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Robust R-S-T Digital Control
and
Open Loop System Identification
A Brief Review

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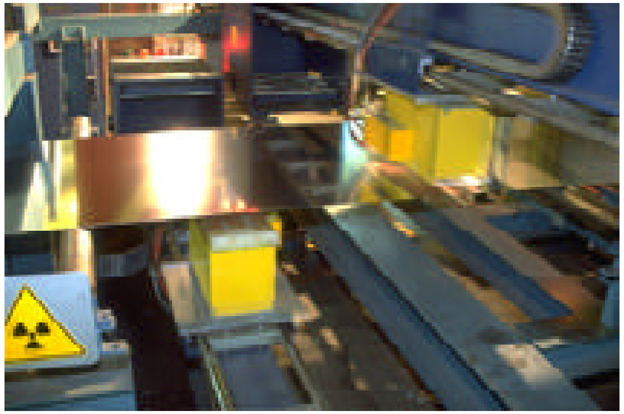
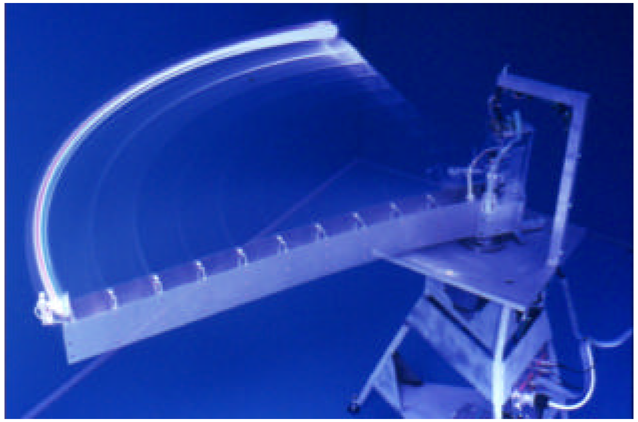
Peugeot (PSA)

Double Twist Machine
(Pourtier)

Applications of R-S-T Controllers



Sollac (Florange)
Hot Dip Galvanizing



360° Flexible Arm (LAG)

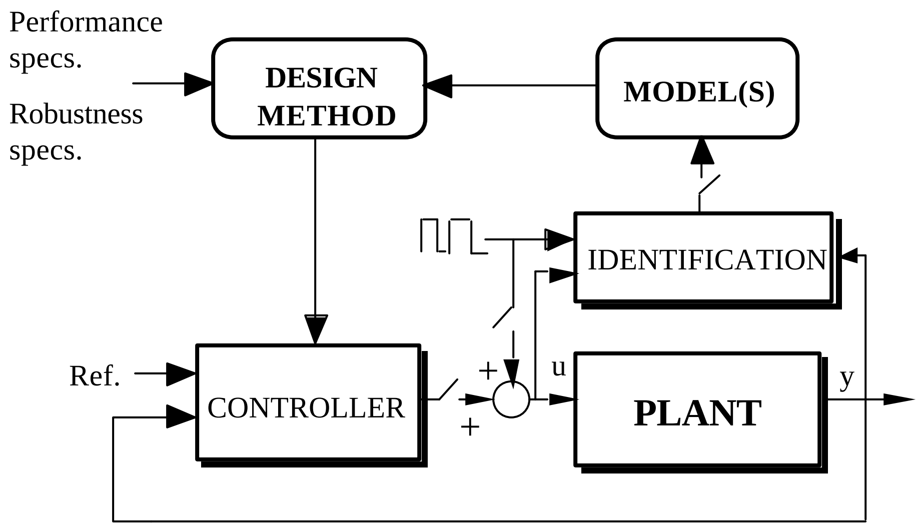
Implementation of R-S-T Digital Controllers

PLC Leroy implements
R-S-T digital controllers and
Data acquisition modules

ALSPA 320 ALSTOM

ALSPA 320 implements
R-S-T digital controllers and
Data acquisition modules

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)

Outline

Robust digital control

-The R-S-T digital controller

-Basic design

-Robustness issues

-An example

Open loop system identification

-Data acquisition

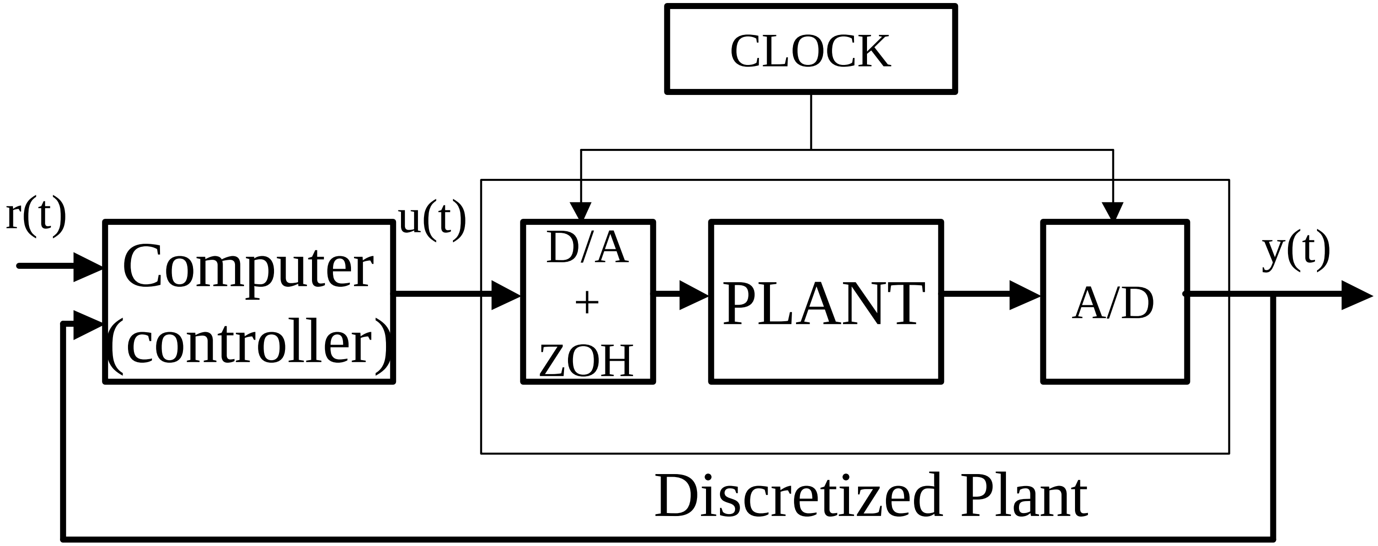
-Model complexity

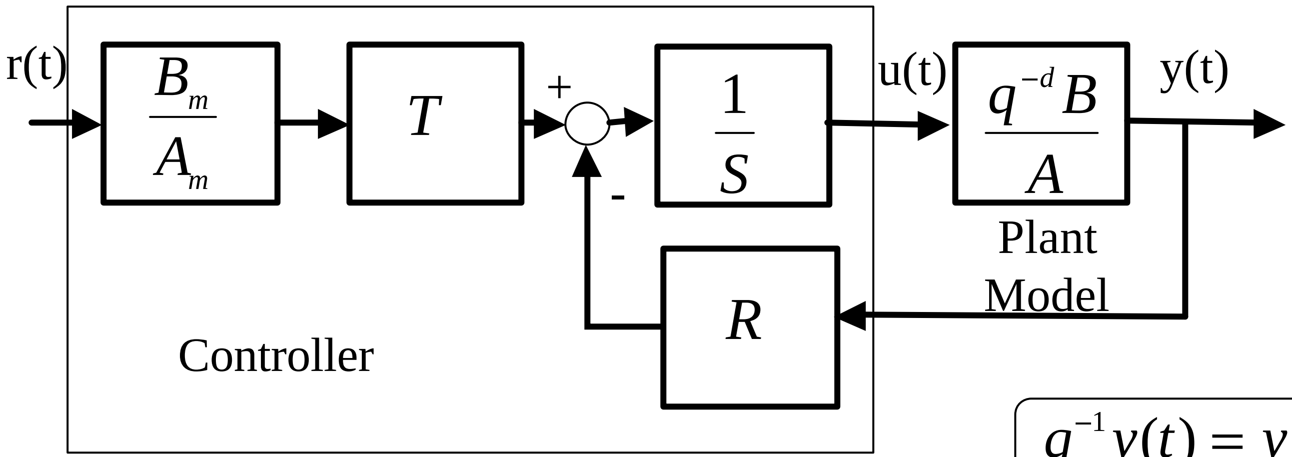
-Parameter estimation

-Validation

Robust Digital Control

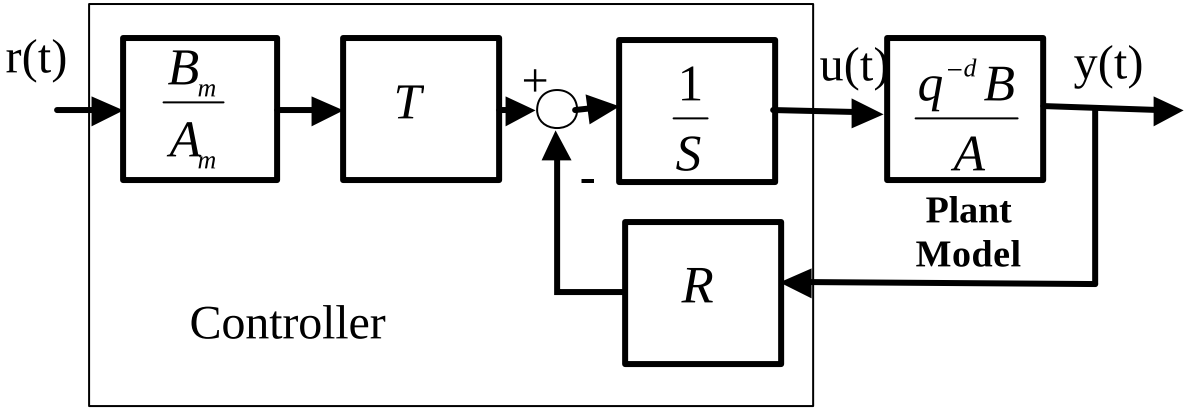
The R-S-T Digital Controller





$$q^{-1}y(t) = y(t-1)$$

The R-S-T Digital Controller



Plant Model:
$$G(q^{-1}) = \frac{q^{-d}B(q^{-1})}{A(q^{-1})} = \frac{q^{-d-1}B^*(q^{-1})}{A(q^{-1})}$$

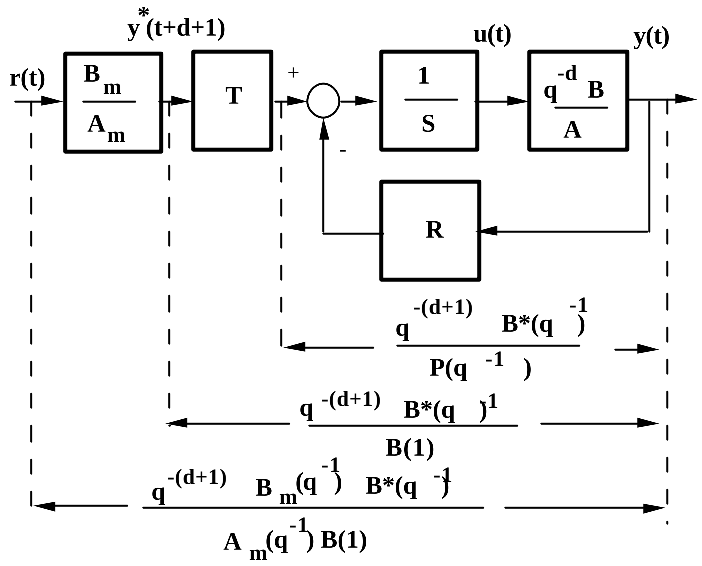
$$A(q^{-1}) = 1 + a_1 q^{-1} + \ldots + a_{n_A} q^{-n_A} \quad B(q^{-1}) = b_1 q^{-1} + \ldots + b_{n_B} q^{-n_B} = q^{-1}B^*(q^{-1})$$

R-S-T Controller:
$$S(q^{-1})u(t) = T(q^{-1})y^*(t+d+1) - R(q^{-1})y(t)$$

Characteristic polynomial (closed loop poles):

$$P(q^{-1}) = A(q^{-1})S(q^{-1}) + q^{-d}B(q^{-1})R(q^{-1})$$

Pole Placement with R-S-T Controller



Controller : $R = H_R R' ; S = H_S S'$ $H_R, H_S :$ fixed parts

Regulation: R' and S' solutions of: $AH_S S' + q^{-d} BH_R R' = P = P_D P_F$

dominant poles auxiliary poles

Tracking : $T = P / B(1)$

Reference trajectory: y^* → computer file
→ $y^* = (B_m / A_m) r$

Connections with other Control Strategies

- Digital PID : $n_R = n_S = 2; H_S = 1 - q^{-1}$

-Tracking and regulation with independent objectives(MRC):

$$P = B^* P_D P_F$$

(Hyp.: *B* has stable damped zeros)*

- Minimum variance tracking and regulation (MVC):

$$P = B^* C$$

noise model

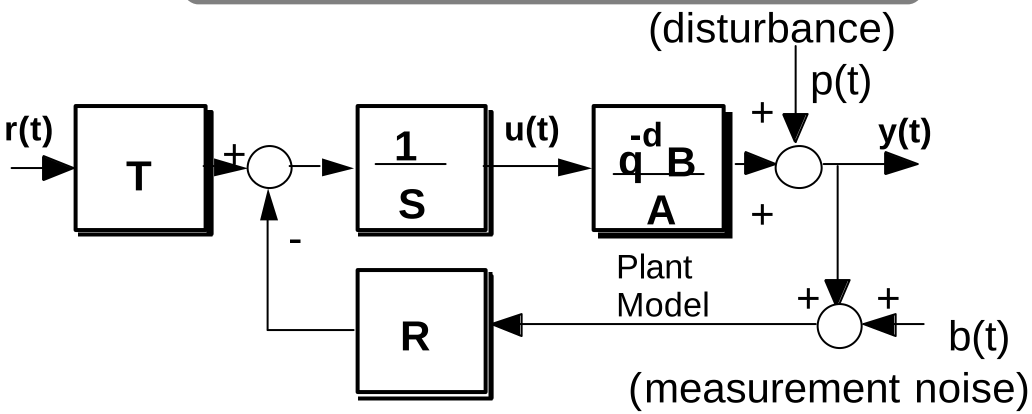
(Hyp.: *B* has stable damped zeros)*

- Internal Model Control (IMC):

$$P = AP_F$$

(Hyp.: *A has stable damped poles)*

The Sensitivity Functions



Output sensitivity function (p -> y)

$$S_{yp}(q^{-1}) = \frac{AS}{AS + q^{-d}BR} = \frac{AS}{P}$$

Input sensitivity function (p -> u)

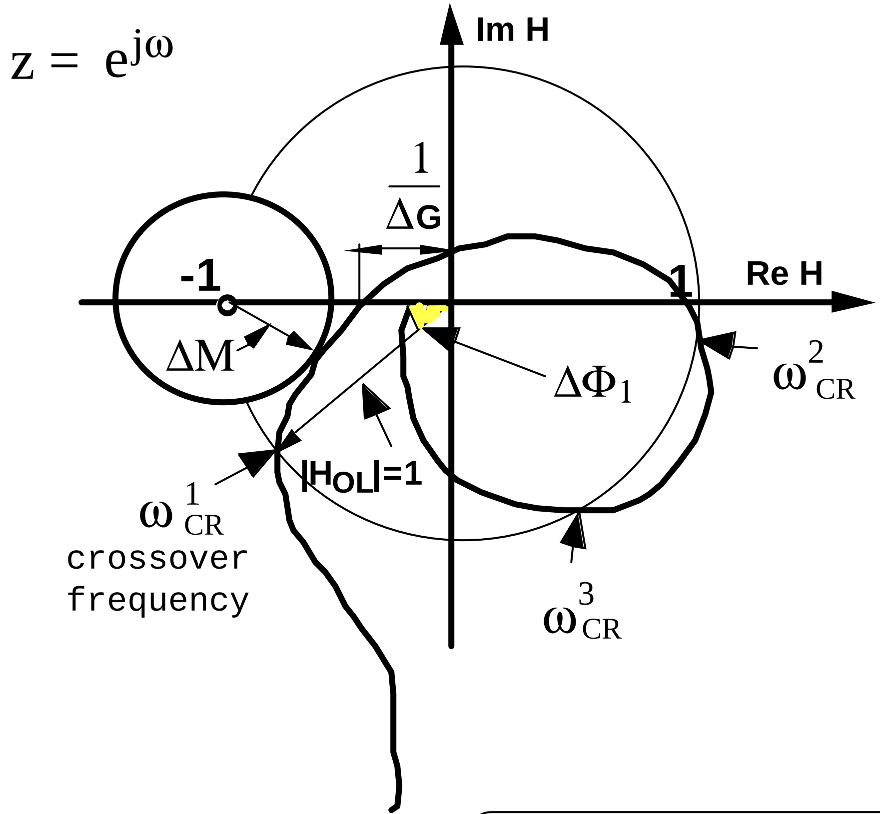
$$S_{up}(q^{-1}) = -\frac{AR}{AS + q^{-d}BR} = -\frac{AR}{P}$$

Noise sensitivity function (b -> y)

$$S_{yb}(q^{-1}) = -\frac{q^{-d}BR}{AS + q^{-d}BR} = -\frac{q^{-d}BR}{P}$$

$$S_{yp} - S_{yb} = 1$$

Robustness Margins



Typical values:

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

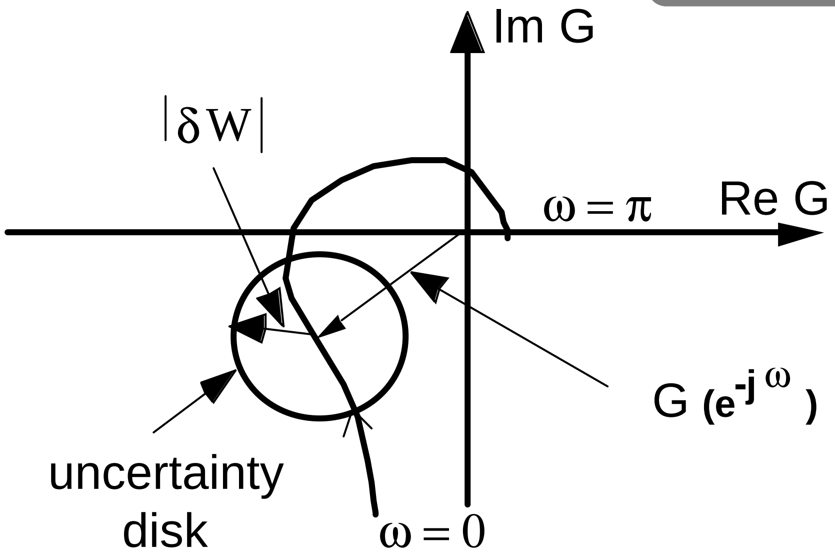
$\Delta M \geq 0.5 \Rightarrow \Delta G \geq 2 \; ; \; \Delta\Phi > 29°$

The inverse is not necessarily true!

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: $\Delta\tau = \min_i \frac{\Delta\Phi_i}{\omega_{CR}^{i}}$

Robust Stability



Family of plant models:

$$G' \in F(G, d, W_{xy})$$

$$G - \textit{nominal model;}\ \|d(z^{-1})\|_\infty \leq 1$$

$$W_{xy}(z^{-1})\text{- } \textit{size of uncertainty}$$

Robust stability condition:

a related sensitivity function

a type of uncertainty

$$\|S_{xy} W_{xy}\|_\infty < 1$$

$$\Downarrow$$

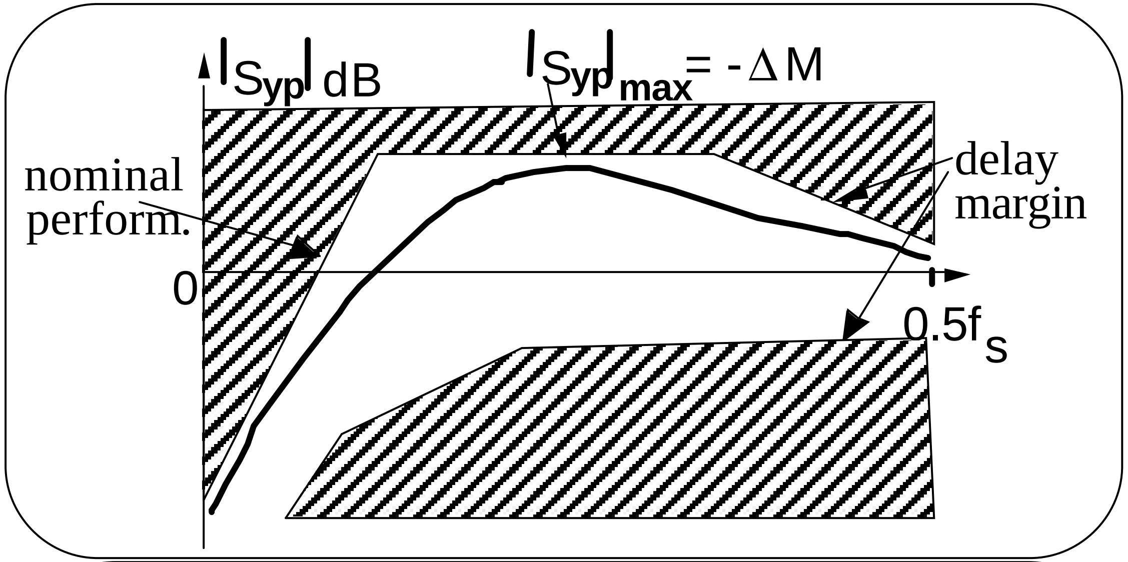
defines the size of the tolerated uncertainty

$$|S_{xy}| < |W_{xy}|^{-1}$$

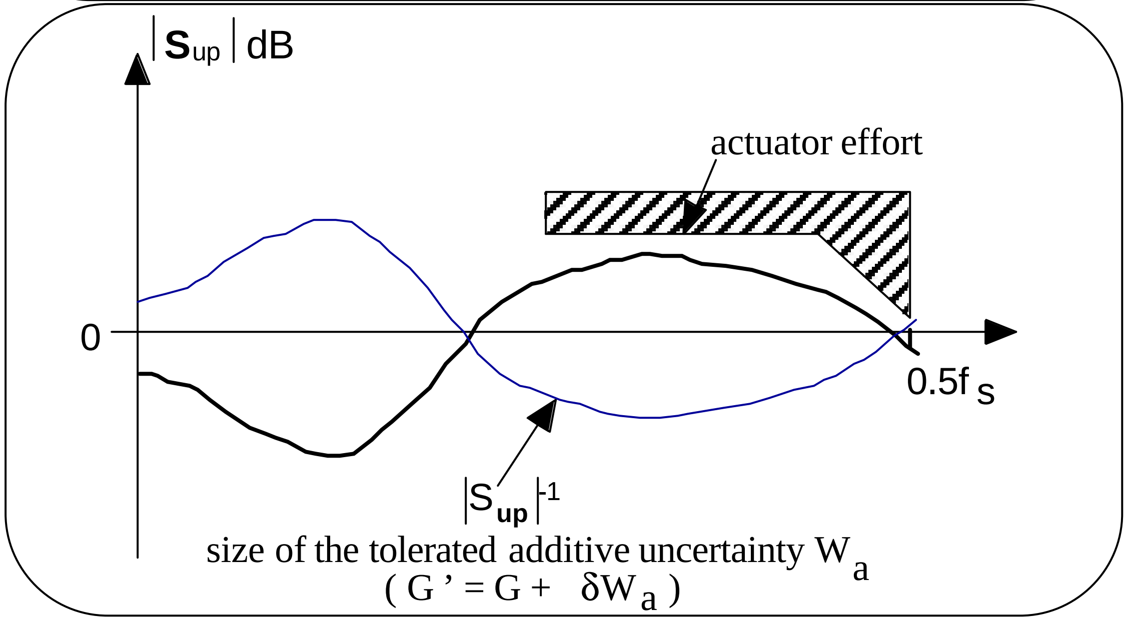
defines an upper template for the modulus of the sensitivity function

There also lower templates (because of the relationship between various sensitivity fct.)

Templates for the Sensitivity Functions



Output Sensitivity Function



Input Sensitivity Function

Robust Controller Design

Pole placement with sensitivity functions shaping

Nominal performance: P_D *and part of* H_R *and* H_S

$$P = P_D P_F$$
$$R = R' H_R$$
$$S = S' H_S$$

Allow to shape the sensitivity functions

Several approaches to design :

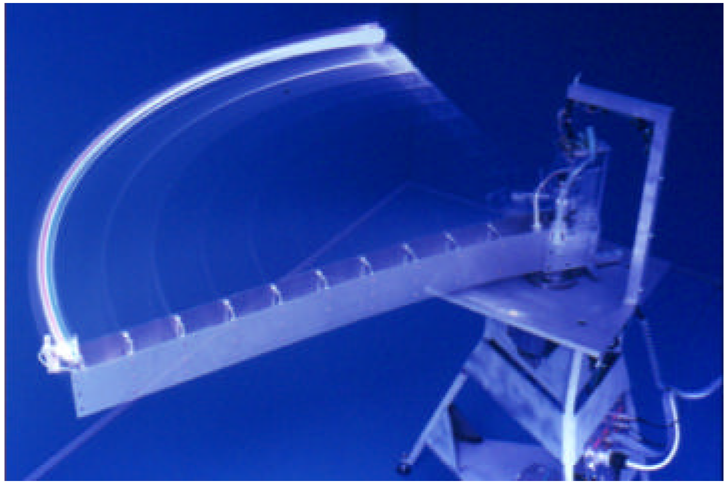
-Iterative

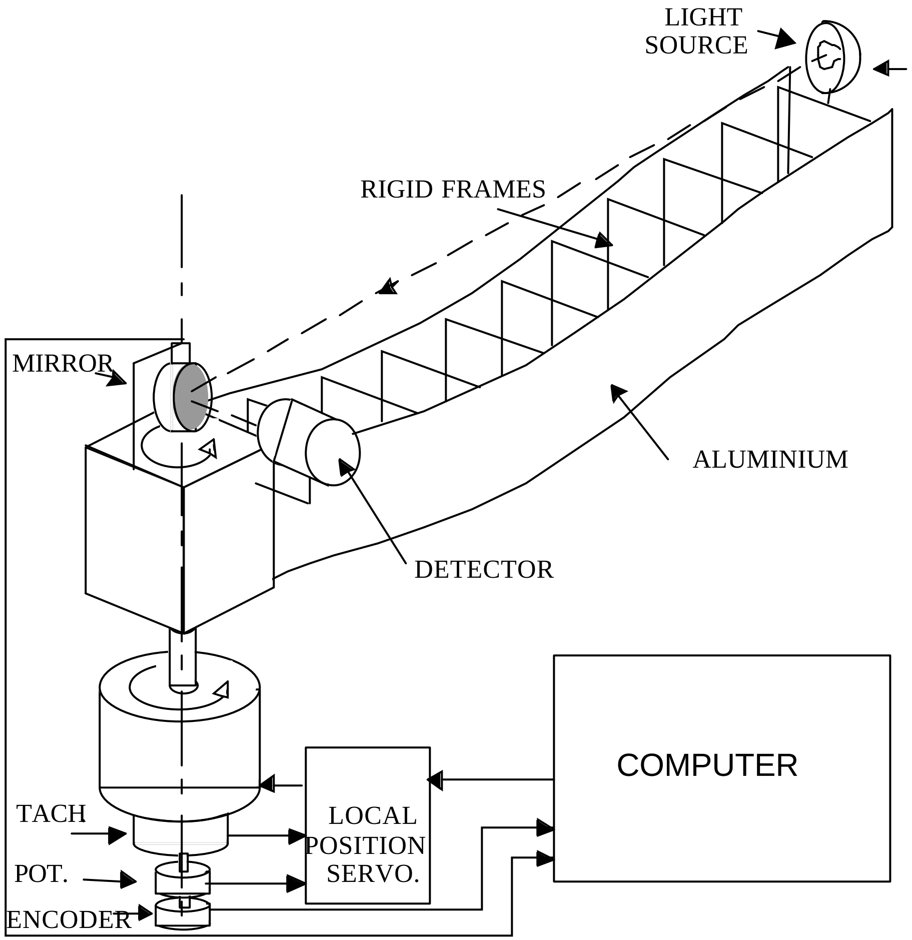
Choosing P_F *and using band stop filters* H_{Ri} / P_{Fi} , H_{Sj} / P_{Fj}

-Convex optimization

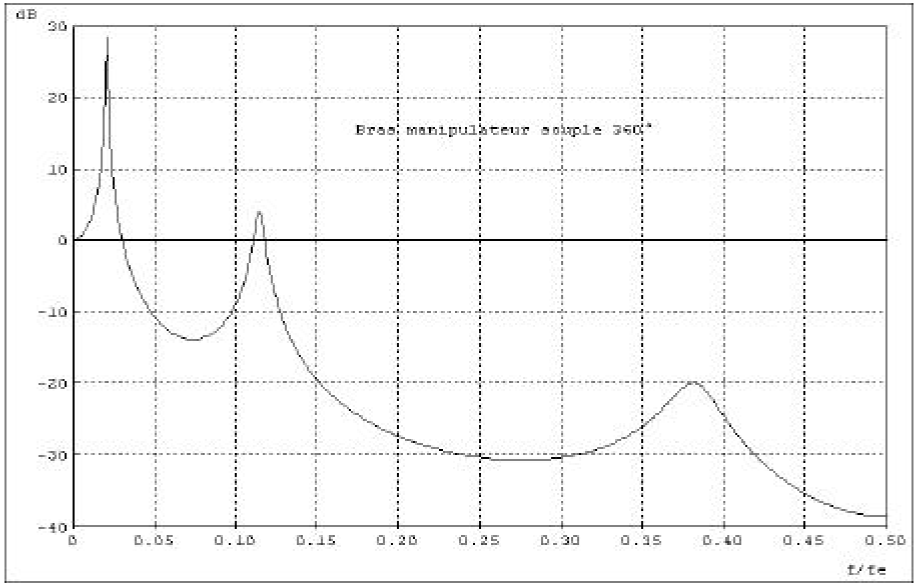
(see Langer, Landau, Automatica, June99, *Optreg* (Adaptech))

360° Flexible Arm

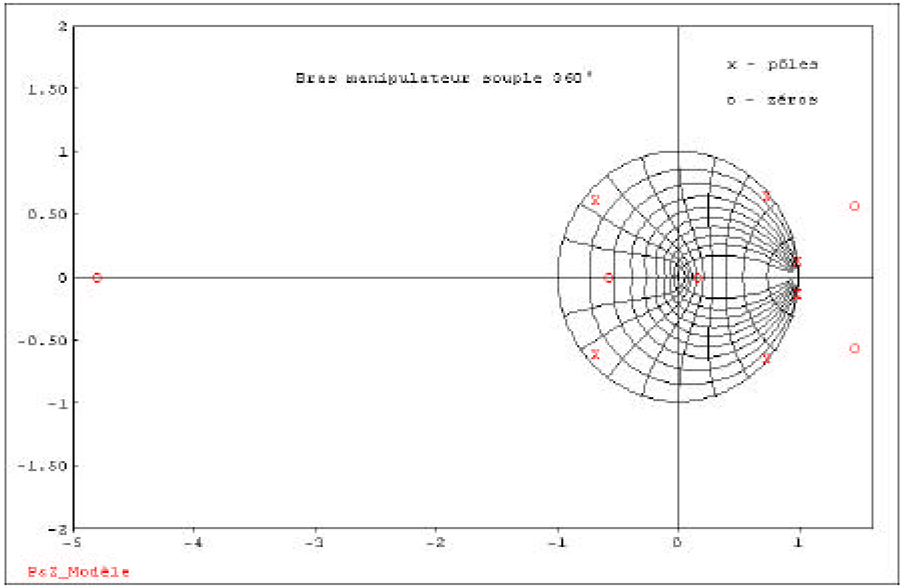




360° Flexible Arm



Frequency characteristics

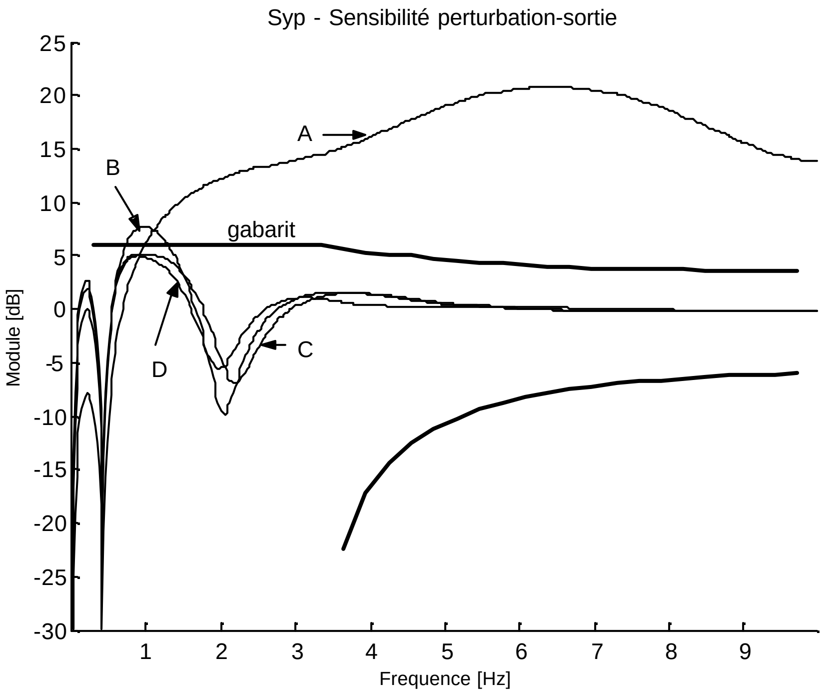


Poles-Zeros

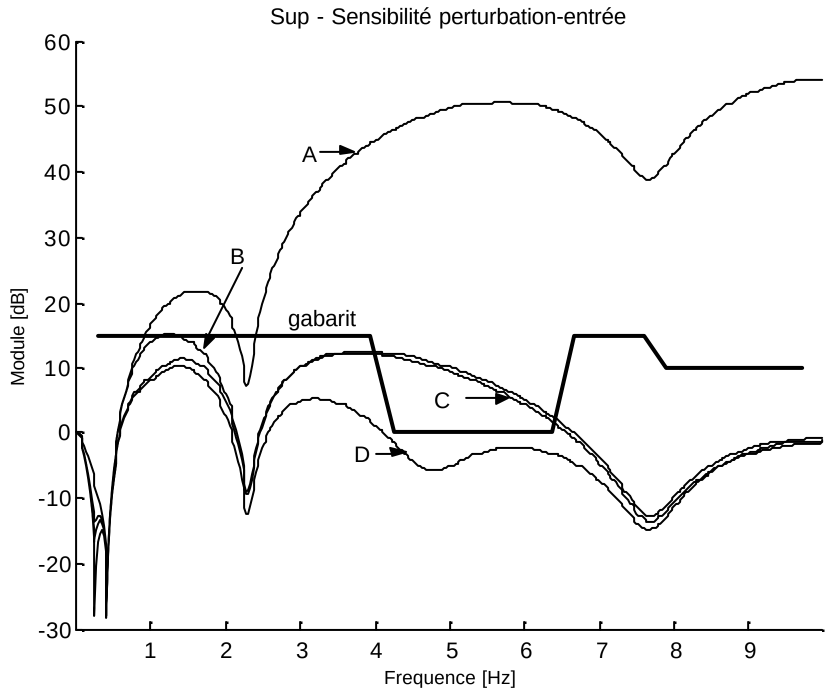
(Identified Model)

Shaping the Sensitivity Functions

Output Sensitivity Function - S_{yp}



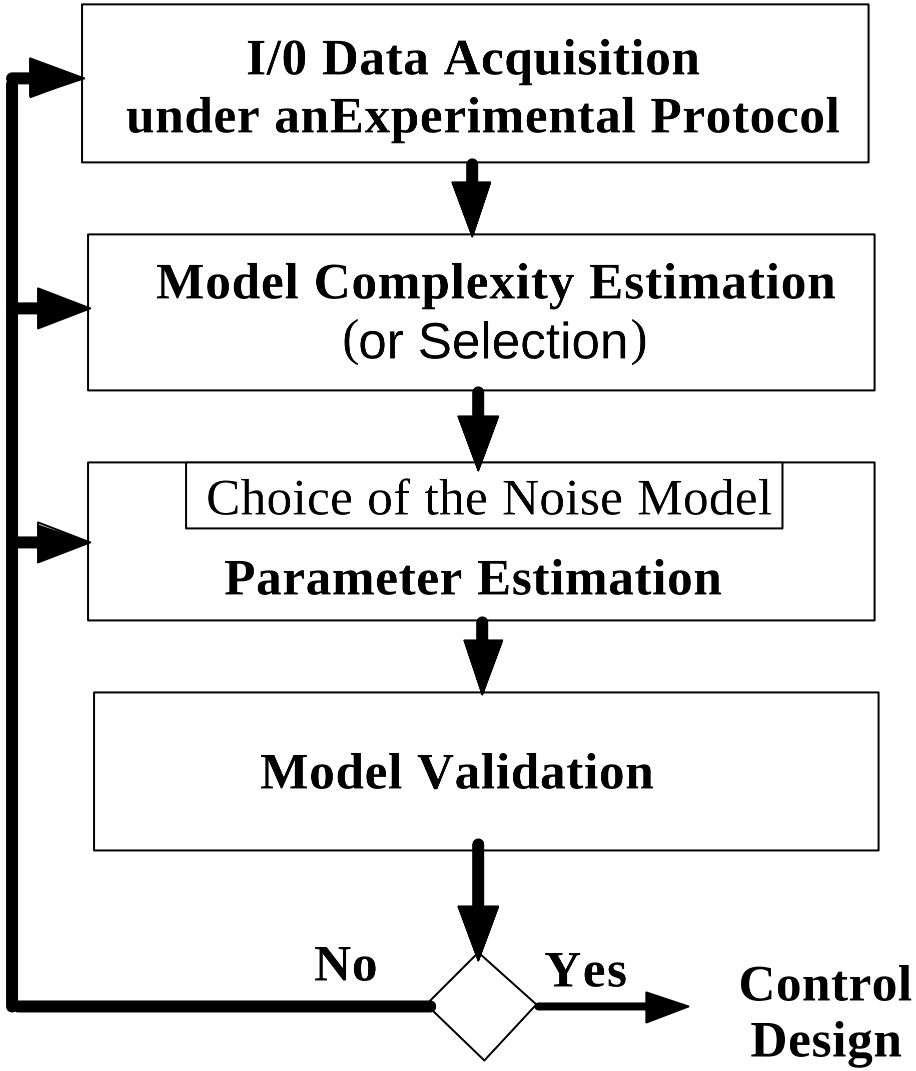
Input Sensitivity Function - S_{up}



A- without auxiliary poles
B- with auxiliary poles
C- with stop band filter H_{S1} / P_{F1}
D- with stop band filter H_{R2} / P_{F2}

Open Loop System Identification

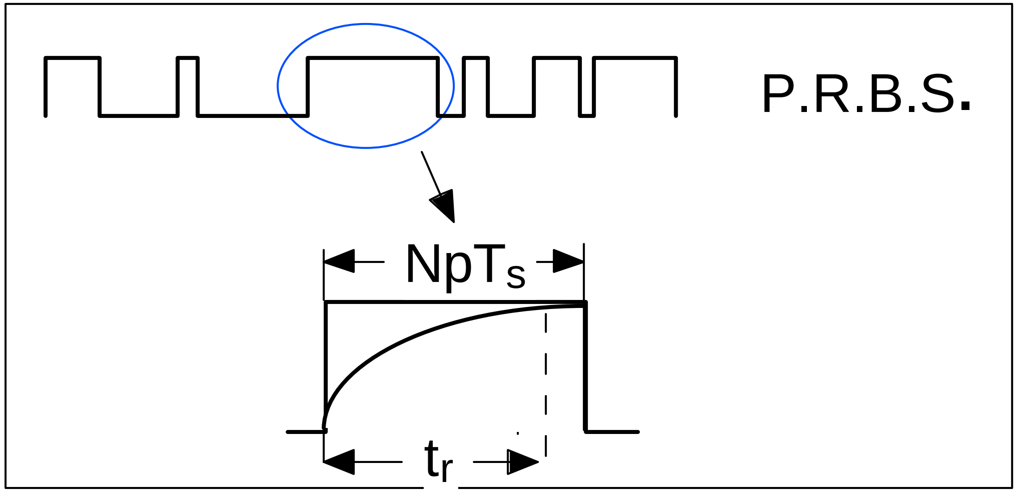
System Identification Methodology



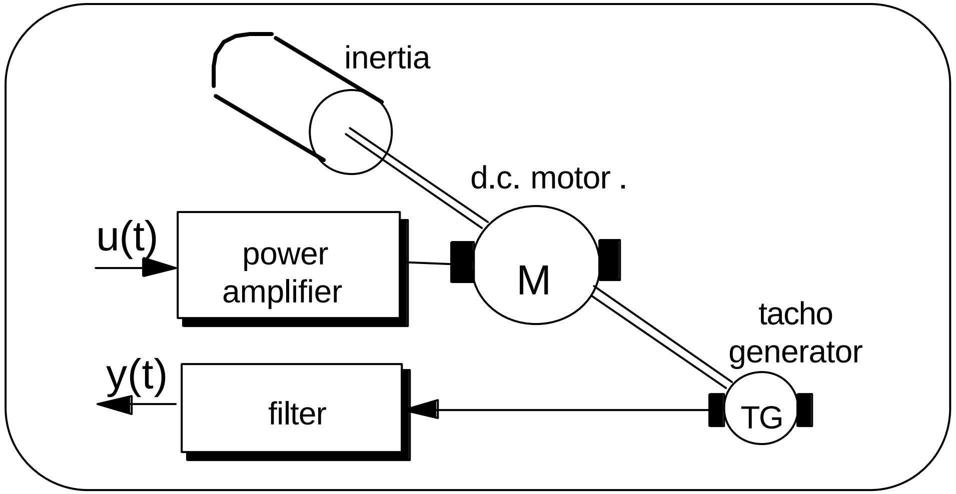
I/O Data Acqusition

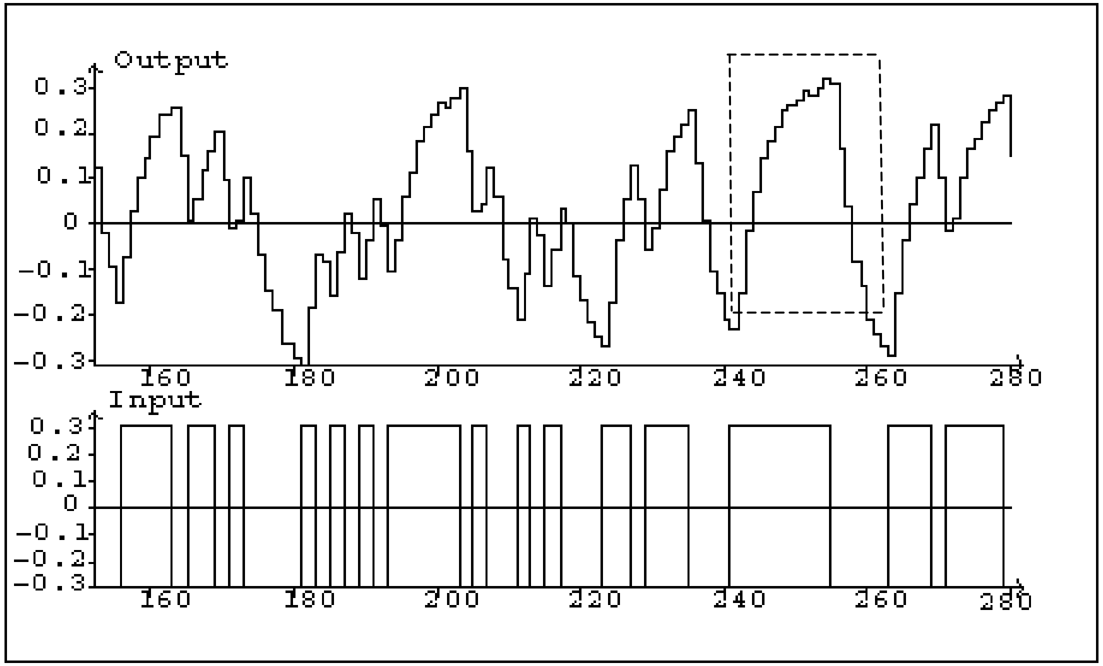
Signal : *a P.R.B.S sequence*
Magnitude : *few % of the input operating point*
Clock frequency : $f_{clock} = (1/p) f_s$; $p = 1, 2, 3$ (f_s = *sampling frequency*)
Length : $(2^{N-1} - 1) pT_s$; N = *number of cells*, $T_s = 1/f_s$
Largest pulse : NpT_s

Length : < allowed duration of the experiment
Largest pulse : $\geq t_R$ (rise time)



An I/O File


inertia
d.c. motor .
u(t)
power
amplifier
M
tacho
generator
y(t)
filter
TG


Output
Input
0.3
0.2
0.1
0
−0.1
−0.2
−0.3
160
180
200
220
240
260
280

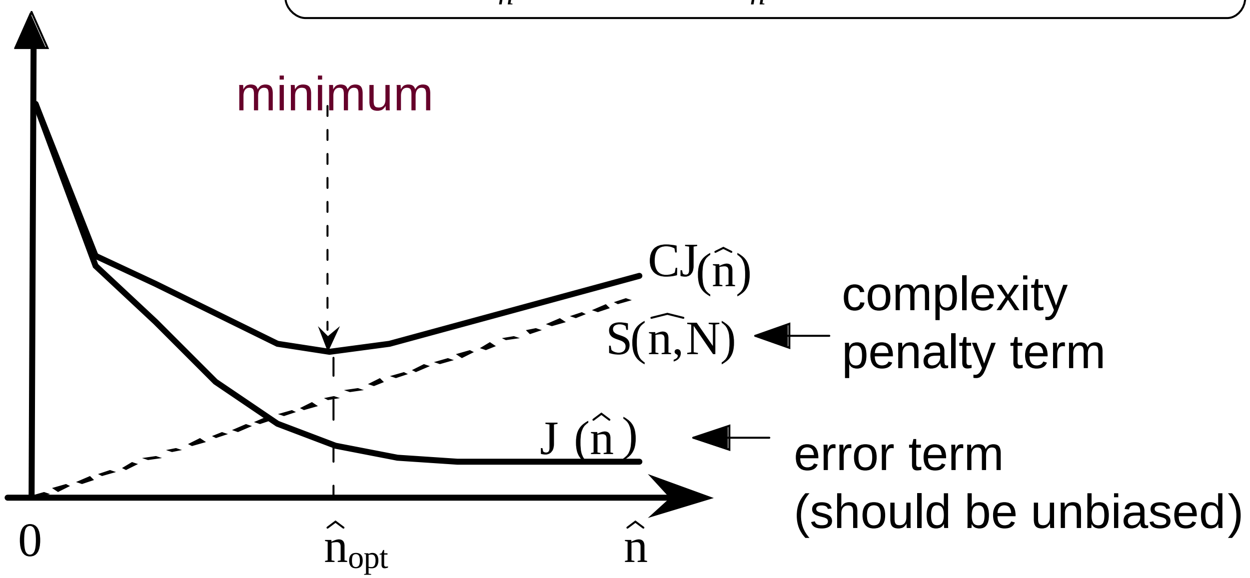
Complexity Estimation from I/O Data

Objective :

To get a good estimation of the model complexity (n_A, n_B, d) directly from noisy data

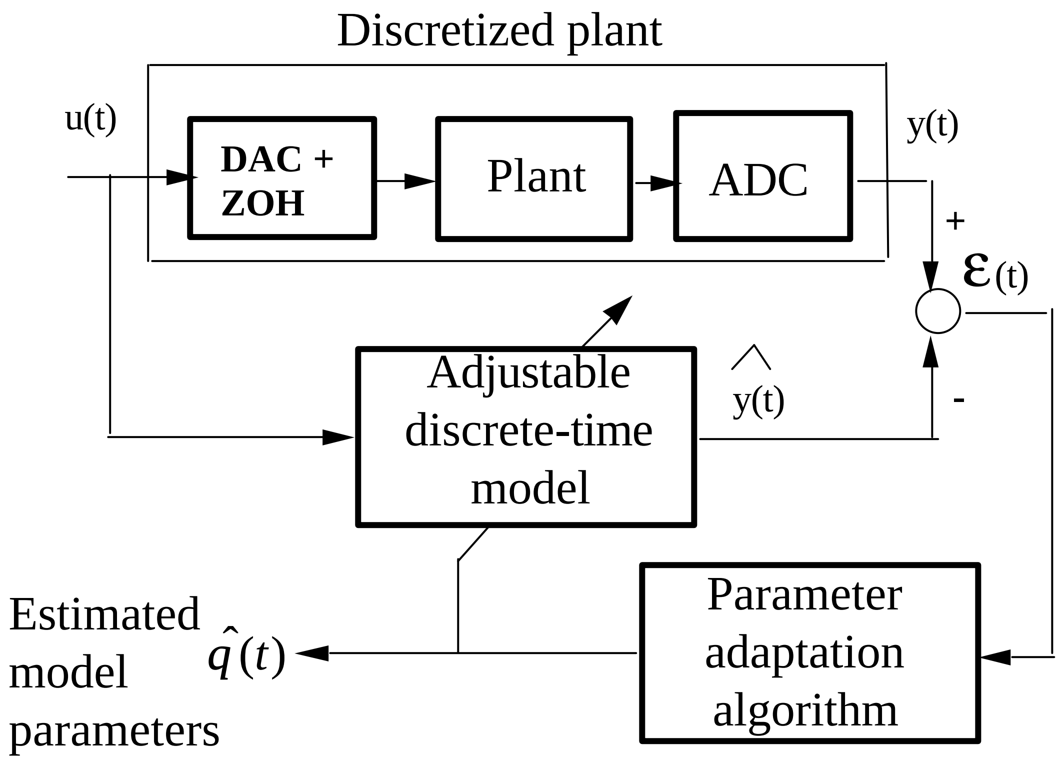
$$n = \max(n_A, n_B + d)$$

$$\hat{n}_{opt} = \min_{\hat{n}} CJ = \min_{\hat{n}} \left[J(\hat{n}) + S(\hat{n}, N) \right]$$



To get a good order estimation, J should tend to the value for noisy free data when $N \to \infty$ *(use of instrumental variables)*

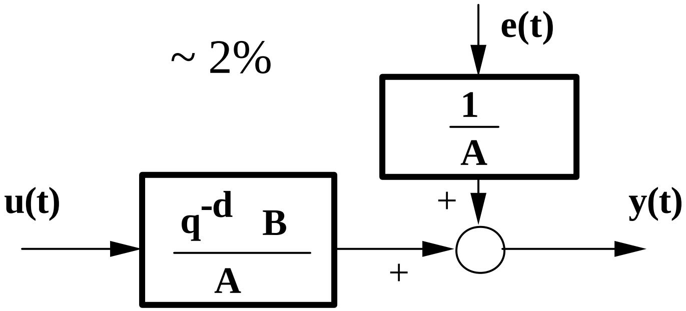
Parameter Estimation



«Plant + Noise » Models

$$S1: A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t) + e(t)$$

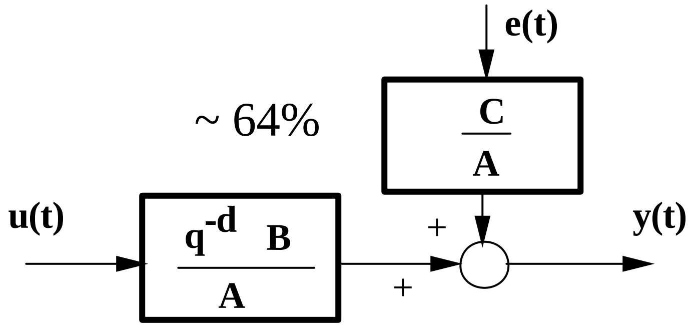
~ 2%



(Recursive) Least Squares

$$S3: A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t) + C(q^{-1})e(t)$$

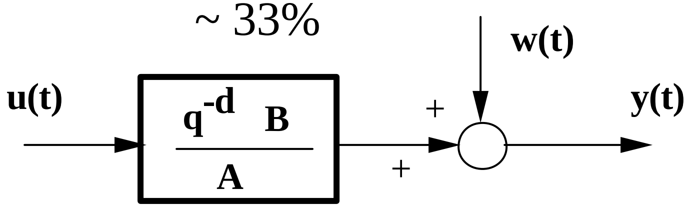
~ 64%



Extended Least Squares
O.E. with Extended Prediction Model
(Recursive) Maximum Likelihood

$$S2: A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t) + A(q^{-1})w(t)$$

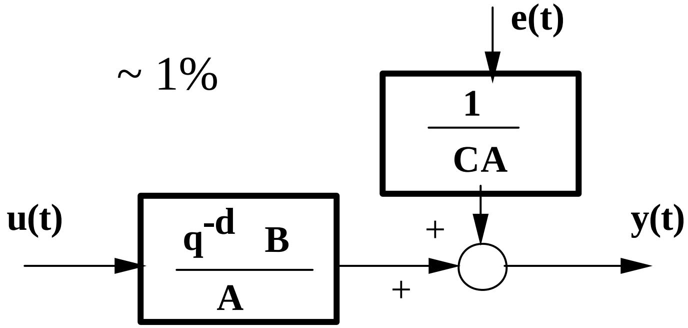
~ 33%



Ouput Error(O.E.)
Instrumental Variable…

$$S4: A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t) + [1/C(q^{-1})]e(t)$$

~ 1%



Generalized Least Squares

Parameter Estimation Methods

Plant Model

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

$$q - parameter\ vector ; y - measurement\ vector$$

Estimated model

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

$$\hat{q} - estimated\ parameter\ vector ; f - observation\ vector$$

Prediction error

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

Parameter adaptation algorithm

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

$$F^{-1}(t+1) = l_1(t)F^{-1}(t) + l_2(t)\Phi(t)\Phi^T(t)$$

$$0 < l_1(t) \le 1 ; 0 \le l_2(t) < 2$$

$$\Phi(t) = f\left[f(t)\right]$$

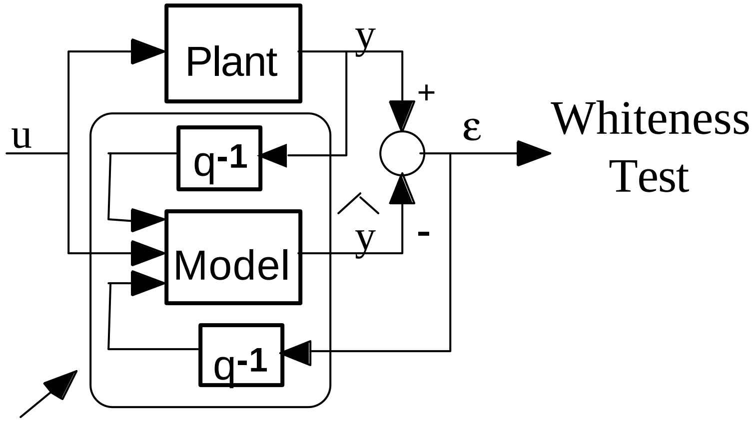
Parameter Estimation Methods

I- *Based on the asymptotic whitening of the prediction error*
(Recursive Least Squares, Extended Least Squares, Recursive Max. Likelihood, O.E. with Extended Prediciton Model)

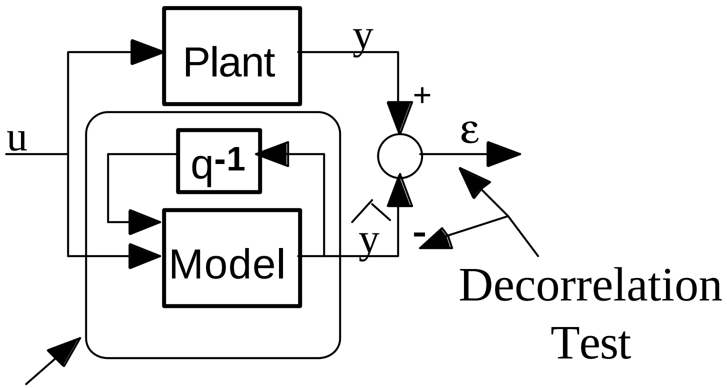
II- *Based on the asymptotic decorrelation between the prediction error and the observation vector*
(Output Error, Instrumental Variable)

Validation of Identified Models

Statistical Validation



ARMAX (ARARX) predictor

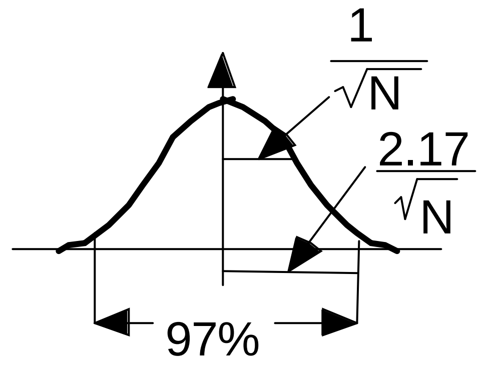


Output Error Predictor

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

normalized crosscorelation

number of data



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

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

Software Tools for Implementing the Methodology

System Identification
-Winpim (Adaptech)
identification in open loop and closed loop operation
-CLID (Adaptech)
identification in closed loop (Matlab Toolbox)

Controller Design
-Winreg (Adaptech)
design and optimisation of R-S-T digital controllers
-Optreg (Adaptech)
automated design of robust digital controllers (under Matlab)

Real-time implementation
-Wintrac (Adaptech): cascade digital control

« Personal » References

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