An Advanced Fault Detection Tool (FDT) for Predictive Maintenance of a Fleet of Industrial Gas Turbines

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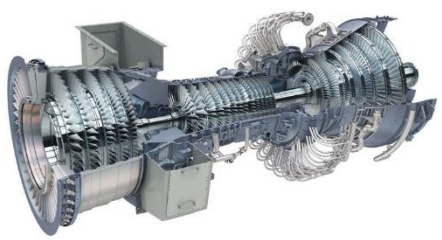
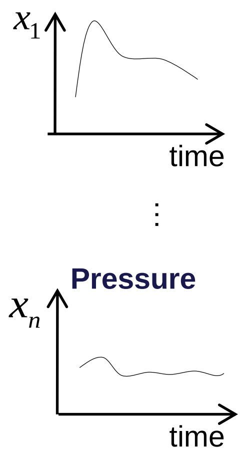
Ambient & Operating Conditions

Industrial Systems and Processes



Sensor signals

Vibration



Fault Detection

Normal

Abnormal

- Maximum Availability
- Minimum LCC
- Business Continuity

Safety Improvement
Cost Saving
New Business

Fault Detection Tool: KPI

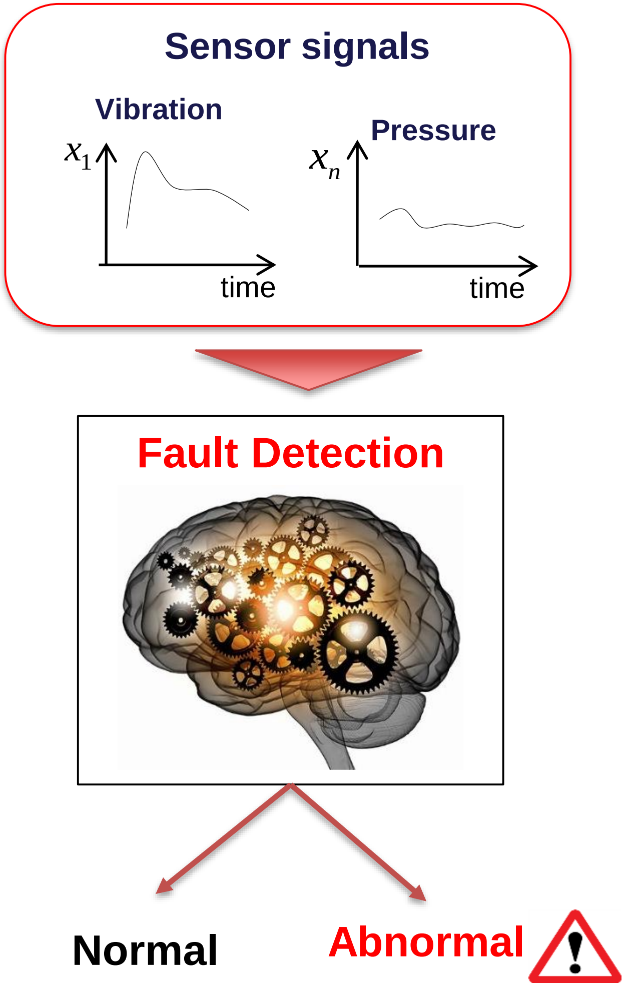
- **Missed Alarm Rate**

  (False Negative)


- **False Alarm Rate**

  (False Positive)

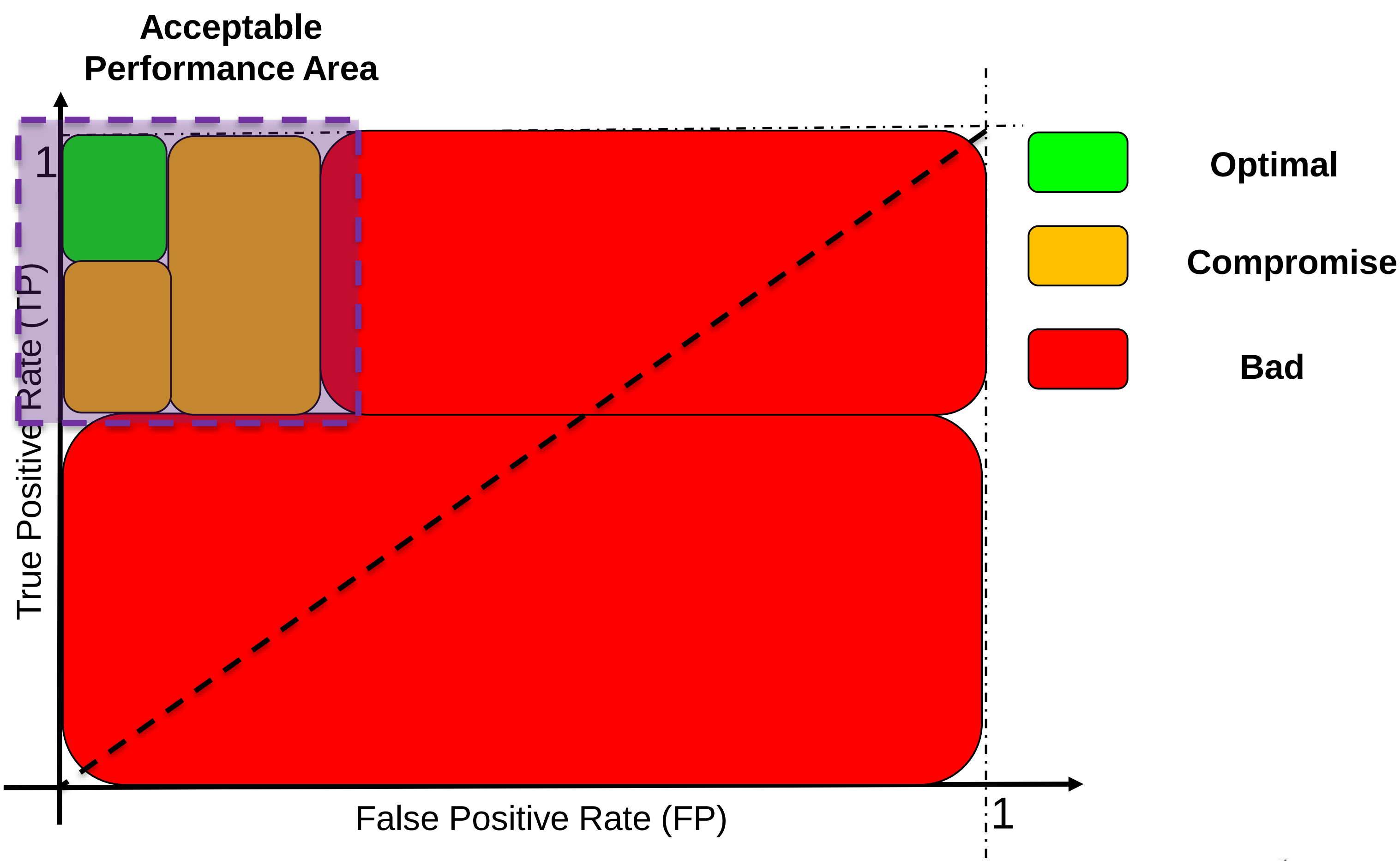

- **Time necessary to identify the abnormal condition**



Receiver Operating Characteristic (ROC) Curve

True Positive $TP = \frac{\#RightDetection}{\#Failure}$

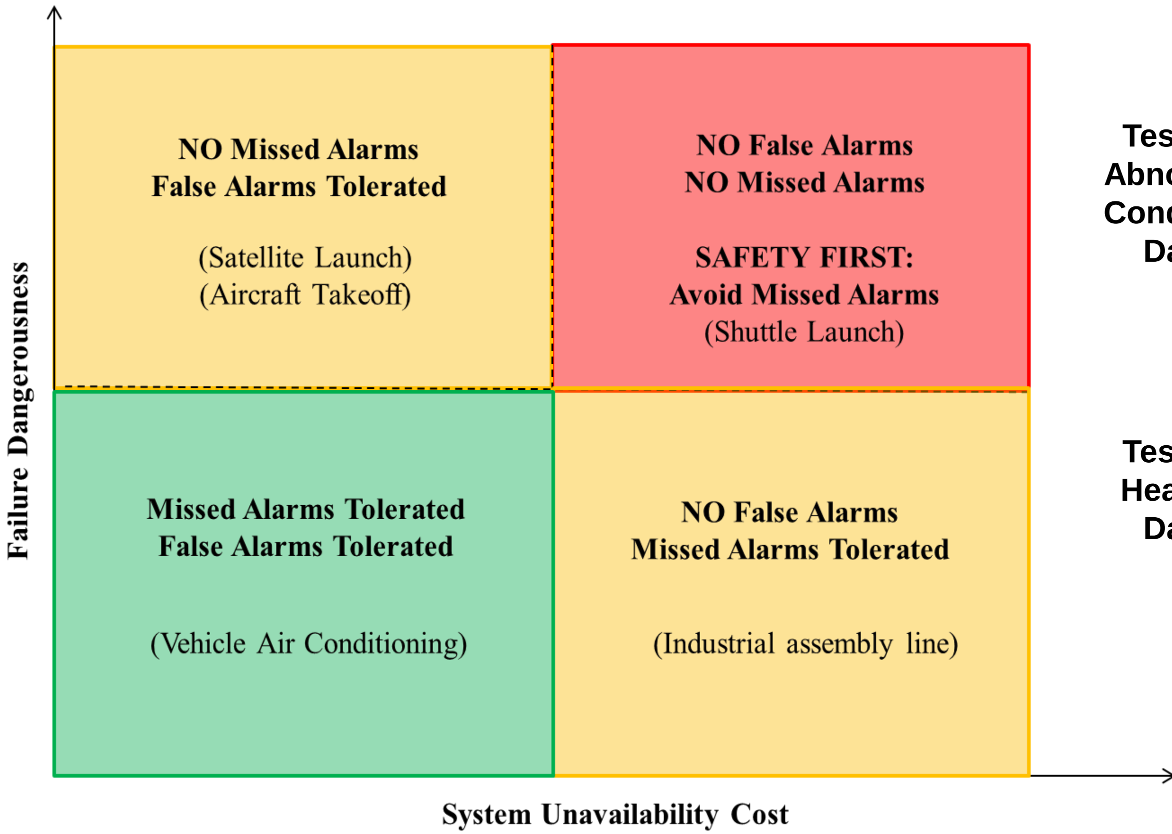
False Positive $FP = \frac{\#FalseAlarm}{\#Healthy}$



Unsupervised Fault Detection: Performance Evaluation

Desired Fault Detection Performance

Depends on the specific situation!



Test on Abnormal Condition Data ▶ **True Positive Rate (TPR)**

$$\frac{\#\,Detection}{\#\,Test\ Trajectories}$$

Test on Healthy Data ▶ **False Positive Rate (FPR)**

$$\frac{\#\,Detection}{\#\,Test\ Trajectories}$$

Fault Detection Tool: Real Industrial Context

Fault Detection Application for Industrial Gas Turbines

Situations characterized by different information availability

<u>UNSUPERVISED FDT</u>

Only Healthy Data Available

(e.g., new turbine fleets)

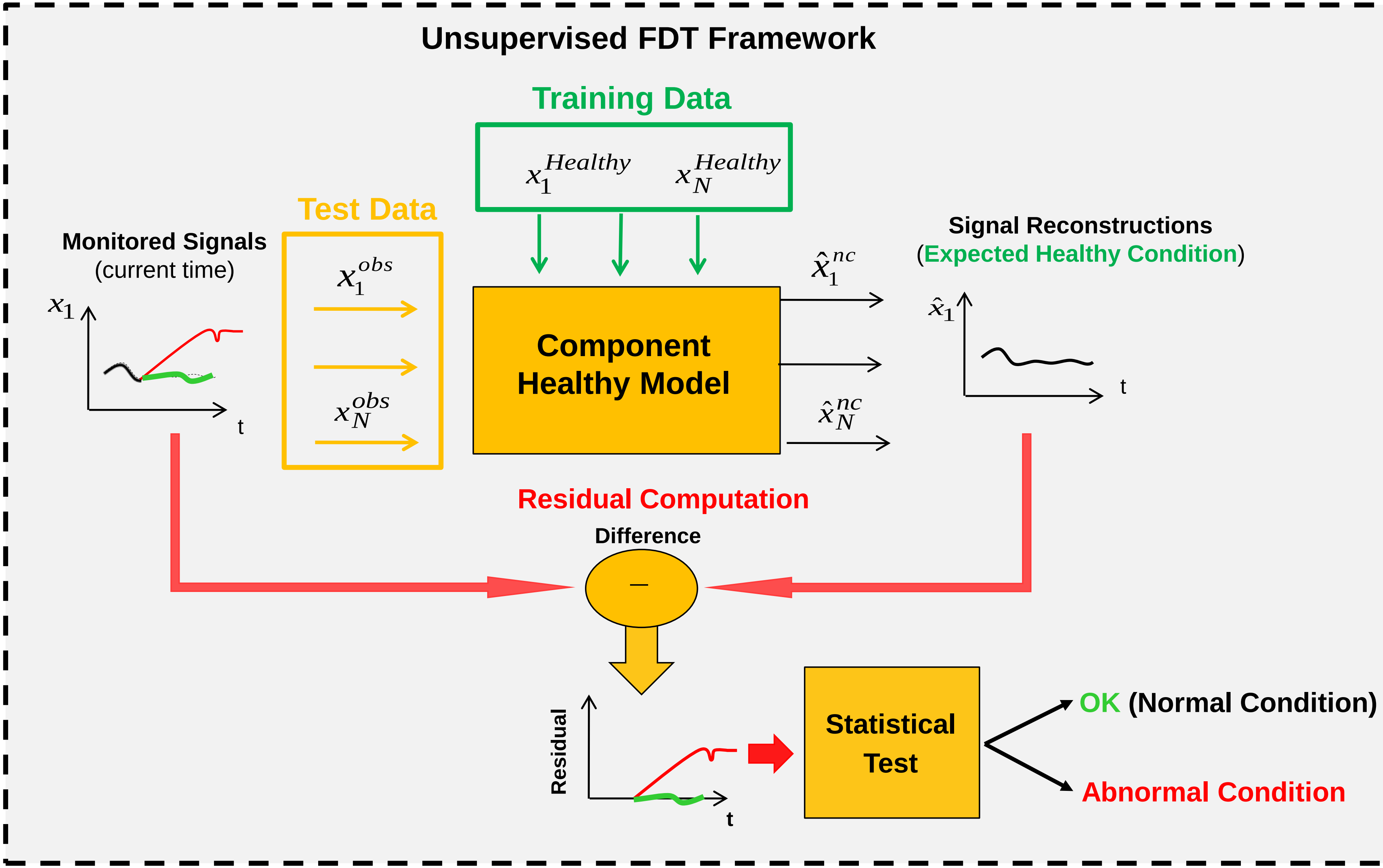
<u>SUPERVISED FDT</u>

Both Healthy and Degraded Data Available

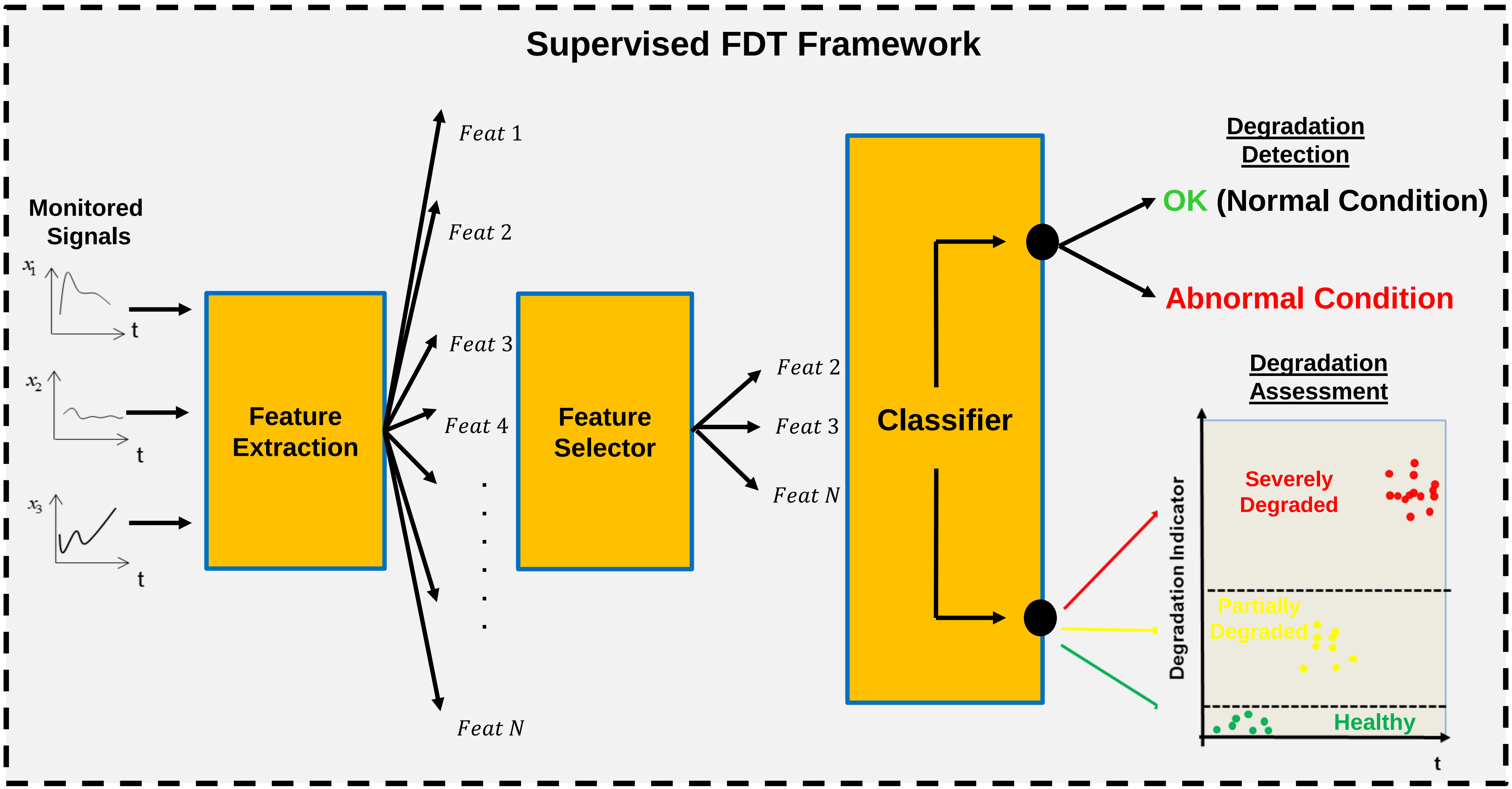
(e.g., historical turbine fleets)

The best approach to choose depends on the type of available data and information

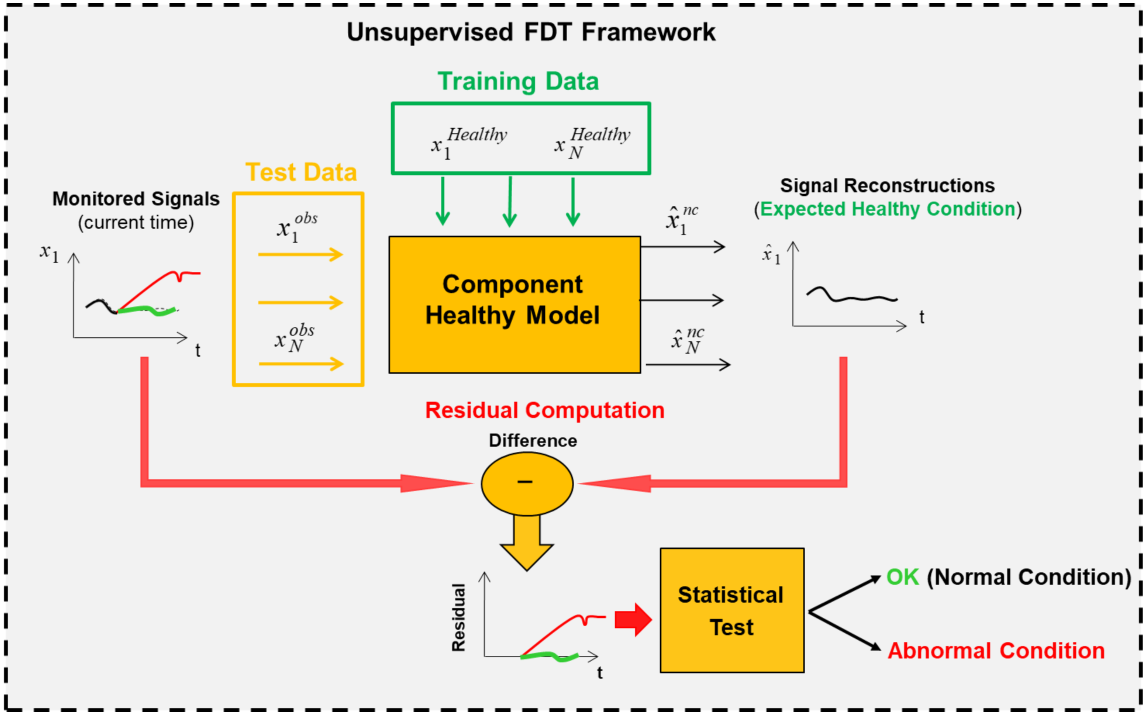
Unsupervised FDT: only healthy data available

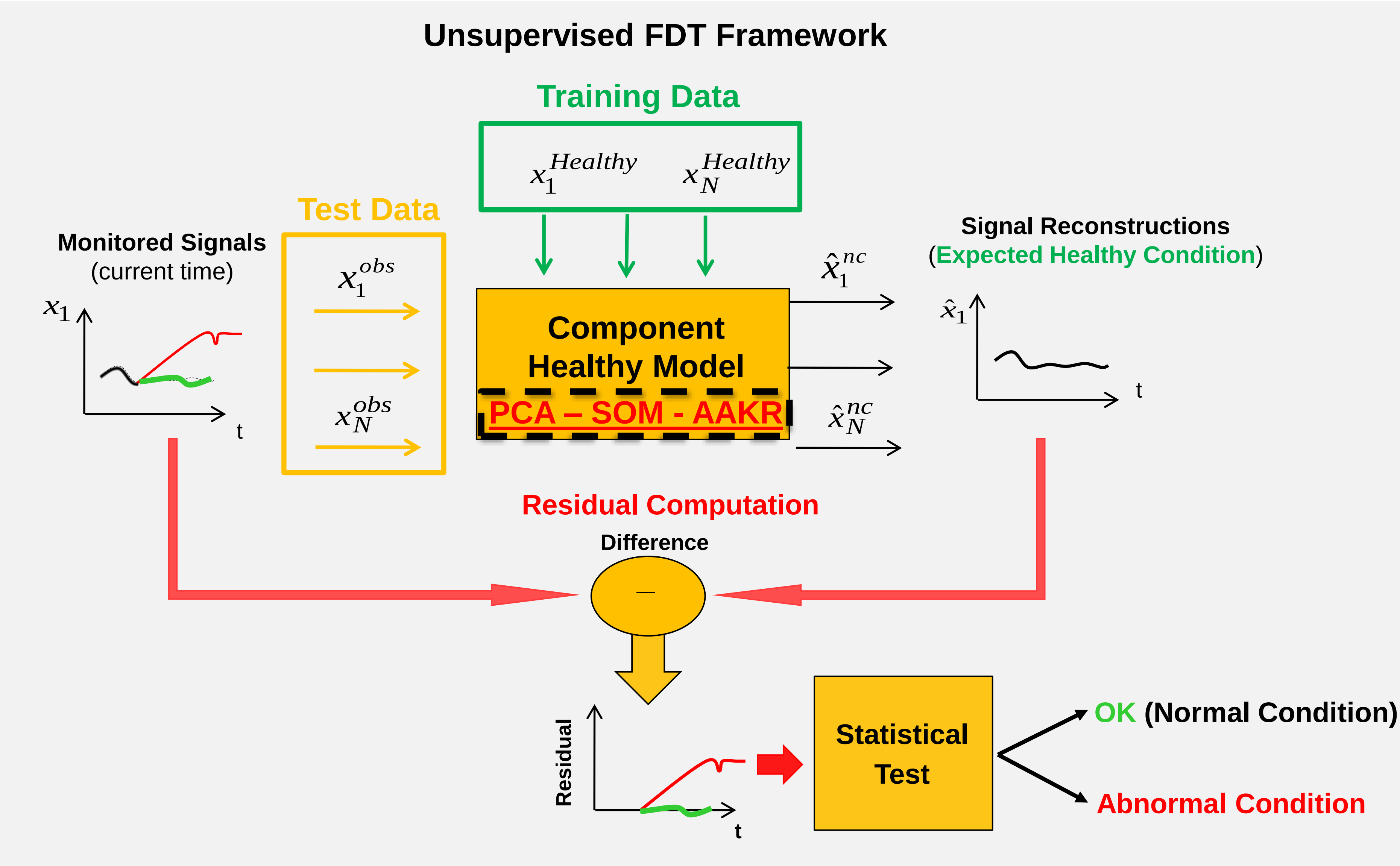


Supervised FDT: healthy and degraded data available



Unsupervised Fault Detection Tool

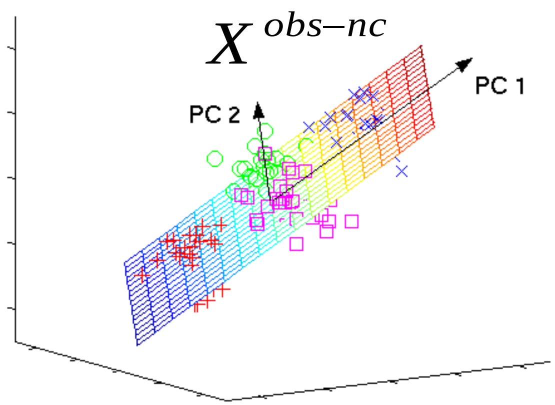



Unsupervised FDT Framework
Training Data
$x_1^{Healthy}$ $x_N^{Healthy}$
Test Data
x_1^{obs}
x_N^{obs}
Monitored Signals
(current time)
x_1
t
Component Healthy Model
PCA – SOM - AAKR
$\hat{x}_1^{nc}$
$\hat{x}_N^{nc}$
Signal Reconstructions
(Expected Healthy Condition)
$\hat{x}_1$
t
Residual Computation
Difference
–
Residual
t
Statistical Test
OK (Normal Condition)
Abnormal Condition

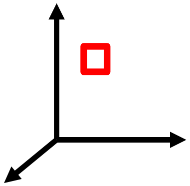
❑ PCA

Historical Signal Measurements

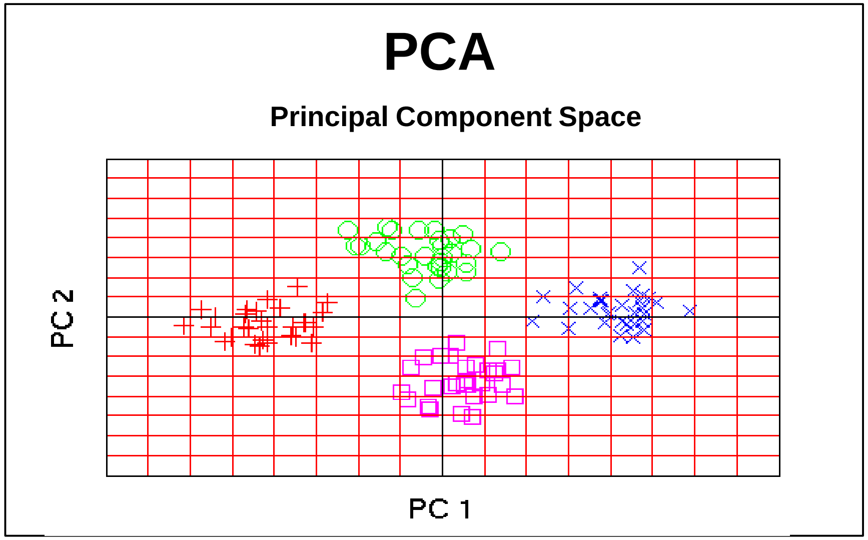
original data space



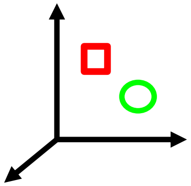
- Signal Measurements
- Signal Reconstruction



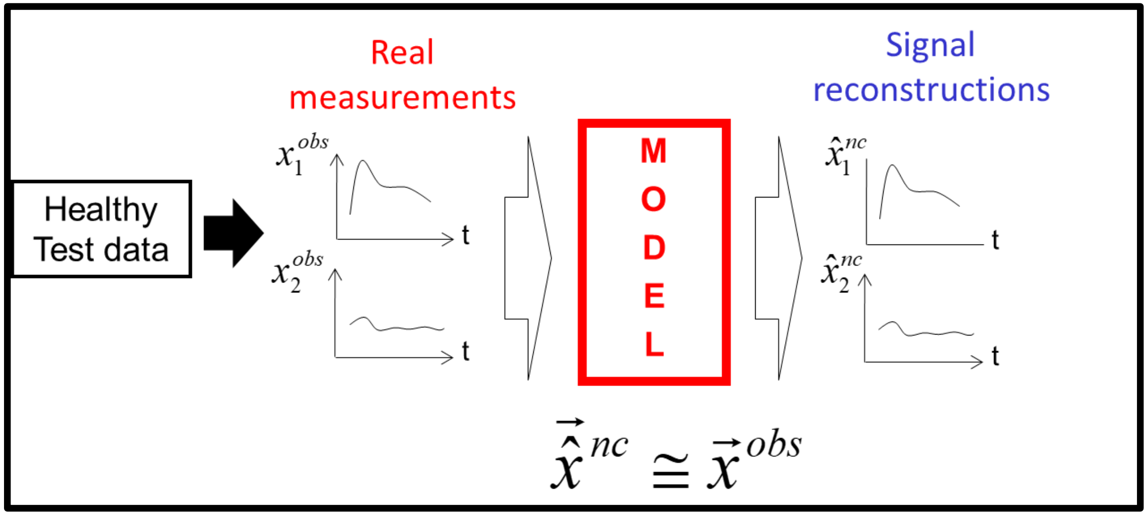
x_1^{obs} →
x_2^{obs} →
x_n^{obs} →

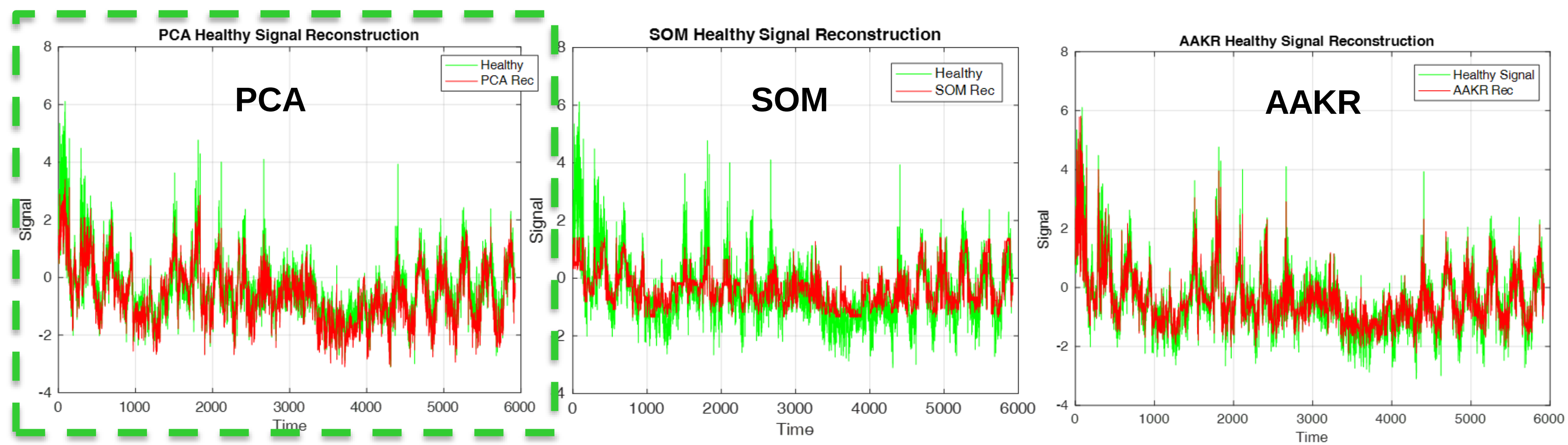


$\hat{x}_1^{nc}$ →
$\hat{x}_2^{nc}$ →
$\hat{x}_n^{nc}$ →



Signal Reconstruction Accuracy

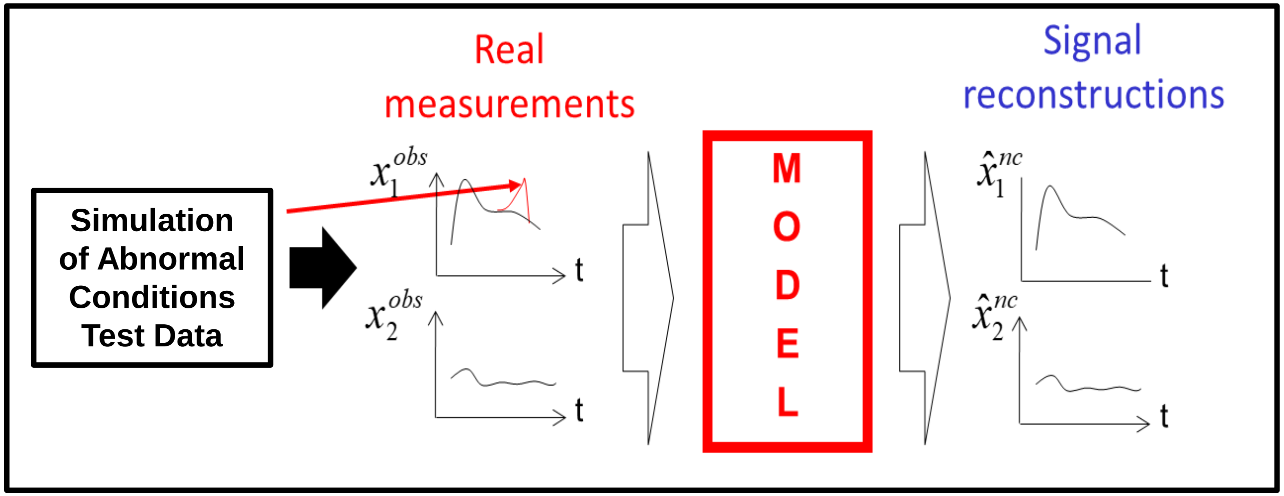


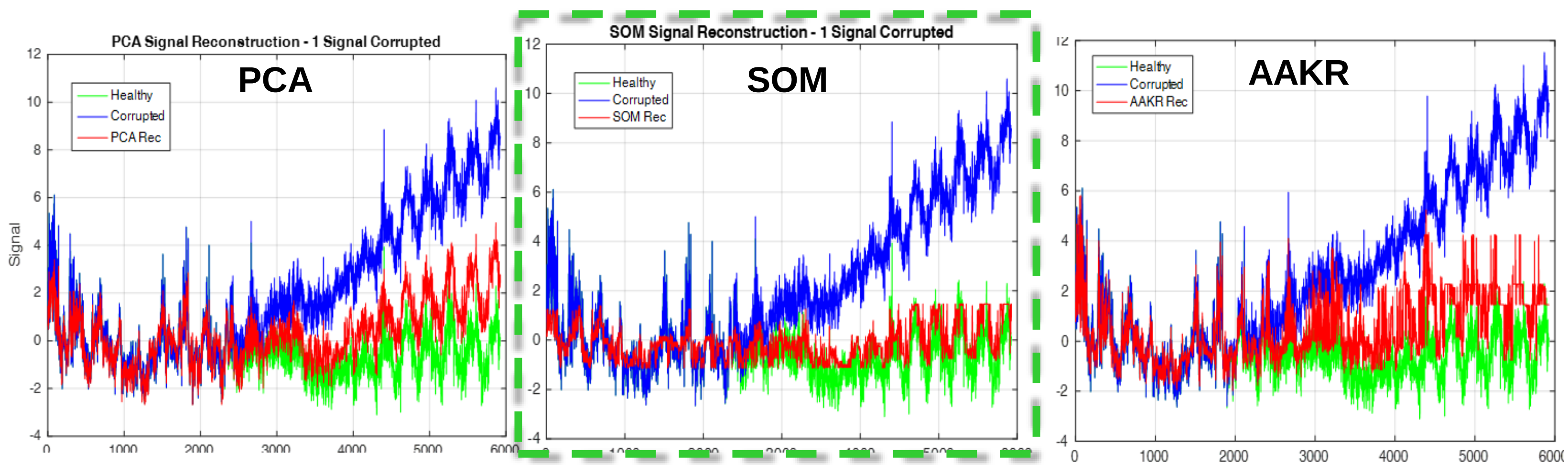


Accuracy	Capability of accurately reconstructing the healthy signals behavior

Best Accuracy: (PCA) → **Avoid False Alarms**

Signal Reconstruction Robustness

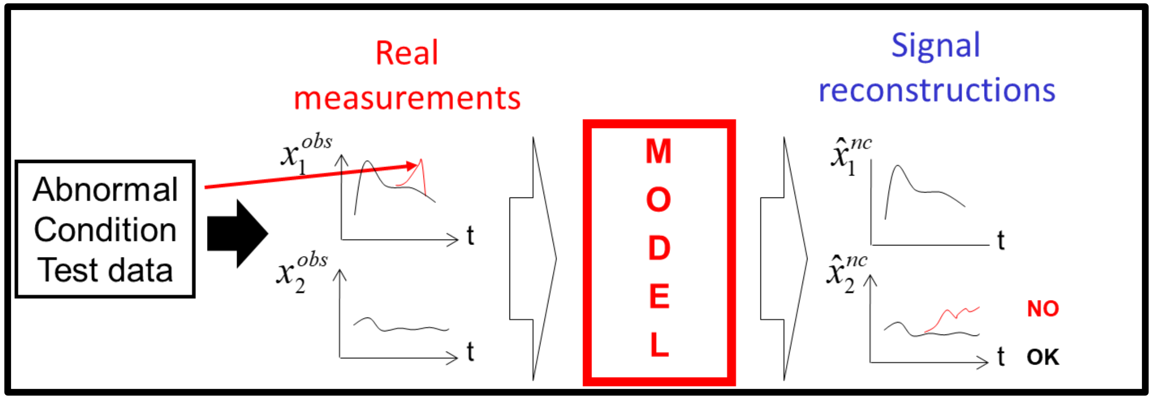


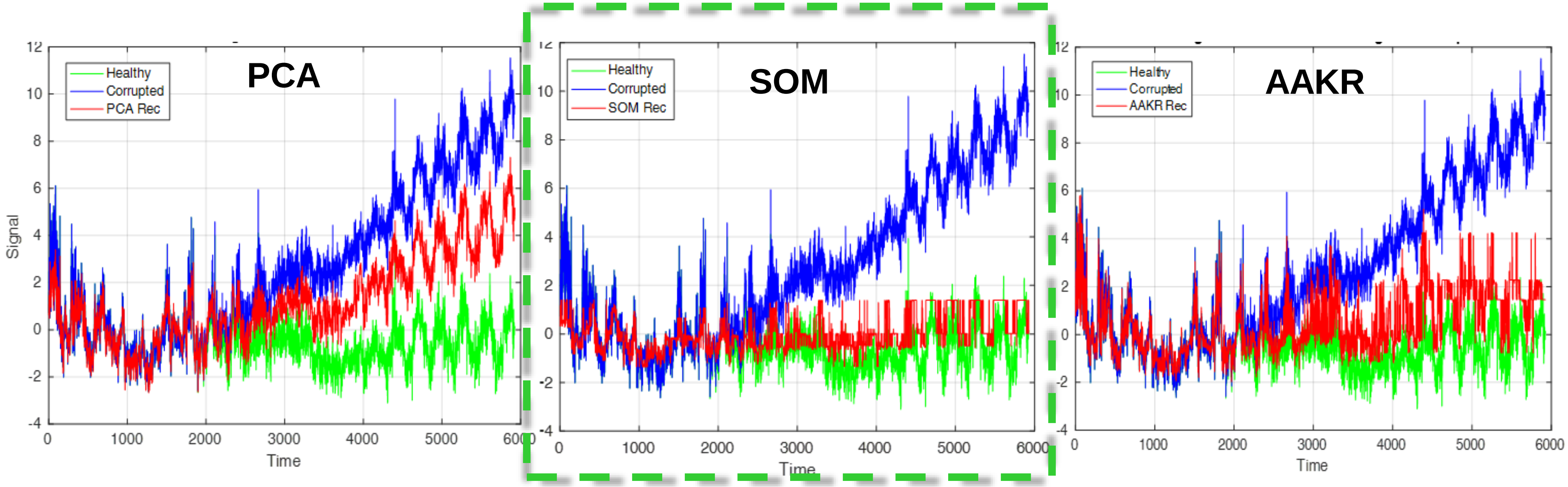


Robustness	Capability of accurately reconstructing the healthy signal in presence of anomalies: the difference between the healthy reconstruction and the corrupted signal allows detecting the anomaly

Best Robustness: (SOM) → **Avoid Missed Alarms**

Signal Reconstruction Spillover





Spillover	Capability of accurately reconstructing a healthy signal in presence of other anomalous signals in the dataset

Best Spillover: (SOM) → **More precise diagnosis of the anomaly**

Statistical Test for Anomaly Detection: Z-Test

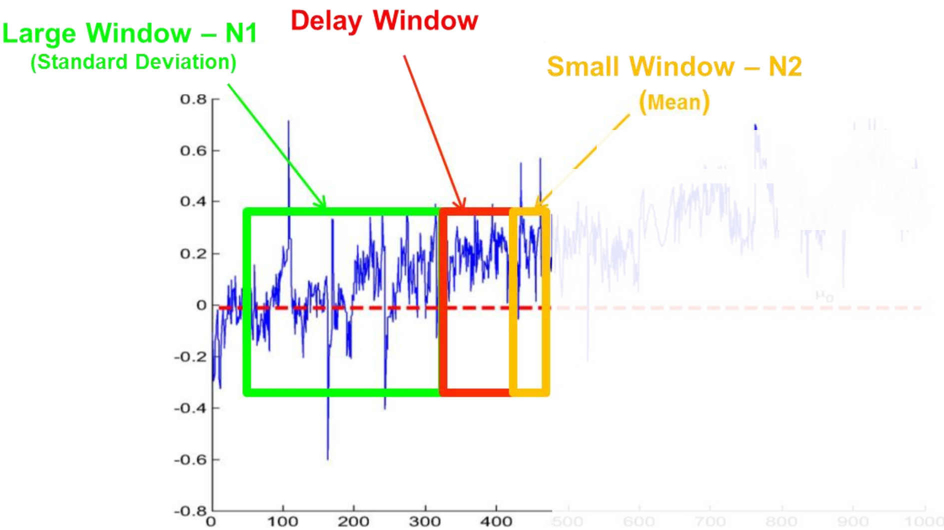
Problem: is the residual distribution changing?

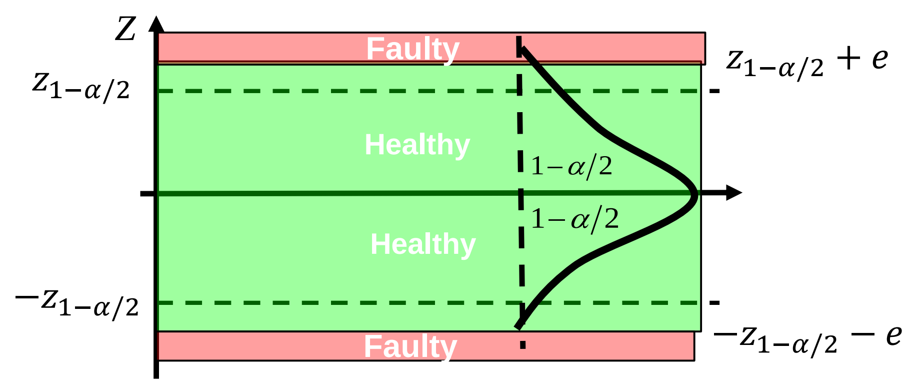
- **Functioning → 2 Hypothesis**

$$\begin{cases} H_0 : \mu_{N_2} = \mu_{N_1} \longrightarrow \text{Healthy} \\ H_1 : \mu_{N_2} \neq \mu_{N_1} \longrightarrow \text{Abnormal} \end{cases}$$

➤ Test Index= $\hat{\mu}_{N_2}(t) = \frac{1}{N_2} \sum_{i=t-N_2+1}^{t} r_i$

$$Z = \frac{\hat{\mu}_{N_2} - \hat{\mu}_{N_1}}{\hat{\sigma}_{N_1} / \sqrt{N_2}} \sim N(0,1)$$

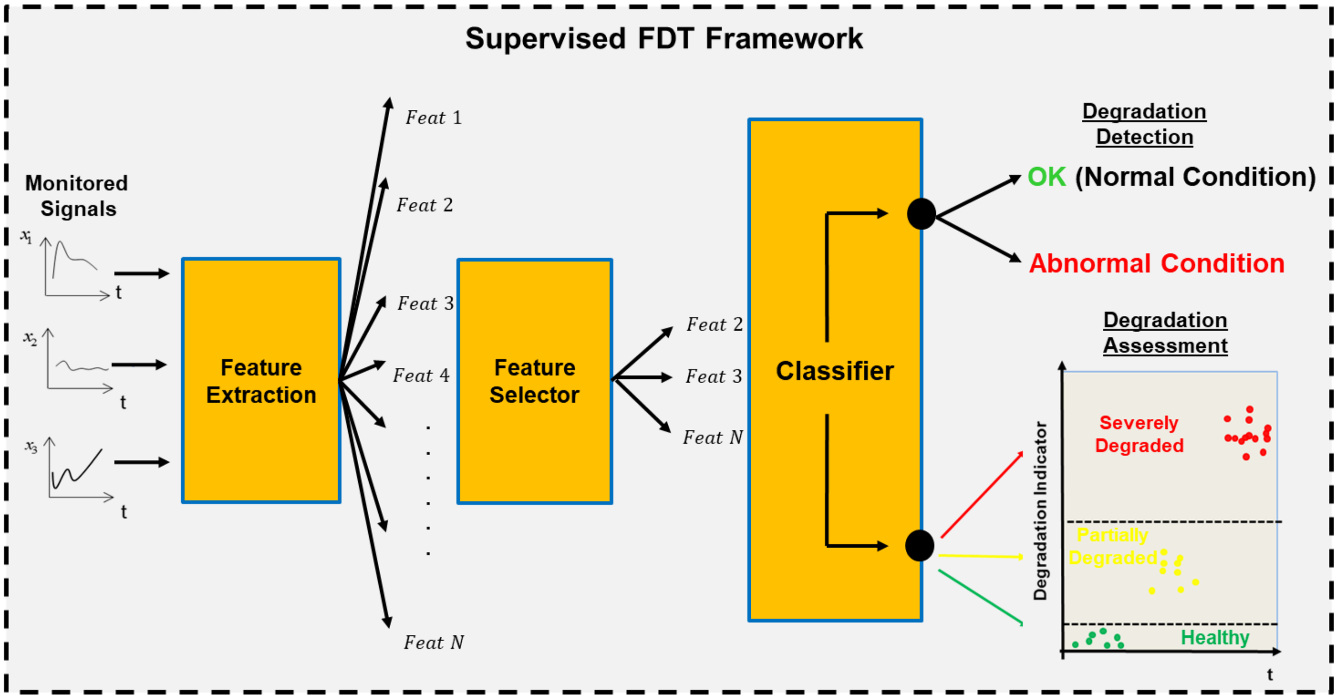




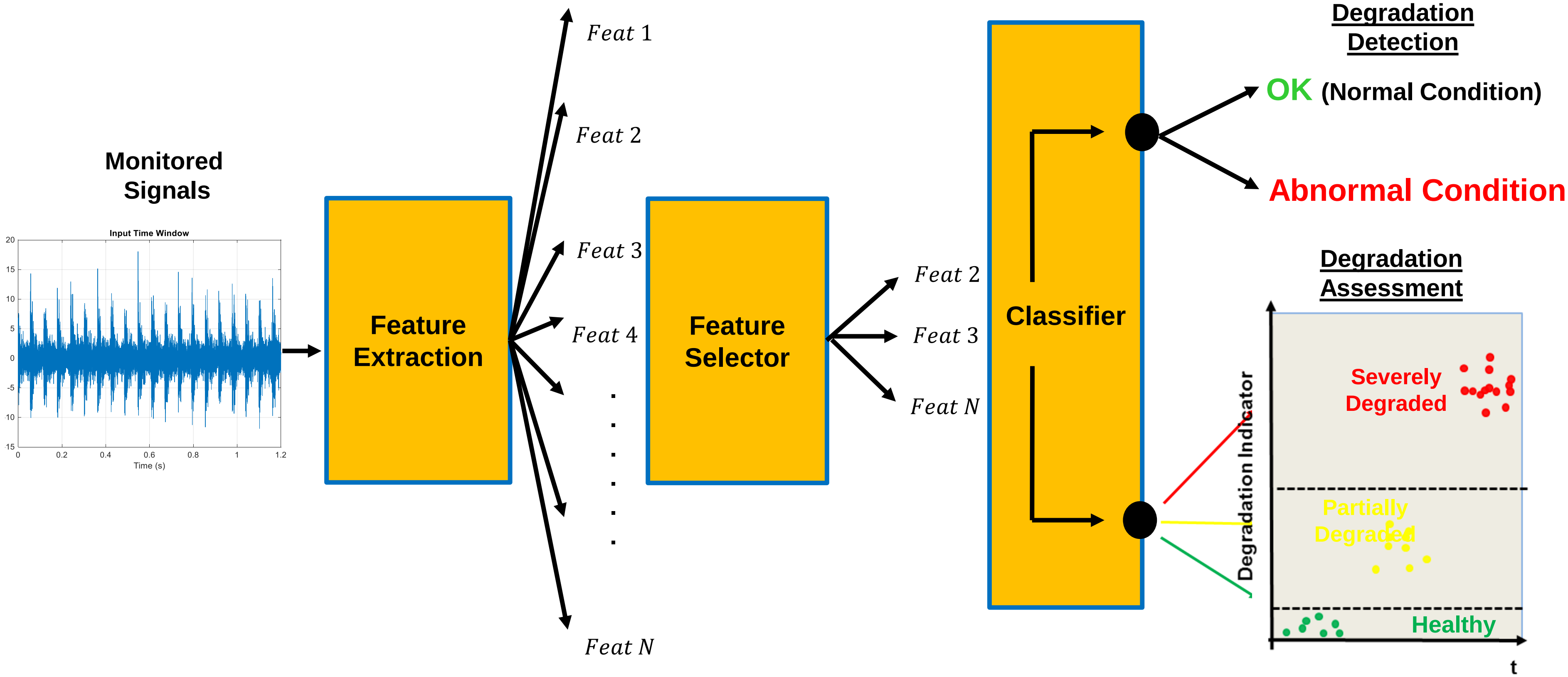
Parameters to optimize

- ➤**N1** → Large Window Width
- ➤**N2** → Small Window Width
- ➤**N_Delay** → Delay Window Width
- ➤**(1–α)** → Coverage
- ➤**e** → Tolerance Factor

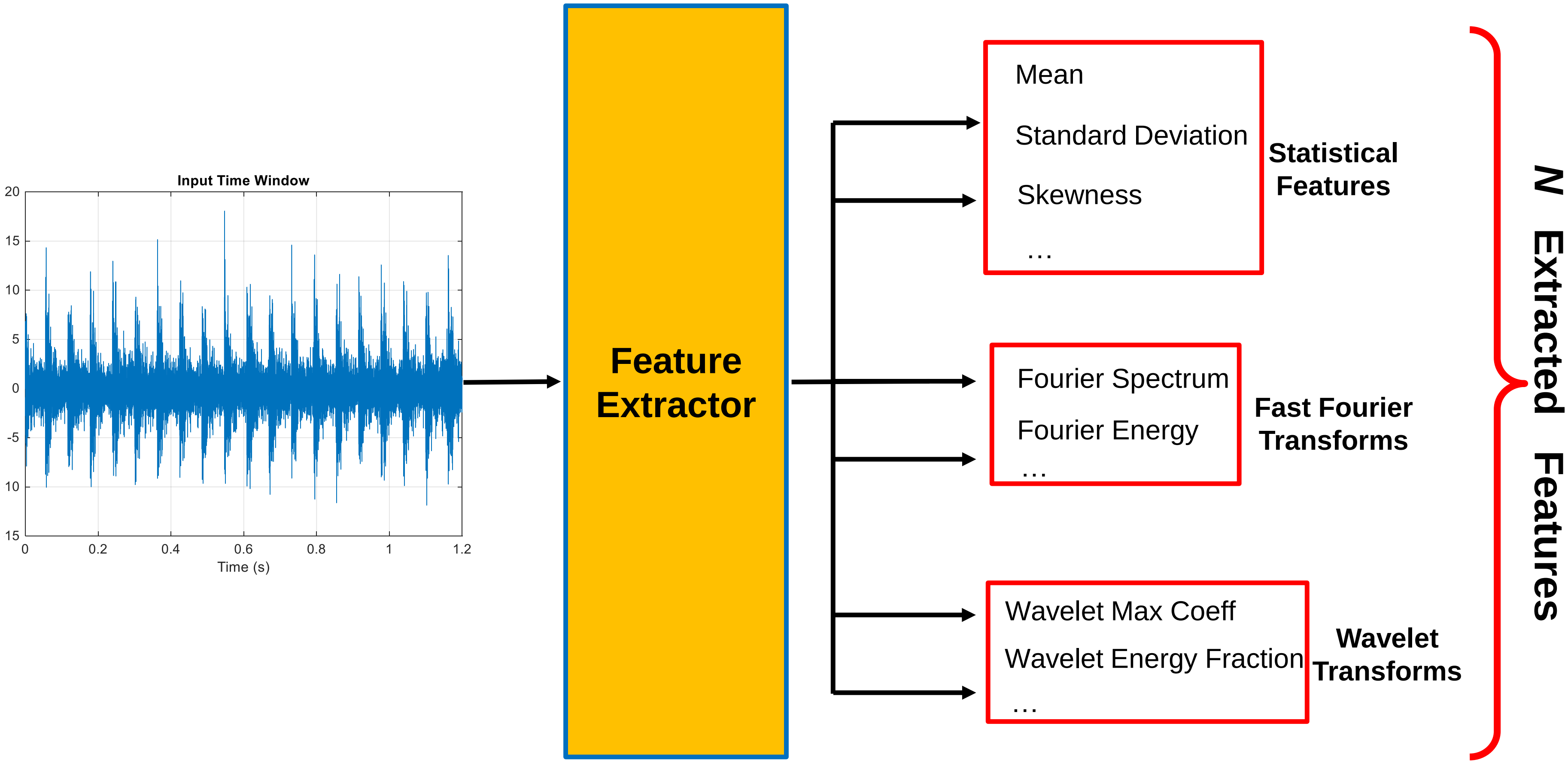
Supervised
Fault Detection Tool



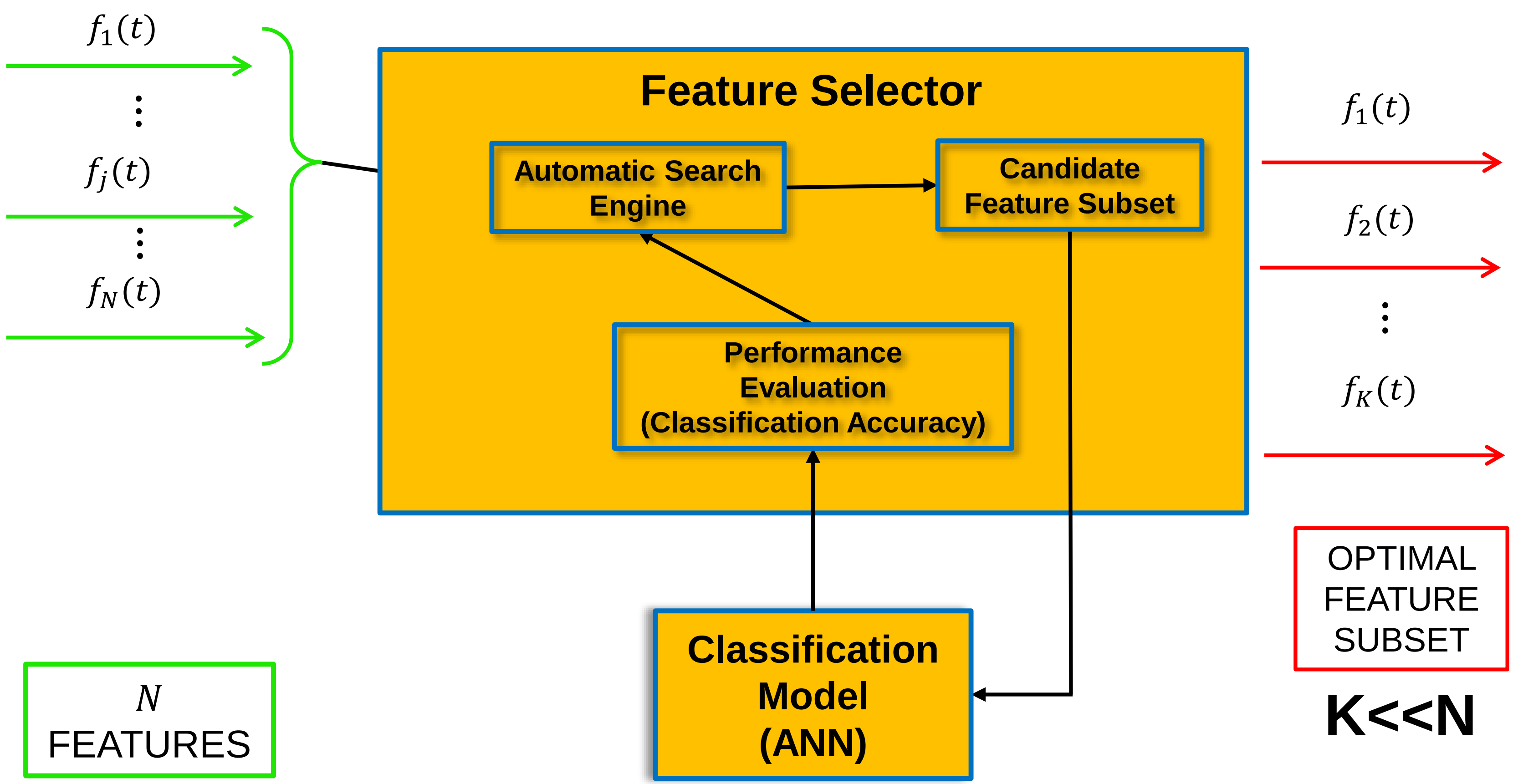
Supervised FDT Framework



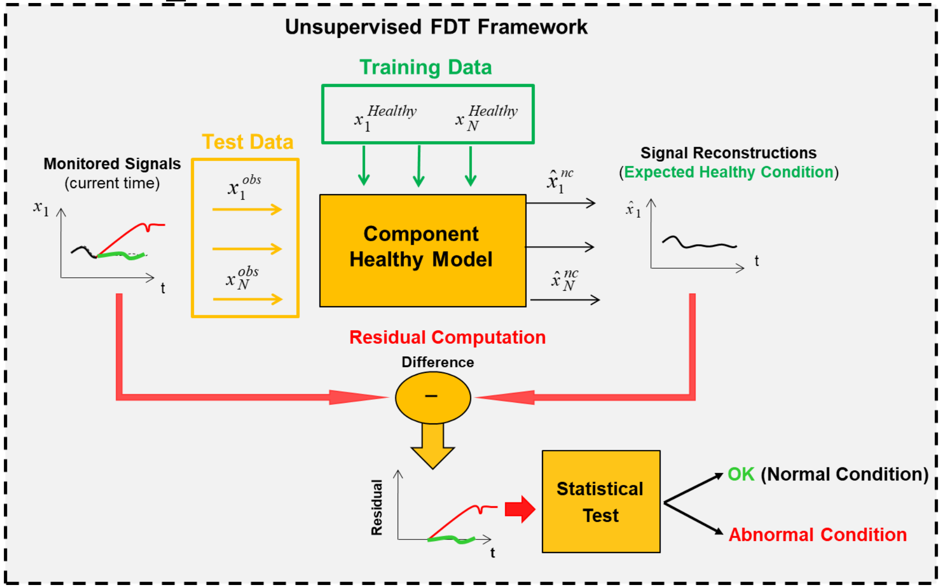
Feature Extraction



Feature Selection: Wrapper Approach



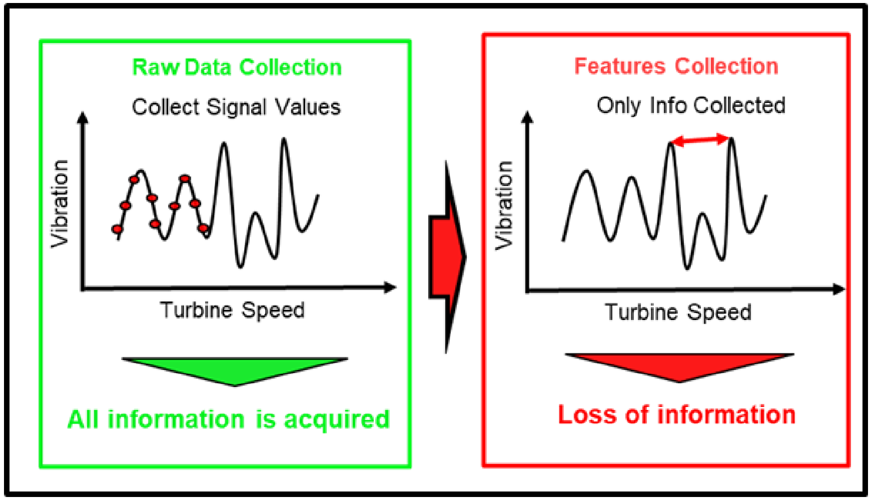
Unsupervised FDT



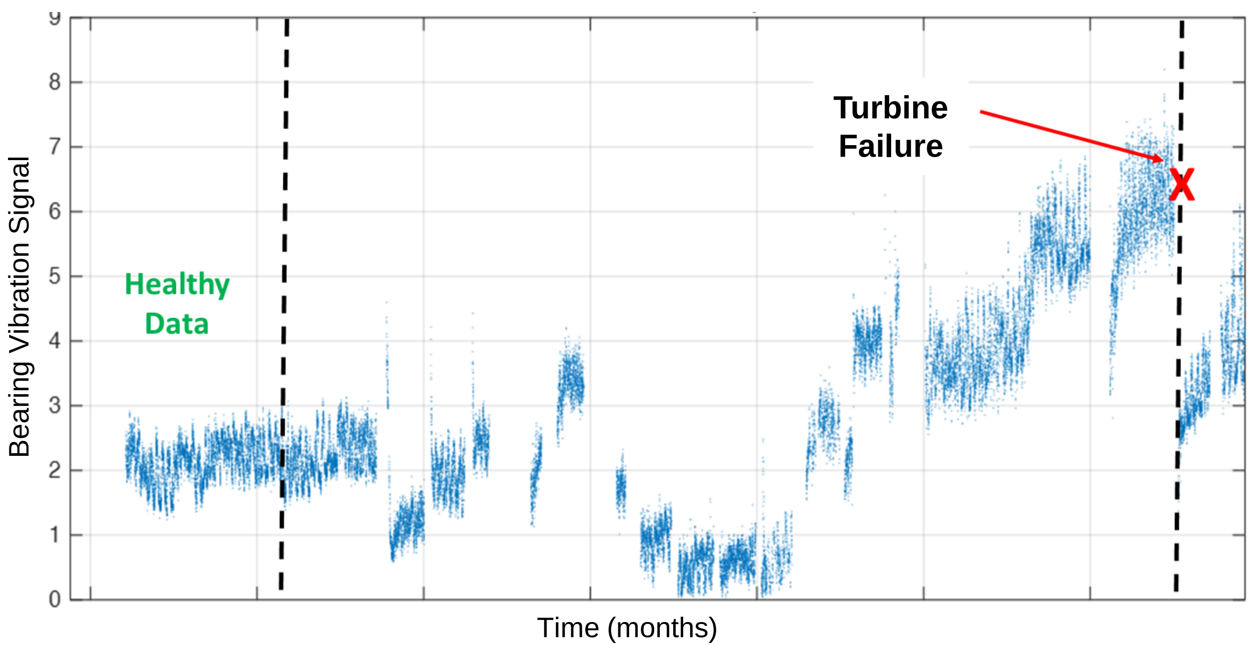
Industrial Application

Gas Turbine Degradation Detection

- **Monitored Period: 8 months**
- **Monitored Signals (155)**
  - 98 Operating Condition
  - 32 Vibrations [Feature extracted from raw data]
  - 25 from Combustion Chamber

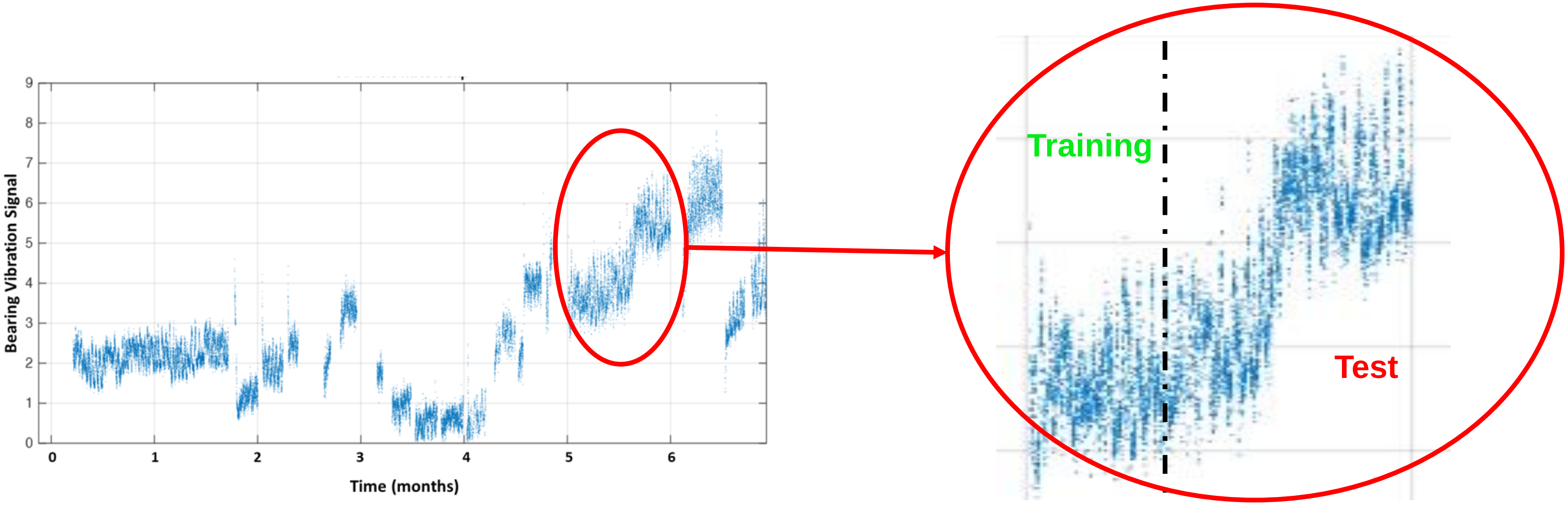


- **Operating Conditions**
  - **Stationary (Regime)**
    - 40101 patterns (1 every 5 minutes)



- **Which data should be used for model training?**

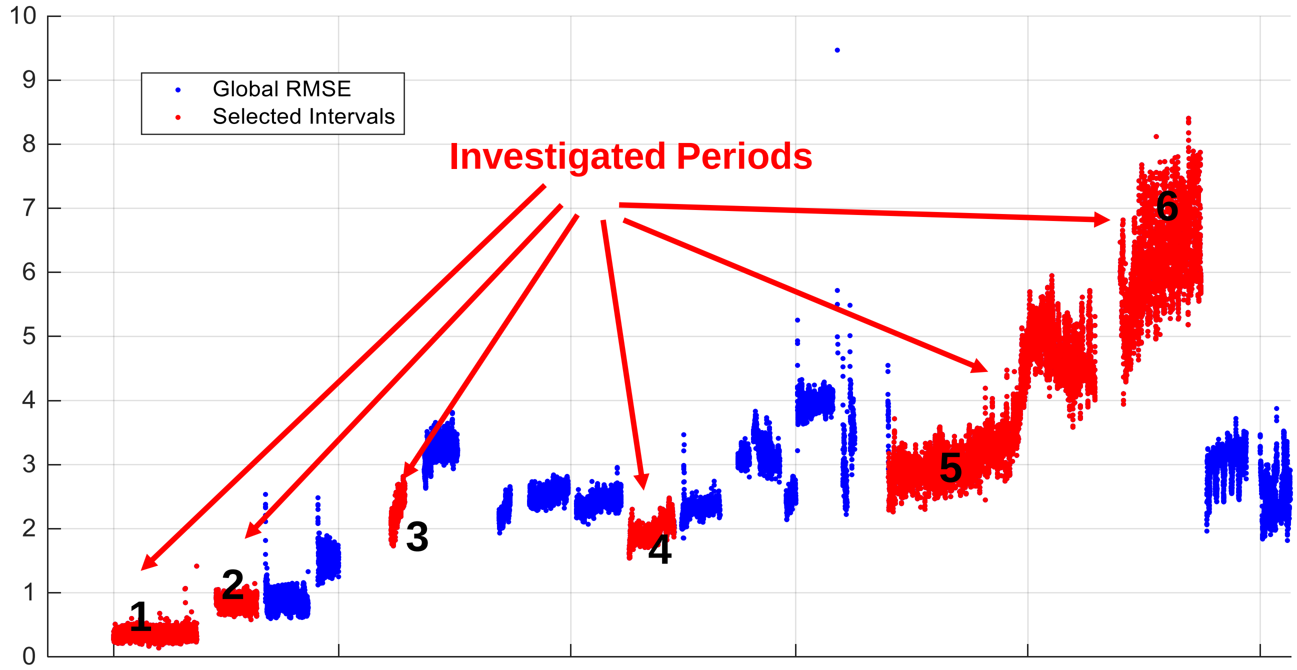
Different signal ranges each time the turbine is turned on



Training Set: data at the beginning of the usage period (just after turbine is turned on)

Training Set dynamically changes

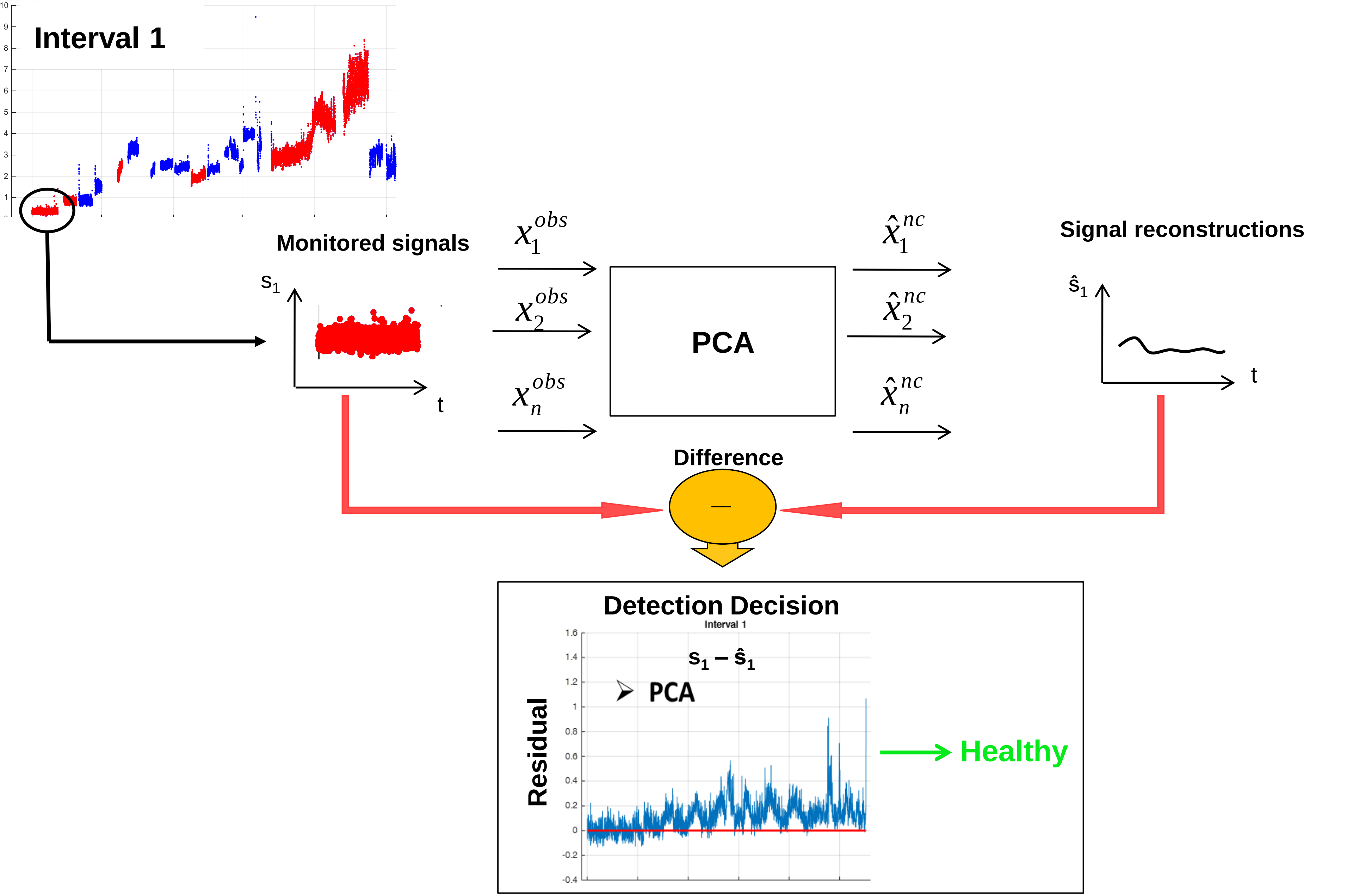
Gas Turbine Degradation Detection: Residual Approach Results



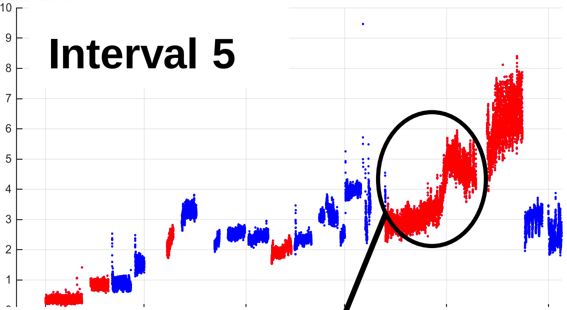
Training Procedure (to be repeated each time turbine is turned on):

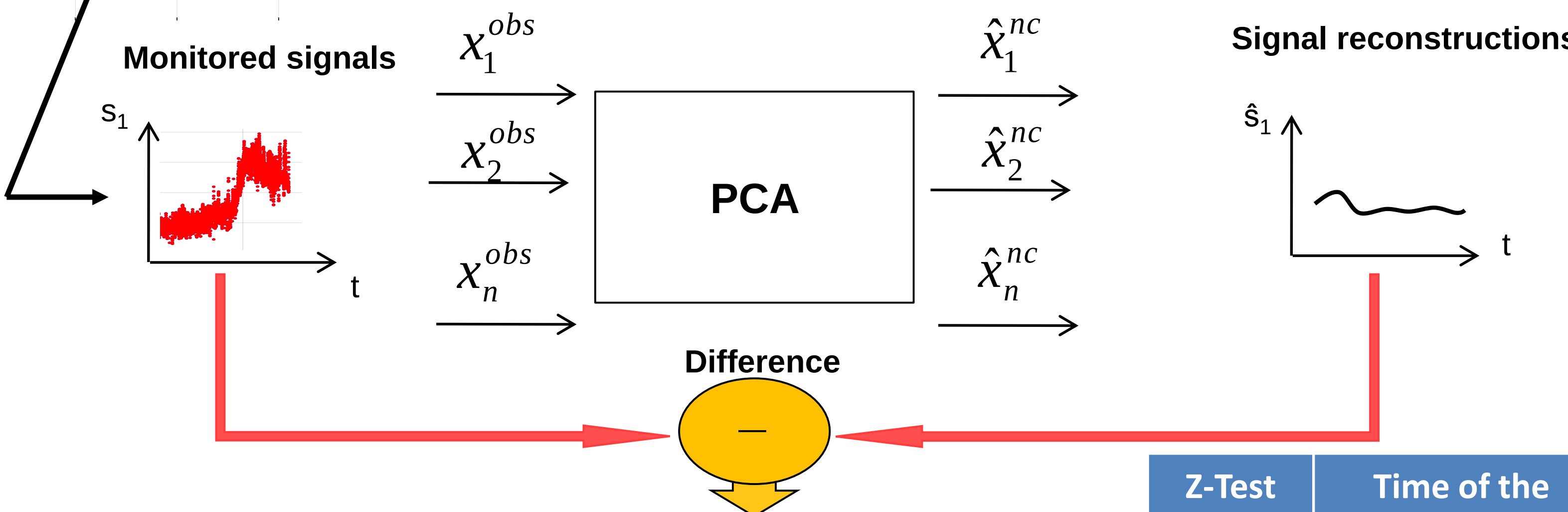
- Collect the data for a short period (e.g. 3 days) → Training Set

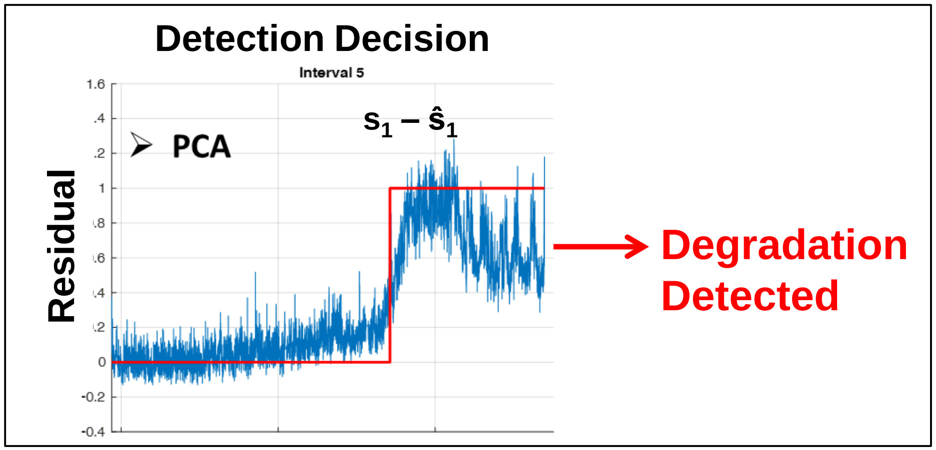
- Develop the PCA model → On-line signal reconstruction


Interval 1
Monitored signals
s1
t
x_1^{obs}
x_2^{obs}
x_n^{obs}
PCA
$\hat{x}_1^{nc}$
$\hat{x}_2^{nc}$
$\hat{x}_n^{nc}$
Signal reconstructions
ŝ1
t
Difference
–
Detection Decision
Interval 1
s1 – ŝ1
PCA
Residual
Healthy

Gas Turbine Degradation Detection: Residual Approach Results (III)



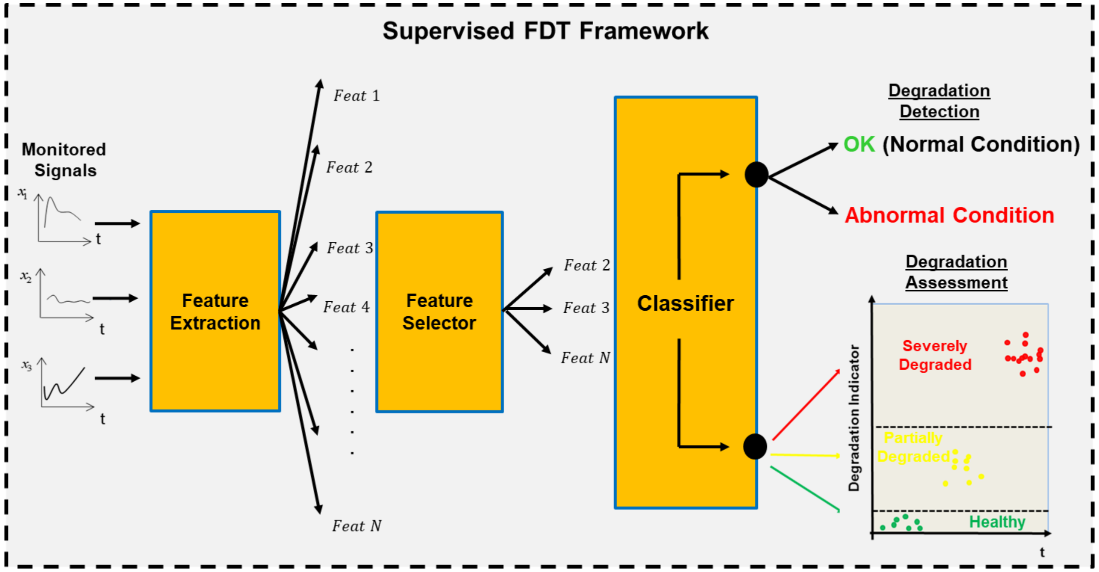




Z-Test	Time of the Alarm
PCA	21/4/2015

Detection of the degradation onset one month and a half in advance with respect to the turbine failure

Supervised FDT



Industrial Application

Gas Turbine Degradation Assessment

Supervised FDT: Gas Turbine Degradation Assessment

❑ Monitored Period: 8 months

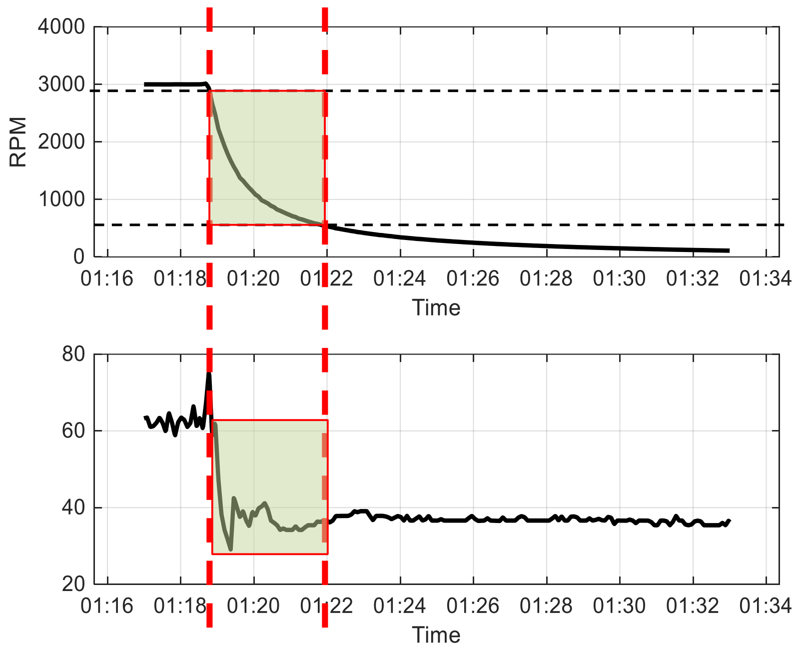
❑ Monitored Signals (155)

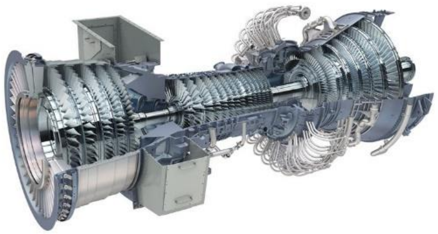
- 98 Operating Conditions
- 32 Vibrations
- 25 from Combustion Chamber

❑ Operating Conditions

➢ Transient

- 61 transients
  - ➢ 31 Shutdown
  - ➢ 21 Cold Start-up
  - ➢ 9 Hot Start-up
- 54793 patterns (1 every second)
  [Feature Values (No raw data)]

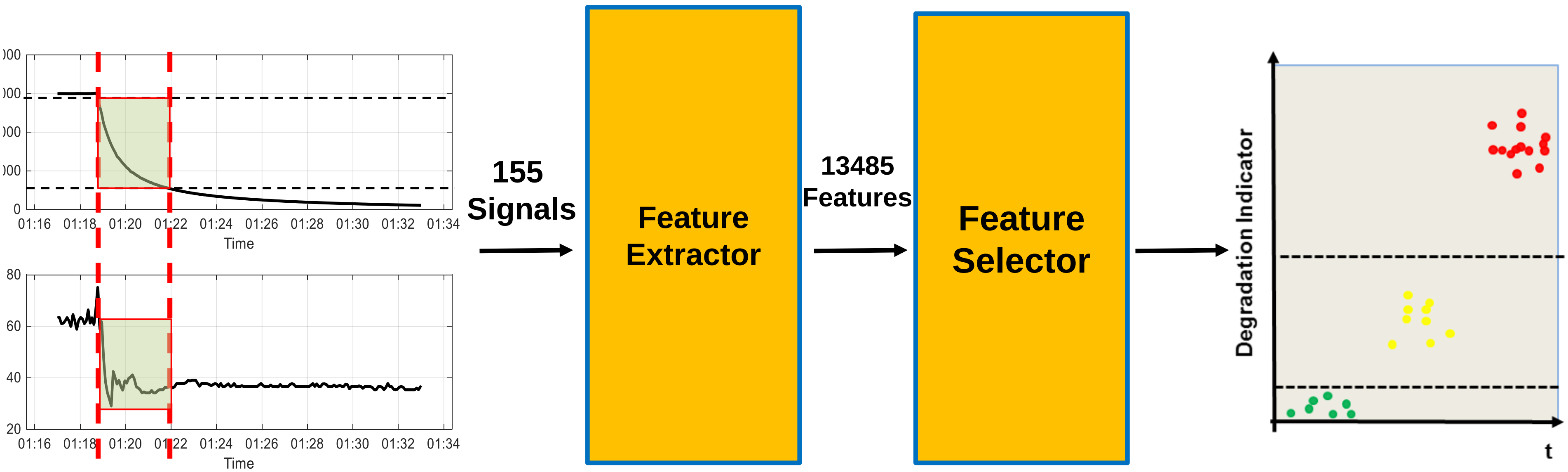




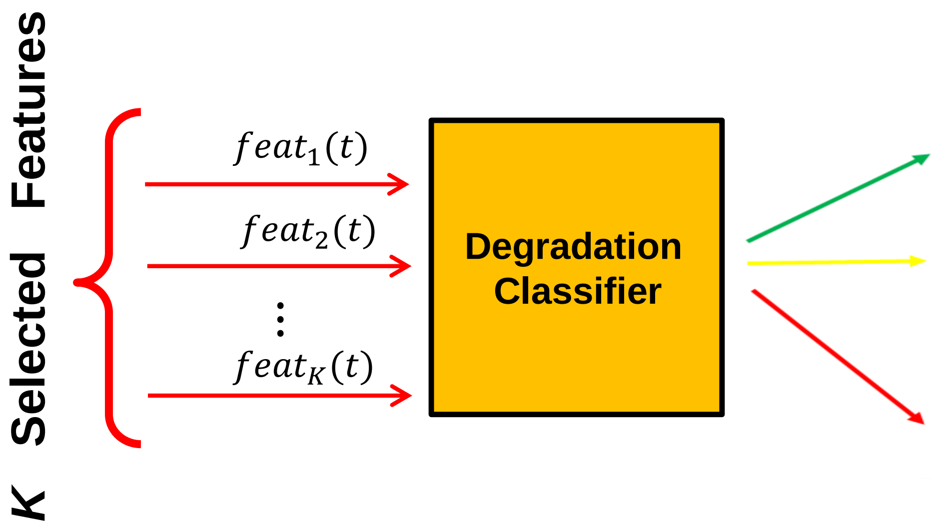
Gas Turbine Degradation Assessment: Feature Extraction and Selection

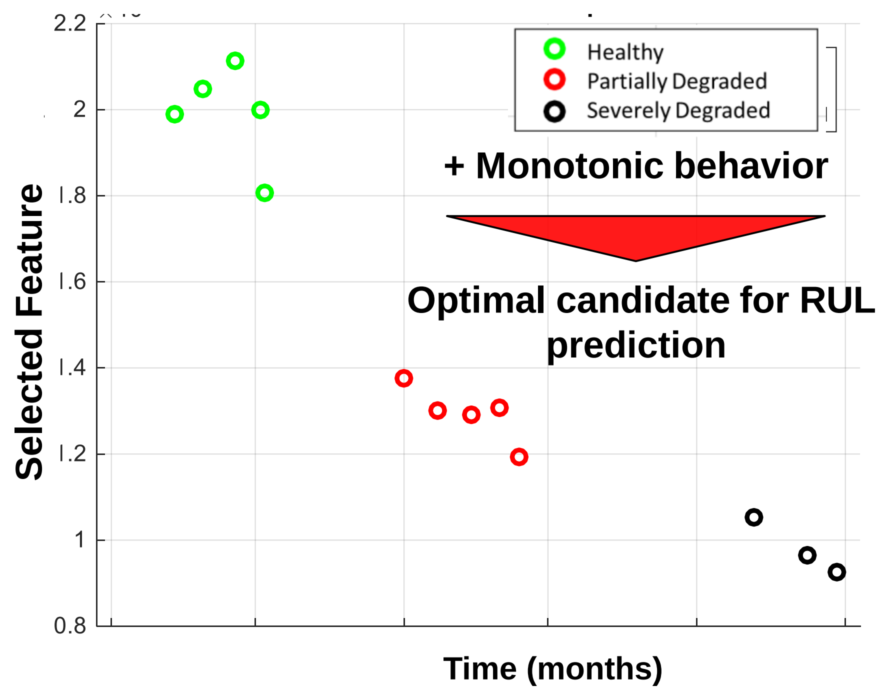
1 Transient = 155 Signals

1 Transient = 155 signals x 87 Features = 13485 Features



- Shutdown transients
- 3 KNOWN classes (in accordance to previous analysis):
  - **Healthy**
  - **Partially Degraded**
  - **Severely Degraded**





Fault Detection Tool (FDT) for Predictive Maintenance

Unsupervised FDT (Only healthy data)

- **Modules:** Signal Reconstruction + Residual Statistical test
- **Application**: Turbine degradation onset detection
- **Results**: Degradation onset detection one month and a half in advance with respect to the turbine failure

Supervised FDT (Both healthy and degraded data)

- **Modules:** Feature Extraction + Feature Selection + Classification
- **Application**: Turbine degradation assessment
- **Results**: Accurate degradation classification. Identification of a monotonic degradation indicator to be used for failure prediction.

Questions & Answers

Thank You!

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Predictive Maintenance Ultimate Goal: Integration into the Business Model