HYDROCARBON PROCESSING®

MARCH 2006

HPIIMPACT

Industry seeks more tech interoperability

Distillate demand to recover

SPECIALREPORT

INSTRUMENTS AND NETWORKS

Abnormal situation prevention and improving safety

BONUSREPORT

Demise and keys to the rise of process control

Why the industry declined and ways to improve it

www.HydrocarbonProcessing.com

Reprinted from:
HYDROCARBON PROCESSING®
March 2006 issue, pgs 41–48
Used with permission.
www.HydrocarbonProcessing.com

Abnormal situation prevention through smart field devices

High-speed data capture and analysis can detect many process anomalies

E. ERYUREK, P. SHARPE and **D. WHITE,** Emerson Process Management, Houston, Texas

Avoiding abnormal situations remains a key foundation in the process industries' pursuit of operational excellence. Abnormal situations can vary widely in severity and consequences from slightly off-specification products to catastrophic equipment failures. These events can be expensive, sometimes dangerous, and occasionally cause environmental and health issues. Three hundred seventy-nine abnormal events in the hydrocarbon industries with individual event losses exceeding $10 million were identified in the period 1970 to 1999.[1] Average losses per year were approximately $700 million with 25 of these events having individual losses exceeding $150 million. Unfortunately, some of these incidents involved loss of life plus serious injuries as well as large environmental releases. Regulatory actions often followed. The US Chemical Safety and Hazards Investigation Board (CSB) Website[2] lists approximately 50 abnormal incidents a month in the US process industries that are noteworthy enough to generate a published news story.

For this article we will define abnormal situations as a disturbance or series of disturbances in a process that cause plant operations to deviate from their normal operating state and require operator intervention to compensate, with potential impacts on (in order of concern):

- Personnel safety
- Environmental emissions
- Equipment damage
- Product quality
- Throughput
- Production cost.

Abnormal situations are then nonroutine incidents that the normal plant control system does not handle. Of course, safety shutdown systems may intervene to bring the plant to a safe state but by that time some economic losses have already been experienced. Further, abnormal situations require an operations and/or maintenance response involving both correct detection and diagnosis of the problem(s) and correct action(s) to compensate. Of particular concern is the case where a relatively minor failure initiates a cascade of other failures leading to a major problem. For example, failure of a valve in a process unit, such as an FCC, can cause a shutdown of the entire unit (Fig. 1). In some process plants, loss of a key unit, such as an FCC would necessitate shutdown of the entire plant, which might cause release of a large amount of flammable material. Detecting the initial failure early enough to take corrective action obviously has high potential value.

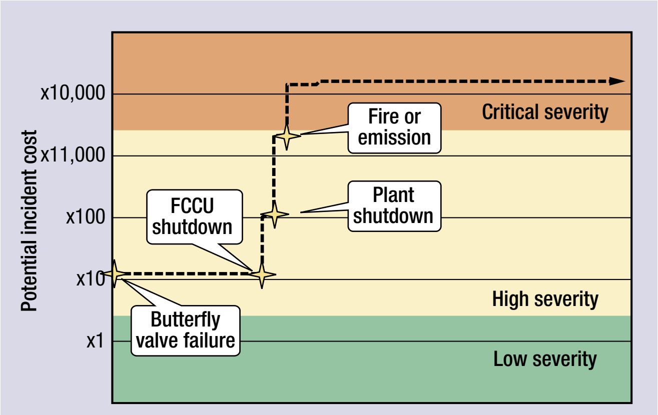

FIG. 1 Incident costs can be reduced by detecting failures earlier.

The catastrophic events mentioned are certainly important but the pure financial implications of less severe abnormal events can also be significant. Unplanned shutdowns and slowdowns of process equipment can result in lost revenue and margin for production-limited plants. High maintenance costs are also associated with these events. Unexpected increases in duration for planned shutdowns also have an economic effect. Multiple studies have indicated that the average loss in potential maximum production for process plants due to these events is in the range of 3–7%, a range also confirmed by the authors' experience. For example, at 14 million barrels per day processing in the US and a $3 per barrel net operating margin, a 1% increase in overall capacity due to reduced abnormal situations is worth $150 million per year to the domestic oil refining industry in increased margin.

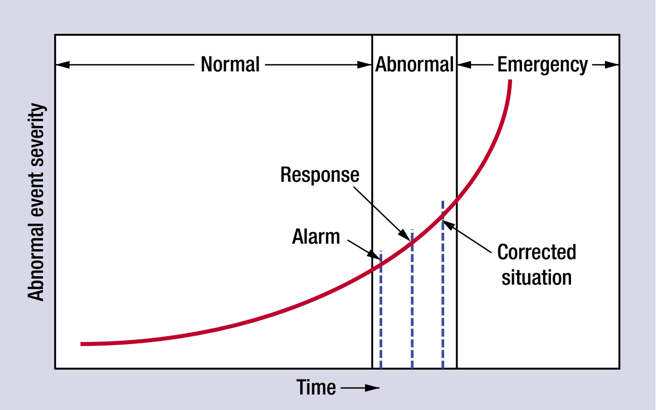

FIG. 2 The longer an abnormal event goes undetected, the more severe the consequences are likely to be.

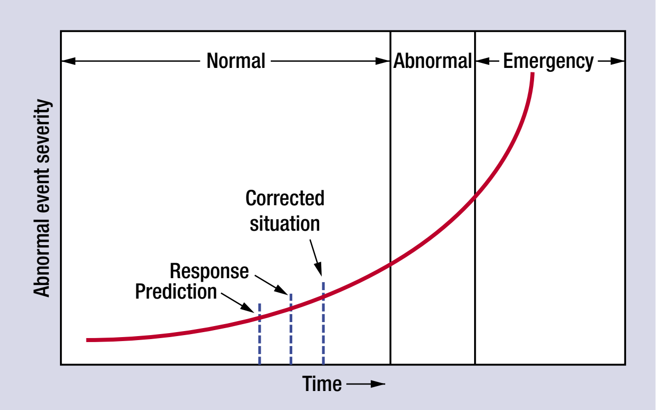

FIG. 3 If the operator can take action earlier, potential consequences can be avoided.

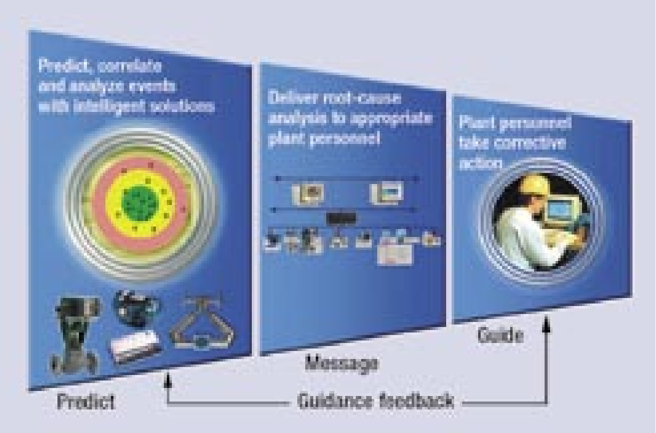

FIG. 4 Three steps are required to deploy ASP.

What then are the sources of these events? Belke[3] and Delguid,[4] among others, examined a large number of abnormal incidents in the process industries to determine their causes. Their conclusions were that multiple factors including design and construction decisions, equipment condition, change control questions, and inadequate operational training and procedures contributed to the incidents. Most of the incidents had more than one cause. The incident investigation database at the CSB supports these conclusions.

With these results, there have always been programs to reduce the frequency and severity of incidents. Some of these programs focus on improved training, others on improved Hazop analysis, and others on better maintenance procedures.

Detecting faults as quickly as possible—preferably before an event actually occurs—diagnosing the underlying problem, and providing assistance to plant operations and maintenance to correct the problem are the goals of abnormal situation prevention (ASP) technology. In this article we will discuss improved and earlier detection of potential incidents based on better process and equipment monitoring and analysis with associated assistance to the operator on the correct action to take to overcome the problem. Previous work in this area includes that of the ASM consortium[5] with recent academic work summarized in Venkatasubramanian et al.[6] and discussed also in Young,[7] Henry[8] and Isermann.[9]

The concept behind this work is straightforward. Consider the action of normal process alarming as illustrated in Fig. 2.

The abscissa of the graph is time and the ordinate is severity of a potential abnormal event. The longer an abnormal event goes undetected, the more severe the consequences are likely to be. With standard alarming, when the process variable reaches a region that is outside the normal operating range, an alarm sounds, the operator responds with an action and hopefully the situation returns to normal before the abnormal event becomes severe.

However, if we can find techniques to detect a potential abnormal situation earlier, to "predict" a potential incident, the operator can take action earlier and better avoid the potential consequences of the situation (Fig. 3):

Recent developments permit enhanced computing and communication capabilities to be included in actual field instrumentation. This incorporation allows much higher speed data capture and analysis of this high-speed data. As discussed later, this development yields new insights into process behavior and allows discovery of anomalous conditions not previously detected and earlier prediction of potential abnormal events.

Assessing previous incidents to determine how earlier detection and action might have affected the outcome is, of necessity, subjective and requires engineering judgment. However, many of the events had less severe precursor events or conditions that went undetected, some for long periods. Our review of the Belke and Delguid incident databases[3,4] and potential amelioration indicate that improved process measurements and real-time analysis/detection might have prevented, or at least substantially reduced, the damage from approximately 25% to 40% of these incidents. Examining the CSB database of incidents yields similar conclusions. This is certainly enough to justify serious evaluation of possible technology improvements.

Smart device technology for abnormal situation prevention. "Smart" devices are field instruments with enhanced computing and communication capabilities that permit them to perform situational analysis not previously possible. They also have the advantage of providing the necessary information directly to the control system via digital buses as anomalies develop during process operation, enabling operators to take necessary steps to either prevent an unnecessary shutdown before the problem becomes serious or schedule maintenance on the problematic process unit. More discussion of the smart plant and smart devices is presented in White.[10] Steps for

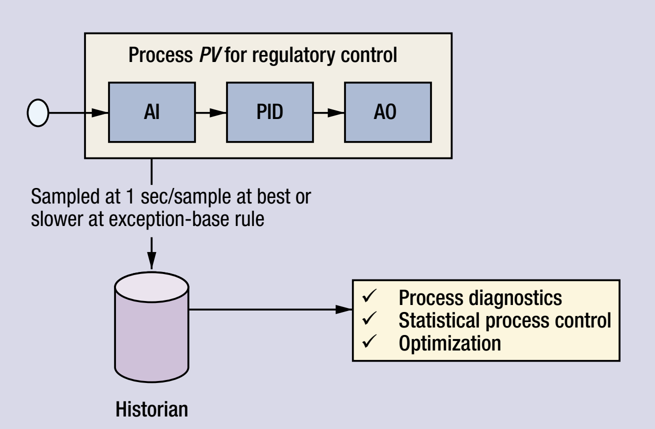

FIG. 5 These advanced software applications typically receive their input from historians.

ASP are shown in Fig. 4. First, there is predicting an impending event. Next, the predicted condition must be sent to the correct organizational unit responsible for corrective action and then assistance should be provided to the individual(s) in determining the proper response.

Traditionally, fault detection has been part of the control system where analysis is done using the data collected by the process historians. There are various reasons for this implementation choice; most important is that the field devices previously could not handle the computations required for fault detection algorithms. However, with the help of the advances in computing and measurement device technologies and advances in communication such as the digital fieldbus technologies, today's smart transmitters are capable of providing much more information regarding the process and its conditions than simply process variable (*PV*) information.

Fig. 5 shows a conventional *PV* and its use in various process diagnostics applications, statistical process control and optimization algorithms. In many process plants, these advanced software applications receive their inputs from historians that may be saved at frequencies from once per minute to at best once per second. Generally historian data are stored when preset change limits are exceeded, which limits its diagnostic usefulness.

Since the field devices include enhanced capabilities for signal processing and data analysis, more and more diagnostics opportunities are becoming available. These new advanced signal processing capabilities at the field device level have proven to be useful for detecting various process operations-related abnormal situations. Data that are used for such diagnostics methods are generally different than the traditional *PV* used for process control. The data generated through these new signal processing capabilities provide insight to fast-changing process behaviors that previously could not be observed simply by looking at the historian-based data.

Recently the advanced information processing capability and the data it generates has been referred to as "diagnostics *PV*," since it was designed to be used for advanced diagnostics and monitoring applications such as ASP.

Fig. 6 shows the diagnostics *PV* that has become available through the "ASP Block" within new smart devices.

Fig. 7 shows a smart *PV* transmitter with some of the questions that can be addressed with the use of diagnostics *PV*.

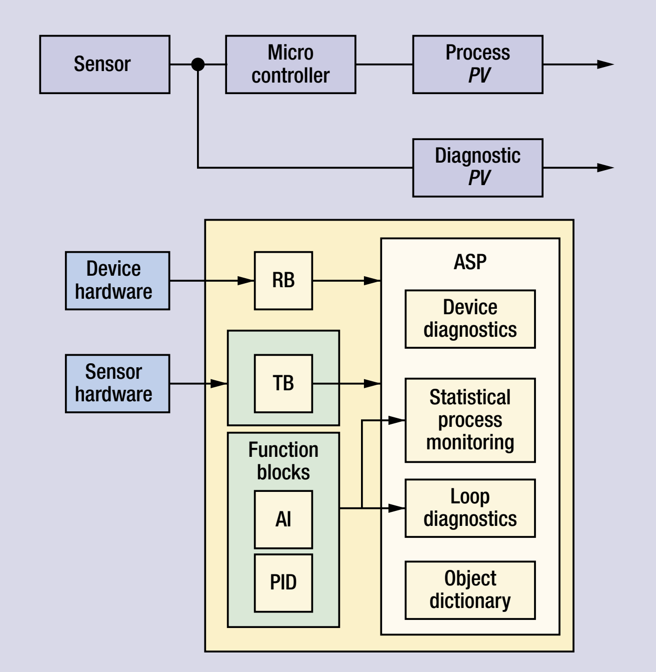

FIG. 6 A diagnostics *PV* is available through the ASP block within smart devices.

Statistical process monitoring (SPM) in smart devices. The abnormal situation prediction method developed and implemented in some of the fieldbus transmitters is a generic process anomaly detection tool called SPM. Many process anomalies can be analyzed and correctly diagnosed by an expert eye or by an expert system where necessary process expertise and possible conditions and rule-base are present.

Process anomalies generally cause a predictable pattern and can be categorized into five distinct patterns. These patterns are common for all sensor types and processes: pressure, temperature, flow, level and others. Using advanced pattern recognition and statistical analysis methods, fieldbus transmitters and smart valves can now detect drift, bias, noise, spike and stuck behaviors of each sensor such as (Fig. 8):

- Drift: sensor/process output changes gradually
- Bias: sensor/process output shows a level change
- Noise: dynamic variation in the sensor/process output is increased
- Spike: sensor/process output is momentarily very high or low
- Stuck: dynamic variation in the sensor/process output is decreased.

The approach and key features of the developed local anomaly detection technology that make it applicable to a broad range of industrial processes are:

- No redundancy in the measurement system is assumed
- No mathematical model of the process is necessary
- No mathematical model of the sensor is required.

The analysis system consists of two phases: learning and monitoring. During the learning phase, normal signal properties such as mean, variance and maximum rate of change are established. These features can be updated when necessary. The signal properties determined in this phase are then used during the monitoring phase to detect possible sensor/process anomalies.

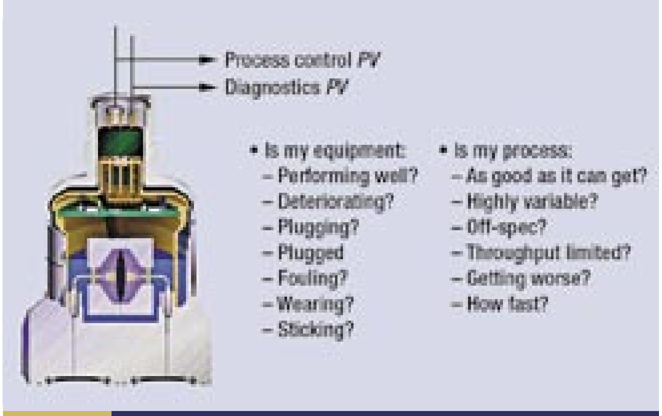

FIG. 7 Many questions can be addressed with the use of diagnostics *PV*.

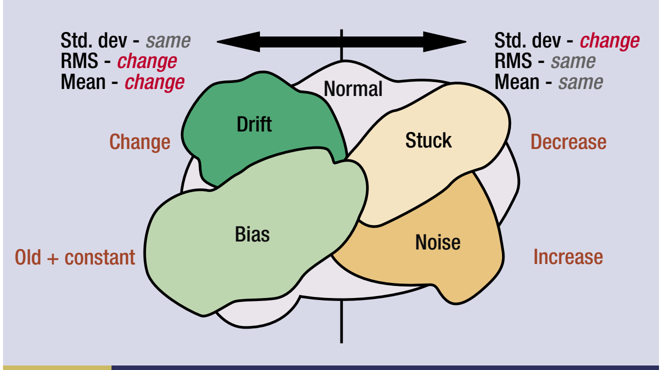

FIG. 9 Many process anomalies can be detected through pattern recognition.

An example of a simple way for extracting information from a signal is analyzing statistical properties of raw data since they are available at a higher rate from the sensor. These statistical values are mean, variance and signal range. They are given by the following expressions:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

$$S^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2$$

$$\Delta R = X_{\max} - X_{\min}$$

where:

$\bar{x}$ is the sample mean
S_2 is the sample variance
S is the standard deviation
N is the total number of points in the sample
ΔR is the range of data points in a sample.

*PV*s, the output of the sensors, are first evaluated as previously mentioned. Statistical parameters and other calculations are used to determine the state of the process. Similar analyses take place throughout the transmitter operation and the data generated are made available continuously to the decision-making system in the DCS. When a discrepancy is detected, operators as well as the decision-making system are informed of the status changes along with the data generated.

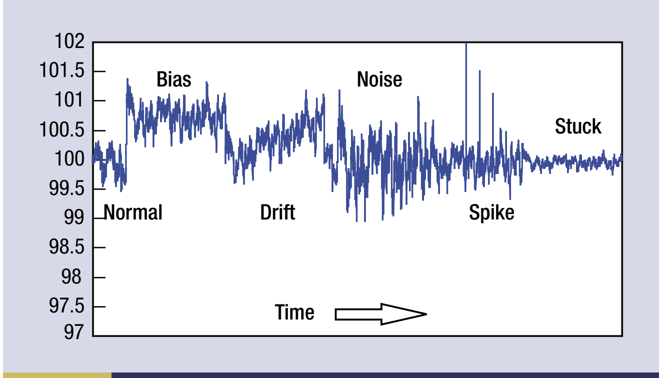

FIG. 8 Fieldbus transmitters and smart valves can detect drift, bias, noise, spike and stuck sensors.

Understanding the dynamics of the process is completely automated in this anomaly detection technology. Parameters that determine the process dynamics are repeatedly verified until process consistency is demonstrated. It is certainly possible that the process can be so erratic that the anomaly detection routines cannot determine a window where the process is stable enough for useful detection. In this case the transmitter will inform the operator appropriately.

Extensive testing and analysis of various operational cases have demonstrated that various process anomalies may be detected with simple pattern recognition algorithms as these conditions start to occur.

The logic behind anomaly detection is represented in Fig. 9. Four of the most common types of anomalies: drift, bias, noise, and stuck are mapped onto four quadrants. Commonalties of these anomalies further divide these four quadrants distinctly into left and right planes. For instance, commonality drift and bias are similar in that standard deviation is constant, while root-mean squared *(RMS)* and mean values change. Similarly, stuck and noise behaviors exhibit varying standard deviation, while the *RMS* and mean values do not change. These characteristic behaviors have been utilized and embedded into smart fieldbus transmitters to predict developing anomalies to warn operators of catastrophic problems.

High-speed data capture and analysis. Although there are cases where using low-speed historian data versus high-speed device data may not make any difference, many process applications have fast-changing noise patterns and the high-speed device data have proven to be beneficial. Ironically, prior to these capabilities available through these new smart fieldbus transmitters, most of the abnormal conditions would have been detected only after they cause considerable damage or disruption to operations. Those who have adopted these technologies as part of their process automation have validated the benefits.[11]

A comparison of high-speed device data and low-speed historian data highlights the potential detection capabilities of these embedded techniques.

The test environment is a controlled air pressure process with an I/P transducer. Using an I/P transducer a noisy pressure process was created and superimposed on top of a 3.5 Hz sine wave. The faulty conditions introduced to the system during the first half of

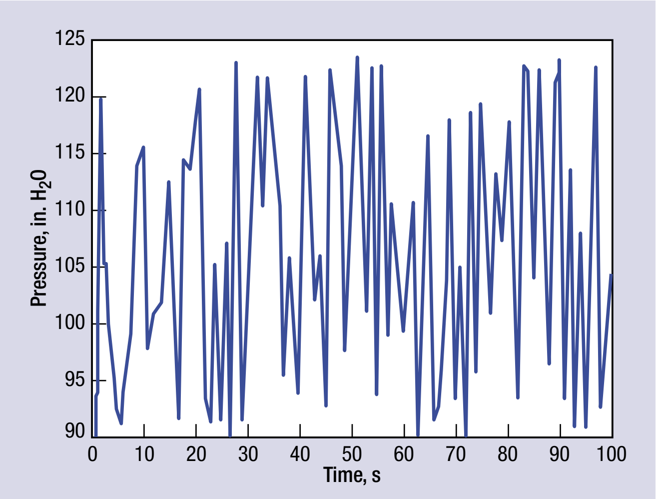

FIG. 10 A one sample/sec rate is typically the best an historian can do.

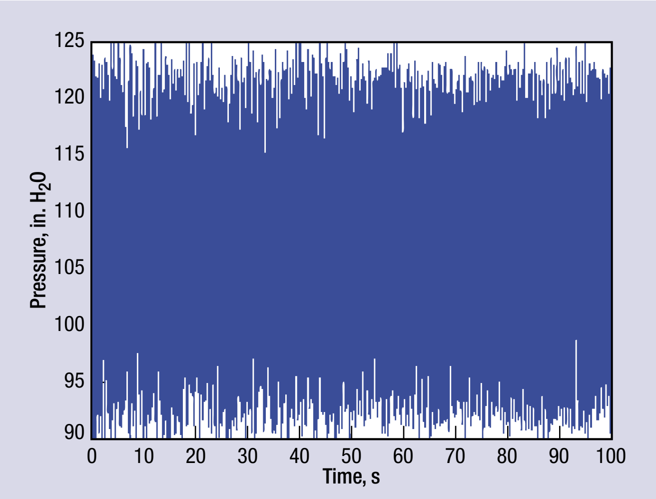

FIG. 11 A fieldbus pressure transmitter can sample process data much quicker.

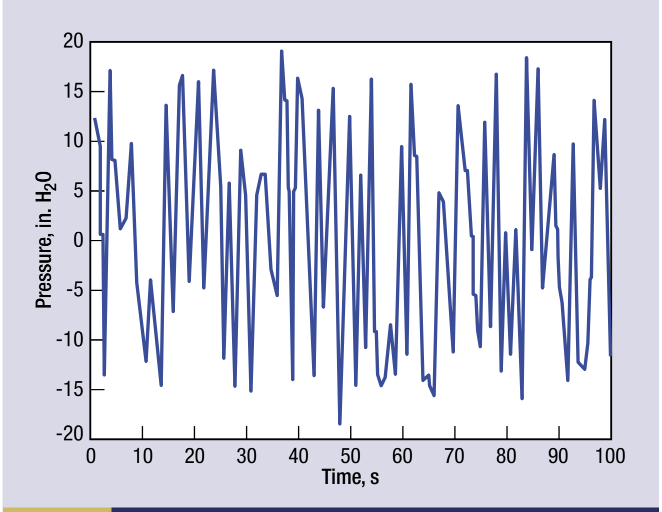

FIG. 12 The fault condition cannot be detected using the low-speed historian data.

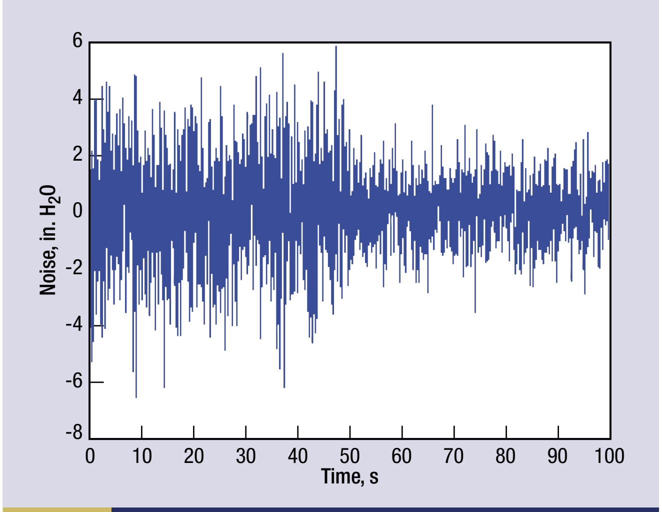

FIG. 13 The fault condition can be detected using the high-speed device data.

the test (0 to 50 seconds) were roughly twice as much as the noise introduced in the second half (50 to 100 seconds) of the test.

During this test the pressure was measured using a fieldbus pressure transmitter with the highest available sampling rate among industrial pressure transmitters with digital bus communication capabilities, and the *PV*s were recorded using an historian at one sample/sec (Fig. 10), a rate that is typically the best that an historian or OPC server can do. Normally historians have preset thresholds for data change and the data are recorded if the thresholds are exceeded, which can make the data even less useful.

Similarly, high-speed device data (Fig. 11) coming from the ASP block of the device were collected through a special data acquisition system to compare the historian-based *PV* to high-speed device data.

As observed in these figures, the process signal seems to be normal during all 100 seconds of the testing. Both historian and device data indicate that the process signal has a mean value around 106 in. H_2O with normal fluctuations, when in fact the first 50 seconds of this data are normal and the second 50 seconds are faulty.

Means and standard deviation calculations for these cases using the historian and device data are given in Table 1. Mean and standard deviations of the first 50 seconds of normal data and the second 50 seconds of faulty data sets are very close and, therefore, cannot be used for fault detection.

To detect process anomalies and changes in a process signal,

TABLE 1. Comparison of process signatures using high- and low-sampled data, all units are inches of water

	High-speed device data			Low-speed historian data		
	Normal 0–50s	Faulty 50–100s	% change	Normal 0–50s	Faulty 50–100s	% change
Mean	106.78	106.84	0.05	105.12	106.84	1.63
STD	11.18	11.10	−0.71	10.56	11.43	8.23
Filtered STD	1.95	0.98	−49.74	10.93	11.06	1.00

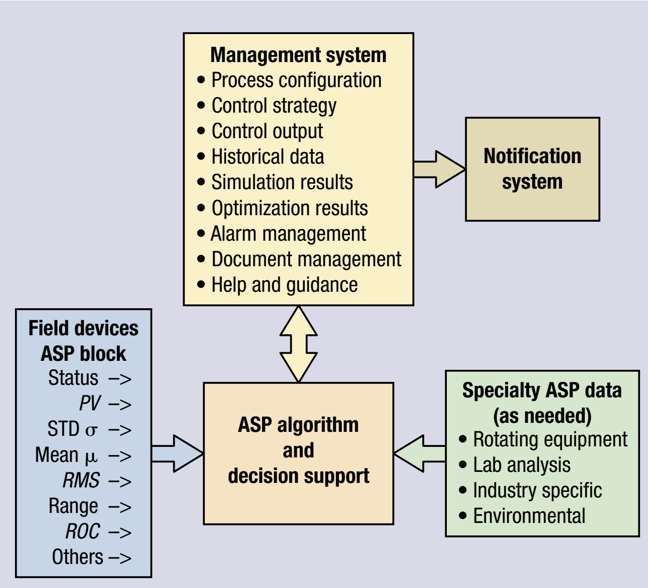

FIG. 14 Detailed functional diagram of ASP.

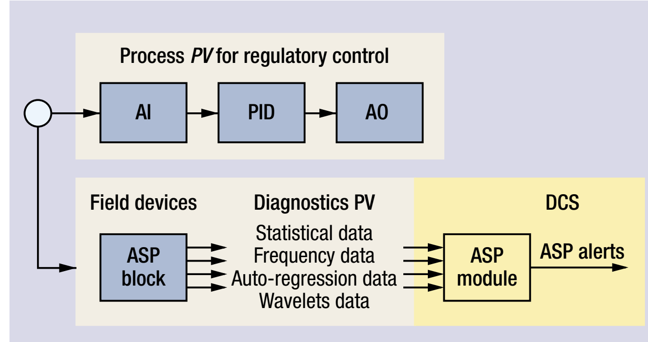

FIG. 15 The ASP block and module are key ASP enablers.

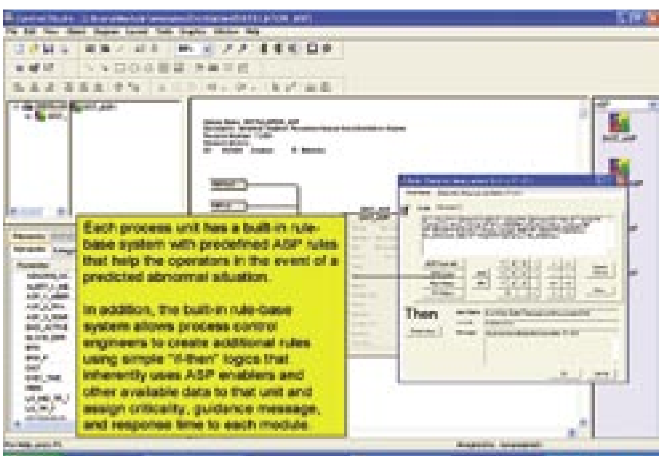

FIG. 16 A rule-base system with predefined ASP rules can help operators in the event of a predicted abnormal situation.

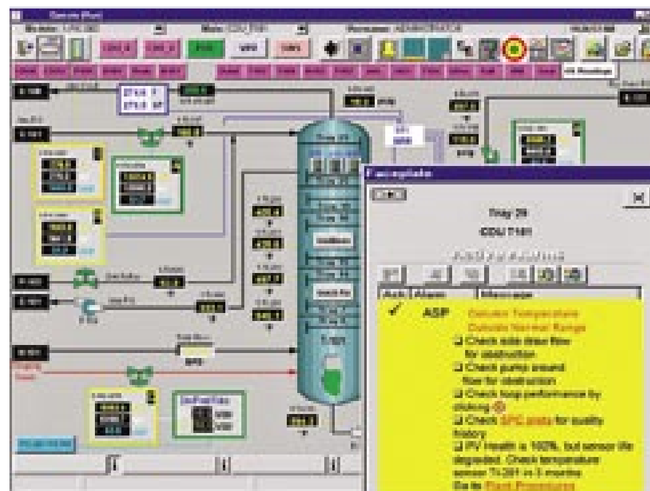

FIG. 17 Along with the ASP alert as much detail as possible is provided on the detected condition.

the slowly varying portion of the signal is generally removed using a digital filter. This filter essentially removes slow trends and transients from the process measurement that indicates load changes, seasonal effects and setpoint changes. This portion of the signal, also referred as the DC portion, is not used for diagnostics and anomaly detection. The faster part, where the high variation of the signal is present, is referred to as the AC part of the signal.

Fig. 12 shows the filtered process signal of the historian data and Fig. 13 the device data of the same process signal as it is filtered within the fieldbus transmitter with ASP block, where the filter is applied to the 4 Hz section of the signal to remove natural process fluctuations introduced by the sine wave.

Comparing Figs. 12 and 13, it is easy to see that the fault condition cannot be detected using the low-speed historian data. However, the same fault condition can easily be detected and observed by using the high-speed device data.

Fig. 12, however, shows that there is almost no change in the signal variation, which is why historian-based analysis systems would miss this type of process anomalies.

Fig. 13 shows that the device can detect the process anomaly, as it is evident from the signal variation that dropped about 50% during the second half of the testing compared to the first half of the testing which represents the normal portion of the process.

Our experiences have shown that most flow processes have content and noise in the DC to 50 Hz range and, therefore, these processes may not be properly diagnosed using a 1 Hz and slower sampling of the historian data.

It is important to highlight that in some processes slow-sampled historian data will be as useful for monitoring and diagnostics capabilities so it may not be too advantageous to have such advanced capabilities within the field devices.

Enabling technologies. Detecting such variations using the field device data and integrating these detection methods with a high-end system, like the ASP module shown in Fig. 14 and a DCS that is designed to take advantage of FOUNDATION fieldbus capabilities, are the primary enablers of ASP.

Some of the ASP-enabling technologies include the FF devices with built-in signal processing capabilities. These support the enhanced data analysis and anomaly detection described in the previous section with embedded online performance diagnostics capabilities of digital positioners and fieldbus transmitter

FIG. 18 The firebox pressure was measured at a rate of 22 Hz.

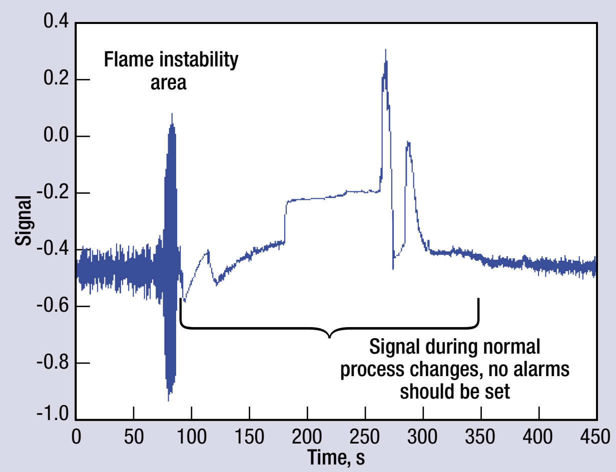

FIG. 19 Flame instability could be predicted from high-frequency variation in the firebox pressure.

that is designed specifically to provide diagnostics on rotating equipment. The smart objects technology from a state-of-the art DCS is the connector between the ASP module and the collaborative diagnostics.

Fig. 15 shows the diagnostics *PV* as generated in the "ASP block" within the fieldbus devices and its use within the ASP module.

Outputs of the ASP block include, but are not limited to, statistical process data obtained using advanced signal processing embedded in the field devices such as:

- Mean, x
- Standard deviation, S
- Root-mean-square, *RMS*
- Rate of change, *ROC*
- A method for spike detection and automatic removal of the spike data from the calculations.

Fig. 16 shows a prototype display of a system with a built-in rule-base system with predefined ASP rules that help the operators in the event of a predicted abnormal situation. In addition, the built-in rule-base system will allow process control engineers to create additional rules using simple "if-then" logic that inherently uses the ASP enablers and other available data to that unit and assign criticality, guidance message and response time to each module.

Once all the loops and units are configured with these smart objects, each of the application modules knows where and how to get the data from the field devices or the ASP modules within loops, subunits and units. Fig. 17 shows an operator user interface. The example depicts an abnormal situation as predicted via the collaborative diagnostics efforts of pressure and temperature devices across the control loops and heater unit, where the temperature transmitter is also indicating that the *PV* health is 100%; however, there is sensor degradation, and recommending a check in three months.

The loops and measurement points highlighted in yellow indicate the locations of the abnormal situations. Even though these conditions have been detected at various levels such as field devices, control loops and subunit levels, only one alert is presented to the operator. The rest are not even shown by the alarm management system since they are related and the corrective actions suggested by the ASP module include necessary steps to mitigate the situation for all of the related indicators.

The ASP alert is presented in a similar fashion and mechanism to the operator. Along with the ASP alert as much detail as possible is provided on the detected condition, with detailed advice on what needs to be done, the correct sequence and embedded links to the specific "plant procedures" as well as links to other embedded applications such as "loop diagnostics and performance" or "SPC plots." These help operators better understand the conditions and assess their impact and take the necessary actions.

Case studies. The ASP technology has been successfully tested on several industrial process units including an FCCU and a process heater. In 2004, ExxonMobil reported using ASP technology to detect anomalies such as plugged impulse lines and catalyst circulation problems.[12] In the latter case, ASP technology was used to detect a change in the reactor standpipe pressure variability. It was found that high-frequency pressure fluctuations revealed when the FCC catalyst bed was about to lose fluidization—30 minutes before conventional measurements identified there was a problem. The company also documented a case where faulty instrument readings were detected due to loss of purge gas and smart transmitter diagnostics were able to properly identify all plugged impulse line tests.

A second test of the technology was recently performed on a major process heater to detect flame instability. Many process plants collect and burn a wide variety of slop oils, vent gases and fuel streams from various process units. Disturbances in any process unit can significantly affect fuel composition and heating value for the process heaters that are burning these streams. For efficient and stable combustion, air flow, draft and atomizing steam must be adjusted to compensate for these changes in composition. Insufficient air, poor mixing, and fuel pressure fluctuations can all lead to unstable flame conditions. If not corrected, flame instability can potentially lead to burner flameout, resulting in an unsafe condition. The test run involved varying fuel Btu content and heater conditions over a wide range to initiate an unstable flame.

The process heater used in this test is shown in Fig. 18 along with the pressure transmitter connected via FF. The firebox pressure was measured with a smart transmitter at a rate of 22 Hz, passed through a high-pass filter and transferred for storage and trending. Special software was used to handle the historization and trending of the high-speed data as well as trigger an alert for the operator.

As shown in Fig. 19, test results showed that flame instability could be predicted from high-frequency variation in the firebox pressure. This high-frequency data collection is best performed by the smart devices themselves with diagnostic signals sent back to the DCS as alerts to the operator. It can be seen from this chart that the sensor was able to correctly identify the flame instability region over a wide range of operating conditions.

Advances in communication and computing, and most particularly the miniaturization of these components, has permitted deploying high-powered computing capabilities in field instrumentation. This deployment enables new analysis and diagnostic algorithms to be implemented based on high-speed data capture. This high-speed data capture and analysis are necessary to detect many process anomalies. **HP**

ACKNOWLEDGEMENT

Revised and updated from an earlier presentation at the NPRA Annual Meeting, San Francisco, March 2005 (Paper AM-05-49).

LITERATURE CITED

[1] Marsh Risk Consulting; "Large Property Damage Losses in the Hydrocarbon Industries, A Thirty Year Review," February, 2001.
[2] US Chemical Safety and Hazards Investigation Board Incidents Reports, www.csb.gov, 2004.
[3] Belke, J. C., "Recurring Causes of Recent Chemical Accidents," htttps://www.denix.osd.mil/denix/Public/Intl/MAPP/Dec99/Belke/belke.html, 1999.
[4] Duguid, I., "Take this Safety Database to Heart," *Chemical Engineering,* July, 2001, pp. 80–84.
[5] Nimmo, I., "Abnormal Situation Management," 1995 NPRA Computer Conference, Paper CC-95-129.
[6] Venkatasubramanian, V., R. Rengaswamy, K. Yin and S. N. Kavuri, "Review of Process Fault Diagnosis—Parts I, II, III," *Computers and Chemical Engineering,* 27(3), 2003, pp. 293–346.
[7] Young, S. K., "Signal Processing in Local Sensor Validation," Report No QUEL 1971/93, University of Oxford, Department of Engineering Science, 1993.
[8] Henry, M. P. and D. W. Clarke, "The Self-Validating Sensor: Rationale, Definition and Examples," Report No QUEL 1978/93, University of Oxford, Department of Engineering Science, 1993.
[9] Isermann, R., "Process Fault Detection Based on Modeling and Estimation," *Automatica,* Vol. 20, No. 4, 1984, pp. 387–404.
[10] White, D. C., "Creating the smart plant," *Hydrocarbon Processing,* October 2003, pp. 41–50.
[11] Refining Center, http://www.emersonprocess.com/solutions/refining/index.asp, 2005.
[12] Szanyi, R., M. Raterman and E. Eryurek, "Diagnostics capabilities of FOUNDATION fieldbus pressure transmitters," *Hydrocarbon Processing,* April 2003, pp. 53 ff.

Evren Eryurek now works for General Electric. He worked for Emerson Process Management when this article was prepared and was the director of PlantWeb technology, responsible for developing and coordinating technologies for PlantWeb across Emerson Process Management divisions. He was a member of the PlantWeb Leadership team and the leader of the PlantWeb Diagnostics Council. Mr. Eryurek has 15 issued patents and over 20 pending patent applications. He is a senior member of ISA and resides in Minneapolis, Minnesota.

Pete Sharpe is a principal consultant for Emerson Process Management's Advanced Applied Technologies team in the Systems and Solutions Division. He holds a BS degree in chemical engineering from the University of Colorado and an MBA from the University of Houston. Mr. Sharpe started as a process engineer for Exxon Chemicals, Baytown, Texas, before joining Setpoint in 1982, later acquired by AspenTech in 1996. Over his 23 years in the industry, he has implemented over 50 projects using a variety of APC and RTO technologies, primarily in the refining and petrochemical industries.

Douglas C. White is vice president, APC Services, for the Process Solutions Division of Emerson Process Management. Previously, he held senior management and technical positions with MDC Technology, Profitpoint Solutions, Aspen Technology and Setpoint. In these positions, he has been responsible for developing and implementing state-of-the-art advanced automation and optimization systems in process plants worldwide and has published more than 40 technical papers on these subjects. He has a BChE from the University of Florida, an MS from California Institute of Technology, and an MA and PhD from Princeton University, all in chemical engineering.