Fault Detection and Diagnosis in Dynamic Systems with Maximal Sensitivity

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Sensor Fault Detection and Isolation

- Extensive literature exists in fault detection:
  - Fault detection based on parity relations and observers/Kalman filters
  - Gross error detection methods, often based on first principles models
  - Statistical correlation based methods (PCA, PLS, etc.)
- Sensor validation: detect, identify, and reconstruct faulty sensors using statistical and/or first principles models.

Outline

- Here we present a subspace model based approach for dynamic fault detection and identification
  - Structured residual approach
  - Steady state FDD with maximal sensitivity
  - A boiler process example
  - Dynamic structured residuals with maximal sensitivity
  - An industrial case study
  - Conclusions and Acknowledgments

Models for Fault Detection

$$\mathbf{Bx} = \mathbf{0} \quad \text{(First Principles, PLS, PCA, etc.)}$$

Actual: $\mathbf{e} = \mathbf{Bx}$ (noise, or equation error)

Fault: $\mathbf{x}_i = \mathbf{x}^* + \xi_i f$; e.g., $\xi_i = [0 \quad 1 \quad \ldots \quad 0]^T$

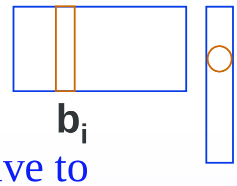
Error: $\mathbf{e}_i = \mathbf{Bx}_i = \mathbf{Bx}^* + \mathbf{B}\xi_i f = \mathbf{e}^* + \mathbf{b}_i f$

Fault Detection: $d = \|\mathbf{e}_i\|^2$

We can determine a confidence limit for d.

Structured Residuals Approach

- Start from a normal model, $e(t) = Bx(t)$
- Design a set of structured residual, $r_i(t)= w_i^T e(t)$
- Design w_i such that one residual (r_i) is not sensitive to one group of faults, but sensitive to others
- Estimate fault magnitude
- Isolate from process faults

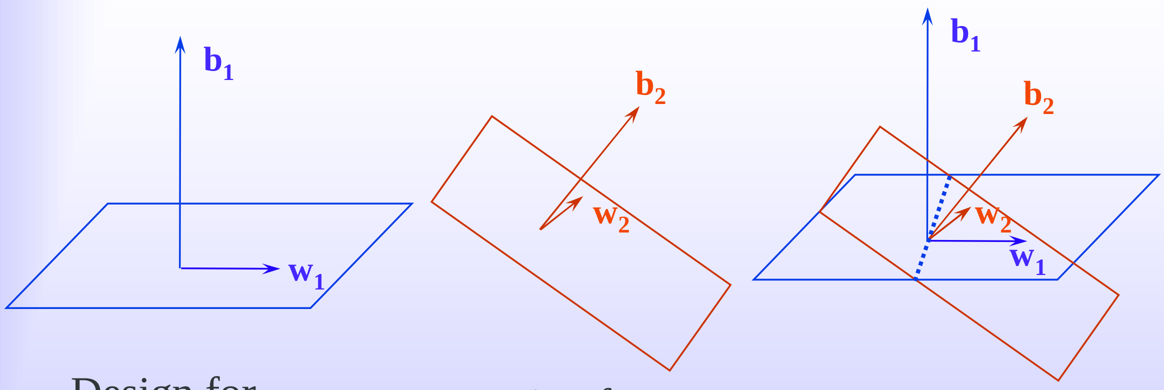


	$f_1(t)$	$f_2(t)$	$f_3(t)$	$f_4(t)$	$f_5(t)$	$f_6(t)$
$r_1(t)$	**0**	**0**	**1**	**1**	**1**	**1**
$r_2(t)$	**1**	**0**	**0**	**1**	**1**	**1**
$r_3(t)$	**1**	**1**	**0**	**0**	**1**	**1**
$r_4(t)$	**1**	**1**	**1**	**0**	**0**	**1**
$r_5(t)$	**1**	**1**	**1**	**1**	**0**	**0**
$r_6(t)$	**0**	**1**	**1**	**1**	**1**	**0**

Degrees of Freedom or Redundancy

- There is a limit on the number of zeros one can choose in each column; this is determined by the degrees of freedom or analytical redundancy in the model
- If one specifies the maximum number of zeros in each column, the weighting vector is unique. However, this is often not a good approach as other non-zero elements can be close to zero
- Usually the number of specified zeros is less than the degrees of freedom. This gives more flexibility in choosing the weighting vector, but it is not unique

Geometric Properties of Structured Residuals



Design for column 1

Design for column 2

Put them together

Structured Residuals with Maximal Sensitivity

Design a structured residual:

$r_{ij} = \mathbf{w}_i^T \mathbf{e}_j$ is NOT sensitive to $\mathbf{b}_i$

but MOST sensitive to $\mathbf{b}_j$ $(j \neq i)$

for i,j=1,2, ... n

Multiple sensor faults can also be handled similarly.

Solution Approach

- The problem is equivalent to

$$\max \sum_{j \neq i} (\mathbf{w}_i^T \mathbf{b}_j)^2$$

$$\text{subject to: } \mathbf{w}_i^T \mathbf{b}_i = 0$$

$$\text{and: } \|\mathbf{w}_i\| = 1$$

- The solution is an eigen-problem:

$$\mathbf{B}_i^\circ \mathbf{B}_i^{\circ T} \mathbf{w}_i = \lambda \mathbf{w}_i$$

$$\text{where } \mathbf{B}_i^\circ = (\mathbf{I} - \mathbf{b}_i^\circ \mathbf{b}_i^{\circ T}) \mathbf{B}^\circ$$

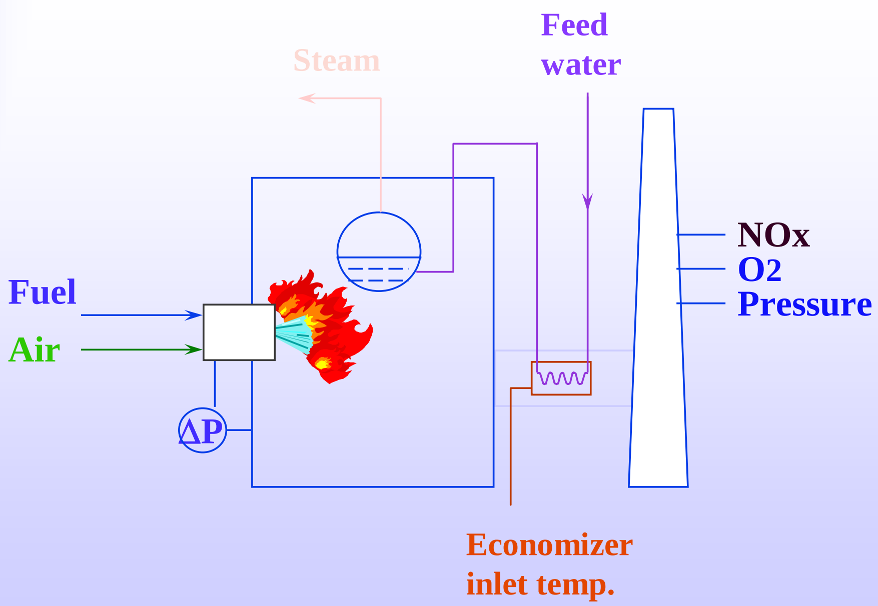
and $\mathbf{B}^\circ$ is $\mathbf{B}$ after column - normalization

Other Issues

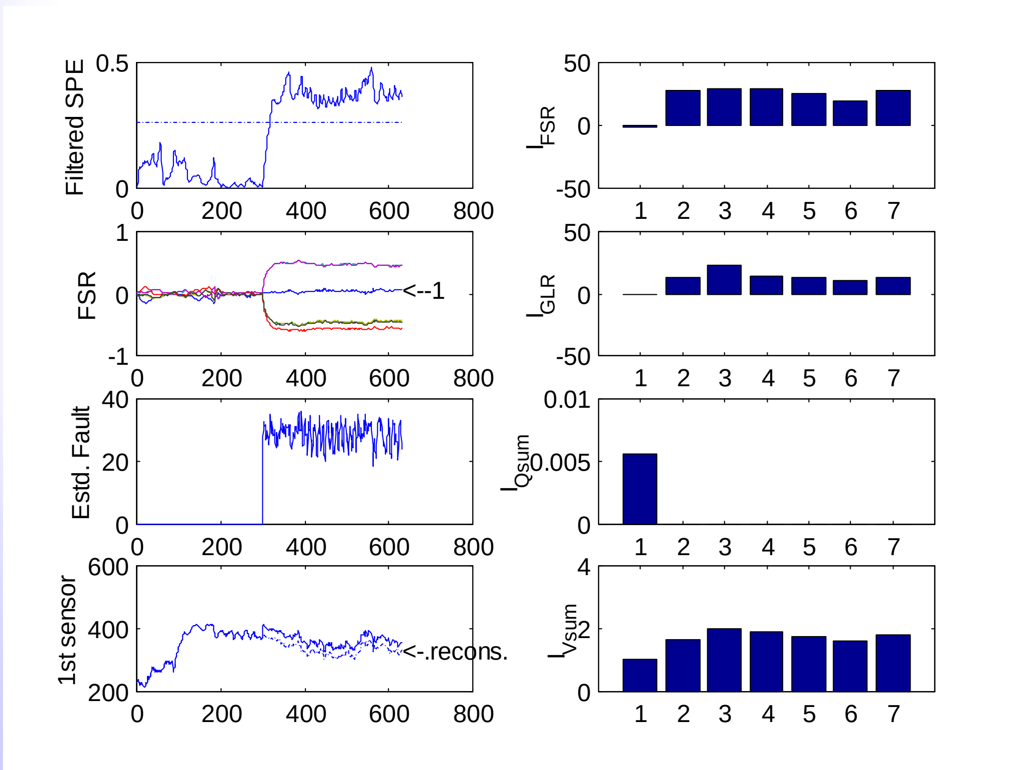
- Filtering the Detection Index
- Fault Identification Indices
  - EWMA-filtered structured residuals
  - Generalized likelihood ratio (GLR)
  - Cumulative sum of residuals (Qsum)
  - Cumulative variance (Vsum)
- Estimating of the fault magnitude
- Classifying types of faults: bias, drift, frozen, variance degradation
- Isolating sensor faults from process disturbances/faults

Example: Boiler Process

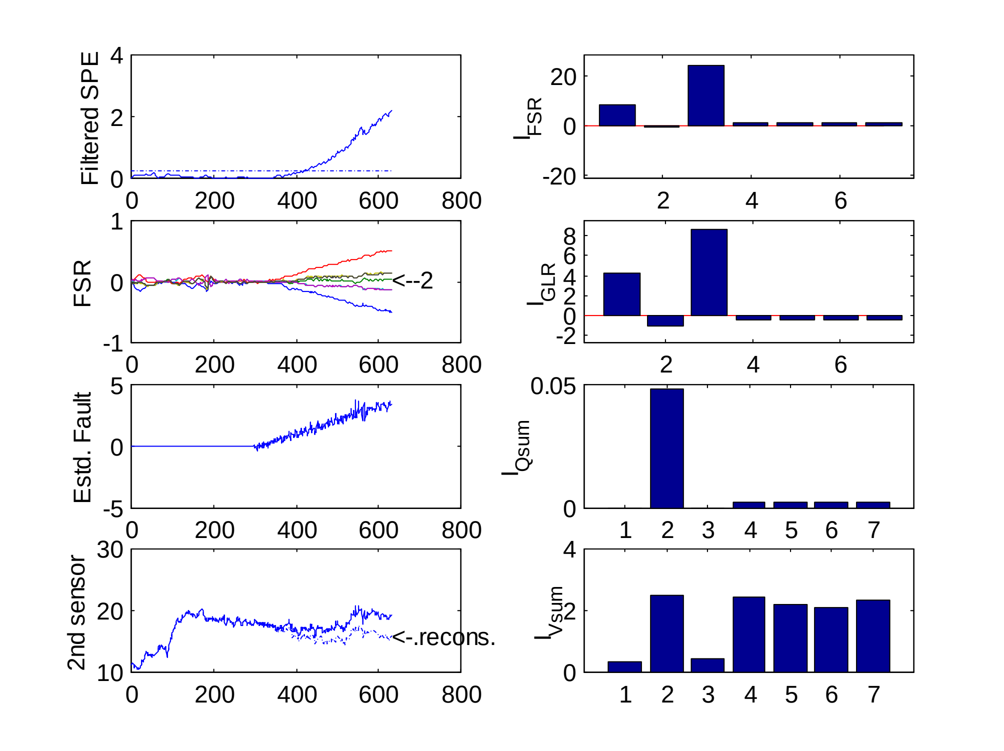
- Faults tested: bias, drift, complete failure, and precision loss



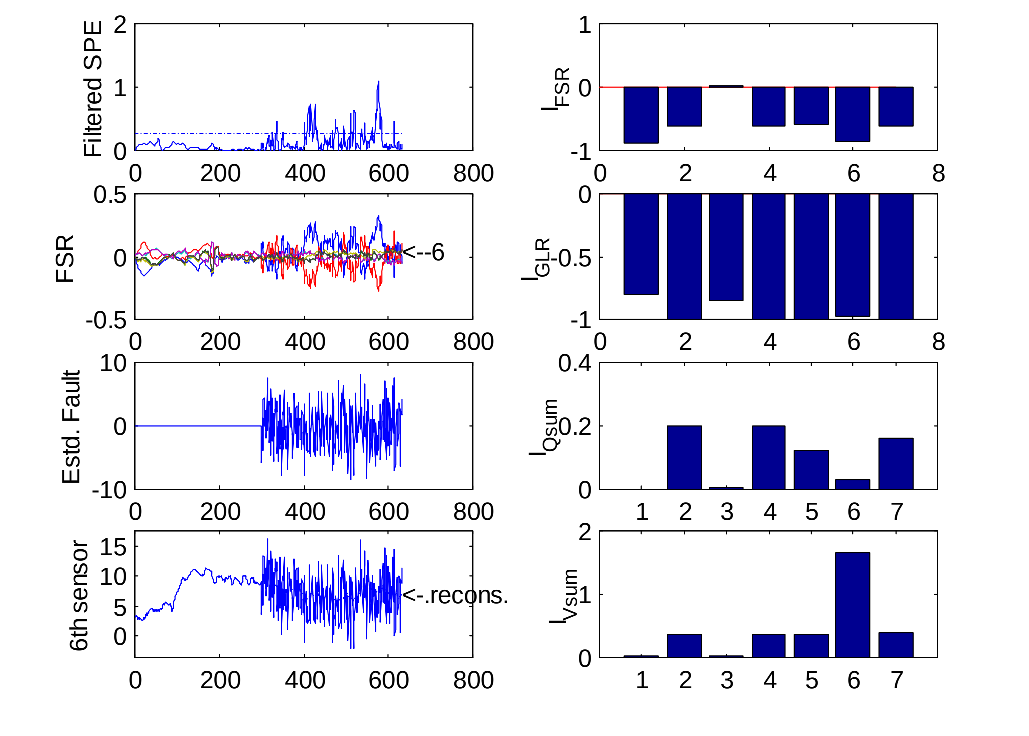
Bias in Airflow (28KPPH)



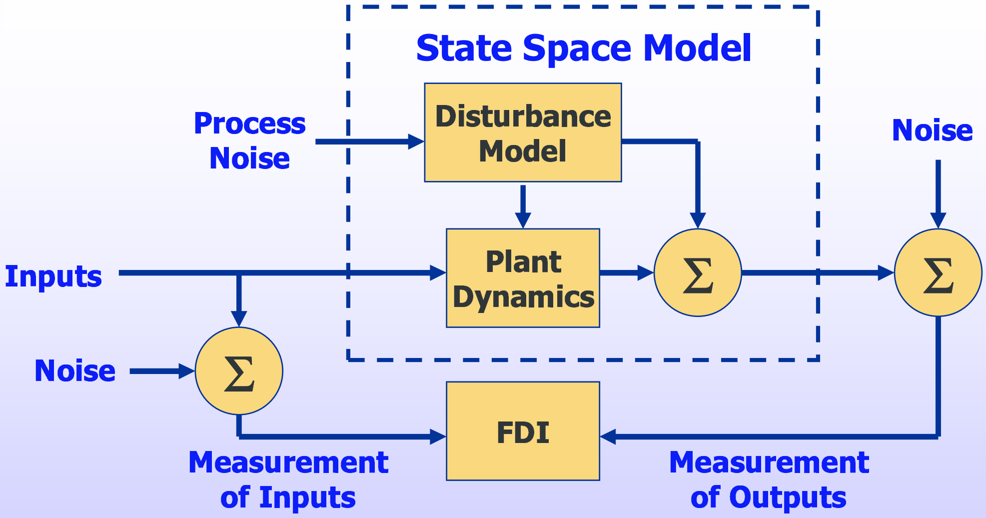
Drift in Fuel Flow (0.01%)



Precision Loss in Windbox Pressure



Errors-in-Variables Dynamic System



Dynamic Process Models

For a deterministic-stochastic system:

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \mathbf{w}_k$$
$$\mathbf{y}_k = \mathbf{C}\mathbf{x}_k + \mathbf{D}\mathbf{u}_k + \mathbf{v}_k$$

with

$$E\left[\begin{pmatrix}\mathbf{w}_k \\ \mathbf{v}_k\end{pmatrix}\begin{pmatrix}\mathbf{w}_l^T & \mathbf{v}_l^T\end{pmatrix}\right] = \begin{pmatrix}\mathbf{Q} & \mathbf{S} \\ \mathbf{S}^T & \mathbf{R}\end{pmatrix}\delta_{kl} \geq 0$$

Extended State Space Model

Iterating the state space model yields the following extended model:

$$\mathbf{y}_f(k) = \mathbf{\Gamma}_f \mathbf{x}_k + \mathbf{H}_f \mathbf{u}_f(k) + \mathbf{G}_f \mathbf{w}_f(k) + \mathbf{v}_f(k)$$

Where the augmented vector is organized as

$$\mathbf{u}_f(k) = \begin{bmatrix} \mathbf{u}_k \\ \mathbf{u}_{k+1} \\ \vdots \\ \mathbf{u}_{k+f-1} \end{bmatrix}$$

The extended observability matrix

$$\mathbf{\Gamma}_f = \begin{bmatrix} \mathbf{C} \\ \mathbf{CA} \\ \vdots \\ \mathbf{CA}^{f-1} \end{bmatrix}$$

and the (deterministic) Toeplitz matrix

$$\mathbf{H}_f = \begin{bmatrix} \mathbf{D} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{CB} & \mathbf{D} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{CA}^{f-2}\mathbf{B} & \mathbf{CA}^{f-3}\mathbf{B} & \cdots & \mathbf{D} \end{bmatrix}$$

Residual Form

- Implicit matrix form:

$$\begin{bmatrix}\mathbf{I} & -\mathbf{H}_f\end{bmatrix}\mathbf{z}_f(k) = \mathbf{\Gamma}_f\mathbf{x}(k) + \varepsilon_f(k)$$

- Eliminating the state vector,

$$(\mathbf{\Gamma}_f^{\perp})^T\begin{bmatrix}\mathbf{I} & -\mathbf{H}_f\end{bmatrix}\mathbf{z}_f(k) = (\mathbf{\Gamma}_f^{\perp})^T\varepsilon_f(k)$$

we obtain:

$$\mathbf{e}(k) = \tilde{\mathbf{P}}^T\mathbf{z}_f(k)$$

where

$$\tilde{\mathbf{P}}^T = (\mathbf{\Gamma}_f^{\perp})^T\begin{bmatrix}\mathbf{I} & -\mathbf{H}_f\end{bmatrix}; \qquad \mathbf{e}(k) = (\mathbf{\Gamma}_f^{\perp})^T\varepsilon_f(k)$$

- The model does not requires A,B,C,D explicitly and thus can use intermediate results from subspace identification

Related Issues

- f=n+1 will suffice due to the Cayley-Hamilton Theorem
- The impact of a single sensor fault is multi-dimensional.
- For example, for a SISO process with f=3, a fault in Sensor 1 (output) is

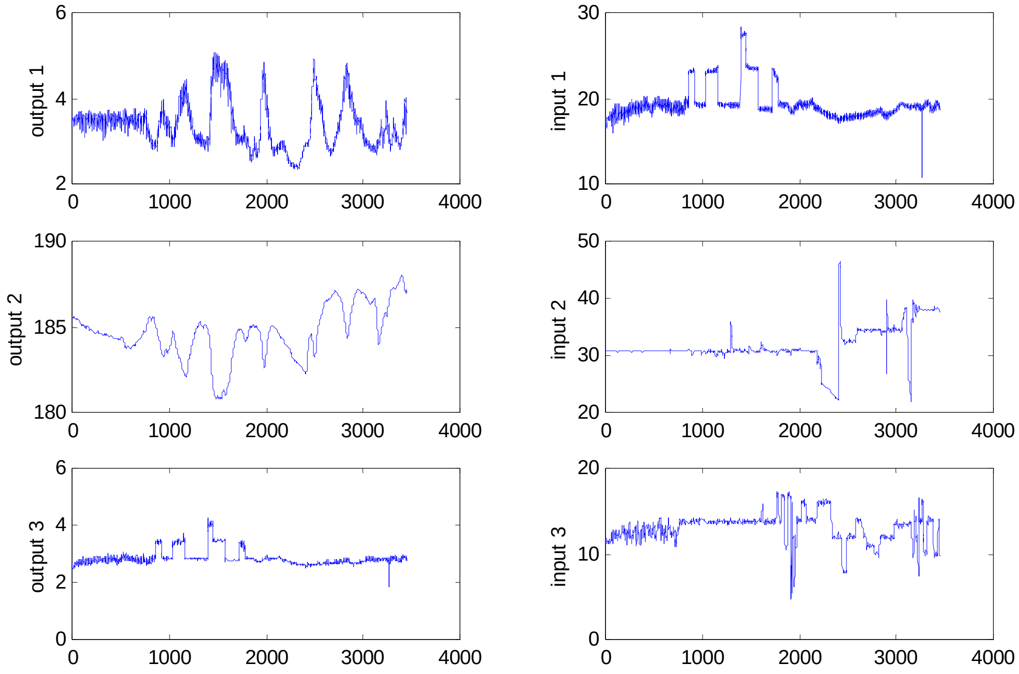
$$\mathbf{z}_f(k) = \mathbf{z}_f^*(k) + [\,f_1(k) \quad 0 \quad f_1(k-1) \quad 0 \quad f_1(k-2) \quad 0]^T$$
$$= \mathbf{z}_f^*(k) + \mathbf{\Xi}_1\mathbf{f}_{1f}(k)$$

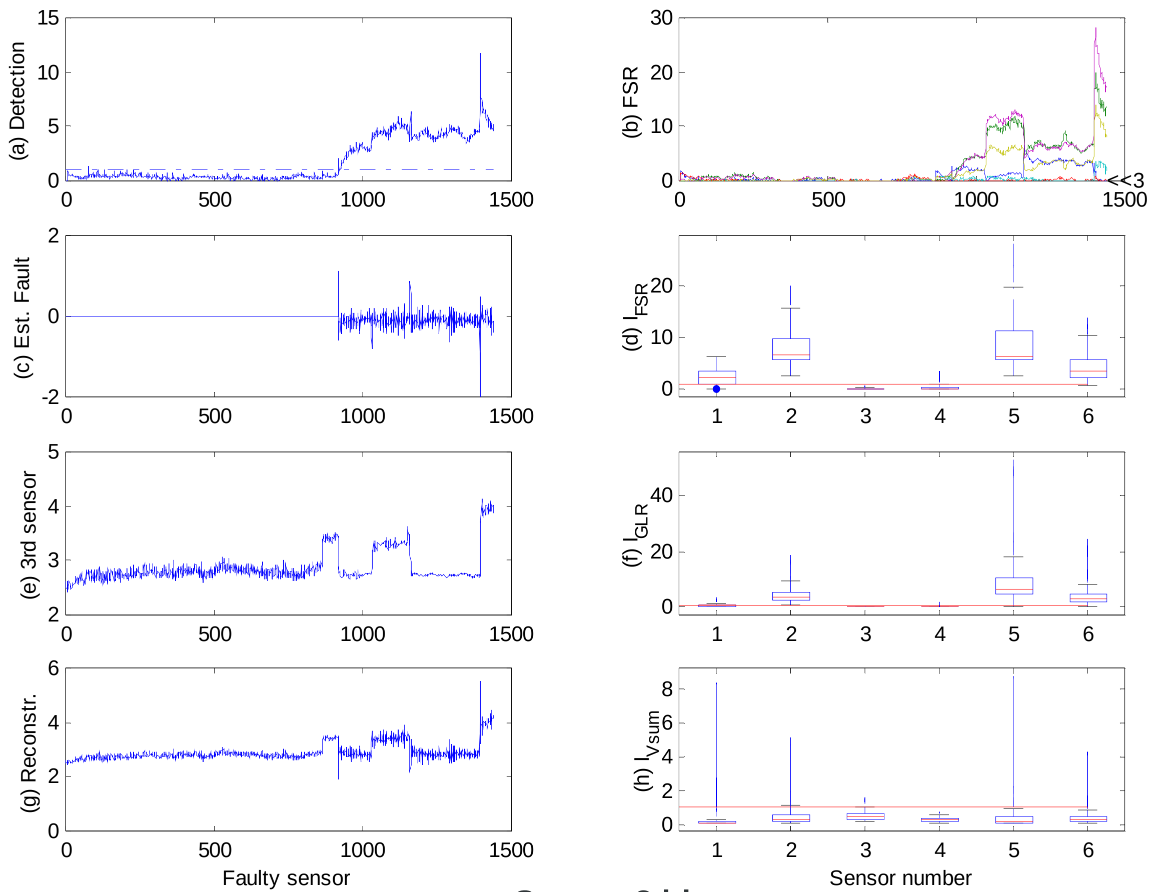
where

$$\mathbf{\Xi}_1^T = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}; \text{ and } \mathbf{f}_{1f}(k) = \begin{bmatrix} f_1(k) \\ f_1(k-1) \\ f_1(k-2) \end{bmatrix}$$

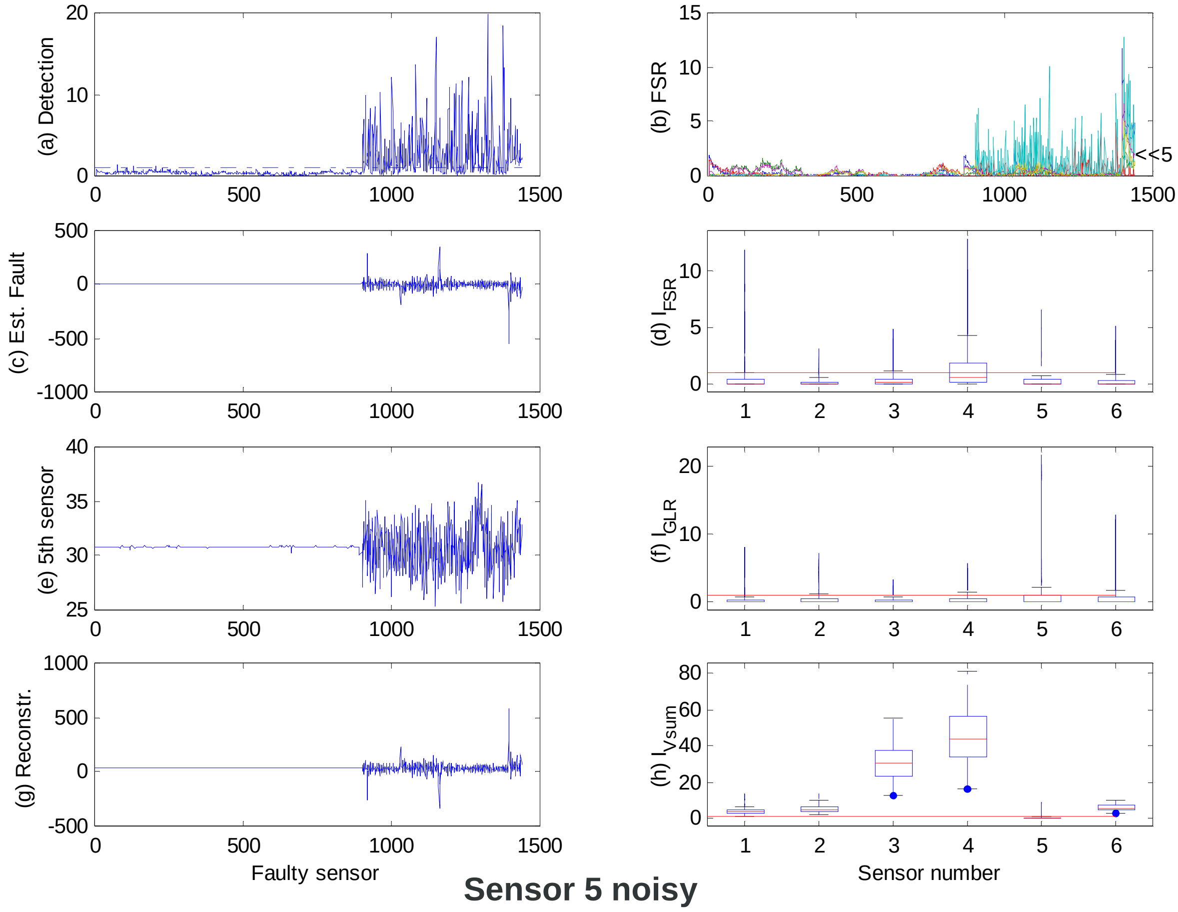
- If the fault type is known, the dimension can be reduced

Industrial Case: 3x3 Process Data





Sensor 3 bias



Sensor 5 noisy

Concluding Remarks

- Proposed a new structured residual design with maximized sensitivity
- The solution of the SRAMS design is an eigen-problem
- Applications to industrial process data are successful.
- Subspace identification approaches can be effective in modeling for fault diagnosis
- Future issues include the optimal structure of the incidence matrix table for a given problem

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