Automated process monitoring in injection molding via representation learning and setpoint regression

SDS2024, May 31, 2024

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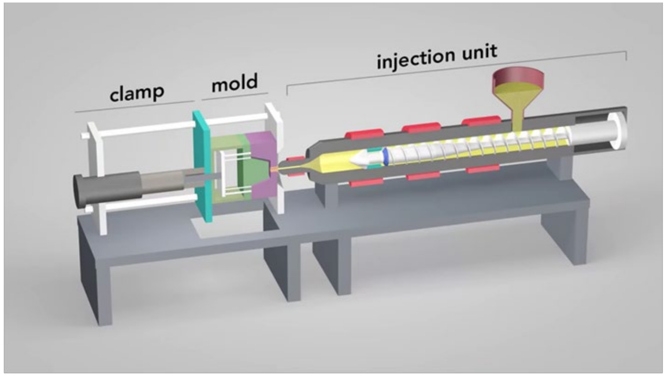
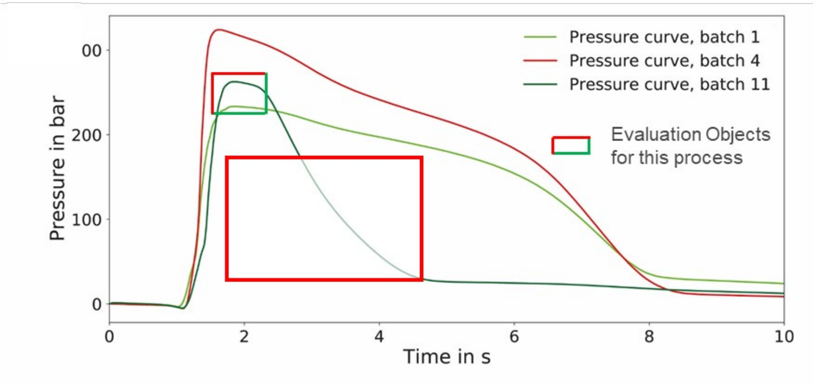
Outline

- Problem statement
- Concept underlying the proposed solution
- Methods and results
- Practical implementation

Problem statement:
State of the art quality control





-Optical inspection of every produced part is possible but extremely expensive

-The good news / state of the art: Process parameters and quality “fingerprint” are encoded in the cavity **pressure curve**

-Experts can then define Evaluation Objects (EOs) reflecting an anomaly-free operation

-In case of errors: experts are needed to find causes and remove them

Motivation: Personnel shortage determines lack of mandatory experts → Market for automation

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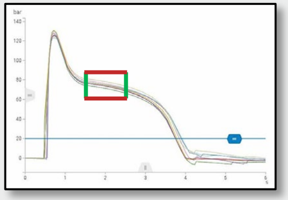
Well-trained operators / experts are requested for

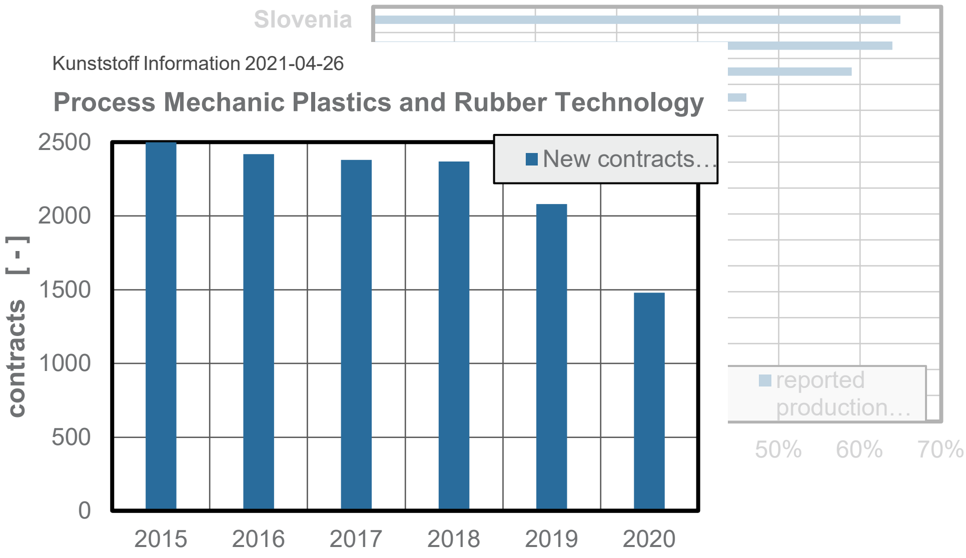
- drift detection
- error identification
- parameter adjustment



But:

- Increasing number of machines
- Decreasing number of capable operators

VDMA report, 2022:
EU 27: Shortage of labor in mechanical engineering



Kunststoff Information 2021-04-26

"Dramatic shortage of apprentices continues"

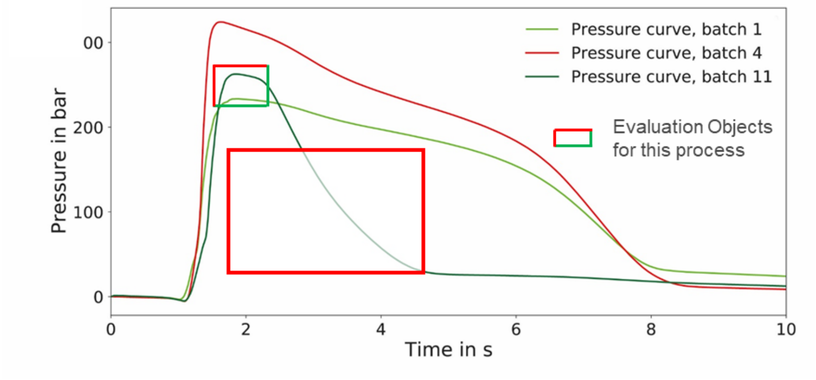
Kunststoff Information 2022-05-05
Ralf Olsen†, CEO Pro-K

"Interest in apprenticeships in the plastics sector continues to decline"

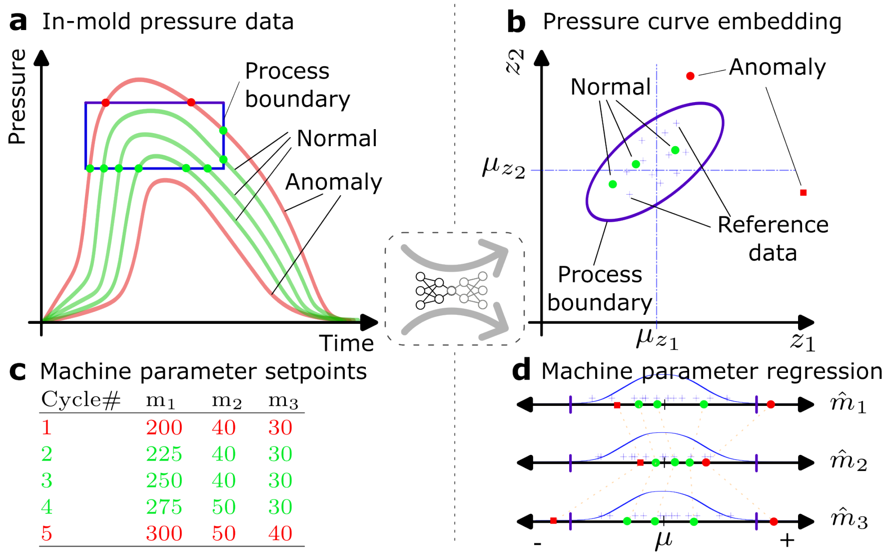
Kunststoff Information 2023-04-14
Ralf Olsen†, CEO Pro-K

Conceptualization of problem statement

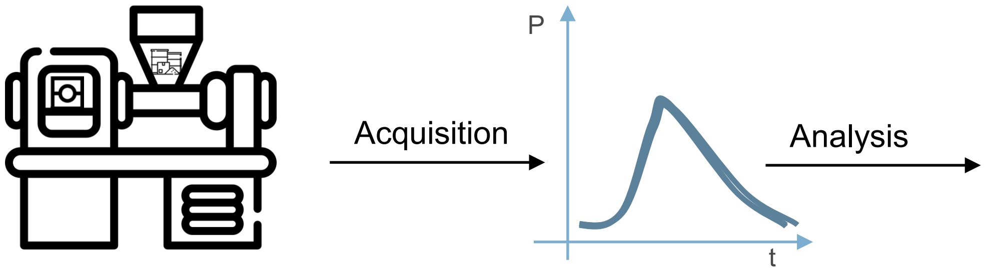
Manual process monitoring **without** root cause indication



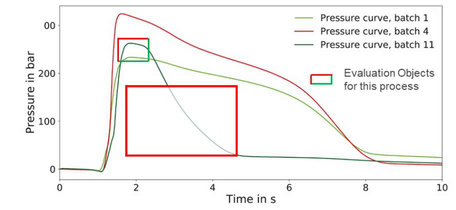
Automated process monitoring **with** root cause indication



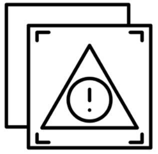
Conceptualization of problem statement
Phase I: Formalize the task



Manual approach with EO labels



AI Task I:
Anomaly detection



AI Task II:
Root cause indication

Conceptualization of problem statement
Phase II: Identify current limitations and challenges for new solution

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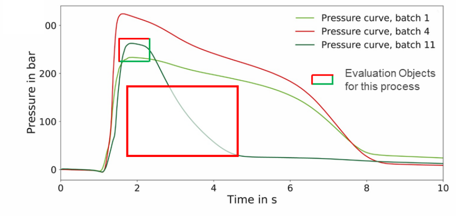
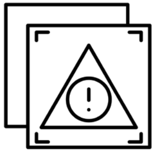
Manual approach with EO labels



- Requires specialized personal
- Implicit knowledge from experience
- Skill-dependent effectiveness
- Sensitivity and specificity indirectly controlled
- Low reproducibility

AI Task I: Anomaly detection



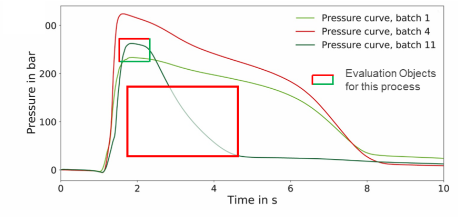
- It is *a priori* not known what is "normal"
- The system must cope with different data sources, parts, materials, etc.
- Anomalies/failures are rare
- No supervised training of the anomaly detection task possible

AI Task II: Root cause indication

- Anomalies are rare events and root cause is not recorded
- System must cope with different data sources, parts, materials, etc.
- No supervised training of the root cause indication task possible

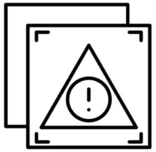
Conceptualization of problem statement
Phase III: Formulate principal solution

Manual approach
with EO labels



- **Operational bounds** set via EO labels
- Labels set based on experience
- Binary output
- **Sensitivity and specificity** implicitly controlled
- No root cause indication
- No way to account for or detect drifts

AI Task I:
Anomaly detection



- **Operational bounds** set in a data-driven way
- Continuous output related to **sensitivity and specificity**
- Direct control of **sensitivity and specificity**

AI Task II:
Root cause indication

- Expression of **interpretable** variables
- Link specific changes in variables **to specific root causes**

Conceptualization of problem statement
Phase IV: Draft specific solution

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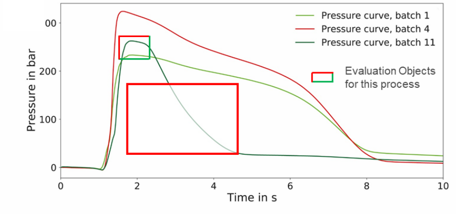
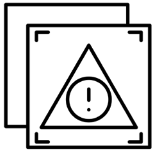
Manual approach
with EO labels



- Manually set control boxes (EO labels)
- Positive (must pass through) edge
- Negative (must not pass through) edge
- Trigger anomaly based on positive/negative rule

AI Task I:
Anomaly detection



- Map pressure curve into low dimensional space

➔ Representation learning leveraging historic data
- Compare the observed curve with that of the previous curves

➔ Parametric density estimation (calibration)
- Trigger anomaly based on configurable threshold

➔ Analytically derived false positive rate

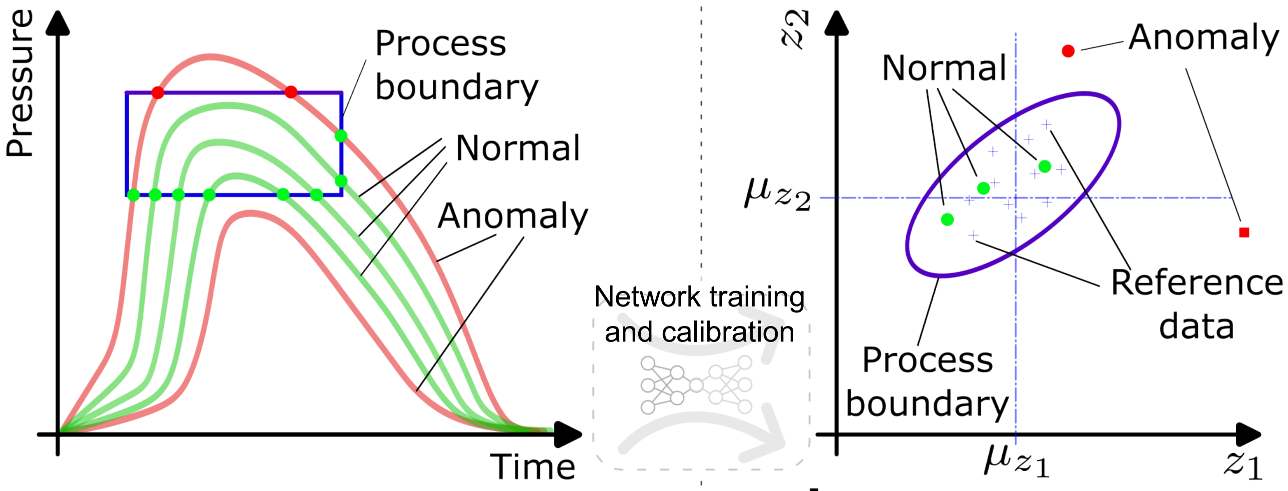
AI Task II:
Root cause indication

- Supervised prediction of external variables that can be controlled
- Acquire training data set with systematic design of experiments
- Use domain knowledge to link specific changes to possible causes

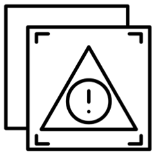
Conceptualization of problem statement
Overview

a In-mold pressure data

b Pressure curve embedding



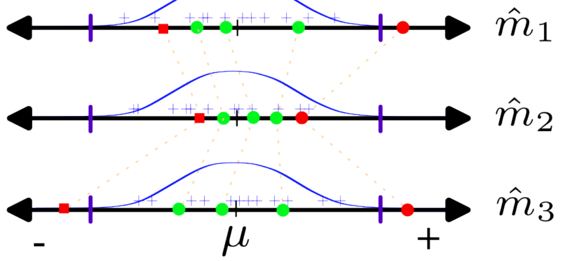
AI Task I:
Anomaly detection



c Machine parameter setpoints

Cycle#	m_1	m_2	m_3
1	200	40	30
2	225	40	30
3	250	40	30
4	275	50	30
5	300	50	40

d Machine parameter regression



AI Task II:
Root cause indication

Method

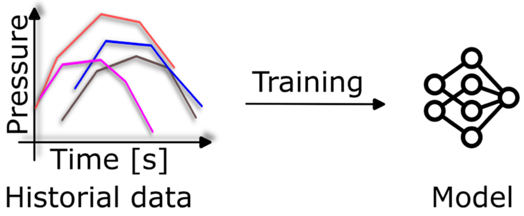
Off-line training phase

Dynamic calibration phase

Online monitoring phase

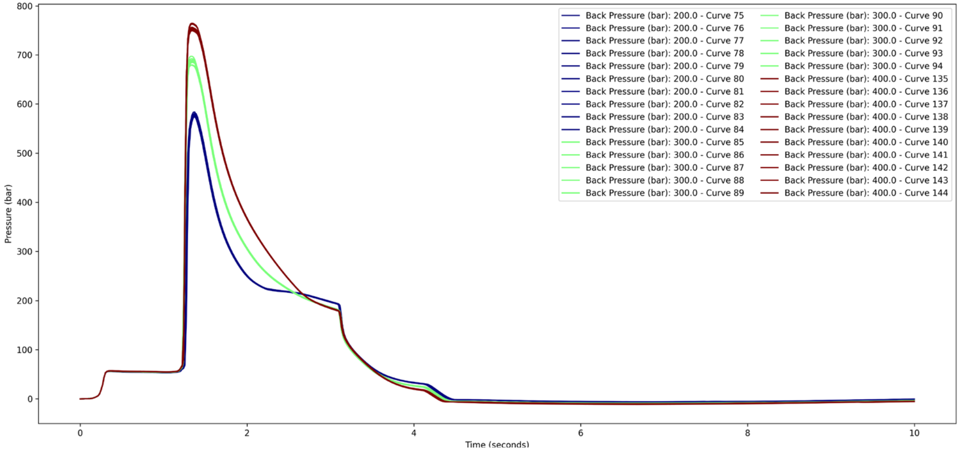
Method

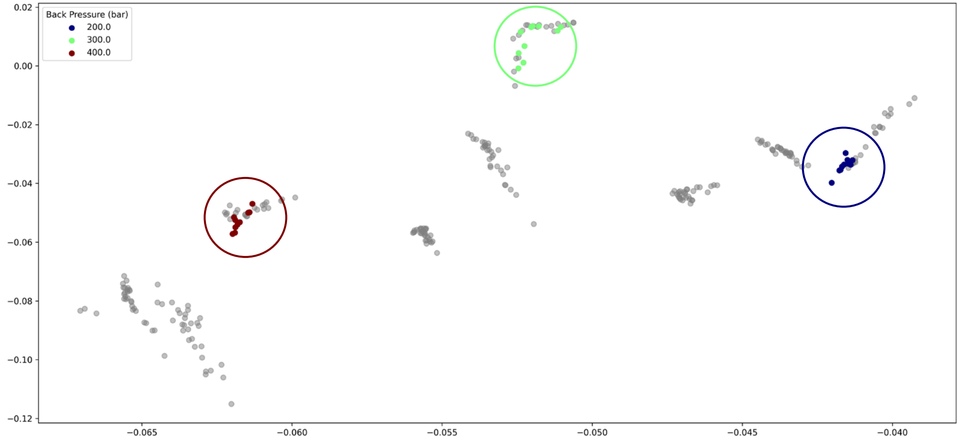
Off-line training phase



Learn representation of the pressure curves

Learn the representation of the pressure curves

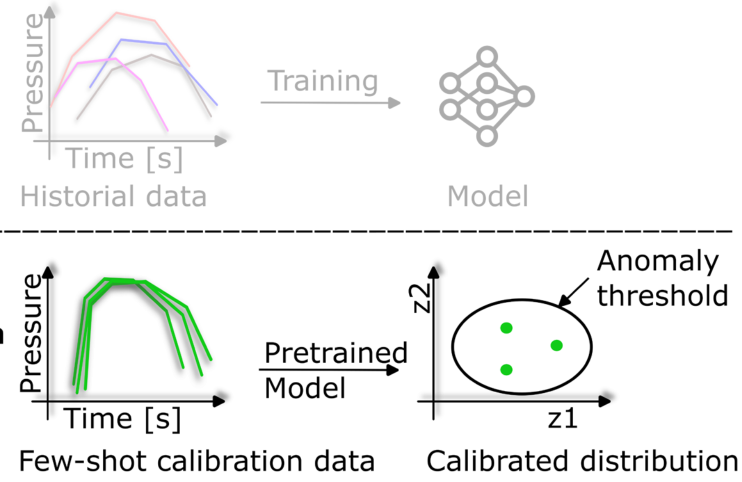




Method

Off-line training phase

Dynamic calibration phase



Learn representation of the pressure curves

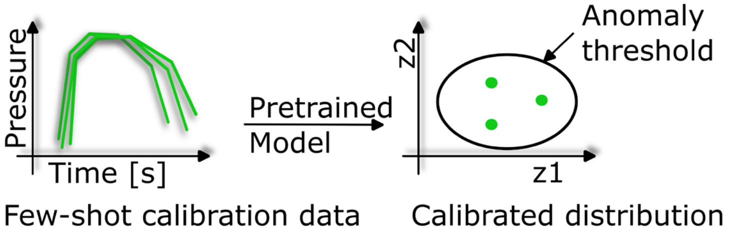
Set up the calibration process

Method

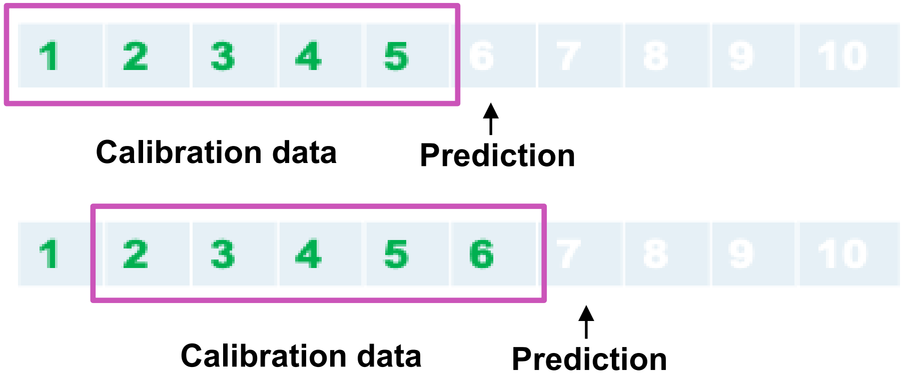
Off-line training phase

Learn representation of the pressure curves

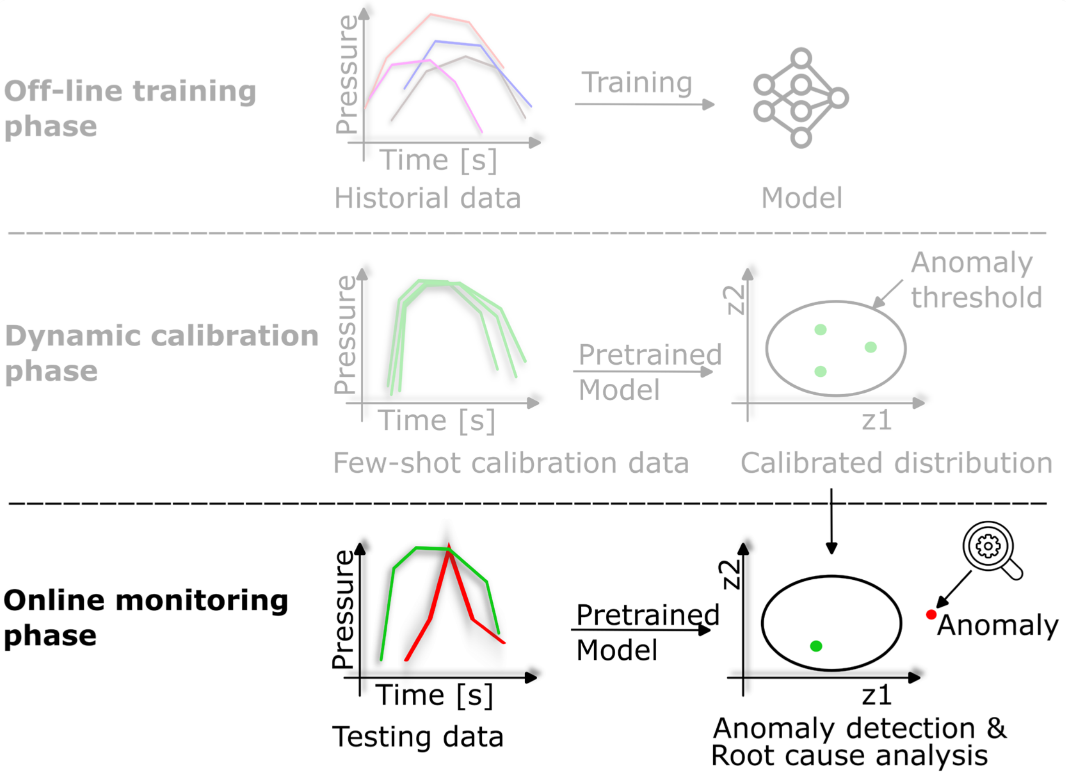
Dynamic calibration phase



Set up the dynamic calibration process



Method

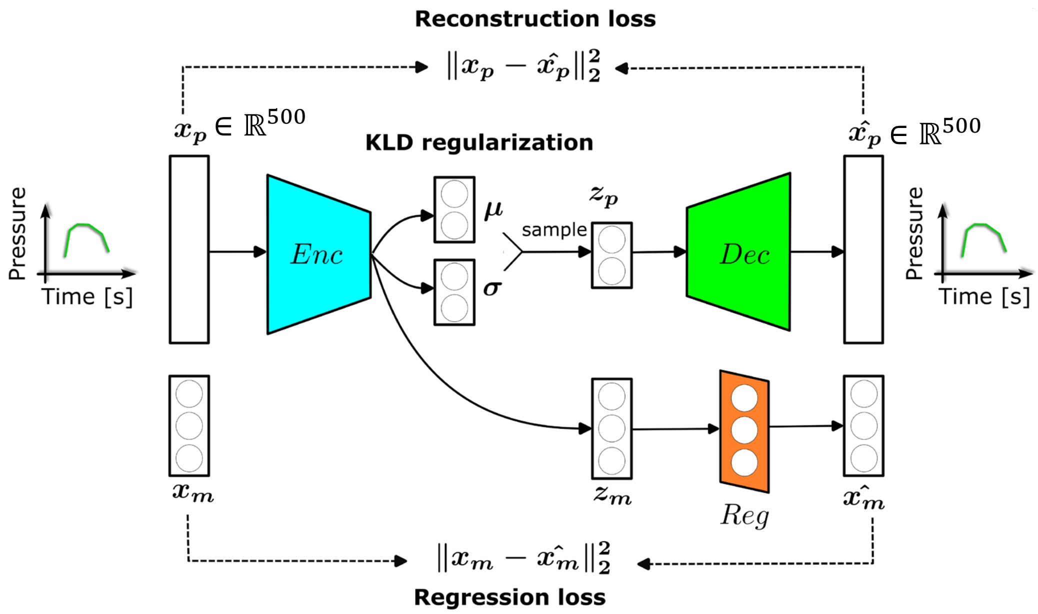


Learn representation of the pressure curves

Set up the calibration process

Anomaly detection process

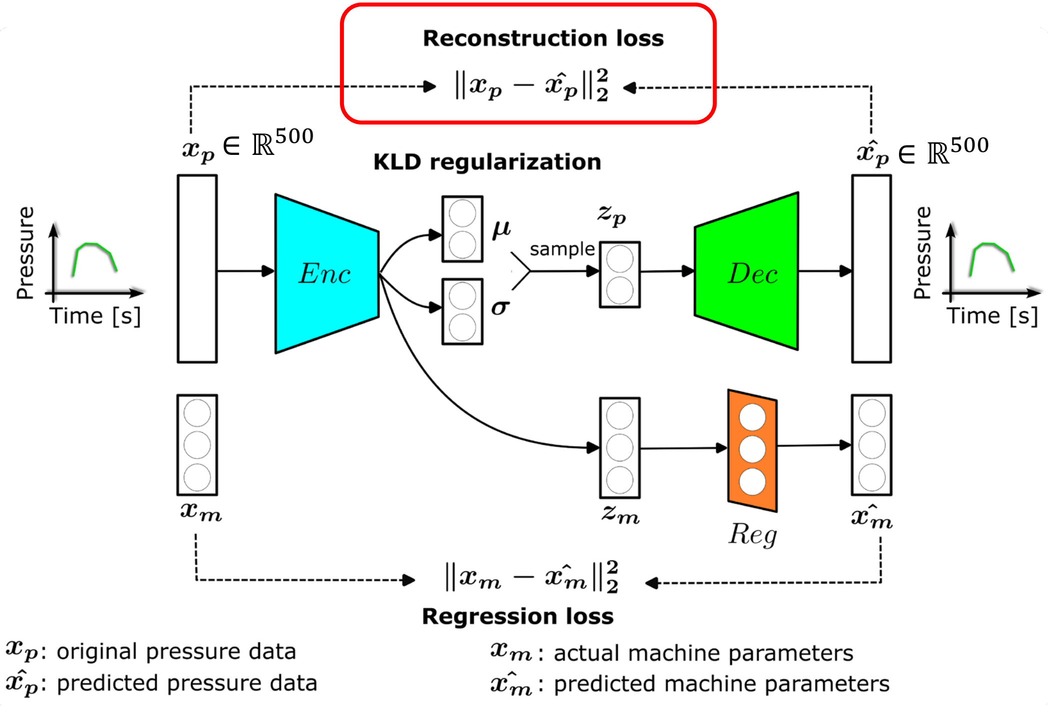
Deep Learning Model



x_p: original pressure data
$\hat{x_p}$: predicted pressure data

x_m : actual machine parameters
$\hat{x_m}$: predicted machine parameters

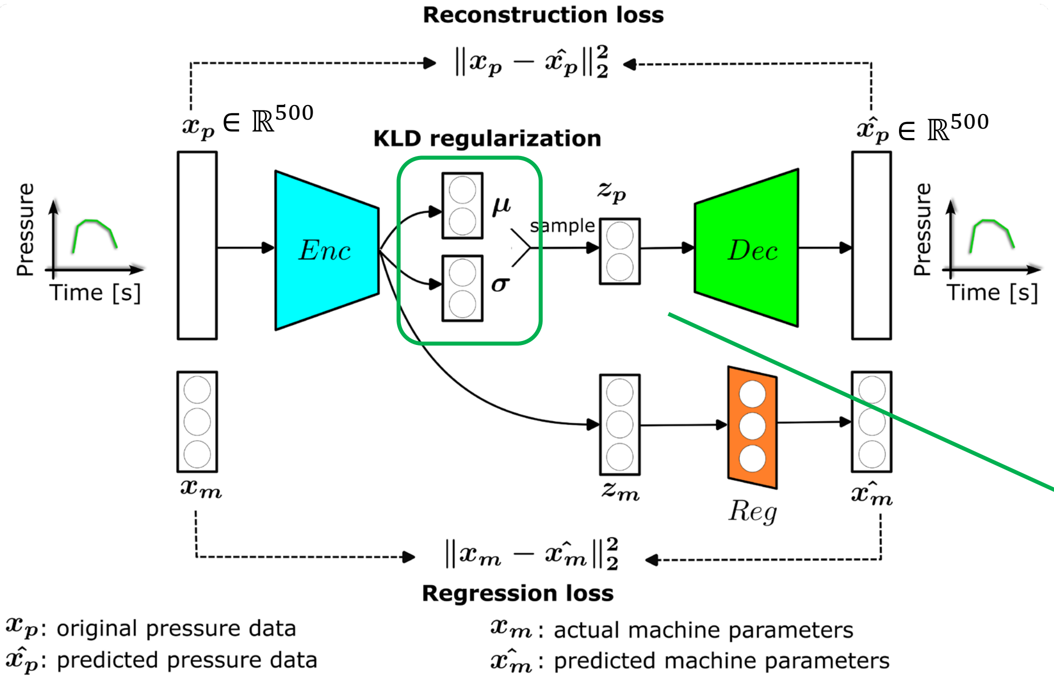
Deep Learning Model



Training:

- Reconstruction loss

Deep Learning Model



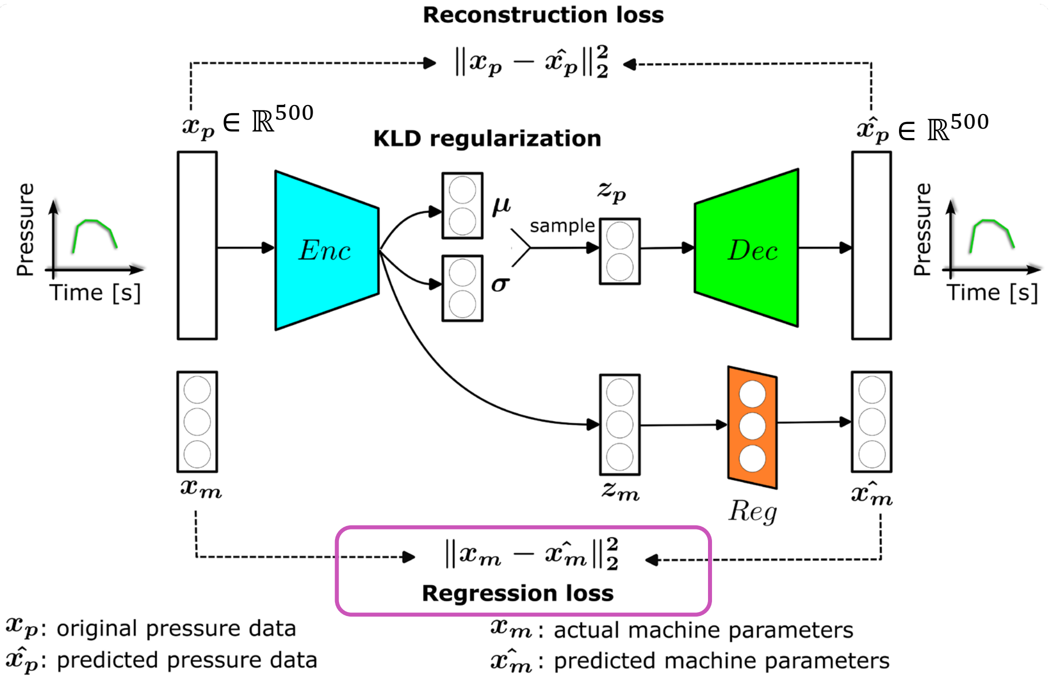
Training:

- Reconstruction loss
- KLD regularization

KLD: $D_{KL}(\mathcal{N}(\mu_x, \sigma_x) \parallel \mathcal{N}(\mathbf{0}, \mathbf{I}))$

- Similarity between standard Gaussian distribution and estimated distribution

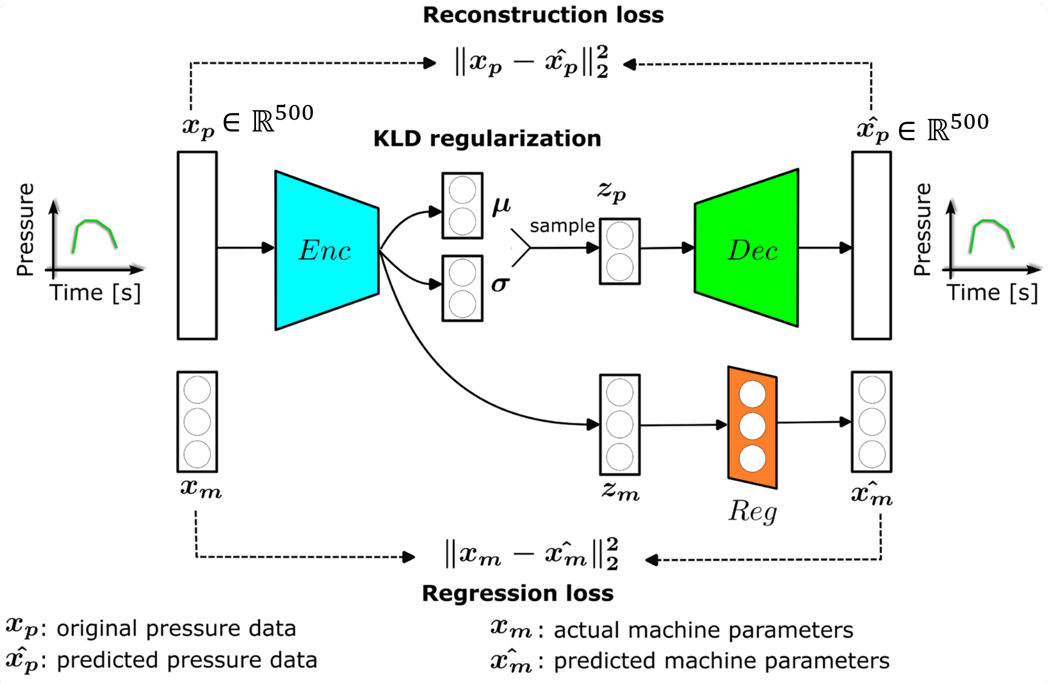
Deep Learning Model



Training:

- Data without machine parameters
  - Reconstruction loss
  - KLD regularization
  - **Regression loss**

Deep Learning Model



Advantages:

- Light-weight model
- Low-dimensional representation
- Short reference time

Results - Anomaly Detection

TABLE II: Evaluation of anomaly detection performance on four different datasets.

Dataset	**AUC**		**Recall** ($B = 0.95$)		**Specificity** ($B = 0.95$)		**Odds Ratio** ($B = 0.95$)	
	One-batch calibration	Dynamic calibration	One-batch calibration	Dynamic calibration	One-batch calibration	Dynamic calibration	One-batch calibration	Dynamic calibration
D1	0.9039	**0.9974**	**1.0**	**1.0**	0.2266	**0.8729**	1.4002	**5.8545**
D2	0.9620	**0.9974**	**1.0**	**1.0**	0.3146	**0.8593**	1.5769	**6.9487**
D3	**0.9980**	**0.9980**	**1.0**	**1.0**	0.6823	**0.8614**	**7.4856**	3.1971
D4	0.9425	**0.9998**	**1.0**	**1.0**	0.2245	**0.8809**	1.4151	**7.7862**
Avg	0.9516	**0.9982**	**1.0**	**1.0**	0.3620	**0.8686**	2.9695	**5.9466**

Results - Anomaly Detection

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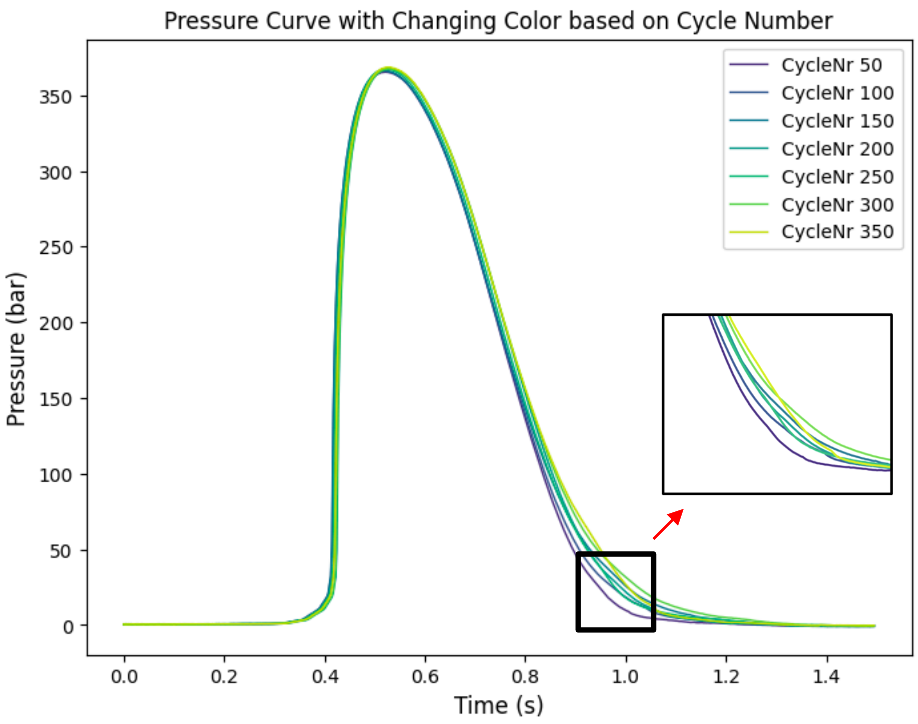
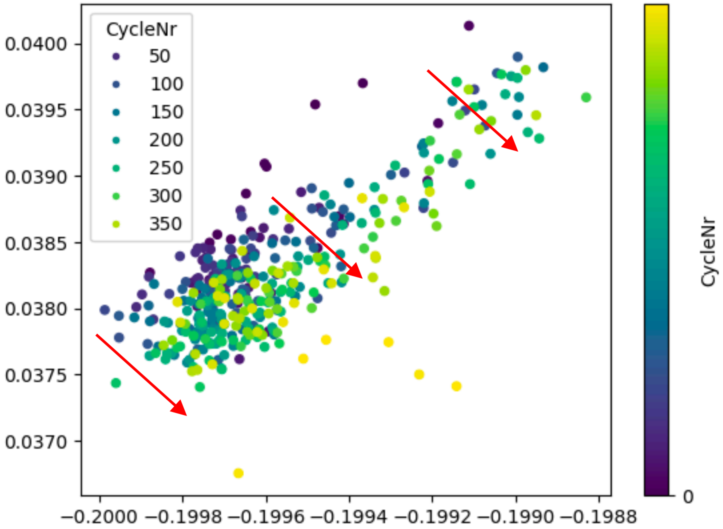
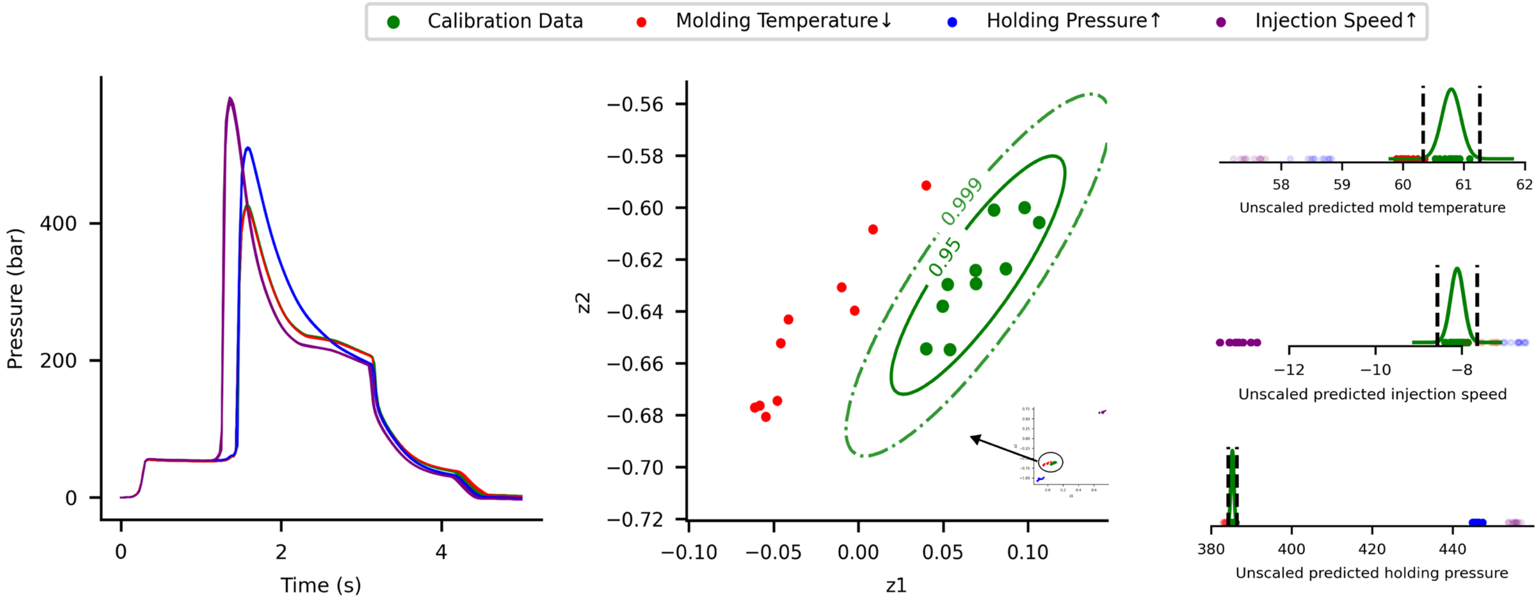
- Dynamic calibration process outperforms one-batch calibration over multiple datasets

Results - Drift Detection





Results - Root Cause Indication



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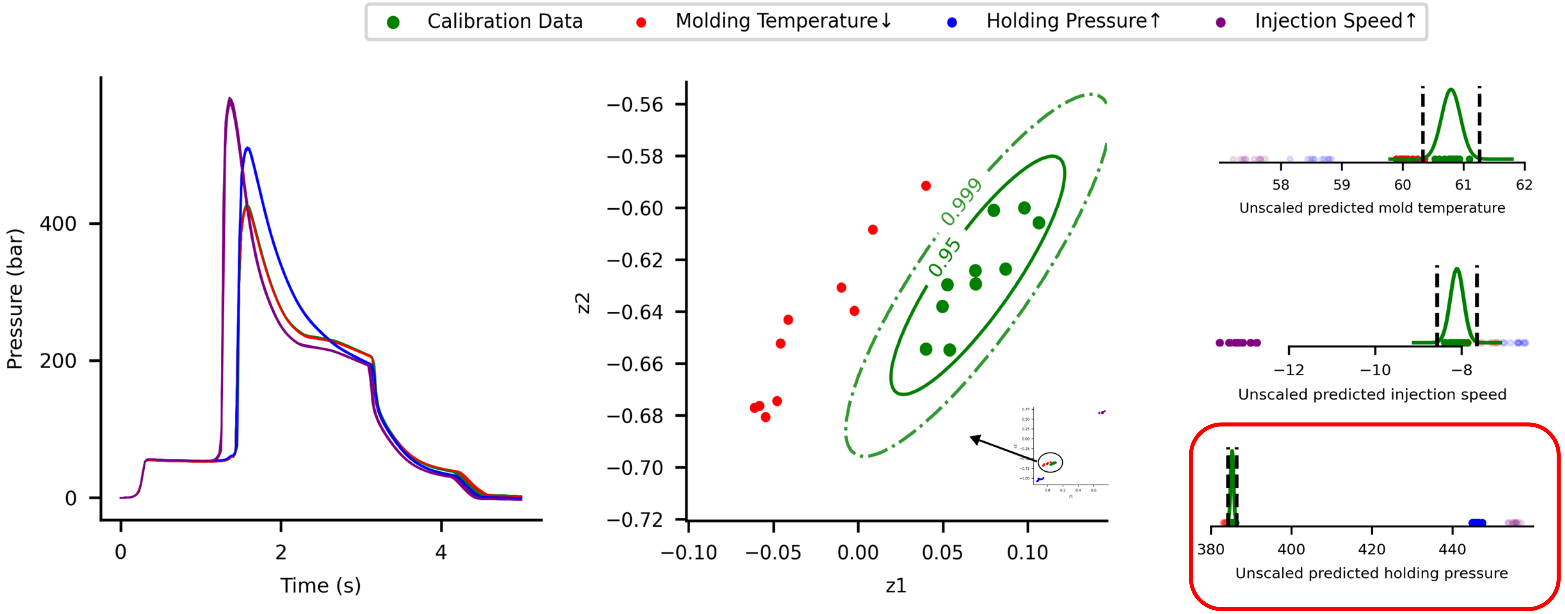

Summary of the model

Summary

- Autoencoder learns a low-dimensional representation from large data set
- Sensitive to subtle changes
- Dynamic calibration of reference density to account for drifts
- Operational bounds are set to detect anomalies and root cause analysis
- Computationally lightweight inference
- Insufficient specificity of machine parameter prediction

➔ A better solution has been implemented in the meantime.

Outlook

- Improve and test generalizability
- Evaluate the effectiveness of root cause indication in production

From the lab to the shopfloor: Technology Readiness Levels

Scale developed by NASA for evaluating technologies for space applications

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Where we are now

Where we started

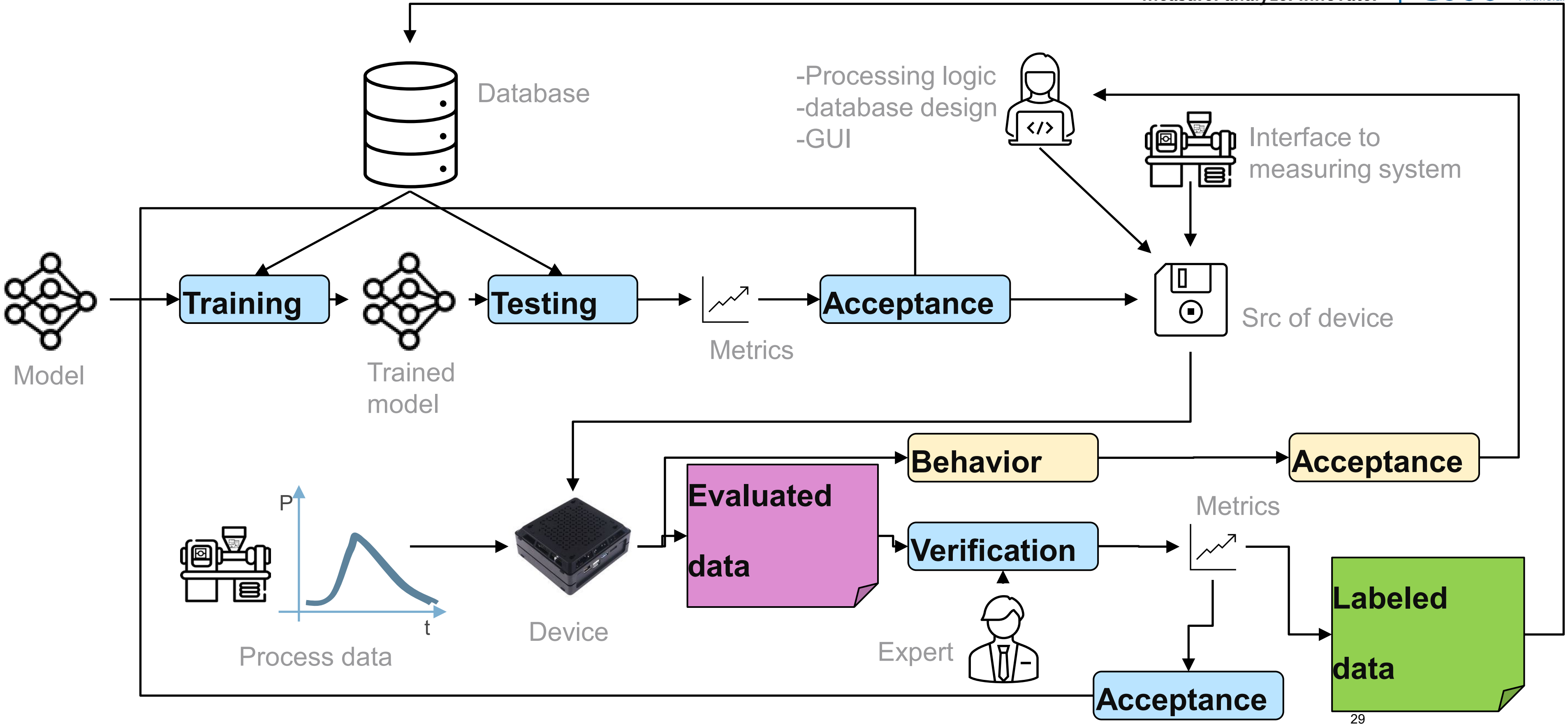
TRL evaluation

-Suitable for evaluating development state of new technologies

-Not just the model, but the entire system (Sensor, data processing, model, output)

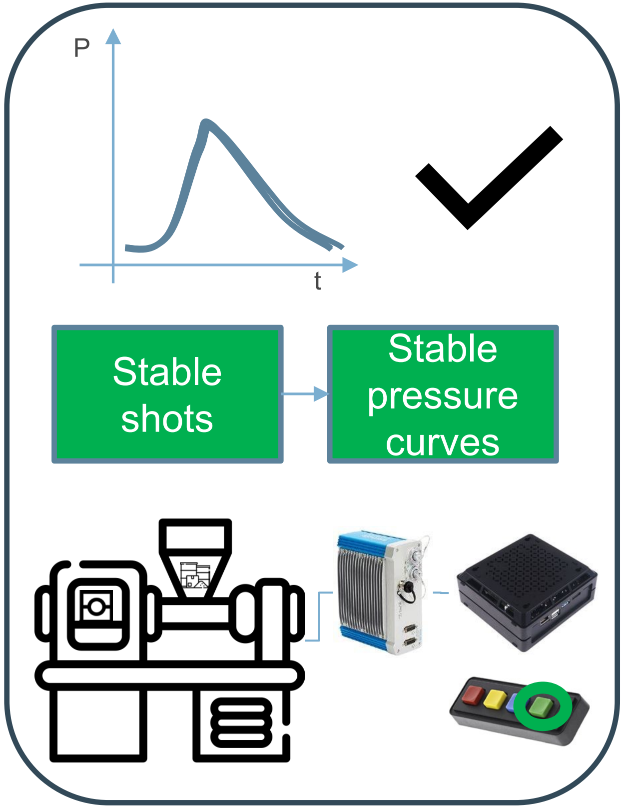
-Something marketable

From the lab to the shopfloor:
Development Process to reach TRL 6+

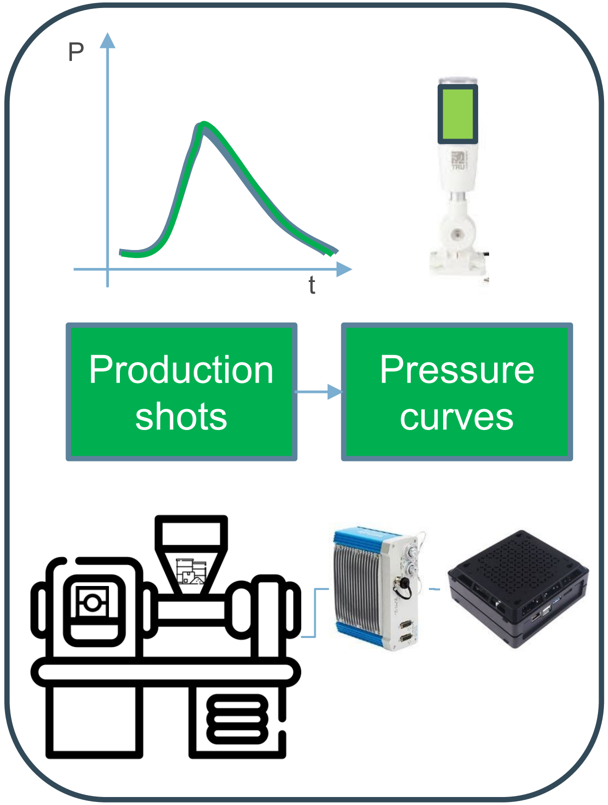


From the lab to the shopfloor: Vision for TRL 6+

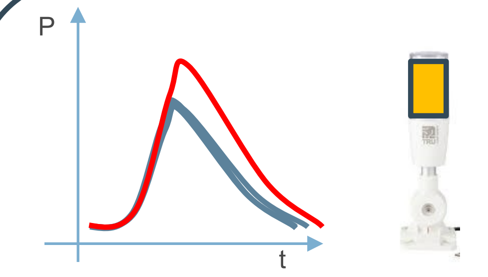
Start of production / calibration



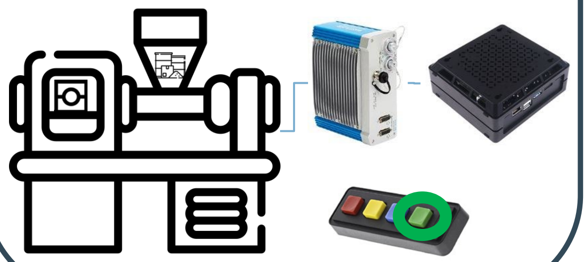
Regular production



Process needs attention



- ✓ Option for user label
- ✓ Option to recalibrate after inspection / process correction
- ✓ Option to adjust model sensitivity



From the lab to the shopfloor:
TRL 3: Proof of concept demo to peer group

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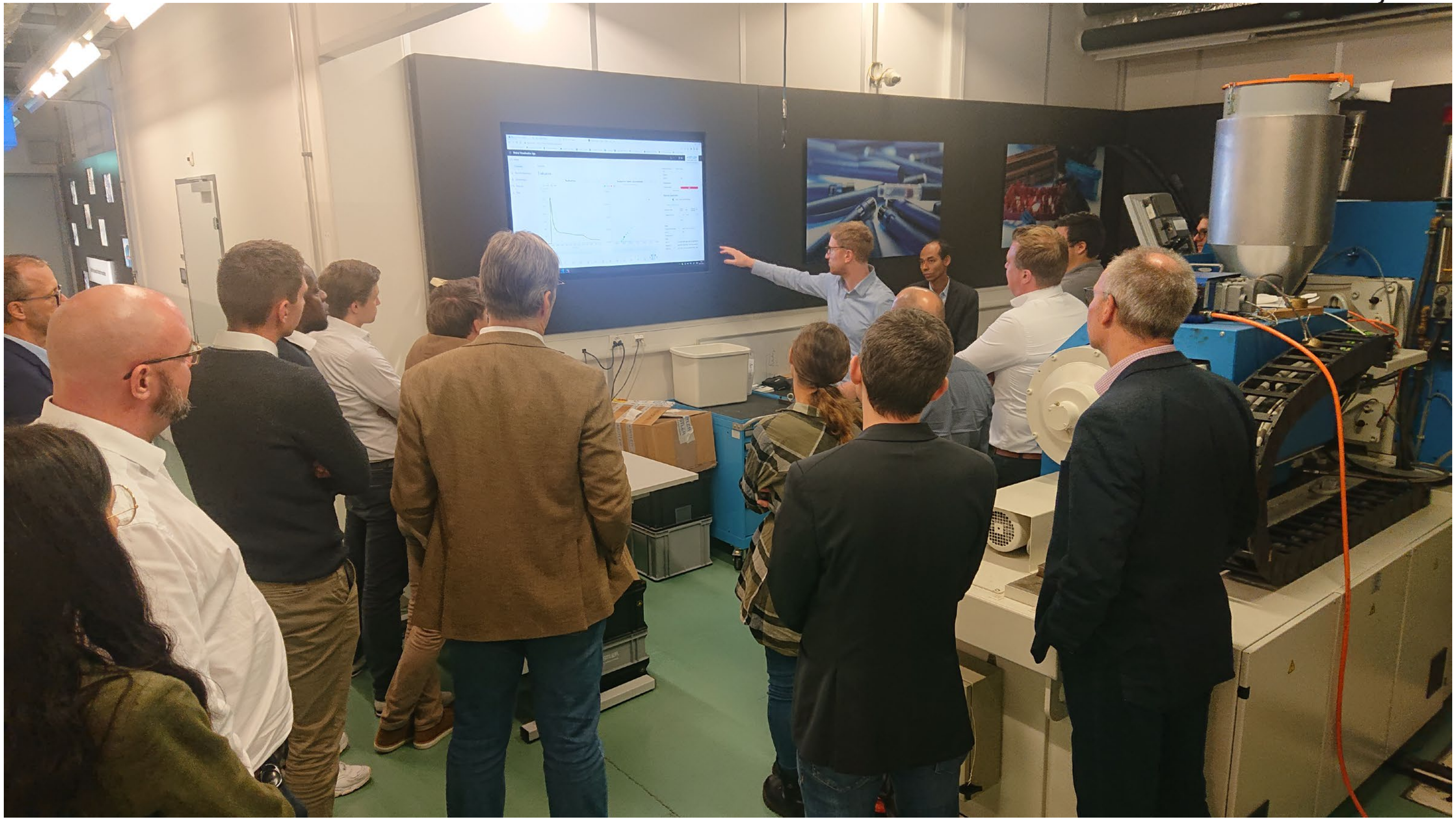

Conclusion

- Basic concept of solution is promising
- Anomaly detection is effective
- Iterative improvement of model
- Regular evaluation in real environment
- Enrichment of training data with validation data from previous iterations