# An Integrated Data-driven Prognostics Approach: from Critical Components Identification to Remaining Useful life Prediction

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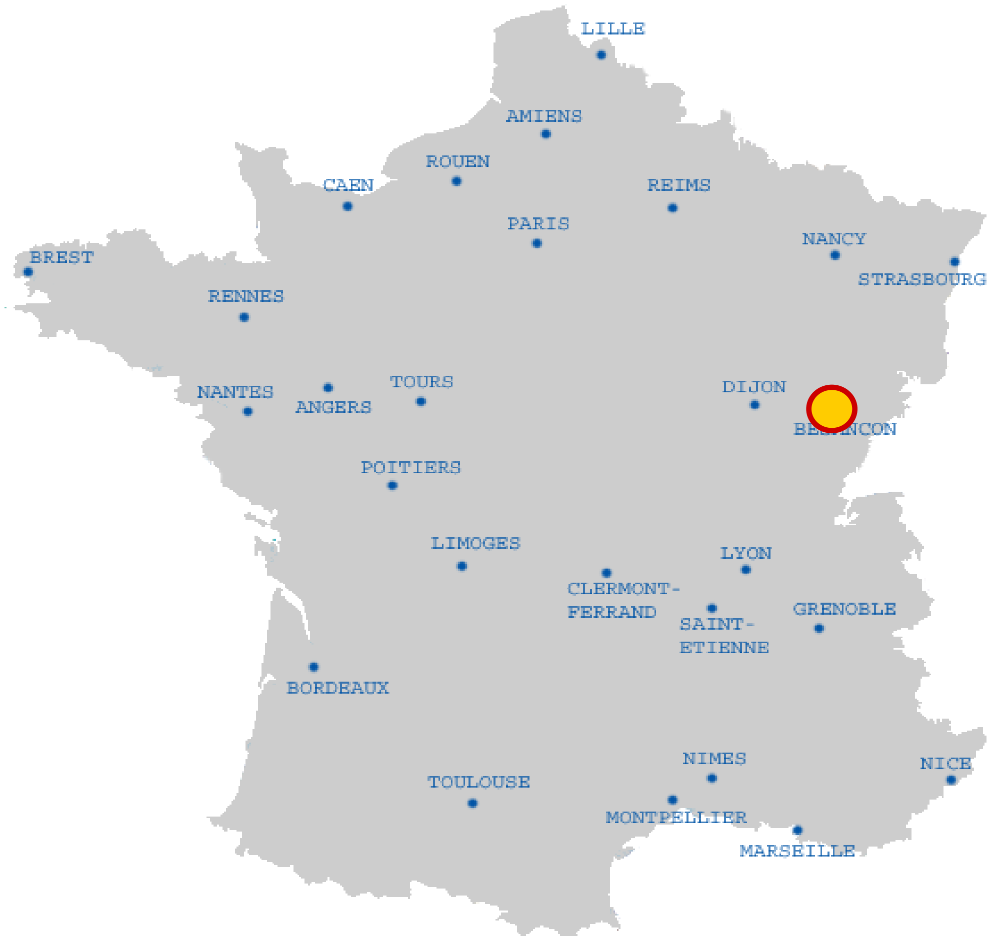
2015 ICRSE & PHM – Beijing

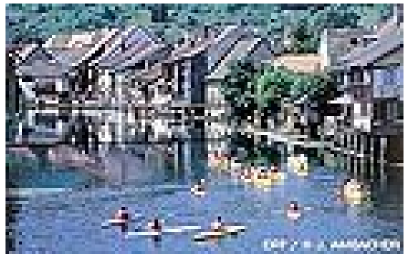
# Overview

1. Motivation
2. Prognostics & Health Management
3. Failure prognostics
4. Problematics & main contributions

# FEMTO-ST Institute





# FEMTO-ST Institute

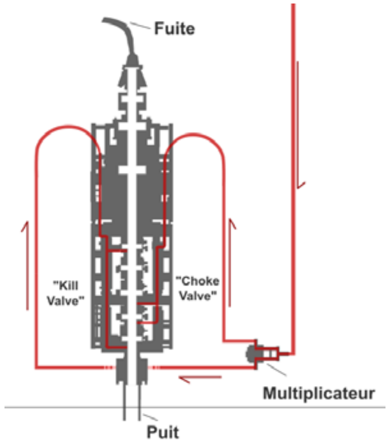
~700 persons (230 Researchers, Professors and Associate Professors, 225 PhDs, 95 Engineers, Technicians and Administratives).

- AS2M: Automatic Control and Micro-Mechatronic Systems
- DISC: Computer Science for Complex Systems
- ENISYS: Energy & Multiphysics Systems
- MEC'APPLI: Applied Mechanics
- MN2S: Micro Nano Sciences & Systems
- OPTIQUE: Optics
- TF: Time & Frequency

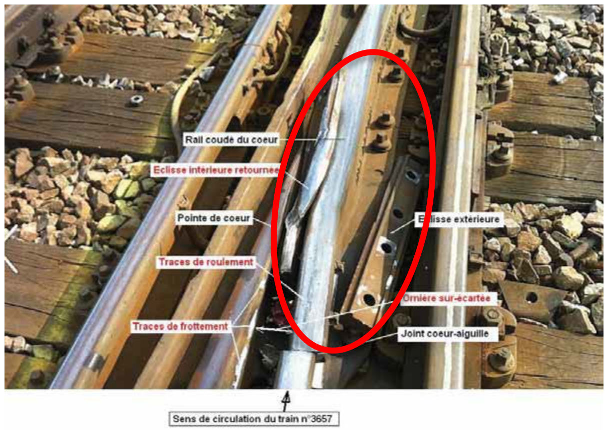
# Motivation

Explosion of the platform Deepwater Horizon in the Golf of Mexico (USA) in April 2010 (source: sciencesetavenir.fr)

Train derailment in Brétigny-sur-Orge in July 2013




Probable cause: leak in the oil pumping system




Cause: failure of a fishplate (source: Bureau d'enquêtes sur les accidents de transport terrestre)

- According to the « Network Rail » in United Kingdom, faults and failures in railway transports are responsible of about 14 millions of minutes of delay per year
- In civil aviation, delays du to technical problems cost 22 Billions of $ in 2011
- Losses due to failures in petrochemical industry were estimated to 2 millions of $ per day
- In automobile domain, failures cost around 288 millions of $ per day

Sources: Keynote de Pierre Dersin at PHM Europe 2014, Muller et al. 1996, Sovacool 2008, Tzanakakis 2013

# Motivation


➡ Need to monitor – assess – anticipate – act

↗ Reliability ↗ Availability ↗ Security ↘ Costs

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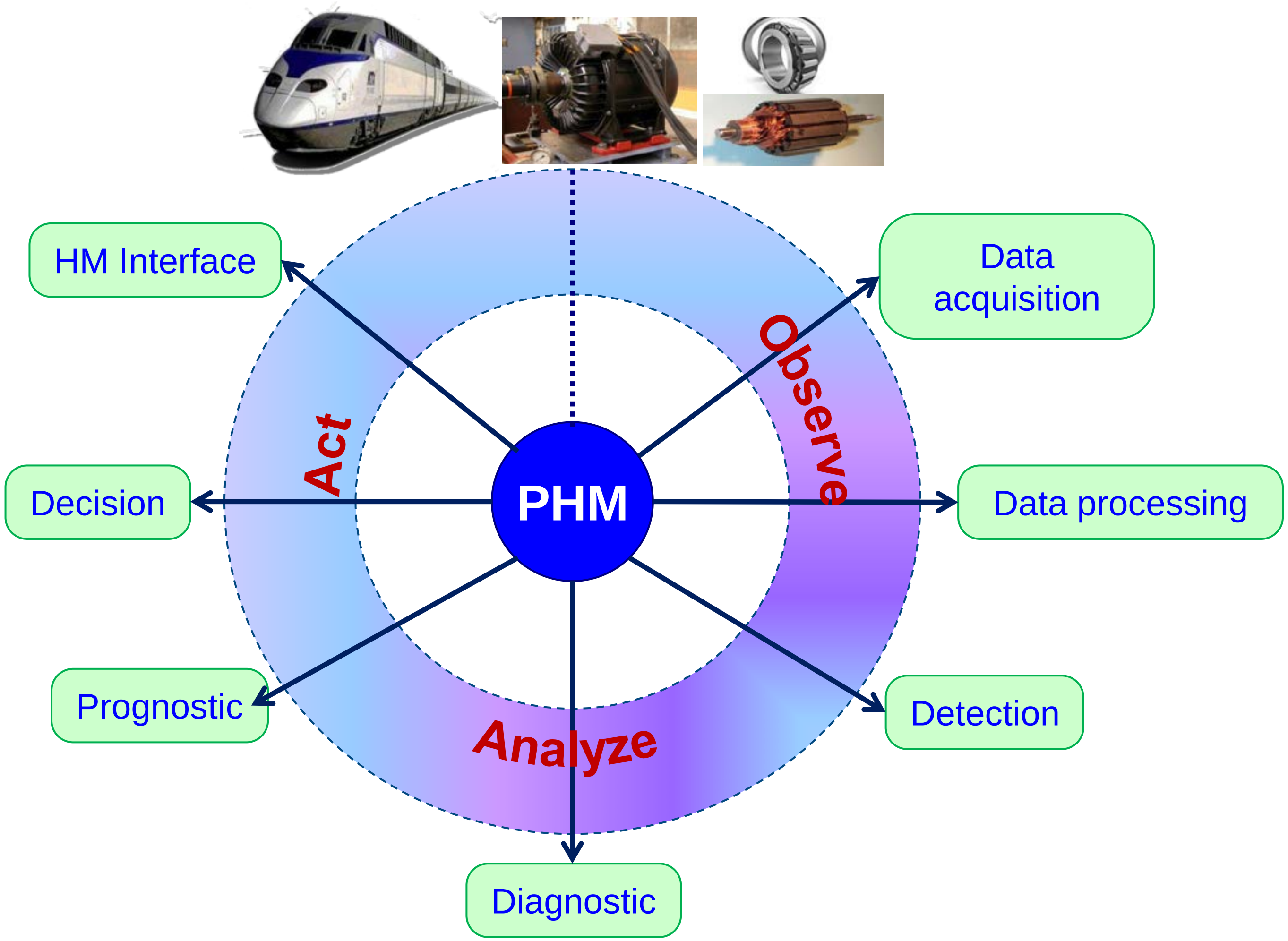
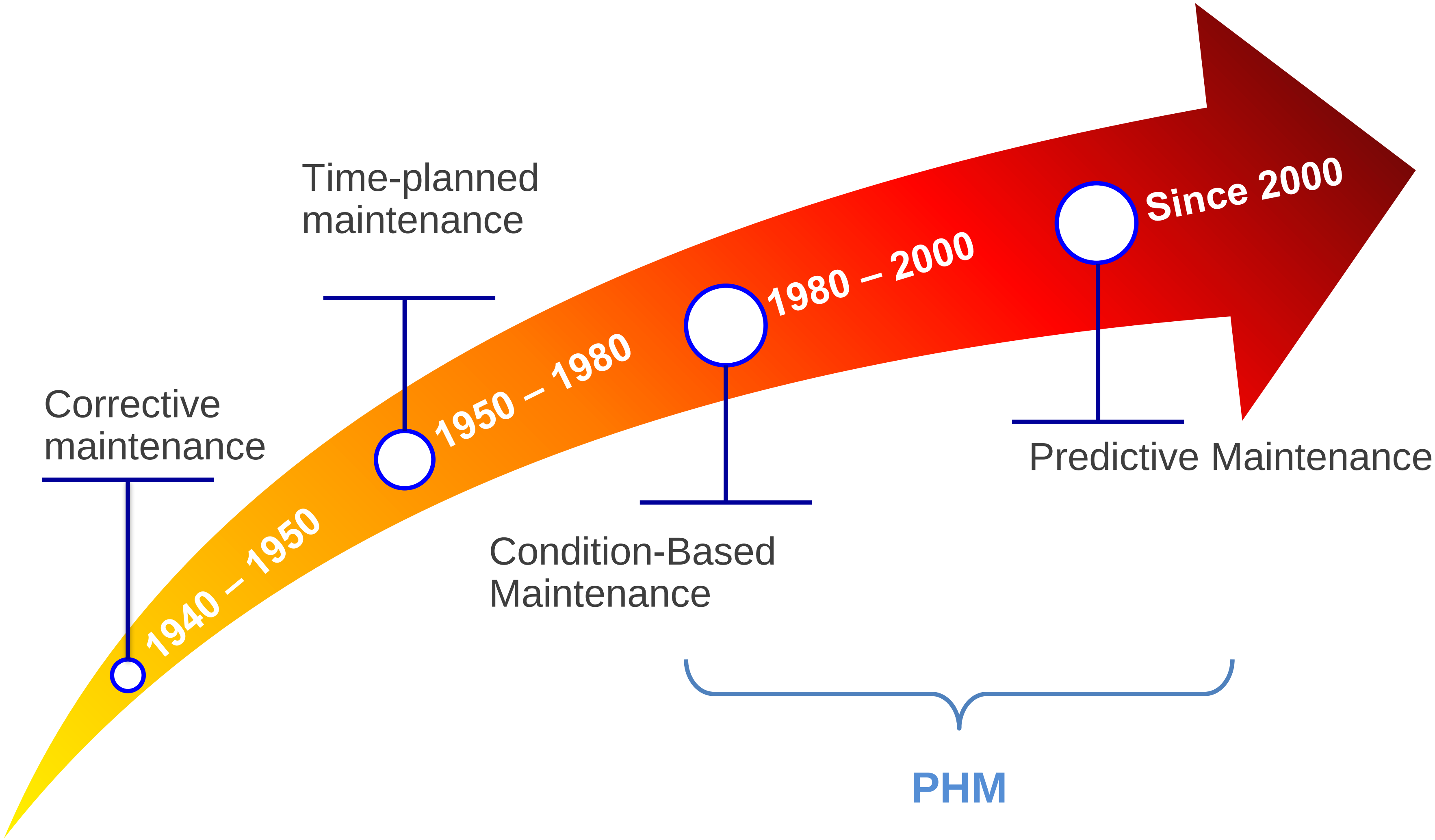
# Prognostics & Health Management

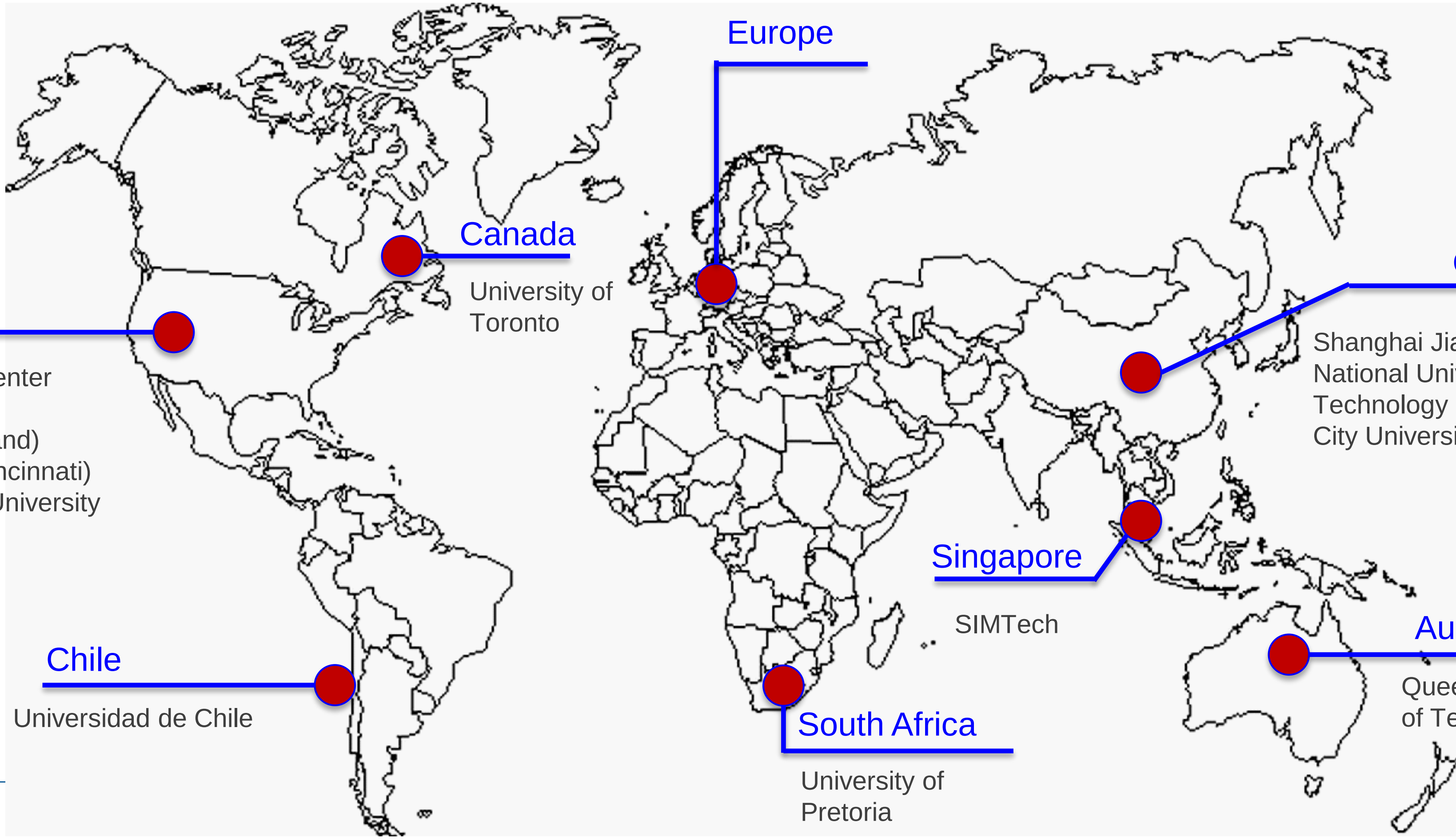


# PHM vs Maintenance



# PHM in the world

Femto-ST, CRAN, Centrale-Supélec, LSIS, Gipsa Lab…(France)
IVHM (Cranfield, UK)
Politecnico di Milano (Italy)
Fraunhofer-Chalmers Centre (Sweeden)
Antalya International University (Turkey)
Tekniker (Spain)



# PHM in industry

## Aerospace

## Energy

## Railway transport

## Automobile

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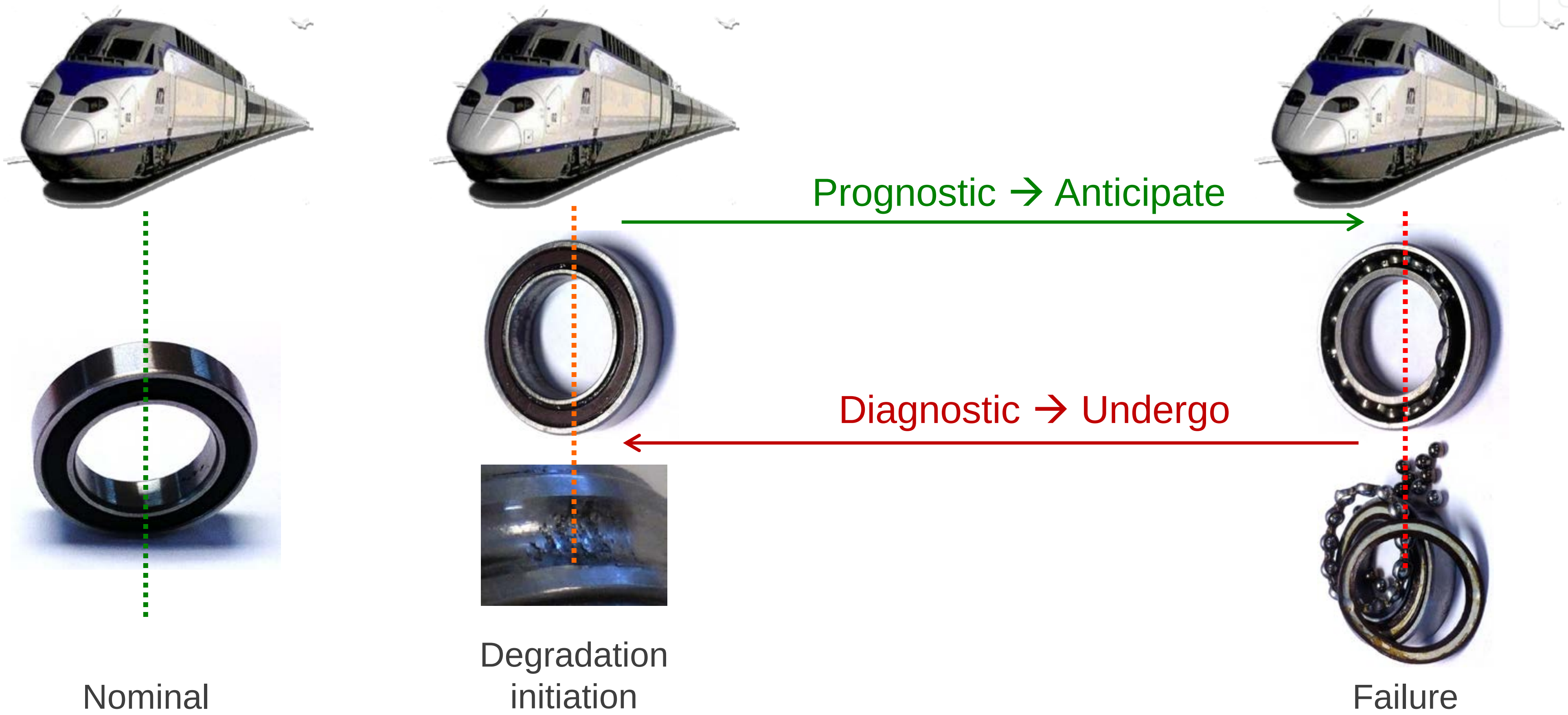
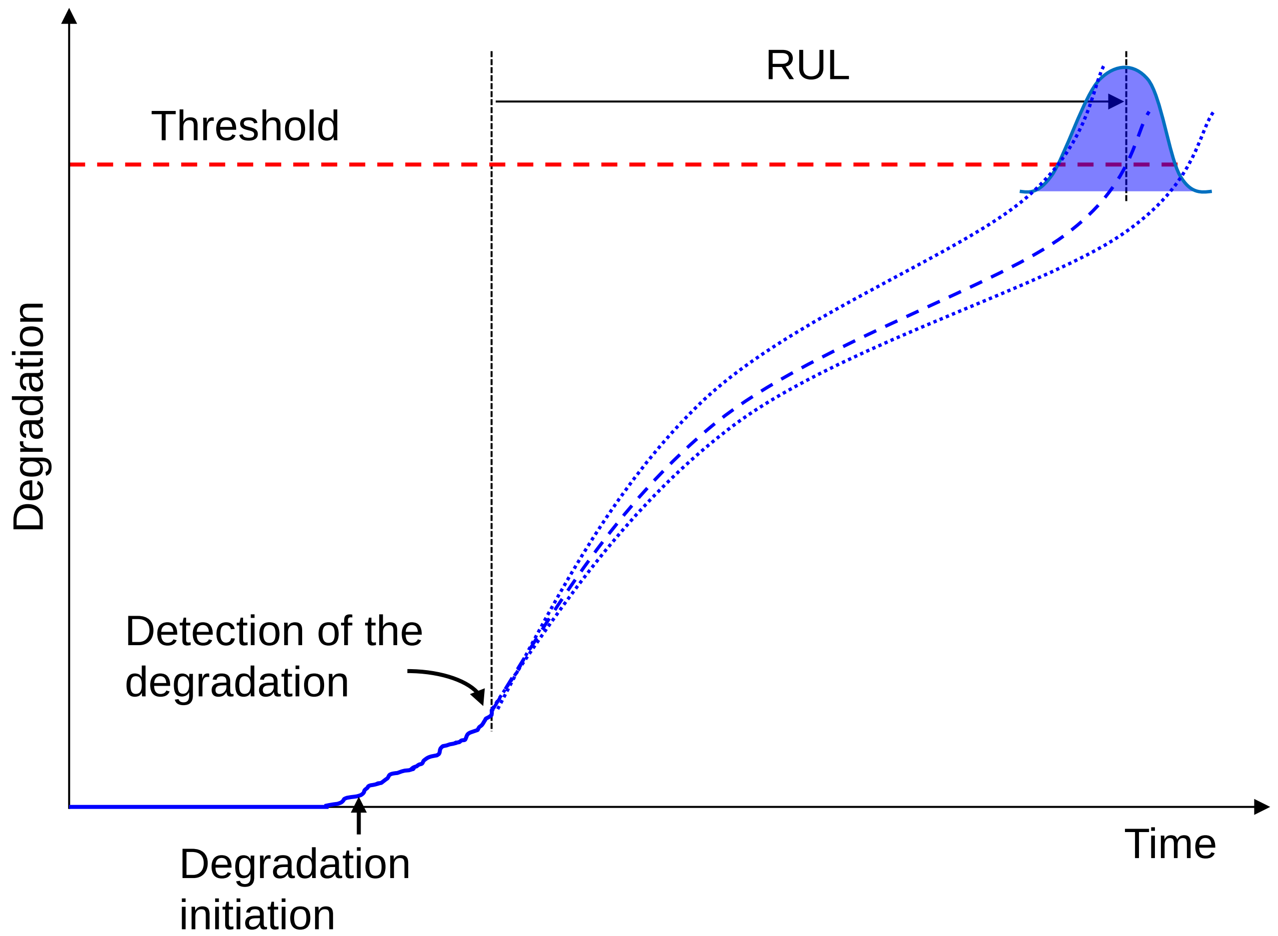
# Failure prognostics



# Definition of failure prognostic

**Prognostic :** prediction of the remaining useful life (RUL) of a system based on its current health state and its future operating conditions



# Prognostic approaches

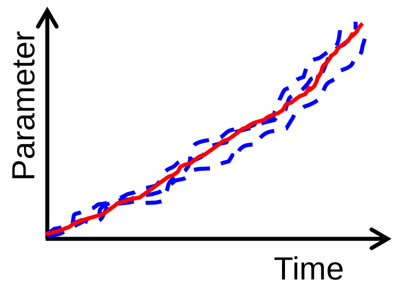
Prognostic approaches

Physics of failure approach

Hybrid approach

Data-driven approach

$$
\begin{cases}
\dot{x} = \phi(x, \theta, u) \\
\dot{\theta} = g(\theta, x) \\
y = h(x, u)
\end{cases}
$$



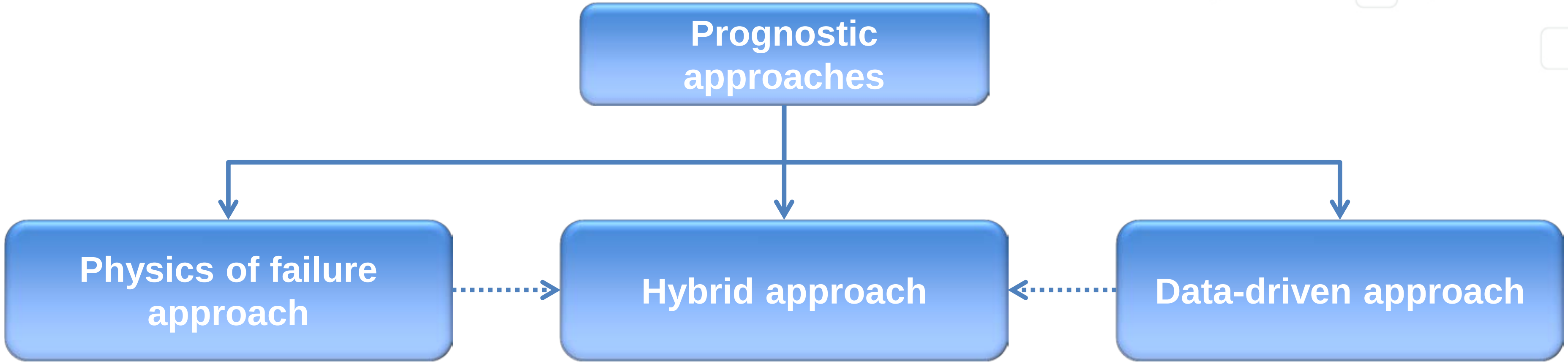

Physical modeling

- Algebro-differential equations
- Fatigue, corrosion, wear… models
- Paris-Erdogan laws

Data oriented modeling

- Trend analysis and regressions
- Artificial Neural Networks
- Probabilistic/stochastic (DBN, HMM)

# Prognostic approaches




+

- Physical approach: quantification of the degradation
- Reuse of models

-

- Simplifying assumptions ⇒ reduced applicability
- High implementation cost

+

- Easy to implement
- Less assumptions
- Low implementation cost

-

- Need of lot of data
- Absence of physical interpretation

# Prognostic approaches

Prognostic approaches

Physics of failure approach → Hybrid approach ← Data-driven approach

**Physics of failure approach**

\+
- Physical approach: quantification of the degradation
- Reuse of models

\-
- Simplifying assumptions ⇒ reduced applicability
- High implementation cost

**Data-driven approach**

\+
- Easy to implement
- Less assumptions
- Low implementation cost

\-
- Need of lot of data
- Absence of physical interpretation

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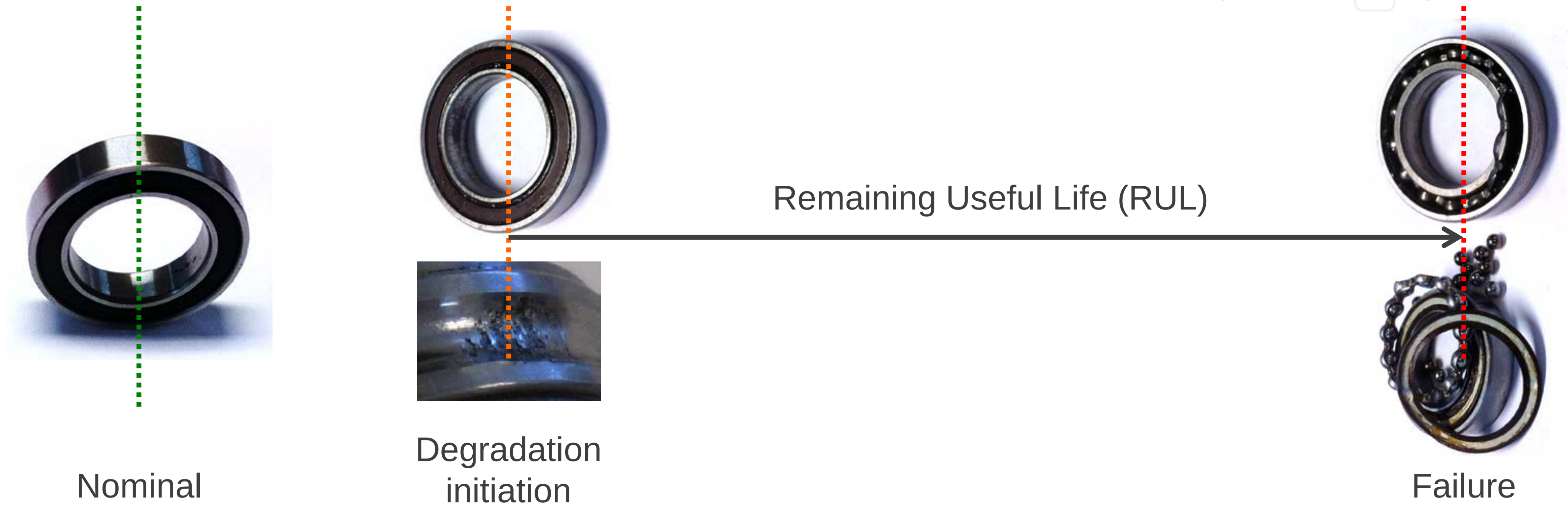
# Scientific issues




1. Quality of data
2. Data transformation
3. Degradation modeling
4. RUL prediction

# Main contributions

Critical components identification & data acquisition → Data processing: feature extraction & health indicators construction → Degradation modeling → Health assessment & RUL prediction → RUL

**Critical components identification & data acquisition**
- Expertise manufacturer / operator
- Exploitation of experience feedback
- Dependability tools (FMECA, fault tree…)

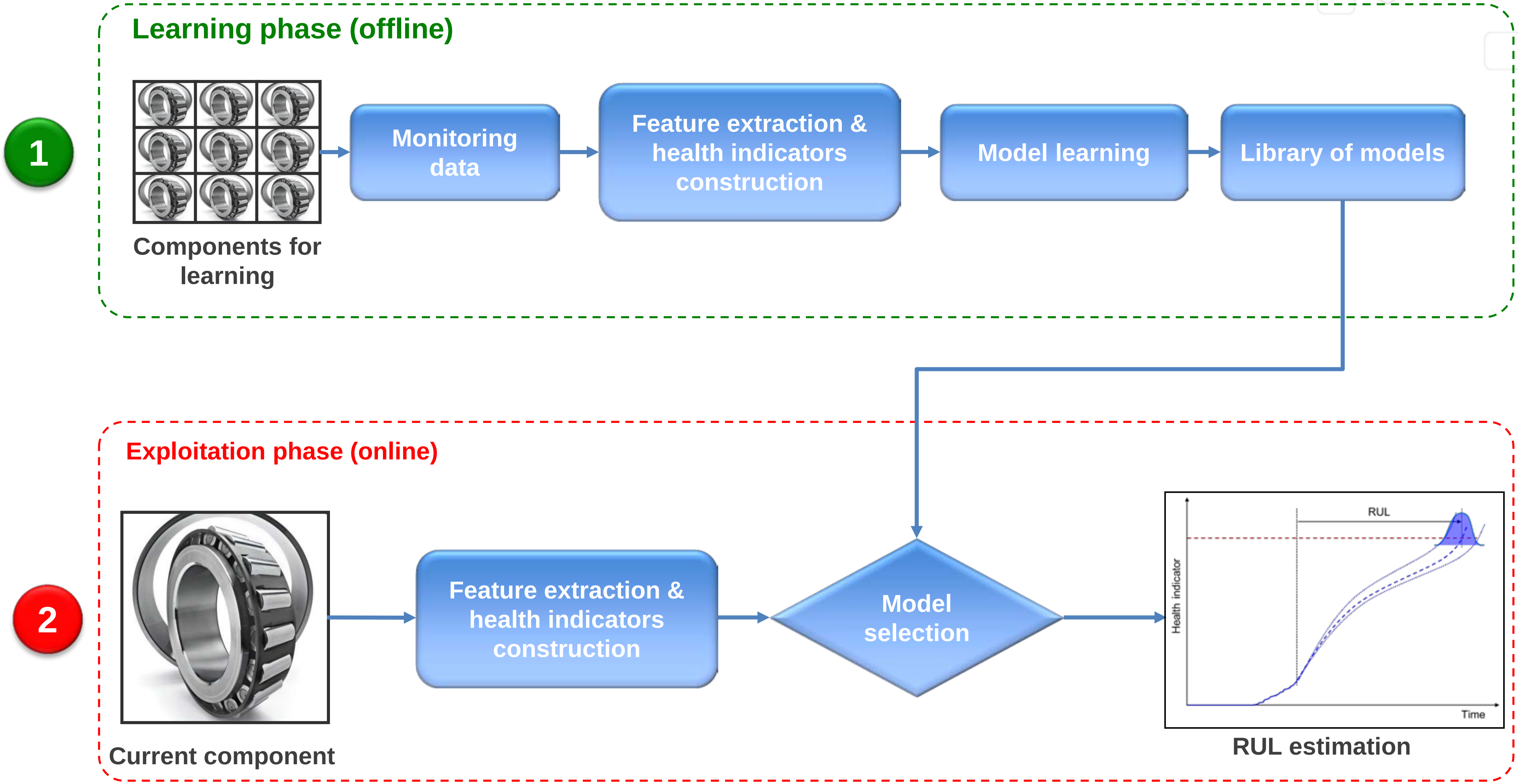
**Data processing: feature extraction & health indicators construction**
- Signal processing (statistical parameters, temporal analysis, time-frequency analysis…)
- Data reduction (PCA, ISOMAP)

**Degradation modeling**
- Dynamic Bayesian Networks
- Support Vector regression
- Gaussian Process Regression

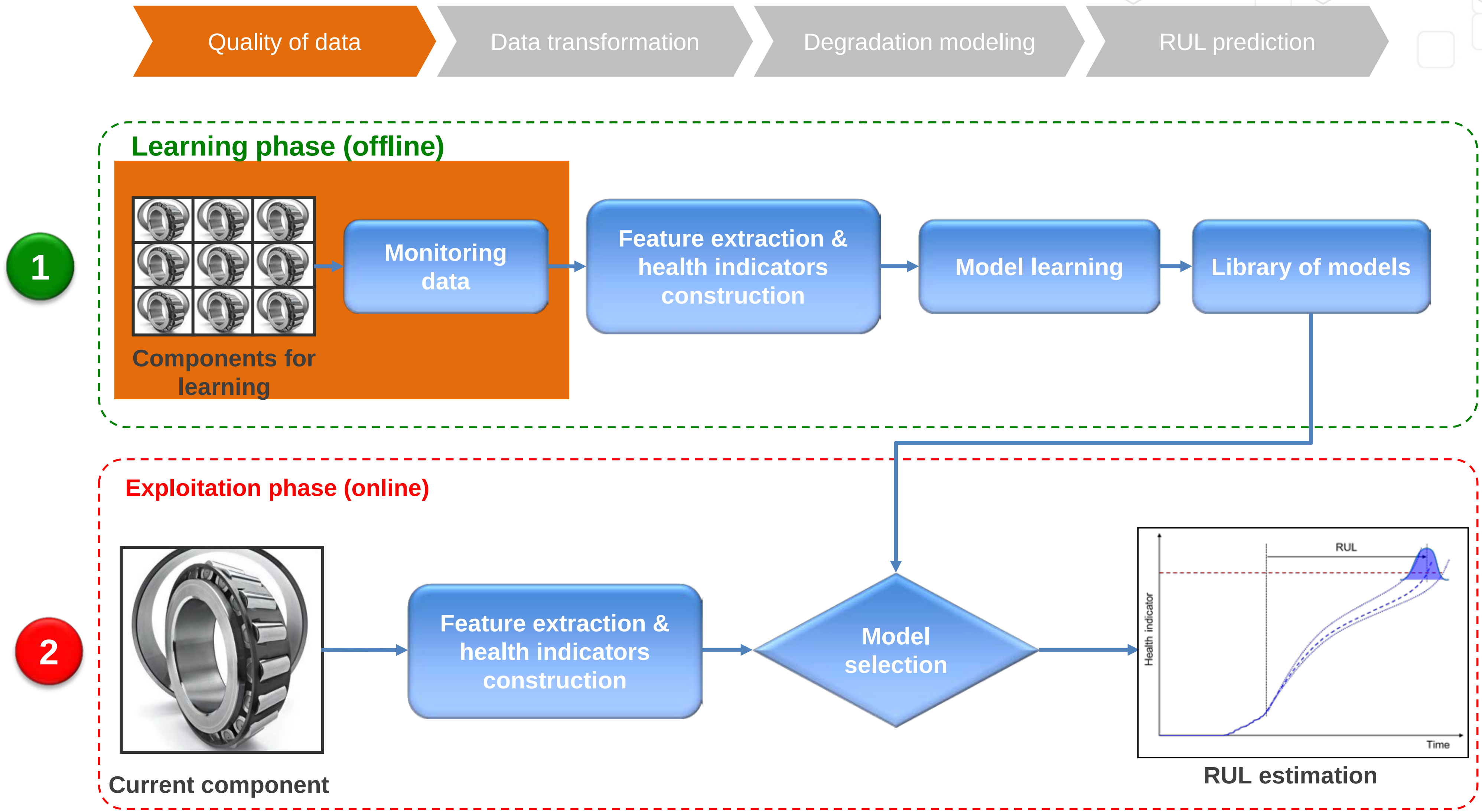
**Health assessment & RUL prediction**
- Exploitation of models
- Definition of fault thresholds
- Prognostic metrics

**Transform the data to models to estimate the RUL**

# Integrated data-driven prognostic approach



# Critical components & data for PHM



# Critical components & data for PHM

- Is it necessary to monitor all system components?
- The degradations are they observables?
- What are the implementation constraints?

1 Choice of critical components → 2 Representative data → « observability » of the degradations

- **Engineering steps (important & indispensables)**
- **Close collaboration with industrials**

# Critical components & data for PHM

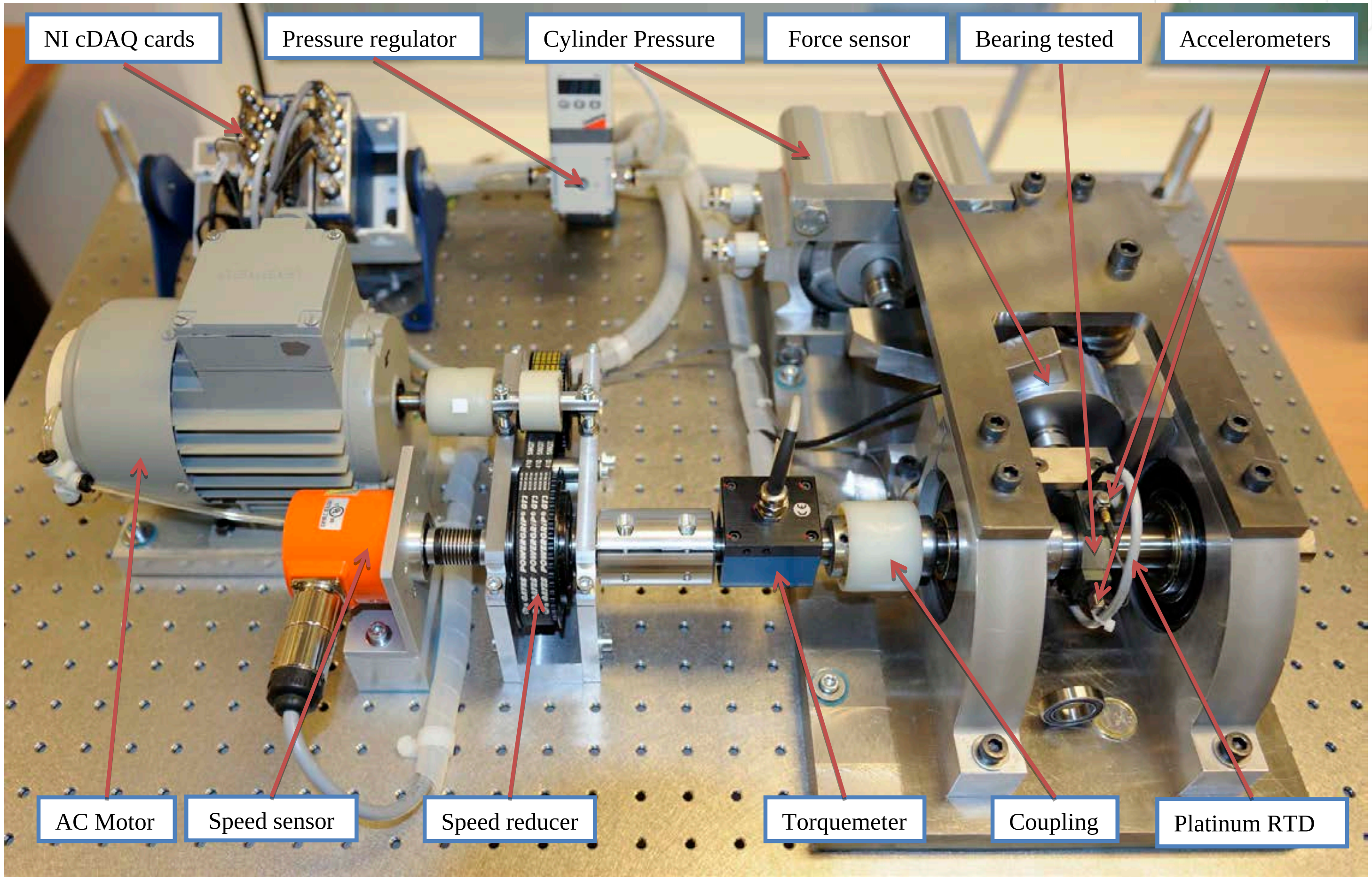
- Industrial projects

ALSTOM

TORNOS


- INTERREG project (with EPFL)

# Experimental platform: PRONOSTIA



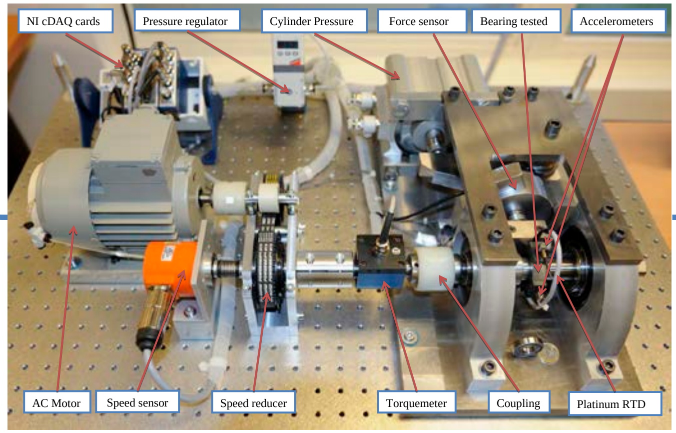

- Test & validation of PHM algorithms
- Organization of PHM Data Challenge 2012 http://www.femto-st.fr/ieee-PHM2012-data-challenge
- Data available at http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/

# Experimental platform: PRONOSTIA

Data

Scientific developments

Validation




PRONOSTIA

# Data processing

Quality of data → **Data transformation** → Degradation modeling → RUL prediction

**Learning phase (offline)**

1

Components for learning

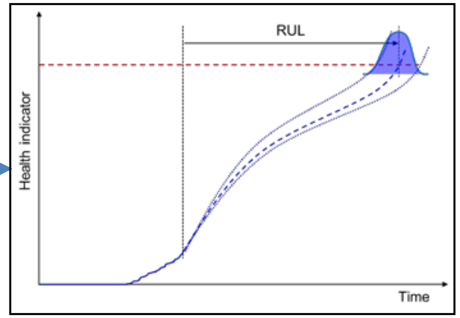
Monitoring data → Feature extraction & health indicators construction → Model learning → Library of models

**Exploitation phase (online)**

2

Current component

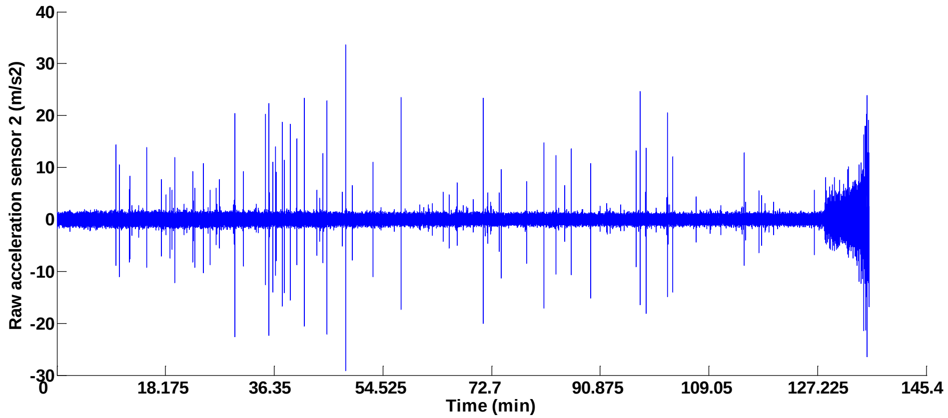
Feature extraction & health indicators construction → Model selection →




RUL estimation

# Data processing

➡ Feature extraction and health indicators construction to track the component degradation

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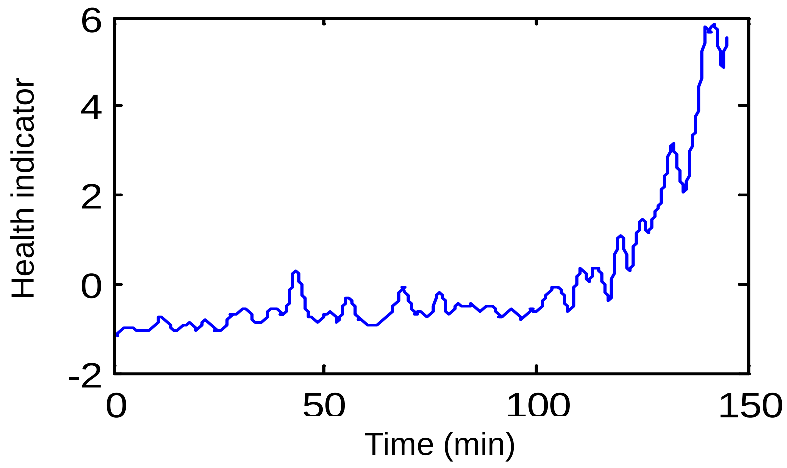
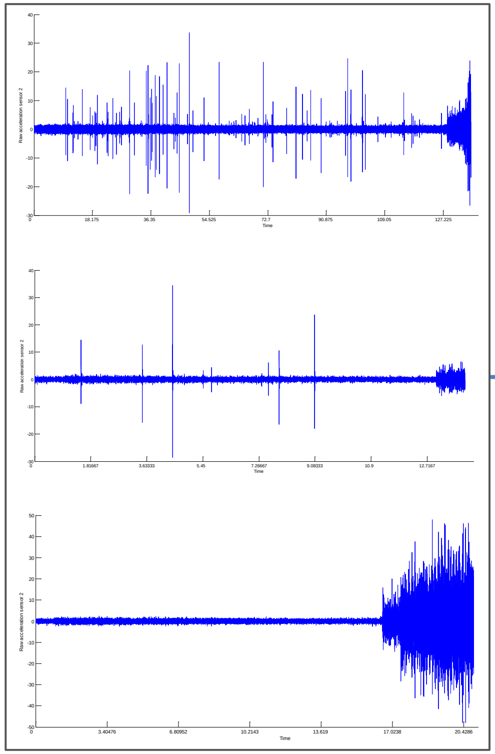
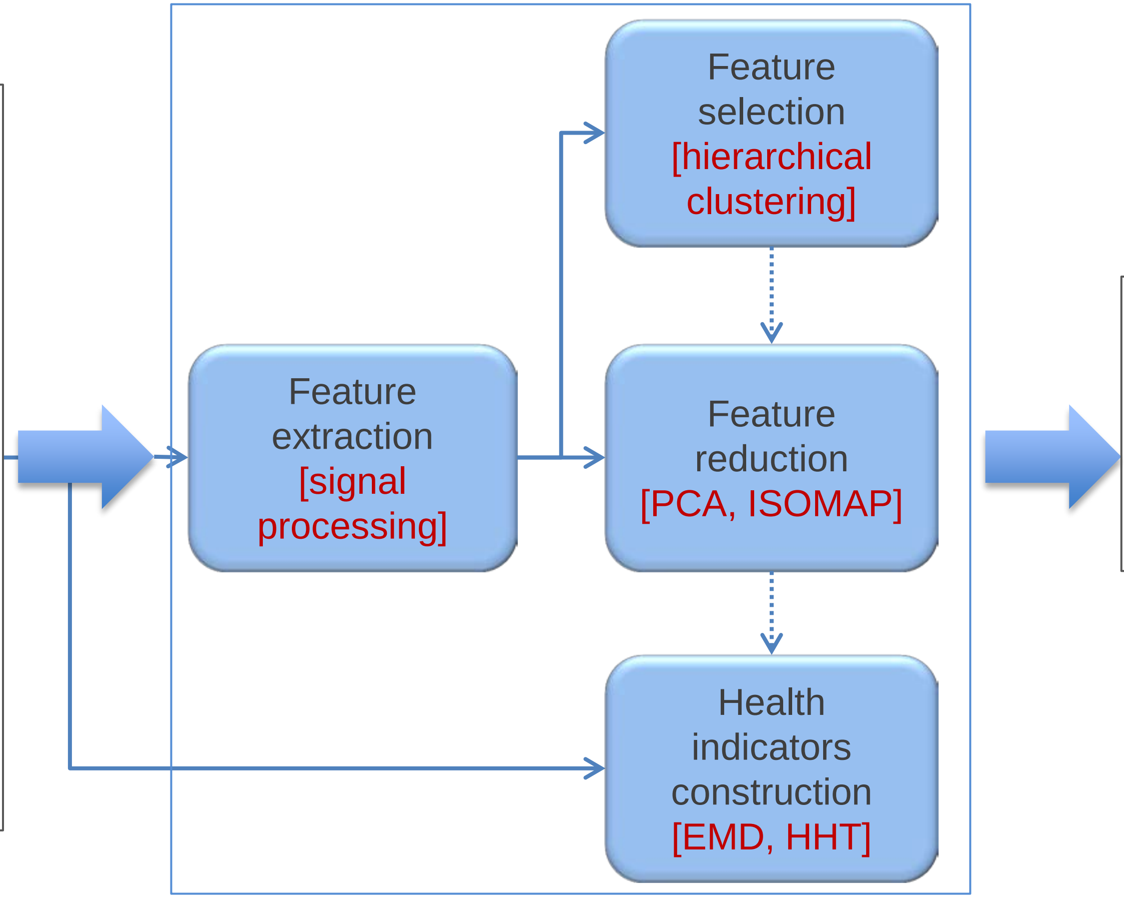


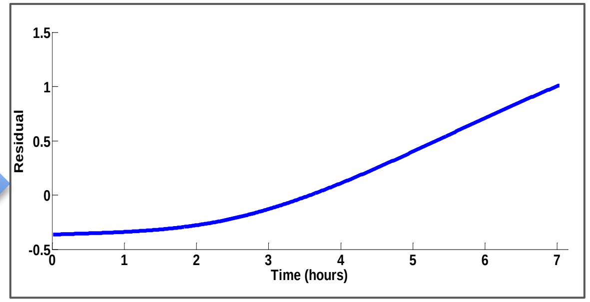

- Which feature to extract?
- Which health indicator to build?

# Data processing



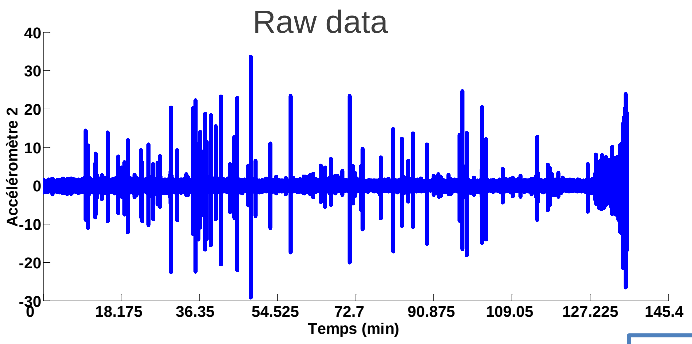
Raw signals



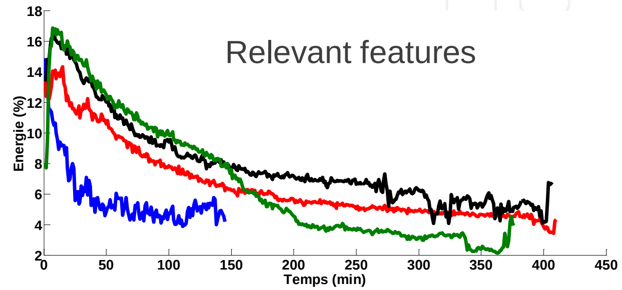




- Relevant features
- Health indicators

# Feature extraction




Feature extraction




## Stationary signals

### Temporal domain

- RMS
- Mean
- Crest
- Skewnnes
- Kurtosis
- Defect factor
- Correlation
- Convolution

### Frequency domain

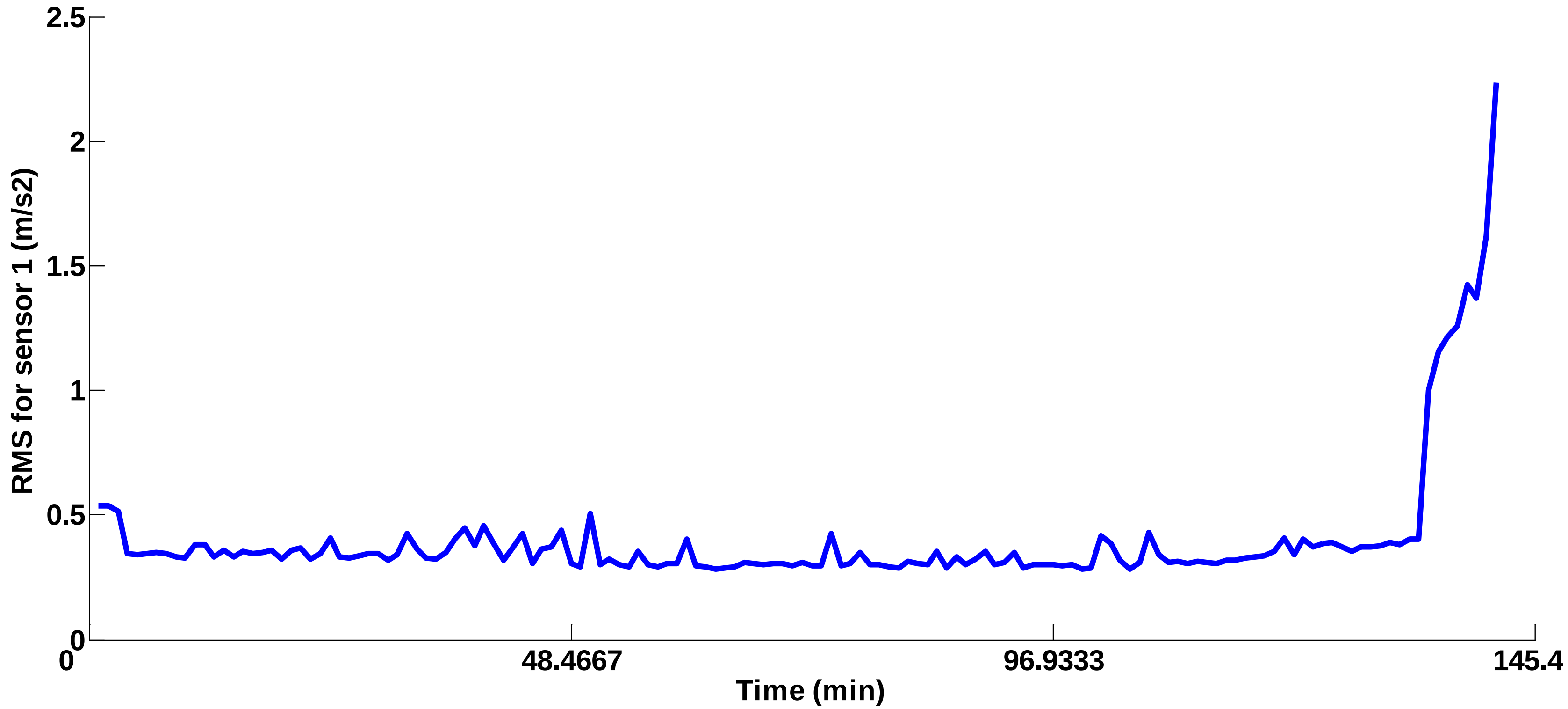
- Spectral analysis
- Envelop analysis
- Cepstrum

## Non stationary signals

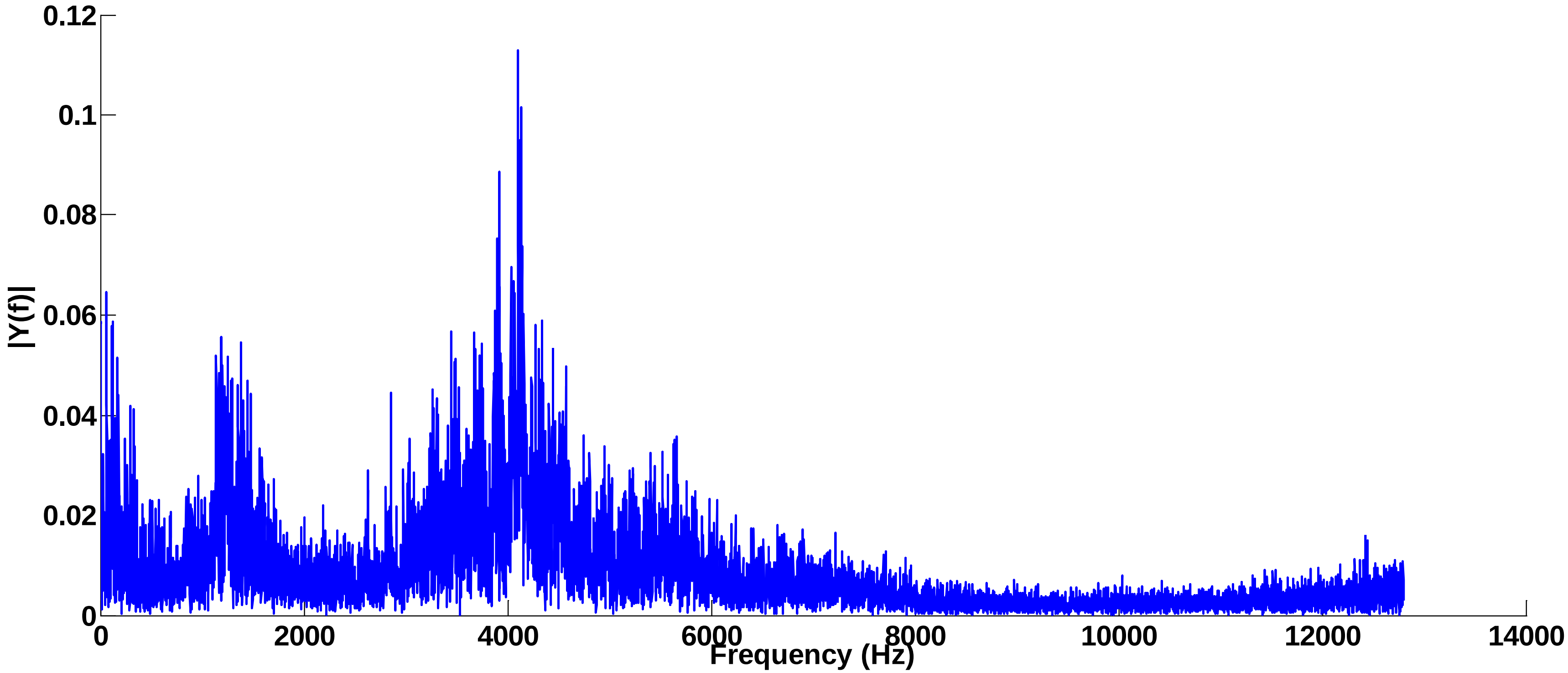
### Time-frequency

- Short Time Fourier Transform
- Cyclostationary analysis
- Wigner-Ville distribution
- Empirical Mode Decomposition (EMD)
- Wavelets
- Wavelet Packet Decomposition (WPD)
- Hilbert-Huang transform

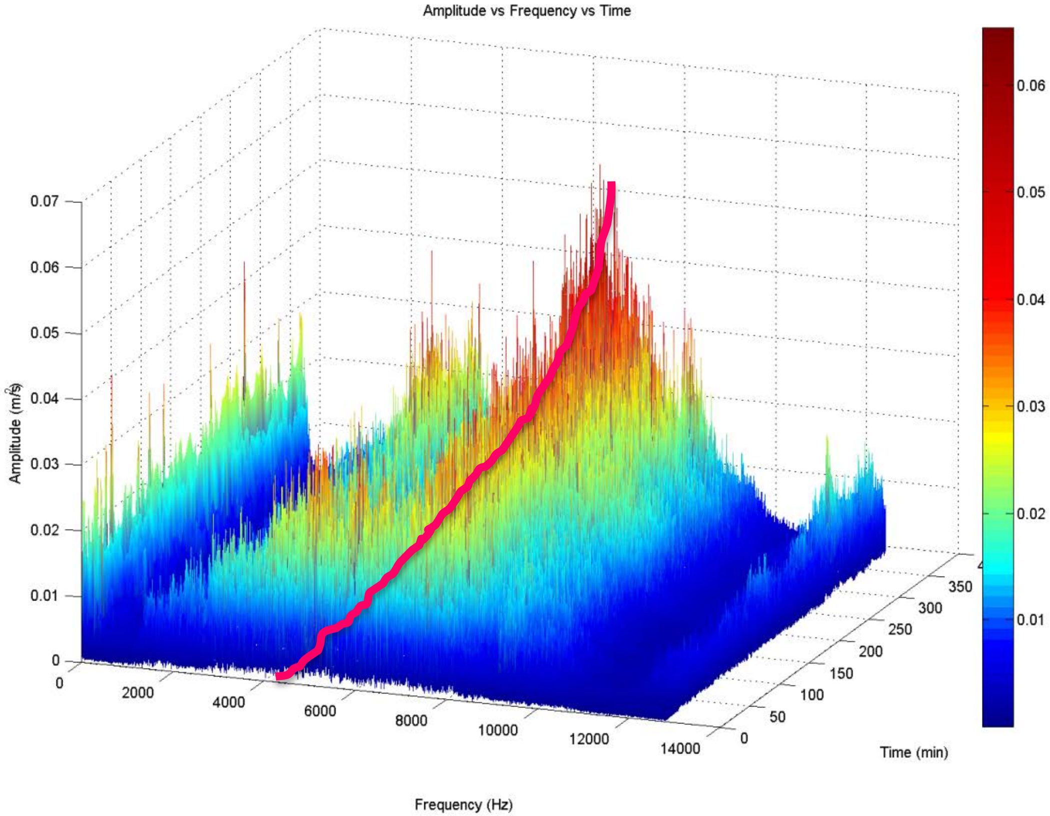
# Temporal feature



# Frequency feature

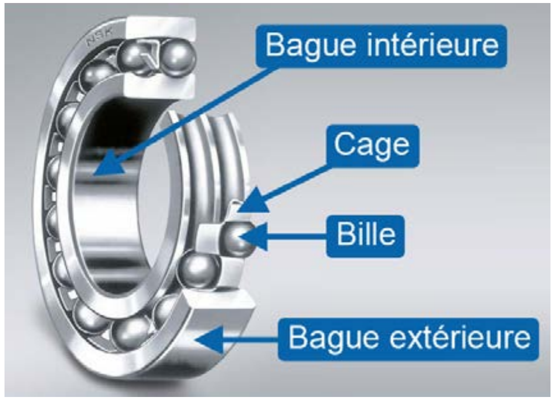


# Time-Frequency feature




Health indicator

# Health indicator




Inner race frequency

$$f_{ir} = \frac{n_b}{2} \cdot f_r \cdot \left[1 + \frac{DB}{DP} \cdot \cos\psi\right]$$

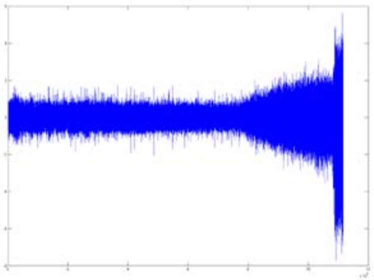
Outer race frequency

$$f_{or} = \frac{n_b}{2} \cdot f_r \cdot \left[1 - \frac{DB}{DP} \cdot \cos\psi\right]$$

Ball frequency

$$f_b = \frac{DP}{DB} \cdot f_r \cdot \left[1 - \frac{DB^2}{DP^2} \cdot \cos^2\psi\right]$$

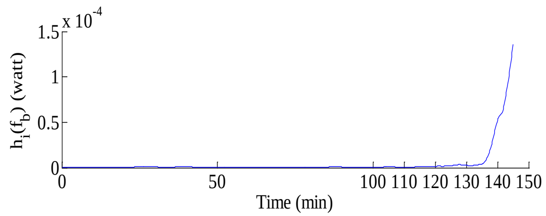
Bearing frequency
$f_{or}$, $f_{ir}$, $f_b$



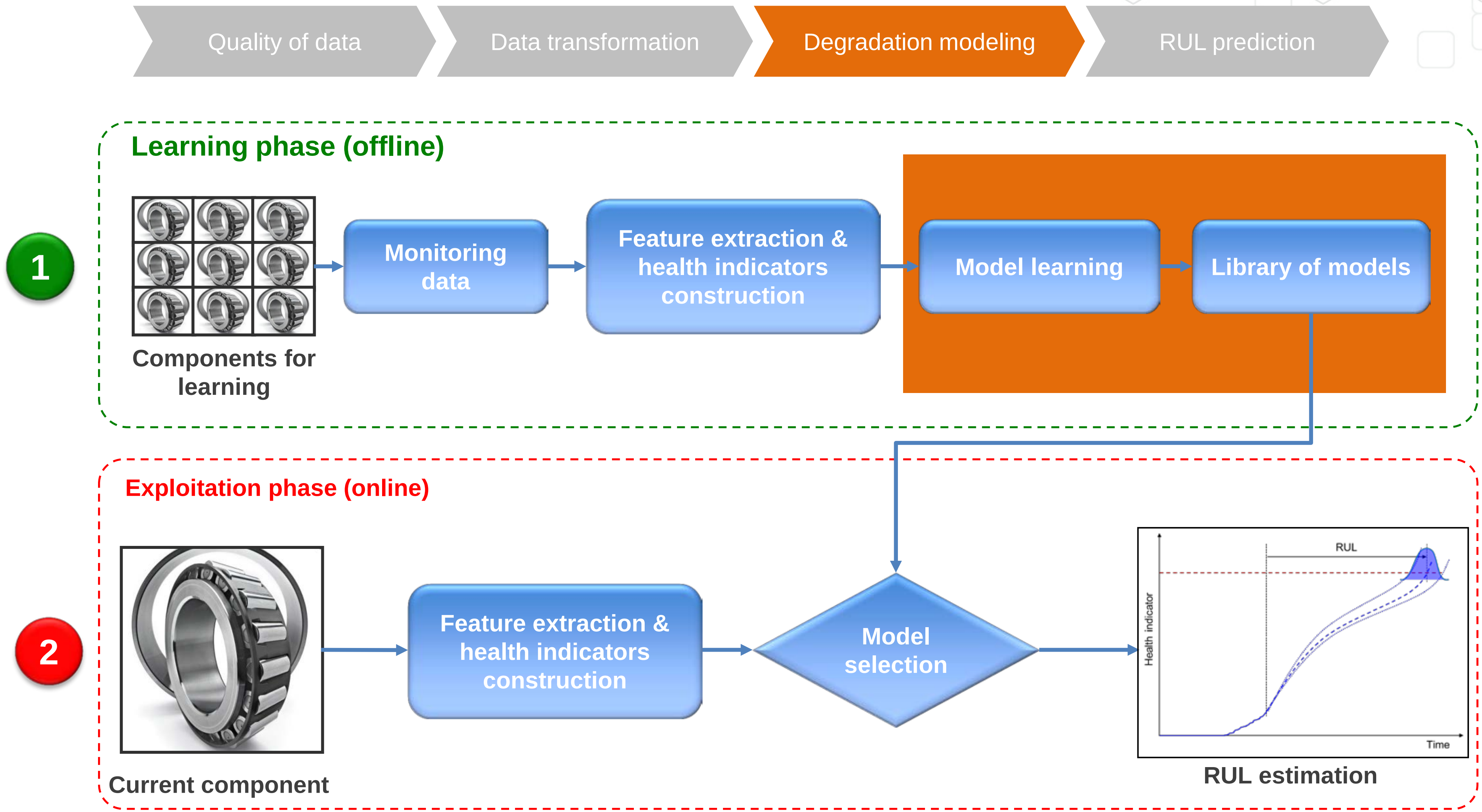
Raw signal

EMD → $IMF_1$, $IMF_2$, $IMF_3$, $IMF_{...}$, $IMF_n$ → HT → $a_i(t)$, $f_i(t)$ $1 \le i \le n$ → Hilbert spectral density $h_i(f)$ $1 \le i \le n$ → IMF selection $c_i(t)$ → max $[h_i(f_{or}, f_{ir}, f_b)]$

$h_i(f_{or})$ – $h_i(f_{ir})$ – $h_i(f_b)$

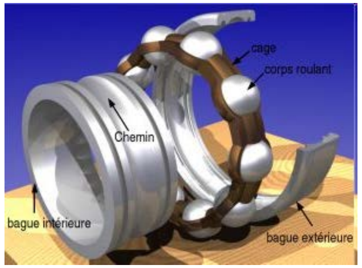


# Degradation modeling

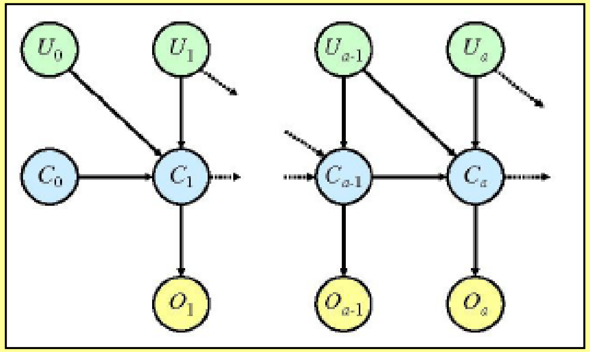


# Degradation modeling

Transform the monitoring data into degradation models

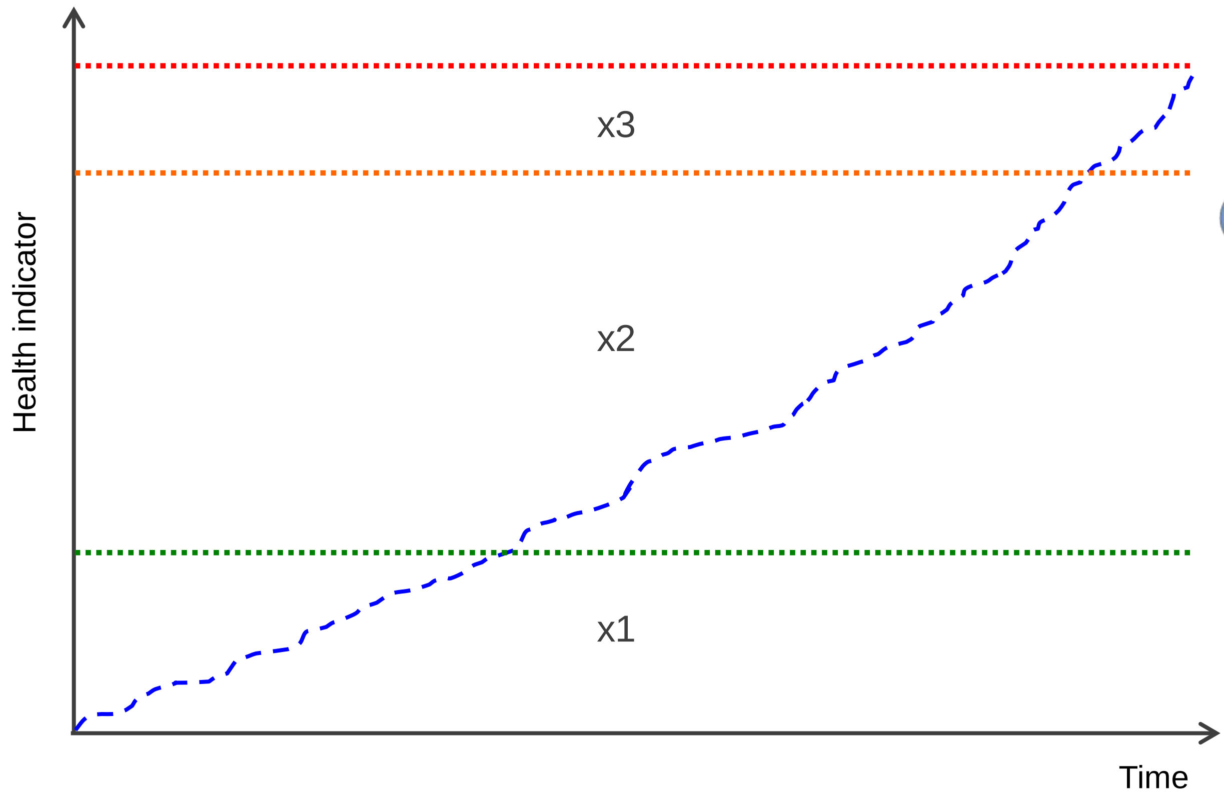



Monitoring data




**Degradation model for prognostics**

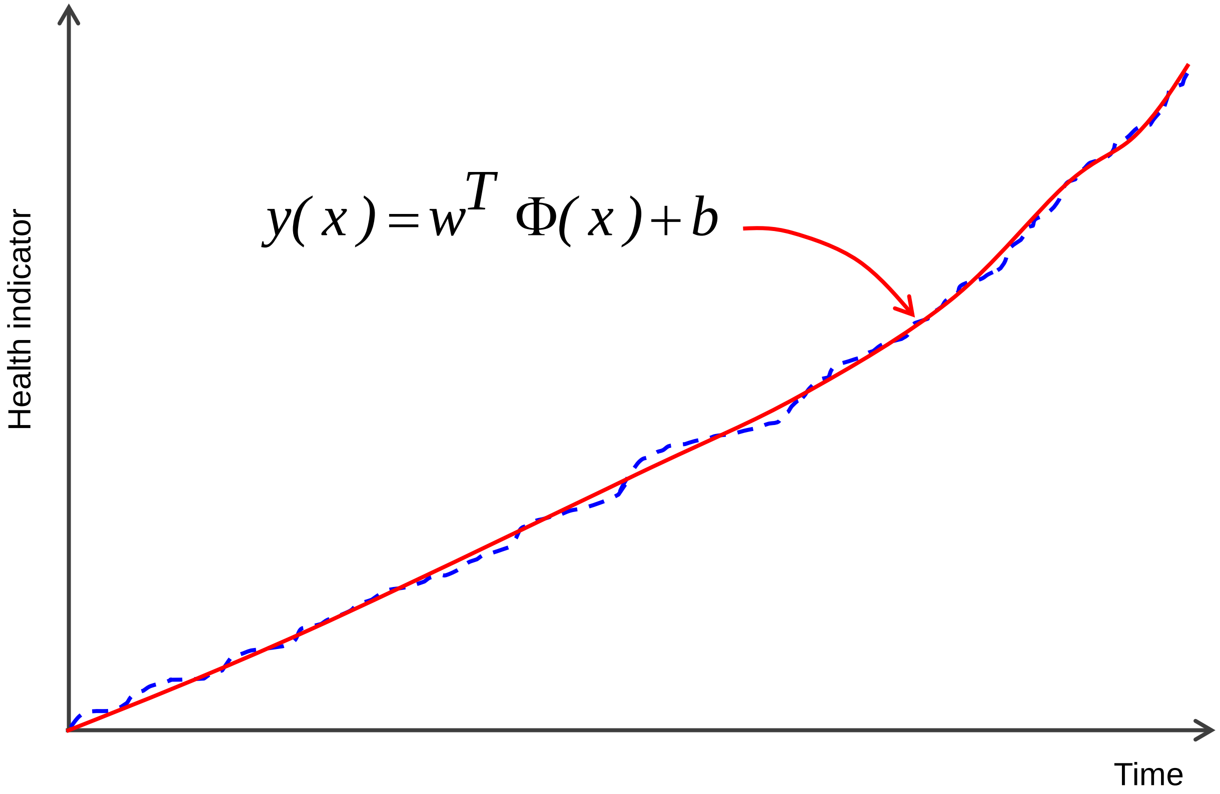
# Degradation modeling





- Probabilistic/stochastic representation
- Taking into account variability of data
- Learning and inference time
- Simplicity of representation
- Generalization of HMM and Kalman filters

# Degradation modeling

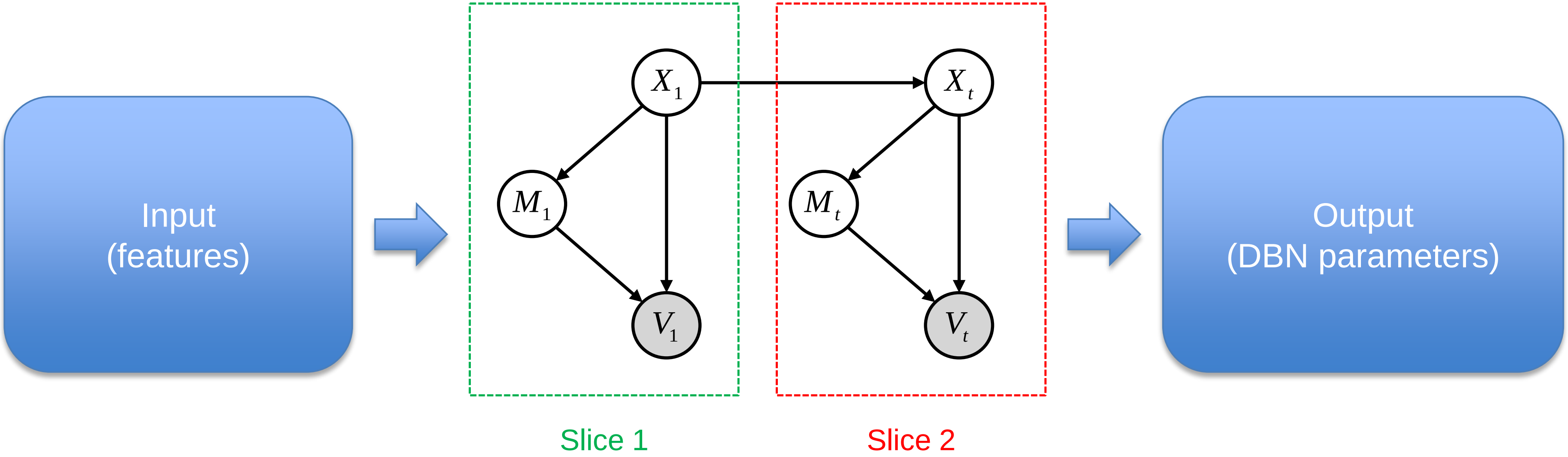



Regression models (GPR, SVR)

- Modeling of uncertainty
- Taking into account of nonlinearities and nonstationarities
- Sparse regression
- Simplicity of implementation

# Dynamic Bayesian Networks

$$\lambda_{RBD} = \{\pi, A, B, M\}$$




**Learning: Baum – Welch algorithm**

$$\{\pi, A, B, M\} | O$$

**recognition: Forward – Backward algorithm**

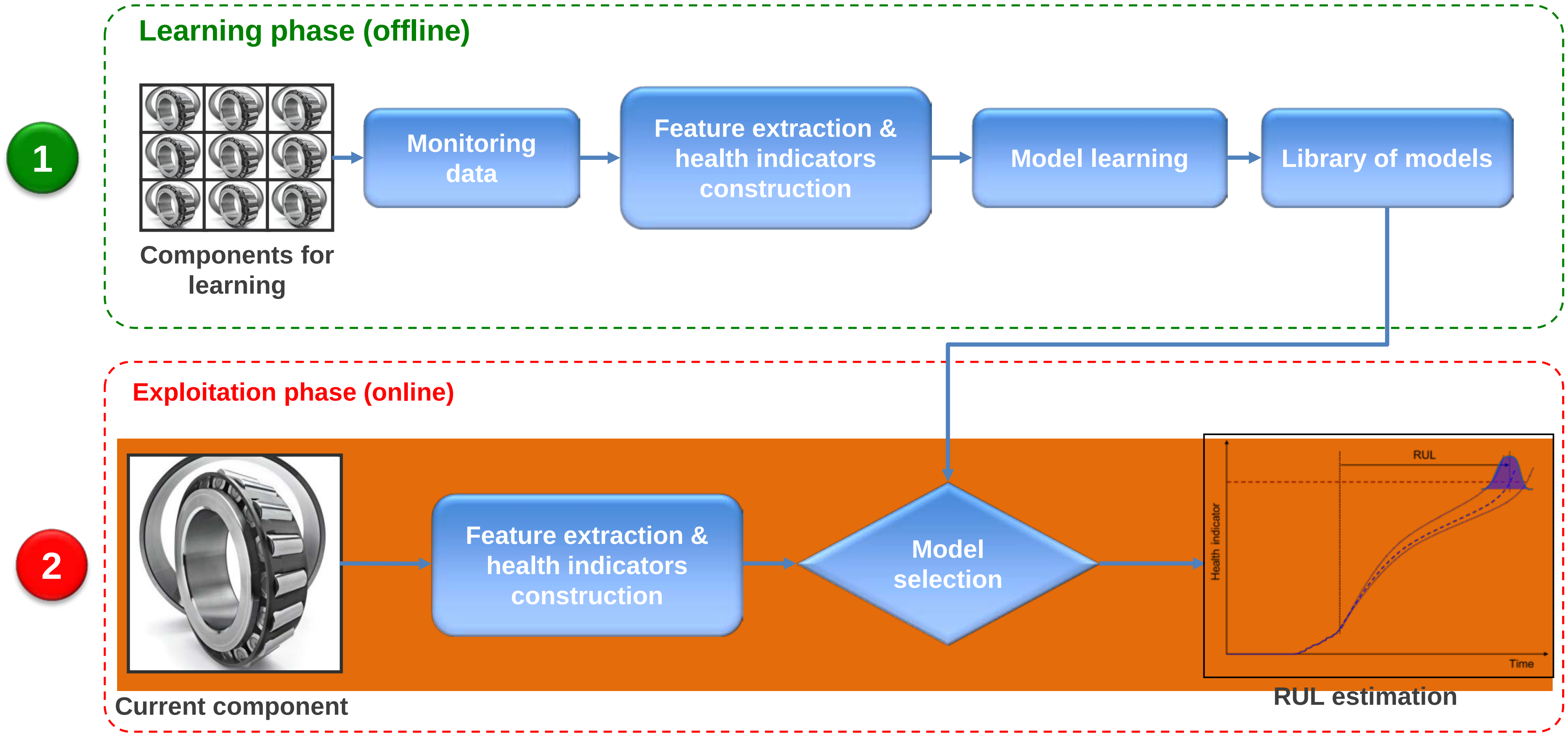
$$P[O|\lambda]$$

**Identification of hidden states: Viterbi algorithm**

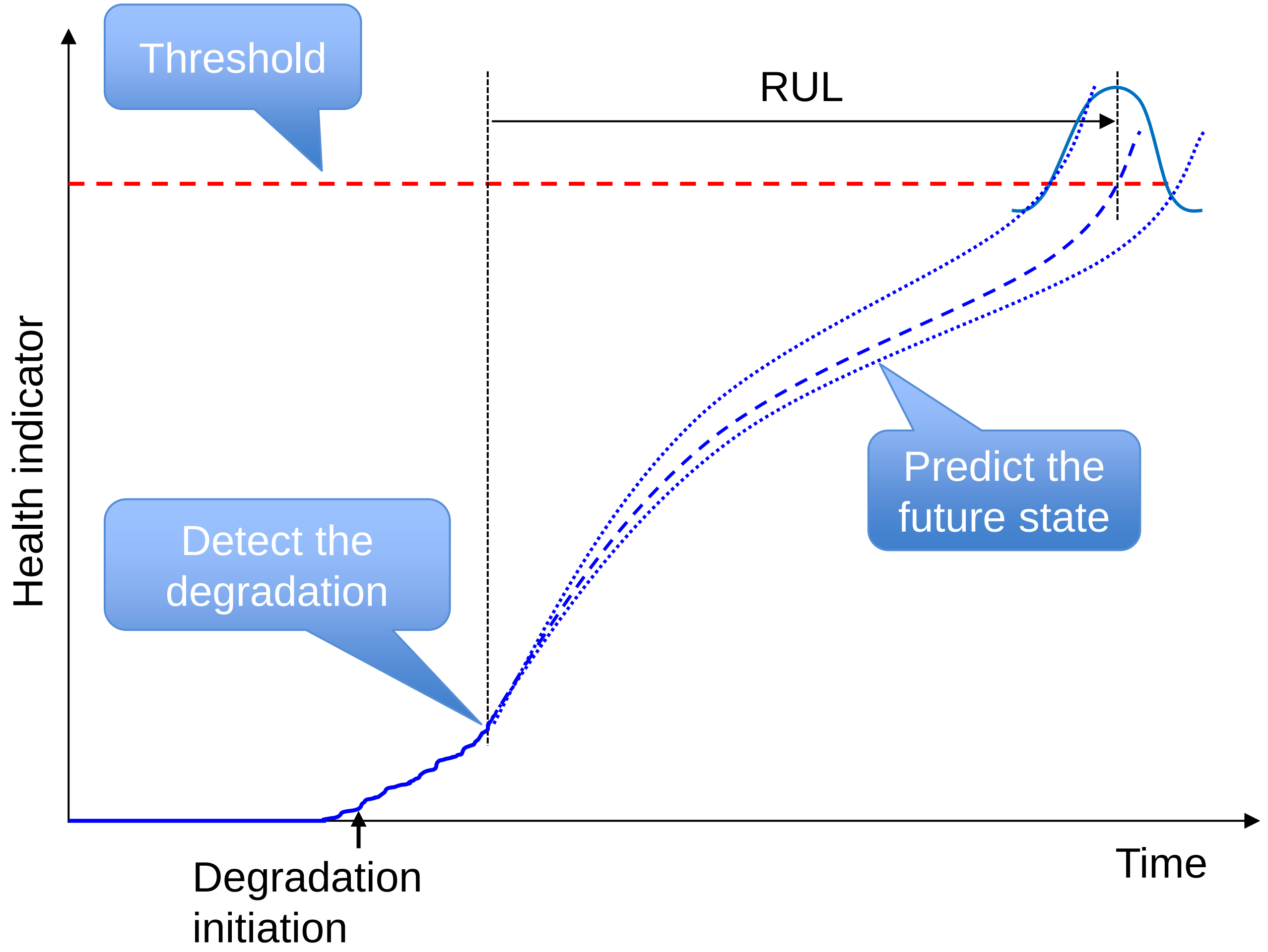
$$\{X = x_1, x_2, x_t, \ldots, x_T\} | O, \lambda$$

# Health assessment & RUL

Quality of data → Data transformation → Degradation modeling → **RUL prediction**



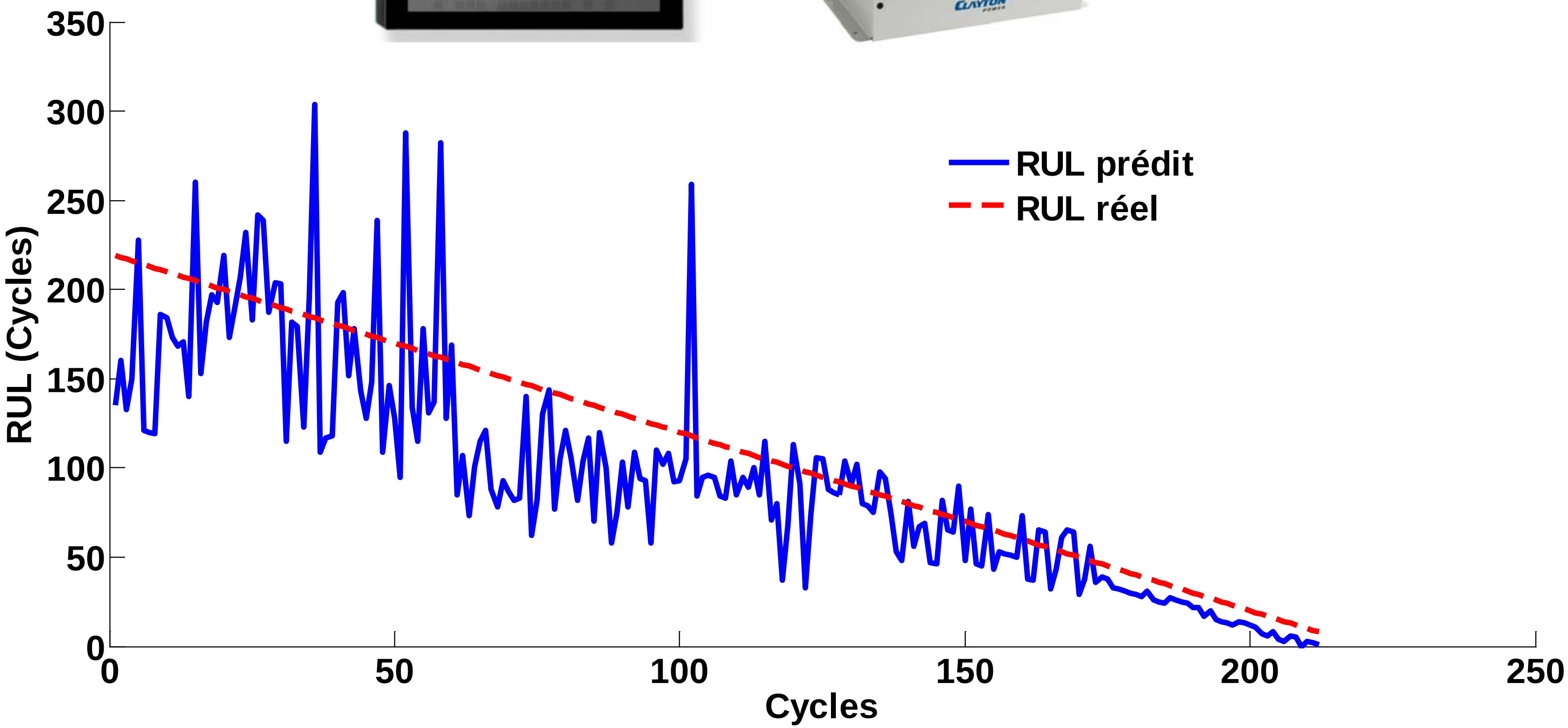
# Health assessment & RUL



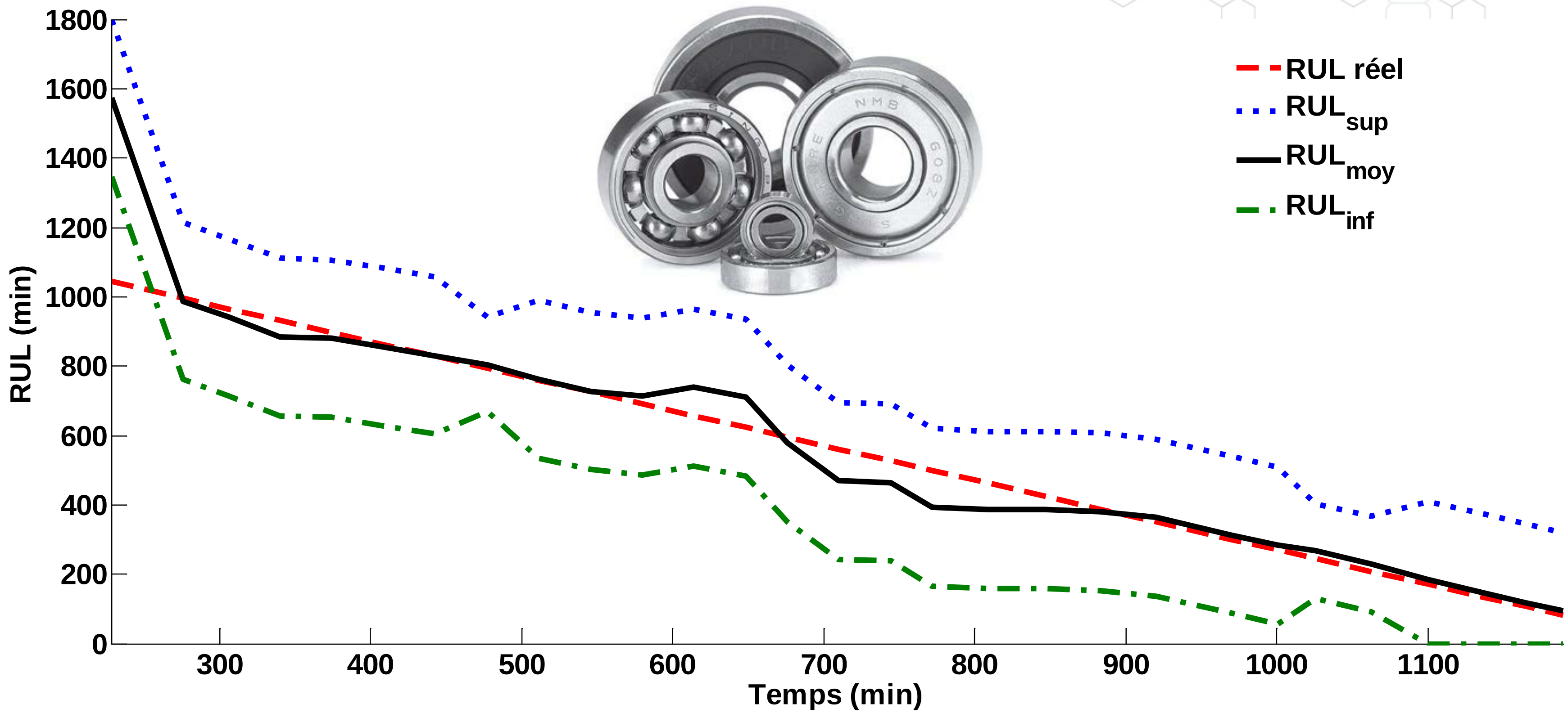
# RUL results


ULTRALIFE
Lithium-Ion Rechargeable Battery


100Ah
Lithium Ion Battery
12VDC 100Ah
CLAYTON

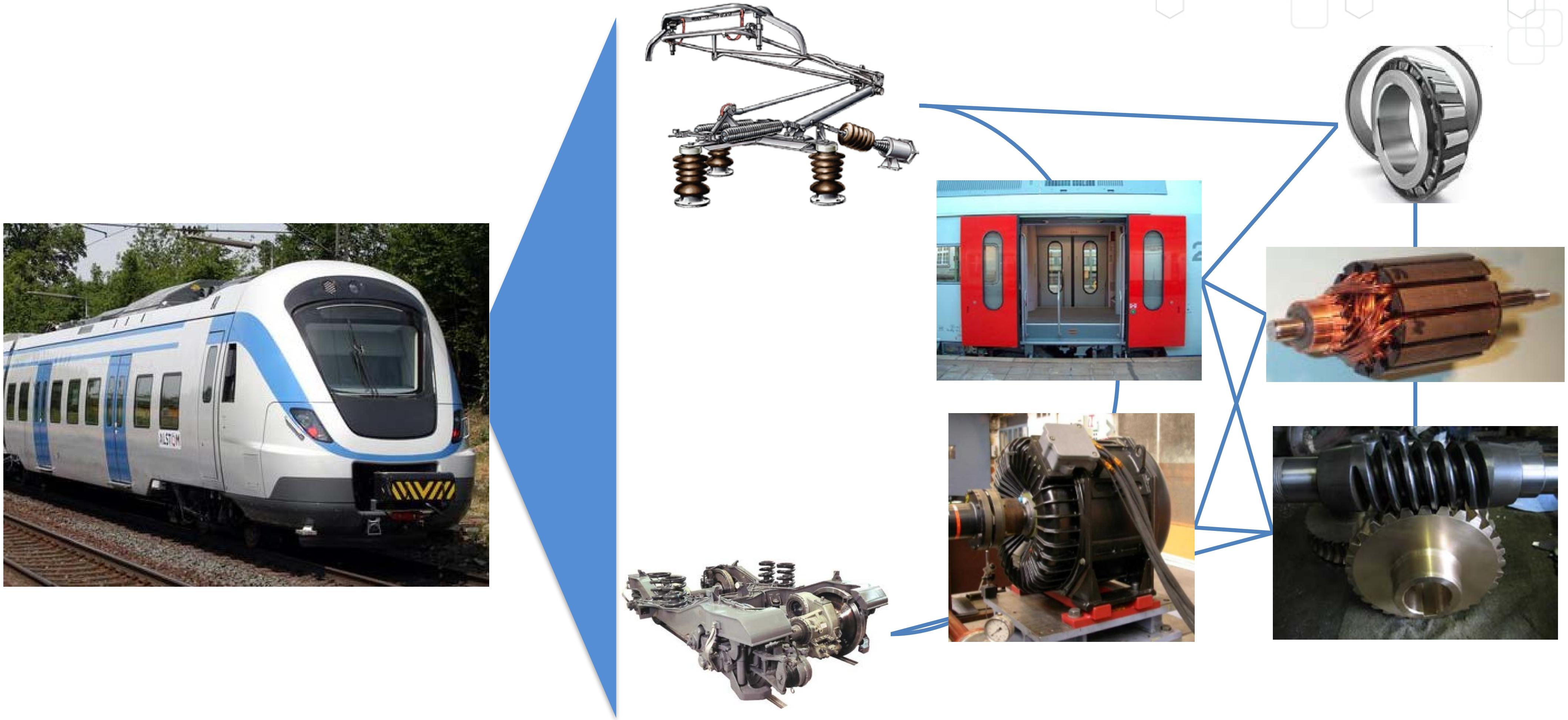

RUL prédit
RUL réel
RUL (Cycles)
Cycles
0
50
100
150
200
250
300
350
0
50
100
150
200
250

# Résultats de RUL



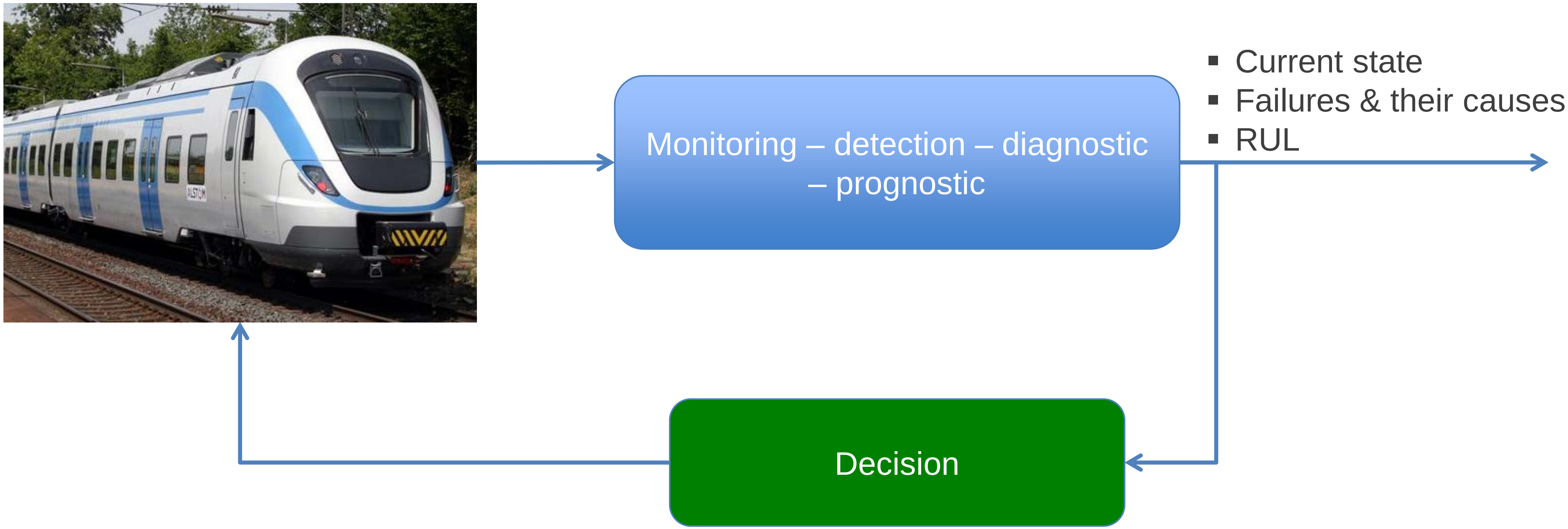

| | Accuracy | Precision | MAPER | HP | $P_{\alpha_c-\lambda_c}$(0.2-0.5) | ER [0.25 0.5 0.75] |
|---|---|---|---|---|---|---|
| $RUL_{sup}$ | 0.5987 | 111.1 | 64.89 | 913 | Yes | [0.81 0.75 0.20] |
| $RUL_{moy}$ | 0.9224 | 108.1 | 8.52 | 913.6 | Yes | [0.98 0.83 0.95] |
| $RUL_{inf}$ | 0.6238 | 116.1 | 50.44 | 961.1 | No | [0.84 0.43 0.28] |

# PHM of complex systems



- Model the interactions between components
- Assess the global heath state of the system
- Predict the global RUL of the system

# Decision


Current state
Failures & their causes
RUL
Monitoring – detection – diagnostic – prognostic
Decision

# Conclusion & Perspectives

- **Dependency between components**
- Observability of the degradations

- Universal features/indicators
- **Physical health indicators**

- **Physical models**
- Validation of the models

- Uncertainty associated to predictions and to RUL
- **Adaptive thresholds**

Critical components identification & data acquisition → Data processing: feature extraction & health indicators construction → Degradation modeling → Health assessment & RUL prediction

**What about decision?**

« Automation » – Implementation – validation on real systems

# Conclusion & Perspectives

## PHM designed systems

Self-monitoring, self-detection, self-diagnostic, self-prognostic

Self-reconfiguration, fault tolerant…

***Towards smart monitoring for more availability & safety…***

# Questions?

Thank you for your attention!

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