UNIVERSITY OF TWENTE.

Netherlands Defence Academy
Ministry of Defence

Predictive Maintenance

Combining Data and Physics

Prof. dr. ir. Tiedo Tinga
t.tinga@mindef.nl

Background

- **NLDA**
  - *Professor Life Cycle Management*
  - Predictive Maintenance based on physical models
  - Smart Maintenance knowledge center with RNLN
  - Focus on military systems (ships, helicopters, vehicles)

- **University of Twente**
  - *Prof. Dynamics based Maintenance* ~ 15 pp
  - Predictive Maintenance + Structural Health & Condition Monitoring
  - Focus on civil applications (windturbines, bridges, train/track)

  - Part of **Maintenance Consortium TIME**
    - Collaboration 8 research groups @UT

TIME

UNIVERSITY OF TWENTE.

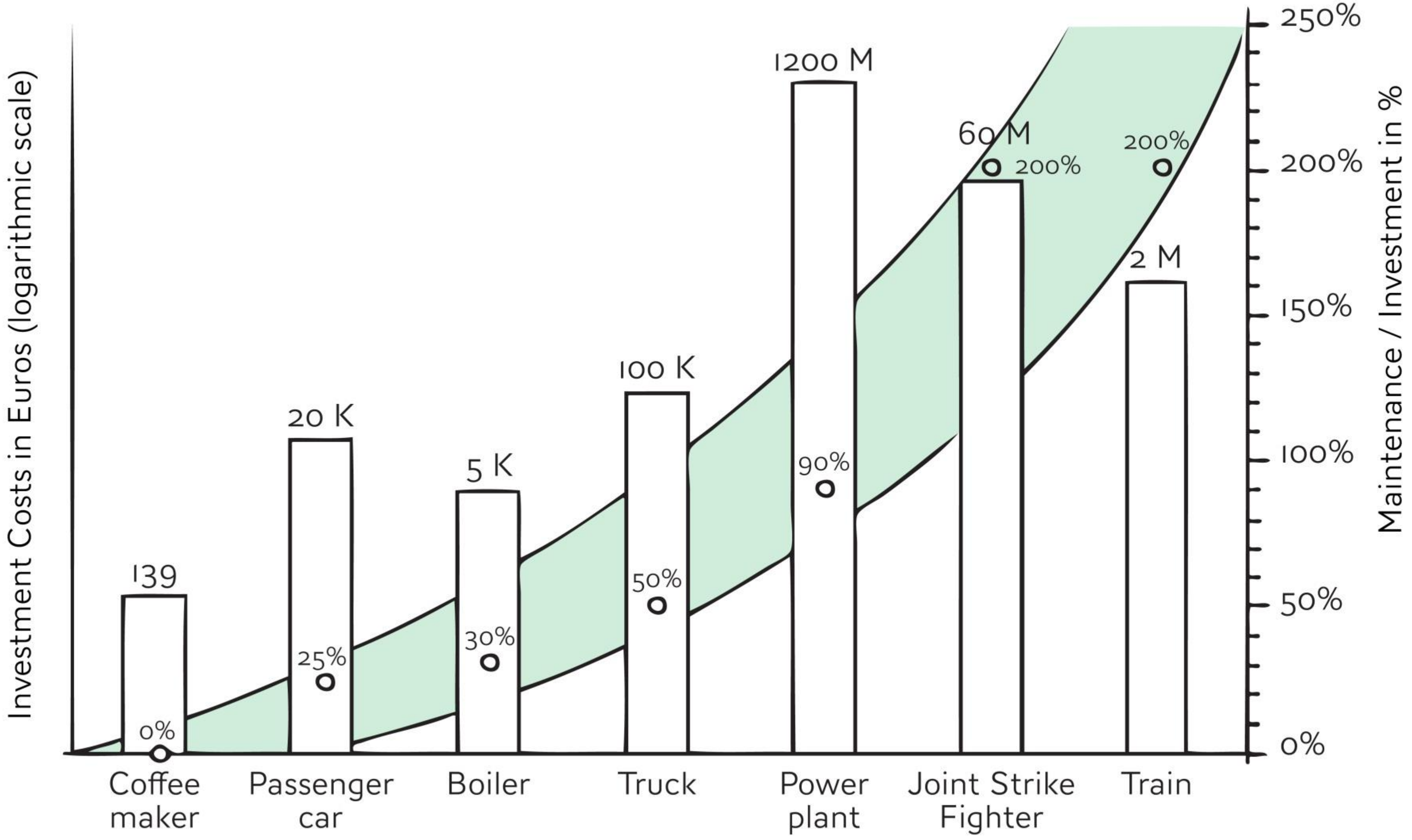
Outline

- **Introduction & motivation**
- **Predictive Maintenance → what & why ?**
- **Approaches**
  - Data-driven
  - Physics of failure
  - Combining data & physics
- **Challenges & conclusion**

Why Predictive Maintenance, and how ?

MAINTENANCE BASICS

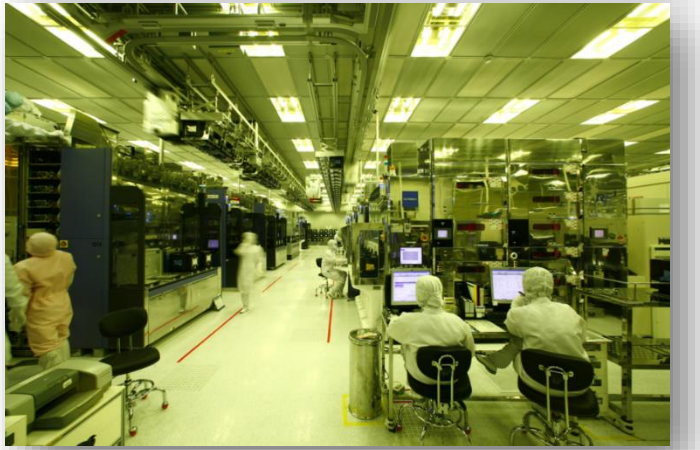
Costs of Maintenance



Costs of (no) maintenance

- A day of downtime in the **process** industry costs **hundreds of thousands of euros**

- An hour of downtime in **semiconductor** manufacturing costs **tens of thousands of euros**



Military systems

Challenging Life Cycle Management

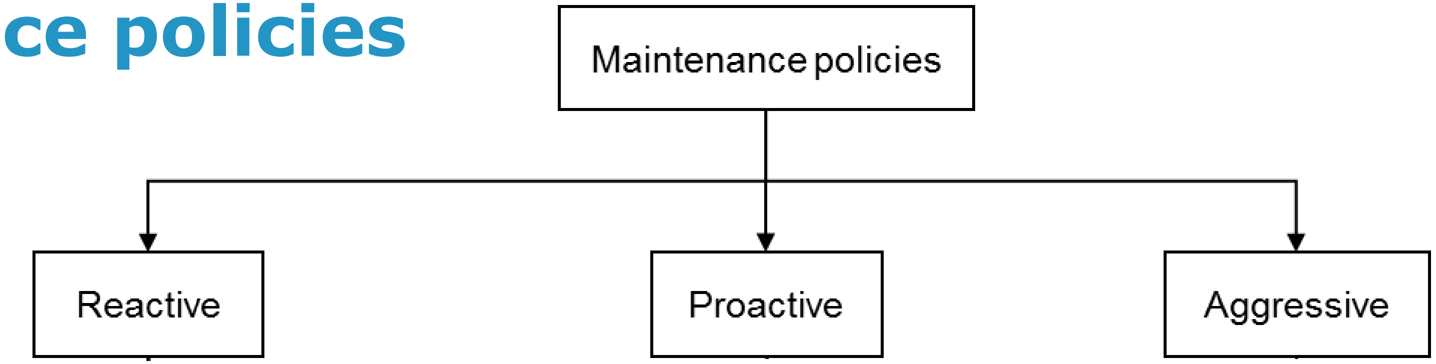
- 20-30 yrs in use → sustainment costs > initial investment
- Highly technological and complex
- Variable operational conditions
- High requirements for availability

→ Requires smart approach to LCM

Maintenance is important

***Predictive* maintenance even better !**

Maintenance policies



Predictive

The maintenance challenge

- **Preventive maintenance ➔ length of service intervals**
- **Balance between**
  - not too early
    - high costs
    - spare parts, repairs, man hours
  - not too late
    - *unexpected* failures
    - low reliability / availability

- **Optimal solution**
  - on-condition maintenance (just-in-time)
  - both *efficient* (costs) and *effective* (no failures)

→ Reliability = proper design + suitable maintenance

Just-in-time Maintenance

- **Health & Condition monitoring**
  - Determine actual condition with sensors / **measurements** → *condition / performance monitoring*
  - Predictions based on trends / extrapolation

  − Reaction time often short → P-F interval
  − Extrapolation inaccurate at varying usage
  + Present condition always accurately known

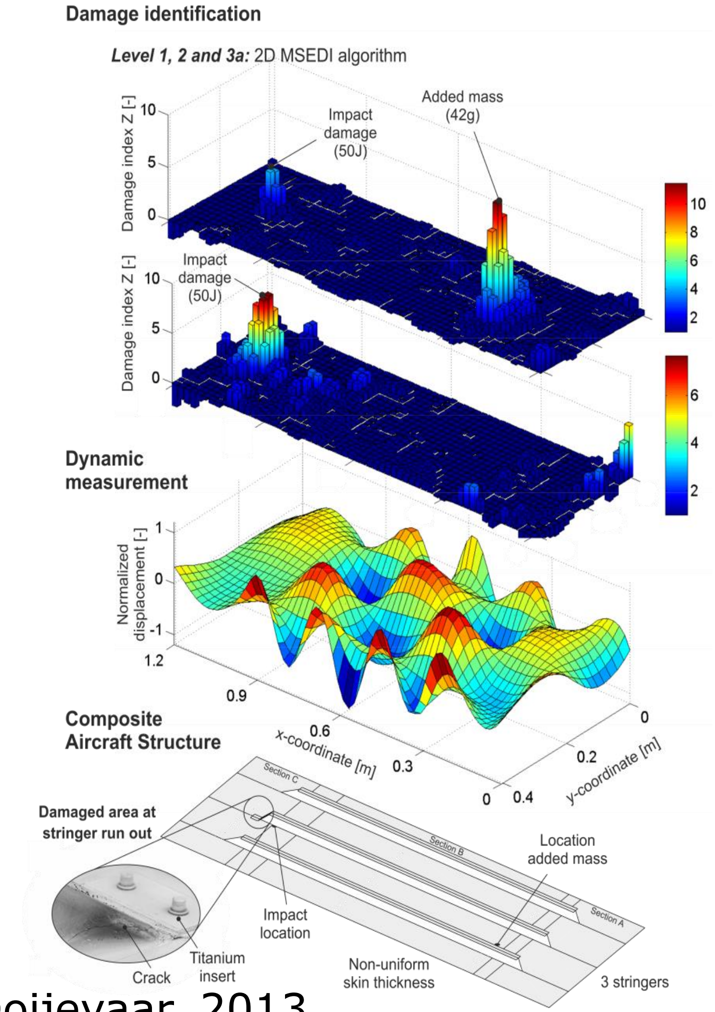
- **Predictive Maintenance & Prognostics**
  - **Calculation** of (remaining) life time based on model or experience (statistics)
  - Measured or assumed usage profile required

  − Only certainty at failure, before: actual condition unknown
  + Varying usage can be accounted for
  + Good model enables predictions far into future (planning !)

1. Health / Condition Monitoring

- **Condition monitoring**
  - Vibration analysis
  - Oil analysis
  - Thermography
  - Electrical current signature analysis
  - → *Developments*:
    - From periodic to in-line / continuous measurements
    - Automation of analysis → AI: pattern recognition, clustering

- **Structural Health Monitoring**
  - Vibration analysis on structures
  - Interpretation challenging !
  - Requires advanced signal processing / data analysis
  - → *Developments*:
    - New sensor types → optical fibres
    - Improved analysis with AI



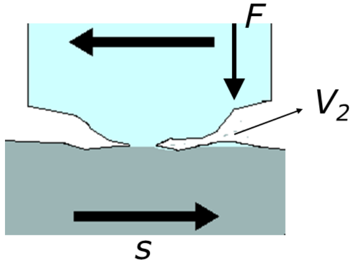
Ooijevaar, 2013

2. Prognostics

- **Experience-based (traditional)**
  - Estimate future usage (OEM) → conservative
  - Collected data → not always available
  - Experience from past → not always representative

- **Data-driven**
  - Derive relations from (big) data sets (e.g. registrations, sensors)
    → sometimes unexpected relations, but is often *black box*
    → not always representative

- **Model-based**
  - Model of physical failure mechanism
  - Input from monitored usage / loads
    → always representative
    → modeling takes large effort



DATA-DRIVEN APPROACH

Data-driven diagnostics & prognostics

- **Lot of potential due to**
  - Large increase in sensor availability
  - Almost no limitation to data storage
  - Lots of Artificial Intelligence (AI) algorithms

  → Considered by many to solve all maintenance problems soon !

- **However: fundamental challenge of applying AI in maintenance**
  - AI / machine learning algorithms require large numbers of examples for training

    ⇕

  - Maintenance aims to minimize number of failures

  → *Per definition* only limited failure data sets !

- **Only limited amount of *generic* solutions for prognostics**

Various levels

- **Detection of failures**
  - Is something wrong ?
  - Anomaly detection, but could be *contextual*
  - Built-in warnings / alarms → often with fixed threshold
    - False alarms, operator faults, …

- **Diagnosing systems**
  - What exactly is wrong ?
  - After failure: indicate where to find the problem (fault finding)
  - Before failure: what is present condition (~ health check)

- **Prognostics**
  - When is the system expected to fail ?
  - *Holy grail* in PdM, but challenging / (still) too ambitous
    - Limited number of failures / training examples

Potential solutions

- **Combine data-driven approaches with physics of failure**
  - Physics of failure based on laws of physics
    - Many relations already well-known
    - Can be used as starting point or to strengthen AI algorithms → hybrid approaches

- **Generate additional failure data for training**
  - Accelerated testing → costly, not always representative
  - **Fleet leader** concept
    - Reason: actual failures invisible due to prev. maintenance (PM)
    - Generate failure data in controlled way:
      - Postpone PM for small fraction of systems
      - These systems must lead the fleet (age)
      - Consequences of failure must be limited
    - Benefits
      - Rest of fleet → PM closer to actual life time
      - Additional sensor data collected → reveals patterns related to failures

Example: Anomaly detection in diesel engines

- **Use engine data to detect bearing failures**
- **Challenges**
  - Select engine parameters (sensor) that relates to bearing condition
    - Bearing (oil) temperature

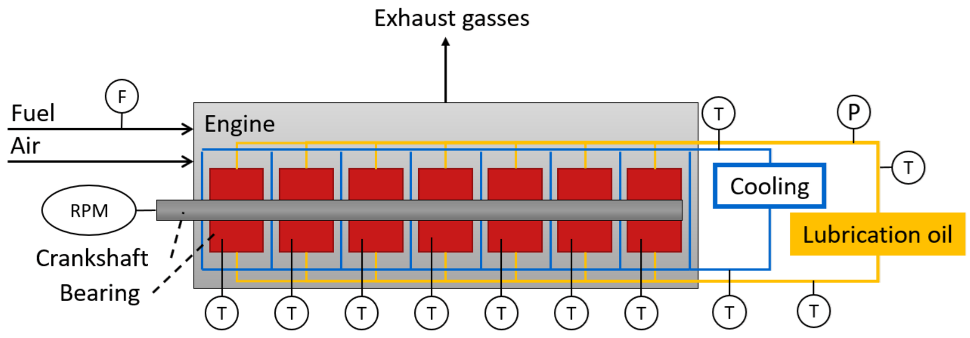
  - How to separate bearing degradation from other causes for T increase ?
    - *Contextual anomalies*
    - Also include rpm, sea state, fuel flow, … ? How to select ?

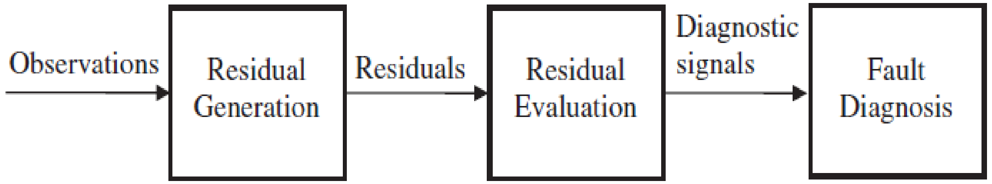
  - How to train model ?
    - Requires at least some failures

- **Methods**
  - Regression models
  - Statistical Process Control

Diagnosis of diesel engine

- **Detect (upcoming) bearing failures in diesel engines**
- **Multiple Linear Regression**





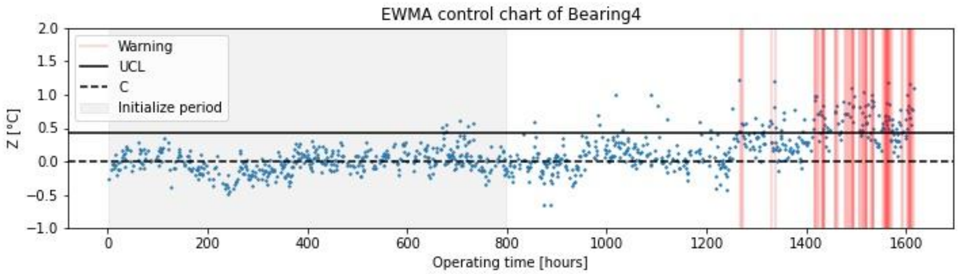
General flowchart of a model-based approach (Jardine et al., 2006)

D. Heek, 2021

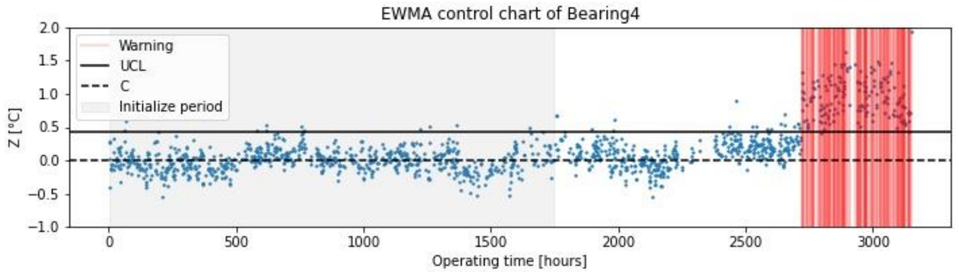
$$T_b = \beta_{1,b} + \beta_{2,b} * x_{RPM} + \beta_{3,b} * x_{RPM}^2 + \beta_{4,b} * x_{Oil} + \beta_{5,b} * x_{RPM\_TC} + \beta_{6,b} * x_{RPM\_TC}^2,$$
$$b \in \{1, .., 7\}$$

Diagnosis of diesel engine (2)

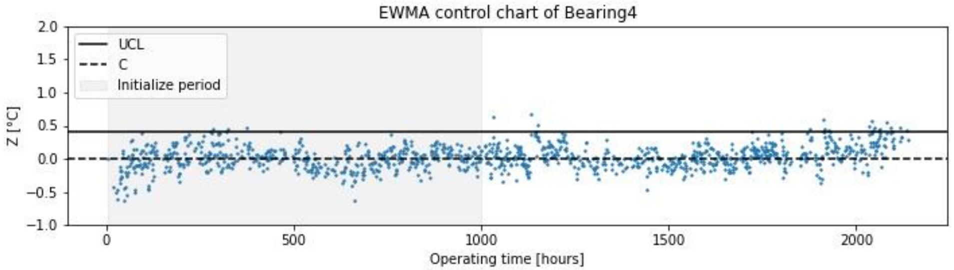
- **Initialize period**
  - Learning MLR
  - Setting UCL
- **Application**
  - Check whether T stays within control limits
- **Challenges**
  - different operating modes



Case I – to defect



Case II – to defect, other maintenance to engine at ~2700



Case III – another engine, no defect

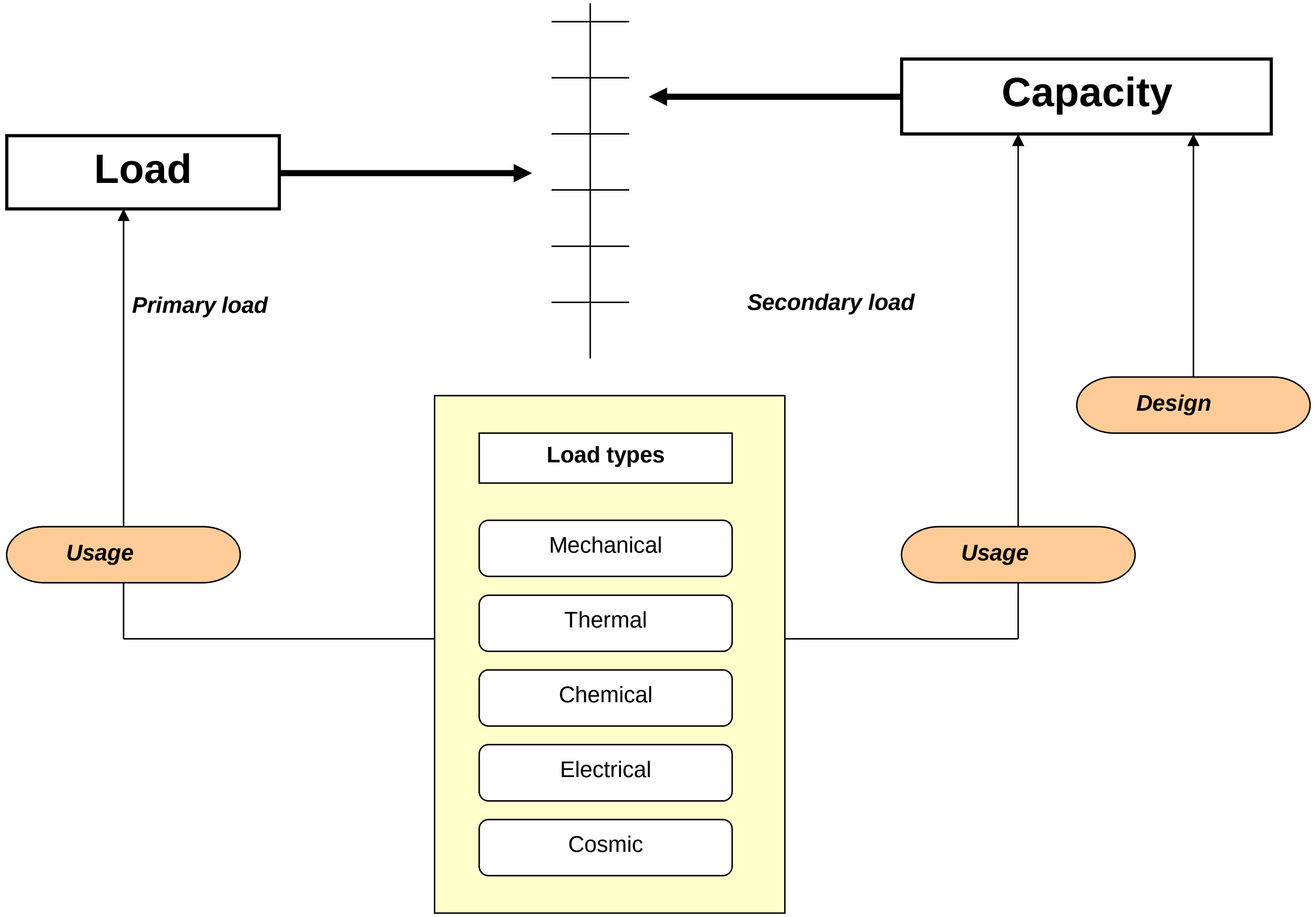
D. Heek, 2021

Understanding failures

PHYSICS OF FAILURE

Balance

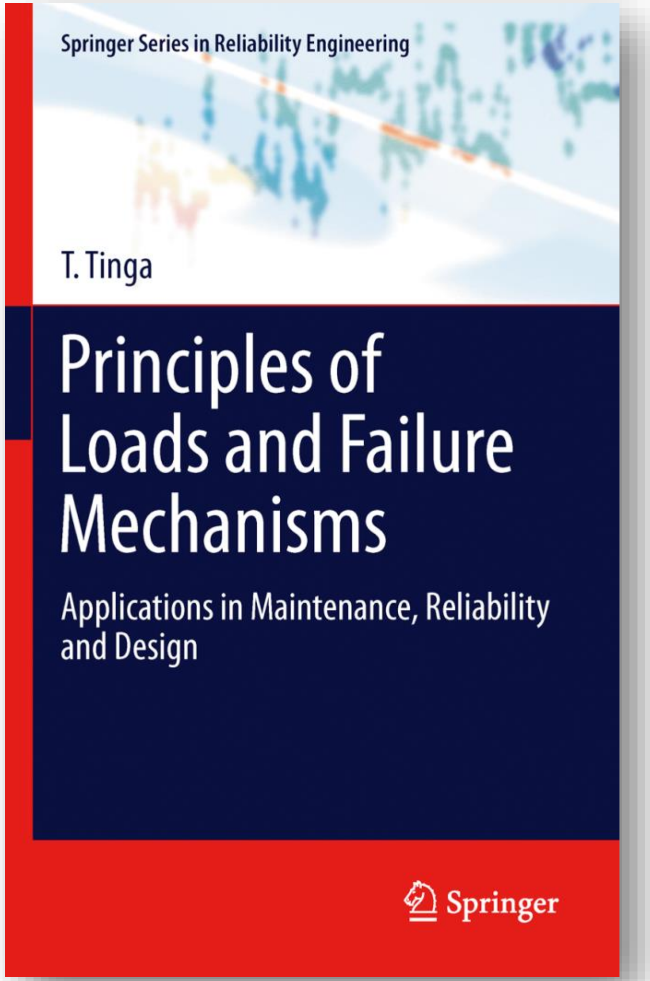
- **Load versus load-carrying capacity**



Failure mechanisms

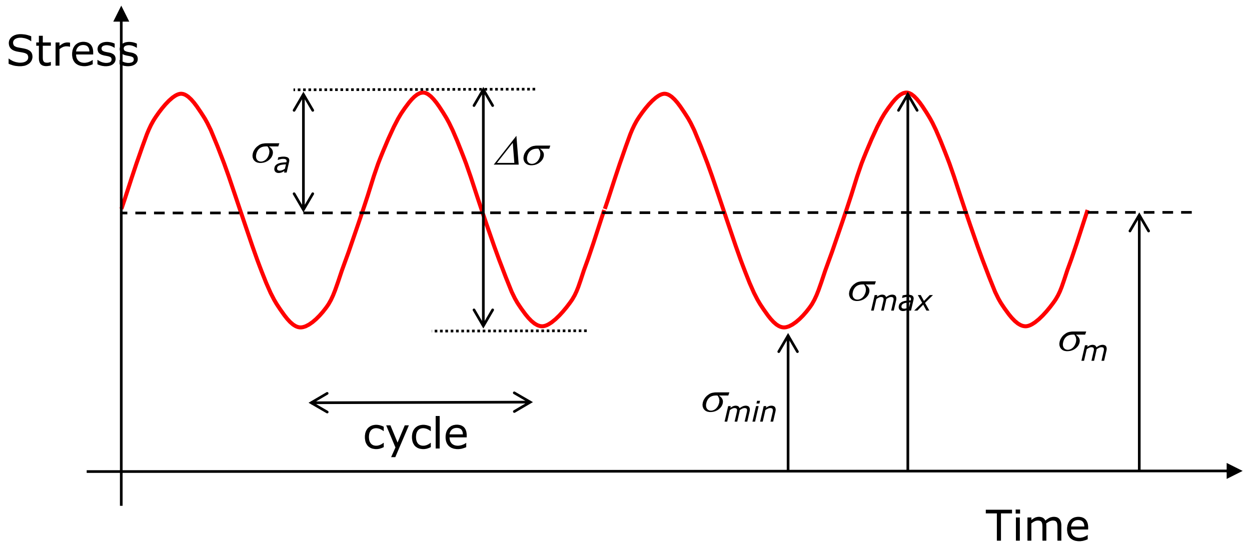
- ***Static overload***
- **Deformation**
- ***Fatigue***
- **Creep**
- ***Wear***
- **Melting**
- **Thermal degradation**
- **Electric failures**
- **Corrosion**
- **Radiative failures**

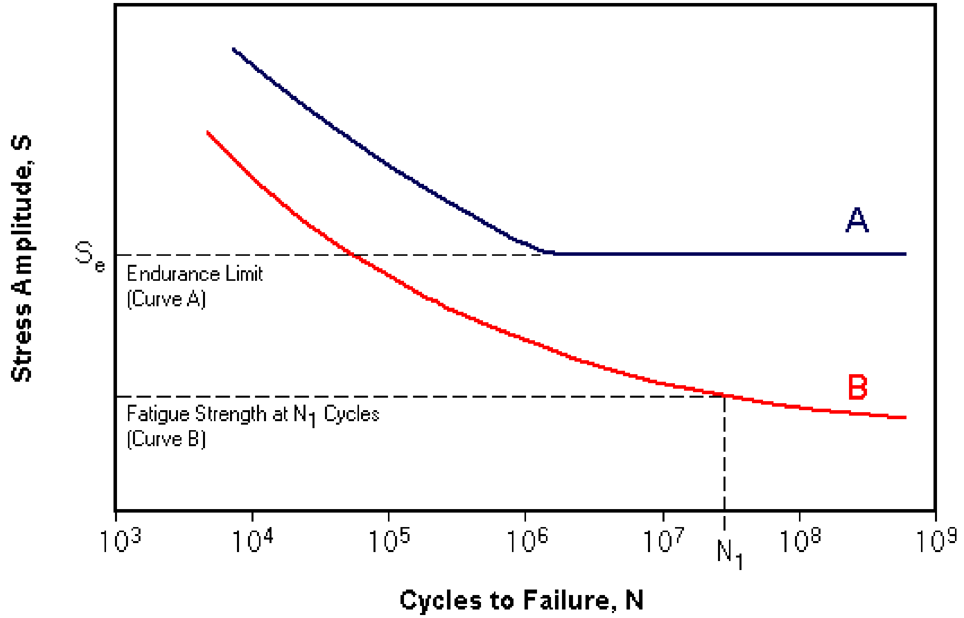
- **Complete overview:**



Fatigue

- **Caused by cyclic load (< tensile strength !)**
- **Failure after large number of cycles ($10^4 - 10^7$)**
- **Life time related to $\Delta\sigma$ → Wöhler curve**





Wear

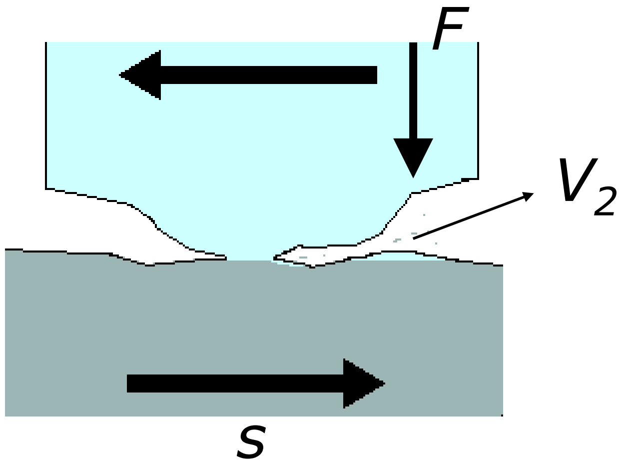
- **Parts sliding against other parts**

- **Archard's law**

$$V_i = k_i F s$$

  - *k* [mm^3/Nm] is specific wear rate (different for two bodies)

  - *k* depends on
    - » material combination
    - » surface roughness
    - » contact temperature
    - » hardness
    - » lubrication



ROLE IN MAINTENANCE

Application in (smart) maintenance

Knowledge on failure (mechanisms) can be used …

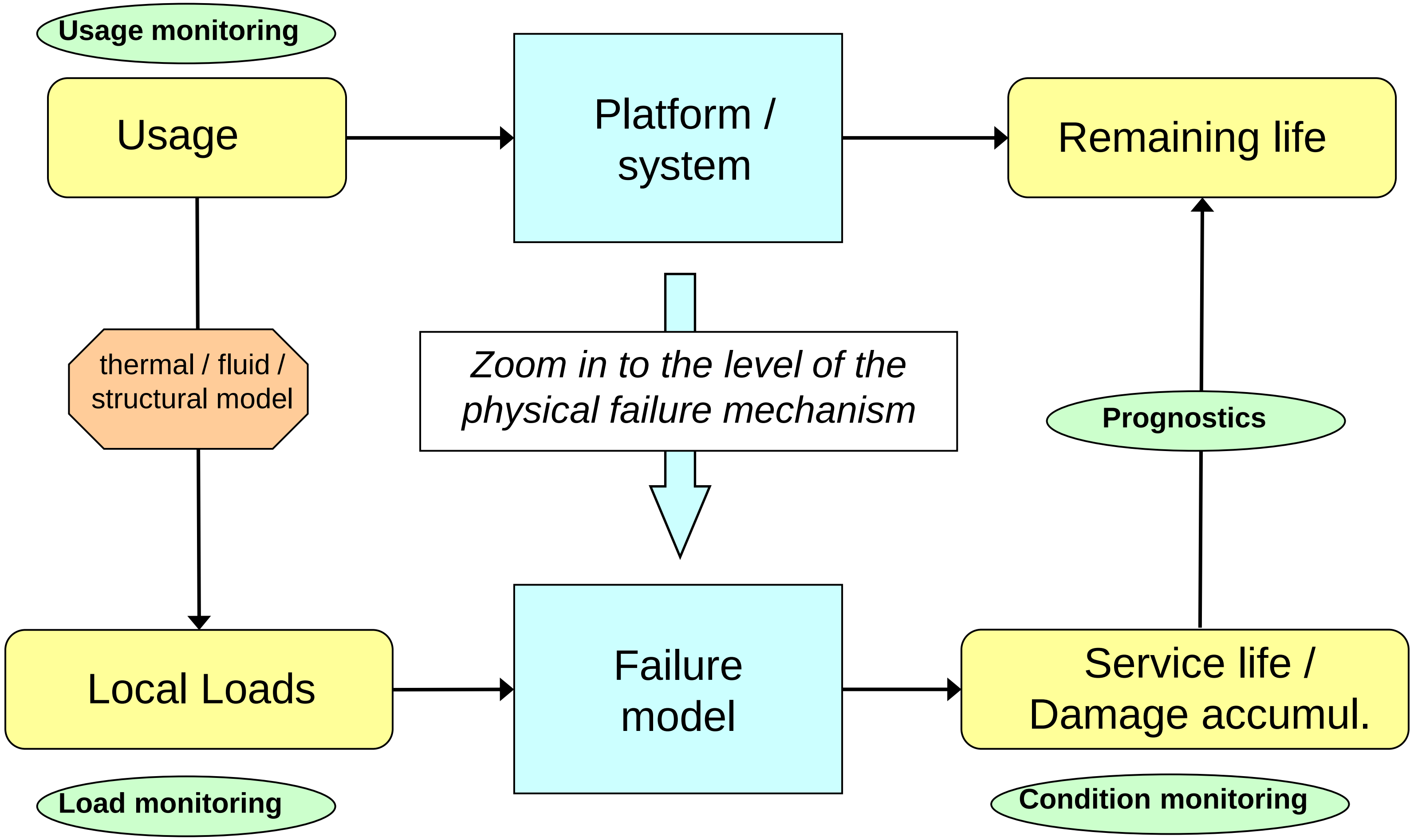
- **before failures occur**
  - Identify critical components → FMECA → Design for Maintenance !
  - Predict time to failure → determine optimal maintenance intervals: **PdM**
  - Develop efficient condition monitoring → **smart sensoring**

- **after failure has occurred**
  - Why did component fail ?
  - How can future failures be prevented ?
  - Root Cause Analysis

- **when a fraction of a (larger) population has failed**
  - Quantify failure behaviour → Reliability Engineering
  - Find Relevant Failure Parameter (RFP)

MODEL-BASED PROGNOSTICS

Model-based: relation usage – life time



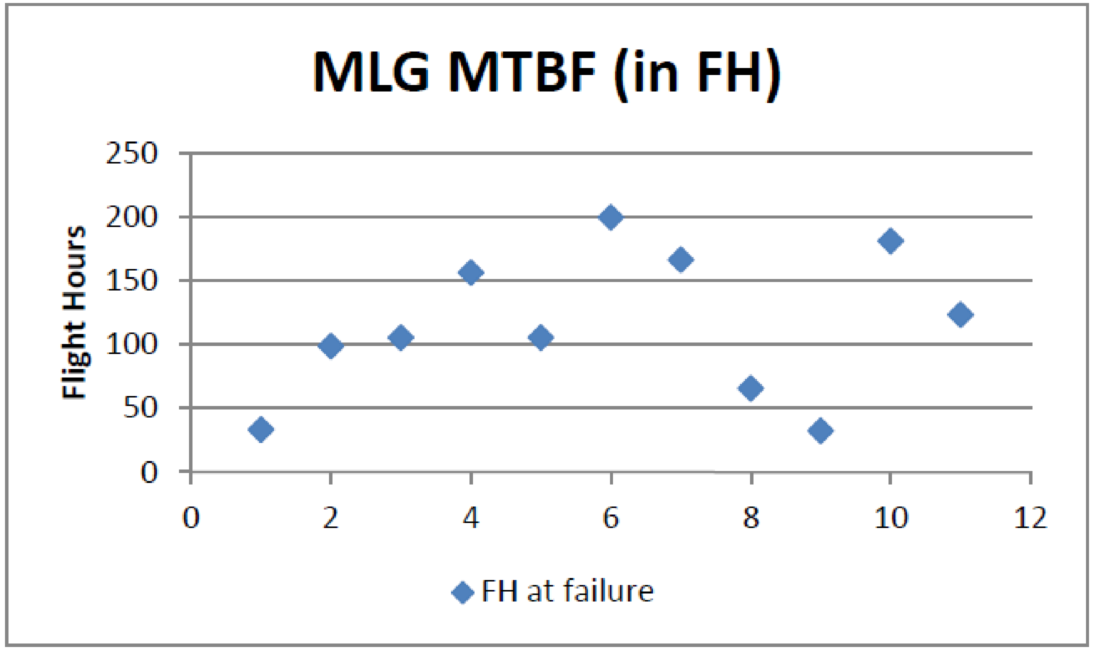
NH-90 helicopter prognostics

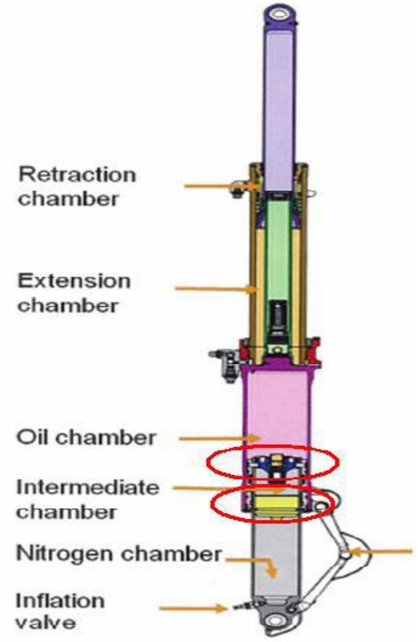
Heerink, 2013

- **HUMS system available for monitoring**
  - Usage → flight hours, landings, conditions, etc.
  - Health → mainly vibrations
- **Maintenance primarely related to flight hours**
- **Identified critical components (Pareto + CMMS)**
  - Cost drivers
  - Availability killers
- **Determined failure mechanism + governing loads**

NH-90 helicopter prognostics (2)

- **Landing gear shock absorber is critical**
- **Time to failure not correlating to FH**
- **Develop prognostic method**



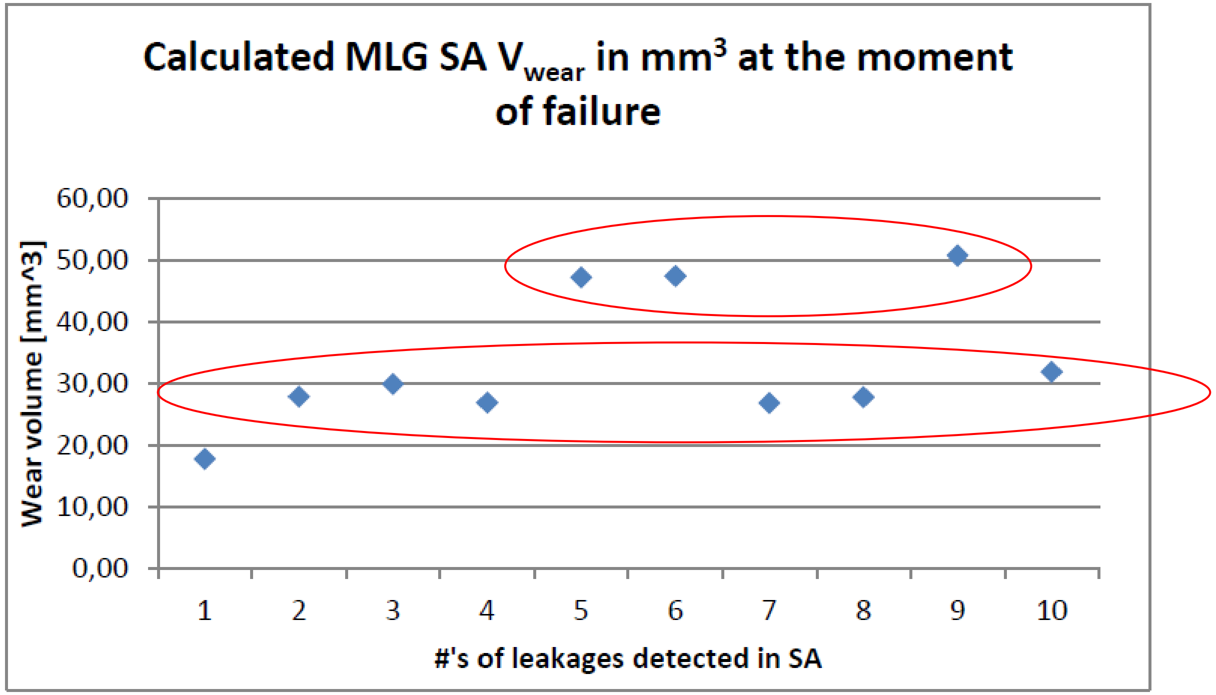


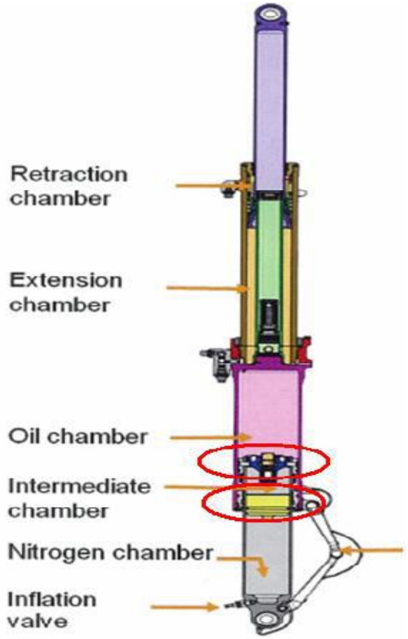
NH-90 helicopter prognostics (3)

- **Mechanism: wear of seal (oil leakage)**

$$V_i = k_i F s$$

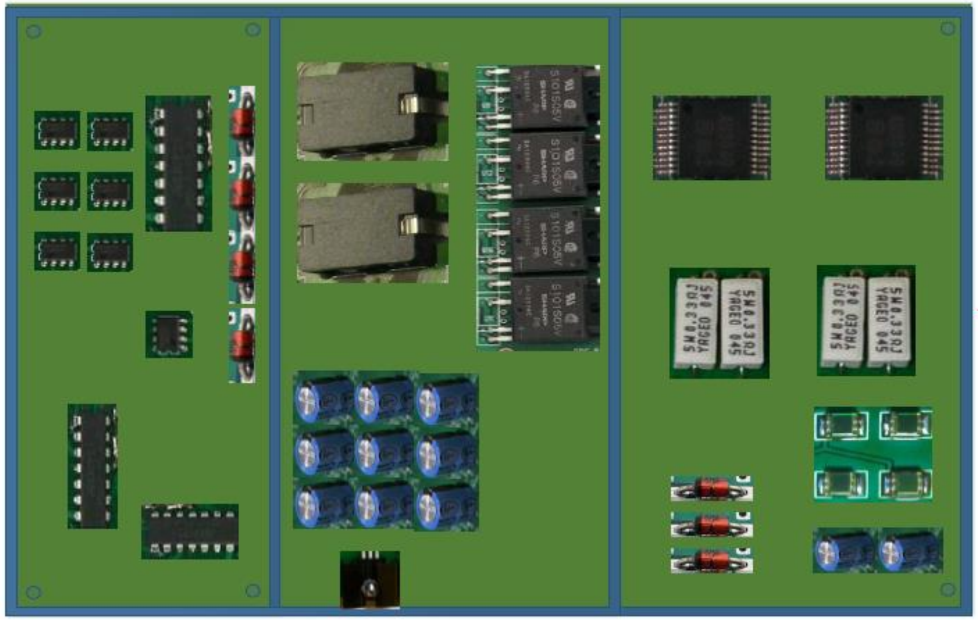
- **Relevant Failure Parameter: travelled distance → # landings + weight**





Predictive maintenance electronics

- **Failures of electronic components often considered to be random**
- **Service life depends on**
  - Vibration level
  - Humidity
  - Temperature (changes)
- **Models available in literature**



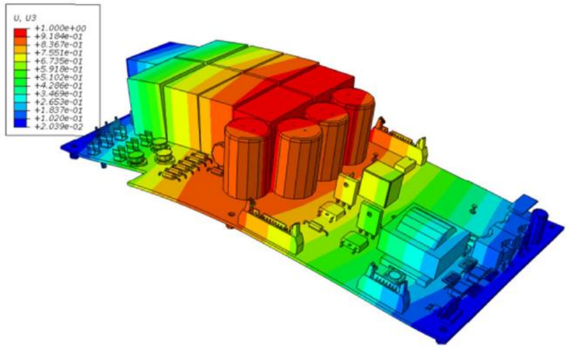
- **Developed a tool to predict service life (APAR)**
- **Performed tests to quantify loads**

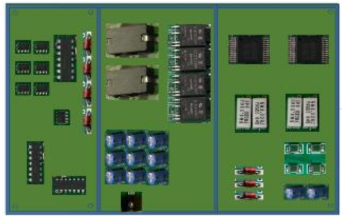
Politis, Ten Zeldam 2015/2016

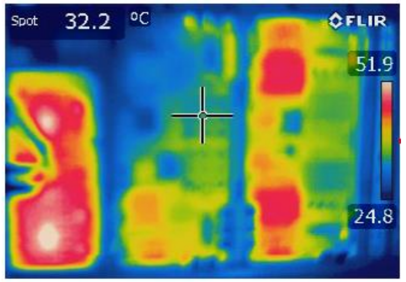
Service life PCBs radar systems

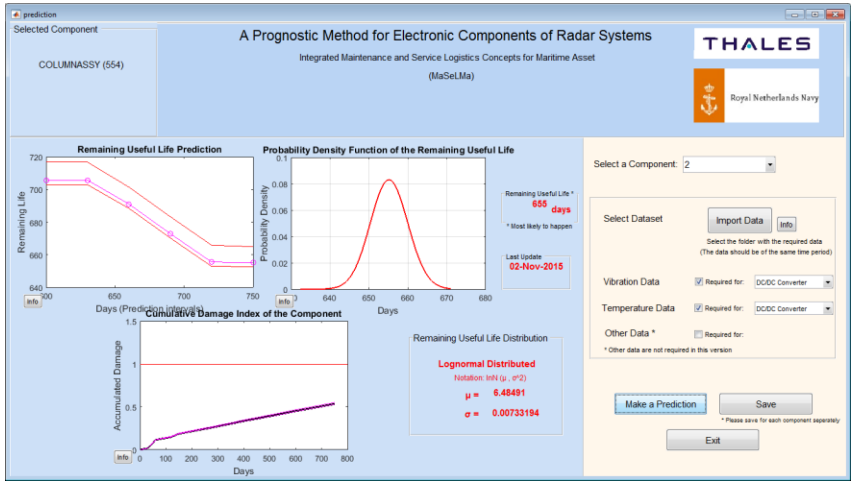
$$N = A \cdot f^{a} \cdot \Delta T^{-b} \cdot G(Tmax)$$

$$N_0 = N_c * \left(\frac{Z_c}{Z_0}\right)^{6,4}$$









Politis, Ten Zeldam 2015/2016

Physical model → Actual usage → Degradation rates

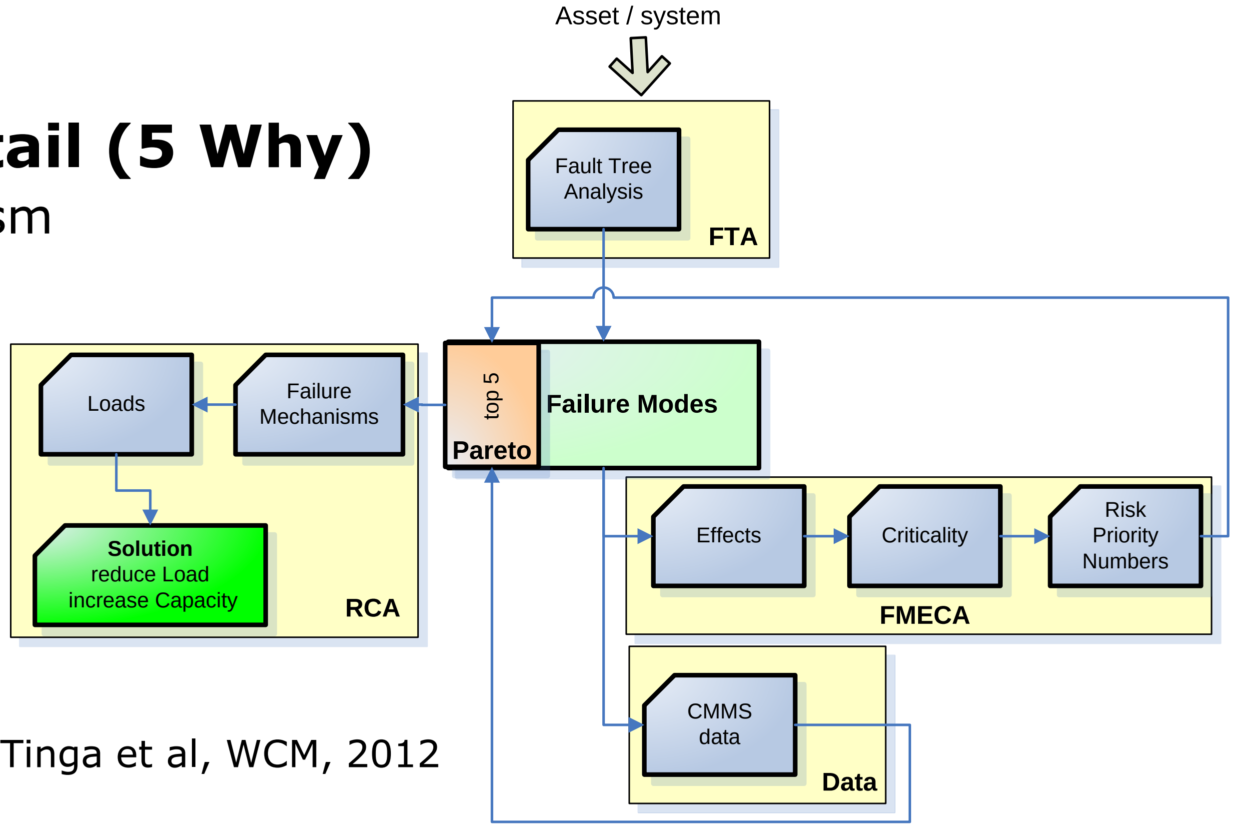
ROOT CAUSE ANALYSIS

Root Cause Analysis

- **Aims to find root cause of any failure**
  - Prevent that only symptoms are tackled
  - Provide real solution to problem

- **Challenge: sufficient level of detail (5 Why)**
  - Should be until level of failure mechanism
  - Load ←→ Capacity

- **Mechanism based Failure Analysis (MBFA)**



Tinga et al, WCM, 2012

Hybrid approaches

COMBINE WITH DATA ANALYSIS

Failure mechanism and data analysis ?

- **Any failure mechanism is governed by the load + usage**

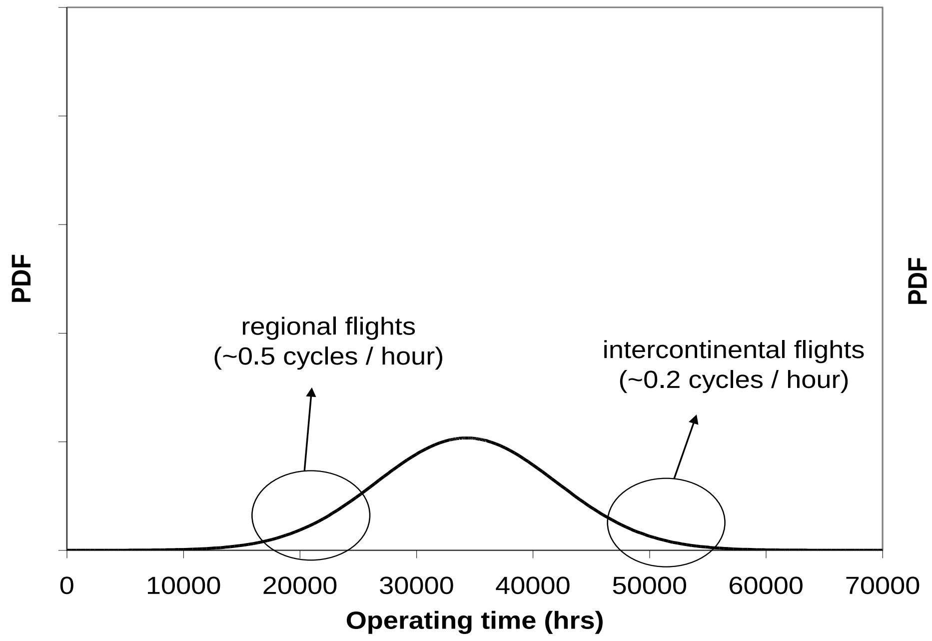
- **Knowledge of failure mechanism provides insight in required data / parameters**

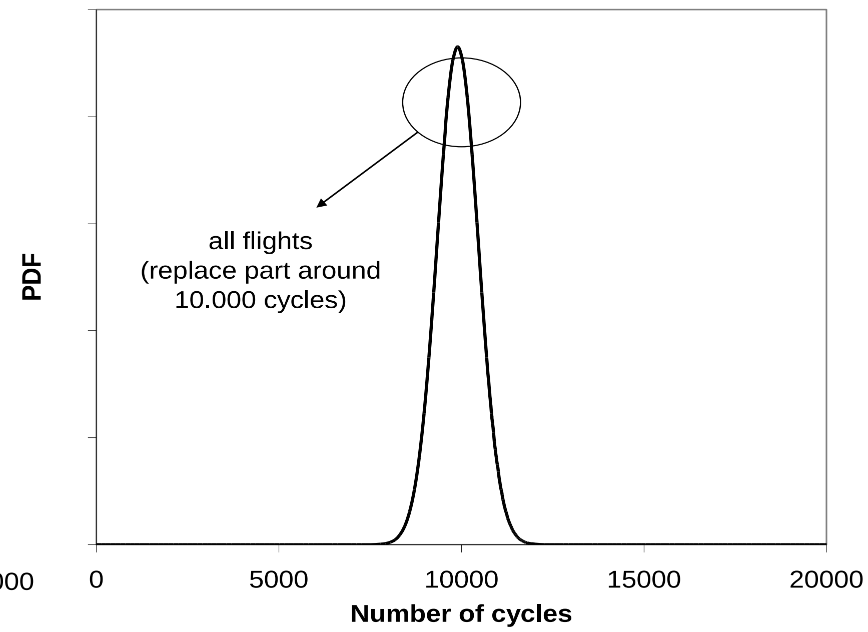
  → relevant failure parameter (RFP)

- **Advantage**
  - Variation in RFP gets smaller → better prediction of life time
  - More accurate reliability assessment

Relevant Failure Parameter - example

- **Airliner with fleet of aircraft**
- **Part fails due to fatigue (~ 10.000 cycles)**

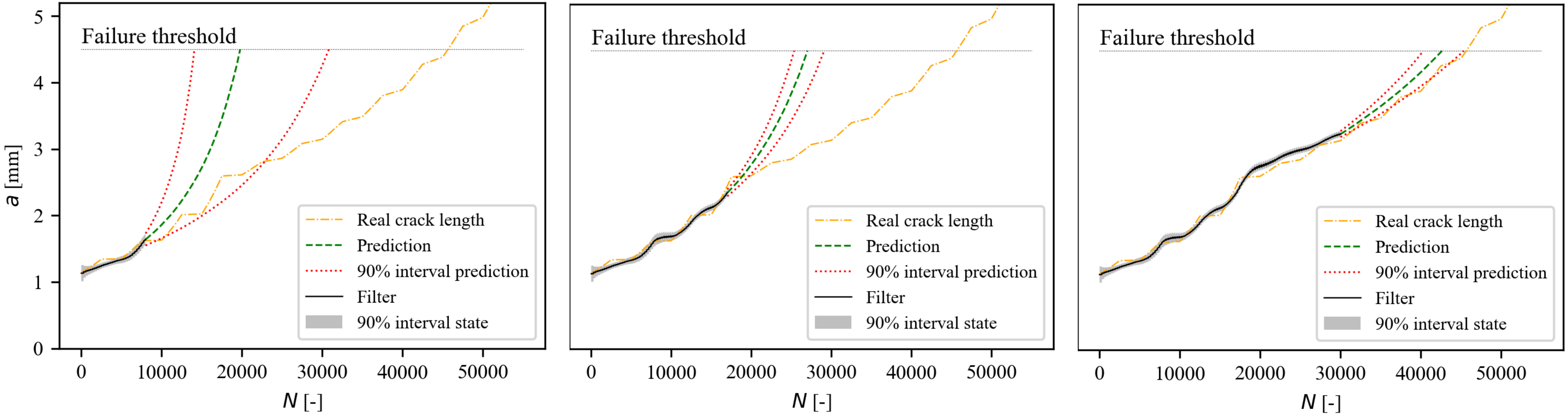




- **Uncertainty reduced with better RFP**

Hybrid prognostic methods

- **Use Unscented Kalman Filter to tune physical model**
  - Physical model for crack propagation
  - Measurements (crack length, loads) for tuning



Keizers et al, IJPHM, 2021

CHALLENGES / EXPERIENCE

Challenges in Predictive Maintenance

1. Critical part selection

- Which (sub)system is most suitable for PdM ?

2. Predictive modelling / prognostics approach

- Which approach is most suitable ?

3. Monitoring / data collection

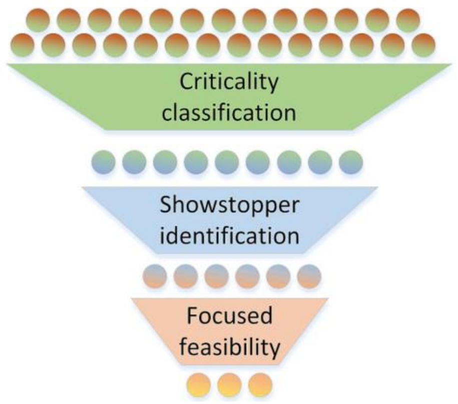
- Which data / parameter to measure / store ?

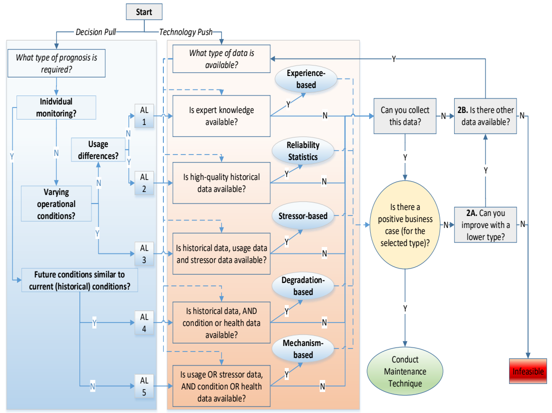
4. Data analysis

- Which algorithm / how to combine with domain knowledge ?

5. Model validation

- What data + history (usage) is needed ?





Conclusion

- **Smart Maintenance & Reliability has lot of potential & gets lot of attention**

- **Ultimate ambition is 100% prediction of failures**

- **Lots of data and AI allow for interesting analyses, but ....**

- **.... knowledge of Physics of Failure is essential for**
  - Designing mantainable systems
  - Developing Predictive Maintenance concepts
  - Learning from failures (RCA)

Further reading

- **Check our publications on**
  - https://www.utwente.nl/en/et/ms3/research-chairs/dbm/publications/
  - https://research.utwente.nl/en/persons/tiedo-tinga