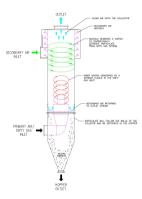
# System identification

Kjartan Halvorsen

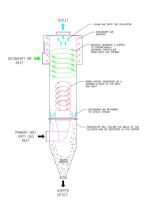
July 14, 2022

### A complicated process

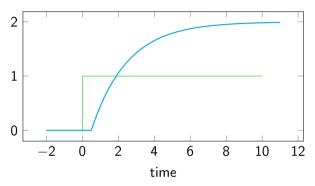


From Wikipedia "Cyclonic separation"

### A complicated process



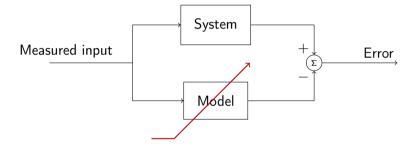
From Wikipedia "Cyclonic separation"



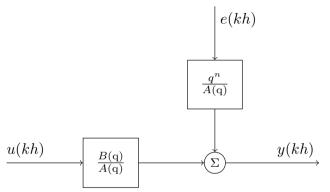
Fit model

$$G(s) = \frac{k e^{-s\theta}}{\tau s + 1}$$

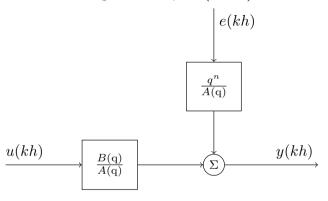
## System identification



## The Auto-Regressive with eXogenous input (ARX) model



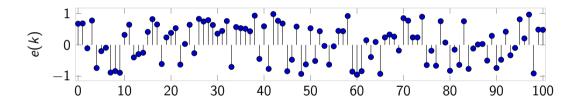
## The Auto-Regressive with eXogenous input (ARX) model



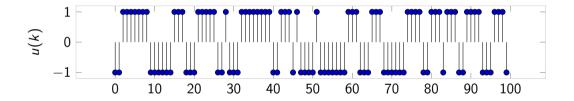
$$A(q)y(k) = B(q)u(k) + e(k+n)$$

The error signal e(k) is a zero-mean white noise sequence representing perturbations and modeling errors.

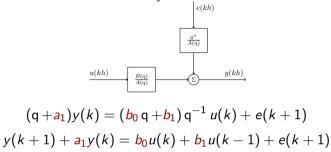
### White noise



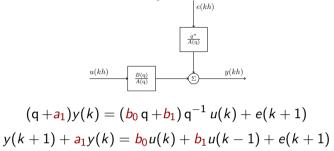
## Random binary signal



### First-order ARX model with one delay



First-order ARX model with one delay



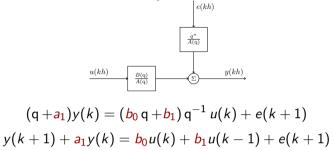
Using the model to predict the output one step ahead:

$$\hat{y}(k+1) = -a_1 y(k) + b_0 u(k) + b_1 u(k-1) = \underbrace{\left[ \underbrace{b_0 b_1}_{\varphi_{k+1}^T} \right]}_{\theta}$$

$$=\varphi_{k+1}^T \theta$$



First-order ARX model with one delay



Using the model to predict the output one step ahead:

$$\hat{y}(k+1) = -a_1 y(k) + b_0 u(k) + b_1 u(k-1) = \underbrace{\left[-y(k) \quad u(k) \quad u(k-1)\right]}_{\varphi_{k+1}^{\mathsf{T}}} \underbrace{\begin{bmatrix} a_1 \\ b_0 \\ b_1 \end{bmatrix}}_{\theta}$$

#### Parameter estimation - Least squares

#### Objective Given observations

$$\mathcal{D} = \{(u_1, y_1), (u_2, y_2), \dots, (u_N, y_N)\}\$$

and model  $\mathcal{M}$ :  $y(k+1) = -ay(k) + b_0u(k) + b_1u(k-1) + e(k+1)$ , obtain the parameters  $(a, b_0, b_1)$  which gives the best fit of the model to the data.

#### Parameter estimation - Least squares

Given observations

$$\mathcal{D} = \{(u_1, y_1), (u_2, y_2), \dots, (u_N, y_N)\}\$$

and model 
$$\mathcal{M}: \ y(k+1) = -\frac{a}{2}y(k) + \frac{b_0}{2}u(k) + \frac{b_1}{2}u(k-1) + e(k+1).$$

1. Form the one-step ahead prediction

$$\hat{y}_{k+1} = -\mathbf{a}_1 y_k + \mathbf{b}_0 u_k + \mathbf{b}_1 u_{k-1} = \underbrace{\begin{bmatrix} -y_k & u_k & u_{k-1} \end{bmatrix}}_{\varphi_{k+1}^T} \underbrace{\begin{bmatrix} \mathbf{a}_1 \\ \mathbf{b}_0 \\ \mathbf{b}_1 \end{bmatrix}}_{\theta}$$

and the prediction error

$$\epsilon_{k+1} = y_{k+1} - \hat{y}_{k+1} = y_{k+1} - \varphi_{k+1}^T \theta.$$

### Parameter estimation - Least squares

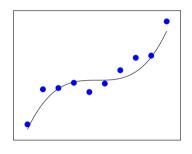
2. Combine all the observations  $y_k$  and predictions  $\hat{y}_k$  on vector form

$$\epsilon = \begin{bmatrix} \epsilon_{3} \\ \epsilon_{4} \\ \vdots \\ \epsilon_{N} \end{bmatrix} = \begin{bmatrix} y_{3} \\ y_{4} \\ \vdots \\ y_{N} \end{bmatrix} - \begin{bmatrix} \hat{y}_{3} \\ \hat{y}_{4} \\ \vdots \\ \hat{y}_{N} \end{bmatrix} = \begin{bmatrix} y_{3} \\ y_{4} \\ \vdots \\ y_{N} \end{bmatrix} - \begin{bmatrix} \varphi_{3}^{T} \theta \\ \varphi_{4}^{T} \theta \\ \vdots \\ \varphi_{N}^{T} \theta \end{bmatrix}$$

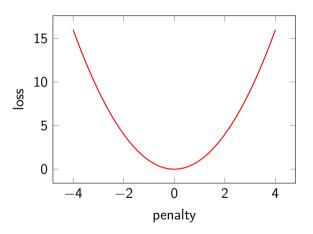
$$= y - \underbrace{\begin{bmatrix} \varphi_{3}^{T} \\ \varphi_{4}^{T} \\ \vdots \\ \varphi_{N}^{T} \end{bmatrix}}_{\Phi} \theta = y - \Phi \theta$$

3. Solve arg min  $J(\theta) = \frac{1}{2} \epsilon^T \epsilon = \frac{1}{2} \sum_{i=3}^N \epsilon_i(\theta)^2$ 

## The problem with least squares



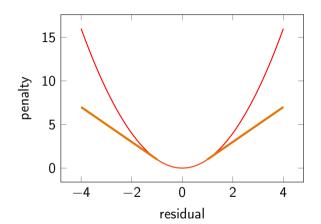
minimize 
$$\sum_k g(\epsilon_k)$$
 where  $g(u)=u^2$ 



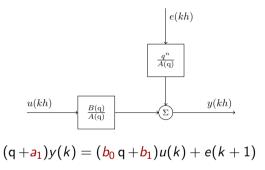
#### More robust: The Huber loss function

Also known as robust regression

minimize 
$$\sum_k g_{hub}(\epsilon_k)$$
 where  $g_{hub}(u) = egin{cases} u^2 & |u| \leq M \ M(2|u|-M) & |u| > M \end{cases}$ 



### First-order ARX model without delay



#### Activity

- 1. Determine the one-step ahead predictor  $\hat{y}_{k+1}$  and the prediction error  $\epsilon_{k+1}$ .
- 2. Form the system of equations  $\Phi\theta = y$

#### The ARMAX model

$$A(q)y(k) = B(q)u(k) + C(q)e(k)$$

Activity Fill the empty blocks.

