

# *Fault Detection using Parameter Estimation applied to a Winding Machine*

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# Outline

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## Objective

### Identification

Choice of a model structure

and an estimation method

Consequence of a fault on parameter estimates

Actuator fault example

### Diagnosis

Residual generation **for detection**

Residual fuzzyfication

Signature table generation **for isolation**

Symptom Aggregation

Isolation Function by **fuzzy inference**

Isolation Function by **distance computation**

Diagnosis task architecture

## Application

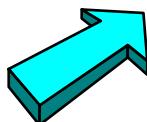


## Objective

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Diagnosis using Parameter estimation  
applied to a complex process!

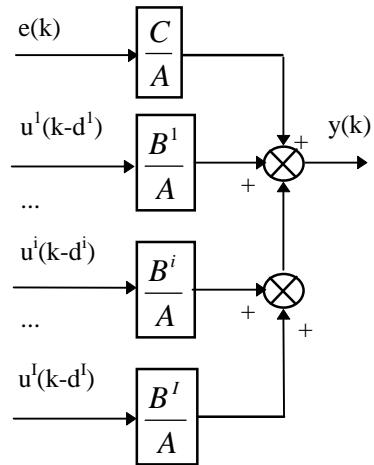


- No physical parameters
- No additive signal !
- A fast and simple estimation method



## Choice of a model structure and an estimation method

### ► ARMAX MISO discrete model



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

- ☺ **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**



## Consequence of a fault on parameter estimates

### Two kinds of faults

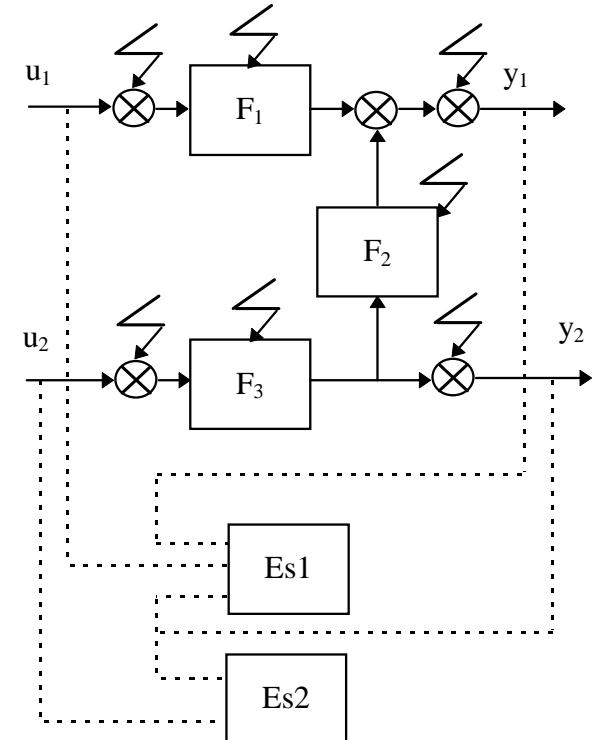
$$\begin{aligned}y_1 &= F_1 u_1 + F_2 y_2 \\y_2 &= F_3 u_2\end{aligned}$$

process fault

**variation of static or dynamic characteristics**

➡  actuator or sensor fault

*a global perturbation of all parameters  
and variance increase*





## Residual generation for detection

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The reference model

$$Es^l = \begin{bmatrix} \Theta_1 & \dots & \Theta_p \end{bmatrix} \rightarrow \text{summing junction}$$

long horizon  
estimate vector with  $\lambda = 1$

The tracking model

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

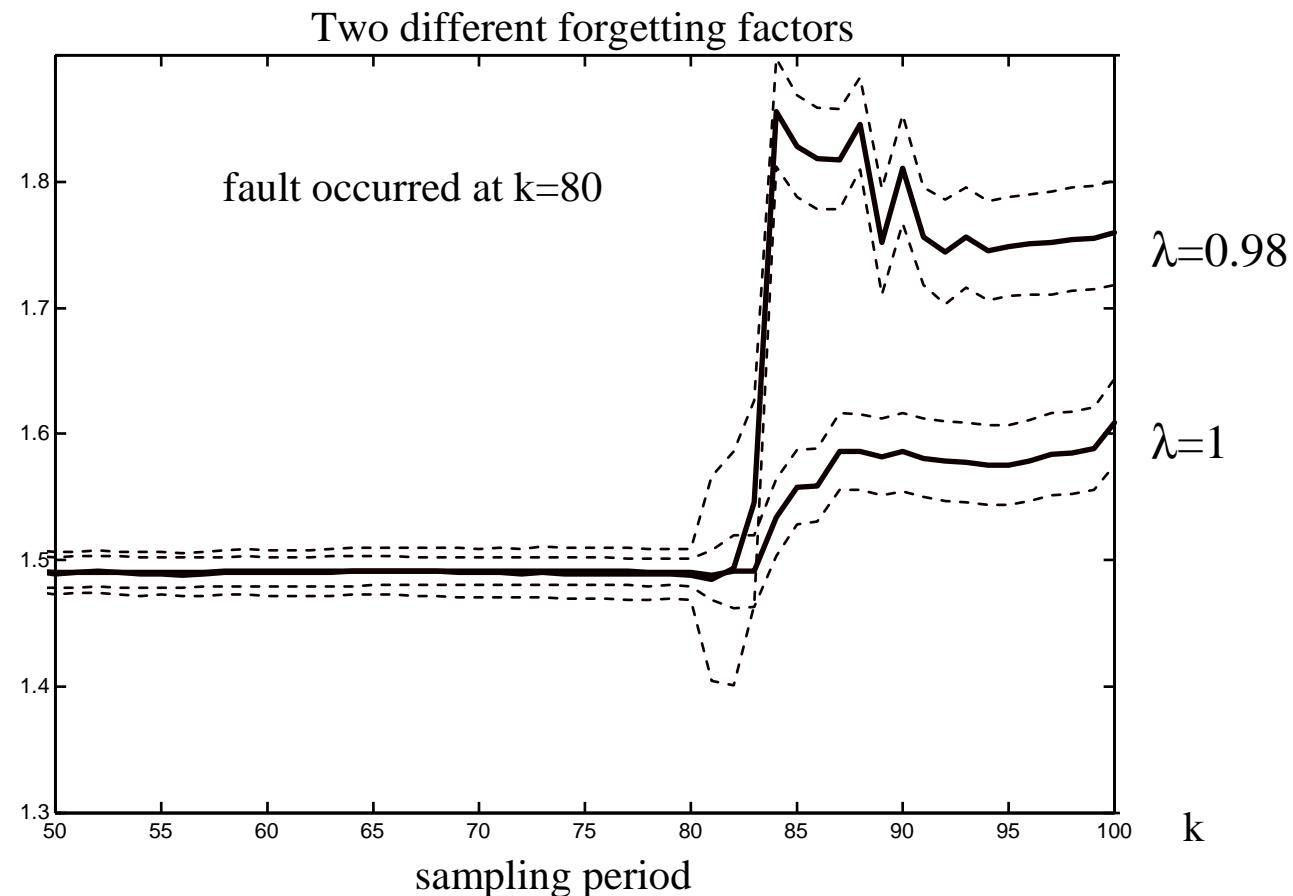
short horizon  
estimate vector with  $\lambda = 0.99$

RESIDUALS

$$r_j = \Theta_j - \theta_j$$

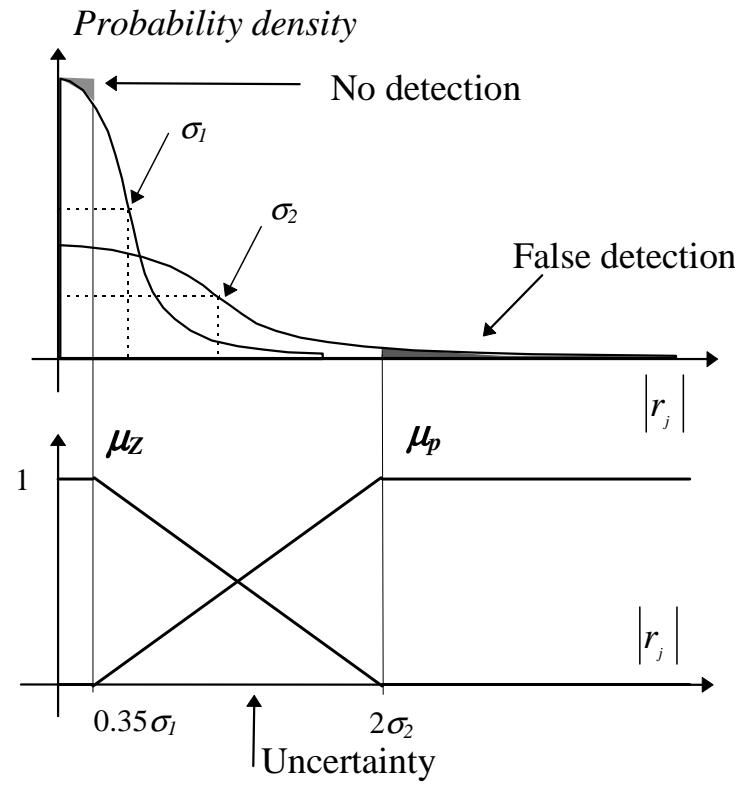
$$E\{r_j\} = E\{\Theta_j\} - E\{\theta_j\} \longrightarrow 0 \text{ if no fault occurred !}$$

## Actuator fault example





## Residual fuzzyfication



$$\text{Variance} \quad \sigma_{r_j}^2 \leq \sigma_{\theta_j}^2 \leq \sigma_2^2$$

$$\sigma_1^2 = \sigma_{\theta_j}^2 + \sigma_{\theta_j}^2 \quad \sigma_2^2 = (\sigma_{\theta_j} + \sigma_{\theta_j})^2$$

The membership function of the fuzzy sets

POSITIVE residual and ZERO residual :

$$\mu_p(|r_j|) = \min\left(1, \max\left(0, \frac{|r_j| - 0.35 \cdot \sigma_1^2}{2 \cdot \sigma_2^2 - 0.35 \cdot \sigma_1^2}\right)\right)$$

$$\mu_z(|r_j|) = 1 - \mu_p(|r_j|)$$



## Signature table generation for isolation

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

$y_1 = F_1 u_1 + F_2 u_2$ $y_2 = F_3 u_1 + F_4 u_2$	model m1 model m2	$y_1 = F_5 u_1 + F_6 y_2$	model m3	
Fault on	$D(n,h)$	$Es_1^s$	$Es_2^s$	$Es_3^s$
$u_1$	$Sg_1$	1	1	1
$u_2$	$Sg_2$	1	1	0
$y_1$	$Sg_3$	1	0	1
$y_2$	$Sg_4$	0	1	1

isolation

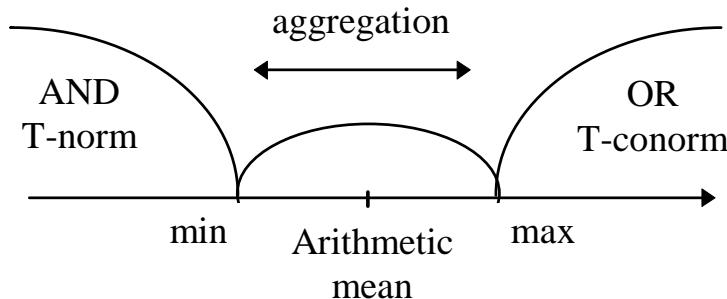


## Symptom Aggregation

**FAULT**



a global perturbation of residuals for the model  $m_h$



The symptom  $s_{m_h}$  is based on the residual vector :  $\left[ \left| r_1^h \right| \dots \left| r_{p^h}^h \right| \right]$

The symptom is defined by two complementary fuzzy sets :

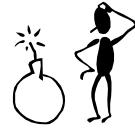
$G_p$  ↗ Globally perturbed  
 $N_p$  ↗ Not perturbed

The membership functions for each model are computed by an aggregation

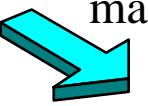
$$\mu_{G_p}(s_{m_h}) = \frac{1}{p^h} \sum_{j=1}^{p^h} \mu_p(\left| r_j^h \right|) \quad \text{and} \quad \mu_{N_p}(s_{m_h}) = 1 - \mu_{G_p}(s_{m_h})$$

Aggregated symptom vector

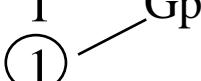
$$Sp = \left[ \mu_{G_p}(s_{m_1}) \dots \mu_{G_p}(s_{m_H}) \right]$$



## Isolation function by fuzzy inference (in single fault case)

$Sp$              $Sg_n$

$\mu_{Fn}(Sp) = 0$	no fault $F_n$
$0 < \mu_{Fn}(Sp) < 1$	fault $F_n$ suspicion
$\mu_{Fn}(Sp) = 1$	fault $F_n$

$D(n,h)$	$Es_1^s$	$Es_2^s$	$Es_3^s$	The rule for $Sg_2$
$Sg_1$	1	1		
$Sg_2$	<b>1</b>	<b>1</b>		IF $s_{m1}$ is Gp
$Sg_3$	1	0		and $s_{m2}$ is Gp
$Sg_4$	0	1		and $s_{m3}$ is Np
				THEN the fault is $F_2$

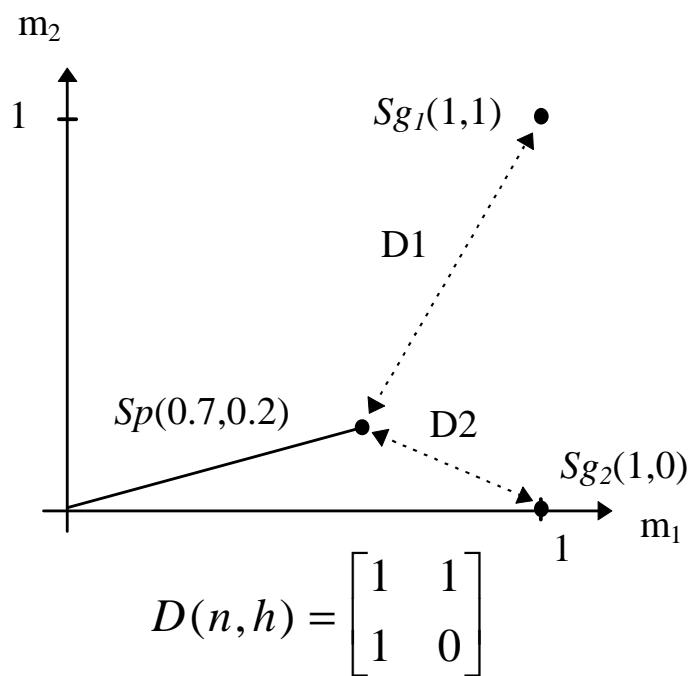
and is a T-norm computed by a min operator, the rule becomes :

$$\mu_{F2}(Sp) = \min \{ \mu_{Gp}(s_{m1}), \mu_{Gp}(s_{m2}), \mu_{Np}(s_{m3}) \}$$

## Isolation function by distance computation

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



$$F(Sp, Sg_n) = 0 \quad \text{no fault n}$$

$$0 < F(Sp, Sg_n) < 1 \quad \text{fault n suspicion degree}$$

$$F(Sp, Sg_n) = 1 \quad \text{fault n}$$

General formula by distance computation

$$F(Sp, Sg_n) = 1 - \frac{1}{\omega} \left( \sum_{h=1}^H |\mu_{G_p}(s_{m_h}) - D(n, h)|^q \right)^{\frac{1}{q}}$$

**Hamming distance**  $q=1$   $\omega=\text{space dimension}$

$$F(Sp, Sg_n) = 1 - \frac{1}{H} \sum_{h=1}^H |\mu_{G_p}(s_{m_h}) - D(n, h)|$$

## Isolation function by distance computation

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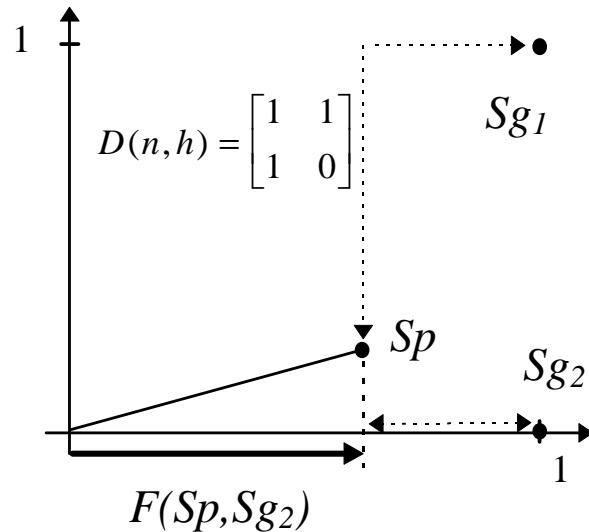
No fault

$$Sp = \begin{bmatrix} 0 & 0 \end{bmatrix} \quad \Rightarrow \quad F(Sp, Sg_2) = 1 - \frac{1}{2}[|0 - 1| + |0 - 0|] = 0.5$$



eliminate insensitive dimensions

$$F(Sp, Sg_n) = 1 - \frac{1}{W_n} \sum_{h=1}^H \{ |\mu_{Gp}(s_{m_h}) - D(n, h)| \cdot D(n, h) \}$$



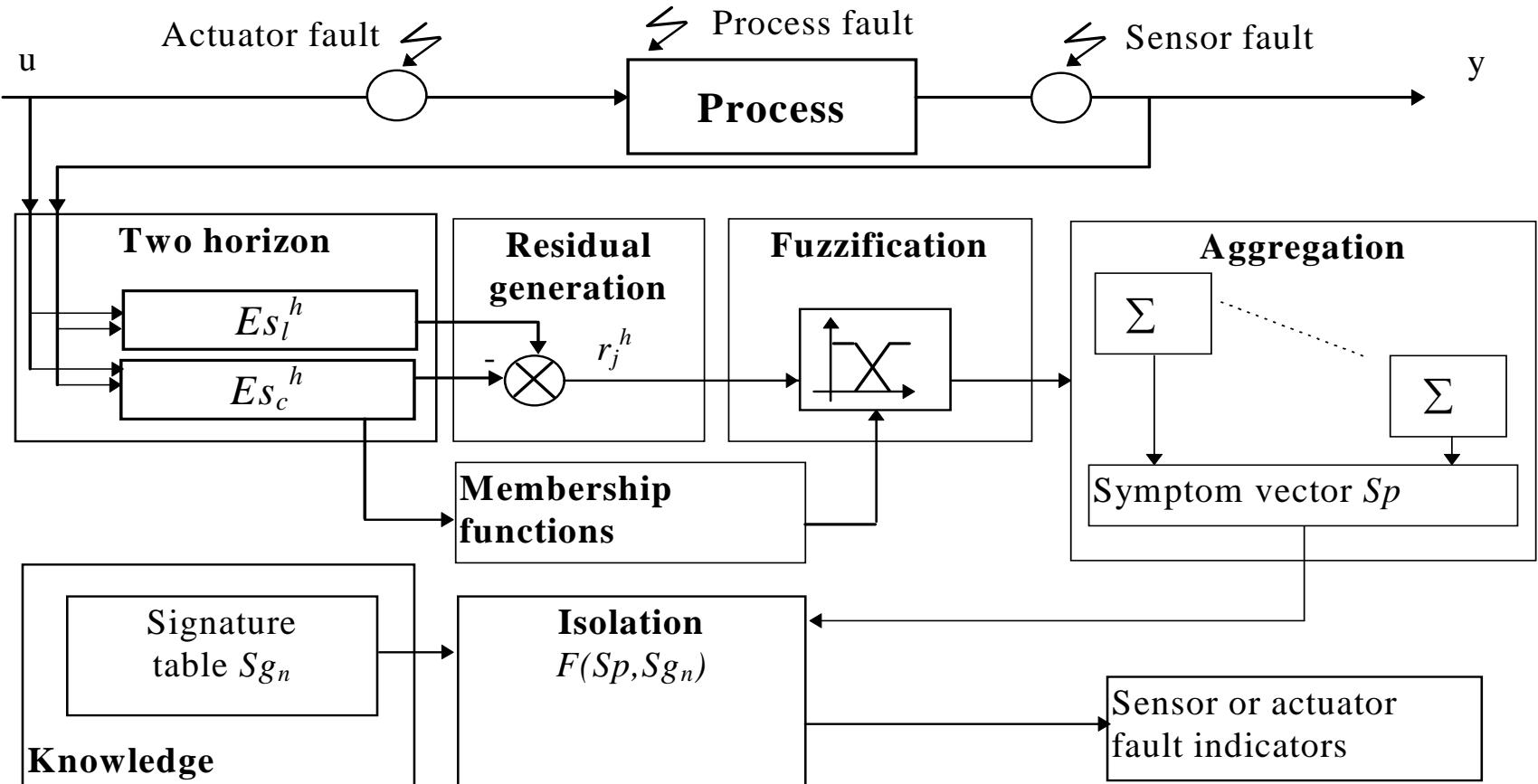
$$Sp = \begin{bmatrix} 0 & 0 \end{bmatrix} \quad F(Sp, Sg_1) = 0 \quad F(Sp, Sg_2) = 0$$

$$Sp = \begin{bmatrix} 0.7 & 0.2 \end{bmatrix} \quad F(Sp, Sg_1) = 0.45 \quad F(Sp, Sg_2) = 0.7$$

$\Rightarrow$  Useful too for multiple fault analysis



## Diagnosis task architecture



# Application

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After off line parameter estimation:

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

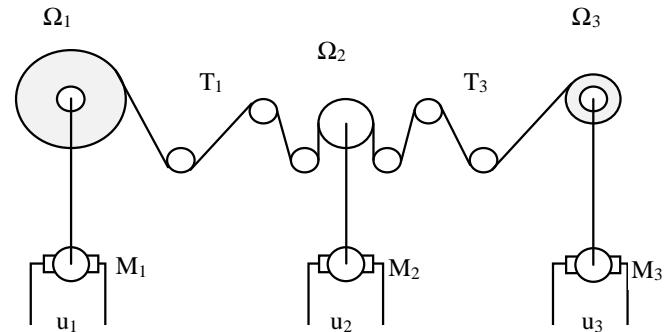
$$A_2(q^{-1}) \cdot \Omega_2(k) = B_{2u2}(q^{-1}) \cdot u_2(k-d_{2u2})$$

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

Redundant transfer function generation:

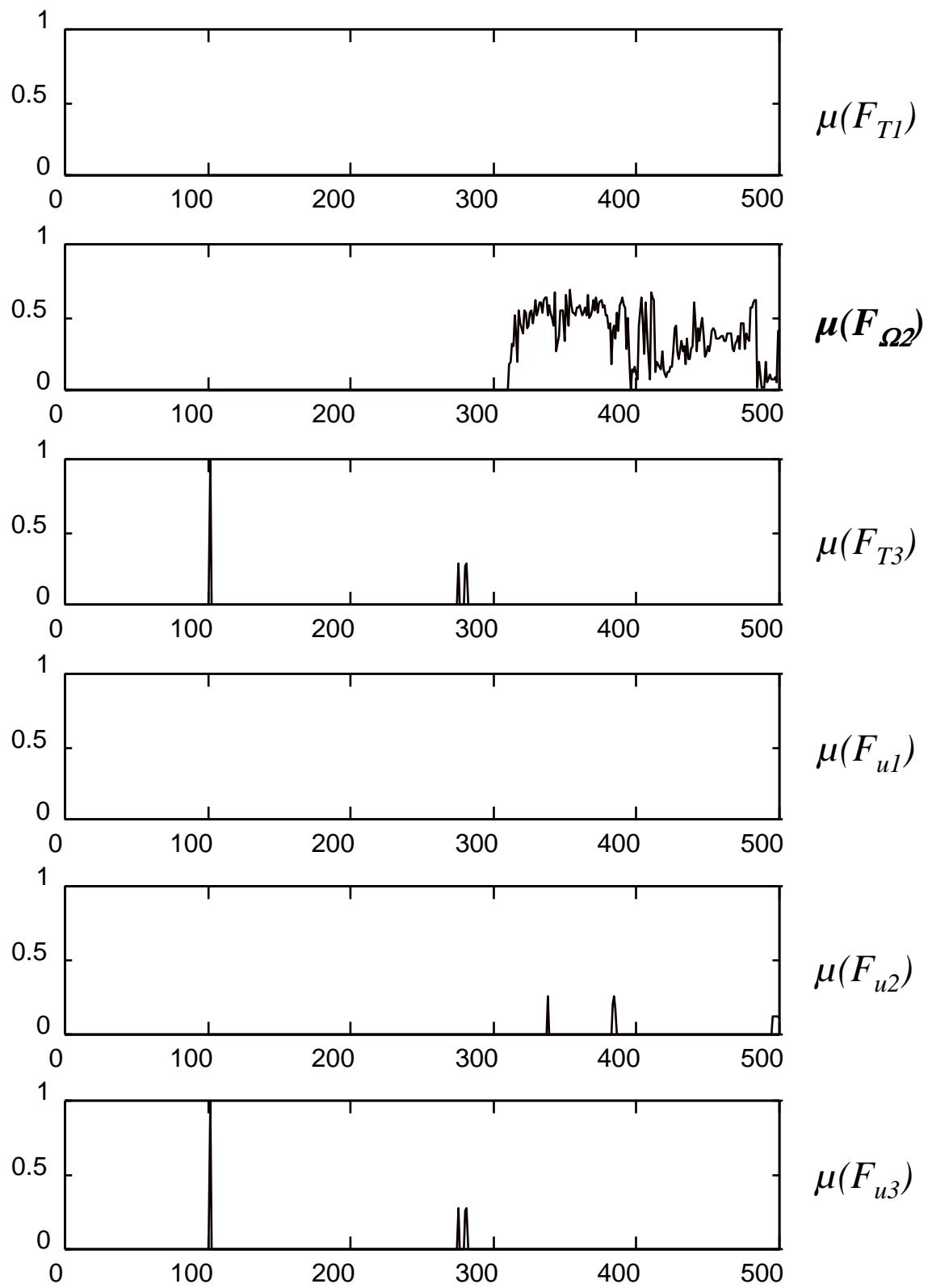
$$A_{11}(q^{-1}) \cdot T_1(k) = B_{11u2}(q^{-1}) \cdot u_2(k-d_{11u2}) + B_{11u1}(q^{-1}) \cdot u_1(k-d_{1u1})$$

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

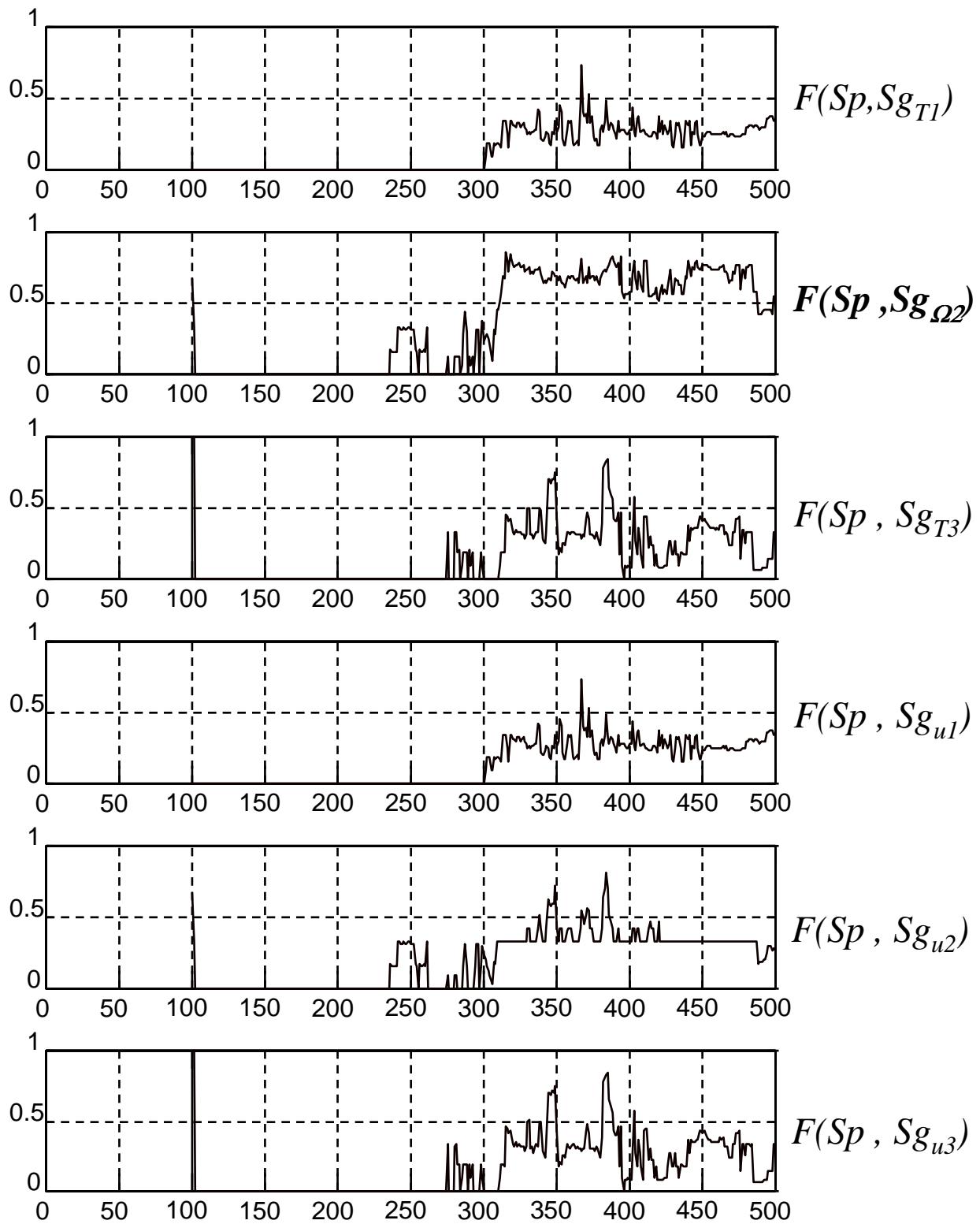


Bias on	<b>D</b>	Es <sub>1</sub>	Es <sub>2</sub>	Es <sub>3</sub>		Es <sub>4</sub>	Es <sub>5</sub>
T <sub>1</sub>	Sg <sub>T1</sub>	1	0	0		<b>1</b>	<b>0</b>
$\Omega_2$	Sg <sub><math>\Omega_2</math></sub>	1	1	1		<b>0</b>	<b>0</b>
T <sub>3</sub>	Sg <sub>T3</sub>	0	0	1		<b>0</b>	<b>1</b>
u <sub>1</sub>	Sg <sub>u1</sub>	<b>1</b>	<b>0</b>	<b>0</b>		1	0
u <sub>2</sub>	Sg <sub>u2</sub>	<b>0</b>	<b>1</b>	<b>0</b>		1	1
u <sub>3</sub>	Sg <sub>u3</sub>	<b>0</b>	<b>0</b>	<b>1</b>		0	1

## Fault suspicion degree using fuzzy rules



## Fault isolation function evolution



## Conclusion

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### Fault detection and isolation of sensor or actuator FAULTS

- transfer function redundancy  $\Rightarrow$  better isolation performance
- fuzzy residual evaluation  $\Rightarrow$  taking uncertainty into account
- symptom aggregation  $\Rightarrow$  allows comparison with the fault signature table
- the result with a classical fuzzy inference system in a single fault case  $\Rightarrow$  method validation
- the result with distance computation for classification  $\Rightarrow$  possibility of multiple faults isolation

## Future work

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### **Parameter estimation method with adaptive forgetting factor**

using information like

condition number,

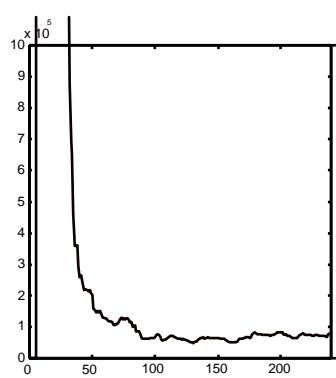
prediction error,

**to solve the non-persistent excitation problem**

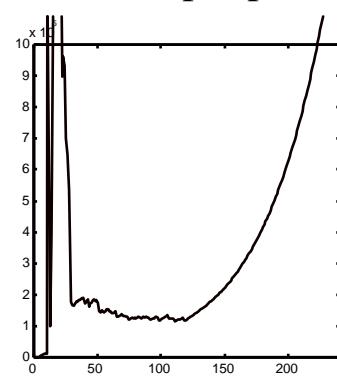
### **Find an optimal signature table**

### **Closed loop application**

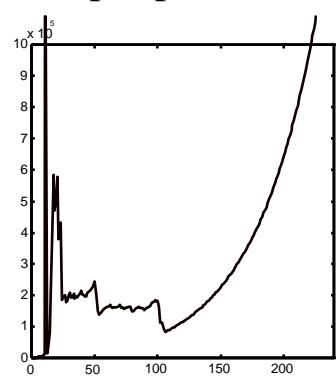
PRBS



Step input



Step input +fault

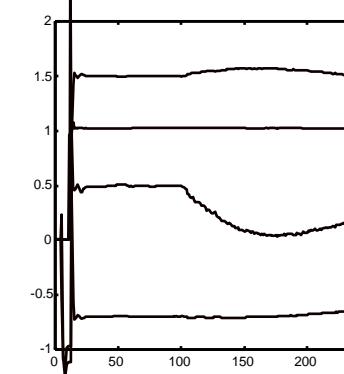
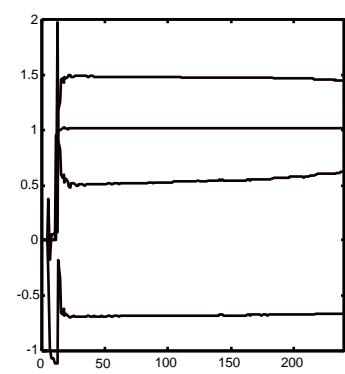
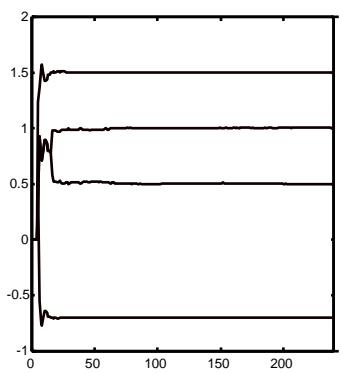
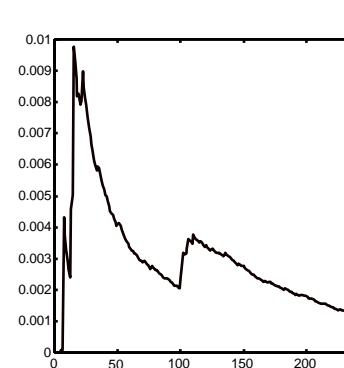
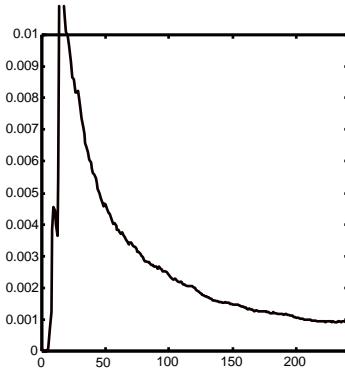
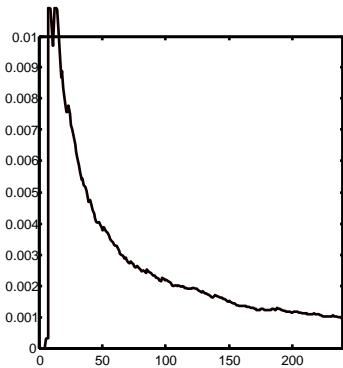
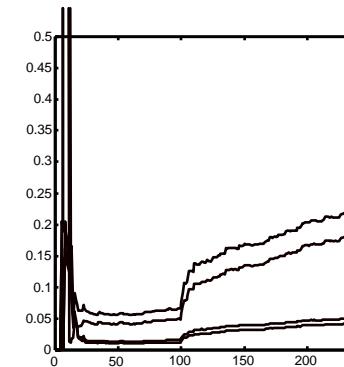
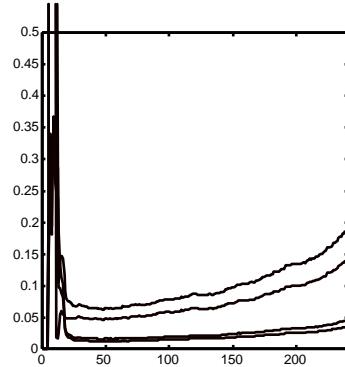
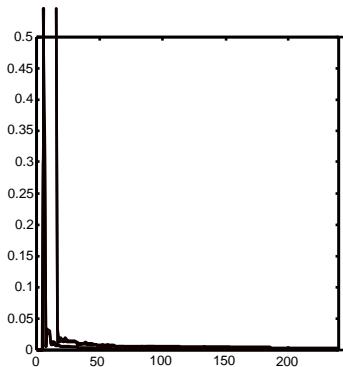


conditioning number

Variance

Prediction error

Parameters



On line conditioning number evolution

