From Reactive to Proactive: Machine Learning Drives Better Business Outcomes

aspentech | Case Study

We have embarked on a digital journey, and the ability to bring transparency to all our operating processes is a priority for us. Aspen Mtell® predictive maintenance software's ease of implementation will allow us to develop data analytics, including pattern recognition and early anomaly detection, in all operating functions, leading to increased performance in safety, quality, reliability and overall improved performance in manufacturing.

27 days

of advance warning for central valve failure

CHALLENGE

Failures of the hypercompressors in an LDPE process were resulting in high maintenance costs and the risk of missing orders.

SOLUTION

Aspen Mtell was deployed on the unit to increase the notification period. For a problem with the HP packing seal, it was able to provide 48 days of notice by including additional upstream sensors from the HP recirculation process.

BENEFITS

This pilot provided proof of three significant capabilities:

- Longer-lead-time detection of repeating failures
- Transfer of learning
- The ability to capture fast-moving failures

Aspen Mtell has demonstrated an ability to detect faults inside the hypercompressor with the increased lead time needed to remediate the problem and reduce the potential for losses.

Overview

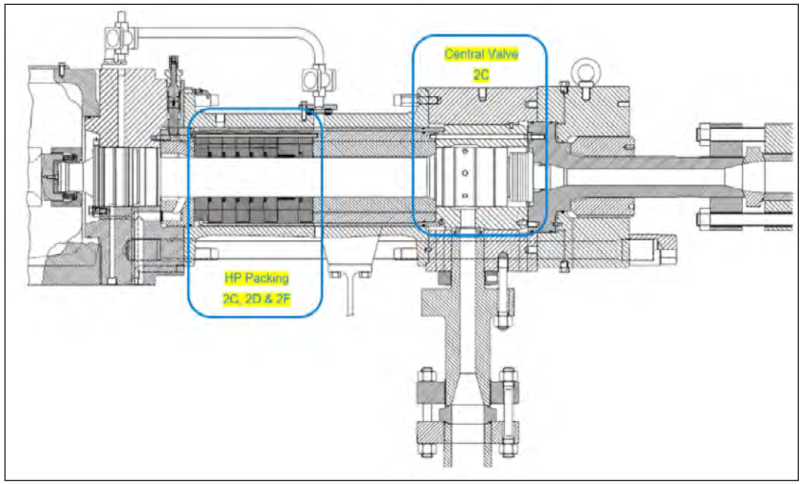
At this plant that produces speciality plastics for energy supply, oil and water pipeline projects, tight margins are the norm — and unplanned downtime can quickly impact the profitability of the business.

The company was evaluating potential solutions to reduce downtime on a problematic piece of equipment in their LDPE production process, a hypercompressor that pressurizes feed to 2800 bar. There were several failure mechanisms contributing to high unplanned downtime, so the organization decided to evaluate Aspen Mtell as a way to predict asset failures earlier and with greater accuracy.

They engaged in a pilot project with the following goals:

- Demonstrate the Aspen Mtell methodology. Show how the solution accurately detects precise patterns of normal behavior, failures and anomalies.
- Demonstrate self-learning of precise signatures. Indicate early warning or lead time from point of detection to actual failure.
- Demonstrate early, accurate detection. Depending on the data content, capture a failure signature and use it to detect failures in unseen data on the same assets and/or similar assets.

Two failure modes were the focus of the pilot project: problems with the central valve and with the HP packing.



The packing problem was a bit of a mystery. The packing was developing leaks, but with an unexpected pattern and progression. The hypothesis was that the failure was associated with startup and shutdown.

The central valve problem was a case of the poppet valves grinding into their seats. After some period, the valve head would degrade to the point where it was sucked into the discharge orifice. This is a rapid failure that occurs in milliseconds and results in catastrophic failure and shutdown of the unit. The early lead time can be used to reschedule production and prevent blowdown of the reactor, which would result in significant loss of product.

Repairs were expensive, but the production losses were typically five to 10 times greater than the repair costs.

A New Approach

As part of its digitization strategy, the company was looking for predictive maintenance technology that could deliver critical capabilities:

- Provide longer notice periods than existing technology. They needed at least two days of notice, but with a week of notice they could optimize their response by rescheduling production to avoid missed orders and/or a reduction in saleable product.
- Accurately predict fast-moving failure types.
- Do the above without false positives.

Aspen Mtell proved its ability to provide an early warning for the failures studied during the pilot. For the central valve problem, Aspen Mtell was able to provide 27 days of notice. After tuning the agents, all false positives were eliminated.

For the packing seal problem, it was able to provide 48 days of notice by including additional upstream sensors from the HP recirculation process.

Benefits

With these increases in warning time, the plant staff was able to reduce their maintenance costs and had time to complete the re-planning workflow. The technology will provide ongoing benefits in eliminating unplanned downtime, reducing asset damage (and hence, maintenance costs) and the ability to remediate asset downtime problems in a business-optimal way.

The pilot project described here occurred over a period of just a few weeks. The quick timeline is possible because of the approach of finding failure signatures, as opposed to analyzing asset performance models. Further work is being done to evaluate rollout plans. This will also highlight a key capability of Aspen Mtell — its capacity for transfer learning, where signatures developed on one asset can be transferred to identical assets.

Technology That Loves Complexity

AspenTech is a leading software supplier for optimizing asset performance. Our products thrive in complex, industrial environments where it is critical to optimize the asset design, operation and maintenance lifecycle. AspenTech uniquely combines decades of process modeling expertise with machine learning. Our purpose-built software platform automates knowledge work and builds sustainable competitive advantage by delivering high returns over the entire asset lifecycle. As a result, companies in capital-intensive industries can maximize uptime and push the limits of performance, running their assets faster, safer, longer and greener.

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