UNIVERSITY OF TWENTE.

Netherlands Defence Academy
Ministry of Defence

Predictive Maintenance
Promises & practical challenges

WCM jaarevent ‘samen slimmer’

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Outline

- **Introduction**
- **Predictive Maintenance**
  - Approaches
  - The promise
- **Challenges in (application of) PdM**
- **Solutions**

Introduction

- **Industry & governments**
  - Increasing demands for availability and reliability of critical assets
  - Abundant (sensor) data → Industry 4.0



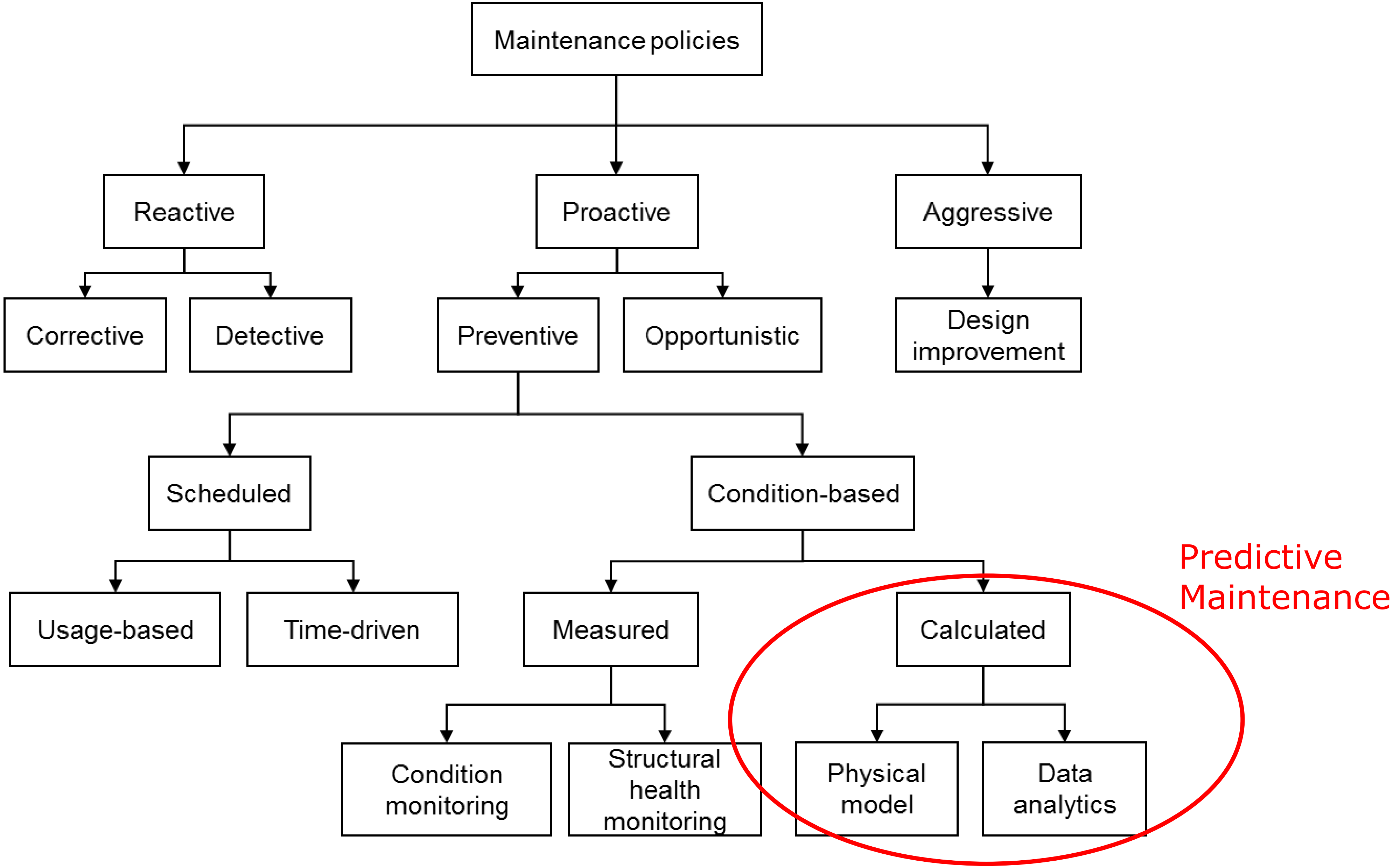


- **Potential & demand for data-driven maintenance**
  - Diagnostics → Condition based Maintenance (CBM)
  - Prognostics → Predictive Maintenance (PdM)

- **Despite available methods and scientific papers**

  → application of PdM in (industrial) practice limited

Maintenance policies



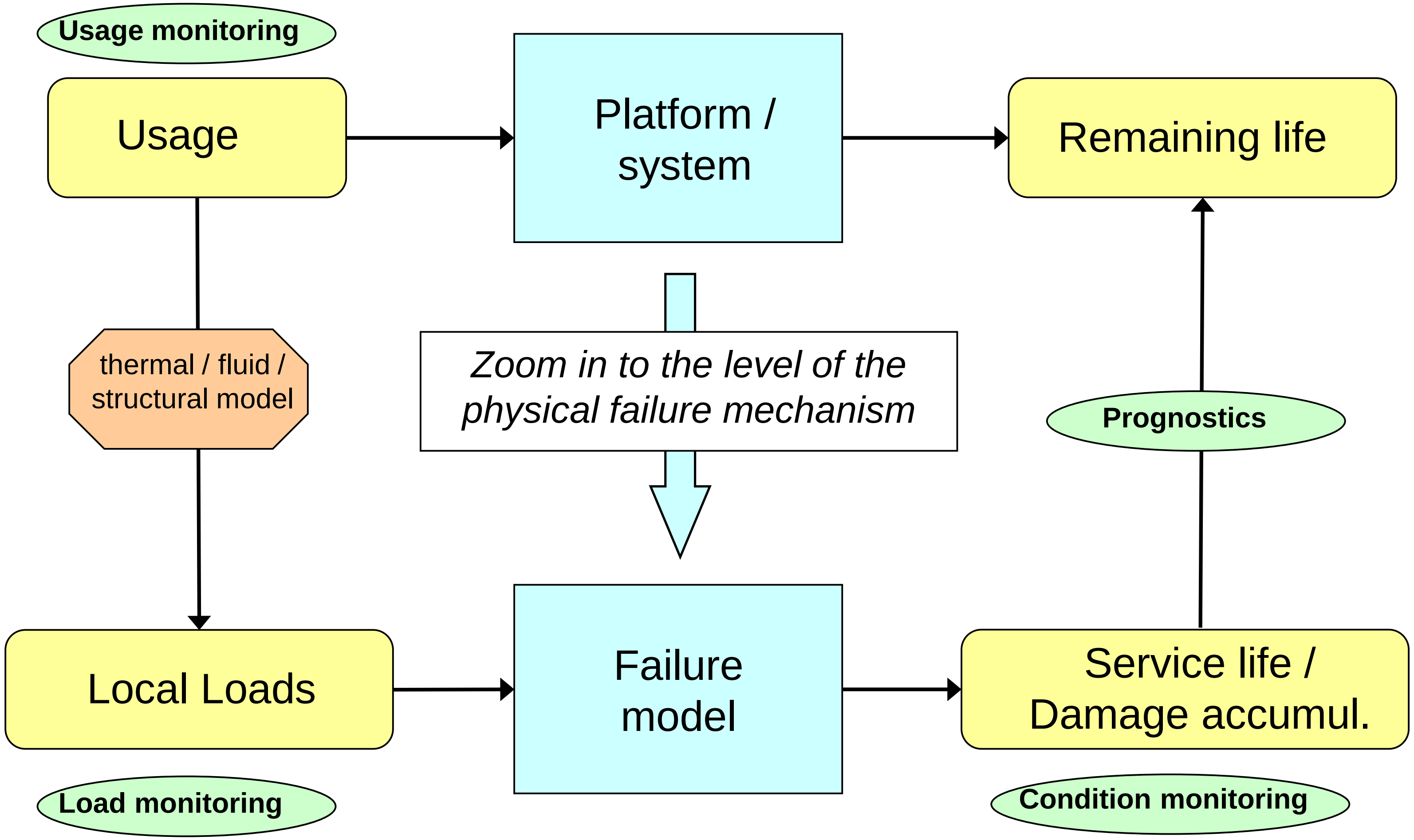
Prognostics – approaches

- **Experience-based (traditional)**
  - Experience from past / collected data
    → often conservative
    → not always available (registration, PM)
    → Not always representative

- **Data-driven**
  - Derive relations from big data sets (e.g. sensors)
  - Use AI / Machine Learning
    → Sometimes unexpected relations, but is *black box*
    → not always representative

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

Model-based: relation usage – life time



Tinga, RESS 2009

The promise of Predictive Maintenance...

- **All failures can (and will) be prevented**
- **100% predictability of failures**
- **Data is abundant, everything is connected**
- **AI will solve everything**

Why limited application of PdM ?

- **Ambitioned Maturity Level vs Data Requirements**

1. Detection: *is something wrong?*
    - Anomaly Detection
    - only requires unlabeled (sensor) data

2. Diagnosis: *what is wrong?*
    - Classification
    - requires labeled data (supervised learning) for all faults

3. Health assessment: *how wrong is it?*
    - Condition monitoring
    - requires dedicated CM sensors & threshold value

4. Prognosis: *when is it expected to go wrong?*
    - Regression, Prediction
    - requires run-to-failure data & operational history

Two main barriers identified

1. **Mismatch ambition level and available data + knowledge**
   - Often unaware → frustrates developments

2. **Lack of relevant data in industrial practice**
   - No labelling
     - *lack of failures & low quality registration*
   - No condition measurements
     - *not many CM sensors, indirect methods*
   - No threshold value
     - *especially for indirect CM, often trial-and-error*
   - No run to failure data
     - *failures prevented for critical systems (→ simulations, benchmark, CMAPSS)*
   - No operating history
     - *not registered, changing configurations*

Solution directions

1. **Accept**
   finding the most suitable approach given the (limited) data

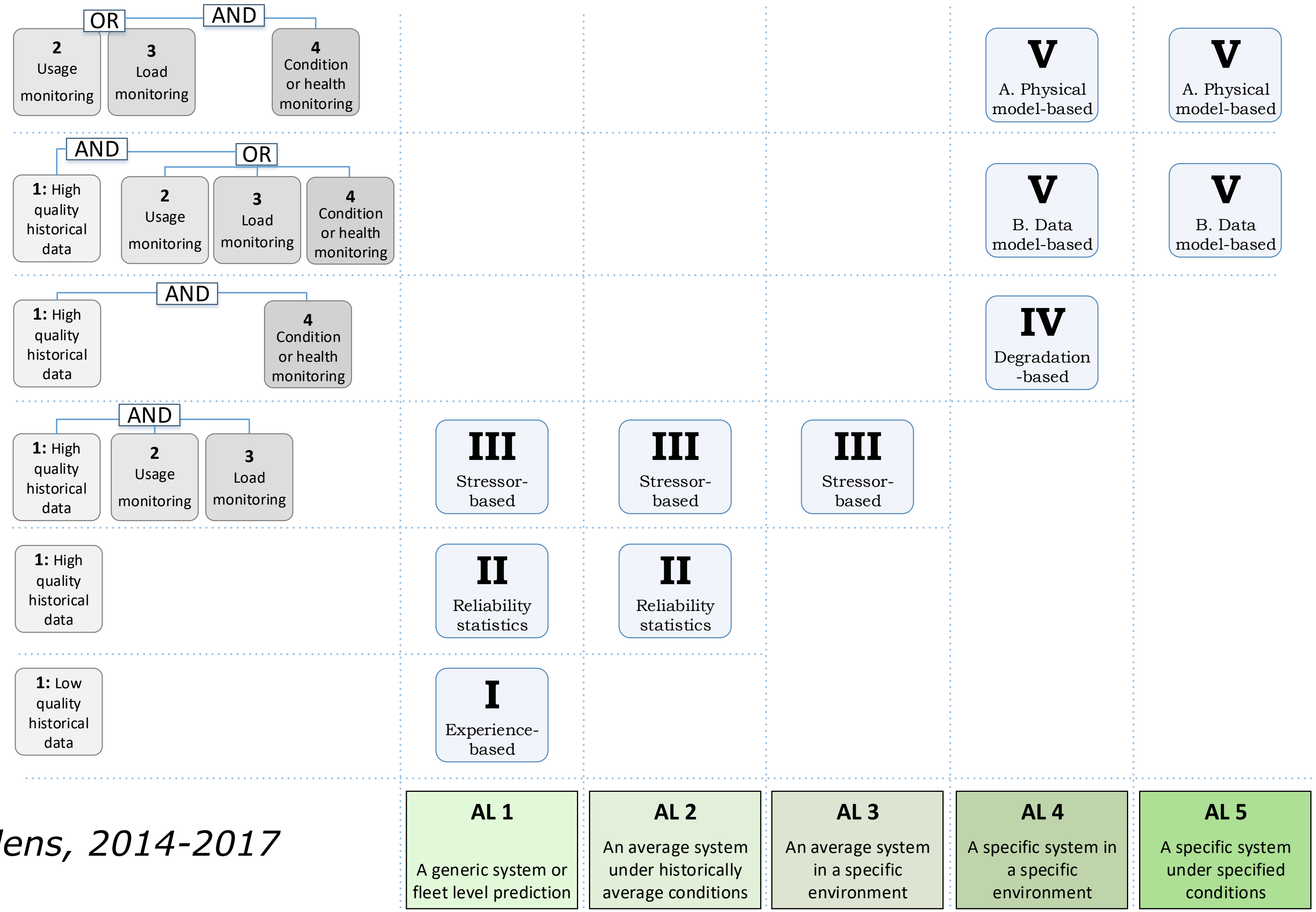
2. **Circumvent**
   combine limited data with physical models

3. **Extend**
   collect additional (relevant) data

Matching ambition and data

ACCEPT

Fitting PdM ambition to data



Tiddens, 2014-2017

PdM scoring method

- **Suitability**
  - match with ambition
- **Feasibility**
  - match with data / knowledge
- **Expert system**
  - Pre-filled with questions and scores per MT

Silveira, 2023

Answers		EB	RS	CE	SB	DA	PB
Is the selected approach required to provide lifetime prediction…	*Answer*	Result score					
(A1) … for individual systems? (No for fleet average values).	Yes	0	0	2	2	2	2
(A2) … for generalized cases?	No	2	2	1	1	1	1
(A3) … for varying operational conditions?	Yes	0	0	1	2	2	2
(A4) … for operational conditions that were not observed previously?	No	2	2	2	2	2	2
(B1) … with only limited accuracy (i.e. a rough estimate)?	Yes	2	2	0	1	0	0
(B2) … including insight into which parameters play an important role in the prediction?	Yes	0	0	0	2	2	2
(C1) Is an expert with practical experience available?	No	Ø	0	0	0	0	0
(C2) Is a specialist/ analyst available?	No	0	0	0	0	0	Ø
(C3) Is a data scientist available?	Yes	0	1	1	1	2	0
(D1) Are the (physical) degradation mechanism and the parameter(s) describing its evolution known ?	Yes	0	0	2	0	0	2
(D2) Is a stressor-base model available?	Yes	0	0	0	2	0	0
(D3) Is a physical model available?	No	1	1	1	0	1	Ø
(E1) Is run-to-failure sensor data available?	Yes	1	2	1	2	1	1
(E2) Is load/usage data available? Such data should cover the entire analyzed system.	Yes	0	0	1	1	2	1
(E3) Is historical failure data available?	Yes	1	1	2	2	2	2
(E4) Is a threshold value available?	No	0	0	Ø	0	0	0
(E5) Is real-time or periodic condition monitoring information available?	No	0	0	Ø	0	0	0
(E6) Are systems monitored individually (usage, loads, situation)?	Yes	0	0	2	0	2	2
(E7) Future operational conditions similar to past?	Yes	2	2	2	1	2	2
Total (T_S)		Ø	0.62	Ø	0.76	0.81	Ø
Suitability (S_S)		0.55	0.55	0.60	1.00	0.82	0.82
Feasibility (F_S)		Ø	0.70	Ø	0.60	0.80	Ø

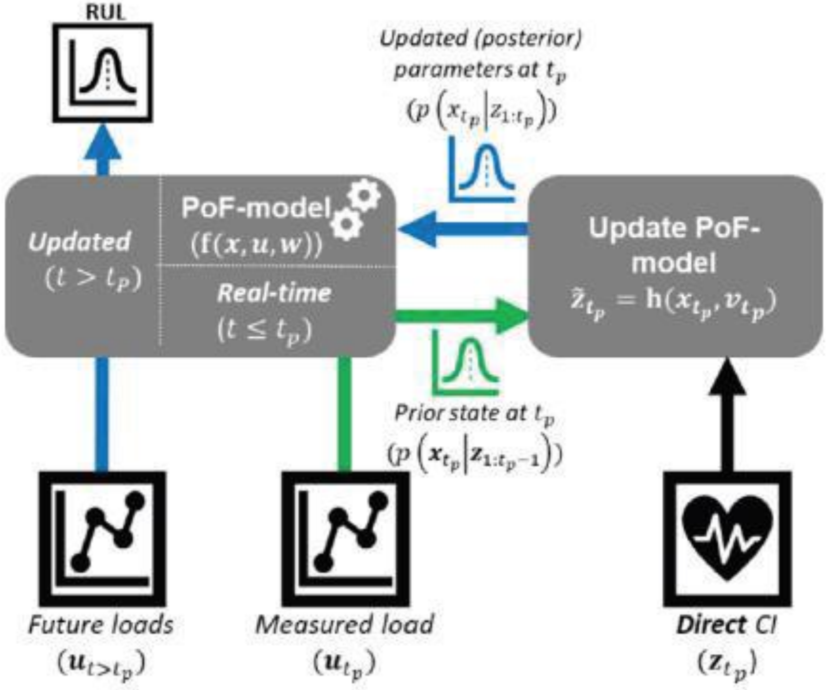
Combine data & models

CIRCUMVENT

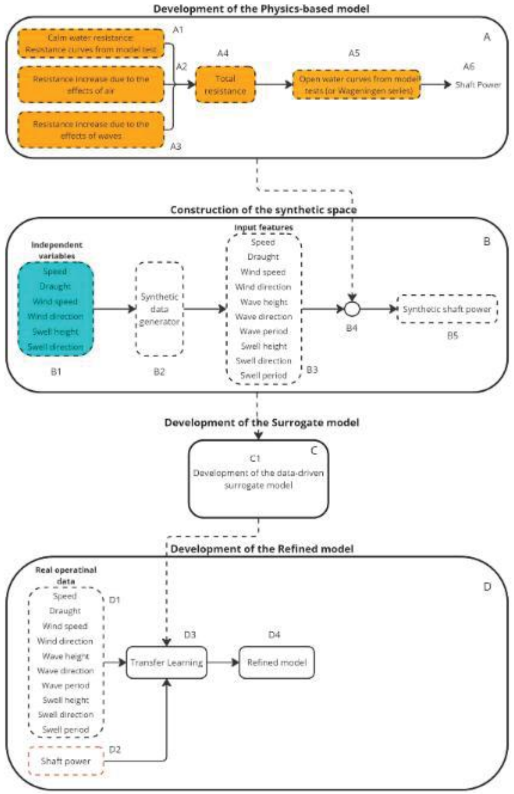
Complement data with models

- **Data-driven approach often infeasible**
  - limited failure data and lack of labelling
- **Physics-of Failure models**
  - contain relations for degradation
  - only need 'fitting parameters' → use data
    + Particle Filter

or Transfer Learning



Keizers, 2024

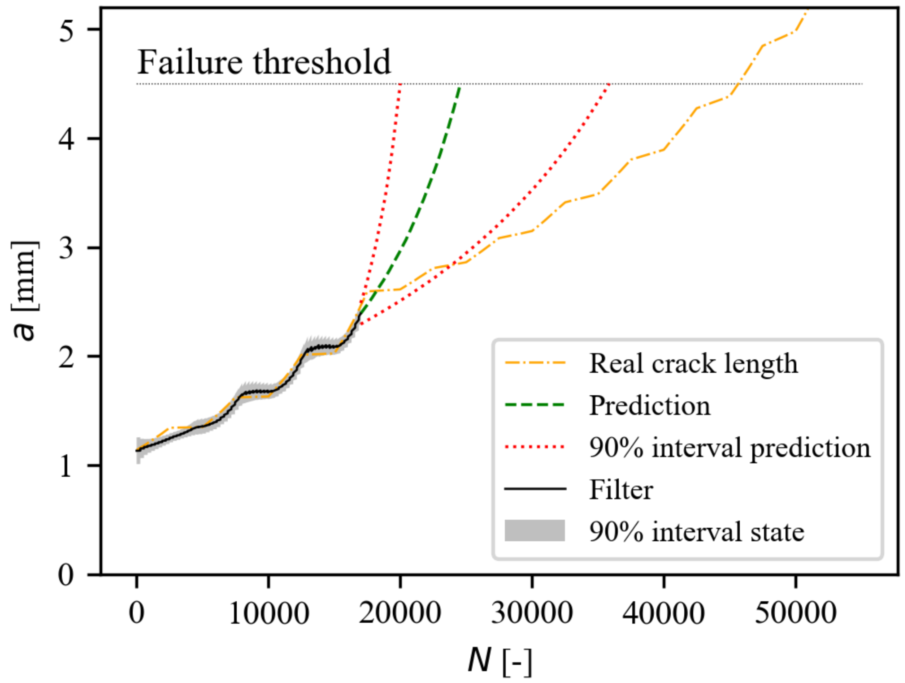


Mavroudis, 2024

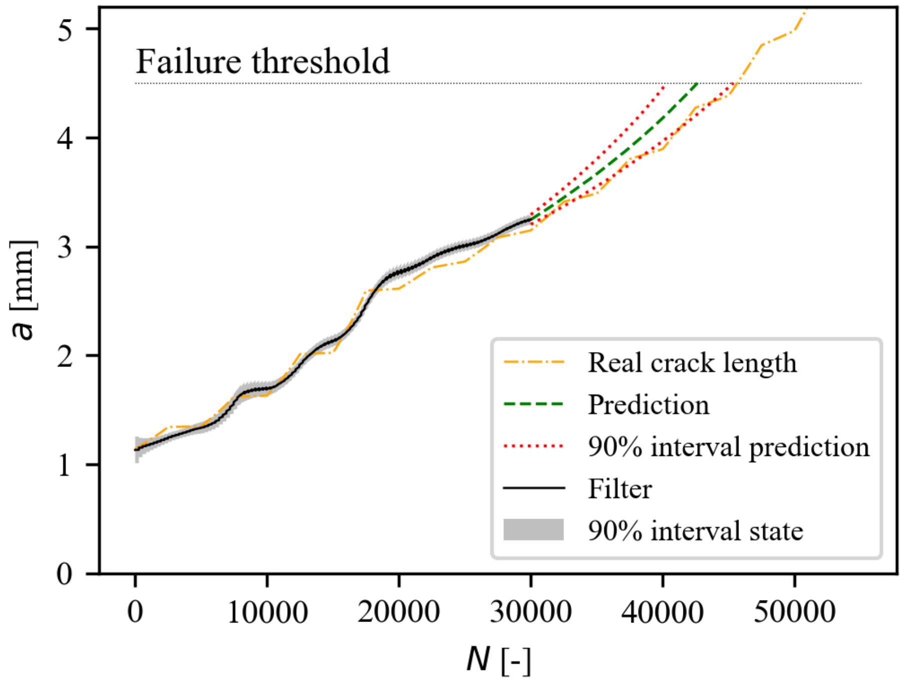
Hybrid approaches

- **Combine physics/monitoring**
  - Physics for (long term) prediction
  - Data to keep model 'on track'

Keizers, 2021



Prediction before load change

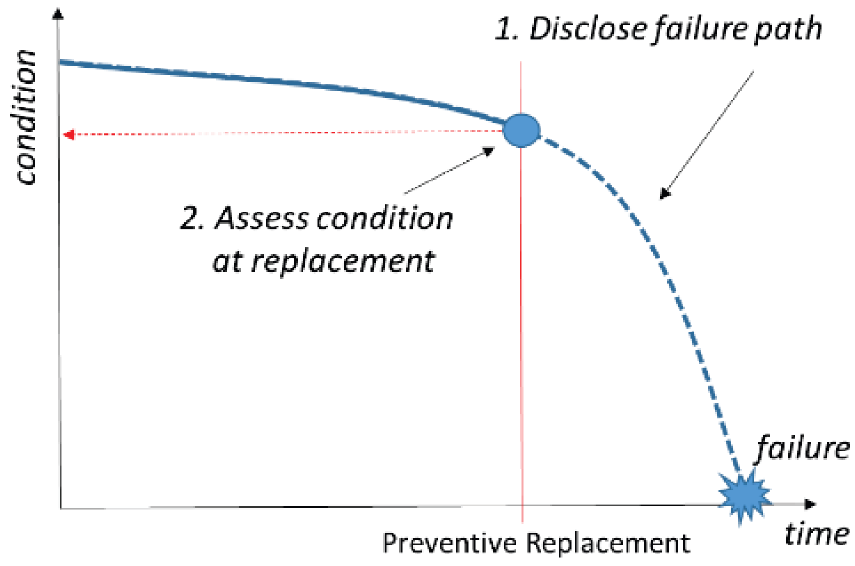


Prediction after load change

Collect additional data

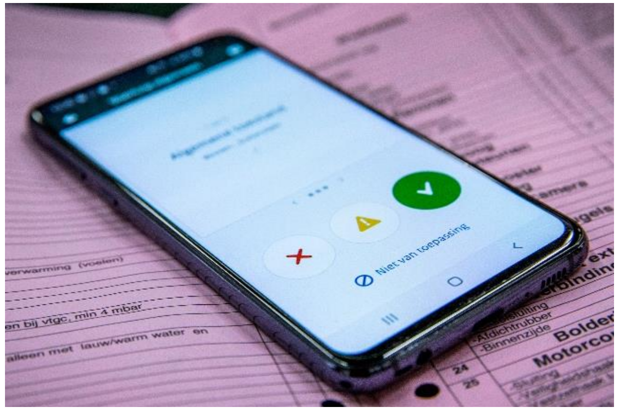
EXTEND

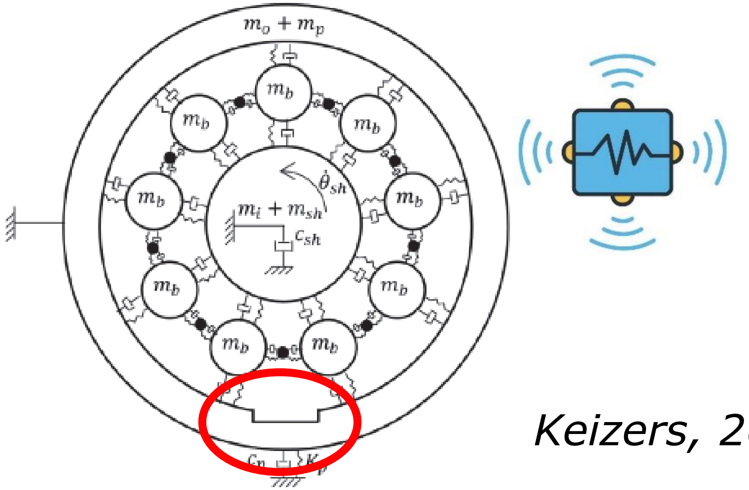
Generation of labeled (failure) data



- **Missing info**
  - Run-to-failure part
  - Condition at replacement

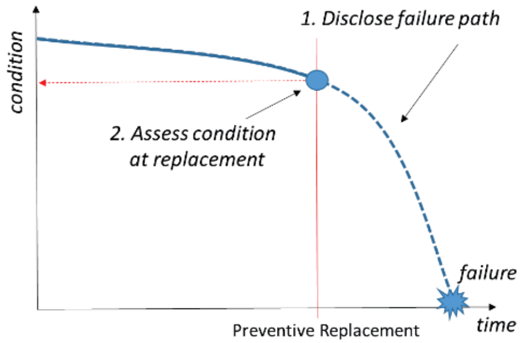
- **Assess condition**
  - Experts register condition of replaced parts
  - Use numerical models to translate indirect into direct CI





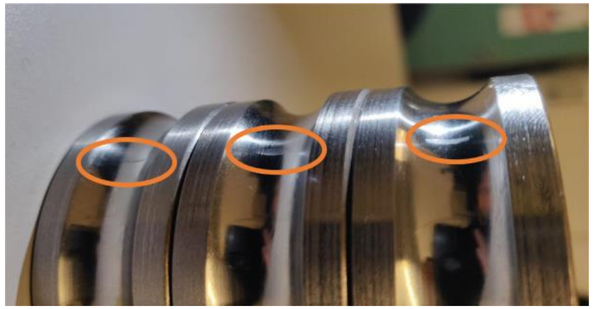
Keizers, 2024

Generation of labeled failure data



- **Testing in laboratory setting**
  - accelerated testing + run-to-failure
  - fully controlled → all potential faults
  - completely labeled dataset (NLN-EMP)

Bruinsma, 2024



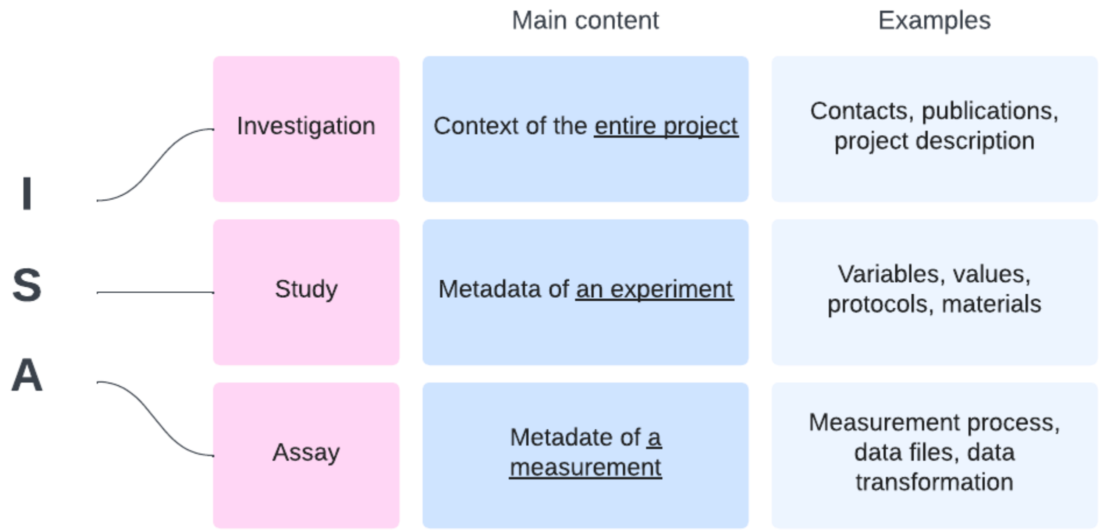
- **Test in field → *Front runner***
  - Postpone PM for small fraction of systems
  - Ensure to lead the fleet (age) + limit failure effects → **failures !**
- Benefits
  - Rest of fleet → PM closer to actual life time
  - Additional (sensor) data reveals patterns related to failures

Dutch Prognostics Lab

- **Public datasets (CMAPSS, CWRU, FEMTO-ST, ...)**
  - Limited # sets, with large faults
  - Format & labeling heterogeneous
  - → Difficult to use for AI method development

- **Distributed testing**
  - More labeled run-to-failure data - 6 (research) organizations in NL

- **Standardize labeling - ISA-PHM**
  - Metadata format (from biology)
    - *Diagnostic / prognostic*
    - *Fault type(s)*
    - *Operational conditons*
  - Upload test data in database
  - Retrieve data for modeling
  - See www.ISA-PHM.com



Conclusion

- **Predictive Maintenance has potential in increasing availability / reducing costs**

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

- **Both data science / AI and physics of failure play an important role**

But:

- **Not the easiest application field for data science**
- **Challenges in transfer from theory to practice (data !)**
- **Hybrid approaches seem to be suitable to solve this**

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