Machine Learning Applications

Predictive Maintenance (band saw application, neural networks for condition monitoring and prediction)

Prof. Dr. Ing. Joachim Metternich, Tobias Biegel M.Sc.
Darmstadt | 23.01.2020

Agenda

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AI encompasses various methods…?

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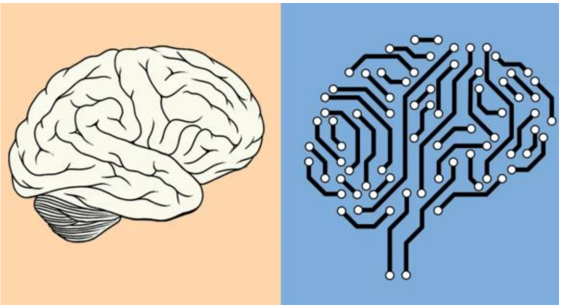
Artificial Intelligence

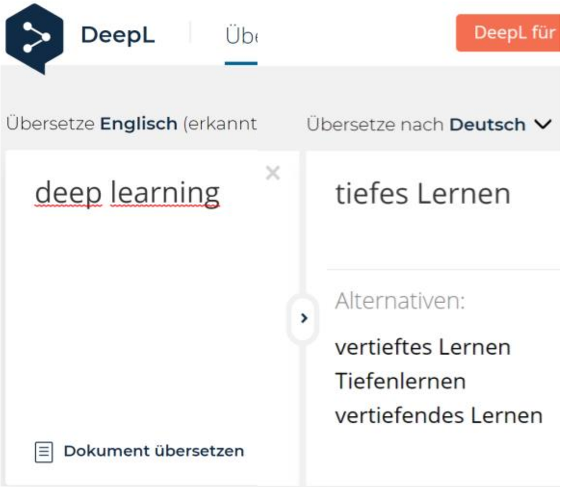
Machine Thinking (i.e. based on logic)

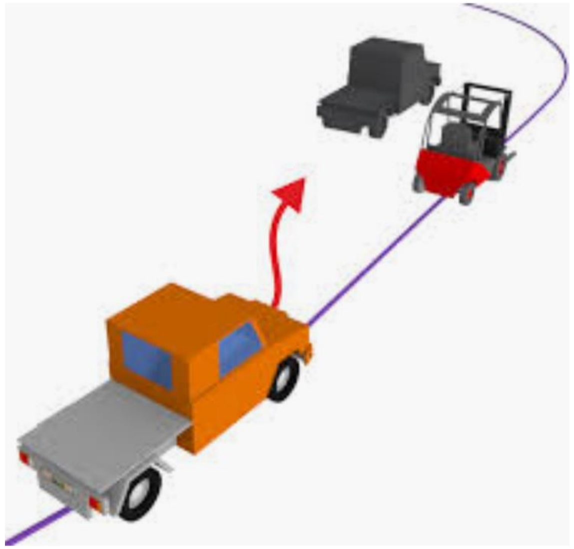
Natural Language/ Voice Processing

Automated Planning

Machine Learning







= create a mathematical model by training with data

AI encompasses various methods…?

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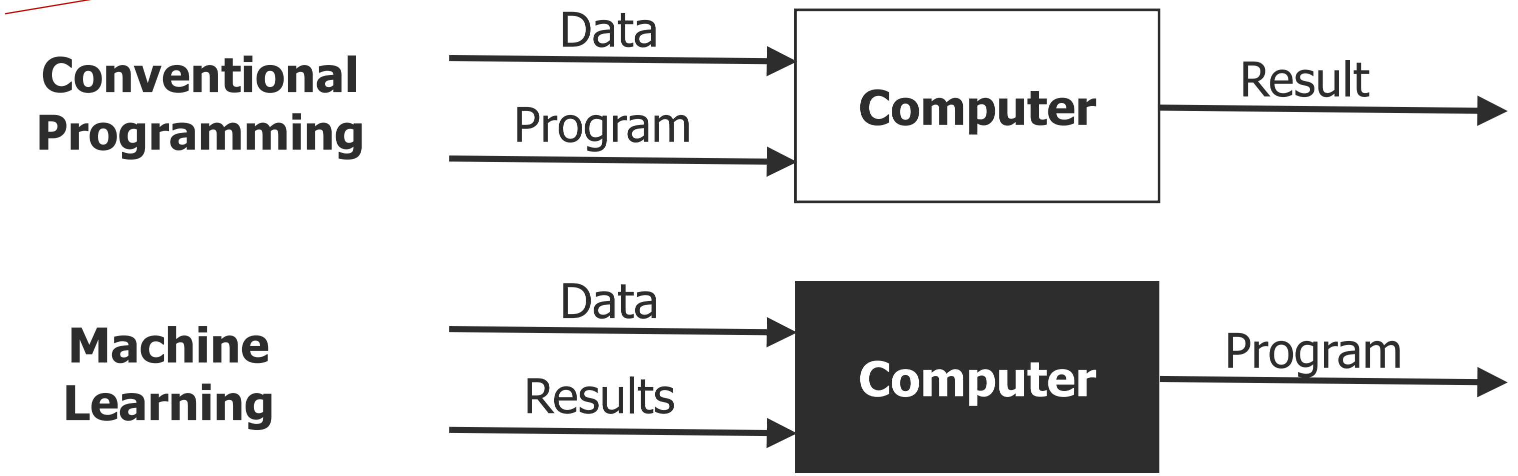
Artificial Intelligence

- **Machine Thinking (i.e. based on logic)**
- **Natural Language/ Voice Processing**
- **Automated Planning**
- **Machine Learning**



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1	Introduction AI
2	**Potentials of AI in production technology**
3	Extension of CRISP-DM: DMME
4	Use Case: Predictive Maintenance

What is changed by the application of AI based methods, especially machine learning?

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Conventional Data Analysis

Domain Knowledge
- Experience
- Technical Dependencies
- Historical quality data

Program/ Rules — Decisions based on domain knowledge

Data Analysis via AI

Process data
- E.g. current, pressure, temperature, …

Quality data
- E.g. Good & Bad parts, measurement results

Trained Algorithm — Decisions based on historical data

Combination of domain knowledge and expert knowledge

Typical problem sets for Machine Learning

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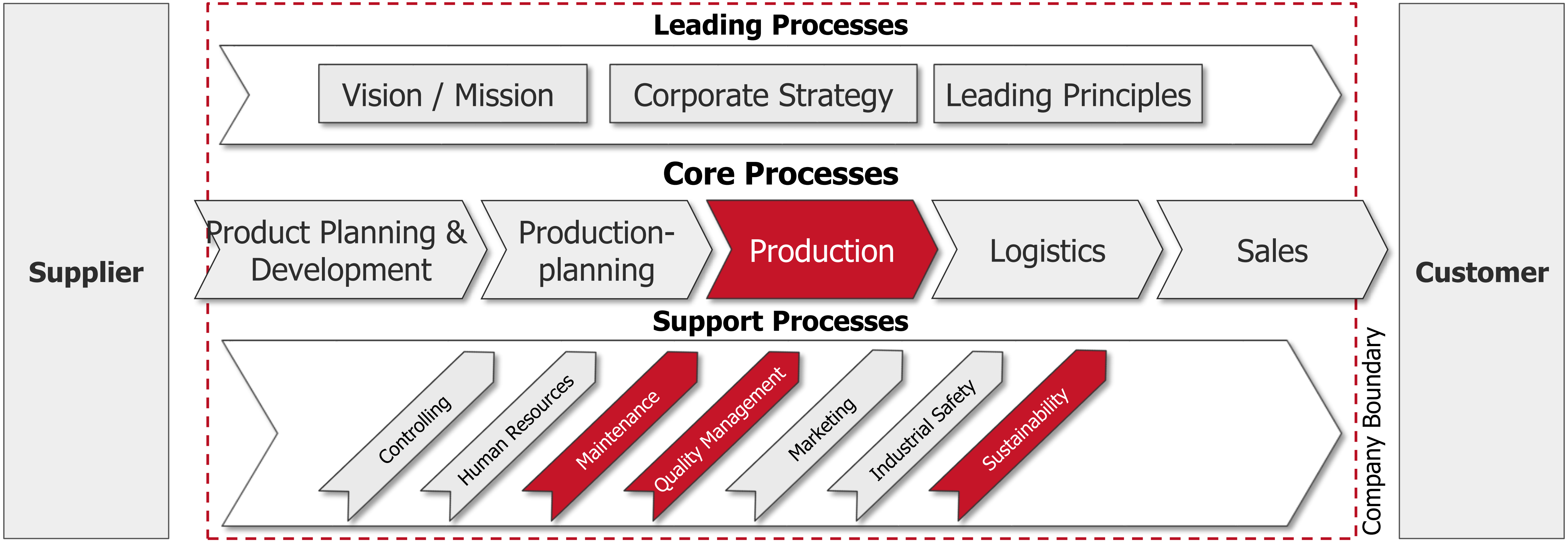
	Issues from the practice:		Machine Learning Task:	
	**Condition** Is the tool/component worn or not?	▶	Clustering of data	**„Unsupervised"**
	**Remaining Lifetime** How long will the tool/part last?	▶	Recognition of patterns to predict target variables	**„Supervised"**
	**Decision/Problem Solving** Is strategy A or B better to process the part?	▶	Influence behaviour through feedback on success or failure	**„Reinforcement"**

AI in production technology
Application potentials for AI



In Anlehnung an: https://refa.de/blog-industrial-engineering/407-gestaltung-von-unternehmensnetzwerken

Potentials for companies through application of AI?

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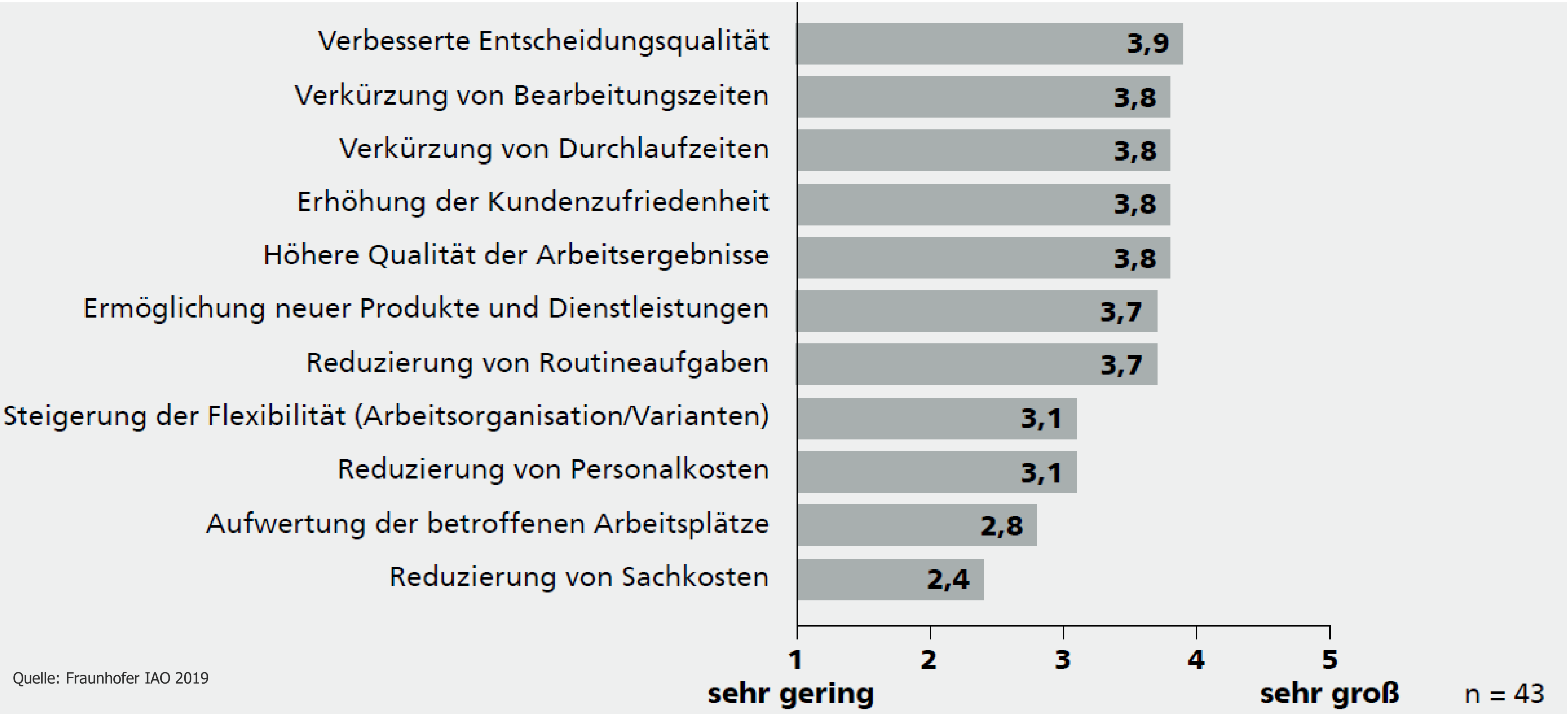


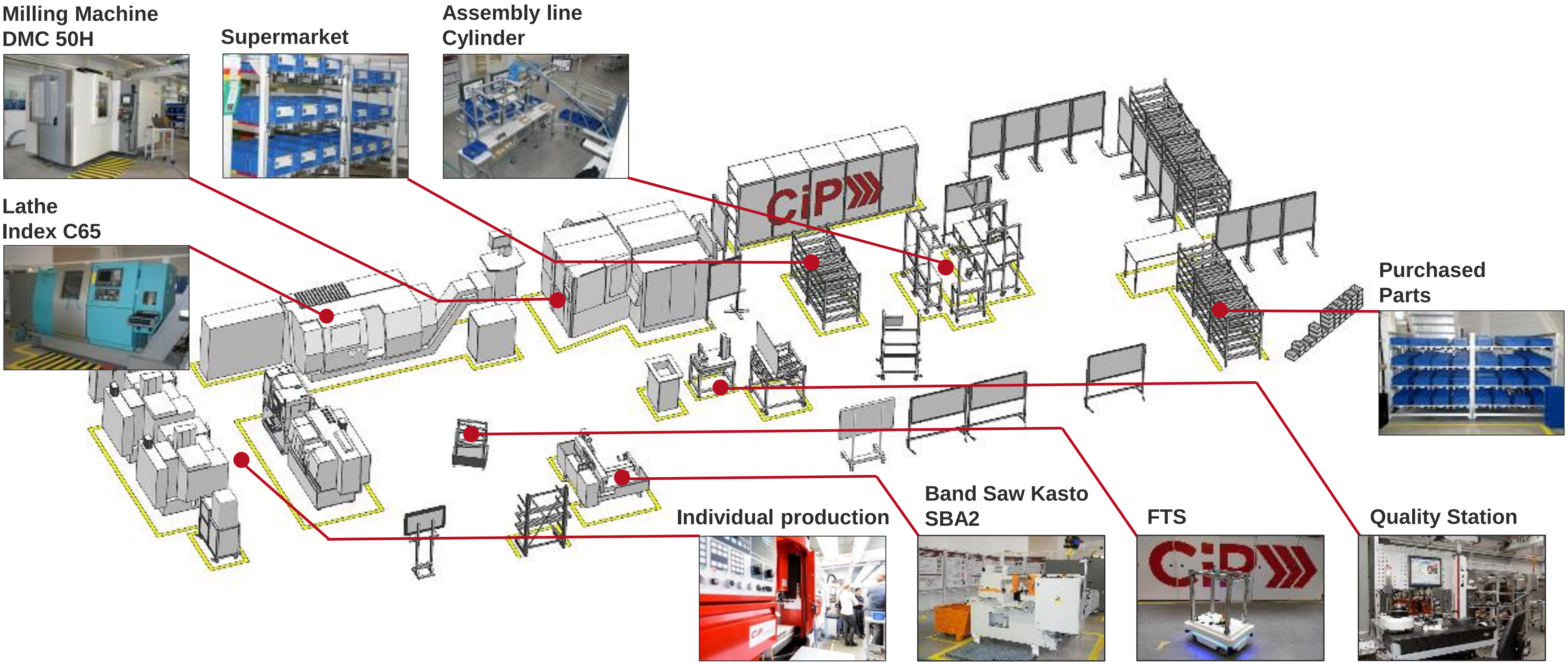
Quelle: Fraunhofer IAO 2019

AI in production technology
Application areas of AI at PTW

Instandhaltung	Qualitätsmanagement	Prozesseffizienz	Energie und Nachhaltigkeit
Vorhersage der Ausfallzeit des Sägebands zur Reduzierung der Instandhaltungskosten	Vorhersage der Qualitäts-merkmale im Bohrprozess zur Optimierung der **Qualitätssicherung**	**Bauteilindividuelle Prozess-parameter** zur Verbesserung der Prozessstabilität und Produktivität	**Energieeffizienter und -flexibler Betrieb** von Produktion und Versorgungstechnik

Datenschutz und -sicherheit

Process Learning Factory CiP
Realistic Production Environment



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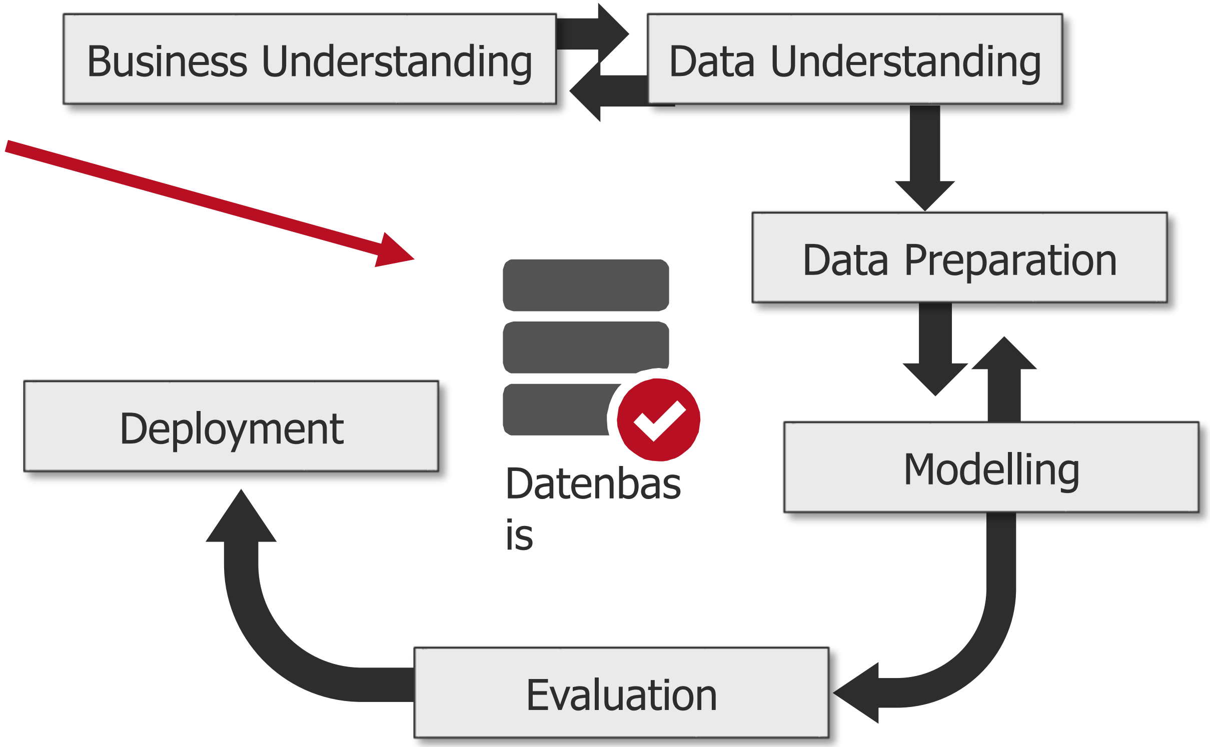
Completing AI projects with the help of CRISP-DM
Cross Industrie Standard Process for Data Mining

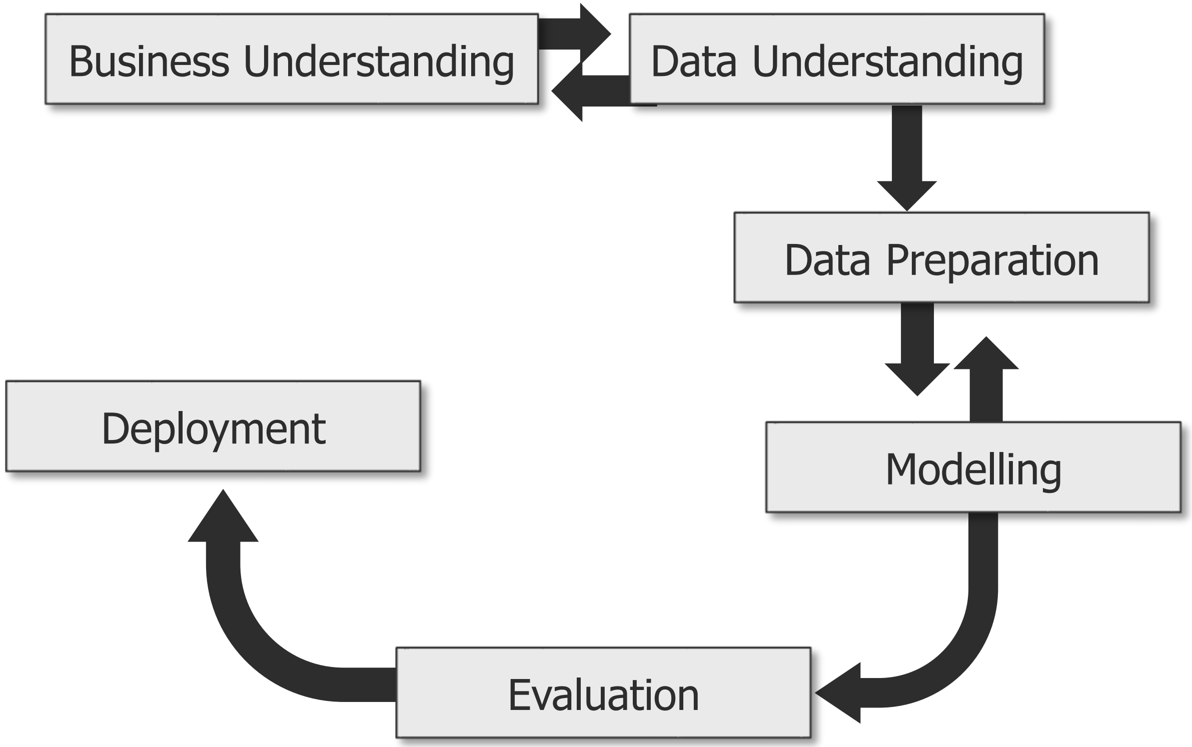
Data collection is one of the biggest issues in production technology



R. Wirth; J. Hipp, "CRISP-DM: Towards a standard process model for data mining," in Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining

Completing AI projects with the help of CRISP-DM

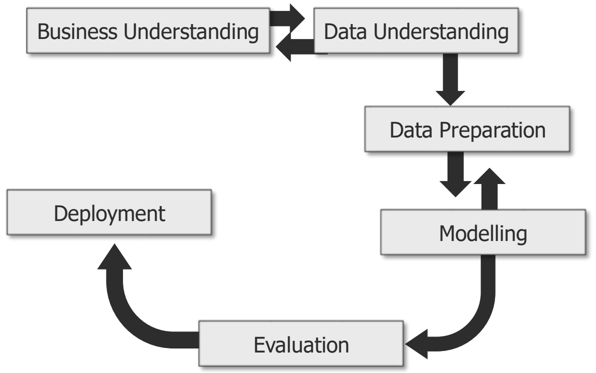
Cross Industrie Standard Process for Data Mining

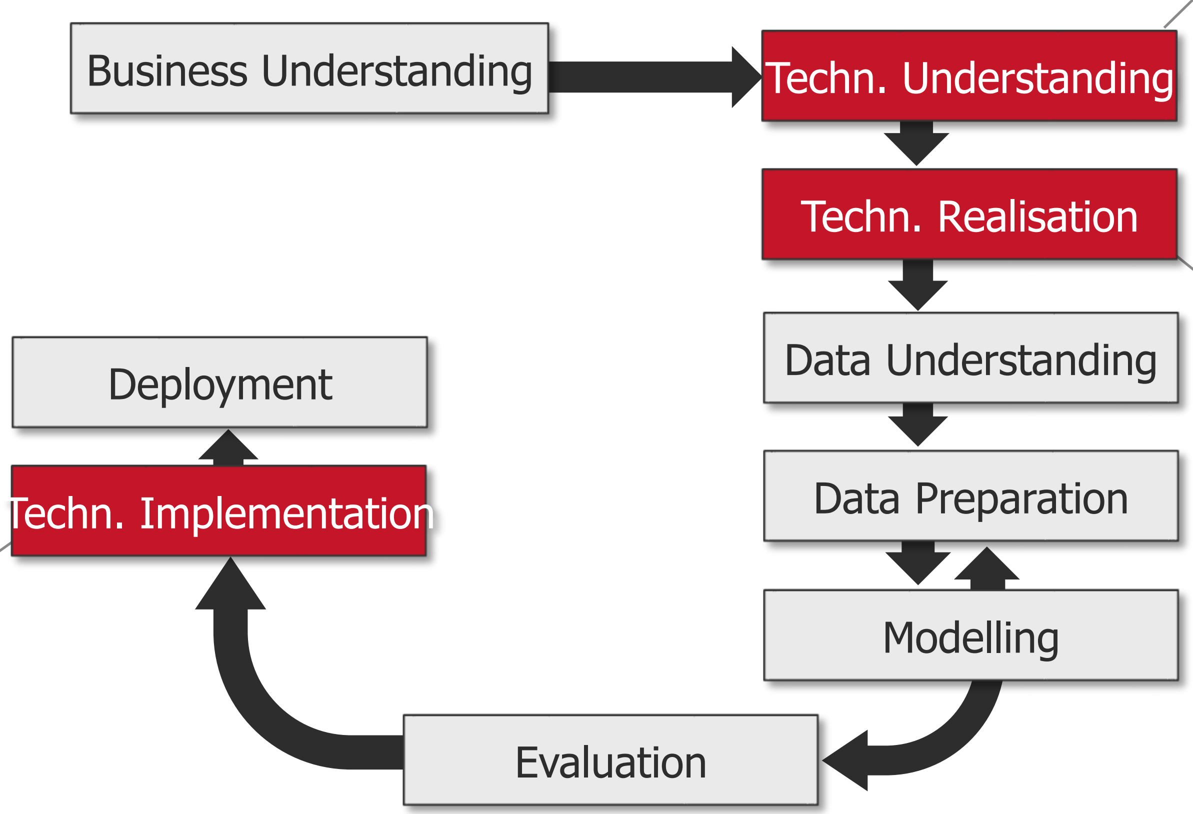


R. Wirth; J. Hipp, "CRISP-DM: Towards a standard process model for data mining," in Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining

DMME Process for AI projects in production technology

Data Mining Methodology for Engineering Applications





- Measurable technical targets
- Domain knowledge
- Experimental design

- Measuring concept
- Conduct Experiments

- Fit sensor concept to production environment
- Software integration

Huber, Wiemer et al. 2019 – DMME: Data mining methodology

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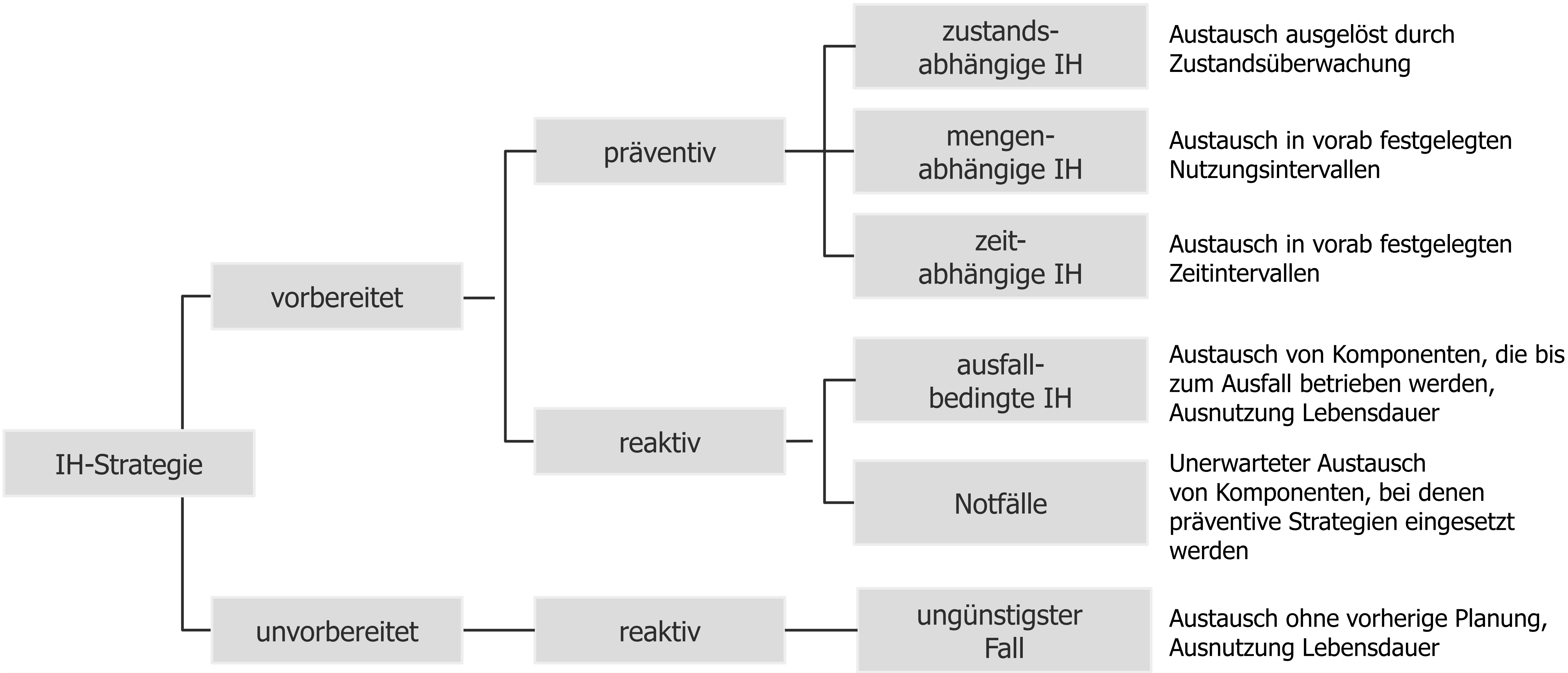
Einordnung verschiedener Instandhaltungsstrategien



Different models for maintenance and necessity for action

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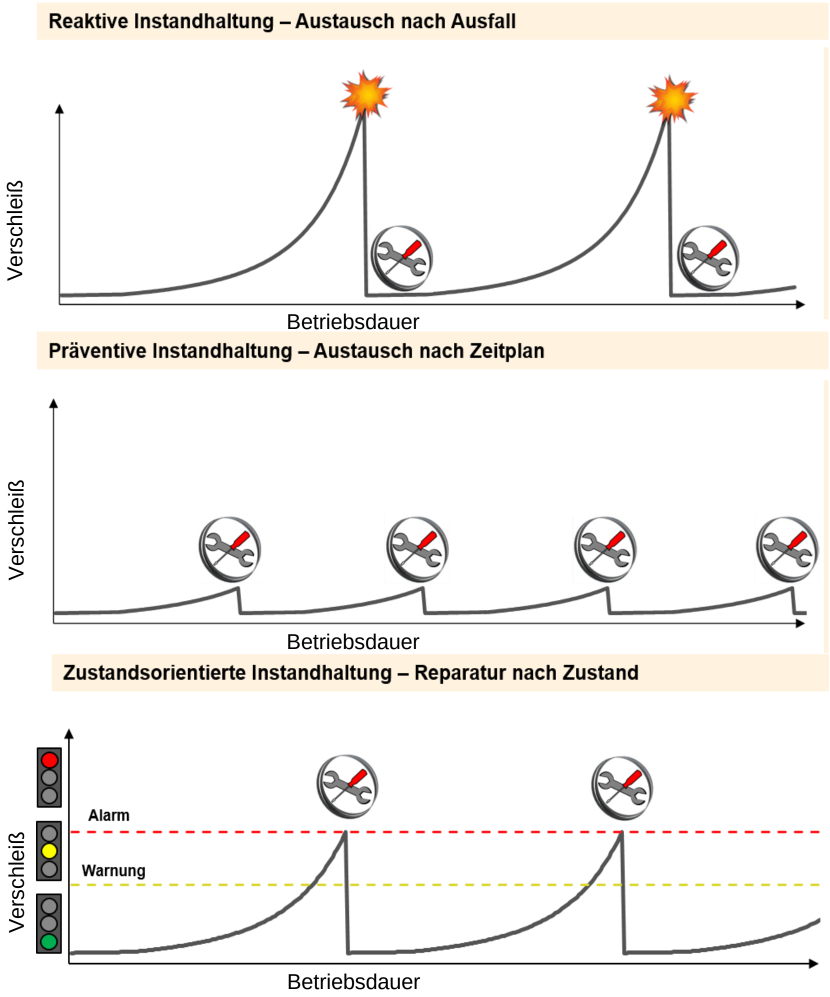

Reactive maintenance:
- Maintenance after machine failure
- Unplanned, after shutdown
- Best possible utilisation of the lifetime

Time-based, Quantity-based, preventive maintenance:
- Maintenance according to fixed intervals
- True machine condition remains unnoticed: Exchange often not necessary

Condition-based, predictive maintenance:
- Indication of imminent failures
- Best possible utilization of the "machine life"

Use Case Band Saw in the Process Learning Factory CiP
DMME: Business Understanding und Technical Understanding

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Reasons to rethink data-based maintenance...

- Sensors and data evaluation can quickly become expensive
- Not every component failure is important
- Some component failures happen (statistically) very regularly and do not require monitoring
- Some components do not fail, just need regular maintenance

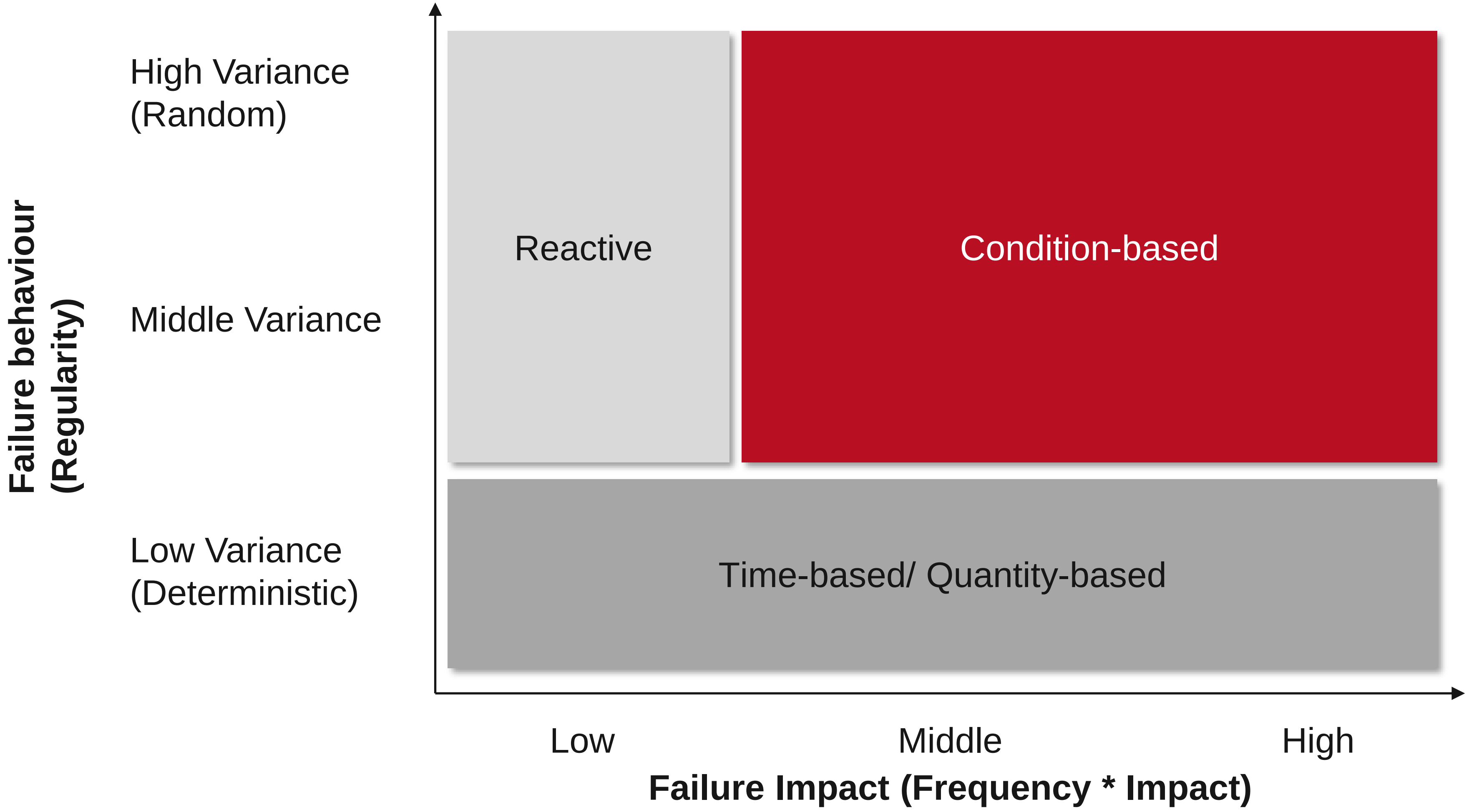
Basically: Data-based maintenance only where it pays off!

Based on a machine analysis, the essential components can be differentiated according to suitable maintenance strategies

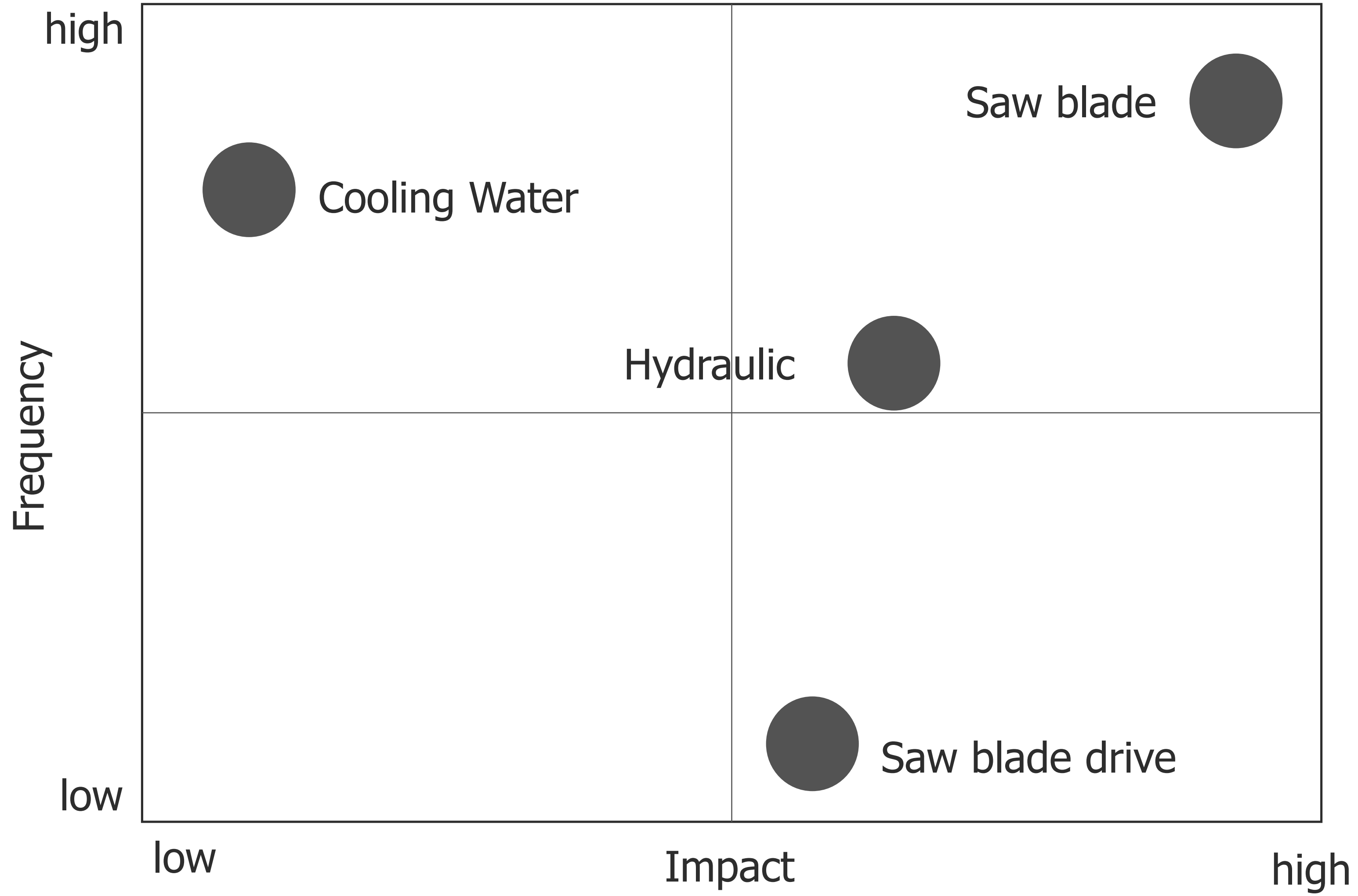
Three questions are of particular relevance:

- Which essential (functional) components does the machine consist of?
- What is the importance of a component failure?
- How often & how reliably do these components fail?

Simple decision rules for maintenance strategies



Use Case Band Saw in the Process Learning Factory CiP
DMME: Business Understanding und Technical Understanding



Use Case Band Saw in the Process Learning Factory CiP:
Failures of the saw blade

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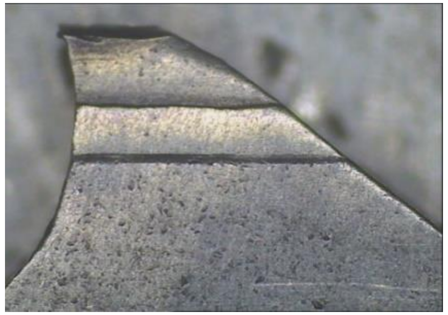
Wear

- saw blade



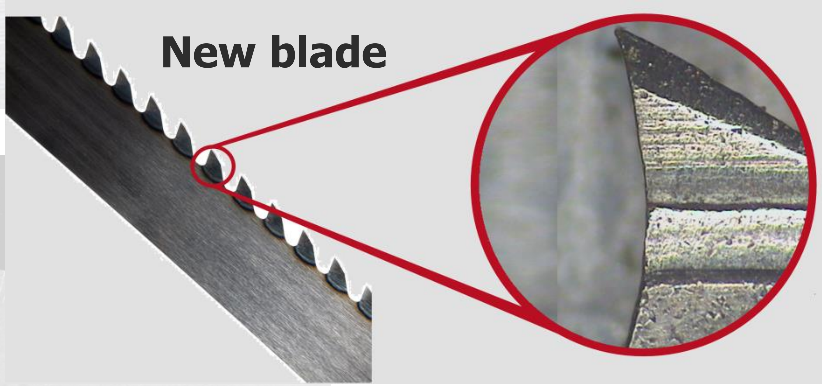
Focus area

Break

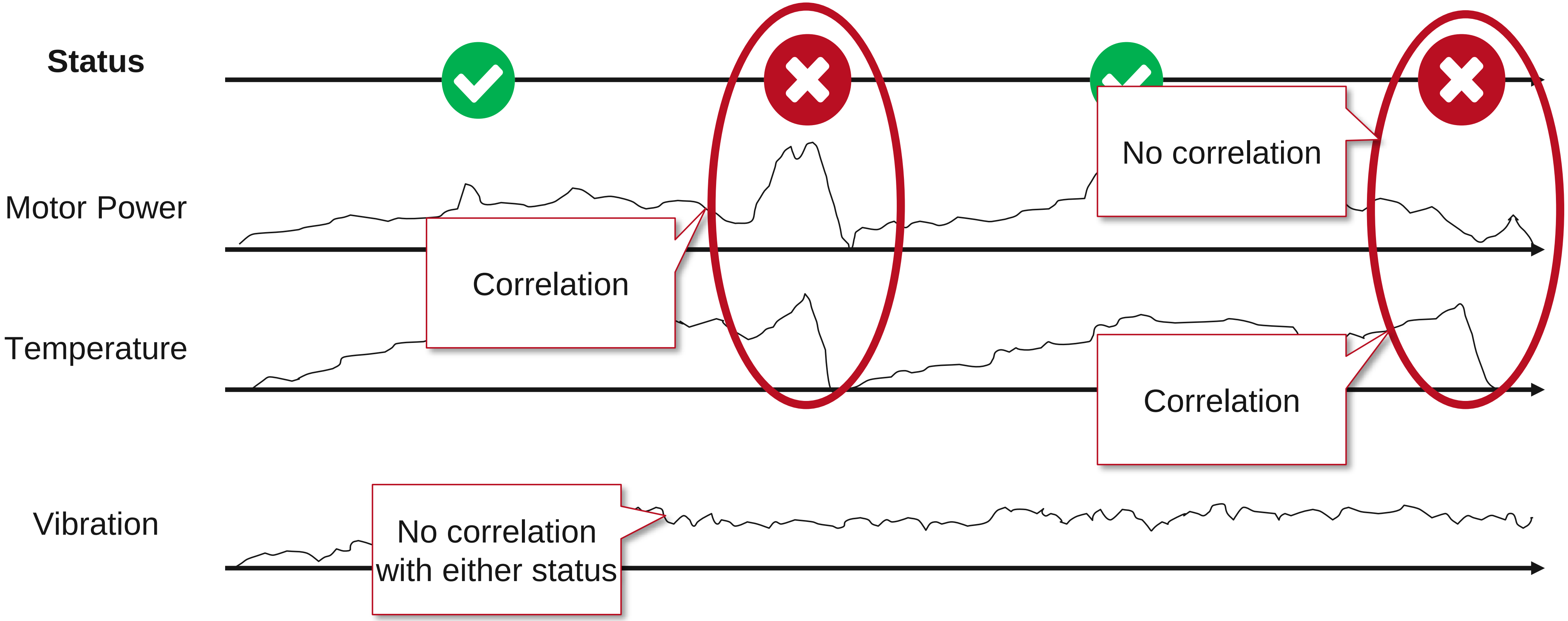
- Weakening of the strip (often in the weld seam) leads to strip tearing within a short time

Defects

- Broken teeth lead to "knocks during sawing" and locally increased wear



Search for dependencies within the data to explain machine failure



Use Case Band Saw in the Process Learning Factory CiP

DMME: Technical Realisation

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Choose appropriate sensor technology depending on the failure hypotheses :

- Which physical parameters describe the symptoms?
  - Vibrations / structure-borne sound
  - Temperature
  - Power consumption, etc.
- What demands does the process make on the sensor technology?
  - Frequency/Sampling rate
  - safety requirements, etc.
- Other signals that are important to understand the system behavior?
  - Start/stop signal of the process
  - "Counter", how often was produced, etc

Komponente	Messgrößen																	
	Temperatur	Temperaturverteilung (Thermographie)	Feuchtigkeit	Beschleunigung/ Vibrationen	Akustische Signale	(Motor-)Drehzahl	(Dreh-)Geschwindigkeit	Bewegungswinkel	(Verschleiß-)Partikel	Achsverschiebung	(El.) Leistungsaufnahme	(El.) Spannung	(El.) Stromstärke	(Isolations-)widerstand	(El.) Kapazität	(El.) Induktivität	Teilentladungen	Volumenstrom (Durchfluss)	Druck
Elektromotor	x	x		x	x		x		x	x	x	x	x	x			x	x	
Generator	x	x		x					x		x			x					
Turbinen	x		x	x	x	x	x				x							x	x
Frequenzumrichter	x		x								x	x	x						
El. Kabel u. Verbinder	x	x		x										x	x	x			
Transformatoren		x												x	x	x			
Kondensator	x	x			x						x	x	x					x	
Lager	x			x		x	x		x		x								x
Getriebe	x		x			x					x							x	x
Pumpen	x	x		x	x				x		x		x	x				x	x
Pumpendichtung			x	x	x														x
Ventile		x	x		x													x	x
Lüfter	x			x	x	x							x	x		x		x	
Ionenimplanter												x	x						x
Kompressor	x			x	x						x		x					x	x
Bohrer				x	x	x	x												

Quelle: Wöstmann, R. et al. (2017): Predictive Maintenance in der Produktion, in: wt Werkstatttechnik online, jahrgang 107 (201), H. 7/8

Use Case Band Saw in the Process Learning Factory CiP
DMME: Technical Realisation

Error	Symptoms (Hypotheses)	Sensor
 **Wear**	Drive power increases	Power sensor
	Feed force increases	Hydr. Feed pressure
	Cutting duration increases	Position sensor
	Temperature at tooth mesh increases	IR-Thermometer Temperature sensor
	Gearbox temperature increases	Temperature sensor
	Band velocity increases	Light barrier
	Hydraulic temperature increases	Temperature sensor
	Vibrations increase	Accelerometer x,y,z

Use Case Band Saw in the Process Learning Factory CiP
DMME: Technical Realisation

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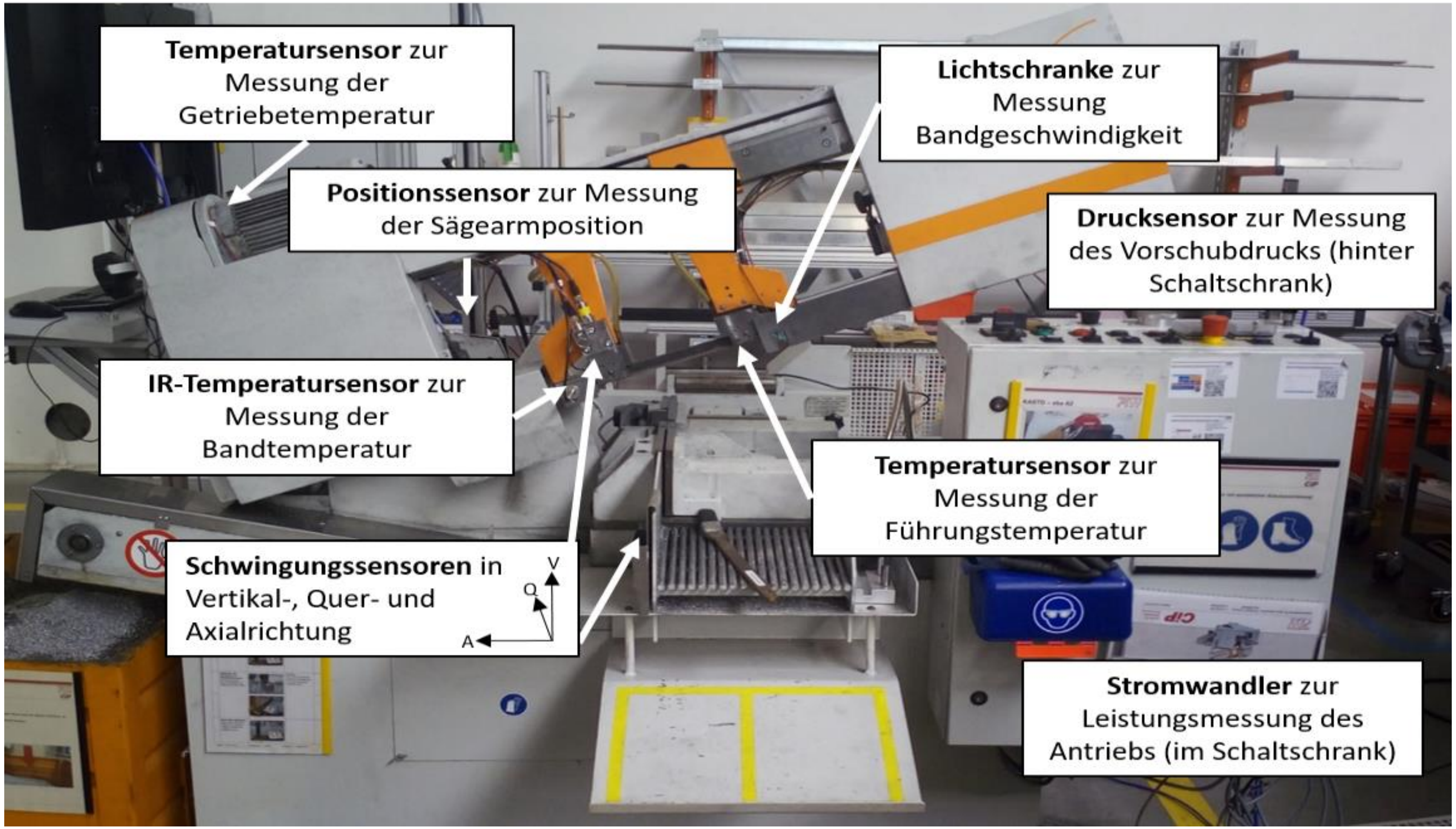
Sensorkonzept der Bandsäge



Use Case Band Saw in the Process Learning Factory CiP

DMME: Data Understanding und Data Preparation

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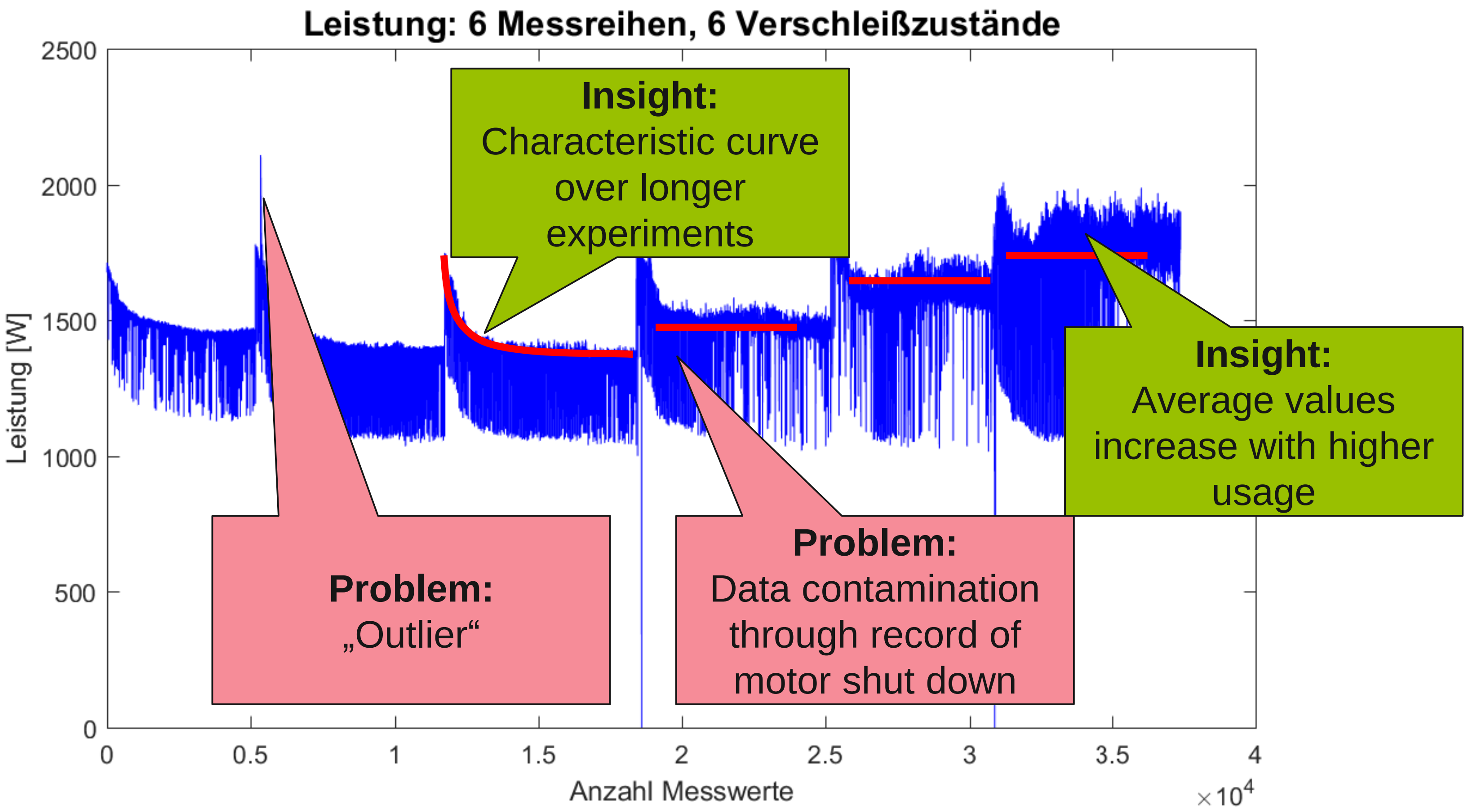
Values of multiple measuring series (Example: Motor Power, 1 Measurement every 0,5s)



Use Case Band Saw in the Process Learning Factory CiP
DMME: Data Understanding und Data Preparation

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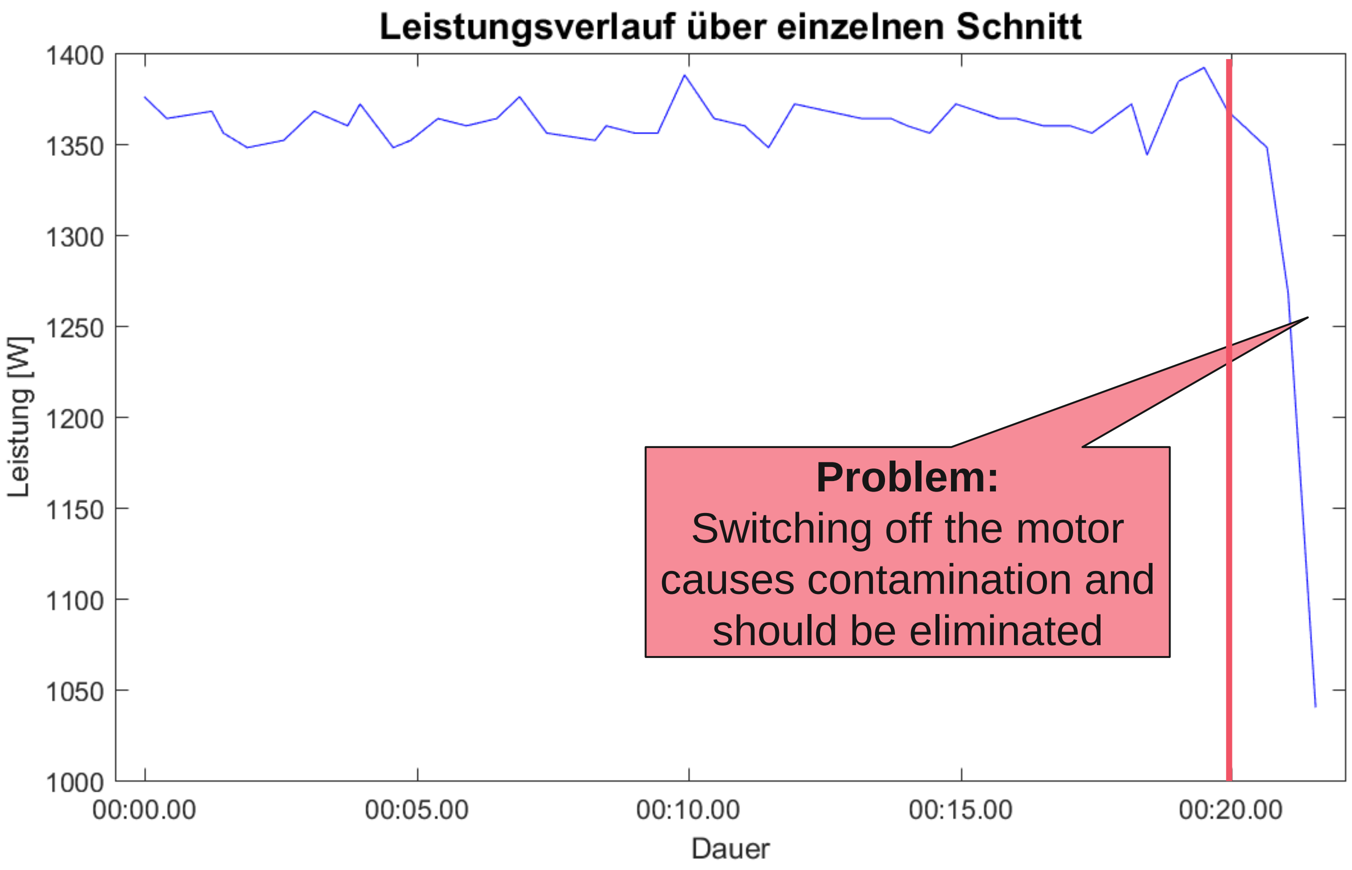
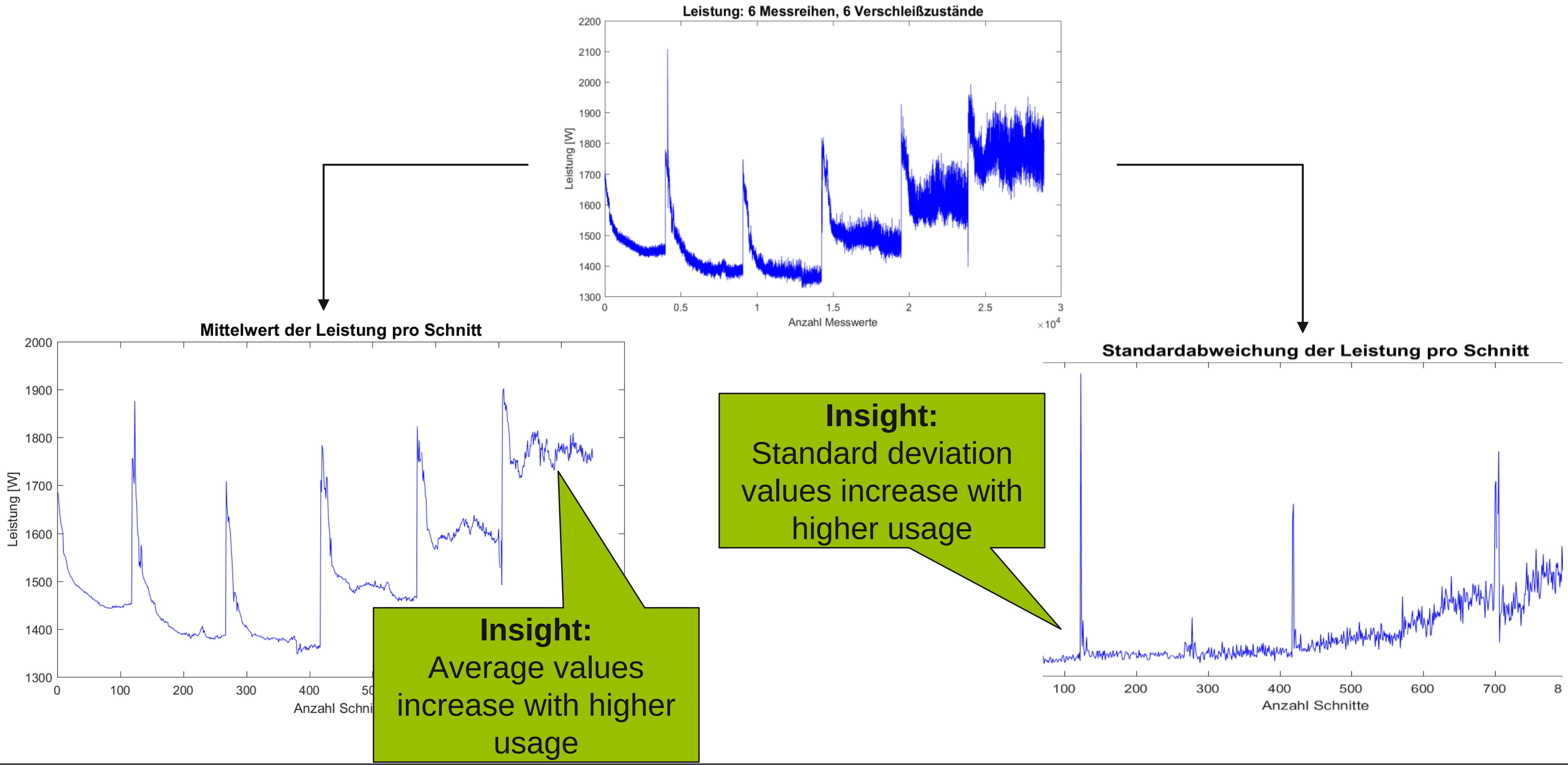
Values during a single cut (Example: Motor Power, 1 Measurement every 0,5s)



Use Case Band Saw in the Process Learning Factory CiP

DMME: Data Understanding und Data Preparation



Feature selection using unsupervised neural networks
The Self Organising Map

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What to do when sensors are life and data are collected?

- How do we know which data are relevant for the intended application?
- What kind of preprocessing of data do we need?
- Which software packages/toolboxes shall we use?

Unsupervised Learning

K-Means Clustering

Principal Component Analysis (PCA)

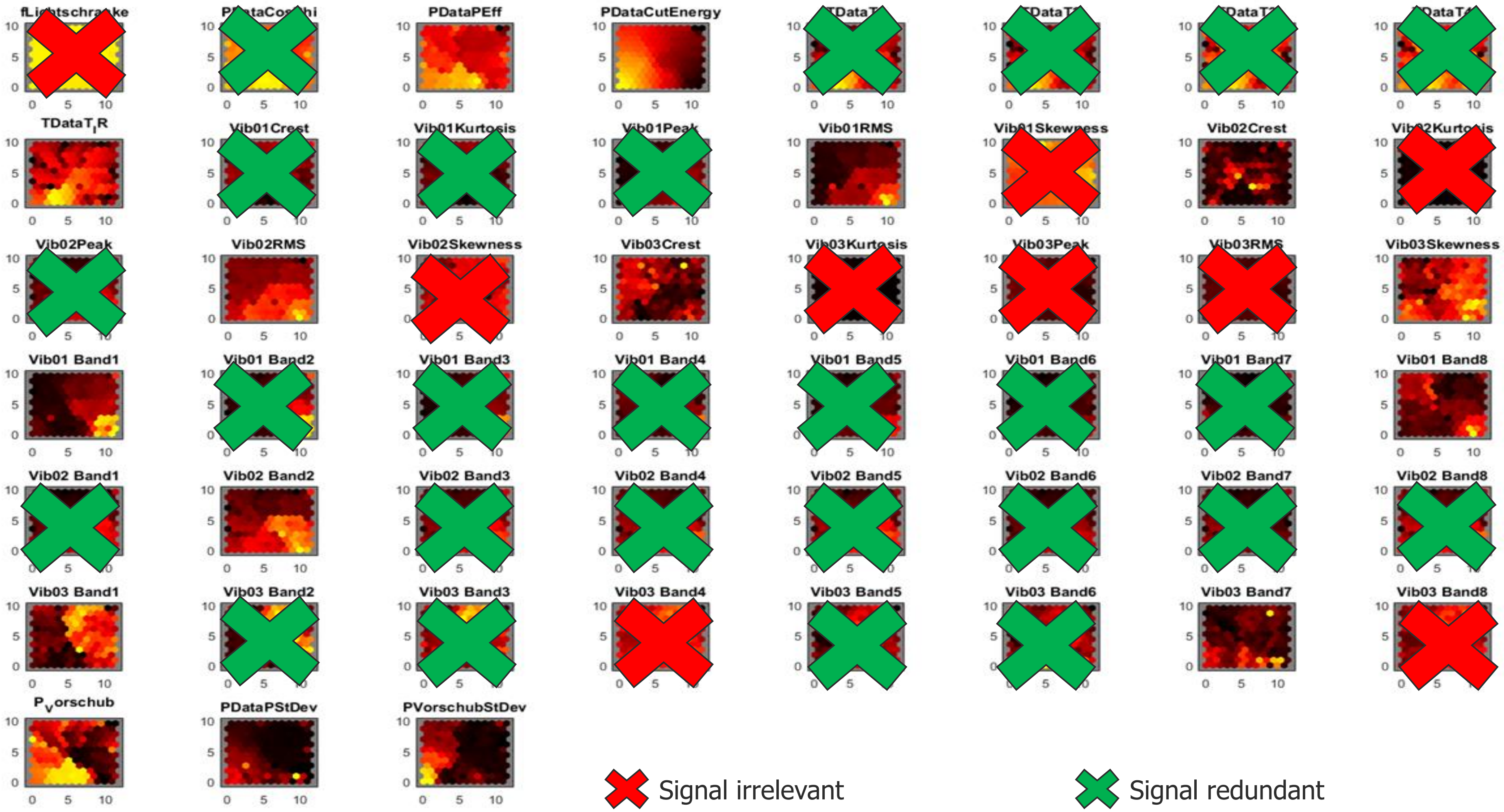
Self-Organizing Map

etc.

Jupyter Notebook

Use Case Band Saw in the Process Learning Factory CiP

DMME: Data Understanding und Data Preparation

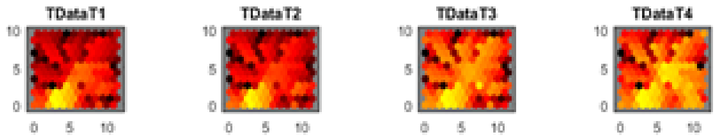


Use Case Band Saw in the Process Learning Factory CiP
DMME: Data Understanding und Data Preparation

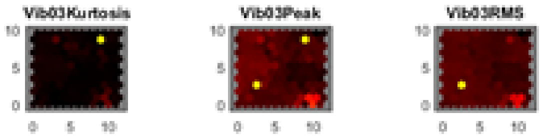
Elimination of redundant and useless Information:

- Light barrier leads to separation, but this is due to a special effect when a saw blade is retracted

- Influences of T1, T2, T3, T4 as well as T_IR almost identical, as temperature increases similarly



- Signals with low contrast (explanatory component) can be eliminated, such as "Vib03Kurtosis".



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DMME: Data Understanding und Data Preparation

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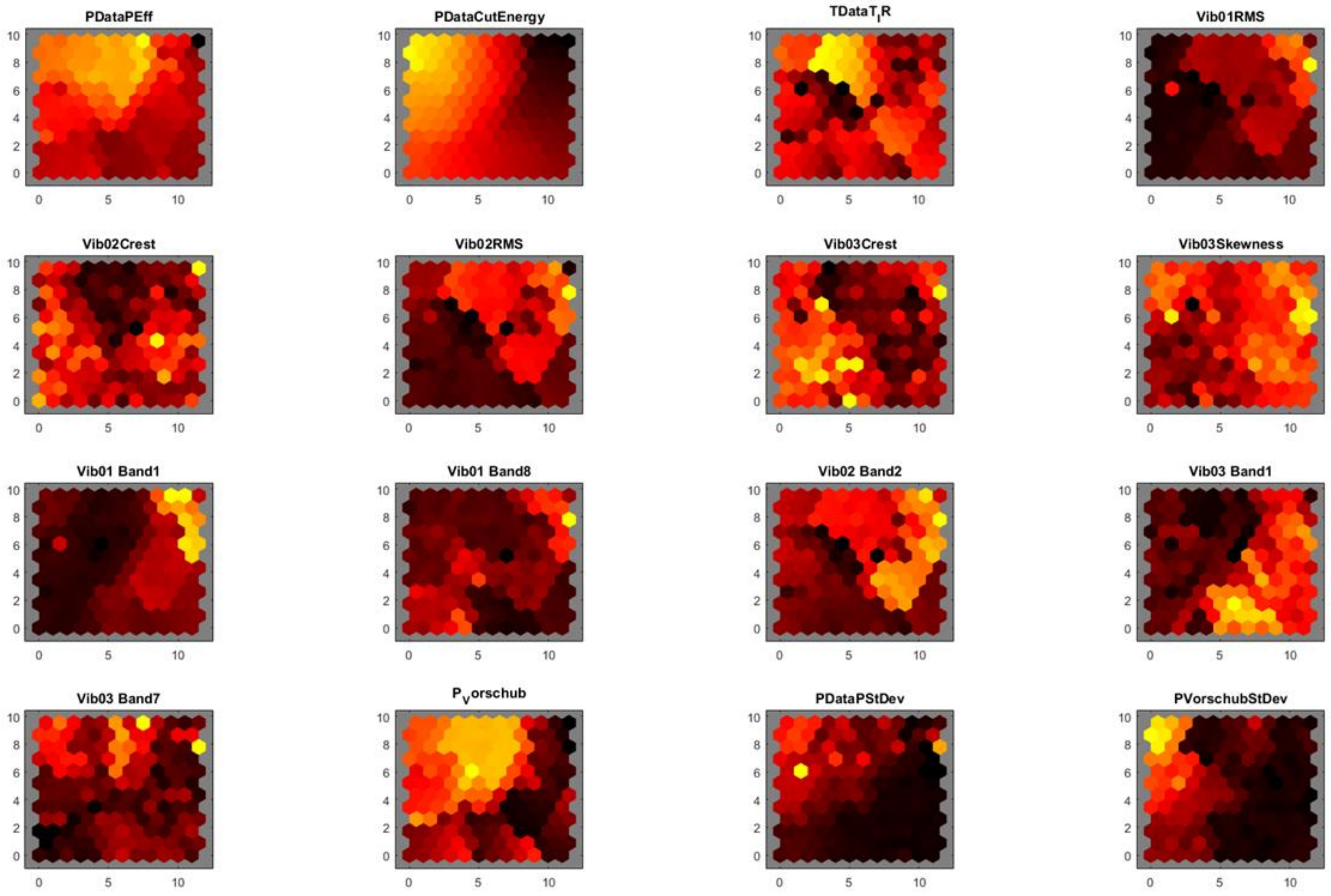
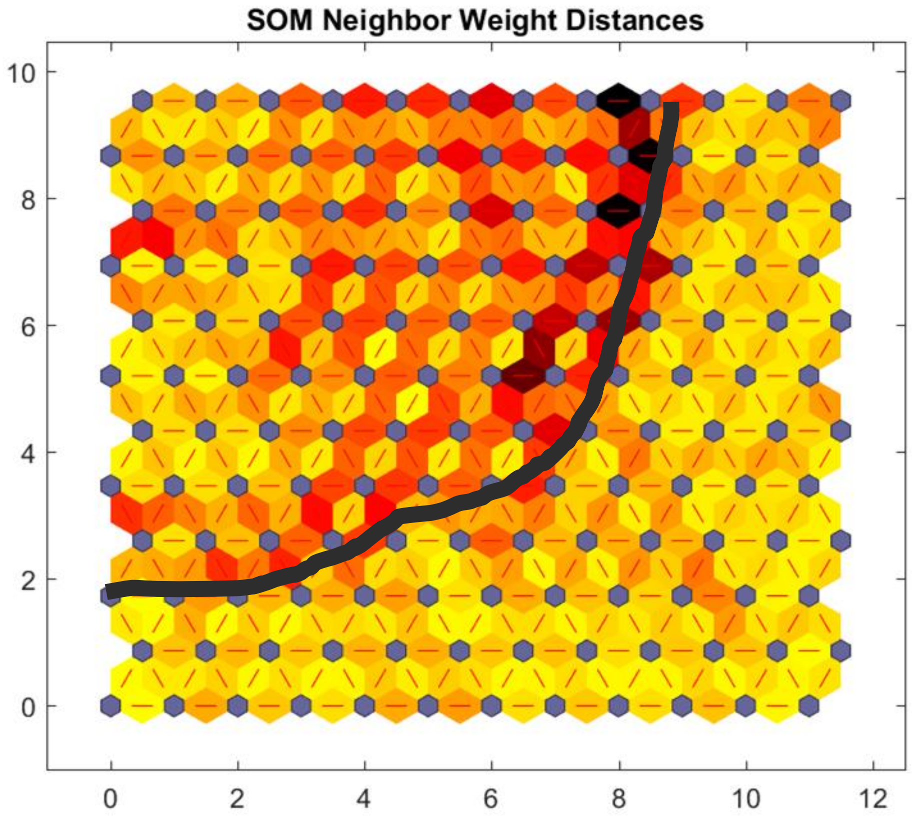


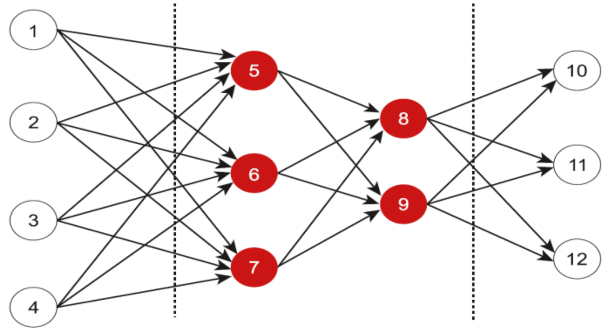


Supervised Learning: Neuronale Netze for state recognition

Training and Evaluation

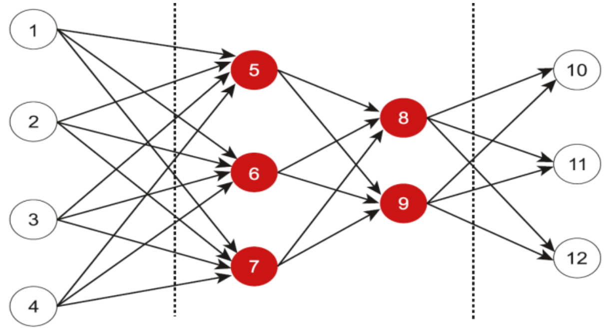
- Input vector $\vec{p}$ and corresponding output values $\vec{t}$ given
- Neuronal net trained till output values $\vec{t}$ will be approximated through $\vec{y}$ with little error

$$\overrightarrow{E_p} = \begin{pmatrix} t_1 - y_1 \\ \vdots \\ t_m - y_m \end{pmatrix} \rightarrow \min.$$



Implementation

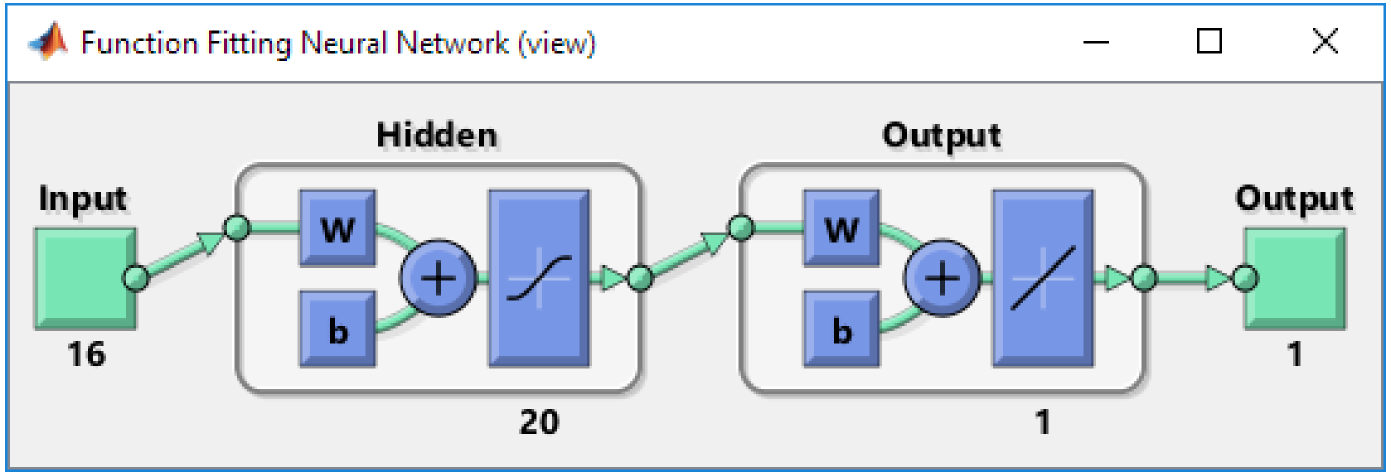
- Input vector $\vec{x}$ from runnig process
- $\vec{y}$ predicted



Use of a neural network for approximation

As input values $\vec{t}$ for training the percentage condition values determined during the wear measurement are used :

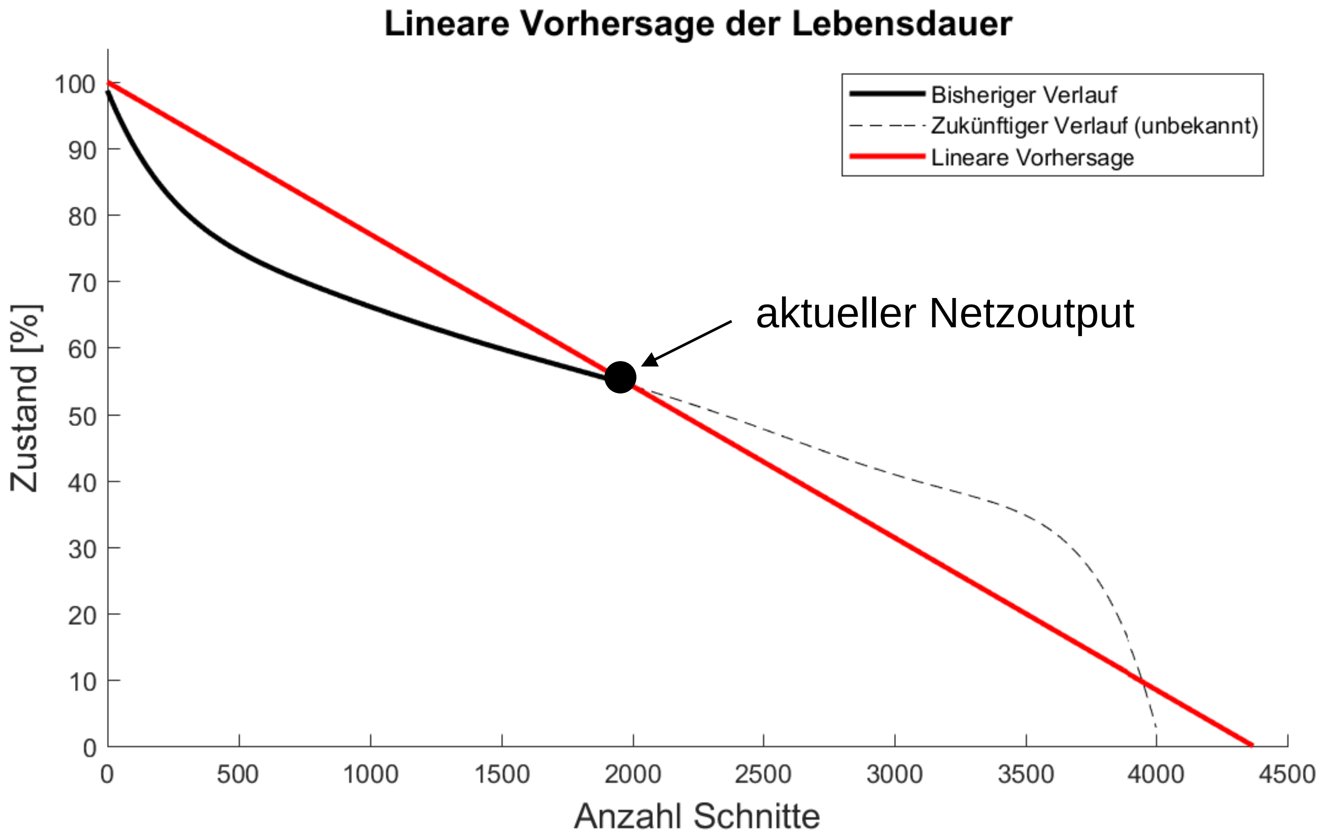
$$\boldsymbol{Condition = 100\% - wear\ in\ percent}$$



Bildquelle: Matlab

Split of data: 40% of the data for training, 20% as validation data set and the remaining 40% for testing.

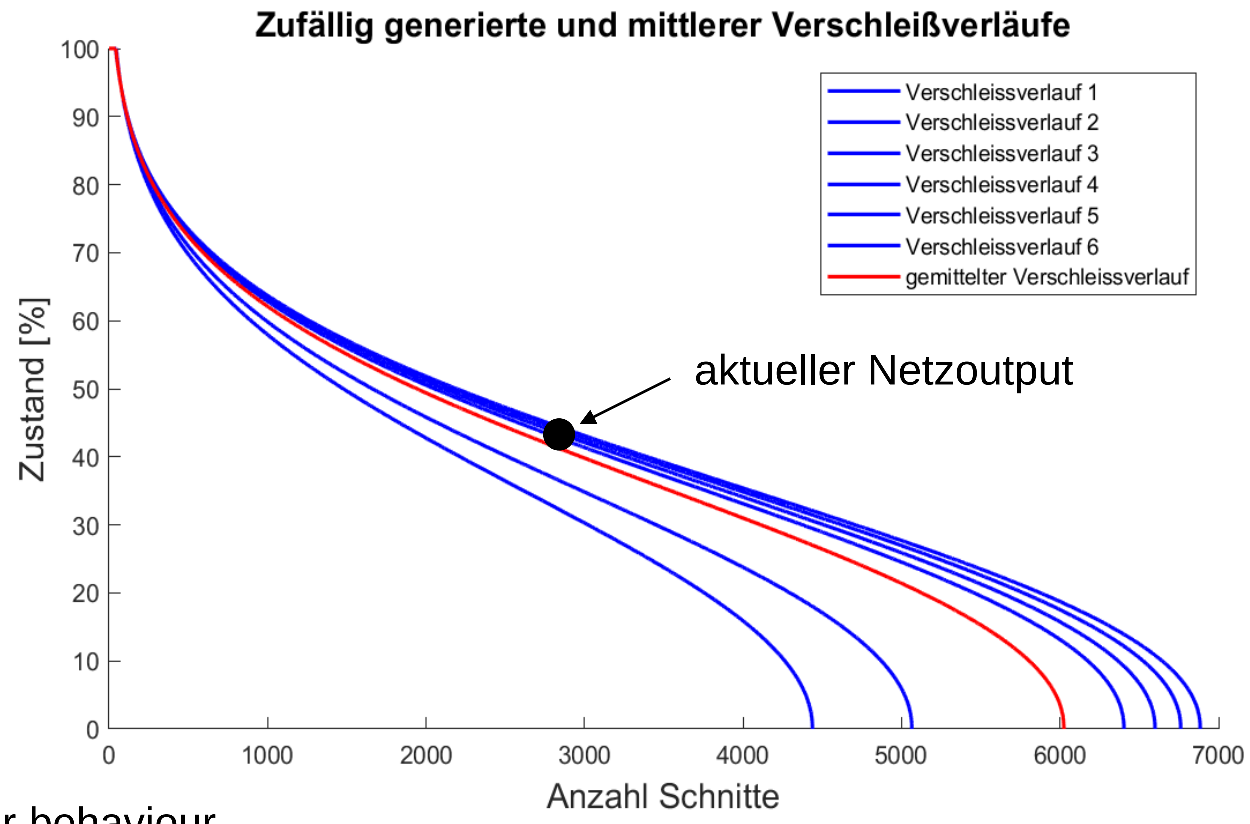
Prediction of the future:
(1) linear



Advantage:
- Ease of implementation

Disadvantage:
- Assumption of a linear wear behaviour

Prediction of the future:
(2) approximation



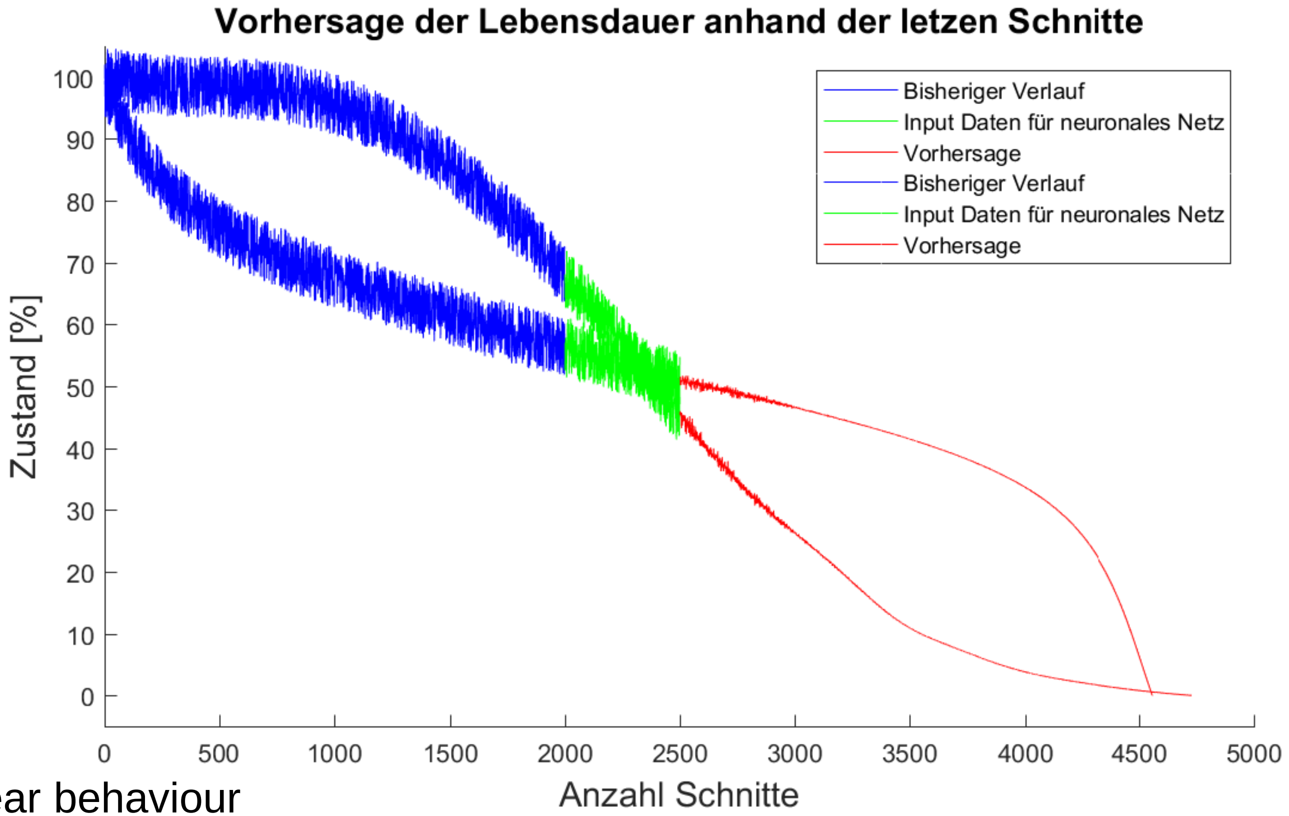
Advantage:

- Prediction of the real wear behaviour
- Valid, even if boundary conditions (material, cutting speed, feed rate) have been changed before the estimation

Disadvantage:

- Only valid if current and future boundary conditions correspond to the curve.

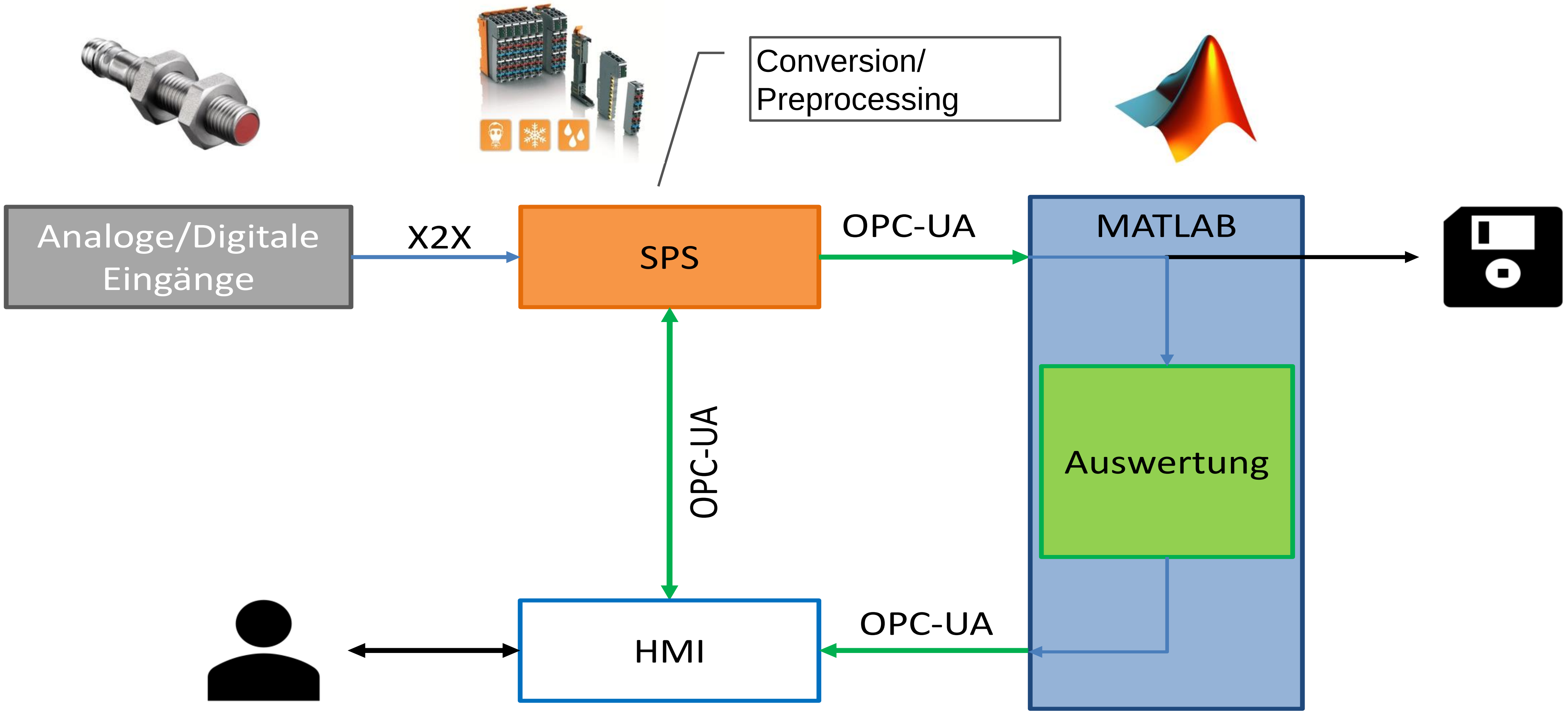
Prediction of the future:
(3) Time series prediction with neural networks



Advantage:
- Prediction of the real wear behaviour
- Can recognize and distinguish different wear behavior

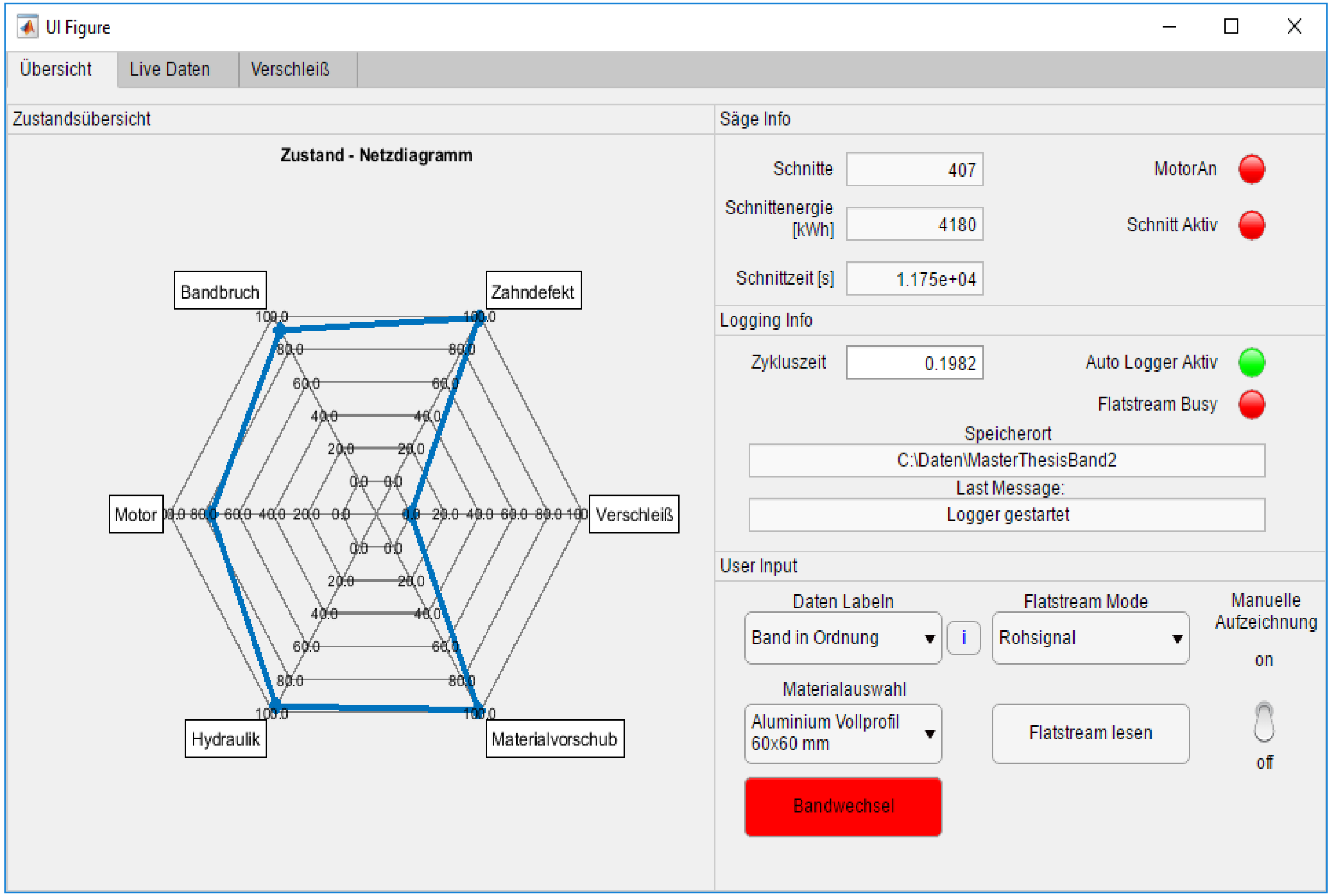
Disadvantage:
- At least one continuous wear curve must be available for each case
- Data of the last cuts (in the example 500 cuts) must be available.

Use Case Band Saw in the Process Learning Factory CiP
DMME: Technische Implementation



Use Case Band Saw in the Process Learning Factory CiP

DMME: Deployment in a GUI with Matlab



Conclusion

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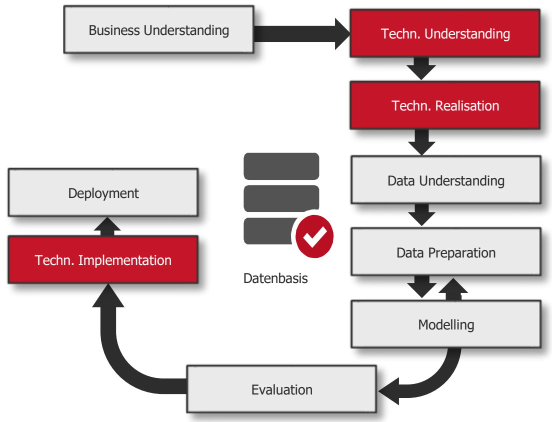
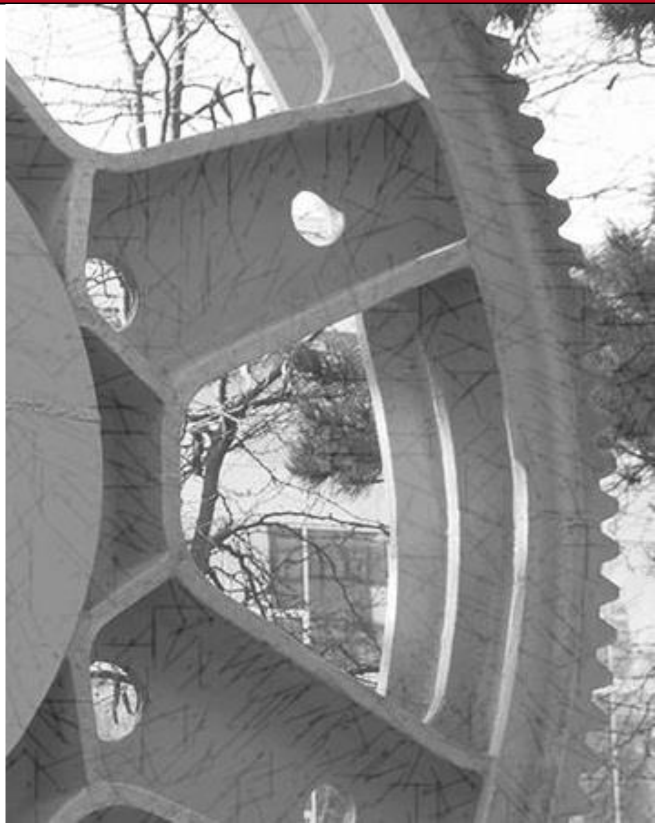
- Initial technical effort is high, especially when cause-effect relationships are unclear
- Data technical competence necessary (sampling frequencies, measuring times, etc.)
- Industry already offers powerful tools ("Edge Computing"), yet: individual data cleansing and reduction necessary
- After identification of the meaningful measured values, sensor expenditure and investment is rather low
- Targeted combination of different procedures necessary (unsupervised/supervised), but not trivial
- Setting up and training machine learning is time-consuming and requires prior knowledge and suitable "labels".
- It does not (yet) work without trial and error
- The expected added value of a functioning system is high



Thank you for your kind attention!!

If you have any questions, do not hesitate to contact us.



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