Machine Learning Applications

TECHNISCHE UNIVERSITÄT DARMSTADT

Wintersemester 2019/2020

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Lecture X

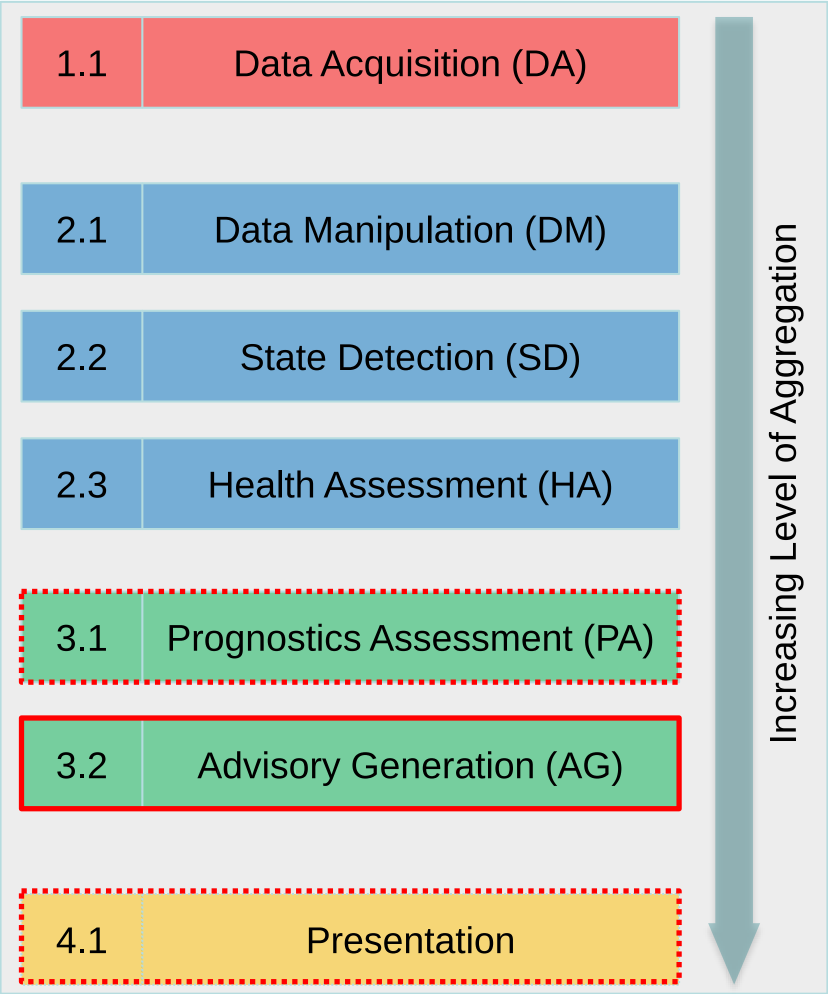
PHM for Complex Systems

What should you be able to take out of the lecture today?

- **Introduction to complex systems**:
  - The relevance of machine learning and PHM for large and complex systems
  - Challenges for those systems
- **PHM as a decision support tool**
- **Introduction to reliability engineering (as baseline approach)**
- **Chances for improvement by combining PHM/ML with reliability techniques**
- **Motor monitoring example**
- **Application example within research project SiFliegeR**
- **Visualization techniques**
- **Realization/Implementation**

Advisory generation at the end of the OSA-CBM process

Open System Architecture for Condition Based Maintenance



- AG combines result of PA with system/expert knowledge

  Which actions and when should I take for the component?
- AG can be used to address different scopes
  - Safety concerns
  - Cost optimization (predictive maintenance)
  - Increased availability
  - Short / long term planning
- Results of AG (and previous) steps will be presented to different user groups → visualization techniques are required
- Special scope: Complex systems

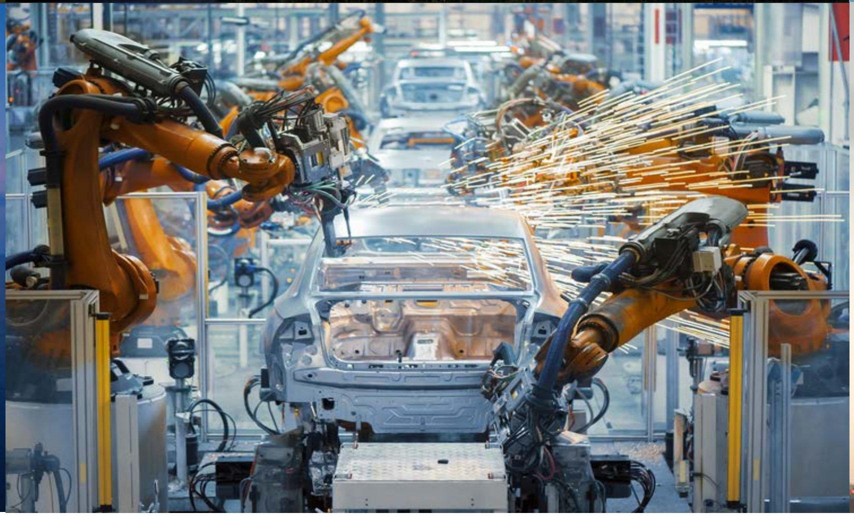
Introduction and Motivation

COMPLEX SYSTEMS

Complex Systems

Examples…

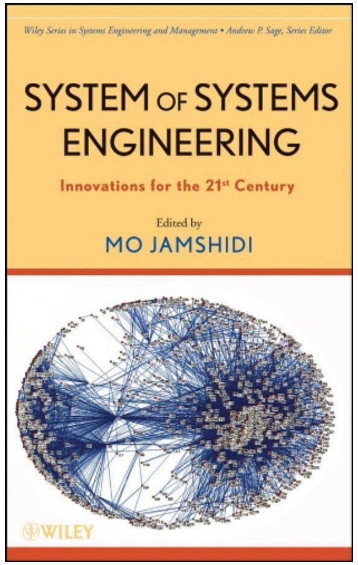



Complex Systems
Definition…

… there is no common definition, but: **Complex Systems** are often characterized by similar attributes, which are:

- Complex system structure with interdependencies and interconnections
- Multiple system states (operating states, performance level)
- Different domains (mechanical-, electrical-, hydraulic-subsystems, software etc.)
- Embedded uncertainties (operational, failure and degradation)
- High level of automation (+decision support)



[Mo Jamshidi, 2008]

Systems composed of multiple complex systems are categorized as **System of Systems** (SoS). These systems are categorized by

- Large-scale integrated systems that are heterogeneous and independently operable on their own, but are networked together for a common goal [Mo Jamshidi, 2008]
- Large Systems of geographical distribution

Complex Systems

Performability = Performance + Dependability

Performance
ability of a system to accomplish its intended services within given non-functional constraints (e.g. time)

Timeliness
ability of the system to provide a service according to given time requirements

Precision
ability of the system to provide the same results under unchanged conditions

Accuracy
ability of the system to provide exact results

Capacity
ability of the system to hold a certain amount of data

Throughput
ability to handle a certain amount of operations

Dependability
ability of a system to provide its intended services in a justifiable way

Availability
readiness for correct service

Reliability
continuity of correct service

Safety
absence of catastrophic consequences

Integrity
absence of improper system state alterations

Maintainability
ability to undergo modifications and repairs

[Bertolino, 2011]

Complex Systems

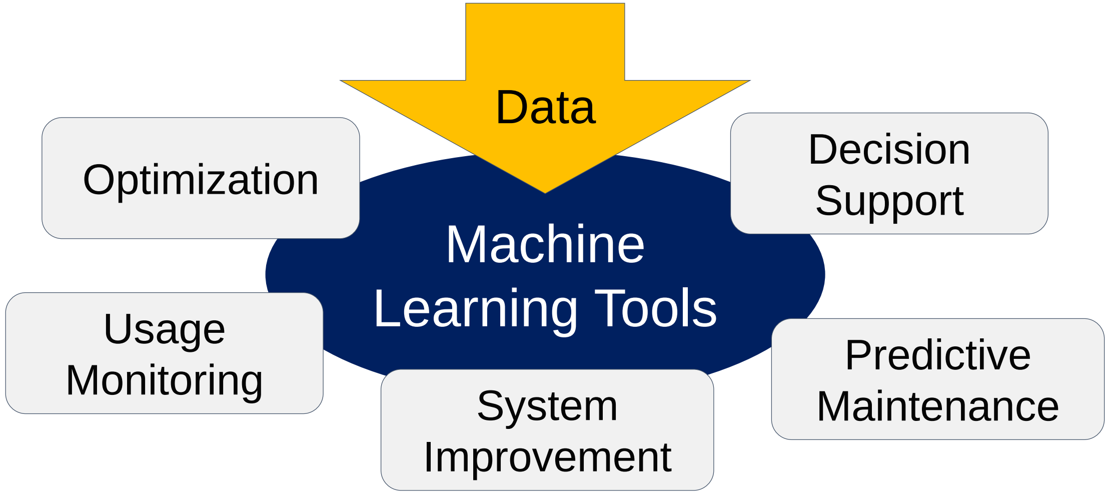
Why do we need prognostics (PHM)

Complex systems are used in versatile scenarios and changing environments. The Performability (outcome) of such a system is thus subject to embedded uncertainties.

On the other hand:

- High demand for availability
- Minimized (maintenance) costs
- High safety requirements

→ Use prognostics as a decision support

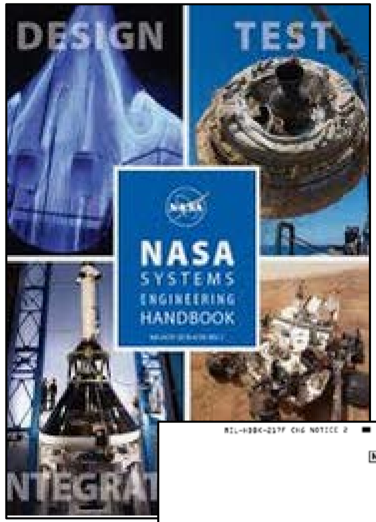


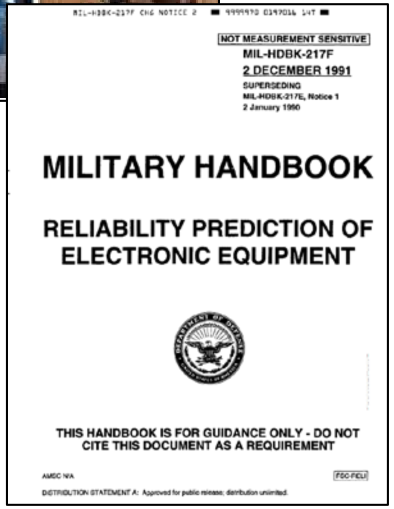
Complex Systems

What are the challenges?

- Different Domains (Electronics / Hydraulics / Structures etc.)
- Different Approaches in different Industries (HUMS, Testing, Standards)

- <u>Technical Issues → Research:</u>
  - Development of Methods and Tools for data aggregation (combine PHM results)
  - Realization (available hardware and software)
  - Visualization

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https://www.panasonic.com

PHM AS A DECISION SUPPORT TOOL

PHM as decision support

From “data” to “information” (OSA-CBM)

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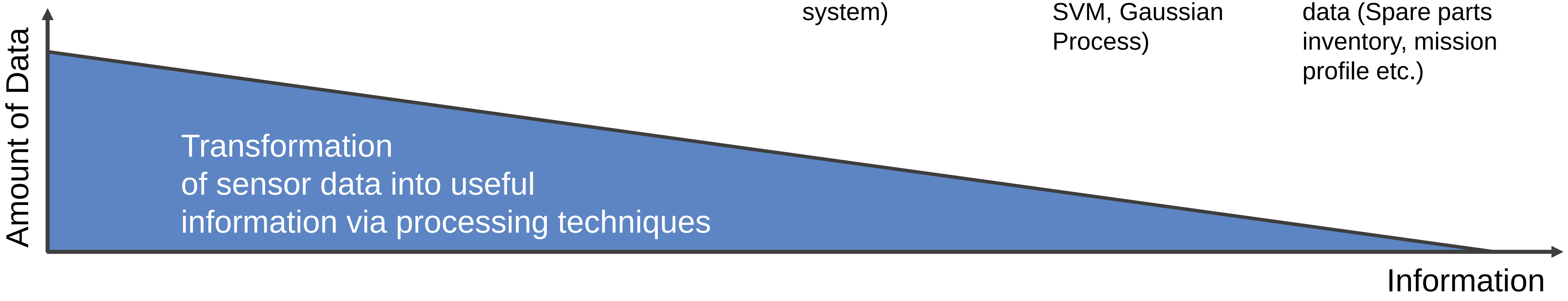
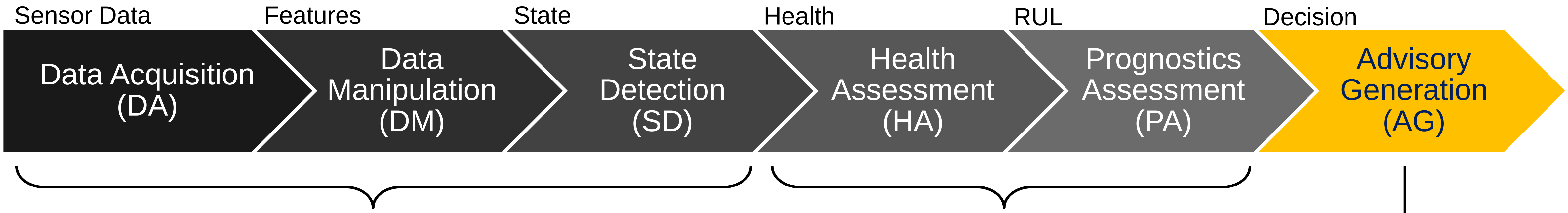
Sensor Data	Features	State	Health	RUL	Decision
Data Acquisition (DA)	Data Manipulation (DM)	State Detection (SD)	Health Assessment (HA)	Prognostics Assessment (PA)	Advisory Generation (AG)
• Temperature, Vibration, Power Consumption etc.	• Signal filtering • Time Domain (thresholds, statis-tics, min max, etc.) • Frequency Domain (FFT, Wavelet)	• Clustering • Filtering (Kalman filter, particle filter etc.)	• Expert Systems • Threshold based (Compare SD data with historic failure data to derive health state of the system)	• Prediction models based on physical, hybrid or data based system models (e.g. Neural Networks, SVM, Gaussian Process)	• Visualization • Reasoning (Bayesian networks, Expert Systems etc.) • Input additional data (Spare parts inventory, mission profile etc.)



PHM as decision support

AG comes at a cost – required inputs by the process



Your engineering expertise required:

- Knowledge of failure modes and mechanisms
- Knowledge of suitable failure precursors
- Selection of appropriate sensors and DAQ

Data required:

- Run to failure data
- (labeled) data with anomalies

Depending on scope and system:

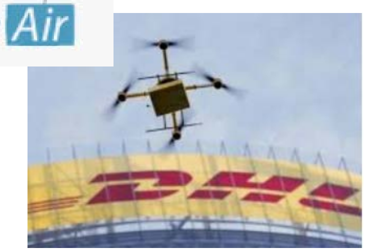
- System structure
- Connected systems and processes
- Design rules (e.g. level of automation)
- …

PHM as decision support

Different scope depending on considered decision level

[FSR/Acorus]

[roboticsbusinessreview.com/]



Unit/Aircraft

- Short term decisions
- Usually operation/mission specific
- e.g. safe operation possible for the current mission

System/Fleet

- Medium term planning
- Consideration of multiple connected systems
- E.g. availability of system in near future (task / job planning)

Organization/Airline

- Long term planning and decisions
- Affects considered systems and connected processes
- E.g. general improvement of product, cost optimizations, integration into processes

Excursion to safety and reliability

RELIABILITY ENGINEERING

Reliability Engineering
Historical background and current challenges





1950s	1960s	1970s	1980s	Since 1990s
Initial problem statement	Component focus	System focus	Man-Made desasters	High reliability organization

Current Situation

- Reliability assessment largely based on historical events and data
- Failure data is (mostly) statistically processed with classical reliability methods
- No direct feedback of individual health state

New Challenges

- Diversified operations in changing environments (e.g. UAVs)
- Varying loads and conditions
- New business models require accurate reliability predictions (e.g. perf. based contracting)

→ dynamic reliability assessment


[NASA]

Reliability Engineering
Definitions

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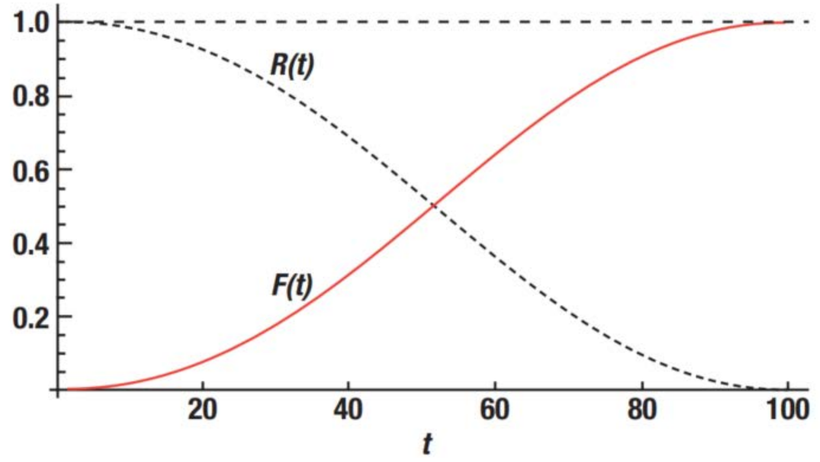
Status Quo: *”Reliability engineering is* [… the discipline …] *to develop methods and tools to evaluate and demonstrate reliability, maintainability, availability, and safety of components, equipment, and systems, as well as to support development and production engineers in building in these characteristics.”* [Birolini, 2010]

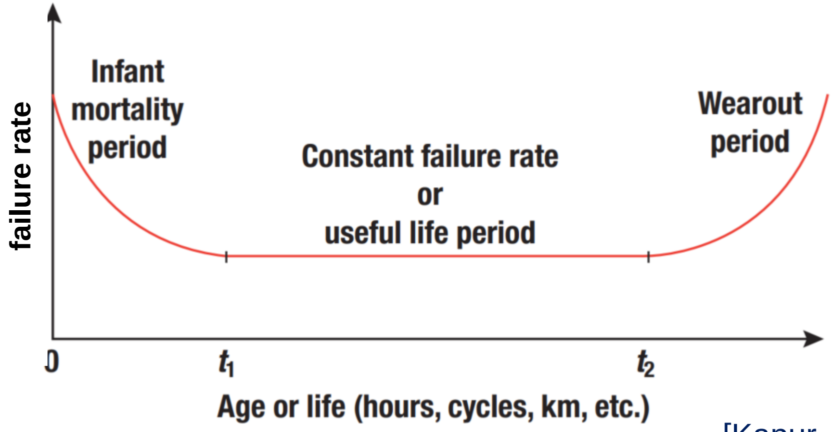
Reliability
Probability that the required function will be provided under given conditions for a given time interval. [Birolini, 2010]

Safety
Ability of the item to cause neither injury to persons, nor significant material damage or other unacceptable consequences. [Birolini, 2010]

Reliability Engineering
Reliability for a single component

Definition	Formula
Failure probability density function (PDF)	$f(t) = \frac{F(t)}{dt}$
Failure probability (CDF)	$F(t) = \int f(t)dt$ $F(t) = 1 - R(t)$
Reliability probability (CDF)	$R(t) = 1 - F(t)$
Failure rate	$\lambda(t) = \frac{f(t)}{R(t)} = -\frac{R(t)}{dt}\frac{1}{R(t)} \quad \left[\frac{1}{h^*}\right]$
Mean Time to Failure (MTTF) [only if λ=const]	$MTTF = \frac{1}{\lambda}$

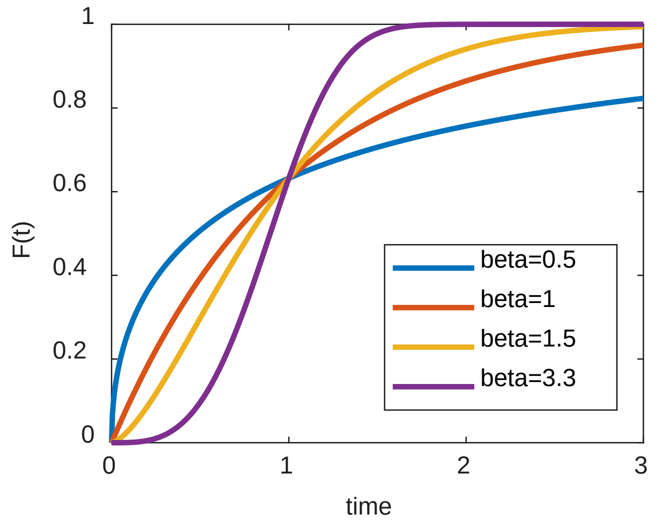


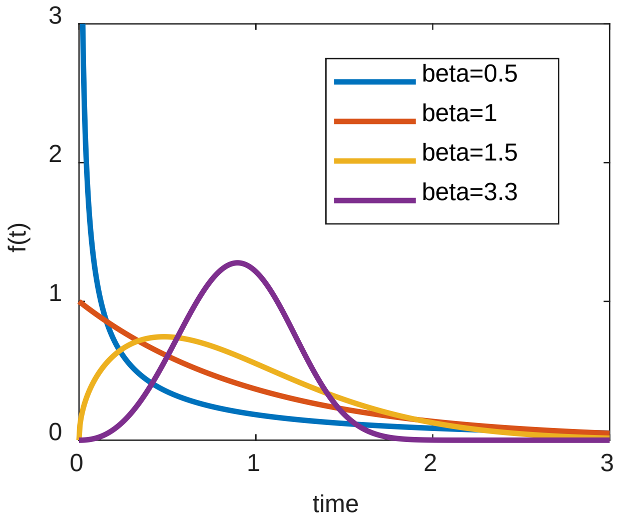


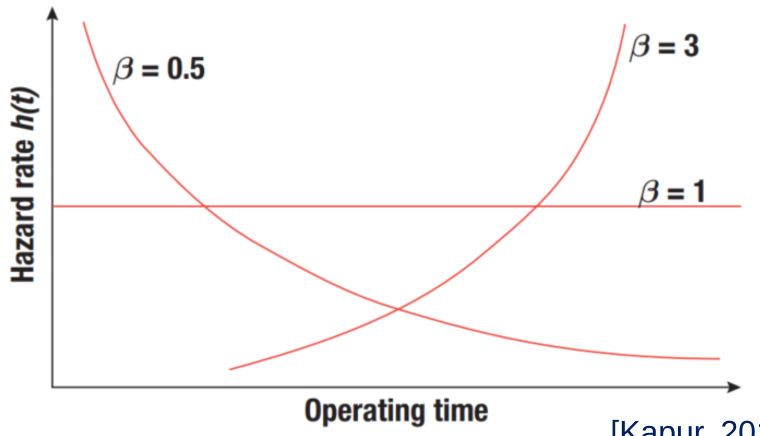
[Kapur, 2014]

Reliability Engineering

Reliability for a single component – Common failure distributions







[Kapur, 2014]

Exponential (failure) distribution:

For constant failure rates (random failures, e.g. electronic equipment):

$F(t) = 1 - e^{-\lambda t}$

λ → Failure rate

Weibull distribution:

Can be parameterized and thus be used to model different failure characteristics (parts of the bathtub curve):

$F(t) = 1 - e^{-(\frac{t}{\eta})^{\beta}}$

η → Scale parameter

β → shape parameter (β=1 → Exp-Distribution)

Reliability Engineering

How to obtain failure rates?

Example: Failure rate estimation based on the MIL-HDBK-217F (1991) for a rotating resolver/encoder

MIL-HDBK-217F CHG NOTICE 2

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MIL-HDBK-217F
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12.2 ROTATING DEVICES, SYNCHROS AND RESOLVERS

DESCRIPTION
Rotating Synchros and Resolvers

$$\lambda_p = \lambda_b \pi_S \pi_N \pi_E \text{ Failures}/10^6 \text{ Hours}$$

[MIL-HDBK-217f, 1991]

Size Factor - π_S

DEVICE TYPE	π_S Size 8 or Smaller	π_S Size 10-16	π_S Size 18 or Larger
Synchro	2	1.5	1
Resolver	3	2.25	1.5

Number of Brushes Factor - π_N

Number of Brushes	π_N
2	1.4
3	2.5
4	3.2

Base Failure Rate - λ_b

T_F (°C)	λ_b	T_F (°C)	λ_b
30	.0083	85	.032
35	.0088	90	.041
40	.0095	95	.052
45	.010	100	.069
50	.011	105	.094
55	.013	110	.13
60	.014	115	.19
65	.016	120	.29
70	.019	125	.45
75	.022	130	.74
80	.027	135	1.3

$$\lambda_b = .00535 \exp\left(\frac{T+273}{334}\right)^{8.5}$$

T_F = Frame Temperature (°C)

If Frame Temperature is Unknown Assume T_F = 40 °C + Ambient Temperature

Environment Factor - π_E

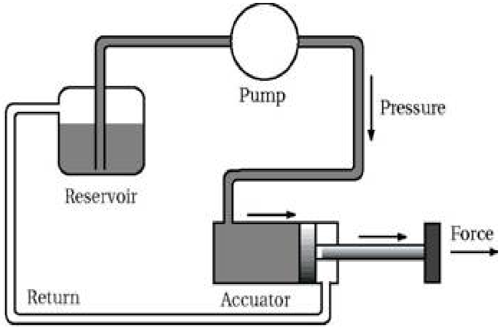
Environment	π_E
G_B	1.0
G_F	2.0
G_M	12
N_S	7.0
N_U	18
A_{IC}	4.0
A_{IF}	6.0
A_{UC}	16
A_{UF}	25
A_{RW}	26
S_F	.50
M_F	14
M_L	36
C_L	680

Reliability Engineering

Reliability calculation for multiple components

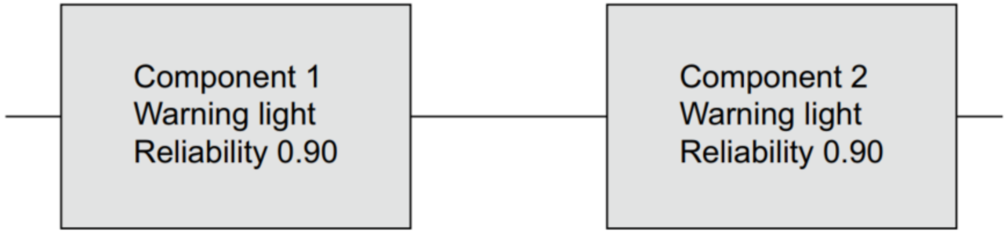
Series configuration

- Example: Hydraulic circuit
- A single failure of one of the components will lead to failure of the complete system
- Logical <u>OR</u>



[hwcorp.com]

$$F(t) = 1 - \prod R_i(t)$$

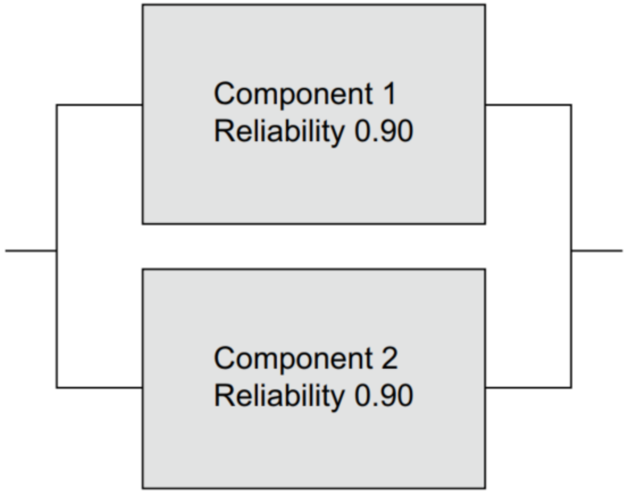


Parallel configuration:

- Example: Aircraft Engines
- (Hardware) redundancy is used to improve reliability of a system
- Logical <u>AND</u>

[wikipedia]

$$F(t) = \prod F_i(t)$$



Reliability Engineering

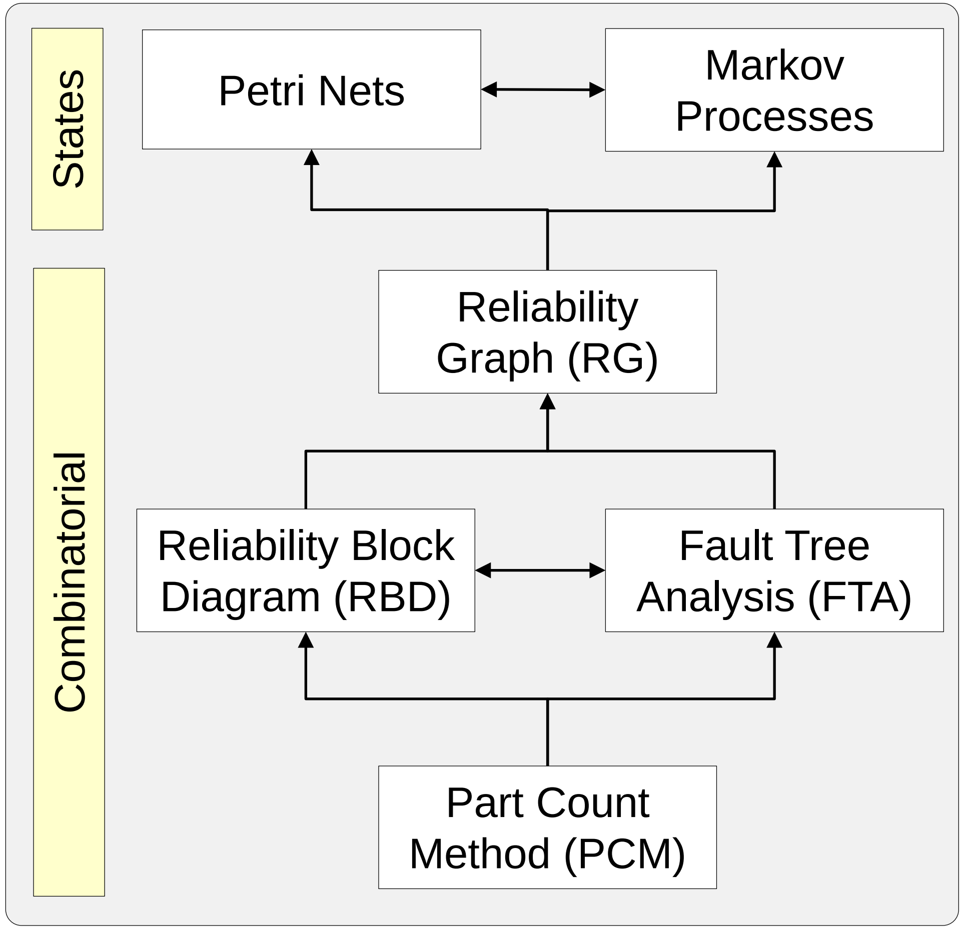
System reliability models (an overview)

Reliability Models:

System reliability models are used to aggregate failure probabilities and to model a system's RAMS (Reliability, Availability, Maintainability, Safety) estimates. Common models are:

- Part Count Method
- Reliability Block Diagram
- Fault Tree Analysis
- Reliability Graph
- Petri Nets
- Markov Models / Processes

→ Models can be expressed in a hierarchy according to their modelling power (see figure on the right)



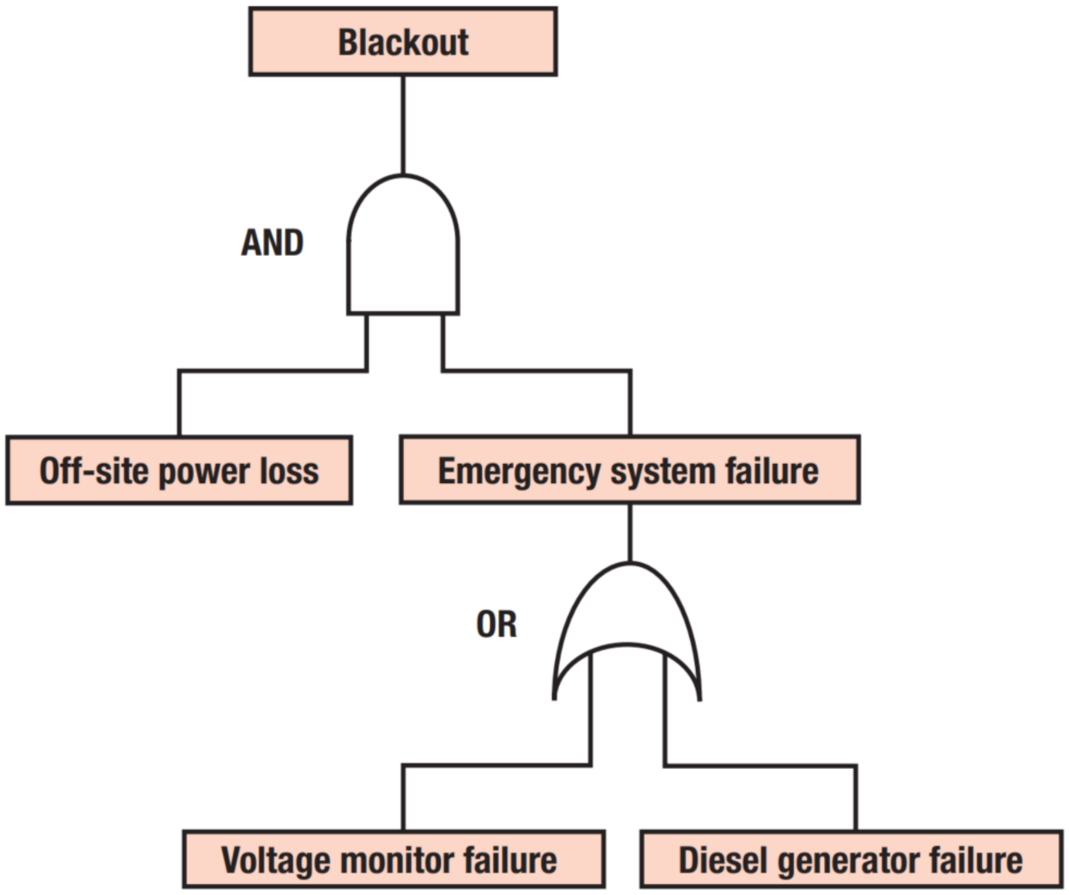
[Malhotra 1994 & Everdij 2003]

Reliability Engineering

System reliability models → Fault Tree Analysis

Fault Tree Analysis (FTA): Engineering tool to model failure dependencies for multicomponent systems based on a tree structure with the following characteristics:

- Can be used for qualitative and quantitative system safety and reliability analysis
- Widely used and accepted in the aerospace domain
- Top-down approach
- Combinatorial model (and/or combinations)
- Can be solved analytically or via simulation (Monte Carlo Simulation)
- Two state output (probability that system has failed or not)



[Kapur, 2014]

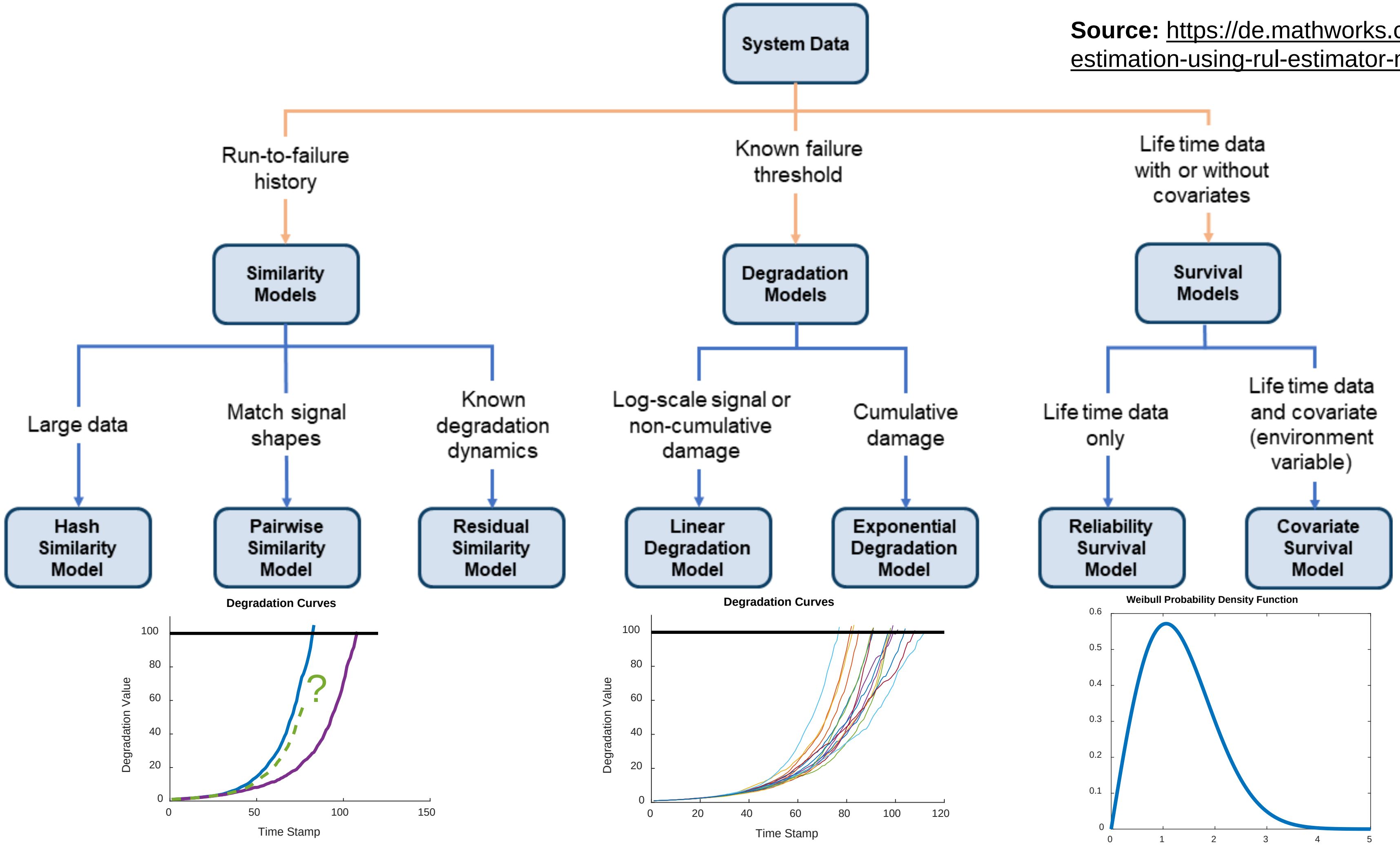
Comparison

PHM VS RELIABILITY

PHM & Reliability

Recap PHM <> Reliability Engineering

Source: https://de.mathworks.com/help/predmaint/ug/rul-estimation-using-rul-estimator-models.html

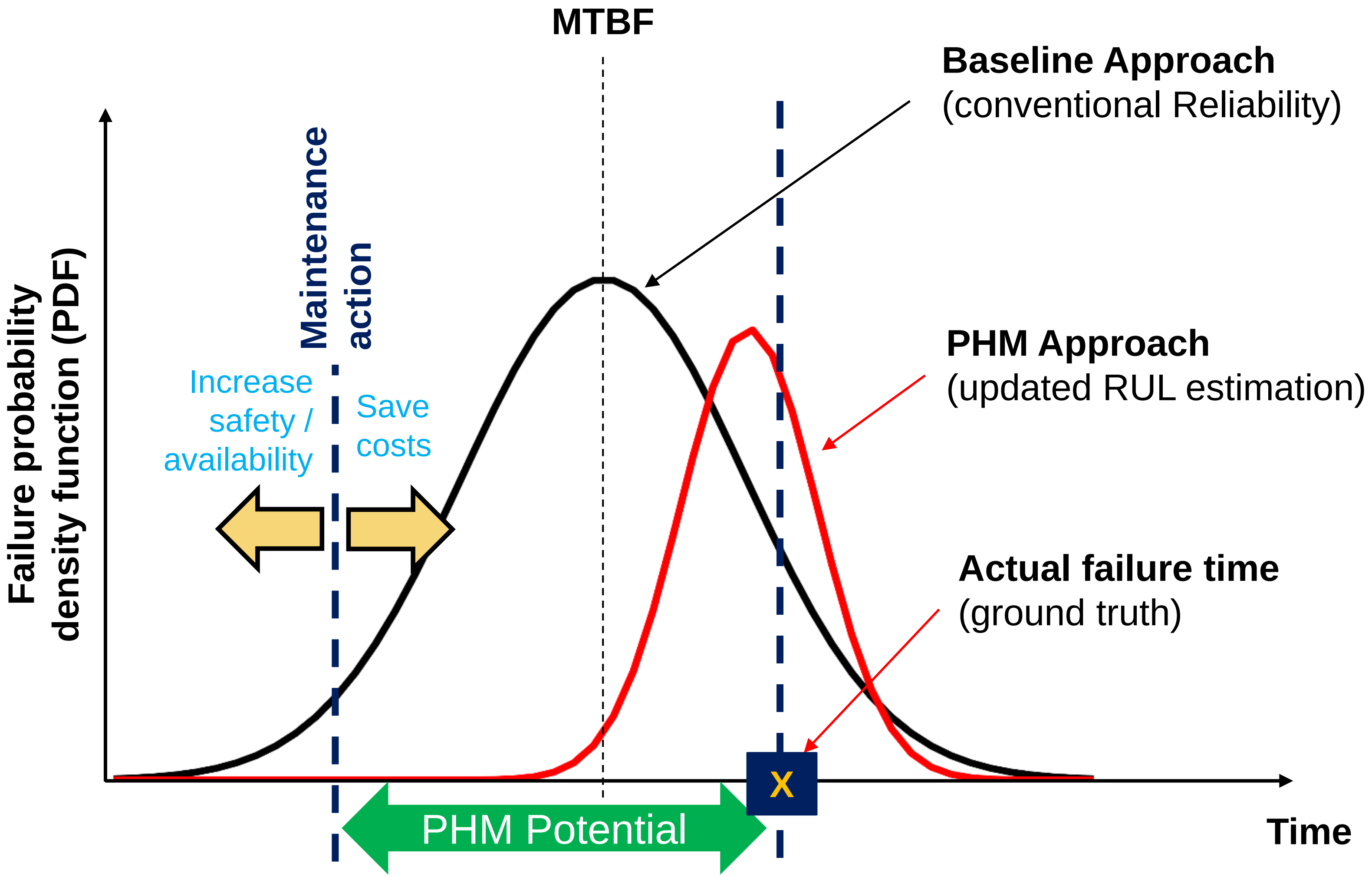


PHM & Reliability

Recap: Why PHM

PHM: Key-enabler for predictive maintenance:

- Find optimum time for maintenance action (decision support)
- Increase safety + availability @ optimum costs

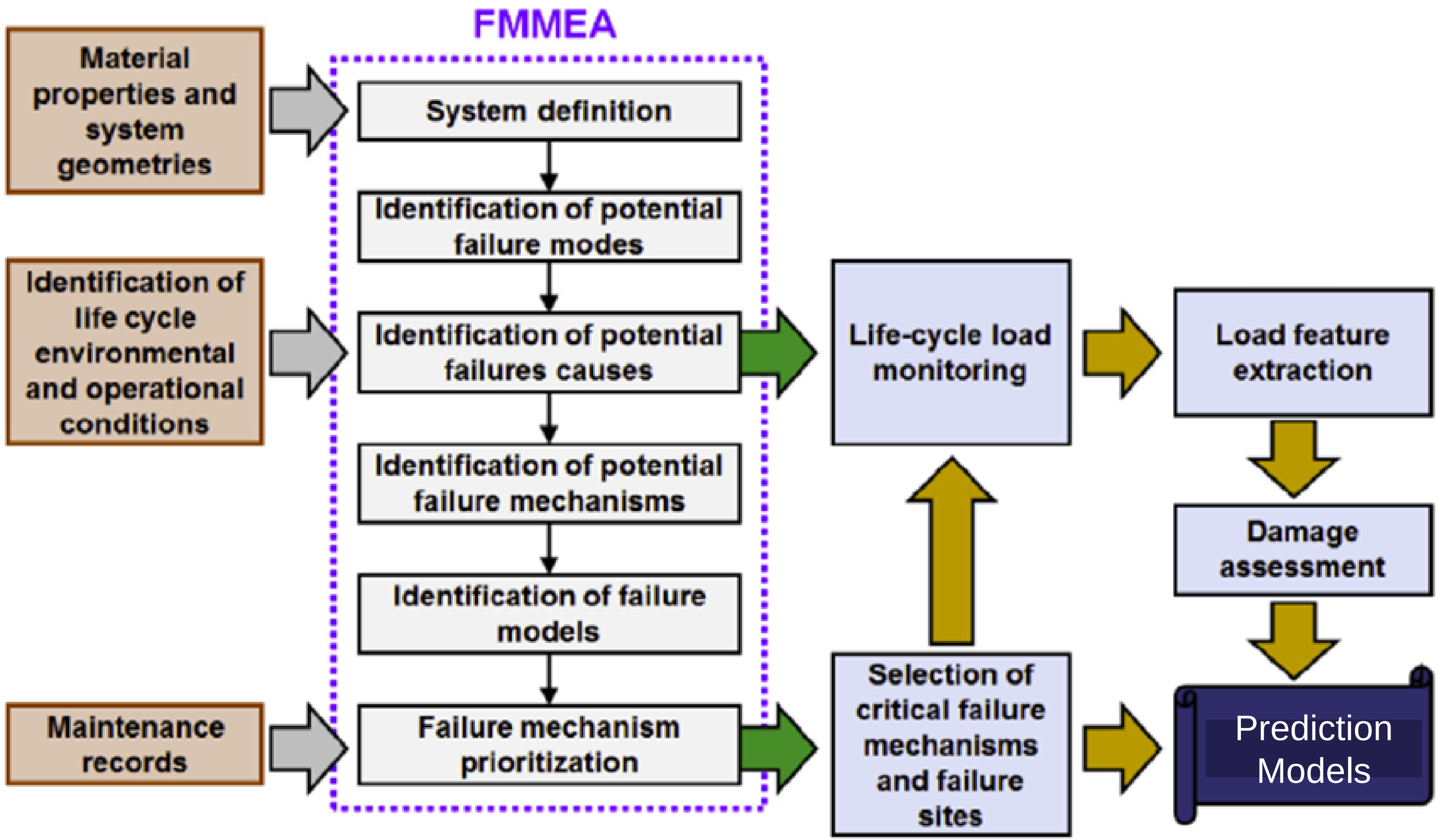


PHM & Reliability

General approach

How to identify suitable PHM monitoring strategy

- Run failure modes, mechanisms and effects analysis
- Identification of relevant (physical) failure precursors
- Select feasible diagnosis/prognosis scheme



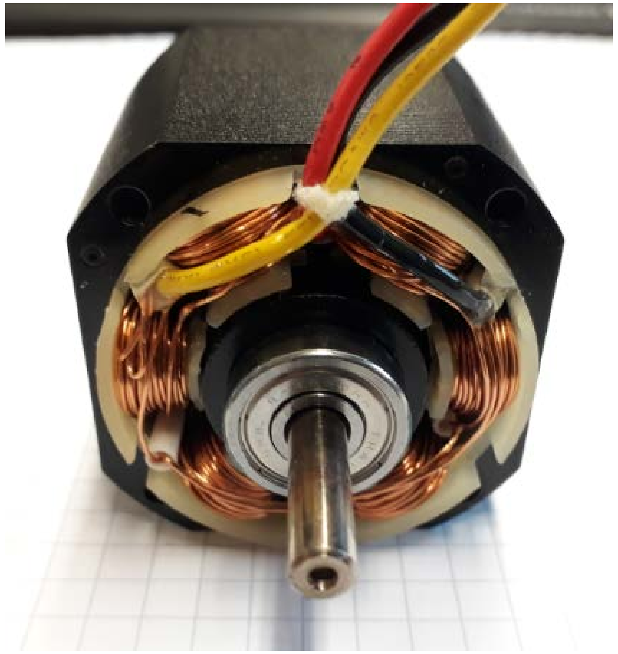
[M. Pecht, 2018]

PHM & Reliability

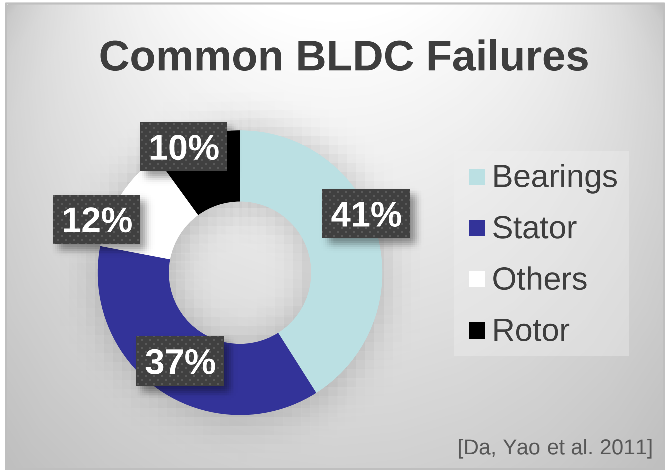
Example: Failure Mechanisms of an electrical motor

Known failure modes:

- Bearing degradation due to overload / excessive cycling
- Eccentricity / unbalanced rotor
- Winding shorts due to thermal / mechanical stress
- Partial demagnetization (over heating)



[Da, Yao et al., 2011]



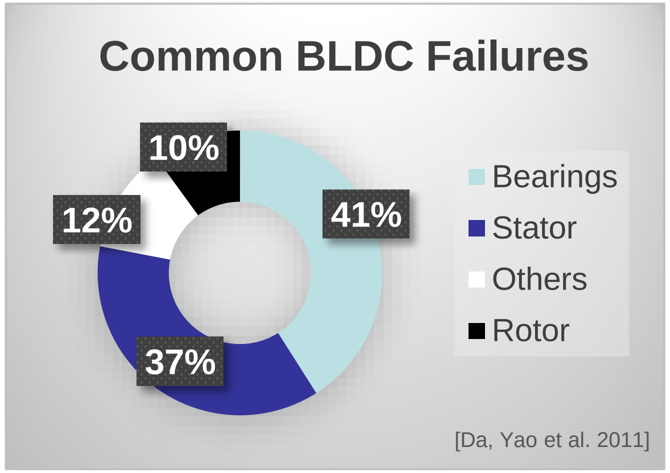
Types of methods	Types of Failures				Hardware Requirement	Drawbacks
	Bearing	Eccentricity	Winding short circuit/open circuit	Partial Demagnetization		
Current frequency Analysis	√	√	√	√	Current sensor, Raster encoder	Not good for various speed operated machines. Eccentricity and demagnetization have same frequency signature.
Vibration/Noise frequency Analysis	√	√			Accelerometer/Sound recorder, Raster encoder	
Parameter estimation based on current and voltage monitoring			√	√	Current sensor, Raster encoder	Fault-free machine accurate parameters are required.
Temperature Monitoring			√		Thermograph	Temperature is affected by many factors.
Direct Flux Monitoring		√	√	√	Search coils, Raster encoder	Additional built-in flux sensors are required.

Example

PHM FOR BLDC MOTORS

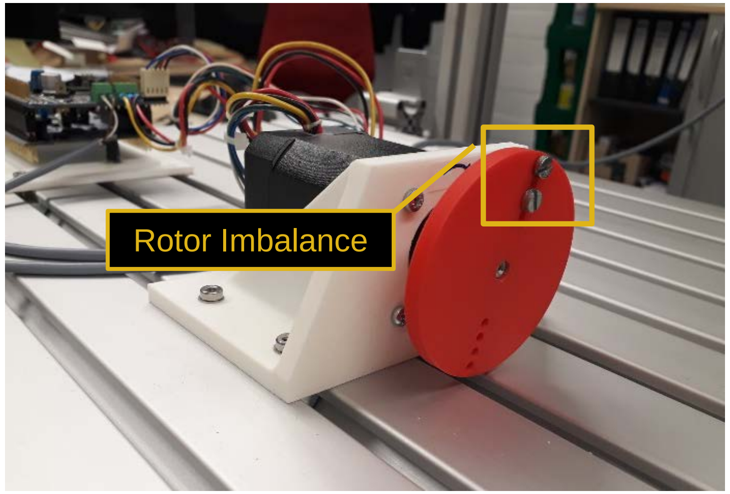
PHM for BLDC motors

Custom Test-rig for research



Scope

- BLDCs widely used in industry with increasing relevance in aerospace applications
- Research of failure mechanisms and monitoring schemes for brushless DC motors [BLDC]



Realization

- HW/SW: Testbed with 48VDC + closed case, STM32 Nucleo MCUs, Custom Motor Controller, DAQ via UDP and Soundbook/Notebook
- Low-Cost components (1xBLDC ~60$)
- Simplified and flexible configurations:
  - Imbalanced rotor
  - Overload / thermal stress
  - Artificially induced faults (winding shorts, increased motor resistance)

PHM for BLDC motors

Custom Test-rig for research

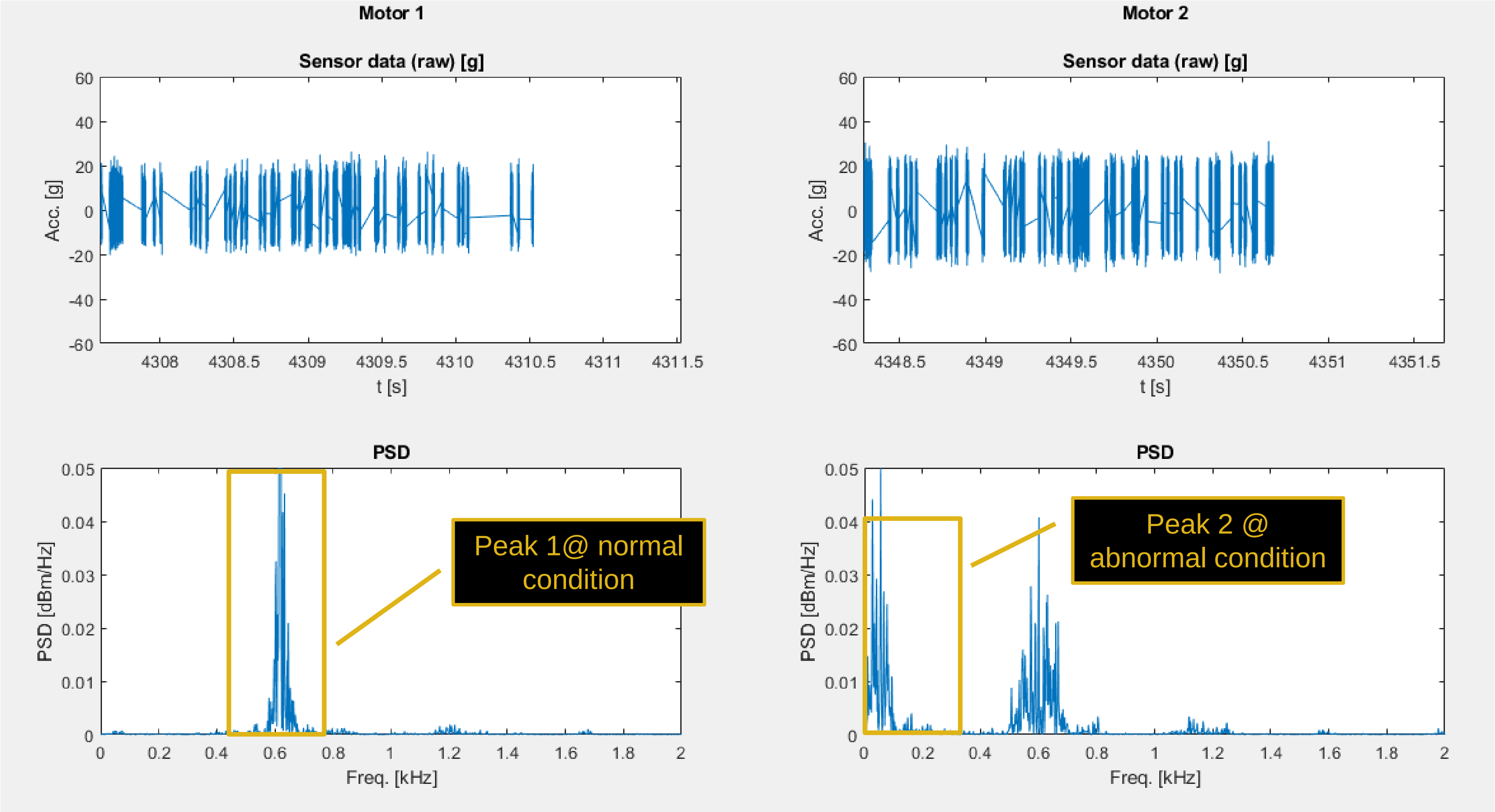
DEMO

PHM for BLDC motors

Data output and feature generation (1)

Expected outcomes:

- Raw sensor data only shows amplitude
- Feature engineering via FFT
- Different characteristic frequencies become visible
- Power spectral density (PSD) signal can be used to generated robust features

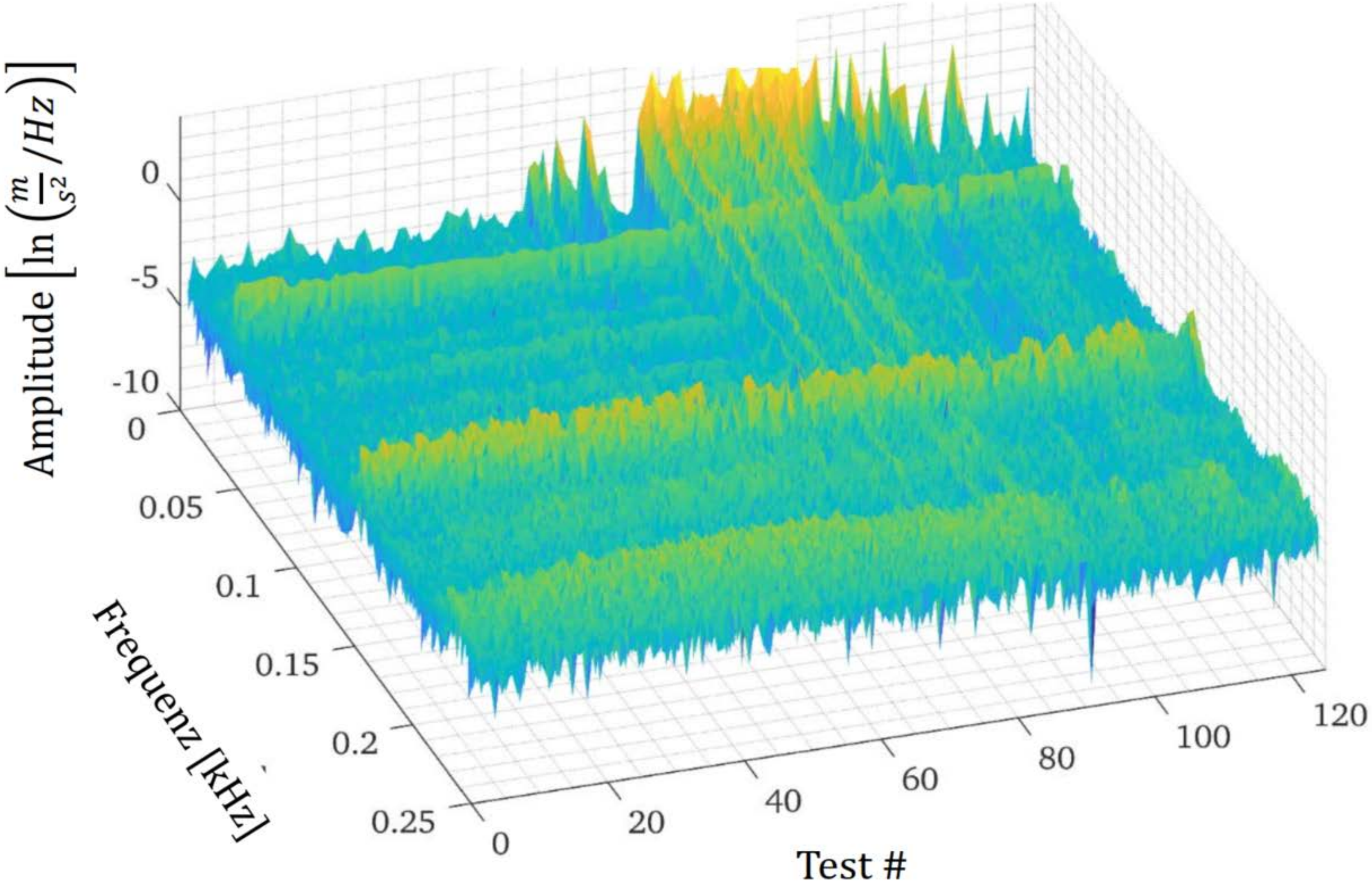


PHM for BLDC motors

Data output and feature generation (2)

Exemplary FFT (research project)

- Accelerated life test of motor + gearbox
- 120 datasets (over time)
- Changes in frequency spectrum clearly visible



Case study for the Quadcruiser’s control surface actuation system

DYNAMIC RELIABILITY ASSESSMENT

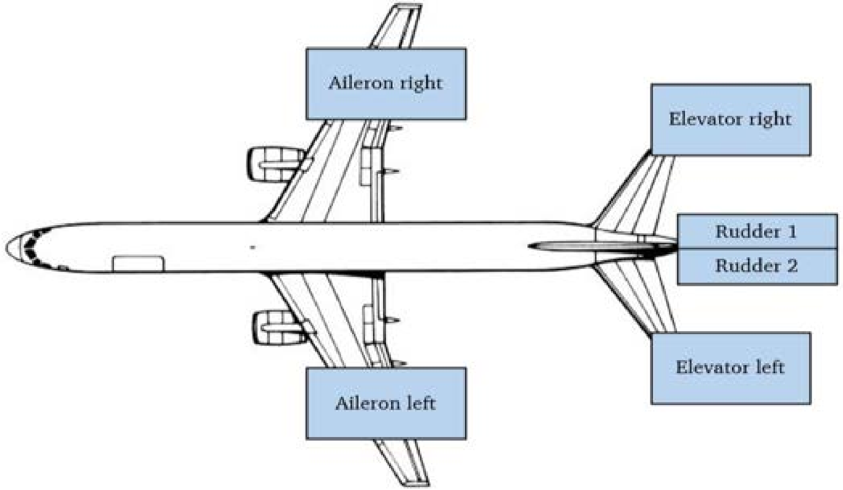
Dynamic reliability assessment
Case study - introduction

Airbus Quadcruiser

- Hybrid unmanned aerial vehicle (UAV)
- Aerodynamic flight + VTOL/hoovering
- Increased safety requirement (certification)
- Idea: Use PHM as decision support + monitoring of the AC control actuation system.

Control surface actuation system

- 6x electromechanical actuator (EMA)
- Redundant setup → 2 actuators per axis
- Different failure severities depending on failure combination



Dynamic reliability assessment

Problem description

1.) **PHM on system level**

"*Most PHM publications focus on the development of algorithms to monitor and estimate the health condition of individual components. However, estimating the Remaining Useful Life (RUL) of complex systems comprising multiple components is a more relevant topic for the industry.*"

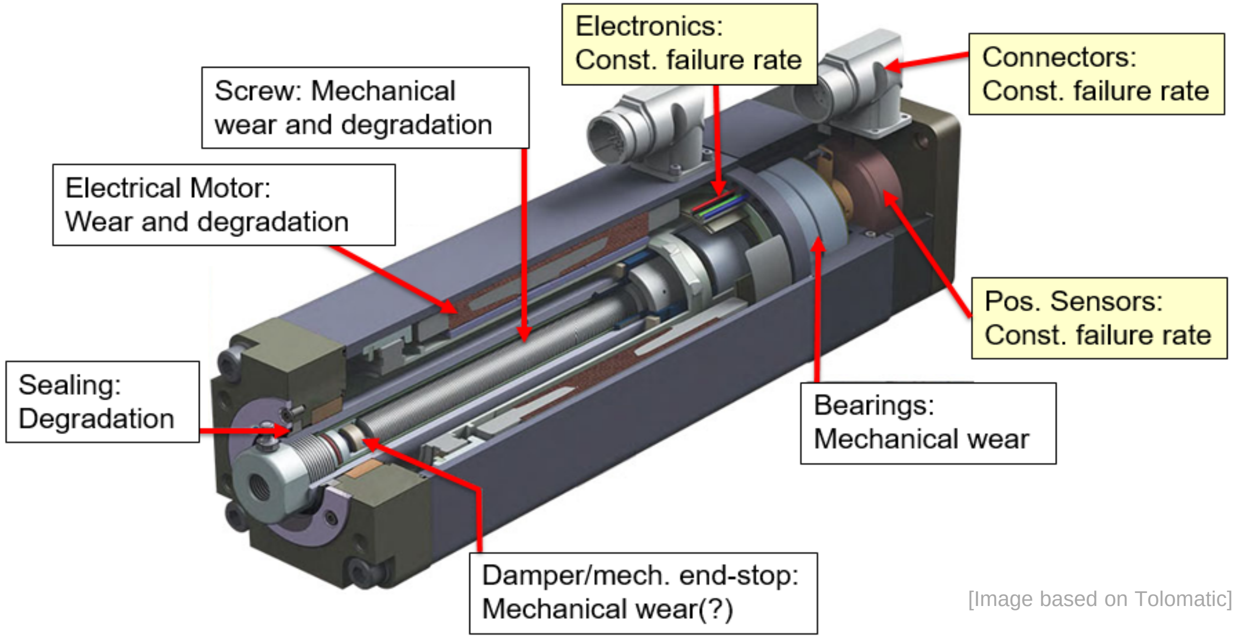
(Leonardo Rodrigues, "*Remaining Useful Life Prediction for Multiple-Component Systems Based on a System-Level Performance Indicator*", June 2017)

2.) **PHM approach not always feasible**

Components are often a composition of multiple parts with <u>different failure characteristics:</u>

a) Random failures (e.g. electronics)

b) Degradation (e.g. mechanical parts)

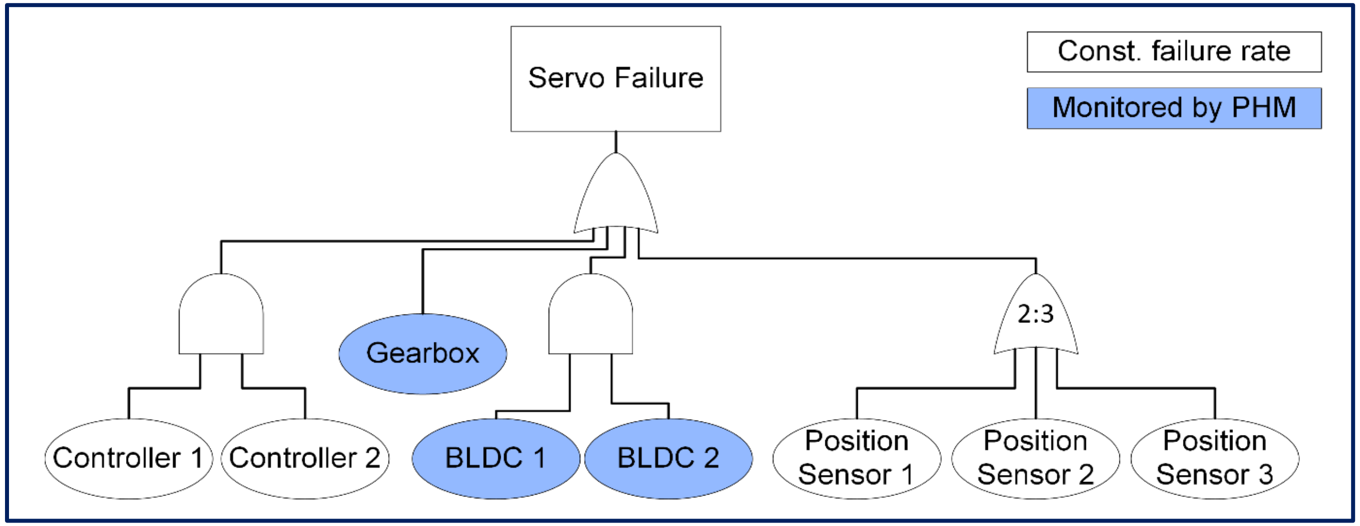


[Image based on Tolomatic]

Dynamic reliability assessment
Case study - introduction

Electromechanical Actuator

- 28VDC with dual brushless motor drive
- Attached gearbox with rotary output
- Rated Torque: 4Nm (135°/sec)
- Stall Torque: 7Nm



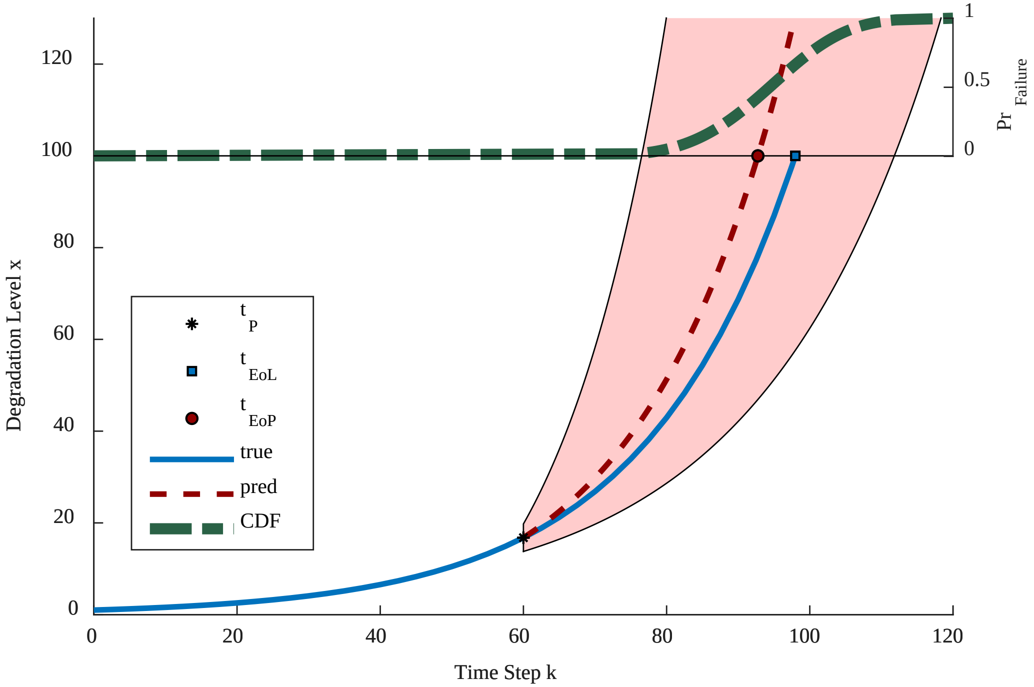
Fault Tree Analysis (FTA)

- Functional decomposition of one actuator
- Mechanical and electronic parts
- Monitoring / PHM foreseen for both BLDCs and the Gearbox

Dynamic reliability assessment

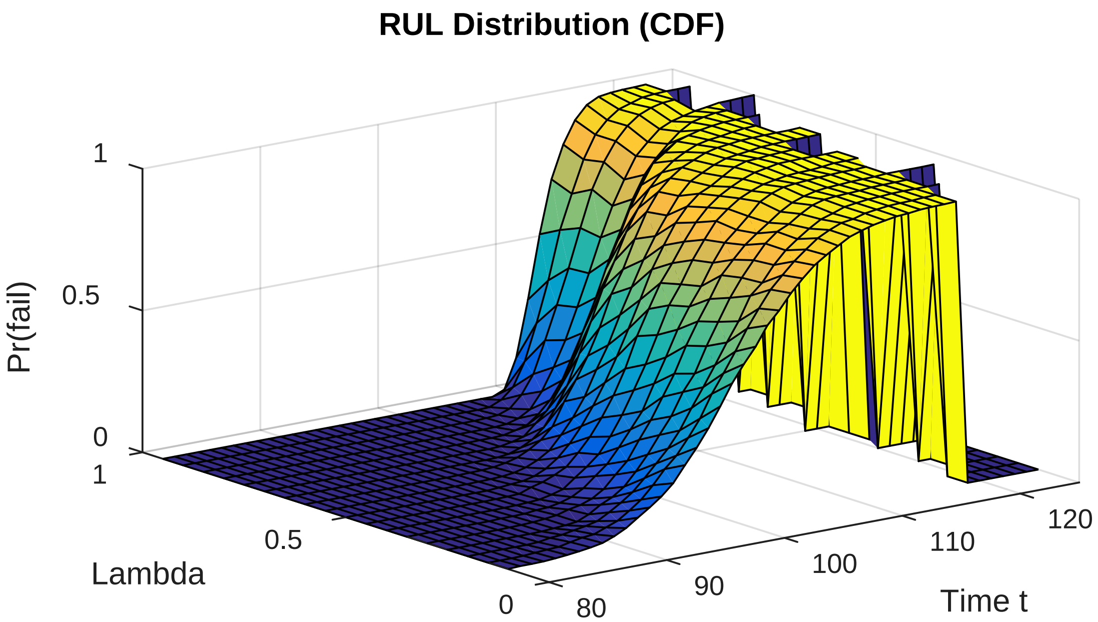
PHM Input Data

- Use the prediction algorithm's uncertainty measure to derive a probability measure (CDF)
- Update this CDF on a frequent basis



Characteristics:

- Only for prediction algorithms with uncertainty bound
- Can lead to a zero failure probability for early intervals
- CDF will change for each prediction



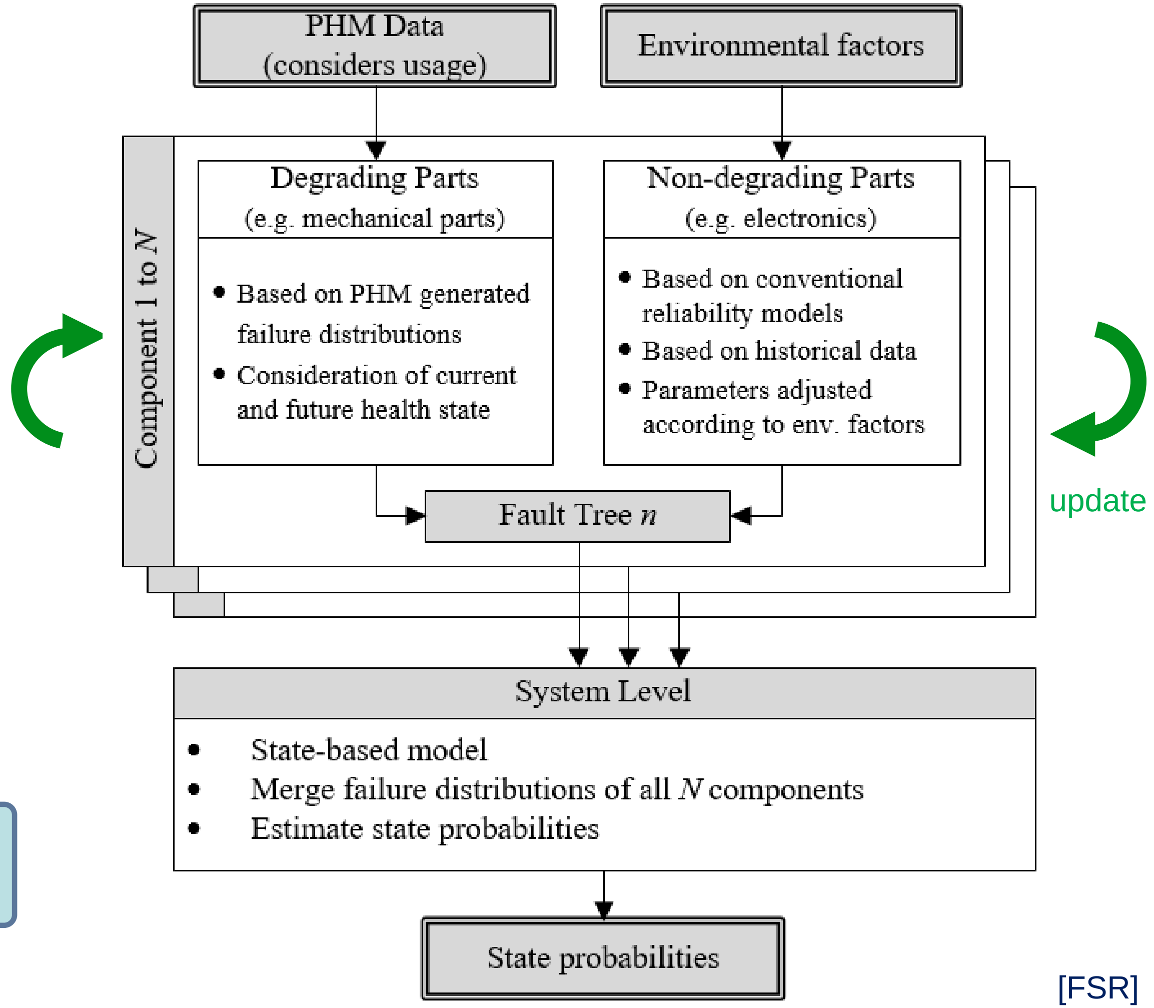
Dynamic reliability assessment

PHM based dynamic reliability model

Hybrid reliability model:

- One Fault Tree for each component (component level)
- Split each component into degrading (→ mechanical) and non-degrading (→ electronic) parts
- Use available PHM data for degrading parts, use life distributions (Exp., Weibull-Dist. etc.) for non-degrading parts
- Aggregate all components in a state-based model (system level)
- Update the model by recalculating it once new data becomes available → dynamic reliability assessment

Model output: Probability (CDF) for each system state (no RULs!)



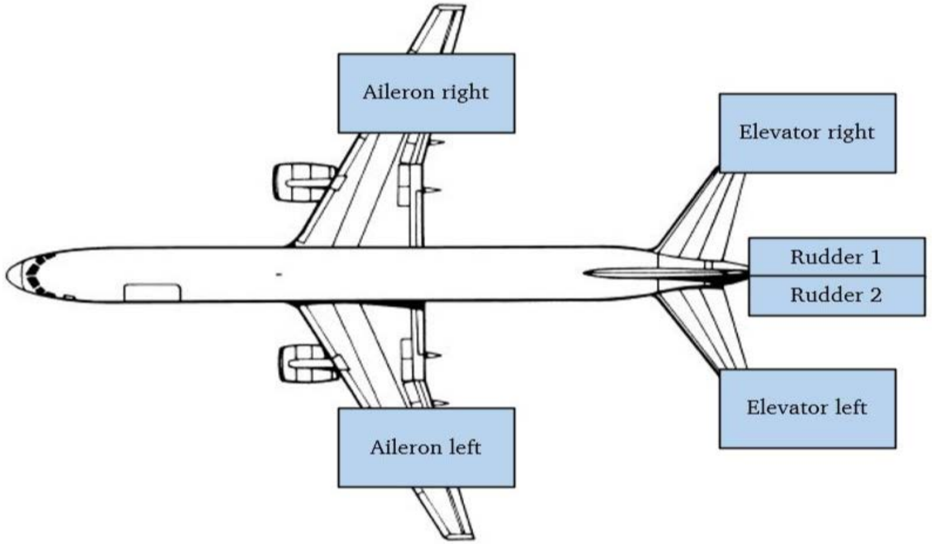
[FSR]

Dynamic reliability assessment

Application to actuation system

- On System-level all EMAs work collaborative, thus multiple states must be considered
- Depending on the overall failure combination different states with different criticalities must be distinguished

Translate system into a state model



State	Failure State	Effect	Criticality
S1	No Failure	Normal Operation	None
S2	1-Axis Degraded	Reduced Perf.	Low
S3	2-Axis Degraded	Reduced Perf.	Medium
S4	3-Axis Degraded	Reduced Perf.	Medium (very unlikely)
S5	Axis-failure	Loss of Control	High

Dynamic reliability assessment

Comparison base-line to PHM model

Scenario 1:

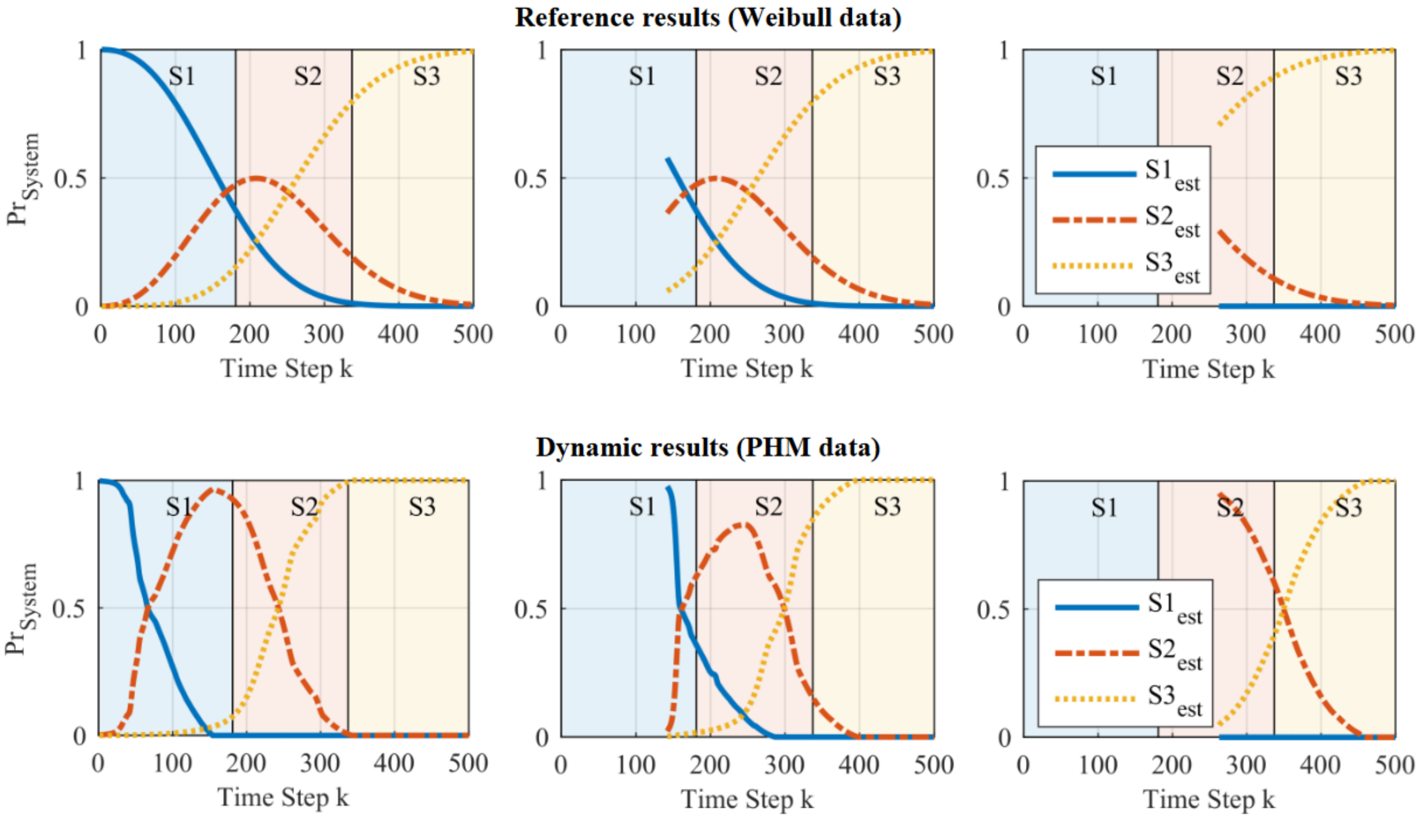
Weibull based CDF instead of PHM data (conventional approach)

- State probabilities remain constant
- Probability for state 2 is max. 50%

Scenario 2:

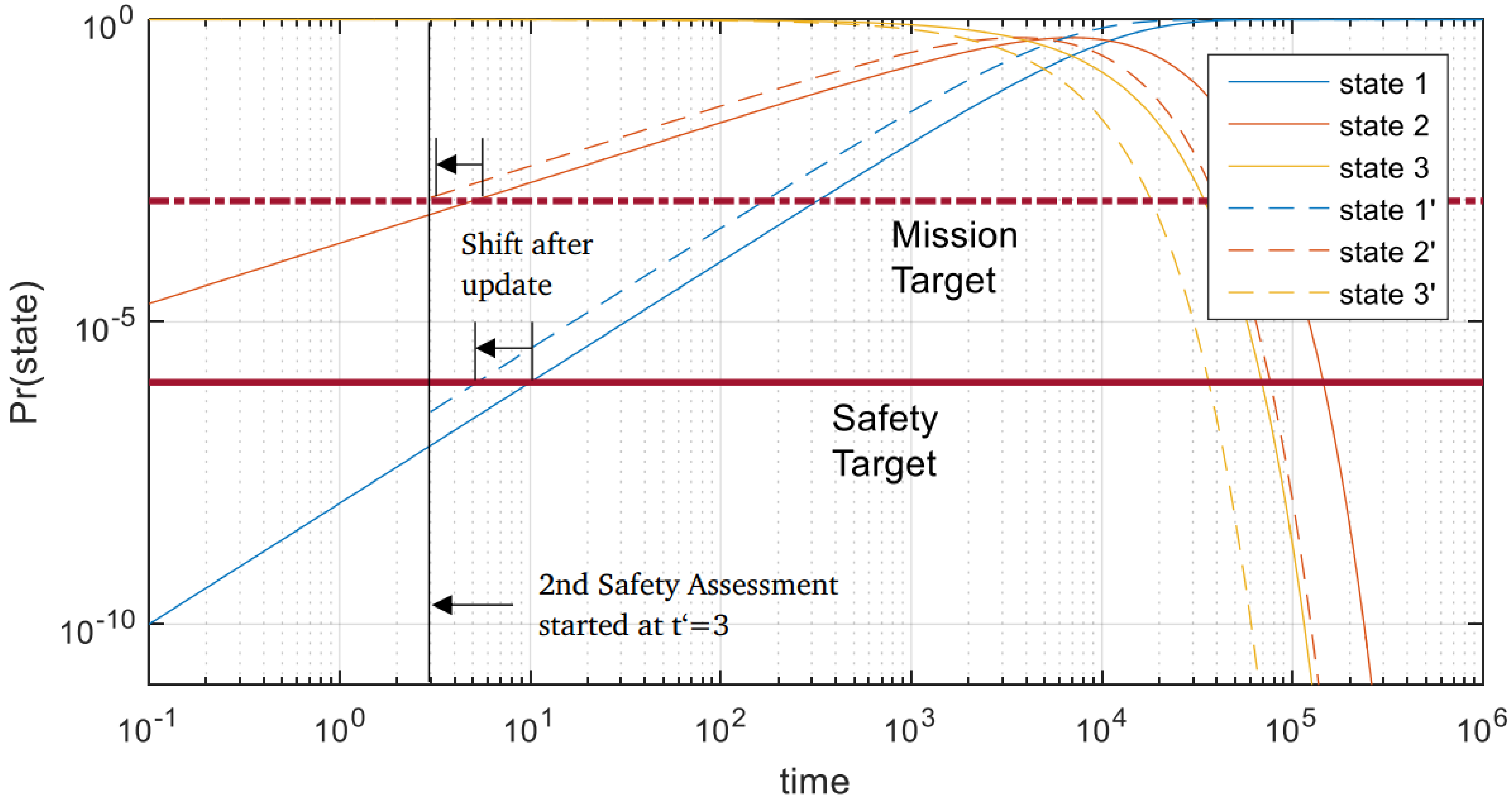
Use PHM results as inputs to model

- State probabilities are adapted according to PHM output
- State 2 is better captured (it is very likely that state 2 will be entered)



Dynamic reliability assessment

Estimated state probabilities

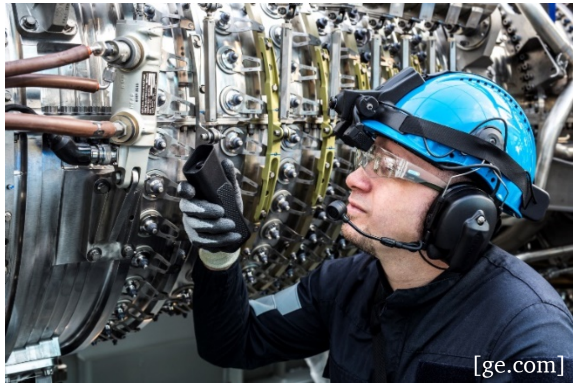


Decision support requires

VISUALIZATION

Visualization

Decision support → Different requirements and scopes



Operator

- Short term decisions
- Intuitive and easy
- Technical depth
  → as low as possible
- Focus: Complete Aircraft
  → System still safe?

Technician

- Time is money
  → as fast as possible
- Technical depth
  → What is wrong / how bad is it
- Focus: Component / unit (Line replaceable units / LRUs)

Organization

- Long term decisions
- High level information on aggregated data
- Focus: Fleet performance

Different requirements → How to choose visualization/representation format?

Visualization
Choosing the right display format (examples – 1)

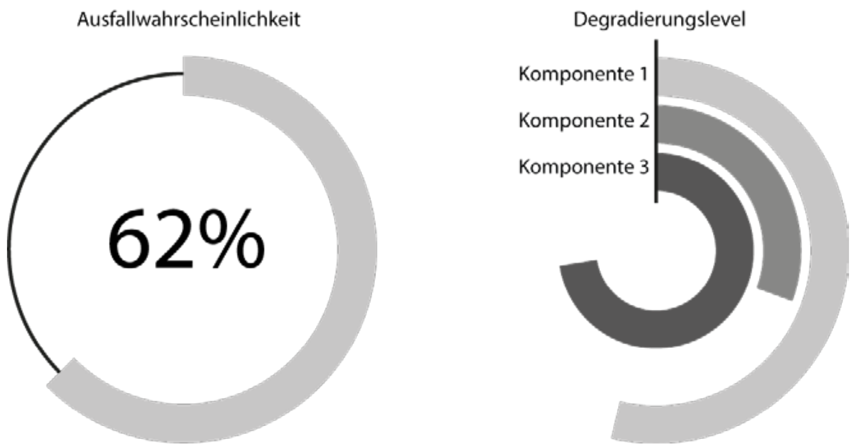
Circular bar chart:

Pro

- Degradation levels as well as default probabilities can be displayed
- Probability of default in % can be displayed similarly

Con

- Degradation level only visible for the current time
- Due to different lengths of the bars, an uneven perception is caused
- Not useful for displaying RUL



Circular bar chart

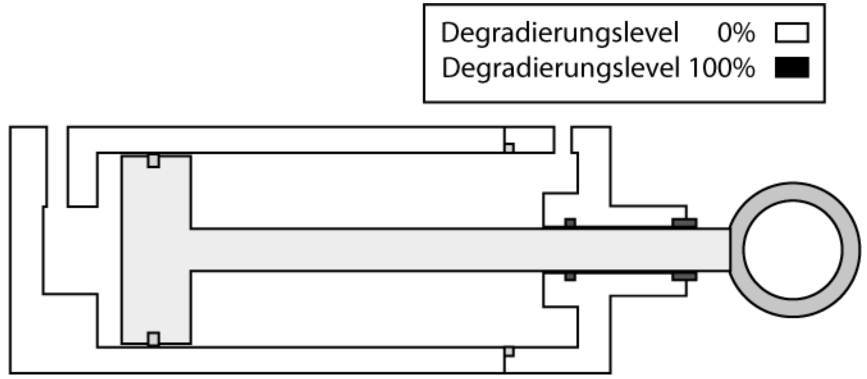
Component Model:

Pro

- Clear association of the data to the components
- Values in % can be visualized

Con

- Degradation level only visible for the current time
- High visualization generation effort



Model (simplified representation)

[FSR]

Visualization

Choosing the right display format (examples – 2)

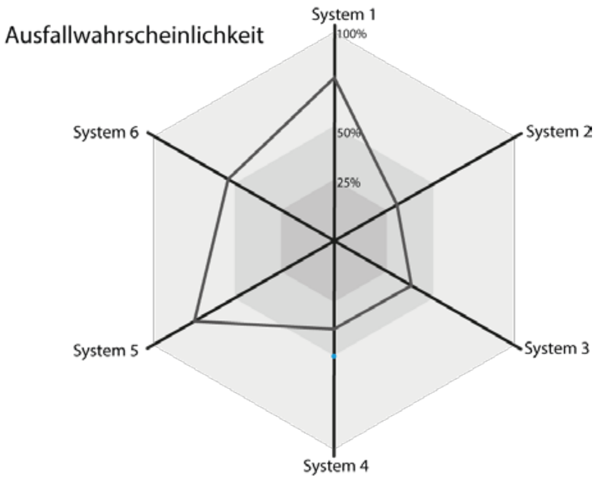
Network diagram:

Pro

- Large number of systems and components can be displayed
- Degradation levels as well as default probabilities can be displayed
- Each system has it’s own scaling

Con

- Only for normalized data, not useful for displaying RUL
- Comparability is difficult due to the round arrangement of the scales around the center point



Network diagram

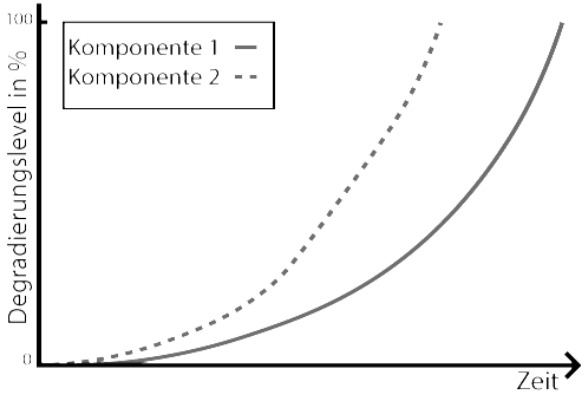
Line chart:

Pro

- Displays historical data, shows trends
- Allows combining prognosis and diagnosis data

Con

- Visualizations are getting confusing with an increasing number of components or systems



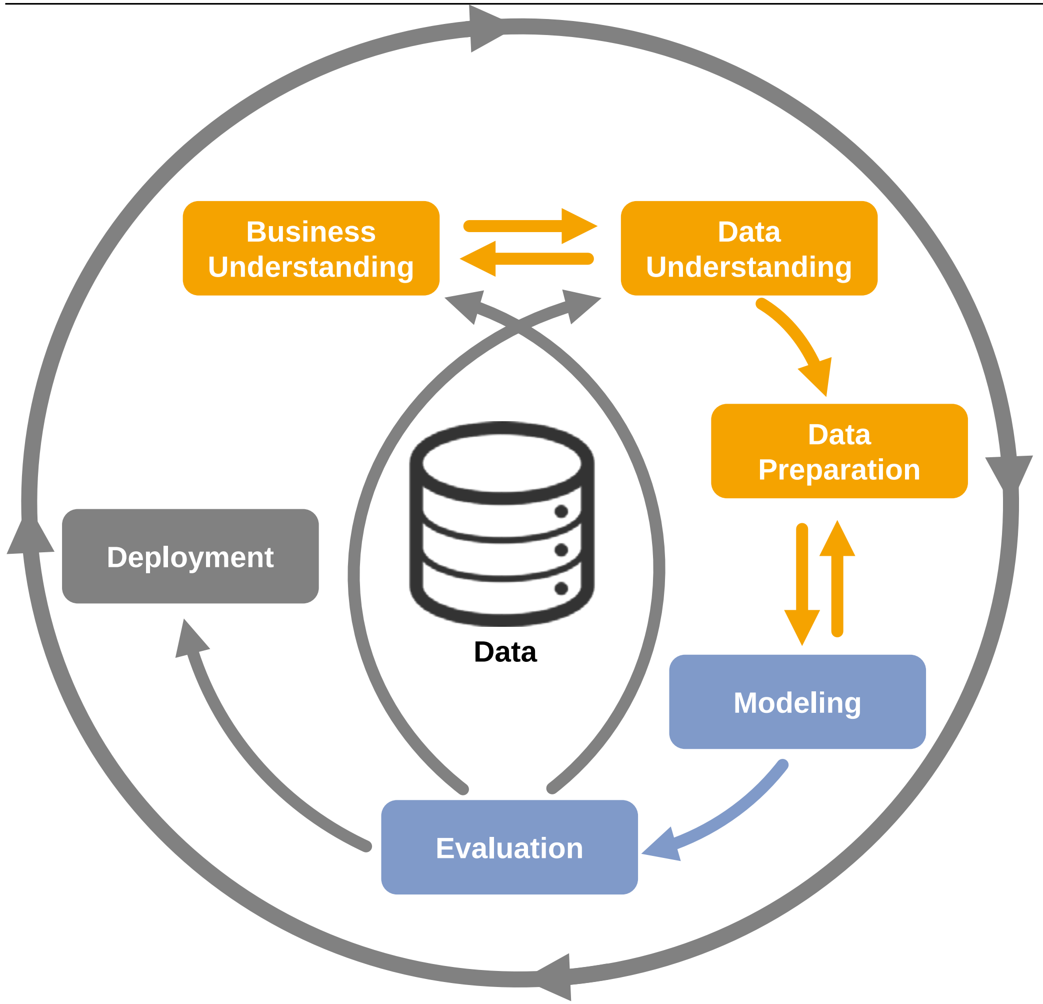
Line chart

[FSR]

REALIZATION

Realization

Towards deployment…



… as we are getting closer towards deployment, IT solutions become necessary…

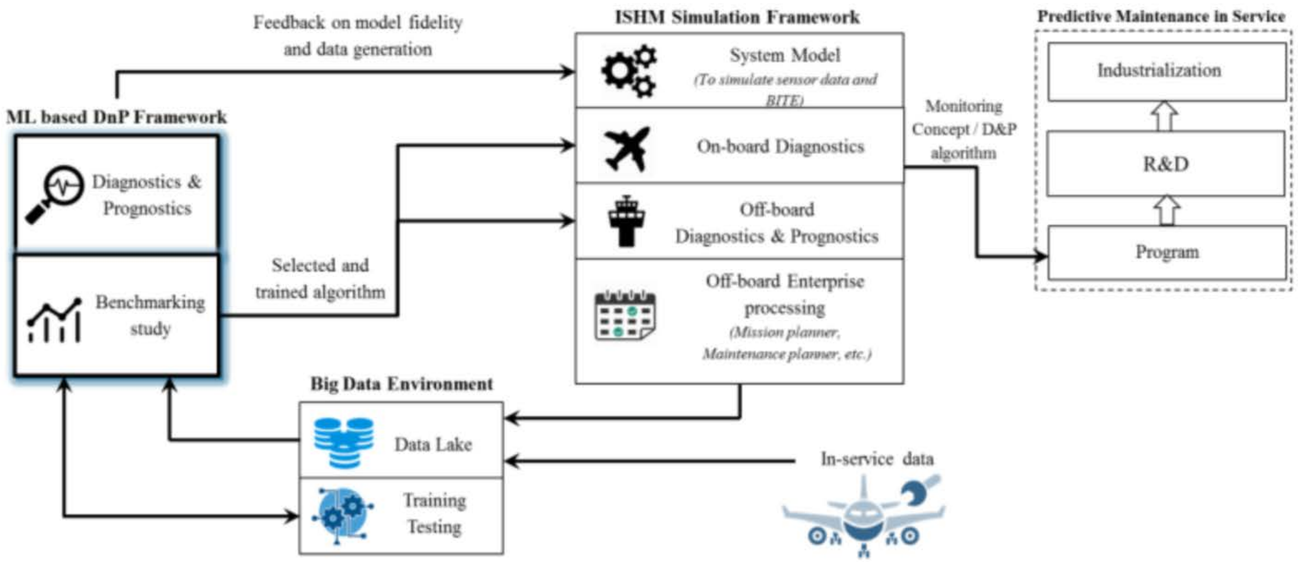
Challenges

- Data flow (especially for large and distributed systems)
- Data consolidation and aggregation
- Hardware resources
  - Limited Bandwidth
  - Limited Processing Power
  - Limited Storage Power

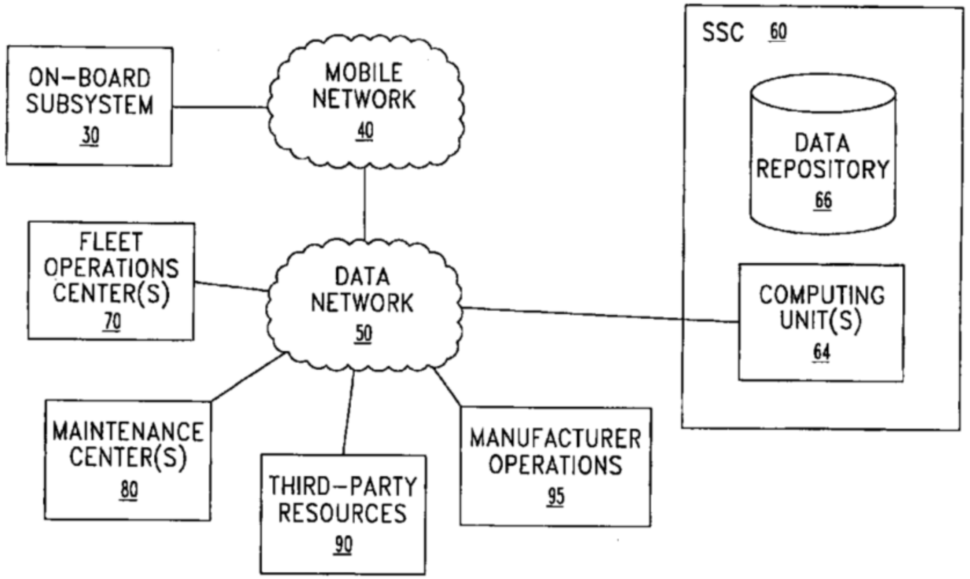
Sources: https://www.ibm.com/support/knowledgecenter/en/SS3RA7_15.0.0/com.ibm.spss.crispdm.help/crisp_deployment_phase.htm | https://www.sv-europe.com/crisp-dm-methodology/#modeling

Realization

PHM architectures in literature (selected examples)



[Adhikari, 2018]



[Wilson, 2004]

Realization challenges

- No general solution…
- However, similar entities (data storage, networks, computing units)

Realization

Data & AI Landscape 2019

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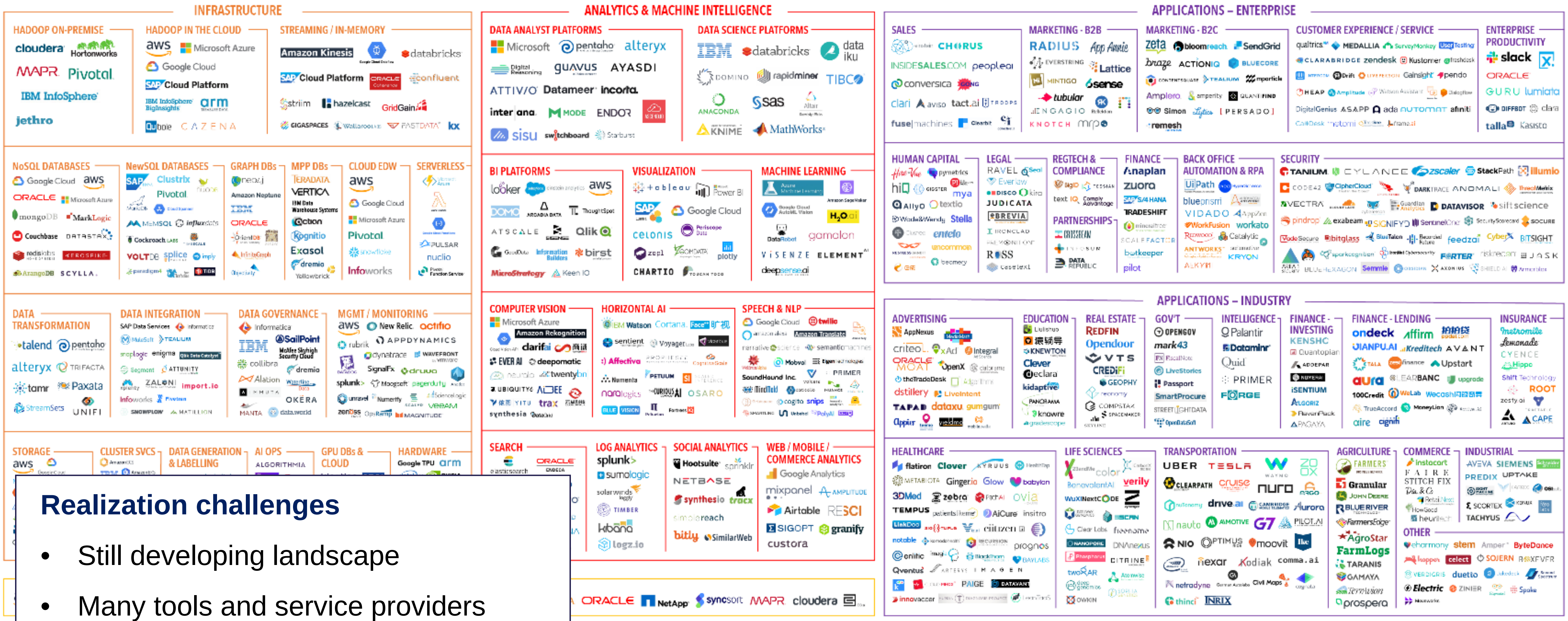

Realization challenges

- Still developing landscape
- Many tools and service providers

[mattturck.com]

Realization

Conclusions…

- as we come closer towards deployment, algorithms and ML solutions might be integrated into existing systems
- There are many technical solutions especially from the IoT domain
- There is no one-fits-all solution, chosen technologies and implementation will result from requirements and existing eco system

→ Be careful, many solutions advertise with “predictive maintenance”, however there are sometimes large differences

[aisoma.de]

SUMMARY AND CONCLUSIONS

Key Findings

- The efficient operation of complex systems can be challenging due to many interactions and uncertainties
- Machine learning and prognostics can be used to support the decision making process for operators via an automated processing of onboard data
- Different aspects (safety / reliability / logistics / operations etc.) can be addressed, **BUT** system knowledge is required (→ bring in your engineering skill-set)
- PHM/ML for complex systems can/will run on different levels
  - Decision support for different user groups → different visualization tools required
  - Different system levels require multiple interacting hard- and software tools to merge and process data (IOT/cloud etc.)

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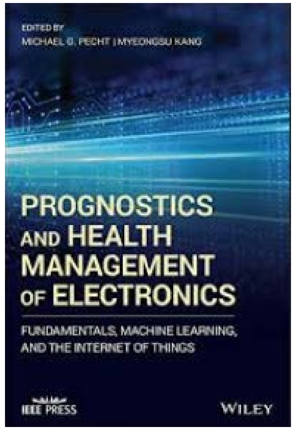

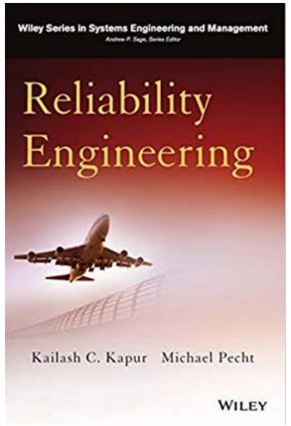

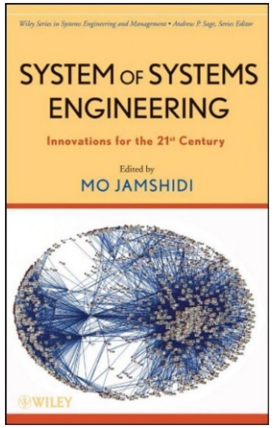

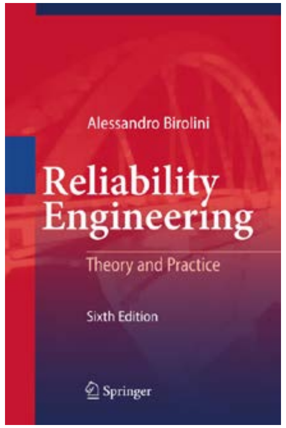


THANK U