

Wanneer Artificiële Intelligentie gebruiken voor predictief onderhoud van gebouwen?

Jan Verhasselt

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yazzoom helps you create **value** from your **data**

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Years

Data Science

AI – Machine Learning
Prescriptive Analytics
Optimization algorithms
Data and Process Mining

Engineering

PID control
Vision and Sensors
Physics - Mechatronics
Advanced Process Control

Scope

Consulting and Services
End to end data projects
Software products
Custom made software

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People



PURPOSE OF THIS TALK

Inspire

- Using examples from AI-based predictive maintenance in Industry

Educate

- Explain AI-based and more traditional predictive maintenance

Motivate

- Further reflexion, discussion and refinement

PLANNING MAINTENANCE

Several ways to “plan” maintenance (RCM2 terminology)

- Scheduled maintenance – Preventive maintenance
 - Each X weeks
 - After X running hours
- Condition based maintenance – Predictive maintenance
 - Based on dedicated local measurements and dedicated decision logic, e.g. vibrations (aka “condition monitoring”)
 - By combining several (available) measurements in mathematical computations to derive metrics indicating maintenance need, e.g. normalized energy efficiency, probability of failure, anomaly scores,... (aka “multivariate condition based maintenance”)

FIRST RULE ON WHEN TO USE AI-BASED PREDICTIVE MAINTENANCE

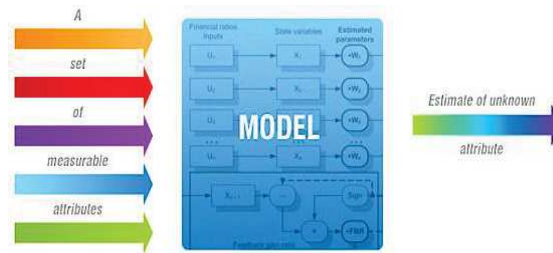
- Only when it makes sense to use predictive maintenance ...instead of reactive or preventive maintenance, or redesign
- Reliability Centered Maintenance is a methodology to decide when that is the case (see literature, e.g. book John Moubray on RCMII)
- However, RCM2 takes into account ao. the technical feasibility and cost of predicting maintenance need
→ so if AI can help to reduce cost or improve accuracy of predicting maintenance need, it will influence decision

SO IF YOU DON'T LIKE TO LEARN SOMETHING NEW I HAVE GOOD NEWS...AND BAD NEWS

- The GOOD NEWS is...
 - Fundamentally HOW you decide when to use predictive maintenance or not does not change:
 - Just apply the RCM2 principles
- The BAD NEWS is...
 - The outcome of the decision can be different if you have access to AI based predictive maintenance techniques
 - So you need to learn a bit about these techniques and how much they cost and when they are useful
 - So stay tuned 😊



USING MATHEMATICAL MODELS FOR CONDITION BASED MAINTENANCE



- **Example:**

- output = a metric indicating maintenance need, e.g. asset efficiency, product quality, probability of failure, anomaly scores...
- inputs = voltage, current, pressure, flow, outside temperature, solar irradiation...
- model = arithmetic and logical operations to compute the output from the inputs

TYPES OF MATHEMATICAL MODELS

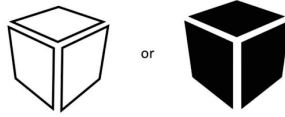
A. **White box models:** mathematics written by human expert

1. Simple man-written rules, e.g. acceptable ranges on sensor values
2. Dedicated statistics and algorithms for detecting specific issues, e.g. control loop oscillation, vibration harmonics exceeding threshold,...
3. Dedicated more complex models, e.g. efficiency of a compressor as a function of operating point

B. **Black box models:** model derived from data using machine learning (AI)

1. Supervised learning: requires examples of target output function to learn model (delivered by human “supervisor”)
2. Unsupervised learning: makes assumption that most of the data used for training represents normal operation. That normal operation is modelled and subsequently an anomaly is detected if something with low probability happens

WHITE BOX or BLACK BOX MODELS? EXPERT BASED OR AI BASED PREDICTIVE MAINTENANCE?



White Box modeling advantages

- Needs no or less historical data and data science skills
- Generalizes better to previously unseen situations
- Better understanding of why the model makes a certain prediction/recommendation

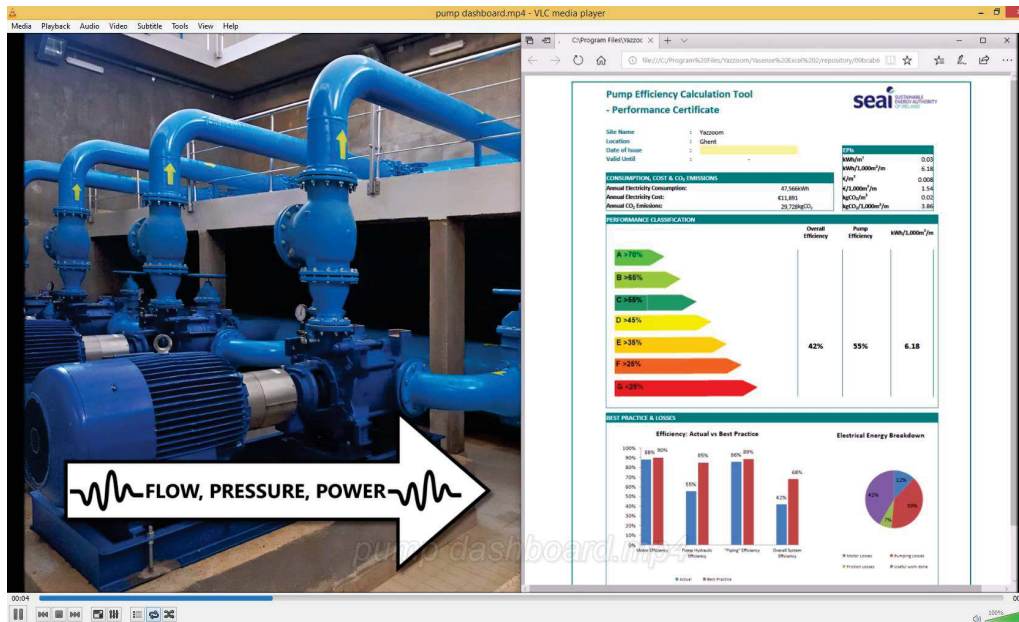
Black Box modeling advantages

- No need to know scientific laws expressed in mathematics
- Can learn non-linear, complex and non-formulaic relationships
- Can have better accuracy
- Easier to maintain if what is modelled changes frequently

White Box models applied to buildings, e.g for HVAC: what & how?

- Continuous monitoring of energy efficiency of heating, ventilation and cooling equipment
- If efficiency drops below threshold: alert maintenance team
- By means of virtual sensors that use power, temperatures and presence detectors as input

Example: virtual sensor for pump efficiency



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Virtual sensor for HVAC: value, cost, risk, maintenance

- **Value**
 - Energy savings
 - Comfort increase
 - Lower maintenance cost
- **Risks**
 - Missing sensors; overlap with existing solutions from HVAC vendors
- **Maintenance needs**
 - After replacement of HVAC by other type or dimension

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BLACK BOX MATHEMATICAL MODELS

- A. White box models:** mathematics written by human expert
 - 1. Simple man-written rules, e.g. acceptable ranges on sensor values, acceptable maximal time of a process step
 - 2. Dedicated statistics and algorithms for detecting specific issues, e.g. control loop oscillation, valve stiction,...
 - 3. Dedicated more complex models, e.g. efficiency of a compressor as a function of operating point
- B. Black box models:** model derived from data using machine learning (AI)
 - 1. Supervised learning: requires examples of target output function to learn model (delivered by human “supervisor”)
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A definition of AI

“If a machine/computer shows intelligent behavior and you cannot figure out whether it is performed by a human or a machine”

A definition of ML

“Machine Learning is a **family of software algorithms and computer models** that **automatically learn** from example **data**”

Learning = extract **structure and patterns**

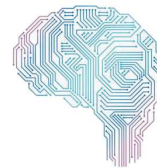
What is different about Machine Learning?

Traditional software



- Behaviour is programmed by software developers
- Contains a few parameters that control its behaviour
- Those parameters are set by experts or users

ML software



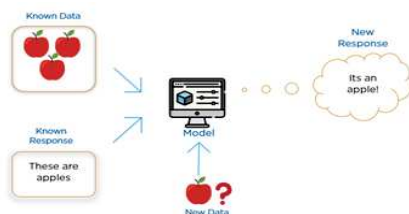
- Behaviour is learned from examples
- Contains very many parameters that control its behaviour
- Those parameters are learned from data

Is Machine Learning = AI?

- No: “ML < AI”
- Artificial Intelligence encompasses other disciplines besides machine learning:
 - Search algorithms
 - Optimization algorithms
 - Expert systems
 - ...
- In general:
 - AI = a science that has as objective to create a machine/computer/software that shows a form of intelligence.
 - ML = a science that lets a machine/computer/software learn from examples.

Supervised versus unsupervised learning

Supervised learning



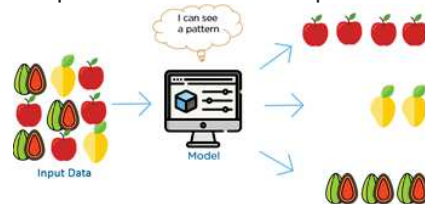
- All data points are labelled with desired output
- In practice not always possible/economical to obtain

“Virtual sensing” of maintenance need

Output of model is probability of failure within X minutes or a proxy of that e.g. prediction of fouling

Trained on examples of failures

Semi-supervised or unsupervised learning



- Data points are not explicitly labelled, or consist only of ‘normal’ examples
- Can also detect unknown ‘labels’

“Anomaly detection” of maintenance need

Output of model is anomaly score = estimate of probability that system is operating abnormally

Trained on examples of normal operation

How much data do you need?

This influences technical feasibility of AI based predictive maintenance

- For virtual sensing (i.e. predicting specific failures): typically at least 100 examples of each specific failure (in different operating conditions)
- For anomaly detection: data of all normal operation conditions during which you want anomaly detection
 - Example 1: dedicated punching machine: minutes
 - Example 2: entire power plant or a building: at least one year

When to use anomaly detection instead of virtual sensing?

- When it is not economically feasible to deliver enough labelled training examples of the failures that need to be predicted
- When early detection of failures that never happened before is desired
- When it is acceptable that the remaining useful lifetime until failure is not (always) predicted

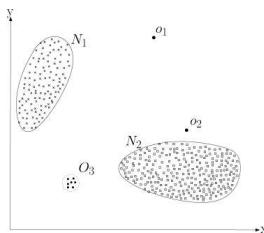
→ A mix of the two AI-based approaches (+ traditional monitoring) can be preferred: complementarity!

Let's dig a bit deeper

What is anomaly detection?

Anomaly detection is the identification of data points, items, observations or events that do not conform to the normal, expected behavior

Types of anomalies



Point anomaly

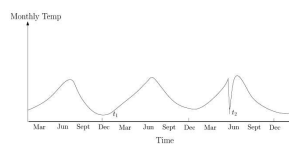


Fig. 3 Contextual anomaly t_2 in a temperature time-series. Note that the temperature at time t_1 is same as that at time t_2 , but occurs in a different context and hence is not considered as an anomaly.

Contextual anomaly

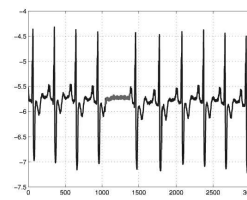


Fig. 4 Collective anomaly corresponding to an Atrial Premature Contraction in an human electrocardiogram output.

Collective anomaly

Each of these can be univariate or multivariate

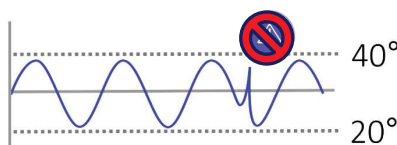
When is predictive maintenance using ML appropriate?

- When there is no human expert that can write down the mathematical model (e.g. the alarm rules)
 - by lack of knowledge, or
 - when it is not economically feasible to create and maintain the model
- Indicators of this situation:
 - When dealing with high-dimensional data
 - When dealing with changing (non-stationary) data
 - When normal system/machine behavior is also influenced by the interaction with other systems that are outside of your control/expertise

Traditional ways of detecting anomalies or outliers

Traditional monitoring

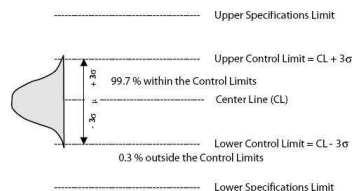
1. Hand-written rules



3. Dedicated sensors



2. Descriptive statistics



4. KPI's and dashboards



Anomaly detection compared to traditional monitoring



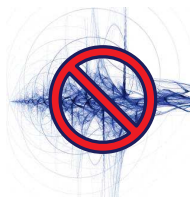
Detect unknown problems, abnormal trends and patterns, external sources



Scale easily to more data, new sensors, changes, variable components or subsystems...



Detect issues in control software execution



Handle complex signals with better detection of issues and less false alarms



Take context into account (outside temperature, working day/holiday,...)

Doesn't replace traditional approaches. It comes in **complement**.

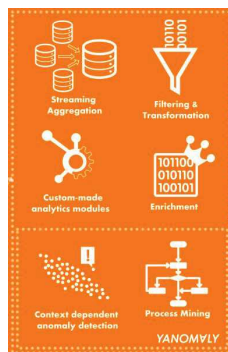
Anomaly detection for predictive maintenance

- Anomaly detection can help in identifying issues with assets early, by
 - Signaling deviations from normal behavior
 - Giving indications of which measurements are the cause of the deviation
- Requires human expertise, investigation or intervention to interpret the signals
- Can be seen as generic, asset-agnostic condition monitoring
- Can be applied to systems of arbitrary complexity
- Does not require specific (physical) models for that asset, only data of 'mostly' normal operation
- Anomaly detection currently does not (yet) predict:
 - Probability of Failure (POF)
 - Remaining useful lifetime (RUL)
 - For predicting these two properties, annotated example data is necessary

How do we make it easy for non data scientists to apply unsupervised anomaly detection?

1. **Dedicated tool for a specific task:** We have created a dedicated big data software for ML-based anomaly detection “Yanomaly”
2. We integrate the Yanomaly software in existing data monitoring platforms → no new platform to learn, no new privacy/secrecy concerns
3. We provide easy web based GUI for selecting data, training computer model, validating it and deploying it
4. **Some initial help:** Our project approach involves Yazzoom’s data scientists in Proof of Concept phase → this knowledge is transferred to the customer in subsequent Pilot phase

YANOMALY



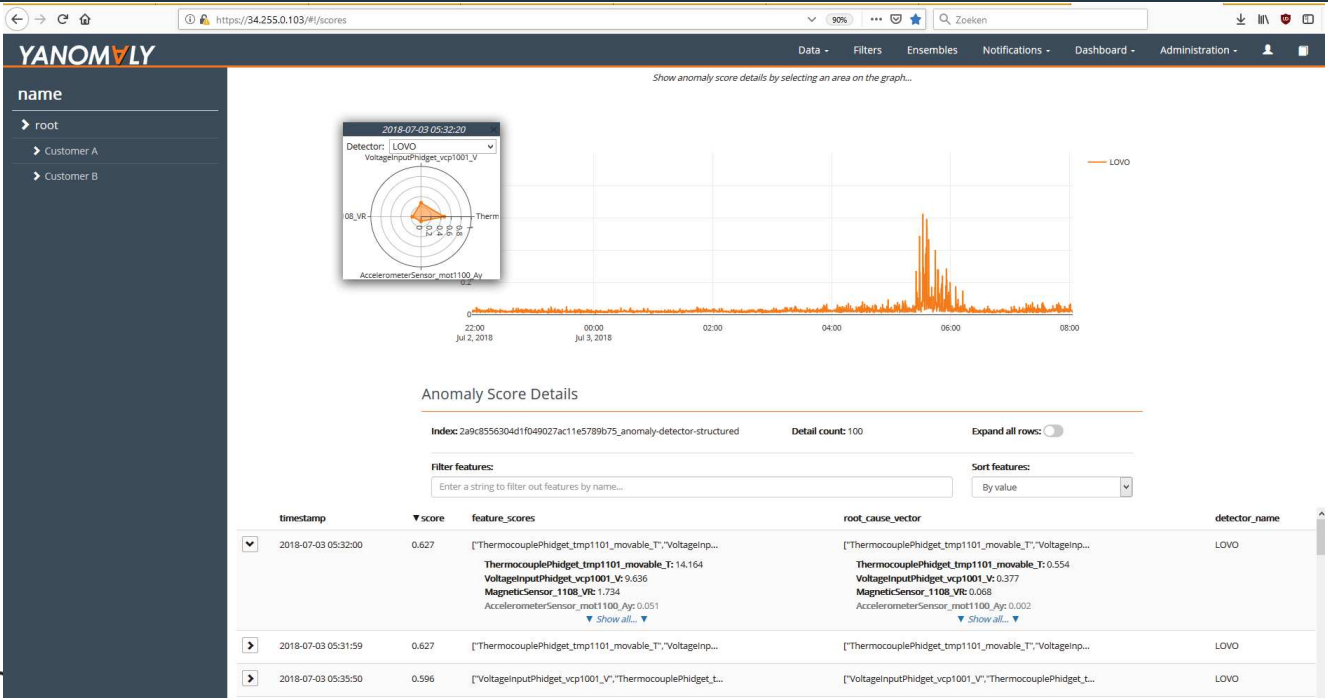
YANOMALY

Big Data solution for Unsupervised Anomaly Detection

For data of Machines & Production Lines & Utilities

- Sensor data: univariate and multivariate anomaly detection
- Event log data: process mining

Use case: Multivariate Numerical Anomaly Detection on CHP: realized with customer



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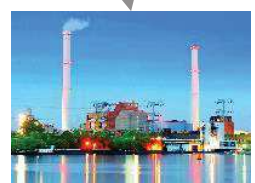
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Anomaly Detection Solution



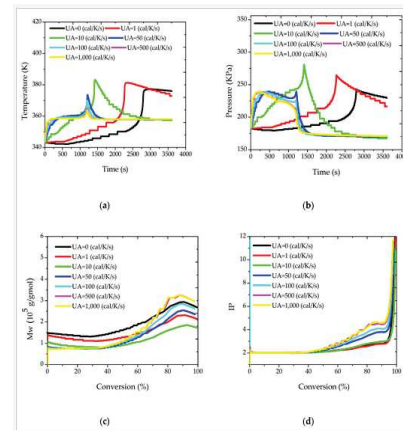
Use case 2: Multivariate anomaly detection on batch chemical process to refine silver, realized with customer



Yanomaly learns automatically the normal evolution over time of each of the sensor signals in the different phases of the batch process, as well as the normal dynamic relationship between the different sensors

Case: incident with exothermal reaction in 2017 was caused by temperature sensor that occasionally gave 10° to 20° wrong reading

Result: Yanomaly discovered abnormal relationship between temperature, steam flow and acid flow two weeks ahead of incident, leaving sufficient time for investigation and maintenance



Note: sensor curves above are from a different (public) process

Relation with building monitoring: every day (24 hour period) can be considered a “batch” of building usage

Anomaly detection applied to buildings: what & how?

- Let the **AI algorithms learn the normal relations** between building sensors and event logs in ICT system of building and external info like weather, time of day, day of week,...
- Let AI **continuously monitor** building and **raise alert** if something unlikely happens, e.g.
 - Lights on at abnormal moments for particular office/room
 - Temperature abnormal given outside temperature and solar irradiation + window/door/gate signals + airco signals

Anomaly detection: value, cost, risk, maintenance

- **Value**
 - Energy savings
 - Comfort increase: predictive maintenance, lower MTTR
 - Safety increase: detection of abnormal presence, overheating/fire
- **Risks**
 - Missing sensors, possible false alarms
- **Maintenance needs**
 - After major modifications to building/ICT infrastructure, otherwise self-learning

Some misconceptions about unsupervised Anomaly Detection...

Doesn't replace traditional approaches. It comes in **complement**.

Can use **human input**: learn faster, get feedback and become better.

Doesn't need a **supercomputer** to run.

Doesn't need to be **in the cloud**.

SUMMARY

- Two types of Machine Learning based predictive maintenance:
 - “virtual sensing” (if you have sufficient examples of the failures you want to predict)
 - anomaly detection” (if you don’t)
- Both require data, but type and amount of data differs
- Does not replace all traditional techniques, but comes in complement
- Decision when to apply it can be determined using RCMII principles
 - like for any other maintenance technique
 - Because power of ML makes predicting or early detection of certain failures feasible and economically viable whereas they weren’t using traditional approaches, it has increased the applicability of predictive maintenance

Questions? Contact Yazzoom:
info@yazzoom.com
www.yazzoom.com