













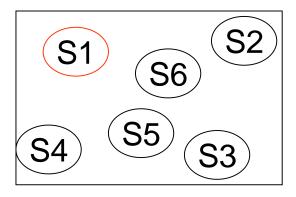
Exercises on Advanced regression techniques of signal analysis for fault detection:

### **PCA**

Federico Antonello federico.antonello @polimi.it



### Component

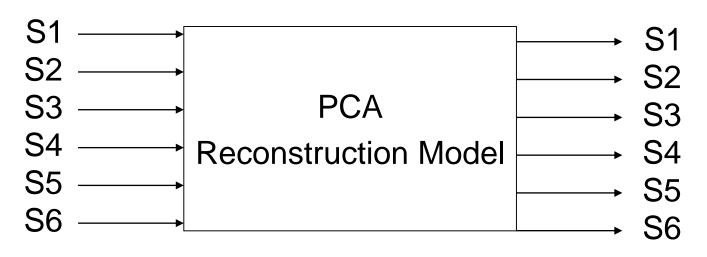


Real

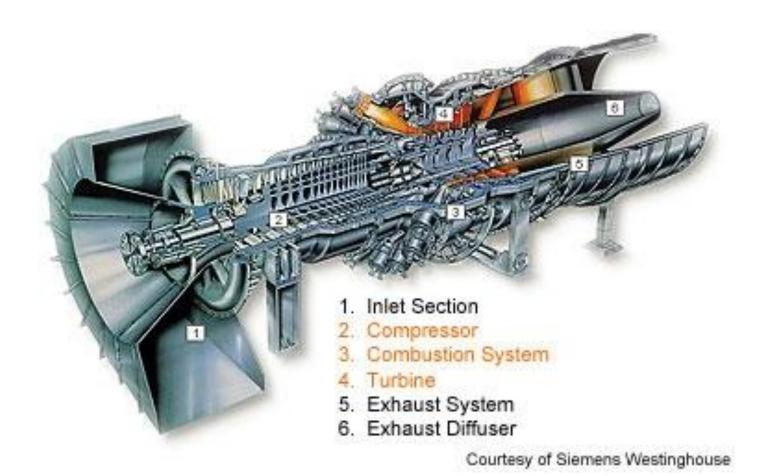
#### measurements

Signal Reconstructions

Expected signal values in normal conditions









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



# PCA



Fill the missing parts of the code PCA\_to\_be\_filled.m

Some useful matlab commands:

- COV
- eig

## **Exercise 1 TRAINING PHASE:** P matrix

% STEP 1: find the matrix P whose column are the eigenvectors ordered

from the largest (column 1) to the smallest (column n)

% SIZE of P is [n,n]



## **Exercise 1 TRAINING PHASE:** P matrix Solution

```
V=cov(train_data_n); % Covariance matrix of the normalized data
%compute eigenvalues and eigenvectors of the Covariance matrix V
[P_rev,D] = eig(V);
eig_val_rev = diag(D); %found eigenvalues are ordered from the smallest to the largest
[a,b]=sort(eig_val_rev);
%change the ordering of eigenvalues and eigenvectors: from the largest to the smallest
for ii=1:n
 P(:,ii)=P_rev(:,b(n-ii+1));
 eig_value(ii)=eig_val_rev(b(n-ii+1));
End
```



# **Exercise 1 TRAINING PHASE: PCA Approximation**

### % STEP 2: perform the PCA approximation

% keep a number (lambda) of eigenvestors such that they represent at least perc\_var of the total data variance

- % Find the matrix P\_lambda whose columns are the first lambda aigenvectors

- How\_many principal components should be considered?
  - Untill variance reaches var\_th (the variance of a single component is equal to its eigenvalue)



# **Exercise 1 TRAINING PHASE: PCA Approximation Solution**

```
STEP 2: perform the PCA approximation
sum_eig=sum(eig_value);
n PC=0;
sum_var=0;
while sum var<var th;
 n PC=n PC+1;
 sum_var=sum_var+eig_value(n_PC)/sum_eig;
 if n_PC==n % to avoid numerical problem from the sum of the eigenvalues
   sum var=1
 end
end
%-----Keep only the first n_comp principal components
P_{\text{lambda}}=P(:,1:n_{\text{PC}});
%end training phase
```

### Exercise 1 TEST PHASE: RECONSTRUCT THE TEST PATTERNS

% STEP 3: RECONSTRUCT THE TEST PATTERNS

% TO BE FILLED

% RECONSTRUCT THE TEST PATTERNS

% Call 'test\_data\_rec\_n' the matrix containing the reconstruction of



### Exercise 1 TEST PHASE: RECONSTRUCT THE TEST PATTERNS Solution

% STEP 3: RECONSTRUCT THE TEST PATTERNS

%-----

%Reconstruct the test patterns by projecting in the trasformed basis, keep only the % principal components and antitrasform

test\_data\_rec\_n=test\_data\_n\*P\_lambda\*P\_lambda';





Consider the patterns in file 'train.dat' to develop a PCA reconstruction model. The file contains data collected during normal conditions. They are 6 temperature signals, 5200 measuraments/year.

- Develop the PCA reconstruction model
- Perform the reconstruction of the file 'validation.dat'. The file contains data collected during normal conditions

#### Hints:

- Perform the computation considering different numbers of Principal Components
- Consider the root mean square error as a performance measure.Two tests should be performed:
  - *Input = normal condition signals*
  - Input = simulated abnormal conditions

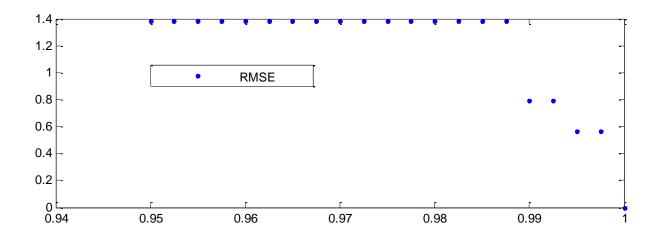
[test\_reconstruction,n\_PC]=PCA\_reconstruction('train.dat','validation.dat',0.95)

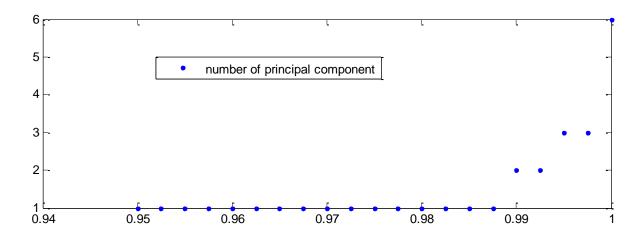


```
Clear all
Close all
true_signal=load('validation.dat');
[N,n]=size(true_signal);
v=[0.98,0.99,0.995,1]
for i=1:4;
 [test_reconstruction,n_PC(i)]=PCA_reconstruction('train.dat','validation.dat',v(i));
% Compute the root mean square error:
 rmse(i)=sqrt(sum(sum((test_reconstruction-true_signals).^2))/(n*N));
close all
end
figure(1)
% subplot(211)
plot(v,n PC,'.')
legend('number of principal components')
figure(2)
plot(v,rmse,'r.')
legend('RMSE')
```

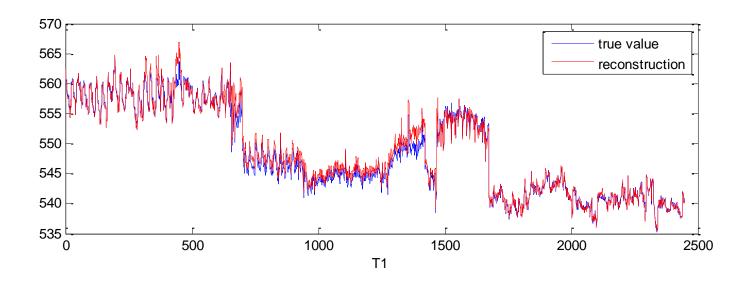


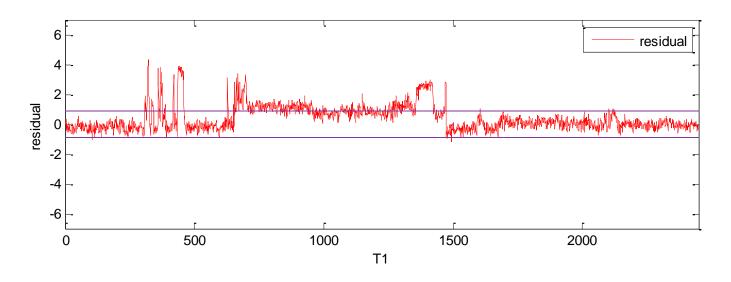
# Exercise 2: Optimal Choice of the number of Principal components (test for the accuracy)



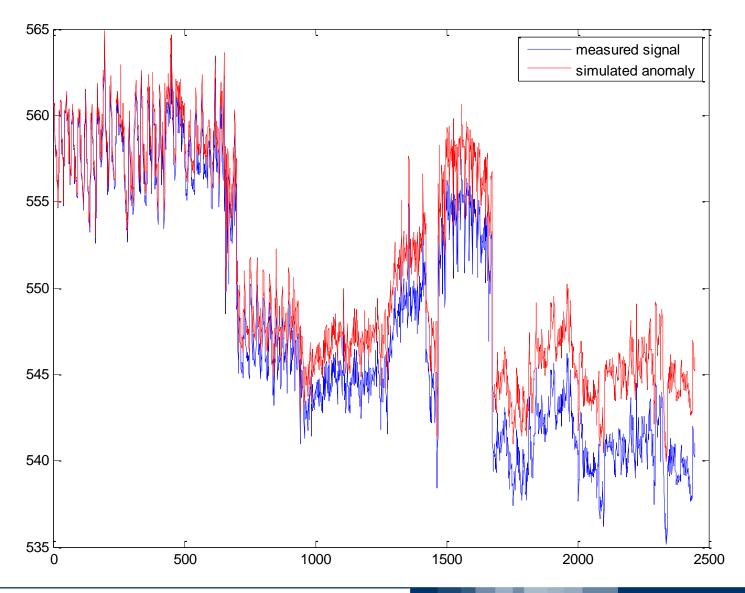




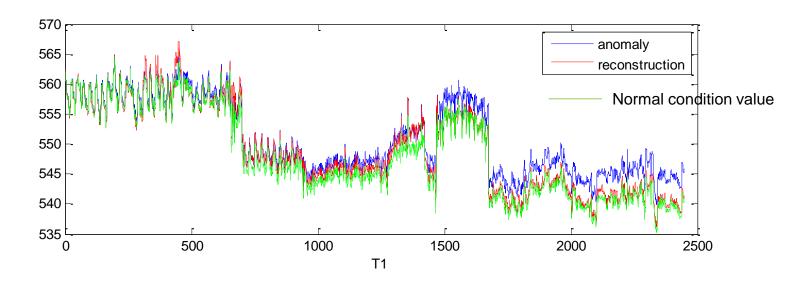


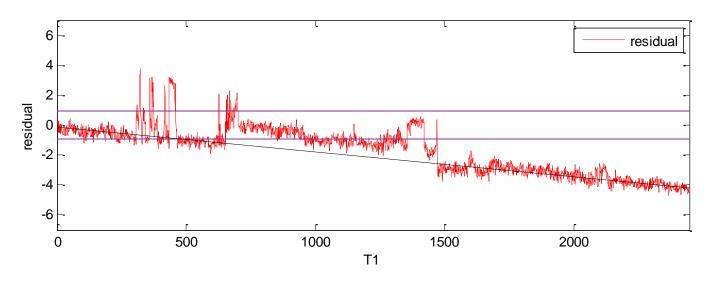




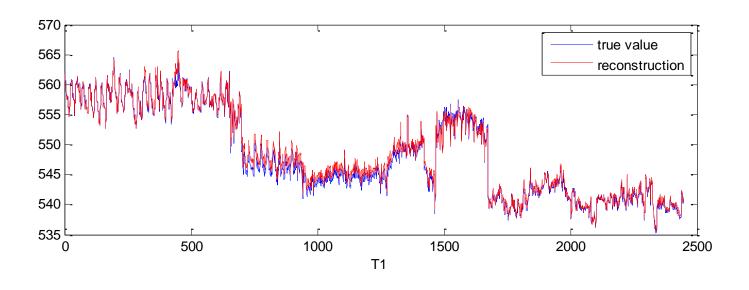


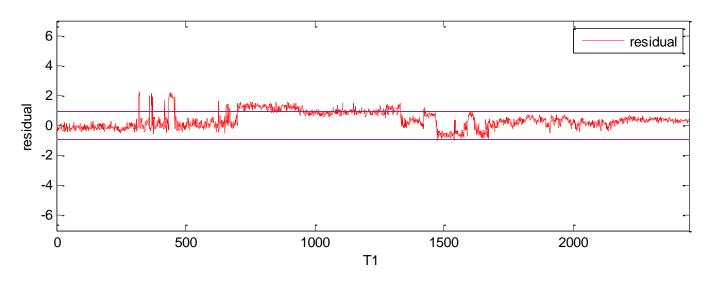




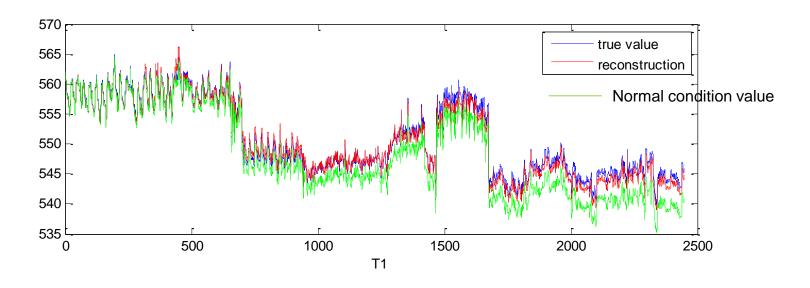


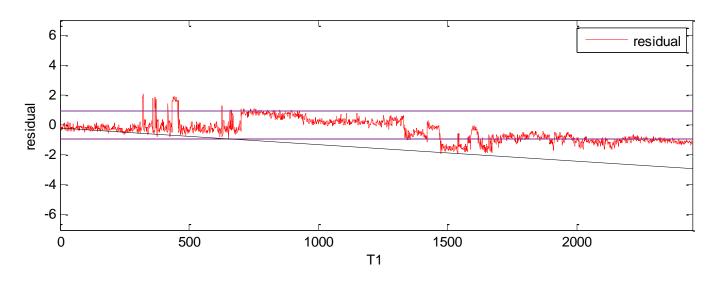








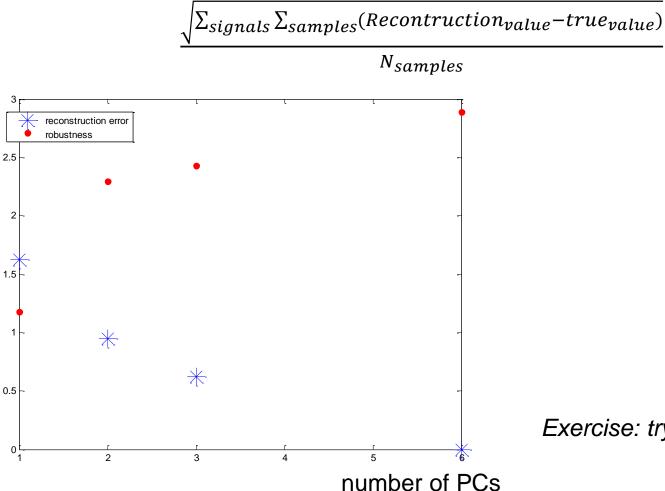






# **Accuracy and robustness Versus Number of Principal Components**

#### Measure for robustness:



Exercise: try to plot this figure



# **Accuracy and robustness Versus Number of Principal Components**

```
true_signal=load('validation.dat');
[N,n]=size(true signal);
v=[0.98,0.99,0.995]
for i=1:4;
  [test_reconstruction,n_PC(i)]=PCA_reconstruction('train.dat','validation.dat',v(i));
 rmse(i)=sqrt(sum(sum((test_reconstruction-true_signals).^2))/(n*N));
  [test_reconstruction,n_PC(i)]=PCA_reconstruction('train.dat','val_anomaly.dat',v(i));
 robustness(i)=sqrt(sum(sum((test_reconstruction(:,1)-true_signal(:,1)).^2))/(N));
 close all
end
figure
% subplot(211)
plot(n PC,rmse,'.')
hold on
plot(n_PC,robustness,'r.')
legend('reconstruction error', 'robustness')
```





- Perform the reconstruction of the signal measurements in the 3 files test\_1.dat, test\_2.dat, test\_3.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