PHM for Rail Maintenance Management: at the cross-roads between data science and physics

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Designing fluidity

Presentation outline

- Introduction: the benefits of Predictive Maintenance
- The promise of Data Science
- Condition-based Detection, Diagnostics & Prognostics
- PHM Virtual Prototyping
- Virtual Prototyping for Railway Systems
- Conclusions

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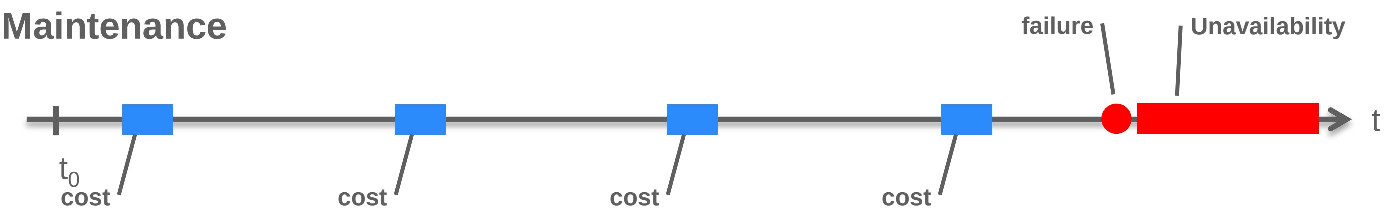
Benefits of Predictive Maintenance

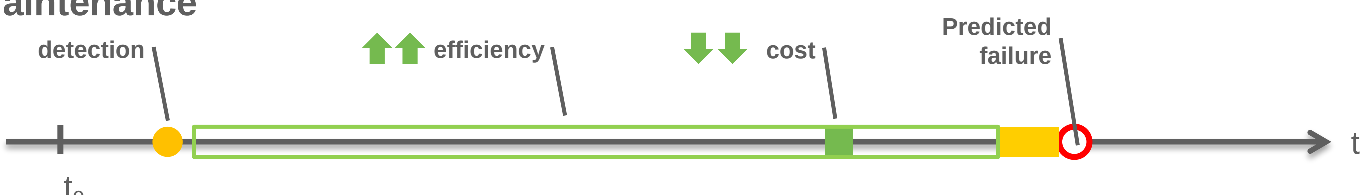
Corrective Maintenance

Scheduled Maintenance

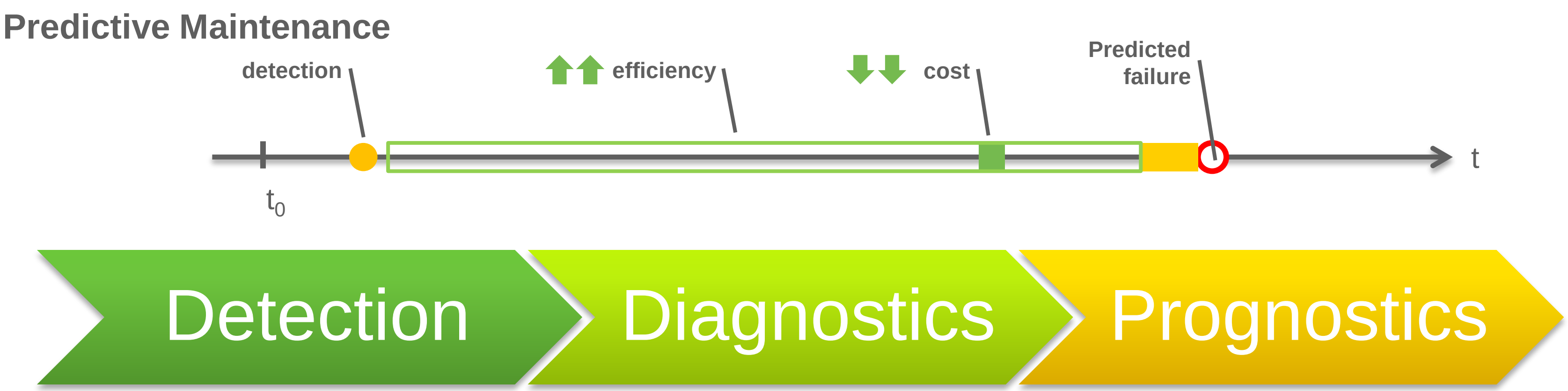


Condition Based Maintenance

Predictive Maintenance



Predictive Maintenance



Detecting that there is an anomaly in the behavior of the monitored component

Diagnosing the type of problem occurring, identifying the affected components

Predicting the probability of the monitored component failing within a time frame

- Being able to identify when a failure is about to occur: no unexpected failures
- Specific target actions identified for affected components
- Less troubleshooting time
- Fewer maintenance interventions necessary
- Minimal inspections on field
- Reduced downtimes
- An efficient tool for scheduling maintenance operations

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The Promise of Data Science

- Difference with respect to classical statistics:

  Classical statistics:

  - Estimate p parameters from n samples (p << n). Usually p is quite small
  - Test a hypothesis about data . Example : gaussian distribution

  ‘Big Data’:

  - Estimate p parameters from n samples ,but p can be very large
  - Discover structures without a priori knowledge

- Successes of Data Science:
  - Data Analysis : Clustering, Visualization
  - Learning: Classification, Regression
  - Ability to manage and store huge amount of data (e.g. Map/ Reduce, Spark, Hadoop)
  - In progress: ‘deep learning’

- Limitations of Data Science for PHM today:

  - Requires typically much larger data sets than are available from field (learning normal and abnormal operations: continuous analog measurements)
  - Mathematical challenge of high-dimensional spaces (large p)

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Motivation

- PHM goal: detection, diagnostics and prognostics of a target component in presence of different sources of uncertainty.

  - present uncertainty (e.g. noisy measurements)
  - future uncertainty (e.g. loading and operating conditions)
  - modeling uncertainty (e.g. model parameters, unmodeled dynamics).

- Availability of a robust set of data is crucial for design of effective PHM algorithms.

- Field data only are generally not informative enough for the purpose of designing a PHM algorithm:

  - Time for degradation excessively long, evolution difficult to track.

- Therefore Prototyping approach is proposed to address the issue of lack of representative data.

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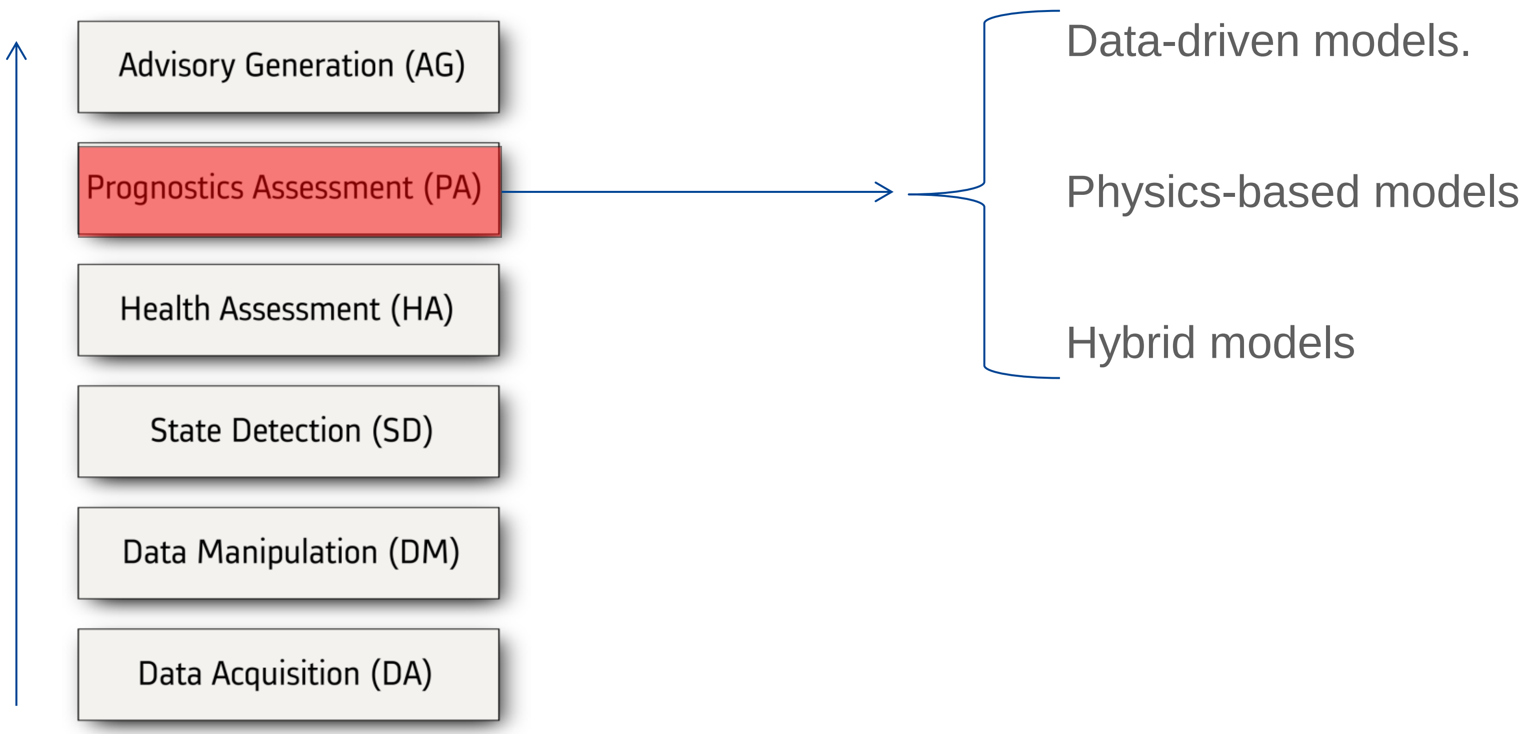
CBM International Standard

- Open System Architecture for Condition-Based Maintenance.
- OSA-CBM is an implementation of ISO-13374 functional standard.



Data-driven (DD) prognostics models

- Use condition monitoring data and/or historical event data collected from the asset to automatically learn a model of system behavior and to predict failures.

  Example techniques: ANN, SOM, SVM, HMM, regression analysis, etc.

☺ Relatively easy to implement, flexible, cost-effective.

☹
- Large amount of data required (healthy and deteriorated conditions)
- Performance highly dependent on the quality of operational data
- Computational load can be demanding
- No physical understanding

- Application of data-driven techniques entails:

(i) Learning/training: mapping (M1) from features to damaged state

mapping (M2) from operational conditions to damage growth rate

(ii) Prediction: use M1 to assess health based on latest measurements

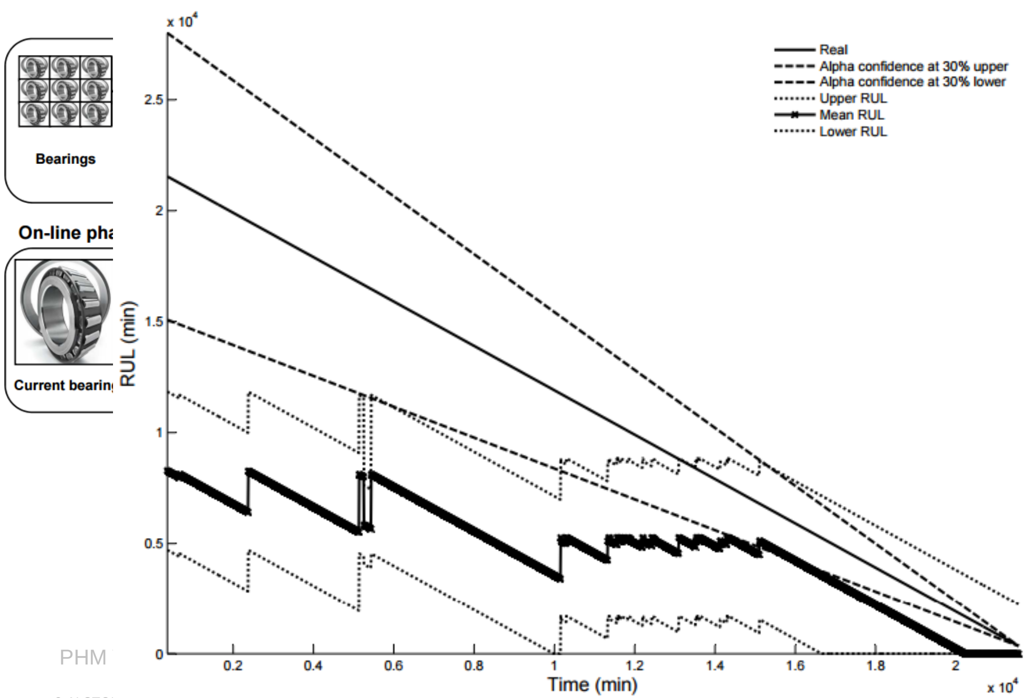
use M2 to estimate future damage evolution based on a future mission profile

Example: data-driven prognostics for bearings

- Tobon et al. 2012: “A Data-Driven Failure Prognostics Method based on Mixture of Gaussians Hidden Markov Models”
- Two phases:

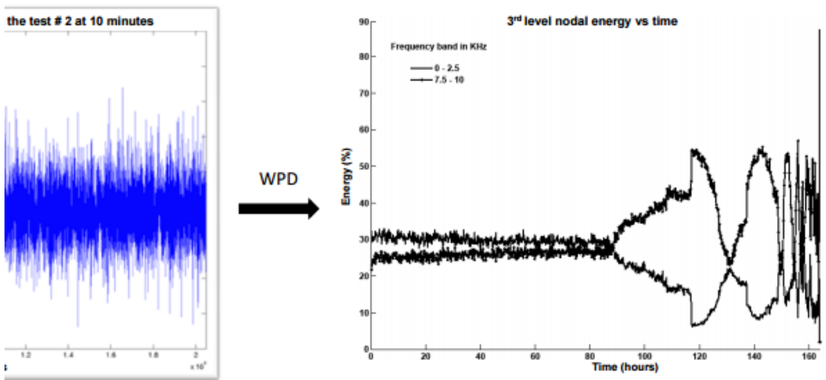
(i) Off-line: sensor data processed to extract features (Wavelet Packet Decomposition coefficients), learning of MoG-HMMs for different initial states/operating conditions.

(ii) Online: assessment of current state (Viterbi algorithm) and RUL estimation.



RUL upper limit estimate inside confidence interval 11 days before the failure of the bearing

Features extraction from test bench data



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Physics-based (PB) prognostics models

- Accurate mathematical model for component degradation (e.g. crack growth) required for each failure mechanism.

  Examples: equations derived from fundamental laws of physics, empirical models, FE, etc.

  - Intuitive results.
  - Limited amount of data required (e.g. calibration).
  - Accurate predictions achieved if detailed knowledge about failure mechanism is available.

  - Lack of knowledge about physics of failure.
  - Implementation costly compared to DD.
  - Component- and failure mechanism-specific, limited flexibility

- Mathematical model used to predict future process evolution:

$$\dot{\mathbf{x}}(t) = \mathbf{f}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{v}(t))$$
$$\mathbf{y}(t) = \mathbf{h}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{n}(t))$$

  - Degradation parameters (subset of Θ) tracked using filtering techniques (e.g. particle filters, Kalman filter, etc) or pre-calculated (e.g. look-up tables) for efficient online implementation.

- Uncertainty management schemes to account for model approximations/simplifications.
- Field/Experimental data may be required for model tuning and validation.

Hybrid models

- Combine knowledge about the physical process and information from sensor readings to enhance prognostics capabilities.

- Integration of measured data and physics can lead to a reduction of uncertainty (e.g. adjust predictions from model using observed data).

- Integration can be implemented at different levels of the PHM process:

  - Online model parameters updating.
  - Model predictions correction based on observed data.
  - Measure current damage level and propagate.
  - Build empirical degradation models from data.

Virtual Prototyping (VP) for PHM Applications

Prognostics models are tuned based on available data (healthy and degraded conditions).

- For the cases where accessing these data is not feasible/expensive (e.g. deterioration evolution), Virtual Prototyping (VP) methodology can be conveniently applied.

- Virtual Prototyping (VP): design of a digital model (software-based) to simulate the dynamics of interest of an asset (both healthy and degraded conditions).

- VP goal: simulate the behavior of the target component under a wide range of operating conditions that the system is expected to encounter during its operational life.

- The data generated by the VP are then used to drive a prognostics model.

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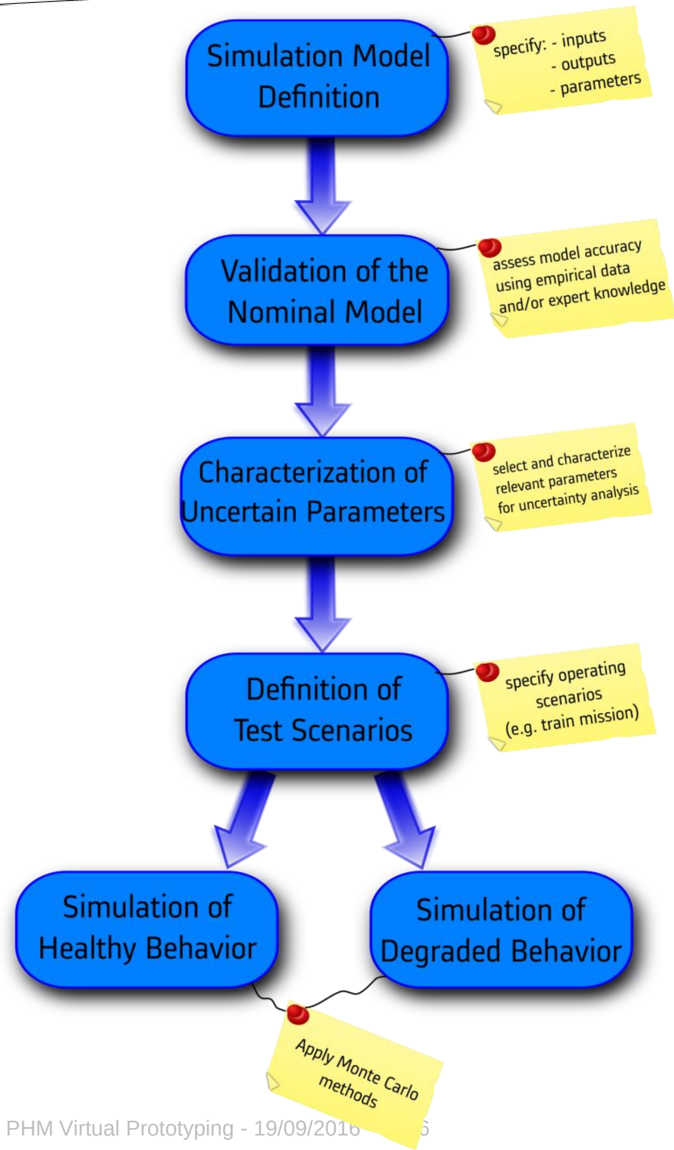
Virtual Prototyping Methodology



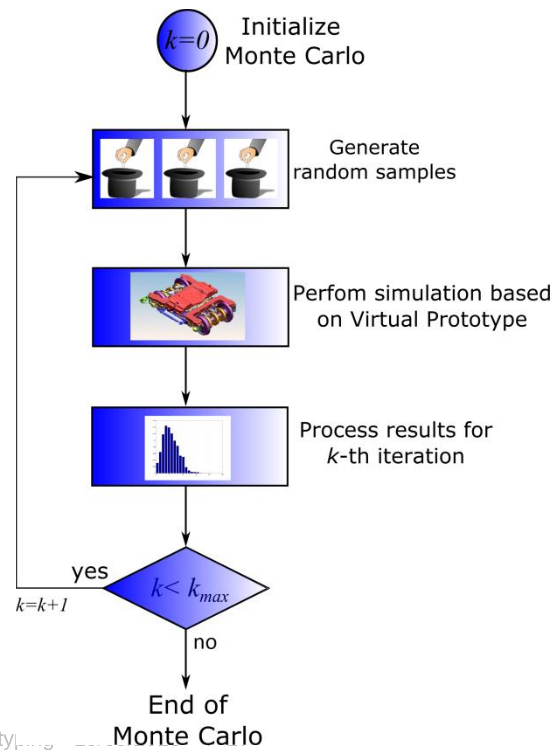
- High level of flexibility
- Reduced cost of experiment
- Safe evaluation of extreme states
- Cost-effective generation of a variety of failure modes based on "FMMEA" (Failure Modes, Mechanisms and Effects Analysis").

Challenges:

- Model validation
- Uncertainty representation/quantification
- Simulation speed (computational feasibility)

Uncertainty in Prognostics

- Appropriate schemes need to be put in place for uncertainty quantification and propagation for RUL estimation (either data-driven or physics-based models).
- For the virtual prototype to be realistic, the sources of uncertainty need to be accurately incorporated in the simulation model.
- Computational framework for uncertainty propagation in VP: Monte Carlo Simulation



Sampling methods:

- Importance Sampling
- Latin Hypercube Sampling
- ...

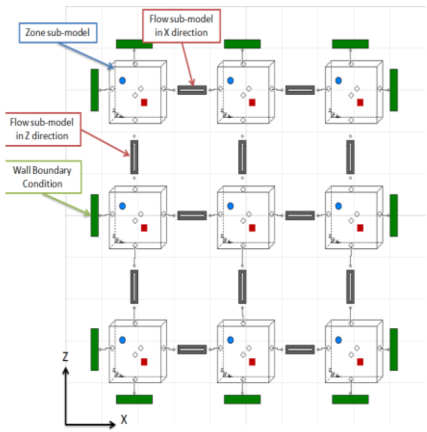
Virtual Prototyping for Railway Systems - Example HVAC

- Model definition
- Model validation
- Model reduction (computational efficiency)
- Simulation of HVAC degraded conditions (clogged filter)

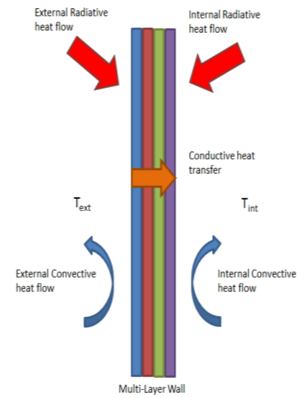
HVAC Virtual Prototype definition

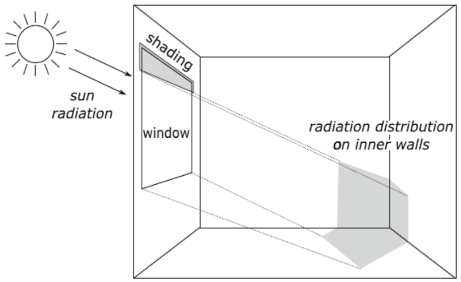
- HVAC system in a Rail car modeled including:

Airflows between thermal zones

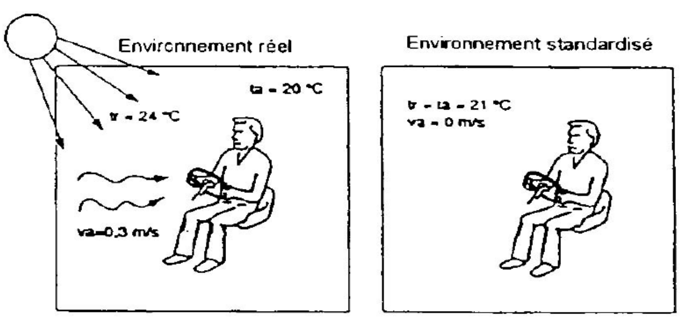


Tramway walls and windows

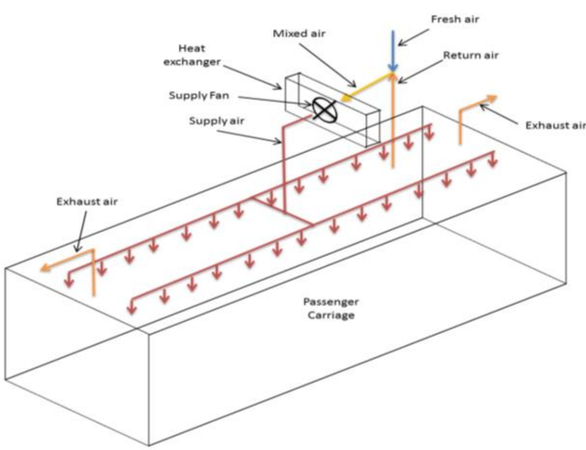




Passenger occupation and seats

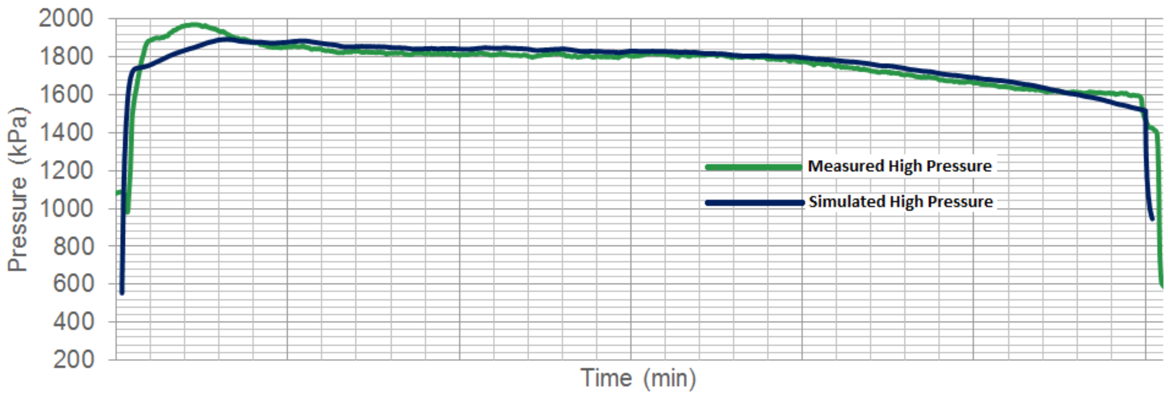


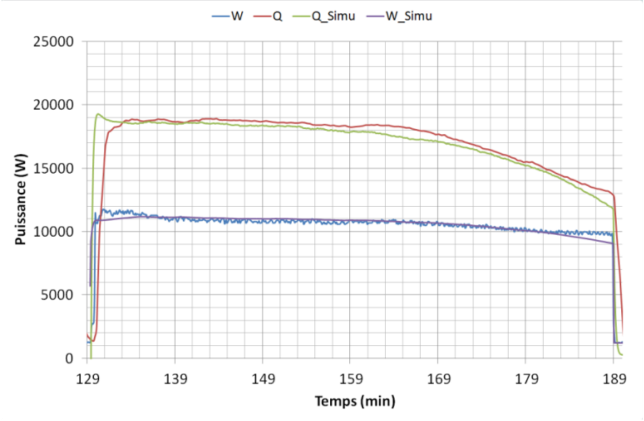
Air ducts and air handling units

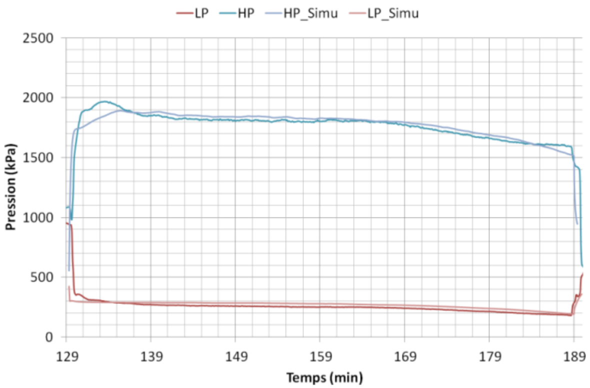


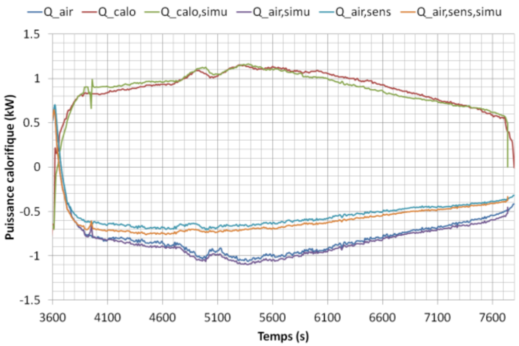
HVAC Virtual Prototype validation

- Virtual Prototype validated through a series of test performed on a real HVAC unit (Alstom's CORADIA Continental).
- Different variables of interest validated against sensor measurements.







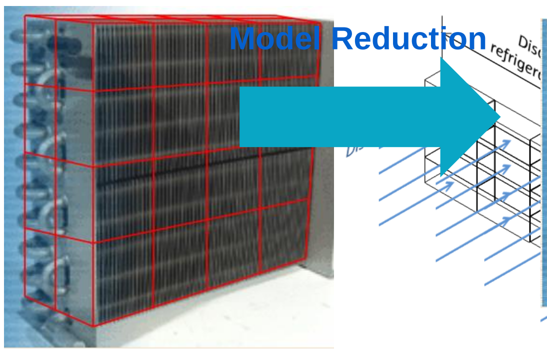


HVAC Virtual Prototype reduction

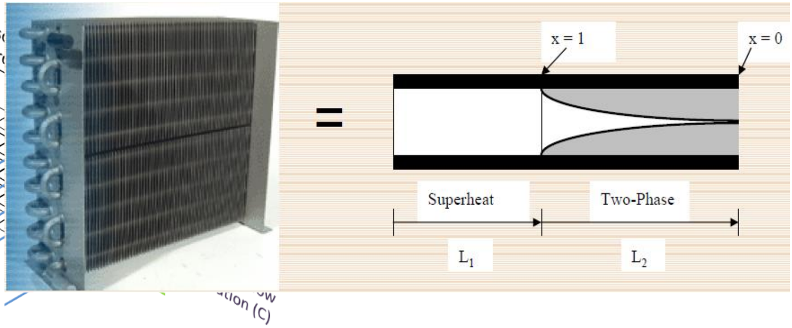
- Reduction of the computational load is vital to be able to perform extensive simulation campaigns.
- Optimize the digital model by:

  - reducing the number of states used to represent the physical model (therefore decreasing the computational time for running the simulation)

  - preserving the accuracy of the model within acceptable limits.
- Example: improved vapor compressor cycle model:
  - Finite Volume (FV) formulation: accurate results but computationally expensive (4x4x2=32 cells, 96 states, high dynamic order)
  - Moving Boundary (MB) formulation: level of accuracy preserved, significant reduction of simulation time (9 states, low dynamic order)



Heat exchanger discretization in a finite volume modelling paradigm



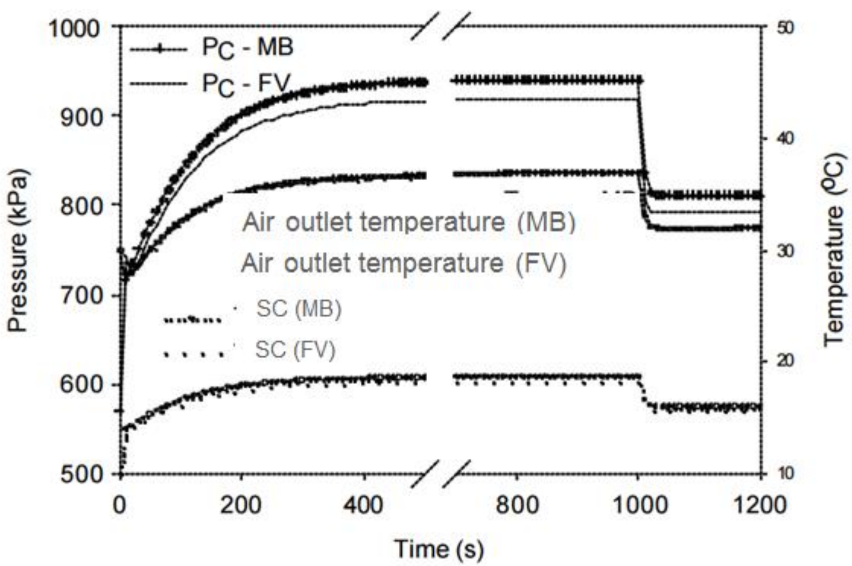
Equivalent pipe representation of a heat exchanger in a moving boundary modelling paradigm

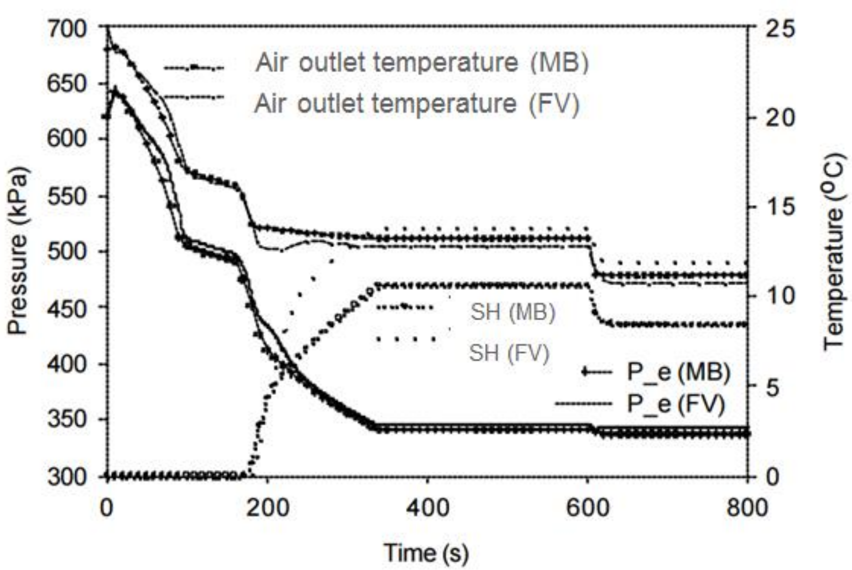
HVAC Virtual Prototype reduction: Finite Volume vs Moving Boundary

- Simulation of evaporator: MB about 10-15 times faster than FV
- Simulation of condenser: MB about 6 times faster than FV
- Example: under the same simulation scenario:

 - Simulation time FV = 183 s

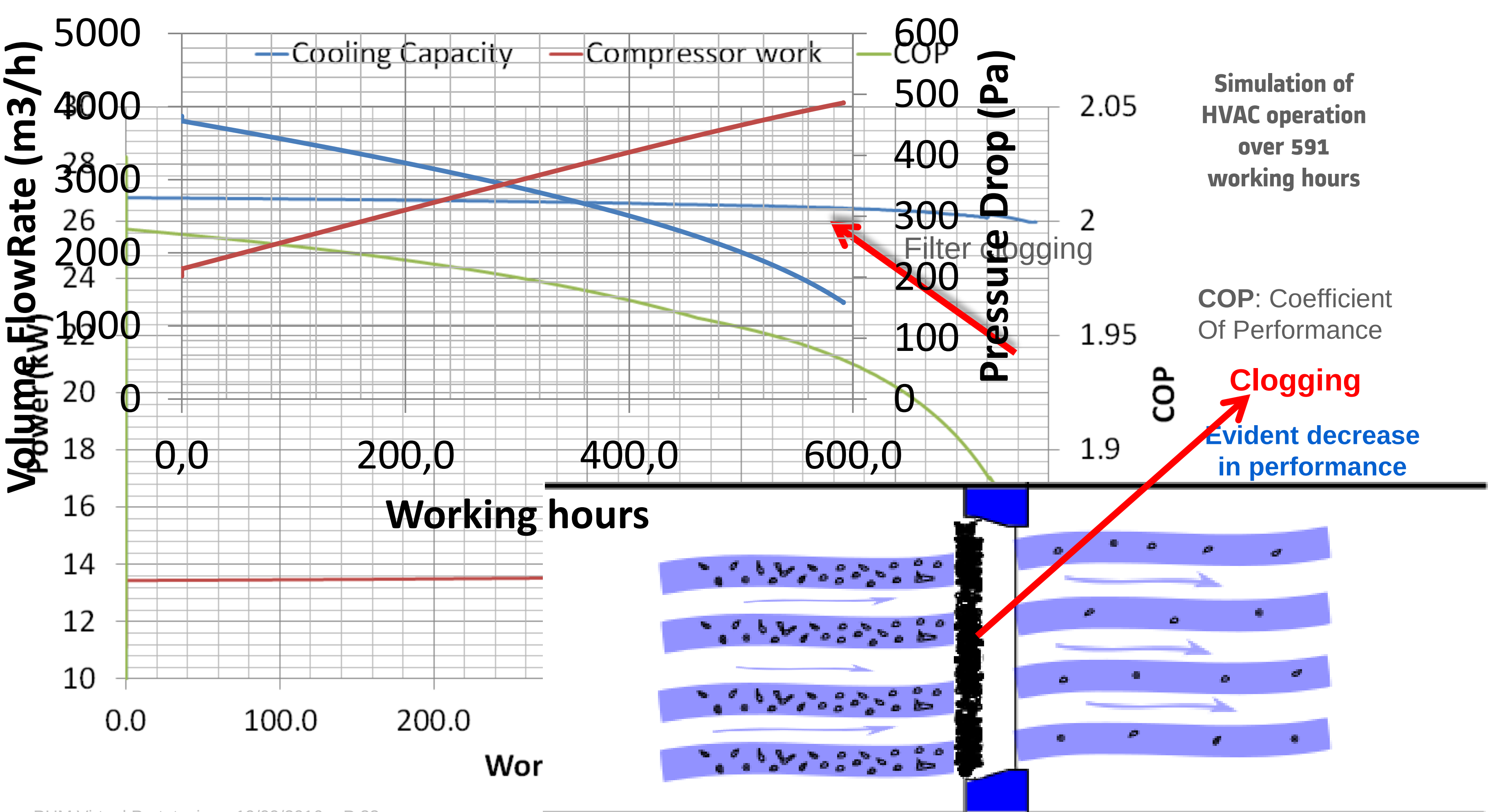
 - Simulation time MB = 31 s (about 84% reduction)





HVAC performance under degraded conditions

- Accumulation of dust and aging effects modify the air duct characteristic curve with increased pressure drop/decreased air flowrate supply.



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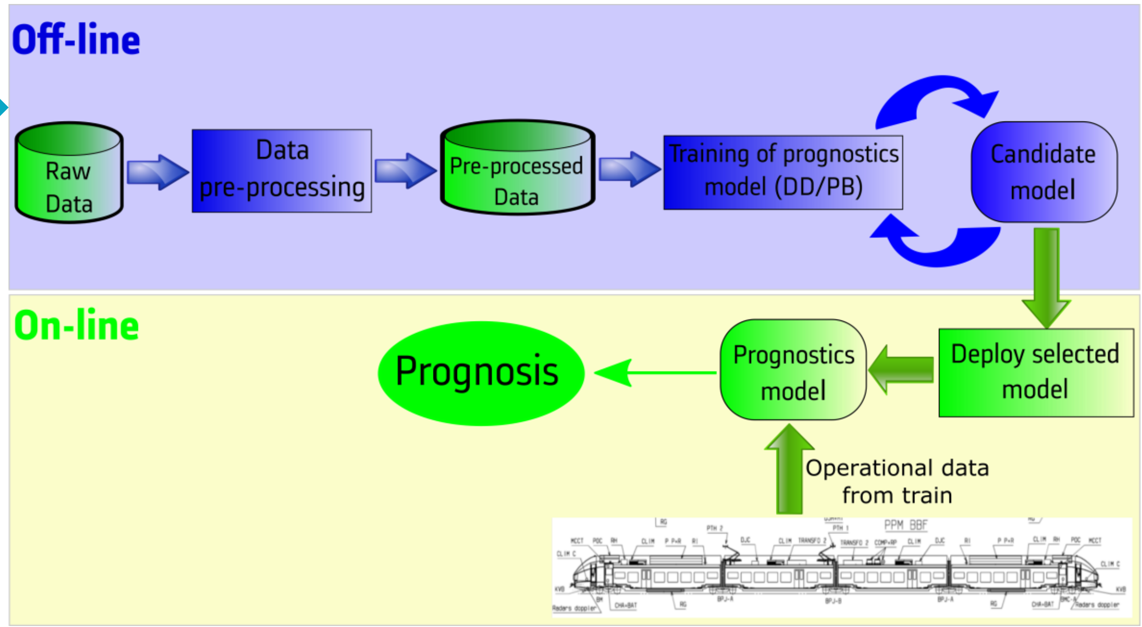
Conclusions

- *We Don't Need Big Data; We Need Wise Data!* (*Stephen Hall, President/CEO at Celeris Aerospace*)
- Wise data: data that have been thoughtfully identified as having the potential to shed light on a given problem or identify potential causal factors that may result in structural or system failures.
- The development of effective and robust prognostics models requires availability of “wise data”

Virtual Prototype (designed to generate “wise data”)



- Integration of VP into the PHM methodology (considering associated benefits and challenges) Initial applications indicate promising results for PHM of rail assets.

Future Perspectives

- Promising developments of machine intelligence
  - Deep Learning (multi-layered neural networks)
  - High-dimensional multi-variate statistics
  - Reinforcement Learning
- Combination of those evolving data-driven methods with expert-based and physics-based methods:
  - Expertise illuminates data
  - Data feeds expertise
- Closer link between PHM approaches and classical reliability engineering approaches (e.g. proportional hazard models)

Acknowledgement

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