \dots, t_N$  be some time moments in arithmetic progression,  $t_{i+1} - t_i = T_s$ , with the ratio being the sampling time. We denote the output of the process by the letter  $y$  and the input of the process by the letter  $u$ . Furthermore, for simplicity of notation, let  $y_k = y(t_k)$  and  $u_k = u(t_k)$ , that is the output of the process which is measured at the time moment  $t_k$  respectively the input which is given to the process at the time moment  $t_k$ .

Then let

$$\mathcal{Y}(z) = \sum_{k \in \mathbb{Z}} y_k \cdot z^{-k} \quad \mathcal{U}(z) = \sum_{k \in \mathbb{Z}} u_k \cdot z^{-k} \quad (1)$$

be the so called  $\mathcal{Z}$  transforms of the sequences  $(y_k)_{k \in \mathbb{Z}}$  and  $(u_k)_{k \in \mathbb{Z}}$  with  $y_k = 0$  for an integer  $k \leq 0$  and  $u_k = 0$  for an integer  $k < 0$ .

The ARX method considers the following input-output relation:

$$\mathcal{Y}(z) = \frac{B(z)}{A(z)} \cdot z^{-n_p} \cdot \mathcal{U}(z) + \frac{1}{A(z)} \cdot \mathcal{E}(z) \quad (2)$$

where

$$\begin{aligned} B(z) &= b_1 \cdot z^{-1} + \dots + b_{n_b} \cdot z^{-n_b} \\ A(z) &= 1 + a_1 \cdot z^{-1} + \dots + a_{n_a} \cdot z^{-n_a} \end{aligned} \quad (3)$$

with  $n_a, n_b, n_p \in \mathbb{N} \cup \{0\}$ . Multiplying both sides by  $A(z)$  and applying the inverse  $\mathcal{Z}$  transform, one obtains:

$$y_k + a_1 \cdot y_{k-1} + \dots + a_{n_a} \cdot y_{k-n_a} = b_1 \cdot u_{k-n_p-1} + \dots + b_{n_b} \cdot u_{k-n_p-n_b} + e_k \quad (4)$$

hence it is obtained:

$$y_k = \begin{bmatrix} -y_{k-1} & \dots & -y_{k-n_a} & u_{k-1-n_p} & \dots & u_{k-n_b-n_p} \end{bmatrix} \cdot \begin{bmatrix} a_1 \\ \vdots \\ a_{n_a} \\ b_1 \\ \vdots \\ b_{n_b} \end{bmatrix} + e_k \quad (5)$$

Letting  $k$  successively take the values  $1, 2, \dots, N$  in (5), one obtains:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} -y_0 & \dots & -y_{1-n_a} & u_{-n_p} & \dots & u_{1-n_b-n_p} \\ -y_1 & \dots & -y_{2-n_a} & u_{1-n_p} & \dots & u_{2-n_b-n_p} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ -y_{N-1} & \dots & -y_{N-n_a} & u_{N-1-n_p} & \dots & u_{N-n_b-n_p} \end{bmatrix} \cdot \begin{bmatrix} a_1 \\ \vdots \\ a_{n_a} \\ b_1 \\ \vdots \\ b_{n_b} \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_N \end{bmatrix} \quad (6)$$

Let  $Y = [y_1 \ \dots \ y_N]$  be the vector of measurements,  $\Phi$  be the resolvent matrix in the above equation (6),  $\theta = [a_1 \ \dots \ a_{n_a} \ b_1 \ \dots \ b_{n_b}]^T$  and  $E = [e_1 \ \dots \ e_N]^T$ . Then, (6) is rewritten as follows:

$$Y = \Phi \cdot \theta + E \iff E = Y - \Phi \cdot \theta \quad (7)$$

Let us then consider the quantity  $J = E^T \cdot E$ . It is easy to see that once the inputs and outputs are given, that is  $y_k$ s and  $u_k$ s, for different values of  $\theta$ , there will be different values of  $J$ . We search for  $\theta$  such that  $J = E^T \cdot E$  is the smallest. One can observe that

$$J = e_1^2 + \dots + e_N^2 \quad (8)$$

For this, consider the operator:

$$\frac{\partial}{\partial \theta} = \left[ \frac{\partial}{\partial a_1} \quad \dots \quad \frac{\partial}{\partial b_{n_b}} \right]^T \quad (9)$$

that is a column vector of partial derivatives with respect to the components of  $\theta$ . We require

$$\frac{\partial}{\partial \theta} J = [0 \quad \dots \quad 0]^T = 0_{(n_a+n_b) \times 1} \iff \begin{cases} \frac{\partial J}{\partial a_1} = 0 \\ \vdots \\ \frac{\partial J}{\partial b_{n_b}} = 0 \end{cases} \quad (10)$$

that is

$$\frac{\partial}{\partial \theta} J = \frac{\partial}{\partial \theta} (E^T \cdot E) = \begin{bmatrix} \frac{\partial J}{\partial a_1} \\ \vdots \\ \frac{\partial J}{\partial b_{n_b}} \end{bmatrix} = \begin{bmatrix} \frac{\partial E^T \cdot E}{\partial a_1} \\ \vdots \\ \frac{\partial E^T \cdot E}{\partial b_{n_b}} \end{bmatrix} = 2 \cdot \frac{\partial E^T}{\partial \theta} \cdot E \quad (11)$$

because, one obtains, for instance, for the first component:

$$\frac{\partial E^T \cdot E}{\partial a_1} = \frac{\partial E^T}{\partial a_1} \cdot E + E^T \cdot \frac{\partial E}{\partial a_1} = 2 \cdot \frac{\partial E^T}{\partial a_1} \cdot E \quad (12)$$

and even more:

$$\frac{\partial E^T}{\partial \theta} = \begin{bmatrix} \frac{\partial e_1}{\partial a_1} & \dots & \frac{\partial e_N}{\partial a_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial e_1}{\partial b_{n_b}} & \dots & \frac{\partial e_N}{\partial b_{n_b}} \end{bmatrix} = \begin{bmatrix} \frac{\partial E^T}{\partial a_1} \\ \vdots \\ \frac{\partial E^T}{\partial b_{n_b}} \end{bmatrix} \quad (13)$$

In equation (7), let  $C_1, \dots, C_{n_a+n_b}$  denote the columns of matrix  $\Phi$ . Then

$$E^T = Y^T - [a_1 \quad \dots \quad a_{n_a} \quad b_1 \quad \dots \quad b_{n_b}] \cdot \begin{bmatrix} C_1^T \\ \vdots \\ C_{n_a+n_b}^T \end{bmatrix} \quad (14)$$

therefore it is easy to see that

$$\frac{\partial E^T}{\partial a_1} = C_1^T \quad \dots \quad \frac{\partial E^T}{\partial b_{n_b}} = C_{n_a+n_b}^T \quad \Rightarrow \quad \frac{\partial E^T}{\partial \theta} = \begin{bmatrix} C_1^T \\ \vdots \\ C_{n_a+n_b}^T \end{bmatrix} = \Phi^T \quad (15)$$

From (12) one obtains:

$$0_{n_a+n_b,1} = \frac{\partial E^T}{\partial \theta} \cdot E \iff \Phi^T \cdot (Y - \Phi \cdot \theta) = 0_{n_a+n_b,1} \quad (16)$$

therefore

$$\theta = (\Phi^T \cdot \Phi)^{-1} \cdot \Phi^T \cdot Y \quad (17)$$

**Remark 1.1** A further improvement can be made to (17) from the numeric point of view, by letting  $L_k$  denote the  $k$ 'th line of matrix  $\Phi$ . In this case  $\Phi^T \cdot \Phi = \sum_{k=1}^N L_k^T \cdot L_k$  and  $\Phi^T \cdot Y = \sum_{k=1}^N L_k^T \cdot y_k$  therefore (17) becomes

$$\theta = \left( \sum_{k=1}^N L_k^T \cdot L_k \right)^{-1} \cdot \sum_{k=1}^N L_k^T \cdot y_k \quad (18)$$

## 2 Implementation

Assume the available data for identification is composed out of two arrays  $Y = [y_0 \ y_1 \ \dots \ y_N]^T$  and  $U = [u_0 \ u_1 \ \dots \ u_N]^T$ . Next, one has to decide on the orders of the system, and choose  $n_a, n_b, n_p$ , see equations (2) and (3). Once this information is available, one will simply form the matrix  $\Phi$  (using  $Y$  and  $U$  and equation (6)) and then apply the formula given in equation (17) or (18) to obtain  $\theta$ . Next, the coefficients of the  $A, B$  polynomials are extracted from  $\theta$  according to (5),(6).

In the following, a *MATLAB*<sup>®</sup> code is provided to implement just that:

```
% arx offline algorithm

% clear console, clear workspace, close figures
clc;
clear all
close all

% Load the data: data is in .mat format and in the working directory.
% The file is provided by the laboratory assistant.

data = load('lab6_2');
u = data.id.u;
y = data.id.y;

% plot the data, just for visualization
plot(u);
hold on
plot(y,'r');
title('initial data');
xlabel('time [s]');
legend('u','y');

% choose parameters: ... somehow ...
na = 1;
nb = 1;
np = 0;

% pad with zeros to account for negative indexes
y_ = [zeros(na+nb+np,1);y]';
u_ = [zeros(na+nb+np,1);u]';

% initialize the sums with zero matrices of appropriate size
S_1 = zeros(na+nb);
S_2 = zeros(na+nb,1);

% begin iterations
for i = na+nb+np+1:length(y_)
% get a line in matrix Phi
L = [-y_(i-1:-1:i-na) u_(i-1-np:-1:i-nb-np)];
% update the sums
S_1 = S_1 + L'*L;
```

```

    S_2 = S_2 + L'*y_(i);
end

% find theta
th = inv(S_1)*S_2;

% extract polynomials
A = [1 th(1:na)'];
B = [zeros(1,np), 0, th(na+1:end)'];

% validate:Ts is needed here
figure
sys_ = idpoly(A,B,1,1,1,0,data.val.ts);
compare(data.val,sys_);

% -----
% ----- matlab solution
% -----

figure
marx = arx(data.id,[na,nb,1]);
compare(marx,data.val);

```

**Remark 2.1** Sometimes, if the identification data does not meet the ARX assumptions (about the error model), then higher orders are required for a good fit.

### 3 Results

Upon running the above code the following figures are obtained:

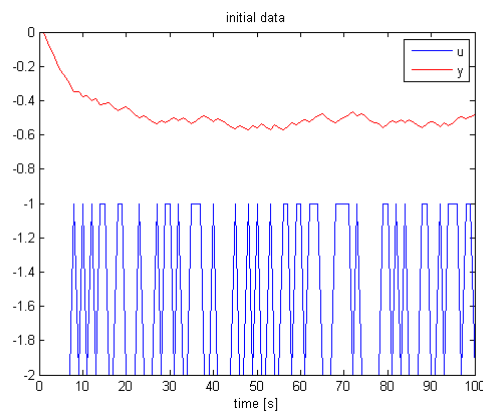


Figure 1: Initial Data

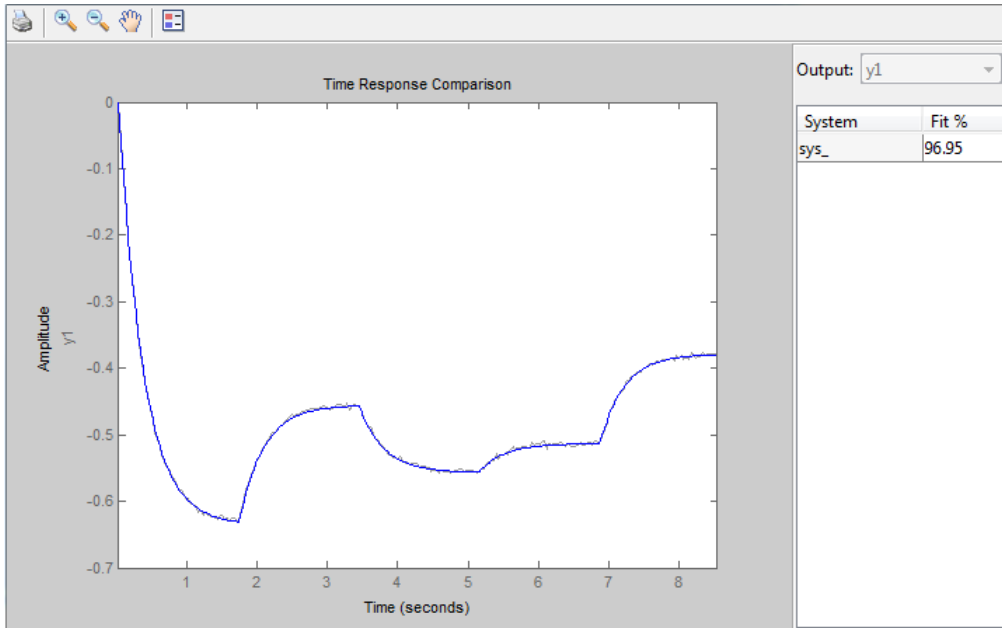


Figure 2: Compare Results: the proposed code

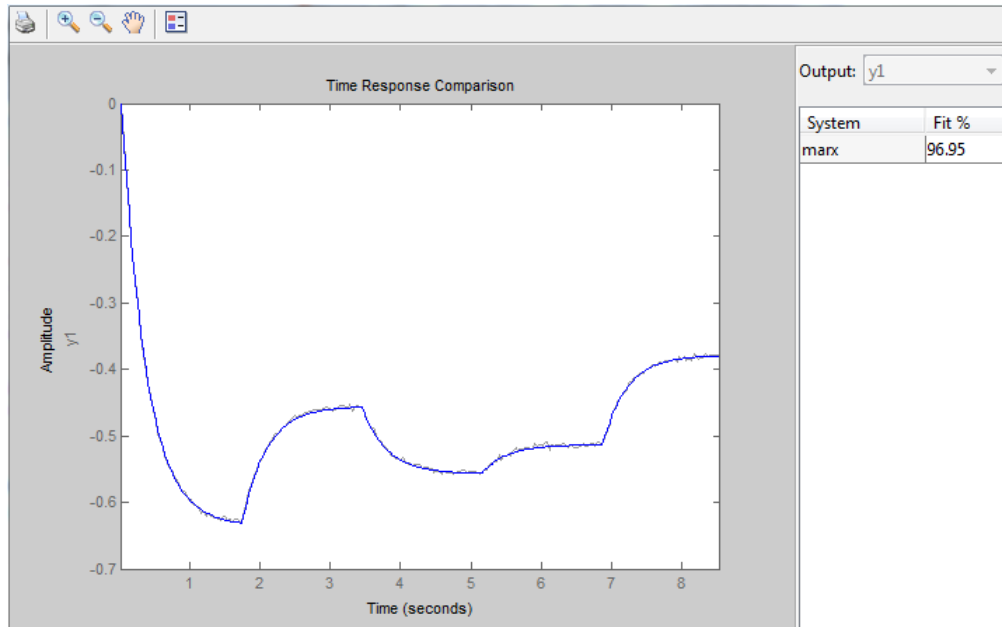


Figure 3: Compare Results: matlab solution