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Predictive maintenance: Successes and challenges for the next 10 years

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Collaboration with many colleagues!

TU/e Technische Universiteit Eindhoven University of Technology

Where innovation starts

Background of myself

- 1990: MSc degree in Applied Mathematics, TU/e
- 1995: PhD degree in Operations Research, TU/e
- 1994-1998: Assistant professor at Mechanical Engineering, Univ. Of Twente (group of Henk Zijm)
  - Involved in large maintenance project with Royal Netherlands Navy
- Since 1999: At Industrial Engineering, TU/e
  - Since 2008 as full professor
  - Started collaboration with multiple OEM's in 2000 (ASML, Philips, Vanderlande, Océ, Stork Food Systems)
  - Started with predictive maintenance in 2010 (ProSeLo project, Dinalog)
- Current projects on predictive maintenance, besides PrimaVera:
  - Real-time, data-driven maintenance (2017-2022, NWO)
  - DayTime (2018-2021, EU)
  - Marconi (2019-2022, NWO)

Trend for capital goods

Higher system availabilities

Lower TCO

Opportunity

Predictive maintenance

= Data-driven maintenance

≈ Condition-Based Maintenance (CBM)

Perspective that we take

A company that maintains a fleet of capital goods

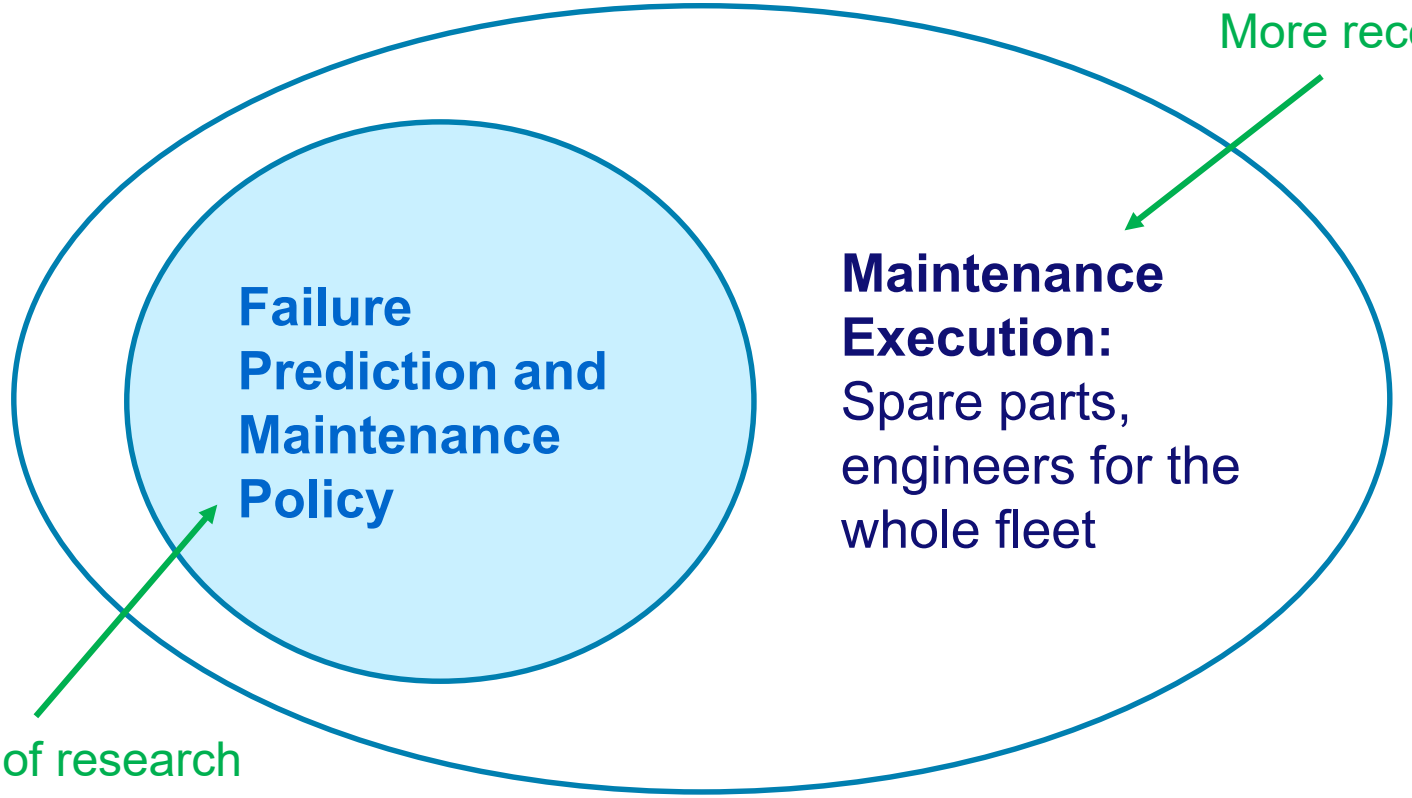
E.g.: Philips, Royal Netherlands Navy, ASML, Dutch Railways

TOPIC OF THIS TALK

How to develop your predictive maintenance policy?

What has been learned in the past 10 years?

What are important research topics for the next 10 years?

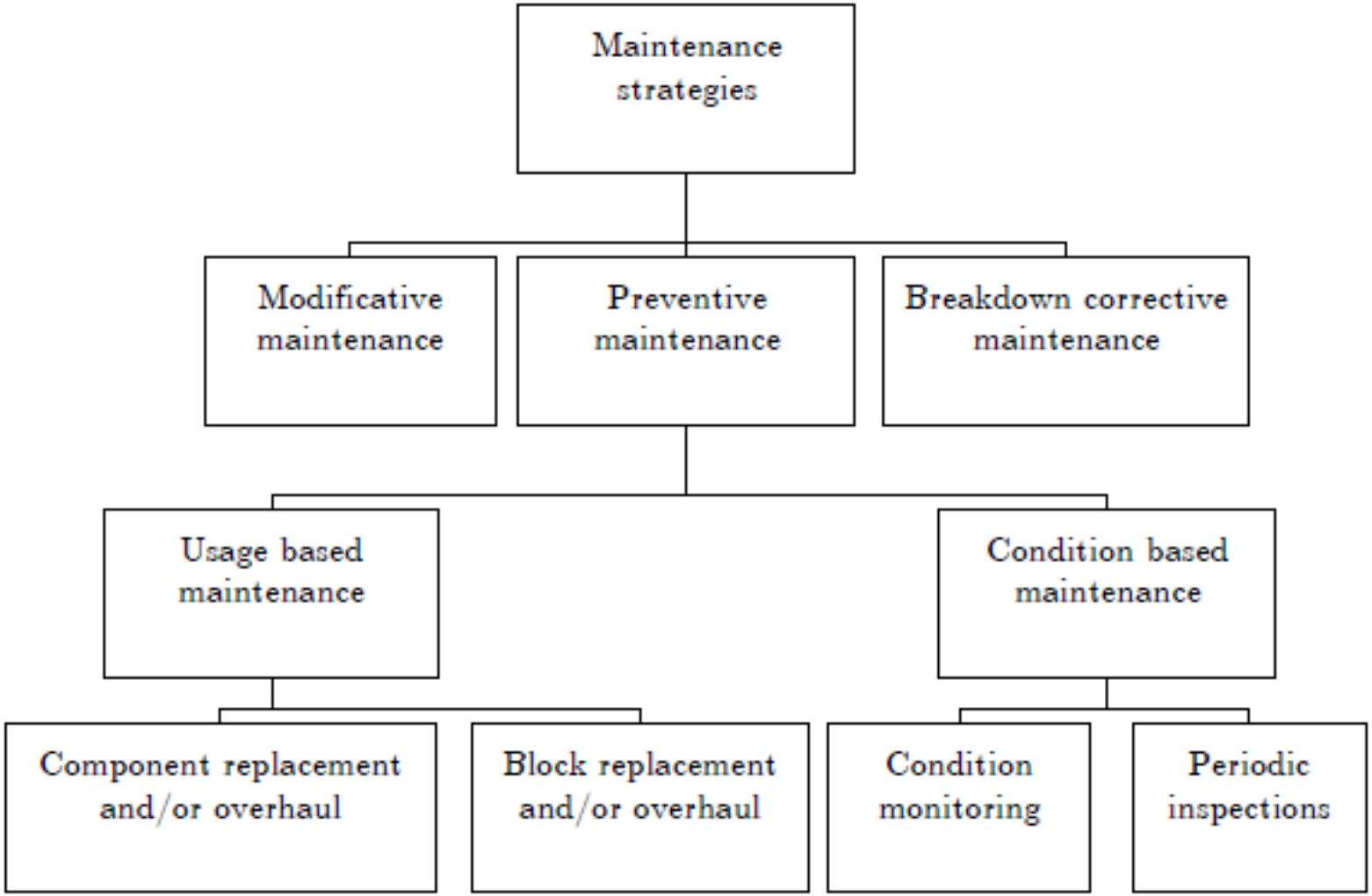

More recent
Failure Prediction and Maintenance Policy
Maintenance Execution:
Spare parts, engineers for the whole fleet
Focus of research in past 10 years

Contents

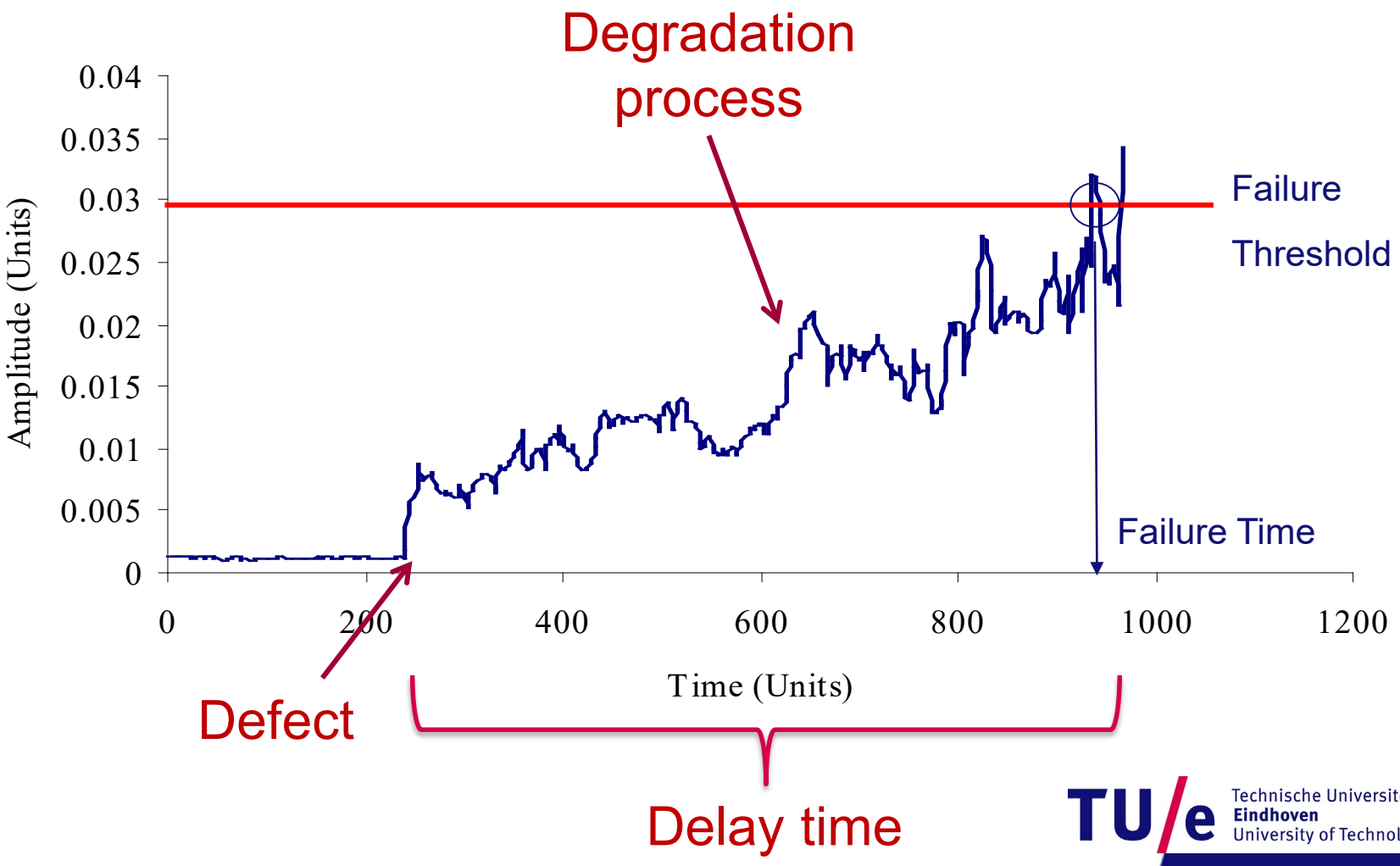
1. Introduction
2. Some Basics
3. Failure Prediction
4. Discussion – Part I
5. Maintenance Policy
6. Maintenance Execution
7. Discussion – Part II

2. Some Basics

Maintenance policies for components



Basic idea behind CBM



Many variants to model degradation en come to Remaining Useful Life estimates

Picture from Si, Wang, Hu, and Zhu (EJOR, 2011):

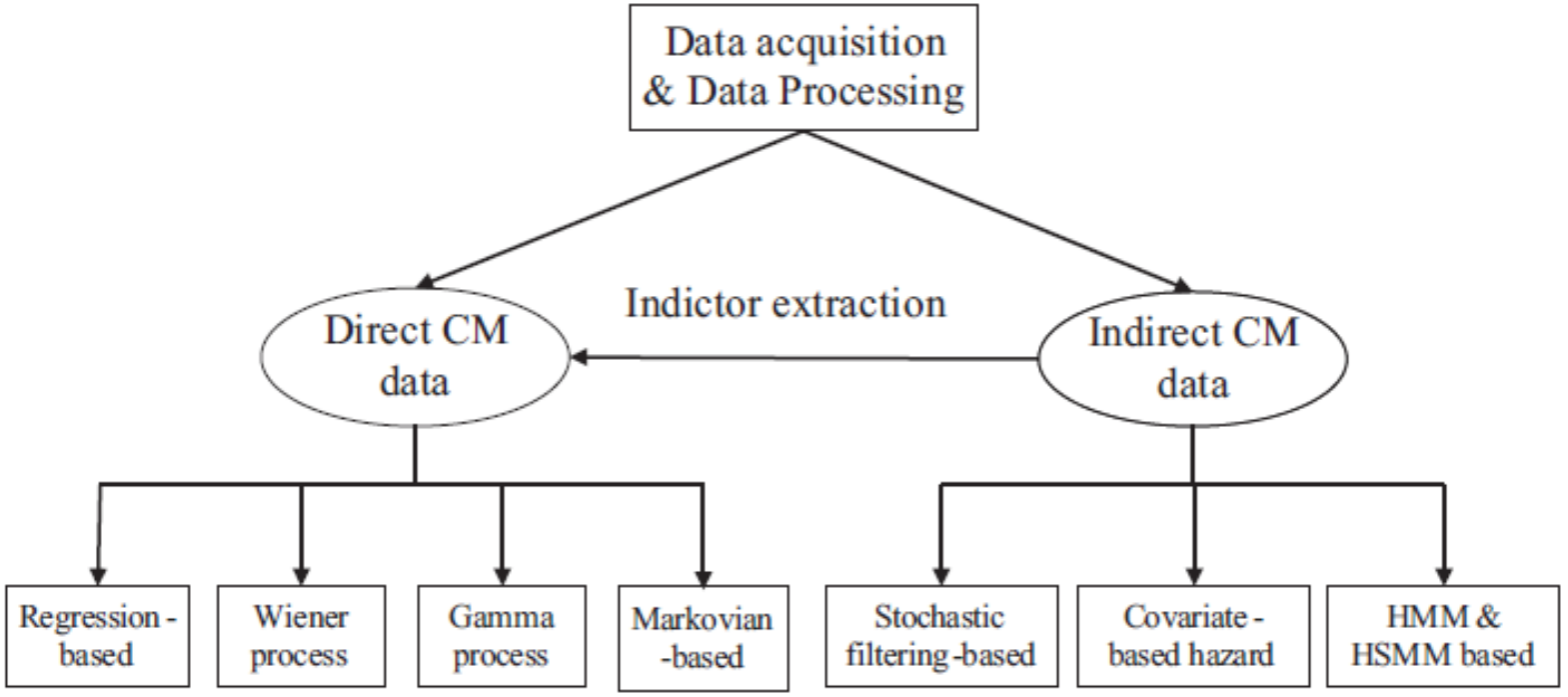
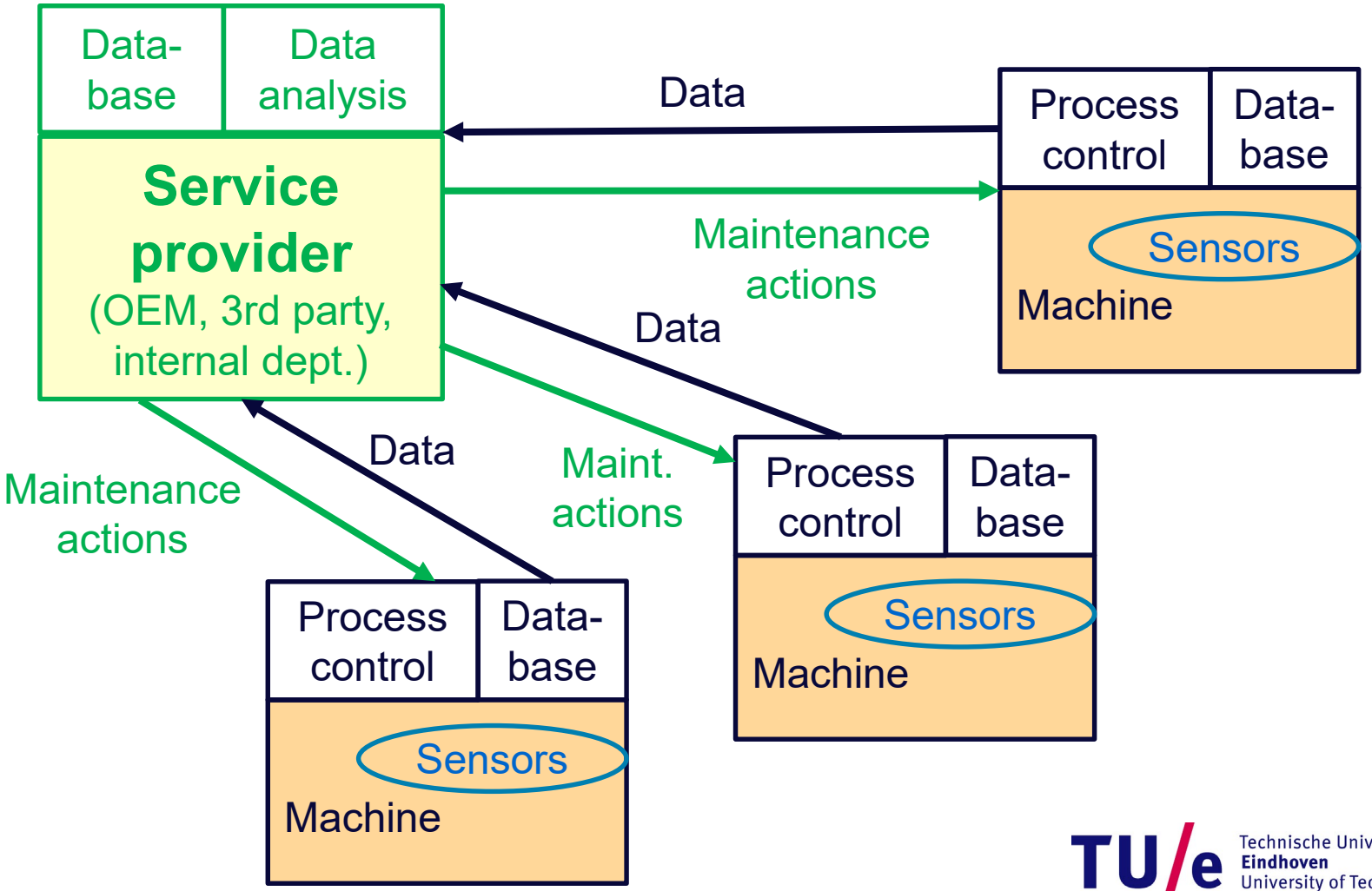
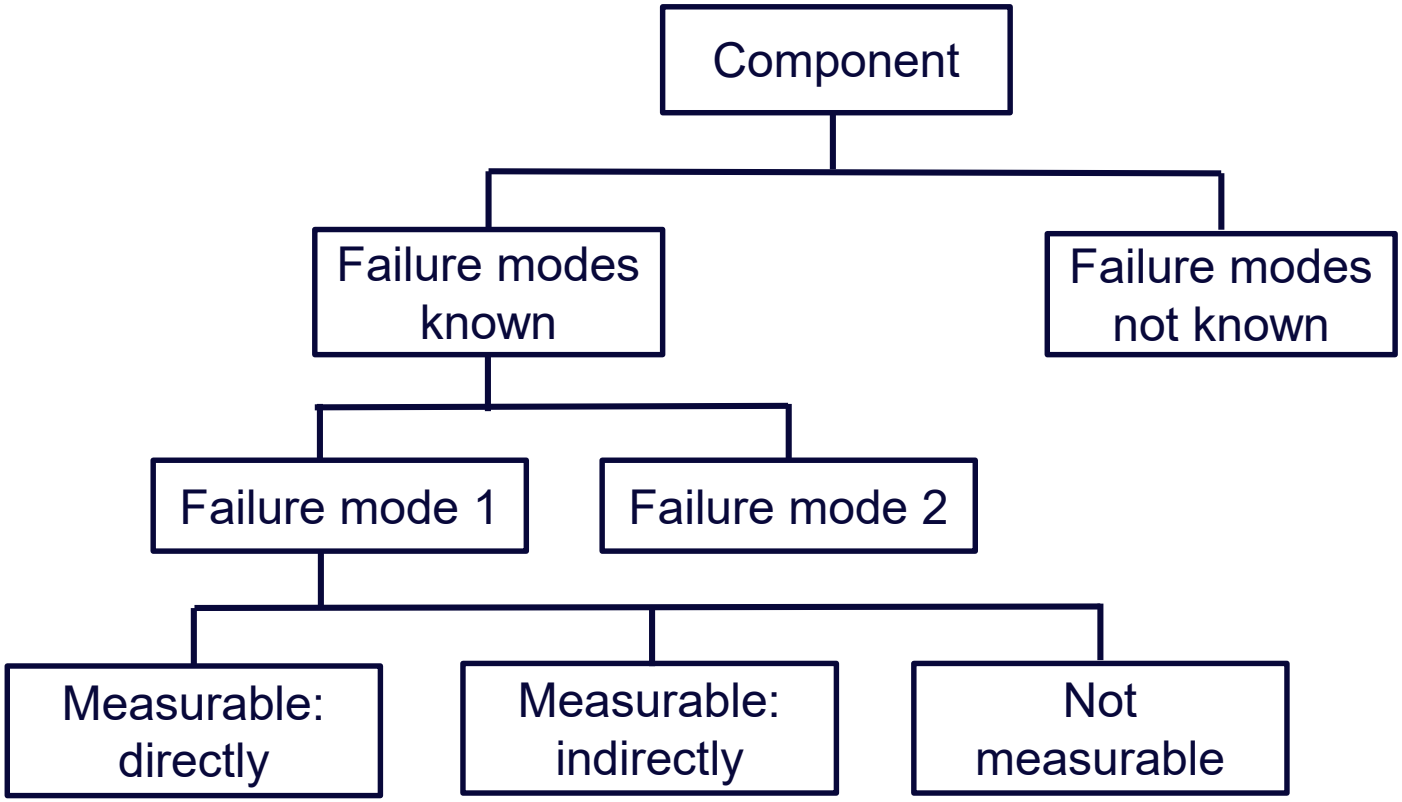


Fig. 1. Taxonomy of statistical data driven approaches for the RUL estimation.

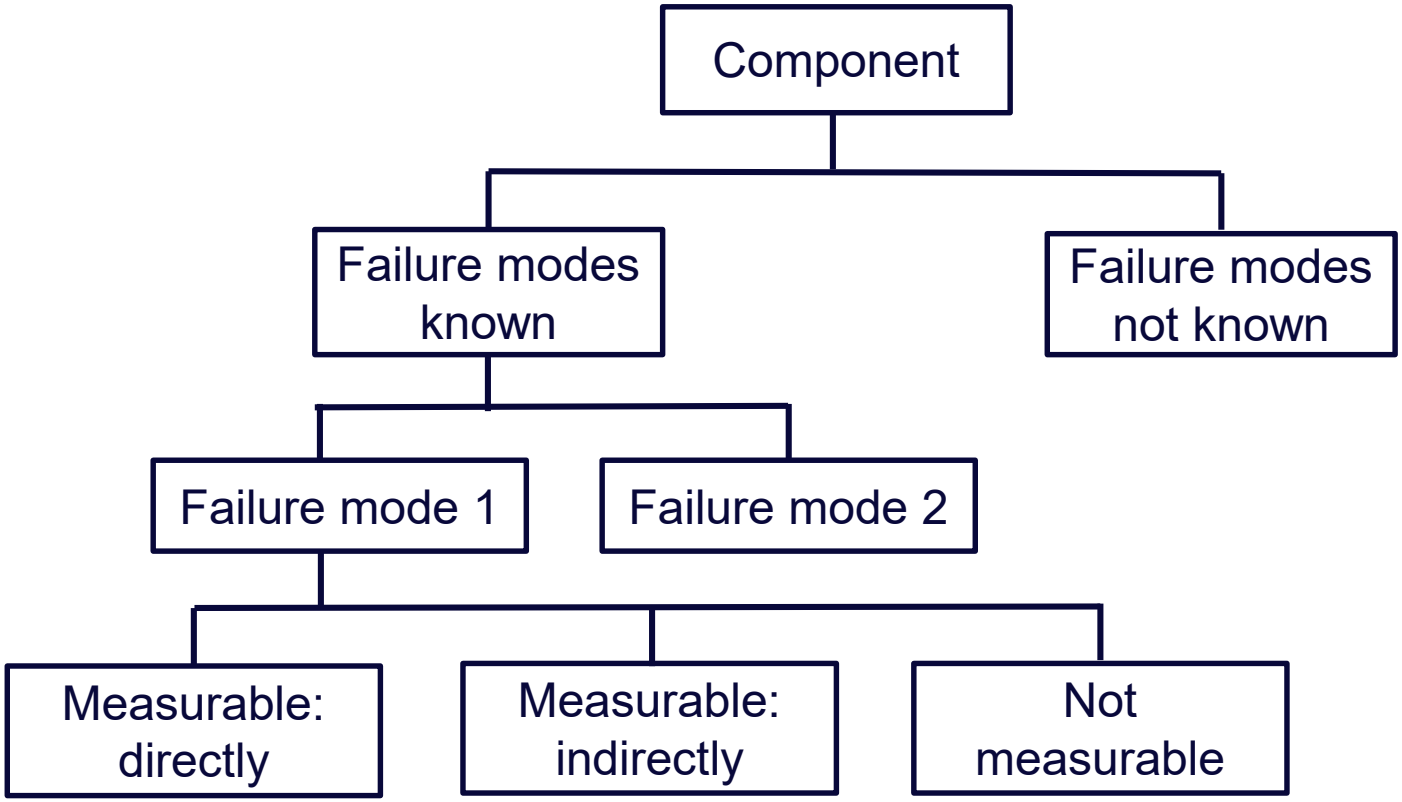

Data-
base
Data
analysis
Service
provider
(OEM, 3rd party,
internal dept.)
Data
Maintenance
actions
Process
control
Data-
base
Sensors
Machine
Data
Maintenance
actions
Data
Maint.
actions
Process
control
Data-
base
Sensors
Machine
Process
control
Data-
base
Sensors
Machine

3. Failure Prediction

Multiple ways to get to failure predictions



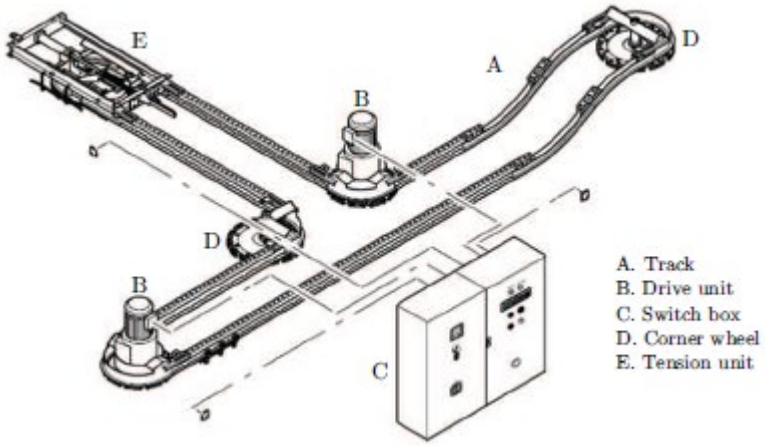
Multiple ways to get to failure predictions



Best option

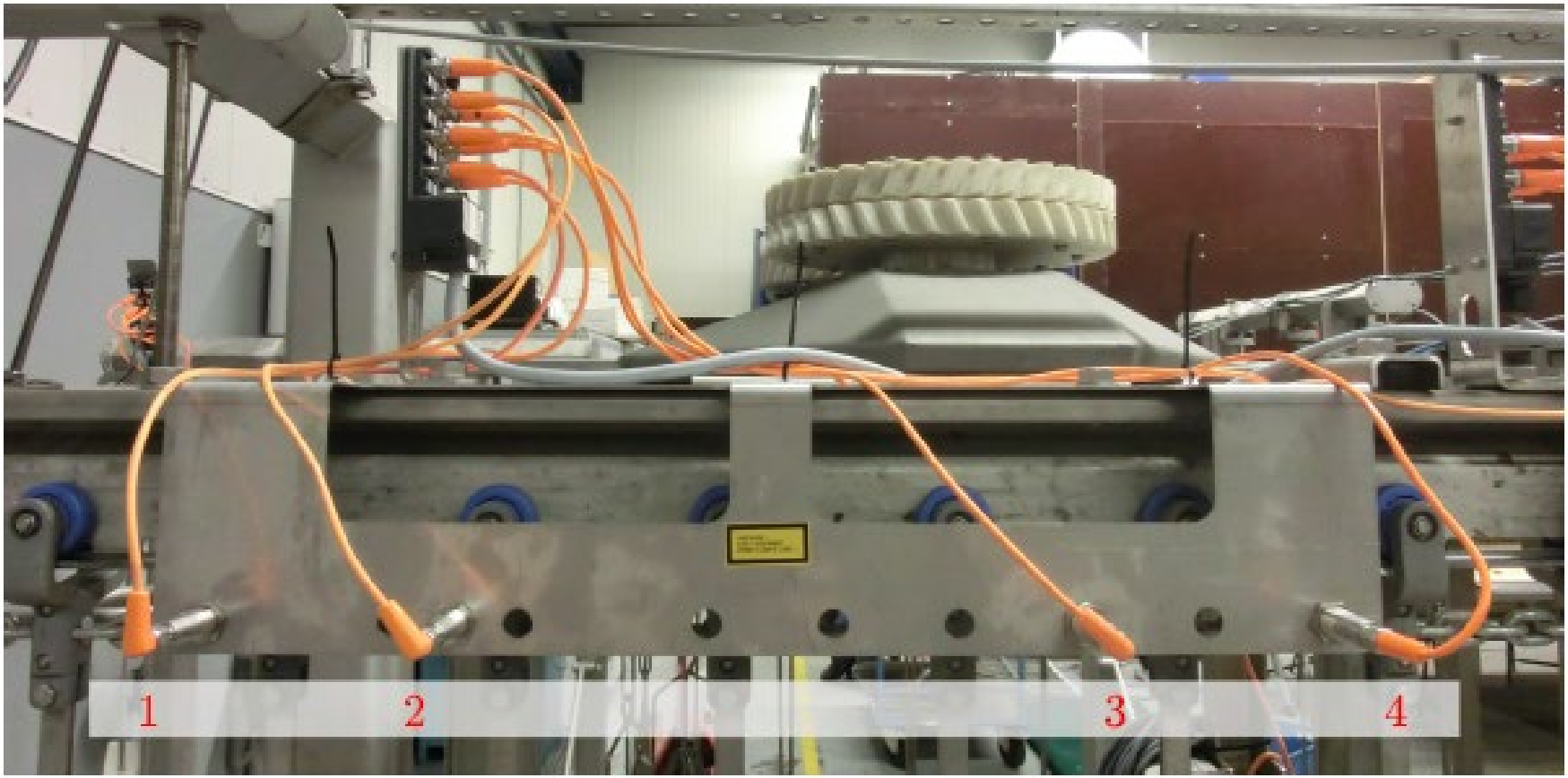
Case Van Dorst: At Marel Stork

Component:
Chain of a chicken slaughtering line

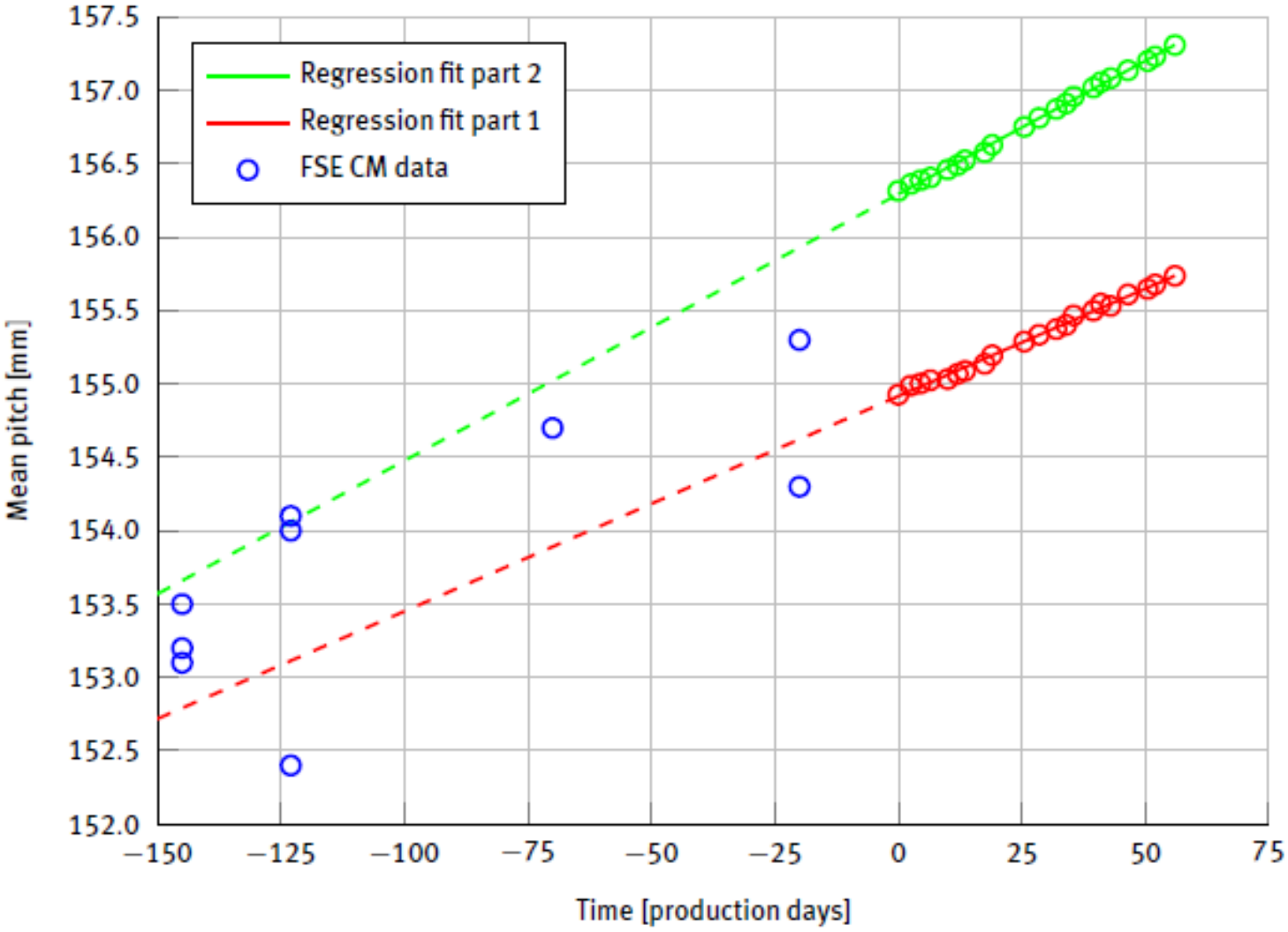


To be measured:
'Pitch'': Distance between two trolleys

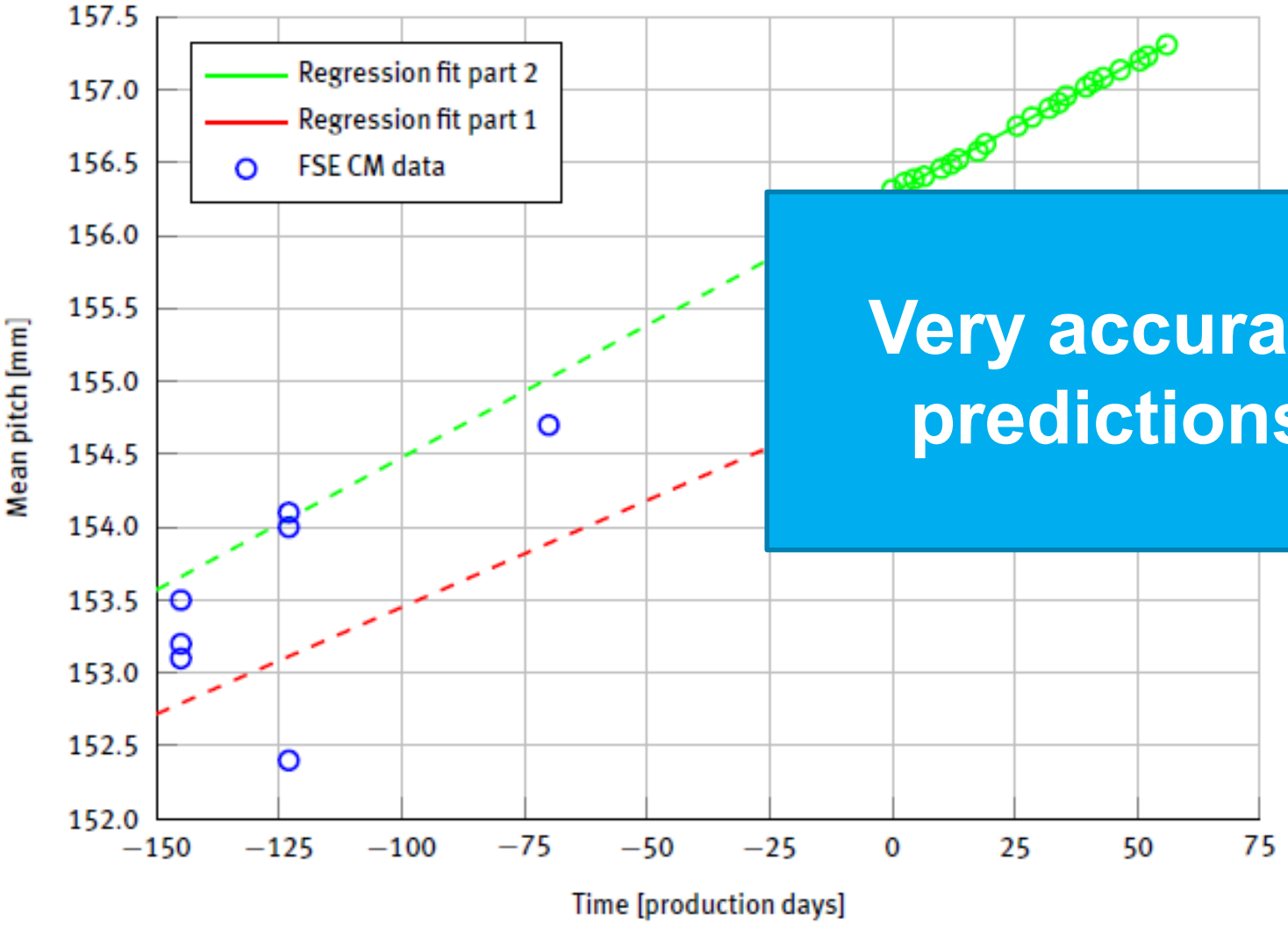
Case Van Dorst: New measurement construction



Case Van Dorst: Measurements

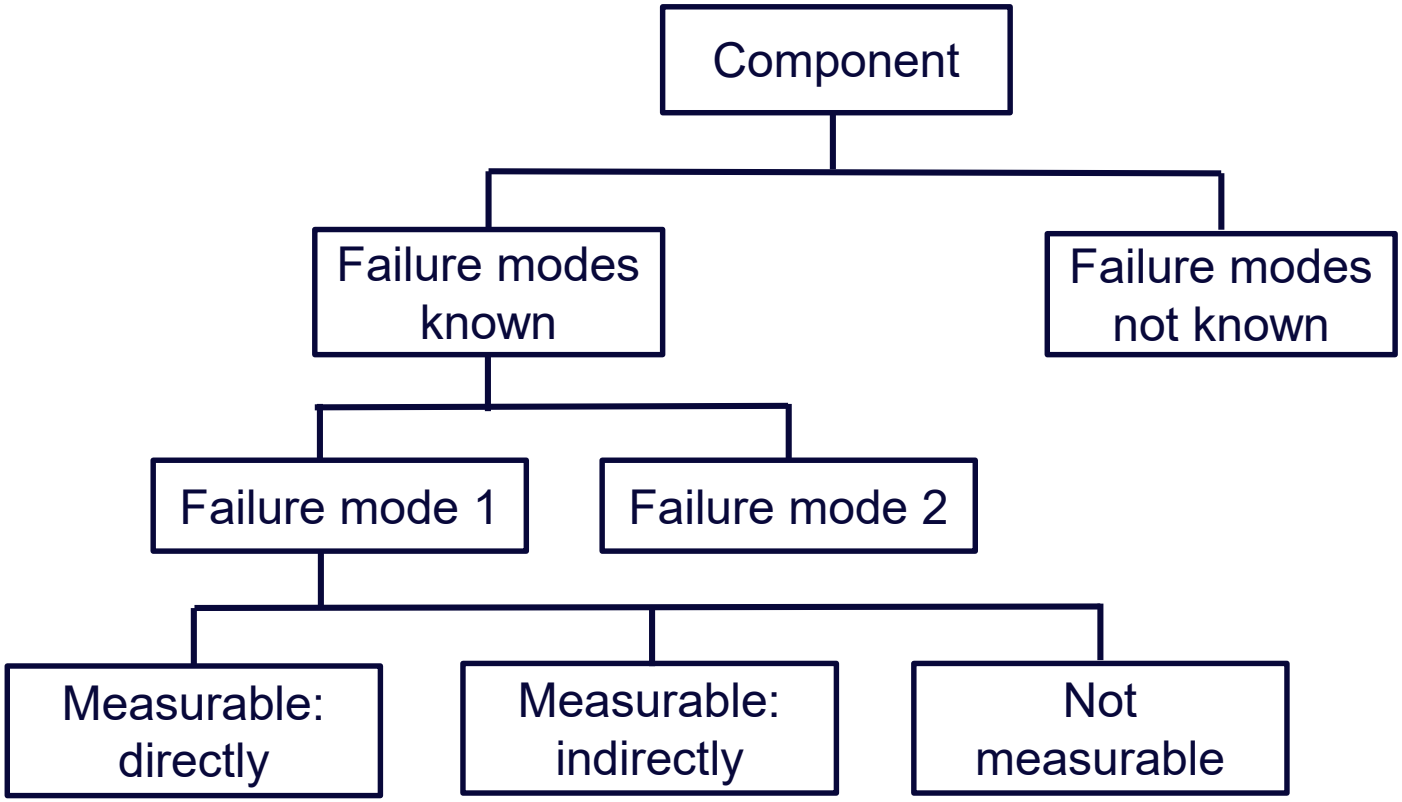


Case Van Dorst: Measurements



Very accurate predictions

Multiple ways to get to failure predictions



Best option

2nd best option

Case Politis: At Thales and Royal Netherlands Navy

Component:
ColumnAssy of the APAR radar system
(price: 300 k€)

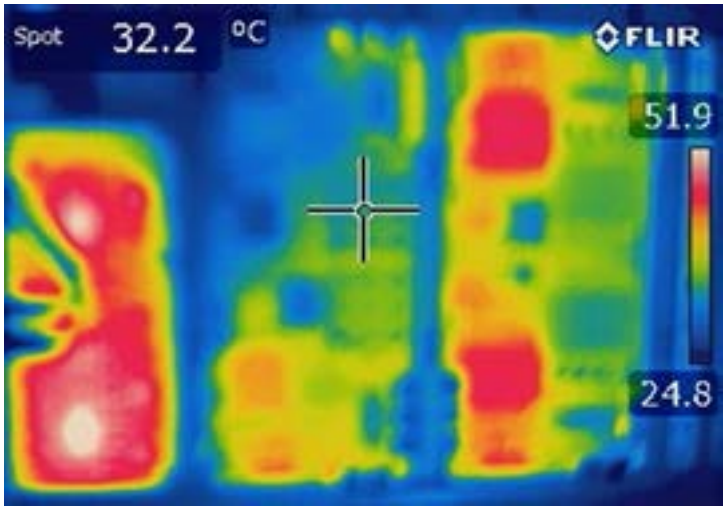
Based on:

- Physics of failures
- Actual application conditions

Case Politis: Approach

Most severe failure mechanisms:

- Thermal fatigue
- Vibration fatigue



Coffin Manson model
(for thermal fatigue)

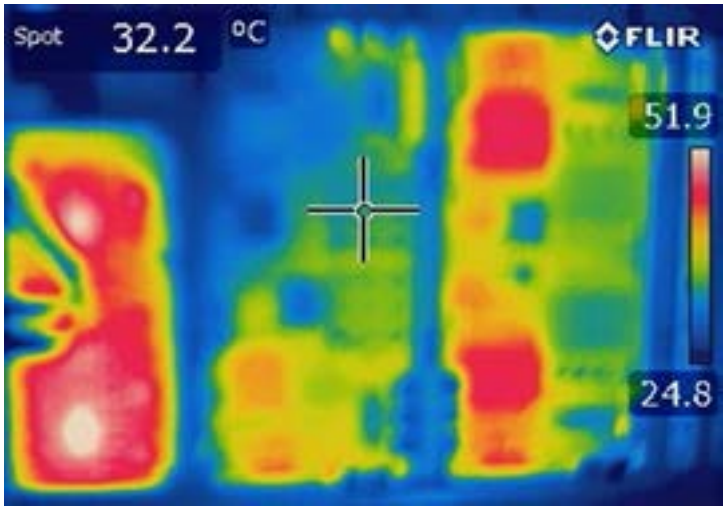
$$N = A \cdot f^{a} \cdot \Delta T^{-b} \cdot G(Tmax)$$

- Considers 3 factors:
  - Maximum temperature
  - Temperature change
  - Cycling frequency
- Number of cycles to fail

Case Politis: Approach

Most severe failure mechanisms:

- Thermal fatigue
- Vibration fatigue



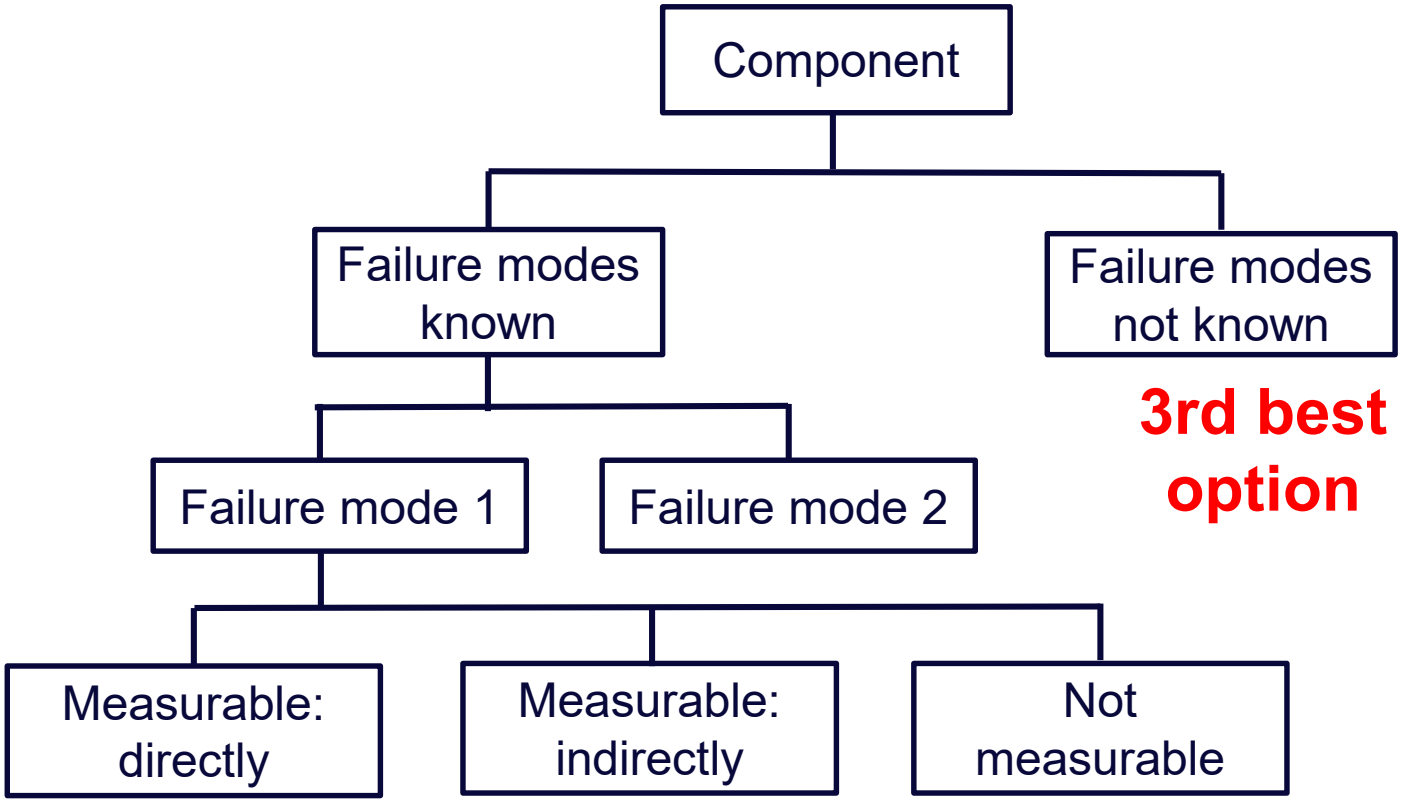
Coffin Manson model
(for thermal fatigue)

$N =$

- Cycling frequency
- Number of cycles to fail

Inaccurate predictions

Multiple ways to get to failure predictions



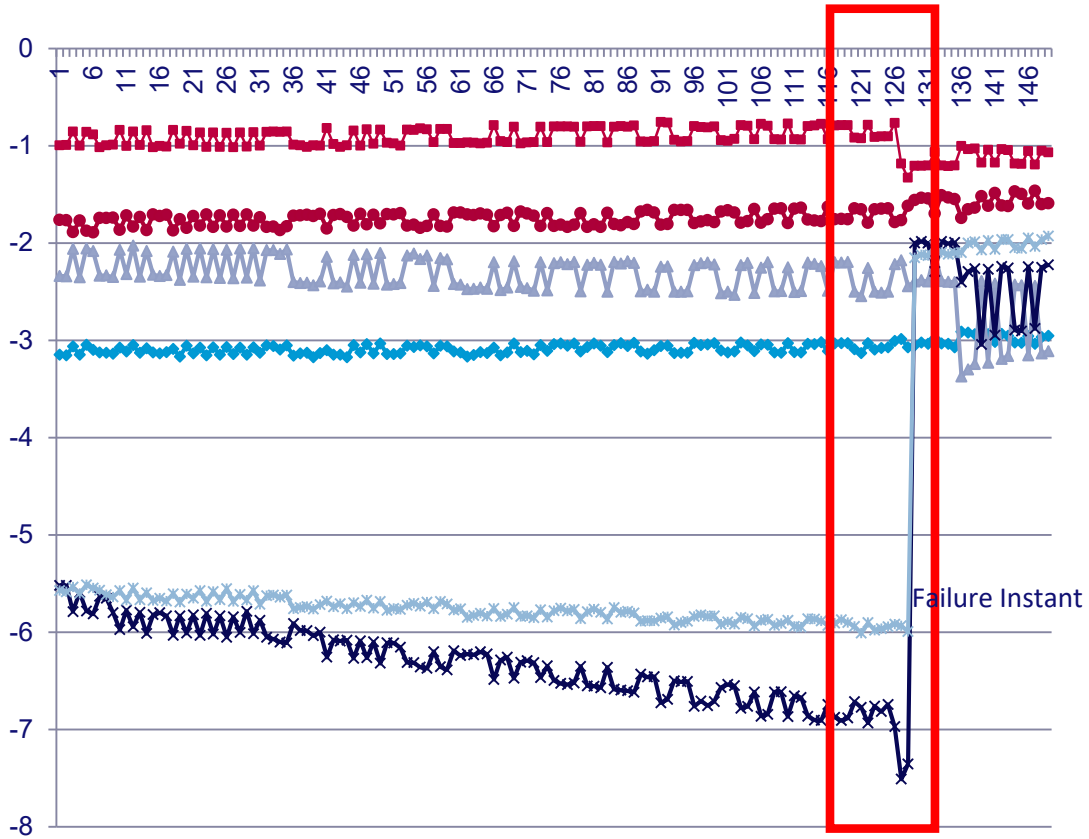
Case Çakir: Data mining

- **Condition data: parameters which are directly or indirectly related with the health state of Module X**
- **Failure data: failure time**

Sample Data: Collected at central level, for one critical unit

MACHINE NUMBER	TIME STAMP	VALUE	MACHINE TYPE	SITE ID	CUSTOMER CONTINENT	CUSTOMER COUNTRY	CUSTOMER NUMBER	PARAM ID
M1297	17-Dec-09	-8.856	T0010	1288	Asia	South Korea	188	3756
M2572	22-Oct-09	-8.9597	T0005	665	Asia	Singapore	2046	990
M2488	30-Jul-09	-3.9977	T0083	755	Other	Other	OT01	981
M0822	14-Jul-09	-4.0141	T0016	1284	Asia	South Korea	188	960
M1621	08-May-09	-3.8854	T0010	1294	Asia	South Korea	1146	957
M1647	23-Oct-09	-3.9167	T0001	277	North America	USA	196	966
M0003	21-Jul-09	-3.873	T0010	1291	Asia	South Korea	188	990
M0004	21-Feb-09	-3.8264	T0010	1291	Asia	South Korea	188	966
M2862	27-Aug-09	-3.7398	T0004	629	Asia	Taiwan	222	993
M2631	06-Jan-09	-8.551	T0004	801	Europe	France	192	972
M1141	10-Aug-09	-6.8885	T0011	1290	Asia	South Korea	1146	966
M3241	22-Apr-09	-8.551	T0010	629	Asia	Taiwan	222	963
M0051	05-Sep-09	-8.9597	T0008	1178	Asia	Taiwan	386	996
M1171	28-Feb-09	-3.9977	T0006	629	Asia	Taiwan	222	987
M1171	12-Aug-09	-6.8885	T0006	629	Asia	Taiwan	222	990
M1614	04-Dec-09	-8.551	T0007	1284	Asia	South Korea	188	990
M1951	16-Jul-09	-8.9597	T0019	1286	Asia	South Korea	188	960
M2785	05-Jul-09	-3.9977	T0010	1291	Asia	South Korea	188	996

Coupling with failure data



STRONG CORRELATION BETWEEN FAILURE AND CONDITION DATA

Results

- A ‘black box’ prediction method has been developed that predicts 70% of the failures
- No false predictions
- Timing of the failure can be predicted a few weeks in advance.
- Method outperformed the prediction model based on physical behavior

Results

- A ‘black box’ prediction method has been developed that predicts 70% of the failures
- No false predictions
- Timing of the failure advance.
- Method outperforme physical behavior

- **False negatives**
- **Often, also false positives**
- **Only works when you have many failures per component**

4. Discussion – Part I

Reflection w.r.t. Failure Prediction

- User is not happy with preventive replacements if false predictions are generated
  - You can still do condition-based spare parts supply
  - Case ASML: Can be very beneficial (Topan et al., IISE Tr, 2019)
- What if prediction methods generate warnings and inspection is needed to say more?
  - Seen at Philips, see work of Xiao et al. (WP, in progress)
- Predicting failure for modules might be easier than for components
  - Could be useful for diagnosis

Statement

The required reliability of failure predictions depends on what you want to do with them:

- **For preventive replacements: 100% reliability required**
- **For diagnosis, inspections, and predictive spare parts supply: low reliability may also be OK, avoid too many false negatives**

*Comments from discussion: The first part of the statement may hold for the case of an OEM and their customers who have to pay for the preventive maintenance action. In the case of Dutch Railways or Royal Netherlands Navy, it may be different. Then the costs of a preventive maintenance and a failure are important as well. And, if a system has to be prepared for a mission, then you also will use less reliavle predictions to preventively replace parts.

5. Maintenance Policy

Complexity

- Many components
- Tailored modeling of degradation per component with a condition-based policy
- Mix of components with condition-based, age-based and failure-based policy
- Economic dependency between components:

  High set-up cost per maintenance action

$\Rightarrow$ *Use Scheduled Downs (SD-s) at time points T, 2T, 3T, …; Gives a decomposition!*

Note: Also convenient for user

Complexity

- Many components
- Tailored modeling of degradation per component with a condition-based policy
- Mix of components with condition-based, age-based and failure-based policy
- Economic d

  High set-u

⇒ *Use Schedu*

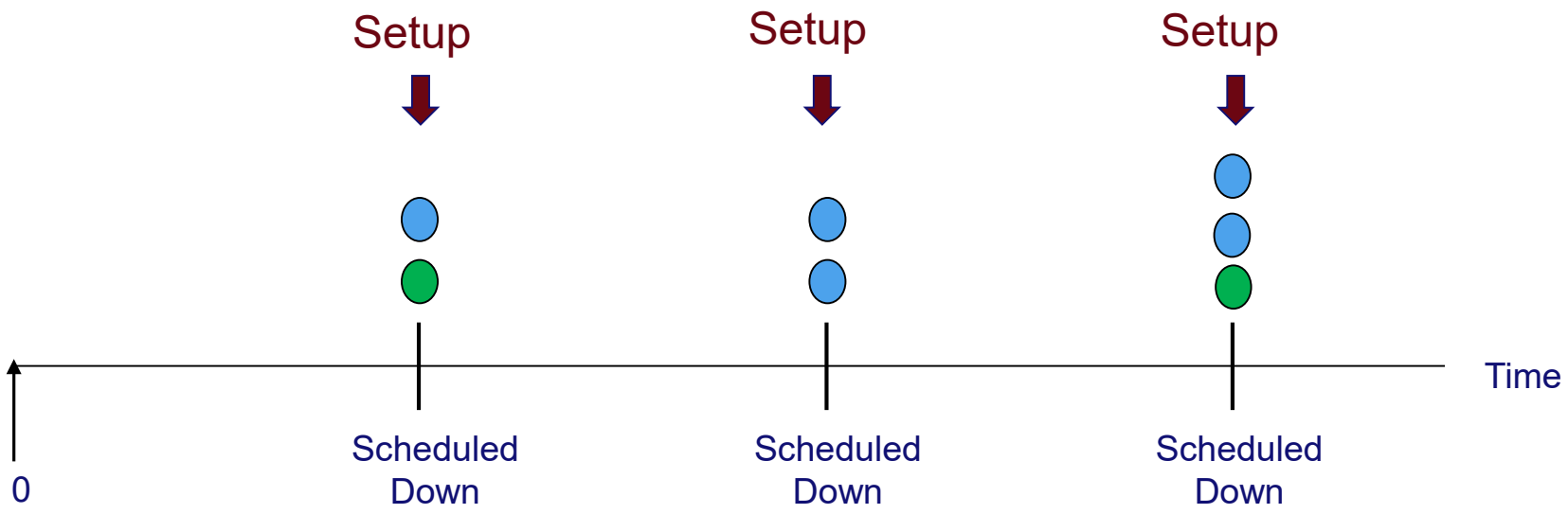
  2*T*, 3*T*, …

Note: Also conv

Maintenance papers with Scheduled Downs:

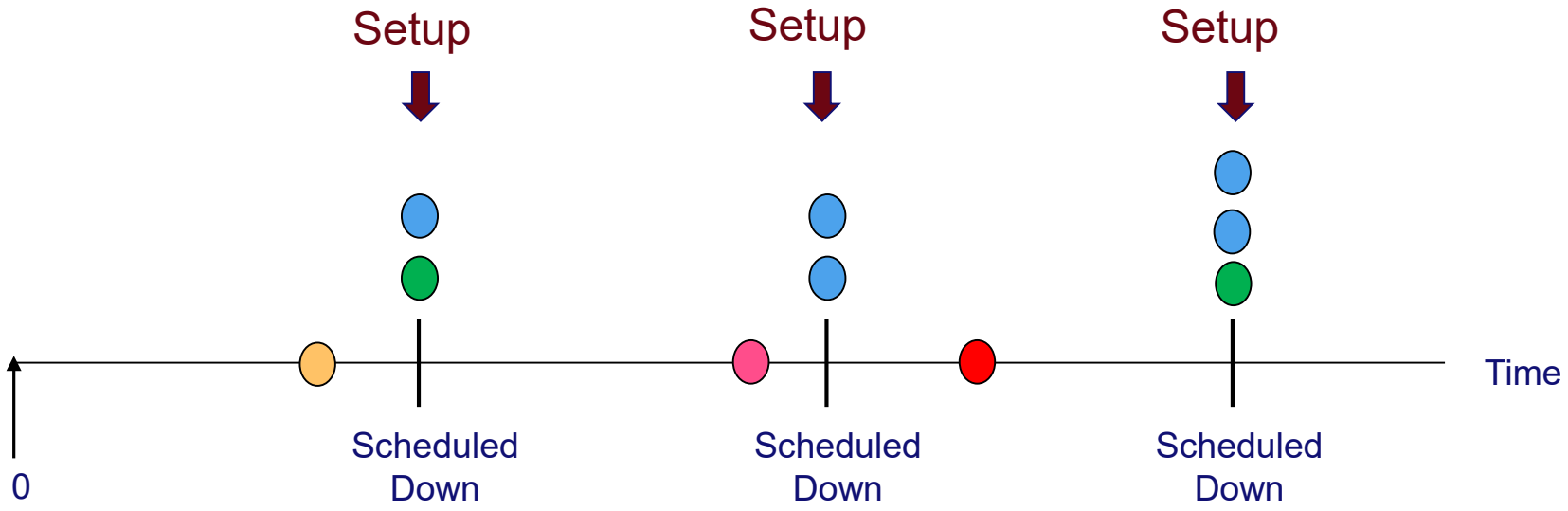
- Zhu, Peng, and Van Houtum (OR Spectrum, 2015)
- Bajestani and Banjevic (IIE Tr, 2016)
- Zhu, Peng, Timmersmans, and Van Houtum (IJPE, 2017)
- Poppe, Boute, and Lambrecht (EJOR, 2018)

Maintenance policy for the system (cont.)



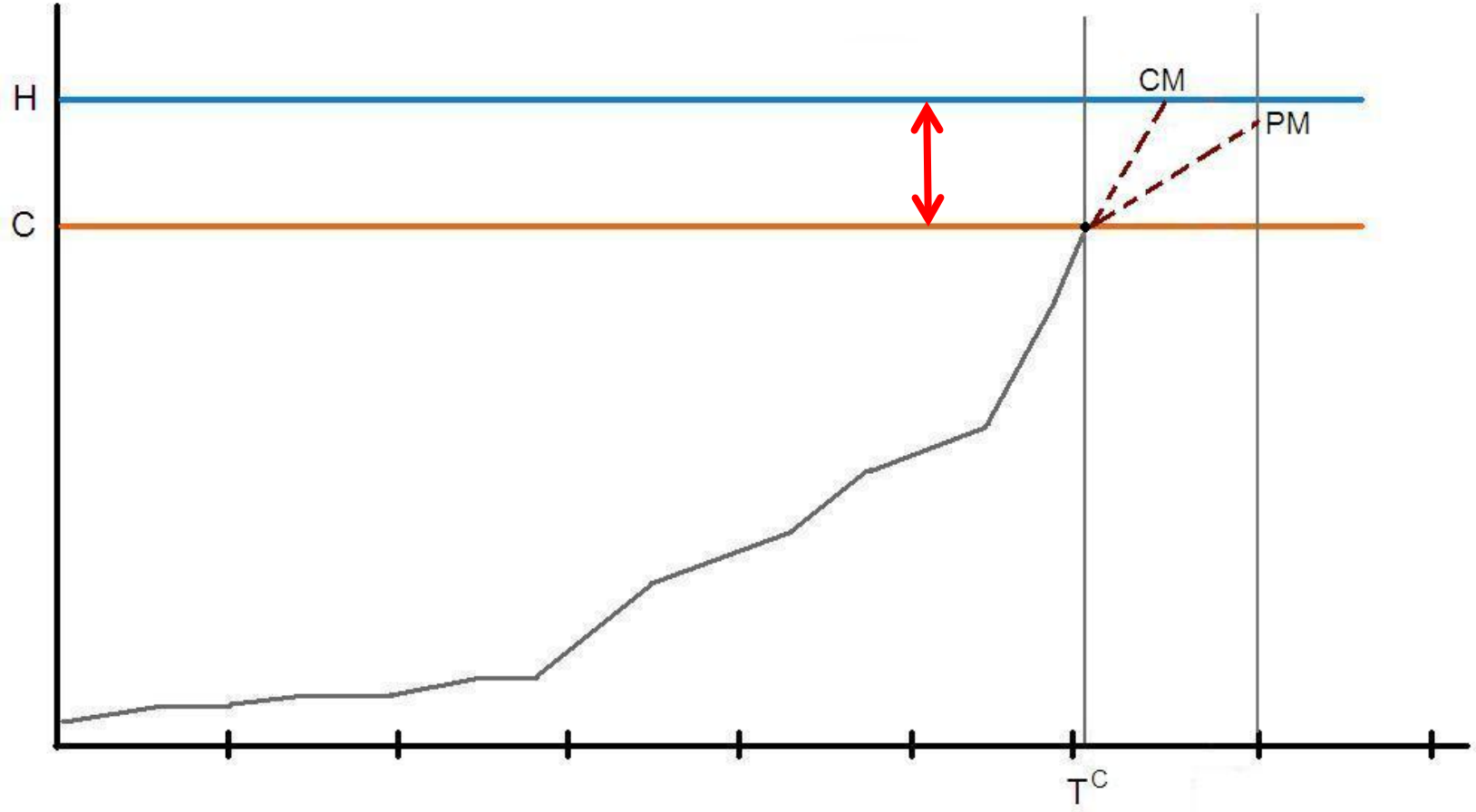
- Preventive action for a condition-based component
- Preventive action for a age-based component

Maintenance policy for the system (cont.)



- Preventive action for a condition-based component
- Corrective action for a condition-based component
- Preventive action for a age-based component
- Corrective action for a age-based component
- Corrective action for a failure-based component

Parameter optimization: Condition-based component



Scientific challenges

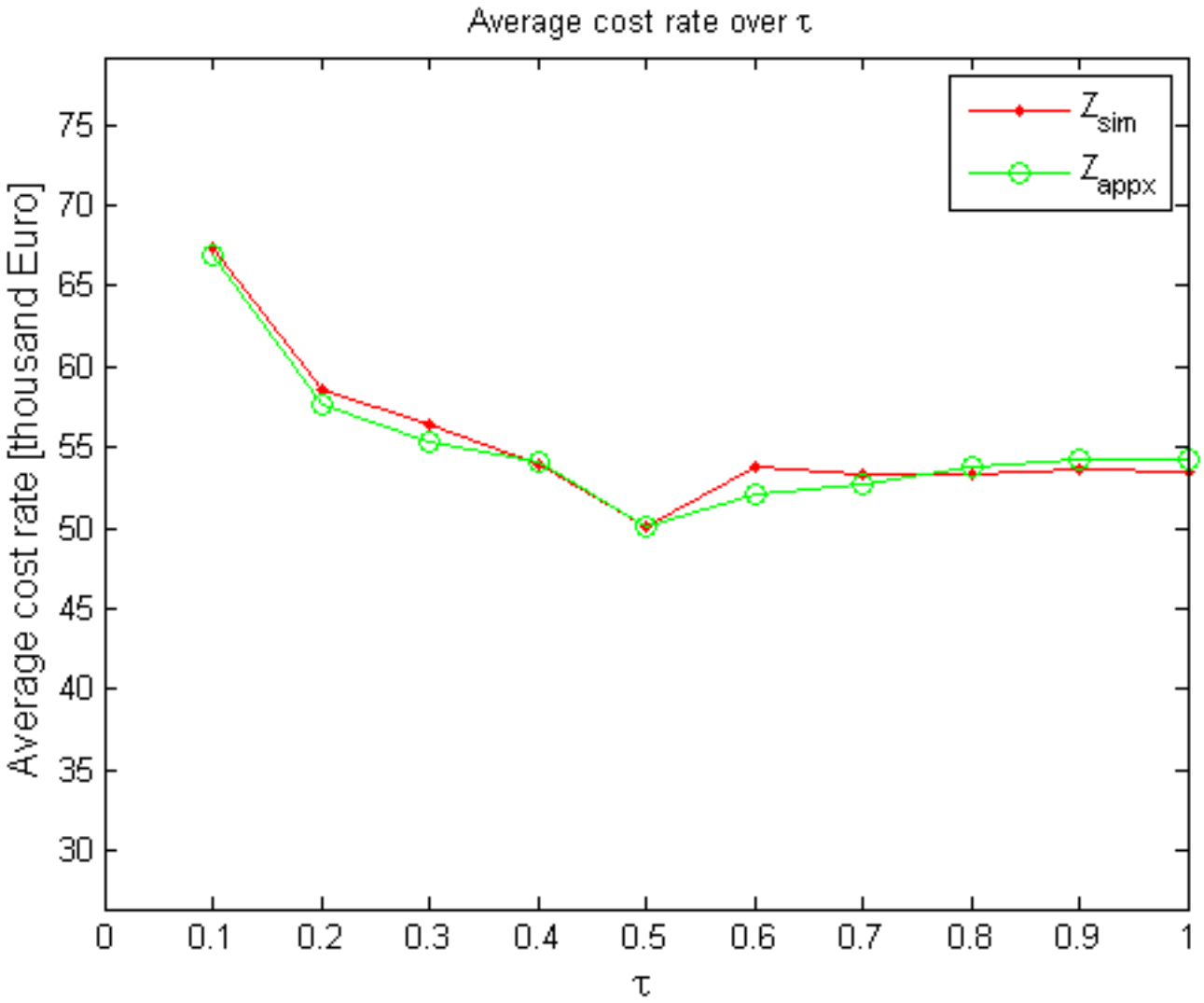
- Development of a fast (approximate) evaluation and optimization procedure of a condition-based policy under given SD-s:
  - Possibly also Unscheduled Downs can be used
  - For multiple degradation process (see Zhu et al. (*IJPE*, 2017) when a Gamma process or Random Coefficent Model is used)
- Similarly for an age-based policy
- Similarly for an inspection-based policy
- Development of a fast (approximate) evaluation and optimization procedure for the system as a whole

Example: Input parameters

(cf. Zhu, Peng, and Van Houtum, Proceedings Railway Conference, 2014)

Parameter	Explanation	$i \in I_{AB}$	$i \in I_{CB}$
c_i^{PM-USD}	PM cost at unscheduled down [thousand Euro]	$\{2.0, 2.1, 2.2, 2.3, 2.4\}$	$\{2.5, 2.6, 2.7, 2.8, 2.9\}$
c_i^{PM-SD}	PM cost at scheduled down [thousand Euro]	$\{1.00, 1.05, 1.10, 1.15, 1.20\}$	$\{1.25, 1.30, 1.35, 1.40, 1.45\}$
$c_i^{Rep} + S^{USD}$	Replacement cost with additional unscheduled setup cost [thousand Euro]	$\{10, 10.5, 11.0, 11.5, 12.0\}$	$\{12.5, 13.0, 13.5, 14.0, 14.5\}$
S^{SD}	Scheduled setup cost [thousand Euro]	3	3
α_i^{AB}	Scale parameter of Weibull distribution (for age-based components)	$\{1.13, 1.24, 1.35, 1.46, 1.58\}$	-
β_i^{AB}	Shape parameter of Weibull distribution (for age-based components)	$\{2.10, 2.31, 2.52, 2.73, 2.94\}$	-
α_i^{CB}	Scale parameter of Weibull distribution (for condition-based components)	-	$\{1.13, 1.24, 1.35, 1.46, 1.58\}$
β_i^{CB}	Shape parameter of Weibull distribution (for condition-based components)	-	$\{6.01, 6.61, 7.21, 7.81, 8.41\}$
H_i	Replacement threshold (for condition-based components)	-	$H_i = 100\%$

Example: Total average costs as a function of the SD interval



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Summary and Reflection

Approach:

- Development of failure prediction model per component
  - Good situation: If 80% of the failures is generated by a limited number of components
- Decomposition for system as a whole via Scheduled Downs

Optimization is done at tactical planning level. You can deviate at executional level.

Summary and Reflection

Complications in practice:

- Interaction with production schedule of user
- Availability of spare parts and engineers may be problem if you have to act fast

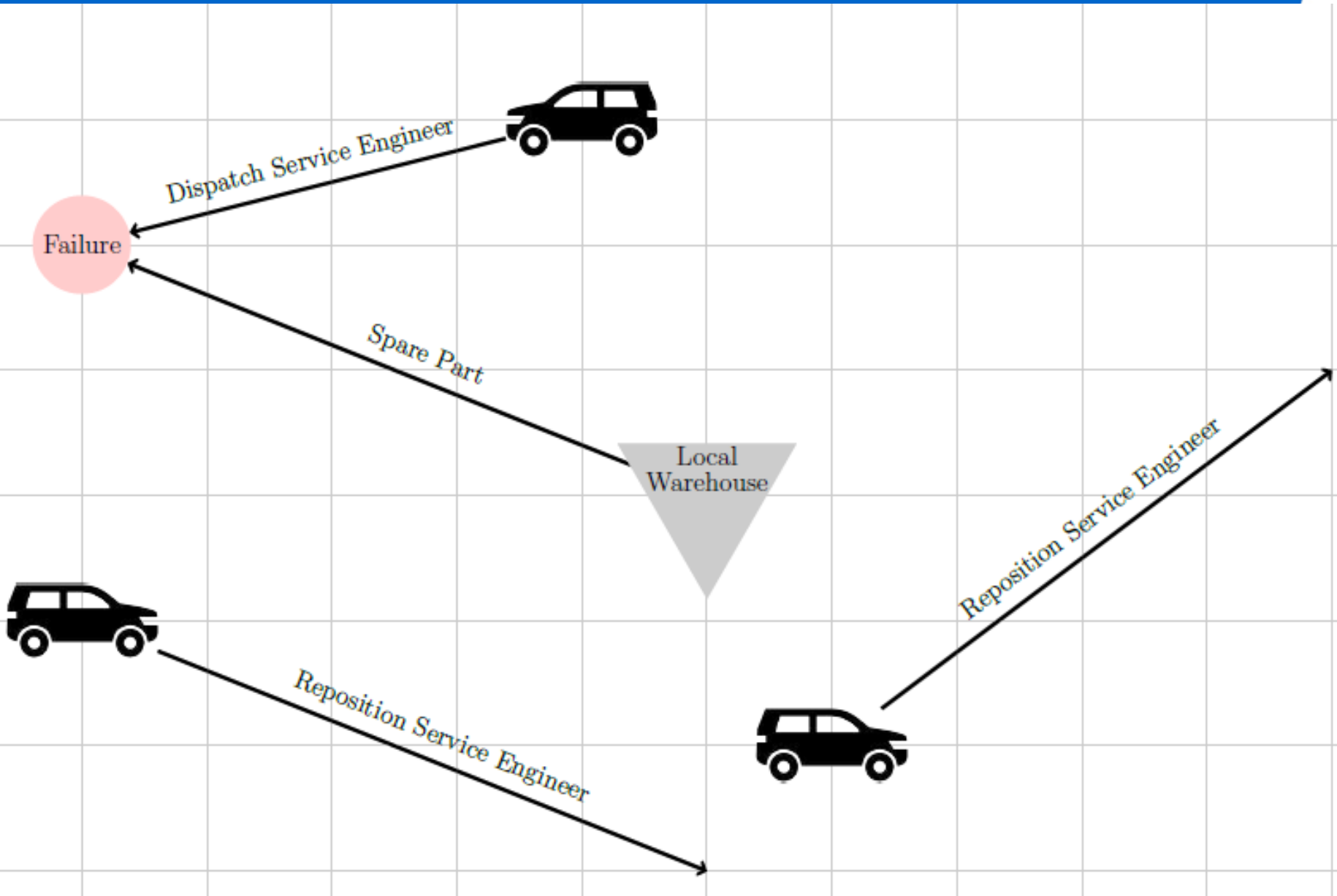
6. Maintenance Execution

Execution: Via maintenance network

Main resources: Engineers, spare parts

Possible concept per service region

(cf. Drent, Olde Keizer, and Van Houtum, EJOR, 2020)



Decision Making: Control Towers

Decision Making: Control Towers

Actual status systems and components

Maintenance plan per system

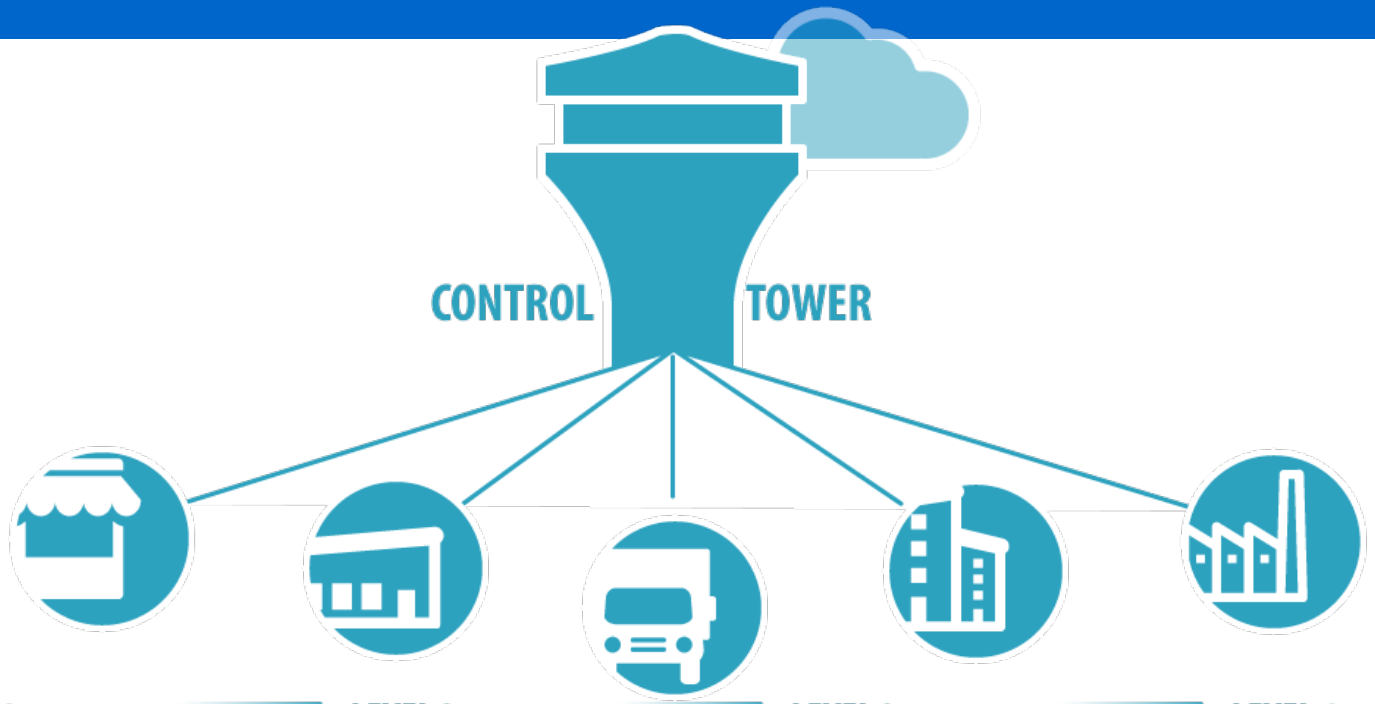
Schedule and actual positions service engineers

Actual inventory levels spare parts

Production schedules at users

Current contract performance

Control towers: Development stages



LEVEL 1 VISIBILITY
You have visibility to all the events and milestones you want track across the entire network.

LEVEL 2 ALERTS
You receive alerts based on the SLAs and lead times tagged to all events and milestones, and you collaborate to resolve them in real time.

LEVEL 3 DECISION-SUPPORT
You now execute transactions within the control tower, and the users make decisions based on recommendations from the intelligent agents.

LEVEL 4 AUTONOMOUS
The intelligent agents imbedded in the execution layer run the supply network without human intervention.

7. Discussion – Part II

What are the big challenges at companies to realize control towers?

- Completely new maintenance process
- Much more decision making is done in the control towers
- Organization has to change
- How to get all information into one system?

What are the big research challenges?

- From data to maintenance actions in one step
- Decision support models for executional level (online decision making)
- Visualization of data to support decisions
- Interaction between decision support systems and human decision makers
- Tradeoff automated-human decision making
- Interaction tactical-executional decision level
- …