Soft Computing in Fault Detection and Isolation

PART V

Case studies - industrial applications

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8 października 2012

OUTLINE

➥ DAMADICS benchmark - valve actuator case study

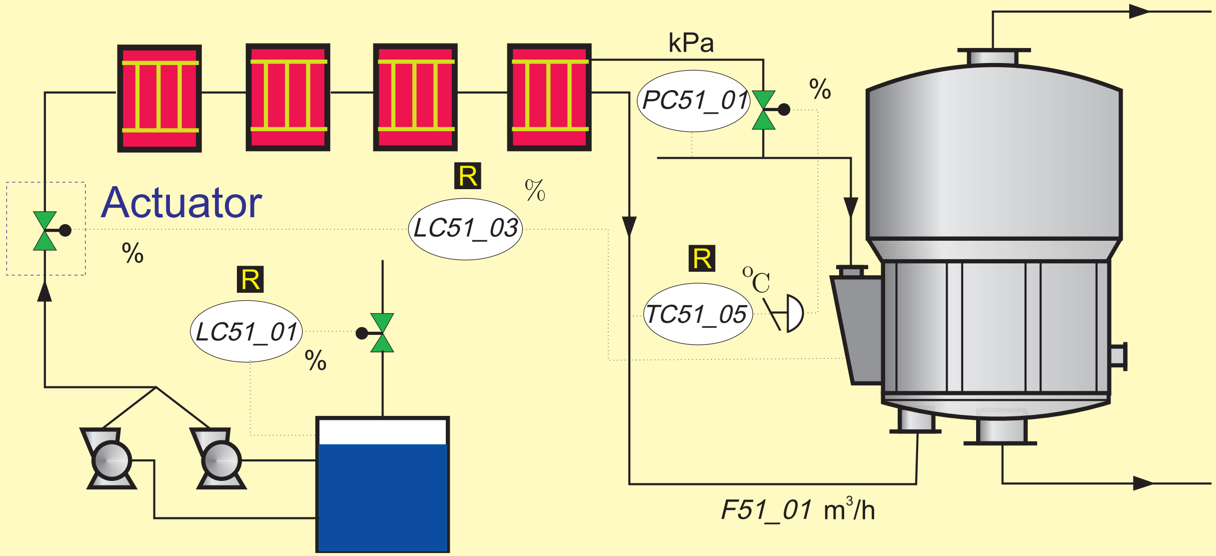
- Robust fault detection with GMDH models
- Genetic programming and extended unknown input observer
- Fault detection with Takagi-Sugeno models and adaptive threshold approach

➥ Induction motors

- State observation of an induction motor
- Unknown input decoupling with EUIO
- Sensor fault detection and isolation example
- Fault detection system for DC engine

☛ DAMADICS BENCHMARK - VALVE ACTUATOR CASE STUDY

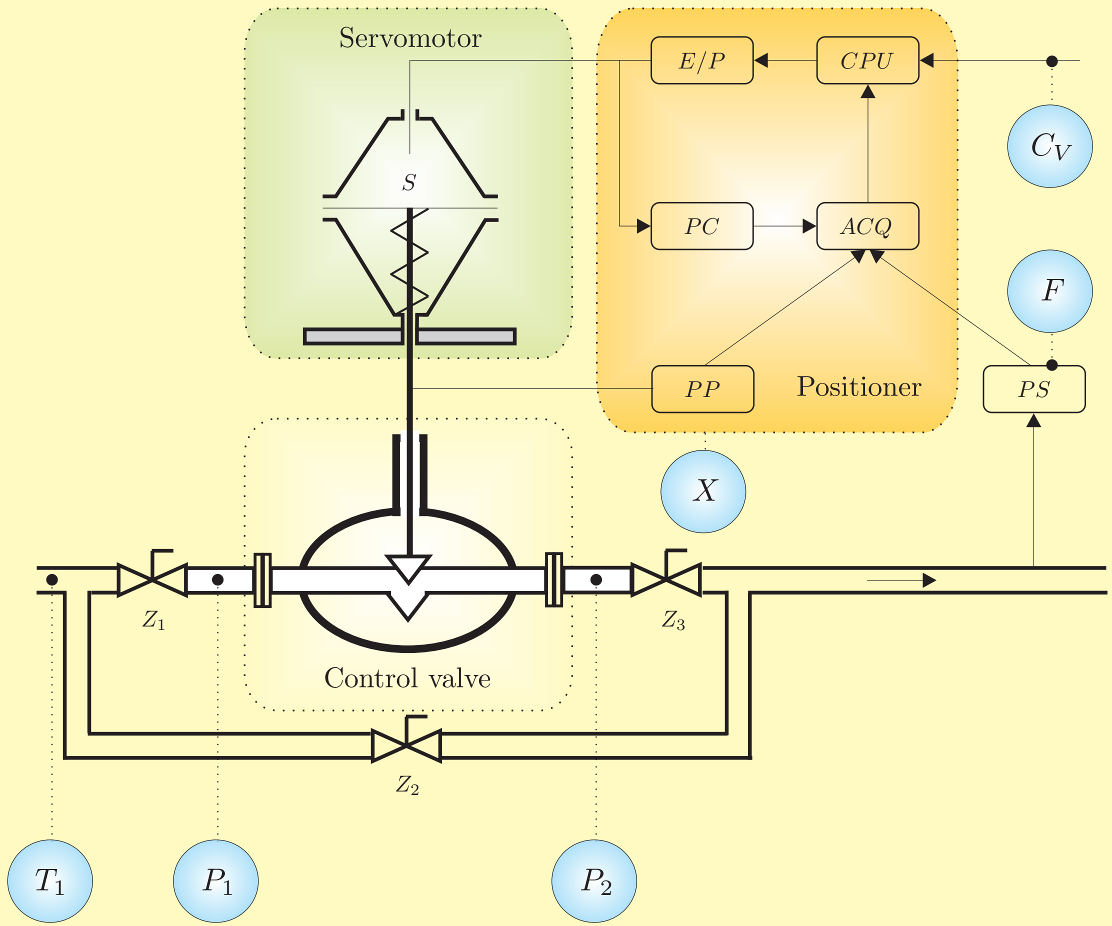
- Realization: FP5 EC, RTN DAMADICS, 2000-2004
- Industry: Lublin Sugar Factory (Cukrownia Lublin S.A.)



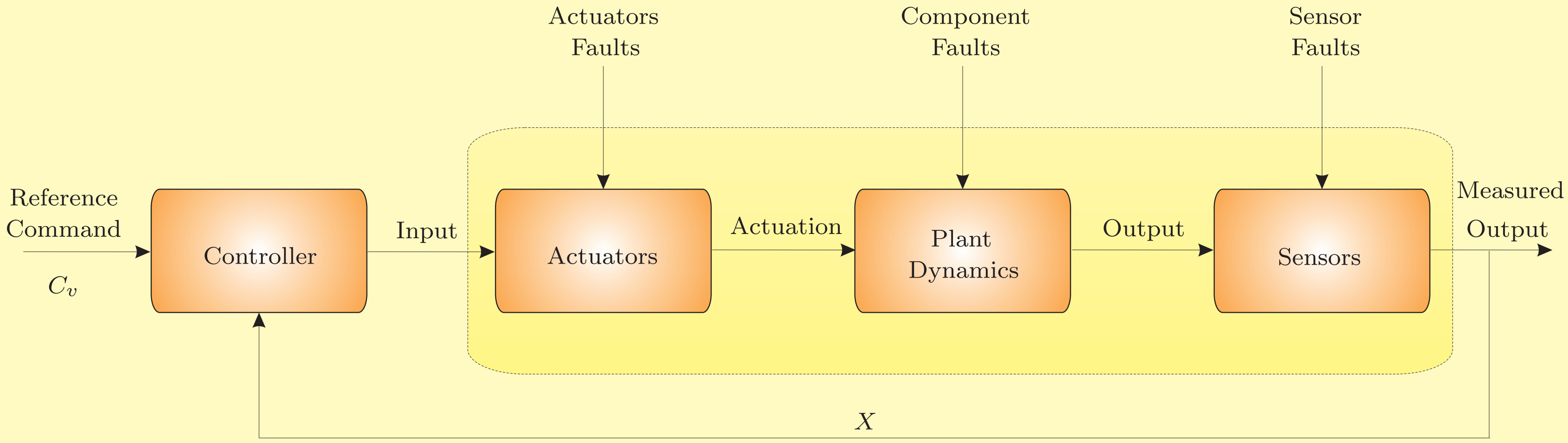
➜ The scheme of the intelligent actuator

ACQ – data acquisition unit
CPU – positioner central processing unit
E/P – electro-pneumatic transducer
z_1, z_2, z_3 – bypass valves
DT – displacement
PT – pressure
FT – value flow transducer

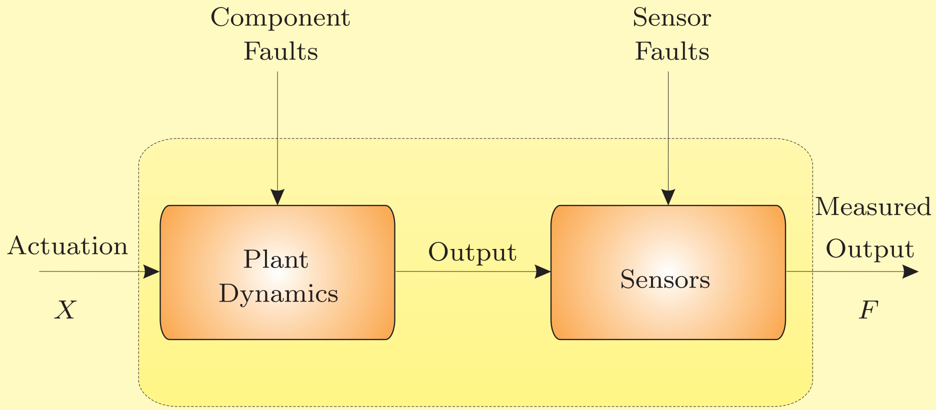
F – juice flow (valve outlet)
X – servomotor rod displacement
C_V – control value
T_1 – juice temperature
P_1 – juice pressure (valve inlet)
P_2 – juice pressure (valve outlet)



- Model of the positioner and the pneumatic motor $X = r_X(C_V, P_1, P_2, T_1)$



- Model of the control valve $F = r_F(X, P_1, P_2, T_1)$



➜ Fault descriptions

Fault	Description	S	M	B	I
f_1	Valve clogging	x	x	x	
f_2	Valve plug or valve seat sedimentation			x	x
f_3	Valve plug or valve seat erosion				x
f_4	Increased of valve or busing friction				x
f_5	External leakage				x
f_6	Internal leakage (valve tightness)				x
f_7	Medium evaporation or critical flow	x	x	x	x
f_8	Twisted servomotor's piston rod	x	x	x	
f_9	Servomotors housing or terminals tightness				x

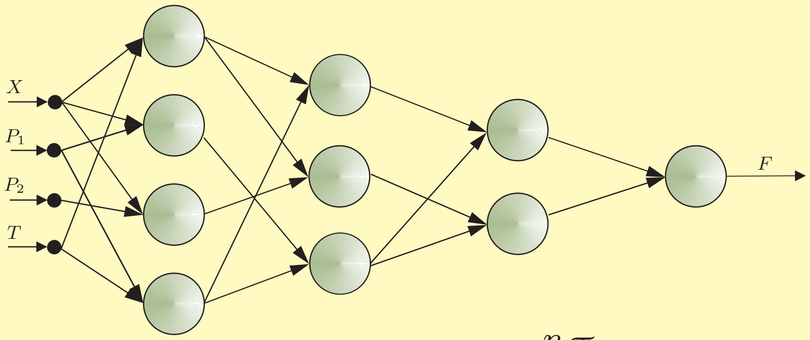
Fault	Description	S	M	B	I
f_{10}	Servomotor's diaphragm perforation	x	x	x	
f_{11}	Servomotor's spring fault				x
f_{12}	Electro-pneumatic transducer fault	x	x	x	
f_{13}	Rod displacement sensor fault	x	x	x	x
f_{14}	Pressure sensor fault	x	x	x	
f_{15}	Positioner feedback fault			x	
f_{16}	Positioner supply pressure drop	x	x	x	
f_{17}	Unexpected pressure change across the valve			x	x
f_{18}	Fully or partly opened bypass valves	x	x	x	x
f_{19}	Flow rate sensor fault	x	x	x	

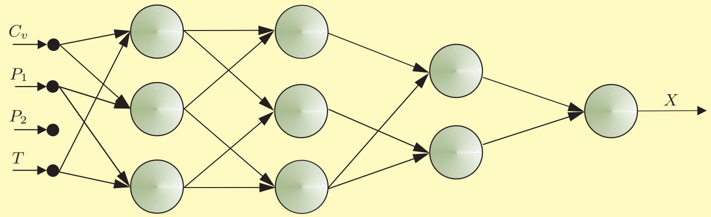
➜ Robust fault detection with GMDH models

The data used for system identification and fault detection

Fault	Range (samples)	Fault/data description
No fault	1–10000	Training data set
No fault	10001–20000	Validation data set
f_{16}	57475–57530	Positioner supply pressure drop
f_{17}	53780–53794	Unexpected pressure drop across the valve
f_{18}	54600–54700	Fully or partly opened bypass valves
f_{19}	55977–56015	Flow rate sensor fault

➜ The final structure of $F = r_F(\cdot)$ and $X = r_X(\cdot)$ GMDH models



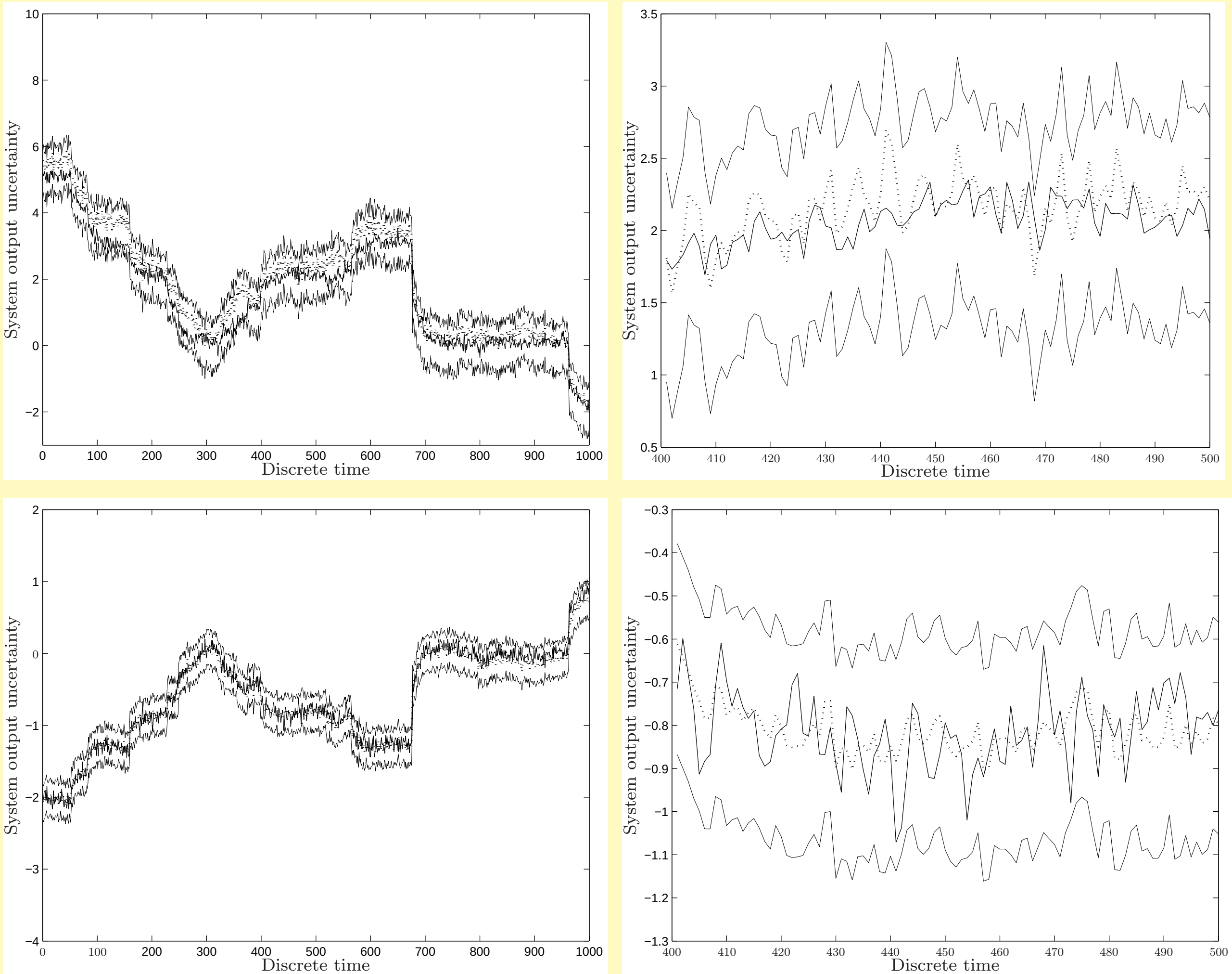


$$Q_{\mathcal{T}} = \frac{1}{n_{\mathcal{T}}} \sum_{k=1}^{n_{\mathcal{T}}} \left| \left(\hat{y}^M(k) + \varepsilon^M(k)\right) - \left(\hat{y}^m(k) + \varepsilon^m(k)\right) \right|$$

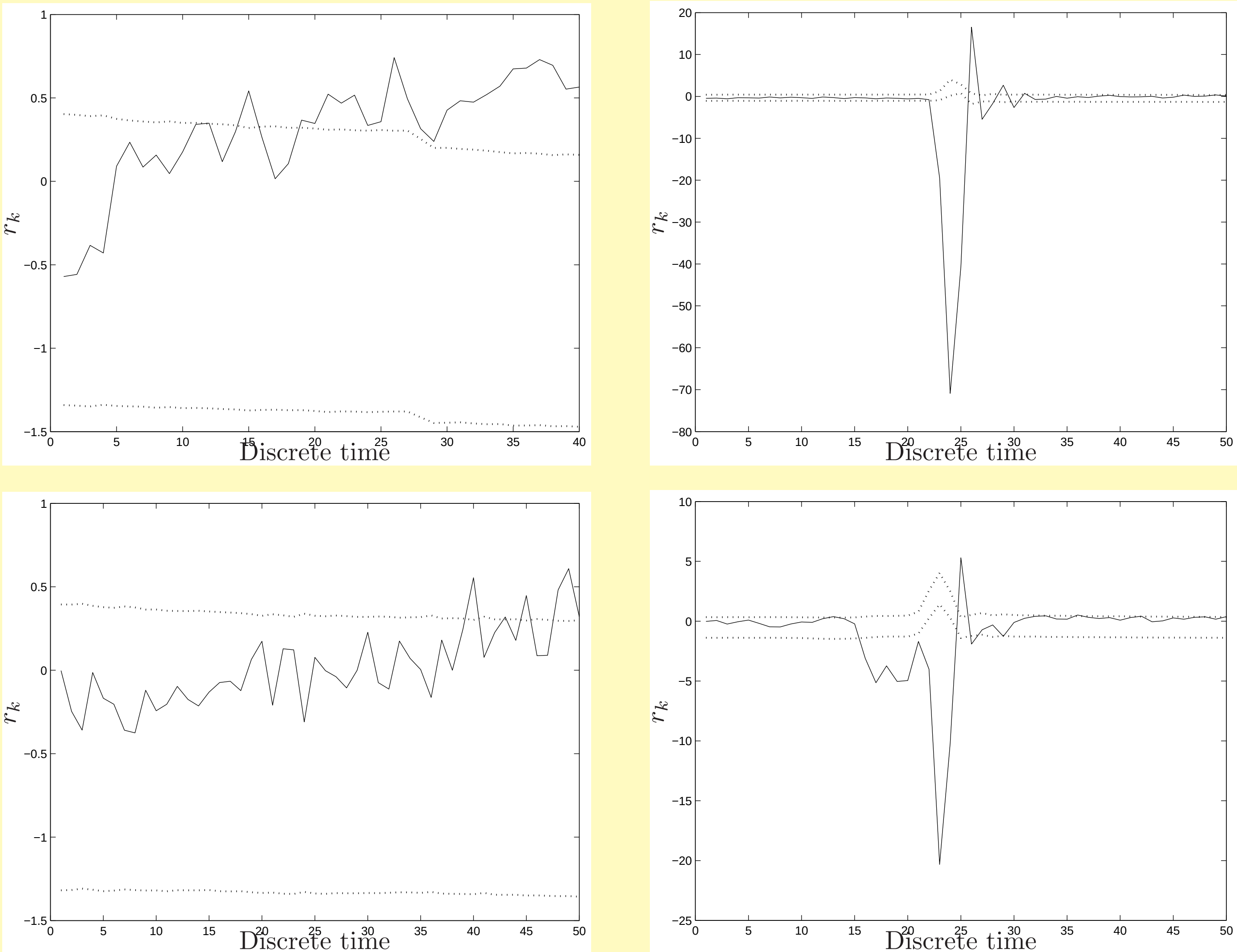
Layer	$r_F(\cdot)$ $Q_{\mathcal{T}}$	$r_X(\cdot)$ $Q_{\mathcal{T}}$
1	1.5549	0.5198
2	1.5277	0.4914
3	1.5047	0.4904
4	1.4544	0.4898
5	1.4599	0.4909

➜ The modelling abilities of the GMDH models $F = r_F(\cdot)$ and $X = r_X(\cdot)$

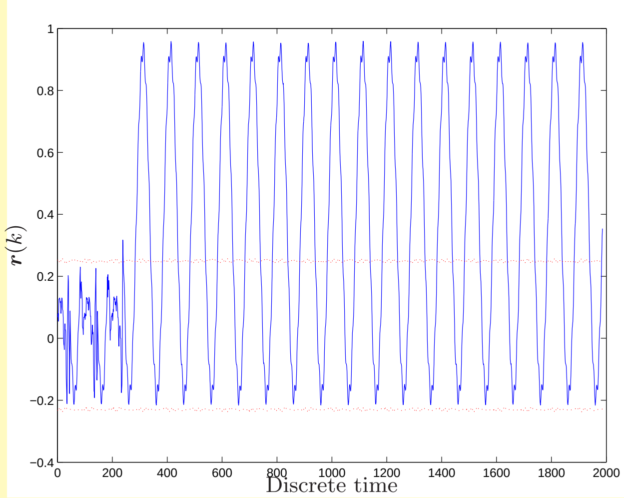
- Model and system outputs as well as the corresponding system output uncertainty

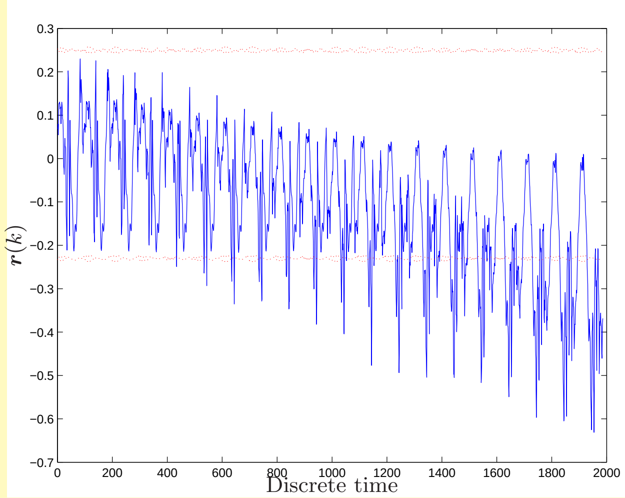


➜ Residual for faults f_{16}, f_{17}, f_{18} and f_{19}

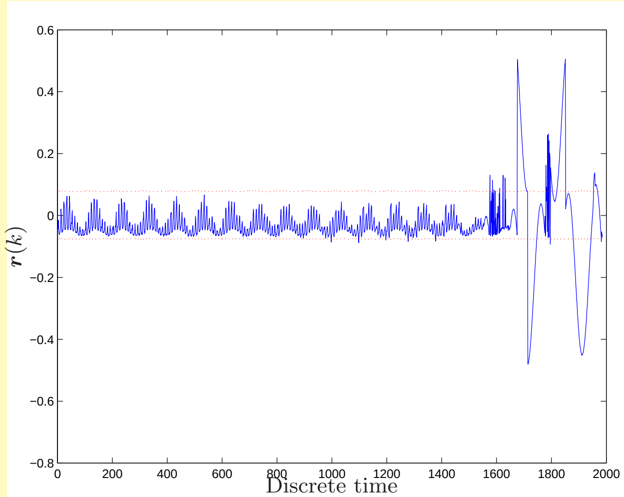


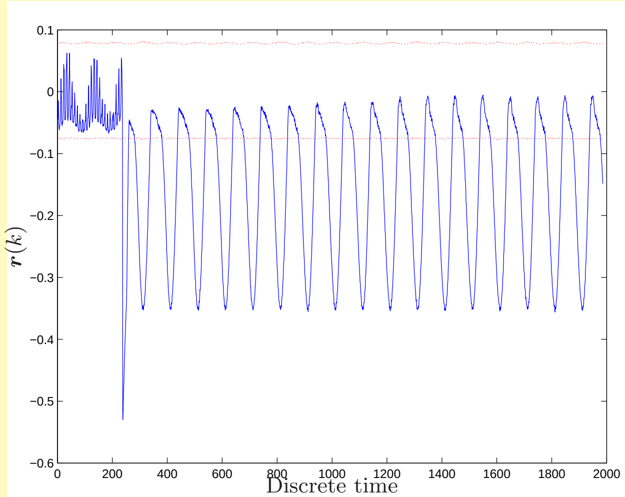
- Residual for the big abrupt fault f_1 (left) and incipient fault f_2 (right)





- Residual tor the incipient fault f_4 (left) and the abrupt medium fault f_7(right)





➜ Genetic programming and extended unknown input observer

- A general form of the modelled relation

$$\boldsymbol{y} = f(\boldsymbol{u}), \quad \boldsymbol{y} = (X, F), \quad \boldsymbol{u} = (P_1, P_2, T_1, CV)$$

- Linear state-space models?

- The non-linear state-space model designed with GP

  The terminals and functions sets

$$\mathbb{T}_A = \{\hat{\boldsymbol{x}}_k\}, \quad \mathbb{T}_h = \{\boldsymbol{u}_k\}$$
$$\mathbb{F} = \{+, *, /\}.$$

The non-linear state-space model

$$\hat{\boldsymbol{x}}_{k+1} = \begin{bmatrix} \boldsymbol{A}_F(\hat{\boldsymbol{x}}_k) & 0 \\ 0 & \boldsymbol{A}_X \end{bmatrix} \hat{\boldsymbol{x}}_k + \begin{bmatrix} \boldsymbol{h}(\boldsymbol{u}_k) \\ \boldsymbol{B}_X \boldsymbol{u}_k \end{bmatrix}$$

$$\hat{\boldsymbol{y}}_{k+1} = \boldsymbol{C}\hat{\boldsymbol{x}}_{k+1}$$

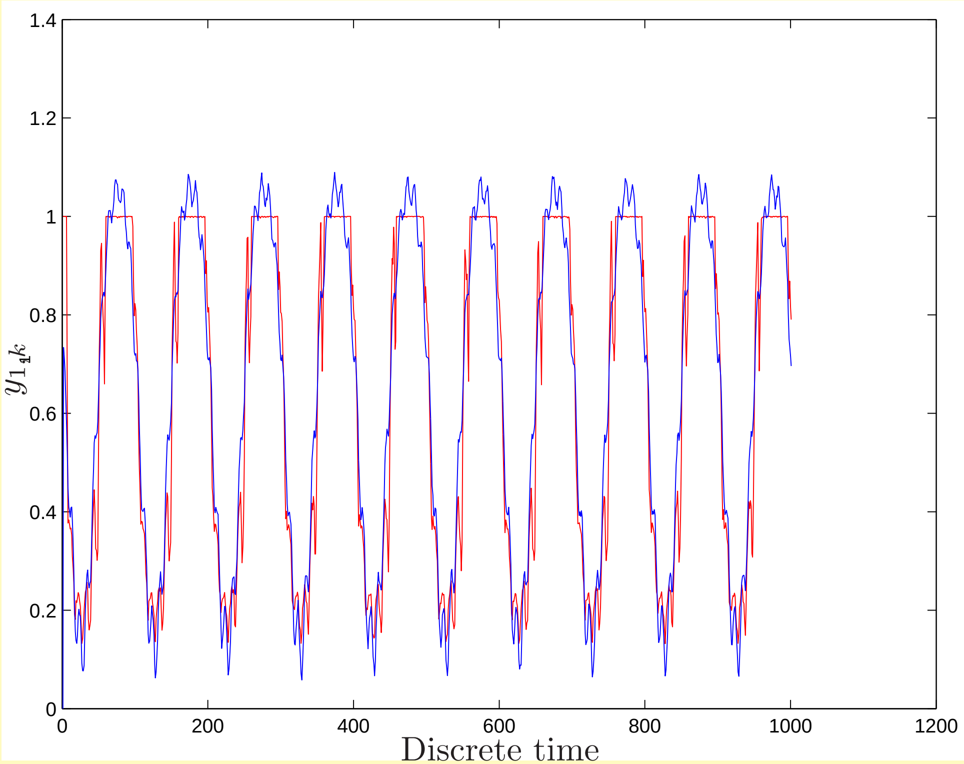
where

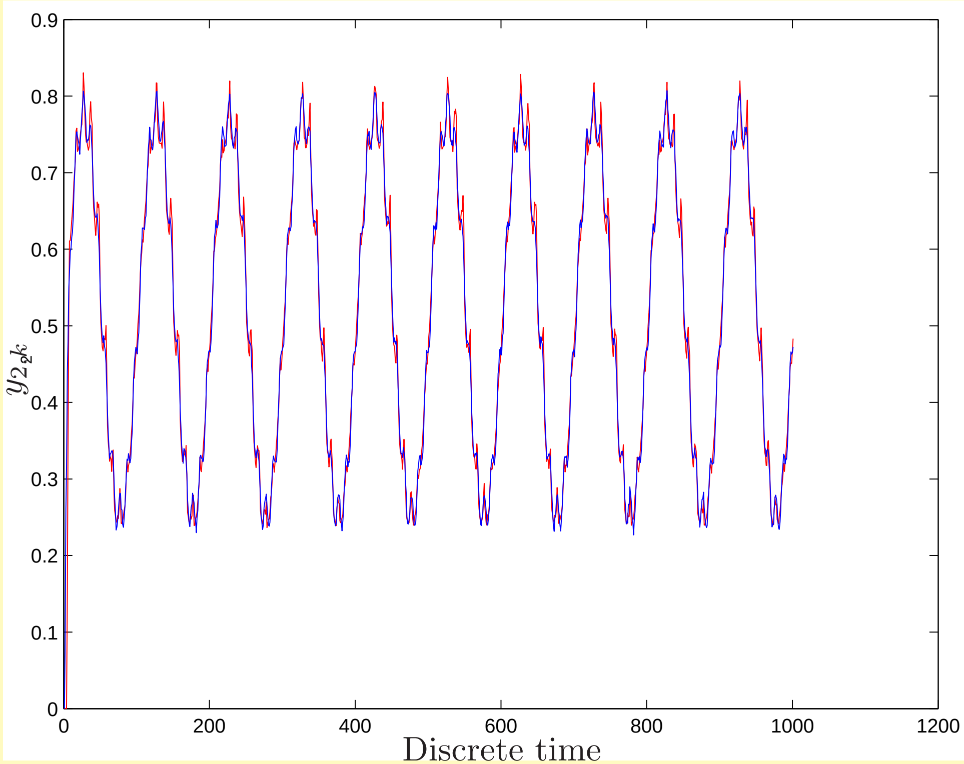
$$\boldsymbol{A}_F(\hat{\boldsymbol{x}}_k) = \begin{bmatrix} 0.3\tanh\left(10\hat{x}_{1,k}^2 + 23\hat{x}_{1,k}\hat{x}_{2,k} + \frac{26\hat{x}_{1,k}}{\hat{x}_{2,k}+0.01}\right) & 0 \\ 0 & 0.15\tanh\left(\frac{5\hat{x}_{2,k}^2+1.5\hat{x}_{1,k}}{\hat{x}_{1,k}^2+0.01}\right) \end{bmatrix}$$

$$\boldsymbol{A}_X = \begin{bmatrix} 0.78786 & -0.28319 \\ 0.41252 & -0.84448 \end{bmatrix} \boldsymbol{B}_X = \begin{bmatrix} 2.3695 & -1.3587 & -0.29929 & 1.1361 \\ 12.269 & -10.042 & 2.516 & 0.83162 \end{bmatrix}$$

$$\boldsymbol{h}(\boldsymbol{u}_k) = \begin{bmatrix} -1.087u_{1,k}^2 + 0.0629u_{2,k}^2 - 0.5019u_{3,k}^2 - 3.0108u_{4,k}^2 \\ +0.9491(u_{1,k}u_{2,k} - u_{1,k}u_{3,k}) - 0.5409\frac{u_{1,k}u_{4,k}}{u_{2,k}u_{3,k}+0.01} + 0.9783 \\ -0.292u_{1,k}^2 + 0.0162u_{2,k}^2 - 0.1289u_{3,k}^2 - 0.7733u_{4,k}^2 \\ +0.2438(u_{1,k}u_{2,k} - u_{1,k}u_{3,k}) - 0.1389\frac{u_{1,k}u_{4,k}}{u_{2,k}u_{3,k}+0.01} + 0.2513 \end{bmatrix}$$

- Comparison between the model (blue) and system (red) output





- Estimation of the unknown input distribution matrix for EUIO

$$\hat{\boldsymbol{d}}_k^* = \arg \min_{\hat{\boldsymbol{d}}_k \in \mathbb{R}^q} \boldsymbol{\varepsilon}_{k+1}^T \boldsymbol{\varepsilon}_{k+1}$$

Since $\boldsymbol{\varepsilon}_{k+1} = \boldsymbol{y}_{k+1} - \hat{\boldsymbol{y}}_{k+1}$, where:

$$\boldsymbol{x}_{k+1} = \boldsymbol{g}(\boldsymbol{x}_k) + \boldsymbol{h}(\boldsymbol{u}_k) + \boldsymbol{d}_k$$
$$\boldsymbol{y}_{k+1} = \boldsymbol{C}_{k+1}\boldsymbol{x}_{k+1}$$

and:

$$\hat{\boldsymbol{x}}_{k+1} = \boldsymbol{g}(\hat{\boldsymbol{x}}_k) + \boldsymbol{h}(\boldsymbol{u}_k) + \hat{\boldsymbol{d}}_k$$
$$\hat{\boldsymbol{y}}_{k+1} = \boldsymbol{C}_{k+1}\hat{\boldsymbol{x}}_{k+1}$$

- The solution is given by

$$\hat{\boldsymbol{d}}_k^* = \arg\min_{\hat{\boldsymbol{d}}_k \in \mathbb{R}^q} \left\| \boldsymbol{C}_{k+1}^T \boldsymbol{C}_{k+1} \hat{\boldsymbol{d}}_k - \boldsymbol{C}_{k+1}^T \left[\boldsymbol{y}_{k+1} - \boldsymbol{C}_{k+1} [\boldsymbol{g}(\hat{\boldsymbol{x}}_k) + \boldsymbol{h}(\boldsymbol{u}_k)] \right] \right\|$$

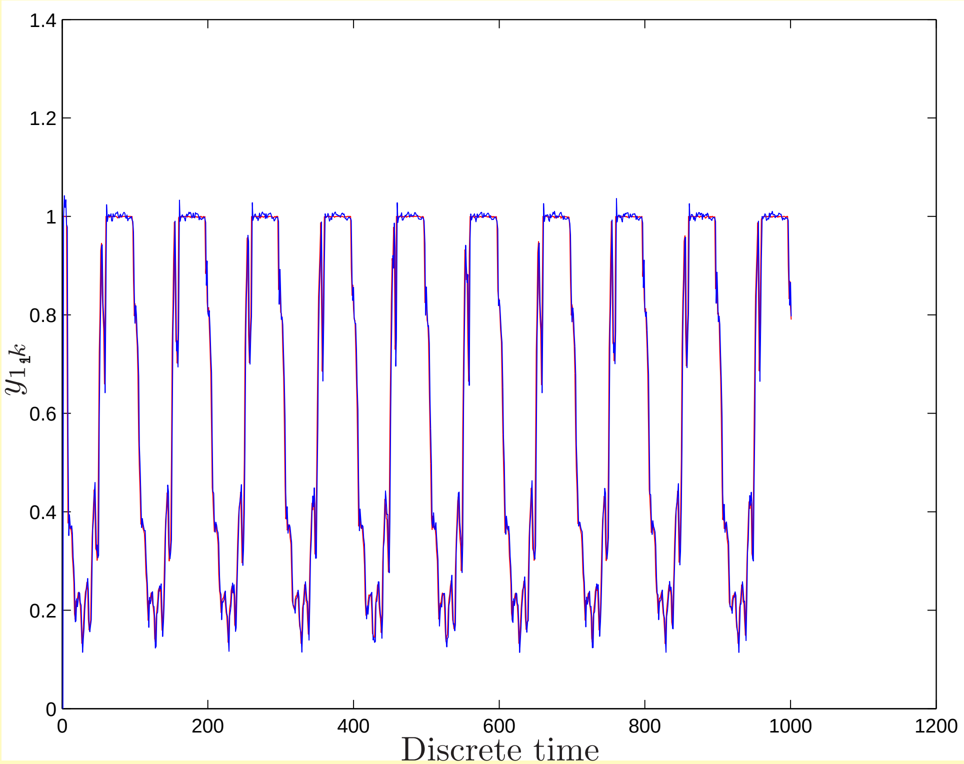
- If the sequence

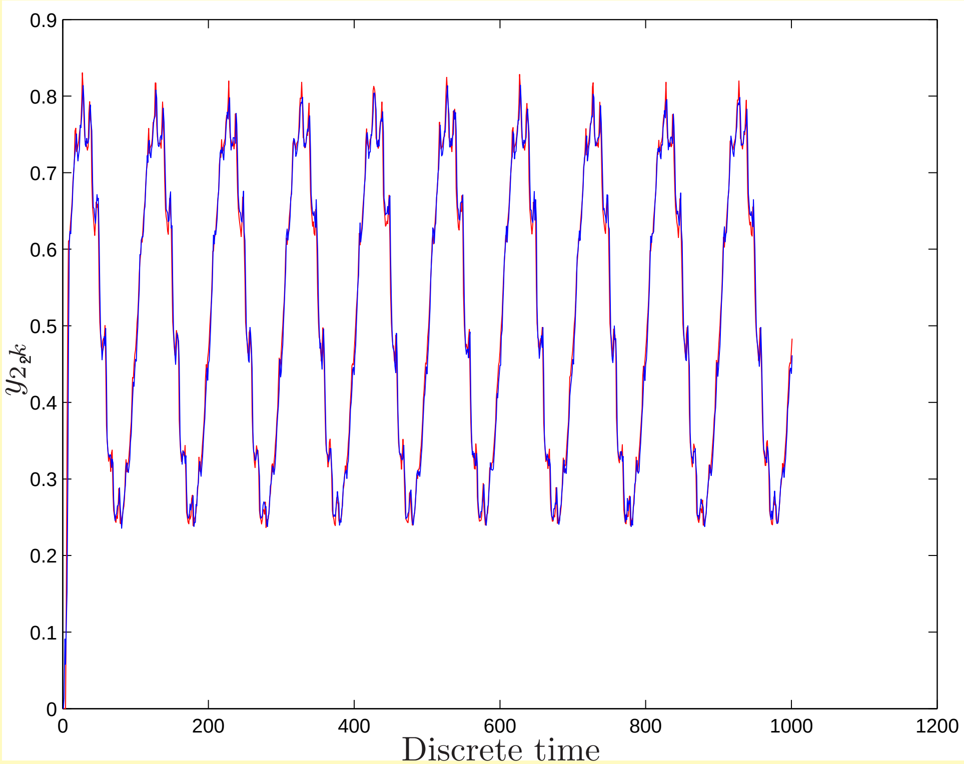
$$\hat{\boldsymbol{d}}_k, \quad k = 1, \ldots, n_t$$

is known then using the approach of (Chen and Patton, 1999) it is possible to estimate the unknown input distribution matrix

$$\boldsymbol{H}_k = \begin{bmatrix} 0.2074 & 0 & 0 & 0 \\ 0.3926 & 0 & 0 & 0 \end{bmatrix}$$

- Comparison between the EUIO (blue) and system (red) output





D - detected, N - not detected

Fault	Description	S	M	B
f_1	Valve clogging	D	D	D
f_2	Valve plug or valve seat sedimentation			D
f_7	Medium evaporation or critical flow	D	D	D
f_8	Twisted servomotor's piston rod	N	N	N
f_{10}	Servomotor's diaphragm perforation	D	D	D
f_{11}	Servomotor's spring fault			D
f_{12}	Electro-pneumatic transducer fault	N	N	D
f_{13}	Rod displacement sensor fault	D	D	D
f_{15}	Positioner feedback fault			D
f_{16}	Positioner supply pressure drop	N	N	D
f_{17}	Unexpected pressure change across the valve			D
f_{18}	Fully or partly opened bypass valves	D	D	D
f_{19}	Flow rate sensor fault	D	D	D

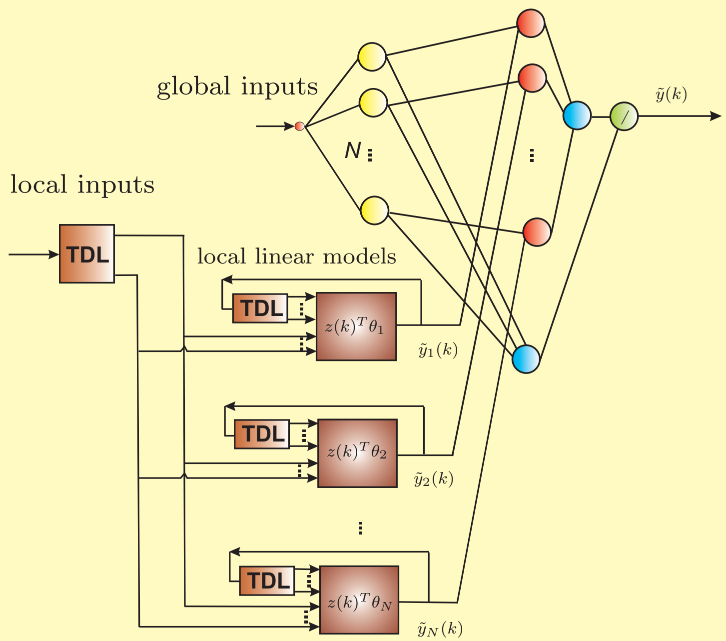
Fault	Description	
f_1	Valve clogging	not isolted
f_2	Valve plug or valve seat sedimentation	not isolted
f_7	Medium evaporation or critical flow	isolted
f_{10}	Servomotor's diaphragm perforation	not isolted
f_{11}	Servomotor's spring fault	isolted as a group
f_{12}	Electro-pneumatic transducer fault	of faults
f_{15}	Positioner feedback fault	not isolted
f_{16}	Positioner supply pressure drop	not isolted
f_{17}	Unexpected pressure change across the valve	not isolted
f_{13}	Rod displacement sensor fault	isolted
f_{18}	Fully or partly opened bypass valves	as a group
f_{19}	Flow rate sensor fault	of faults

➜ Fault detection with Takagi-Sugeno models and an adaptive threshold approach

- Structures of the Takagi-Sugeno N-F models

	$F = r_F(\cdot)$	$X = r_X(\cdot)$
global inputs	X	C_V
local inputs	X, P_1, P_2, T_1	C_V, P_1, P_2, T_1
no. fuzzy rules	7	3

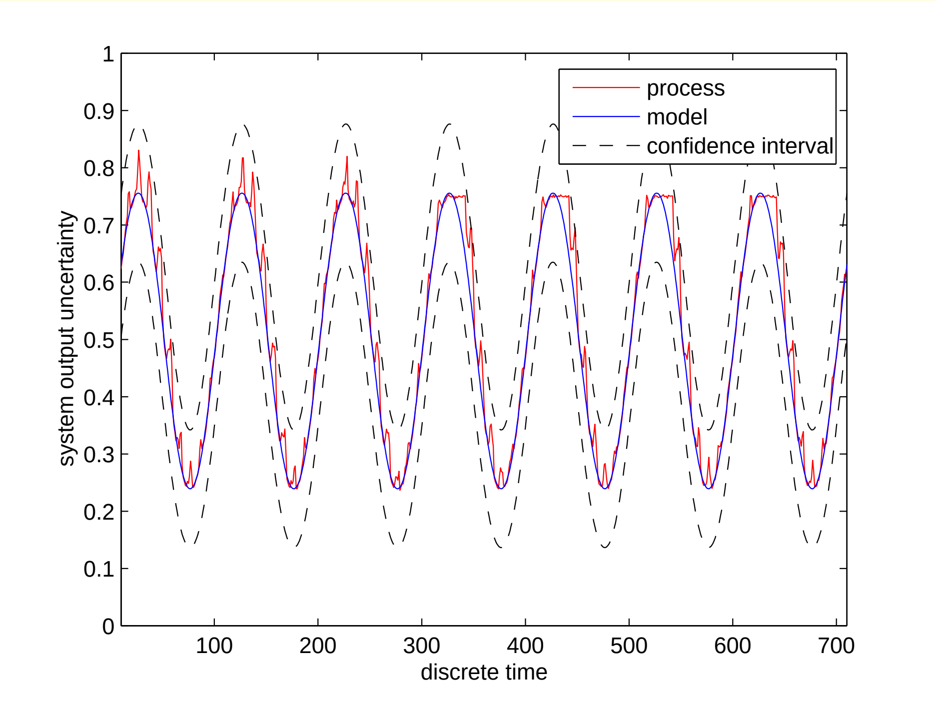
TDL-Tapped Delay Line

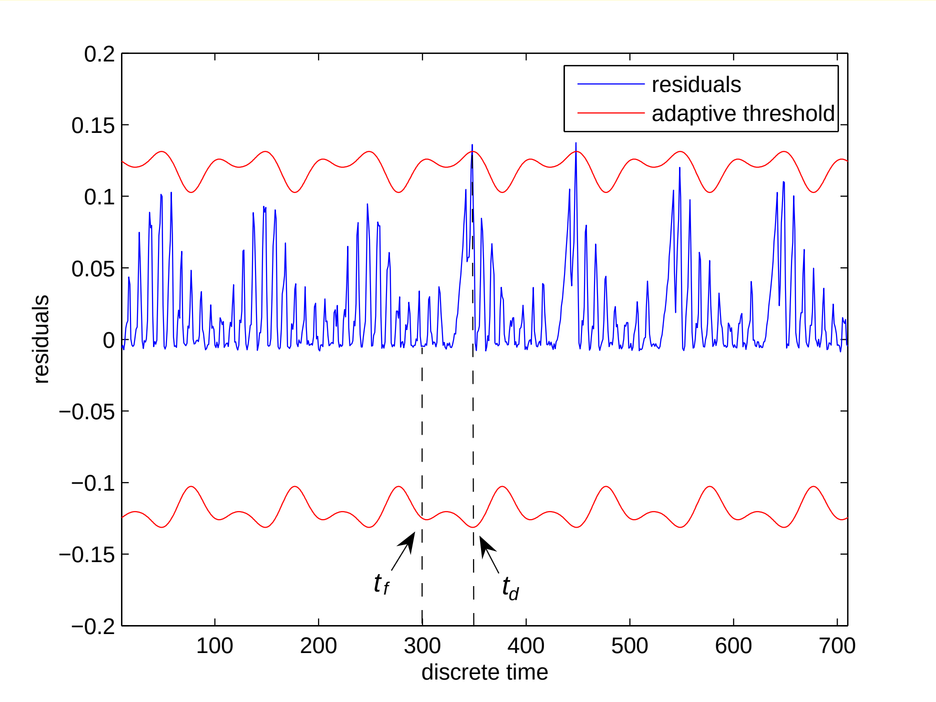


- dynamics is introduced in local linear models
- models was tuned using algorithm, which is based on Bounded Error Approach: Kowal and Korbicz (2005): Proc. of 16th IFAC World Congress

➜ Experimental results for Takagi-Sugeno models

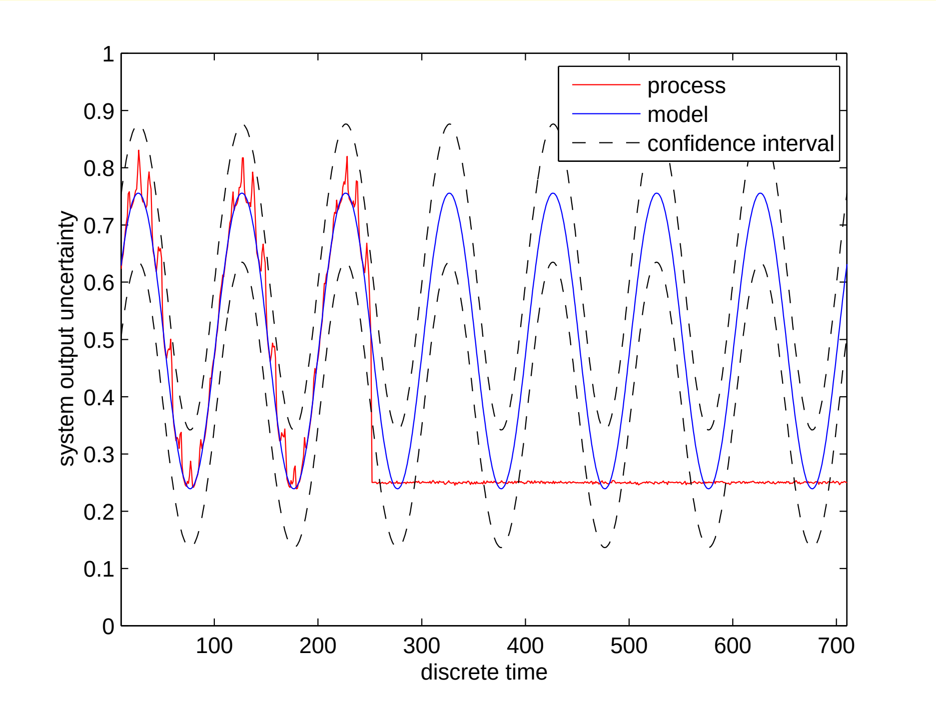
- Model and system output as well as corresponding confidence interval and residuals for small fault f_1

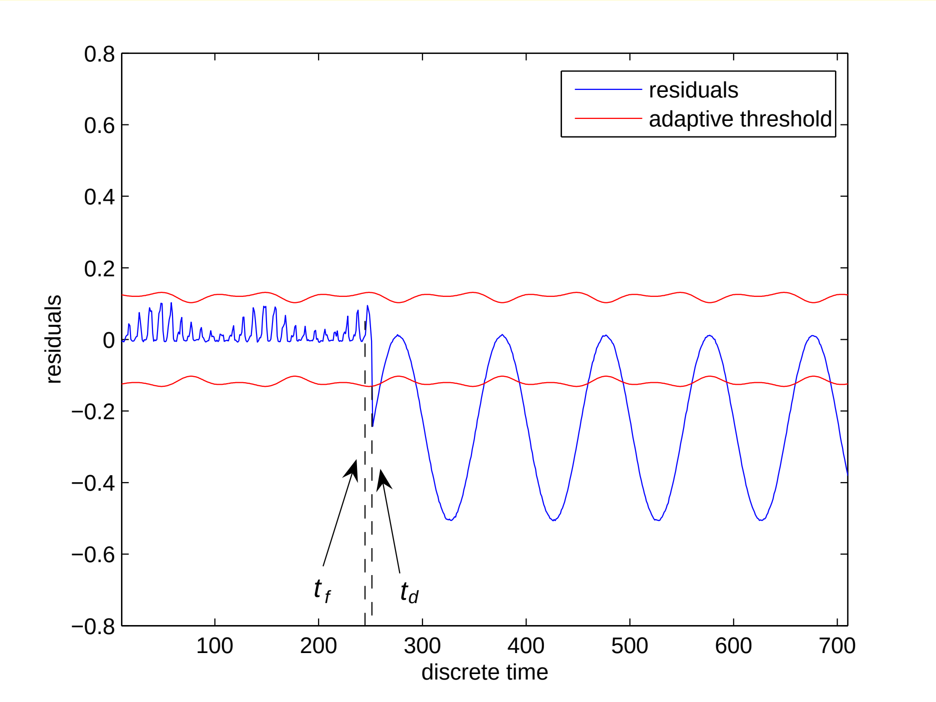




➜ Experimental results for Takagi-Sugeno models

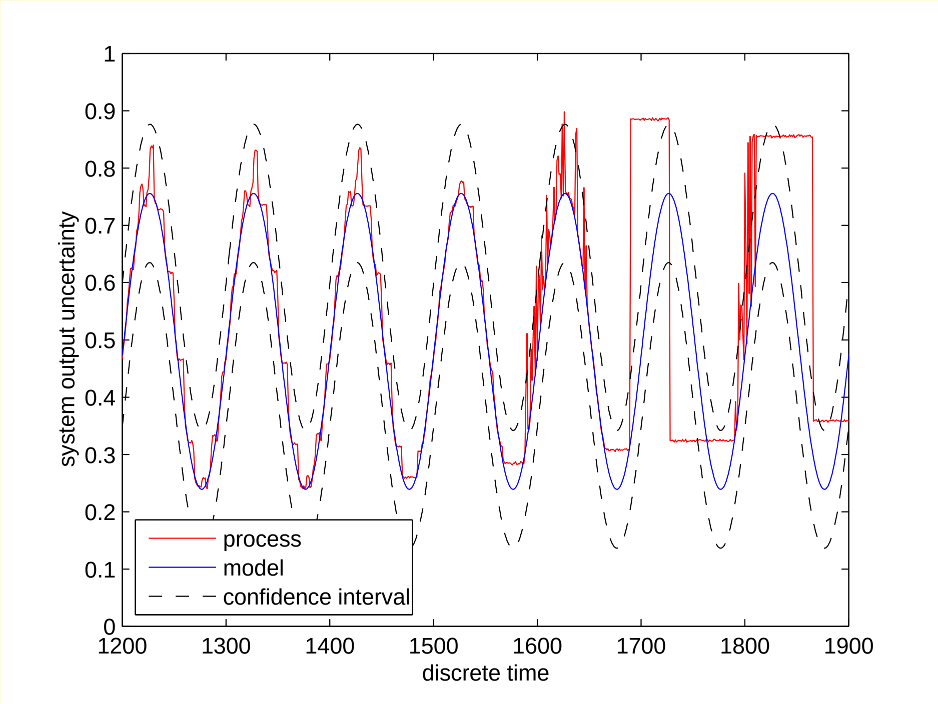
- Model and system output as well as corresponding confidence interval and residuals for big fault f_1

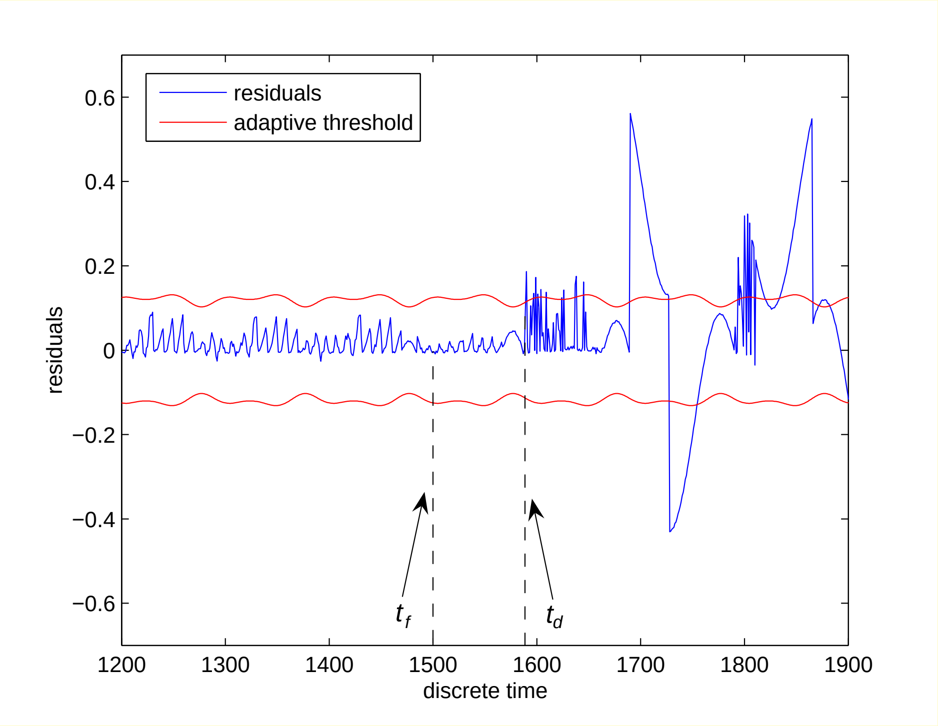




➜ Experimental results for Takagi-Sugeno models

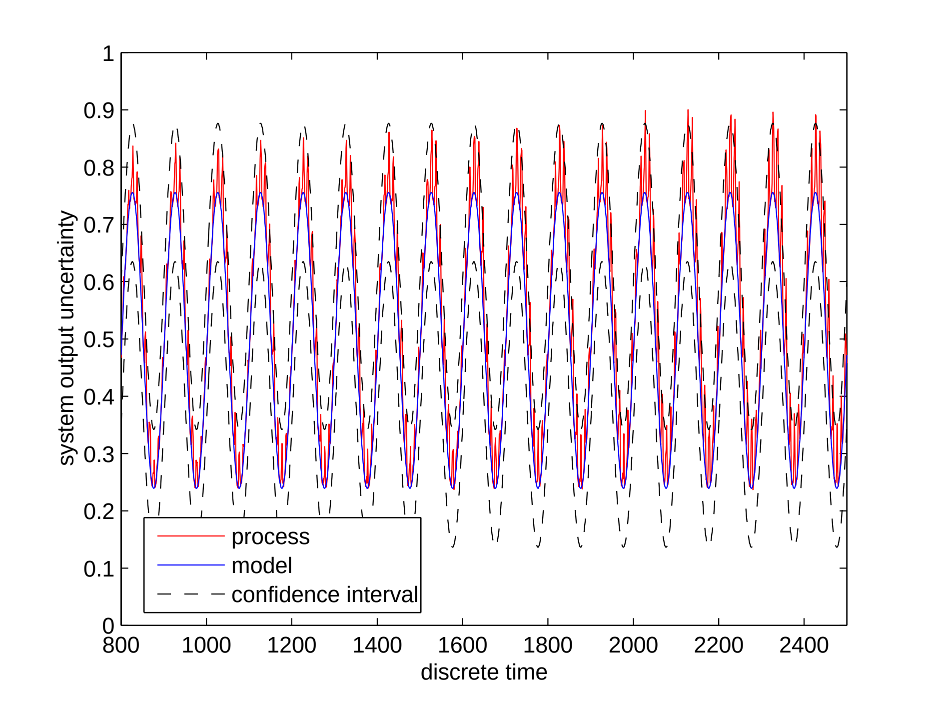
- Model and system output as well as corresponding confidence interval and residuals for incipient fault f_4

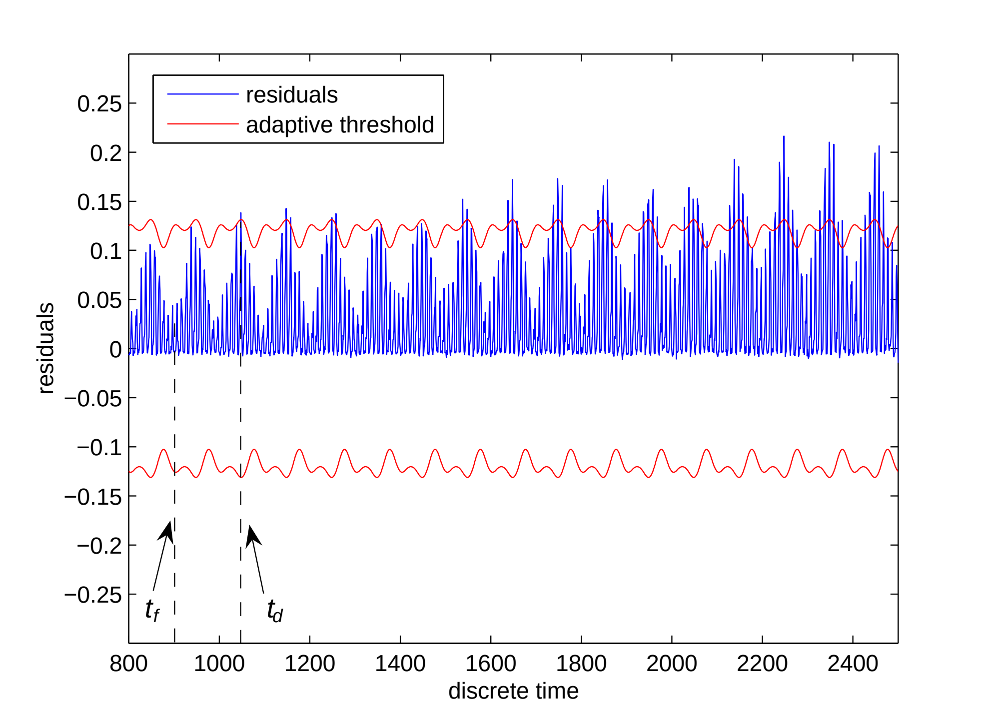




➜ Experimental results for Takagi-Sugeno models

- Model and system output as well as corresponding confidence interval and residuals for incipient fault f_{11}





☛ INDUCTION MOTORS

➜ State observation of an induction motor

The complete discrete-time model in a stator-fixed (a,b) reference frame

$$
\begin{aligned}
x_{1,k+1} =& x_{1,k} + h(-\gamma x_{1k} + \frac{K}{T_r}x_{3k} + Kpx_{5k}x_{4k} + \frac{1}{\sigma L_s}u_{1k}) \\
x_{2,k+1} =& x_{2,k} + h(-\gamma x_{2k} - Kpx_{5k}x_{3k} + \frac{K}{T_r}x_{4k} + \frac{1}{\sigma L_s}u_{2k}) \\
x_{3,k+1} =& x_{3,k} + h(\frac{M}{T_r}x_{1k} - \frac{1}{T_r}x_{3k} - px_{5k}x_{4k}) \\
x_{4,k+1} =& x_{4,k} + h(\frac{M}{T_r}x_{2k} + px_{5k}x_{3k} - \frac{1}{T_r}x_{4k}) \\
x_{5,k+1} =& x_{5,k} + h(\frac{pM}{JL_r}(x_{3k}x_{2k} - x_{4k}x_{1k}) - \frac{T_L}{J}) \\
y_{1,k+1} =& x_{1,k+1}, \; y_{2,k+1} = x_{2,k+1}
\end{aligned}
$$

- Testing the relevance of an appropriate selection of the instrumental matrices

Assumptions: $\boldsymbol{x}_0 = \boldsymbol{0}$, $\boldsymbol{d}_k = \boldsymbol{0}$, $\hat{\boldsymbol{x}}_k = (200, 200, 50, 50, 300)$

Case 1: Classical approach (constant values), i.e.

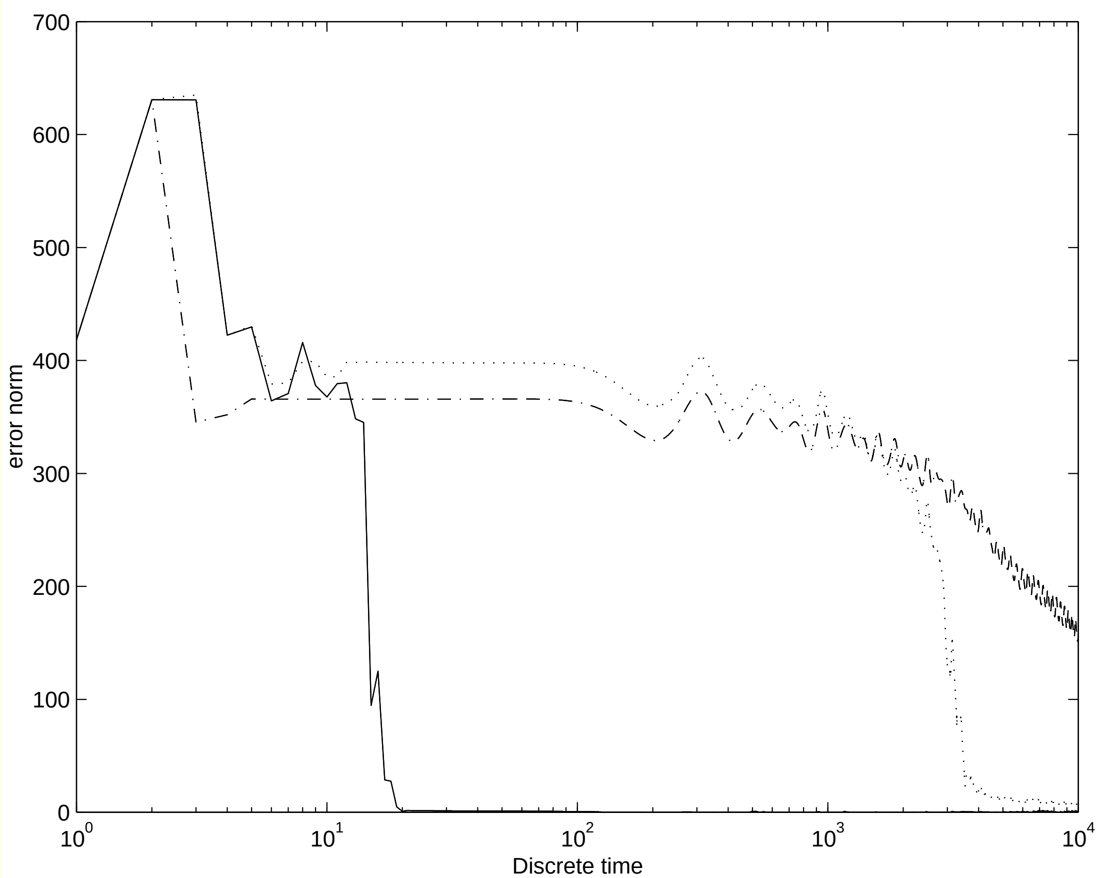
$$\boldsymbol{Q}_{k-1} = 0.1, \quad \boldsymbol{R}_k = 0.1$$

Case 2: Analytic solution, i.e.

$$\boldsymbol{Q}_{k-1} = 10^3 \boldsymbol{\varepsilon}_{k-1}^T \boldsymbol{\varepsilon}_{k-1} \boldsymbol{I} + 0.01\boldsymbol{I}, \quad \boldsymbol{R}_k = 10\boldsymbol{\varepsilon}_k^T \boldsymbol{\varepsilon}_k \boldsymbol{I} + 0.01\boldsymbol{I}$$

Case 3: Genetic programming design of $\boldsymbol{Q}_{k-1}$ and $\boldsymbol{R}_k$

- The state estimation error norm $\|\boldsymbol{e}_k\|_2$ for Case 1 (dash-dot line), Case 2 (doted line), Case 3 (solid line)



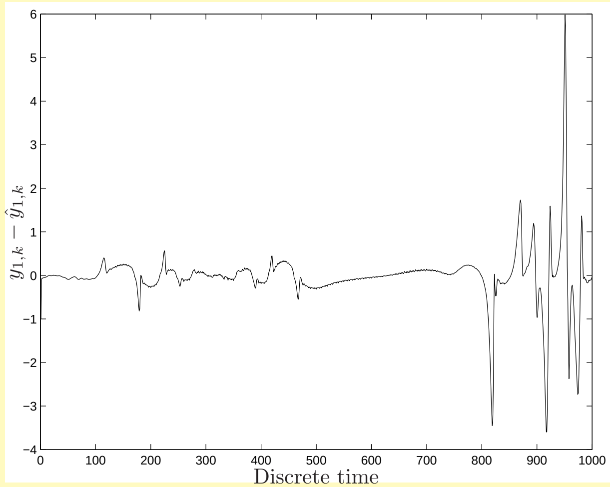
➜ Unknown input decoupling with EUIO

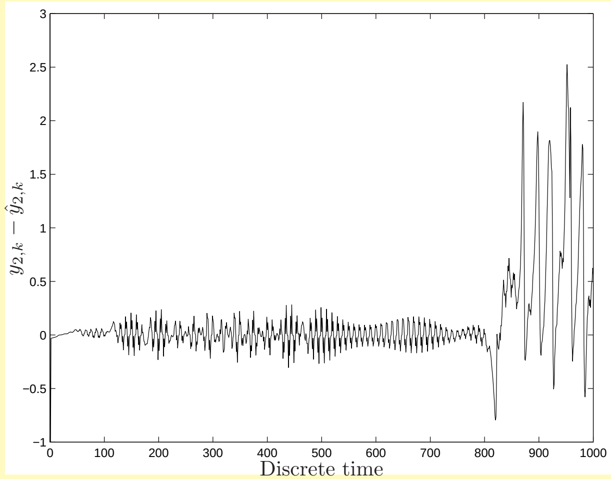
Assumptions: $\boldsymbol{x}_0 = \mathbf{0}$, $\hat{\boldsymbol{x}}_0 = \mathbf{1}$

$$\boldsymbol{E}_k = \begin{bmatrix} 0.1 & 0 & 1 & 0 & 0 \\ 0 & 0.1 & 0 & 1 & 0 \end{bmatrix}^T,$$

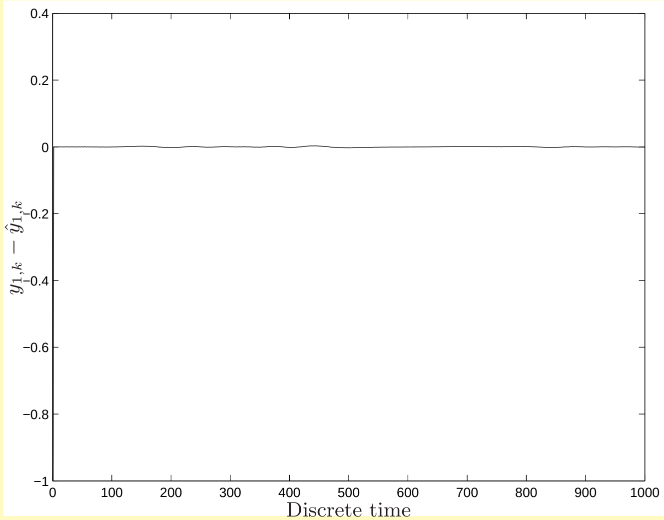
$$d_{1,k} = 0.09\sin(0.5\pi k)\cos(0.3\pi k), d_{2,k} = 0.09\sin(0.01k);$$

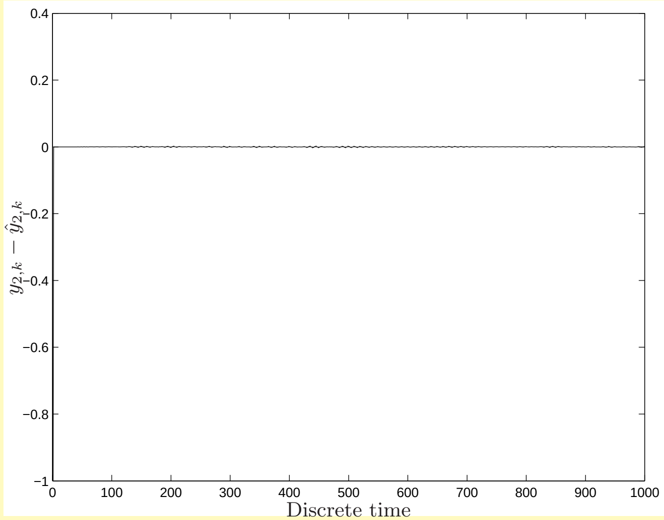
- Residuals for an observer without unknown inputs decoupling





- Residuals for an observer with unknown inputs decoupling



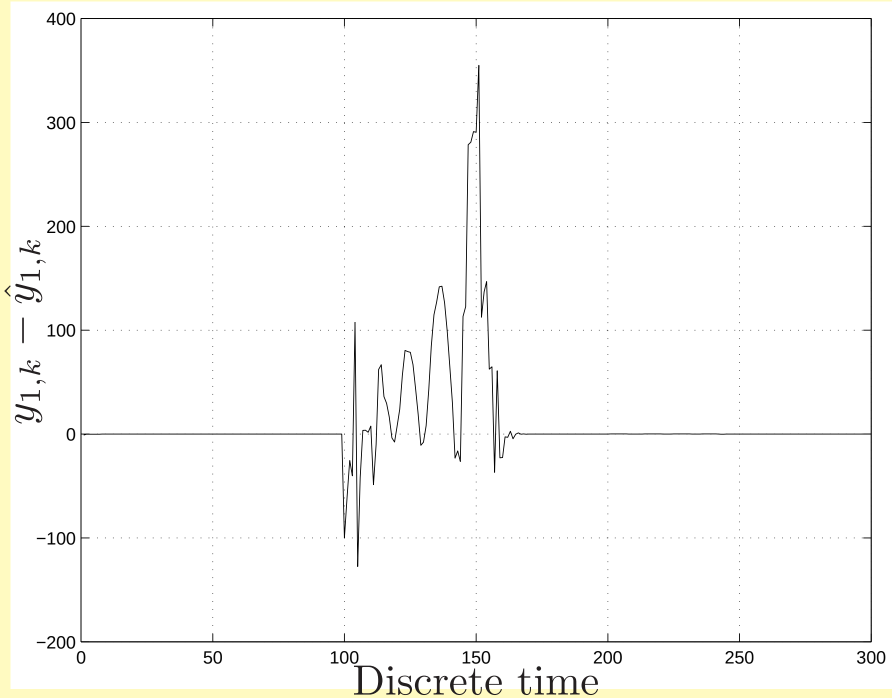


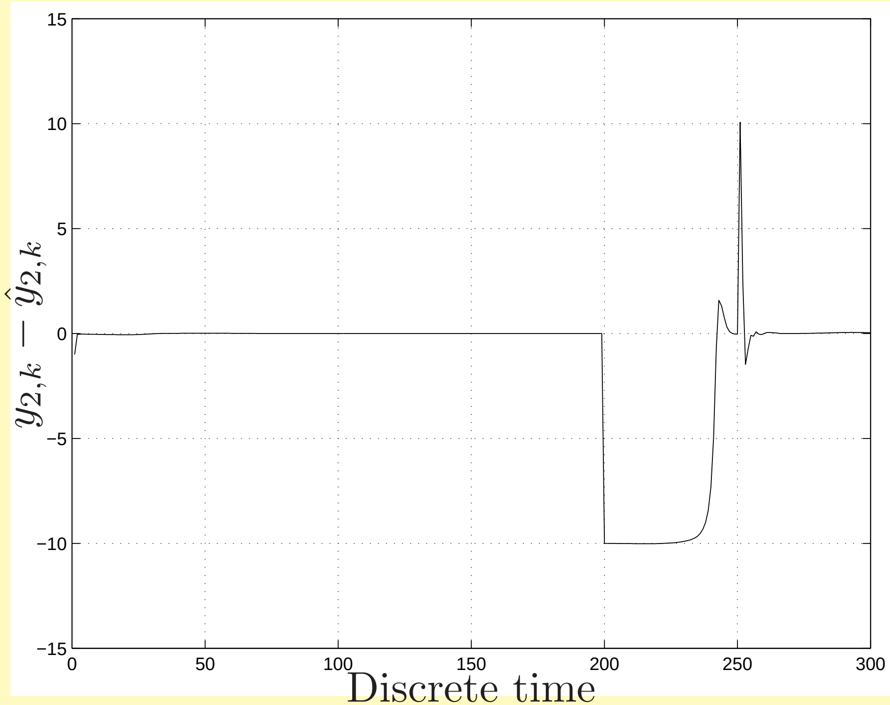
- A fault scenario

$$f_{1,k} = \begin{cases} -100, & k = 100, \dots, 150, \\ 0, & \text{otherwise}, \end{cases}$$

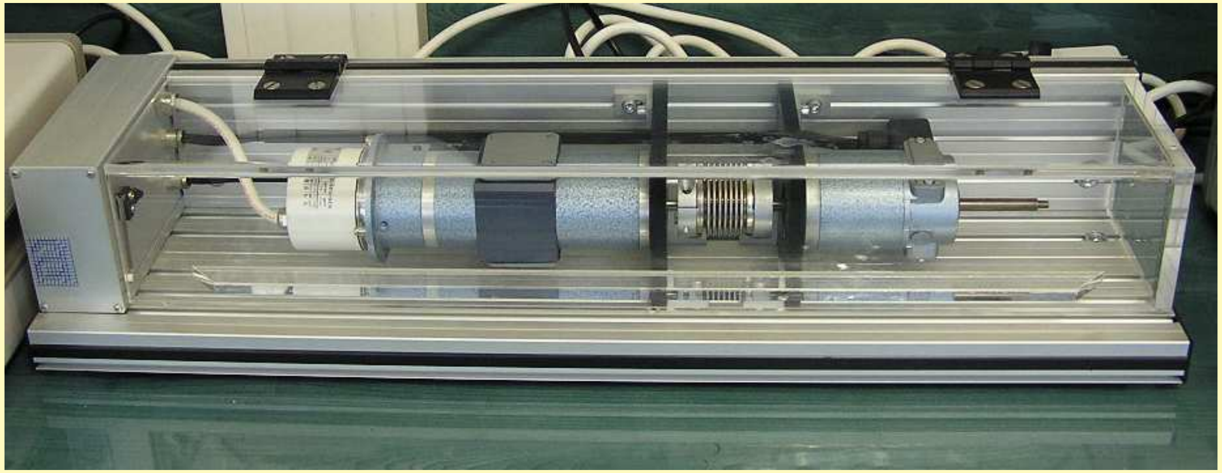
$$f_{2,k} = \begin{cases} 10, & k = 200, \dots, 250, \\ 0, & \text{otherwise}. \end{cases}$$

➜ Sensor fault detection and isolation example





➜ Fault detection system for DC engine



- Laboratory stand consists of five main elements
  - DC engine M_1
  - DC engine M_2
  - two engine-speed indicators
  - clutch K
- The shaft of the engine M_1 is connected with the engine M_2 by the clutch K
- Engine M_2 works in generator mode

➜ Laboratory system technical data

Engine M_1

variable	value
rated voltage	24 V
rated current	2 A
rated power	30 W
rated speed	3000 ob/min
rated moment	0.096 Nm
moment of inertia	$17.7 * 10^{-6}$ Kgm^2
resistance	3.13 Ω

- The engine M_1 is controlled using the servo-amplifier, where the control signal has the form of the voltage from range -10V – +10V
- input variable: aramture current
- output variable: rotational speed

➜ Fault descriptions

No	Description	S	M	B	I
f_1	Tachometer fault	•	•	•	•
f_2	Mechanical fault of the engine	•	•		•

- Faults can be incipient (I) or abrupt and abrupt faults are divided into small (S), medium (M) and big (B)

➜ Fault detection using Takagi-Sugeno model

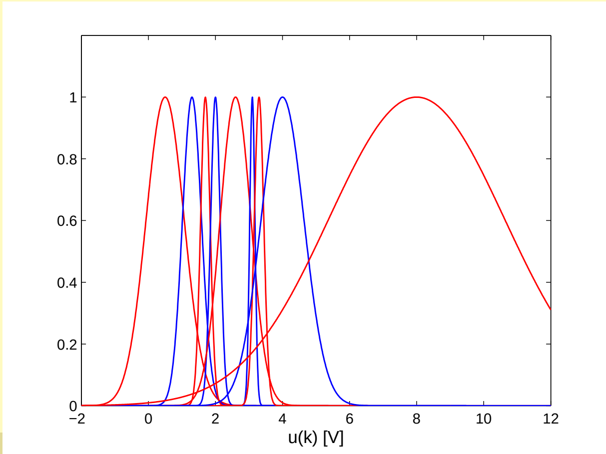
- Fuzzy model consists of 9 rules

$$R_i: \text{ IF } u(k) \text{ is } A_i \text{ THEN } y_i(k) = \boldsymbol{z}_i^T(k)\boldsymbol{\theta}_i, \;\; i = 1, \dots, 9$$

where $u(k)$ - voltage, $y(k)$ - rotational speed, $\boldsymbol{\theta}_i$ - parameters of the local linear model and

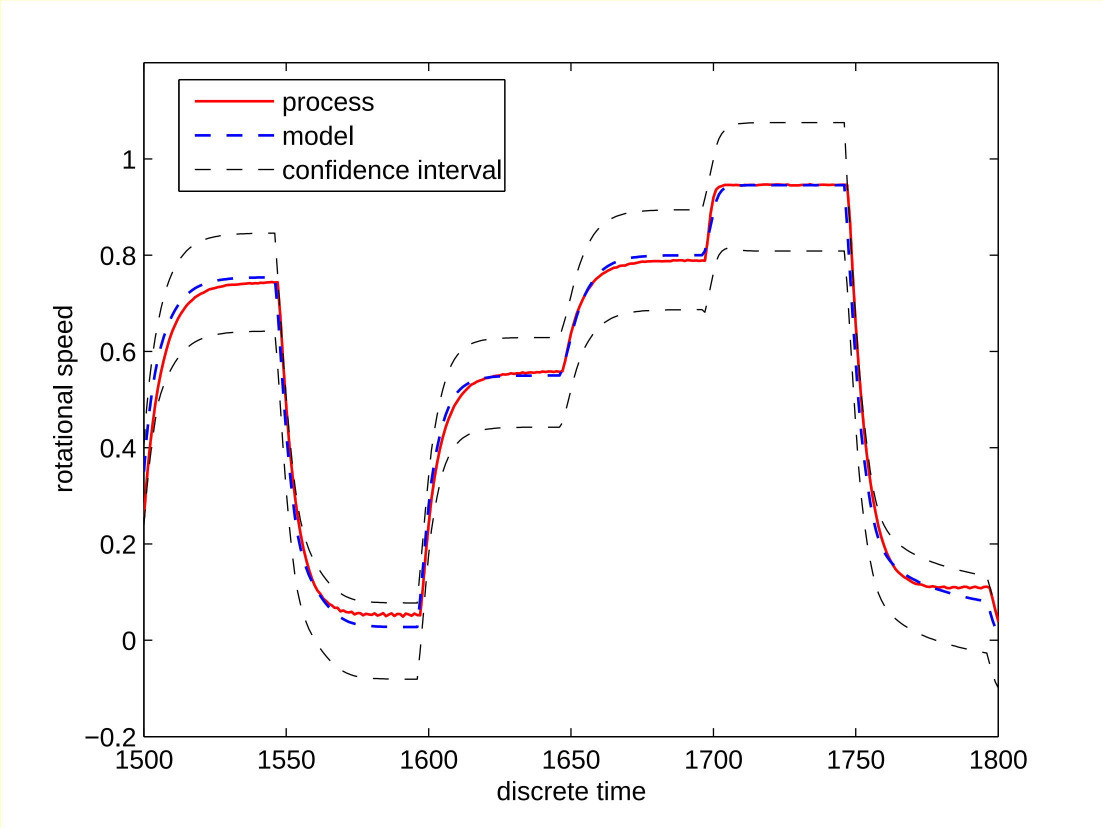
$$\boldsymbol{z}_i(k) = \begin{bmatrix} y_i(k-1) \\ u(k-1) \\ u(k-2) \\ u(k-3) \\ u(k-4) \end{bmatrix}, \boldsymbol{\theta}_i = \begin{bmatrix} a_i \\ b_i^{(1)} \\ b_i^{(2)} \\ b_i^{(3)} \\ b_i^{(4)} \end{bmatrix}.$$

- Fuzzy sets A_i after tuning procedure



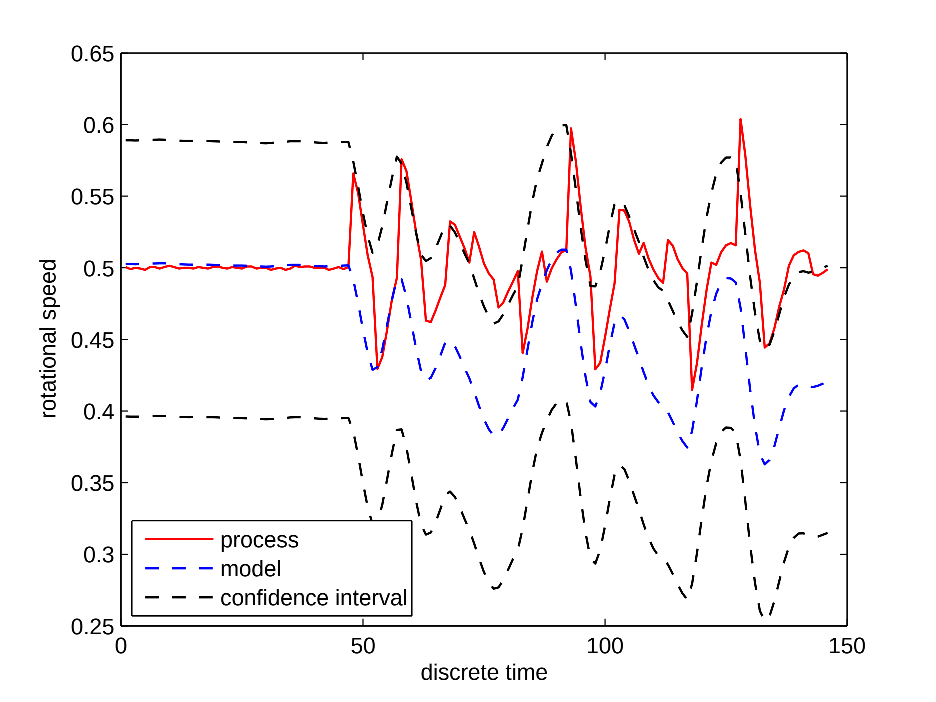
➜ Experimental results

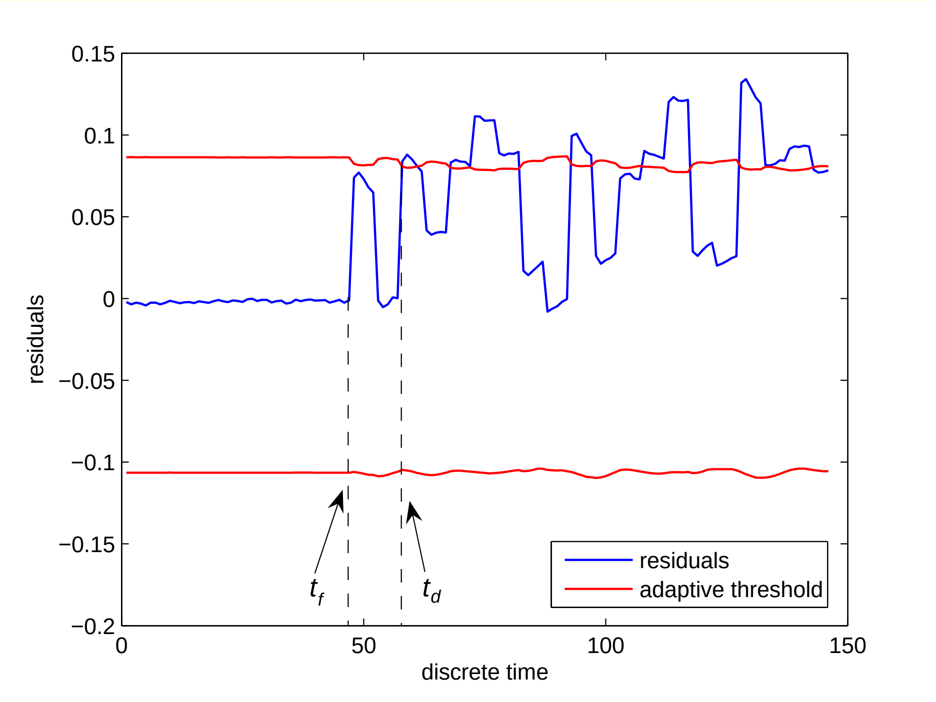
- Model and process outputs as well as corresponding confidence interval for fault-free mode



➜ Experimental results

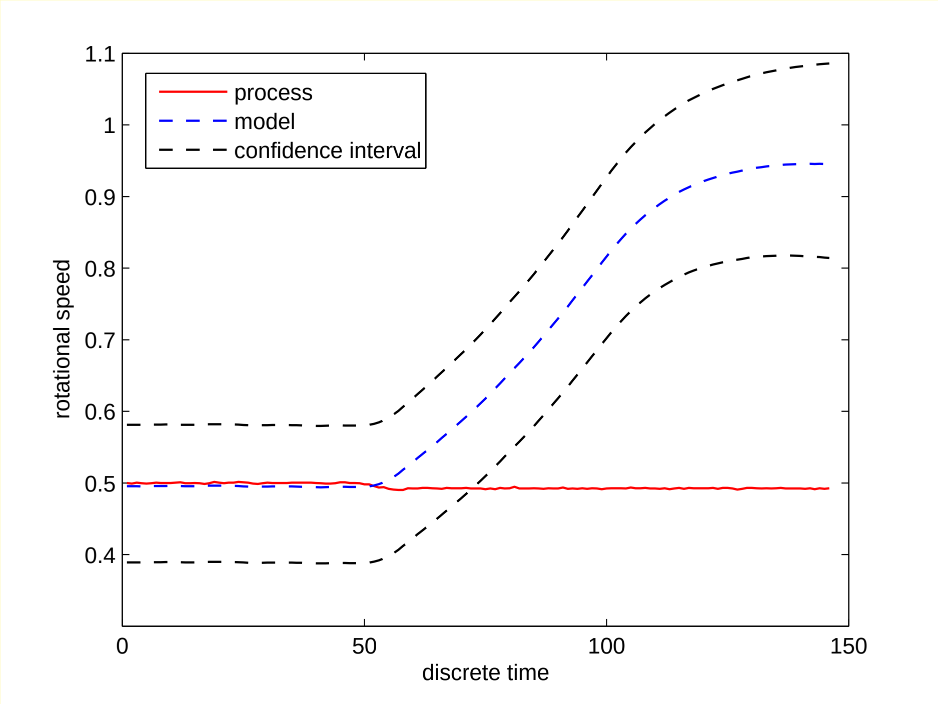
- Process and model outputs as well as corresponding confidence interval and residuals for small fault f_1

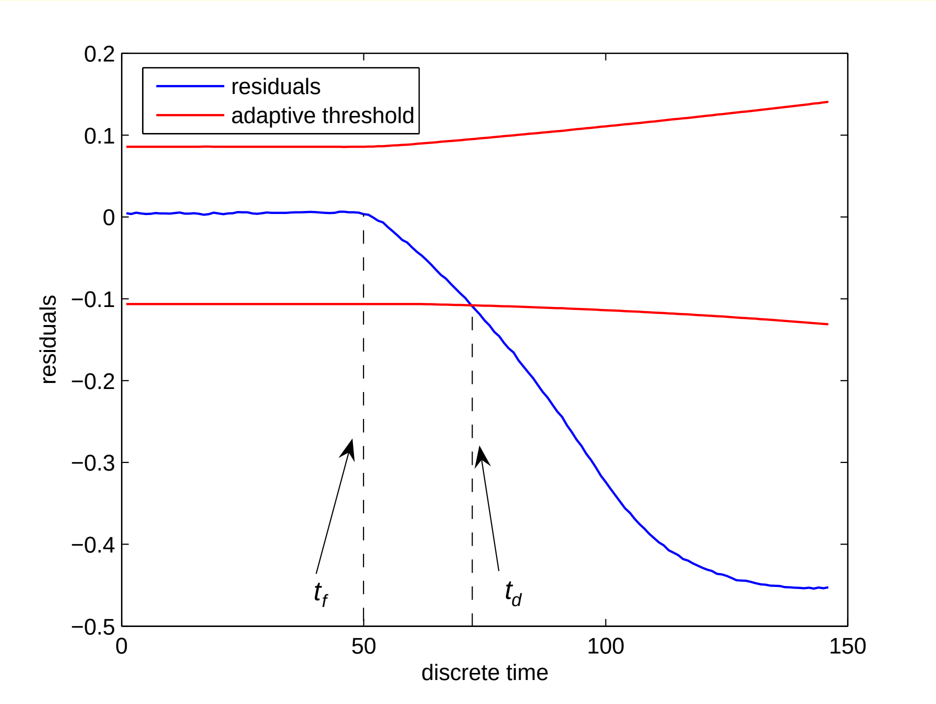




➜ Experimental results

- Process and model outputs as well as corresponding confidence interval and residuals for incipient fault f_2





☛ CONCLUDING REMARKS

- ❒ The proposed GMDH-based approach constitutes an excellent tool for passive fault detection
- ❒ Genetic programming makes it possible to develop non-linear state-space models that can be applied for robust observer design
- ❒ Extended unknown input observers supported with genetic programming can effectively be used for FDI
- ❒ Takagi-Sugeno fuzzy models can be effectively employed for fault detection if their uncertainty is considered in detection procedure

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Thank you