VROC

Whitepaper

The Business Case for Machine Learning in Predictive Maintenance

The total cost of downtime across different process industries varies, however experts estimate that large industrial facilities lose more than a day's worth of production each month (1), with unplanned downtime costing $50 billion annually.(2)

Maintenance and reliability professionals continuously work to reduce downtime and improve the reliability and performance of their equipment. To reduce the financial impact of unplanned downtime, it is important to regularly review maintenance methods and eliminate outdated maintenance procedures which lead to increased costs.

In this paper we highlight the business case for adopting machine learning-based predictive maintenance and explore how this is different to rules-based predictive maintenance using condition monitoring.

Contents

Introduction	2
Maintenance comparison	3
How does machine learning predictive maintenance work?	4
Benefits of machine learning predictive maintenance	8
Summary	11

Predictive Maintenance Comparison

Due to the growing popularity of predictive maintenance, we have split the category into two distinct approaches. Rules-based predictive maintenance and Machine learning-based predictive maintenance.

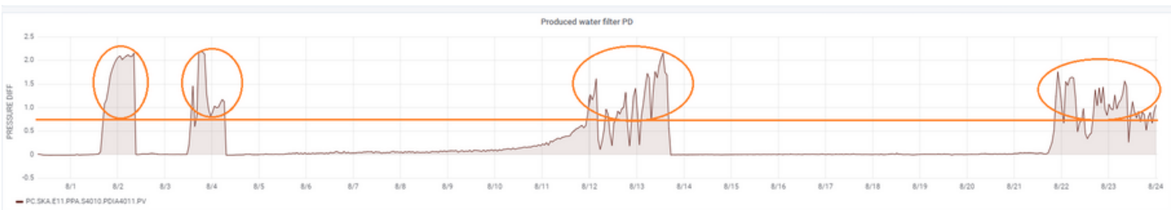
Rules-based predictive maintenance

Rules based predictive maintenance utilises equipment sensor data, condition monitoring and pre-defined threshold limits to predict when maintenance is required. The challenge with rule-based predictive maintenance is that only 20 percent of anomalies can be predicted (4) due to the limitations of conforming to an expected failure pattern. Unfortunately, these pre-defined threshold limits can result in a high rate of alerts which may not necessarily be true indicators (false positives) that maintenance is required, using up valuable resources. For accurate alerts, thresholds are often only exceeded just prior to a failure, limiting the ability for early intervention. In a number of cases, especially with changes in input conditions and operating parameters, it is highly likely that there are missing alarms and anomalies that exist un-detected.

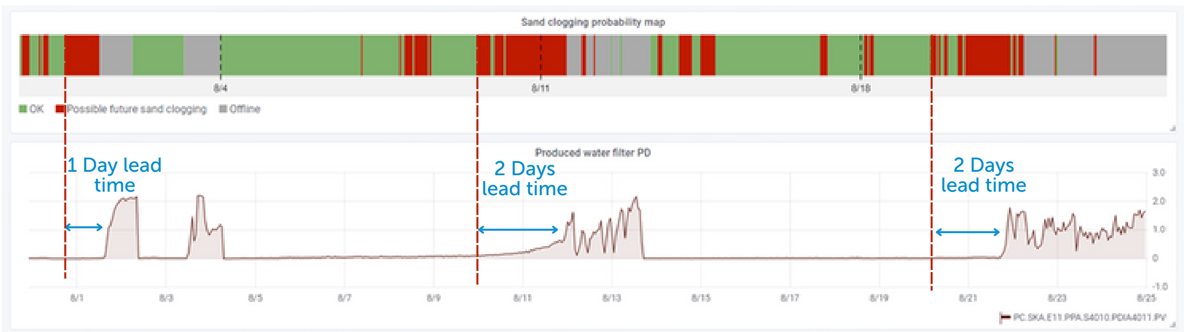
Machine learning-based predictive maintenance

Machine-learning based predictive maintenance uses equipment sensor data, advanced analytics and machine learning to detect anomalies and predict failures using a risk and/or criticality approach so that maintenance teams can make informed decisions on carrying out maintenance prior to a failure or mitigating the situation itself. This method continuously ‘learns’ and studies patterns leading to anomalies and faults to proactively alert teams as an equipment’s operating envelope deviates from the predicted norm, with the goal of reducing unplanned downtime and improving asset availability and performance.

We’ll continue to highlight the core differences, advantages and disadvantages throughout this paper, so that you can evaluate and prepare a business case specific to your own asset.



Without AI, Operators know there is a clogging event once the pressure has already reached the threshold



With AI, Operators are alerted to possible clogging events in advance

Image 1: Produced Water filter machine learning prediction, model visualisations

How does Machine Learning Predictive Maintenance work?

This technology works by understanding how an entire asset behaves at different operating conditions, how individual sensors are affected by or affect other sensors and is then able to predict a value for each sensor in real time based on a holistic model of the asset. Any variation or deviation between an individual predicted value and the real-time sensor reading triggers an alert showing the deviation but also the root causes and contributing factors that have triggered this change.

Holistic data connectivity and analysis

Machine learning models analyse live and historic data which is gathered from connected machines via diverse sources, such as critical equipment sensors, industrial control systems, enterprise resource planning (ERP) systems, computerized maintenance management systems (CMMS), and production systems. The benefit of using a holistic approach is that machine learning models can detect seemingly unconnected processes and inter-related problems to predict failures, contributing factors and root causes.

When equipment is monitored individually based on its sensors alone using threshold alerts, not all failures can be predicted, in some situations the equipment may not present with a deviation until an imminent failure, at which point it is too late for intervention. Other equipment sensors however may show a deviation, and which may be indicators for a predicted failure in a different section of the process.

For example: Multiple AI models are created for a 3-phase oil and gas process shown below. In the event of an impending process issue, the models can predict a drop in the output at the custody transfer meter and highlight the root cause and contributing factors simultaneously across the entire process allowing the operations team intervene early enough to avoid the drop in production. The models automatically adjust once the maintenance or mitigation work is completed, accurately predicting normal future production.

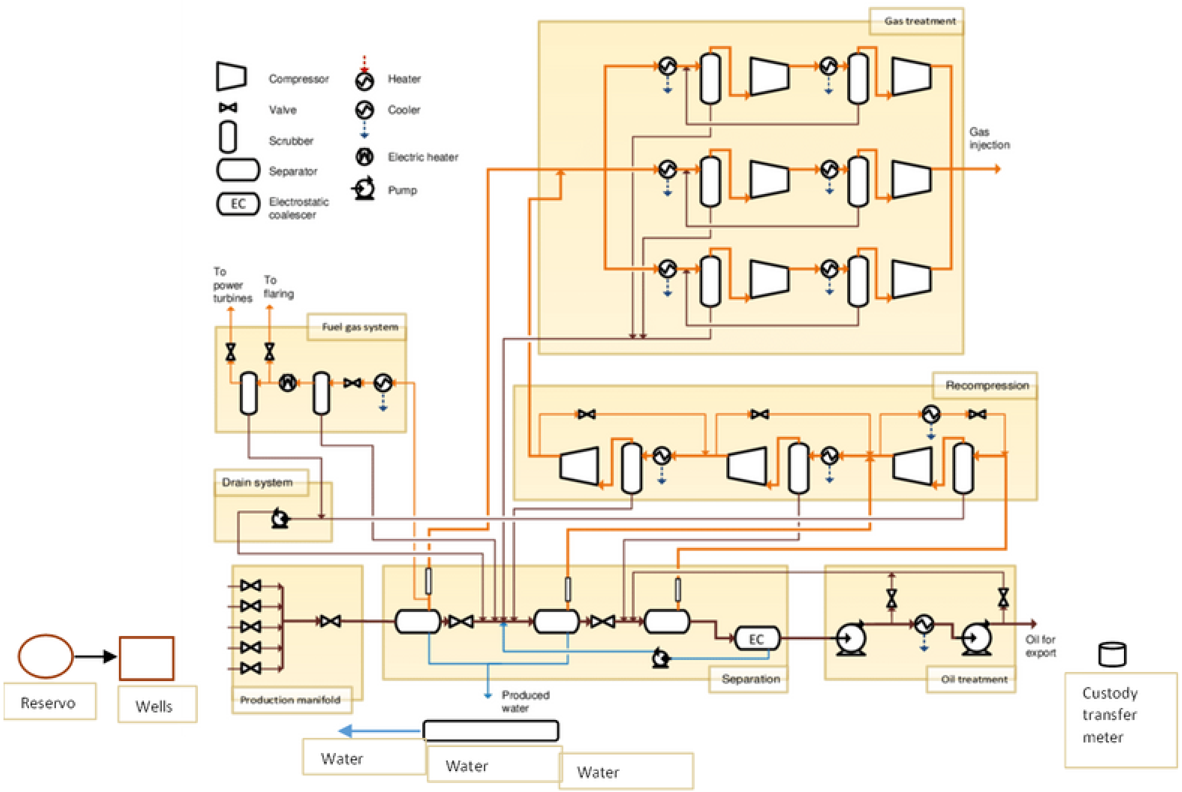


Image 2: 3-phase oil and gas process

Predicting time to failure

In this visualisation of an actual failure, a turbine was failing repeatedly due to the wrong maintenance being undertaken (blue line actual TTF).
The AI models were able to predict each of the failures well in advance as seen from the timeline (orange line predicted time to failure).

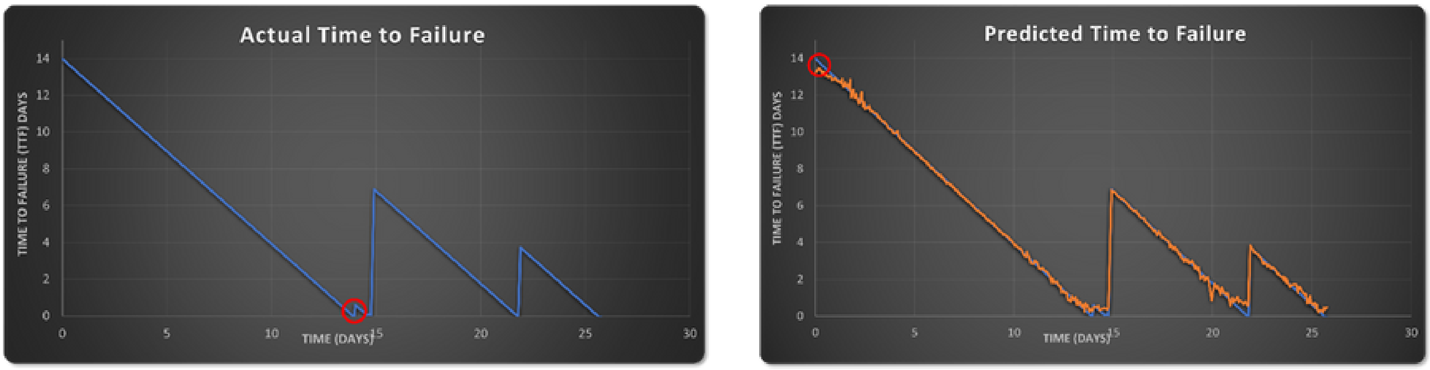


Image 3: Time to failure graphs with actual and predicted comparison

Detecting failures without equipment sensors

Using data from across the whole plant or facility, it is possible for machine learning to detect a failure even if the specific sensor for the failing component is not available, as other sensors tend to show deviations prior to any such occurrence.

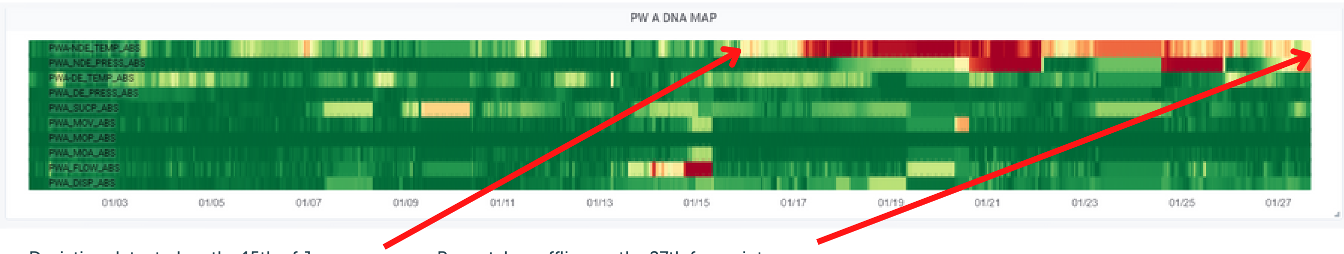
This has been proven in many examples, one in particular with a Turbine Generator where models were created for the speed, power and bearing temperature, however there was no sensor data available for the cooling-fan belt. Despite this, a machine learning model (which was comprised of 65 AI Models) raised an alarm for the increased generator enclosure temperature. The team were able to bring another generator into service before the faulty generator tripped, avoiding a critical blackout. The team concluded that a loose cooling fan belt was causing the generator to work harder, resulting in an increase in temperature without proper cooling.

Image 4: Turbine Generator model visualisation

Predictions on new assets with no failure history

Machine learning models can also be used on new assets without failure history, predicting asset deviation earlier than threshold alerts. One example of this is on a new build FPSO, whereby two years of historical data (over 30000 sensor tags) and live streaming of data were used to model the rotating equipment. The models detected a significant deviation from normal operating condition on the Produced Water Pump, identifying the root cause as a leaking non-driven end mechanical seal. The team had five days leading indication from the models and were able to schedule a pump changeover before the seal failed, preventing a plant shutdown and major loss of production.

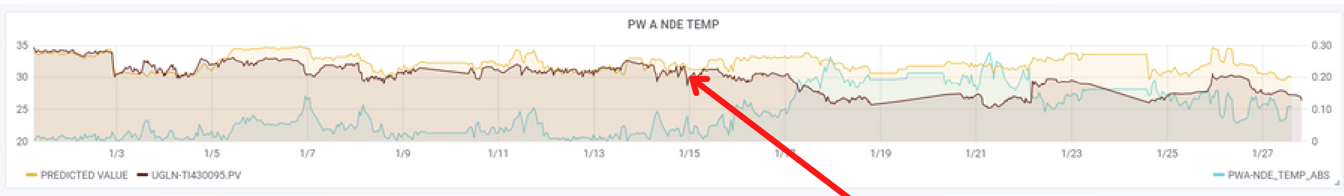
Sensor Tags Summary DNA Map



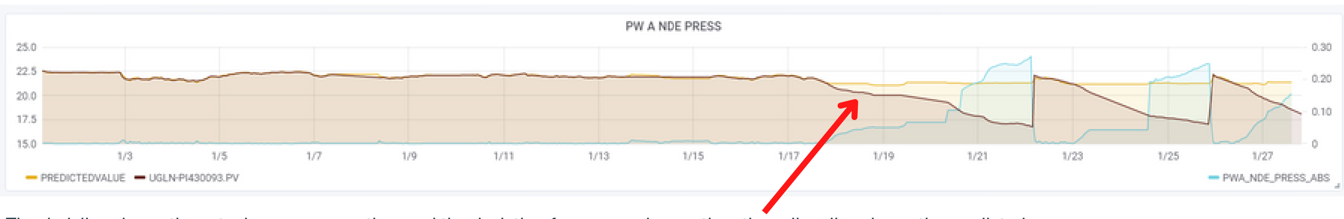
Deviation detected on the 15th of January.

Pump taken offline on the 27th for maintenance.

Detailed Deviation Plots



The dark line show the actual temperature reducing over time, the yellow shows the predicted temperature had the pump been operating optimally.



The dark line shows the actual pressure over time and the deviation from normal operation, the yellow line shows the predicted pressure.

Image 5: FPSO Produced Water Pump model visualisations

Physics vs Machine Learning modelling

Physics based models require complex analysis which are challenging to model in real time to get insights into the process, therefore in most cases physics-based models are used to provide post-mortem results. These models are also separate for each type of asset – static, rotating, pipeline, chemical reaction, thermodynamic, multi-phase, etc. Data based modelling is agnostic to the asset itself and relies solely on connections between different data points over time. This allows AI models to provide real-time predictive insights as a stand-alone solution or they can be used to support, verify and fine tune physics-based models.

Eliminating bias

Traditional industrial maintenance methodology takes a physics-based approach to model data, which is based on the original equipment manufacturers' (OEM) design specifications, thus limiting the analysis to only data from the equipment being investigated.

If we continue this approach when using machine learning, we introduce a bias into our algorithms. We restrict the machine learning models to an area of data which we have already assumed will identify the problem or contain the fault.

By broadening the scope of our investigation and looking at all available data (that’s real-time data from historian, DCS, SCADA or other sensors, CMMS, ERP, technical information, and even external data such as weather), the machine learning algorithms learn how the whole facility, processes and equipment work together under all different operating conditions and are not blinded by seeing only part of the picture.

By analysing the entire plant data, errors and faults from seemingly unrelated processes can be detected, which wouldn’t normally be detected from a traditional data science approach.

Real-time feedback loop

Utilising machine learning insights for predictive maintenance works in a continuous loop. Operators are alerted when maintenance is required, once the maintenance is completed, the models refresh, and if work has been carried out correctly, the models will predict a normal operating state. If the work hasn’t been implemented correctly, the models will detect it immediately after start-up and highlight the root causes of the problem. This can help maintenance and operating teams have confidence in their work. It is important to note however, that with a holistic approach, the root cause is detected at a macro component level initially meaning that maintenance can be completed accurately first time.

Benefits of Machine Learning Predictive Maintenance

Reduced planned and unplanned downtime

Rule-base predictive maintenance cannot eliminate unplanned downtime. Machine learning-based predictive maintenance, which continually looks for new patterns and trends in the data across the whole facility, is highly effective for the prevention of unplanned downtime and reduction of planned downtime with root cause analysis. At VROC we have had one client who suffered from frequent reliability issues over a number of years, with the help of machine learning predictive maintenance they were able to increase uptime and save $21.7M USD in just four months. These savings are not in isolation, McKinsey has estimated that predictive maintenance is estimated to create between 260 and 460 billion dollars(4) in economic value to the global manufacturing use case setting. Also, Deloitte estimate that predictive maintenance can help increase equipment uptime and availability by 10-20 percent(5).

Improved maintenance planning

Machine learning predictive maintenance gives maintenance teams additional time to plan essential maintenance activities safely. With so many complex processing plants in remote locations, such as offshore oil and gas platforms or remote mining sites, maintenance planning is critical to minimising cost. This includes the time to order spares if necessary, limiting high freight costs and the scheduling and logistics of technical personnel. Planned maintenance also allows for the planned switch over of equipment so that if the equipment fails there is a back-up already in place and there is no effect on production. Planned maintenance is by far the safest and most cost effective, with unplanned maintenance costing more, and breakdown maintenance typically costing three to four times as much as planned maintenance(6). It is in every businesses interest to increase the percentage of planned maintenance to reduce maintenance costs and increase safety.

Lower spares inventory

For processes with frequent failures, predictive maintenance can help identify the root cause of failures so that maintenance can be carried out on the right component and reduce the necessity and cost of large spares inventories. This was proven by one of the largest port operators, who were able to improve their crane availability with a decrease in spares inventory(7) and associated costs.

Increased manpower utilization

With machine learning-based predictive maintenance, teams are focused on tasks which they know are a high priority and have a high impact on operations, and as such they are more efficient.

Reduced personnel on site or switch to remote operations

Machine learning predictive maintenance can be used to assist companies switch to remote operations. The real time data provides an accurate picture of current operations as well as how operations will be performing twelve hours, twenty-four hours, forty-eight hours, five days or even two to four weeks into the future. An offshore oil and gas platform in the North Sea relied on machine learning predictive maintenance insights during COVID-19 lockdowns which restricted its reliability team from being on-site. During this time the platform continued production and actually improved its reliability(8). Reliability engineers were able to liaise with the limited on-site team to advise on necessary actions based on data insights obtained in real-time.

Many complex processing plants are remotely located or propose safety risks for personnel to be on-site. There is an increased push from many industries to switch to remote operations, and if these can be reliably operated from a centralised location, it provides for a safer, more cost-effective approach.

Improved environmental outcomes

Unplanned maintenance and breakdowns often have environmental risks, such as flaring, contamination, leakage, and a higher rate of emissions. Machine learning predictive maintenance helps operators maintain a steady state, reducing breakdowns and increasing environmental compliance. An oil and gas producer in Southeast Asia was able to use the technology to solve major integrity issues on one of its platforms, resulting in an improved flaring compliance from 50% to 100%. The producer was able to minimise production loss, as well as avoid compliance penalties and reputational damage(9). In another example a company was able to avoid a significant safety incident through the rapid identification of the cause of moisture content on hydrocarbon. The avoidance of the incident saved the company one million USD11(10).

Reduce energy consumption and improve energy efficiency

Machine learning predictive maintenance can be used to improve the energy efficiency of complex processes, identifying excessive energy consumption or causes for loss of energy production. It can also be used to create accurate baselines for energy usage and identify areas for optimisation. A coal-fired plant used machine learning predictive maintenance to compare two identical air supply units to isolate the root cause as to why one was deviating from optimal performance. The models detected a pressure loss in the boiler and pressure entry to the gas heater which was causing the excessive energy consumption and reliability issues. An air heater seal repair was completed which led to a 0.5% in plant heat retention, which for a 200MW plant can translate to $280,000 USD per/annum in fuel cost savings(11). With rising energy costs and the urgent need to reduce carbon emissions, machine learning insights can provide both a maintenance benefit as well as an environmental benefit.

Optimise processes

A subsequent benefit of machine learning predictive maintenance are the insights that can be used to optimise processes into the future. Examples have been shown where ML models identify previously unknown critical thresholds, such as a speed band on a gearbox(13) , this information was then used to avoid trips and damage to equipment. Another example which was not picked up by standard reliability analysis is a situation where equipment was being operated in the incorrect mode(14). By optimising processes, operators can avoid equipment damage as well as improve the production quality and/or quantity.

Extend asset useful life

Maintaining asset integrity and reliability as assets age is critical to profitability, as is the ability to extend an assets useful life due to the cost of replacement and decommissioning. Machine learning models can provide insights to ensure the on-going reliability of ageing equipment, alerting teams when maintenance is required. This ensures that damage isn't occurring unnoticed which can have a longer-term impact on useful life. Machine learning models can also be used to determine the length of useful life that remains, as well as opportunities such as adjusting settings so that the asset is optimised to last for longer, perhaps just at a slightly reduced effort than when it was first commissioned. Two late life assets in the North Sea that adopted machine learning predictive maintenance were able to reduce their production loss by 80% and 83% respectively from previous experienced downtime(12).

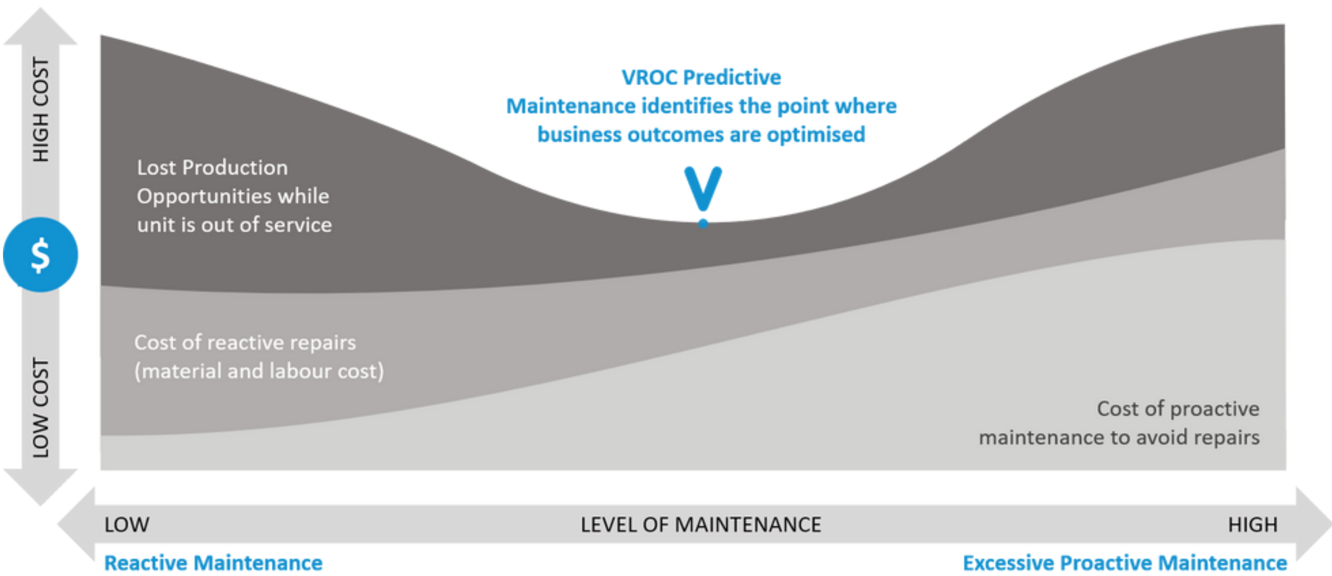


Image 6: Level of maintenance vs maintenance cost illustration

Summary

- Machine learning technology has evolved to a state where real time insights are successfully predicting maintenance requirements on equipment well in advance of traditional methods.
- AI models for individual equipment and processes can be built using a no-code holistic approach by any stakeholder to focus on their own particular areas of interest.
- The business case for the use of this technology for any real-time process is now well established and can be implemented in a very short time with a quick ROI.

References

1. https://www.continuitycentral.com/index.php/news/business-continuity-news/6416-machine-failures-result-in-27-hours-average-downtime-per-month-for-industrials
2. https://partners.wsj.com/emerson/unlocking-performance/how-manufacturers-can-achieve-top-quartile-performance
3. https://www.arcweb.com/blog/improve-asset-uptime-industrial-iot-analytics
4. https://www.mckinsey.com/~/media/mckinsey/business%20functions/mckinsey%20digital/our%20insights/iot%20value%20set%20to%20accelerate%20through%202030%20where%20and%20how%20to%20capture%20it/the-internet-of-things-catching-up-to-an-accelerating-opportunity-final.pdf
5. https://www2.deloitte.com/us/en/insights/focus/industry-4-0/using-predictive-technologies-for-asset-maintenance.html/#endnote-sup-1
6. https://www.plantengineering.com/articles/maintenance-planning-scheduling-deliver-to-the-bottom-line/
7. https://vroc.ai/case_study/reduction-in-spares-inventory/
8. https://vroc.ai/case_study/reducing-pob-with-real-time-remote-monitoring/
9. https://vroc.ai/case_study/increased-reliability-for-oilfield/
10. https://vroc.ai/case_study/lopc-avoidance/
11. https://vroc.ai/case_study/generator-optimization/
12. https://vroc.ai/case_study/opex-reduction-in-late-life-assets/
13. https://vroc.ai/case_study/oil-rig-gearbox-failure-prevention/
14. https://vroc.ai/case_study/2000x-faster/

For more information or a demonstration of VROC's Machine Learning Solution for Predictive Maintenance, please contact us directly:

E. solutions@vroc.ai
W. www.vroc.ai
T. +61 1300 VROC AI (1300 876 224)