Signal Cruncher
[Embedded Realtime Analytics]

Predictive Maintenance and More

Application and benefits

Predictive Maintenance (PdM) uses data analysis to predict the failure of machines and their components. It also recommends when and, if necessary, what type of maintenance is required to avoid the predicted failure.

Predictive maintenance thus promises cost savings over routine or time-based preventive maintenance because maintenance is performed only when actually necessary. Unexpected failures are detected in good time and can be (largely) avoided.

PdM utilises predominantly non-destructive testing technologies (camera, infrared, acoustic, vibration, etc.) via sensors, recently in combination with the measurement of different process parameters. A wide variety of process data can be incorporated into the analysis; the analytical method itself determines the most informative attributes.

A variety of statistical processes are used in the analysis including the detection of outliers, principal component analysis and clustering. However, scoring is by far the most important. This will be described later.

The benefits of predictive maintenance vary depending on the application and data situation. The XONBOT was able to reduce failures by 8%.

According to a study conducted by the World Economic Forum and the Accenture consulting company, even 12 percent could be saved on planned repairs and almost 30 percent on maintenance costs compared to unplanned repairs. The amount of unplanned downtime could be reduced by 70 percent.

The benefits of the XONBOT, however, go far beyond that, as seen below: If a scoring model is first used to describe the probability of failure, it is possible to study which of the parameters (so-called attributes) are particularly relevant to the failure. This heightens the understanding of the failure pattern. Beyond that, these attributes can then be adjusted - assuming they can be influenced - to lower the probability of failure.

What's more, XONBOT allows for process control via these control attributes (e.g. radiation intensity, coolant supply, movement velocities) in real time to continuously minimize the probability of failure. This brings the process from pure prediction to automated control!

All in real time - XONBOT

Practically all PdM systems now use the so-called 4-phase model, which is based on the storage of all data and offline analyses.

In the first phase, the current parameter values are usually collected by sensors. This data is saved to a central repository (e.g. data warehouse) in the second phase. In the third phase a scoring model is taught to this data and from that the next failure date is predicted. Based on that date, the next servicing session is scheduled in the fourth phase. Once that is complete we go back to the first phase.

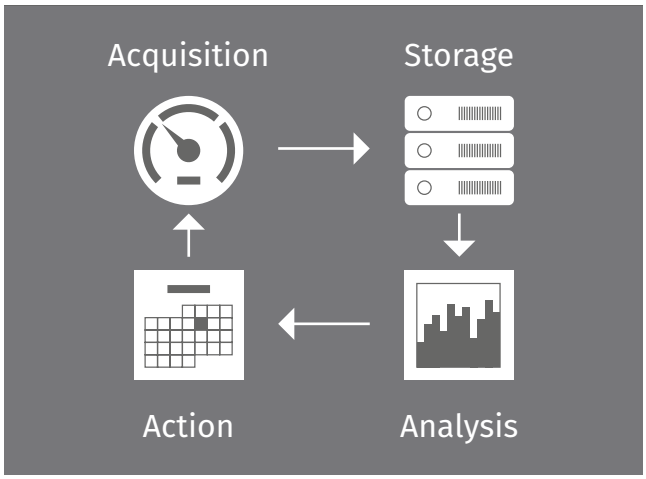


Fig: The four phases of conventional predictive maintenance.

After all, we are dealing with a classical offline analytical process. It is complex and expensive as all relevant measurements must be centrally stored. It is also a slow process as unexpected accidents are always only detected at the time of the next data analysis (which is then potentially already too late).

However, the last disadvantage is increasingly addressed by frequently using the analysis model in real time (and only learning occurs offline). Nevertheless, the model can quickly become obsolete with severe changes in behaviour. And the problem of data retention remains.

The XONBOT, on the other hand, learns online. In other words it learns continuously. The analysis model is then incrementally updated with each new dataset. There is no need to save transaction data. On top of that, the data model is continuously updated and evaluated. But at the first sign of impending failure the next servicing is initiated.

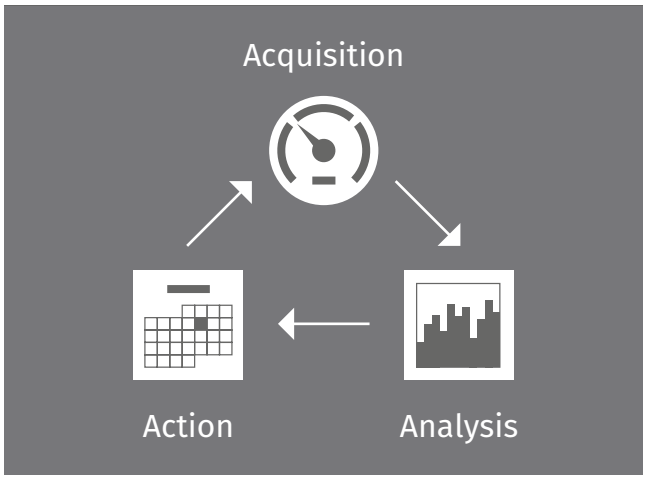


Fig: Continuous learning with online predictive maintenance.

The XONBOT can also learn offline from stored data. This is especially helpful for pilot analyses and for initialising a scoring model. However, afterwards is it also possible to switch back to the online mode as described to take full advantage of the system advantages.

How it works

The main modelling consists of using a scoring model - typically based on regression - to model the probability of failure depending on its influencing parameters.

To do this always requires a flat table featuring lines to represent the data vectors - the data points of the measurements - and columns to represent the attributes - the measured parameters. One of the attributes refers to the time of failure and is called the target attribute. The purpose of the regression process is to establish a functional relationship between the input attributes and the target attribute. As such, a prediction for the time of failure can be made for each data vector.

As the XONBOT is designed for real time analysis, it considers the table as a stream whose incoming data vectors are processed immediately. Each new data vector in the pre-processor first undergoes pre-processing, in other words it is transformed, normalized etc.

Further, attributes can contain keys to other tables whose attribute values are joined via the aggregator in the dataset. Beyond that, the aggregator can calculate synthetic attributes from the existing ones or from their development.

The learner then updates the regression model with the new dataset. The learning can also be delayed, e.g. following completion of a session.

The regression model always takes on the form of a function

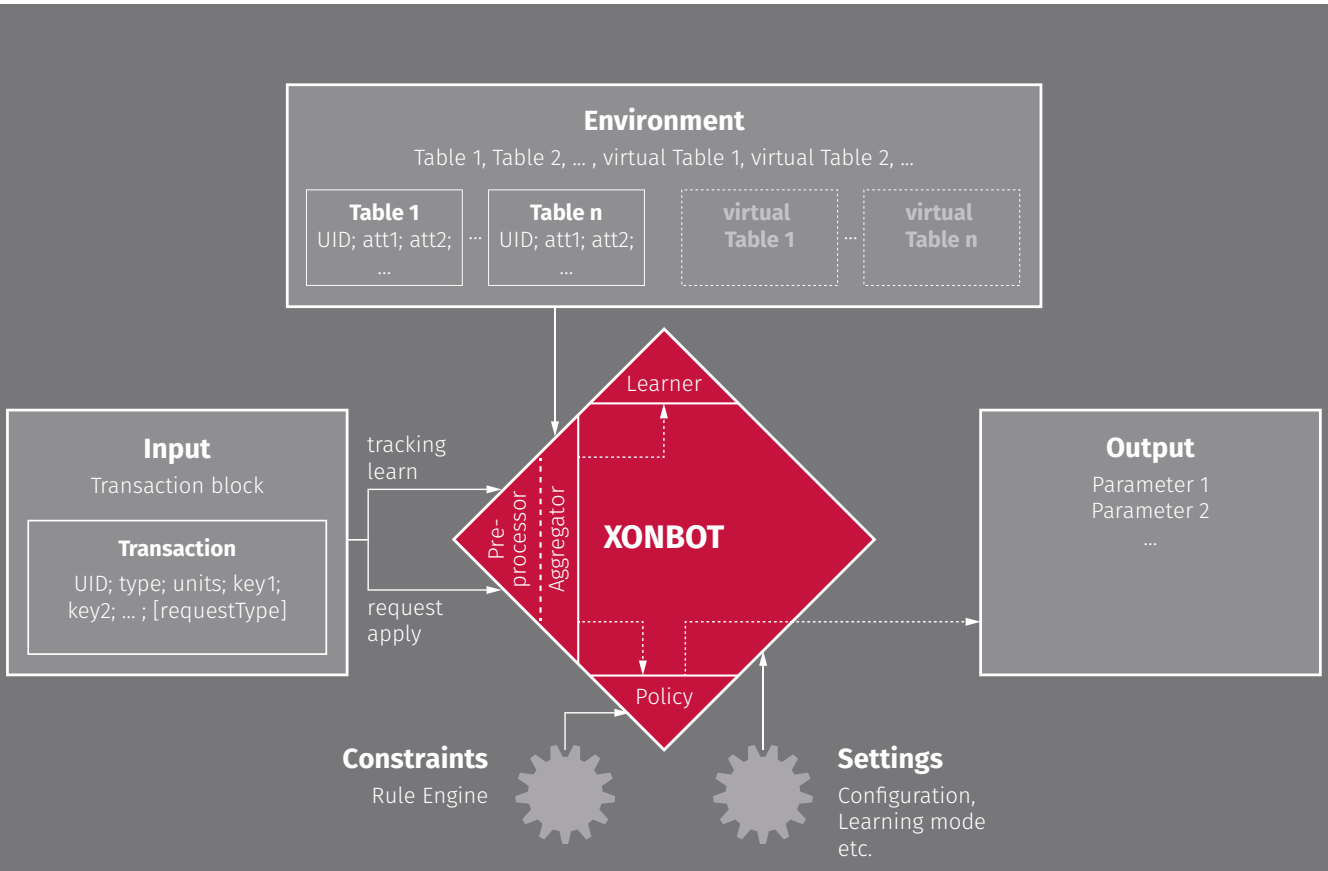
$$f(x)=y,$$

where the predicted value of its target attribute is assigned to each data vector x.

The XONBOT provides different learning processes such as regression trees, neuronal networks ("deep learning"), support vector machines and sparse grids.

Ultimately, the XONBOT predicts a time of failure of the machine for each incoming data vector.

Fig: Setup and operation of the XONBOT



More than just predictive maintenance

The regression function $f(x)$ is not only used to predict the time of failure. It can also be used to analyse the influence of individual attributes of the data vector x on the failure.

If some of these attributes - the control attributes - can be influenced (current, cooling temperature, etc.) the question remains as to the optimal choice. In other words, how must the values of the control attributes $x_c^1, \ldots, x_c^k$ be selected in relation to the other attribute values in order for the failure time to be as great as possible:

$$f(x) \xrightarrow[x_c^1, \ldots, x_c^k]{} \max ?$$

To solve this complex problem, the XONBOT features Policy, which calculates the optimal control values in real time and returns them as output.

In practice this problem is compounded because the values for the control attributes cannot be freely selected but can only be selected from certain ranges and sometimes complex relationships - the constraints. These constraints can be flexibly specified in the XONBOT using a set of rules.

This puts the XONBOT in the position to suggest preventative measures in real time to reduce the probability of failure or other variables such as maximisation of yield.

Conclusion

Predictive Maintenance is a key component for Industry 4.0 Due to its revolutionary real-time architecture, the XONBOT is in a position to solve this problem in a particularly cost-saving and efficient way.

It can be tested first on existing data in offline pilot analyses. During productive operation it is then switched over to online learning where it continuously updates its analysis model and there is no need to save transaction data.

The XONBOT can also be used to control process parameters in real time to reduce the probability of failure.

The XONBOT can solve much more complex problems using its integrated reinforcement learning. We would be glad to provide you with more information!

Fig: XONBOT applications in various industries

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