Angewandte Digitalisierung in der Industrie

L04: Injection moulding in times of digitalization

Curdin Wick MSc.

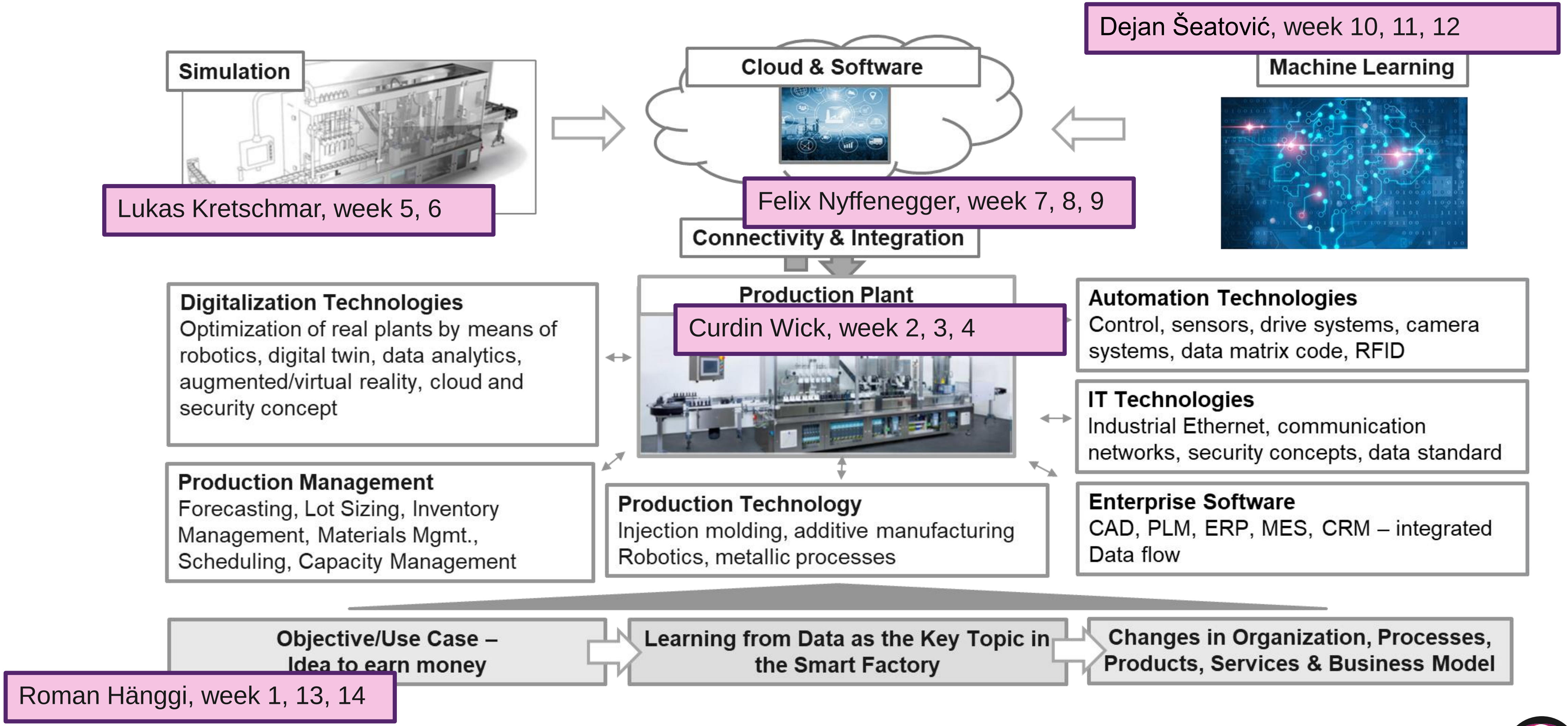
15. März 2022

Ostschweizer Fachhochschule

Time Table – Lecture schedule

Datum	Thema	Vorlesung v1: 15:10 - 16:50 Uhr	Praktika 1 p11: 17:00 - 18:40 Uhr	Durchführung
22.02.2022	Einführung & Strategie	Roman Hänggi	Roman Hänggi	Techpark
01.03.2022	Smarte Fabrik: Prod. Techn.	Curdin Wick	Curdin Wick	Techpark
08.03.2022	Smarte Fabrik: Prod. Techn.	Curdin Wick	Curdin Wick	Techpark
15.03.2022	Smarte Fabrik: Prod. Techn.	Curdin Wick	Curdin Wick	Techpark
22.03.2022	Diskrete Event Simulation	Lukas Kretschmar	Lukas Kretschmar	Techpark
29.03.2022	Diskrete Event Simulation	Lukas Kretschmar	Lukas Kretschmar	Techpark
05.04.2022	IT Architektur - IoT	Felix Nyffenegger	Samuel Helbling	Techpark
12.04.2022			Frühlingsferien	
19.04.2022			Unterrichtsfrei	
26.04.2022	IT Architektur - IoT	Felix Nyffenegger	Samuel Helbling	Techpark
03.05.2022	IT Architektur - IoT	Felix Nyffenegger	Samuel Helbling	Techpark
10.05.2022	Machine Learning	Dejan Šeatović	Dejan Šeatović	Techpark
17.05.2022	Machine Learning	Dejan Šeatović	Dejan Šeatović	Techpark
24.05.2022	Machine Learning	Dejan Šeatović	Dejan Šeatović	Techpark
31.05.2022	Real World bei Geberit	Roman Hänggi	Curdin Wick	Geberit
07.06.2022	Zusammenfassung	Roman Hänggi	Curdin Wick	Techpark

Complexity needs to be managed



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Recap Week 3

Overview: injection moulding as application example

Level of automation	Data basis / commonness
Process management	
Process monitoring	
Process control	

Week	Date	Lecture v1: 15:10 - 16:50 Uhr	Exercise p11: 17:00 - 18:40 Uhr
02	01.03.2022	**L04: Process basics and process management** • Repetition injection moulding • Setting up the process • Statistical design of experiments	**E04: Correlation of setting parameters and quality characteristics** Practical training on the SG machine with Stasa QC
03	08.03.2022	**L05: Process monitoring** • Motivation for process monitoring • Process monitoring with cavity pressure (incl. presentation of ComoNeo)	**E05: process monitoring with ComoNeo** Practical training on the SG machine with Como Neo
04	15.03.2020	**L06: Injection moulding in times of digitalization** • Uses Cases for injection moulding • Smart Factory@Techpark • Creating a database (signals, data quality, data recording) • Handling of data (curve data / KPI)	**E06: Processing and evaluation of process data** Practical training with own laptop with ibaAnalyzer

Week 4: Goals of this weeks lecture / exercise

The students can…

- … explain possible use cases for injection moulding which are made possible through digitalization
- … define which recording rate is useful for which signals
- … understand how to get data out of machines and how to deal with different machines and devices
- … highlight the possibilities of the SmartFactory@OST
- … calculate KPI's out of raw data and set up an automated process protocoll

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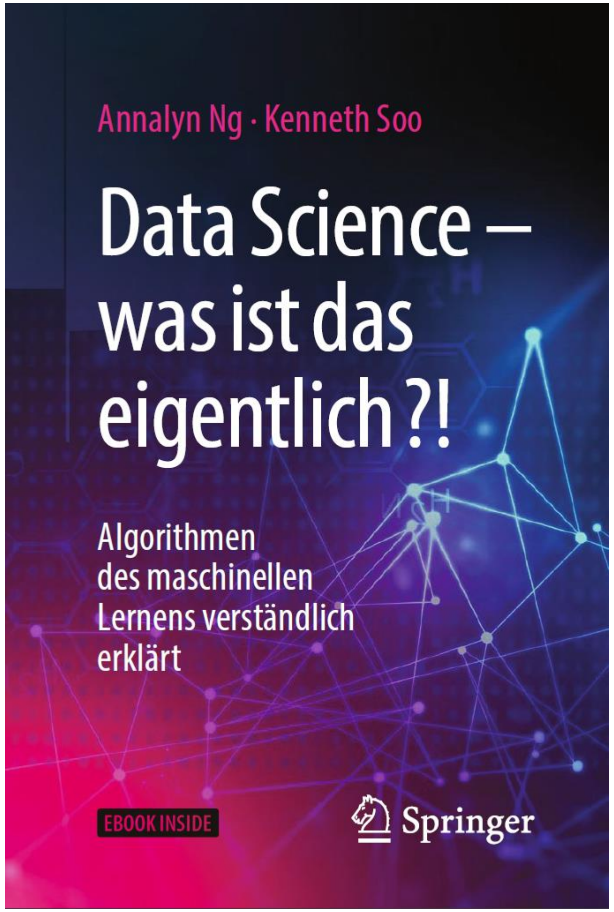
L04: Injection moulding in times of digitalization

1. Data driven injection moulding
2. Dealing with Big Data in injection moulding
3. Data Acquisition
4. Uses Cases for injection moulding
5. Smart Factory@OST

Exercise:

- Processing and evaluation of process curve data

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

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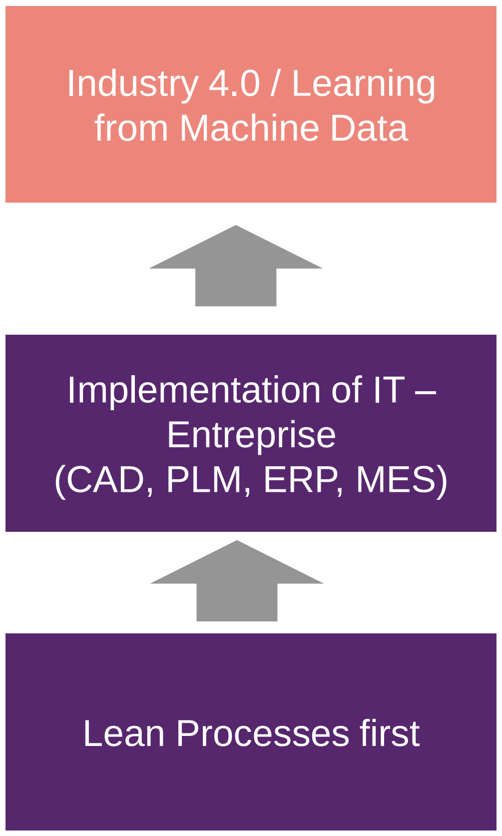
Data driven injection moulding

Digitalization in injection moulding

- To implement Industry 4.0 in injection moulding companies, data must be collected, analyzed and also predicted.
- Inevitably, the term "big data" cannot be ignored. Big data is a term that has already been around for a few years, but continues to attract a great deal of attention with regard to various aspects.
- Questions that injection moulding companies are getting in touch with:
  - How can I use my data?
  - How can I increase my added value through data?
  - What exact examples are there and how can I learn from them?



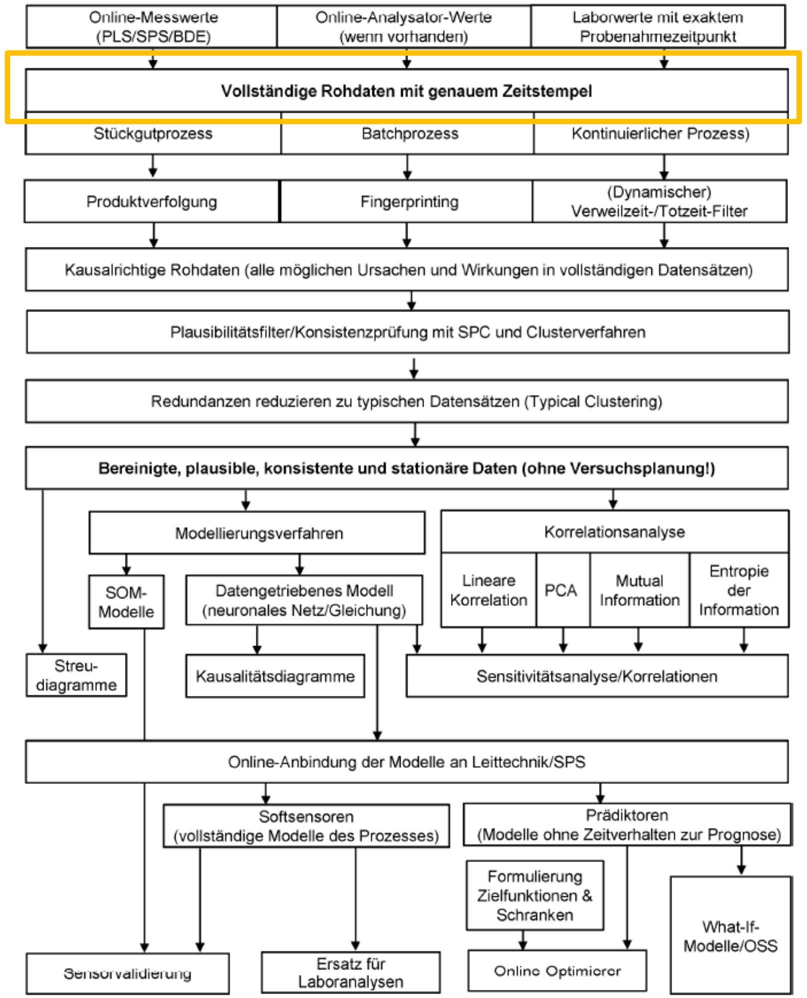
- Additional data from the machine
- Combining machine data with data from IT Entreprise solutions (orders)

- 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

Challenges for successful implementation of Industry 4.0

Challenges for successful implementation of Industry 4.0



[VDI-Statusreport – Chancen mit Big Data Best Practice]

- Some of the possibilities for data analysis are shown in the adjacent flow chart.
- However, the first stumbling block is usually already the database. Problems that arise:
  - What data do I need?
  - Is the data available in sufficient quality? What data quality do I need at all?
  - How do I get the data out of my machine?
  - How do I synchronise data from different machines and devices?
- The development of a data acquisition system for several injection moulding machines at the IWK serves as an example for the existing challenges.
  - Different injection moulding machines (Krauss Maffei, Engel, Arburg, Fanuc, Battenfeld)
  - Different data storage solutions (Database, Cloud)

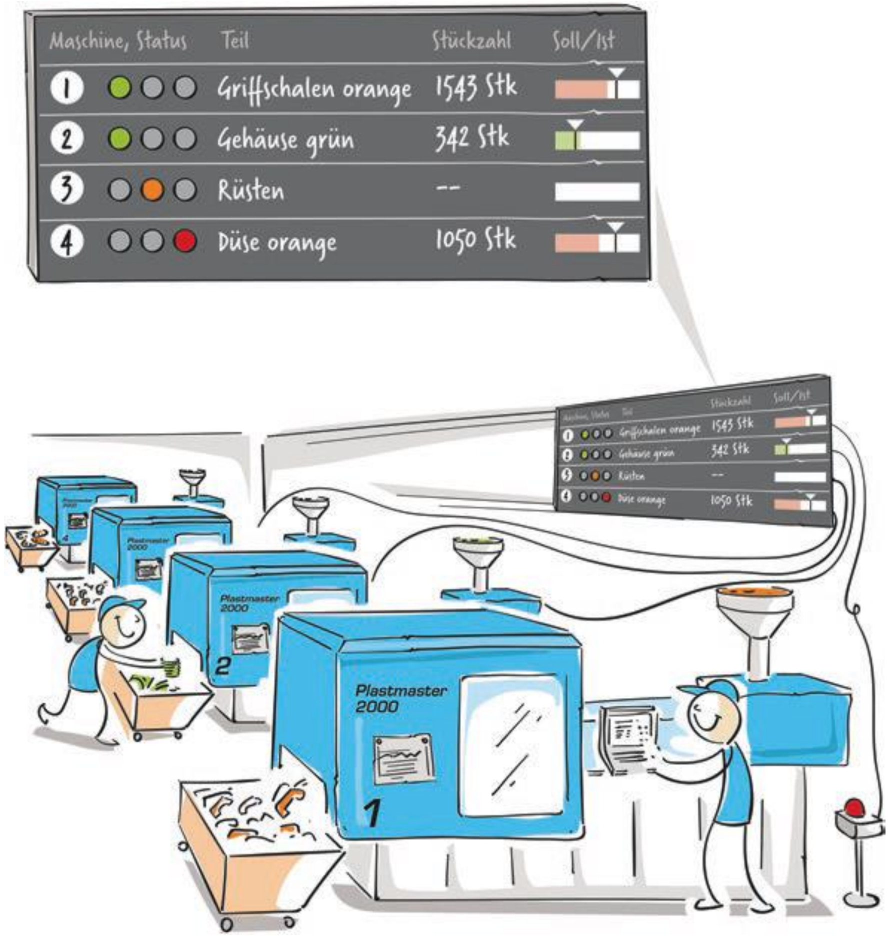
Data is the new gold

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

Peter Drucker, American economist

Injection moulding in times of digitalization

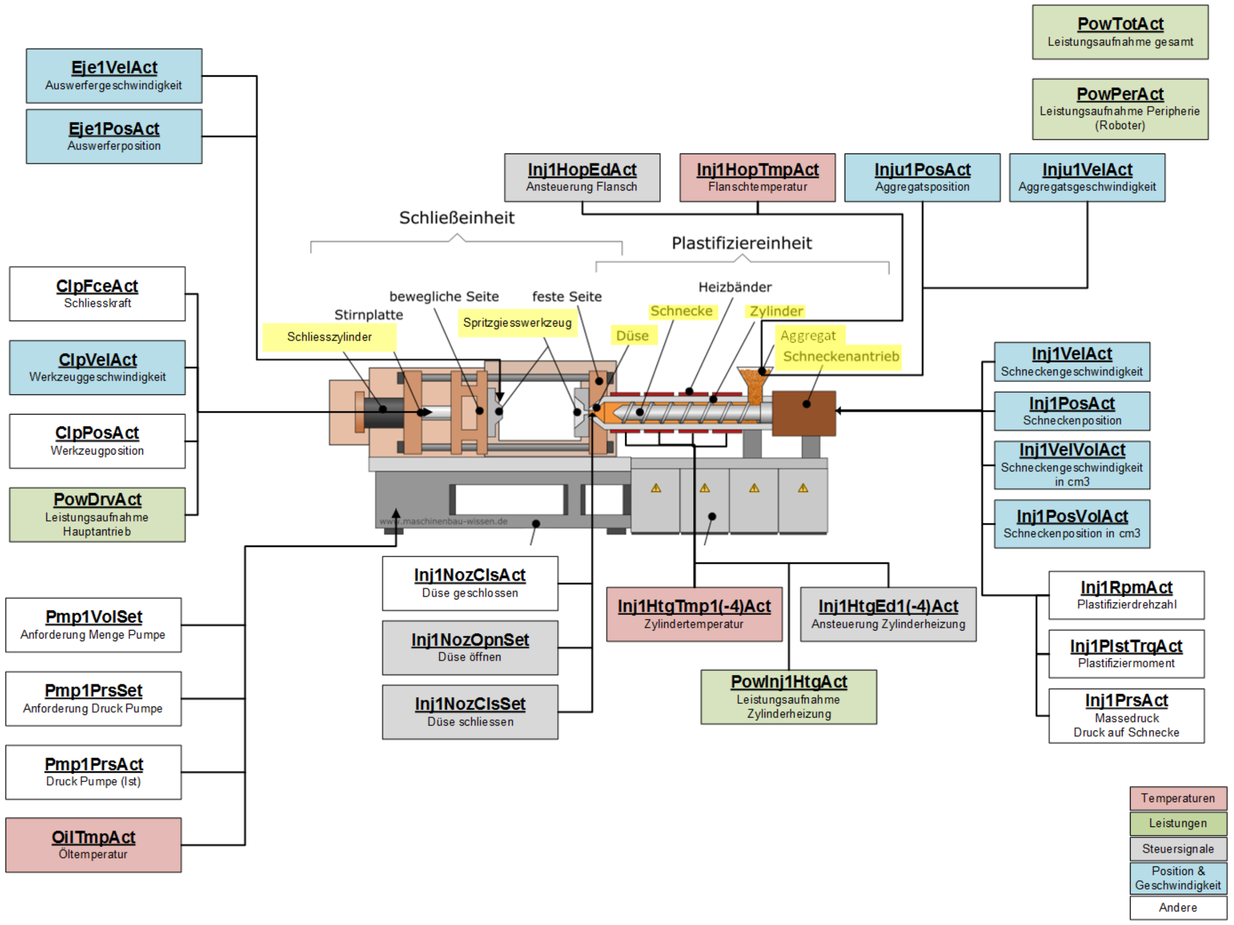
- If you know the exact actual state of your machines you can work on optimization of the process.
- There is a **improved data availability on injection moulding machines**. Few machines are already offering the export of process signals as curve data, most of the new machines provide at least cyclical parameters.
- In combination with Artificial Intelligence (AI), which currently experiences a boom because it is **made possible by affordable computing power**, there are improved possibilities for process monitoring:
  - employees will be able to look after a larger machine park
  - lower scrap rates
  - higher productivity



[LEAN Production]

Injection moulding machine with improved data availability

- Krauss Maffei Injection moulding machine PX 120-380 at the IWK-lab with DataXplorer which enables the recording of:
  - more than 50 different process signals with a sampling frequency of 200 Hz
  - setting parameters of the injection moulding machine with a sampling frequency of 0.6 Hz



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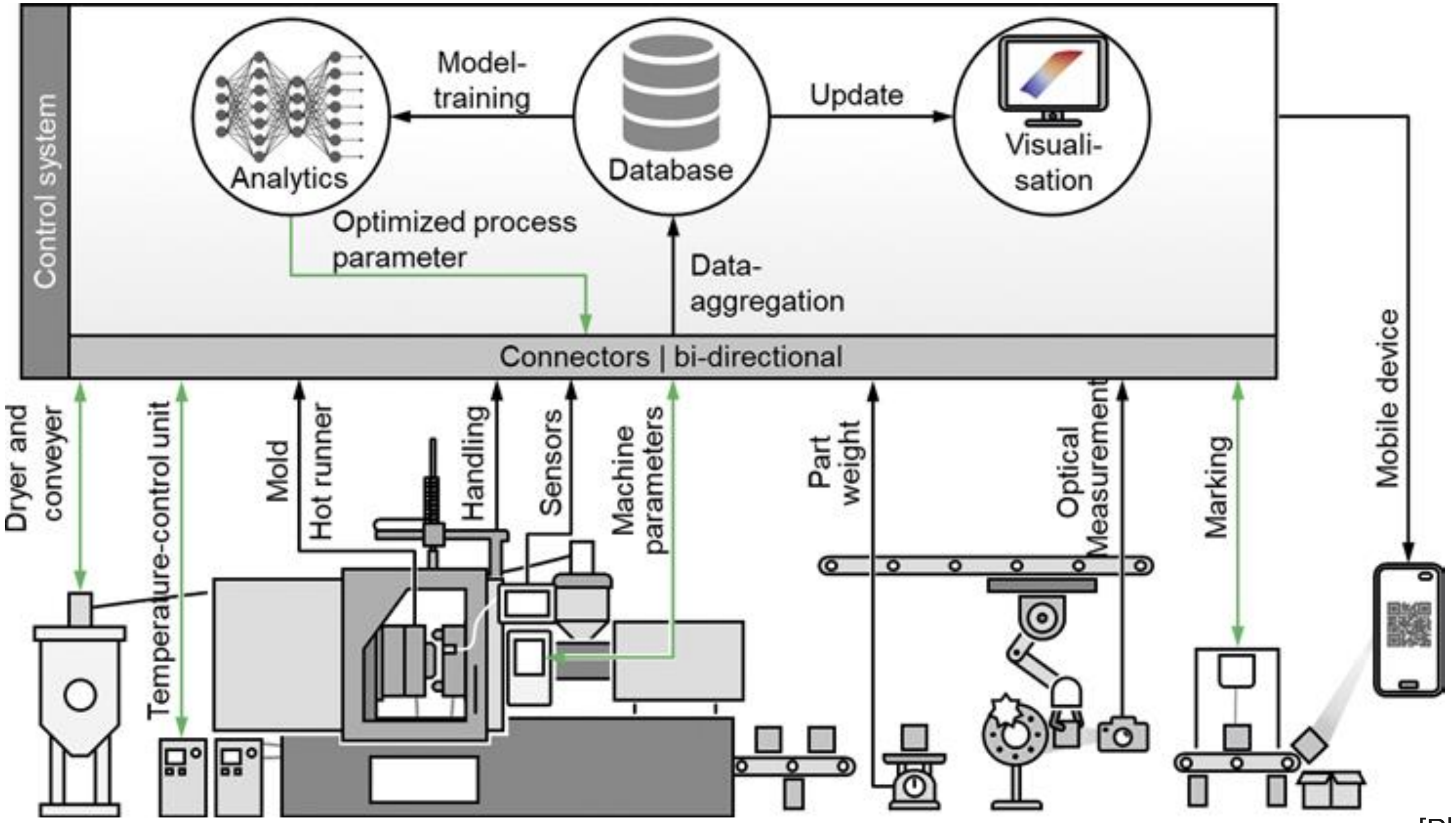
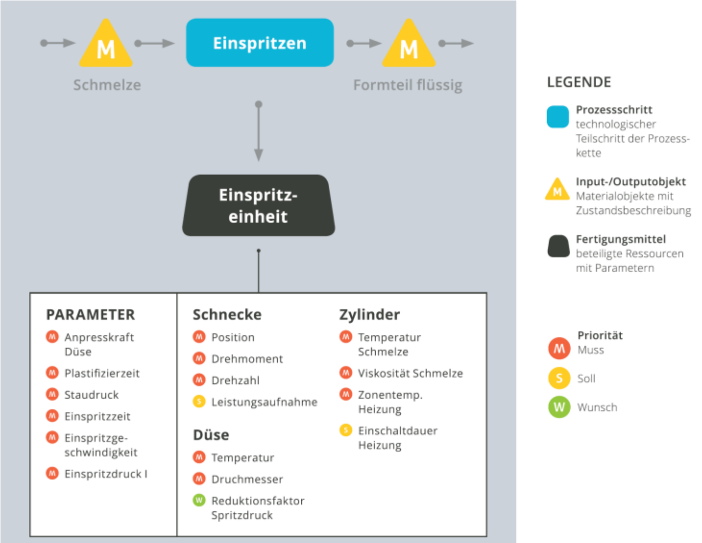
Possible application: Fully connected production cell for automated process setup

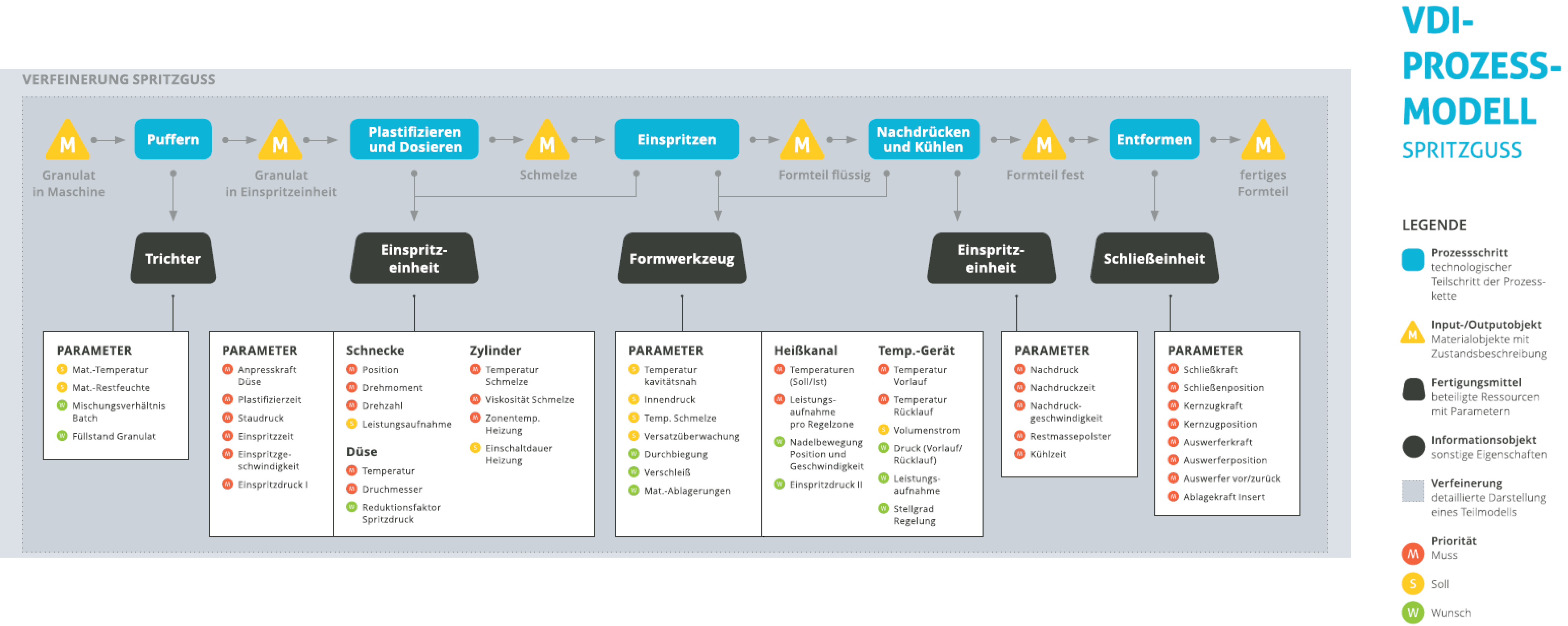


[Plastics Industry 4.0]

Dealing with Big Data in injection moulding



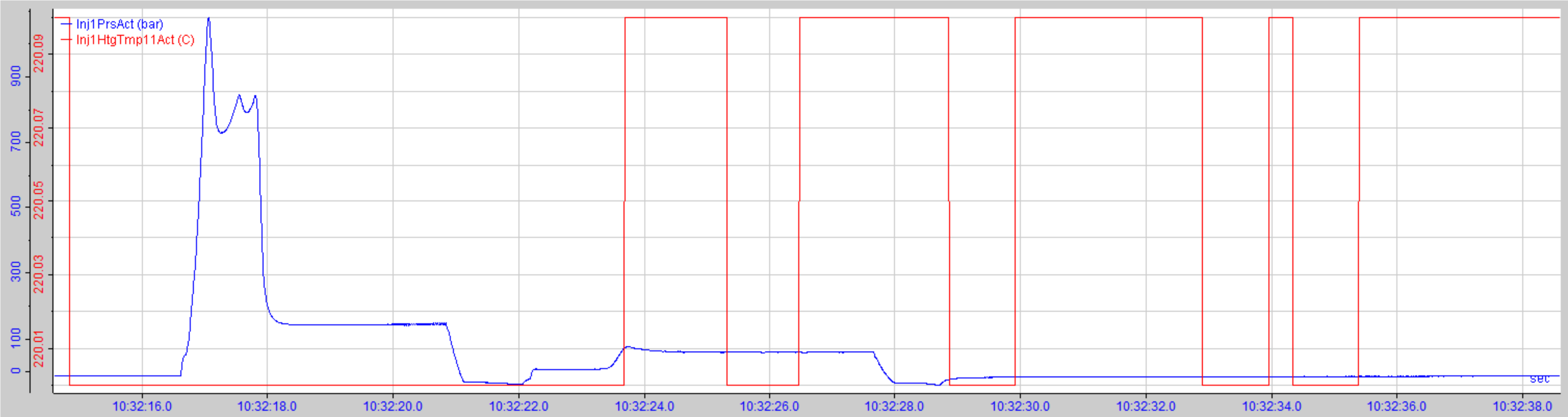
Which data do I need? - Injection moulding process database



[VDI-Statusreport – Industrie 4.0 in Spritzgießunternehmen]

What data quality do I actually need?

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



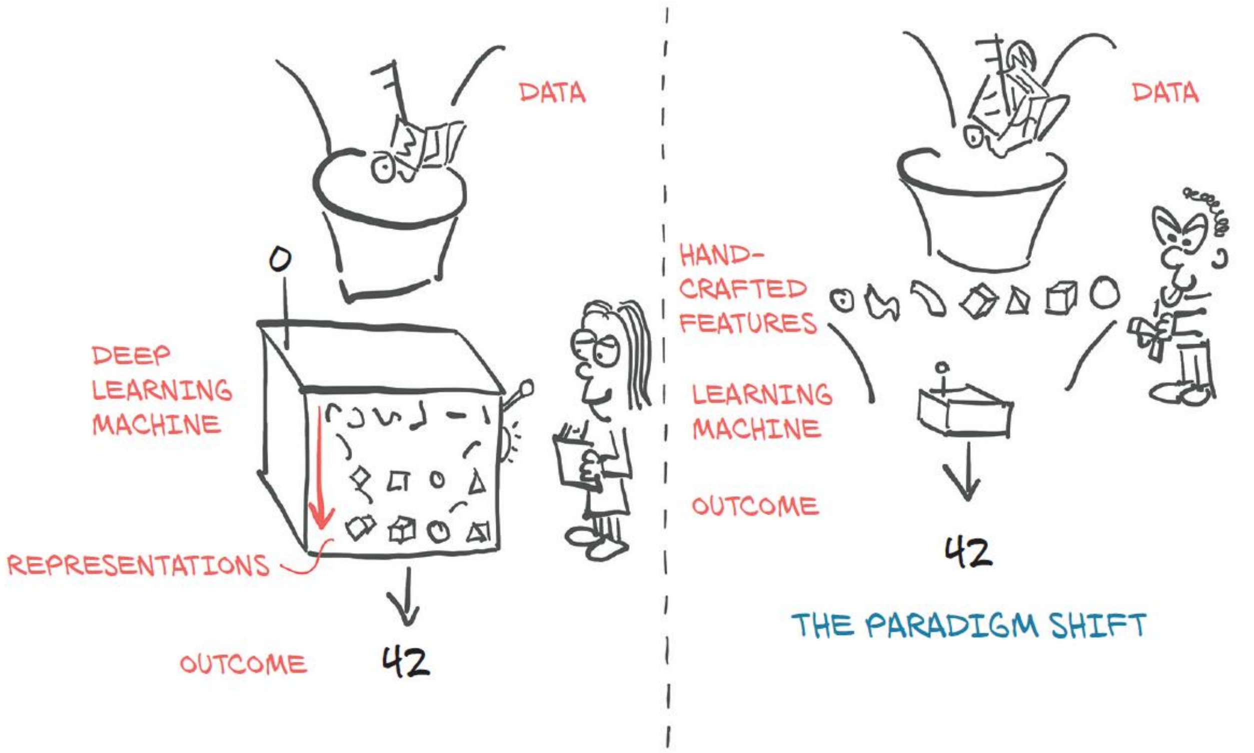
- If, for example, the injection pressure can only be recorded at low frequency, valuable information is lost (e.g. maximum)

What data quality do I actually need?

- The data recorded by the injection moulding machines is used for machine learning purposes.
- In a first step, therefore, as much data as possible should be recorded, recommendation for machine learning: curve data of various process signals
  - with 100-200Hz sampling frequency: injection pressure, screw position, plasticizing torque, screw speed, mould position, ejector position and force, WID signals, trigger signals for process phases (injection, holding pressure, etc.)
  - with 1Hz sampling frequency: cylinder temperatures and power consumption (per zone), temperatures and mould heating (per zone), data temperature control units (temperatures, flow), ambient conditions
- In addition to the process parameters, the setting parameters should also be exported, so that direct changes to the process can also be detected.

Data preparation

- For machine learning you can either work directly with these data curves, means with curve-based methods, or with feature-based methods.



[Deep Learning with Py-Torch]

Data preparation

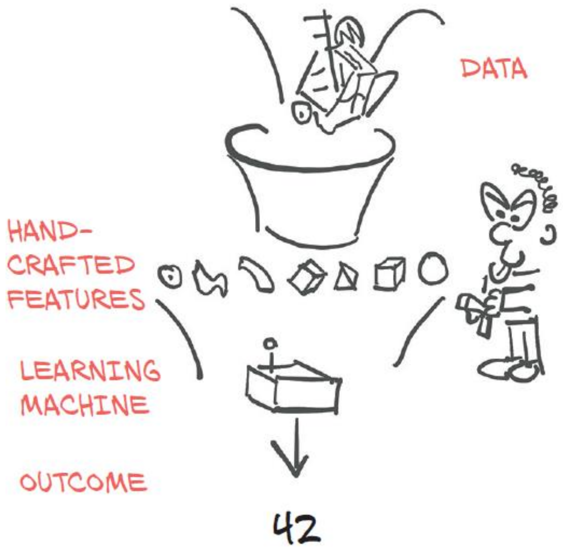
The large amounts of data (Big Data) can be reduced by feature building to work with feature-based methods for machine learning.

The goal is to reduce curve data (or image data) to as few features as possible while retaining as much information as possible.

Possible methods:

- Statistical feature building (local and global features)
- KPI based on expert knowledge

Feature based-methods are easier for implementation und better understandable.



[Deep Learning with Py-Torch]

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

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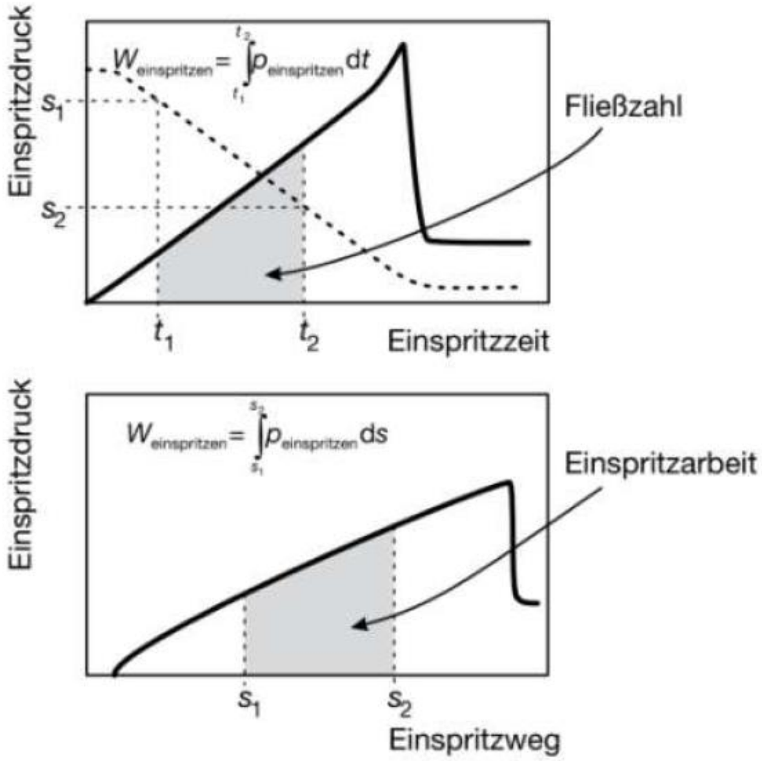
Feature building: KPI based on expert knowledge

- 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.



[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

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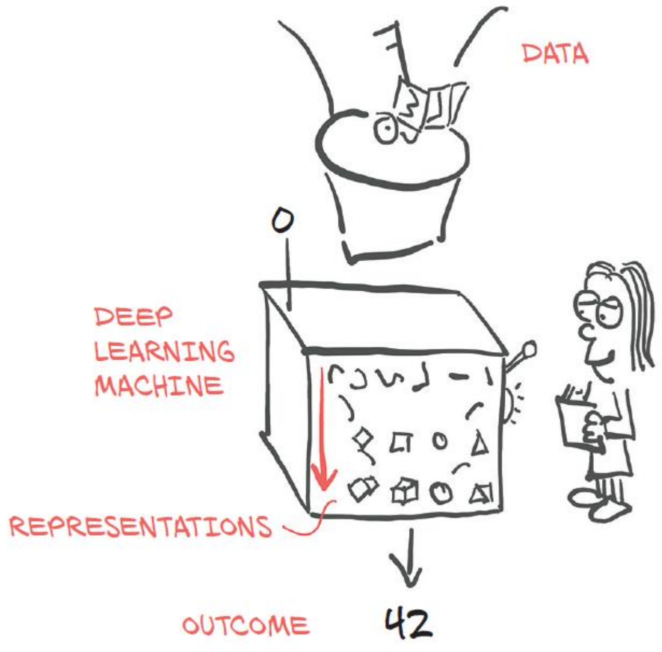
Data preparation

The other approach is to work directly with curve data.

- A big advantage of curve-based models is that the features do not have to be found by the user, but are learned implicitly by the network.
- Thus, for example, curve progressions (or correlations) that can only be represented by complicated features can also be taken into account quite simply.
- Disadvantage of these models is the depending upon enormous memory and computation effort which is needed. In addition, the debugging of a non-functioning model is also very difficult.
- The most well-known applications for curve-based models are language models (since information is to have influence partly over sentences) or for example temperature or stock price forecasts.



[Deep Learning with Py-Torch]

Data acquisition in injection moulding

How do I get the data out of my machine?

In the field of injection moulding, standardised interfaces / communication protocols offer a possibility for "simple" data export:

- 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

Data storage / upload

To ensure that the data can be recorded and exported in the desired quality, device-specific solutions must often still be implemented. Thus, there is a different solution for data recording for each injection moulding machine at the IWK.

IPCs from Siemens and a DAQ-C system from iba are used for data 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

Implementation: Cloud & platform solution and specific DB solution

Different data export / connectivity options as well as different data storage solutions will be demonstrated. Therefore, the following two main solution variants will be developed:

Variant 1 (Cloud- & Plattformlösung)

- Siemens Mindsphere

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

Variant 2 (specific local database solution)

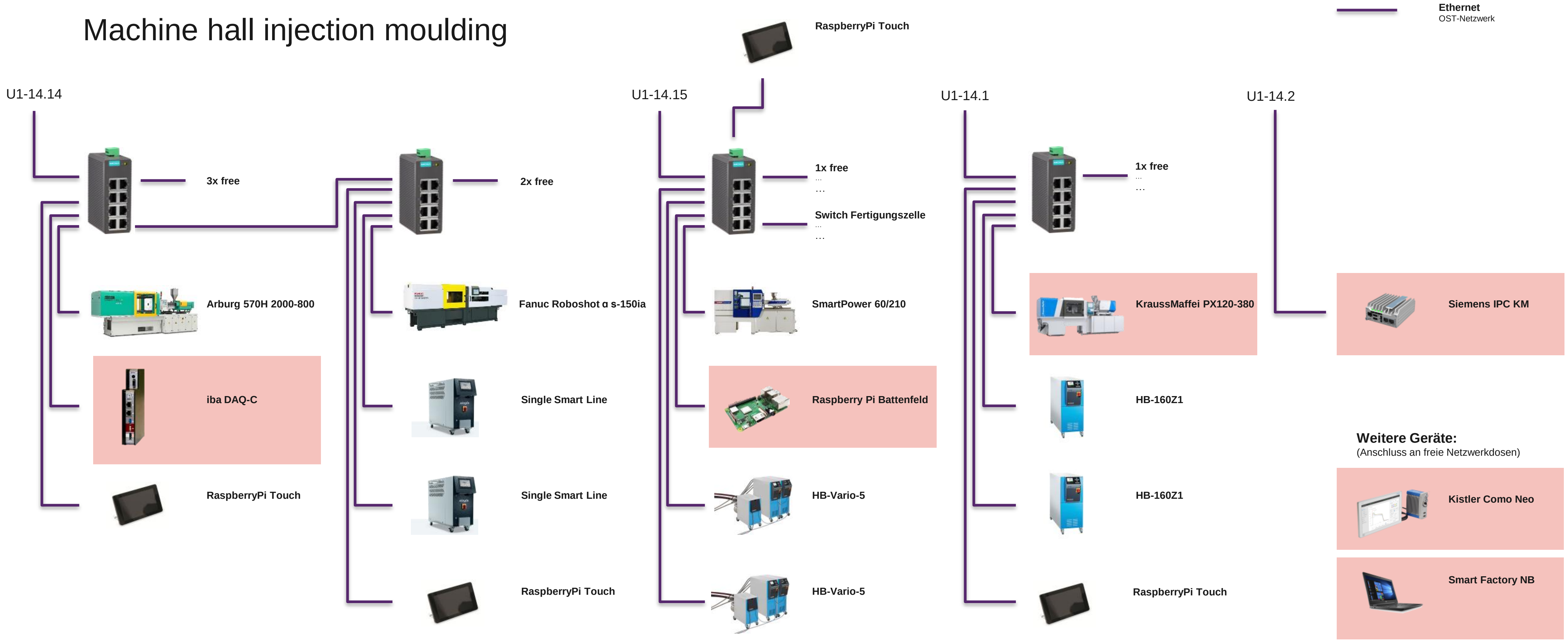
- Solution from the company iba

Microsoft® SQL Server® +

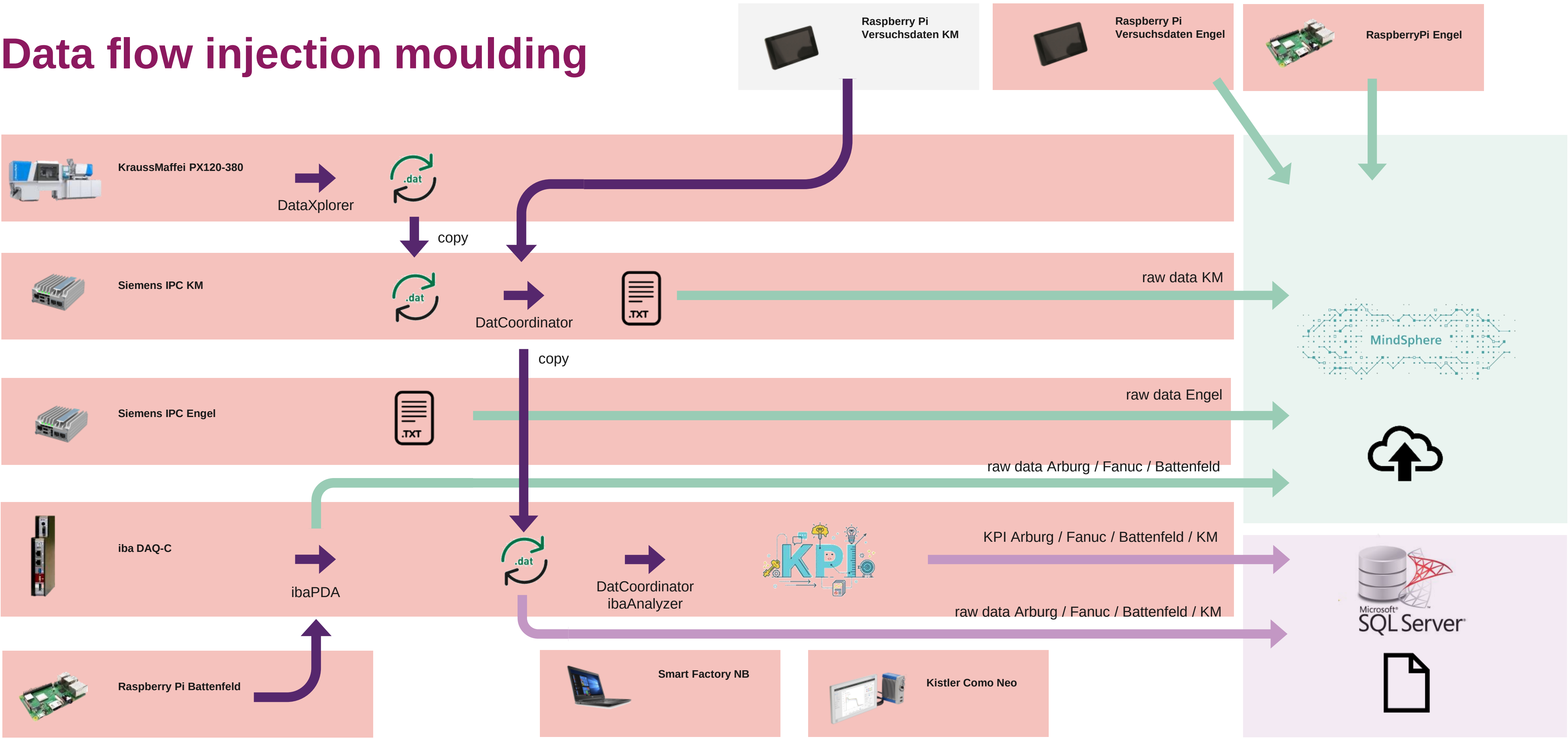
- All process data as "raw data" and calculated process parameters in a database
- Visualisation of process parameters with ibaDaVIS

Networkplan – OST-network

Machine hall injection moulding



Data flow injection moulding



Battenfeld Smart Power 60/210

Data recording with iba DAQ-C

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

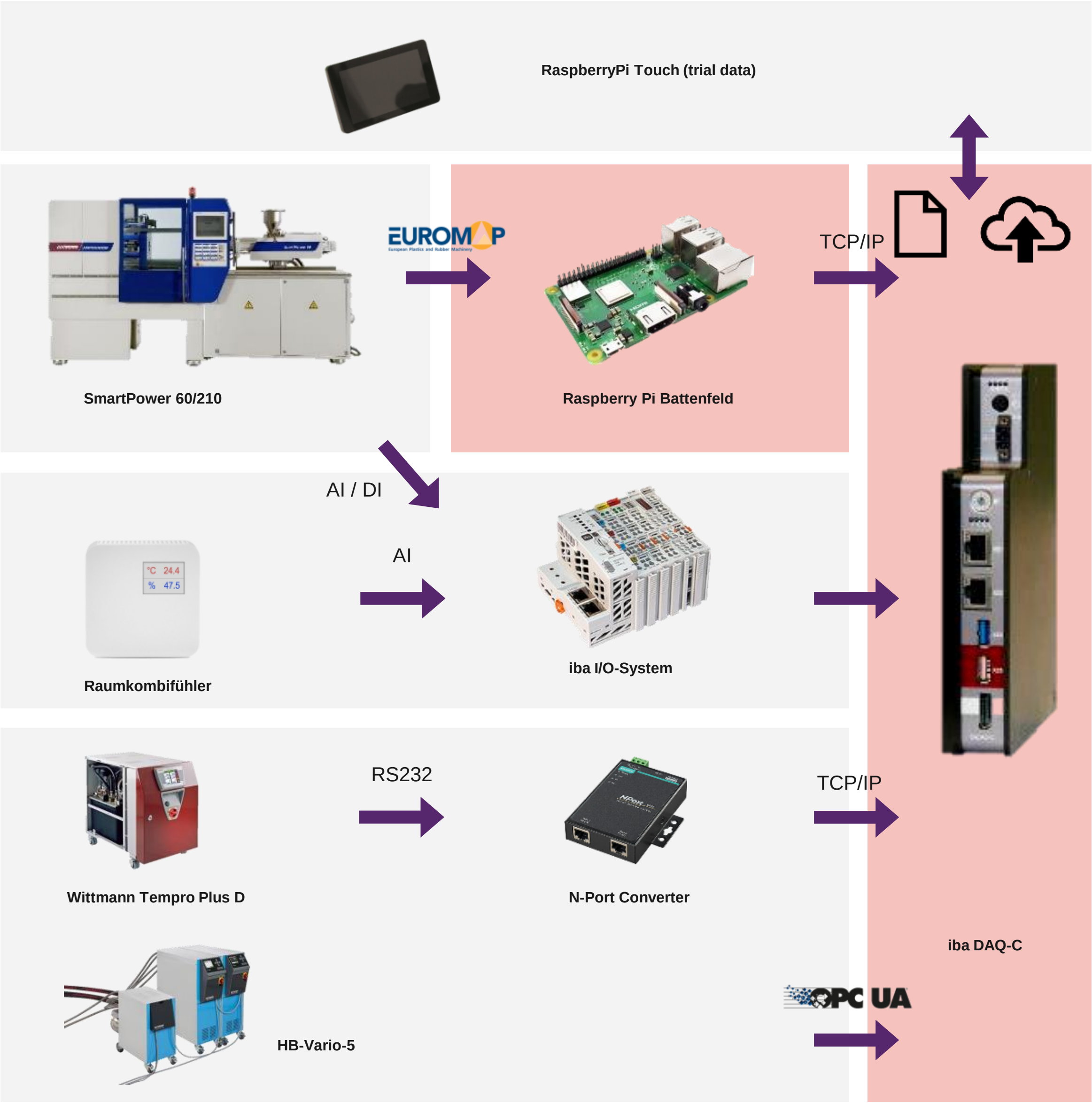
- Cavity pressure sensors 1 channel
  - Curve signals with max. 1kHz sampling frequency (via control cabinet and I/O module)

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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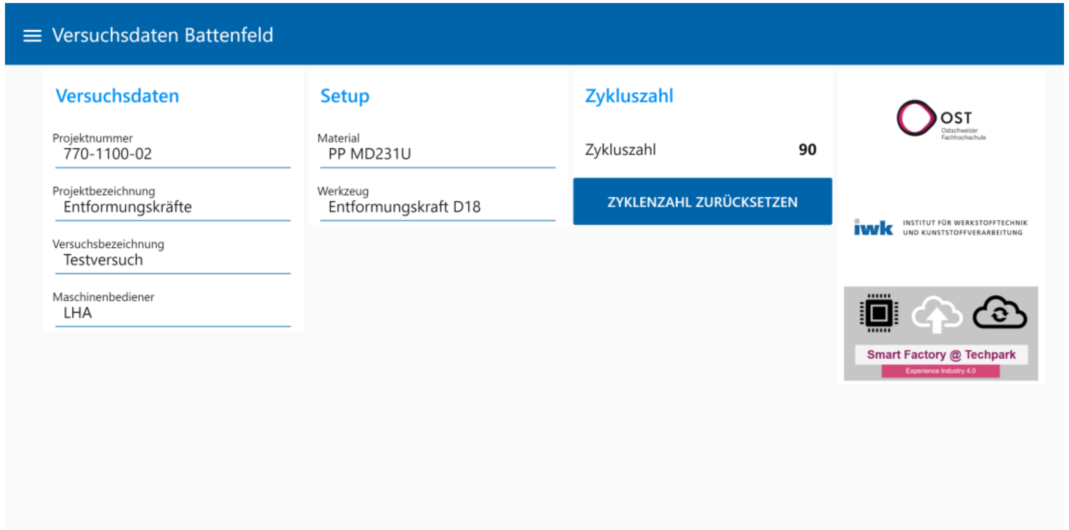
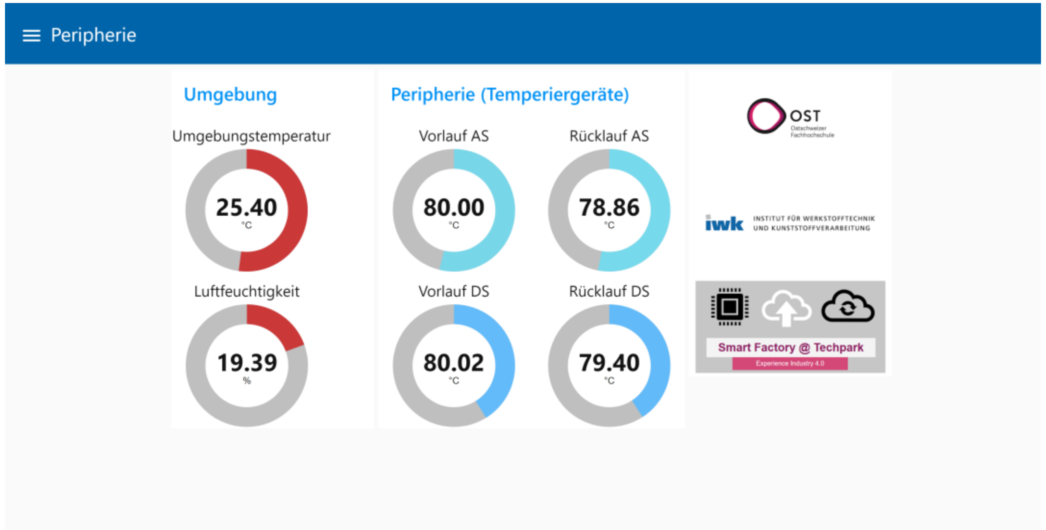
Input for manual / trial data

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.

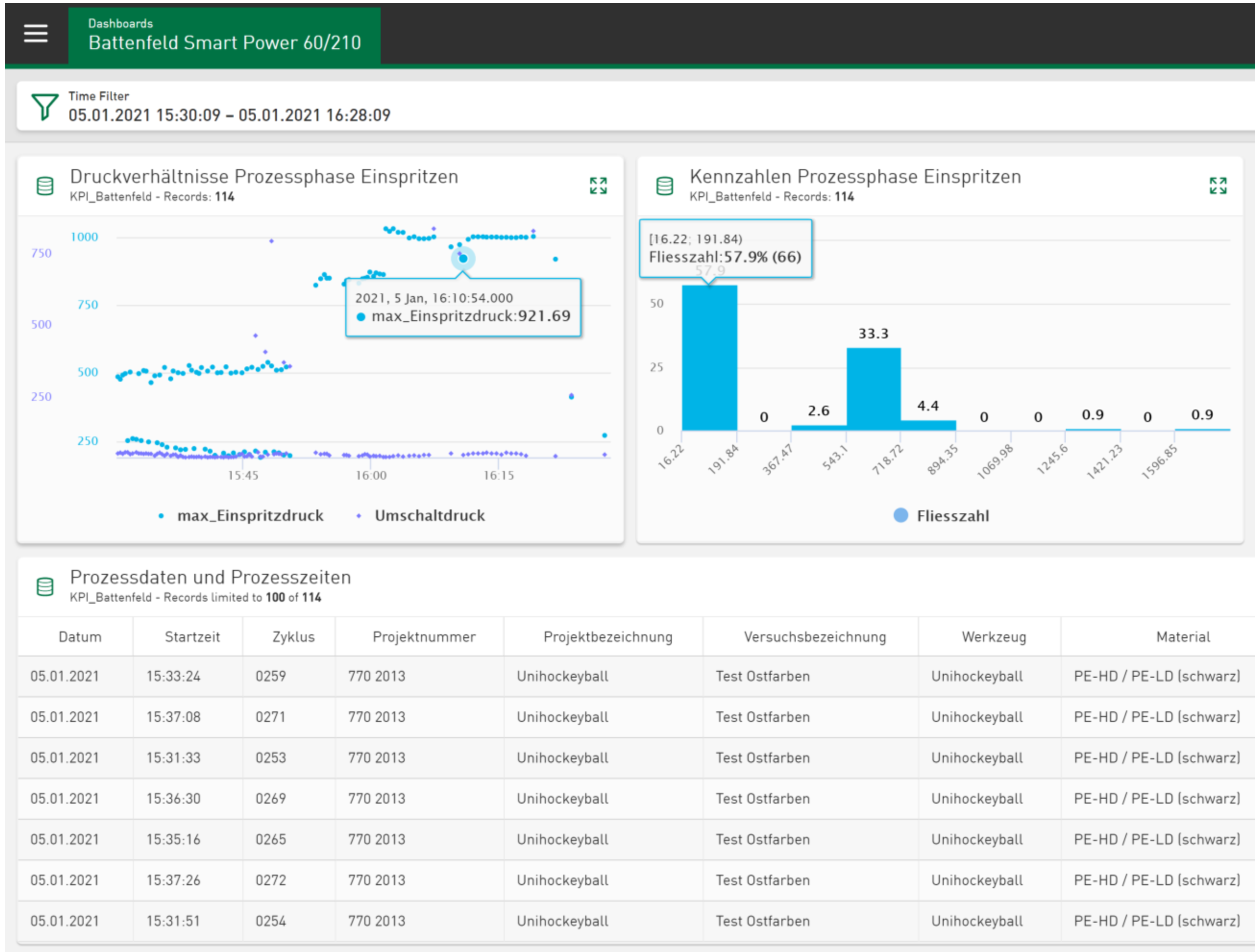




Data visualisation

In addition to data recording, the visualisation of the data is also a central objective:

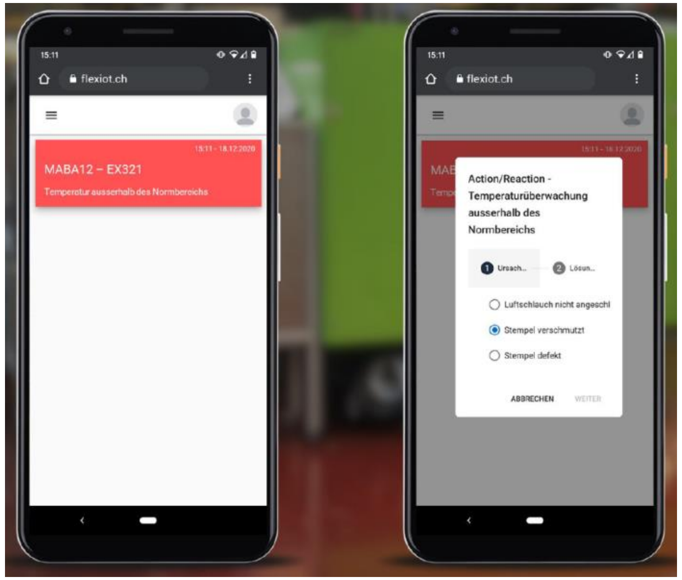
- Edge2Web application in Siemens Mindsphere
- data from the local database can be visualised with ibaDaVIS (picture on the right).



Notifications

- 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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Further use of the recorded data

The created database also provides other possibilities, for example automated process protocols:

1. Automated calculation of process parameters
2. Creation of the protocol for a given cycle

Inclusion of trial data, process curves, process parameters, setting parameters and also images of the process.

This guarantees that the process is documented completely and always in the same way. In addition, the exact settings and parameters for each cycle are documented.

Data acquisition in injection moulding

Further use of the recorded data

OST Ostschweizer Fachhochschule — iwk INSTITUT FÜR WERKSTOFFTECHNIK UND KUNSTSTOFFVERARBEITUNG

SPRITZGIESSPROTOKOLL

Maschinendaten

Maschine / Modellnummer	Battenfeld Smart Power 60/210	300210
Steuerung / Version	Unilog B6P	19.51
Schneckendurchmesser	25 mm	
Düse	Verschlussdüse ø 3 mm	

Versuchsdaten / -bedingungen

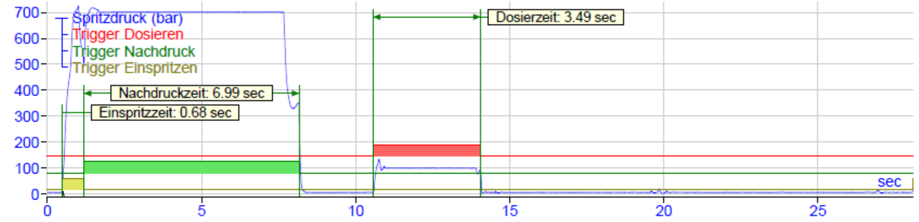
Projektnummer	771 3348
Projektbezeichnung	Haftungsversuche TKP
Versuchsbezeichnung	TrÃ¤gerbauteil
Maschinenbediener	LOI

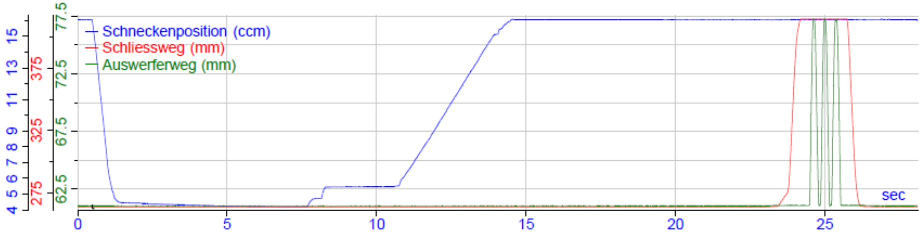
Datum	29.01.2021
Uhrzeit	14:34:26
Zykluszahl	0008
dat-File	Battenfeld_0008_2021-01-29_14.34.26

Werkzeug	Haftungspruefkoerper 1. Komponente
Material	Ultramid B3WG10

Umgebungstemperatur	27.40	°C
Luftfeuchtigkeit	23.02	%

Kurvendaten / Prozessphasen





Prozesskennwerte (Ist-Parameter)

Phase Einspritzen

max. Einspritzdruck	720.55	bar
Einspritzgeschwindigkeit *	7.44	ccm/s
Fliesszahl	351	bar*s
Einspritzarbeit	10	J
Umschaltdruck	511.07	bar
Umschaltweg	5.19	ccm

Phase Nachdruck

Nachdruckintegral	4'740	bar*s
mittlerer Nachdruck	677.24	bar
Nachdruckarbeit	355	J
Massepolster	4.16	ccm

Phase Dosieren

Dosierweg	16.12	ccm
Drehzahl *	81.44	rpm
Staudruck *	98.19	bar

weitere Kennzahlen / Prozesszeiten

Zykluszeit	27.61	s
Kühlzeit	22.50	s
Leistungsaufnahme Maschine	2'738	W

Werkzeugtemperierung

Feste Seite (VL/RL) *	105.04	103.82	°C
Bewegl. Seite (VL/RL)	104.99	103.84	°C

Zylinderheizung

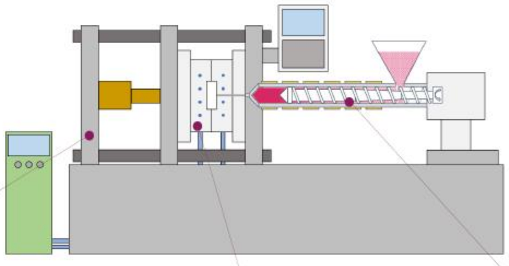
Temperatur Düse *	300.00	°C
Temperatur Zylinderkopf *	300.00	°C
Temperatur Einzugszone *	301.00	°C
Temperatur Flansch *	31.00	°C

Werkzeugheizung

Temperatur Zone 1 *	750.00	°C
Temperatur Zone 2 *	750.00	°C
Temperatur Zone 3 *		°C
Temperatur Zone 4 *		°C

* = über den Zyklus gemittelte Werte

Einstellparameter (Soll-Parameter)



Schliesseinheit

Werkzeug schliessen

Schliesskraft		kN

Werkzeug öffnen

Geschwindigkeit	500.00	mm/s

Werkzeug und Peripheriegeräte

Werkzeugheizung

Temperatur Zone 1	270.00	°C
Temperatur Zone 2	270.00	°C
Temperatur Zone 3		°C
Temperatur Zone 4		°C

Werkzeugtemperierung

	Feste Seite		Bewegl. Seite	
Vorlauftemp.	105.00	°C	105.00	°C
Hersteller	HB-Therm		HB-Therm	
Modell	HB180Z3		HB140Z3	
Seriennummer	213-1849		606-7597	

Plastifiziereinheit

Zylinderheizung

Temperatur Düse	300.00	°C
Temperatur Zylinderkopf	300.00	°C
Temperatur Einzugszone	300.00	°C
Temperatur Flansch	40.00	°C

Einspritzen

Einspritzvolumen	10.8	ccm
Einspritzgeschwindigkeit	6.00	ccm/s
Umschaltvolumen	5.20	ccm

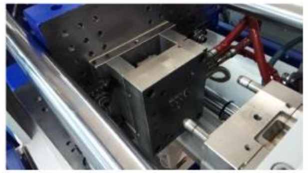
Nachdruck

Nachdruck Stufe 1	700.00	bar
Nachdruckzeit Stufe 1	0.50	s
Nachdruck Stufe 2	700.00	bar
Nachdruckzeit Stufe 2	6.00	s

Dosieren

Dosierhub	15.00	ccm
Dosiergeschwindigkeit (Umfang)	150.00	mm/s
Dekompressionsvolumen	1.00	ccm

Production View



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Uses Cases for injection moulding

Overview: 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

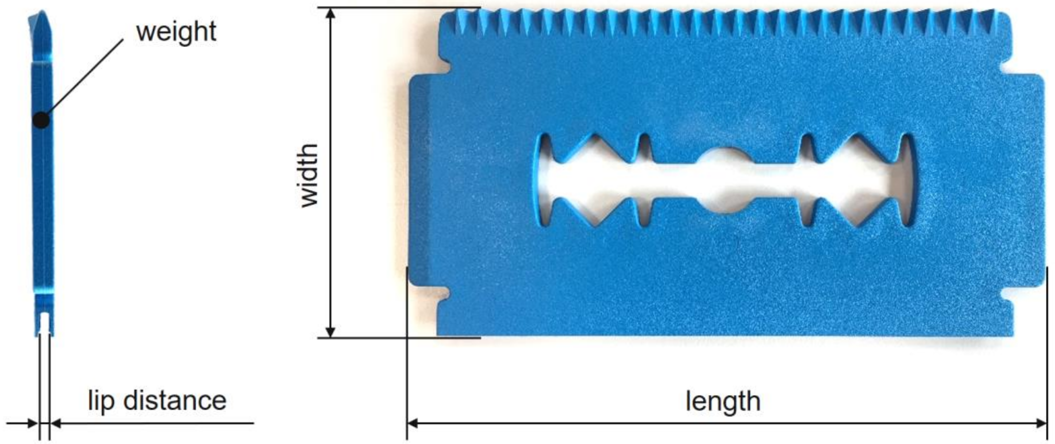
Use case 3: preventive and predictive maintenance

- 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

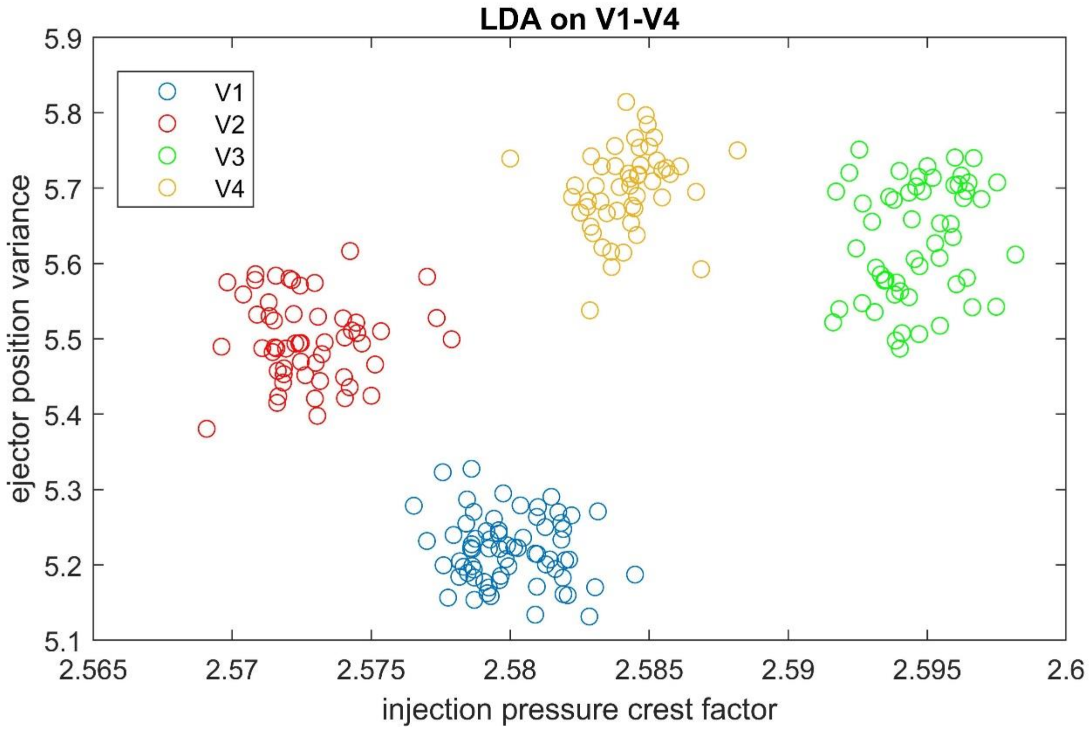
- 4 test series, part: ice scraper, material: PP
  - Trial series 1 (72 parts) - reference trial series → ice scrapers lie within the tolerances
  - Trial series 2 (56 parts) - calcified cooling channels → temperature of the mould temperature medium increased
  - Trial series 3 (57 parts) - batch fluctuation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

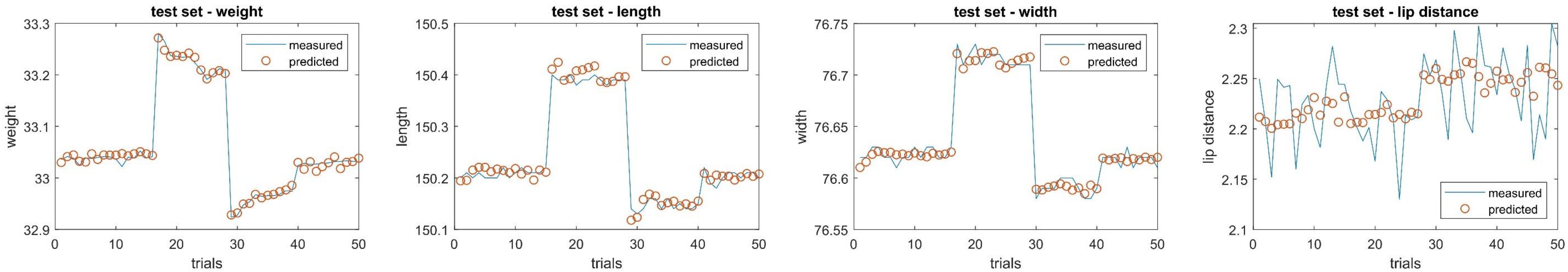
- Can ML be used to anticipate process anomalies based on internal measurement signals?



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)

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.



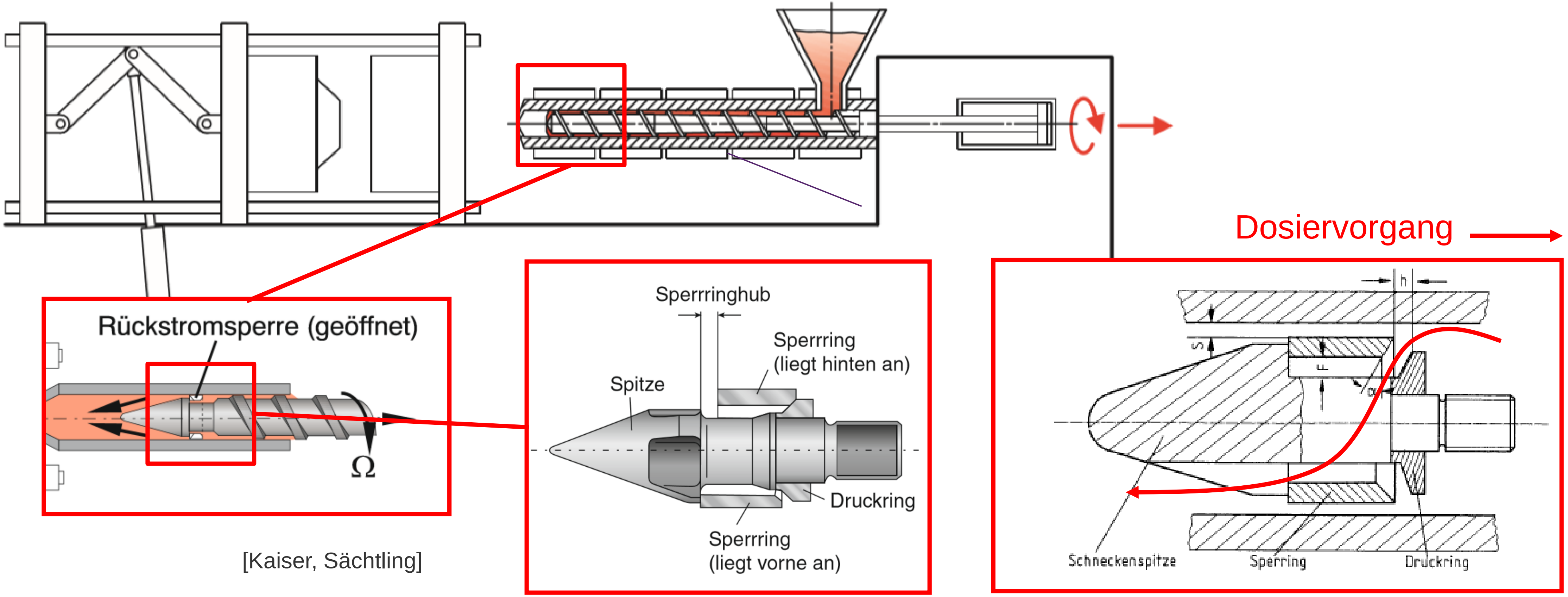
	weight	length	width	lip distance
STD-Error $\boldsymbol{\sigma}$	0.009 g	0.017 mm	0.014 mm	0.032 mm
$\boldsymbol{CV = \frac{\sigma}{\mu}}$	0.03 %	0.02 %	0.02 %	1.38 %

➡ 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



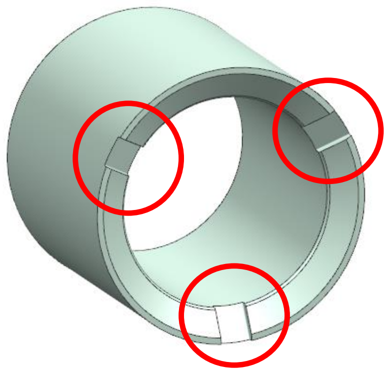
[Kaiser, Sächtling]

[IKV]

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

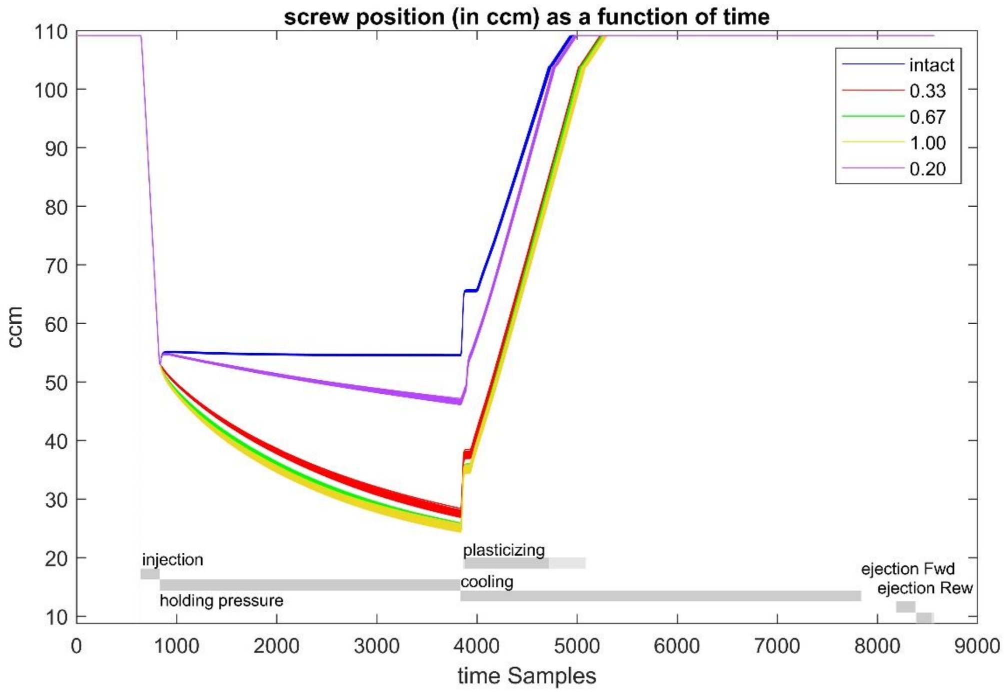


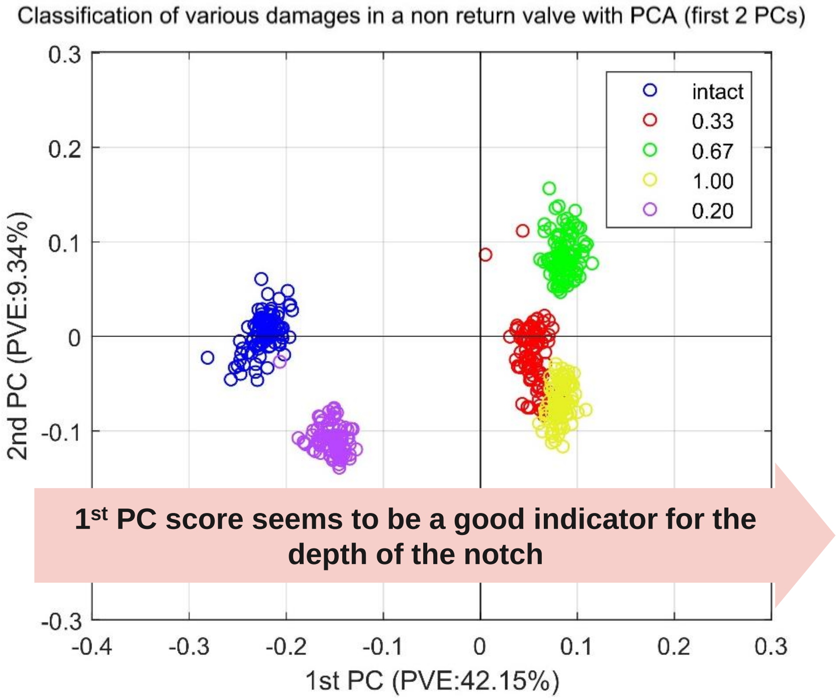
non-return valve with machined notches

- 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



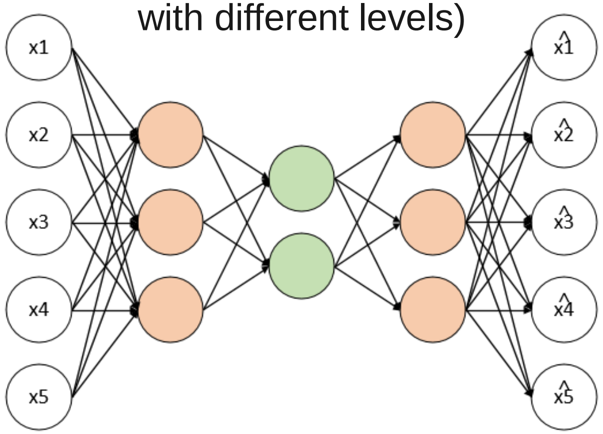


The wear of the non-return valve can be clearly detected with the component scores of a PCA → probably the damage can even be reliably estimated

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)



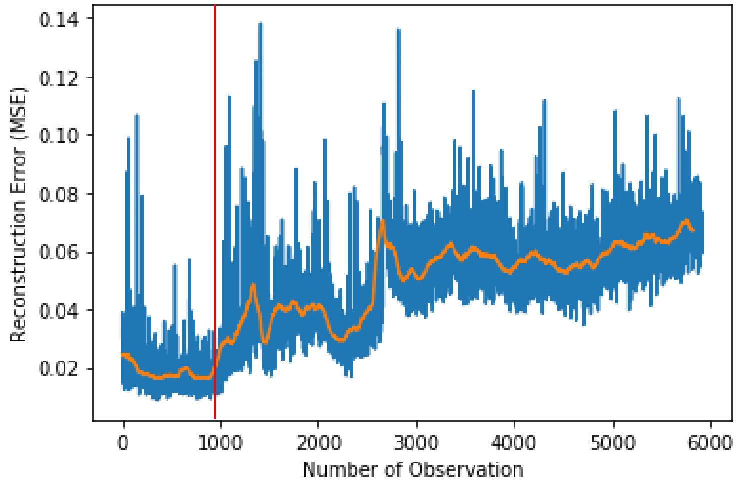
features

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

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

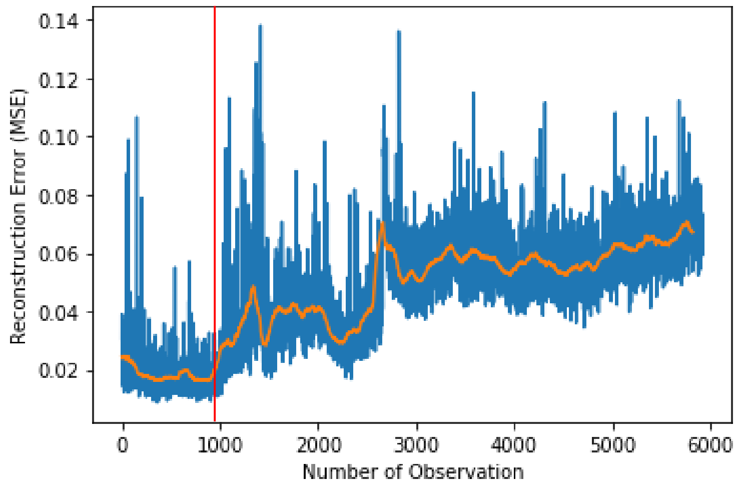
reconstruction error

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

Smart Factory @ OST

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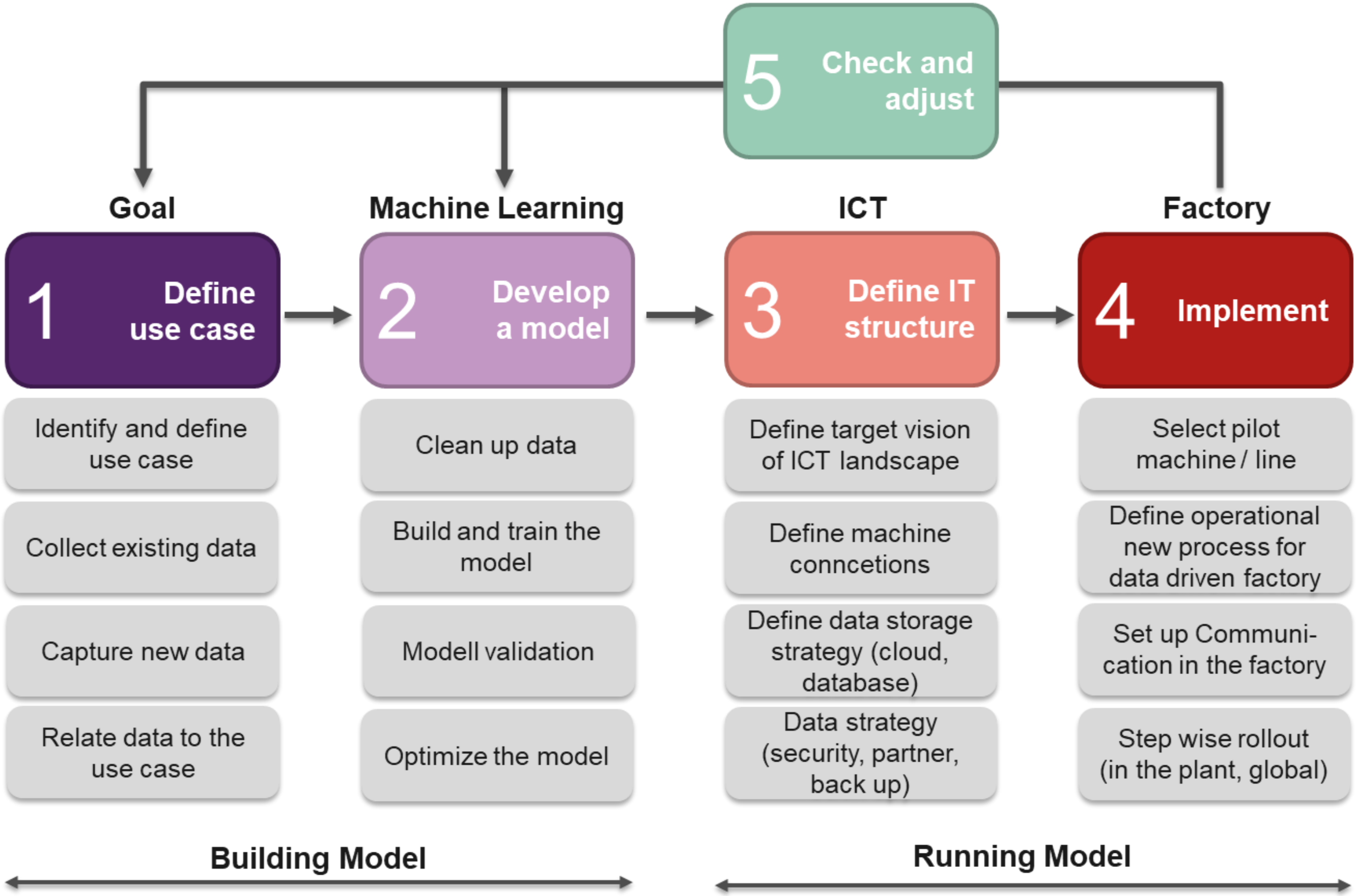
Model for the implementation of machine learning in the factory

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



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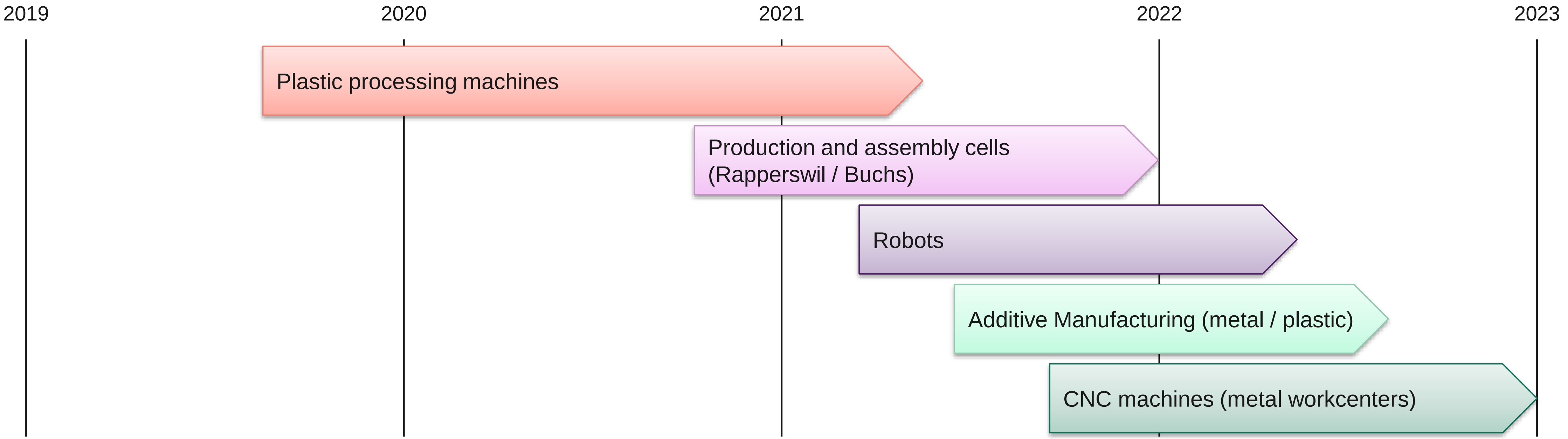
Smart Factory components and roadmap

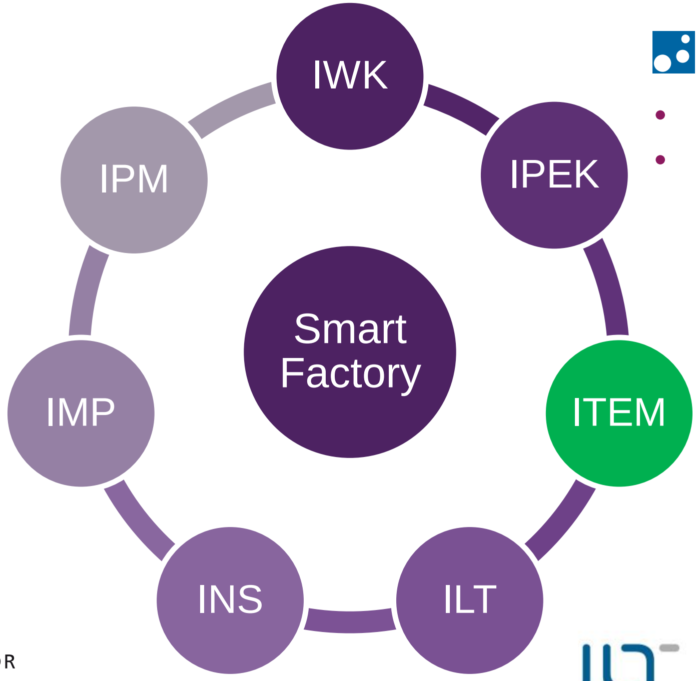
- Due to the existing knowledge in the field of plastic production technologies and robotics, these areas also serve as central elements of the smart factory.
- The networking and the development of data export for the machines of the IWK served as the initiation for the development of the smart factory,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

Institut für Technologiemanagement
Universität St.Gallen

- Production strategy
- Business models

IMP Institut für Mikrotechnik und Photonik

- Mechatronic systems

INSTITUTE FOR
NETWORKED SOLUTIONS

- Network and cloud infrastructure
- Security

INSTITUTE FOR LAB AUTOMATION
AND MECHATRONICS

- Robotics
- Automation solutions

Outlook: production cell

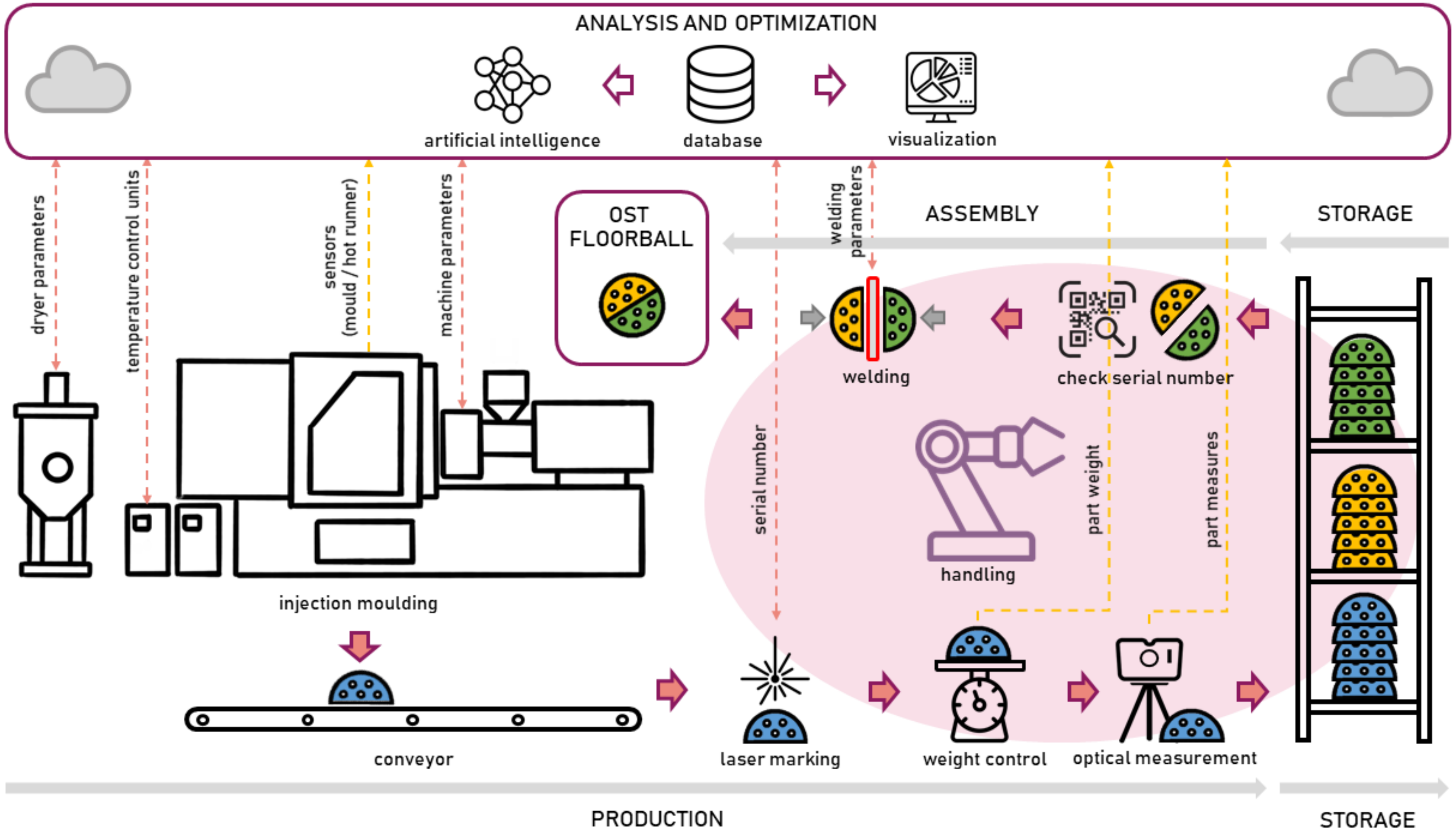
A manufacturing cell is / was set up in the Techpark for the production of

- a floorball with individual color configuration starting from quantity 1.
- an OST-gadget (wireless charger)

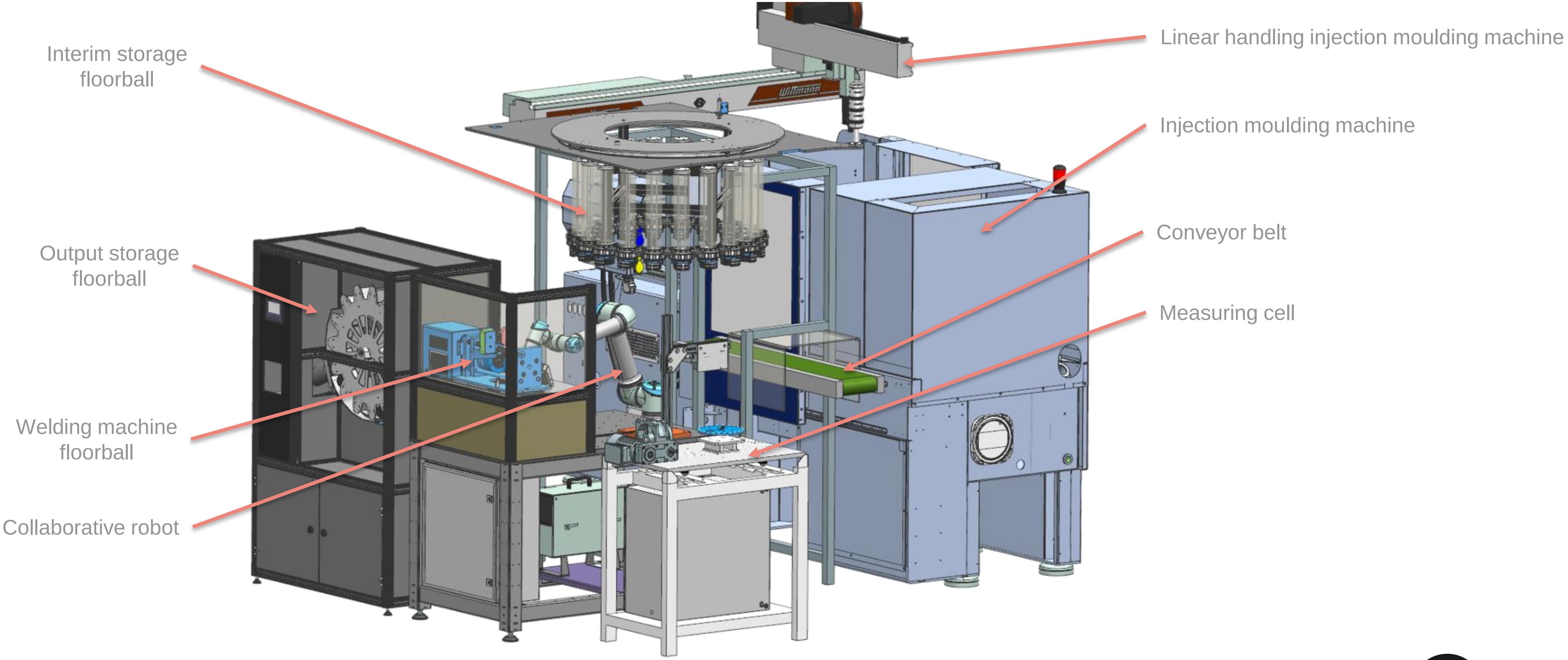
Goals:

- Demonstration of the possibilities of an automated production cell with continuous data acquisition
- Complete product traceability
- Complete coupling with an SAP system

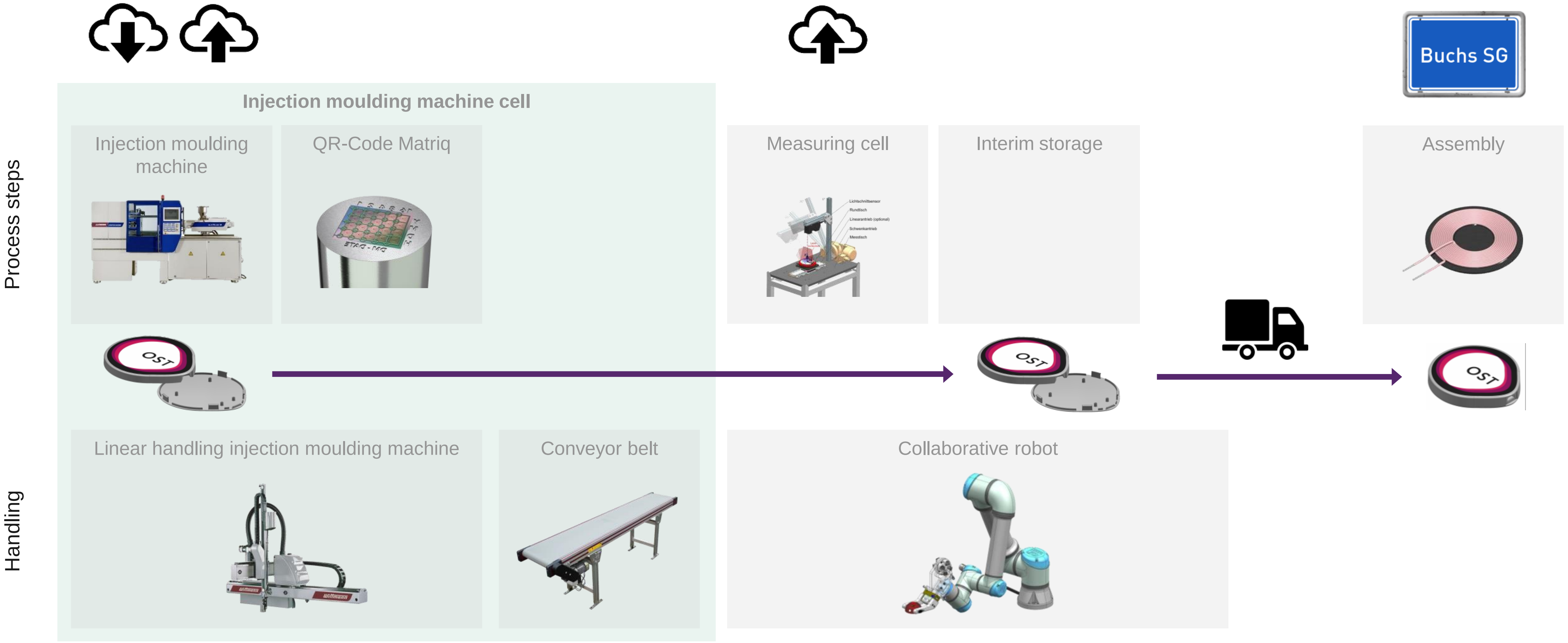
Manufacturing cell floorball



Outlook: production cell floorball - overview



Outlook: production cell - production flow OST-gadget



Assembly cell OST-Gadget @ Campus Buchs

Outlook to Exercise 04

E04 – Processing and evaluation of process data

Practical course with ibaAnalyzer (on own laptop):

- Analysis of curve data (data from preliminary tests on the injection moulding machines)
- Calculation of KPIs
- Creation of automated process protocol

Thank you for your attention

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