Model-Based Fault Diagnosis for Dynamic Processes Using Identification Techniques

Silvio Simani
Department of Engineering
University of Ferrara
Via Saragat, 1E - 44100 Ferrara (FE)
ITALY
Ph: +39 0532 97 4844
Fax: +39 0532 97 4870
URL: **www.ing.unife.it/simani**
Email: **silvio.simani@unife.it**

Projects & Research Topics

- *Turbocharged Diesel Engine Modelling for Nonlinear Controller Design (2007-2009)*
- *Computerised Decision Support Systems* for Oral Anticoagulant Treatment (OAT) Dose Management (2005-2007)
- Development of *Fault Tolerant NGC (Navigation, Guidance & Control)* Algorithms for CUAV (Civil Unmanned Aerial Vehicle) Patrolling & Rescue Missions in Harsh Environment (2004-2008, 2009-2011)
- Wind turbine FDI and FTC (2010-2012)

Fault Diagnosis Issues

- In practical situations, the straightforward application of model-based FDI techniques can be difficult, due to the dynamic model complexity
- Viable procedure for the practical application of FDI techniques is really necessary
- Possible solutions...

Main Points

- ***Dynamic model identification*** **for FDI is successfully used**
  - **the requirement for physical modelling is obviated**
- ✓ **Linear and nonlinear dynamic prototypes**
  - **Linear identified models**
    - Monitoring of the operation and performance of the system w.r.t. an expected working condition
  - **Nonlinear identified models**
    - Different working conditions

Main Points (Cont'd)

- The main challenges are to provide a technology for signalling the onset of faults before expensive failure occurs
- Methodology considered along with maintenance schedules with an aim to cut down maintenance cost, while steadily improving the reliability of the system
- Important implication on the use of on-line FDI and diagnostic tools once the dynamic process is under customer operation
- Structural simplicity when compared with different schemes

Industrial Example: Related Project (2007-2009)

- ✓ **Control scheme calibration and tuning for commercial diesel engines (boats, ships, farm tractors, ...)**
  - **Diesel engine modelling and identification**
    - **grey-box**: analytical approach and identification (~1 year)
    - **black-box**: fuzzy modelling and identification (~1 week!)
  - ***BOSCH* Electronic Control Unit (ECU)**

Physical Modelling

✓ **State parameters**
- P, T, ρ, c, W, ...
- N (speed)
- X (chemical composition)
- ...

✓ **Variables**
- ...

✓ **Equations**
- Mass conservation
- Energy conservation
- Momentum conservation
- Motion quantity conservation
- State equations
- Transformation equations

FDI Application Review

- About 250 documents (Springer, Blackwell, Elsevier conference proceedings, and journals) – years: 1995 – 2009 + IEEE/IEE (journals, transactions, letters, magazines, conference proceedings, and standards) – years: 1969 – 2009

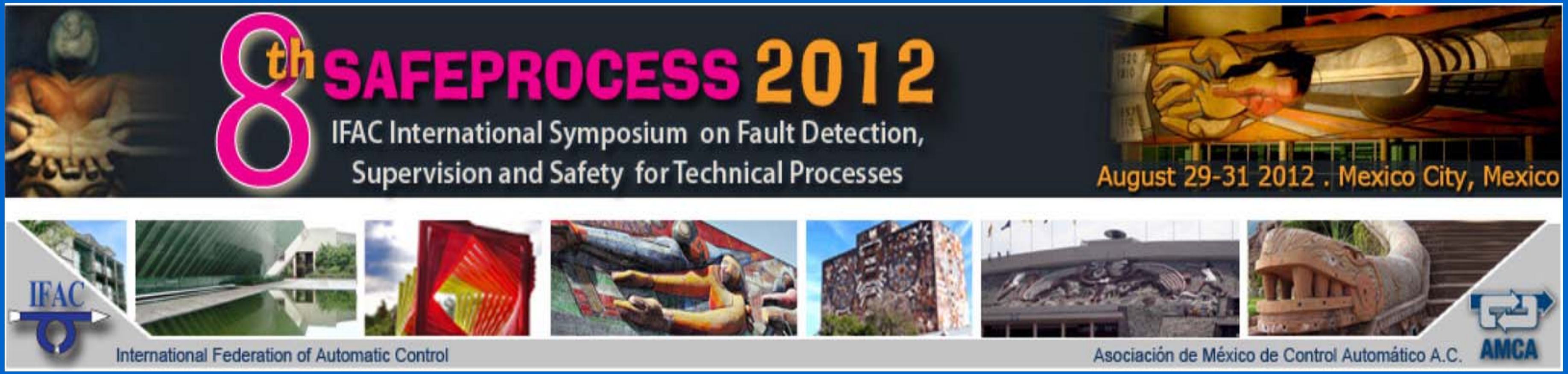
PROCESS MODEL		CONTRIBUTIONS
Real Process Data		29%
Simulation Models		28%
Linearised (Approximate) Models		15%
Identification/Estimation	Linear Regression Models	8%
	Nonlinear Models	8%
	Fuzzy Prototypes	4%
	Neural Networks	8%

FDI Application Review (Cont'd)

FAULT DETECTION METHOD	CONTRIBUTIONS
Observer/Filter	9%
Parameter Estimation	5%
Frequency Spectral Analysis	20%
Fuzzy Techniques	6%
Neural Networks	9%
Statistical Methods	17%
Geometrical Methods	28%
Wavelet Analysis	6%

REASONING STRATEGIES	CONTRIBUTIONS
Bayes Method	15%
Decision Trees	17%
Fuzzy Logic	16%
Neural Networks	20%
Geometrical Methods	32%

Forthcoming Event



IFAC

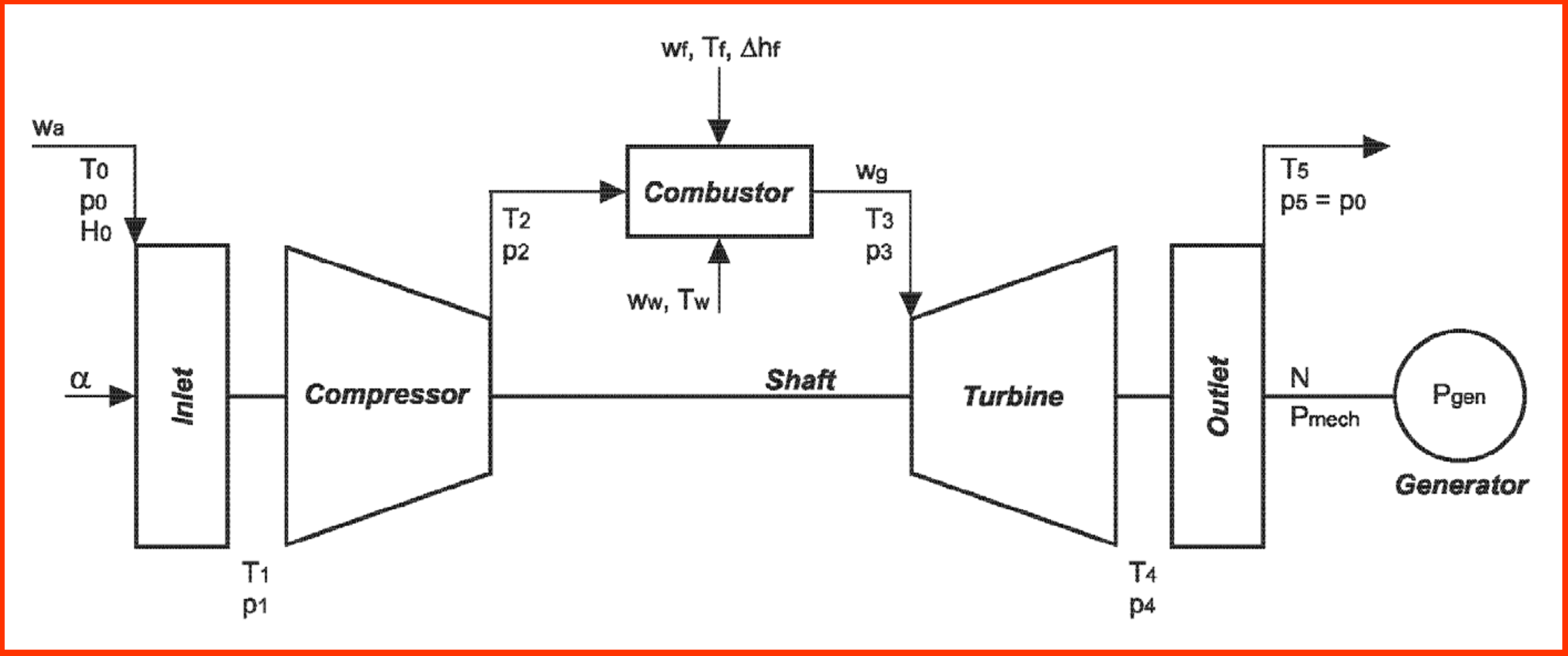
Invited session proposals
September 30, 2011
Submission of draft papers
October 15, 2011
Notification of acceptance
March 12, 2012
Final paper submission
May 15, 2012
Early registration
May 15, 2012

This Talk: Introduction

- **Simulation models**
  - **Industrial gas turbine: *Example 1* - Linear approach**
  - **Wind turbine: *Example 2* – Nonlinear scheme**
- **Dynamic system identification & residual generator design**
- **Actuator & sensor FDI**
- **Simulation results**
- **Reliability & robustness analysis**
- **Comparisons with different FDI schemes**

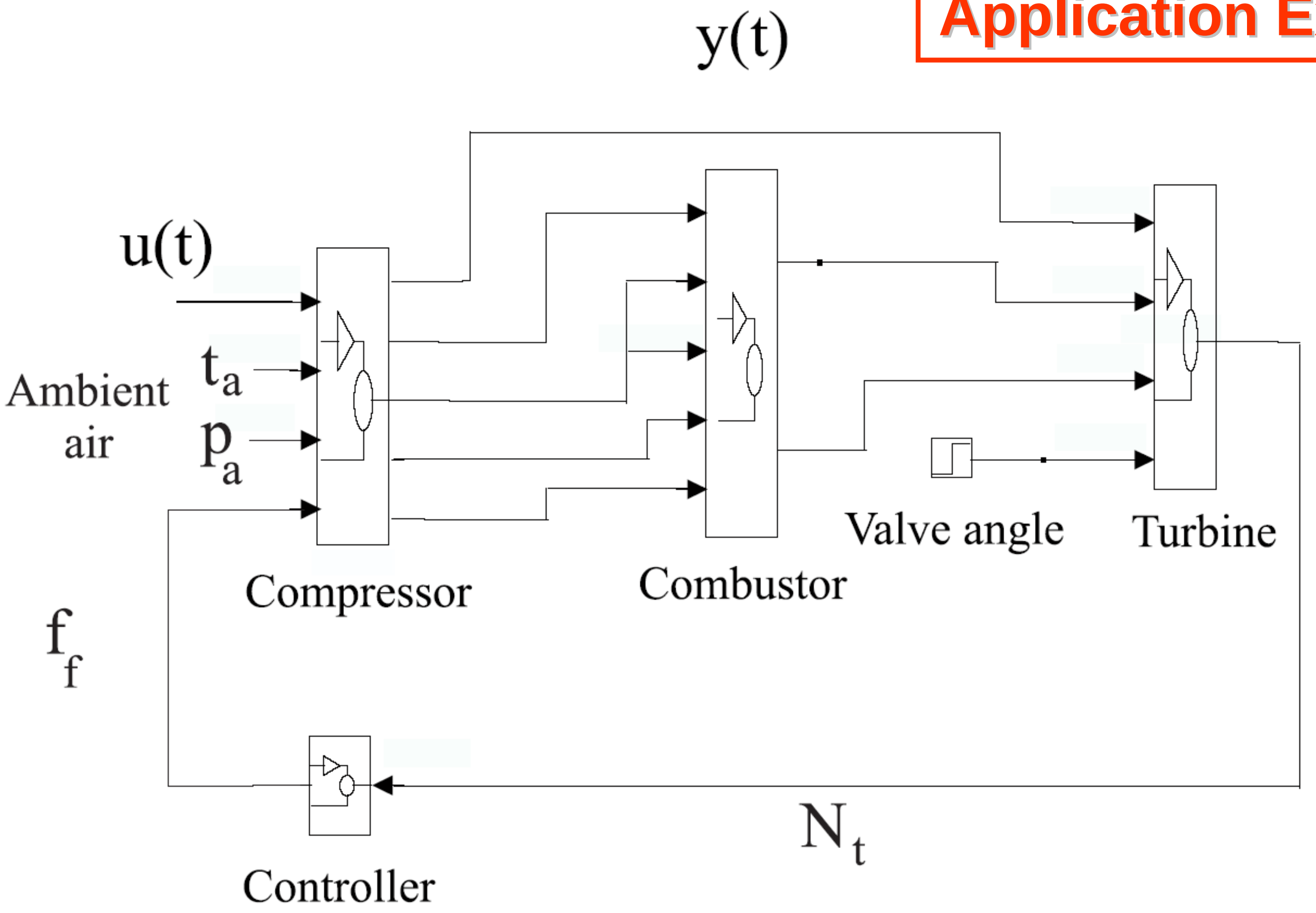
Gas Turbine Scheme (Example 1)

- Main components of the gas turbine simulator

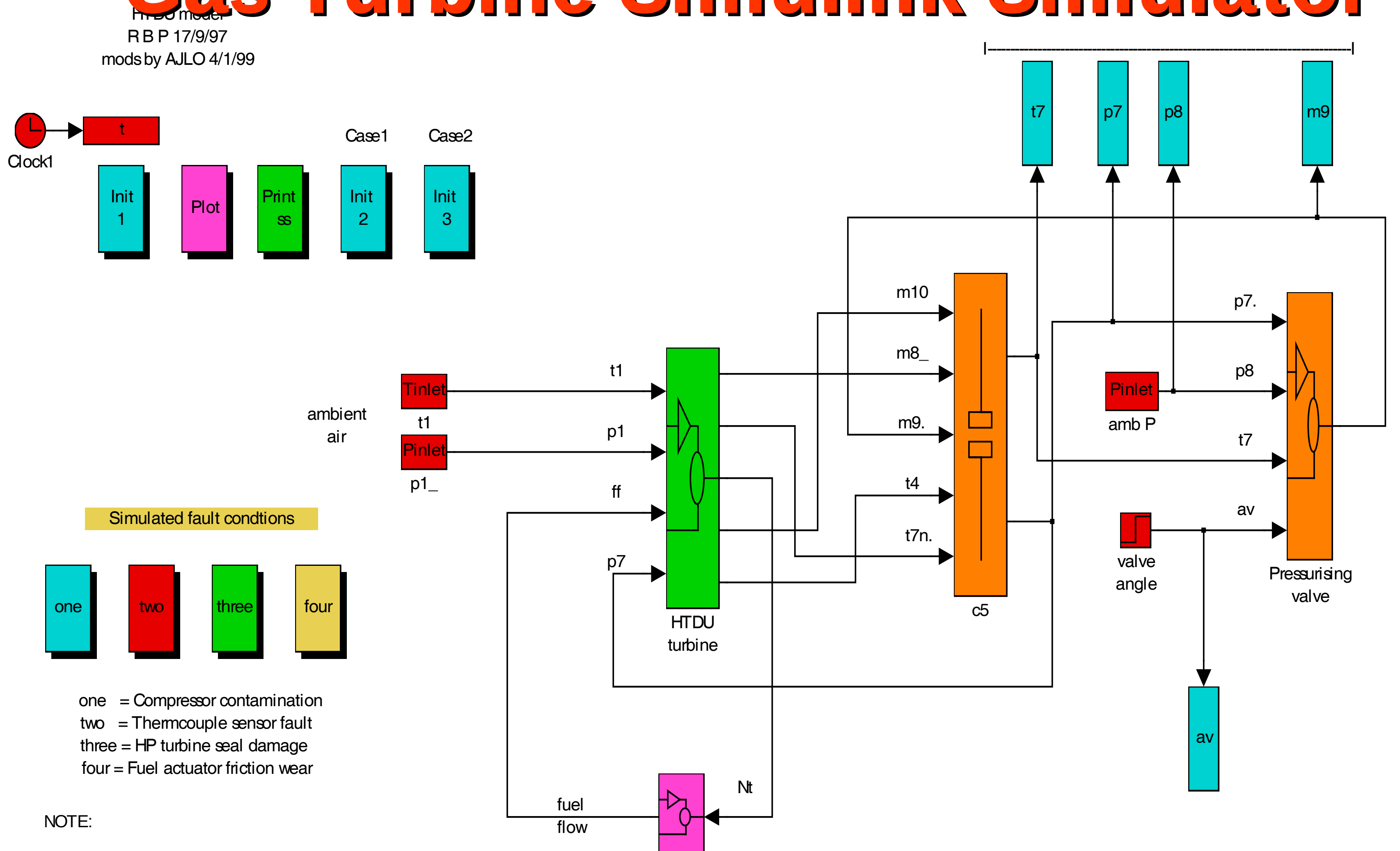


Gas Turbine Simulation Model

Application Example 1

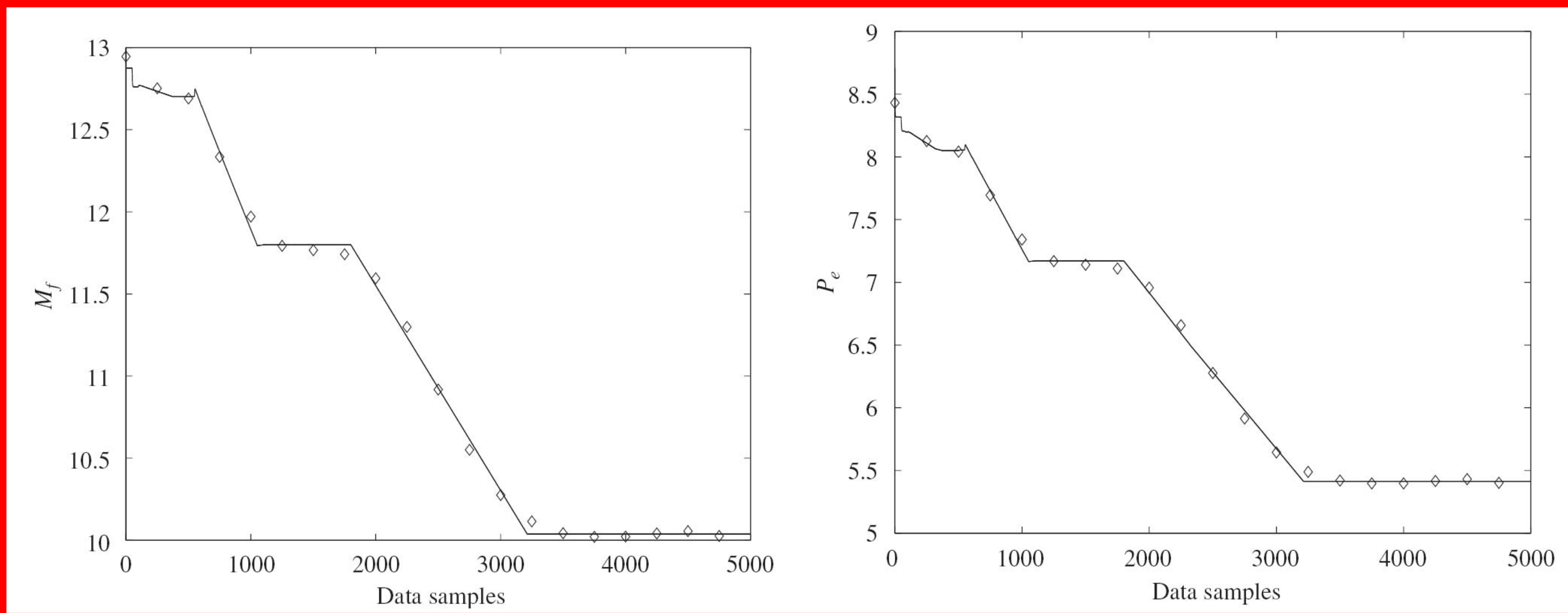


Gas Turbine Simulink Simulator



Application Example 1

Model Validation



Fuel flow rate M_f and electrical power P_e

I / O Measurement Accuracy

Control input signal accuracy

Variable	Name	Accuracy
T_a	Amb. air temp.	$\pm 0.4\,K$
p_a	Amb. air press.	$\pm 1\%$
M_f	Fuel flow	$\pm 5\%$
a_v	Valve angle	$\pm 2\%$

FMEA analysys

Variable $y_i(t)$	Name	Accuracy (%)
m_5	Mass flow	10
p_5	Pressure	15
q_3	Torque	10
t_3	Temperature	3
w_t	Speed	10

Output measurement accuracy

Tools and Techniques

- **Linear dynamic state-space model**
  - Prediction Error Method (PEM)
    - ARX models – Output observers
  - Subspace technique (N4SID)
    - SS models – Kalman filters
- **Practical Tools**
  - Matlab® System Identification Toolbox™
  - Simulink® for predictor implementation

FDI Techniques

- **Residual generation**
  - Dynamic observers
  - Kalman filters
  - *Used as output predictors*

$$\begin{cases} \hat{x}_{k+1} = \mathbf{A}\,\hat{x}_k + \mathbf{B}\,u_k + \mathbf{H}\,e_k \\ \hat{y}_k = \mathbf{C}\,\hat{x}_k + e_k \end{cases}$$

- **Residual evaluation**
  - Geometrical analysis
  - Statistical tests (*e.g.* standard deviation, mean value, correlation analysis, whiteness, χ^2-test)

$$\begin{cases} J(r_k) \le \varepsilon, & \text{fault-free case} \\ J(r_k) > \varepsilon, & \text{faulty case} \end{cases}$$

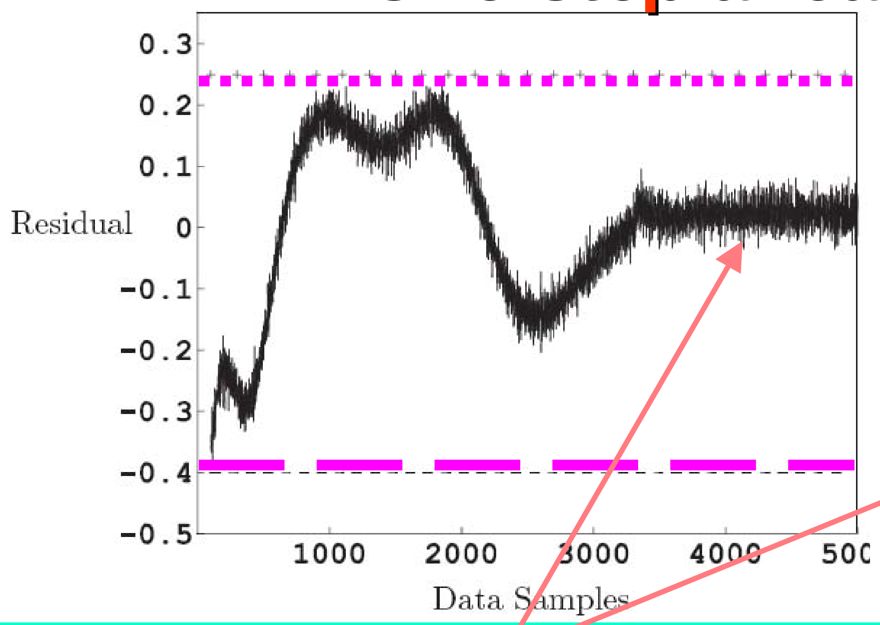
Considered Fault Conditions (Ex. 1)

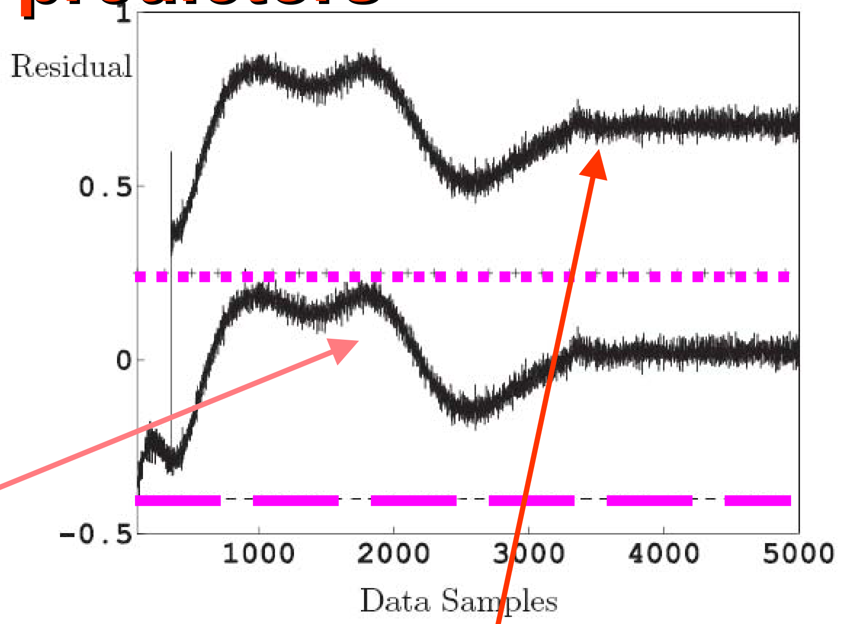
- **Fault "case 1"**: malfunctioning of a thermocouple in the turbine gas path: thermocouple fault, i.e. *output sensor fault*. The fault development rate is set to 5% error in the measured actual temperature per hour

- **Fault "case 2"**: malfunctioning of the actuator of the turbine, *i.e.* the *actuator fault*. It leads to the loss of performance due to the wear of the fuel valve actuator, thus causing a slower response to flow rate demands. Modelled as a simple first order lag on the resulting fuel flow. The actuator response time constant increases linearly with the time in order to represent a progressive damage to the actuator

Simulated Results (Ex. 1)

- Dynamic observer example: *abrupt fault*
- One-step ahead predictors



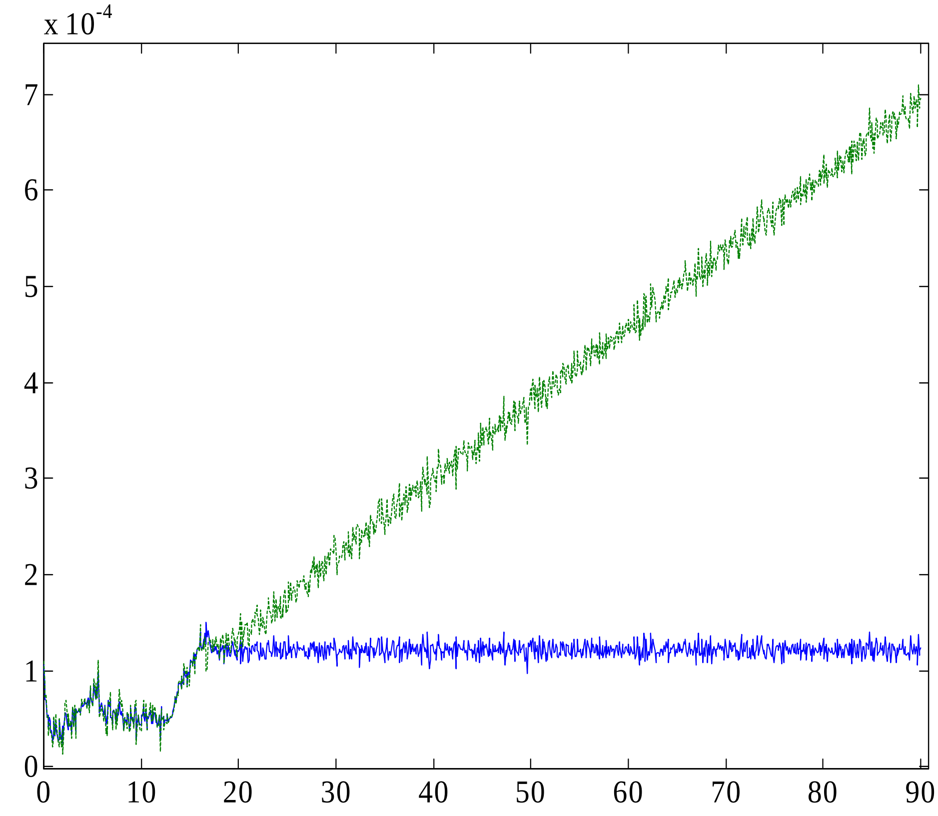


Fault free residual

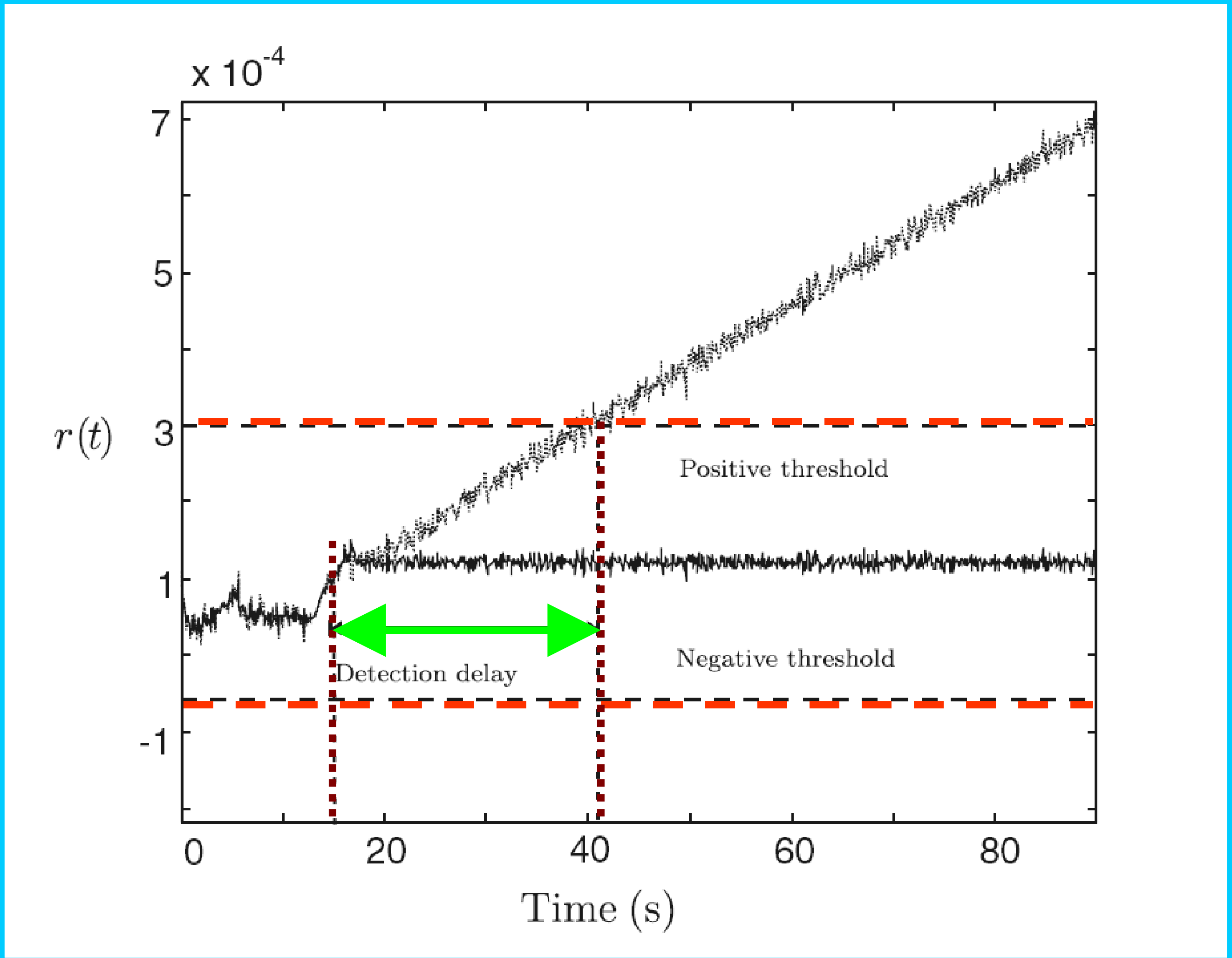
Fault-free & faulty residuals

Simulated Results (Cont’d)

Kalman filter residuals: termocouple sensor **incipient fault**



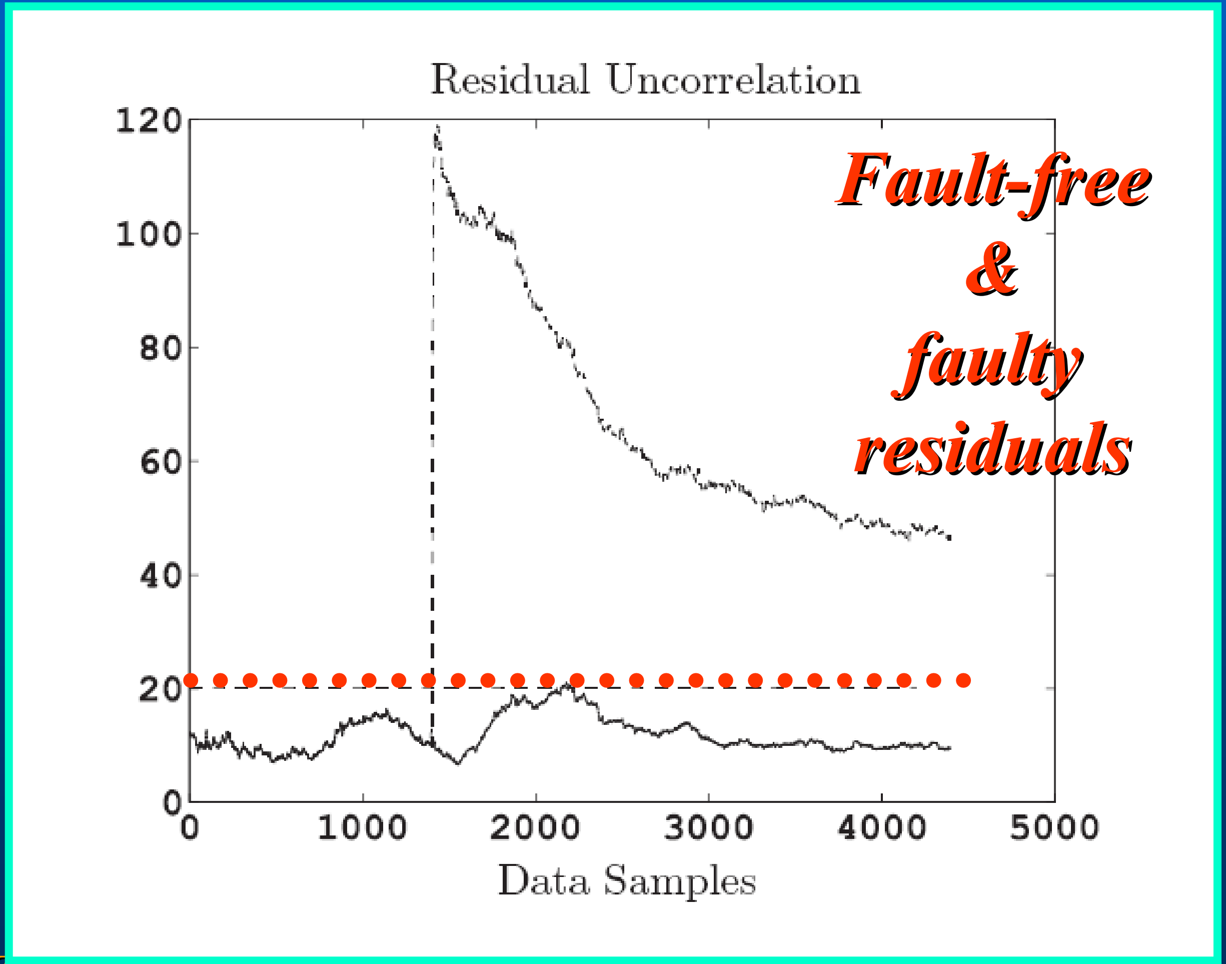
Simulated Results (Cont'd)



Detection delay with positive and negative thresholds

Simulated Results (Cont'd)

Kalman filter residuals: whiteness test (example)



Simulated Results (Cont'd)

- **Monte Carlo analysis**
  - False alarm rate
  - Missed fault rate
  - True detection/isolation rate
  - Mean detection/isolation delay time

Variable	Reference value	Error (%)
p_a	101325	1.0
T_a	288.16	0.5
RH	60%	3.0
e_c	0.87673	1.0
e_t	0.79353	3.0

Simulated turbine uncertainties

Fault	r_{fa}	r_{mf}	r_{td}, r_{ti}	τ_{md}, τ_{mi} (s)
Case 1	0.002	0.003	0.997	27
Case 2	0.001	0.001	0.999	18

Simulated Results (Cont'd)

- **Comparison with:**
  - Unknown Input Kalman Filters (UIKF)
  - Neural Networks (NN)

Fault case\FDI method	UIKF (%)	NN (%)
Case 1	10	12
Case 2	12	14

Application Example 2

- Detection and isolation of sensor faults for *a wind turbine benchmark*
- Wind turbine simulator
  - Measurement noise & realistic fault cases
- *Nonlinear modelling*
  - Aerodynamic torque, control strategy
  - Uncertain measurements (*e.g.* wind speed)

State-of-the-Art

- Linear or linearized model techniques
- Fault detection observer
- Kalman filtering/EKF
- Unknown Input Observer
  - Fault isolation
  - Nonlinearity disturbance de-coupling
- Adaptive filters

Data-Driven Model-Based FDI

- ✓ Input-output measurements from the fault free system
- ✓ Data partitioning
- ✓ Identification of a piecewise affine prototype
  - *Hybrid* or *switching* models
- ✓ Residual generation with process simulator
- ✓ Fixed threshold residual evaluation

Nonlinear PWA Modelling

Piecewise affine prototype

$$y(t+n) = \sum_{j=0}^{n-1} \alpha_j^{(i)} y(t+j) + \sum_{j=0}^{n-1} \beta_j^{(i)} u(t+j) + b^{(i)},$$

$$X_k^{(i)} = \begin{bmatrix} y(k) & \mathbf{x}_k^T(0) & 1 \\ y(k+1) & \mathbf{x}_k^T(1) & 1 \\ \vdots & \vdots & \\ y(k+N_i-1) & \mathbf{x}_k^T(N_i-1) & 1 \end{bmatrix}$$

$$\Sigma_k^{(i)} = \left(X_k^{(i)}\right)^T X_k^{(i)}$$

Data matrices and covariance matrices

Parameter Estimation

$$\Sigma_2^{(i)}, \quad \Sigma_3^{(i)}, \quad \ldots \quad \Sigma_k^{(i)}, \quad \ldots$$

Sequence of matrices in each region

Singularity condition for $k = n$ and parameter estimation (*ideal case with white noise*)

$$\Sigma_n^{(i)} \begin{bmatrix} -1 \\ \mathbf{a}_n^{(i)} \end{bmatrix} = 0$$

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

Errors-In-Variables (EIV) framework: equivalent additive (“white”) noise affecting input-output measurements

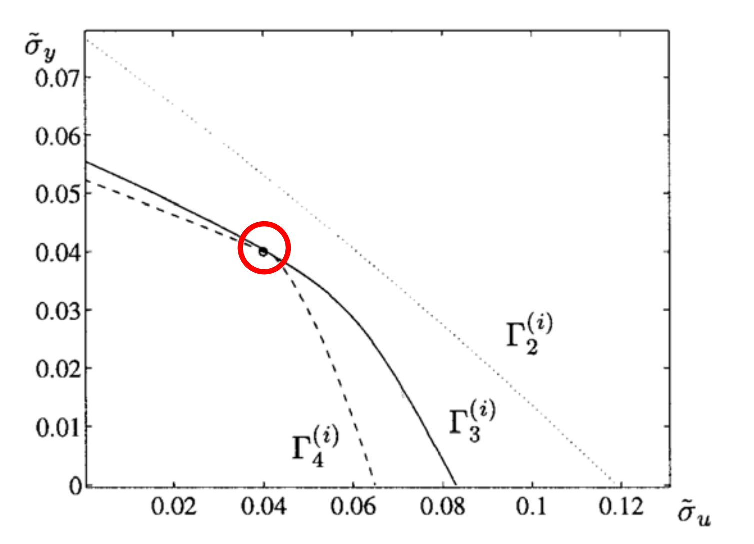
"Real" Case Estimation

$$\Sigma_k^{*(i)} = \Sigma_k^{(i)} - \tilde{\Sigma}_k \geq 0$$

Data sequences are modified according to the EIV description

"Noise" covariance matrix representing the model-process mismatch

$$\tilde{\Sigma}_k = \mathrm{diag}[\tilde{\sigma}_y I_{k+1}, \tilde{\sigma}_u I_k, 0]$$



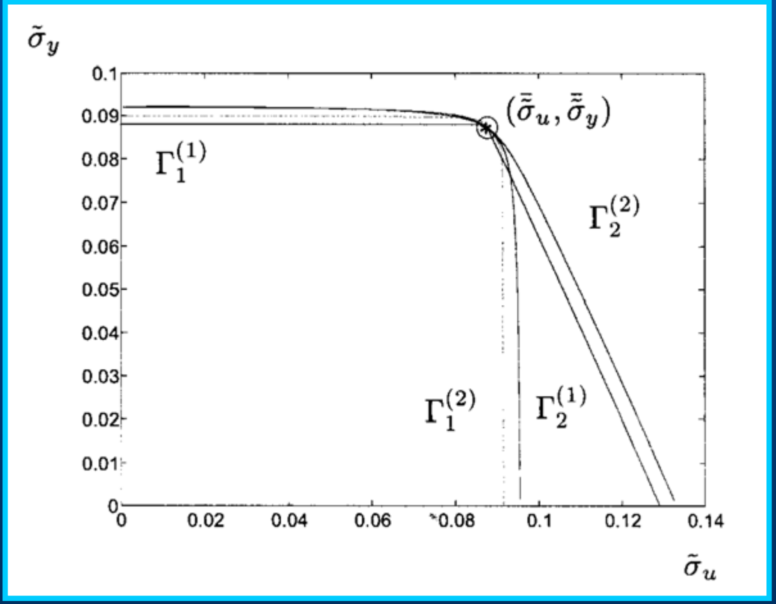
Singularity curves $\Gamma_k^{(i)}$ in the noisy space: in the ideal case, they share a common point, corresponding to the noise affecting the data

It holds for white noise!

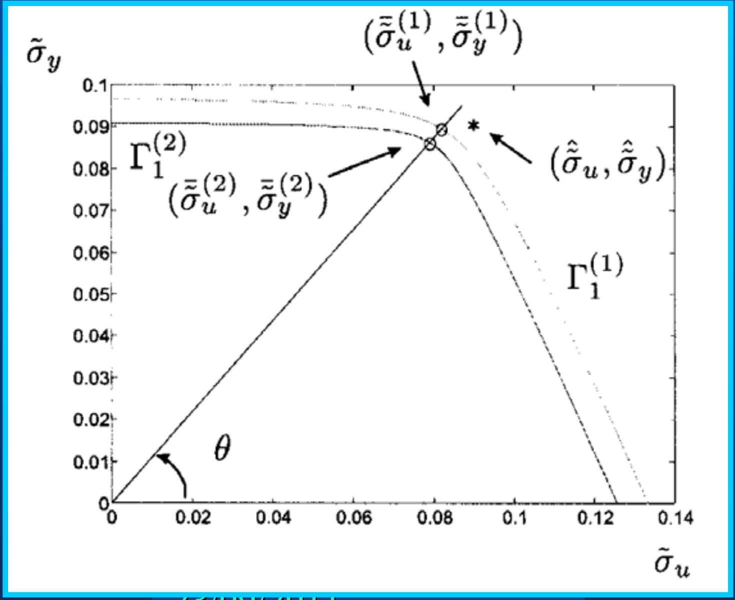
Optimization Problem

$$J\left(\left(\bar{\tilde{\sigma}}_u^{(1)}, \bar{\tilde{\sigma}}_y^{(1)}\right), \ldots, \left(\bar{\tilde{\sigma}}_u^{(M)}, \bar{\tilde{\sigma}}_y^{(M)}\right)\right) = d\left(\left(\bar{\tilde{\sigma}}_u^{(1)}, \bar{\tilde{\sigma}}_y^{(1)}\right), \ldots, \left(\bar{\tilde{\sigma}}_u^{(M)}, \bar{\tilde{\sigma}}_y^{(M)}\right)\right) + \left(C_n A_n\right)^{\mathrm{T}} H C_n A_n$$

Best solution consistent with the ideal case: single point condition and continuity of the model



Singularity curves in the ideal and real cases



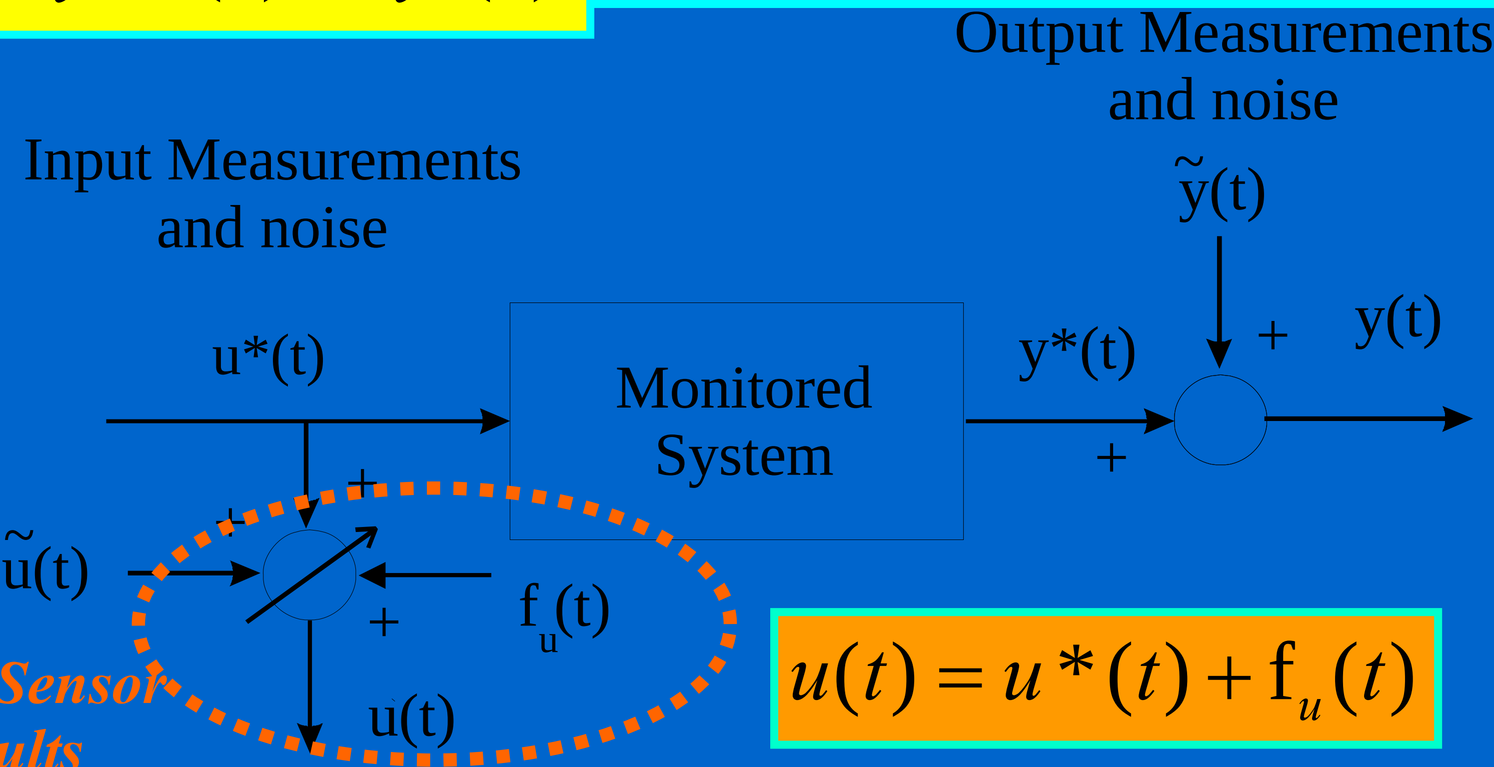
Tools and Techniques

- **Nonlinear modelling**
  - Hybrid prototypes
    - Piece-Wise Affine models
  - Data clustering/partitioning
    - EIV local affine model identification (EIV)
- **Practical Tools**
  - Matlab® Fuzzy Modelling and Identification Toolbox™ (FMID)
  - Simulink® for predictor implementation

Models for FDI: Input Faults

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

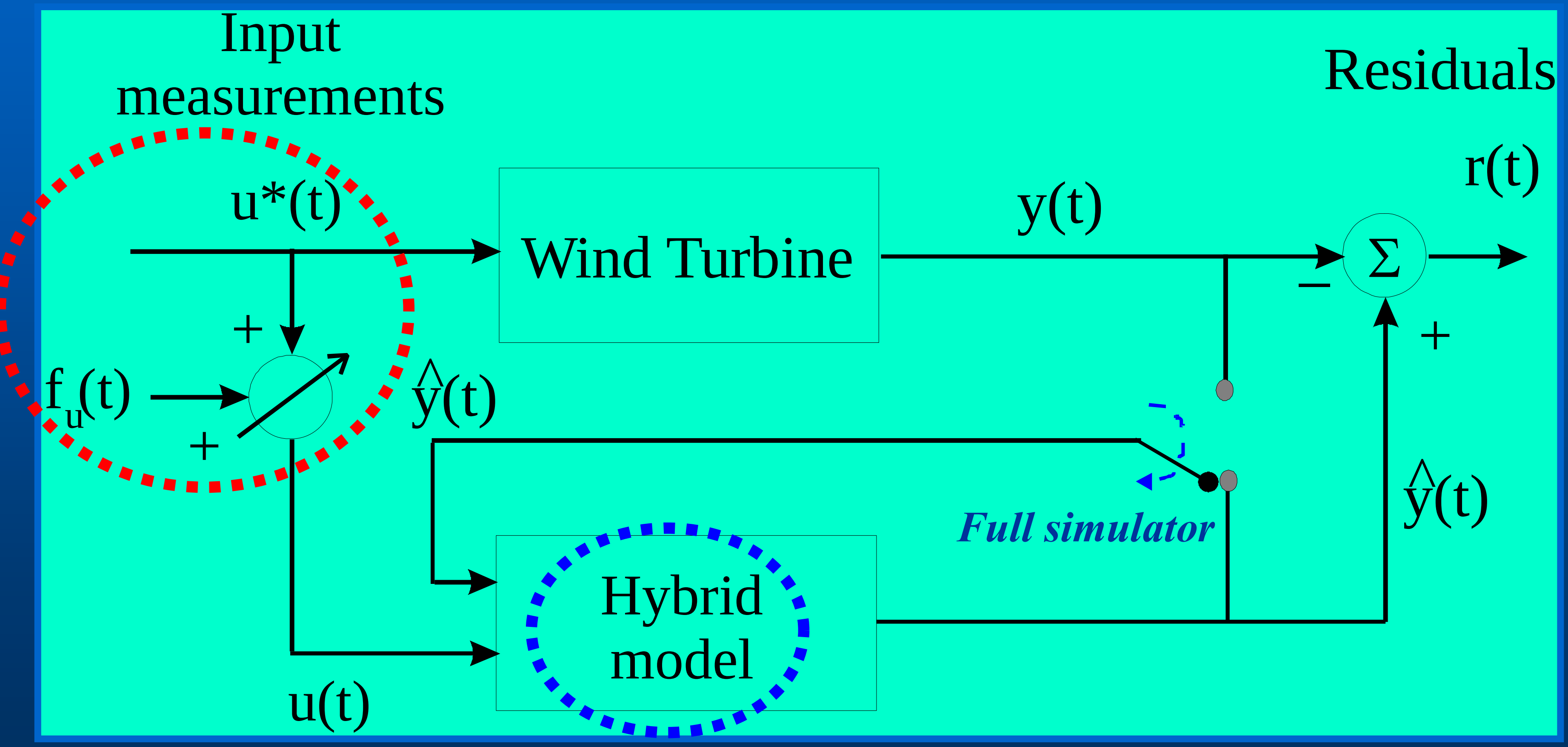
Additive noise, according to the EIV framework



$$u(t) = u^*(t) + f_u(t)$$

Input Fault FDI Scheme

Input sensor additive faults

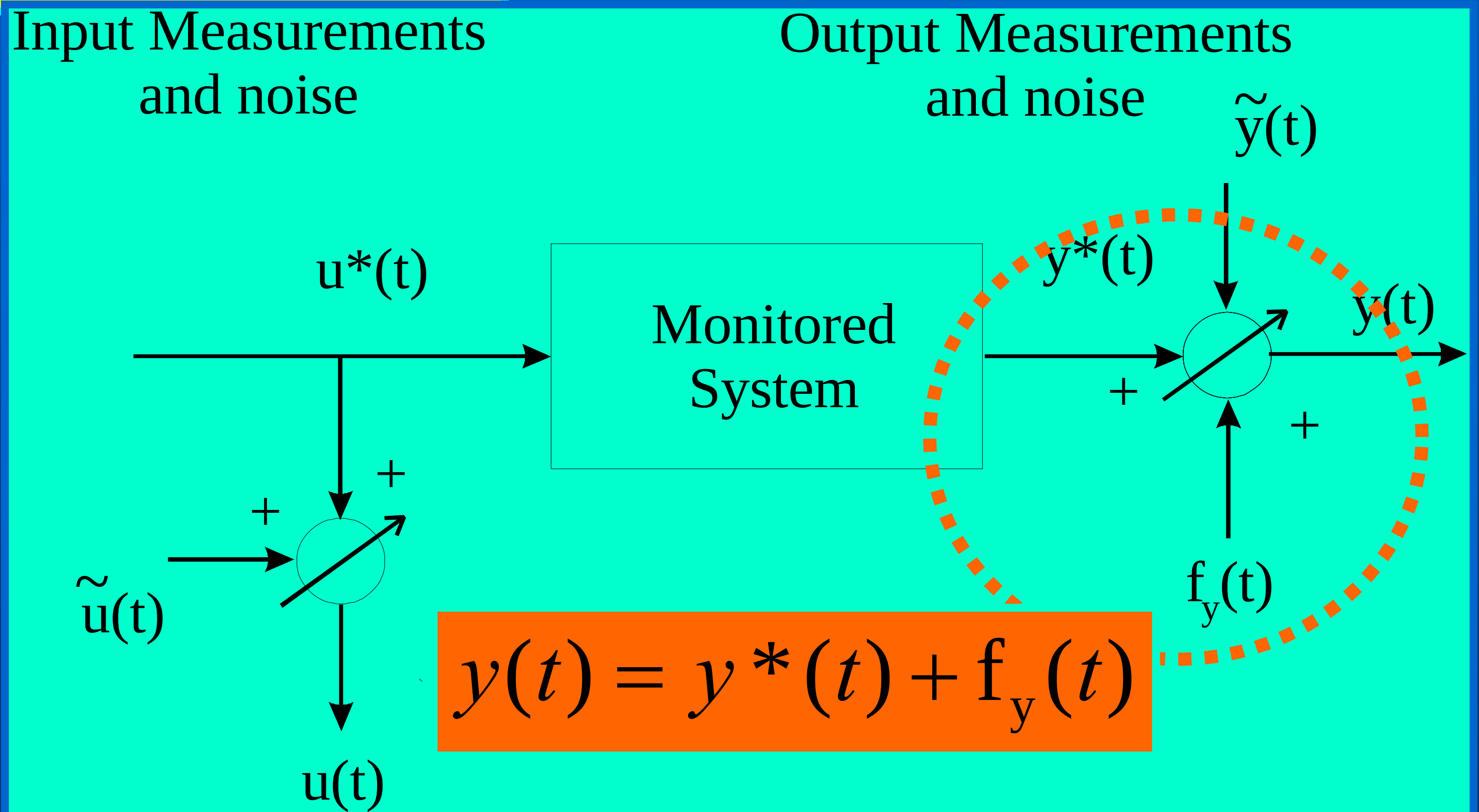


Models for FDI: Output Faults

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

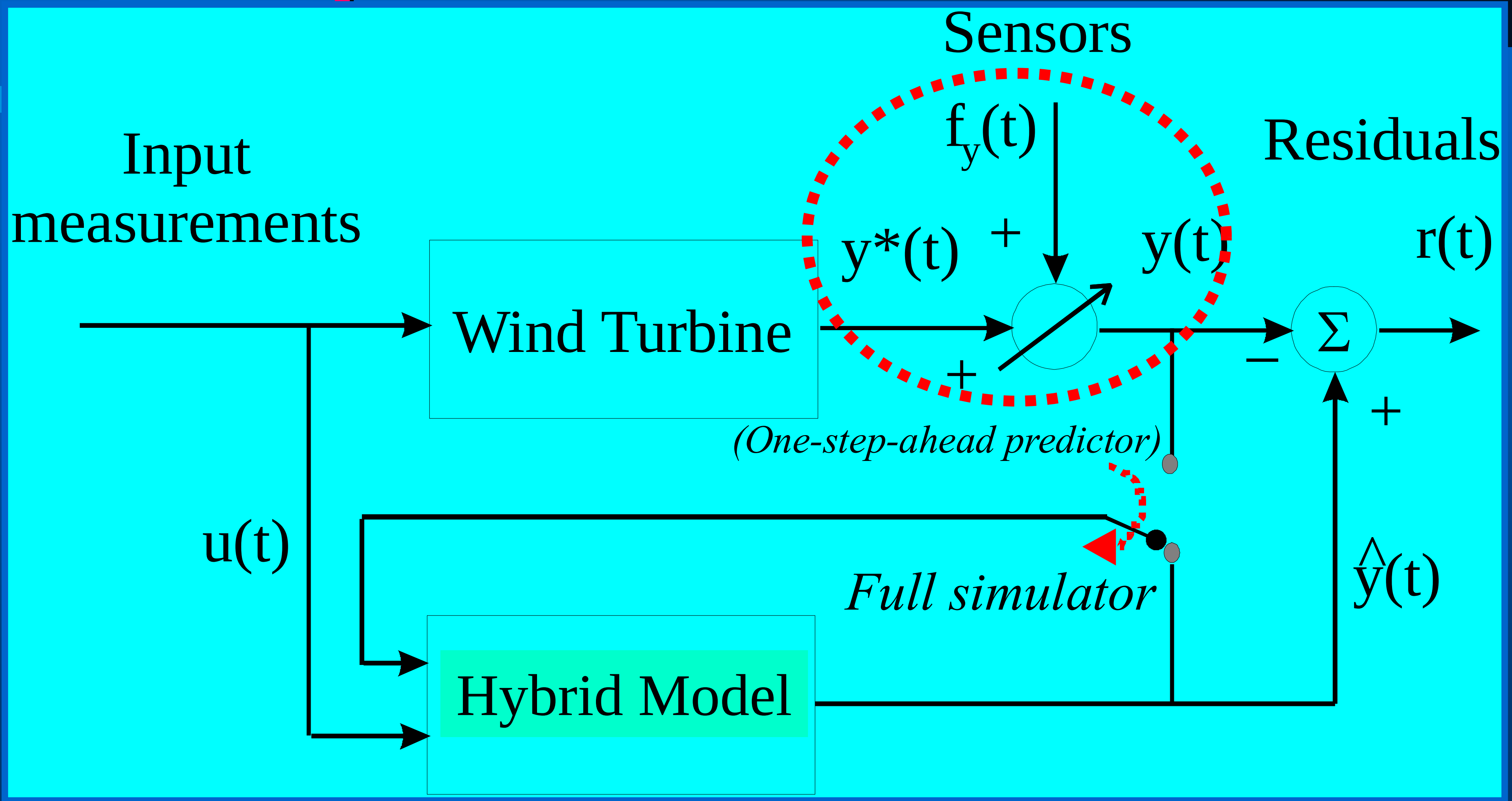
Additive noise, according to the EIV framework

Fault model



$$y(t) = y^*(t) + f_y(t)$$

Output Fault FDI Scheme



Model used as "full simulator"

Residual Evaluation

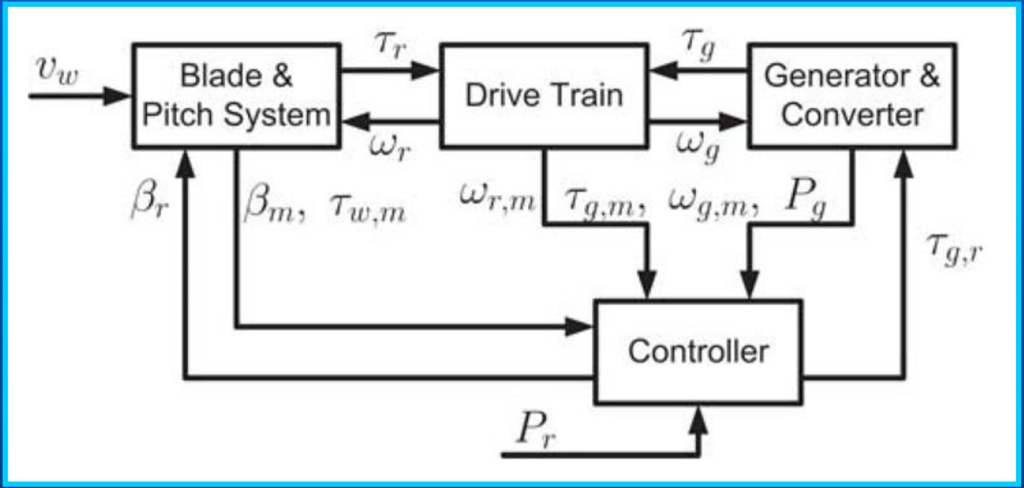
$$|r(t)| \begin{cases} \leq \text{Threshold} \ , \text{ in fault–free conditions,} \\ > \text{Threshold} \ , \text{ in faulty conditions.} \end{cases}$$

$$\begin{cases} \bar{r} - \nu\,\sigma_r \leq r(t) \leq \bar{r} + \nu\,\sigma_r \ , \text{ in fault–free conditions;} \\ \\ r(t) < \bar{r} - \nu\,\sigma_r \\ \quad \text{or} \qquad\qquad\qquad\qquad\qquad , \text{ in faulty conditions.} \\ r(t) > \bar{r} + \nu\,\sigma_r \end{cases}$$

Fixed threshold selection: ν settled in order to minimise false alarm & missed fault rates, while maximising fault detection rate

Wind Turbine Description

- Three blade horizontal axis turbine
- Rotor shaft moved by wind. A gear box is used

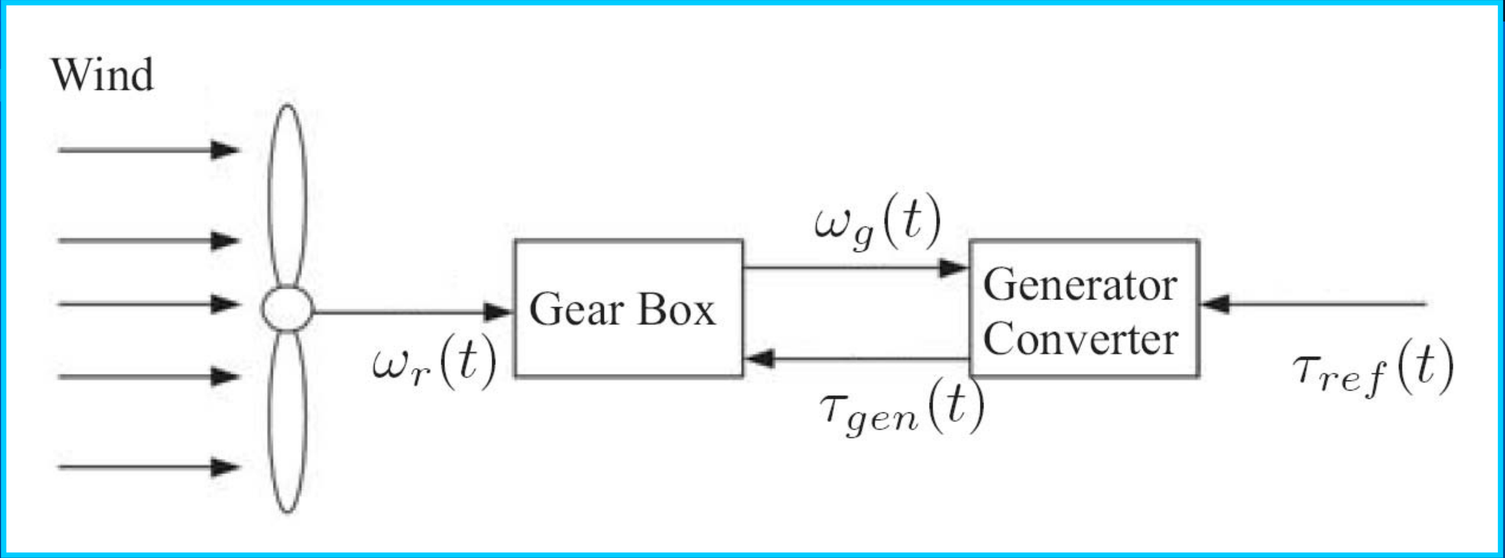


- The rotational speed & the generated power regulated with 2 control strategies

Turbine Control Description

- **2 control strategies:**
  - **Converter torque & pitch angle of the turbine blades**
  - **Power generation optimisation**
- Partial load region: **a specific ratio between the blade tip speed and wind speed is maintained**
  - **Rotational speed and converter torque are controlled**
- Full power region: **converter torque kept constant**
  - **rotational speed is adjusted by controlling the pitch angle of the blades**

Wind Turbine Aerodynamics



$$\tau_{aero}(t) = \frac{\rho\, A\, C_p\,(\beta(t),\ \lambda(t))\ v^3(t)}{2\,\omega_r(t)}$$

Aerodynamic torque and tip-speed ratio

$$\lambda(t) = \frac{\omega_r(t)\, R}{v(t)}$$

Wind speed is not unknown, but measured but highly noisy

Wind Turbine Sub-Models

$$\dot{\omega}_r(t) = \frac{1}{J}\left(\tau_{aero}(t) - \tau_{gen}(t)\right)$$

$$\dot{\tau}_{gen}(t) = p_{gen}\left(\tau_{ref}(t) - \tau_{gen}(t)\right)$$

Drive-train model

Hydraulic pitch system

$$\frac{\beta(s)}{\beta_r(s)} = \frac{\omega_n^2}{s^2 + 2\,\zeta\,\omega_n\,s + \omega_n^2}$$

$$\frac{\tau_g(s)}{\tau_{g\,r}(s)} = \frac{\alpha_{gc}}{s + \alpha_{gc}}$$

Generator & converter models

$$P_g(t) = \eta_g\,\omega_g(t)\,\tau_g(t)$$

WT Control Strategy

- 2 main working conditions: switching between (i) power optimisation & (ii) constant power production

(i) $\tau_{g\,r} = K_{opt}\,\omega_r^2$

$\beta_r = 0$

$$K_{opt} = \frac{1}{2}\,\rho\,A\,R^3\,\frac{C_{p_{\max}}}{\lambda_{opt}^3}$$

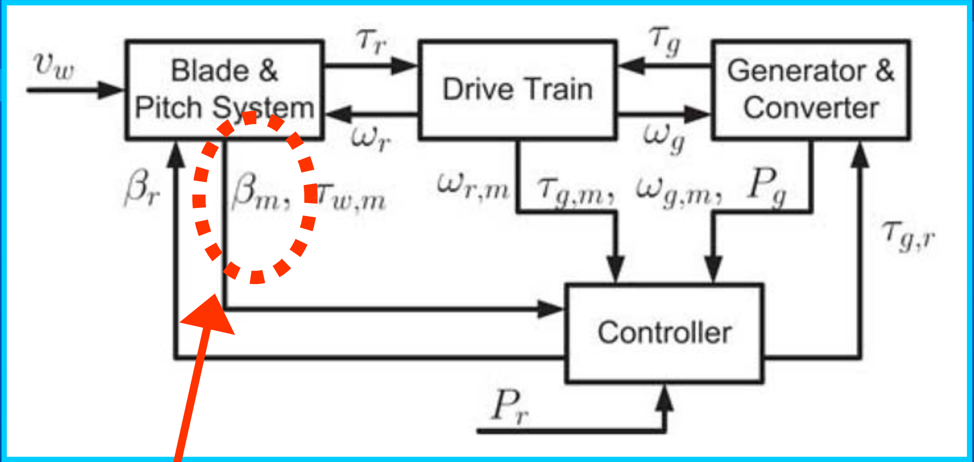
(ii) PI controller

$$\begin{cases} \beta_r\,[n] &= \beta_r\,[n-1] + k_p\,e\,[n] + (k_i\,T_s - k_p)\,e\,[n-1] \\ e\,[n] &= \omega_r\,[n] - \omega_{nom} \end{cases}$$

(ii)

- **Measurement sensors modelled by adding the actual variable values with stochastic Gaussian noise processes. Mean and standard deviation values depend on the considered measurements**

Wind Turbine Benchmark



Wind turbine scheme & considered fault cases

Fault Signal	Description
Fault_1	Fixed value on Pitch 1 position sensor 1
Fault_2	Scaling error on Pitch 2 position sensor 2
Fault_3	Fixed value on Pitch 3 position sensor 1
Fault_4	Fixed value on Rotor speed sensor 1
Fault_5	Scaling error on Rotor speed sensor 2 & Generator speed sensor 2
Fault_6	Changed pitch system response pitch actuator 2 – high air content in oil
Fault_7	Changed pitch system response pitch actuator 3 – low pressure
Fault_8	Offset in Converter torque control
Fault_9	Changed Dynamics Drive train

Fault Models (WT Benchmark)

- $Fault_1$ or $Fault_3$: fixed values on pitch 1 or 3 position sensors #1
  - $f_u(t)$ **affecting the** $\beta_1(t)$ **or** $\beta_3(t)$ **sensors; their measurements stuck to** 5^o **or** 10^o **for** $100\ s$**.**
  - $2000\ s. < t < 2100\ s.$ **or** $2600\ s. < t < 2700\ s.$
- $Fault_2$: $\beta_2(t)$ sensor gain change #2
  - **from *1* to *1.2***
  - **active between** $2300\ s. < t < 2400\ s.$

Modelling & FDI Strategy

- 3 identified hybrid models

1) $u(t) = [\tau_{ref}(t), v_{hub}(t), \beta_i(t)]^T$, $y(t) = \omega_r(t)$, $i = 1$ (Fault$_1$)

2) $u(t) = [\tau_{ref}(t), v_{hub}(t), \beta_i(t)]^T$, $y(t) = \omega_r(t)$, $i = 2$ (Fault$_2$)

3) $u(t) = [\tau_{ref}(t), v_{hub}(t), \beta_i(t)]^T$, $y(t) = \omega_r(t)$, $i = 3$ (Fault$_3$)

- **440×10^3 samples & 100 Hz sampling rate**
- Clustering algorithm with

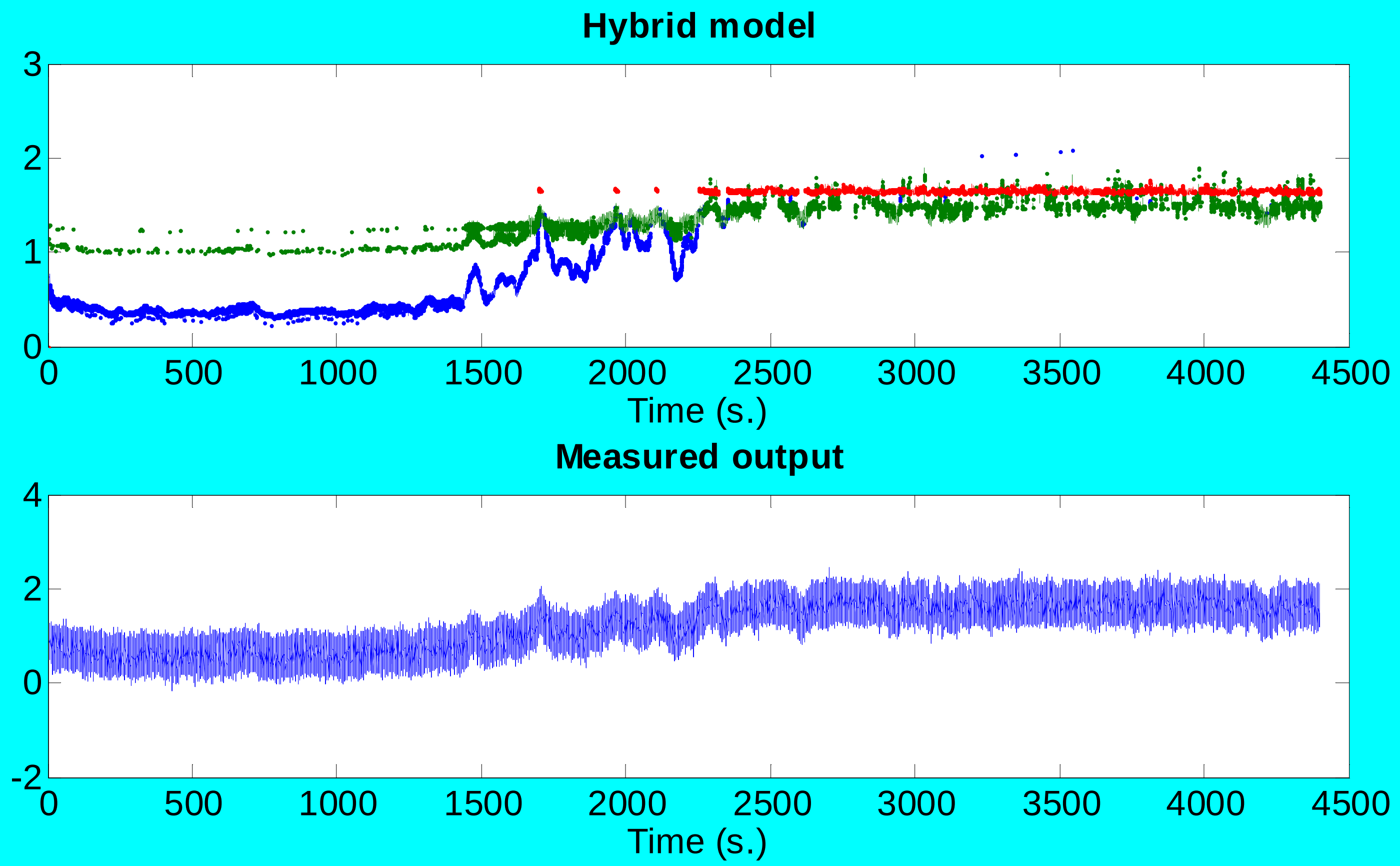
1) ***M* = 3 clusters & *n* = 3 for** $\{\tau_{ref}(t), v_{hub}(t), \beta_i(t), \omega_r(t)\}$

- Identification and validation data
  - **VAF (Variance Accounted For) > *90%***
  - **Optimisation of the loss function (hybrid model prediction error)**

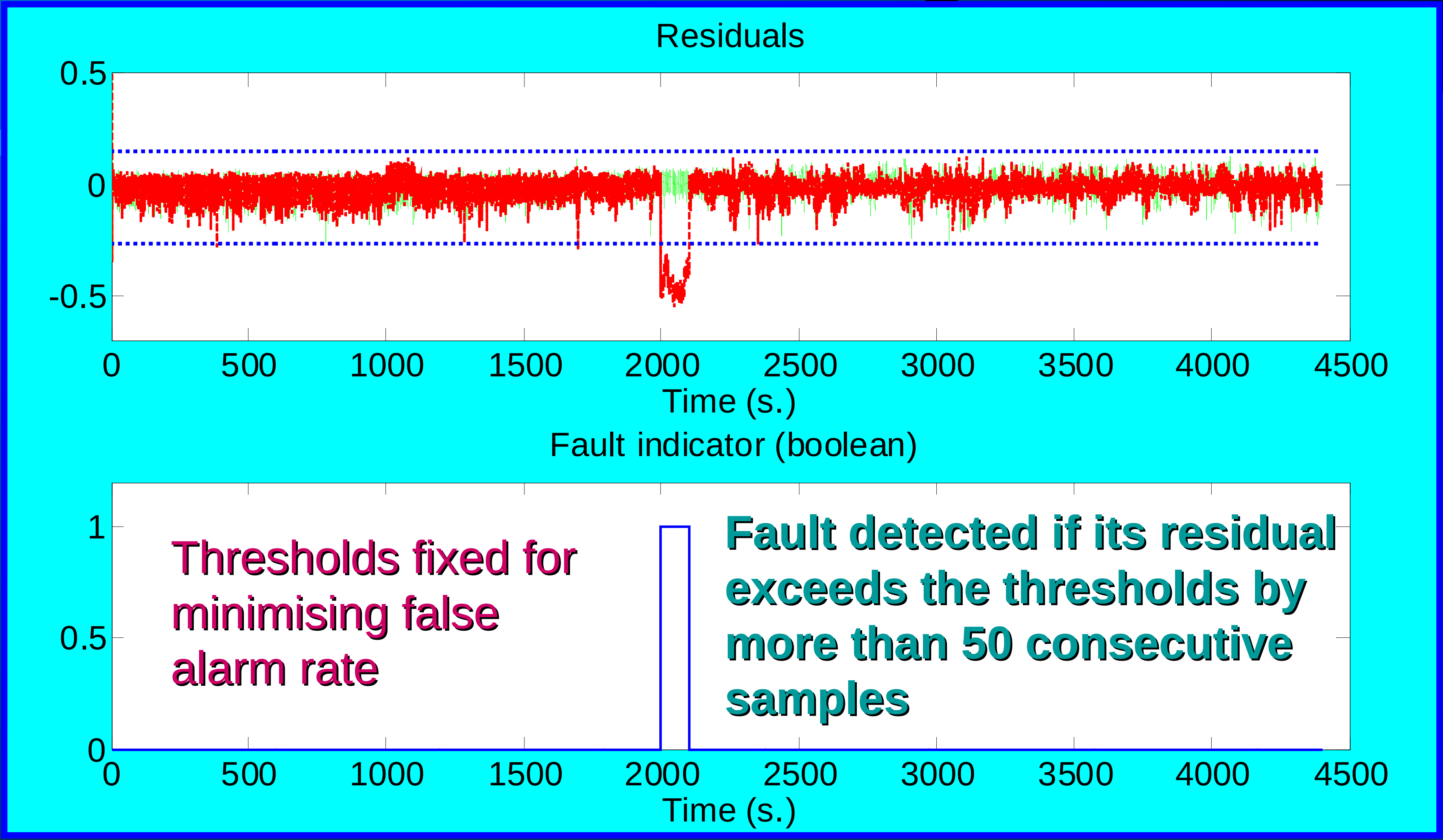
Hybrid Modelling Results

$$y(t+n) = f(\mathbf{x}_n(t)) = \sum_{i=1}^{M} \chi_i(\mathbf{x}_n(t))[\mathbf{x}_n(t), 1]^T \mathbf{a}_n^{(i)}$$

Each colour corresponds to a local identified affine model

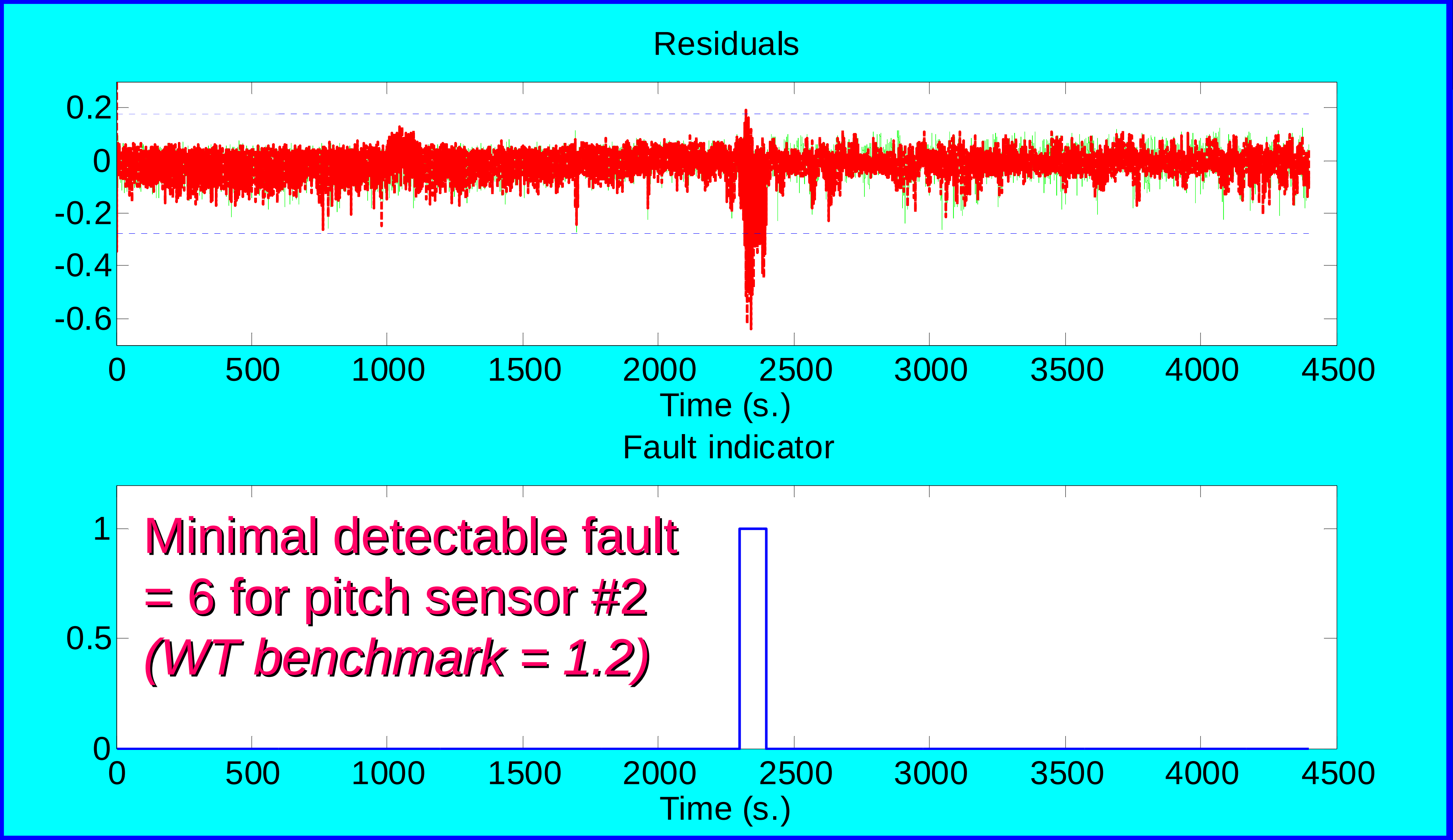


Results for Fault$_1$



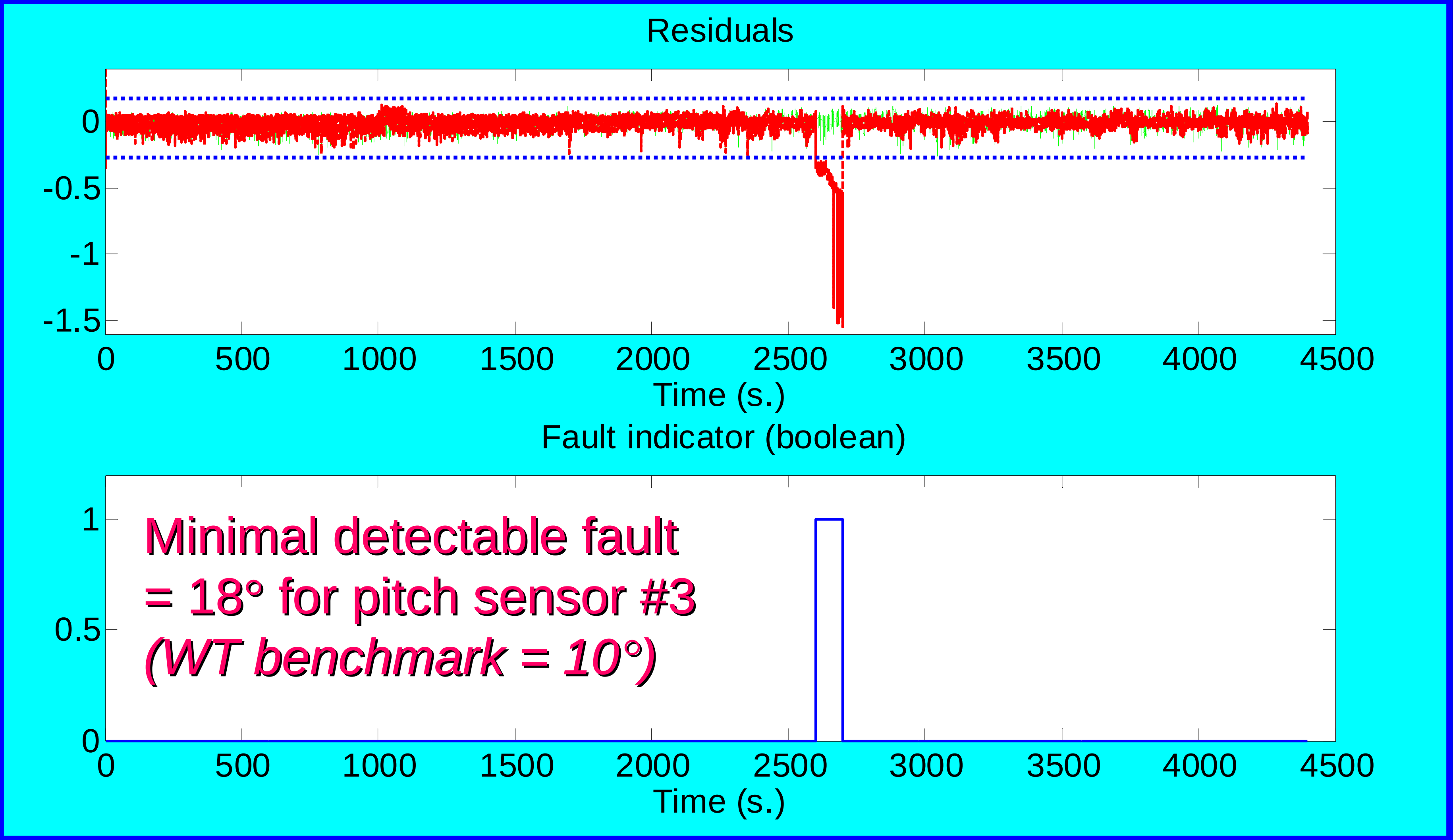
$\beta_1(t)$ sensor fault residuals $r(t)$, and the fault indicator function

Results for $Fault_2$



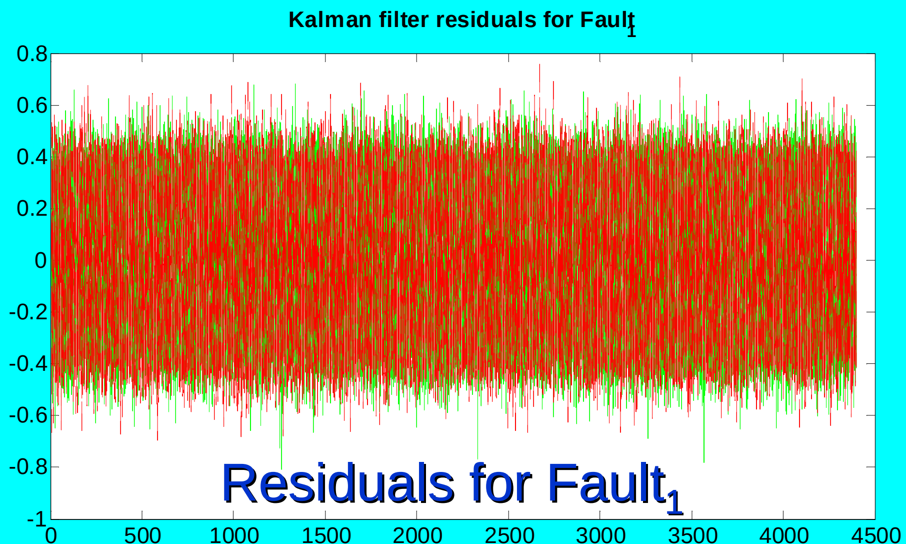
$\beta_2(t)$ sensor fault residuals $r(t)$, and the fault indicator function

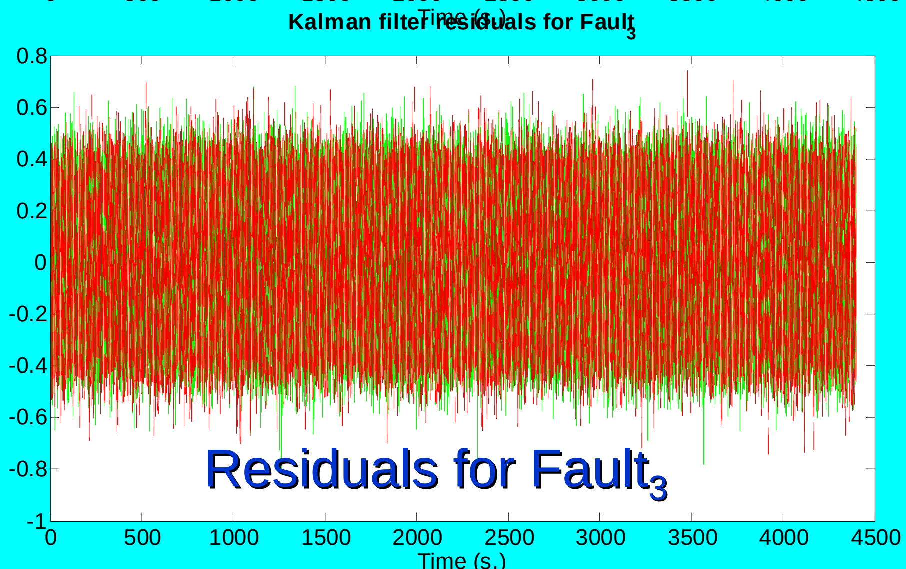
Results for Fault_3



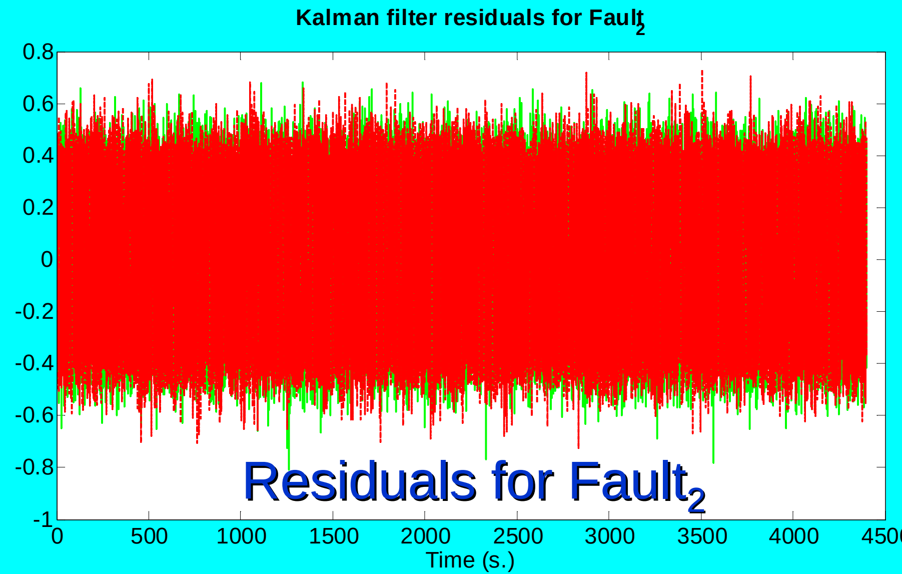
$\beta_3(t)$ sensor fault residuals $r(t)$, and the fault indicator function

Comparisons with Linear KFs



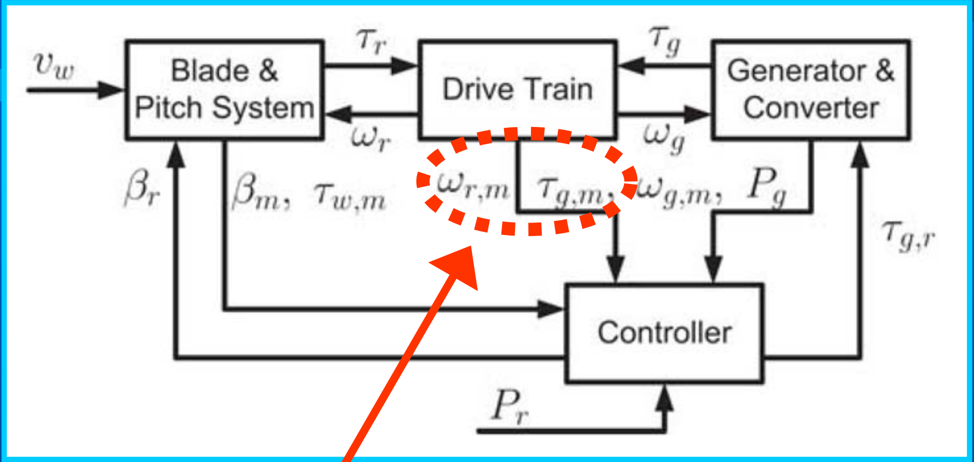


Kalman filter residuals…



… do not allow fault detection!

Wind Turbine Benchmark



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Fault_1	Fixed value on Pitch 1 position sensor 1
Fault_2	Scaling error on Pitch 2 position sensor 2
Fault_3	Fixed value on Pitch 3 position sensor 1
Fault_4	Fixed value on Rotor speed sensor 1
Fault_5	Scaling error on Rotor speed sensor 2 & Generator speed sensor 2
Fault_6	Changed pitch system response pitch actuator 2 – high air content in oil
Fault_7	Changed pitch system response pitch actuator 3 – low pressure
Fault_8	Offset in Converter torque control
Fault_9	Changed Dynamics Drive train

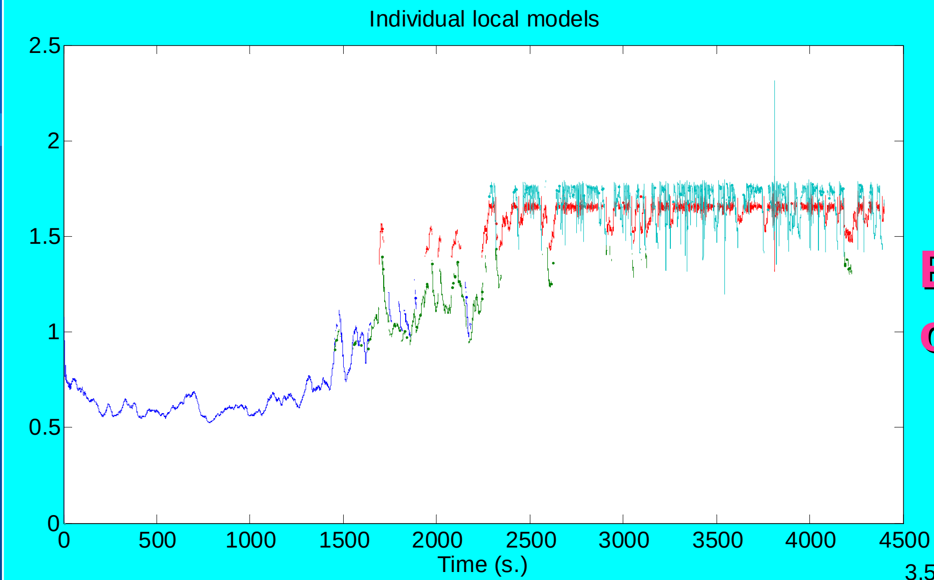
Fault Models

- WT Benchmark
- **Fault$_4$: fixed value on rotor *speed sensor 1***
  - ***$f_y(t)$* affecting the *$\omega_r(t)$* sensor; its measurement stuck to *1.4 rad/s***
  - ***1500 s. < t < 1600 s.***
- **Fault$_8$: offset in *converter torque* $\tau_{gen}(t)$ control**
  - ***$f_y(t)$*, converter fault active for *100 s.***
  - ***3800 s. < t < 3900 s.***

Nonlinear Modelling

- 2 identified hybrid models
  1) $u(t) = [\tau_{ref}(t), \tau_{aero}(t)]$, $y(t) = \omega_r(t)$
  2) $u(t) = [\tau_{ref}(t), \tau_{aero}(t)]$, $y(t) = \tau_{gen}(t)$
- **440×10^3 samples & 100 Hz sampling rate**
- Data clustering algorithm with
  1) **$M = 4$ clusters & $n = 2$ for $z=\{\tau_{ref}(t), \tau_{aero}(t), \omega_r(t)\}$**
  2) **$M = 2$ clusters & $n = 2$ for $z=\{\tau_{ref}(t), \tau_{aero}(t), \tau_{gen}(t)\}$**
- Identification and validation data
  - **VAF (Variance Accounted For) > *90%***
  - **Loss function minimisation for different *M* and *n***

Nonlinear Modelling Results

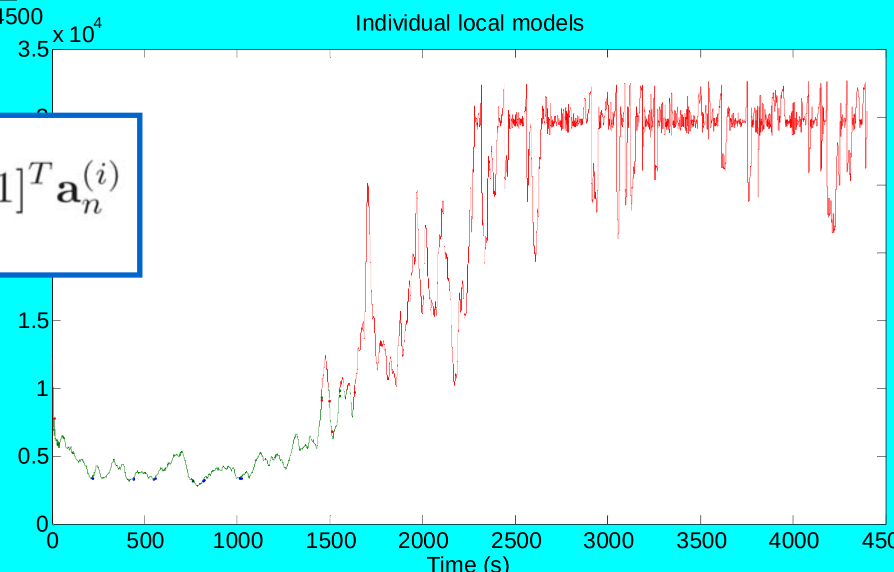


$\omega_r(t)$ output and local models with $M = 4$, $n = 2$

Each colour corresponds to the output of the *i*-th local affine model

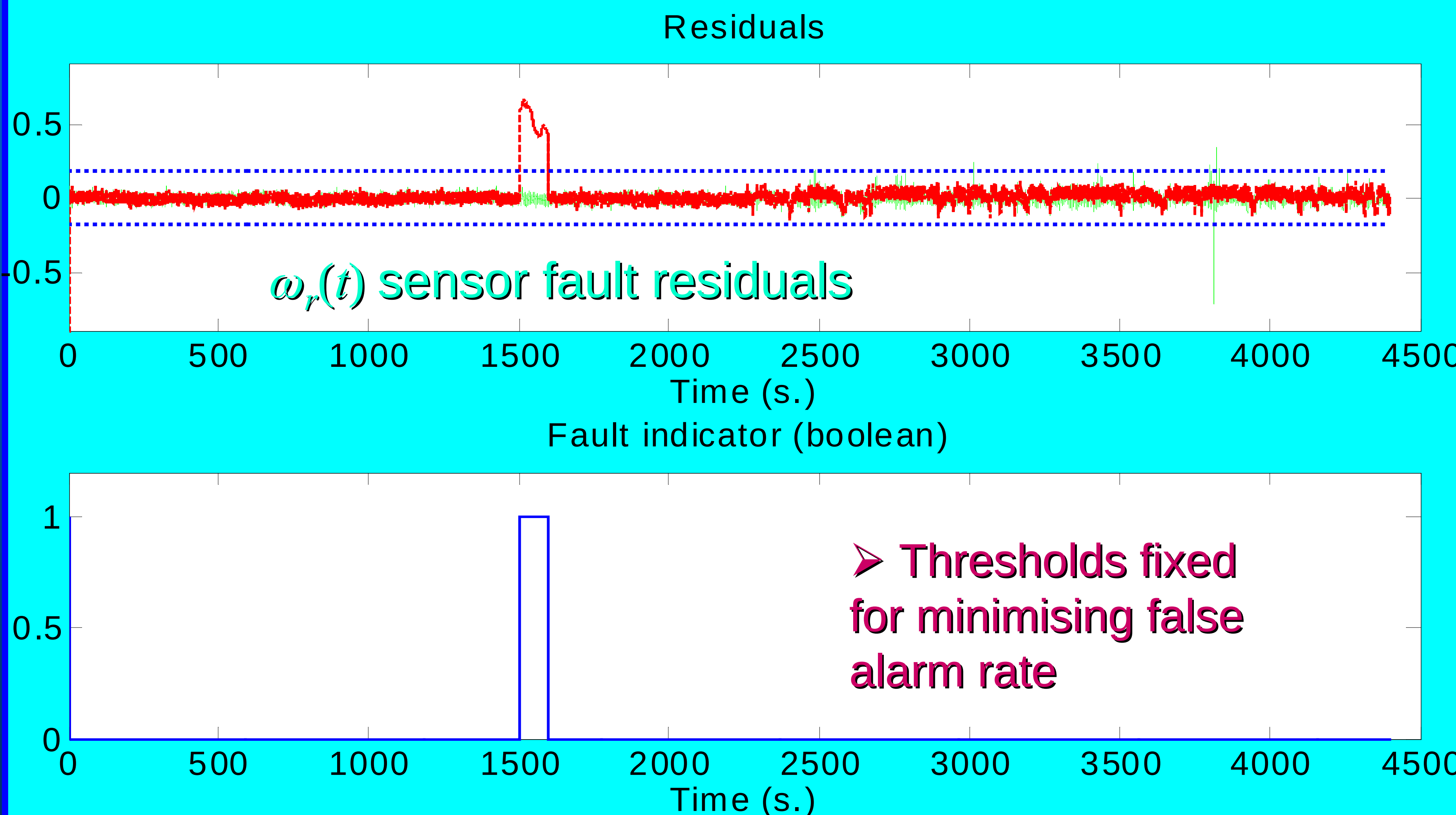
$$y_i(t) = \theta_i^T\, x_i(t)$$

$$y(t+n) = f\big(\mathbf{x}_n(t)\big) = \sum_{i=1}^{M} \chi_i\big(\mathbf{x}_n(t)\big)\,[\mathbf{x}_n(t), 1]^T\, \mathbf{a}_n^{(i)}$$



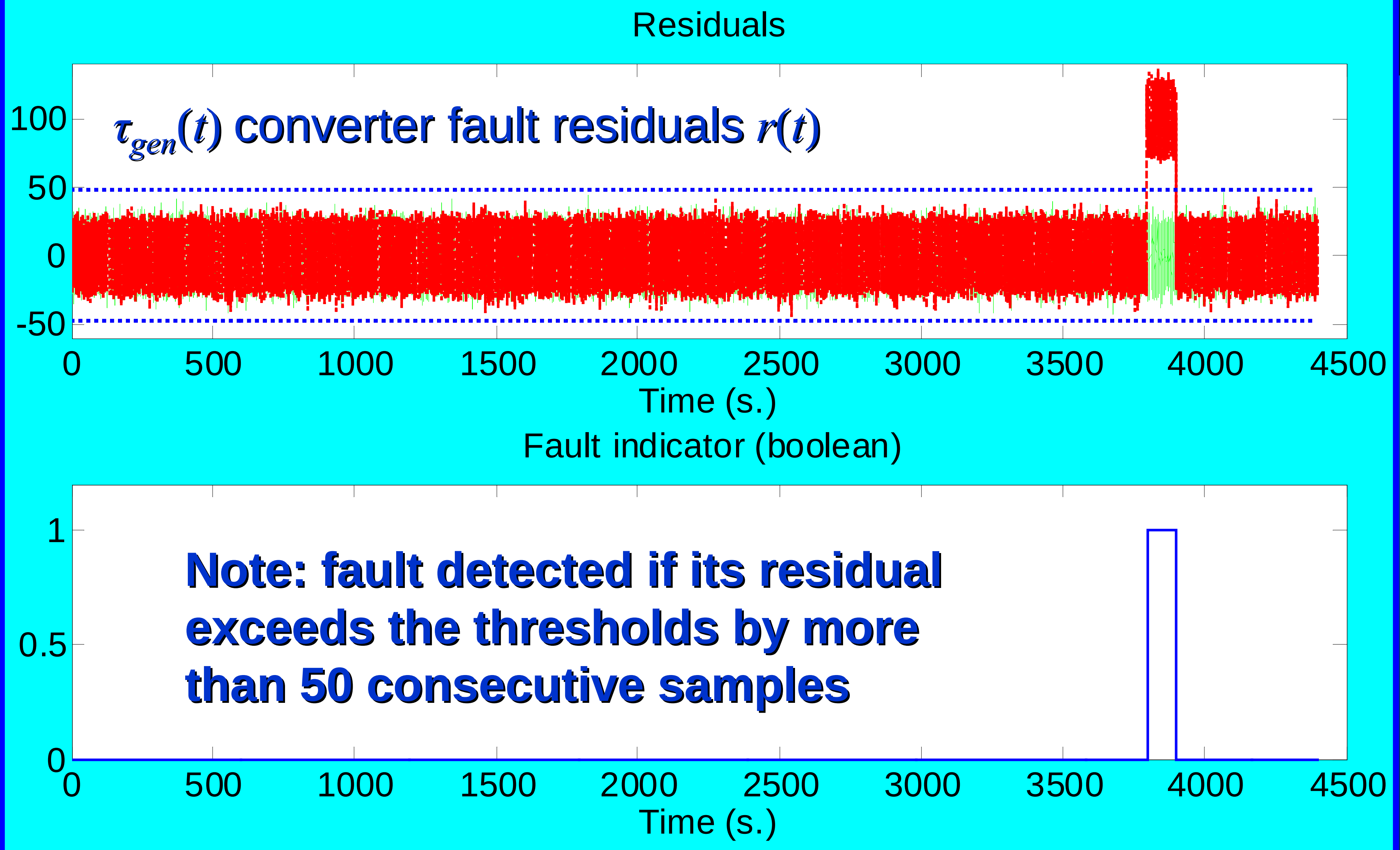
$\tau_{gen}(t)$ output and local models with $M = 2$, $n = 2$

Results for Fault_4

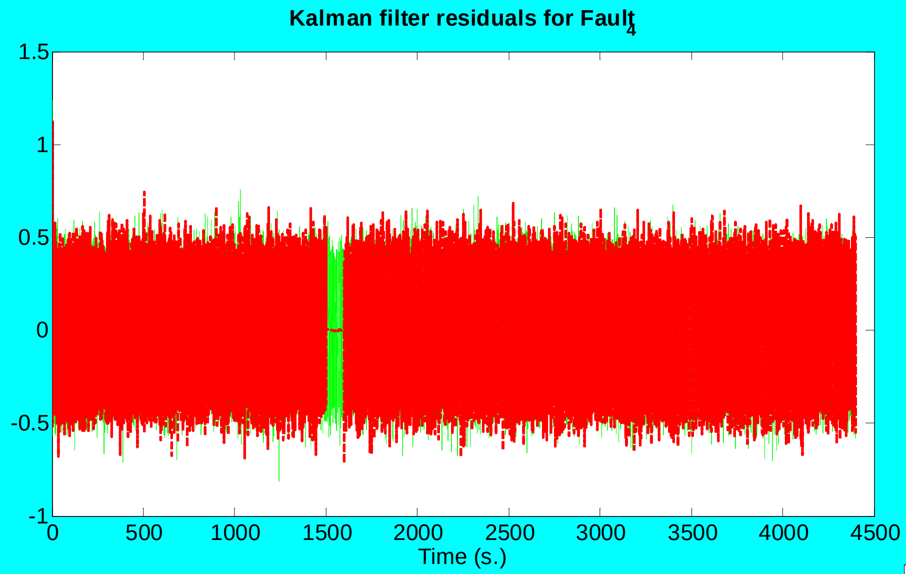


$\omega_r(t)$ sensor fault residuals $r(t)$, and the fault indicator function

Results for $Fault_8$

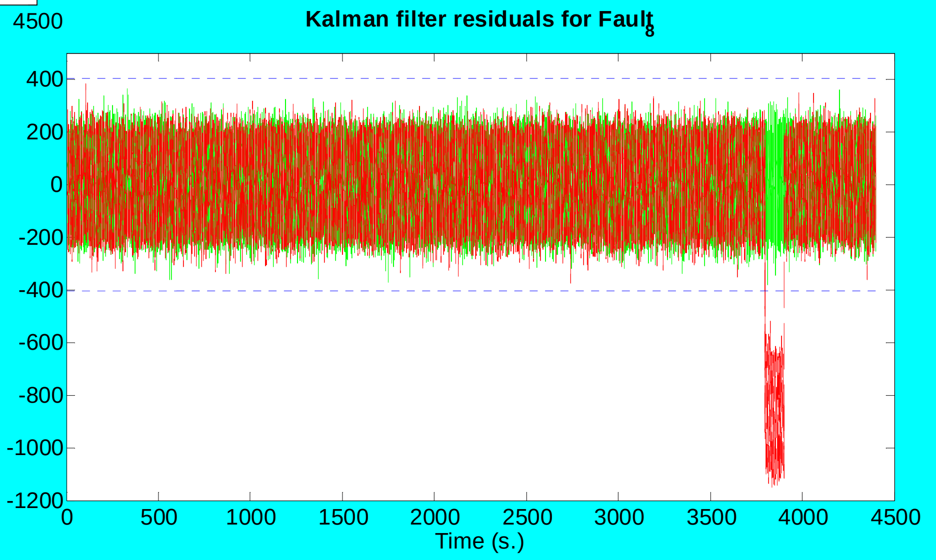


Comparison with Linear KF



$\omega_r(t)$ sensor fault residuals from KF: output prediction errors

$\tau_{gen}(t)$ converter fault residuals from KF: output prediction errors



Concluding Remarks

- ✓ Practical results in actuator and sensor FDI
  - Identified model-based FDI approach
- ✓ Simplicity of the FDI structure
- ✓ Algorithmic simplicity is seen as a very important aspect when considering the need for verification and validation of a demonstrable scheme for industrial certification and practical process FDI
- ✓ The more complex the computations required to implement the scheme, the higher the cost and complexity in terms of certification

Concluding Remarks (Cont'd)

- ✓ Modelling uncertainty and measurement error seem to be well tackled
- ✓ The achieved results highlight the potential of using such a method in real applications
- ✓ Extensive simulations for estimating the reliability of the developed FDI scheme and the final performance
- ✓ Studies have been carried out to evaluate the effectiveness of the approach when applied to real data

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Thank you for your attention!

We are well behind and still have a long way to go...