Plant Services
SPECIAL REPORT

How machine learning is revolutionizing FMEA

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Conventional failure analysis technique gets an intelligent upgrade

A revamp is underway of a widely revered strategy to avoid or mitigate industrial equipment failures. The failure modes and effects analysis (FMEA), originally a military procedure and later adopted into other industries, is a core Six Sigma tool for improving processes and products. Recent technology advancements are breathing new life into this longtime, largely unchanged best practice.

For reliability engineers, FMEA is a step-by-step process for identifying and tracking the various ways an asset or equipment can fail, along with the causes and consequences of each failure mode and priorities for corrective action. But despite its proven merits, FMEA's labor-intensive nature means it is often reserved for only the most critical equipment. It relies heavily on opinion-based decisions, and it primarily focuses on mechanical wear and tear, overlooking the more prevalent threat of damage-inducing process conditions that contribute to random asset failures.

With advanced analytics creating new possibilities for process modernization, solutions are emerging to make FMEA more automated, data-driven, and accurate. They aim to detect problems much earlier by analyzing unseen behavioral patterns and use machine learning (ML) to continuously self-learn and improve.

Ultimately, these "smart" FMEA solutions equip reliability engineers to intervene earlier and more effectively when failure signals are spotted, thus reducing costly downtime and maintenance, and improving performance and safety.

WHY NOW?

Industry 4.0 is epitomized by a plethora of digital solutions working together to make manufacturing smarter. Today, companies can deploy an industrial internet of things (IIoT) platform, connected machine and process sensors, and intelligent analytics based on AI and ML to streamline and continually improve crucial work processes and make data-based decisions.

Applying these technologies to FMEA helps to automate the identification and analysis of both equipment and process abnormalities while substantially widening

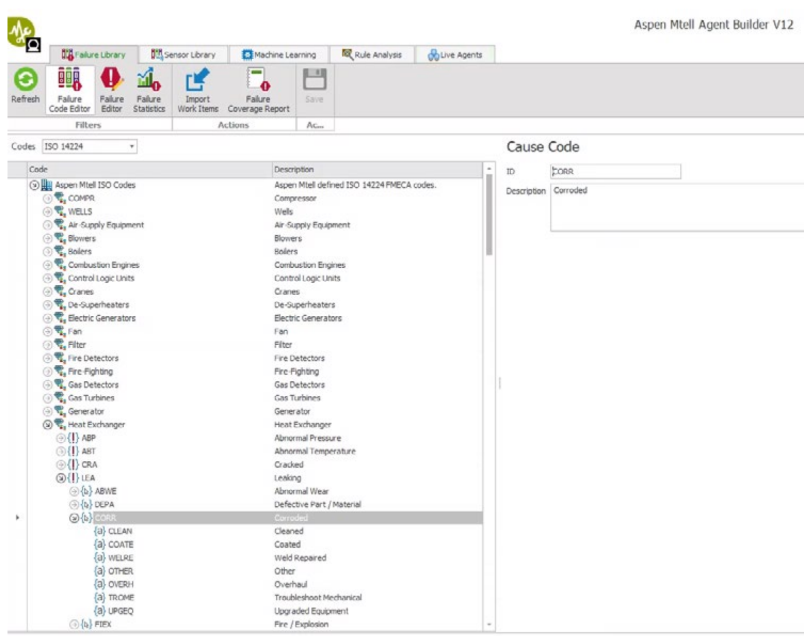

Figure 1. Aspen Mtell Agent Builder: A selection of Failure Codes, Causes, and Resolutions per different asset classes is available while building Agents.

the pool of data from which maintenance and process conclusions are derived.

Incorporating process sensor data into equipment failure analysis is necessary to identify process issues caused by operator error or equipment operating outside of safety and design limits. These are far more common root causes of machine failure than equipment conditions such as worn bearings or corroded pipes.

Fortunately, modern AI analytics can overcome inherent process data complexities, such as:

- Upstream process effects can be so miniscule or random that they're barely detectable.
- The sensor contributions coming from the beginning of a process are very different from the ones that contribute at the end.
- The machine will behave differently in different parts of the process.

AUTONOMOUS ML AGENTS DRIVE SMART FMEA

- Failure agents: Built from past failures
- Anomaly agents: Built from "normal" baseline data
- Condition-based agents: Built based on engineering knowledge

Since smart FMEA constantly learns from changes in patterns in the condition data, it gains an increasingly nuanced understanding of data subtleties like the above and refines the failure modes, effects, priorities, and corrective actions accordingly.

By comparison, conventional FMEA is based on judgement, experience, probability, and inductive rather than deductive reasoning. "It is mostly failure related and not cause related, and it can miss interventions," says Mike Brooks, Global Director of APM Solutions at AspenTech (www.aspentech.com).

SYNTHESIZING FMEA AND SMART ANALYTICS

Software providers working to upgrade FMEA include AspenTech, whose asset performance management (APM) solution, Aspen Mtell, was recently enhanced to include FMEA integration. Designed to forecast equipment degradation and failures and prescribe timely corrective actions, it now also leverages data-driven AI capabilities to provide insight into failure patterns based on multiple signals over far more dimensions than humans can see.

Using both supervised and unsupervised learning, it monitors sensor data trends 24/7 to discover patterns and predict problems well ahead of condition-based maintenance (CBM). It alerts the maintenance team with early and precise warnings of looming threats, and prescribes the actions

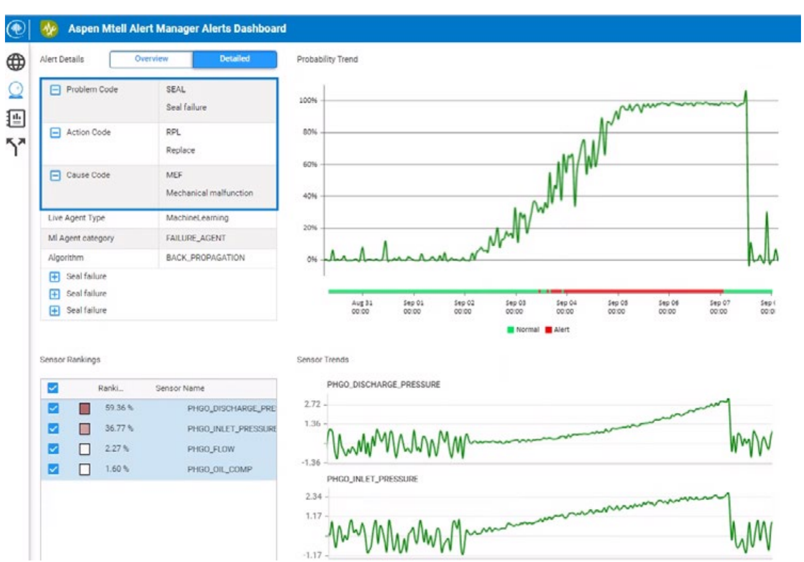

Figure 2. Aspen Mtell Alert Manager: Agents report associated failure codes, cause codes and potential resolutions.

recommended for the failure mode when associated with the agent.

The autonomous ML "agents" that identify anomalies and predict failures are tied to data that exists within the customer's own FMEA library. Aspen Mtell also has a set of generic, pre-defined failure agents and FMEAs for common assets such as rotating machinery. The library's data is continually enhanced as new FMEA data for additional assets is compiled. Reliability engineers can rapidly build three types of agents. Each serves a different purpose, but all perform very specific pattern recognition and self-learn and adapt over time.

Failure agents are built from past failures in the customer's FMEA library, providing a tie-in to the failure mode, cause, and actions to take. Problem alerts include prescriptive guidance and a time to failure and are attached to a work order to expedite completion.

Anomaly agents are built from customer-provided baseline or "normal" process data. They are trained to look for deviations from normal and send an alert indicating which sensor(s) spotted the abnormal process or equipment behavior, so the condition can be investigated. If a problem is confirmed and FMEA is performed, a failure agent can be created to watch for future occurrences.

Condition-based agents can be created as needed in Aspen Mtell or the DCS, based on the customer's engineering knowledge, to detect and be alerted to known problem conditions such as an increase in temperature or drop in pressure. Alerts include one or more choices of actions to take.

Additionally, "transfer learning" allows ML to occur across equipment of the same type with the same or similar sensor configurations. If a problem is found on one asset, an agent created to learn from it can watch for it in other assets of the same kind.

"We use pattern recognition, not models, because we discovered over the years that the causality and failure mode are directly linked into the failure signatures perceived in changing behavior patterns," explains Brooks. "You may not know what the causality or failure mode is, but if a root cause analysis is done, you've linked them together, so we can tell you precisely what it is the next time that pattern appears."

AspenTech is currently working to minimize human intervention for new anomalies. By systematically getting deeper into binding the relationship between process and mechanical changes, they hope to get closer to the root cause.

THE FUTURE OF SMART FMEA

With AI-powered FMEA, assets and equipment have the potential to benefit from continually improving failure pattern detection, analysis, and response. The positive impacts on equipment reliability, maintenance efficiency, safety, and the bottom line are likely to be substantial. ☐