

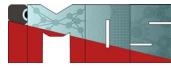


Prof. Dr. Olga Fink

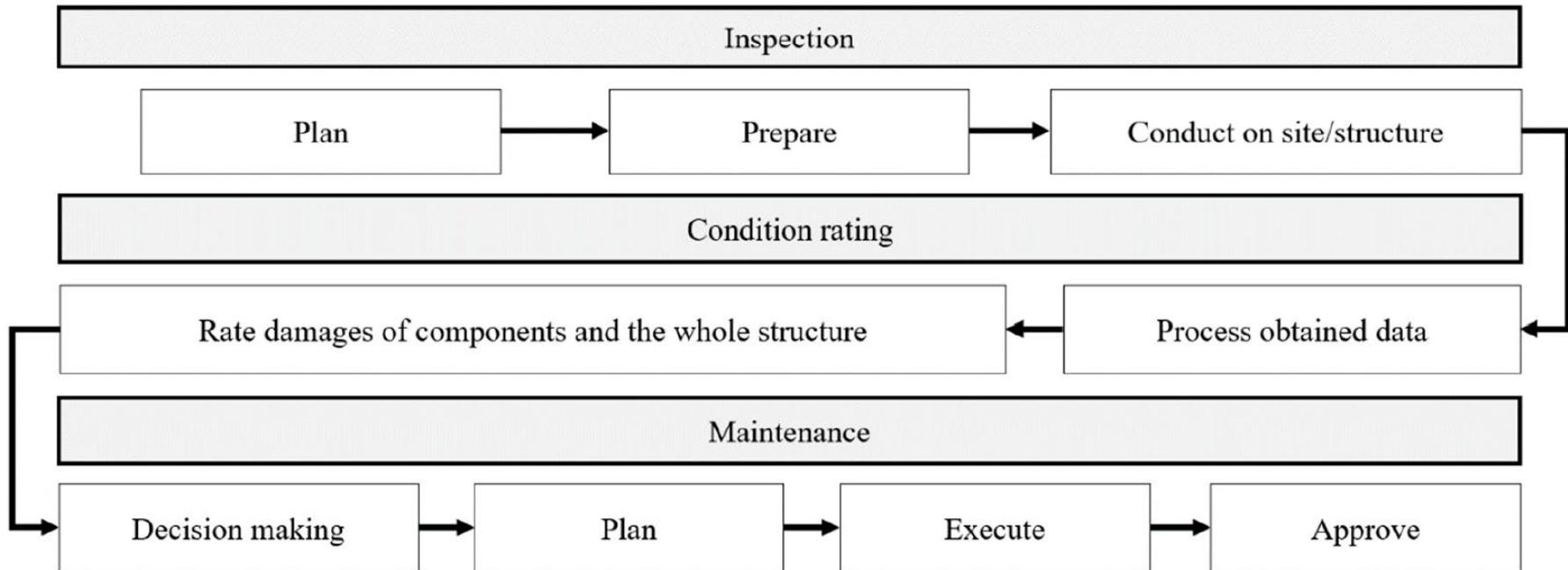
Data Science for Infrastructure Condition Monitoring: Decision support systems



May 2025



Process of Structural Health Monitoring



- Sensing
- Data Acquisition
- Data Processing
- Feature Extraction
- Damage Detection, Diagnosis, Prognosis
- Decision Making

- Measurement technology
- Accuracy of the monitored parameters
- Feasibility of monitoring
- Operating conditions during measurement
- Measuring interval
- Data acquisition rate
- Registration of the monitored parameters
- Measuring points
- Preliminary warning and alarm criteria
- Reference values

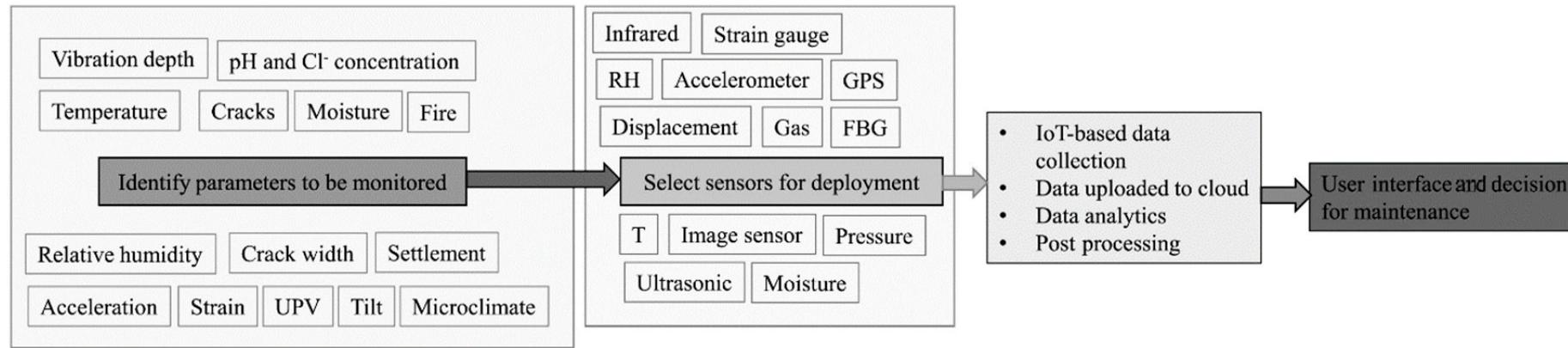
Considerations in the selection of measuring points (repetition)

- Safety,
- Selection of the transducers,
- Signal conditioning,
- High sensitivity to error changes,
- Low sensitivity to other influencing variables,
- Repeatability of the measurements,
- Attenuation or signal loss,
- Accessibility,
- Ambient conditions,
- Costs

- Measurement and trend analysis
- Quality of the measurement
- Comparison of the measurement results with the warning and alarm criteria
- Diagnostics and prognosis
- Improving the reliability of diagnoses and/or forecasts

- Noise filtering and normalization
- Data fusion from multiple sources
- Managing missing or corrupted data

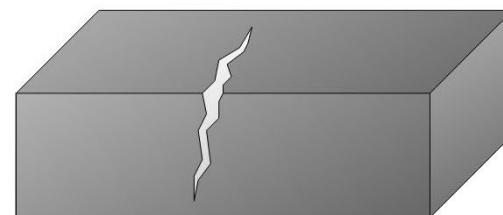
SHM approach to infrastructure assessment and decision-making.



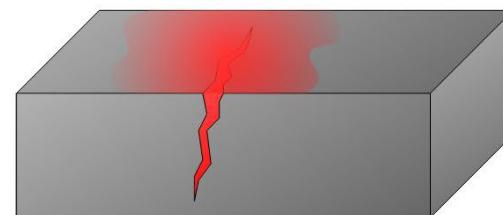
NDE Category	Approach
Visual Inspection	Dye Penetrant
Acoustic Wave-based	Ultrasonic Testing
Optical Techniques	Thermal Barrier Coatings Based on Infrared Thermography
Imaging Techniques	Digital Radiograph
Electromagnetic Fields	Eddy Current Testing



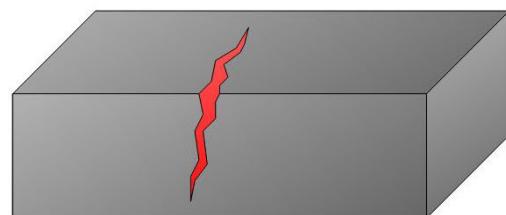
1) contaminated workpiece



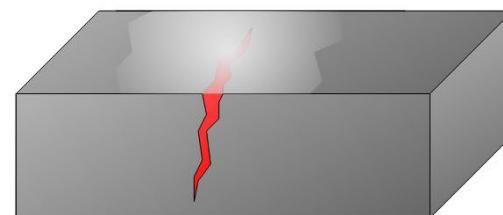
2) cleaning the workpiece



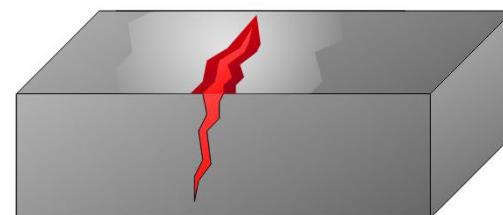
3) applying the flaw detection ink



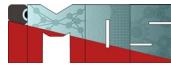
4) rinsing the workpiece



5) applying the dye developer



6) inspecting the crack



Sensor placement

- The Sensor Placement Problem involves determining:
- How many sensors to use, and
- Where to place them on a structure
- to maximize monitoring effectiveness while minimizing cost and redundancy.

- Poor placement → missed faults or false positives.
- Good placement → better signal coverage, earlier fault detection, lower cost.
- Especially critical in **large-scale systems** (e.g., bridges, aircraft, wind turbines).

- Maximize fault detectability
- Enable damage localization
- Capture key dynamic behaviors (e.g., mode shapes)
- Minimize information redundancy
- Maintain robustness to sensor failure
- Optimize cost-performance tradeoff

- **Heuristic Methods**

- Greedy algorithms, expert rules, trial-and-error.
- **Fast but suboptimal.**

- Optimization-Based Approaches

$$\max_{x \in \{0,1\}^n} J(x) \quad \text{subject to:} \quad \sum x_i \leq k$$

- Where x_i indicates sensor at location i , and $J(x)$ is an objective like:
 - Fisher Information Matrix (FIM)
 - Mutual information
 - System observability/controllability

- Mutual Information (MI) quantifies the amount of information that one random variable (sensor measurements) contains about another (system state or damage state).

$$I(X;Y) = H(X) - H(X|Y)$$

- Where:
- X: Random variable representing the system state (e.g., damage location, severity).
- Y: Sensor measurements.
- $H(X)$: Entropy (uncertainty) of the system state.
- $H(X|Y)$: Remaining uncertainty in the system state after observing the sensors.

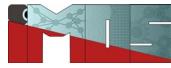
Select a set of sensor locations $S \subset \mathcal{L}$ (possible locations) such that:

$$\max_{S, |S| \leq k} I(X; Y_S)$$

where Y_S is the measurement vector from the selected sensor locations.

Why Use MI for Sensor Placement?

- Data-driven and model-agnostic.
- Can naturally handle nonlinear, high-dimensional systems.
- Accounts for redundancy: avoids placing sensors that provide overlapping information.
- Robust in probabilistic settings (e.g., under uncertainty in system state or noise).



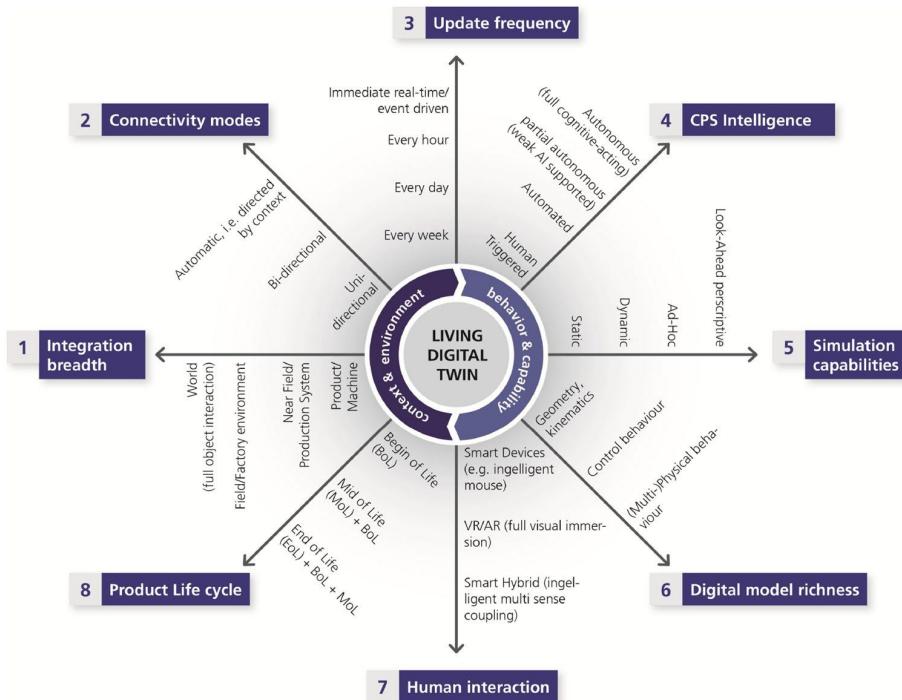
Digital Twins

1. Definition: Digital twins

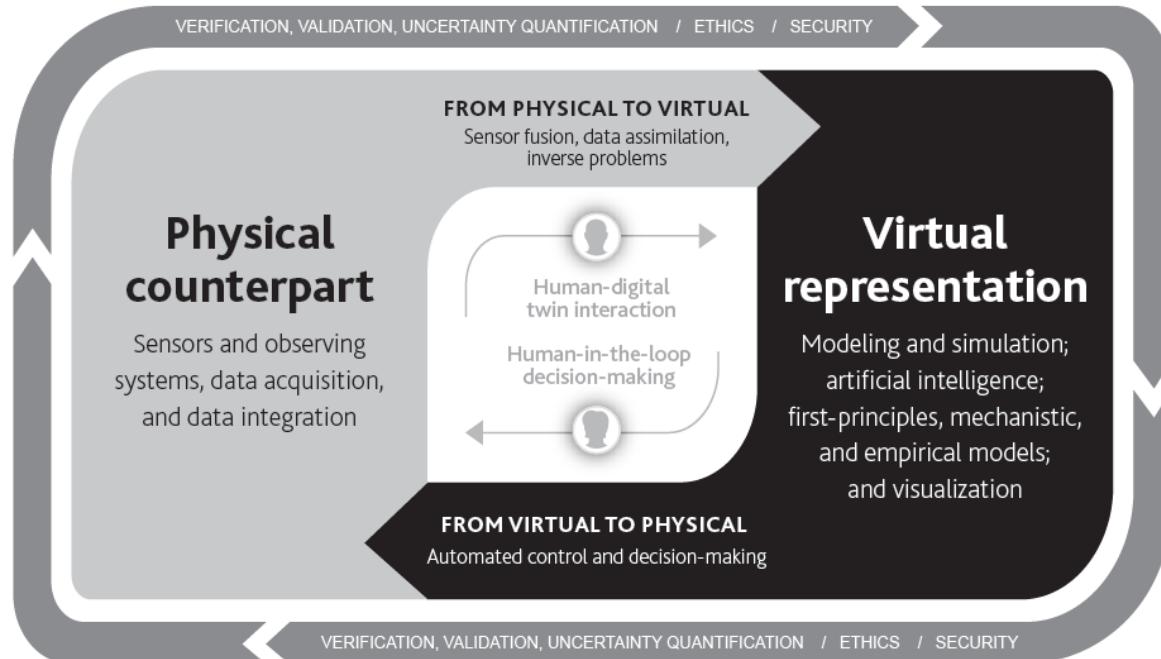
- A digital twin is defined as “a living model of the physical asset or system, which continually adapts to operational changes based on the collected online data and information, and can forecast the future of the corresponding physical counterpart”.

2. Definition: Digital twins

- *A digital twin is a set of virtual information constructs that mimics the structure, context, and behavior of a natural, engineered, or social system (or system-of-systems), is dynamically updated with data from its physical twin, has a predictive capability, and informs decisions that realize value. The bidirectional interaction between the virtual and the physical is central to the digital twin.*



R. Stark, C. Fresemann, and K. Lindow, "Development and operation of Digital Twins for technical systems and services," *CIRP Ann.*, vol. 68, no. 1, pp. 129–132, Jan. 2019.



Digital twin of a patient

REAL WORLD PATIENT

The patient and the tumor from which data is gathered using various clinical assessments to inform the digital twin.

VVUQ →
Verification, validation,
and uncertainty quantification
As the patient and tumor are constantly evolving and the data collection can also change over time, VVUQ must occur continually for digital twins.
Uncertainty quantification needs to be addressed for all aspects of the digital twin, including the patient's data, modeling and simulation, and decision making.

DIGITAL TWIN

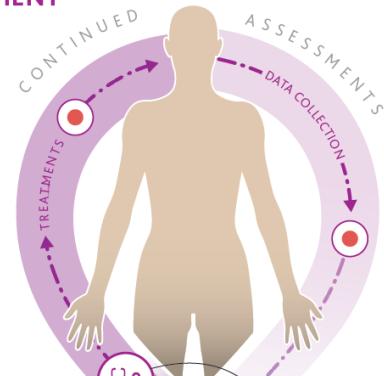
The virtual representation comprised of models describing temporal and spatial characteristics of the patient and tumor with dynamic updates using data from the real world patient.



Modeling

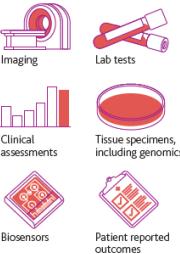
Models spanning a range of fidelities and resolutions may be utilized and potentially integrated together.

As new observed data are acquired, the data are assimilated and the models are calibrated, updated, and estimated.



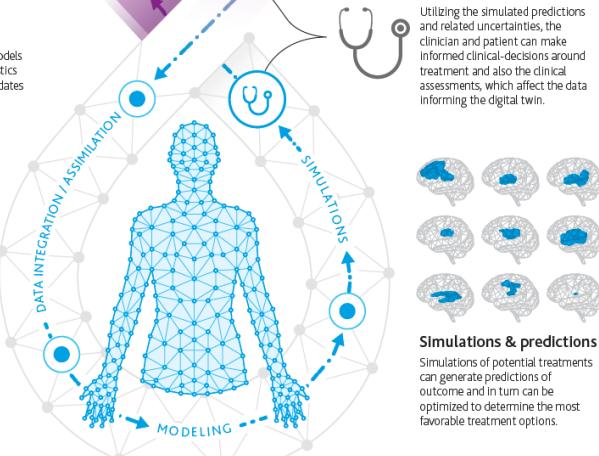
Clinical assessments

Data are collected in many ways:



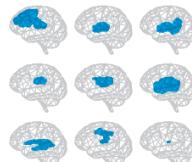
Human and digital twin interaction

Utilizing the simulated predictions and related uncertainties, the clinician and patient can make informed clinical decisions around treatment and also the clinical assessments, which affect the data informing the digital twin.



Simulations & predictions

Simulations of potential treatments can generate predictions of outcome and in turn can be optimized to determine the most favorable treatment options.



Verification, Validation, Uncertainty Quantification

- **Verification:** Does a computer program correctly solve the equations of the mathematical model?
- **Validation:** To what degree is a model an accurate representation of the real world, from the perspective of the intended model uses?
- **Uncertainty Quantification:** What are uncertainties in model calculations of quantities of interest?

Application cases of DT in SHM

Real-Time Structural Monitoring

Predictive Maintenance

Damage Localization & Assessment

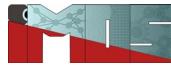
Scenario Simulation (e.g. simulates "what-if" stress, load, or disaster scenarios)

Post-Event Assessment

Life-Cycle Performance Prediction

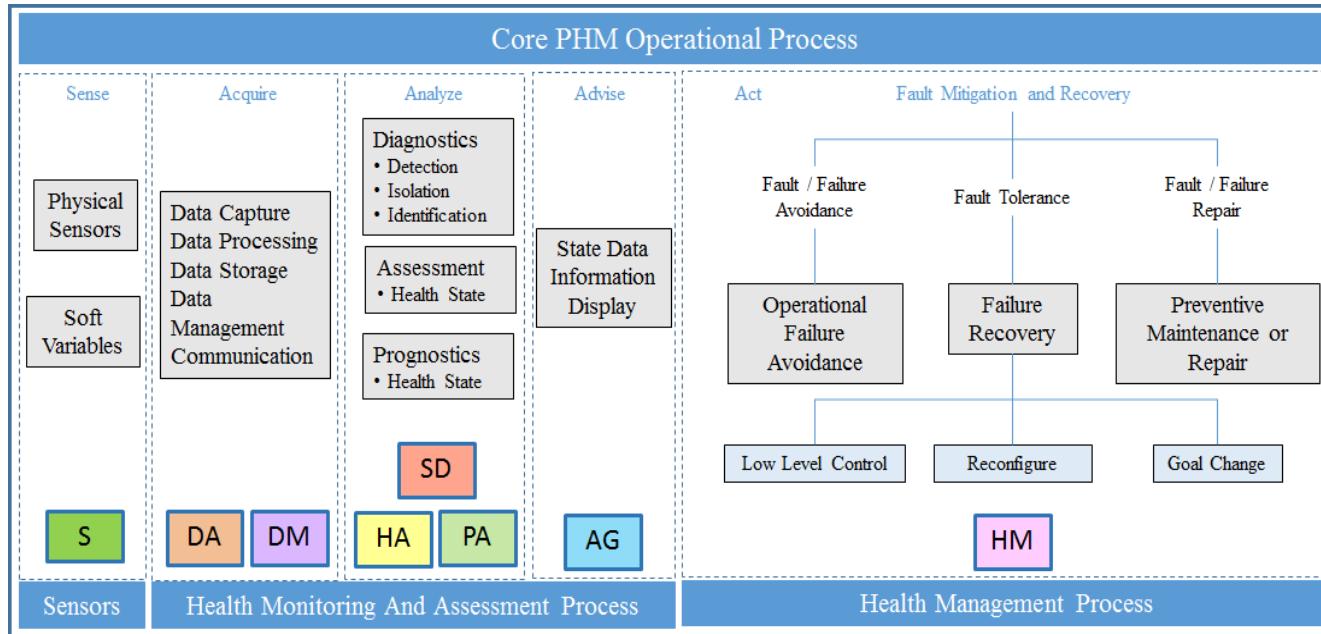
Decision Support for Asset Management

- **Balancing required fidelity for prediction, available resources, and acceptable costs**
- Different digital twin purposes drive different fitness requirements related to modeling fidelity, data availability, visualization, time-to-solution, etc.
- For many potential use cases, achieving fitness-for-purpose is currently intractable

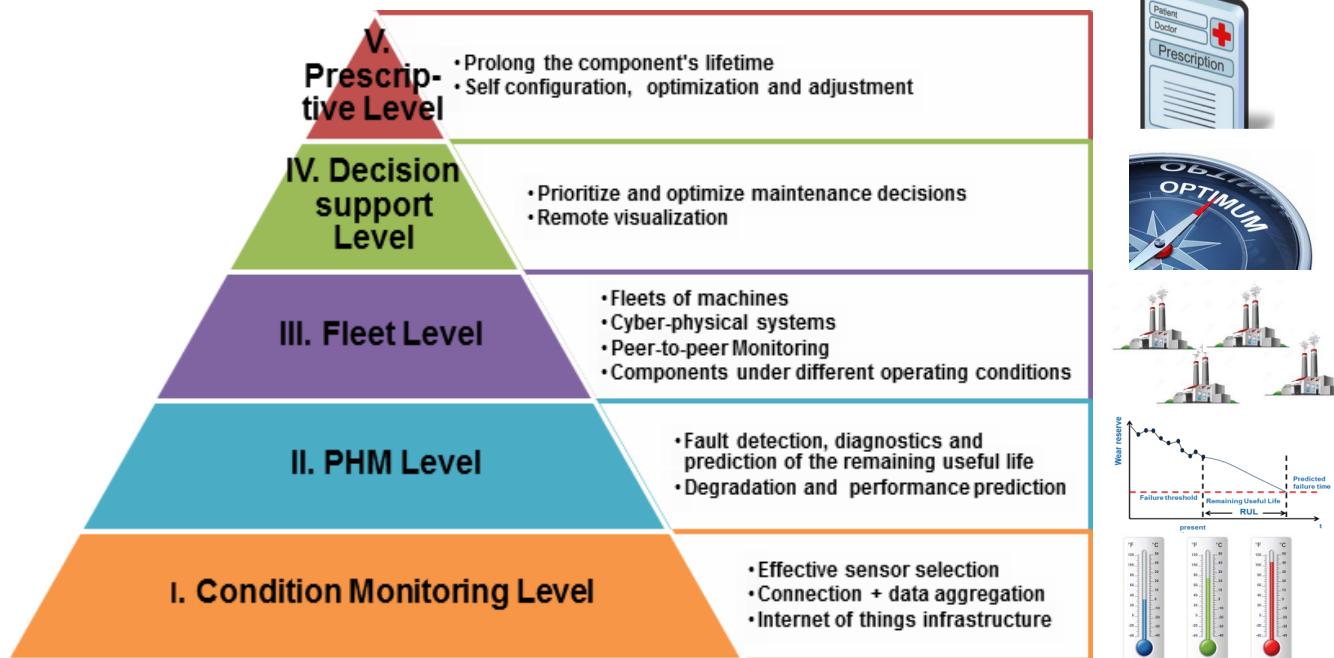


Decision support

Reminder: PHM system operational view



Five levels of condition-based and predictive maintenance



- Required recommendation at system, fleet and enterprise level:
 - Optimal specific action (what needs to be done)
 - Optimal point in time
 - Required resource usage (including personnel, tools and material)
 - Under the given constraints from the resource availability and operational requirements

- Health management utilizes prognostic information to make **decisions** related to safety, condition-based maintenance, ensuring adequate inventory, and product life extension.
- Health management goes beyond the predictions of failure times
 - supports optimal maintenance and logistics decisions
 - by considering the available resources +
 - the operating context +
 - the economic consequences of different faults.
- Health management process of taking timely and optimal maintenance actions based on outputs from diagnostics and prognostics, available resources and operational demand

Aggregate information at the system level (taking boundary conditions into consideration)

Health-aware control → operation

Adjustment of operations with respect to the equipment's health state

Optimization of maintenance scheduling

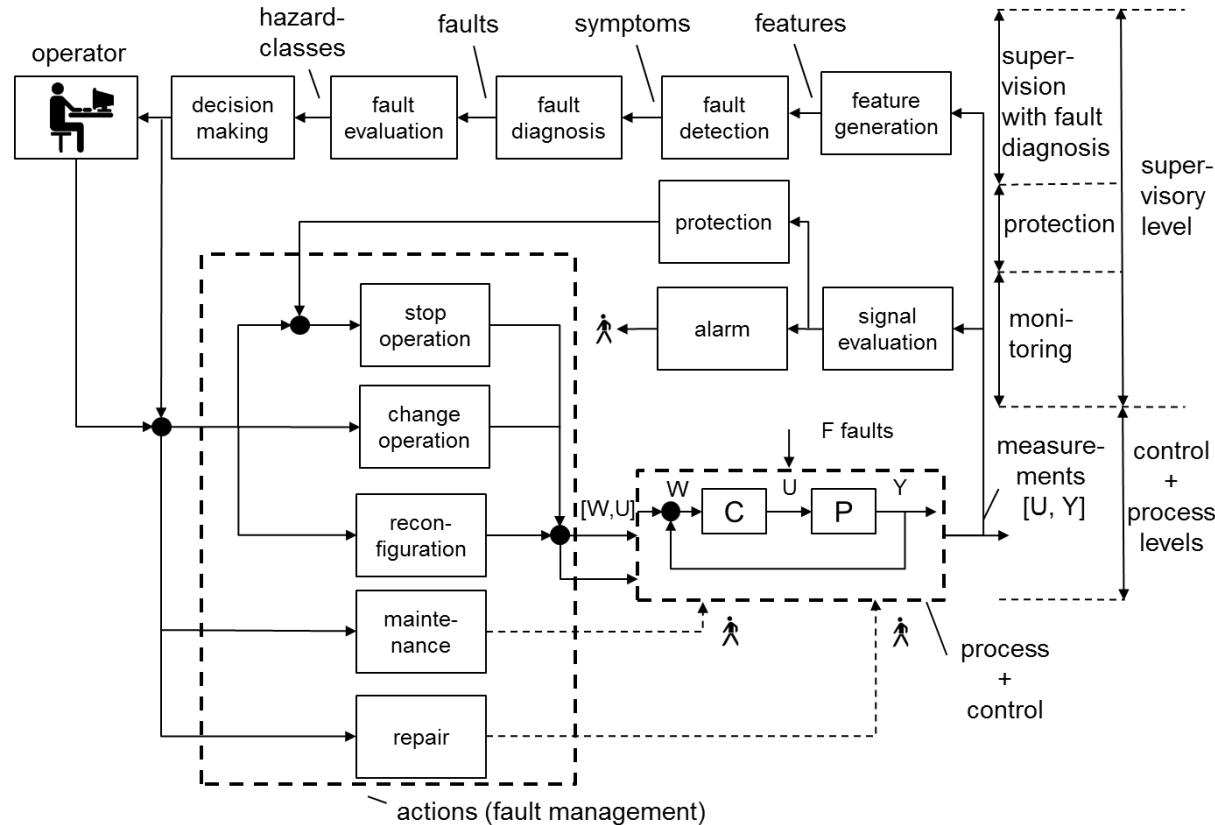
Take decision at fleet level (e.g. mission scheduling)

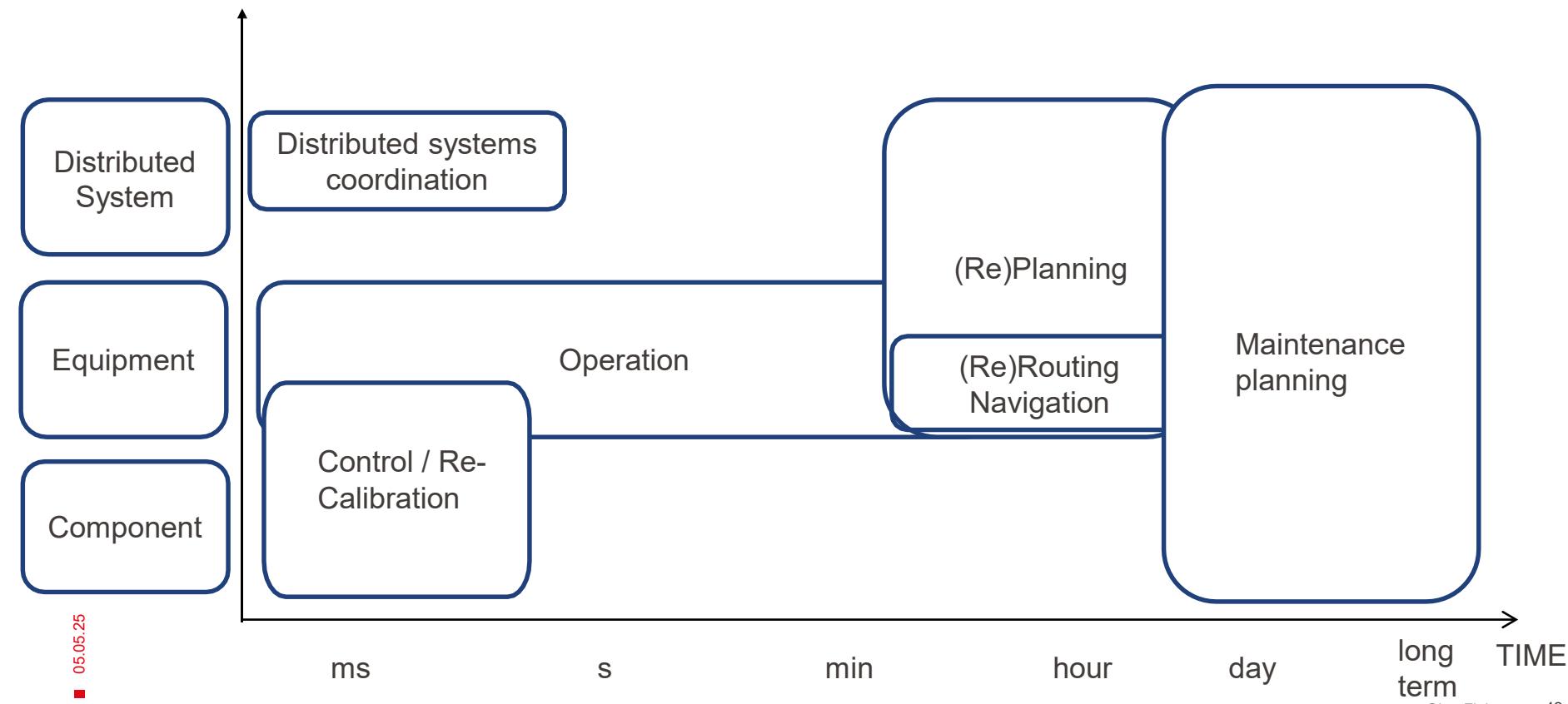
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- **Rule-Based Systems:** Simple thresholds, decision logics
- **Probabilistic Models:** e.g. Bayesian networks
- **Optimization-Based Decision Support:** Maintenance scheduling, resource allocation.
- **Learning-based Systems:** Reinforcement learning for maintenance optimization
- **Multi-Criteria Decision Analysis (MCDA)**
 - Trade-offs between safety, cost, downtime.

- **Optimization Algorithms:** Determining the most cost-effective maintenance schedules and resource allocations.
- **Scenario Analysis:** Evaluating the impact of different maintenance strategies or operational changes.
- **Risk Assessment:** Assessing the likelihood and consequences of potential failures to prioritize actions.

- Formulate maintenance and inspection as an optimization problem.
- **Cost-Based Optimization**
 - **Objective:** Minimize total life-cycle cost (inspection + repair + downtime + risk).
 - **Constraints:** Safety, regulatory limits, resource availability.
 - **Techniques:** Linear/nonlinear programming, mixed-integer programming.
- **Partially Observable Markov Decision Processes (POMDPs)**
 - **Context:** Damage is not directly observable.
 - **Advantage:** Balances cost of monitoring vs. cost of failure.
 - **Example:** Decide whether to inspect, repair, or wait based on belief states updated from sensor data.





- Establish objectives (e.g. availability, reliability, safety, performance and energy consumption), constraints (e.g. resources), decision variables
- Incorporate operational and maintenance requirements on single system and on the fleet level (plus possible flexibility)
- Establish priorities and decision variables
- Quantify critical metrics
- Perform trade-off study incl. risk

Fleets of different assets (being composed of different components) incl. their criticality

Health indicators or RULs, detection alarms (ideally including the uncertainty level)

Scheduled maintenance + inspections (e.g. due to safety requirements)

Maintenance resources (maintenance infrastructure, tools, spare parts, logistics)

Human resources (incl. qualification)

Missions / operational requirements

Decision support system

Performance objectives (availability, cost targets, efficiency ...)

Operational schedules

Maintenance planning + schedule (grouping of several components / systems)

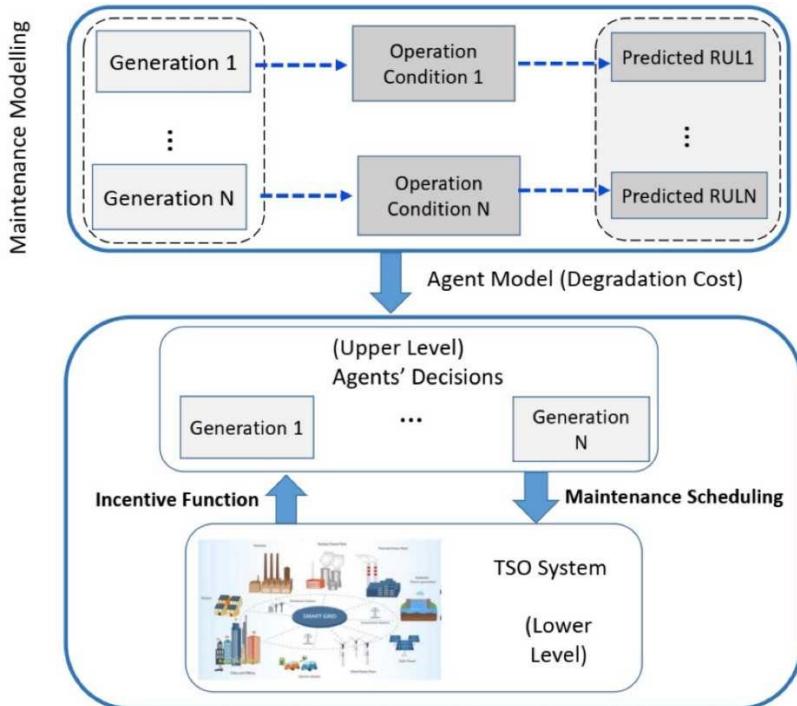
Personnel planning

Requirements for spare parts /logistics

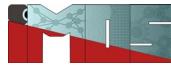
Occupation of maintenance infrastructure

Performance indicators (costs, operational availability, efficiency, product quality, quality of service, etc.)

Multi-agent predictive maintenance scheduling in an electricity market



Rokhforoz, P., Gjorgiev, B., Sansavini, G., & Fink, O. (2021). Multi-agent maintenance scheduling based on the coordination between central operator and decentralized producers in an electricity market. *Reliability Engineering & System Safety*, 210, 107495.



Business models

Possible business models in predictive maintenance

Sensors a service

Subscription

Performance based contracting

Pay per use

Guaranteed availability

Freemium

Add-on

Solution provider