Digital Manufacturing

Injection Moulding in a Smart Factory

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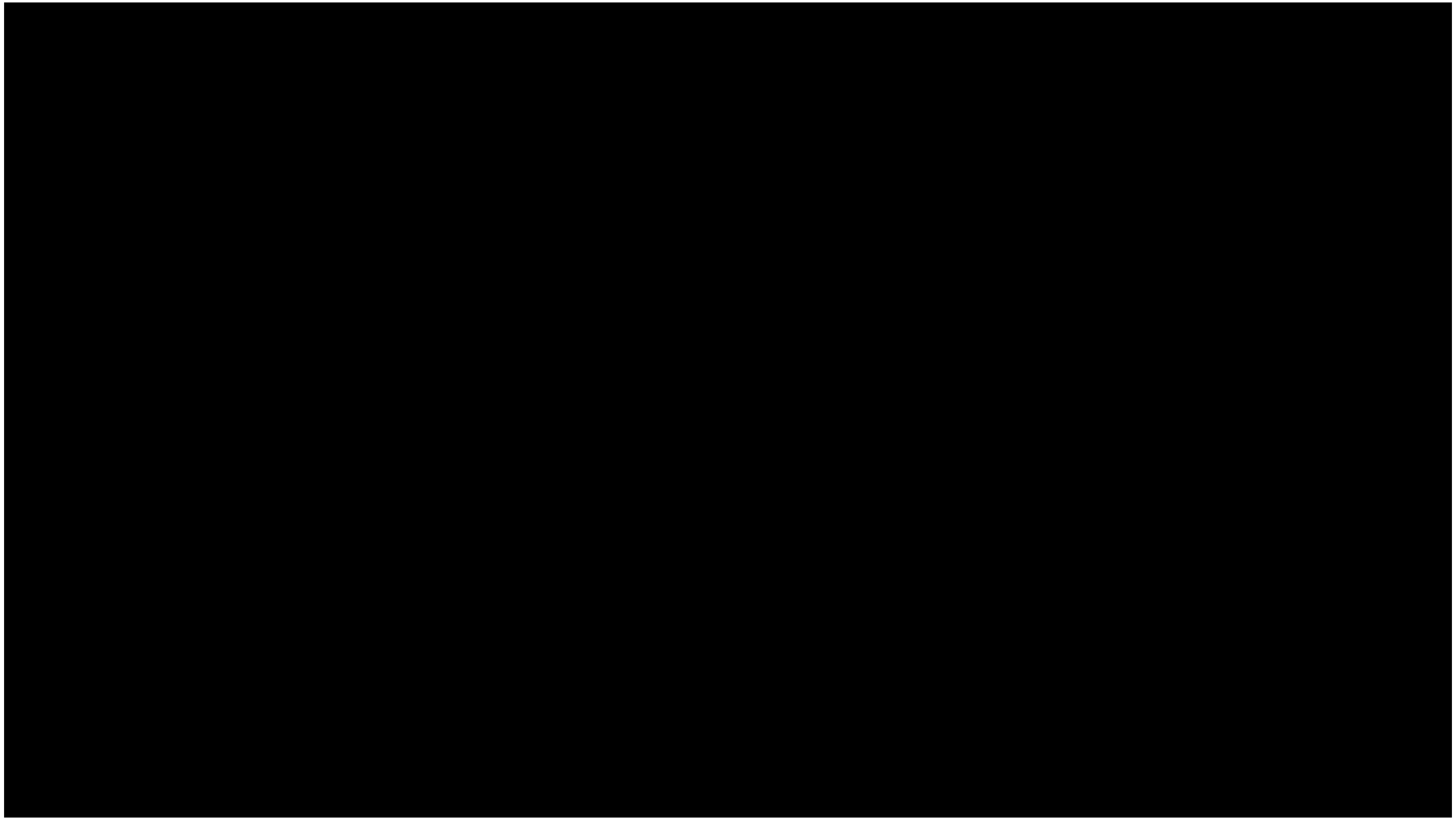
Ostschweizer Fachhochschule

What is a Smart Factory and why is it the future?

*" Future state of a **fully connected factory**, which leads the **interaction of man - machine** in the focus. The smart factory generates, receives and processes **data** to realize the **production of all kinds of goods in a data-driven way**."*

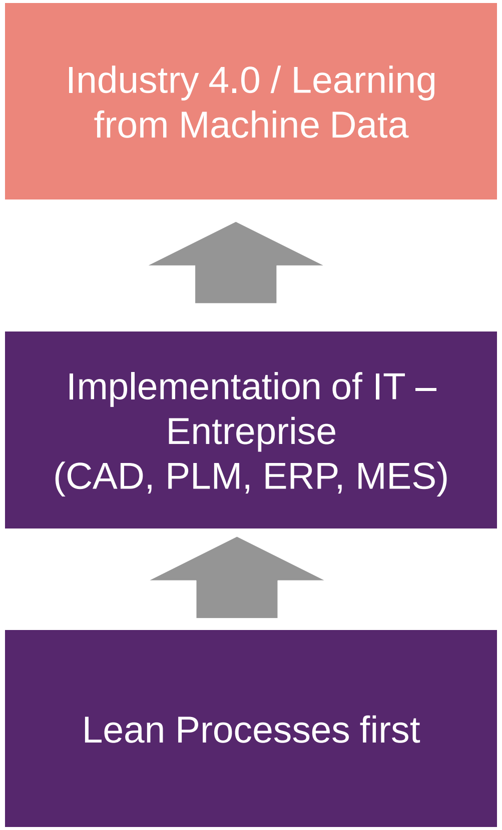
Source: Osterrieder, Budde & Friedli (2019): The Smart Factory as a key construct of Industry 4.0: A systematic literature review

Smart Factory @ OST – floorball production



Injection moulding in times of digitalisation

- Everyone is talking about digitalization, the smart factory and Industry 4.0, and these topics are also becoming increasingly relevant for injection moulding.
- In order to implement Industry 4.0 in injection moulding companies, data must be collected and analysed in order to make predictions.
- However, the data-driven monitoring, optimization or operation of an injection moulding production is still often a dream today.



- Additional data from the machine
- Combining machine data with data from IT Entreprise solutions (orders)

- IT Entreprise Solutions focus on integrated process & data flow
- Key Information / data for a company

- Stable & robust processes are the base
- Reduction of Waste
- Lean Principle focus on the important digital needs

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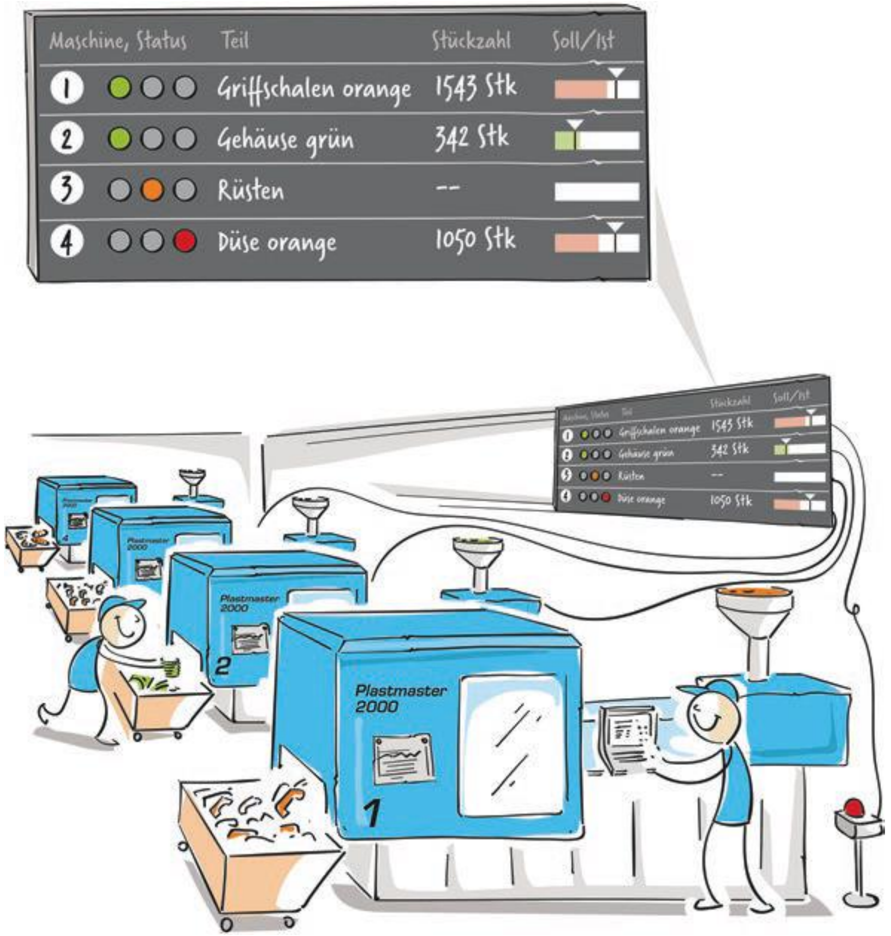
Learning from data

The main goal of the smart factory is to optimize production by learning from data.



"What you can't measure, you can't control"

Peter Drucker, American economist

Only if the exact actual condition of the machines and peripheral equipment is known work on optimizing the processes can be done.

Source: LEAN Production

Challenges in implementing Industry 4.0

There are two main challenges in implementing Industry 4.0 today.

- **lack of awareness** in practice, both **for possible applications and for the necessity of a implementation**. We are talking about the actual target orientation or also use case definition for the smart factory. This concretization must be oriented to the following questions:
  - How can I increase my value creation by using data?
  - How can I use my data? What is the goal?
  - What data do I need to implement a specific use case?

- learning from data requires a **complete data base**. Some questions arise here as well:
  - Which signals do I need? Which signals are available at all?
  - What quality of data do I need? Is the data available in this required quality?
  - How do I get the data out of my machine?
  - How do I synchronize data from different machines and devices?

Learning objectives of this lecture

The students can…

- … apply the concept for learning from data in the smart factory
- … identify difficulties in its implementation

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Injection Moulding in a Smart Factory

1. Implementation of machine learning in the factory
2. Use Cases for injection moulding

Exercise:

- Experience the floorball manufacturing cell

Additional reading

Plastics Industry 4.0

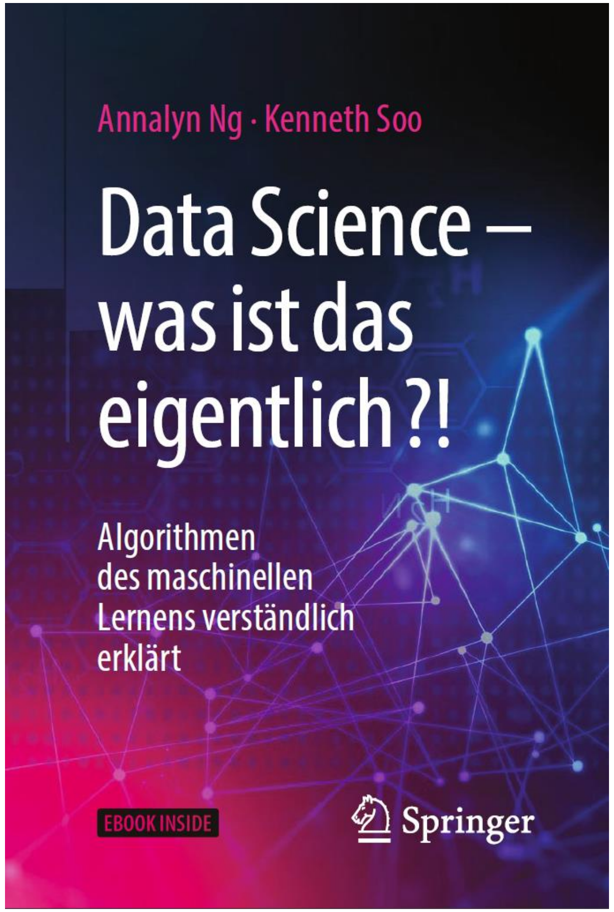
Potentials and Applications in Plastics Technology

Christian Hopmann, Mauritius Schmitz

Print ISBN: 978-1-56990-796-2
eISBN: 978-1-56990-797-9

https://www.hanser-elibrary.com/doi/10.3139/9781569907979.fm

Additional reading



Data Science – was ist das eigentlich?!

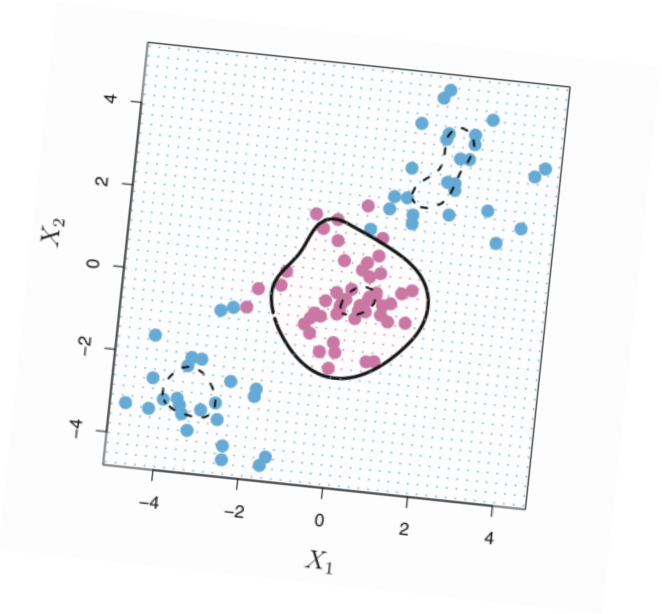
Algorithmen des maschinellen Lernens verständlich erklär

Annalyn Ng, Kenneth Soo

Print ISBN: 978-3-662-56775-3
eISBN: 978-3-662-56776-0

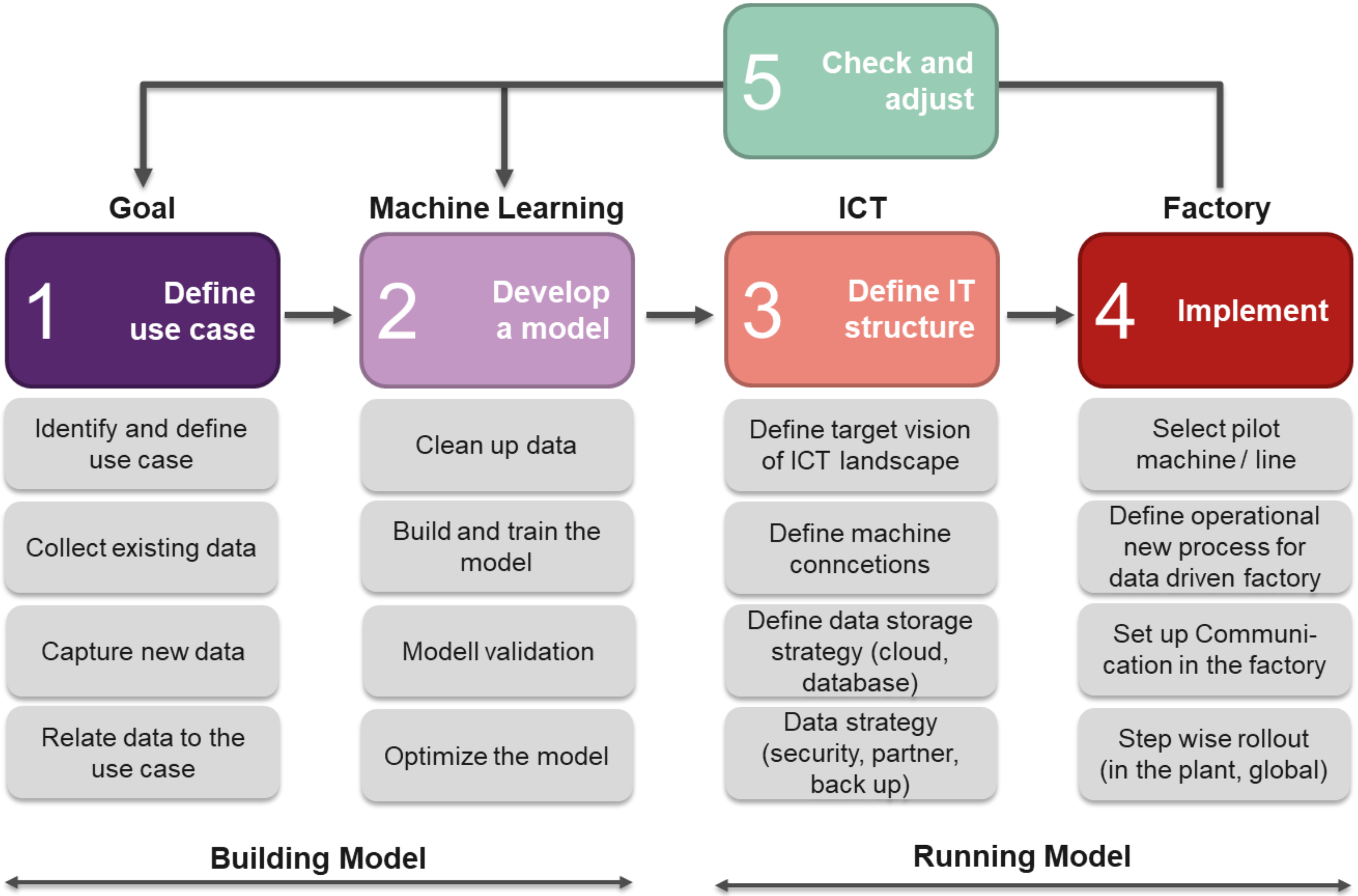
https://link.springer.com/book/10.1007/978-3-662-56776-0

Implementation of machine learning in the factory



Model for the implementation of machine learning in the factory

Investigations showed that a **step-by-step approach** to implement Industry 4.0 in plastics processing is target-oriented.



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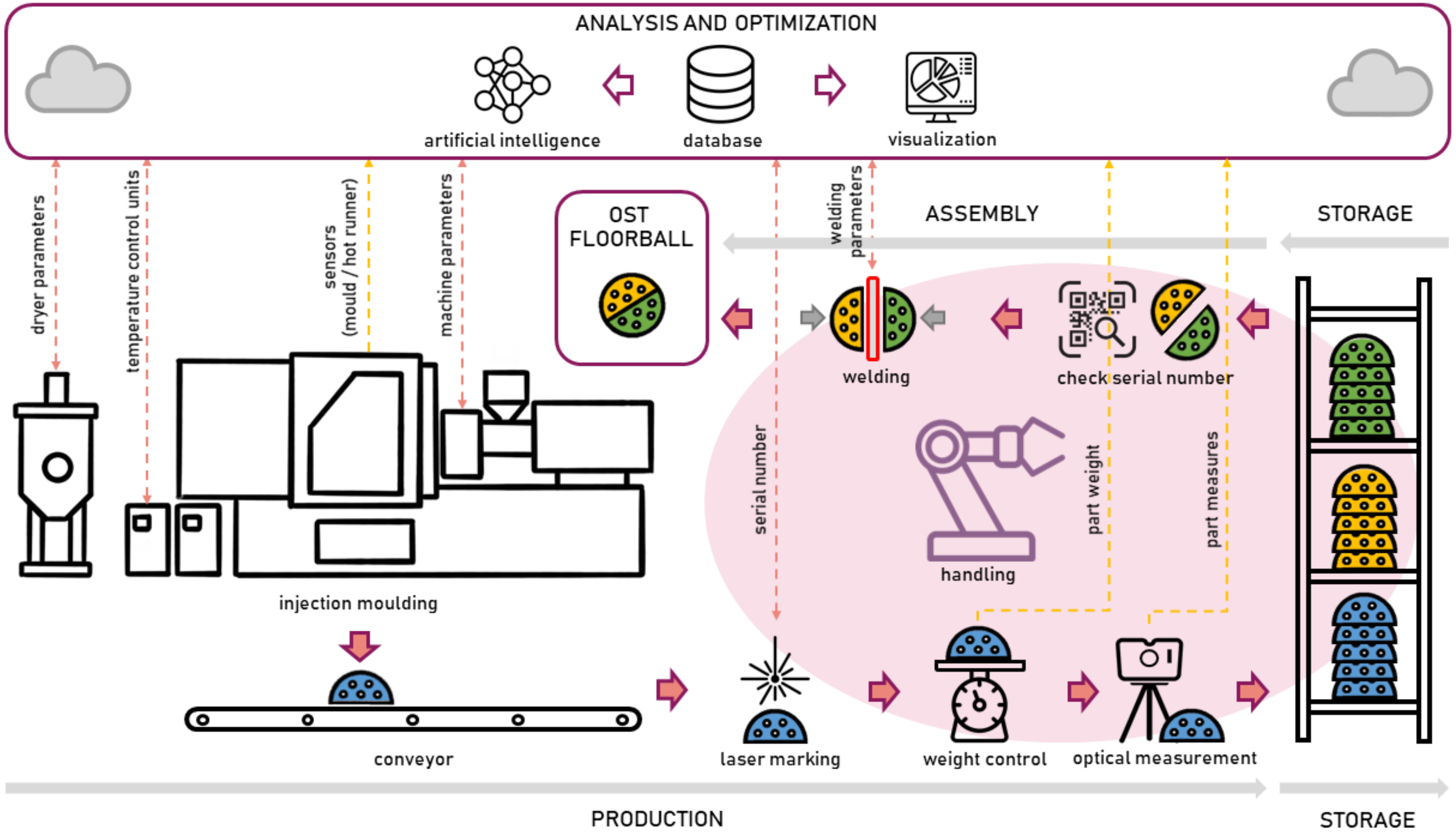
Manufacturing cell floorball



From Smart Factory use case patterns to specific use-cases

Goal

1 **Define use case**

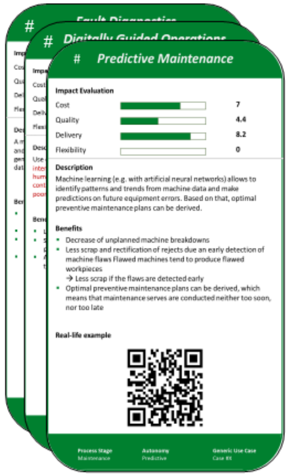
Identify and define use case

Collect existing data

Capture new data

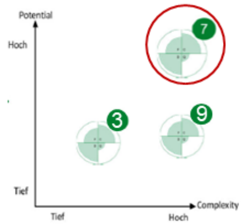
Relate data to the use case

1. Cards with generic smart factory use cases serve as a foundation



2. Apply/adapt the use cases in your specific context

3. & 4. Classification in Potential/Complexity Chart & Prioritization



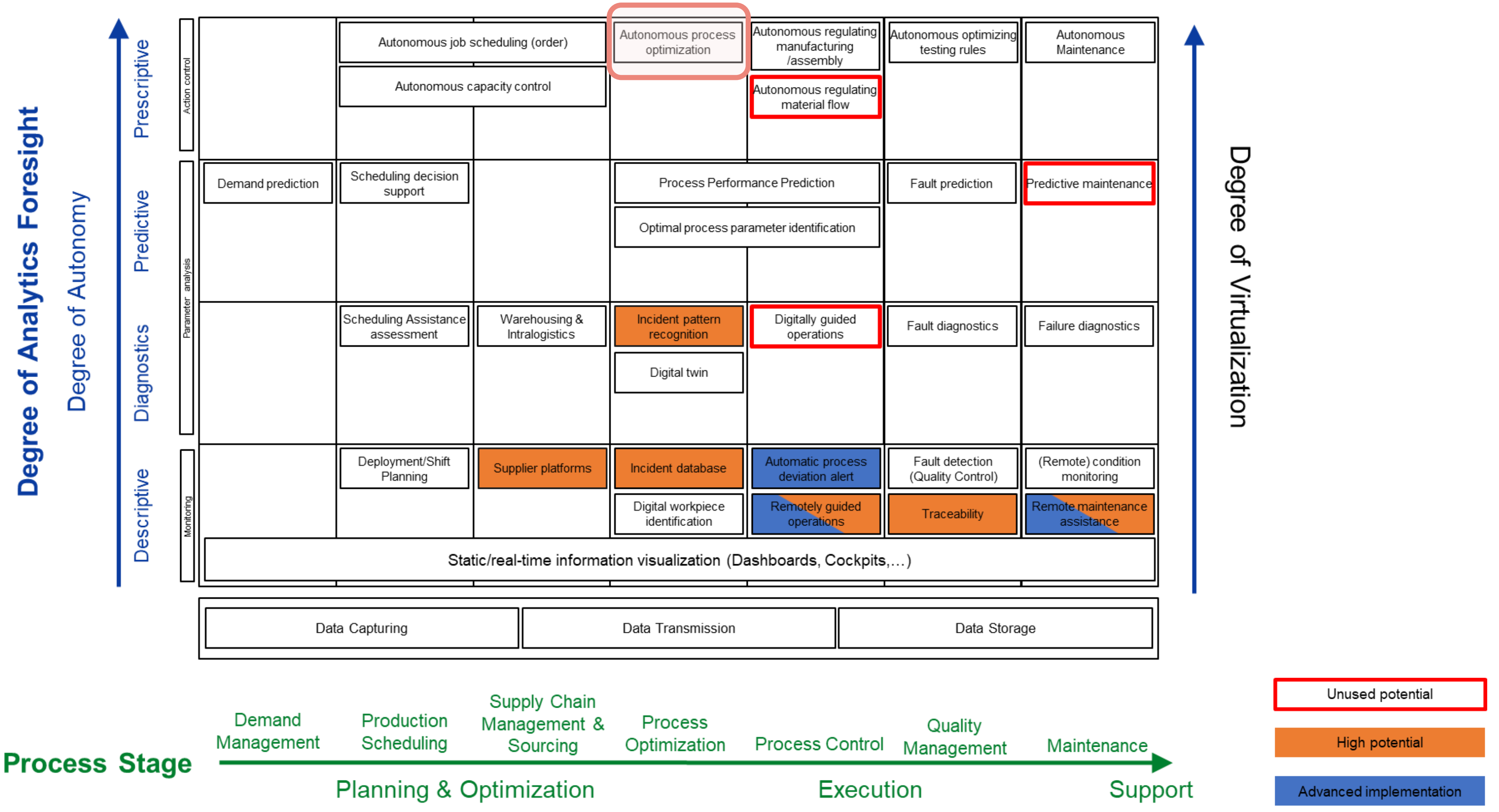
5. Creation of a roadmap (Multi project planning)

6. Implementation of a specific project

Goal

1 Define use case

Classification of digitalization use cases



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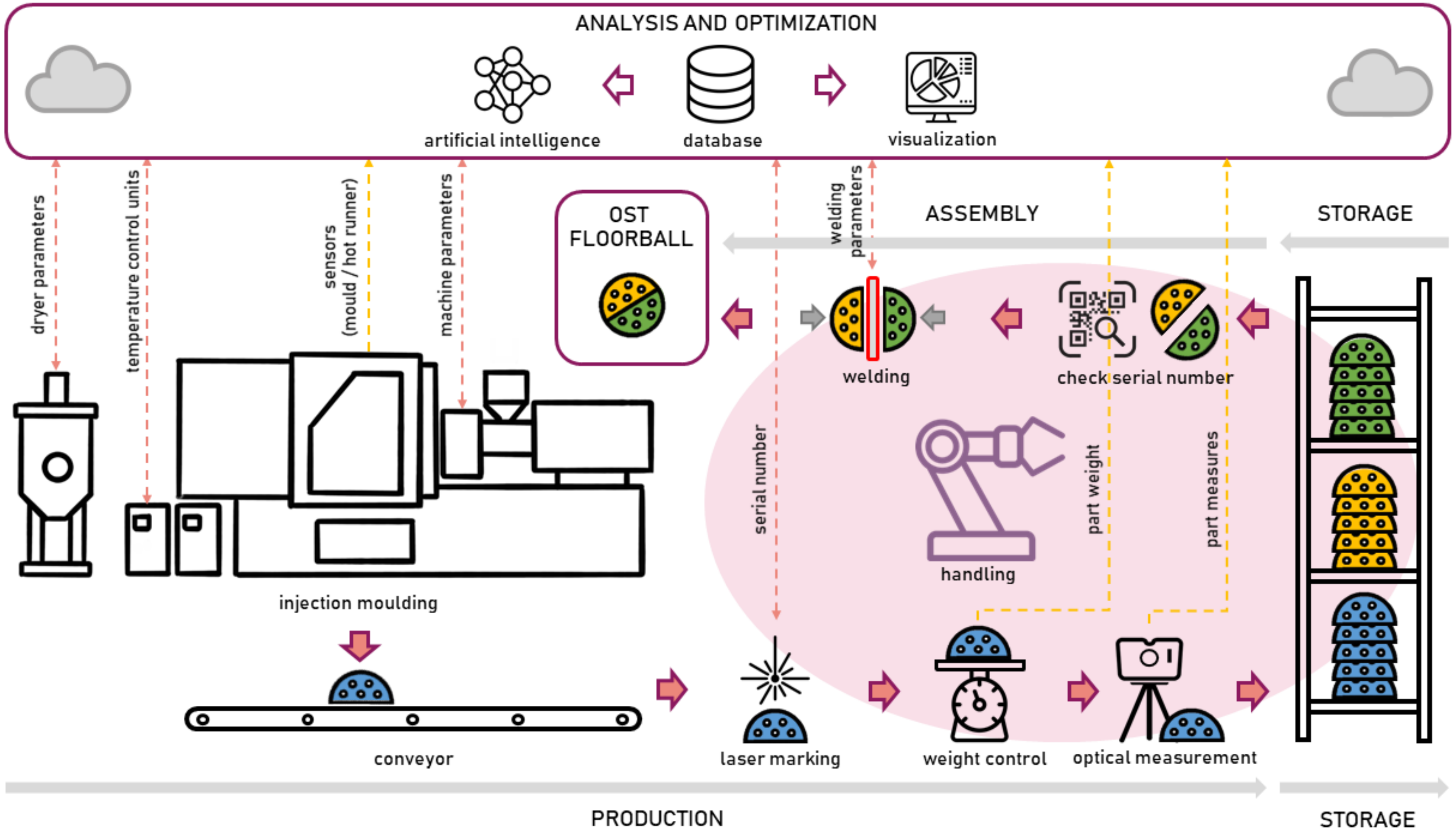
Goal

1 Define use case

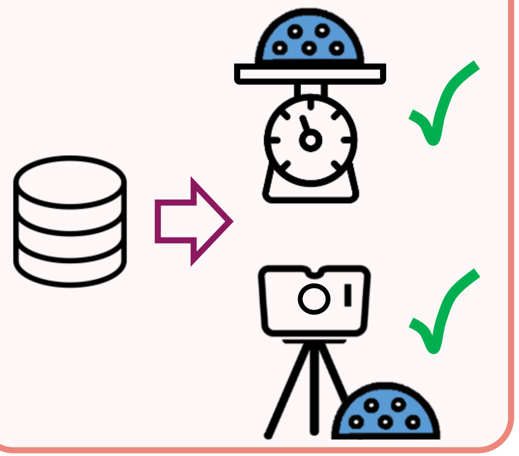
Which data do I need? - Injection moulding process database

Source: VDI-Statusreport – Industrie 4.0 in Spritzgießunternehmen

Build and train your model



Use case:
Autonomous process optimization



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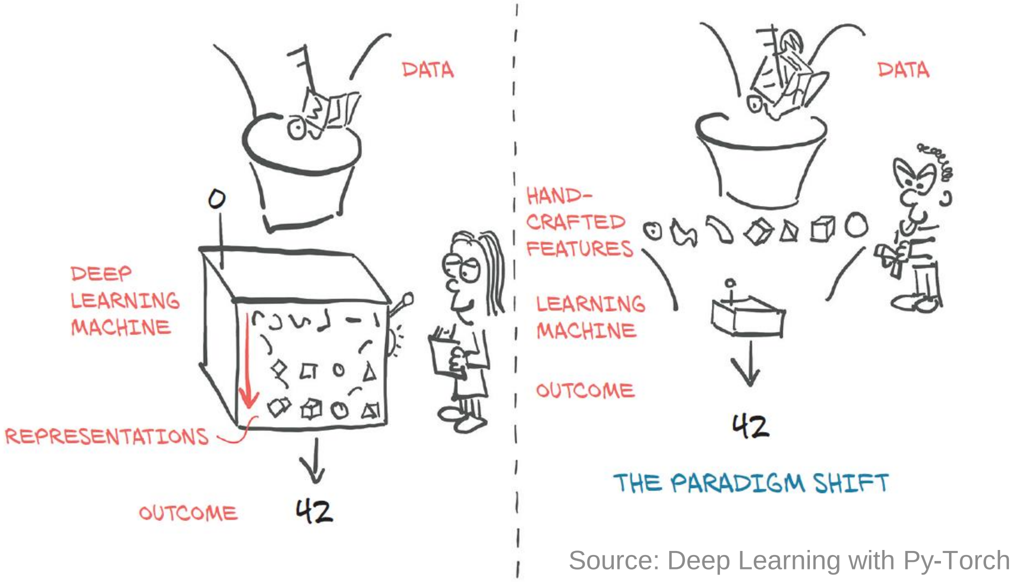
Data preparation

- Advantage:
  - data can be reduced by feature building
  - easier for implementation und better understandable
- Disadvantage
  - possibly loss of information
  - additional data handling



Source: Deep Learning with Py-Torch

Possible methods for feature engineering:
- Statistical feature building (local and global features)
- KPI based on expert knowledge

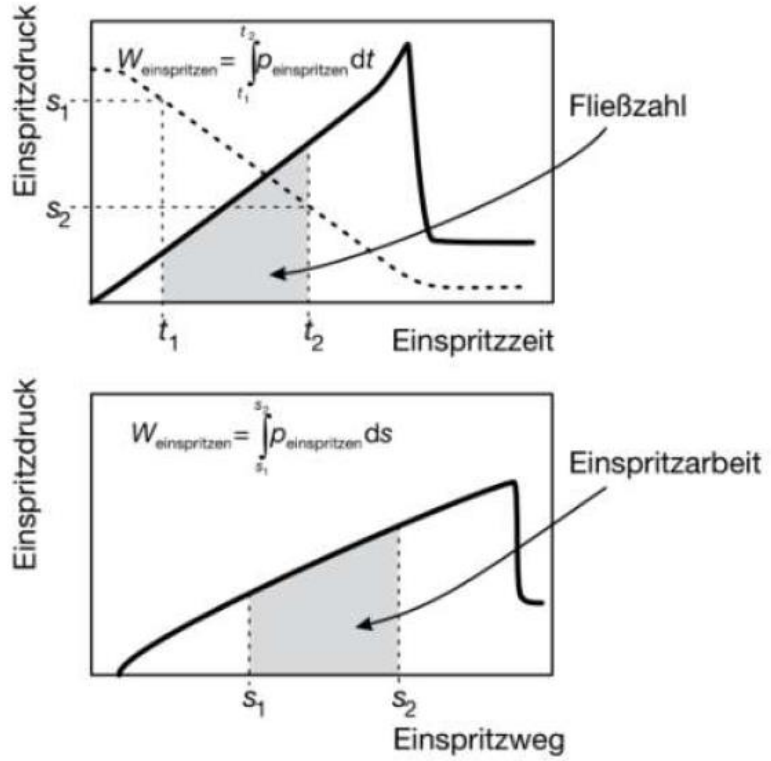
- Advantage:
  - features do not have to be found by the user, but are learned implicitly by the network.
  - Correlations that can only be represented by complicated features can also be taken into account quite simply.
- Disadvantage
  - depending upon enormous memory and computation effort which is needed
  - debugging of a non-functioning model is also very difficult.

Feature building: Statistical Features

- Global features (applied to the whole time signal)
  - Global maximum $s_{j_{max}}(o) = max\left(s_j(o, kT)\right)$
  - Global minimum $s_{j_{min}}(o) = min\left(s_j(o, kT)\right)$
  - Mean $s_{j_{mean}}(o) = \frac{1}{n}\sum_{k=0}^{n-1}\left(s_j(o, kT)\right)$
  - RMS $s_{j_{rms}}(o) = \sqrt{\frac{1}{n}\sum_{k=0}^{n-1}\left(s_j(o, kT)^2\right)}$
  - Variance $s_{j_{var}}(o) = Var\left(s_j(o, kT)\right)$
  - Crest factor $s_{j_{var}}(o) = \frac{s_{j_{max}}(o)}{s_{j_{rms}}(o)}$
- Local features (applied on on limited time intervals, e.g. injection phase)
  - Same calculations methods as for global features

Feature building: KPI based on expert knowledge

- Another approach is to work directly with process parameters (e.g. injection work, flow coefficient, integral WID, changeover pressure, etc.).
- These parameters are based on expert knowledge from the plastics industry and can often be calculated and recorded directly by the machines. These process parameters can also be calculated from the curve data described above, if they can be recorded.



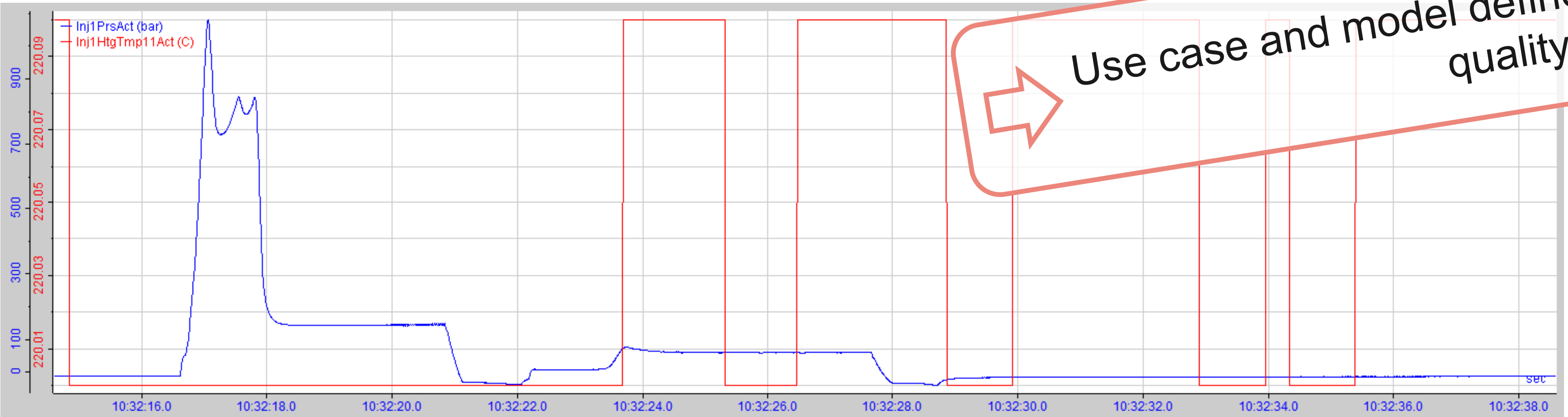
Source: Handbuch Spritzgiessen

Feature building: KPI based on expert knowledge

Beschreibung	Einheit	Berechnung	Anzahl Werte pro Zyklus
Fliesszahl	[bar*s]	Integral Massedruck über Einspritzzeit	1
Einspritzarbeit	[J]	Integral Massedruck über Einspritzweg	1
Nachdruckarbeit	[J]	Integral Massedruck über Nachdrucksweg	1
Maximaler Einspritzdruck	[bar]	Max Einspritzdruck während Einspritzphase	1
Umschaltdruck	[bar]	Druck bei Ende Einspritzen	1
Umschaltpunkt	[mm]	Schneckenposition bei Ende Einspritzen	1
Massepolster	[mm]	Schneckenposition bei Ende Nachdruck	1
Massedruck beim Nachdruck	[bar]	Mittelwert Massedruck während Nachdruckphase	1
Einspritzzeit	[s]	Sumvalid Trigger Einspritzen	1
Dosierzeit	[s]	Sumvalid Trigger Plastifizieren	1
Zykluszeit	[s]		1
Drehzahl	[1/min]	Mittelwert Drehzahl beim Plastifizieren	1
Drehmoment	[Nm]	Mittelwert Drehmoment beim Plastifizieren	1
Staudruck	[bar]	Mittelwert Massedruck beim Plastifizieren	1
Maximaler Werkzeuginnendruck	[bar]	Maximaler Werkzeuginnendruck	Entspricht Anzahl Kavitäten
Werkzeuginnendruckintegral		Integral Werkzeuginnendruck	Entspricht Anzahl Kavitäten
Einschaltdauer jeder Zylinderheizung	[%]	Mittelwert Ansteuerung Zylinderheizung	5
Temperatur jeder Zylinderheizung	[°C]	Mittelwert Zylindertemperatur	5
Einschaltdauer Heisskanal	[%]	Mittelwert Ansteuerung Werkzeugheizung	6
Temperatur Werkzeugheizung	[°C]	Mittelwert Temperatur Werkzeugheizung	6
Temperatur Temperiergeräte	[°C]	Mittelwert Temperatur Temperiergeräte	2
Durchfluss Temperiergeräte	[l/min]	Mittelwert Durchluss Temperiergeräte	2
Maxmimale Werkzeugtemperatur	[°C]	Maximum der Werkzeugtemp	Entspricht Anzahl Kavitäten
Werkzeugtemperatur Einspritzphase	[°C]	Werkzeugtemp zum Start der Einspritzphase	Entspricht Anzahl Kavitäten
Umgebungstemperatur	[°C]		1
Luftfeuchtigkeit Umgebung	[%]		1

What data quality do I actually need?

- High-frequency signals vs. slow signals
  - Injection pressure [bar]
  - Nozzle temperature [°C]

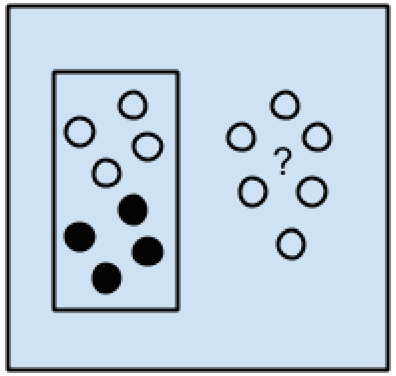


Use case and model define the data quality you need

- If, for example, the injection pressure can only be recorded at low frequency, valuable information is lost (e.g. maximum)

Build and train your model

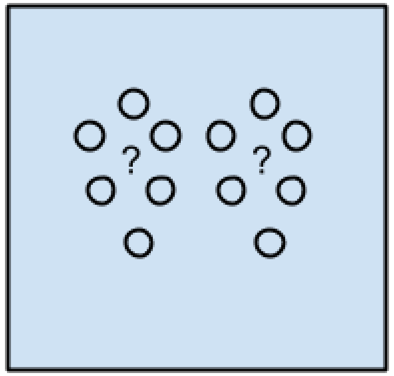
Supervised Learning



Supervised Learning Algorithms

- A model is prepared through a training process in which it is required to make predictions and is corrected when those predictions are wrong.
- The training process continues until the model achieves a desired level of accuracy on the training data.

Unsupervised Learning



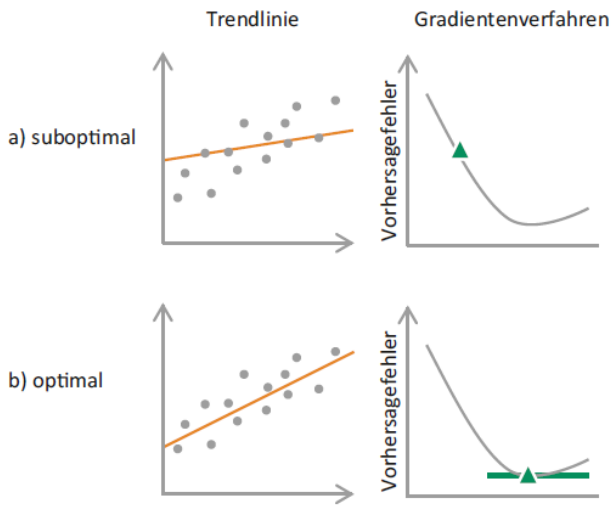
Unsupervised Learning Algorithms

- A model is prepared by deducing structures present in the input data. This may be to extract general rules.
- It may be through a mathematical process to systematically reduce redundancy, or it may be to organize data by similarity.

Source: https://machinelearningmastery.com/a-tour-of-machine-learning-algorithms/

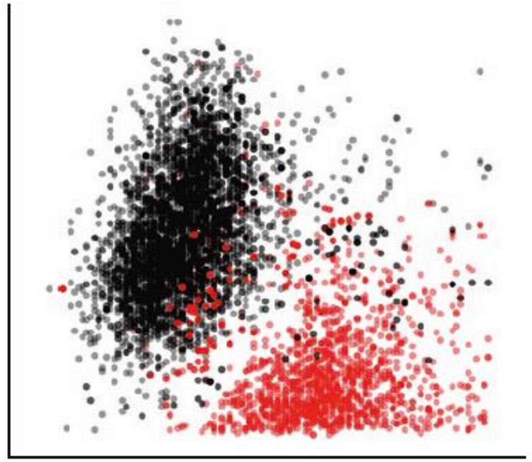
Build and train your model

Linear Regression



- finds the "best fit trend line" that touches as many data points as possible, or at least comes as close to them as possible.
- Works best when there is little correlation between predictors and no outliers

K-Nearest Neighbors

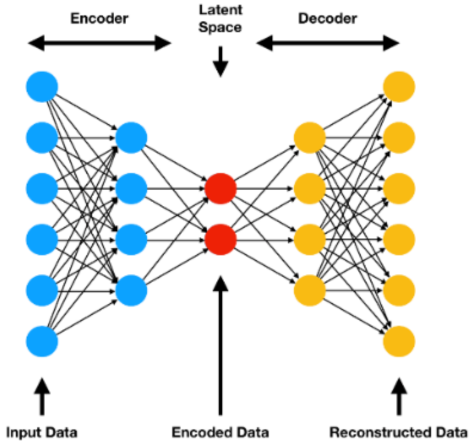


- classifies data points based on the values of neighboring data points.
- k is the number of data points considered, reasonable values for this parameter are obtained by cross-validation

Source: Data Science – Was ist das eigentlich?

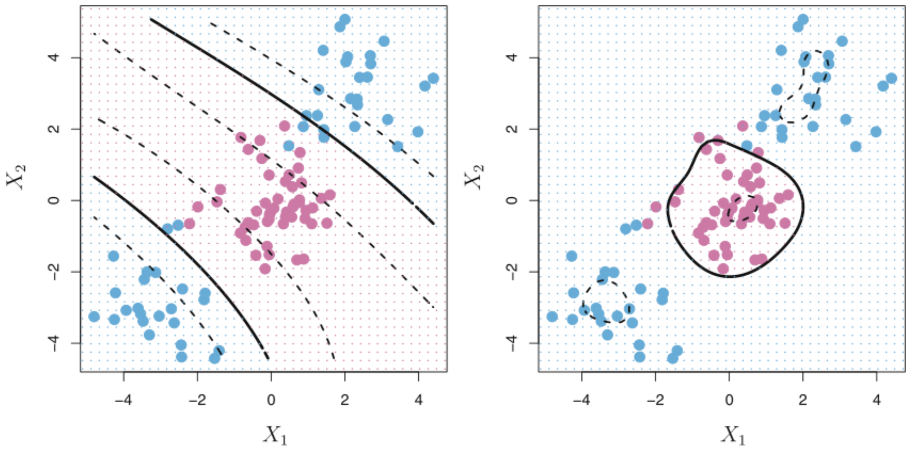
Build and train your model

Neuronal networks



- the **weights in the encoder and decoder are adjusted** so that there is as little error as possible between input and output.
- work best when large data sets and powerful computers are available

Support Vector Machine

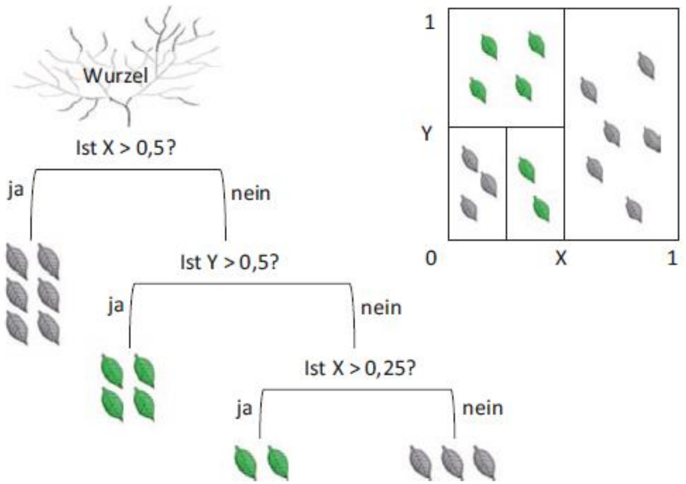


- classifies data points into two groups by drawing a boundary line midway between the boundary points, here called support vectors.
- SVM is insensitive to outliers, since it uses a buffer zone

Source: Data Science – Was ist das eigentlich?

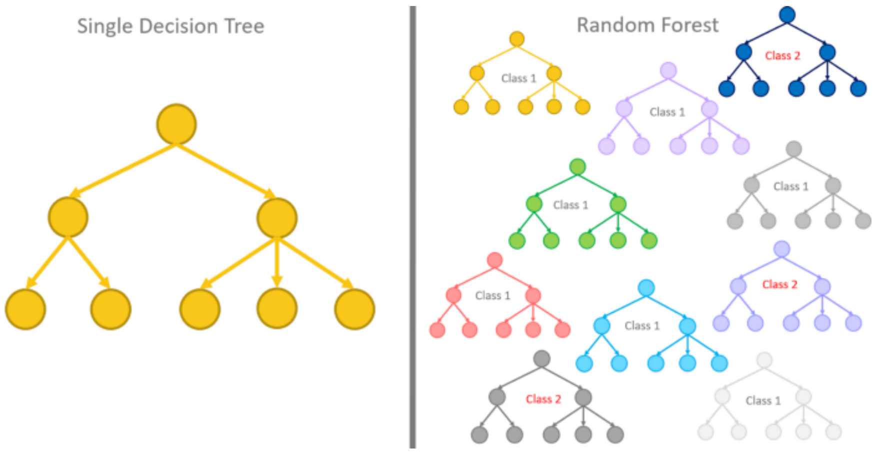
Build and train your model

Decision Tree



- makes predictions based on a sequence of binary questions.
- In this way, the data are gradually divided until they break down into a number of sufficiently homogeneous groups.

Random Forests

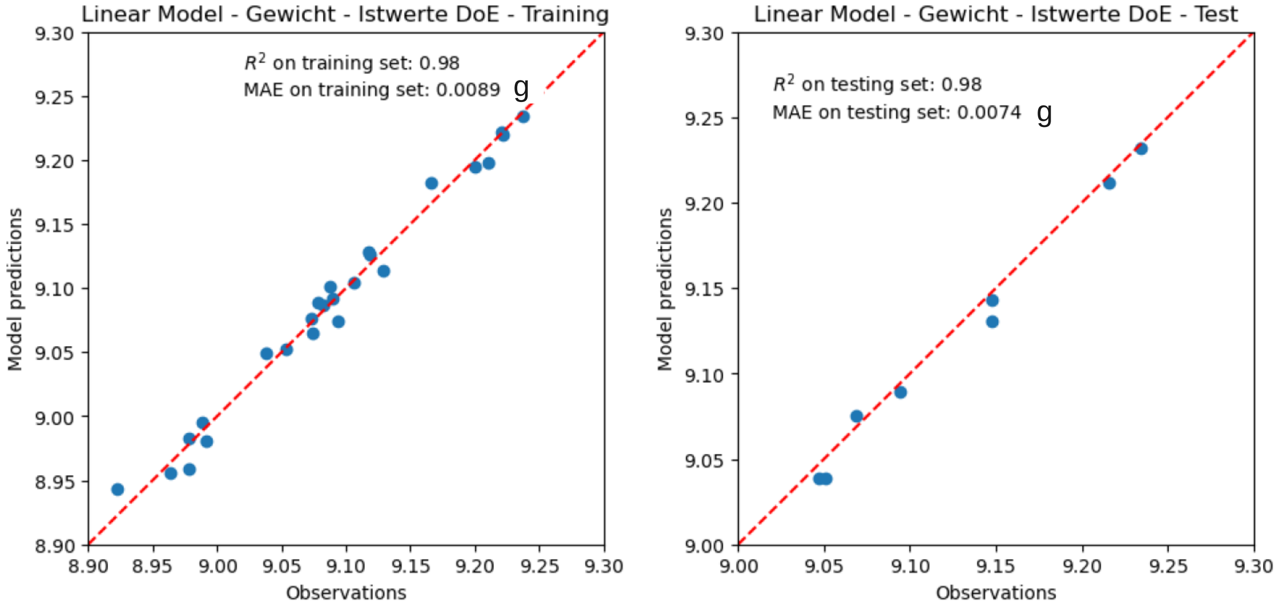


- has usually better prediction accuracy than individual decision trees.
- Used where they are easy to implement - especially where predictive accuracy is more important than interpretation of results.

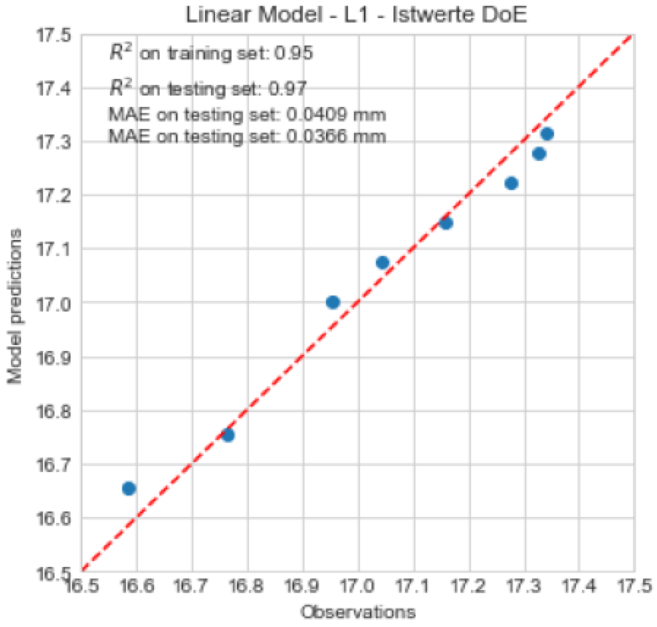
Source: Data Science – Was ist das eigentlich?

Model validation

- Building a different model with linear and polynomial regression for different materials and quality features
- Validation of the model with a test set and evaluation metrics (not used for the training of the model)
- Very good prediction for the quality features and weight just with a few important features found by feature selection

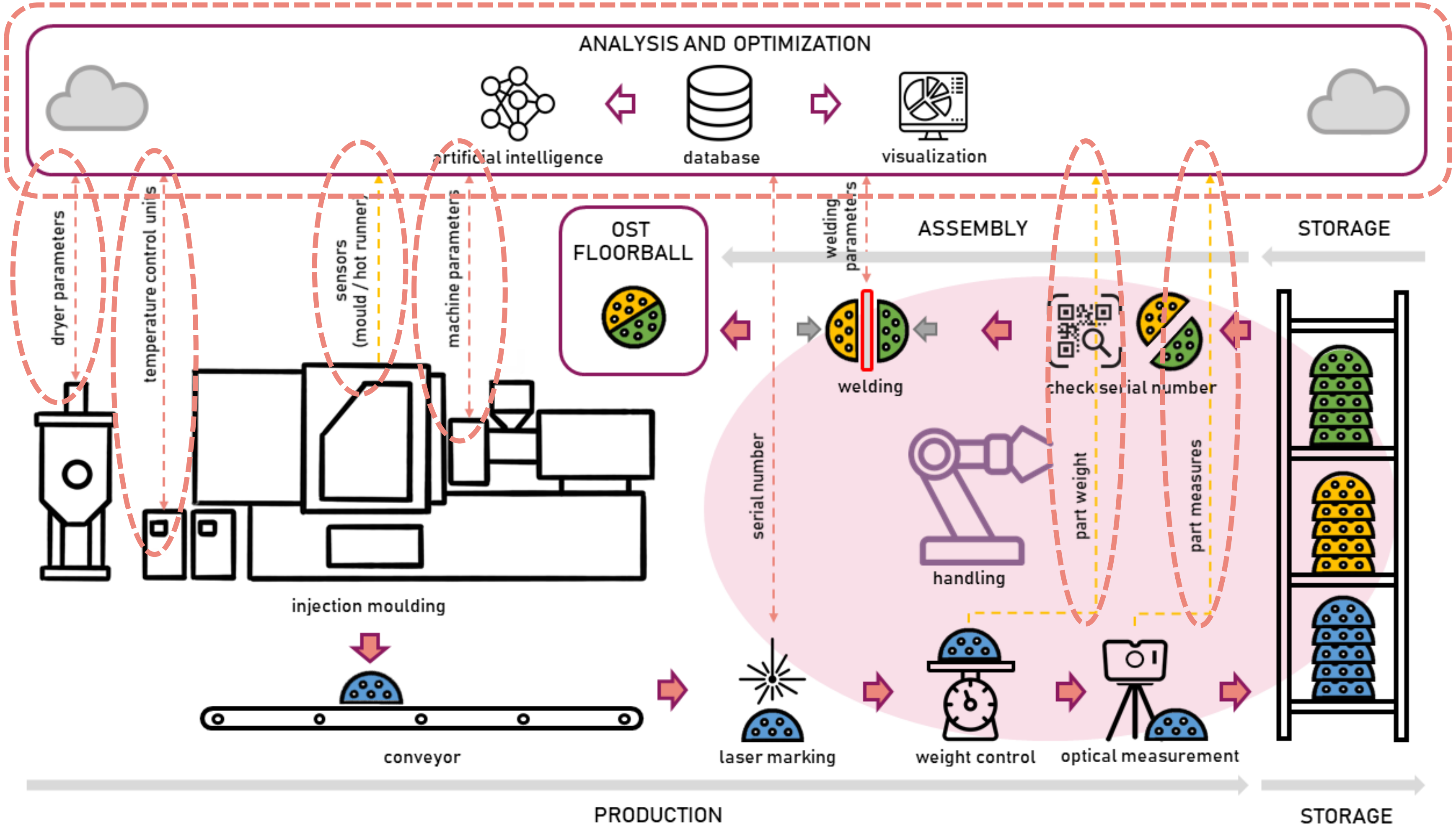


(a) Training (b) Testing



Test set for the polynomial regression model for quality feature including parameters of the training

Define your IT structure



ICT

3 Define IT structure

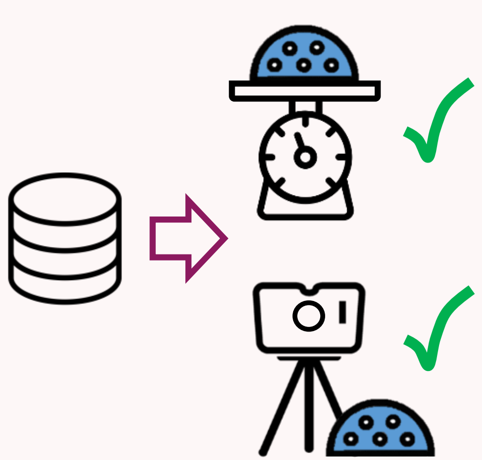
Define target vision of ICT landscape

Define machine conncetions

Define data storage strategy (cloud, database)

Data strategy (security, partner, back up)

Use case:
Autonomous process optimization



Cloud & platform solution and specific DB solution

Different data export / connectivity options as well as different data storage solutions will be demonstrated:

Variant 1 (Cloud- & platform solution)

- Siemens Mindsphere

MindSphere

- All process data as "raw data" in the cloud
- Visualisation of process parameters

Variant 2 (specific local database solution)

- Solution from the company iba

Microsoft SQL Server +

- All process data as "raw data" and calculated process parameters in a database
- Visualisation of process parameters with ibaDaVIS

Challenges in setting up the data acquisition

A number of challenges has to be overcome in order to set up this type of data acquisition for machine learning:

- Often **device-specific solutions** had to be implemented so that the data could be exported and recorded in the desired quality.
- Another difficulty is the **synchronization of data from different machines** and devices (e.g. injection molding machine, temperature control units, ambient conditions).
- The **allocation of data from different pre or post-processes** is also an issue.
  - data acquisition differs between continuous processes, e.g. material drying, in which continuous time series are recorded, and discontinuous processes such as injection
  - data from pre-process steps must be able to be clearly assigned to the later data of the part.

ICT

3 Define IT structure

Data storage / upload

In the Smart Factory @ OST different devices are used for data acquisition, storage and upload:

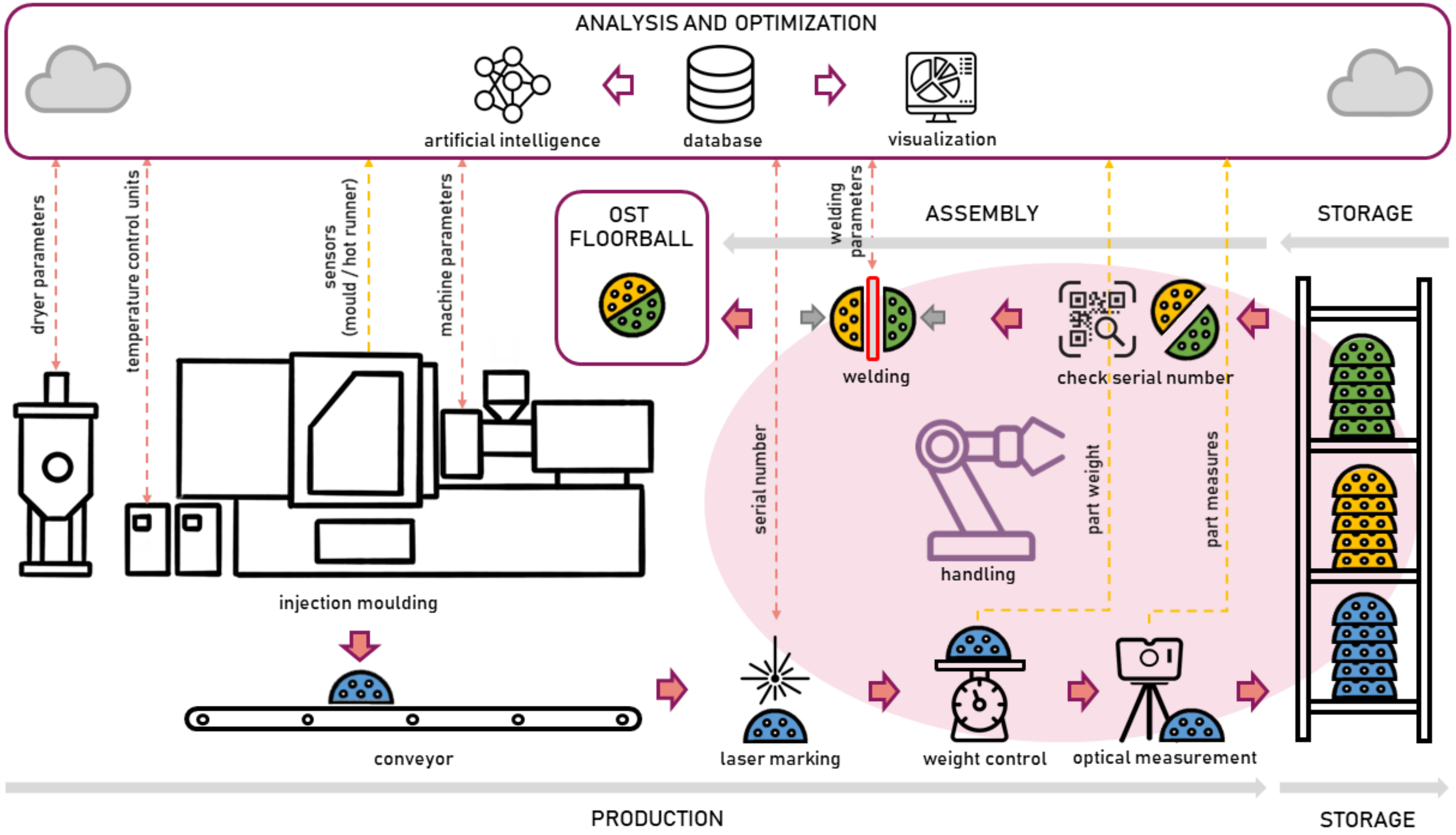
System	Siemens IPC	iba DAQ-C	Raspberry Pi
			
Data recording	no	yes	yes
Data upload	yes, manual programming	yes, through ibaPDA	yes, manual programming
timestamp	from machine	from DAQ-C for all devices	from Raspberry Pi

How do I get the data out of my machine?

For the cyclic export of process parameters, the Euromap 63 and Euromap 77 (OPC-UA) interfaces play an important role:

- Euromap 77 (OPC UA)
  - simple standardised data exchange, but the sampling frequency is limited to approx. 2 Hz (depending on the subscription the machine or device allows)
  - currently only available on very new machines
  - developed for the cyclic export of process parameters
- Euromap 63
  - less standardised and the sampling frequency is also limited (maximum is approx. 1 Hz)
  - widely used on newer machines
  - also developed for the cyclic export of process parameters

Implementation: manufacturing cell



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Battenfeld Smart Power 60/210

Data from the injection moulding machine

- Euromap 63 (via Raspberry Pi)
  - Curve signals with 0.5 Hz sampling frequency rather cyclical values
  - Process parameters and setting parameters
- Sensor signals from the machine control cabinet
  - Curve signals with max. 1kHz sampling frequency (via I/O module)

Data from the tool

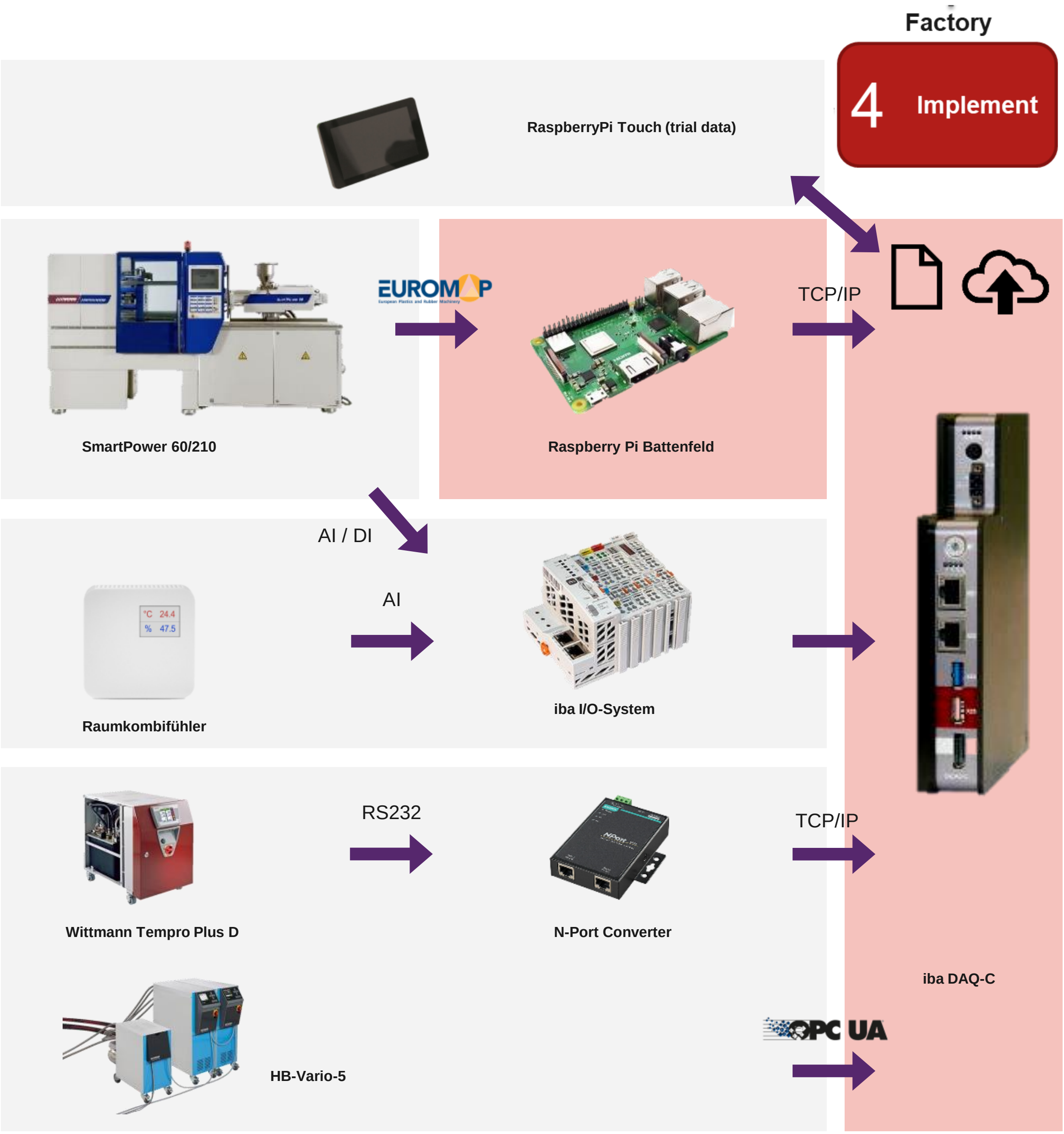
- Cavity pressure sensors 1 channel
  - Curve signals with max. 1kHz sampling frequency (via control cabinet and I/O module)

Peripheral and environmental data

- Temperature control units Wittmann Tempro Plus D (via RS232 & NPort)
  - Curve signals with 1Hz sampling frequency
- HB-Vario 5 unit (via OPC UA)
  - Curve signals with 1Hz sampling frequency
- Ambient temperature and humidity (via I/O module)
  - Curve signals with max. 1kHz sampling frequency (via I/O module)

Trial data

- Input via touch screen (via TCP/IP)



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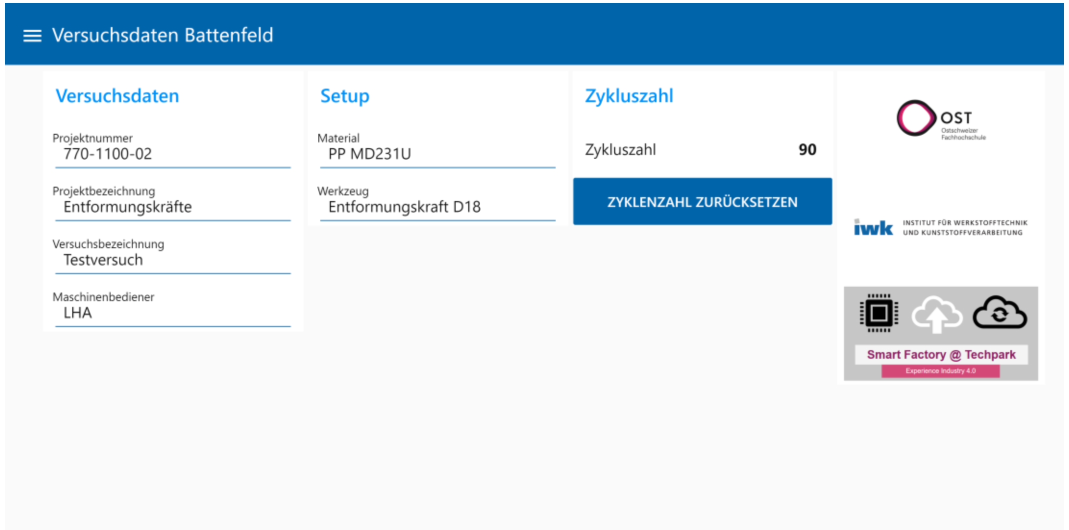
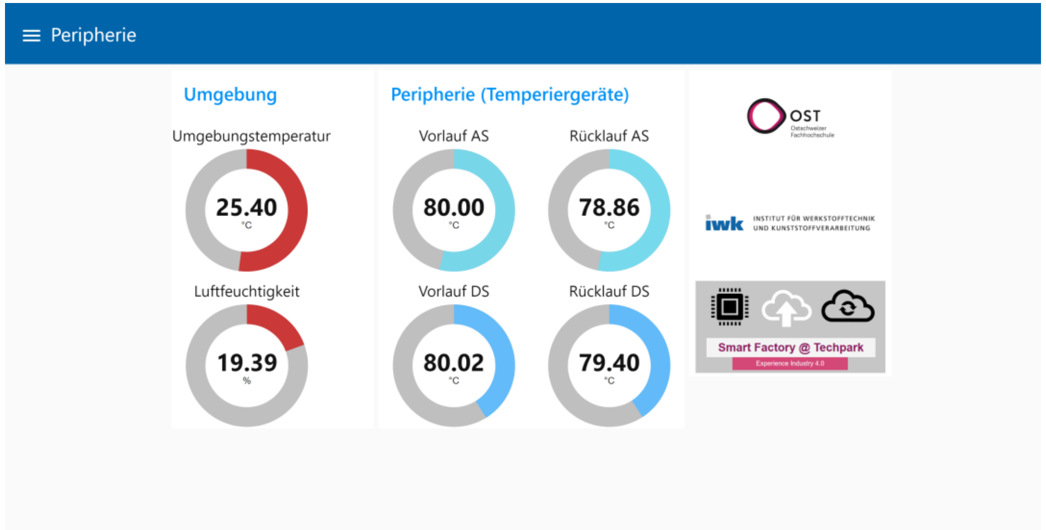
Input for manual / trial data

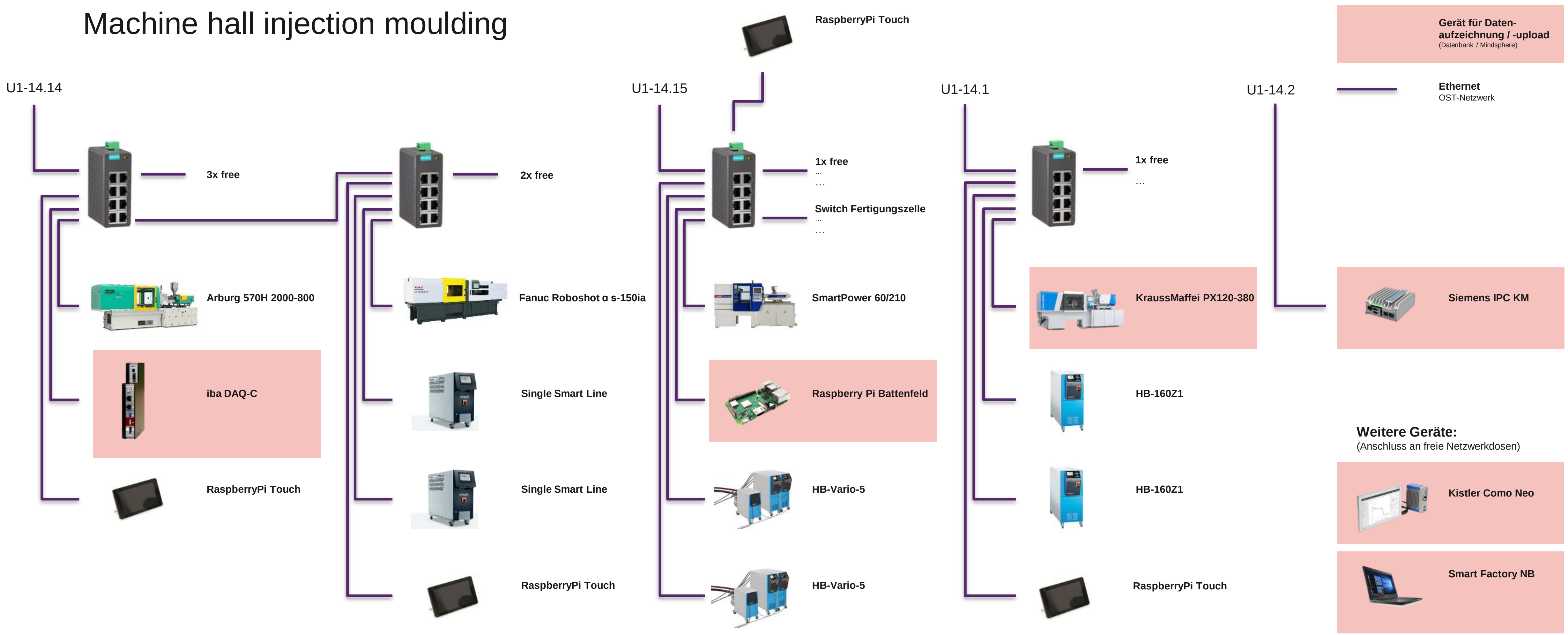
To ensure that the recorded data can also be assigned to the corresponding trials, information on the trials is required in addition to the process data. For this purpose, each machine was equipped with a touch display with which the test data can be recorded but also the process data can be visualised.





Networkplan

Machine hall injection moulding



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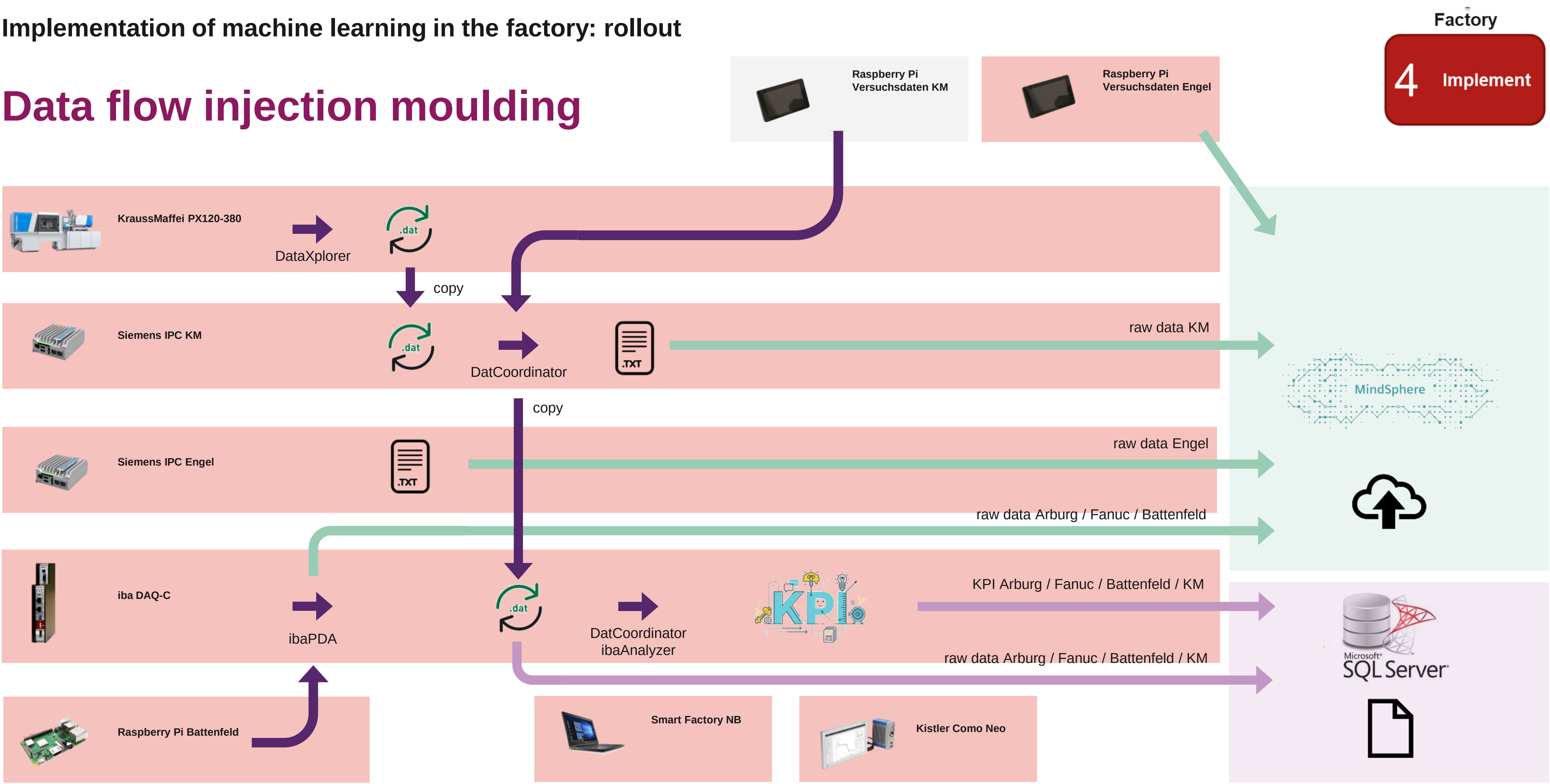
Data flow injection moulding



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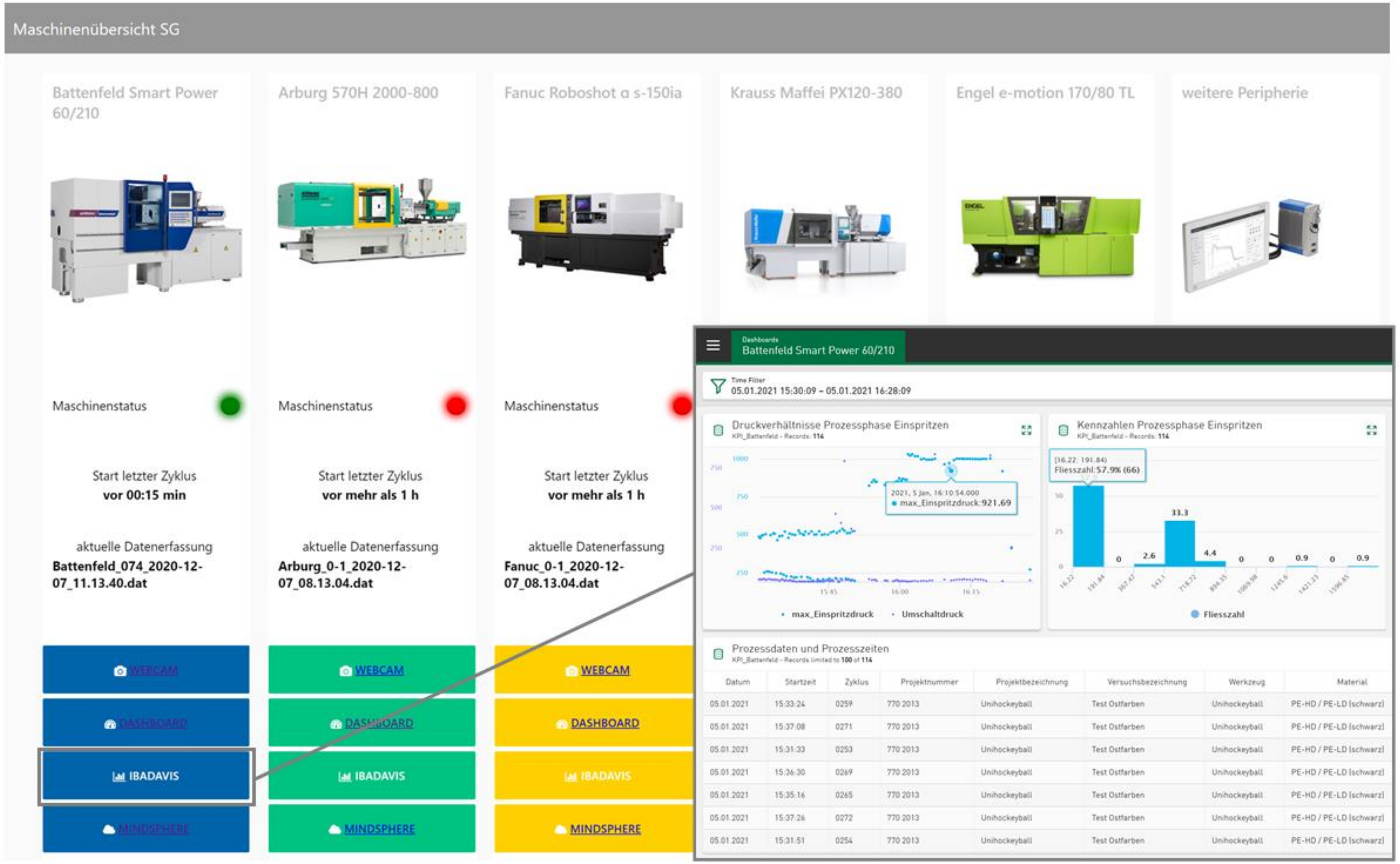
Dashboard injection moulding machines



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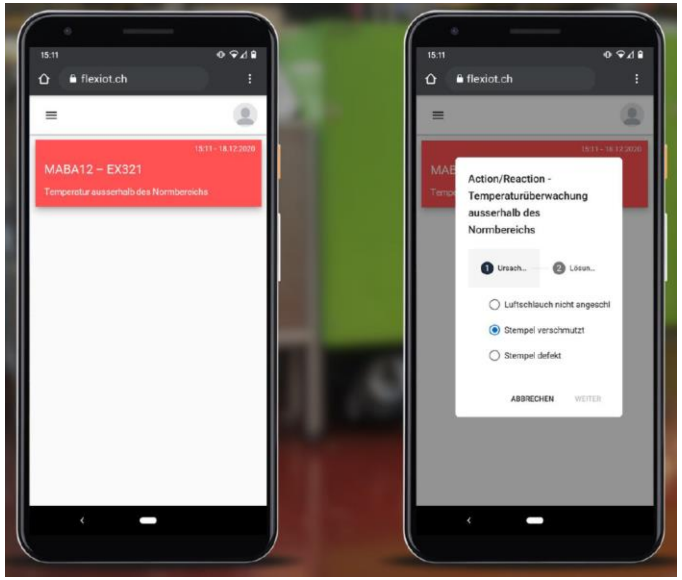
Factory

4 Implement

Notifications for shop floor

- Highly automated , increasingly connected production environments and constantly growing amounts of «industrial data »
- Several applications with complex information dashboards and for concrete maintenance tasks available, but …

- How can manufacturing workers at the shop floor be informed about the current production status and potential interventions?



[PRISM Preventive Intervention in Smart Manufacturing]

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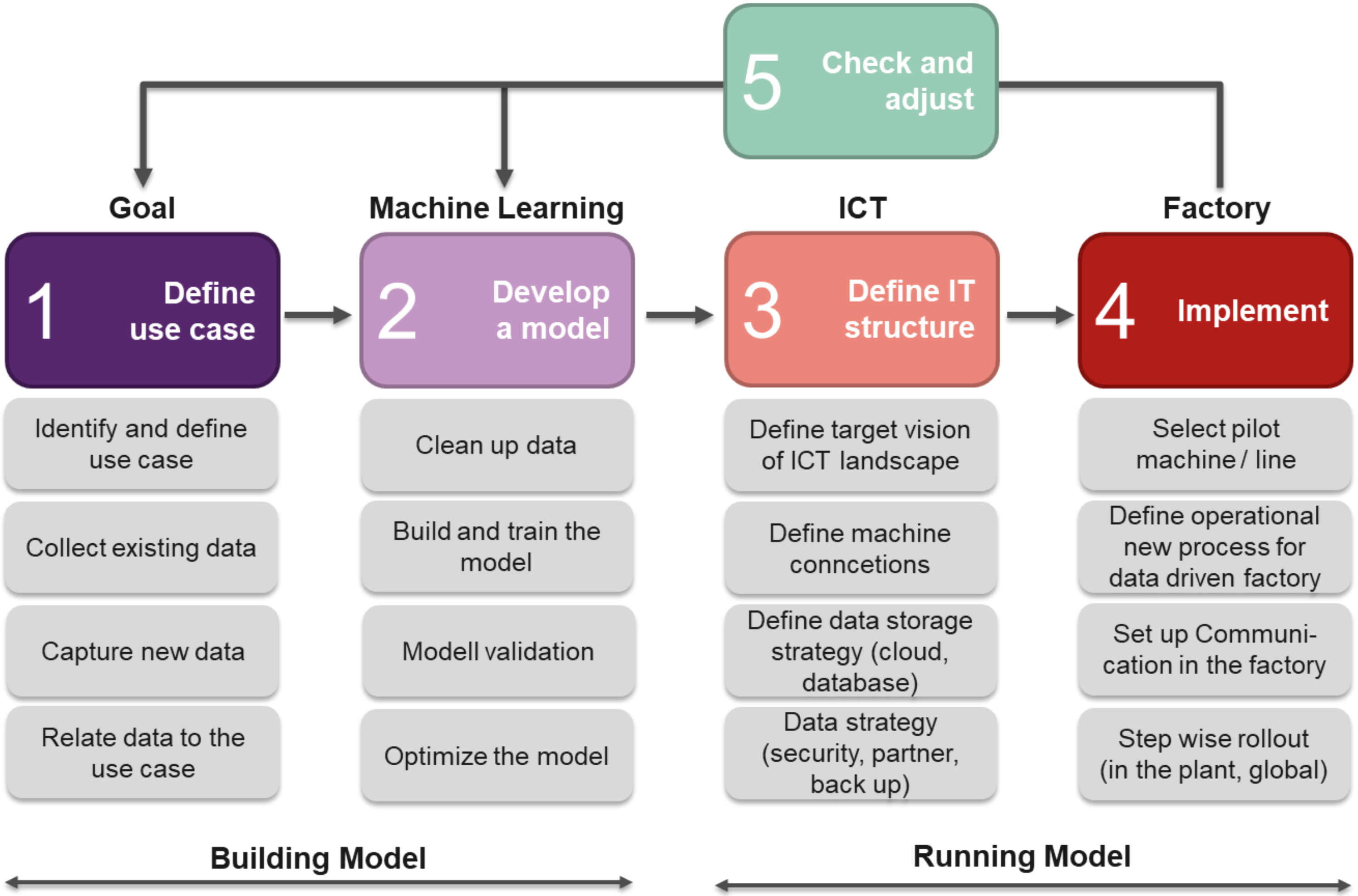
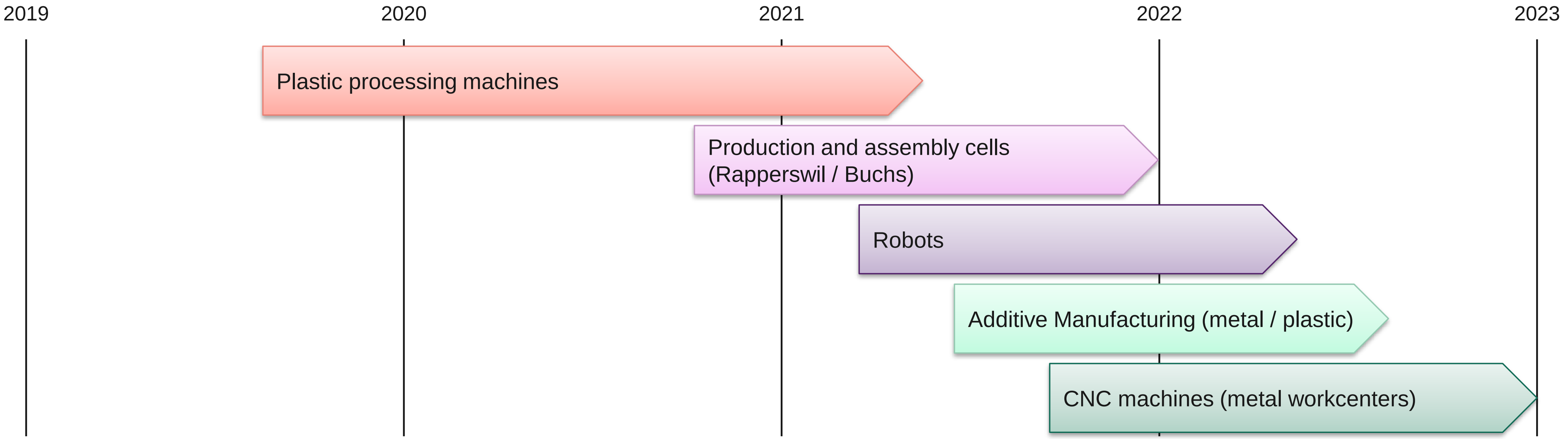
Validate your model

Model for the implementation of machine learning in the factory



Smart Factory components and roadmap

- Due to the existing knowledge in the field of plastic production technologies and robotics, these areas also serve as central elements of the smart factory.
- The networking and the development of data export for the machines of the IWK served as the initiation for the development of the smart factory, which is now to be continuously and diversely expanded.



Implementation partner: competencies united

INSTITUT FÜR WERKSTOFFTECHNIK UND KUNSTSTOFFVERARBEITUNG

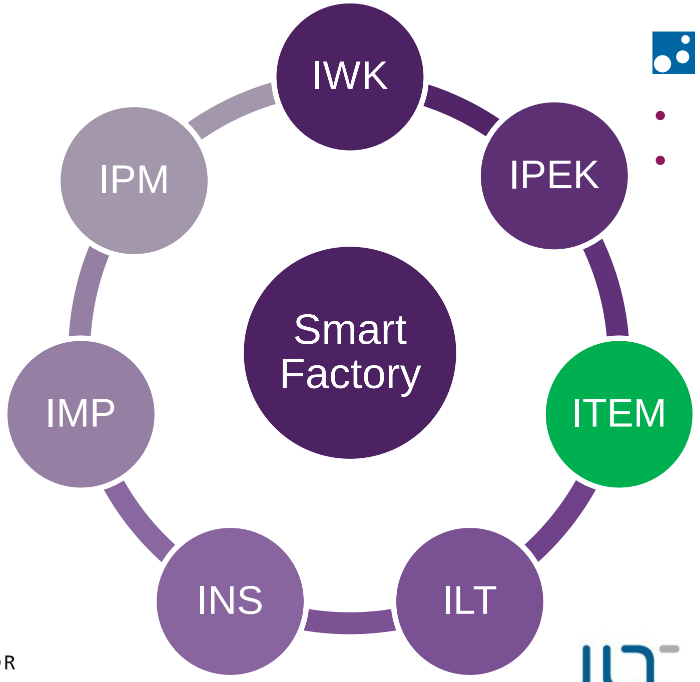
- Plastics processing
- Data acquisition and processing

INSTITUT FÜR PRODUKTDESIGN, ENTWICKLUNG UND KONSTRUKTION

- Industry 4.0
- Information and communication technology

IPM Institut für Informations- und Prozessmanagement

- SAP



IMP Institut für Mikrotechnik und Photonik

- Mechatronic systems

Institut für Technologiemanagement

Universität St.Gallen

- Production strategy
- Business models

INSTITUTE FOR NETWORKED SOLUTIONS

- Network and cloud infrastructure
- Security

INSTITUTE FOR LAB AUTOMATION AND MECHATRONICS

- Robotics
- Automation solutions

Further Use Cases for injection moulding

Use cases for injection moulding @ OST

Use case 1: anomaly detection

- Use of internal machine data for anomaly detection and logging events at occurrence
- Proposal of an appropriate countermeasure

Use case 2: quality data prediction

- Use of internal machine and tool data (cavity pressure) to predict quality of injection moulded parts

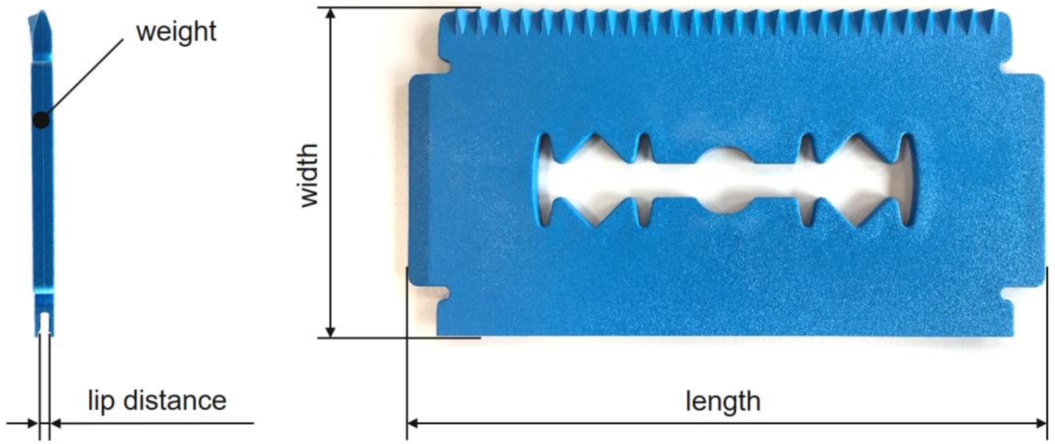
Use case 3: preventive and predictive maintenance

- Use of internal machine data for the evaluation of the condition of key components of an injection moulding machine (e.g. non return valve)
- Determination of the time for a replacement

Anomaly detection: trial design

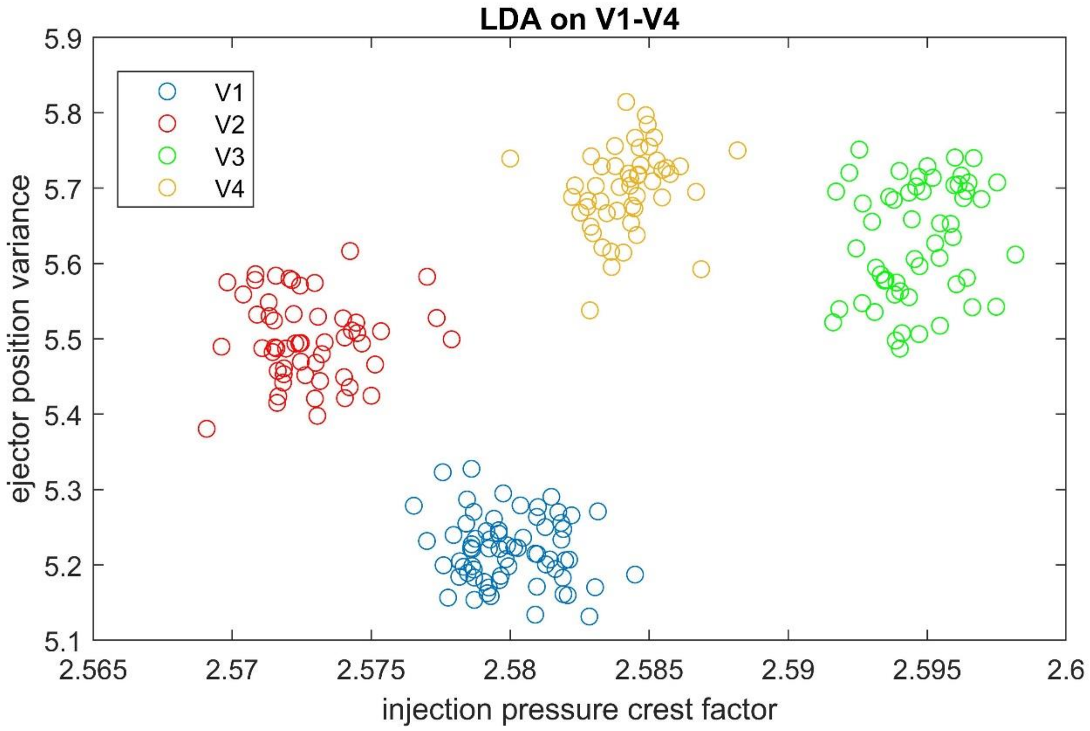
- 4 test series, part: ice scraper, material: PP
  - Trial series 1 (72 parts) - reference trial series → ice scrapers lie within the tolerances
  - Trial series 2 (56 parts) - calcified cooling channels → temperature of the mould temperature medium increased
  - Trial series 3 (57 parts) - batch fluctuation → cylinder temperature increased
  - Trial series 4 (52 parts) - wrong material → 10% foreign material added

- Database
  - Process curves recorded with the DataXplorer
  - Additionaly the corresponding quality data were measured (shown in picture on the right)



Anomaly detection: classification of trial series

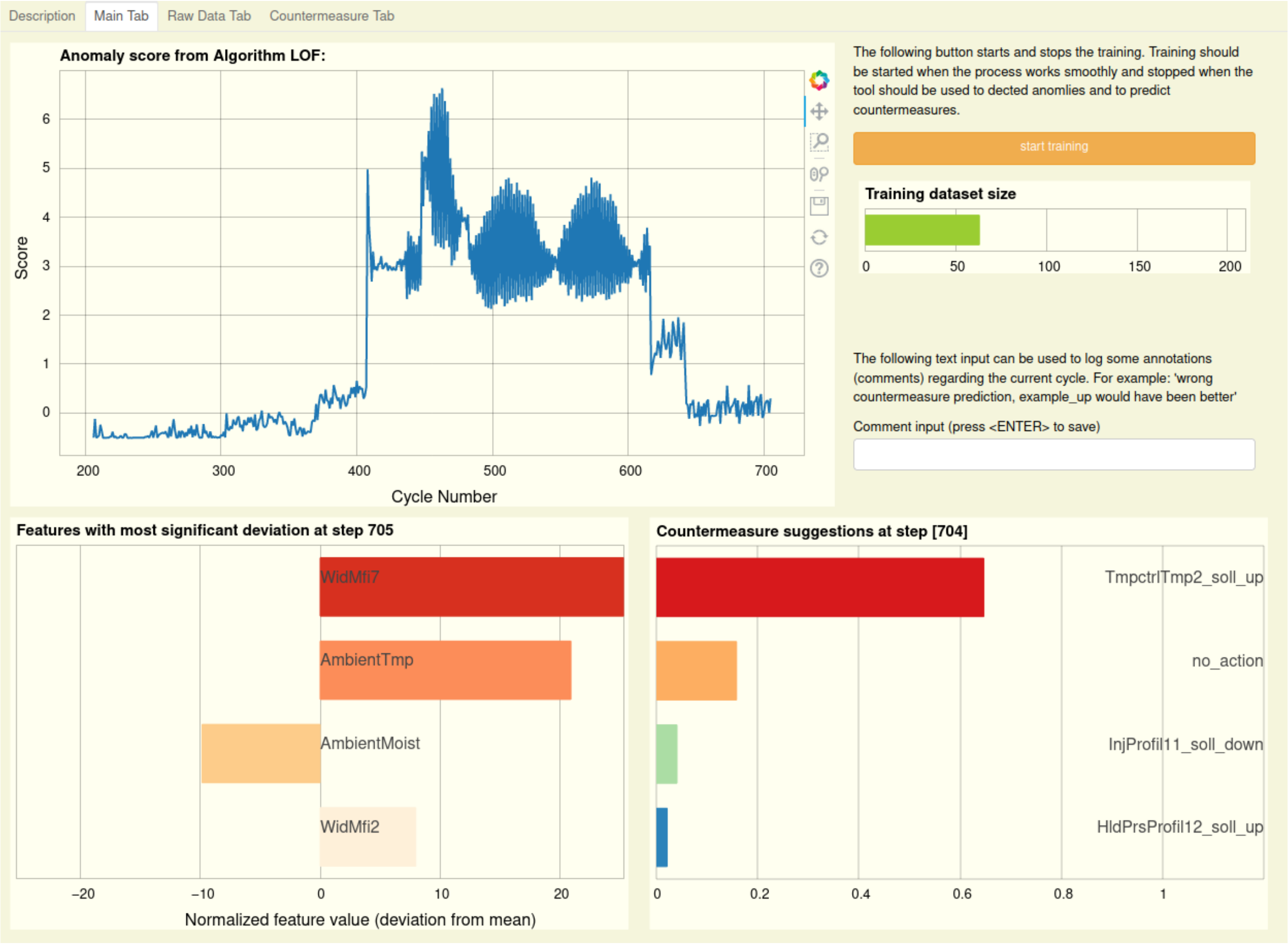
- Can ML be used to anticipate process anomalies based on internal measurement signals?



→ trial series V1-V4 can be completely classified with just two important features (a linear discriminant analysis (LDA) was used for the actual classification of the trial series)

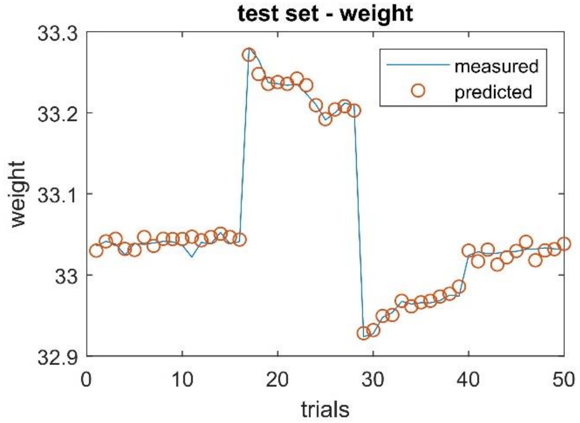
Anomaly detection: application in practice

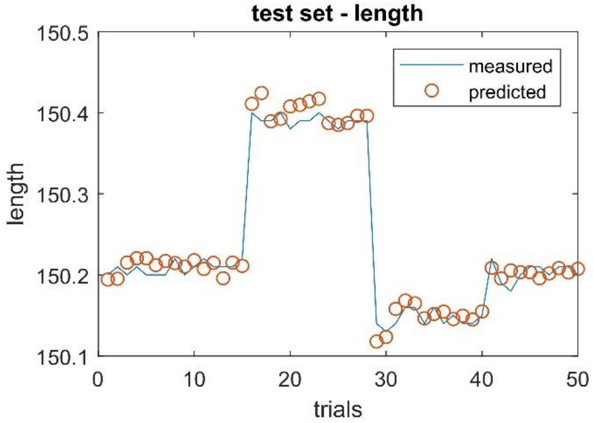
- When the anomaly score increases, a recommendation for action is suggested to the operator (Fig. 5, bottom right), which can be used to correct the process again.

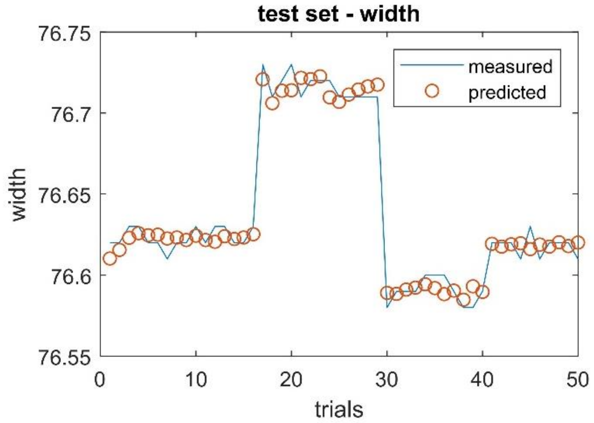


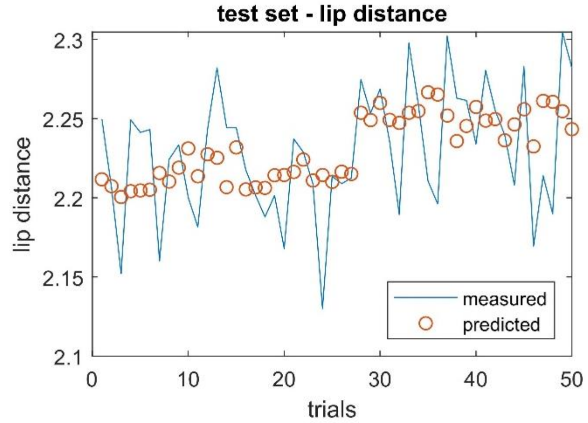
Quality data prediction: results

- Test sets (random data from the trial series that were not used for the development of the models) were used to test the models by predicting the quality data of the already moulded parts.









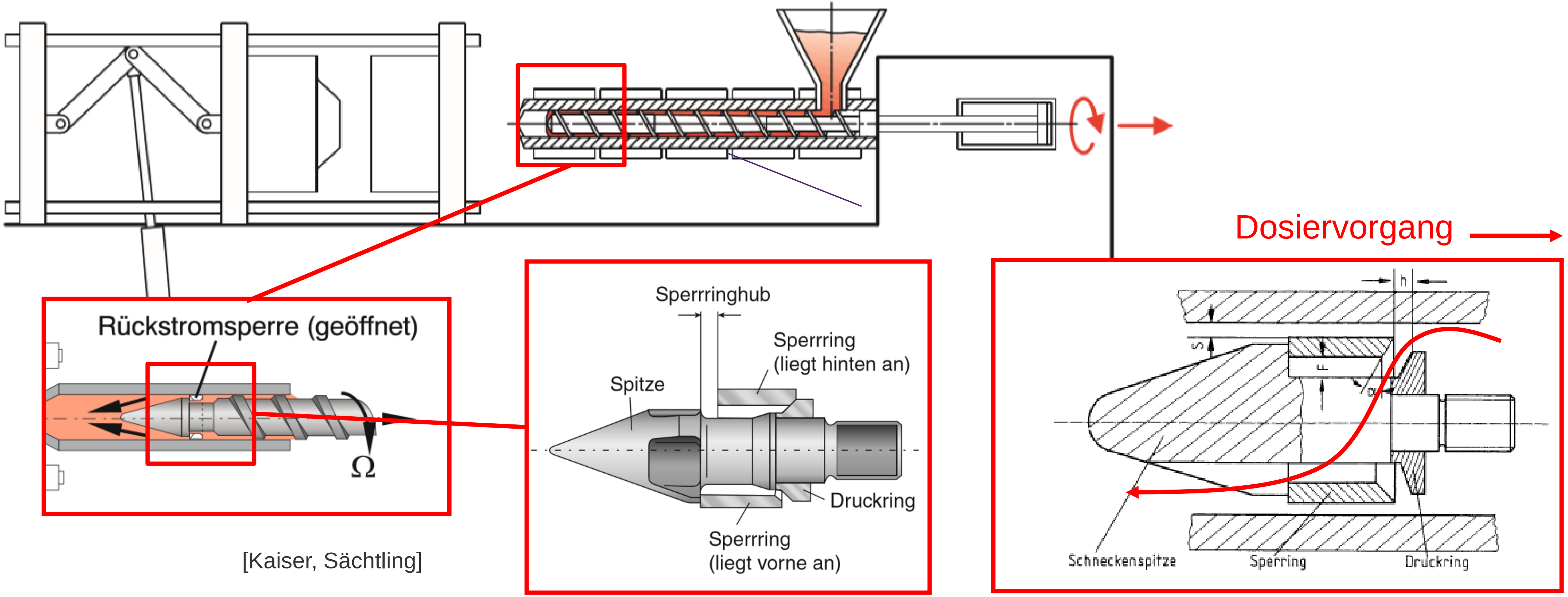
	weight	length	width	lip distance
STD-Error $\boldsymbol{\sigma}$	0.009 g	0.017 mm	0.014 mm	0.032 mm
$\boldsymbol{CV = \frac{\sigma}{\mu}}$	0.03 %	0.02 %	0.02 %	1.38 %

➡ Very good prediction of quality data of NEW components, based only on internal machine data

Predictive maintenance: defect non-return valve

Operating principle non-return valve: prevents the melt from flowing back over the screw bars

→ Otherwise no reproducible production is possible; undefined dwell time of the material in the cylinder



[Kaiser, Sächtling]

[IKV]

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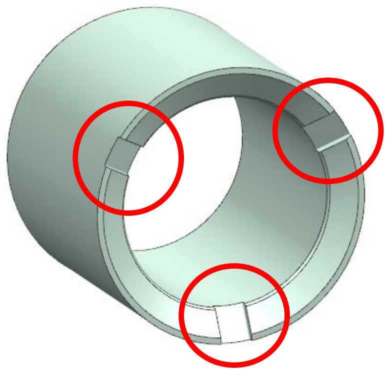
Predictive maintenance: trial design

- A well-known anomaly in the injection moulding process is the wear of non-return valve
  - To simulate this anomaly the ring of a non-return valve was artificially damaged, means notches with different depths were milled

- 5 test series, part: ice scraper, material: ASA
  - Trial series 1 – intact non-return valve
  - Trial series 2 – damaged non-returned valve, notch depth 0,20 mm
  - Trial series 3 – damaged non-returned valve, notch depth 0,33 mm
  - Trial series 4 – damaged non-returned valve, notch depth 0,67 mm
  - Trial series 5 – damaged non-returned valve, notch depth 1,00 mm

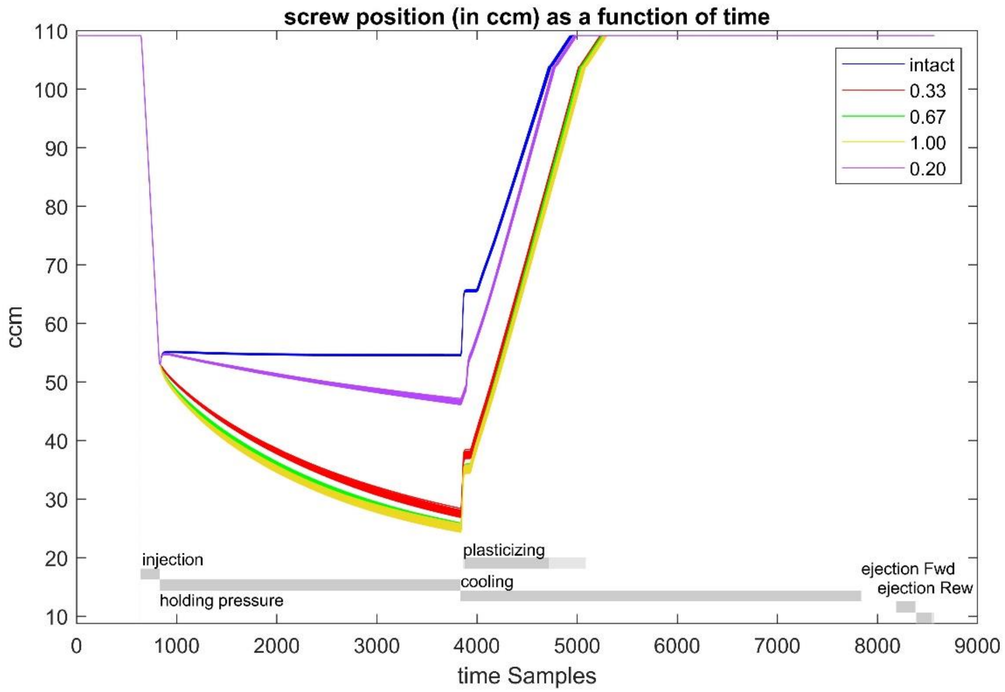


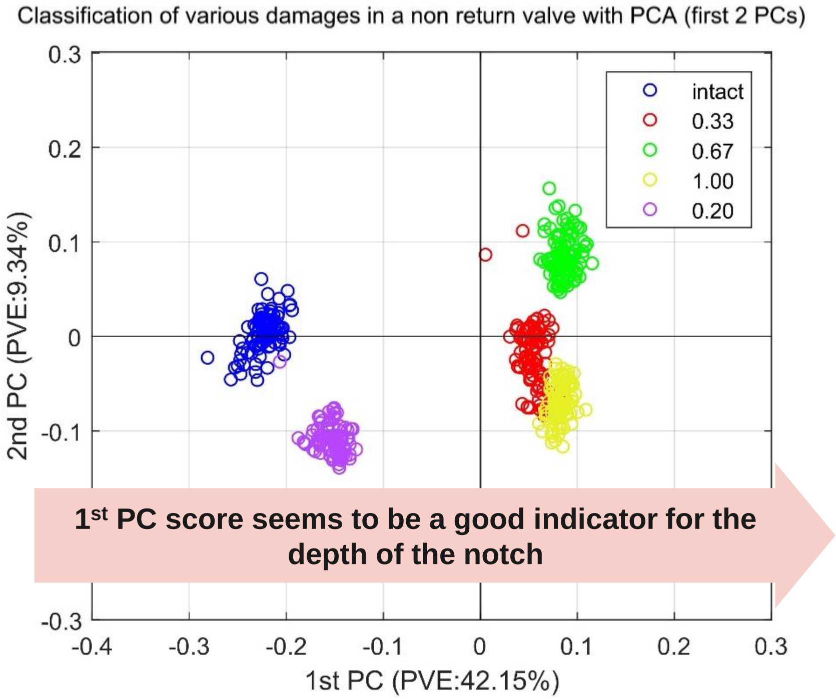
non-return valve with machined notches

- Database
  - Process curves recorded with the DataXplorer

Predictive maintenance: classification of trial series

- With damaged non-return valves the screw covers significantly longer distances during holding pressure phase, scattering increases with higher wear → already known in industry



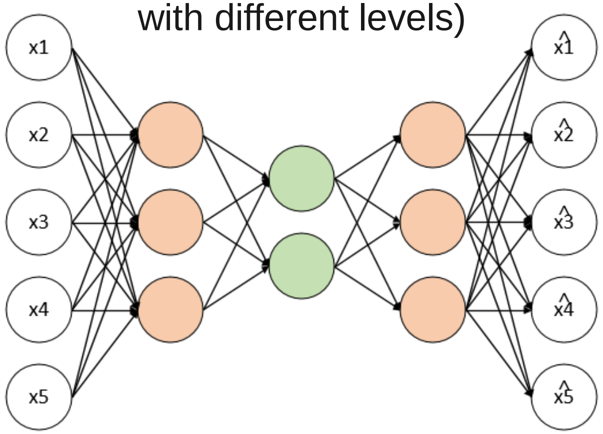


→ The wear of the non-return valve can be clearly detected with the component scores of a PCA → probably the damage can even be reliably estimated

Predictive maintenance: use of an auto encoder

- Can ML detect these anomalies even before the machine operator and determine the time for a replacement?
  - Results of additional trials with an unhardened non-return valve and high reinforced PPA material:

Auto encoder (neural network with different levels)



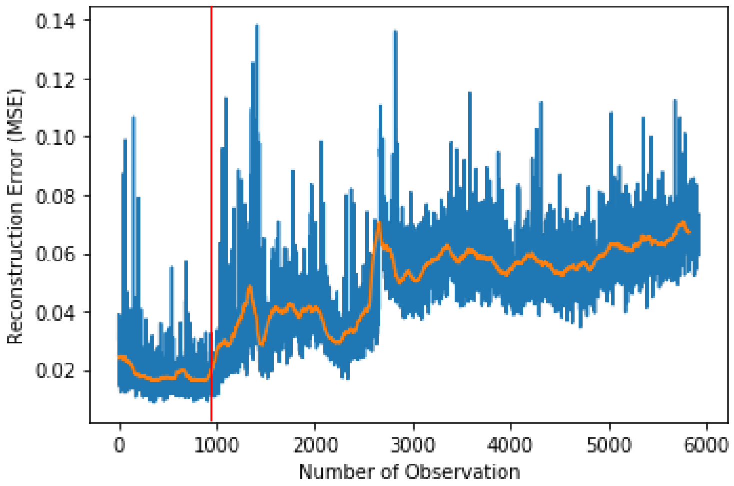
features

recalculated features

Reconstruction error calculation with RMS

$$f_{rms} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left((\widehat{x_k} - x_k)^2\right)}$$

Reconstruction error in function of cycle number



Yes, anomaly can be detected right from the start

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Predictive maintenance: use of an auto encoder

- Can ML detect these anomalies even before the machine operator and determine the time for a replacement?
  - Results of additional trials with an unhardened non-return valve and high reinforced PPA material:

Identification of anomalies

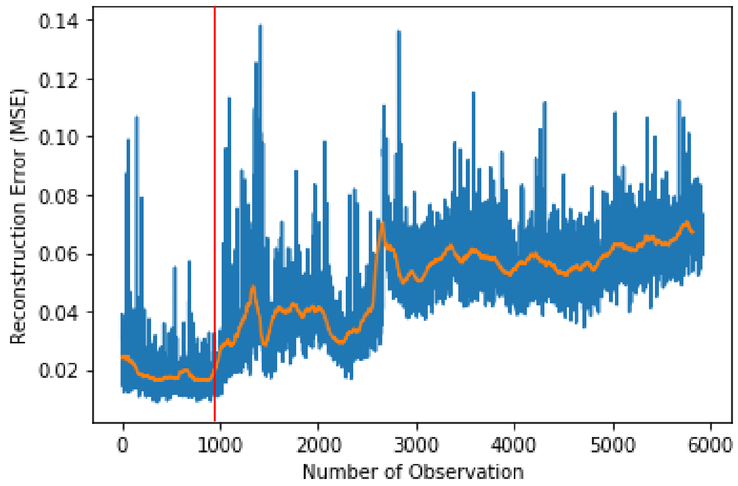
reconstruction error

Index	0_caller	1	2	3	4
64	11.9467	13.4402	19.2116	18.4646	16.2018
68	12.3311	13.7234	18.4835	17.8316	15.9617
195	9.8003	11.2507	14.3728	14.0198	12.7106
191	9.70302	11.2043	14.3134	13.6768	12.5816
85	6.73853	7.81164	11.6803	10.2961	10.9288

number of cycles

1. minimal screw position = melt cushion
2. variance screw position

Reconstruction error in function of cycle number



→ Reason for anomaly can also be identified by comparing and ranking the reconstruction error of the used features

Thank you for your attention

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