Revolutionizing Predictive Maintenance: How AI-Driven Solutions Enhance Efficiency and Reduce Costs Across Industries

András Zsombók, Imre Zsombók

AK-S Ltd.
Email: *zsombok[at]ak-s.hu*

Abstract: ***Thanks to the soaring cost of monitoring technology and new predictive analytics, it is now easier - and cheaper - than ever to avoid pumps, electronics and other systems failing. New stand-alone predictive maintenance solutions like the ones in our trials can be integrated into new and existing applications across a wide range of industries. AI enables fast and efficient processing, analysis and prediction of data. Algorithms analyse the data and can identify correlations, patterns and regularities on the basis of which predictions or decisions are made. AI is able to analyse data in a comprehensive way, enabling it to solve complex problems that are too complex or contain too much data to be processed using traditional methods. In addition to data analysis, AI is also capable of continuous learning and automation, which improve the efficiency and accuracy of analysis. The application of data-driven AI can improve efficiency and increase productivity, reduce costs and improve quality.***

Keywords: AI, maintenance, monitoring, charging station, sustainability

1. Introduction

Predictive maintenance is a strategy that relies on data and analysis to try to predict potential failures or breakdowns of a machine or piece of equipment. This approach allows for optimisation of maintenance activities and timely intervention, reducing unplanned downtime and costs.

Predictive maintenance is based on data collection and data analysis. Using sensors, monitors or other sensing devices, data on machine operation and performance is continuously collected and analysed. This data can then be used for AI and machine learning algorithms that can detect patterns and correlations between data.

The benefits of predictive maintenance:

a) **Reduced downtime:** based on forecasts, the timing of maintenance can be optimised, minimising unplanned downtime of machines or equipment.
b) **Cost savings:** more accurate maintenance scheduling and preventive interventions before parts are replaced reduce repair costs.
c) **Improved performance and lifetime:** timely maintenance interventions can increase the efficiency and lifetime of machinery or equipment.
d) **Data-driven decision making:** analysing data to make more accurate and efficient decisions on maintenance processes.

It is important to stress that predictive maintenance is not only about collecting and analysing data, but also about taking appropriate action to prevent or address predicted problems. In industries, predictive maintenance is becoming more widely available and applicable as AI and data analytics evolve, contributing to more efficient and cost-effective operations.

Combining preventive maintenance with artificial intelligence (AI) can bring significant benefits across industries and sectors. Preventive maintenance is all about maintaining equipment, machines or systems in a timely manner and based on predictable problems before major failures or breakdowns occur.

With the help of AI technologies, it is possible to make preventive maintenance more efficient and accurate, because AI algorithms can:

Analyse data and build predictive models: AI can learn about the behaviour and performance of equipment or machines based on data. It can learn how machines and machines can learn the behaviour and performance of machines and equipment.

a) **Fault prediction:** AI-based systems can monitor signals from different sensors or data sources that may indicate system faults or problems. These predictions can be used to take timely action for maintenance or repair.
b) **Optimised maintenance scheduling:** MI allows you to optimise maintenance cycles and schedules. It can do this by using data to make tailored recommendations for maintenance intervals, minimising unnecessary maintenance and repairs.
c) **Detailed diagnostics:** AI systems can provide detailed analytical information on the condition of equipment or machinery, helping engineers or maintenance staff to identify and solve problems faster.

AI-based preventive maintenance systems can make businesses run more efficiently and effectively by minimising unplanned downtime, reducing repair costs and increasing the lifespan of machinery or equipment. This can lead to long-term cost savings and productivity gains.

Overall, data analytics using artificial intelligence offers many opportunities in business and science, but there is a need for regulation and responsible use to maximise the positive impact of the technology and minimise the risks.

What a difference a sensor makes
Monitoring pumps and associated process piping is nothing new. Regulations require monitoring of well poles to prevent pollution and harmful emissions.

In the field of fuel trading and servicing, the use of technology common in other industries is not common, so it is not possible to predict when a system failure is imminent. To ensure reliable forecasting, existing systems should be retrofitted with data acquisition and storage systems.

To obtain this kind of data, operators traditionally need to contract with another party to assess the circumstances around the technology. The data they collect can later be compared with previous reports to identify signs of deterioration. However, since in our case the data is collected only periodically (typically it was sampled annually), it is difficult, if not impossible, to determine exactly when or how a particular problem occurred.

The planned advanced remote monitoring system can provide all this and more. By adding a sensor, the flow meter, to motors, pumps and other equipment, it is now possible to collect continuous, real-time data that indicates if a pump is approaching an unexpected shutdown or if conditions are occurring that could negatively impact the performance of the suction recovery process. Depending on the application, this data can include anything from flow and temperature monitoring.

This is exactly the kind of information that a maintenance company or its own staff can use to prevent unexpected and costly equipment failures, improve performance and extend equipment life.

This advanced form of monitoring is of even greater value when the equation is coupled with predictive analysis. Algorithms can be used to model the data collected through monitoring to identify patterns that help users not only intervene in the event of impending failures, but also to predict future behaviours and events. With predictive analytics, experts can use this data to pinpoint the root causes of past problems and identify the best next steps for impending problems.

The monitoring system can also be designed to warn the user if the characteristic values start to change and approach the threshold set by legislation. Knowing that operating conditions are changing, maintenance staff can take preventive corrective action to address any trend in operating deviations.

Real-time remote condition monitoring provides end-users with a new, intelligent tool for early management of wellhead degradation. Combined with data analysis, these systems help determine the optimal time and scope of maintenance and potentially identify the root cause of problems, making service providers even more valuable to their customers.

Ultimately, they result in lower running costs and longer life. The bottom line: if the cost and revenue loss of shutting down well poles is significant, the payback of a standalone remote monitoring and analytics solution is usually well worth the price.

2. Plan

The possibility of predicting failures and implementing proactive solutions can also be attractive for operators, as our theoretical calculations show a clear return on investment. Predictive maintenance is also becoming increasingly important in industries and applications due to rising energy prices, labour costs and the harder availability of skilled labour. Our vision, based on industry experience, is to develop a similar solution to prevent losses from malfunction and complex, time-consuming and costly failures, such as the real-world troubleshooting before they occur, based on the measurement of characteristic properties already implemented in many production lines. AK-S Ltd's customers are faced with regular failures of fuel dispensers, and the failures are worsening as a number of well column components wear out, causing a significant loss of revenue.

3. Experiment

We conducted a theoretical comparison of the most popular machine learning methods used to solve similar problems, which were tested to predict the failure of gasoline vapor recovery piston pumps and other wellhead components. This study attempts to address the problem of predicting in-service failure of the pump and critical components that fundamentally affect its proper operation. Failures in our case do not mean a complete inoperability of the pump, but a deviation of the measured values from the legal limit. In such cases, high repair costs must be expected, especially if the fault is not known before the repair is started, and the location of the filling stations is an additional cost-increasing factor.

The use of machine learning techniques allows us to anticipate the need for repairs by detecting operational anomalies in time, as measured by our VRM system, and to carry out maintenance before the failure occurs.

In our experiments we predict the wear of the vapour recovery pump based on parameters recorded in real time during operation. To compile the dataset, we collected real data between 2018 and 2022, resulting in a dataset of more than 10 000 for training and validation.

First, each model tested was applied to a dataset collected from a real working system and evaluated.

4. Evaluation Criteria

In order to compare different forecasting models, the literature defines a set of metrics that are calculated from the error between the actual value and the estimated value.

Of course, the model may overfit the initial data and not work well, i.e. the error will be too large. For this reason, testing the value of the training error is not a good way to measure how predictive models will perform in the real world. Therefore, to validate the model, we need to use the same data that we extract from the flow meter.

Using artificial intelligence is another approach to analysing data. AI algorithms are based on machine learning, which allow algorithms to learn on data and process it automatically. AI algorithms can handle large amounts of complex and unstructured data and are able to identify correlations and patterns that would be difficult or impossible tasks for analytical analysis. The advantage of AI is that it is more adaptive, as algorithms can learn from the data and adapt to changing environmental conditions. However, MI algorithms are generally more time consuming and complex, and often require higher levels of computational power.

Overall, there are advantages and limitations to both analytical and AI approaches to data analysis. Analytical analysis allows for fast and efficient analysis of large amounts of structured data, while AI can be used to analyse large amounts of and/or unstructured data and to identify the relationships in the data.

5. Evaluation

In our development work, we focused on analytical data analysis at the beginning of the project, as we considered the causal relationships of the data that could be extracted from the tool to be reasonably certain. A more thorough analysis of the measurement results, as well as the failures during the test run - which occurred both for the device and the well columns - led us to the conclusion that it is worthwhile to investigate and take into account other, not directly derivable errors and effects. For example, pump wear/wear, which can be clearly seen from the reduction in suction return performance, does not always hold true, as our experience has shown that the non-obvious maintenance needs of different components (filters, condensate separators, electronics) in a cycle have also shown similar results. These faults could not be clearly deduced from the measurement results, but by recording additional data (operating time, amount of material flow, recording of infeed data), it is 92 % probable that the cause of a faulty measurement for other reasons can be predicted/indicated and defined before maintenance is started, simply by analysing the data.

The calculation of the cost of maintenance usually depends on a number of factors, including the cost of parts, the cost of labour and the maintenance time. Below is a summary of how to calculate the cost of maintenance.

a) Cost of parts: the first step is to identify the parts that need to be replaced during maintenance. The cost of parts can vary and depends on the state of stock, location and the procurement strategy used. In some cases, the company may already have a stock of spare parts, which can mean significant savings.
b) Cost of labour: the next step is to determine the cost of labour. This amount is calculated based on the wages of the service technicians, travel costs, equipment rental, equipment maintenance and repair, etc.
c) Maintenance time: the duration depends on the maintenance task, the problem, the condition of the asset and the skills of the workforce. Duration also affects maintenance cost, as the longer the duration, the more labour costs are incurred.

With this information, the cost of maintenance can be calculated as follows:

Maintenance cost = Parts cost + Labour cost x Maintenance time

Determining the cost-effectiveness of planned preventive maintenance also depends on several factors. The essence of preventive maintenance is that by regularly checking, cleaning and maintaining equipment, the chance of failure and the time and cost of repair can be reduced. However, the costs of preventive maintenance can also be significant and the cost-effectiveness can be determined by comparing the costs and savings.

Calculating the economics of preventive maintenance:

a) **Cost of planned maintenance:** this includes the cost of parts, labour and tools, as well as preparation and planning costs.
b) **Saving on repair costs:** preventive maintenance aims to reduce the number and cost of repairs. Savings in repair costs can be estimated using repair data from the previous period.
c) **Savings on production losses:** production losses due to errors and breakdowns can also be estimated on the basis of data from the previous period.

The economics of preventive maintenance are calculated as follows:

Savings = (Savings on repair costs + Savings on production losses)

Economy = Savings / Planned maintenance cost

For example, if the cost of a planned preventive maintenance programme was 500 000 HUF, the average repair cost in the previous period was 800 000 HUF and the average production loss was 300 000 HUF, the savings would be as follows:
Savings = HUF 800 000 + HUF 300 000 = HUF 1 100 000
And the economics are:
Economy = HUF 1 100 000 / HUF 500 000 = 2,2

The cost of loss due to failure includes the loss of production and the cost of repairing the asset. In order to determine the total downtime cost, the downtime and the time taken to repair the asset, as well as the cost of materials and labour, should be taken into account.

The calculation of the stranded costs due to equipment failure is as follows.

a) **Production loss costs:** the cost of production loss depends on the role of the asset in the production process. The cost of lost production includes lost revenue due to unfilled orders and unused production capacity.
b) **Asset repair costs:** repair costs are defined as the cost of parts, labour and tools.

Paper ID: SR231214124830 DOI: https://dx.doi.org/10.21275/SR231214124830

c) **Other costs:** in the event of equipment failure, additional costs may be incurred, such as transport costs, rental costs and rental foregone costs.

The stranded costs are determined as follows:

Downtime cost = Production downtime costs + Asset repair costs + Other costs
For example, if the average daily loss of production due to the failure of an asset is HUF 10 000 000 and the cost of repairing the asset is HUF 3 000 000, the cost of the loss would be:

Loss cost = 10 000 000 HUF + 3 000 000 HUF = 13 000 000 HUF

For each model, we take into account the time taken for training and scoring processes to provide an additional parameter for later practical use.

Typical scatter plots of the models are shown below. On the horizontal axis is the real "y" (value given by the well column), on the vertical axis is the prediction of the backscatter "ŷ". The most correlated models were DLM and GBT.

AI-enabled maintenance, driven by artificial intelligence and data analytics, offers significant benefits in maintenance processes. AI-enabled systems enable real-time monitoring of the condition of machinery and equipment, predicting potential failures and breakdowns based on data, and optimising scheduled maintenance.

6. Conclusion

Minimise unplanned downtime
AI-supported maintenance allows machines and equipment to be repaired or serviced in a timely manner, reducing the risk of unplanned downtime and lost production.

Saving costs and increasing efficiency: through data-driven decision making and predictive analytics, AI-enabled maintenance optimises maintenance cycles and reduces costs, improving machine performance and lifetime.

More accurate and efficient maintenance: AI can predict problems based on data analysis, enabling detailed and timely interventions that increase machine reliability and efficiency.

7. Future development opportunities

With the continued development of AI and data-driven maintenance systems, there are further opportunities to increase efficiency, scalability and machine reliability.

AI-enabled maintenance is a key innovation for industry, as the technology enables intelligent monitoring and maintenance of machines and equipment, optimising operations and improving productivity. AI and data analytics-driven maintenance solutions are becoming more widespread and play a key role in increasing business competitiveness and creating sustainable operations.

References

[1] Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on ambient air quality and cleaner air for Europe, Official Journal L 152, 11.06.2008; http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2008:152:0001:0044:en:PDF.
[2] András Zsombók, Imre Zsombók VOC vapour recovery controls and technology 2023 IJSR
[3] András Zsombók Zsombók, Imre Zsombók Research and development in the life of small businesses 2023
[4] Zsombók András Zsombók, Zsombók Imre Zsombók Legal background of steam recovery and control at filling stations
[5] Peter Szalata, TÜV SÜD Industrie Service GmbH, Vapour recovery at filling stations, TankTec 07. 11. 2013.
[6] OPW Fueling Components Group, Total Vapour Solution TVS,
[7] TST electronics GmbH, The green petrol station, VarecoVent, www. tste.eu.
[8] VDI 4502 Sheet 3: Measurement and test methods for the assessment of vapour recovery systems in filling stations - Dry method of measurement.2003-11
[9] Directive 2004/42/EC of the European Parliament and of the Council of 21 April 2004 on the limitation of emissions of volatile organic compounds due to the use of organic solvents in certain paints and varnishes and vehicle refinishing products and amending Directive 1999/13/EC (Decopaint Directive).
[10] Simonsen-Industrietechnik, Retrofitting a petrol station, http:// www.simonsen-industrietechnik.de/tankstelle.html.
[11] Dr. Anikó Németh University of Szeged Data analysis with statistical methods
[12] Falus I., Ollé J.: The practice of empirical research, National Textbook Publishing House, Budapest, 2008.
[13] SN EN 228, Automotive fuels - Unleaded petrol - Requirements and test methods