WHITEPAPER

PREDICTIVE MAINTENANCE

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Predictive Maintenance

Basic Concepts

AI, Machine Learning and Deep Learning

Machine Learning is a field of study concerned with algorithms, statistical models and computer systems. The goal of ML is to give computers the ability to learn some task without being explicitly programmed to do so. This happens by creating ML models that are trained to recognize patterns in historical data in order to make predictions about the future. One of the ML model classes that has made major breakthroughs in the creation of AI since 2010 are artificial neural networks, or simply neural networks for short.

Neural networks that have a complex shape are called deep neural networks. The creation of deep neural networks is known as **deep learning**, and this has proven to be extremely powerful in a number of areas. For example, most intelligent machine translation systems like Google Translate have a neural network as a motor.

Artificial Intelligence refers to two things. On the one hand, it is a scientific subject area that studies the intelligence of machines. The creation of artificial intelligence has been a dream of mankind for centuries, but the academic research about its creation has been around since 1956. Second, AI refers to machines or computer systems that show intelligent behaviour. Intelligent machines and systems are already used in a lot of areas. Recently, the vast majority of such intelligent machines and systems have been created by ML methodologies, so now it is essentially AI = ML + x. There are some areas where the use and advancement of AI has received particular attention, and these have become important sub-areas of AI.

Natural Language Processing is the process of programming computers to analyse, understand, and generate large amounts of human natural language. This subject is a mixture of computer science, linguistics and AI and is e.g. Critical to the development of personal virtual assistants or chatbots.

The explanations of terms listed are an extract from the book:
"The Ultimate Data & AI Guide" by Alexander Thamm, Alexander Borek and Michael Gramlich.

1.Data is now available in most Smart Factories

In 2011, the term Industry 4.0 was coined by the German Federal Ministry of Economics and with it, Predictive Maintenance as a prominent use case. But in the years that followed, disillusionment set in for many. Often, insufficient data was available, such as only error codes or data from the control unit. This has changed in recent years, however, as many companies have now implemented the necessary data infrastructure. The falling costs of sensors and increased bandwidth, coupled with new technological advances, have made Predictive Maintenance (PdM) a far more viable option that could also be scaled across the enterprise.

Technological advances

increased bandwidth

Falling costs of sensors

2.Predictive Maintenance in a Nutshell

In the past, maintenance was always carried out according to fixed, predefined intervals. Today, you can realize predictive maintenance scenarios with the help of AI models. These models can compare current sensor data with historical data and thus recognize unusual behaviour patterns in components of a machine that would otherwise remain hidden. In this way, measures can be taken at an early stage to prevent a downward trend in product quality, a deterioration or even a failure of the machine.

The condition-based approach refers to the continuous monitoring of the equipment's state, usually through sensors. Its goal is to identify changes that indicate potential damage, so repairs can be performed before a failure gets the chance to occur. In place of trusting in mean-time-to-failure statistics to schedule maintenance activities, direct monitoring of the mechanical conditions is executed. The primary idea is to take action when components of a machine show certain behaviors that usually result in a downtrend in product quality, machine degradation, or failure. It indicates the need for maintenance steps before the actual damage occurs or product quality drastically changes. The foundation of this approach is the collection of a huge amount of machine data collected by sensors. Parts are replaced when a measurement or a calculated value reaches a certain threshold beyond which normal functioning of the system is not ensured.

PdM is an evolution of the condition-based approach because its analysis of the current state goes one step further. The goal is no longer the early detection of degenerative processes alone, but rather the additional deeper diagnosis in order to predict the expected anomalous process behavior. Then, it is possible to anticipate how a manufacturing facility might degrade, and the maintenance can be scheduled according to these expectations.

3.PdM Projects in our daily Business

Predictive Maintenance and condition monitoring (CM) are often used as synonyms. Not least because of its use as a marketing term. However, behind this are very different concepts, uses of AI models and use cases. In many of our customers' projects, we see a lack of orientation in the buzzword jungle. From a data science point of view, we may understand the term predictive maintenance in a different way than the customer.

As an example, one project can be mentioned here in which only highly aggregated error codes of a machine were available. The customer was not aware that this data set did not show the ageing process of the machine at all and thus the most important building block for creating a predictive model was missing. For the project, however, this did not automatically mean that no added value could be created based on this data. With a root cause analysis, we were able to find the cause of the most frequent machine failures and still achieve the goal of the use case (reduce machine failures). However, there are also customers who have far more data available due to a more modern machine park or due to retro-fitting of older machines. In short, the starting point for predictive maintenance projects could not be more different.

In order to deal with this very heterogeneous situation in the best possible way, we have developed a maturity model. On the one hand, it helps us to better discuss the current status quo with our customers and develop use cases. On the other hand, it enables us to proceed iteratively within projects in order to create added value right from the beginning.

4. [at]'s PdM Maturity Level Framework

1.

Maturity Level 1: Condition Monitoring

In the classic understanding of condition monitoring, AI does not yet play a role at this point. The focus here is on the presentation of sensor data in the form of dashboards. However, it is possible that domain-specific logic for call-to-action functionality is integrated, such as an alarm when limit values are exceeded.

2.

Maturity Level 2: AI conducted anomaly detection

From this level onwards, machine learning methods are used to recognise changes in the data patterns. The goal is to identify changes that indicate potential damage, so repairs can be performed before a failure gets the chance to occur. This layer is not about predicting the point of failure, but about detecting anomalies in order to perform maintenance steps near the potentially imminent failure.

3.

Maturity Level 3: AI conducted anomaly detection incl. fault diagnostic

This level extends the anomaly detection to the point of fault diagnosis. After a degradation is recognized by machine learning algorithms, the diagnosis component is triggered. This component is designed to enable fast and targeted maintenance by using Explainable AI to localise the root cause.

4.

Maturity Level 4: AI conducted prediction of remaining useful life

In the highest maturity level, the pure detection of the ageing process is extended by the prediction of the expected process behaviour. The problem to be solved is now no longer a classification problem (machine condition is ok / not ok), but a regression problem with the prediction of the point in time of the machine failure. With this knowledge, the choice of the time of maintenance can then be made in the best possible way.

5. Key Enablers for Predictive Maintenance

The following two enablers can be seen as upstream levels in the maturity level mentioned above. In order to be able to address the analytical question at all, these two technical prerequisites must be met. Never underestimate the complexity of IT infrastructure that is required to run predictive maintenance activities. It employs multiple hardware and software modules as well as cloud technologies.

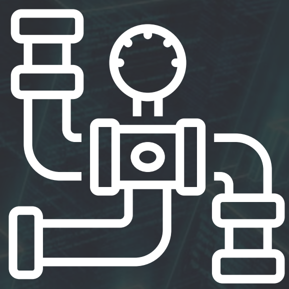
Data Acquisition Layer

Predictive maintenance is inconceivable without comprehensive data. However, data can vary greatly in terms of quality and level of detail. This has a major influence on the development of AI models, as they can only achieve good results if the data have a large information volume. In the case of production machines, the data is often available in different levels of detail:

Raw data | **Event-based data** | **High-level information** | **High-level actions**

The most obvious possibility is the storage of raw data. The system stores the data from different sensors without further calculation steps. All possible information remains in the data without aggregation, and the data can be reused for different contexts. The biggest disadvantage of this storage form is the huge amount of data that has to be stored.
Another alternative is the event-based storage method. In this storage paradigm, only changes in sensor data are stored, so that less storage space is needed.
With storage type High Level Information, the data is first transformed so that only a condensed information content is stored. There is a risk that information is lost and the data can no longer be used for another context.
The fourth method, High Level Actions, provides for the highest degree of aggregation in the storage of data. In the storage, the focus is no longer on the sensor data, but on the significant actions of environmental changes.
For the development of AI models, it makes a big difference whether only error codes or the raw data from the sensors are available. A common problem is often the lack of important contextual information. Different batches of 2 kg and 2.5 kg workpiece weights have different effects on the sensor data and must be taken into account so that these differences are not wrongly classified as an anomaly.

Data infrastructure and Storage



A frictionless data processing and the use of trained AI models for maintenance optimisation is only possible through an orchestrated interaction of several systems.

Here is a brief overview of the different components needed for an infrastructure:

- A connectware to connect sensors or machines from different manufacturers to a unified system
- Scalable data storage and a Big Data processing engine to handle streaming data (if real-time data is required)
- Computing resources and environments for training AI models
- Services to deliver the predictions of the AI models to the end user

A common problem in predictive maintenance is the large number of sensor manufacturers with different protocols for transmitting data. Together with partners in the field of connectware, this challenge can be overcome.

End-user centered application

User-centricity is important for all products with an AI component. Often, black box solutions are built that are not trusted in daily use. Human in the loop is the central approach here. In a dashboard for the machine operator or in the control center, it must be clear why certain forecasts or anomaly detections were made. By implementing AI technology, existing processes and ways of working are always changed. That's why change management always plays an important role in the success of our customers project.

6. Domain Knowledge Matters

A deep understanding in the fundamentals of machine learnings should every data scientist know. What important assumptions does each algorithm have? Why does variance and bias tradeoff matters or how can one avoid the pitfalls of information leakage during training? Even if some companies suggest that they can offer machine learning as a commodity, in reality the picture is frequently different. This is usually due to a lack of domain knowledge and the attempt to solve the problem without a basic understanding of the process and the data generated from it. Through the numerous projects we have completed in the PdM area, we have had the opportunity to gather necessary domain knowledge that is necessary for the formulation of concrete use case and the implementation of machine learning algorithms.

In the following, a small subset of problem areas and the related questions to asked are highlighted.

Carlo Voß
Senior Data Scientist

Is the time window between the start of the degradation process and the failure of the machine of sufficient length?

Due to early detection of anomalies, maintenance steps can be performed while the degenerating machine still produces and are not executed sequentially after the failure occurred. In the context of spare part management, predictive maintenance only makes sense if an anomaly can be detected in a early stage of degradation. Then, there is enough time for ordering the machine component and the plant can still be used until the spare parts are available and maintenance measures are carried out. In the best case scenario, the time of all these processes is less than the time span between anomaly detection and machine failure. As a consequence, the main premise is that malfunctions develop over a certain period and do not occur abruptly.

Are different recipes with batch-size-n run on the machine or is it individual piece production?

Predictive maintenance mostly makes sense for those areas that carry out series production. The influence of system variables or products is important. Either these system variables can be included in the data set as categorical features or separate models can be trained for individual characteristics. The consideration of the categorical feature ‘recipe ID’ is important because the system behavior will be highly recipe-dependent. Therefore all data points except those from this recipe are discarded to train a recipe specific model. In individual piece production, you would have too many different framework conditions that would all have to be taken into account in the model.

What changes have there been to the machine over the period of the historical data?

Historical data over a long period of time is wonderful, but only if the context has not changed heavily. For example, if extensive repairs are carried out on a machine, the pattern in the data can change without an anomaly being present. In addition to the historical sensor data, the (automated) documentation of error cases is therefore also beneficial.

Carlo Voß
Senior Data Scientist

What features can be taken into account in addition to the sensor data?

The influence of system variables or products is important, and variations in these variables are often the root cause of mechanical problems. These system variables from e.g. ERP systems can be included. Furthermore, engineering knowledge can be take into account by feature engineering or signal pre-processing with methods like fourier or wavelet transformation. In this way domain knowledge can be incorporated into the machine learning process.

How to add a root cause analysis to the system?

Localization is more difficult than someone might expect. If a sensor measures an unusual value, the corresponding component is not automatically responsible for the anomaly. For instance, a growth of any vibration-based indicator calculated from a sensor theoretically indicates a fault of this system's part. Nevertheless, such an assumption is not always valid, because a working part is not an autonomous system, but it is mechanically connected and therefore influenced by other mechanical elements. Various methods in the field of explainable AI can be used here.

7. How to define the unknown?

In addition to the correct selection of algorithms, the art is to correctly formulate the automation task as a machine learning problem. This applies in particular to the area of anomaly detection. The fundamental issue of anomaly detection is the lack of a definition of how different a novelty has to be before one classifies it as abnormal. Labeled data for the training of models is often not available in the context of PdM. Either it is not feasible to observe normal and anomalous behavior in all possible ways, or it is too expensive to gain specific labels.

Framing the problem as a one-class problem is one way to tackle this challenge. With this approach, a model of normality is trained in an unsupervised manner on a data set containing sensor signals representing the machines normal behavior.

In the second step, the model receives a sequence of past observations and predicts the next sensor signal based on the learned pattern of the normal machine behavior. The prediction of sensor values is just an interim step; the goal is the classification of a measure into normal or abnormal.

In the third step, one compares the actual sensor values of the machine with the predicted value in order to detect novel behavior. If degradation occurs, a deviation between prediction and observation should be noticeable because the real sensor values drift away from the predictions. By applying this one-class classification approach, there is a way to bypass the problem of not knowing all kinds of anomalies.

Carlo Voß
Senior Data Scientist

How to evaluate the performance of the ML model?

Training data is essential for machine learning tasks. However, test data is not less important because it is necessary for checking the performance of different approaches and models. We face the problem of annotation again because anomalies must be present in a test data in order to check whether the model can distinguish between new patterns and the normal state sufficiently.

Since contextual anomalies usually occur during degeneration processes, it does not make sense to mark individual values as anomalies, but rather to mark a defined sequence as either normal or abnormal. But a human can label only the time of the failure of the machine because this event is observable for him. The exact beginning of the degeneration process is not known. Of course, a certain period before failure can be marked as an anomaly, but the time span would then only be a pure estimate.

The multivariate time series constitute a further challenge in the evaluation of models due to a large number of sensors. In most real-world data sets, one will have only one annotation for the entire machine state in the test data set. However, the model predicts the next value for each sensor, which results in a classification for each sensor's time series. As a consequence, several individually classified time series by a model need to be compared with labels representing the whole machine state. One possibility would be to calculate the evaluation metrics between each time series and the labels of the overall machine condition and finally average them across all sensors. However, this procedure could distort the result. Not all parts may be involved in the degeneration process of the entire machine. A model could then predict specific sensor values with sufficient accuracy and then correctly label them as normal. If every single classified time series of a sensor is then compared with the labels that describe the entire machine condition, one would include FN values unjustifiably in the calculation.

8. Financial Implications and Cost Justification

The primary objective of maintenance is to increase plant availability by avoiding unplanned machine failures and material damage. It has a direct impact on a company's value creation by ensuring that production runs reliably. Concerning the life cycle of a plant, the operation costs and maintenance exceed the acquisition and disposal costs. This fact shows the importance of maintenance.

The advantages of CM / PdM are also accompanied by higher installation and operating costs. The cost of implementing a data acquisition layer can be quite high, especially if the goal is to monitor already installed equipment. Creating models requires much expert knowledge from different areas. In order to use capital-intensive CM / PdM profitably in a company, its necessity must be assessed for each plant. Several factors are influencing the selection of maintenance. Examples are interlinking and redundancy of the plants, quality and safety standards, spare parts availability, and material buffer between the plants.

In order to quantify the advantages of CM / PdM financially, an estimation of savings caused by less downtime, less troubleshooting, and less quality control problems must be obtained by all departments involved in that production process. It is necessary because there can be no satisfactory cost justification without financial data.

9. [at]'s Data Journey in context of PdM

Is the prediction of maintenance steps really necessary or is an early detection of the degeneration process sufficient? Scoping is important at the beginning of each project. For most customer requests, the detection of the degeneration process is completely satisfactory from a business case point of view. Another important question is what level of maturity the use case should reach. Should a first proof of concept be created or an existing one be put into production?

What is the current data infrastructure? If, for example, sensor data has not yet been processed at all, the very complex implementation of a data infrastructure is necessary first. In order to be able to generate the first added values as early as possible, an iterative approach can be useful. By initially setting up a condition monitoring system, the machine status can be visualised for the machine operators and create initial added value. Insights can then be used for a PdM use case in the further course.

Take a closer look at the [at] data journey, where our philosophy of creating value from data is translated into a framework.

PREDICTIVE MAINTENANCE

USE CASES

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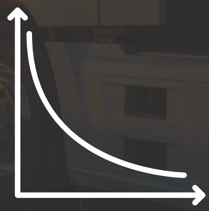
USE CASE

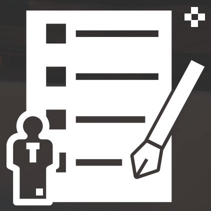
Predictive Maintenance @ MAN

With telematics data, it is possible to detect issues at an early stage and make preventive fixes.

Prevention of 92% of all injector failures



Reduction of warranty costs



Reduced penalties and securing of follow-up orders

Challenge

If a fully loaded truck breaks down on the road, for example due to injector damage, the component failure must be repaired, which incurs costs that usually have to be paid by the manufacturer. Late delivery results in convention penalties and a drop in quality ranking, which is bad for follow-up orders.

Solution

Based on the telematics data, fault memory entries and repair information, a data set is built to predict failures. The developed algorithm identifies patterns in the ECU data that can be used to distinguish healthy from failed vehicles. With the pattern learned and validated, predictions can be made for all vehicles in the future as to the likelihood of injector failure.

Result

With the current status, 92% of injector failures can be correctly predicted.This leads to lower warranty costs in the long term, delay penalties are prevented and follow-up orders can be secured.

USE CASE

Predictive Car Maintenance

Predictive maintenance helps to significantly reduce and control costs and risks.

Reduction of warranty costs by over 50%

Prevention of costly recall actions

Increase customer satisfaction

Challenge

Vehicles with a potential defect should be identified in advance, before the failure actually occurs, in order to reduce or avoid warranty costs.

Solution

By combining measured value data, master data of the vehicle and diagnostic data, a prognosis model can be created that can reliably predict the occurrence of faults (predictive car maintenance). With the help of the specialist department and other specialists, errors can be detected and identified in advance.

Result

The forecasting model identifies 75% of the affected vehicles in advance. Testing costs and any extensive recall campaigns can be avoided. Warranty costs are reduced by over 50%. Customer satisfaction will be increased.

About [at]

Alexander Thamm GmbH is one of the leading providers of data science and artificial intelligence in the German-speaking area. We generate real added value for and with our customers from data, so that they are also competitive in the future. To this end, we develop and implement data-driven innovations and business models. The service portfolio covers the entire data journey - from the data strategy to the development of algorithms and the construction of IT architectures to maintenance and operation.

Contact Carlo Voß or Simon Decker for a free consultation.

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