Application Examples of Fault Detection and Isolation Strategies using System Identification Approaches

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Summary

- Introduction
- System Identification Methods for FDI
- Case study examples
- Conclusions & Further Researches

Introduction

- Problem and challenges for FDI
- Industrial case examples
  - CSTR simulated process
  - CSTR plant (realistic)
  - Sugar factory (*not included in this talk*)
- Parameter changes and fault effects

The Need for Multiple Model

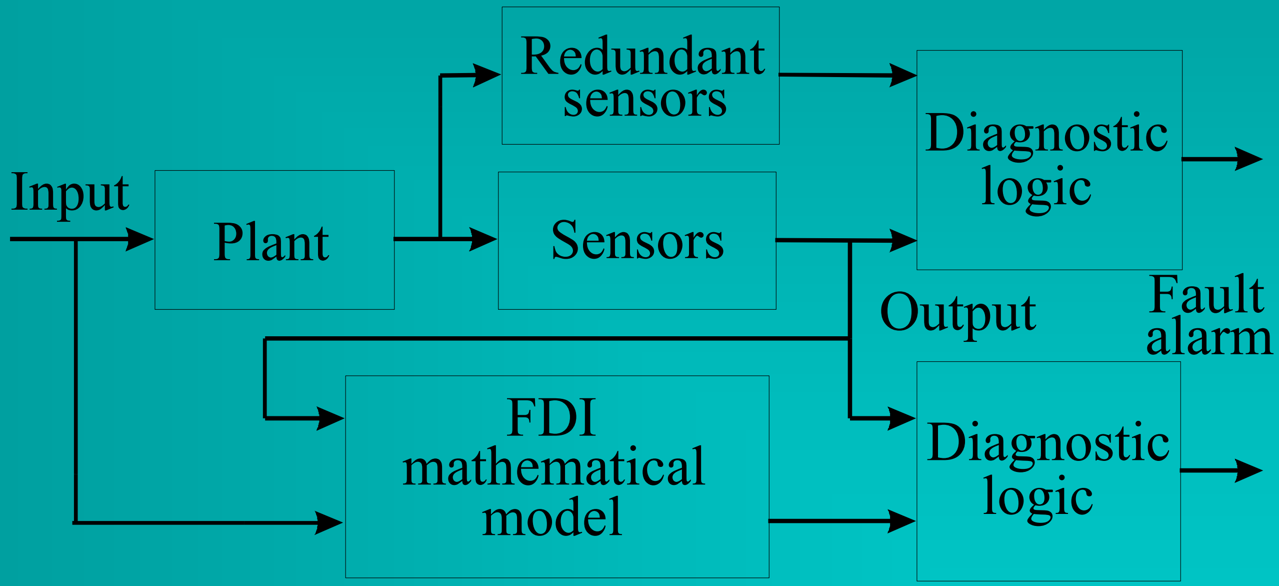
- Models and interpolation
- Fuzzy clustering
- Takagi-Sugeno/Mamdani/State-Space
- Global stability problem for Observers and State-Space models
- Optimal cluster numbers

Hint...

Monitoring

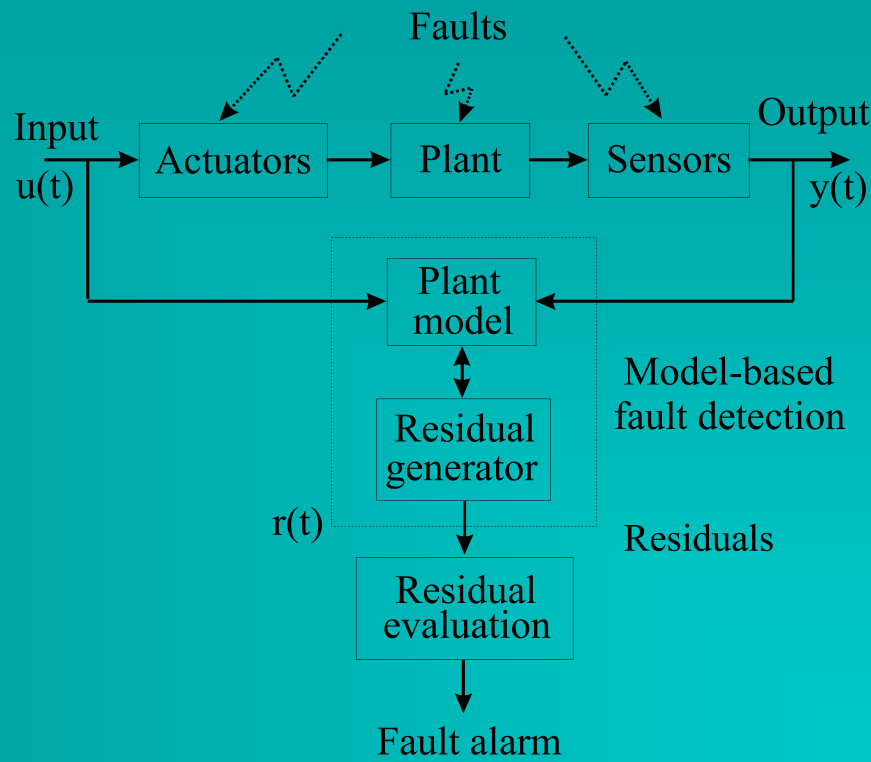
A continuous real-time task of determining the conditions of a physical system, by recording information, recognising and indication anomalies in the behaviour.

Fault Detection and Diagnosis Methods



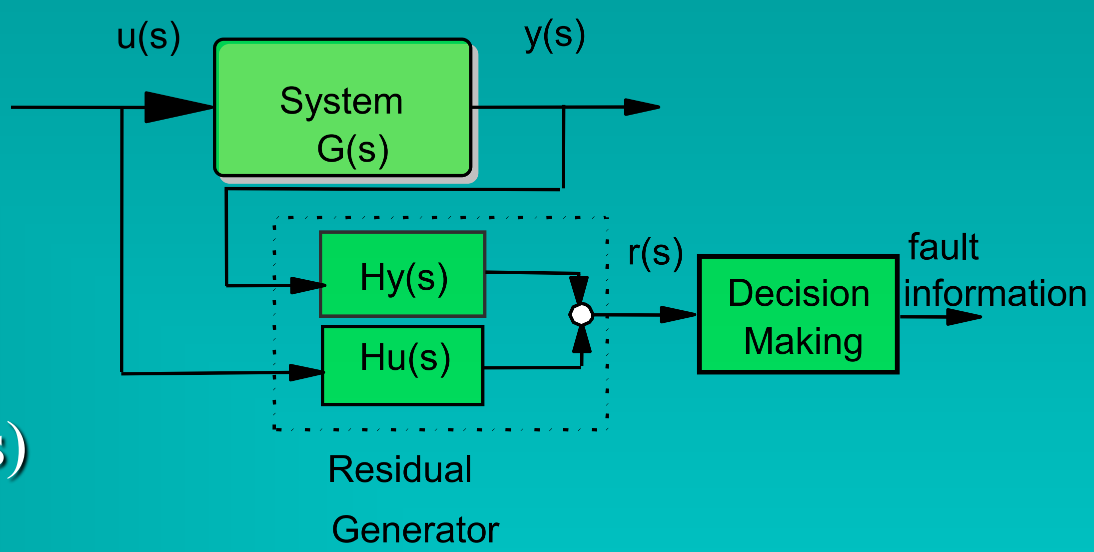
Comparison between hardware and analytical redundancy schemes.

Model-Based fault Detection Methods



Scheme for the model-based fault detection.

Model-Based FDI Principles



Residual Signal:

$r(s) = H_u u(s) + H_y y(s)$

Objectives:

choose H_u & H_y so that

$r(s) = 0$ when no fault occurs

$r(s) \neq 0$ when a fault occurs

Model-Based FDI Principles

Residual Generation

Algorithm which processes measurable I/O of system to generate residual signal.

Decision Making

- Residuals are examined for likelihood of faults
- Decision rule applied to determine if any fault has occurred

Observers

- Estimate system O/P from available I/O (Patton *et al*, 1989)
- Residual → weighted difference b/w estimated and actual O/P
- Flexibility in selecting observer gain → rich variety of FDI schemes

Model-Based FDI : Observers

Parity Relations

based on either

- direct redundancy *(making use of static algebraic relations b/w sensors & actuator signals)* or upon
- temporal redundancy *(when dynamic relations b/w I/P & O/P are used)*

Parameter Estimation

- Component faults of dynamic system reflected in **physical parameters** e.g. friction, mass velocity resistance
- Faults detected by estimating parameters of non-parametric models

Model-Based FDI

Requirement of Precise Analytical Model

- Precise and accurate analytical model required for traditional FDI…….. **Difficult for Real Systems**
- Design robust algorithms where **disturbances effects** on residual are **minimised** and **sensitivities to faults** are **maximised**
- Unknown I/P observer, Eigen. assignment (Patton *et al,* 2000), Frequency domain (Edelmeyer et al, '97)
- Resulting error affects FDI performance
- Non-linear systems represent majority of real processes
- The following can be used:
  - *more abstract models based on qualitative physics*
  - *Fuzzy-logic rules*

Model-Based fault Detection Methods

Basic process model-based FDI methods:

(1) Output observers (O/p observers, estimators, filters)
(2) Parity equations,
(3) Identification & parameter estimation.

If only output signals y(t) can be measured, signal model-based methods can be applied.
Typical signal model-based methods of fault detection:

(4) Bandpass filters,
(5) Spectral analysis (FFT),
(6) Maximum-entropy estimation.

Model-Based fault Detection Methods

- **Characteristic quantities or features from fault detection methods show stochastic behaviour with mean values & variances.**
- **Deviations from the normal behaviour have then to be detected by methods of change detection (residual analysis) like:**

(7) Mean and variance estimation,
(8) Likelihood-ratio test, Bayes decision,
(9) Run-sum test.

Fault Diagnosis methods

- **If several symptoms change differently for certain faults, a first way of determining them is to use classification methods which indicate changes of symptom vectors.**
- **Some classification methods are:**

(10) Geometrical distance and probabilistic methods,
(11) Artificial neural networks,
(12) Fuzzy clustering.

Fault Diagnosis methods

- **By forward and backward reasoning, probabilities or possibilities of faults are obtained as a result of diagnosis.**
- **Typical approximate reasoning methods are:**

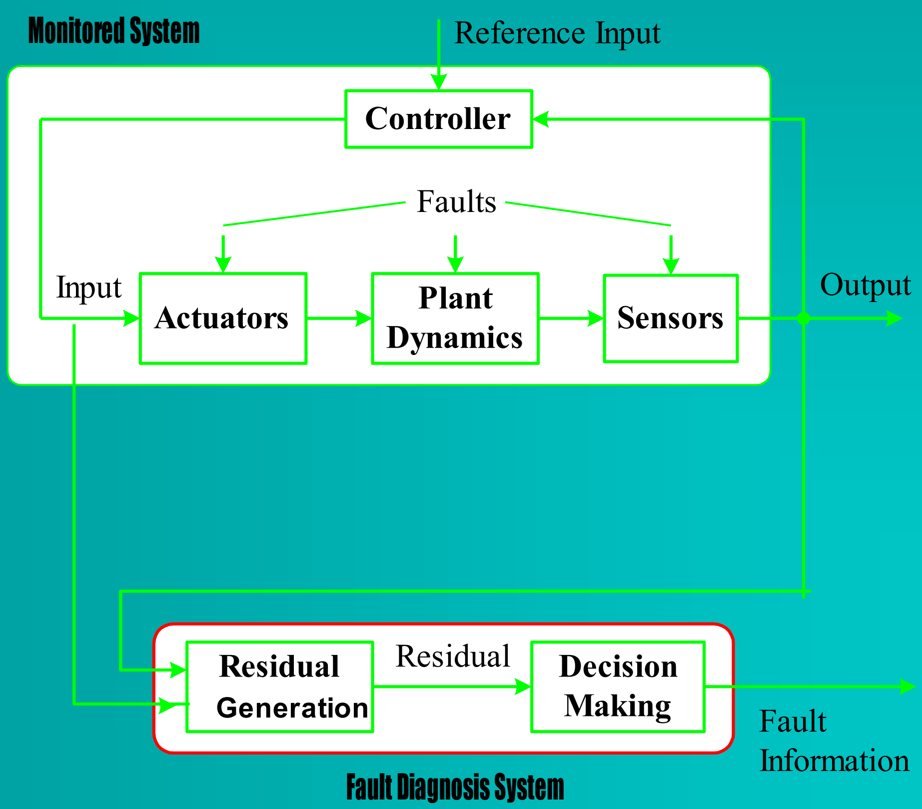
(13) Probabilistic reasoning,
(14) Possibilistic reasoning with fuzzy logic,
(15) Reasoning with artificial neural networks.

Summary of FDI Applications

Number of contributions IFAC FDI-related Conferences
Applications of model-based fault detection

Milling and grinding processes	41
Power plants and thermal processes	46
Fluid dynamic processes	17
Combustion engine and turbines	36
Automotive	8
Inverted pendulum	42
Miscellaneous	61
DC motors	25
Stirred tank reactor	27
Navigation system	33
Nuclear process	10

Model Based Fault Diagnosis



Schematic diagram of an FDI system

Residual Generation

System with possible faults is then described as:

$$\mathbf{y}(s) = G_u(s)\,\mathbf{u}(s) + G_f(s)\,\mathbf{f}(s)$$

Residual generator can be generally expressed as:

$$\mathbf{r}(s) = H_u(s)\,\mathbf{u}(s) + H_y(s)\,\mathbf{y}(s)$$

$H_u(s)$ and $H_y(s)$ **are transfer matrices which are realisable using stable linear systems. To make the residual to becomes zero for the fault free,** $H_u(s)$ and $H_y(s)$ **must satisfy the condition:**

$$H_u(s) + H_y(s)G_u(s) = 0$$

ROBUSTNESS

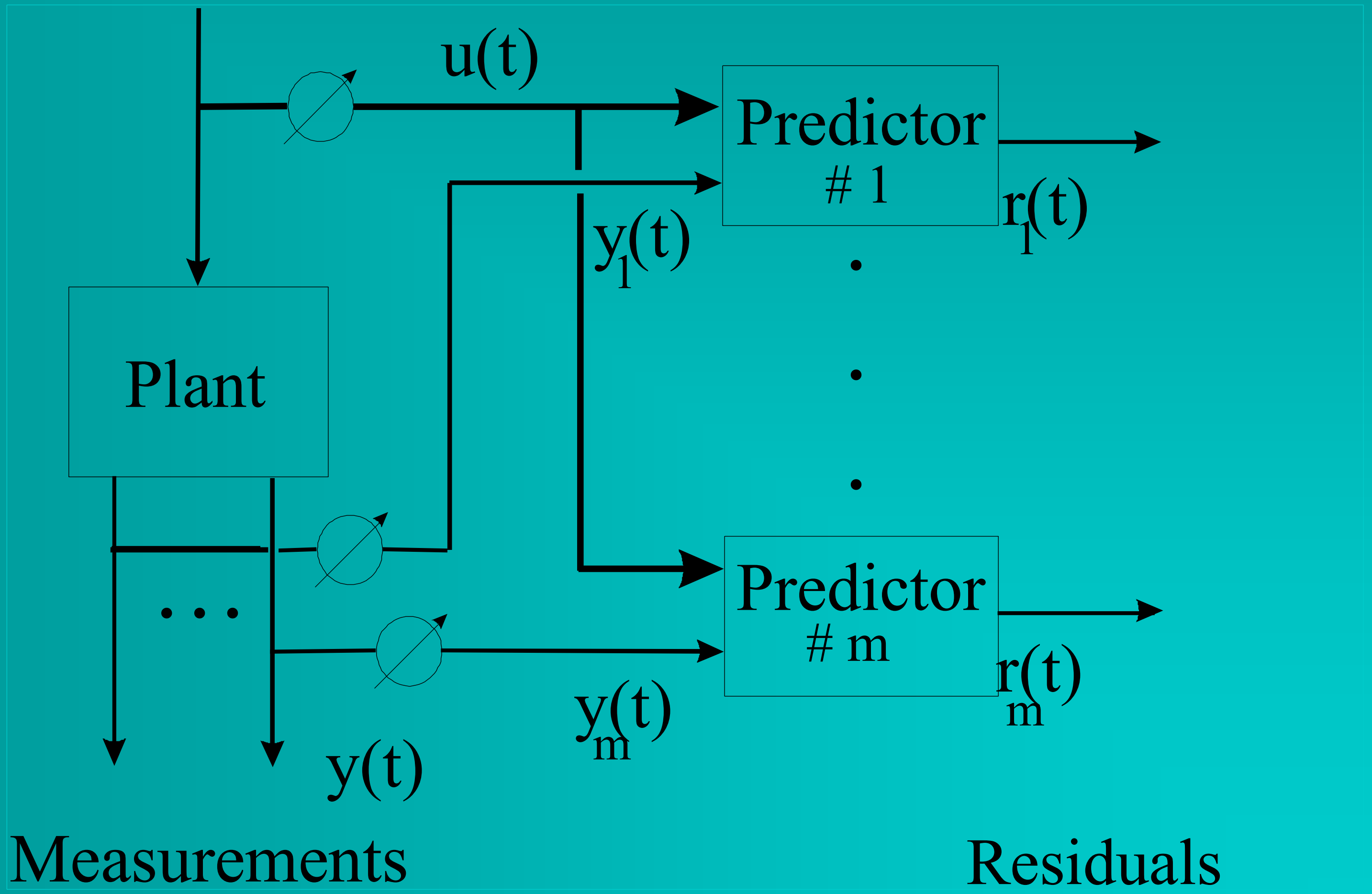
Model-based FDI makes use of mathematical models of the supervised system.

Hence potential danger of false alarms caused by model-system mismatches .

Case study I - CSTR system

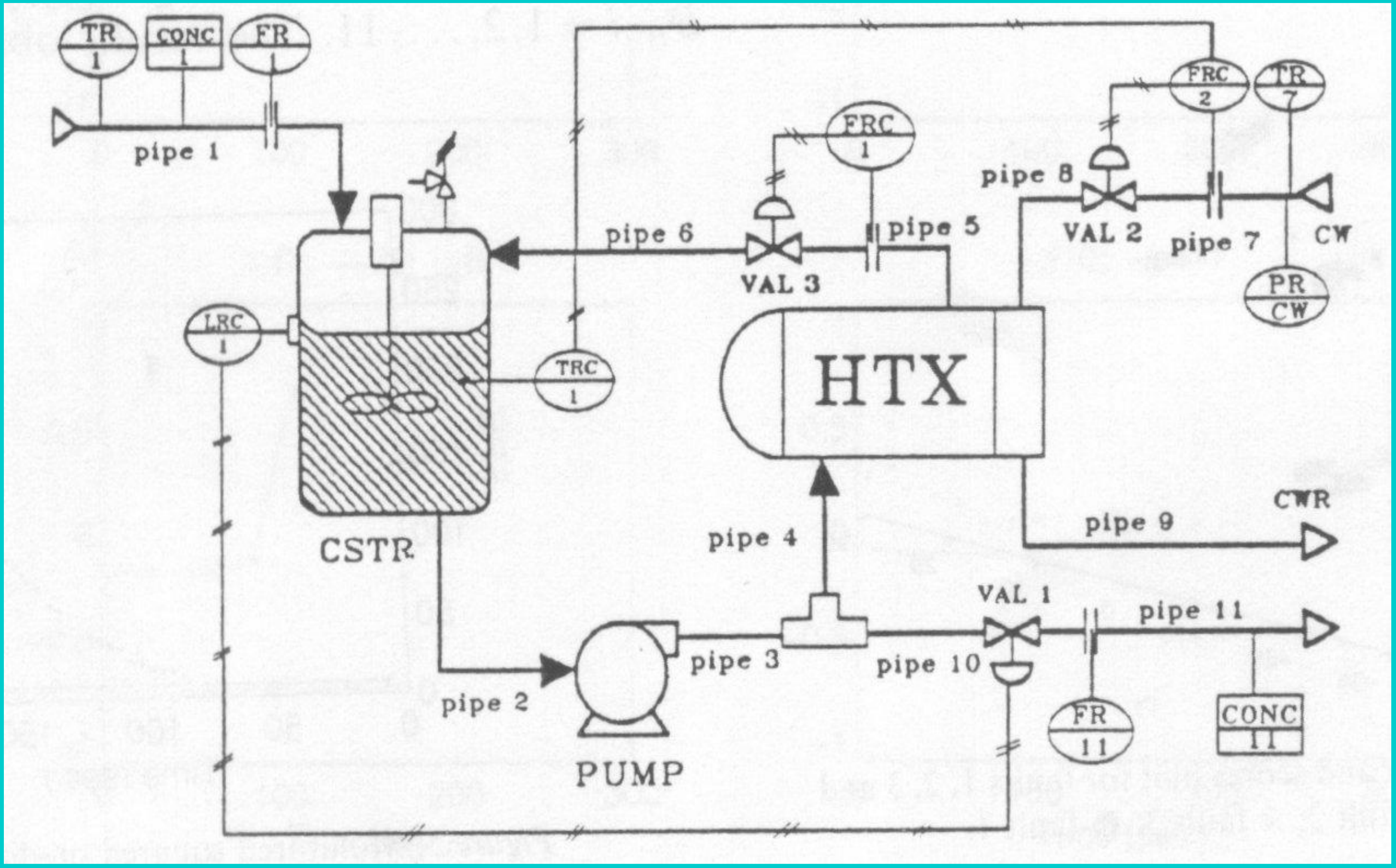
- Introduction
- FDI scheme
- Model description
- Identification techniques
- Results

Residual generation



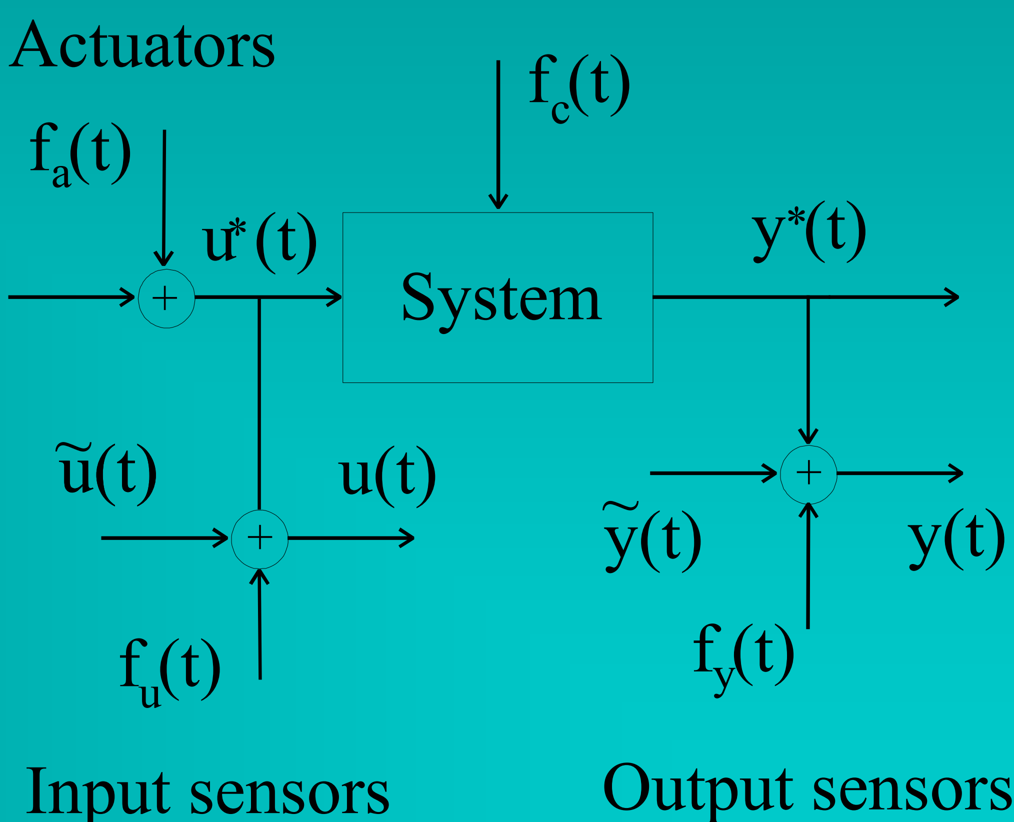
Residual generation: DOS

CSTR system description



The measurement process (1)

- Actuators $f_a(t)$
- Sensors $f_u(t)$ $f_y(t)$
- Components $f_c(t)$
- **Sensor noises**
- **u(t), y(t)** available measurements
- **u*(t), y*(t)** inaccessible inputs and outputs



Nomenclature

CSTR fault conditions

- 1 Pipe 1 blockage
- 2 External feed reactant flow rate too high
- 3 Pipe 2 or 3 are blocked or pump 1 fails
- 4 Pipe 10 or 11 is blocked
- 5 External feed reactant temperature abnormal
- 6 Control valve 1 fails high
- 7 Pipe 7, 8 or 9 blockage or control valve 2 fails low
- 8 Control valve 1 fails high
- 9 Pipe 4, 5 or 6 blockage or control valve 3 fails low
- 10 Control valve 3 fails high
- 11 External feed reactant concentration too low

Dynamic system identification

- Input and output sequences **u(t)** and **y(t)**
- ✓ Equation error models → linear ARX systems (steady state conditions)
- Multi-model approach → TS non-linear systems (different working points)

Equation error models

$$\hat{y}_i(t) = \sum_{k=1}^{n} \alpha_{ik} \hat{y}_i(t-k) + \sum_{j=1}^{r} \sum_{k=1}^{n} \beta_{ikj} \hat{u}_j(t-k) + \varepsilon_i(t)$$

- High signal to noise ratios $\tilde{\mathbf{u}}(t) \cong \mathbf{0}$, $\tilde{\mathbf{y}}(t) \cong \mathbf{0}$

- From the sequences **u(t)** and **y(t)** determine α_{ik} , β_{ikj} and **n.**

ARX MISO model identification

- $\theta = \begin{bmatrix} \alpha_n & \cdots & \alpha_1 & \beta_n & \cdots & \beta_1 \end{bmatrix}^T$ parameters
- $J(\theta) = \frac{1}{N} \sum_{t=n+1}^{L} \left(\hat{y}(t) - y(t) \right)^2$ mean square error

$$\mathbf{H}_n(u) = \begin{bmatrix} u(1) & \cdots & u(n) \\ \vdots & \ddots & \vdots \\ u(L-n) & \cdots & u(L-1) \end{bmatrix}, \quad \mathbf{H}_n(y) = \begin{bmatrix} y(1) & \cdots & y(n) \\ \vdots & \ddots & \vdots \\ y(L-n) & \cdots & y(L-1) \end{bmatrix}$$

Hankel matrices

ARX to state space model

$$\mathbf{x}_i(t+1) = \mathbf{A}_i \mathbf{x}_i(t) + \mathbf{B}_i \hat{\mathbf{u}}(t) + \mathbf{B}_{\omega_i} \varepsilon_i(t)$$

$$\hat{\mathbf{y}}_i(t) = \mathbf{C}_i \mathbf{x}_i(t) + \mathbf{D}_{\omega_i} \varepsilon_i(t), \quad t = 1,2,\ldots$$

- A_i , B_i , $B_{\omega i}$, C_i , $D_{\omega i}$ are matrices depending on ARX parameters and order
- Each i-th output

ARX identification: results

- Optimal value of the model orders
- Residual whiteness (~ $\aleph^2_{8,0.95}$ distribution with 8 d.o.f and 95% confidence level)
- Correlation between inputs and residual (~ Gaussian distribution with 8 d.o.f.)
- One step ahead predictive model (~ 1%)
- Identified model in **full-simulation** (~ 7%)
- **Model validation** in full simulation

Non-linear fuzzy identification

Local Takagi-Sugeno rules:

$y_i(t)$: ***If*** $x(t)$ *is* R_i ***then***

Global fuzzy non-linear model:

$$y(t) = \frac{\sum_{i=1}^{M} \mu_i(x(t))\, y^{(i)}(t)}{\sum_{i=1}^{M} \mu_i(x(t))}, \quad y^{(i)}(t) = F^{(i)} x(t) + b^{(i)}$$

Non-linear fuzzy identification

"State vector"

$$\mathbf{x}(t) = \left[\mathbf{u}(t-1),\cdots,\mathbf{u}(t-n),\cdots,\mathbf{y}(t-1),\cdots,\mathbf{y}(t-n)\right]^T$$

Parameters to identify

$$\mu_i(.) : C \subset \Re^{nxn} \longrightarrow [0,1]$$

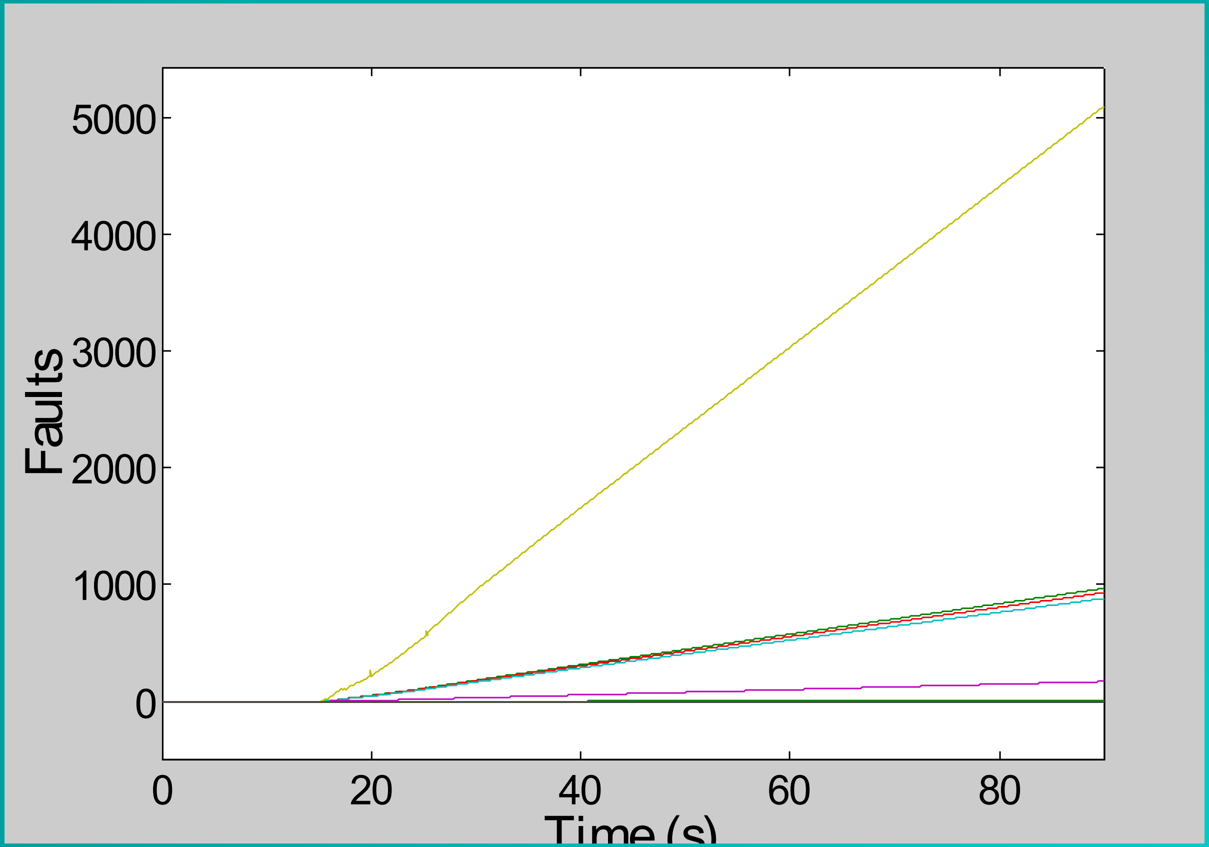
$$F^{(i)}, b^{(i)} \; and \; n$$

Identification & FDI steps

- ✓ ARX linear/TS fuzzy non-linear
  model identification
- Output estimator design
  residual generation/output sensitivity
- FDI analysis
  fault signature

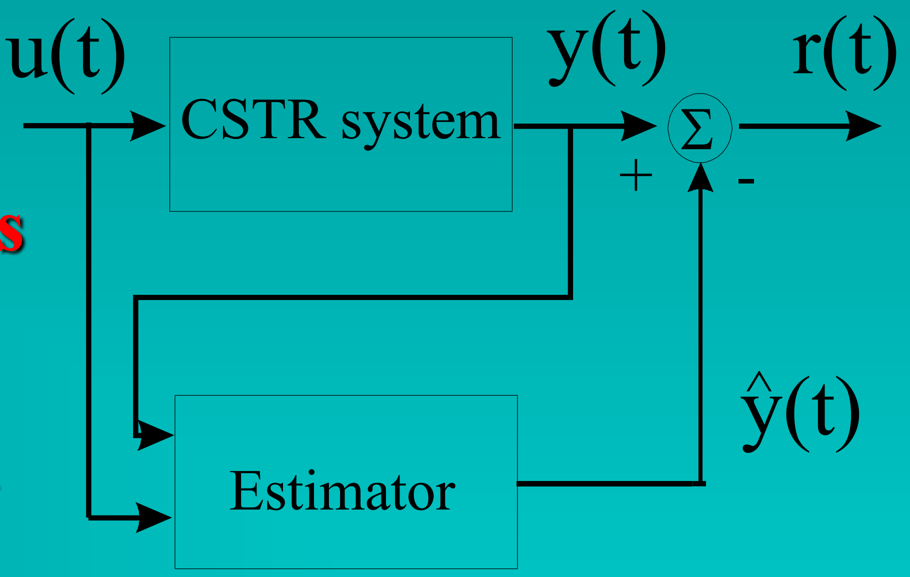
Residual sensitivity analysis

The most sensitive residual to a fault



Residual generation

- **Estimator**
  - **observers**
  - **fuzzy predictors**
- **Residual analysis**
  - **fault sensitivity**
- **Fault signature**
  - **fault isolation**



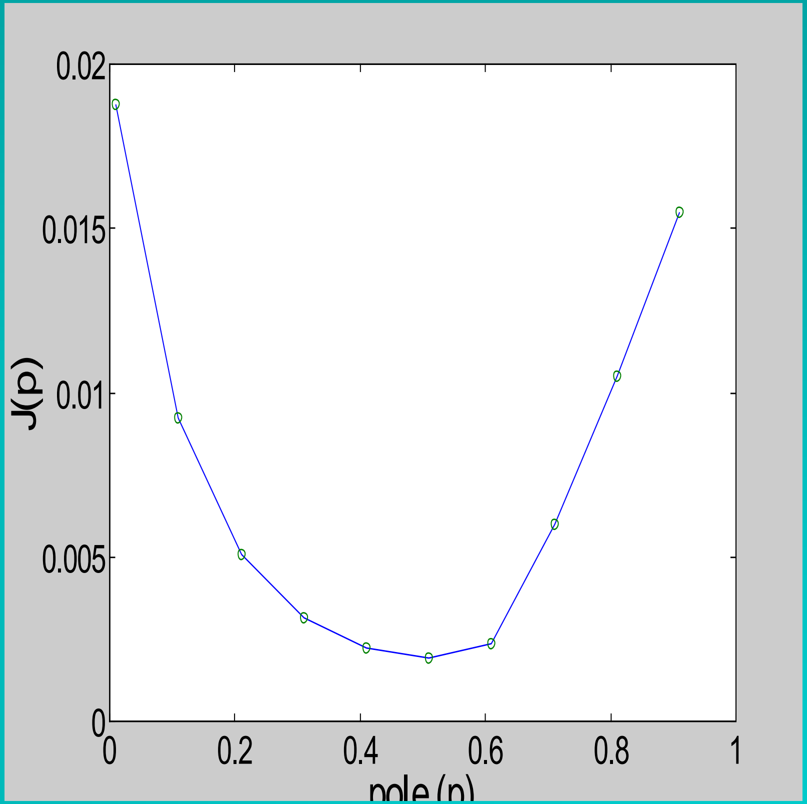
Residual generator

Output observer design

- I/O ARX to state space model
- Pole placement: **J(p)** optimization technique

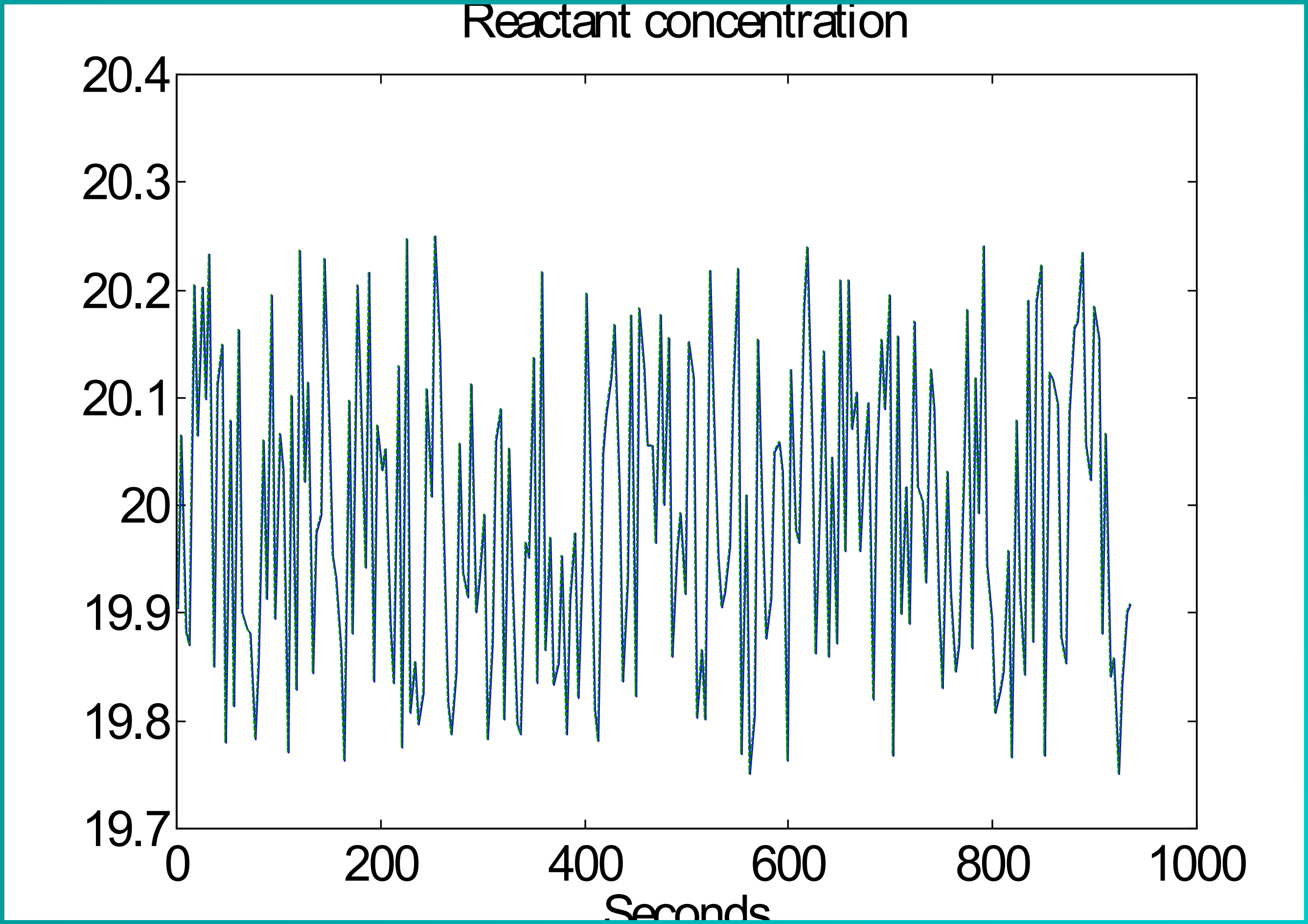
$$\min_{\mathbf{p}} J(\mathbf{p})$$

$$J(\mathbf{p}) = \|r(t,\mathbf{p})\|^2_h \Big/ \|r(t,\mathbf{p})\|^2_f$$



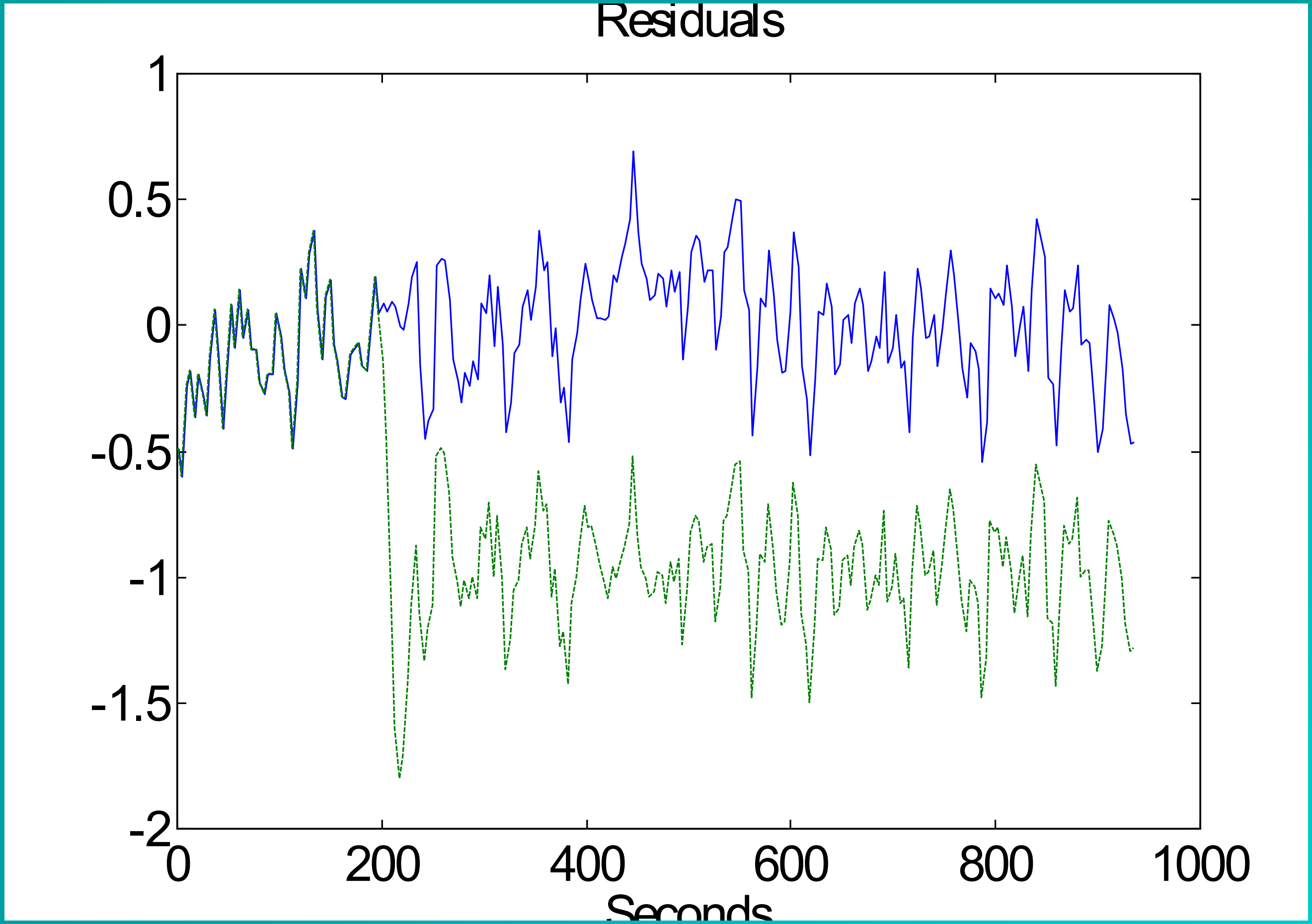
Cost function versus pole position

Fault case #1: pipe 1 blockage



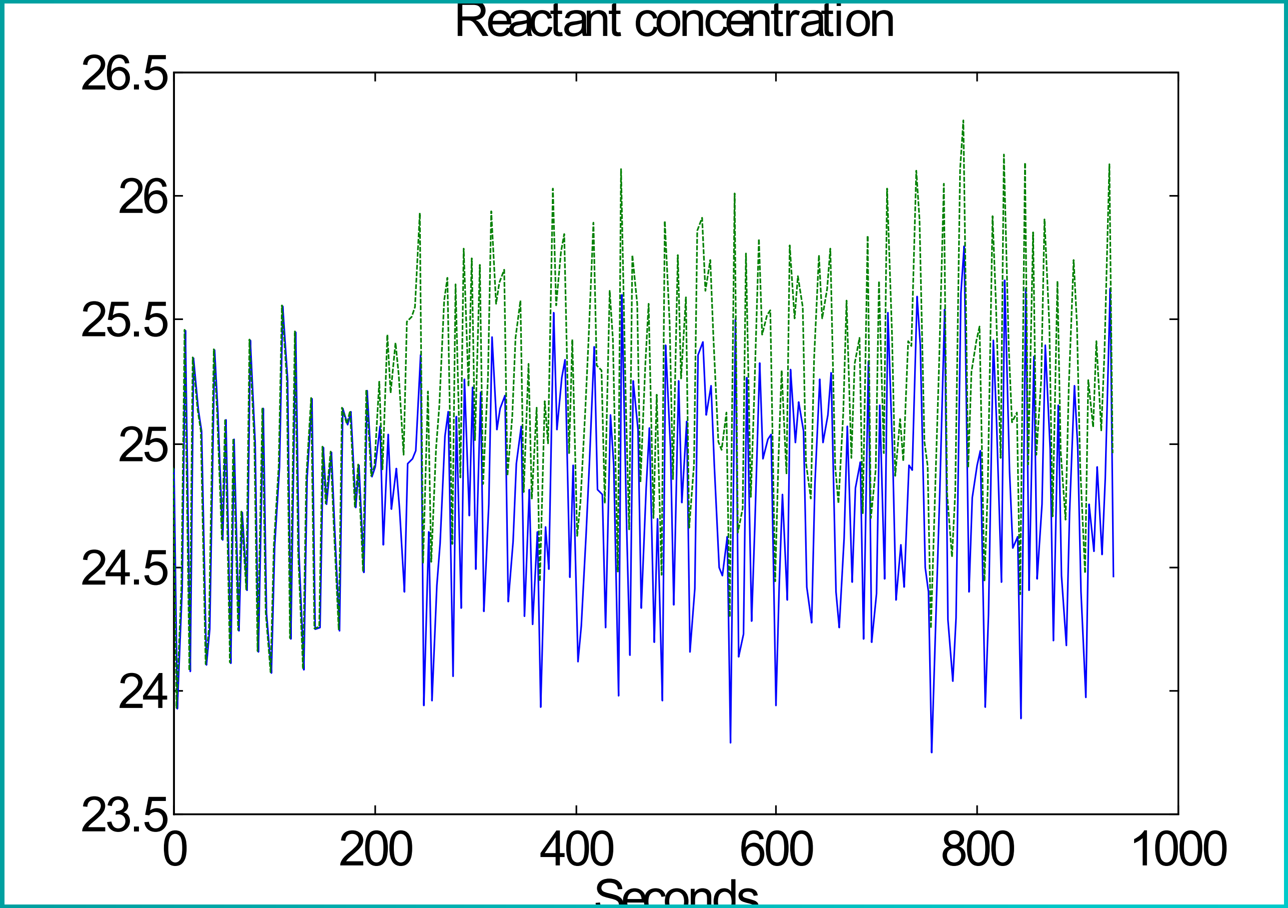
Output #3: reactant concentration in the reactor

FDI with observers: fault case #1



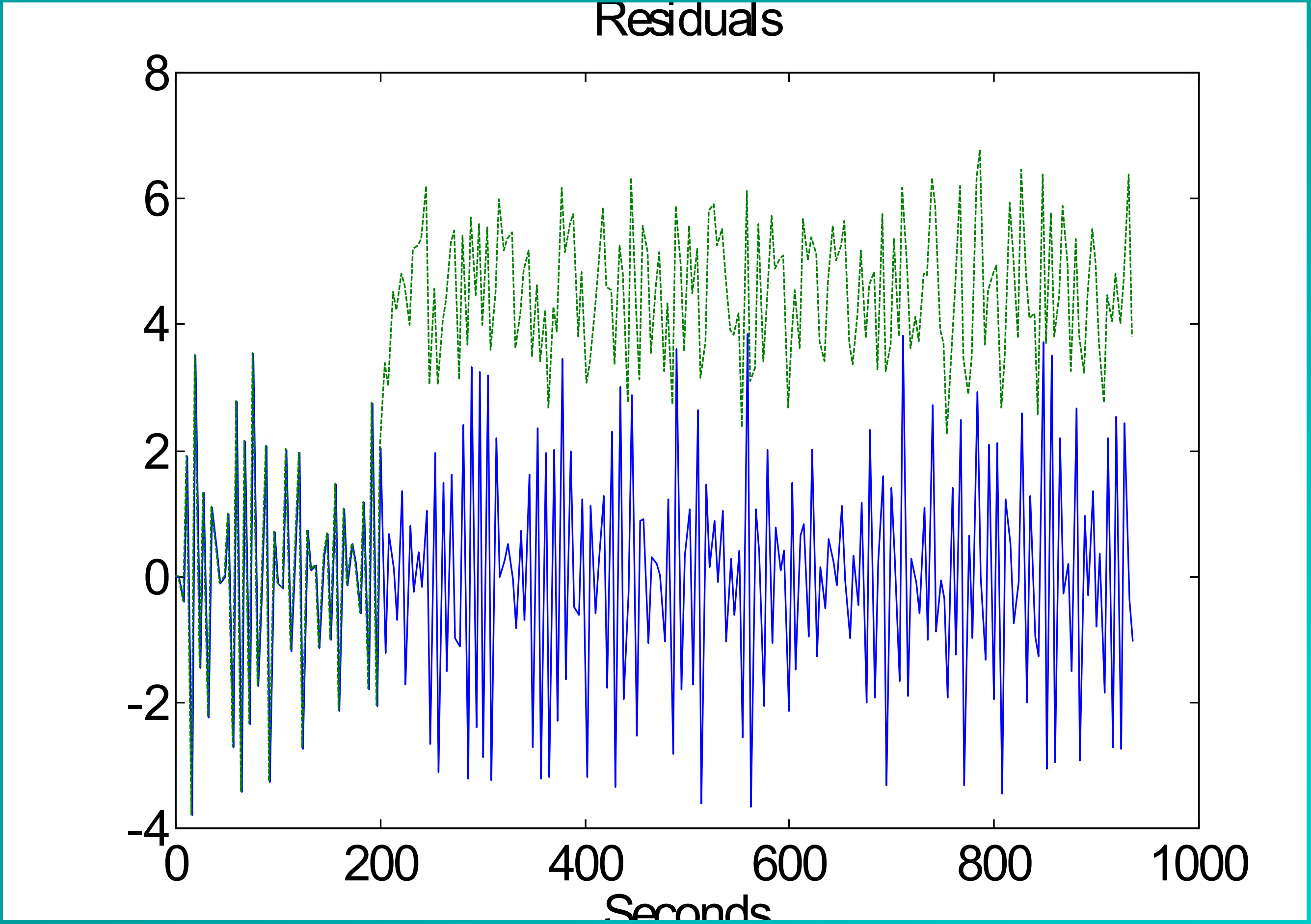
PPCRE ~ 5%. PCRRE ~ 0.3%. Fault size = 30%

TS fuzzy model: case #1 pipe 1 blockage



Output #5: controller output of the level controller

FDI with TS fuzzy model: case #1



VAF ~ 98.7% . PCRRE ~ 7.4%. Fault size = 25%

Fault Isolability (non-linear case)

Fault signature: the most sensitive measurement

Fault case	Residual and output #							Sensitive output
	#1	#2	#3	#4	#5	#6	#7	
1	0	0	1	0	1	0	0	5
2	1	1	1	1	0	0	1	7
3	1	1	0	1	1	1	1	4
4	1	1	1	1	1	1	0	1

‘0’ if residual is not sensitive to a fault

‘1’ if residual is sensitive to a fault

Conclusion I

- Actuator, component, sensor FDI of a simulated chemical process
- Linear (ARX) and non-linear (fuzzy TS) identification techniques
- Output estimation approach (observer and predictors)
- Minimal detectable fault

Further works

- Non-linear identification techniques (NARX, hybrid models, neural networks)
- Fuzzy observers, UIO
- Disturbance de-coupling
- Multiple faults
- Measurements affected by noise
- Measurement availability

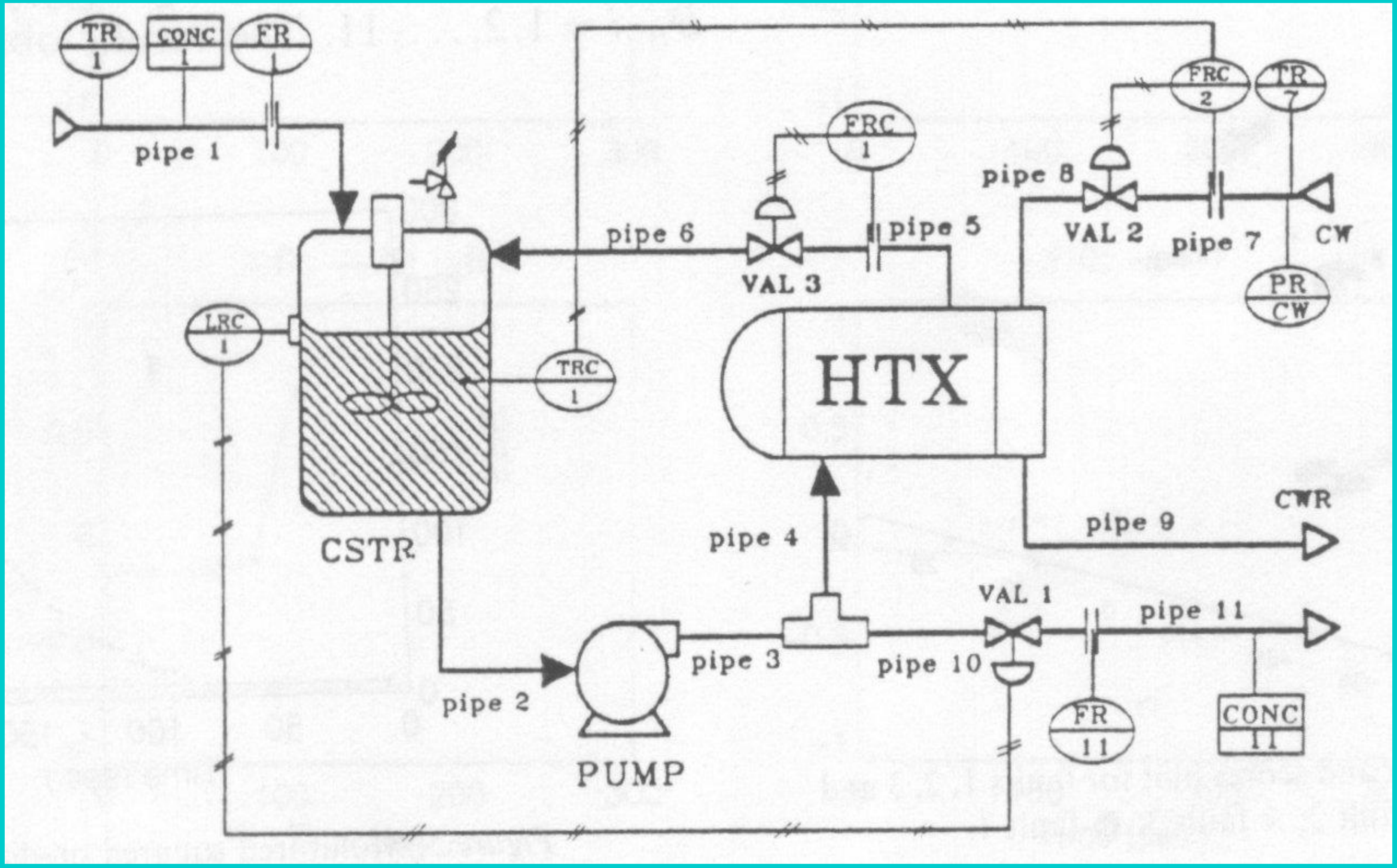
Case Study II: CSTR

Application example about the use of non-linear identification

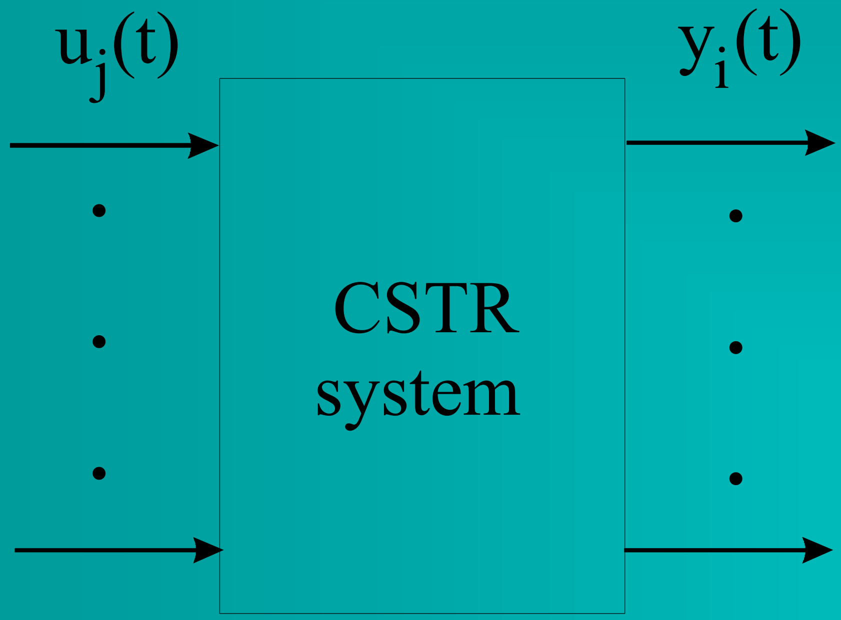
Introduction

- FDI in dynamic systems
  - model-based/observer-based methods
  - linear/non-linear systems
- Dynamic system identification
  - linear/non-linear models

CSTR system description



CSTR system layout



Input and output selection

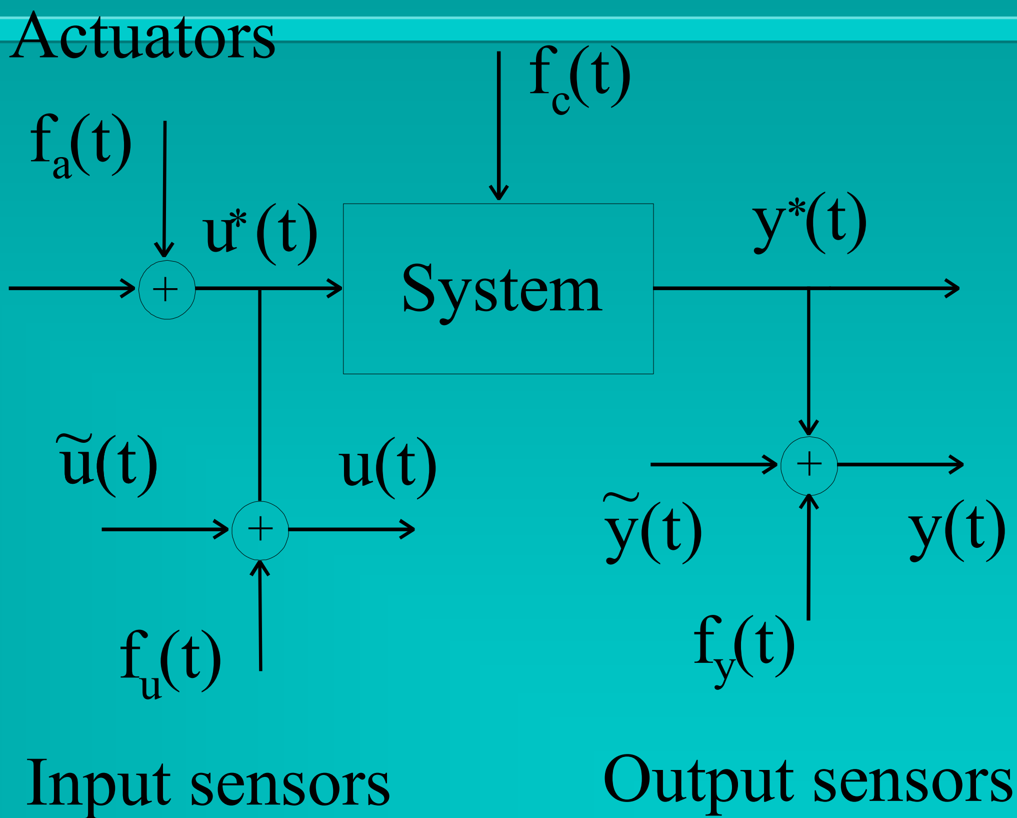
- 6 inputs, $\mathbf{u}_j(t)$
- 7 outputs, $\mathbf{y}_i(t)$
- closed-loop system
- input-output analysis

CSTR inputs and outputs

1	Tank temperature	O
2	Tank level	O
3	Temperature of feed	I
4	Feed rate through pipe 1	I
5	Flow rate of recycled reactant	I
6	Flow rate of cooling water	I
7	Flow rate of product	I
8	Reactant concentration in the reactor	O
9	Reactant concentration in the feed	I
10	Pressure	O
11	Controller output of the level controller	O
12	Primary control loop output of the temperature controller	O
13	Secondary control loop output of the temperature controller	O

Measurement process

- Actuators, $f_a(t)$
- Sensors, $f_u(t)$, $f_y(t)$
- Components, $f_c(t)$
- **Sensor noises**
- **u(t), y(t)** available measurements
- **u*(t), y*(t)** inaccessible inputs and outputs



Nomenclature

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- ✓ 1 Pipe 1 blockage
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- 5 External feed reactant temperature abnormal
- 6 Control valve 1 fails high
- 7 Pipe 7, 8 or 9 blockage or control valve 2 fails low
- 8 Control valve 1 fails high
- 9 Pipe 4, 5 or 6 blockage or control valve 3 fails low
- ✓ 10 Control valve #3 fails high
- 11 External feed reactant concentration too low

Dynamic system identification

- Input and output sequences **u(t)** and **y(t)**
- Equation error models ➡ linear ARX/SS systems (steady state conditions)
- Multi-model approach ➡ TS non-linear systems (different working points)

Equation error models (ARX)

$$\hat{y}_i(t) = \sum_{k=1}^{n} \alpha_{ik} \hat{y}_i(t-k) + \sum_{j=1}^{r} \sum_{k=1}^{n} \beta_{ikj} \hat{u}_j(t-k) + \varepsilon_i(t)$$

- High signal to noise ratios $\tilde{\mathbf{u}}(t) \cong \mathbf{0}$, $\tilde{\mathbf{y}}(t) \cong \mathbf{0}$
- From the sequences **u(t)** and **y(t)** determine α_{ik} , β_{ikj} and **n.**

ARX to State Space model

$$\begin{cases} \mathbf{x}_i(t+1) = \mathbf{A}_i \mathbf{x}_i(t) + \mathbf{B}_i \hat{\mathbf{u}}(t) + \mathbf{B}_{\omega_i} \varepsilon_i(t) \\ \hat{\mathbf{y}}_i(t) = \mathbf{C}_i \mathbf{x}_i(t) + \mathbf{D}_{\omega_i} \varepsilon_i(t), \qquad t = 1,2,\ldots \end{cases}$$

- A_i , B_i , $B_{\omega i}$, C_i , $D_{\omega i}$ are matrices depending on ARX parameters and order
- Each *i*-th output

Linear identification: results

- Optimal value of the model orders
- Residual whiteness (~ $\aleph^2_{8,0.95}$ distribution with 8 d.o.f and 95% confidence level)
- Correlation between inputs and residual (~ Gaussian distribution with 8 d.o.f.)
- One step ahead predictive model (~ 1%)
- Identified model in **full-simulation** (~ 7%)
- **Model validation** in full simulation

Non-linear identification: results

- Optimal value of the model orders *n* and *M*
- *Per Cent Reconstruction Error* and "*VAF*"

$$VAF\% = 100 \times \left[1 - \frac{\mathrm{std}\left(\hat{y}(t) - y(t)\right)}{\mathrm{std}\left(y(t)\right)} \right]$$

- One step ahead predictive model (~ 0.1%) or in **full-simulation**
- **Model validation** in full simulation

Non-linear fuzzy identification

- Local Takagi-Sugeno rules:

$y_i(t)$: ***If*** $x(t)$ *is* R_i ***then*** $y_i(t) = \theta_i^T x(t)$

- Global fuzzy non-linear model:

$$y(t) = \frac{\sum_{i=1}^{M} \mu_i\big(x(t)\big)\; y_i(t)}{\sum_{i=1}^{M} \mu_i\big(x(t)\big)}$$

where $y_i(t) = \theta_i^T\, x(t)$

Non-linear fuzzy identification

"State vector"

$$\mathbf{x}(t) = \left[\mathbf{u}(t-1),\cdots,\mathbf{u}(t-n),\cdots,\mathbf{y}(t-1),\cdots,\mathbf{y}(t-n)\right]^T \in \Re^p$$

Parameters to identify
(*FMID Matlab Toolbox*)

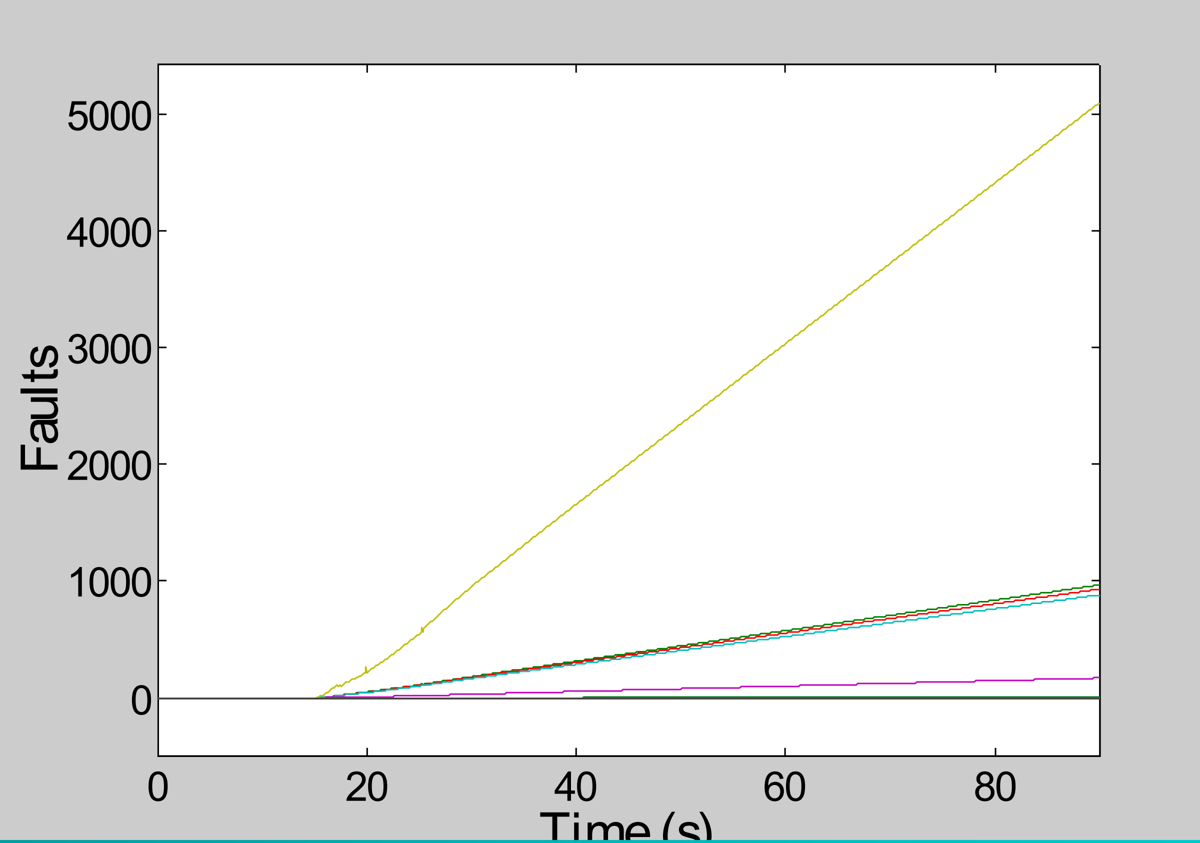
$\mu_i(.) : C \subset \Re^p \rightarrow [0,1]$ identify θ_i and n

Identification & FDI steps

- ARX linear/TS fuzzy non-linear
  model identification
- Output estimator design
  residual generation/output sensitivity
- FDI analysis
  fault signature

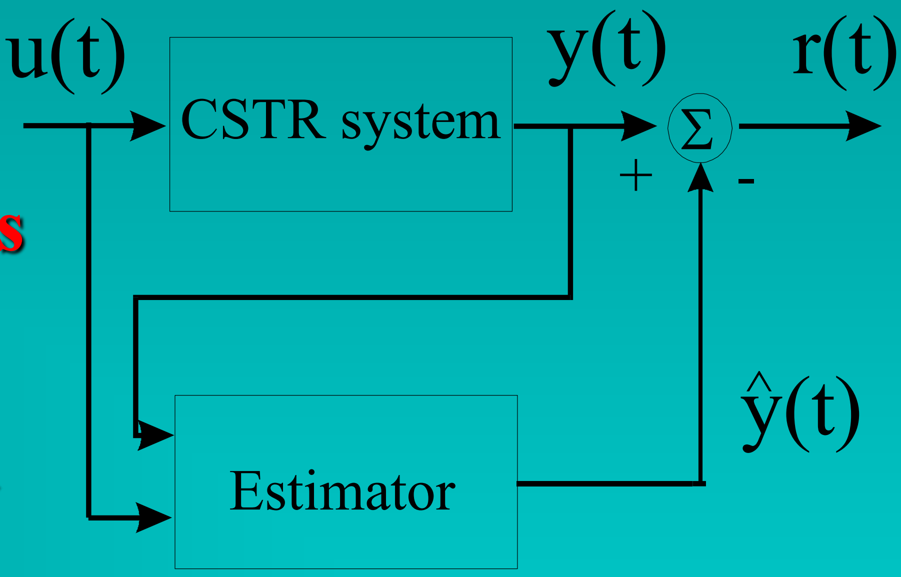
Residual sensitivity analysis

The most sensitive residual to a fault



Residual generation

- Estimator
  - ➡ observers
    fuzzy predictors
- Residual analysis
  - ➡ fault sensitivity
- Fault signature
  - ➡ fault isolation



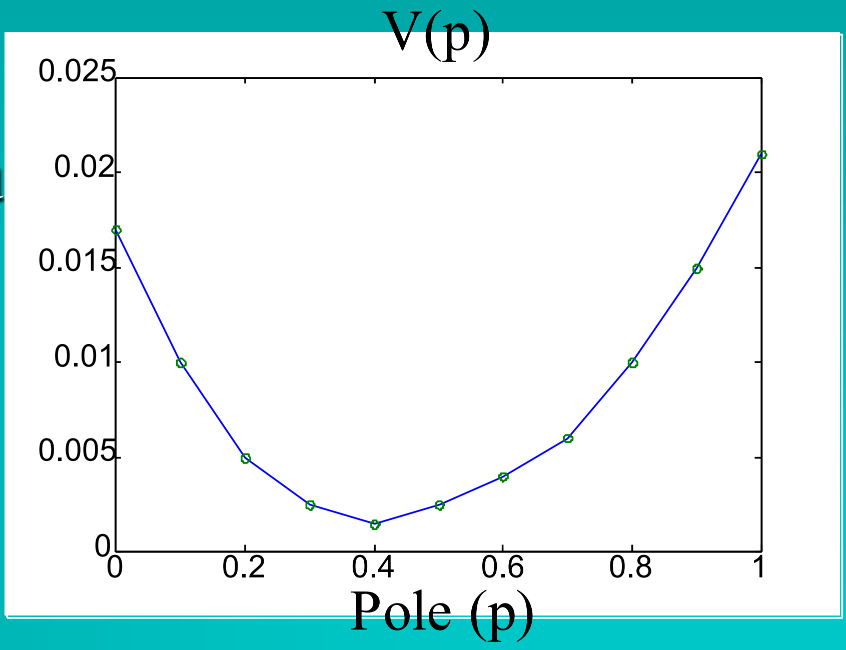
Residual generator

Robust output observer design

- State space model
- Pole placement: J(p) optimization techniqu

$$\min_{\mathbf{p}} J(\mathbf{p})$$

$$J(\mathbf{p}) = {\left\| r(t,\mathbf{p}) \right\|^2}_h \Big/ {\left\| r(t,\mathbf{p}) \right\|^2}_f$$



Cost function versus pole position

Application examples

Fault Case 1a:

30% blockage in Pipe 1 due to actuator problem (linear case).

Fault Case 1b:

15% blockage in Pipe 1 due to actuator problem (non-linear case).

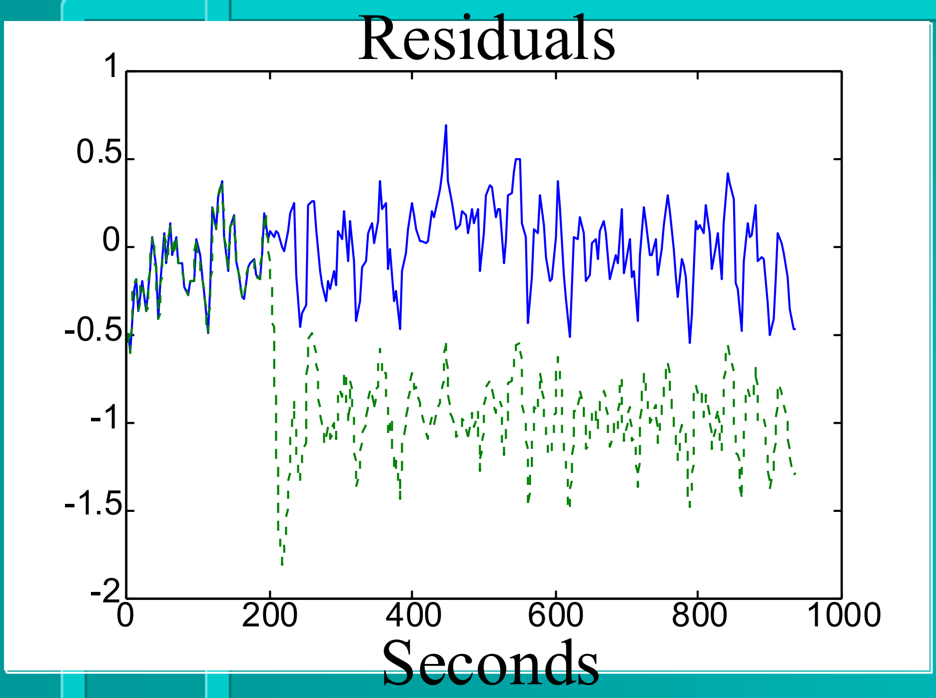
Fault Case 2a:

Control valve #3 fails high (linear case)

Fault Case 2b:

Control valve #3 fails high (non-linear case)

Fault case : Actuator fault



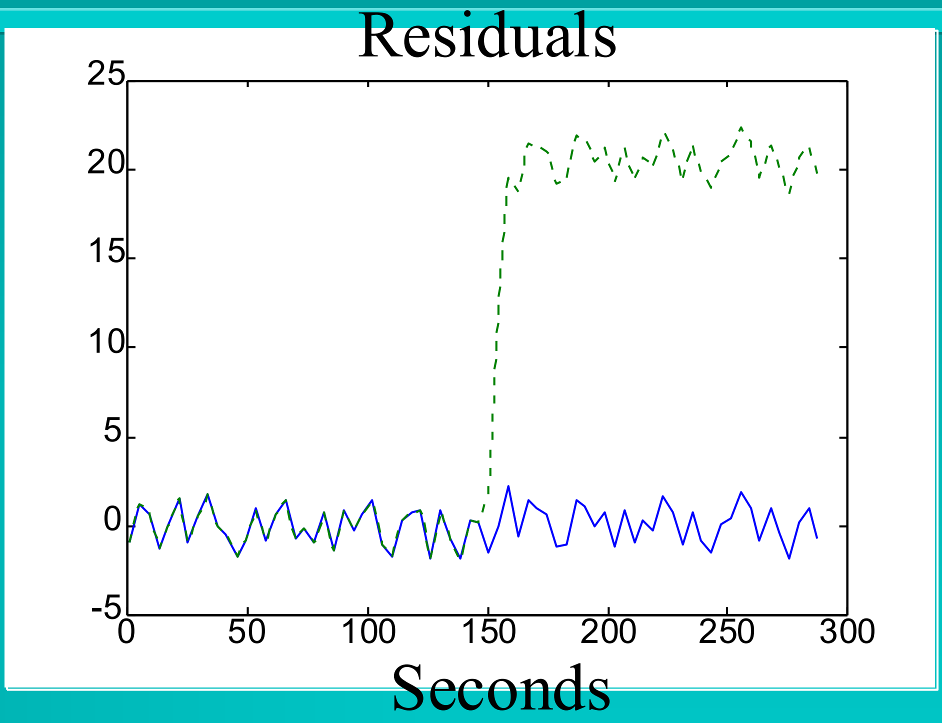
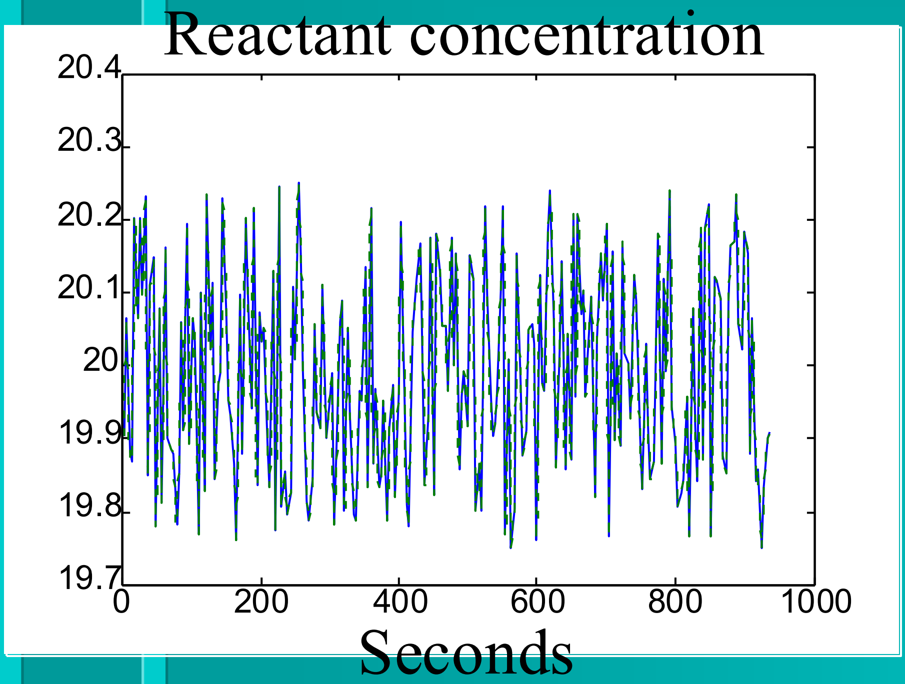
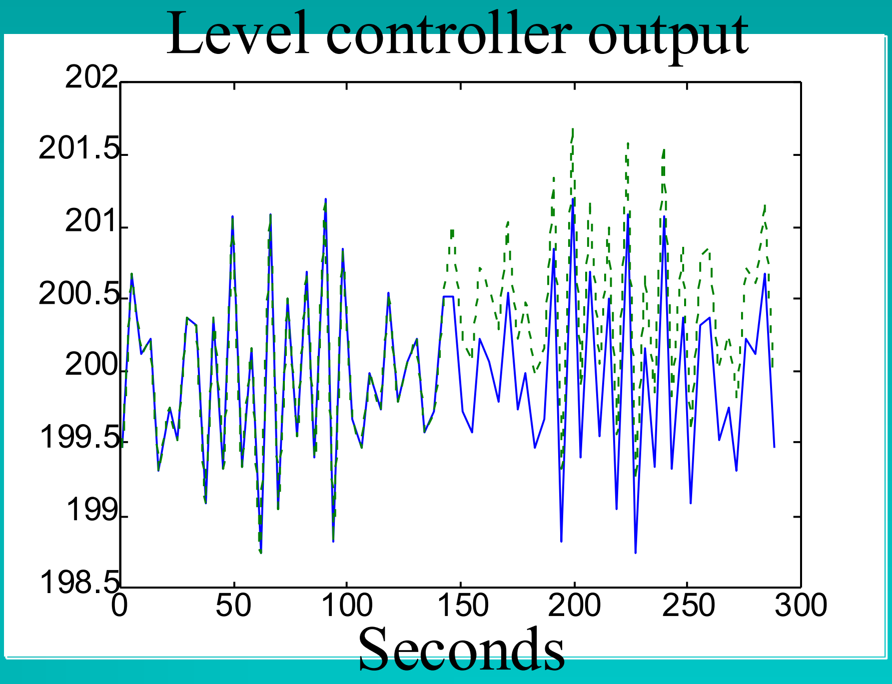


Figure : Residuals for the actuator fault *Case 1a (Left)*; Residuals for control valve *Case 2a (Right)*

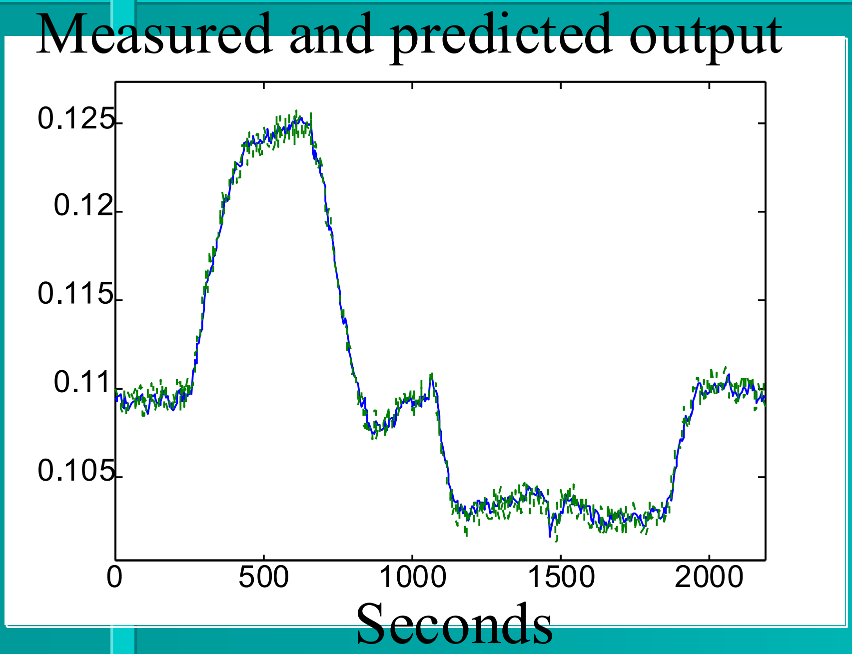
Monitored outputs for FDI

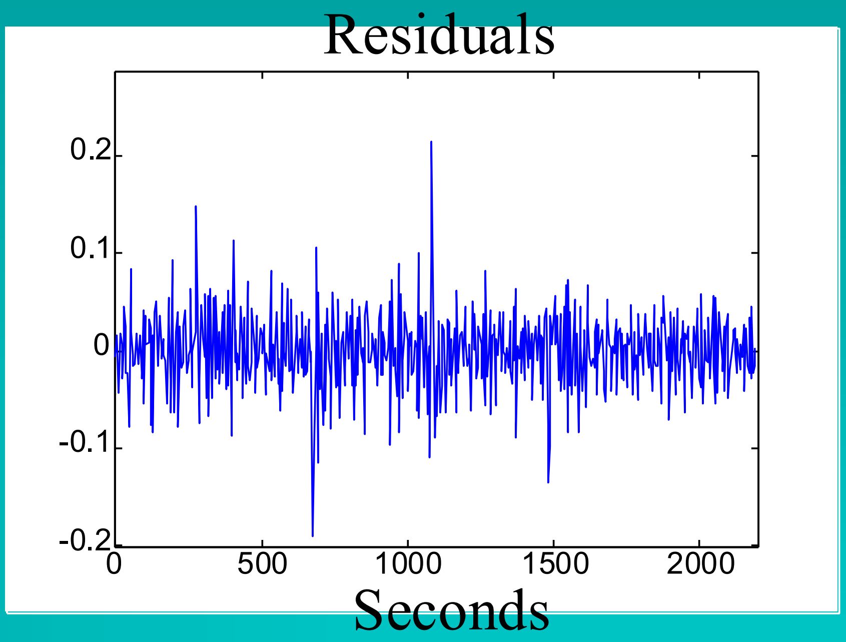




Predicted and measured outputs #3 and #5

Multiple operating point detection

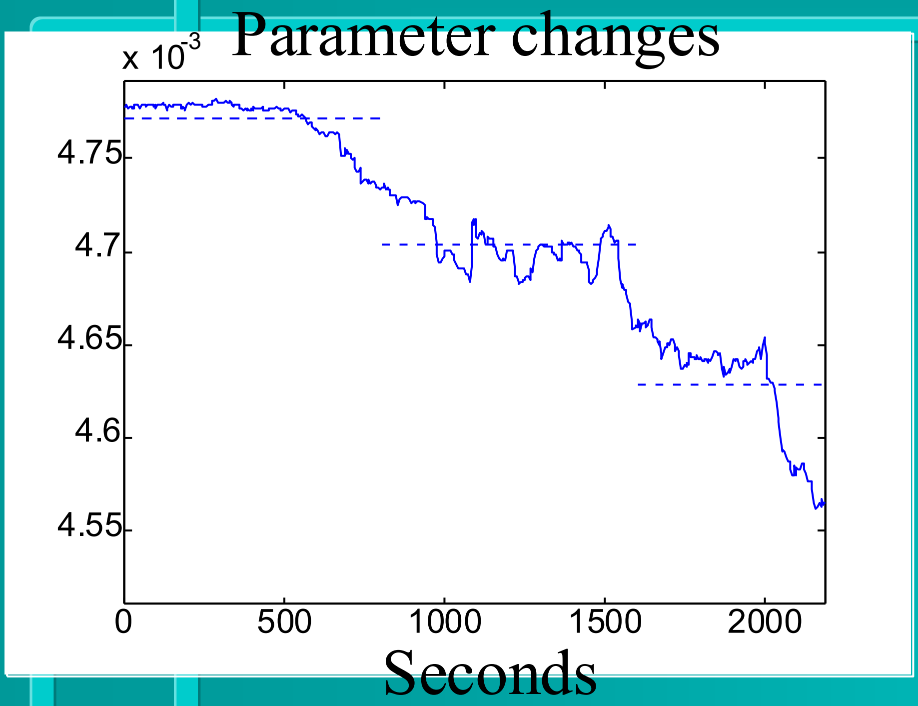


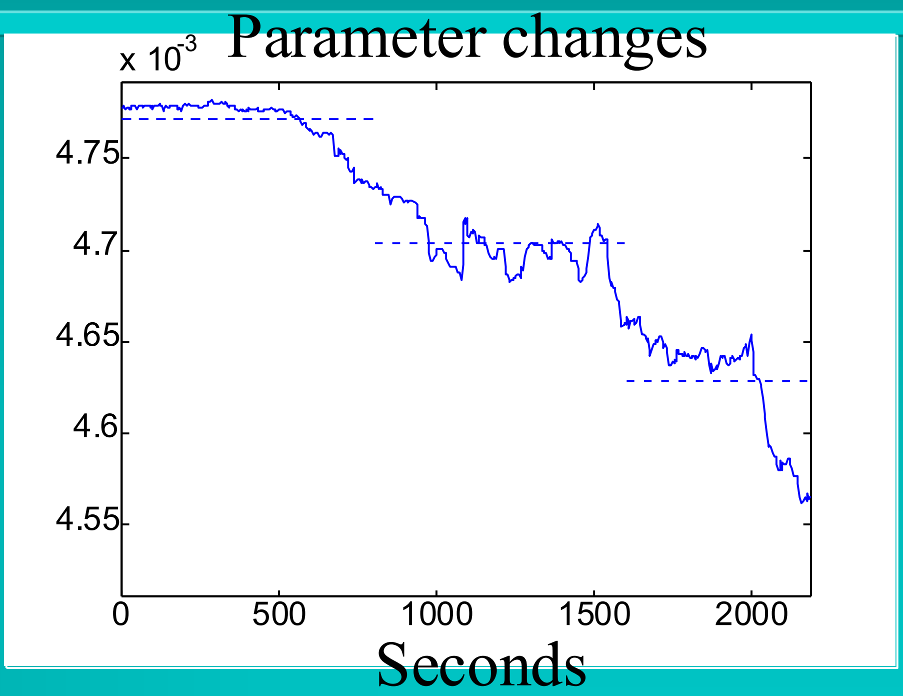


Measured and predicted output #3.

Kalman filter residual.

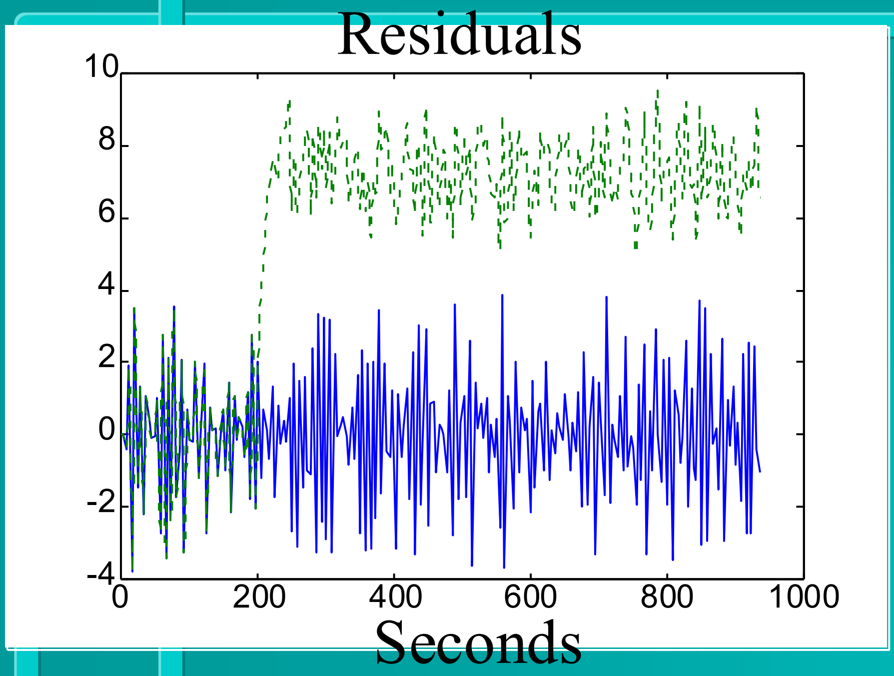
Multiple operating point detection





Parameters of a non-stationary ARX model for different working regions

TS fuzzy model: fault detection



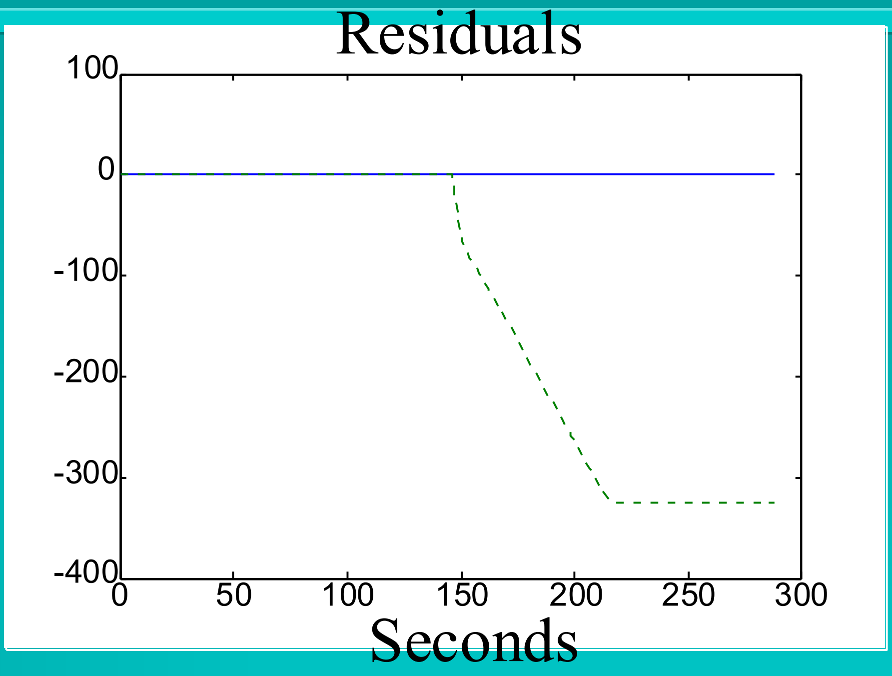
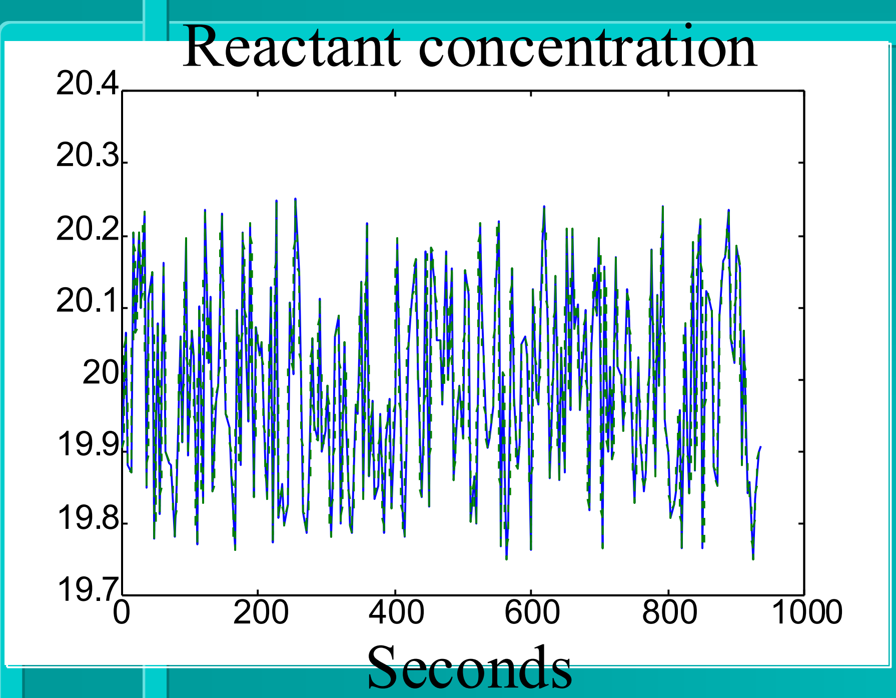


Figure : Residual functions for the fuzzy model *Case1b* (Left); Residuals for *Case 2b* (Right)

TS fuzzy model: Fault isolation



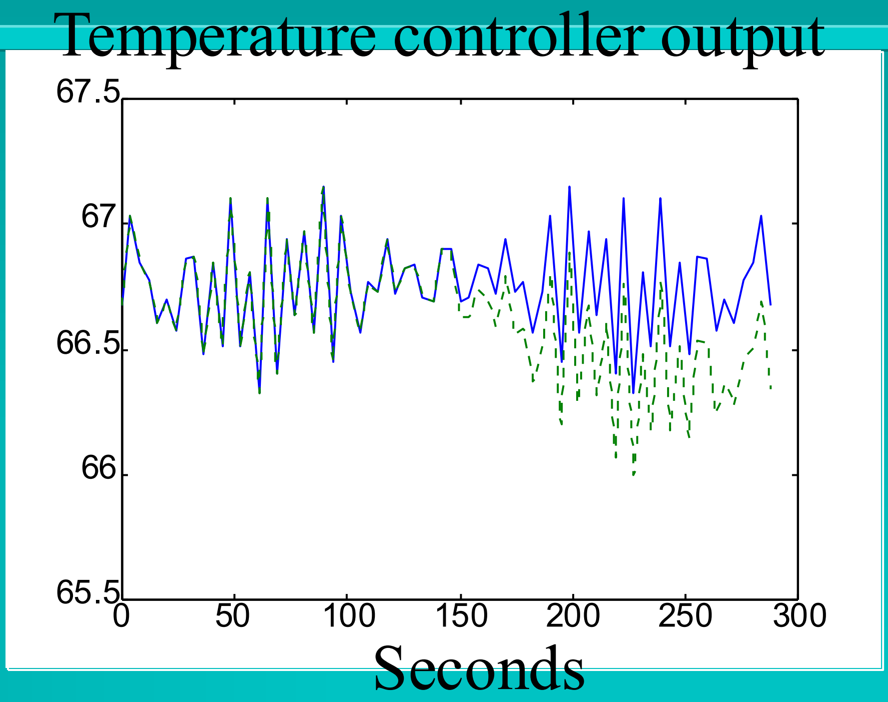


Figure : Output for fault *Case 1b* (Left);
Output for fault *Case 2b* (Right)

Fault Detection: results

- **Minimal detectable faults**

Fault Case	**Minimum detectable fault**	**PPCRE**	***VAF***
Case 1a	30%	5%	×
Case 2a	15%	0.3%	×
Case 1b	2%	0.5%	99.2%
Case 2b	0.5%	0.1%	98.7%

- ✓ Fault detection performance improvement

Fault Isolability (linear case): 1

Fault signature: the most sensitive measurement

Fault case	Residual and output #							Sensitive output
	#1	#2	#3	#4	#5	#6	#7	
1	1	1	1	0	0	0	0	3
2	1	1	1	1	1	0	0	2
3	1	1	1	0	1	1	1	6
4	0	1	1	1	1	1	1	7

'0' if residual is not sensitive to a fault

'1' if residual is sensitive to a fault

Fault Isolability (linear case): 2

Fault signature: the most sensitive measurement

Fault case	Residual and output #							Sensitive output
	#1	#2	#3	#4	#5	#6	#7	
5	1	0	1	0	1	0	1	1
6	0	0	1	0	0	1	1	3
7	0	0	0	0	0	0	1	7
8	1	1	1	1	1	1	1	4
9	1	0	0	0	1	1	1	6
10	1	0	1	0	1	1	1	5
11	1	1	0	0	1	0	0	2

‘0’ if residual is not sensitive to a fault

‘1’ if residual is sensitive to a fault

Fault Isolability (non-linear case): 1

Fault signature: the most sensitive measurement

Fault case	Residual and output #							Sensitive output
	#1	#2	#3	#4	#5	#6	#7	
1	0	0	1	0	1	0	0	5
2	1	1	1	1	0	0	1	7
3	1	1	0	1	1	1	1	4
4	1	1	1	1	1	1	0	1

‘0’ if residual is not sensitive to a fault

‘1’ if residual is sensitive to a fault

Fault Isolability (non-linear case): 2

Fault signature: the most sensitive measurement

Fault case	Residual and output #							Sensitive output
	#1	#2	#3	#4	#5	#6	#7	
5	1	0	1	**1**	0	0	1	4
6	**1**	0	1	1	0	0	1	1
7	0	0	**1**	0	0	0	1	3
8	1	**1**	1	1	1	0	1	2
9	1	0	1	0	0	**1**	1	6
10	1	0	0	0	0	**1**	0	6
11	1	0	1	0	0	0	**1**	7

‘0’ if residual is not sensitive to a fault

‘1’ if residual is sensitive to a fault

Conclusions II

- Actuator, component, sensor FDI of a simulated chemical process: *application study*
- Linear (ARX/SS) and Multiple Model identification techniques (fuzzy TS)
- Output estimation approach

  dynamic observer and *fuzzy* predictors
- Minimal detectable faults for CSTR justify use of T-S fuzzy approach, compared to ARX based estimation approaches.
- Fault isolability and size estimation

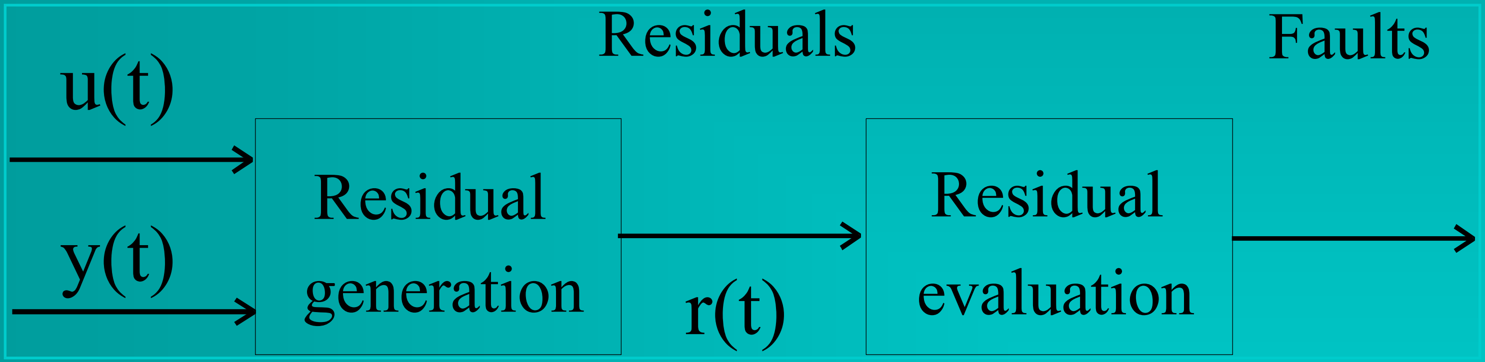
  ⇨ application to the real process

Case Study III: FDI of a simulated model of gas turbine prototype

FDI approach for this case study

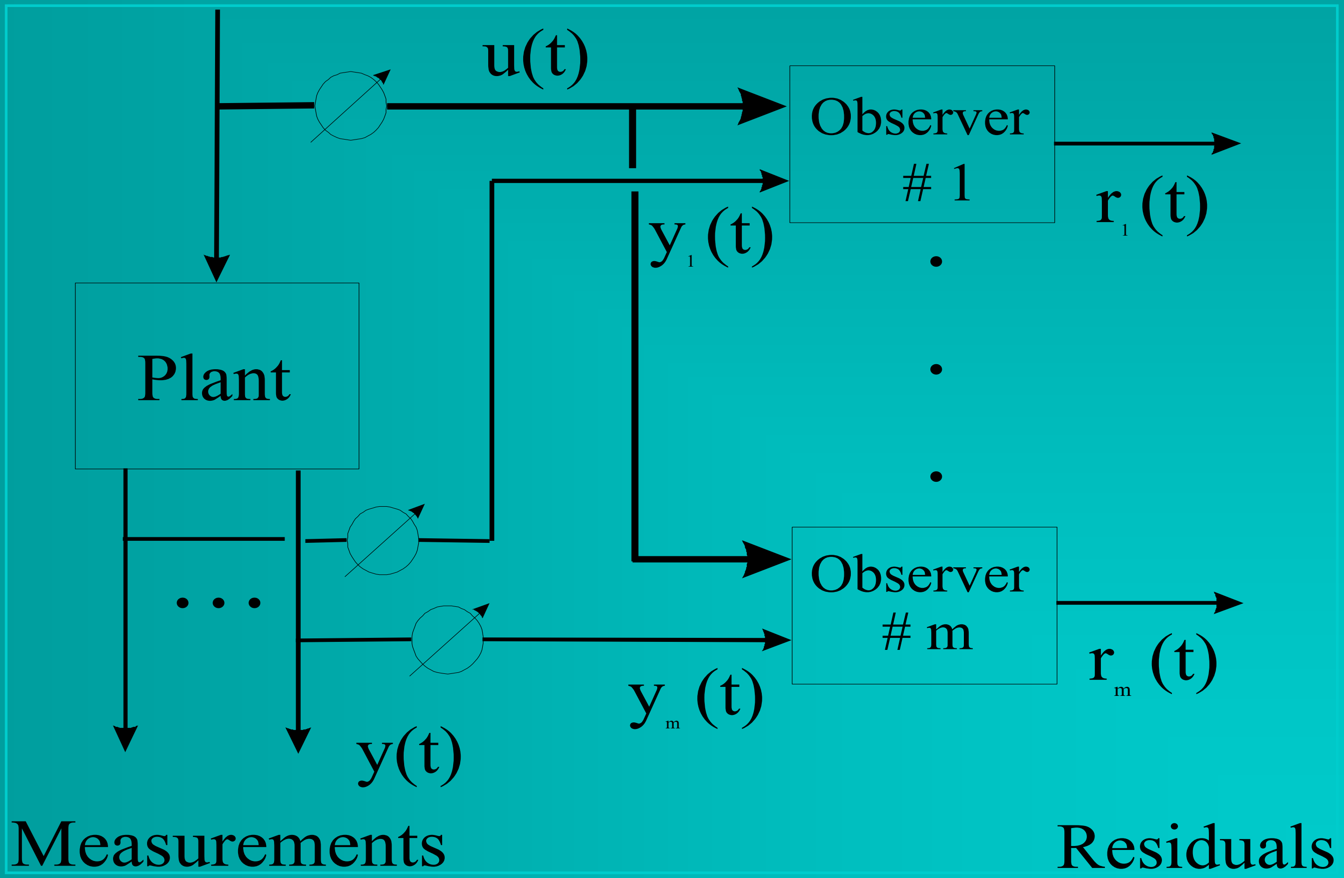
- Residual generation:
  - Luenberger observers or Kalman filters.
- Residual evaluation:
  - Geometrical or statistical tests;
  - Neural networks.

FDI scheme



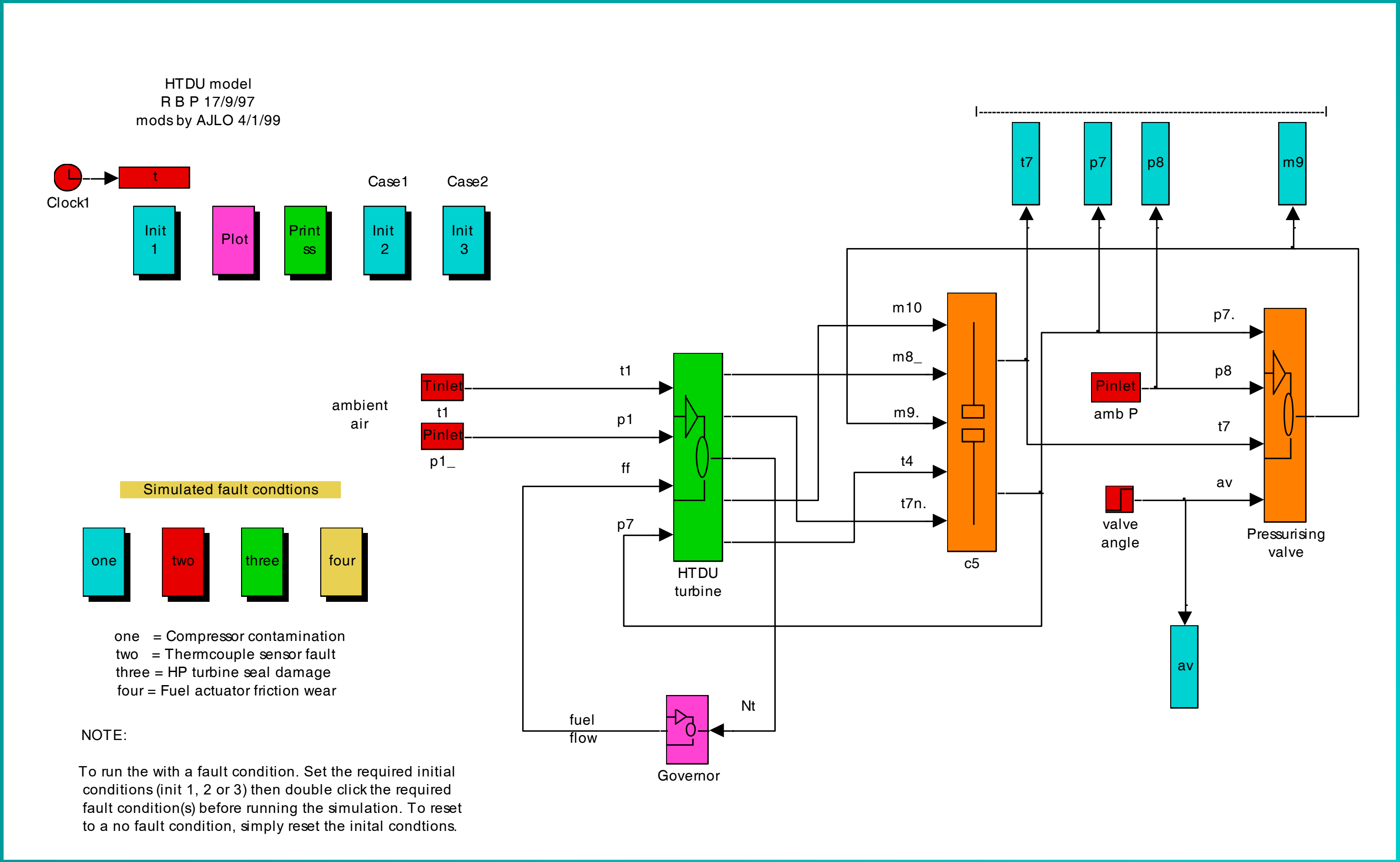
Logic diagram of the FDI system

Residual generation

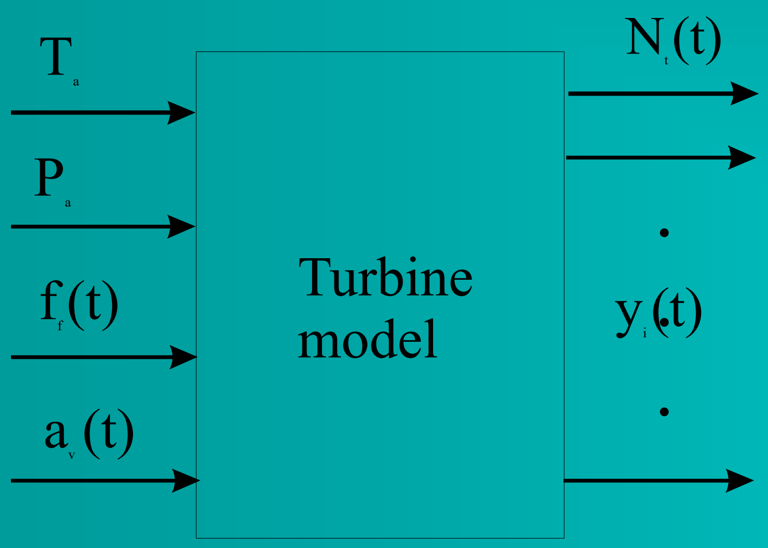


Residual generation: DOS

Model description



Turbine layout



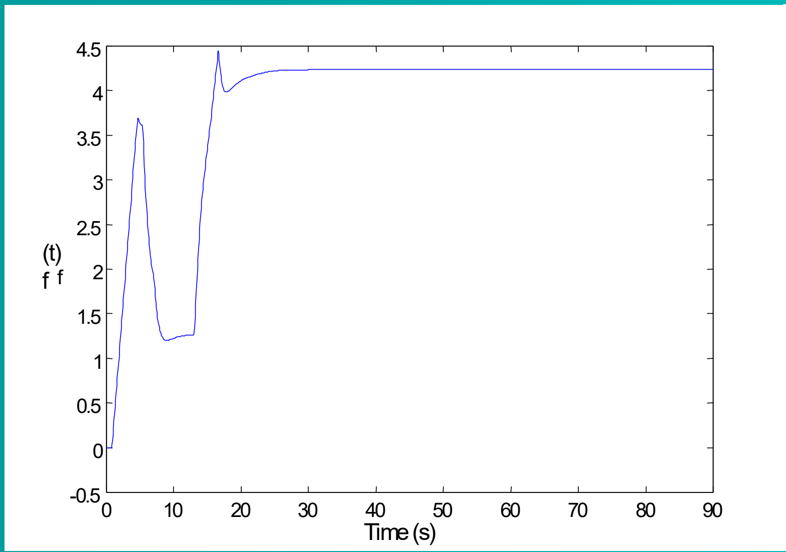
- T_a , P_a fixed as boundary conditions
- $a_v(t)$ pressurizing valve angle
- $f_f(t)$ manipulated control input
- $N_t(t)$ controlled variable
- $y_i(t)$ gas turbine measurements

Turbine model

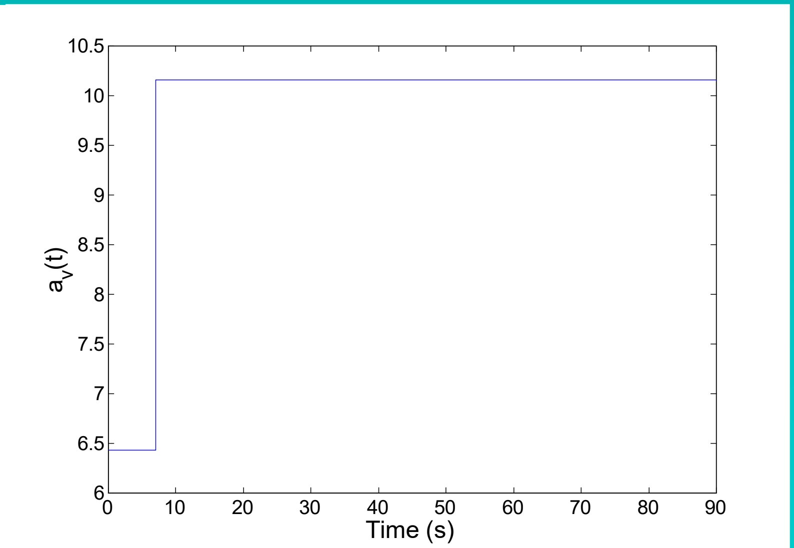
- Simulink dynamic model supplied, based upon an ALSTOM experimental test rig.
- 1%-5% model accuracy.
- Steady state validation.

Turbine inputs and outputs

Measure	$a_v(t)$	Torque	$f_f(t)$	Temp.	Press.	Mass
Accuracy	$\pm 2\%$	$\pm 1\%$	$\pm 5\%$	$\pm 1.5^o$	$\pm 1\%$	$\pm 5\%$



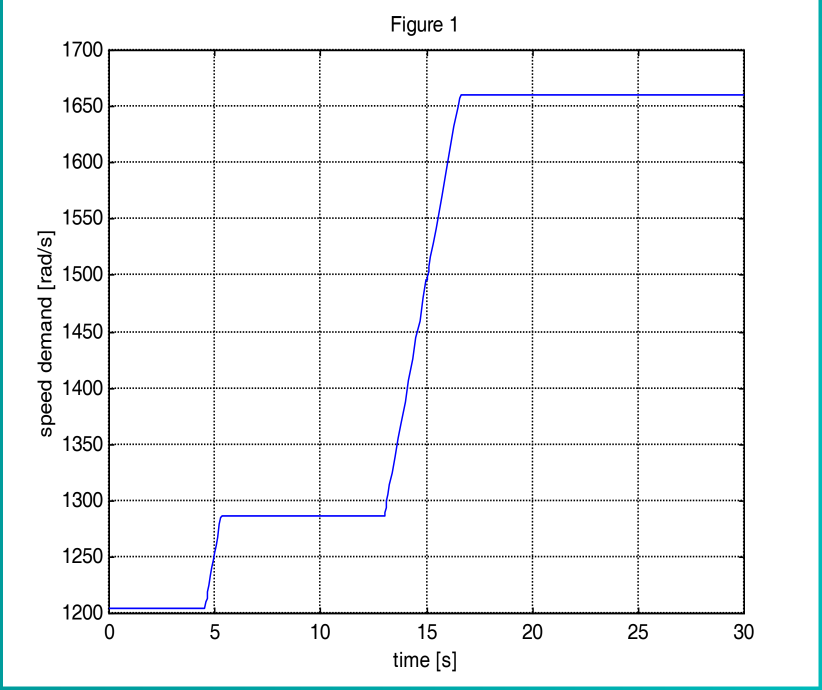
$f_f(t)$

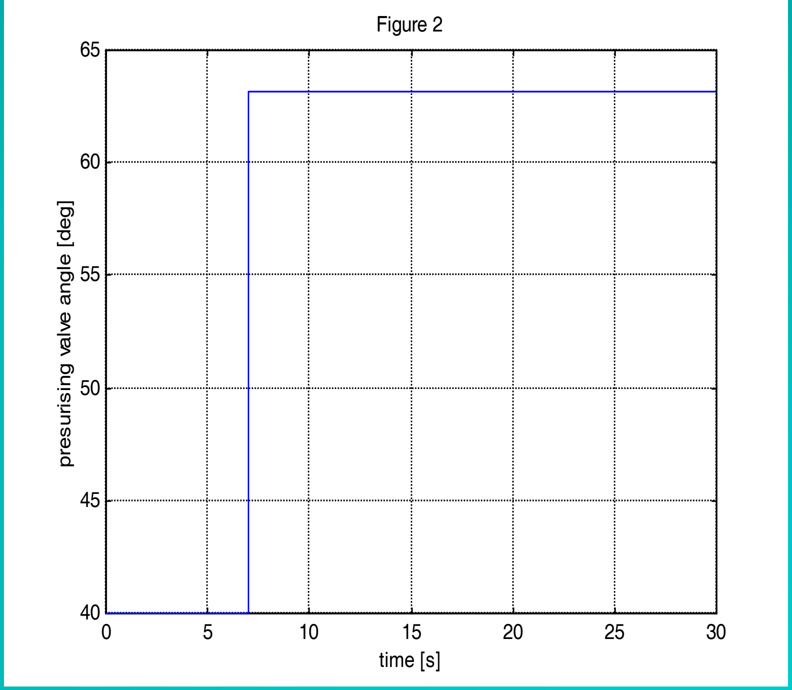


$a_v(t)$

Turbine dynamic performance run

Speed demand and valve angle sequencing in transient conditions.

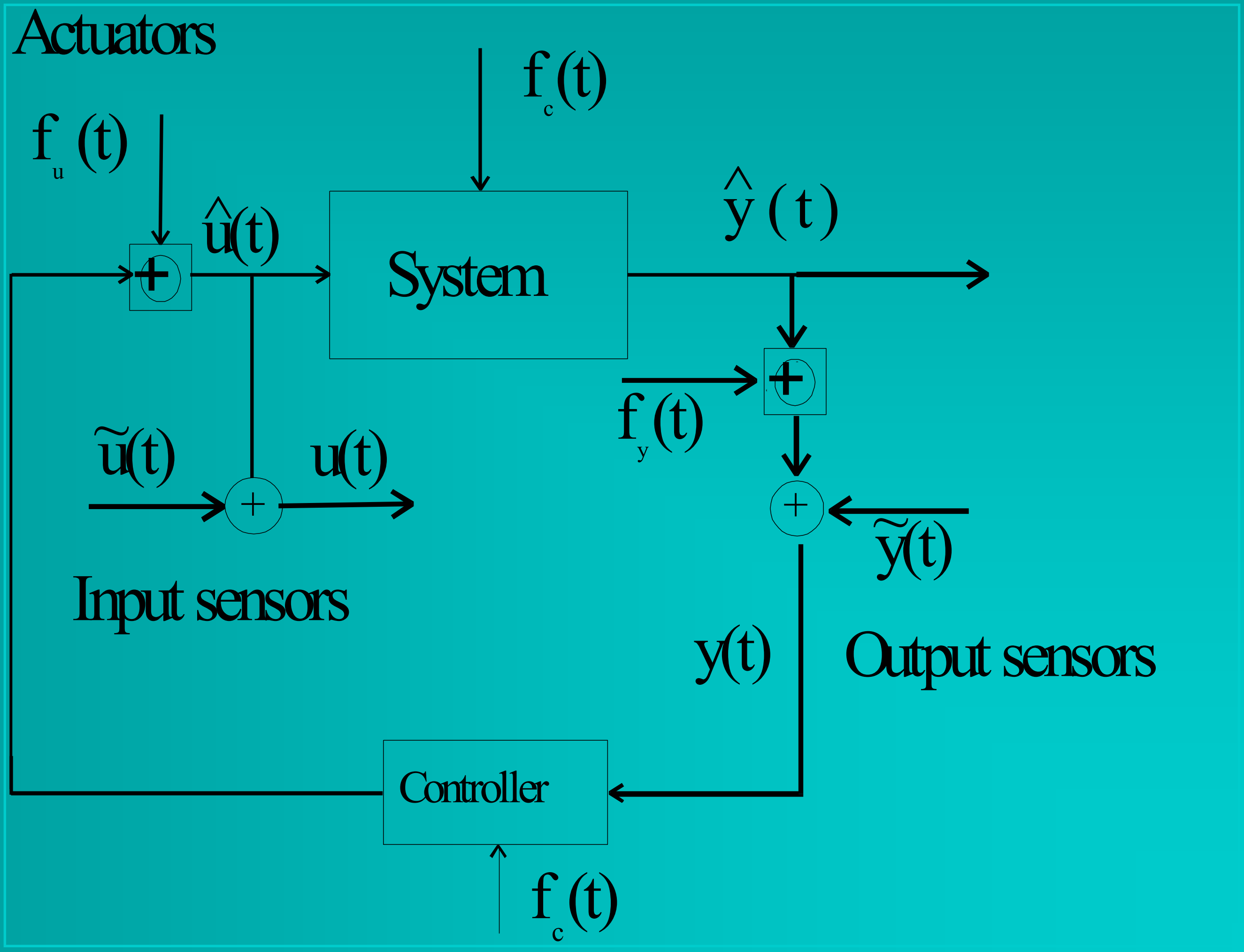




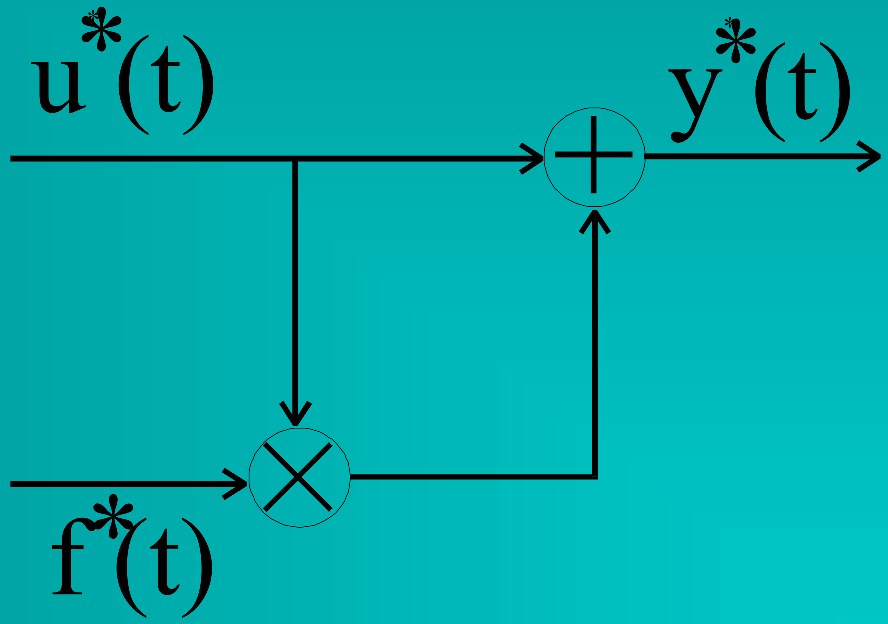
Speed demand

Valve angle

The measurement process



The fault model



$$y^*(t) = u^*(t) + u^*(t)\, f^*(t)$$

$$(\text{ vs. } y^*(t) = u^*(t) + f^*(t) \text{ })$$

Fault conditions

Four gradually developing faults:

1) Compressor contamination (*core engine* performance deterioration)
2) Thermocouple *sensor* fault
3) High Pressure turbine seal damage (*core engine* performance deterioration
4) Fuel *actuator* friction wear

Dynamic system identification

- Input and output sequences **u(t)** and **y(t)**
- Deterministic environment ➡ equation error models: ARX
- Stochastic environment ➡ errors in variables models: dynamic Frisch Scheme

Equation error models

$$\hat{y}_i(t) = \sum_{k=1}^{n} \alpha_{ik} \hat{y}_i(t-k) + \sum_{j=1}^{r} \sum_{k=1}^{n} \beta_{ikj} \hat{u}_j(t-k) + \varepsilon_i(t)$$

- High signal to noise ratios $\tilde{\mathbf{u}}(t) \cong \mathbf{0}$, $\tilde{\mathbf{y}}(t) \cong \mathbf{0}$

- From the sequences **u(t)** and **y(t)** determine α_{ik} , β_{ikj} and **n.**

ARX MISO model identification

- $\theta = \begin{bmatrix} \alpha_n & \cdots & \alpha_1 & \beta_n & \cdots & \beta_1 \end{bmatrix}^T$ parameters
- $J(\theta) = \frac{1}{N} \sum_{t=n+1}^{L} \left(\hat{y}(t) - y(t) \right)^2$ mean square error

$$\mathbf{H}_n(u) = \begin{bmatrix} u(1) & \cdots & u(n) \\ \vdots & \ddots & \vdots \\ u(L-n) & \cdots & u(L-1) \end{bmatrix}, \quad \mathbf{H}_n(y) = \begin{bmatrix} y(1) & \cdots & y(n) \\ \vdots & \ddots & \vdots \\ y(L-n) & \cdots & y(L-1) \end{bmatrix}$$

Hankel matrices

LS - ARX parameter estimation

$$\begin{bmatrix} \hat{y}(n+1) \\ \vdots \\ \hat{y}(L) \end{bmatrix} = \begin{bmatrix} \mathbf{H}_n(y) & \mathbf{H}_n(u) \end{bmatrix} \theta = H_n \theta$$

$$\hat{\theta} = \mathbf{H}_n^+ \begin{bmatrix} y(n+1) \\ \vdots \\ y(L) \end{bmatrix} = \mathbf{H}_n^+ y_n^o$$

$\mathbf{H}_n^+$ is the pseudo-inverse of $\mathbf{H}_n$

ARX order estimation

$$\mathbf{H}_k^* = \left[\mathbf{H}_k(y) \quad \mathbf{H}_k(u) \quad y_k^o \right]$$

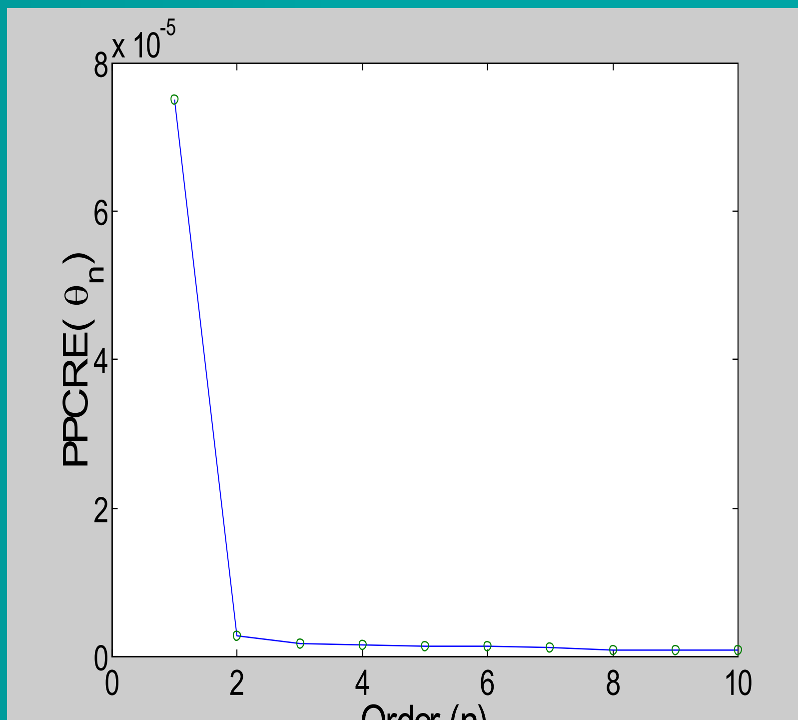
$$rank\left(\mathbf{H}_k^*\right) = 2k+1 \quad for\ 2k+1 < n,$$

$$rank\left(\mathbf{H}_k^*\right) = 2k \qquad for\ 2k \geq n.$$

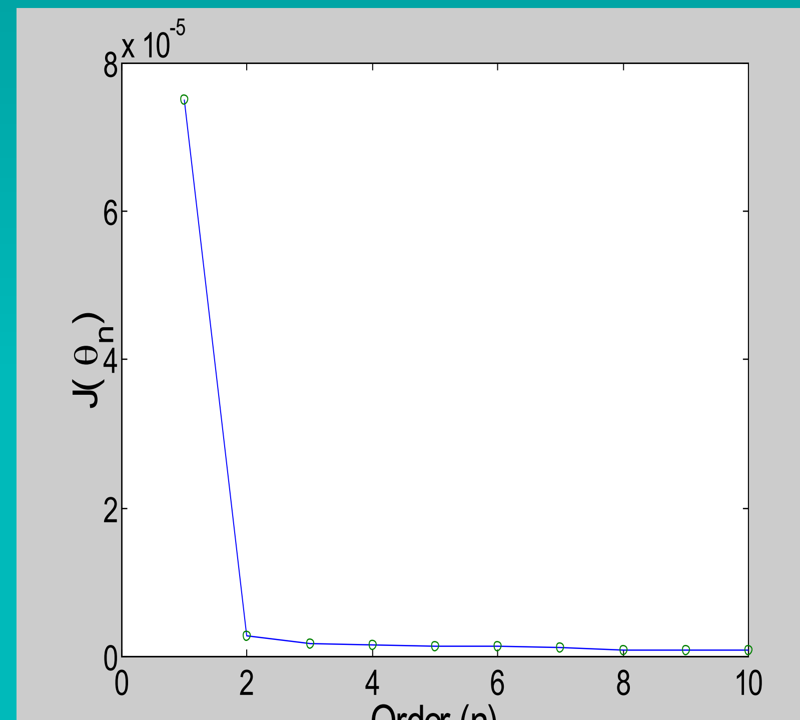
$$\sigma_{\varepsilon_k} = \sqrt{\frac{\det\left(\mathbf{S}_k\right)}{N \det\left(\mathbf{H}_k^T \mathbf{H}_k\right)}}$$

$$\sigma_{\varepsilon_k} > \sigma_{\varepsilon} \quad \text{if} \quad k < n \quad \& \quad \sigma_{\varepsilon_k} \cong \sigma_{\varepsilon} \quad \text{if} \quad k \geq n$$

ARX order estimation



$PPCRE(\theta_n)$



$J(\theta_n)$

ARX to state space model

$$\mathbf{x}_i(t+1) = \mathbf{A}_i\mathbf{x}_i(t) + \mathbf{B}_i\hat{\mathbf{u}}(t) + \mathbf{B}_{\omega_i}\varepsilon_i(t)$$

$$\hat{\mathbf{y}}_i(t) = \mathbf{C}_i\mathbf{x}_i(t) + \mathbf{D}_{\omega_i}\varepsilon_i(t), \quad t = 1,2,\ldots$$

- A_i , B_i , $B_{\omega i}$, C_i , $D_{\omega i}$ are matrices depending on ARX parameters and order
- Each i-th output

Identification in stochastic environment

- Plant inputs and outputs are affected by noises (four inputs).
- Dynamic Frisch Scheme to estimate model parameters and noise variances (Kalman, 1982; 1990. Beghelli *et al*., 1990; 1992).
- Kalman filter to generate residuals.

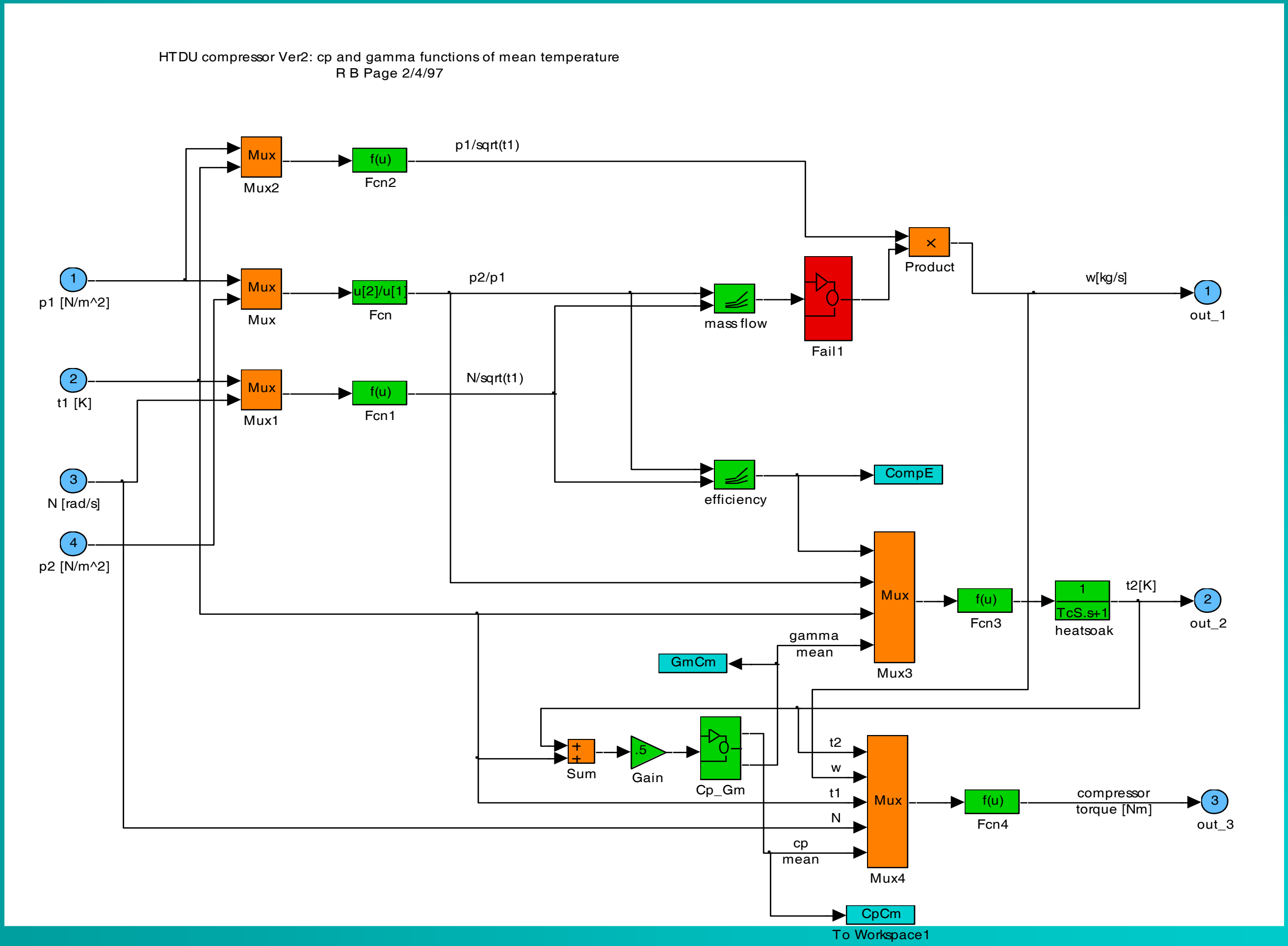
Turbine fault detection

- Single fault: four cases. Component, output sensor and actuator malfunctions.
- Ramp functions, slowly increasing faults.

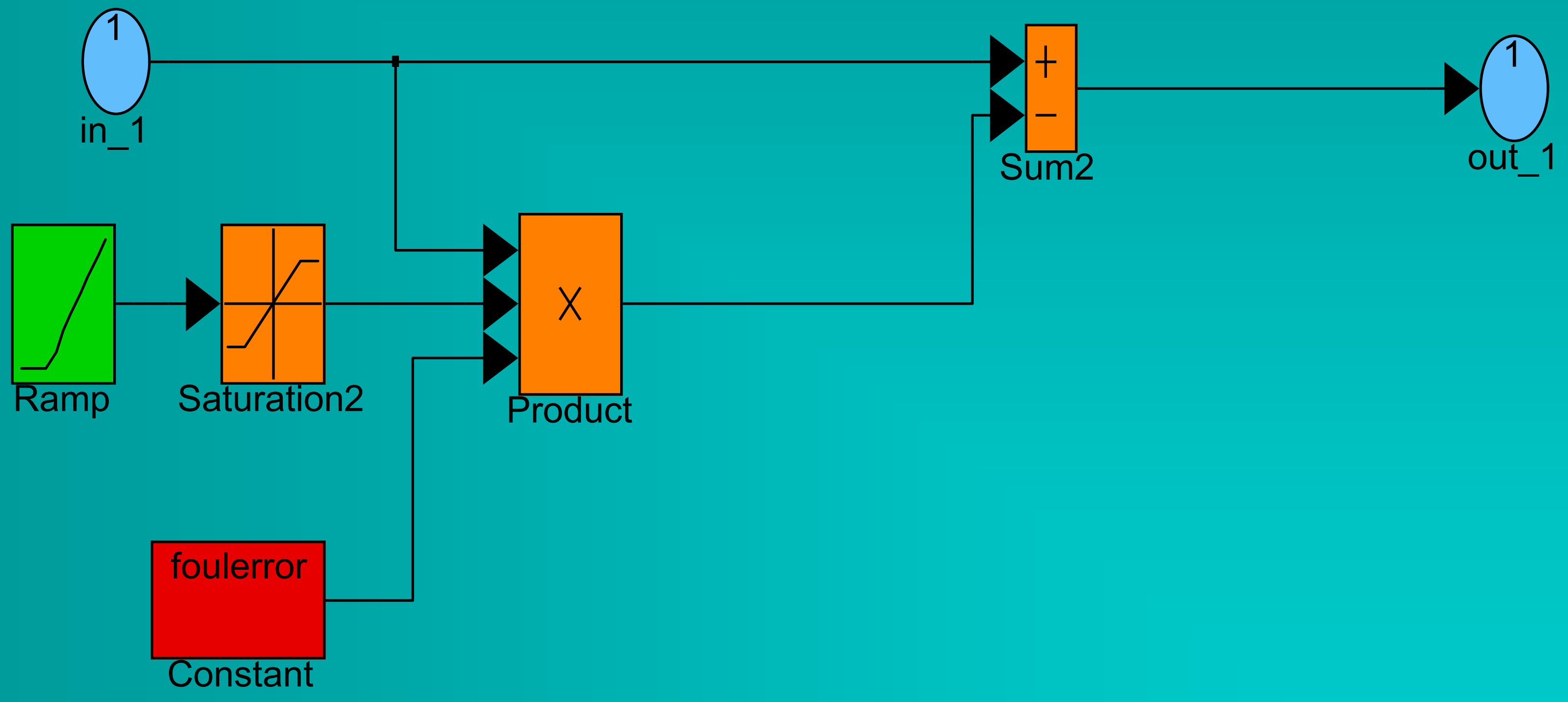
Compressor contamination (1)

- **Fault 1: Compressor contamination**
- It represents fouling of the surfaces of the compressor blades.
- The failure is modeled as a gradual decrease in mass flow rate for a given pressure ratio.

Compressor contamination (1)

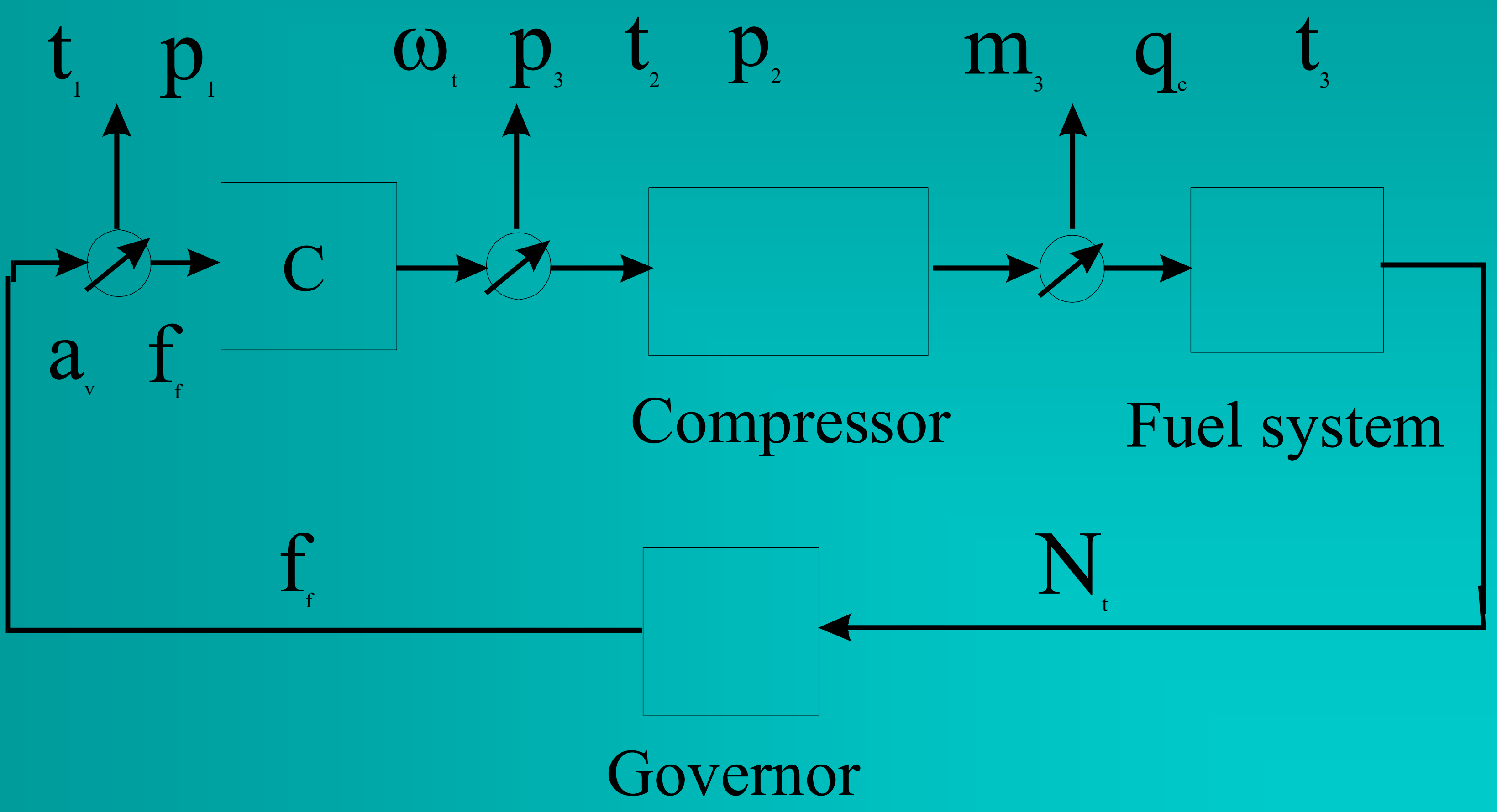


Compressor contamination (1)



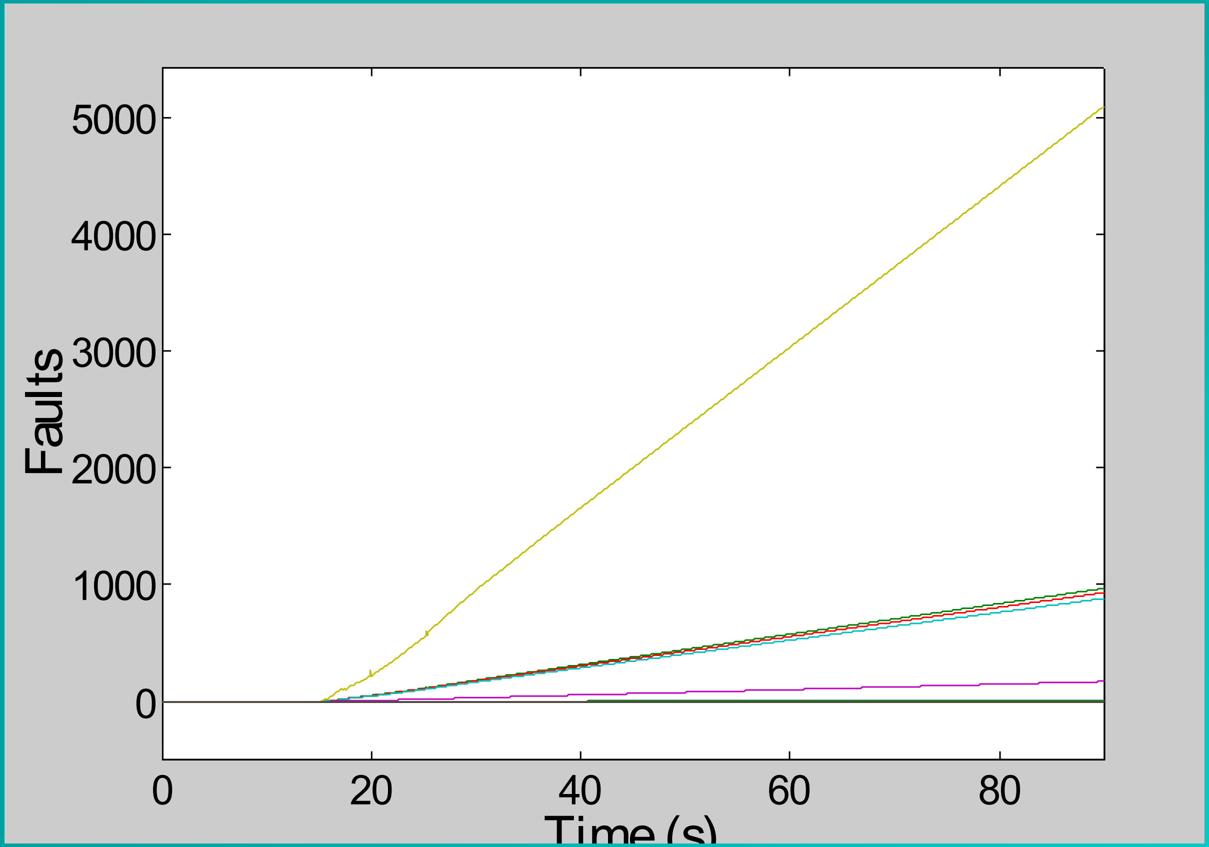
Block location: **compressor** submodel.

Turbine logic scheme



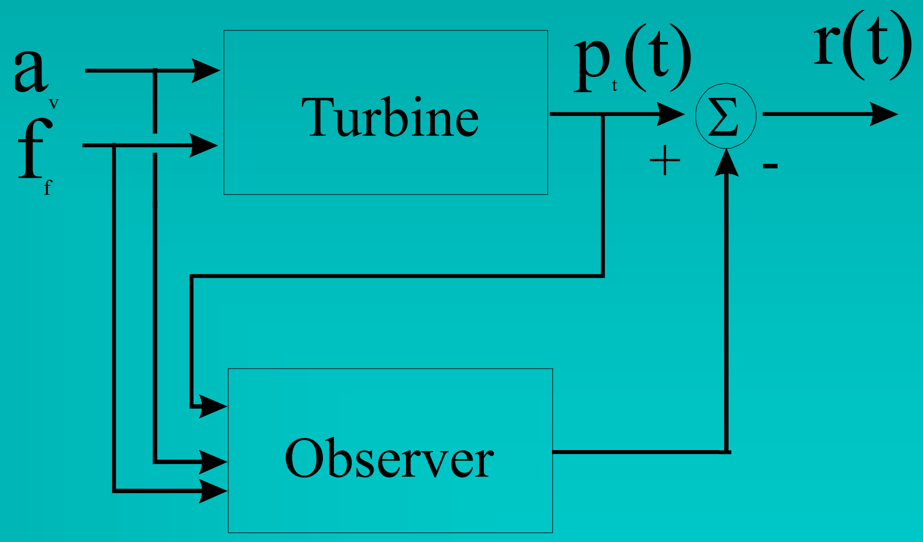
Residual sensitivity analysis

The most sensitive residual to a fault



Compressor contamination (1)

- Mainly affects
  p_3 , p_4 , p_5 , p_t
- **$p_t(t)$** output observer
- Observer inputs:
  $f_f(t)$, $a_v(t)$, $p_t(t)$
- residual generation
  $r_{13}(t)$

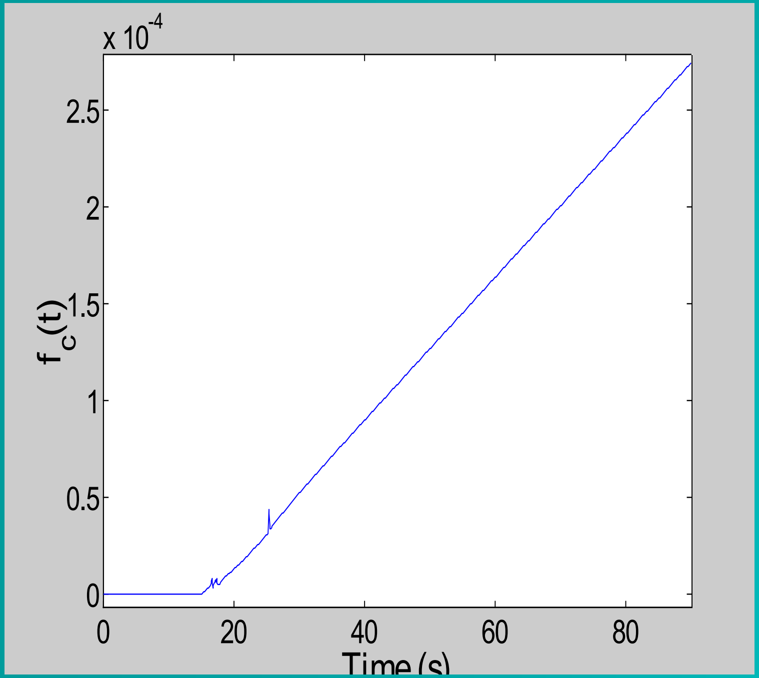


ARX MISO identification (p_t)

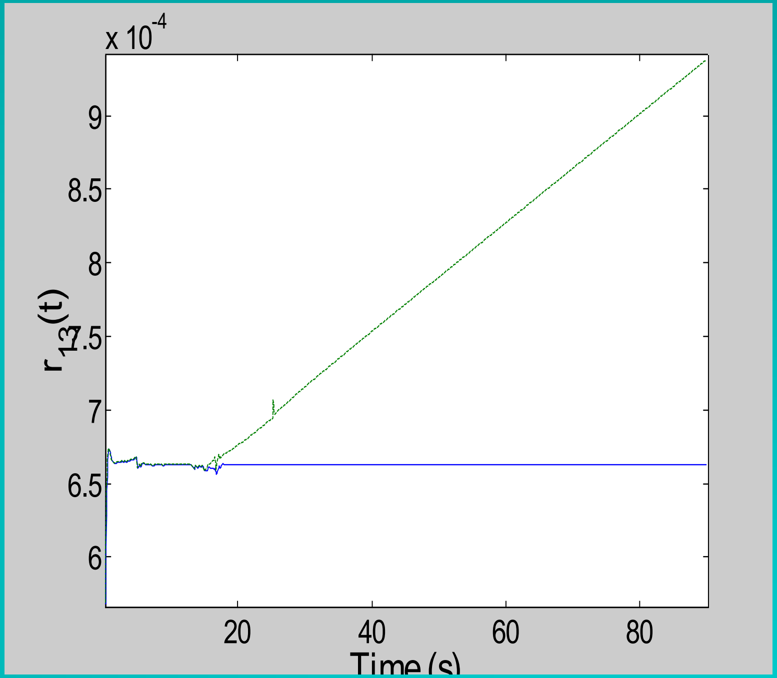
- Two inputs - one output ARX model.
- Second order ARX model (n=2).
- $J_2(\theta) = 2.98 \times 10^{-5}$.

Component (1) fault detection

Residual generation



Fault estimate



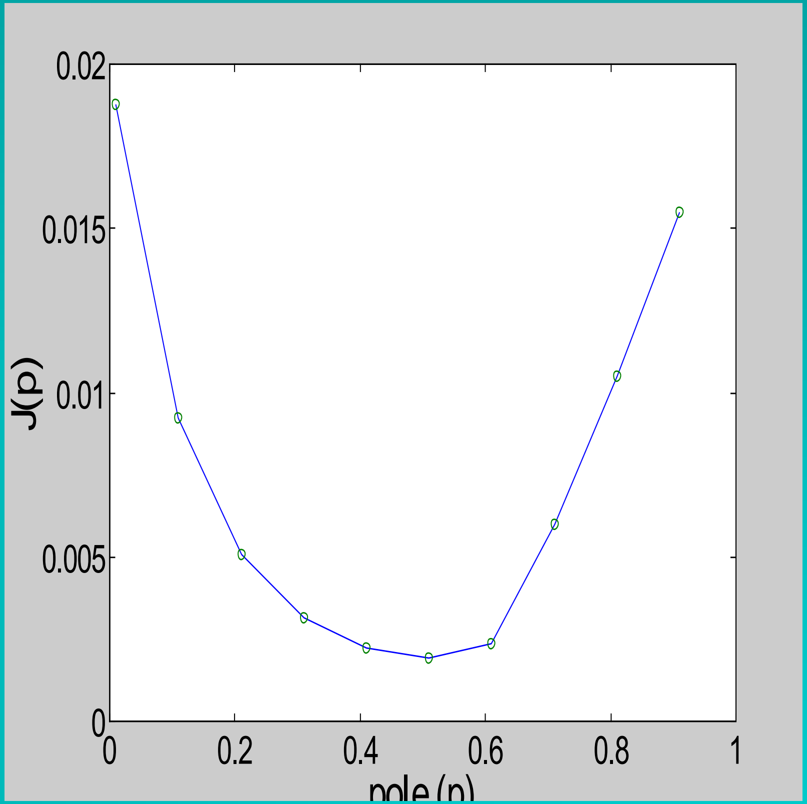
Fault free and faulty residual

Output observer design

- I/O ARX to state space model
- Pole placement: **J(p)** optimization technique

$$\min_{\mathbf{p}} \; J(\mathbf{p})$$

$$J(\mathbf{p}) = \left. \|r(t,\mathbf{p})\|^2_h \middle/ \|r(t,\mathbf{p})\|^2_f \right.$$



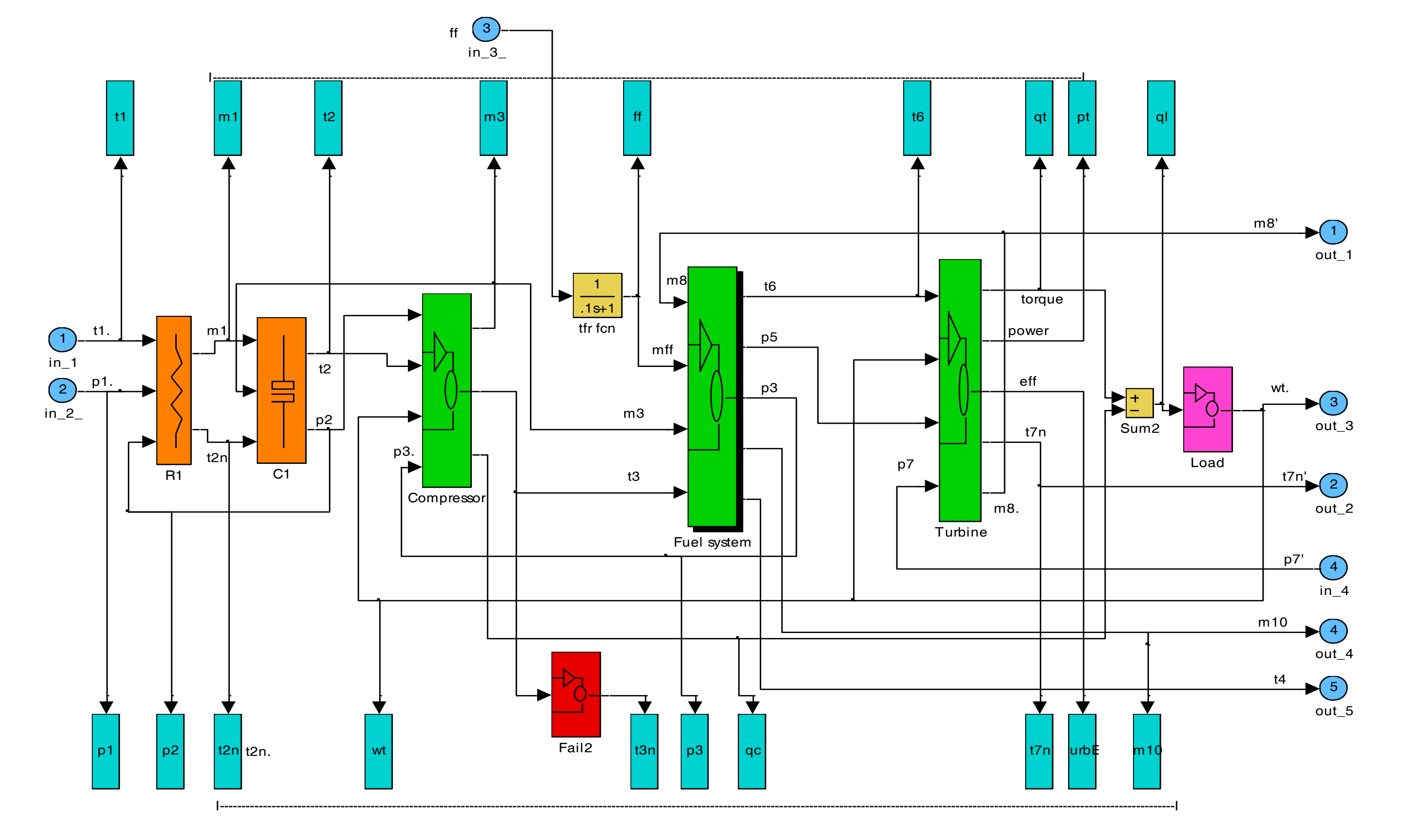
Thermocouple sensor (t_{3n}) fault

- **Fault 2: output sensor fault**

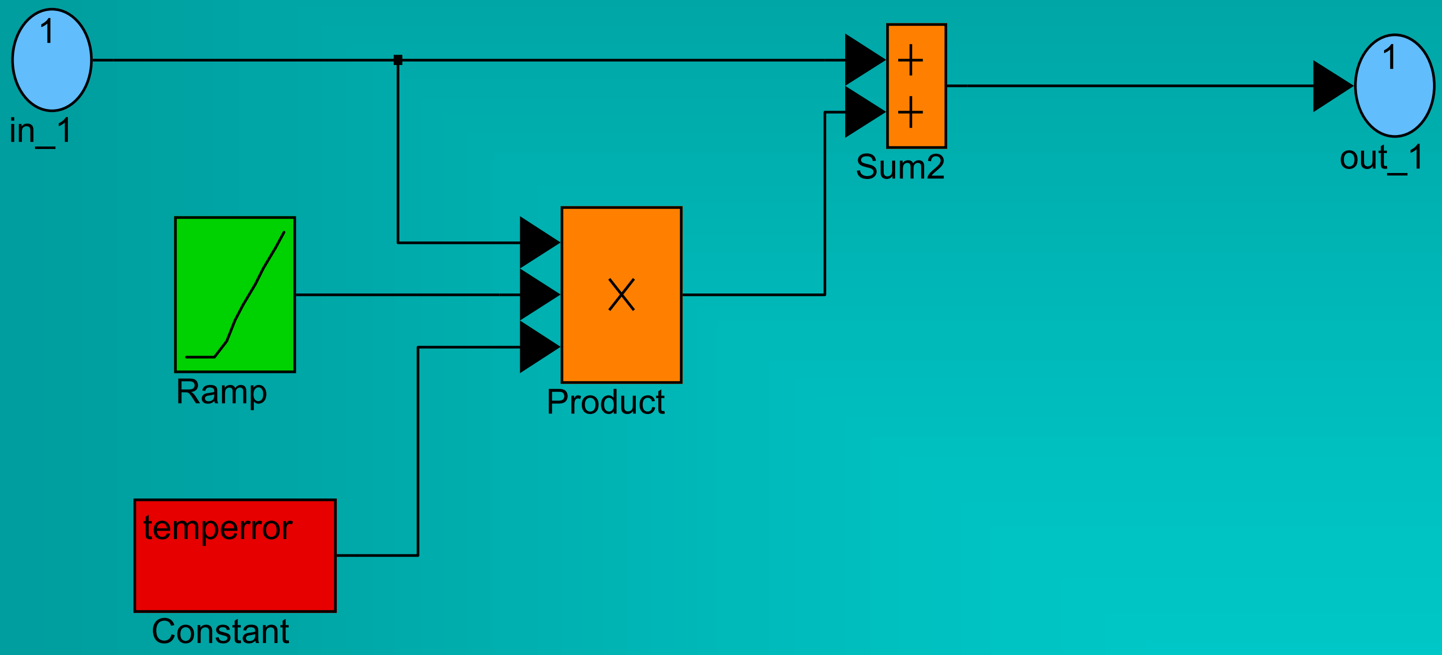
- Failure case 2 represents the malfunctioning of a thermocouple (t_{3n}) in the gas path.

- It leads to a slowly increasing or decreasing reading over time.

Thermocouple sensor (t_{3n}) fault



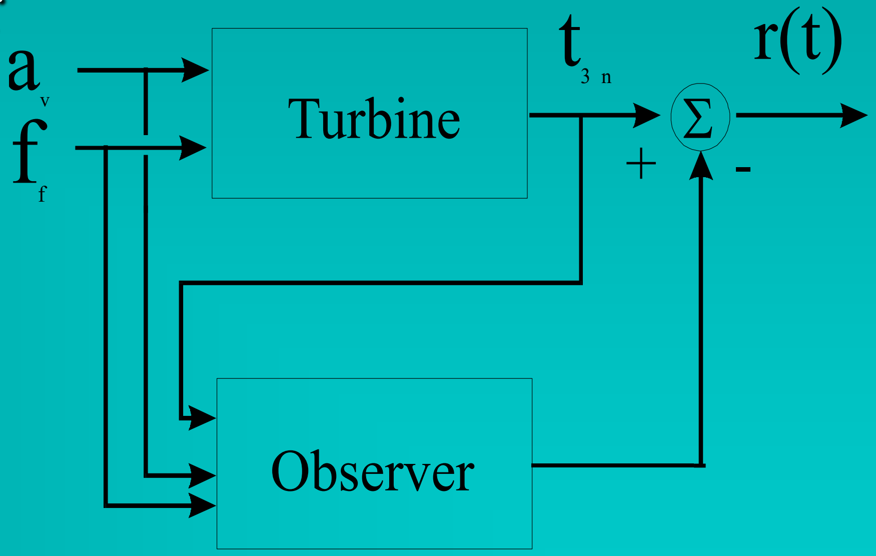
Thermocouple sensor (2) fault



Block location: **HTDU turbine** submodel.

Thermocouple sensor (2) fault

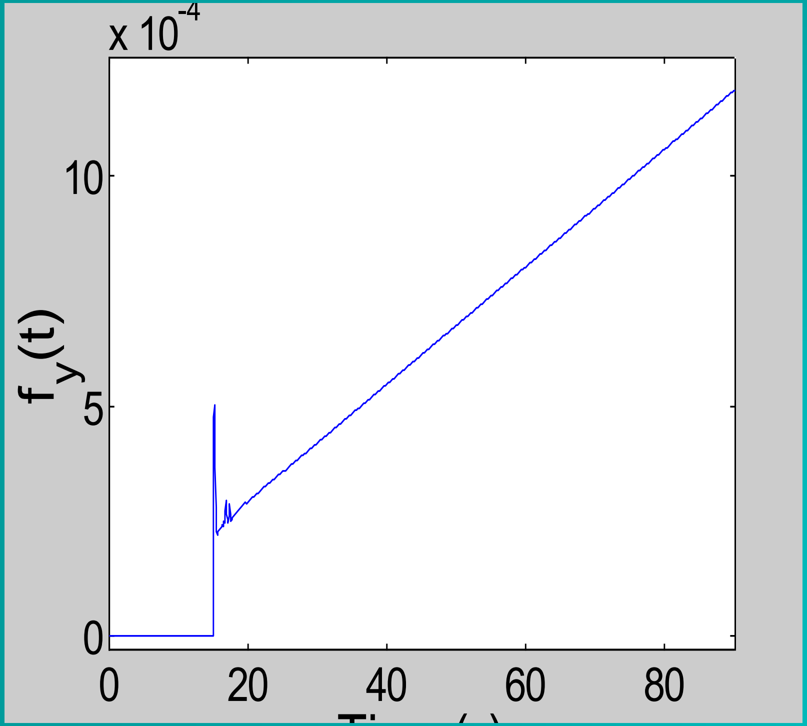
- It affects only t_{3n}
- $t_{3n}(t)$ output observer
- Observer inputs: $f_f(t)$, $a_v(t)$, $t_{3n}(t)$
- residual generation $r_{18}(t)$



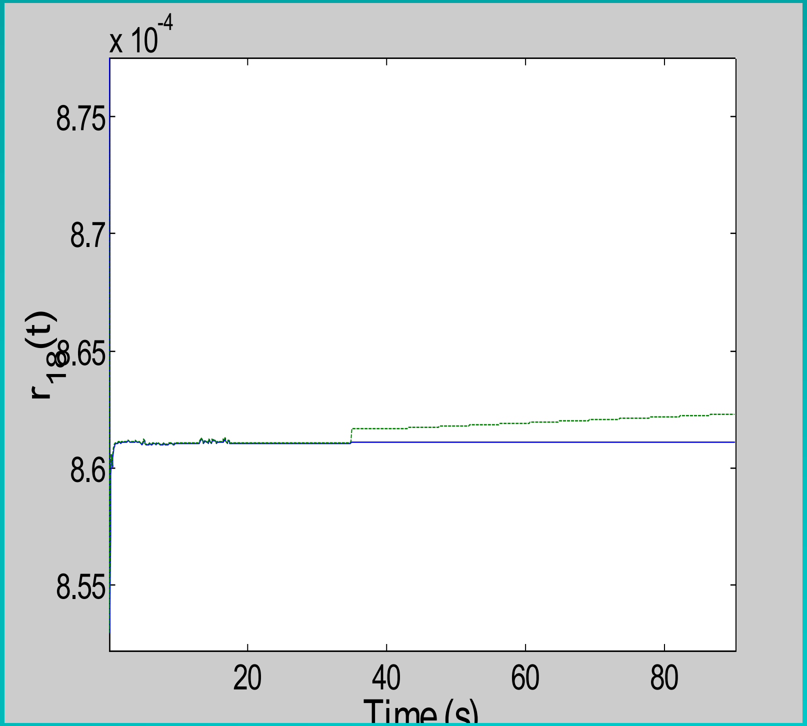
ARX MISO identification (t_{3_n})

- Two inputs - one output ARX model.
- Second order ARX model (n=2).
- $J_2(\theta) = 1.13 \times 10^{-5}$.

Output sensor (2) fault detection



Fault estimate

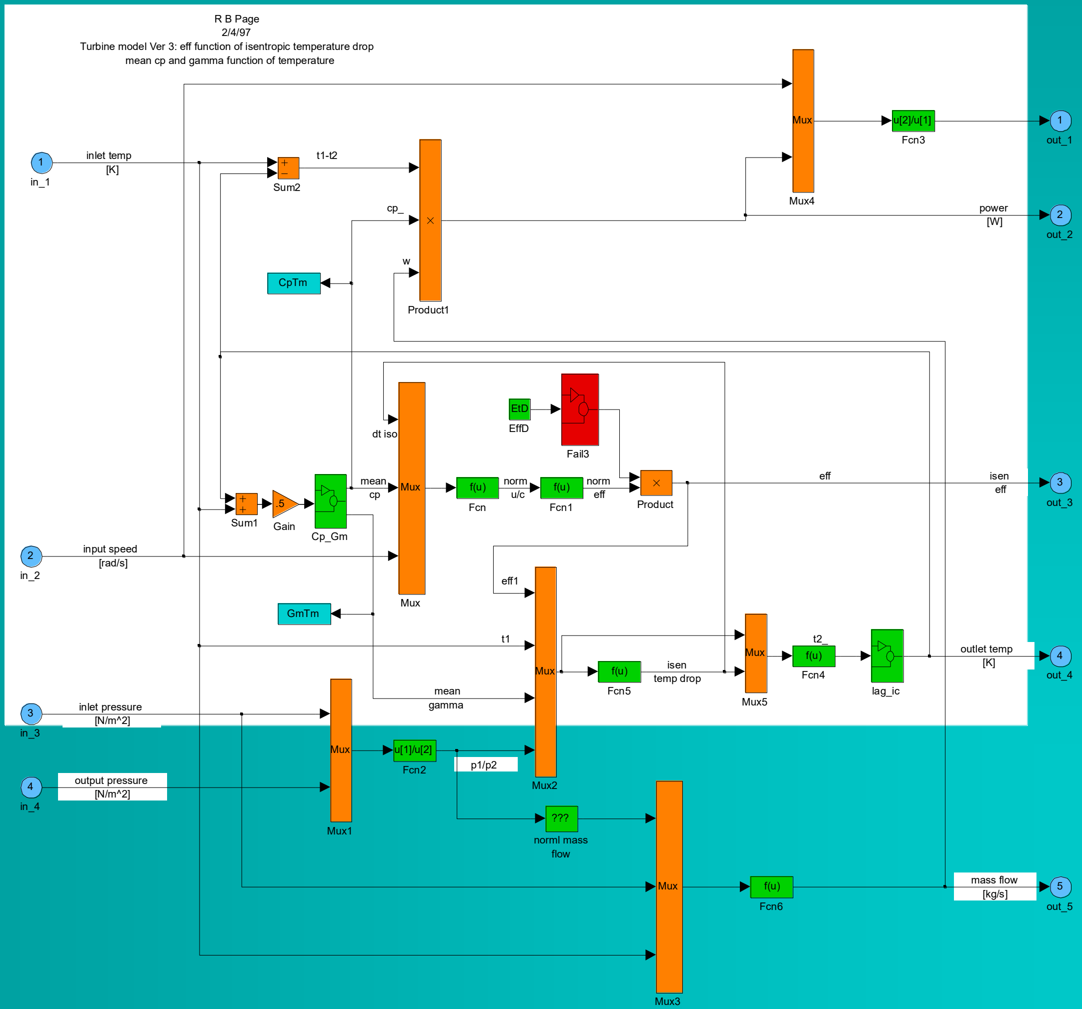


Fault free and faulty residual

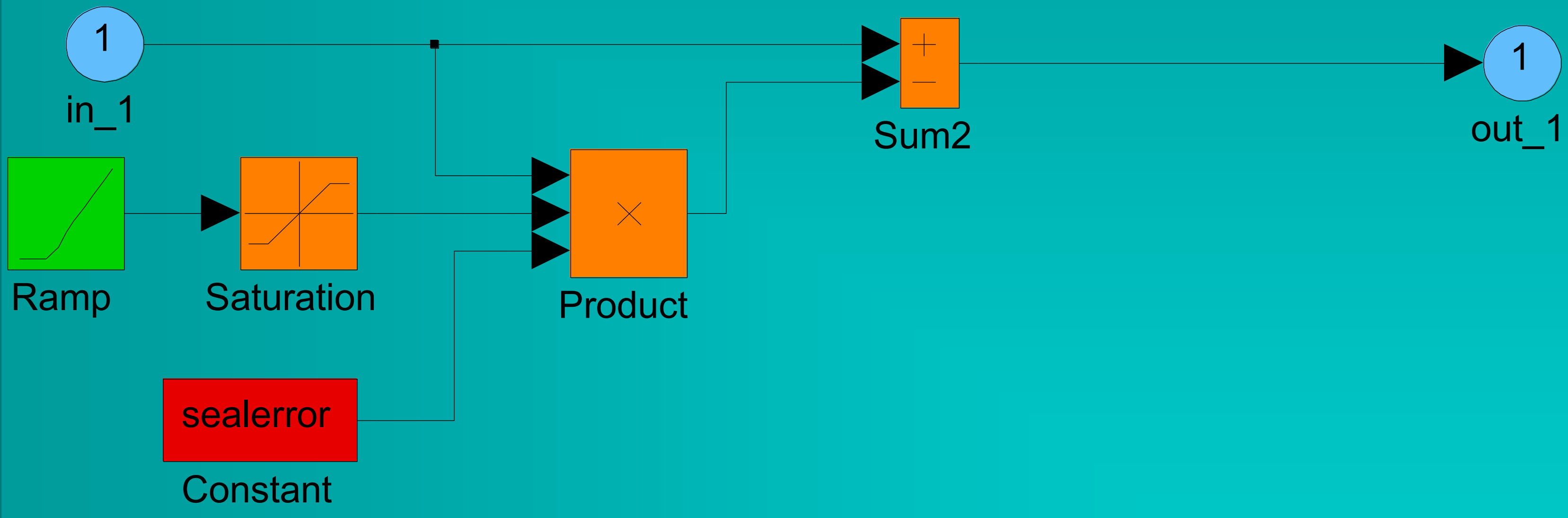
High pressure turbine seal damage

- Failure case 3: failure of an HP turbine seal.
- This results in a reduction in turbine efficiency.
- The fault is modeled as a gradual reduction in turbine efficiency over time.

High pressure turbine seal damage



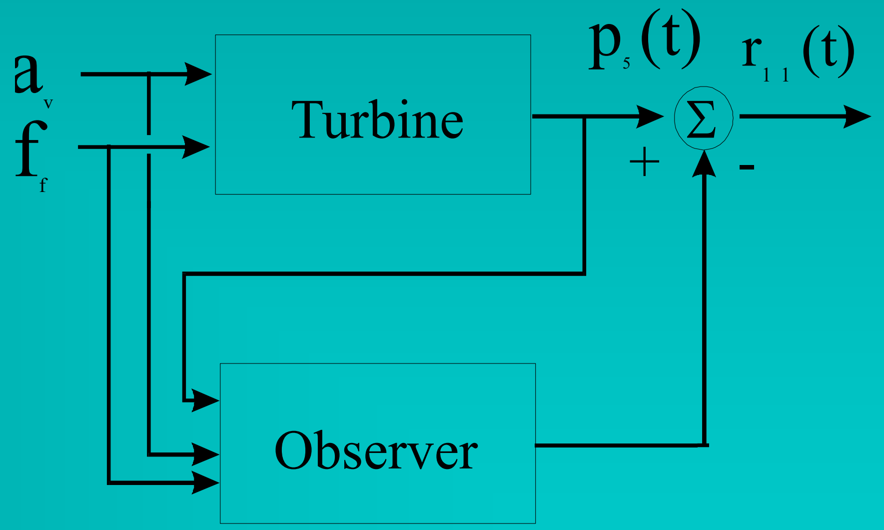
Turbine seal damage (3)



Block location: **turbine** submodel.

Turbine seal damage (Case 3)

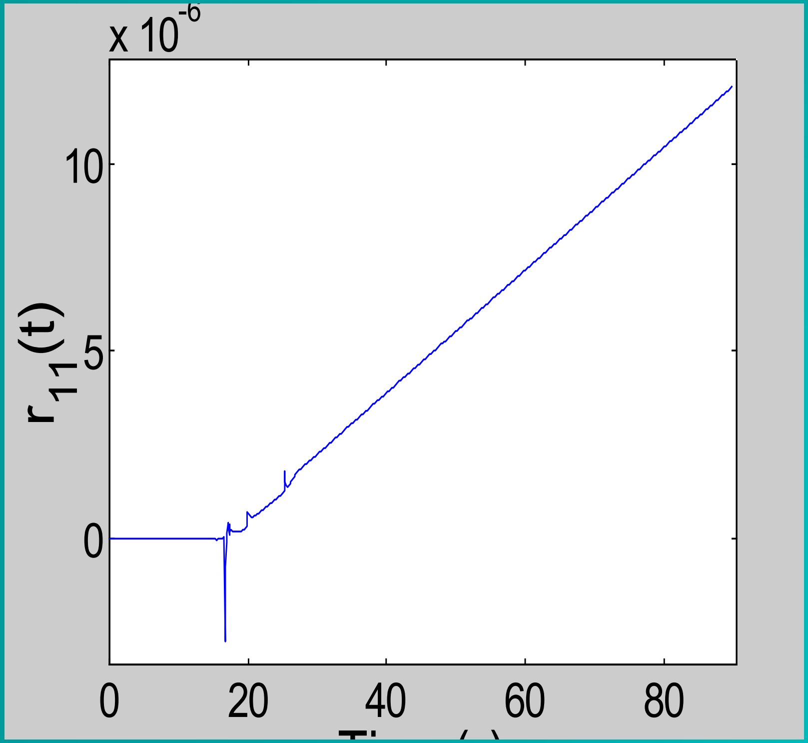
- Mainly affects p_3 , p_4 p_5 , p_7 , p_t , t_5 , t_6 .
- $p_5(t)$ output observer
- Observer inputs: $f_f(t)$, $a_v(t)$, $p_5(t)$
- residual generation $r_{11}(t)$



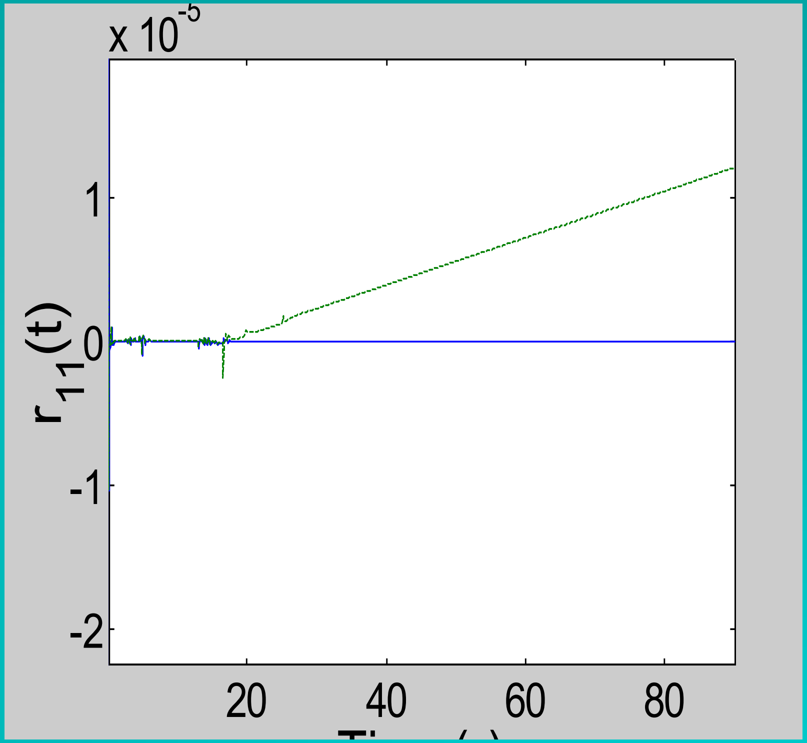
ARX MISO identification (p_5)

- Two inputs - one output ARX model.
- Second order ARX model (n=2).
- $J_2(\theta)= 2.30 \times 10^{-5}$.

Component (3) fault detection



Fault estimate



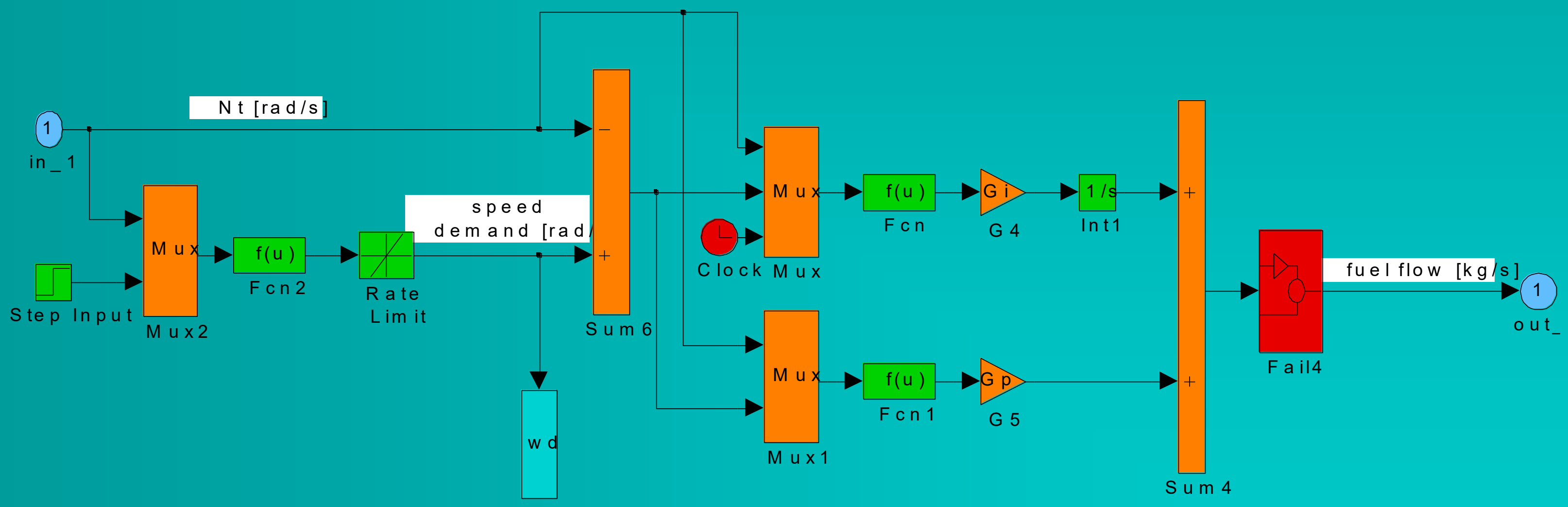
Fault free and faulty residual

Fuel *actuator* friction wear (4)

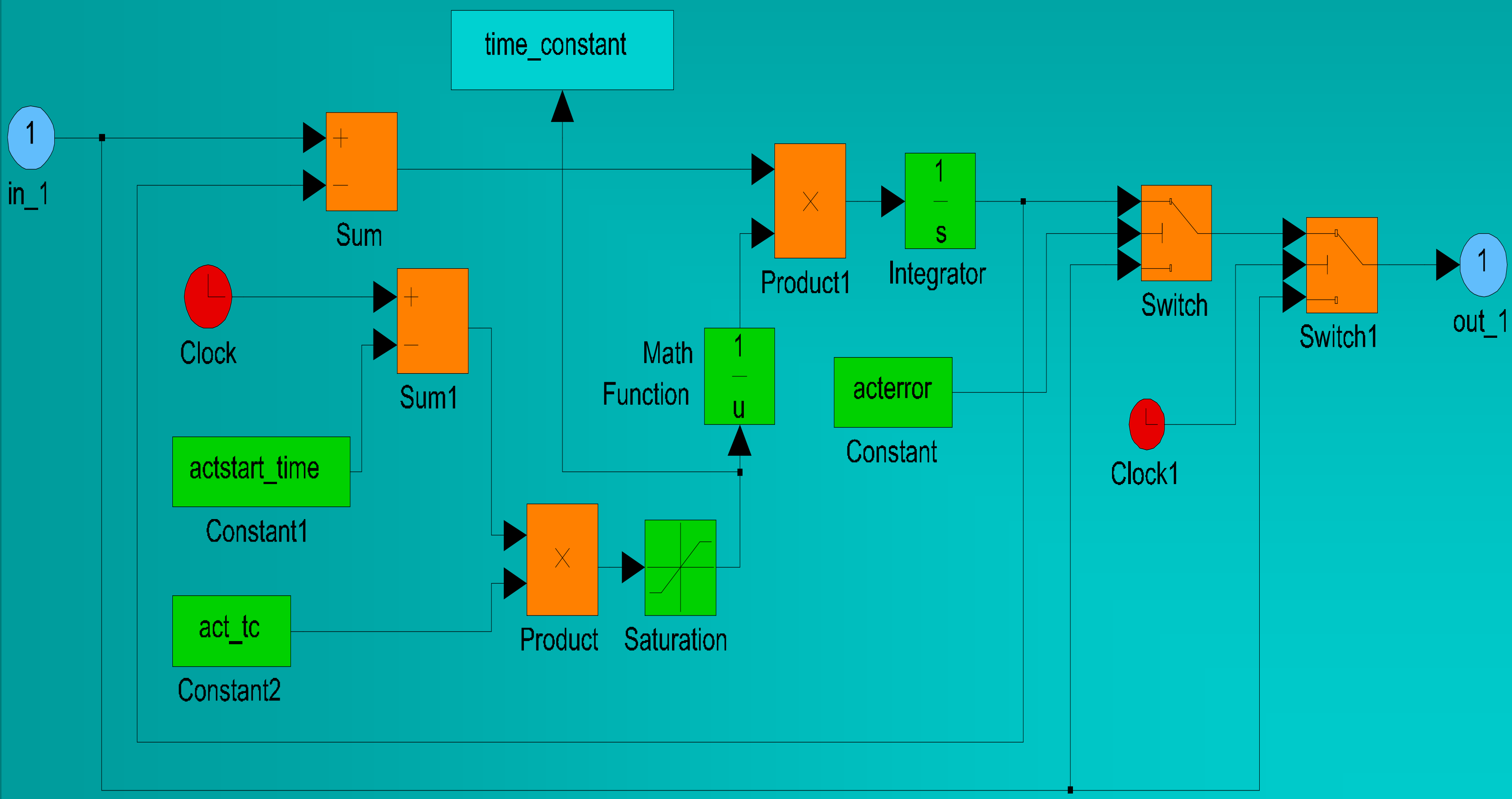
- Failure **case 4**: loss of performance due to wear of the fuel valve actuator.
- The effect of actuator wear causes slower response to demanded flow rates.
- It is modeled as a simple first order lag.

  The time constant increases linearly with time to represent progressive wear damage to the actuator.

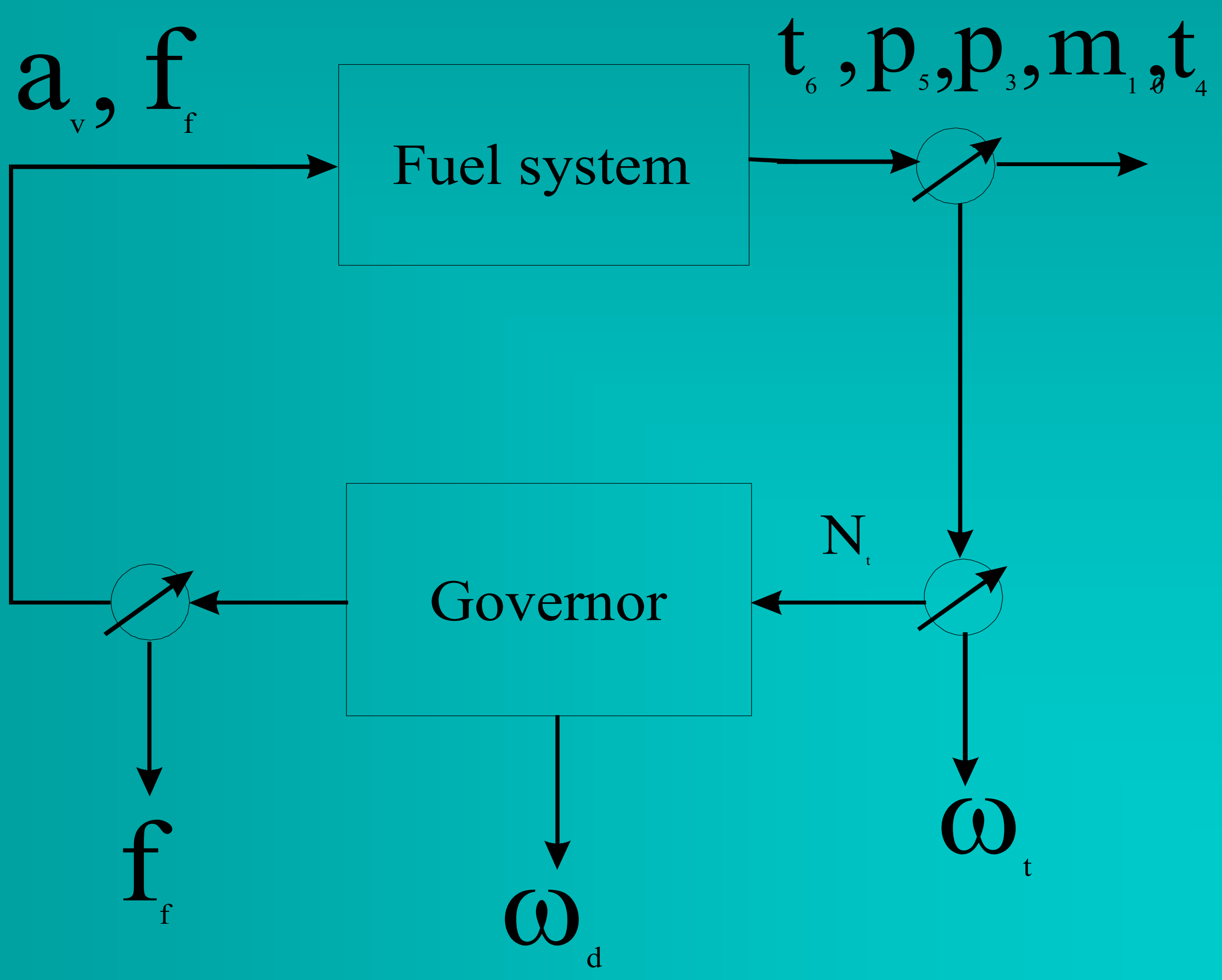
Fuel *actuator* friction wear (4)



Fuel actuator friction wear (4)

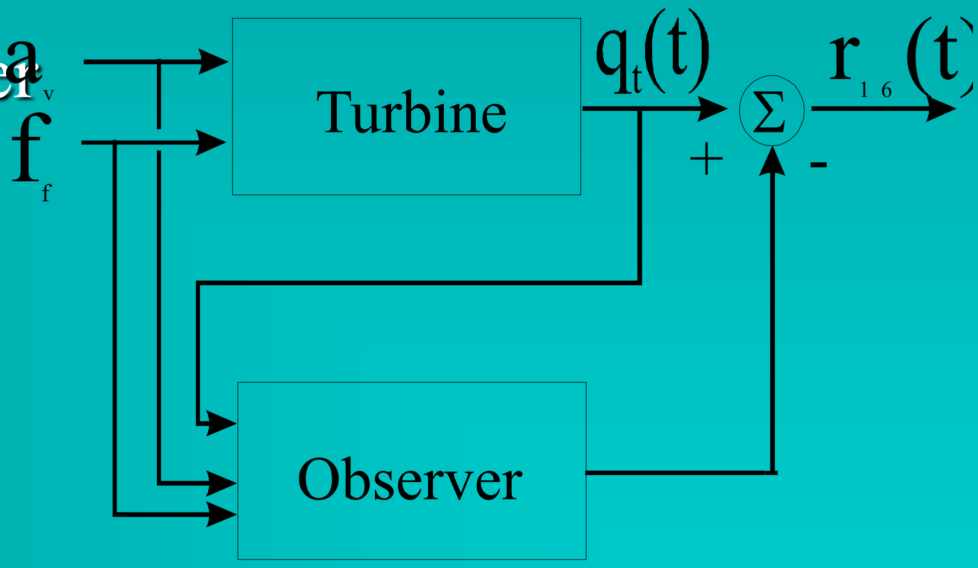


Turbine logic scheme



Fuel actuator friction wear (4)

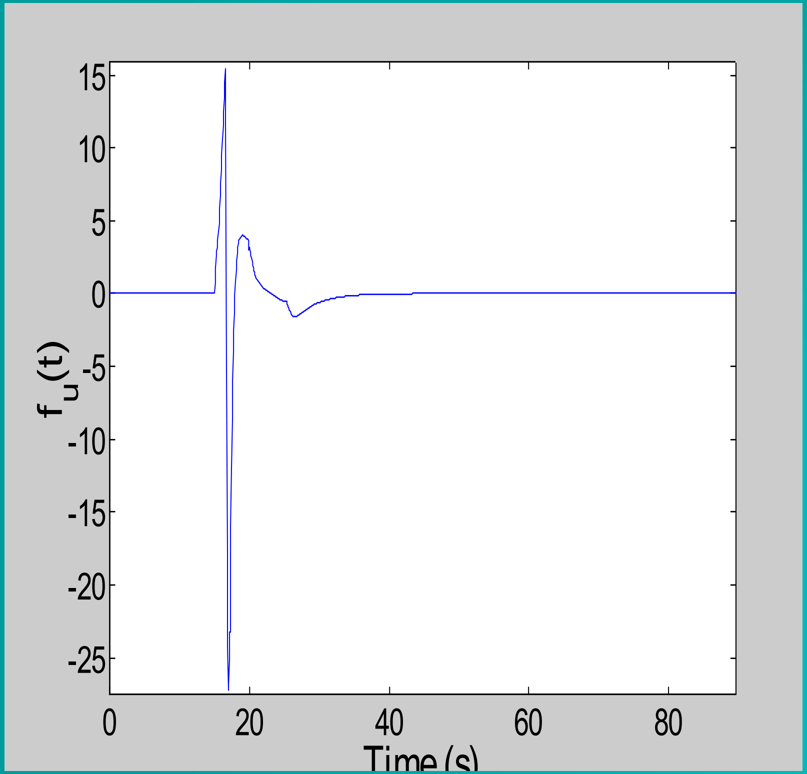
- Mainly affects p_3 , p_4 p_5 , p_t , q_a , q_c , q_t .
- $q_t(t)$ output observer
- Observer inputs: $f_f(t)$, $a_v(t)$, $q_t(t)$
- residual generation $r_{16}(t)$

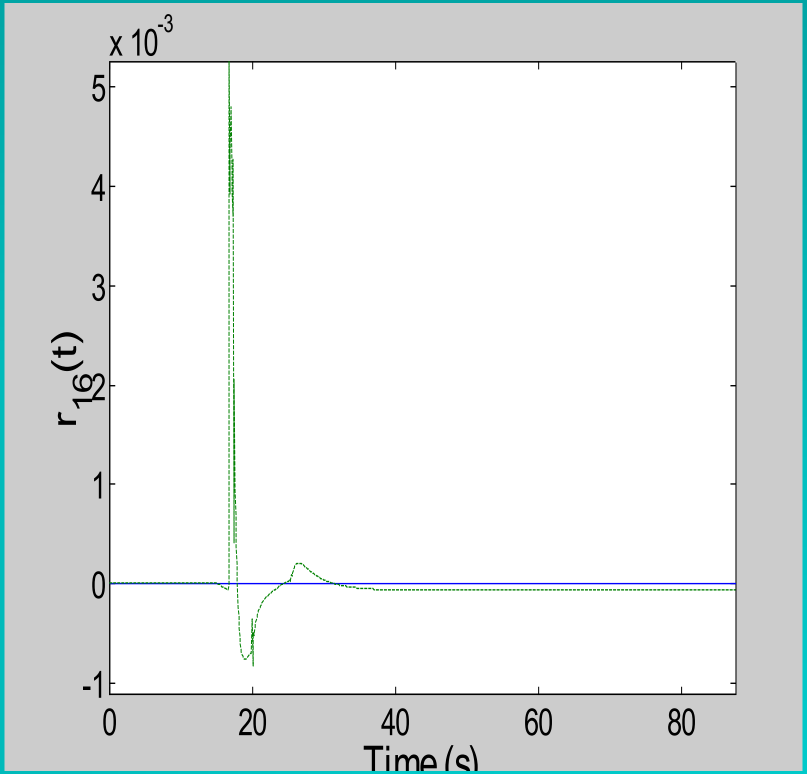


ARX MISO identification (q_t)

- Two inputs - one output ARX model.
- Second order ARX model (n=2).
- $J_2(\theta) = 4.64 \times 10^{-5}$.

Actuator (Case 4) fault detection





Fault signal

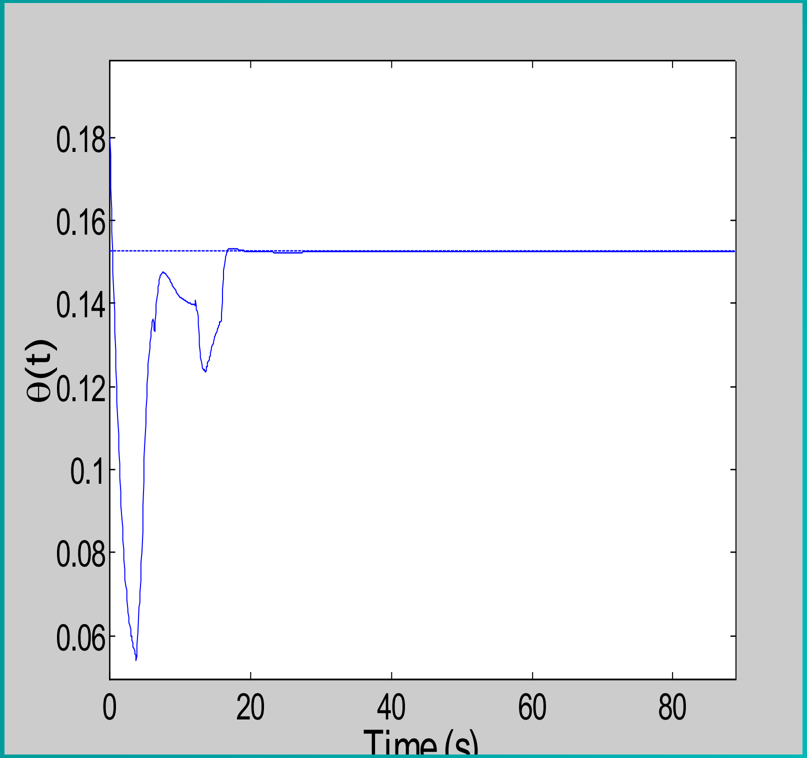
Fault free and faulty residual

Kalman filter as parameter estimator

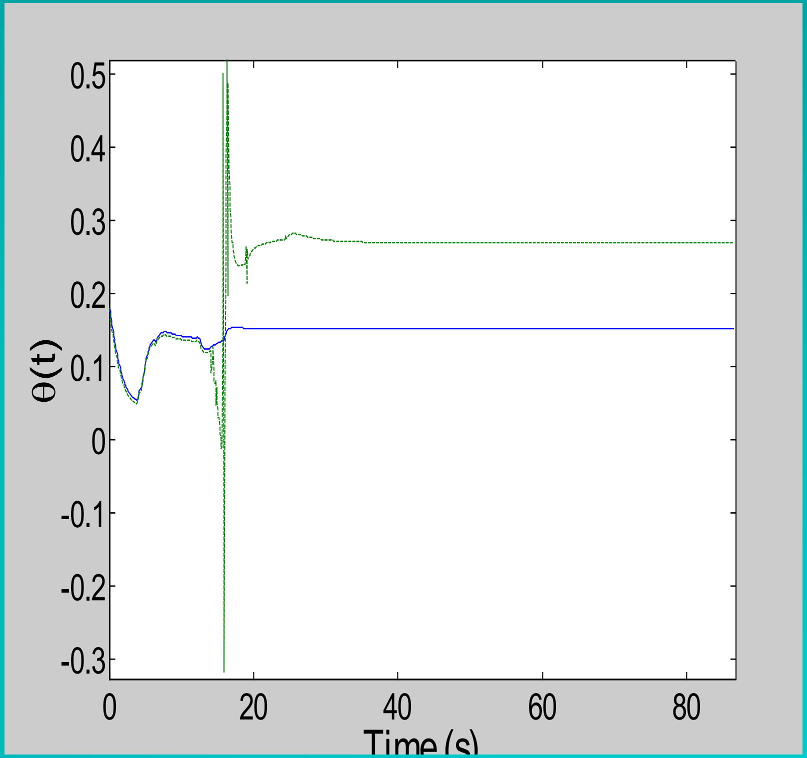
$$\begin{cases} \theta(t+1) = \theta(t) + \omega(t) \\ y(t) = \mathbf{C}(t)\theta(t) + e(t) \end{cases}$$

- θ(t) parameter vector
- **C**(t) measurement vector
  $$\mathbf{C}(t) = \left[y(t-n) \ldots y(t-1), u(t-n) \ldots u(t-1) \right]$$
- ω(t) white process, e(t) equation error term

KF parameter estimation



Fault free parameter (LS)



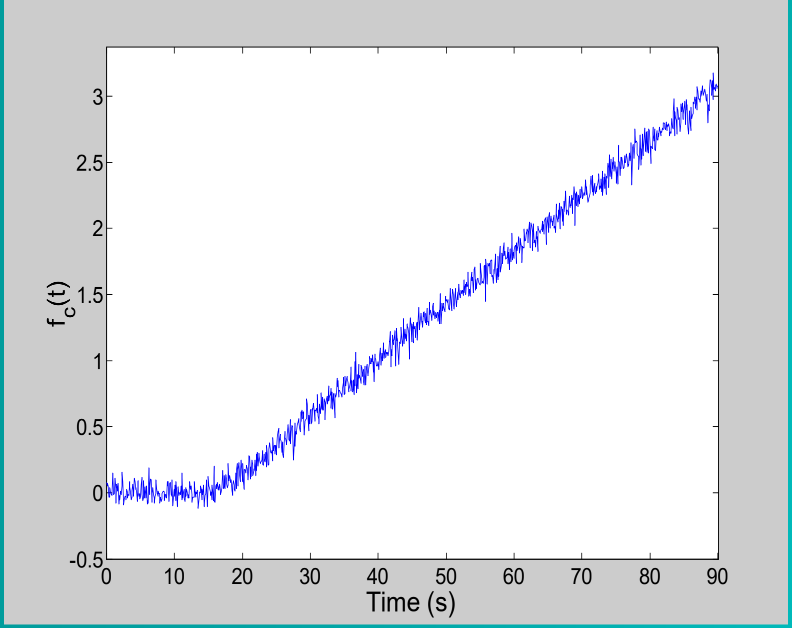
Fault free and faulty parameter

FDI in stochastic environment

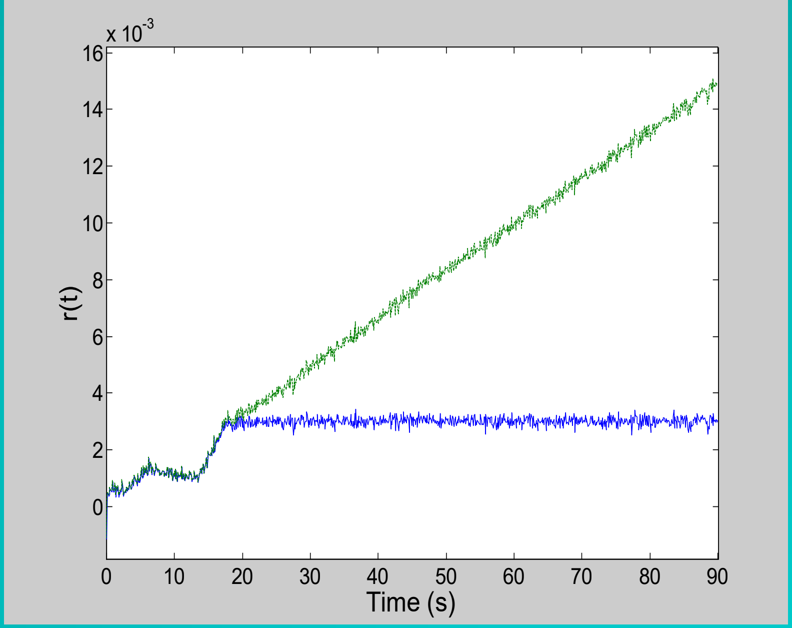
- Measurements affected by noises.
- Frisch Scheme identification.
- Kalman filter design.
- Residual evaluation.

Compressor contamination (Case 1)

$p_t(t)$ residual generation using a Kalman filter



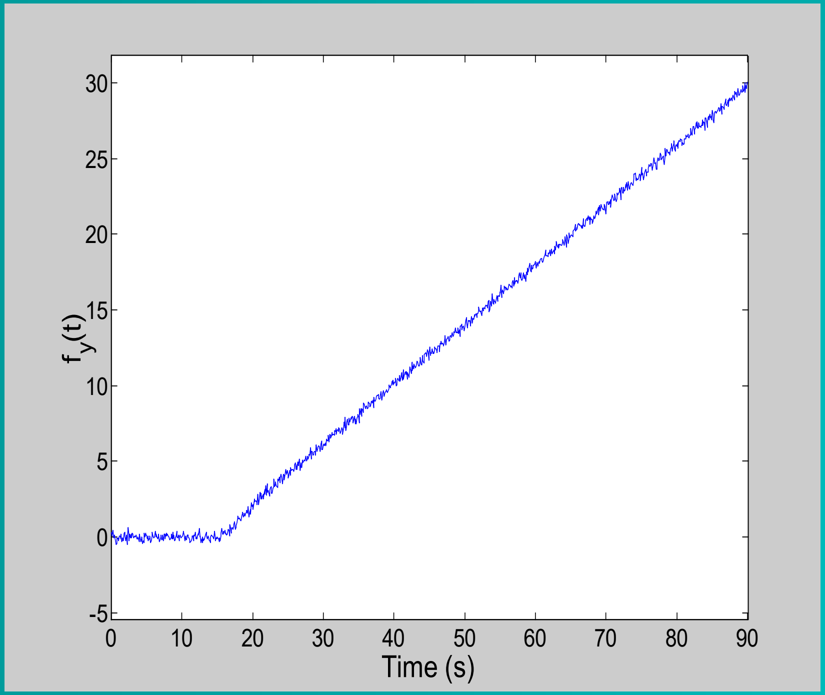
Faulty signal

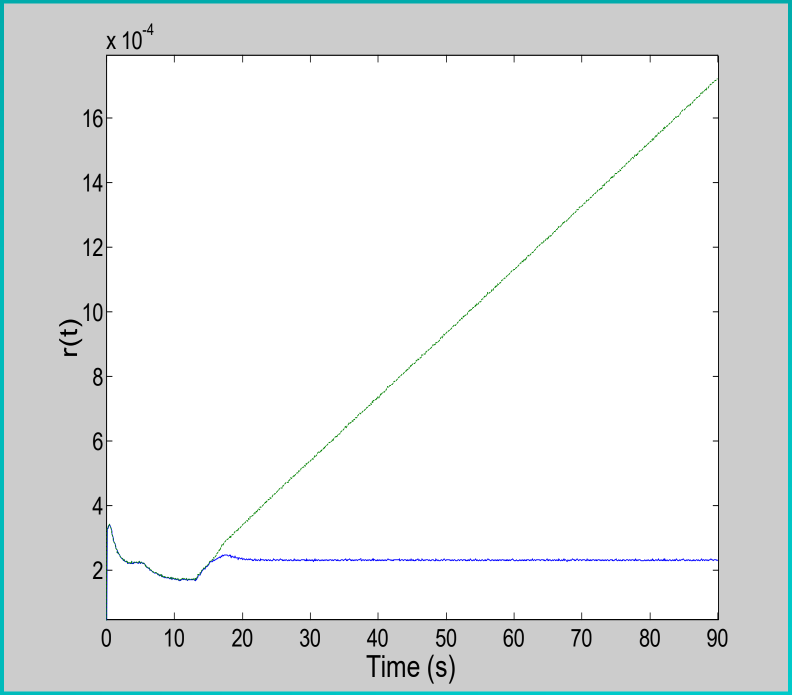


Fault free and faulty residual

Thermocouple sensor (Case 2) fault

t_{3n} residual generation using a Kalman filter



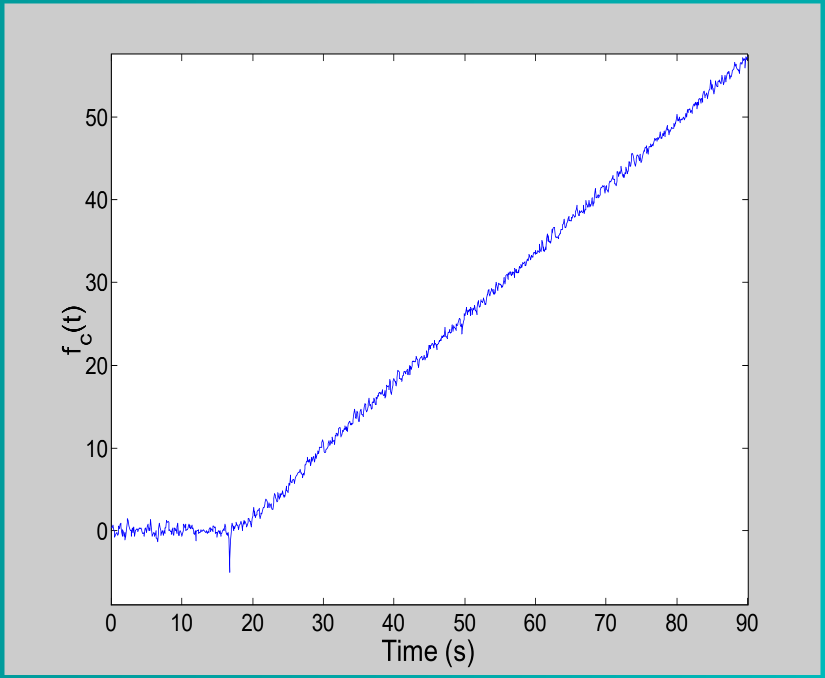


Faulty signal

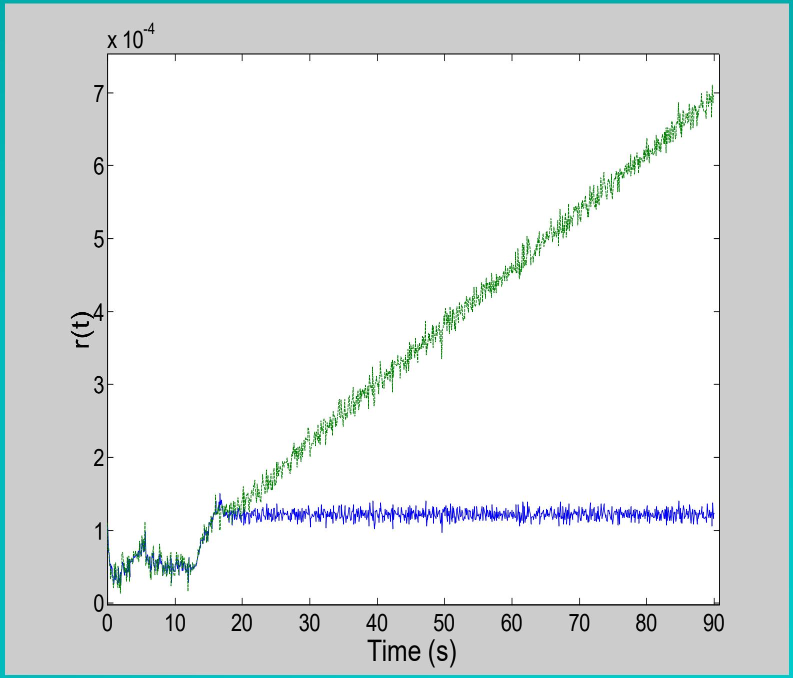
Fault free and faulty residual

High pressure turbine seal damage (Case 3)

$p_5(t)$ residual generation using a Kalman filter



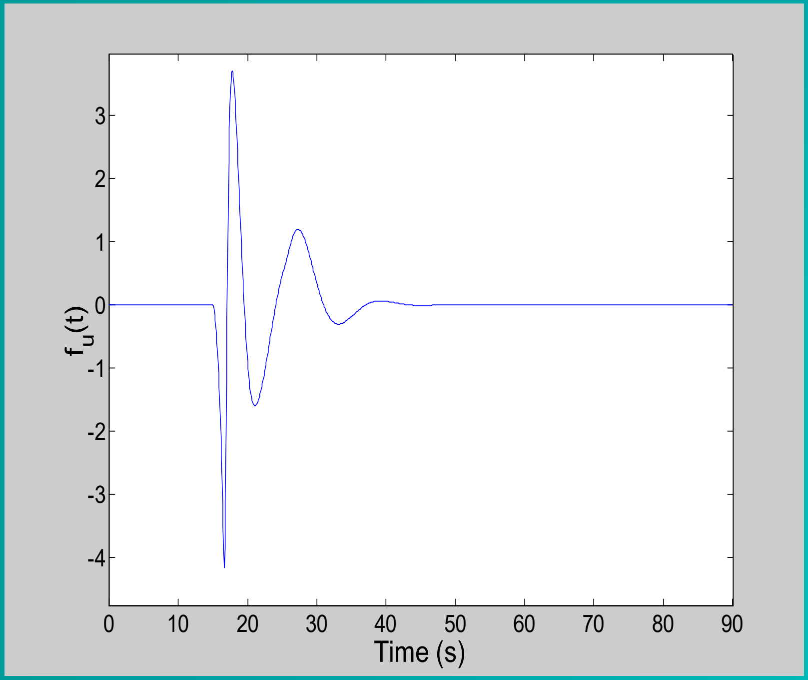
Faulty signal

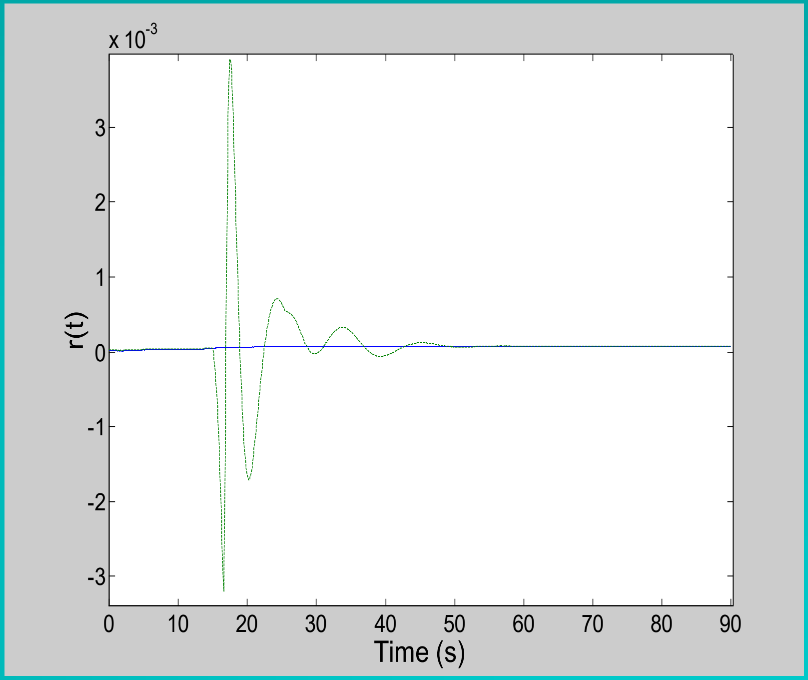


Fault free and faulty residual

Fuel *actuator* friction wear (Case 4)

$q_t(t)$ residual generation using a Kalman filter





Faulty signal

Fault free and faulty residual

Fault Isolability

Fault signature: the most sensitive measurement

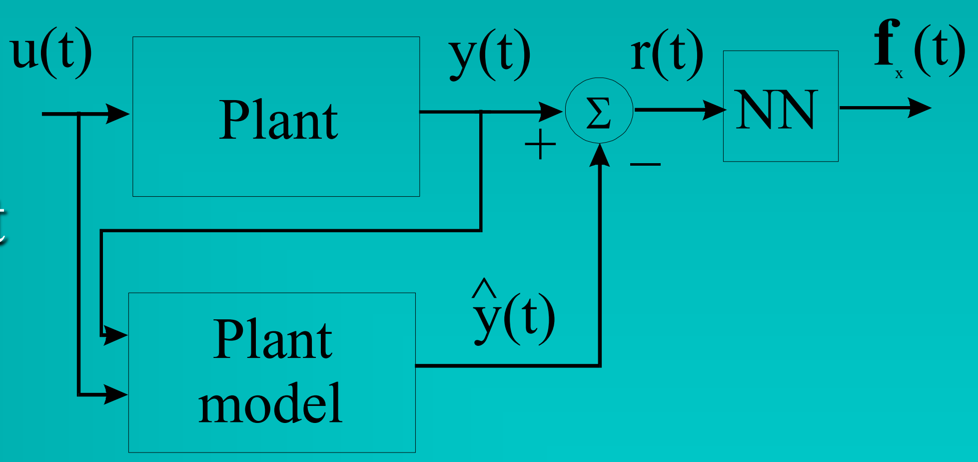
Fault/ $r(t)$	p_3	p_4	p_5	p_7	p_t	q_a	q_c	q_t	t_{3n}	t_5 t_6	
Case 1	1	1	1	0	1	0	0	0	0	0	0
Case 2	0	0	0	0	0	0	0	0	1	0	0
Case 3	1	1	1	1	1	0	0	0	0	1	1
Case 4	1	1	1	0	1	1	1	1	0	0	0

‘0’ if residual is not sensitive to a fault

‘1’ if residual is sensitive to a fault

Residual classification NN

- NN is as nonlinear function approximator
- Static nonlinear mapping between residuals and fault size.
- Feed-forward MLP NN



Minimum detectable faults

Fault case	Deterministic environment	Stochastic environment
Case 1	5%	11%
Case 2	5%	8%
Case 3	5%	9%
Case 4	5%	8%

- Faults expressed as per cent of the signals.
- Minimum delay FDI

Conclusions III

- Actuator, component, sensor FDI of an industrial process simulated model
- Identification techniques in deterministic and stochastic environment
- Observer and filter based approach for residual generation
- Minimal detectable fault

General Conclusions

- AI approaches very effective in enhancing powerful detection and isolation capabilities of quantitative model-based methods.
- Integrate qualitative and quantitative strategies to minimise probability of false-alarms and missed-alarms in fault decision-making.
- Improve level of heuristic information available for the Human operator.
- Increase inn use of NN as alternative to model-based/observer/ estimator for FDI
- NN needs no explicit model of system but is an implicit or "Black Box" model.

General Conclusions

- FL provide reasoning and transparency
- FL methods are rapidly becoming a powerful alternative to use of artificial expert systems.
- Combining together fuzzy rule-based strategy with a NN, some powerful diagnostic results can be obtained.
- The T-S approach to multiple-model observer design for FDI, incorporated fuzzy rules, based on easily understood premise variables, with state space models dependent on point of operation
- Combination of FL and quantitative modelling provides a robust solution for FDI.