

Fault Detection and Isolation using Multiple Model Parameter Estimation

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Objective	Identification	Diagnosis	Application
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Outline

Objective

Identification

Choice of a model structure

and an estimation method

Consequence of a fault on parameter estimates

Diagnosis

Residual generation **for detection**

Residual fuzzyfication

Signature table generation **for isolation**

Symptom Aggregation

Isolation Function by **distance computation**

Application

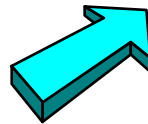
Winding machine

Objective



Diagnosis using Parameter estimation

applied to a physical process.

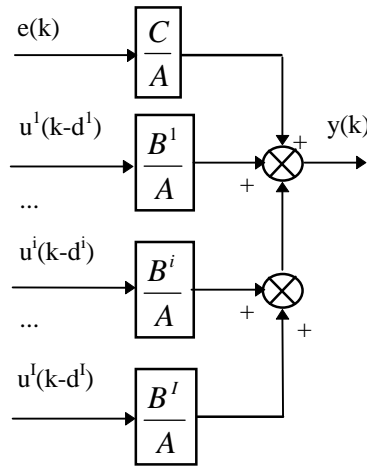


- ✗ No knowledge on the physical parameters
- ✗ No additive signal !
- ✗ A fast and simple estimation method

Objective	Identification	Diagnosis	Application
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Choice of a model structure and an estimation method

✘ ARMAX MISO discrete model

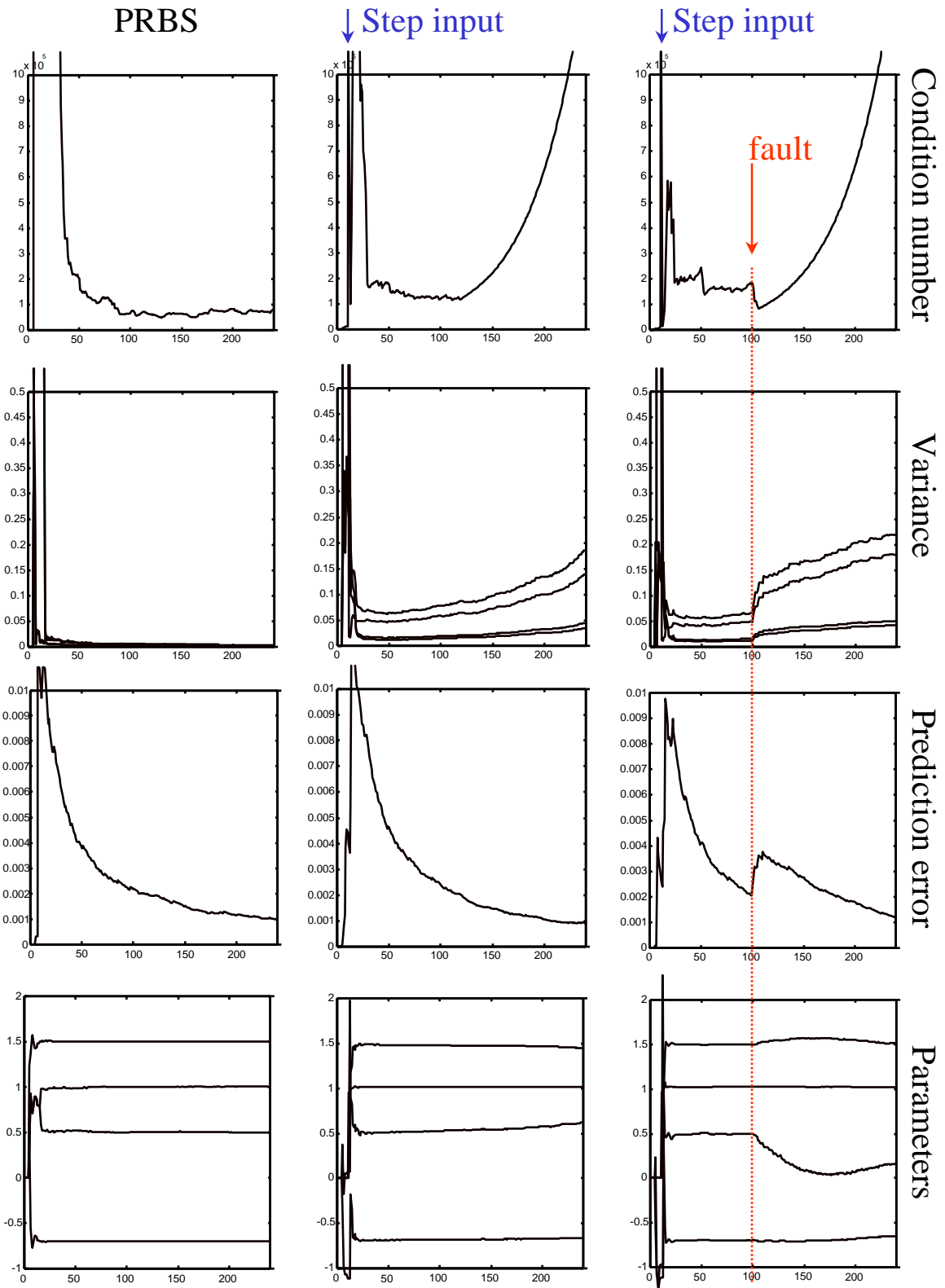


$$A(q^{-1}) \cdot y(k) = \sum_{i=1}^l B^i(q^{-1}) \cdot u^i(k - d^i) + C(q^{-1}) \cdot e(k)$$

- ☺ **transfer function** parameter estimation
- ☺ **low complexity**
and no biased parameters

✘ RELSE with forgetting factor achieved by **Orthonormal Transformation**

- ☑ **on line** variance and parameter estimation
- ☑ **good numerical properties**



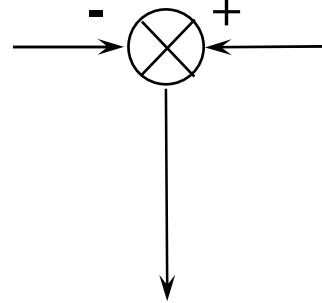
On line condition number evolution with $\lambda < 1$

Residual generation for detection

The tracking model

$$Es^s = \begin{bmatrix} \theta_1 & \dots & \theta_p \end{bmatrix}$$

short horizon
estimate vector with λ



The reference model

$$Es^l = \begin{bmatrix} \Theta_1 & \dots & \Theta_p \end{bmatrix}$$

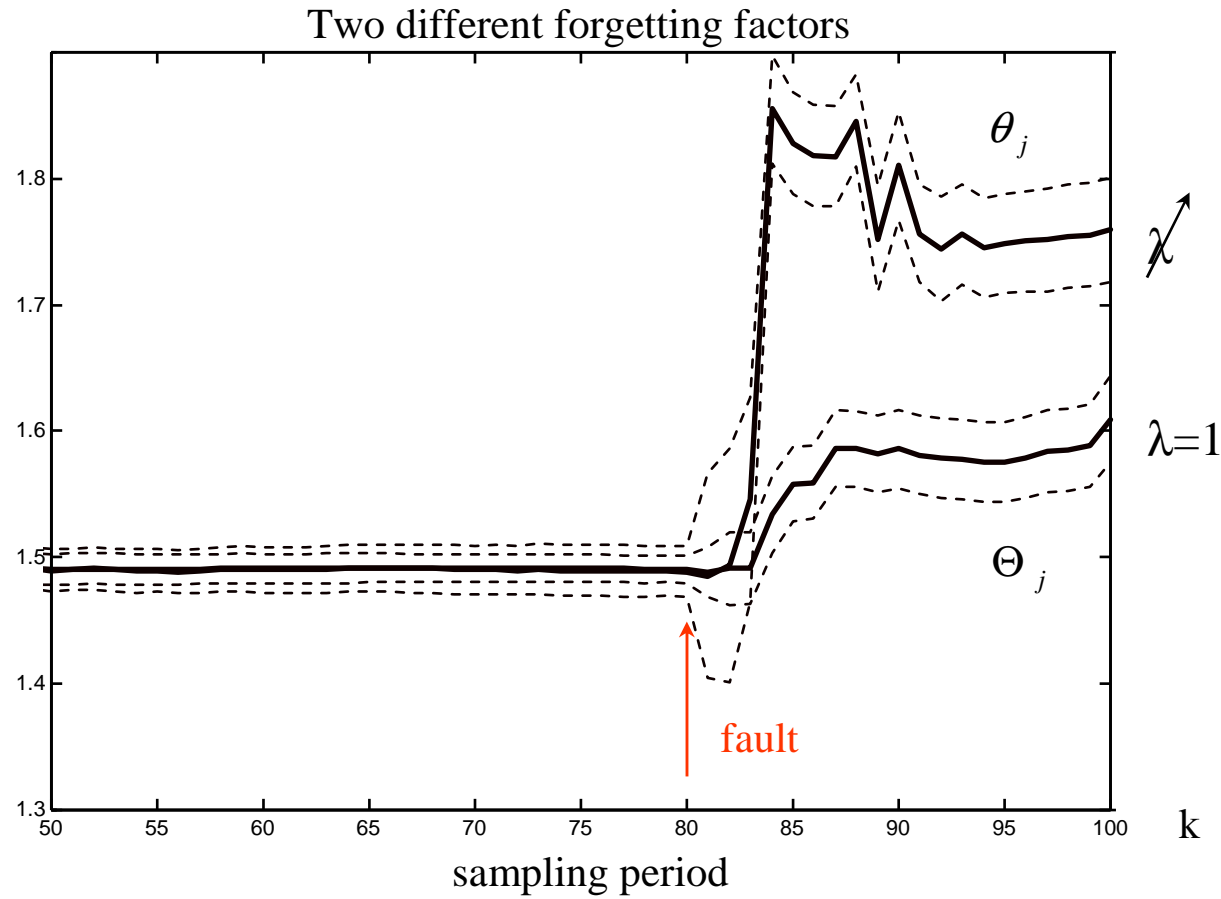
long horizon
estimate vector ($\lambda = 1$)

RESIDUALS

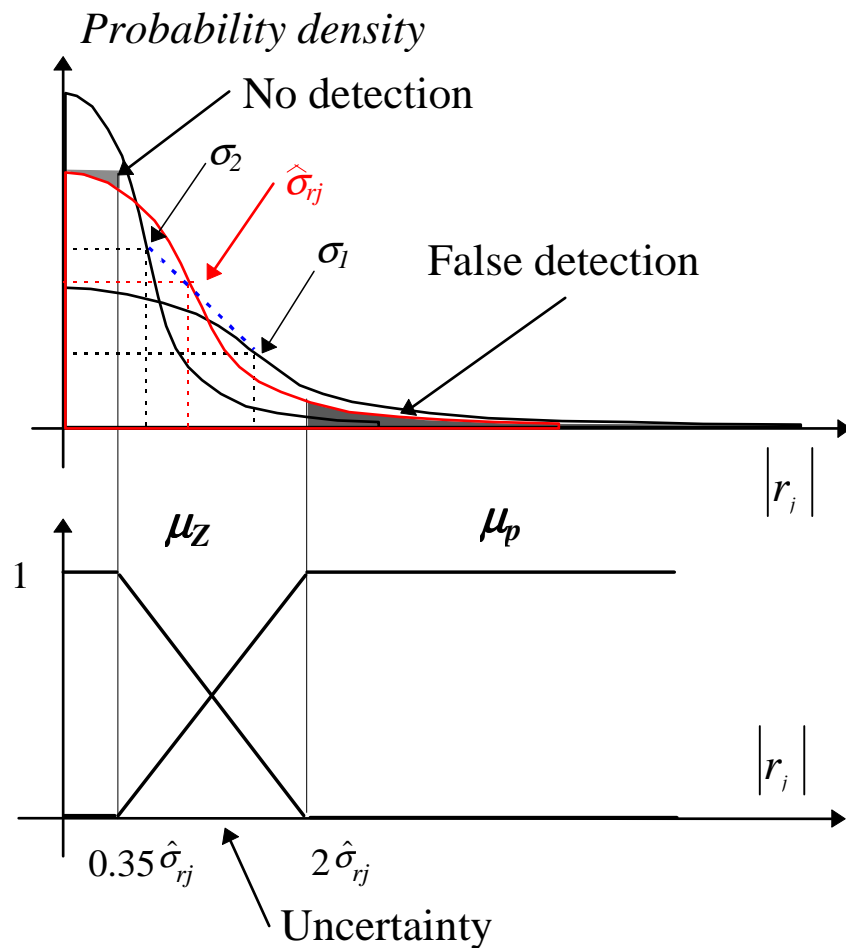
$$r_j = \Theta_j - \theta_j$$

$$E\{r_j\} = E\{\Theta_j\} - E\{\theta_j\} \longrightarrow 0 \text{ if no fault occurred!}$$

Actuator fault example



Residual fuzzyfication



Variance

$$\sigma_2^2 \leq \sigma_{r_j}^2 \leq \sigma_1^2$$

The membership function of the fuzzy sets POSITIVE and ZERO :

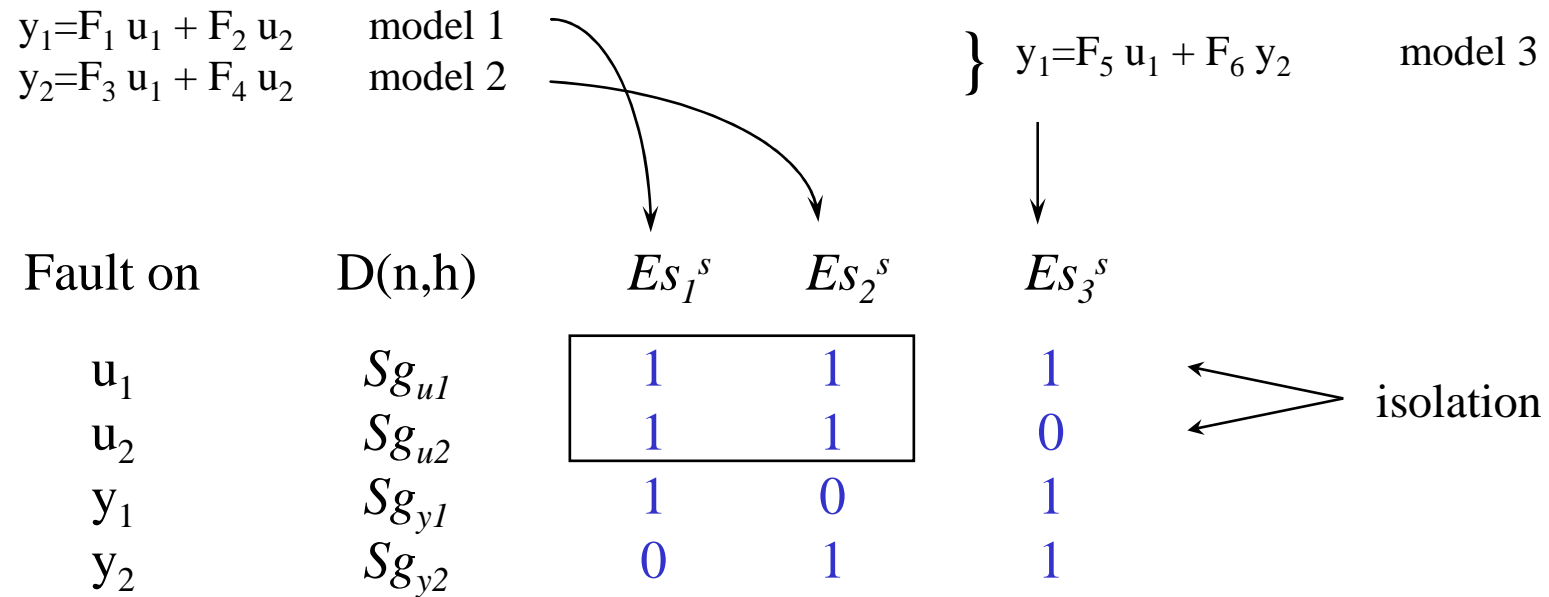
$$\mu_P(|r_j(k)|) = \min \left(1, \max \left(0, \frac{|r_j(k)| - 0.35 \cdot \hat{\sigma}_{r_j}(k)}{2 \cdot \hat{\sigma}_{r_j}(k) - 0.35 \cdot \hat{\sigma}_{r_j}(k)} \right) \right)$$

$$\mu_Z(|r_j(k)|) = 1 - \mu_P(|r_j(k)|)$$

Membership functions

Signature table generation for isolation

The signature table $D(n,h)$ defines the relation between faults and short estimate vector Es_h^s



Symptom Aggregation


FAULT  a global perturbation of residuals for the model h (1...H)

The symptom s_h is based on the residual vector :

$$s_h = \left[\left| r_1^h \right| \dots \left| r_{p^h}^h \right| \right]$$

The symptom is defined by two complementary fuzzy sets :

Gp  Globally perturbed


Np  Not perturbed

The membership functions for each model are computed by an aggregation

$$\mu_{Gp}(s_h) = \frac{1}{p^h} \sum_{j=1}^{p^h} \mu_P(|r_j^h|) \quad \text{and} \quad \mu_{Np}(s_h) = 1 - \mu_{Gp}(s_h)$$

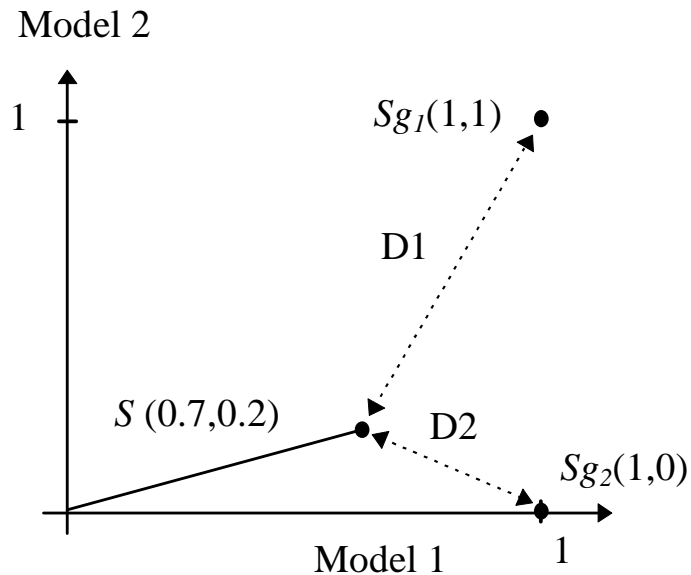
Aggregated symptom vector

$$S = \left[\mu_{Gp}(s_1) \dots \mu_{Gp}(s_H) \right]$$

S  match?
 Sg_n

Isolation function by distance computation

The Isolation Function $F_I(S, Sg_n)$ represents a degree of **likeness** between S and the fault signature Sg_n



$$D(n, h) = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$$

- $F_I(S, Sg_n) = 0$ no fault n
- $0 < F_I(S, Sg_n) < 1$ fault n suspicion degree
- $F_I(S, Sg_n) = 1$ fault n

Using the Hamming distance

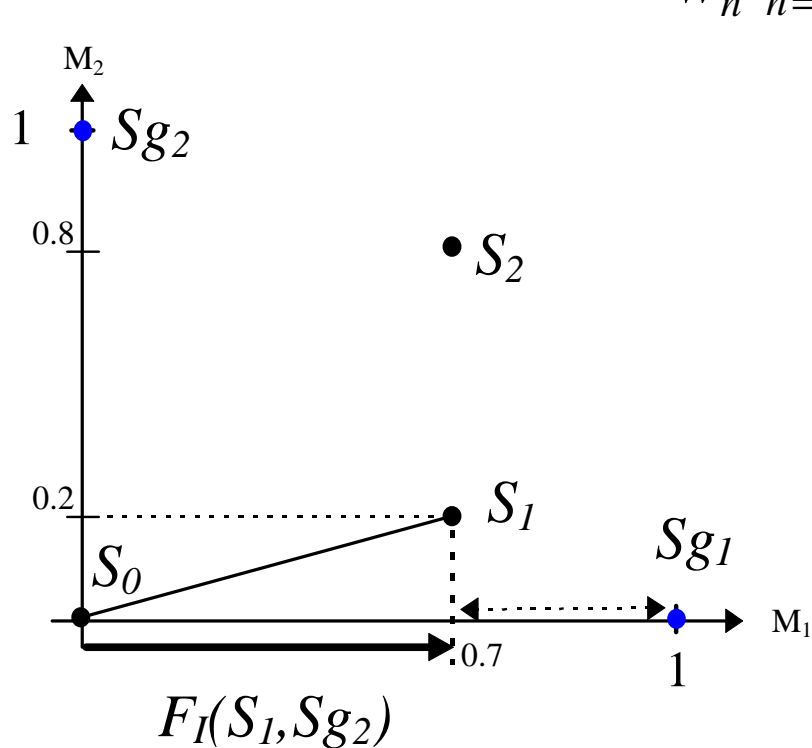
$$F_I(S, Sg_n) = 1 - \frac{1}{H} \sum_{h=1}^H |\mu_{Gp}(s_h) - D(n, h)|$$

Isolation function by distance computation



elimination of insensitive dimensions is useful for multiple fault analysis

$$F_I(S, Sg_n) = 1 - \frac{1}{W_n} \sum_{h=1}^H \{ |\mu_{Gp}(s_h) - D(n, h)| \cdot D(n, h) \}$$



$$D(n, h) = \begin{bmatrix} M_1 & M_2 \\ 1 & 0 \\ 0 & 1 \\ \hline 1 & 1 \end{bmatrix}$$

Sg_1

Sg_2

← no combination

$$S_0 = [0 \quad 0]$$

$$S_1 = [0.7 \quad 0.2]$$

$$S_2 = [0.7 \quad 0.8]$$

● $F_I(S_0, Sg_1) = 0$

● $F_I(S_0, Sg_2) = 0$

● $F_I(S_1, Sg_1) = 0.7$

● $F_I(S_1, Sg_2) = 0.2$

● $F_I(S_2, Sg_1) = 0.7$

● $F_I(S_2, Sg_2) = 0.8$

Application

After off line parameter estimation:

$$A_1(q^{-1}).T_1(k)=B_{12}(q^{-1}).\Omega_2(k-d_{12})+B_{1u1}(q^{-1}).u_1(k-d_{1u1})$$

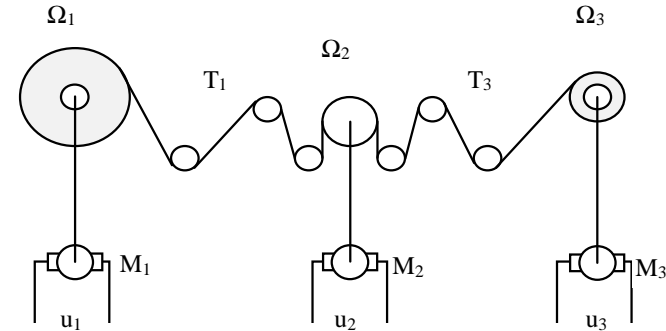
$$A_2(q^{-1}).\Omega_2(k)=B_{2u2}(q^{-1}).u_2(k-d_{2u2})$$

$$A_3(q^{-1}).T_3(k)=B_{32}(q^{-1}).\Omega_2(k-d_{32})+B_{3u3}(q^{-1}).u_3(k-d_{3u3})$$

Redundant transfer function generation:

$$A_{11}(q^{-1}).T_1(k)=B_{11u2}(q^{-1}).u_2(k-d_{11u2})+B_{11u1}(q^{-1}).u_1(k-d_{1u1})$$

$$A_{33}(q^{-1}).T_3(k)=B_{33u2}(q^{-1}).u_2(k-d_{33u2})+B_{33u3}(q^{-1}).u_3(k-d_{3u3})$$



Fault on	D	Es ₁	Es ₂	Es ₃		Es ₄	Es ₅
T ₁	Sg _{T1}	1	0	0		1	0
Ω ₂	Sg _{Ω2}	1	1	1		0	0
T ₃	Sg _{T3}	0	0	1		0	1
u ₁	Sg _{u1}	1	0	0		1	0
u ₂	Sg _{u2}	0	1	0		1	1
u ₃	Sg _{u3}	0	0	1		0	1

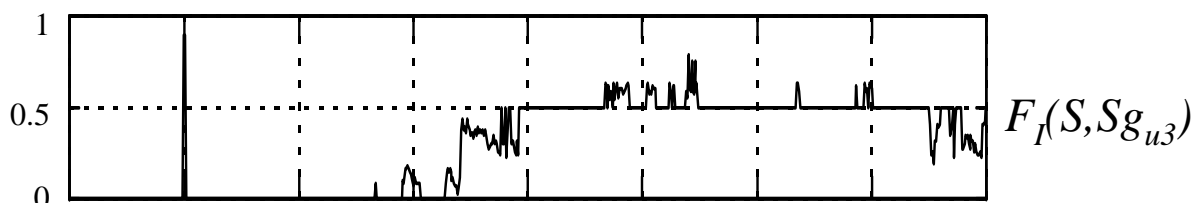
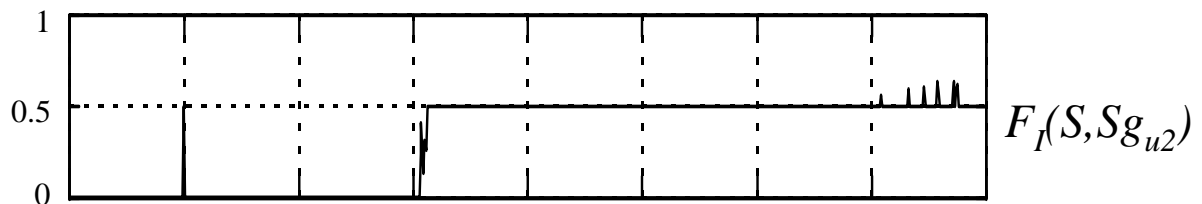
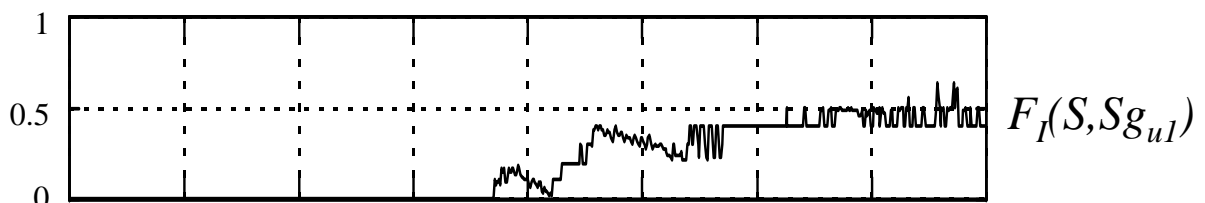
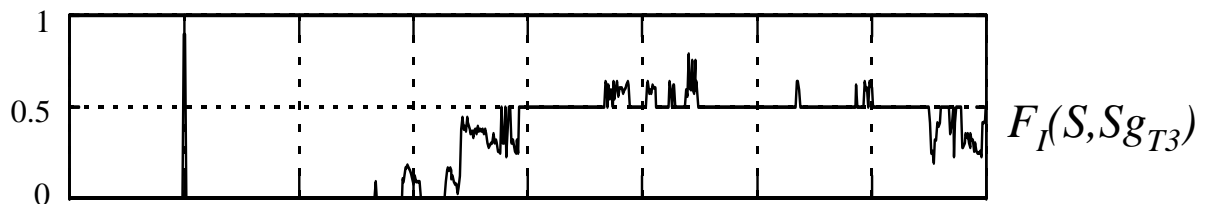
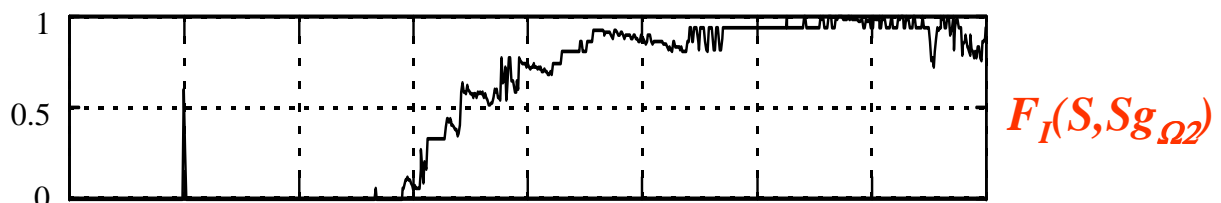
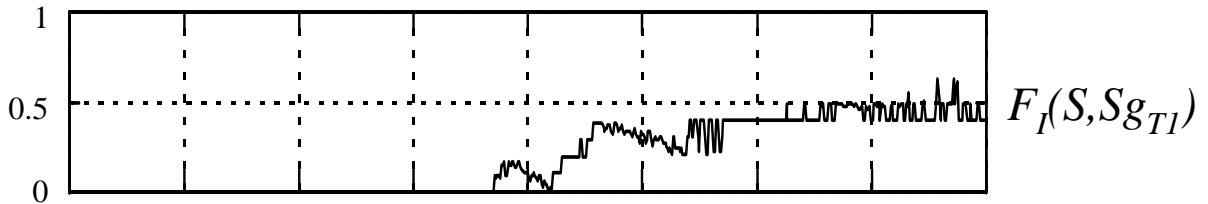
Fault isolation function evolution

CESA 1998

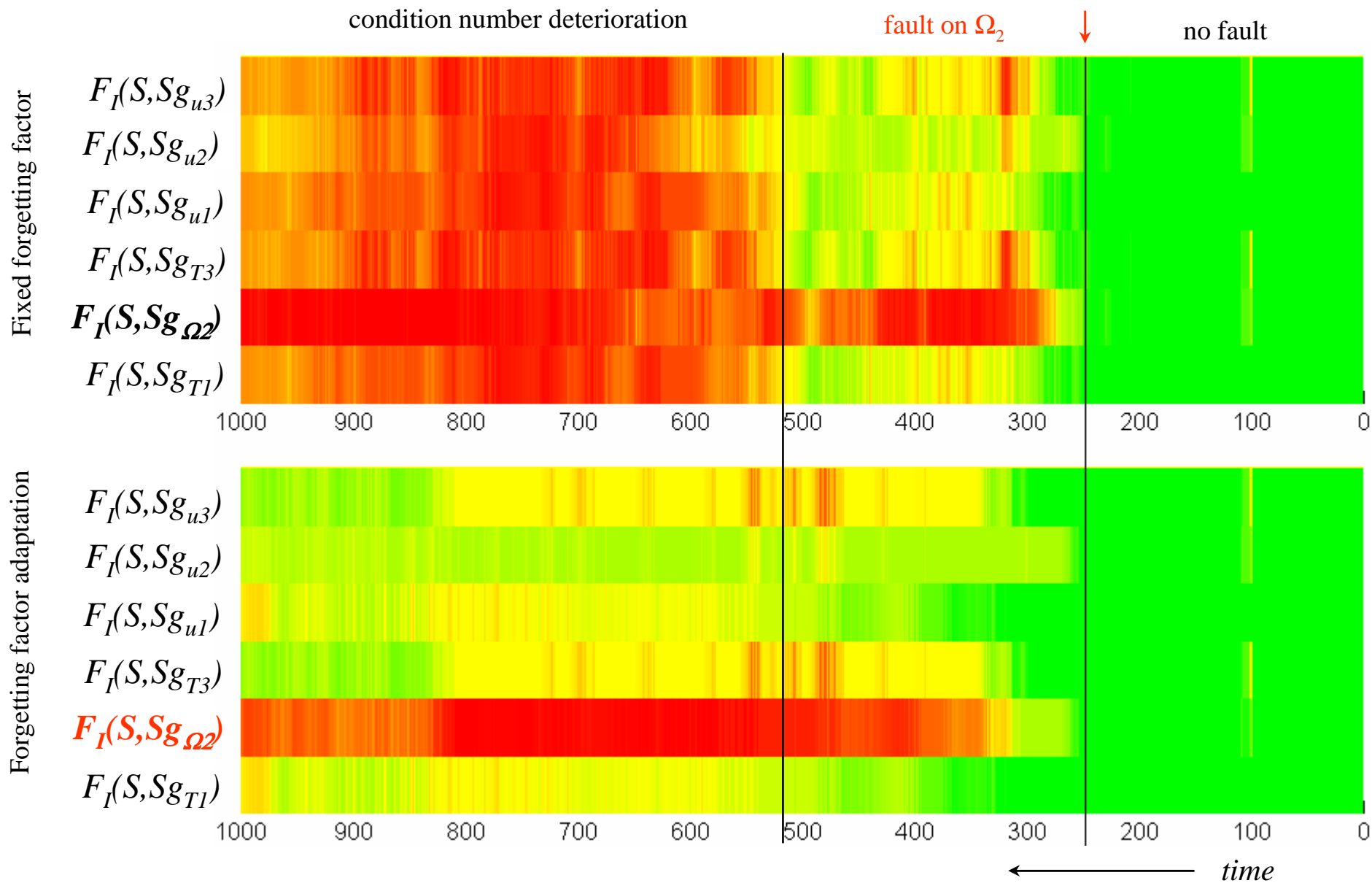
no fault



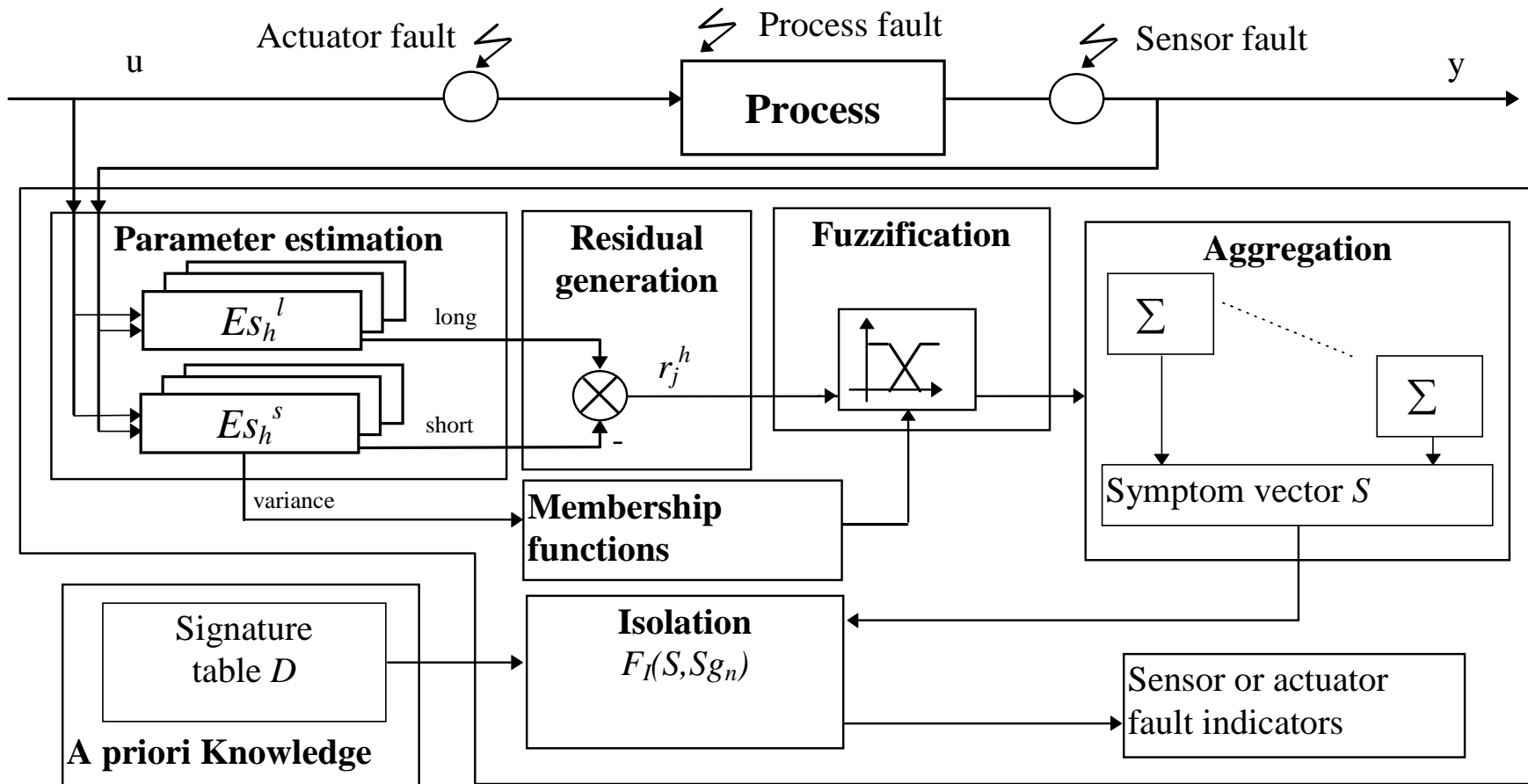
fault on Ω_2



Fault Detection and Isolation using
Multiple Model Parameter Estimation



Conclusion



Future work

Parameter estimation method using prediction error to a Box-Jenkins model structure

allows decoupling transfert function estimations

	Es^s_1	Es^s_2
fault x	1	0



	Es^s_1		Es^s_2	
	F_{11}	F_{12}	F_{21}	F_{22}
fault x	1	0	0	0

Actuator fault example

