SHL MEDICAL

2024/03/07

Florian Josselin / Senior Data Scientist

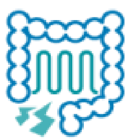
Real-time Anomaly Detection in Injection Molding: Leveraging Autoencoder Models To Define The Future Of Quality Control

Introduction

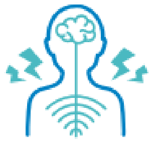
Florian Josselin

We enable patients' independence

As a **pioneer** of the **modern autoinjector**, **we enable patients' independence** through partnerships with **leading pharma and biotech companies** in providing groundbreaking drug delivery solutions. Since our inception in 1989, our **winning combinations** have been delivered across **global markets** for use in a wide range of **therapeutic areas.**



Inflammatory bowel disease

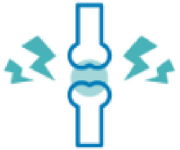


Multiple sclerosis

Postmenopausal osteoporosis

Weight management

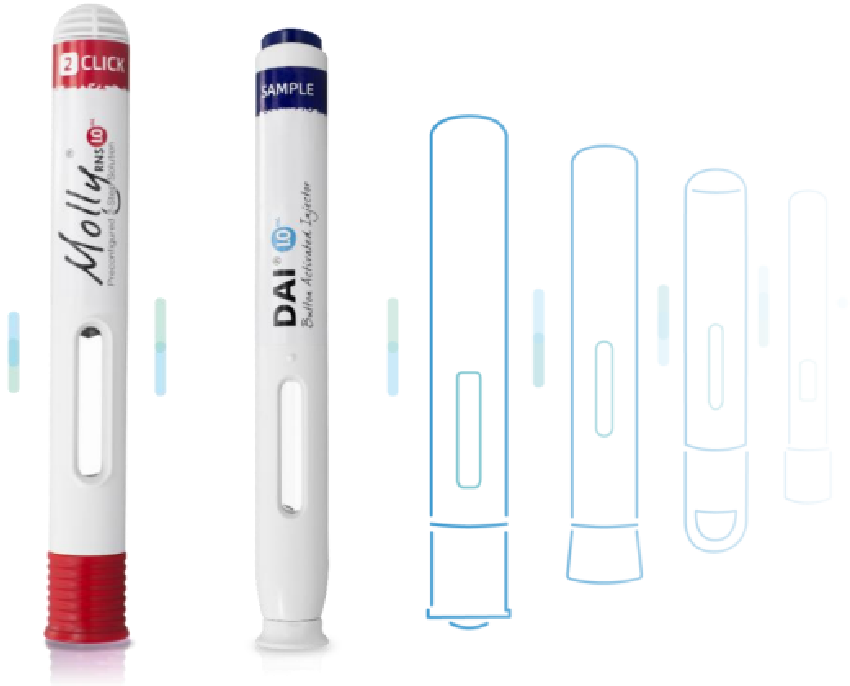
Migraine



Rheumatoid arthritis

Type 2 diabetes

Atopic disorders



We operate across the globe

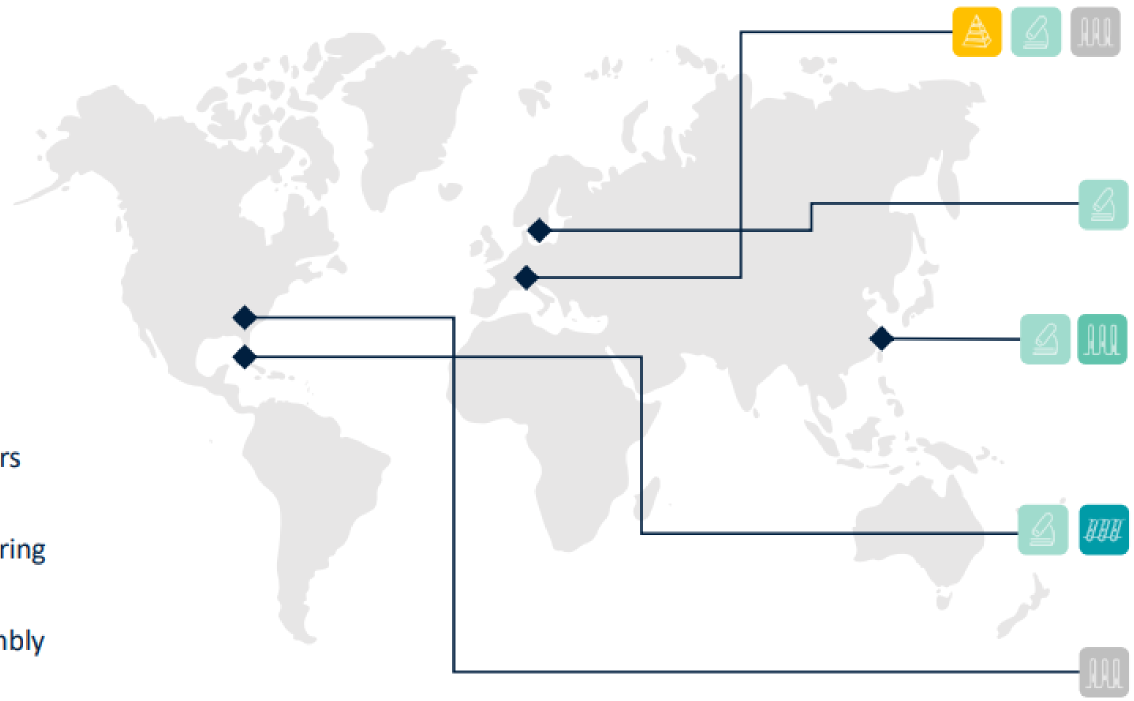
SHL Medical provides support across **multiple time zones** with **streamlined processes** to deliver excellent customer-centric services. All projects abide by the **ISO 13485 quality management system** standards to ensure consistent, high-quality products. This approach **facilitates quality local execution while enabling global coordination**.

Global HQ

R&D Centers

Manufacturing

Final Assembly



Zug, Switzerland

- 1,790 m² office established in 2018
- New HQ and manufacturing site expected in 2026

Stockholm, Sweden

- 2,560 m² office space established in 2004

Taoyuan, Taiwan

- 161,135 m² office and facility space across 5 locations

Florida, USA

- 5,195 m² office and facility since 2010

South Carolina, USA

- 25,000 m² new manufacturing site expected in 2024

BIG CHALLENGE

What our approach needs:

1) Solve a quality prediction problem, cost-effectively, with limited or expensive labelled data, and SC-Ambiguity -> Unsupervised Anomaly Detection foundation.

2) Wanted Anomaly Detection that works for different kind of manufacturing equipment and across different sectors of our company.

3) Wanted flexibility to achieve diverse business targets.

Context

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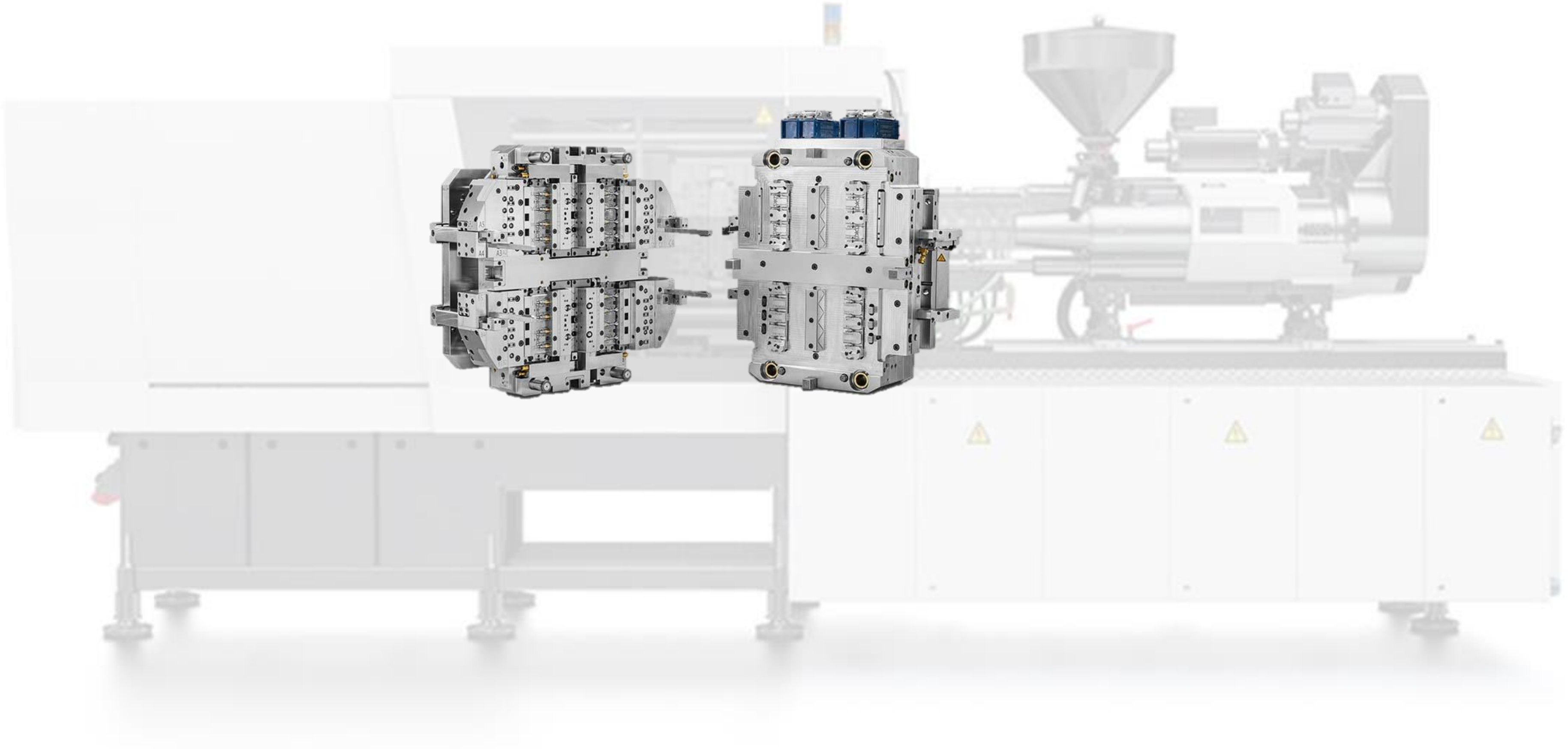
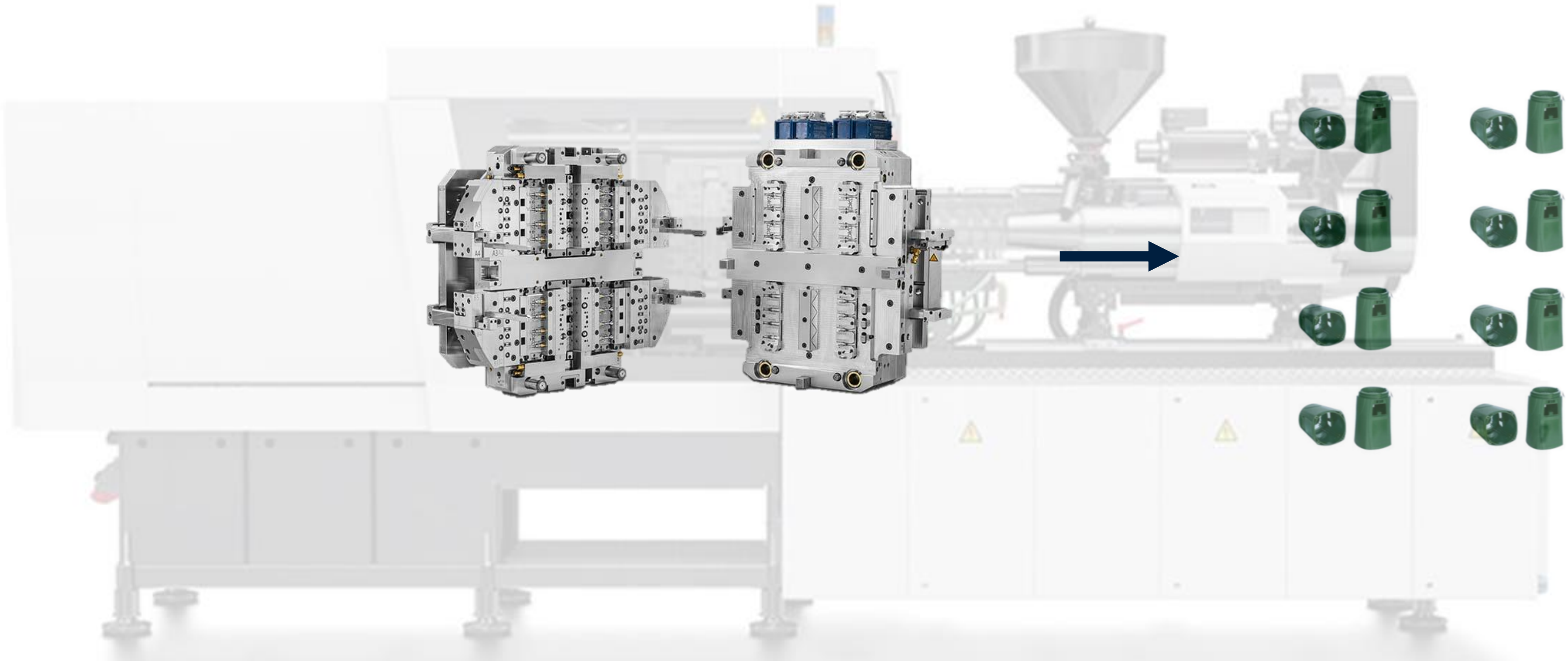
INJECTION MOLDING
PROCESS AND PRODUCT



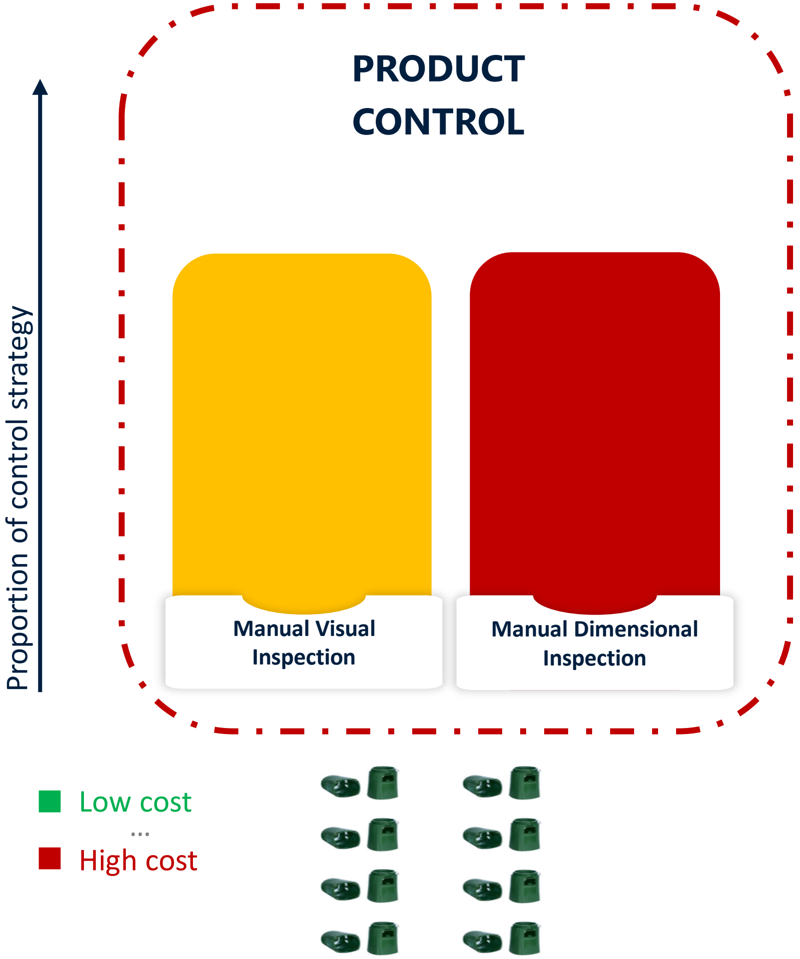
INTRODUCTION TO INJECTION MOLDING: THE PRODUCT

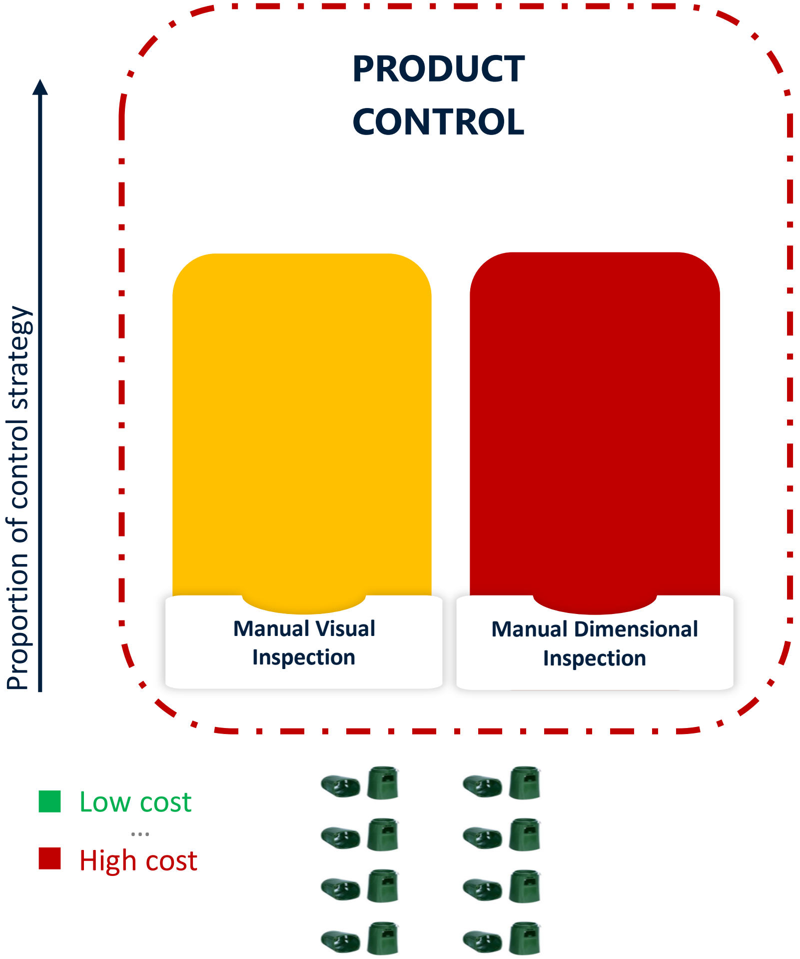


INTRODUCTION TO INJECTION MOLDING: THE FINAL ASSEMBLED PRODUCT

QUALITY CONTROL AND THE NEED FOR CHANGE

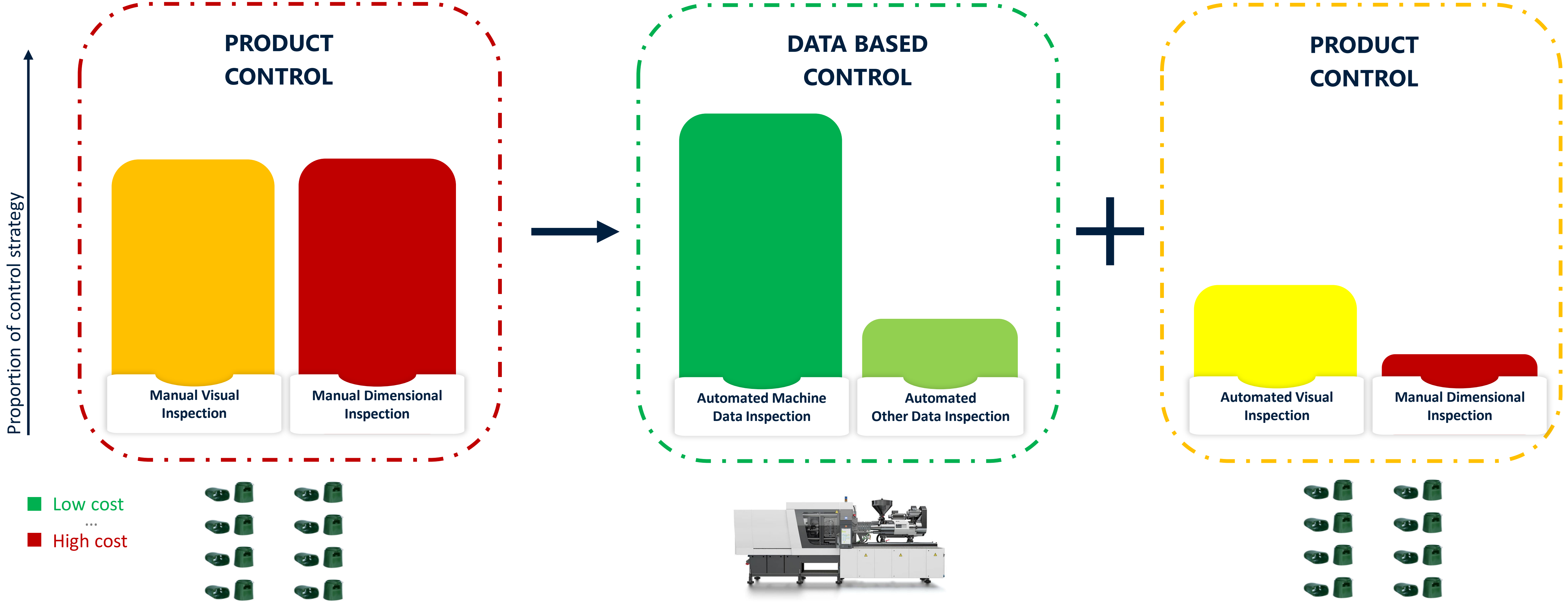
CURRENT QUALITY CONTROL METHOD




PRODUCT CONTROL
Proportion of control strategy
Manual Visual Inspection
Manual Dimensional Inspection
Low cost
...
High cost

Challenges

DESIRED QUALITY CONTROL METHOD



Evaluated at min **8.6m $** of savings per year

Solutions

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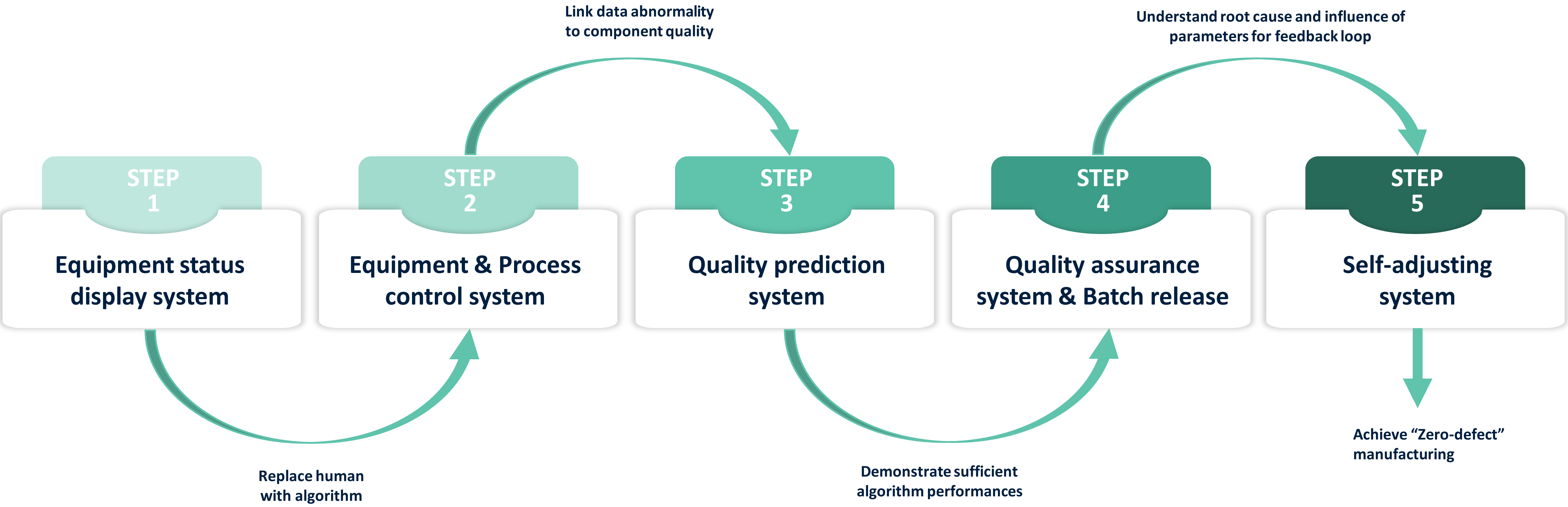
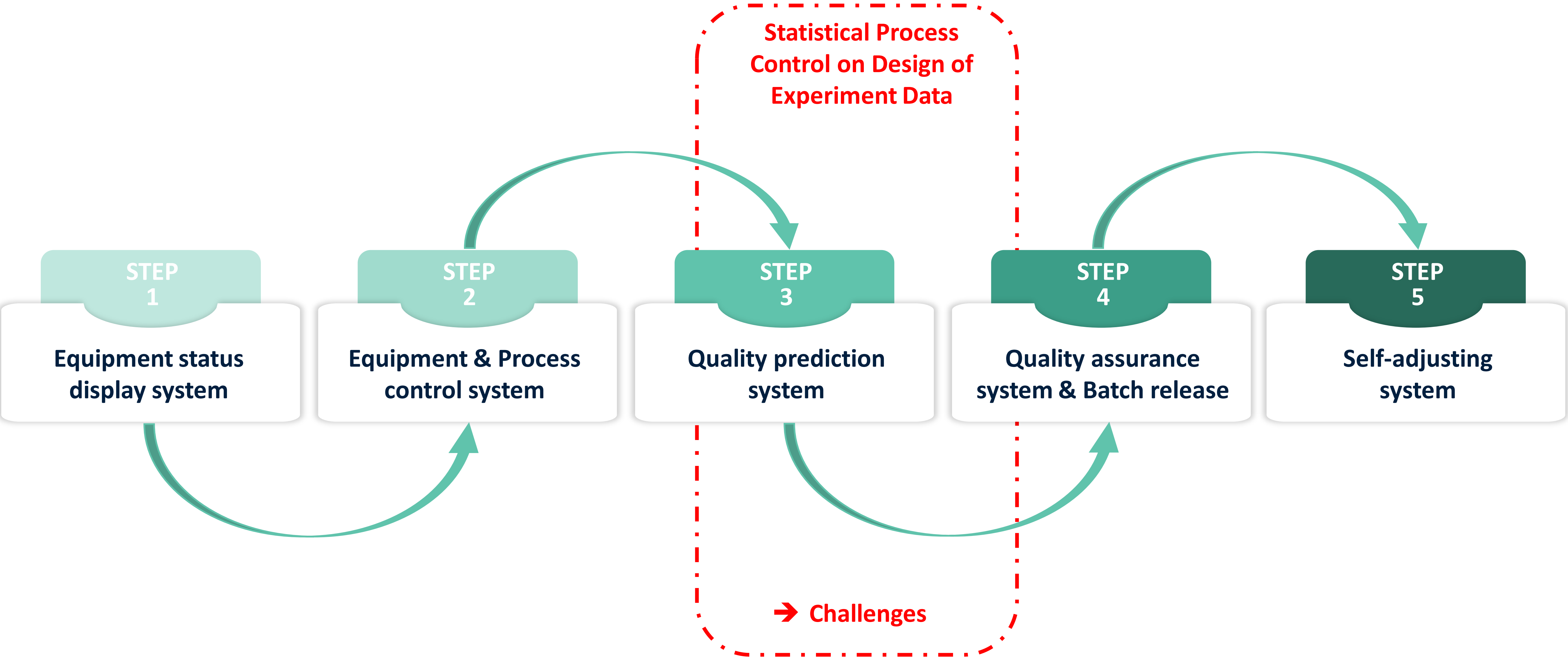
DECOMPOSE DATA BASED CONTROL

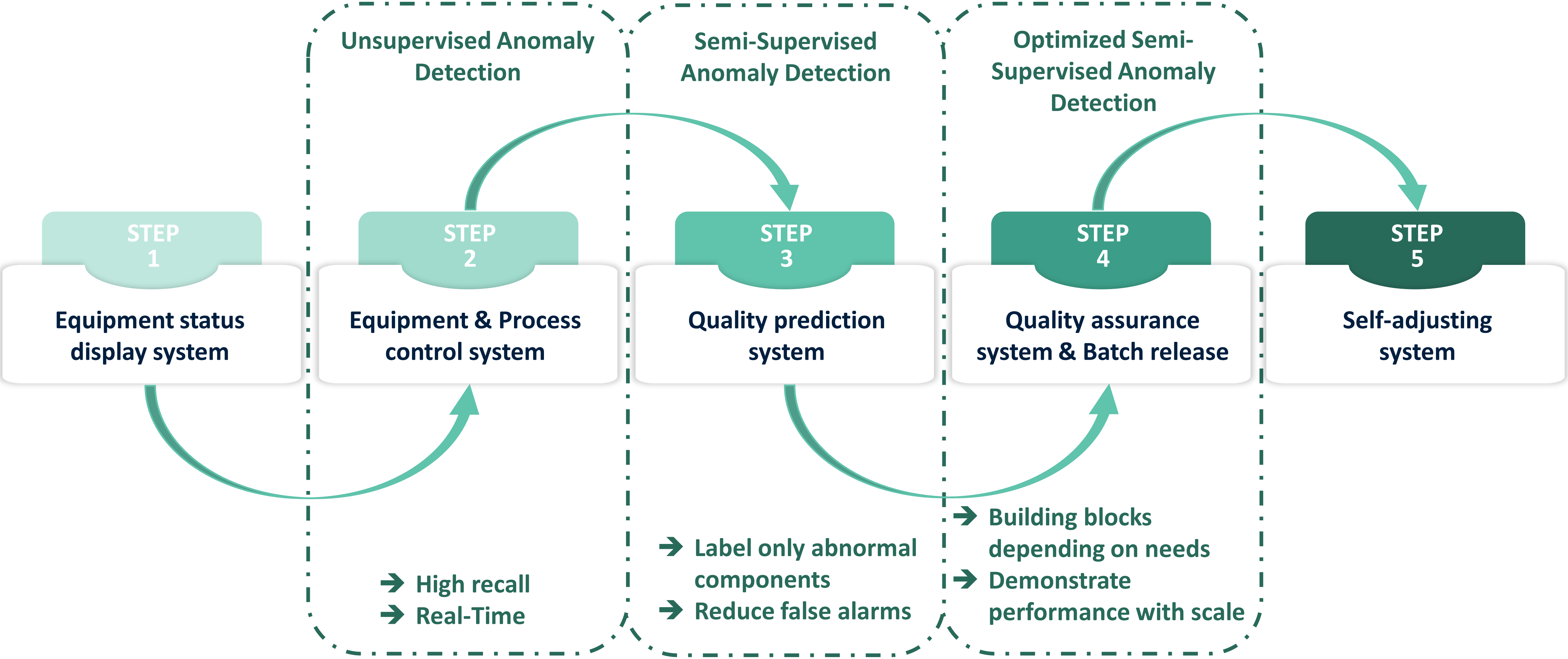
DECOMPOSITION OF DATA BASED CONTROL IN DIFFERENT STEPS



TRADITIONAL APPROACH FOR DATA BASED CONTROL

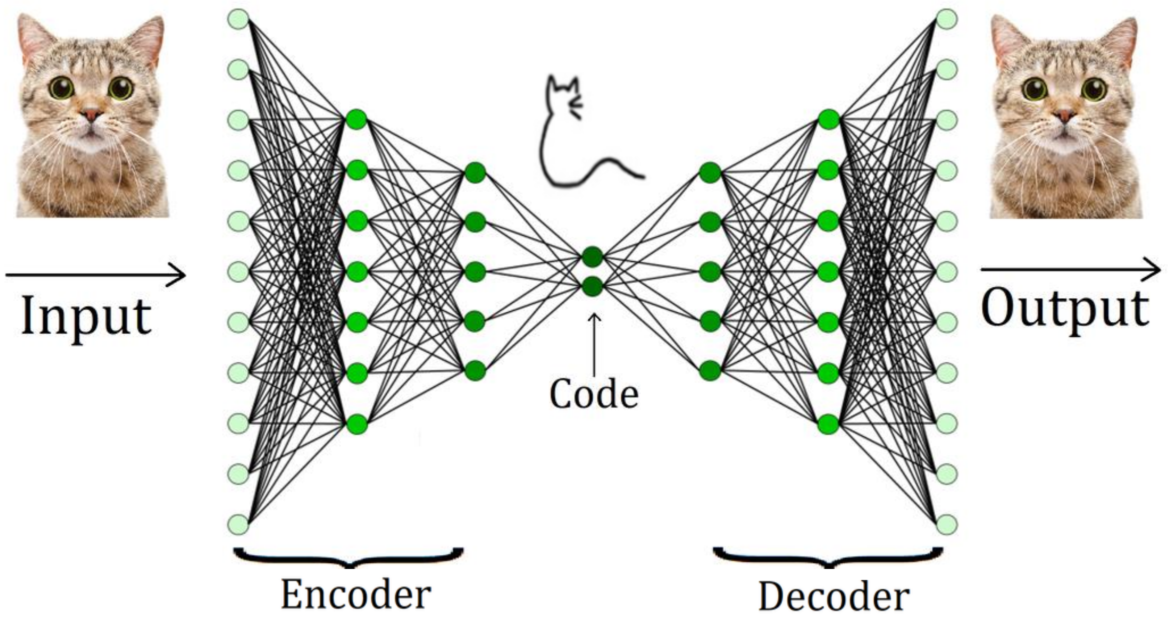


INNOVATIVE APPROACH TO TRY TO ACHIEVE QUALITY ASSURANCE



Auto-Encoders

Florian Josselin



Auto-Encoders:

- Learns pattern behind majority of the data
- The best algorithm for anomaly detection in the injection molding industry according to research literature review*

	Accuracy	Precision	Recall	F1-Score
Autoencoder	0.9959	0.9469	1.0000	0.9727

Recall 1 = 125/125 defects detected

- Allows with additional building blocks to achieve steps 2, 3 and 4 according to slide 22
- Cost effective and flexible as needed in introduction
- Can take many parameters and model complex relationships
- Can be fine-tuned to adjust to new normal State/Context
- Threshold on the reconstruction error is used to detect normal from abnormal shots

*See reference 1. slide 41

Engineering Study
PoC Results

Florian Josselin & Jesse Wu

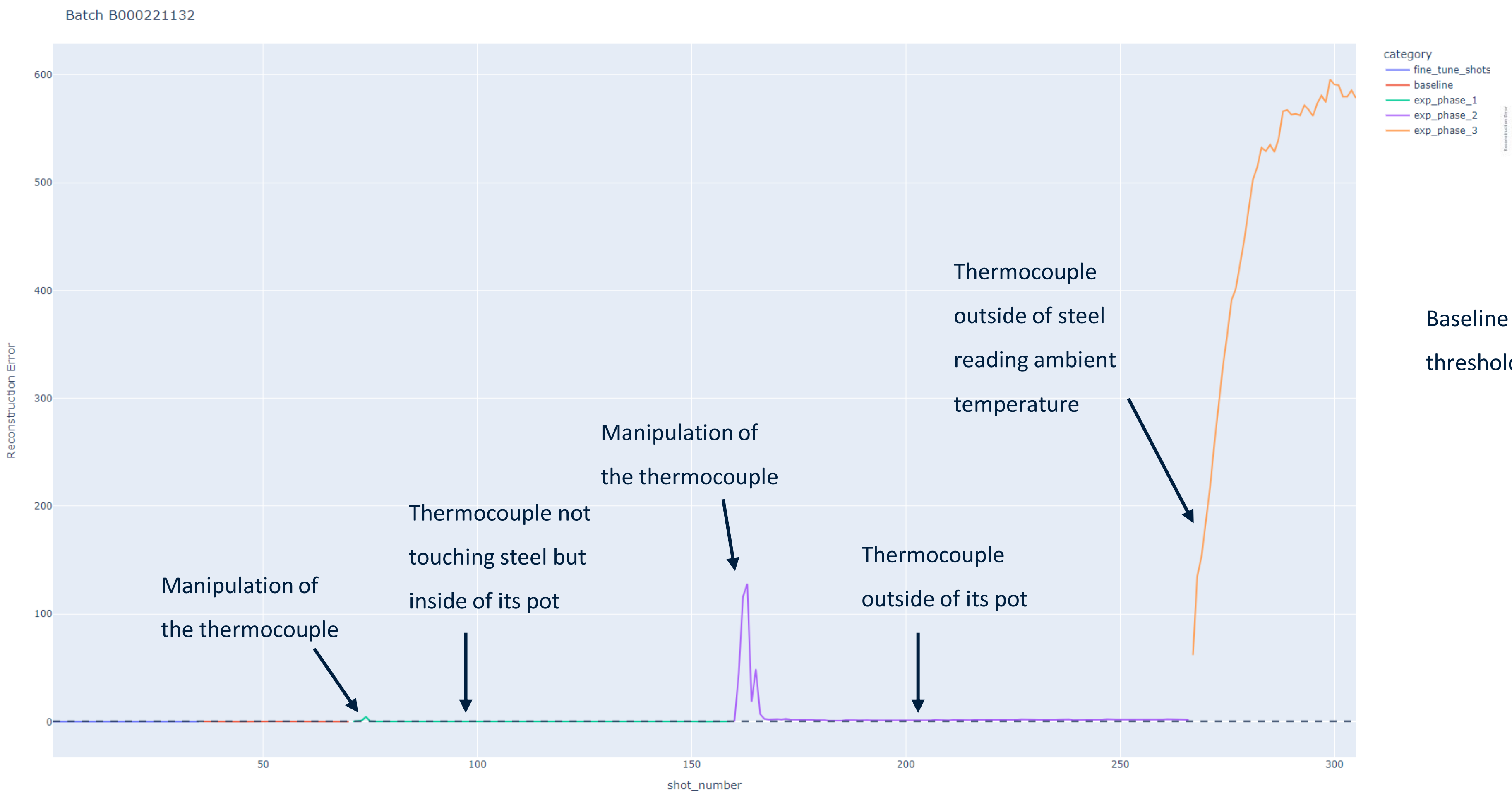
Performance

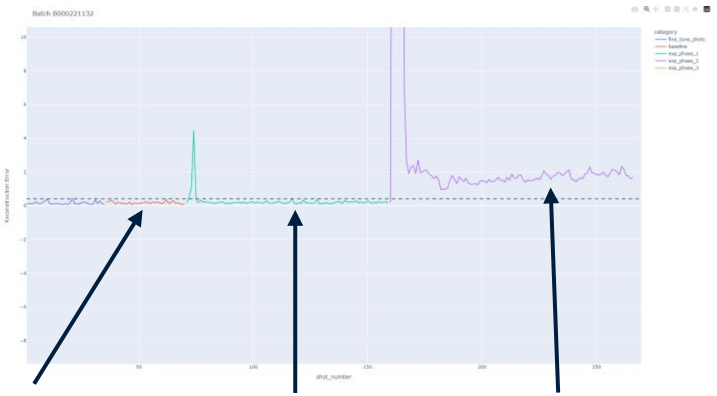
The current model detected **8/8 Fault scenarios from a specifically designed Engineering Study**:

- The experiments were designed to ensure the scenarios are representative of real abnormal manufacturing situations.
- 2 scenarios of the 10 were eliminated from results due to problems in the data generation.
- 97.8% of generated visual defects and 100% of generated dimensional defects were detected.
- FP rate is 5.42% and similar to literature review.
- We used a basic Auto-Encoder model that can still be optimized.

Batch	Visual defect shots	Visual defects detected	Visual defect detection rate	Dimensional defect shots	Dimensional defects detected	Dimensional defect detection rate
B34	53	53	100 %	84	84	100 %
B37	7	9	77,8 %			
B38	29	29	100 %			
Total	89	91	97.8 %	84	84	100 %

FAULT SCENARIO 5: THERMOCOUPLE RUNNING WILD



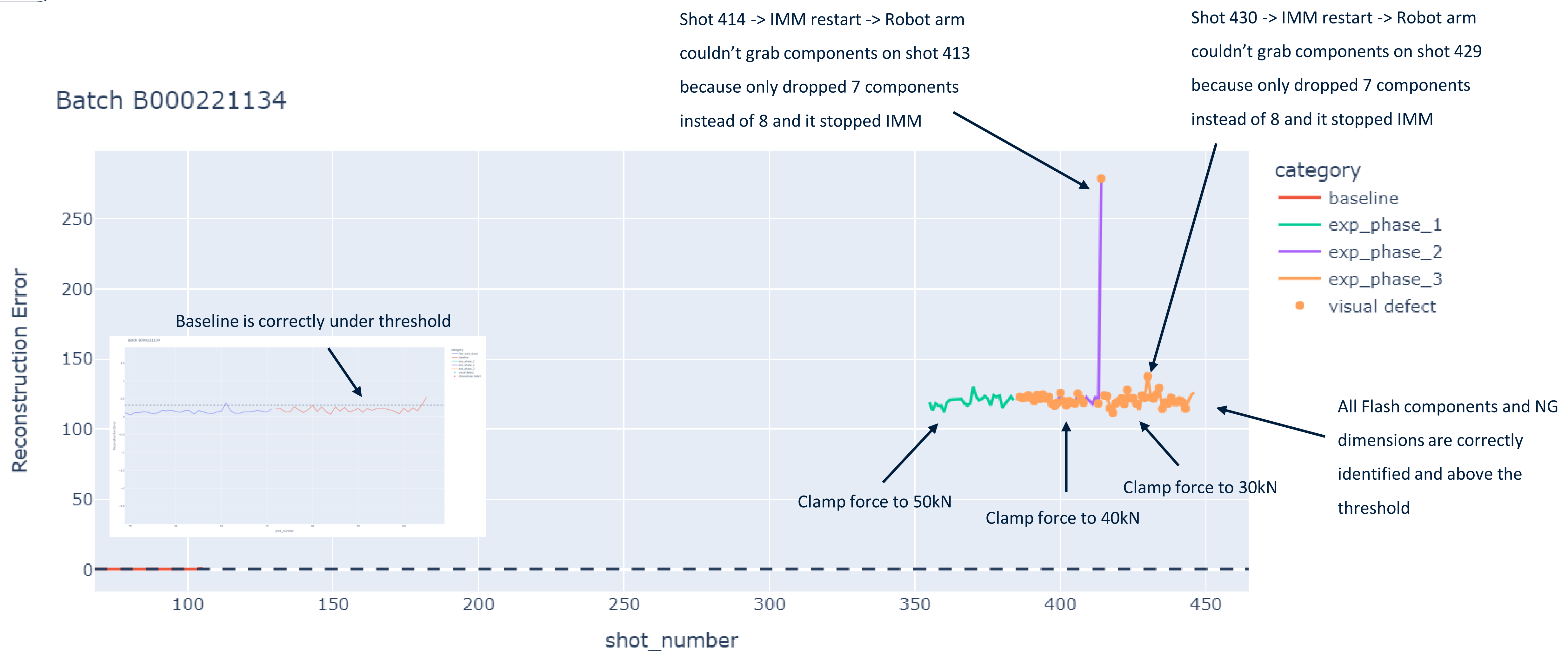


Baseline is bellow threshold

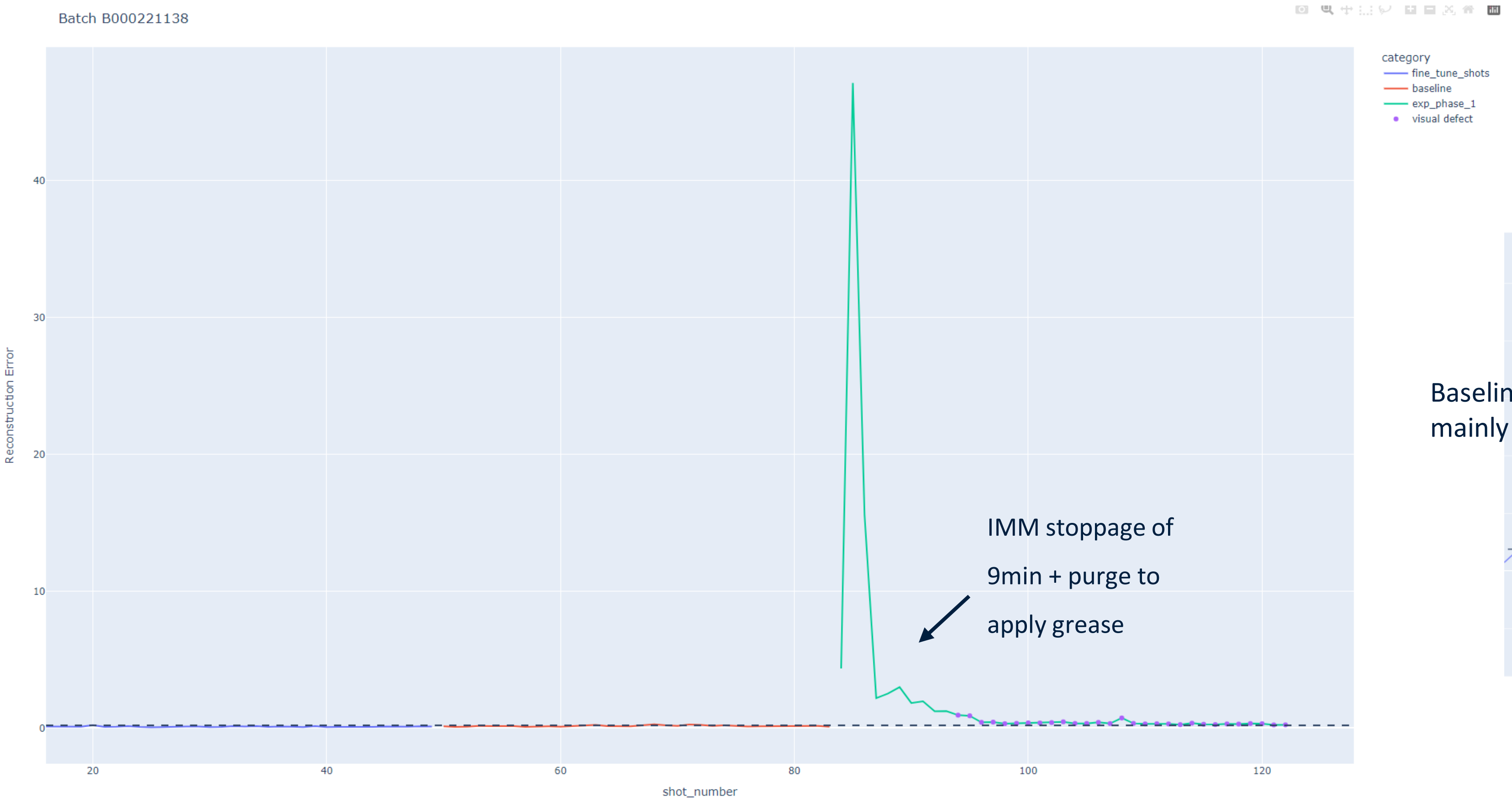
Inside of pot sensor has no significant difference in temperature measures so expect no significant difference in reconstruction error

Outside of pot sensor with abnormal temperature has higher reconstruction error correctly identified by the model

FAULT SCENARIO 6: REDUCE CLAMP FORCE



FAULT SCENARIO 10: AIR VENT BLOCKING WITH GREASE



IMM stoppage of 9min + purge to apply grease

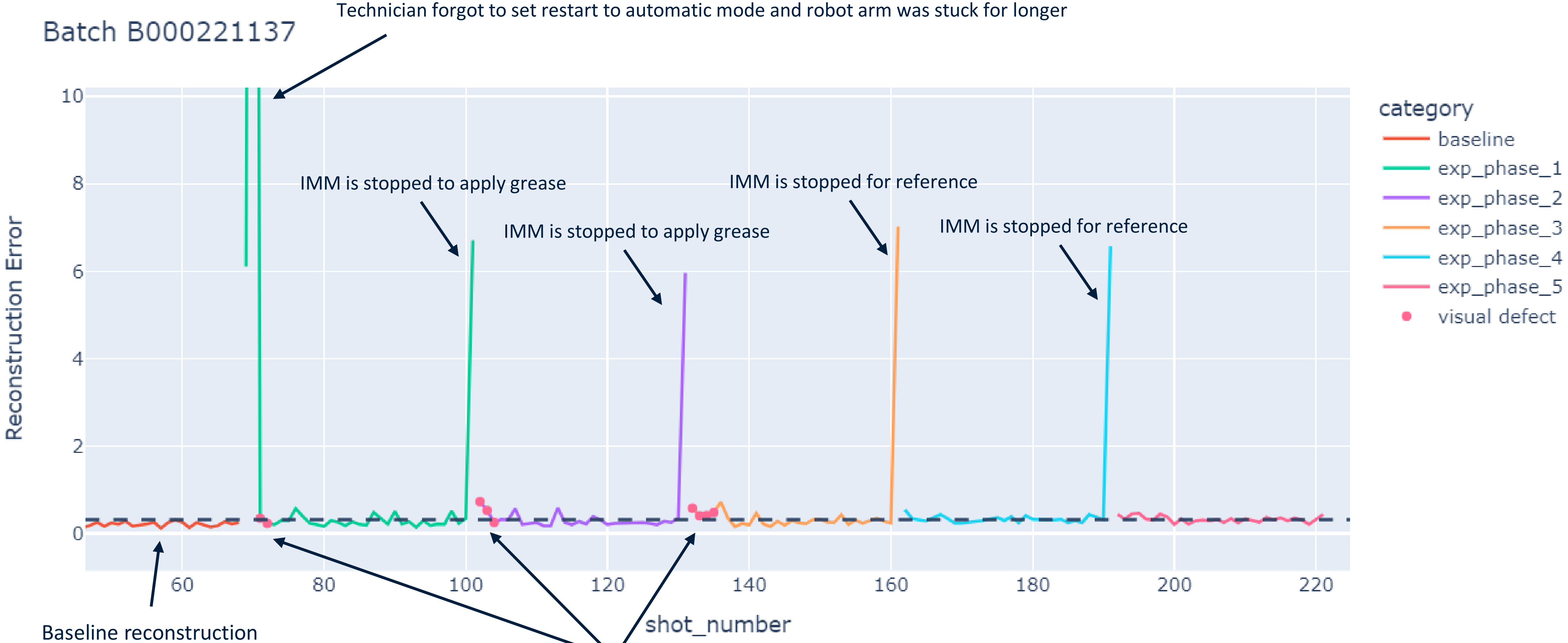
Baseline reconstruction error is mainly under threshold

Point until here have defect 'Short shot' and are all identified correctly with the higher reconstruction error above the threshold

FAULT SCENARIO 7: APPLY GREASE INSIDE OF CAVITIES

IMM is stopped to apply grease -> higher reconstruction error than other stoppages because

Technician forgot to set restart to automatic mode and robot arm was stuck for longer



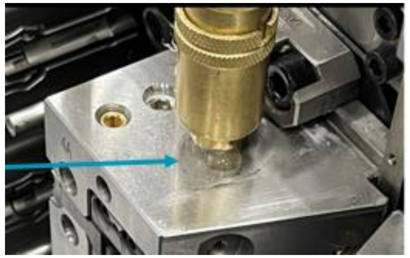
Baseline reconstruction error is under threshold

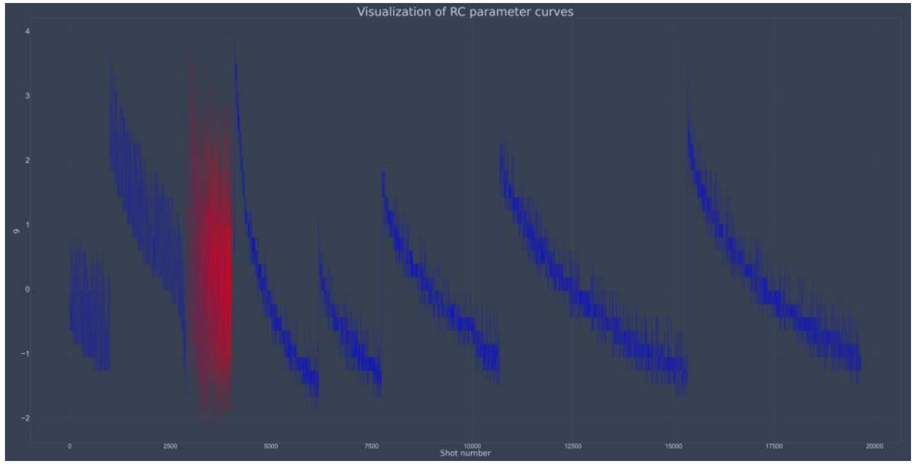
Defects are ‘Contamination: oil-grease’, as well as first on purple and orange have defect ‘Dent’ -> model detects them

Example Of A Complex Real Case

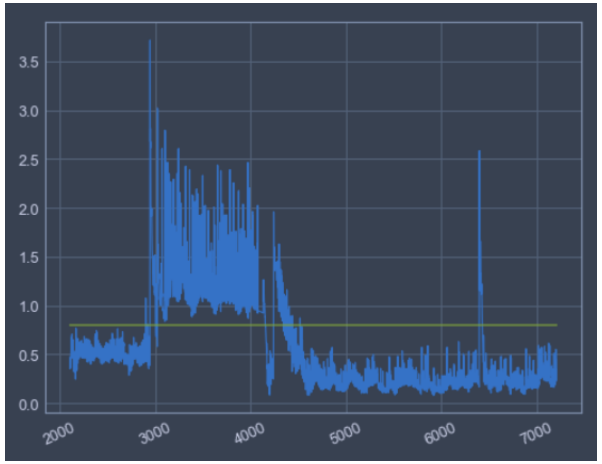
Florian Josselin

Case study example: Short Shots due to water leakage on 08/01/2022:

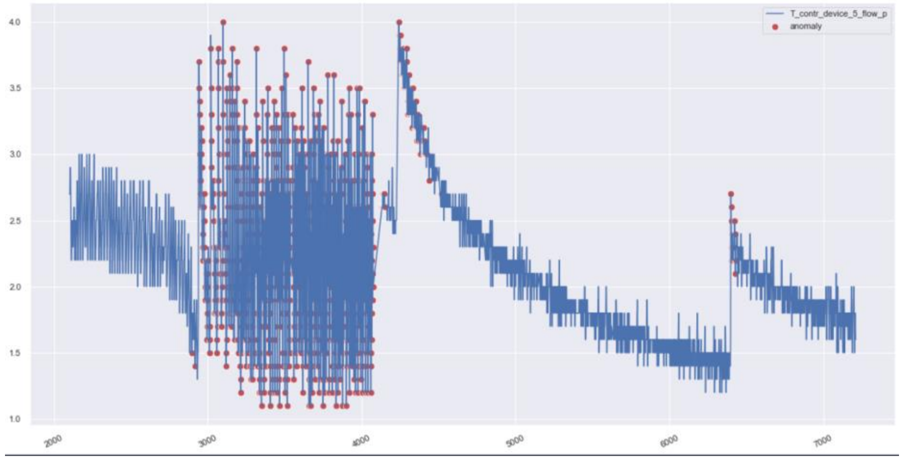




Plot of the Temperature control device 5 flow pressure. Shots in red are the ones presenting Short Shots defects during water leakage. Shots in blue are all good shots from the batch.



Anomaly score for shots ≈ 2000-7000 containing good and bad samples. All short shots have higher reconstruction error and therefore are detected as anomalies. Abnormal shots are also present after machine restart which is expected behavior.

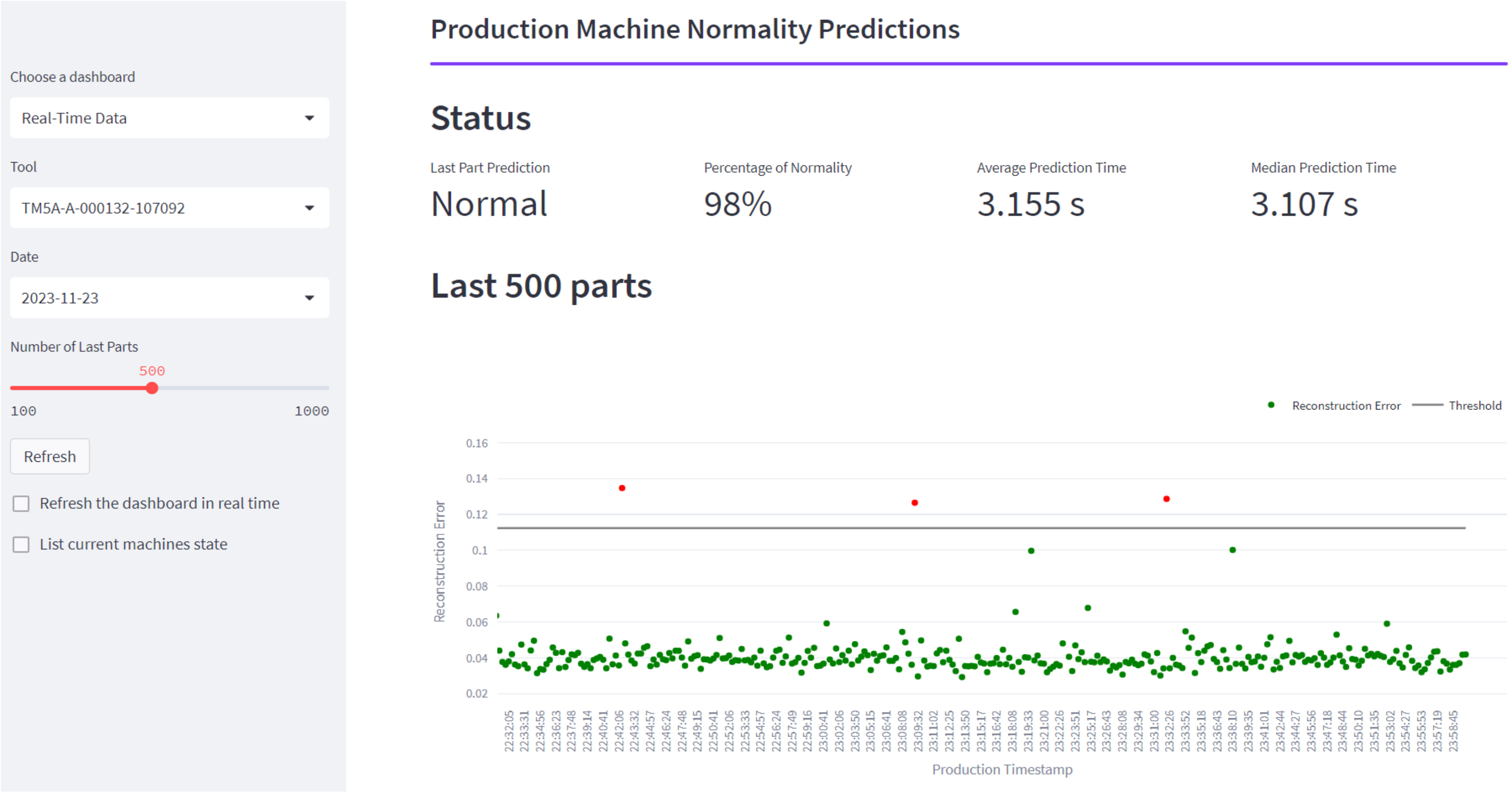


Plot of the Temperature control device 5 flow pressure for shots ≈ 2000-7000 where all short shots are identified correctly as anomalies in an unsupervised way.

An LSTM Auto-Encoder needed to be used instead of a classic Auto-Encoder to detect these anomalies.

The Need For A Real-Time Cloud Pipeline

Florian Josselin & Joy Hsu



- 1 point on the graph = 1 injection molding shot
- The reconstruction error (y-axis) represents how normal (stable) the machine is producing, the higher the value the more abnormal (unstable) the production is
- The reconstruction error = Mean Squared Error (MSE) between the reconstructed input data and the original input data

Ongoing Development

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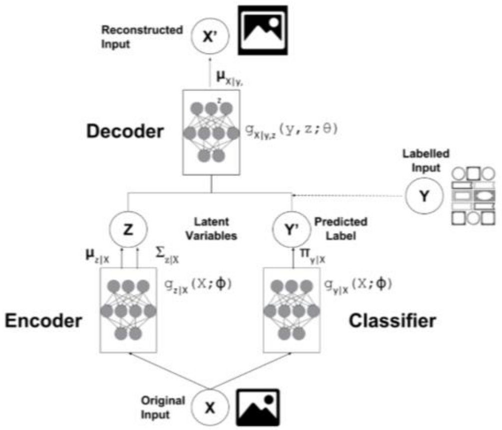
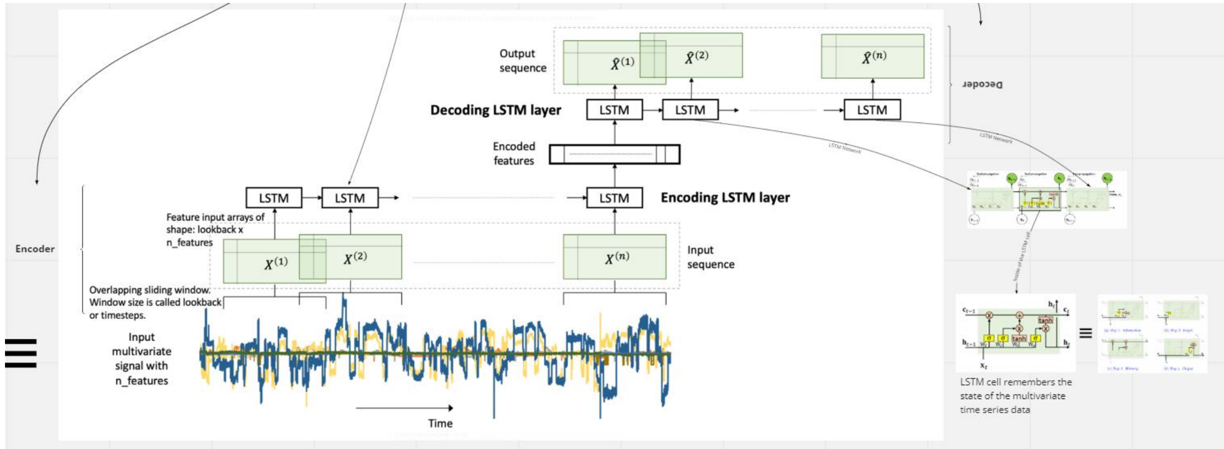
Semi-supervised Auto-Encoder:



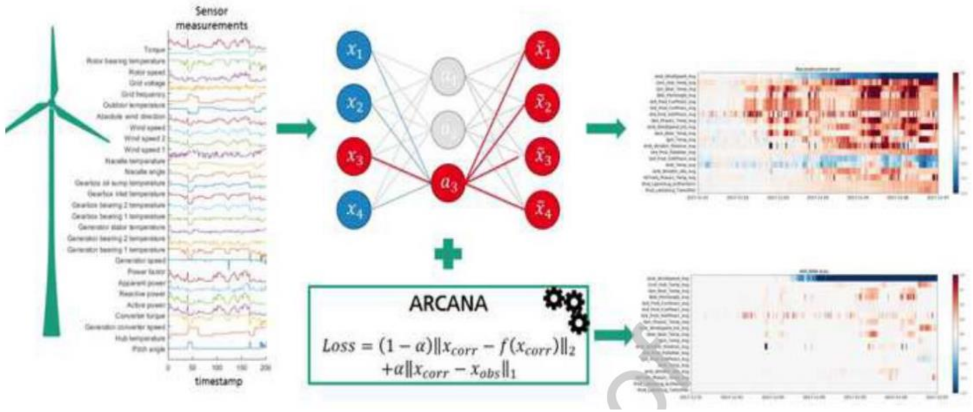
*See reference 2. slide 41

LSTM Auto-Encoder:



*See reference 3. slide 41

ARCANA – Auto-Encoder Root Cause Analysis:



*See reference 4. slide 41

Summary

Florian Josselin

Executive Summary:

1) Need switch from product control to data based control

2) Data based control problem can be decomposed in 5 steps

3) Auto-Encoders can be used as a foundation for anomaly detection & quality prediction to overcome the challenges faced by traditional methods

4) Auto-Encoder model lead to high recall during POC (step 2)

5) Building blocks (Semi-Supervised, LSTM, RCA, etc..) can be added onto the Auto-Encoder (step 2 to 3, and 3 to 4)

6) Need of pipeline and scalability to demonstrate performance (step 3 to 4)

Put together:

A practical cost-effective way to try to achieve quality assurance capable of generating business value along the way

Questions

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References

Florian Josselin

References:

1. Hail Jung & Jinsu Jeon & Dahui Choi & Jung-Ywn Park, 2021. "Application of Machine Learning Techniques in Injection Molding Quality Prediction: Implications on Sustainable Manufacturing Industry," Sustainability, MDPI, vol. 13(8), pages 1-16, April.

2. https://bjlkeng.io/posts/semi-supervised-learning-with-variational-autoencoders/

3. https://processminer.com/lstm-autoencoder-keras/

4. Roelofs, Cyriana & Lutz, Marc-Alexander & Faulstich, S. & Vogt, Stephan, 2021. "Autoencoder-based Anomaly Root Cause Analysis for Wind Turbines", Energy and AI. 4. 100065. 10.1016/j.egyai.2021.100065.

Enabling patients' independence

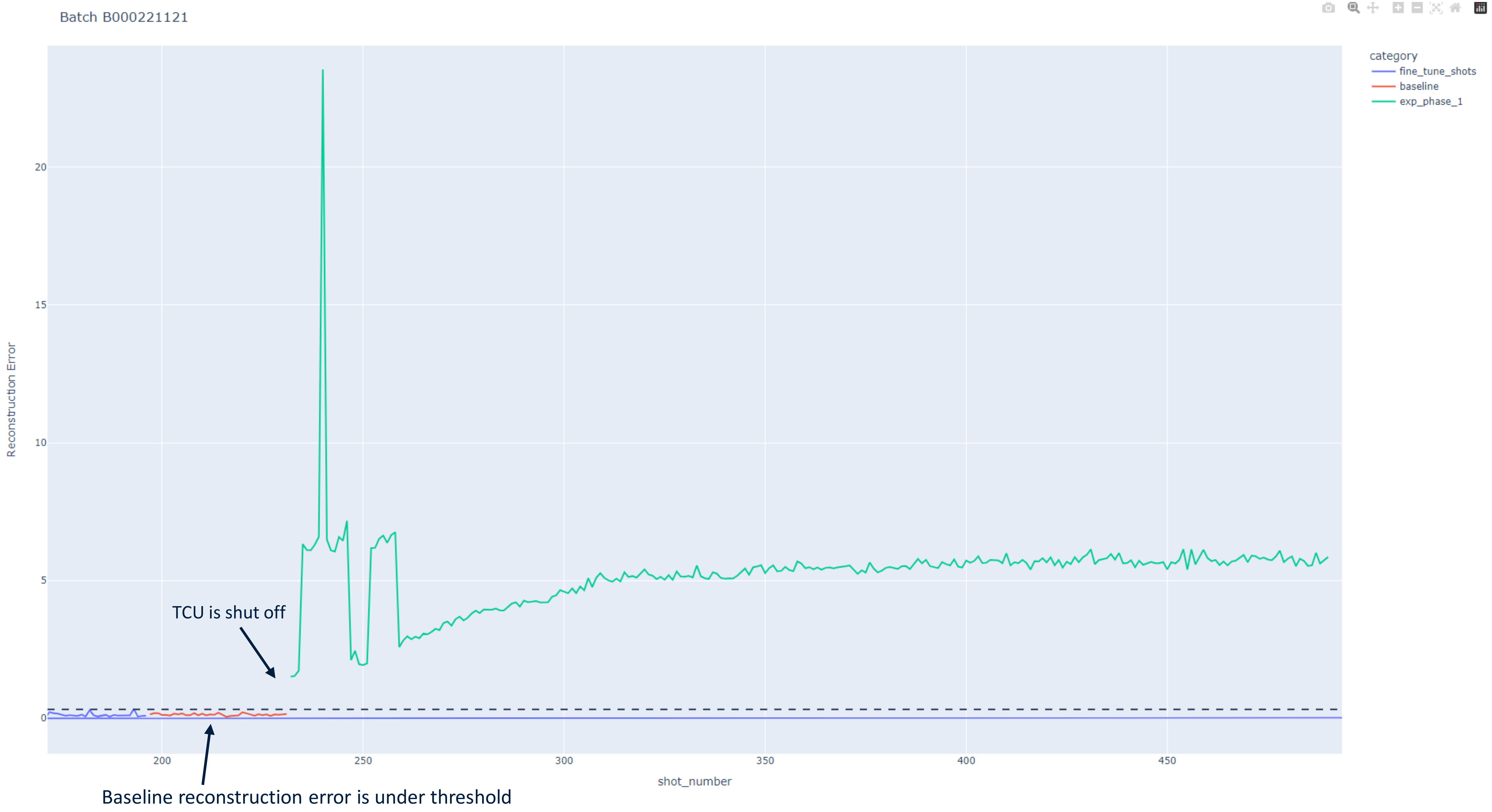
Appendix

Jesse Wu & Florian Josselin

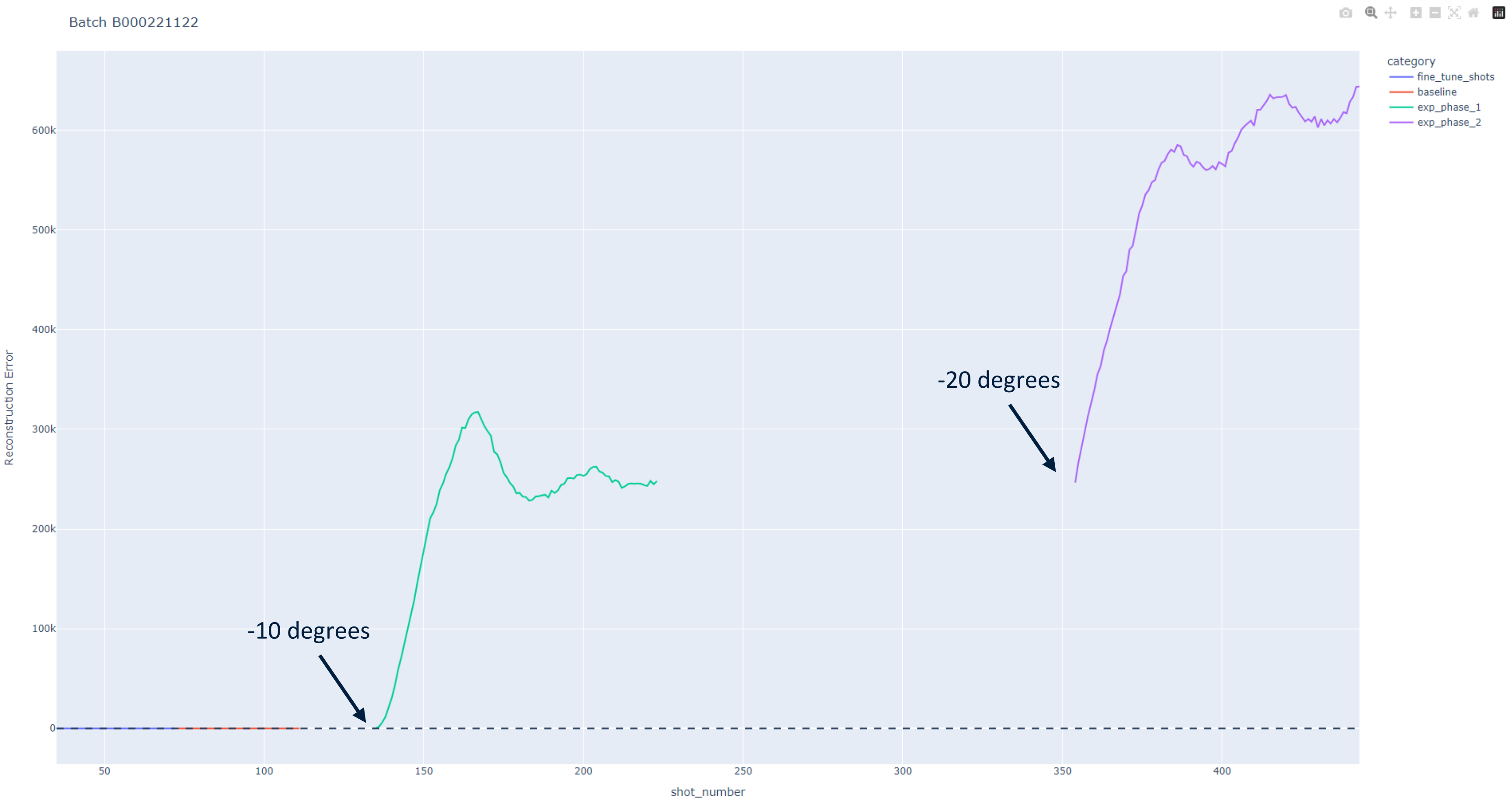
Engineering Study PoC results: rest of the scenario’s

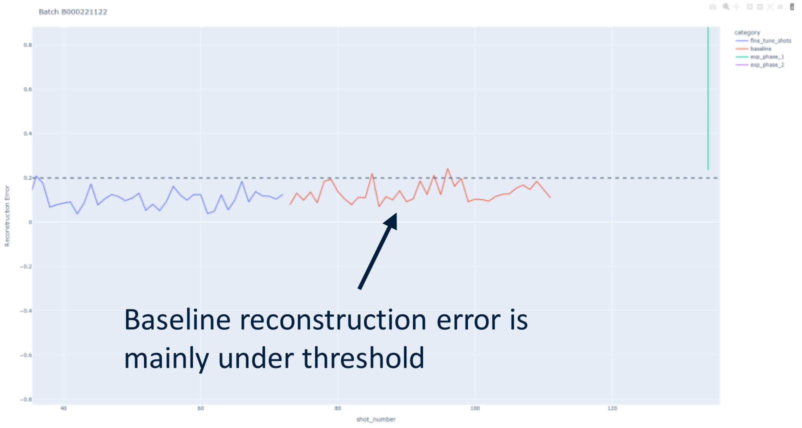
Jesse Wu & Florian Josselin

Fault Scenario 1: TCU Shut Off



Fault Scenario 2: Temperature drop of hot half (core+cavity) by 10-degree steps





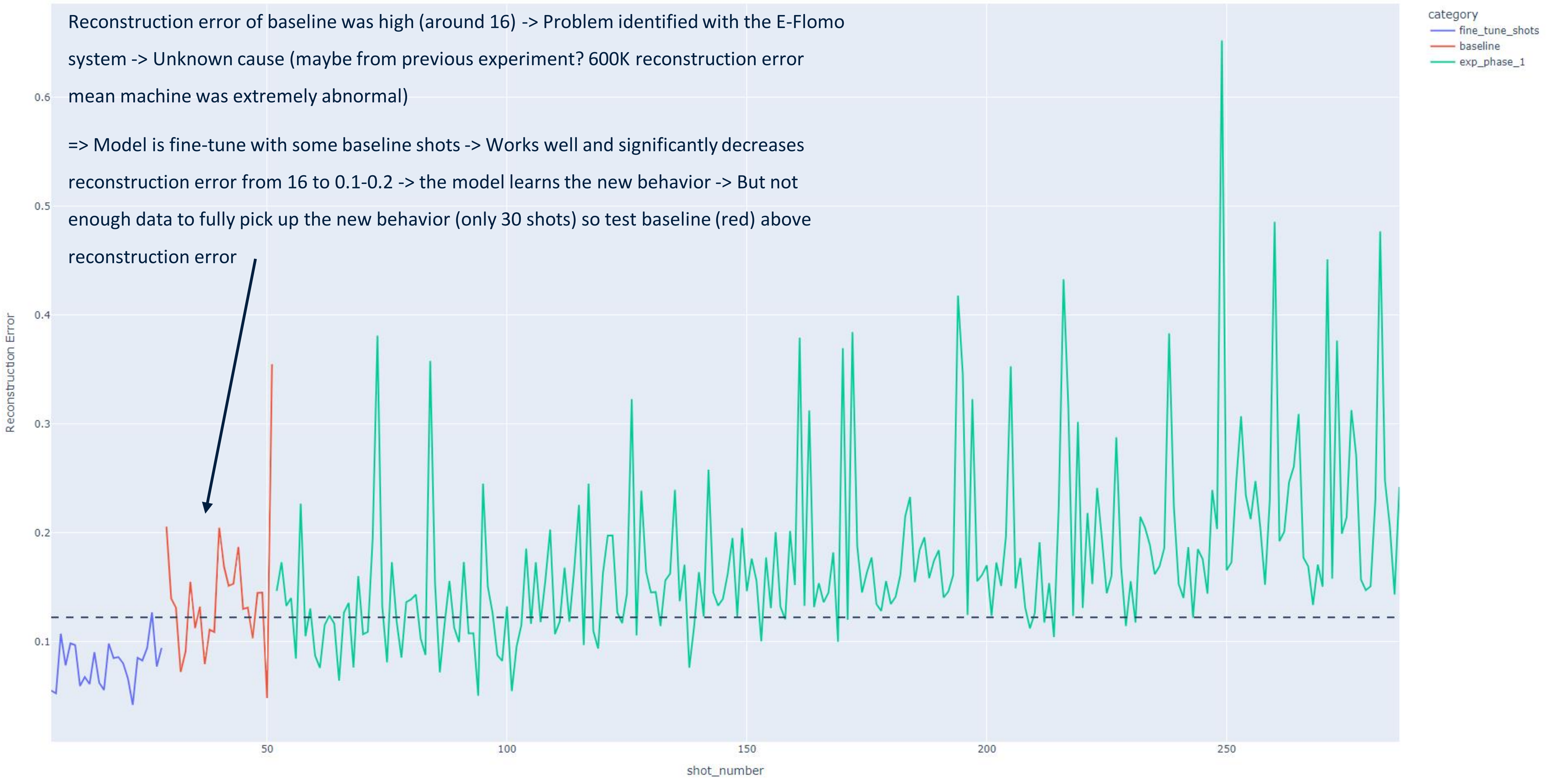
Not usuable

Fault Scenario 3: Overexposed Material (48hrs) with increased moisture content (> 0.1%)

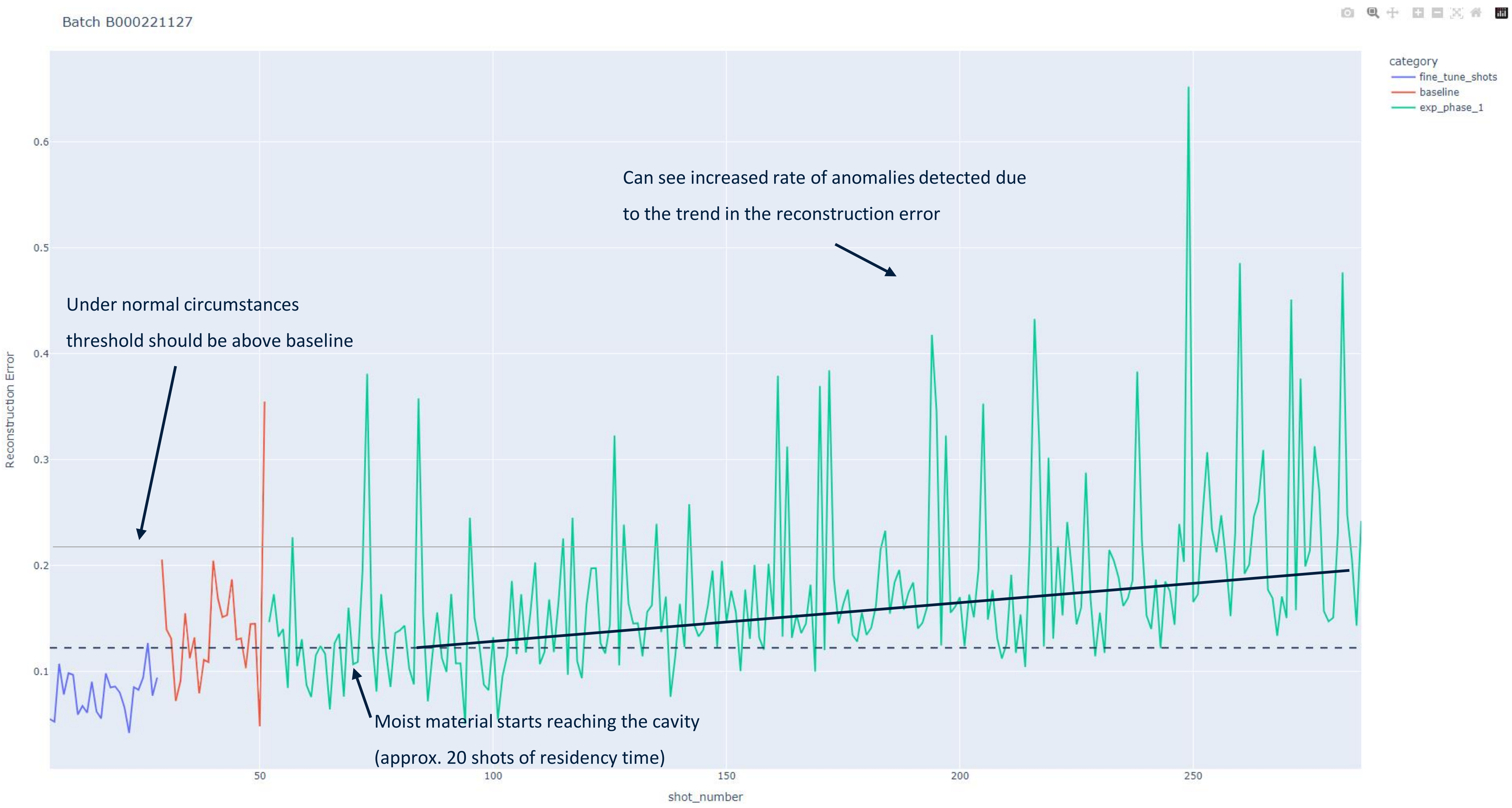
Batch B000221127

Reconstruction error of baseline was high (around 16) -> Problem identified with the E-Flomo system -> Unknown cause (maybe from previous experiment? 600K reconstruction error mean machine was extremely abnormal)

=> Model is fine-tune with some baseline shots -> Works well and significantly decreases reconstruction error from 16 to 0.1-0.2 -> the model learns the new behavior -> But not enough data to fully pick up the new behavior (only 30 shots) so test baseline (red) above reconstruction error



Fault Scenario 3: Overexposed Material (48hrs) with increased moisture content (> 0.1%)

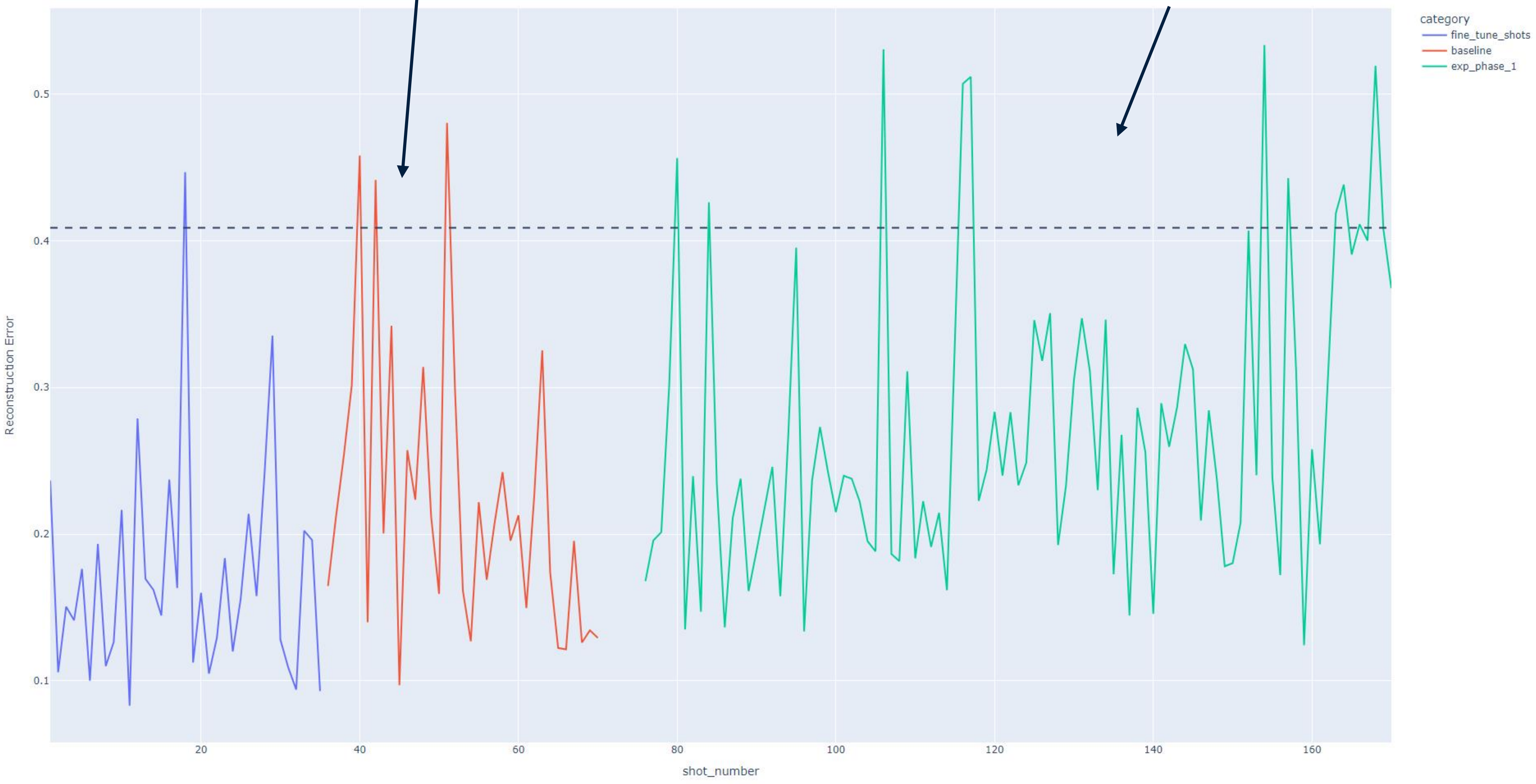


Fault Scenario 4: Overdried material (48 hrs) with decreased moisture level (<0.008%)

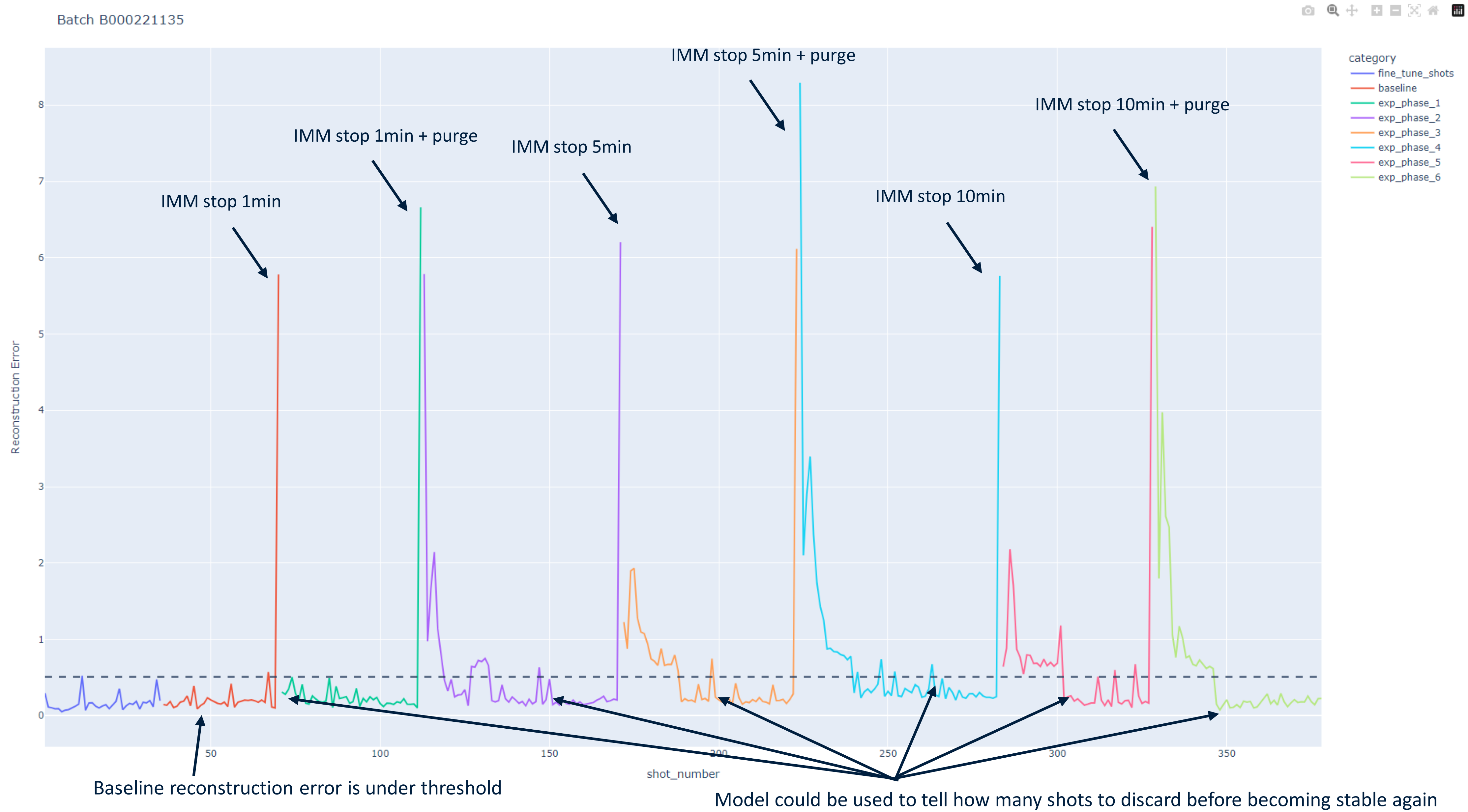
Same challenge on baseline -> reconstruction error was high but now test baseline works better because was already fined tune on previous experiment -> saw more data to learn the pattern from abnormal E-Flomo

No change between Overdried material and normal production -> why? -> Because the tested moisture content of overdried material was comparable to the moisture of normal production batches and was moister than certain normal production baselines -> so it is expected to not see any significant change

Batch B000221123



Fault Scenario 8: IMM stoppages



Fault Scenario 9: Decrease cooling time and increase hot runner nozzle temperature