CONTROL

WHITE PAPER

The three top use cases for process AI

How real-time artificial intelligence and machine learning can improve plant performance and enable increasingly autonomous operations

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Even as the process industries' production of data has exploded in recent years, our ability to understand it has lagged. And while the tools and technology for analyzing time-series data, such as that produced in process manufacturing environments, have become more powerful and easier-to-use, their application has often been focused on a manual search for meaning in off-line, historical data sets—not the information streaming in real-time from process instrumentation.

Enter artificial intelligence (AI) and machine learning (ML). When paired with automated, real-time data analytics, AI/ML methodologies can identify variations from normal processs conditions much earlier than human operators, ultimately enabling closed-loop machine intelligence and increasingly autonomous operations.

AI algorithms are particularly adept at detecting deteriorating equipment performance that may presage unscheduled downtime as well as sub-optimal operating conditions that erode overall efficiency and adversely affect product quality or throughput.

Use case #1: Predict equipment failures earlier

With rotating equipment such as compressors and pumps, abrasion and deterioration of parts can occur more quickly than detected through periodic maintenance checks. Predicting these types of problems and taking effective countermeasures early on can prevent costly unplanned shutdowns and reactive repair work.

While direct detection of rotating equipment problems can be made using vibration and power consumption data, simple observation of these variables is insufficient for the early prediction of future problems. Machine learning can be used to develop a model that effectively amplifies early stage changes among various process variables during abnormal operations, allowing impending failures to be detected much earlier.

Use case #2: Find sources of performance degradation

Performance degradation due to fouling of heat exchangers, corrosion of piping and tanks, clogging of equipment due to polymerization and other issues can often be detected early through root cause analysis.

This is typically done by analyzing differences between periods of normal operation and periods when degraded performance occurred, referred to as abnormal conditions. To identify the root cause, a hypothesis is made and then verified using process data. When abnormal condition data can be collected in sufficient quantities, machine learning algorithms can show which process variable contributed most to the abnormality.

One issue with this approach is that abnormal condition data may be limited, largely because plants strive to avoid operating in such adverse conditions. In this case, operational states can be divided into several groups using a technique called clustering, with the group including the abnormal operation state examined in detail. Based on the characteristics of this group, the condition in which the possibility of abnormality is high can be derived.

Another machine learning technique that can be used to determine which cluster is abnormal is by teaching to the model the features associated with normal data, then applying those learnings to the dataset clusters under evaluation. When a cluster is determined to be abnormal, the process variables with highest contribution can be identified and ranked.

For example, when corrosion and clogging occur in piping associated with a distillation column, separation performance decreases and production is hindered. Although it is possible to detect the situation in which the abnormality occurs by observing an increase of differential pressure or changes in many other process variables, the method described above can be used to rank the contribution of each variable to the problem, producing more actionable results.

Use case #3: Model product quality parameters

Product quality may vary due to differences in raw materials and changing environmental conditions. These metrics, however, are often not available in real time because samples must be pulled and analyzed in a lab.

To overcome this delay—and avoid producing large amounts of off-spec product in the mean time—use an AI model to predict product quality in real-time based on process data. These techniques predict product quality problems before they occur by applying a linear regression model or a nonlinear machine-learning model to real-time process inputs.

Sometimes, however, problems arise because the prediction model was created from past data. If the state of process has shifted, for example, due to catalyst degradation or raw material variations, the product quality prediction will be offset as well. If, however, this offset is reproducible it can be corrected with a just-in-time (JIT) model to improve prediction accuracy.

Overcoming dataset limitations

If the number of available datasets to train an AI/ML algorithm is small, the expected benefits are often not obtained. This issue can be addressed by using an accurate process simulator to generate the data required for learning. With these simulations, various combinations of input conditions can generate thousands or tens of thousands of cases, and the model then learns from that generated data.

After this step, the machine learning model can rapidly carry out tasks such as prediction, case-study generation and optimization. In addition, when the ML model detects a process abnormality, it is possible to use the process simulation to come up with effective countermeasures.

At present, extensive human intervention is often required to develop advanced AI/ML applications, often referred to as human-driven AI. But in the future, data-driven AI will be able to examine data and discover and solve problems more autonomously. Eventually, knowledge-driven AI will create knowledge by examining one unit or process, and then applying these learnings in other situations.