Ramp up Reliability With Low-Touch Machine Learning for Hyper Compressor Monitoring

Robert Golightly, Sr. Manager, Product Marketing, Aspen Technology, Inc.
Mike Brooks, Sr. Director, Business Consulting, Aspen Technology, Inc.

White Paper

Hyper Compressor Reliability Issues

Reliability is top-of-mind for many executives today. Eliminating unplanned downtime is an obvious, and potentially dramatic, driver of better financial performance. This is certainly the case regarding the hyper compressors used in low-density polyethylene (LDPE) production.

LDPE was discovered by ICI in 1933, and the autoclave process technology followed in 1938. BASF developed the first tubular process. Today, there are many different licensors of both autoclave and tubular processes.

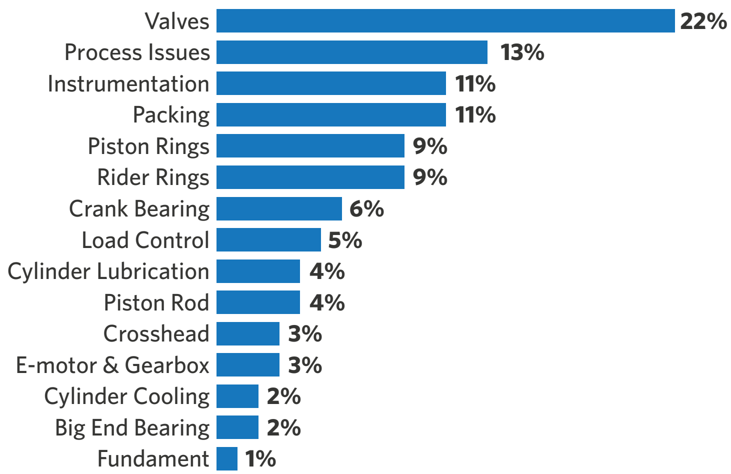


Figure 1: Most frequent failure modes of hyper compressors (source: *DIAGNOSTYKA, 2018, Vol. 19, No. 1*)

Hyper Compressors and Overall Plant Reliability

There are several common failure modes for hyper compressors. Compressor valves are the weakest component and the most frequent failure mode, accounting for almost half the maintenance cost. Also noteworthy is the second-most-frequent failure, process issues. We'll come back to that in a minute.

Reciprocating compressors are designed to handle clean gas and cannot satisfactorily handle liquids and solid particles that may be entrained in the gas. Liquids are non-compressible, and their presence could rupture the compressor cylinder or cause other major damage.

Safety is a significant concern with these compressors, due to the extreme pressures and the feeds involved.

Mechanical Monitoring

The quality of a production system is primarily characterized by adequacy, reliability, safety, durability and efficiency. Monitoring of mechanical conditions via vibration analysis, pressures, temperatures, position sensors and accelerometers is a common approach to improving the reliability aspect.

Condition monitoring systems provide some warning based on mechanical condition, but have no ability to sense the incipient fault — the process conditions that cause most failures. Recall that “process issues” ranked as the second-most-common failure category (see Figure 1). That limits the degree of warning that can be delivered (length of time and accuracy).

These monitoring systems can only identify degradation once the condition has progressed to the point that vibrations, temperatures and other mechanical signals are anomalous. Process-induced conditions such as liquid carryover can only be detected by these systems once the damage has reached a point where repairs are already unavoidable. Early prediction helps reduce the scope of required maintenance by detecting undesirable operating conditions before significant damage is done.

Monitoring solutions have delivered benefits, but there are still significant losses associated with unplanned downtime. Figure 2 comes from a vendor of mechanical monitoring systems and shows their claim regarding the initial and remaining cumulative unplanned repair costs where mechanical monitoring has been implemented.

There’s significant improvement, but more than half of the potential benefit has not been captured. More to the point: what’s missing in this analysis is the degree to which the monitoring system provided warning in time to avoid production disruptions, order spare parts, line up the repair labor, schedule the downtime and, possibly, reschedule production to minimize missed orders.

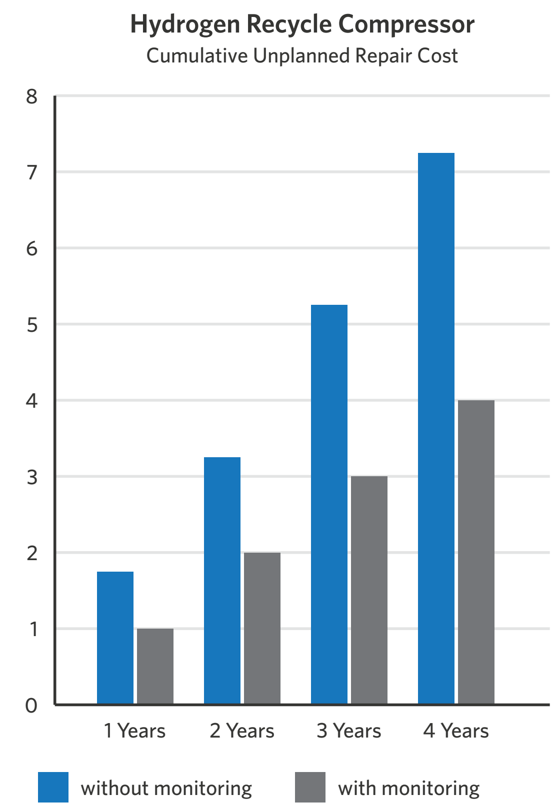


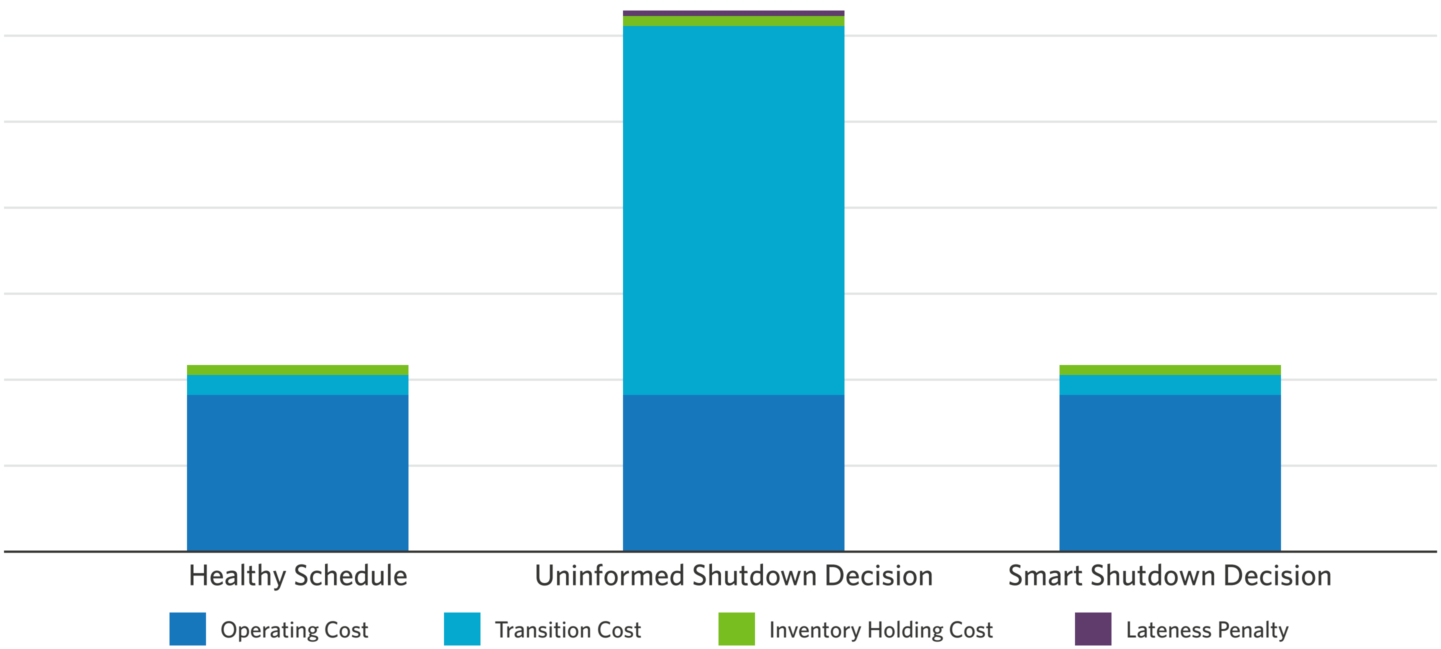
Figure 2: Even with monitoring, there is an opportunity to capture more cost benefits. (Source: A Self-Organized Fault Detection Method for Vehicle Fleets, Yuantao Fan, Halmstad University, 2016)

The Costs of Unplanned Downtime

When hyper compressors fail, the losses in production can be many times greater than the maintenance costs. Those costs can range from tens of thousands to millions of dollars per occurrence. Beyond the safety issues are environmental considerations, as ethylene flaring is common when hyper compressors fail.

As an example, one major producer of LDPE has experienced multiple failures — up to 15 unplanned events per year. Each failure results in a maintenance spend of at least $25,000 plus the loss of production for the outage period. **Using a heuristic of production loss being at least 2X the maintenance costs, these failures resulted in more than $500,000 in losses per hyper compressor each year.** These are highly conservative estimates.

In another case, a company wanted to increase the pre-failure notification period. Their business goal was to use the increased notification time to reschedule production, thereby reducing late orders and improving financial performance.



Financial Gains From Rescheduling

Figure 3: In this example, the grade that was scheduled for the period after repair of the compressor was a grade that required a long ramp-up to produce. By rescheduling, a different grade was scheduled for the period, resulting in significantly lower costs.

Incipient faults often generate very subtle signals that are obscured in traditional approaches. Machine learning, especially deep learning approaches, have proven themselves highly capable of detecting those subtleties.

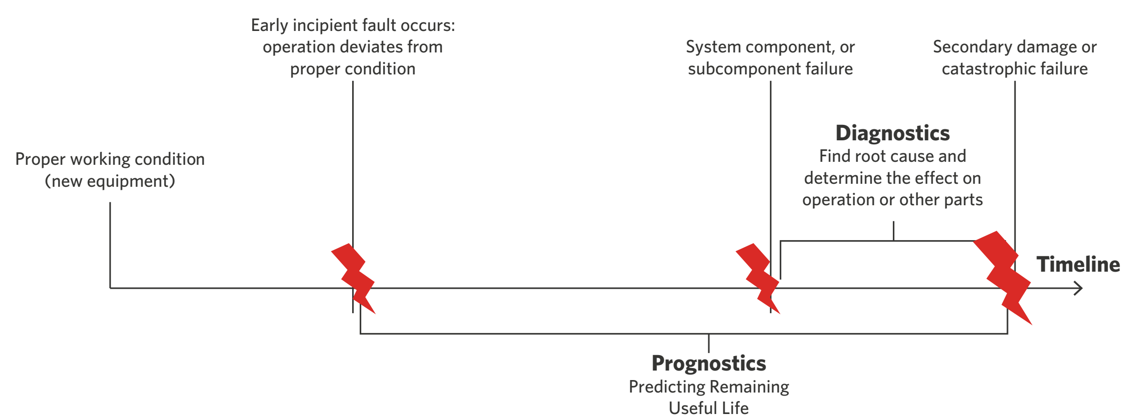
Limitations of Condition Monitoring

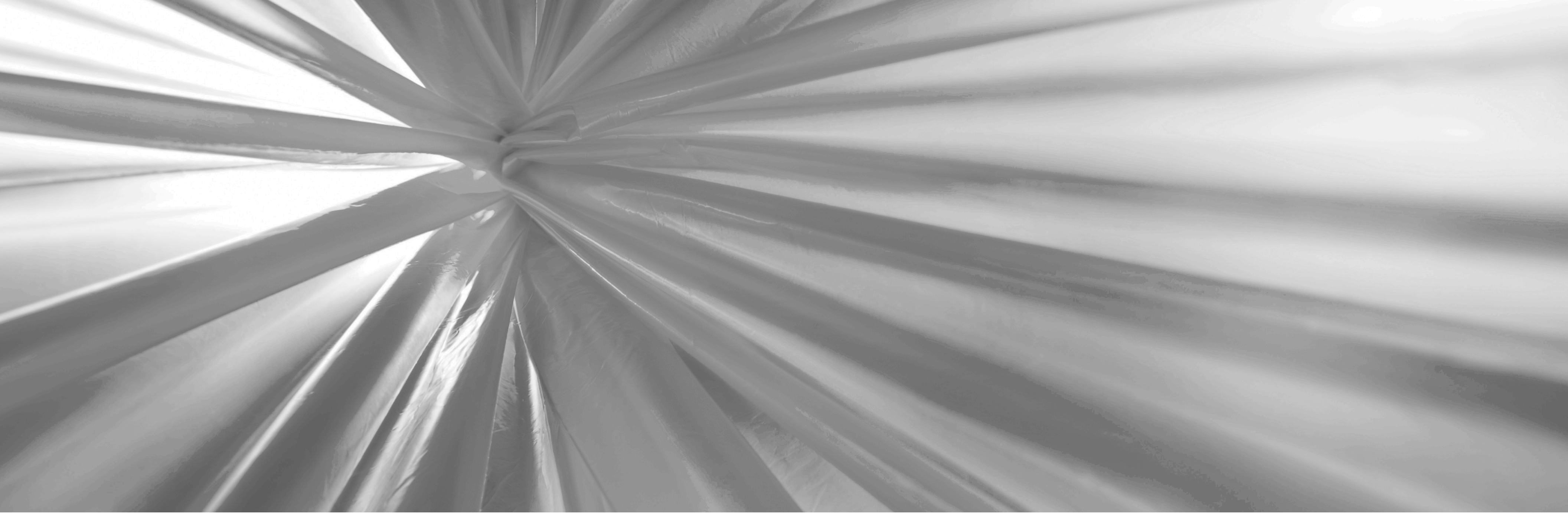
To increase the notification period, we need to be sensing farther upstream to find the operating behaviors that reduce reliability. Condition monitoring systems have no connection to process data, so they are limited to the late-stage indicators of thermal profiles, vibration analysis and position sensing.

The problem we are trying to solve can be classified as a temporal multivariable analysis. We need to be able to correlate potentially small signals that occurred days or weeks earlier with the actual machine breakdown or degradation. Incipient faults often generate very subtle signals that are obscured in traditional approaches. Machine learning, especially deep learning approaches, have proven themselves highly capable of detecting those subtleties. The idea is akin to finding the cancer while it's still small.

A large part of the functionality gap in current solutions is an artifact of the quality of the data. Misclassification of failures, missing data, bad instrumentation and other factors result in data that requires significant human intervention for conditioning before analysis can begin. In fact, users report that data gathering and conditioning easily consume half of the time devoted to analyses.

Traditional CBM systems utilize a rules engine driven by Boolean logic to indicate the conditions to perform maintenance when the need arises. Just finding people with the skills to interpret the information from condition monitoring systems can be a challenge. The market leader for condition monitoring of hyper compressors has a team of experts who do the interpretation and provide the monitoring as a service. That is not only an issue with costs of scaling, but it also introduces potential delays in communicating and reacting to alarms.





Aspen Mtell® Delivers Better Business Outcomes

Hyper compressor failures can result in significant production disruptions. The number of options for remediating those disruptions are proportional to the length of the notification — i.e., the shorter the notice period, the fewer options the business has at its disposal to deal with the problem.

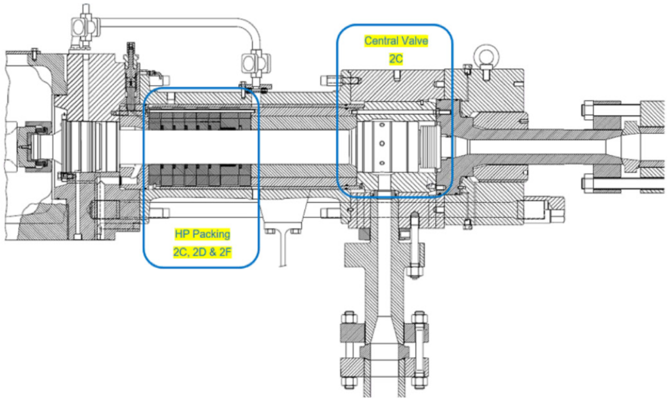
The best option is to avoid the liquid carryover completely. The second-best option is to get away from liquid carryover as soon as possible.

Typical remediation efforts involve obtaining spare parts, locating skilled labor to perform the repairs and scheduling those repairs. With additional notification comes a broader set of options.

In one case, the success criteria for compressor monitoring was to provide enough notice to reschedule production to minimize missed orders. Aspen Mtell delivered **26 days of notice of valve failures and more than 46 days of notice for packing failures**. Even for fast-moving events like suction valve failures, Aspen Mtell provided weeks of notice that enabled a more business-optimal response.

Case Study

A plastics producer needed to reduce downtime on a problematic piece of equipment in their tubular low-density polyethylene (LDPE) production process, a hyper compressor that pressurizes feed to the reactor. There were several failure mechanisms contributing to high unplanned downtime.



Specifically, the company had several goals:

- **Demonstrate the 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.
- **Predict failures with enough time to re-schedule production to minimize missed orders.**

Two failure modes were the focus: problems with the central valve and with the high-pressure packing. The packing was developing leaks, but with an unexpected pattern and progression.

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.

Aspen Mtell Finds the Failure Mechanisms

Hyper Compressor Cylinder(s)	Failure Type	Lead Time (Days)
2F	Methodology and Training HP Packing – High Plunger Displacement	29
2C	Detection of Repeating Failure HP Packing – High Plunger Displacement	Up to 60
2C	Fast-Moving Failure – 5min dataset Central Valve – High Discharge Temp	27
2C, 2D, 2F	Transfer Learning HP Packing – High Plunger Displacement	30, 18, 27
2C	Upstream Detection HP Packing – High Plunger Displacement Includes HP Recirc, 2nd Stage CYL 2C	Up to 78

How Aspen Mtell Works

Aspen Mtell uses advanced pattern recognition with statistical and machine learning techniques on current operational data and historical records. It is the most sophisticated, fully automated solution available, and it executes with little human involvement — inline, in real-time, automatically learning and adapting to operational changes and new failure conditions.

Aspen Mtell is a low-touch application with an automated methodology based on Autonomous Agents that abstract all technical aspects of machine learning. It includes ease-of-use constituents to ensure the system installs using the end user's current skill set. It's fast to implement, it's scalable and repeatable, and it learns and adapts automatically. **It is the solution that provides extremely early warnings, and to date is the only solution that focuses on the process issues that lead to most equipment damage.**

The designers of Aspen Mtell set out to build a product that was accessible for personnel at current manufacturing process plants — without them needing to acquire new skills in maintenance methodologies, intense mathematical or engineering model-building, data science or information technology (IT) skills. Consequently, people who can build a display in an automation system, configure an historian or program a PLC (programmable logic controller) are well-suited to rapidly learn to set up an Aspen Mtell system and build and deploy Autonomous Agents.

Aspen Mtell finds degradation conditions that others cannot — and it finds them earlier, allowing more lead time to determine the appropriate action to take. The capability of Autonomous Agents to determine precise time-to-failure with great accuracy is a technique that eludes other products, which primarily carry out only anomaly detection.

Aspen Mtell finds degradation conditions that others cannot — and it finds them earlier, allowing more lead time to determine the appropriate action to take.

Aspen Mtell Autonomous Agents

What's an Agent?

Simply stated, an Autonomous Agent is a software component that does machine learning so that you don't have to!

An Autonomous Agent monitors only one asset, comparing incoming data patterns with its internal signature/pattern. Each asset uses several Autonomous Agents, detecting normal behavior and specific patterns leading up to failures in bearings, drive-couplings, seals and other components. Autonomous Agents send messages and initiate action when an asset behaves abnormally, and they learn and adapt over-time.

Autonomous Agents automatically execute intense technical and analytical work in real time, announcing issues with long lead times the second they are detected. They work continuously, 24/7, constantly learning and adapting, and they retain absorbed knowledge forever.

There are two Autonomous Agent types, which provide two ways to find degrading or failure conditions: *Anomaly Agents* and *Failure Agents*. Anomaly Agents ask, "Is this normal behavior?" Consequently, they can recognize excursions that are previously unseen failures, as well as legitimate process excursions that may be classified as "new" normal behavior.

Anomaly Agents are intensely accurate because their formation comes from a technically comprehensive and very pure understanding of what normal behavioral patterns "look" like. They know precise patterns of normal far better than competing techniques. As a result, Anomaly Agents detect failures early and with greater accuracy than modeling techniques, and even machine learning techniques that use simple human-driven approximations of normal or threshold methods that are not grounded in the waveform and pattern exclusion procedures deployed in Aspen Mtell.

Additionally, Anomaly Agents automatically adapt to changes in process behavior to ensure the accuracy of all detected failures without false alarms. In other solutions, failure mode models are libraries of estimated failure conditions, and they do not work as well.

Failure Agents are trained by measuring the actual behavioral patterns that begin early in root cause conditions that lead to very specific failures (e.g., a bearing failure). As a result, by constantly scanning incoming data to detect recurrences, Failure Agents provide far more accuracy, and much earlier warnings of machine and process behavioral issues. All Autonomous Agents can send notifications via text messages, emails and dashboard alerts. Failure Agents can send detailed descriptive information about the failure and advise prescriptive action to eliminate or minimize production interruptions from impending failures.

Anomaly Agents

An Anomaly Agent autonomously assesses incoming patterns of data on its defined data collection set for one specific piece of equipment against. It then compares those patterns with an accurate signature of normal behavior that it carries for that equipment.

Simply described, an anomaly is a deviation from normal behavior, and is detected by answering the question, "Is this normal?" Because of the waveform, pattern exclusion and machine learning used to define "normal," Aspen Mtell detection of anomalies is far more precise and warns earlier than contemporary systems — and when it detects a deviation, it is real and accurate for any failure or new normal condition.

The signature carried by an Anomaly Agent is determined by the probability waveform process, which includes the Aspen Mtell proprietary non-normal pattern exclusion technique. A machine learning analysis of the precise multivariate and temporal patterns carried in minuscule, non-human detectable changes between sensor time series data and across time assesses the complex patterns making up the signature.

When a deviation is declared to be a "new normal" behavior — that is, something never seen before — the Anomaly Agent retrains itself, with human involvement, to add the new pattern to its internal signature. Going forward, it will recognize the new behavior and will not send out false alarms. In this way, Anomaly Agents learn and retrain, capturing and retaining all the behavioral knowledge of changes in operations.

An Anomaly Agent also stimulates dispatch of alerts by text, email and dashboard messages to warn end users, and it can also stimulate the entry of an inspection work request directly into the asset management system.

Note: An Anomaly Agent is not a model! Its content, the signature, was described by machine learning techniques, and its duty is to compare incoming patterns against the patterns it knows. This is very different from models that try to estimate what the results should be.

Failure Agents

A Failure Agent assesses incoming patterns of data on its defined data collection set for a specific machine, and then compares those patterns against a signature of a very specific failure (often tied to an explicit root cause) for that machine. The failure signature carried by a Failure Agent describes the precise multivariate and temporal patterns carried in minuscule, non-human-detectable changes between sensor time series data and across time.

The pattern of degradation leading to a failure with a root cause is very specific, and Aspen Mtell analyzes data using machine learning to "fingerprint" the precise patterns for a specific root cause. Failure Agents are trained using Aspen Mtell's proprietary data conditioning and sophisticated machine learning algorithms — all "under the covers" to keep it simple for end users.

Most contemporary systems only use anomaly detection for attempting to find failures, and they cannot approach the performance of Failure Agents for earliness or accuracy of warnings. Standard anomaly detection is normally fraught with inaccuracies and false alarms, and it always requires human intervention — unlike Aspen Mtell Anomaly Agents that are framed by the precision and accuracy of the probability waveform process.

Where anomaly detection asks, "Is this normal?" a Failure Agent asks, "What is the exact pattern that led up to this failure?" So the Failure Agent technique is based on actual failure patterns, proving to detect earlier and find more issues earlier, with greater accuracy than all contemporary systems to which it has been compared.

A Failure Agent also stimulates alerts by text, email and dashboard messages to warn end users, and can send a precise work order into the asset management system, alerting the exact root cause and stimulating corrective action to remediate the impending failure.

The differentiating feature of Autonomous Agents concerns their capability to learn precise patterns from the time-series data from sensors on and around machines.

What's So Special About Agents' Detection Capabilities?

The differentiating feature of Autonomous Agents concerns their capability to learn precise patterns from the time-series data from sensors on and around machines. Such patterns do not emanate from models, determined by humans from thermodynamic, stoichiometric, physics, heat and material balance (or other mathematical/statistical equations and approximations). They are determined from the precise behavior of the machines, declared in the time-series data streams from the sensors that monitor them.

Agent signatures are not "hygienically clean" models which strip out nuance, but they are accurate representations based on all the minuscule distinctions contained in the "digital shadows" in one data stream, across data streams and across time (very important!). Additionally, the proprietary probability waveform analysis and comprehensive procedures for excluding patterns that deviate from normal assure that Anomaly Agents carry the purest signature of normal behavior derived in any solution today. That means that when an Anomaly Agent sends an alert, the recipient it assured it is a definite deviation that is always true and trustworthy — and not a false alert.

Greater accuracy also originates from Aspen Mtell's industrialized use of machine learning as the capability to look for deterministic patterns through time, not just at one time-slice at a time. What's even more special is that both Anomaly Agent and Failure Agent signatures are not simple thresholds, statistical boundaries, or even defined operating envelopes.

Aspen Mtell Autonomous Agents are very complex multi-dimensional and temporal patterns that humans are not equipped to see. On a piece of equipment with 40 sensors, Aspen Mtell Agents can "see" 41 distinct dimensions to derive patterns that humans cannot detect. Humans only see three dimensions well and struggle to recognize a cause and effect over more than a few seconds.

Conclusion

Aspen Mtell reduces unplanned downtime for hyper compressors, catching problems before damage progresses to reduce repair scope and costs. Periods of disruption to production are shortened, which reduces operational losses. Aspen Mtell has proven its ability to recognize the early indications of the faults that impact hyper compressors, successfully identifying patterns associated with valve, packing and piston faults — without false positives. Further, it has shown the ability to identify upstream process conditions that reduce hyper compressor reliability.

The value Aspen Mtell delivers to hyper compressors can be seen in improvements in RONA, ROCE and OEE metrics. The solution improves safety by providing earlier and more accurate warnings of asset failures. Further, the potential improvements from integrating with other workflows, like plant scheduling, can significantly improve performance.

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.

www.aspentech.com