POLITECNICO DI MILANO

ARAMIS
reliable innovation

Modern Reliability and Maintenance Engineering for Modern Industry

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Politecnico di Milano, Department of Energy, Italy
ARAMIS Srl, Italy

ARAMIS & LASAR : the identity card

Advanced Reliability Availability & Maintenance for Industries and Services

History

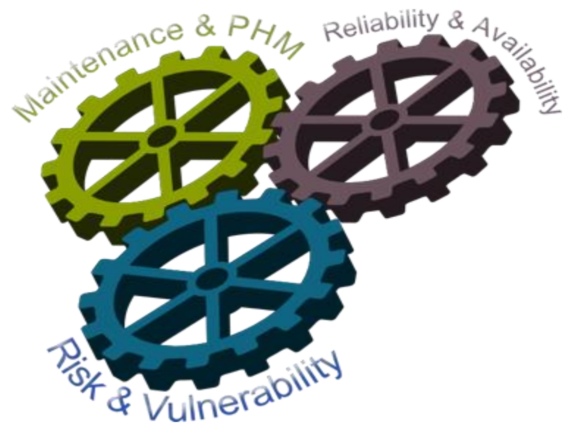
laboratory of signal and risk analysis

POLITECNICO MILANO

Research & Innovation consulting approach

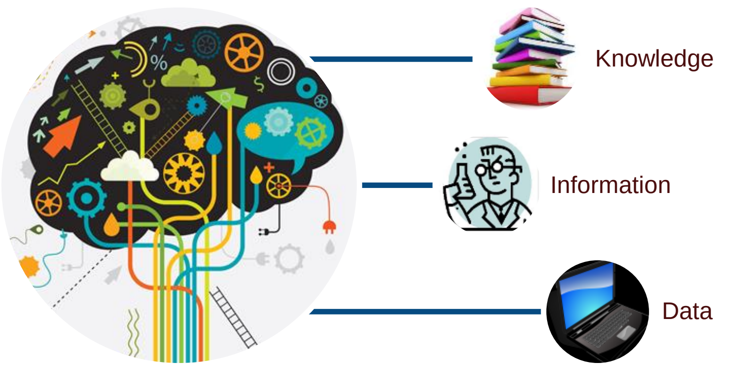
Large amount of deployed algorithms
(more than 20yrs R&D)

Main Intervention Areas



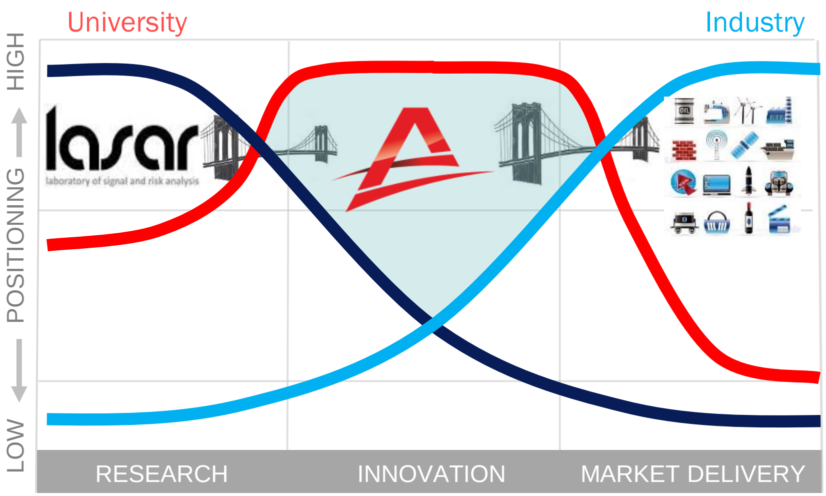
Approach

SMART KID



Simulation, **M**odeling, **A**nalysis, **R**esearch
for **T**reasuring **K**nowledge, **I**nformation and **D**ata

Mission



The Team

LASAR Members (3):

- Piero Baraldi (Associate Professor, PhD)
- Francesco Di Maio (Assistant Professor, PhD)
- Enrico Zio (Full Professor, PhD)

LASAR Post-Docs (3):

- Michele Compare (PhD)
- Rodrigo Mena (PhD)
- Sameer Al Dahidi (PhD)

LASAR PhD students (7):

- Marco Rigamonti
- Francesco Cannarile
- Wei Wang
- Zhe Yang
- Shiyu Chen
- Alessandro Mancuso
- Edoardo Tosoni

+ MSc students (10-12/y)
+ Visiting (4-6/y)

ARAMIS Members (7):

- Enrico Zio (President)

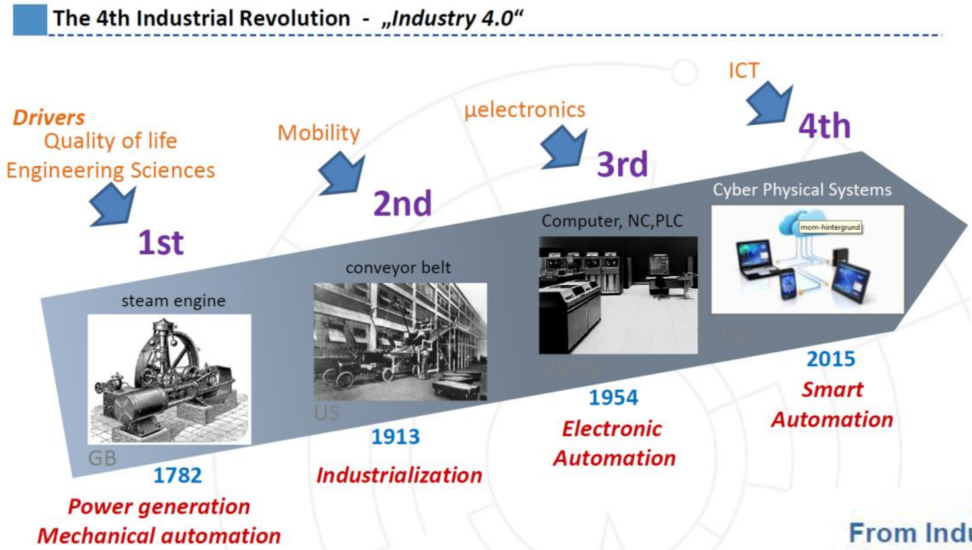
- Michele Compare (Partner, CEO)

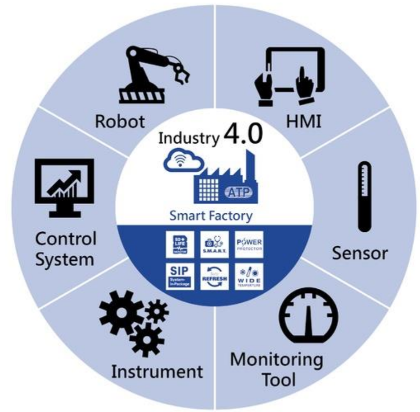
- Piero Baraldi (Partner)
- Francesco Di Maio (Partner)
- Giovanni Sansavini (Partner)

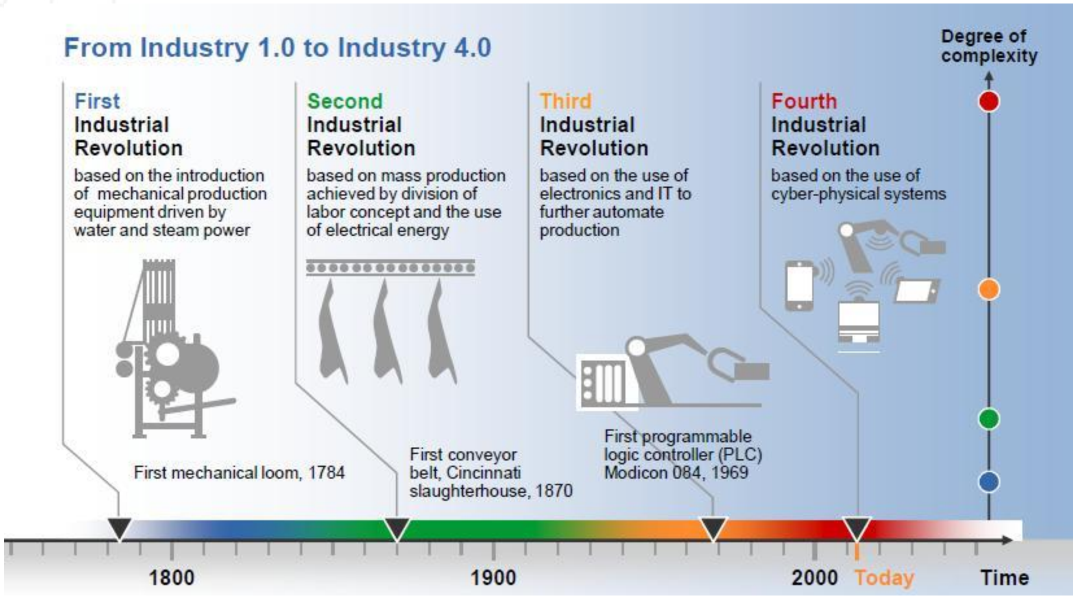
- Francesco Cannarile (Research consultant)
- Rodrigo Mena (Research consultant)

+ Network of senior experts on specific technical areas

Industry 1-2-3-4





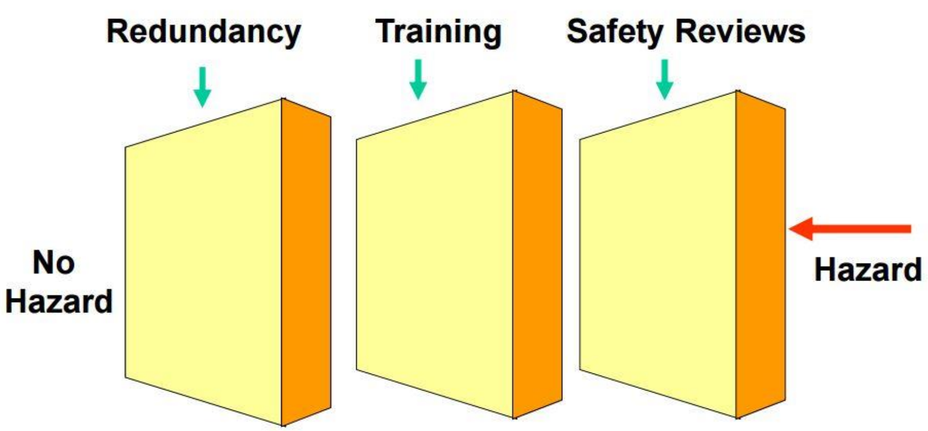


Problem statement

Failures

Prevented by

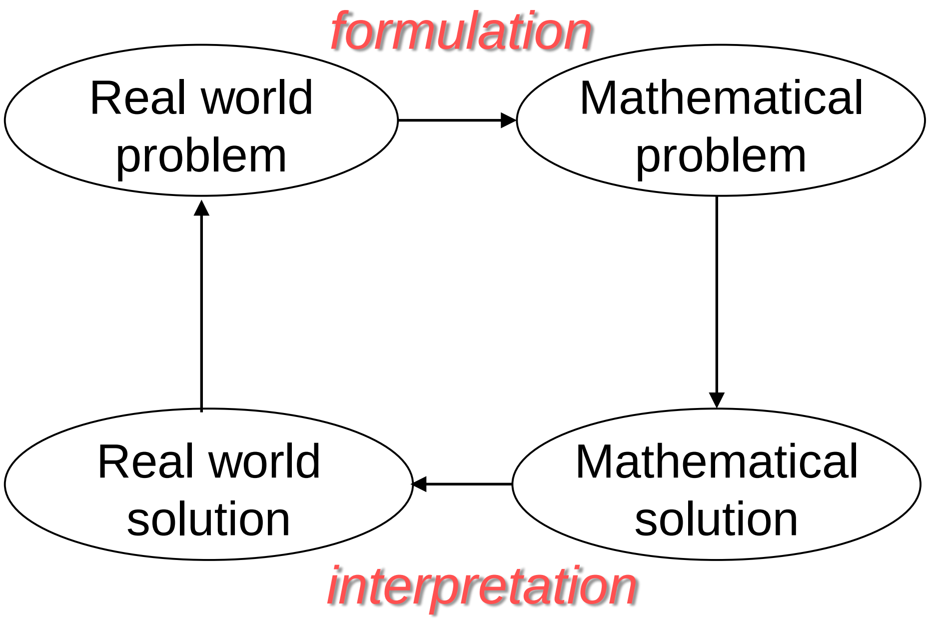
Design for Reliability | **Maintenance**



(SMART) Reliability Engineering

The Big KID

Big Knowledge(ID)



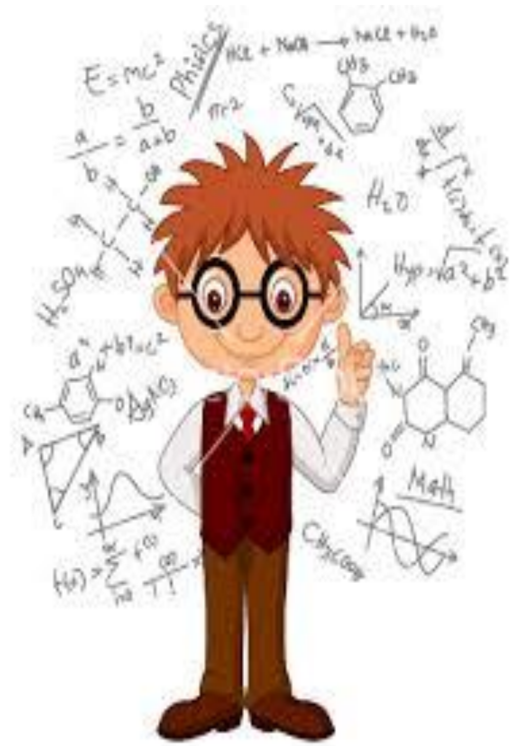
$$
\begin{aligned}
v_q &= -r_s i_q + \frac{\omega_r}{\omega_b}\Psi_d + \frac{p}{\omega_b}\Psi_q, \\
v_d &= -r_s i_d - \frac{\omega_r}{\omega_b}\Psi_q + \frac{p}{\omega_b}\Psi_d, \\
v_o &= -r_s i_o + \frac{p}{\omega_b}\Psi_o, & p\theta_r &= \omega_r, \\
0 &= r_{aq} i_{aq} + \frac{p}{\omega_b}\Psi_{aq}, & p\theta_e &= \omega_e, \\
v_f &= r_f i_f + \frac{p}{\omega_b}\Psi_f, & \delta &= \theta_r - \theta_e, \\
0 &= r_{ad} i_{ad} + \frac{p}{\omega_b}\Psi_{ad}, & \omega_m &= \frac{2}{p}\,\omega_r, \\
T_e &= \frac{3}{2}\,\frac{P}{2}\,\frac{1}{\omega_b}(\Psi_d i_q - \Psi_q i_d), \\
p\omega_r &= \frac{P}{2J}\,(T_a - T_e),
\end{aligned}
\qquad (1)
$$

Big (K)Information(D)

Big (KI)Data

1110101001010001011100100101011000010101001
1101110111011101010010100010111001001010110
0001010100111011101111011101010010100101110
0100101011000010101001110111011101110101001
0100010111001001010110000101110101001010001
0111001001010110000101010011101110111011101
0100101000101110010010101100001010100111011
1011101110101001010001011100100101011000010

Can the Big KID become SMART for Reliability Engineering ?



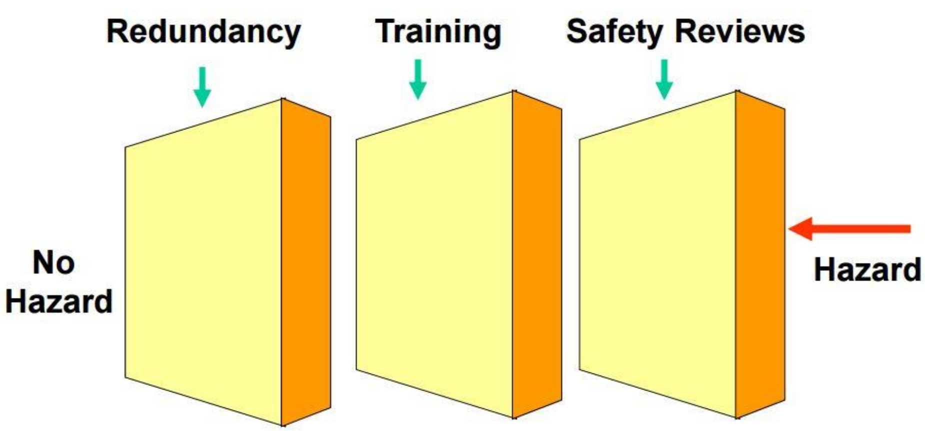
Problem statement

Failures

Prevented by

Design for Reliability

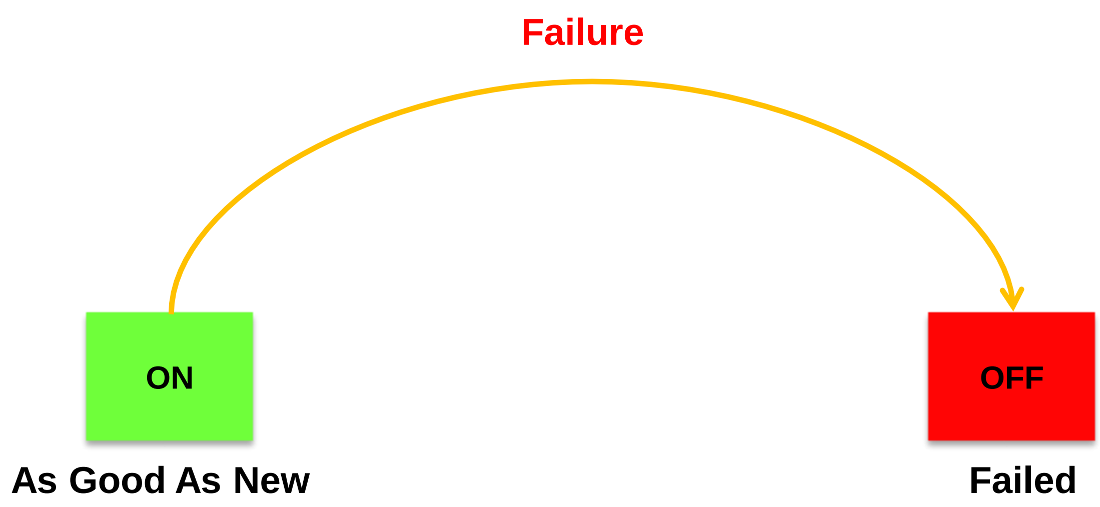
Maintenance

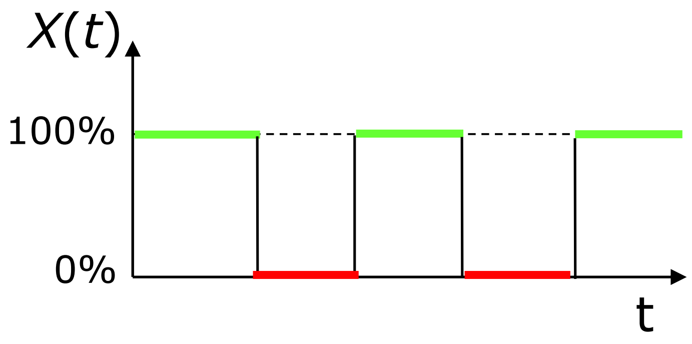


Reliability analysis for Design for Reliability:

From (binary) failure modeling to degradation-to-failure modeling

Failure modelling (binary)

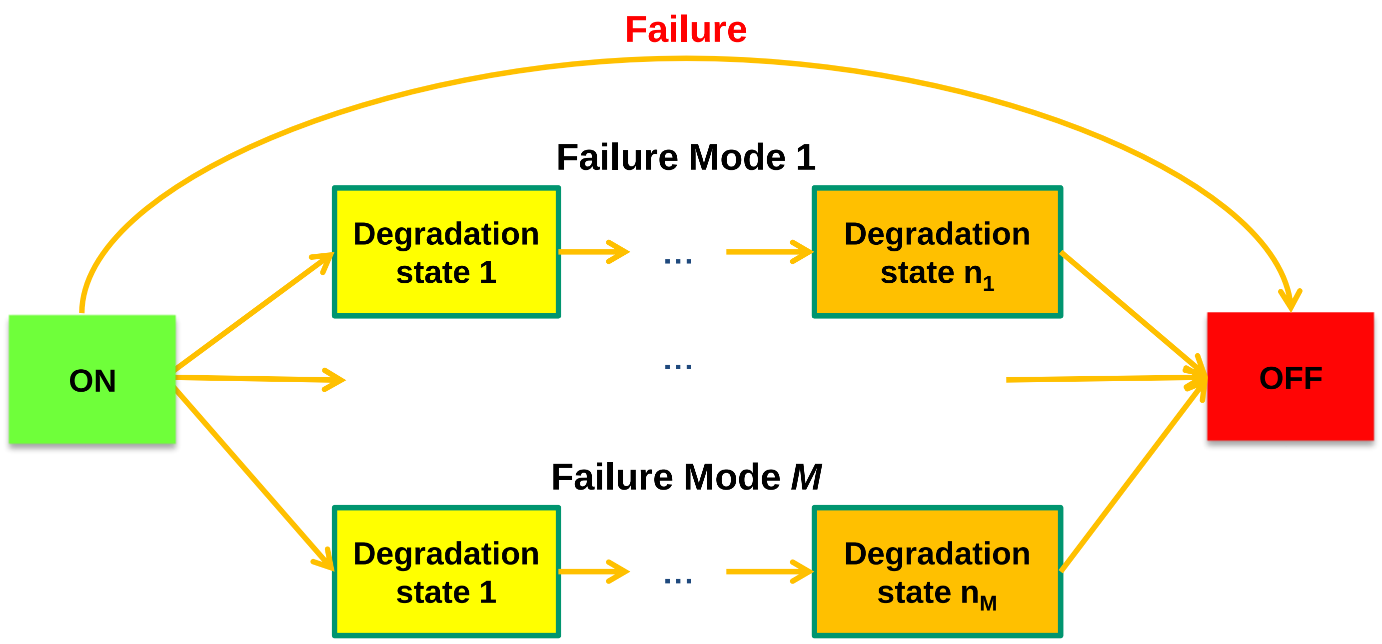


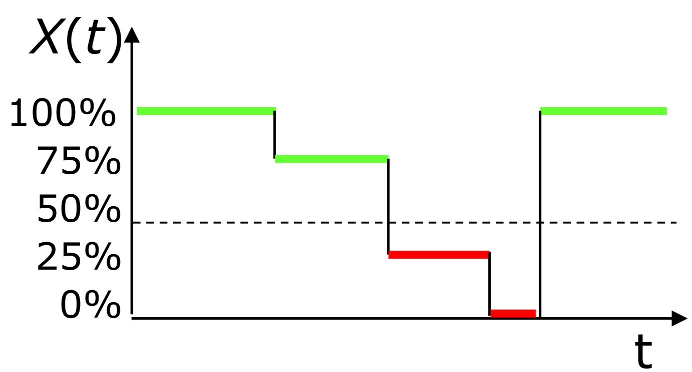


System unavailability $U(t) = \Pr[X\ (t) < 100\%]$

$U(t) = \Pr[X\ (t) = 0\%]$

Multi-state:



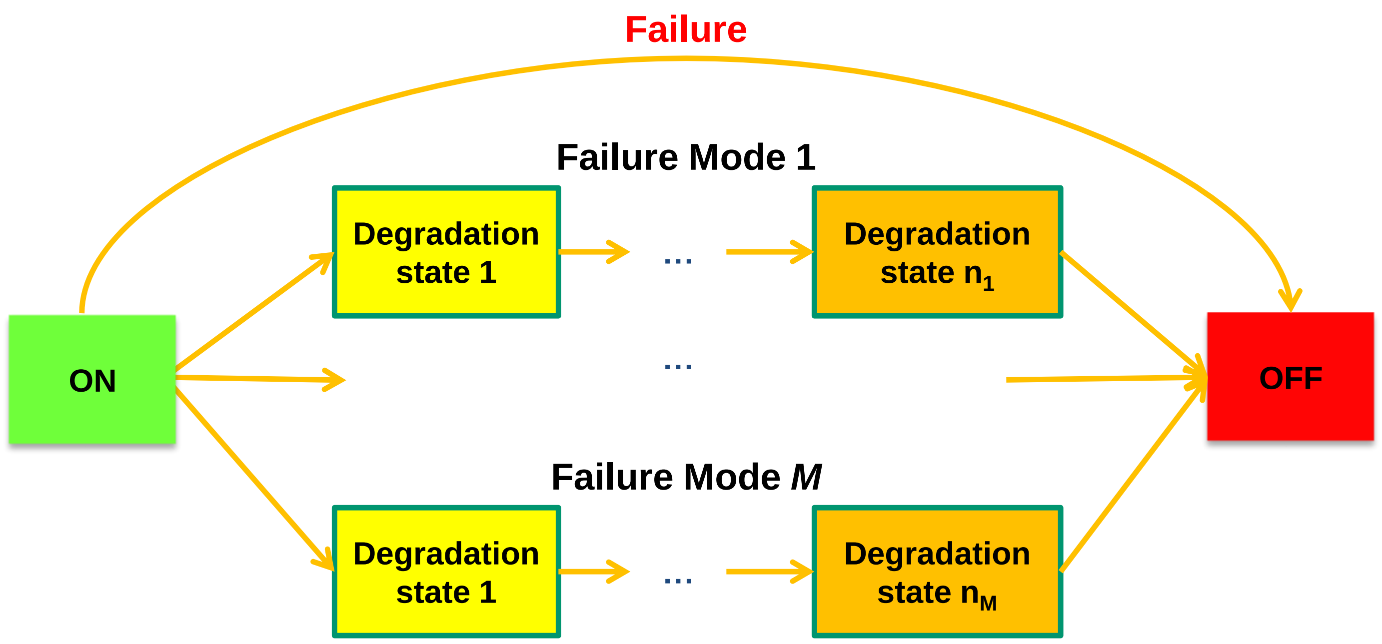


Demand of system performance $D(t)$

System unavailability $U(D,t) = \Pr[X(t) < D(t)]$

Degradation-to-failure modeling

Multi-state:



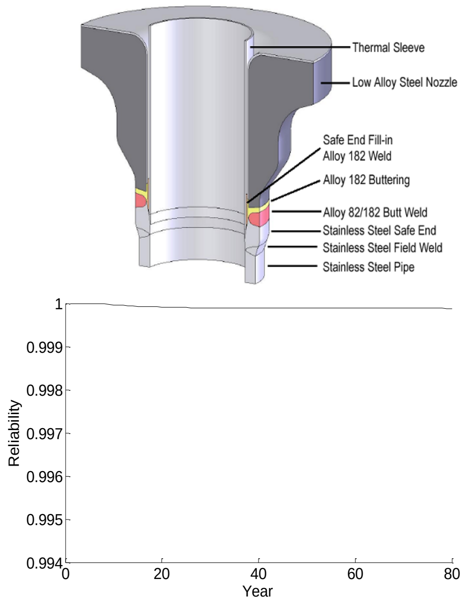
How to represent and model the item behavior?

Integrating physics-of-failure knowledge in reliability models

Multi-State Physic-Based Models

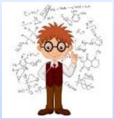
Alloy 82/182 dissimilar metal weld of piping in a PWR primary coolant system

Reliability ?



Highly reliable

KID



(Knowledge, Information, Data)

Model

Sufficient failure data

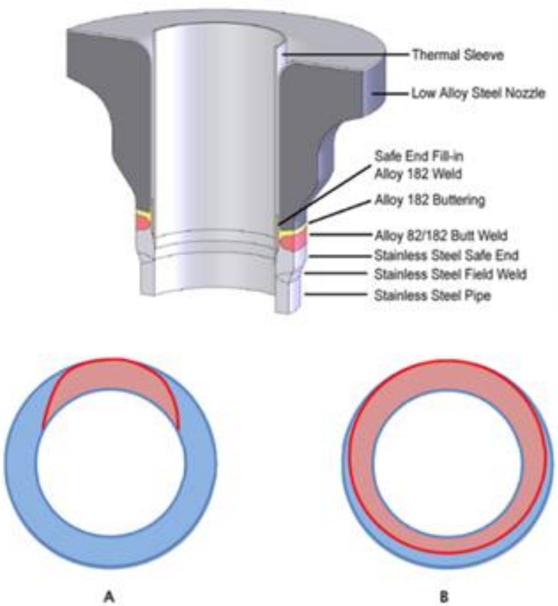
- Statistical models of time to failure
- Stochastic process models

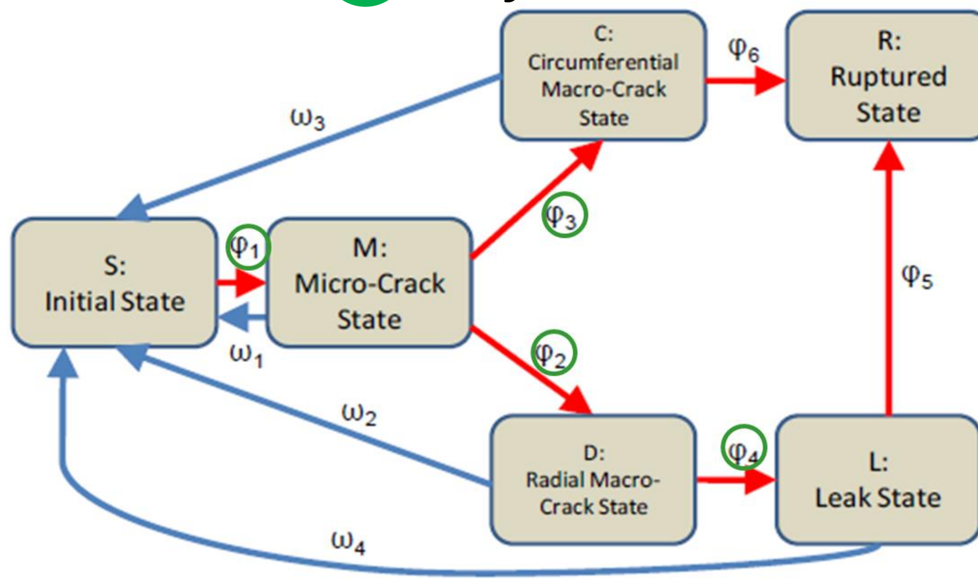
Physics knowledge
Expert judgment
Field data

- Physics-based models
- Multi-state models

Alloy 82/182 dissimilar metal weld of piping in a PWR primary coolant system

Physical laws





Multi-state physics model of crack development in Alloy 82/182 dissimilar metal weld

$$\varphi_1 = \int \left(\frac{b}{\tau}\right) \cdot \left(\frac{t}{\tau}\right)^{b-1} \cdot f_{PDF}(\tau, b)\, d\tau db$$

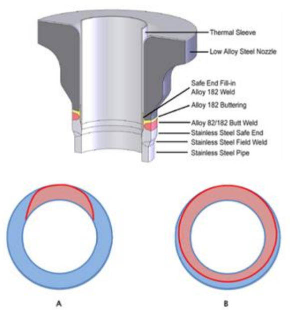
$$\varphi_2 = \begin{cases} \frac{a_D P_D}{\dot{a}_M u^2 (1 - P_D (1 - a_D/(u \dot{a}_M)))}, & if\ u > a_D/\dot{a}_M \\ 0, & else \end{cases}$$

$$\varphi_3 = \begin{cases} \frac{a_C P_C}{\dot{a}_M u^2 (1 - P_C (1 - a_C/(u \dot{a}_M)))}, & if\ u > a_C/\dot{a}_M \\ 0, & else \end{cases}$$

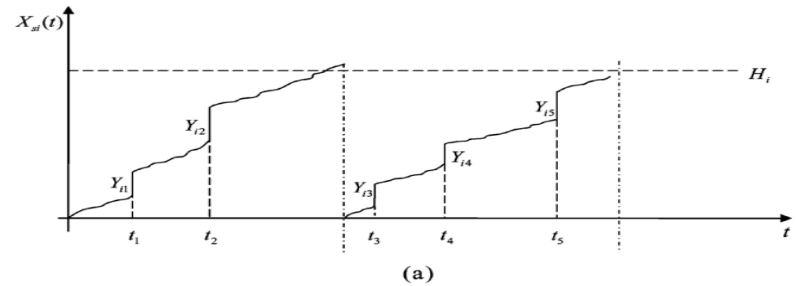
$$\varphi_4 = \begin{cases} \frac{1}{w}, & if\ w > (a_L - a_D)/\dot{a}_M \\ 0, & else \end{cases}$$

SMART Reliability Engineering Opportunities

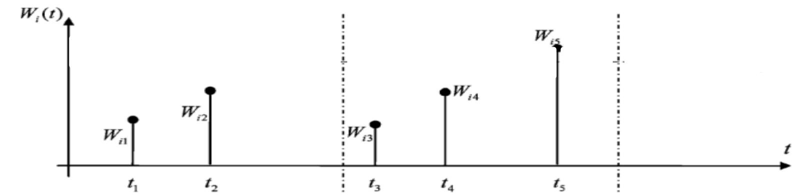
1) Random shocks



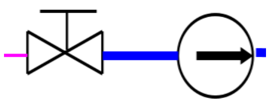
Degradation process



Random shock process



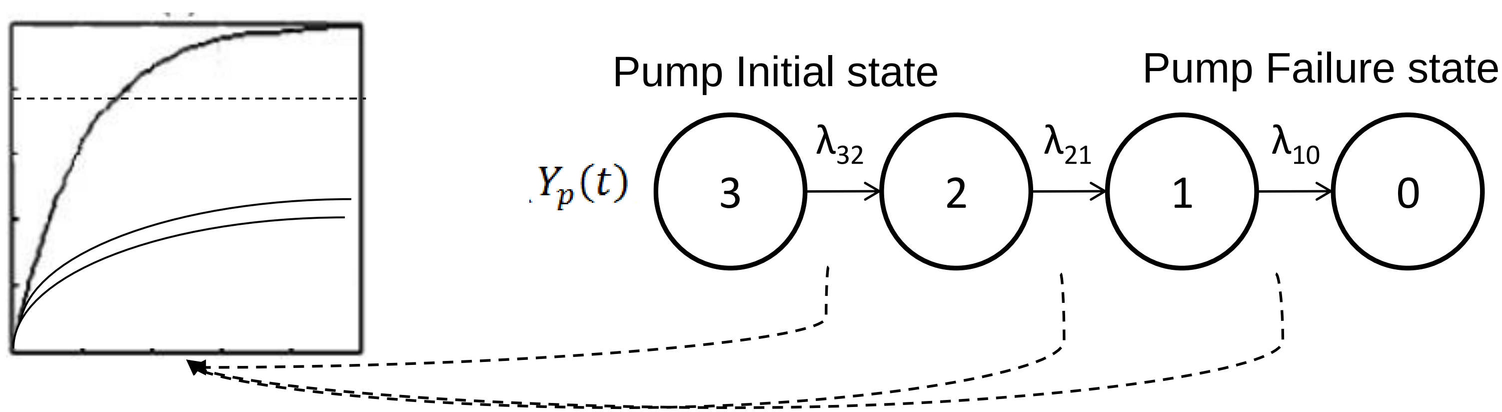
2) Dependences in degradation processes



Valve Internal leak

$D_b(t)$

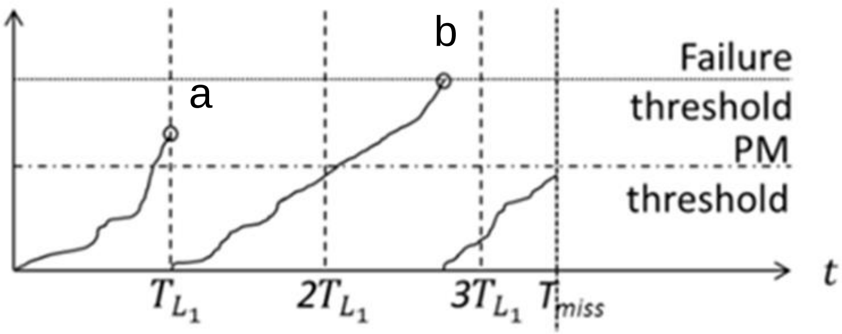
$$\dot{D}_b(t) = \omega_b(1 + \beta_{Y_p(t)})$$



SMART Reliability Engineering Opportunities

3) Maintenance

Degradation process

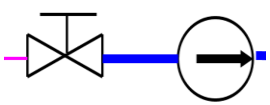


Preventive maintenance (a)

Corrective maintenance (b)

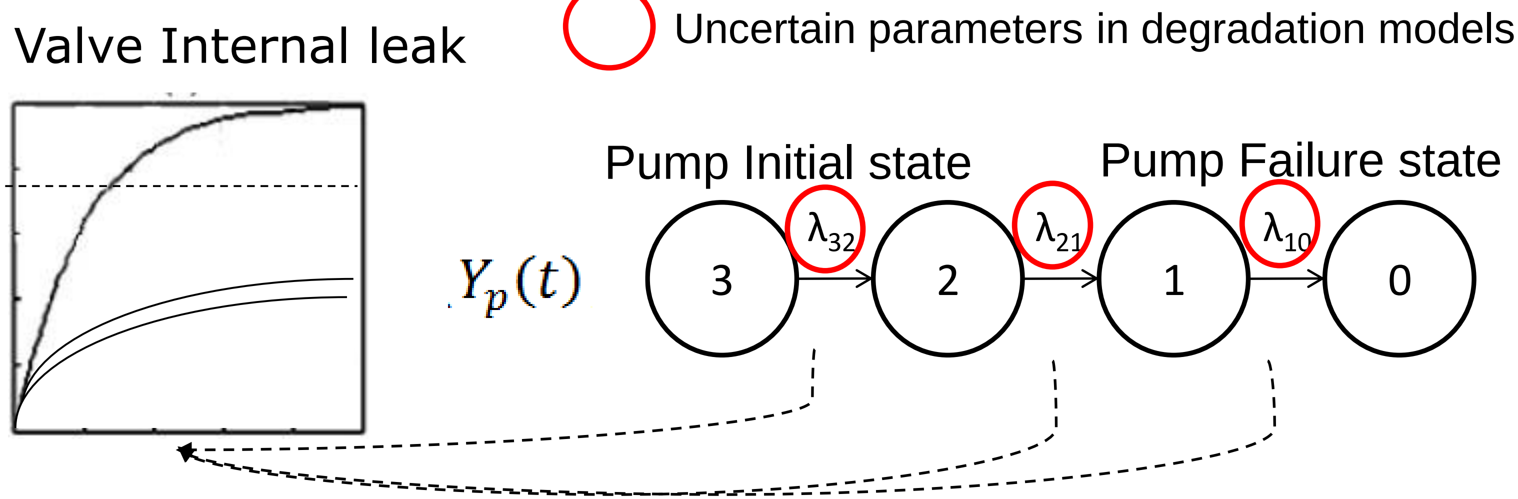
4) Uncertainty

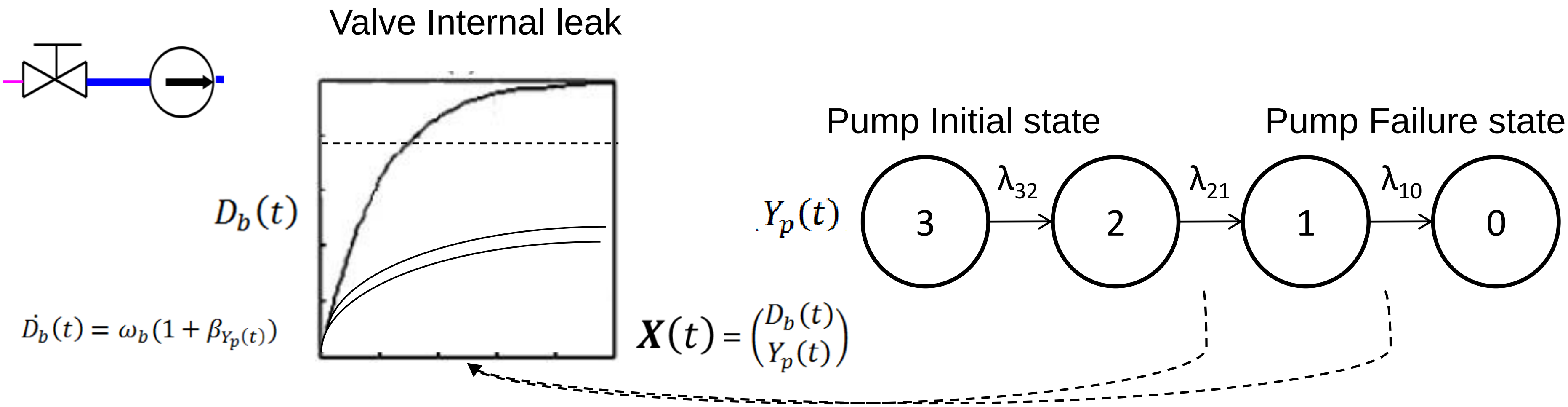
Uncertain parameters in degradation models



$D_b(t)$

$\dot{D_b}(t) = \omega_b(1 - \beta_{Y_p(t)})$





$$\boldsymbol{X}(t) \qquad \dot{\boldsymbol{X}}(t) = \begin{pmatrix} \dot{\boldsymbol{X}}_{L_1}(t) \\ \vdots \\ \dot{\boldsymbol{X}}_{L_M}(t) \end{pmatrix} = \begin{pmatrix} \boldsymbol{f}_{L_1}{}^{Y(t)}(\boldsymbol{X}(t), t \mid \boldsymbol{\theta}_{L_1}) \\ \vdots \\ \boldsymbol{f}_{L_M}{}^{Y(t)}(\boldsymbol{X}(t), t \mid \boldsymbol{\theta}_{L_M}) \end{pmatrix} = \boldsymbol{f}_L{}^{Y(t)}(\boldsymbol{X}(t), t \mid \boldsymbol{\theta}_L)$$

Piecewise-deterministic Markov process (PDMP)

Finite-volume integration schemes

$$\boldsymbol{Y}(t) \qquad \lim_{\Delta t \to 0} P(\boldsymbol{Y}(t + \Delta t) = j \mid \boldsymbol{X}(t), \boldsymbol{Y}(t) = i, \boldsymbol{\theta}_K) / \Delta t = \lambda_i(j \mid \boldsymbol{X}(t), \boldsymbol{\theta}_K), \forall\, t \geq 0, i, j \in \boldsymbol{S}, i \neq j$$

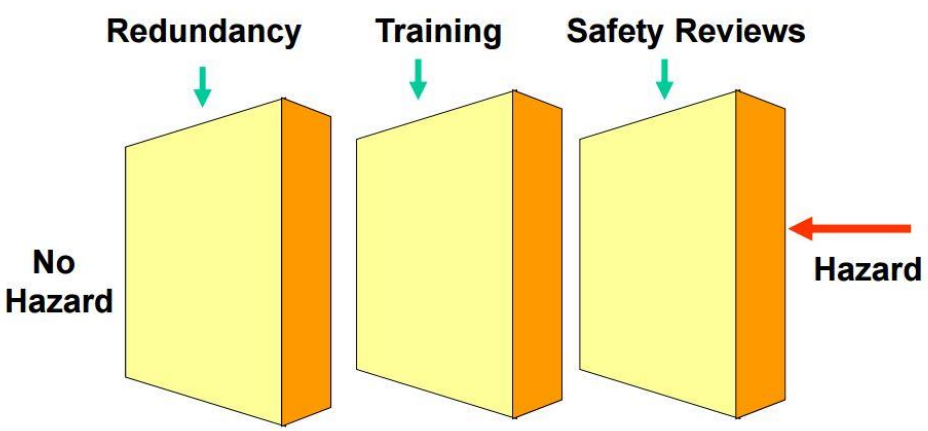
Monte Carlo (MC) simulation

Problem statement

Failures

Prevented by

Design for Reliability | **Maintenance**



Maintenance Engineering Objectives

- Optimization of the maintenance of production assets:
  - Maximize reliability (**R**)
  - Maximize production availability (**A**)
  - Minimize personnel, material, inventory costs
  - Maximize efficiency/effectiveness of maintenance interventions (**M**)
  - Trade-off internal/external maintenance efforts (M)
  - Fulfill safety/regulatory constraints (**S**)
  - Fulfill budgetary constraints (**C**)
  - …

In other words…

RAMS(+C)

for

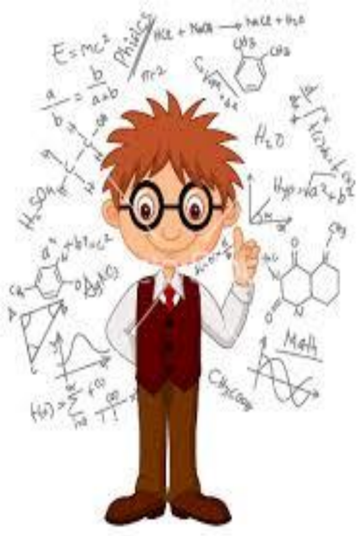
BETTER PERFORMANCES WITH LOWER COSTS

How to achieve the objectives

Integrated maintenance process, supported and informed by knowledge of components/systems/process behaviors through

- high-quality data, real-time information
- effective models and methods to process the information
- effective organizational processes to implement the solutions

KID + Intelligence



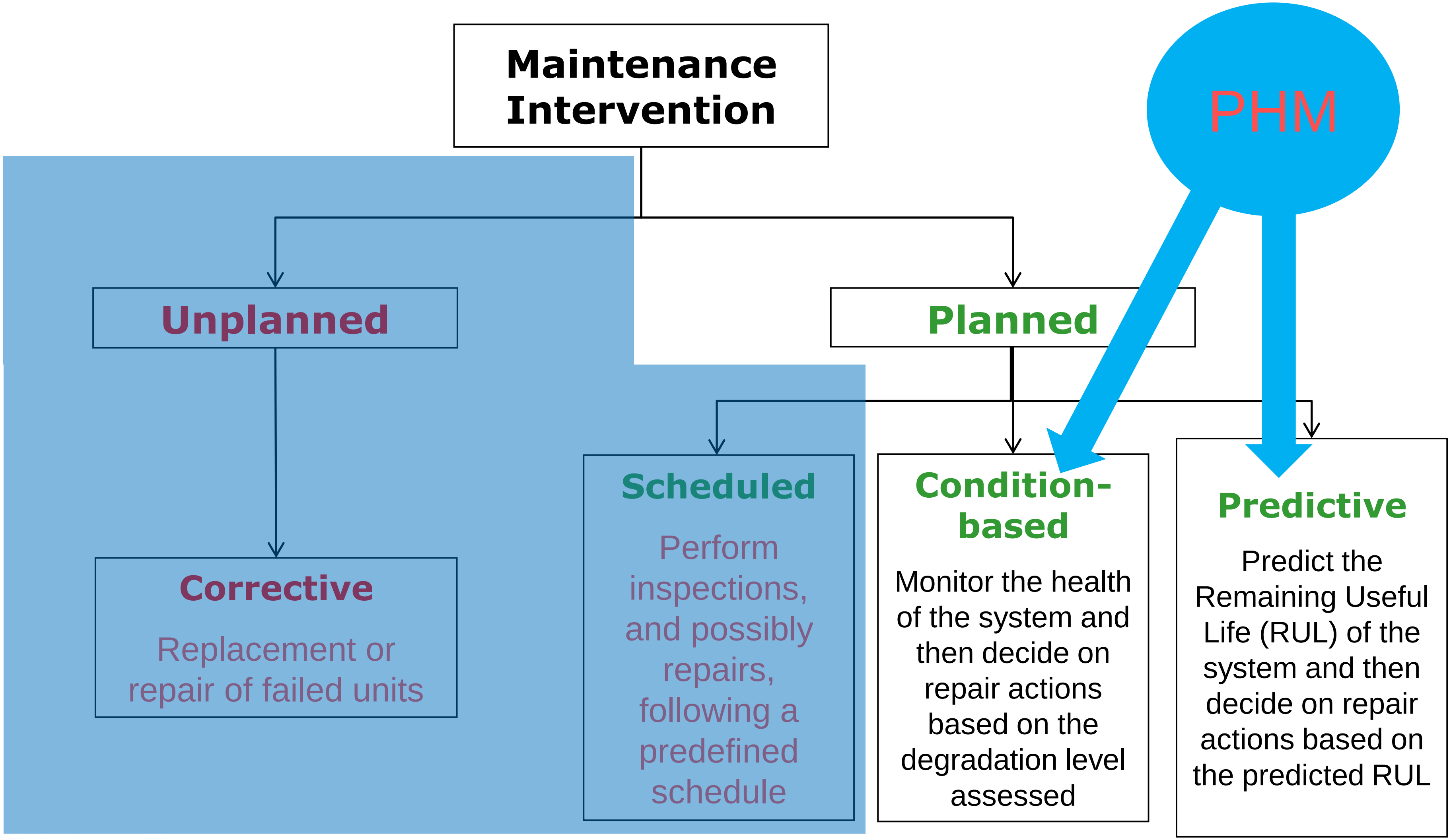
Maintenance:

Integrating physics knowledge and data:

- **Prognostics and Health Management (PHM)**

Maintenance Intervention Approaches

Modelling is in support to proper maintenance planning and



Maintenance

1950 — Corrective Maintenance

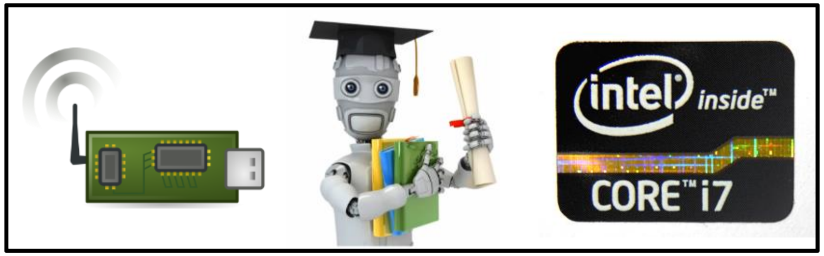
1980 — Planned Periodic Maintenance

2000 — Condition Based Maintenance (CBM)

2016 — Predictive Maintenance (PrM)

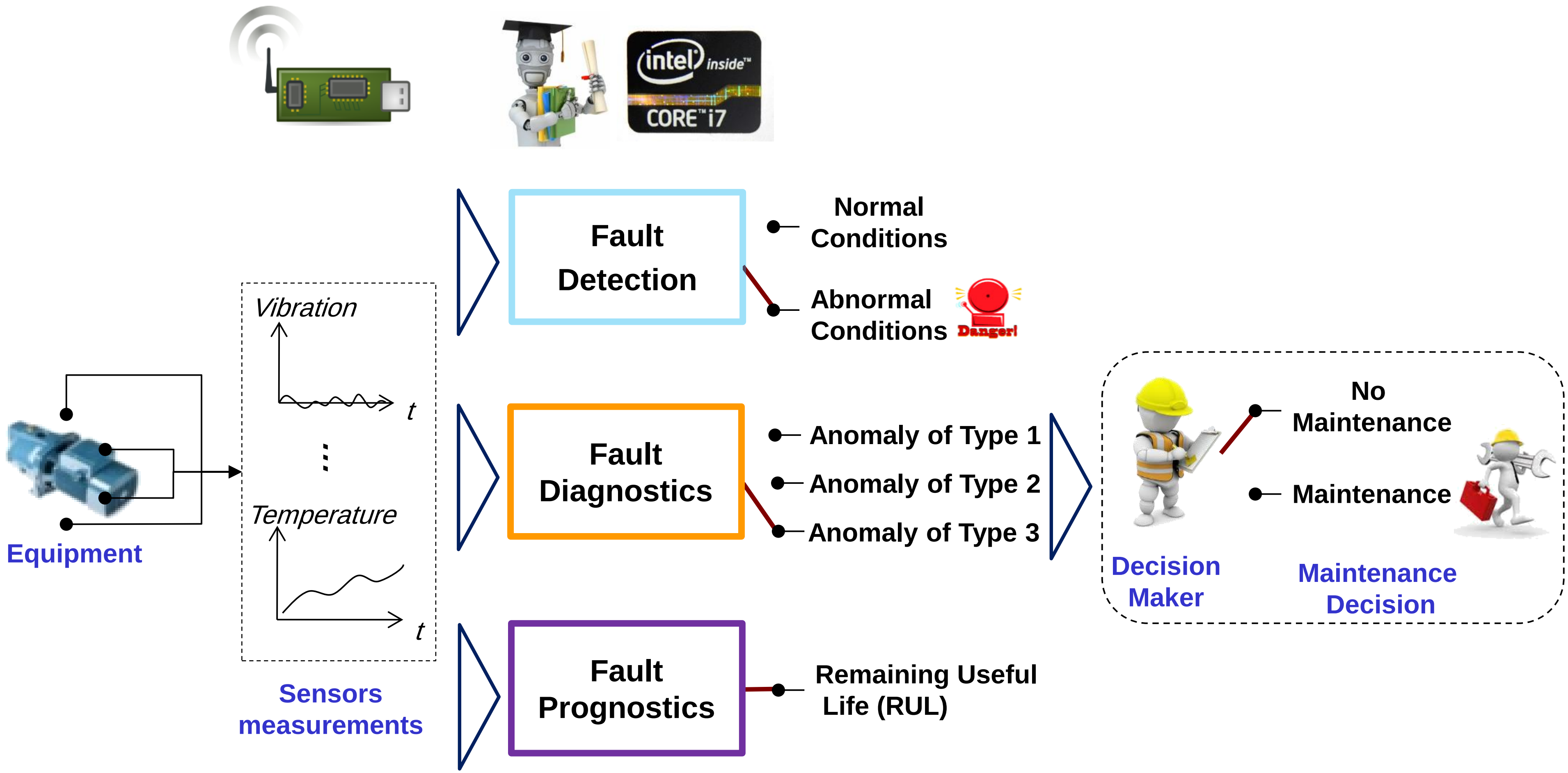
Prognostics and Health Management (PHM)

PHM is fostered by advancements in:



Sensor **Algorithm** **Computation power**

PHM in support to CBM and PrM



PHM: why? (Industry)

- **Increase** maintainability, availability, safety, operating performance and productivity

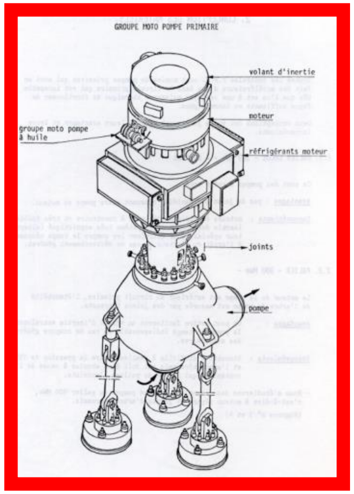
- **Reduce** downtime, number and severity of failure and life-time cost

PHM: why? (Business)

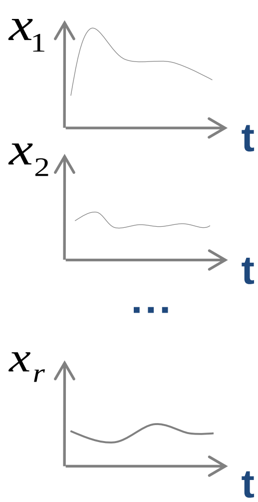
- **Improve** cash flow, profit stream and utilization of assets
- **Guarantee** long term business
- **Increase** market share

PHM: how? (Fault detection)

Feedwater Pump



Measured Signals



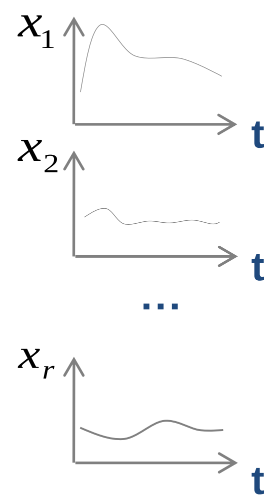
Auto Associative kernel regression

Artificial Neural Networks

PCA

MODEL OF EQUIPMENT BEHAVIOR IN NORMAL CONDITION

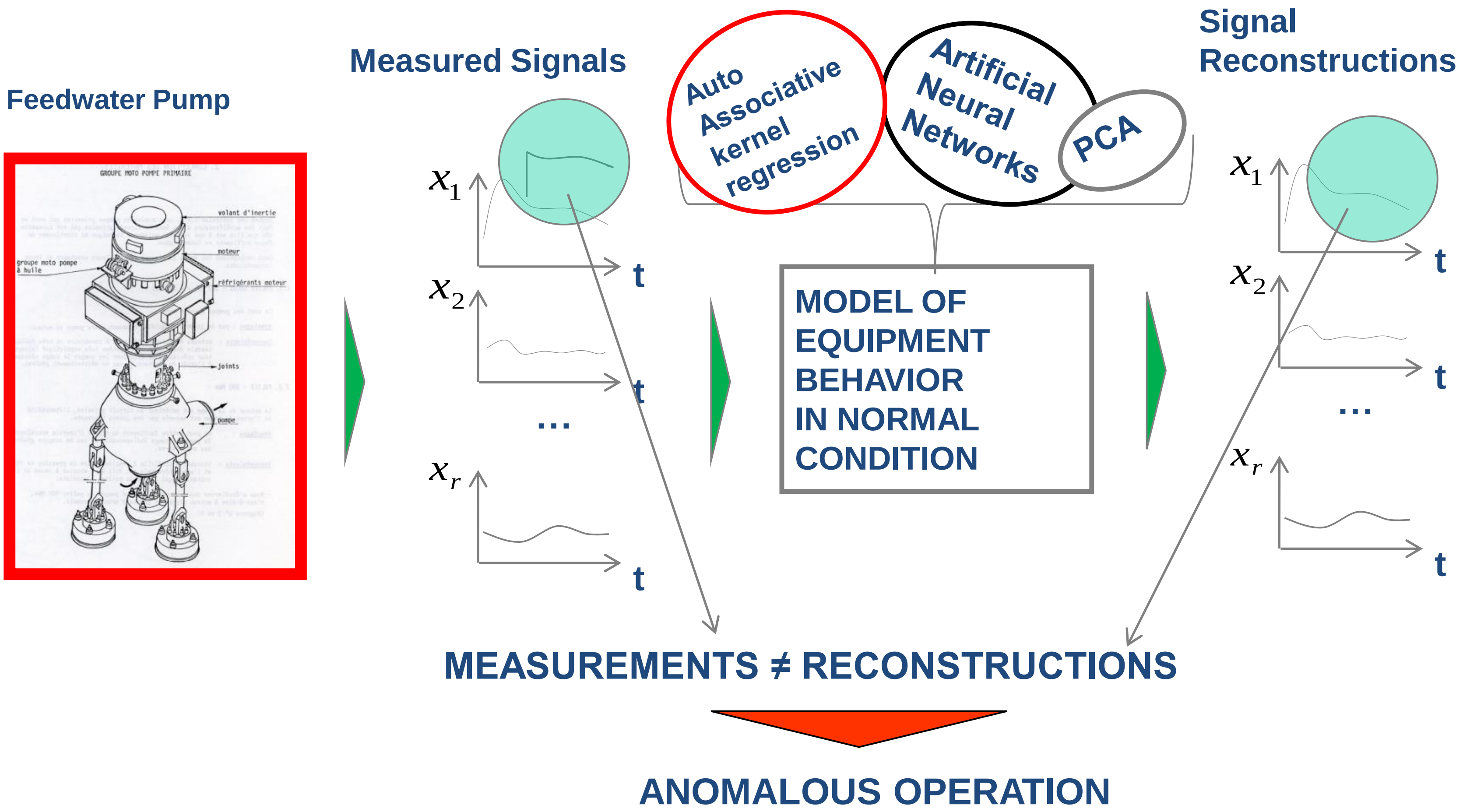
Signal Reconstructions



MEASUREMENTS = RECONSTRUCTIONS

NORMAL OPERATION

PHM: how? (Fault detection)



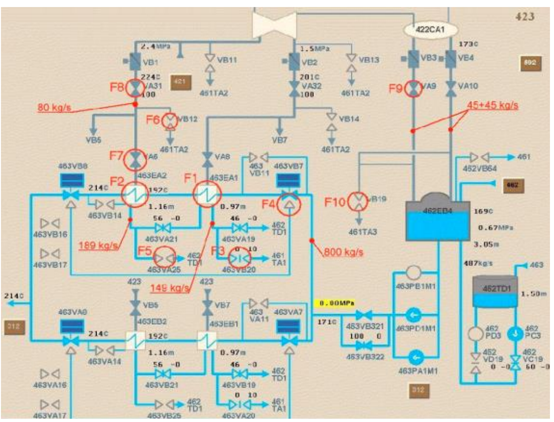
P. Baraldi, F. Di Maio, L. Pappaglione, E. Zio, R. Seraoui, “Condition Monitoring of Electrical Power Plant Components During Operational Transients”, Proceedings of the Institution of Mechanical Engineers, Part O, Journal of Risk and Reliability, 226(6) 568–583, 2012.

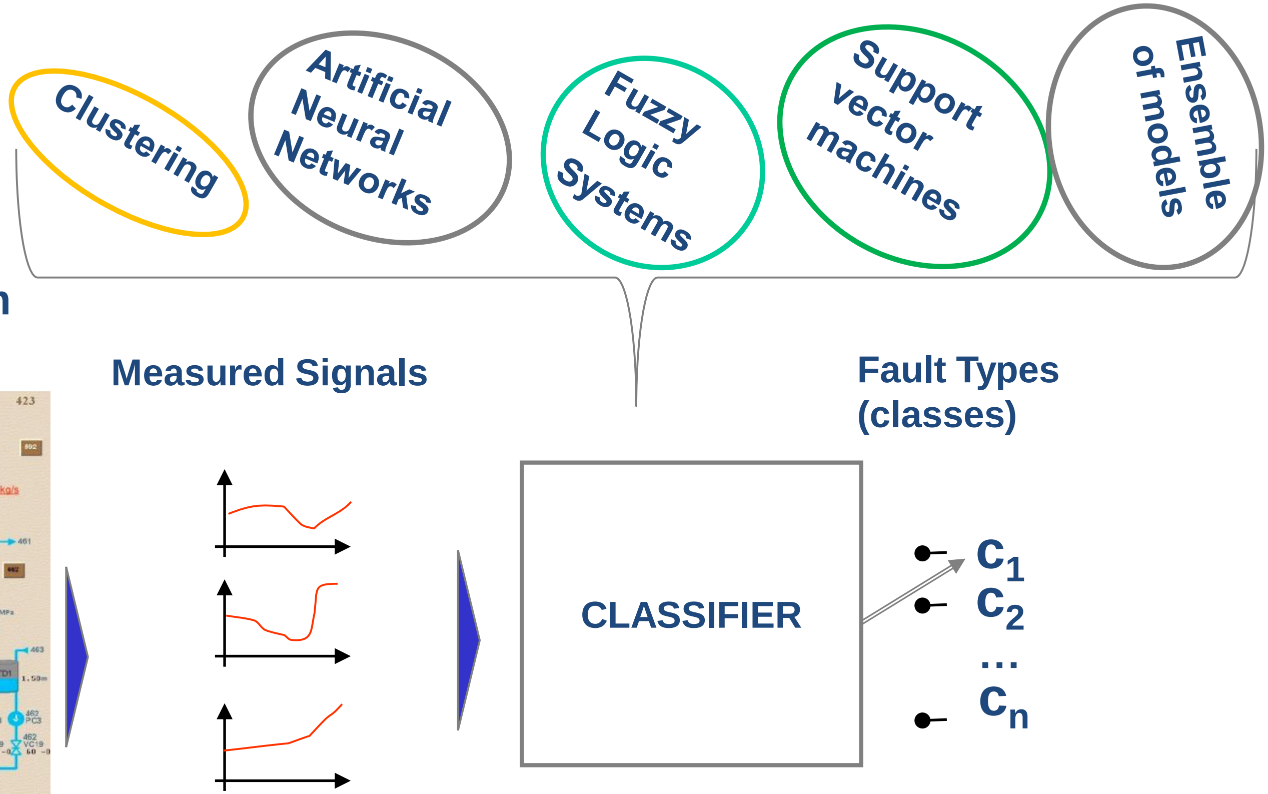
Baraldi, P., Canesi, R., Zio, E., Seraoui, R., Chevalier, R. Genetic algorithm-based wrapper approach for grouping condition monitoring signals of nuclear power plant components (2011) Integrated Computer-Aided Engineering, 18 (3), pp. 221-234.

PHM: how? (Fault diagnostics)

- Signal measurements representative of the fault classes: «$c_1, c_2, \ldots c_n$, class»

BWR feedwater system (Swedish Forsmark-3)

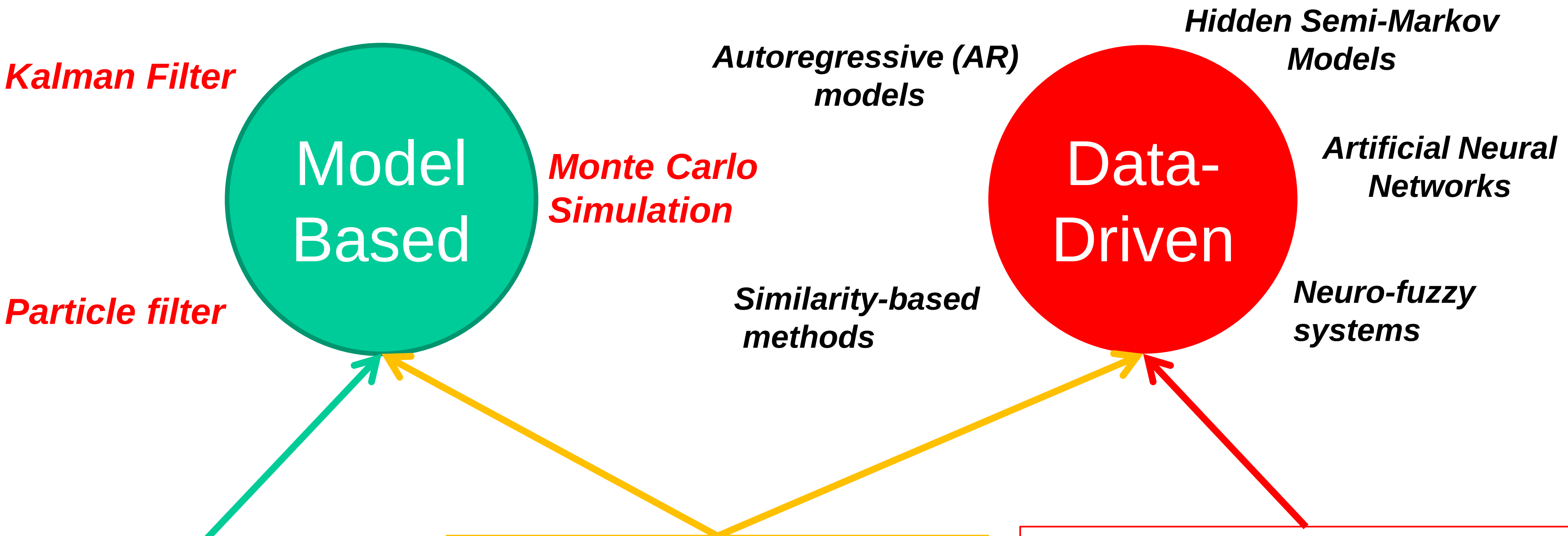




Baraldi, P., Razavi-Far, R., Zio, E., "Classifier-ensemble incremental-learning procedure for nuclear transient identification at different operational conditions", (2011) Reliability Engineering and System Safety, 96 (4), pp. 480-488.

F. Di Maio, J. Hu, P. Tse, K. Tsui, E. Zio, M. Pecht, "Ensemble-approaches for clustering health status of oil sand pumps", Expert Systems with Applications, Volume 39, pp. 4847–4859, doi: 10.1016/j.eswa.2011.10.008

PHM: how? (Fault prognostics)



- Physics-based model of the degradation process
- Measurement equation

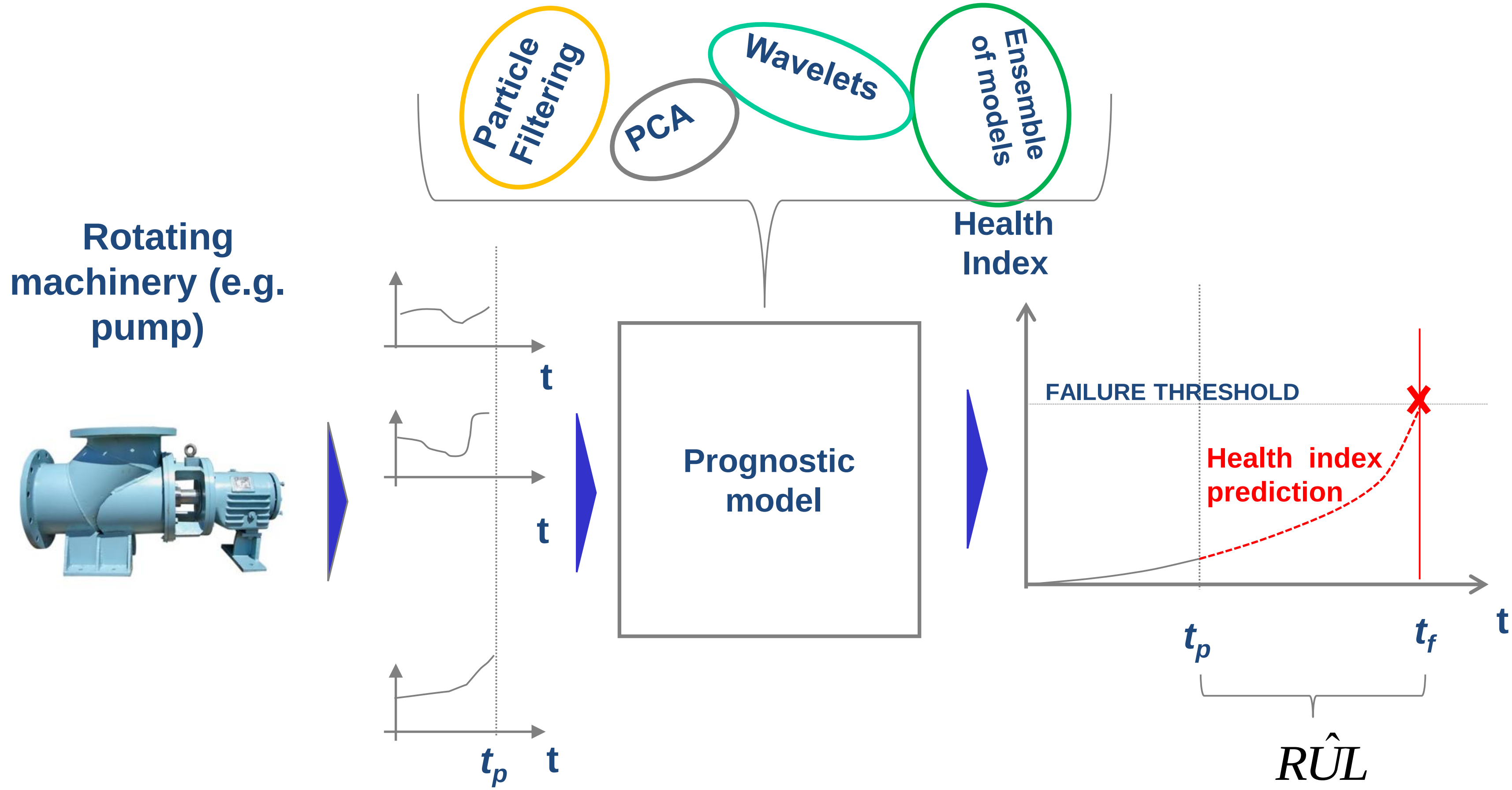
- Current degradation trajectory
- A threshold of failure
- External/operational conditions

Degrading component

- Degradation trajectories of similar components
- Life durations of a set of similar components

Similar components

PHM: how? (Fault prognostics)



Baraldi, P., Cadini, F., Mangili, F., Zio, E. Model-based and data-driven prognostics under different available information (2013) Probabilistic Engineering Mechanics, 32, pp. 66-79.

E. Zio, F. Di Maio, “A Data-Driven Fuzzy Approach for Predicting the Remaining Useful Life in Dynamic Failure Scenarios of a Nuclear Power Plant”, Reliability Engineering and System Safety, RESS, 10.1016/j.ress.2009.08.001, 2009.

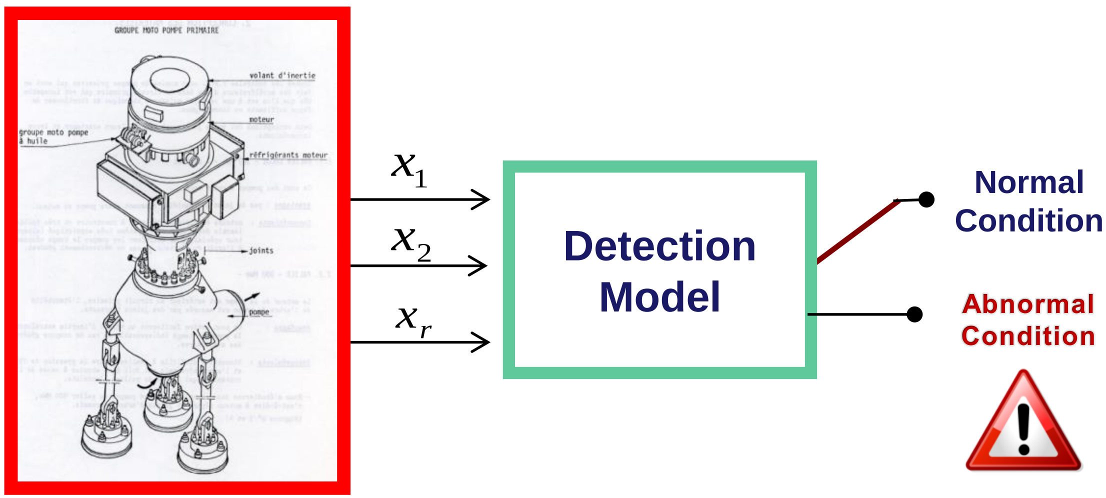
F. Di Maio, K.L. Tsui, E. Zio, “Combining Relevance Vector Machines and Exponential Regression for Bearing RUL estimation”, Mechanical Systems and Signal Processing, Mechanical Systems and Signal Processing, 31, 405–427, 2012.

PHM: performance ?

- Accuracy

PHM: performance ? (detection)

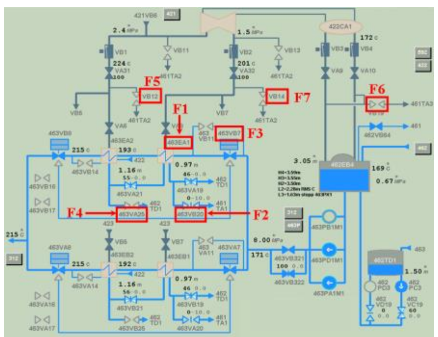
- Accuracy
  - Fault Detection:
    - Low rate of False Alarms
    - Low rate of Missing Alarms

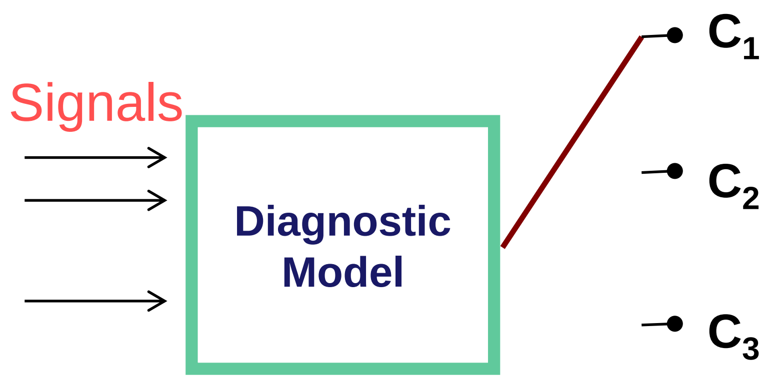


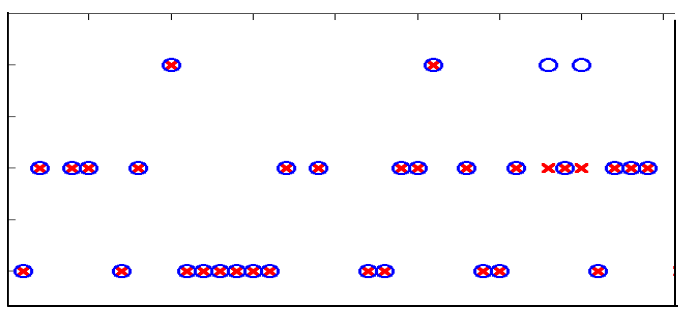
False Alarm Rates	Missing Alarm Rates
0.54%	0.98%

PHM: performance ? (diagnostics)

- Accuracy
  - Fault diagnostics:
    - Low Misclassification rate





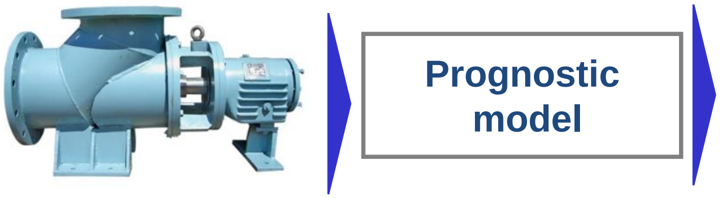


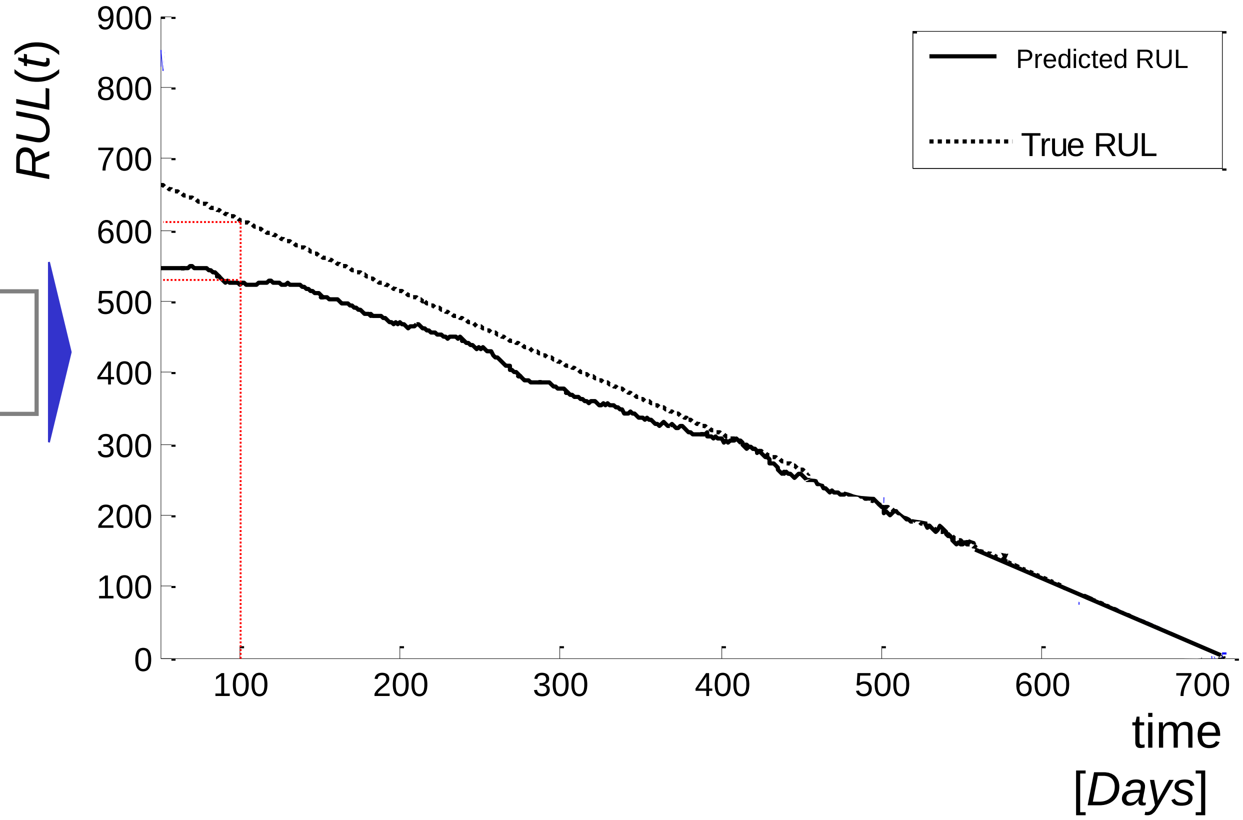
Misclassification rate = 2.58%

o = true
× = diagnostic model

PHM: performance ? (prognostics)

- Accuracy
  - Prognostics

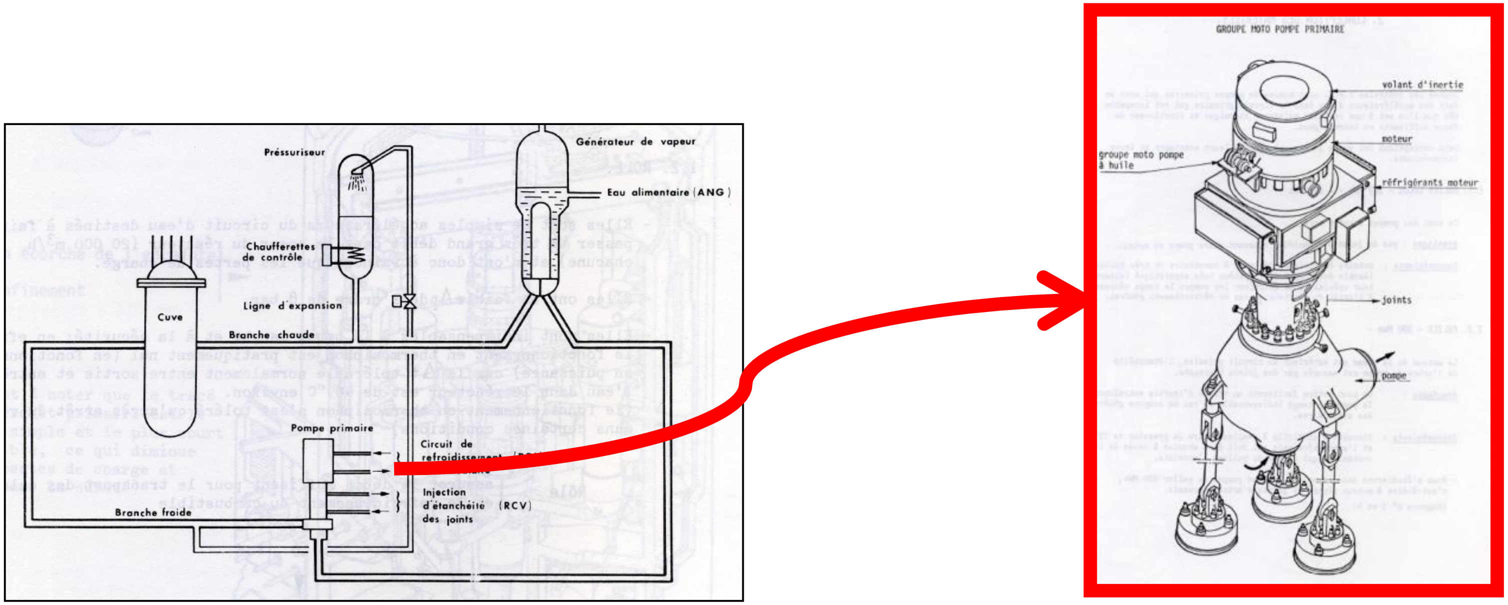




FAULT DETECTION

Application: NPP feedwater pumps

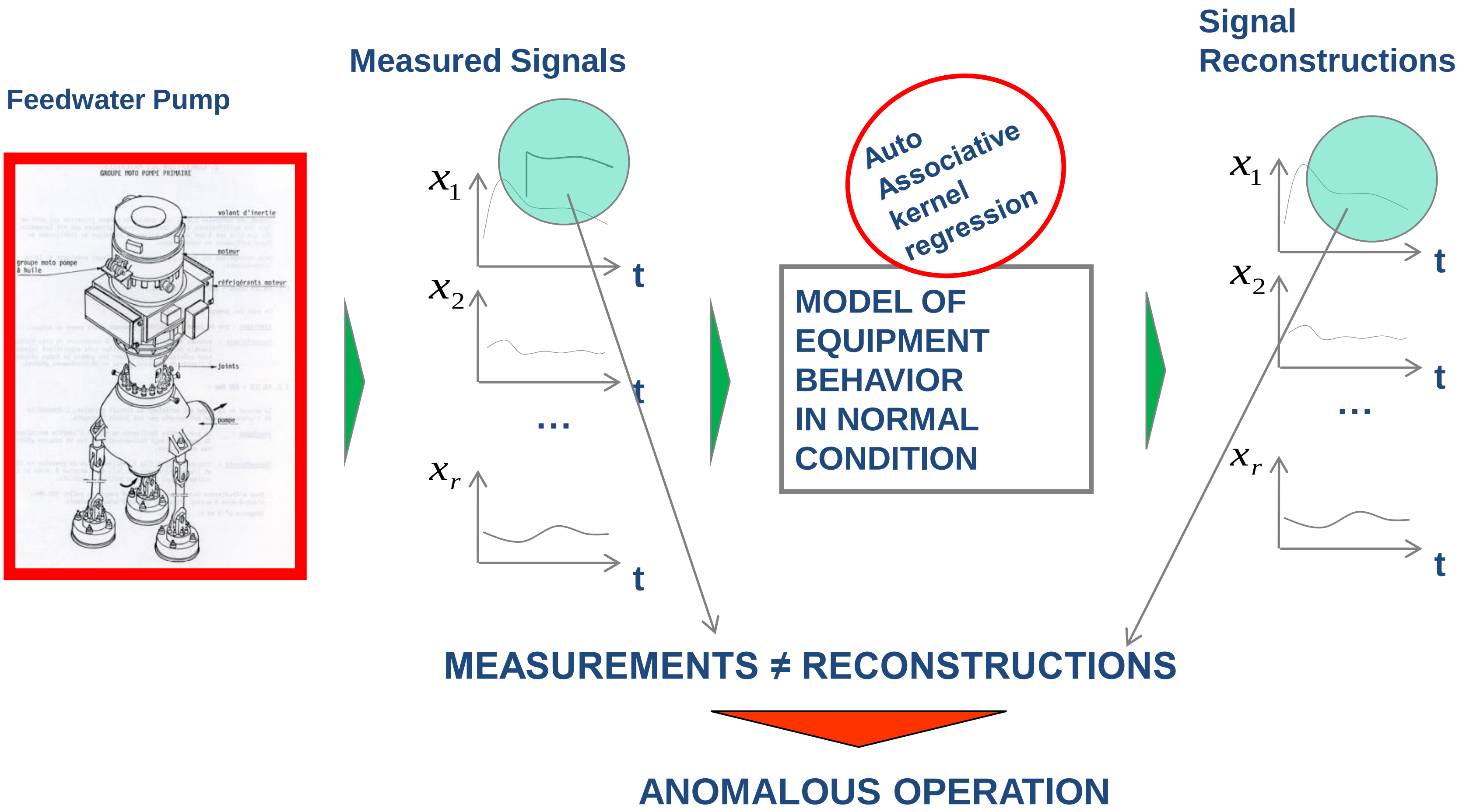
- Reactor Coolant Pumps of a PWR NPP



x4

P. Baraldi, R. Canesi, E. Zio, R. Seraoui, R. Chevalier, "Generic algorithm-based wrapper approach for grouping condition monitoring signal of nuclear power plant components". Integrated Computer-Aided Engineering, Vol. 18 (3), pp. 221-234, 2011

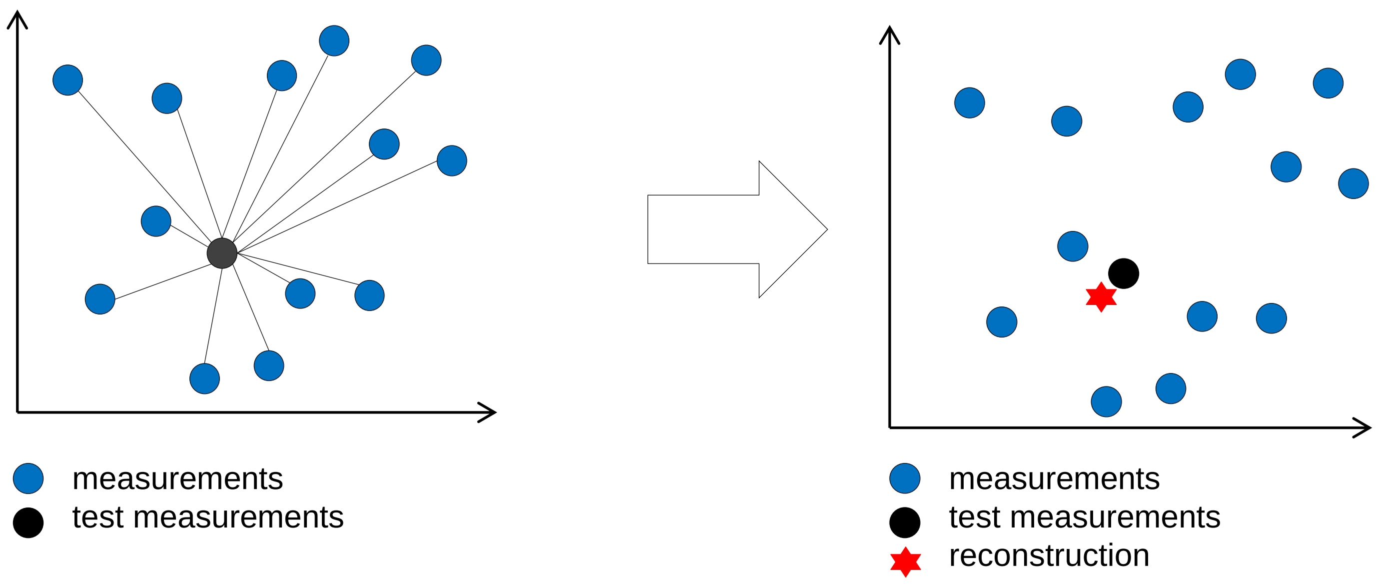
PHM: how? (Fault detection)



The Auto-Associative Kernel Regression (AAKR)

Empirical modeling refers to any kind of (computer) approximated modeling based on empirical observations rather than on mathematically describable relationships of the system modeled

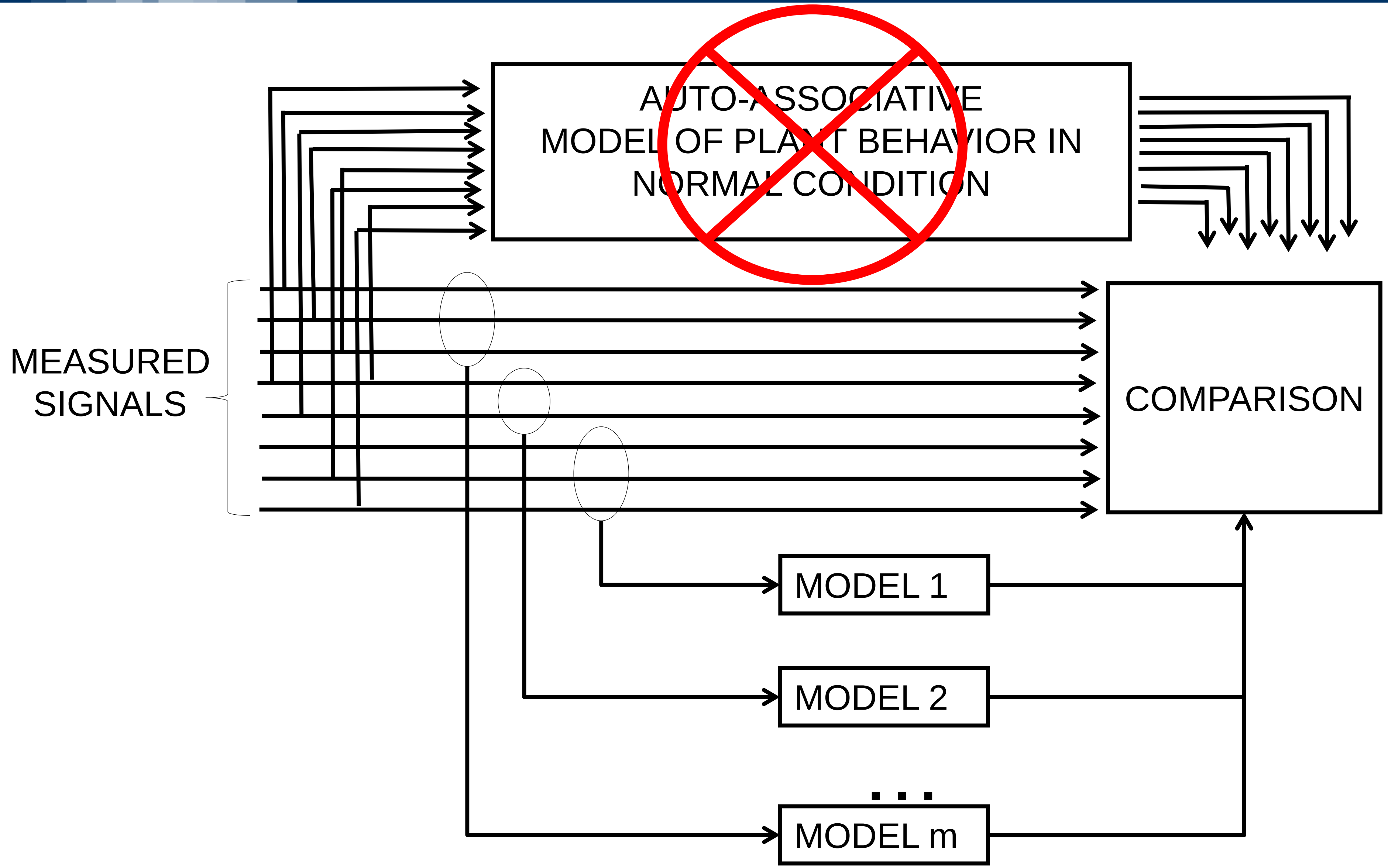
1. Collect data measurements representative of the system behavior
2. Develop the empirical model using as **training set** the collected data



Available information

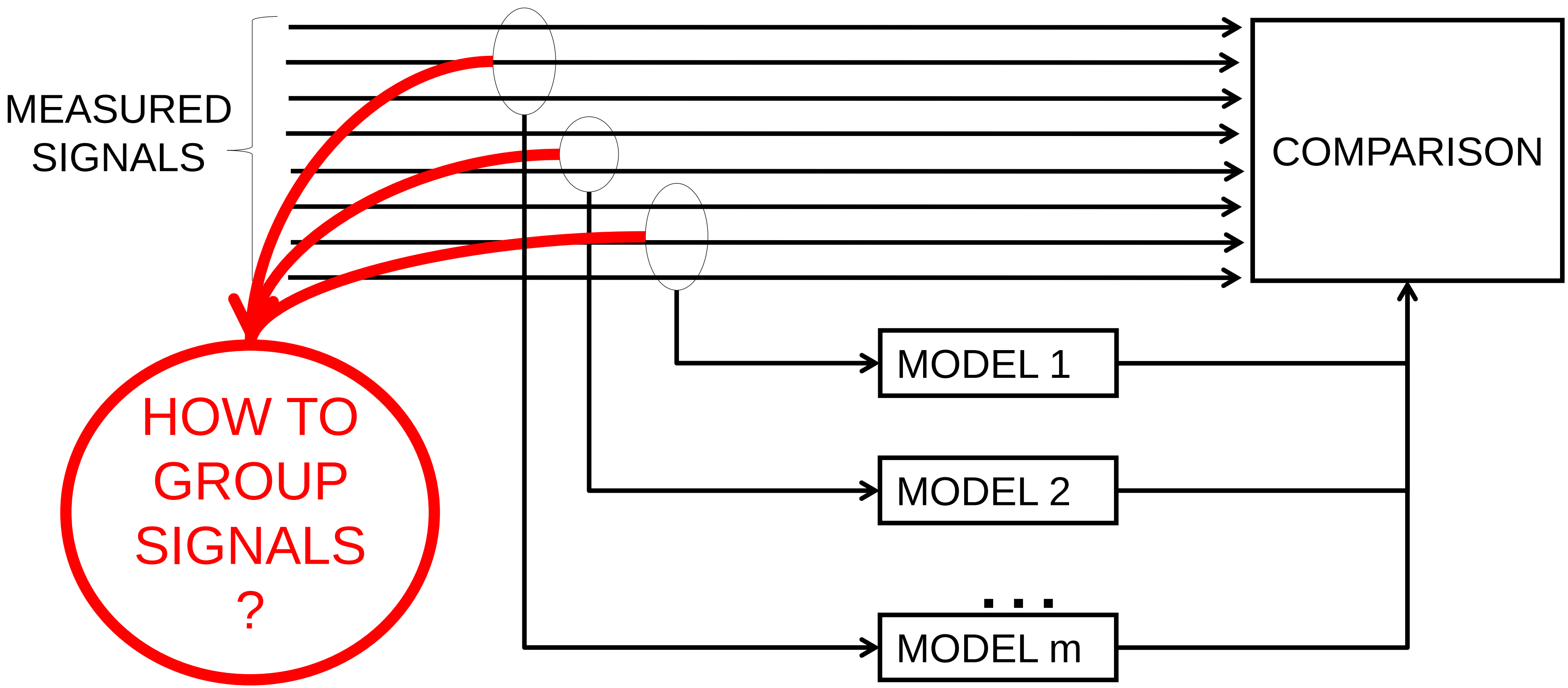
- Historical measurements of 94 stationary signals during 1 year of operation
- EDF experts have considered 48 of the 94 measured signals as the most important for the component condition monitoring

Signal Grouping



Challenge: Optimal Grouping

Requirement: each signal should belong to only 1 group



Approaches to signal grouping

HOW TO SPLIT THE SIGNALS INTO SUBGROUPS?

A-PRIORI CRITERIA
(signals divided on the basis of…)

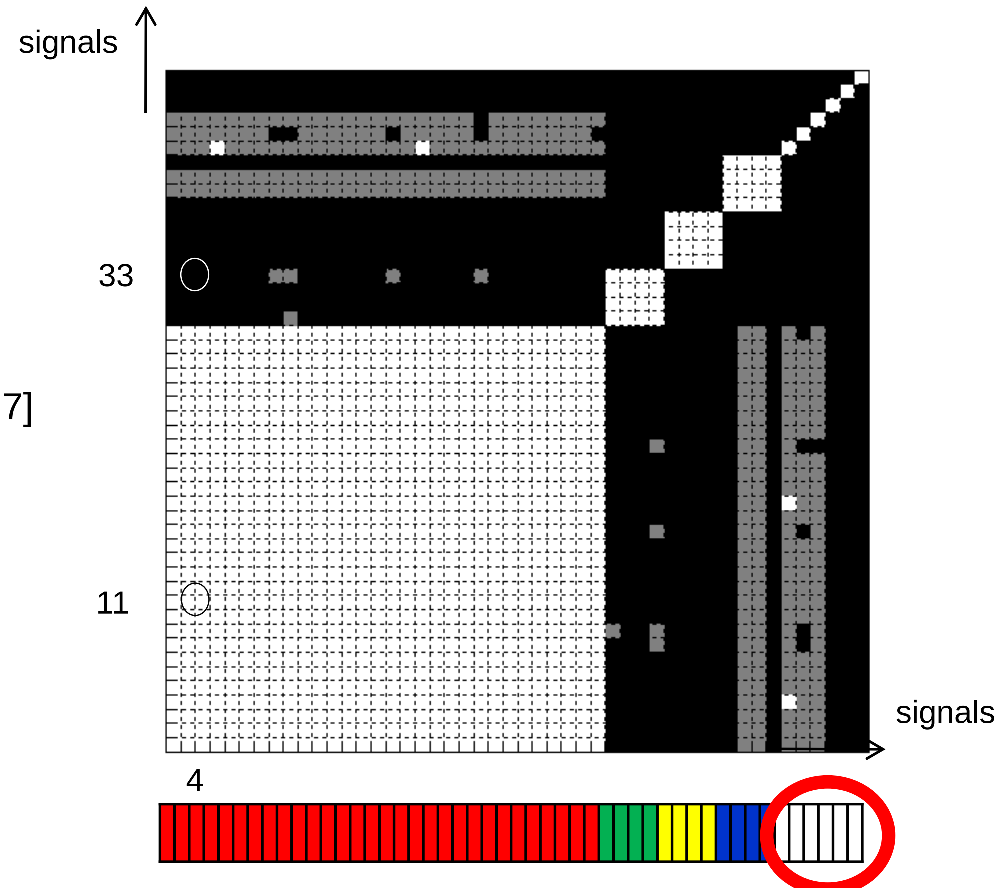
- physical homogeneity
- location in the power plant
- correlation
- others

BEST A-PRIORI GROUPING: “correlation”

WHITE: high correlation (0.7 1]

GREY: medium correlation (0.4 0.7]

BLACK: low correlation [0 0.4]



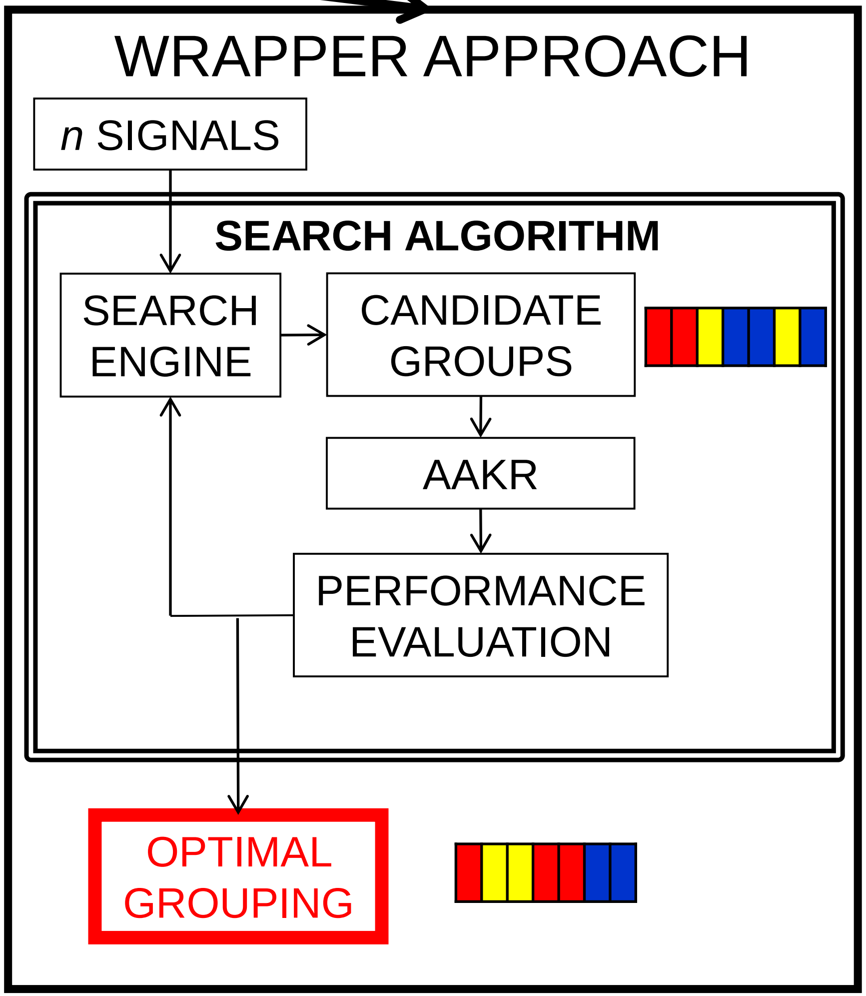
signal belonging to group 1
signal belonging to group 2
signal belonging to group 3
signal belonging to group 4
signal belonging to group 5

CRITICALITY: how to group the signals which have a low degree of correlation with all the others?

HOW TO SPLIT THE SIGNALS INTO SUBGROUPS?

A-PRIORI CRITERIA
(signals divided on the basis of…)

- location in the power plant
- correlation
- physical homogeneity
- others



SEARCH ENGINE
Genetic Algorithms

CHROMOSOME

n genes = *n* signals

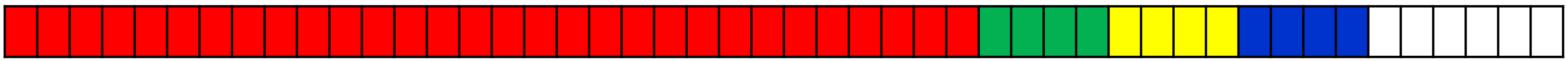
GENE	signal 1	signal 2	signal 3	…	signal *i*	…	signal *n*
GROUP LABEL (integer number)	1	1	2	3	3	2	3

PERFORMANCE EVALUATION
fitness = Accuracy

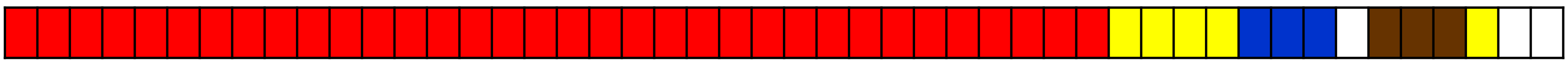
Results

OBTAINED GROUPINGS

correlation

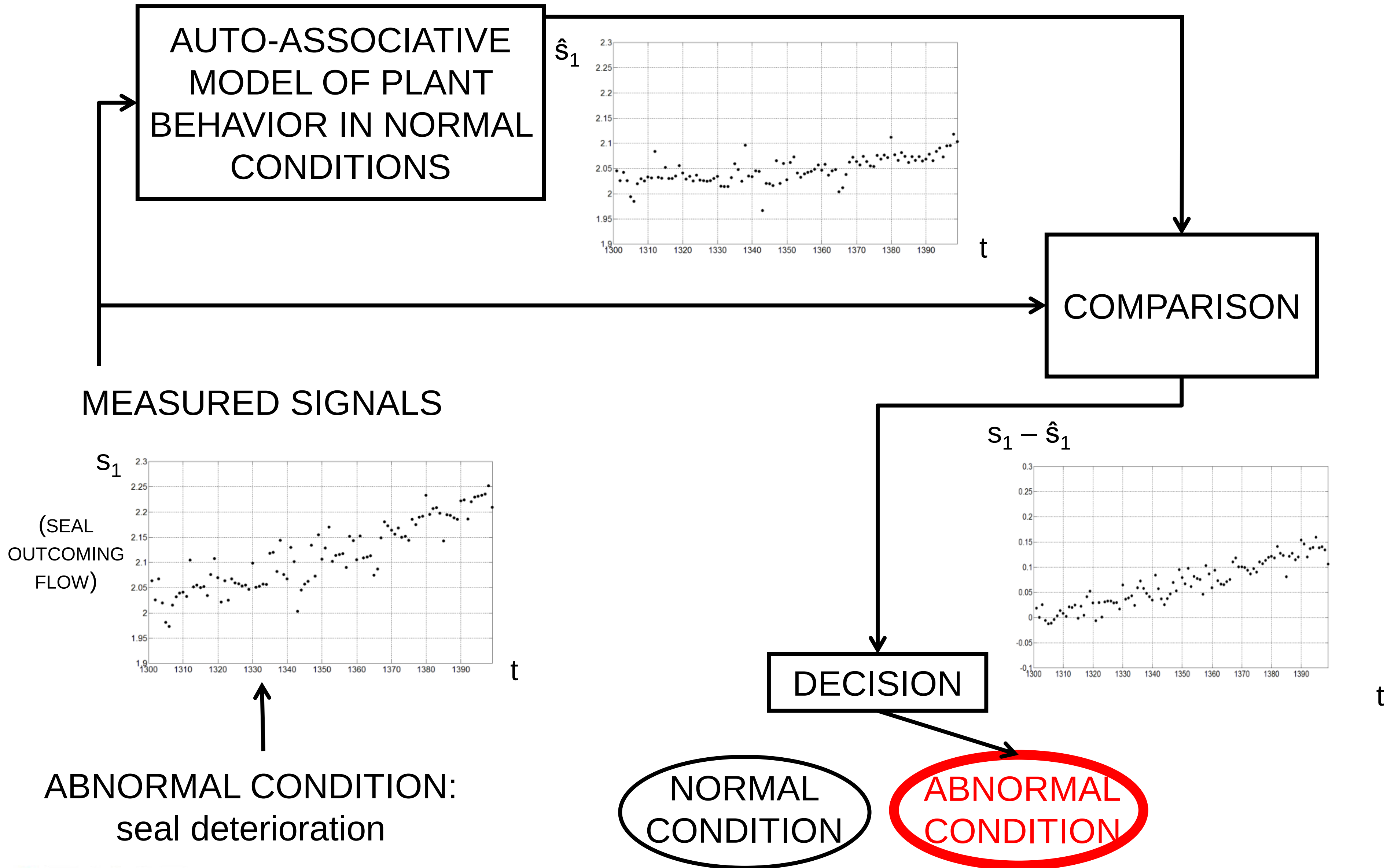


GA



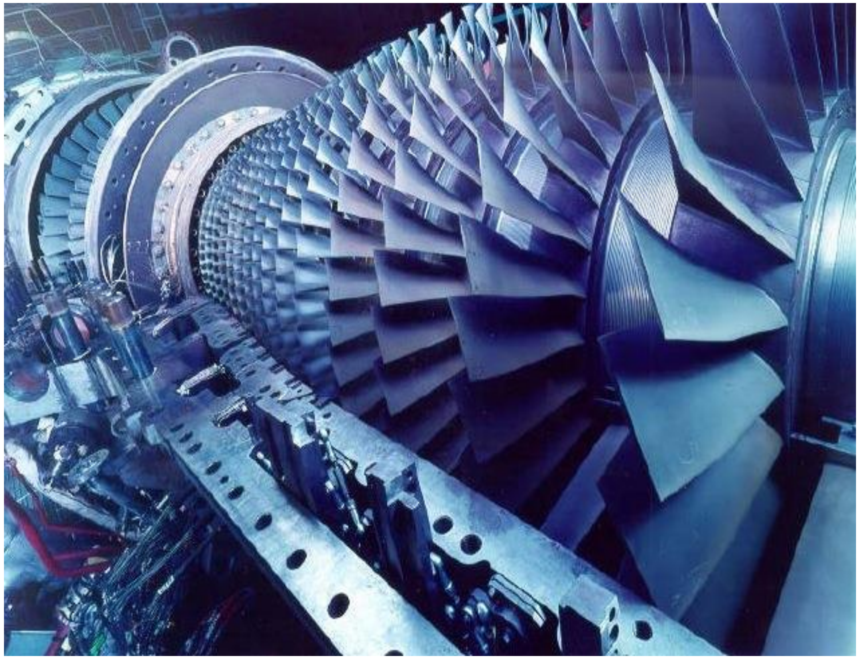
MAIN DIFFERENCE:
signals which have a low degree of correlation are divided in groups and/or mixed with signals with a high degree of correlation

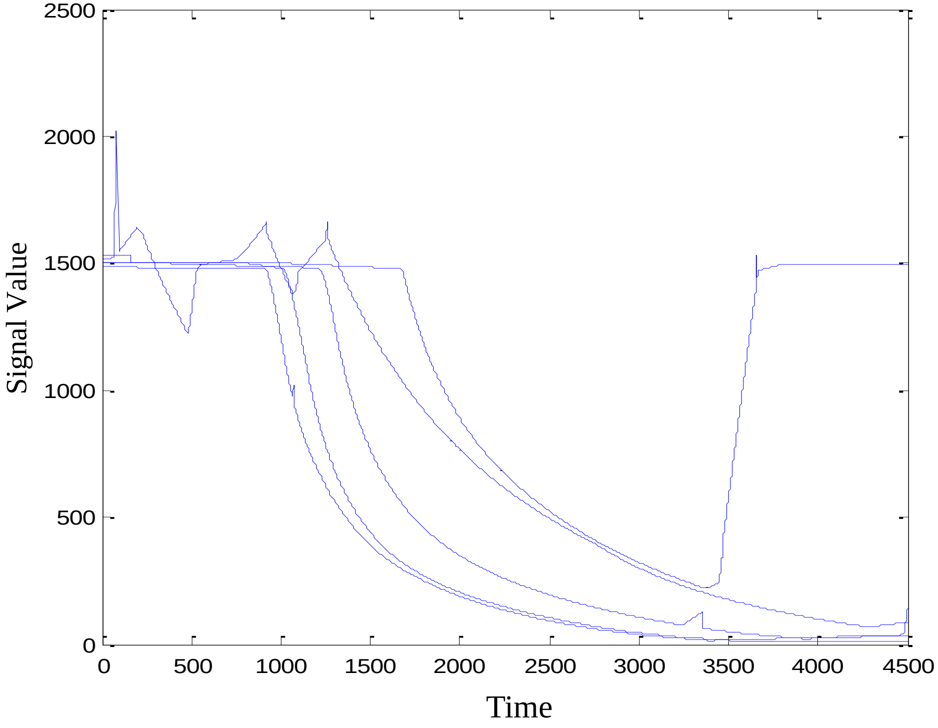
Results: Wrapper Approach



FAULT CLASSIFICATION

Application: NPP turbine





AVAILABLE DATA:

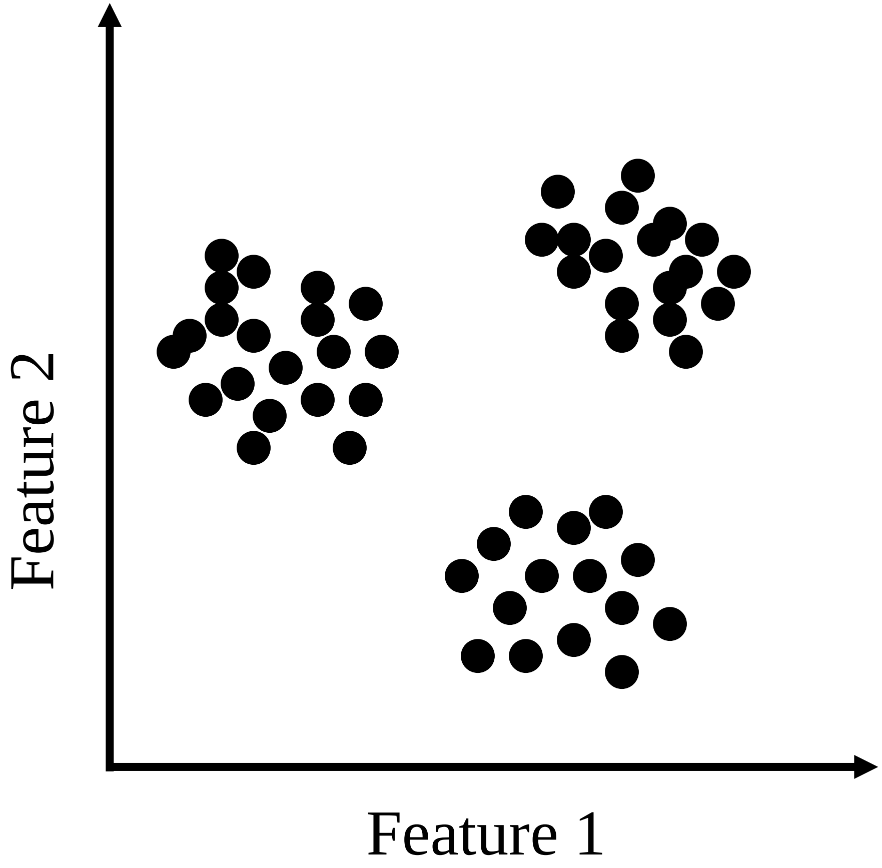
• Number of transients: N=115
• Transient time length: 4500t
• Number of vibration signals: K=7

The problem

• examples are unlabeled

Scope

Find hidden structure in data

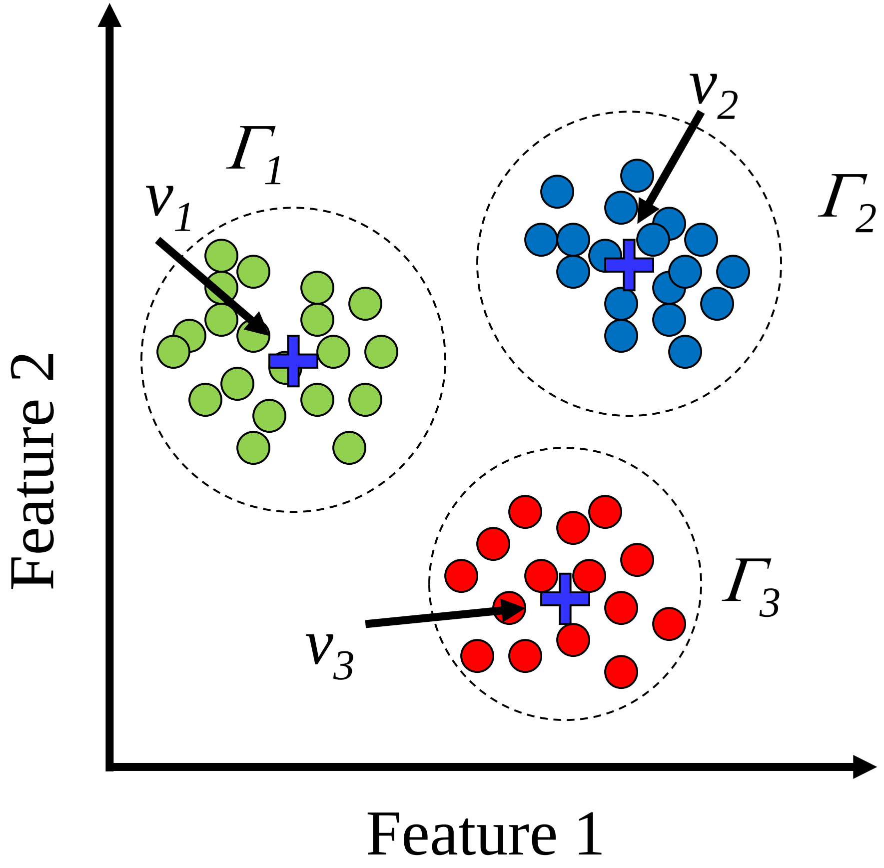


The problem

- examples are unlabeled
- there is no error or reward to evaluate a potential solution

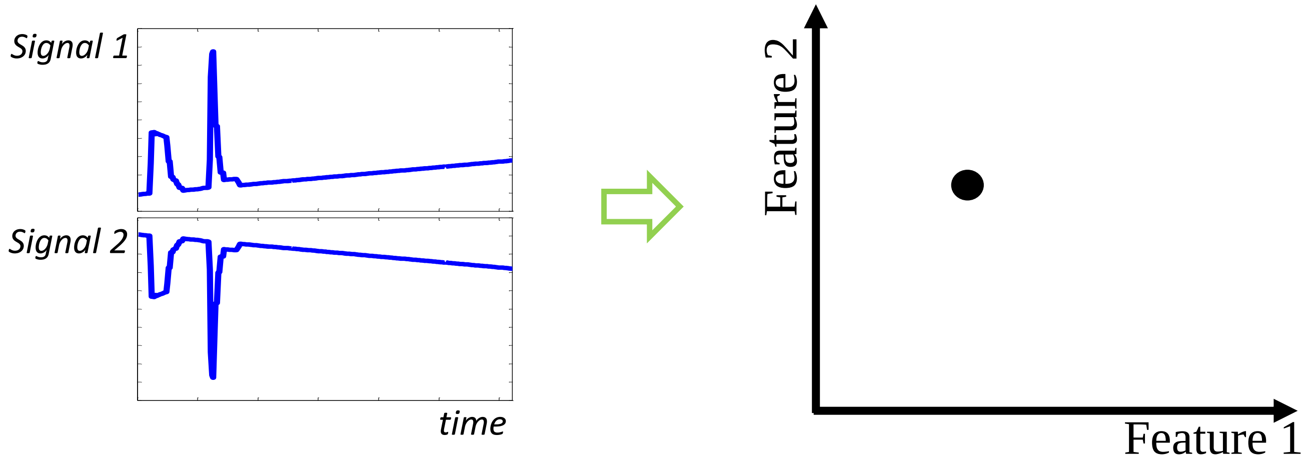
⇩

unsupervised clustering

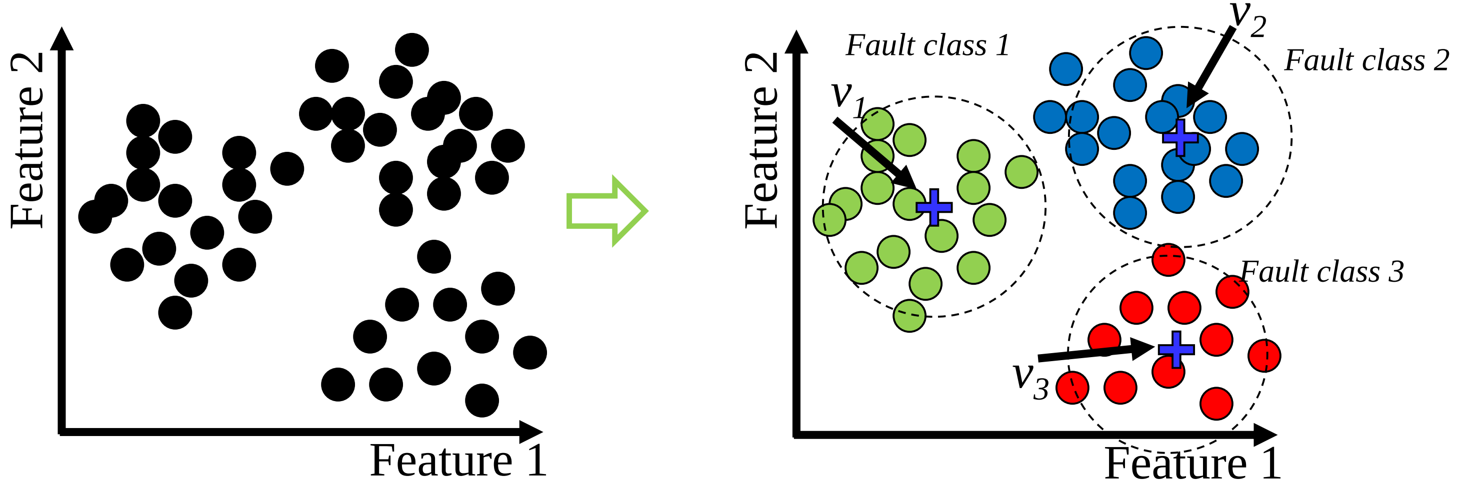


Methodology

STEP 1: feature extraction

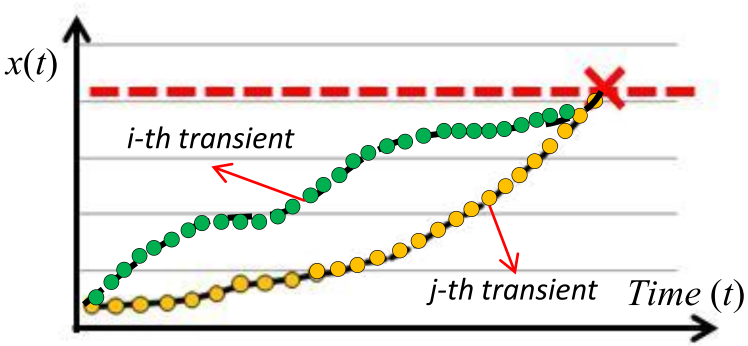


STEP 2: unsupervised clustering



Feature Extraction: Fuzzy Similarity Analysis (1-D)

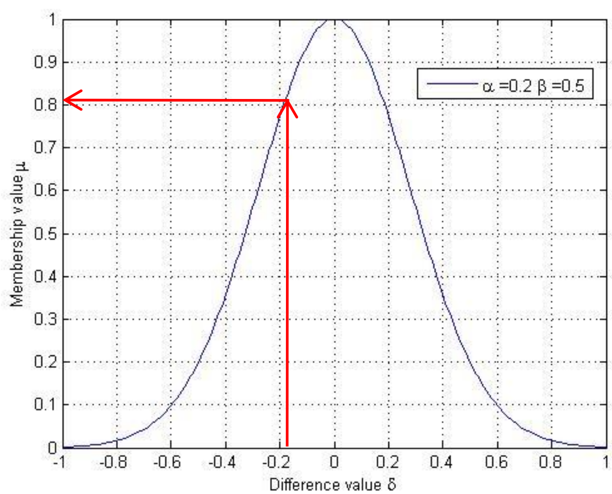
1- Transients pointwise difference computation:



$$\delta(i,j)=\sqrt{\sum_{t=i}^{T}\left(x_i(t)-x_j(t)\right)^2} \quad i=1,2,\dots,N \quad j=1,2,\dots,N$$

j-th transient *i-th transient*

2- Transients pointwise similarity computation:



μ (i,j) is the membership value of the distance δ (i,j) to the condition of "approximately zero"

3- *Similarity Matrix W definition*:

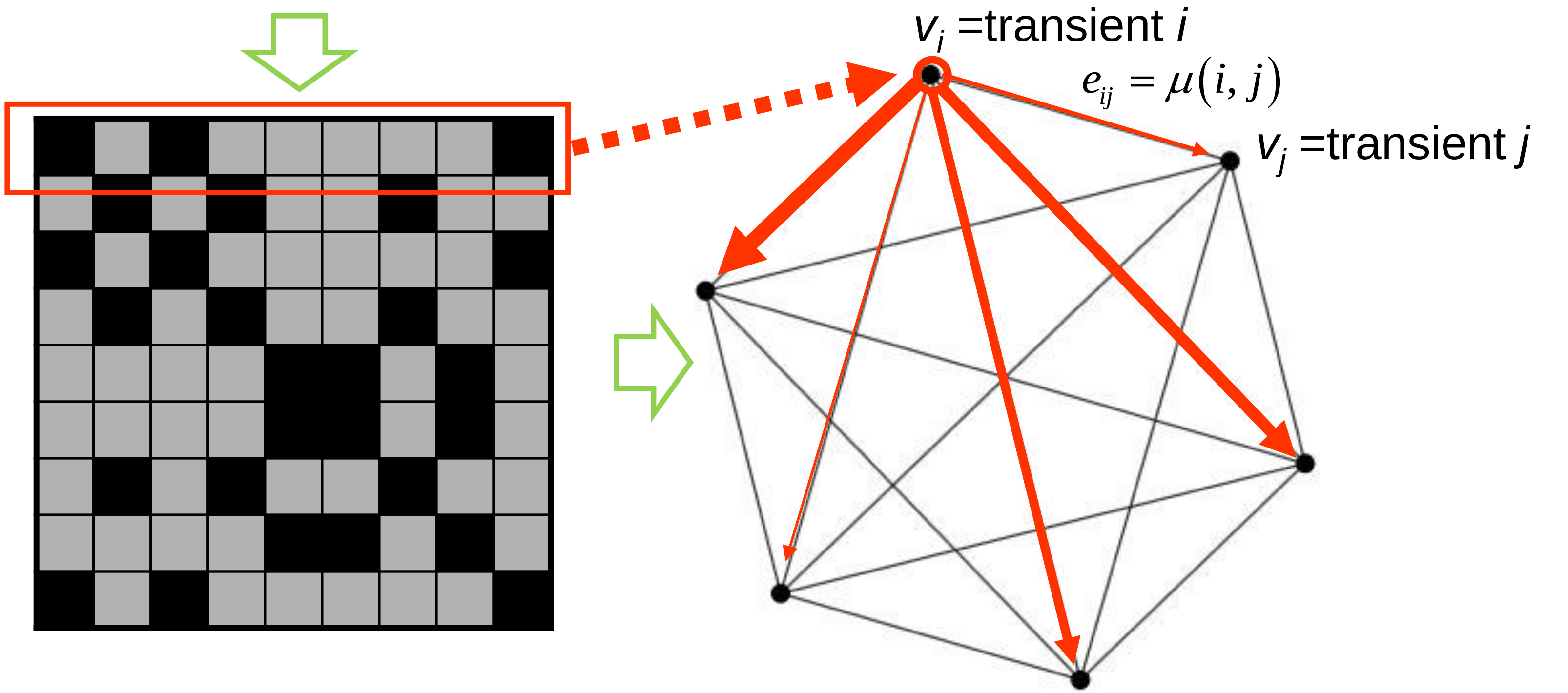
$$\begin{array}{cc} & \text{N columns} \Rightarrow \\ \text{N rows} \Downarrow & \begin{bmatrix} 1 & \mu(1,2) & \dots & \mu(1,N) \\ \mu(2,1) & 1 & \mu(2,3) & \dots \\ \dots & \mu(3,2) & \dots & \mu(N-1,N) \\ \mu(N,1) & \dots & \mu(N,N-1) & 1 \end{bmatrix} \end{array}$$

Similarity between transients 2 and 3

Feature Extraction: Spectral Analysis

1- Similarity matrix *W* → Fully connected graph $G(v_i,e_{ij})$

$$\begin{bmatrix} 1 & \mu(1,2) & \dots & \mu(1,9) \\ \mu(2,1) & 1 & \mu(2,3) & \dots \\ \dots & \mu(3,2) & \dots & \mu(8,9) \\ \mu(9,1) & \dots & \mu(9,8) & 1 \end{bmatrix}$$

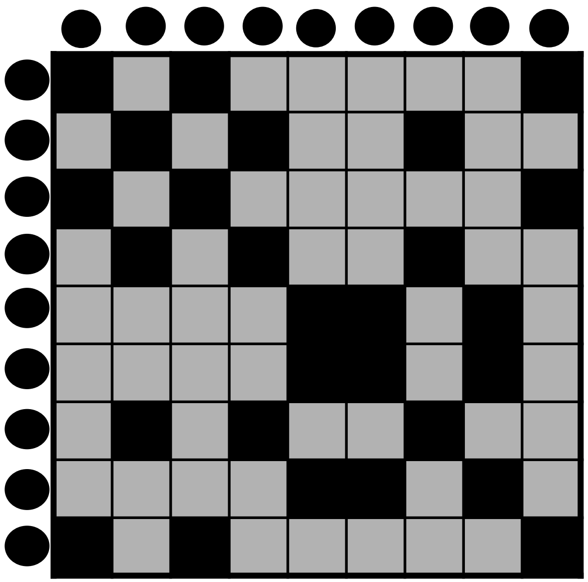


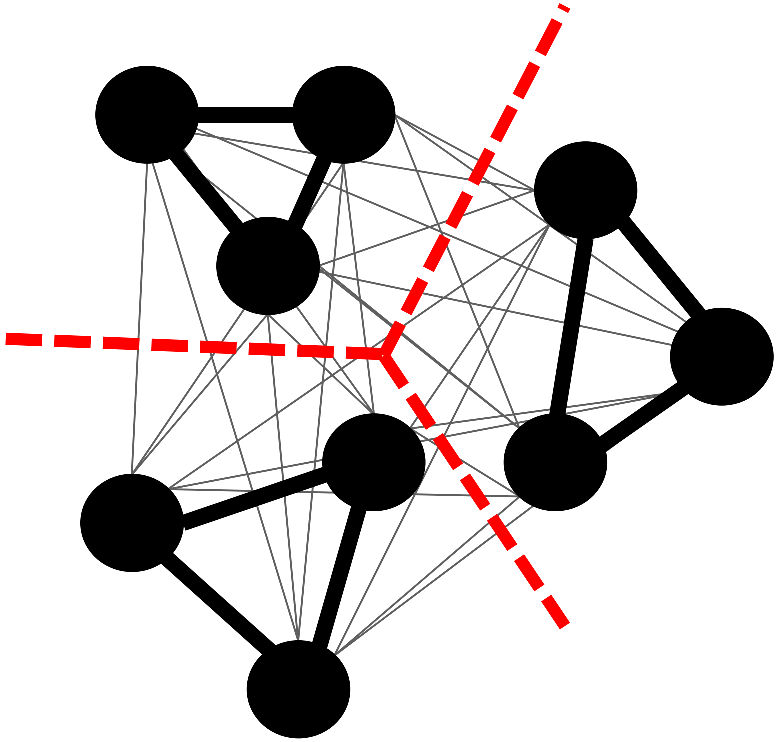
Spectral Analysis: the scope

Identify the most appropriate features for

- partitioning the graph $G(v_i,e_{ij})$

Similarities

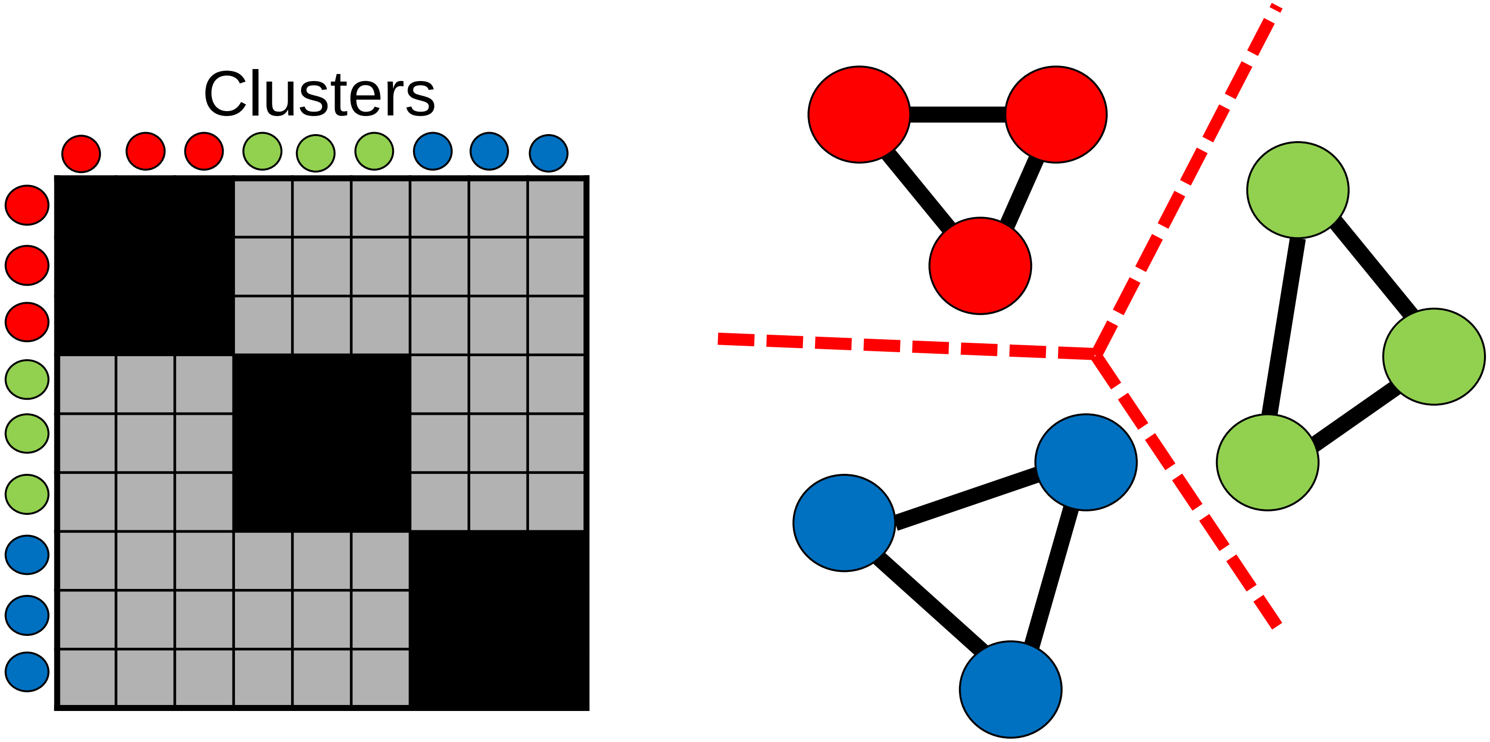




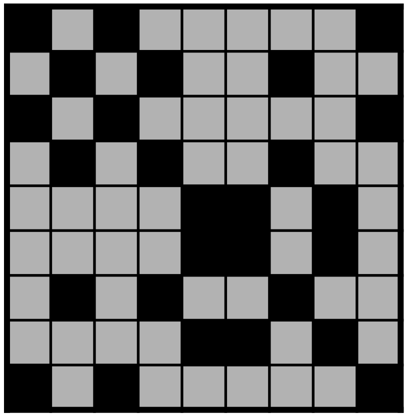
Identify the most appropriate features for

- partitioning the graph $G(v_i,e_{ij})$

- shuffling matrix W to highlight blocks of similarity



Spectral Analysis: The procedure for feature selection



2- Compute the degree matrix D: $d_{ii} = \sum_{j=1}^{N} \mu(i,j)$

3- Compute the Normalized Laplacian matrix L_{sym}:

$$\overline{\overline{L}}_{sym} = \overline{\overline{D}}^{-1/2}\,\overline{\overline{L}}\,\overline{\overline{D}}^{-1/2} = \overline{\overline{I}} - \overline{\overline{D}}^{-1/2}\,\overline{\overline{W}}\,\overline{\overline{D}}^{-1/2}$$

4- Compute the first C eigenvalues of L_{sym}

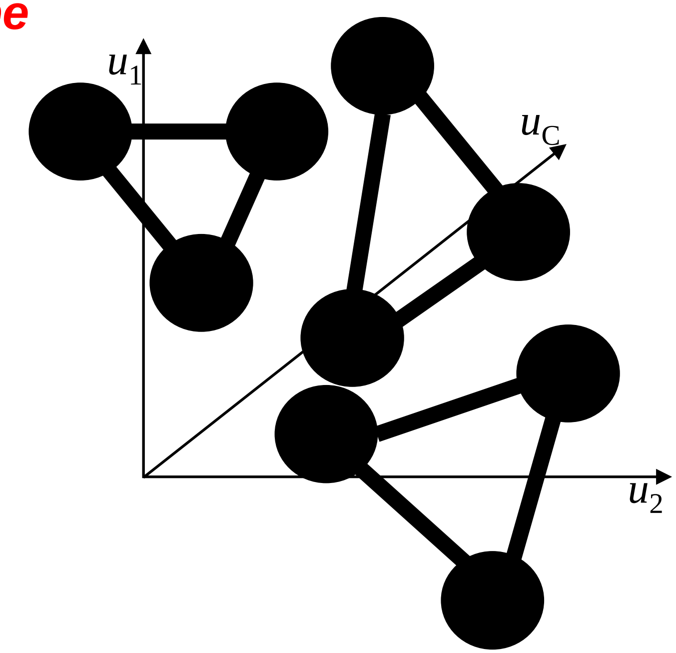
($\lambda_1, \lambda_2, \ldots, \lambda_C$ are very small, but λ_{C+1} is relatively large)

5- Compute the first C eigenvectors $\vec{u}$ of L_{sym}

	u^1	u^2	…	u^C
1	.71	0		0
2	.14	.69		0
3	.69	-.14		0
…	0	.71		0
…	0	0	…	.5
…	0	0		.5
N	…	…	…	…

Patterns to be clustered

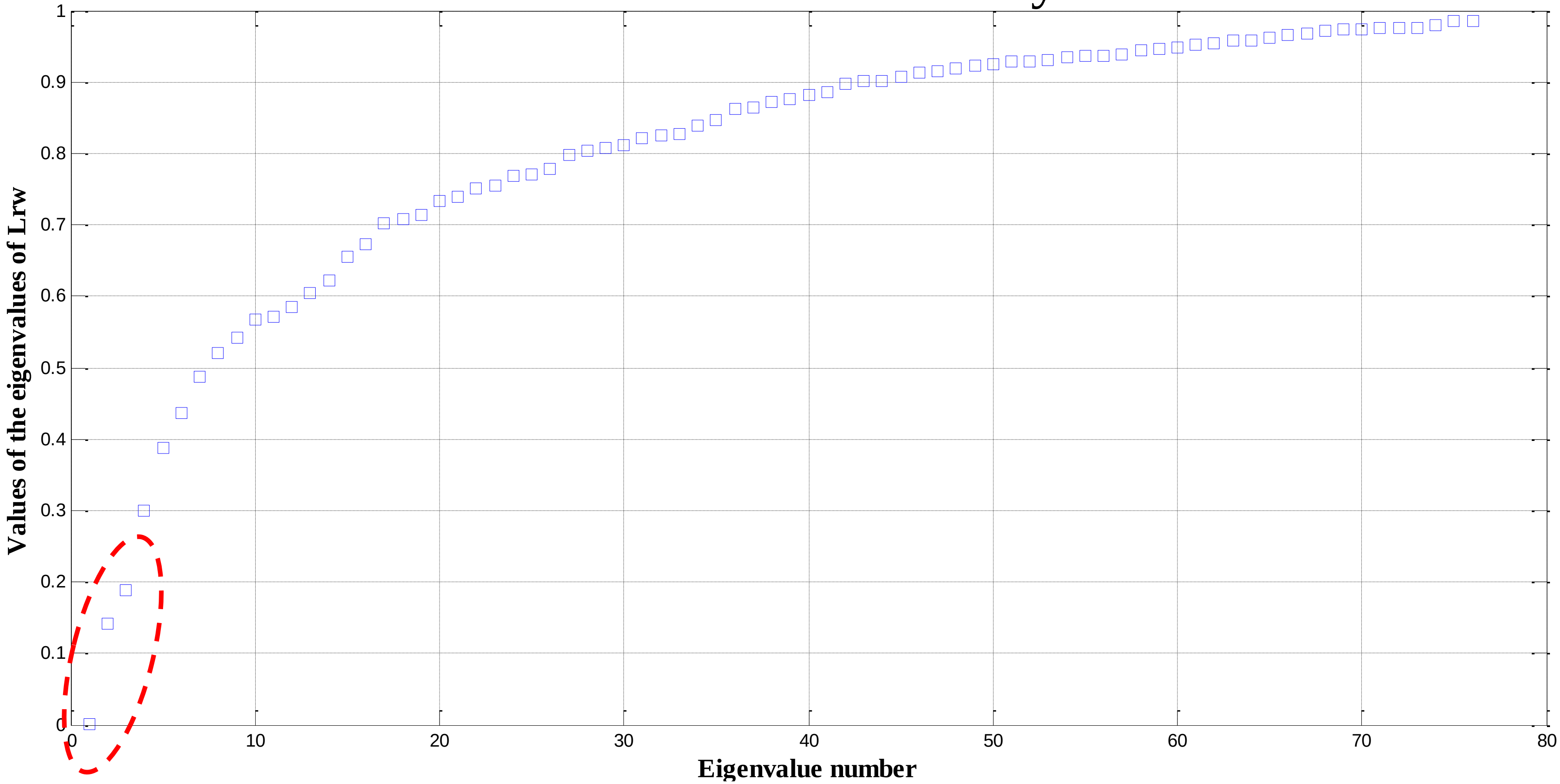
$\vec{u}_i,\ i = 1, \ldots, N$



New Features

Eigenvalues Plot

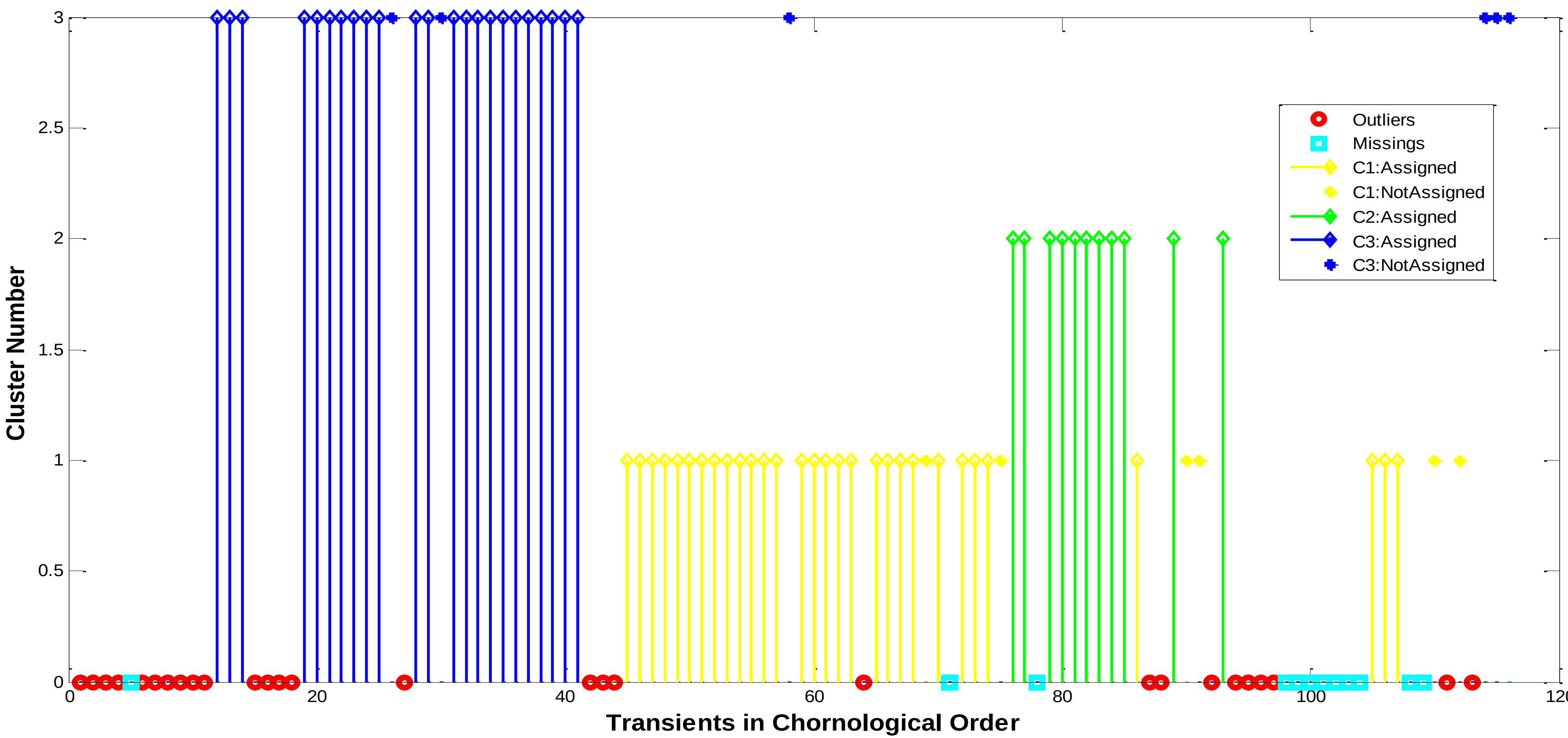
76 eigenvalues obtained by applying spectral analysis method to the 76*76 similarity matrix



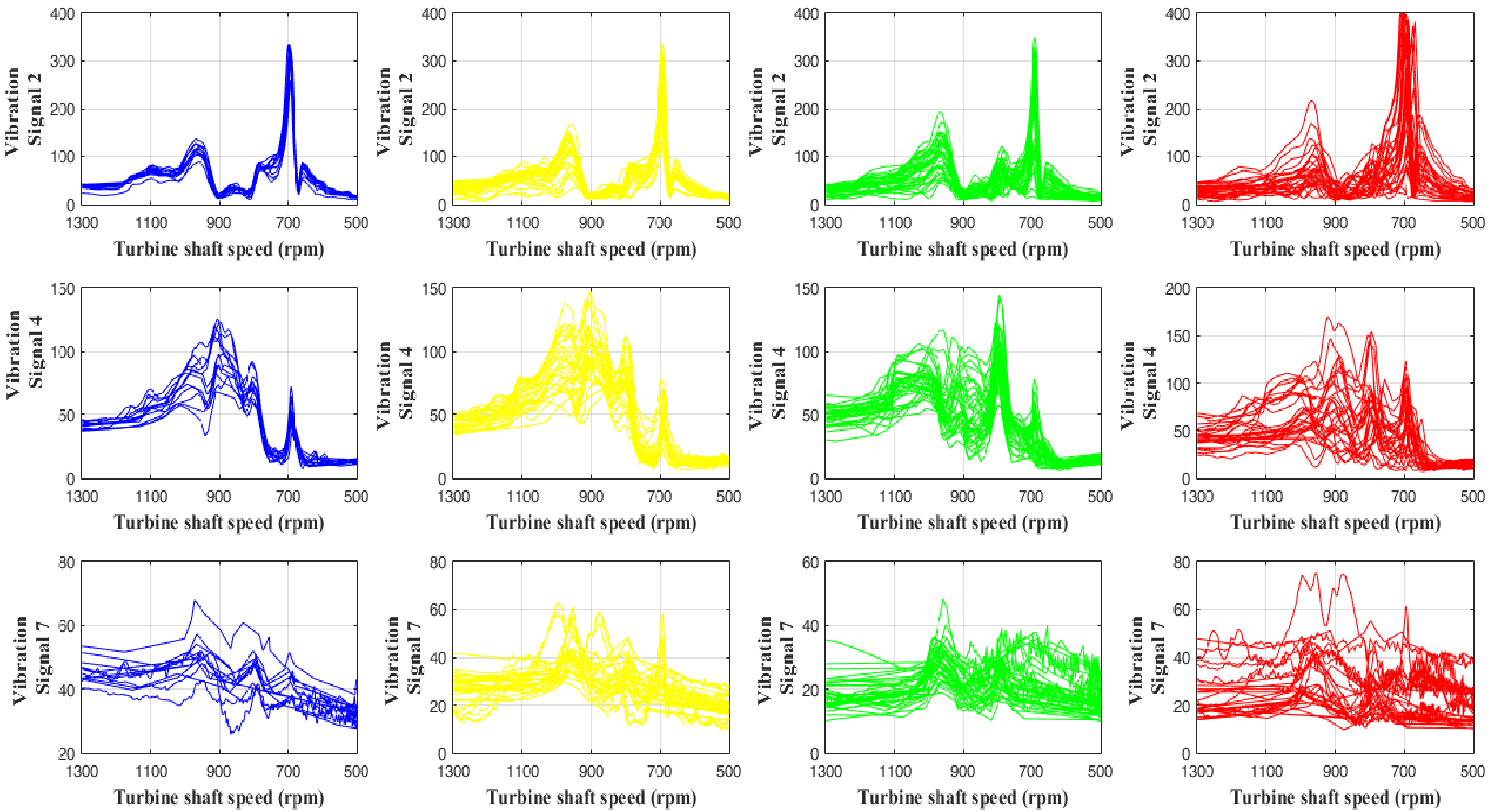
→ 3 Clusters

Result discussion

- The obtained clusters are representative of different operational conditions /maintenance actions done on the component (i.e., chronological order of the transients):



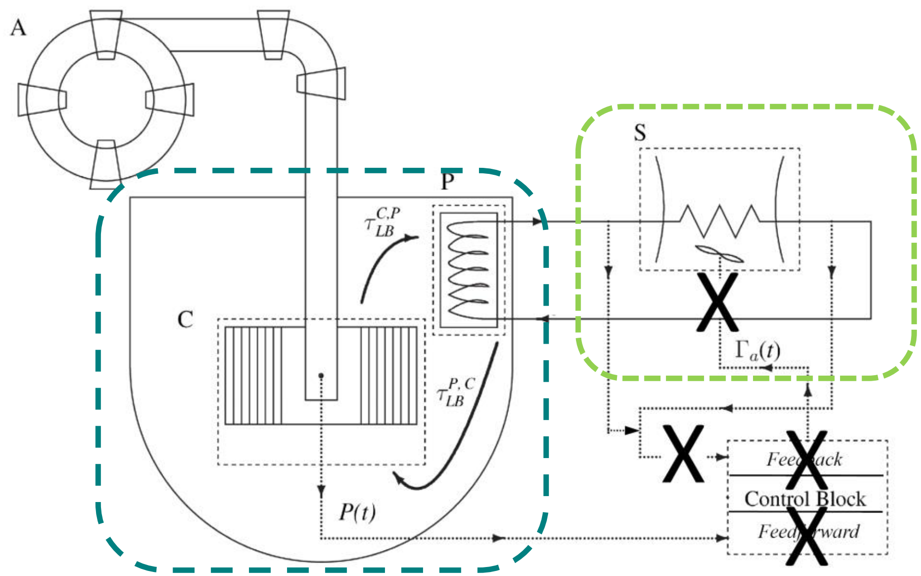
Results: Spectral clustering

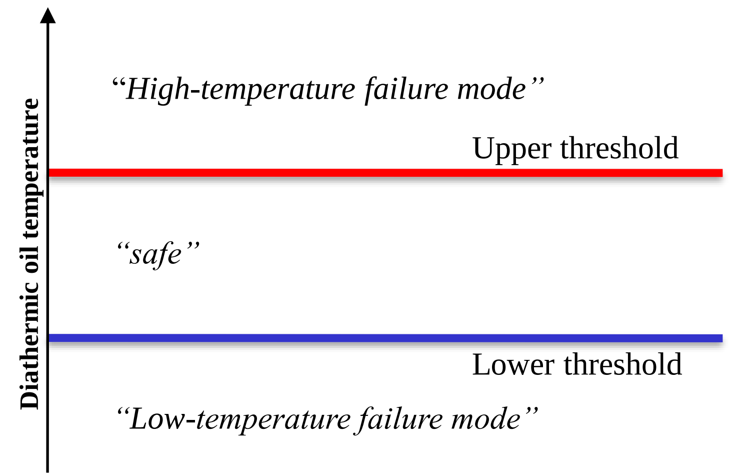


FAULT PROGNOSTICS

Case study: LBE-XADS

The model of the LBE-XADS has been embedded within an MC-driven fault injection engine to sample component failures.





4 control/actuator faults

64 accident scenarios

Data-driven Fuzzy Similarity Approach

Similarity-based approach for prognostics of the available Remaining Useful Life

Library of reference trajectory patterns

Data from failure dynamic scenarios of the system

Fuzzy-similarity comparison

New developing accidental scenario

prediction

Remaining Useful Life (RUL)

Methodology: Fuzzy Similarity Analysis

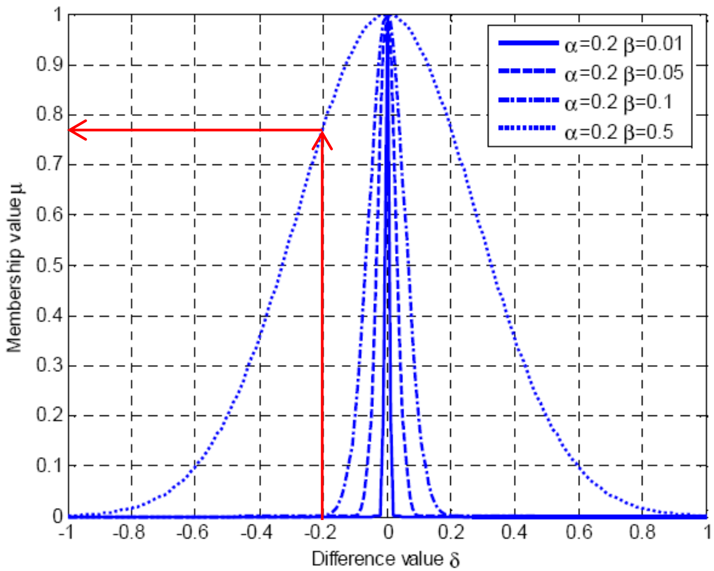
1- Trajectory pointwise difference computation:

$$\delta(i,j) = \tilde{f}(t) - r(i,j), \quad i = 1,2,\ldots,N, \quad j = 1,2,\ldots,k$$

n-long test trajectory pattern (Fig.1)

n-long , j-th interval of the i-th treference trajectory pattern (Fig. 1)

2- Trajectory pointwise similarity computation:



$\mu(i,j)$ is the membership value of the distance $\delta(i,j)$ to the condition of "approximately zero"

3- $RUL_i(t)$ estimation:

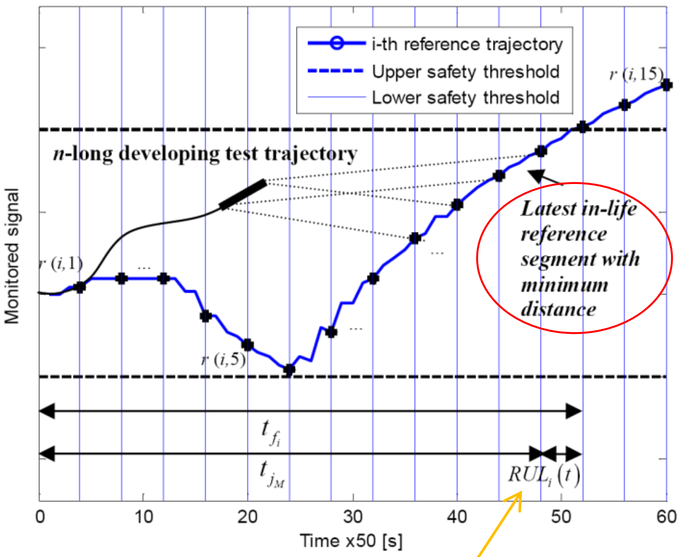


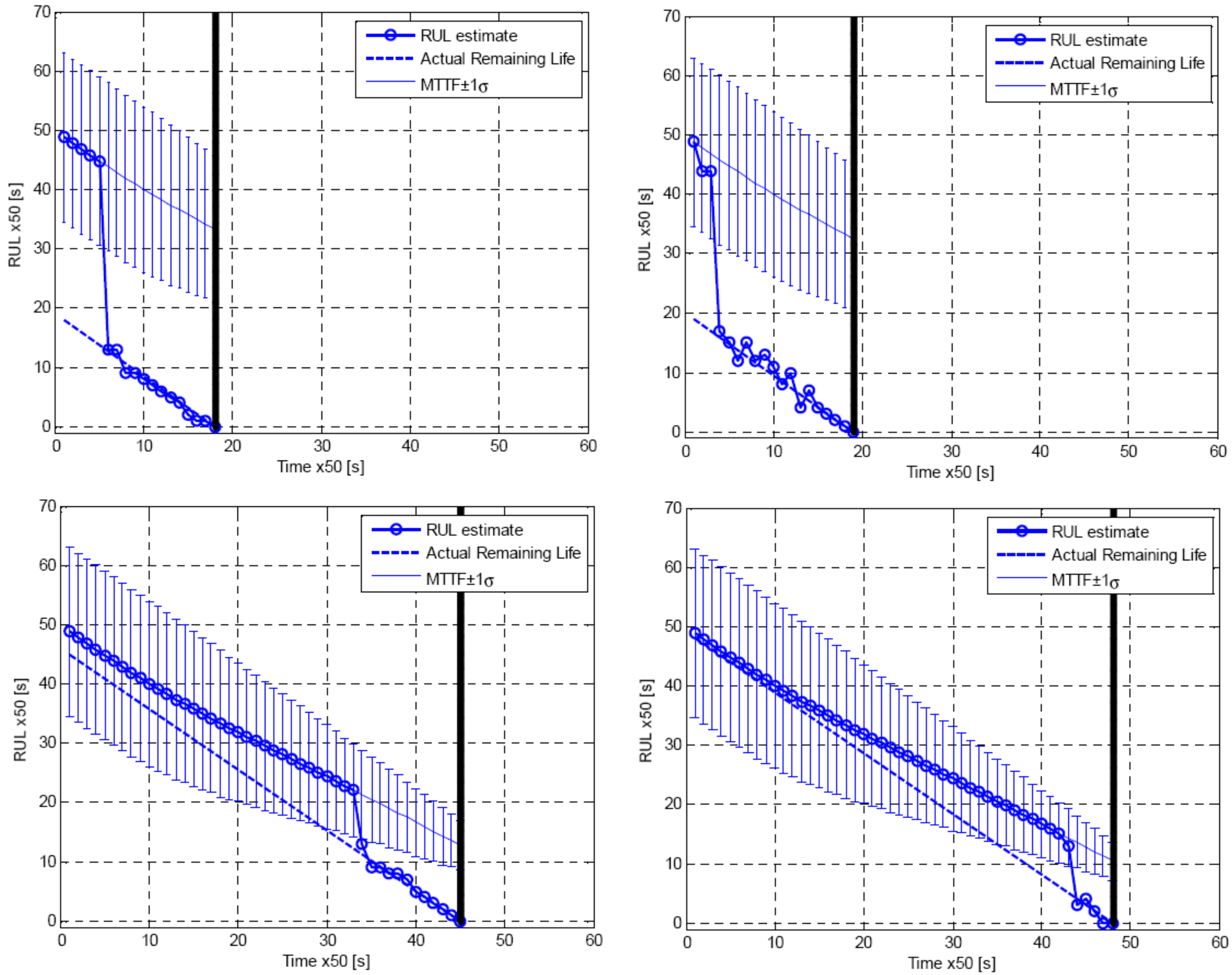
Figure 1

4- *RUL* estimation:

Weighted sum of the RUL_i , i=1,2,…,*N*

$$RUL = w_i \cdot RUL_i \text{ with } i=1,2,\ldots,N$$

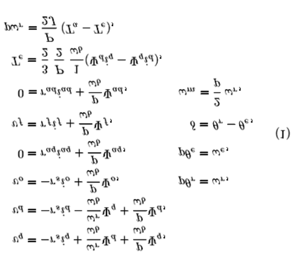
Results

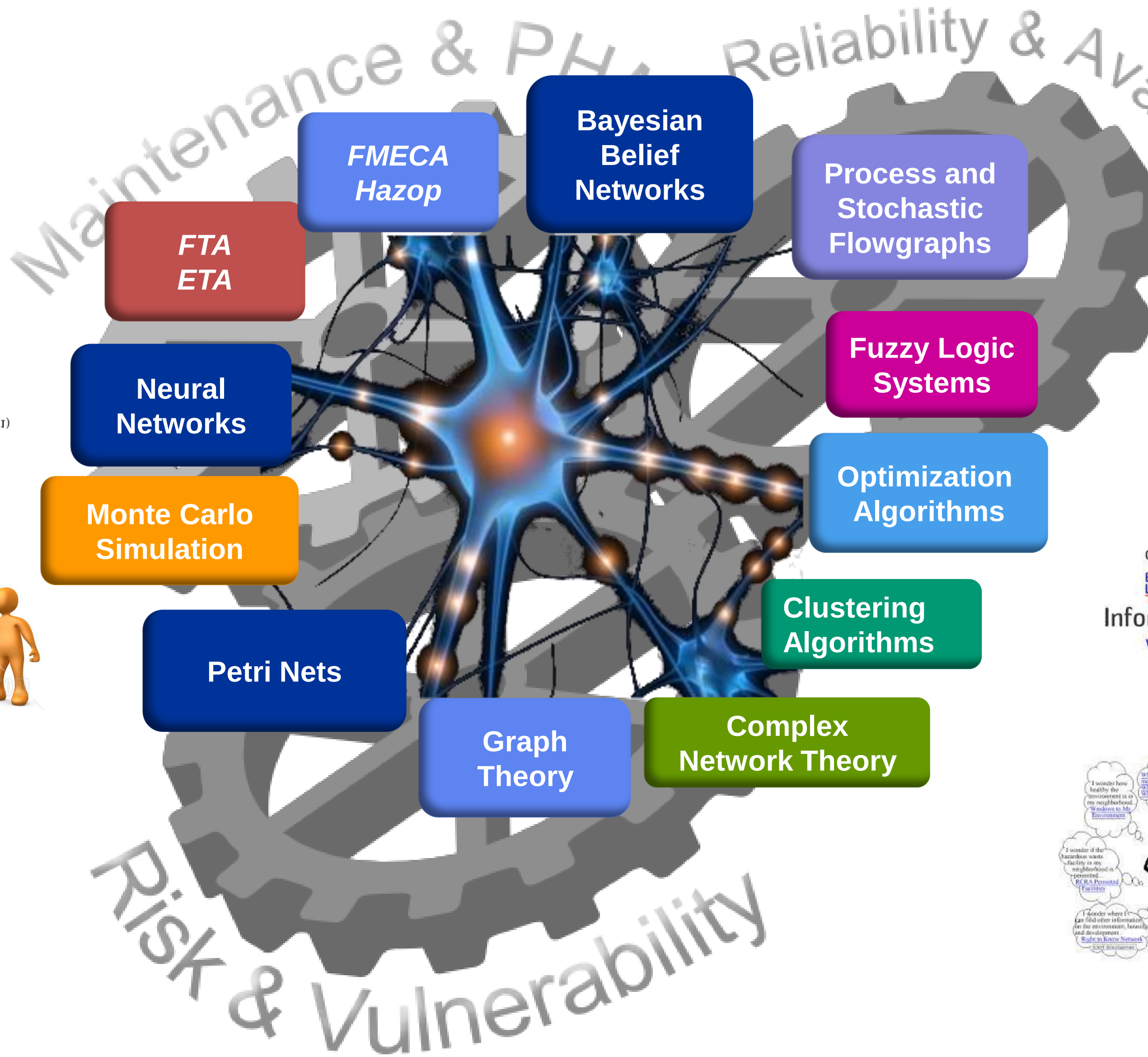


RUL estimate
Actual Remaining Life
MTTF±1σ
RUL x50 [s]
Time x50 [s]
0
10
20
30
40
50
60
70


Maintenance & PHM
Reliability & Availability
Risk & Vulnerability

Tools for a SMART Reliability and Maintenance Engineering for Modern Industry





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