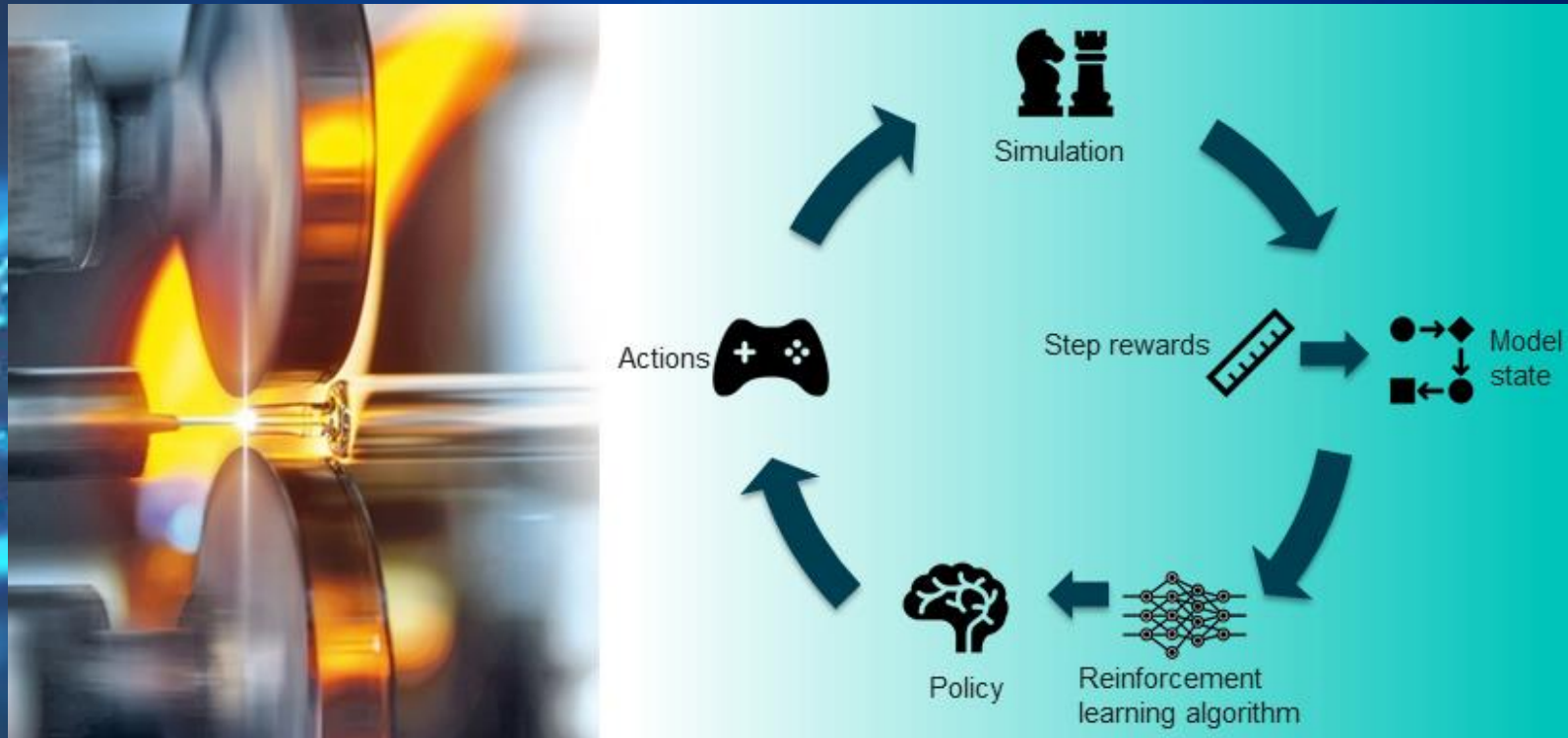


Werkstattgespräch bei Gerresheimer

Prozess-Stabilisierung mit KI



Gefördert durch:



Bundesministerium
für Wirtschaft
und Klimaschutz

aufgrund eines Beschlusses
des Deutschen Bundestages

Agenda

- 1 Begrüßung und Einführung
- 2 Vorstellung IIP und Gerresheimer
- 3 Fertigungsprozess: Wie wird das Glas zur Spritze?
- 4 Wie funktioniert der Einstieg in Künstliche Intelligenz in einem Unternehmen?
- 5 Einblick in die Entwicklung für KI basierten Lösungen in der pharmazeutischen Produktion
- 6 Q&A Session 1
- Pause*
- 7 KI-Praxisbeispiele
- 8 Digitaler Zwilling der Glasformung
- 9 Q&A Session 2
- 10 Expertengespräch: Was sagen die Experten zu KI in der Produktion?
- 11 Zusammenfassung und Ausblick



Vorstellung IIP-Ecosphere



IIP-Ecosphere

IIP-Ecosphere – Ein offenes Ökosystem

Ziel: Aufbau eines offenen **KI-Ökosystems** für die intelligente Produktion



Vereinfachter Zugang zu KI-Lösungen



IIP-Ecosphere IIoT-Plattform



KI-Methoden für die Produktion



Unterstützung bei der Innovation von KI-Geschäftsmodellen





IIP-Ecosphere

IIP-Ecosphere auf einen Blick

slashwhy gerresheimer Lenze

SIEMENS



SENNHEISER



KIPROTECT

GILDEMEISTER



VDW



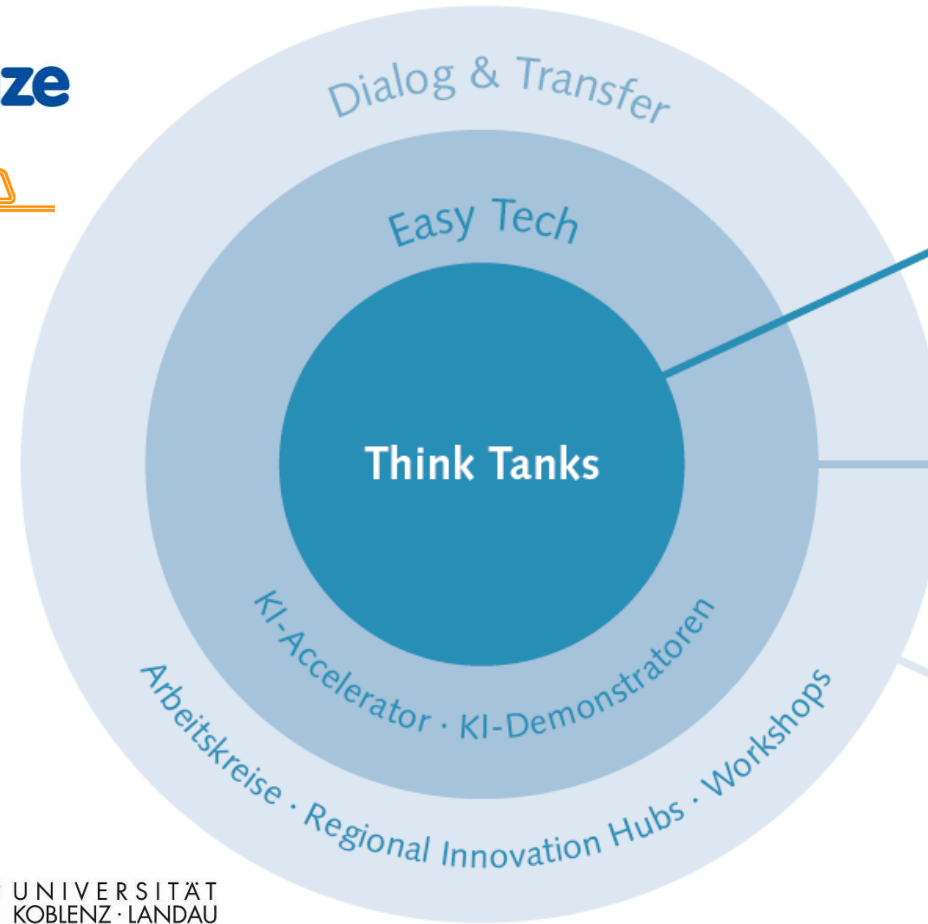
Nutzfahrzeuge



BITMOTEC



FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG



Anwendungsorientierte Forschung

Vereinfachter Zugang zu KI durch:

- Demonstratoren
- KI-Beschleunigung
- Best Practices

Einbindung von Stakeholdern,
Events, Wissens-Transfer



IIP-Ecosphere

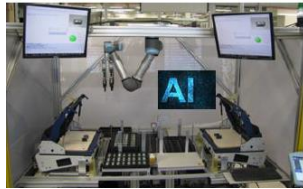
Die IIP-Demonstratoren



Prozessstabilität bei der Glasumformung

gerresheimer

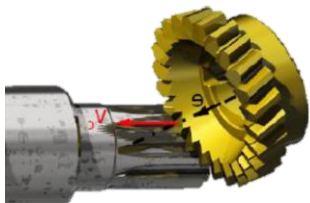
Demonstrator
Prozess-
stabilität



Autonome Endprüfung von Platinen

 SENNHEISER

Demonstrator
Autonome
Endprüfung



Überwachung und Parametrierung von
Wälzschälprozessen


GILDEMEISTER

Demonstrator
Zyklus-
optimierung



Optimierung von Taktzeiten in der Karosseriefertigung



Nutzfahrzeuge

Easy Tech

Think Tank »KI & Pro

Think Tank »Geschäftsmodelle«

Inno-
vation
Core

Think Tank »Plattformen

gerresheimer

Vorstellung Gerresheimer

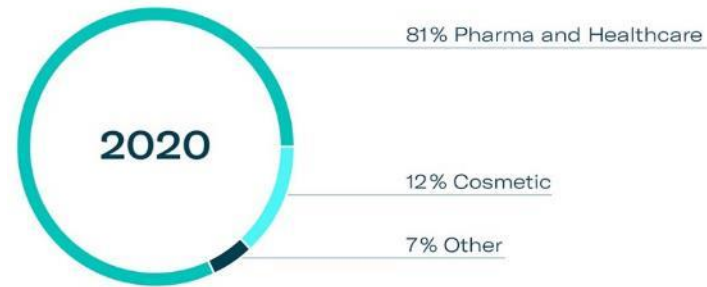


Gerresheimer

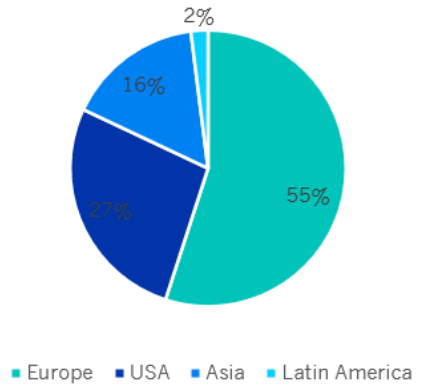
A leading partner for the pharma & healthcare industry

Revenues by market segment

Revenues at constant exchange rates financial year 2020 EUR ~ 1.4 bn



Revenues by region



MARKET LEADER in primary packaging
for injectables / drug delivery devices

15.5 bn

pieces sold p.a.

1

in prescription &
injectables
in the US

**STRONGLY DIVERSIFIED
CUSTOMER BASE**

OVER
1500
customers

Supplying all of
Top 10
Pharma companies

PRODUCING in 14 countries

Selling in
100
countries

Over
5
continents

gerresheimer

Gerresheimer product overview

A leading partner for the pharma & healthcare industry in packaging

Prefillable syringes



~ 600m pieces

Plastic bottles
(incl. Centor)



~ 5.5bn pcs

Pharma glass bottles



~ 2.5bn pcs

Cosmetics



~ 1bn pcs

Gerresheimer is manufacturing 16bn products a year

Injection vials



~ 4bn pcs

Ampoules



~ 2bn pcs

Inhalers



~ 100m pcs

Cartridges



~ 1bn pcs

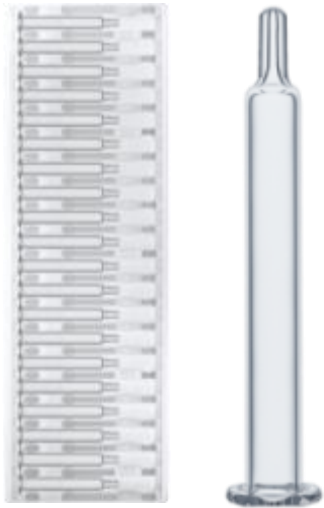
Product overview MDS

Prefillable syringes and pen cartridges

Glass syringes: bulk

Gx[®] bulk

- Washed, sterilized and filled by the customer;
- Delivery of the unsterilized syringe bodies in flat trays (Rondo Trays)



Glass syringes: ready-to-use

Gx RTF[®]

- Washed, siliconized, pre-assembled with closure system and sterilized with ethylene oxide (EtO);
- Delivery of syringes completely prepared for aseptic filling



Plastic syringes

Gx RTF[®] ClearJect[®] ClearJect[®]

- Innovative drug delivery platform based on COP (Cyclic Olefin Polymer)
- For highly demanding drug products like sensitive biotech formulations



Pen cartridges

Gx[®] pen cartridges

- Cartridges for insulin (glass type I)



Customized solutions

Primary Packaging

Definition, categories & requirements

Definition

- Contains drug product
- Direct contact to drug product
- Designed to handle and withdraw drug product
- Protects from environmental influence
- Protects from loss of filled goods
- Does not or hardly interact with content

Packaging categories

- Primary packaging: e. g. blister, vial, syringe
- Secondary packaging: e. g. individual carton box, label pen system
- Tertiary packaging: pallet, shrink wrap, big carton box

Protection	Compatibility	Safety	Performance
Temperature	Adsorption	Leachables	CCI
Light	pH change	Extractables	Drug Delivery
Water loss	Precipitation	Toxicity	NS pull off
Loss of solvent	Colour change	Glue or ink migration	Break loose and Gliding
Oxygen	Packaging brittleness		Elderly people, children
Microbial ingress			Connections

Material properties

Why is glass most common?

Glass

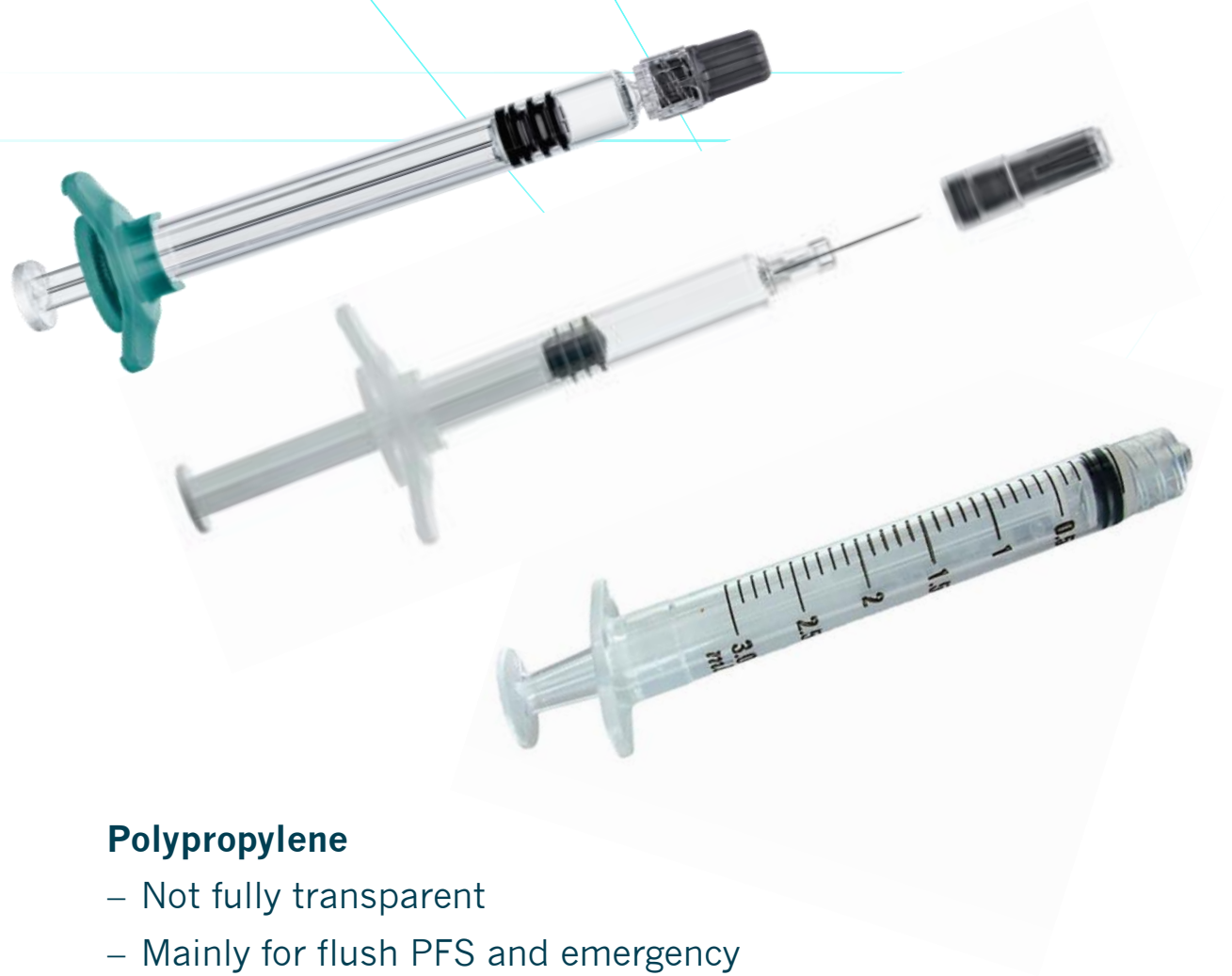
- Gas tight, suited for long term storage
- Transparent (visual inspection)
- Very well analyzed and well suited for long-term storage
- Track record for many decades
- Inert in most cases
- accepted in Pharmacopoeia USP, EP, JP

COP and COC

- Glass like transparency
- Not gas tight
- No pH shift
- No delamination

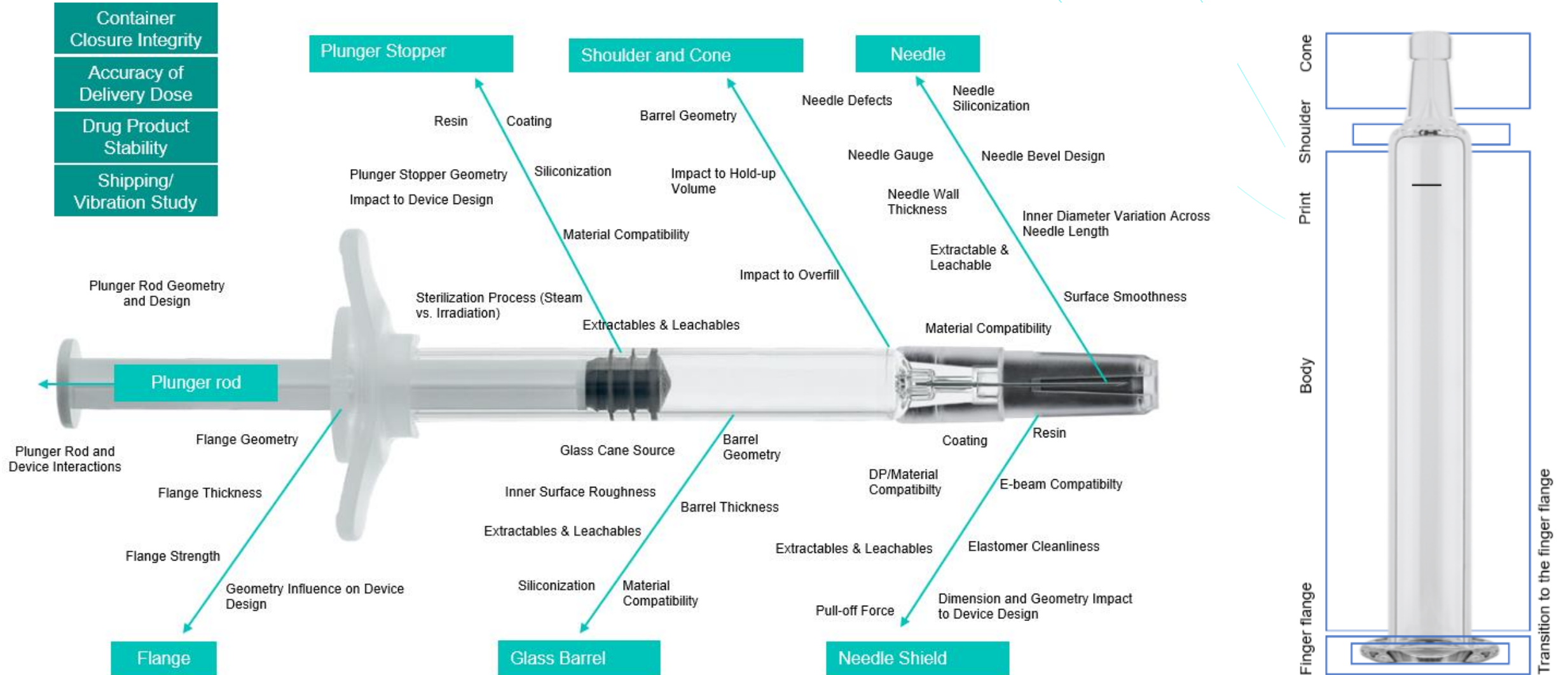
Polypropylene

- Not fully transparent
- Mainly for flush PFS and emergency applications
- Disposable syringes to be used with a glass vial



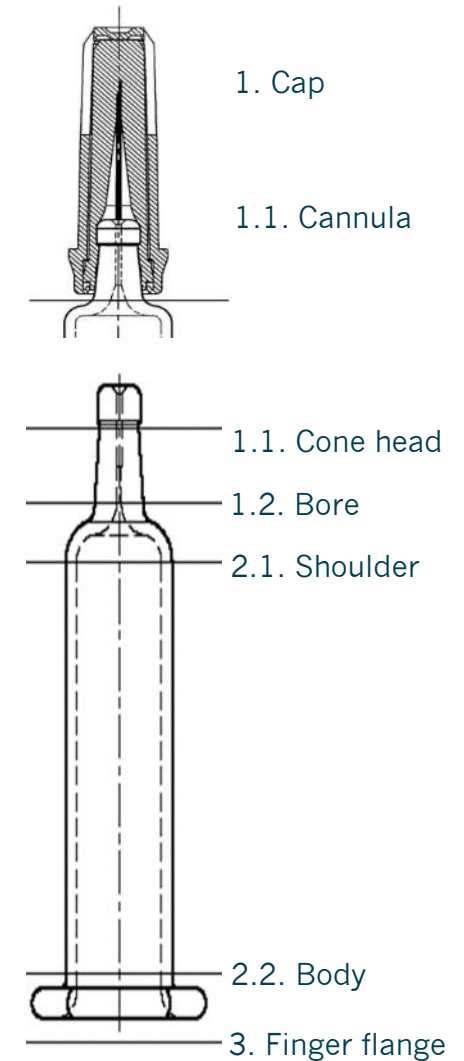
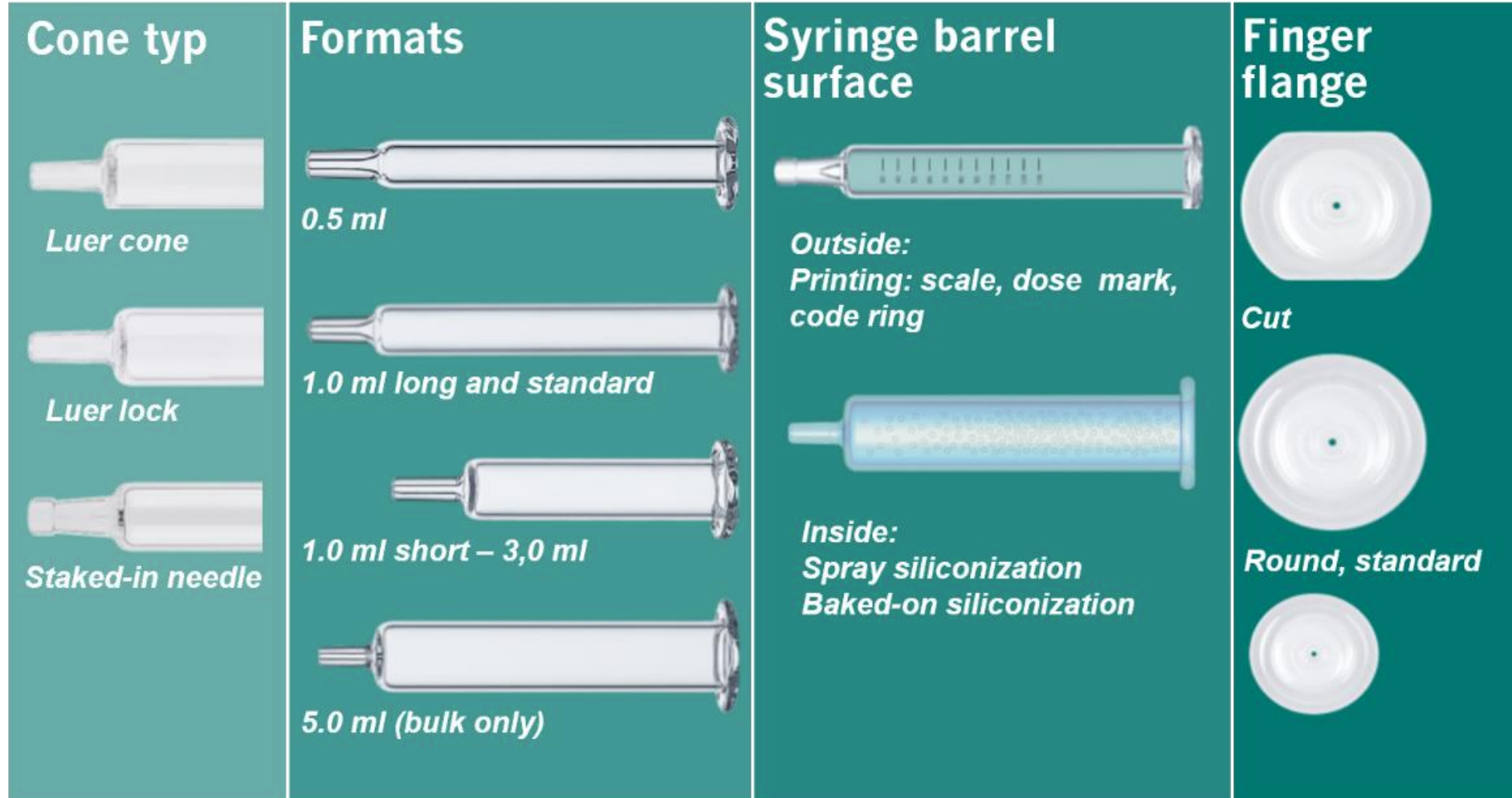
Quality features

Functionality, Geometry and Cosmetics



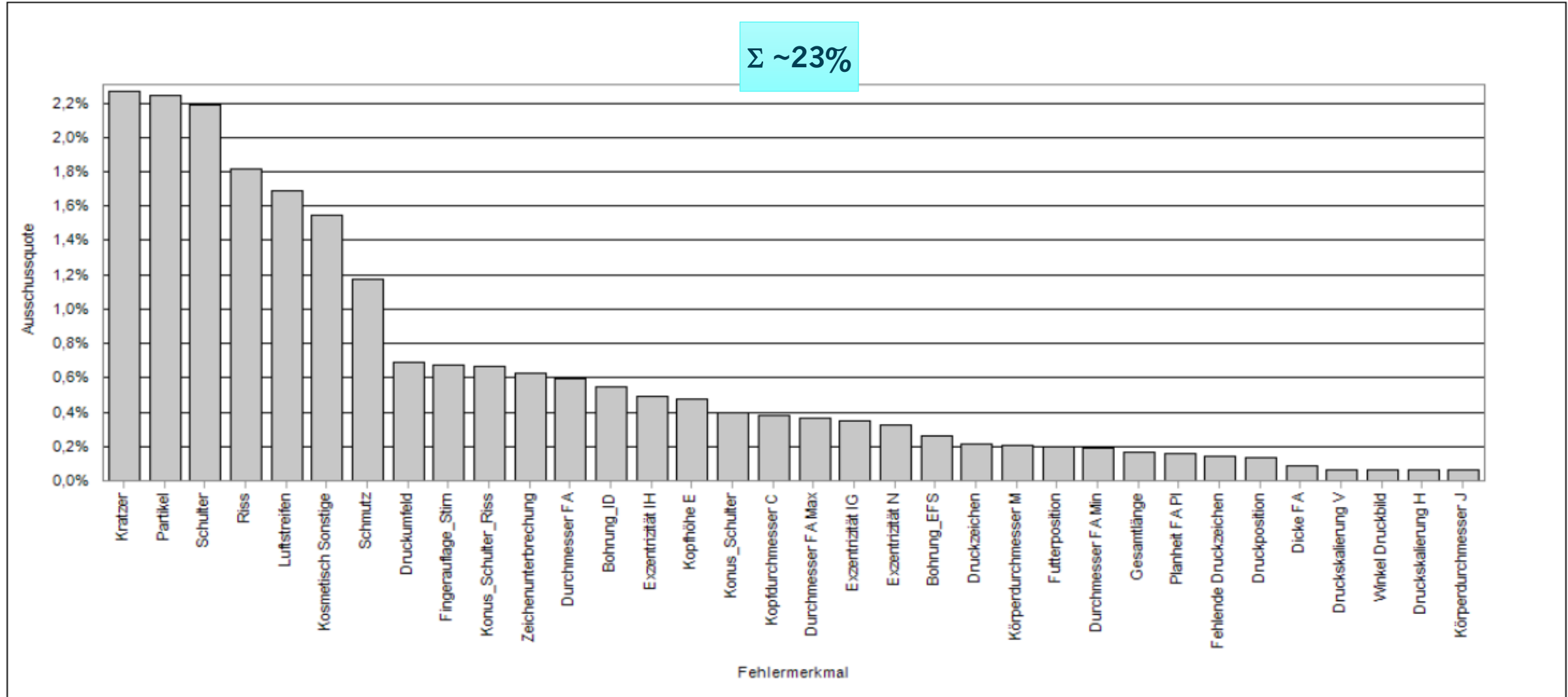
Product overview Buende

Syringes: Glass barrel features



Failure rate

For syringes produced in Buende



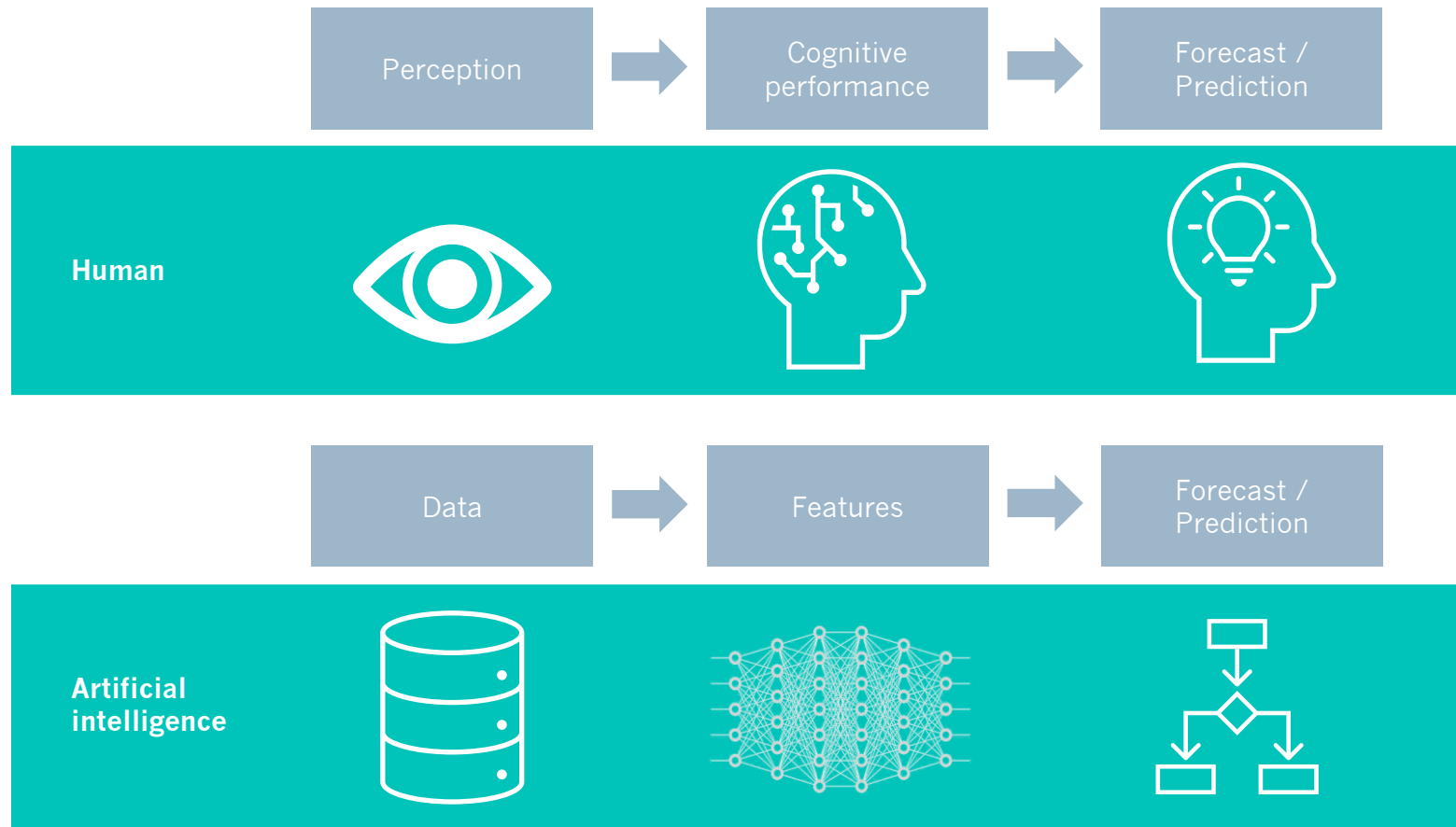
Fertigungsprozess: Wie wird das Glas zur Spritze?

Glasspritzen-Fertigung

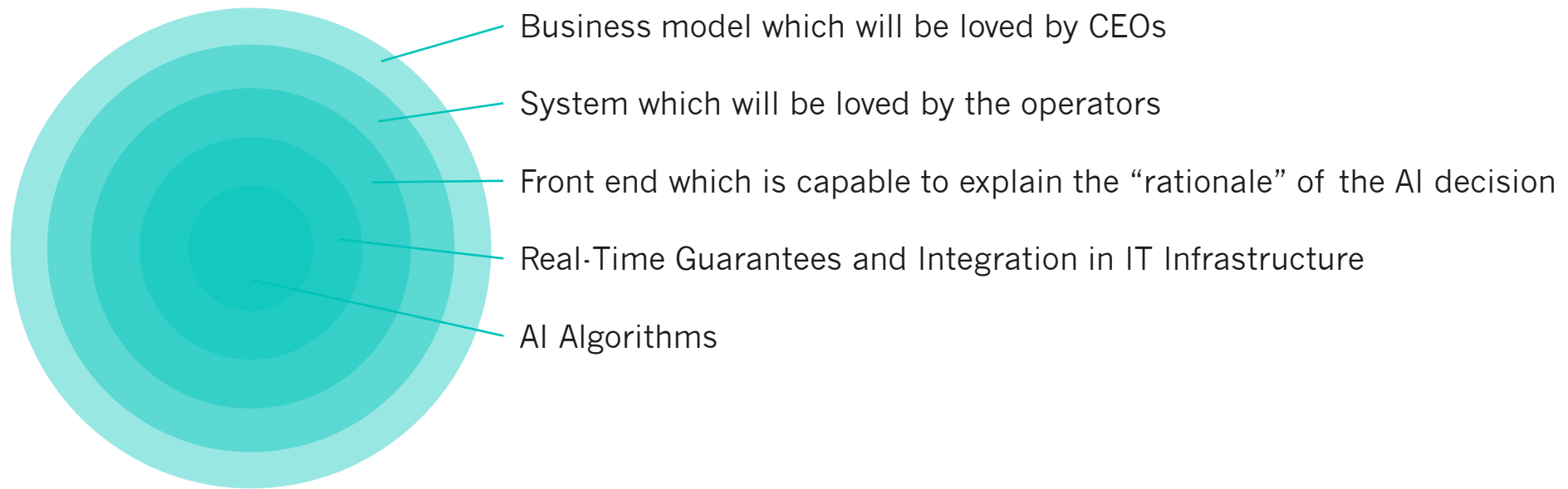


Wie funktioniert der Einstieg in Künstliche Intelligenz in einem Unternehmen?

Artificial Intelligence in General

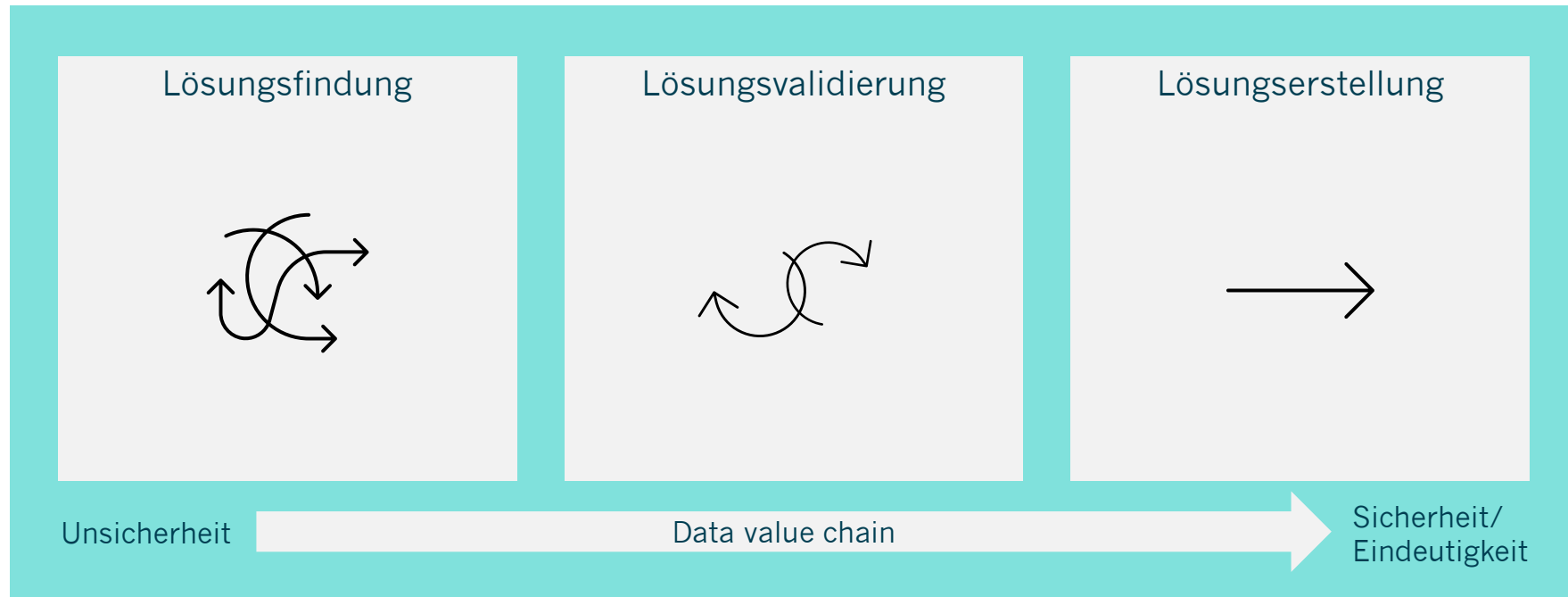


Strategic way to go with AI



(inspired by Leo Spenner's talk at the 2nd KEEN workshop 2019)

Unser Ansatz für eine gesamtheitliche Lösung aus Projektsicht



Our approach to reach the goal

Global view

Development Strategy



Scaling

- Deployment of models
- Evaluation in a broader field



Pilot Testing

- Online analysis: Working with streaming data of a machine
- Evaluation in practical environment



Prototype Development

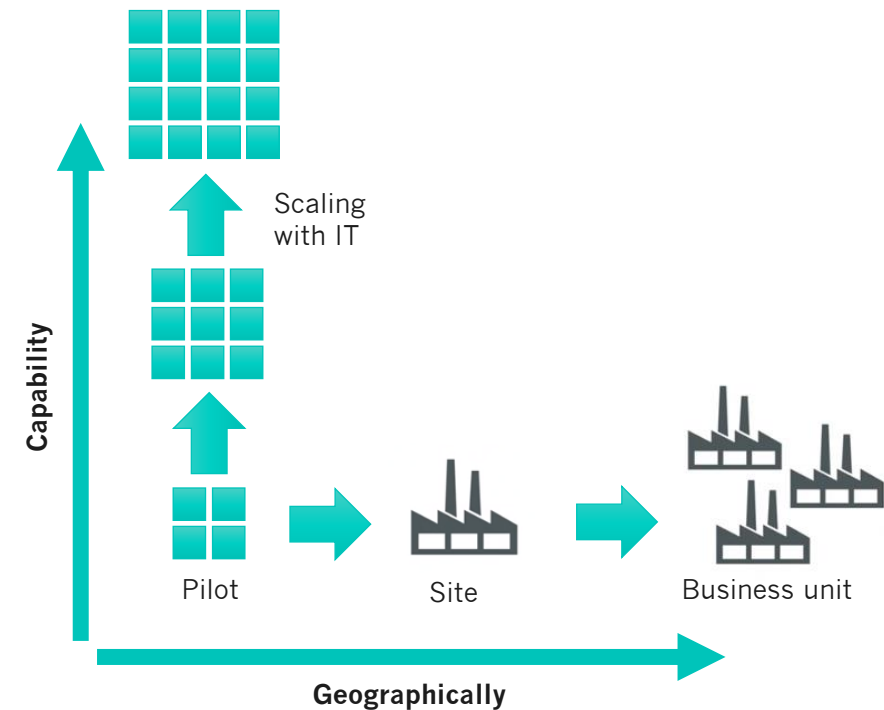
- Model Testing
- Offline analysis
- First performance evaluation
- Project visions



Exploration

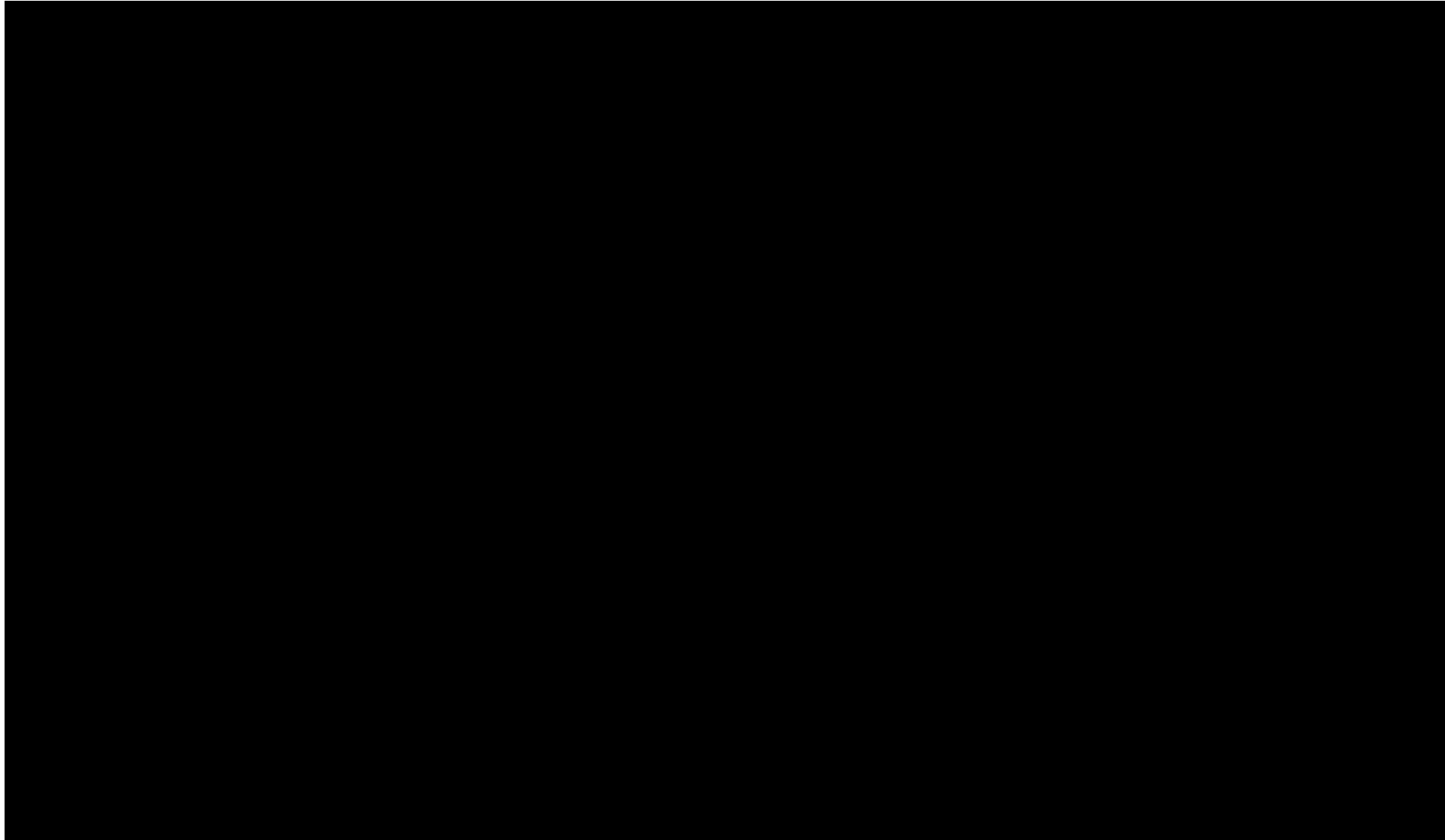
- Data acquisition
- Data exploration
- Use case definition

Deployment and Modification Strategy



Einblick in die Entwicklung für KI basierten Lösungen in der pharmazeutischen Produktion

KI im Glasspritzen-Fertigungsprozess



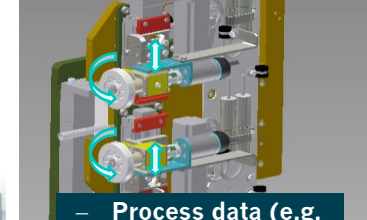
Inside Automation System Development – IoT G3 Platform

Business model and Use Case

- Reduce scrap
- Increase machine availability
- Increase power efficiency



Internal Automation Engineering



- Process data (e.g. from sensors in the field)
- Machine data



- Machine – Logs
- Event data

Self-Controlled Machine

IT Infrastructure

Hybrid architecture



Local real-time applications



Huge computing power and big data storage

IoT-Platform and AI Expertise

G3 IoT Platform

Look back

Future

Descriptive

- What happened?

Diagnostic

- Why it happened?

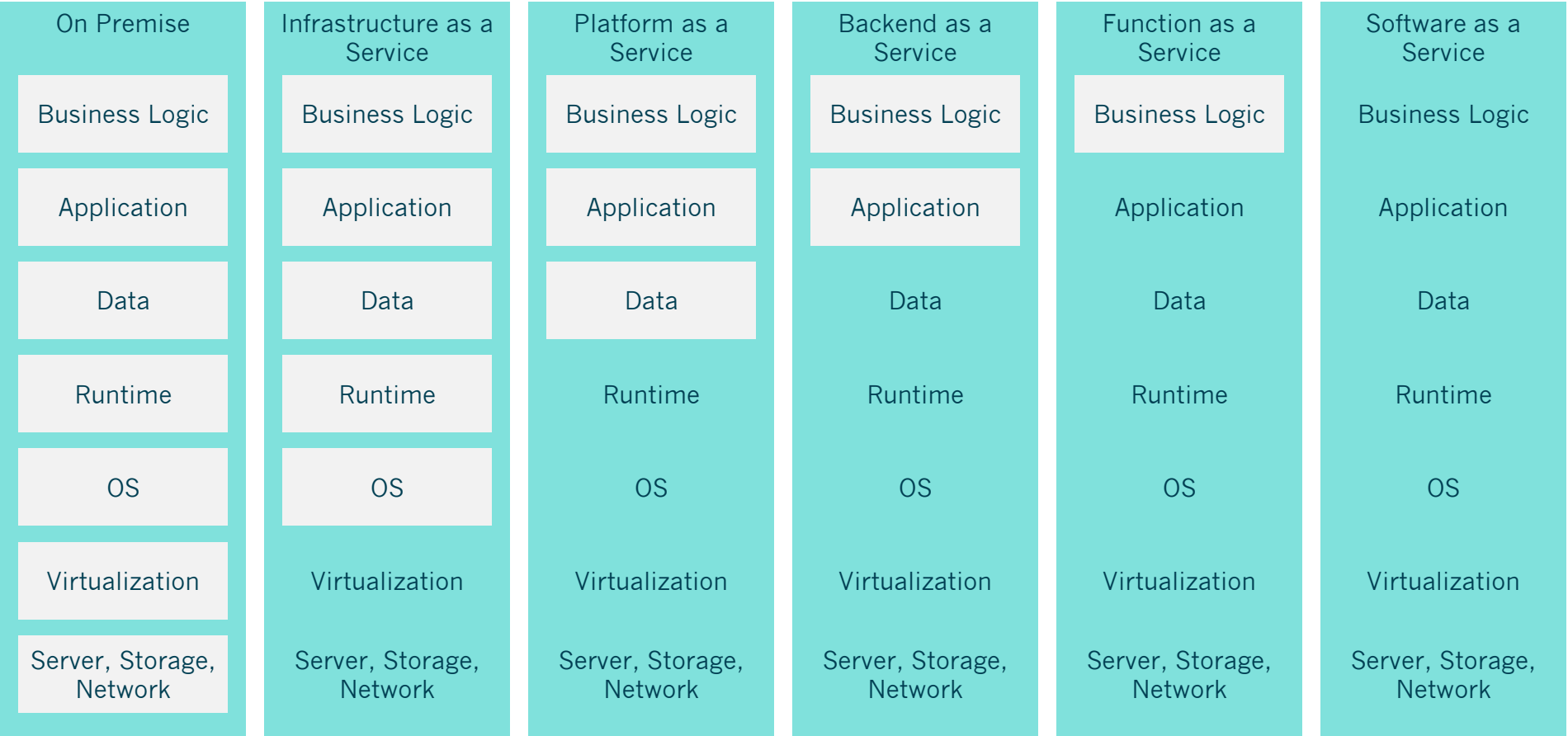
Predictive

- What will happen?
- What will happen, if a parameter is modified?

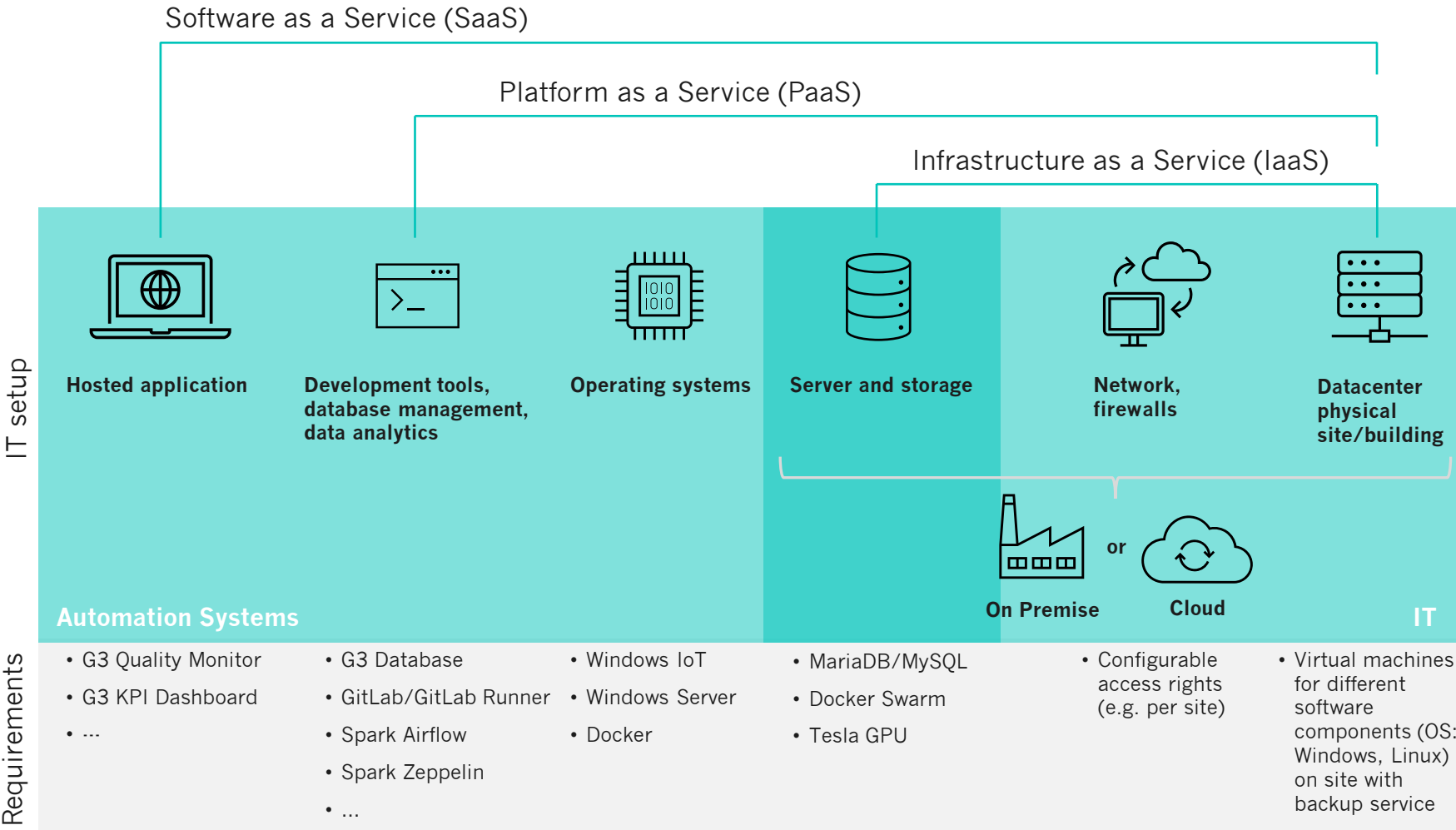
Prescriptive

- What action to take to solve the problem?

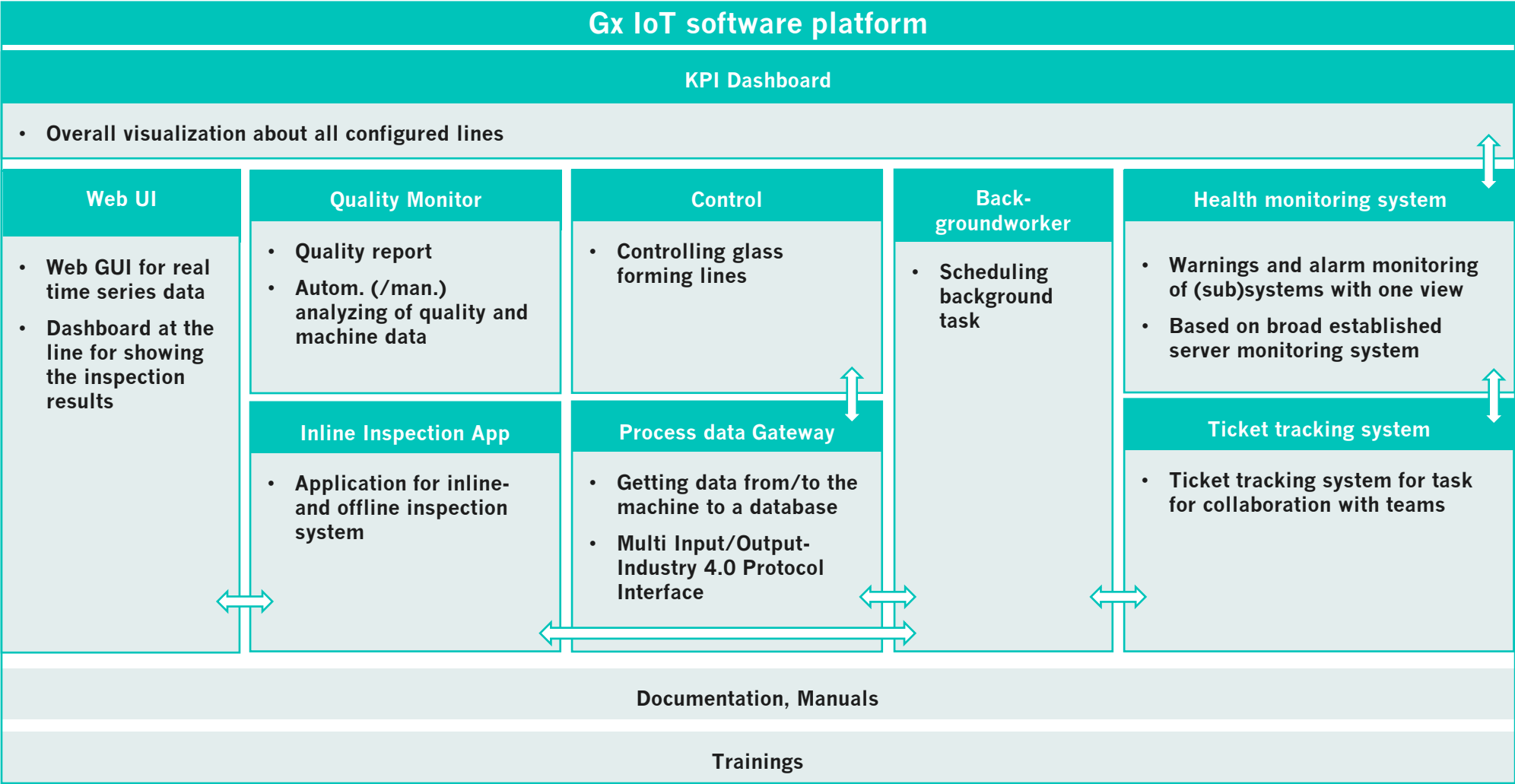
Service Level



G3 Software as a Service - Responsibility

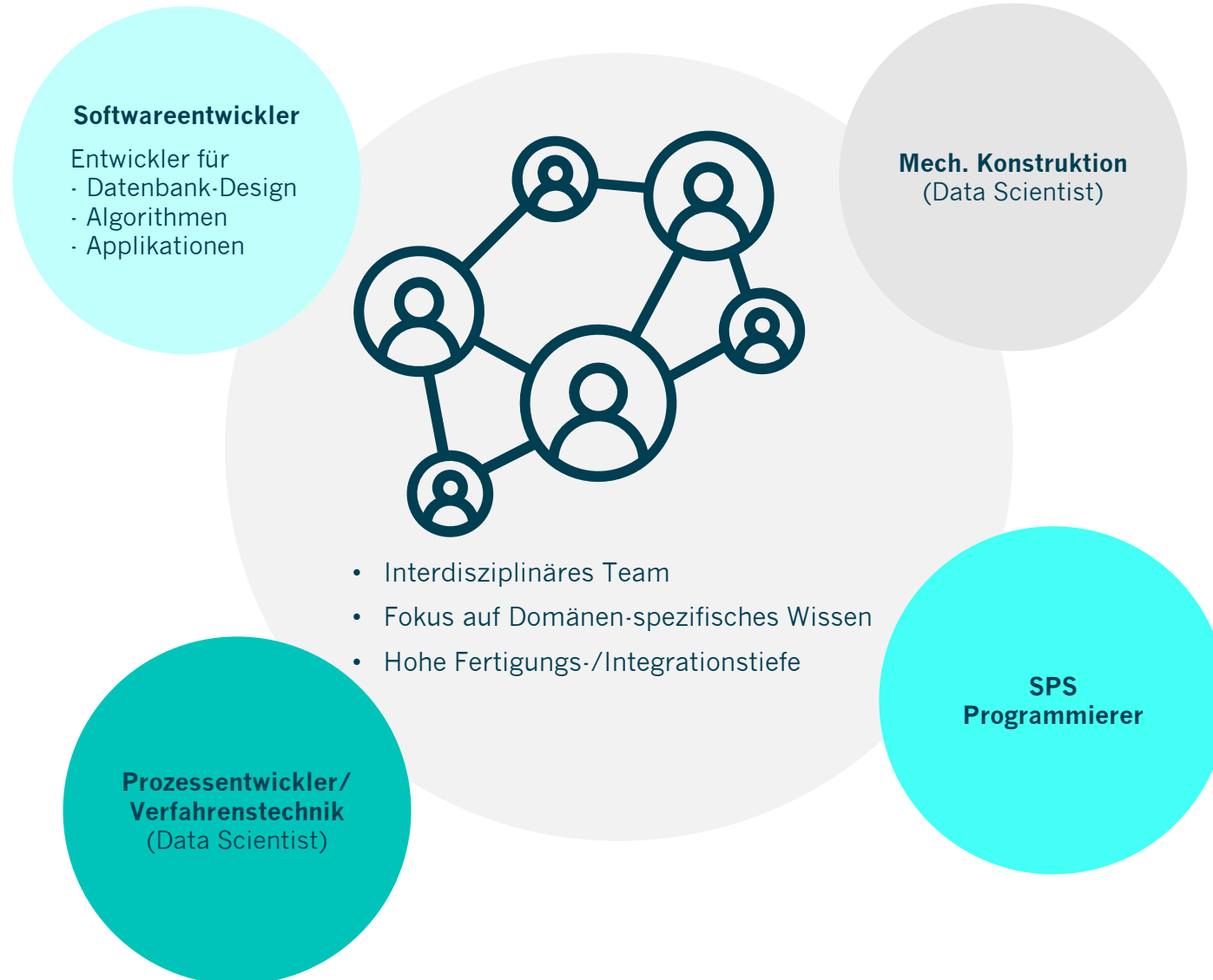


Target picture of G3 Platform

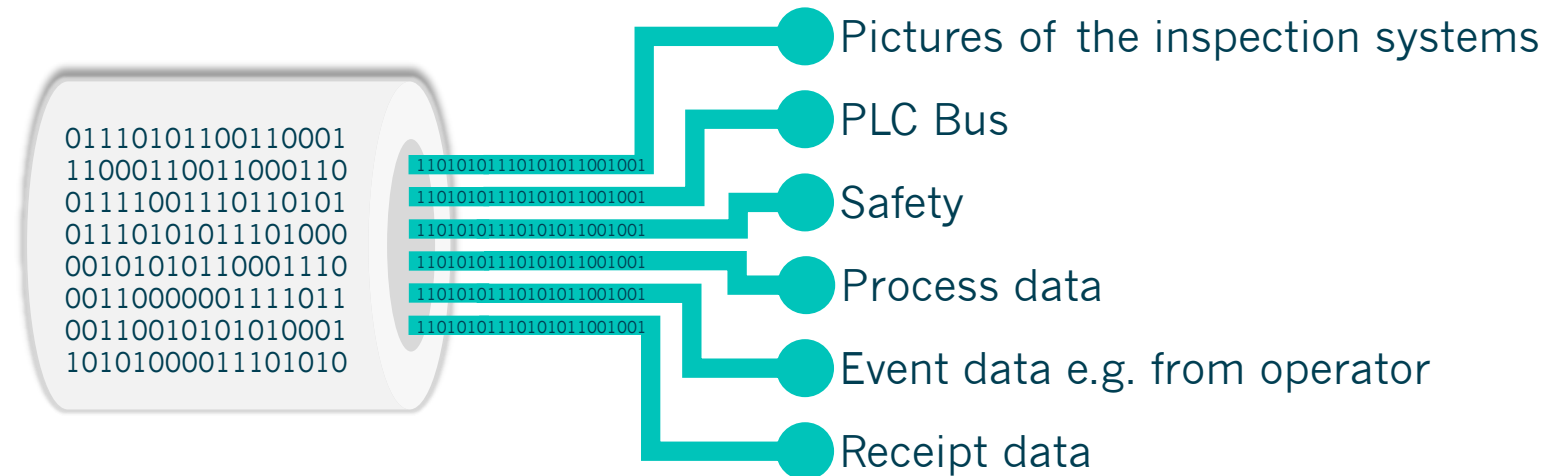


Legend Additional APIs

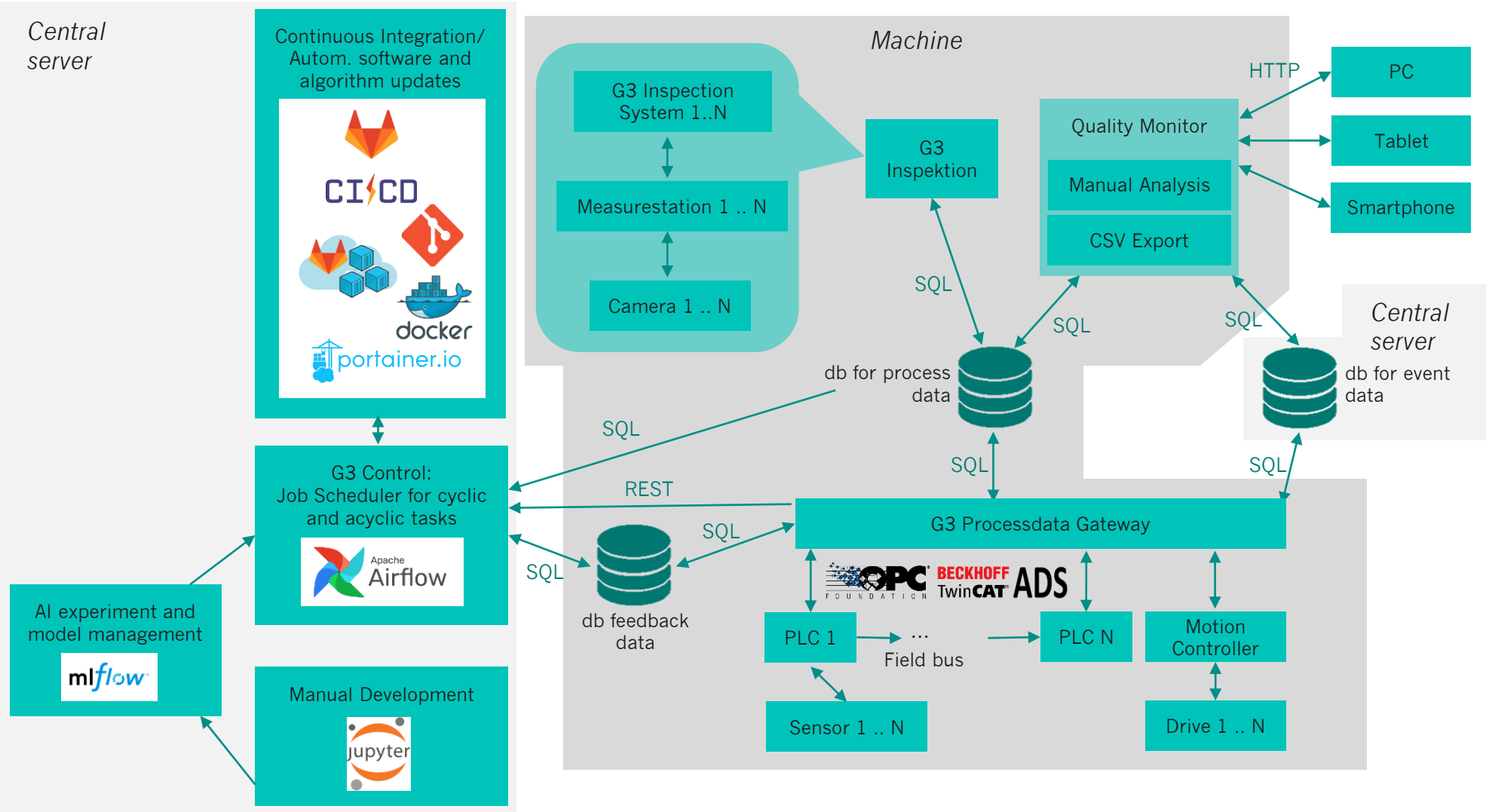
Das Team



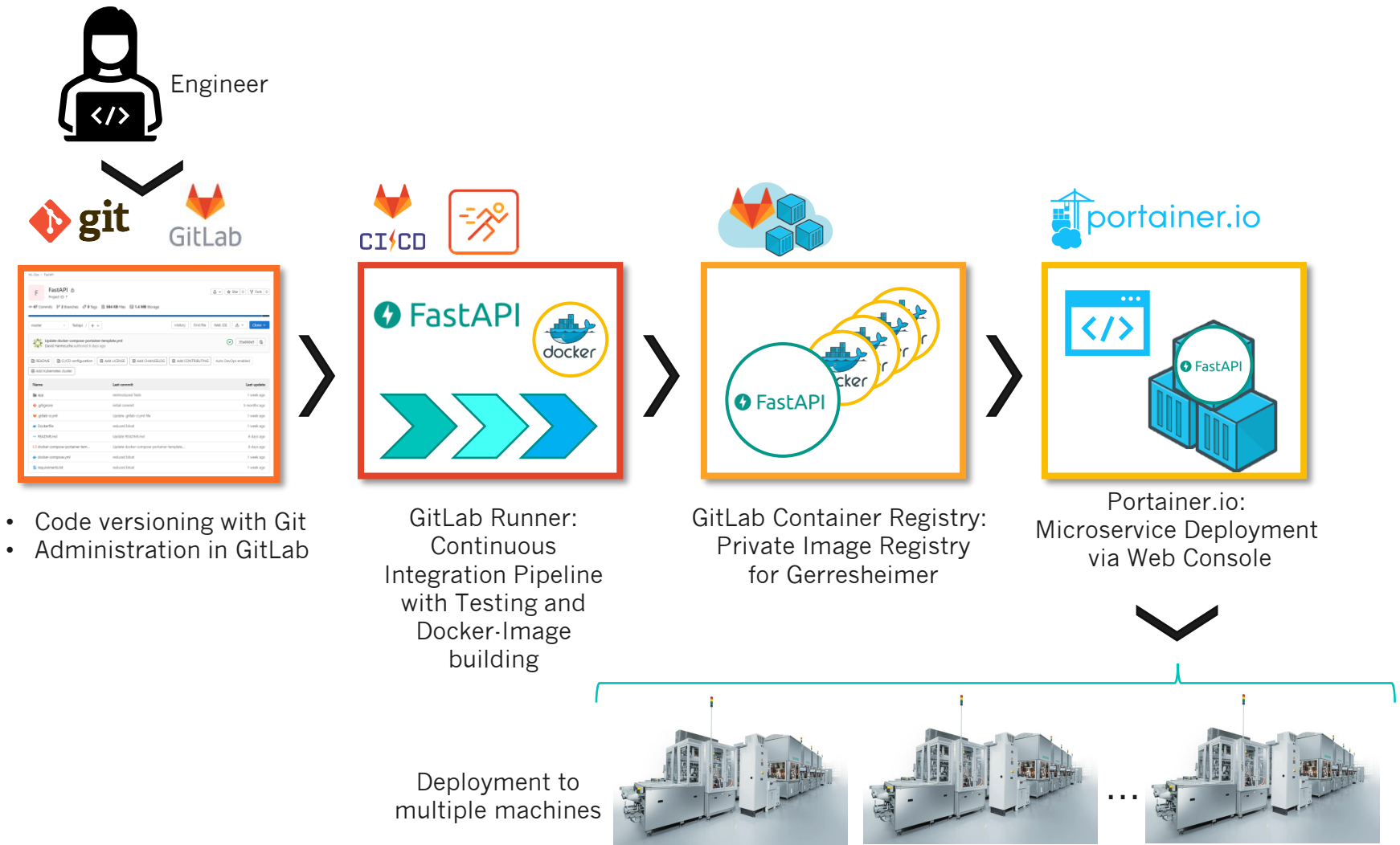
Datenströme



Technical perspective - concept



CI/CD Platform for deploying updates to multiple machines



gerresheimer

Q&A Session 1

Umfrage

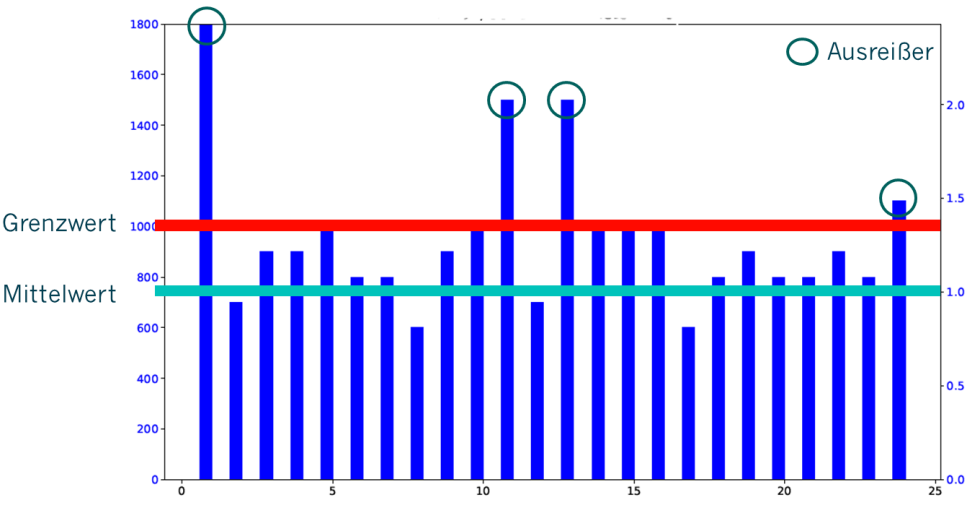
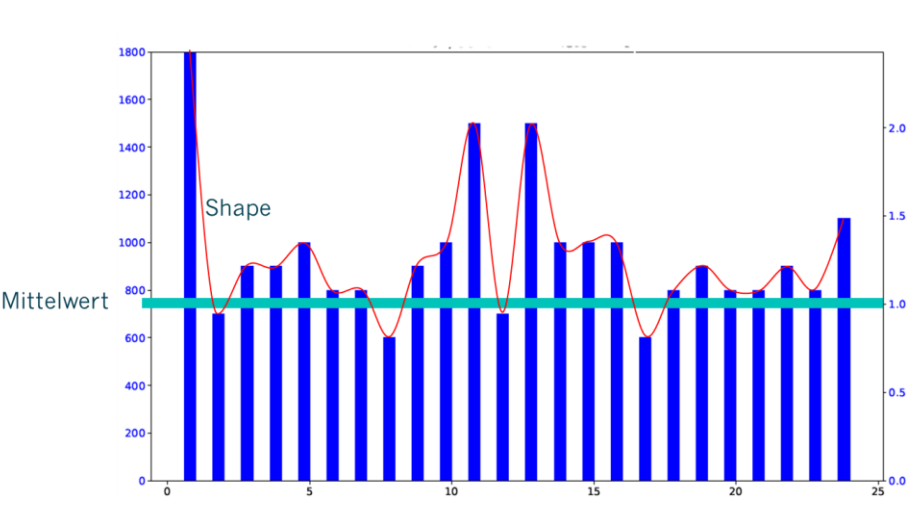
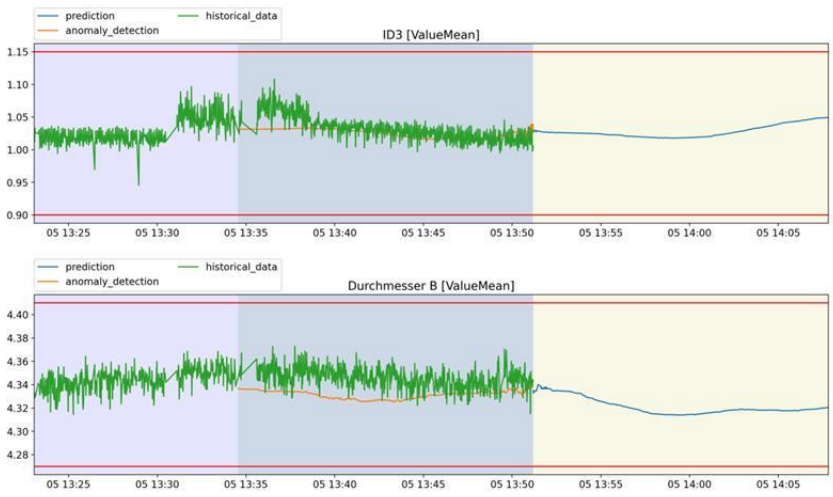
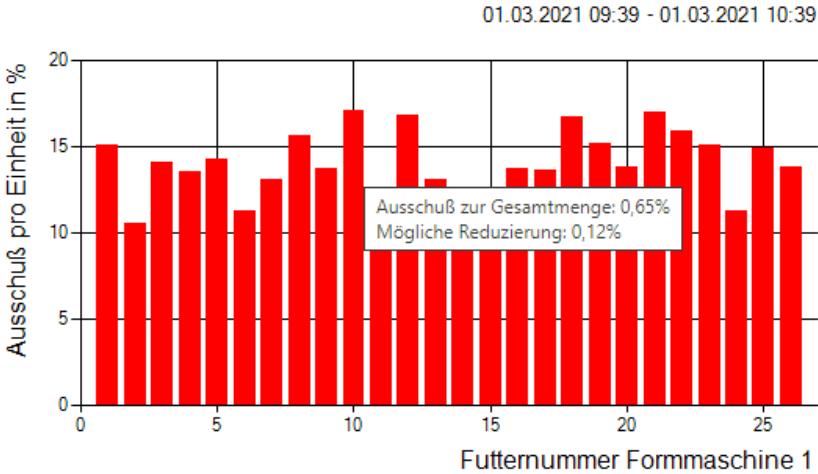
Pause

15:00

KI-Praxisbeispiele

Anwendungsfälle im Überblick

Ausschussübersicht: Kopfhöhe E, Futternummer Formmaschine 1
Seite Blau



Remaining Useful Life (RUL) of the cone forming pin (1/4)

Motivation

- Application: glass forming with high deterioration of mechanical parts
- Forecasting the fading of mechanical components → remaining useful life (RUL)
- Estimation of RUL before breakdown

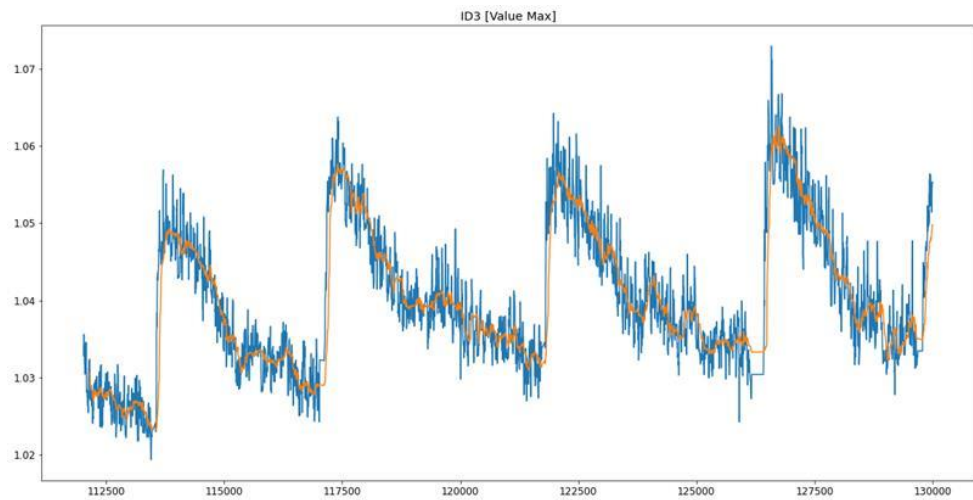
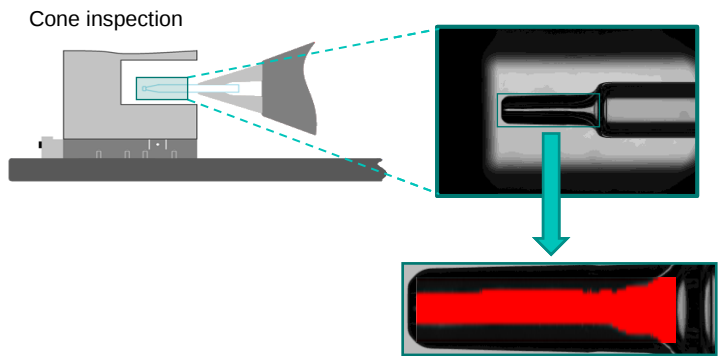
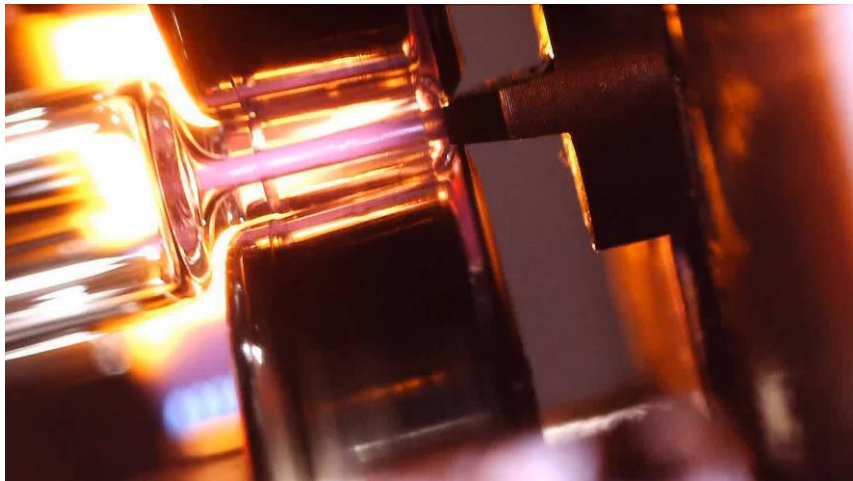
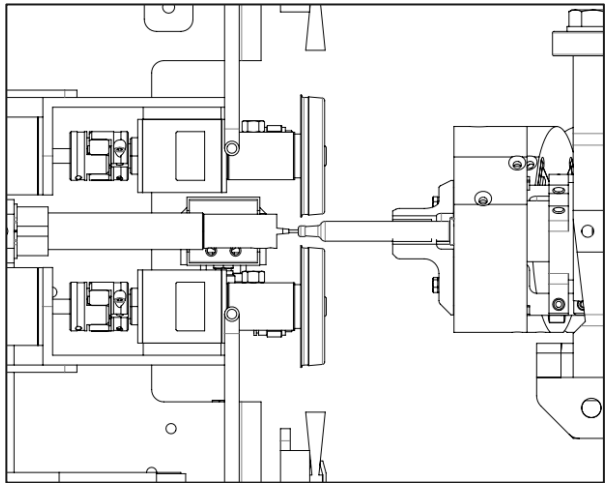
Challenges in practice

- Dynamic environment of industrial manufacturing sites: product derivatives, operator impact, different machine setups (e.g. sampling rates)
- Faulty setting leads without any contextual information to mismatches in RUL estimations
- Early-stage replacement because of missing ground truth of the wear

Key contributions of this work

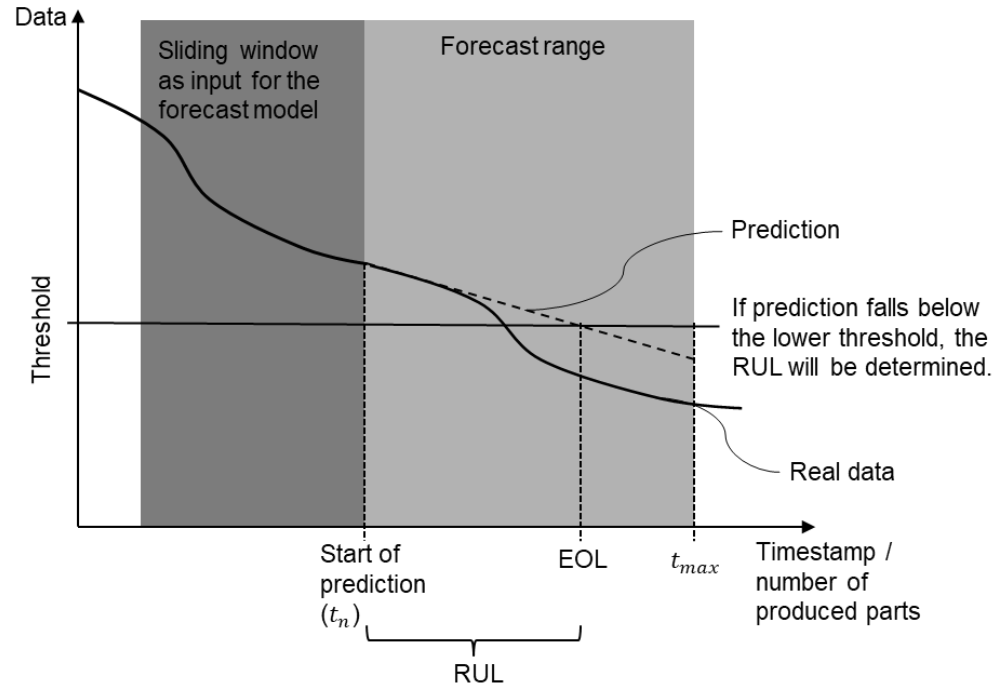
- Degradation forecast by an autoencoder alike structure with limited noisy data and unknown real RUL
- Calculation of an end of life threshold independent of the individual product specification limits and health of the forming tool
- Scaling ability to similar machines and products without the need of re-training for all machines in the field having different mechanical and dynamic conditions

Remaining Useful Life (RUL) of the cone forming pin (2/4)



Remaining Useful Life (RUL) of the cone forming pin (3/4)

Novel method RUL estimation and anomaly detection

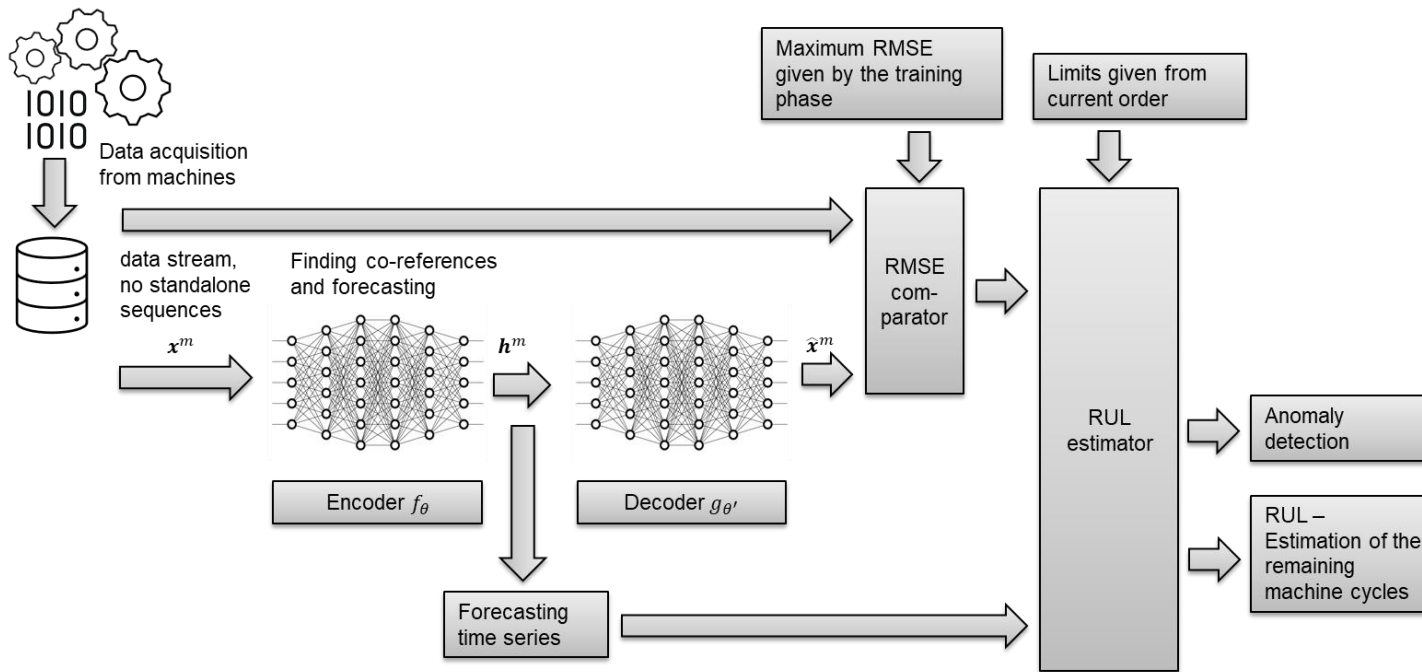


$$RUL(t_n) = EOL(t_n) - t_n$$

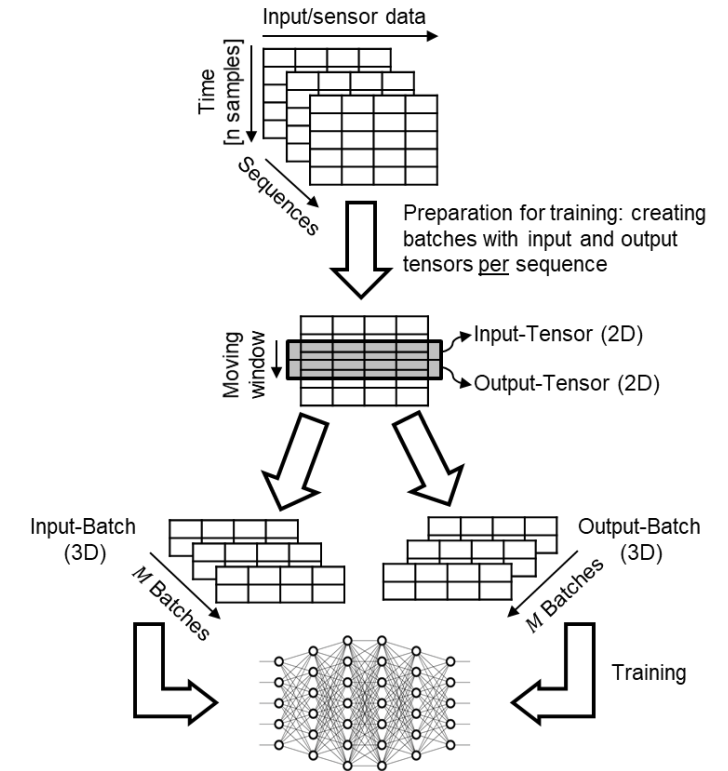
Short cut	Name, Description
RUL	Remaining Useful Life, Amount auf time left before system health fails below a defined failure threshold
EOL	End of Life, Time index of actual end of life or time of failure
EOP, t_{max}	End of Prediction, max. time index of the prediction horizon

Remaining Useful Life (RUL) of the cone forming pin (4/4)

Architecture of the autoencoder health estimation algorithm



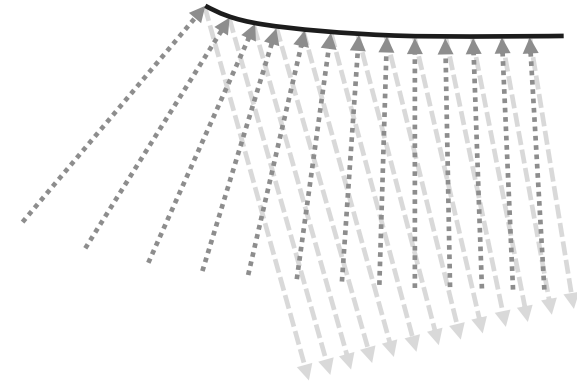
Data preparation for the training



Time resolution warping (1/5)



Beam path of the side mirror (top view)

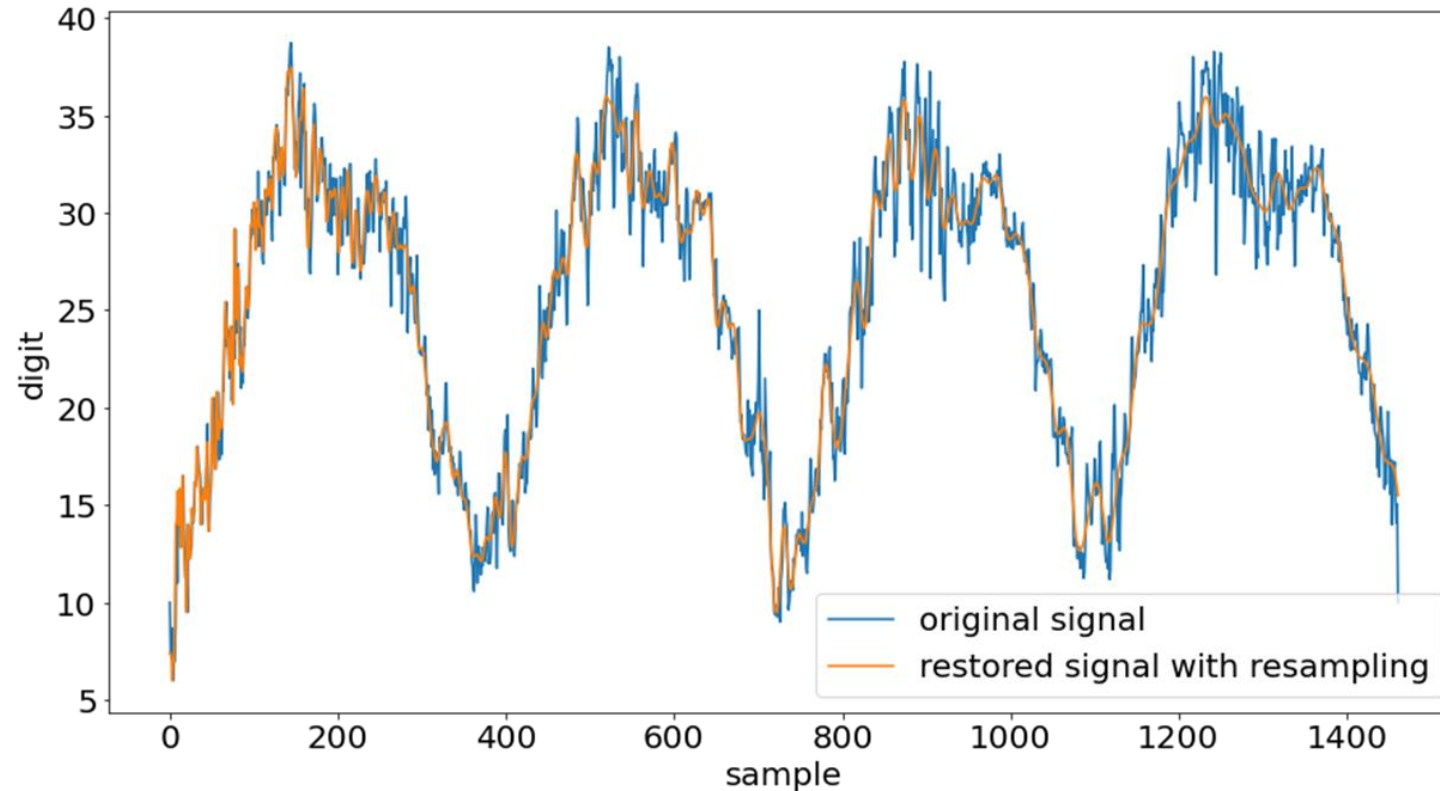


→ Focus is set to the relevant areas, other areas are compressed

Time resolution warping (2/5)

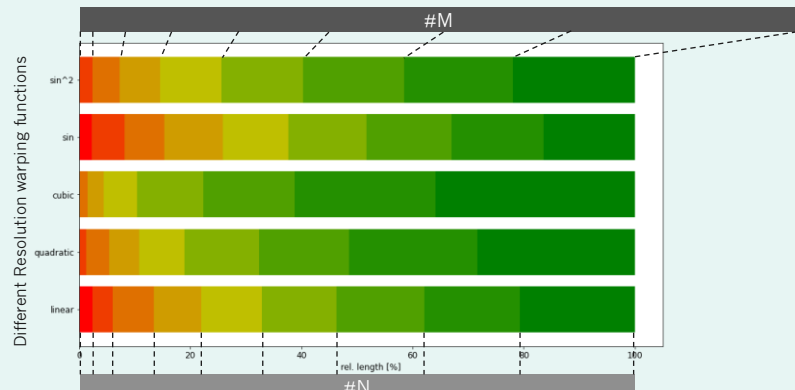
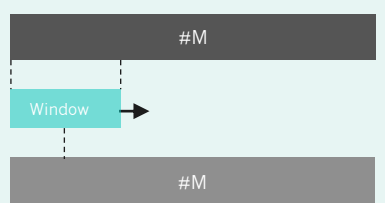
Example time series:

Comparison between original and restored signal starting at sample 0



Time resolution warping (3/5)

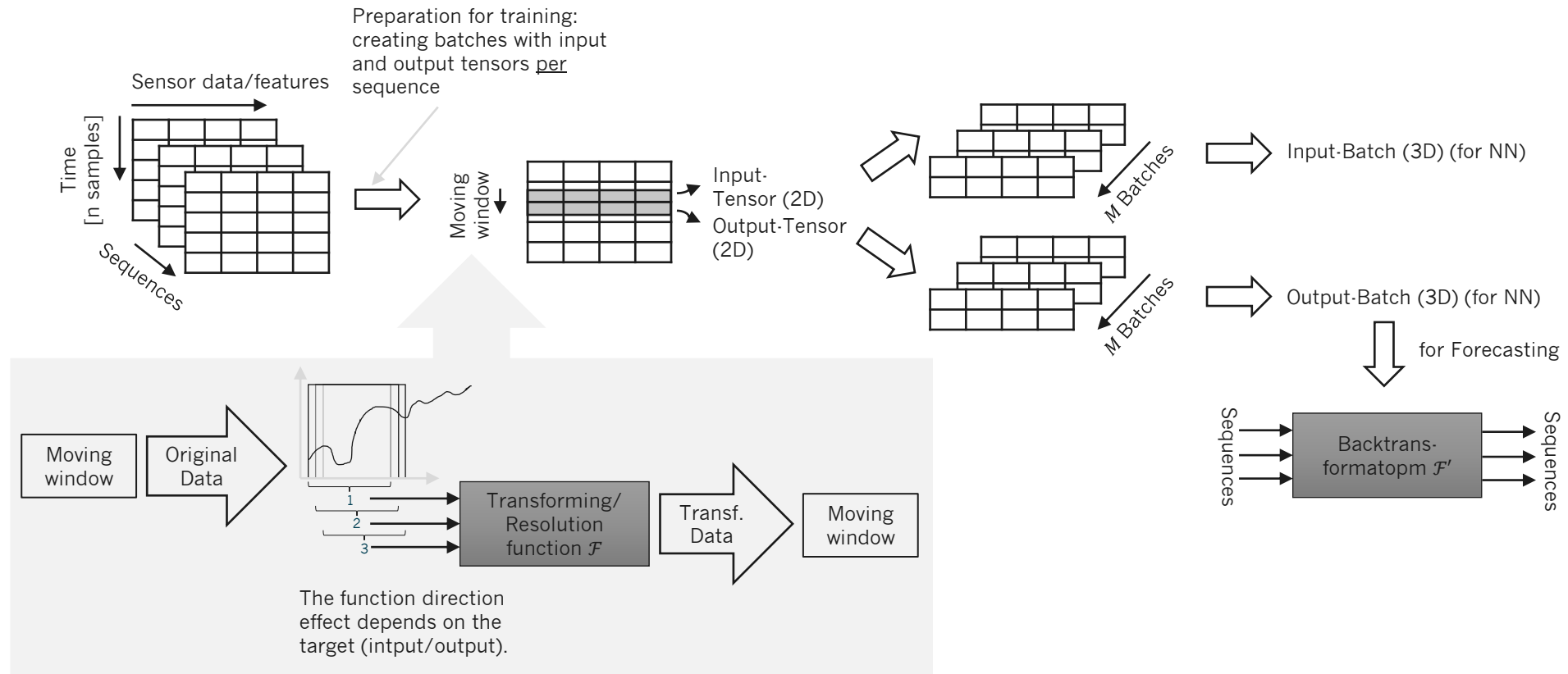
Comparison Temporal resolution warping vs SMA, EMA

Temporal resolution warping	SMA, EMA
Sliding window for filtering	
Time → Step 1: [Dropped data] [Input data] [Output data] Step 2: [Dropped data] [Input data] [Output data] Step 3: [Dropped data] [Input data] [Output data] Step 4: [Dropped data] [Input data] [Output data] Input M values are transformed to N values. Transformation:  The window size is a function of the distance to the current timestamp. Compared to EMA current values are considered more strongly.	Time → Step 1: [Dropped data] [Input data] [Output data] Step 2: [Dropped data] [Input data] [Output data] Step 3: [Dropped data] [Input data] [Output data] Step 4: [Dropped data] [Input data] [Output data] Input M values are transformed M values. Transformation: e.g. center oriented 

Time resolution warping (4/5)

Using temporal resolution warping for time series forecasts

- Using this compressing technique to obtain reliable on a rather long-term forecasting horizon
- Without increasing the complexity of the network
- Temporal resolution warping can be used for input and/or output applicable



Time resolution warping (5/5)

Evaluation of the calculation vs. ML model complexity

- The effectiveness in terms of the trade-off between time compressing and forecast accuracy is evaluated for FNNs and CNNs
- Evaluation on different real-world datasets with different characteristics



Conclusion

- We use the resolution factor to enhance the prediction horizon of the NN without increasing the size of it.
- Temporal resolution warping can be used as pre-processing to reduce computation time of forecasting
 - By 27% for small FNNs and 26% for small CNNs

Deriving a Wear Metric without Ground Truth

Determine Wear of Print Screen

Print Screen wears out during printing

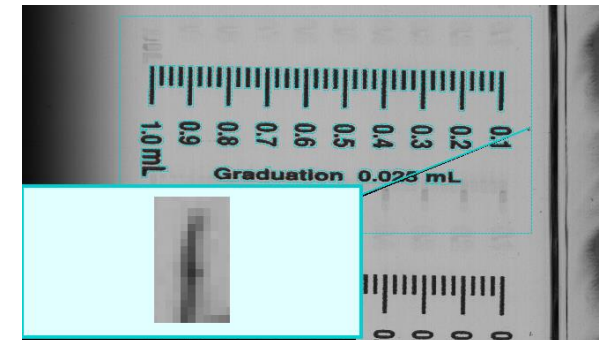
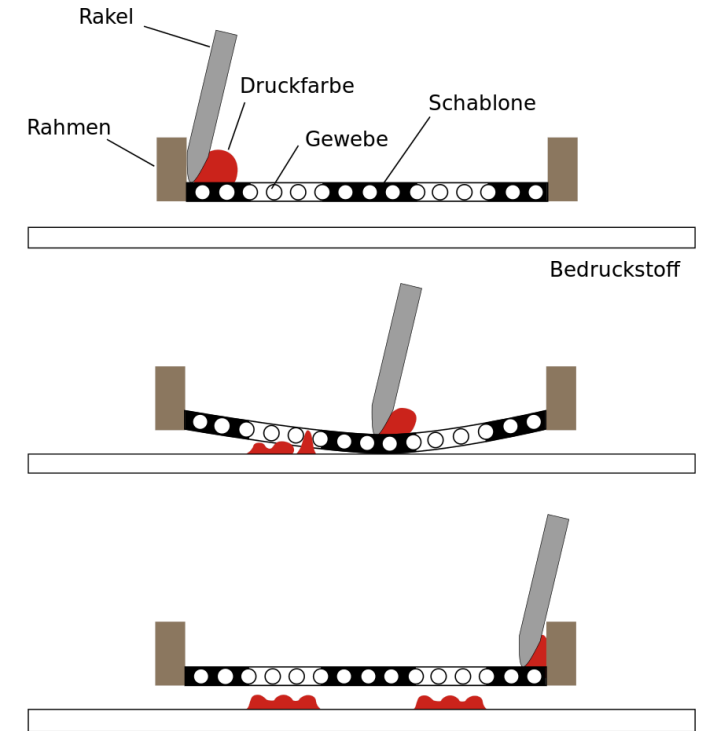
Question: when would be the best time to change it?

- too early: high costs and down time
- too late: rejected parts, ripped print screen

Problem: no measure of wear available – no ground truth

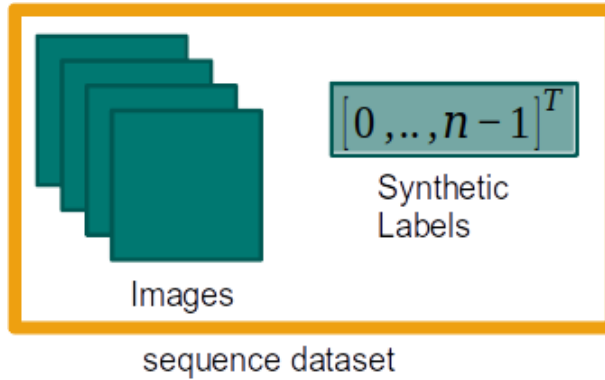
Idea: learn wear metric from inspection images automatically

- data available: number of prints done by print screen
- Compare prints of fresh screen with prints from worn out screen
- But: time of print screen changes not (reliably) available

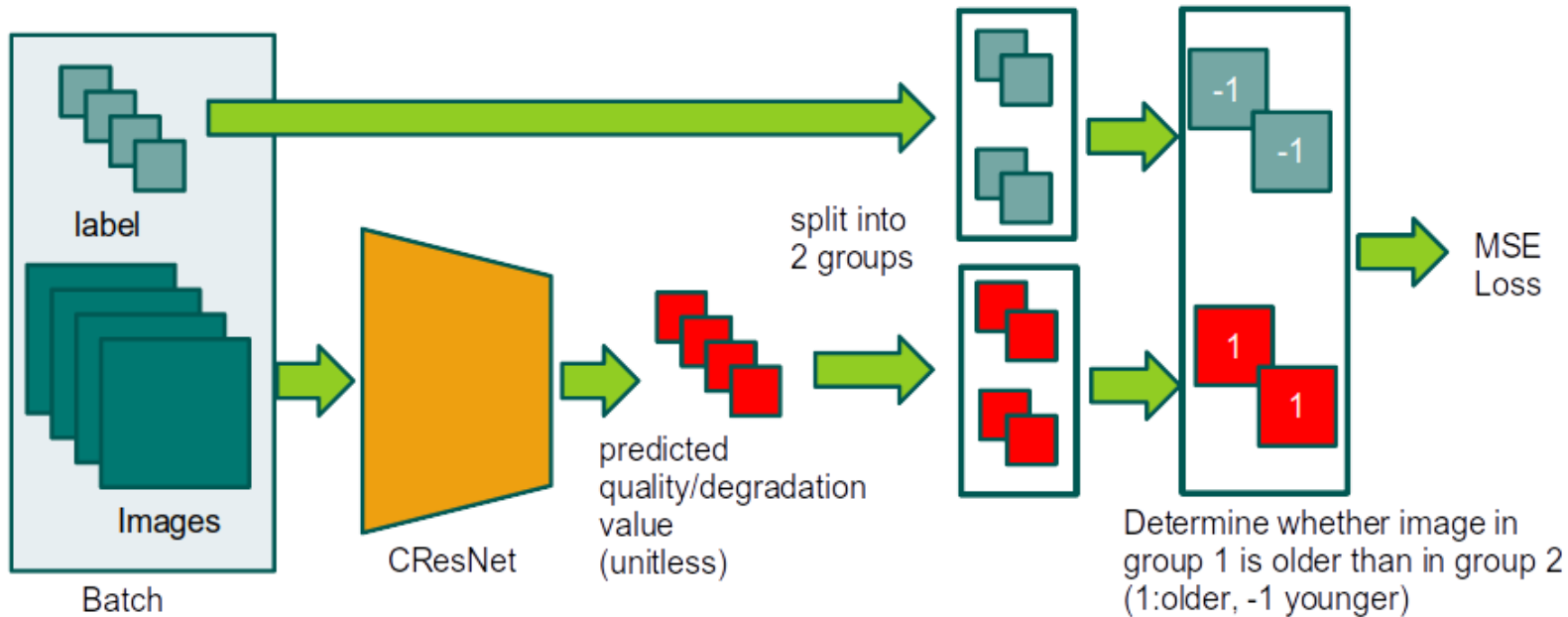


Deriving a Wear Metric without Ground Truth

Learning from Comparing

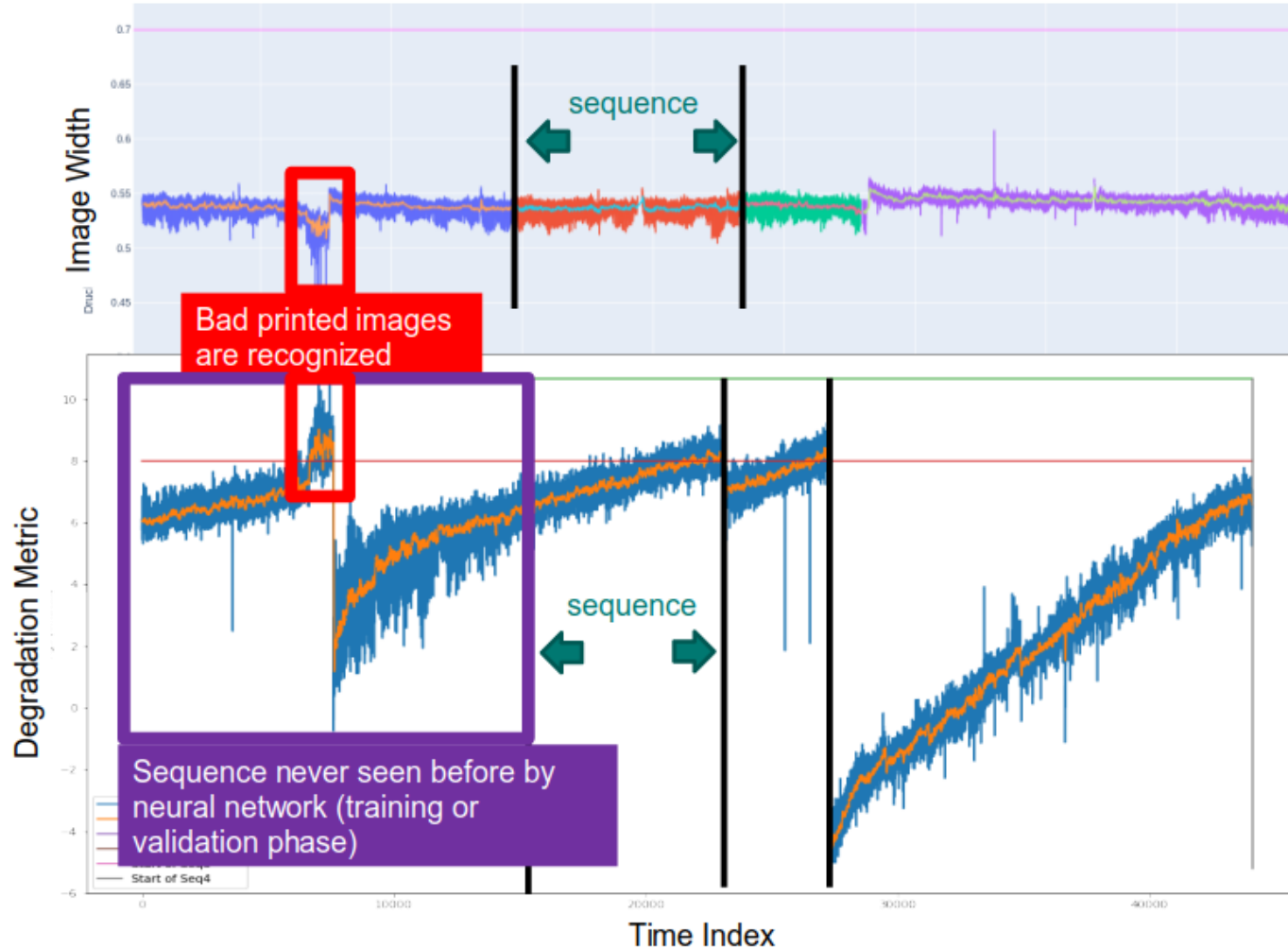


- Images from the same sequence are compared to enable neural network to learn degradation metric.
- Loss Hard Hyperbolic Tangent function and MSE are used only during training
- For deployment, degradation value can be inferred from each image



Deriving a Wear Metric without Ground Truth

Promising Results

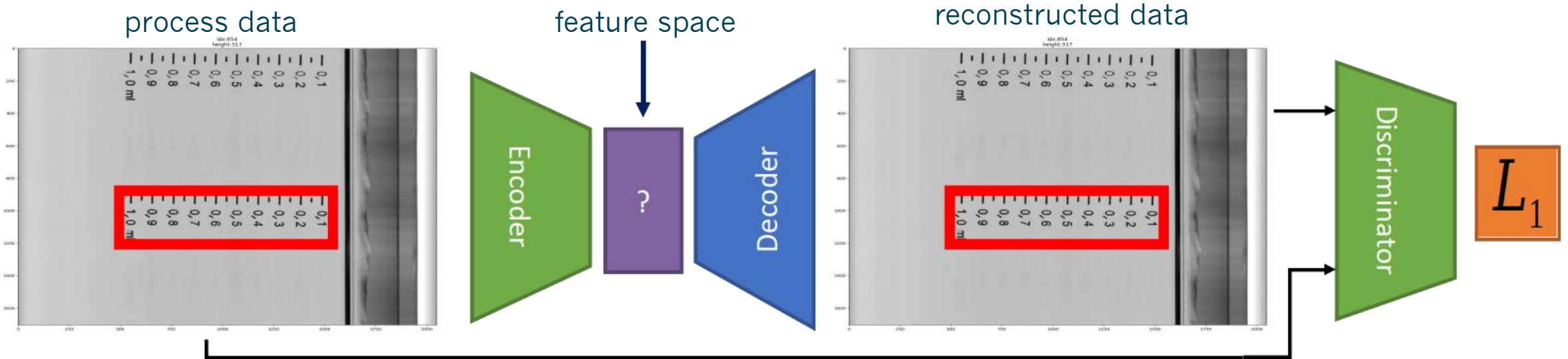


Practical issues:

- live image data needed => huge data load
- retrieval /storing of images was not implemented => new API for access
- print screen change data not available => added door switch to machine
- synchronization of asynchronous datagrams

Explainability

What did we Learn?

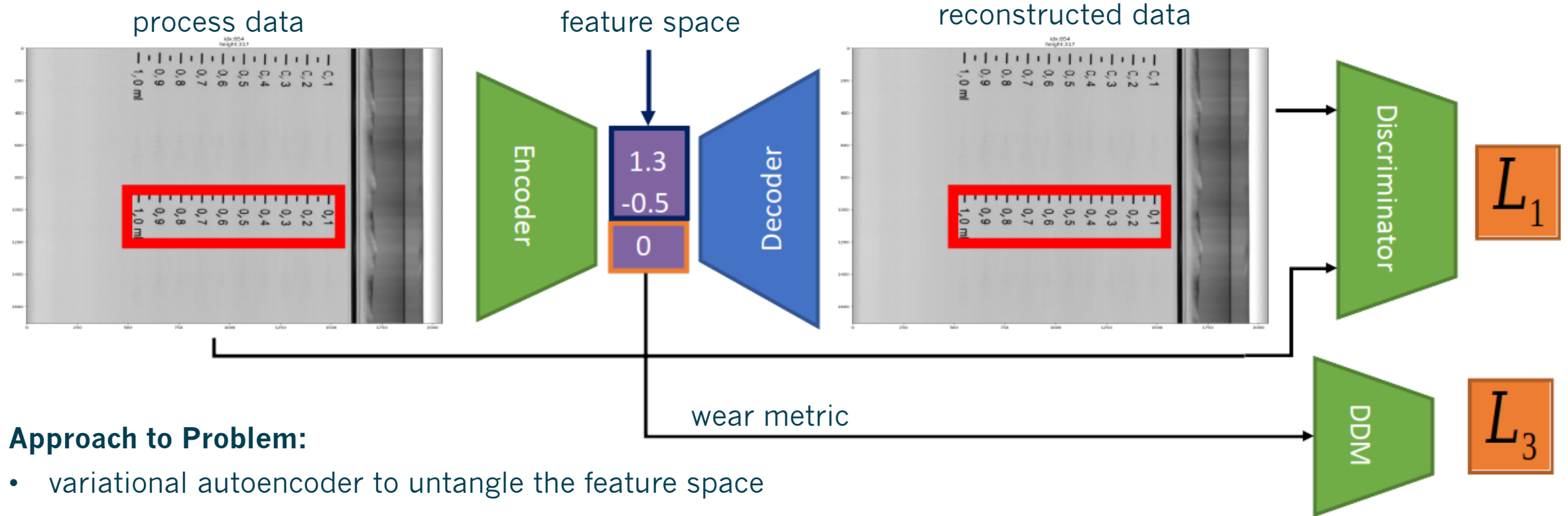


Problems of Neural Networks:

- feature space is a black box
- information of interest is contained but hidden inside

Explainability

What did we Learn?



Approach to Problem:

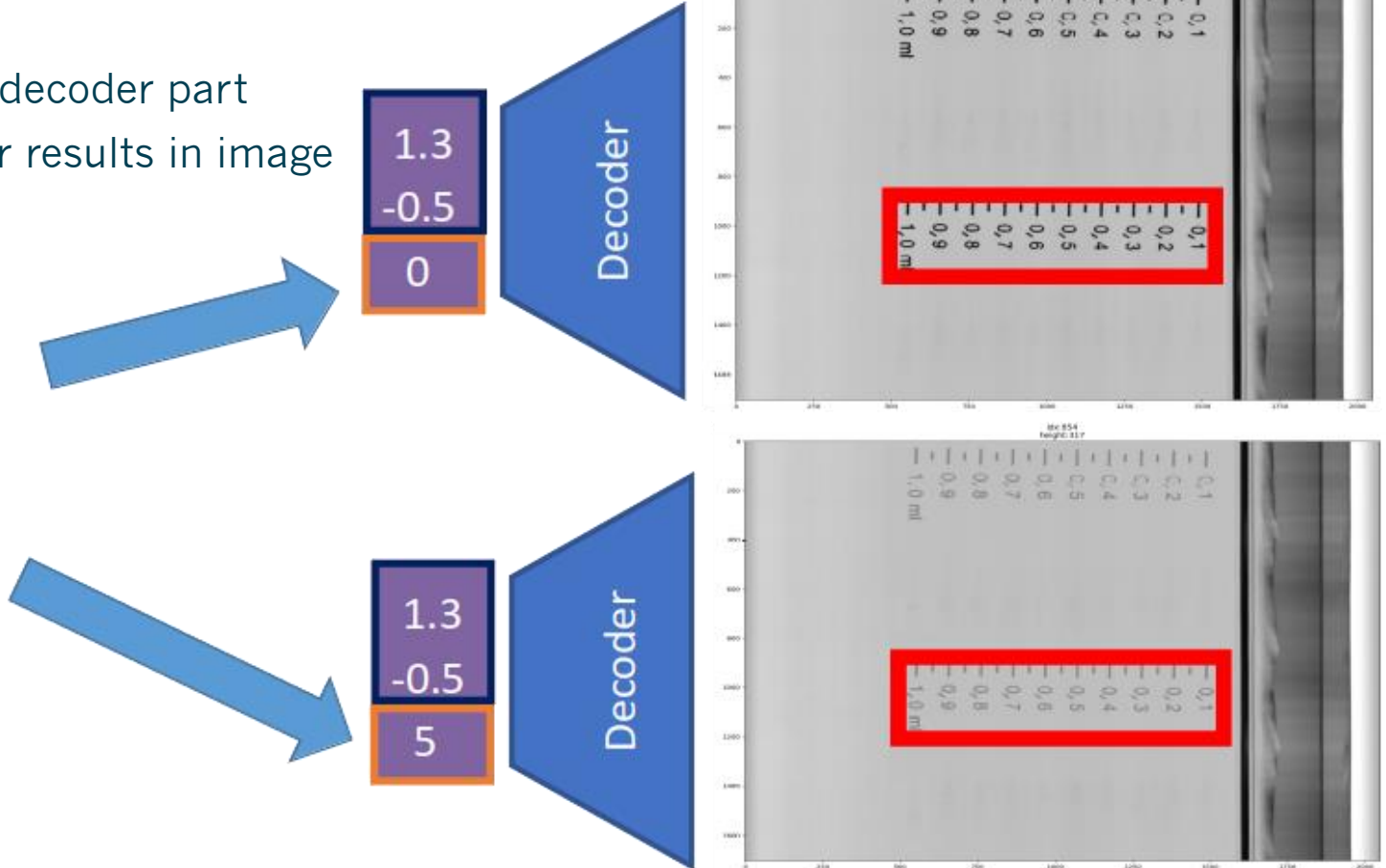
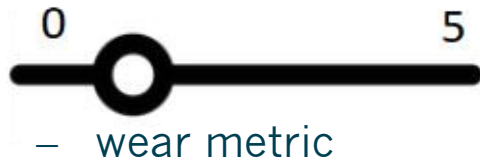
- variational autoencoder to untangle the feature space
- information of interest is now contained in single feature vector entries

Explainability

What did we Learn? Visualization of Learned Knowledge

Benefit:

- knowledge can be visualized using the decoder part
- forcing specific entries in feature vector results in image

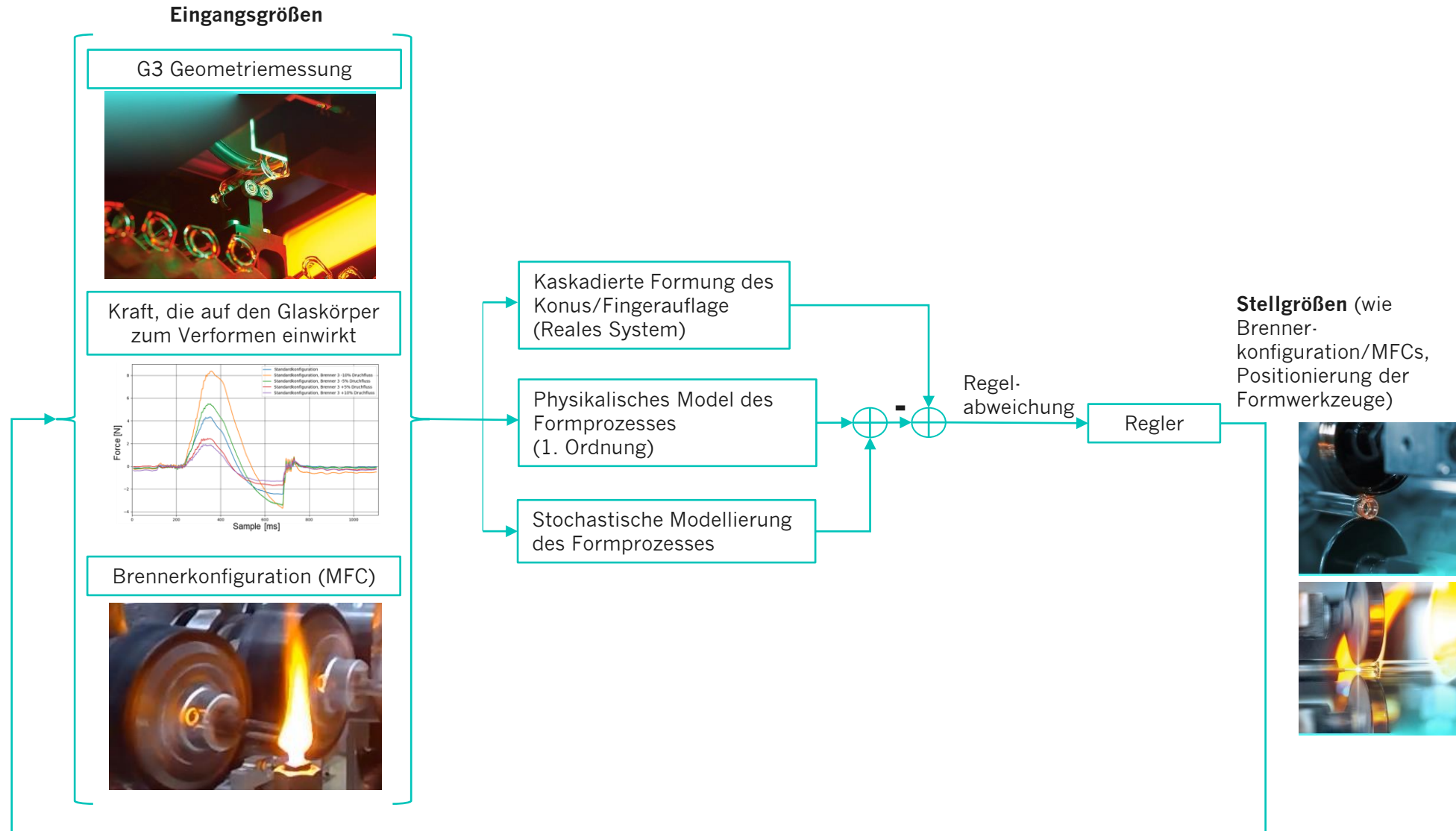


Publications for a Deep Dive

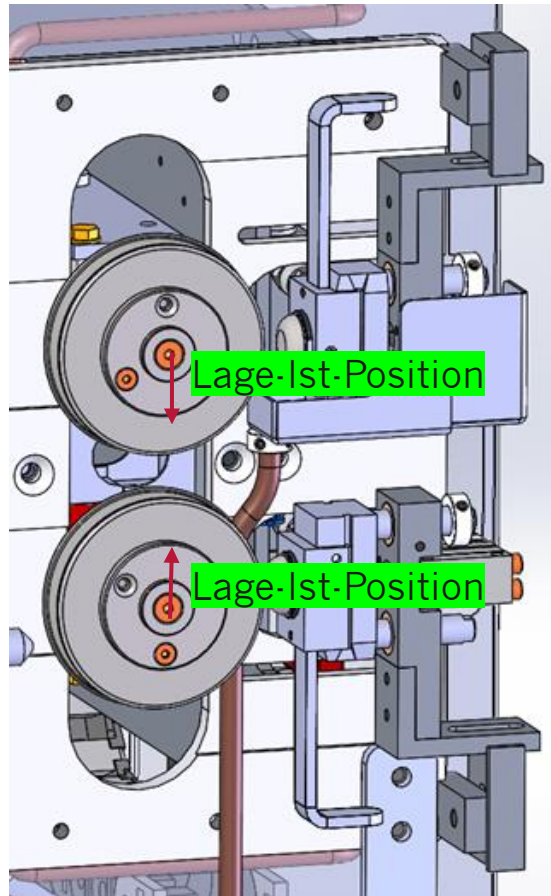
Conference	Title	Abstract
<i>Procedia CIRP, 2020</i>	Estimation of unknown system states based on an adaptive neural network and Kalman filter (Kellermann, C.; Ostermann, J.)	In the field of industry 4.0 the number of sensors increases steadily. The sensor data is often used for system observation and estimation of the system parameters. Typically, Kalman filtering is used for determination of the internal system parameters. Their accuracy and robustness depends on the system knowledge, which is described by differential equations. We propose a self-configurable filter (FNN-EKF) which estimates the internal system behavior without knowledge of the differential equations and the noise power. Our filter is based on Kalman filtering [...]. Applications are denoising sensor data or time series. Several bouncing ball simulations are realized to compare the estimation performance of the Extended Kalman Filter to the presented FNN-EKF.
<i>IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), 2021</i>	Introduction to an Adaptive Remaining Useful Life Prediction for forming tools (Kellermann, C.; Adhisantoso, Y. G.; Neumann, E.; Munderloh, M.; Ostermann, J.)	As key components in the field of industry 4.0, data of sensors is often used for checking and observing the quality of subsystems. [...] In this paper a system based on an autoencoder alike structure to forecast the deterioration of components is introduced. It is capable to predict the RUL based on the historical stress and usage conditions and identify anomalies like occurring faults by predicting the future with the encoder part, projecting it backwards with the decoder part, and then comparing it with the original data. The degradation forecast is estimated with respect to direct measurable parameters and not using a virtual health index. Our approach estimates the RUL on limited and noisy data and does not require knowledge of the true RUL. With the proposed setup our model is scalable to other production line configurations and product derivatives with different given production or quality thresholds without the need of a new training. [...]
International Symposium on Computer Science and Intelligent Control (ISCSIC), 2021	A new preprocessing approach to reduce computational complexity for time series forecasting with neuronal networks: Temporal resolution warping (Kellermann, C.; Neumann, E.; Ostermann, J.)	In modern manufacturing environments huge amount of sensor data of machines have to be analyzed in the time domain. Applications for process control are to observe the stability, to predict behavior of mechanical components or to detect abnormal behavior of the manufacturing process. For that, time series forecasting is important to make manual or automated decisions. In this work, we introduce a preprocess method which we call “temporal resolution warping” (TRW). It is used for signal pre- and post-processing before and after applying to the neural network. Thus, the computation complexity of the used network is reduced by compressing the time series in a certain way. We will show the computation reduction capability of our approach. For verification of our approach feed forward and convolution neural networks with residual layers are used to forecast reference time series of different applications. We will demonstrate that the training is speed up more than 10% by with our pre- and post-processing technique.

Digitaler Zwilling der Glasformung

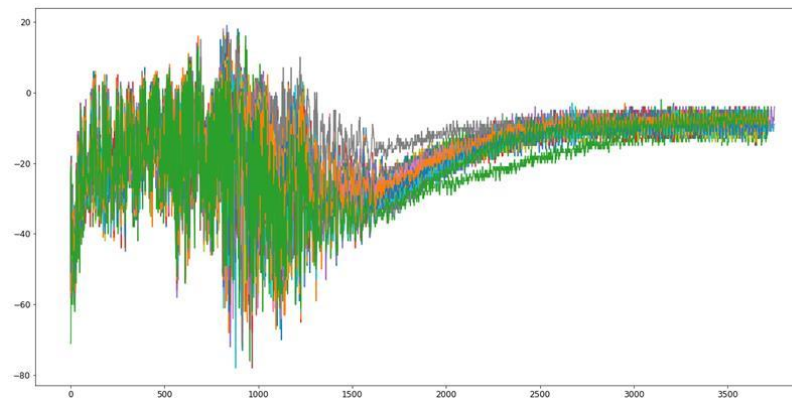
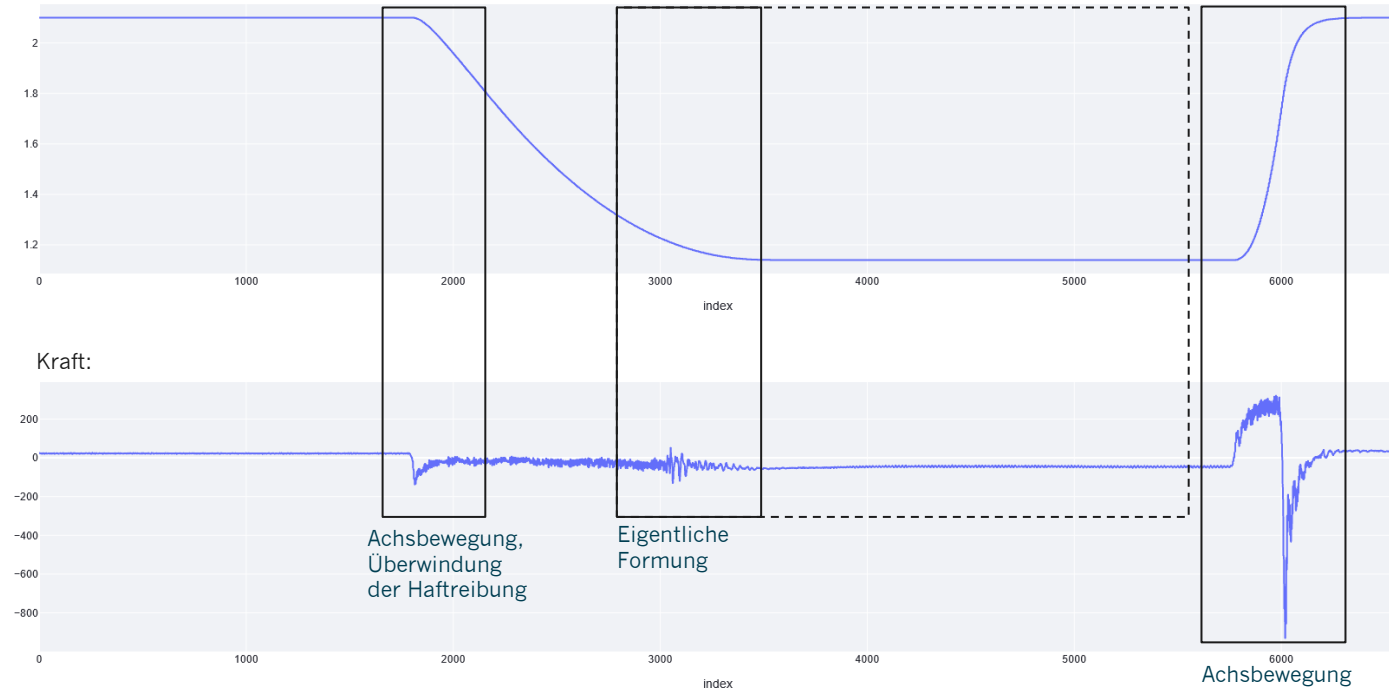
Digitaler Zwilling



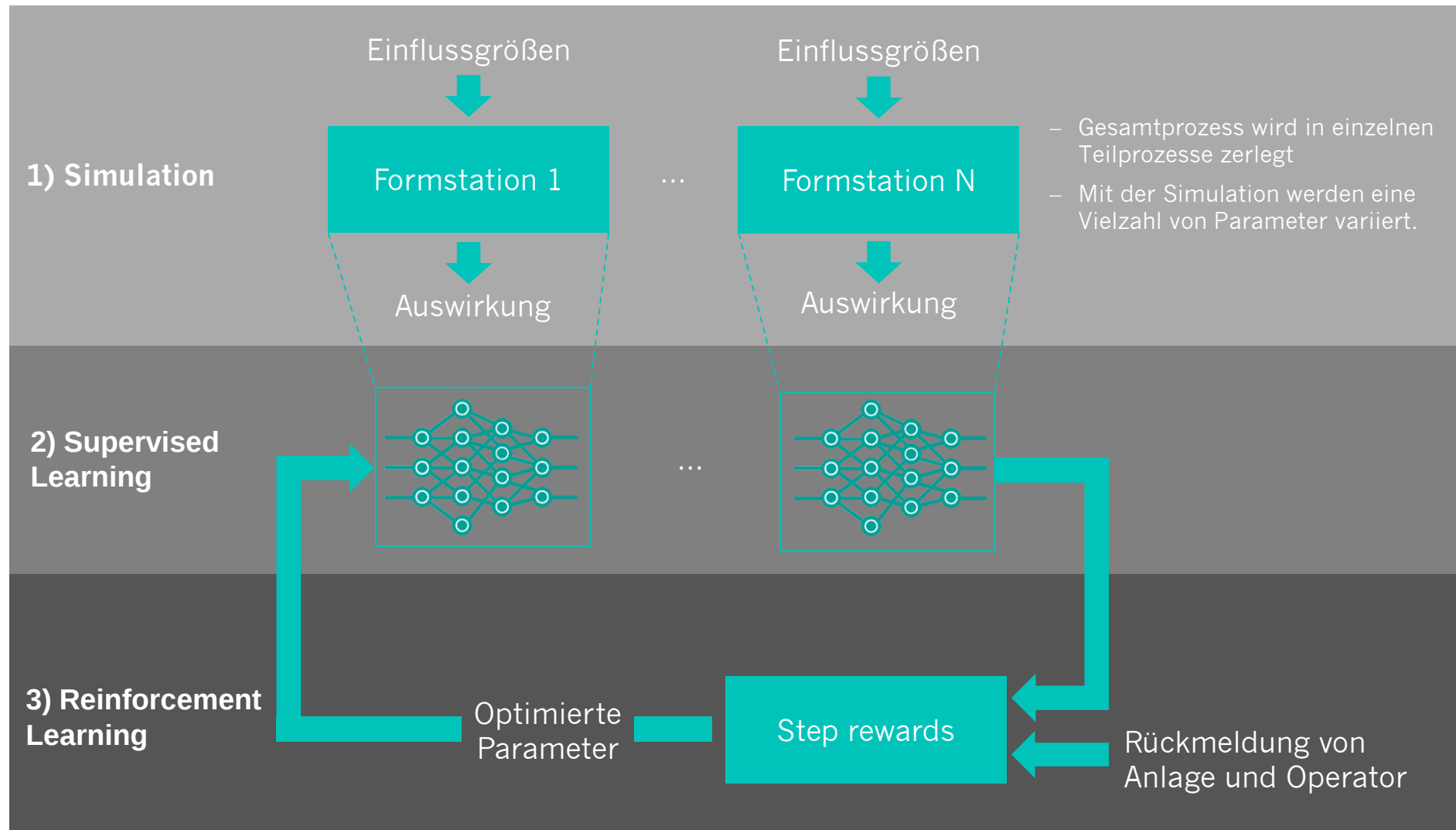
Digitaler Zwilling



Lage-Ist-Position:



Digitaler Zwilling – Grober Aufbau



Q&A Session 2

Pause

5:00

Expertengespräch: Was sagen die Experten zu KI in der Produktion?

Moderator: Prof. Ostermann

Teilnehmer:

- Matthias Hellmich
- Christoph Kellermann
- Marco Munderloh

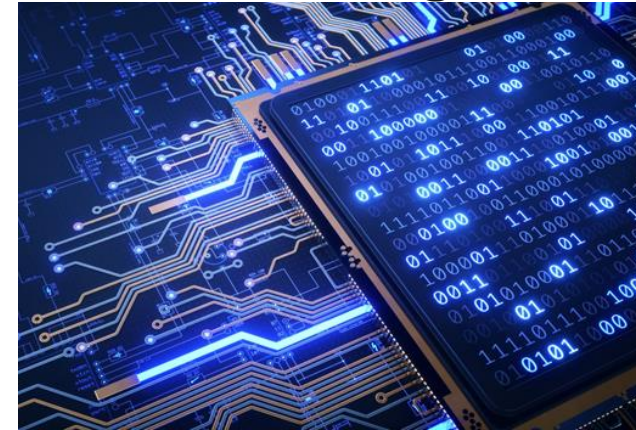
Zusammenfassung und Ausblick

AI Capabilities in the field of production @ Gerresheimer

Real world – real machine



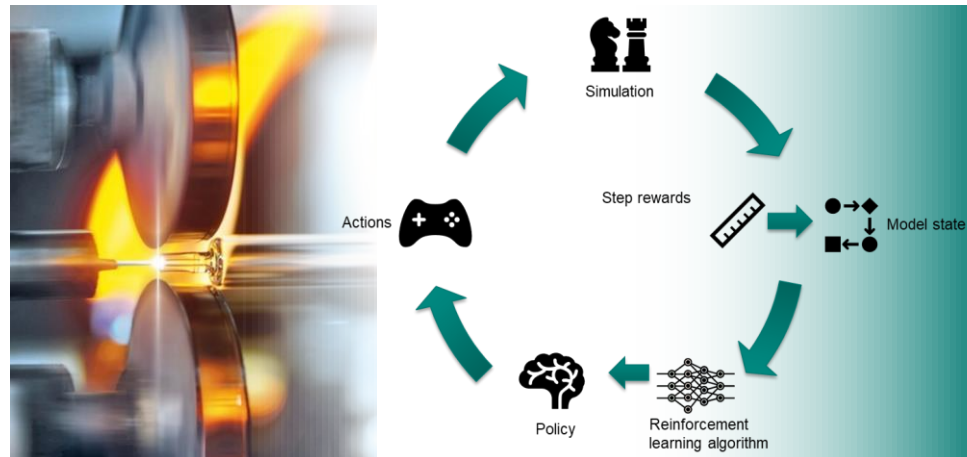
Virtual world – digital twin



Realtime simulation – Close loop control



Merging the real world with the virtual world for **optimal parameter settings**.



Advantages of highly automatic production:

- Fast ramp up
- Minimal scrap
- Increase machine availability

Werde Teil unseres Teams!

Wir suchen...

- Elektrotechnik mit Schwerpunkt optische Messsysteme
- Abschlussarbeiten (Bachelor, Master)
 - Maschinenbau
 - Elektrotechnik
 - Informatik
- Praxisintegriertes Studium Bachelor of Engineering (m/w/d) mit Fachrichtung Maschinenbau & Elektrotechnik
- Initiativbewerbung





IIP-Ecosphere

Safe the Date!

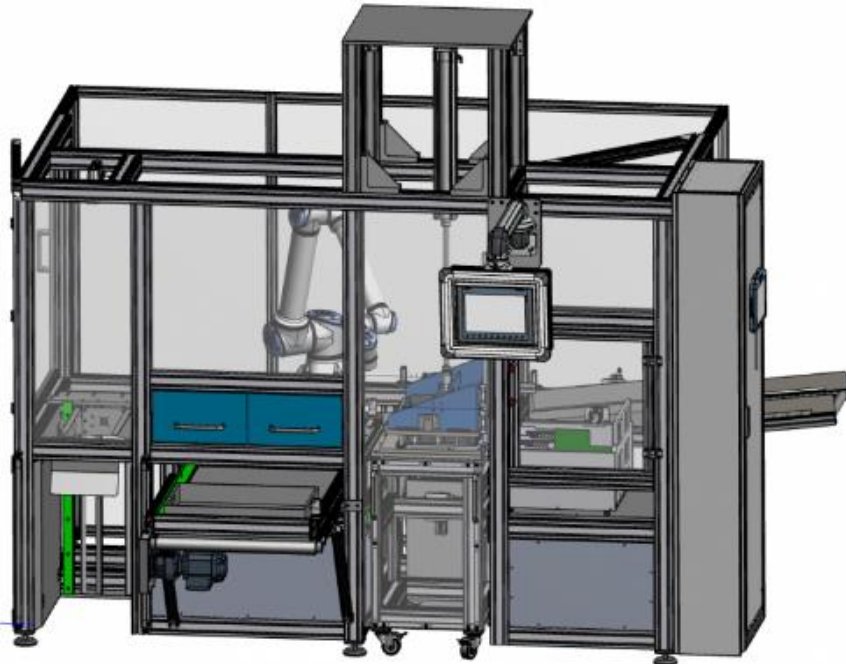


2. Werkstattgespräch mit Sennheiser

am 22. oder 23. März 2022

- Autonome Roboterzelle zur Endprüfung von Platinen
- KI zur Erkennung von Fehlern und Pseudofehlern

Alle Infos über unsere Newskanäle!



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Offene Fragen (1/2)

Wie werden Use Cases identifiziert?

Basierend auf ersten Einschätzungen der Fachabteilungen wie mechanischer und elektrischer Konstruktion werden Hypothesen formuliert. In ersten Prototypen wird dann die Umsetzung getestet und anschließend an Hand von Punkten wie Aufwand/Kosten, tech. Schwierigkeit und Nutzen bewertet. Nur Use Cases mit den vielversprechendsten Prognosen werden umgesetzt.

Wie tief ist Ihre Wertschöpfung in der Softwareentwicklung?

Wir arbeiten mit einem breit aufgestelltem Team Softwareentwicklern an der Lösungsfindung. Dazu gehören Experten, die sich mit BUS-Systemen und hardwarenahen Protokollen im Industrieumfeld auskennen bis hin zu Datenbankexperten und Applikationsentwicklern. D.h. wir stellen dadurch eine tiefe Wertschöpfung für den Bereich der Datenakquise und Datenverarbeitung dar. Hingegen greifen wir auf gängige Visualisierungsframeworks mit für uns geringer Wertschöpfung zurück. Grundlagenentwicklungen werden mit Universitäten wie zum Beispiel im IIP-Projekt geschaffen.

Offene Fragen (2/2)

Wie sind Sie mit Zeitverläufen in den Eingangsdaten in Kombination mit statischen Werten umgegangen?

Statische Werte wie Maschinenparameter werden nur gelegentlich verändert, haben aber einen durchaus signifikanten Einfluss auf den Produktionsprozess. Aus diesem Grund werden sie als Zeitreihe aufbereitet und den Netzen zugeführt. D.h. synchrone Produktionsdaten, die individuell für jedes Fertigungsteil sind, werden mit den asynchronen Maschinenparametern oder Maschinenbediener-Eingaben als Zeitreihe vereinigt.

Sind die Modelle, die beim digitalen Zwilling verwendet werden, übertragbar zwischen unterschiedlichen Maschinen oder müssen die Modelle neu angelernt werden?

Auf unseren Maschinen werden unterschiedliche Produkte mit unterschiedlichen Fertigungsanforderungen produziert. Einige Modelle sind nicht abhängig von Anlagen und Produktspezifikationen; diese müssen nur gelegentlich nachtrainiert werden um Parameterdrifts zu erlernen. Die Produktflexibilität erfordert allerdings bei einigen Modellen die Nutzung von Transfer-Learning.

Frage zum Thema Generalisierung: Lässt sich beispielsweise der Ansatz zur Verschleißbewertung als eine Art „Baustein“ übertragen auf andere Use Cases?

Einige Ansätze können auch als Baustein verwendet werden, da sie ein generelles technisches Problem adressieren. In unseren Publikationen haben wir die Generalisierung dieser Probleme gezeigt.

gerresheimer

innovating for a better life