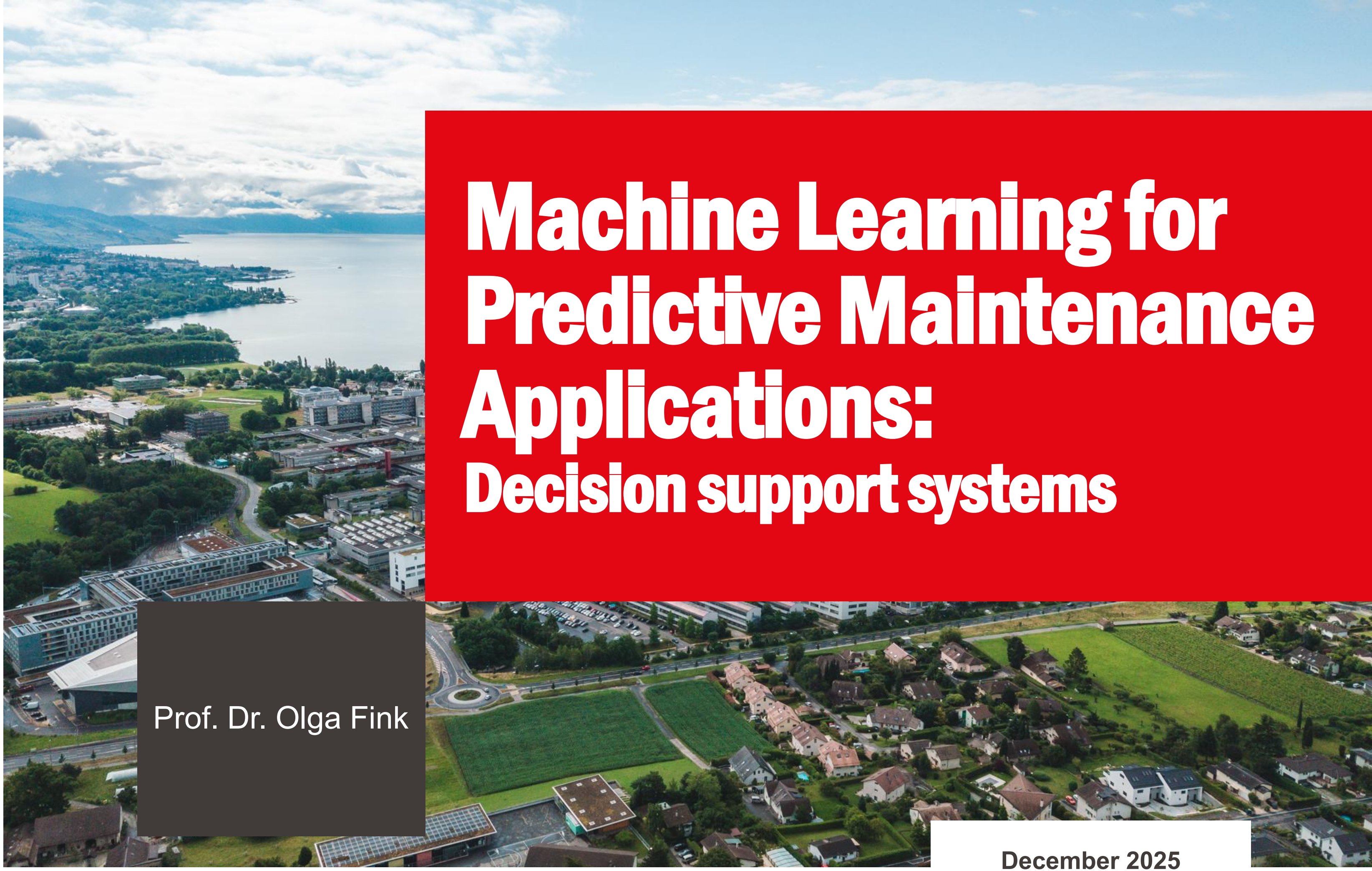
EPFL



Machine Learning for Predictive Maintenance Applications:

Decision support systems

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École polytechnique fédérale de Lausanne

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

Decision support

PHM Process

Data Acquisition (DA)

Data Manipulation (DM)

State Detection (SD)

Health Assessment (HA)

Prognostics Assessment (PA)

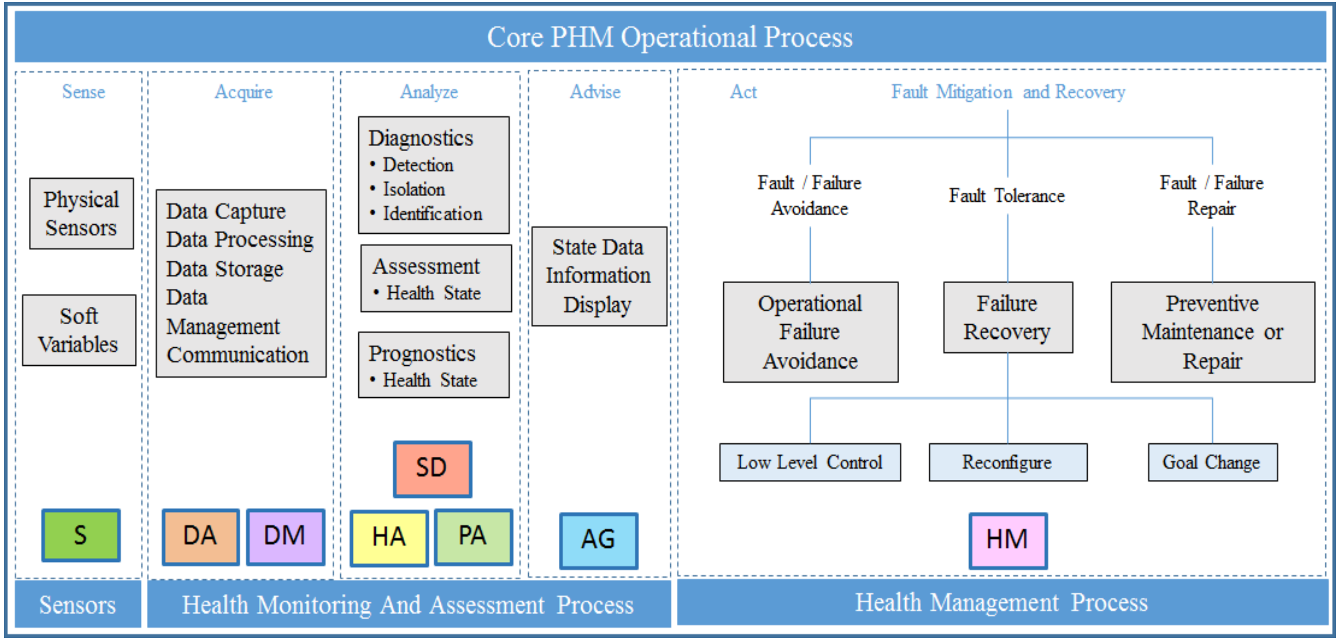
Advisory Generation (AG)

What we focused on up to now

- Up to now:
  - Generate an alarm in case of an anomaly
  - Provide information which fault type has occurred (or at least which signals have shown the largest deviation from normal behaviour)
  - Provide a prediction of the remaining useful life

  → Overcoming challenges of the lack of labels, diversity of operating conditions, uncertain measurements…
- Predictions / detections at component / (sub-)system level

Reminder: PHM system operational view



Source: P1856™/D31 Standard

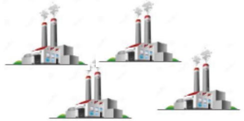
EPFL

Five levels of condition-based and predictive maintenance

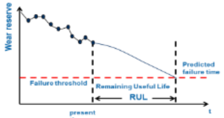
V. Prescrip-tive Level
- Prolong the component's lifetime
- Self configuration, optimization and adjustment

IV. Decision support Level
- Prioritize and optimize maintenance decisions
- Remote visualization

III. Fleet Level
- Fleets of machines
- Cyber-physical systems
- Peer-to-peer Monitoring
- Components under different operating conditions



II. PHM Level
- Fault detection, diagnostics and prediction of the remaining useful life
- Degradation and performance prediction



I. Condition Monitoring Level
- Effective sensor selection
- Connection + data aggregation
- Internet of things infrastructure

Why decision support systems for PHM required?

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

(Prognostics and) Health Management

- 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

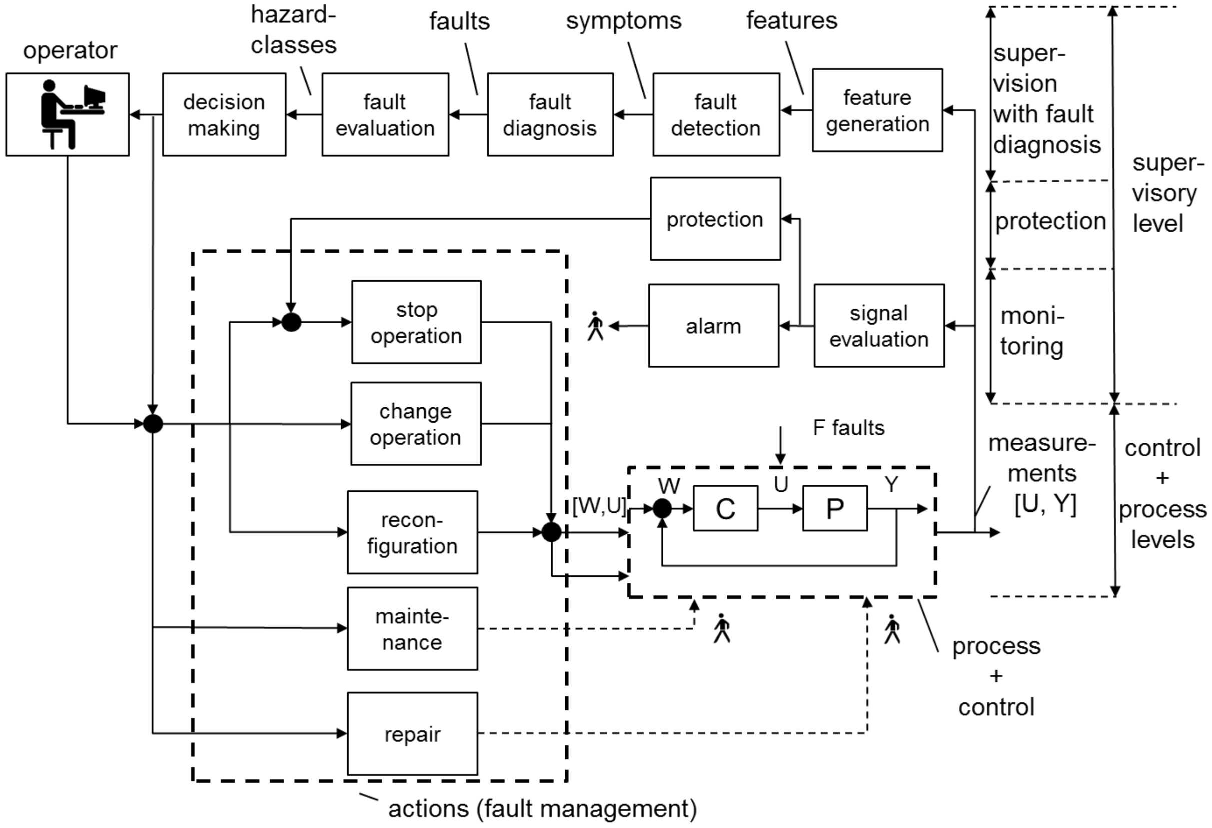
Types of decisions

- 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)
- …

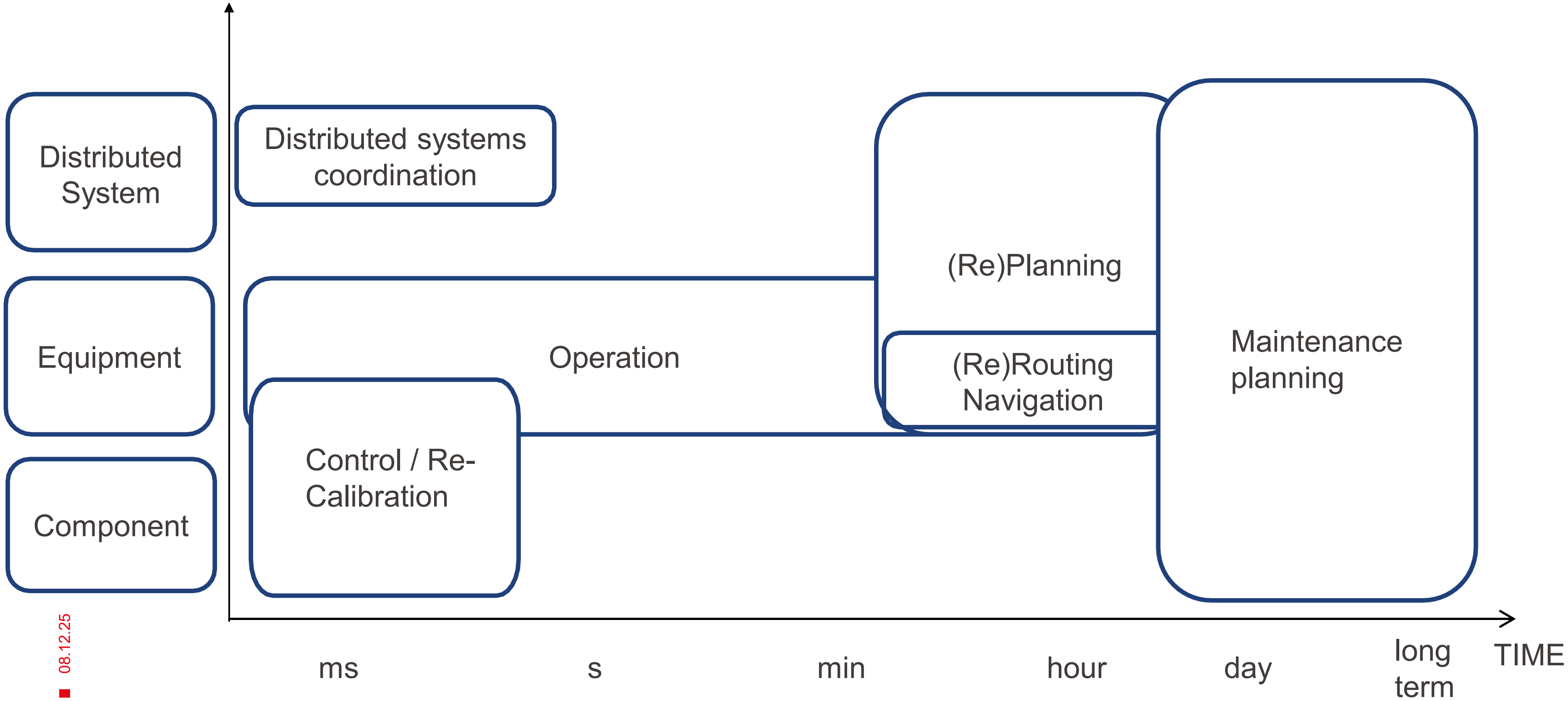
Decision-Making Tools

- **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.

Health management



Decision making in complex systems



Steps to perform

- Establish objectives (e.g. availability, reliability, safety, performance and energy consumption), constraints (e.g. ressources), 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

Elements of decision support systems

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 ressources (maintenance infrastructure, tools, spare parts, logistics)

Human ressources (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

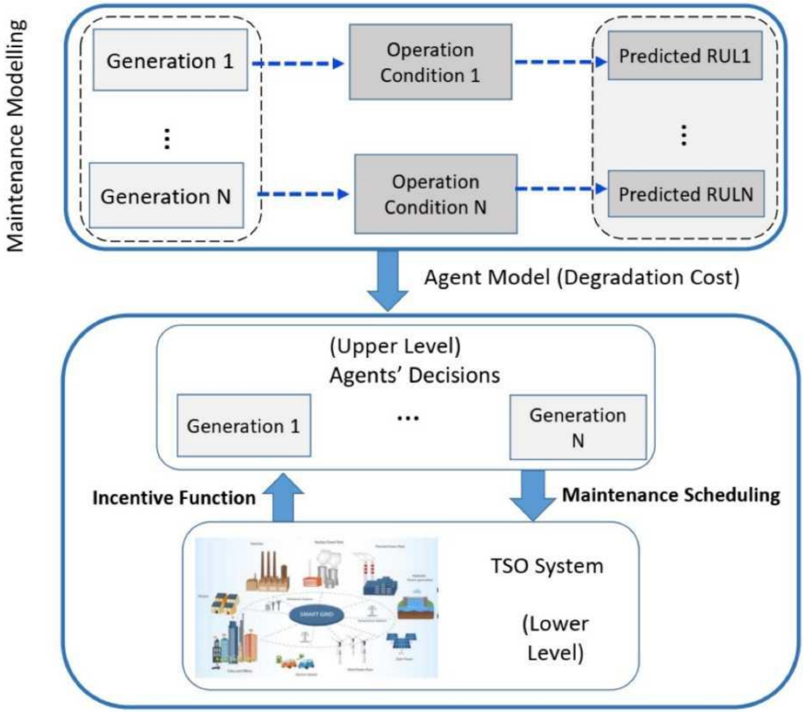
Requirements for spare parts /logistics

Occupation of maintenance infrastructure

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

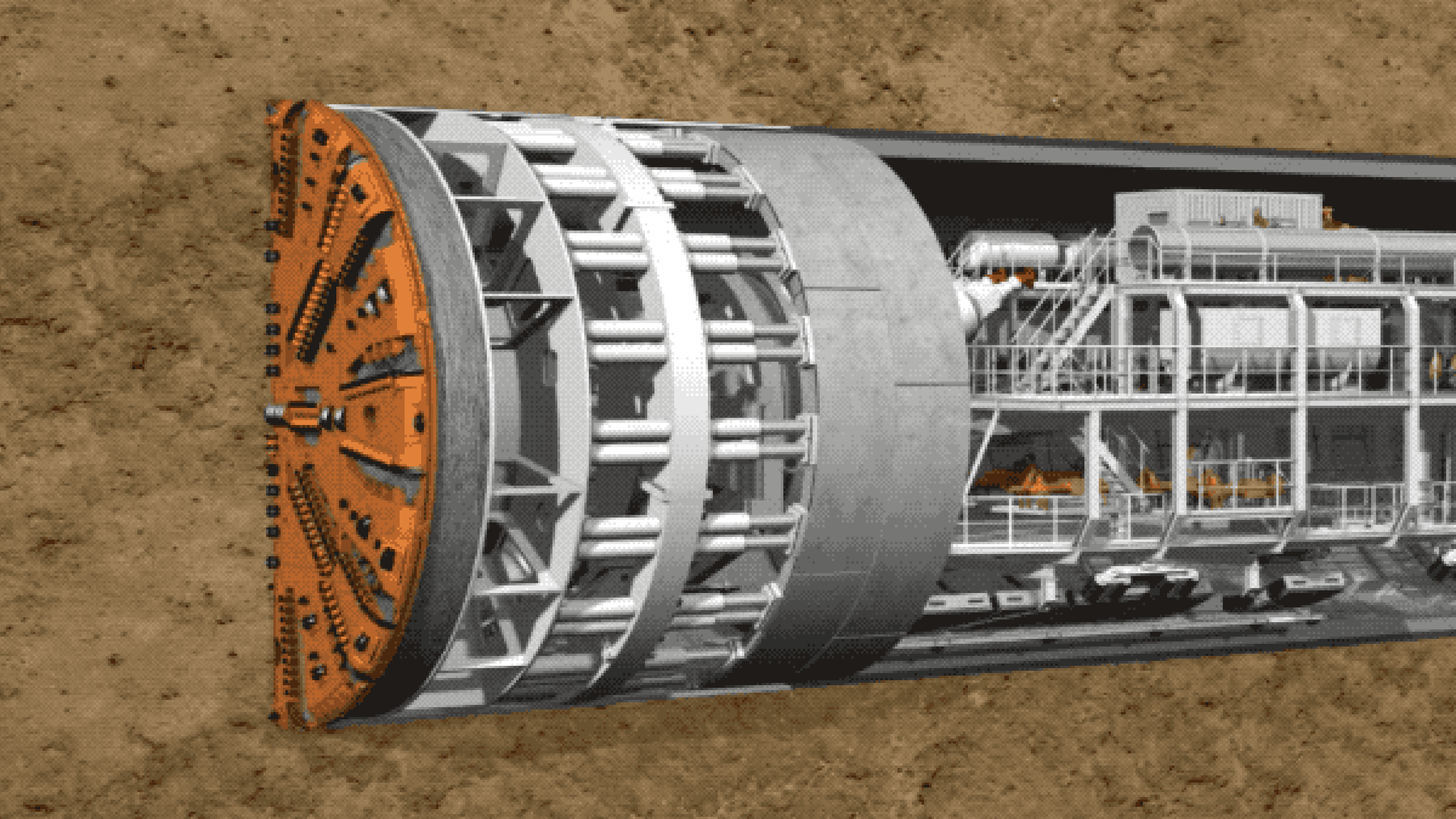
EPFL

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.

Decision support for optimal operation



Consequences of uncertainty?

High uncertainty + high complexity → often cost and time overruns (+safety critical risks)

Importance of experienced and skilled operators

Drilling efficiency differs between different operators and often depends on the level of expertise and experience → difficult to train novices

Tasks with incomplete observations / high uncertainty

How can we leverage the the experience and expertise of domain experts?

Under the condition that we don't know how good the decisions / actions are

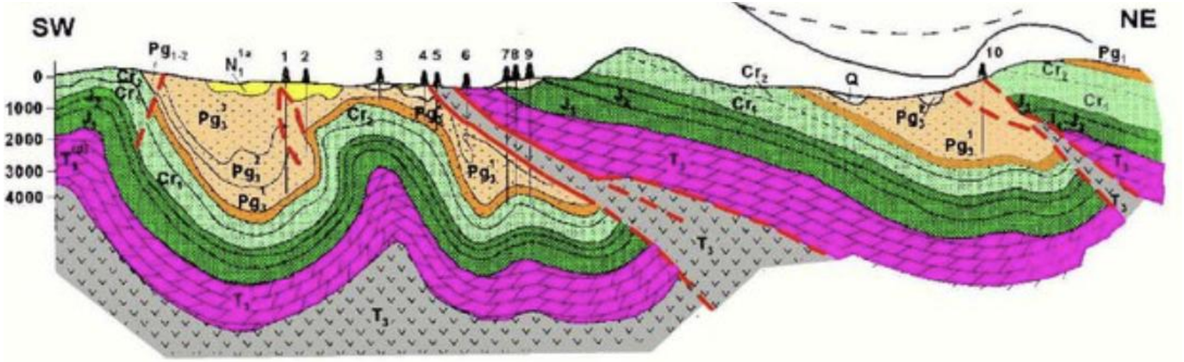
By only observing the data that their decisions generate

Mechanized tunneling: Tunnel construction using Tunnel Boring Machines (TBMs)

- Massive machines employed to build critical infrastructure for modern life
- Large number of sensors installed on a TBM (torque, rotational speed, thrust, ...)
- Geology affects sensor values

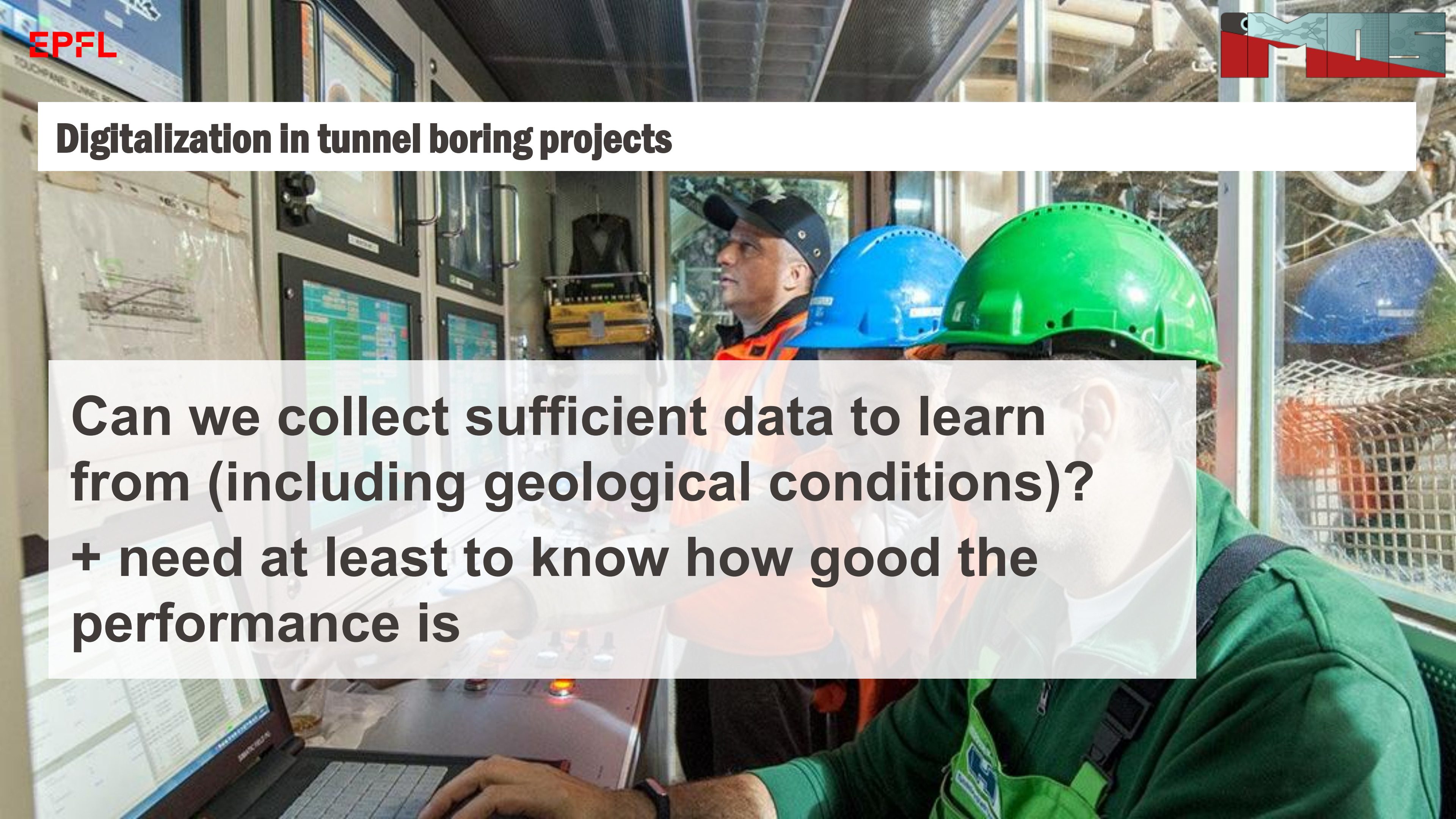
Image credit: https://www.theb1m.com/video/first-tbm-for-grand-paris-express-launched

Geological conditions



Source: Bushati S. et al. , «Gophysical outlook on structure of the Albanides»

Digitalization in tunnel boring projects



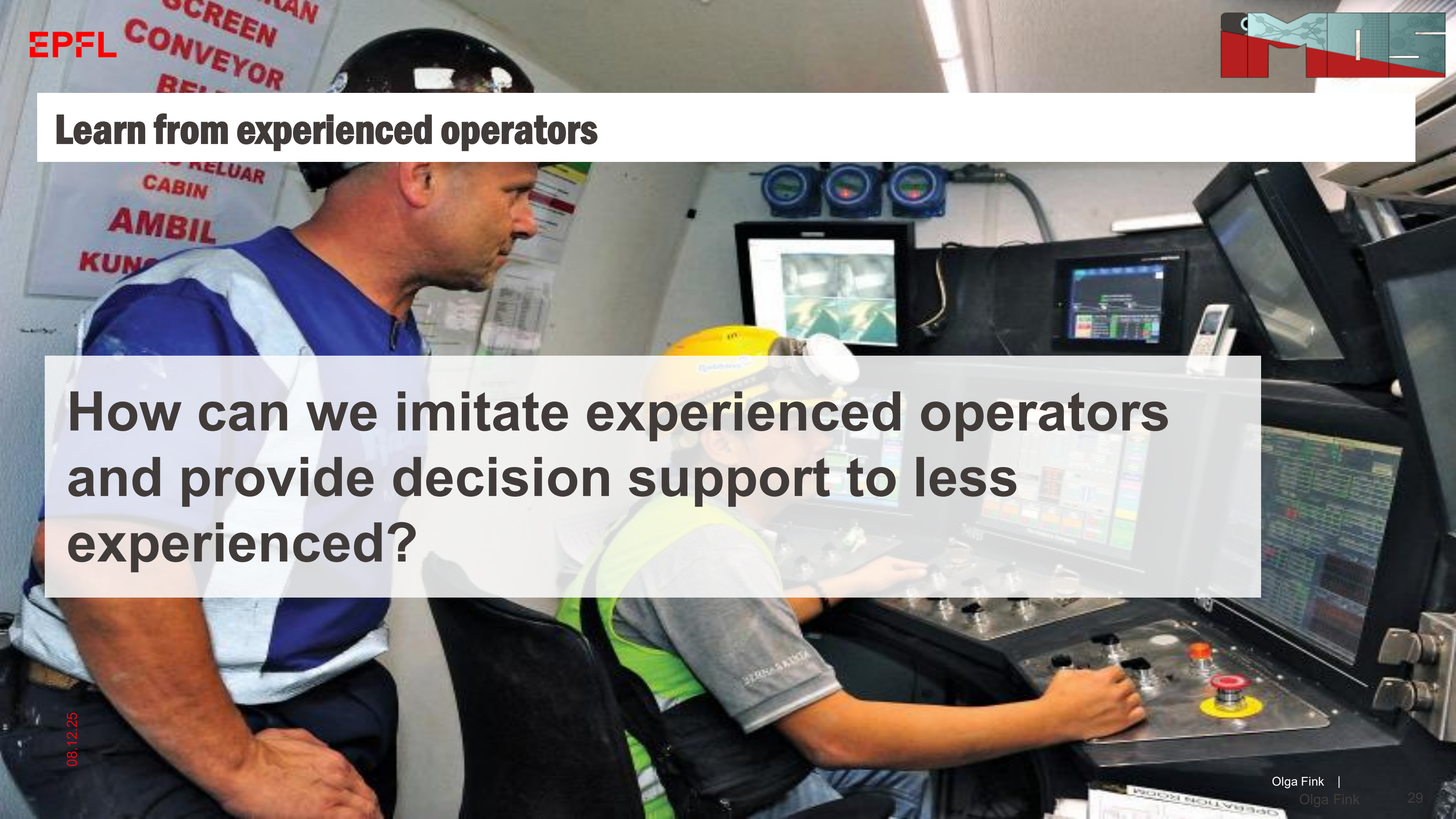
Can we collect sufficient data to learn from (including geological conditions)?

+ need at least to know how good the performance is

Humans – AI - Humans

Learning from observing the decision of domain experts → support novices

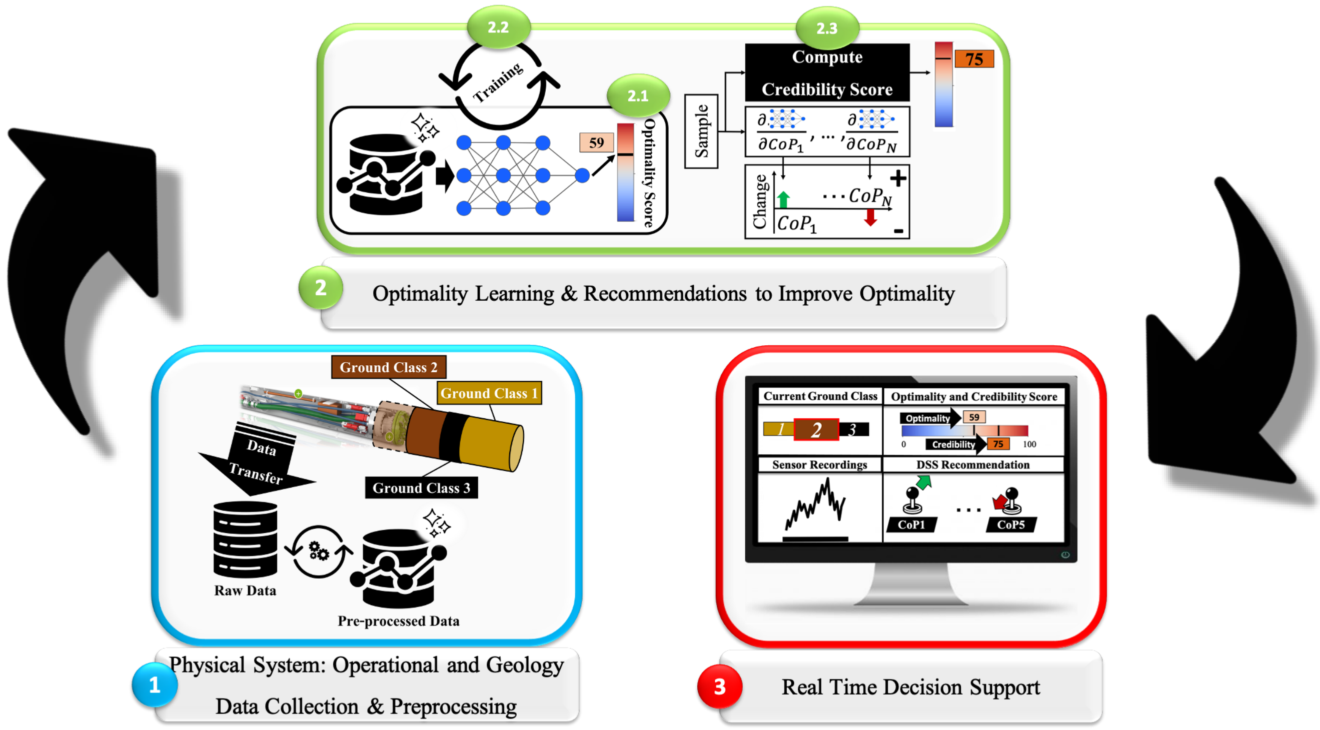
Learn from experienced operators



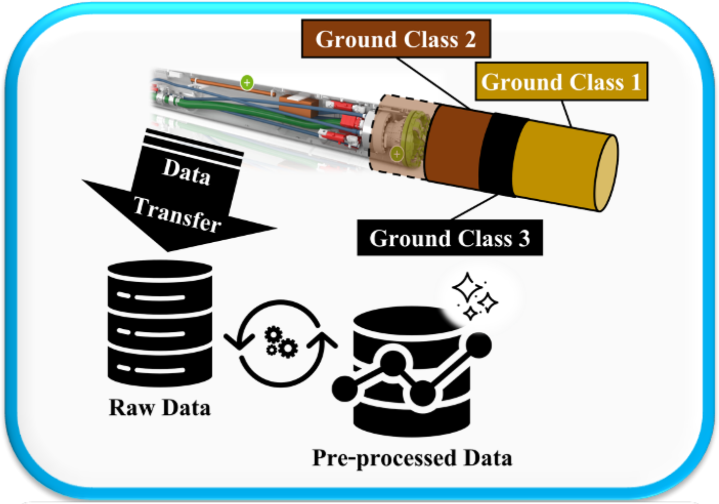
How can we imitate experienced operators and provide decision support to less experienced?

Olga Fink

Decision support system for an intelligent operator of utility tunnel boring machines → resembles imitation learning



Framework



1

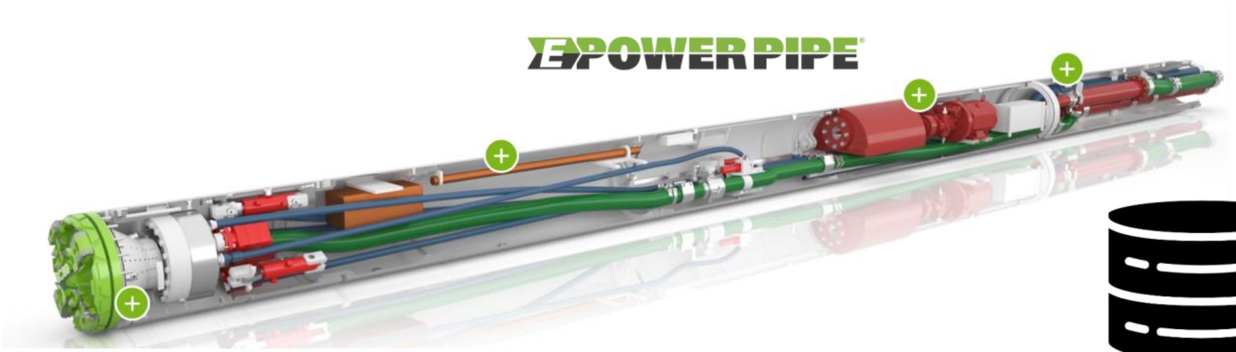
Physical System: Operational and Geology

Data Collection & Preprocessing

Use Case

Collect raw sensor data

1



Cutting Wheel Rot Speed	Feed pump Pressure	…	Oil Temperature
20.1012	1.29482	…	50.1232
21.0333	1.22112	…	50.21999

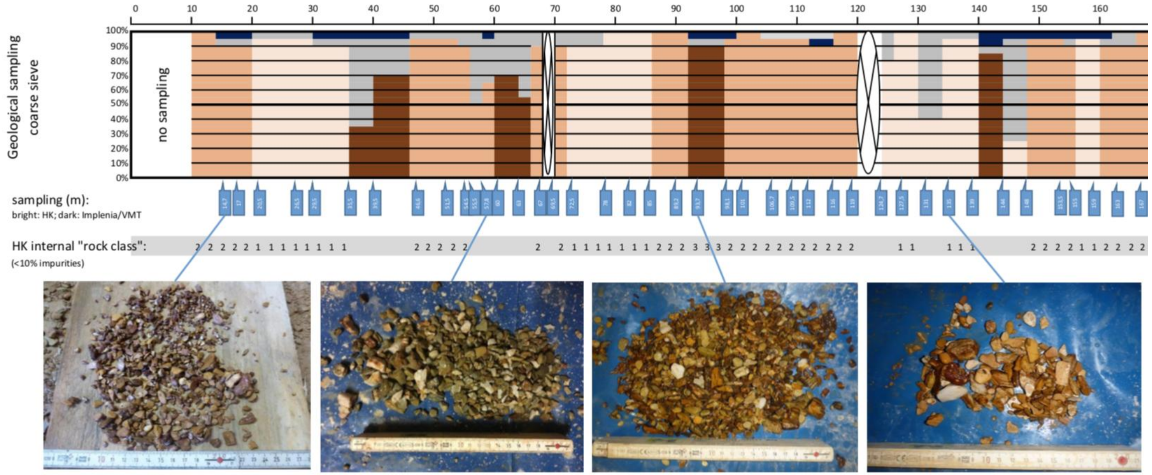
Use Case: Utility tunnels

Geology Profiles

1

- Highly weathered schist (HWS)
- Moderately weathered schist (MWS)
- Slightly weathered Schist (SWS)
- Quartzite
- Iron (hydr-)oxide
- No Material

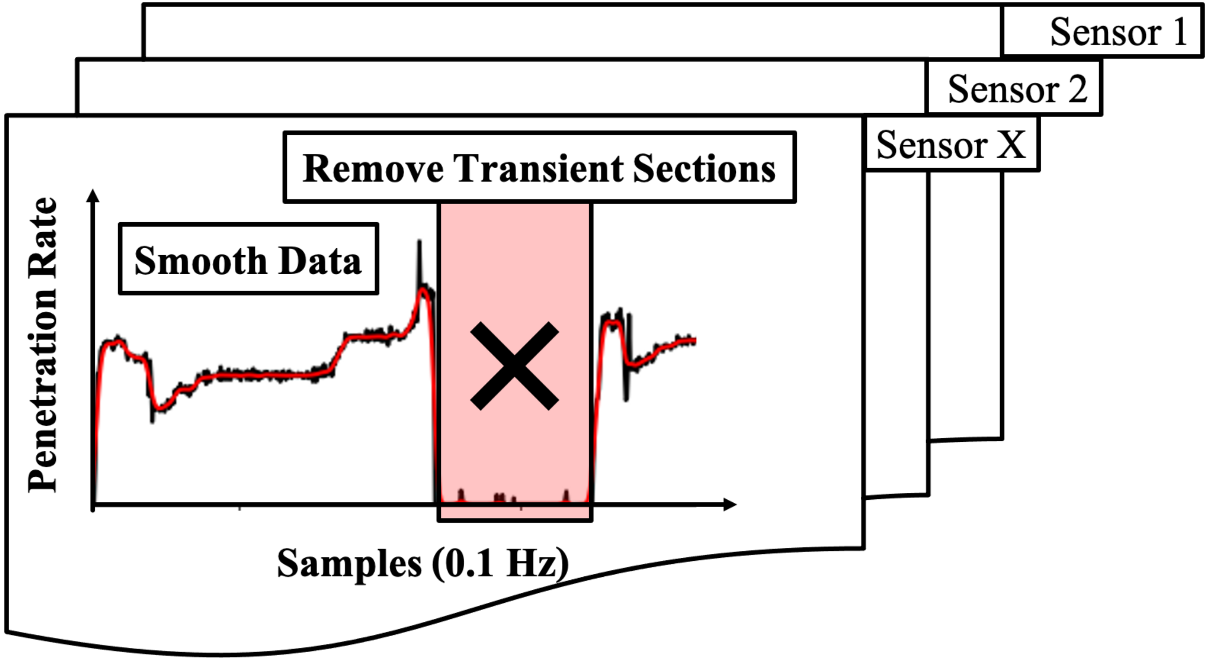
$$GC_1 = Homogeneous\ HWS$$
$$GC_2 = Homogeneous\ MWS$$
$$GC_3 = Homogeneous\ SWS$$



Garcia, G. R., Michau, G., Einstein, H. H., & Fink, O. (2021). Decision support system for an intelligent operator of utility tunnel boring machines. *Automation in Construction*, *131*, 103880.

Use Case
Data Preprocessing

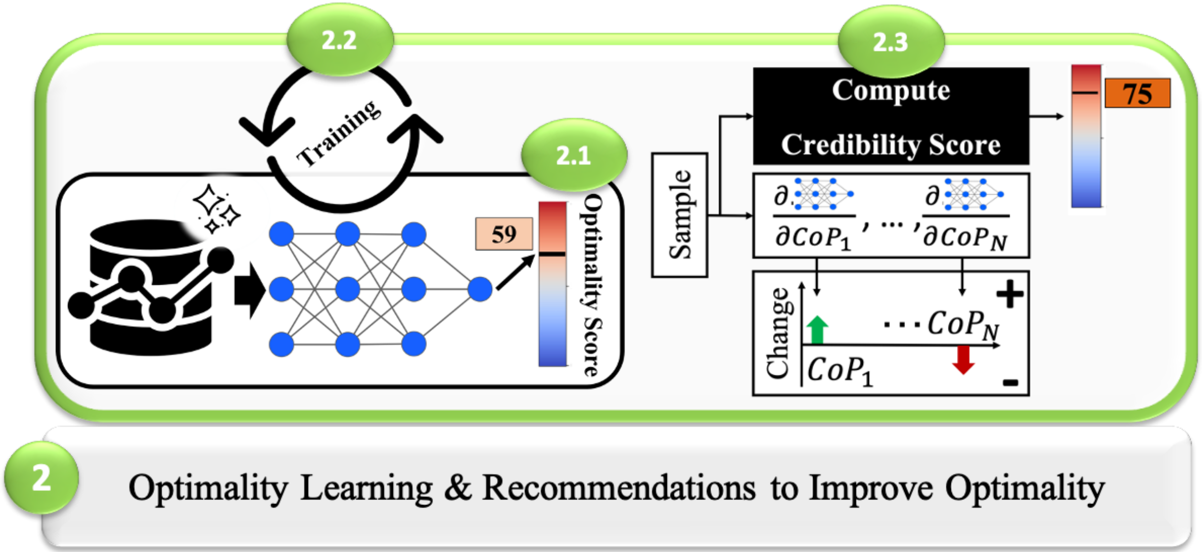
1



List of selected parameters

Parameter Name	Unit
Context Parameters (CxP)	
Steering cylinder 1 pressure	bar
Steering cylinder 2 pressure	bar
Steering cylinder 3 pressure	bar
Steering cylinder 3 pressure (3-B)	
Feed line pressure (on TBM)	bar
Feed line pressure (on pump)	bar
Suction line pressure	bar
High pressure pump pressure (on pump)	
Bentonite pump pressure	bar
Feed line flow rate	m^3/s
Drive line flow rate	m^3/s
High pressure nozzle flow rate	m^3/s
High pressure pump rotational speed	rpm
Bentonite pump rotational speed	rpm
Steering cylinder 1 extension	mm
Steering cylinder 2 extension	mm
Steering cylinder 3 extension	mm
Machine oil temperature	celsius
TBM axial rotation	degrees
Control Parameters (CoP)	
Cutter head rotational speed (CoP_1)	rpm
High pressure water nozzle speed (CoP_2)	bar
Drive line pressure (CoP_3)	bar
Jacking frame thrust (CoP_4)	kN
Feed pump rotational speed (CoP_5)	rpm
Target Parameters (TP)	
Working pressure	bar
Penetration rate	mm/min
(Optimality)	–

Framework

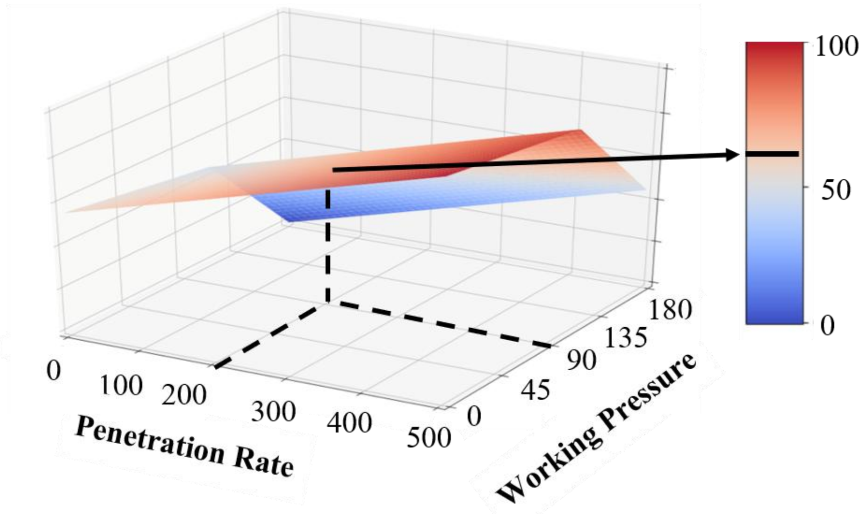


2.2
Training
2.1
59
Optimality Score
2.3
Sample
Compute
Credibility Score
75
$\frac{\partial}{\partial CoP_1}, \cdots, \frac{\partial}{\partial CoP_N}$
Change
CoP_1
$\cdots CoP_N$
+
-
2
Optimality Learning & Recommendations to Improve Optimality

Use Case
Define Optimality

2.1

$$f^{opt}_{GC_i}(t) = \begin{cases} \frac{AR_t}{MAR_i} - w_1 \cdot \frac{WP_t}{UB} & \text{if } WP_t \leq MB_i, \\ \frac{AR_t}{MAR_i} - w_1 \cdot \frac{MB_i}{UB} - w_2 \cdot \frac{WP_t - MB_i}{UB} & \text{otherwise.} \end{cases}$$



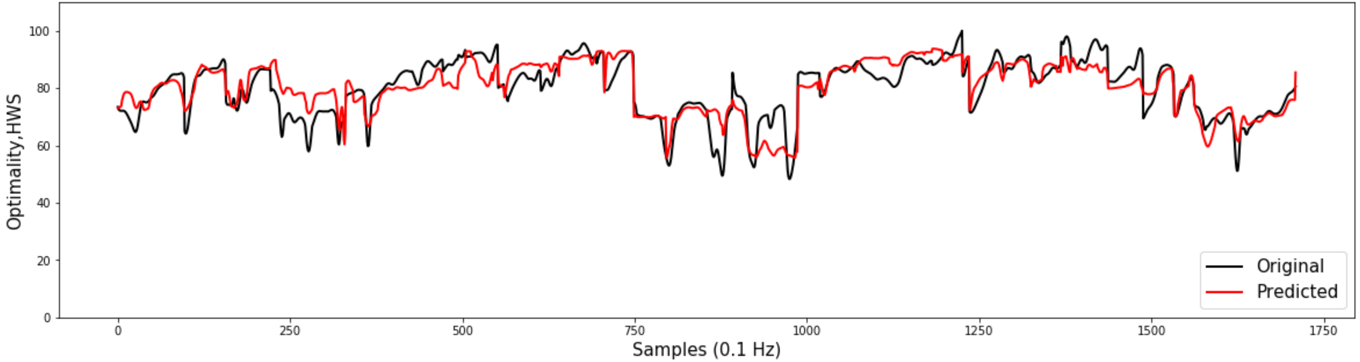
- AR_t is the advance rate [mm/min] at time t
- WP_t is the working pressure [bar] at time t
- UB is the upper bound of the working pressure (safety threshold before automatic shutdown)
- MB_i is the working pressure margin bound [bar] defined as the observed 90th percentile for the i-th ground class
- MAR_i is the observed maximum advance rate within i-th ground class
- w_1 is the negative penalizing weight on the working pressure when the working pressure is below the margin bound MB_i.
- w_2 is the negative penalizing weight on the working pressure when the working pressure is above the margin bound MB_i. Typically we have $w_2 \gg w_1$.

Garcia, G. R., Michau, G., Einstein, H. H., & Fink, O. (2021). Decision support system for an intelligent operator of utility tunnel boring machines. *Automation in Construction*, *131*, 103880.

Use Case

Predict Optimality

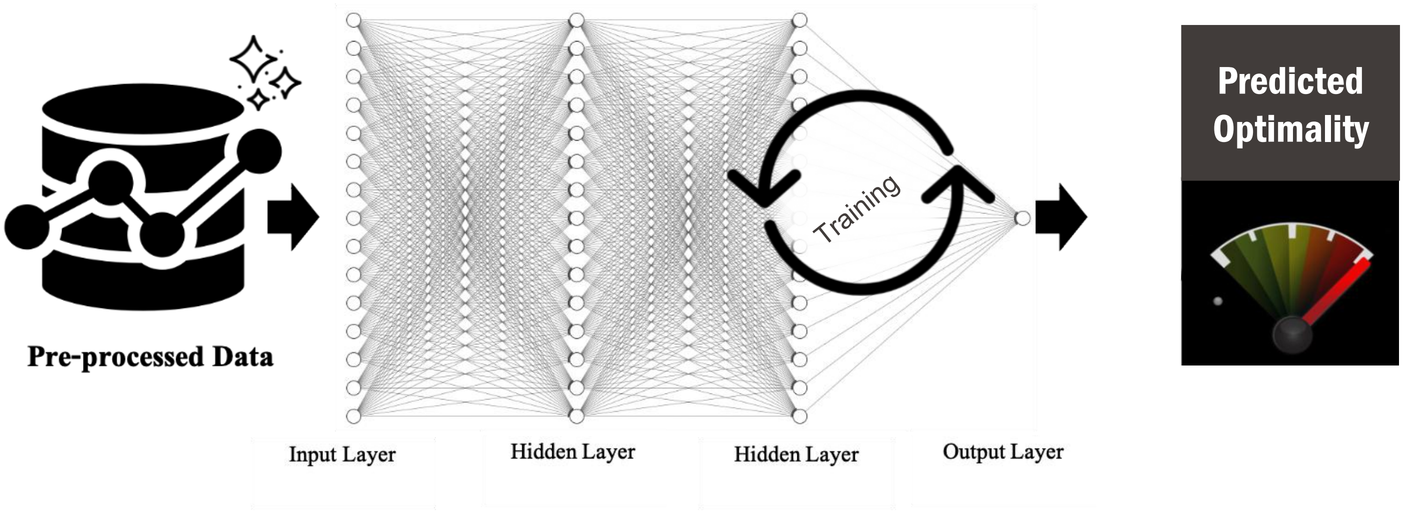
2.2



Use Case

Train the Neural Network

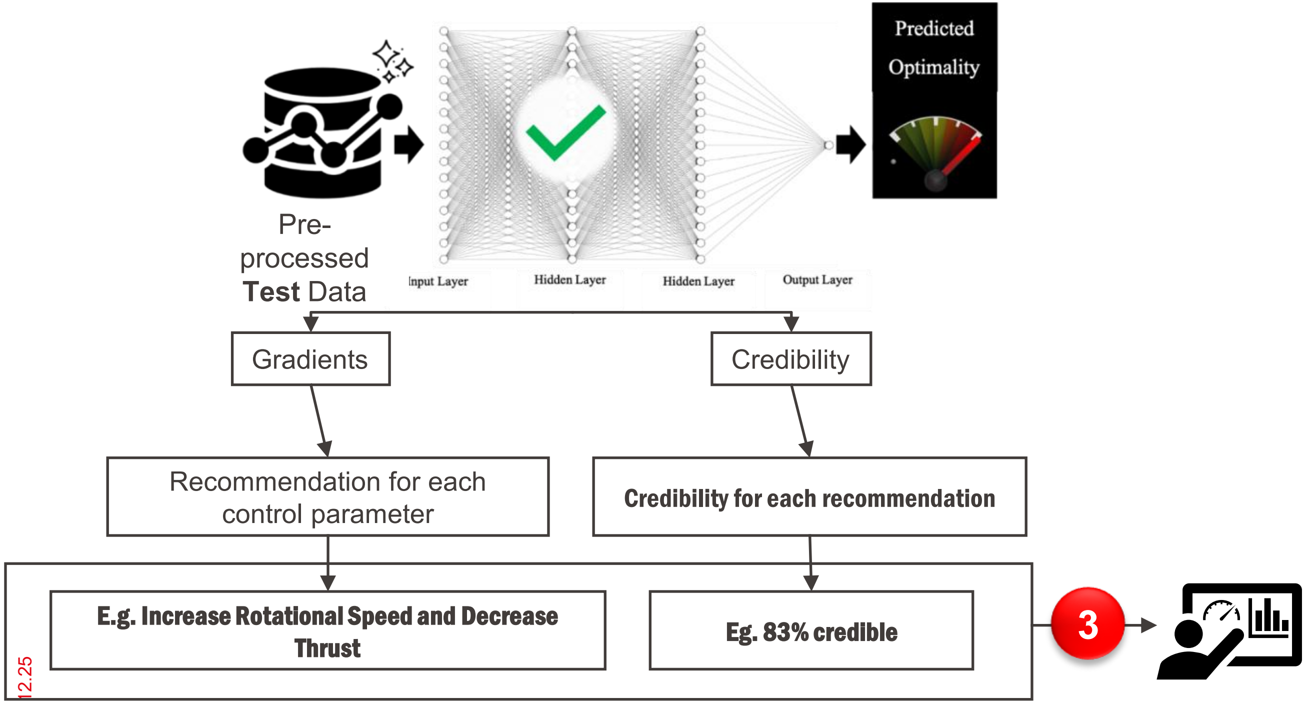
2.2



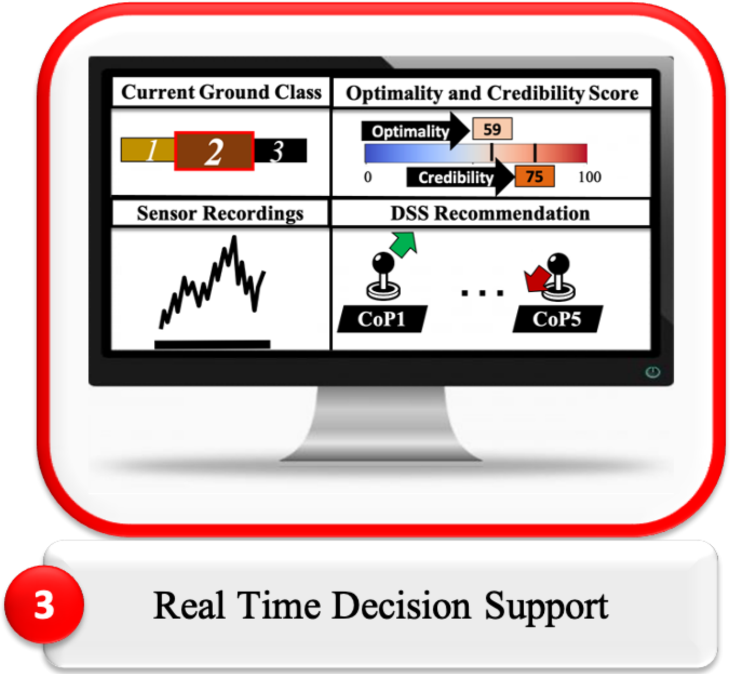
Use Case

Make recommendations and assess Credibility

2.3

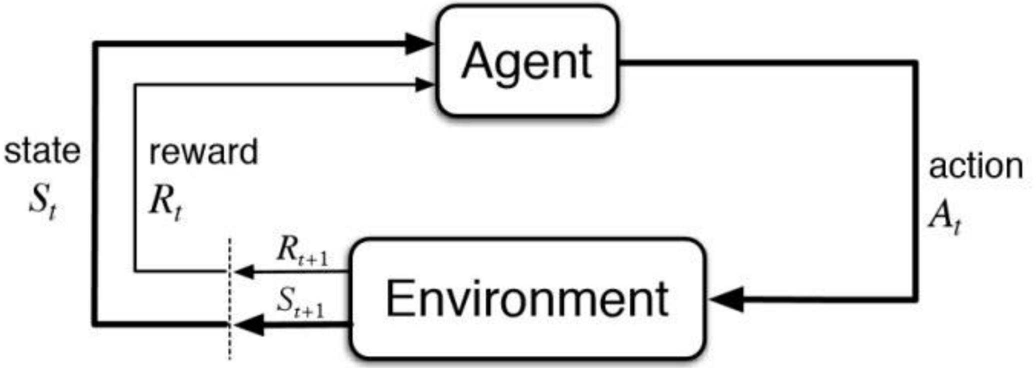


Framework


Current Ground Class
1
2
3
Optimality and Credibility Score
Optimality
59
0
Credibility
75
100
Sensor Recordings
DSS Recommendation
CoP1
. . .
CoP5
3
Real Time Decision Support

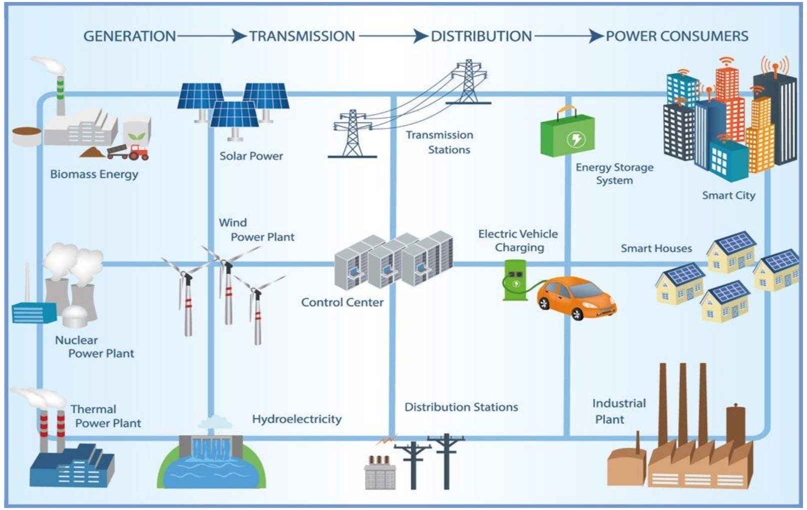
Safe multi-agent deep reinforcement learning for joint bidding and maintenance scheduling of generation units

Reminder: Reinforcement Learning



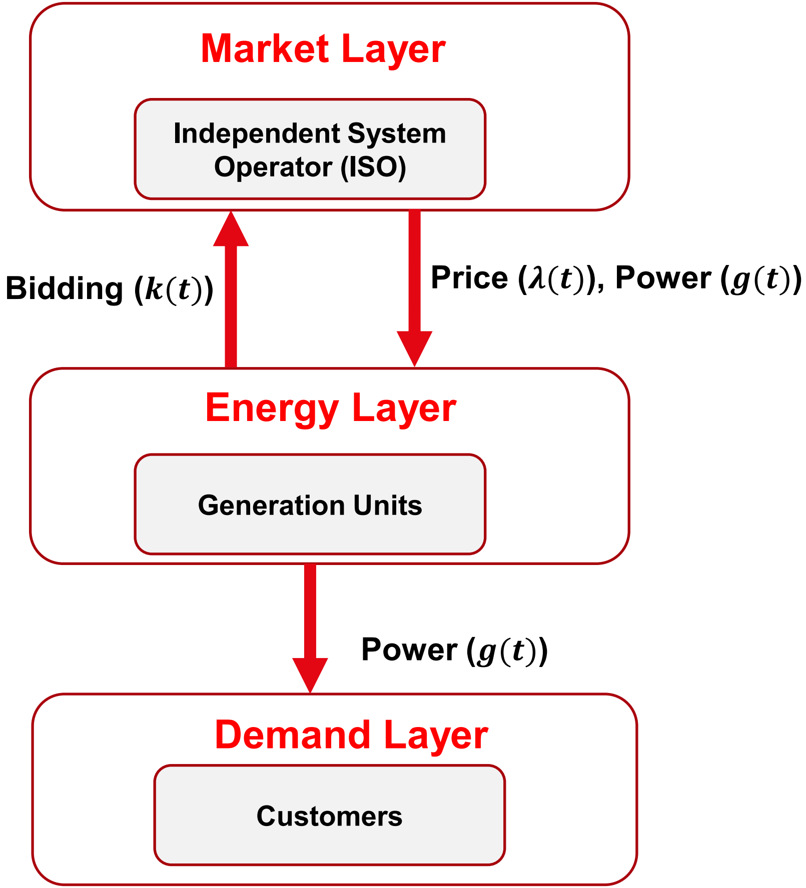
Optimal maintenance scheduling of generation units (combined with bidding)?

- Maximize the system's reliability
- Maximize the profit of the generation units
- Consider the system's constraints
- Fulfillment of the energy demand



Rokhforoz, P., Montazeri, M., & Fink, O. (2023). Safe multi-agent deep reinforcement learning for joint bidding and maintenance scheduling of generation units. *Reliability Engineering & System Safety*, 109081.

Problem formulation



$$\max_{k_i,u_i} \sum_{t\in\mathcal{T}} \left(\lambda(t)g_i(t) - \lambda_{i,m}(t)g_i(t) - c_i(t)u_i(t) - C_i^U(t) - C_i^D(t) \right)$$

subject to :

$$A_1 : 1 \le k_i(t) \le k_i^{\max}, \quad \forall t \in \mathcal{T},$$

$$A_2 : \sum_{t\in\mathcal{T}} u_i(t) \ge H_i,$$

$$A_3 : u_i(t) - u_i(t-1) \le u_i(t + D_i - 1), \quad \forall t \in \mathcal{T}.$$

$$A_4 : u_i(t) = \{0, 1\}, \quad \forall t \in \mathcal{T},$$

$g_i(t)$: Power generation of generation unit i at time t (MW)

$\lambda(t)$: Electricity market price at time t ($\frac{\$}{\mathrm{MW}}$)

$u_i(t)$: Maintenance decision of generation unit i at time t

$k_i(t)$: Bidding decision of generation unit i

$C_i^U(t), C_i^D(t)$: Start-up/shut-down cost incurred by generation unit i at time t

c_i: Maintenance cost of unit i

$\lambda_{i,m}$: Marginal cost of generation unit i ($\frac{\$}{\mathrm{MW}}$)

$k_i^{\max}$: Maximum bidding of generation unit i

H_i: Required duration of preventive maintenance of generation unit

EPFL

ISO Optimization problem

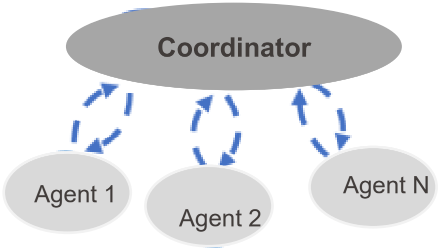
$$
\begin{aligned}
&\min_{X} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{N}} \left(k_i(t)\lambda_{i,m}(t)g_i(t) + C_i^U(t) + C_i^D(t) \right) \\
&\text{s.t. :} \\
&C_1 : \sum_{i\in\mathcal{N}} g_i(t) - \sum_{r\in\Gamma_l} B_{l,r}(\theta_l(t) - \theta_r(t)) = d(t) : \quad \lambda(t), && \forall t \in \mathcal{T}, \forall l \in \mathcal{J}, \\
&C_2 : (1 - u_i(t))g_i^{\min} \le g_i(t) \le (1 - u_i(t))g_i^{\max}, && \forall i \in \mathcal{N}, \forall t \in \mathcal{T}, \\
&C_3 : g_i(t) - g_i(t-1) \le R_i^U, && \forall i \in \mathcal{N}, \forall t \in \mathcal{T}, \\
&C_4 : g_i(t-1) - g_i(t) \le R_i^D, && \forall i \in \mathcal{N}, \forall t \in \mathcal{T}, \\
&C_5 : \quad -F_{l,r} \le B_{l,r}(\theta_l(t) - \theta_r(t)) \le F_{l,r}, && \forall r \in \Gamma_l, \forall l \in \mathcal{J}, \\
& && \forall i \in \mathcal{N}, \forall t \in \mathcal{T}, \\
&C_6 : C_i^U(t) \ge 0, && \forall t \in \mathcal{T}, \\
&C_7 : C_i^D(t) \ge 0, && \forall t \in \mathcal{T}, \\
&C_8 : C_i^U(t) \ge \big(u_i(t) - u_i(t-1)\big)K_i^U, && \forall t \in \mathcal{T}, \\
&C_9 : C_i^D(t) \ge \big(u_i(t-1) - u_i(t)\big)K_i^D, && \forall t \in \mathcal{T},
\end{aligned}
$$

Solution and challenges

- ➢ **Decentralized optimization method (Agent's based modelling)**

  Challenges

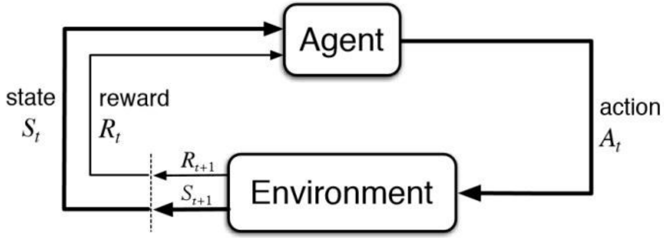
  - Agents are not aware of the other agents' decisions
  - Agents are not aware of the price of the market



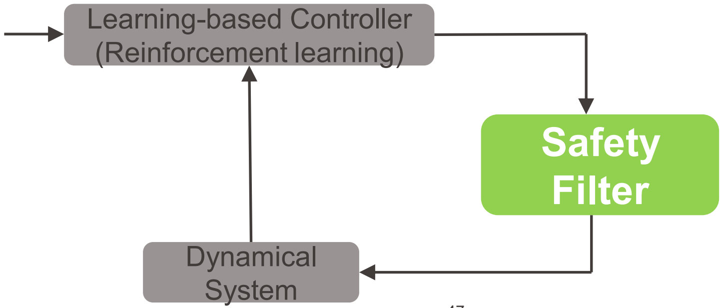
- ➢ **Decentralized reinforcement learning**

  Challenges

  - System's safety constraint

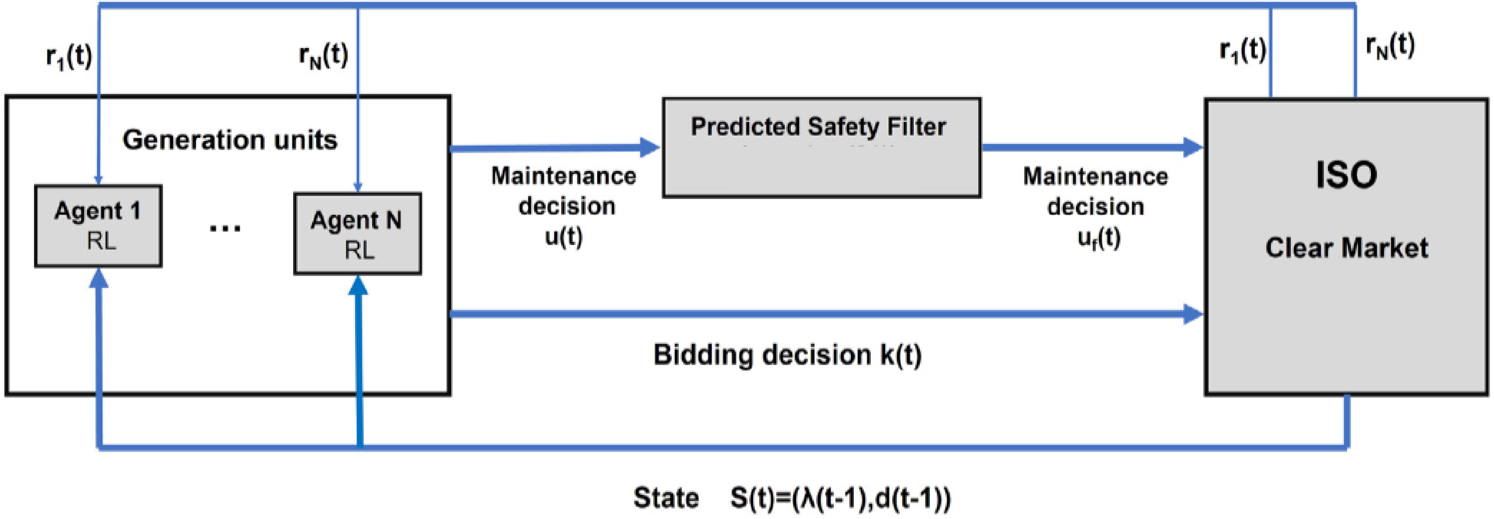


- ➢ **Decentralized safe reinforcement learning**



47

Proposed solution methodology

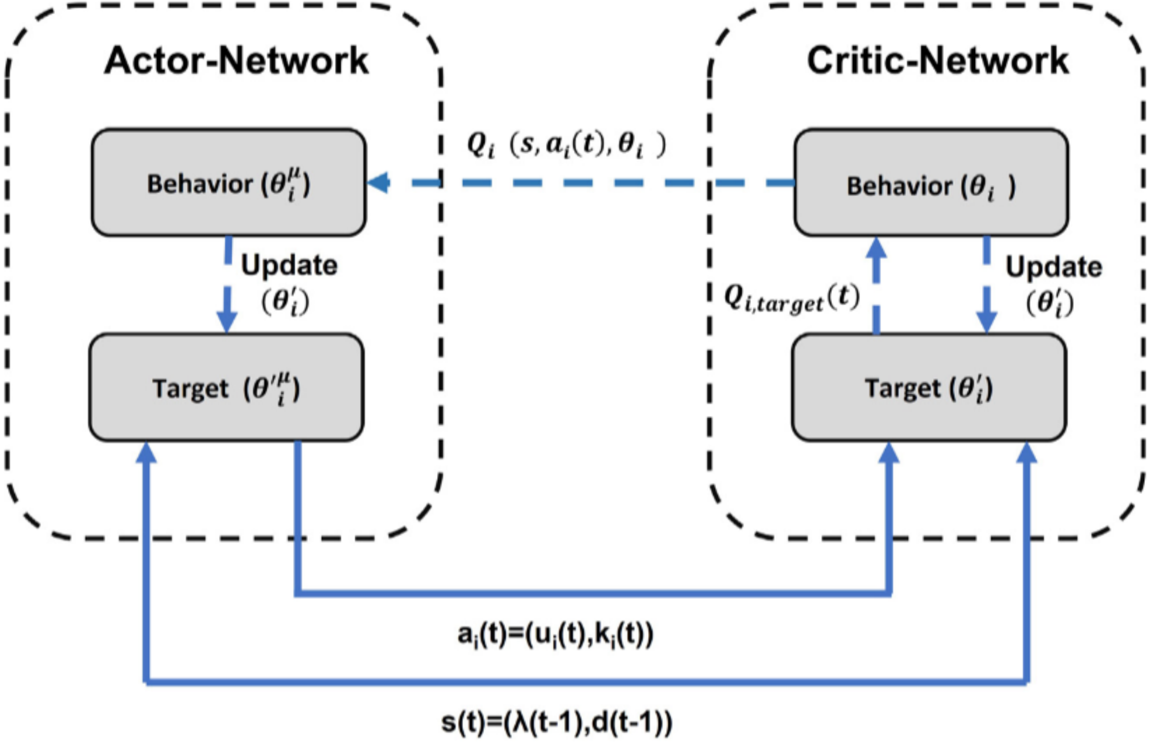


$$r_i(t) = \lambda(t)g_i(t) - \lambda_{i,m}g_i(t) - c_i u_i(t) - C_i^U(t) - C_i^D(t).$$

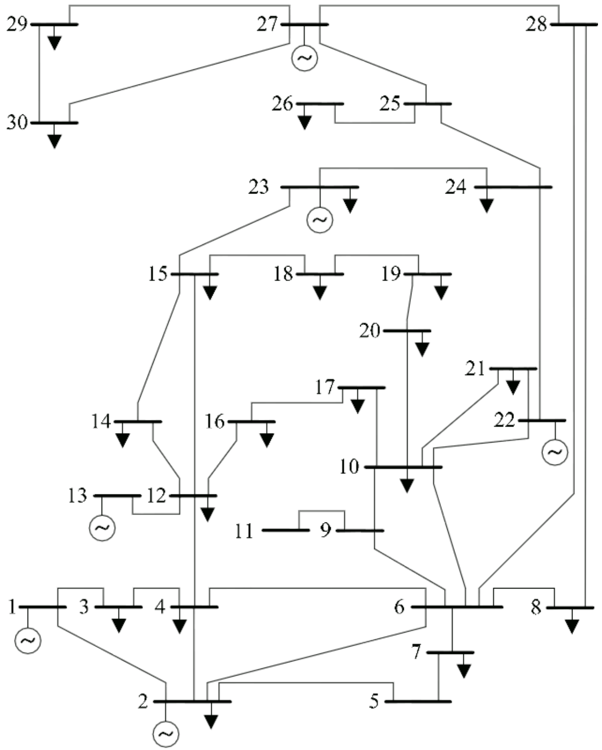
$$\min_{u_{f,i}} \sum_{i \in \mathcal{N}} \|u_{f,i}(t) - u_i(t)\|^2$$

Inspired by: Wabersich, K. P., & Zeilinger, M. N. (2021). A predictive safety filter for learning-based control of constrained nonlinear dynamical systems. *Automatica*, *129*, 109597.

Schematic of the DDPG algorithm for one unit (Deep Deterministic Policy Gradient)

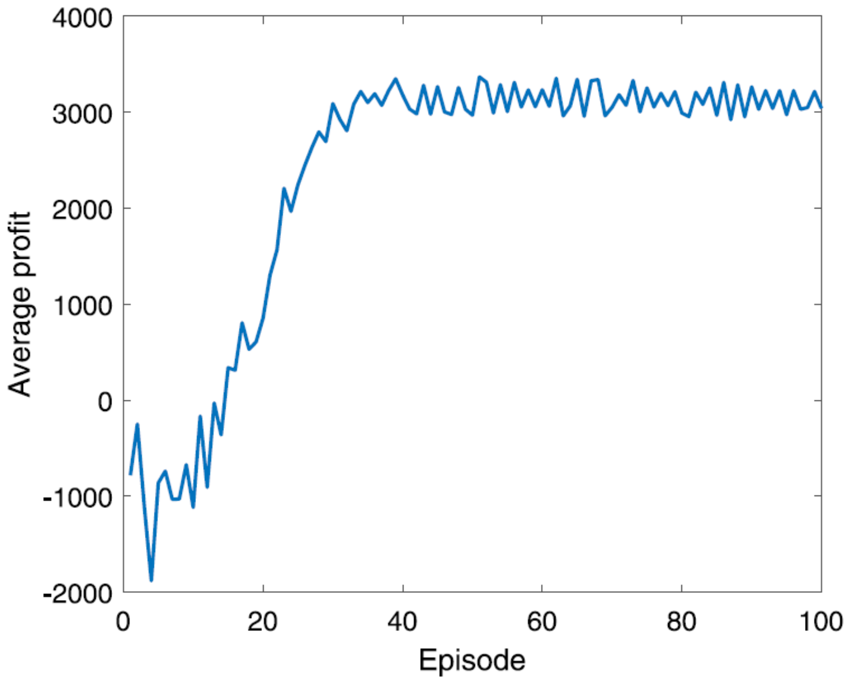


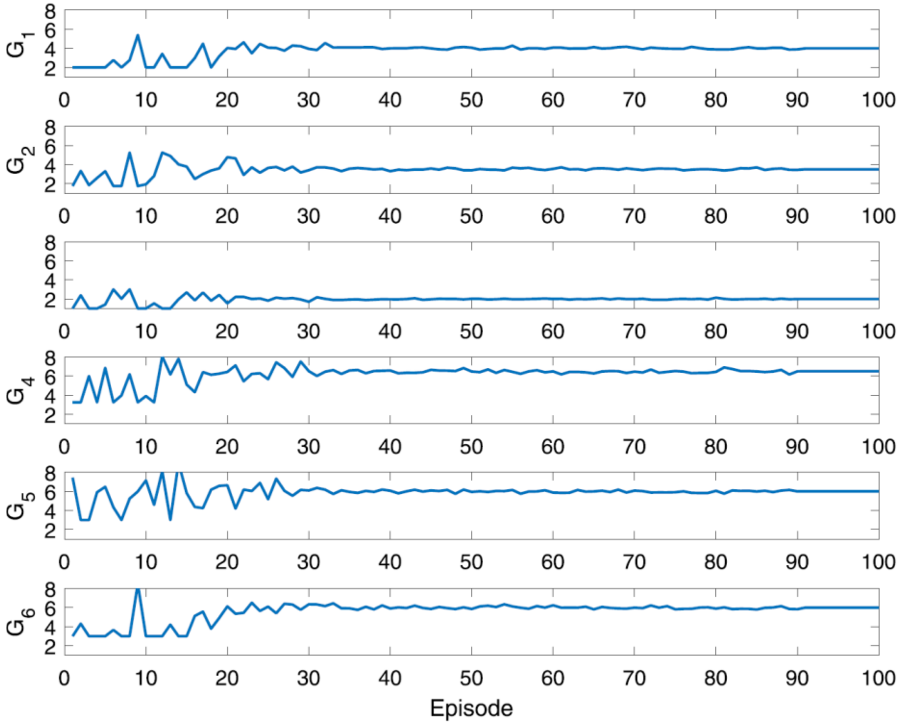
Case study: IEEE 30-bus system with 6 generation units



Generation unit	$\lambda_{i,m}$ $[\frac{\$}{MWh}]$	$g_i^{\max}$ $[MW]$	$g_i^{\min}$ $[MW]$	c_i [$]	H_i
1	2	80	5	120	65.4
2	1.75	80	5	135	54.5
3	1	50	5	142	52.4
4	3.25	55	5	125	60.3
5	3	30	5	175	60.7
6	3	40	5	165	50.8

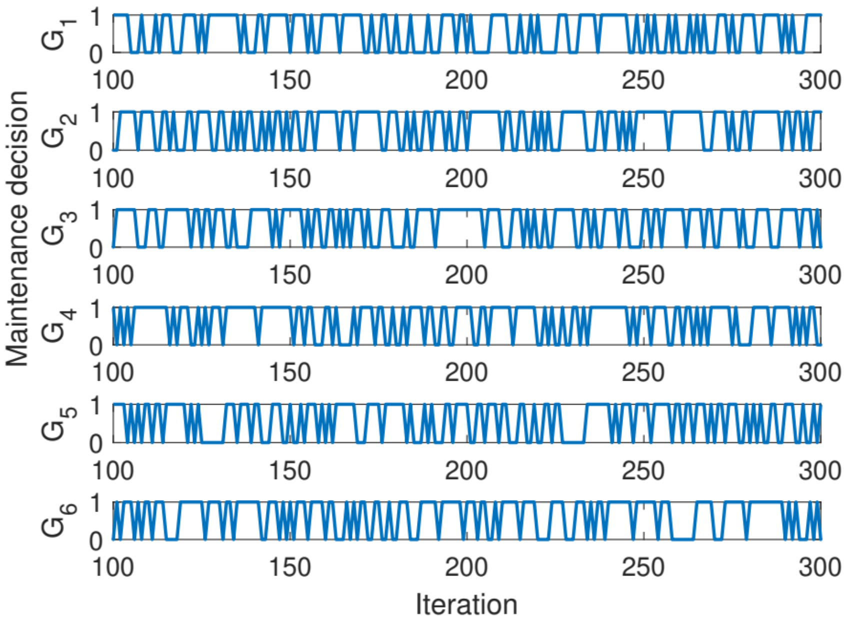
Bidding strategies



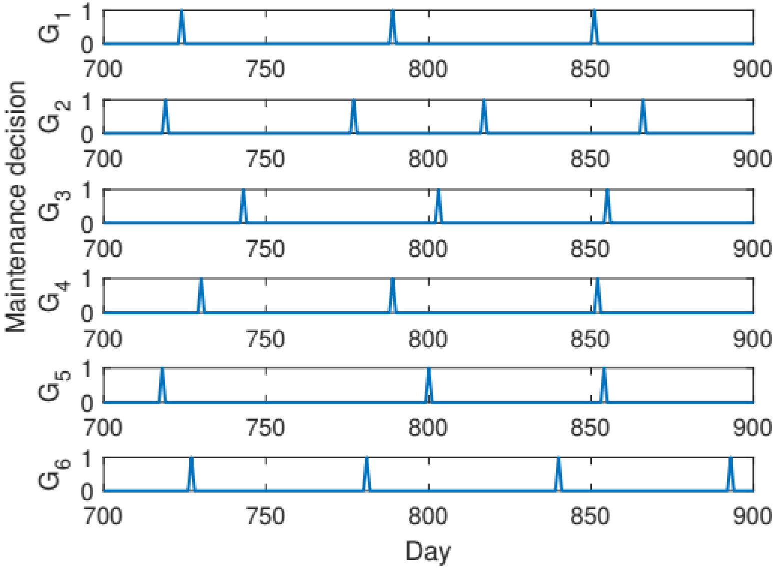


Effect of safety filter

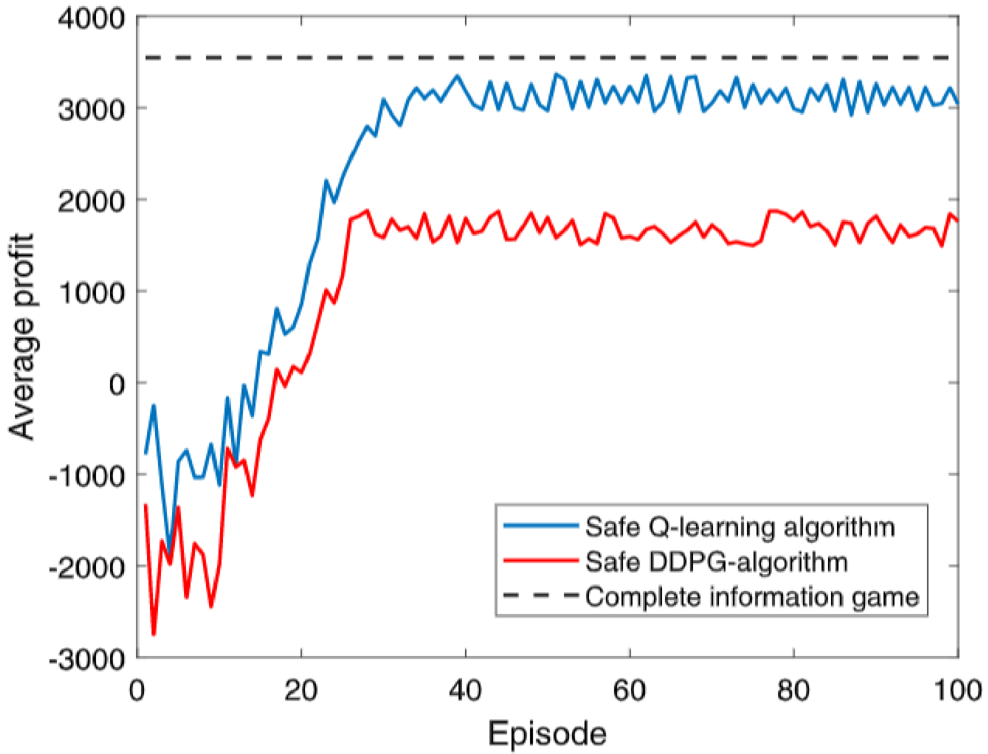
Without safety filter



Effect of safety filter



Performance comparison



Conclusion

- Safe deep reinforcement learning for joint bidding and maintenance scheduling of generation units.

- The results show that the proposed approach can handle the safety constraints.

- Reinforcement learning leads to a higher profit than Q-learning algorithm.