



Prognostics and Health Management

From monitoring to remaining useful life prediction

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Motivation



➡ Need to monitor – assess – diagnose – anticipate – act

↗ Reliability ↗ Availability ↗ Security ↘ Costs

Prognostics & Health Management (PHM)

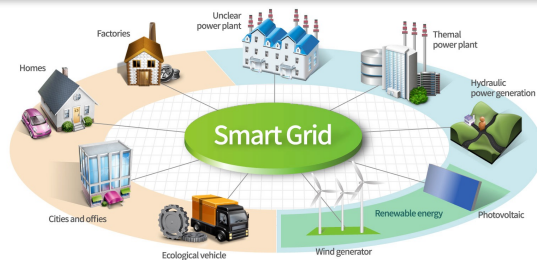
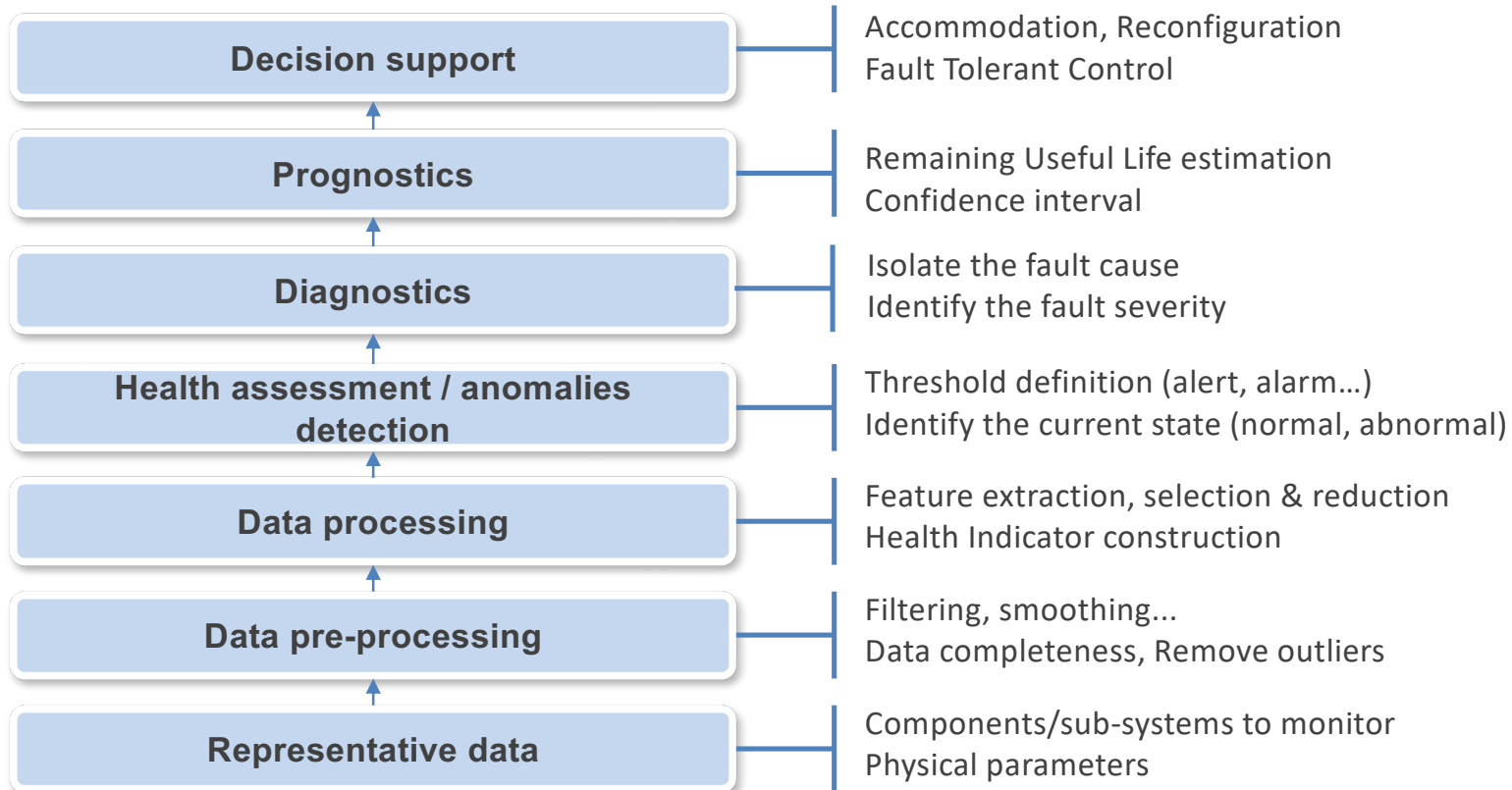
Definitions

PHM: *means to predict and protect the integrity of equipment and complex systems, and avoid unanticipated operational problems leading to mission performance deficiencies, degradation, and adverse effects to mission safety.* [CALCE Center]

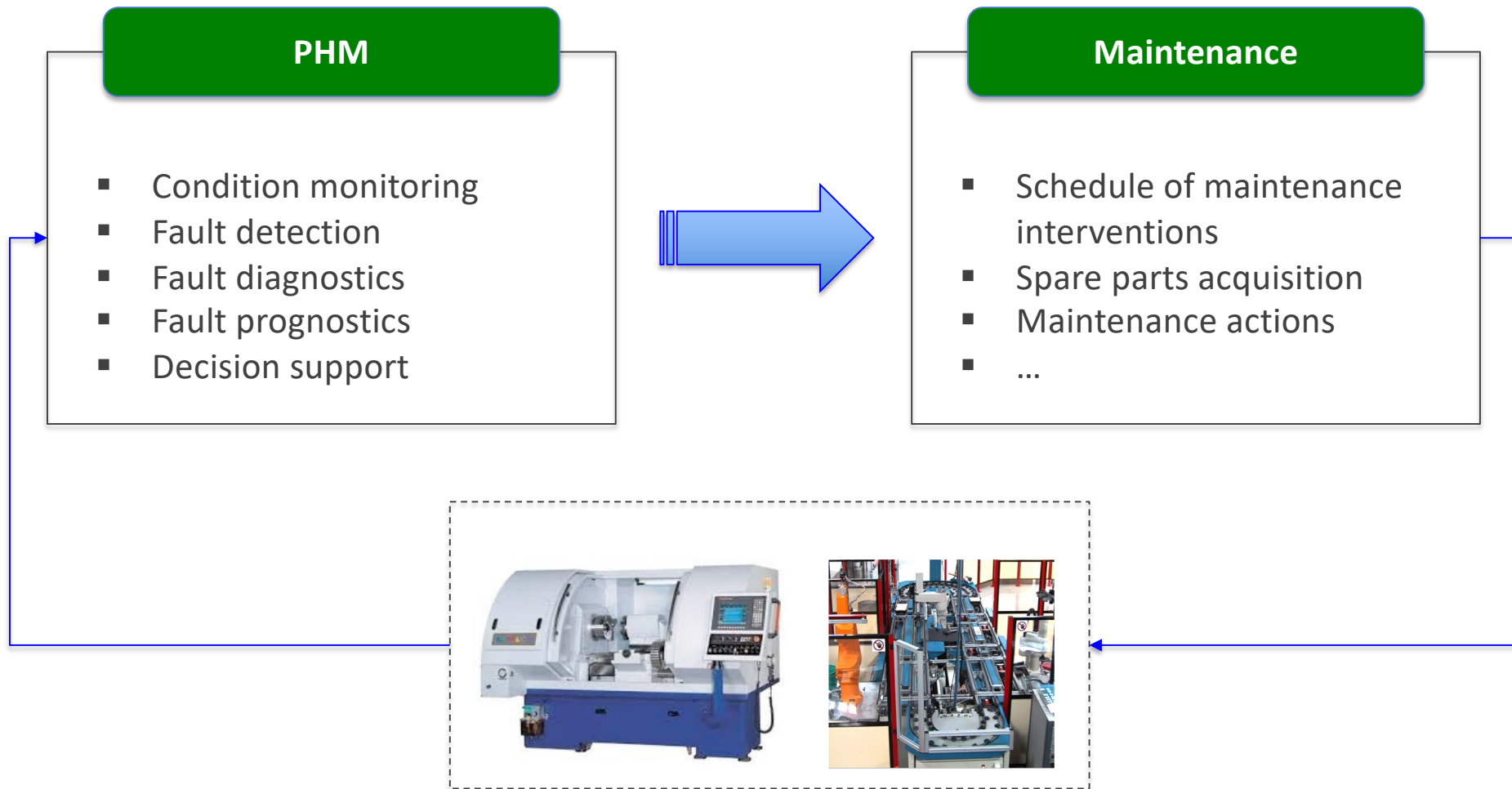
PHM: *discipline that links studies of failure mechanisms to system lifecycle management. PHM uses information to allow early detection of impending or incipient faults, remaining useful life calculations, and logistical decision-making based on predictions.* [D. Stark, SEMATECH Inc.]

PHM: *field of research and application which aims at making use of past, present and future information on the environmental, operational and usage conditions of an equipment in order to detect its degradation, diagnose its faults, predict and proactively manage its failures.* [E. Zio, 2012]

Prognostics & Health Management (PHM)



PHM vs Maintenance



Reliability vs PHM

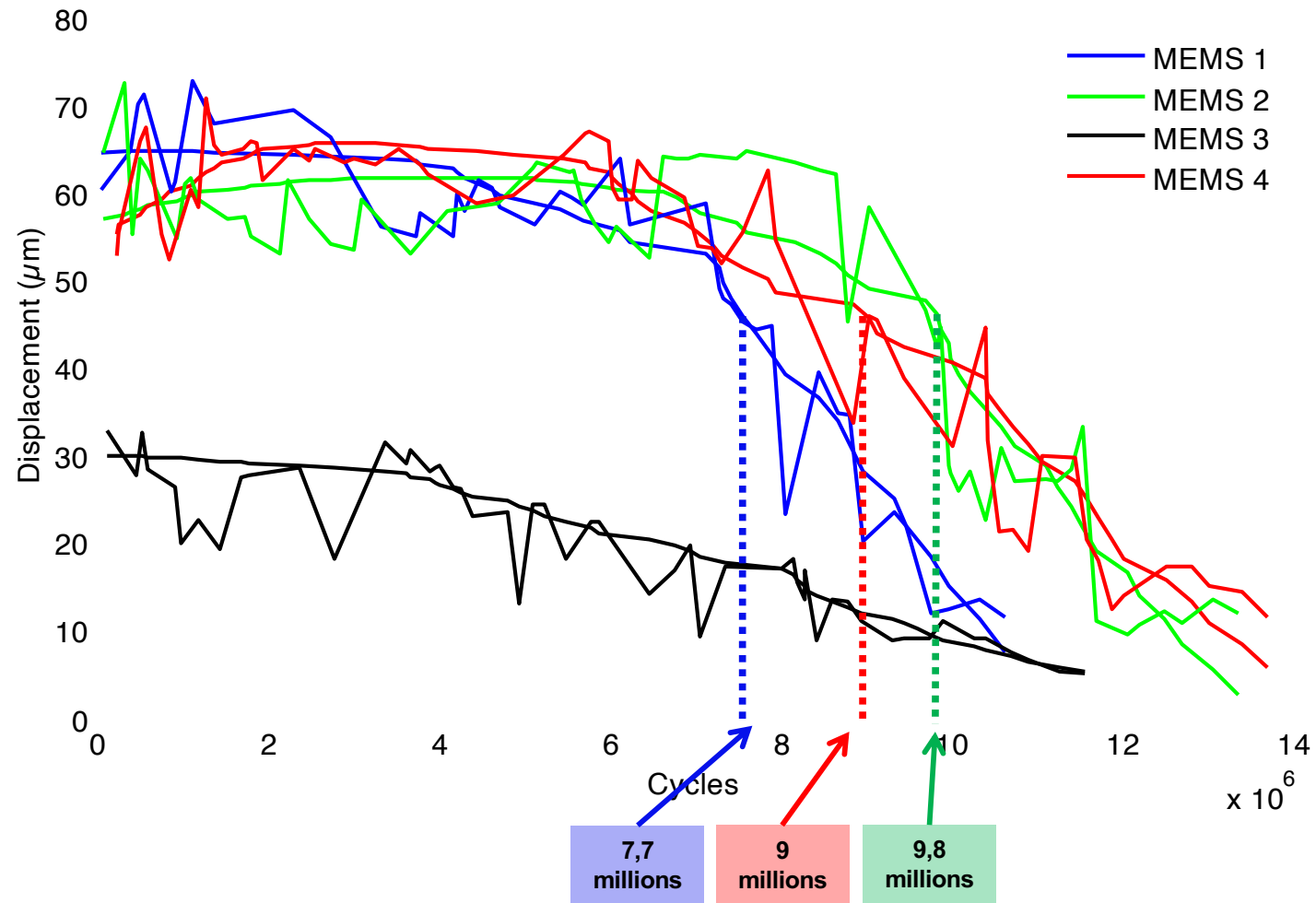
Reliability: probability that a machine will perform its required functions without failure for a specified time period when used under specified conditions.

- Specified time period, specified conditions
- Reliability models: obtained from statistical data on representative samples of systems.
- No update of the reliability models once derived.

PHM: means to predict and protect the integrity of equipment and complex systems, and avoid unanticipated operational problems leading to mission performance deficiencies, degradation, and adverse effects to mission safety.

- Continuous monitoring and health state assessment of the system (individually).
- Model parameters update as new observations are acquired.
- Remaining Useful Life prediction by taking into account current and future operating conditions.

Reliability vs PHM



For information: the manufacturer guarantees the micro-valve MEMS for 8 million cycles

PHM in industry

Aerospace



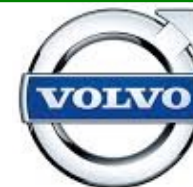
Energy



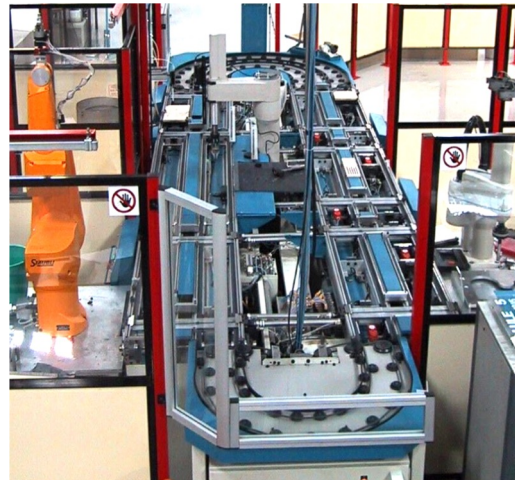
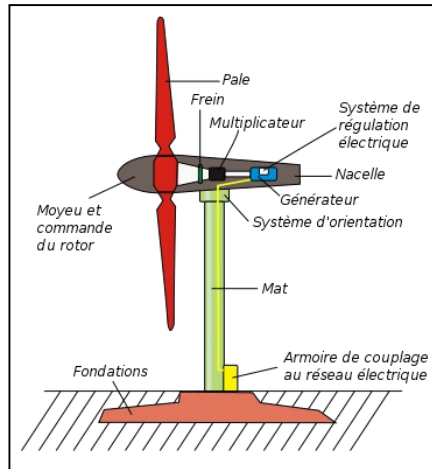
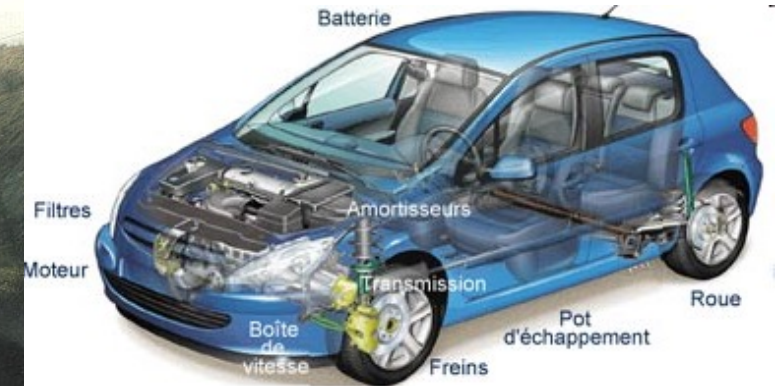
Railway transport



Automobile

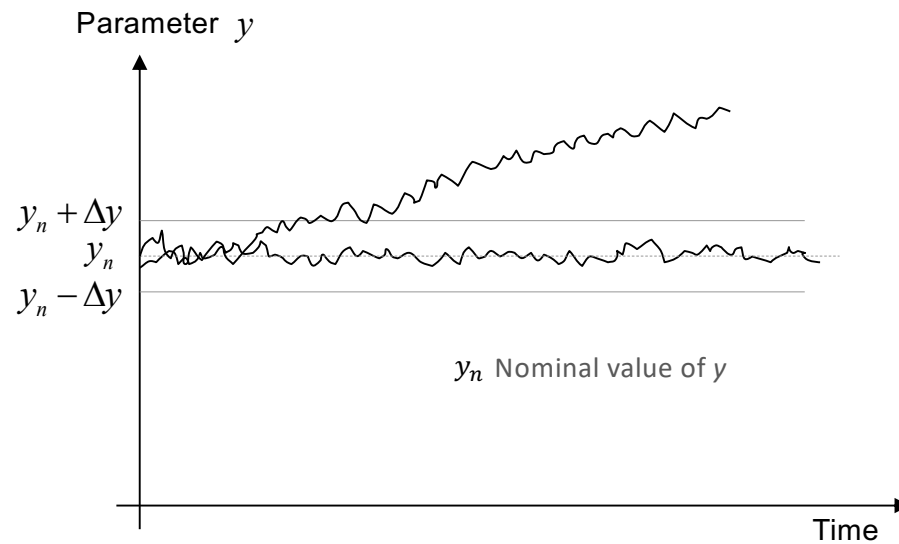


PHM in industry



Condition Monitoring

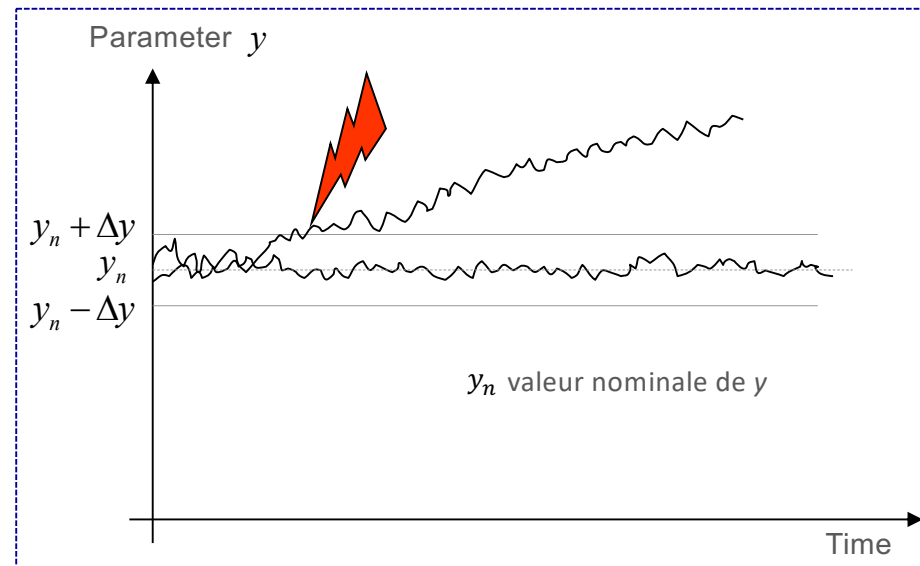
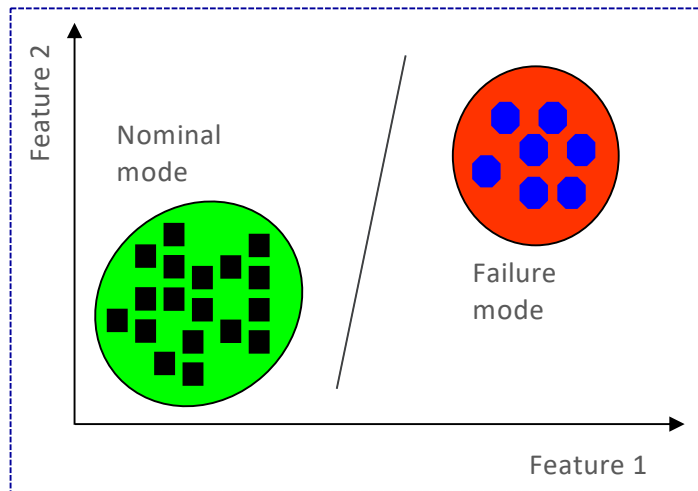
Acquisition and processing of information and data that indicate the state of a machine over time.



Monitoring or observation of a parameter

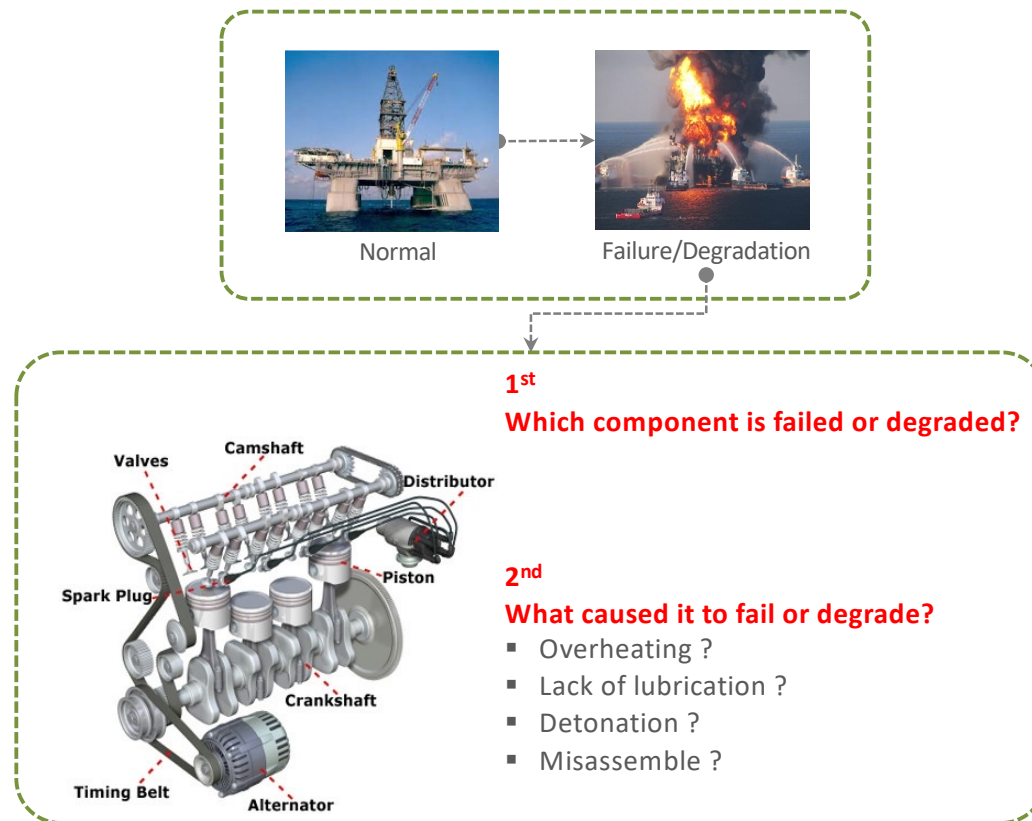
Fault detection

Fault (or failure) detection consists of deciding whether a system is in its nominal operation (state) or not. [NF E90-372, NF ISO 13372 : 2012-12]



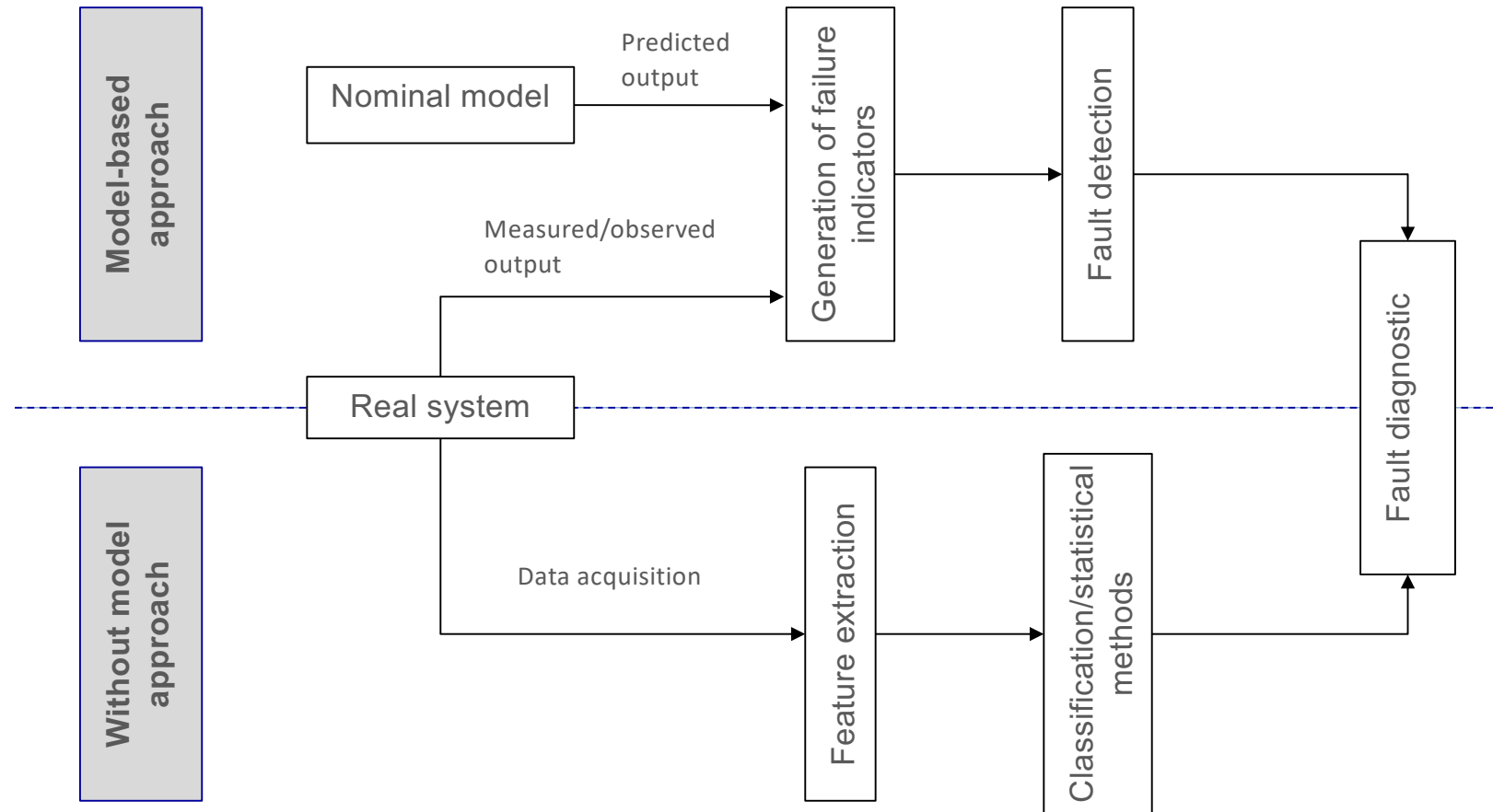
Fault diagnostics

Examination of symptoms and syndromes to determine the nature of faults or failures (kind, situation, extent). [NF E90-372, NF ISO 13372 : 2012-12]



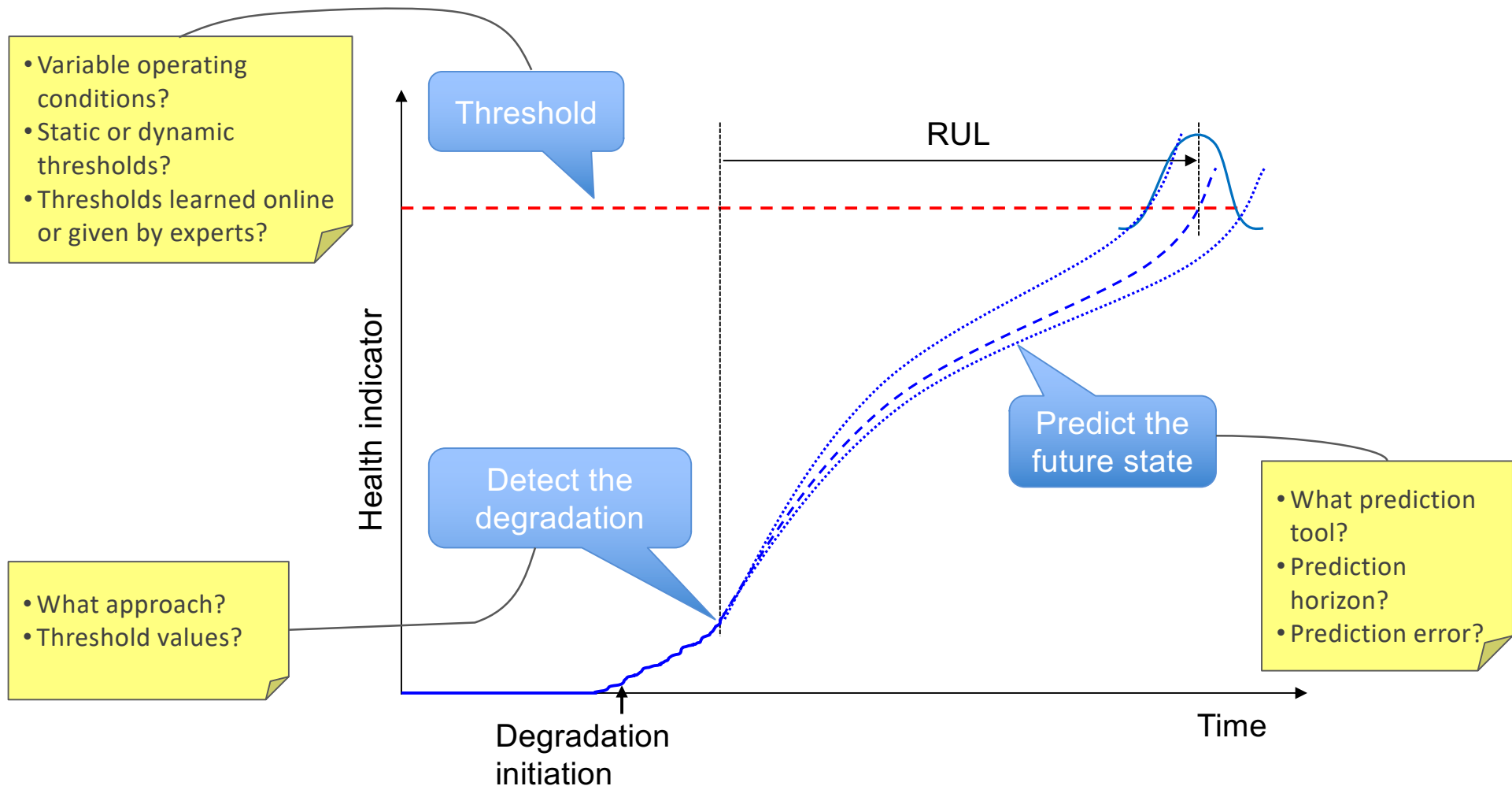
Fault diagnostics

Diagnostic approaches [Kawthar ALAMEH, 2017]

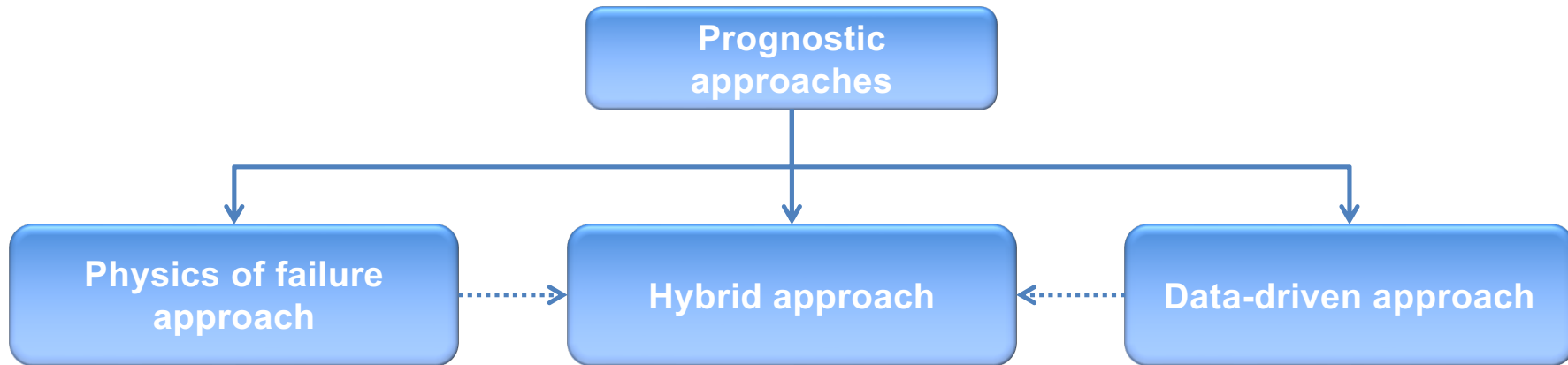


RUL prediction (Prognostics)

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



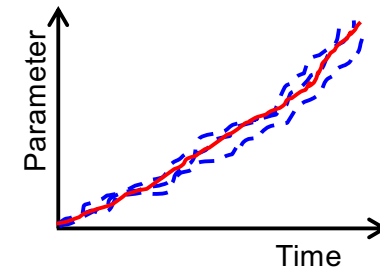
Prognostic approaches



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

Physical modeling

- Algebra-differential equations
- Fatigue, corrosion, wear... models
- Paris-Erdogan laws



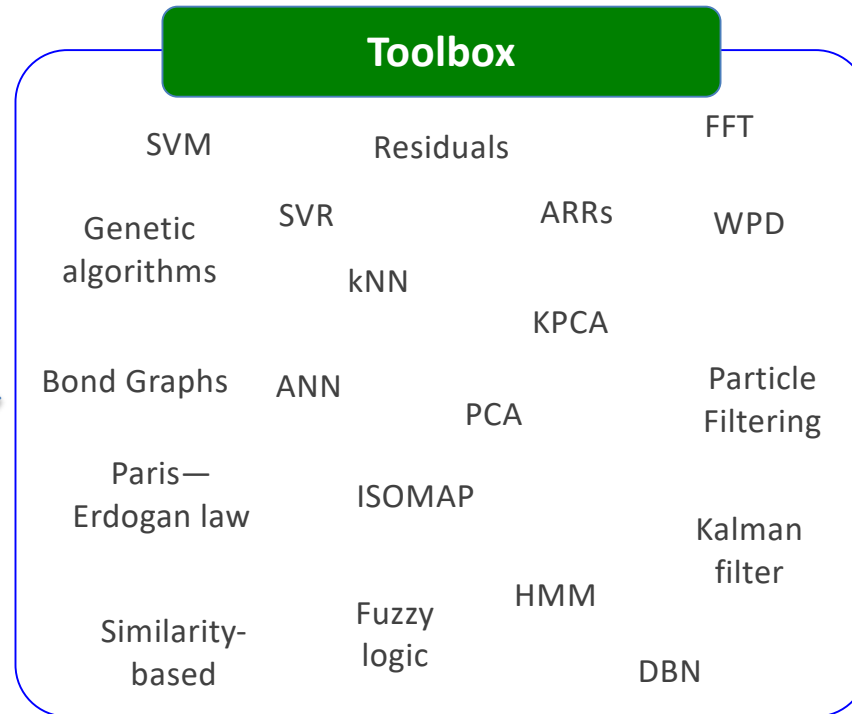
Data oriented modeling

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

Prognostic tools



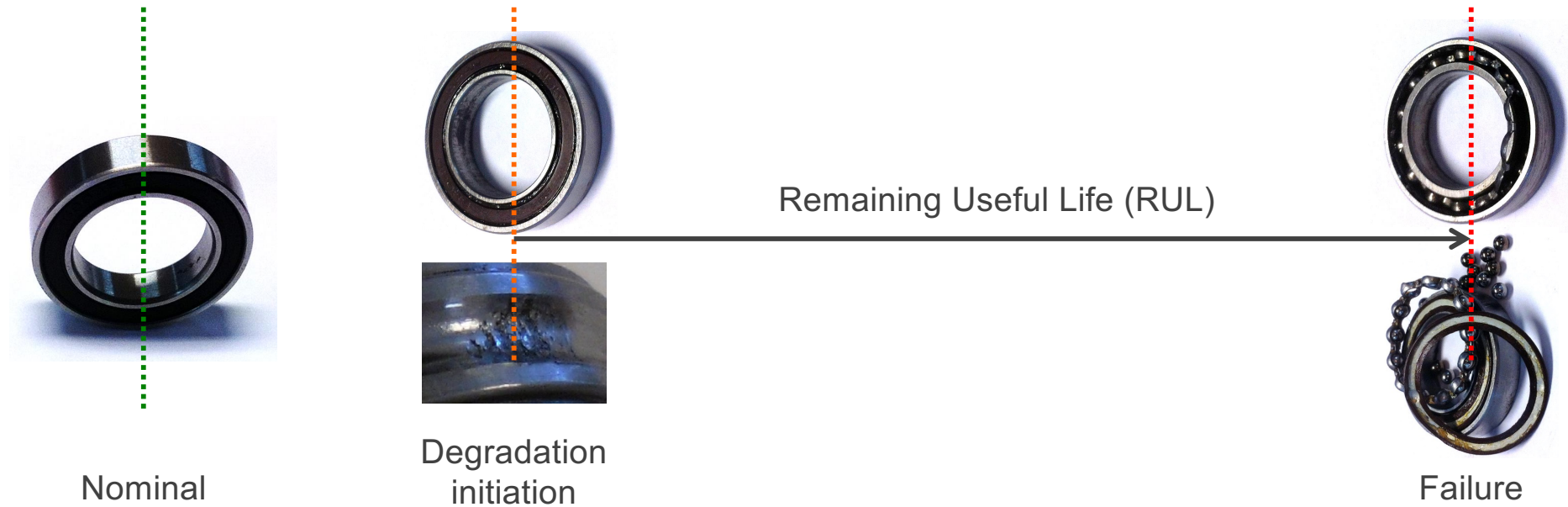
Data &
expert
knowledge



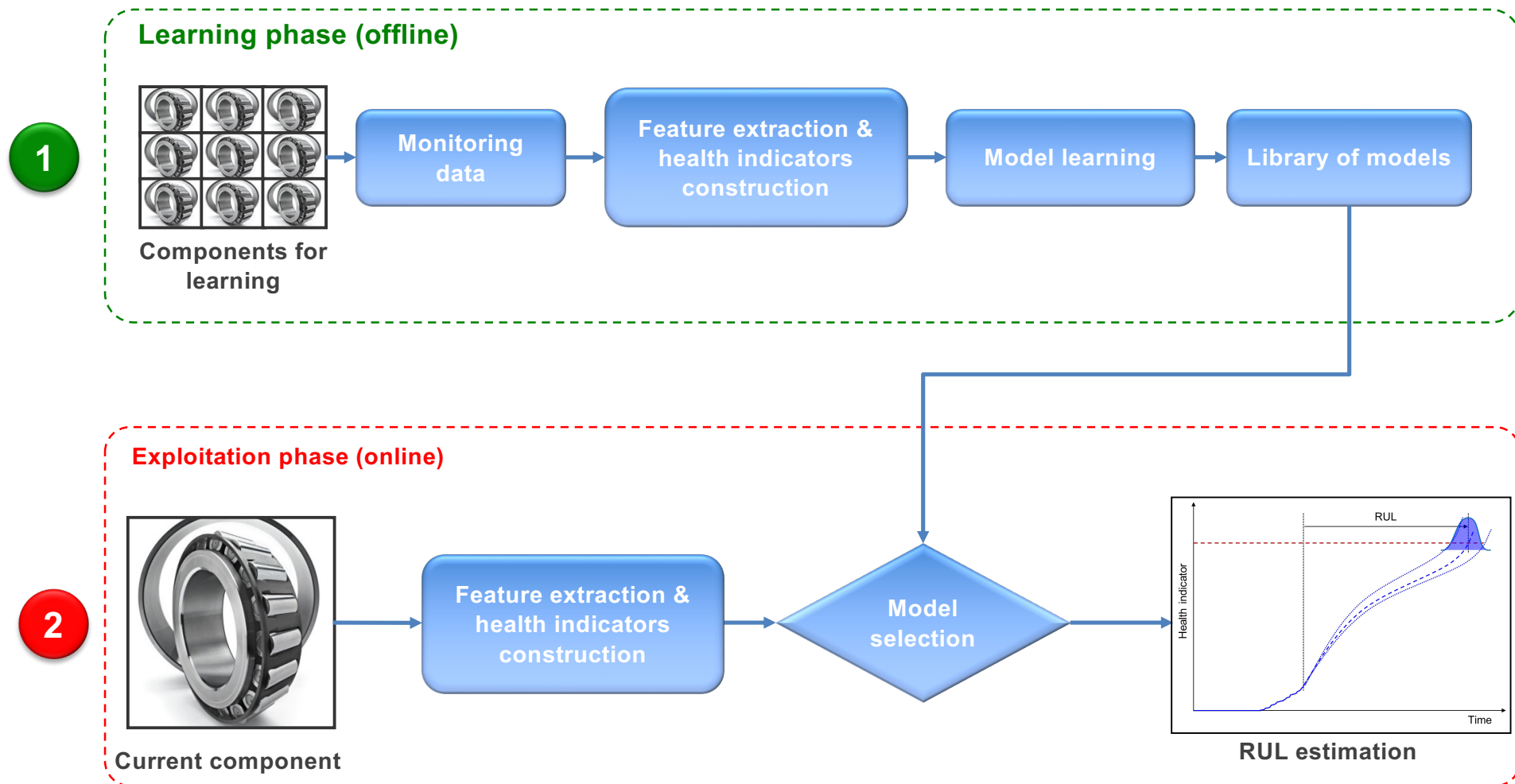
- Fault detection
- Fault diagnostics
- Fault prognostics
- Decision support

Data-driven prognostic approach

Scientific issues



Data-driven prognostic approach

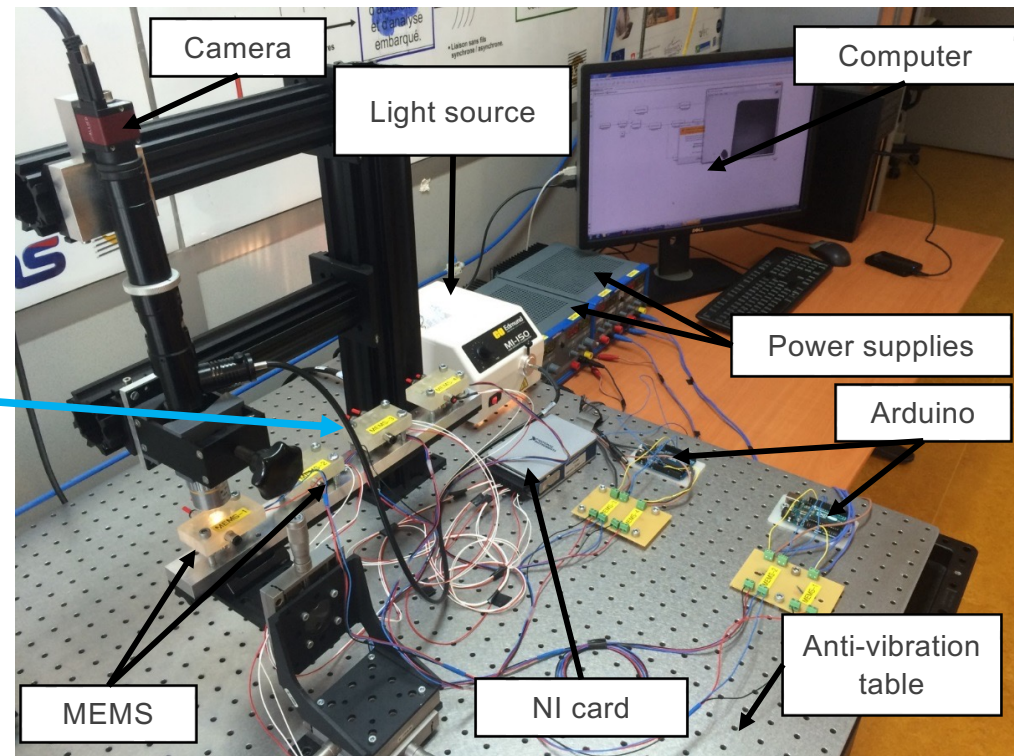
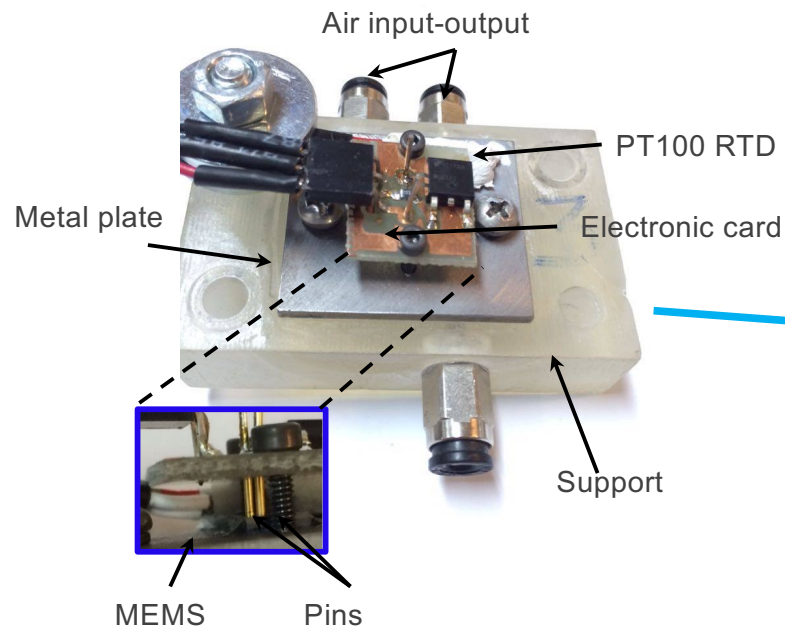


Case study

MEMS

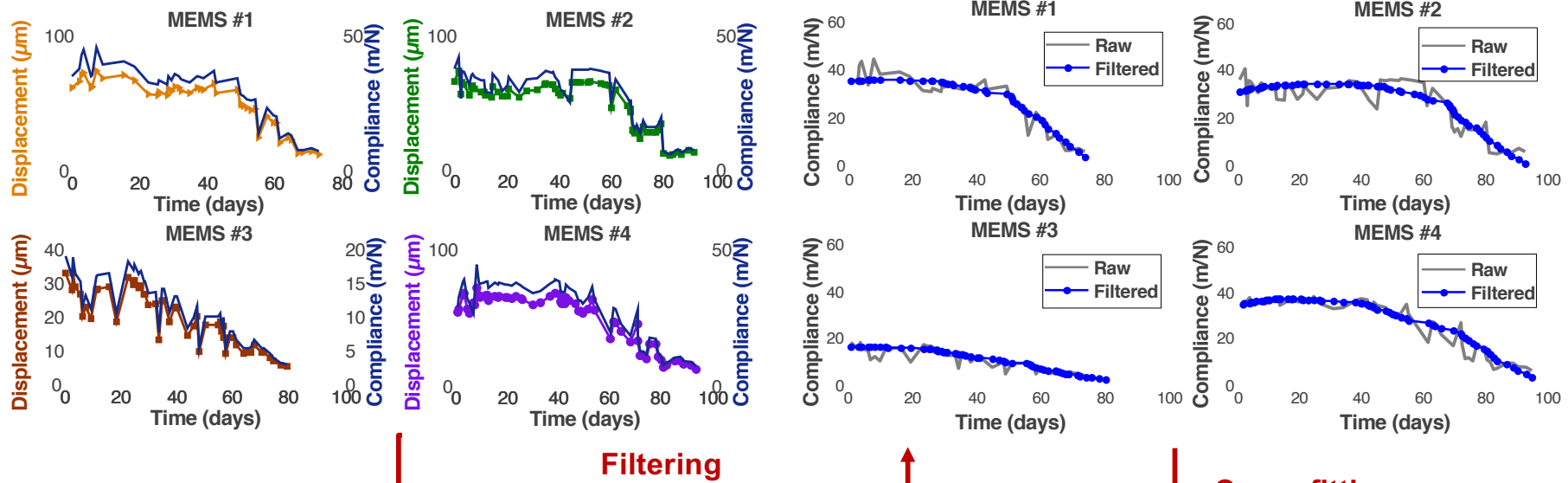


Support to fix the MEMS



Case study

Built Health Indicators



Coefficient of determination ($0 < R^2 < 1$)

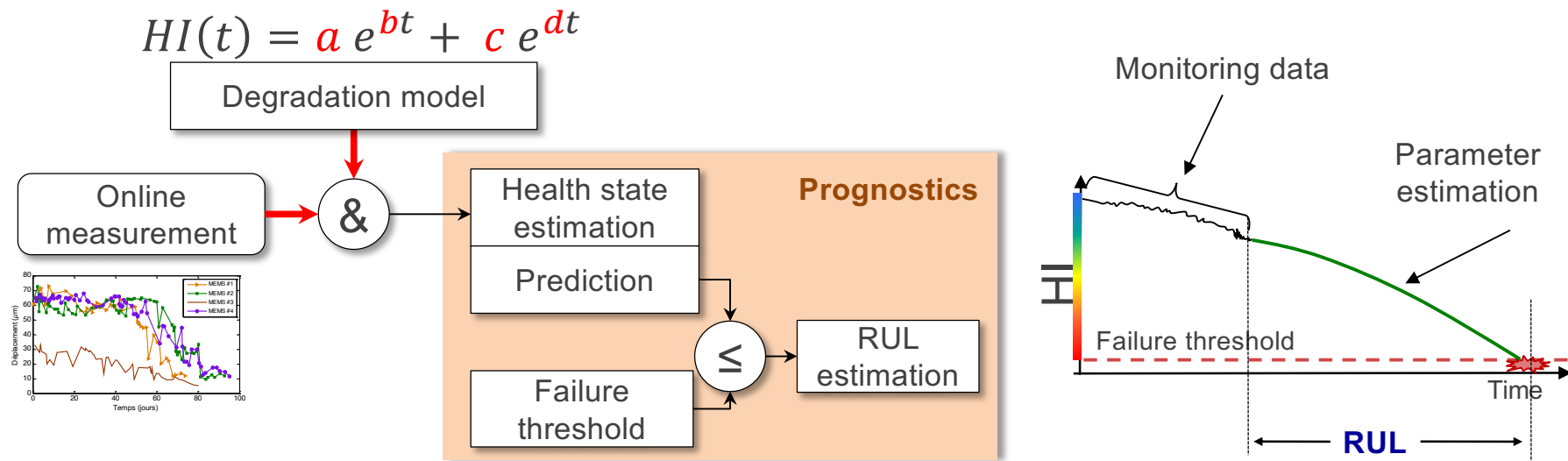
Campaign	MEMS 1	MEMS 2	MEMS 3	MEMS 4
2	0.993	0.989	0.989	0.992
3	0.981	0.973	0.964	0.972
4	0.978	0.983	0.970	0.979

Curve fitting

Degradation model

$$HI(t) = a e^{bt} + c e^{dt}$$

Case study



1. Kalman filter

2. Extended Kalman filter

3. Particle filter

- Estimate and adjust parameters



- Propagate the estimated state in the future
- Estimate the RUL



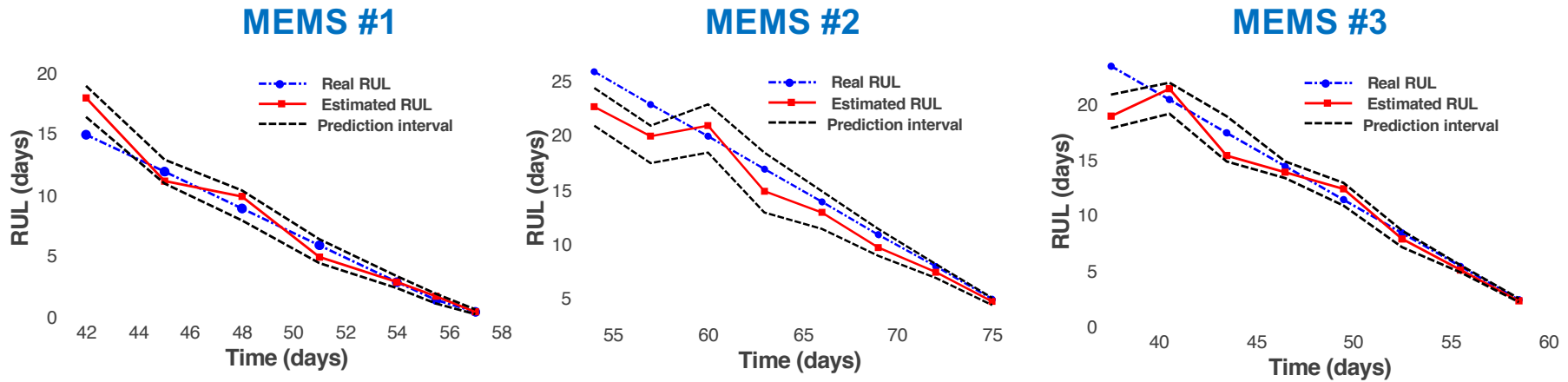
Non-linear models and non-Gaussian noises



Uncertainties in the parameters

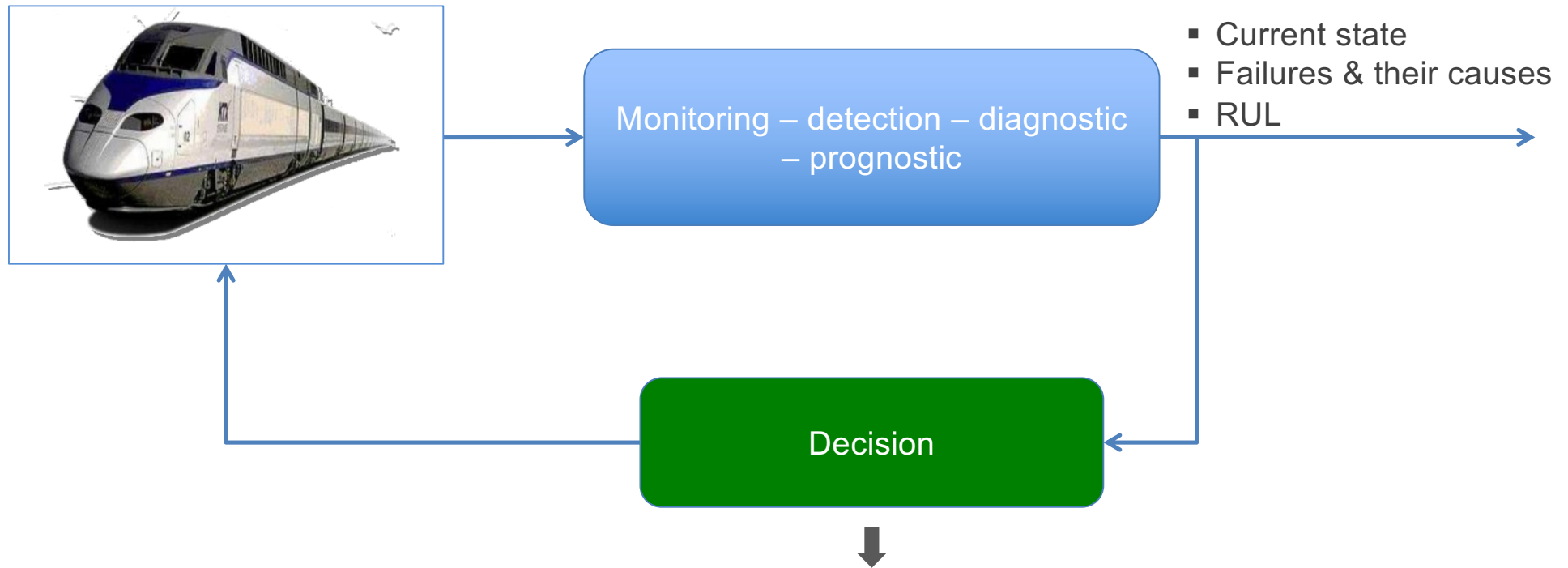
Case study

Prognostics Results



MEMS	App.> than (days)	Max. error (days)	Horizon (days)	Error (%)
1	44	1	13	<10%
2	59	2	16	<12%
3	40	2	18	<9%

Decision support



Operational

- Maintenance interventions
- Hardware and software (control) reconfiguration → impact on the health state and on the RUL
- Fault Tolerant Control (FTC)

Feedback to design

- Adding and/or replacement of sensors → observability
- Re-design and/or repositioning of components → maintainability

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