PROGNOSTICS AND HEALTH MANAGEMENT: MERITS AND CHALLENGES

by:

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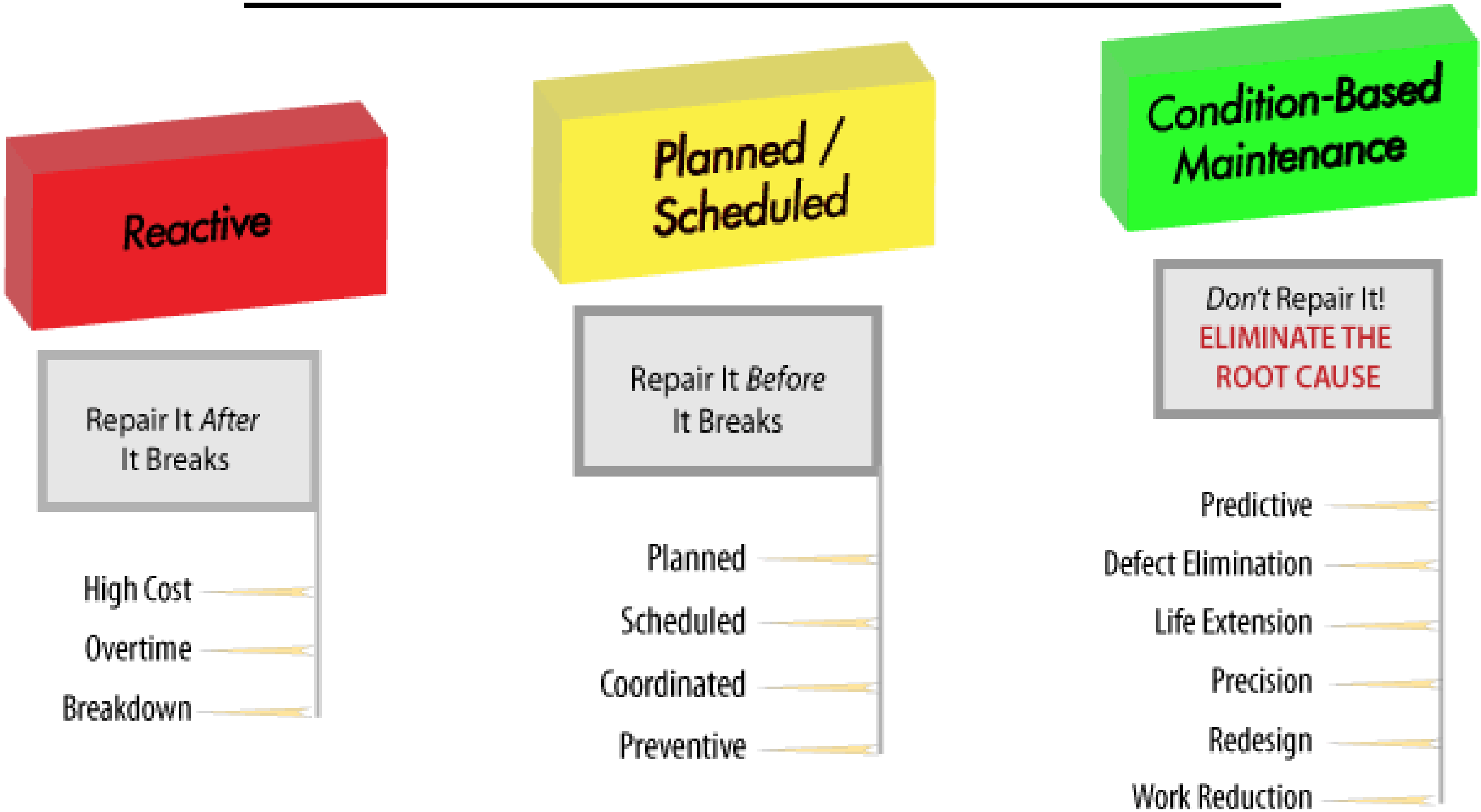
Summary

- ✓ Condition based maintenance and prognostics
- ✓ Fundamentals of prognostics
- ✓ Case study

Condition Based Maintenance and Prognostics

Evolution of the concept of maintenance



Paradigm shift

Objective: ensure system availability

Conventional maintenance

- Periodical inspections
- Scheduled maintenance

Innovative maintenance

- Based on condition
- Connected to logistic support

Paradigm shift

Monitoring for prognostics and health management

Canary doesn't feel well → air in the mine is getting worse:

- More time to manage the failure
- Canary can be reused

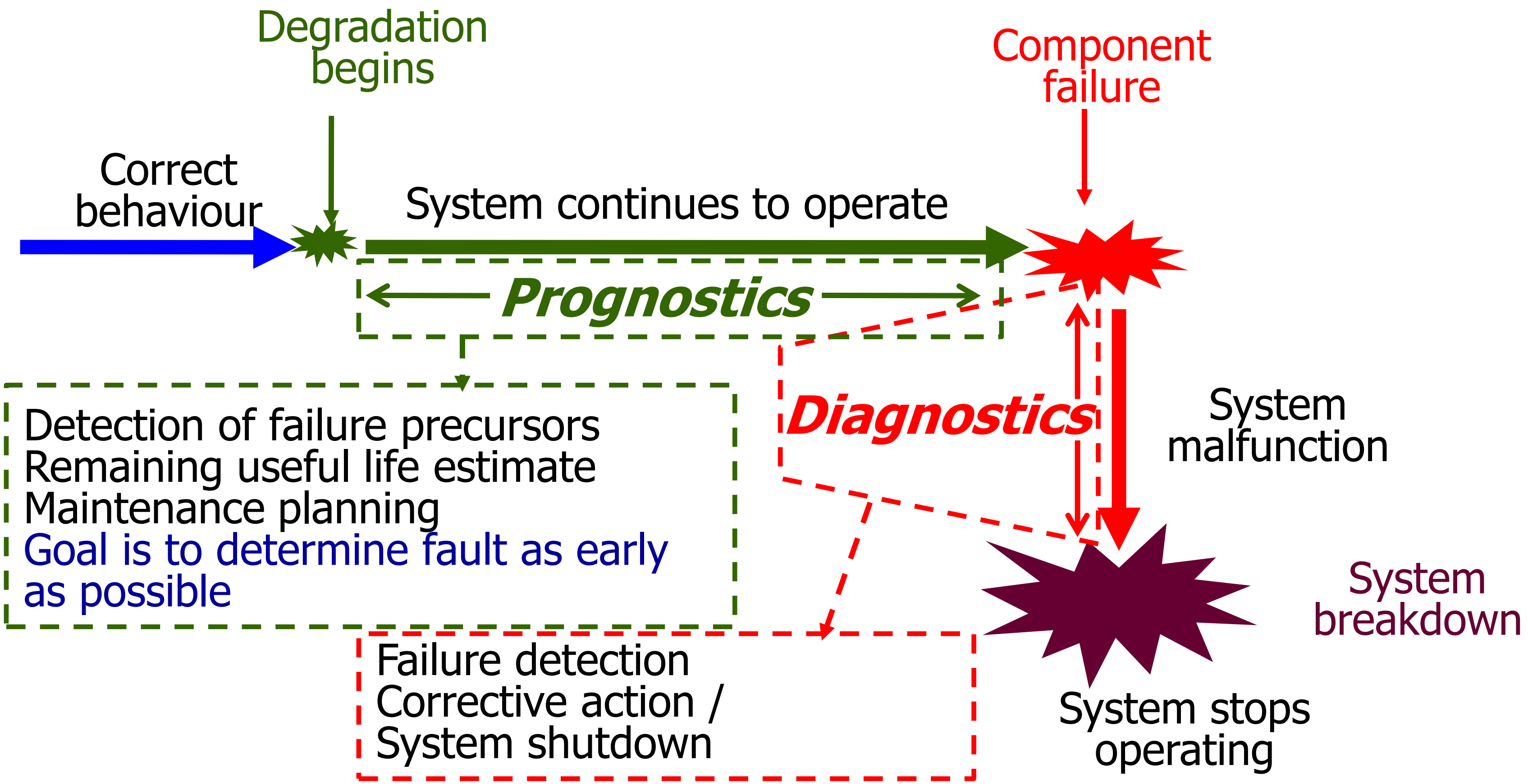
Monitoring for Diagnostic

Canary died → air in the mine was bad

Condition based maintenance and prognostics

- ✓ ***Diagnostics:*** Detection of anomalous conditions (faults or failures) and isolation of the relevant subsystem or component
- ✓ ***Prognostics:*** Prediction of the future behaviour of a system, or component, after a fault is detected and estimation of remaining useful life (RUL) ➔
  PHM = Prognostics and Health Management
- ✓ ***Condtion Based Maintenance (CBM):*** Scheduling maintenance according to expected failure and RUL

Progression from fault to failure



Condition Based Maintenance

- It is "opportunistic"
- Does not wait for a failure to occur....
- ....but it is not either performed periodically
- It is based on prognostics

→ Detects the precursors of a failure

→ Calculates the remaining useful life

→ Alerts the logistic support chain

→ Plans the system shutdown and the maintenance actions

PHM Keywords

Prognostics refers to the capability to predict and manage the progression of the fault condition to component failure synthesised by the concept of RUL (Remaining Useful Life)

Key words:

- Prediction
- Progression
- Fault condition
- RUL (Remaining Useful Life)
- Manage

PHM Keywords

Prediction implies **Uncertainty**

✓Precision → Confidence level

Progression implies **Predictions that evolve with time →**

✓Dynamic stochastic process

Fault Condition implies **Defining a measure of the actual components health status or damage level**

- Reliable
- Accurate

PHM Keywords

RUL → amount of probable time, in terms of operating hours, cycles, or other measures, for which the component will continue to meet its design specifications

Manage implies **Capability of dealing with uncertain and dynamic information**

✓Redesign of:
- Maintenance processes
- Logistic support

✓Goal: → Optimal exploitation of RUL estimate

What is necessary for a PHM system

- Identify the significant failure modes
- Identify the failure precursors and the degradation paths (fault-to-failure mechanisms)
- Develop suitable algorithms for predicting the remaining useful life

Merits of a PHM system

General objectives

Maximize the system operating time

Minimize operating and maintenance costs

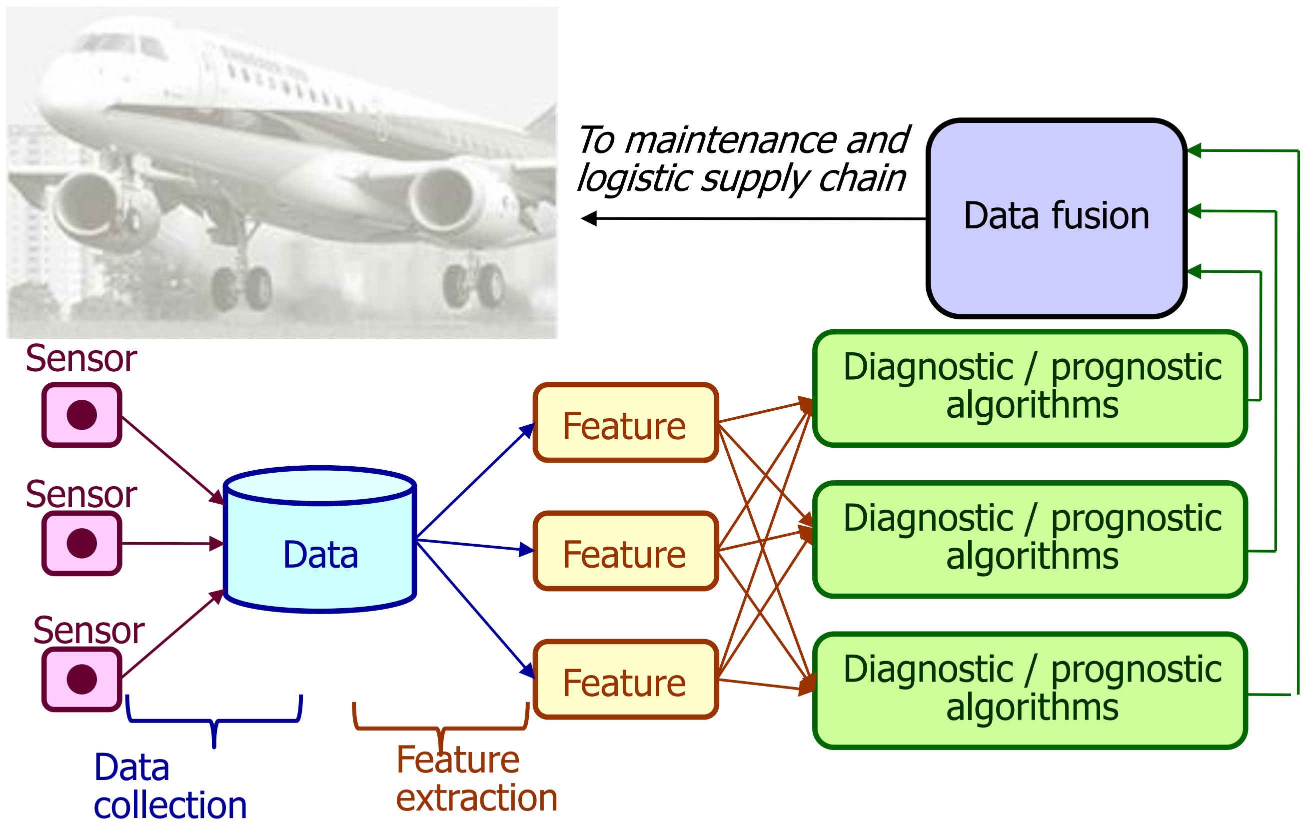
- Reduction of system downtime
- No more scheduled maintenance

In particular....

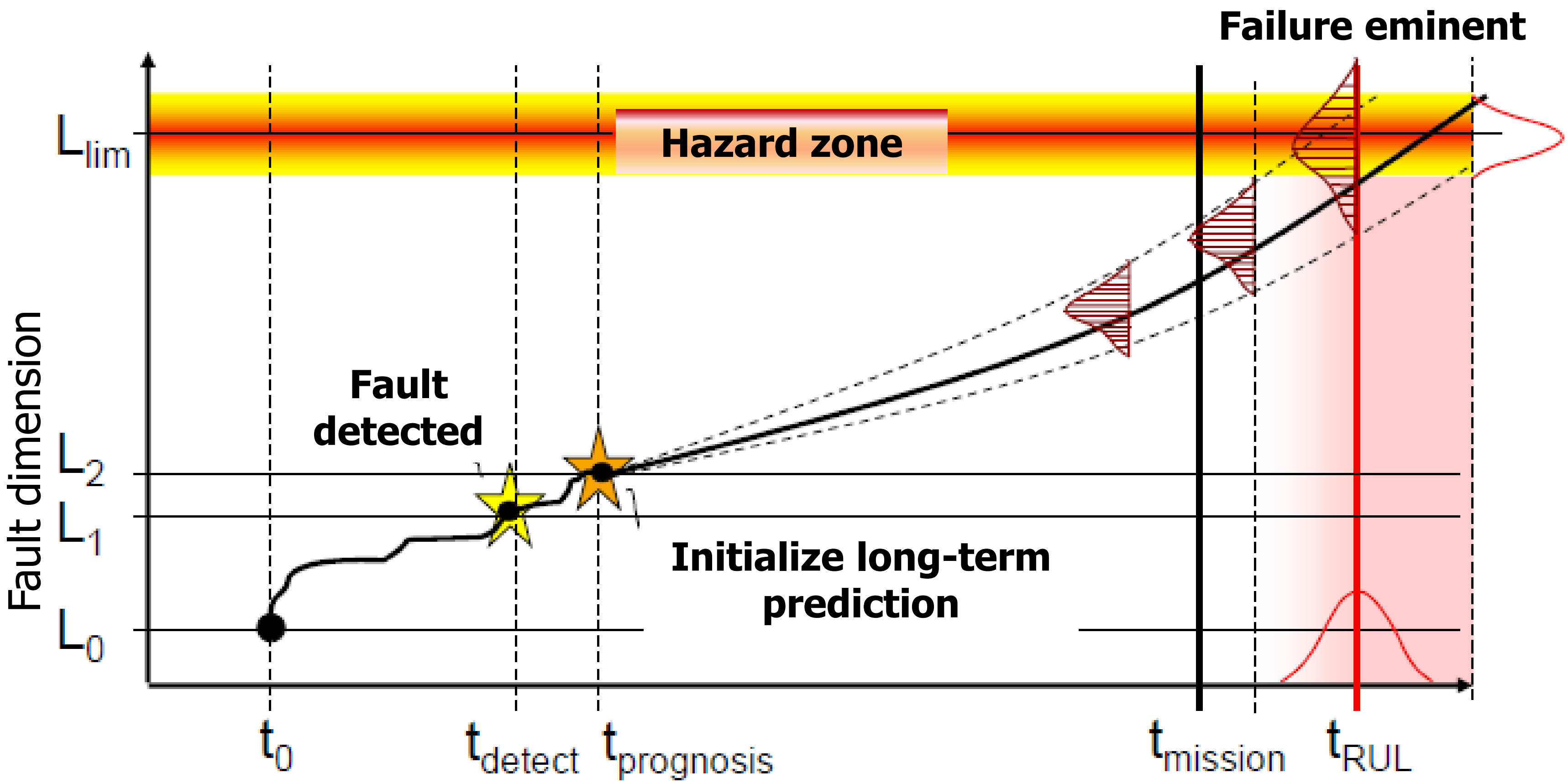
- Increased system availability
- Lower inspections time
- Minimum probability of system damage
- Minimum system downtime
- Reduction of number of spare parts

Fundamentals of prognostics

Logic flow of a PHM system



Prediction of Remaining Useful Life



Prediction of Remaining Useful Life - Critical issues

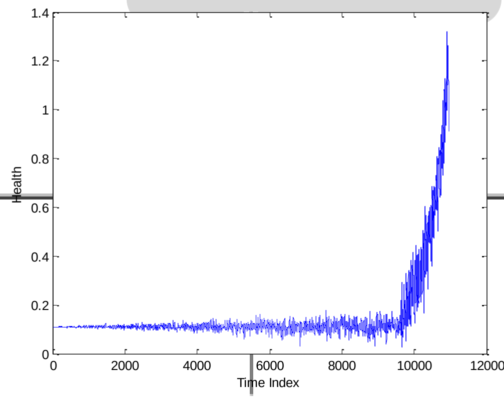
Environmental Conditions (T, P etc..)

Operational Condition (C, ω, P etc…)

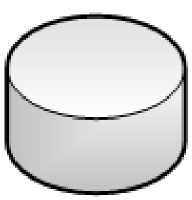
Condition Monitoring

T = 0

T = t



Degradation measure is affected by **noise** → accuracy and precision pattern are expected to be **non linear**



Historical time to failure data

Time zero :
model the failure distribution based upon historical component's failure data - Estimate RUL

Component's actual quality

Developing a PHM System - Step 1

Identify the failure modes

Importance of the different types of failures

Failures critical for the operation

Failure critical for the maintenance

Failures critical for the supply of spare parts

Developing a PHM System - Step 2

Identify the failures precursors

- Establish how a component failure can be identified
- Define the symptom in the "measurable" domain
- Smart use of all normally available information
- Possible adding of new sensors

Developing a PHM System - Step 3

Identify the degradation paths

- How a degradation propagates progressively and becomes a failure
- Develop mathematical models able to:
  - →Describe the physical phenomenon
  - →Predict the progression of the fault
  - →Estimate the remaining useful life

Developing a PHM System - Step 4

Provide an alert of the fault progression

- Indication of the fault progression process and remaining useful life must be given to the maintenance personnel in the most appropriate way
- Need to avoid **missed** and **false alarms**

Developing a PHM System - Step 5

Assess the cost effectiveness

For which failures does prognostics provide an economical advantage?

↓

Need to fuse in a unified model data relevant to:

↓

- Reliability
- Maintainability
- Cost of manpower
- Cost of storage
- Cost of system downtime
- Investment costs
- Costs of missed failures and false alarms

PHM cost issue

Investment costs

✓Experimental tests (Accelerated degradation tests)

✓High R&D expenses required, to be replicated for each new/different component

✓System development (IT infrastructure, hardware, software, systems integration)

✓ Processes reengineering

→ **Very high fixed costs**

Prognostics algorithms

Can be grouped in two main types:

- Model based
- Data driven
- PHM algorithms can also be built which are a combination of the two types

Model based prognostics

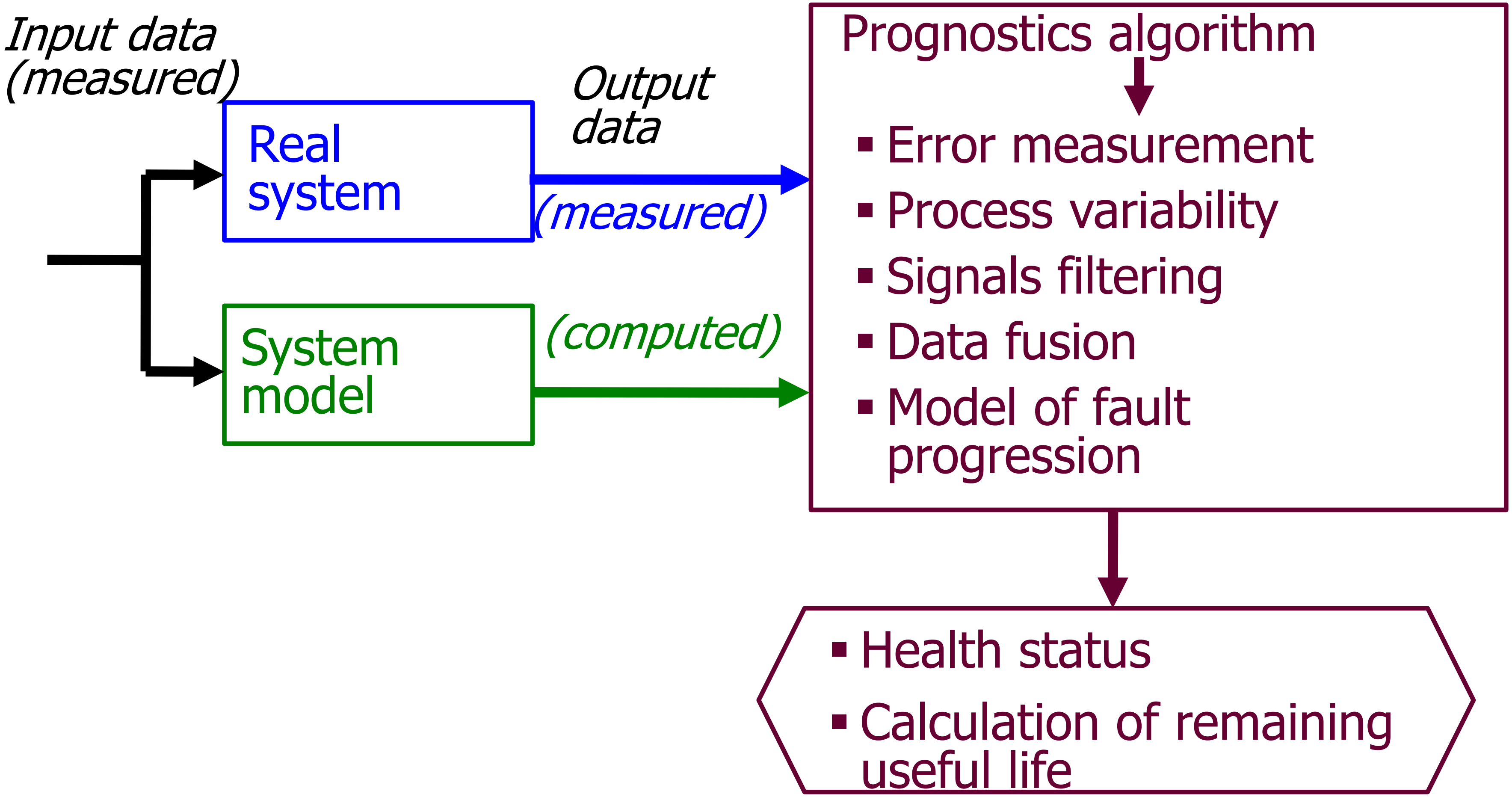
Model-based prognostics uses a dynamic model describing the process which characterizes the system operation

The system dynamic model can be built in two ways:

- Creation of a "physical" model of the system, in which system variables and parameters are interrelated by a set of algebraic and differential equations
- System identification by means of autoregressive techniques

It consists of assuming a given expression for the system dynamic model and adapt its parameters as a function of the measured values of the output variables

Flow chart of model based prognostics

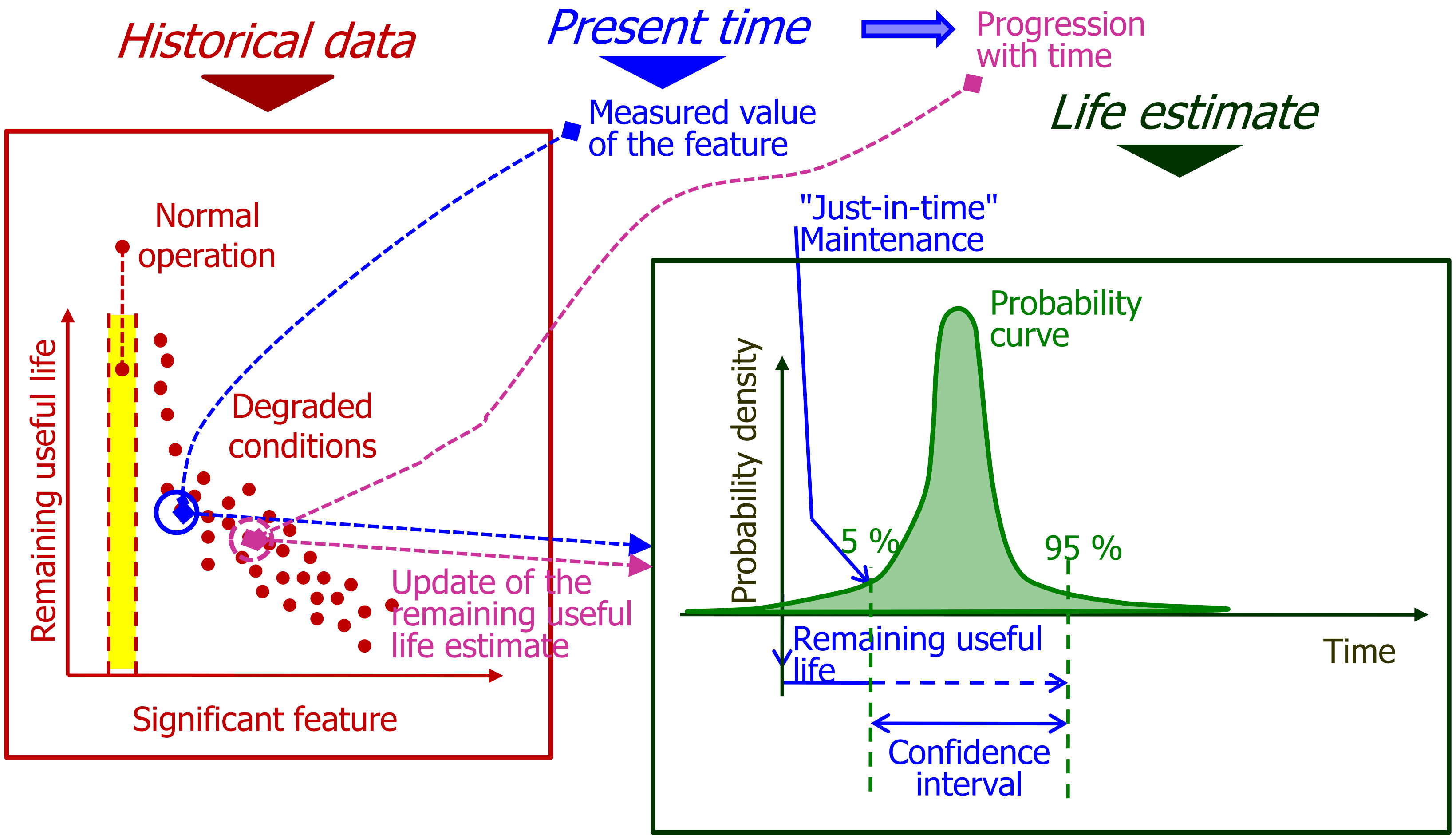


Data driven prognostics

It does not uses a mathematical model of the system, but is based on:

- Historical data for the type of system under study
- Definition of the probability density function
- Definition of the confidence limits

Significant diagrams for data driven prognostics

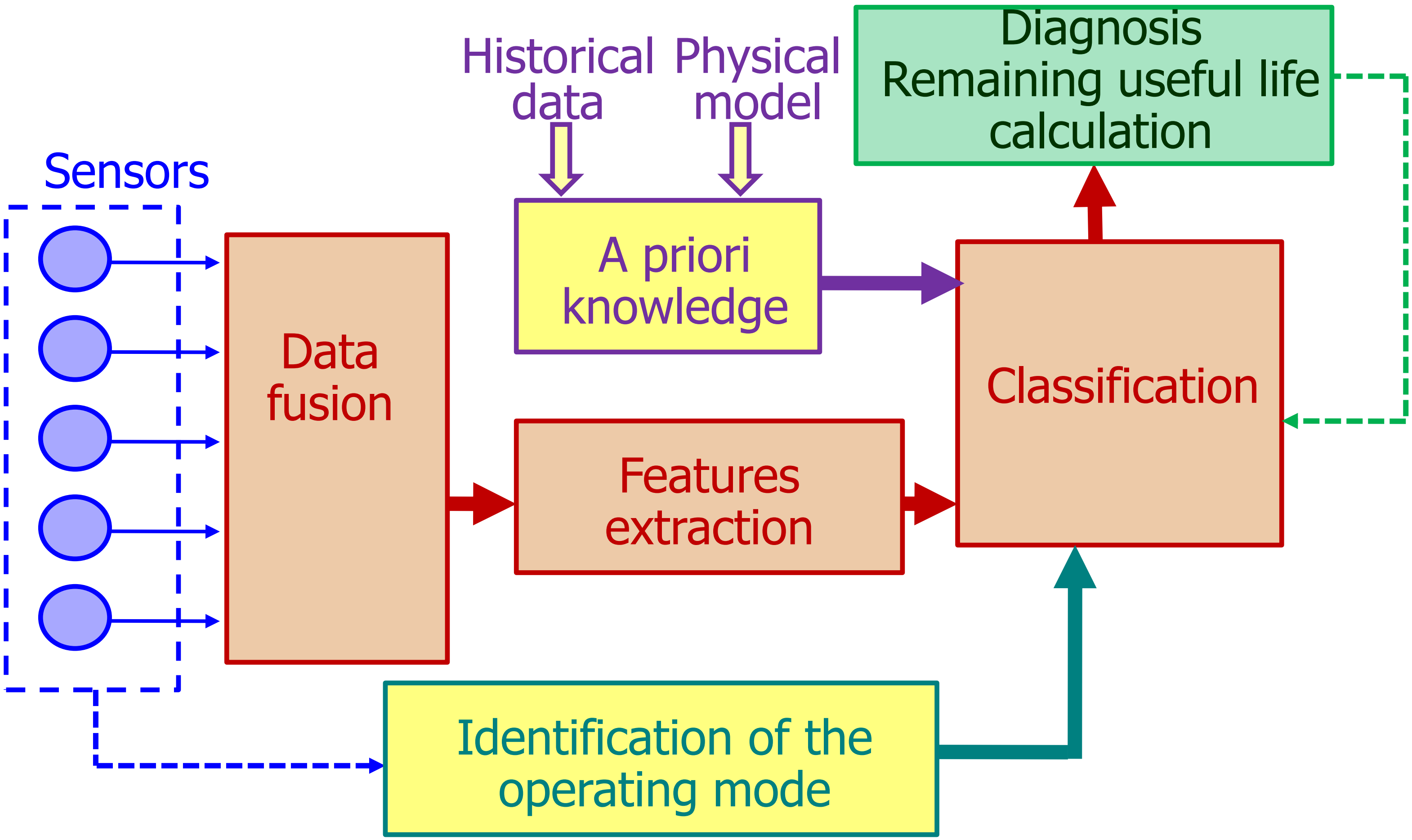


Use of neural networks in prognostics

Neural networks can be a useful tool for prognostics when a system failure can be caused by several possible combinations of faults of the system parts.
Most often, neural networks are based on a mix of model-based and data-driven algorithms

The neural network is auto-adaptive, learns from examples and aims at capture the significant relations among the data

Concept block diagram of neural networks in prognostics



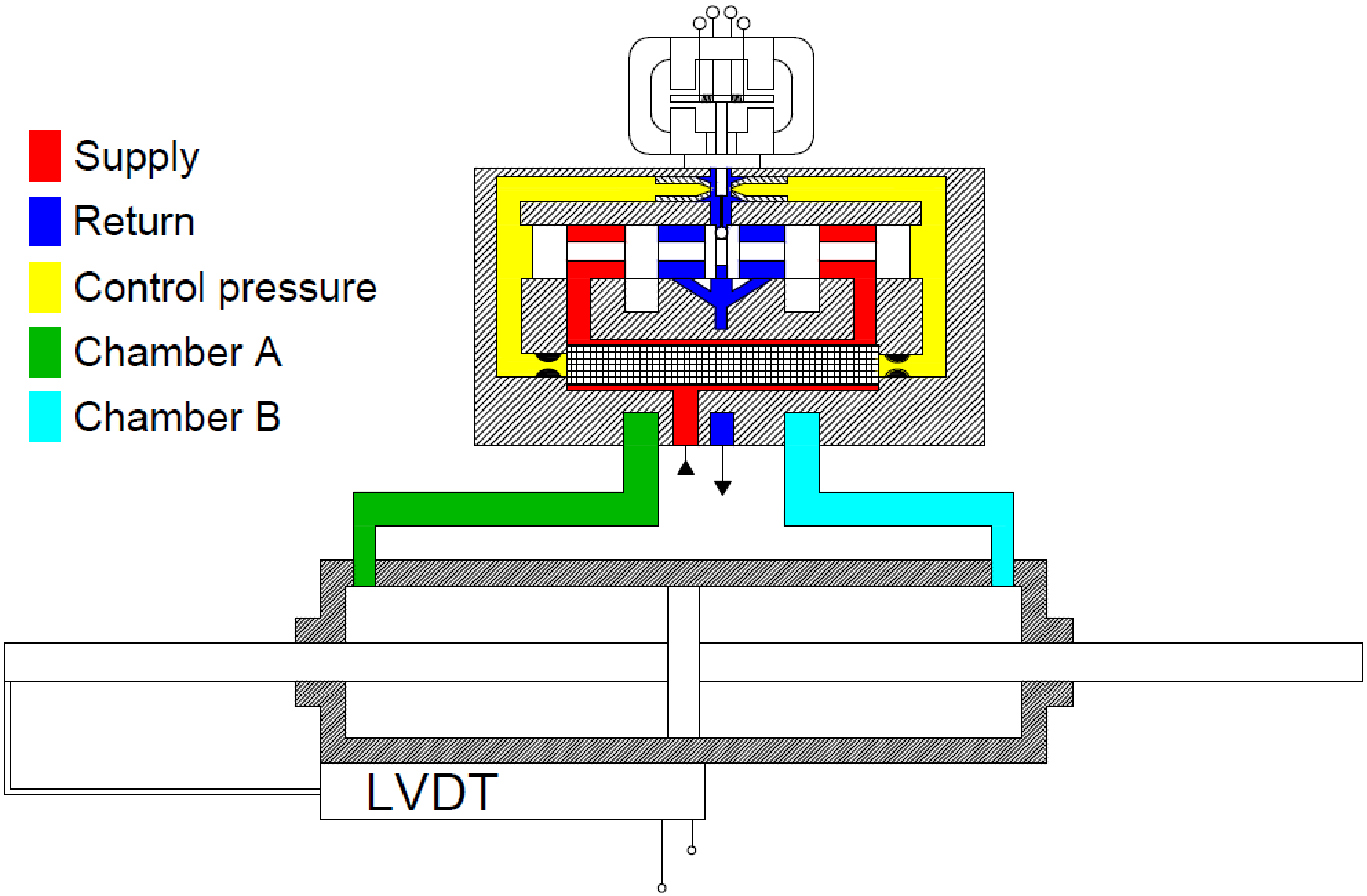
Case study

Development of a PHM system for electrohydraulic servoactuators
Primary flight controls

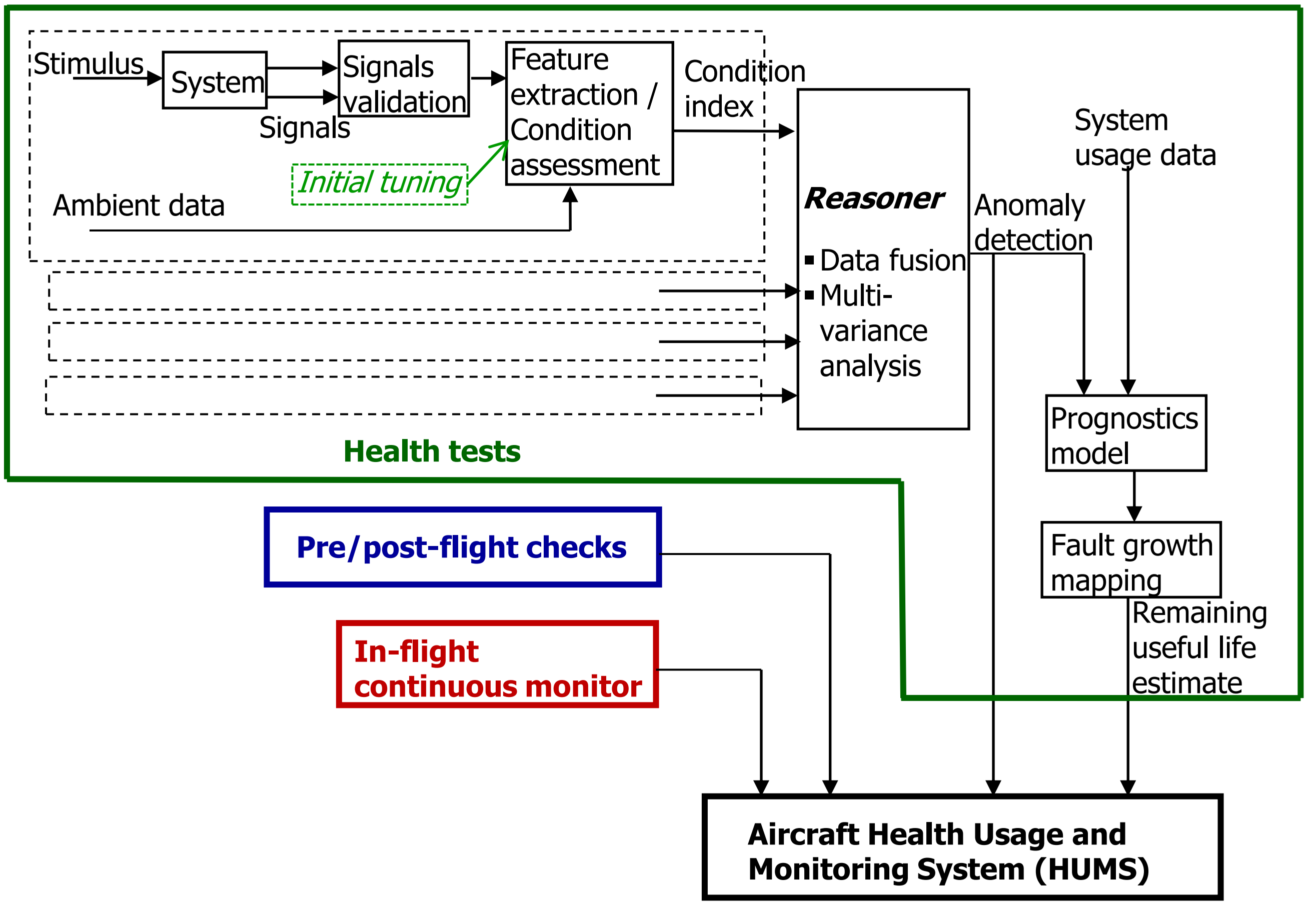
Development of the PHM system will require research effort in:

1) Servoactuator assessment
   - Define the reference configuration of the EHSA for the research activity
   - Virtual hardware (high fidelity model)
   - Real-time model
2) Definition of servoactuator health monitoring system
   - Failure modes, reliability and maintainability
   - Identify health indexes making up significant features for the EHSA health status
   - Define health status based on the variation with time of health indexes
3) PHM system assessment
   - Definition of a representative operational scenario for the EHSA
   - Perform extensive simulations to validate PHM system
   - Define a merit index for the PHM system

Electrohydraulic servoactuators schematic



Health monitoring strategy



Fault detection strategy

Experimental data:
- **F/B Position**
- **Current**

Position command

Position and current signals processing

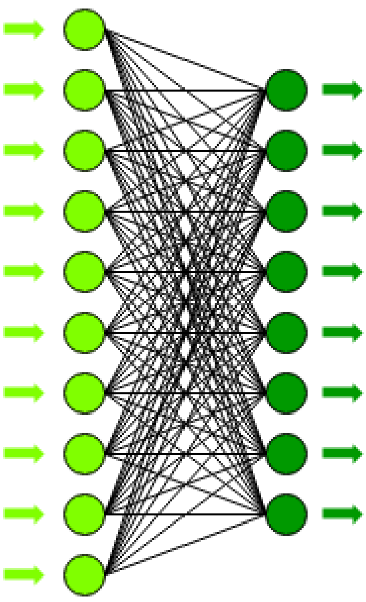
Health indexes

Comparison of health index with nominal variation range

Nominal health indexes

Operative conditions

Evaluated nominal health indexes variation range



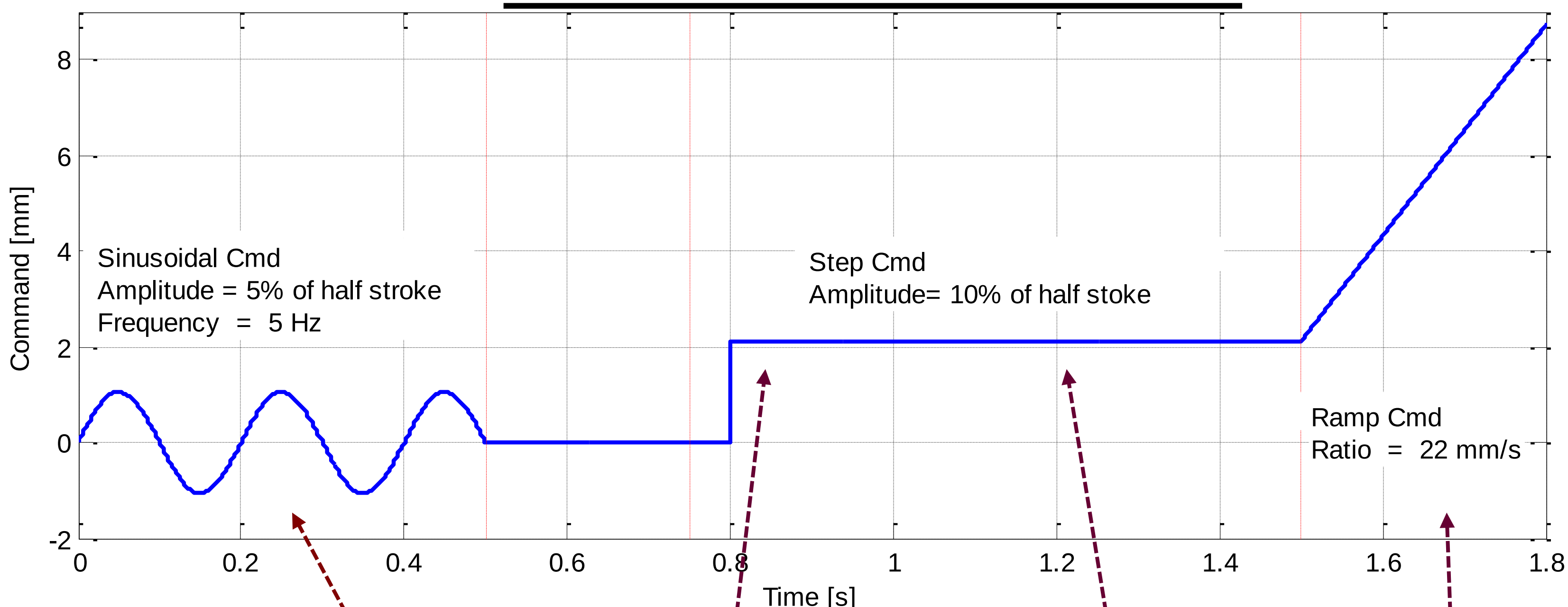
Neural Networks

OUTPUT

Type of degradation

Some initial results

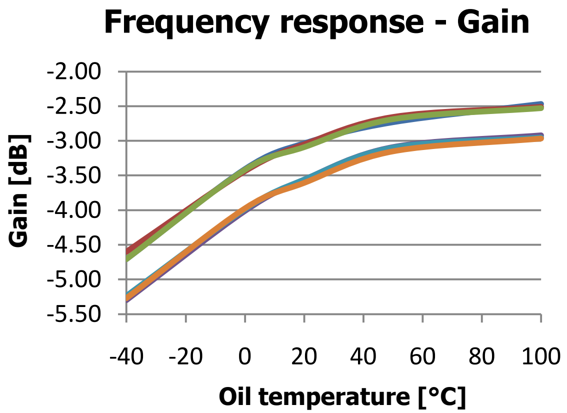
Selected stimuli injection
preflight or postflight health tests

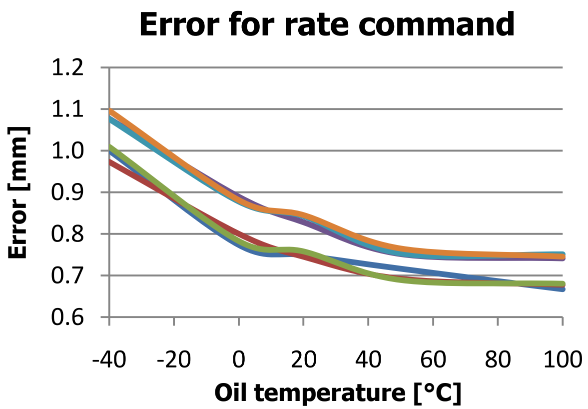


Condition indexes position	**Gain and phase**	**Rise time**	**Instability**	**Steady state error**
Condition indexes current	**I_{cmd} servovalve Max. Min. Mean**	**Time decrease I_{cmd}**	**Instability**	**I_{cmd} ramp Max.**

Some initial results

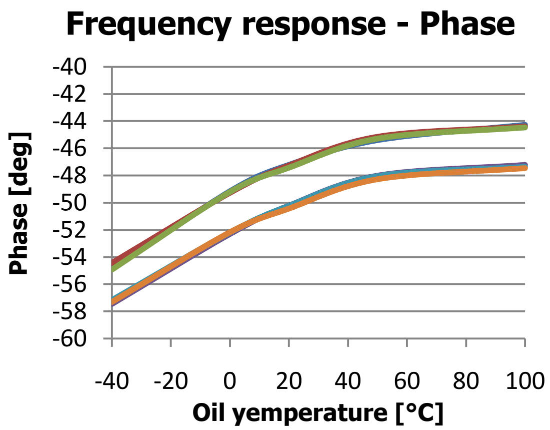
Assessment of normal variation range of condition indexes position

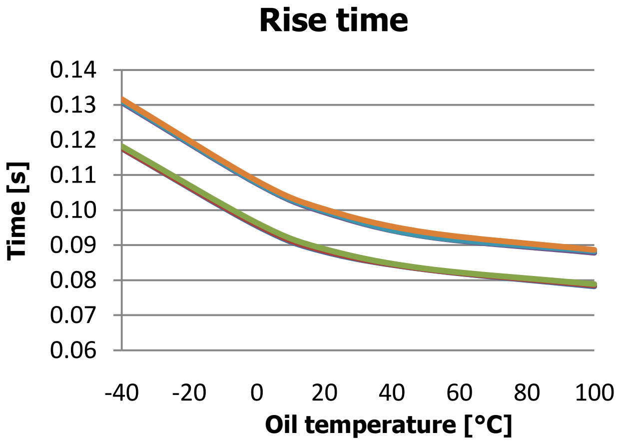




Diagrams curves correspond to different interface conditions for the EHSA

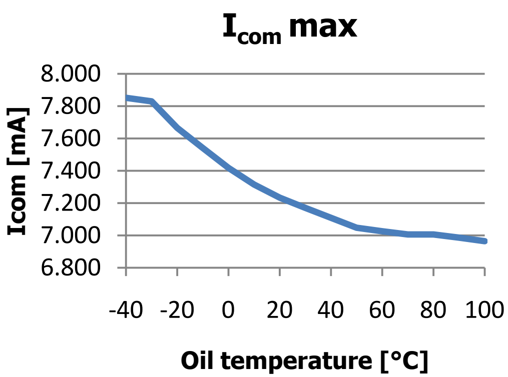
- Supply pressure
- Air content in the hydraulic fluid
- Flight control surface load (wind, gust, turbulence)
- Electrical noise

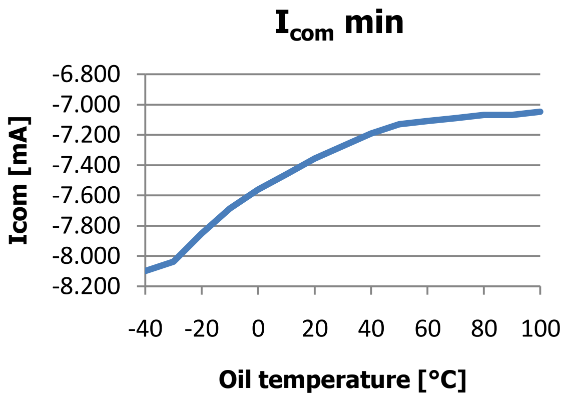




Some initial results

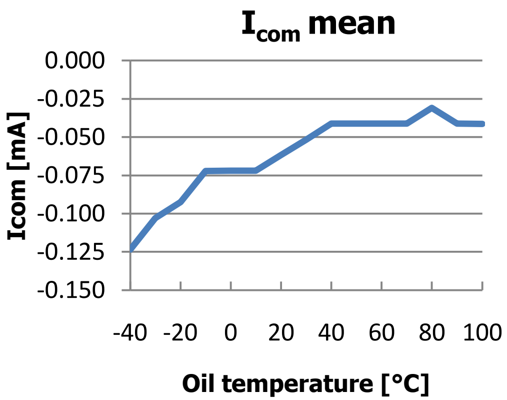
Assessment of normal variation range of condition indexes current

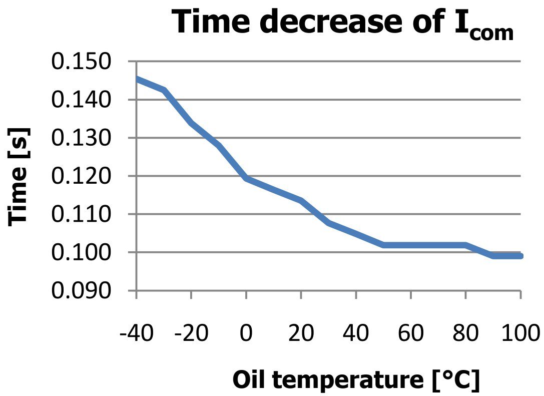


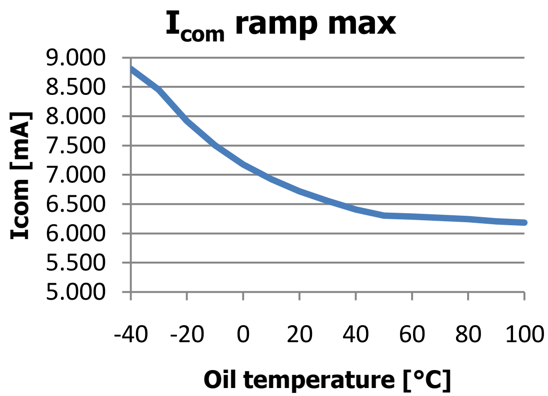


Diagrams curves correspond to below interface conditions for the EHSA

- Supply pressure: 18 MPa
- Air content in the hydraulic fluid
- Flight control surface load (wind, gust, turbulence)
- Electrical noise







Some initial results

Inject degradations ➔ fault growth mapping

Already addressed:

- ✓ Torque motor degradation
- ✓ EHSV spool friction increase
- ✓ Increase of radial clearance between EHSV spool and sleeve
- ✓ EHSV feedback spring degradation (partial yielding, backlash increase)
- ✓ Progressive clogging of an EHSV nozzle

Under investigation:

- ✓ Contamination of the EHSV inlet filter
- ✓ Actuator seals damage
- ✓ Actuator friction increase
- ✓ Actuator spherical bearings damage (friction / backlash increase)
- ✓ LVDT degradation (change of sensitivity)

Some initial results

Inject degradations ➔ fault growth mapping

Fault growth

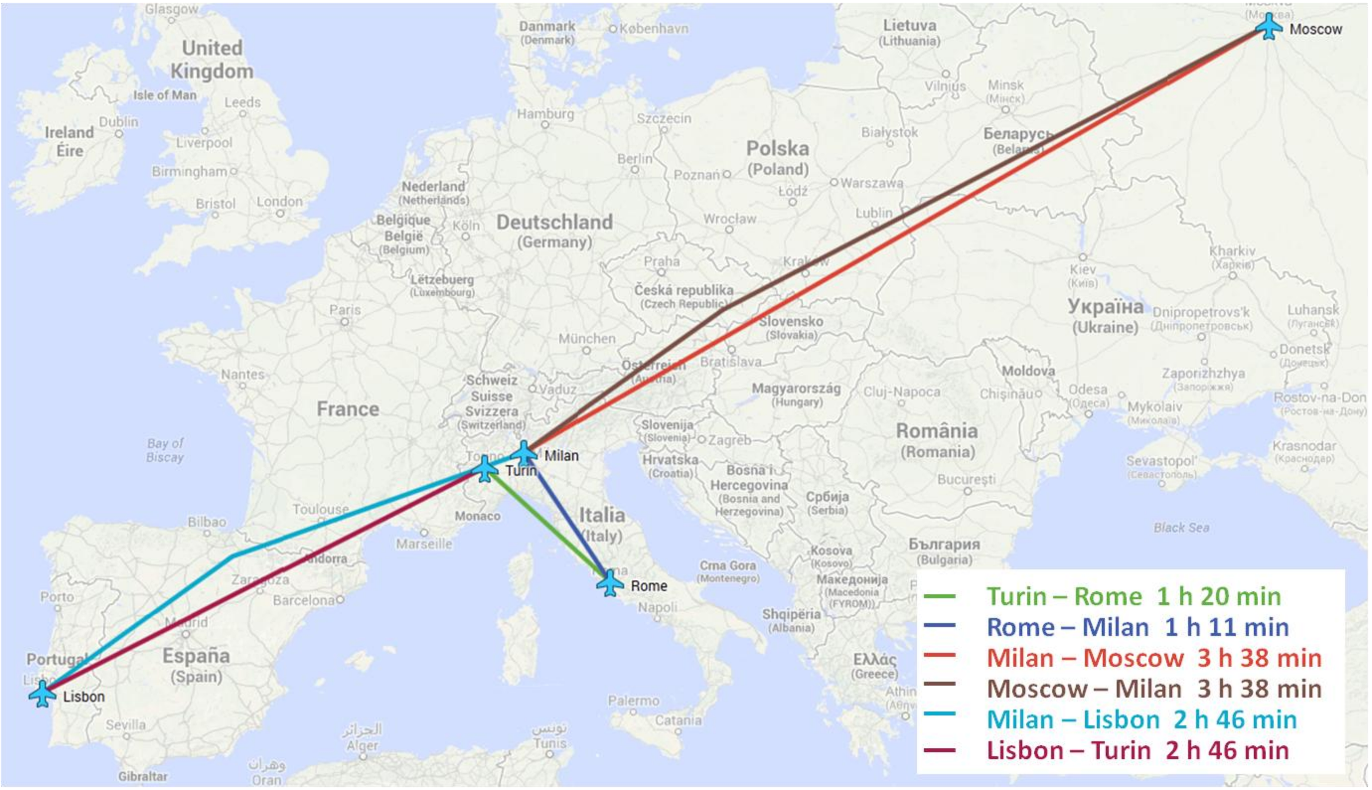
Initial assumptions:

- Fault growth is in general dependent upon both usage time and amplitude / frequency of commands
- Relative importance of usage time and amplitude / frequency of commands depends on fault type
- Effects of single faults were considered
- Progression of a degradation provisionally assumed to be linear with either usage time, or amplitude / frequency of commands, or both

Some initial results

Test PHM in an operational scenario

Test case: Commercial aircraft operating in a european network

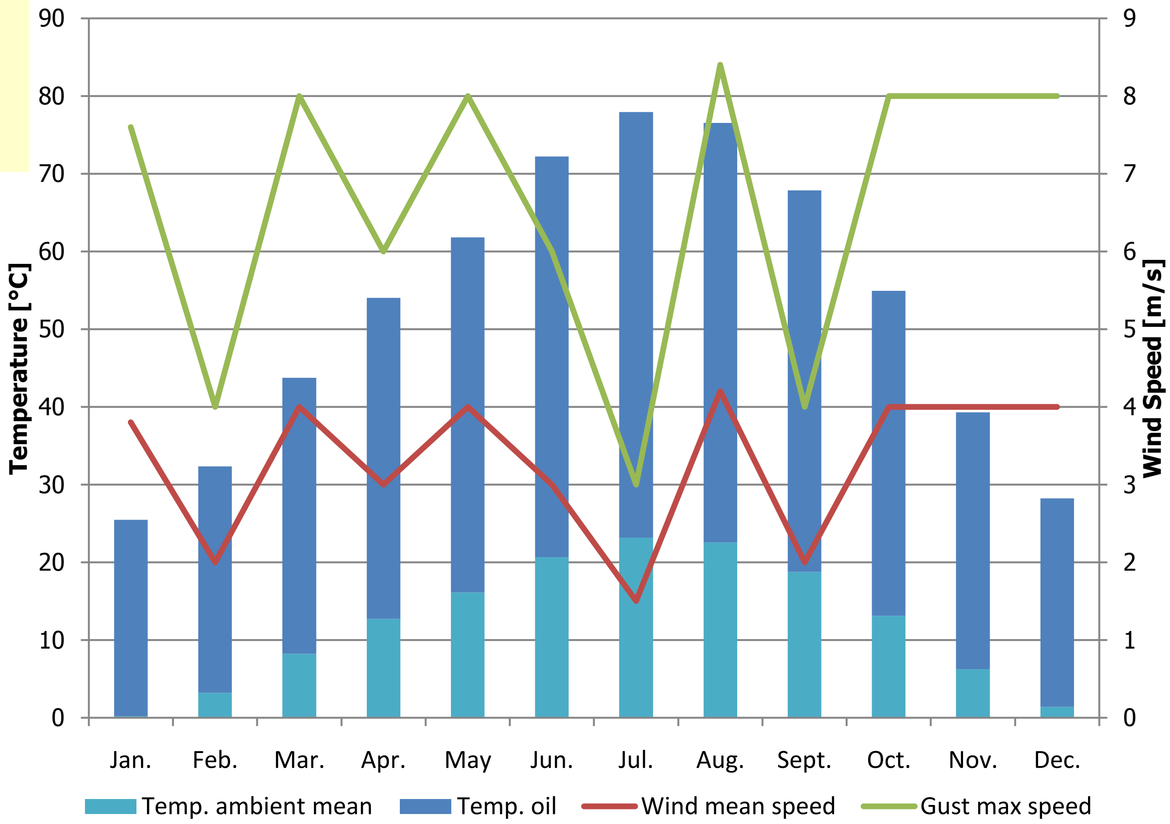


Some initial results

Test PHM in an operational scenario

Definition of ground conditions when test stimuli are injected

- Prevailing temperature and wind conditions at Turin airport - Daily random fluctuations over mean values considered in the analysis
- Similar diagrams used for the other locations



Some initial results

Test PHM in an operational scenario

Reference time history of commands / loads during flight

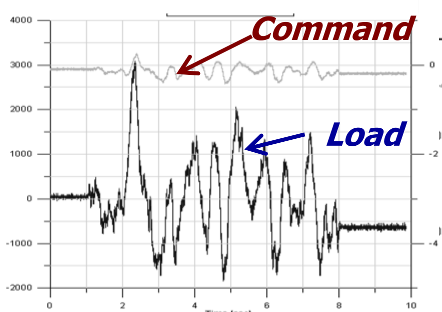
Basic manoeuvres ➔

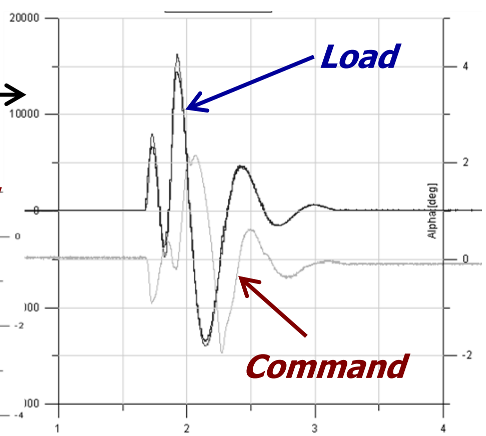
Load ➔ $F_{aer} = C_{1eq} \rho V^2 (1 + K x_L)$

Corrective commands in response to:

⇩

- Gusts ⟶
- Turbulence



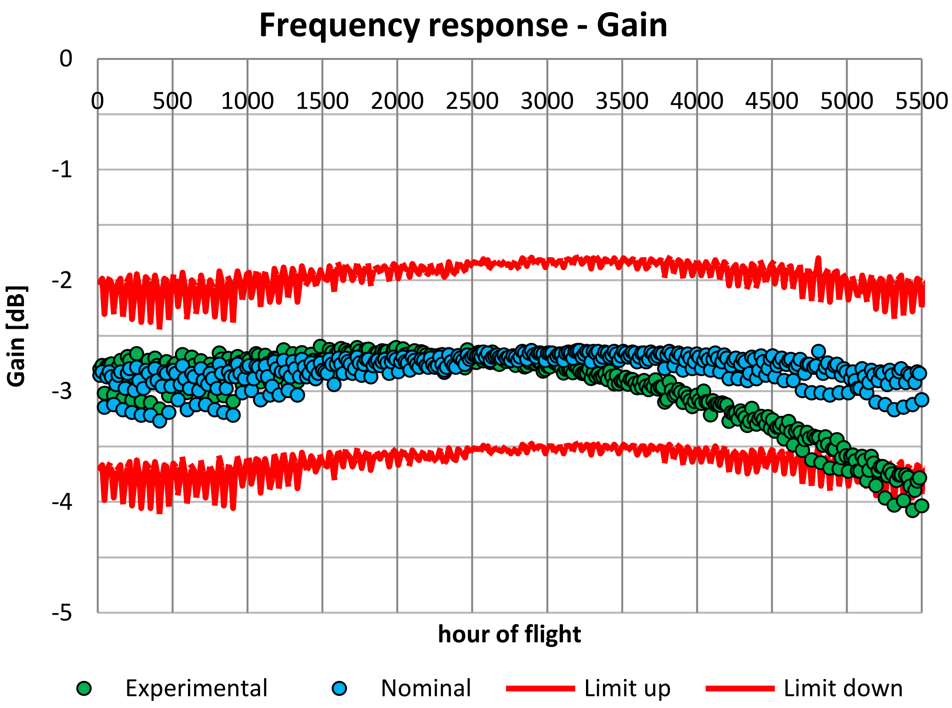


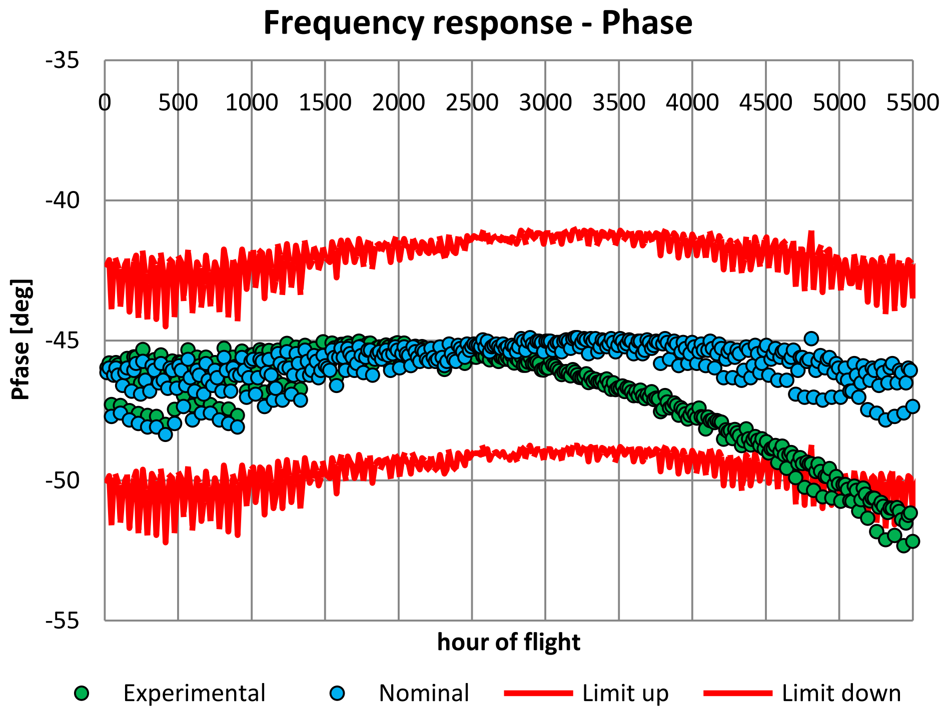
Phase of flight	Stroke	Cycle
Preflight	±20%	1
Taxiing	0%	0
Climb	±70%	2
	±40%	3
	±20%	4
Cruise	±50%	1 per hour
	±25%	2 per hour
Descent	±20%	2
Loiter	±30%	1 every 4 minutes
Approach	±60%	1
	±30%	2
	±10%	3
Landing	0%	0

Some initial results

Test PHM in an operational scenario

Example of fault case:
Increase of radial clearance between spool and sleeve





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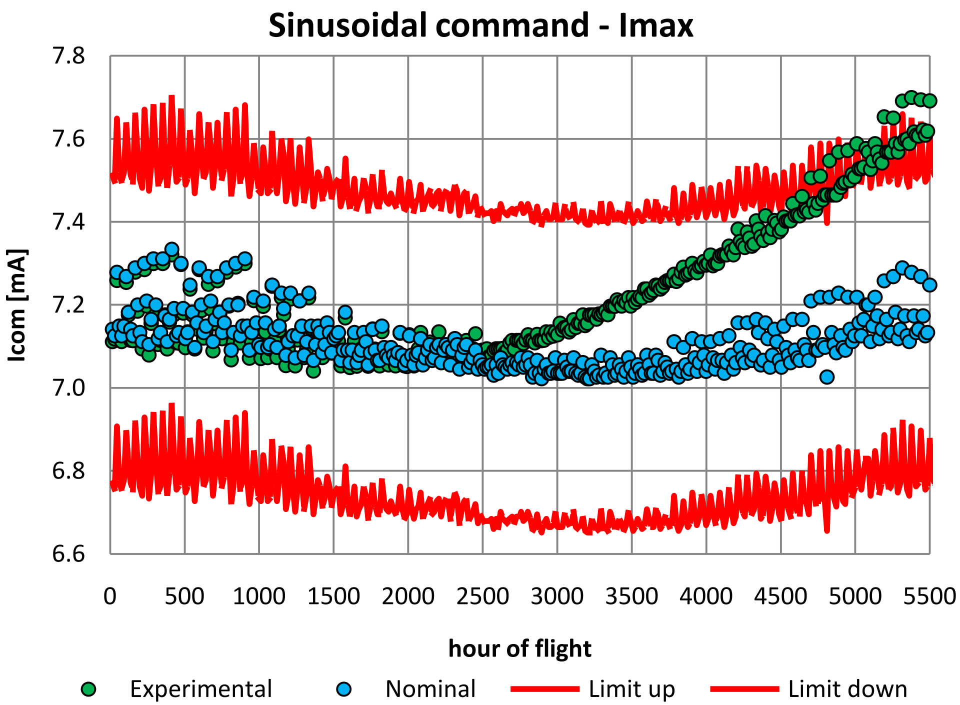
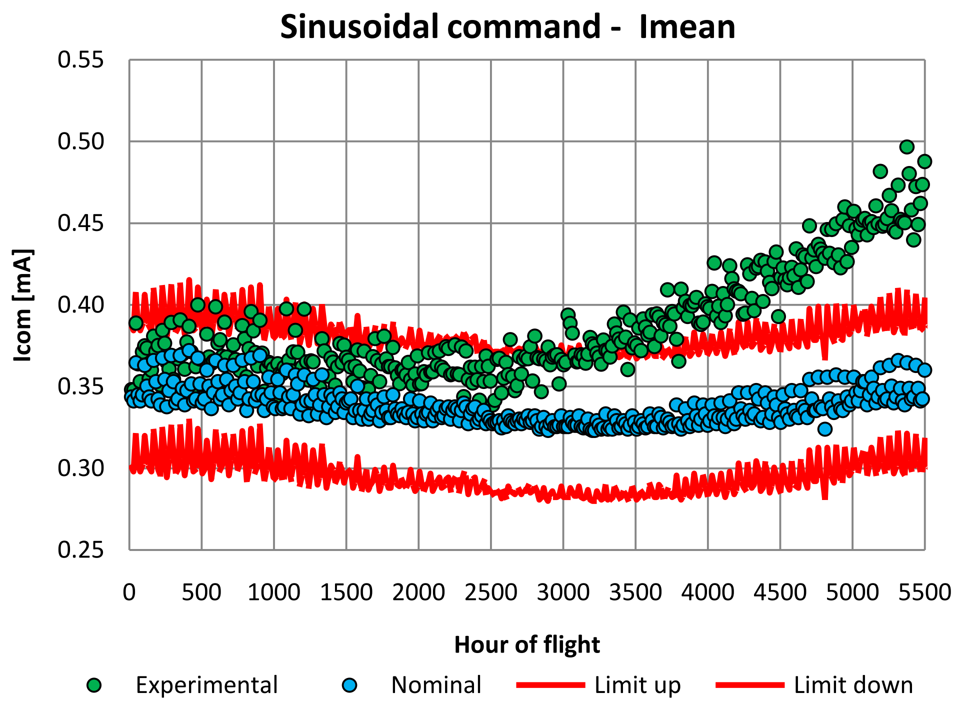


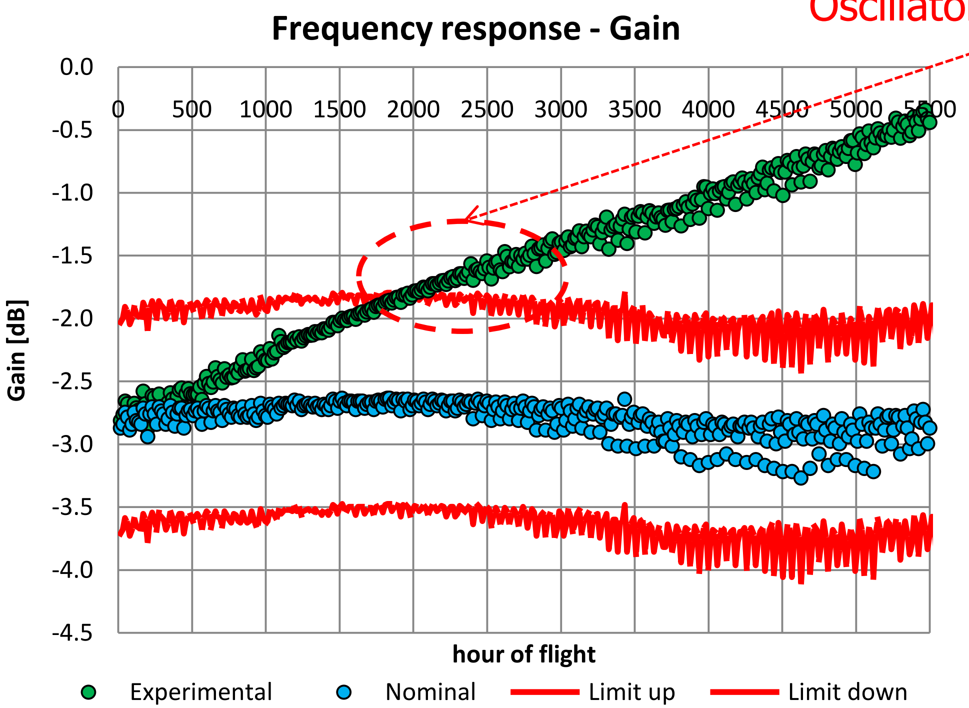


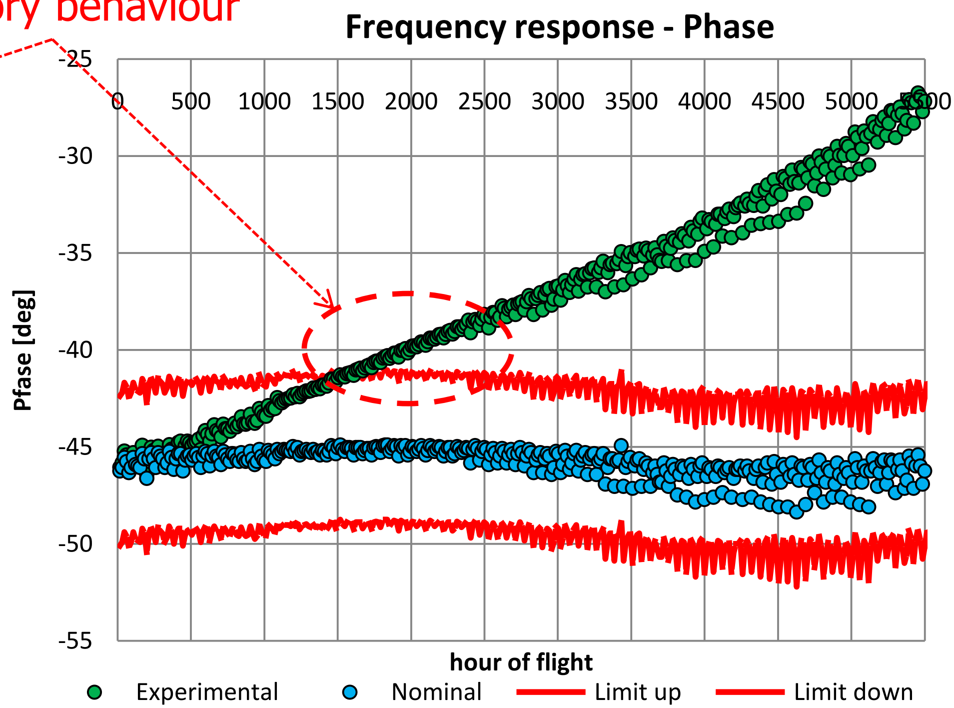
Some initial results

Test PHM in an operational scenario

Example of fault case:
Decrease of feedback spring stiffness

Oscillatory behaviour

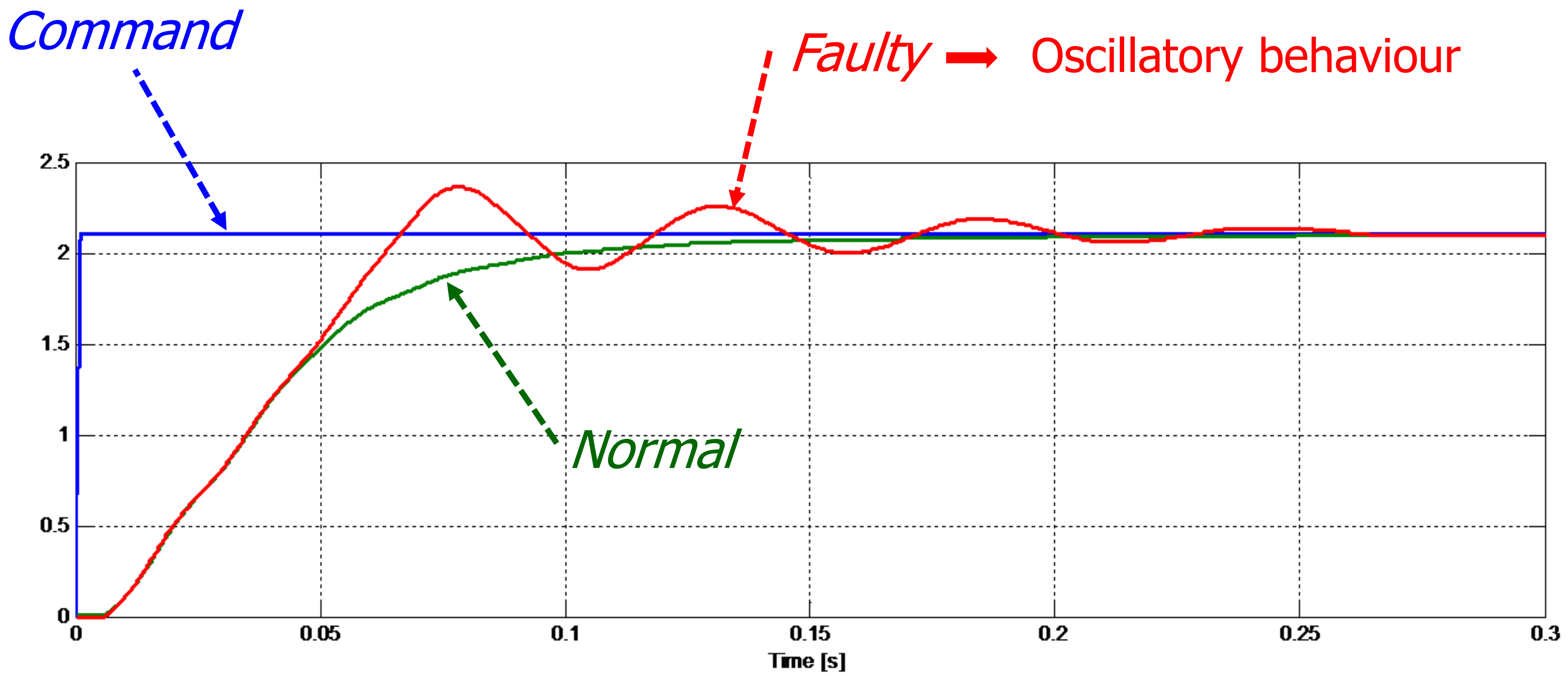




Some initial results

Test PHM in an operational scenario

Example of fault case:
Decrease of feedback spring stiffness



Remarks

- Initial results are encouraging
  - ✓ High-fidelity and real time models showed good accuracy
  - ✓ Injection of selected stimuli in pre/post flight seems able to pick up several possible faults of servovalves
  - ✓ Boundaries can be defined to allow fault recognition with minimum risk of false alarms
- A long way to go before reaching TRL 4 (*Component and/or breadboard validation in laboratory environment*)

First degradation classification

The classification of first degradation is based on a neural network; the algorithm is based on the difference between the experimental health index and the nominal health index

Each degradation induces a unique combination of indexes variation. Therefore it is possible to determine the type of degradation by simply analyzing the variation of the indexes

Confusion Matrix

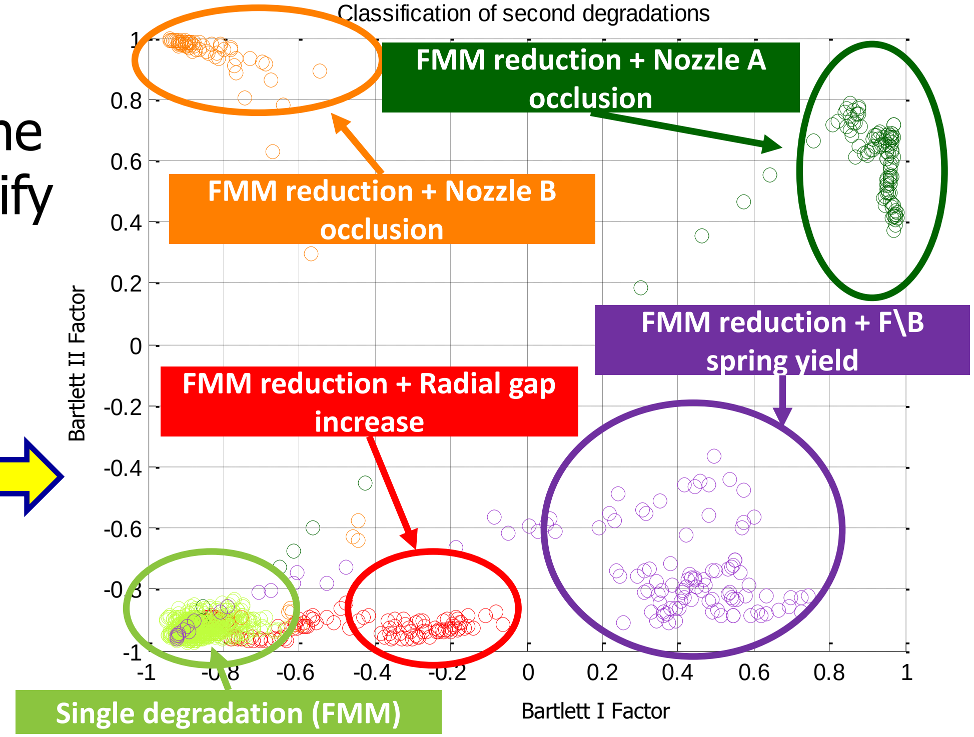
Output Class \ Target Class	FMM	Yield	Backlash	Nozzle A	Nozzle B	Radial gap	Friction	Total
FMM	1868 13.7%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	31 0.2%	1 0.0%	98.3% 1.7%
Yield	0 0.0%	2167 15.9%	3 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	99.9% 0.1%
Backlash	0 0.0%	0 0.0%	1355 9.9%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
Nozzle A	0 0.0%	0 0.0%	0 0.0%	2257 16.6%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
Nozzle B	0 0.0%	0 0.0%	0 0.0%	0 0.0%	2355 17.3%	0 0.0%	0 0.0%	100% 0.0%
Radial gap	3 0.0%	0 0.0%	0 0.0%	0 0.0%	2 0.0%	1539 11.3%	2 0.0%	99.5% 0.5%
Friction	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	2048 15.0%	100% 0.0%
Total	99.8% 0.2%	100% 0.0%	99.8% 0.2%	100% 0.0%	99.9% 0.1%	98.0% 2.0%	99.9% 0.1%	99.7% 0.3%

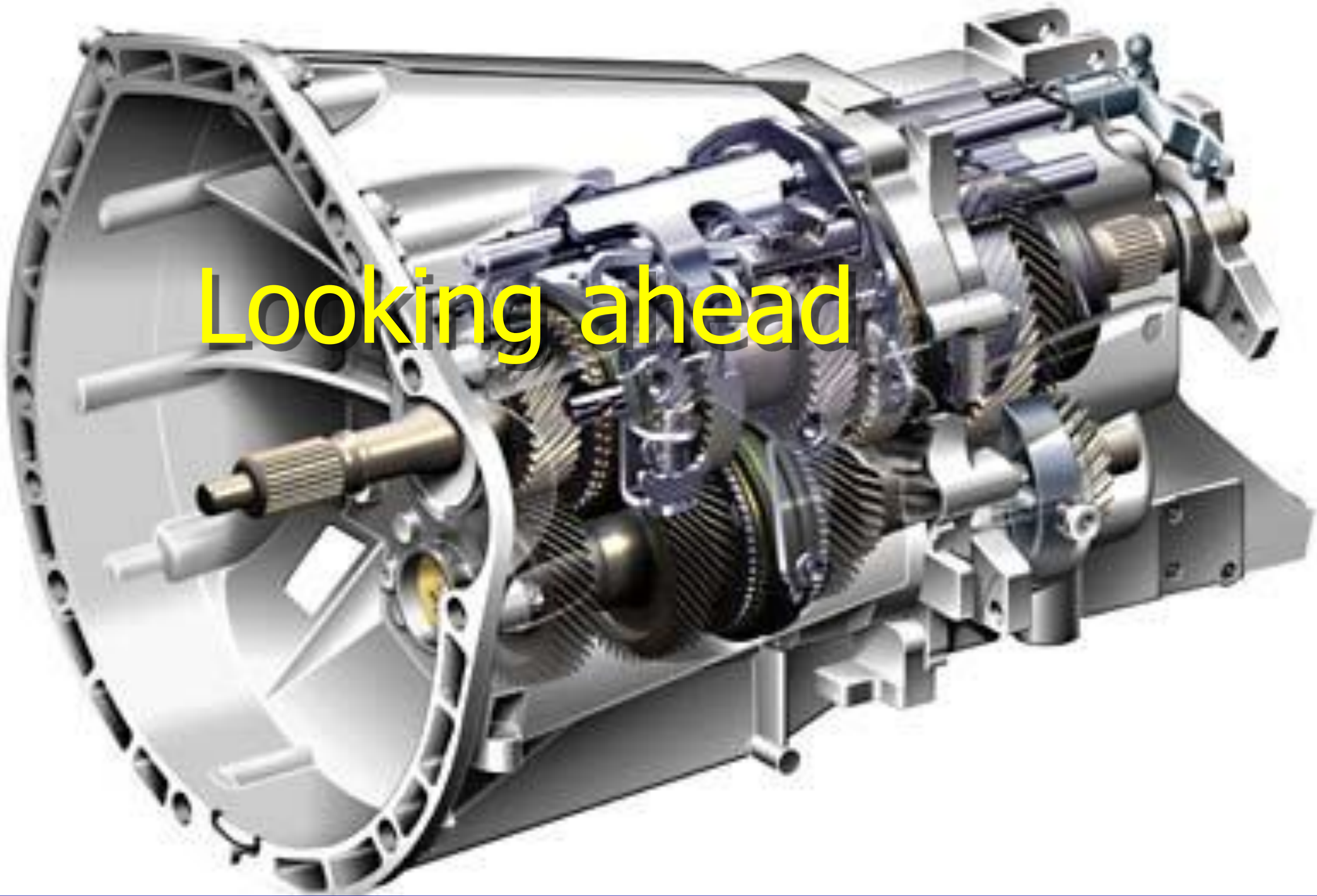
Additional degradation classification

In presence of a single degradation the correlations between the different health indexes are well defined, but such relationships are greatly changed upon the onset of a second degradation

By performing a factor analysis of the health indexes it is possible to identify and classify a new degradation

Test case:
Torque motor degradation followed by a second degradation of different type





Looking ahead