IDENTIFICATION IN CLOSED LOOP
A powerful design tool
(better models, simpler controllers)

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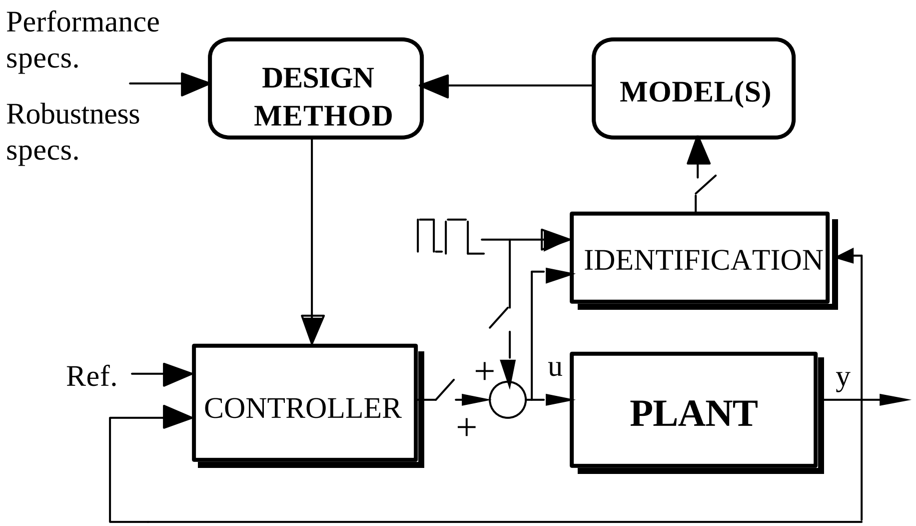
Outline

- Introduction
- An example (flexible transmission)
- Objectives of identification in closed loop
- Basic Schemes
- The CLOE Algorithms (closed loop output error)
- Properties of the algorithms
- Properties of the estimated models
- Validation of models identified in closed loop
- Iterative identification in c. l. and controller re-design
- Experimental results (flexible transmission)
- Filtered open loop identification algorithms
- Conclusions

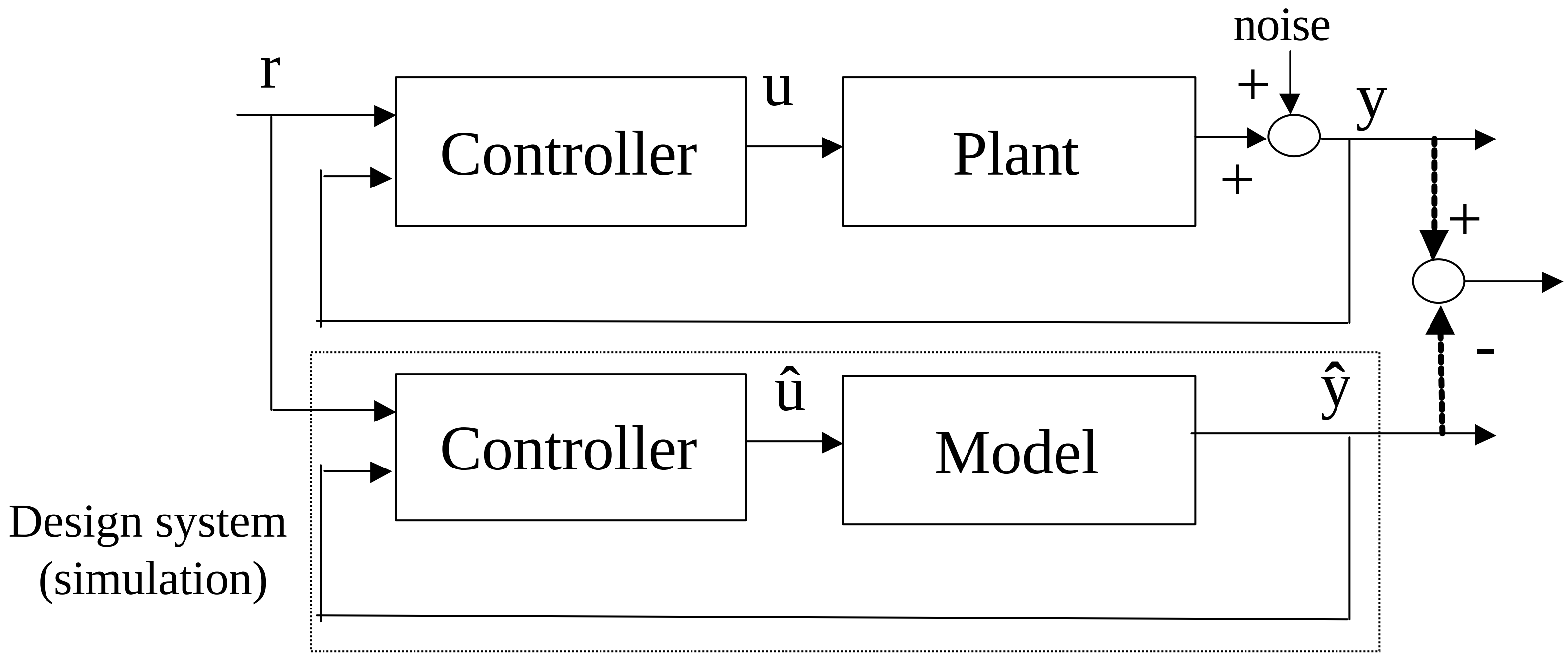
Controller Design and Validation



1) Identification of the dynamic model
2) Performance and robustness specifications
3) Compatible controller design method
4) Controller implementation
5) Real-time controller validation
   (and on site re-tuning)
6) Controller maintenance (same as 5)

(5) and (6) require
identification in closed-loop

Real-Time Controller Validation



Comparison of « achieved » and « desired » performances

A useful interpretation :

Check to what extent the **model** used for design allows achievement of:
- desired nominal performances
- desired robustness specs.(sensitivity functions)

Real-Time Controller Validation

If the results are not satisfactory:

Plant model identification in *closed loop*
+
Controller redesign

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

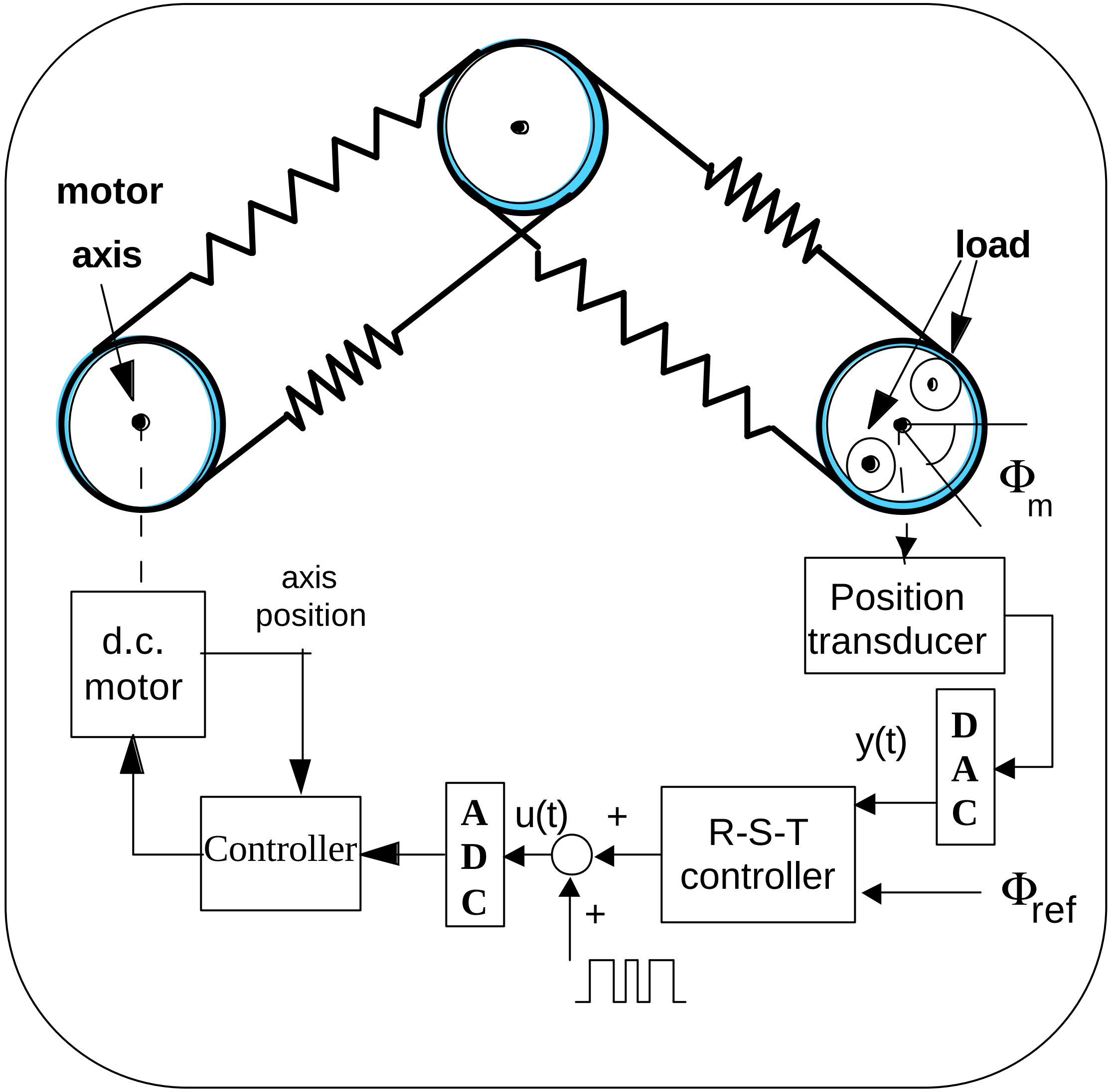
Iterative identification and controller redesign

May provide better « design » models

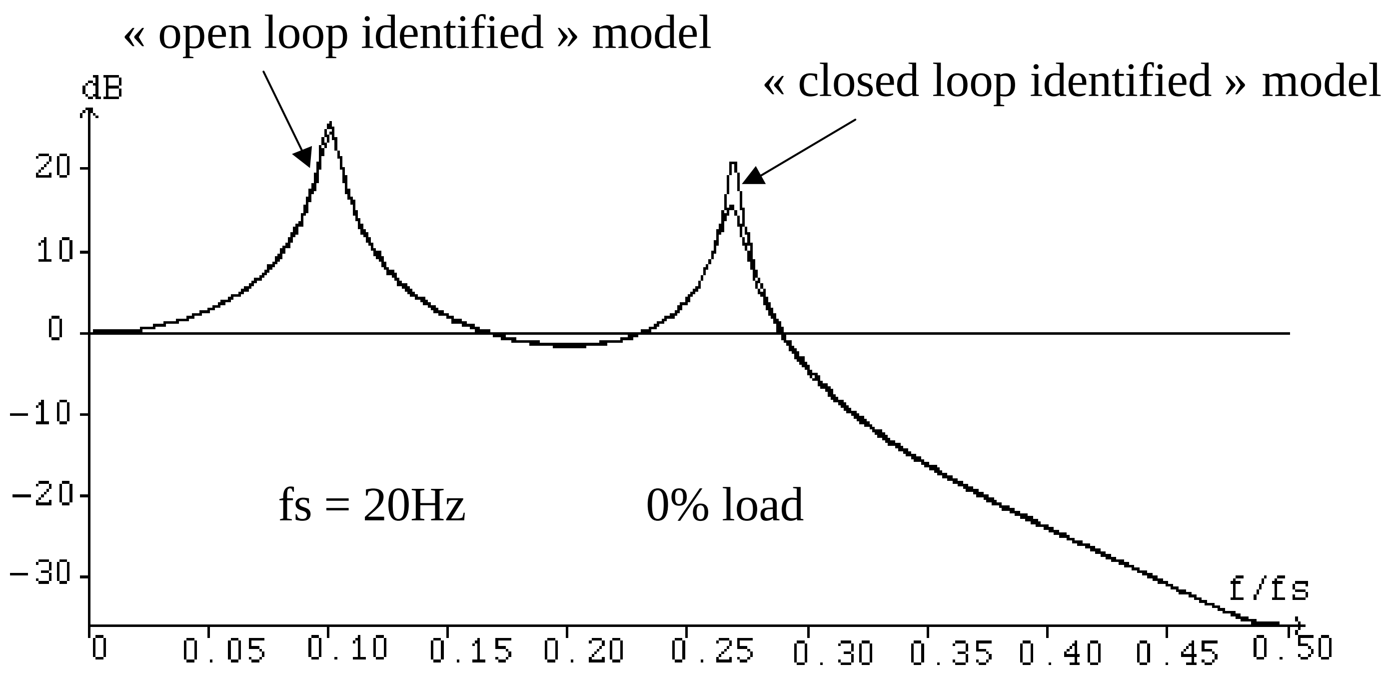
Cannot be dissociated from the controller and robustness issues

Identification in Closed Loop

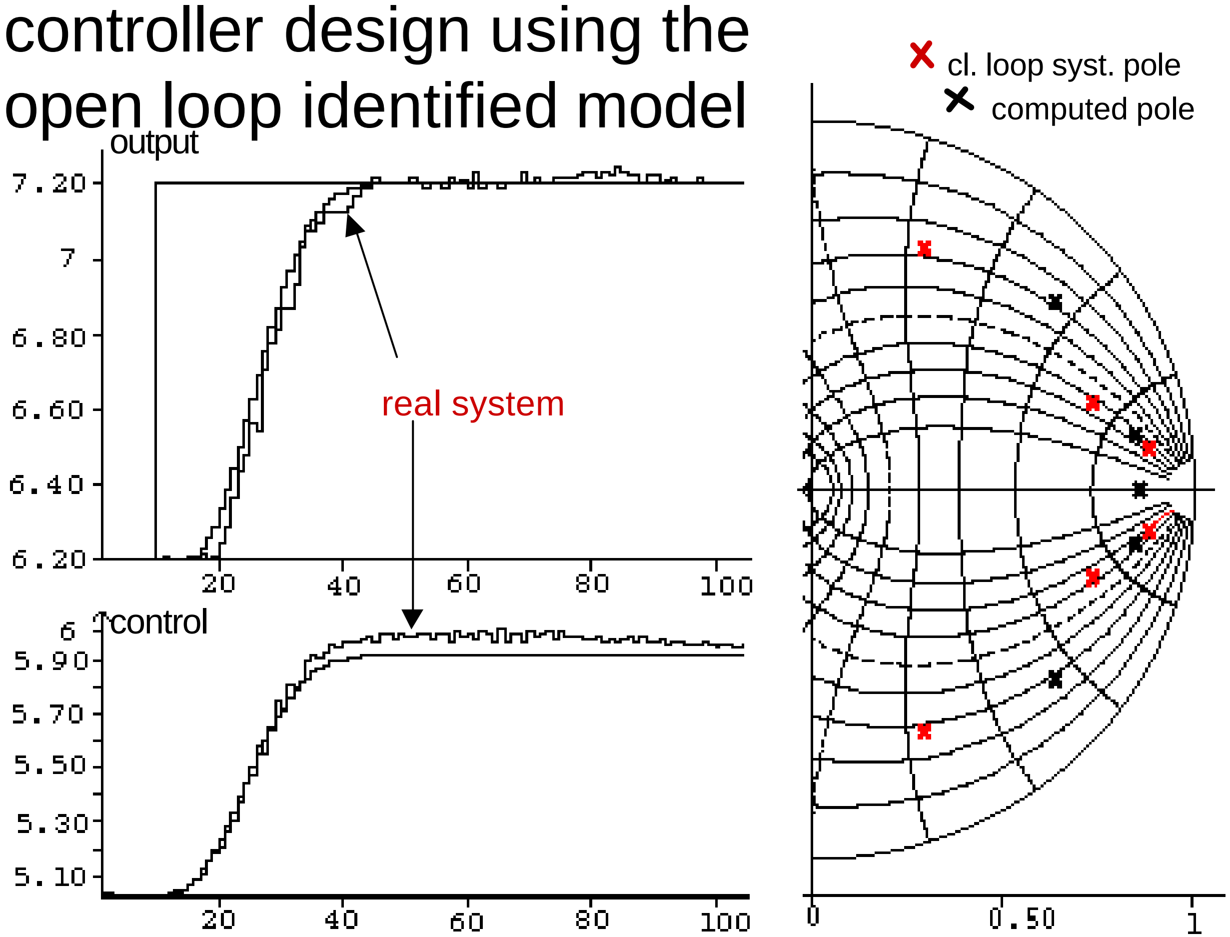
The flexible transmission



What is the *good* model ?

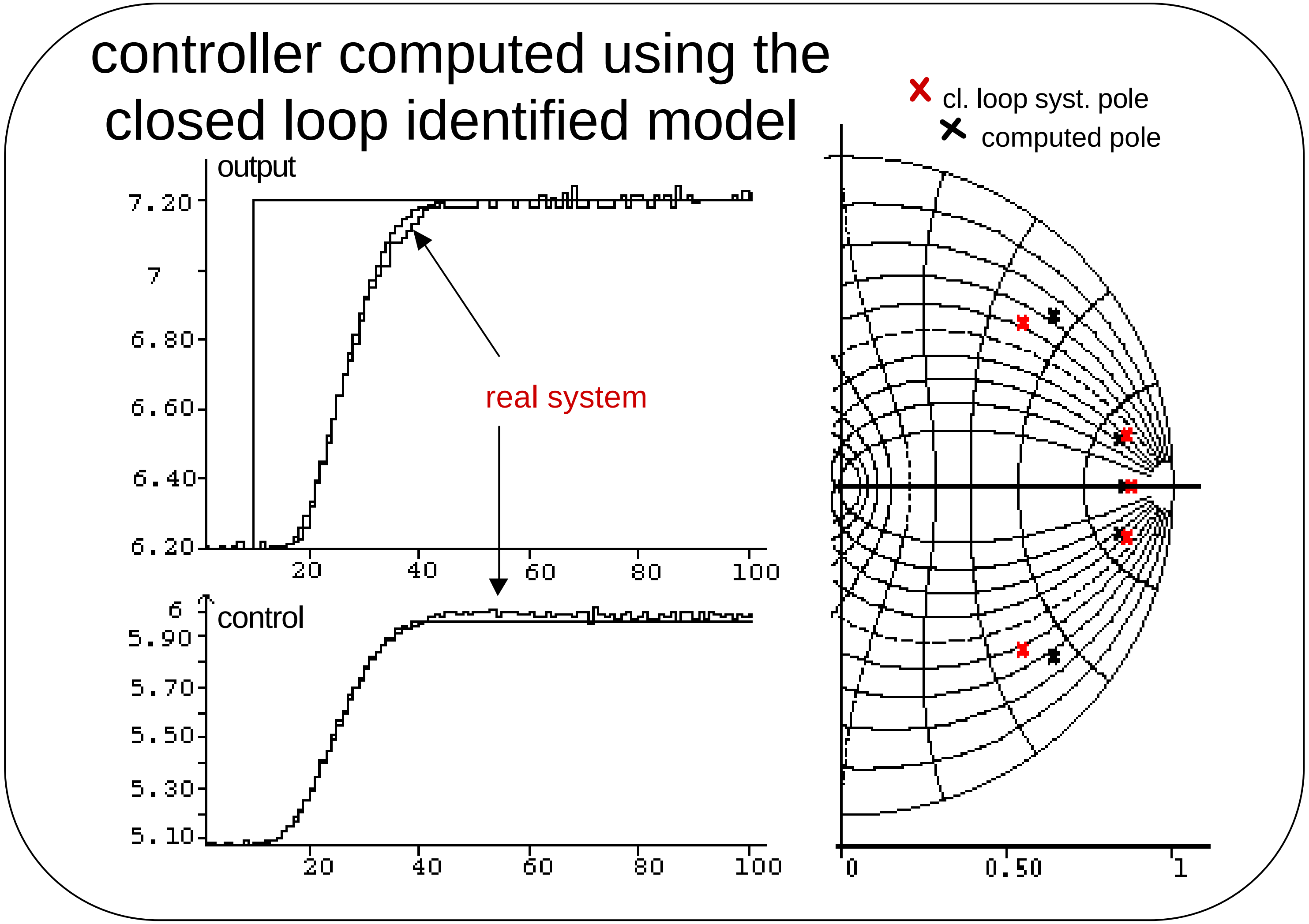


Benefits of identification in closed loop (1)



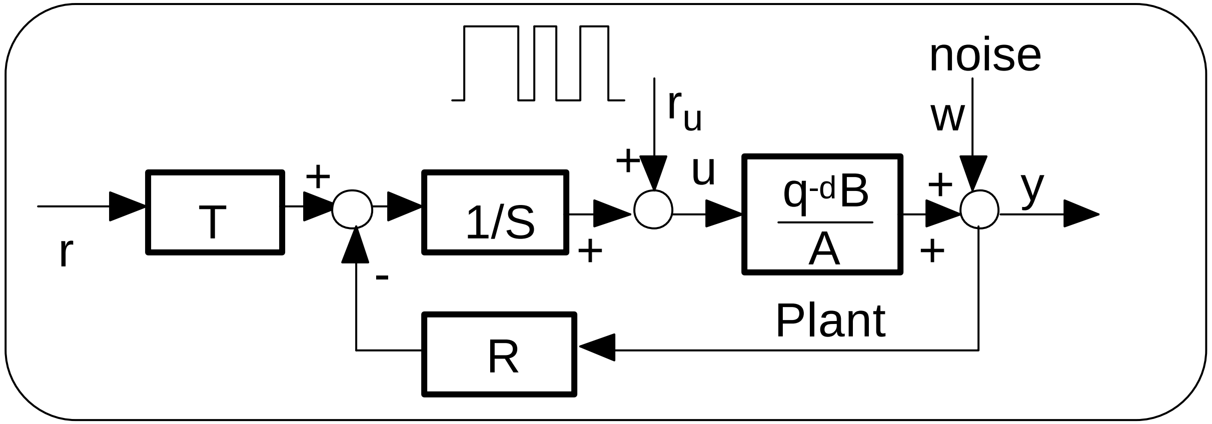
The pattern of *identified closed loop poles* is different from the pattern of *computed closed loop poles*

Benefits of identification in closed loop (2)

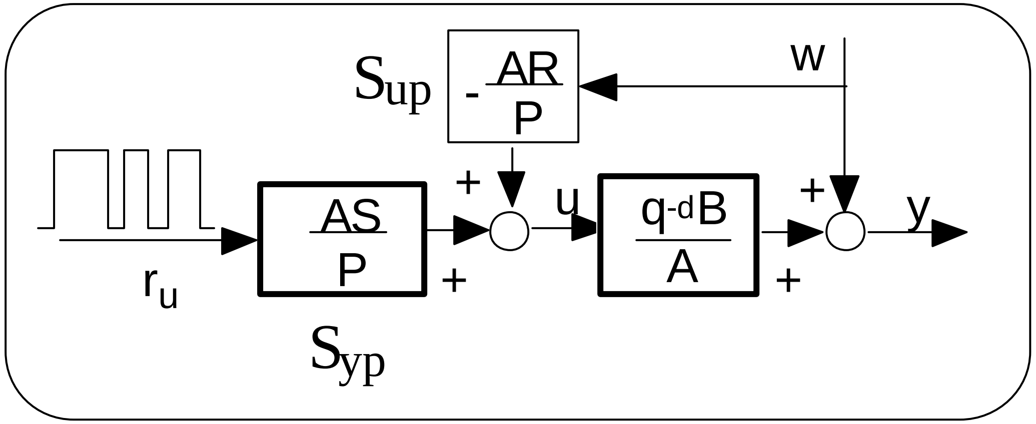


The *computed* and the *identified* closed loop poles are very close

Identification in Closed Loop



Open loop interpetation



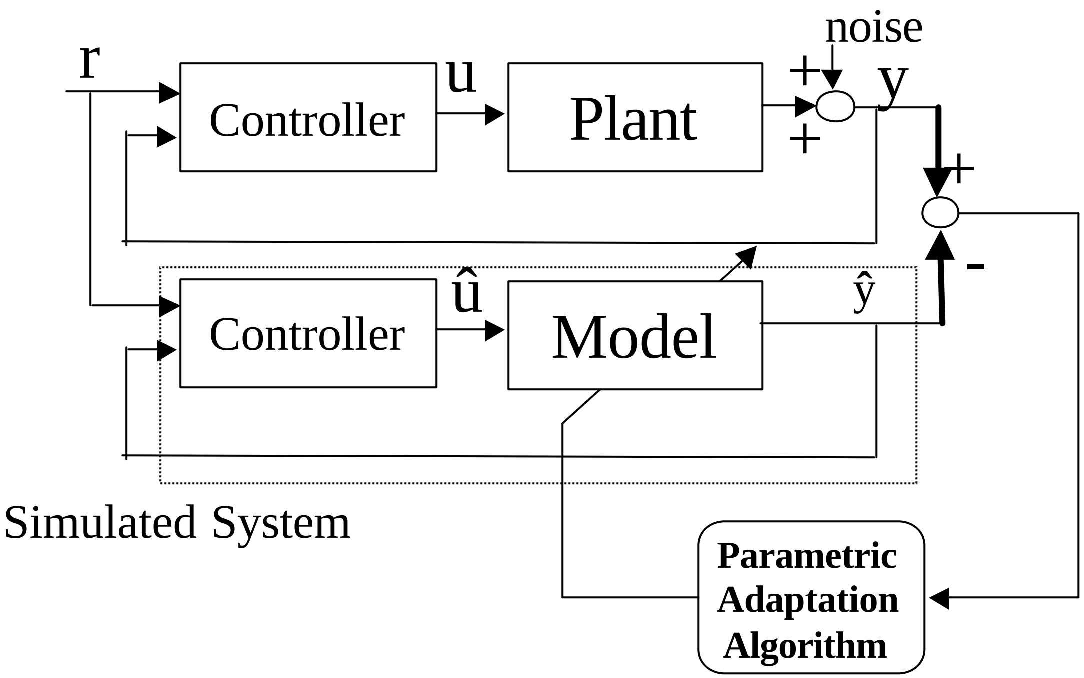
Objective : development of algorithms which:

- 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.

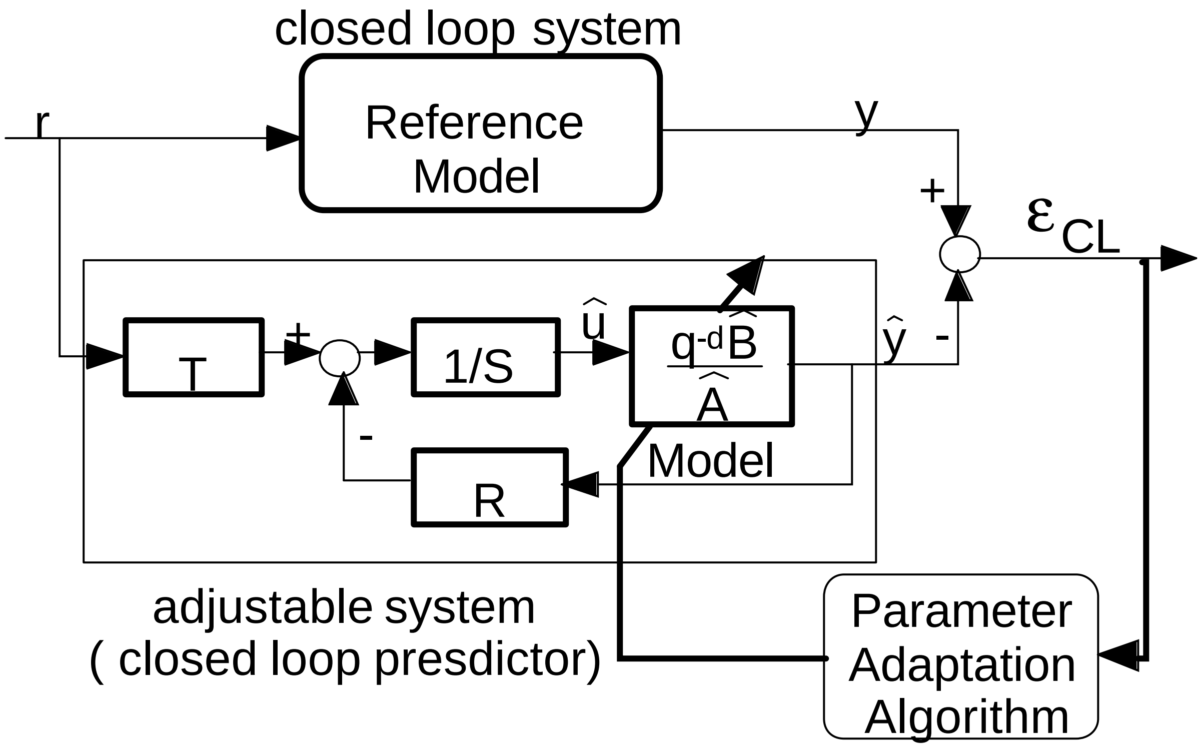


CLOE Algorithms

Closed Loop Output Error

Identification in Closed Loop

- *M.R.A.S. point of view :*

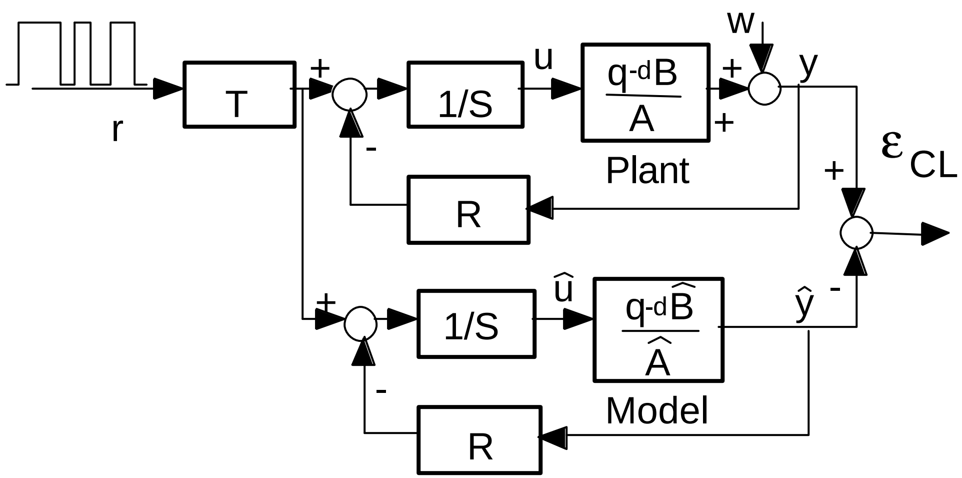


- *Identification point of view :*

A re-parametrized adjustable predictor of the closed loop

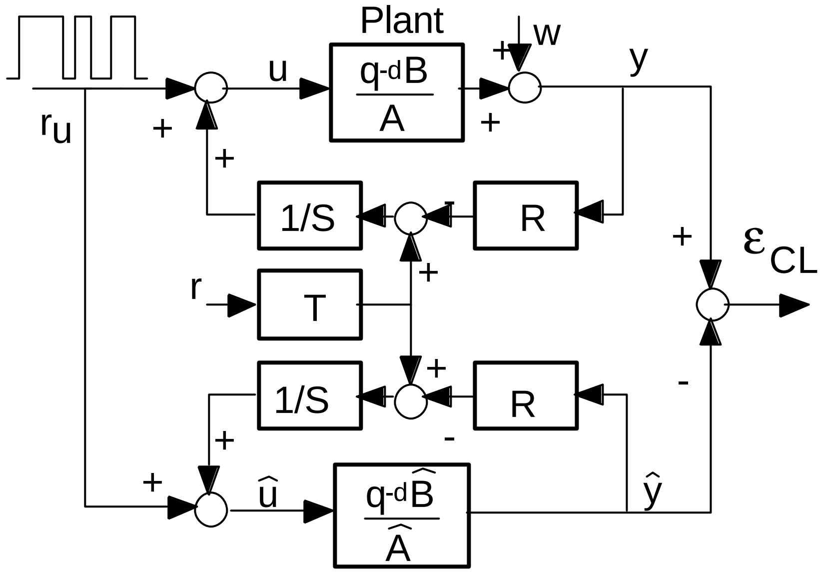
Closed Loop Output Error Identification Algorithms (CLOE)

Excitation added to reference signal



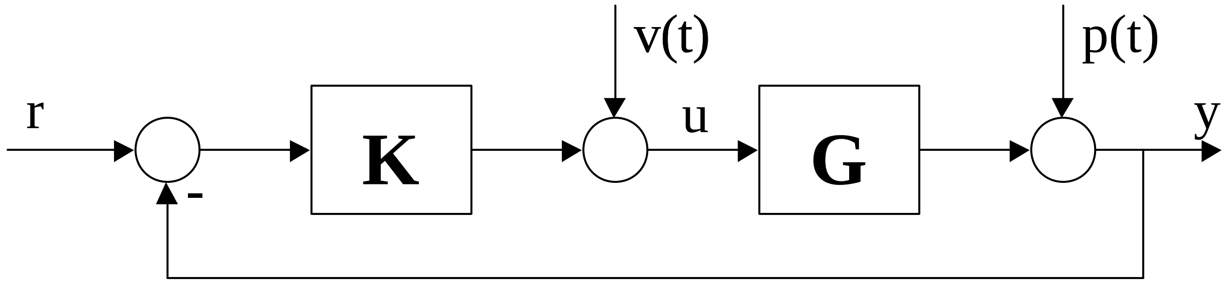
$$u = -\frac{R}{S}y + \frac{T}{S}r \qquad \hat{u} = -\frac{R}{S}\hat{y} + \frac{T}{S}r$$

Excitation added to controller output



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

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 :

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

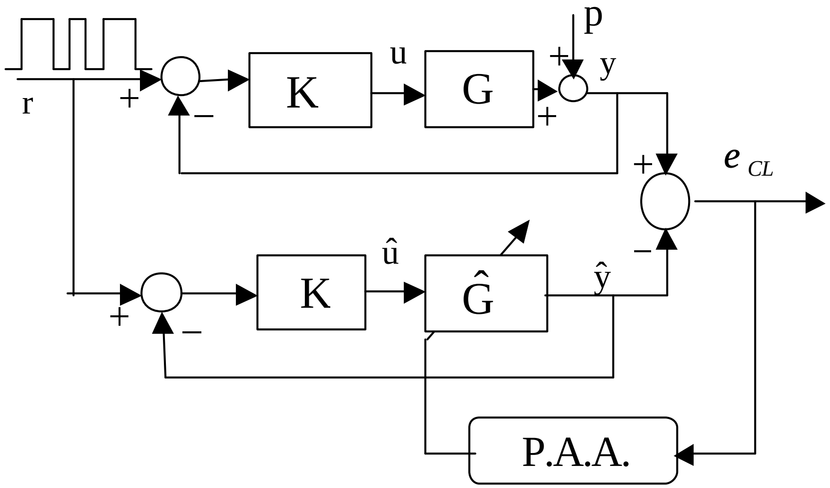
Closed loop poles : $P(z^{-1}) = A(z^{-1})S(z^{-1}) + z^{-d}B(z^{-1})R(z^{-1})$

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

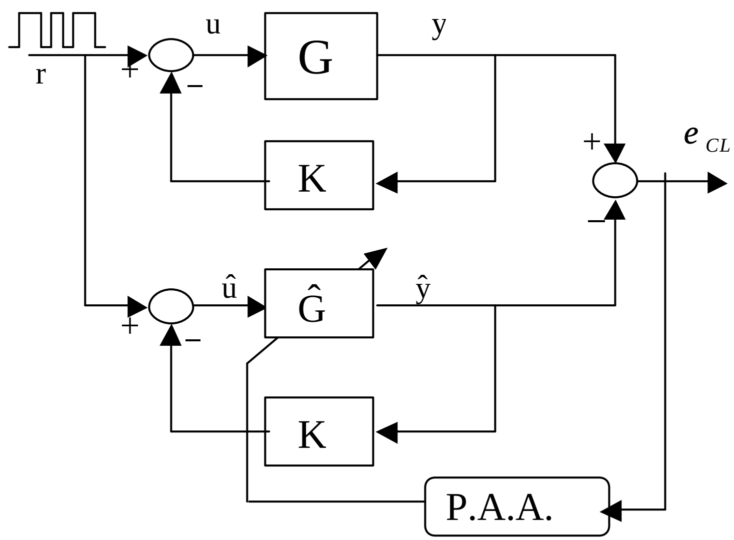
Nominal simulated(estimated) closed loop : $(K,\hat{G}), \hat{P}, \hat{S}_{xy}$

Closed Loop Output Error Identification Algorithms (CLOE)

Excitation added to reference signal

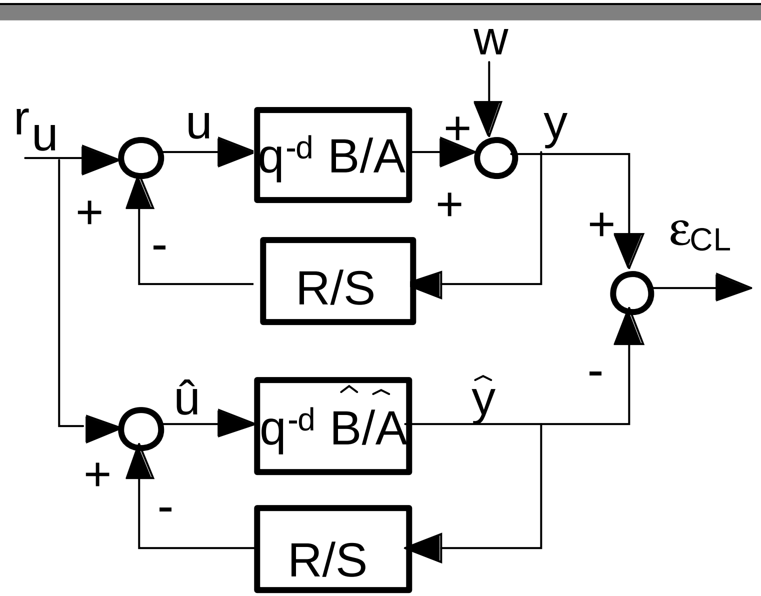


Excitation added to controller output



Same algorithm but different properties of the estimated model

Closed Loop Output Error Algorithms (CLOE)



The closed loop system:

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

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

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

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

CLOE

Adjustable predictor (closed loop)

$$\hat{y}^{\circ}(t+1) = \hat{q}^{T}(t)f(t) \qquad \hat{y}(t+1) = \hat{q}^{T}(t+1)f(t)$$

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

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

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

The Parameter Adaptation Algorithm

$$e^{0}_{CL}(t+1) = y(t+1) - \hat{q}^{T}(t)f(t) = y(t+1) - \hat{y}^{0}(t+1)$$

$$\hat{q}(t+1) = \hat{q}(t) + F(t+1)\Phi(t)e^{0}_{CL}(t+1)$$

$$F^{-1}(t+1) = l_1(t)F^{-1}(t) + l_2(t)\Phi(t)\Phi^{T}(t)\ ;\ 0 < l_1(t) \leq 1\ ;\ 0 \leq l_2(t) < 2$$

$$\Phi(t) = f(t)$$

CLOE Algorithms

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

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

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

CLOE Properties

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

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

CLOE $S/P - l/2$
F-CLOE $\hat{P}/P - l/2$
AF-CLOE *none*

→ *Strictly positive real tr. fct.*

$$\max_t l_2(t) \leq l < 2$$

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

See the next slides

Properties of the Estimated Model (1)

Excitation added to controller output

$$\hat{q}^{*} = \arg\min_{q} \int_{-p}^{p} [\left|S_{yv} - \hat{S}_{yv}\right|^{2} f_{r}(w) + \left|S_{yp}\right|^{2} f_{p}(w)]dw$$

$$= \arg\min_{q} \int_{-p}^{p} \left|S_{yp}\right|^{2} [\left|G - \hat{G}\right|^{2} \left|\hat{S}_{yp}\right|^{2} f_{r}(w) + f_{p}(w)]dw$$

- $\hat{G}$ 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

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

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

- $\hat{G}$ 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

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.)

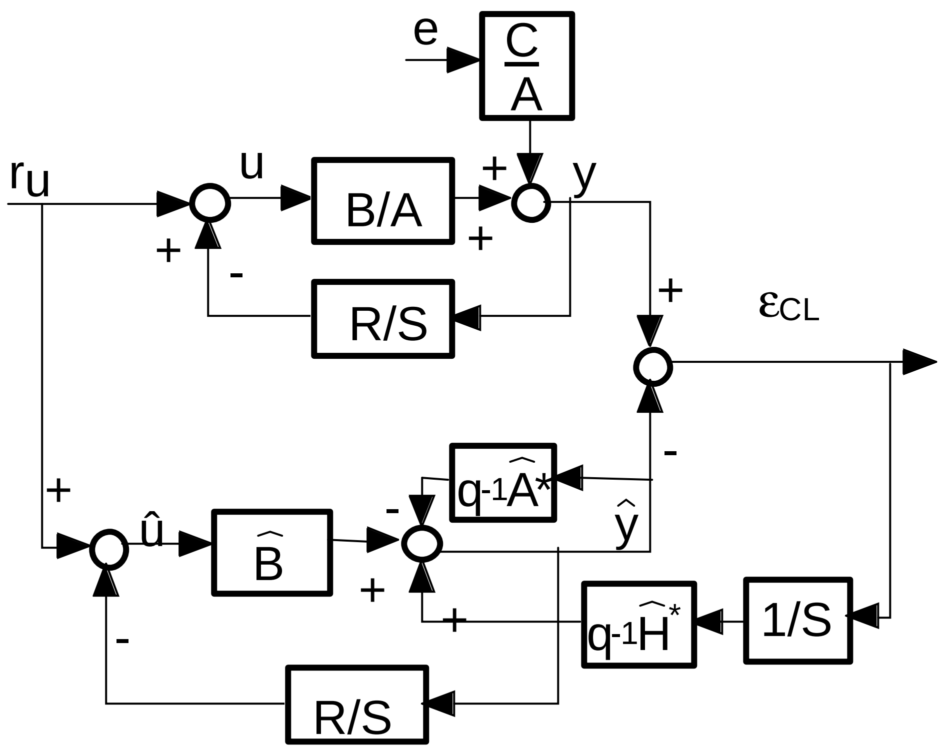
$$\text{CLOE} \quad \hat{q}^* = \arg\min_q \int_{-p}^{p} \left|S_{yp}\right|^2 [\left|G - \hat{G}\right|^2 \left|\hat{S}_{yp}\right|^2 f_r(w) + f_p(w)] dw$$

$$\text{OLOE} \quad \hat{q}^* = \arg\min_q \int_{-p}^{p} [\left|G - \hat{G}\right|^2 f_r(w) + f_p(w)] dw$$

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

Identification in Closed Loop of ARMAX Models

X-CLOE



Extended Closed Loop Output Error

Validation of Models Identified in Closed Loop

Controller dependent validation !

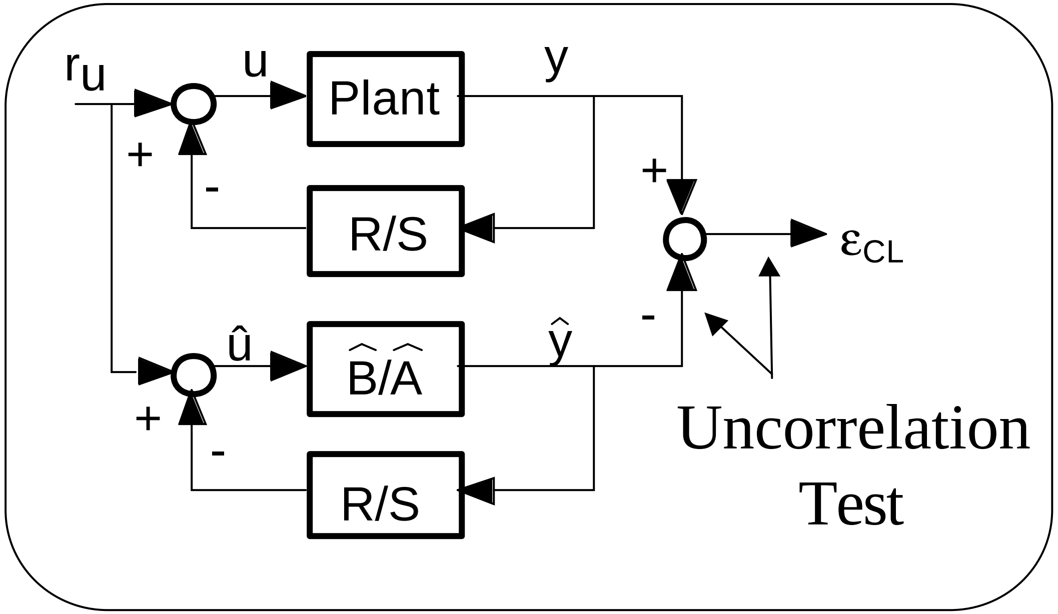
1) Statistical Model Validation

2) Pole Closeness Validation

3) Time Domain Validation

Identification in Closed Loop

Statisitical Model Validation

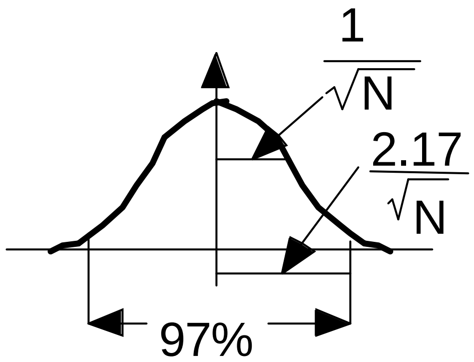


Controller dependent validation !

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

normalized crosscorelation

number of data



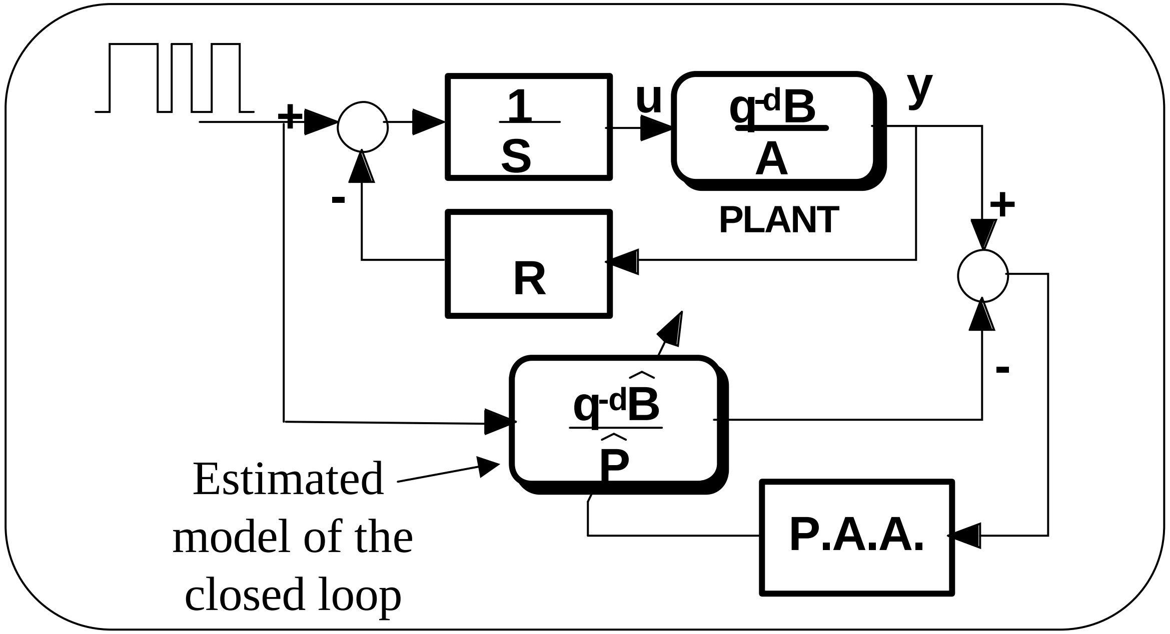
$$N = 256 \rightarrow |RN(i)| \leq 0.136$$

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

Identification in Closed Loop

Pole Closeness Validation

Closeness tests of achieved and desired (computed) *poles* and/or *sensitivity functions by* **identification of the closed loop**



Rem:

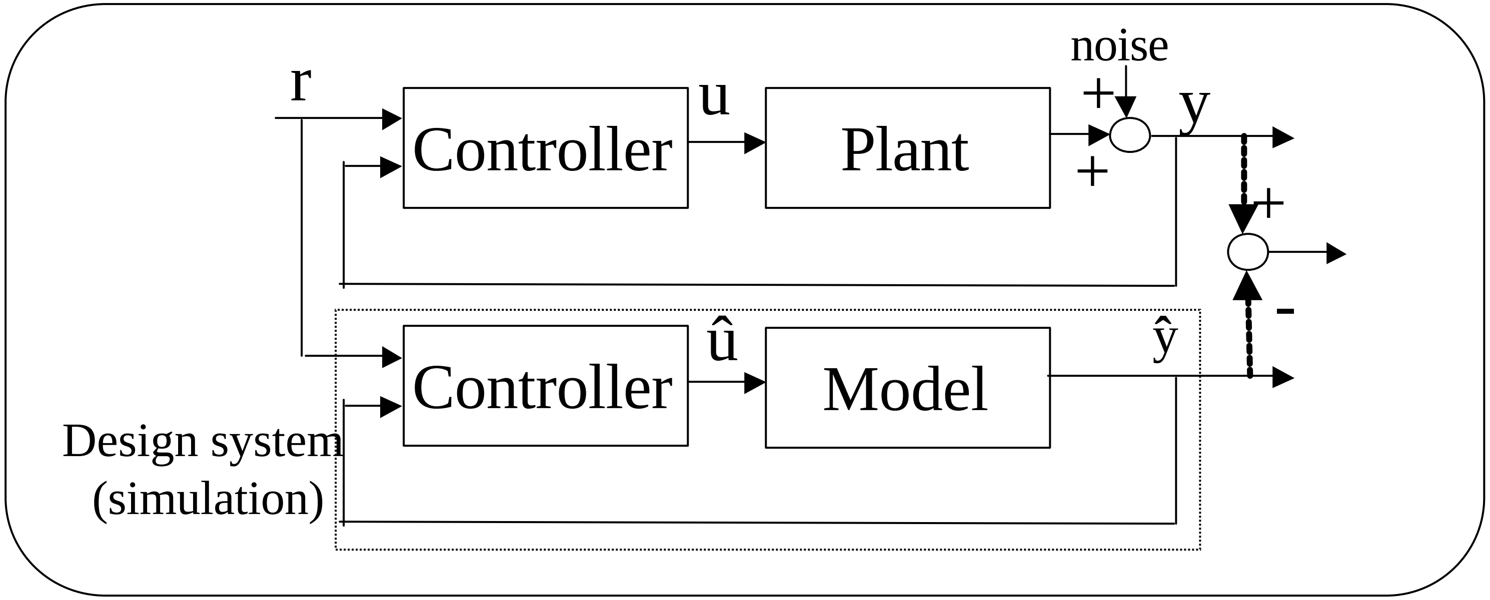
-use of open loop identification algorithms

-same signals as those used for the identification of the *plant model* in closed loop operation

Identification in Closed Loop

Time Domain Validation

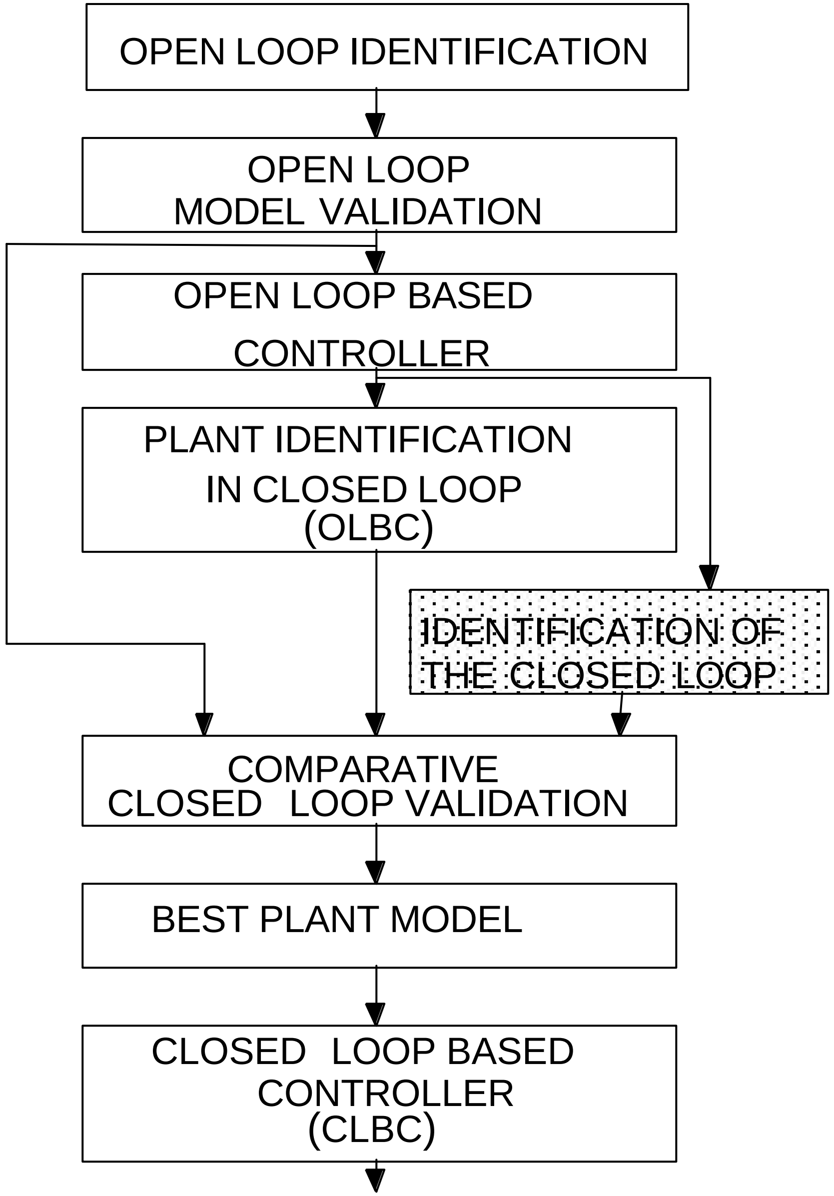
Comparison of « achieved » and « simulated » performance in the time domain



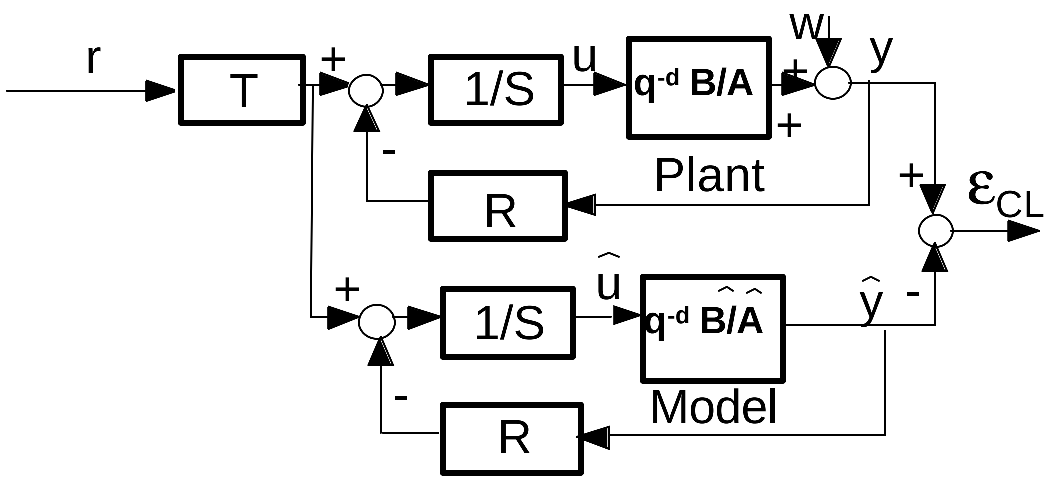
Rem:

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

Methodology of Plant Model Identification in Closed Loop



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,…

Experimental Results

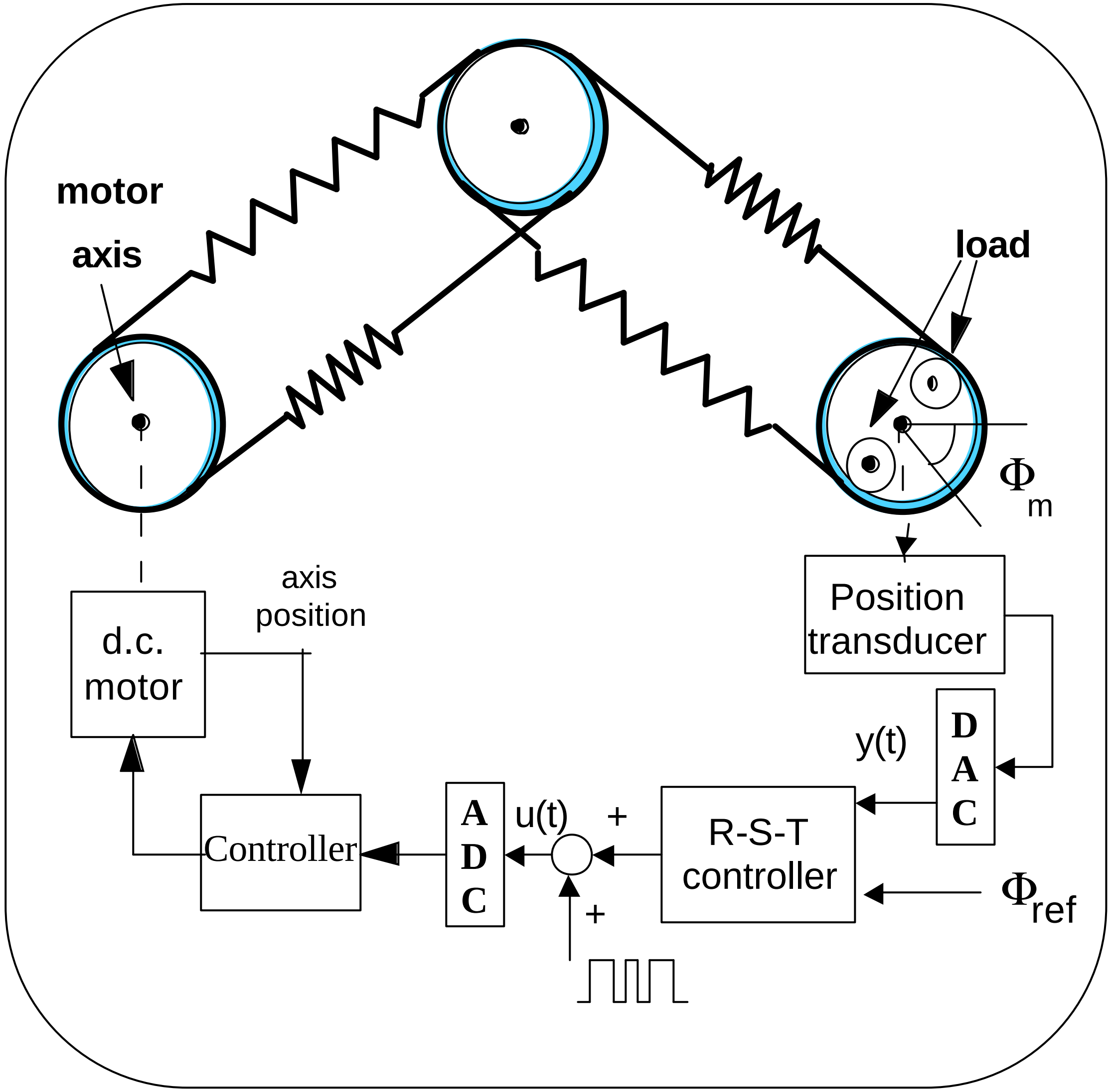
Identification in closed loop and controller re-design

for

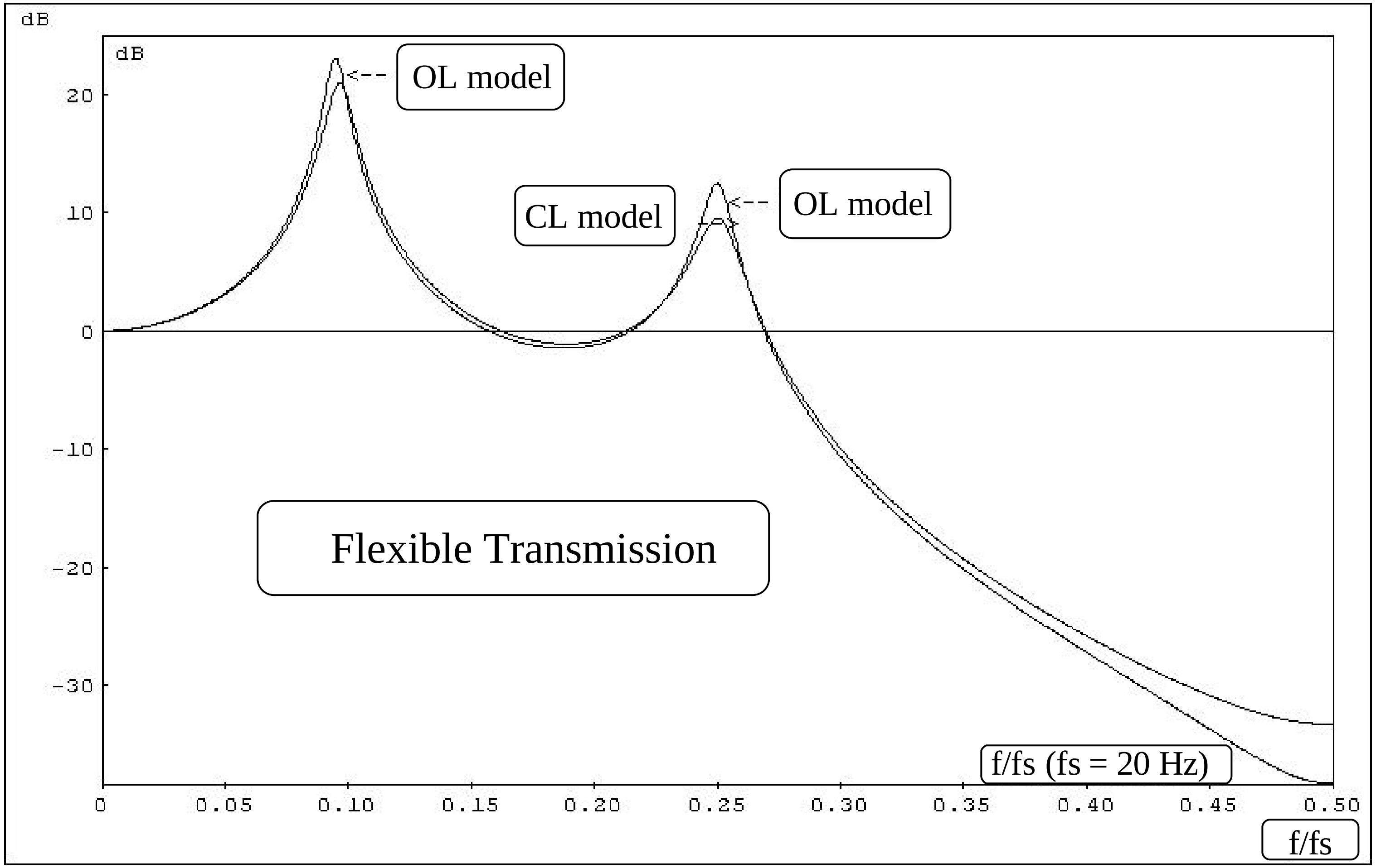
a flexible transmission

Identification in Closed Loop

The flexible transmission

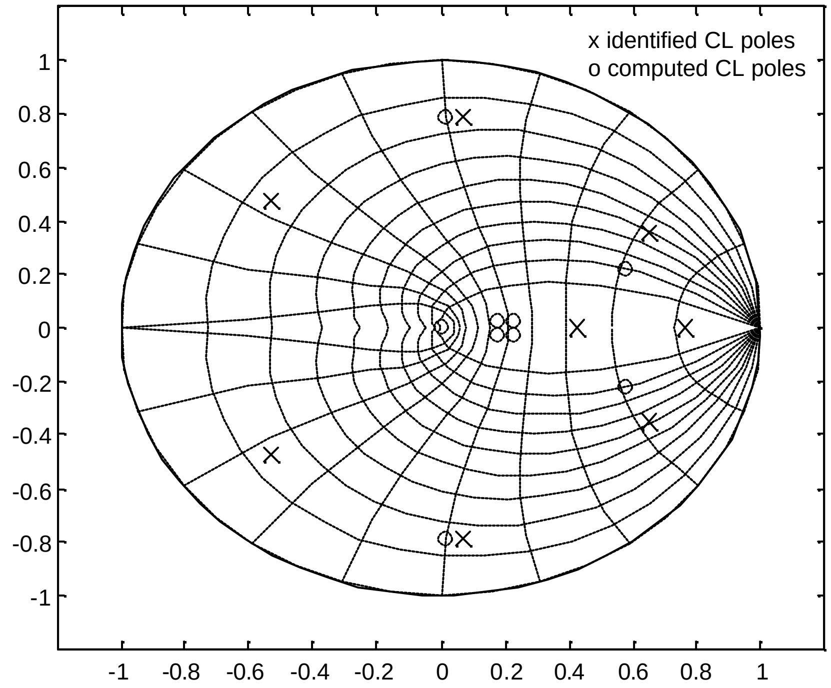


Flexible Tranmission
Frequency Characteristics of the Identified Models

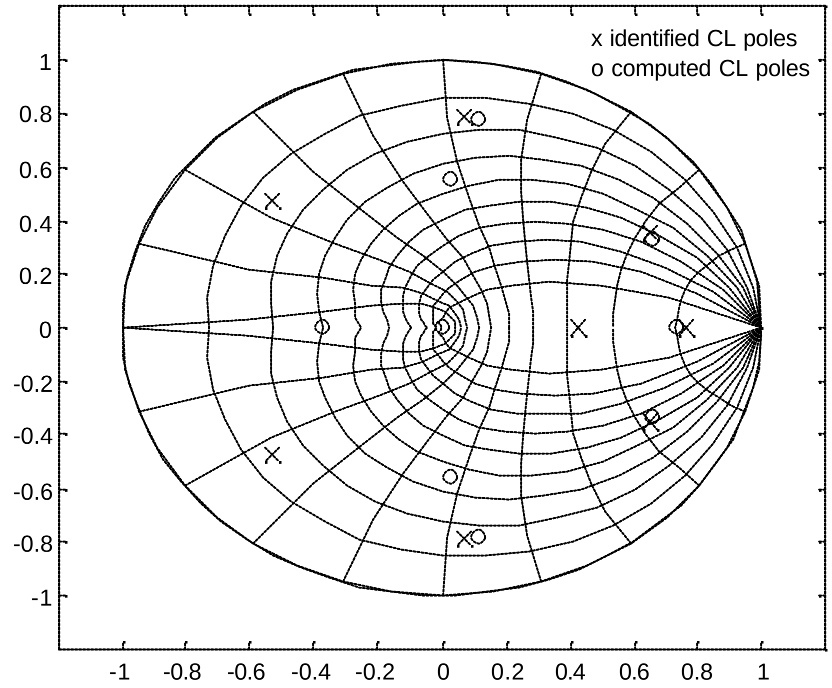


Model Validation in Closed Loop

Poles Closeness Validation



Model identified in open loop



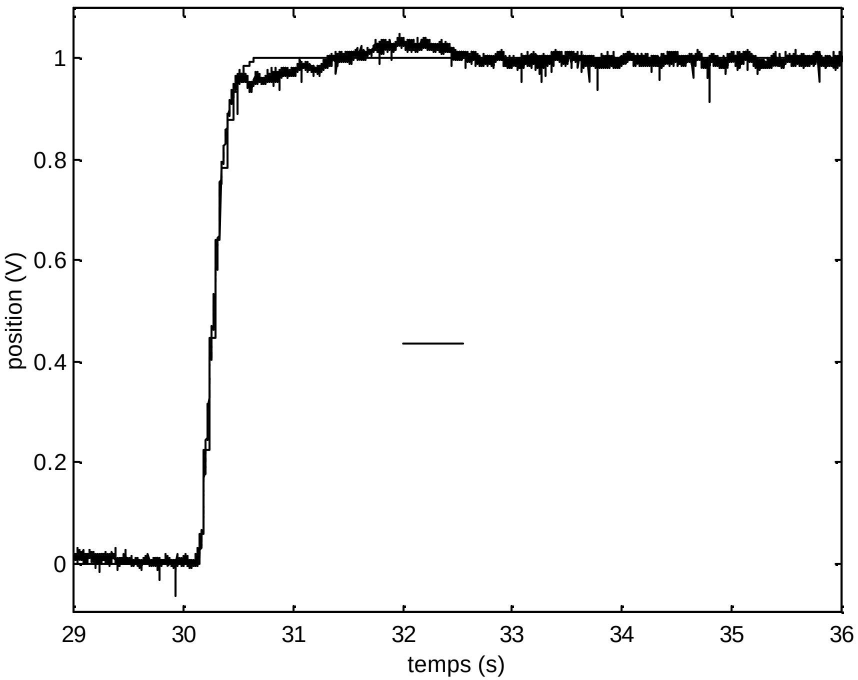
Model identified in closed loop

The model identified in closed loop provides « computed » poles closer to the « real » poles than the model identified open loop

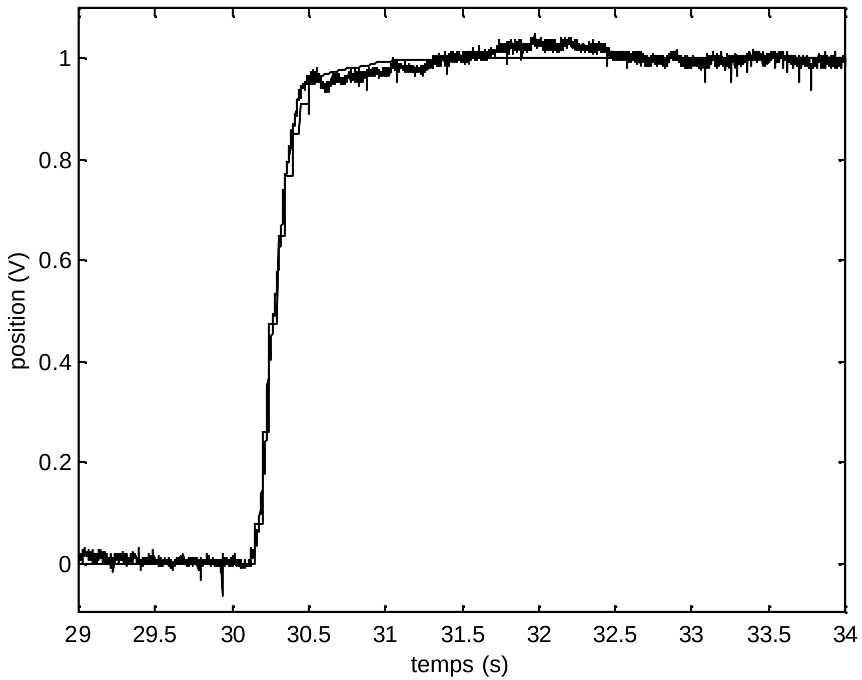
Model Validation in Closed Loop

Time Domain Validation

O.L.B.C.



Model identified in open loop

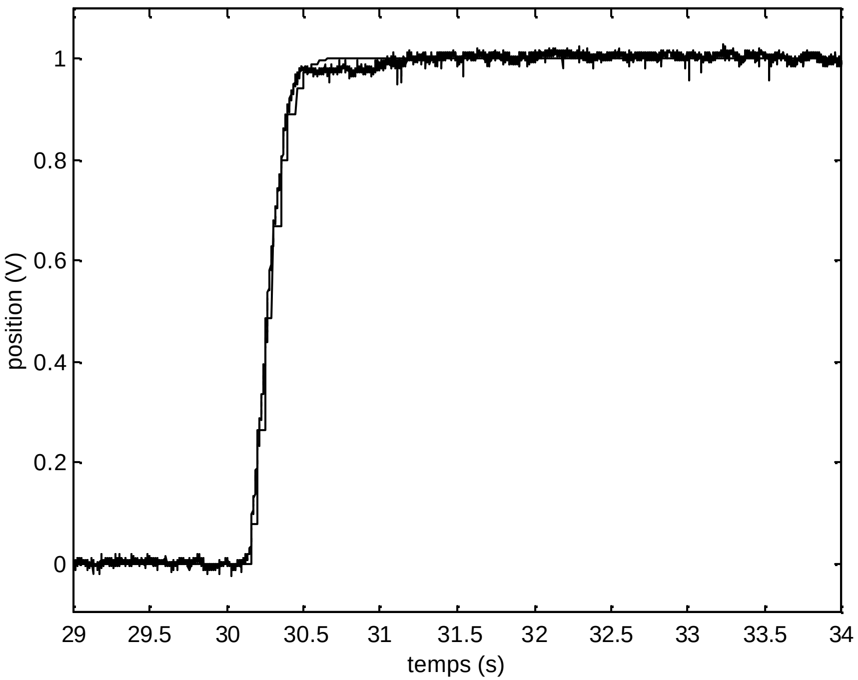


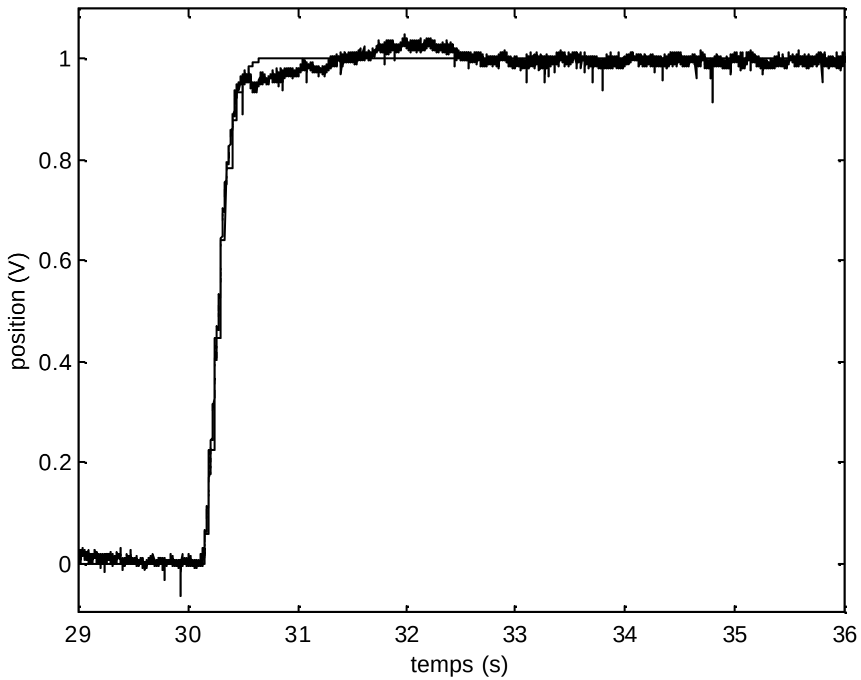
Model identified in closed loop

The simulation using the model identified in C.L. is closer to the real response than the simulation using the O.L.identified model

Controller Re-design Based on the Model Identified in Closed Loop

(on-site controller re-tuning)



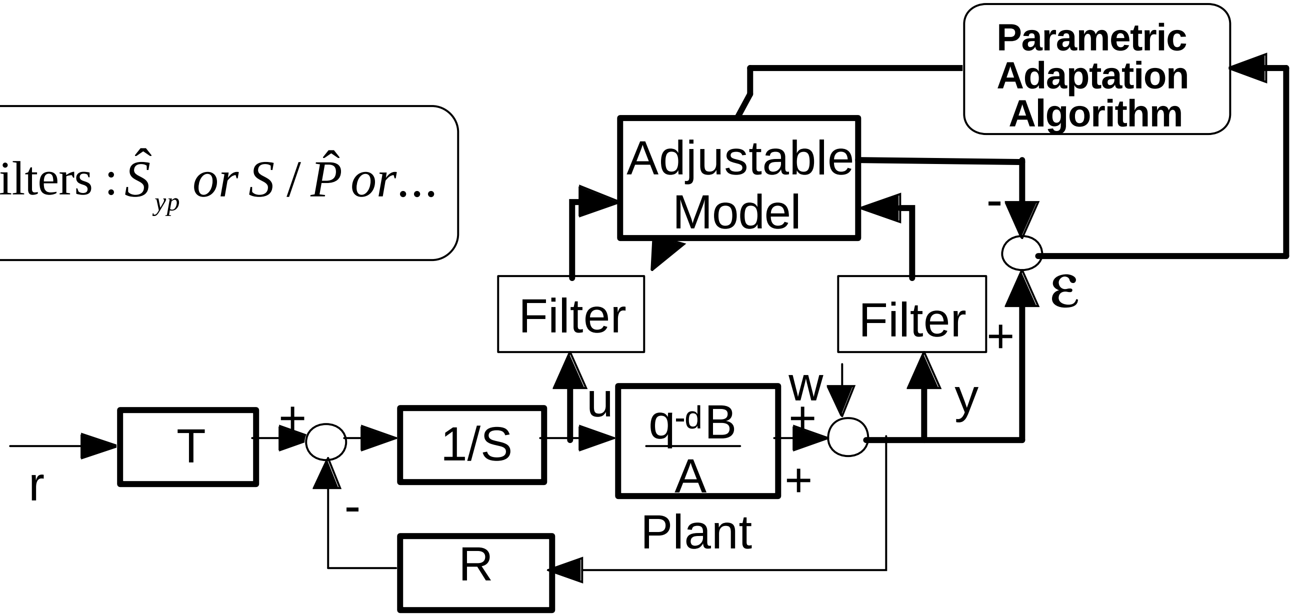


Re-designed controller (CLBC) Initial controller (OLBC)

The CLBC controller provides performance which is closer to the designed performance than that provided by the OLBC controller

Identification in Closed Loop
Filtered Open Loop (FOL)Identification Algorithms

I/O Data Filters : $\hat{S}_{yp}$ or $S/\hat{P}$ $or...$



-Biased estimates
-Require (theoretically) time varying filters
-FOL alg. can be seen as approximations of CLOE alg.
-Are used instandard indirect adaptive control

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
-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
-Identification in closed loop can be used for “model reduction”
-By duality arguments one can use the algorithms for controller reduction
- **Successful use in practice**
- A MATLAB Toolbox is available (CLID)
-A stand alone software is available (WinPIM/Adaptech)

« Personal » References

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.

Landau I.D., Lozano R., M'Saad M., (1997) : *Adaptive Control*, Springer, London,U.K.

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

Landau I.D., (2002) *Identification et Commande des Systèmes*, 3rd edition, Hermes, Paris (June)