2000 SAFEPROCESS

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IFAC

- Sensor failure detection of air quality monitoring network.

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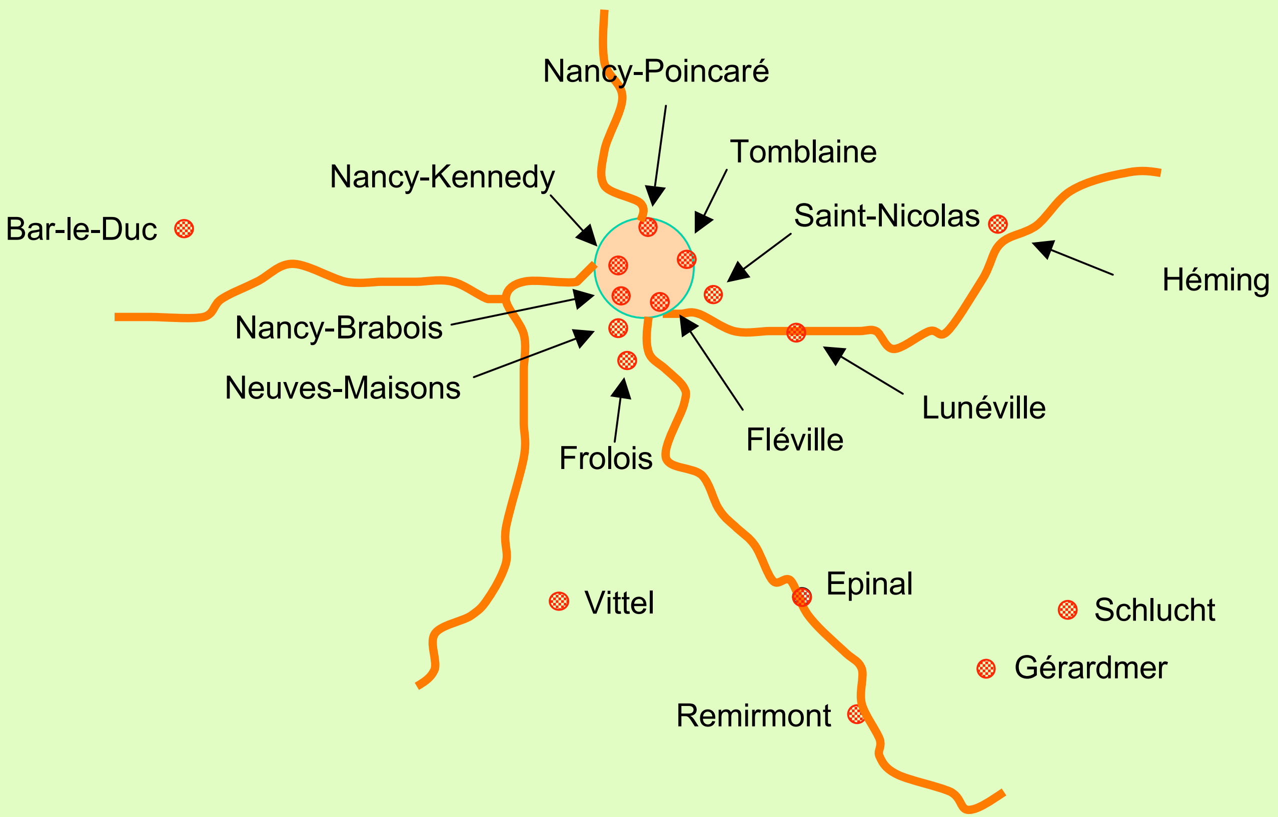
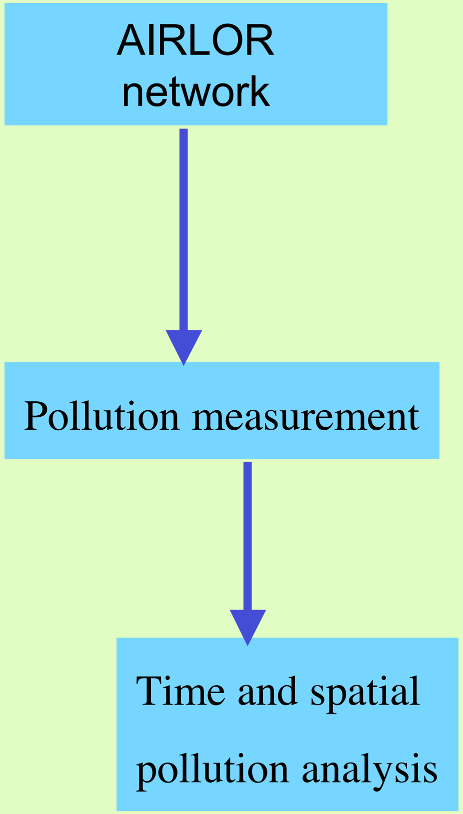
Sensor failure detection of air quality monitoring network

- Objectives of the study and process description
- PCA concepts
- PCA application to data reconstruction
- PCA application to fault detection
- PCA application to fault isolation
- Some numerical results
- Extensions end conclusion

1. Sensor failure detection of air quality monitoring network

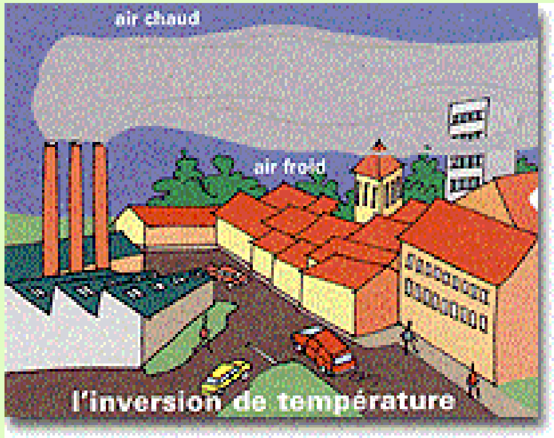




1. Objectives of the study « air quality monitoring »

Available data

Since	1995
Around Nancy :	16 stations
Data acquisition :	every 15 mn
Measurement :	O3, NO, NO2, SO2 ...
	P, H, T, Wd, Wf ...



Objectives

Permanent information of population

Prediction of pollution

Methods

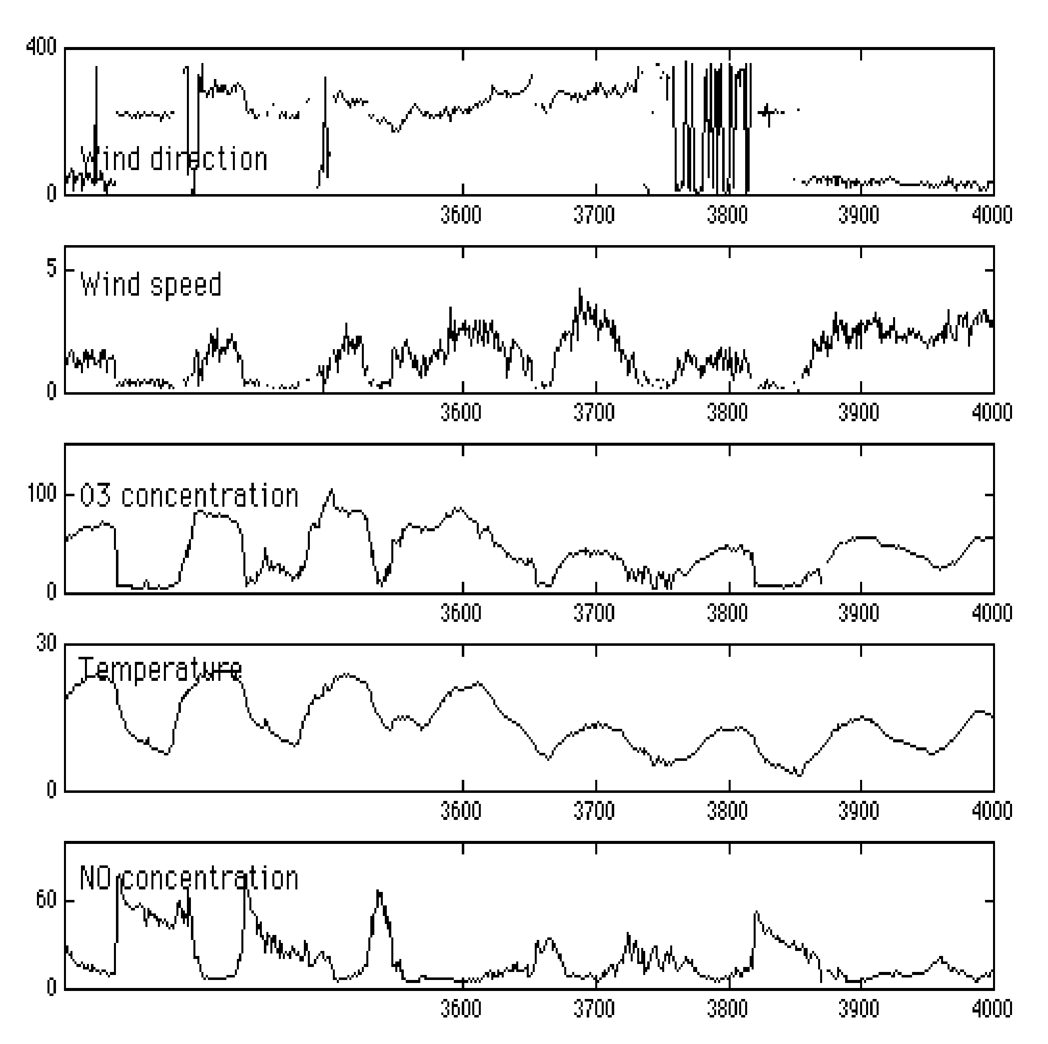
Data validation

Modelization

1. Objectives of the study « air quality monitoring »

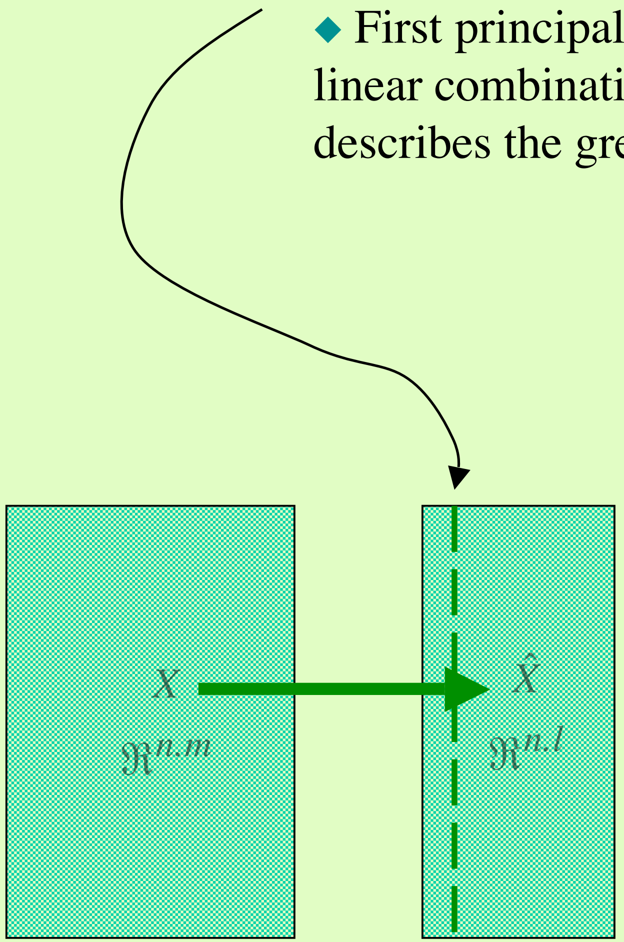
Measurements and difficulties

missing values
jumps in data
Noisy values



2. PCA first objective : data reduction

- First principal component
linear combination of the columns of X
describes the grestest amount of variability of X



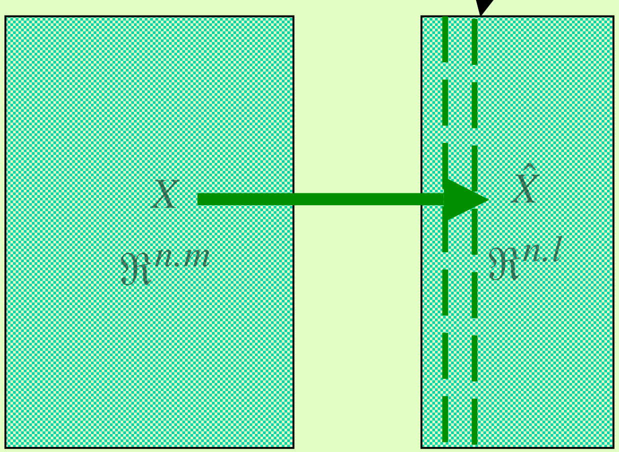
$$\begin{cases} t_1 = Xp_1 \\ \|p_1\|^2 = 1 \end{cases}$$

$$\Phi = \|Xp_1\|^2 + \lambda\left(1 - \|p_1\|^2\right)$$

p_1 is the eigenvector associated
to the greatest eigenvalue of $X^T X$

2. PCA first objective : data reduction

- Second principal component
linear combination of the columns of X
describes the next grestest amount of variability of X

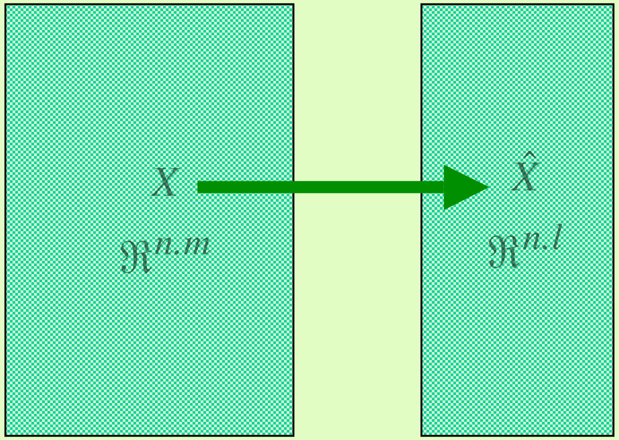


$$\begin{cases} t_2 = Xp_2 \\ t_2 \perp t_1 \\ \|p_2\|^2 = 1 \end{cases}$$

$$\Phi = \|Xp_2\|^2 + \lambda\left(1 - \|p_2\|^2\right) + \mu t_2^T t_1$$

p_2 is the eigenvector associated
to the next greatest eigenvalue of $X^T X$

2. PCA first objective : data reduction



- Decomposition of the X matrix

$$X = \sum_{i=1}^{m} t_i \, p_i^T$$

$$\begin{cases} X = TP^T \\ T = XP \end{cases}$$

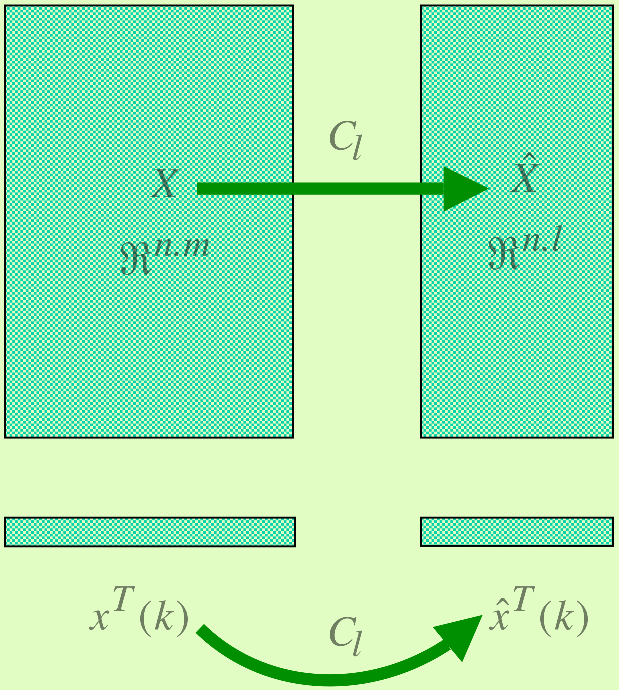
- Approximated decomposition

$$\hat{X} = \sum_{i=1}^{l} t_i \, p_i^T$$

$$\begin{cases} \hat{X} = T_l \, P_l^T \\ T_l = XP_l \end{cases} \qquad \begin{cases} \hat{X} = XP_l \, P_l^T \\ \hat{X} = XC_l \end{cases}$$

$$X = \hat{X} + E$$

2. PCA first objective : data reduction

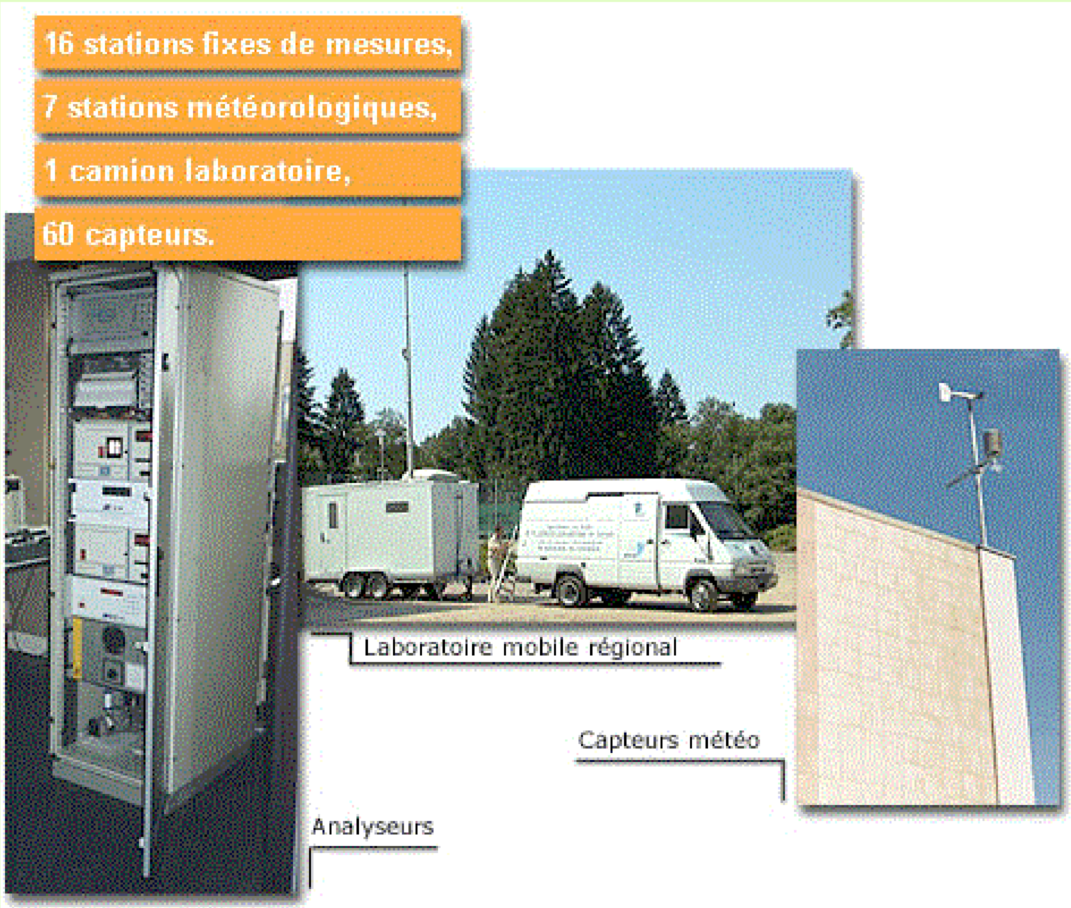


- Decomposition of a new observation

$$x(k) = \hat{x}(k) + \tilde{x}(k)$$
$$\hat{x}(k) = C_l x(k)$$
$$\tilde{x}(k) = \left(I - C_l\right) x(k)$$

- Selection of the number of PC

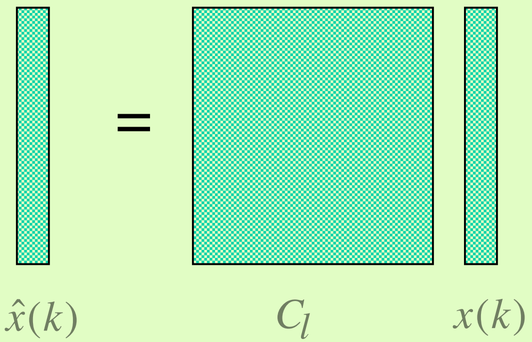
1. Objectives of the study « air quality monitoring »

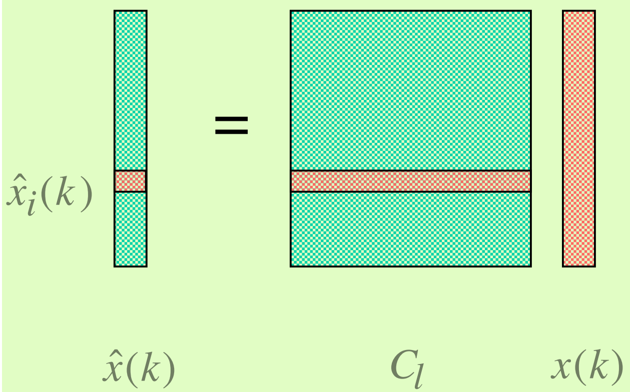


Measurement devices

Mobile system
Fixed system

3. PCA second objective : data estimation





- Decomposition of a new observation

$$\hat{x}(k) = C_l x(k)$$

- Data estimation (ith variable)

using all the sensor $\hat{x}_i(k) = C_{l,i} x(k)$

without using the ith sensor $\hat{x}_i(k) = \dfrac{\begin{pmatrix} c_{-i} & 0 & c_{+i} \end{pmatrix}}{1 - c_{ii}} x(k)$

- Diagnosis application

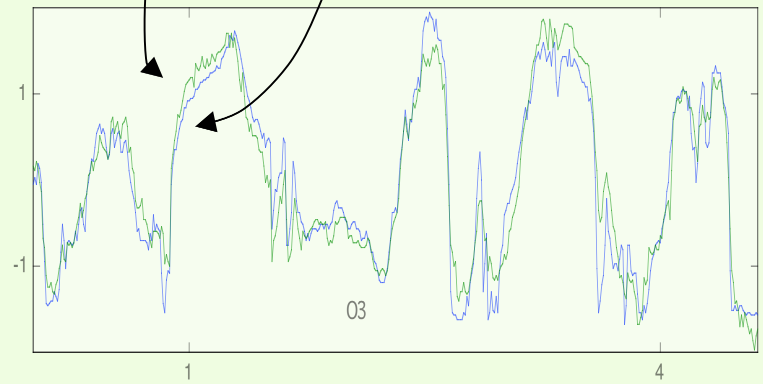
residual analysis $r_i(k) = \hat{x}_i(k) - x_i(k)$

3. PCA second objective : data estimation

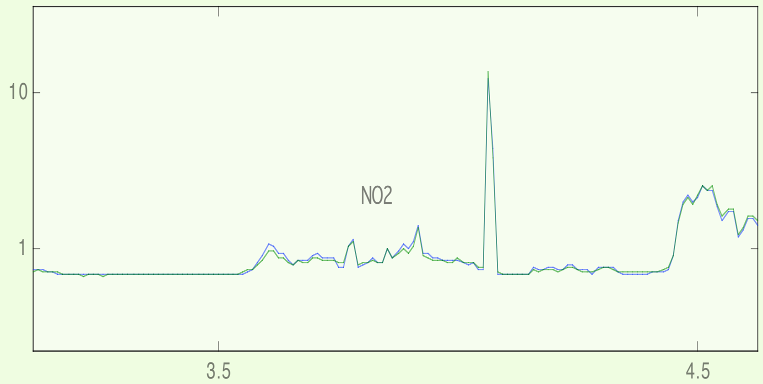
18 variables { 6 stations with O3, NO2, NO

PCA estimation
measurement

O3 estimation
(l=8 PC)



NO2 estimation
(l=8 PC)



4. PCA third objective : fault detection

Residuals nalysis

$$x(k) = \hat{x}(k) + \tilde{x}(k)$$

$$SPE(\tilde{x}(k)) = \|\tilde{x}(k)\|^2$$

$$\delta = \theta\left(1 + \frac{c_\alpha\sqrt{2\theta_2 h^2}}{\theta_1} + \frac{\theta_2 h(h-1)}{\theta_1^2}\right)$$

$$\theta_i = \sum_{j=l+1}^{m} \lambda_j^i \quad ; \quad h = 1 - 2\theta_1\theta_3 / \left(3\theta_2^2\right)$$

c_α Confidence limit

λ_j Eigenvalues of $X^T X$

Detection

Normal conditions

$$SPE(\tilde{x}(k)) \le \delta$$

Abnormal conditions

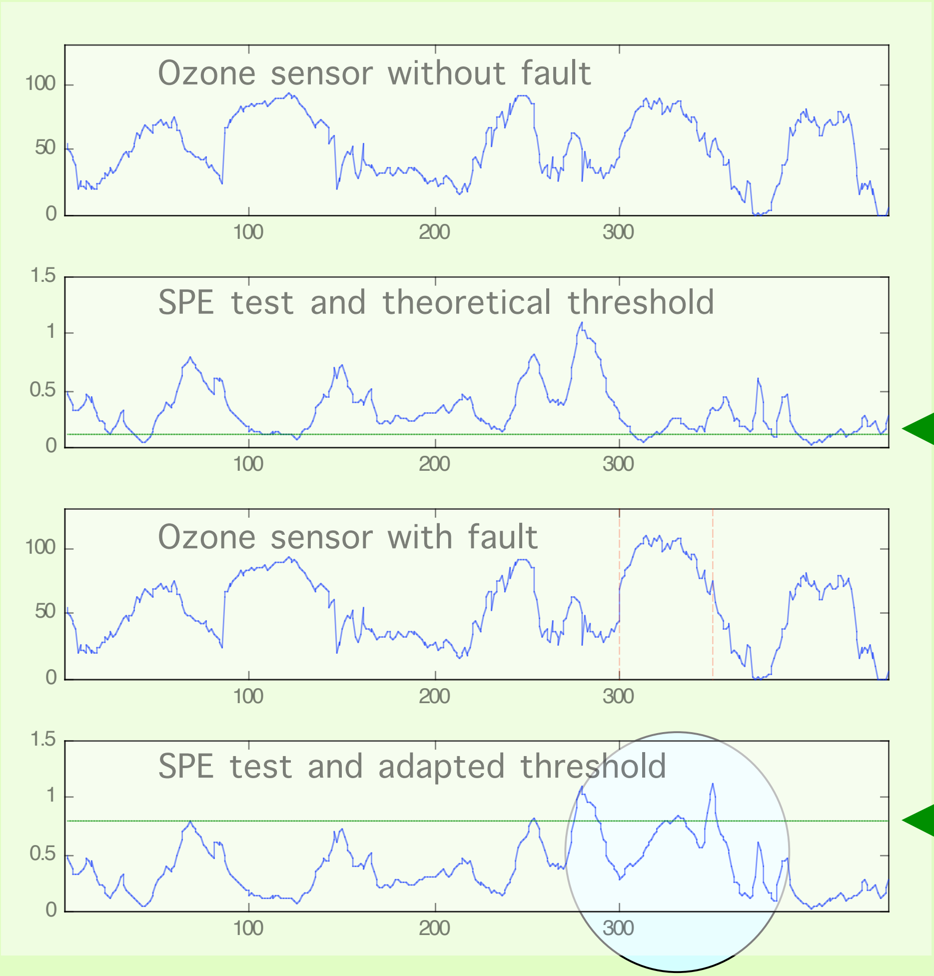
$$SPE(\tilde{x}(k)) > \delta$$

False alarm filtering

$$\tilde{\tilde{x}}(k) = (I - \Gamma)\tilde{\tilde{x}}(k) + \Gamma\tilde{x}(k)$$

$$SPE(\tilde{x}(k)) \Rightarrow SPE\left(\tilde{\tilde{x}}(k)\right)$$

4. PCA third objective : fault detection



Theoretical threshold

Empirical threshold

5. PCA fourth objective : fault isolation

Analysis :
jth sensor reconstruction

$$x^T(k) = \begin{pmatrix} x_{-j}(k) & x(k) & x_{+j}(k) \end{pmatrix}$$

$$\tilde{x}(k) = (I - C_l)x(k)$$

$$z(k) = \frac{\begin{pmatrix} c_{-j} & 0 & c_{+j} \end{pmatrix}}{1 - c_{jj}} x(k)$$

$$\bar{x}^T(k) = \begin{pmatrix} x_{-j}(k) & z(k) & x_{+j}(k) \end{pmatrix}$$

$$\tilde{\bar{x}}(k) = (I - C_l)\bar{x}(k)$$

Isolation of fault i

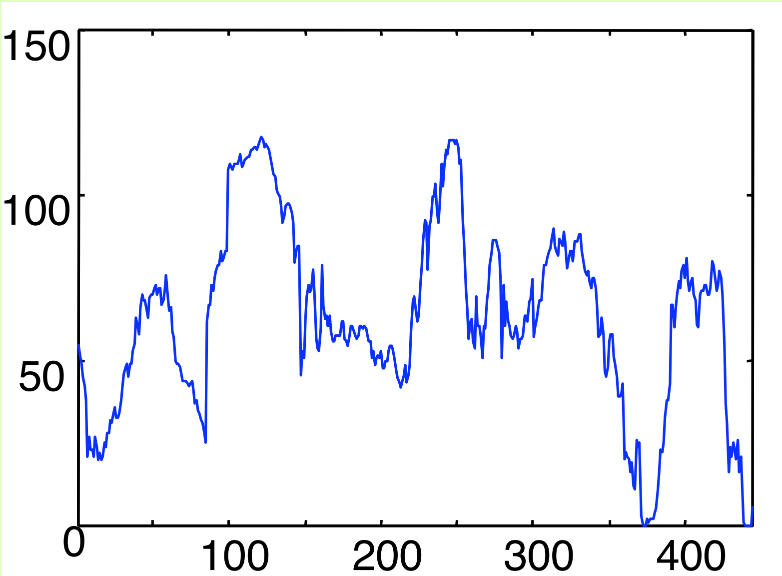
If j = i,
we have a good reconstruction of x(k)

$$SPE\left(\tilde{\bar{x}}(k)\right) < SPE\left(\tilde{x}(k)\right)$$

If j ≠ i,
The reconstruction of x(k) is bad

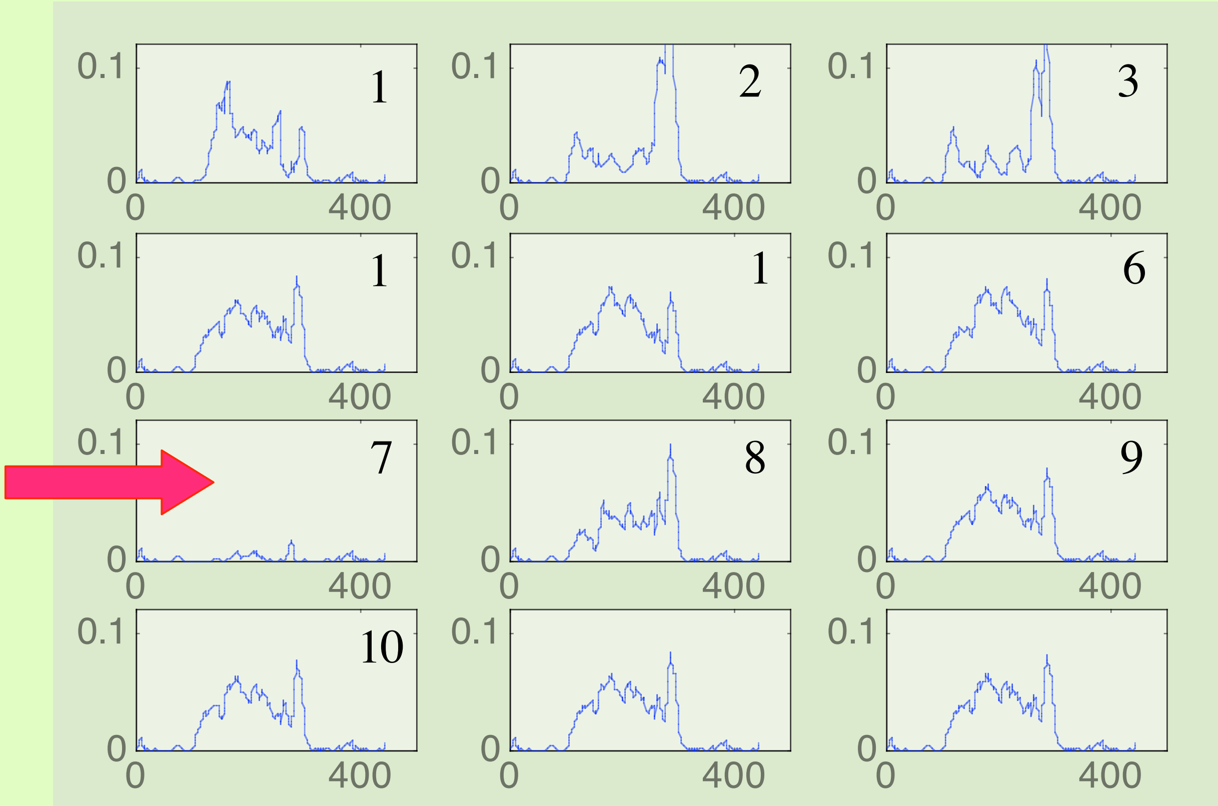
$$SPE\left(\tilde{\bar{x}}(k)\right) \approx SPE\left(\tilde{x}(k)\right)$$

5. PCA fourth objective : fault isolation



6. Some results

Some of the 18 $\tilde{t}^{2}_{1,j}$ after reconstructing one of the 18 the variables

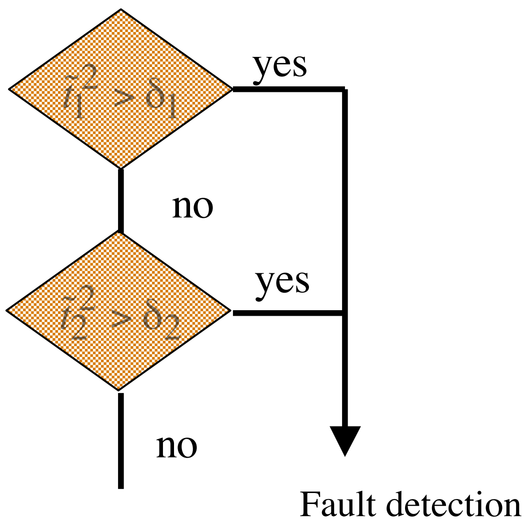


Proposition

Compute the sum of squares of the last PC

$$t = Xp \quad \begin{cases} \tilde{t}_1^2 = t_m^2 \\ \tilde{t}_2^2 = t_m^2 + t_{m-1}^2 \\ \tilde{t}_3^2 = t_m^2 + t_{m-1}^2 + t_{m-2}^2 \\ \ldots \end{cases}$$

FD : compare them to a threshold



Compute the sum of squares of the last PC
Using reconstructed values

$\tilde{t}_{1,j}^2$ using reconstructed variable j

……

FI : compare them to a threshold

if $\tilde{t}_{1,j}^2 < \delta_1$
then the jth variable is suspected

7. Conclusion

☛ Diagnosis has been achieved by using a combination of :

PCA data compression
data reconstruction
projection analysis

☛ Application to air monitoring

data validation
sensor supervision

☛ Future work

Generalized reconstruction
multiple fault detection
real time constraint