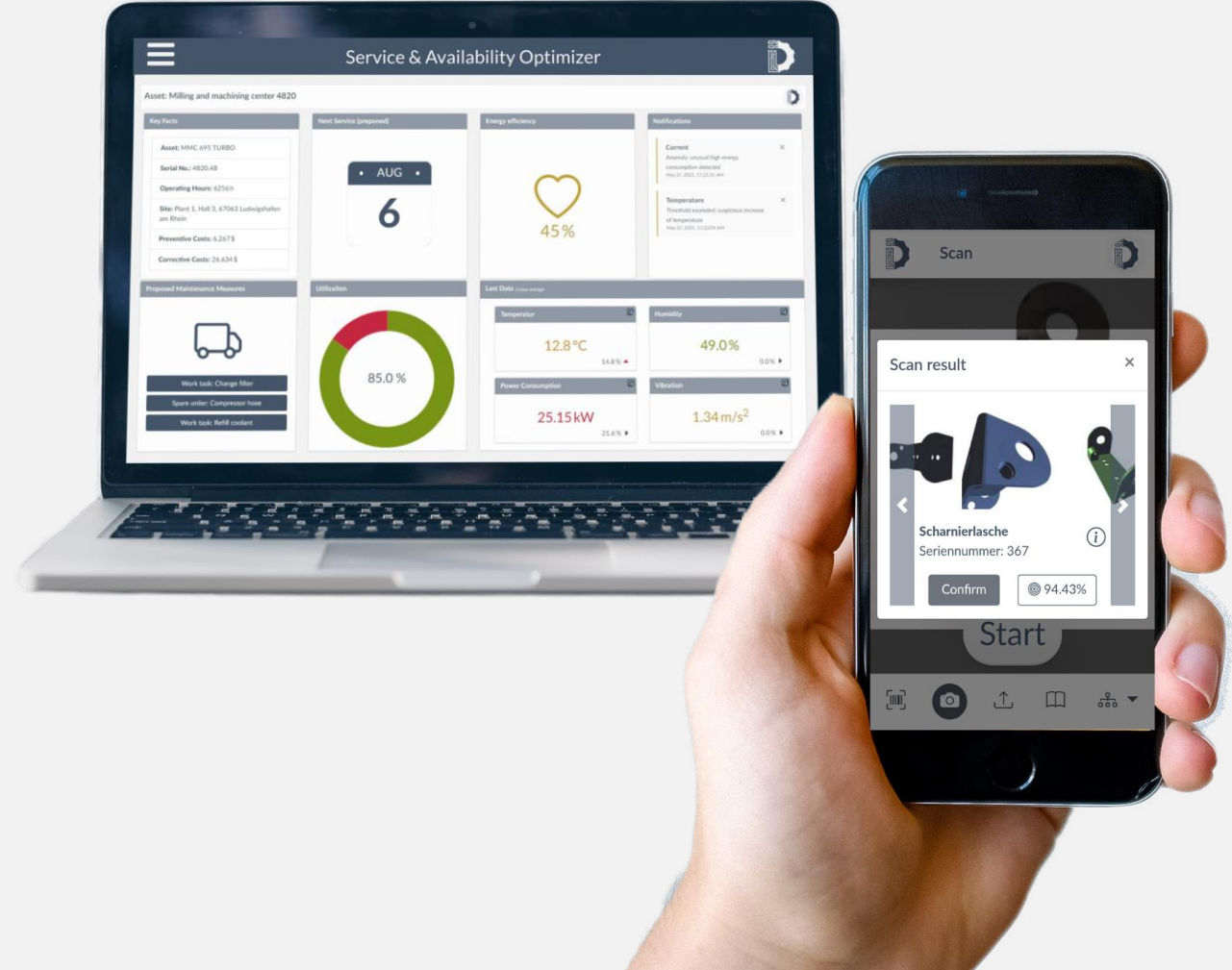# DATAbility.ai

Engineering know-how meets artificial intelligence.

Solutions for predictive operation and service automation
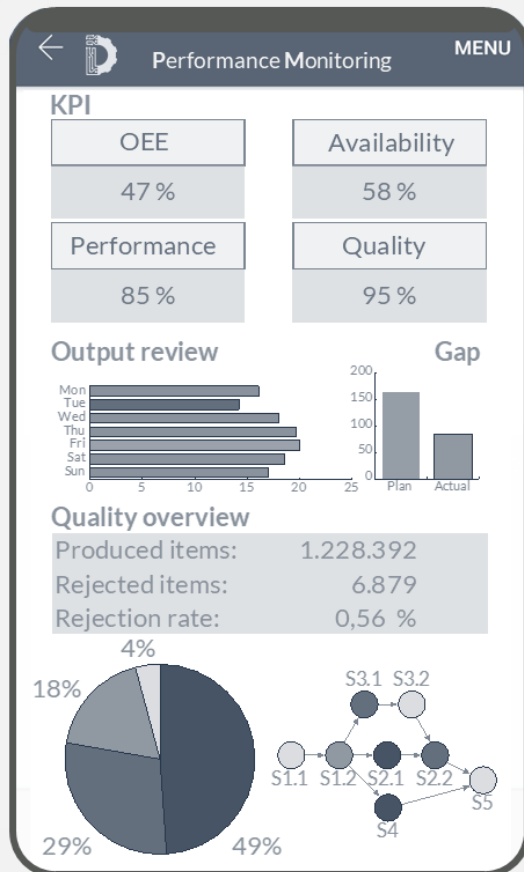
DATAbility´s vision: Enabling a seamless human-machine collaboration!

We support your team-up: Get clear insights and recommendations.

System analytics

Condition monitoring and maintenance planning

Spare & troubleshoot support

Meet our core: (PhD) engineers approaching downtime with strategy & AI!

Sebastian Baumann

MD & Founder

Uwe Klingauf

Advisor & Founder
Prof. Dr.-Ing.

Christian Preusche

TD & Founder

Simon Mehringskötter

Anett Horváth

DB · DB Cargo · EWIKON · DUNLOP TECH GmbH · PFALZWERKE Pfalzwerke Gruppe · SCHEIDT&BACHMANN · ZK simply genius · HÜBNER · MAN · KRONE · entega · vodafone

Evolution: The job profile of an engineer is changing!

Technical domain

Digital capabilities & tools

Conventional methods & principles

Mediator:
Programming / Computer
Science
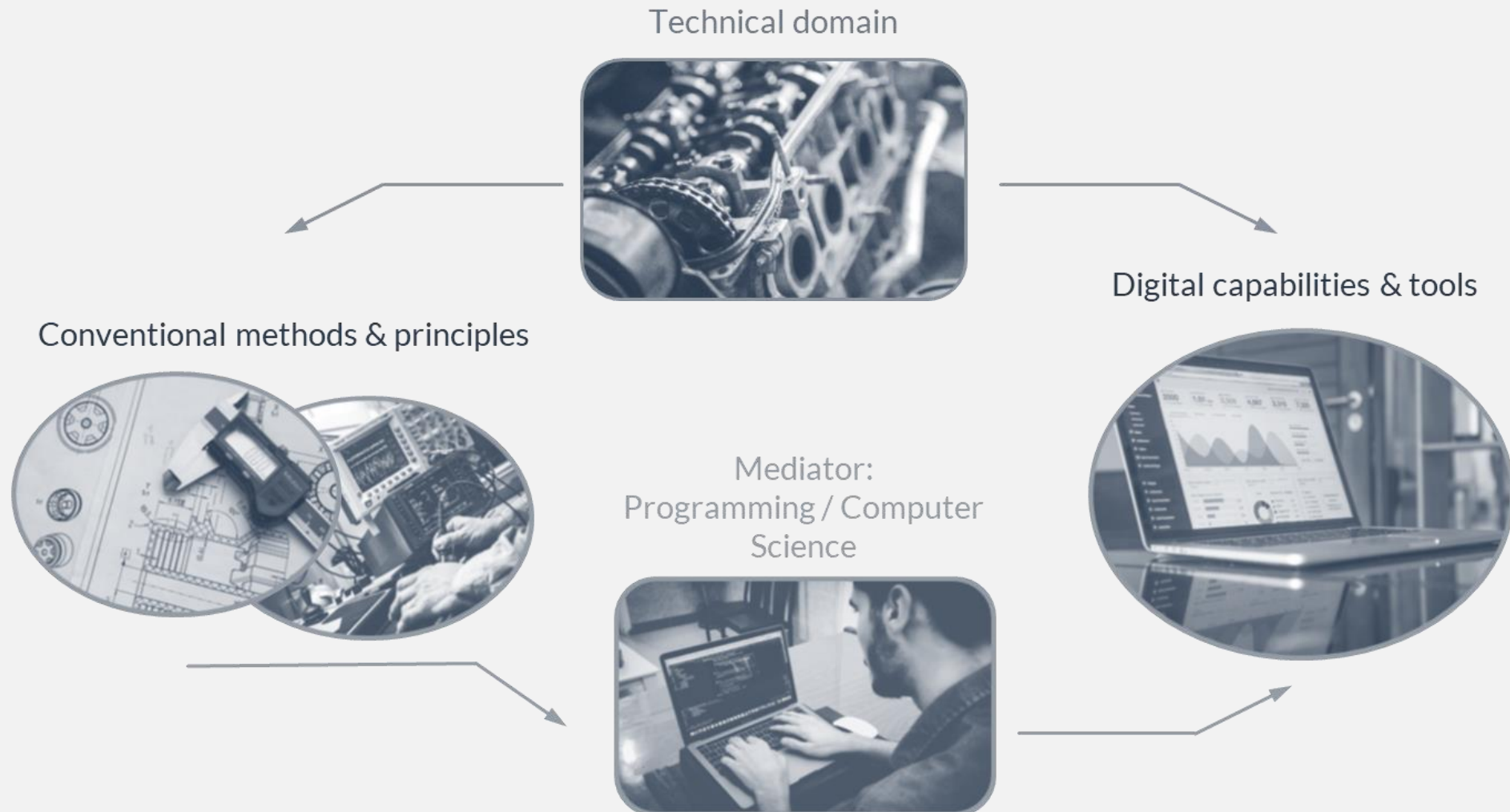
Challenge: Downtimes are cost-intensive and workflows are laborious!

Logistics

Production

Mobility

Reactivity on site causes...

...manual efforts and unavailability...

... which leads to an efficiency gap of 20%!

Cross-industry affects? Yes, it is omnipresent!
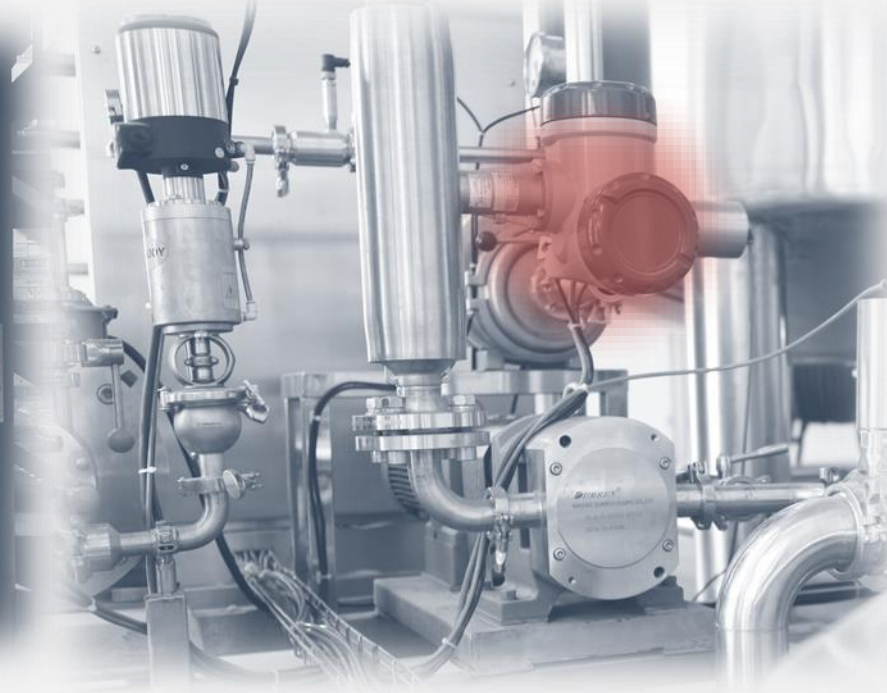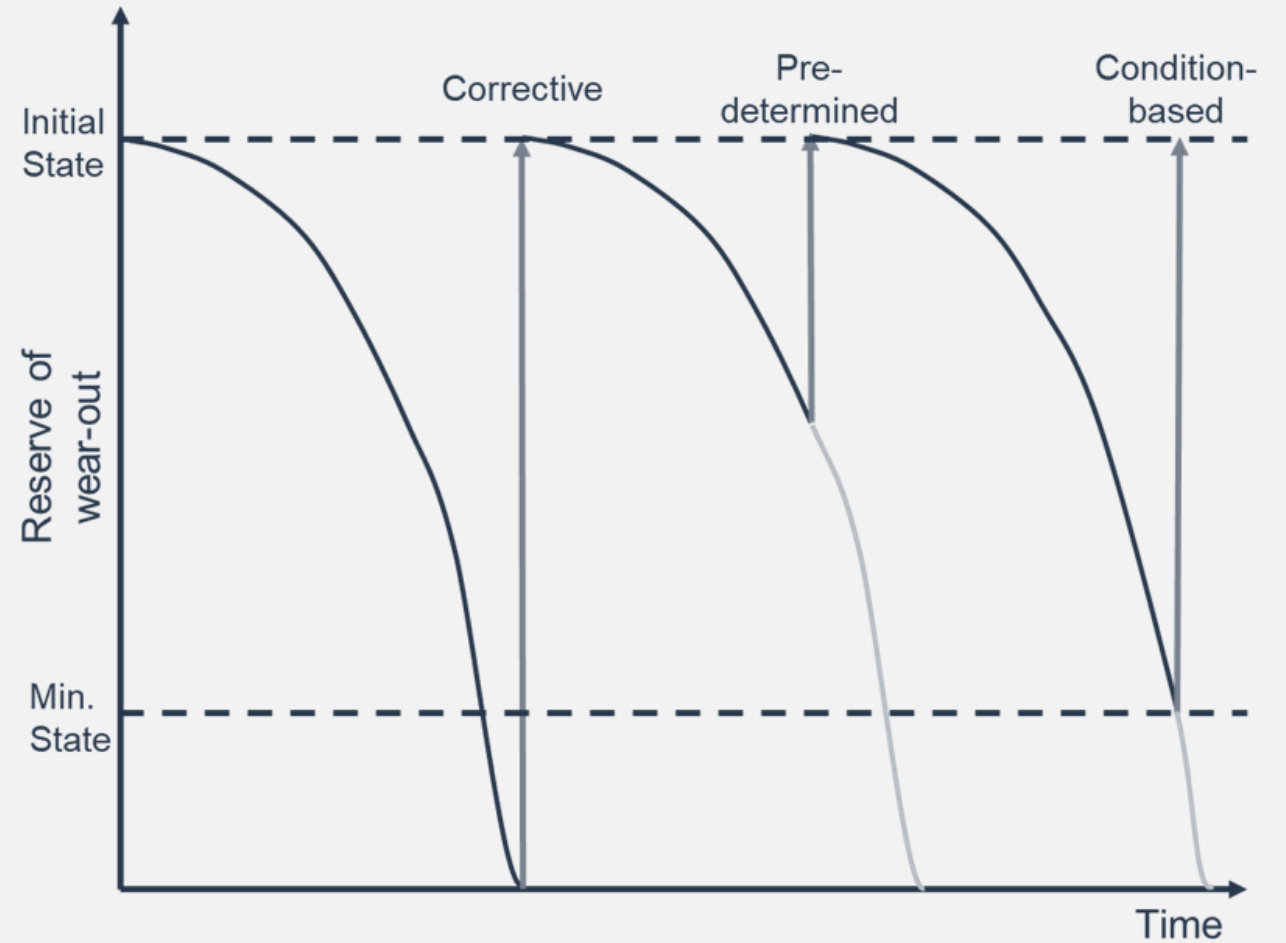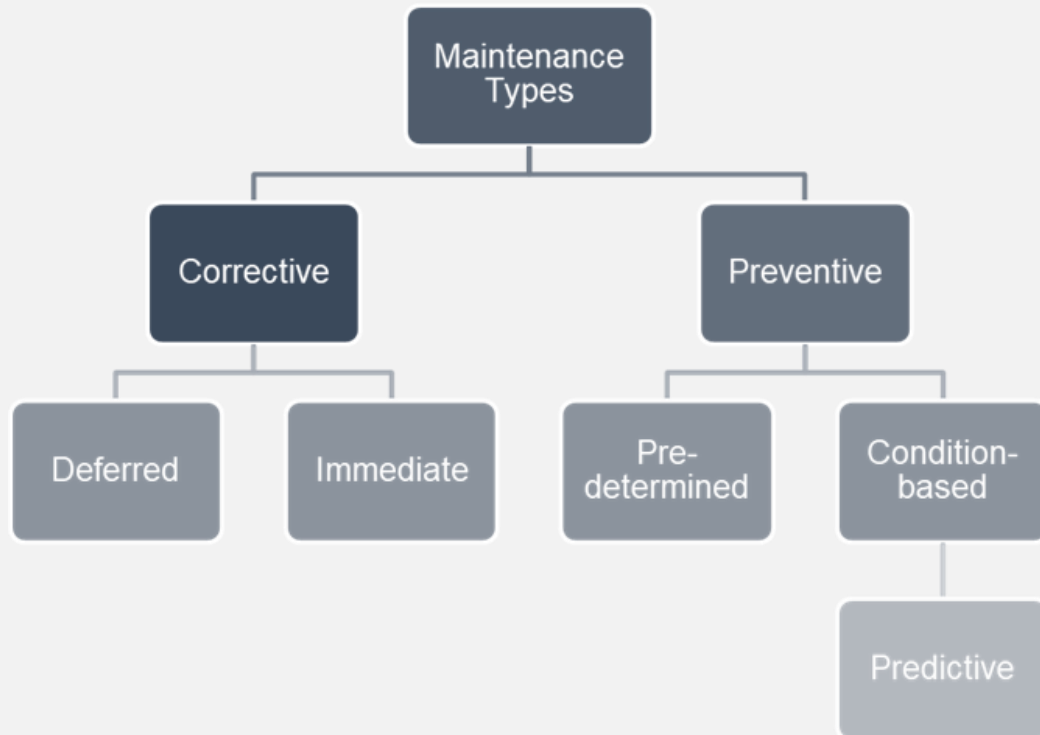
Predictive maintenance: It´s all about interpretation & prevention!

Current gaps: Workflows are manual, laborious and inefficient!

Operators

Service agents

Responsibles
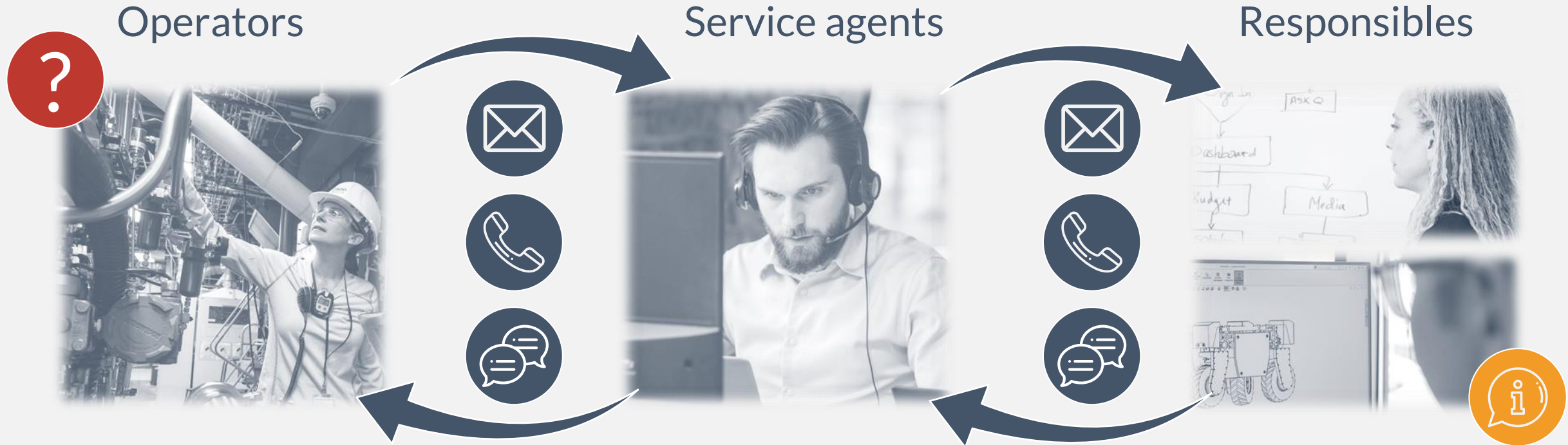
ML & AI capability: Taking manual efforts to automation!

Operators

Service agents

Responsibles
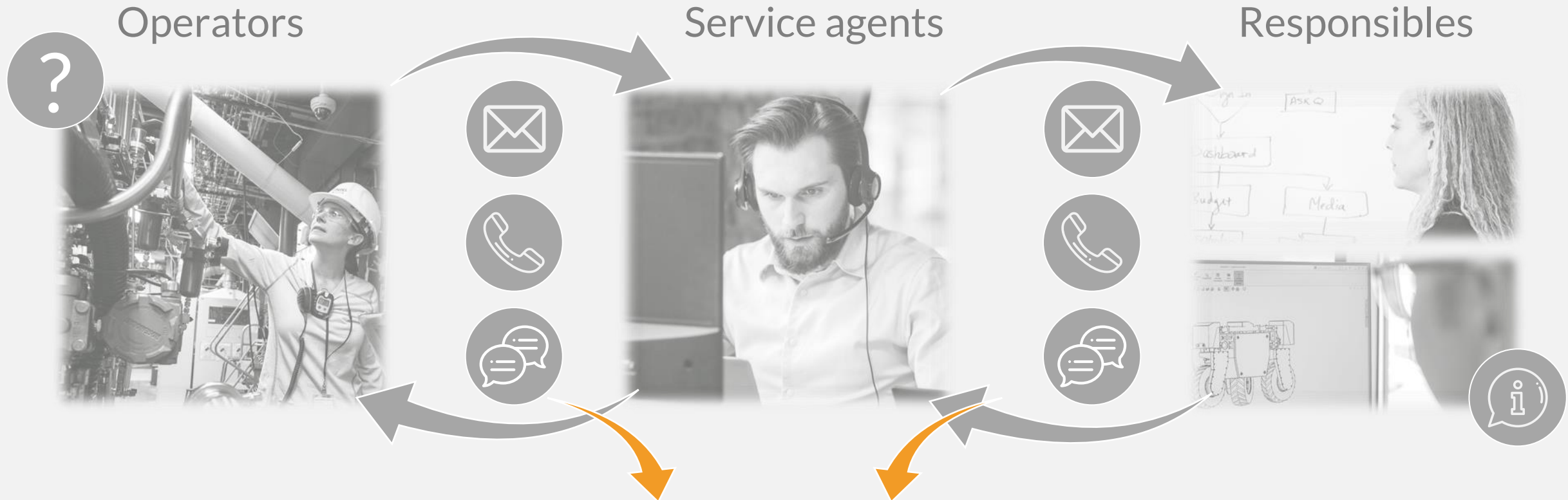
✓ **Shorten process times by more than 95 %.**

✓ **Increase availability & cut SLA penalties by more than half.**

✓ **Reduce workload and scale service quality.**

Our strategy: We merge data, engineering methods & AI algorithms!

Explainability

AI

Expert knowledge & Engineering methods
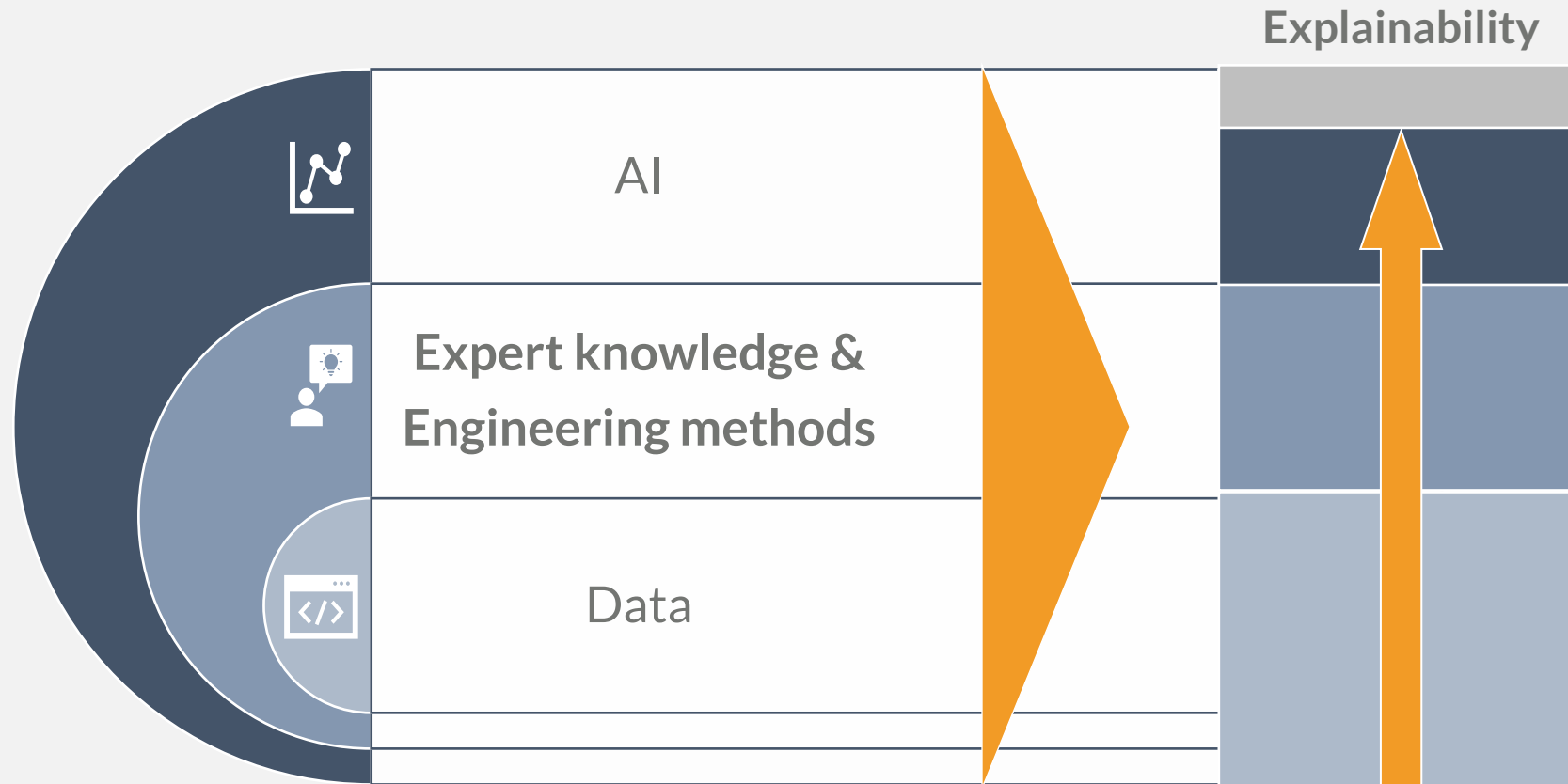
Data

Benefits: Data-based strategies are gaining popularity for replicating complex systems.
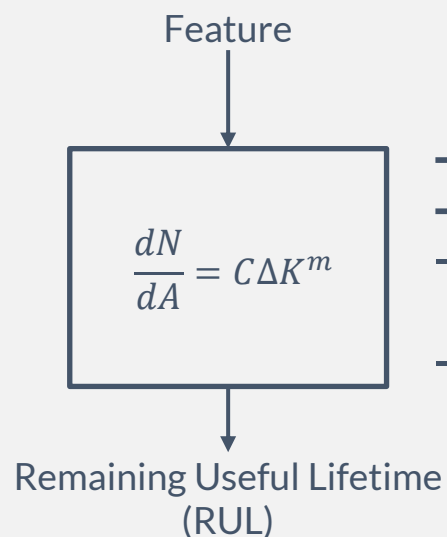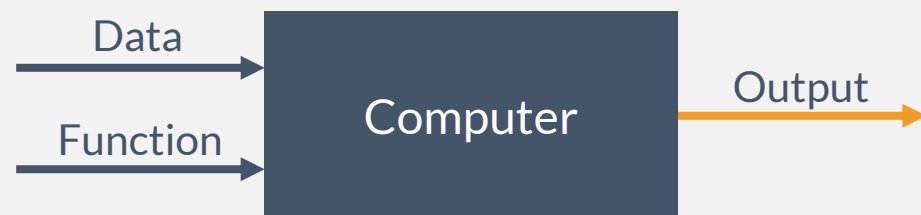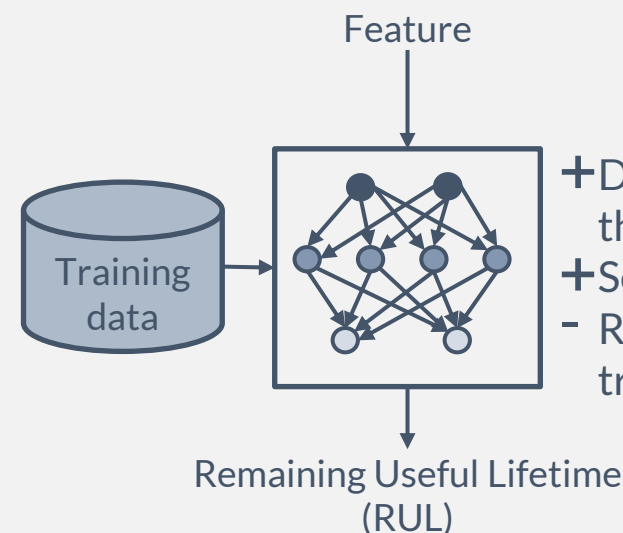
Physical / analytical models
(white-box)

Data-based / Iteratively learned models
(grey/black-box)

Data → Computer → Output

Function →

Feature

$$\frac{dN}{dA} = C\Delta K^m$$

+ Traceability
+ Stability verification
− Deep domain knowledge necessary
− High effort / high model complexity

Remaining Useful Lifetime
(RUL)

Data → Computer → Function

Output →

Feature
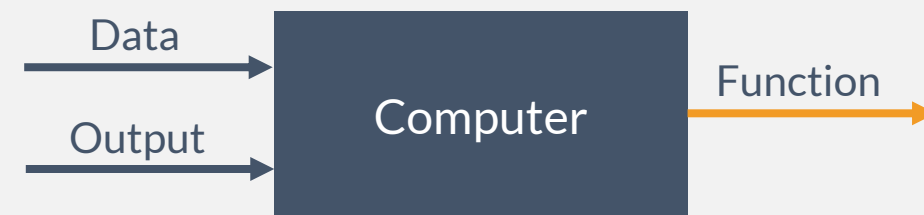
Training data

+ Data availability increases through digitalisation
+ Self-learning algorithms
− Requires meaningful training data

Remaining Useful Lifetime
(RUL)

Lessons learned: Data must be enriched!

Investment Trade-Off

Costs

Cost optimum

Data quality

Optimization
- Acquisition
- Preprocessing

Securing
- Auditing
- Self-testing
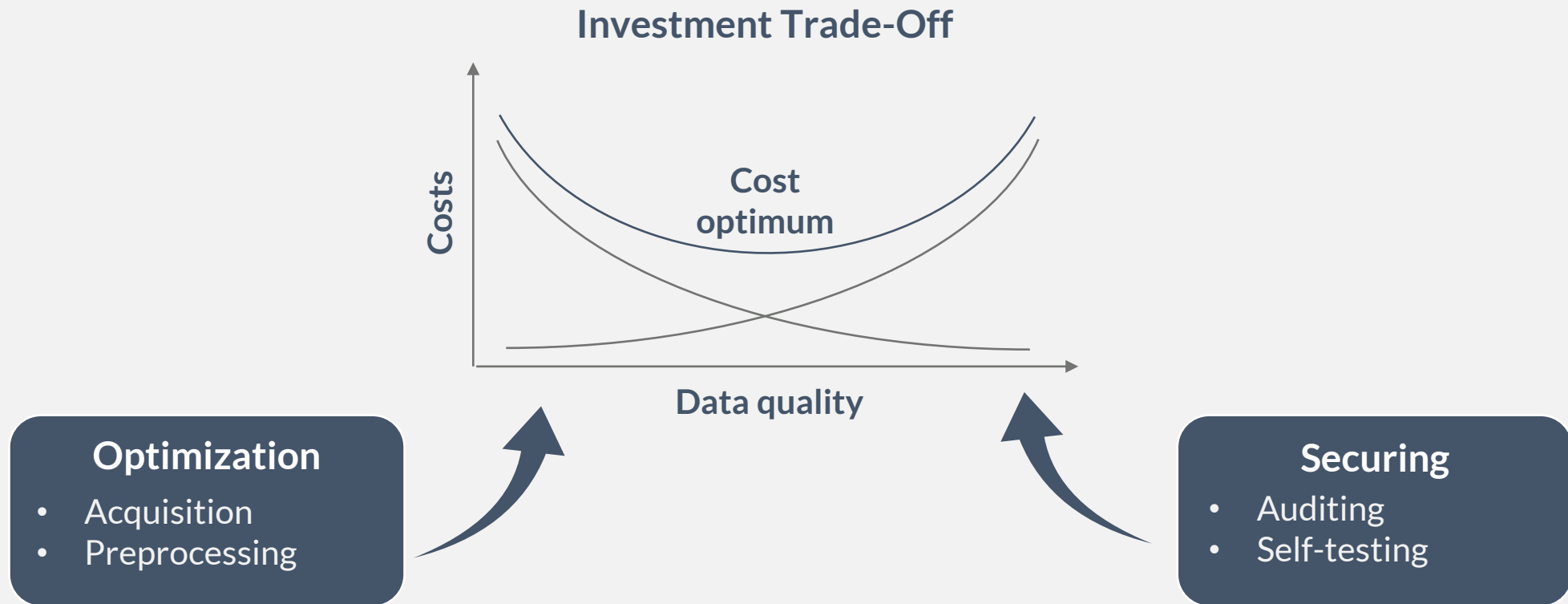
Lessons learned: Established methods & principles must be included!

Data ❯ Value ❯ Quality ❯ Trust

GET AN IDEA

Common case: Bearings, coupling, gearbox are frequent error sources.

Damage → **Bearing** — Misalignment → **Rotor/Stator** — Imbalance → **Downtime**
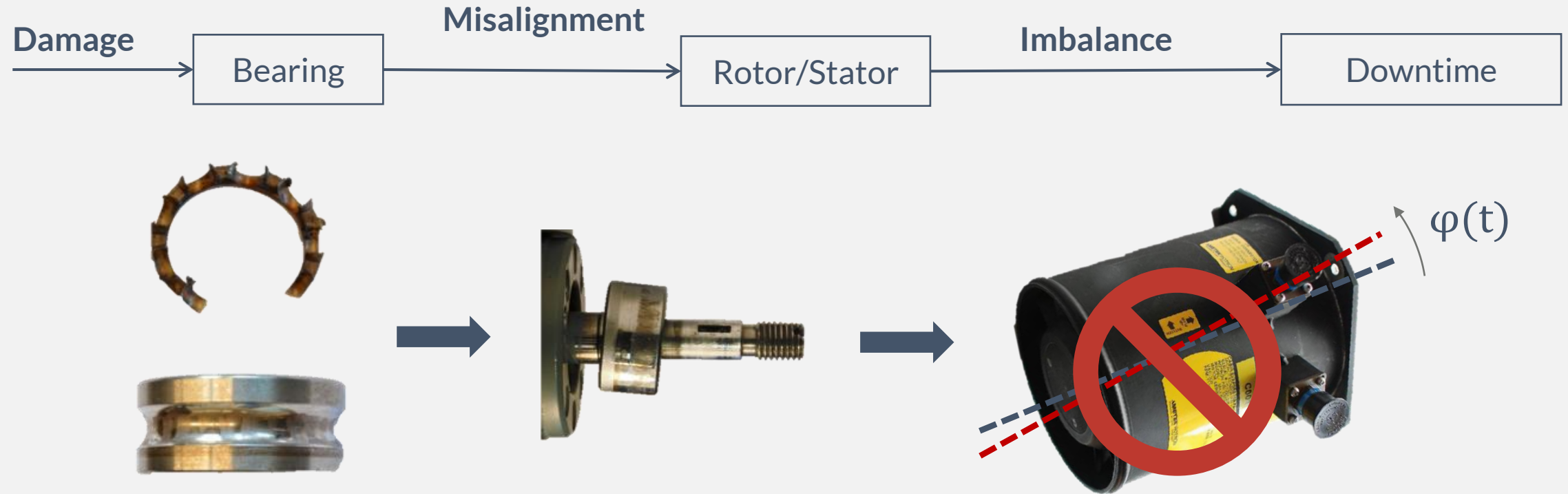
$\varphi(t)$
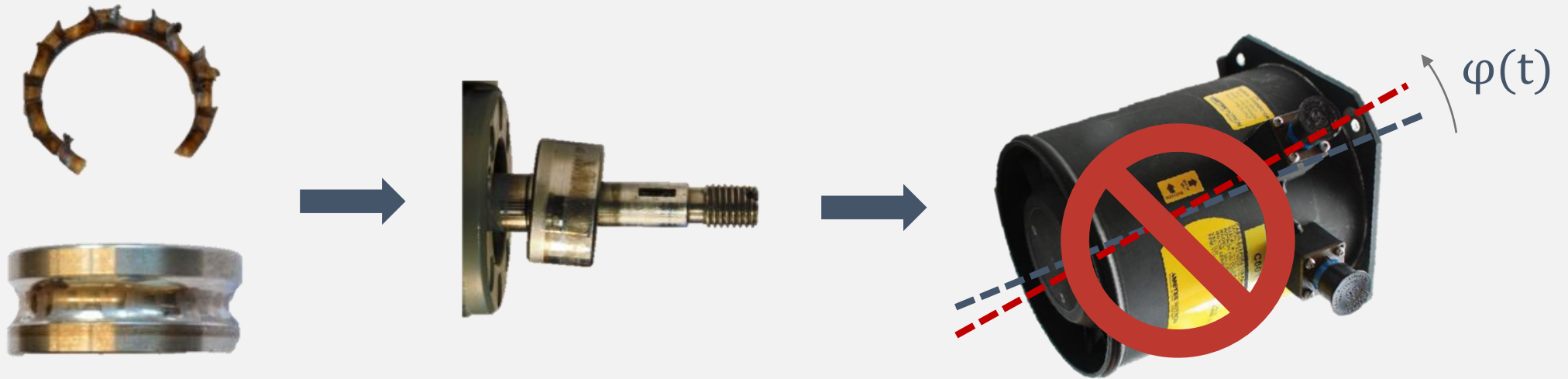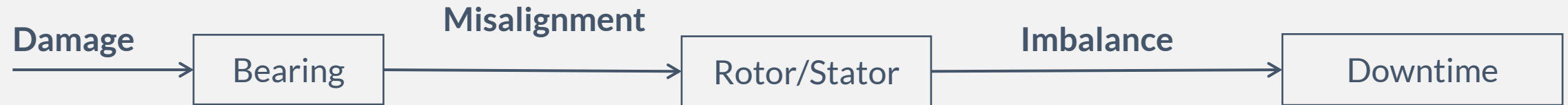
🚫 **Conditions can only be determined by visual inspections.**

🚫 **Disassembly is time-consuming and requires field service.**

Common case: Bearings, coupling, gearbox are frequent error sources.

Damage → Bearing → **Misalignment** → Rotor/Stator → **Imbalance** → Downtime
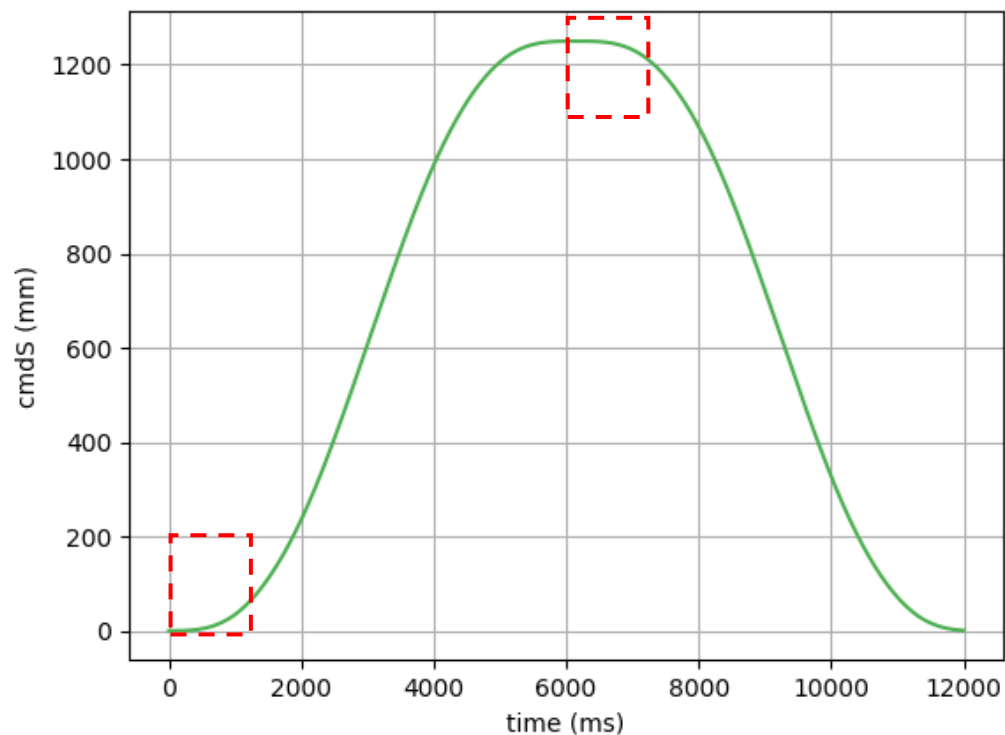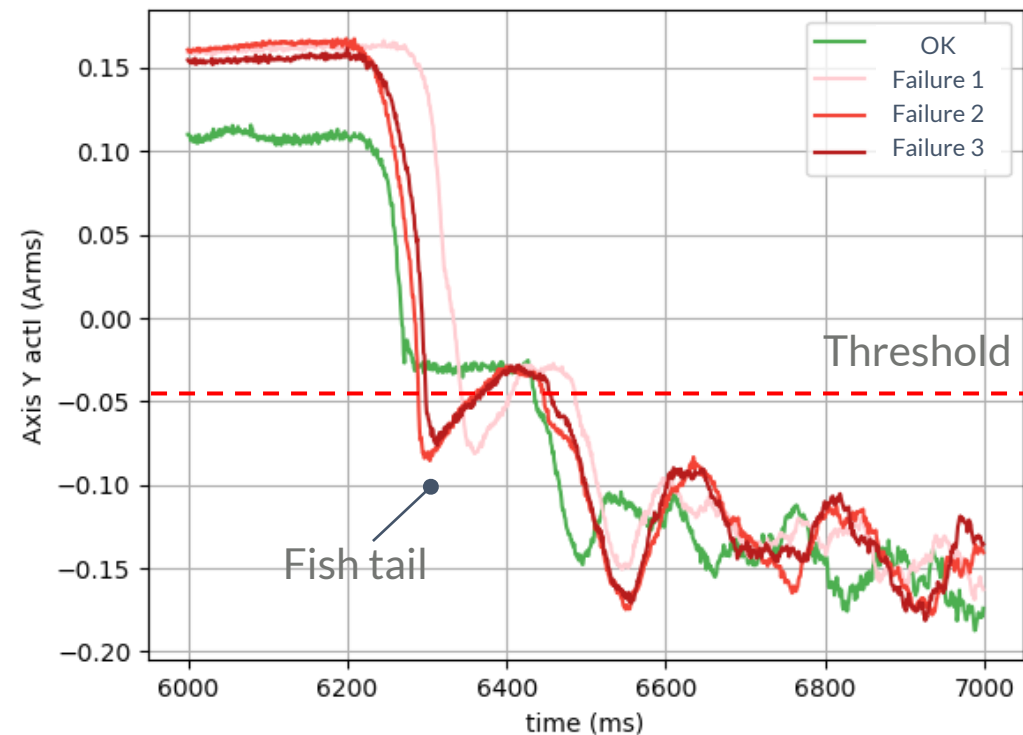
$\varphi(t)$

Possible strategies

- Make components more intelligent using (more) sensor technology
- **Intelligent use of existing information**

Example: Failures in operation are not always easy to identify. Digitization pays off!
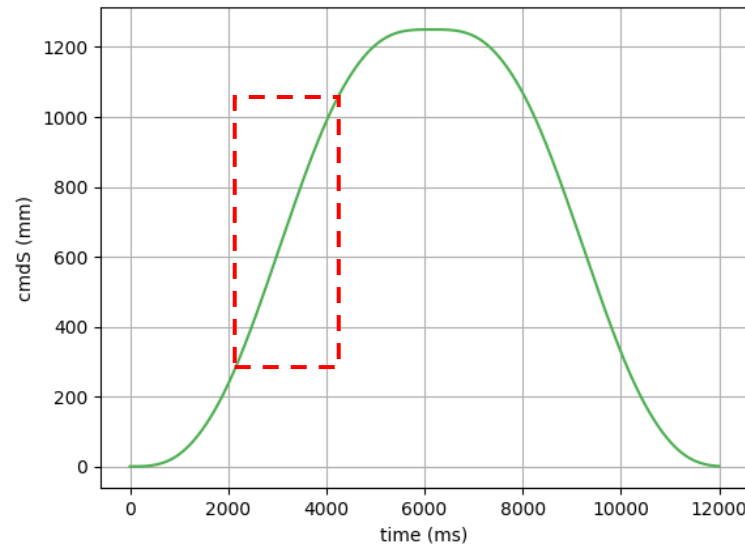

Start of a system movement (commanded position)

Measured signal of the movement (current)

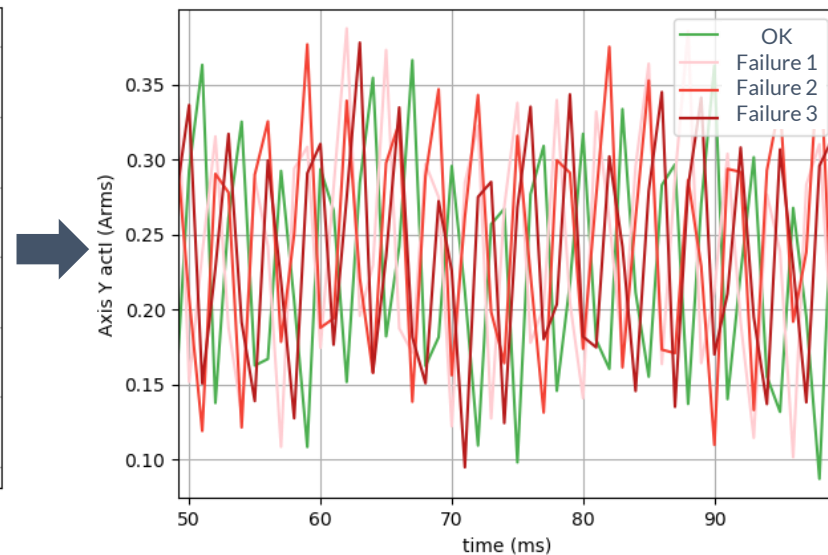Threshold

Fish tail

OK
Failure 1
Failure 2
Failure 3

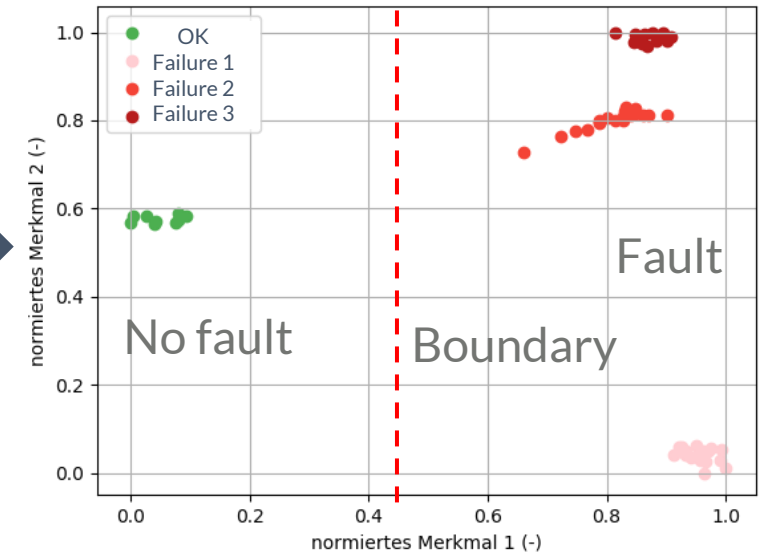# Example: AI-based systems can distinguish complex issues.

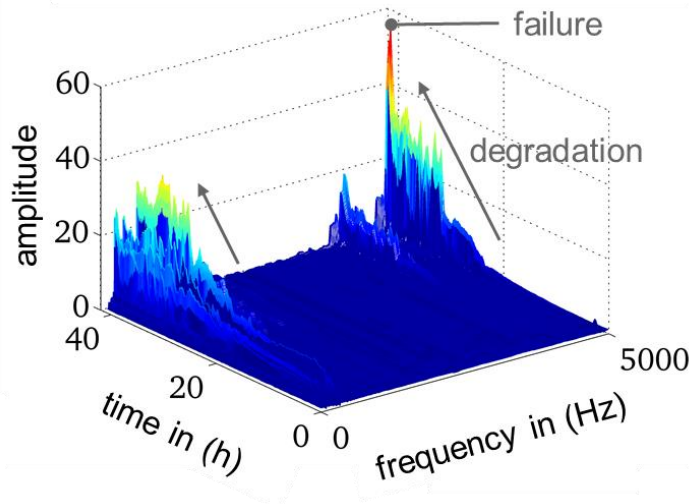Unaccelerated system movement (commanded position)

Measured signal of the movement

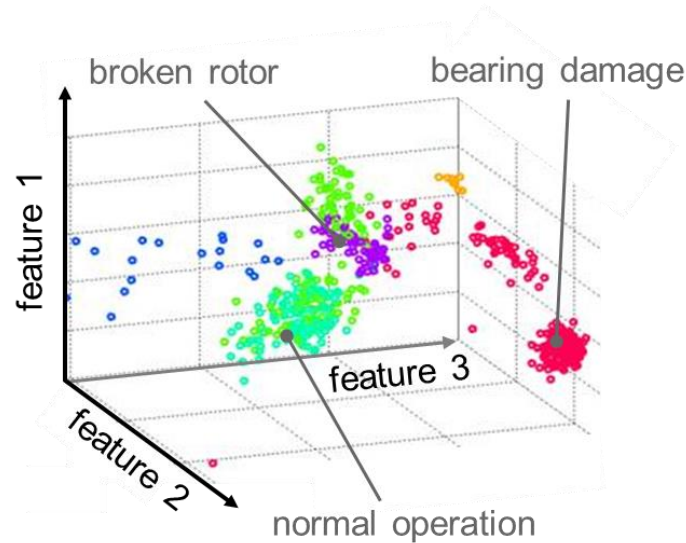AI-based separation by characteristic features

Approach: Predictions require three steps and are based on diagnoses.
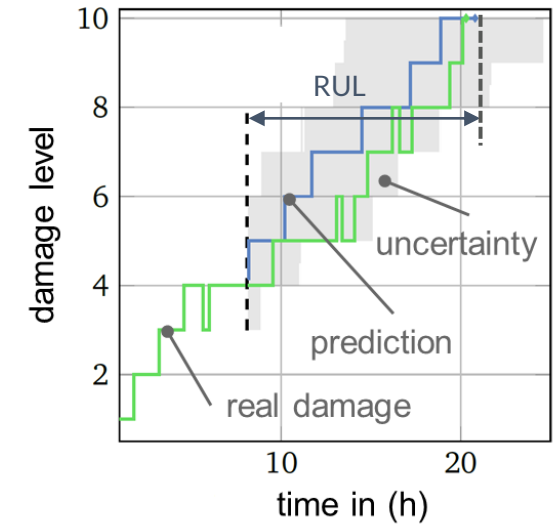
Data acquisition and processing

Description and identification of relevant features (measured, event based, modeled or simulated)

Diagnosis of the operating status

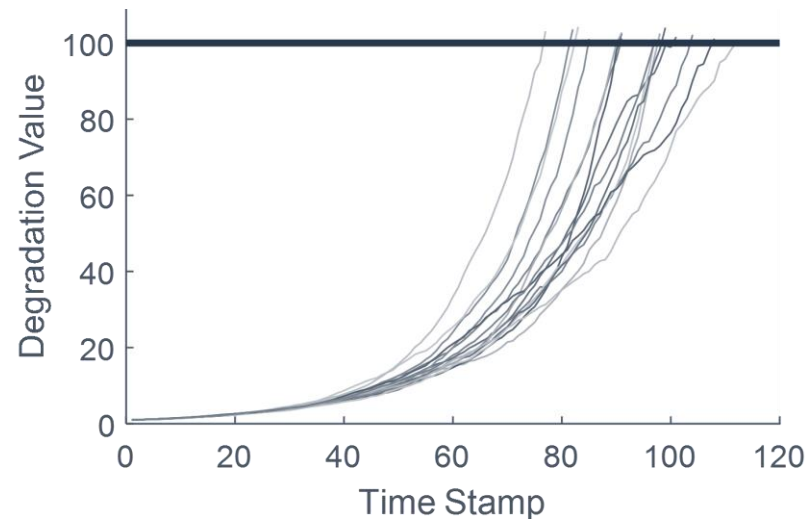Description of current operating and system states

Forecast of remaining useful lifetime

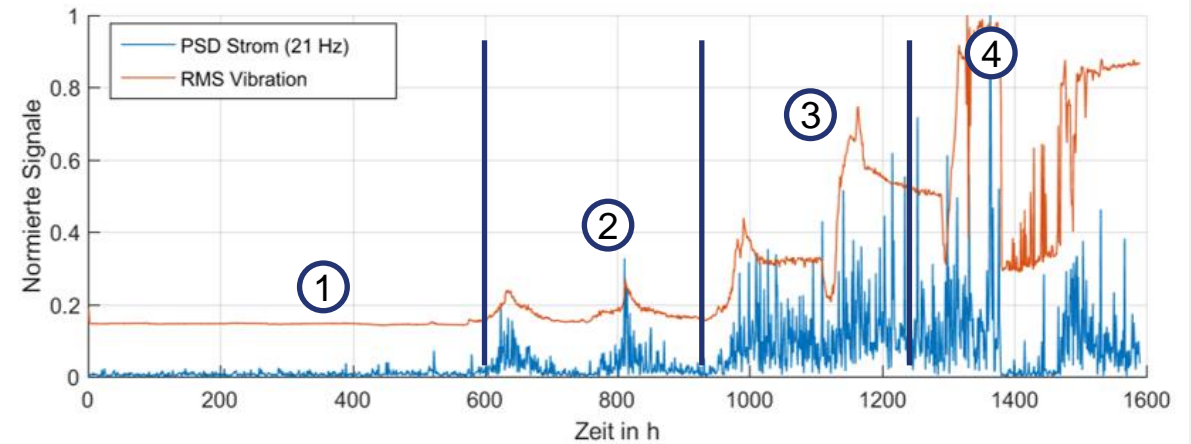Determination of future states based on usage scenarios and tackling uncertainties

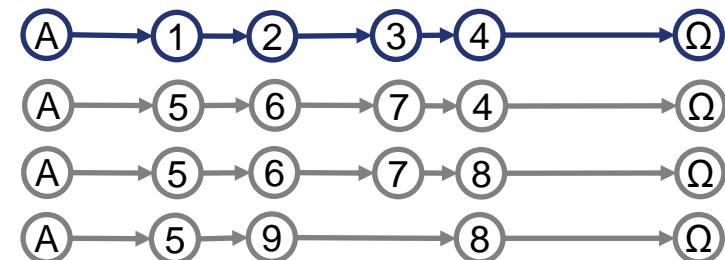# Model example: Data-based damage models are learned from the sensor data.

Qualitative damage progression

Real progression and aggregation to a state model

Deriving state models (e.g. Markov chains)

Usage for transactional forecasts: Identification of drivers for temporal occurrence and magnitude.
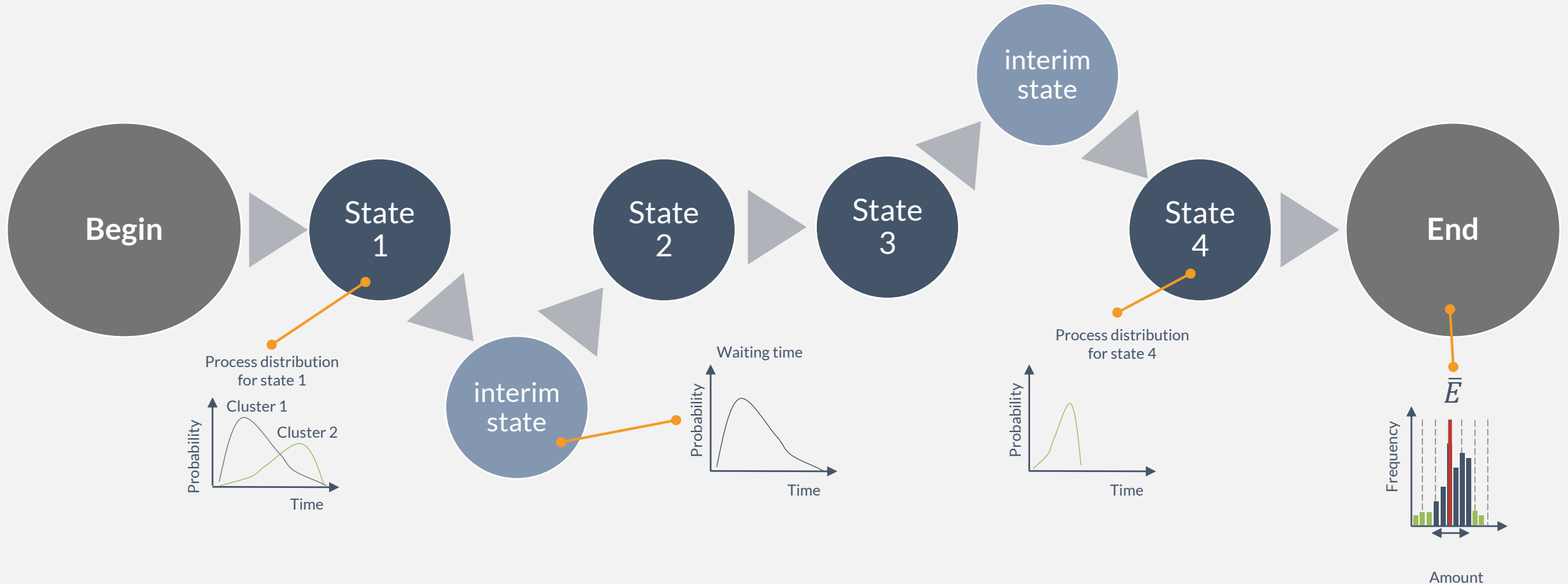
Insights in the use

Big picture: We provide platform-independent smart analytic capabilities!

Computer science approach

Engineering approach

"Best of both worlds"

blue box

black box

white box

- Patterns & correlations
- AI/ML algorithms & learning frameworks

- Mathematical / physical models
- (analog) SME knowledge

Retrofit-ready for

servicenow

Azure

SAP

aws

24

Enabling predictability: Comprehensible trends and future estimations!
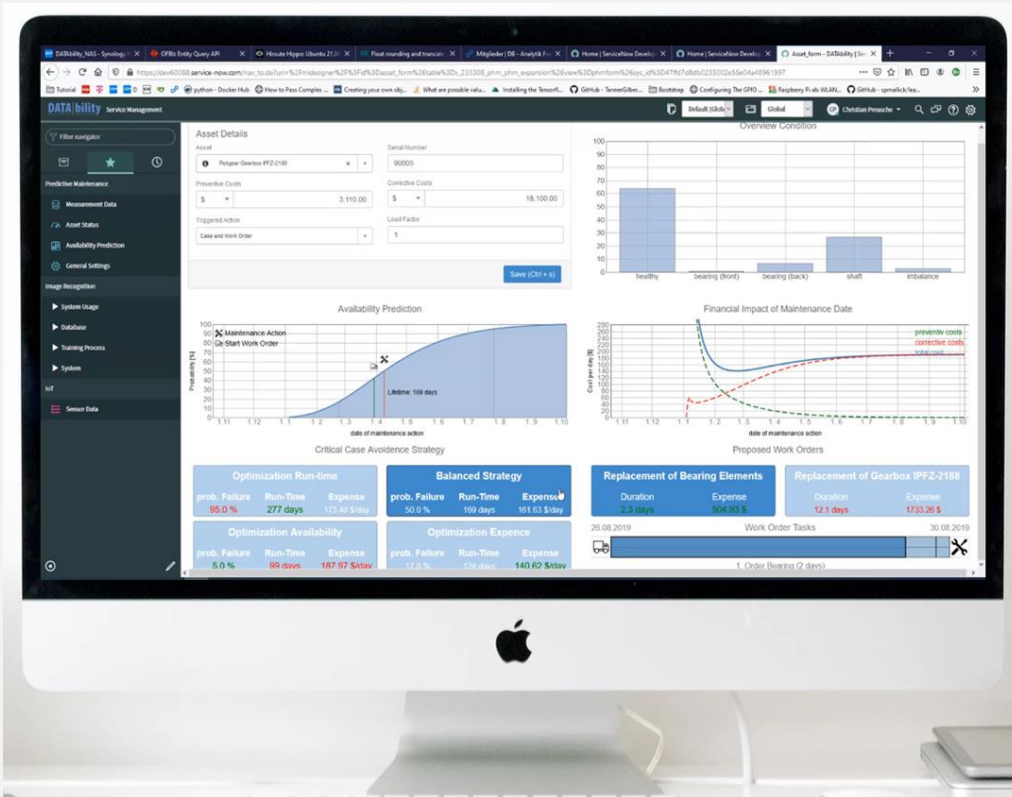
✓ Detailed system insights & information!

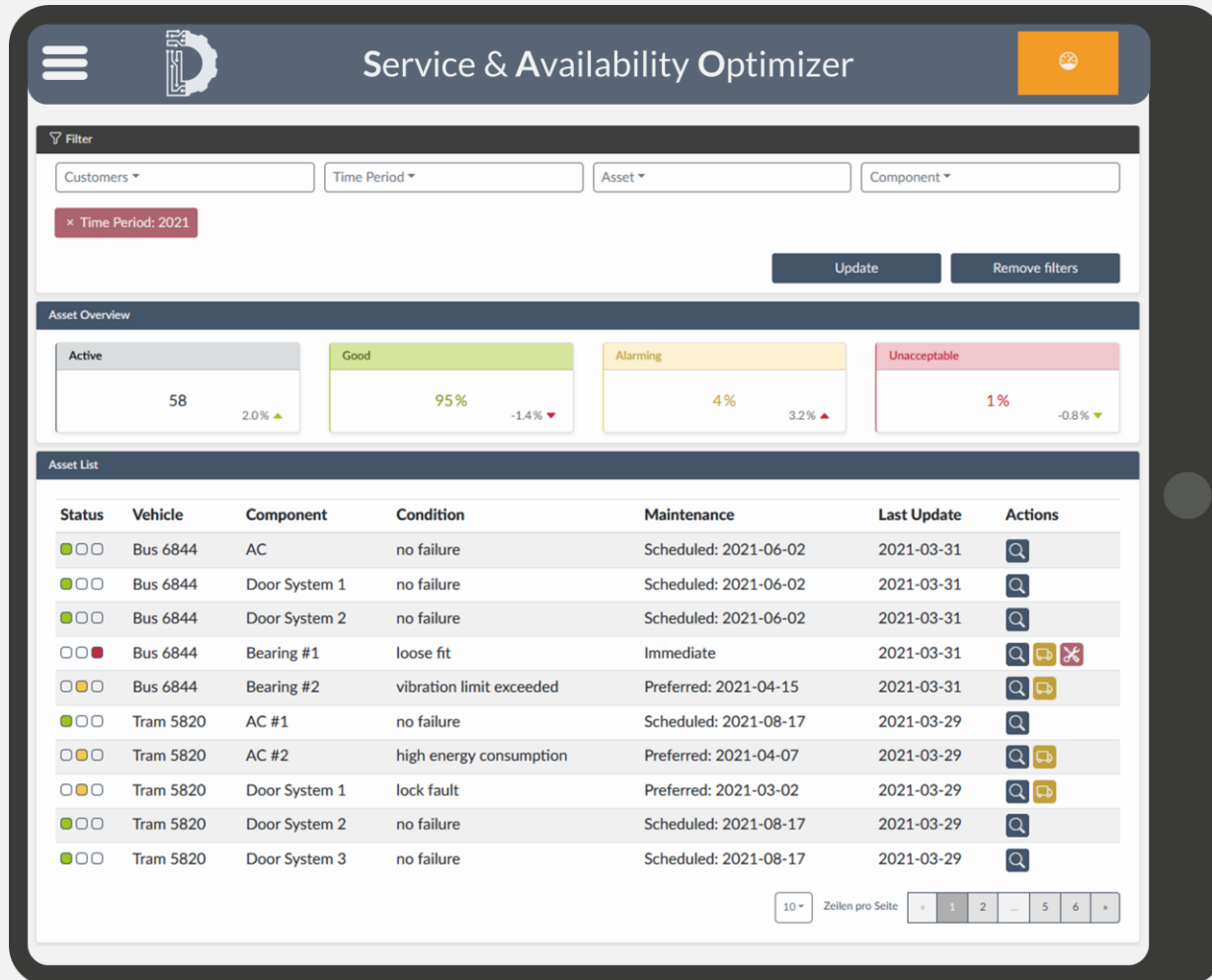✓ Increase availability by more than 25%!

✓ Avoid deficient service level agreements!

Watch it live by following this link!

Asset management: Fleet monitoring and decision support made simple!

Relevant key values at a glance!

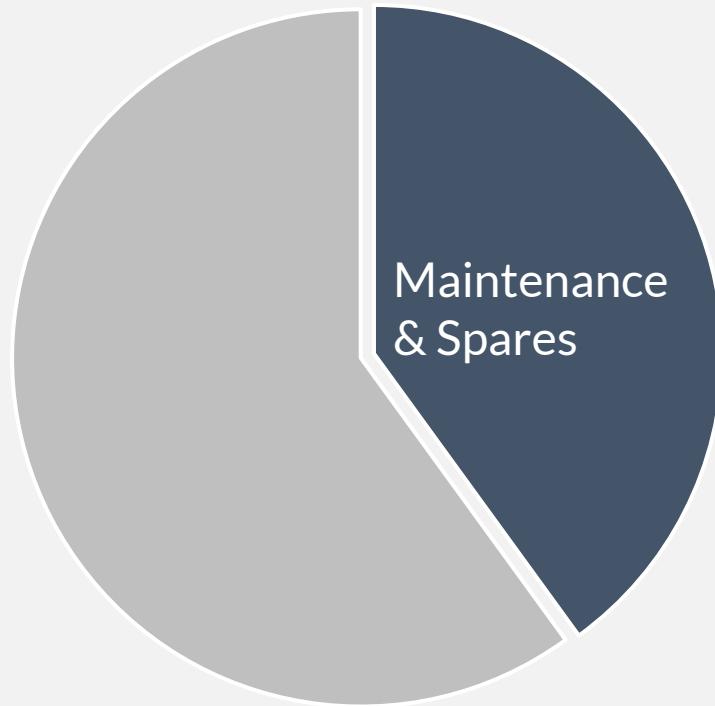Actionable insights & workflows!

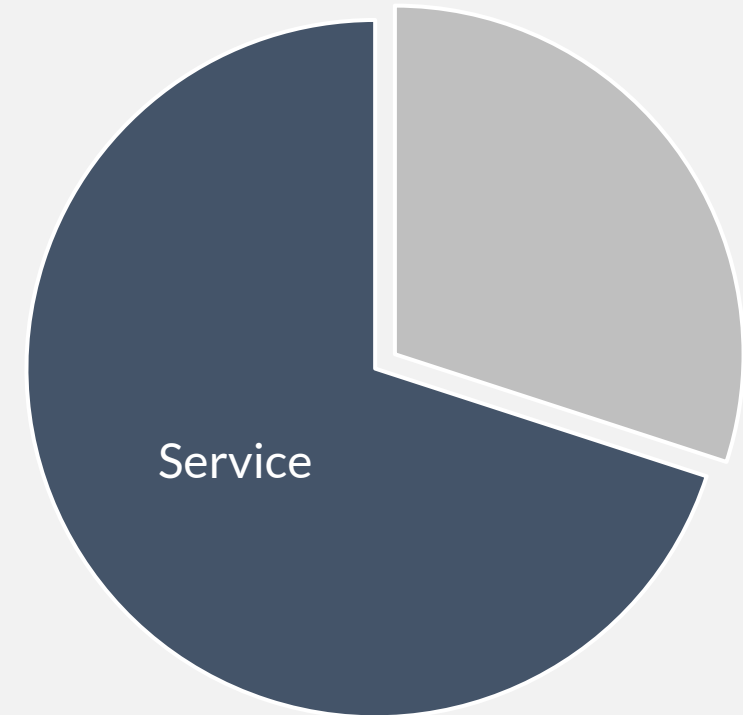Monitor & manage with a click!

Watch it live by following this link!

We got you: Benefit as operator or manufacturer to become future-proof!

Reduce operative efforts in maintenance

Maintenance & Spares

Increase profitability in production & after sales

Service

■ Share
■ Others

Source: Illner et al.: *Leitfaden Fit for Service*. VDMA (2017) and *Digitale Produkte und Services lassen sich zu Geld machen*. VDMA (2019)

We are looking forward to work with you!

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in sebastian-oliver-baumann

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