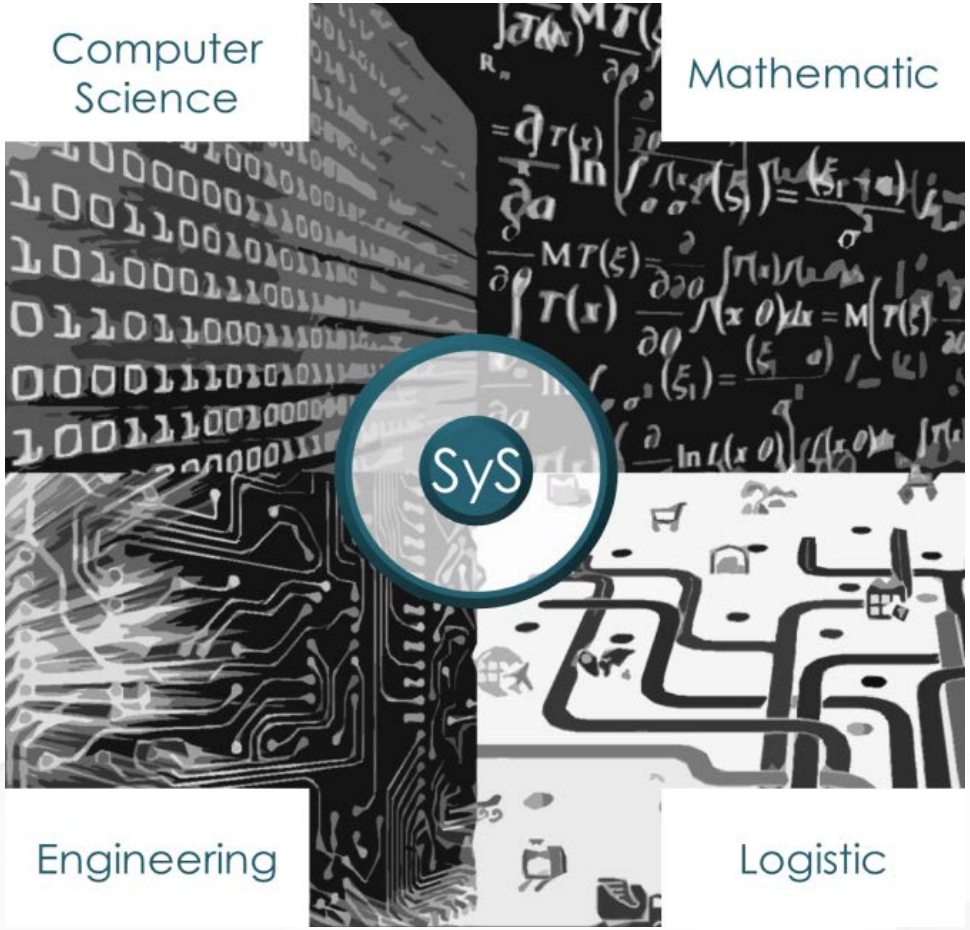

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Challenges of Supervised Learning Algorithms in the Predictive Maintenance Context

Smart Maintenance Conference in ZHAW Winterthur

Daniel Jaroszewski

5th of September 2017

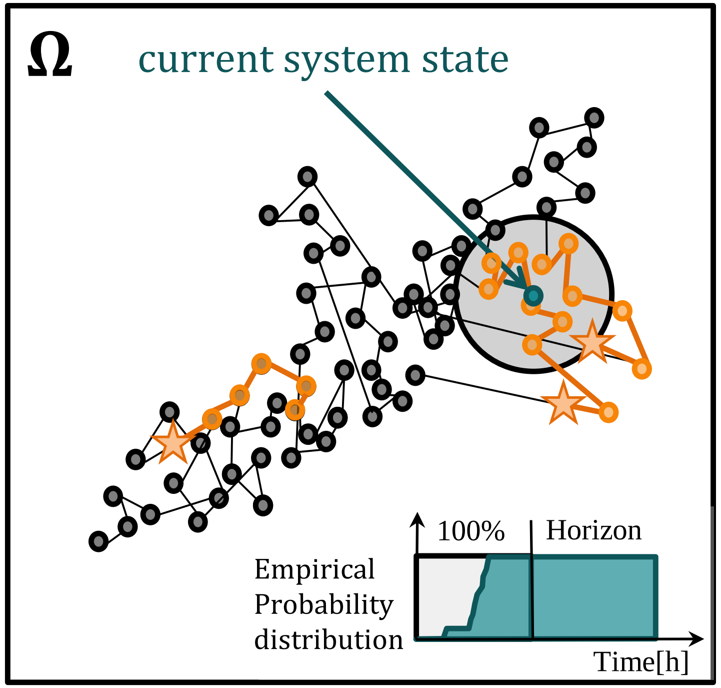
Principal Issue in the Supervised Learning Context

Algorithm/ Regression/ Classification

$$Y_{t+H} = f(X_t)$$

Response Variables depending on horizon

Input Variables



The probability that a critical event will occur within the prediction horizon H is computed based on comparable states in the training data

$$P(T_Y < t + H \mid X_t = x)$$

$$= P\left(\text{Event Y will occur within the next H time units} \mid \text{State vector of system at time t}\right)$$

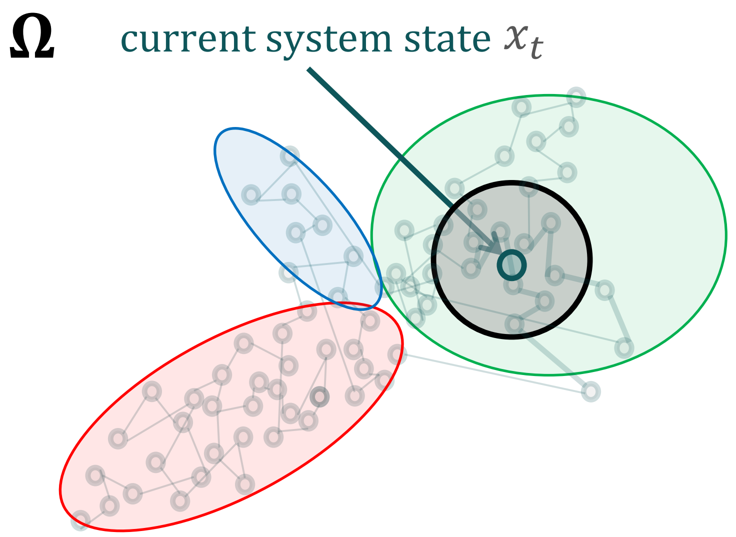
State Space Aggregation

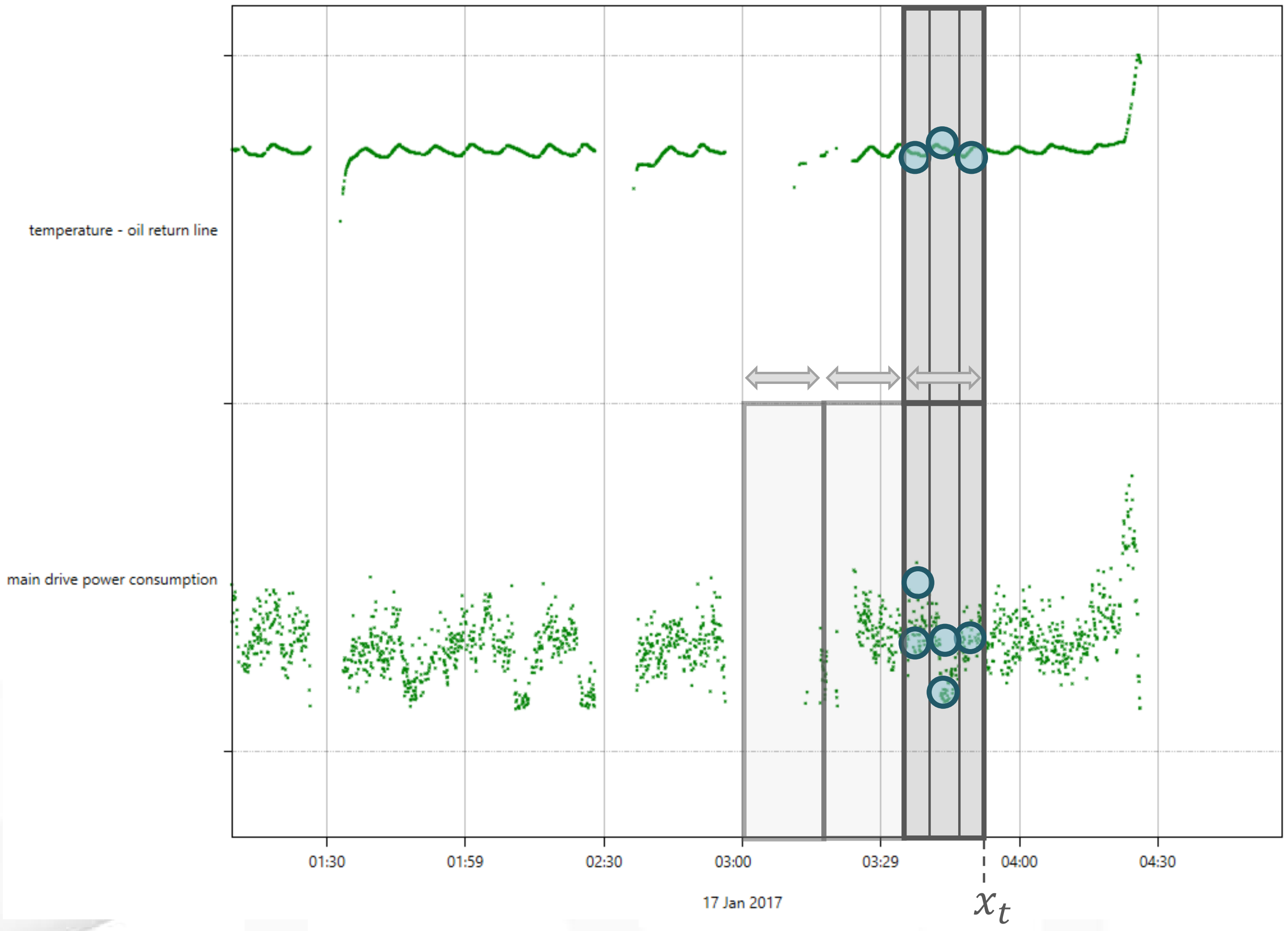
What is the right choice of the state space?

$$Y_{t+H} = f(X_t)$$

Input Variables

Definition of observation points (X_t)?





Preferences for the State Space

Aggregation (Min, Max, Avg, Max Diff,…)
Parameter Selection
Step Size (Monitoring Frequency)
Embedding Window
Operating Modes
Data Source (Fault memory, Sensors)

Auxiliary Power Converters (Rail)
Fault memory data

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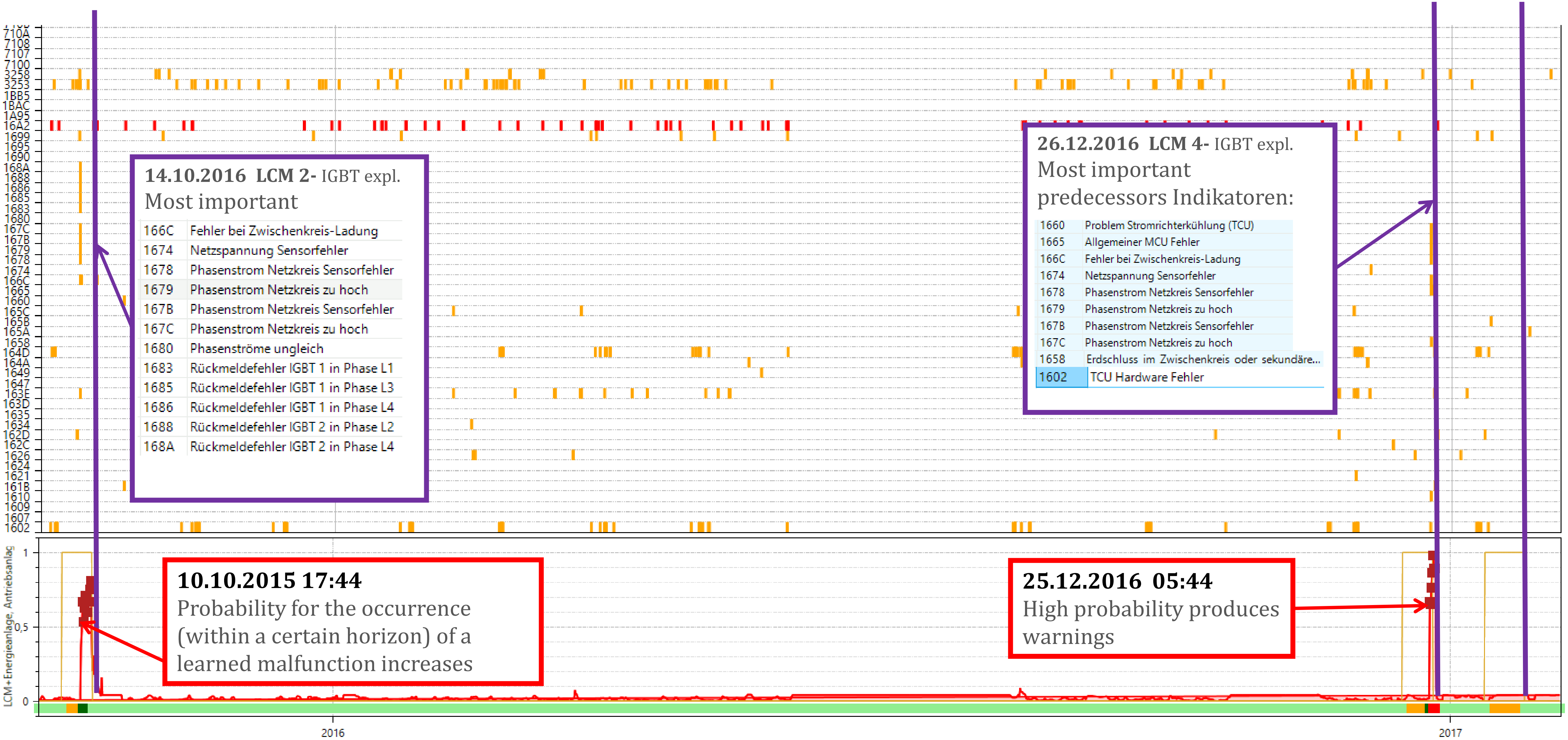


State Space Classifier

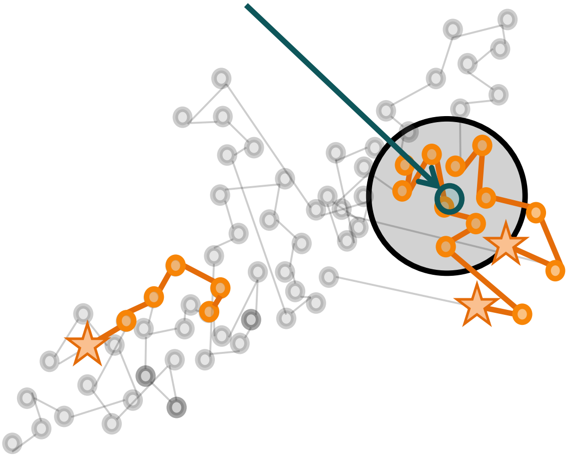
Which ingredients can I use for the definition of an appropriate output?

$$Y_{t+H} = f(X_t)$$

Response Variables depending on horizon

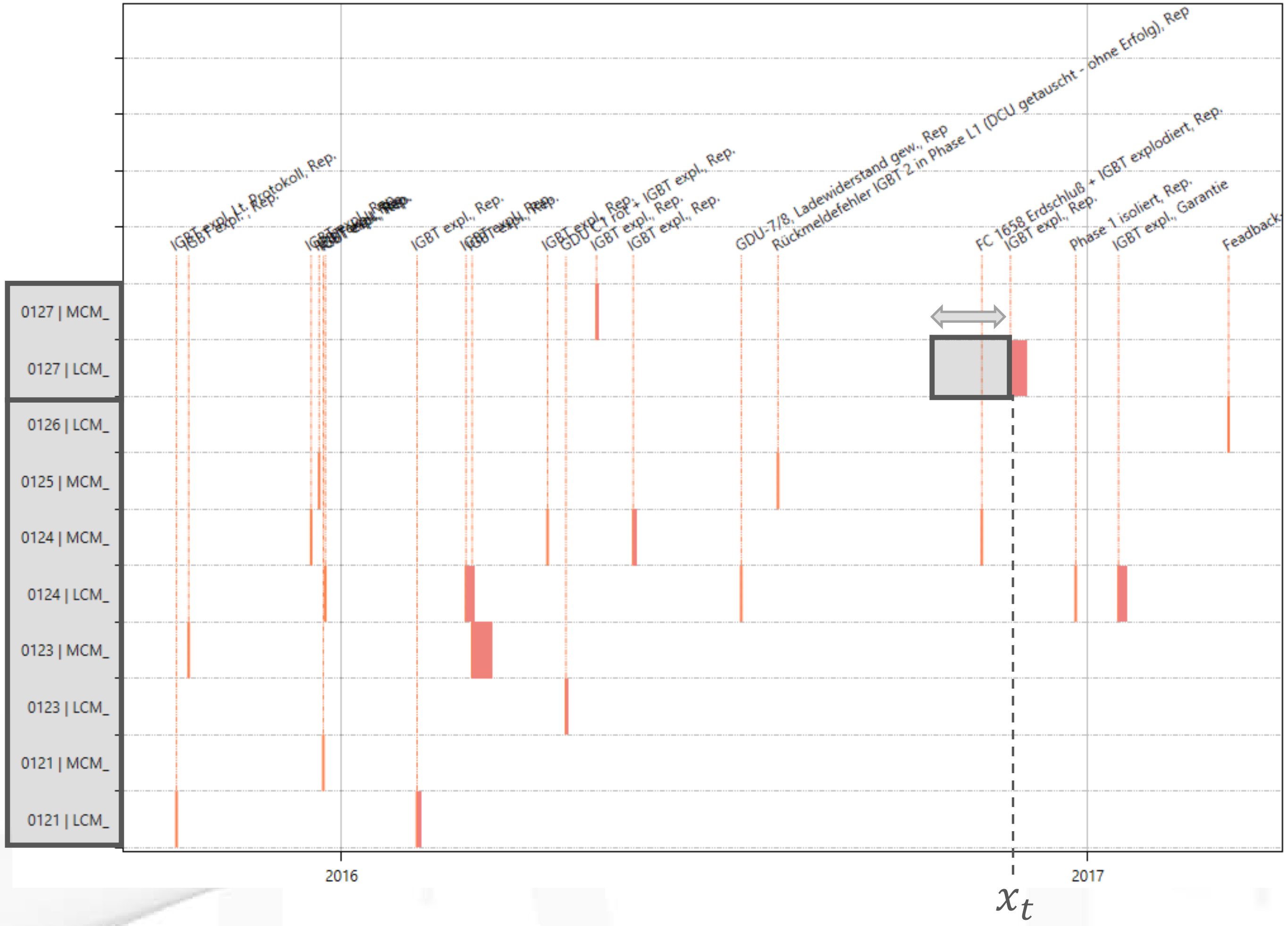
Definition of critical points (Y_{t+H})

Ω current system state



Preferences for the Output

Aggregation (Binary, Forward Time)
Horizon
Categorization (Hierarchical Structure)
Reference data (Comparable Assets)



Hierarchical Structuring of the Input Data

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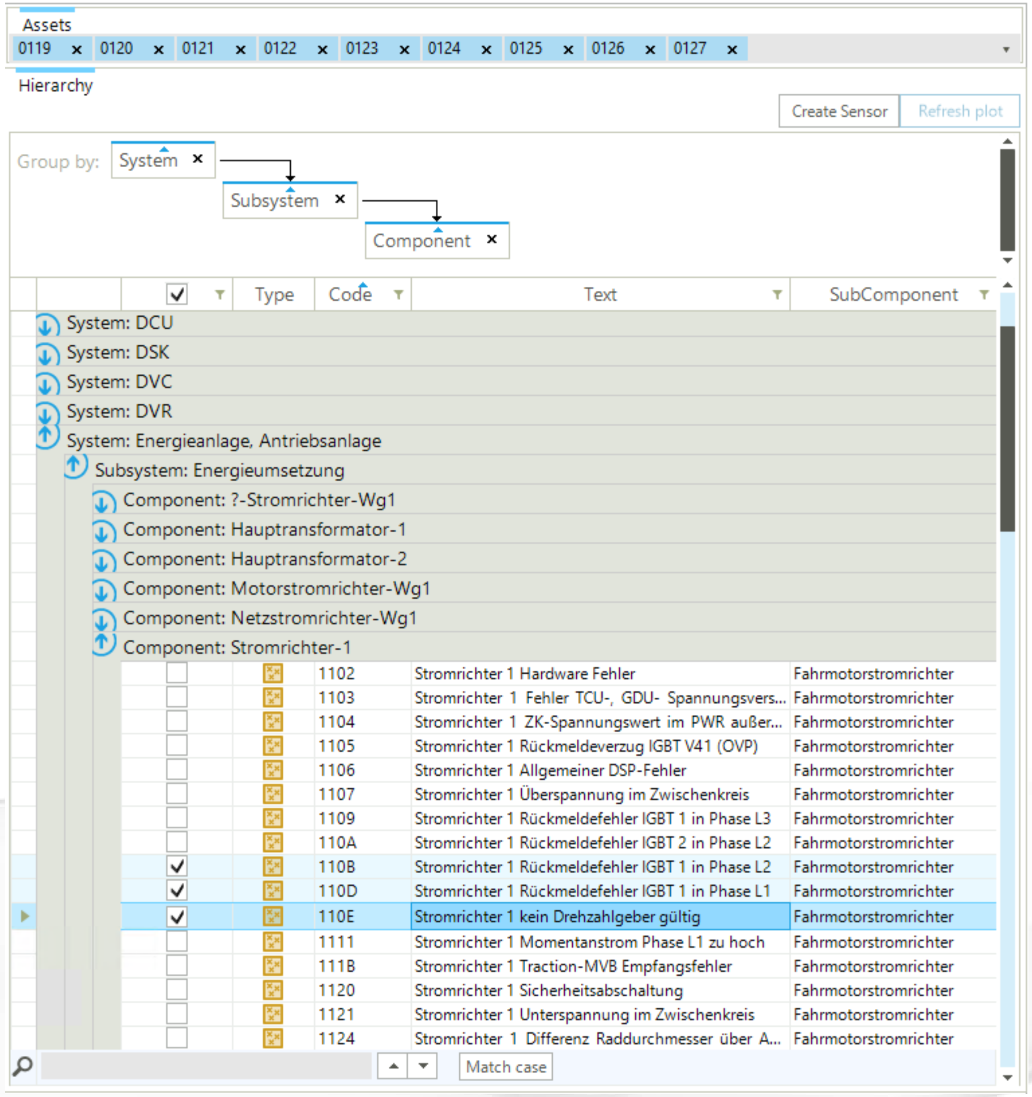
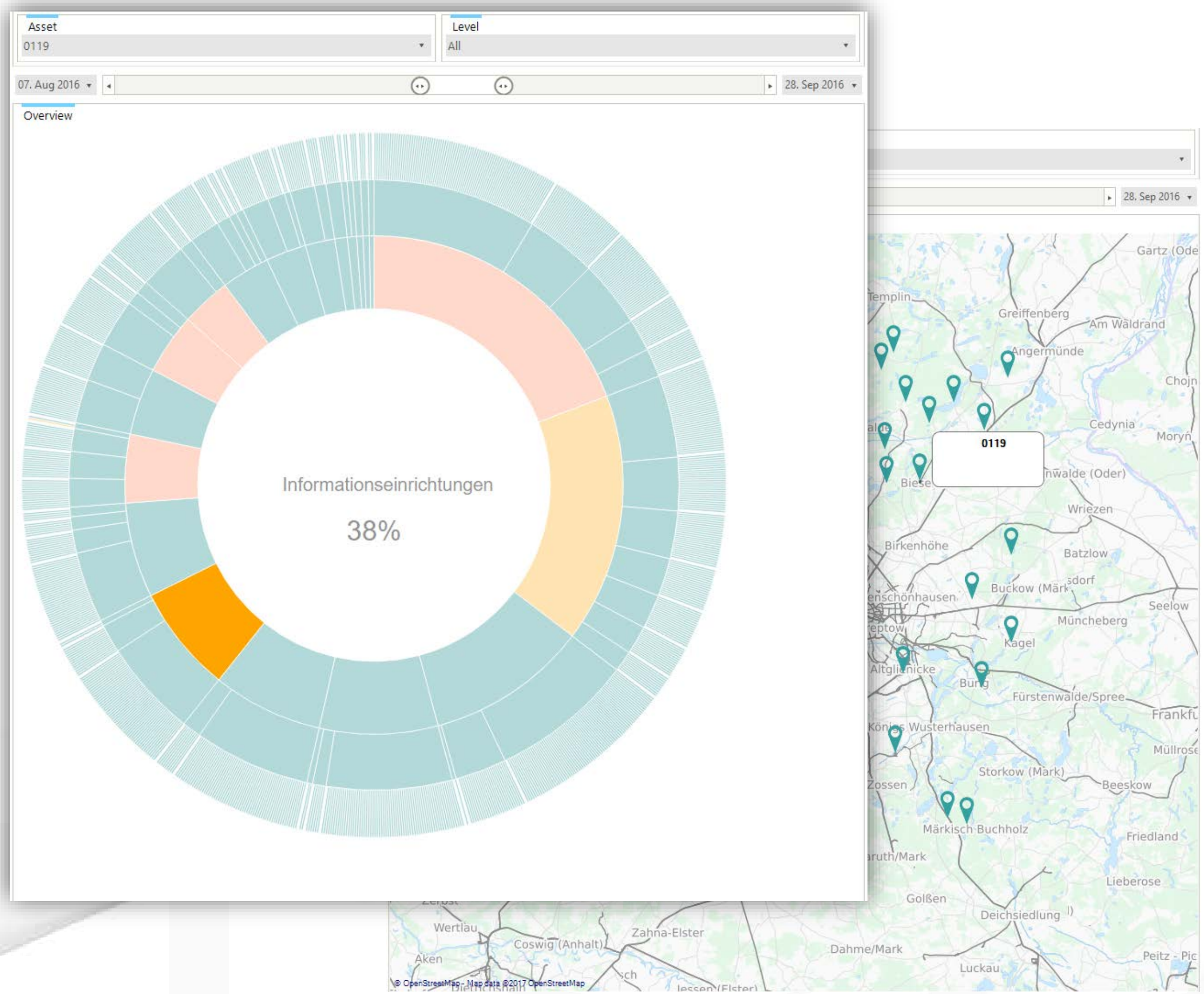




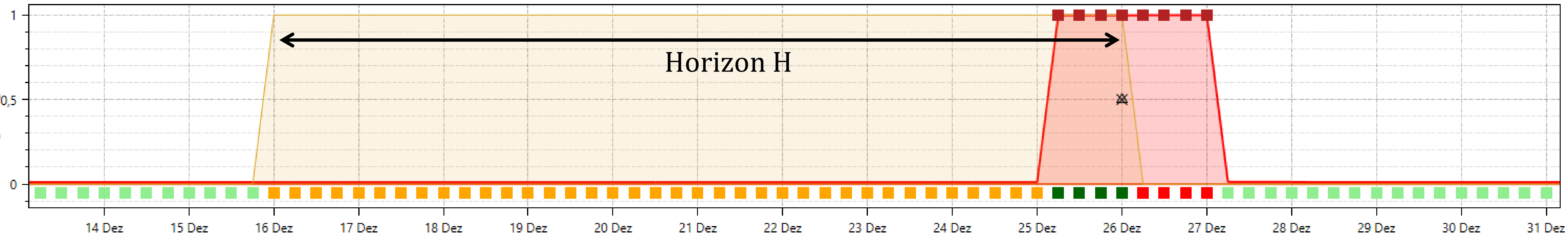
Supervised Learning Algorithms

How much impact do the algorithm on the KPI’s?

Algorithm/ Regression/ Classification

$$Y_{t+H} = f(X_t)$$

Definition of Statistical KPI‘s (1/2)



KPIs	Actual false	Actual true
Prediction false	#TN	#FN
Prediction true	#FP	#TP

Classification Features

- ***#TN* (Number of True Negatives):** Number of Intervals, in which **no** event are predicted in the next H hours and actually **no** event occurs
- ***#TP* (Number of True Positives):** Number of Intervals, in which **an** event is predicted in the next H hours and actually **an** event occurs
- ***#FN* (Number of False Negatives):** Number of Intervals, in which **no** event is predicted in the next H hours and actually **an** event occurs
- ***#FP* (Number of False Positives):** Number of Intervals, in which **an** event is predicted in the next H hours and actually **no** event occurs

Type 2 Error
False Negative

$$\frac{\#FN}{\#FN+\#TP}$$

Type 1 Error
False Positive

$$\frac{\#FP}{\#FP+\#TN}$$

Definition of Statistical KPI's (2/2)

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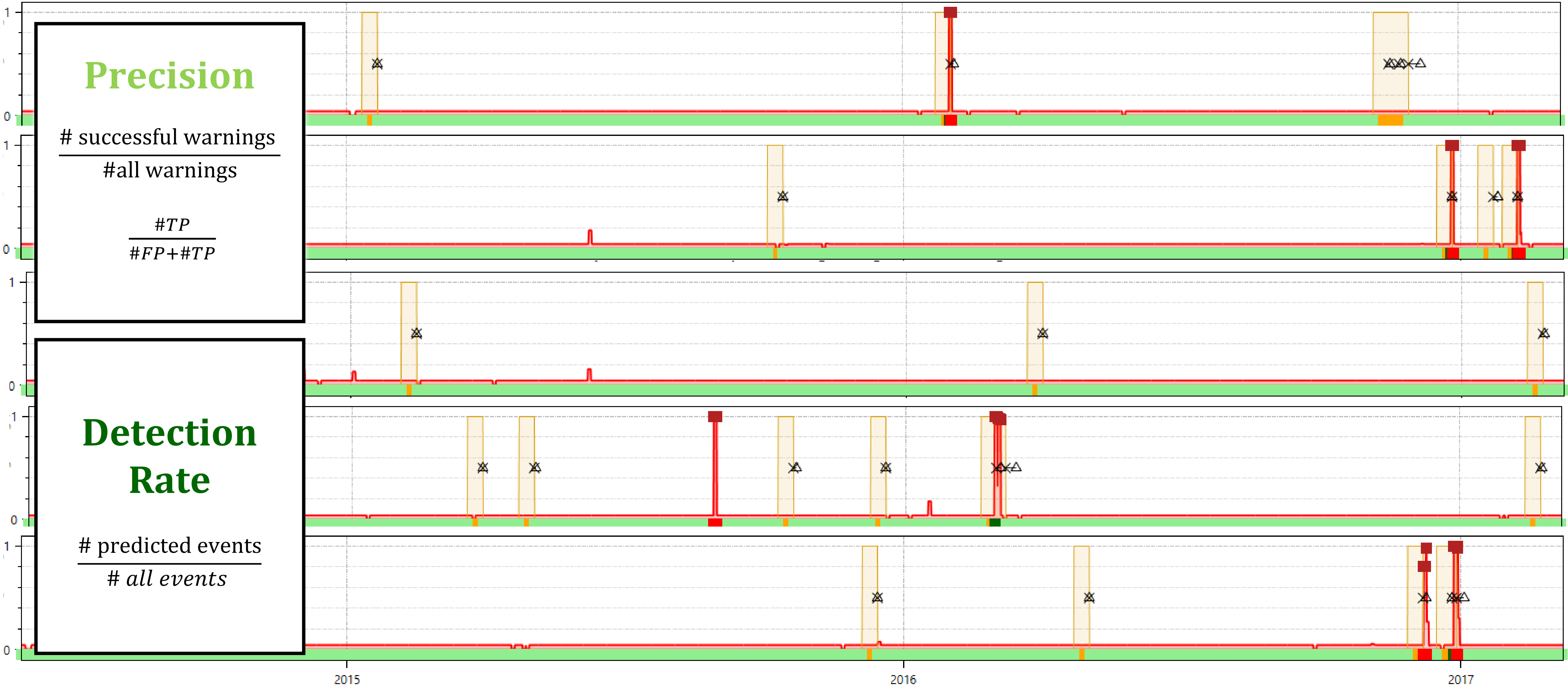
BR442 129, 131, 141, 323, 333 | LCM&MCM | 6-hour Rate



Precision

$$\frac{\text{\# successful warnings}}{\text{\#all warnings}}$$

$$\frac{\#TP}{\#FP + \#TP}$$

Detection Rate

$$\frac{\text{\# predicted events}}{\text{\# all events}}$$

Impact of algorithms

Mobility Networks Logistics

DB Systemtechnik

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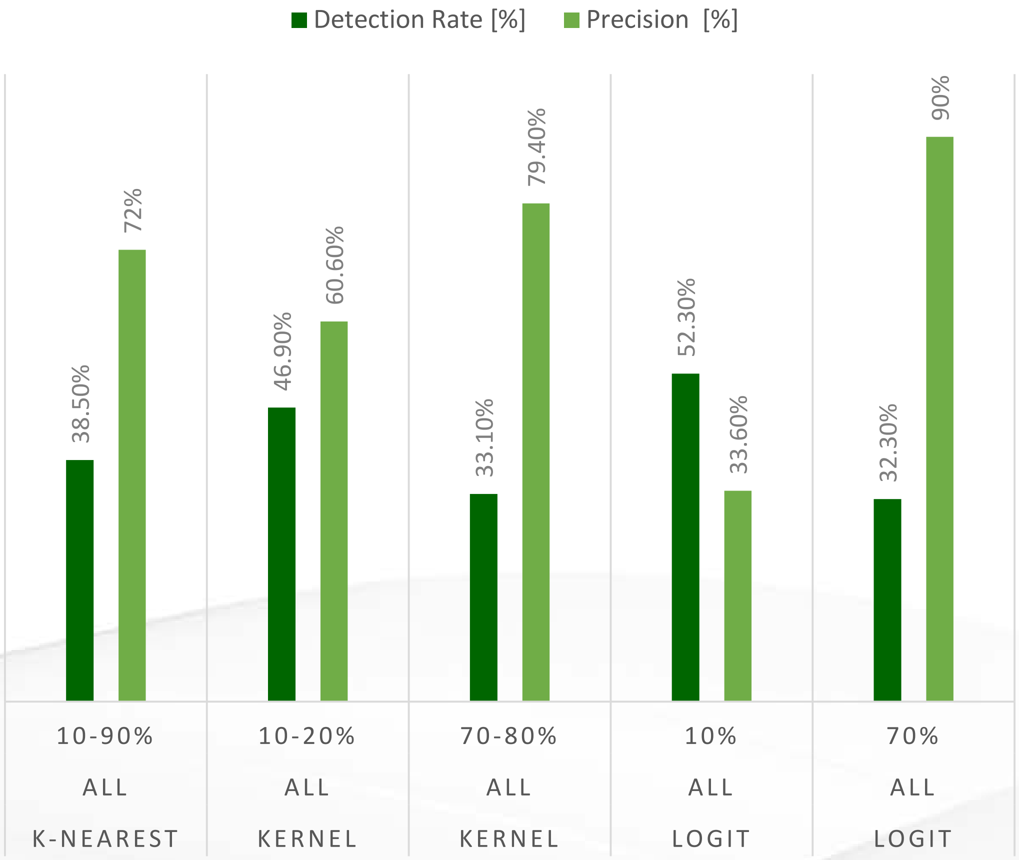
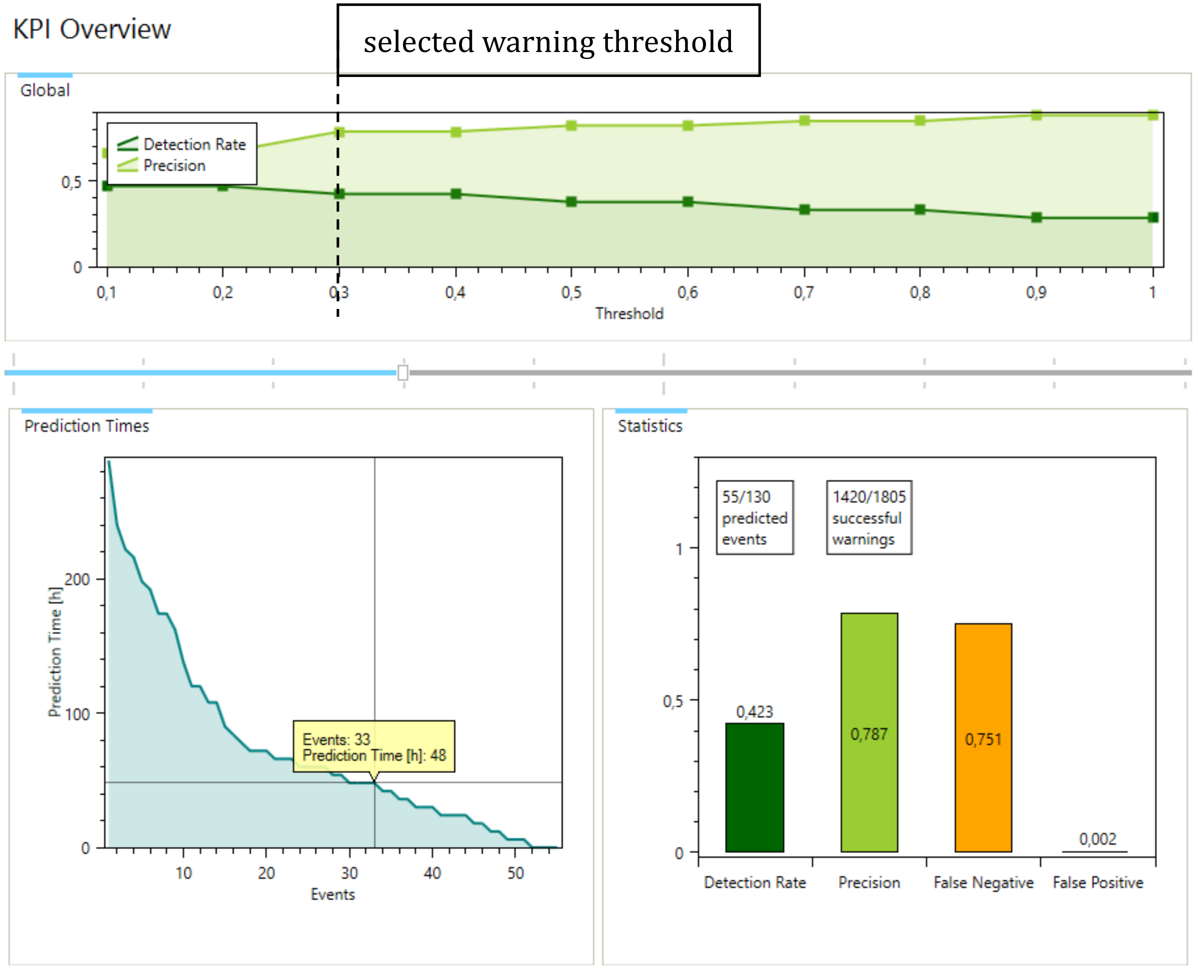
PROGNOSIS KPI'S OF 130 MAINTENANCE ACTIONS (LCM&MCM) OVER A FLEET OF 43 VEHICLES



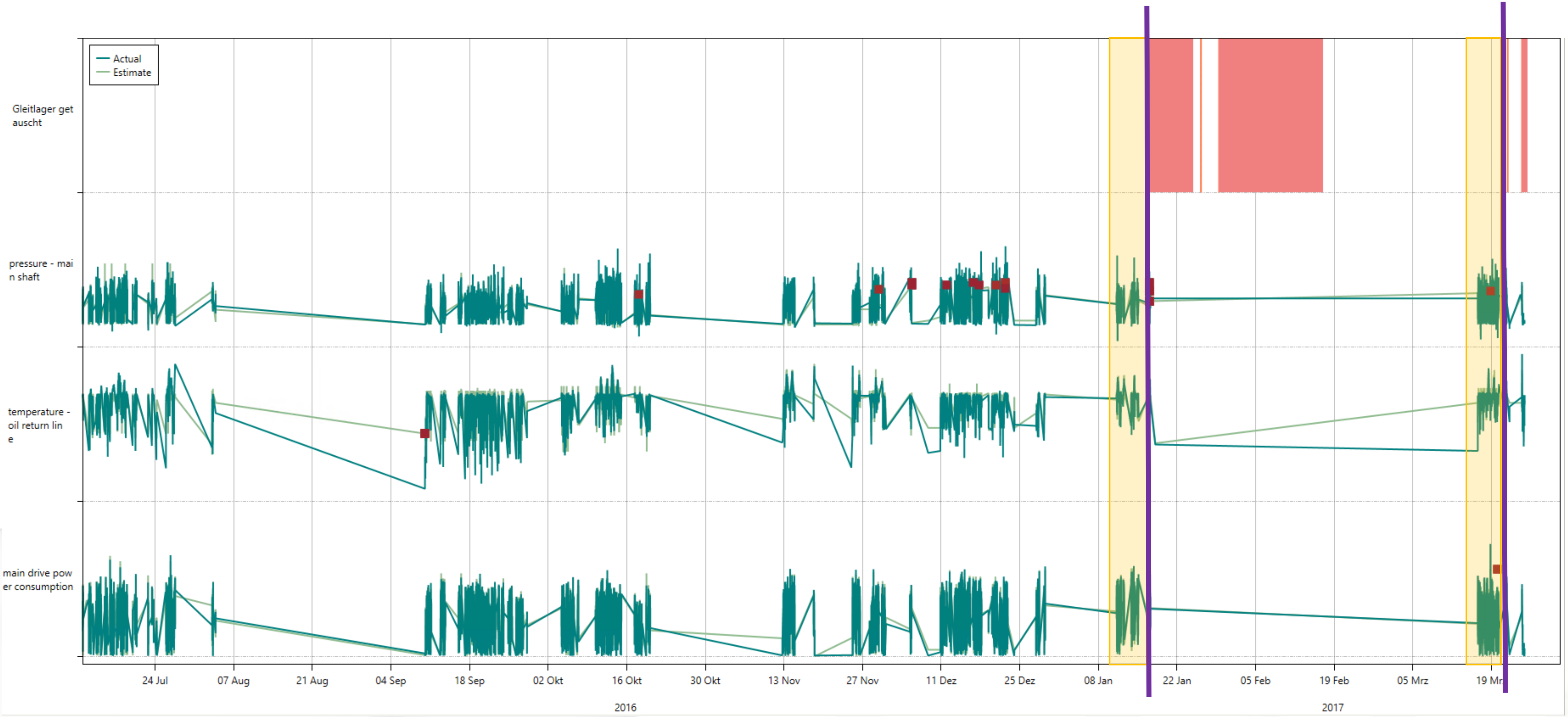
DEPENDENCIES BETWEEN THE KPI'S, THE PREDICTION TIMES AND THE WARNING THRESHOLD



Challenges of Supervised Learning Algorithms

What are the lessons learned?

Crusher (mining industry)
From anomaly detection to supervised learning



Crusher (mining industry)

Example: Friction Bearing

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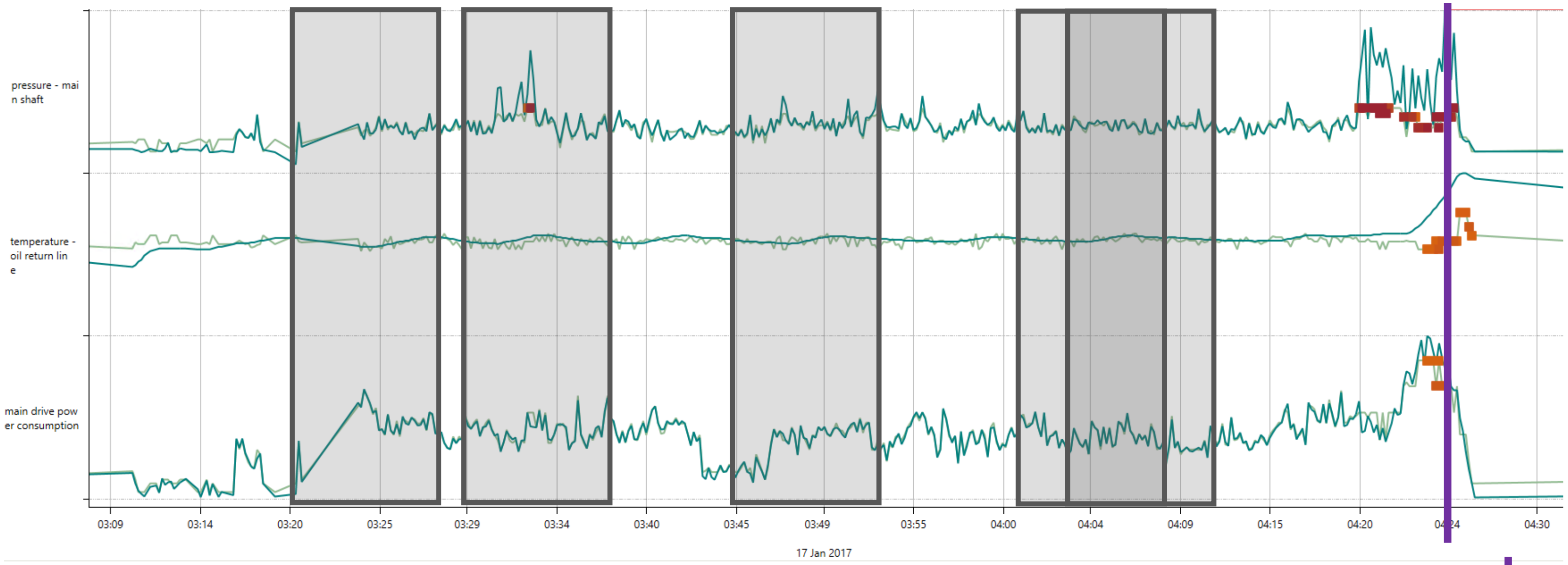
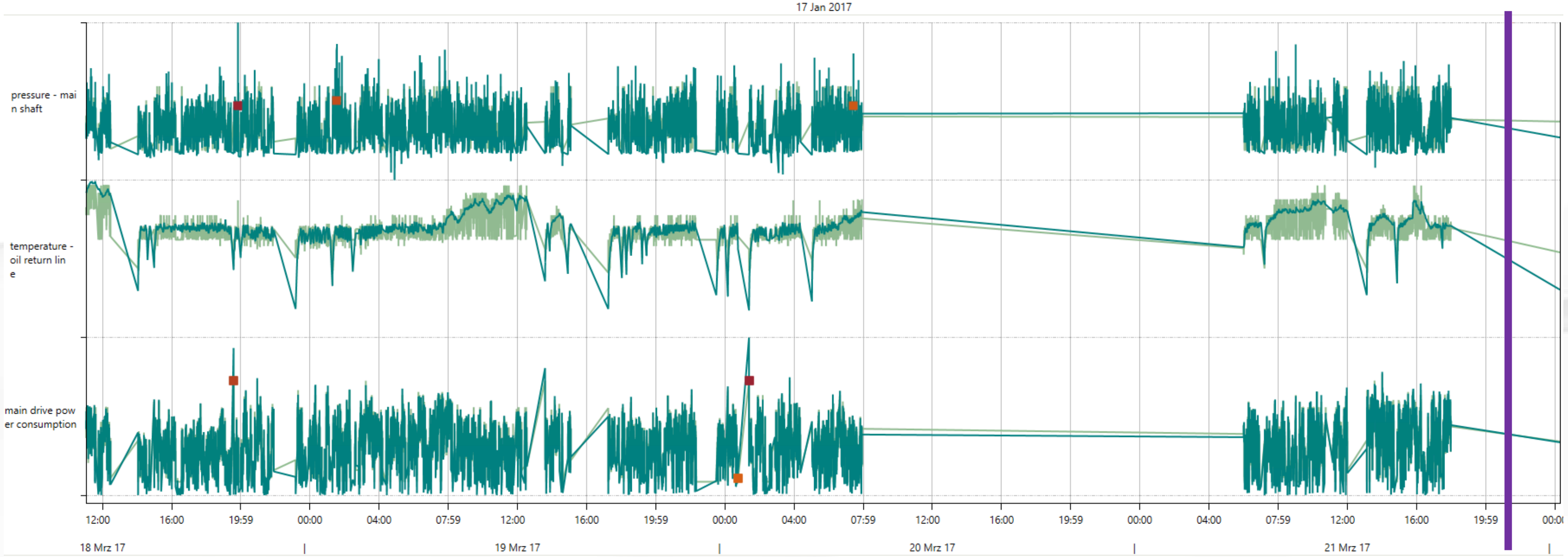
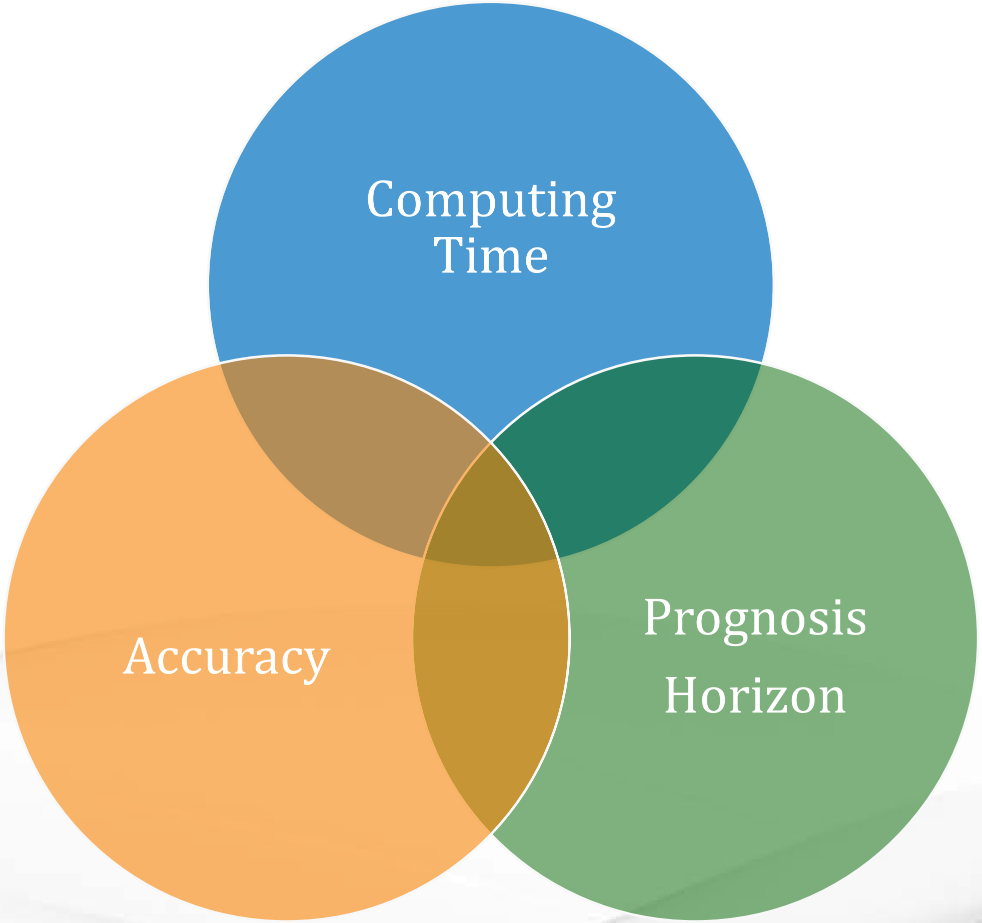




Source: https://cloud.google.com/blog/big-data/2016/09/experience-googles-machine-learning-on-your-own-images-voice-and-text#showImage

Impact of all preferences

Goal: Generate models with less computing time, high accuracy and large forecasting horizon



Preferences for the State Space

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Parameter Selection
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Embedding Window
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Preferences for the Output

Aggregation (Binary, Forward Time)
Horizon
Categorization (Hierarchical Structuring)
Reference data (Comparable Assets)

Algorithms

Approach Selection
Sensitivity (Warning Threshold)

Suggestion for the predictive maintenance community

Operators

- Exact capturing and categorization of maintenance actions
- Knowledge transfer to data scientists
  - Ambient influencing factors, which are currently not measured, should be taken in account (Usage of open data)

Data Scientists

- Algorithms has to be "fast"
  - GPU computing
  - Quantum computing
- Algorithms has to be "smart"
  - Fast filters for relevant data points
  - Development of appropriate classification techniques
- Comprehensibility of results

Thank You!

Appendix

IH-Generik | Predictive Maintenance Project

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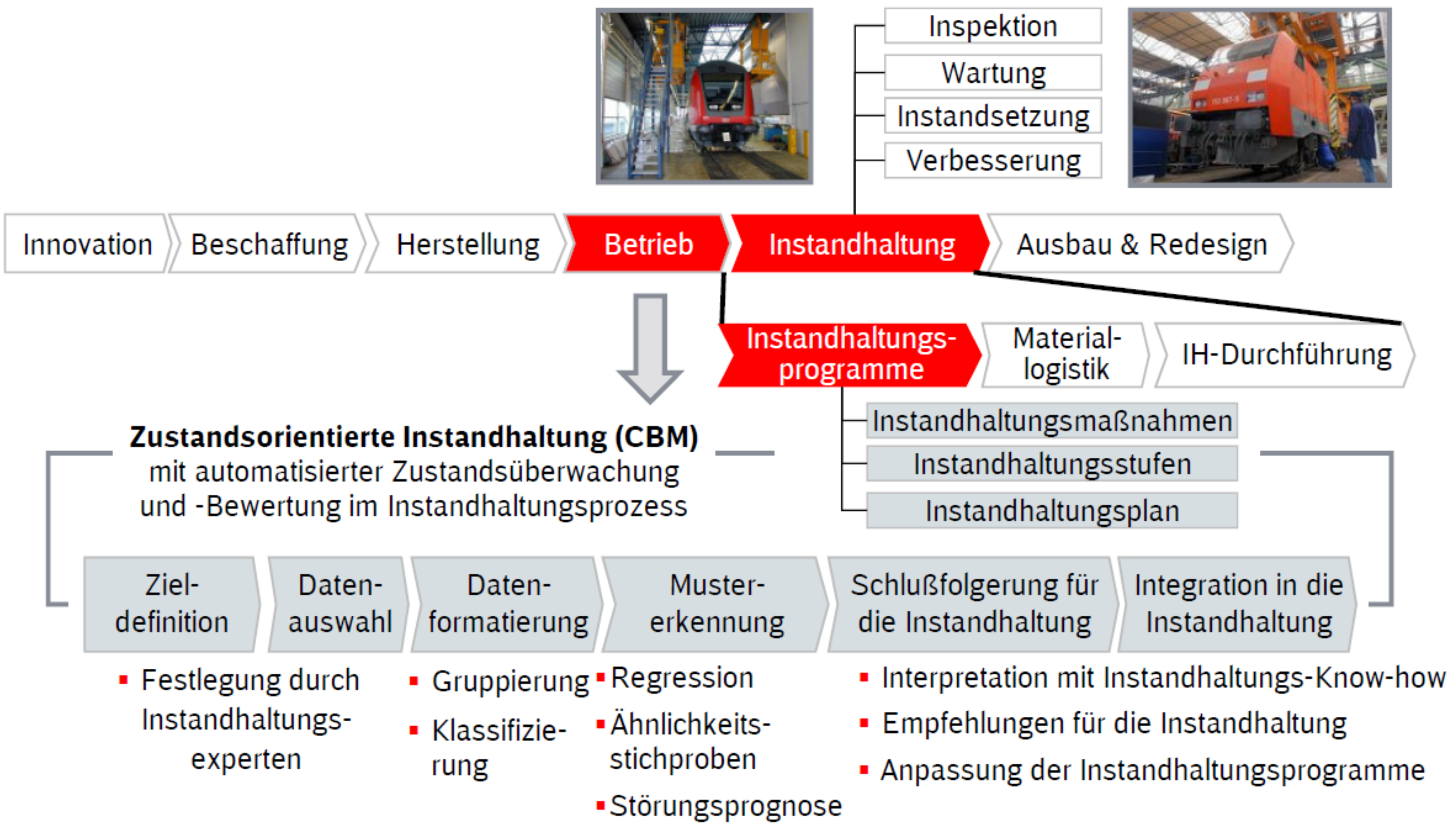
DB Mobility Networks Logistics

Einsatzbereich „Fahrzeug überwacht sich selbst“

Das Projekt will ein Verfahren der automatisierten Zustandsüberwachung in den Instandhaltungsprozess integrieren.



BR442 | Auxiliary Power Converter

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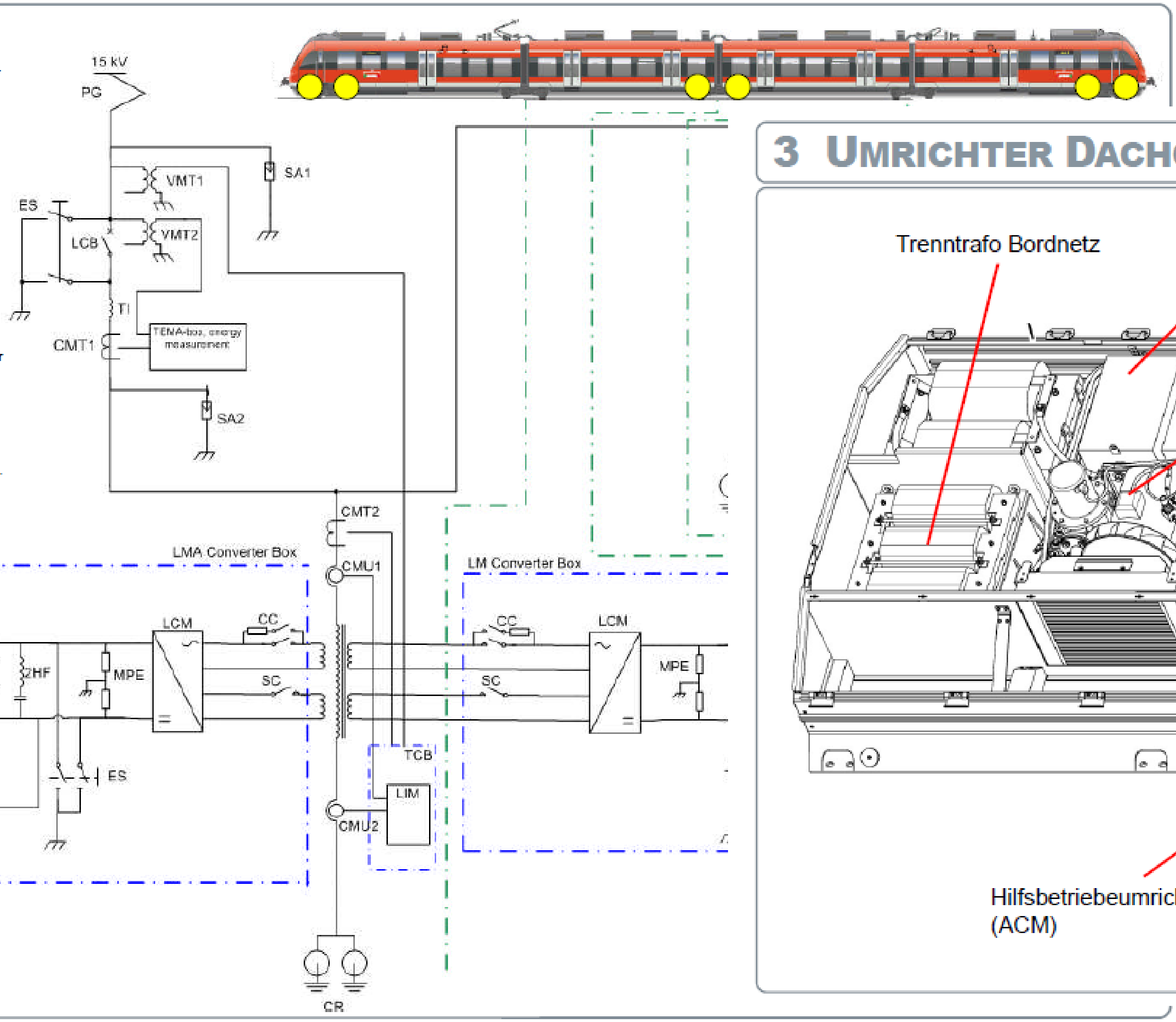
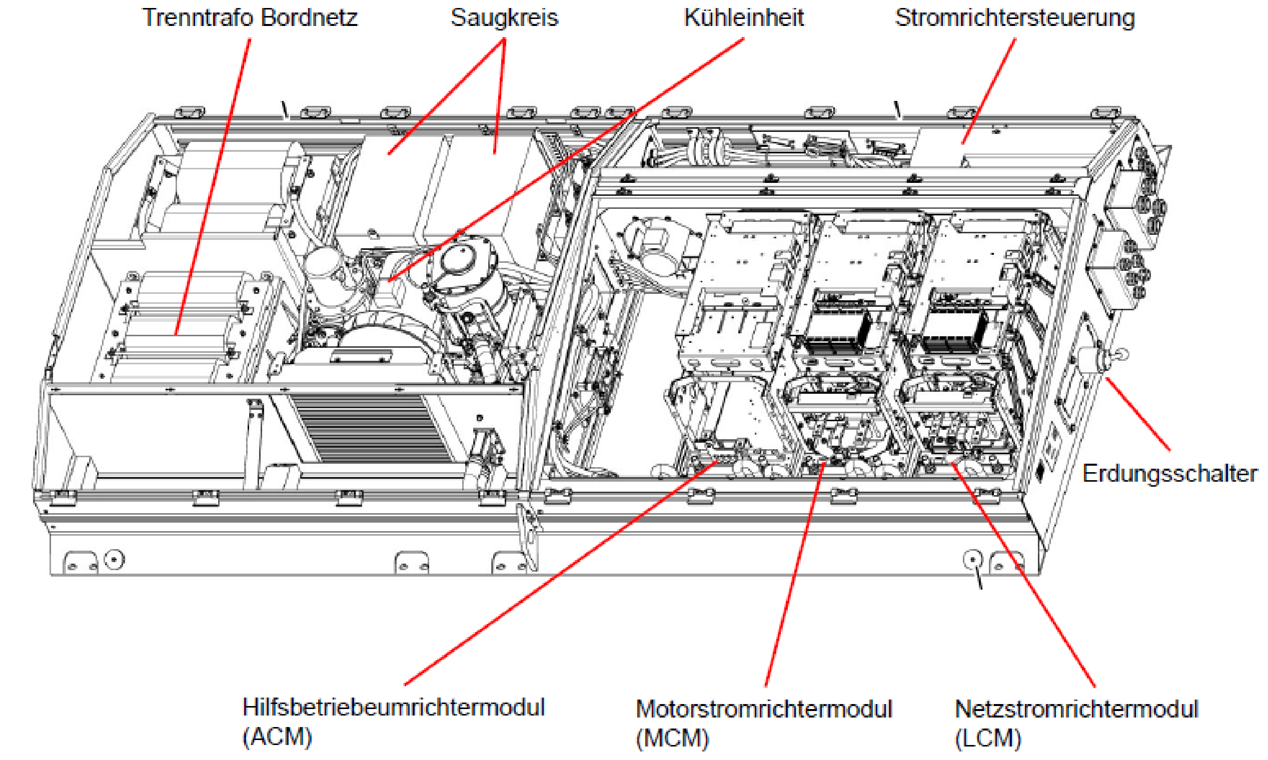
3 Antriebs- und Hilfsbetriebeausrüstung (4-Teiler)

2HF 2nd Harmonic Filter
ACM Auxiliary Converter Module
CC Charging Circuit
CMT1 Current Measuring Transformer Energy meas.
CMT2 Current Measuring Transformer Prop control
CMU1 Current Sensor LIM, Over current, diff current
CMU2 Current Sensor LIM, 100 Hz
CR Current Return (not PPC scope)
DS Disconnector Switch
EF Earth Fault Detector
ES Earthing Switch
LCB Line Circuit Breaker
LCM Line Converter Module
LIM Line Interference Monitor
LM Line Module
LMA Line Module Auxiliary
MCM Motor Converter Module
MPE Midpoint Earthing
OVR Over Voltage Resistor
PG Pantograph (not PPC scope)
SA1 Surge Arrester Protection of HV system
SA2 Surge Arrester Protection of Main Transformer
SC Separation Contactor
TCB Trafo Control Box
TI Transient Inductor
TM Traction Motor
TRF Main Transformer
VMT1 Voltage Measuring Transformer Prop control
VMT2 Voltage Measuring Transformer Energy meas.



3 Umrichter Dachcontainer



Predictive Maintenance Methodologies

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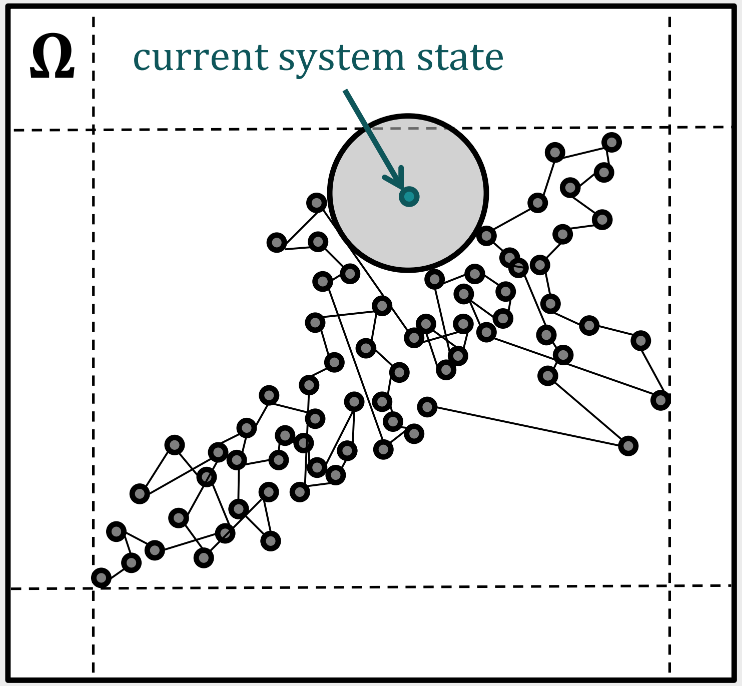
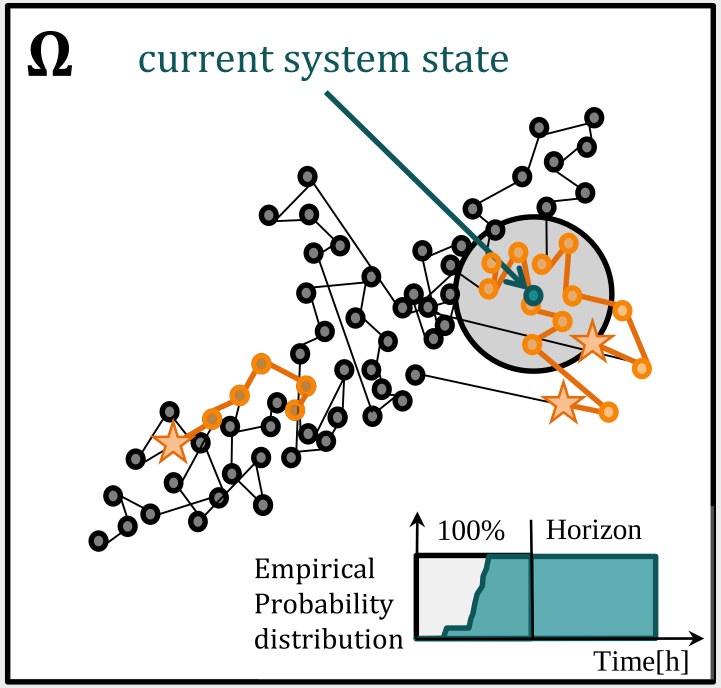


Anomaly rate based on the distance between actual value and expected value (calculated by AAKR methods) for given operating mode

Anomaly Detection

$$E(X_t^N | X_t = x)$$

$$= E\left(\text{Expected operating point} \mid \text{Actual operating point} \right)$$



The probability that a critical event will occur within the prediction horizon *H* is computed based on a sample within an environment of comparable states in the training data

Supervised Learning

$$P(T_Y < t + H \, | X_t = x)$$

$$= P\left(\text{Event Y will occur within the next H time units} \mid \text{State vector of system at time t} \right)$$