Artificial Intelligence Expands Frontiers in Asset Management

Condition Monitoring and Predictive Maintenance Systems Make AI Pay Off With Lower Maintenance Costs, Improved Forecasting, and Fewer Unplanned Shutdowns

By Bob Waterbury, Senior Editor
November 16, 2000

What is the cost of a process upset? According to Mark Allen, director of product marketing, Gensym Corp., Cambridge, Mass., the most expensive industrial disaster in U.S. history occurred at a Gulf Coast petrochemical plant. The total cost of the explosion and fire cost an estimated $1.6 billion dollars.

Most process upsets and abnormal situations don't cost nearly that much. However, even poor asset management can cost thousands of dollars a minute in lost productivity. Sometimes losses are measured simply in dollars. In extreme circumstances they may be measured in terms of human lives.

In either case, the cost can be significant. That is why asset management has evolved as a higher function of process control. It incorporates elements of control with predictive modeling-- and more recently artificial intelligence (AI) -- to better manage plant asset operation and maintenance.

According to a recent study published by ARC Advisory Group, Dedham, Mass., the market for condition monitoring and plant asset management systems is expected to grow 10% annually through 2003. The ability to monitor the health of plant assets in real time is the key to plant optimization, says ARC. Factors driving this development include the need to lower maintenance costs, improve forecasting and production, and minimize unplanned shutdowns due to equipment failure. This type of knowledge is becoming ever more critical at the management and business systems level--thus the rise of new software products that ARC refers to as Plant Asset Management (PAM) systems.

Why Artificial Intelligence?

Methods, targets, and equipment settings for normal steady-state operations are well understood. Most plants have software and instrumentation that handle this quite nicely. Outside of normal operating conditions, however, control system efficiency may deteriorate rapidly as alarms seem to cascade into uncontrollable system breakdown. Sometimes algorithms and equation-based software solutions can handle these abnormal situations. But as systems become more complex and interconnected, artificial intelligence techniques are used increasingly to predict failures before they occur, and to deal with process upsets before human and financial costs spiral out of control.

If process conditions could always be determined and modeled in advance, then normal equation-based modeling and software techniques would be sufficient. However, process upsets and abnormal situations often entail a certain degree of unpredictability. It is the unknowns and unpredictable behavior of processes operating in combination with one another that call for advanced techniques known variously as artificial intelligence.

In Brazilian offshore oil field production, for example, oil and gas from as many as 30 wells may be directed to a single platform where a processing plant separates the oil, gas, and water. Part of the gas is used locally to supply the electricity for platform activities. Dependence of the platform activities and of the production itself on produced oil turns the plant automation process into a complex problem. Local control at the vessels, pumps, and compressors requires supervision by an intelligent system that can predict abnormal and unsafe operating conditions.

Brazil's state-run Petrobras decided to implement a system that combined conventional PLC control with an intelligent supervisory module called MODIG, based on G2 expert system technology from Gensym Corp., Cambridge, Mass. MODIG was put into operation at a large offshore platform, Petrobras Platform XXIV, Campos Basin, Brazil. Operating results have documented an 80% reduction in plant shutdown frequency.

Currently, Petrobras is implementing neutral networks and fuzzy logic control (FLC) to replace PLC logic. The reason, according to plant management, is that FLC speaks a language more commonly understood by engineers and technicians than PLC logic. FLC logic uses rules of the type, "if pressure is high and level is low, then pressure valve aperture is medium and level valve aperture is low," which is highly intuitive to the operator. Supervisory decision making is supported by the fuzzy logic. And actual pieces of data are matched against prototypical knowledge of the behavior of the operating variables.

"The difference between expert systems and fuzzy logic or neural networks is that the latter two normally express results in terms of a percentage possibility or confidence level," says Brad Law, strategic marketing manager, Bently-Nevada, Minden, Nev. "Our customers typically need results that are categorically absolute -- in effect black or white. That's why we use expert systems. If there is a mass imbalance on a wet gas compressor, then we want to know if that is due to dirty steam or some other cause. If dirty steam is the cause, then the operator is advised that he needs to shut down the machine and conduct a turbine wash. Normal diagnosis and corrective action might take days in some cases, but with an expert system it often takes only a few minutes. This not only minimizes damage to the machinery, but ensures steady production."

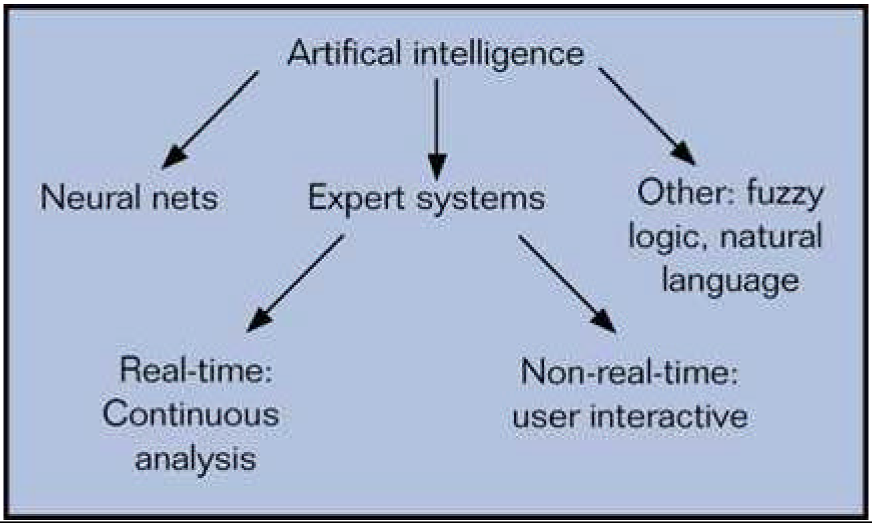
Law adds that many solutions sold today as asset management systems don't really control or manage assets at all. Instead, they are often informational or advisory in nature. Certain condition monitoring, enterprise asset management, or computerized maintenance management systems may fall into that category. Asset management systems, he asserts, do not have to be online and real-time. It depends on the nature of the equipment, its function, and criticality. For instance, it is not necessary to constantly monitor the condition of all pumps in real time. They can be checked periodically and offline as required. By his definition, however, asset management consists of more than data historian software and techniques, although they may be integrated into the solution.

As general guidelines, Law suggests that neural networks and fuzzy logic should be applied when the process is not entirely known and/or understood. Conversely, expert systems are best used when the process or system is well known and understood. This allows expert systems to be fully characterized for optimum results.

What Is Artificial Intelligence?

Traditional artificial intelligence techniques deal with the unknown or unpredictable. These techniques consist of neural networks, expert systems, and fuzzy logic (Figure 1). Other subcategories consist of real-time and non-real-time expert systems, and natural languages other than fuzzy logic. In application, these techniques may be combined with other elements such as predictive models, algorithms, and model-free software.

Figure 1: AI Landscape



Artificial intelligence techniques cover both online real-time and offline functions.

A neural network is a system of programs and data structures that approximates operation of the human brain. It involves a large number of processors operating in parallel, each possessing its own sphere of knowledge and access to data in its local memory. It incorporates large amounts of data and rules about those data relationships, for example, a person's grandfather must be older than his father.

The neural network (NN) is used to perform such tasks as pattern recognition, data mining, classification, and process modeling. The most common type of neural network used in process control is known as the feed-forward, back propagation neural network. Although in existence for more than 50 years, the NN has found practical application only recently due to the intense computational demands satisfied only by high-speed, low-cost computers.

Fuzzy logic, on the other hand, is based on set theory or what could be considered "degrees of truth" as opposed to true-false or Boolean logic on which the computer is based. Although numbers 0 and 1 can be used to represent extreme degrees of truth or falsehood, fuzzy logic normally assigns a percentage or degree of an attribute. An example might be 0.38 of closure.

Fuzzy logic works similar to the brain by aggregating a number of partial truths into a higher-level truth. When this threshold or level of truth is exceeded, it may trigger further results such as a motor reaction or sensor alarm. It recognizes degrees such as slow, slower, medium, and faster.

Expert systems are programs that simulate the judgment and experience of a human or a set of organized expert knowledge in a particular field. Typically, an expert system includes a knowledge base that contains accumulated expertise, and a set of rules that is used to apply the knowledge base to a particular application. Both the knowledge base and the rules can be revised or enhanced to apply to new or changing circumstances.

Expert systems that play chess and assist in diagnosing medical conditions are common everyday applications. According to Allen, typical applications in the process control industries might include prediction of process variables and product quality, calculation of setpoints for process optimization, sensor validation and backup, improved process knowledge, and plant safety.

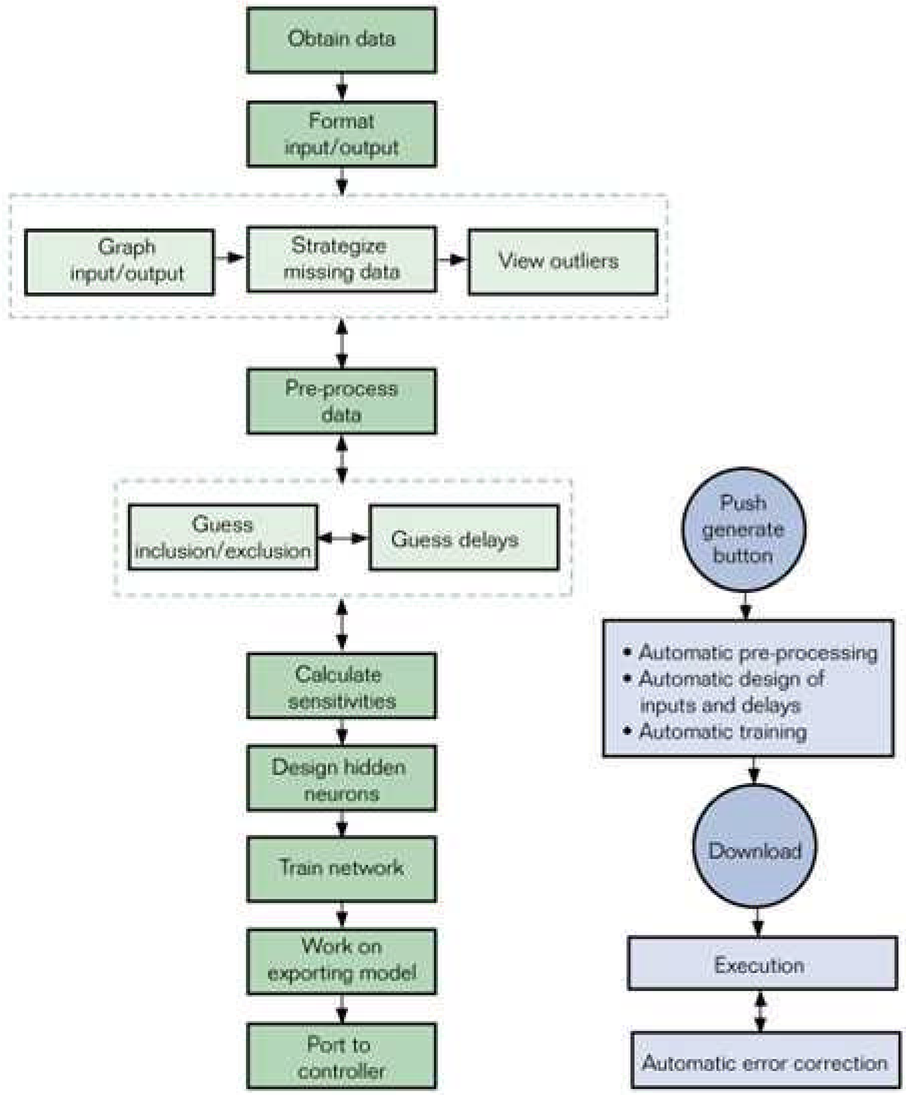
Recent Developments in AI

Artificial intelligence techniques have been quietly developed, refined, and applied to advanced process solutions over the last several decades. One of the newer areas where artificial intelligence is being applied is in cross-validation of physical sensors, or where outputs must be determined by a series of lab analyses.

"Neural networks are being structured as function blocks that automate the process of collecting data, preprocessing, training, verifying the model, and downloading the generated model to a real-time controller," says Jay Colclazier, product manager, Fisher-Rosemount, Austin, Texas. "An intelligent sensor, commonly known as a soft sensor, uses software techniques to determine the value of a process variable as opposed to a physical sensor that directly measures the process variable's value. The soft sensor is a highly trained neural network that can process inputs and spit out current values of the process variable online. It also can be manipulated to predict future values."

This concept involves modeling a neural network as a function block (capable of execution in a controller) to which trained models can be downloaded. Soft sensors are used in situations where a physical sensor is not practical, as a crosscheck for their online physical counterparts, as inexpensive online predictors of operating results, and as if-then analyzers for predicting future values. Figure 2 shows a methodology that allows a neural network model to be generated automatically for faster controller processing.

Figure 2: Easy Nets



Automated versus traditional approaches to neural network generation.

One of the newest solutions based on artificial intelligence provides advanced pattern recognition capability for the surveillance of sensors and sensor network data. Software from SmartSignal Corp. Lisle, Ill., uses microprocessor technology to gather information from sensor signals within a system or device. It then uses that information to construct a model of the signal. The model is used to detect changes or deviations that may warn of device or sensor failure.

The core SmartSignal technology was developed at Argonne National Laboratory, Batavia, Ill., under a 10-year research effort to improve early warnings of potentially expensive or dangerous problems in a nuclear power plant. It quickly became clear, however, that the technology had implications far beyond electric power generation. In 1996, ARCH, the technology development arm of Argonne and the University of Chicago, founded SmartSignal to further commercialize and apply the technology.

Using a stored standard operating protocol or building a model of the current operation based on previous operating history, the software detects and diagnoses deviations in operating characteristics. The signal value is monitored closely as are the statistical characteristics of the removed "noise" for changes in variance, bias, or skewness.

"By identifying the onset of sensor degradation or impending process irregularities," says Alan Wilks, SmartSignal's vice president of technology, "the software actually distinguishes between sensor failure and true system faults. This eliminates false alarms and prevents unnecessary operating disruptions. The technology also provides a precise replacement signal for failed sensors in order to continue operations and understand the state of your system during sensor replacement."

SmartSignal's software integrates a number of techniques based on artificial intelligence. It combines pattern recognition, optimization, noise removal, and predictive algorithms to provide a highly sensitive, comprehensive signal analysis capability. Furthermore, the technology can be applied in standalone configurations, integrated into other smart devices, incorporated into instruments and equipment, embedded into leading control software platforms, or built into an application specific integrated circuit (ASIC) chip set.

Recent alliances with Crossbow Technology and Think and Do Software have opened up additional opportunities for this technology in the equipment condition monitoring (ECM) market. It is being applied in embedded measurement sensor and control subsystems, and also in manufacturing downtime tracking and management.

AI in Action

Artificial intelligence techniques have been quietly embedded into plant solutions throughout the process industries. Often, we are simply unaware of their presence or their function unless specifically pointed out.

For example, the Amoco Oil Petroleum Products refinery in Texas City, Texas, takes more than 400,000 barrels of preheated crude oil daily as a feed and separates it into five streams: naphtha, kerosene, diesel, vapor recovery, and bottom stream. Amoco has to know the exact composition of each stream at all times. However, the on-stream analyzers are subject to a delay of more than 30 minutes.

"By applying Gensym's G2 Diagnostic Assistant and three neural network models, we were able to create a control system featuring soft sensor values for the compositions," says David Middleton, the Amoco computer specialist who implemented the system. "The net result is that we went from no endpoint control to more than 95% closed-loop utilization of our assets and an estimated savings of $500,000 annually in recovered product. The ability to deliver quality values in real time makes it possible to run this advanced control solution more tightly. By learning of the outcome early, we can maintain final boiling point specifications of the separate streams within tight limits. It also keeps product from drifting off spec."

The three NeurOnline models of naphtha, kerosene, and diesel production use between 44 and 46 inputs each. Amoco has run duplicate nets totaling 268 input nodes with no noticeable computer loading. "Best of all, there's no need to spend months researching neural nets," says Middleton. "Once the data sets are built, NeurOnline allowed us to use its built-in configurator to develop the required models."

SmartSignal equipment condition monitoring (ECM) is keeping the paper line rolling for a North American manufacturer. The plant ECM engine works by monitoring multiple signals from a mill and alerting operators to any abnormal conditions.

The ECM uses an aggregate of existing signals from the paper line to calculate expected readings. Then, for each new reading of a signal, ECM calculates an estimated or expected value that is compared to the actual value. The detection engine determines if a pattern of change is occurring or if the real-time signals are normal.

"This is the first time that this manufacturer has had advance warning of breaks," says Bill Nieman, senior application engineer at SmartSignal. "The plant operators now have more than one hour warning of a developing paper break condition, and enough time to take corrective action. "With an estimated loss of $7,500 per hour of downtime, the SmartSignal ECM enables the plant to eliminate more than 260 hours of downtime valued at more than $2 million annually."

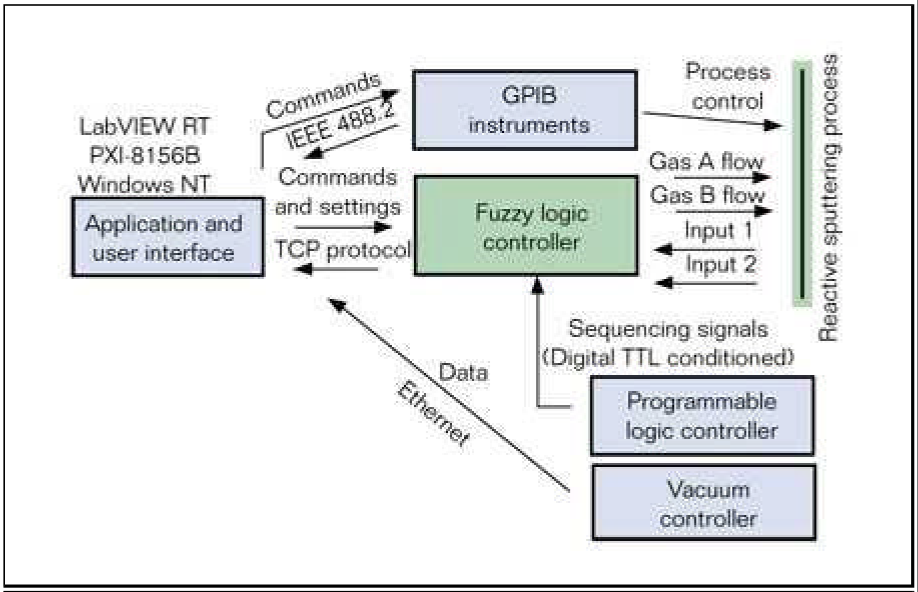
The Marathon Ashland Petroleum refinery in Catlettsburg, Ky., is a highly automated example of process control. However, even with a high level of automation, the site periodically experienced abnormal operations resulting in damaged equipment and lost production.

"Advanced control applications regulated very well when the units were operating normally, but they were not effective during abnormal situations, which resulted in damaged equipment and lost production," says Jack Stout, president, Nexus Engineering, Kingwood, Texas. "Estimated losses from these periodic abnormal situations totaled $75 million over a five-year period. Just two major losses in 1996 alone were estimated at $25 million. By implementing an abnormal situation management (ASM) system, however, the plant increased its equipment utilization, reduced production losses, improved its automatic process control and optimization applications, and improved overall asset management."

The Nexus ASM solution based on Gensym's G2 was developed on a hierarchy of requirements starting with sensor validation. At the basic level, the sensor validation consisted of data analysis for the high/low limit checking, blipped, dead, and simple model inferences. Longer term, the solution is addressing advanced modeling schemes and neural network-based pattern recognition.

Roger Kring, project engineer, Cal-Bay Systems, San Rafael, Calif., implemented a fuzzy logic-based system (Figure 3) to control the thickness of frequency filtering and anti-glare coatings applied to optical lenses. These in turn are used in solar cells, liquid crystal displays, and CRTs. Strict tolerances, multiple variables, and the need for uniform, consistent coatings prompted him to implement the system using LabView RT and LabView Fuzzy Logic toolkit.

Figure 3: Focus on Fuzzy



Fuzzy logic control of reactive sputtering makes coatings consistent on optical lenses.

To achieve sputtering, plasma is sustained in an evacuated vessel. A high-energy field causes a reaction within the vessel that results in ejection of the coating material and deposition on another surface. In a reactive sputtering process, oxygen is also introduced to oxidize the coating material. If silicon is being sputtered, it reacts with the oxygen to produce silicon dioxide or quartz. Multiple layers of materials are deposited on a lens to obtain anti-reflective and anti-glare properties. "Fuzzy logic allows intuitive operator knowledge to be used in a controller employing imprecise linguistic terms," says Kring. "The fuzzy controller, however, is completely deterministic; for any set of input values there is a unique set of outputs."

Kring reports that the fuzzy logic controller improves asset management by allowing quicker changeover and implementation of process variables such as heating, cooling, and coating materials. It also provides more uniform, higher quality coatings.

Assessing the Need for AI

The ability to monitor the health of manufacturing assets in real time is a major function in plant asset management. Whether the goal is to reduce maintenance expenses, improve utilization and output of manufacturing equipment, increase production, or improve product quality, plant asset management is a major key.

Abnormal situations will continue to produce unpredictable conditions that one cannot reasonably identify and program for in advance. Likewise, costs associated with time, manpower, productivity, and capital utilization will come under increasing scrutiny as global markets continue to tighten and become more competitive in the era of e-commerce. Thus, artificial intelligence is destined to play an increasing role in long-term process control, optimization, and management solutions--not only in new green-field plants, but in wringing the most bang for the buck from existing assets.