

# LASAR<sup>3</sup>

 POLITECNICO DI MILANO

## *Exercises Session on Fault Detection*

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## Exercise 1

*Method: AAKR (Signal Reconstruction)+SPRT (Decision)*

*Component: Gas Turbine*

## Exercise 2

*Method: PCA*

*Component: Gas Turbine*

## Exercise 3 (take home)

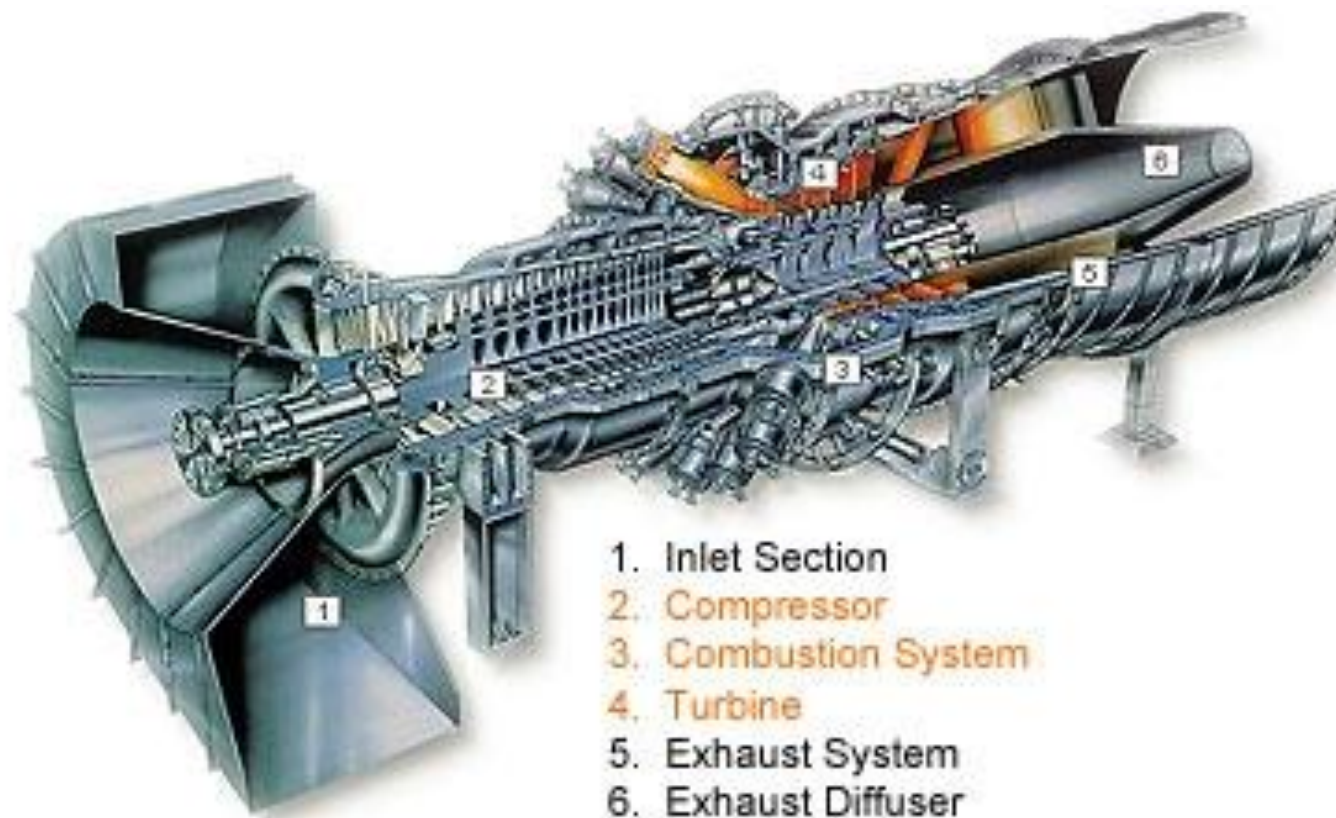
*Method: you choose*

*Component: Wind Turbine*



# Exercise 1

*Component: Gas Turbine*



1. Inlet Section
2. Compressor
3. Combustion System
4. Turbine
5. Exhaust System
6. Exhaust Diffuser

Courtesy of Siemens Westinghouse

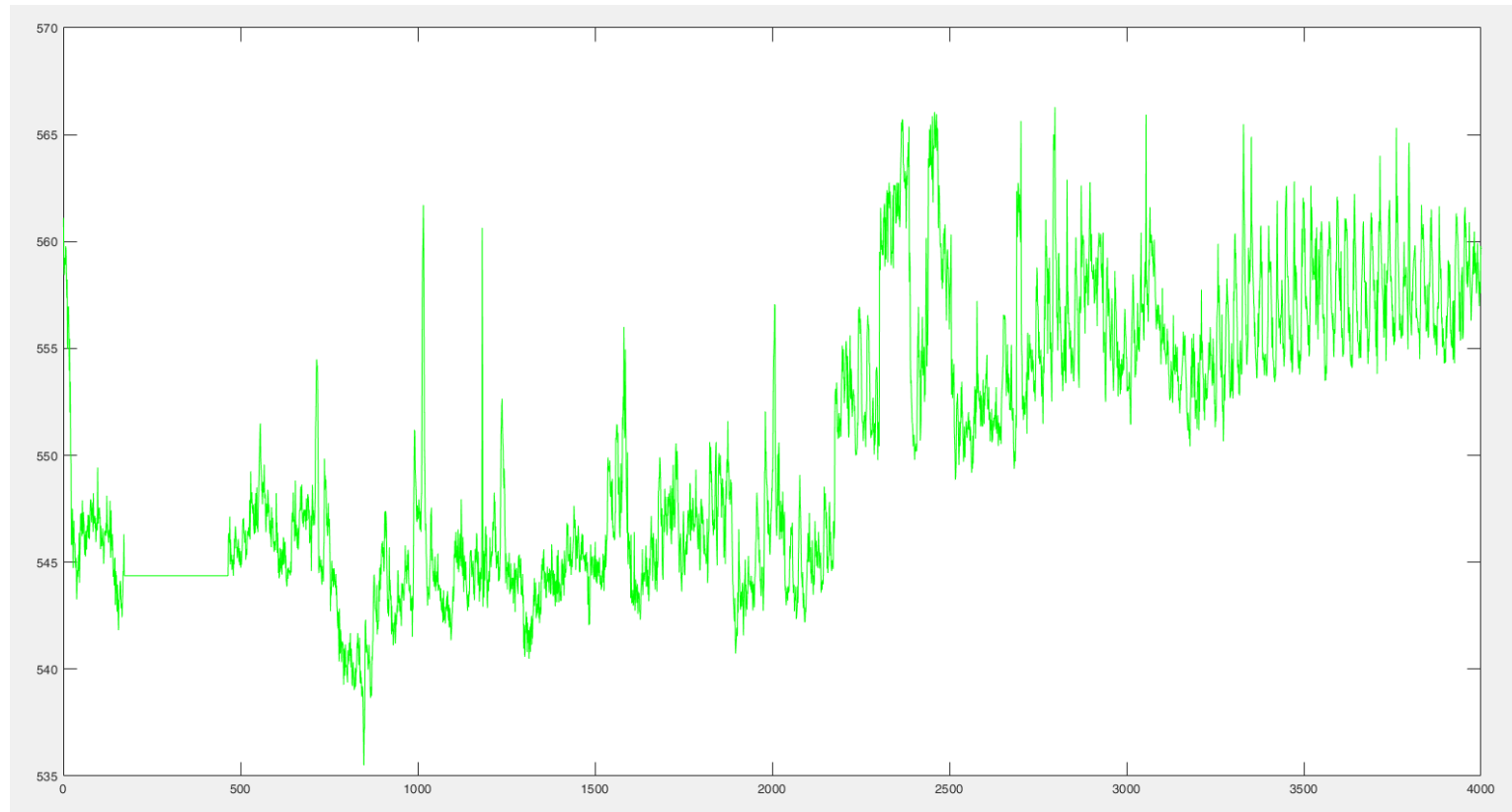


Temperature location 1 (°C)
Temperature location 2 (°C)
Temperature location 3 (°C)
Temperature location 4 (°C)
Temperature location 5 (°C)
Temperature location 6 (°C)



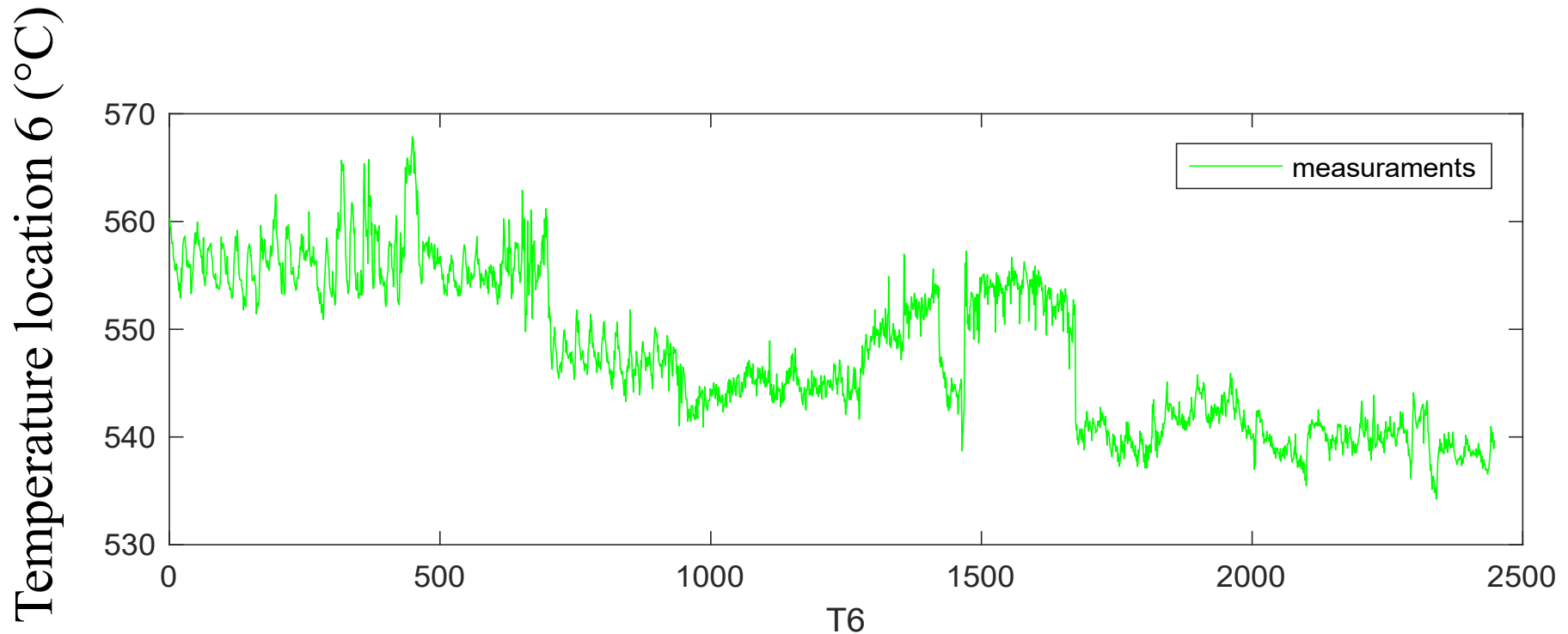
- Train.dat → Normal condition data [6 signals, 4000 data points, frequency: 5200 measurements/year]

Temperature location 6 (°C)





- Validation.dat → Normal condition data [6 signals, 2500 data points, frequency: 5200 measurements/year]



# Exercise 1

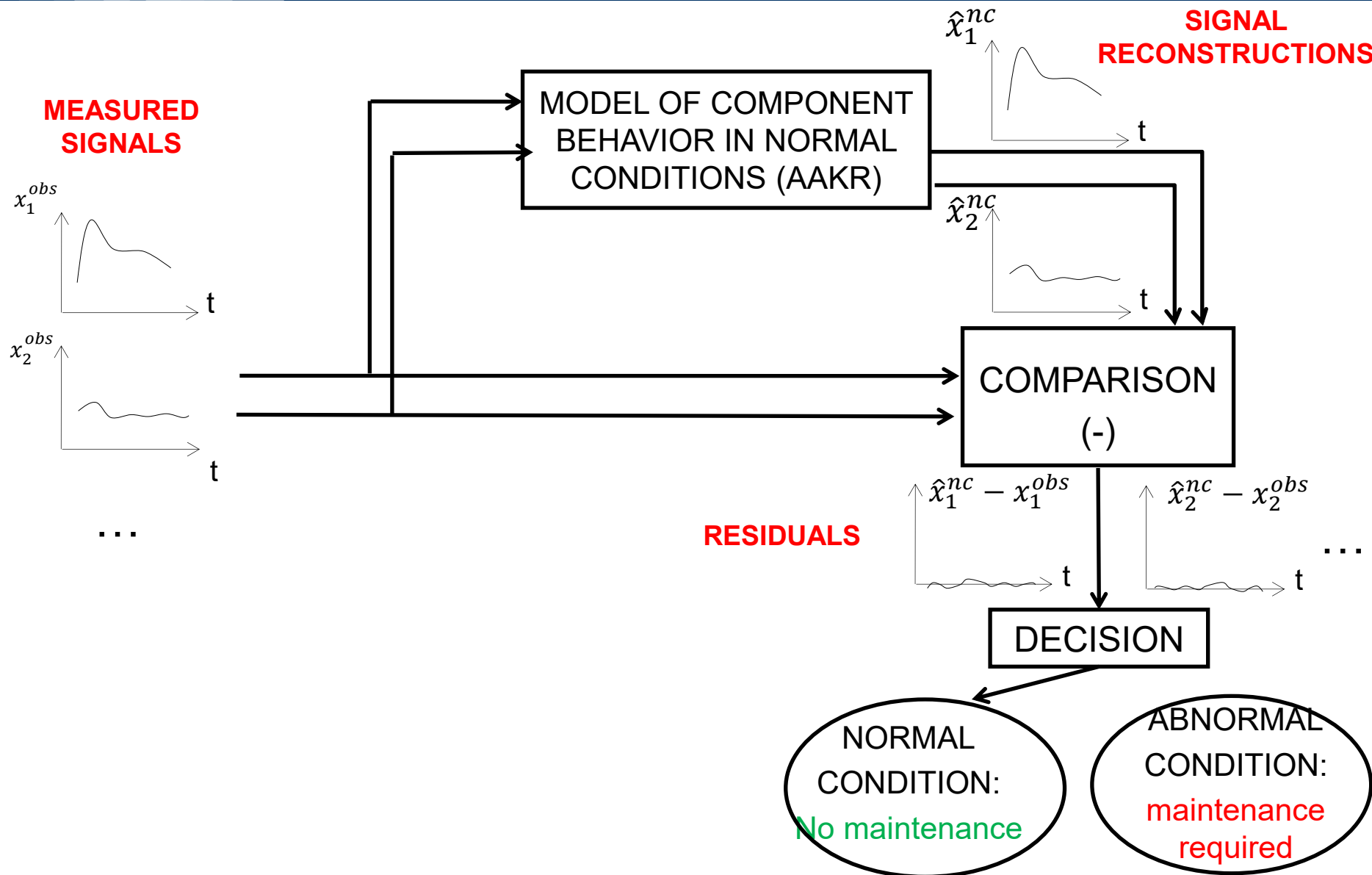
*Method: AAKR (Signal Reconstruction)+SPRT (Decision)*





# Fault Detection using AAKR for signal reconstruction

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# The AAKR code in Pyhon (.ipynb): how to run the code?

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Open **AAKR\_reconstruction\_ex.ipynb**

jupyter AAKR\_reconstruction\_ex Last Checkpoint: 3 minutes ago (unsaved changes)  Logout

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3

Save + Copy Paste Undo Redo Run Stop Restart Code

```
In [3]: ▶ import numpy as np
import matplotlib.pyplot as plt
from AAKR_reconstruction_ex import AAKR_reconstruction_ex

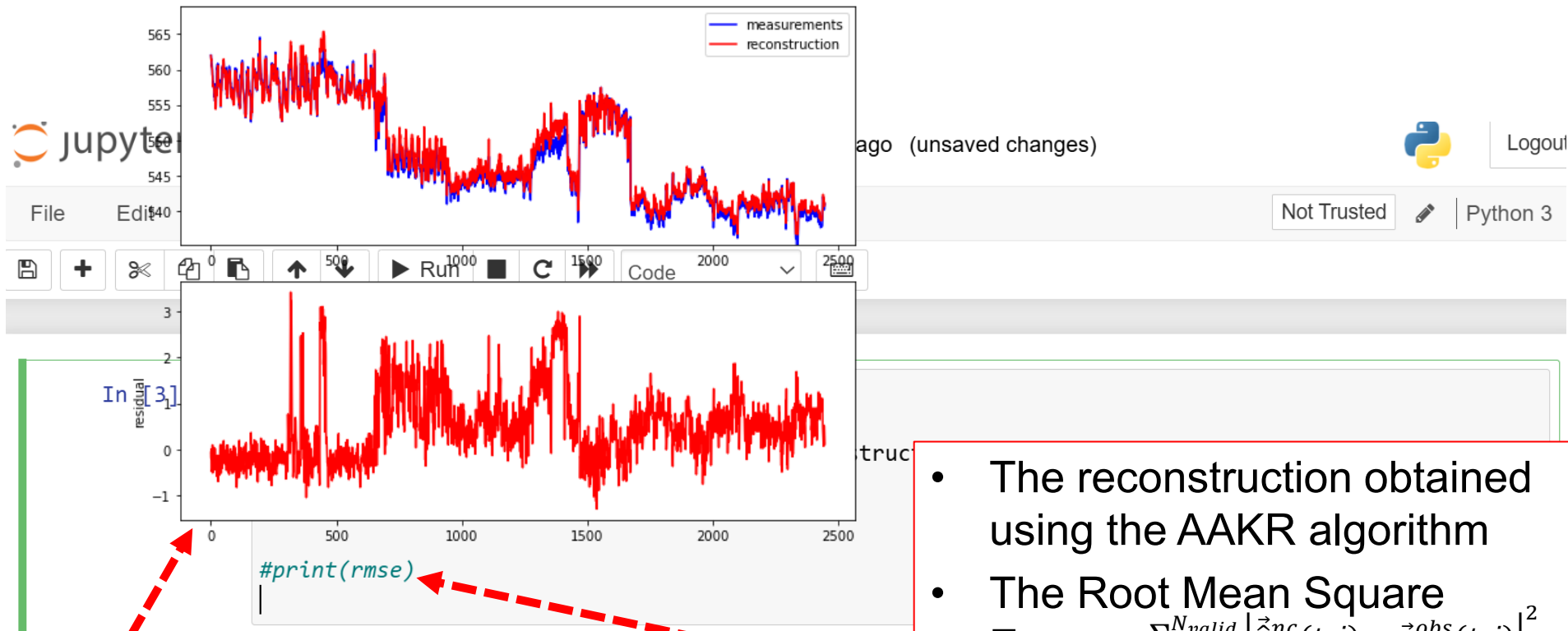
#print(rmse)
|
```

Run type and the code:

`test_data_rec, RMSE=AAKR_reconstruction_ex('train.dat', 'validation.dat', h, plot)`

`h`: bandwidth parameter

`Plot`: logical value (True/False), indicating whether to provide the plots of reconstructions and residuals or not




One figure for each signal representing:

- The original data and the reconstruction obtained using the AAKR algorithm
- The residual for each data point

- The reconstruction obtained using the AAKR algorithm
  - The Root Mean Square Error:
- $$RMSE = \frac{\sum_{j=1}^n \frac{\sum_{t=1}^{N_{valid}} |\hat{x}^{nc}(t,j) - \hat{x}^{obs}(t,j)|^2}{N_{valid}}}{n}$$



5 minutes

jupyter AAKR\_reconstruction\_ex Last Checkpoint: 3 minutes ago (unsaved changes)  Logout

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3

Run

```
In [3]: ▶ import numpy as np
import matplotlib.pyplot as plt
from AAKR_reconstruction_ex import AAKR_reconstruction_ex

#print(rmse)
|
```

**Run the algorithm considering the bandwidth parameter  $h=0.1$**

Execute the code:

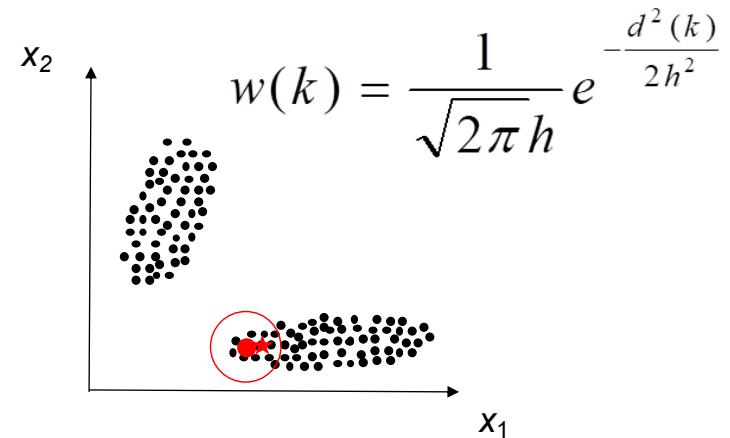
```
test_data_rec, RMSE=AAKR_reconstruction_ex('train.dat', 'validation.dat', h, plot)
```

# Exercise 1

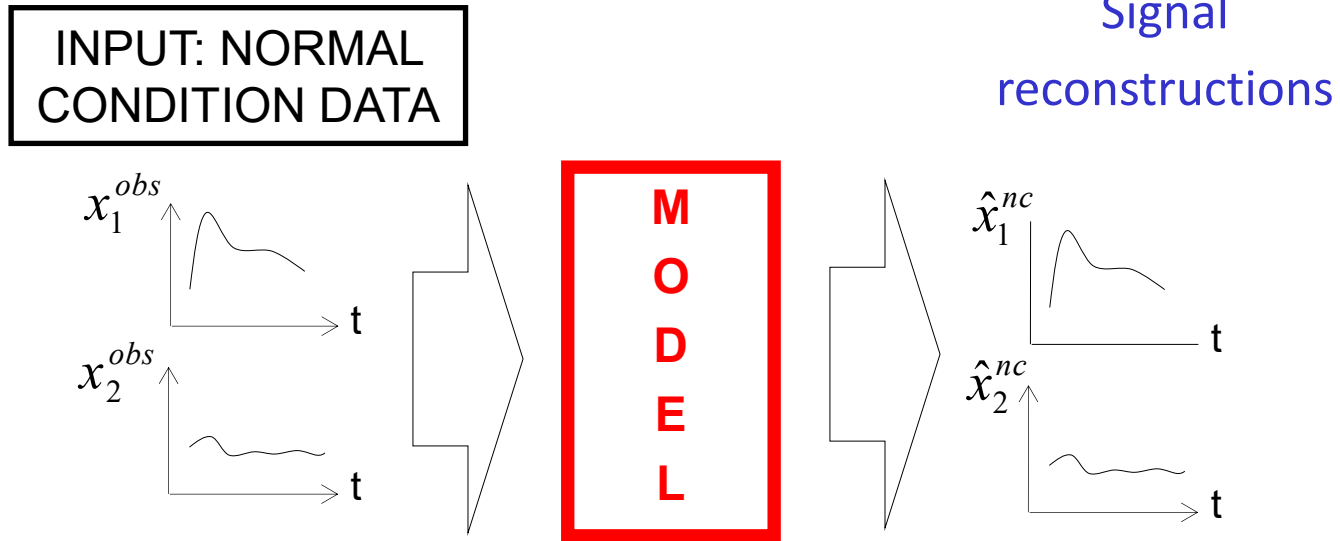
*Method: AAKR*

*Setting the model parameter:*

- *$h$  = bandwidth parameter*



- Objective: ACCURATE and ROBUST reconstruction model

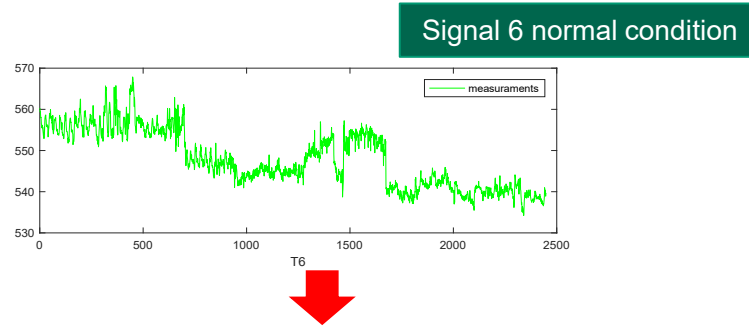
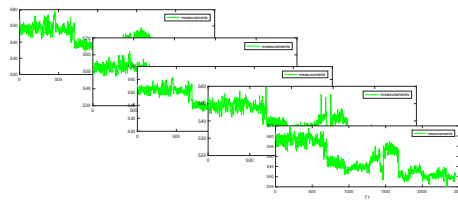


- **Accurate** reconstruction model if:

$$\vec{\hat{x}}^{nc} \cong \vec{x}^{obs}$$

- Metric to measure accuracy: Root Mean Square Error (*RMSE*):

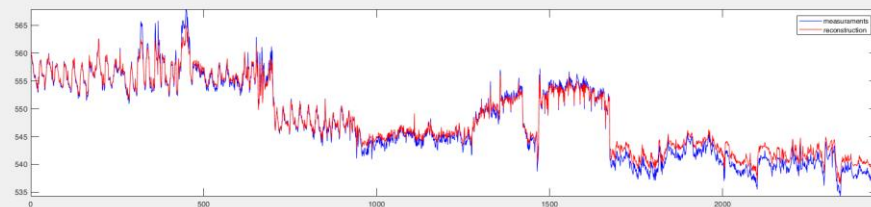
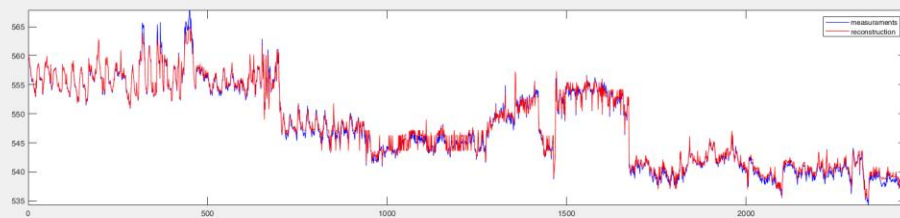
$$RMSE = \frac{\sum_{j=1}^n \frac{\sum_{t=1}^{N_{valid}} \left| \vec{\hat{x}}^{nc}(t,j) - \vec{x}^{obs}(t,j) \right|^2}{N_{valid}}}{n}$$



**AAKR**

$h=0.05$

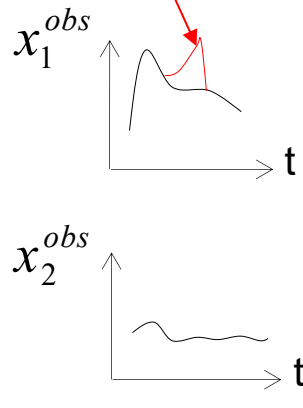
$h=0.4$



**$h=0.05$  results in a more accurate model**

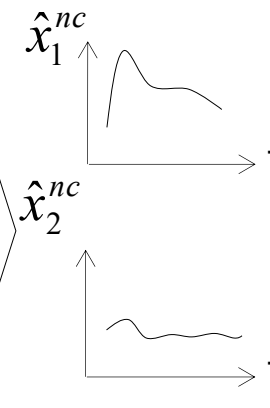


INPUT: ABNORMAL  
CONDITION DATA  
(Typically simulated)



**M  
O  
D  
E  
L**

Signal  
reconstructions

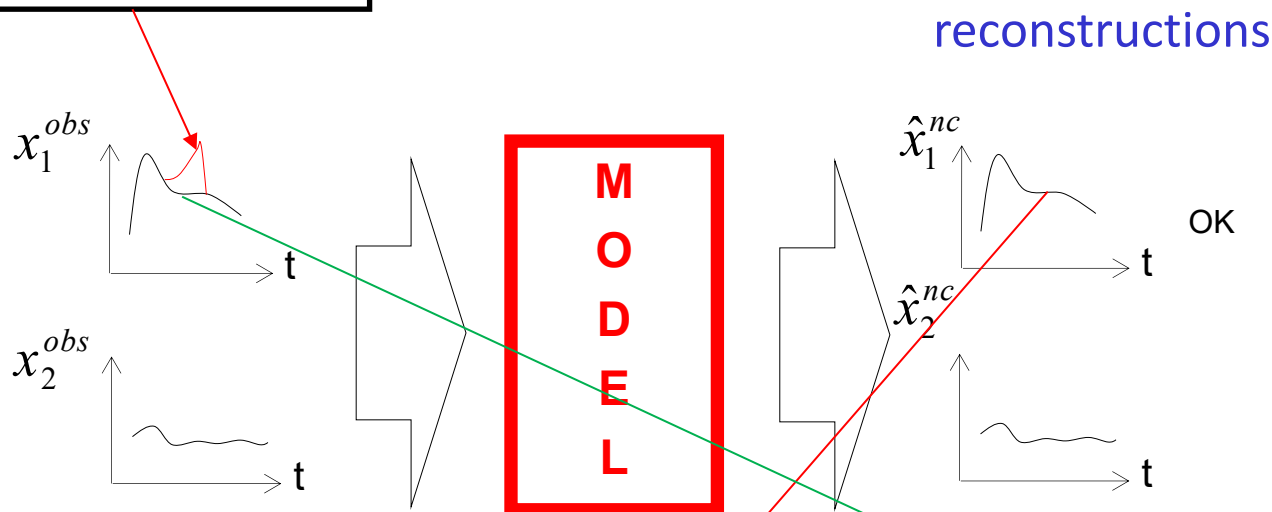


- Robust reconstruction if:  $\vec{\hat{x}}^{nc} \cong \vec{x}^{obs-nc}$





INPUT: ABNORMAL  
CONDITION DATA  
(Typically simulated)



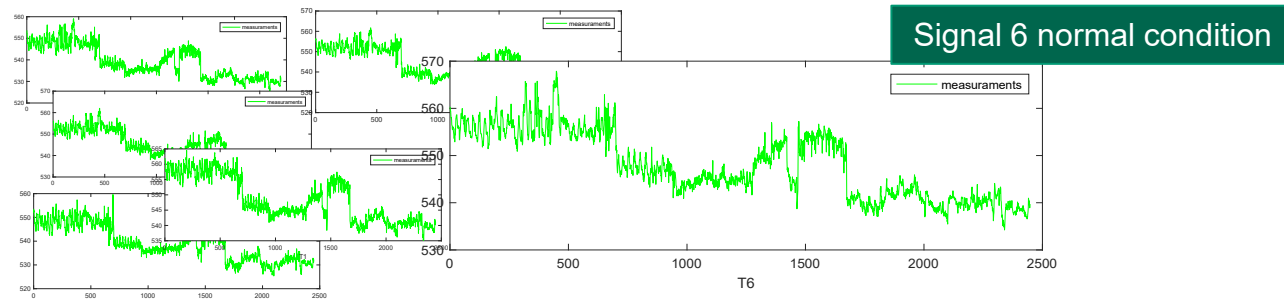
- Robust reconstruction if:  $\vec{\hat{x}}^{nc} \cong \vec{x}^{obs-nc}$

- Metric to measure Robustness:

Reconstruction  
of the anomaly

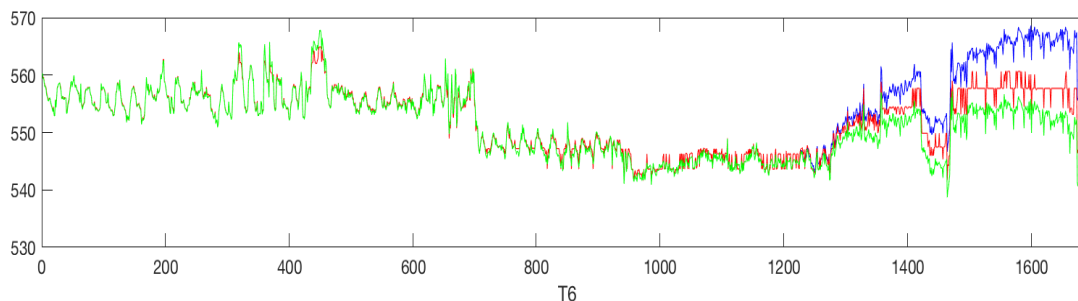
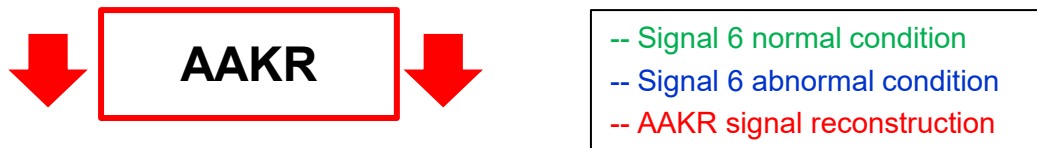
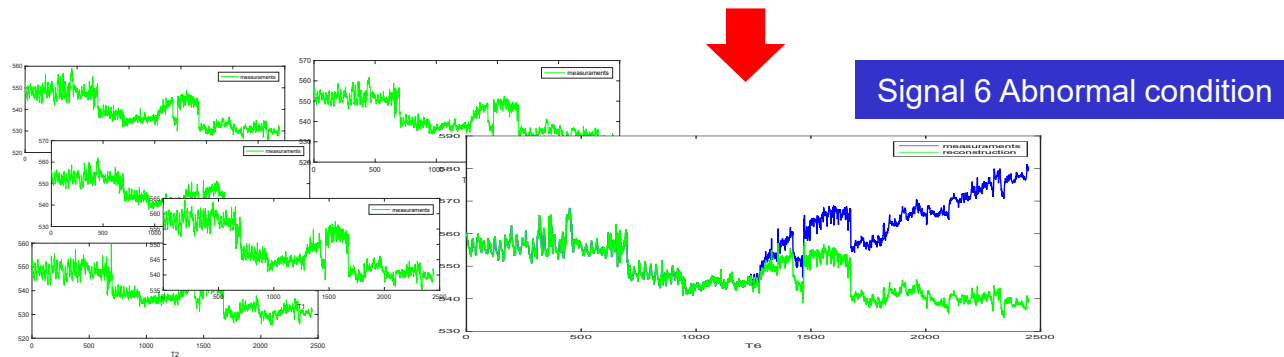
Normal condition data (before  
anomaly simulation)

$$\text{Robustness} = \sqrt{\frac{\sum_{t=1}^{N_{valid}} \left| \hat{x}_1^{nc}(t) - \vec{x}_1^{obs-nc}(t) \right|^2}{N_{valid}}}$$

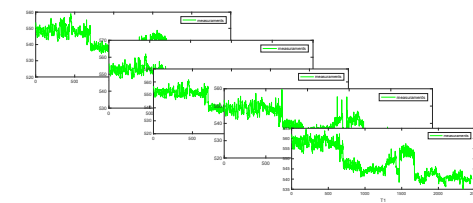


Artificial simulated abnormal condition on signal 6

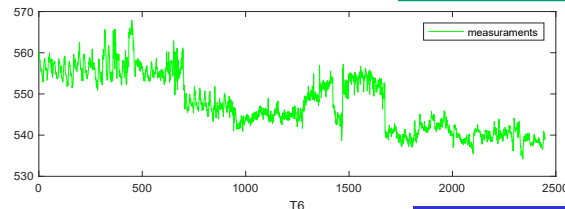
The other signals remain in normal condition



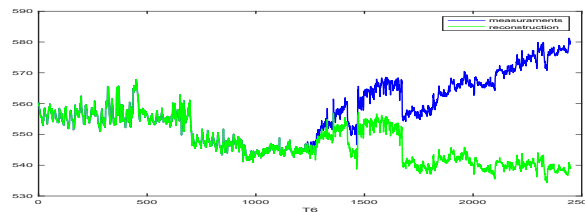
The method is robust if AAKR reconstruction is equal to the signal in normal condition



Signal 6 normal condition



Signal 6 Abnormal condition



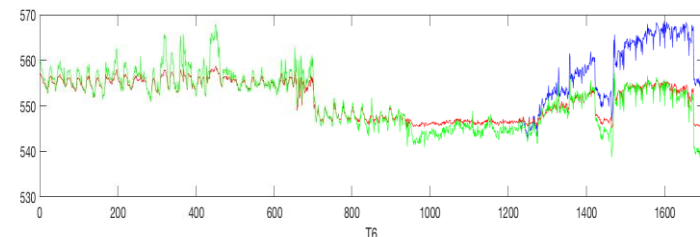
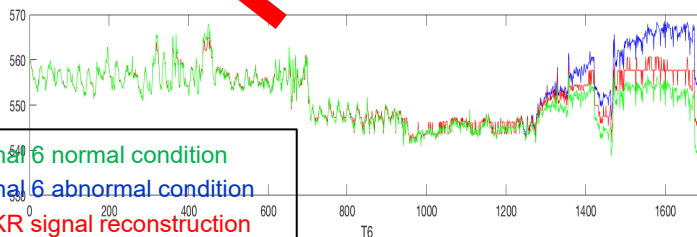
not robust  
but accurate

$h=0.05$

AAKR

$h=0.4$

More robust  
but less  
accurate



Optimal value of  $h$  is a trade off between accuracy and robustness



```
val = np.loadtxt('validation.dat')
anomaly = np.loadtxt('validation_sim.dat')

npat, nsig = val.shape

test_reconstruction, _ =
AAKR_reconstruction_ex('train.dat', 'validation_sim.dat',
0.05)
error = test_reconstruction[:, 5] - val[:, 5]
robustness = np.sqrt(np.sum(error**2) / npat)
```



- Set the bandwidth parameter ( $h$ ) of the AAKR-based reconstruction model

You can use the following files:

- Validation.dat → data in normal condition

30-40 minutes

- Validation\_sim.m → data containing a simulated abnormal condition on signal 6

```
val = np.loadtxt('validation.dat')
anomaly = np.loadtxt('validation_sim.dat')

npat, nsig = val.shape

test_reconstruction, _ =
AAKR_reconstruction_ex('train.dat', 'validation_sim.dat',
0.05)
error = test_reconstruction[:, 5] - val[:, 5]
robustness = np.sqrt(np.sum(error**2) / npat)
```



- Perform the reconstruction of the signal measurements in the 4 files test\_1.dat, test\_2.dat, test\_3.dat and test\_4.dat.
- In which files can you detect abnormal conditions? Do you have any hypothesis on the type of abnormal condition?
- Draw your conclusions on the possibility of using the developed model for fault detection.

30 minutes



# Analyze residuals with *SPRT*



## Exercise 1.3: Hints

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$$SPRT_{Index} = SPRT(test_{name}, test\ rec_{name}, \alpha, \beta, \mu_{H_0}, \sigma_{H_0}, \mu_{H_1}, \sigma_{H_1})$$

Function  $SPRT \rightarrow$  Computes the  $SPRT$  index value from the residuals of a test data and their reconstructions and stores them in the  $N$ -by-1 vector  $SPRT_{Index}$ .

### INPUTS:

- $test_{name}$  =  $N$ -by-1 data matrix containing all patterns as rows and one signal in column of a test data
- $test\ rec_{name}$  =  $N$ -by-1 data matrix containing all reconstructed patterns as rows of one signal in column for the test patterns of  $test_{name}$ .
- $\alpha$  = False alarm rate
- $\beta$  = Missed alarm rate.
- $\mu_{H_0}$  = the mean of the Gaussian distribution of  $H_0$  hypothesis (the component is working in normal conditions).
- $\sigma_{H_0}$  = variance of Gaussian distribution  $H_0$
- $\mu_{H_1}$  = the mean of the Gaussian distribution of  $H_1$  hypothesis (the component is working in abnormal conditions).
- $\sigma_{H_1}$  = variance of Gaussian distribution  $H_1$





- Verify the capability of the SPRT method of detecting normal and abnormal conditions in evolution of signal 5 in “test\_4A.dat” and “test\_4B.dat” files. With respect to the parameters of the SPRT we suggest to use:

➤  $\alpha = 0.01$

➤  $\beta = 0.01$

and Gaussian distributions for the two hypothesis  $H_0$  and  $H_1$  with parameters:

➤  $\mu_{H_0} \approx 0, \sigma_{H_0} = 0.15$

➤  $\mu_{H_1} = 1, \sigma_{H_1} = 0.15$

- In which file do you detect the abnormal condition? When?
- Compare the results with those of a threshold-based method with threshold = 1.
- Draw your conclusions on the possibility of using the SPRT in decision-making for fault detection.



## Exercise 1.3: Hints

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$$SPRT_{Index} = SPRT(test_{name}, test\ rec_{name}, \alpha, \beta, \mu_{H_0}, \sigma_{H_0}, \mu_{H_1}, \sigma_{H_1})$$

Function  $SPRT \rightarrow$  Computes the  $SPRT$  index value from the residuals of a test data and their reconstructions and stores them in the  $N$ -by-1 vector  $SPRT_{Index}$ .

### OUTPUTS:

- $SPRT_{Index}$  =  $N$ -by-1 vector of the  $SPRT$  values

### EXAMPLE:

$SPRT_{Index}$   
=  $SPRT('test\_4A\_meas\_S5.dat', 'test\_4A\_rec\_S5.dat', 0.01, 0.01, 0, 0.15, 1, 0.15)$



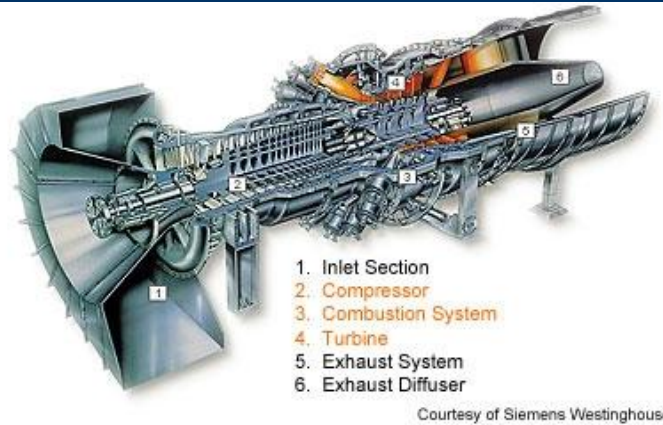
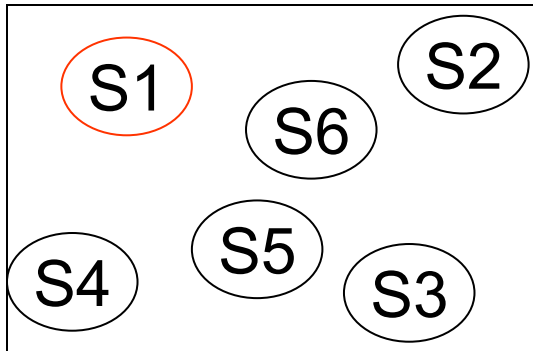
# Exercise 2

*Fault detection with PCA considering turbine data*

1. *Optimize the PCA to achieve:*
  - a. *Accuracy*
  - b. *Robustness*
2. *Apply the PCA model on test datasets*
3. *Compare AAKR and PCA results*



## Component

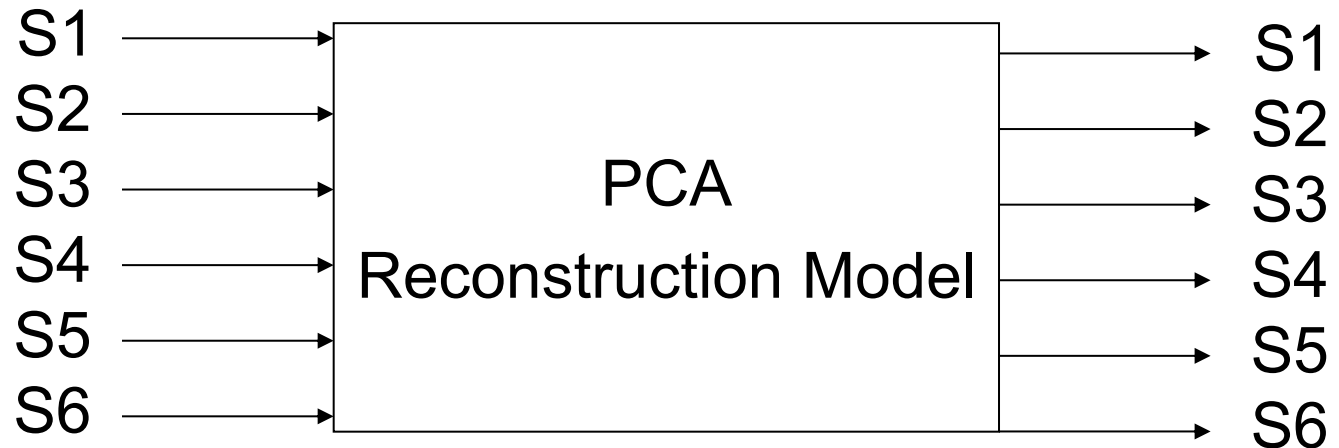


Real  
measurements

Signal  
Reconstructions

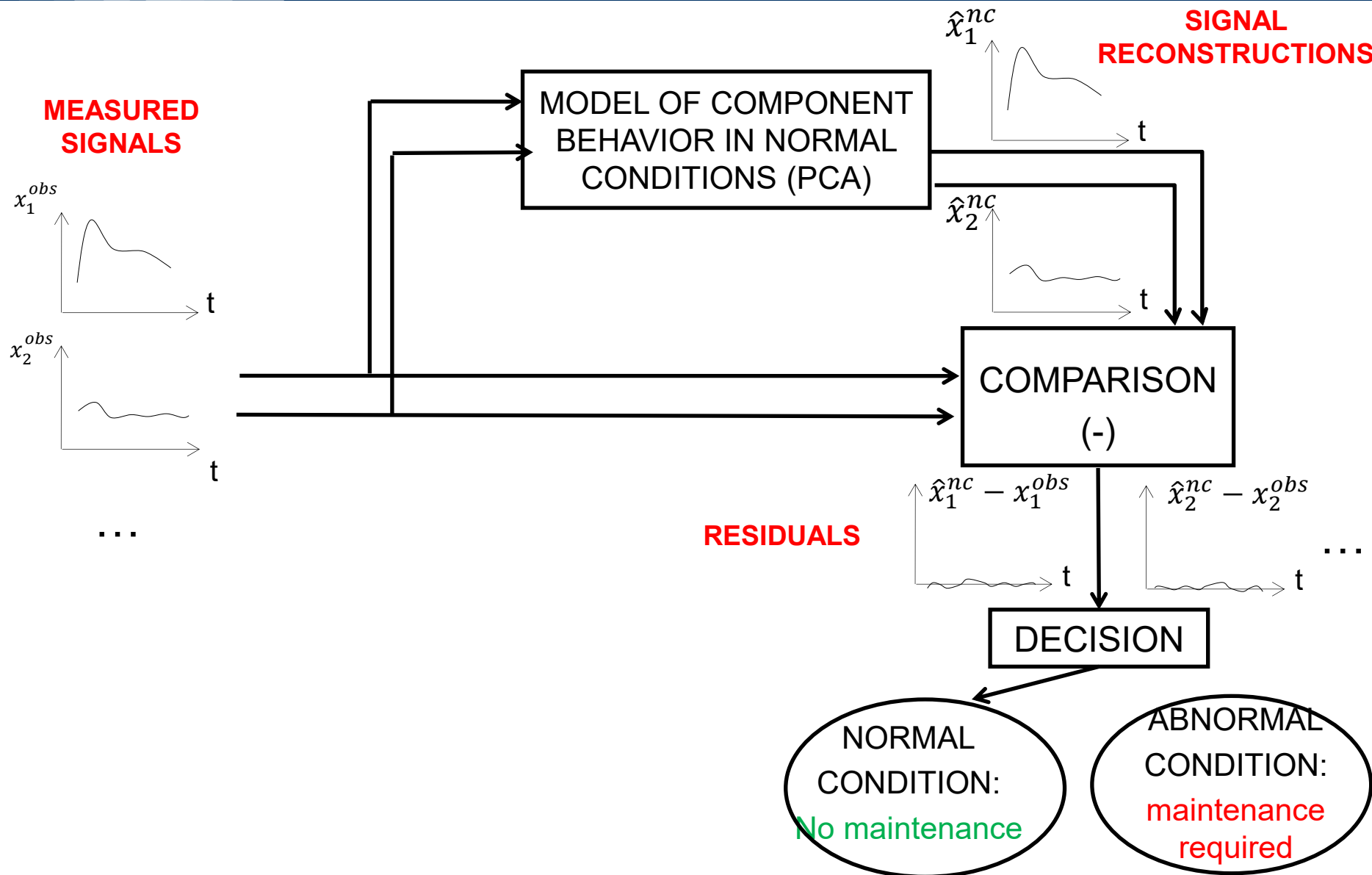
=

Expected signal values in  
normal conditions





# PCA





# The PCA code in Python (.ipynb): how to run the code?

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Open **PCA\_reconstruction\_ex.ipynb**

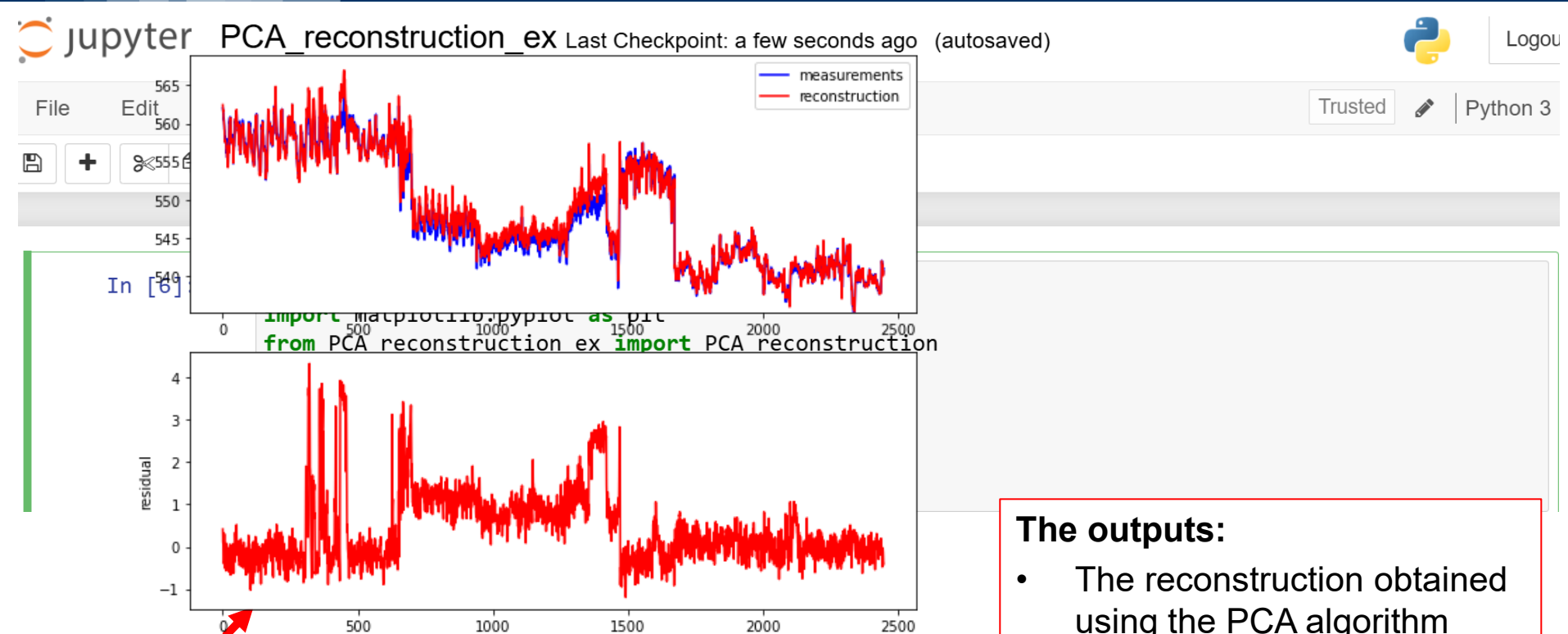
The image shows the Jupyter Notebook interface. At the top, the file name 'PCA\_reconstruction\_ex' is displayed. Below it is a menu bar with options: File, Edit, View, Insert, Cell, Kernel, Widgets, Help. To the right of the menu bar are buttons for 'Trusted', a pencil icon, and 'Python 3'. Below the menu bar is a toolbar with icons for saving, adding, deleting, copying, pasting, undo, redo, and a 'Run' button. A red dashed arrow points from the 'Run' button to the code cell below.

```
In [6]: ▶ import numpy as np
import matplotlib.pyplot as plt
from PCA_reconstruction_ex import PCA_reconstruction

#print(rmse)
```

Execute the code:

`test_data_rec, PCs, RMSE = PCA_reconstruction('train.dat', 'validation.dat', perc_var, plot)`  
`perc_var`=minimum percentage of variance to be represented in the PCA space [e.g., 0.95]  
`plot`=logical value (True/False), indicating whether to provide the plots of reconstructions and residuals or not



One figure for each signal representing:

- The original data and the reconstruction obtained using the PCA algorithm
- The residual for each data point

### The outputs:

- The reconstruction obtained using the PCA algorithm
- The number of principal components corresponding to the selected variance
- The RMSE





Consider the same data used in Exercise 1 ('train.dat', 'validation.dat', 'test\_1.dat', 'test\_2.dat', 'test\_3.dat', 'test\_4.dat')

1. Optimize the PCA reconstruction model to achieve:
  - a. Accuracy
  - b. Robustness
2. Apply the PCA model on test datasets: test\_1.dat, test\_2.dat, test\_3.dat and test\_4.dat.
3. Compare AAKR and PCA results on test\_3.dat

40 minutes

Hints:

- Consider different numbers of Principal Components by trying different values for the parameter  $v$  = *minimal percentage of variance considered in the PCA space*
- Consider the root mean square error as a performance measure and compute it on test data under normal condition and simulated abnormal condition

```
[test_reconstruction,n_PC, RMSE]=PCA_reconstruction('train.dat','validation.dat',0.95)
```

# Exercise 3 (take home)

*Method: you choose*

*Component: Wind Turbine*

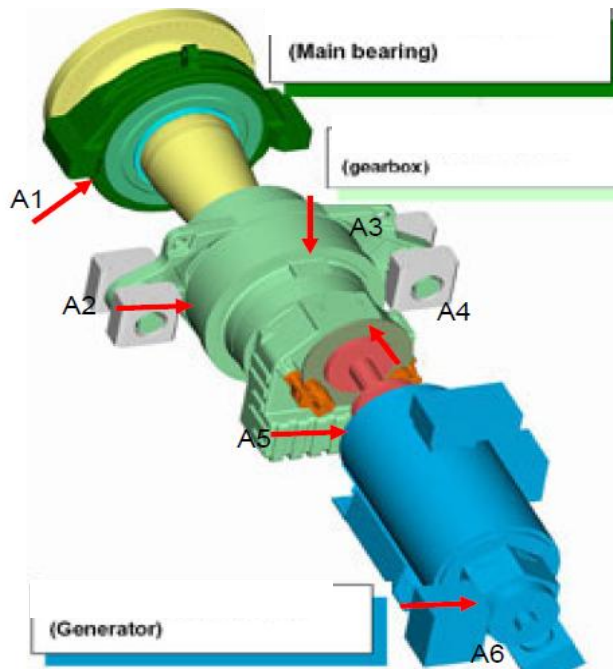


# The Monitoring System

Wind turbine farm built in 2002.

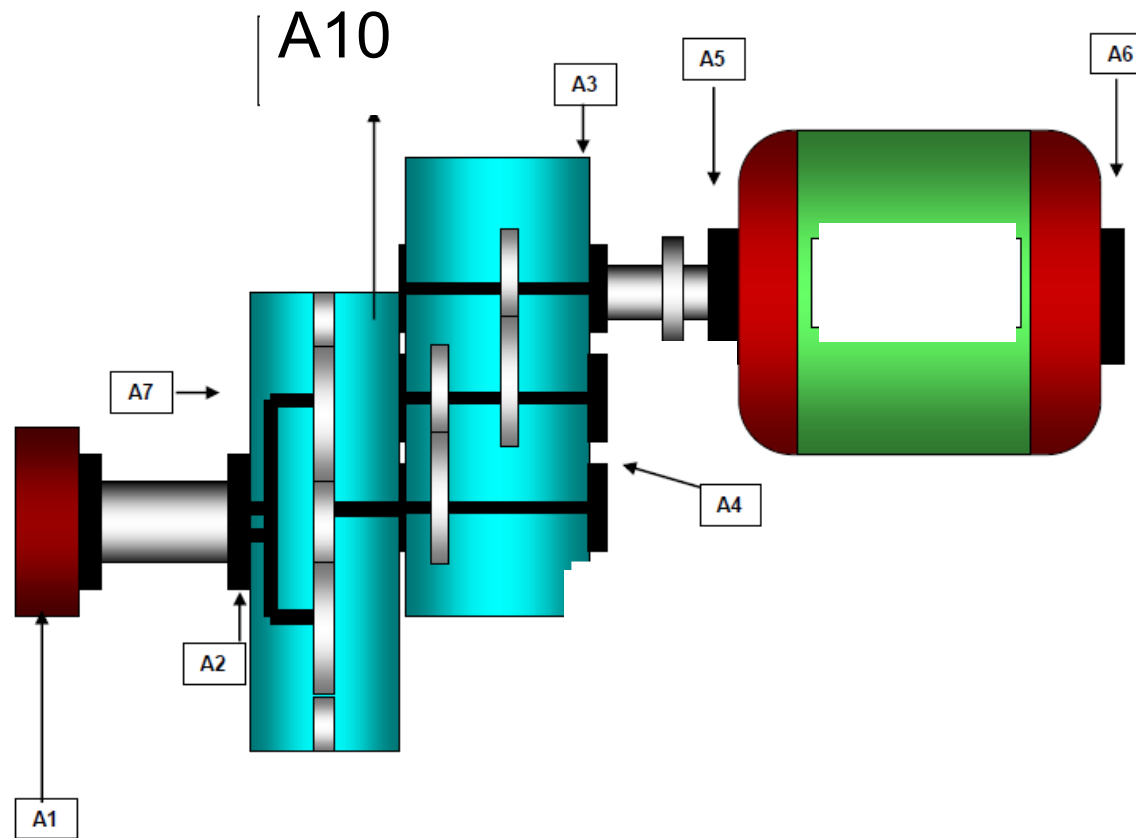


- Main Bearing+ Planetary Gear box + Gearbox + Generator



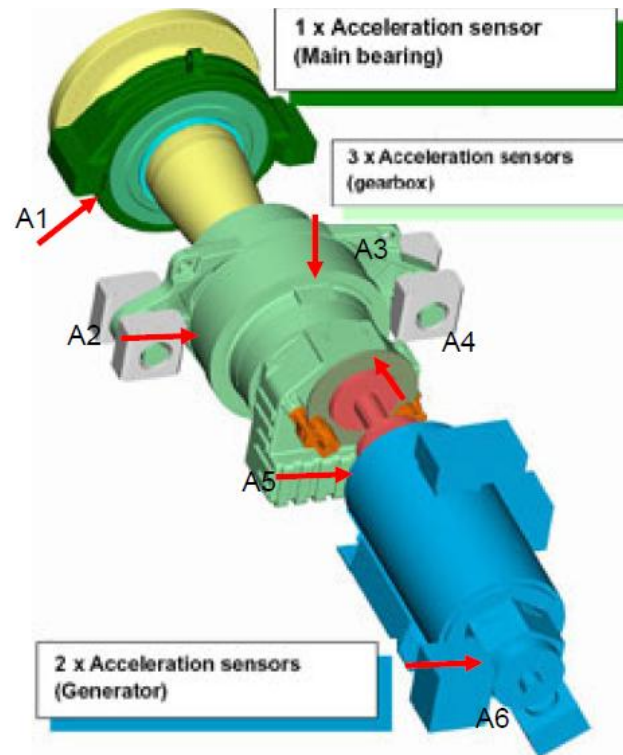
# The Monitoring System

- Monitoring system: 6 accelerometers and 1 sensor measuring the rotating speed

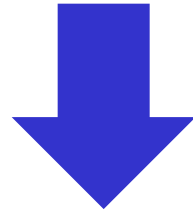


# Failures Modes

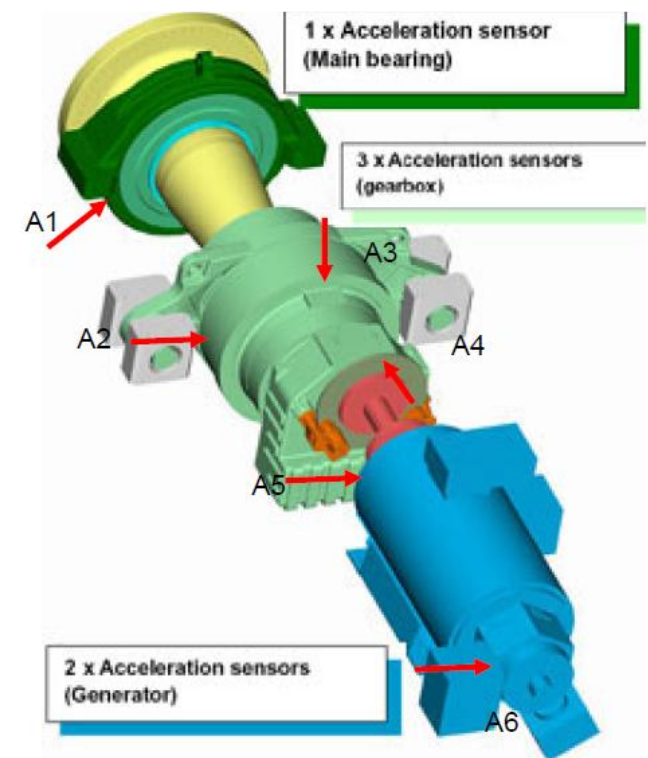
- a) Crashing of the highspeed shaft of the gear box
- b) Breaking of teeth in the planetary stage
- c) Misalignment between the generator and the gearbox shafts
- d) Wearing of the rear bearing housing of the generator



## Gearbox-Generator Failure



- Three months of turbine downtime
- Intervention of expensive tools



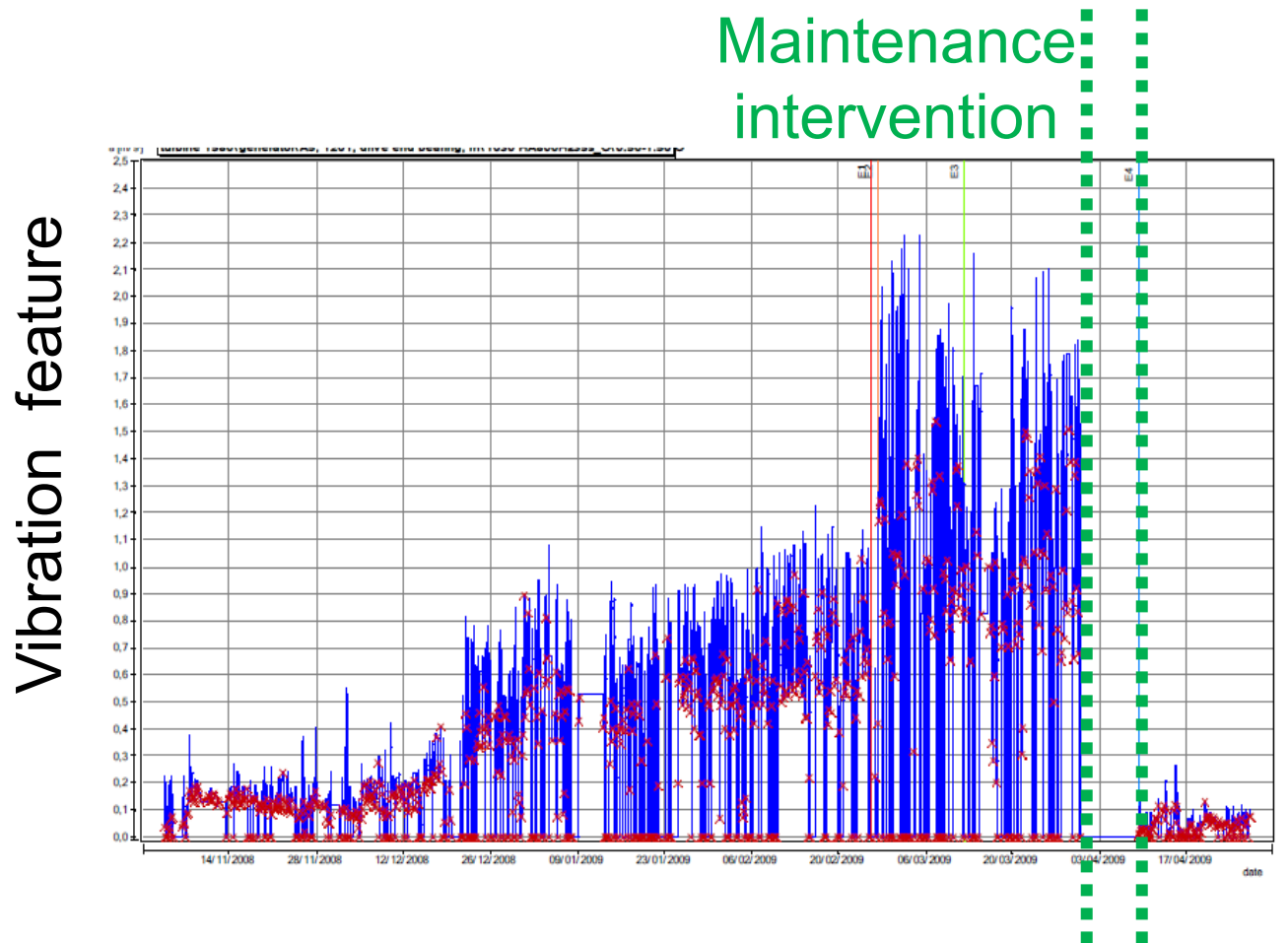
# Current Diagnostic Protocol

- 1) Data sent to the field operator and the diagnostic center
- 2) Filed operator & expert in vibration signal analysis isolate anomalies.
  - Expert knowledge required
  - e.g. considering thresholds on vibration levels at different rotating speeds of the highspeed shaft
- 3) Maintenance center assign a priority level (Green, Yellow, Red) for the intervention and plan the maintenance intervention

Machine :	Priorité 1	Priorité 2	Priorité 3	Conclusion
<a href="#">EOLIEENNE MV01</a>				Pas de mesures depuis le 19 février 2019.
<a href="#">EOLIEENNE MV02</a>			➡	Fonctionnement acceptable de cet ensemble. Pas d'évolution notable sur les défauts déjà suivis. Suivant présence d'une trappe de visite, sur la partie épicycloïdale du multiplicateur, un contrôle visuel de l'état des dents des satellites et couronne est recommandé sans urgence
<a href="#">EOLIEENNE MV03</a>		➡		Fonctionnement anormal de cet ensemble. Malgré une baisse significative des vibrations sur les paliers de la génératrice, les roulements présentent des défauts avérés sur la cage de maintien des éléments roulants avec une propagation sur ces derniers. Le risque de rupture de la cage est important et il est nécessaire de prévoir le remplacement des roulements de la génératrice
<a href="#">EOLIEENNE MV04</a>		➡		Fonctionnement acceptable de cet ensemble. Un contrôle de la lubrification du palier côté opposé au roulement de la génératrice est à prévoir à la réception Le jeu de fond de denture du train MV/PV semble légèrement trop faible et un contrôle visuel de la denture sur ce secteur est toujours conseillé
<a href="#">EOLIEENNE MV05</a>			➡	Fonctionnement de cet ensemble Y-a-t'il eu une intervention sur la génératrice expliquant la baisse observée sur les tests d'usure des roulements?
<a href="#">EOLIEENNE MV06</a>			➡	Fonctionnement normal de cet ensemble. Pas d'évolutions nettes sur l'alternateur. Néanmoins, une amélioration de l'alignement de l'alternateur après une période d'enregistrement en LIVE TREND, permettra de réduire les contraintes et ainsi d'augmenter la durée de vie des roulements.
<a href="#">EOLIEENNE MV07</a>				Pas de mesures depuis le 15 mai 2019.
<a href="#">EOLIEENNE MV08</a>		➡		Fonctionnement de cet ensemble est stable et acceptable. Il est indispensable de récupérer des mesures spectrales particulièrement sur l'alternateur afin de suivre l'évolution des défauts déjà observés

# Example

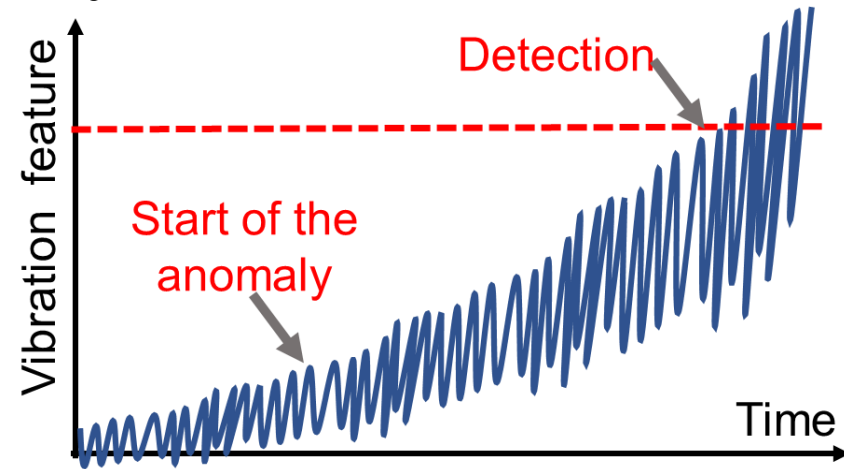
- Wearing of the rear bearing housing of the generator



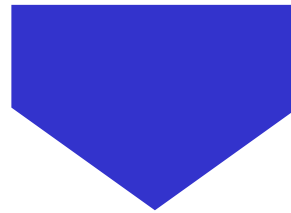


# Limitation of the Current Approach

## Detection and Diagnosis Delays



Human errors



Develop an “**automatic**” system  
for anomaly detection and  
diagnostic

# DESCRIPTION OF THE DATASET

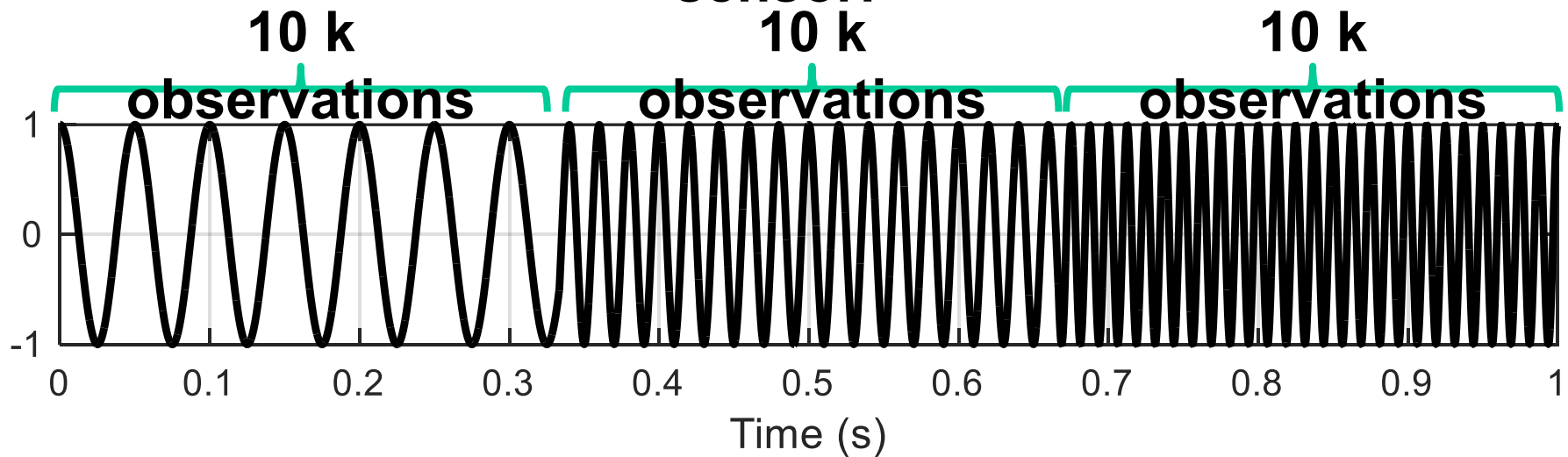
A file contains 5 seconds of measurements of the accelerator at a frequency of 5.0kHz is collected each time at 'Meas Time' in the file.

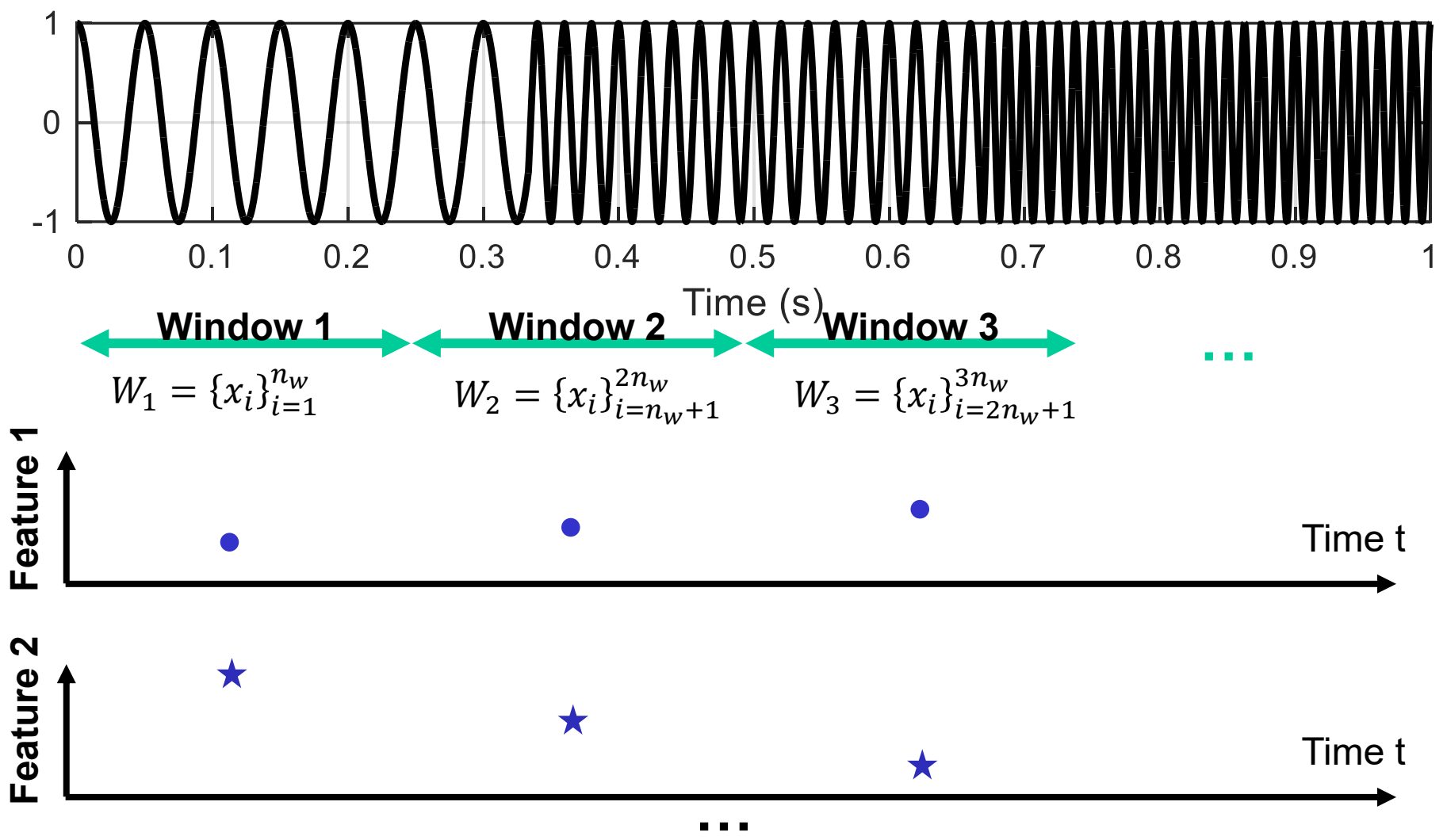
The screenshot shows an Excel spreadsheet with the following structure:

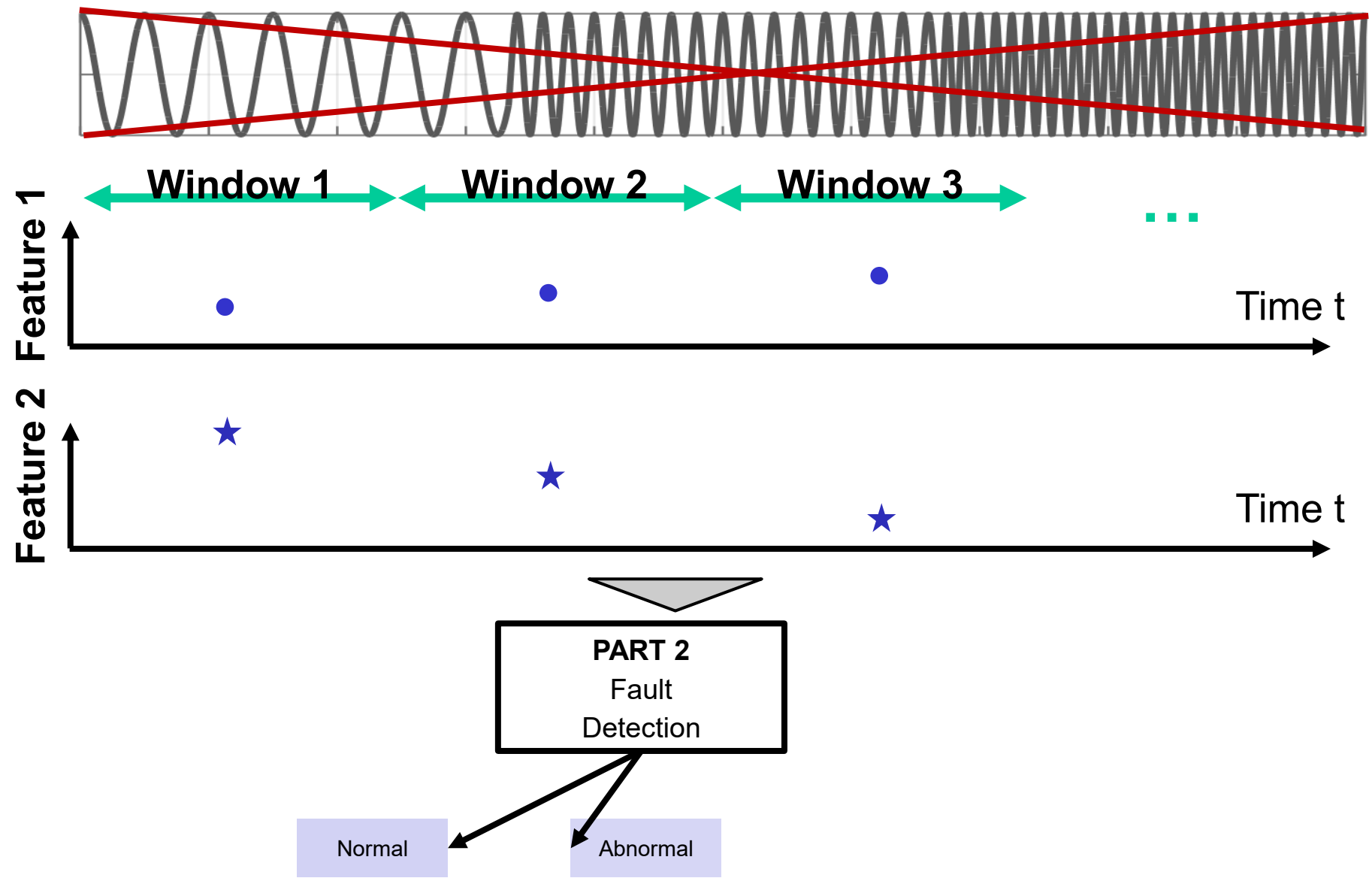
	A	B	C	D	E	F	G	H
1	Path	FITOU ERELIA / 1379_MV3 / Multiplicateur / A3, Å	Stage spur, rv / 1007 CA3.2kHz35s_F					
2	ID	-2113443231						
3	Unit	m/s <sup>2</sup>						
4	Meas Time	2013-09-04T11:26:34Z	Meas Time	2013-09-04T11:43:41Z	Meas Time	2013-09-04T11:26:09Z	Meas Time	2013-09-27T11:12:14Z
5	Reference Speed	2.507.069.969.177.240	Reference Speed	25.057.832.717.895.500	Reference Speed	16.709.163.665.771.400	Reference Speed	16.663.54
6	Samplerate	819.197.998.046.875	Samplerate	819.197.998.046.875	Samplerate	819.197.998.046.875	Samplerate	819.19
7	Time	Signal 1	Signal 2	Signal 3	Signal 4			
8		0	0	0	0	0	0	0
9	0.00012207061809	0.00012207061809	0.00012207061809	0.00012207061809	0.00012207061809	0.00012207061809	0.00012207061809	0.00012207061809
10	0.00024414123618	0.00024414123618	0.00024414123618	0.00024414123618	0.00024414123618	0.00024414123618	0.00024414123618	0.00024414123618
11	0.000366211868823	0.000366211868823	0.000366211868823	0.000366211868823	0.000366211868823	0.000366211868823	0.000366211868823	0.000366211868823
12	0.000488282472361	0.000488282472361	0.000488282472361	0.000488282472361	0.000488282472361	0.000488282472361	0.000488282472361	0.000488282472361
13	0.000610353075899	0.000610353075899	0.000610353075899	0.000610353075899	0.000610353075899	0.000610353075899	0.000610353075899	0.000610353075899
14	0.000732423737645	0.000732423737645	0.000732423737645	0.000732423737645	0.000732423737645	0.000732423737645	0.000732423737645	0.000732423737645
15	0.000854494341183	0.000854494341183	0.000854494341183	0.000854494341183	0.000854494341183	0.000854494341183	0.000854494341183	0.000854494341183
16	0.000976564944722	0.000976564944722	0.000976564944722	0.000976564944722	0.000976564944722	0.000976564944722	0.000976564944722	0.000976564944722
17	0.001098635606468	0.001098635606468	0.001098635606468	0.001098635606468	0.001098635606468	0.001098635606468	0.001098635606468	0.001098635606468
18	0.001220706151798	0.001220706151798	0.001220706151798	0.001220706151798	0.001220706151798	0.001220706151798	0.001220706151798	0.001220706151798
19	0.001342776813544	0.001342776813544	0.001342776813544	0.001342776813544	0.001342776813544	0.001342776813544	0.001342776813544	0.001342776813544
20	0.00146484747529	0.00146484747529	0.00146484747529	0.00146484747529	0.00146484747529	0.00146484747529	0.00146484747529	0.00146484747529
21	0.001586918020621	0.001586918020621	0.001586918020621	0.001586918020621	0.001586918020621	0.001586918020621	0.001586918020621	0.001586918020621
22	0.001708988682367	0.001708988682367	0.001708988682367	0.001708988682367	0.001708988682367	0.001708988682367	0.001708988682367	0.001708988682367
23	0.001831059227698	0.001831059227698	0.001831059227698	0.001831059227698	0.001831059227698	0.001831059227698	0.001831059227698	0.001831059227698
24	0.001953129889444	0.001953129889444	0.001953129889444	0.001953129889444	0.001953129889444	0.001953129889444	0.001953129889444	0.001953129889444
25	0.002075200434774	0.002075200434774	0.002075200434774	0.002075200434774	0.002075200434774	0.002075200434774	0.002075200434774	0.002075200434774
26	0.002197271212935	0.002197271212935	0.002197271212935	0.002197271212935	0.002197271212935	0.002197271212935	0.002197271212935	0.002197271212935
27	0.002319341758266	0.002319341758266	0.002319341758266	0.002319341758266	0.002319341758266	0.002319341758266	0.002319341758266	0.002319341758266
28	0.002441412303597	0.002441412303597	0.002441412303597	0.002441412303597	0.002441412303597	0.002441412303597	0.002441412303597	0.002441412303597
29	0.002563483081758	0.002563483081758	0.002563483081758	0.002563483081758	0.002563483081758	0.002563483081758	0.002563483081758	0.002563483081758

**High frequency**

**sensor:  
10 k**







- Each 5 sec signal data are divided in 40 segments(windows) in order to extract features
- The following statistical features are considered:  
Mean, standard deviation, Kurtosis, Skewness, min, max, 2<sup>nd</sup> moment, 3<sup>rd</sup> moment
- A window contains  $N$  values  $W = \{x_i\}_{i=1}^N$ , the corresponding Statistical Features are:

Sample Mean:

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$

Sample Variance:

$$\sigma^2 \approx s^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2$$

Standard Deviation:  $\sigma$

$k$ -th Moments:

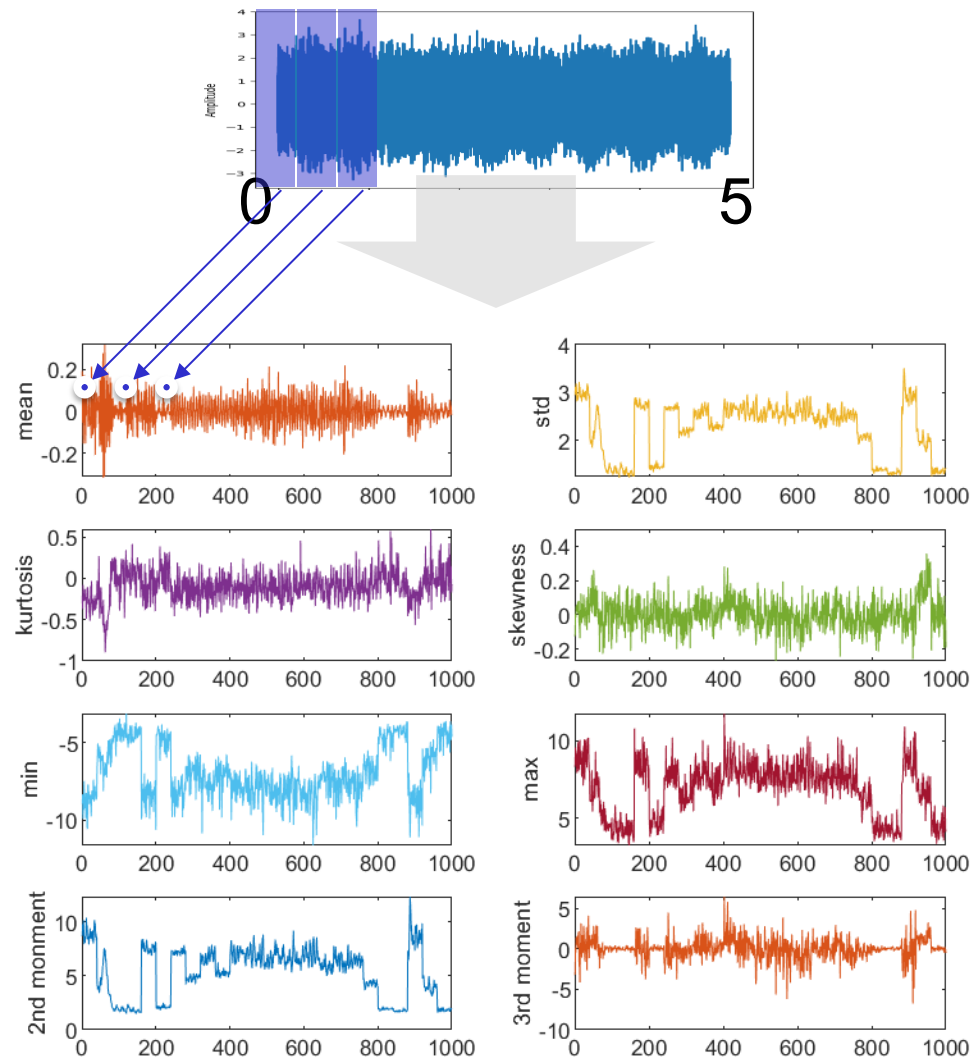
$$\mu_k \approx \frac{1}{N} \sum_{i=1}^N x_i^k$$

Skewness → “asymmetry”  
(the third standardized moment)

$$\frac{\mu_3}{\sigma^3}$$

Kurtosis → “peak”  
(the fourth standardized moment)

$$\frac{\mu_4}{\sigma^4}$$



# EXERCISE 3 DEVELOPMENT OF A FAULT DETECTION TOOL FOR A WIND TURBINE GENERATOR

## Given:

- 1) The file 'train.dat' contains the features already extracted in normal condition
- 2) The file 'validation.dat' contains the features already extracted in normal condition
- 3) The file 'validation\_sim.dat' contains the features in simulated abnormal condition

train								
800x8 double								
	1	2	3	4	5	6	7	8
1	0.1918	2.9473	-0.2172	-0.1264	-8.9417	8.3333	8.6760	-3.2251
2	-0.0553	3.1255	-0.3734	0.0047	-8.3208	9.5974	9.7568	0.1444
3	-0.0273	3.0340	-0.0800	-0.0165	-9.9243	8.4782	9.1938	-0.4595
4	-0.1549	3.1874	-0.2684	0.0424	-8.4574	9.1952	10.1471	1.3688
5	0.0066	3.0410	-0.2734	0.0520	-9.3214	8.4448	9.2366	1.4564
6	0.1720	2.8165	-0.1769	0.0581	-7.4707	7.9281	7.9228	1.2936
7	-0.0533	2.9428	-0.1788	0.0175	-9.2303	9.3448	8.6492	0.4444
8	0.1164	2.8412	-0.1314	0.0722	-8.2652	9.2579	8.0627	1.6507
9	-0.0958	2.8827	-0.2671	0.0034	-8.6233	9.9347	8.2996	0.0815
10	-0.1537	2.9199	-0.2698	0.0793	-8.7042	8.0308	8.5154	1.9674
11	0.0615	2.9858	-0.2282	0.0806	-9.8658	9.6261	8.9039	2.1387
12	-0.0193	3.2212	-0.4878	-0.0667	-8.2399	8.1581	10.3633	-2.2198
13	0.0821	3.0265	-0.2508	-0.0710	-8.5418	9.9236	9.1485	-1.9599
14	0.0416	3.1149	-0.1363	-0.1381	-10.4691	10.0679	9.6909	-4.1581
15	0.0044	2.9303	-0.1060	0.0274	-10.5794	8.6044	8.5764	0.6874
16	-0.0010	2.8905	-0.1156	0.0113	-7.7779	8.4754	8.3445	0.2727
17	-0.0743	2.9348	-0.3117	0.1239	-7.6838	9.3669	8.6025	3.1201
18	-0.0671	2.9080	-0.2487	-0.0200	-8.6593	8.2900	8.4459	-0.4903
19	0.0190	2.8127	-0.2573	-0.0495	-8.1409	7.6882	7.9017	-1.0966
20	0.0753	2.9773	-0.3975	0.0638	-8.9418	8.6402	8.8533	1.6776

mean      std      kurtosis      skewness      min      max      2<sup>nd</sup> Moment      3<sup>rd</sup> Moment

## You are required to:

- 1) **Develop** a fault detection tool for the turbine generator [you can use AAKR or PCA, as you prefer];
- 2) **Apply the developed tool** to the data in the files 'test\_1.dat' and 'test\_2.dat'. Identify possible abnormal condition period.



### **Exercise 3.1**

*Fault detection with AAKR*

1. *Optimize the AAKR to achieve Accuracy and Robustness*
2. *Apply the AAKR model on test data*

Use data and code (AAKR) in folder 'second case study'

### **Exercise 3.2**

*Fault detection with PCA*

1. *Optimize the PCA to achieve Accuracy and Robustness*
2. *Apply the PCA model on test data*

Use data and code (PCA) in folder 'second case study'