



# ***SUPERVISION & CONDITION MONITORING STRATEGIES FOR TECHNICAL PROCESSES: MODEL- BASED & DATA-DRIVEN METHODS***

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# Lecture Main Topics

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- General introduction
  - State-of-the-art review
  - Fault diagnosis nomenclature
- Main methods for fault diagnosis
  - **Parameter estimation methods**
  - Observer and filter approaches
  - Parity relations
  - **Neural networks and fuzzy systems**
- Application examples
- Concluding remarks



# Programme Details

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- Introduction: Course Introduction
- Issues in Model-Based Fault Diagnosis
- Fault Detection and Isolation (FDI) Methods based on Analytical Redundancy
- Model-based Fault Detection Methods
- The Robustness Problem in Fault Detection
- Fault Identification Methods
- Modelling of Faulty Systems



# Programme Details (Cont'd)

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- Residual Generation Techniques
- The Residual Generation Problem
- Fault Diagnosis Technique Integration
- Fuzzy Logic for Residual Generation
- Neural Networks in Fault Diagnosis





# Programme Details (Cont'd)

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- Observers for Robust Residual Generation
- Residual Robustness to Disturbances
- Application Examples



# Annual Meetings on FDI

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- IFAC SAFEPROCESS Symposium
- *Fault Detection Supervision & Safety for Technical Processes*
  - 1<sup>st</sup> held in Baden–Baden, Germany in 1991
  - 2<sup>nd</sup> in Espo, Finland in 1994
  - 3<sup>rd</sup> at Hull, UK in 1997
  - 4<sup>th</sup> held in Budapest, Hungary in 2000
  - 5<sup>th</sup> at Washington DC, USA, July 2003
  - 6<sup>th</sup> in Beijing, P.R. China, August 2006
  - 7<sup>th</sup> in Barcelona, Spain, July 2009
  - 8<sup>th</sup> in Mexico City, Mexico, August 2012
  - 9<sup>th</sup> in Paris, France, 2015
  - 10<sup>th</sup> in Warsaw, Poland, 2018
  - 11<sup>th</sup> in Cyprus, Greece, June 2022
  - 12<sup>th</sup> in Ferrara, Italy, 4-7 June, 2024



# Nomenclature

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## 1. *States and Signals*

### **Fault**

An unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable, usual or standard condition.

### **Failure**

A permanent interruption of a system's ability to perform a required function under specified operating conditions.

### **Malfunction**

An intermittent irregularity in the fulfilment of a system's desired function.

### **Error**

A deviation between a measured or computed value of an output variable and its true or theoretically correct one.



# Nomenclature (cont'd)

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## 1. *States and Signals*

### **Disturbance**

An unknown and uncontrolled input acting on a system.

### **Residual**

A fault indicator, based on a deviation between measurements and model-equation-based computations.

### **Symptom**

A change of an observable quantity from normal behaviour.



# Nomenclature (Cont'd)

## 2. *Functions*

### **Fault detection**

Determination of faults present in a system and the time of detection.

### **Fault isolation**

Determination of the kind, location and time of detection of a fault.  
Follows fault detection.

### **Fault identification**

Determination of the size and time-variant behaviour of a fault. Follows fault isolation.

### **Fault diagnosis**

Determination of the kind, size, location and time of detection of a fault. Follows fault detection. Includes fault detection and identification.

### **Monitoring**

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

### **Supervision**

Monitoring a physical and taking appropriate actions to maintain the operation in the case of fault.



# Nomenclature (Cont'd)

## 3. *Models*

### **Quantitative model**

Use of static and dynamic relations among system variables and parameters in order to describe a system's behaviour in quantitative mathematical terms.

### **Qualitative model**

Use of static and dynamic relations among system variables in order to describe a system's behaviour in qualitative terms such as causalities and IF-THEN rules.

### **Diagnostic model**

A set of static or dynamic relations which link specific input variables, *the symptoms*, to specific output variables, the faults.

### **Analytical redundancy**

Use of more (not necessarily identical) ways to determine a variable, where one way uses a mathematical process model in analytical form.



# Nomenclature (Cont'd)

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## Reliability

Ability of a system to perform a required function under stated conditions, within a given scope, during a given period of time.

## Safety

Ability of a system not to cause danger to persons or equipment or the environment.

## Availability

Probability that a system or equipment will operate satisfactorily and effectively at any point of time.



# Nomenclature (Cont'd)

## 5. *Time dependency of faults*

### **Abrupt fault**

Fault modelled as stepwise function. It represents bias in the monitored signal.

### **Incipient fault**

Fault modelled by using ramp signals. It represents drift of the monitored signal.

### **Intermittent fault**

Combination of impulses with different amplitudes.

***NOTE: Incipient fault (slowly developing fault)= hard to detect !!!***





# Nomenclature (Cont'd)

## 6. *Fault terminology*

### Additive fault

Influences a variable by an addition of the fault itself. They may represent, *e.g.*, offsets of sensors.

### Multiplicative fault

Are represented by the product of a variable with the fault itself. They can appear as parameter changes within a process.



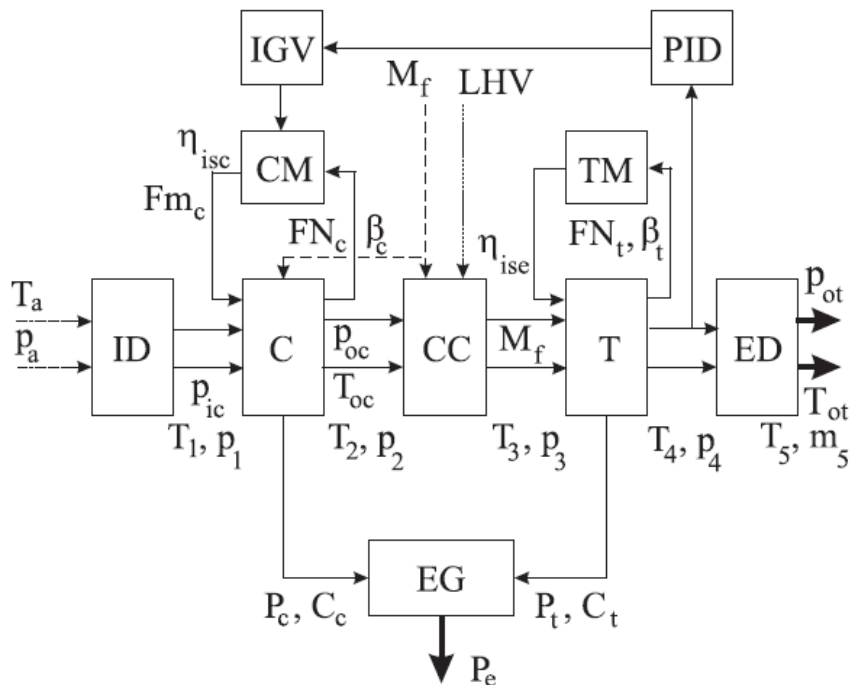
# Application Examples

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- Simulated case studies
- Identification/FDI applications
- Real processes
- Research works
- Undergraduate theses topics

# Simulated Application Examples

## Simulated Gas Turbine

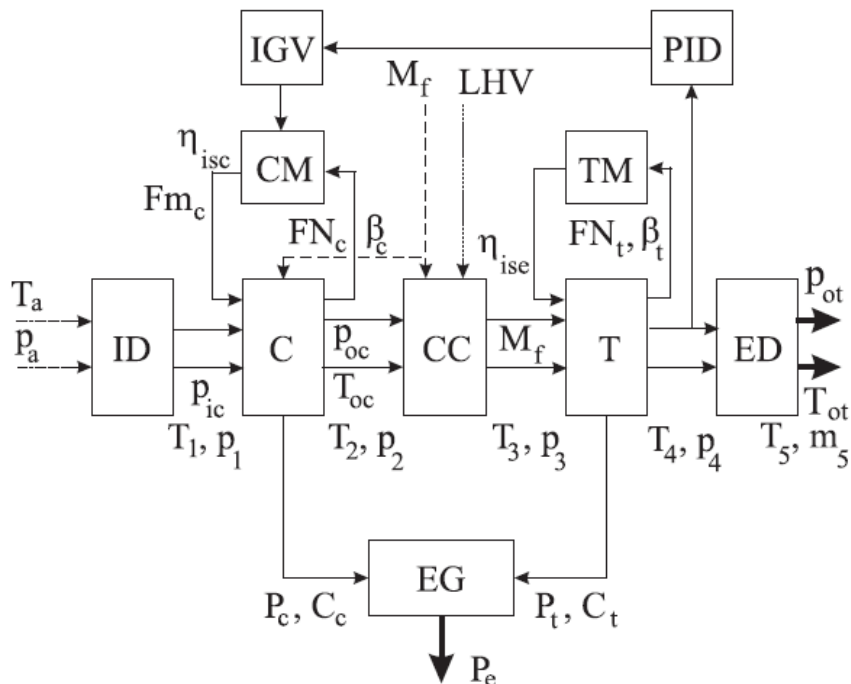


C	Compressor
CC	Combustor (Combustion Chamber)
CM	Compressor Map
ED	Exhaust Duct
EG	Electric Generator
ID	Intake Duct
IGV	Inlet Guide Vanes
PID	Proportional Integral Derivative Controller
T	Turbine
TM	Turbine Map

Figure 5.2: Block diagram of the single-shaft gas turbine.

# Simulated Application Examples (Cont'd)

## Simulated Gas Turbine

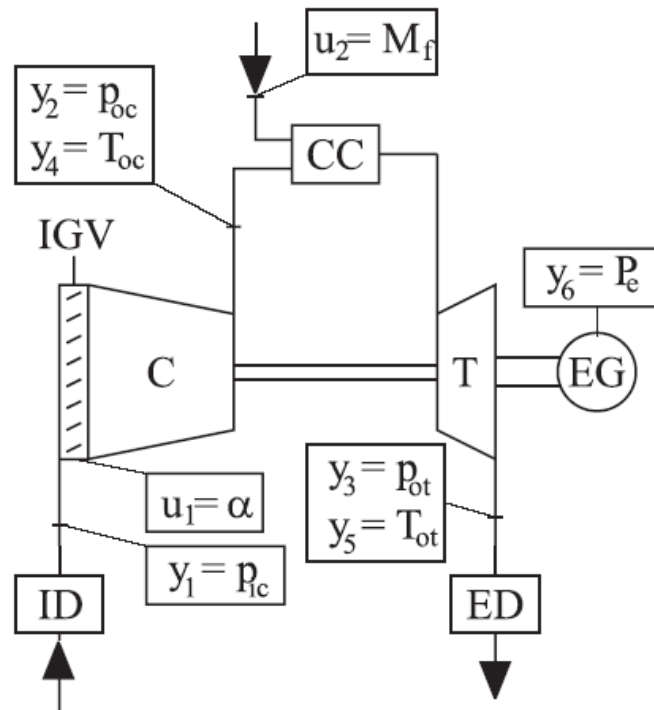


$M_f$	Fuel mass flow rate
$LHV$	Lower Heating Value
$\eta_{isc}$	Isentropic compressor efficiency
$Fm_c$	Compressor mass flow function
$FN_c$	Compressor rotational speed function
$\beta_c$	Compressor pressure ratio
$\eta_{ise}$	Isentropic expansion efficiency
$FN_t$	Turbine rotational speed function
$\beta_t$	Turbine pressure ratio
$T_i$	$i$ -th section (module) temperature ( $i = 1, \dots, 5$ )
$p_i$	$i$ -th section (module) pressure ( $i = 1, \dots, 5$ )
$m_5$	5-th module mass flow rate
$T_a$	Ambient temperature
$p_a$	Ambient pressure
$P_c$	Compressor power
$P_t$	Turbine power
$C_c$	Compressor torque
$C_t$	Turbine torque
$P_e$	Electrical power

Figure 5.2: Block diagram of the single-shaft gas turbine.

# Simulated Application Examples (Cont'd)

## Simulated Gas Turbine



$u_1(t)$ , Inlet Guide Vane (IGV) angular position ( $\alpha$ );

$u_2(t)$ , fuel mass flow rate ( $M_f$ ).

$y_1(t)$ , pressure at the compressor inlet ( $p_{ic}$ );

$y_2(t)$ , pressure at the compressor outlet ( $p_{oc}$ );

$y_3(t)$ , pressure at the turbine outlet ( $p_{ot}$ );

$y_4(t)$ , temperature at the compressor outlet ( $T_{oc}$ );

$y_5(t)$ , temperature at the turbine outlet ( $T_{ot}$ );

$y_6(t)$ , electrical power at the generator terminal ( $P_e$ ).

# Simulated Application Examples (Cont'd)

## Simulated Gas Turbine (SIMULINK®)

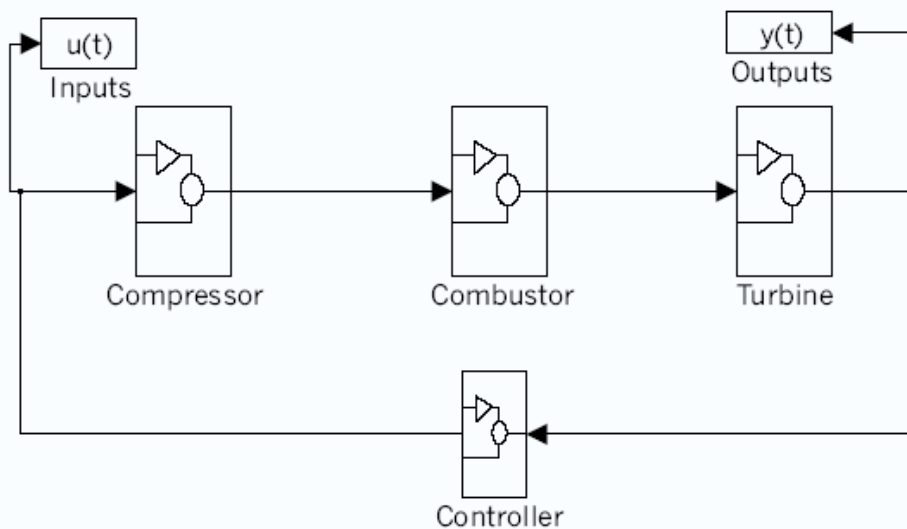


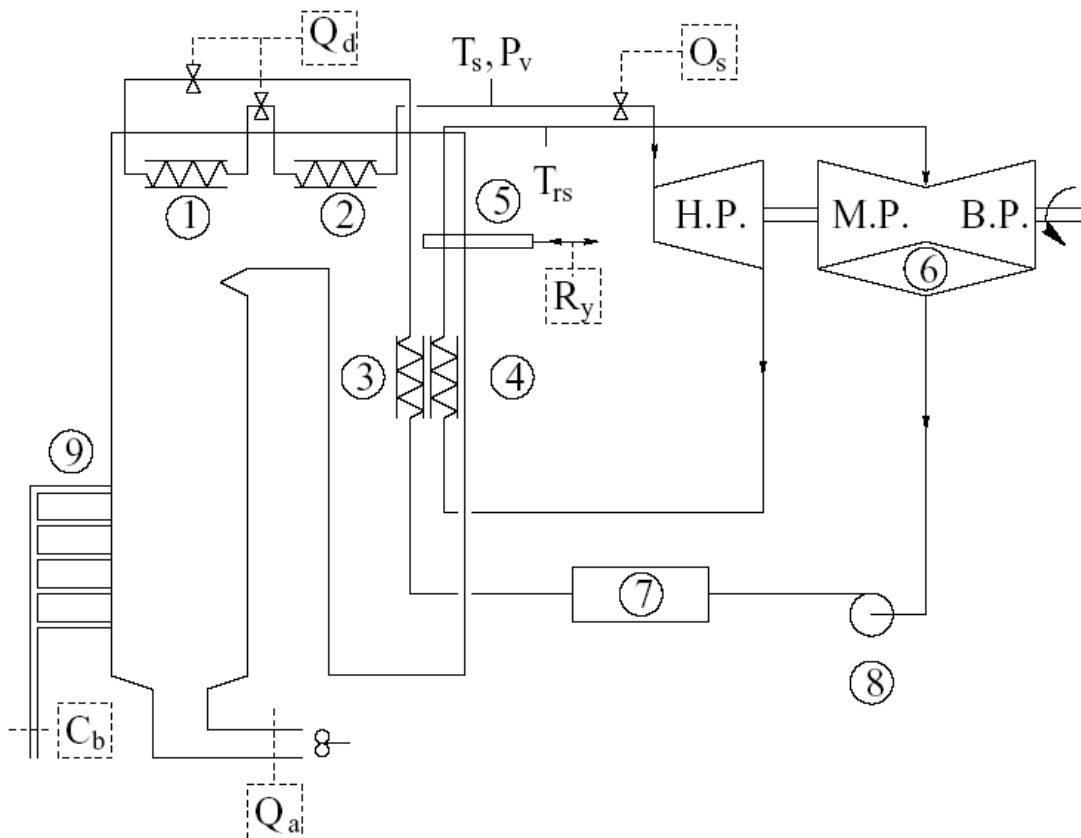
Figure 5.7: SIMULINK block diagram of the process.

Gas turbine main cycle parameters (ISO design conditions).

Air mass flow rate [kg/s]	24.4
Cycle pressure ratio ( $P_{oc}/P_{ic}$ )	9.1
Electrical power ( $P_e$ ) [kW]	5220
Exhaust temperature ( $T_{ot}$ ) [K]	796
Fuel mass flow rate ( $M_f$ ) [kg/s]	0.388
IGV angle range ( $\Delta\alpha$ ) [deg]	17

# Simulated Application Examples (Cont'd)

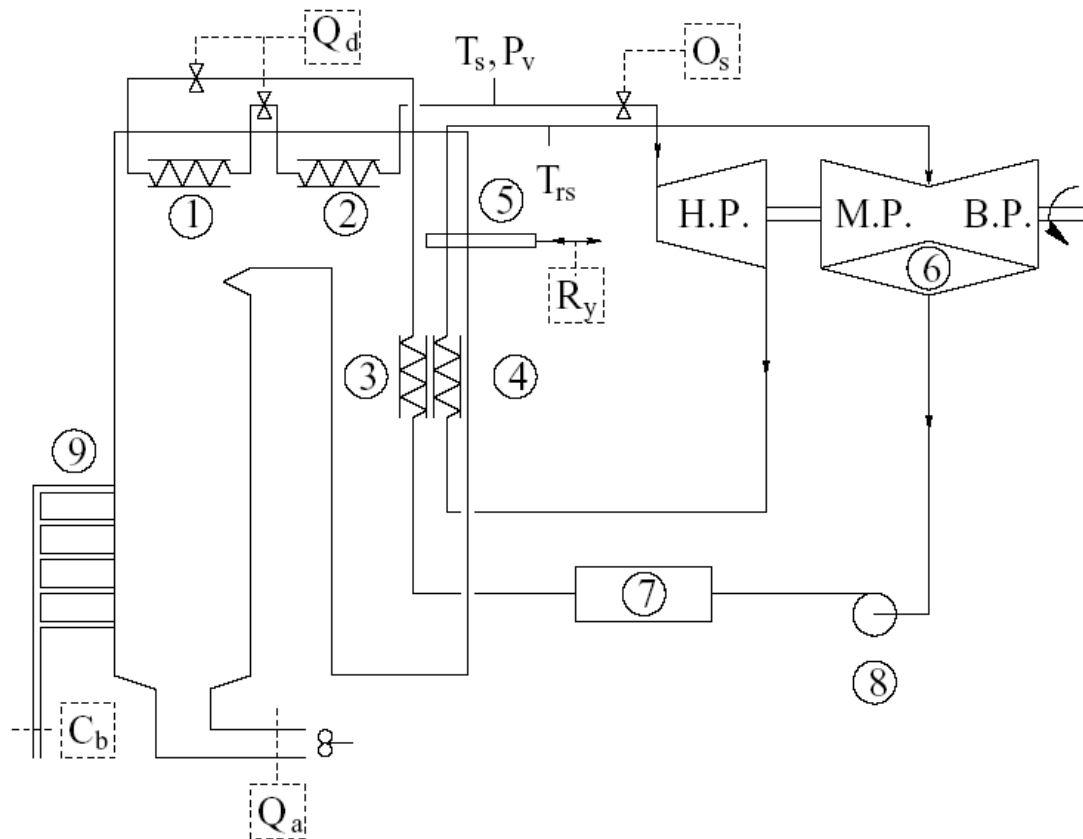
## Simulated Power Plant: *Pont sur Sambre*



1. super heater (radiation);
2. super heater (convection);
3. super heater;
4. reheater;
5. dampers;
6. condenser;
7. drum;
8. water pump;
9. burner.

# Simulated Application Examples (Cont'd)

## Simulated Power Plant: *Pont sur Sambre*



$u_1(t)$	$C_b$	gas flow
$u_2(t)$	$O_s$	turbine valves opening
$u_3(t)$	$Q_d$	super heater spray flow
$u_4(t)$	$R_y$	gas dampers
$u_4(t)$	$Q_a$	air flow
$y_1(t)$	$P_v$	steam pressure
$y_2(t)$	$T_s$	main steam temperature
$y_i(t)$	$T_{rs}$	reheat steam temperature



# Simulated Application Examples (Cont'd)

## Simulated Gas Turbine

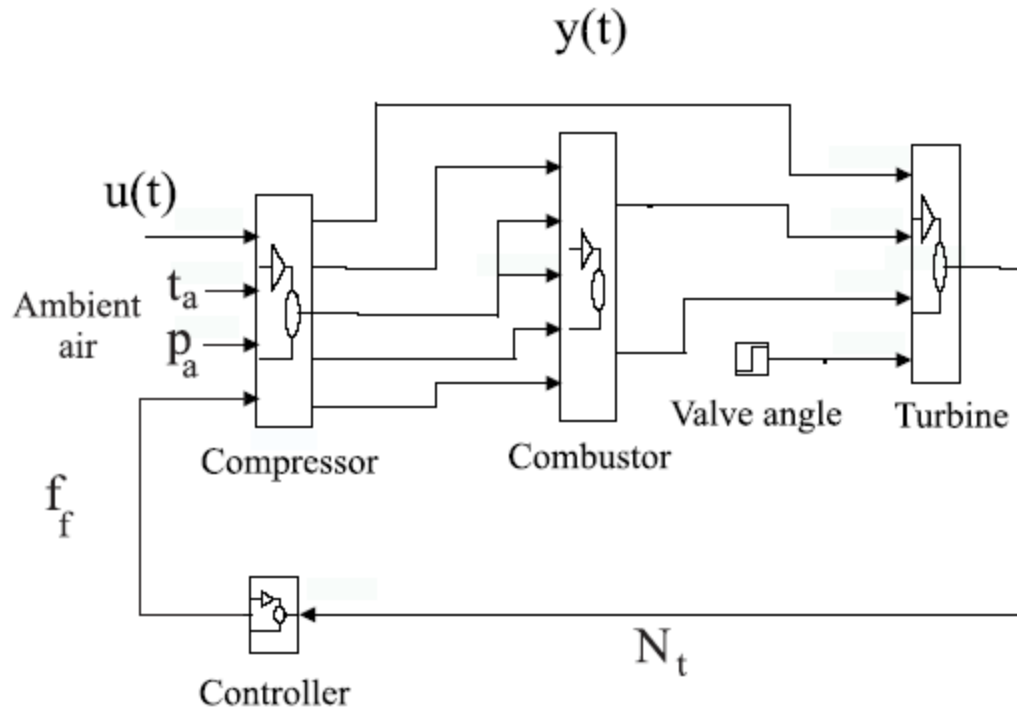


Figure 5.44: The monitored system.

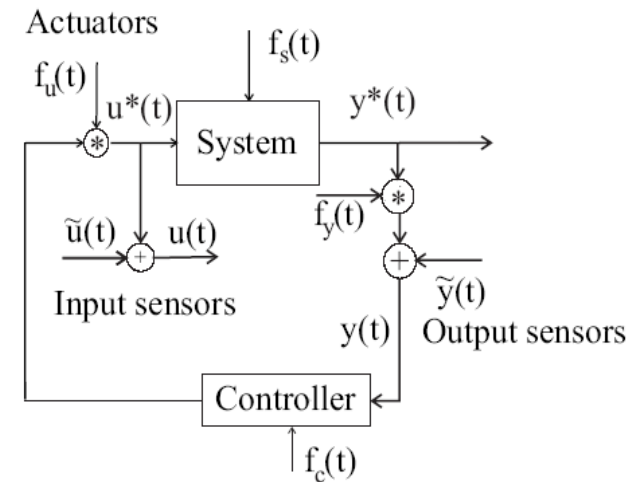


Figure 5.46: Turbine closed-loop scheme.

# Simulated Application Examples (Cont'd)

## Small Aircraft Model



Piper Malibu

Table 1: Nomenclature

$V$	True Air Speed (TAS)	$H$	altitude
$\alpha$	angle of attack	$\delta_e$	elevator deflection angle
$\beta$	angle of sideslip	$\delta_a$	aileron deflection angle
$P$	roll rate	$\delta_r$	rudder deflection angle
$Q$	pitch rate	$\delta_{th}$	throttle aperture percentage
$R$	yaw rate	$\gamma$	flight path angle
$\phi$	bank angle	$g$	acceleration of gravity
$\theta$	elevation angle	$m$	airplane mass
$\psi$	heading angle	$I_x, I_y, I_z$	principal-axis inertia moments
$n$	engine shaft angular rate	$d_t$	distance of c.g. from the Thrust line

# Simulated Application Examples (Cont'd)

## Small Aircraft Model

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# Simulated Application Examples (Cont'd)

## 6.1 SATELLITE OVERVIEW

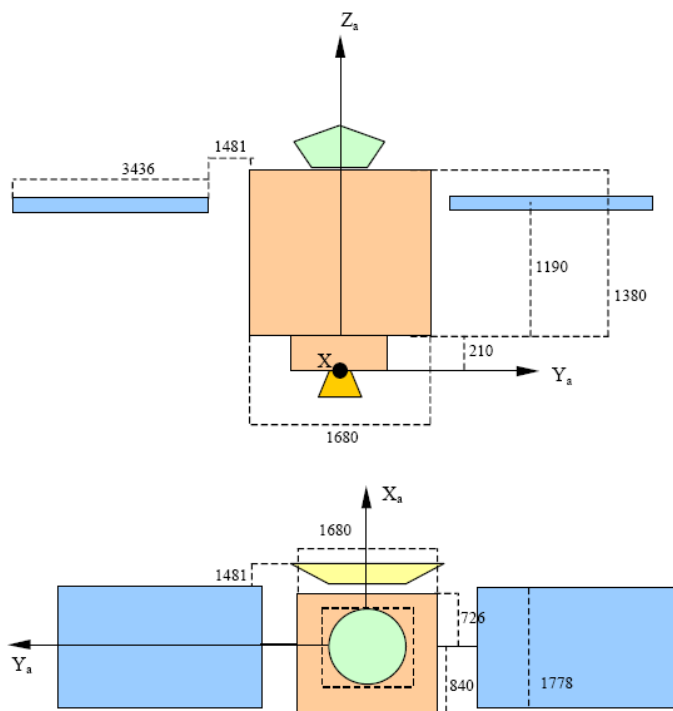


Figure 6-1: Satellite dimensions

## 6.4 SOLAR ARRAYS DYNAMICS

A GLOBALSTAR solar array has been selected. Its dimensions are recalled on the Figure 6-2.

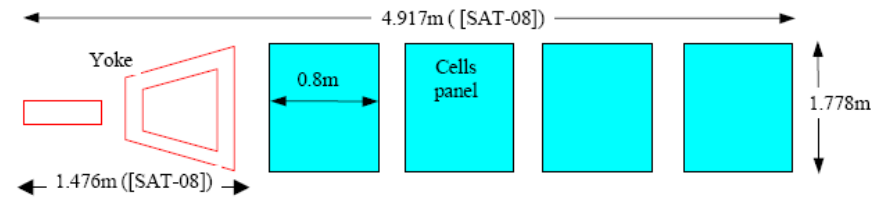


Figure 6-2: MARS-EXPRESS solar array

Simple SA model

**Aerospace Satellite**

# Simulated Application Examples (Cont'd)

## Aerospace Satellite

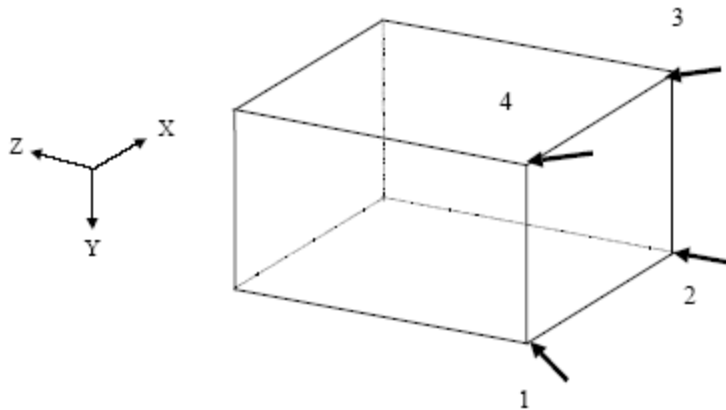


Figure 6-3 : Thrusters implementation

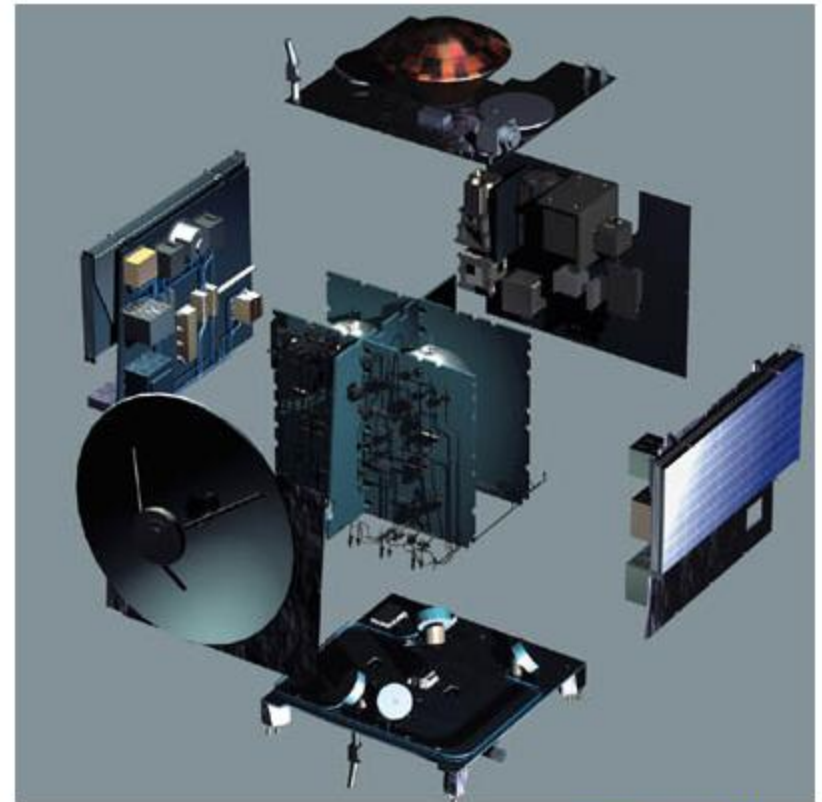
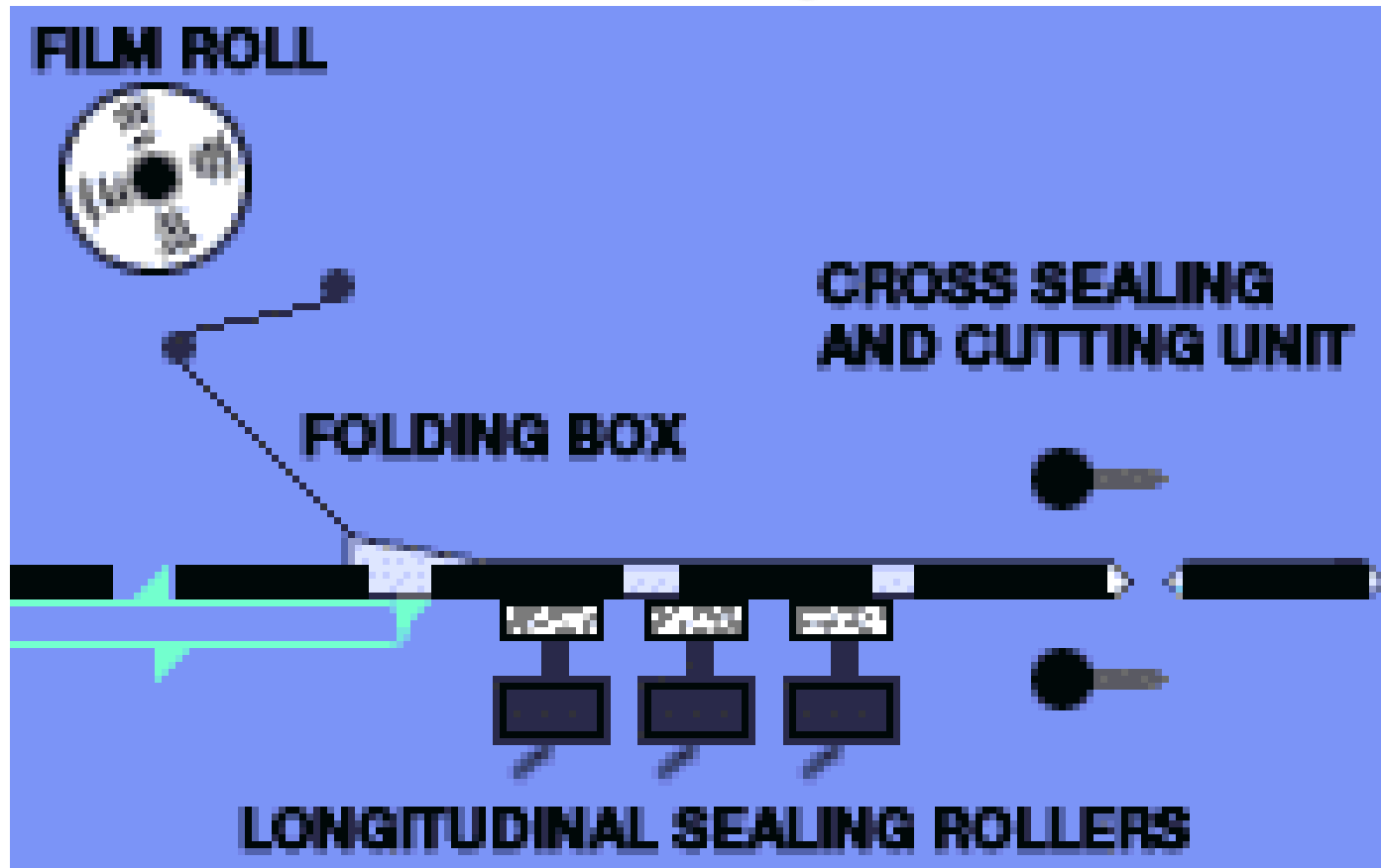


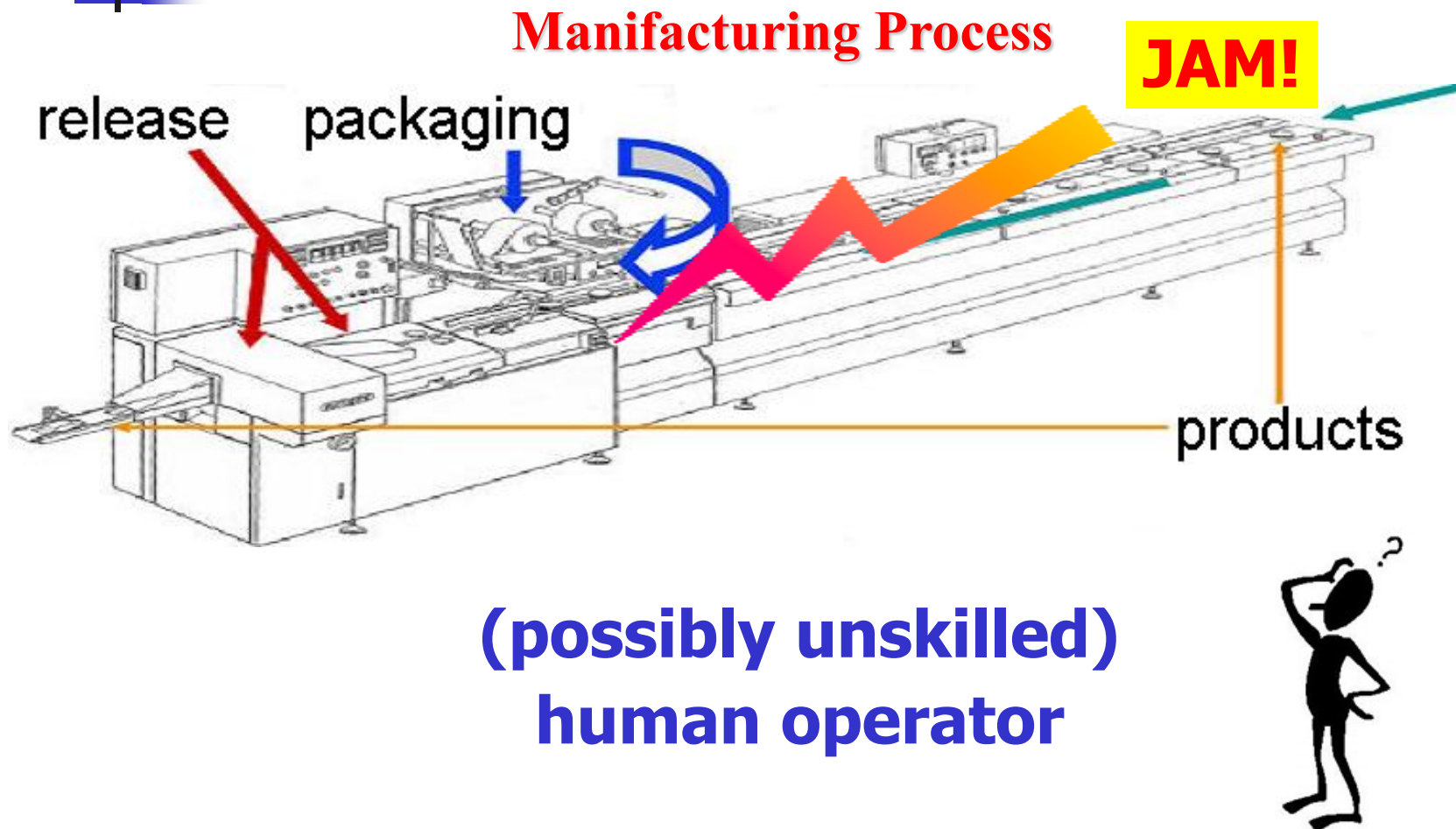
Fig. 1: Mars Express spacecraft (MEX) ([www.esa.int](http://www.esa.int))

## Simulated Application Examples (Cont'd)

### Manufacturing Process



## Simulated Application Examples (Cont'd)



# Introduction

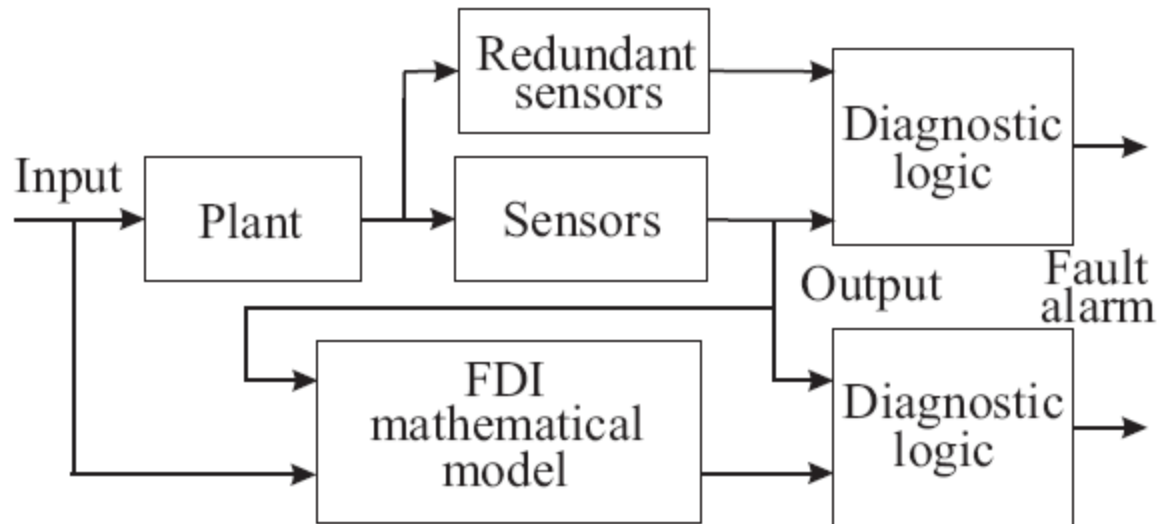


Figure 1.1: Comparison between hardware and analytical redundancy schemes.



# Introduction (Cont'd)

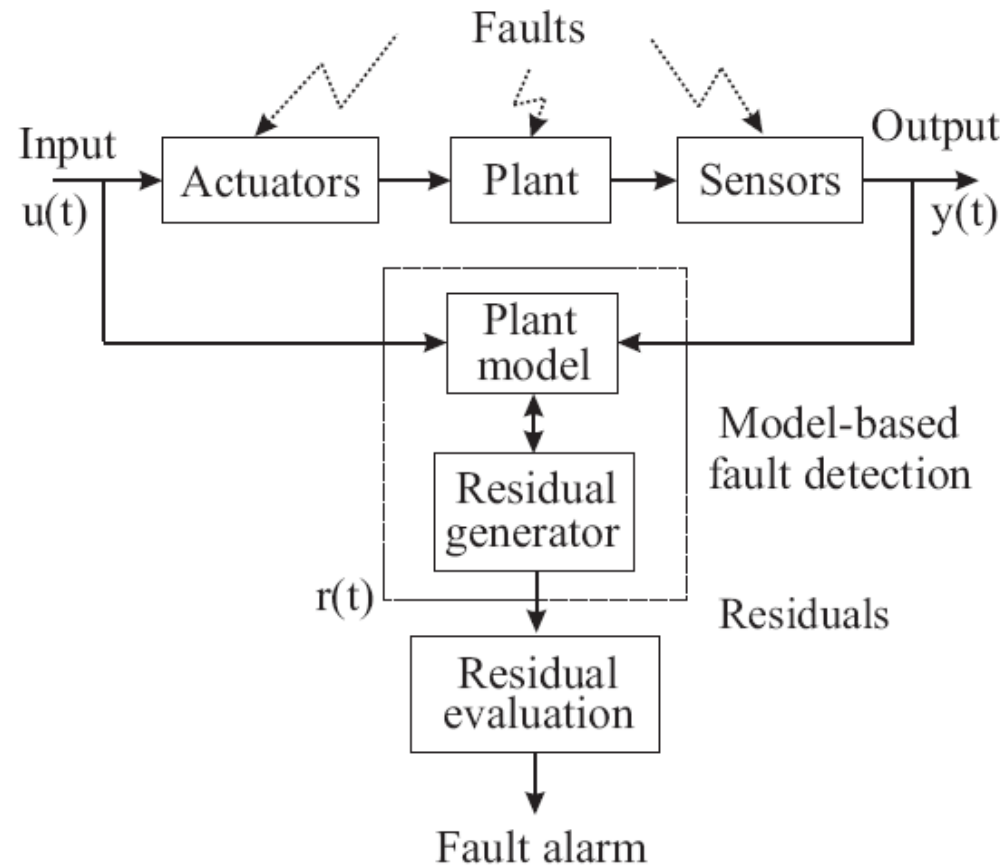


Figure 1.2: Scheme for the model-based fault detection.



# Residual Generation

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- This block generates residual signals using available inputs and outputs from the monitored system
- This residual (or fault symptom) should indicate that a fault has occurred
- Normally zero or close to zero under no fault condition, whilst distinguishably different from zero when a fault occurs



# Residual Evaluation

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- This block examines residuals for the likelihood of faults and a decision rule is then applied to determine if any faults have occurred
- It may perform a simple threshold test (geometrical methods) on the instantaneous values or moving averages of the residuals
- It may consist of statistical methods, e.g., generalised likelihood ratio testing or sequential probability ratio testing



# Introduction (Cont'd)

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## ■ Model-Based FDI Methods:

1. Output observers (OO, estimators, filters);
2. Parity equations;
3. Identification and parameter estimation.



# Introduction (Cont'd)

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- **Signal Model-Based Methods:**

1. Bandpass filters;
2. Spectral analysis (FFT);
3. Maximum-entropy estimation.

- **Change Detection: Residual Analysis**

1. Mean and variance estimation;
2. Likelihood-ratio test, Bayes decision;
3. Run-sum test.



# Introduction (Cont'd)

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- Model Uncertainty and FDI
  - Model-reality mismatch
  - Sensitivity problem: incipient faults!
- Robustness in FDI
  - Disturbance, modelling errors, uncertainty
  - UIO and Kalman filter: robust residual generation
- System Identification for FDI
  - Estimation of a reliable model
  - Modelling accuracy
  - Disturbance estimation



# Introduction (Cont'd)

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- Fault Identification Methods

- Fault nature (type, shape) & size (amplitude)

1. Geometrical distance and probabilistic methods;
2. Artificial neural networks;
3. Fuzzy clustering.

- Approximate Reasoning Methods:

1. Probabilistic reasoning;
2. Possibilistic reasoning with fuzzy logic;
3. Reasoning with artificial neural networks.

# Introduction (Cont'd)

## ■ FDI applications status & review

Table 1.1: FDI applications and number of contributions.

Application	Number of contributions
Simulation of real processes	55
Large-scale pilot processes	44
Small-scale laboratory processes	18
Full-scale industrial processes	48

Table 1.2: Fault type and number of contributions.

Fault type	Number of contributions
Sensor faults	69
Actuator faults	51
Process faults	83
Control loop or controller faults	8



# Introduction (Cont'd)

## ■ FDI applications status & review

Table 1.3: FDI methods and number of contributions.

Method type	Number of contributions
Observer	53
Parity space	14
Parameter estimation	51
Frequency spectral analysis	7
Neural networks	9

Table 1.4: Residual evaluation methods and number of contributions.

Evaluation method	Number of contributions
Neural networks	19
Fuzzy logic	5
Bayes classification	4
Hypothesis testing	8

# Introduction (Cont'd)

## ■ FDI applications status & review

Table 1.5: Reasoning strategies and number of contributions.

Reasoning strategy	Number of contributions
Rule based	10
Sign directed graph	3
Fault symptom tree	2
Fuzzy logic	6

Table 1.6: Applications of model-based fault detection.

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

# Model-based FDI Techniques

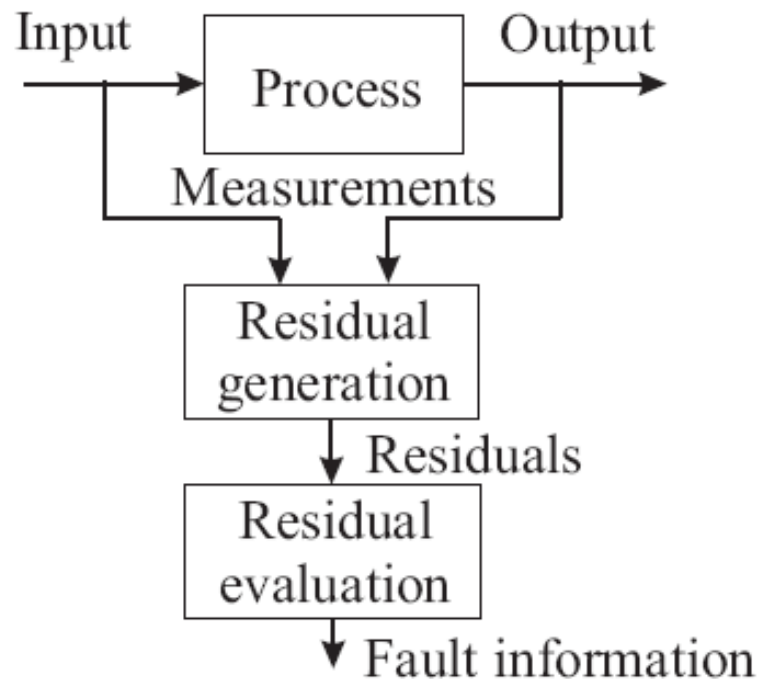


Figure 2.1: Structure of model-based FDI system.



## Model-based FDI Techniques (Cont'd)

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1. **Residual generation:** this block generates residual signals using available inputs and outputs from the monitored system. This residual (or fault symptom) should indicate that a fault has occurred. It should normally be zero or close to zero under no fault condition, whilst distinguishably different from zero when a fault occurs. This means that the residual is characteristically independent of process inputs and outputs, in ideal conditions. Referring to Figure 2.1, this block is called *residual generation*.
2. **Residual evaluation:** This block examines residuals for the likelihood of faults and a decision rule is then applied to determine if any faults have occurred. The *residual evaluation* block, shown in Figure 2.1, may perform a simple threshold test (geometrical methods) on the instantaneous values or moving averages of the residuals. On the other hand, it may consist of statistical methods, *e.g.*, generalised likelihood ratio testing or sequential probability ratio testing [Isermann, 1997, Willsky, 1976, Basseville, 1988, Patton et al., 2000].

## Model-based FDI Techniques (Cont'd)

### ➤ Modelling of Faulty Systems

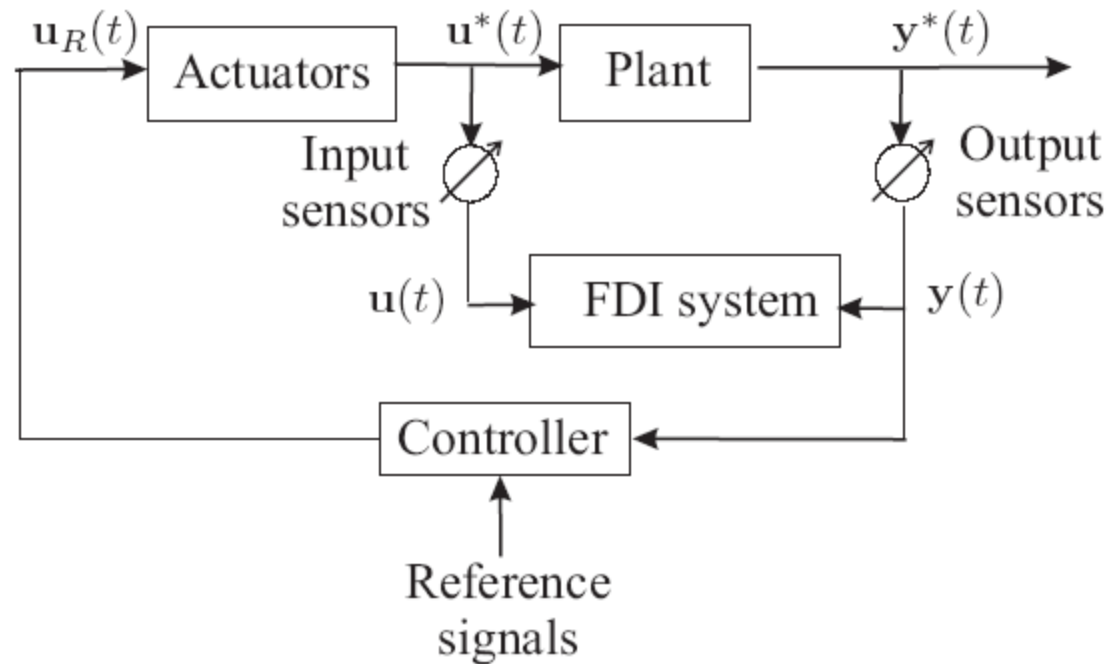


Figure 2.2: Fault diagnosis in a closed-loop system.

## Model-based FDI Techniques (Cont'd)

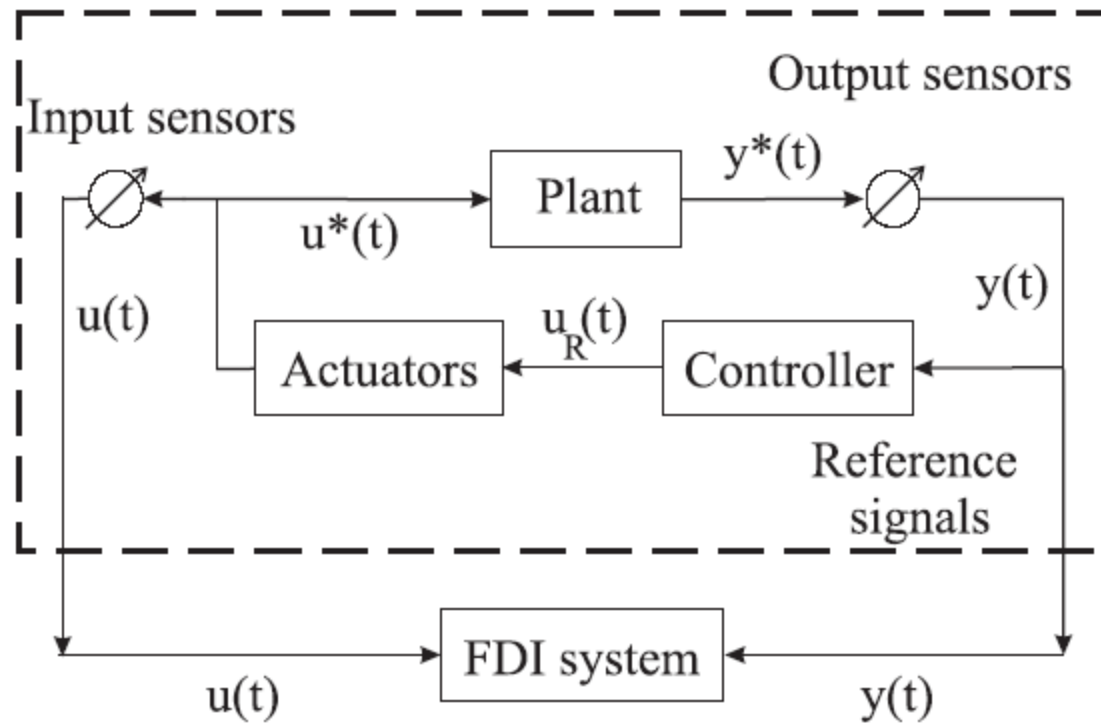


Figure 2.3: The rearranged fault diagnosis scheme.

## Model-based FDI Techniques (Cont'd)

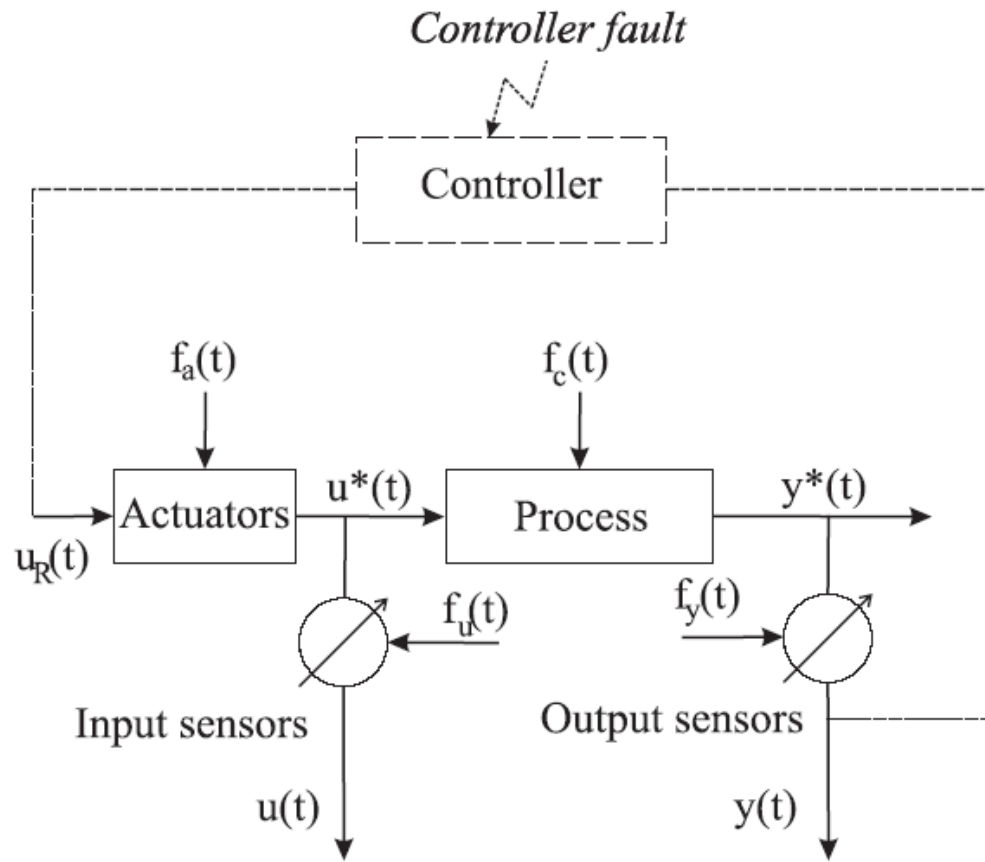


Figure 2.4: The controlled system and fault topology.

## Model-based FDI Techniques (Cont'd)

### Fault Location:

- Actuators
- Process or system components
- Input sensors
- Output sensors
- Controllers

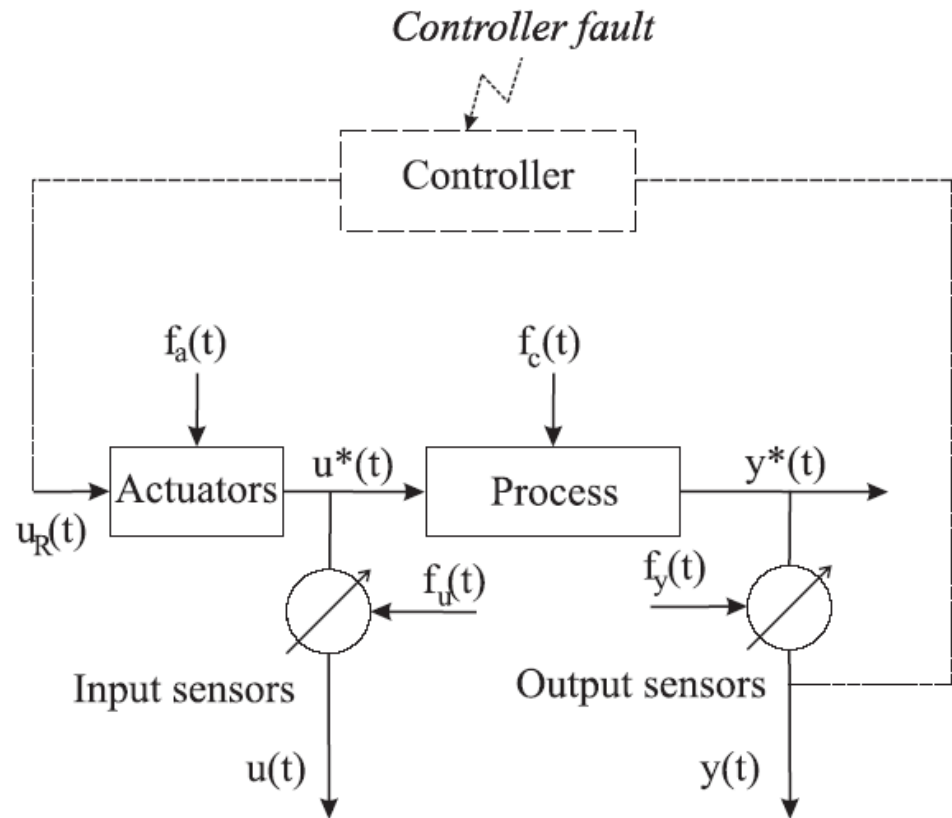


Figure 2.4: The controlled system and fault topology.



# Model-based FDI Techniques (Cont'd)

## Fault and System Modelling

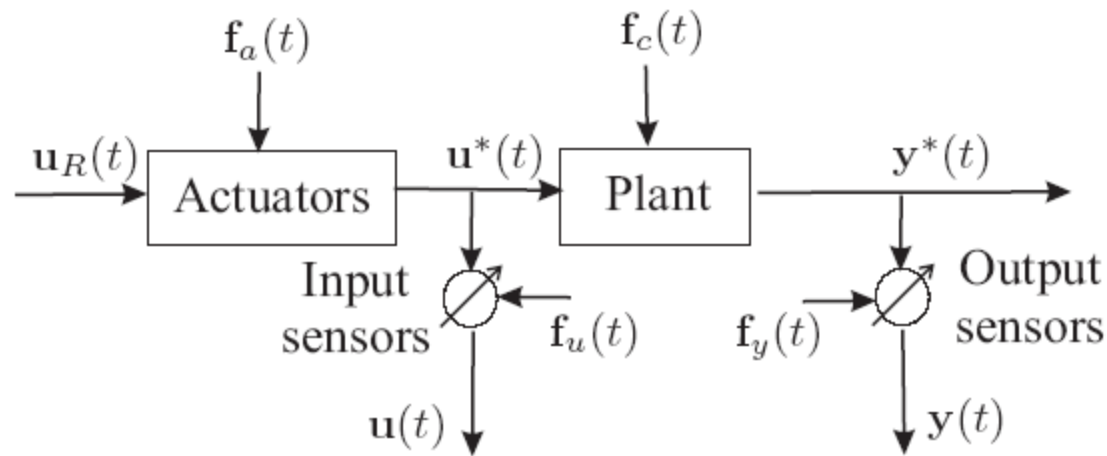


Figure 2.5: The monitored system and fault topology.

$$\begin{cases} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}^*(t) \\ \mathbf{y}^*(t) &= \mathbf{C}\mathbf{x}(t) \end{cases}$$

# Model-based FDI Techniques (Cont'd)

## Fault and System Modelling

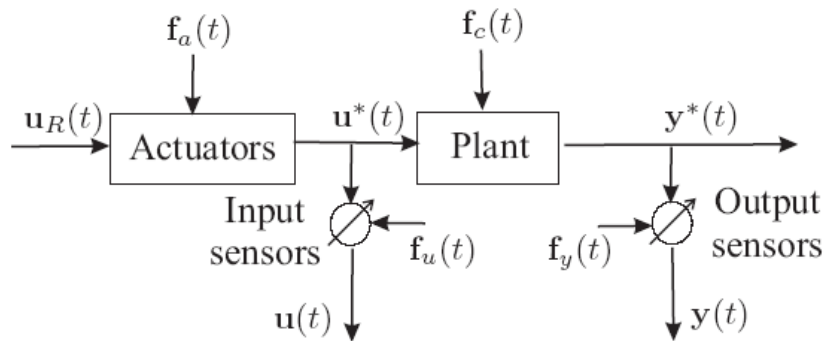


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$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}^*(t) + \mathbf{f}_c(t)$$

$$\mathbf{f}_c(t) = I_i \Delta a_{ij} x_j(t)$$

$$\begin{cases} \mathbf{u}(t) &= \mathbf{u}^*(t) + \mathbf{f}_u(t) \\ \mathbf{y}(t) &= \mathbf{y}^*(t) + \mathbf{f}_y(t) \end{cases}$$

# Model-based FDI Techniques (Cont'd)

## Fault and System Modelling

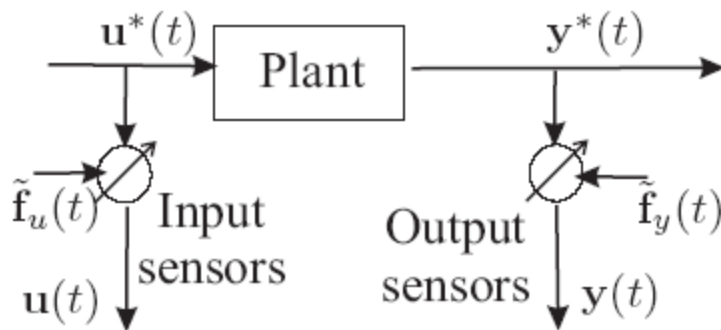


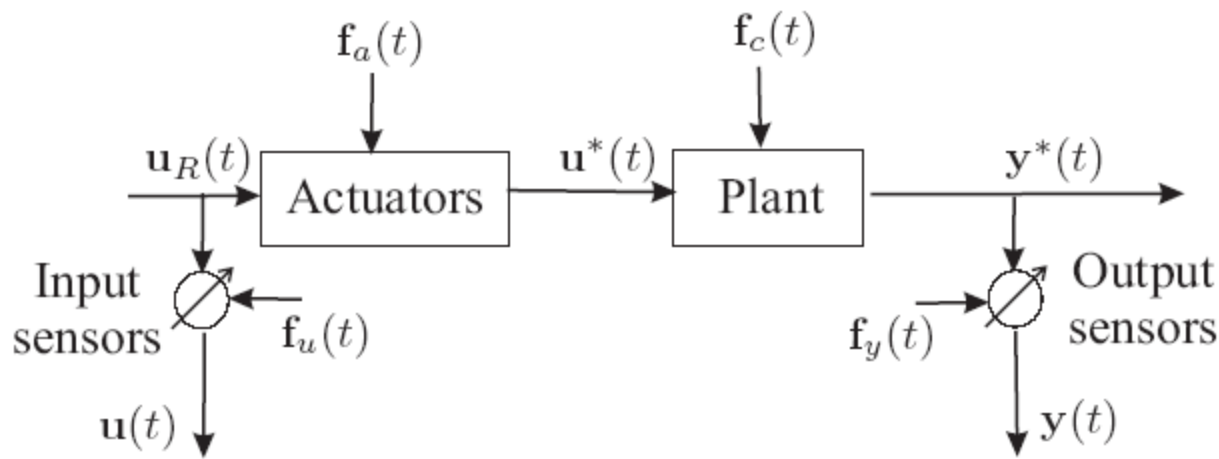
Figure 2.6: The structure of the plant sensors.

$$\begin{cases} u(t) &= u^*(t) + \tilde{u}(t) \\ y(t) &= y^*(t) + \tilde{y}(t) \end{cases}$$

$$\begin{cases} u(t) &= u^*(t) + \tilde{u}(t) + f_u(t) \\ y(t) &= y^*(t) + \tilde{y}(t) + f_y(t) \end{cases}$$

# Model-based FDI Techniques (Cont'd)

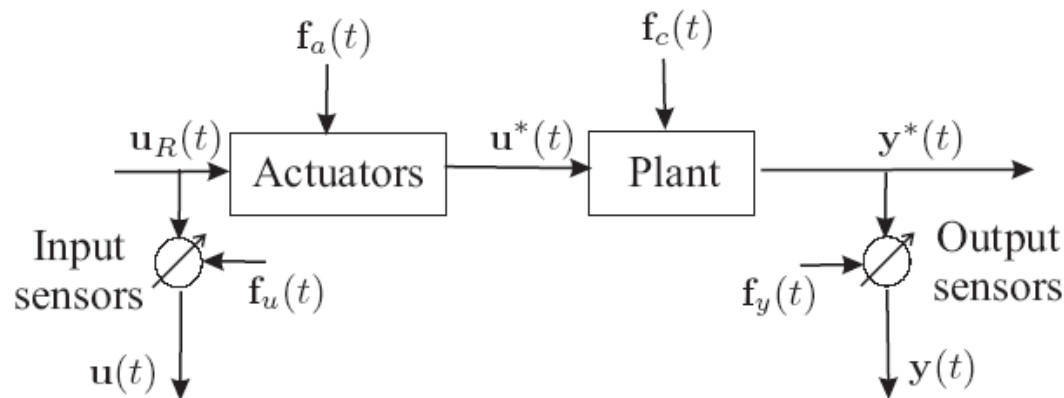
## Fault and System Modelling



$$u^*(t) = u_R(t) + f_a(t)$$

$$\begin{cases} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{f}_c(t) + B\mathbf{u}^*(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{f}_y(t) \\ \mathbf{u}(t) &= \mathbf{u}^*(t) + \mathbf{f}_u(t) \end{cases}$$

# Model-based FDI Techniques (Cont'd)

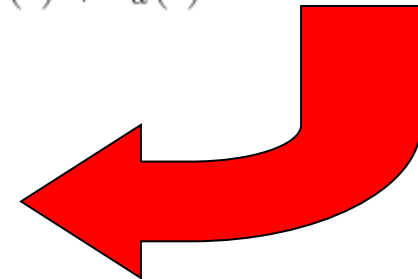


## ■ Modelling of Faulty Systems

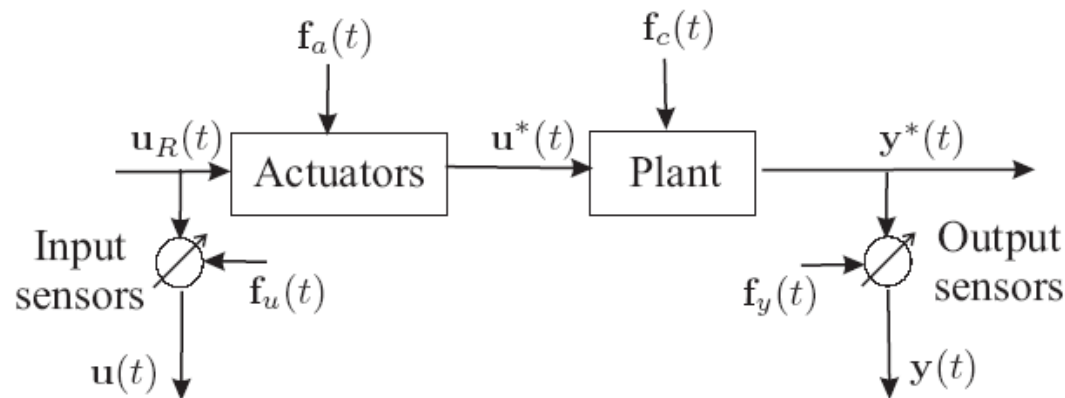
Figure 2.7: Fault topology with actuator input signal measurement.

$$\mathbf{f}(t) = [\mathbf{f}_a^T, \mathbf{f}_u^T, \mathbf{f}_c^T, \mathbf{f}_y^T]^T \in \mathbb{R}^k \quad \begin{cases} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{f}_c(t) + \mathbf{B}\mathbf{f}_a(t) + \mathbf{B}\mathbf{u}^*(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{f}_y(t) \\ \mathbf{u}(t) &= \mathbf{u}^*(t) + \mathbf{f}_u(t) \end{cases}$$

$$\begin{cases} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}^*(t) + \mathbf{L}_1\mathbf{f}(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{L}_2\mathbf{f}(t) \\ \mathbf{u}(t) &= \mathbf{u}^*(t) + \mathbf{L}_3\mathbf{f}(t) \end{cases}$$



# Model-based FDI Techniques (Cont'd)



## ■ Modelling of Faulty Systems

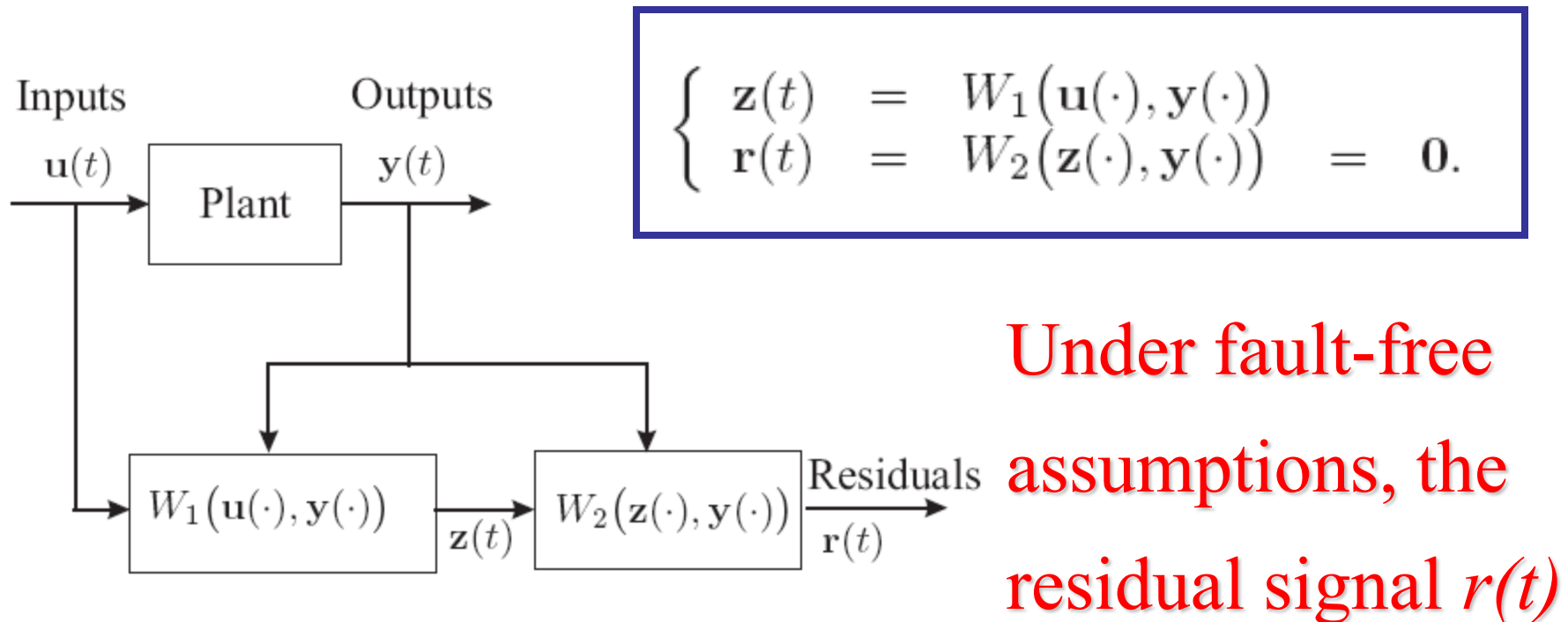
Figure 2.7: Fault topology with actuator input signal measurement.

$$y(z) = G_{yu^*}(z)u^*(z) + G_{yf}(z)f(z)$$

## ■ Transfer function description:

$$\begin{cases} G_{yu^*}(z) &= C(zI - A)^{-1}B \\ G_{yf}(z) &= C(zI - A)^{-1}L_1 + L_2 \end{cases}$$

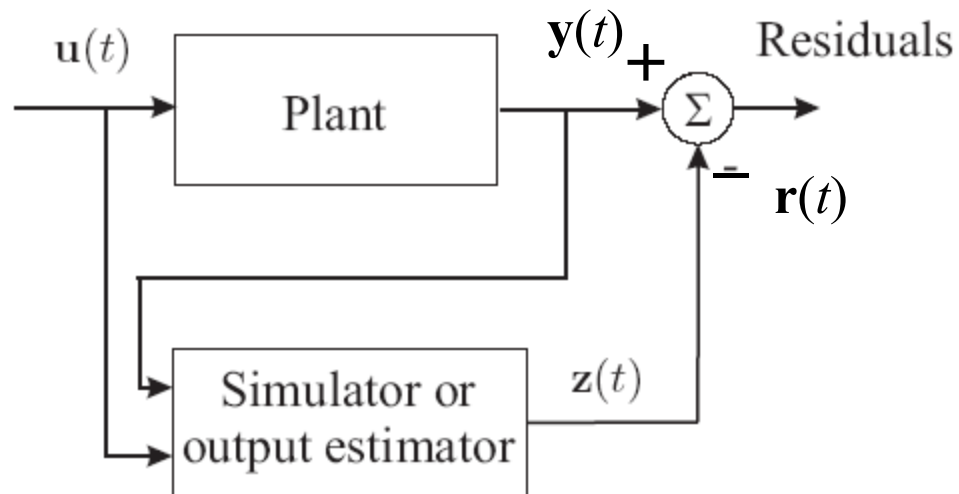
# Residual Generator Structure



Under fault-free assumptions, the residual signal  $r(t)$  is “almost” zero

Figure 2.8: Residual generator general structure.

## Residual General Structure (Cont'd)



Residual generation  
via *system simulator*

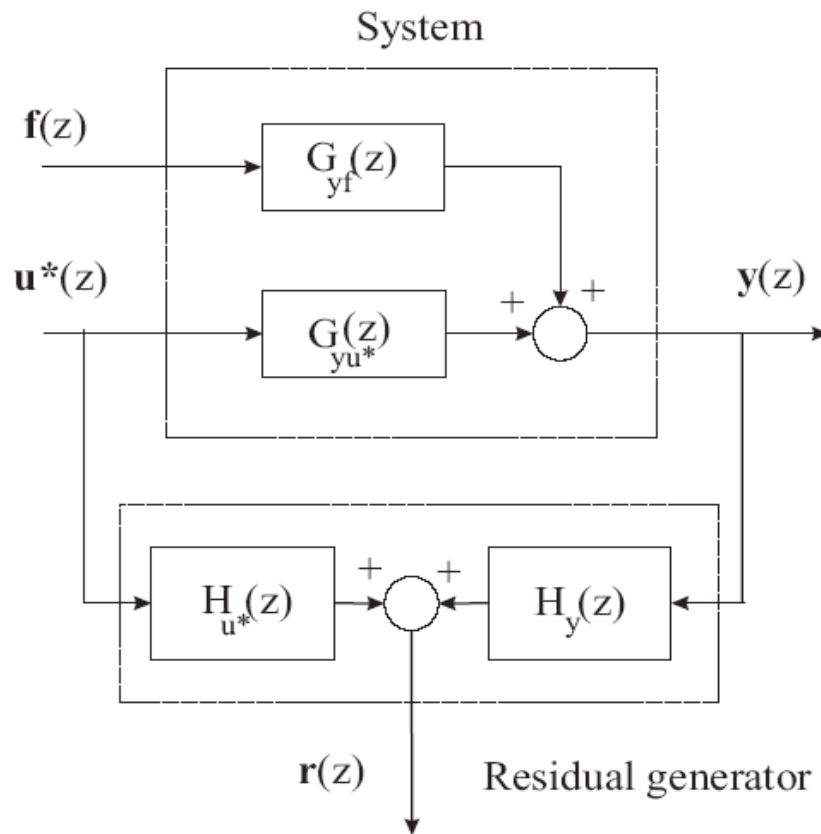
$$\mathbf{r}(t) = \mathbf{y}(t) - \mathbf{z}(t)$$

Figure 2.9: Residual generation via system simulator.

$z(t)$  is the *simulated plant output*



# Residual General Structure (Cont'd)



$$y(z) = G_{yu^*}(z)u^*(z) + G_{yf}(z)f(z)$$

**Residual generator:**

$$r(z) = \begin{bmatrix} H_{u^*}(z) & H_y(z) \end{bmatrix} \begin{bmatrix} u^*(z) \\ y(z) \end{bmatrix} =$$

$$= H_{u^*}(z)u^*(z) + H_y(z)y(z)$$

$$r(t) = 0 \text{ if and only if } f(t) = 0$$

**Constraint conditions:** *design*

$$H_{u^*}(z) + H_y(z)G_{yu^*} = 0$$

Figure 2.10: Residual generator general structure.

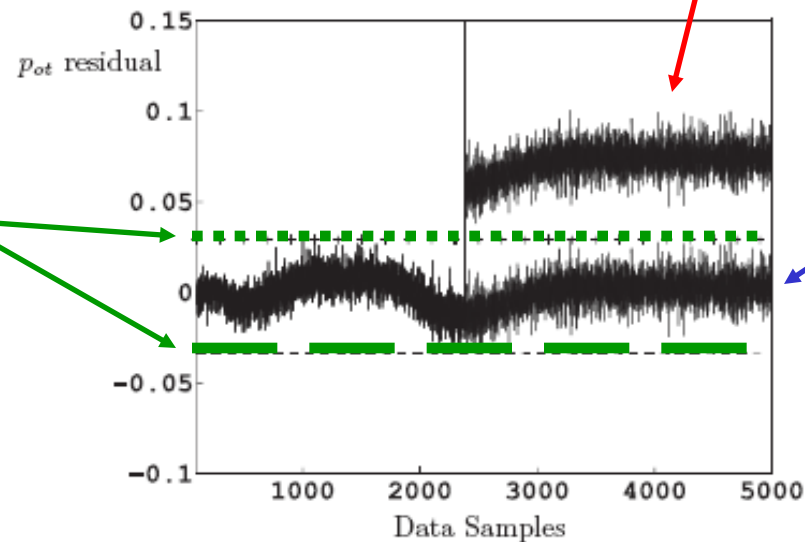
# General Residual Evaluation

$$\begin{cases} J(\mathbf{r}(t)) \leq \varepsilon(t) & \text{for } \mathbf{f}(t) = \mathbf{0} \\ J(\mathbf{r}(t)) > \varepsilon(t) & \text{for } \mathbf{f}(t) \neq \mathbf{0} \end{cases}$$

Detection thresholds  
 $\varepsilon(t)$

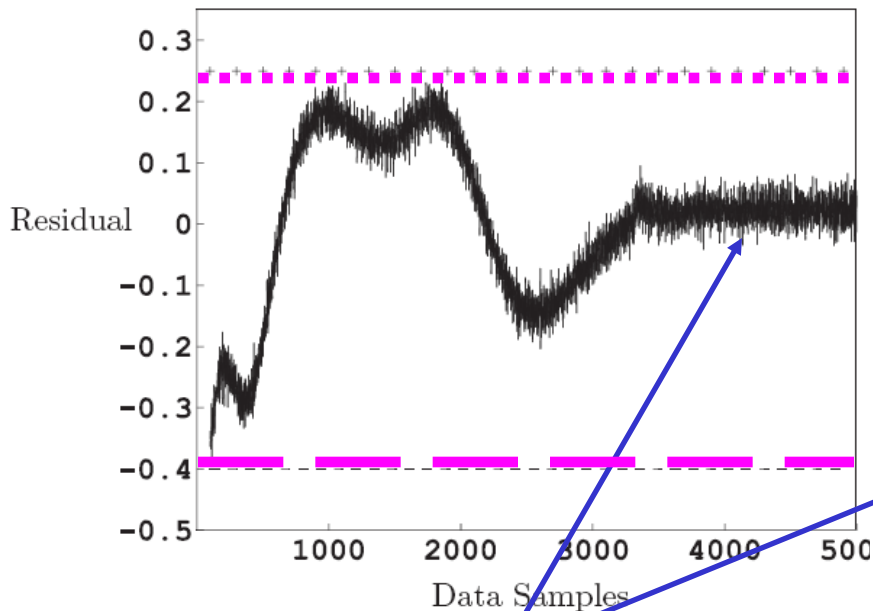
Faulty residual

Fault free residual

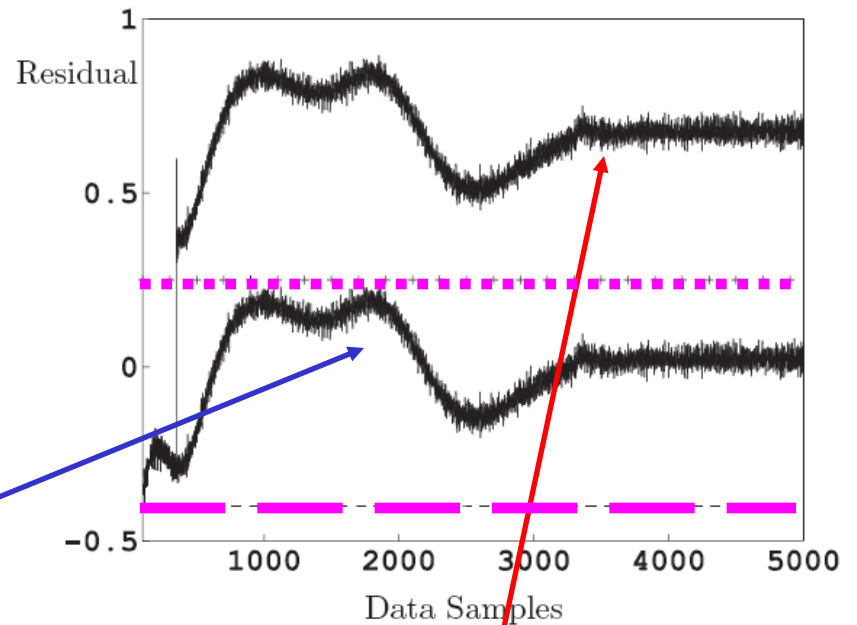


# General Residual Evaluation (*example*)

## *Detection thresholds*



**Fault free residual**



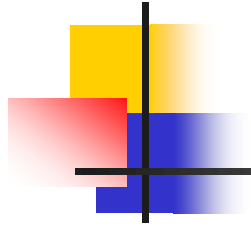
**Fault-free & *faulty* residuals**



# Residual Generation Techniques

---

- **Fault detection via parameter estimation**
- **Observer-based approaches**
- **Parity (vector) relations**



# **Fault Detection via Parameter Estimation**



# Parameter Estimation

---

- Parameter estimation for fault detection
- The process parameters are not known at all, or they are not known exactly enough. They can be determined with parameter estimation methods
- The basic structure of the model has to be known
- Based on the assumption that the faults are reflected in the physical system parameters
- The parameters of the actual process are estimated on-line using well-known **parameter estimations methods**



## Parameter Estimation (Cont'd)

---

- The results are thus compared with the parameters of the reference model obtained initially under fault-free assumptions
- Any discrepancy can indicate that a fault may have occurred
- **An approach for modelling the input-output behaviour of the monitored system will be recalled and exploited for fault detection**



# Equation Error (EE) Approach

---

- SISO model

$$y(t) = \Psi^T \Theta$$

- Parameter vector

$$\Theta^T = [a_1 \dots a_n, b_1 \dots b_n]$$

- Regression vector

$$\Psi^T = [y(t-1) \dots y(t-n) \quad u(t-1) \dots u(t-n)]$$





# Equation Error Method

---

- *Equation error*

$$e(t) = y(t) - \Psi^T \Theta$$

- Model of the process (Z-transform)

$$\frac{y(t)}{u(t)} = \frac{B(z)}{A(z)}$$

- Estimated polynomials

$$e(t) = \hat{B}(z)u(t) - \hat{A}(z)y(t)$$



## Equation Error Method (Cont'd)

---

- Estimation of the process model: **LS**

$$\hat{\Theta} = [\Psi^T \Psi]^{-1} \Psi^T y$$

- LS minimisation

$$\begin{cases} J(\Theta) &= \sum_t e^2(t) = e^T e \\ \frac{d J(\Theta)}{d \Theta} &= \mathbf{0}. \end{cases}$$

# Equation Error Method (Cont'd)

- Estimation of the process model: **RLS**

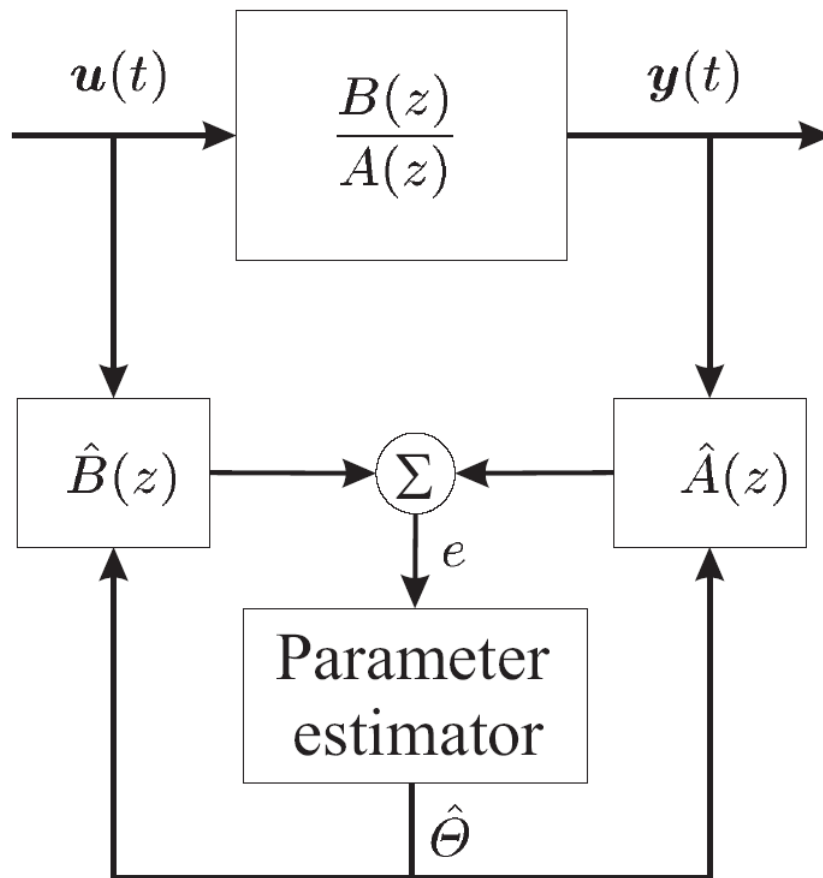
$$\hat{\Theta}(t+1) = \hat{\Theta}(t) + \gamma(t) \left[ y(t+1) - \Psi^T(t+1) \hat{\Theta}(t+1) \right]$$

- Estimate recursive adaptation

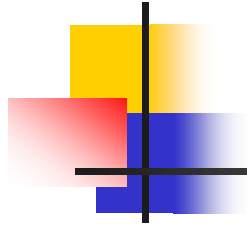
$$\begin{cases} \gamma(t) &= \frac{1}{\Psi^T(t+1) P(t) \Psi(t+1) + 1} P(t) \Psi(t+1) \\ P(t+1) &= [I - \gamma(t) \Psi^T(t+1)] P(t). \end{cases}$$

*Note: see on-line estimation approach*

# Parameter Estimation via EE



- Recursive estimation of the transfer function polynomials
- Equation error
- Parameter estimation via recursive algorithm
- **RLS**



# **Links Between Input- Output and State-Space Discrete-Time LTI Models**



# Input-Output Model (EE)

- The input to output discrete-time model behaviour can be mathematically described by a set of ARX Multi-Input Single-Output (MISO) models

$$y_i^*(t) = \sum_{j=1}^n \alpha_{i,j} y_i^*(t-j) + \sum_{j=1}^r \sum_{k=1}^n \beta_{i,j,k} u_j^*(t-k) + \varepsilon_i(t) , \quad i = 1, \dots, m$$



# Input-Output Model (EE)

- $m$  is the number of the output variables
- The order  $n$  and the parameters  $\alpha_{i,j}$  and  $\beta_{i,j,k}$  with  $i = 1, \dots, m$ , of the model are determined by the identification approach
- The term  $\varepsilon_i(t)$  takes into account the modelling error (EE)

$$y_i^*(t) = \sum_{j=1}^n \alpha_{i,j} y_i^*(t-j) + \sum_{j=1}^r \sum_{k=1}^n \beta_{i,j,k} u_j^*(t-k) + \varepsilon_i(t) , \quad i = 1, \dots, m$$



# State-Space Equivalent Model

- The input-output EE model has a state space “realisation” as follows:

$$\begin{cases} \mathbf{x}_i(t+1) &= \mathbf{A}_i \mathbf{x}_i(t) + \mathbf{B}_i \mathbf{u}^*(t) + \mathbf{B}_{\omega_i} \varepsilon_i & i = 1, \dots, m \\ \mathbf{y}_i^*(t) &= \mathbf{C}_i \mathbf{x}_i(t) + \mathbf{D}_{\omega_i} \varepsilon_i, & t = 1, 2, \dots \end{cases}$$

- The matrices  $(\mathbf{A}_i, \mathbf{B}_i, \mathbf{C}_i, \mathbf{B}_{\omega_i}, \mathbf{D}_{\omega_i})$  of a state space representation in canonical form of the  $n$ -th order system are defined as follows:





# State-Space Matrices

$$\mathbf{A}_i = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \alpha_{i,1} & \alpha_{i,2} & \alpha_{i,3} & \cdots & \alpha_{i,n} \end{bmatrix},$$

$$\mathbf{C}_i = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix},$$

# State-Space Matrices (Cont'd)

$$\begin{bmatrix} B_i & B_{\omega_i} \\ \mathbf{0} & D_{\omega_i} \end{bmatrix} = S_i^{-1} \begin{bmatrix} \beta_{i,1,1} & \cdots & \beta_{i,r,1} & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \beta_{i,1,n} & \cdots & \beta_{i,r,n} & 0 \\ 0 & \cdots & 0 & 1 \end{bmatrix}$$

$$S_i = \begin{bmatrix} -\alpha_{i,1} & -\alpha_{i,2} & \cdots & -\alpha_{i,n} & 1 \\ -\alpha_{i,2} & -\alpha_{i,3} & \cdots & 1 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -\alpha_{i,n} & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Note that the matrix  $S_i$  is always non-singular



# State-Space Matrices (Cont'd)

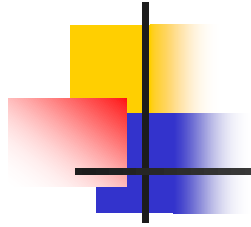
---

## In Matlab:

TF2SS Transfer function to state-space conversion.

`[A,B,C,D] = TF2SS(NUM,DEN)` calculates the state-space representation from a single input. Vector DEN must contain the coefficients of the denominator in descending powers of  $s$ . Matrix NUM must contain the numerator coefficients with as many rows as there are outputs  $y$

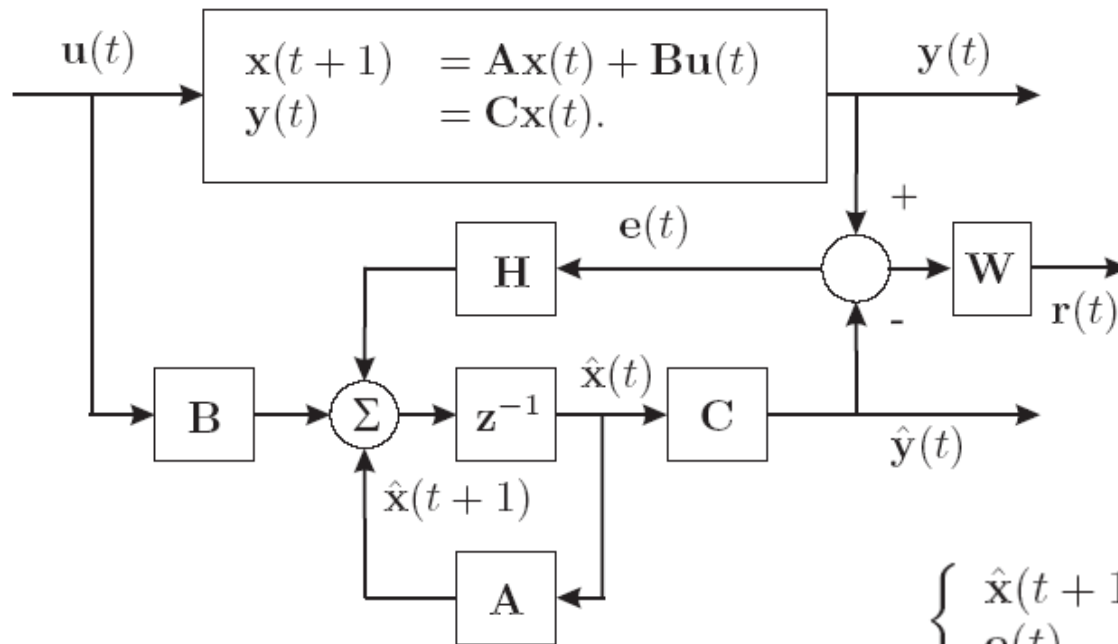
**Note: for MIMO models, use `ss` and `tf` functions**



# Observer-based Approaches

# Residual General Structure

## ■ Observer-based approach



Plant model

$$\begin{cases} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t). \end{cases}$$

Observer model

$$\begin{cases} \hat{\mathbf{x}}(t+1) &= \mathbf{A}\hat{\mathbf{x}}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{H}\mathbf{e}(t) \\ \mathbf{e}(t) &= \mathbf{y}(t) - \mathbf{C}\hat{\mathbf{x}}(t). \end{cases}$$

*Output estimation approach!*



# Residual Generator Structure

---

Plant model

$$\begin{cases} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t). \end{cases}$$

Observer model

$$\begin{cases} \hat{\mathbf{x}}(t+1) &= \mathbf{A}\hat{\mathbf{x}}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{H}\mathbf{e}(t) \\ \mathbf{e}(t) &= \mathbf{y}(t) - \mathbf{C}\hat{\mathbf{x}}(t). \end{cases}$$

State estimation model

$$\begin{cases} \mathbf{e}_x(t) &= \mathbf{x}(t) - \hat{\mathbf{x}}(t) \\ \mathbf{e}_x(t+1) &= (\mathbf{A} - \mathbf{H}\mathbf{C})\mathbf{e}_x(t). \end{cases}$$

State estimation property

$$\lim_{t \rightarrow \infty} \mathbf{e}_x(t) = \mathbf{0} \quad (\text{fault-free case!!!})$$

# Residual Generator Property

**+ disturbance signals and fault**

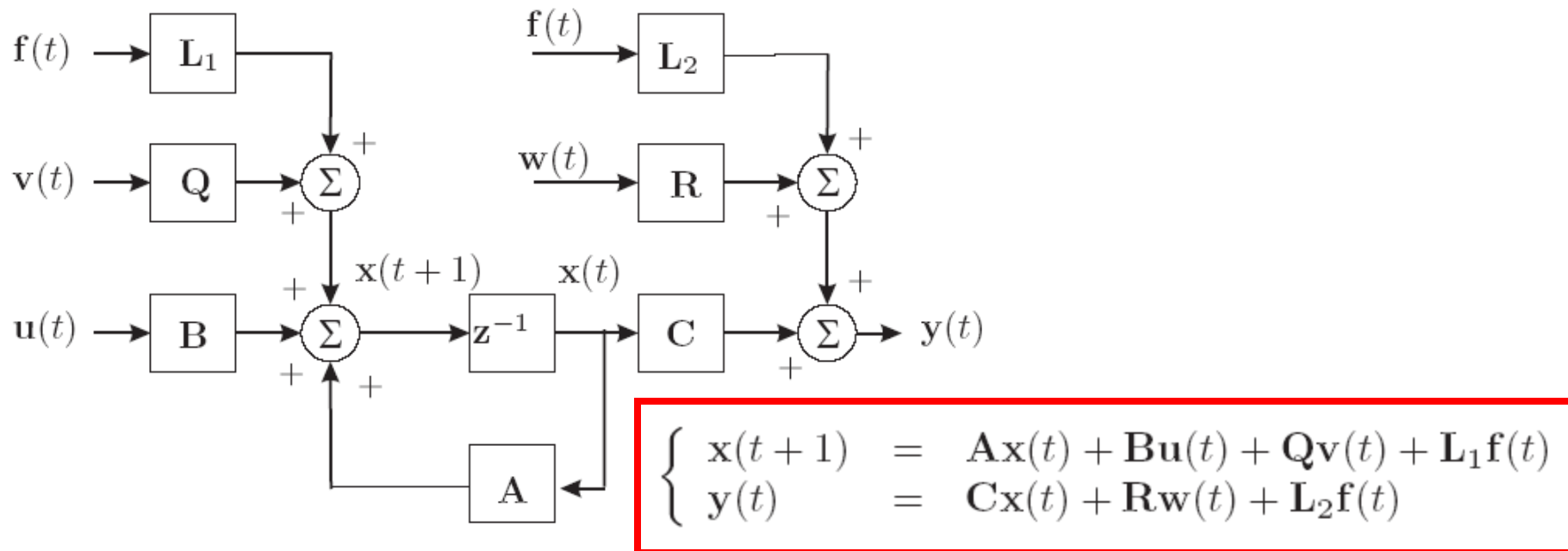


Figure 2.14: MIMO process with faults and noises.



## Residual Generator Property (Cont'd)

*+ fault signals*

System model

$$\begin{cases} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{Q}\mathbf{v}(t) + \mathbf{L}_1\mathbf{f}(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{R}\mathbf{w}(t) + \mathbf{L}_2\mathbf{f}(t) \end{cases}$$

Observer model

$$\mathbf{e}_x(t+1) = (\mathbf{A} - \mathbf{H}\mathbf{C})\mathbf{e}_x(t) + \mathbf{L}_1\mathbf{f}(t) - \mathbf{H}\mathbf{L}_2\mathbf{f}(t)$$

Output estimation error  
with faults *but noise-free*

$$\mathbf{e}(t) = \mathbf{C}\mathbf{e}_x(t) + \mathbf{L}_2\mathbf{f}(t).$$

Both  $\mathbf{e}(t)$  and  $\mathbf{e}_x(t)$  are suitable residuals!



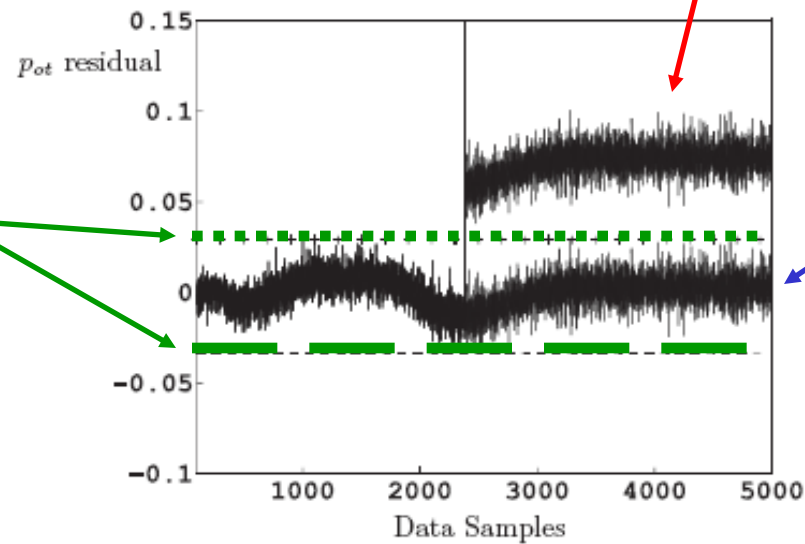
# General Residual Evaluation

$$\begin{cases} J(\mathbf{r}(t)) \leq \varepsilon(t) & \text{for } \mathbf{f}(t) = \mathbf{0} \\ J(\mathbf{r}(t)) > \varepsilon(t) & \text{for } \mathbf{f}(t) \neq \mathbf{0} \end{cases}$$

Detection thresholds  
 $\varepsilon(t)$

Faulty residual

Fault free residual



# Change Detection & Residual Evaluation

$$\begin{cases} J(\mathbf{r}(t)) \leq \varepsilon(t) & \text{for } \mathbf{f}(t) = \mathbf{0} \\ J(\mathbf{r}(t)) > \varepsilon(t) & \text{for } \mathbf{f}(t) \neq \mathbf{0} \end{cases}$$

$$J(r(t)) \equiv |r(t)|$$

Detection thresholds

$\varepsilon(t)$

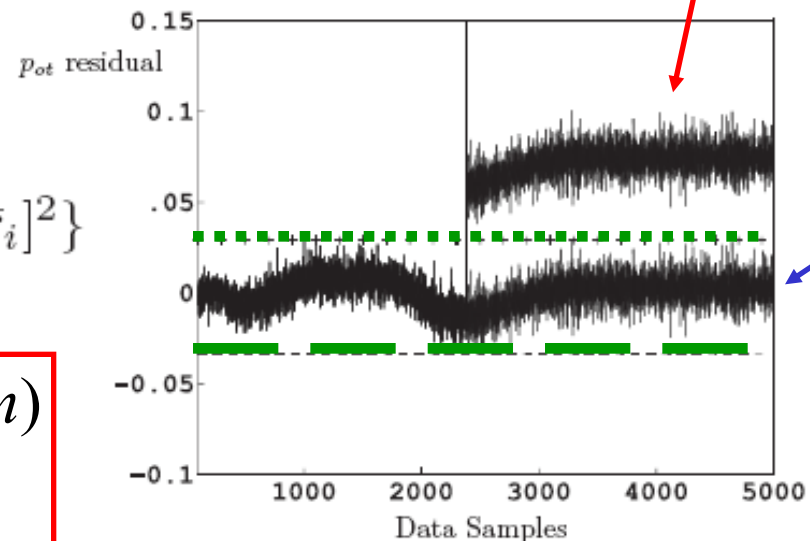
$$\bar{r}_i = E\{r_i(t)\}; \quad \bar{\sigma}_i^2 = E\{[r_i(t) - \bar{r}_i]^2\}$$

$$\varepsilon(t) = \bar{r}_i \pm \delta \times \bar{\sigma}_i \quad (i = 1, \dots, m)$$

with  $\delta \geq 3$

Faulty residual

Fault free residual





# Residual Generation

---

- ✓ Output Observers
  - Recall the output observer design
- ✓ Fault Detection
  - Fault Isolation, *i.e. where is the fault?*

# Output Observer

## Process model with faults

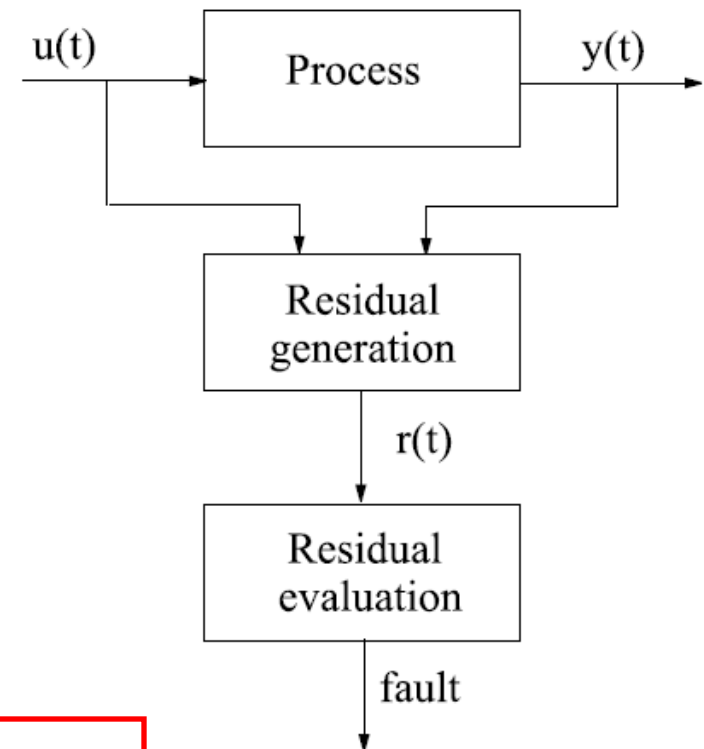
$$\begin{aligned} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}(\mathbf{u}(t) + \mathbf{f}_c(t)) + \mathbf{f}_s(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t), \end{aligned}$$

## Input-output sensor faults

$$\left. \begin{aligned} \mathbf{u}(t) &= \mathbf{f}_u(t) + \mathbf{u}^*(t) \\ \mathbf{y}(t) &= \mathbf{f}_y(t) + \mathbf{y}^*(t) \end{aligned} \right\}$$

## Observer for the i-th output $y_i(t)$

$$\mathbf{x}^i(t+1) = \mathbf{A}_i \mathbf{x}^i(t) + \mathbf{B}_i \mathbf{u}(t) + \mathbf{K}_i (y_i(t) - \mathbf{C}_i \mathbf{x}^i(t))$$



$(A_i, B_i, C_i)$  is the state-space process model



# Output Observer for *Fault Detection*

---

Given the observer model

$$\mathbf{x}^i(t+1) = \mathbf{A}_i \mathbf{x}^i(t) + \mathbf{B}_i \mathbf{u}(t) + \mathbf{K}_i (y_i(t) - \mathbf{C}_i \mathbf{x}^i(t))$$

Under fault-free assumptions

$$r_i(t) = y_i^*(t) - \hat{y}_i(t) = \mathbf{C}_i (\mathbf{x}_i(t) - \mathbf{x}^i(t)) \text{ is equal to zero.}$$

Fault detection logic

fixed threshold  $\epsilon$ ,

$$\left. \begin{array}{ll} \mathbf{r}(t) \leq \epsilon & \text{for } \mathbf{f}(t) = \mathbf{0} \\ \mathbf{r}(t) > \epsilon & \text{for } \mathbf{f}(t) \neq \mathbf{0} \end{array} \right\}$$

$\mathbf{f}(t)$  being a generic failure vector.

# Output Observer for *Fault Isolation*

$$\left. \begin{aligned} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{B}\mathbf{f}_u(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{f}_y(t) \end{aligned} \right\}$$

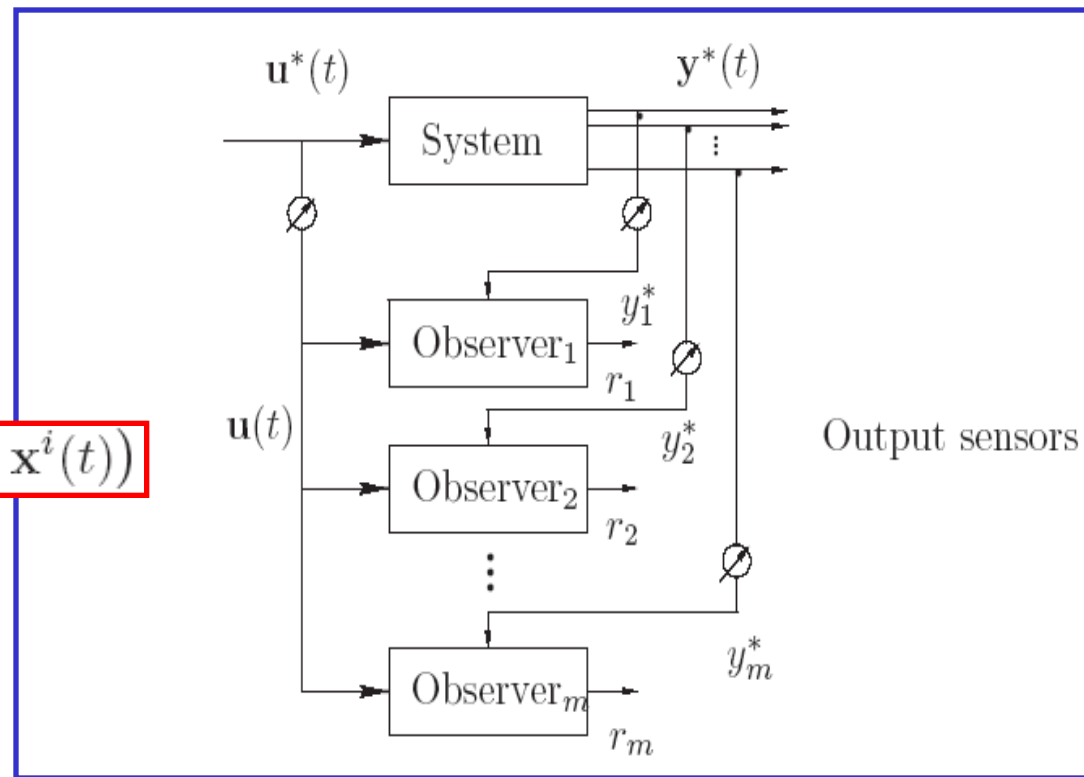
Process model

$$\begin{aligned} \mathbf{x}^i(t+1) &= \mathbf{A}_i \mathbf{x}^i(t) + \mathbf{B}_i \mathbf{u}(t) + \\ &+ \mathbf{K}_i (y_i(t) - \mathbf{C}_i \mathbf{x}^i(t)) \end{aligned}$$

$$r_i(t) = y_i^*(t) - \hat{y}_i(t) = \mathbf{C}_i (\mathbf{x}_i(t) - \mathbf{x}^i(t))$$

$$y_i(t) = y_i^*(t) + f(t)$$

**Bank of output observers**



Output sensors

## Output Observer for *Fault Isolation* (Cont'd)

### Bank of output observers

$$\mathbf{x}^i(t+1) = \mathbf{A}_i \mathbf{x}^i(t) + \mathbf{B}_i \mathbf{u}(t) + \mathbf{K}_i (y_i(t) - \mathbf{C}_i \mathbf{x}^i(t))$$

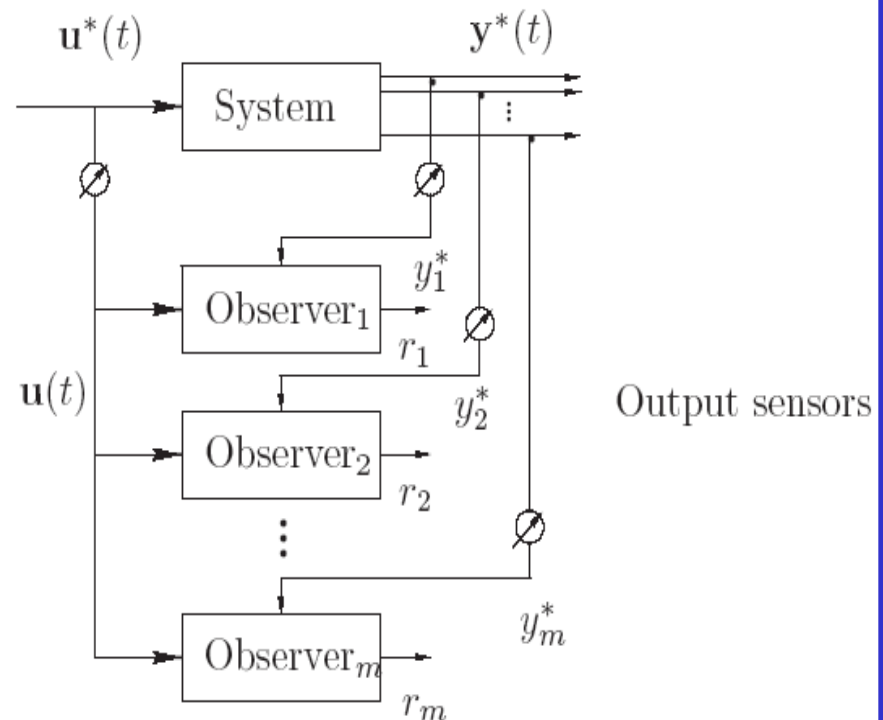
$$r_i(t) = y_i^*(t) - \hat{y}_i(t) = \mathbf{C}_i (\mathbf{x}_i(t) - \mathbf{x}^i(t))$$

*Fault-free case:*

$$\lim_{t \rightarrow \infty} r_i(t) = \lim_{t \rightarrow \infty} (y_i(t) - \mathbf{C}^i \mathbf{x}^i(t)) = 0$$

*Faulty case*

$$y_i(t) = y_i^*(t) + f(t)$$



# Output Observer for *Fault Isolation* (Cont'd)

Table 4.1: Fault signatures.

	$u_1$	$u_2$	$\dots$	$u_r$	$y_1$	$y_2$	$\dots$	$y_m$
$r_{O_1}$	1	1	$\dots$	1	1	0	$\dots$	0
$r_{O_2}$	1	1	$\dots$	1	0	1	$\dots$	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$r_{O_m}$	1	1	$\dots$	1	0	0	$\dots$	1

$$\mathbf{x}^i(t+1) = \mathbf{A}_i \mathbf{x}^i(t) + \mathbf{B}_i \mathbf{u}(t) + \mathbf{K}_i (y_i(t) - \mathbf{C}_i \mathbf{x}^i(t))$$

*Fault-free case:*

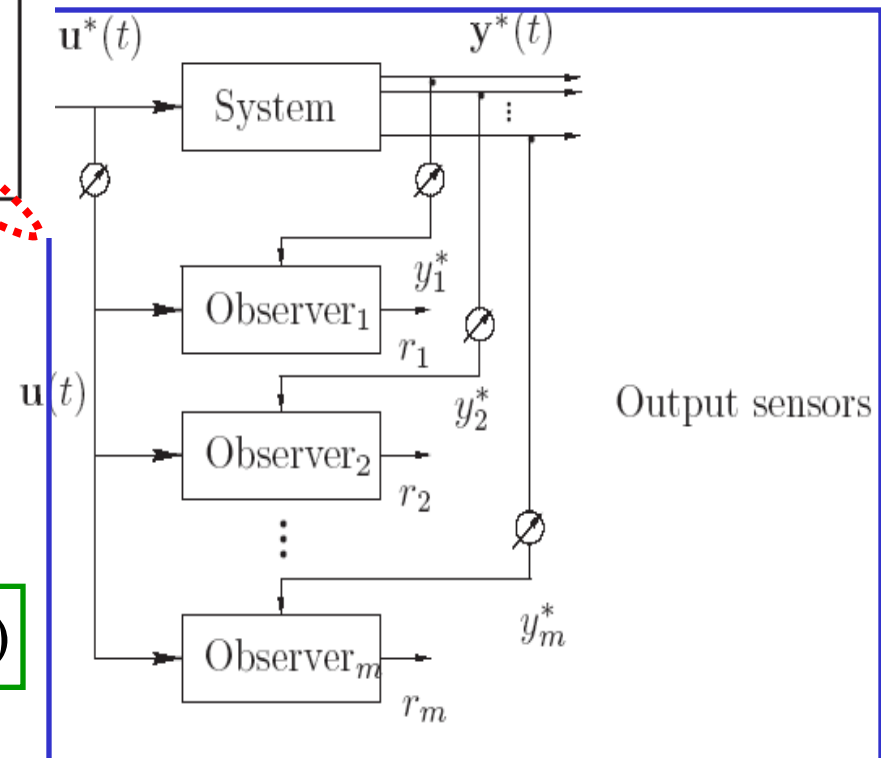
$$\lim_{t \rightarrow \infty} r_i(t) = \lim_{t \rightarrow \infty} (y_i(t) - \mathbf{C}_i^i \mathbf{x}^i(t)) = 0$$

*Faulty case*

$$y_i(t) = y_i^*(t) + f(t)$$

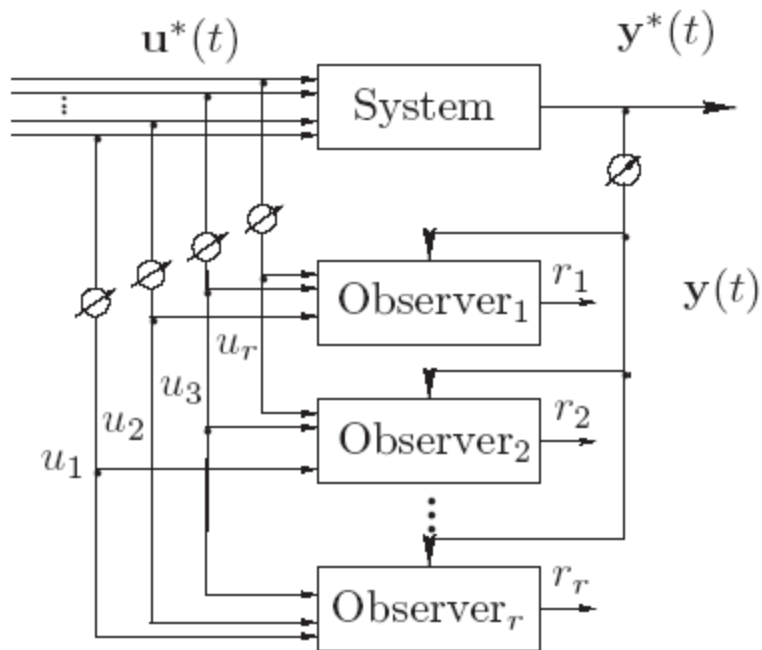
$$\lim_{t \rightarrow \infty} r_i(t) \neq 0$$

## Bank of output observers

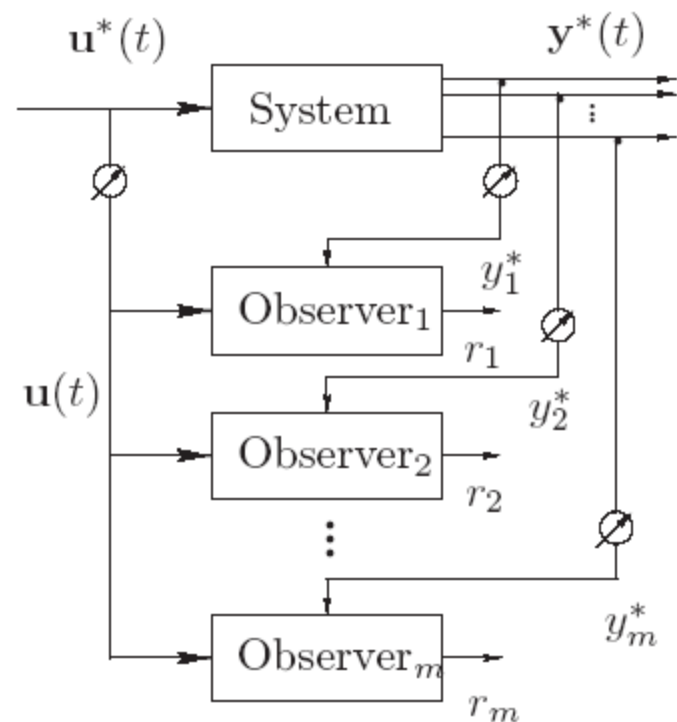




# Multiple FDI



***Input sensor FDI***



***Output sensor FDI***

# Residual Disturbance *Robustness*

- Residuals decoupled from disturbance
- Robust residual generator
- Disturbance effect minimisation
- Measurement errors

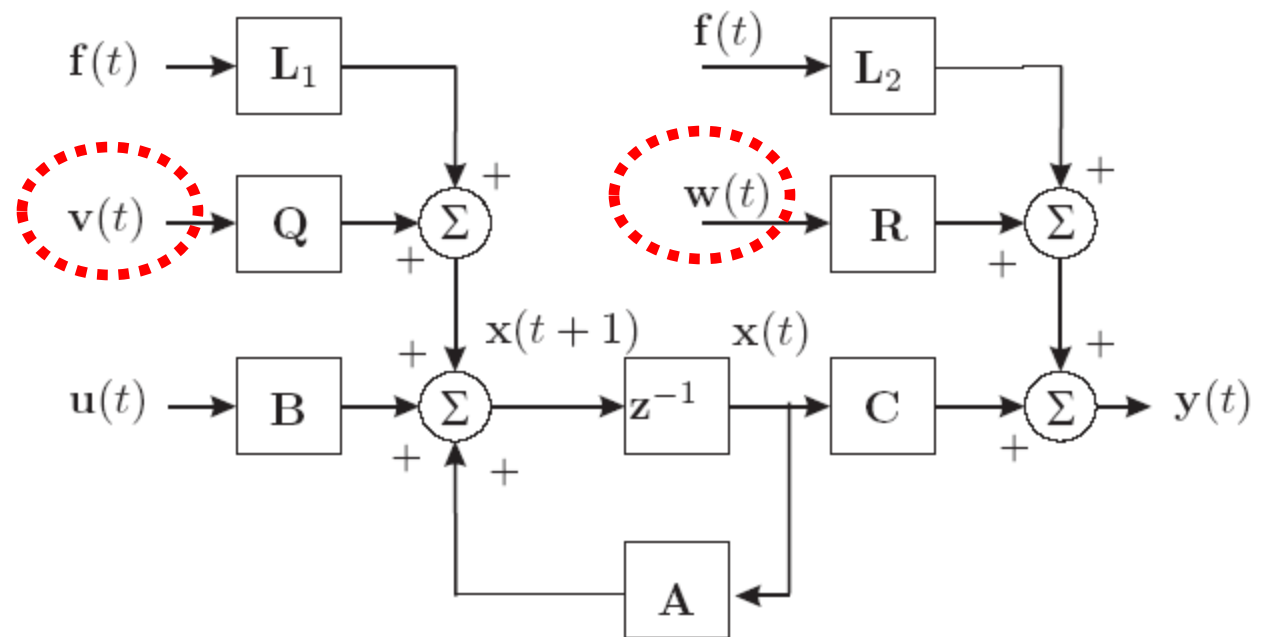


Figure 2.14: MIMO process with faults and noises.



## FDI with *Noisy Measurements*

$$\begin{cases} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{Q}\mathbf{v}(t) + \mathbf{L}_1\mathbf{f}(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{R}\mathbf{w}(t) + \mathbf{L}_2\mathbf{f}(t) \end{cases}$$

✓ Model with fault and noise

$$\begin{cases} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{Q}\mathbf{v}(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{R}\mathbf{w}(t) \end{cases}$$

➤ Model with noise only: Kalman filter!



---

# Fault Detection with Parity Equations



# Parity Relations for Fault Detection

---

- The basic idea of the parity relations approach is to provide a proper check of the **parity (consistency)** of the **measurements** acquired from the monitored system
- In the early development of fault diagnosis, the **parity vector (relation)** approach was applied to static or parallel redundancy schemes, which may be obtained **directly from measurements (hardware redundancy) or from analytical relations (analytical redundancy)**



# Parity Relations for Fault Detection

---

- In the case of hardware redundancy, two methods can be exploited to obtain redundant relations
- The first requires the use of **several sensors** having identical or **similar functions to measure the same variable**
- The second approach consists of **dissimilar sensors** to measure different variables but with **their outputs being relative to each other**
- **Analytical forms of redundancy**



# Analytical Redundancy

---

- Model ( $M$ ) and process ( $P$ )

$$G_M(z) = \frac{\hat{A}(z)}{\hat{B}(z)} \quad G_P(z) = \frac{A(z)}{B(z)}$$

- Error vector

$$\boldsymbol{r}(z) = \left( \frac{A(z)}{B(z)} - \frac{\hat{A}(z)}{\hat{B}(z)} \right) \boldsymbol{u}(z)$$



# Analytical Redundancy (**OE**)

---

- Models, if:

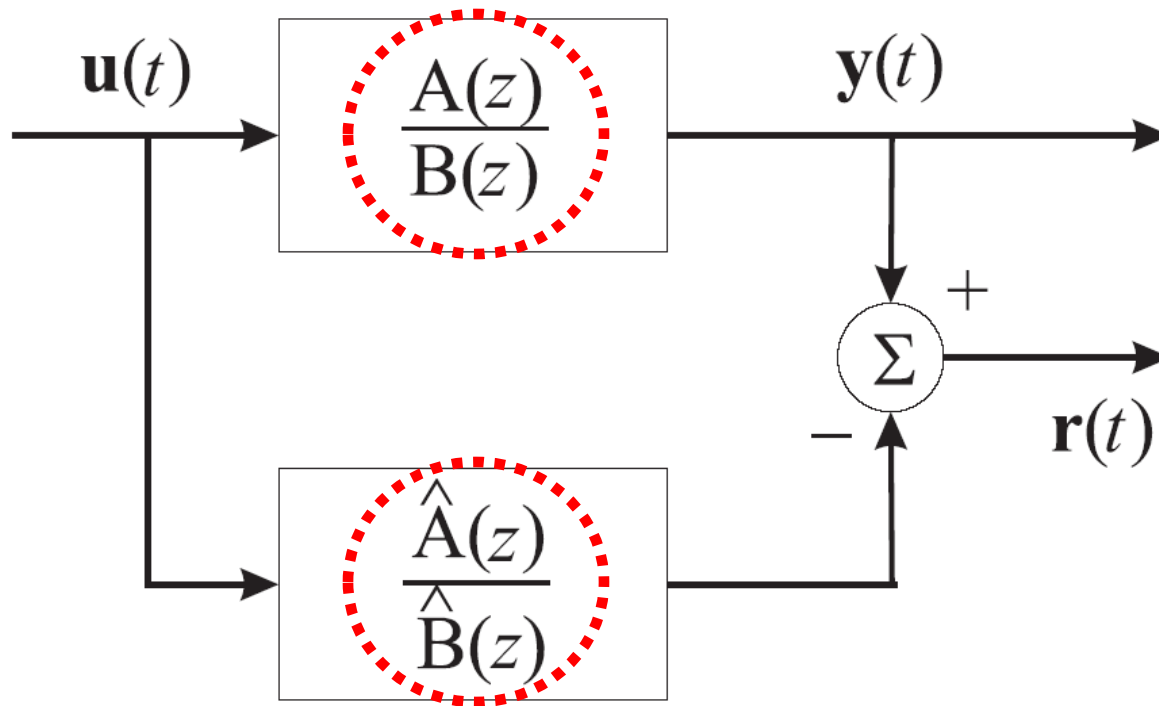
$$\mathbf{G}_M(z) = \mathbf{G}_P(z) \text{ i.e. } \frac{\hat{\mathbf{A}}(z)}{\hat{\mathbf{B}}(z)} = \frac{\mathbf{A}(z)}{\mathbf{B}(z)}$$

- Residual, with input and output faults

$$\mathbf{r}(z) = \frac{\mathbf{A}(z)}{\mathbf{B}(z)} \mathbf{f}_u(z) + \mathbf{f}_y(z)$$

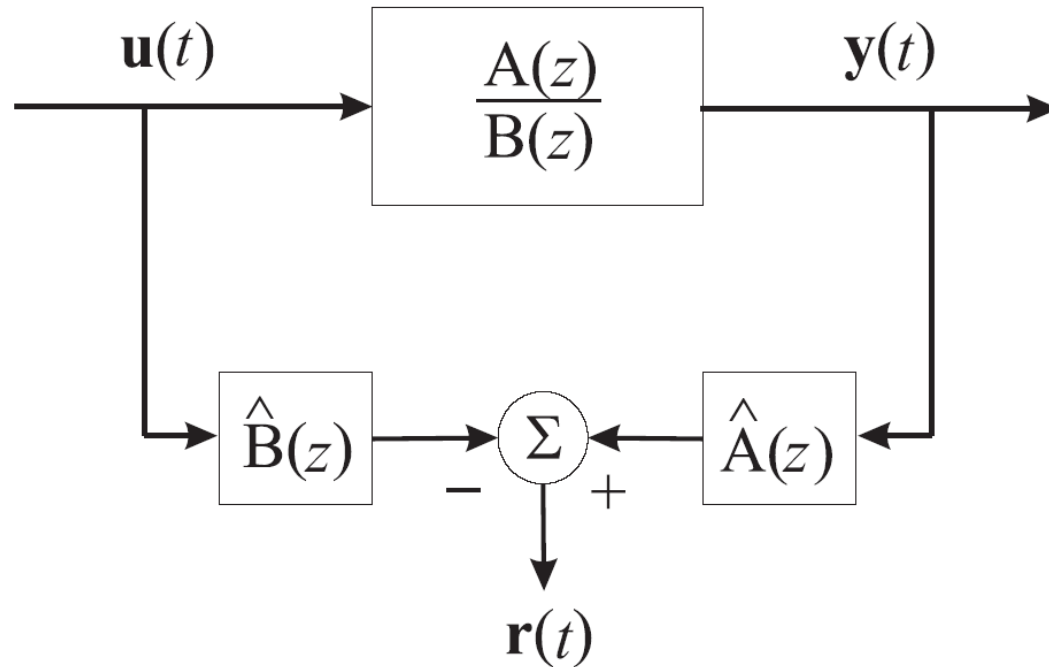


# Analytical Redundancy (**OE**)



(a) Output error

# Parity Relation (**EE**)



(b) Equation error



## Parity Relations via **EE**

---

- According to EE, another possibility for generating a polynomial error:

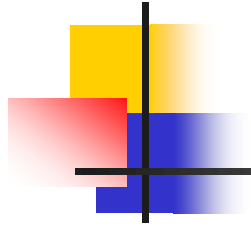
$$\begin{aligned} \boldsymbol{r}(z) &= \hat{\boldsymbol{A}}(z)\boldsymbol{y}(z) - \hat{\boldsymbol{B}}(z)\boldsymbol{u}(z) \\ &= \boldsymbol{B}(z)\boldsymbol{f}_u(z) + \boldsymbol{A}(z)\boldsymbol{f}_y(z) \end{aligned}$$



# Parity Relations

---

- The previous equations that generate residuals and are called parity equations under the assumptions of fault occurrence and **of exact agreement between process and model**
- However, within the parity equations, the model parameters are assumed to be known and constant, whereas the **parameter estimations** can vary the parameters of the polynomials in order to minimise the residuals



# Change Detection and Symptom Evaluation



# Residual Evaluation

---

- When the residual generation stage has been performed, the second step requires the examination of symptoms in order to determine if any faults have occurred
- A decision process may consist of a simple threshold test on the instantaneous values of moving averages of residuals



## Residual Evaluation (Cont'd)

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- On the other hand, because of the presence of noise, disturbances and other unknown signals acting upon the monitored system, the decision making process can exploits statistical methods
- In this case, the measured or estimated quantities, such as signals, parameters, state variables or residuals are usually represented by stochastic variables



# Residual Evaluation (Cont'd)

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- Mean and standard values

$$\bar{r}_i = E\{r_i(t)\}; \quad \bar{\sigma}_i^2 = E\{[r_i(t) - \bar{r}_i]^2\}$$

- Residuals or symptoms

$$\Delta r_i = E\{r_i(t) - \bar{r}_i\}; \quad \Delta \sigma_i = E\{\sigma_i(t) - \bar{\sigma}_i\}$$





## Residual Evaluation (Cont'd)

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- Fixed threshold selection

$$\Delta r_{tol} = \epsilon \bar{\sigma}_r, \quad \epsilon \geq 2$$

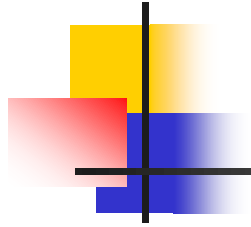
- By a proper choice of  $\epsilon$ , a compromise has to be made between the detection of small faults and false alarms
- More complex residual evaluation schemes



# Residual Generation Problem

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- **Robustness issues!**
- Two design principles:
  - Uncertainty is taken into account at the residual design stage: **active robustness in fault diagnosis**
  - **Passive robustness** makes use of a residual evaluator with proper threshold selection methods (fixed or adaptive)



# **Fault Diagnosis Technique Integration**



# FDI Technique Integration

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- Several FDI techniques have been developed and their application shows different properties with respect of the diagnosis of different faults in a process
- To achieve a reliable FDI technique, a good solution consists of a proper integration of several methods which take advantages of the different procedures
- Exploit a knowledge-based treatment of all available analytical and heuristic information



## **Fuzzy Logic** for Residual Generation

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- Classical fault diagnosis model-based methods can exploit state-space of input-output dynamic models of the process under investigation
- Faults are supposed to appear as changes on the system state or output caused by malfunctions of the components as well as of the sensors
- The main problem with these techniques is that the precision of the process model affects the accuracy of the detection and isolation system as well as the diagnostic sensitivity



## Fuzzy Logic for Residual Generation (Cont'd)

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- The majority of real industrial processes are nonlinear and cannot be modelled by using a single model for all operating conditions
- Since a mathematical model is a description of system behaviour, accurate modelling for a complex nonlinear system is very difficult to achieve in practice
- Sometimes for some nonlinear systems, it can be impossible to describe them by analytical equations

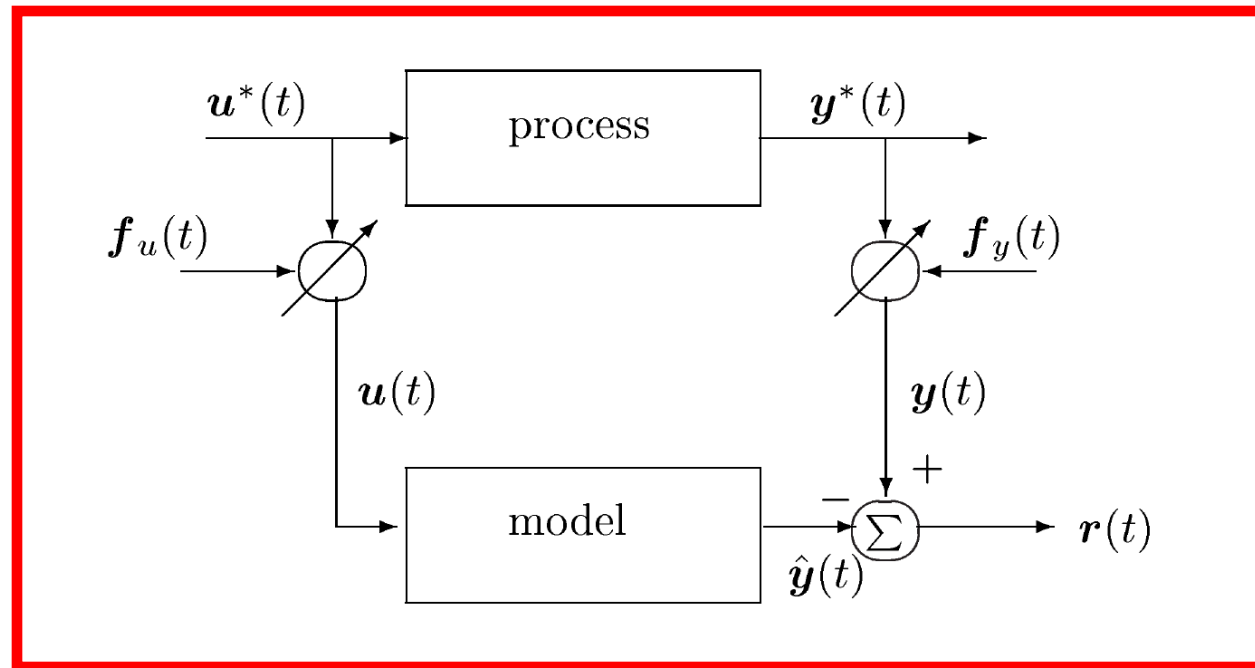


## Fuzzy Logic for Residual Generation (Cont'd)

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- Sometimes the system structure or parameters are not precisely known and if diagnosis has to be based primarily on heuristic information, no qualitative model can be set up
- Because of these assumptions, fuzzy system theory seems to be a natural tool to handle complicated and uncertain conditions
- Instead of exploiting complicated nonlinear models, it is also possible to describe the plant by a collection of local affine fuzzy models, whose parameters are obtained by identification procedures

# Residual Generation via Fuzzy Models



Residual signals:  $r(t) = y(t) - \hat{y}(t).$





# Neural Networks in Fault Diagnosis

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- Quantitative model-based fault diagnosis generates symptoms on the basis of the analytical knowledge of the process under investigation
- In most cases this does not provide enough information to perform an efficient FDI, *i.e.*, to indicate the location and the mode of the fault
- A typical integrated fault diagnosis system uses both analytical and heuristic knowledge of the monitored system



## Neural Networks in Fault Diagnosis (Cont'd)

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- The knowledge can be processed in terms of residual generation (analytical knowledge) and feature extraction (heuristic knowledge)
- The processed knowledge is then provided to an inference mechanism which can comprise residual evaluation, symptom observation and pattern recognition



## Neural Networks in Fault Diagnosis (Cont'd)

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- In recent years, neural networks (NN) have been used successfully in pattern recognition as well as system identification, and they have been proposed as a possible technique for fault diagnosis, too
- NN can handle nonlinear behaviour and partially known process because they learn the diagnostic requirements by means of the information of the training data



## Neural Networks in Fault Diagnosis (Cont'd)

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- NN are noise tolerant and their ability to generalise the knowledge as well as to adapt during use are extremely interesting properties
- FDI is performed by a NN using input and output measurements
  - NN is trained to identify the fault from measurement patterns
  - Classification of individual measurement pattern is not always unique in dynamic situations
- Fault diagnosis of dynamic plant is not practical and other approaches should be investigated



## Neural Networks in Fault Diagnosis (Cont'd)

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- A NN could be exploited in order to find a dynamic model of the monitored system or connections from faults to residuals
- In the latter case, the NN is used as pattern classifier or nonlinear function approximator
- NN are capable of approximating a large class of functions for fault diagnosis of an industrial plant
- The identification of models for the system under diagnosis as well as the application of NN as function approximator will be shown

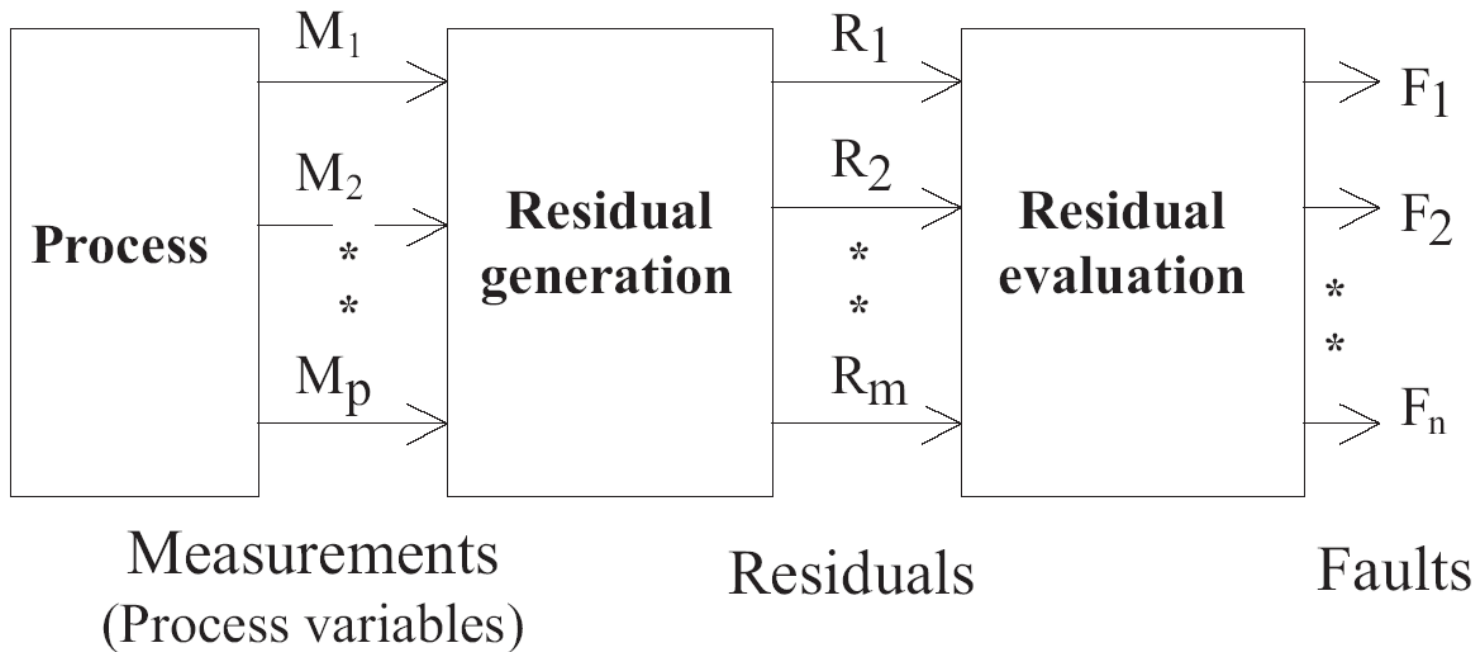


## Neural Networks in Fault Diagnosis (Cont'd)

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- Quantitative and qualitative approaches have a lot of complementary characteristics which can be suitably combined together to exploit their advantages and to increase the robustness of quantitative techniques
- Partial knowledge deriving from qualitative reasoning is reduced by quantitative methods
- Further research on model-based fault diagnosis consists of finding the way to properly combine these two approaches together to provide highly reliable diagnostic information

# FDI with Neural Networks





## FDI with Neural Networks (Cont'd)

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- As described in the figure, the fault diagnosis methodology consist of 2 stages
- In 1<sup>st</sup> stage, the fault has to be detected on the basis of residuals generated from a bank of output estimators, while, in the 2<sup>nd</sup> step, fault identification is obtained from pattern recognition techniques implemented via NN
- Fault identification represents the problem of the estimation of the size of faults occurring in a dynamic system





## FDI with Neural Networks (Cont'd)

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- A NN is exploited to find the connection from a particular fault regarding system inputs and output measurements to a particular residual
- The output predictor generates a residual which does not depend on the dynamic characteristics of the plant, but only on faults
- NNs classify static patterns of residuals, which are uniquely related to particular fault conditions independently from the plant dynamics



## FDI with Neural Networks (Cont'd)

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- NNs have been used both as predictor of dynamic models for fault diagnosis, and pattern classifiers for fault identification
- The most frequently applied neural models are the feed-forward perceptron used in multi-layer networks with static structure
- The introduction of explicit dynamics requires the feedback of some outputs through time delay units



## FDI with Neural Networks (Cont'd)

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- Alternatively to static structure, NN with neurons having intrinsic dynamic properties can be used
- On the other hand, NN can be effectively exploited for residual signal processing, which is actually a static pattern recognition problem



## FDI with Neural Networks (Cont'd)

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- Fault signals create changes in several residuals obtained by using output predictors of the process under examination
- A neural network is exploited in order to find the connection from a particular fault regarding input and output measurements to a particular residual



## FDI with Neural Networks (Cont'd)

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- The predictors generate residuals independent of the dynamic characteristics of the plant and dependent only on sensors faults
- Therefore, the neural network evaluates static patterns of residuals, which are uniquely related to particular fault conditions independently from the plant dynamics



# Conclusion

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- ✓ Model-Based FDI
- ✓ Analytical Redundancy
- ✓ State-Space Models
- ✓ Residual Generation
  - ✓ Dynamic Observers
    - ✓ Output observers
- ✓ Residual Evaluation/Change Detection