

Practical Use Cases for Artificial Intelligence and Machine Learning

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Artificial intelligence (AI) and machine learning (ML) tools are being applied in the process industries to improve a variety of operations and maintenance tasks.

Artificial intelligence (AI) and machine learning (ML) are ready to be deployed on the plant floor. In the past, technical and economic hurdles made application impractical, but those hurdles have been overcome and the chemical process industries (CPI) are now embracing AI and ML technology in their plants for a variety of operations and maintenance use cases. Before getting into more detail about potential applications, let's cover some basics on AI and ML.

It's likely that you are familiar with the general idea of AI, which is defined as "the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings" (1). Fields as diverse as theology, mathematics, philosophy, and writing have speculated about the concept of AI for centuries, even though the term to describe it would not come about until much later (2). The term was officially coined in 1956 as part of the "Dartmouth Summer Research Project on Artificial Intelligence" (3) and is attributed to Dartmouth College's John McCarthy, considered to be one of the founders of AI, and three other researchers involved in the project.

ML is a branch of AI that pertains to the ability of a software application or machine/system to learn through

experience, becoming more intelligent over time through data and algorithms rather than programming. The term ML has been in existence almost as long as the term AI; it was introduced as part of a 1959 article by IBM's Arthur L. Samuel entitled "Some Studies in Machine Learning Using the Game of Checkers" (4).

AI and ML for the process industries

AI and ML have come a long way since its inception at an Ivy League workshop and the use case of winning a game of checkers; in fact, it's now considered industry-ready. In "Prediction Machines: The Simple Economics of Artificial Intelligence," authors Agrawal *et al.* use the example of autonomous vehicles to argue that AI lowers the cost of prediction (5). For many years, autonomous vehicles were programmed with "if/then" statements to behave in specific ways based on the situation. However, an autonomous vehicle can encounter an almost infinite number of situations, making it virtually impossible to code all of them.

The breakthrough for autonomous vehicles came when the problem was converted to a prediction problem. Sensors were installed in human-driven vehicles to collect enormous amounts of data about what drivers did in all types of driv-

ing scenarios. AI analyzed this data to progressively learn what good drivers do and then applied that learning to the mechanical aspects of driving.

It is not too difficult to take this same approach in the CPI. Process automation systems have historically done an excellent job of collecting data, some of which has been used to assist plant operations. However, much of the data goes unused. Now we have a great application for that data — as input into AI. Like the autonomous vehicle example, AI can learn about how a plant operates and start to make correlations between the data and the results. These correlations can be supplemented with plant know-how and applied to various use cases — some of which are covered later in this article — that help to solve basic business issues in areas such as maintenance and operations optimization. AI correlations can be used to keep production lines running and also to help them run more efficiently.

For all of this to happen, several critical pieces must be in place:

- *Data.* Process automation systems are great at collecting data. In addition, many new types of sensors are available for locations where data is needed but has not been available.
- *Communications networks.* It is critical to have communication networks to move data. A combination of wired networks and the ongoing evolution of wireless technologies, such as industrial wireless internet and 5G, are facilitating data movement.
- *Data integration.* Once data has been moved from the sensors on the plant floor to the data analytics engine on a computer or the cloud, it must be seamlessly integrated. The combination of industry standards and commercially available tools are enabling this to happen.
- *Computing power.* Processing the enormous amounts of data needed by AI requires powerful computers that are now commonly available, affordable, and compact.
- *AI- and ML-based tools.* With all of the above pieces in place, suppliers have the motivation to develop AI- and ML-based tools that address key industry drivers and maximize uptime, improve operational efficiency, and support decision accuracy. These tools provide the ability to build asset models, train the models based on ML and domain experience, and use them to generate maintenance and inspection requests. They can also predict equipment condition-related deviations and send an alert when they occur, as well as consolidate expert knowledge to reduce the workload of overextended operators, engineers, and maintenance technicians.

When combined with real-life knowledge, AI and ML can holistically analyze equipment, process areas, and/or entire plants. This provides an intuitive picture of the equipment, process, and plant health; enables remote monitoring; identifies correlations and anomalies; and predicts failures.

Data is the fuel

It is important to understand that AI is only useful with the input of high-quality data. Data is the fuel for AI and is combined with the input of subject matter experts as part of the model building process. Once the models are built utilizing correlations analysis and pattern recognition, the monitoring, evaluation, and diagnosis phases can begin.

Before the Industry 4.0 revolution, transferring data from one level to another or one component to another was more difficult due to the disparate nature of the data and the lack of network infrastructure to support it. Embarking on a digital transformation as part of Industry 4.0 requires breaking down silos to get something useful from the data lake. This involves combining various data sources and their semantics in a meaningful way that can then act as the input to the AI and be used for ML. For example, pre-defined semantics will identify a temperature sensor as having a temperature output. This ontology is used in the connectivity model for various functions and analytics. Automatic contextualization of the data provides an intuitive exploration of the many aspects, alarms, and assets in a specific plant.

The AI algorithm can determine what is currently happening or what is likely to happen based on the usage of historical and statistical data patterns. With the successful integration of AI across a fleet of plants, companies are not only able to optimize and monitor operation from a single plant, but across the entire fleet. In addition, it is possible to monitor the health status of all plant assets, including field network and automation assets, which can lead to improved maintenance. This holistic view of all assets provides transparency of plant modifications and enables synchronization with engineering data.

Next, we look at some specific use cases where AI and ML can be applied in the CPI, including:

- business-target-driven process control
- predictive monitoring for assets and processes
- predictive analytics for batch processes.

Business-target-driven process control

In many of today's companies, the connection between process control, business objectives, and product strategy is not direct. The result is that process control adjustments are not performed with a focus on the company's business targets. A better option is business-target-driven process control, where processes are aligned with business goals and intelligent insight into the production process is gained with AI through anomaly assistance.

AI anomaly assistance begins with using AI and ML to predict future production process issues or anomalies. The next step is to classify the business impact of each anomaly. For example, what is most impacted? Is it quality? (Lab data is often "after the fact" and not readable online.) Or

stability? (Stabilizing the process will save costs on raw materials, equipment, energy, and maintenance resources.) Or, perhaps it's a combination of factors such as the ratio between throughput and quality. Different companies have different business drivers. And, over time, the business drivers will often change within a single company based on business conditions. This information comes from personnel at the company.

Once the anomalies have been identified and the business drivers are known, a mapping between the two is completed to classify each anomaly by business impact. Focusing on the anomalies with the most significant business impact enables process control based on current business drivers. And, as time progresses and more learning is accomplished, ML can continue to refine the relationship between anomalies and business drivers, further increasing the business impact.

The current situation in the CPI involves complex processes with internal relationships or quickly developing issues that often cannot be effectively controlled by the process automation system, monitored by the operators, and/or manually addressed in an acceptable timeframe. AI anomaly assistance provides early detection of production process issues caused by complex internal process behaviors, increasing the time that operators have to respond.

Functionally, this process involves gathering data from the process automation system or historian and then transferring the data to the AI-based tool for analysis, correlation detection, and anomaly detection (Figure 1). This process continues to progressively improve the models. Next, a dashboard presents the anomalies to plant personnel to alert when they occur. From there, the personnel can take a deep dive into the most critical anomalies (*i.e.*, those with the most

significant business impact) to determine which actions will lead to the most positive business impact.

For example, an anomaly dashboard and deep dive summary may include:

- an anomaly history area with the latest anomalies of all controlled processes or of a selected process
- the anomaly level indicating the degree of deviation in the production process (this provides a better understanding of the process to help predict the probability of an anomaly)
- a display of the production process with the latest predicted anomaly on the top of the list of the production processes

• additional useful information (perhaps integrated by links) regarding the production process coming from the process automation system, plant engineers, etc.

The deep dive should use root cause analysis to better understand the issue and explore actions that can reduce the negative business impact. It may include anomaly history and management information, such as:

- business relevance rating (*i.e.*, define the level of importance of the anomaly)
- business impact classification (*i.e.*, define the business target with which the anomaly is associated)
- links to documentation that may support root cause analysis
- trends for the corresponding process values.

Predictive monitoring for assets and processes

With the constant pressure to increase plant efficiency and uptime in a highly competitive environment, condition-based maintenance has become increasingly important for a plant's economic success. In most modern plants,

significant process equipment data is available in the process automation system, but how can it be leveraged to implement efficient and effective condition-based maintenance?

Personnel who have experience in the plant can combine process knowledge with ML capabilities to extract relevant information from the equipment and process status. From an analysis standpoint, it is important to not only monitor the operating data of the equipment itself, but also to analyze the process around it. The result can be early detection of changes in equipment behavior that enables better decisions regarding the opera-



▲ **Figure 1.** An AI anomaly assistant analyzes process data to detect issues early. Anomalies on the left are sorted based on priority (*e.g.*, "Alarm" is a higher priority than "Warning"), and the trend chart on the right depicts the time frame when the selected anomaly occurred (shaded red).

tion of processes and the required maintenance, which is a big step toward implementing advanced predictive maintenance (Figure 2).

One example of where this has been applied is at a refinery in China that was seeking to increase plant availability, avoid unplanned shutdowns, and reduce maintenance through predictive monitoring. The plant chose to implement AI/ML-based condition monitoring on a compressor that had failed in the past. These failures led to unplanned outages that had an average cost of hundreds of thousands of dollars per incident.

The engineers began the process by collecting months of past data from the plant historian and other data sources such as maintenance reports, monitoring systems, etc. In this case, eight months of data were reviewed, including key variables such as compressor speed, input and output pressures, input temperature, output flow, and lube oil level. The facility held a workshop for plant personnel where they defined the models that AI would develop. The models were then developed from the data and refined by examining multiple training periods.

Once the models were defined, analyses of past data could be executed to see where anomalies were detected. Leading up to one of the past compressor failures, the AI-based analysis detected unhealthy behavior on the compressor's output pressure 18 hours before an alarm occurred in the distributed control system (DCS). This would have provided sufficient time for the plant maintenance personnel to address the issue and avoid the shutdown. Over time, ML will continue to improve the models.

Predictive analytics for batch processes

Batch processes have additional complexity due to their sequential nature and the fact that desirable process conditions are continually changing during the batch production process. When combined with process know-how, AI and ML can provide insight into the performance of past batches that can be used to improve the production of future batches



▲ **Figure 2.** AI/ML-based tools can monitor the health status of process equipment and alert operators when issues arise.

and ensure that key metrics around plant production performance, batch variability, and quality are met (Figure 3). A variety of sources are included in the analysis, such as batch data, process data, and lab data.

Visually, the results of the data analysis can be depicted in a way that includes:

- *Production overview.* Display the batches with and without anomalies over a given time period (e.g., per day).
- *Batch details.* From the production overview, dive into any batch for a comprehensive overview that includes information such as the anomalies that occurred per batch phase.
- *Anomalies overview.* From the batch details display, analyze any deviation to compare the measured value to the AI calculated value.

In addition, analyzing data from past batches helps develop models that support operations. The models can be used to detect anomalies and enable real-time fault detection so that prompt action can be taken to prevent off-spec batches.

Building and maintaining a set of models in a library is also essential. Model building should allow for models to be built down to the phase level to produce a golden batch comprising a set of “golden phases.” Retraining the models (i.e., improving the ML) accounts for process conditions that change over time.

Getting started

What is the best way to get started? As a first step, before considering any specific digital and Industry 4.0-based solutions whether they be AI/ML-based or not, it is important that you assess your overall situation and identify what is the best fit. To guide the process, develop a digital



▲ **Figure 3.** AI and ML analyze the performance of past batches to provide insight on how to improve the production of future batches.

transformation framework using these steps:

1. Educate yourself by assessing the current landscape of use cases and tools to address them.
2. Evaluate your current industrial internet of things (IIoT) maturity level through a maturity assessment. This will give you a realistic view of your starting point.
3. Define your desired IIoT future state. What goals are you trying to achieve?
4. Create an IIoT action plan that will take you from Point A, your current IIoT maturity level, to Point B, your desired IIoT future state. This is accomplished through project prioritization and roadmapping to identify low hanging fruit and maximize business impact. The roadmap should include return on investment (ROI) projections, budget planning, and a proposed implementation schedule.
5. Propose solutions that will enable you to complete your IIoT action plan. This will include detailed projects, requirements, and investments. It is important to gain management support to be successful.

The future of AI and ML in the process industries

Now that AI and ML have arrived on the plant floor, the number and types of use cases where the technology can be applied will continue to increase. And, the prevalence of the technology will only continue to expand and improve: more data and better network infrastructures to get the data where it needs to go, better data integration capabilities to enable the ML to process the data and improve its knowledge, faster computers to do the processing, and more tools to address the expanding number of use cases.

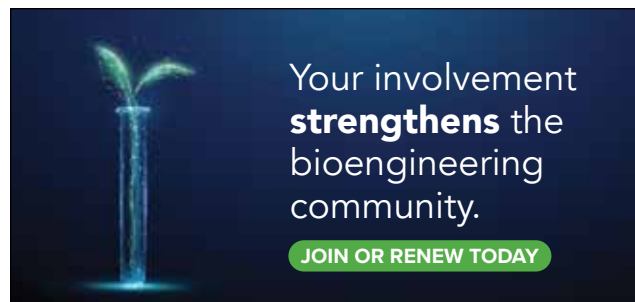
In the very near future, AI and ML will be used on the factory floor to address a wide range of use cases, including many that have not yet been considered. This will occur on such a widespread basis that we will wonder how we ever got by without them in the first place. If you have not yet consid-

ered utilizing AI/ML tools in your plant, there is no time like the present to start learning about them. At some point, all manufacturers in the CPI will evolve to the use of AI and ML in order to gain and keep a competitive edge.

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