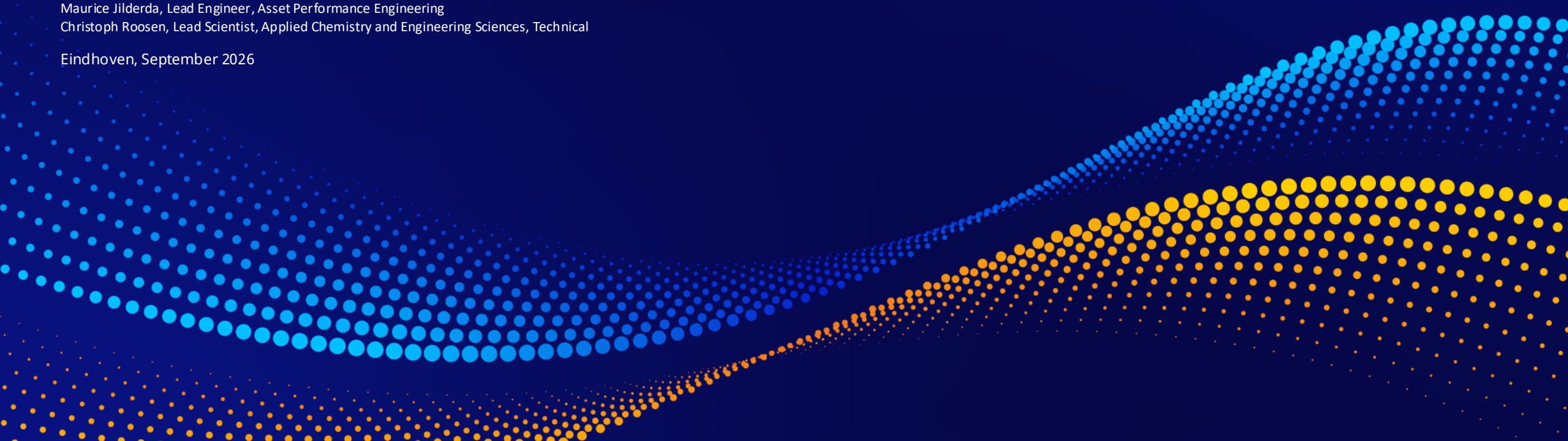


See more. Know sooner. Perform better.

Our journey towards large scale smart plant monitoring

Maurice Jilderda, Lead Engineer, Asset Performance Engineering
Christoph Roosen, Lead Scientist, Applied Chemistry and Engineering Sciences, Technical

Eindhoven, September 2026



“ Imagine an anomaly is
detected in your critical asset.
Would you stop the plant?



Intro

SABIC at a glance



1976

Company
established



26,000+

Employees
around the world



60

Manufacturing/compounding
sites worldwide



Top 2

Chemical Brand Value*



10,700+

Patent portfolio



20

Technology &
innovation centers

The journey

Why smart plant monitoring?

Safety & Reliability

- Increase safety
- Reduce downtime
- Increase quality
- Increase throughput

Shortage skilled employees

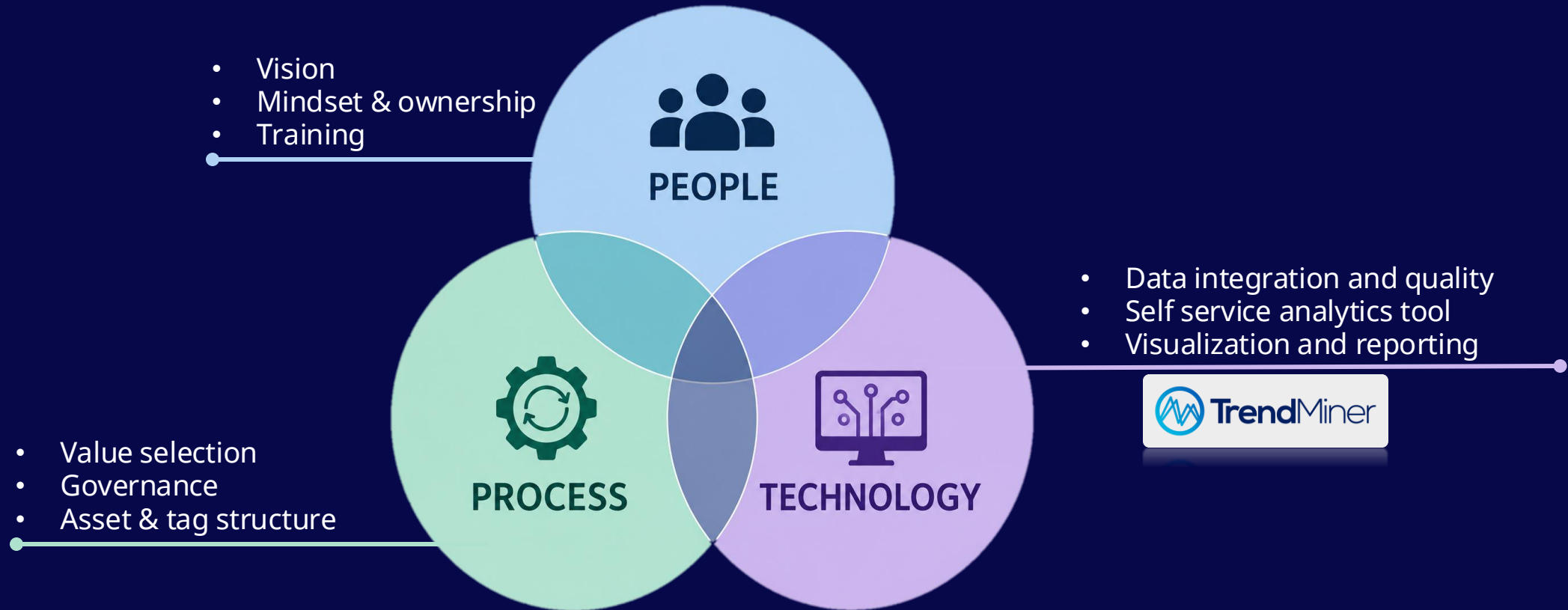
- More efficient usage of hours on monitoring
- Capture knowledge by defining logics and models



Created with AI

The journey

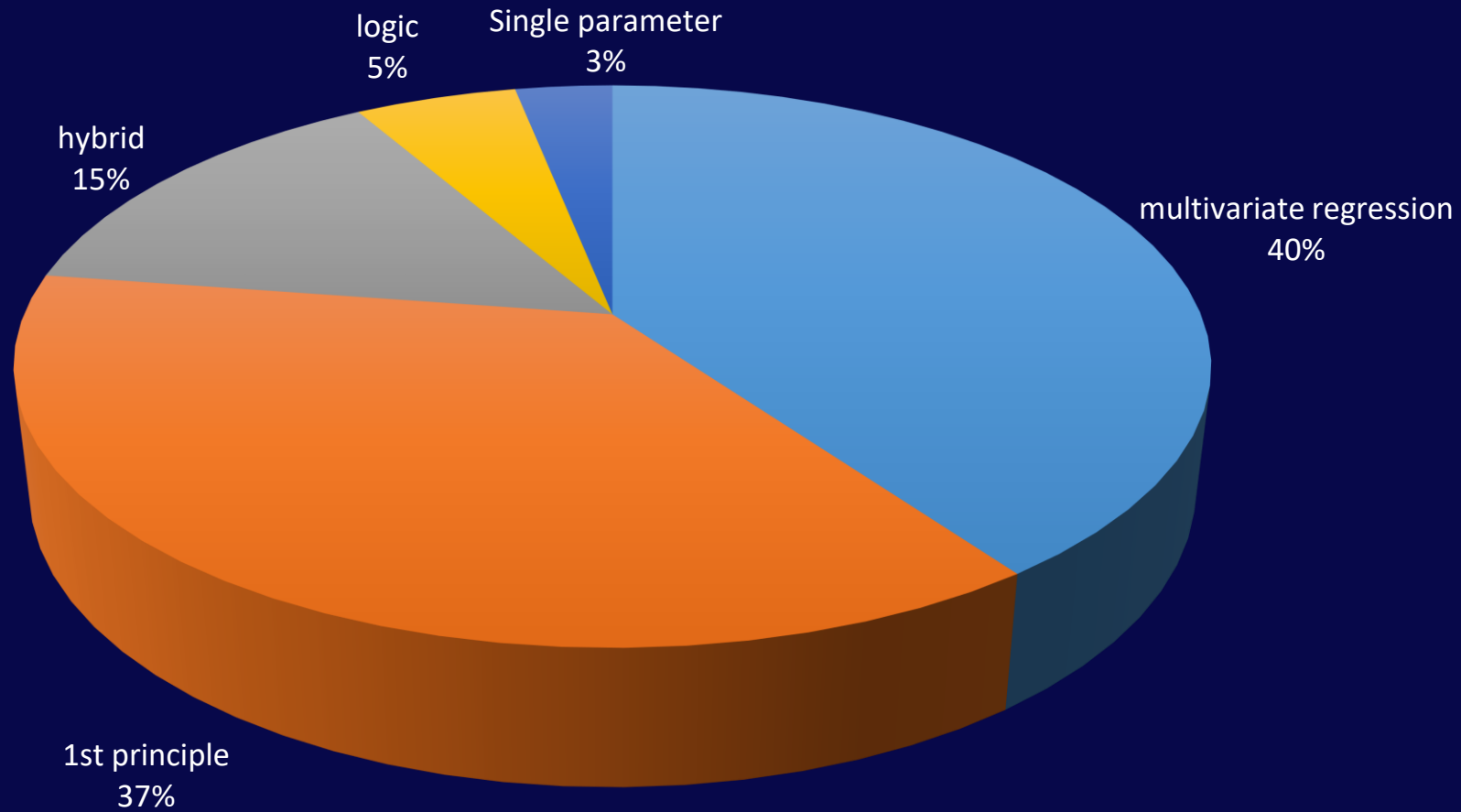
What is your biggest challenge in plant monitoring?



- Source for PPT circles: 1964, Dr. Harold Leavitt's, paper, "Applied Organization Change in Industry"
- Graph generated by AI

The journey

Which **type of algorithm** do you use most?



Of scope 2 plant sections

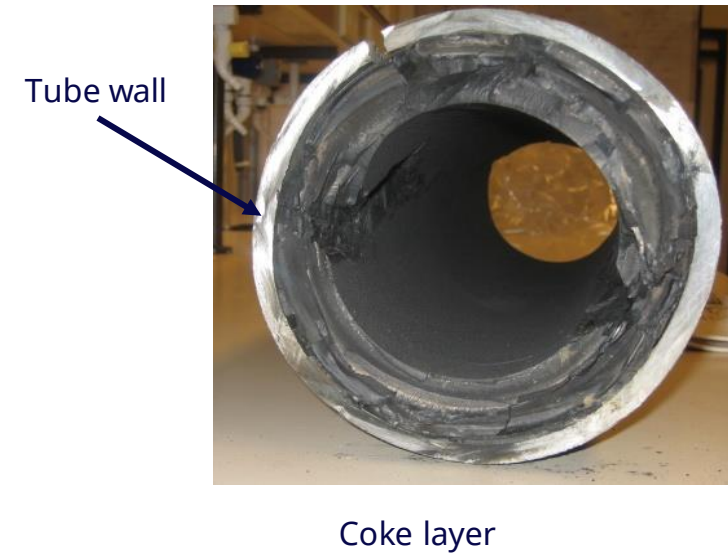
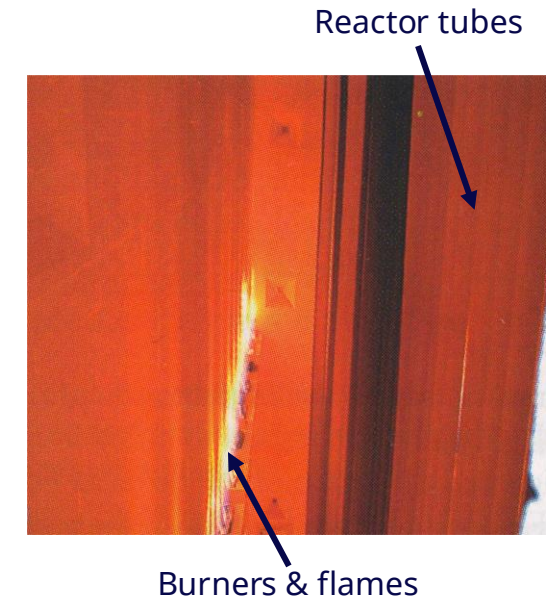
Furnace coil evaluation

Problem:

- Coke build-up inside coil
- New technologies can reduce coking
- Trial evaluation needed

Challenge:

- Dynamic, time series data
- Real plant data
- Comparison of many runs needed
- Tube metal temperature controlled

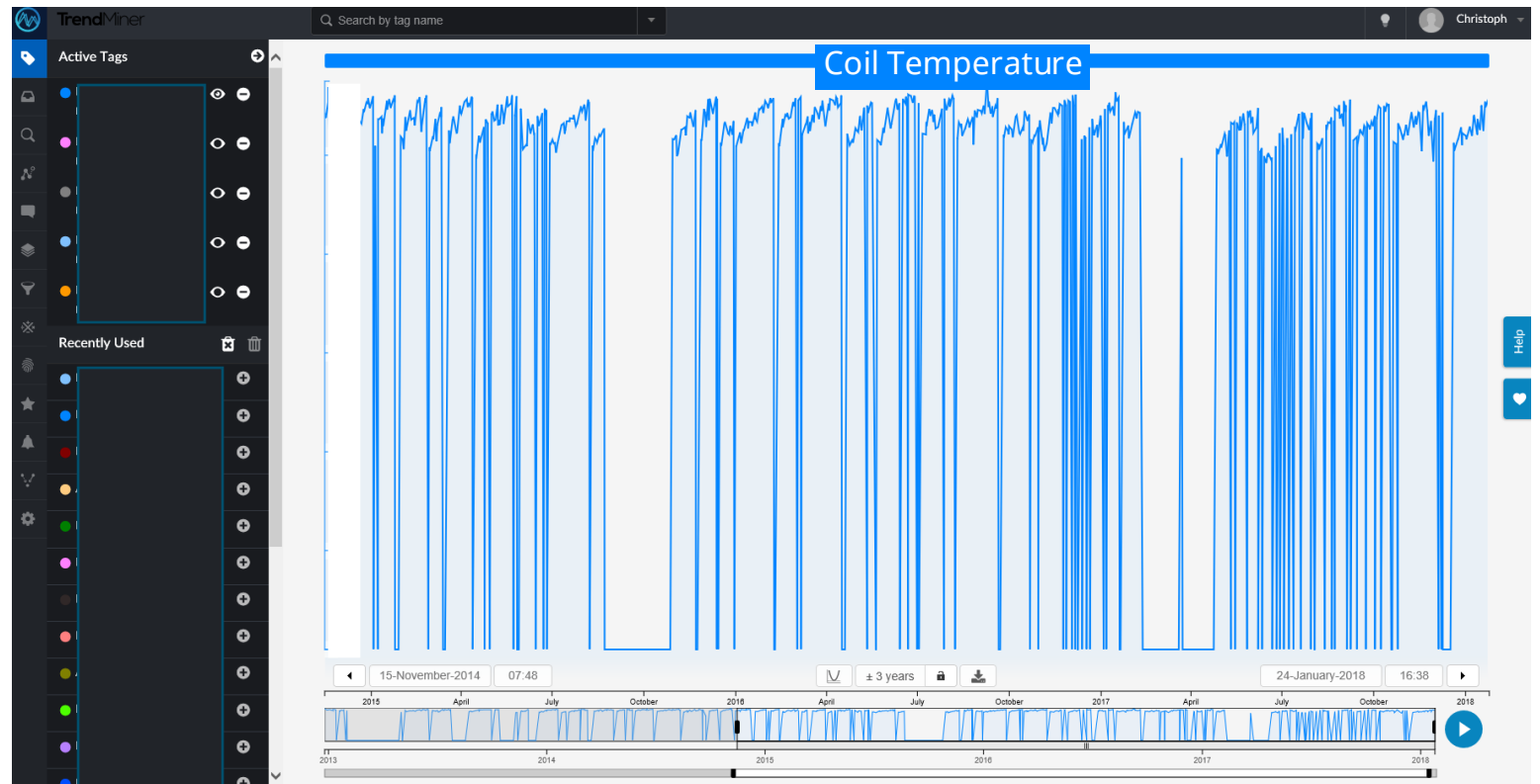


Use Case 1: Furnace coil evaluation

Solution

Step 1:

- Multi-year data
- Semi-batch process



Use Case 1: Furnace coil evaluation

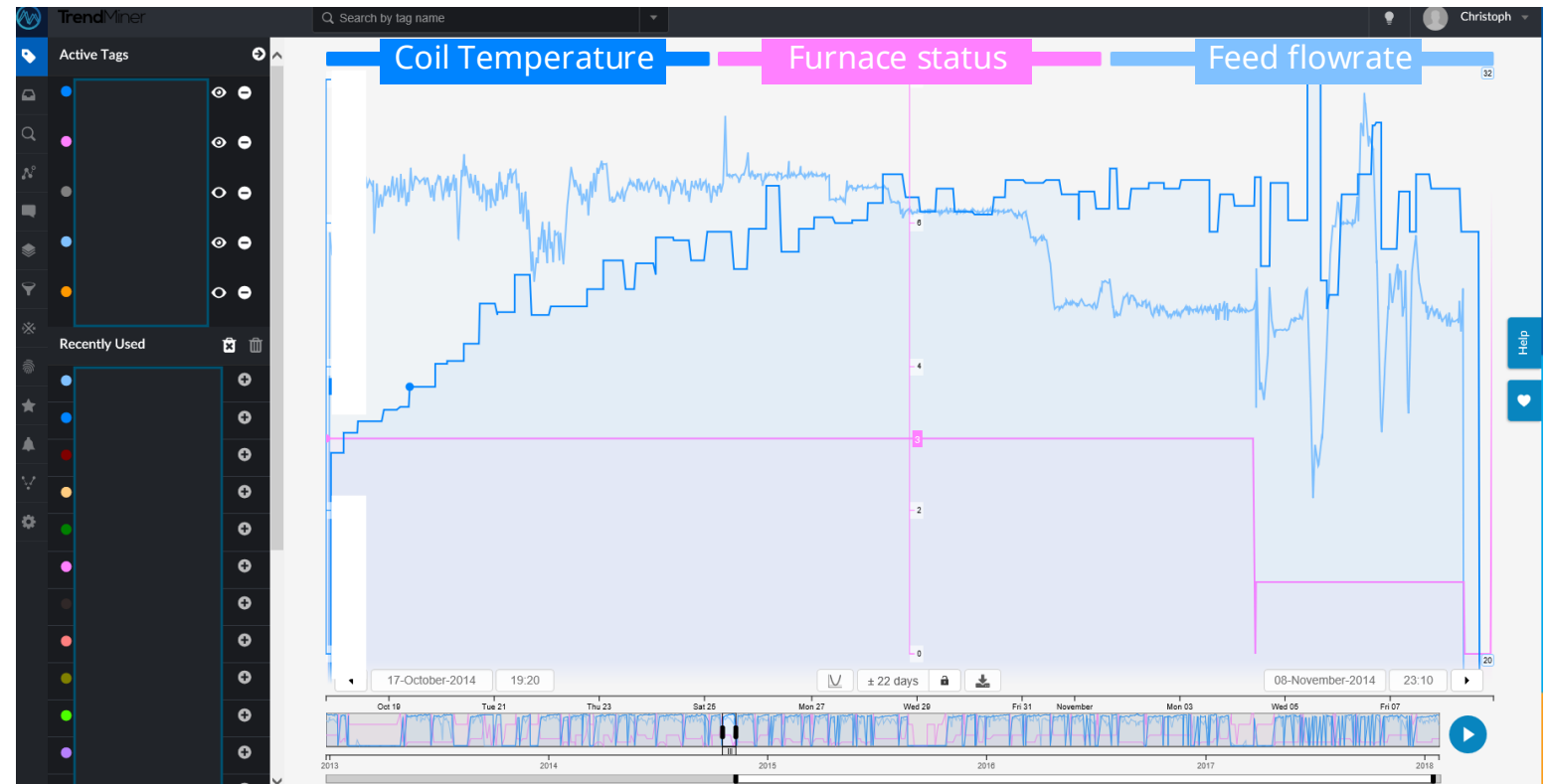
Solution

Step 1:

- Multi-year data
- Semi-batch process

Step 2:

- Find periods with furnace in operation
- Take flowrate and other parameter into account



Solution

Step 1:

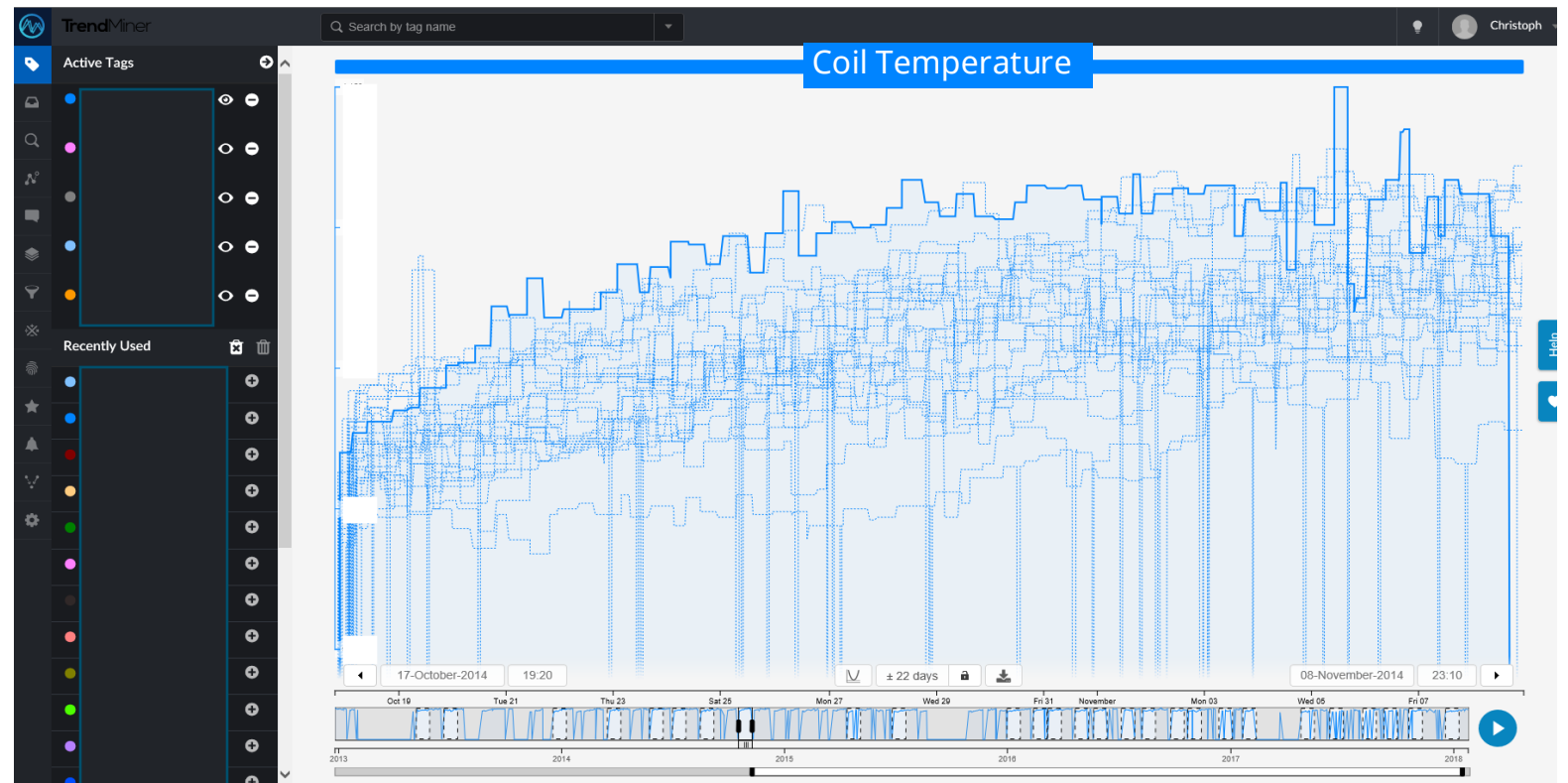
- Multi-year data
- Semi-batch process

Step 2:

- Find periods with furnace in operation
- Take flowrate and other parameter into account

Step 3:

- Build fingerprint and calculate statistical parameter
- Compare before and after



Summary Furnace coil evaluation

Problem:

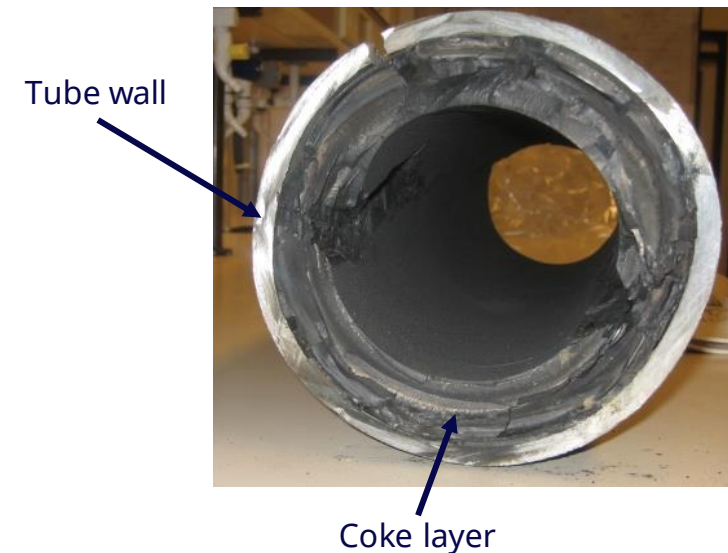
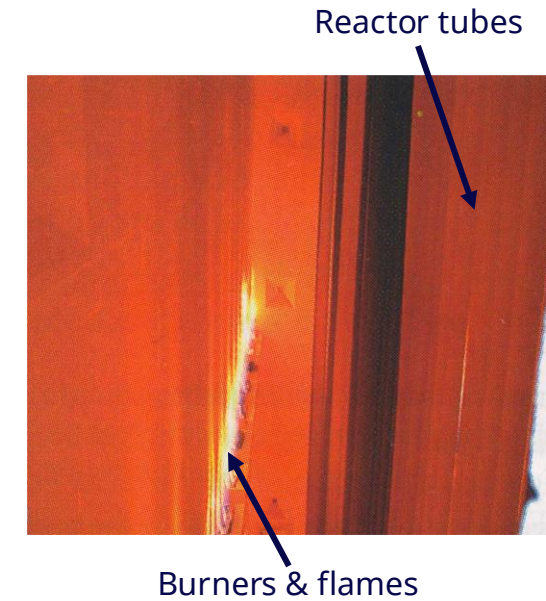
- Coke build-up inside coil
- New technologies can reduce coking
- Evaluation before and after needed

Challenge:

- Dynamic, time series data
- Real plant data
- Comparison of many runs needed
- Tube metal temperature controlled

Benefit of Trendminer:

- Much faster evaluation
- More reliable results
- Easy visualization
- Used for future monitoring to see state of life



Use Case 2: Reduced production losses due to failure prediction

Unplanned stop due to bearing fouling and wear

Problem:

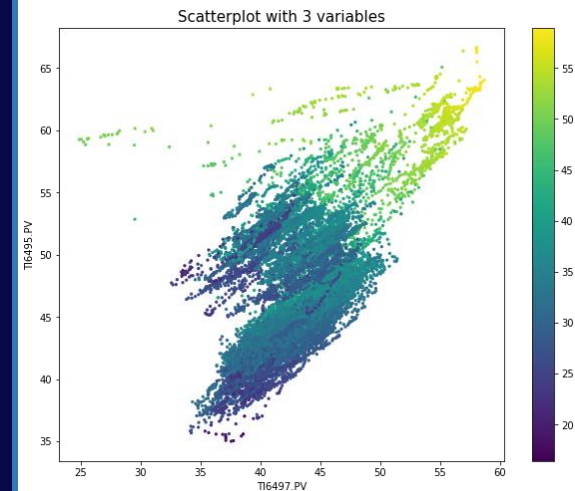
- Fouling and wear of (slow speed) bearing
- Existing early warning was inadequate
- Sometimes turnaround is not reached
- Unplanned shutdown leads to major losses

Challenge:

- No stable signal for bearing vibration and temperature due to environment and process dynamics.
- Multivariable problem

Single variate: Low R^2

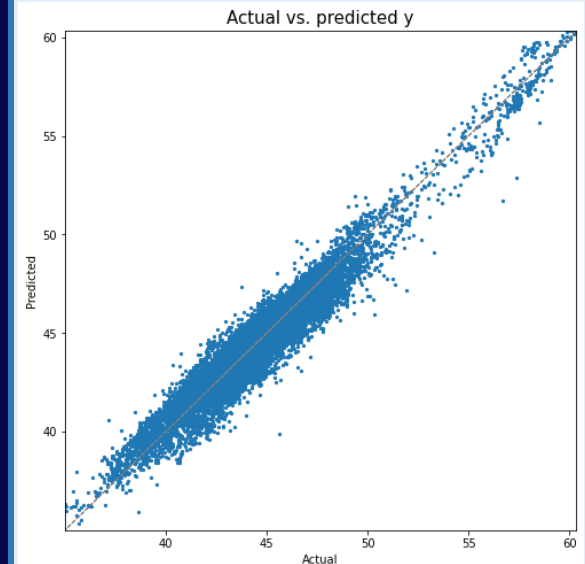
Relation of the 1st and 2nd impact parameter with the bearing temperature: no strong relation.



Not possible to set threshold

Multi variate: High R^2

Multiple parameters: relation model is $>80\%$. Enough to predict the temperature.



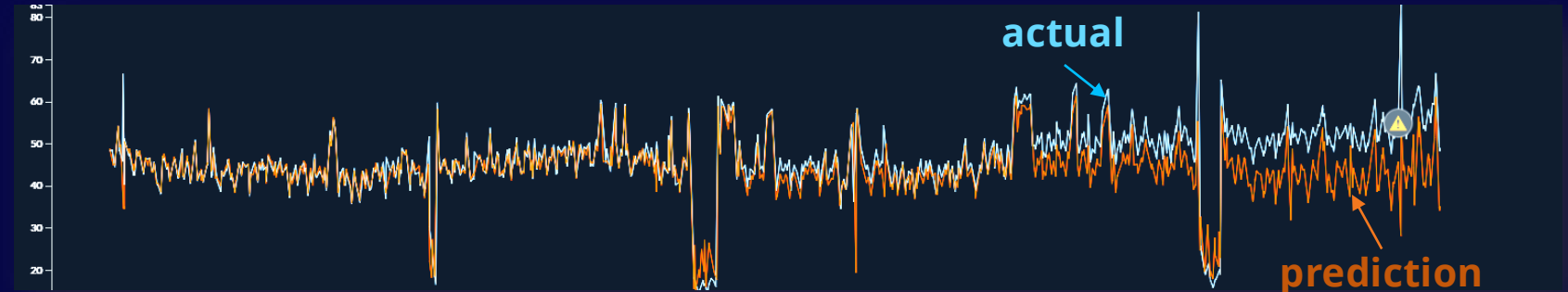
Possible to set threshold

Use Case 2: Reduced production losses due to failure prediction

Build monitor for fouling and wear

Approach & solution:

- Build multivariable regression in TrendHub to predict bearing temperature;
 - Scale-up for all 4 assets
 - Between 8-11 variables per model
 - R^2 sufficient for this application ($>80\%$)
- Alarms via DashHub



Use Case 2: Reduced production losses due to failure prediction

Reduced production losses due to failure prediction

Impact

- We decided to fix the bearing in an earlier planned stop
- Repair was just in time (see picture)
- Prevented losses: > 1 million Euro



Use Case 3: Increased gross margin due to improved quality stability

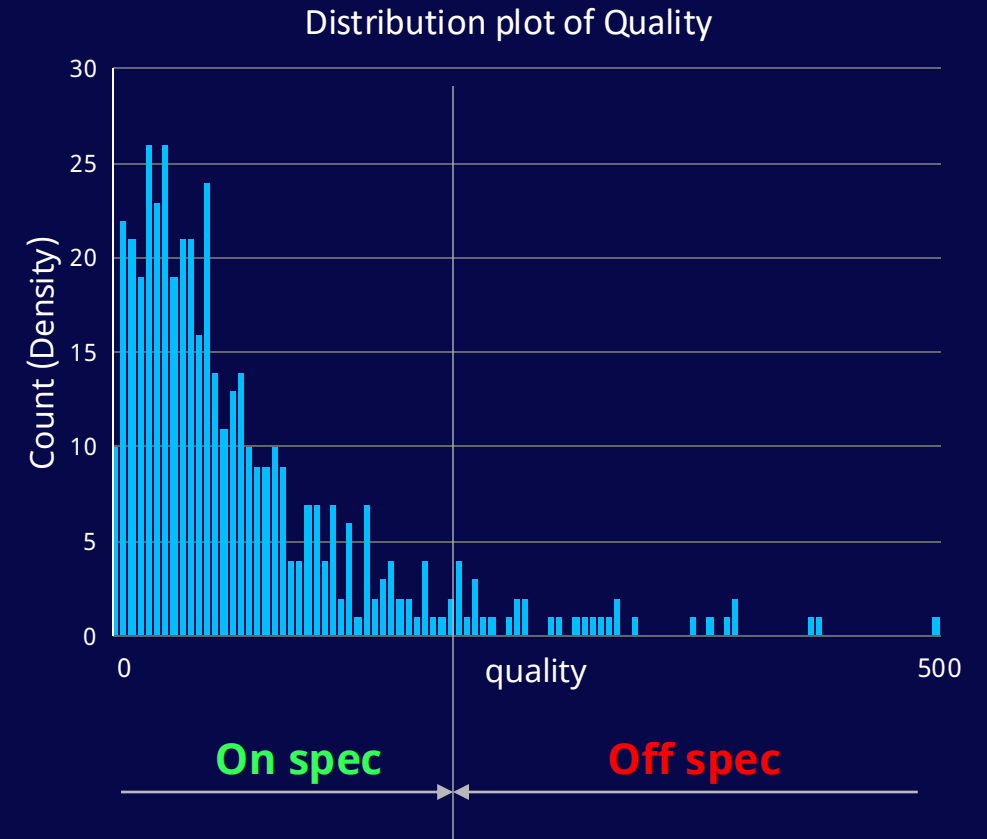
Off spec quality for this product

Problem:

- Unstable quality at normal (high) throughput
- Due to instability lower throughput to avoid off spec
- Led to gross margin loss

Challenge:

- Limited lab data
- Limited data of this product type
- Lab measurement accuracy is relative low
- Lot of changes in process over time



Use Case 3: Increased gross margin due to improved quality stability

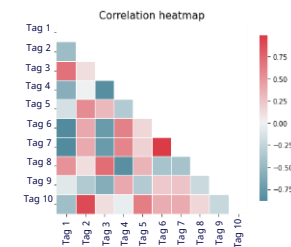
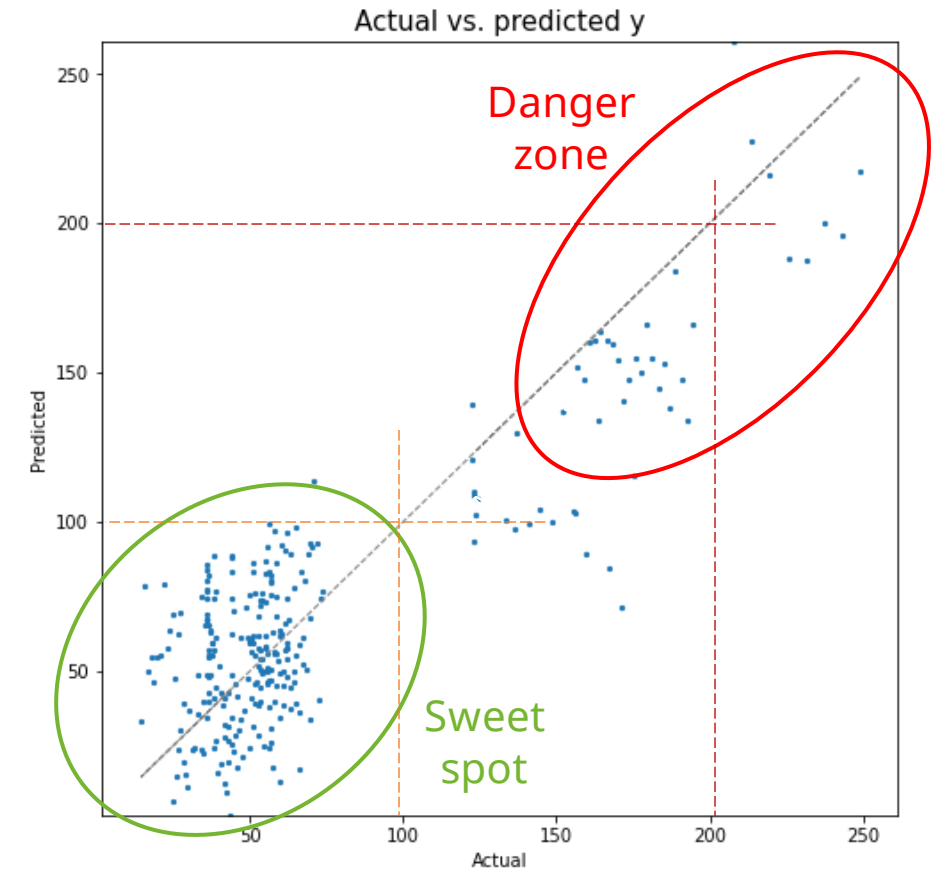
Predict quality and find 'golden' recipe

Approach:

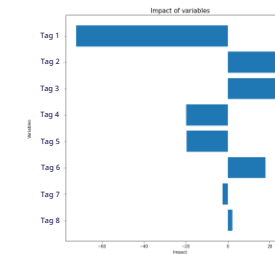
- Prediction of quality with regression
- Find several sweet spot combinations

The algorithm

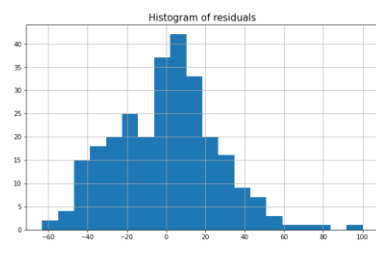
- Prediction with multivariate statistical regression
- 8 input parameters
- R^2 sufficient for this application (73%)



Correlation matrix



Impact parameters



Histogram of residuals

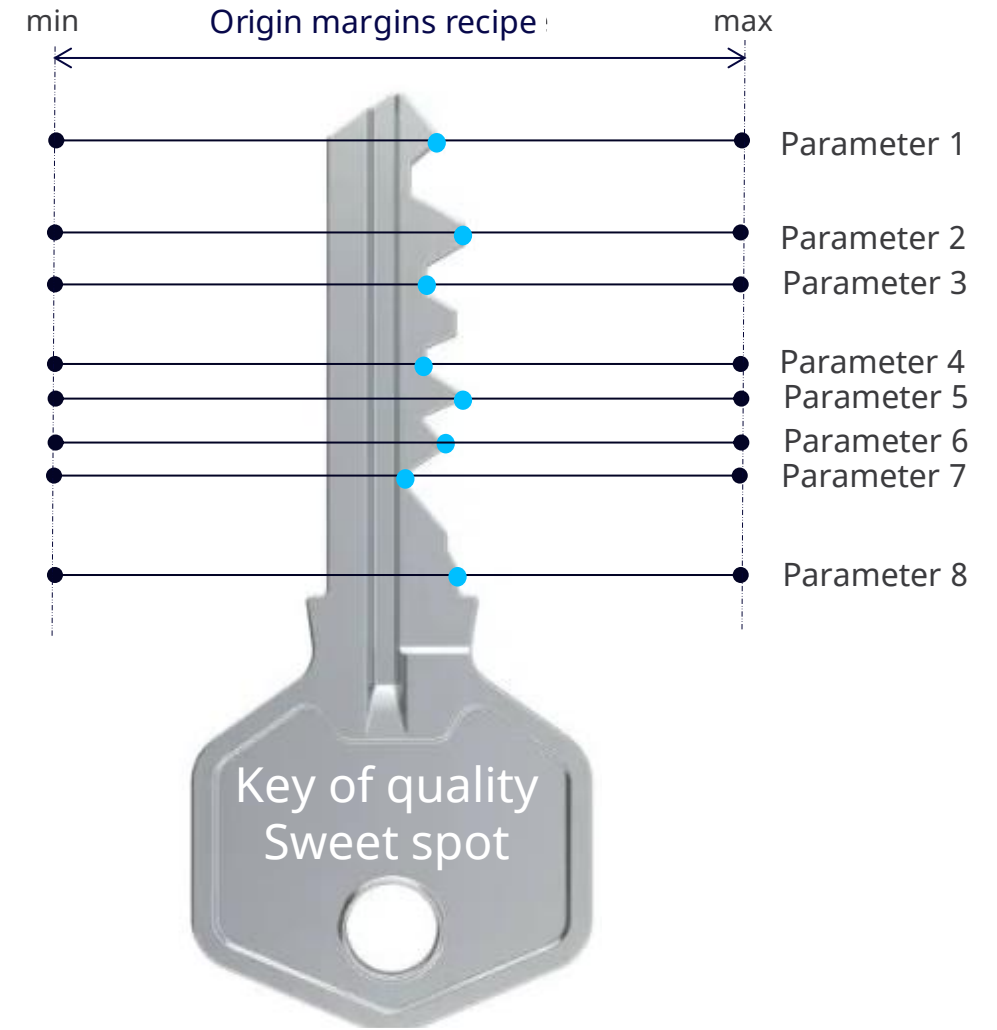
Results: 100% within spec

Solution

- Optimized product recipe
- Prediction in Trendminer with threshold in DashHub
- Multi variable SPC in Trendminer DashHub

Impact

- Quality **100% within spec** since implementation
- Always maximum throughput
- Additional gross margin **> € 500k Euro per year**
- Extend lifetime of asset parts at **€ 200k** with **two years**



Wrap up

Where we are now

- Today's scale of the project:



- Next step is to scale up to the complete Geleen site. (5 times today's scope)



Key Takeaways

- Manage the **total process of monitoring** where people, processes and technology meet.
- Summary of our improvement areas of 2024-2026 for further inspiration:
 - Improved **quality** of specific product grade with effect of 9% increased throughput
 - Reduced **downtime** due to prediction of asset failures (multiple cases, x million Euro GM)
 - Optimize **scheduling** and risk reduction due to better forecast of (complex) fouling
 - **Faster (re)startup** of recovery plant due to real time insights
 - **Time saving** for plant monitoring, root cause analyses and evaluations
 - Installed operator **warnings** for critical anomalies in the process

Thank You

