

## AI als hefboom voor onderhoud en service teams

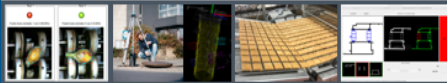
**Dr. Jan Verhasselt, Managing Director  
Yazzoom, a PA-ATS company**

2024



# Yazzoom offer: our 4 activities to create value from data

**DISCOVERING VALUE WORKSHOPS**  
**HOW CAN AI CREATE VALUE FOR YOU?**  
**INSPIRATION + ROI CALCULATION + PRIORITIZATION**



## **MACHINE VISION**

**QUALITY CONTROL**  
**VISUAL INSPECTION**  
**ASSEMBLY CHECK**  
**AUTOMATIC SORTING**  
**MEASUREMENTS & METROLOGY**  
**COLOUR & SHAPE CONTROL**



## **CUSTOM AI SOLUTIONS** **FOR INDUSTRY 4.0**

**DECISION SUPPORT**  
**WHAT-IF ANALYSIS**  
**AUTOMATED OPTIMIZATION**  
**PLANNING RECOMMENDERS**  
**DIAGNOSTIC ANALYTICS**

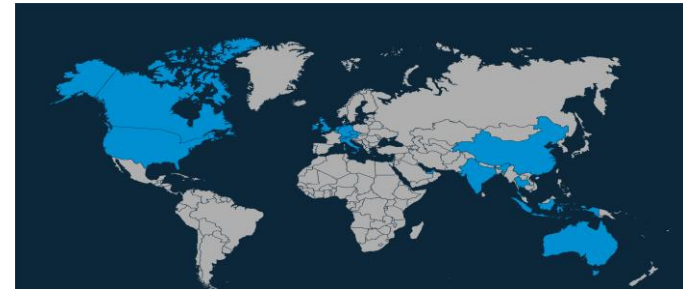


## **YANOMALY** **AI-POWERED ANALYTICS FOR** **INDUSTRIAL DATA PLATFORMS**



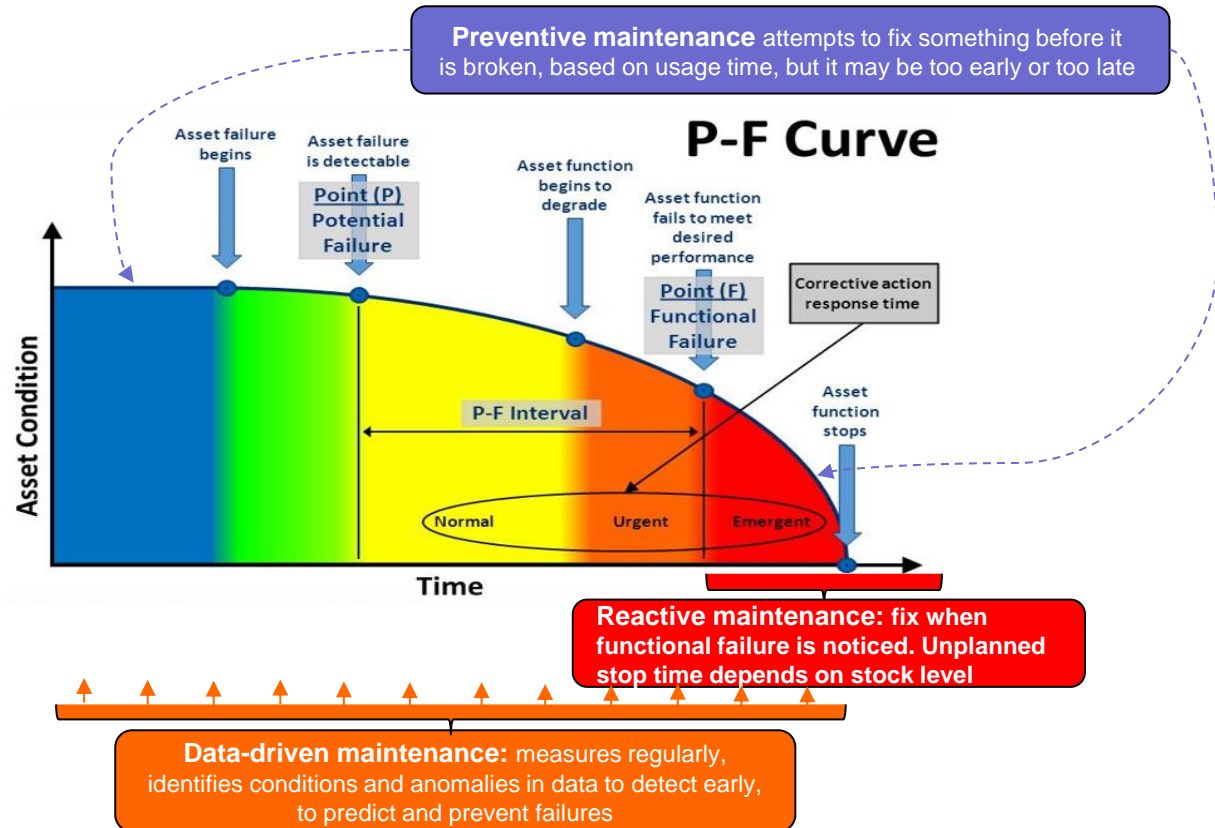
# Corporate Structure

- Yazzoom is daughter company of Process Automation Solutions (<https://pa-ats.com/>)
  - About 1600 people
  - Offers for Industrial Production companies:
    - Consulting
    - Automation
    - Digital solutions
- Process Automation Solutions is daughter of ATS Corporation (<https://atsautomation.com/>)
  - About 7000 people
  - HQ Cambridge, Ontario, Canada
  - Listed on Toronto and New York Stock Exchange
- Locations: 60 manufacturing facilities and over 80 offices in North America, Europe, SE Asia and China

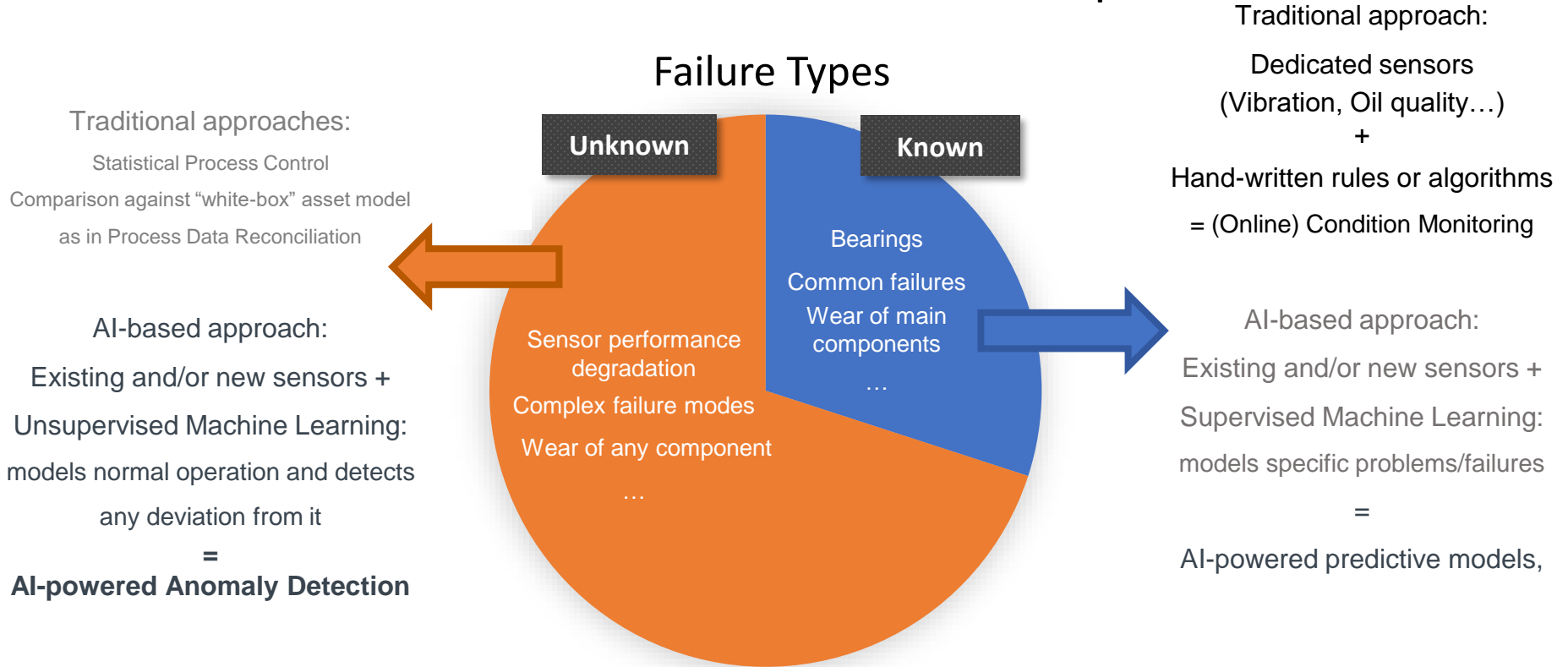


# AI for data-driven maintenance

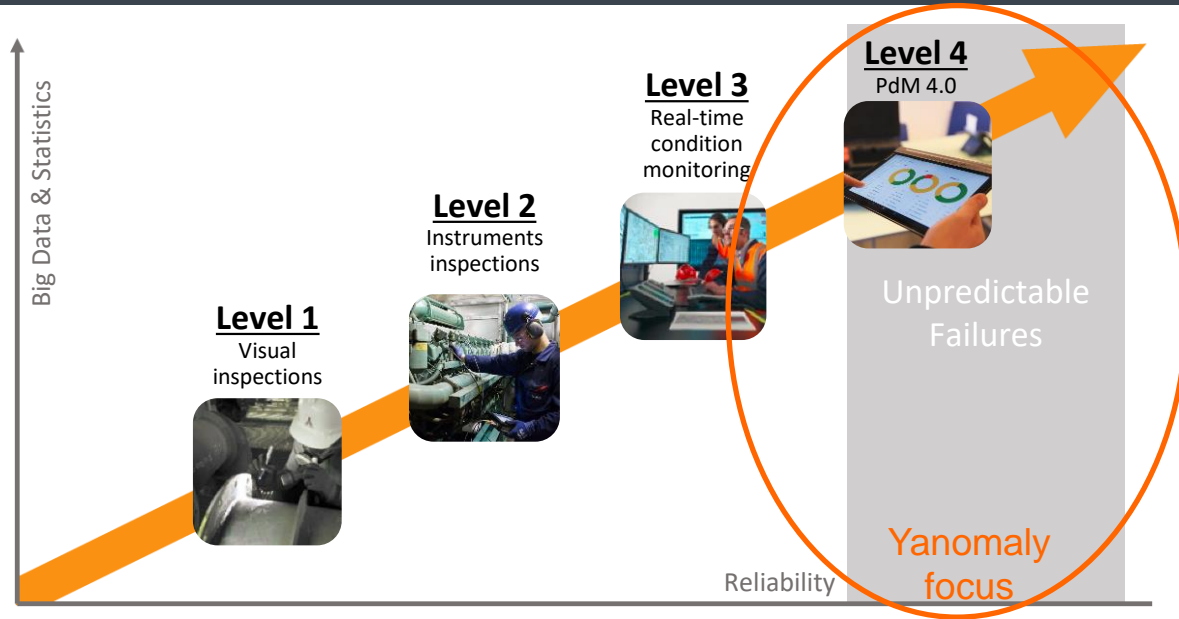
What if you could detect asset health issues in existing machine/process data?



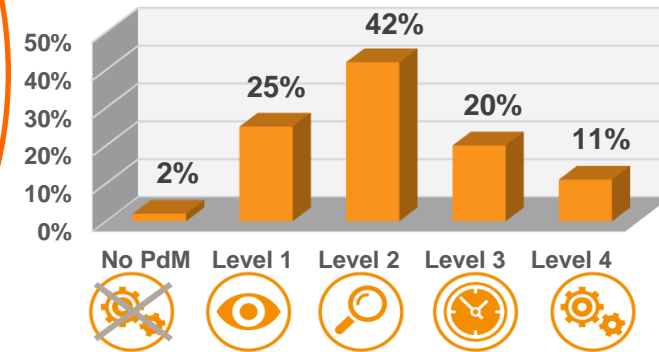
# Data-drive maintenance techniques



# What is your Predictive Maintenance Maturity?



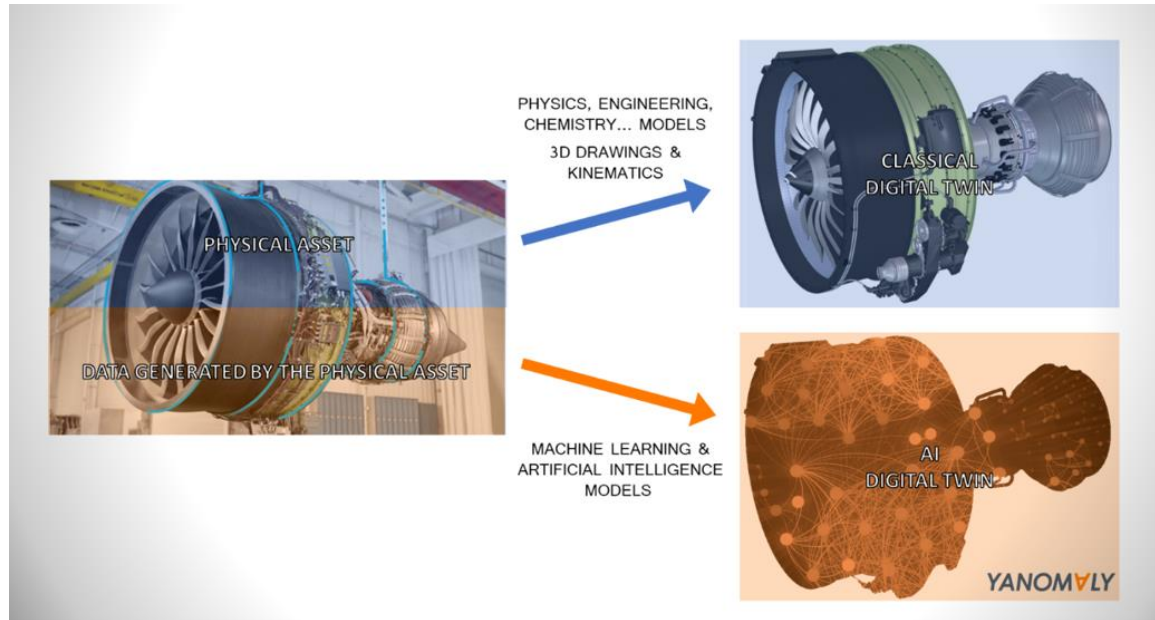
## Current PdM maturity level - EU Industries (2018)



- **Visual inspections:** periodic physical inspections; conclusions based solely on inspector's expertise
- **Instrument inspections:** periodic inspections; conclusions based on a combination of inspector's expertise and instrument read-outs
- **Real-time condition monitoring:** continuous real-time monitoring of assets, with alerts given based on pre-established rules & critical levels
- **Predictive maintenance with big data analytics:** continuous real-time monitoring of assets with alerts sent based on AI techniques such as anomaly detection and regression.

# HOW IS AI-BASED ANOMALY DETECTION DONE?

AI-based anomaly detection is done by letting computer algorithms learn mathematical models (digital twins) of normal operation/data of a machine or system, and then report deviations from normal operation as anomalies



- **Abnormal values**
- **Abnormal dynamics**
- **Abnormal patterns**
- **Abnormal statistics**
- **Abnormal settings**
- **Abnormal changes**
- **Abnormal relations**
- ...

# YANOMALY: OWN SOFTWARE PRODUCT FOR ANOMALY DETECTION...AND MORE



# YANOMALY

Scalable software product for adding AI-based monitoring & analytics to Machines, Production Lines and IoT devices

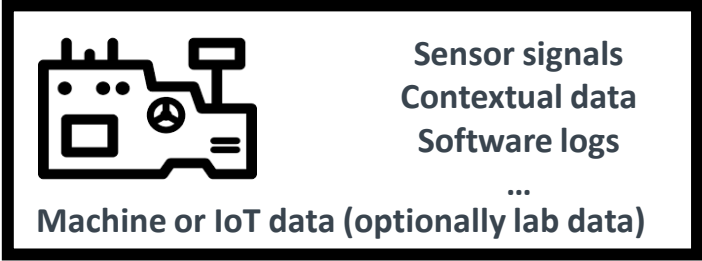
## Included functionalities:

1. Sensor data quality validation
2. Anomaly detection
3. “Golden” production run advisor
4. Predictive models for virtual sensing
5. Micro-stop detection

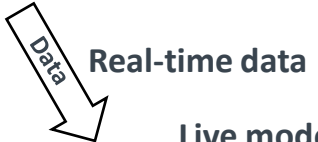
## Used for:

1. Production process improvements
2. Data-driven maintenance
3. Product quality improvements

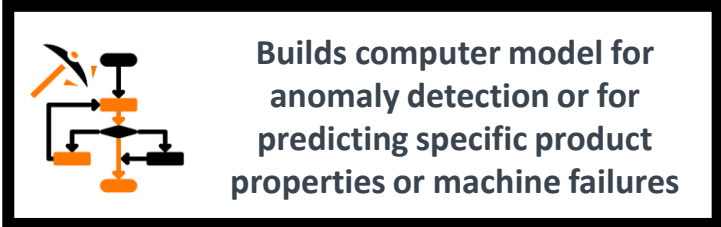




# YANOMALY



Machine Learning



Model Training



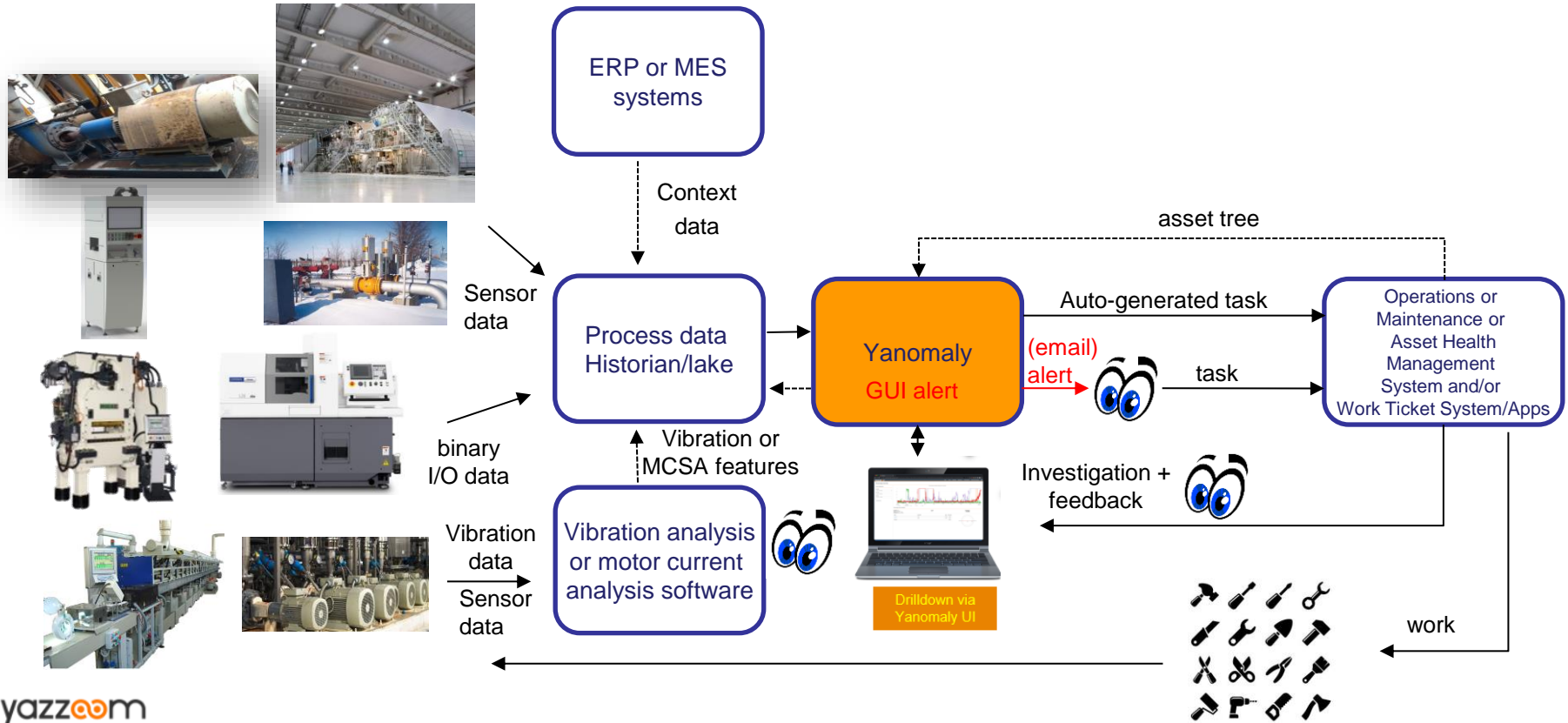
Live model computing

Model Deploying

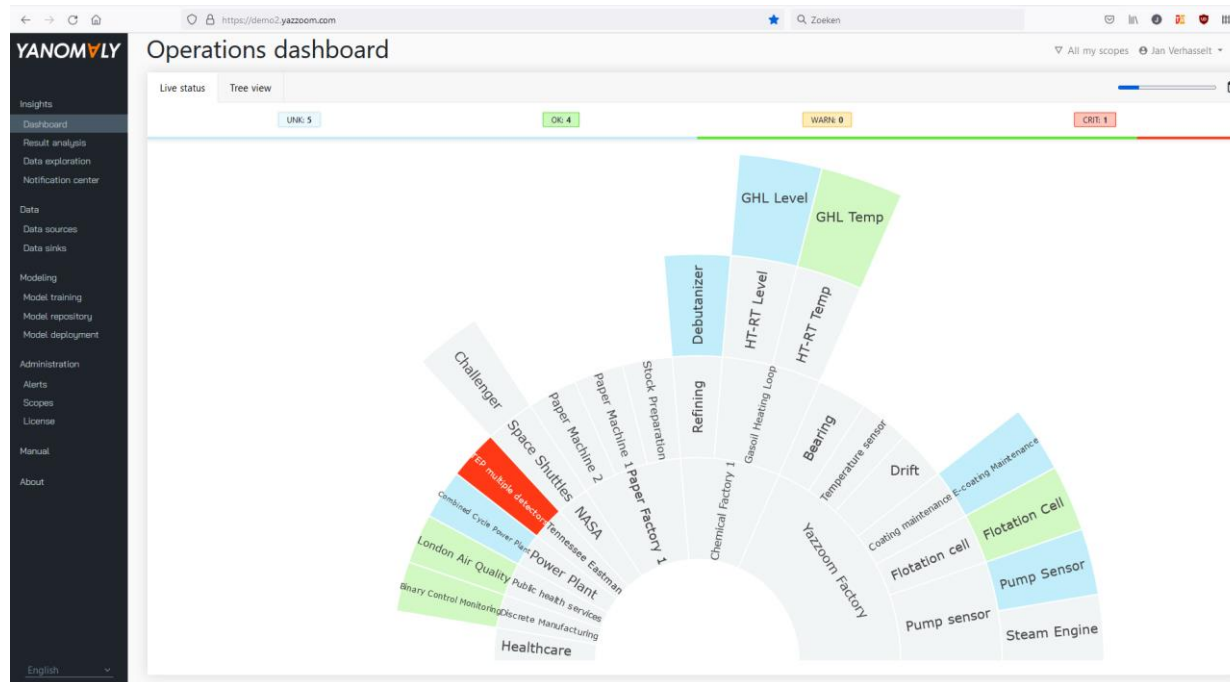
Diagnostic analytics

Anomaly Alerts  
Predictions  
Recommendations

# Example integration in existing IT/OT technology for anomaly detection, with optional vibration/MC analysis



# Live Status Dashboard / Overview Report showing location of biggest issues + allow drill-down



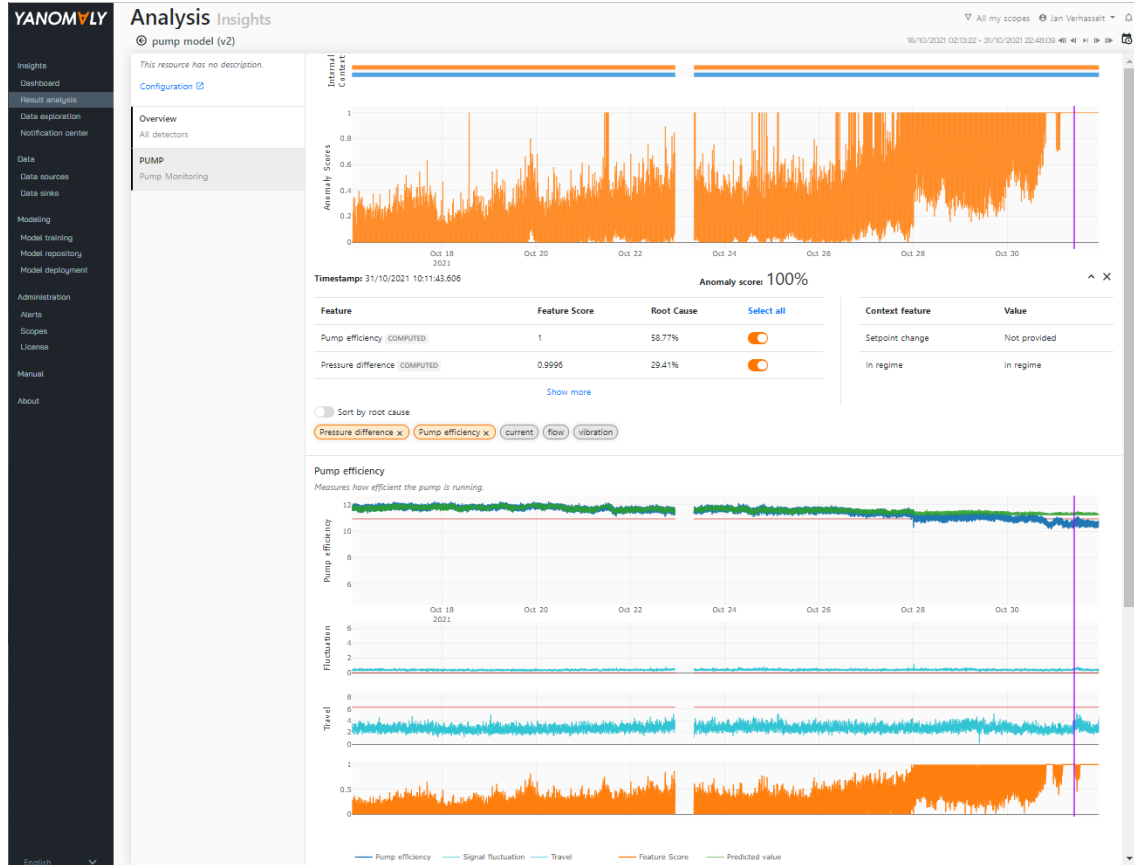
Example of levels: Plant, Line, Machine, Subsection, Control Loops

# 5 different ways AI-based anomaly detection complements traditional condition monitoring

1. Combine traditional predictive maintenance technology (“condition monitoring”) with process data and context data to make an **even earlier or more reliable (less false alarm) detection of specific failures**. Thanks to making the decision to alarm or not on more information about the concrete circumstances.
  - *Example: combining vibration + context + process data in pump monitoring*
2. Detect and remedy issues in the production process that over time would lead to asset degradation. This is before the P-point of that failure. Avoid avoidable asset health degradation by detecting process anomalies.
  - *Example: detect oscillation of control loop caused by bad PID parameters: avoid faster wear of control valve*
3. Detect asset health issues for which there is no condition monitoring technique. Because it is a quite unique installation for which there are not enough examples of failures to build a dedicated sensor and algorithm to detect that failure.
  - *Example: detecting issues in a floatation cell based on multivariate anomaly detection in the sensor data.*
4. Detecting asset health issues for which adding available condition monitoring techniques is too expensive. Instead use existing process data for anomaly detection on many assets. Better than no health monitoring.
  - *Example: Stora-Enso and other large-scale anomaly detection customers.*
5. Detecting asset health issues for which there is no gradual degradation of the health, but a sudden one. In that case the idea of predicting the failure is impossible.
  - *Example: detect mistake made during planned maintenance on pump. Avoid functional failure.*

# Specific hybrid AI anomaly detector for monitoring pumps: Pump monitoring detector:

Example  
from sugar  
producing  
company



## Benefits:

- Reduce unplanned stops
- Save energy
- Avoid bigger damage to pump

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# Example use-case from food industry

## Control Performance Degradation Detection

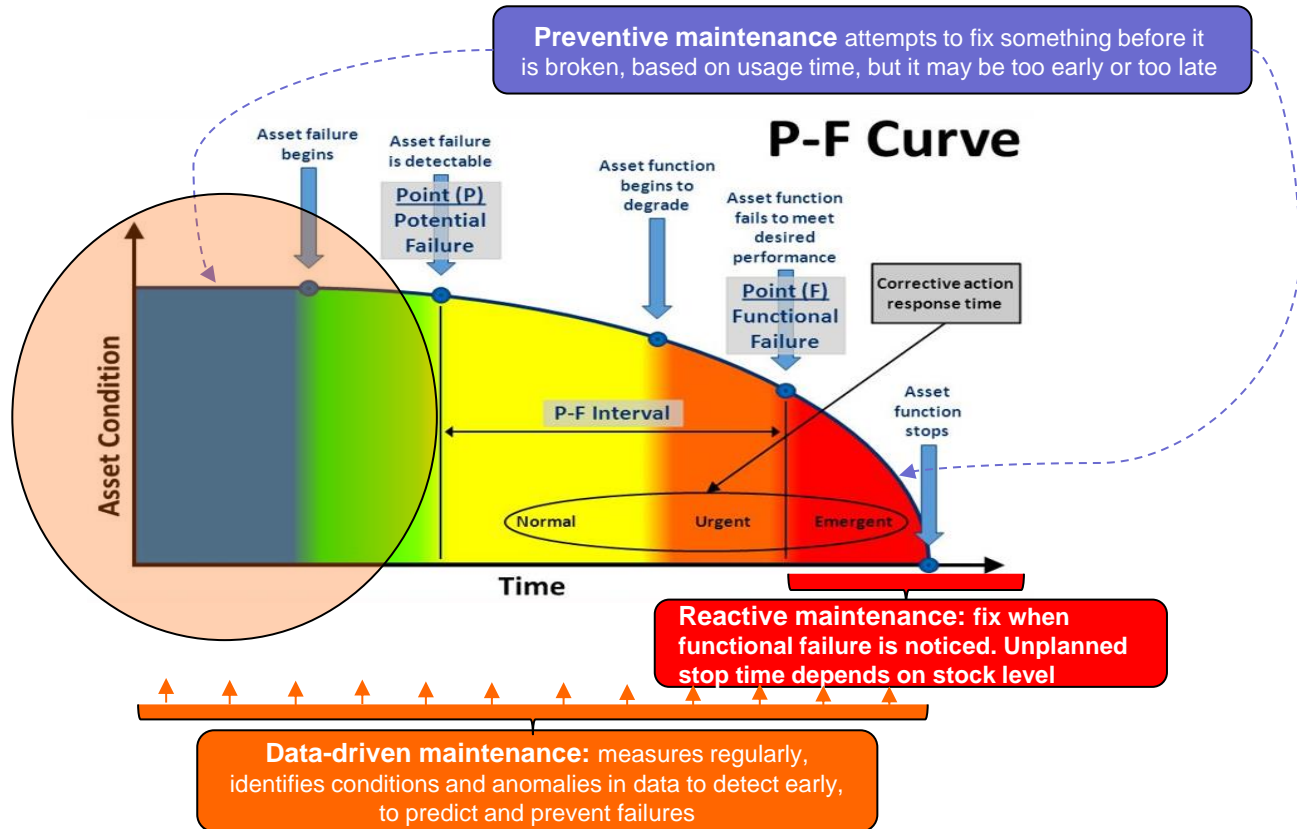
Oscillations detected preceding control valve breakage



- Cause : Ceramic valve of level controller broken
- Risk : No control on level
- Action : Maintenance on the valve during planned stop
- Added value : WinCC is not able to detect oscillations. Yanomaly detected issue 8 days before failure

# AI for data-driven maintenance

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# Evaluation by users @ paper mill with 500 anomaly detecting models on motors, controllers,...

- All (email) notifications by Yanomaly are investigated and classified:
  - False alarm
  - Justified alarm, but not useful
  - Justified alarm and useful
- Actions are coupled to the useful notifications, examples:
  - “Pump doesn’t work without manual intervention, must be replaced”
  - “Re-tune PID controller”
  - “Limit control valve to 20%”
- No vibration sensors used
- Summary statistics after 6 months:

Categories	count	%
False alarm	24	12.12%
Justified alarm but not useful	40	20.20%
Justified alarm & useful	134	67.68%
<b>Total</b>	<b>198</b>	<b>100.00%</b>

# Alert List

Useful for operators/engineers to see most recent alerts, investigate them, and give feedback

●	06/12/2024 10:40:16	43m 50s	Flotation Cell	Abnormal relation	Upstream pH	CRIT
●	06/12/2024 10:40:06	10s	Flotation Cell	Abnormal relation	Upstream pH	WARN
●	06/12/2024 10:39:56	10s	Flotation Cell	Abnormal relation	Upstream pH	CRIT



1) Select alerts from list of recent alerts

**Alert details**

General Feedback

Severity **CRIT**

Start time 06/12/2024 10:40:16

End time 06/12/2024 11:24:06

Duration 43 minutes and 50 seconds

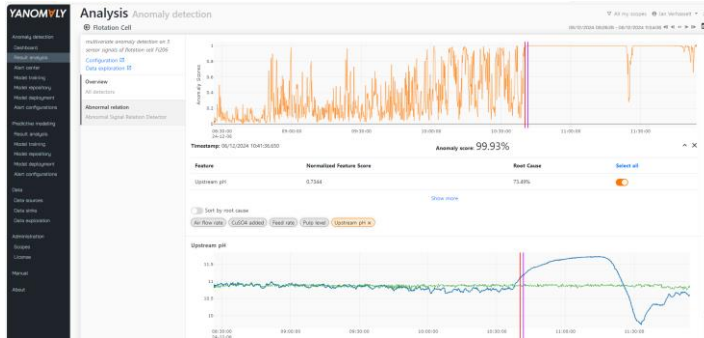
Resolution Unresolved

Suppressed No

The following features contribute the most to this a

**Feature**

Upstream pH



**Alert details**

General Feedback

**Suppression**

Duration\*  Suppress until\*

Reason\*

**Resolution**

Unresolved

True alarm

True alarm but not useful

False alarm

**Comments**

Jan Verhasselt • 06/12/2024 18:16:30 • [Edit](#)

Control valve for pH broken and needs replacement

2) Investigate

3) Give feedback

# Boon Edam case Lifeline security gates PoC

- Status: Currently preparing data collection including normal functioning and failures
- Next: figure out which anomaly detection algorithms applied to which data is best suited for data-driven maintenance



# BEDANKT VOOR JE AANDACHT!

## Meer informatie:

- Jurjen Helmus – Hogeschool van Amsterdam: [j.r.helmus@hva.nl](mailto:j.r.helmus@hva.nl)
- Dr. Jan Verhasselt - Yazzoom: [jan.verhasselt@yazzoom.com](mailto:jan.verhasselt@yazzoom.com)

## FME Platform AI for Industry:

Patrick Blommerde – FME: [patrick.blommerde@fme.nl](mailto:patrick.blommerde@fme.nl)

# FME AI FOR INDUSTRY JAAREVENT



**Bedankt voor  
je aandacht!**