February 2020

WHITEPAPER

Artificial Intelligence: from Predictive to Prescriptive and Beyond

Authored By:

-

James H. Chappell

Vice President – Information Solutions

Executive Summary:

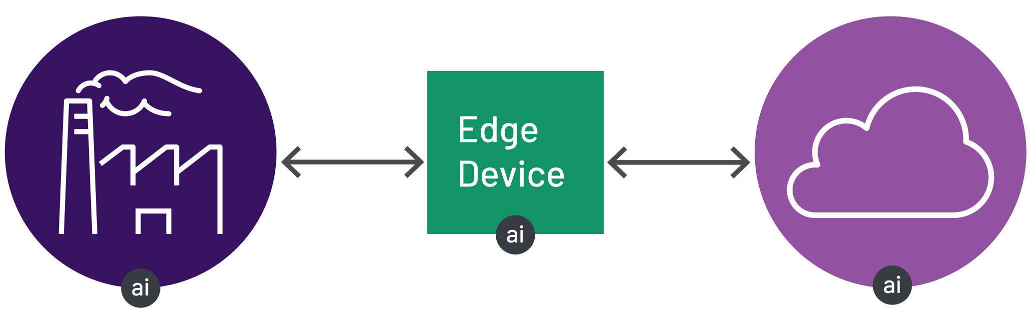
State-of-the-art artificial intelligence technologies improve industrial processes, proactively detect and solve problems, and provide guidance for risk-based decisions resulting in significant cost savings and improved competitiveness for the enterprise.

Artificial Intelligence (AI) has existed for decades, with early technologies in neural nets, game AI, and natural language processing dating back to the 1950's. But these technologies typically required very large computers to operate and mainly existed in computer labs at universities and other major research institutions. With incredible hardware advances over the years, AI in the workplace became a reality. It started slowly but then gained momentum. Today, it is prolific and manifests itself in many forms. Over the past twenty years it has significantly transformed the industrial workplace. However, the challenge remains to bridge the gap between AI technology and human understanding. In order to glean maximum value from AI, there must be a human conduit across this industry-changing technology.

AI is disrupting the workplace through digital transformation, resulting in extensive use of the digital twin. This 'digital twin' is effectively a virtual representation of a physical object or system. As it has evolved, it has come to also encompass larger entities such as buildings, factories, and cities. It includes IOT data, advanced computer systems, digital processes, electronic documents, and advanced analytics which all model physical space. However, AI is necessary in order to get the most value out of the digital twin. The combination of AI with the digital twin results in significantly enhanced productivity. This is not theory; this is a fact and is quantifiable. AI enhances workforce productivity and improves safety, reliability, quality, and security. Through efficiency gains and reduced waste, AI is creating an overall greener environment with enhanced sustainability. AI also helps the workers themselves. Studies show that there is not enough new qualified staff to replace the knowledge of an aging workforce rapidly approaching retirement. AI helps to facilitate and reduce this gap.

This AI-based disruption aids many aspects of the industrial process, from design & engineering to operations to maintenance. AI improves engineering through automated design generation, enabling lower total cost and lower risk in capital projects. After the digital twin is put into production, AI then enhances operations for safe and profitable processes within constraints and regulatory norms. It automates monitoring and control processes through closed-loop analytics for autonomous operational control to ensure safety and performance. Maintenance is greatly improved through many AI techniques to increase longevity and performance of assets while ensuring a safe, reliable environment for the workforce through predictive and prescriptive analytics. And planning/scheduling is optimized through various types of AI to create a self-learning approach for continuous improvement to reduce risk and maximize profitability.

However, AI also disrupts jobs, which sometimes results in the elimination of certain types of occupations. This can be devastating for those impacted. But at the same, it creates a variety of new jobs such as monitoring service technicians, data analysts, data scientists, etc. Forbes estimates that 75 million jobs will be displaced by 2022 due to AI (machines and algorithms). At the same time, 133 million new jobs are expected to be created, resulting in a net increase of 58 million additional jobs in the next 3-4 years. Of course, this is nothing new. The implementation of new technology has been disrupting the workforce for centuries. Ultimately, history has shown that while innovation does eliminate some jobs, it typically adds more than it destroys, resulting in a net increase in the overall workforce. Unfortunately, AI can sometimes create an overall fear of the unknown, including privacy concerns and anxiety of being replaced. Companies must take measures to ensure that these fears are managed, and that proper employee education and communication channels are in place to minimize fear due to misinformation and a general lack of understanding.



In order to accomplish this digital disruption, AI is being deployed on-premises, in the cloud, at the edge, and through many types of hybrid architectures. AI itself is not one thing but comprised of a number of technology types, including neural networks, deep learning (a flavor of neural networks), natural language processing, computer vision, unsupervised machine learning, supervised machine learning, reinforcement learning, transfer learning, etc. These various types of AI are applied in different ways throughout the industrial world to create targeted solutions provided as descriptive, predictive, and prescriptive analytics. A relatively common solution used in a wide range of industries today is predictive analytics in the form of machine learning to identify anomalies with equipment and processes. These anomalies can indicate performance problems or asset health deterioration well in advance of any control system or SCADA warning or alarm. Lead times with predictive analytics can be days, weeks, or even months, allowing operators and maintenance personnel adequate time to react and schedule repairs and corrections. Software tools are becoming more and more sophisticated in order to provide additional insight into these anomalies. This includes identifying which sensors are the key contributors to the problem as well as the probable root cause. With all of this sophistication, issues can be identified and corrected quickly, well before they have a major impact on operations. This results in less downtime, better product quality, reduced risk, and increased overall efficiency and profitability.

From an industrial perspective, AI can be broken down into what AVEVA categorizes as the Four P's of Industrial AI:

- **Predictive**: Based on Machine Learning, this is a type of pattern recognition and anomaly detection leveraging Industrial Big Data to create digital signatures of assets and processes and then to detect both deviations and matching patterns that indicate early warning of pending problems and inefficiencies, as well as errors in the design process. The Big Data can come from a variety of sources, including sensors, data lakes, data historians, calculated values, audio, video, etc.
- **Performance**: Based on first principles analytics (simulation) & machine learning, this is a type of optimization system leveraging industry and asset specific algorithms and modeling techniques (often based on thermodynamic principles) to provide early warning detection of pending problems and inefficiencies when compared to actual sensor values. It is a combination of both online and simulation software that leverages machine learning to baseline performance through advanced pattern analysis in order to ensure the mathematical models accurately match operational reality. From there, deviations can be quickly detected in order that early action is taken to rectify the situation.
- **Prescriptive**: Based on the issues detected in Predictive and Performance analytics, this provides root cause analysis, planning & decision-support, and probabilistic courses of action to best remedy & optimize a given situation.
- **Prognostics**: Leveraging neural net, deep-learning, and reinforcement learning technologies, this provides a forecast of future events. It can be used in monitoring/control and scheduling optimization as well as in determining how long an asset or process can continue to safely operate (after an anomaly has been detected) before failure or significant loss of functionality occurs. It can also provide risk-based insight into decisions such as whether or not an operation should attempt to run to the next planned maintenance outage.

By applying AI to Big Data, a vast amount of information has resulted and is growing at increasing rates, year over year. In order to make this information useful, Knowledge Graphs are becoming increasingly prevalent in various capacities to help apply context. Unbeknownst to many, Knowledge Graphs have been implemented by a number of widely used sites, including Google, Facebook, and LinkedIn. In the industrial space, AVEVA provides Knowledge Graphs to contextualize this information with an ontology that spans engineering (CapEx) as well as operations and maintenance (OpEx) aspects of an industrial asset's entire life cycle.

This breadth is unique in the industrial world and allows users to capture, organize, infer, and expose this information for maximum value and ease of use.

With all the capabilities and complexity of the various types of AI techniques available today, it can be overwhelming and somewhat intimidating for the human workforce. Further, it is important that the complexities of AI technology be translated into something that is easily understood and, more importantly, actionable in order to gain useful business value. This is especially important with an aging workforce and the need to capture and convey knowledge in business context. Besides acting as an AI bridge for human understanding, this can also be an excellent training aid for workforce improvement and advancement.

Although there are many types of AI, predictive analytics in the form of machine learning has become one of the more common advanced technologies used in industry today. Although referred to as "predictive," it is actually a very effective method of anomaly detection in near-real-time. It is a type of advanced pattern recognition where the digital signatures of normal behavior of an asset or process are captured and used as a basis of comparison with incoming, real-time data from SCADA and other control systems. Real-time data from sensors is collected and compared to the expected data signature of a given asset or operational scenario. Deviations from normal behavior can be detected days, weeks, and even months before a traditional SCADA or control system alarm would trigger. This provides companies adequate time to take the appropriate actions to rectify the asset or operational problem before it's too late.

The prevalence of predictive analytics is largely due to its general applicability to huge volumes of time-series data, often referred to as Industrial Big Data. With the advent of the Industrial Internet of Things (IIoT), the cost of sensors has greatly decreased, allowing companies to install various types of online meters where they never would have previously. This allows more values to be measured and recorded in data historians and data lakes, both on-premises and in the cloud. Contained in the myriad of data that is archived in these repositories are valuable patterns and knowledge insight that can be used in a variety of applications including training simulators and operations & maintenance optimization.

In order to extract and capture this knowledge, advanced analytics such as machine learning is leveraged. Many techniques are used, including proprietary data clustering algorithms that help suppress "noise" so that core patterns are better detected and analyzed. Today, there are two primary types of machine learning: unsupervised and supervised. With unsupervised, data is automatically analyzed, relationships among data are systematically determined, and deviations from patterns of normal behavior are identified with no human intervention. With supervised machine learning, assets and operations are modeled by humans selecting relevant sensors (tags) that are statistically related and selected periods of archived Big Data that represent "good behavior" so that the software can create a digital signature of what is considered to be proper operation. Incoming real-time data is then compared to this digital signature, and deviations are identified as possible early warnings of asset or operational degradation. Further, the primary contributing sensors to each anomaly are automatically identified in order to allow humans to better track down the root cause of the issue and correct it before it becomes a major operational problem.

Examples of successful predictive analytics include sophisticated turbine "catches" where there were step changes of vibration reductions (not increases). Each time, the manufacturer told the customer it was OK because it was a reduction in vibration, not an increase. With this particular situation, it turned out to be due to the beginning of blade separation within the turbine stages. The system was nowhere near a control system alarm or warning. However, had it gone on, it would have resulted in a catastrophic failure that could have destroyed the turbine, caused extensive downtime (loss of power production), and a potential for significant injury to personnel. Conservative estimates by the customer showed that over $34 million USD were avoided due to the early warning detection of this issue.

Another example occurred during a major storm with high winds where a transmission grid company leveraged AI and advanced analytics to prevent a catastrophic transformer explosion. The system alarmed due to unusual patterns of dissolved gas analysis (DGA), including methane and carbon dioxide.

The company dispatched technicians to investigate and saw that the breakers had tripped open due to the hurricane, leaving the transformer in an energized state with no load. Had the breakers merely been closed per normal procedure, a major explosion could have resulted, destroying the transformer, potentially injuring people, and causing cascading outages. These types of high-voltage transformers cost in the range of €10 million each, and spares are not typically kept on hand as backup. This was a major "catch" that the customer proudly cites as a huge avoided cost in terms of asset damage, lost transmission, and human safety.

In contrast, the Food and Beverage industry, as a whole, is just beginning to adopt and leverage predictive analytics technologies. Although less mature in predictive maintenance than other industries, they are quickly finding value by monitoring and analyzing their production lines, reducing downtime, and improving quality. Examples of "catches" include irregular motor operation where the electric current runs too high in relation to other monitored values, but not high enough to cause an operational warning. Gas oxidizer issues are another useful area for this technology, as well as conveyor problems with over-tensioned belts, and pumps running hot due to oil and valving issues.

Prescriptive analytics takes this further by providing specific recommended actions that operations and maintenance personnel should take to rectify the issue. For example, prescriptive guidance for oil issues include verifying the calibration of oil temperature sensors, replacing or recalibrating as required. Further, oil analysis is often recommended to check for contamination, sometimes leading to replacement of the oil and oil filter. Other types of prescriptive actions can quickly become much more complicated and involved. As AI becomes more fully integrated into the Food and Beverage industry, more and more success stories will surface, and this technology will continue to rapidly proliferate.

Historically, these types of machine learning "catches" were difficult to identify for novices, sometimes requiring users to write script and manage software code. This is one of the reasons for the advancement and proliferation of programming languages such as Python and R. However, as time went on, machine learning software was developed to the point of being much easier to use, with advanced "drag and drop" graphical user interfaces (GUIs) and simple, easy-to-understand on-screen representations of identified anomalies. This became the first bridge of understanding between the industrial AI and the human.

These enhanced user interfaces were very helpful in allowing AI to penetrate the day-to-day processes of various industries; however, they were limited in their abilities to guide the workforce in how to correct the issues that were detected. A better method of bridging this gap was needed.

Prescriptive analytics became that bridge between AI technologies and humans. It began with condition-based triggers to create a proactive maintenance program, vs calendar-based preventative maintenance. Applied to AI, prescriptive bridges the gap between anomaly detection and the actions needed for resolution. It's critical to both improved asset maintenance and enhanced operational efficiency; consequently, it has become an increasingly important aspect of an overall Reliability Centered Maintenance (RCM) program.

In order to further enhance predictive and prescriptive analytics, prognostics takes AI one step further by forecasting future events, such as operational performance degradation or asset remaining useful life. Prognostics can allow humans to make decisions such as, "can the system make it to the next planned maintenance outage?," or "can the asset make it to next week, or do we need to call in emergency personnel over the weekend on overtime wages to fix the problem?" These are critical decisions that impact both risk and costs. Managing risk is a key part of what AI brings to businesses, and it can significantly help improve the bottom line of industrial operations.

However, without a suitable bridge between AI technology and humans, appropriate actions may not be taken, and the value of this advanced technology could be lost. Prescriptive analytics is the key to making this happen in order that businesses gain maximum value from advanced AI technologies and software investment.

Implementing prescriptive analytics is not trivial. It requires extensive, industry-specific fault diagnostic and resolution action databases that are logically defined based on changing sensor values (and other permutations) so that automatic (programmatic) recommendations can be provided to the user. This requires software to encompass vast industry expertise, experience in types of reliability centered maintenance practices, and predictive analytics. Because of this combined uniqueness, competition in this space is limited and typically targeted to specific industries. With AVEVA's breadth of industrial predictive analytics software expertise and its recent acquisition of MaxGrip (a leader in the industrial Reliability Centered Maintenance space), they are an example of a software leader that is uniquely positioned to offer predictive, prescriptive, and prognostic solutions to the global industrial markets.

As software continues to evolve, integrated processes become more important. Predictive, prescriptive, and prognostic software will increasingly integrate with enterprise asset management (EAM) systems in order to dynamically create work orders and integrate the forecasted remaining useful life of the asset with recommended prescriptive actions needed to rectify the issue. This will provide automation from issue detection, through root cause analysis, to remediation and rectification.

Beyond EAM integration, this type of AI software will also integrate with scheduling systems to recommend the optimal time to perform emergency maintenance within the forecasted remaining useful life window of an asset in order to reduce adverse impacts on operations, minimize overall business risk, and maximize profit. This will then extend to closed-loop, automated process control, where humans merely monitor the fully automated and optimized, end-to-end operations and maintenance processes that are controlled by AI. These technologies exist today, and adoption will increase over time.

Predictive analytics software will continue to be improved and enhanced through prescriptive capabilities in order to detect and prevent problems faster, better maintain industrial operations, optimize scheduling, and enhance process control. From a societal perspective, predictive analytics will be humanized through continued advancements in prescriptive capabilities in order to:

- Better enable & empower the human workforce
- Provide more efficient operations
- Improve work product (less mistakes)
- Facilitate faster/more complete knowledge transfer and learning
- Enhance safety in the workplace
- Create new jobs and business opportunities
- Ultimately, offer a better quality of life for society

An increasing number of industrial companies throughout the world are actively engaged in leveraging artificial intelligence, particularly predictive analytics. This is no longer an option in many industries but often a requirement to keep up with the competition. In order to maximize the benefits, the bridge from predictive AI technology to humans must be as seamless as possible. That's where prescriptive plays a key role, and it is revolutionizing the way work is performed. It enhances workforce productivity and improves safety, reliability, quality, and security. As a result, industrial efficiency is improving in ways it never could before, and new types of jobs are being created. However, AI technology is only in its infancy, and it is greatly advancing each year. The future of AI is extremely exciting, and opportunities to benefit from it are virtually limitless.

About the Author

Jim Chappell oversees AVEVA's overall Artificial Intelligence (AI) strategy and implementation across all business sectors. In addition, he is in charge of the Asset Performance Management (APM) suite of products and related engineering/analytics services. This encompasses Industrial Big Data (data historians), predictive/prescriptive/prognostic analytics, business intelligence, and enterprise asset management. His responsibilities include both on-premises and cloud based (SaaS) offers.

Previously, Jim was a founding partner and managing officer of InStep Software, a global leader in predictive analytics and enterprise data historian software. He oversaw InStep's operations and services for nearly 20 years and helped grow the company from startup to a global leader in its space, ultimately being acquired by Schneider Electric in 2014. His responsibilities included mission-critical system integration, enterprise architecture, cutting-edge analytics, value-added consulting services, customer support, quality assurance, and training. Early in his career, Jim was a U.S. Naval Officer where he was trained to command and control nuclear power plants, including reactor safety operations and nuclear emergencies.

Jim holds a B.S. in Nuclear Engineering from Rensselaer Polytechnic Institute (RPI) in Troy, NY, a M.S. in Nuclear Engineering from the Naval Nuclear Power School in Orlando, FL, and a M.B.A. from Chaminade University in Honolulu, Hawaii. In addition, he graduated from the Civil Engineer Corps Officer's School (CECOS) in Port Hueneme, CA.