Whitepaper

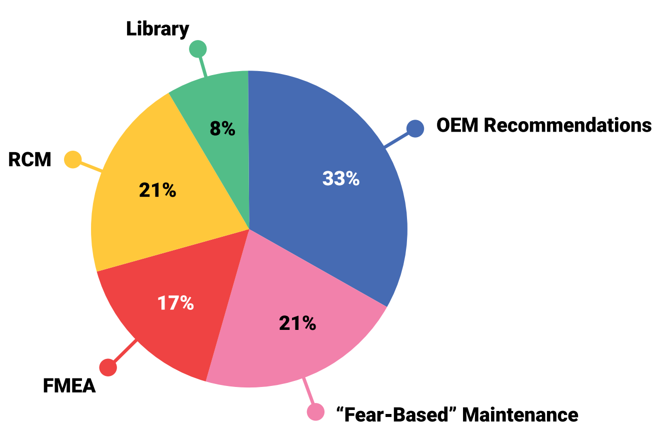
Author: Joe Perino – Industry Analyst, PERTEX

A Common-Sense Approach to APM

The Problem

Today's manufacturers face a host of challenges in the aftermath of the COVID pandemic, the stress on supply chains, and now the renewed emphasis on reshoring manufacturing and the push to grow advanced manufacturing. These include the traditional issues of costs, quality, reliability, productivity, customer satisfaction, employee talent & skills, etc. Among those, reliability has always been the subject of much focus. The simple question is, "Just what does it take to keep things running smoothly so all other objectives can be met?"

Maintenance and inspection practices have long leveraged **Preventative Maintenance (PM)** techniques such as routine, periodic or time-based, and **Condition-based Monitoring (CbM)** to maintain equipment, machines, and devices. Vibration monitoring is a good example of CbM. Even with these approaches, some assets are left in reactive mode, that is in **Run-to-Fail (RtF)** mode. **Reliability-centered Maintenance (RCM)** and **Risk-based Inspection (RBI)** strategies have been widely adopted. Subject matter expertise has also been relied upon to understand the sources of degradation and failure, why, and under what conditions they occur. This expertise can be captured in a **Failure Modes and Effects Analysis (FMEA)** library, though it may not address every possible asset or failure mode. **Computerized Maintenance Management Systems (CMMS)** have also evolved into **Enterprise Asset Management (EAM)** systems, whose primary jobs are to schedule and execute work orders and record the results, including work effort and costs.



What approaches do you use to develop asset strategies?

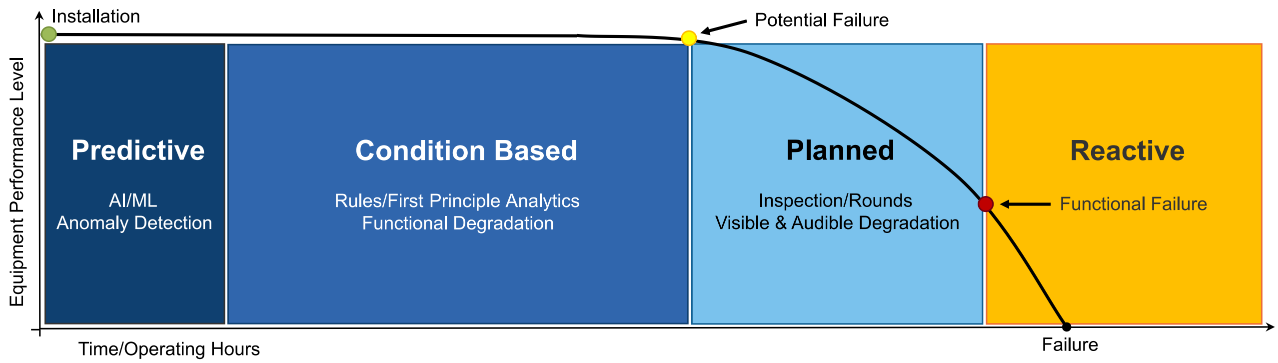
2023 Survey, Asset Management Professionals

In the last ten years, new technology has enabled **Predictive Maintenance (PdM)** and **Prescriptive Maintenance (RxM)** based on **Machine Learning (ML)**, a form of **Correlative Artificial Intelligence (AI)**. In addition, the **Industrial Internet of Things (IIoT)**, including low-cost sensors, Edge computing, advanced analytics, DataOps, networking connectivity (Wi-Fi, 5G Cellular, ISA 100, OPC UA, etc.), and other technologies, have all combined to enable a step change in reliability capabilities.

What is APM?

Asset Performance Management (APM) is a decision-making process to manage assets and improve asset efficiency, availability, reliability, maintainability, and overall lifecycle value while reducing downtime. In essence, it addresses all the elements of strategy, risk assessment, establishing the appropriate maintenance and inspection approaches, and then following through with the processes, procedures, tasks, and technology to carry them out. In short, APM takes a holistic approach to asset management addressing people, processes, and technologies.

As mentioned above, APM is an out-growth of past approaches, with an enlarged scope and enriched by new capabilities. The ability to automatically detect degradation and predict potential failures, perform root cause analysis, and recommend prescriptive actions across a series of assets simultaneously multiplies the capabilities of engineering and maintenance personnel who heretofore had to acquire data, analyze it in spreadsheets, and then recommend corrective actions. Even with historians, CMMS/EAM, and control systems alarming in place, humans were the glue between these systems and other independent CbM solutions e.g., vibration and corrosion monitoring, etc. With APM these systems can be effectively integrated improving analysis accuracy and speeding response, saving time, effort, and cost, and avoiding potentially disastrous consequences i.e., spills, leaks, fires, explosions, loss of life and property, damage to the environment, etc.



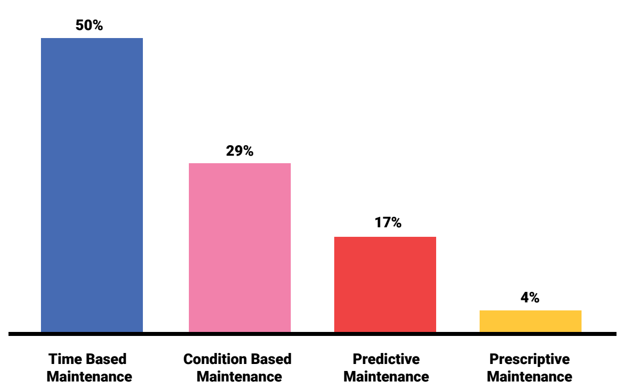
	Predictive	Condition Based	Planned	Reactive
Equipment Risk Profile	Very High to High	High to Low	High to Low	Low
Typical % of Population	<10 %	40%-70 %	30%-60%	20%-30%
Time to react	Best	Better	Minimal	-
Cost to implement	Very High	Low to High	Low	-

P-F Curve

What has been the impact on maintenance approaches? The industry is seeing a shift from a combination of RtF, routine, CbM, and periodic maintenance to a more heavily weighted CbM, along with PdM and RxM applied to the most critical assets. And given low-cost sensors and IIoT, there are few assets today that cannot be monitored cost-effectively. Thus, the number of assets utilizing traditional PM and RtF is going down while CbM, PdM, and RxM are increasing. However, the rate of uptake is uneven across industries, with the large-scale process industries like refining, petrochemicals, chemicals, mining, and power generation leading the adoption. The hybrid/batch and discrete industries tend to lag behind the process industries, though there are notable exceptions, semiconductor manufacturing being a good example.

What techniques are you using to mitigate asset failure risk?

What's next? By the end of this decade and likely sooner, APM is expected to add **Prognostic Maintenance (PxM)** and even learning capabilities, given the advances in **Generative AI** and **Causal AI**. Further, APM will integrate with other systems to help optimize operations and turnaround planning over multi-year time horizons, while minimizing carbon footprint.



2023 Survey, Asset Management Professionals

It's a Crowded and Often Confusing Market

The term APM is widespread. There are over 20 vendors in the space, ranging from numerous start-up companies to large and established ISVs, including EAM and ERP vendors. In addition, there are APM products, sometimes called applications, and APM solutions. However, most APM products tout themselves as APM solutions when in reality they are not solutions. In addition, the term APM is often used interchangeably with Predictive Maintenance. Thus, the market can be confusing to navigate. Let's break this down to better understand the difference between products and solutions.

First, a bit of history. The mathematics of machine learning are well understood and date back to the 1950's. Just to contrast, modern statistics date back to the 17th century, with discussions of probability going back hundreds of years earlier. With today's low-cost, powerful computing capabilities, ML can now consume large amounts of data, and develop and run their models in essentially real-time. This made it possible to apply ML to the prediction of asset performance, that is to predict asset degradation and potential failure. These predictive capabilities are very valuable in and of themselves.

Note that the APM products that have predictive capabilities are often labeled Predictive Maintenance. They may use proprietary or open-source ML algorithms. They work by identifying abnormal behavior in the data stream, hence the term **Anomaly Detection**. The ML models can be trained to identify known patterns of bad asset behavior or just simply detect unknown bad behavior. In either case, the bad behavior implies a root cause of the potential problem. When the behavior can be associated with a known failure mode, such as may be found in an FMEA library, problem identification is quickly facilitated. Some libraries may contain recommended actions to resolve the problem i.e., prescriptions.

Most APM products stop at the predictive point and say that their anomaly detection mechanism is all that one needs. This may be true when analyzing process performance since there are stand-alone analytics software products that allow one to analyze and create an ML model for problem detection based on the user's fundamental understanding of the process.

However, it still falls short of APM solutions that include strategy, risk assessment, and the ability to trigger external actions e.g., work orders and notifications, as well as predictive and prescriptive capabilities. This is the inherent limitation of predictive-only products – they leave the heavy lifting of the analysis and resolution to the manual efforts of engineering and maintenance personnel. Note that there are only a handful of APM vendors who utilize FMEA libraries, either their own or from a third-party supplier.

APM Options

What about products that may appear to overlap APM in functionality? We have already mentioned stand-alone advanced analytics software tools for process manufacturing data e.g., Seeq. There are, of course, open-source sets of algorithms such as TensorFlow and analytics toolkits like MathWorks' MatLab, but these are **Do-It-Yourself (DIY)** and require data science and programming skills to implement.

Another category of APM-related software is called **State Machine Modeling** or simply state modeling. A state machine model is a mathematical model that groups all possible system occurrences, called states. Every possible state of a system is evaluated, showing all possible interactions between subjects and objects i.e., the assets. The idea is to model the entire production system's key assets, specifying various scenarios representing varying degrees of reliability, acknowledging that no asset is available 100% of its lifetime. This allows a design and economic analysis of the system. State modeling is primarily used in an offline mode in the capital design stage as well as when planning modifications, additions, or removals. It is complementary to APM in that once the APM strategies are

developed, they can be modeled under different reliability scenarios to determine the realistic maximum production capacity. It is often paired with other production modeling software in the design stage to optimize the system design.

What about those new **Manufacturing Performance Solutions (MPS)**? By MPS we are referring to software that is designed to optimize the production process by providing analysis and advisory direction to production engineers and plant floor personnel. This is in contrast to the advanced control and optimization techniques used in large-scale process manufacturing, or from **Manufacturing Execution Systems (MES)** and **Manufacturing Operations Management (MOM)**, whose functions are primarily to schedule, execute, track, analyze, and report.

MPS is different. There are two broad types of this software. First, those that focus on machine, tool, and equipment uptime. Improving **Overall Equipment Effectiveness (OEE)**, identifying bottlenecks, and increasing productivity is their objective. They may include Predictive Maintenance functionality. However, the operators are required to label data when tool failures or quality defects occur. Then machine learning algorithms detect patterns from the hundreds of data items collected from each machine. They also lack an FMEA library, although the operators are building a basic version of one as they label data. This type of software is most often used in the discrete industries but is also found in the hybrid/batch.

The second type of MPS takes a broader view of the production process focusing on throughput, quality, energy, and reliability, again providing guidance to production engineers and plant floor personnel. It is equally applicable to processes as well as equipment and can serve the process, hybrid/ batch, and discrete industries. But similar to the previous category, their reliability functionality is limited to predictive capabilities.

The first type of MPS is very focused on machine utilization and downtime minimization and thus is less holistic than the second category. The second category would benefit from an APM solution that complements its remaining production optimization functionality, rather than just being limited to predictive maintenance.

A variation of MPS are those industry-dedicated solutions that combine a data infrastructure with advanced analytics capabilities including asset performance and predictive maintenance.
These are offered as configurable solution development frameworks e.g., XMPro iDTS, or as pre-packaged applications e.g., C3.ai Reliability.

The last category is the full-featured APM solutions. These solutions contain all the elements of an APM solution and are primarily targeted at the large continuous process and other asset-intensive industries. As such large ISVs and automation companies tend to dominate this space e.g., GE Digital, AVEVA, AspenTech, Honeywell, etc. Often encompassing CMMS/EAM with APM functionality, they can be costly to acquire and complex to implement and maintain. Many users do not take advantage of all their many features or in some cases, don't really need them or have the staff to support them. Think of it like Excel – how many of its 450+ functions do we typically use? Amazingly, despite their plethora of features, most of these solutions offer only predictive maintenance capabilities and furthermore, one may have to choose the algorithms to apply to the data. This means that users have to have at least some data science background to configure the reliability portion of the system.

The bottom line is that this category of APM is an elephant gun designed for hunting elephants. If you are not an elephant, what should you do? Or maybe you are an elephant looking for simpler alternatives.

What to Look For in an APM Solution

There is a set of core capabilities that belong in an APM solution. These capabilities separate APM products from APM solutions without requiring the “elephant” approach. Note that these capabilities consist of both services and software. While this is not meant to be a comprehensive and detailed list, all these major elements should be on the user’s shortlist to screen potential vendors.

1. The APM vendor should provide services to help the user (i.e., owner/operator) determine the optimal maintenance and inspection strategies. These services should be supported by some type of risk analysis tool.

2. The output of the risk analysis tool should then drive the appropriate maintenance approach for each asset i.e., RtF, routine, CbM and periodic maintenance, PdM, and RxM. These approaches will also have to be configured for each asset in the CMMS/EAM system.

3. PdM and RxM should be applied to the most critical assets as identified by the risk analysis. One should be able to start out small, with a few assets, and then scale as needed.

4. When configuring the predictive functionality, users should not be required to have a data science background or be expected to choose ML algorithms. The solution should do that for the user automatically behind the scenes.

5. The solution should be easy to configure, meaning no coding, with features like drag’n drop, check boxes and options, fill-in-the-blank, etc. Maintenance technicians as well as engineers should be able to use the software with minimal training effort.

6 The APM solution should have an FMEA library to support root cause analysis and resolution. The user should be able to add custom assets, failure modes, conditions, and actions.

7 The APM solution should easily integrate with popular CMMS/EAMs, historians, third-party CbM, inspection, and rounds systems.

8 The APM should provide a means of alerting, expert collaboration, analysis, reporting, and work order triggering.

9 The solution should be able to run on-premise or run in the Cloud in a Software-as-a-Service (Saas) mode to provide deployment flexibility.

10 Last but not least, the price of the solution should reflect the ability to start small and then scale, meaning no large upfront “elephant” license fees, be it on a perpetual on-premise license basis or delivered by SaaS. Pricing should be flexible to meet the user’s needs such that smaller manufacturers can take advantage of sophisticated APM solutions heretofore limited to the largest of operating companies.

Pitfalls and Challenges

There are five common pitfalls or obstacles frequently encountered in implementing APM.

The first is the lack of the right information infrastructure to collect, store, and provide quality data to the APM solution. Despite their widespread use in the process industries where distributed control systems (DCS) come packaged with a historian, many hybrid/batch and discrete manufacturers lack historian functionality. MES/MOM, **Supervisory Control and Data Acquisition (SCADA)**, and PLC-based control systems tend to have limited data storage capabilities. Today, on-premise and Cloud-based historians are widely available enabling even the smallest manufacturers to cost-effectively manage production data. IIoT and Edge computing devices can easily integrate with this infrastructure.

The second obstacle is that many organizations do not adequately maintain their EAM/CMMS. The asset hierarchies in the EAM/CMMS need to properly align with the historian and control systems, as well as the financial ledger that manages asset amortization,procurement of spare parts and labor hour tracking. These systems need to be cleansed and updated for APM to work properly.

The third challenge is to avoid getting into an algorithm comparison between competing alternatives. While there are proprietary ML algorithms and well-known open-source ones, there are few people i.e., PhD data scientists, that can actually determine the difference and there is no standard for testing them. On a comparative basis, APM solutions in today's market offer very similar first principle models and machine learning algorithms. The real test is the ease of building and deploying the predictive functionality and ensuring it is accurate for a given operating context.

The fourth challenge is finding a vendor with domain experience who really understands the principles, processes, and practices of reliability and asset performance management. Many Predictive Maintenance products are offered by analytics firms that lack deep domain experience. Yes, they know how to make ML algorithms work with data, but as we have been discussing, APM is much more than that.

The fifth challenge is organizational readiness. Given APM's capabilities of PdM and RxM, how will the maintenance, inspection, and operations work processes be impacted? What needs to change? What workforce skills need upgrading? Thus, there is a change management component that should not be overlooked or underestimated.

It is important to address the above before rushing off to try out a solution in a pilot, then later only to find out that the solution did not work as intended, or that one cannot scale the solution. Users are encouraged to get outside help if needed.

Summary and Conclusions

While this white paper is not meant to be a comprehensive analysis of APM nor a detailed competitive comparison, it can help users navigate the crowded and often confusing market when choosing a suitable APM solution. One can achieve a sophisticated, powerful, yet simple, easy-to-use, scalable, and cost-effective solution without falling short in functionality or requiring unnecessary cost and complexity. This is not to say that competing Predictive Maintenance products and APM solutions do not work, only to say that this is the right direction for the largest range of manufacturers seeking an APM solution. So, if you are not an elephant, this is the common-sense approach. And if you are, perhaps you should consider a change for the better and simplify your reliability program.

About the Author

Joe Perino - independent consultant and advisor focused on industrial transformation and operational excellence for the energy, process, and manufacturing industries. Perino founded PERTEX in 2015 to help industrial organizations drive business results. He is actively involved with the Industrial Internet of Things (IIoT), DataOps, advanced analytics (AI/ML), Cloud and Edge computing, Digital Twins, robotic process automation, and blockchain.

Perino started his career as a process engineer in the refining, chemicals, and pipeline sectors. He has worked for operating companies (Phillips Petroleum, Diamond Shamrock, Northern Natural Gas) as well as automation and software firms (Emerson, Honeywell, Blue Yonder) and services firms (IBM, Schlumberger, CGI, and DXC). Before going independent, Perino was a principal analyst for LNS Research, where he was the lead analyst for asset performance management, operational excellence, advanced analytics, autonomous operations, and data management.

He holds a BS in Chemical Engineering from the University of Notre Dame, an MS in Finance from the University of Houston-Clear Lake and has completed executive education programs at the Kellogg School of Management at Northwestern University, and Harvard Business School.

Appendix

Reliability-centered Maintenance (RCM) is a corporate-level maintenance strategy designed to optimize maintenance programs by establishing safe minimum levels of equipment upkeep. RCM emphasizes matching individual assets with the maintenance techniques most likely to deliver cost-effective outcomes.

Risk-based Inspection (RBI) is an optimal maintenance business process used to examine equipment such as pressure vessels, heat exchangers, and piping in industrial plants. RBI is a decision-making methodology for optimizing inspection plans. The RBI concept lies in that the risk of failure can be assessed in relation to a level that is acceptable, and inspection and repair used to ensure that the level of risk is below that acceptance limit.

Artificial Intelligence is the ability of machines to perform tasks that are typically associated with human intelligence, such as learning and problem-solving.

Machine Learning (ML) is a branch of Artificial Intelligence (AI) and computer science that focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. It's an umbrella term for solving problems for which the development of algorithms by human programmers would be cost-prohibitive, and instead, the problems are solved by helping machines 'discover' their 'own' algorithms.

There are several kinds of machine learning. **Unsupervised Learning** analyzes a stream of data and finds patterns and makes predictions without any other guidance. **Supervised Learning** requires a human to label the input data first, and comes in two main varieties: **Classification** (where the program must learn to predict what category the input belongs in) and **Regression** (where the program must deduce a numeric function based on numeric input). In **Reinforcement Learning** the agent is rewarded for good responses and punished for bad ones. The agent learns to choose responses that are classified as "good". **Transfer Learning** is when the knowledge gained from one problem is applied to a new problem. **Deep Learning** uses **Artificial Neural Networks (ANNs)** for all of these types of learning.

ANNs are a branch of machine learning models that are built using principles of neuronal organization discovered by connectionism in the biological neural networks constituting animal brains.

Anomaly Detection is the identification of rare items, events, or observations that deviate significantly from the majority of the data and do not conform to a well-defined notion of normal behavior.

Statistics is the practice or science of collecting and analyzing numerical data in large quantities, especially for the purpose of inferring proportions in a whole from those in a representative sample. There are two main statistical methods: 1) descriptive statistics, which summarize data from a sample using indexes such as the mean or standard deviation, and 2) inferential statistics, which draw conclusions from data that are subject to random variation (e.g., observational errors, sampling variation).

What's the Difference Between Statistics and Machine Learning? According to Professor Shahab D. Mohaghegh, at West Virginia University's Department of Petroleum and Natural Gas Engineering, a simple explanation is (paraphrasing): "With statistics, data is fitted to a mathematical model, while with machine learning, the data is the model."

Asset Performance Management (APM), as defined by Gartner, encompasses the capabilities of data capture, integration, visualization, and analytics tied together for the explicit purpose of improving the reliability and availability of physical assets. APM includes the concepts of condition monitoring, predictive forecasting, and reliability-centered maintenance (RCM).

Gartner defines **DataOps** as a collaborative data management practice focused on improving the communication, integration, and automation of data flows between data managers and data consumers across an organization. The goal of DataOps is to deliver value faster by creating predictable delivery and change management of data, data models, and related artifacts. DataOps uses technology to automate the design, deployment, and management of data delivery with appropriate levels of governance, and it uses metadata to improve the usability and value of data in a dynamic environment.

CMMS vs. EAM. Whereas a **Computerized Maintenance Management System (CMMS)** is used primarily to manage the maintenance of equipment and machinery, **Enterprise Asset Management Software (EAM)** takes a holistic view of the complete asset lifecycle management, which also includes planning, procurement, inventory, operations, and disposal. It maintains information at every stage of the asset life cycle.

Prognostic Maintenance (PxM) is what is exactly what it sounds like, a prognosis of the expected outcome given the prescriptive choices for action. Another way to think about it is the answer to this question, "How well do we resolve the issue given various choices of action?"

Generative AI (GAI) is artificial intelligence capable of generating text, images, or other media, using generative models a.k.a. large language models. Generative AI models learn the probabilistic patterns and structure of their input training data and then generate new data that has similar characteristics.

Generative AI was introduced in the 1960s in chatbots. But it was not until 2014, with the introduction of Generative Adversarial Networks (GANs) -- a type of machine learning algorithm -- that Generative AI could create convincingly authentic images, videos, and audio of real people.

Causal AI (CAI) is an artificial intelligence system that can explain cause and effect. Causal AI technology is used by organizations to help explain decision-making and the causes of a decision.

What is the Difference Between Generative and Causal AI? While only predictive AI (using machine learning which is a form of Correlative AI) can see into the future reliably, only Causal AI can deterministically know the root cause of an issue … and only **Generative AI** can tailor recommendations and solutions to specific problems using advanced probabilistic algorithms.

State Machine Modeling is a mathematical model that groups all possible system occurrences, called states. Every possible state of a system is evaluated, showing all possible interactions between subjects and objects. A state machine is a behavior model. It consists of a finite number of states and is therefore also called a finite-state machine (FSM). Based on the current state and a given input the machine performs state transitions and produces outputs.

Overall Equipment Effectiveness (OEE) is a measure of how well a manufacturing operation is utilized (facilities, time, and material) compared to its full potential, during the periods when it is scheduled to run. It identifies the percentage of manufacturing time that is truly productive. An OEE of 100% means that only good parts are produced (100% quality), at the maximum speed (100% performance), and without interruption (100% availability).

OEE = Availability x Performance x Quality, or
OEE = (Production Time / Potential Production Time) x (Actual Output / Theoretical Output) x (Good Unit Output / Actual Output)

Supervisory Control and Data Acquisition (SCADA) is a control system architecture comprising computers, networked data communications, and graphical user interfaces for high-level supervision of machines and processes.