Building Resilience into Urban Rail Transport Systems

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ASPECT 2019, Delft

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Agenda

1. Introduction: building resilience through design, maintenance and operations
2. Design: a resilient architecture
3. Maintenance: predictive maintenance
4. Operations: adaptive traffic management
5. Conclusion

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Introduction: building resilience through design, maintenance and operations

Introduction

- In large metropolitan areas, growing demand for punctual, reliable and environment-friendly transport services
  - Alstom's answer: URBALIS® communication-based train control (CBTC) system
- Resilience: Ability to recover quickly from non-nominal situations. Returning fast to nominal operation after a disturbance
- URBALIS® designed to deal with:
  - Hardware and Software failures or degradations
  - Disturbances from external perturbations, including passenger usage
  - Malevolent attacks
- Key Levers:
  - Architecture: Highly redundant, in particular for the 'backbone' data communication system
  - Maintenance: Condition-based and predictive where cost-effective (e.g. Point systems)
  - Operations: Adaptive traffic management

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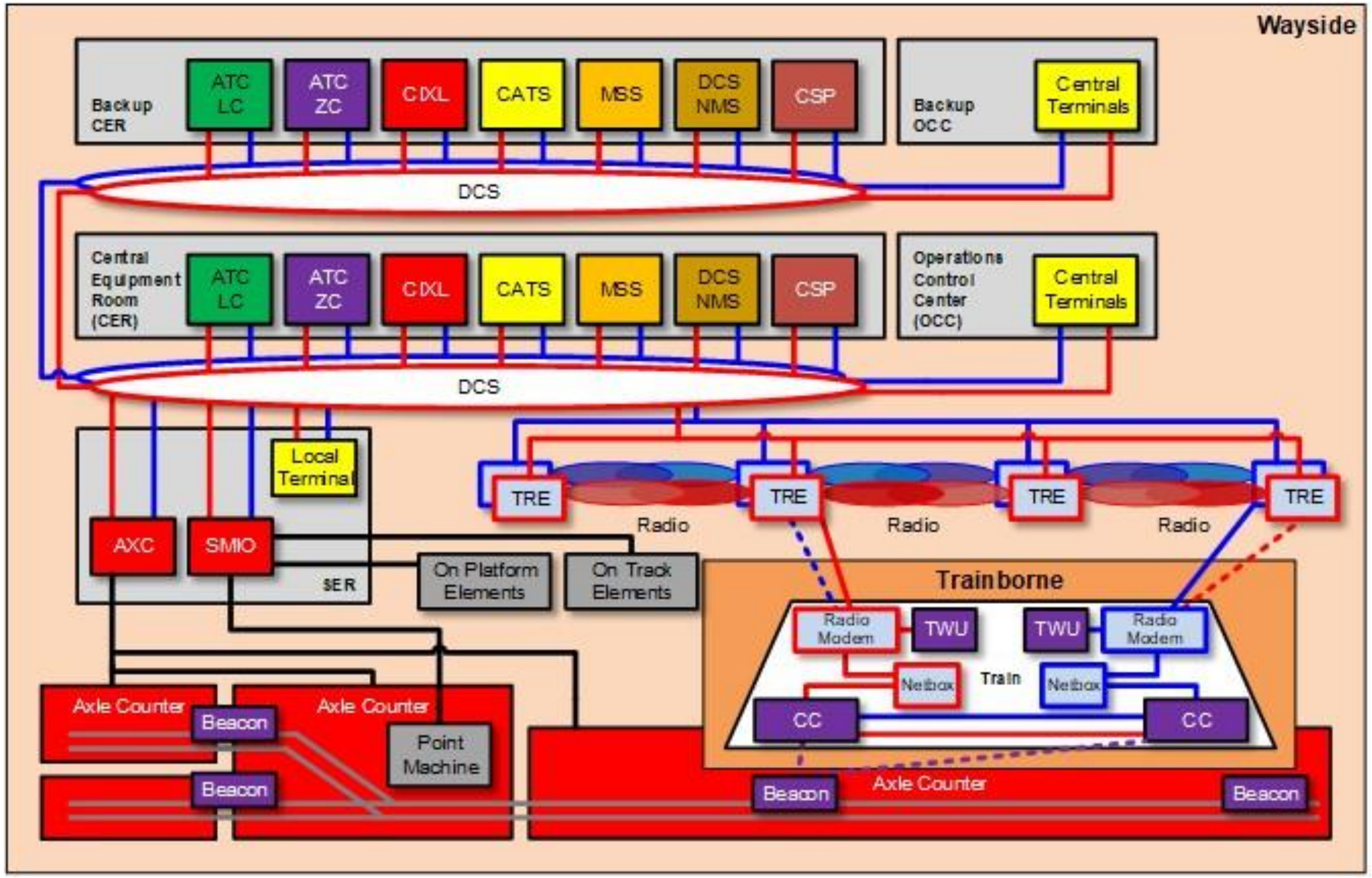
Design: a resilient architecture

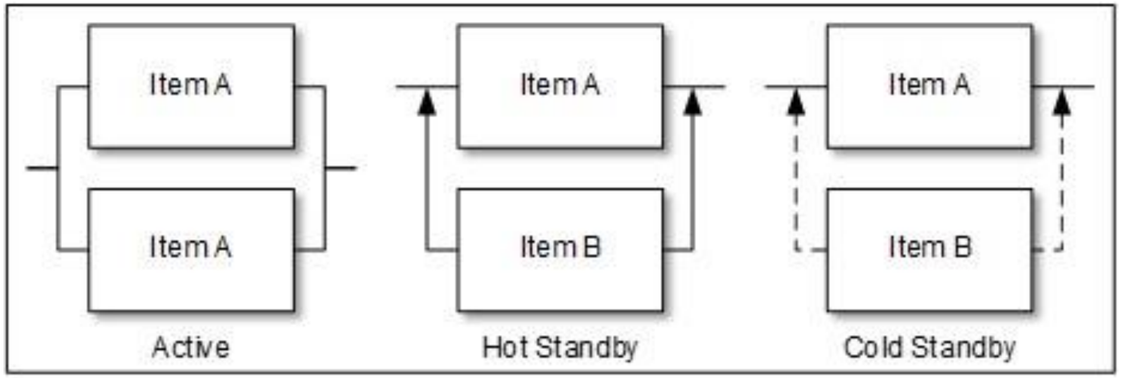
Design: a resilient, highly-redundant architecture

- Duplicated and fully separated wired and radio networks for communications (‘red’ and ‘blue’)
- Nominal communication path is dynamically rerouted in case of failure
- Maximum redundancy:
  - Centralized equipment
  - Remote input/output modules when controlling critical trackside objects
- Geographically duplicated equipment to provide a standby redundancy backup



Design: a resilient, highly-redundant architecture - Redundancy Modelling

- Various types of redundancy:
  - KooN: 1oo2 (one out of two), 2oo3 (two out of three), etc.
  - Active or Standby
  - Hot or Cold

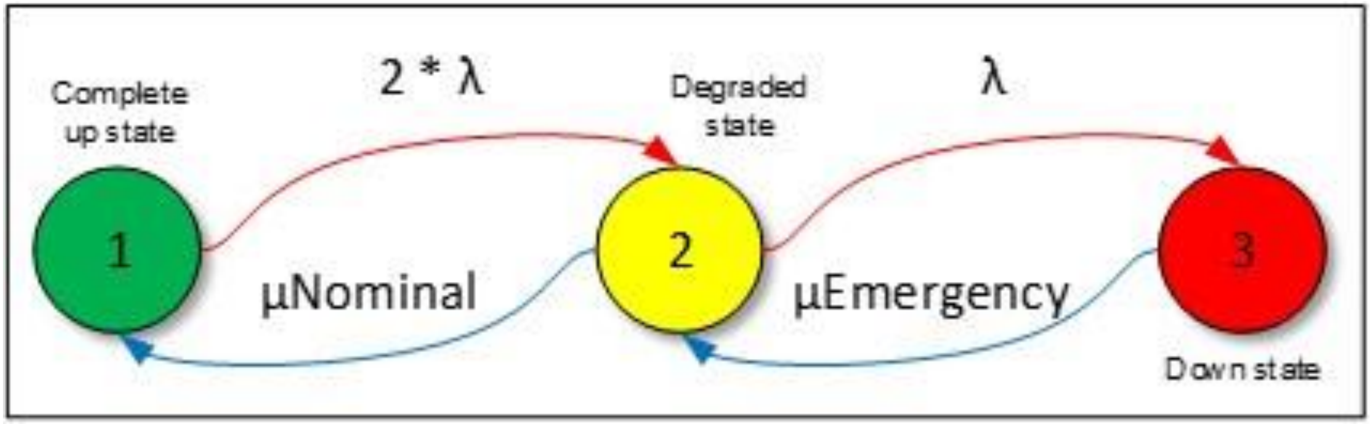


- It is essential to manage redundancy: know when a channel has failed and restore it before function is lost

- → State diagrams (Markov) are a convenient way to model failures and restorations

Design: a resilient, highly-redundant architecture - Redundancy Modelling

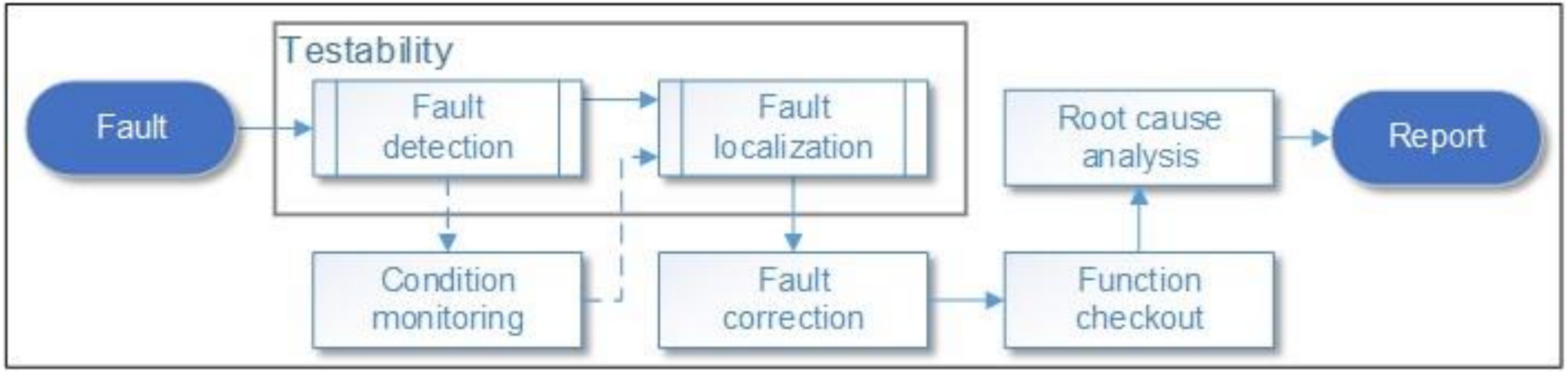
- Modelling an ideal 1-out-of-2 active redundancy (Markov)
  - State 1 - the system “complete up- state” (fully operational): the initial state
  - State 2 - a degraded state: one of the two channels has failed, but the main function is still performed
  - State 3 - a system down state: both channels have failed and therefore the main function is lost



  - Circles represent system states
  - Arrows are failure (λ) or restoration (µ) transitions

Design: a resilient, highly-redundant architecture - Redundancy Modelling

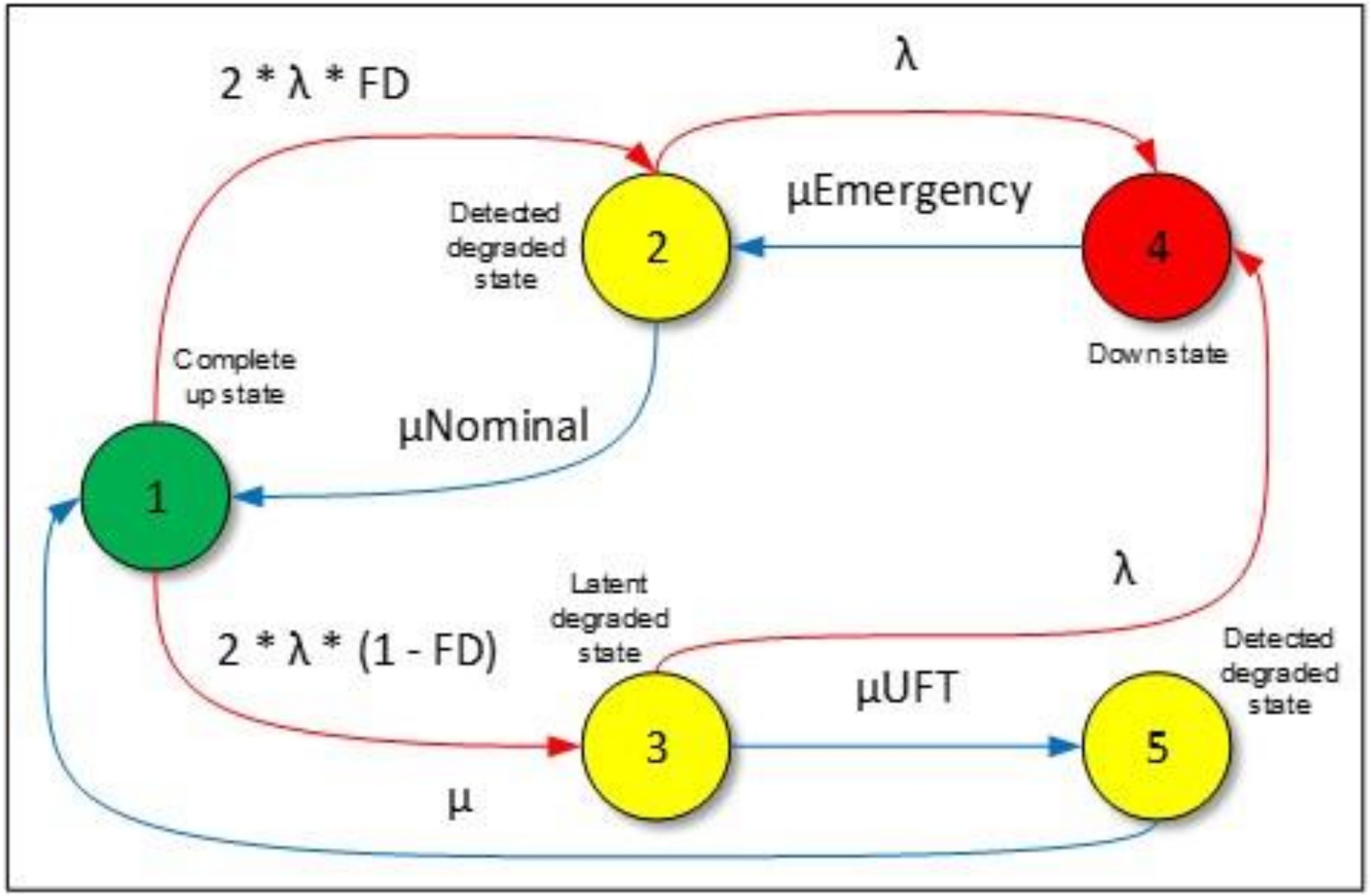
- Testability: a key design characteristic for redundant structures



- If testability is imperfect → first failure might not be detected: latent failure. Then, channel won’t be restored before function loss
- On-line built-in test equipment with high detection capabilities enables detection of partial failures before function loss
- A complementary solution to built-in test: periodic inspection

Design: a resilient, highly-redundant architecture - Redundancy Modelling

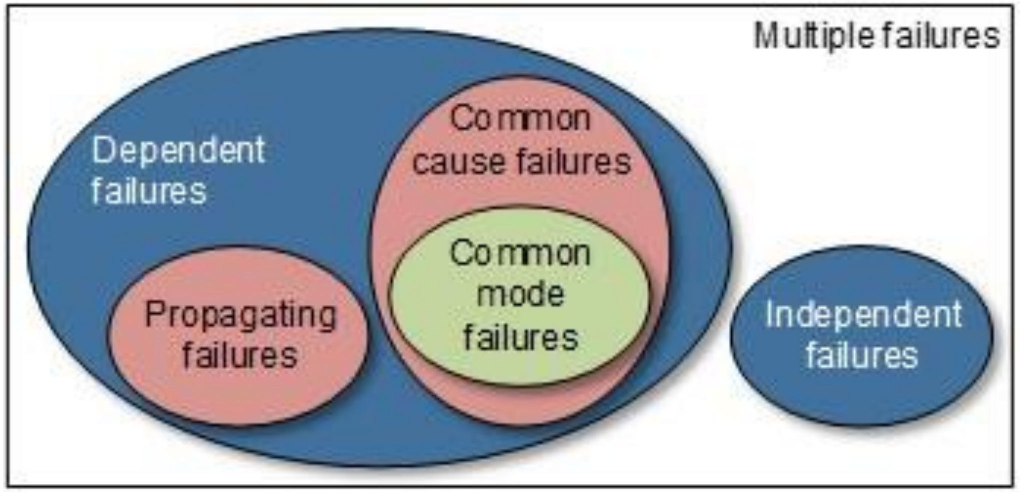
- Markov model of a 1-out- of- 2 active redundancy considering imperfect detection



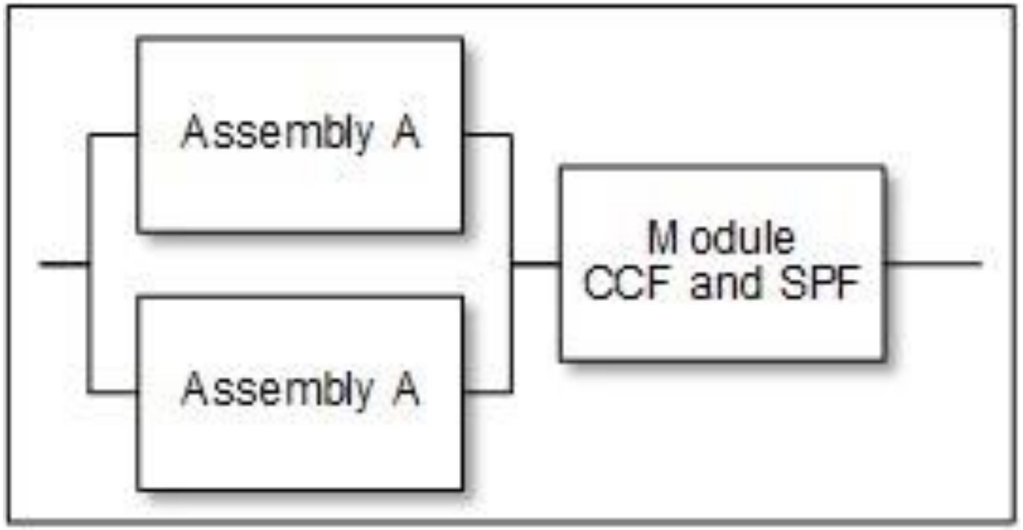
  - FD: fault detection probability
  - UFT: undetected fault time

Design: a resilient, highly-redundant architecture - dealing with common cause failures (CCF)

- Common Cause Failures (CCF) are failures of multiple items resulting from a single cause



- Common Cause Failures (CCF) and Single Point Failures (SPF) drastically reduce the effectiveness of redundancy



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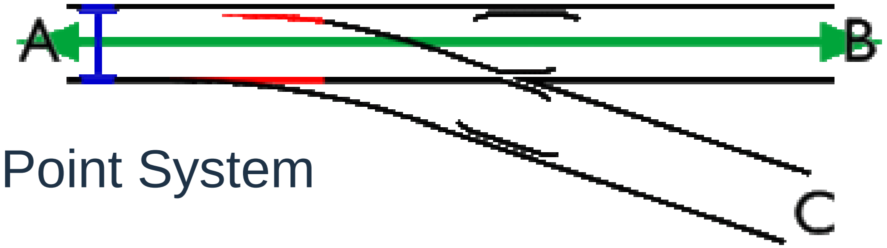
Maintenance: predictive maintenance

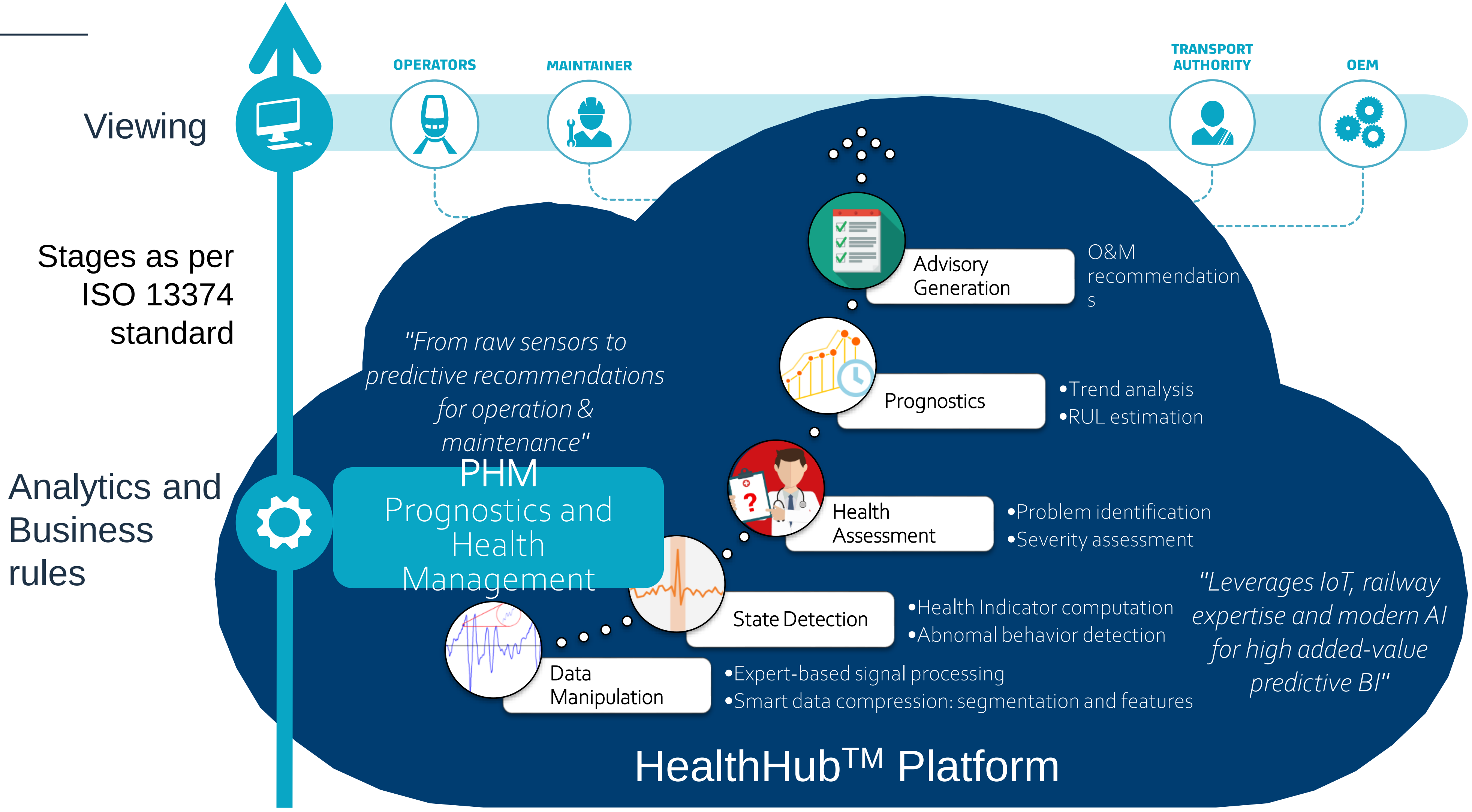
Predictive Maintenance

- For failures that are not sudden but are preceded by progressive degradations, it often makes sense to implement predictive maintenance
- Goal: Detecting degradations and performing preventive maintenance before they result in service-affecting failures
- Benefits:
  - Avoiding failures and their impact on punctuality and unscheduled maintenance costs
  - Avoiding unnecessary costly scheduled maintenance
- For trackside equipment: Point systems are amongst the most critical assets in terms of both maintenance cost and failure impact on operations



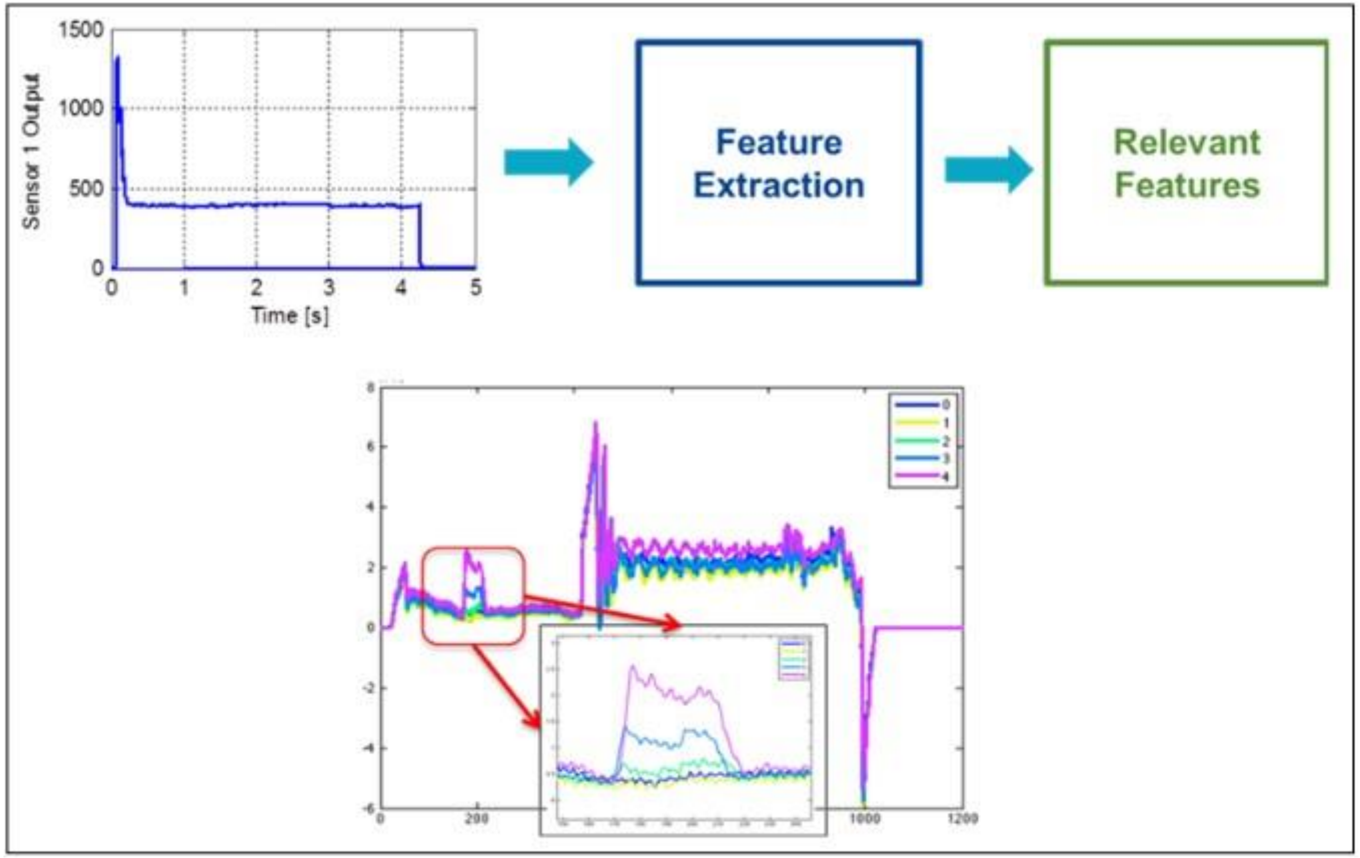
Point System

Alstom's PHM (Prognostics & Health Management) Framework

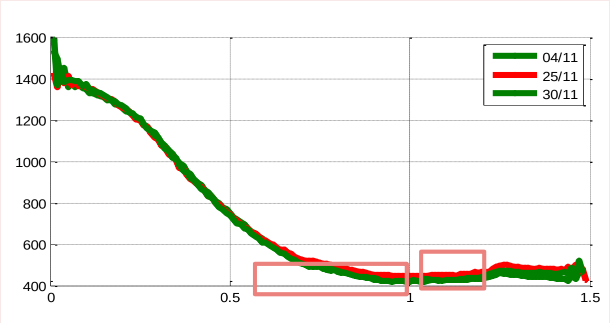
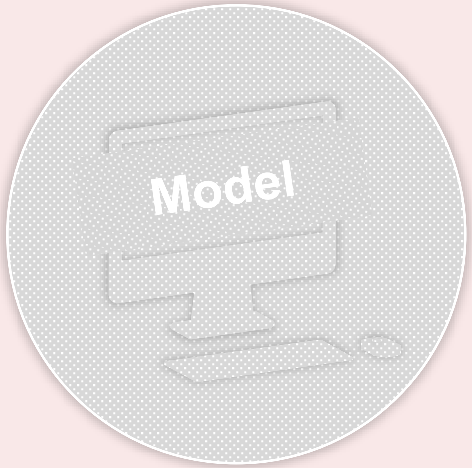
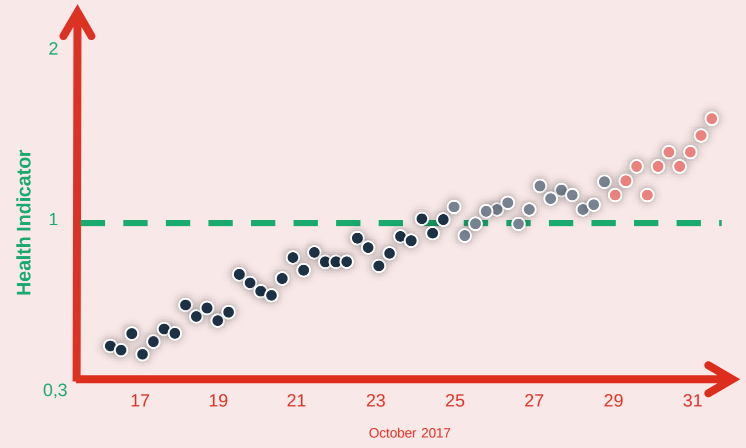


Predictive Maintenance: 1. Data acquisition & manipulation

- From raw physical signals to relevant features

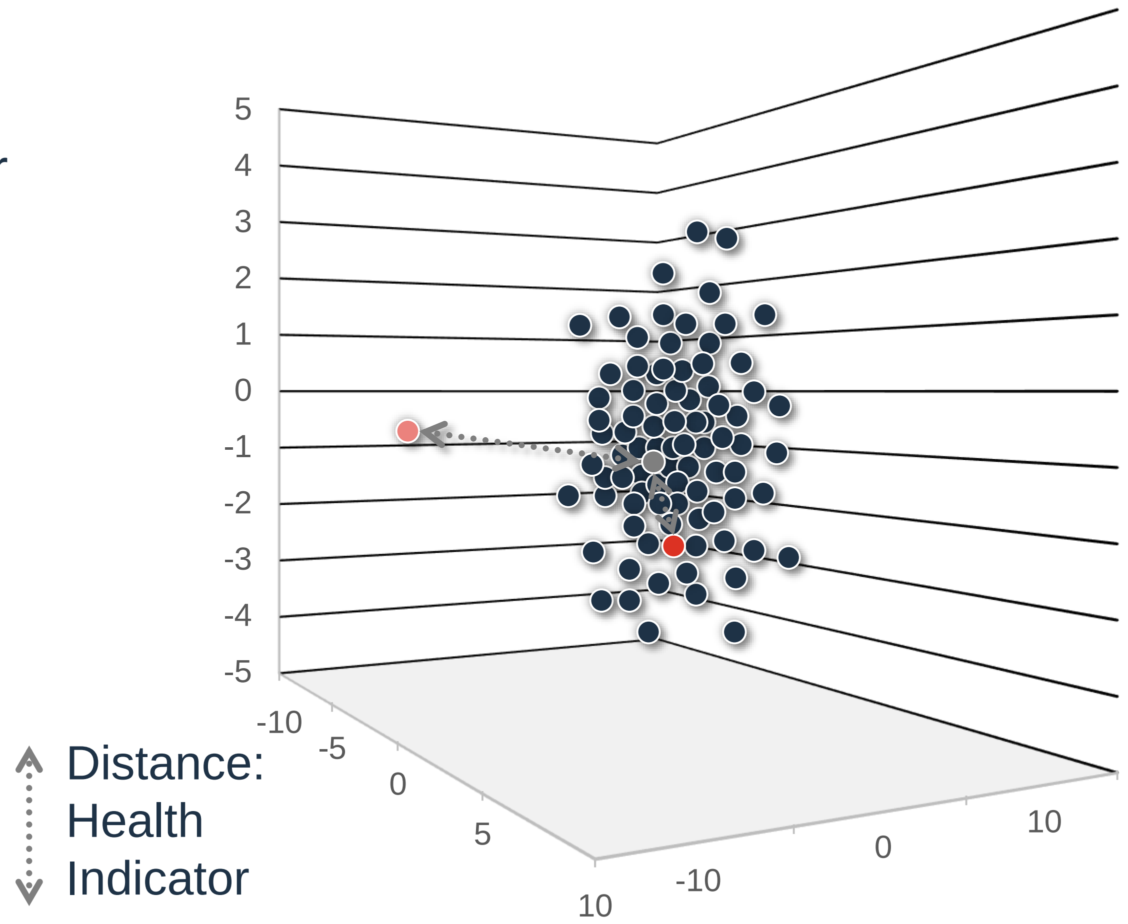


Predictive maintenance: 2. State detection

Raw signals	Machine Learning Model	Health Indicator
 		
• Too many false alarms or too few detections • Requires high accuracy to capture relevant variations	• Domain Knowledge • Customer requirements • Maintainer feedback	• Quantification of distance between the observed state and a healthy condition

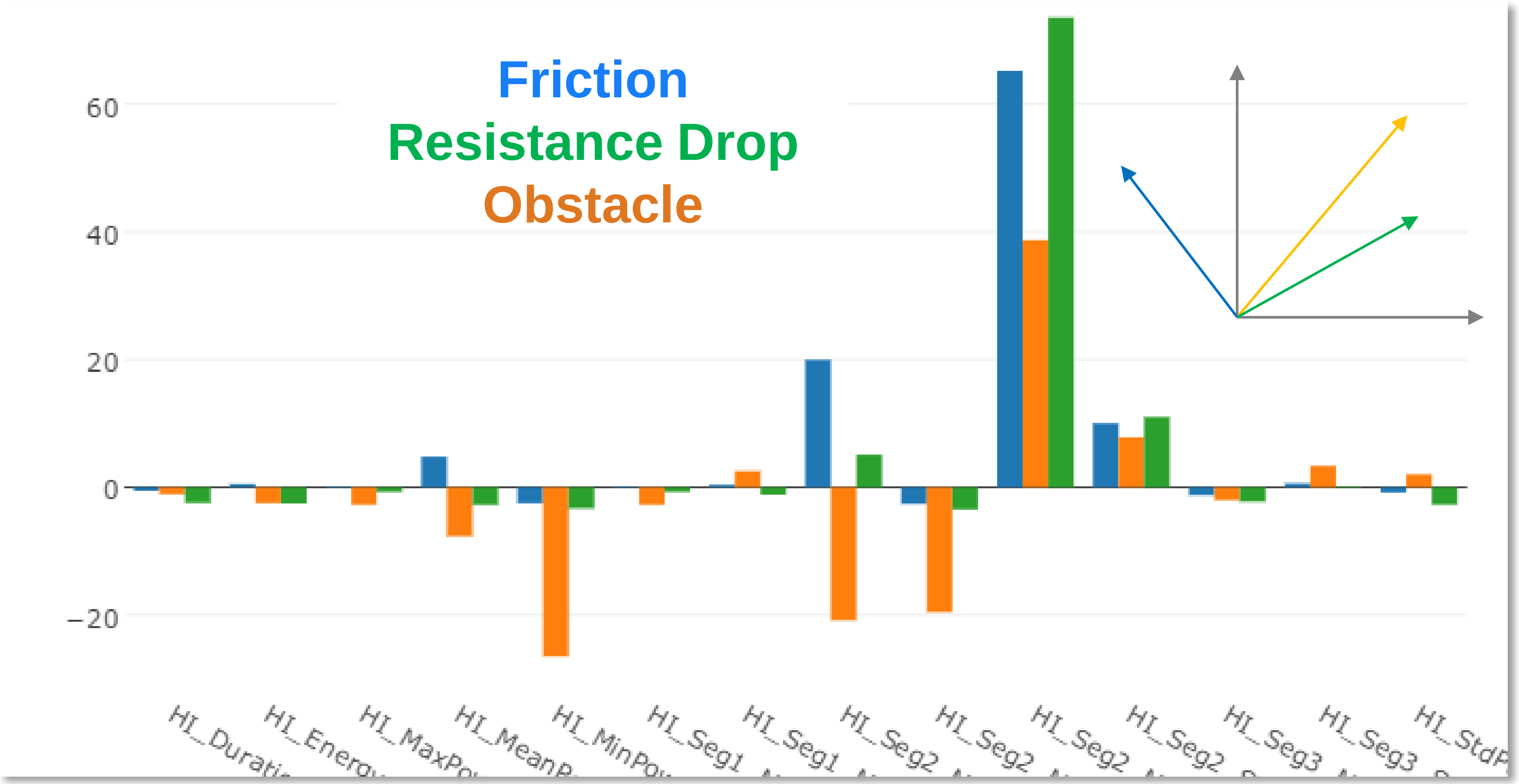
The Health Indicator: the heart of detection, diagnosis and prognosis

- The Health Indicator measures discrepancy between test (observed) data and training data
- The anomaly is visible with the Health Indicator while the raw signals won't always show the anomalies



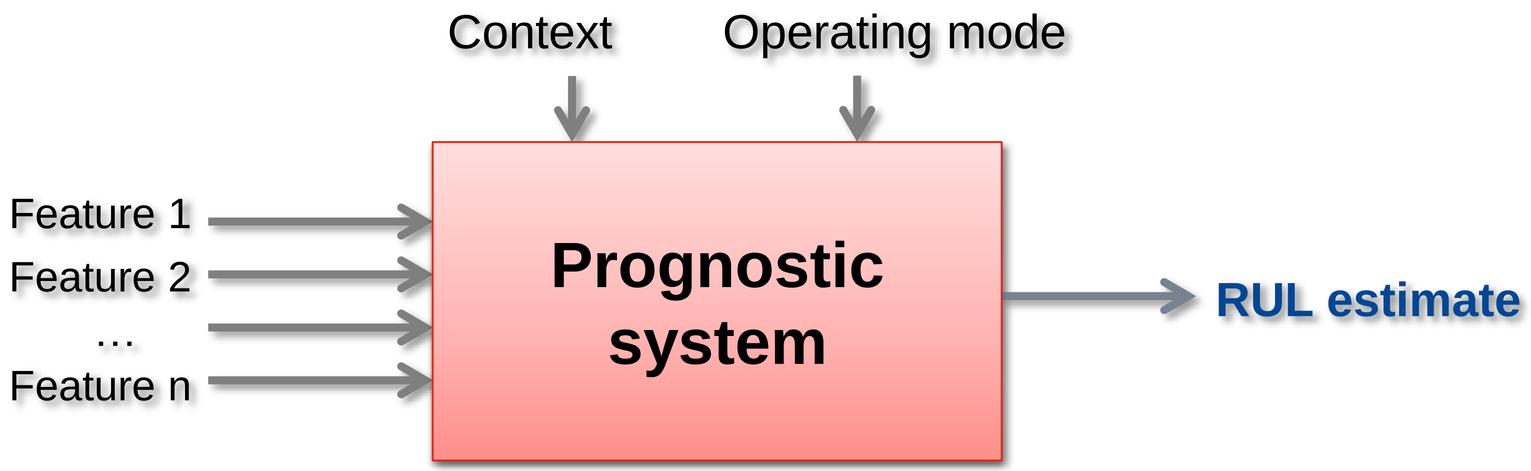
Predictive maintenance: 3. Health Assessment/Diagnosis Step

- Learning the degradation modes (= signature type + localization + severity) from field observations, and classifying the observed symptoms (find signature ‘closest’ to observation)



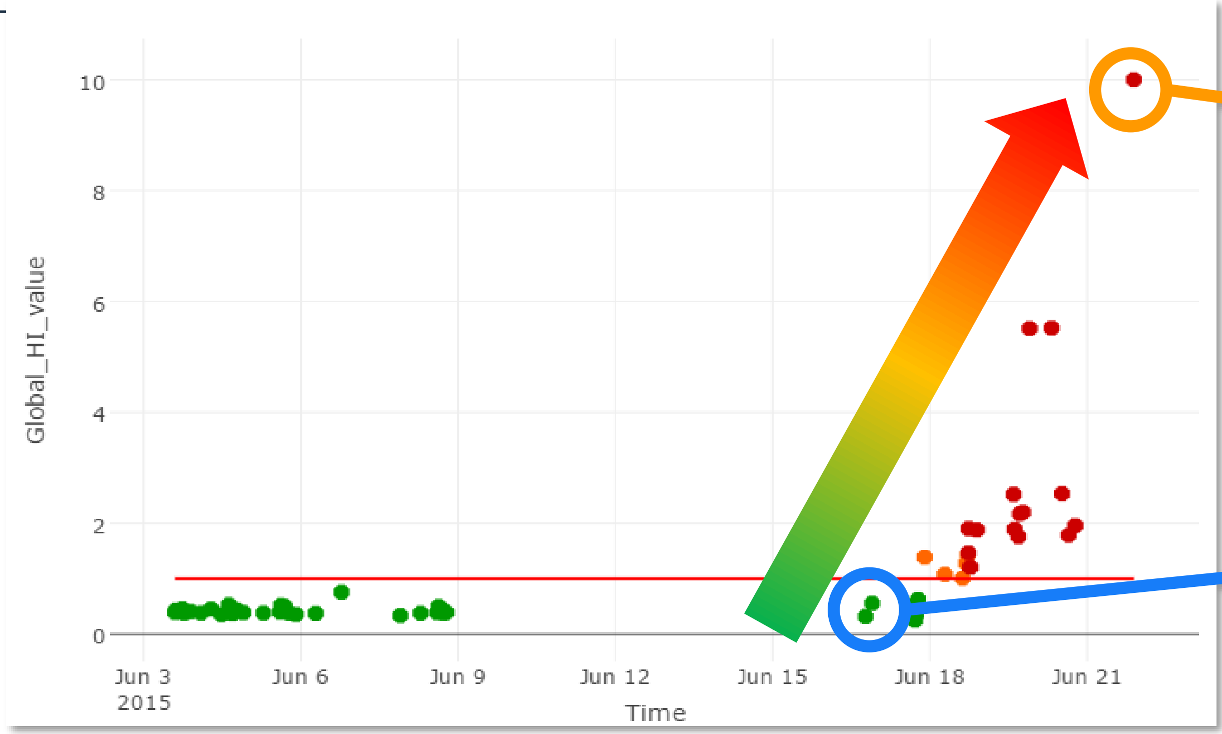
Predictive maintenance: 4. Prognosis Step

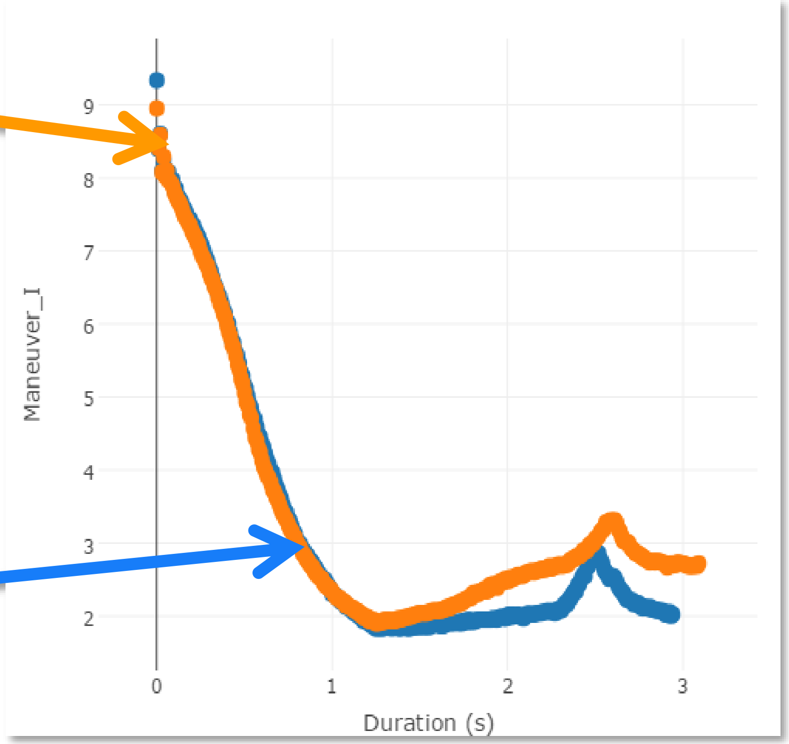
- Prognosis: evaluate current health of an asset and, conditioned on future load, estimate at what point in time the asset will no longer operate within its design specifications



- Prognosis: "Estimation of remaining useful life (RUL) of a component/subsystem"

Example of results for points





Observation:
Progressive rise in health indicator

Maintainers' feedback:
Lack of lubrication

4

Operations: adaptive traffic management

Operations: Adaptive Traffic Management

- Various regulation strategies can be used:
  - Headway regulation (keep headway constant)
  - Schedule regulation (enforce schedule adherence)
  - Mixed regulation
- Perturbations, due not just to technical problems but also to passengers, can destabilise the system → potentially large delays
- Goal-based regulation algorithms take a global view and optimize key performance indicators such as regularity and punctuality
- Control variables: dwell time in stations and speed between stations
- In addition, Alstom has developed a simulation tool that compares the efficiency of various regulation algorithms, i.e. their impact on the KPIs

Simulation tool for Regulation Policies Efficiency Assessment

- Evaluate efficiency of regulation algorithms during design phase.
- Evaluate the robustness of timetables (stability with respect to external perturbations)
- Design more efficient regulation algorithms = optimize key performance indicators

Key Performance Indicators

- The simulation tool calculates the average value of following UITP key performance indicators corresponding to various regulation strategies and thus allows for selecting the best regulation algorithm

$$\text{UITP Punctuality KPI} = \frac{\text{Number of train trips delayed by less than ‘x’ minutes}}{\text{Actual number of train trips}} \quad \text{with x} = 60\text{s}$$

$$\text{UITP Regularity KPI} = \frac{\begin{array}{l}\text{Number of train departures at specified stations complying}\\ \text{with planned headways within ‘x’ minutes}\end{array}}{\text{Actual train departures from specified stations}} \quad \text{with x} = 30\text{s}$$

$$\text{UITP Recovery time from incident KPI: Time to return to normal operation (e.g. nominal headway)}$$

5 Conclusion

Conclusion

- Resilience: Quick and efficient recovery from perturbations (internal or external)
  - A variety of different, complementary risk mitigation measures are necessary
  - Multi-disciplinary, system-wise endeavour
- Urbalis®
  - Relies to that end on hardware and software
  - Addresses the entire scope of design, maintenance and operations
- Future directions: learning system
  - Context-adaptive maintenance and operations policies
  - Reconfiguration algorithms learning from past experience

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