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Dynamic Modeling and Robust Fault Detection of Gas Turbine Engines

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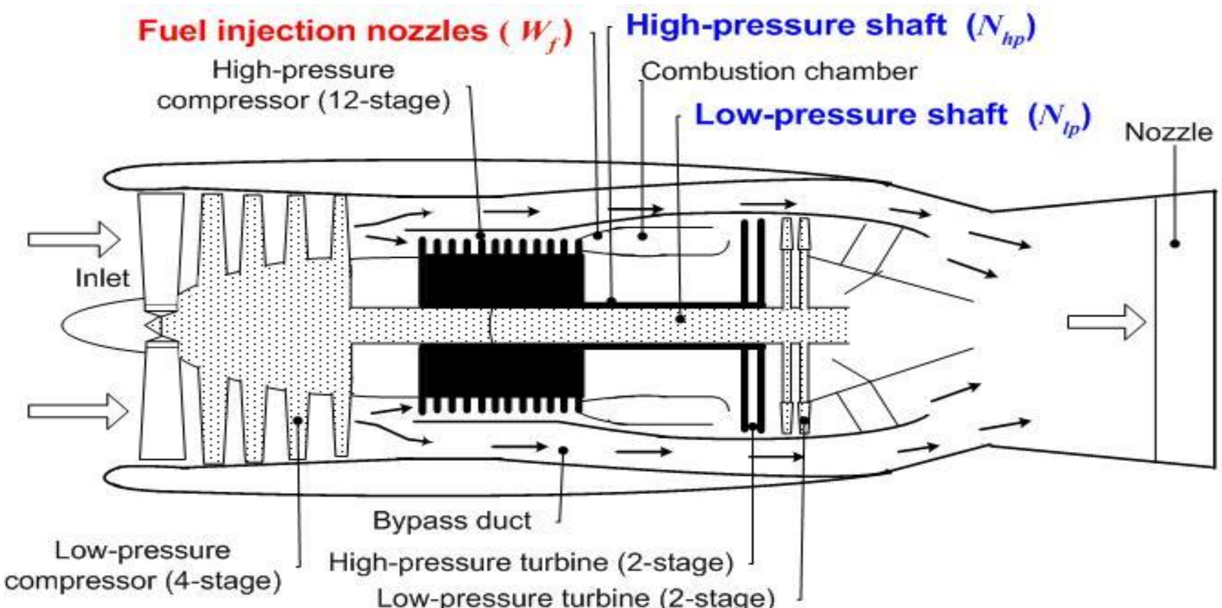
Outline

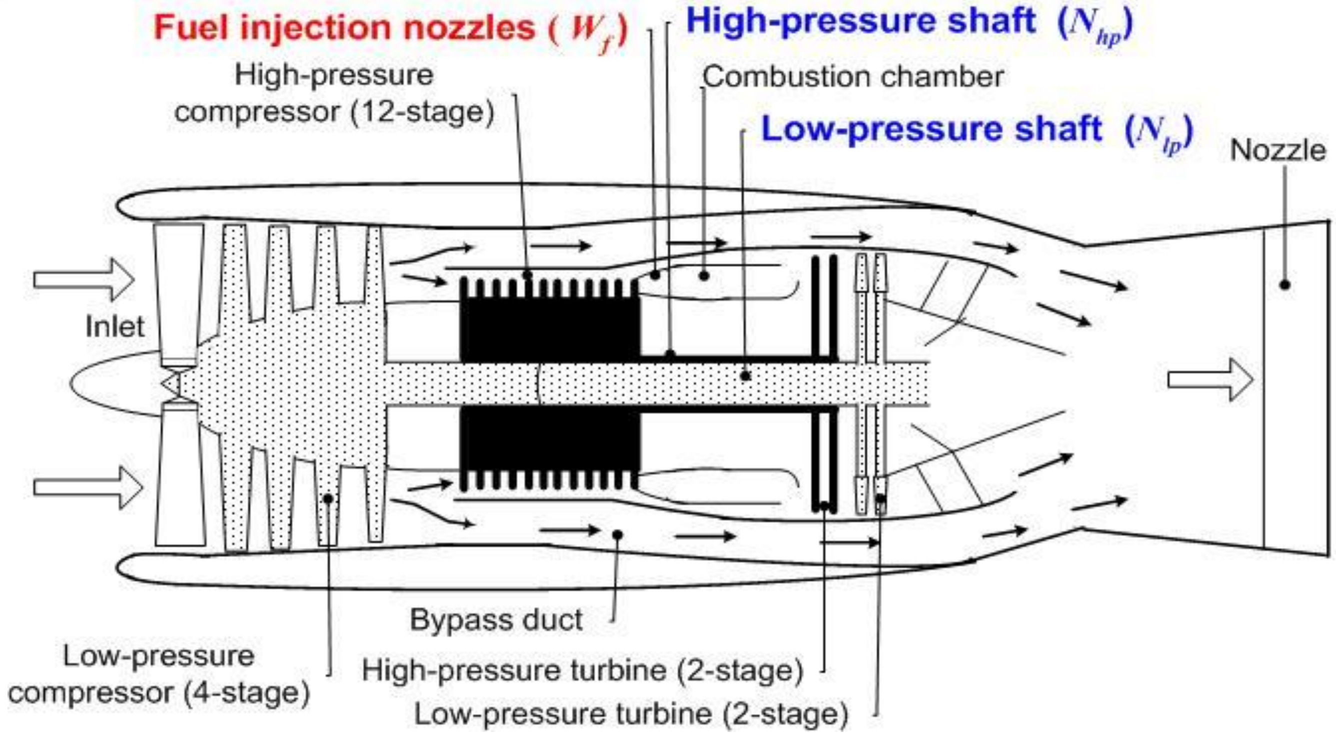
- **1. Problem Statement and Objectives**
- **2. Output Error Modelling**
- **3. Robust Fault Detection Observer Design**
- **4. Application and Results**

1. Problem statement

- Difficulties in on-board modelling and condition monitoring
  1. An Output Error (OE) model is required
  2. Conflicts between iterative identification algorithms and limited on-board computation resources
  3. Being corrupted by the disturbance and/or noise.



Dynamic Modeling and Robust Fault Detection



Around some operating point

- The reheat nozzle area and the angle of the VGVs (Variable guide vanes) are fixed.
- The fuel flow (*Wf*) is the input: $u(t) = W_f(t)$
- The shaft speeds are the primary outputs: $y(t) = [y_1, y_2] = [N_{LP},\ N_{HP}]$

Objectives

- Fitting the parametric model to the data:

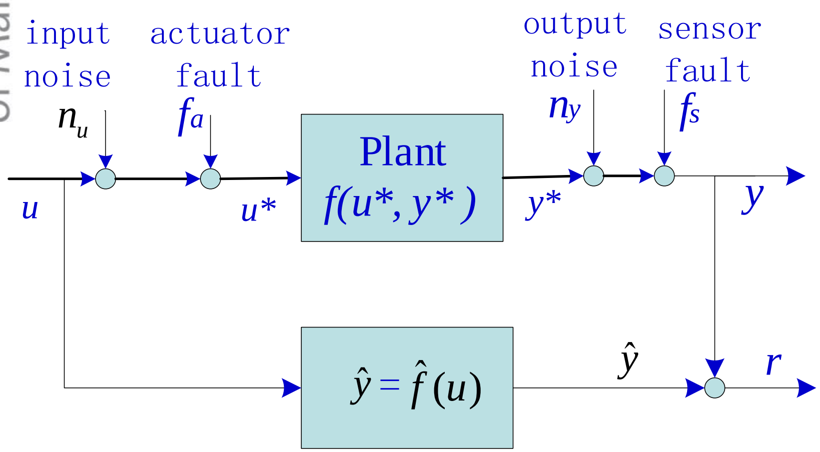
  fast identification algorithm (accelerating the convergence speed)

- Designing the observer (residual generator):

  the residual should be sensitive to the fault, but robust to the disturbances.

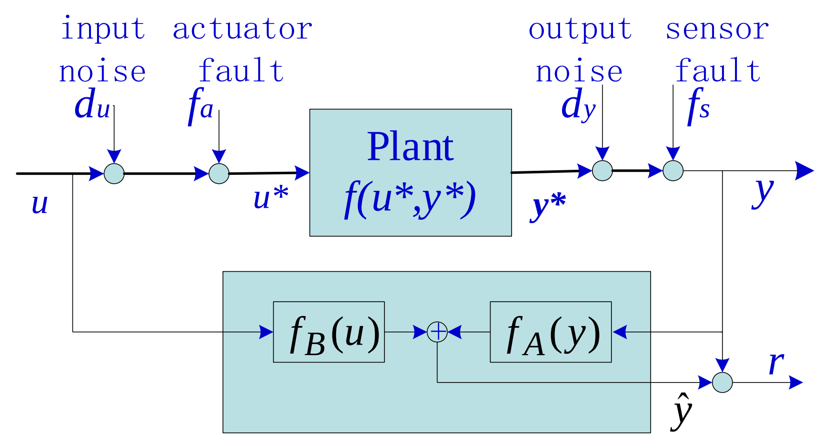
2. EE v.s. OE

(a) parallel connection mode

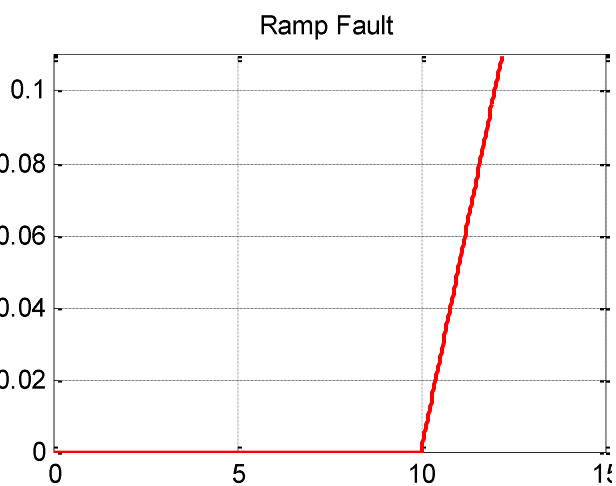


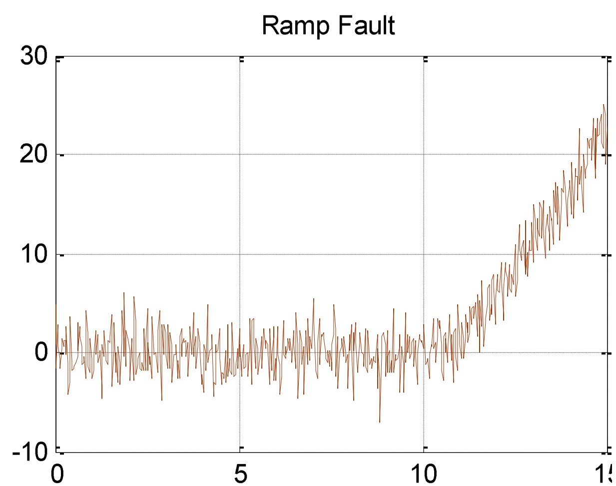
Parallel model

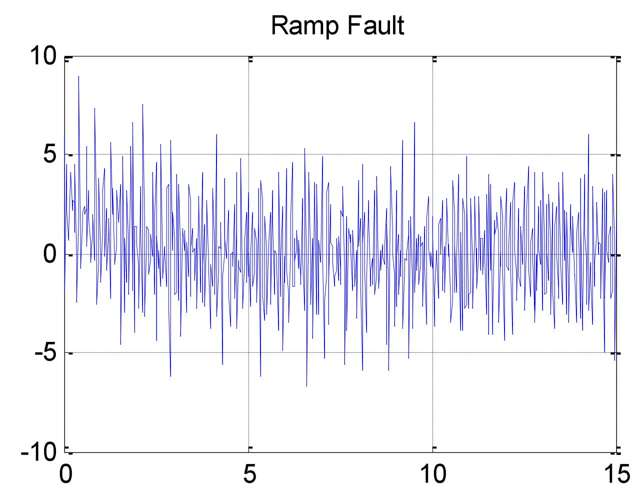
(b) parallel-series connection mode



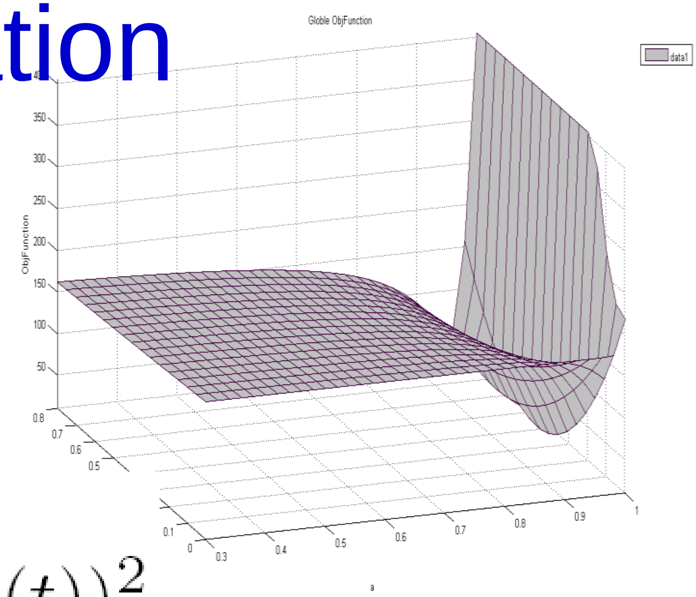
Parallel-series model







OE Identification



$$\hat{y}_i(t) = \frac{\sum_{j=1}^{n} \beta_{i,j} q^{-j}}{1 + \sum_{j=1}^{n} \alpha_{i,j} q^{-j}} u(t)$$

- Aims: minimize MSOE

$$\min_{\theta_i \in \Re^{2n}} E(\theta_i) = \sum_{t=1}^{N} (y_i(t) - \theta_i^T \cdot \hat{z}_i(t))^2$$

- The objective function $E(\theta_i)$ is highly nonlinear
- Some iterative optimization method has to be used, NLS (Nonlinear Least Squares)

$$\theta_i(k+1) = \theta_i(k) - \eta^* \cdot [\mathbf{R}_i(k)]^{-1} \cdot \frac{\partial E(\theta_i(k))}{\partial \theta_i}$$

Correlated Output Errors

a.) Iterative calculation of gradient

$$g_i(t) = \frac{\partial(y_i(t) - \hat{y}_i(t))}{\partial\theta_i}$$
$$= -\hat{z}_i(t) + [g_i(t-1) \cdots g_i(t-n)\ 0 \cdots 0] \cdot \theta_i(k)$$

and

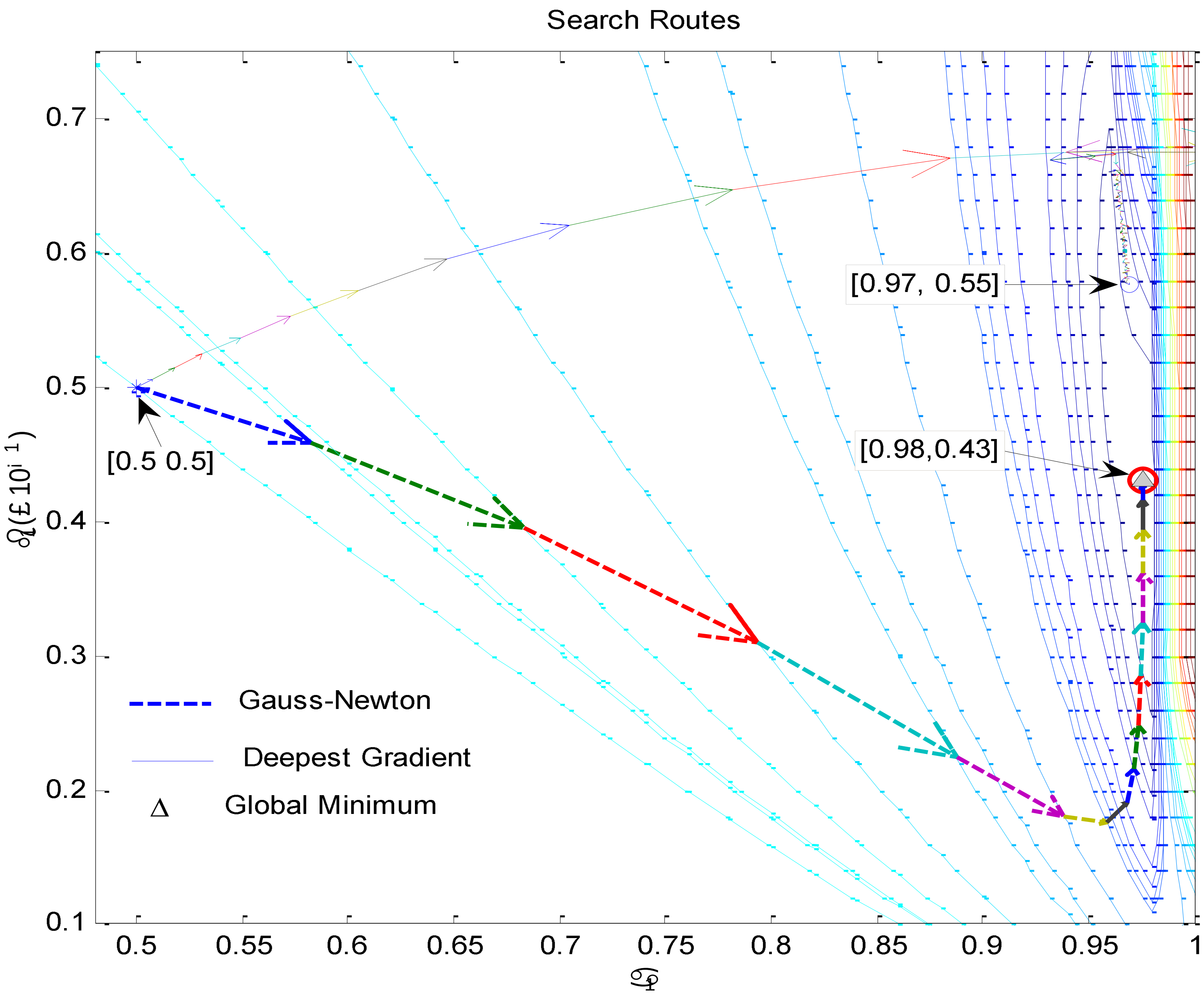
$$\frac{\partial E(\theta_i(k))}{\partial\theta_i} = 2\sum_{t=1}^{N} \varepsilon_i(t) \cdot g_i(t)$$

b.) Approximation of $R_i(k)$

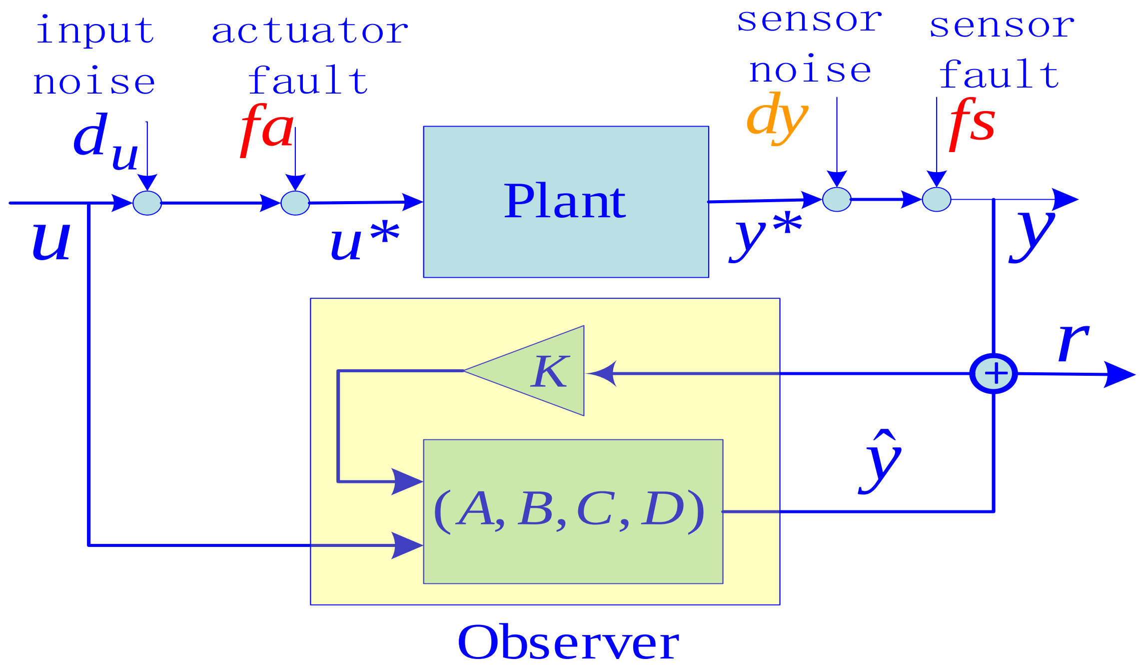
--Gauss-Newton method

$$\mathbf{R}_i(k) \approx \mathbf{H}_i(\theta_i(k)) \approx \mathbf{J}_i^T(k) \cdot \mathbf{J}_i(k)$$

Dynamic Modeling and Robust Fault Detection



3. Robust Fault Detection Observer Design



$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + B_d d(k) + B_f f(k) \\ y(k) = Cx(k) + D_d d(k) + D_f f(k) \end{cases}$$

$$\begin{cases} \hat{x}(k+1) = A\hat{x}(k) + Bu(k) + K(y(k) - \hat{y}(k)) \\ \hat{y}(k) = C\hat{x}(k) + Du(k) \end{cases}$$

TFMs (Transfer Function Matrices)

- The TFMs relating the residual $r(z)$ to the fault $f(z)$ and disturbance $d(z)$ are

$$r(z) = G_f(z) f(z) + G_d(z) d(z)$$

Robustness index

$$\min \; J = \frac{J_1}{J_2}$$

$$\min \; \| G_d(z) \|_{z=e^{jw_r}}$$

$$\max \; \| [G_f(z)] \|_{z=1}$$

Sensitivity index

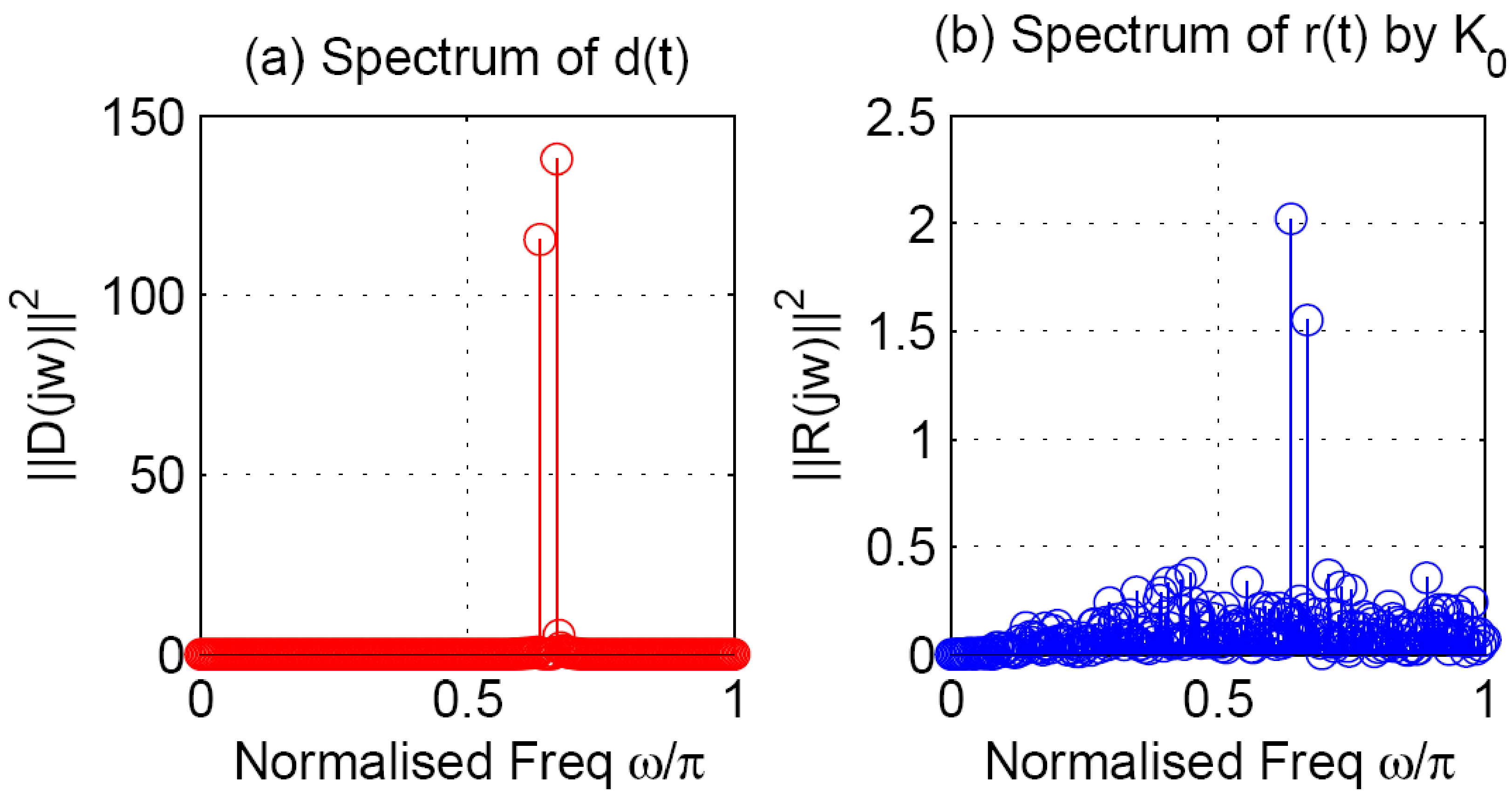
Eigenstructure Assignment and Optimisation

- With the aid of eigen value analysis, the TFMs $G_f(z)$, $G_d(z)$ and the gain matrix ***K*** can be parameterized with a set of eigenvalues and a set of free parameters.

- Using optimisation algorithms results in an optimal observer for fault detection and disturbance attenuation.

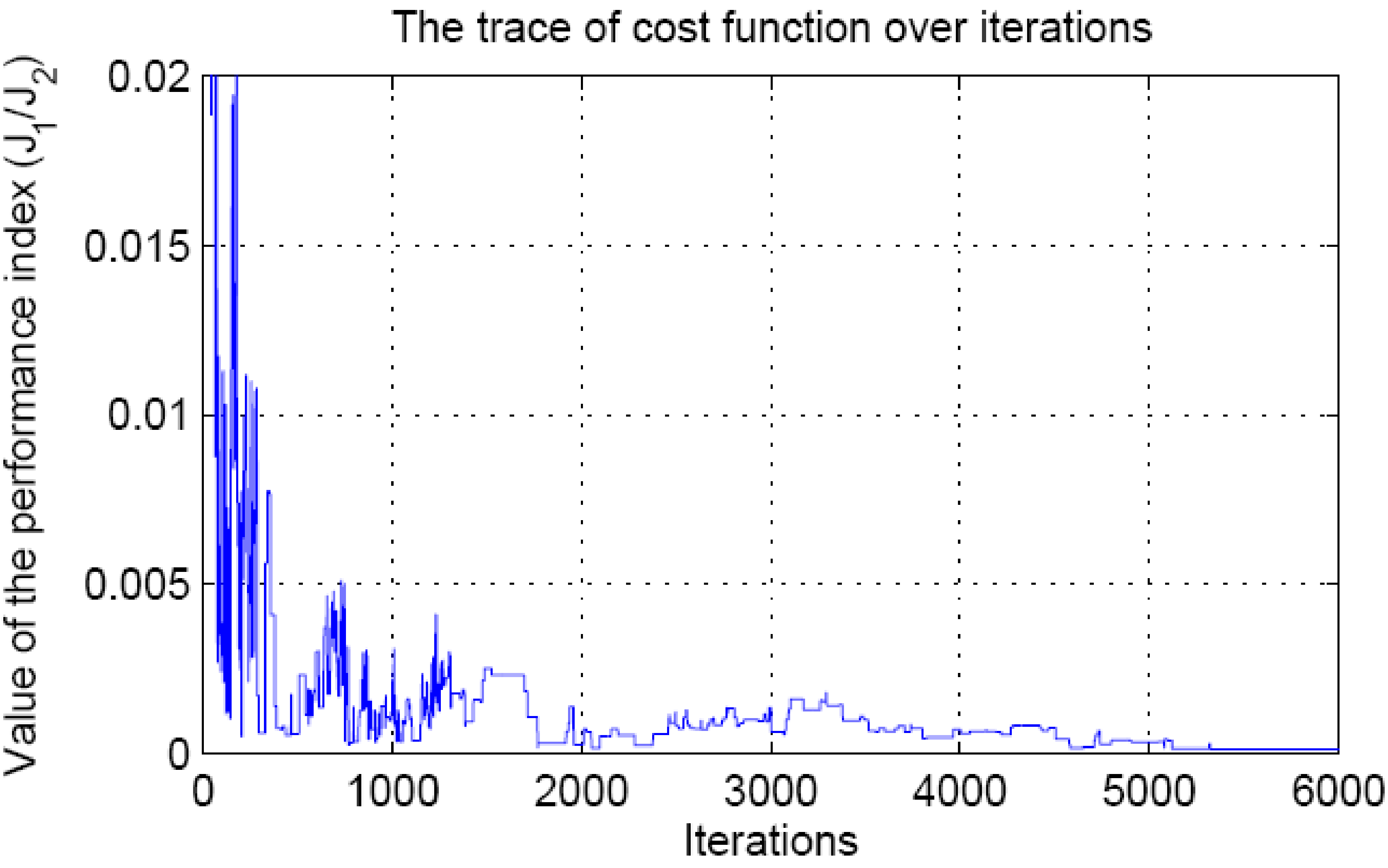
4. Results

- Disturbances injected into the system
- Residual spectrum analysis



Trace of cost function over iteration

-Simulated Annealing

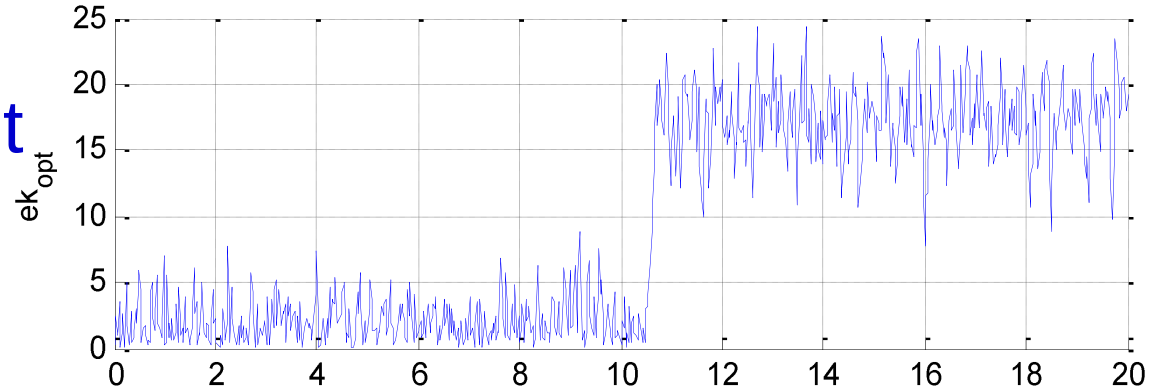


Fault detection

residuals

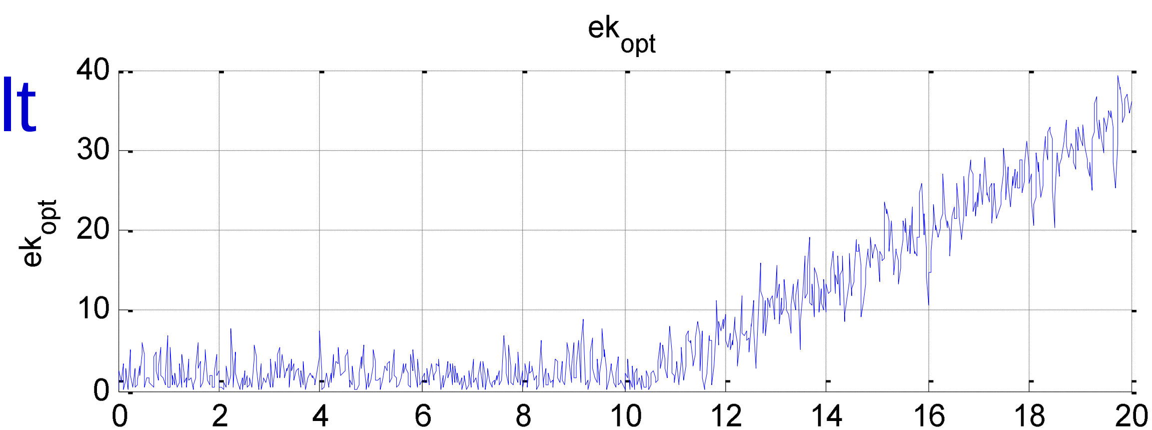
abrupt sensor fault

$$f_s(t) = \begin{cases} 0 & t < 10.5\text{sec} \\ 0.25 & t > 10.5\text{sec} \end{cases}$$

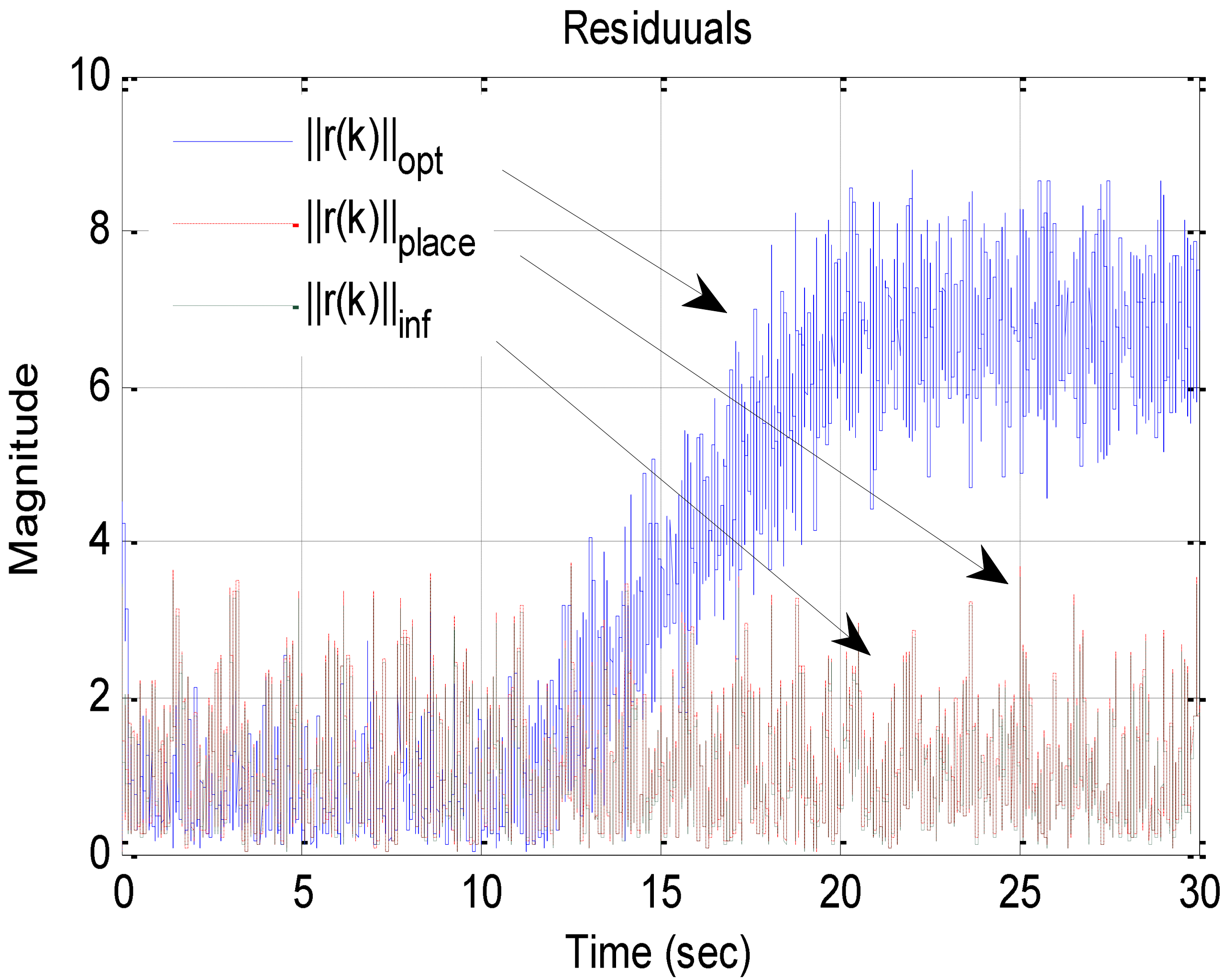


incipient sensor fault

$$f_s(t) = \begin{cases} 0 & t < 10.5\text{sec} \\ 0.5(t - 10.5) & t > 10.5\text{sec} \end{cases}$$



Fault Detection



Thanks