Seeing Into the Future With Prescriptive Analytics: A New Vision for Asset Performance Management

Robert Golightly, Senior Product Marketing Manager, Aspen Technology, Inc.

aspentech | White Paper

Everyone is making big claims about analytics — you hear the buzz words like "machine learning," "predictive" and "prescriptive" — but there are huge differences in approaches and the value they can create for capital-intensive businesses.

In this paper, we'll look at the prevalent deployment model for prescriptive analytics and review some of the challenges that have surfaced just in the past year. We'll present the Aspen Asset Performance Management (APM) technology stack and show how it enables a completely new approach for creating, deploying and managing analytics apps for asset and operational performance. Finally, we'll review some pilot projects recently completed by AspenTech and show how our customers are achieving real bottom-line benefits.

The Objectives of Asset Performance Management

Investor demands to maintain or improve revenue and margins are driving searches for new technologies and applications to drive down costs, improve reliability and increase efficiencies. Equipment failures and process disruptions are creating unplanned downtime that is costing the process industries billions of dollars in lost revenue and profit every year.

This is an area where we commonly see corporate initiatives cropping up around asset performance management and risk management. What these companies are searching for are ways to improve the accuracy of detection and increase the notification period of these events. With more warning, more options become available — and with options comes the opportunity to mitigate the negative impact of those events.

Traditional Approaches Model Machines, Not Failures

Here's the solution most commonly implemented today: take raw, real-time data, feed it through a model that simulates the behavior of the asset, and see if the prediction indicates some abnormal behavior. If it's not a clear-cut case, an expert (data scientist and/or domain expert) will consult. For many commercial offerings, which deliver analytics as a service, those experts are often supported by a rules engine to help them assess quickly and to capture new events. Finally, the information is communicated to the customer so they can implement a remediation plan.

Of course, there are those customers who have the resources to implement their own analytics programs, but the technology model is the same: they still must have an accurate model of the asset, the domain knowledge to understand the data and the resources to keep it all maintained.

We've already seen numerous examples of the difficulty that some organizations face in building and maintaining models of asset behavior. In the last half of 2017, seminal articles in trade publications revealed the struggles of one APM vendor that had to freeze operations to come to grips with problems delivering on their promises. Simply stated, the nature of their particular solution was conducive to false positive alerts that drove down confidence in the solution. The need for deep, expensive domain expertise combined with those problems resulted in a total failure of the business and a loss of billions of dollars in market value.

With asset performance management powered by low-touch machine learning, it's now possible to extract value from decades of design and operations data to perform prescriptive maintenance and optimize asset performance.

New Technologies and a New Approach

Traditional preventive maintenance alone cannot solve the problems of unexpected breakdowns. With asset performance management powered by low-touch machine learning, it's now possible to extract value from decades of design and operations data to perform prescriptive maintenance and optimize asset performance. This disruptive technology deploys precise failure pattern recognition with very high accuracy to predict equipment breakdowns ***months*** in advance.

A new set of technologies is driving a move from creating detailed models of asset behavior to identifying the "signatures" of failures. In recent months, we've worked with numerous clients to complete pilot projects in their facilities. These pilots are demonstrating the value of a new approach to improving asset effectiveness.

The Need for Speed

The first significant difference can be immediately seen in the duration of pilot projects. Competing solutions often take three to six months (or longer) to complete. The summary results in this paper come from pilot projects that were all completed in less than a month and, on average, in about 2 ½ weeks.

Automating the "Grunt Work"

One of the most time-intensive tasks associated with analysis is preparing the data. Aspen Mtell® provides a low-touch machine learning approach that eliminates much of the manual effort involved in "data wrangling."

The competence embedded in the autonomous agents of Aspen Mtell represents a breakthrough in automating data collection, cleansing and analysis to provide prescriptive maintenance protection for equipment. In one case, the solution was built by an engineer with less than five years of experience. With just a few hours of instruction, he completed the development of a new Aspen Mtell agent — including the work to access, extract, clean, organize and prepare data for analysis.

Aspen Mtell automates much of that knowledge work, with interfaces connecting to historians for process data, to the condition-based maintenance system for asset condition data and to the enterprise asset management/maintenance management system for the maintenance histories of assets.

More Than Anomaly Detection

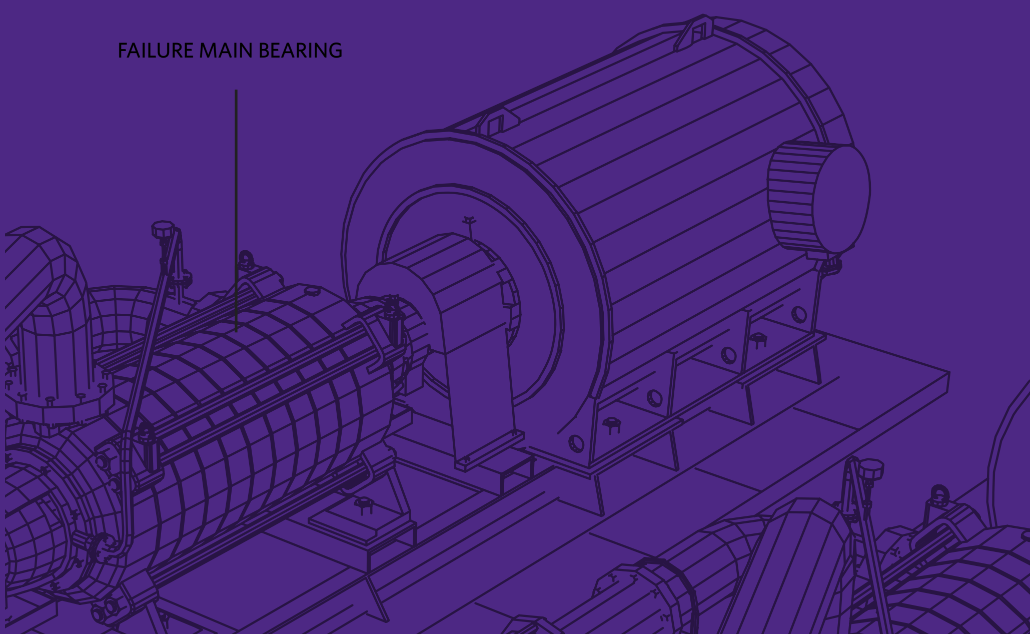
Another significant difference is accuracy. That's because Aspen Mtell agents identify specific failure signatures. With the typical method of anomaly detection, you simply know something is different — and it's still up to you to determine what.

With Aspen Mtell, each agent is responsible for detecting a single, specific signature. That specificity enables automated responses to events.

As a proof point, a Fortune 500 energy company that operates two LNG terminals has implemented Aspen Mtell to prevent equipment failures at both terminals. Aspen Mtell autonomous agents provide the early-warning system, triggering work orders to service and inspect equipment immediately on detection of early-onset degradation, and well before equipment fails and causes a catastrophe.

In the past, the company's asset management system had churned out planned maintenance work orders based on calendar triggers (whether the maintenance was actually needed or not). Aspen Mtell reduced the workload by up to 60 percent compared to scheduling maintenance based on equipment runtime hours.

Aspen Mtell autonomous agents provide the early-warning system, triggering work orders to service and inspect equipment immediately on detection of early-onset degradation, and well before equipment fails and causes a catastrophe.



Earlier Warnings — Finding the Subtle Patterns Humans Can't See

This new approach to asset performance management and predictive analytics has two important capabilities: it finds problems sooner than competing technologies, and it takes faster action to correct the problems.

That improvement highlights another significant difference: the accuracy of failure signatures over anomaly detection. For example, a major oil and gas company was experiencing recurring, unexplained breakdowns of compressors at one of its refineries. The staff was a mature implementer of reliability-centered maintenance methodologies and used state-of-the-art vibration systems, but still the breakdowns occurred.

Frustrated, the company turned to Aspen Mtell. In a rapid implementation spanning just five days, Aspen Mtell autonomous agents were protecting three major compressors and pumps. On the third day of implementation, one anomaly agent alerted and exposed the cause of a compressor failure that had plagued the refinery for over a decade.

In a similar "save," one agent alerted, with eight weeks' warning, to a failure in the third-stage valve of a multi-stage compressor. The operations staff chose to continue unheeded. Seven weeks later, the vibration system announced excursions, and the condition deteriorated rapidly. In three days, the compressor was shut down for maintenance. The tear-down proved that Aspen Mtell had correctly announced the impending failure a full seven weeks before the state-of-the-art vibration system.

Successful Applications of Prescriptive Analytics

The low-touch machine learning approach of Aspen Mtell is proving itself every day in pilots across the energy, chemicals, transportation and water industries — among others. By eliminating the need for models of the asset behavior, Aspen Mtell provides a more scalable approach. And unlike asset-modeling approaches, failure signatures developed on one asset can be used to inoculate similar assets without redevelopment.

Here are some examples of other recent Aspen Mtell pilot projects:

In a **drilling operation**, autonomous agents correctly detected calibration errors on drilling joystick operations that had gone unnoticed. Aspen Mtell provided two to four weeks' warning of impending failures on top-drive, mud pump and draw works components.

A **transportation company** had been plagued by catastrophic failures of locomotives that were going undetected by its current reliability processes. Each line-of-road engine failure typically costs over $1 million USD in repairs, additional operational costs and fines. Aspen Mtell insight discovered both normal behavioral patterns and exact failure patterns, and within approximately four months, agents alerted on 10 "saves" and prescribed corrective action — amounting to more than $10 million USD in saved costs. Aspen Mtell alerted to the situation eight weeks sooner than the company's legacy solution.

A **multinational mining company** implemented Aspen Mtell machine learning and significantly improved production uptime. This customer makes extensive use of autonomous agents for early, heads-up warning of degradation in metals refining processes and equipment, and agents regularly advise a time-to-failure of 40 days on a pump.

In another **industrial facility**, Aspen Mtell agents have detected vibrations in pumps that led to the replacement of mechanical seals before failure, and they also identified signatures that led to the replacement of a high-pressure pump with 39 days of lead time. In the same plant, problems with a wash oil pump were detected 48 days in advance.

A **large, global chemicals company** had been seeking better notification of fouling in a quench oil tower. An Aspen Mtell pilot was completed using fouling data from the previous year, and the agents provided an alert with a 125-day lead time of fouling. Unfortunately, the customer took no action and eventually had to shut down the quench oil tower due to fouling.

In a **European refinery**, vacuum bottom pumps had been affected by repeated seal and bearing failures. Aspen Mtell learned the vacuum bottom pump failure history, which included more than a dozen different failure signatures. The data went back to a known event in 2014. Aspen Mtell provided lead times of 28 and 31 days for future seal failures on the pumps, as well as lead times of 10 and 28 days for future bearing failures. The refinery ignored the warnings from the pilot application and was forced to replace seals and bearings after the failures occurred.

Simplicity in Scaling Up

One constraint on scaling predictive analytics solutions has been in developing the traditional asset behavior models. The problem has been that those behavior models are not often transferable across similar assets, so the work to create and maintain the models must be repeated for each asset. With Aspen Mtell, failure signatures are transferable across assets.

Here are a few examples of how the Aspen Mtell solution has been scaled up:

- The oil driller referenced earlier transferred failure signatures for key assets to over 200 drilling rigs around the world.
- The failure agents for the locomotives mentioned earlier were transferred to more than 600 engines.
- Agents that were trained to identify casing leaks on electric submersible pumps in one facility have been transferred to 18 other pumps.

Conclusion

These pilot results illustrate the ability of Aspen Mtell to provide earlier prediction of asset failures while reducing or eliminating false positives. They have demonstrated the speed at which the solution can be developed using available resources, and they have proven the ability to inoculate similar assets with failure signatures to achieve incredible scalability.

As one pilot participant said, "Improving reliability positively impacts a wide range of issues, from reducing current maintenance costs to planning for abnormal process conditions, avoiding emergency or unplanned shutdowns and successfully managing unpredictable feed and demands. We expect to achieve savings from this initiative, which is part of an important digitalization project."

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