Adaptive Control

Part 3: Iterative identification in closed loop and controller redesign

Outline

- Why identification in closed loop is important ?
- Why models identified in closed loop can be better for control design ?
- Some experimental results
- Brief review of robustness concepts
- Algorithms for identification in closed loop
- Properties of the estimated models
- Validation of models identified in closed loop
- Iterative identification in closed loop and controller re-design
- An “adaptive control” interpretation
- CLID – a toolbox for identification in closed loop

Plant Identification in Closed Loop

Why ?

There are systems where open loop operation is not suitable (instability, drift, ..)

A controller may already exist (ex . : PID)

Re-tuning of the controller

a) to improve achieved performances
b) controller maintenance

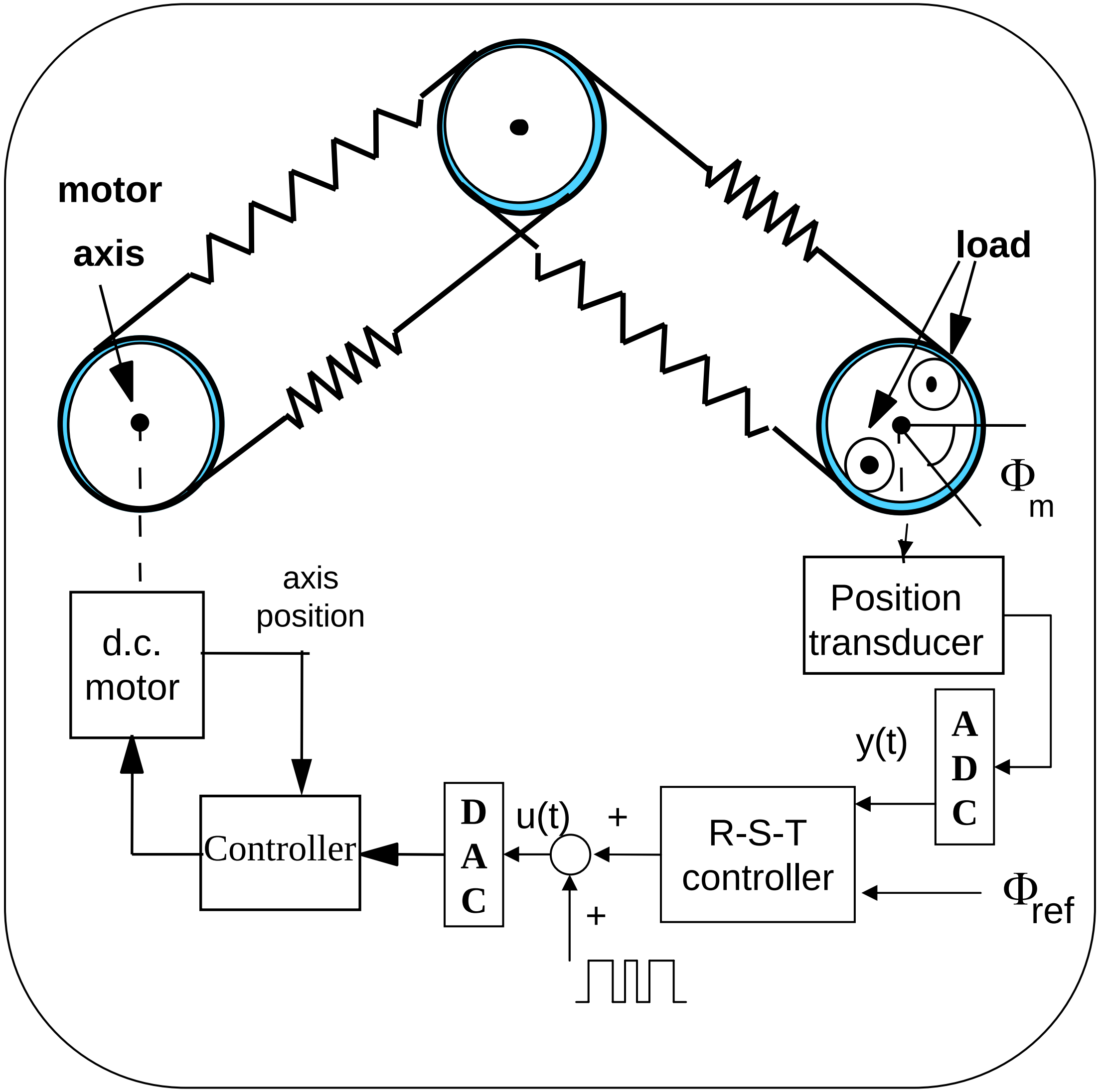
Iterative identification and controller redesign

May provide better « design » models

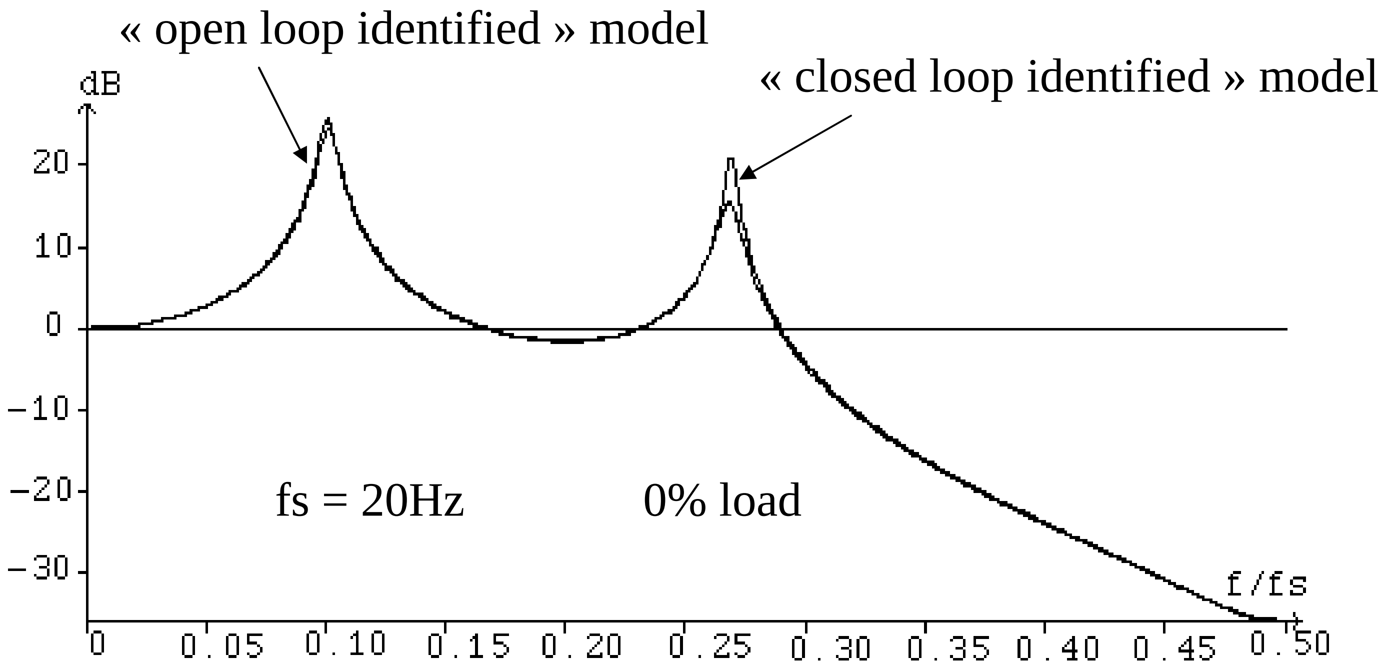
Cannot be dissociated from the controller and robustness issues

Identification in Closed Loop

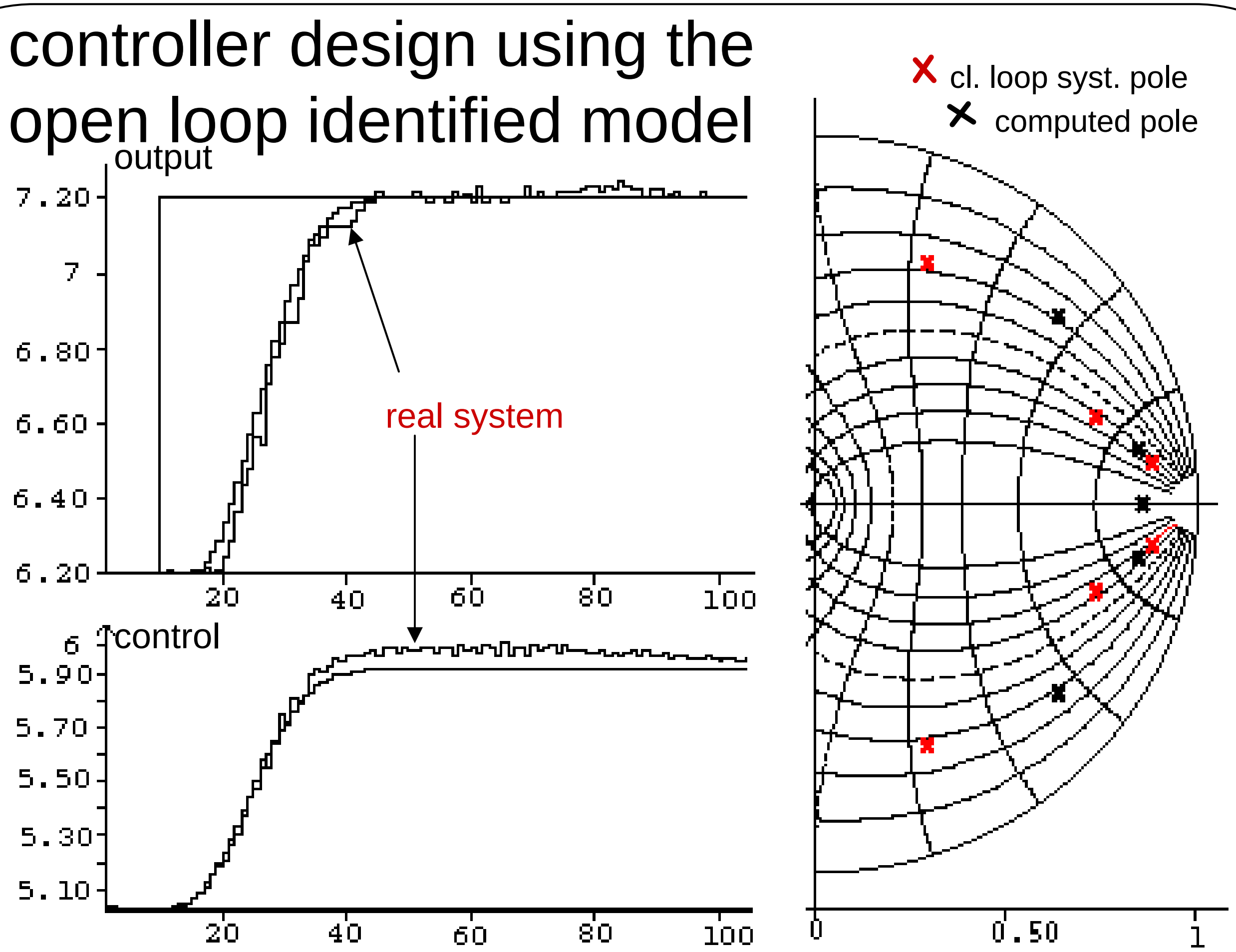
The flexible transmission



What is the *good* model (for control design) ?



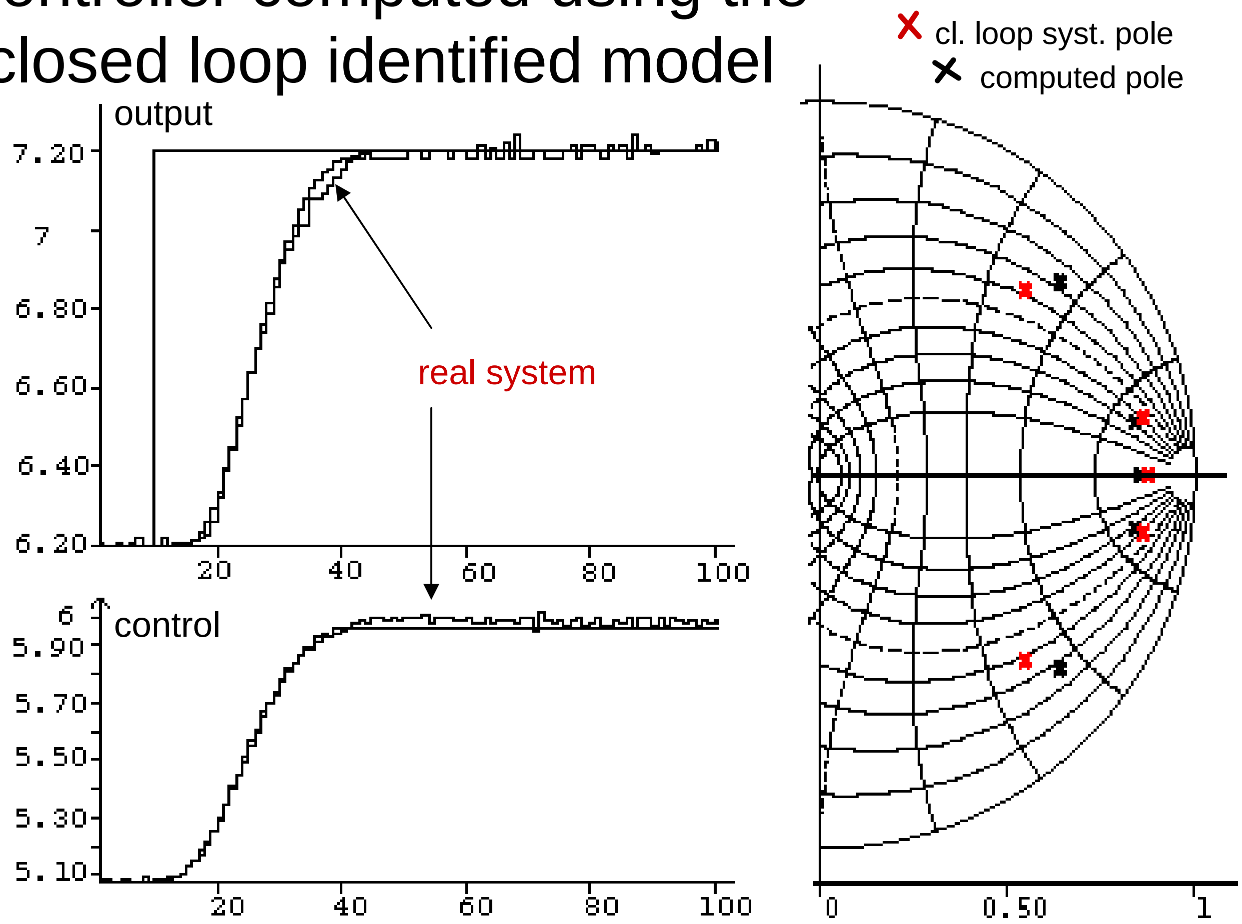
Benefits of identification in closed loop (1)



The pattern of *identified closed loop poles* is different from the pattern of *computed closed loop poles*

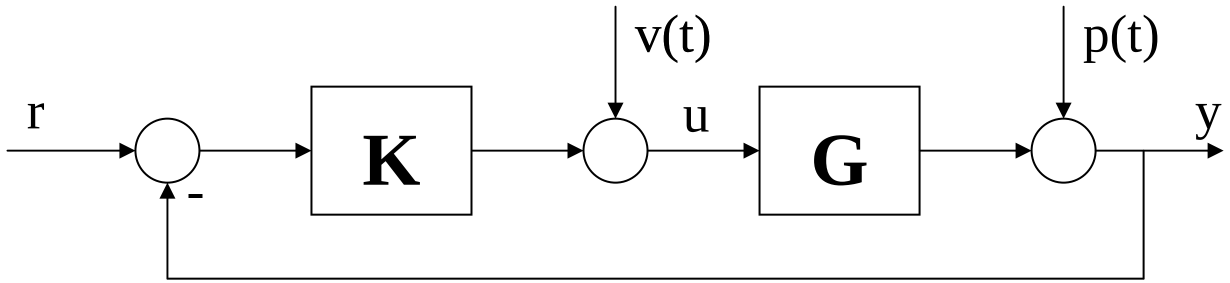
Benefits of identification in closed loop (2)

controller computed using the closed loop identified model



The *computed* and the *identified* closed loop poles are very close

Notations



$$G(q^{-1}) = \frac{q^{-d}B(q^{-1})}{A(q^{-1})} \qquad K(q^{-1}) = \frac{R(q^{-1})}{S(q^{-1})}$$

Sensitivity functions :

$$S_{yp}(z^{-1}) = \frac{1}{1+KG} \;;\; S_{up}(z^{-1}) = -\frac{K}{1+KG} \;;\; S_{yv}(z^{-1}) = \frac{G}{1+KG} \;;\; S_{yr}(z^{-1}) = \frac{KG}{1+KG}$$

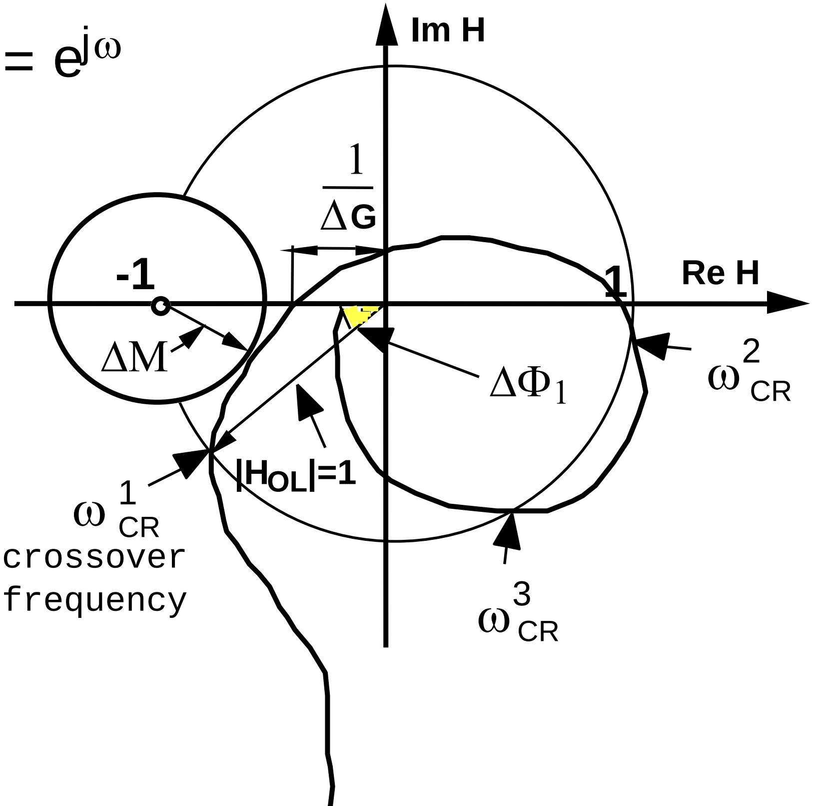
Closed loop poles : $P(z^{-1}) = A(z^{-1})S(z^{-1}) + z^{-d}B(z^{-1})R(z^{-1})$

True closed loop system :(K,G), P, S_{xy}

Nominal simulated(estimated) closed loop :$(K, \hat{G}), \hat{P}, \hat{S}_{xy}$

Robustness Margins

$z = e^{j\omega}$



Typical values:

$\Delta M \geq 0.5$ (-6dB), $\Delta\tau > T_S$

$\Delta M \geq 0.5 \Rightarrow \Delta G \geq 2$; $\Delta\Phi > 29°$

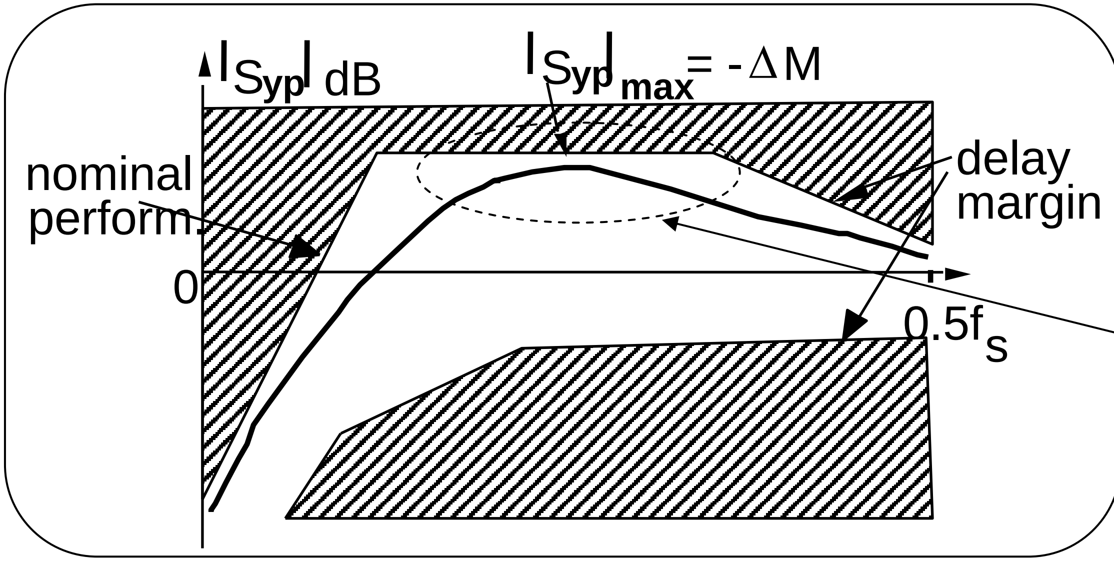
The inverse is not necessarily true!

Critical frequency region for control

Modulus Margin: $\Delta M = \left|1+H_{OL}(z^{-1})\right|_{min} = \left(\left|S_{yp}(z^{-1})\right|_{max}\right)^{-1} = \left(\|S_{yp}\|_{\infty}\right)^{-1}$

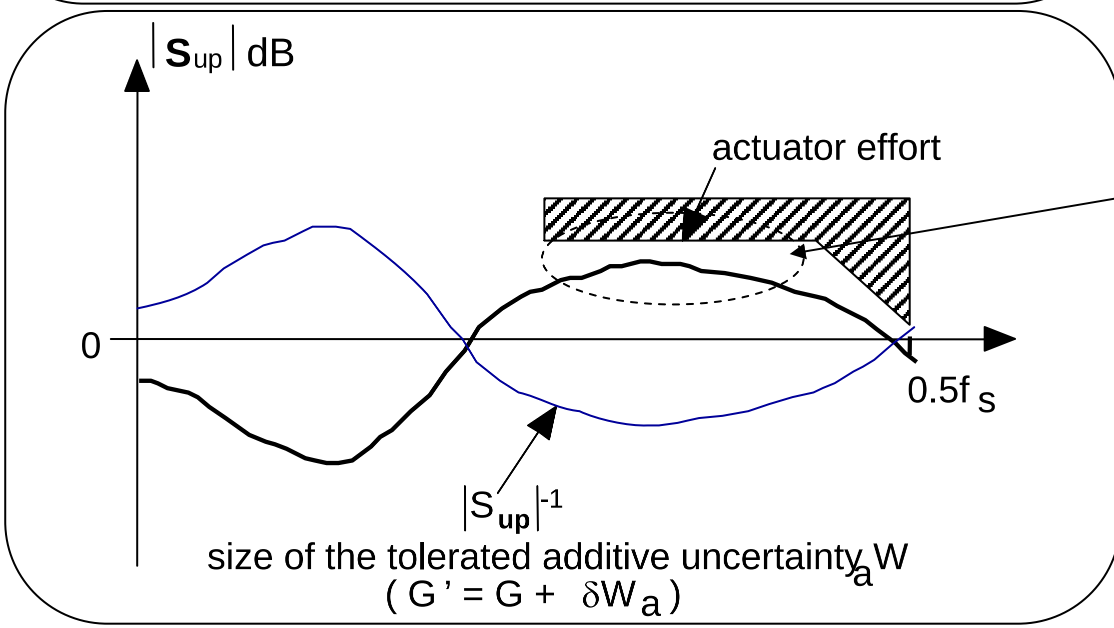
Delay Margin: $\Delta\tau = \min_i \frac{\Delta\Phi_i}{\omega^i_{CR}}$

Templates for the Sensitivity Functions



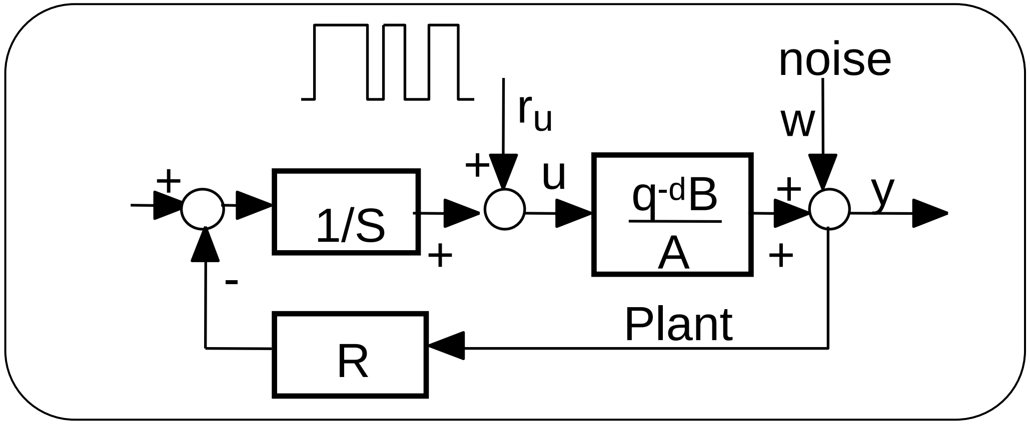
Output Sensitivity Function

Critical frequency region for control

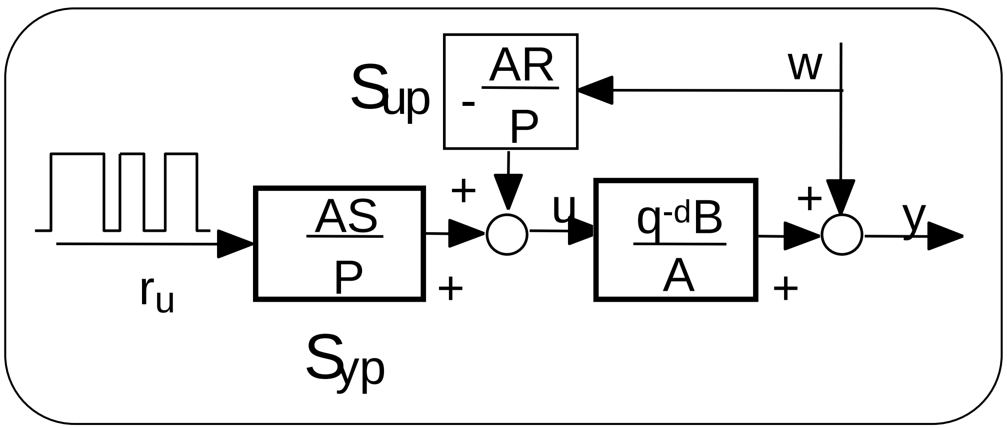


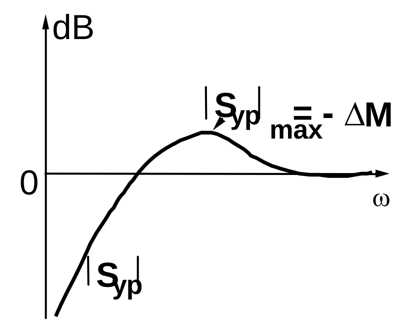
Input Sensitivity Function

Identification in Closed Loop



Open loop interpetation





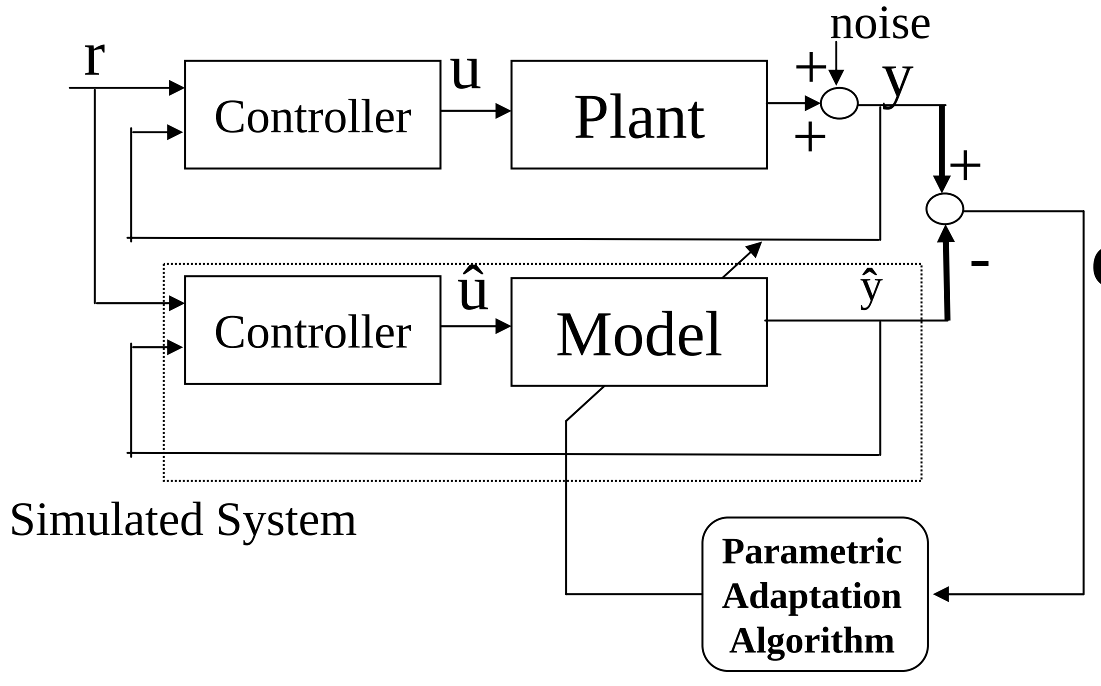
Objective : development of algorithms which:

- take advantage of the « improved » input spectrum
- are insensitive to noise in closed loop operation

Objective of the Identification in Closed Loop

(identification for control)

Find the « plant model » which minimizes the discrepancy between the « real » closed loop system and the « simulated » closed loop system.

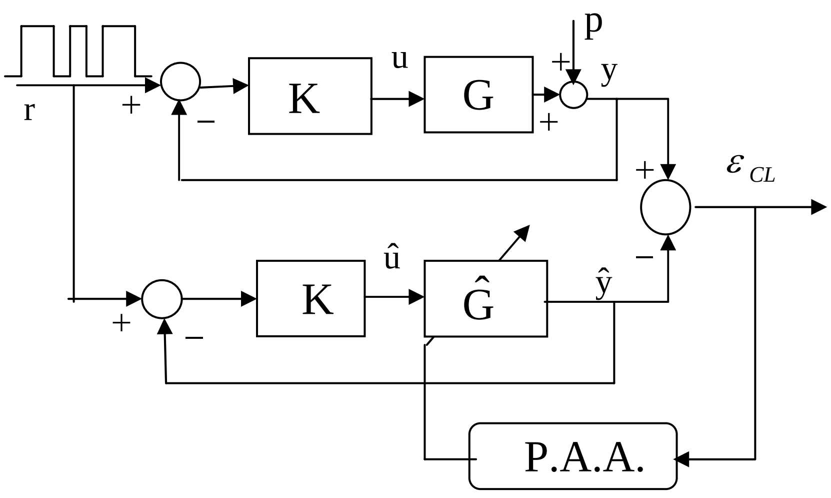


CLOE Algorithms

Closed Loop Output Error

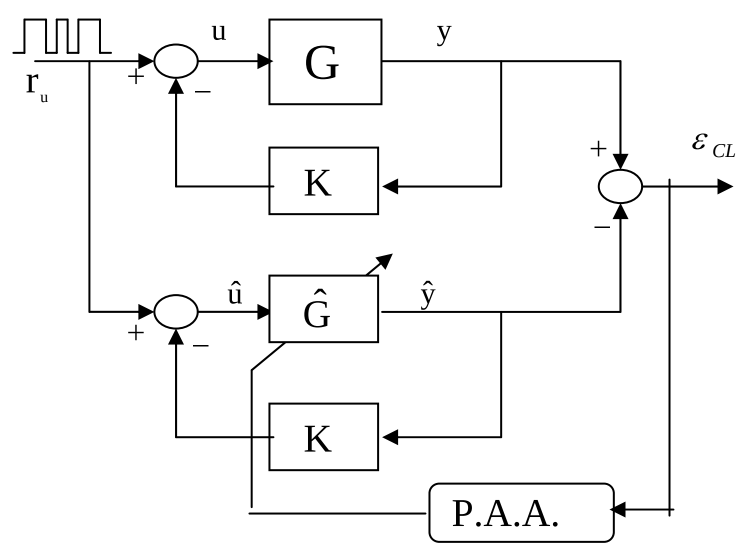
Closed Loop Output Error Identification Algorithms (CLOE)

Excitation added
to reference signal



$$u = -\frac{R}{S}y + \frac{R}{S}r \qquad \hat{u} = -\frac{R}{S}\hat{y} + \frac{R}{S}r$$

Excitation added
to controller output

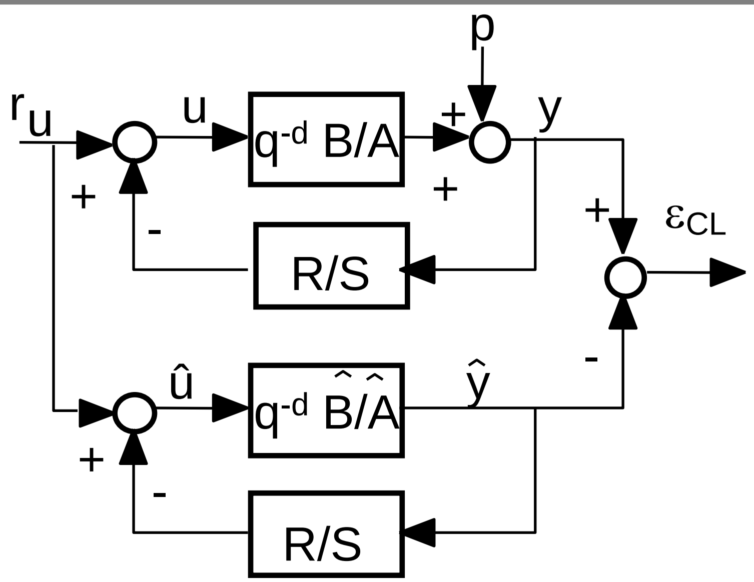


$$u = -\frac{R}{S}y + r_u \qquad \hat{u} = -\frac{R}{S}\hat{y} + r_u$$

Same algorithm but different properties of the estimated model!

Closed Loop Output Error Algorithms (CLOE)

Excitation added to the plant input



The closed loop system (for p = 0):

$$y(t+1) = -A^*(q^{-1})y(t) + B^*(q^{-1})u(t-d) = \theta^T \psi(t)$$

$$\theta^T = \left[a_1, \ldots a_{n_A}, b_1, \ldots b_{nB}\right]$$

$$\psi^T(t) = \left[-y(t), \ldots -y(t-n_A+1), u(t-d), \ldots u(t-d-n_B)\right]$$

$$u(t) = -\frac{R}{S}y(t) + r_u$$

CLOE

Adjustable predictor (closed loop)

Predicted output :

$$\hat{y}^0(t+1) = -\hat{A}^*(t,q^{-1})\hat{y}(t) + \hat{B}^*(t,q^{-1})\hat{u}(t-d) = \hat{\theta}^T(t)\phi(t) \quad \textit{a priori}$$

$$\hat{y}(t+1) = \hat{\theta}^T(t+1)\phi(t) \qquad \textit{a posteriori}$$

$$\hat{u}(t) = -\frac{R}{S}\hat{y}(t) + r_u$$

$$\hat{\theta}^T(t) = \left[\hat{a}_1(t), \ldots \hat{a}_{n_A}(t), \hat{b}_1(t), \ldots \hat{b}_{n_B}(t)\right]$$

$$\phi^T(t) = \left[-\hat{y}(t), \ldots -\hat{y}(t-n_A+1), \hat{u}(t-d), \ldots \hat{u}(t-d-n_B)\right]$$

Closed loop prediction (output) error

$$\varepsilon_{CL}^0(t+1) = y(t+1) - \hat{\theta}^T(t)\phi(t) = y(t+1) - \hat{y}^0(t+1) \qquad \textit{a priori}$$

$$\varepsilon_{CL}(t+1) = y(t+1) - \hat{\theta}^T(t+1)\phi(t) = y(t+1) - \hat{y}\ (t+1) \qquad \textit{a posteriori}$$

CLOE

The Parameter Adaptation Algorithm

$$\varepsilon_{CL}^{0}(t+1) = y(t+1) - \hat{\theta}^{T}(t)\phi(t) = y(t+1) - \hat{y}^{0}(t+1)$$

$$\hat{\theta}(t+1) = \hat{\theta}(t) + F(t+1)\Phi(t)\varepsilon_{CL}^{0}(t+1)$$

$$F^{-1}(t+1) = \lambda_1(t)F^{-1}(t) + \lambda_2(t)\Phi(t)\Phi^{T}(t)\,;\, 0 < \lambda_1(t) \leq 1\,;\, 0 \leq \lambda_2(t) < 2$$

$$\Phi(t) = \phi(t)$$

Updating F(t):

$$F(t+1) = \frac{1}{\lambda_1(t)}\left[F(t) - \frac{F(t)\Phi(t)\Phi(t)^{T}F(t)}{\frac{\lambda_1(t)}{\lambda_2(t)} + \Phi(t)^{T}F(t)\Phi(t)}\right]$$

CLOE Algorithms

CLOE $$\Phi(t) = \phi(t)$$

F-CLOE $$\Phi(t) = \frac{S(q^{-1})}{\hat{P}(q^{-1})}\phi(t)$$ $$\hat{P} = \hat{A}(q^{-1})S(q^{-1}) + q^{-d}\hat{B}(q^{-1})R(q^{-1})$$

AF-CLOE $$\Phi(t) = \frac{S(q^{-1})}{\hat{P}(q^{-1},t)}\phi(t)$$ $$\hat{P}(q^{-1},t) = \hat{A}(q^{-1},t)S + q^{-d}\hat{B}(q^{-1},t)R$$

$$\phi^T(t) = \left[-\hat{y}(t),..-\hat{y}(t-n_A+1),\hat{u}(t-d),..\hat{u}(t-d-n_B)\right]$$

Remarks :

• F-CLOE needs an « estimated model » for filtering. This can be an «open loop model» or a model identified with CLOE or AF-CLOE

• For AF-CLOE « inital estimation » for filtering can be $\hat{A}=1,\ \hat{B}=0$

CLOE Properties

Case 1: The plant model is in the model set
(i.e. the estimated model has the *good order)*

- The controller is constant
- An external excitation is applied
- Measurement noise independent w.r.t. the external excitation

Asymptotic unbiased estimates in the presence of noise
subject to a (mild) sufficient passivity condition

•*CLOE:* $S/P - \lambda/2$

•*F-CLOE:* $\hat{P}/P - \lambda/2$

→ *Strictly positive real transfer fct.*

$$\max_t \lambda_2(t) \leq \lambda < 2$$

•*AF-CLOE:* *none (local)*

CLOE Properties

Case 2: The plant model is not in the model set
(ex.: the estimated model has a *lower order)*

Basic idea for analysis of identification algorithms (Ljung) :
Convert time domain minimization criterion in frequency domain criterion using Parseval th. and Fourrier transforms

See the next slides

Properties of the Estimated Model (1)

Excitation added to controller output

$$\hat{\theta}^* = \arg\min_{\theta} \int_{-\pi}^{\pi} [\left| S_{yv} - \hat{S}_{yv} \right|^2 \phi_{r_u}(\omega) + \left| S_{yp} \right|^2 \phi_p(\omega)] d\omega$$

$$= \arg\min_{\theta} \int_{-\pi}^{\pi} \left| S_{yp} \right|^2 [\left| G - \hat{G} \right|^2 \left| \hat{S}_{yp} \right|^2 \phi_{r_u}(\omega) + \phi_p(\omega)] d\omega$$

- $\hat{G}$ will minimize the 2 norm between the true sensitivity function and the sensitivity function of the closed loop estimator when r(t) is a white noise (PRBS)

-Plant -model error heavily weighted by the sensitivity functions

-The noise does not affect the asymptotic estimation

Properties of the Estimated Model (2)

Excitation added to reference signal

$$\hat{\theta}^* = \arg\min_{\theta} \int_{-\pi}^{\pi} [\left|S_{yp} - \hat{S}_{yp}\right|^2 \phi_r(\omega) + \left|S_{yp}\right|^2 \phi_p(\omega)] d\omega$$

$$= \arg\min_{\theta} \int_{-\pi}^{\pi} \left|S_{yp}\right|^2 [\left|G - \hat{G}\right|^2 \left|\hat{S}_{up}\right|^2 \phi_r(\omega) + \phi_p(\omega)] d\omega$$

- $\hat{G}$ will minimize the 2 norm between the true sensitivity function and the sensitivity function of the closed loop estimator when r(t) is a white noise (PRBS)

-Plant -model error heavily weighted by the sensitivity functions

-The noise does not affect the asymptotic estimation

Properties of the Estimated Model (3)

Excitation added to reference signal

One has: $\left|S_{yp} - \hat{S}_{yp}\right| = \left|S_{yr} - \hat{S}_{yr}\right|$

Therefore one has also :

$$\hat{\theta}^* = \arg\min_{\theta} \int_{-\pi}^{\pi} [\left|S_{yr} - \hat{S}_{yr}\right|^2 \phi_r(\omega) + \left|S_{yp}\right|^2 \phi_p(\omega)] d\omega$$

$$= \arg\min_{\theta} \int_{-\pi}^{\pi} [\left|S_{yp} - \hat{S}_{yp}\right|^2 \phi_r(\omega) + \left|S_{yp}\right|^2 \phi_p(\omega)] d\omega$$

The differences with respect to the output sensitivity function and the complimentary sensitivity function are minimized

Identification in closed loop - Some remarks

- The quality of the identified model is enhanced in the critical frequency regions for control (compare with open loop id.)

CLOE $$\hat{\theta}^* = \arg\min_{\theta} \int_{-\pi}^{\pi} \left|S_{yp}\right|^2 \left[\left|G - \hat{G}\right|^2 \left|\hat{S}_{yp}\right|^2 \phi_r(\omega) + \phi_p(\omega)\right] d\omega$$

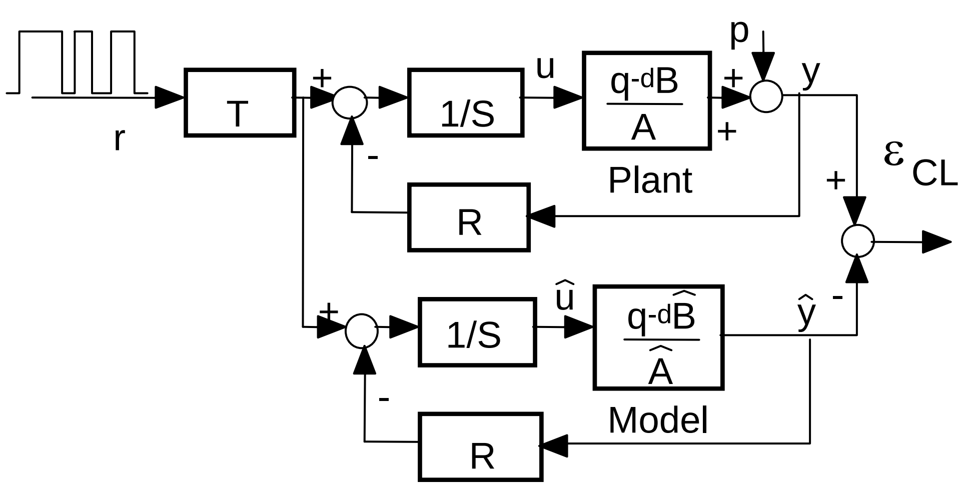
OLOE $$\hat{\theta}^* = \arg\min_{\theta} \int_{-\pi}^{\pi} \left[\left|G - \hat{G}\right|^2 \phi_r(\omega) + \phi_p(\omega)\right] d\omega$$

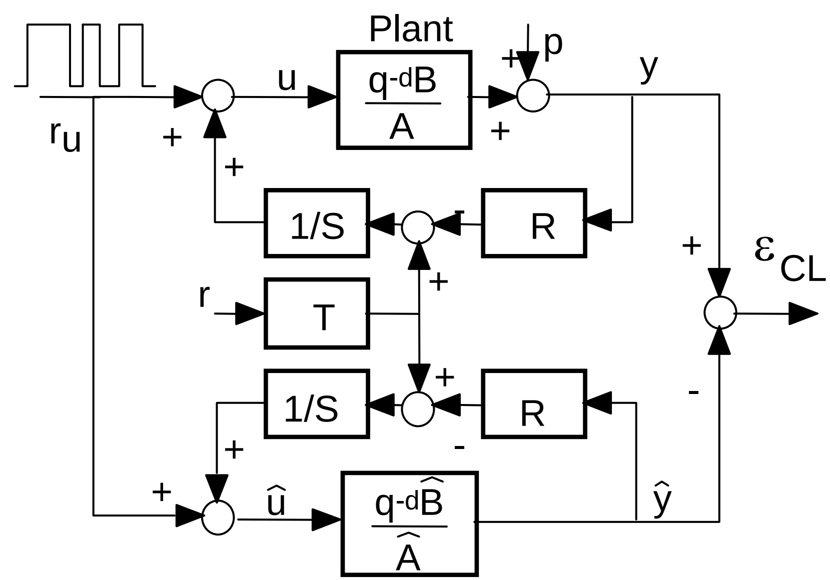
-Identification in closed loop can be used for **model reduction.** *The approximation will be good in the critical frequency regions for control.*

Closed Loop Output Error Identification Algorithms (CLOE)

R-S-T Controller

Excitation added to reference signal	Excitation added to controller output





$$u = -\frac{R}{S} y + \frac{T}{S} r \qquad \hat{u} = -\frac{R}{S} \hat{y} + \frac{T}{S} r$$

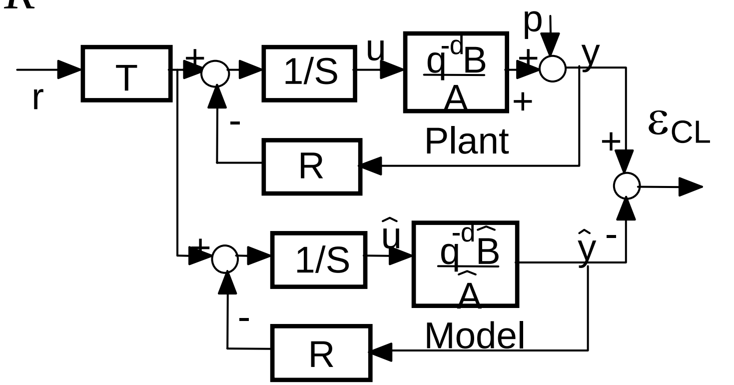
$$u = -\frac{R}{S} y + r_u \qquad \hat{u} = -\frac{R}{S} \hat{y} + r_u$$

Use of the prefilter T (R-S-T controller)

Difference between closed loop transfer functions (excitation through T)

$$\frac{BT}{AS+BR}-\frac{\hat{B}T}{\hat{A}S+\hat{B}R}=\frac{T}{R}\left[\frac{BR}{AS+BR}-\frac{\hat{B}R}{\hat{A}S+\hat{B}R}\right]=\frac{T}{R}\left[S_{yr}-\hat{S}_{yr}\right]$$

$$=\frac{T}{S}\left[\frac{BS}{AS+BR}-\frac{\hat{B}S}{\hat{A}S+\hat{B}R}\right]=\frac{T}{S}\left[S_{yv}-\hat{S}_{yv}\right]$$



Properties of the estimated model:

$$\hat{\theta}^{*}=\arg\min_{\theta}\int_{-\pi}^{\pi}\left[\left|S_{yr}-\hat{S}_{yr}\right|^{2}\left|\frac{T}{R}\right|^{2}\phi_{r}(\omega)+\left|S_{yp}\right|^{2}\phi_{p}(\omega)\right]d\omega$$

$$=\arg\min_{\theta}\int_{-\pi}^{\pi}\left[\left|S_{yv}-\hat{S}_{yv}\right|^{2}\left|\frac{T}{S}\right|^{2}\phi_{r}(\omega)+\left|S_{yp}\right|^{2}\phi_{p}(\omega)\right]d\omega$$

$T=S$ *Excitation added to the plant input (controller output)*

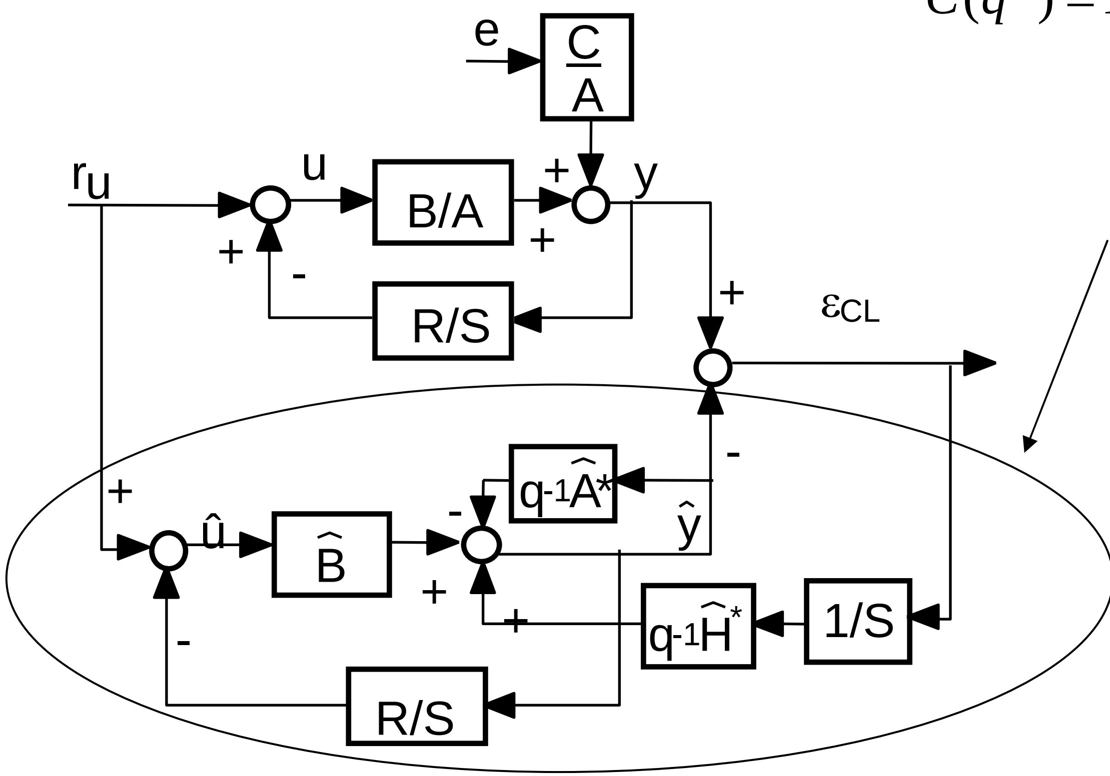
$T=R$ *Excitation added to the controller input (measure)*

Identification in Closed Loop of ARMAX Models

X-CLOE *Extended Closed Loop Output Error*

$$y(t+1) = -A^*(q^{-1})y(t) + B^*(q^{-1})u(t-d) + C^*e(t) + e(t+1)$$

$$C(q^{-1}) = 1 + q^{-1}C^*(q^{-1})$$



Optimal predictor for the closed loop when :

$$\hat{A} = A; \hat{B} = B; \hat{C} = C$$

$$H^* = C^*S - A^*S - B^*R;\ H = 1 + q^{-1}H^*;\ \boxed{nH \cong nP}$$

X-CLOE – the algorithm

Predicted output :

$$\hat{y}^{\circ}(t+1) = \hat{\theta}_e^T(t)\phi_e(t) \qquad \textit{a priori}$$

$$\hat{u}(t) = -\frac{R}{S}\hat{y}(t) + r_u$$

$$\hat{\theta}_e^T(t) = \left[\hat{a}_1(t),\ldots\hat{a}_{n_A}(t),\hat{b}_1(t),\ldots\hat{b}_{n_B}(t),\hat{h}_1(t),\ldots\hat{h}_{n_H}(t)\right]$$

$$\varepsilon_{CLf}(t) = \frac{1}{S}\varepsilon_{CL}(t)$$

$$\phi^T(t) = \left[-\hat{y}(t),.-\hat{y}(t-n_A+1),\hat{u}(t-d),.\hat{u}(t-d-n_B),\varepsilon_{CLf}(t),.\varepsilon_{CLf}(t-n_H+1)\right]$$

Closed loop prediction (output) error

$$\varepsilon_{CL}^0(t+1) = y(t+1) - \hat{\theta}_e^T(t)\phi_e(t) = y(t+1) - \hat{y}^0(t+1) \qquad \textit{a priori}$$

X-CLOE – the algorithm

The Parameter Adaptation Algorithm

$$\varepsilon_{CL}^{0}(t+1) = y(t+1) - \hat{\theta}_e^T(t)\phi_e(t) = y(t+1) - \hat{y}^0(t+1)$$

$$\hat{\theta}(t+1) = \hat{\theta}(t) + F(t+1)\Phi(t)\varepsilon_{CL}^{0}(t+1)$$

$$F^{-1}(t+1) = \lambda_1(t)F^{-1}(t) + \lambda_2(t)\Phi(t)\Phi^T(t)\,;\, 0 < \lambda_1(t) \le 1\,;\, 0 \le \lambda_2(t) < 2$$

$$\Phi(t) = \phi_e(t)$$

X-CLOE Properties

Case 1: The plant model is in the model set

Deterministic case:

• Global convergence does not require any S.P.R. condition *(works allways)*

Stochastic case (noise)

• Asymptotic unbiased estimates

• Convergence condition: $1/C - \lambda/2 =$ S.P.R *(like in open loop for ELS and OEEPM)*

Case 2: The plant model is not in the model set

• Slightly less good « approximation » properties than CLOE

• Provides better results than « open loop » identification alg.

Validation of Models Identified in Closed Loop

Controller dependent validation !

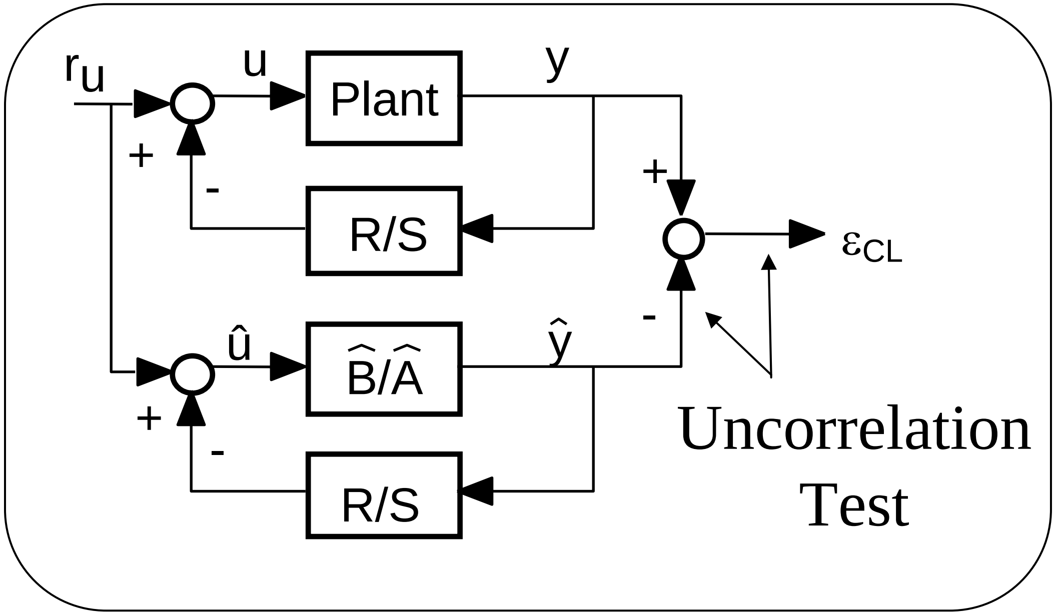
1) Statistical Model Validation

2) Pole Closeness Validation

3) Sensitivity Functions Closeness Validation

4) Time Domain Validation

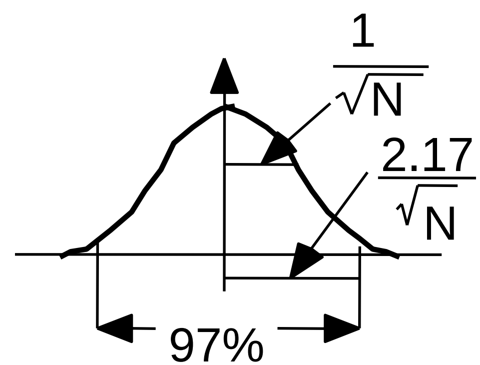
Statistical Model Validation



$$|RN(i)| \le \frac{2.17}{\sqrt{N}}\,;\; i \ge 1$$

normalized crosscorelations

number of data



Controller dependent validation !

$$N = 256 \rightarrow |RN(i)| \le 0.136$$

pratical value : $|RN(i)| \le 0.15$

« Uncorrelation » Test

$\{\varepsilon_{CL}(t)\}$: centered sequence of residual closed loop prediction errors

One computes:

$$R(i) = \frac{1}{N}\sum_{t=1}^{N}\varepsilon_{CL}(t)\hat{y}(t-i) \quad ; \quad i = 0,1,2,...,i_{max} \qquad ; \quad i_{max} = \max(n_A, n_B + d)$$

$$RN(i) = \frac{R(i)}{\left[\left(\frac{1}{N}\sum_{t=1}^{N}\hat{y}^2(t)\right)\left(\frac{1}{N}\sum_{t=1}^{N}\varepsilon_{CL}{}^2(t)\right)\right]^{1/2}} \quad ; \quad i = 0,1,2,...,i_{max}$$

Remark: $RN(0) \neq 1$

Theoretical values: $RN(i) = 0;\ i = 1, 2 \ldots i_{max}$

Real situation:
- Finite number of data
- Residual structural errors (orders, nonlinearities, noise)
- Objective: to obtain « good » simple models

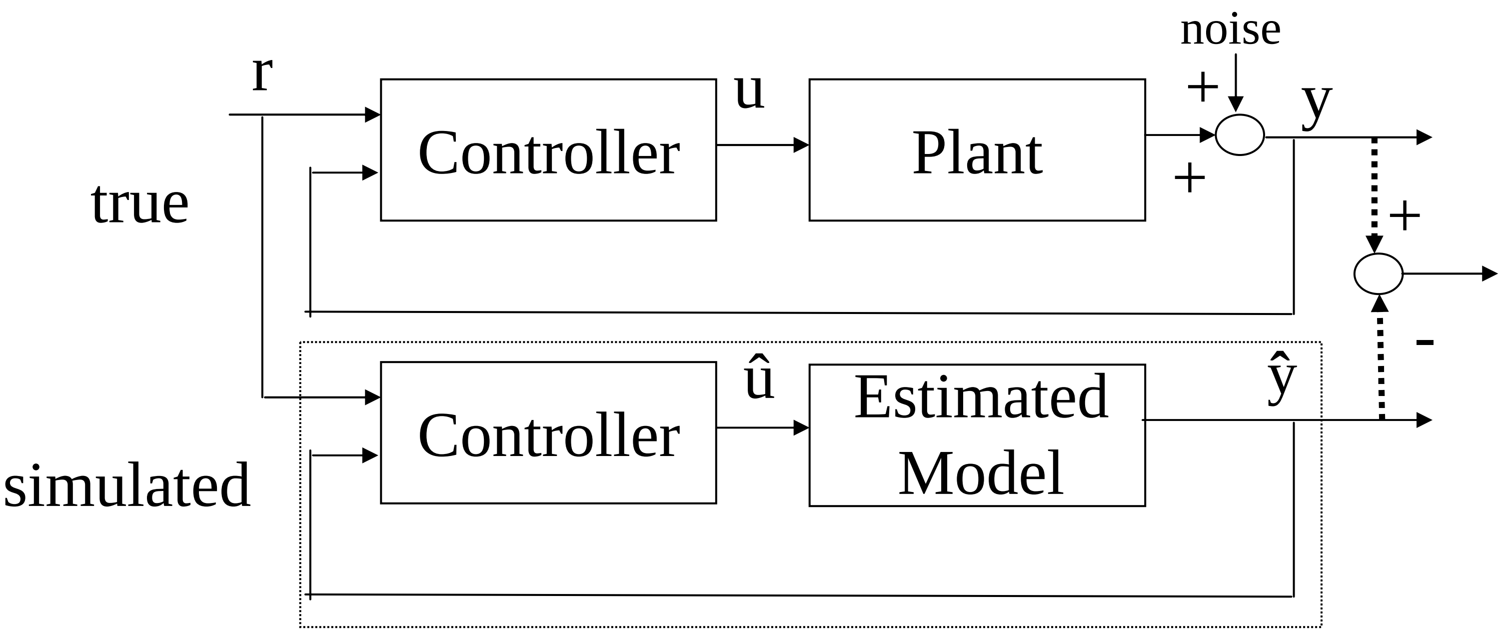
Validation criterion (N = number of data):

$$|RN(i)| \leq \frac{2.17}{\sqrt{N}} \quad ; \quad i \geq 1$$

or: $|RN(i)| \leq 0.15;\ i = 1,...,i_{max}$

Identification in Closed Loop

Pole Closeness Validation



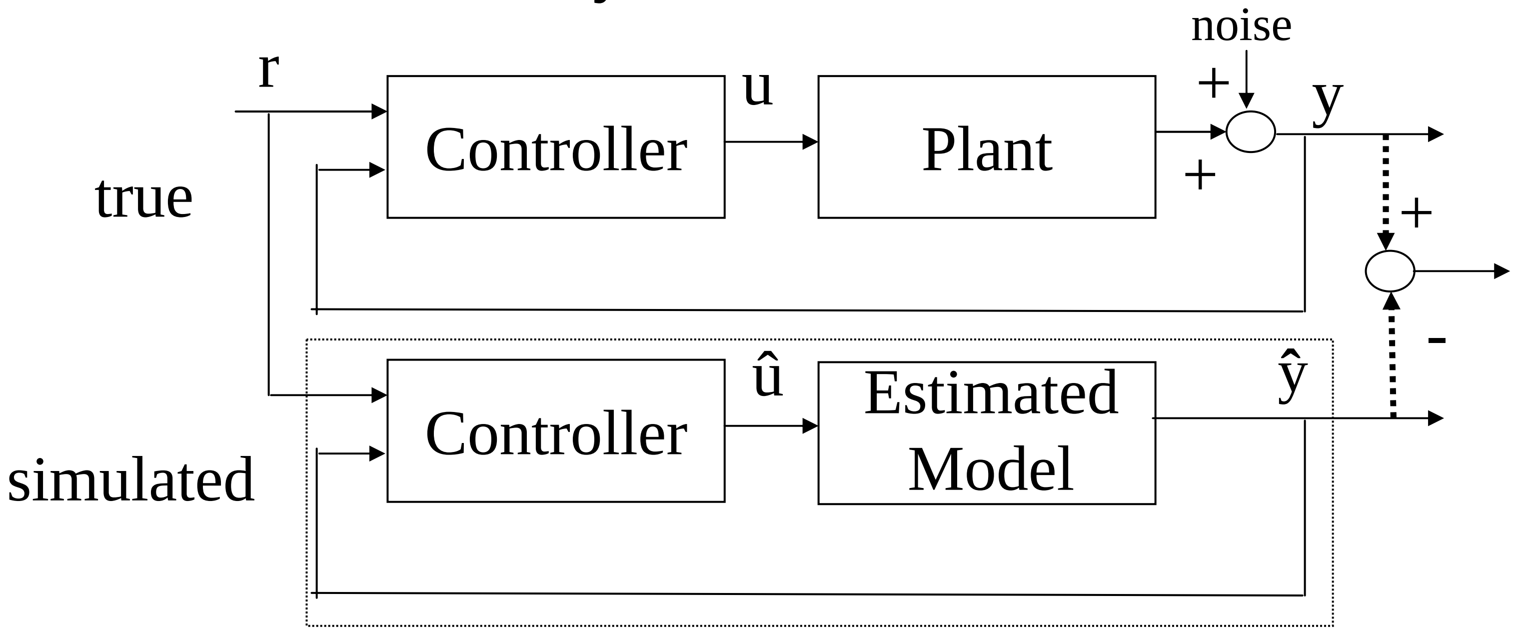
If the estimated model is good, the poles of the « true » loop and of the « simulated » loop should be *close*

•*The poles of the « simulated » system can be computed*

•*The poles of the « true » system should be estimated*

Identification in Closed Loop

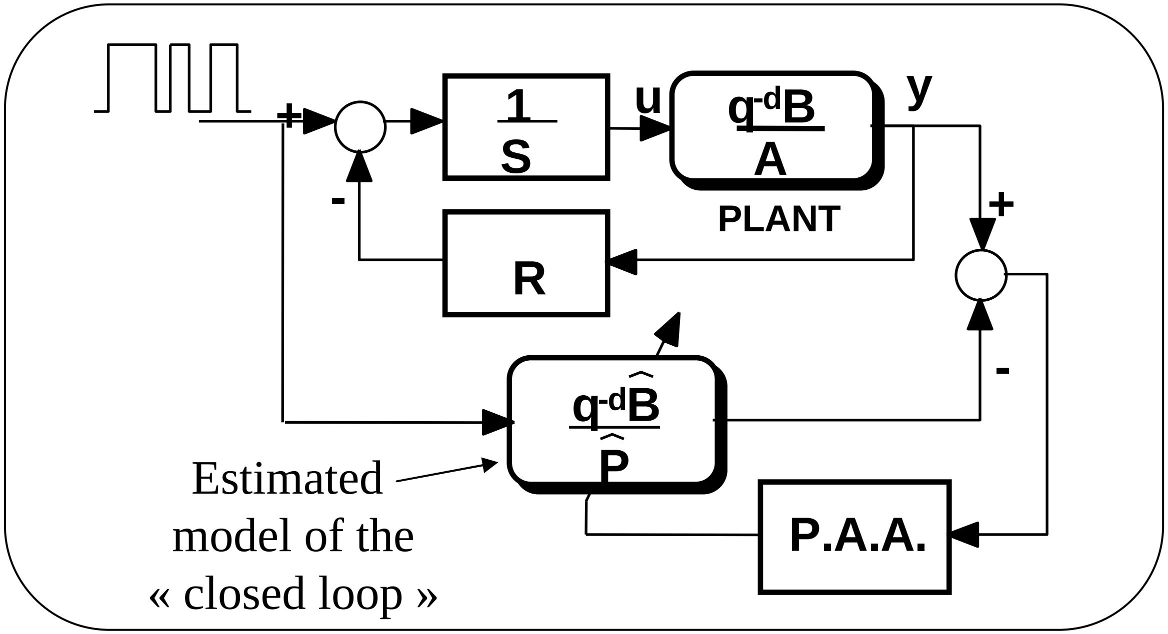
Sensitivity Function Closeness Validation



If the estimated model is good, the sensitivity functions of the « true » loop and of the « simulated » loop should be *close*

- *The sensitivity fct. of the « simulated » system can be computed*
- *The sensitivity fct. of the « true » system should be estimated*

Closed loop poles/Sensitivity functions Estimation



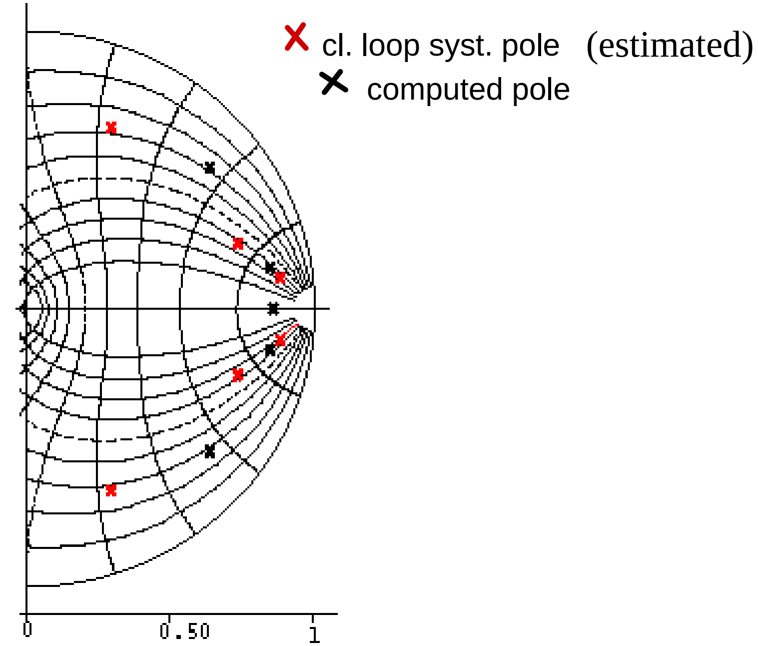
Rem:

- use of open loop identification algorithms
- same signals as those used for the identification of the *plant model* in closed loop operation
- attention to the selection of the order !

How to asses the poles/sensitivity fct. closeness ?

Poles:

- Patterns of the poles map
- Closeness of $1/\hat{P}$ and $1/\hat{\hat{P}}$



Sensitivity functions:

- Closeness of $\hat{S}_{xy}$ and $\hat{\hat{S}}_{xy}$

The closeness of two transfer functions can be measured by the « Vinnicombe distance » (ν gap) (min = 0, max = 1)
(*will be discussed later)*

$\hat{X}$: Closed loop transfer function computed with the estimated plant model

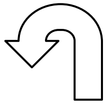
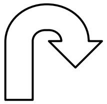
$\hat{\hat{X}}$: Estimated closed loop transfer function

Normalized distance between two transfer functions (G_1, G_2)
(Vinnicombe distance or ν–gap)

The winding number:

$$wno(G) = n_{z_i}(G) - n_{p_i}(G)$$

Unstable zeros — Unstable poles

wno(G)>0  wno(G)<0 

$wno(G)$ = number of encirclements of the origin (winding number)
(+ : counter clock wise , - : clock wise)

One can compares transfer functions satisfying :

$$wno(1 + G_2^* G_1) + n_{p_i}(G_1) - n_{p_i}(G_2) - n_{P_1}(G_2) = 0 \qquad \{w\}$$

G^* = complex conjugate of G $\qquad$ $n_{P_1}(G_2)$ = number of poles on the unit circle

Normalized distance between two transfer functions (G_1, G_2) (Vinnicombe distance or ν–gap)

One assumes that {w} is satisfied.

Normalized difference :

$$\Psi\left[G_1(j\omega), G_2(j\omega)\right] = \frac{G_1(j\omega) - G_2(j\omega)}{\left(1+\left|G_1(j\omega)\right|^2\right)^{1/2}\left(1+\left|G_2(j\omega)\right|^2\right)^{1/2}}$$

Normalized distance (Vinnicombe distance or ν-gap) :

$$\delta_\nu(G_1, G_2) = \left| \Psi\left[G_1(j\omega), G_2(j\omega)\right] \right|_{\max_\omega} = \left\| \Psi\left[G_1(j\omega), G_2(j\omega)\right] \right\|_\infty$$

$$\text{for } \omega = 0 \text{ to } \pi f_s$$

$$0 \le \delta_\nu(G_1, G_2) < 1$$

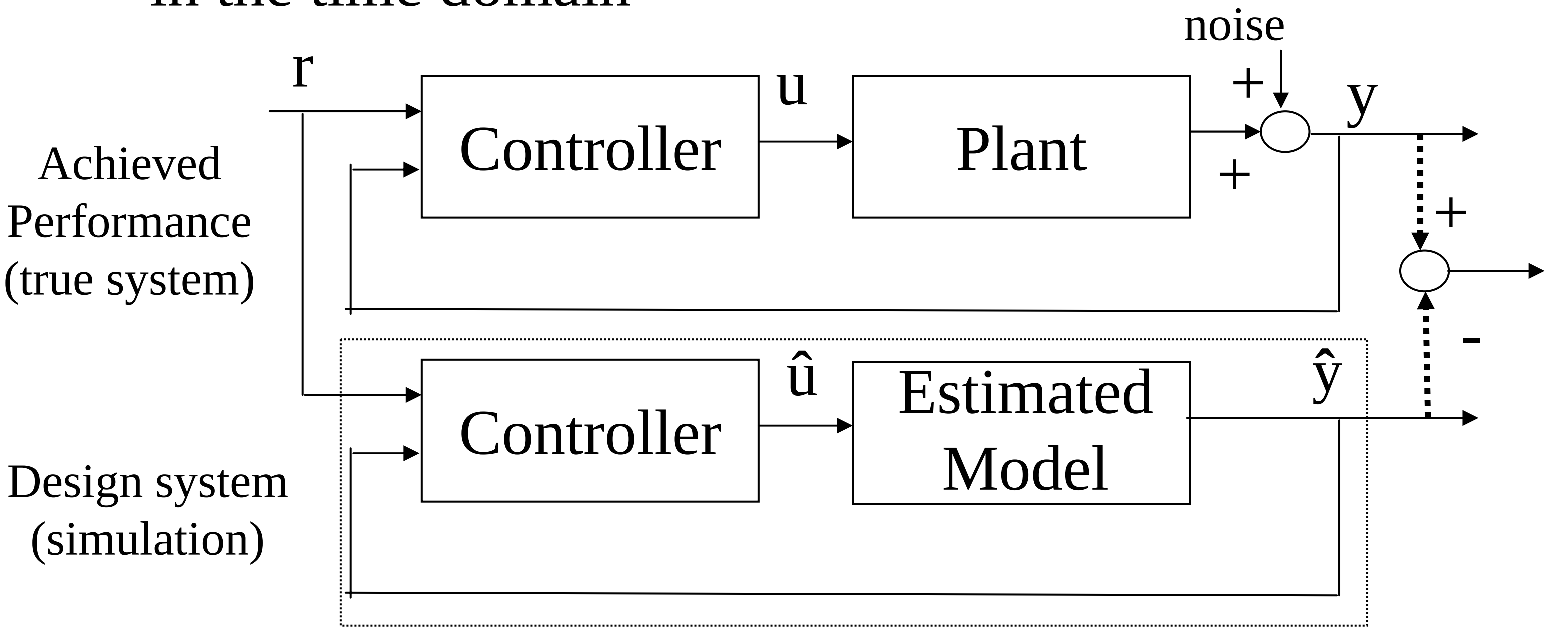
If {w} is not satisfied : $\delta_\nu(G_1, G_2) = 1$

See Landau, Zito “Digital Control Systems… or “Commande des systèmes”

Identification in Closed Loop

Time Domain Validation

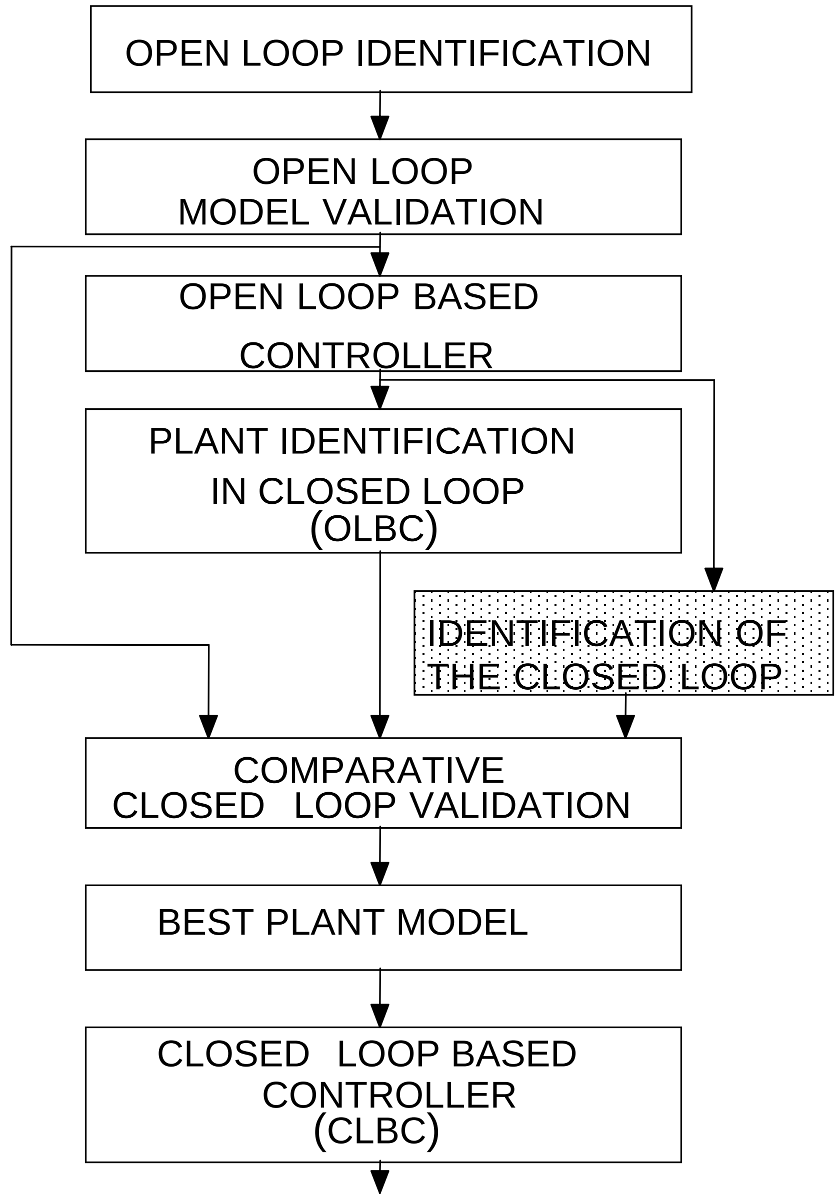
Comparison of « achieved » and « simulated » performance in the time domain



Rem.:

- not enough accuracy in many cases
- difficult interpretation of the results in some cases

Methodology of Plant Model Identification in Closed Loop

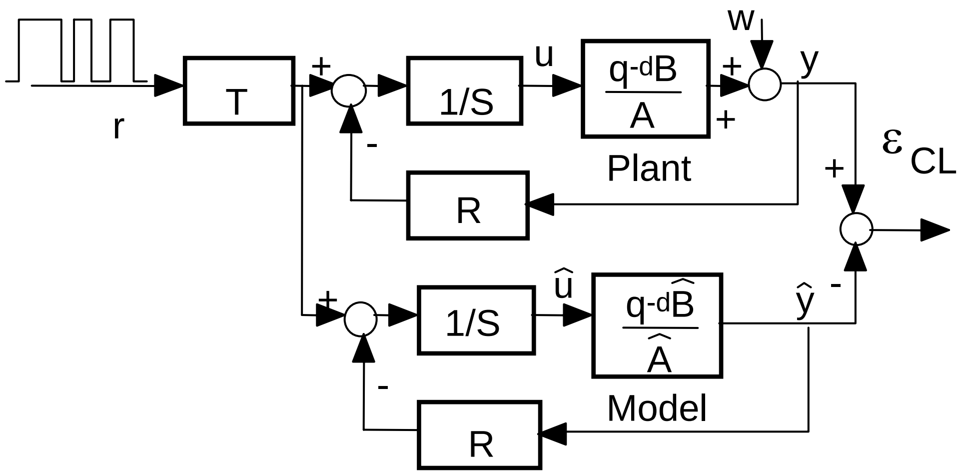


Selection of closed loop identification schemes

Identification criterion	Closed loop identification scheme
$\min\left\| S_{yp} - \hat{S}_{yp} \right\|$ or $\min\left\| S_{yr} - \hat{S}_{yr} \right\|$	CLOE with external excitation added to the controller input equivalent to CLIE with external excitation added to the plant input
$\min\left\| S_{up} - \hat{S}_{up} \right\|$	CLIE with external excitation added to the controller input
$\min\left\| S_{yv} - \hat{S}_{yv} \right\|$	CLOE with external excitation added to the controller output

An interesting connection CL/OL

Open loop identification algorithms are particular cases of closed loop identification algorithms

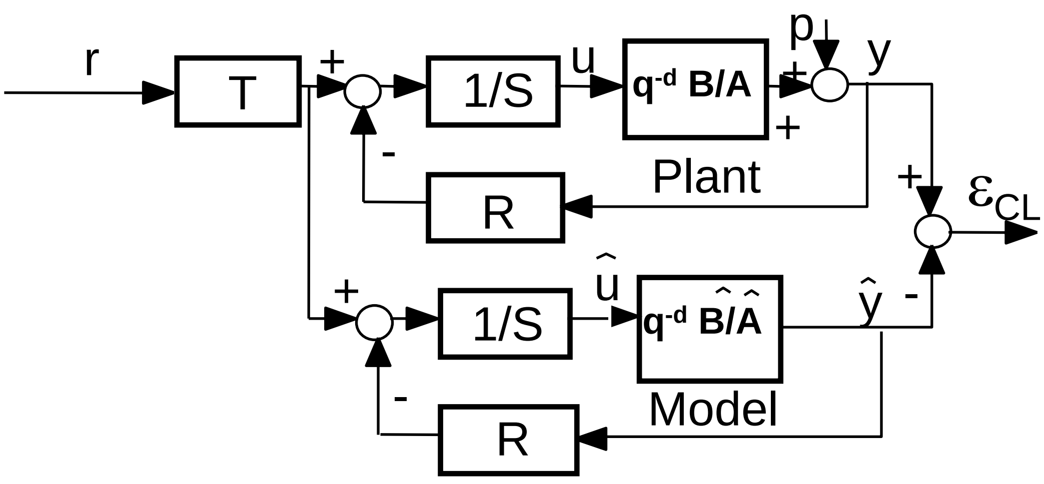


Use R=0, S=T=1 and you get the open loop identification algorithms

CLOE → (OL)OE

X-CLOE → X(OL)OE

Iterative Identification in Closed Loop and Controller Re-Design



Step 1 : Identification in Closed Loop

-Keep controller constant

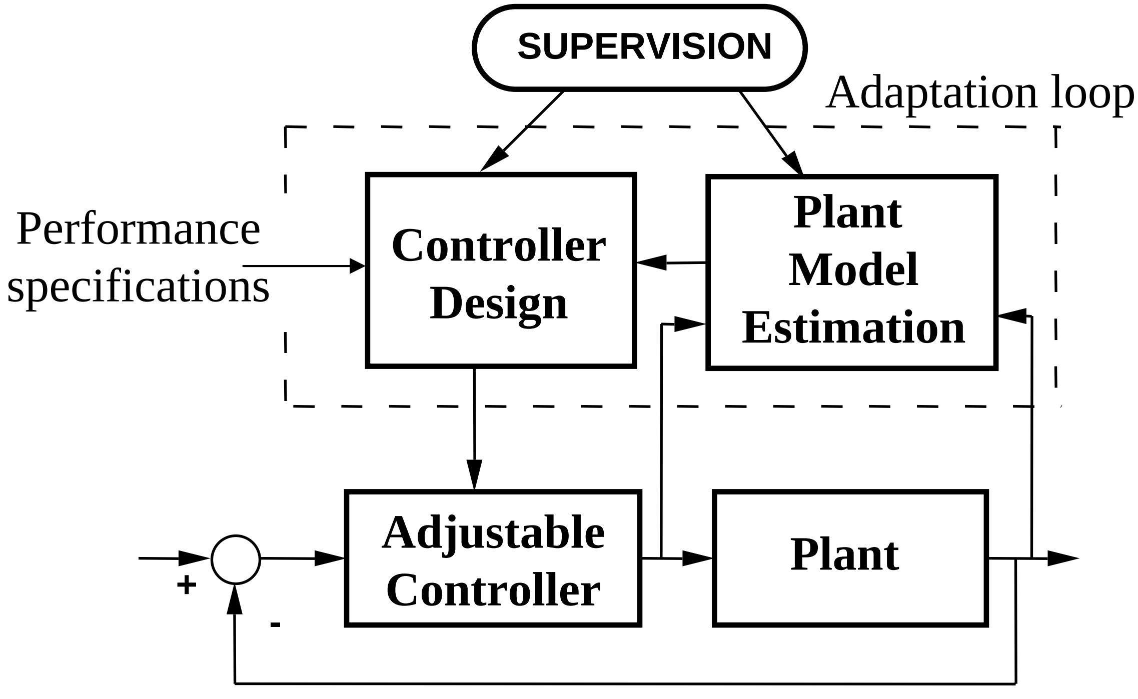
-Identify a new model such that ε_{CL} ↘

Step 2 : Controller Re – Design

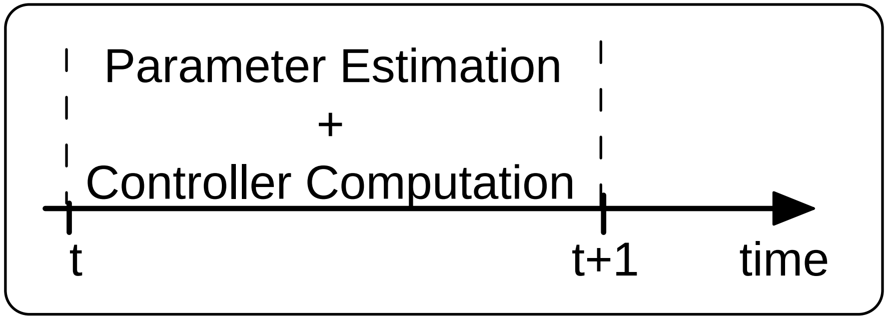
- Compute a new controller such that ε_{CL} ↘

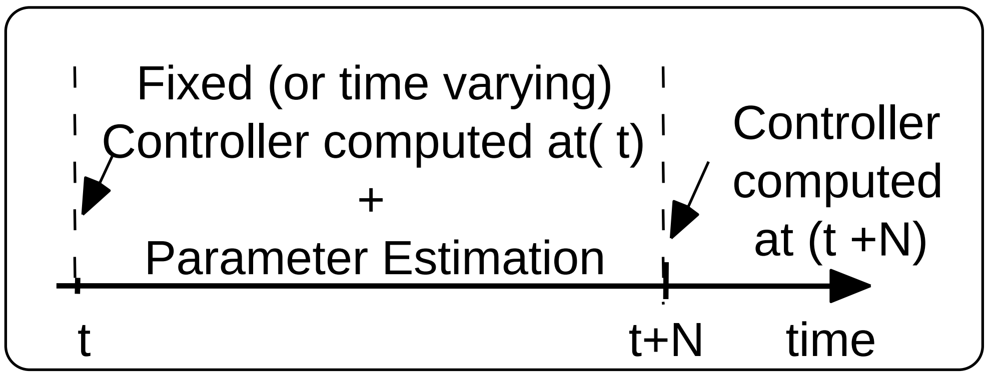
Repeat 1, 2, 1, 2, 1, 2,…

Indirect Adaptive Control – A Basic Scheme



Iterative Identification and Controller Redesign versus (Indirect) Adaptive Control





$N = 1$: Adaptive Control

$N = Small$
Adaptive Control
$N = Large$
Iterative Identification in C.L.
And Controller Re-design
$N \Rightarrow \infty$
Plant Identification in C.L. +
Controller Re-design

The *iterative procedure* introduces a time scale separation between identification / control design

Remarks

- Identification in closed loop combined with controller redesign is a special form of adaptive control
- Use a time scale separation
- Use an external excitation signal
- Controller kept constant during plant model estimation
- Estimation not affected by disturbances
- At supervision level a validation of the model is done

Concluding Remarks

- Methods are available for efficient identification in closed loop
- CLOE algorithms provide unbiased parameter estimates
- CLOE provides “control oriented “reduced order” models (precision enhanced in the critical frequency regions for control)

-The knowledge of the controller is necessary (for CLOE and FOL)

-**In many cases the models identified in closed loop allow to improve the closed loop performance**

-**For controller re-tuning, opening the loop is no more necessary**

-Sequential use of identification in closed loop and controller re-design for tuning on line the controller (adaptive control)

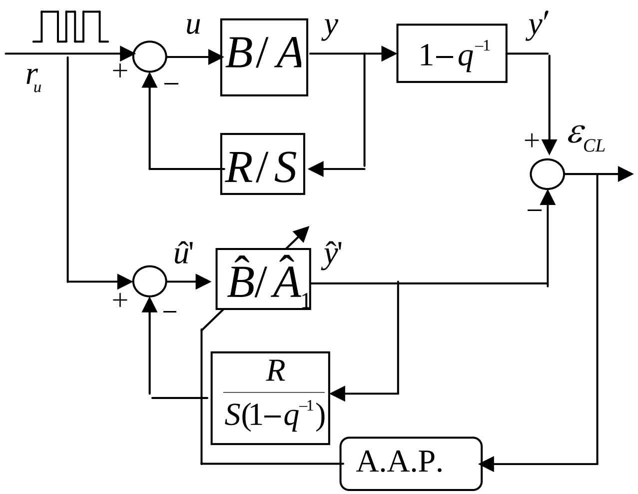
- A MATLAB Toolbox is available (CLID- see website))

-A stand alone software is available (WinPIM/Adaptech)

Appendix

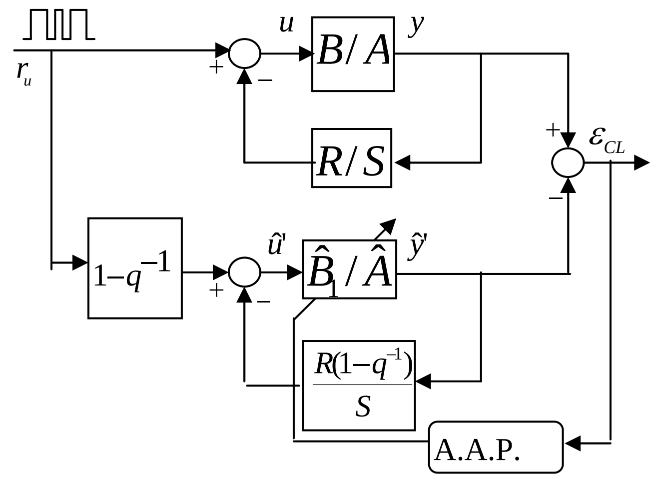
How to identify in closed loop systems with known parts ?

integrator



Replace the measured output by its variations

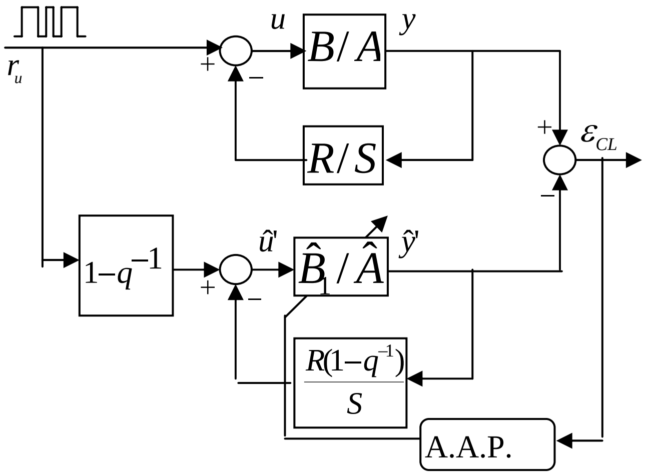
differentiator



Replace the input to the predictor by its variations

Attention :

- the controller in the predictor has to be modified
- one identifies the plant model without the fixed part


u
y
B/A
r_u
+
−
R/S
+
ε_{CL}
−
$1-q^{-1}$
$\hat{u}'$
$\hat{y}'$
$\hat{B}/\hat{A}$
+
−
$\frac{R(1-q^{-1})}{S}$
A.A.P.

CLID^{TM}
(Matlab) Toolbox for Closed Loop Identification

To be downloaded from the web site:
http//:landau-bookic.lag.ensieg.inpg.fr

- files(.p and.m)
- examples (type :democlid)
- help.htm files (condensed manual)

CLID Toolbox

```
>> help clid
```

CLOSED LOOP IDENTIFICATION MODULE
by :
ADAPTECH
4 rue du Tour de l'Eau, 38400 Saint Martin d'Heres, France
info@adaptech.com
Copyright by Adaptech, 1997-1999

List of functions

cloe - Closed Loop Output Error Identification

fcloe - Filtered Closed Loop Output Error Identification

afcloe - Adaptive Filtered Closed Loop Output Error Identification

xcloe - Extended Closed Output Error Identification

clvalid - Validation of Models Identified in Closed Loop using also Vinnicombe gap

clie - Closed Loop Input Error Identification

>> help cloe

CLOE is used to identify a discrete time model of a plant operating in closed-loop with an RST controller based on the CLOE method.

[B,A]=cloe(y,r,na,nb,d,R,S,T,Fin,lam1,lam0)

y and r are the column vectors containing respectively the output and the excitation signal.

na, nb are the order of the polynomials A,B and d is the pure time delay

R, S and T are the column vectors containing the parameters of a two degree of freedom controller. S*u(t)=-R*y(t)+T*r(t)
Remark: when the excitation signal is added to the measured output (i.e. the controller is in feedforward with unit feedback) we have T=R and when the excitation signal is added to the control input (i.e. the controller is in feedback) we have T=S.

Fin is the initial gain F0=Fin*(na+nb)*eye(na+nb) (Fin=1000 by default)

lam1 and lam0 make different adaptation algoritms as follows:

lam1=1;lam0=1 :decreasing gain (default algorithm)
0.95<lam1<1;lam0=1 :decreasing gain with fixed forgetting factor
0.95<lam1,lam0<1 :decreasing gain with variable forgetting factor

See also FCLOE, AFCLOE, XCLOE and CLVALID.
Copyright by Adaptech, 1997-1999

CLOE – closed loop output error identification function

>> help cloe

Model Polynomials (identified)

Model orders

Initial adaption gain (Fin=1000 by default)

[B,A]=cloe(y,r,na,nb,d,R,S,T,Fin,lam1,lam0)

Measured output

Excitation

Controller Polynomials

λ_1

λ_0

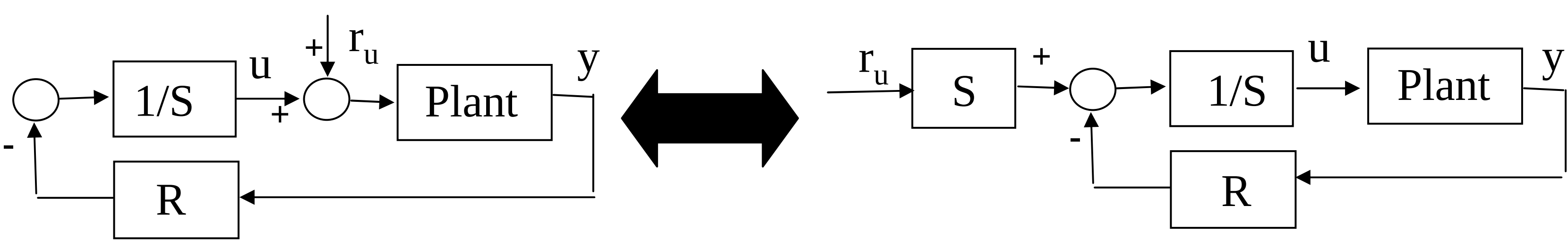
lam1=1;lam0=1 : decreasing gain (default algorithm)

0.95<lam1<1; lam0=1 : decreasing gain with fixed forgetting factor

0.95<lam1,lam0<1 : decreasing gain with variable forgetting factor

•Excitation superposed to the reference: ***Need to specify R, S and T***

• Excitation superposed to the controller output (i.e. plant input): ***Need to take T=S***



CLVALID – closed loop model validation function

>> help clvalid

[lossf,gap,Pcal,Piden,yhat]=clvalid(B,A,R,S,T,y,r,pcl)

B,A: Model Polynomials (identified)

R,S: Controller Polynomials

lossf : $\frac{1}{N}\sum_{1}^{N}\left[y(t)-\hat{y}(t)\right]^2$

gap : Vinnicombe gap metric between *identified* and *computed* closed loop transfer function (BT/P)

Pcal : Computed closed loop poles by given model and controller

Piden : Identified closed loop poles from [y r] data

yhat : Closed loop estimated output

pcl = 1 : performs pole closeness validation (poles map display)
pcl =0; default

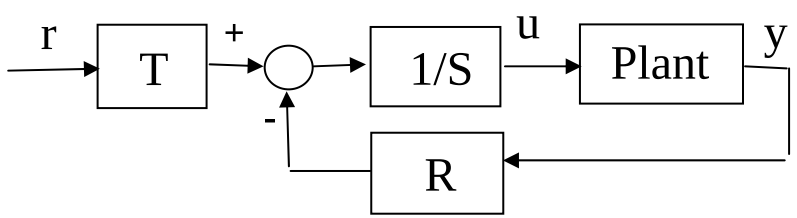
Display also the normalized cross corelations $(r,\hat{y})$
Plots : cross correlations, autocorrelations (validation of the closed loop identified model), identified and computed closed loop transfer function, identified and computed poles

DEMOCLID –demo function

>> democlid

Load excitation(r) (PRBS), output data (y) controller and values for Fin (=1000), lam1(= 1), lam0(= 0)

Data are generated in closed loop with a RST controller
The external excitation is superposed to the reference



Plant model
for data generation
(simubf4.mat)
(r,y,u)

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

$$A(q^{-1}) = 1 - 1.5q^{-1} + 0.7q^{-2}\ ;\quad B(q^{-1}) = q^{-1} + 0.5q^{-2}\ ;\quad d = 0$$

$$C(q^{-1}) = 1 + 1.6q^{-1} + 0.9q^{-2}$$

Controller
for data generation
(simubf_rst.mat)

$$R(q^{-1}) = 0.8659 - 1.2763q^{-1} + 0.5204q^{-2}$$

$$S(q^{-1}) = 1 - 0.6283q^{-1} - 0.3717q^{-2}$$

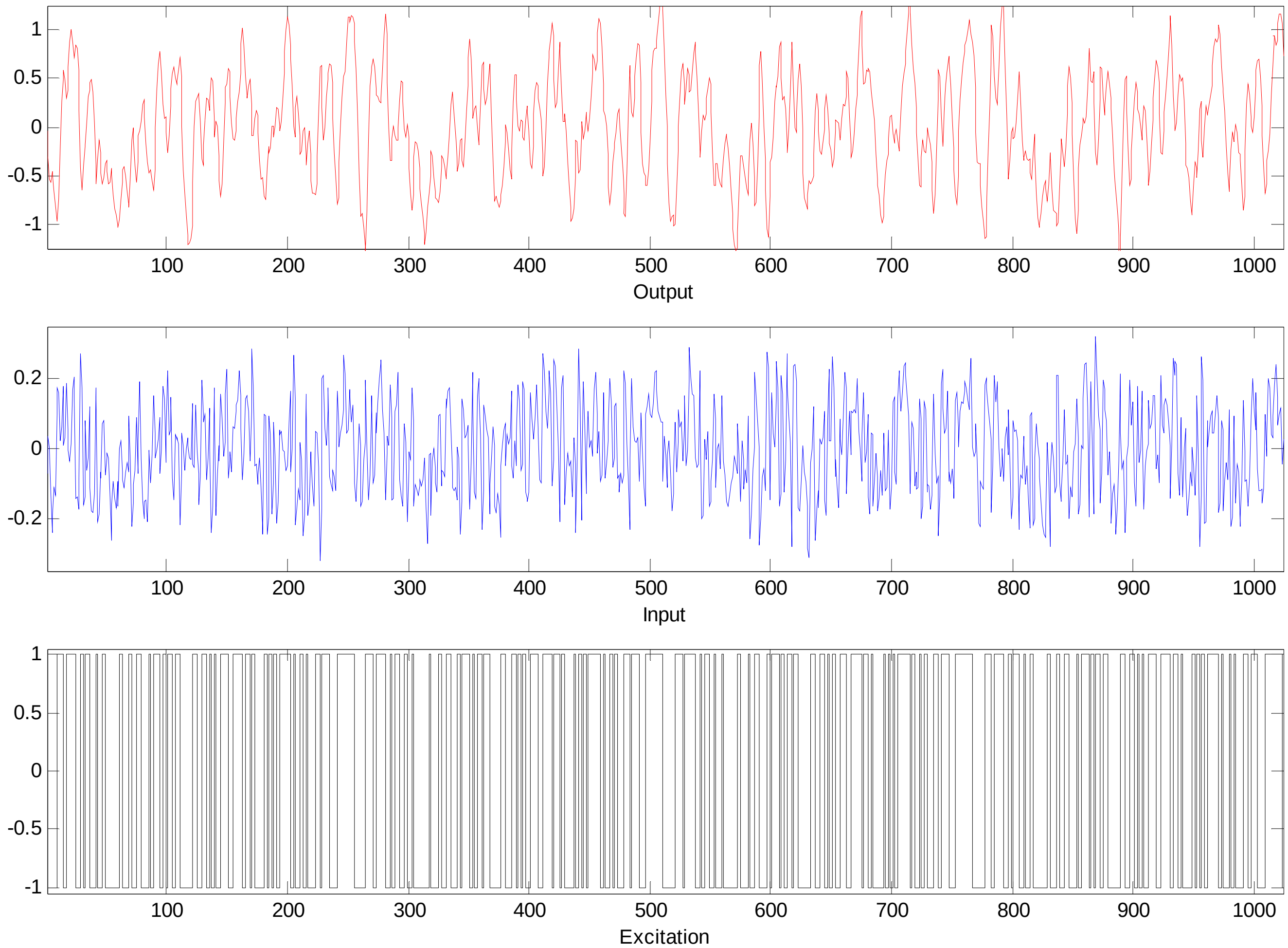
$$T(q^{-1}) = 0.11$$

File SIMUBF

Output (y)

Plant input (u)

External excitation (r)



Excitation superposed to the reference

Identification results

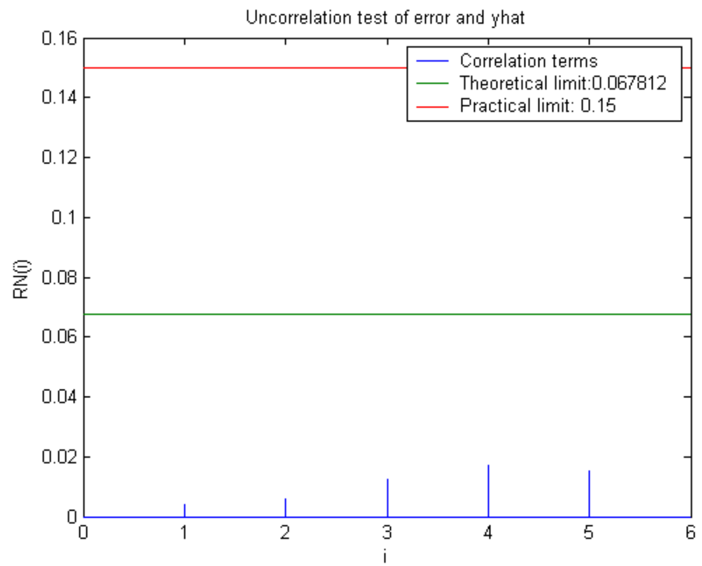
CLOE

```
>> [B,A]=cloe(y,r,na,nb,d,R,S,T,Fin,lam1,lam0)

B =

        0    0.9527    0.4900


A =

    1.0000   -1.4808    0.6716
```

AF-CLOE

```
>> [B,A]=afcloe(y,r,na,nb,d,R,S,T,Fin,lam1,lam0)

B =

        0    0.9684    0.4722


A =

    1.0000   -1.4844    0.6821
```

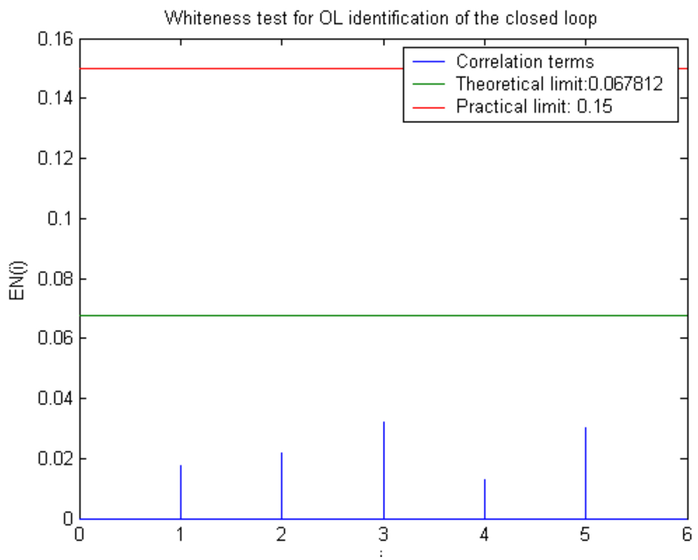
Statistical Validation of the model identified in closed loop



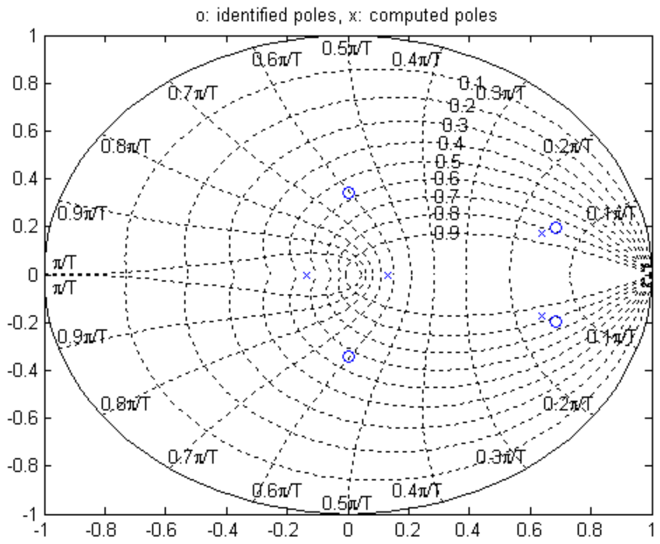
Model of the plant identified in closed loop with AF-CLOE

Is OK. $$|RN(i)| \leq \frac{2.17}{\sqrt{N}} = \frac{2.17}{\sqrt{1024}} = 0.0678; \quad i \geq 1$$

Poles closeness validation and ν-gap validation



Stochactic validation of the identified model of the closed loop
Is OK.
Can be used for poles closeness validation and ν-gap validation



Poles map
o identifed poles of the true CL system
x computed poles of the simulated CL system
Is OK

ν–gap = 0.0105 (min = 0, max =1)

File SIMUBF – comparison of identified models

Closed Loop Statistical Validation

Méthod	a_1	a_2	b_1	b_2	CL Error Varaince R(0)	Normalized Intercorrelations (validation bound 0.068) |RN(max)|.
Nominal Model	-1.5	0.7	1	0.5		
AF-CLOE	-1.4689	0.6699	0.991	0.5276	0.03176	0.0092
CLOE	-1.476	0.6674	0.9592	0.4862	0.03181	0.0284
F-CLOE	-1.4692	0.6704	0.9591	0.5152	0.03175	0.0085
X-CLOE	-1.49	0.6822	0.9668	0.3775	0.0312	0.0237
OL type identification (RLS.)	-1.3991	0.6034	0.975	0.508	0.0323	0.0843

Best results (F-CLOE)

Open loop type identification
(between u and y ignoring the controller)

« Personal » References

Books:

I.D. Landau,G.Zito, "Digital Control Systems – design, identification and implementation" (chapter 9), Springer, London, 2005

I.D. Landau, R. Lozano, M.M'Saad "Adaptive Control", Springer, London 1997

I.D.Landau "Commande de Systèmes - conception, identification et mise en oeuvre" Hermès, Paris, Juin 2002 (Chapter 9)

I.D.Landau, A. Besançon (Editors) "Identification des Systèmes", Traité des Nouvelles Technologies, Hermès, Paris,2001

Web site:

http://landau-bookic.lag.ensieg.inpg.fr

« Slides » for chapters and tutorial can be downloaded
Free routines (matlab, scilab) can be downloaded (including CLID)

« Personal » References

Papers:

Landau I.D., Karimi A., (1997) : « Recursive algorithms for identification in closed -loop – a unified approach and evaluation », *Automatica*, vol. 33, no. 8, pp. 1499-1523.

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Karimi A., Landau I.D.(1998): ”Comparison of the closed-loop identification methods in terms of the bias distribution" *Systems and Control Letters*, 34, 159-167, 1998

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Landau I.D., (2001) : « Identification in closed loop : a powerful design tool (better models, simpler controllers) », *Control Engineering Practice*, vol. 9, no.1, pp.51- 65.

J.Langer,I.D.Landau (1996): “Improvement of robust digital control by identification in the closed loop. Application to a 360° flexible arm” *CEP*, vol 4,no 12, pp. 1637-1646,

I.D.Landau, A. Karimi (1999): "A recursive algorithm for ARMAX model identification in closed loop" IEEE Trans. on Automatic Control 44, 840-843,

I.D. Landau, A.Karimi, (2002) :« A unified approach to closed-loop plant identification and direct controller reduction », *European J. of Control*, vol.8, no.6

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L. Ljung(2002), *System Identification*, Prentice Hall, N.J.2nd ed. 2002

M. Gevers(1993) “Towards a joint design of identification and control” (ECC 93), in (H. Trentelman,J. Willems eds) “*Essays on Control: perspectives in the theory and its application*”, Birkhauser, Boston, pp 111-152

M.Gevers (2004) “Identification for control. Achievements and open problems”. Proc. 7th IFAC Symp. on Dynamics and control of process systems(DYCOPS 2004), Cambridge, Mass. USA, July *(contains an extensive list of references for the interaction between identification and control)*

P.M. Van den Hof, P. Shrama(1995) “Identification and control – closed-loop issues”, *Automatica* 31(12), 1751-1770