THE SHELL JOURNEY TOWARDS global predictive maintenance

Predictive maintenance is an established proactive technical monitoring approach that uses advanced data analytics based on machine learning and artificial intelligence to monitor data from equipment in assets. Machine learning models are trained using historical data to detect any abnormal behaviour that could indicate early signs of failure. By detecting an issue early, timely preventive action can be taken and potential unscheduled deferment or unplanned downtime can be avoided. Shell is rolling out predictive maintenance across its assets to improve their reliability and thus their efficiency.

The challenge

Traditionally, caring for equipment at Shell assets has relied on replacing parts after a set time. This approach sometimes means that parts are replaced while they are still in good condition. An alternative strategy is to wait until something fails. However, equipment failure means that an asset needs to shut down temporarily for repairs, which affects production.

Physics-based models have gone a long way to improving these strategies. They can be used to monitor data from an asset and to help detect issues by determining when readings go above or below a certain point. Such solutions are still considered the best options for equipment with straightforward condition monitoring instrumentation. However, assets are under increasing pressure from the financial and reputational perspectives to increase their reliability. Making use of machine learning and artificial intelligence is the next step on the maintenance journey.

The solution

In a move to improve reliability at a refinery in the Netherlands, the instrument engineering team decided to investigate how artificial intelligence could help to detect control valve issues early on and thus help to avoid unscheduled deferment or unplanned downtime. The team worked with Delft University of Technology, the Netherlands, and the Shell digital team to assess how artificial intelligence could play a role in improving the reliability of Shell assets. Predictive maintenance for control valves was born from this collaboration.

Each Shell asset captures many thousands of data points every minute, far too many for the human brain to analyse or identify patterns in. As a result, Shell data scientists have developed machine learning models that can analyse thousands of data points simultaneously and thus enable engineers and others to draw insights from these data. Using historical data, the machine learning models are trained to recognise anomalies in data sets. Alerts are triggered when small anomalies are detected so that further investigation and more proactive maintenance can occur.

Predictive maintenance machine learning models are currently being trained and rolled out at assets across the company. In 2020, a refinery in the Netherlands reached an important milestone in its predictive maintenance journey: all the suitable control valves across the asset were successfully modelled and being monitored by predictive maintenance applications. Within a short time, the predictive maintenance models gave alerts for 65 control valves that were in need of repair and that would not have been detected using traditional methods. In January 2021, a refinery in Singapore was the next to reach this important milestone, closely followed by assets in the USA and Canada in March. More assets are expected to follow soon.

Integration with work processes

Predictive maintenance models are fully integrated into the central exception-based surveillance work process, part of the ensure safe production process in Shell’s asset management system. For most assets, this means that a remote engineer analyses any alert first, see Figure 1. After this initial investigation, the remote engineer passes on valid findings to either a
remote or a local specialist before going to the asset engineer for a deeper investigation. This process aims to reduce the effort required from the asset and enable engineers to focus on validated alerts. The asset engineers work closely with maintenance teams to assess any issues and take action where necessary.

**Success in Singapore**

In September 2020, a machine learning model was created to monitor a globe control valve at a refinery in Singapore. Such valves are the final control elements used to start, stop and regulate the flow of process fluids. They do so by controlling the position of a movable plug relative to a stationary seat. This controls the area the process fluid can flow through and, therefore, the flow rate. Over time, the mechanical parts of the control valve that interface with the process fluid, such as the plug, the seat and the gland packing, may degrade and cause potential leakages or reduced controllability. This situation is intolerable, especially if the valve has a safety-critical function, i.e., it acts as a barrier that prevents the uncontrolled release of a hazard that could lead to a worst-case-credible scenario. Thus, it is very important to ensure that the control valve is operating appropriately.

As part of the Predictive Maintenance Programme, the project team modelled the expected positioning of the valve based on the process conditions and then began monitoring its actual and predicted positions. Subsequently, the predictive maintenance for control valves application detected a deviation between the valve’s actual position and its predicted position and triggered an alert. In Figure 2, the blue line shows the actual valve position (percentage open) obtained from the distributed control system and the green line shows the C3 AI prediction. The green boxes show when the deviations occurred.
The remote engineer’s initial investigation indicated that the control valve was hunting (oscillating uncontrollably about the set point) and that the impulse line of the differential pressure level transmitter might be choking. The predictive maintenance model was created in September 2020 but was able to show that the erratic valve movement had started several months earlier. Local instrument engineers analysed the report and validated the observations.

The unit maintenance focal point then carried out a site investigation to validate the findings and correct any potential choking. A pump-through was performed on the transmitter’s impulse line to clear the potential choke. The data monitoring for the two subsequent weeks confirmed that the control valve hunting had significantly reduced.

In Figure 3, the green line shows the control valve position from the distributed control system and the blue line indicates the level. The green box shows when the corrective action occurred. It is clear that cleaning the choked impulse line eliminated the valve’s hunting behaviour.

Thanks to early intervention, significant reported value has been confirmed. A failure caused by this control valve problem could have resulted in shutting down the sour-water stripper for cleaning and the need for flaring. It could also have resulted in a period of lower quality product because of the poor controllability of the control valve in the fractionator unit.

**Deepwater platform early warning**

Another interesting issue recently arose on the other side of the world at a deepwater platform in the Gulf of Mexico, where predictive maintenance machine learning models for all the suitable control valves were successfully deployed to monitor and optimise their performance in December 2020.

A few weeks later, the predictive maintenance control valve application detected an anomaly in the data from the positioner valve that controls the flow to the first phase of the vapour recovery unit and triggered an alert. The remote engineer observed deviations between the valve and the feedback from the positioner, which was causing fluctuations in the flow signal. Although the flow was regular, there were some disturbances. The red line in Figure 4 shows the controller output. The green line shows the control valve position feedback and the blue line shows the process variable. The process variable was found to be linear with respect to the valve position feedback, so, in response, the controller output was attempting to bring the process variable back to the set value. Consequently, the engineer contacted the local focal points and recommended an investigation into the health of the control valve.

The investigation revealed that the valve was swinging by 5–10% and up to six times in less than a minute, and then the movement almost stopped only to start again. This was repeating continually. As a result, replacement or repair of the valve positioner is being considered. This early detection of a potential issue means that maintenance to the valve can be proactively planned at the best time for the asset.
What is particularly interesting about this finding is that no other methods detected this issue: other monitoring methods showed 98% compliance because the movement was too fast and too infrequent for traditional monitoring systems to pick up.

Commercialisation
The predictive maintenance solutions were recently released to energy operators in the open market via the Open AI Energy Initiative, which was launched by Shell and partners Baker Hughes, C3 AI and Microsoft. It is an open ecosystem of artificial intelligence based solutions specifically for the energy and process industries.

By bringing its solutions to market and encouraging others to do the same, Shell hopes to accelerate the adoption of artificial intelligence technology across the industry. The Open AI Energy Initiative provides an open framework for building interoperable solutions such as artificial intelligence and physics-based models, diagnostic libraries and services.

We are excited to offer these and additional (future) capabilities to the market and participate in the creation of an open ecosystem that can benefit the entire energy industry.

What’s next
Currently, there are two main products available: one for monitoring control valves and one for rotating equipment. A new application has recently been launched that combines rotating equipment (centrifugal compressors, centrifugal pumps and steam and gas turbines), subsea electric submersible pumps and a recent proof of concept on dry gas seals. With this new application, the time required to assimilate new equipment is expected to reduce significantly. In addition, the replication time across assets for the same equipment type will be shorter.

The Predictive Maintenance Programme is continuously looking for new opportunities to enhance existing products, improve adoption and identify new use cases where machine learning can be applied to improve equipment reliability. Several developments are under way to investigate the possibilities of comparing whole systems such as parallel reactors or liquefied natural gas trains. Another interesting initiative is looking at the possibilities of using machine learning to monitor a whole asset. In parallel, deployments continue worldwide to increase reliability and improve equipment care strategies.

Acknowledgements
The author would like to thank colleagues Marijn Bezuijen and Vijaya Rajan (Predictive Maintenance Programme), Arnold Hes, Ye-Peng Wang, Mervin Masicat, Shane Jarrell, Bo Harris and Nathan Heilman for their help with this article.

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