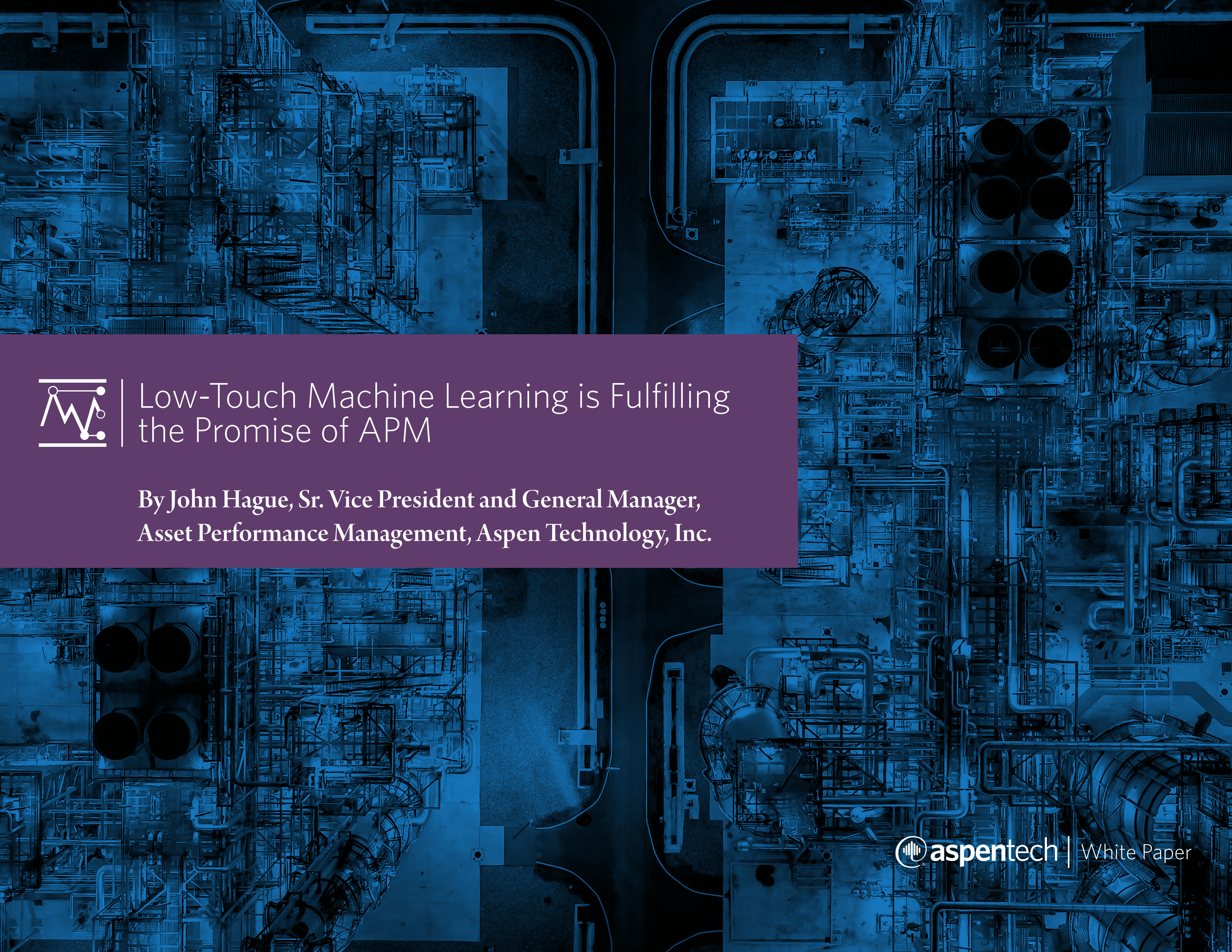

Low-Touch Machine Learning is Fulfilling the Promise of APM

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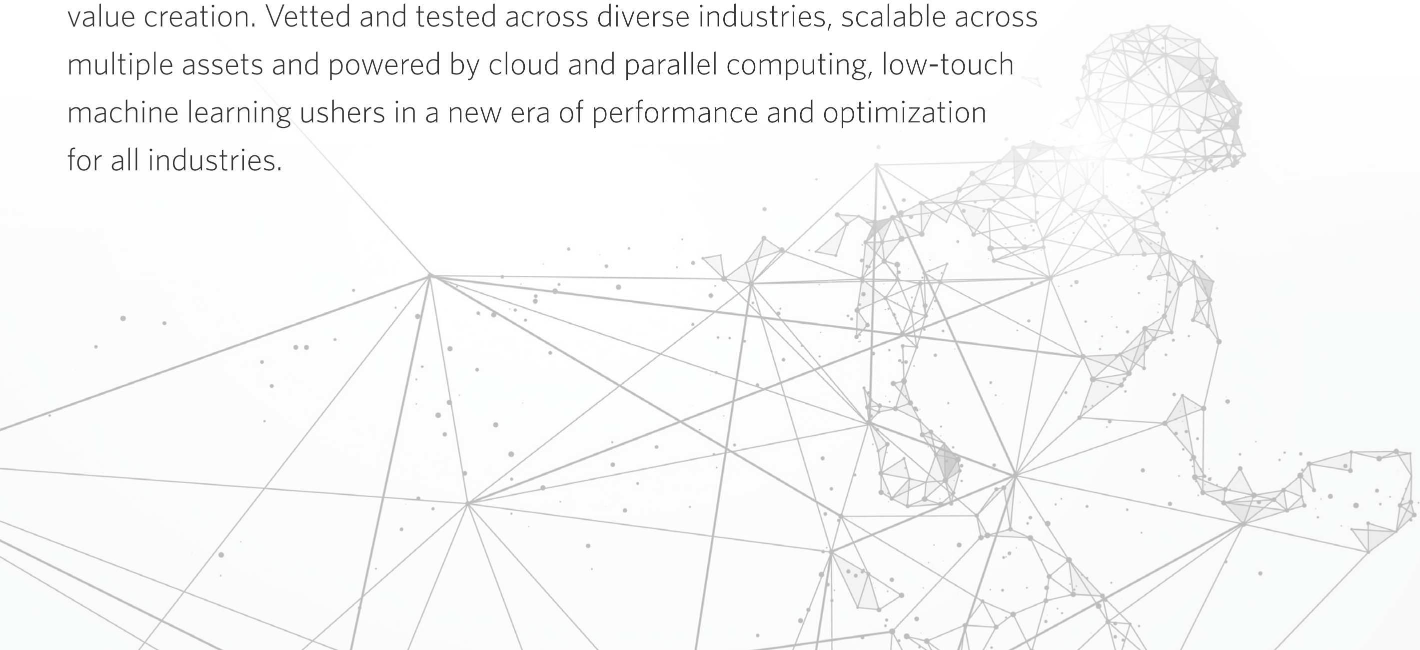
Introduction

New methods and cutting-edge technologies are driving asset performance management (APM) well beyond historical capabilities, rapidly increasing its bottom-line value. Technologies such as cloud computing, data science and machine learning are now being integrated with automated methodologies directly into APM solutions.

This wave of integration firmly places advanced analytical techniques into the hands of operators and engineers with previously unimagined scale and ease of use. The incremental progress in APM over the last 20 years pales in comparison to what's now possible through digital transformation.

Low-touch machine learning is the key catalyst to scale APM's potential well beyond existing first principles-based solutions and "armies" of consultant engineers and data scientists. A widespread integration of machine learning in APM will mark a transition from estimated engineering and statistical models towards measuring actual patterns of asset behavior.

Manufacturing facilities staff can now readily extract value from decades of existing design and operations data to better manage and optimize asset performance. This "low-touch" machine learning method continuously embraces changes in asset behavior, empowering real-time APM value creation. Vetted and tested across diverse industries, scalable across multiple assets and powered by cloud and parallel computing, low-touch machine learning ushers in a new era of performance and optimization for all industries.



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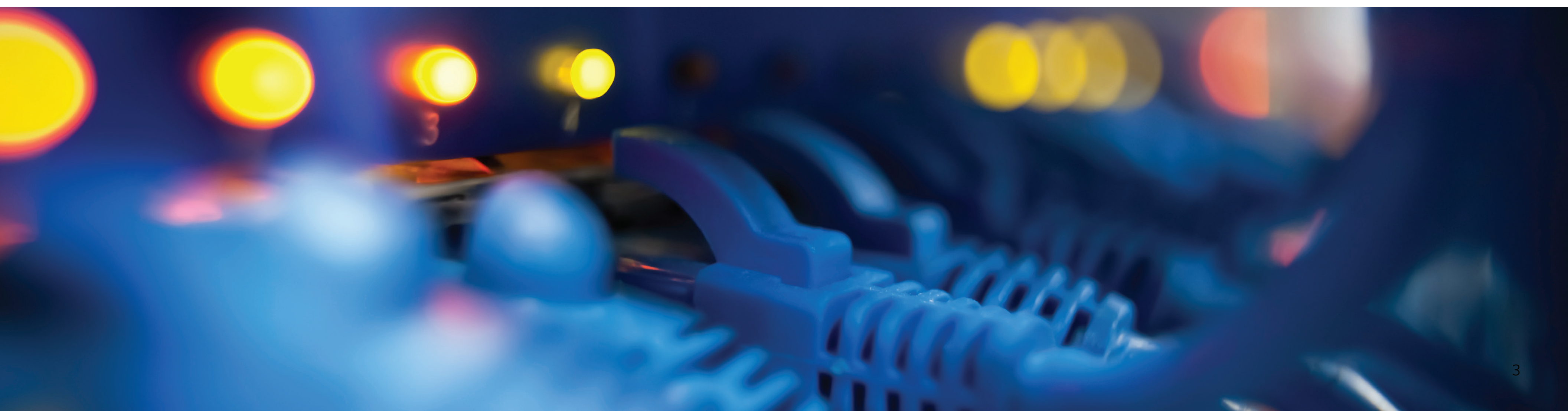
How We Got Here: APM Before Low-Touch Machine Learning

The foundation for realizing a new APM vision already exists, with engineers having applied performance models for decades. Such pioneering APM adopters faced the challenges and constraints of the technologies surrounding their models. Disparate systems evolved to manage and optimize maintenance functions, to develop risk assessment and criticality, and to perform continuous condition monitoring.

These systems were isolated, resulting in limited connectivity and integration, as well as workflow impairments. Due to limited integration, early computers processed small volumes of available related data in batch mode instead of in real time, when insights are most valuable. Outputs came too late, typically in days or weeks. Computational power limited the advancement of new algorithms. And assured static models were fixed, low-frequency and not adaptable to new failure behaviors and incremental operational changes.

As the 2000s arrived, leading industries started to better instrument assets for condition-based monitoring, and computational power continued to increase. Systems were still isolated, but in separate systems, engineers started to see something resembling real-time asset-level data. Although such advances brought additional insights, they also introduced complexities and data quality issues. Computing platforms could not scale adequately and were inordinately expensive for processing massive data volumes. Limited replication was a mechanism to approach data accessibility but again introduced more data quality issues. This meant APM software still didn't yet clearly communicate accurate, reliable diagnoses or clear recommendations.



Even with mechanically based systems achieving some improved reliability through planned maintenance, usage and condition-based monitoring techniques, there was still limited ability to identify or address the main causes of asset breakdowns. The results offered extremely limited actionable insights, and many system alerts delivered false positives — inaccurate declarations of degradation and failure events. Such letdowns overwhelmed engineers and created a negative impression of these approaches.

A good example is illustrated by examining a single system, such as a stand-alone pipeline. Sensors deployed across multiple assets along a pipeline system report regular readings of variable conditions such as temperature, pressure and flow. Classical, model-based or statistical technologies of the 1990s and 2000s were designed only for anomaly detection. Anomaly detection is fraught with errors and always needs expert human intervention to interpret results and separate real alerts from false alerts.

On the pipelines, engineers were inundated with hundreds of undifferentiated false positive leak alerts. Internal staff couldn't ignore these alerts and weren't equipped to accurately assess their validity. Operational integrity suffered, and trust in the systems eroded.

Today, many systems that propose to alert for asset integrity are still designed to only perform anomaly detection. They still require a staff of consultants to intercept and interpret the correct course of action to avoid failure or mitigate risk. In the case of pipeline leak detection, this is overly expensive, resulting in unnecessary maintenance and large consulting fees. Low-touch machine learning is a disruptive technology, deploying precise failure pattern recognition with very high accuracies and months of advanced notice on failures. It eliminates the requirement for substantial resources and expertise to realize the value of the application.

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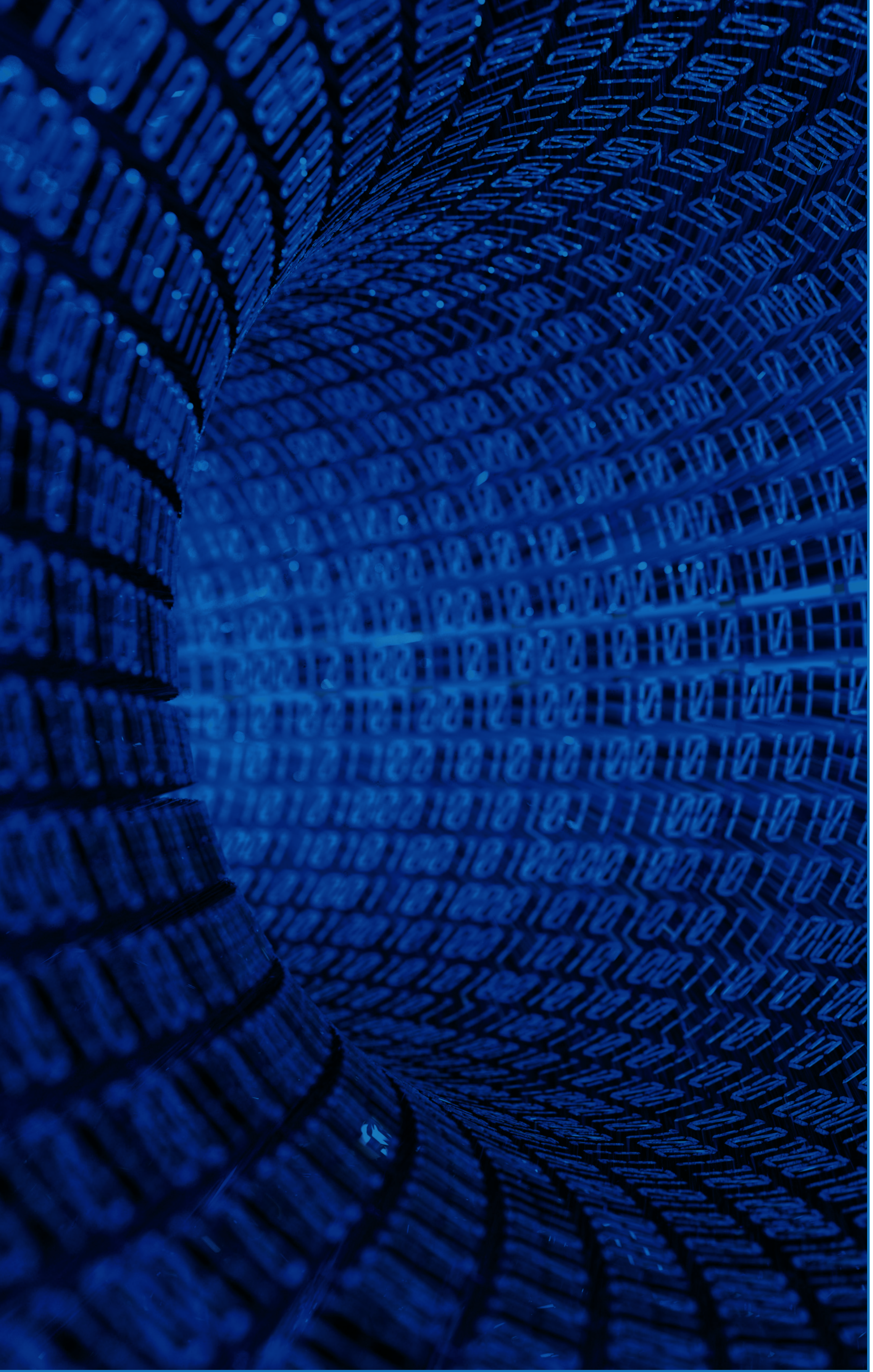

The 2000s Set the Stage

The late 2000s saw multiple parallel technology innovations coalesce into the modern state-of-the-art APM methodology. Best-in-class systems could now incorporate detection of precise patterns of normal and failure behaviors, and perform the computational isolation of key indicators of degradation. Especially important was the 2006 debut of Amazon Web Services for scalable cloud computing. Advances in structured and unstructured databases and operational data pools were tested and improved at the enterprise level during this period.

Around the same time, smart sensors saw a dramatic shift in performance, size, reliability and price. Added to this was a dramatic improvement in the computational and analytical capability of machine learning called "deep belief networks" or "deep learning." This breakthrough was pioneered by Geoffrey Hinton at the University of Toronto, who is now tightly coupled with Google.

The result was a quantum leap in capability, and this has enabled machine learning to surpass the performance of previous analytical techniques, which limited modeling and statistical methods. Machine learning is now the dominant analytical method in all IT fields around the world. It is used for credit card fraud detection, facial recognition by Facebook, voice recognition by Amazon, Apple, and Google, for driving automated cars, medical diagnoses and more.

The smartphone rose in prominence during this period, led by the iPhone debut in 2007, which greatly advanced computer literacy and afforded complex application (app) capabilities for the masses.

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Between 2007 and 2010, culminating with the iPad debut, the process industry workforce moved from experimentation with the industrial internet of things (IIoT) to demands for smart devices and consumer-style applications at work. Industrial software and technology began to update offerings with user interfaces incorporating low-touch, readily navigable applications and displays. Vendors started delivering intuitive software that did not require intense skills and experience to be productive.

At the same time, cross-industry initiatives, sponsored by many owner-operator companies, led to the development of open standards for connecting disparate systems and work process inter-operation — particularly between operations and maintenance systems.

Such initiatives assured comprehensive use of data combinations to address problems and afford solutions that were previously unattainable. Blending such methodologies and automation of technology approaches set the stage for a major leap in APM performance and value.

During this period, emergent techniques for maintenance operations on assets, particularly for mechanical assets, came under scrutiny. The movement from fail-fix — through calendar, usage and condition-based planned maintenance events — all the way to reliability-centered maintenance (RCM) techniques provided incremental improvements. However, the cost, complexity, time and staffing skill-set requirements constrained deployments.

Today, there's a growing realization that maintenance alone cannot solve the problems of unexpected asset breakdowns. According to the ARC Advisory Group[1], 82 percent of mechanical breakdowns display a random failure pattern and are caused by process-induced conditions that current maintenance practices do not monitor.

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Entering the Modern Era of Low-Touch Machine Learning

Data-intensive and complex environments in manufacturing industries are prime candidates to deploy the new advances in reliability management. Deployed coherently, with appropriate automation, machine learning enables greater agility and flexibility to incorporate current, historical and projected conditions from process sensors, as well as from mechanical and process events. Systems become automatic, moving past traditional, consultant-heavy approaches. Instead there are agile, flexible models that learn and adapt to real data conditions, and which incorporate all the nuances of real asset behavior.

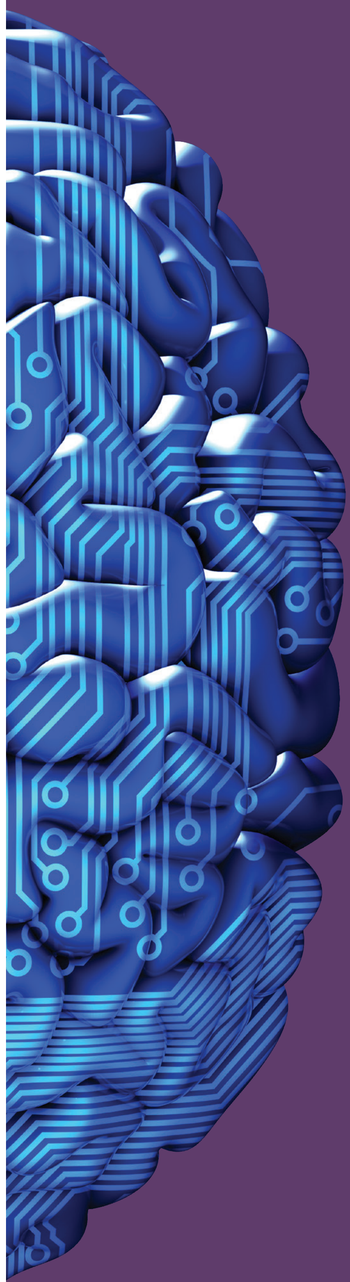
Data capacities and computational capabilities are so great that internal staff can now perform active and accurate management of individual processes and mechanical assets. This management capability can now be applied to combinations of assets — plant-wide, system-wide or across multiple locations.

The pivot in APM's capabilities arrives at an important time for manufacturing in process industries and many other sectors. Organizations are under tremendous economic pressure, and recent conversations with our customers, along with industry-wide estimates, indicate that operations is seeing less than 1 percent in incremental savings year over year due to historical gains already realized. However, current razor-thin operational margins are pushing process industry executives to look to APM for additional return on investment, especially in avoiding unplanned downtime and preventing damage to equipment due to operational issues. Low-touch machine learning APM is ready to deliver that value.

Every process industry organization deals with complex systems, fluctuating conditions and a myriad of assets. A spectrum of pressure points exists, in varying degrees, due to diverse market needs, time criticality, staffing levels and skill sets. Consider the following real-world examples:

- An oil refiner struggles with excessive asset breakdowns. Its compressors are well-instrumented and receive RCM treatment, with regular inspection and service, but unanticipated failures persist.
- A chemicals producer with multiple intermediate storage tanks can suffer intermittent failures on feed pumps. Failures mean extended downtime and lost product.
- The aging and complex electric grid requires a sophisticated analytics approach. Knowing only the average asset lifespan creates maintenance schedules based on guesswork. There's no ability to model future demands that might cause a rolling blackout. This creates costly over-spend on maintenance and doesn't avoid grid performance gaps.

Low-touch machine learning APM can address all of these issues.



Best Practices in Low-Touch Machine Learning APM

Agility, flexibility, adaptability and scale are essential to truly deliver reliability in the process industries. Only low-touch machine learning APM can deliver these capabilities. These are five machine learning best practices that drive state-of-the-art reliability management that is applicable to any asset in any industry at any level, from a single location to a country-wide system.

Five Best Practices for Low-Touch Machine Learning APM

1. Data collection and preparation

2. Condition-based monitoring

3. Work management history

4. Predictive and prescriptive analytics

5. Pool and fleet analytics

Data Collection and Preparation

Over the last two decades, every attempt at massive data analysis from diverse sources of plant data collected from sensors has run into serious issues around collection, timeliness, validation, cleansing, normalization, synchronization and structure issues — "garbage in, garbage out."

Often such data preparation can consume 50–80 percent of the time to execute and repeat data mining and analysis. However, that process is essential to ensure appropriate and accurate data that allow the end-users to trust in the ensuing analytical results. New advances in APM have automated the bulk of the data preparation process to assure trust and to reveal previously undiscovered opportunities with minimal user preparation.

Condition-Based Monitoring

Once data is trustworthy, condition-based monitoring (CBM) can be applied. The plant conditions vary constantly, according to mechanical performance of assets, feedstock variations in quality, weather conditions and production timeline and demand changes. Static models cannot work under such duress. In addition, focusing CBM on mechanical equipment behavior can reveal only a small fraction of the true issues causing degradation and failure[1].

Leading organizations recognize that legacy CBM is now inadequate, since it typically ignores the salient process-induced conditions causing the bulk of the breakdowns. New advances in APM deliver comprehensive monitoring of the all the mechanical and upstream and downstream process conditions that can lead to failure.

Work Management History

The history of work provides the bread crumb trail of past solutions to failure prevention and/or remediation. Problem identification, coding and a standard approach of problem resolution provide an important baseline for the exact failure point in the lifecycle of an asset. OEM data that may live in a big data solution can provide insight into process issues and outliers specific to the configuration and engineering within the plant process.

Forward-thinking organizations understand the importance of this data and how it contributes to hyper-accurate predictions of production degradation that ultimately leads to asset failure.

Predictive and Prescriptive Analytics

Clean data and CBM enable in-place predictive analytics: a process to interpret past behavior and, based upon that analysis, predict future outcomes. In contrast, using engineering and statistical models to estimate the future readings of sensors, and interpret variances from actual readings, is a technique fraught with errors and false positives. Top performers use inline, real-time analysis of the patterns of normal and failure behaviors of process equipment and machines.

When performed correctly, predictive analytics can accurately portray asset lifecycle and asset reliability, and focus on the early root cause of degradation, rather than later-stage detection of damage. The insights available from intense multivariate and temporal pattern analysis provide accurate, critical lead times. This allows time for decisions that can eliminate damage and maintenance or, at the very least, provide preparation time to reduce the time-to-repair and mitigate the consequences.

Best-in-class APM provides prescriptive advice based on established root cause analysis (RCA) and presents information on the approach that will proactively avoid process conditions that cause damage, and/or advise on the precise maintenance required to service the asset.

As a result, predictive and prescriptive capabilities enable asset lifecycle reliability, and they facilitate decisions on when and how to maximize production while proactively avoiding asset and output risks. Such real-time analytics guide maintenance scheduling and asset optimization, eliminating guesswork on future production or asset issues. For C-level executives, this complete picture of plant or site performance enables more confident risk analysis and performance projections for the board level.

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Pool and Fleet Analytics

The next level of analytics allows patterns discovered on one asset in a pool or fleet to be shared, enabling the same safety and shutdown protection for all equipment. Once deployed, companies can rapidly scale solutions from a unit to a site to multiple sites, or even throughout a whole corporation. From all local systems, information roll-up from disparate sites into one larger model provides asset performance comparisons across sites and plants, creating common baselines that highlight areas for improvement.

Conclusion

The manufacturing world has changed. Now, previous maintenance practices can be improved to recognize all issues affecting asset degradation. Operational integrity improves when organizations implement strategies to detect root causes as early as possible, providing extended lead times for good decisions to avoid unplanned downtime.

For every process industry organization, regardless of needs or sophistication, low-touch machine learning APM is ready today to eliminate catastrophic failures on assets, to improve overall reliability and to lift net product output and increase profitability.

References

[1] *Webinar "Improve Reliability of Process Assets with Prescriptive Analytics: Get Results Today featuring ARC Advisory Group," 14 June, 2017.*

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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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