ARAMIS reliable innovation

FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

CentraleSupélec

POLITECNICO DI MILANO

Challenges and opportunities in reliability engineering: the big KID (Knowledge, Information and Data)

Enrico Zio

Chair on Systems Science and the Energy Challenge – CentraleSupelec, Fondation Electricité de France (EDF), France

Energy Department, Politecnico di Milano, Italy

Aramis Srl, Italy

CentraleSupélec

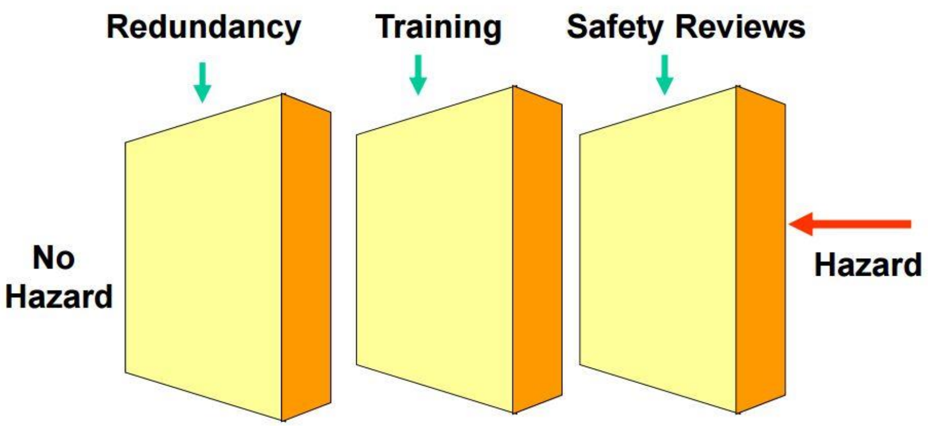
ARAMIS reliable innovation

FONDATION EDF
Science - Enseignement
en partenariat avec l'Institut de France

Failures

Prevented by

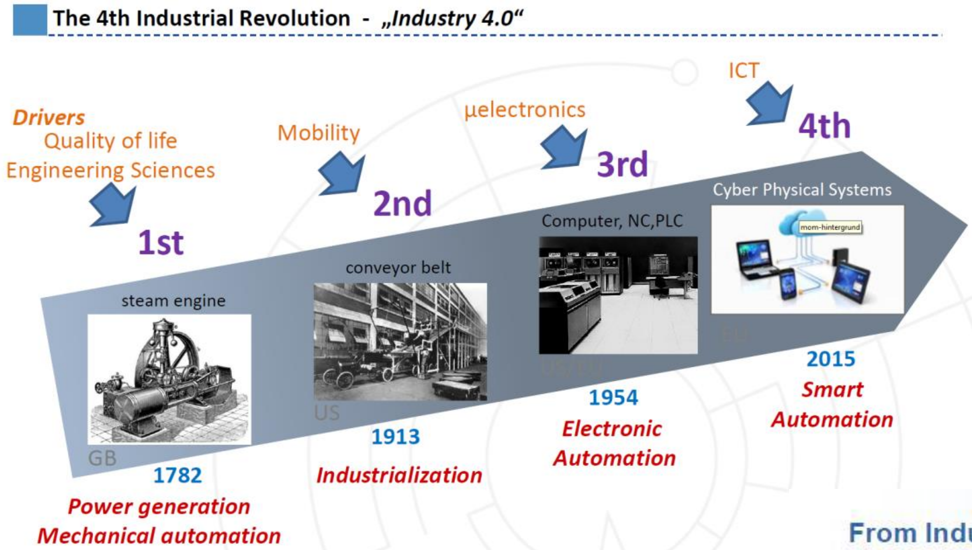
Design for Reliability

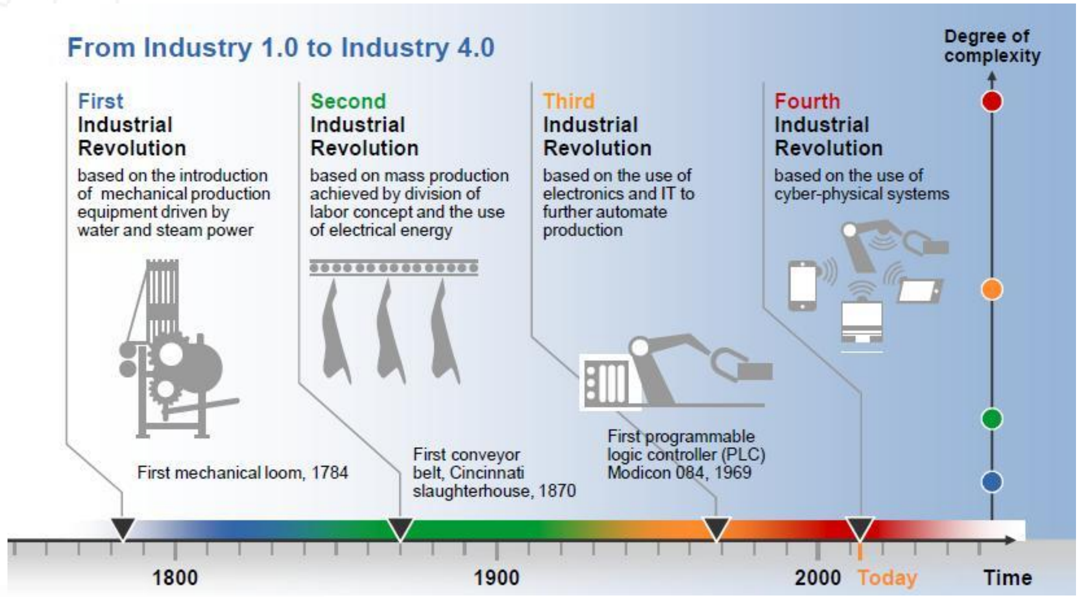


Maintenance

INDUSTRY

Industry 1-2-3-4

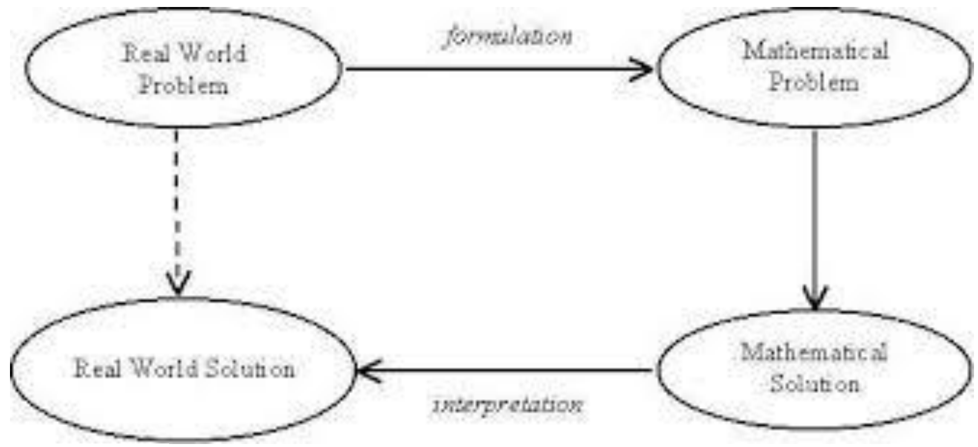




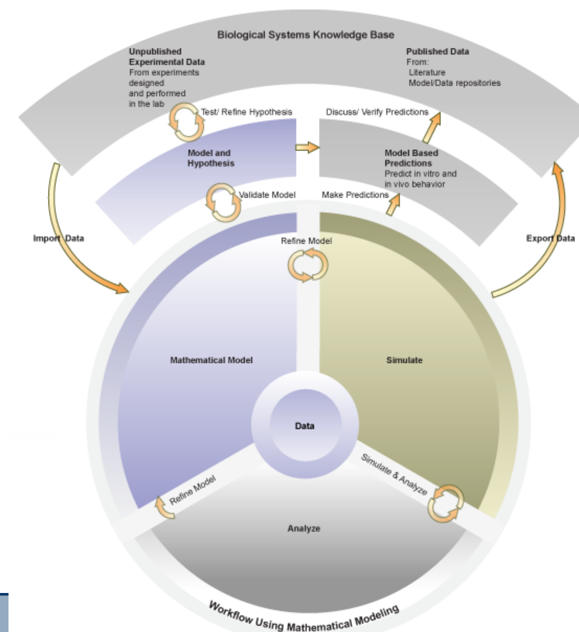
(SMART) Reliability Engineering

The Big KID

Big Knowledge(ID)



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



CentraleSupélec

ARAMIS reliable innovation

FONDATION EDF
Science - Enseignement
en partenariat avec l'Institut de France

Big (K)Information(D)

CentraleSupélec
ARAMIS reliable innovation
FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

Big (KI)Data

1110101001010001011100100101011000010101001

1101110111011101010010100010111001001010110

0001010100111011101110111010100101000101110

0100101011000010101001110111011101110101001

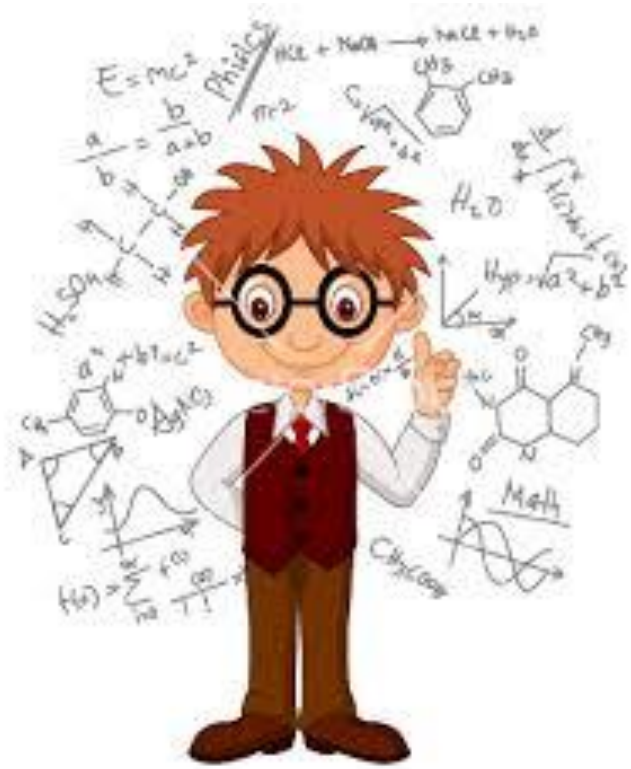
0100010111001001010110000101110101001010001

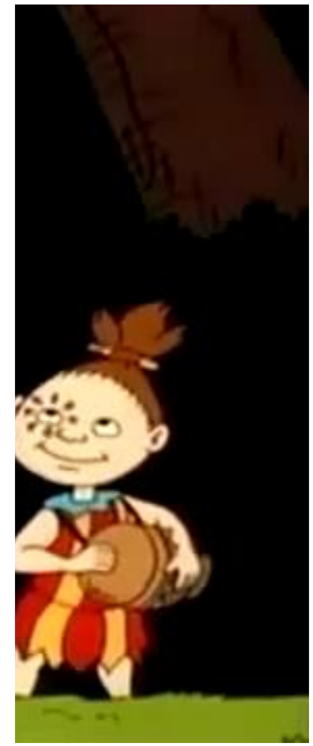
0111001001010110000101010011101110111011101

0100101000101110010010101100001010100111011

1011101110101001010001011100100101011000010

Can the Big KID become SMART for Reliability Engineering ?



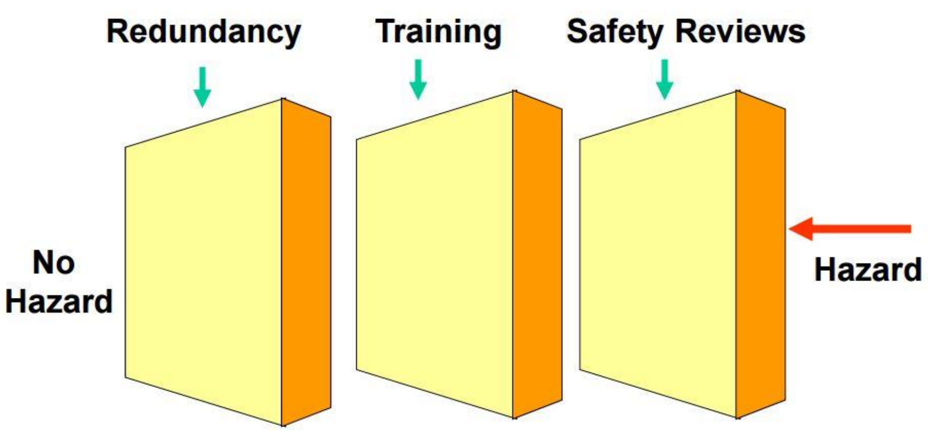


Problem statement

Failures

Prevented by

Design for Reliability | **Maintenance**



Reliability analysis for Design for Reliability:

From failure modeling to degradation-to-failure modeling

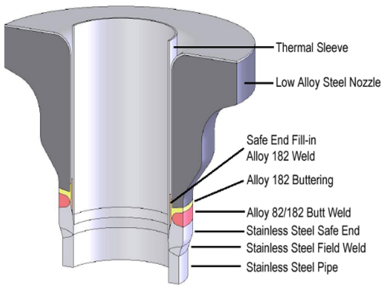
Reliability analysis for Design for Reliability:

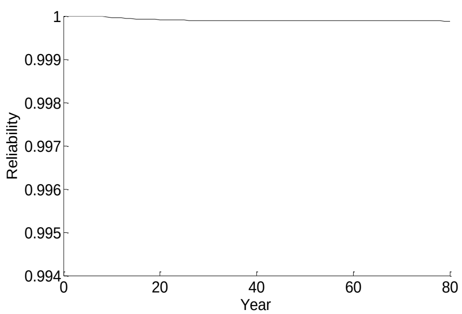
From failure modeling to degradation-to-failure modeling

Integrating physics-of-failure knowledge in reliability models

- Multi-State Physic-Based Models

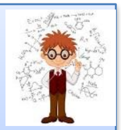
Reliability ?





Highly reliable

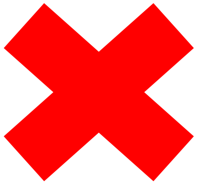
KID
(Knowledge, Information, Data)



Model

Sufficient failure data

- Statistical models of time to failure
- Stochastic process models



Physics knowledge
Expert judgment
Field data

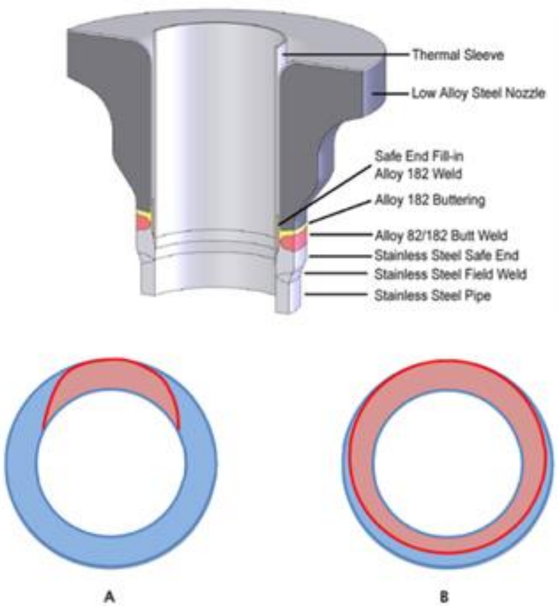
- Physics-based models
- Multi-state models

CentraleSupélec

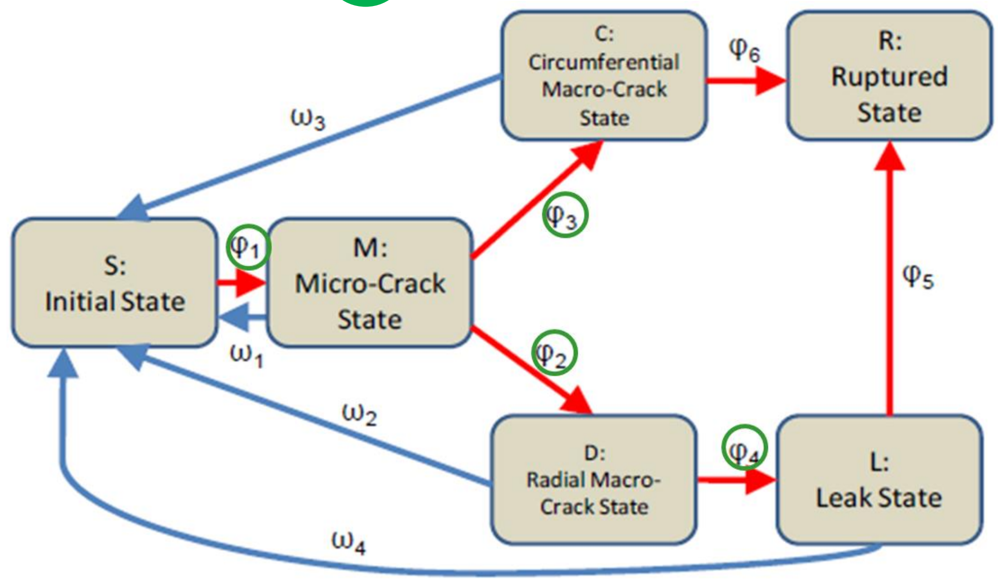
ARAMIS reliable innovation

FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

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

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

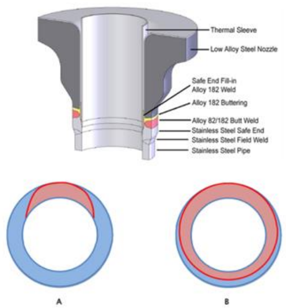
$$\varphi_2 = \begin{cases} \dfrac{a_D P_D}{\dot{a}_M u^2 (1 - P_D(1 - a_D/(u\dot{a}_M)))}, & if\ u > a_D/\dot{a}_M \\ 0, & else \end{cases}$$

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

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

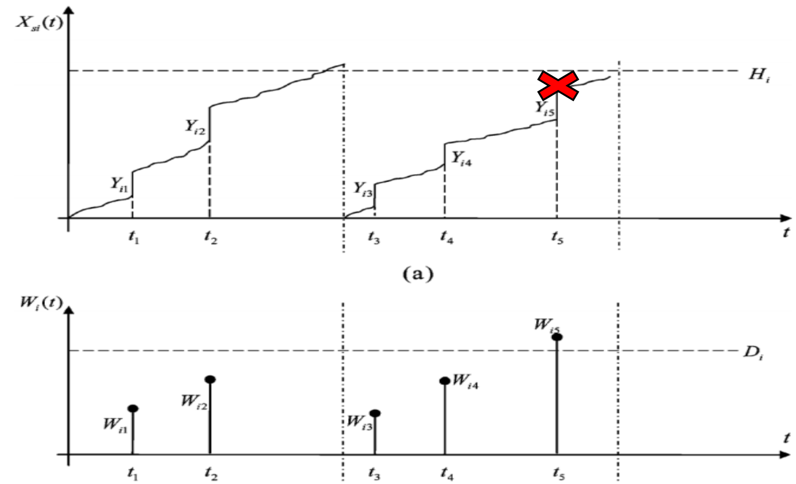
SMART Reliability Engineering – component Opportunities

Random shocks



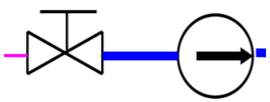
Degradation process

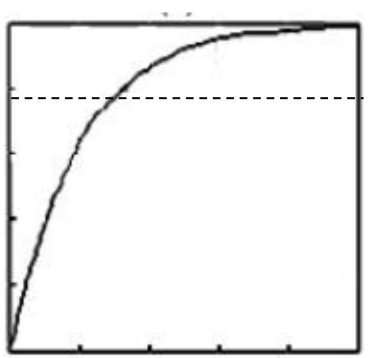
Random shock process



Dependences in degradation processes

Internal leak



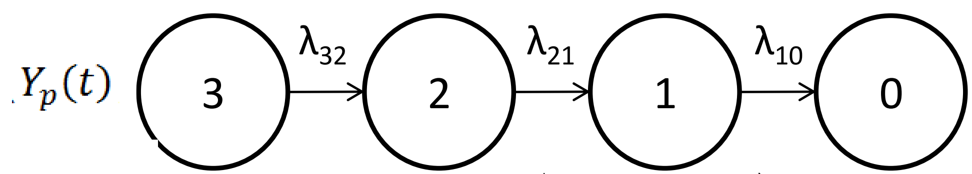


$D_b(t)$

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

Initial state

Failure state



$$Z(t) = \begin{pmatrix} D_b(t) \\ Y_p(t) \end{pmatrix}$$

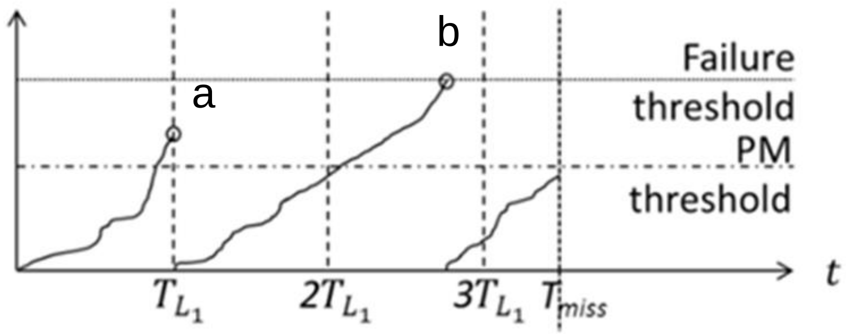
CentraleSupélec

ARAMIS reliable innovation

FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

Maintenance

Degradation process



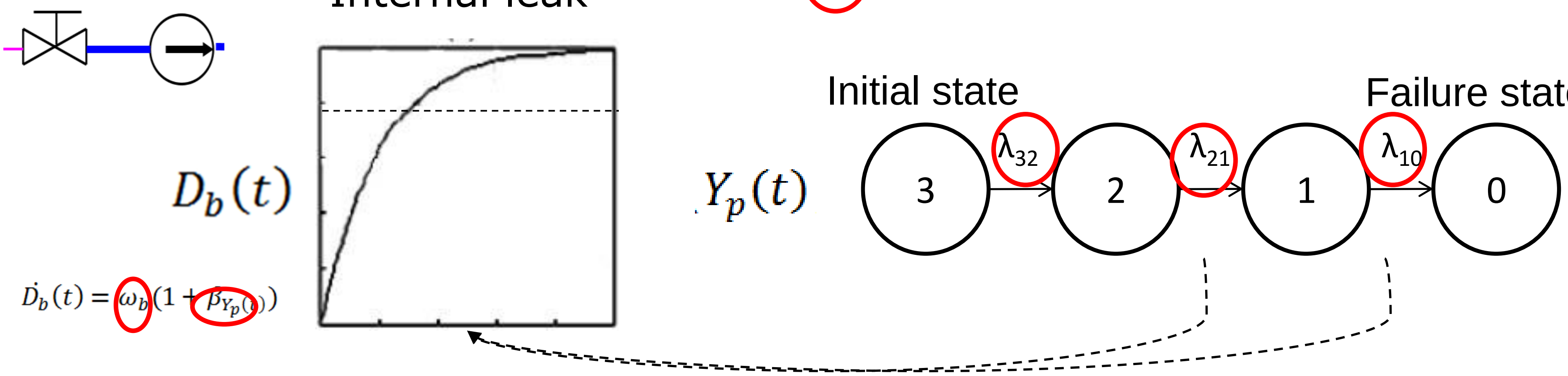
Preventive maintenance (a)

Corrective maintenance (b)

Uncertainty

Uncertain parameters in degradation models

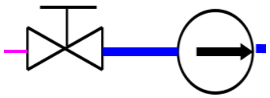
Internal leak

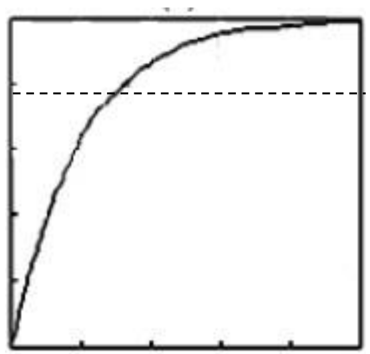


$\dot{D}_b(t) = \omega_b(1 + \beta_{Y_p(t)})$

Degradation processes

Internal leak



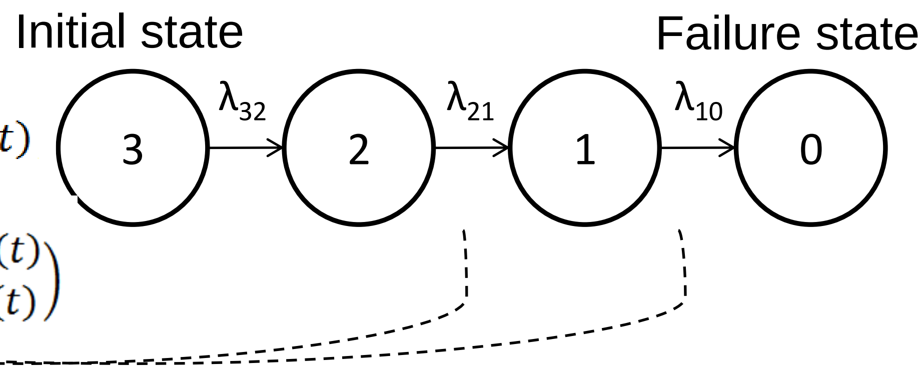


$D_b(t)$

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

$Z(t) = \begin{pmatrix} D_b(t) \\ Y_p(t) \end{pmatrix}$

$Y_p(t)$



Piecewise-deterministic Markov process (PDMP)

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

$$= \boldsymbol{f}_L{}^{Y(t)}(\boldsymbol{X}(t), t \mid \boldsymbol{\theta}_L)$$

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

$$= \lambda_i(j \mid \boldsymbol{X}(t), \boldsymbol{\theta}_K), \forall\, t \geq 0, i, j \in \boldsymbol{S}, i \neq j$$

CentraleSupélec ARAMIS reliable innovation FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

MC Simulation

While $k < N_{max}$

Initialize the system by setting $Z' = \begin{pmatrix} X(0) \\ Y(0) \end{pmatrix}$ (initial state), and the time $T = 0$ (initial system time)

Set $t' = 0$ (state holding time)

While $T < T_{miss}$

Sample a t' by using the probability density function (3.7)

Sample an arrival state Y' for stochastic process $Y(t)$ from all the possible states by using the conditional probability distribution (3.8)

Set $T = T + t'$

Calculate $X(T)$ by using the physics eq. (3.3)

Set $Z' = \begin{pmatrix} X(T) \\ Y' \end{pmatrix}$

If $T \leq T_{miss}$

If $Z' \in \mathcal{F}$

Set $k' = k' + 1$

Break

End if

Else (when $T > T_{miss}$)

Calculate $Z(T_{miss})$

If $Z(T_{miss}) \in \mathcal{F}$

Set $k' = k' + 1$

Break

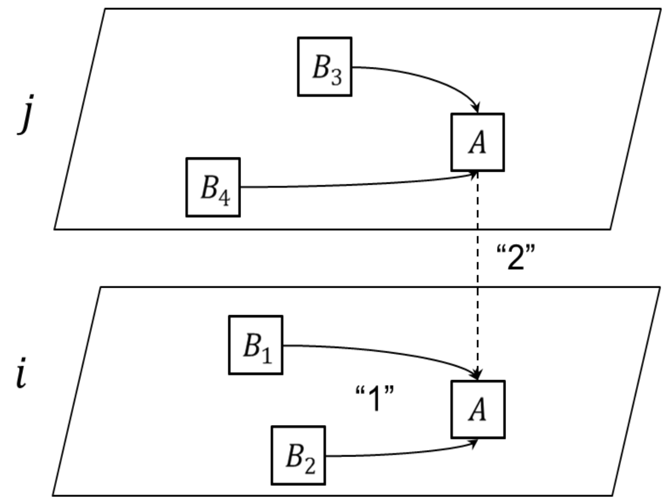
End if

End if

End While

Finite-volume scheme

$$P_{n+1}(A, i \mid \boldsymbol{\theta}) = \frac{1}{1 + \Delta t b_A^i} \widehat{P_{n+1}}(A, i \mid \boldsymbol{\theta}) + \Delta t \sum_{j \in S} \frac{a_A^{ji}}{1 + \Delta t b_A^j} \widehat{P_{n+1}}(A, j \mid \boldsymbol{\theta})$$



Reliability analysis for Design for Reliability:

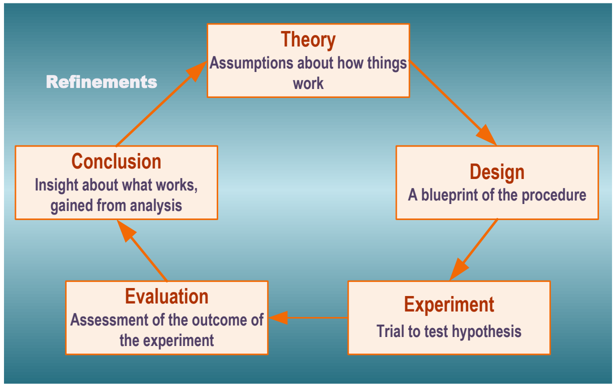
From failure modeling to degradation-to-failure modeling

Integrating physics-of-failure knowledge in reliability models

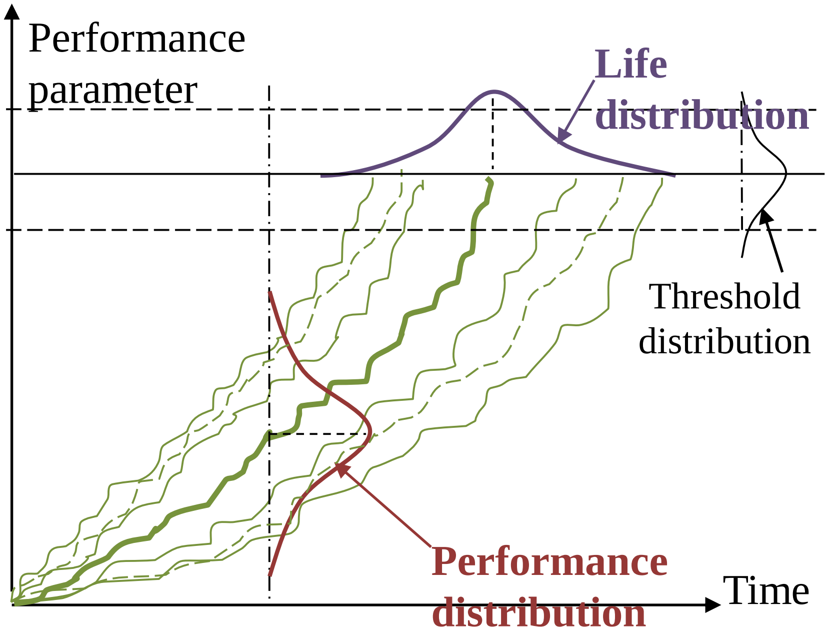
- Multi-State Physic-Based Models

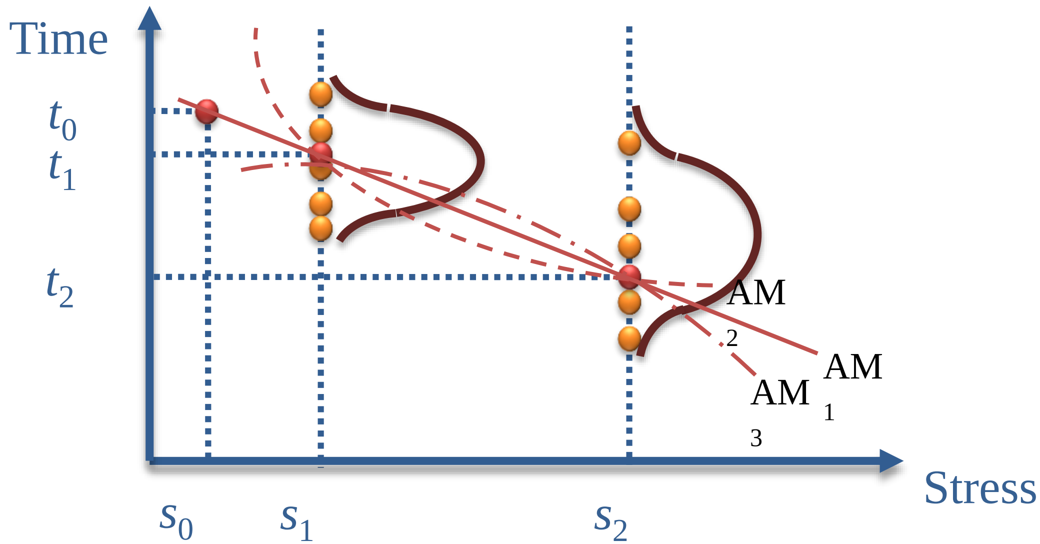
?And the data?

ADT Procedure



General testing procedure





Degradation Model:

Degradation VS Time

<u>Stochastic process or degradation-path:</u>

Wiener process: $Y(t) = \sigma B(t) + d(S)t$

Acceleration Model:

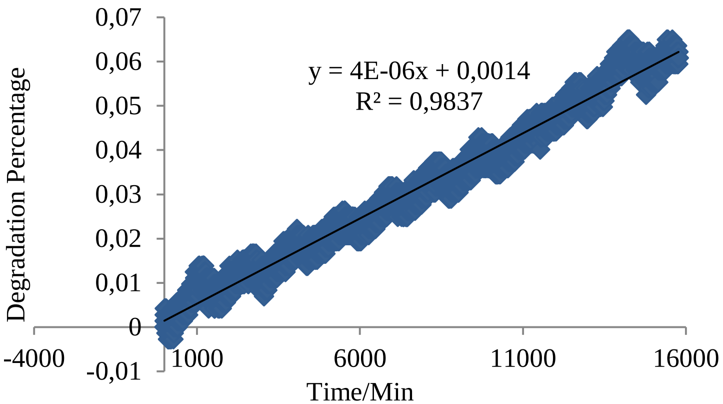
Stress VS Time

<u>Physical or empirical models:</u>

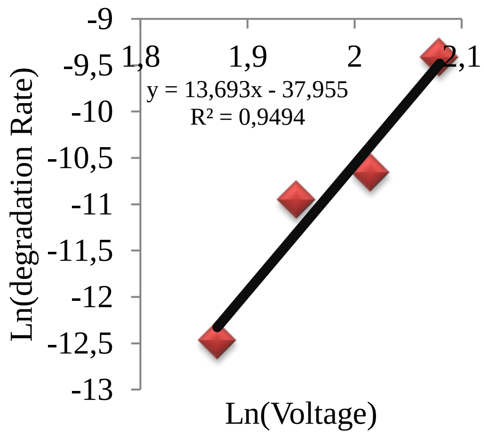
Arrhenius: $d(S) = Ae^{-E_a/kS}$

Data Analysis

Trend analysis & Accelerability Verification:



Degradation VS Time



Time VS Stress

Degradation Process Model

$$Y_l(t)=\sigma B(t)+d(S_l)\cdot t+y_0,\ d(S_l)=\exp[a+b\varphi(S_l)]$$

Maximum Likelihood

$$L(\sigma,a,b)\propto \prod_{l=1}^{k}\prod_{i=1}^{n_l}\prod_{j=1}^{m_l-1}\frac{1}{\sqrt{2\pi\sigma^2\Delta t_{lij}}}\exp\left\{-\frac{\left[x_{lij}-d(S_l)\cdot\Delta t_{lij}\right]^2}{2\sigma^2\Delta t_{lij}}\right\}$$

$$\sum_{l=1}^{k}\sum_{i=1}^{n}\sum_{j=1}^{m_l-1}\left\{x_{lij}-\exp\left[a+b\cdot\varphi(S_l)\right]\cdot\Delta t\right\}=0$$

Degradation Fitting

$$E\left[Y_l(t)\right]=d(S_l)\cdot t+y_0 \xrightarrow{\text{LSE}} d(S_l)$$

$$d(S_l)=\exp\left[a+b\varphi(S_l)\right] \Rightarrow \ln d(S_l)=a+b\varphi(S_l) \xrightarrow{\text{LSE}} \hat{a}+\hat{b}$$

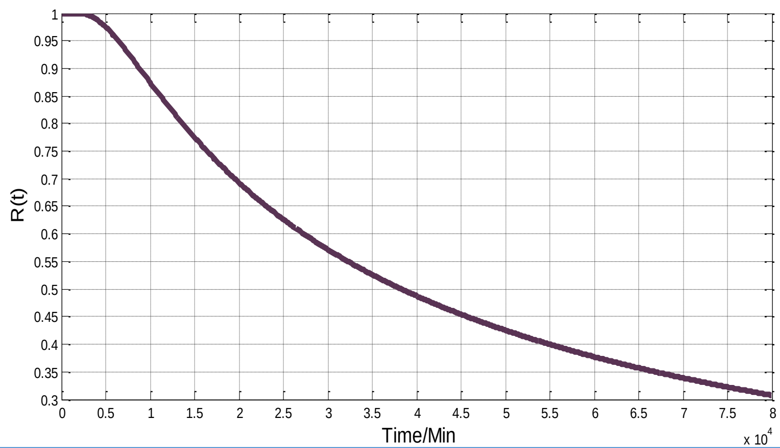
Parameter Estimation

$$\hat{\sigma}^2=\frac{1}{n\cdot(m-k)\Delta t}\cdot\sum_{l=1}^{k}\sum_{i=1}^{n}\sum_{j=1}^{m_l-1}\left[x_{lij}-\exp\left[\hat{a}+\hat{b}\cdot\varphi(S_l)\right]\Delta t\right]^2$$

Parameter estimation:

$\hat{a}$	$\hat{b}$	$\hat{\sigma}^2$
- 36.961	13.112	8.278e-07

Reliability Prediction:



Challenges in ADT

Degradation trend

- The whole trend is defined (linear, exponential, etc.)

Aleatory uncertainty

- Inherent randomness
- Probability

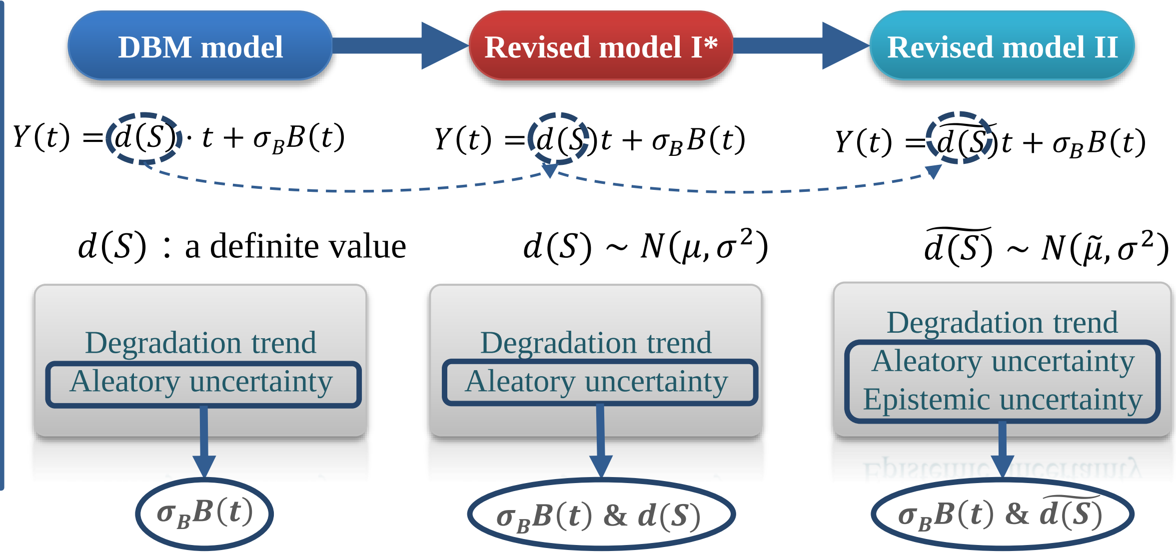
Epistemic uncertainty

- Incomplete knowledge due to limited information
- Interval, possibility, etc.

Challenges:

- ✓ Traditional methods mainly model degradation trend and aleatory uncertainty.
- ✓ Failing to consider epistemic uncertainty may cause serious reliability evaluation problems.

Stochastic Process – some revised models:



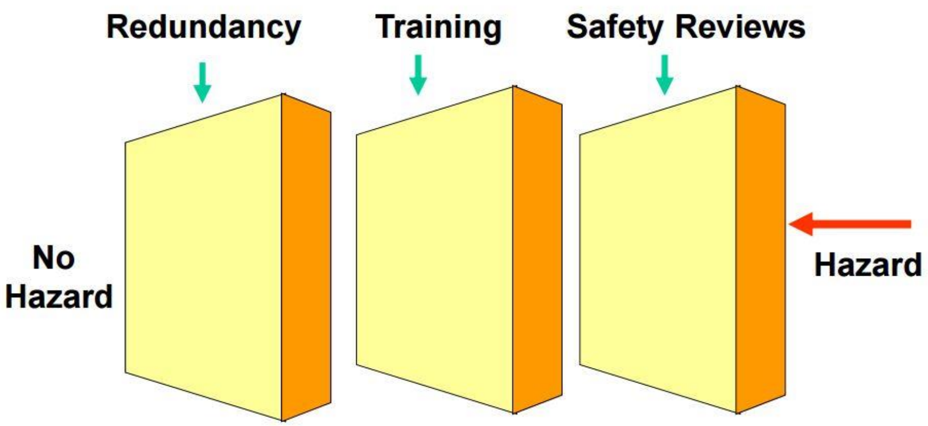
Problem statement

Failures

Prevented by

Design for Reliability

Maintenance



POLITECNICO DI MILANO

Maintenance:

Integrating physics knowledge and data:

- Prognostics and Health Management (PHM)

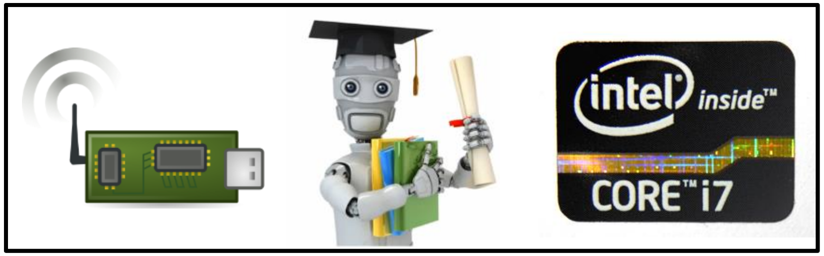
Maintenance

1950	1980	2000	2016

Corrective Maintenance | Planned Periodic Maintenance | Condition Based Maintenance (CBM) | Predictive Maintenance (PrM)

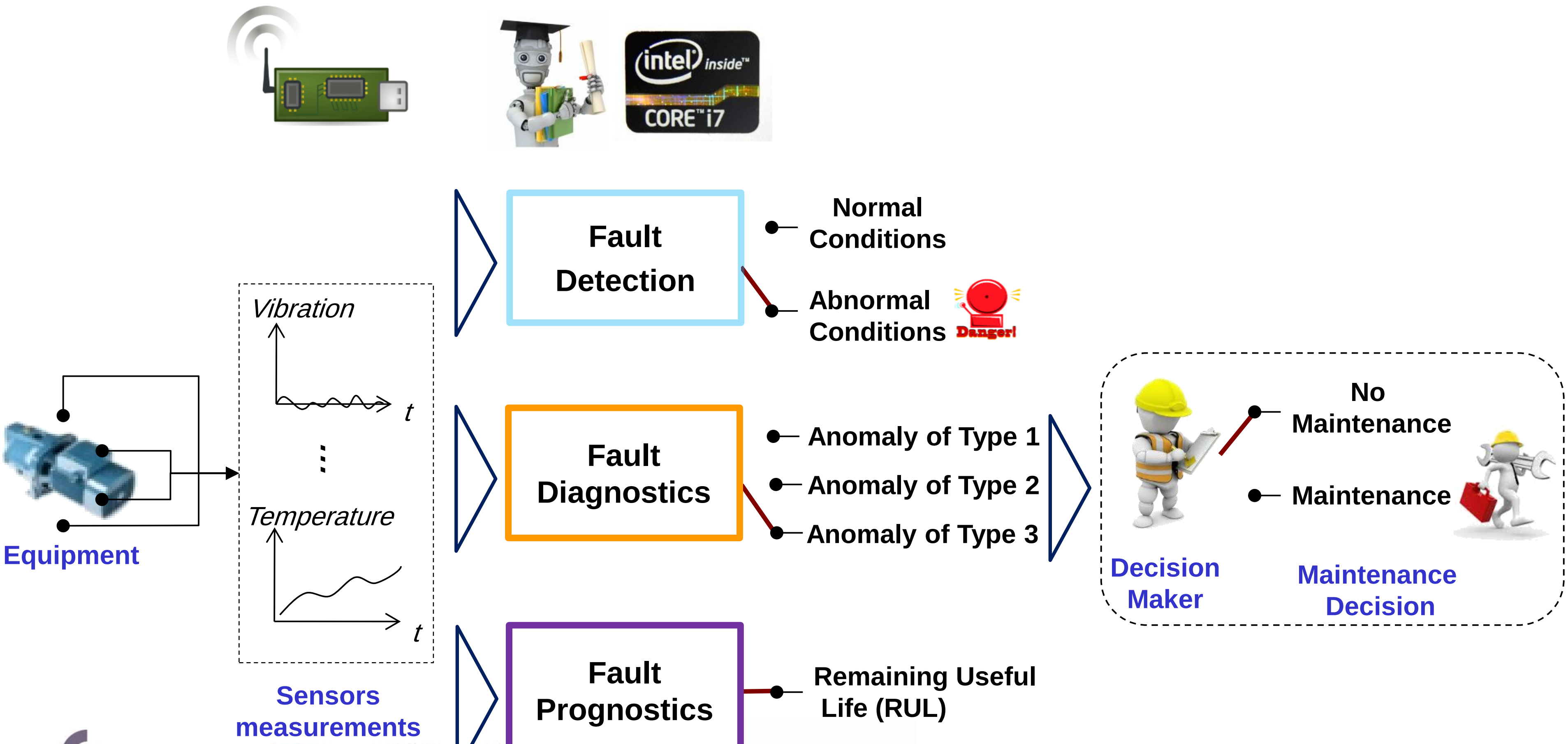
Prognostics and Health Management (PHM)

PHM is fostered by advancements in:



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

PHM in support to CBM and PrM



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

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

PHM: how? (Fault detection)

Signal reconstructions

Real measurements

MODEL OF

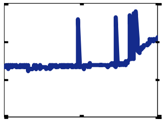
PLANT BEHAVIOR

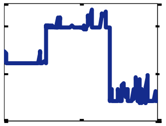
IN NORMAL OPERATION

Nominal Range-based

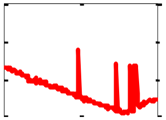
Physics-based

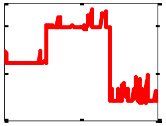
Data-Driven (AAKR, PCA, RNN,…)

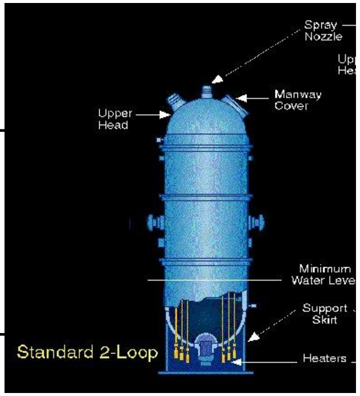




≠







Abnormal Condition

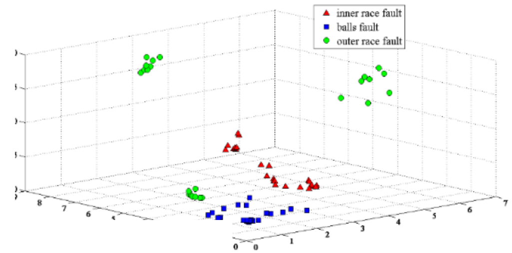
CentraleSupélec

ARAMIS reliable innovation

FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

PHM: how? (Fault diagnostics)

- Signal measurements representative of the fault classes: «x_1,x_2,…x_n, class»



x_1 → x_2 → x_3 →

Empirical Classifier

- **C_1 = Inner race**
- **C_2 = Balls**
- **C_3 = Outer race**

- Empirical classification methods:
  - ***Support Vector Machines***
  - ***K-Nearest Neighbours***
  - ***Multilayer Perceptron Neural Networks***
  - ***Supervised clustering algorithms***
  - ***Ensemble of classifiers***
  - ***…***

CentraleSupélec ARAMIS reliable innovation FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

PHM: how? (Fault prognostics)

Kalman Filter

Particle filter

Model-Based

Monte Carlo Simulation

Autoregressive (AR) models

Similarity-based methods

Data-Driven

Hidden Semi-Markov Models

Artificial Neural Networks

Neuro-fuzzy systems

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

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

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

Degrading component

Similar components

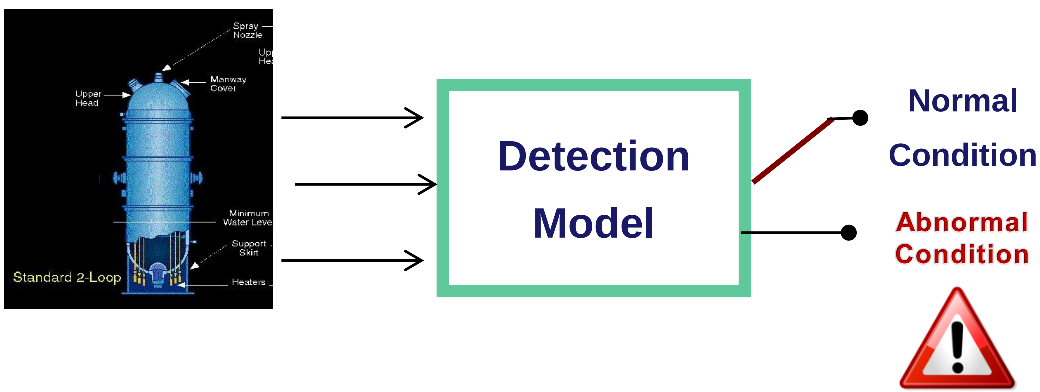
PHM: performance ?

- Accuracy

PHM: performance ? (detection)

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

Example:



False Alarm Rates	Missing Alarm Rates
0.54%	0.98%

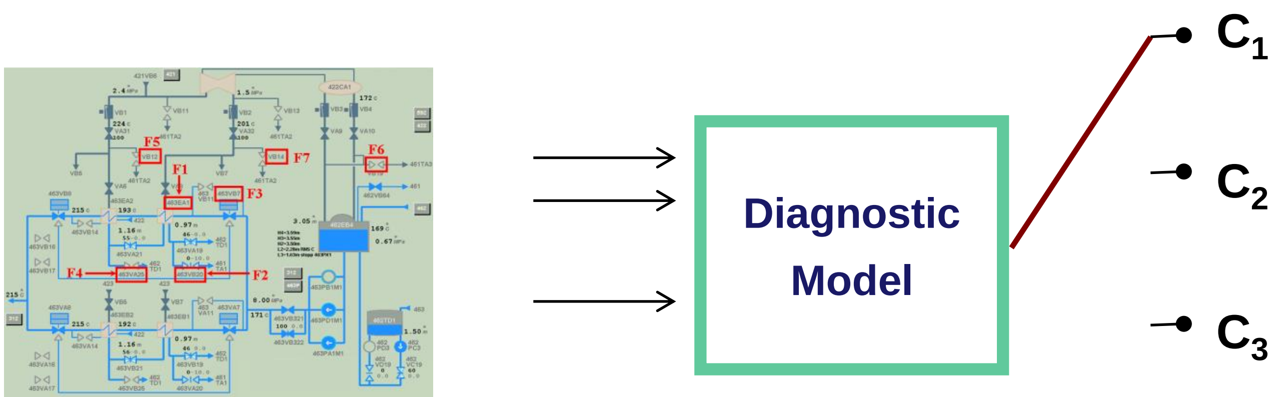
CentraleSupélec

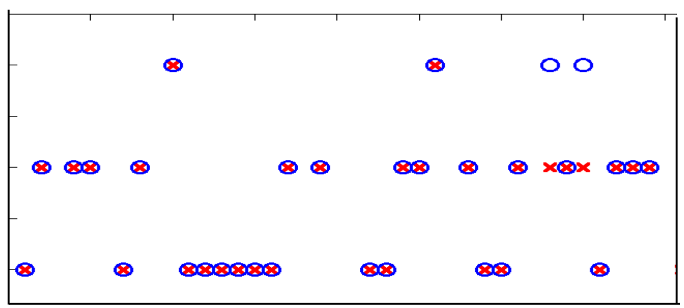
ARAMIS reliable innovation

FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

PHM: performance ? (diagnostics)

- Accuracy
  - Fault diagnostics:
    - Low Misclassification rate

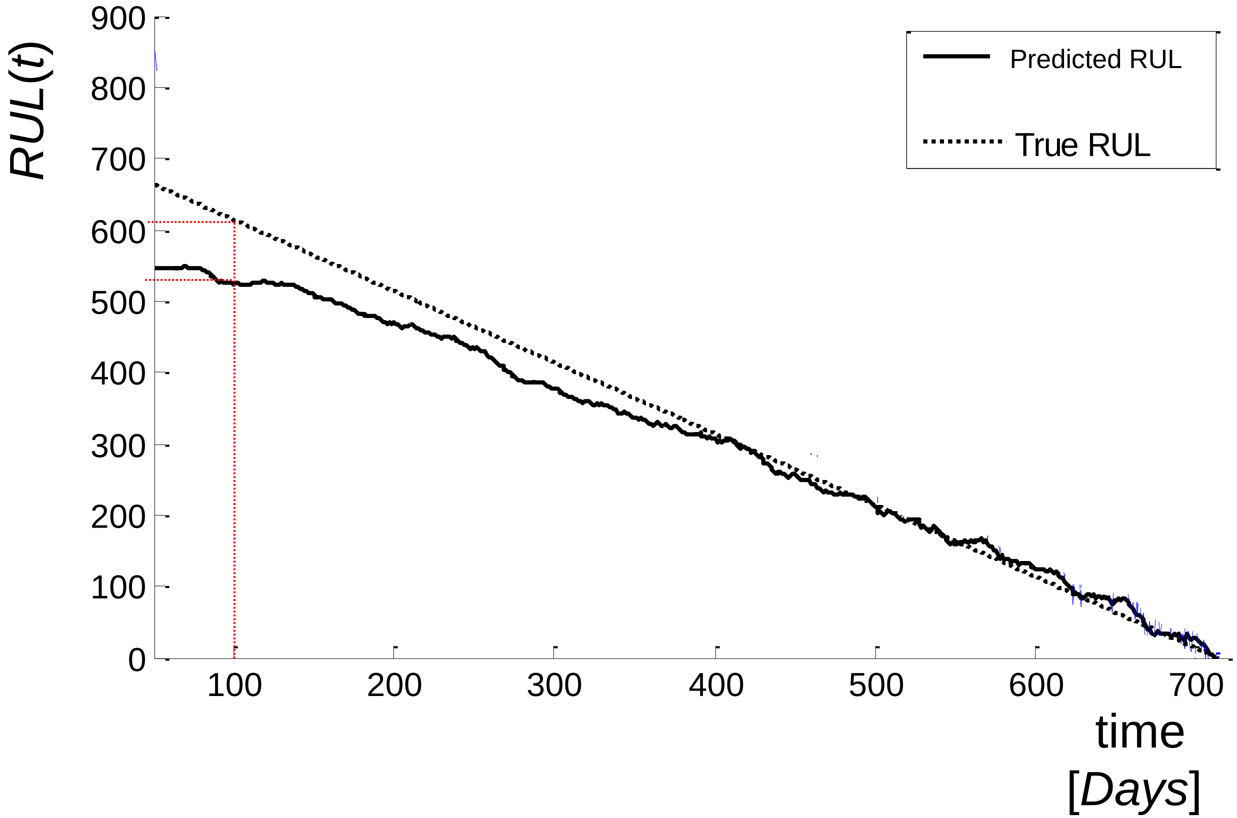




o = true
× = diagnostic model

Misclassification rate = 2.58%

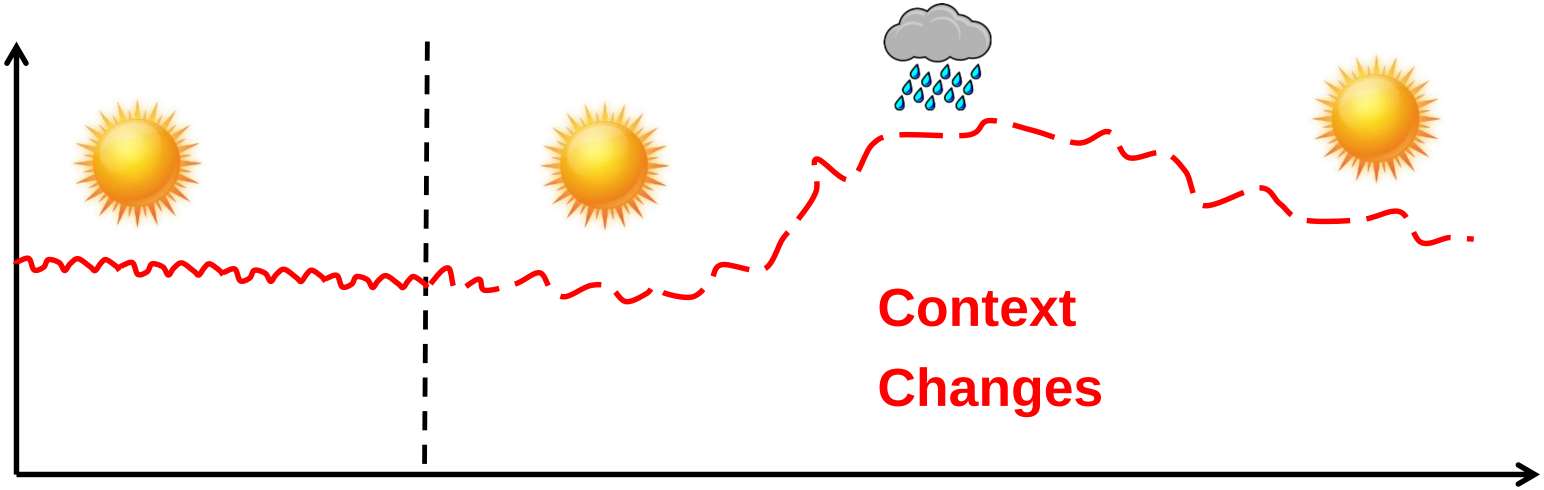
- Accuracy
  - ➢ Prognostics



PHM &

1) Context changing
2) Uncertainty management
3) Fleet
4) Return of Investment
5) Safety

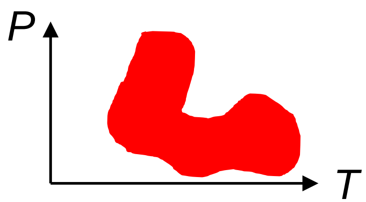
Context changing: concept



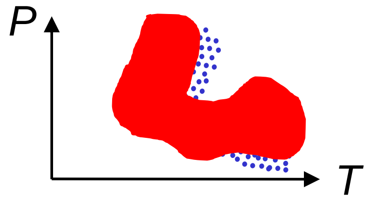
Monitoring components of a (e.g. nuclear power) plant

The detection model should be able to follow the process changes:

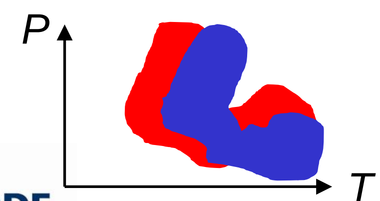
- Incremental learning of the new data that gradually becomes available
- No necessity of human intervention for:
  - selecting recent normal operation data
  - building the new model



New data are coming

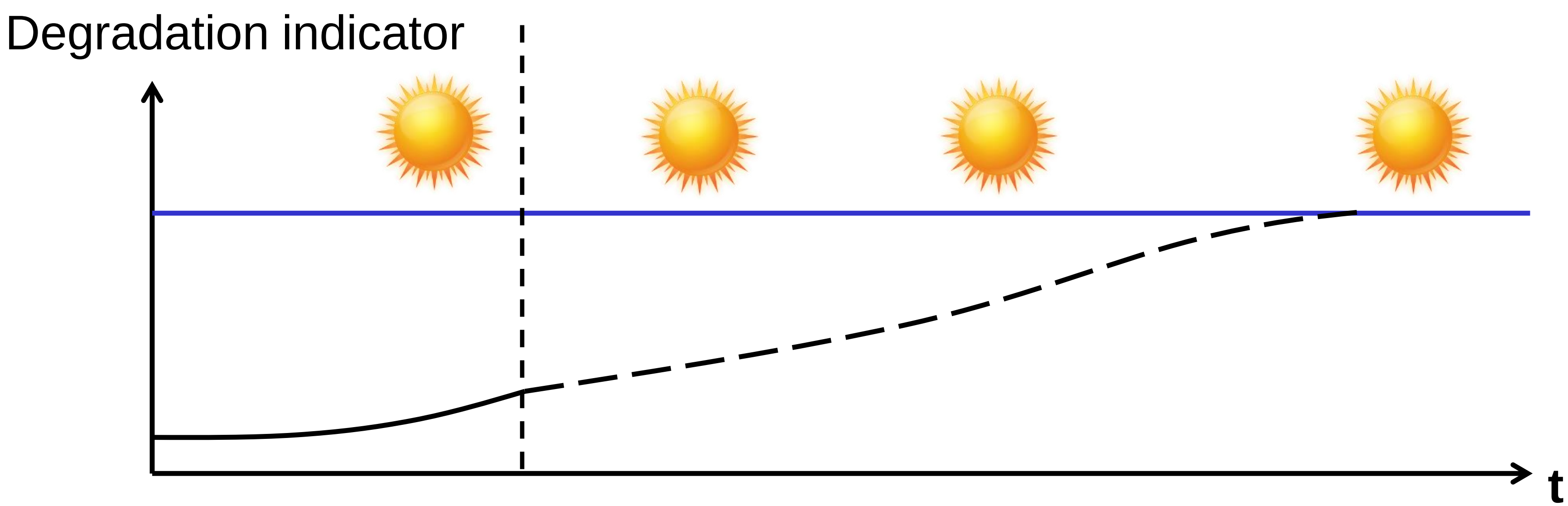


Automatic updating of the model

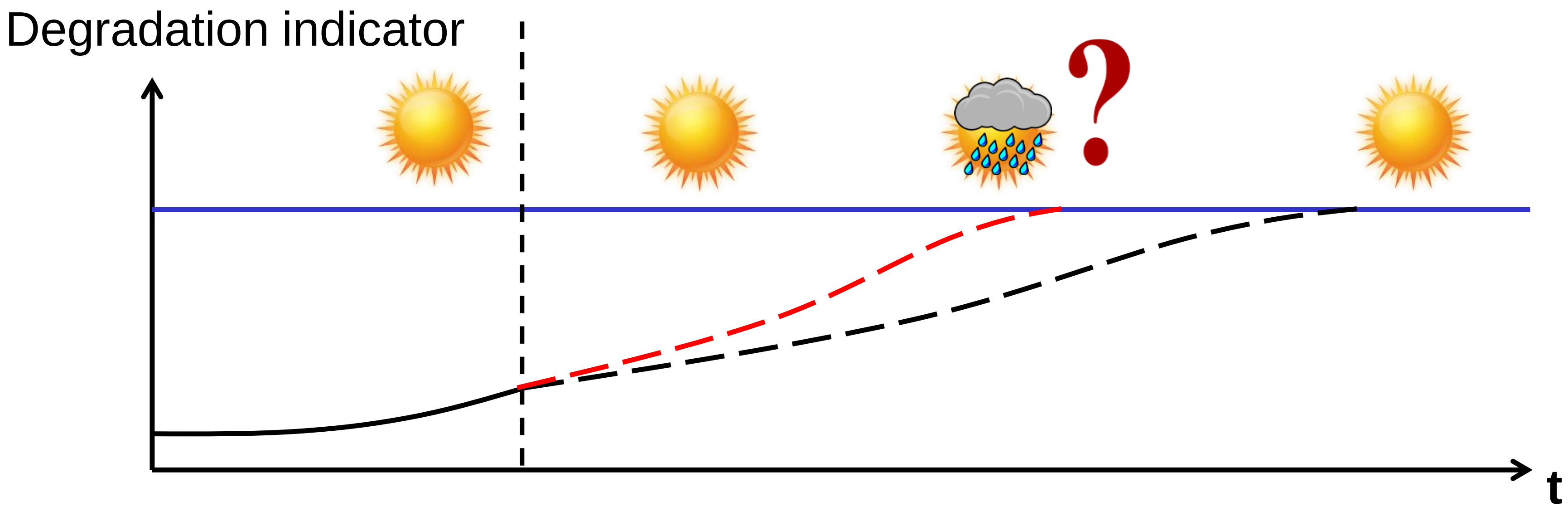


CentraleSupélec ARAMIS reliable innovation FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

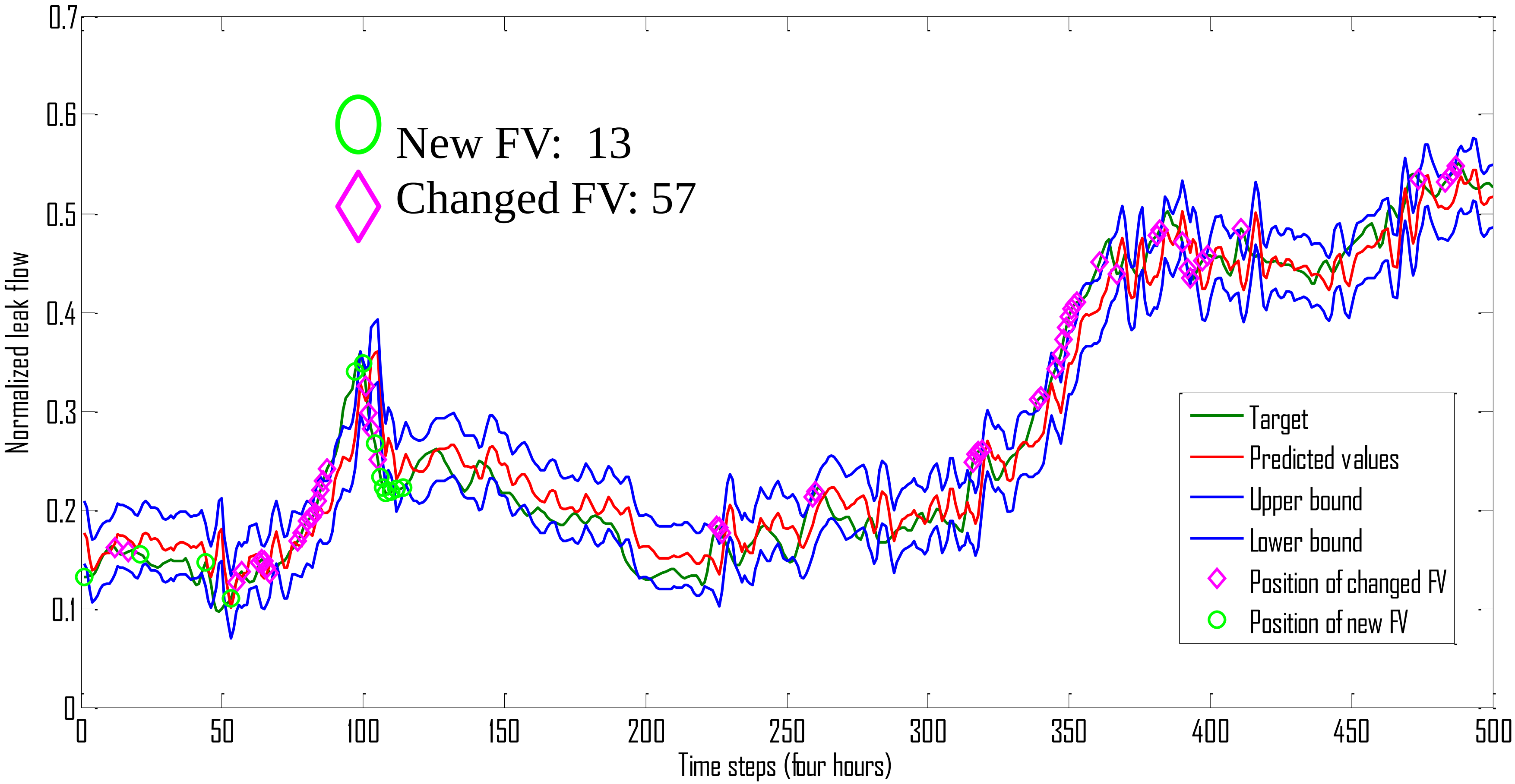
Context changing (fault prognostics)



Context changing (prognostics)



Context changing (fault prognostics)



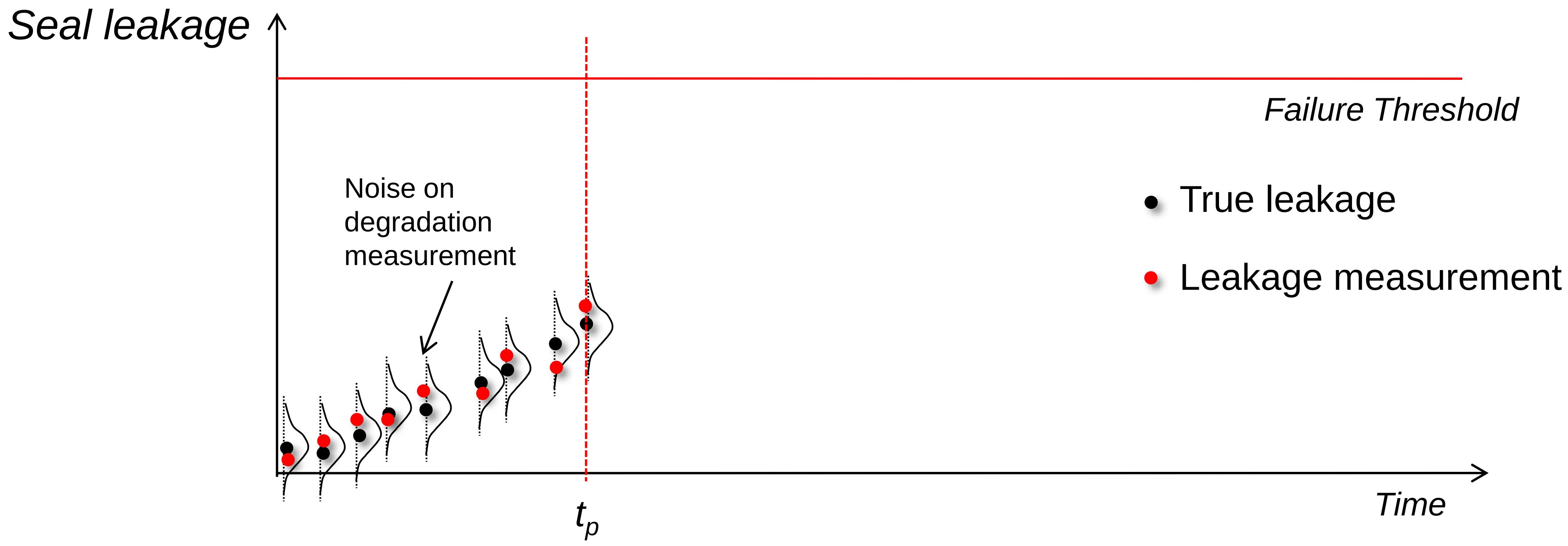
CentraleSupélec
ARAMIS reliable innovation
FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

PHM &

1) Context Changing
2) Uncertainty management
3) Fleet
4) Return Of Investment
5) Safety

Sources of uncertainty:

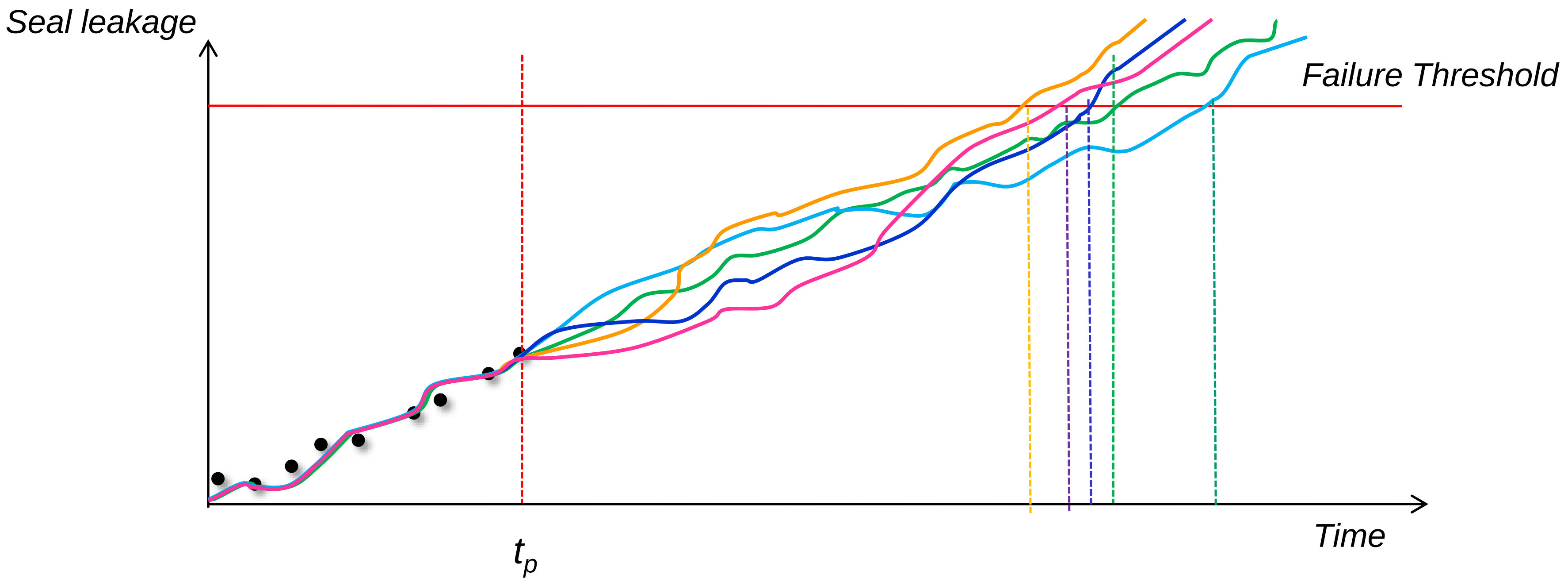
1) noise on the observations (measurements)



Sources of uncertainty:

1) noise on the observations (measurements)

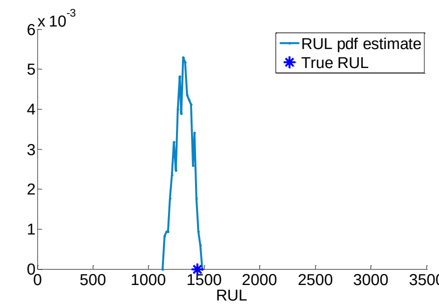
2) intrinsic stochasticity of the degradation process



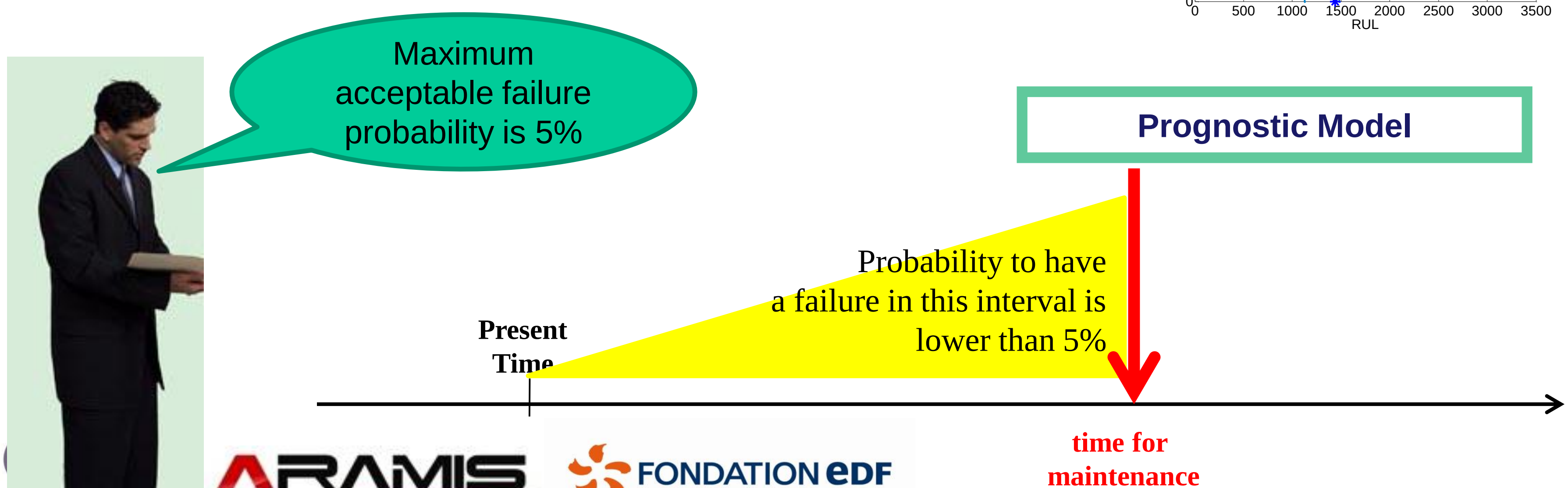
Uncertainty management (prognostics)

Sources of uncertainty:

1) noise on the observations (measurements)
2) intrinsic stochasticity of the degradation process
3) unknown future external/operational conditions
4) Modeling errors, i.e. inaccuracy of the prognostic model used to perform the prediction



Uncertainty on the RUL prediction ?



PHM &

1) Context Changing
2) Uncertainty management
3) $\boxed{\text{Fleet}}$
4) Return of Investment
5) Safety

Fleet (fault diagnostics)

- Can we use data from similar industrial plants of the same fleet to build diagnostic systems?

Failure of Class 1

Failure of Class 2

Failure of Class 3

Plant A

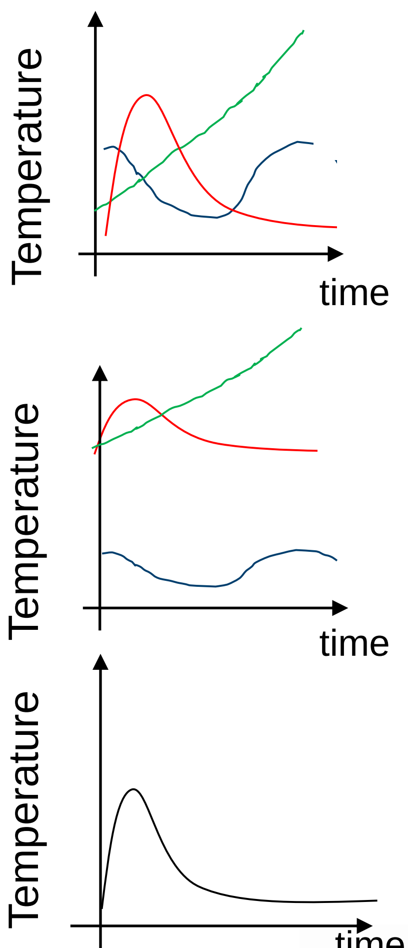
(near the sea)

Plant B

(near a river)

Plant Z

(in a very rainy region)



CentraleSupélec

ARAMIS reliable innovation

FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

PHM &

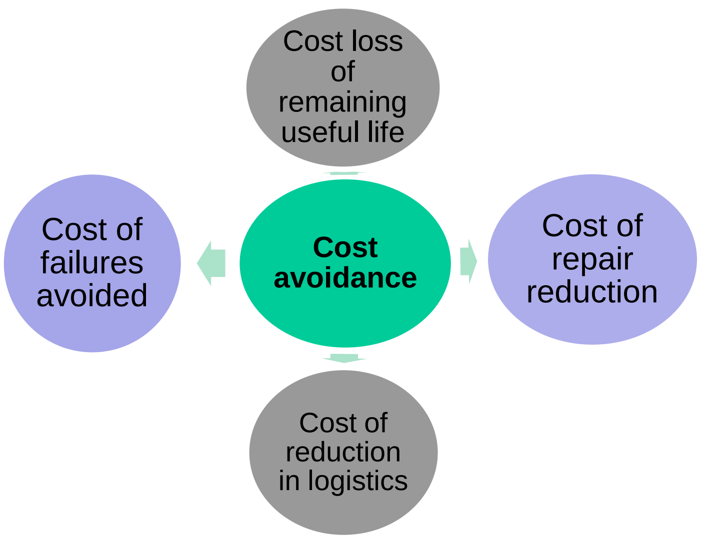
1) Context Changing
2) Uncertainty management
3) Fleet
4) Return of Investment
5) Safety

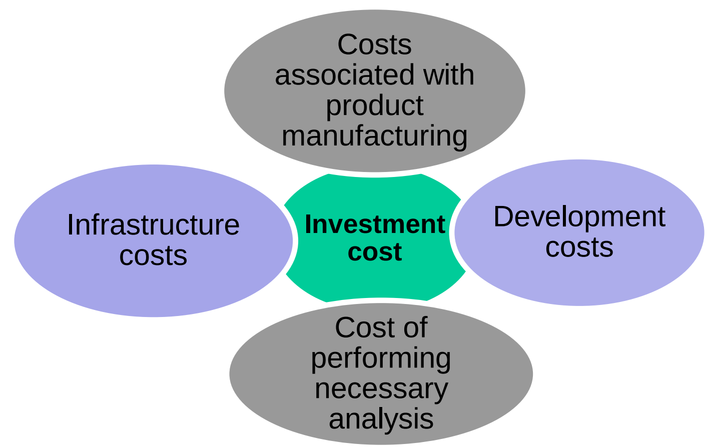
Return Of Investment (ROI)

POLITECNICO DI MILANO

- Most frequently used measure to estimate the economic benefit of PHM:

$$ROI = \frac{Cost\ avoidance}{Investment} - 1$$





Questions:

1- How to reformulate the ROI based on these economic benefits and make the ROI framework general?

2- How the performance indicators will affect the ROI ?

CentraleSupélec ARAMIS reliable innovation FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

PHM &

1) Context Changing
2) Uncertainty management
3) Fleet
4) Return of Investment
5) Safety

PHM & safety

Risk $\rightarrow (p_i, c_i | k)_{i=1,\ldots,N}$

(Terje Aven, ESRA Webinar, What is Risk, March 17, 2016)

PHM

- **Avoided failures thanks to PHM**
- **Reduction of unnecessary maintenance interventions (< human errors in maintenance)**
- **…**
- **Management of abnormal conditions**
- **Missing alarms of the fault detection system**
- **Late RUL predictions of the prognostic system**
- **Unexpected scenarios**
- **…**

PHM System

$\rightarrow (p_i^*, c_i^* | k^*)_{i=1,\ldots,N^*}$

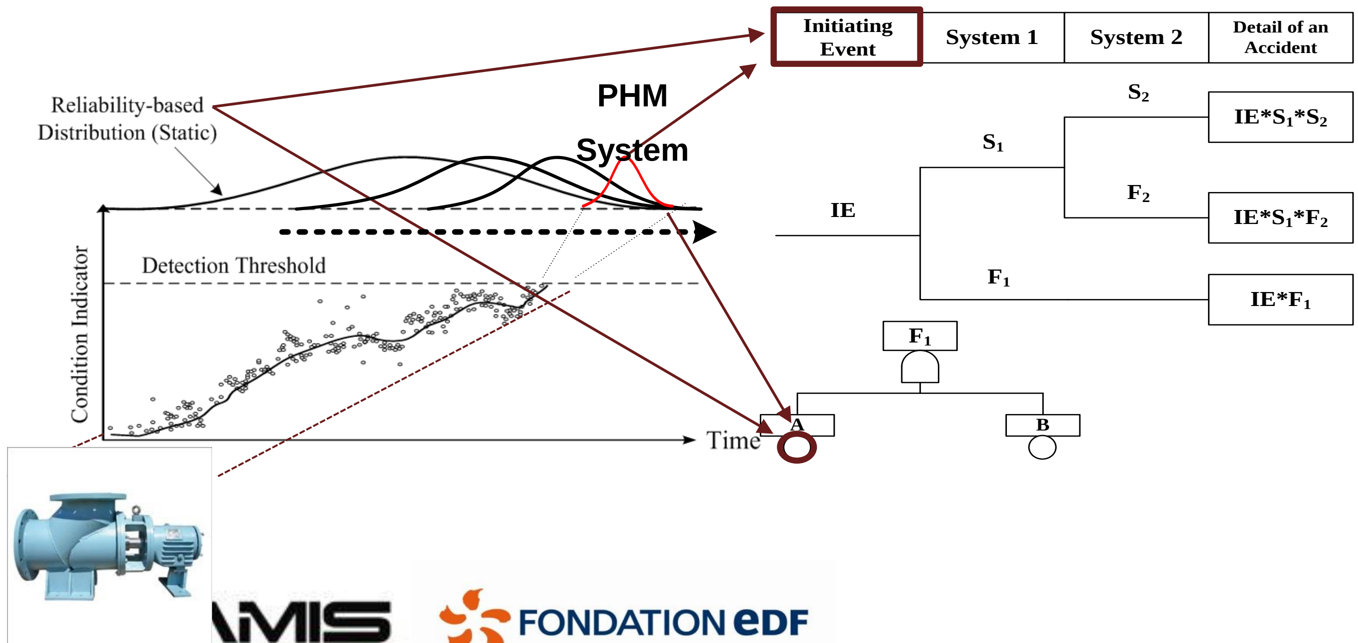
CentraleSupélec

ARAMIS reliable innovation

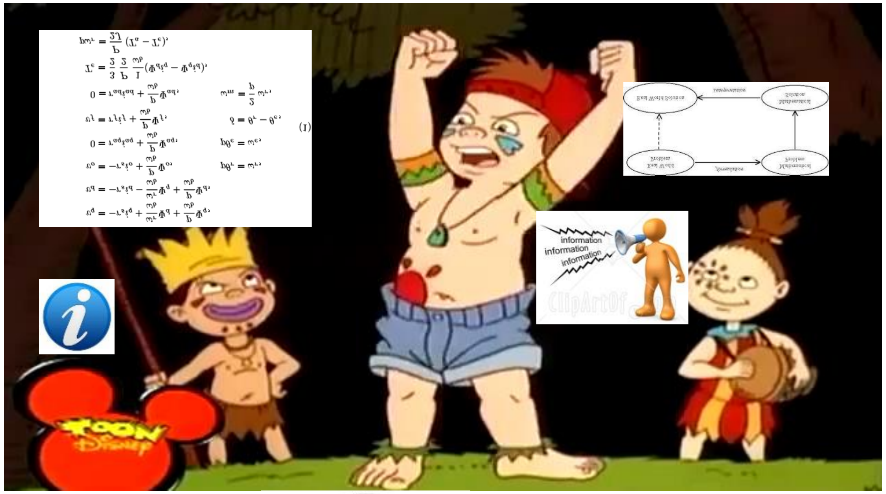
FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

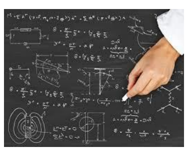
Safety?

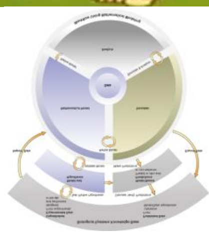
+ PHM System

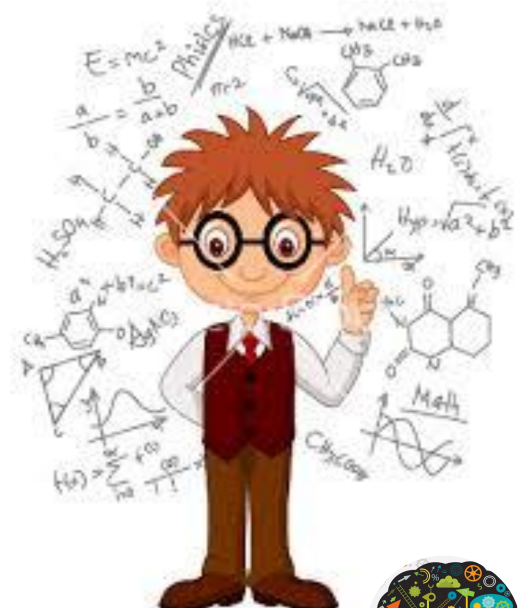


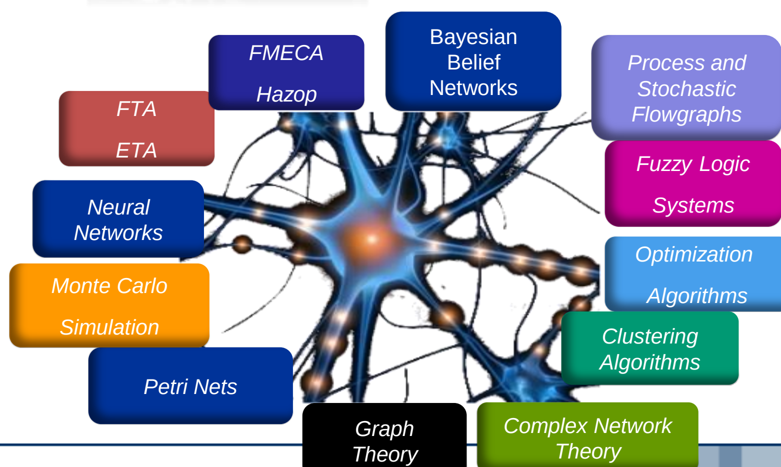
Conclusions: Big KID and Smart KID











SMART KID

Simulation, **M**odeling, **A**nalysis, **R**esearch
for **T**reasuring **K**nowledge, **I**nformation and Data
(for Reliability Engineering)

E. Zio, IEEE Trans on Reliability, 2016

Some challenges and opportunities in reliability engineering

Thanks…

POLITECNICO DI MILANO

…for your outstanding contributions

CentraleSupélec

ARAMIS reliable innovation

FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France

POLITECNICO DI MILANO

…for your attention

CentraleSupélec

ARAMIS reliable innovation

FONDATION EDF Science - Enseignement en partenariat avec l'Institut de France