TECNICHE DI CONTROLLO E DIAGNOSI

Diagnosi Automatica dei Guasti

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Lecture Main Topics

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

Nomenclature

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)

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.

Introduction

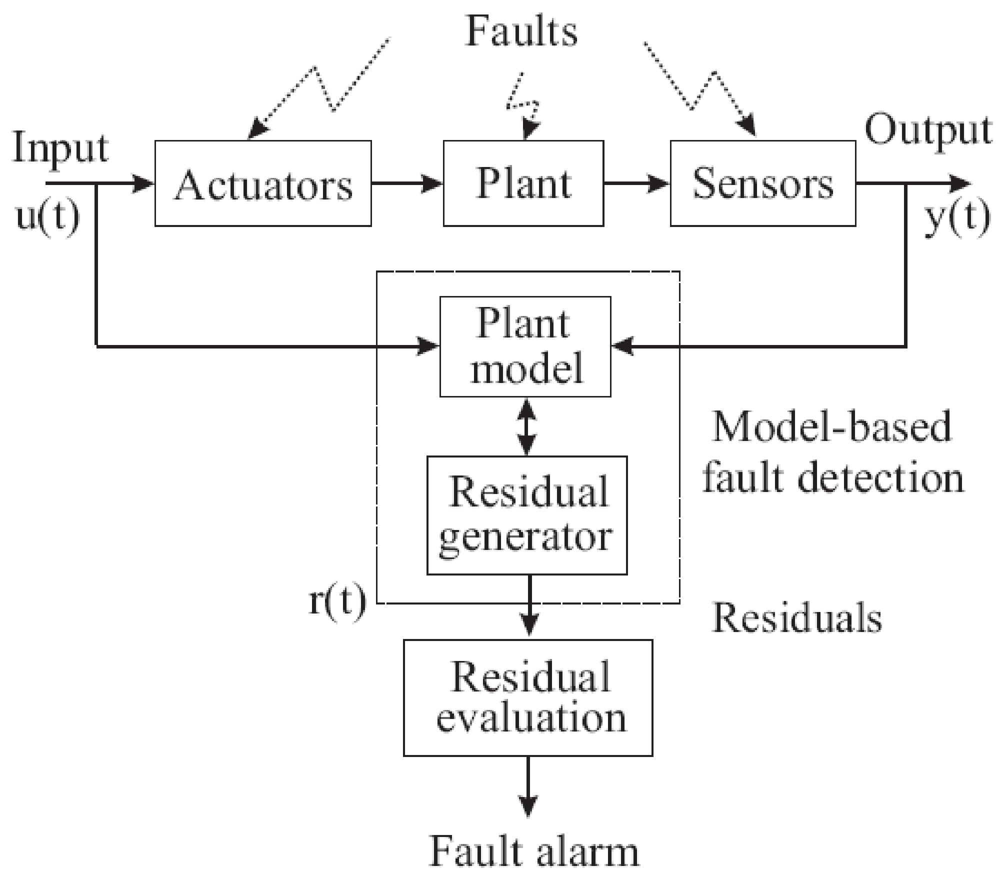


Figure 1.2: Scheme for the model–based fault detection.

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
- Normally zero or close to zero under no fault condition, whilst distinguishably different from zero when a fault occurs

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
- 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)

- Model-Based FDI Methods:

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

Model-based FDI Techniques

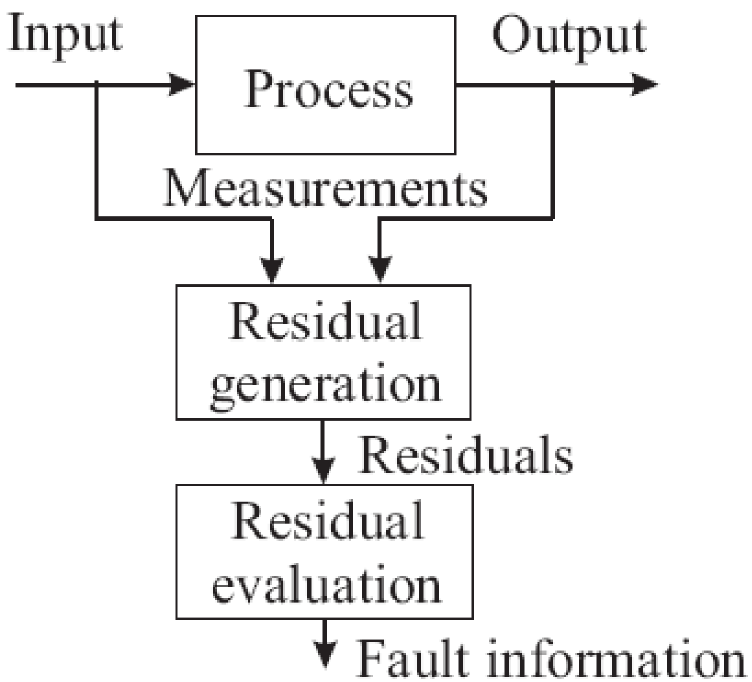


Figure 2.1: Structure of model-based FDI system.

Model-based FDI Techniques (cont'd)

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)

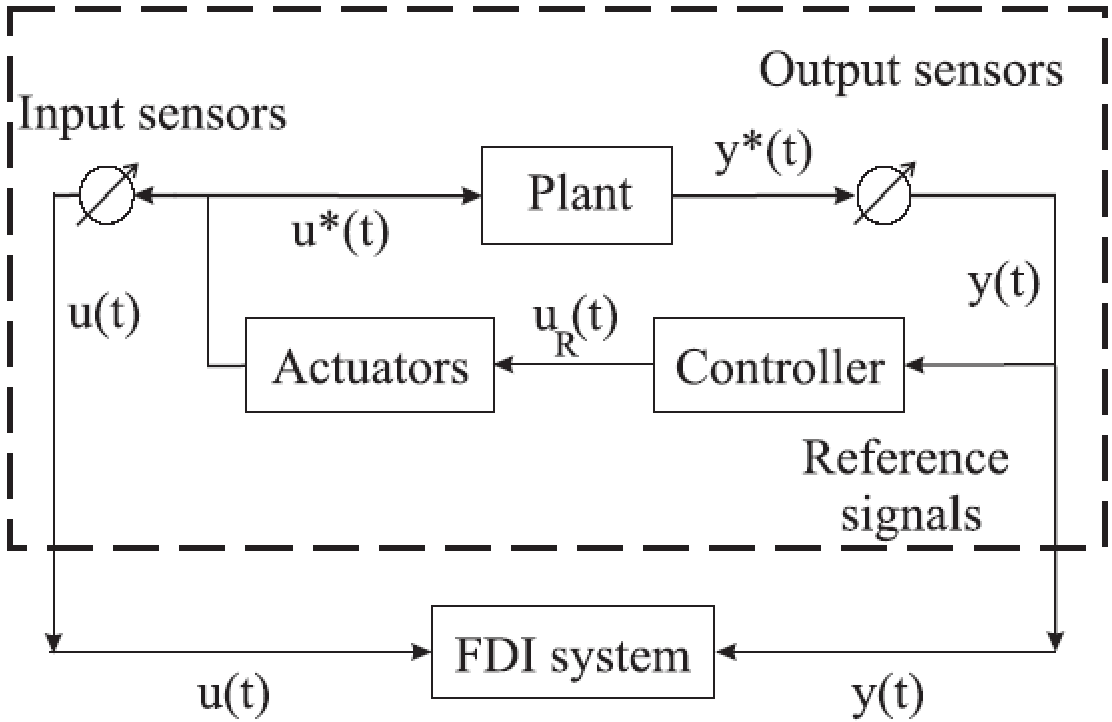


Figure 2.3: The rearranged fault diagnosis scheme.

Model-based FDI Techniques (cont'd)

Fault Location:

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

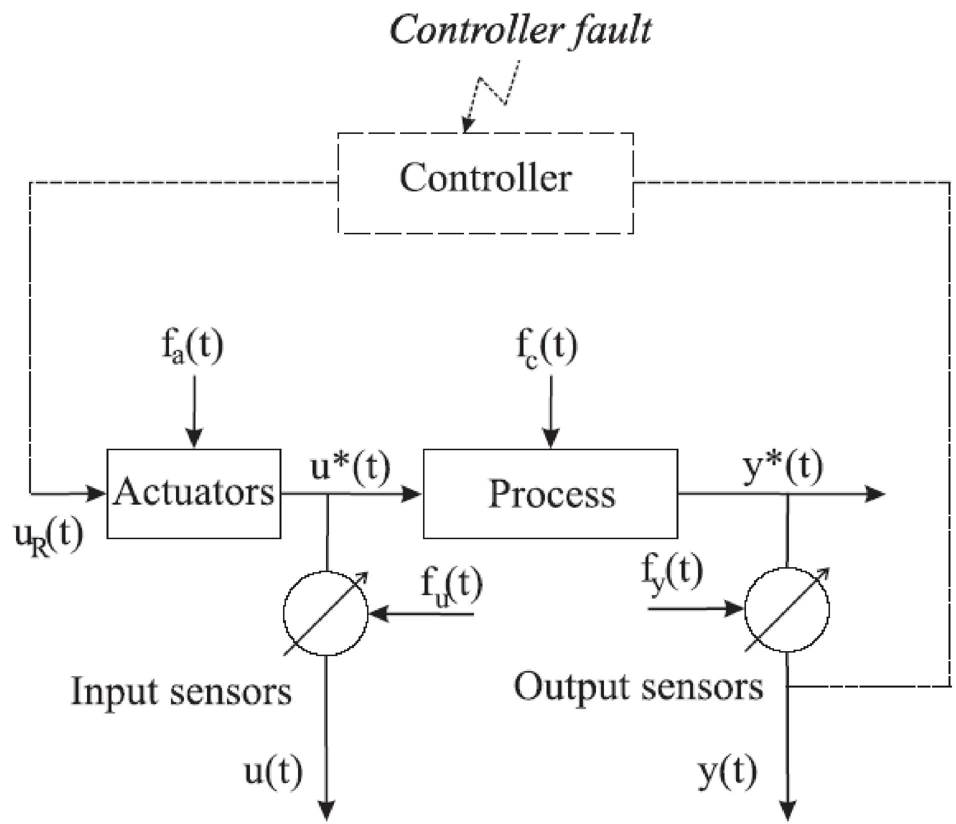


Figure 2.4: The controlled system and fault topology.

Fault and System Modelling

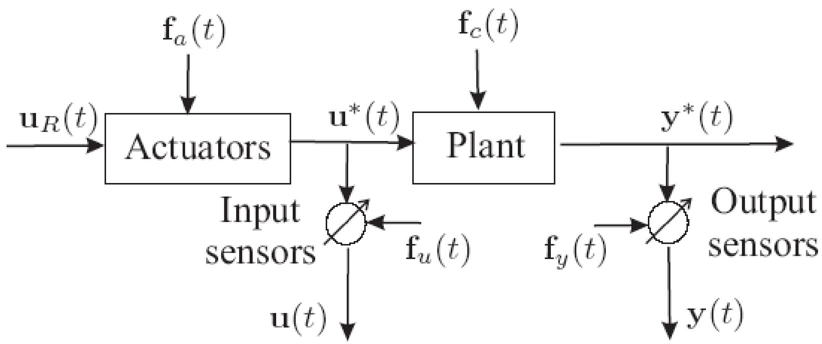


Figure 2.5: The monitored system and fault topology.

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

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

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

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

Fault and System Modelling

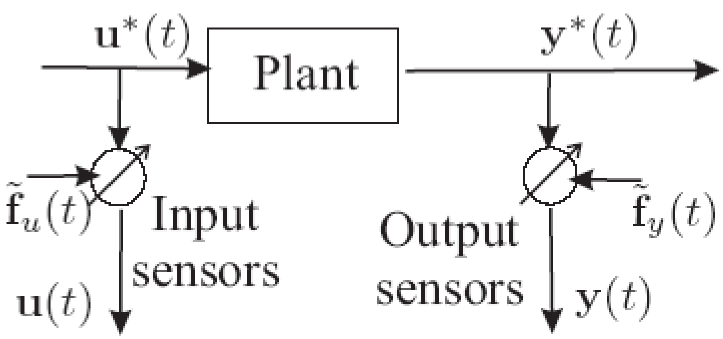
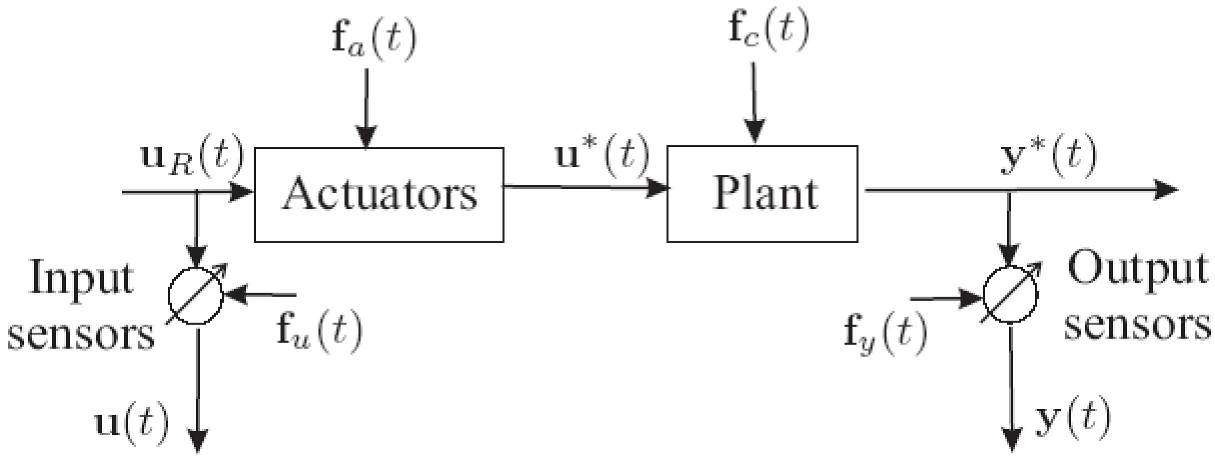


Figure 2.6: The structure of the plant sensors.

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

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

Fault and System Modelling



$$\mathbf{u}^*(t) = \mathbf{u}_R(t) + \mathbf{f}_a(t)$$

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

Model-based FDI Techniques (cont'd)

- Modelling of Faulty Systems

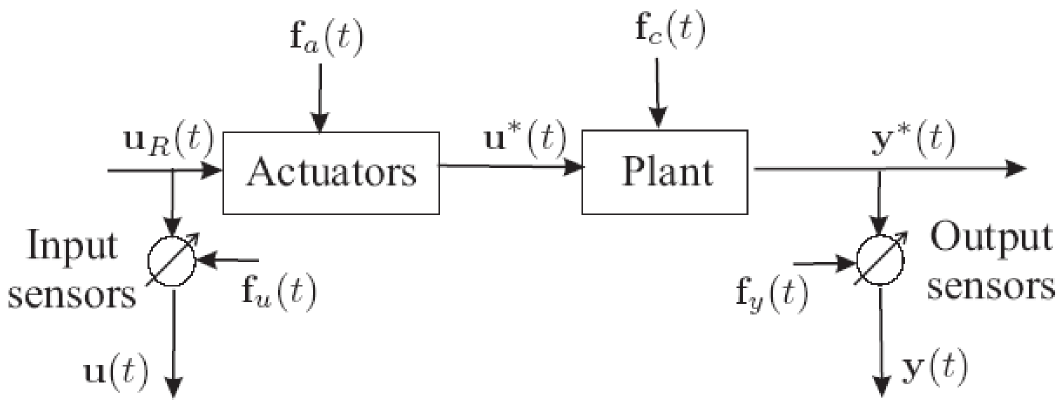


Figure 2.7: Fault topology with actuator input signal measurement.

$$\mathbf{f}(t) = [\mathbf{f}_a^T,\ \mathbf{f}_u^T,\ \mathbf{f}_c^T,\ \mathbf{f}_y^T]^T \in \Re^k$$

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

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

Residual Generator Structure

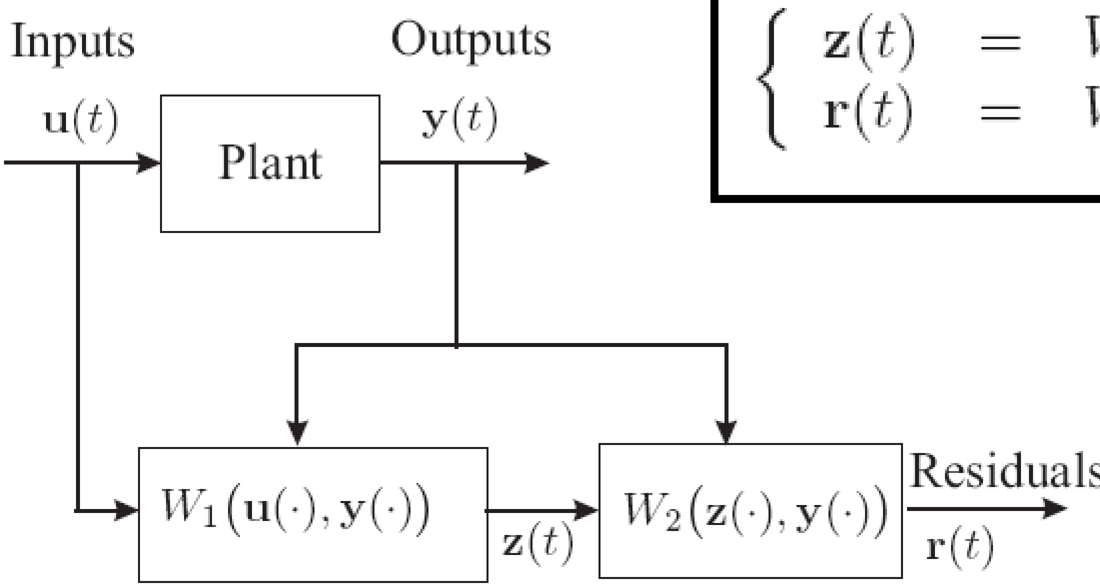


Figure 2.8: Residual generator general structure.

$$\begin{cases} \mathbf{z}(t) = W_1\big(\mathbf{u}(\cdot),\mathbf{y}(\cdot)\big) \\ \mathbf{r}(t) = W_2\big(\mathbf{z}(\cdot),\mathbf{y}(\cdot)\big) = \mathbf{0}. \end{cases}$$

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

Residual General Structure (cont'd)

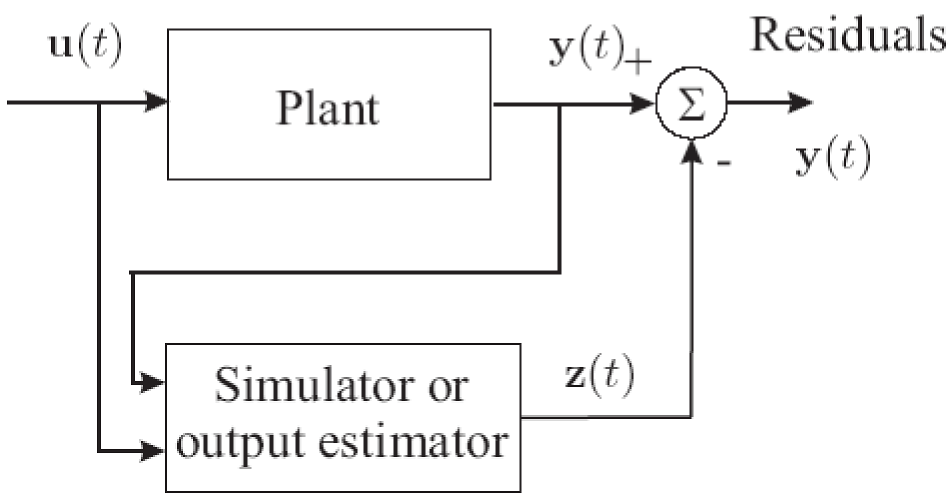


Figure 2.9: Residual generation via system simulator.

Residual generation via system simulator

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

z(t) is the simulated plant output

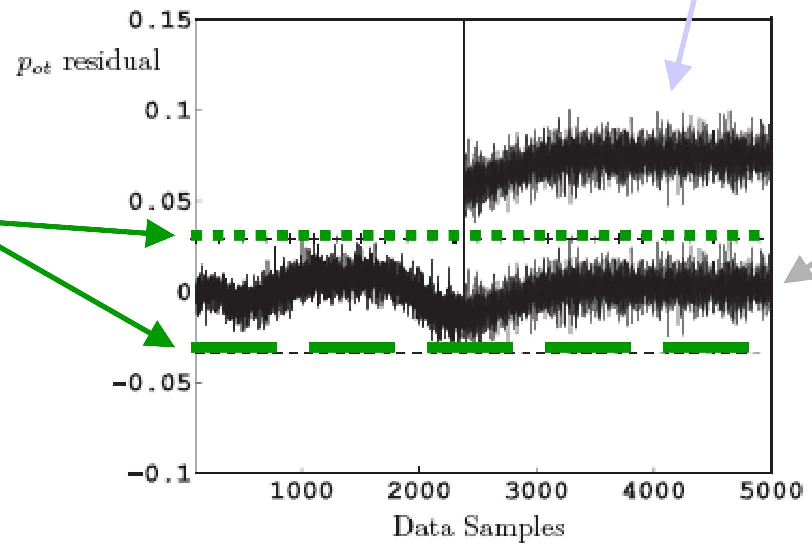
General Residual Evaluation

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

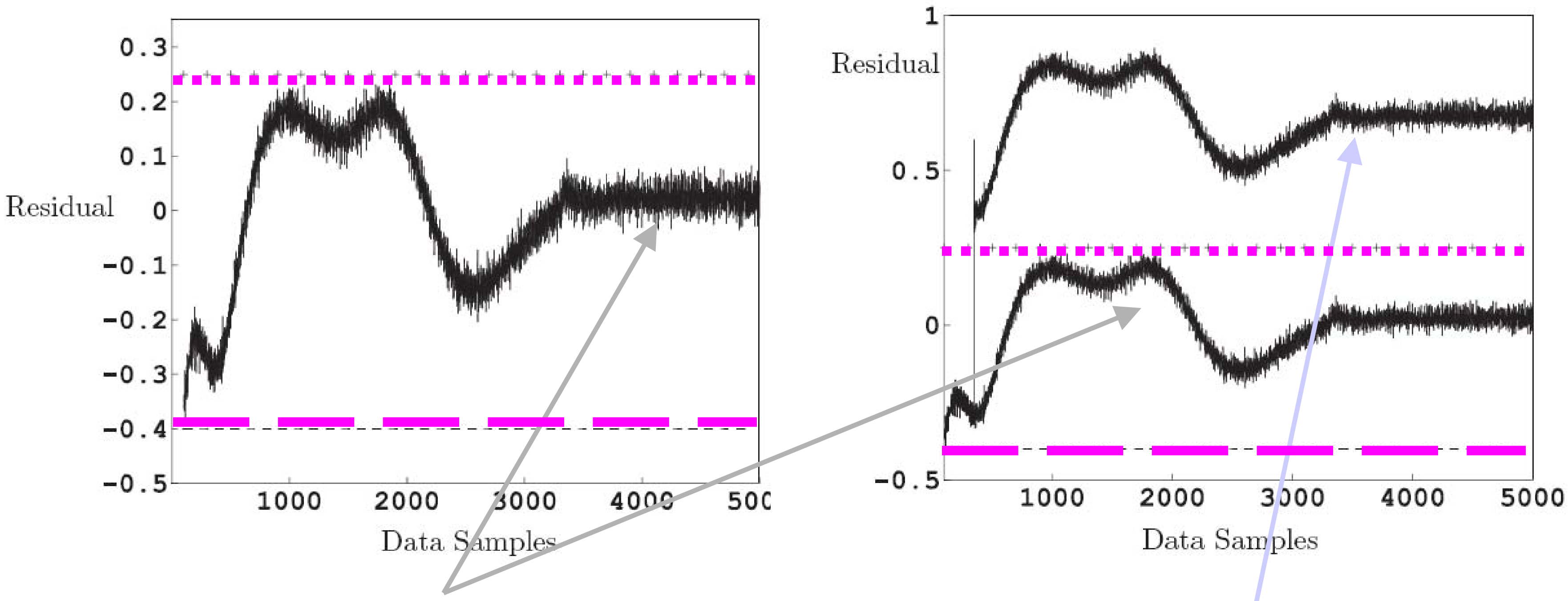
Faulty residual

Fault free residual

Detection thresholds ε(t)



Detection thresholds



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

Residual Generation Techniques

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

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

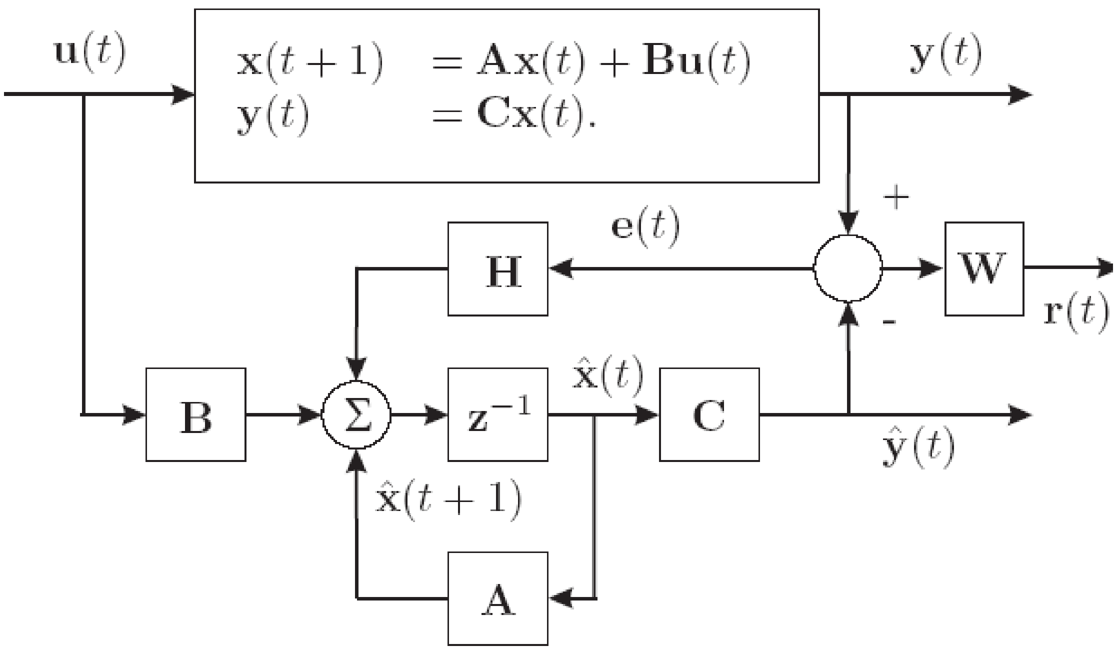
Parameter Estimation (cont'd)

- 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

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

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

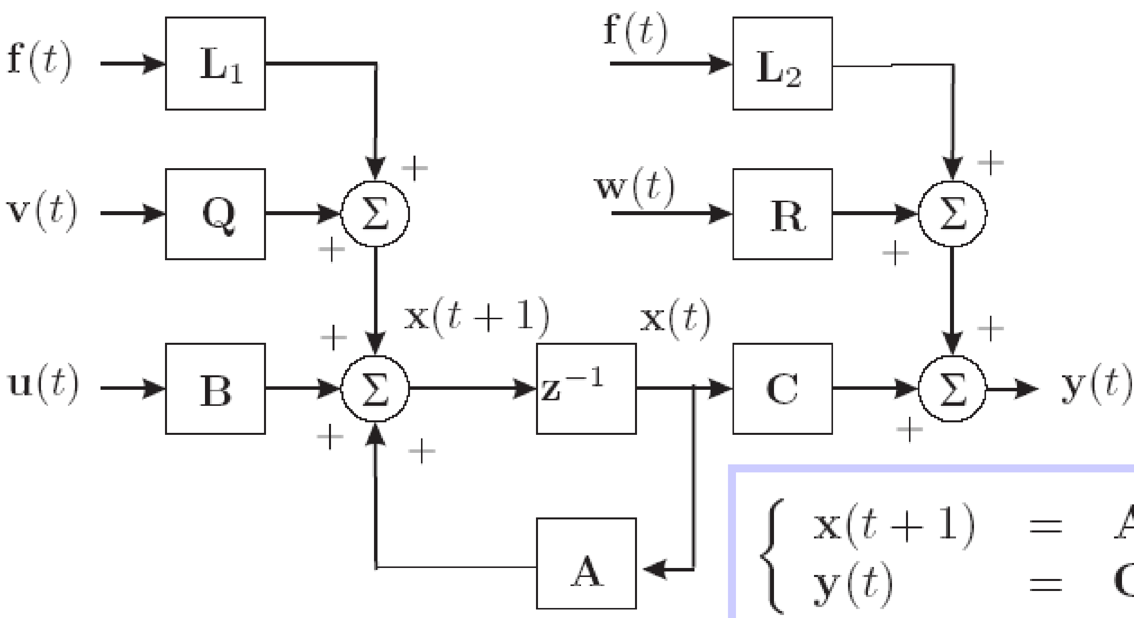
State estimation model

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

State estimation property $\lim_{t \to \infty} \mathbf{e}_x(t) = \mathbf{0}$ *(fault-free case!!!)*

Residual Generator Property

+ disturbance signals and fault



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

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 *e(t)* and e_x(t) are suitable residuals!

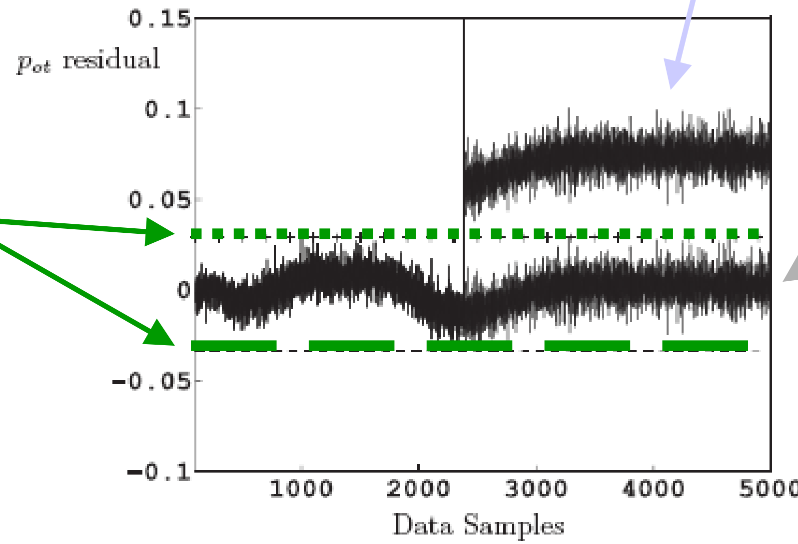
General Residual Evaluation

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

Faulty residual

Fault free residual

Detection thresholds ε(t)



Change Detection & Residual Evaluation

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

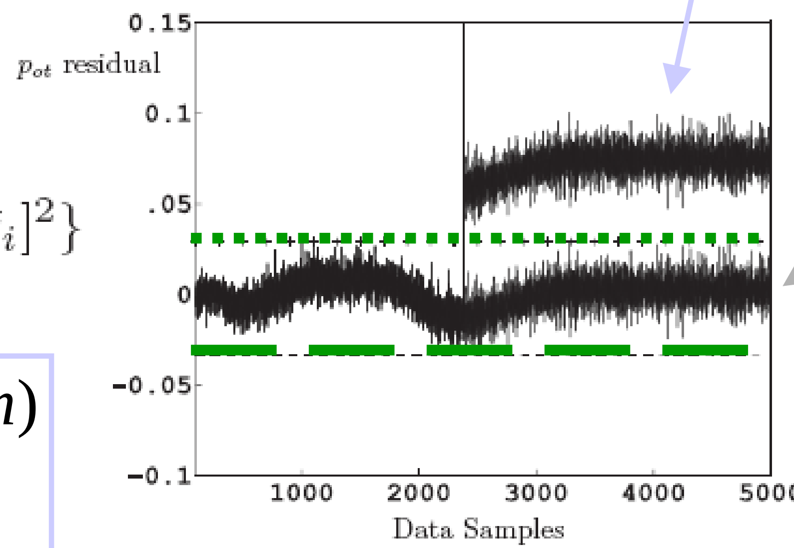
$$J(r(t)) \equiv |r(t)|$$

Detection thresholds $\varepsilon(t)$

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

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

with $\delta \ge 3$



Residual Generation

- ✓ Output Observers
- ➢ Unknown Input Observers
- ✓ Fault Detection

- ❖ Fault Isolation, *i.e. where is the fault*?

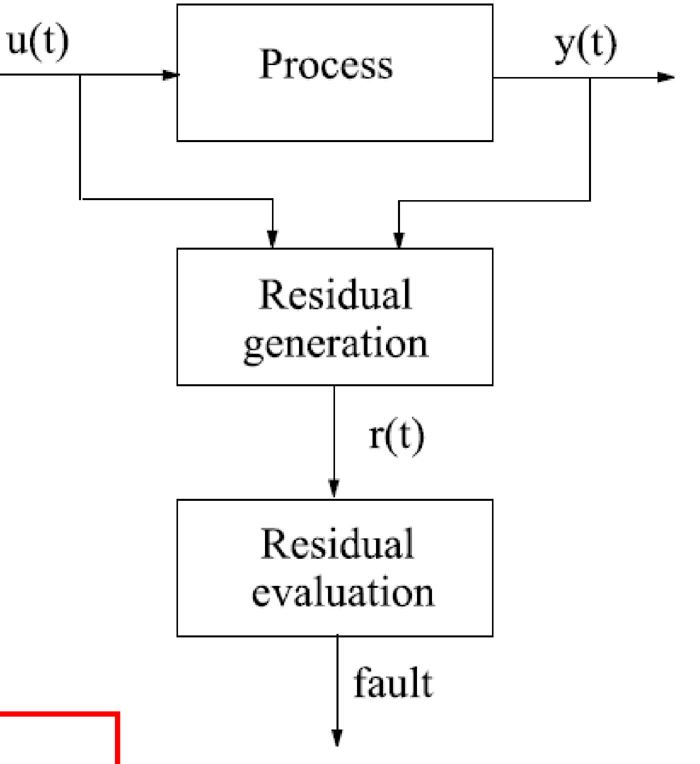
Output Observer

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 $y_i(t)$

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

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

Output Observer for *Fault Detection*

Given the observer model

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

Under fault-free assumptions

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

Fault detection logic

fixed threshold ϵ,

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

$\mathbf{f}(t)$ 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

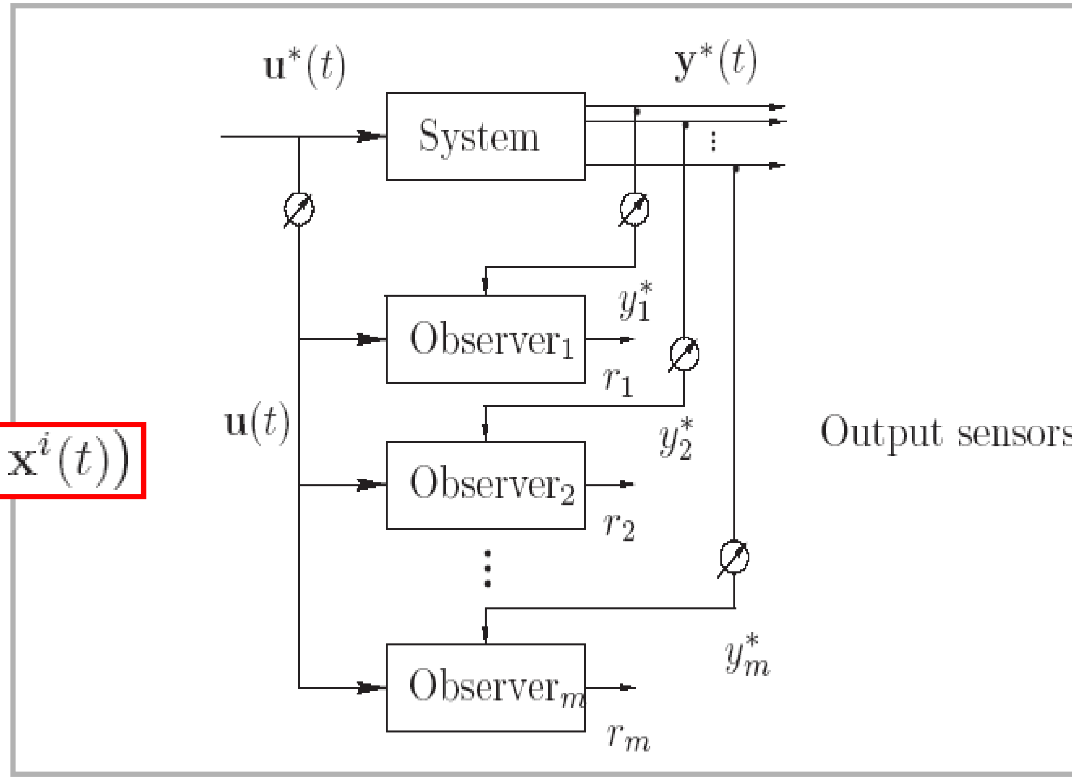
Bank of output observers

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

$$+ \mathbf{K}_i\left(y_i(t) - \mathbf{C}_i\mathbf{x}^i(t)\right)$$

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

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



Output Observer for *Fault Isolation* (cont'd)

Bank of output observers

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

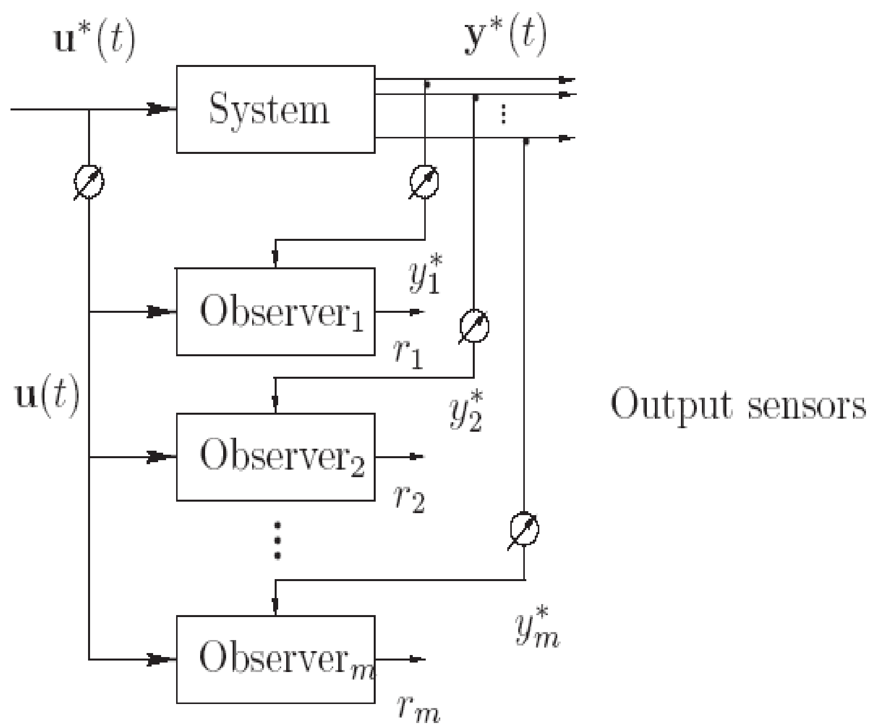
$$r_i(t) = y_i^*(t) - \hat{y}_i(t) = \mathbf{C}_i\left(\mathbf{x}_i(t) - \mathbf{x}^i(t)\right)$$

Fault-free case:

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

Faulty case

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



Residual Disturbance *Robustness*

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

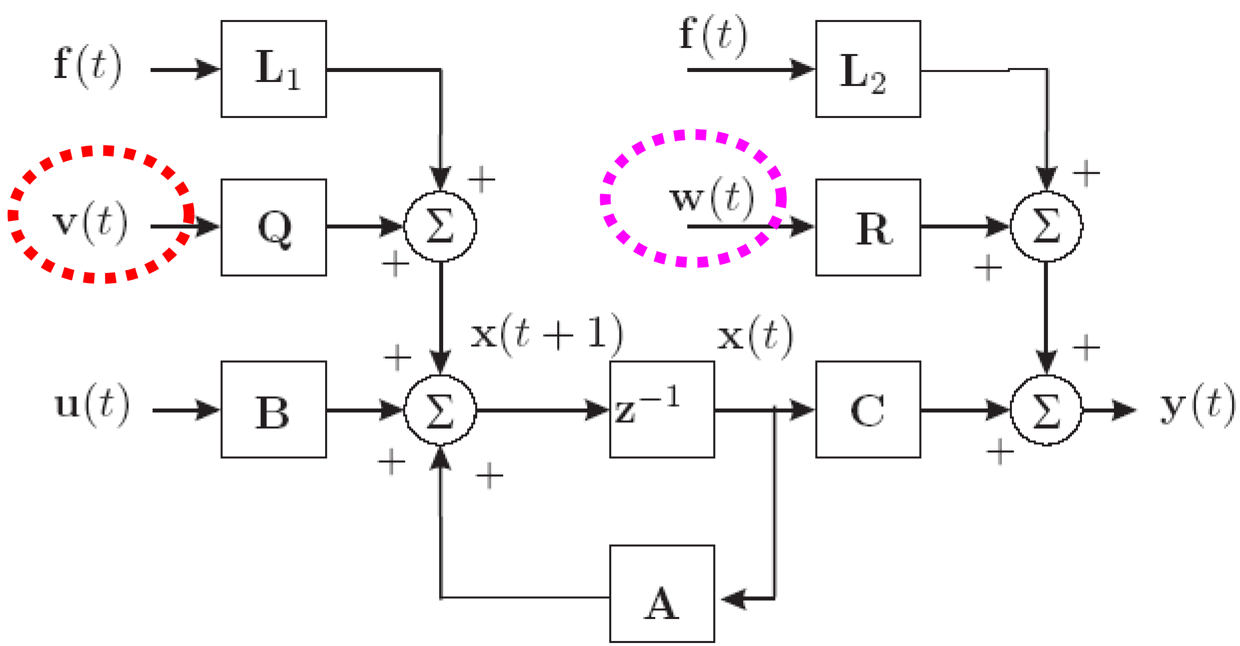


Figure 2.14: MIMO process with faults and noises.

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!

Kalman Filter Properties (cont'd)

- Defined:
  - It minimises: $e(t) = x(t) - \hat{x}(t)$
  - *i.e.* the mean square error & the error covariance matrix $\mathrm{E}\left[e^T(t)\,e(t)\right] \equiv P(t)$
- Filter gain $K(t)$
  - Solution of the difference equation:

$$P(t+1) = -A\,P(t)\,C^T\left[R + C\,P(t)\,C^T\right]^{-1} C\,P(t)\,A^T + \\ + A\,P(t)\,A + Q$$

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

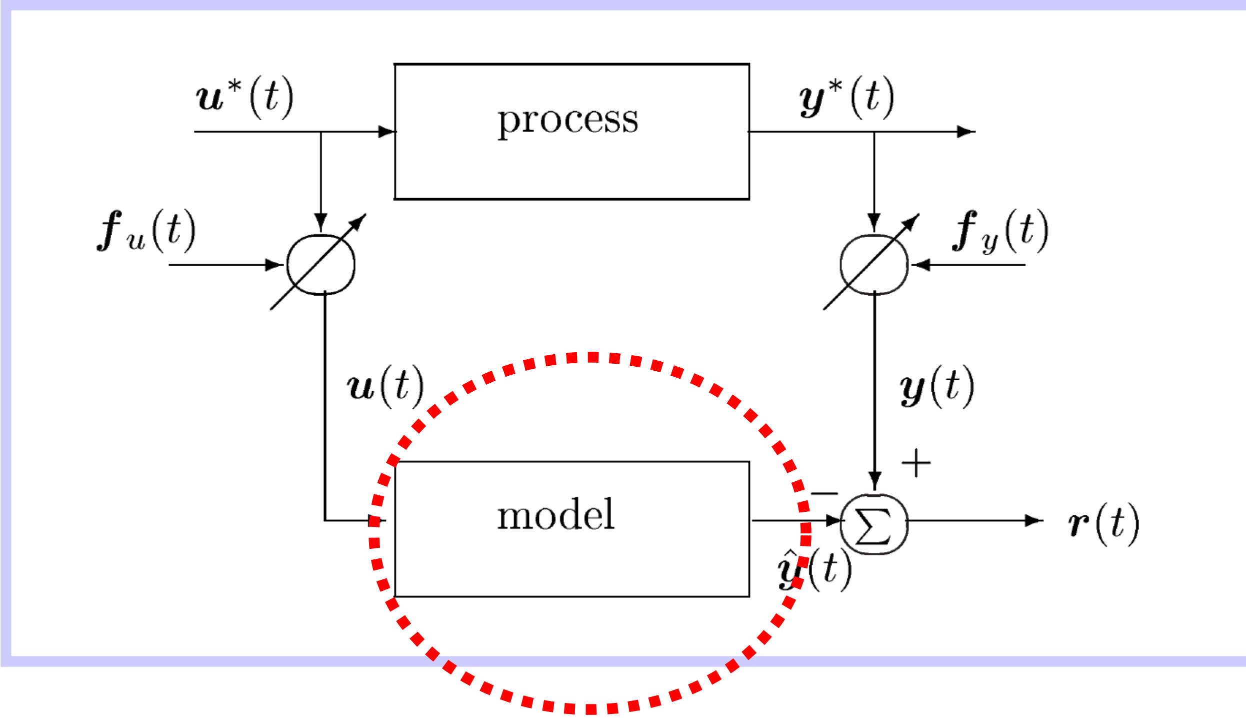
- **Analytical forms of redundancy**

Fault Diagnosis Technique Integration

FDI Technique Integration

- 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

Residual Generation via Heuristic Models



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

Model: fuzzy system or neural network!!!