

# CHEMICAL PROCESSING

LEADERSHIP | EXPERTISE | INNOVATION

## Pressure Instrumentation eHandbook



Take the  
**Pressure Off**  
Your Process

# Shouldn't your sole source of data be reliable?

Pressure gauges are often the sole source of data for monitoring and troubleshooting essential equipment such as pumps. But, 40% of gauges have failed or are close to it.\*

Without accurate measurements like suction and discharge pressures, you could be dealing with repeat equipment failures, costly repairs and downtime.

The experts at WIKAI Instrument, LP can help you be more predictive with the right gauges. Learn how. Contact us at [info@wika.com](mailto:info@wika.com) or 1-888-945-2872.



*\*More than 250 WIKAI Instrument Audits*

# Table of Contents

<b>Is Your Process Whispering To You?</b>	<b>4</b>
Pressure transmitter noise can pinpoint process problems	

<b>Think Straight About Orifice Plates</b>	<b>10</b>
Insufficient flow conditioning often undermines measurement accuracy	

<b>Consider Robust Inferential Sensors</b>	<b>12</b>
Easier-to-develop-and-maintain sensors offer significant benefits for chemical processes	

## Ad Index

<b>Wika</b>	<b>2</b>
<a href="http://www.wika.us">www.wika.us</a>	

<b>Emerson</b>	<b>9</b>
<a href="http://www.rosemount.com/fullpotential">www.rosemount.com/fullpotential</a>	

## Product Releases

<b>Emerson Rosemount</b>	<b>3</b>
<a href="http://www.rosemount.com/3051S">www.rosemount.com/3051S</a>	

### Rosemount 3051S Pressure Transmitter

Design improvements enhance long-term stability and lengthen warranty

**EMERSON PROCESS MANAGEMENT** has improved the stability of the Rosemount 3051S Pressure Transmitter to 15 years and lengthened the coverage of the limited warranty to 15 years. Users can benefit from these improvements through extended calibration intervals and better measurement repeatability over time. The new 15-year long term stability specification is the result of a three-year design effort to further optimize the Rosemount 3051S SuperModule sensor platform. A new process isolating diaphragm design and shaping enhancements coupled with new ultra-high precision manufacturing equipment were key to extending the long-term stability of the Rosemount 3051S.

As a result of the improved design, users can achieve 15+ years of process and measurement repeatability over time under installed operating conditions, resulting in improved batch-to-batch quality and reduced process uncertainty. Calibration intervals can be extended to minimize time and costs spent on maintenance and troubleshooting. An extended 15-year limited warranty also is available and is a testament to the overall quality and reliability of the Rosemount 3051S.

Additional information on the Rosemount 3051S can be found at [www.rosemount.com/3051S](http://www.rosemount.com/3051S)



Emerson Process Management • 800-999-9307 • [www.EmersonProcess.com](http://www.EmersonProcess.com)



# Is Your Process Whispering To You?

Pressure transmitter noise can pinpoint process problems

By Roger K. Pihlaja, Emerson Process Management

**SOME SMART** pressure transmitters include built-in diagnostics that can monitor and alarm problems occurring in the process rather than just within the instrument. The best known application of such external-problem diagnostics is detecting impulse-line plugging via differences in the subsonic noise patterns generated between plugged, partially plugged and clear lines. The technique has become well accepted in process automation.

Recent work by Emerson shows that great opportunity exists for spotting many more process problems via acoustic signatures using the latest fast-sampling pressure transmitters. We have evaluated noise phenomena in a range of process equipment at customer sites, university R&D facilities and private laboratories to detect incipient and actual process problems or failures. Of particular interest is work in

1. Catalyst circulation in fluid catalytic crackers;
2. Pulsation-induced measurement error;
3. Coated or plugged multiport pitot-tube (Annubar) flow meters;
4. Coal-pulverizer fan wear (somewhat afield of chemical processes);
5. Distillation column flooding;
6. Furnace/boiler flame instability; and
7. Wet gas flow.

The first four have been proven and are being used in a few chemical plants and elsewhere.

For instance, an Exxon refinery relies on process noise detected by a fast-sampling pressure transmitter to quickly alarm the beginnings of stick-slip catalyst flow in a fluid catalytic cracker. In the past, the automation system's historian was about 30 minutes

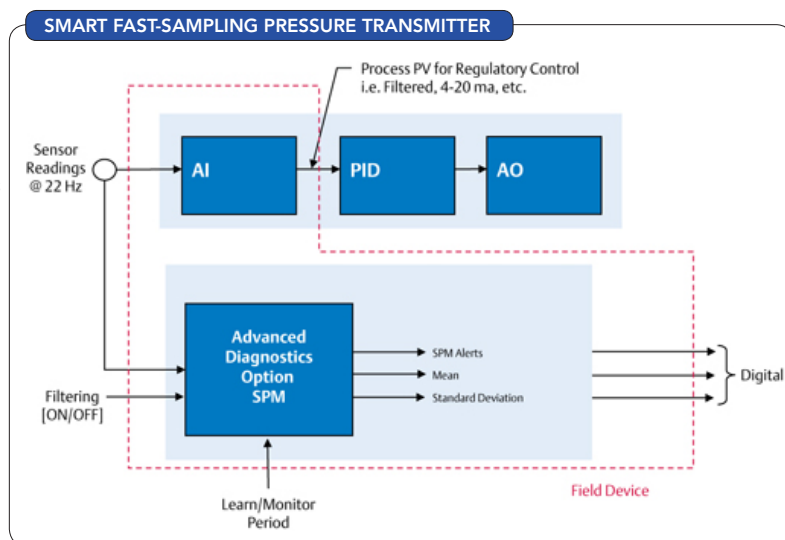


Figure 1. This block diagram shows key elements of a 4–20-mA HART device.

late at conventional regulatory sensor-sampling rates in noting the problem and alarming the tag. This resulted in shutdowns that cost up to \$1 million/day in lost output for up to seven days, plus very expensive equipment repairs. More details on the application are at: [www.emersonprocess.com/rosemount/document/note/00830-0200-4801.pdf](http://www.emersonprocess.com/rosemount/document/note/00830-0200-4801.pdf).

The other three applications are in various stages of advanced development. Less far along is problem detection in aerated liquid flow, agitation, bubbler tank level, process leaks and pump/valve cavitation. Theoretical applications include steam trap failure, turbine blade wear and coating, and wet steam flow.

Today we know what factors must be present for a



reasonable chance of success in both detection and application of process noise to reveal and control process problems.

#### KEY COMPONENT

Vital to detecting problems or failures in process equipment are HART 4–20-mA and Foundation Fieldbus pressure transmitters having fast-sampled (22-Hz) sub-sonic sensor readings (Figure 1). These signals are used two ways: (1) conversion to filtered process variable for regulatory control, and (2) conversion of noise hash into useful acoustic signatures within an on-board advanced diagnostics module based on statistical process control (SPC). Data provided by this module are trailing mean, trailing standard deviation (SD) and calculated coefficient of variation ( $C_v$ ). These three values and the relationships among them — often at particular sensor-reading frequencies — can expose incipient and actual problems before they otherwise would be noted.

The 22-Hz sampling rate is useful for evaluating about 80% of the noise frequencies commonly generated by the large and heavy equipment and relatively slow events found in processes. Unfortunately, per the Nyquist sampling theorem, frequencies from 0 to 11 Hz (22 Hz halved) are the only ones available for evaluation. Above 11 Hz, frequency aliasing leads to garbled information.

#### HELPFUL NOISE

Table 1 lists sources of process noise found useful thus far. Of these, turbulence is most common. Such sources probably are self-evident, except perhaps for burner flame instability, which indicates incorrect air/fuel ratio or impending flame-out in furnaces and boilers.

Trying to identify the source or sources of noise at the beginning of a smart pressure transmitter problem-sensing application project is helpful. However, rigorous

#### SOURCES OF TRANSMITTER NOISE

##### Turbulence

- Primary  $\Delta P$  sensing elements
- Pipe fittings and valves

##### Mechanical Equipment

- Agitators
- Pumps and fans
- Other rotating equipment
- Various process equipment

##### Gas Entrainment

##### Chemical Reactions

- Flame stability

##### Phase Change

- Subcooled nucleate boiling
- Steam hammer
- Cavitation
- Condensation

##### Phase Inversion

- Distillation column flooding
- Particulate solid bed fluidization
- Packed bed breakthrough

##### Flow Path Change

- Fouling or coating
- Flow channel swelling, shrinking or blocking
- Sudden expansion or contraction of flow channel
- Valve throttling
- Leakage
- Water hammer

analysis isn't worth the time and effort. For example, noise reflected off internal surfaces can alternately reinforce or cancel itself out, depending upon conditions,





thereby confusing analyses. Also, the more viscous a fluid is, the more it absorbs sound, which makes transmitter or testing equipment placement a guessing game.

It's best to attempt to identify generally expected trends of what the signal source is doing at any one time versus what the process is doing then or might do later. Detecting an incipient problem or failure is the ultimate goal. Thinking ahead helps speed the development of a testable hypothesis that can be instrumented-up and trended during normal and abnormal operations. It's all quite empirical.

Three signal phenomena deserve particular attention.

Most obvious is a signal that gets stronger or weaker because of an abnormal situation. Impulse line plugging and distillation column flooding (discussed later) fall into this category. The faster the change occurs, the more positive the detection.

Second is where signal strength fluctuates more (or less) during abnormal conditions. Changes in mean and SD make those occurrences stand out graphically.

Less obvious is where the diagnostic signal is simply background process noise, such as from a pump or blower, and of no value of itself. Process-problem detection occurs when this signal, as it passes through a piece of process equipment, is attenuated or amplified during an abnormal situation. Noteworthy examples include: fouling in a heat exchanger and water absorption in a molecular sieve dryer (a swelling sieve changes the flow channel, which muffles the background noise).

### BEST PRACTICES

In addition to trying to identify the source or sources of process-generated noise, an engineer should evaluate the physics of the noise through statistical manipulation to help develop a testable hypothesis.

For instance, in a fluid flow situation it's useful to know what the physics of the fluid are (its Reynolds

### RELATED CONTENT ON CHEMICALPROCESSING.COM

"Technology Targets Towers", [www.ChemicalProcessing.com/articles/2009/075/](http://www.ChemicalProcessing.com/articles/2009/075/)

"Diagnostics Dig Deeper", [www.ChemicalProcessing.com/articles/2007/129/](http://www.ChemicalProcessing.com/articles/2007/129/)

"Plants Smarten Up", [www.ChemicalProcessing.com/articles/2006/077/](http://www.ChemicalProcessing.com/articles/2006/077/)

Number (Re), viscosity, density, etc.), and their impact on noise creation, propagation and suppression — and therefore on transmitter positioning. The same can be said about the effects — good or bad — of orifice plates, venturis, valves and other substantial noise generators.

As a statistical example, a higher flow rate equals higher Re, equals higher turbulence, equals higher SD. Frequently, the SD increases and decreases quite linearly with flow rate. Dividing the SD by the mean (which gives the  $C_v$ ), in effect, filters the SD by providing a  $C_v$  trend curve that stays relatively level compared to a rising and falling SD trend (Figure 2). Under abnormal conditions, the typically abrupt change in the  $C_v$  trend is often the most easily detected and alarmed.

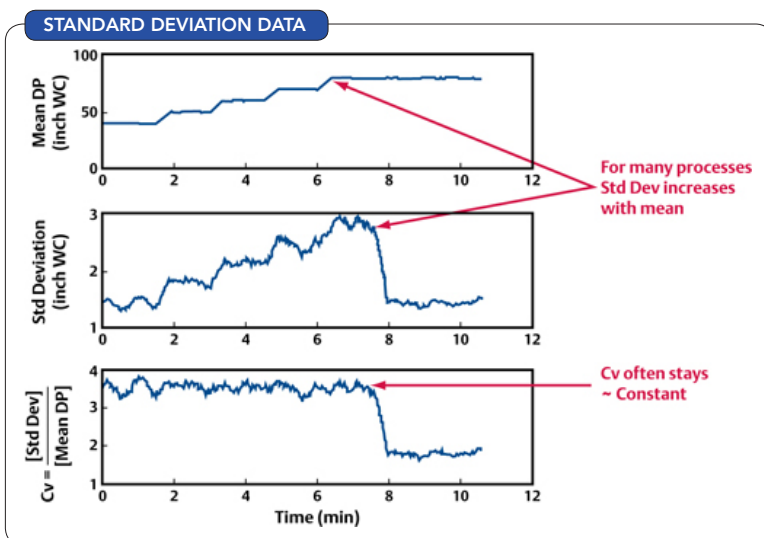


Figure 2. The  $C_v$  trace often provides a better basis for alarming against abnormal situations.



The transmitter, of course, should be located close to the expected diagnostic signal source and far from interfering signal sources. Its impulse lines should be short and purged often. Once the transmitter is in service, it's important to check whether new or intermittently operating process equipment generate noise in the 0–11 Hz range. If so, the transmitter may need retuning for proper operation.

Many more suggestions, tips, do's and don'ts, and the like gained from practical experience exist — more than can be covered in a short article.

### COLUMN FLOODING

Let's now look at some of the thought processes in recent work to spot distillation column flooding.

A smart  $\Delta P$  transmitter used to monitor and control upward vapor flow in the rectification section of a packed distillation column also can serve to detect and alarm, via its noise signature, incipient flooding in that section (Figure 3). The diagnostic technique was developed and proven on a pilot-plant column of the Separations Research Program at the University of Texas at Austin. (See: "Technology Targets Towers," [www.ChemicalProcessing.com/articles/2009/075/](http://www.ChemicalProcessing.com/articles/2009/075/)) It hasn't yet been applied to a full-size tower.

When operating normally in the section's continuous phase, droplets of distilled product fall through the packing while vapor flows upward. Increasing vapor flow creates an aerodynamic drag on the droplets. If drag becomes excessive, the drops can't fall and flooding begins.

Eventually a complete phase inversion occurs; the void space is flooded entirely with a combination of liquid and entrained vapor bubbles being forced up through the liquid. In due course the transmitter's regulatory function would sense a substantial increase in  $\Delta P$  due to flooding throughout and trigger an alarm — but much too late.

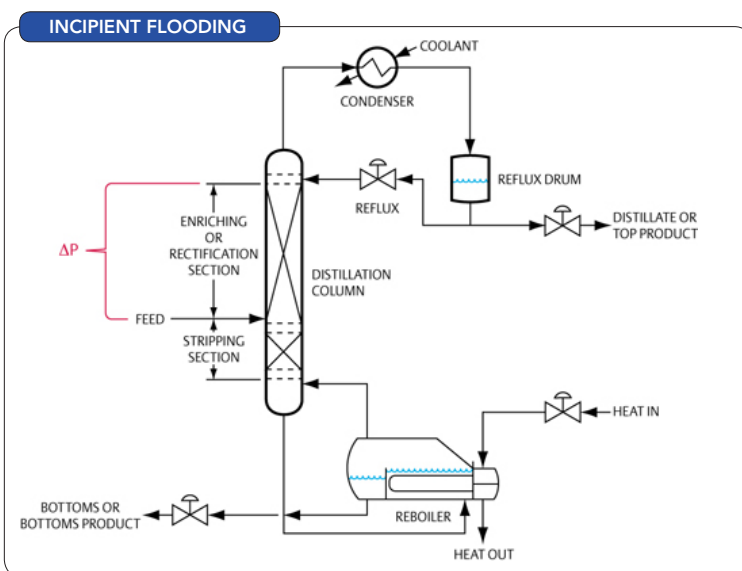


Figure 3. Smart pressure transmitter can quickly detect flooding in rectification section.

The transmitter's diagnostics are configured to detect a change in the emitted noise pattern from the flooded packing caused by the sound of the bubbles randomly nucleating, growing and breaking — not unlike the noise of a carbonated drink.

Figure 4 shows a SD curve of the transmitter's bubble noise signal, modified by an SPC differencing filter, that indicates a relatively sharp increase before settling at a higher level. The one-minute trailing trace is the most graphic indication of the beginning of flooding and the ideal parameter to alarm.

A power spectral density analysis can refine the sensing technique and check possible interference with the transmitter's regulatory function. Figure 5 shows bubble noise during normal and flooded conditions. Note that from 4 to 11 Hz the normal trace runs as





#### POWER SPECTRAL DENSITY

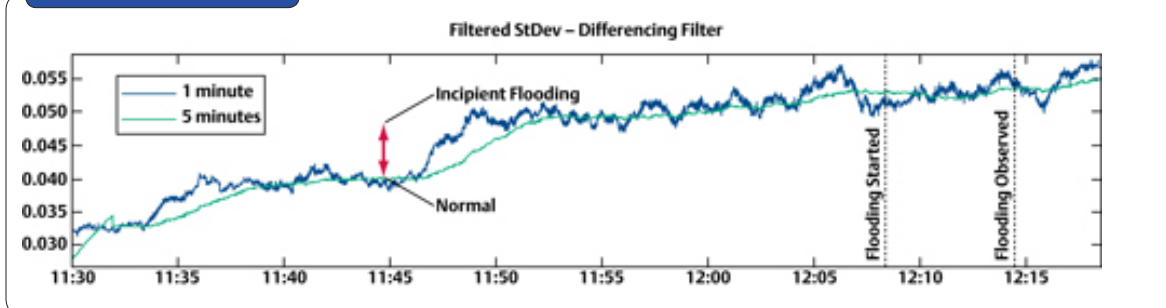


Figure 4. SD curve response at 11:45 indicates start of flooding.

#### POWER SPECTRAL DENSITY ANALYSIS

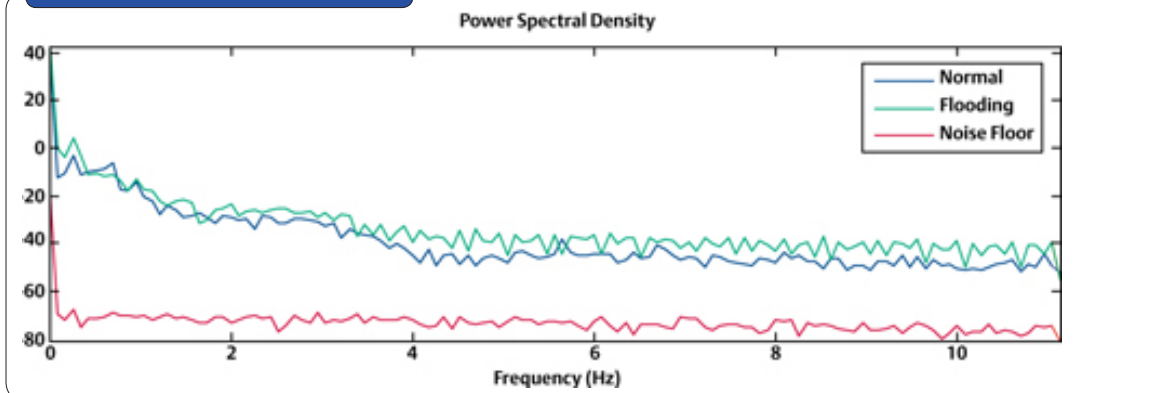


Figure 5. Biggest difference between flooding and normal noise occurs at 4–11 Hz.

much as 10 db quieter than the flooded one, making that range best for flooding detection. Also note that the two traces are quite flat and unspiked, indicating they are “weak white noise,” i.e., noise that minimally affects the accuracy, reliability and repeatability of the regulatory signal.

#### LISTEN TO YOUR PROCESS

Smart fast-sampling pressure transmitters can break apart what appears to be random process noise. What’s discovered within that noise can identify

process problems. While I highlighted early detection of distillation column flooding, a variety of potential applications exist. Each differs in its own way. Additional statistical analysis methods can manipulate process signals to tease out otherwise unknown phenomena and also to establish trailing-mean learn/monitor periods to give the most consistent results. ●

ROGER K. PIHLAJA is principal engineer — process diagnostics for Rosemount, Emerson Process Management, Chanhassen, MN. E-mail him at [Roger.Pihlaja@Emerson.com](mailto:Roger.Pihlaja@Emerson.com).





I get measured on hitting my production targets. I need to get more out of my assets so I can meet my performance goals.

# YOU CAN DO THAT

**ROSEMOUNT®** Discover new efficiencies and achieve unmatched throughput with **Rosemount® instrumentation**. Turn to Emerson measurement experts and Rosemount instrumentation to get more production out of your current equipment, maintain a smarter workflow and operate at your full potential. Our specialists will show you how to use stable, accurate instruments to minimize measurement drift and confidently run your facility as close as possible to critical levels. And with intuitive diagnostic tools and wireless transmitters, you can gather more detailed insights into the health of your entire process without adding infrastructure, so you can stay optimized longer and avoid downtime. To learn how Emerson can help you hit your production targets and maximize the capacity of your assets with measurement instrumentation, see case studies at [Rosemount.com/fullpotential](http://Rosemount.com/fullpotential)



View video with our  
take on efficiency.



**EMERSON™**  
Process Management

The Emerson logo is a trademark and a service mark of Emerson Electric Co. © 2013 Emerson Electric Co.

**EMERSON. CONSIDER IT SOLVED.™**



# Think Straight About Orifice Plates

Insufficient flow conditioning often undermines measurement accuracy

By Andrew Soley, Contributing Editor

**PLANTS FREQUENTLY** rely on differential pressure created by an obstruction in a line to measure flow. Accuracy depends upon two factors: the correctness of the differential pressure measurement obtained via taps upstream and downstream, and the calculation for turning that measurement into a flow rate.

The obstruction placed in the line most often is an orifice plate — a flat plate with a machined orifice. (For more on orifice plates, see: “Remember the Old Reliable Orifice Plate,” [www.ChemicalProcessing.com/articles/2006/132/](http://www.ChemicalProcessing.com/articles/2006/132/); for other differential-pressure flow metering options, see: “Look Beyond Orifice Plates,” [www.ChemicalProcessing.com/articles/2008/253/](http://www.ChemicalProcessing.com/articles/2008/253/).) Orifice plates are cheap and reliable. Moreover, orifice plates manufactured to specific dimensions and tolerances generate known pressure drops for a given flow rate. The International Standards Organization (ISO) has summarized

the dimensional criteria; all reputable orifice-plate manufacturers meet these standards.

ISO standards also cover installation requirements. Proper installation plays a crucial role in achieving accurate orifice-plate measurements. The major criteria include a stable flow pattern, a fluid-filled pipe and an unobstructed flow path (no blockages). If these criteria are met, flow meter calculations can be based on the physical dimensions of the system; no in-place measurement or calibration is required.

Let’s look in detail at the first requirement, a stable flow pattern. An oft-repeated rule of thumb states that a length of straight-run pipe equal to 10–15 piping diameters creates a sufficiently stable flow pattern. How does this compare to the ISO standards?

The ISO standards include multiple upstream piping configurations — from fully open full-bore valves upstream and downstream to multiple right-angle

## ISO INSTALLATION REQUIREMENTS

UPSTREAM CONFIGURATION	β VALUE						
	<0.32	0.45	0.55	0.63	0.70	0.77	0.84
Fully open, full-bore valve	12	12	13	16	20	27	38
Two right-angle bends in same plane, Two or three bends at right angles with straightening vanes	15	18	22	28	36	46	57
Two or three bends at right angles, Flow branch	35	38	44	52	63	76	89
Fully open globe valve	18	20	23	27	32	40	49
Single right-angle bend	10	13	16	22	29	44	56

Table 1. Required number of pipe diameters in upstream straight run generally decreases with β value.

turns to tee-branch connections. They also detail for multiple values of  $\beta$  — the orifice diameter/pipe diameter, in consistent units — the length of straight-run piping required (Table 1). In general, the lower the  $\beta$ , the shorter the pipe run necessary. During piping design, the final  $\beta$  ratio is unknown. So, many engineering standards attempt to reduce overall cost by specifying a maximum  $\beta$  of 0.55 to 0.63.

The best cases are fully open full-bore valves with a straight run upstream of them, and a single right-angle bend upstream. The required piping runs for a 0.55  $\beta$  are 13 diameters for the full-bore valves and 16 diameters for the single right-angle bend. Every other configuration is worse — in some cases, much worse. Higher  $\beta$  values increase upstream requirements.

For two 90° bends in series, an orifice with a 0.55  $\beta$  requires 44 diameters of upstream piping to meet ISO standards. Even with properly installed straightening vanes, this layout needs 22 diameters. A  $\beta$  of 0.84 raises the requirement to 40+ diameters for all types of installations.

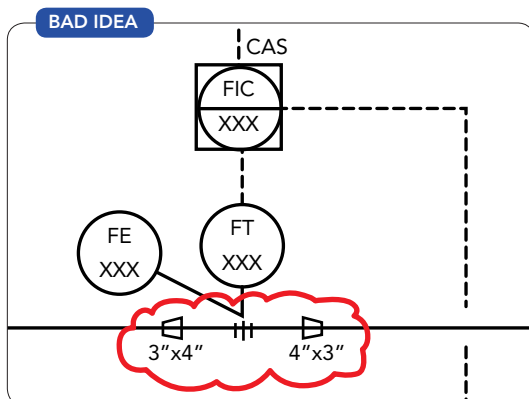


Figure 1. Installing a short section of larger diameter pipe would create flow pattern with unknown impact on meter.

## RELATED CONTENT ON CHEMICALPROCESSING.COM

“Remember the Old Reliable Orifice Plate,” [www.ChemicalProcessing.com/articles/2006/132/](http://www.ChemicalProcessing.com/articles/2006/132/)  
 “Look Beyond Orifice Plates,” [www.ChemicalProcessing.com/articles/2008/253/](http://www.ChemicalProcessing.com/articles/2008/253/)

What this all means is that if your plant needs maximum accuracy, use lots of pipe run upstream of orifice plates. In some cases, 90 diameters are necessary. Additionally, if you’re having flow meter problems, check the installation. I’ve observed many orifice meters inside process units that don’t meet ISO standards. The 10–15-diameters rule only applies to a “best case” — i.e., everything else is done correctly and a low- $\beta$  orifice plate is installed. Most industrial installations require 20+ diameters. Using straightening vanes can help, but doesn’t completely solve the problem. The toughest installations are downstream of flow branches and where multiple elbows in series are at right angles to each other. To paraphrase a quote from pump installation guidelines, the only thing worse than one elbow upstream of a flow orifice is two elbows.

While a plant may start with low- $\beta$  orifice plates, as hydraulics become tighter it may put in new plates with lower pressure drops (and higher  $\beta$  values). Installing a short run of larger diameter pipe doesn’t solve the problem (Figure 1). The upstream expansion creates a flow pattern with unknown effect on the orifice meter.

If the piping configuration doesn’t meet ISO standards, accuracy will suffer. For monitoring unit trends, reduced accuracy may be an acceptable tradeoff for a cheaper meter installation. For high and reliable accuracy, always follow the ISO requirements. ●

**ANDREW SLOLEY**, Contributing Editor  
 ASloley@putman.net





## Consider Robust Inferential Sensors

Easier-to-develop-and-maintain sensors offer significant benefits for chemical processes

By Arthur Kordon, Kordon Consulting, LLC; and Leo Chiang, Zdravko Stefanov and Ivan Castillo, The Dow Chemical Company

**SOME CRITICAL** parameters (composition, molecular distribution, density, viscosity, etc.) in chemical processes are not measured online. Instead, their values are determined either by laboratory samples or offline analysis. However, for process monitoring and quality supervision, the very slow response time of these relatively low frequency measurements (taken every several hours or even days) may cause loss of production due to poor quality control. In situations with potential for alarm showers, lack of critical parameters available online could result in a significant negative impact and eventually could lead to shutdowns. One of the approaches to address this issue is through development and installation of expensive hardware online analyzers. Another solution is to use soft or inferential sensors that deduce the critical parameters from easy-to-measure variables such as temperatures, pressures and flows.

Reference 1 describes the current state of the art of inferential sensors. At a very general level, the sensors fall into two different classes — model-driven and data-driven. Model-driven sensors are developed based on first-principles models, which can be costly and require deep process knowledge. Data-driven sensors are developed based on empirical models derived from plant data. The majority of applied inferential sensors are data-driven.

The data-driven sensor model-development process consists of data gathering, preprocessing, variable selection, model structure design (nonlinear or linear), and model validation. Once the inferential sensor is deployed, model maintenance mechanisms such as diag-

nosis of under-prediction are desirable for quickly tuning the model's parameters or troubleshooting the process.

Several empirical modeling methods are used to extract relevant information from historical manufacturing data to develop inferential sensors. In the case of linear relationships between process and quality variables, multivariate statistical regression models such as partial least squares (PLS) can serve to find these empirical correlations. When dealing with high-dimensional data, a successful variable-selection procedure will improve the interpretation and identification of the underlying process conditions. Reference 2 provides an extensive review of PLS-based variable-selection methods that are effective in an industrial context. An important advantage of PLS is its capability of providing diagnosis where changes in operating conditions and faulty situations can be detected and utilized during the deployment stage.

Since the early 1990s, a more generic approach that captures nonlinear relationships based on artificial neural networks has been used. Neural networks are black-box empirical models designed by mimicking the human nervous system. They have several features that are very appropriate for inferential sensors' design, such as universal approximation, models are developed by learning from data and can be implemented online.

Due to these features, many applied inferential sensors are based on neural networks. However, neural networks have some limitations, such as low performance outside the ranges of process inputs used for model development. Model development



and maintenance require specialized training — and frequent retraining, which significantly increases the maintenance cost. In addition, model deployment demands specialized run-time licenses.

An alternative technology — the robust inferential sensor — has been under development at The Dow Chemical Company since 1997. It is based on genetic programming and resolves most of the issues of neural-network-based inferential sensors. The robust inferential sensors are in the form of explicit algebraic equations automatically generated with an optimal tradeoff between accurate predictions and simple expressions. As a result, they offer more robust performance in the face of minor process changes. Dow facilities, such as the Pittsburg, Calif., plant pictured above, are gaining significant benefits from robust inferential sensors. Reference 3 gives a detailed description of the technology. That paper is based mostly on the experience of applying robust inferential sensors at Dow.

#### IMPORTANT ADVANTAGES

Robust inferential sensors provide both economic and technical benefits.

From an economic standpoint:

- Inferential sensors allow tighter control of the most critical parameters for final product quality and, as a result, enable significant improvement in product consistency.
- Online estimates of critical parameters reduce process upsets through early detection of problems.
- The sensors improve working conditions by decreasing or eliminating laboratory measurements in a dangerous environment.
- Very often such sensors provide optimum economics. Their development and maintenance cost is much lower than that of first-principles models and less than the cost of buying and maintaining hardware sensors.

- Inferential sensors can be used not only for estimating parameters but also for running “what-if” scenarios in production planning.

In addition, compared to competitive inferential sensors based on other data-driven methods such as neural networks or multivariate statistical regression, robust inferential sensors provide a variety of technical advantages:

*Better prediction outside the model development range.* A key issue for neural networks is that they cannot extrapolate outside the range of the data from which they have been trained. Robust inferential sensors with the optimal complexity of their models resolve this problem. In principle, simple models and smooth functions generalize better than complex highly nonlinear models. A second-order polynomial generalizes better than a 15th-order polynomial, which usually captures noise instead of a functional relationship. Based on several implemented cases, selecting models with proper complexity and smoothness can enable reliable performance at 20–25% outside the model development range [3].

*Non-black-box models.* Most production engineers dislike black boxes and are very reluctant to implement them for process monitoring and control. This is one of the reasons why neural-network inferential sensors have not been accepted on a mass scale. Robust inferential sensors are based on explicit algebraic equations, which are more acceptable to users in manufacturing.

*Predictions based on an ensemble of models.* It often is preferable to develop an inferential sensor that does not rely on a single model but instead on an ensemble of models, with the average of the various models used as the final prediction. One advantage of using an ensemble sensor is that the standard deviation of the different models in the ensemble can serve as a model disagreement measure. Another advantage is that the



ensemble enables redundancy. Because inferential sensors mainly are used in processing conditions, frequently one or more of the instruments measuring the input variables may fail. If the ensemble consists of models with different input variables, another model available in the ensemble still can predict.

*Greater suitability for process control and optimization.* Equation-based empirical models can be optimized explicitly and their responses and sensitivities to the inputs can be obtained by applying mathematical operators over the equations. This analytical predictability means that inferential sensors pose less risk than black-box-based models for closed-loop control.

#### APPLICATION AREAS

Industry rapidly realized the economic and technical benefits of inferential sensors. From the early 1990s on, vendors and articles in the literature have reported a spectacular record of successful applications.

Environmental emission monitoring epitomizes the role inferential sensors can play. Traditionally, analytical instruments with high maintenance costs perform such monitoring. The inferential sensor alternative, implemented as a classical neural network, is much cheaper and provides accuracy acceptable for federal, state and local regulations in the United States and the European Union. Process variables enable inferring the level of  $\text{NO}_x$  emissions in burners, heaters, incinerators, etc.

One of the first popular applications of inferential sensors was for estimating product composition in distillation columns. However, the most widespread implementation in the chemical industry is for predicting polymer quality. Several polymer quality parameters, such as melt index, polymerization rate and conversion, are deduced from reactor temperature, jacket inlet and outlet temperatures, and the coolant flow rate through the jacket. Of special interest is the nonlinear controller developed by Rockwell Automation, called

Process Perfecter, that optimizes the transition between different polymer products.

Using inferential sensors for troubleshooting and closed-loop control has become a growing trend in the chemical industry. Today, to cope with rapid changes in demand for particular products, many plants strive for greater flexibility to operate at different production rates and grades. This brings new problems (e.g., increases in maintenance costs, unplanned shutdowns and final product quality deviations) — ones that inferential sensors can solve. For instance, Dow AgroSciences used a soft sensor to rid a herbicide product of an undesirable component, which had started appearing recently but was not present in previous production lots. The soft sensor helped identify the main variables that can predict this undesirable component and then can drill down to the root cause to eliminate it. Furthermore, operating in closed-loop control allows plants to be more flexible. However, the sampling rate used for analytical measurements is not fast enough for most control implementations — inferential sensors are the answer.

Such sensors fill the growing need in industry for sophisticated nonlinear models of process quality parameters. A number of well-established vendors, such as Rockwell Automation, Aspen Technology, Siemens and Honeywell, already have implemented thousands of inferential sensors in a wide variety of industries. The benefit from improved quality and reduced process upsets is estimated in the hundreds of millions of dollars but the potential market is much bigger.

#### SUCCESS STORIES

Let's now look at two examples of their successful application at Dow.

*Distillation tower control.* Obtaining an accurate and fast prediction of a process quality variable (in this case, propylene concentration) can enable better control of a distillation column. The current analyti-



cal technique allows measurement of propylene every 10 minutes, which is not sufficient for control purposes. So, Dow turned to a robust inferential sensor that provides a prediction of propylene concentration every minute.

An ensemble of equation-based models has been derived on a genetic programming toolbox developed internally at Dow. The key criterion for model selection was an optimal balance between performance and low complexity. Satisfying the requirement for robustness to measurement faults favors models with different inputs. This led to the selection of the following three nonlinear models:

$$f1 = a + b \frac{x_8^2 x_{21}^3}{x_4} \quad (1)$$

$$f2 = a + b \frac{x_8^2 x_6^3}{x_4^2} \quad (2)$$

$$f3 = a + b \frac{x_6^2 x_8^4 x_{21}^2}{x_4^3 x_{18}^2} \quad (3)$$

where  $f$  is the predicted propylene concentration from each model and the  $x$ s are the corresponding candidate inputs, such as temperatures, pressures and flows. The models are simple and interpretable by process engineers. The different model inputs increase the robustness of the estimation scheme in case of possible input sensor failure. The model disagreement indicator is the standard deviation of the three models and a critical limit was defined to quantify the effect.

**$NO_x$  emissions monitoring.** Another successful application is for  $NO_x$  emission monitoring of two gas turbines, GT1 and GT2. The turbines operate on variety of fuels, including hydrogen and offgas. In 2004, using the genetic programming toolbox, Dow specialists developed robust inferential sensors

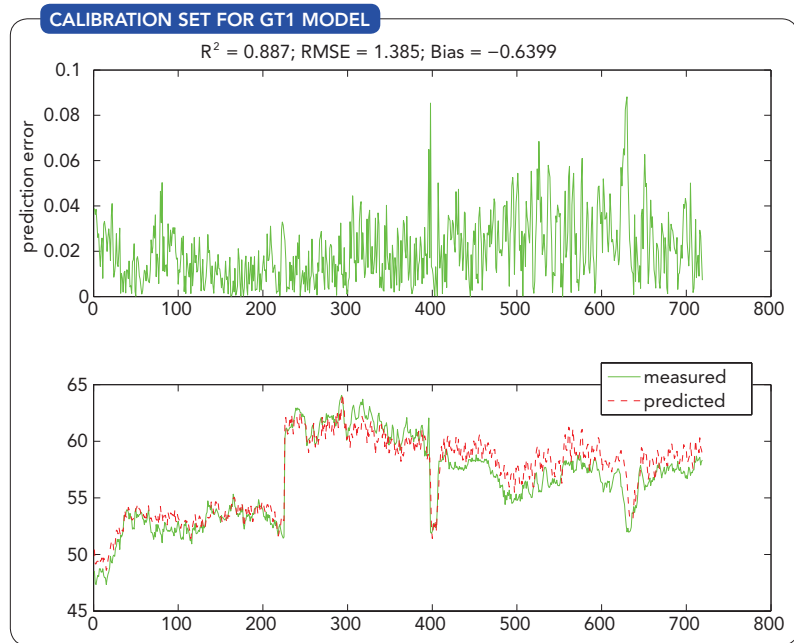


Figure 1. Predictions from model closely matched measured values.

for both turbines. Figures 1 and 2 illustrate the performance of the initial model for GT1. The initial models identified for GT1 and GT2 were:

$$NO_{x_{GT1}} = a_0 + a_1 \frac{a_2 p_2 - x_{12}}{x_3^2 + x_{12}} \quad (4)$$

$$NO_{x_{GT2}} = a_0 + a_1 x_3^2 + a_2 x_{12} + a_3 p_2 \quad (5)$$

where the inputs are process variables, such as steam injection flow, megawatts and offgas mass flow.

Analysis of the two models showed they behaved similarly in the window of operating conditions; so, the simpler formula (5) was fit for both turbines. This is another indication of the superiority of robust inferential sensors, i.e., being analytical functions and the consequent possibility for simplification and superior



model-structure selection.

The sensors have performed excellently. During ten years of operation, they passed relative accuracy test audits (RATAs) annually (the longest period allowed by law) with the single exception of a 6-month schedule case. To achieve an annual schedule, a sensor must pass with better than 7.5% relative accuracy. Both turbines were mechanically rebuilt in 2008; the models still passed RATA with annual schedule without the need to fit a different model structure.

## LIMITATIONS

A robust inferential sensor is not a “silver bullet” for all problems. Like any technique, it has limitations. The most important of these are:

*Requirement for high-quality process data.* The quality of the inferential sensor’s modeling process strongly depends on the quality of the available data. Of special importance is providing suitably wide ranges for both input and output variables. The data should capture the full range of operating conditions — otherwise the empirical model is pushed into extrapolation mode, which always is unreliable with any technique.

*Limited value for significant process changes.* The sensor only can handle minor process changes based on drifts in the operating conditions approximately 20% outside the range of model development. If the process experiences significant changes, such as introduction of a new control system, unit redesign or new type of product, the inferential sensor will not perform adequately under the new conditions; a new model development process is recommended.

*Need for periodic readjustment.* Just as any hardware sensor demands periodic calibration, the robust inferential sensor needs periodic readjustment. Usually, the procedure requires refitting the modeling parameters

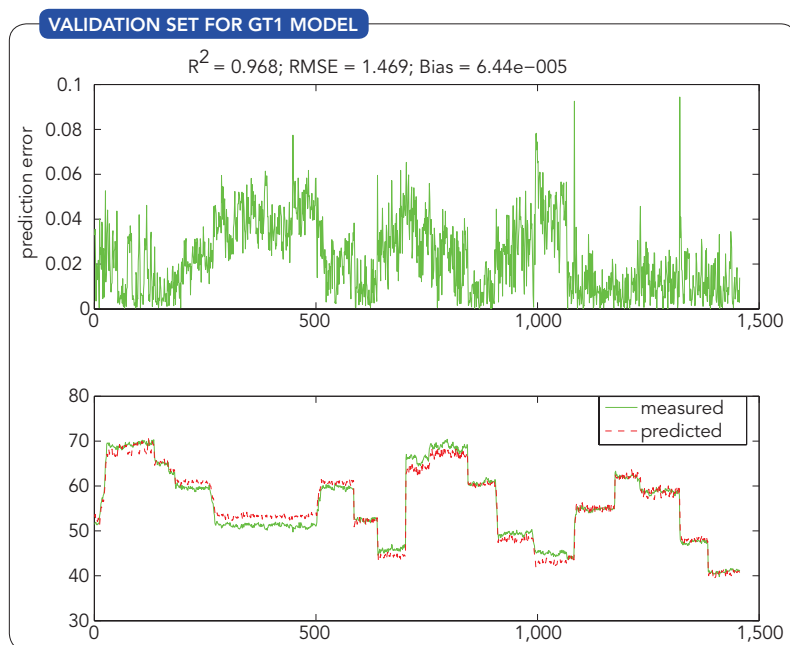


Figure 2. Model consistently provided accurate predictions.

once a quarter or whenever predictions start deteriorating; this can be done without special training.

*Necessity for some risk taking.* Due to its novelty and complexity relative to hardware sensors, opting for the inferential sensor incurs added risk. However, we believe that significant reduction in risk level will occur with the increased number of applications and proven, long-term performance.

*Non-traditional maintenance and support.* The inferential sensor’s maintenance and support require different, more-specialized knowledge, including a skillset in the area of statistics and machine learning. Organizing effective support is one of the biggest challenges for mass-scale applications of this attractive technology.





## THE FUTURE

To minimize inferential sensor maintenance cost and prevent future extrapolation, offline model development should take advantage of the broadest possible ranges of the inputs and outputs from the available historical data. However, for different reasons, such as operating regime fluctuations due to different product demand, control system readjustment or equipment changes, at least 30% of applied inferential sensors are pushed to handle online operating conditions 20% outside of the offline model development range. This very high extrapolation level poses a challenge for any empirical modelling technique. Unfortunately, the high extrapolation level requires model redesign, including derivation of an entirely new model structure.

A possible solution for this key issue with current inferential sensors is to explore the capabilities of a new technology called evolving intelligent systems. It promises self-maintaining (autonomous) inferential sensors — i.e., ones that can adapt and evolve their structure as well as their parameters to follow the data pattern, to retrain and recalibrate. The gradual evolution of the model structure (fuzzy rules) means that a retraining of the sensor when required only will modify (add or replace) one or a few fuzzy rules.

This new type of adaptive, self-calibrating and self-developing inferential sensor (called eSensor) has been tested on a range of case studies from real chemical processes [4]. The proposed eSensors can be trained “on the fly” starting either from scratch or after being primed with an initial rule-base. Also optionally, the eSensor can select online the most relevant and important input variables. The results with data from real chemical processes demonstrate that the evolving inferential sensor is very flexible. It develops its model structure and automatically adapts to sudden changes of operating condition. It does not need any pretraining and specific maintenance and, thus, significantly

## RELATED CONTENT ON CHEMICALPROCESSING.COM

“Cut Your Sensor Count but Not Your Data,” <http://goo.gl/pHGGkj>

“Soft Sensors Win Hard Jobs,” <http://goo.gl/186EG9>

reduces lifecycle costs. In addition, the structure of the eSensor is transparent and interpretable as it is composed of linguistic fuzzy rules. It has great potential for the next generation of low-cost inferential sensors. ●

**ARTHUR KORDON** recently retired from The Dow Chemical Co. and is now CEO of Kordon Consulting, Fort Lauderdale, Fla.

**LEO CHIANG** is senior technical manager, chemometrics and data analytics at the Analytical Tech Center of The Dow Chemical Co., Freeport, Texas. **ZDRAVKO STEFANOV** is lead technical

manager, fundamental problem solving at the Analytical Tech Center. **IVAN CASTILLO** is associate analytical manager, chemometrics and data analytics at the Analytical Tech Center. E-mail them at [arthur@kordon-consulting.com](mailto:arthur@kordon-consulting.com), [Hchiang@dow.com](mailto:Hchiang@dow.com), [Zstefanov@dow.com](mailto:Zstefanov@dow.com) and [Castillo2@dow.com](mailto:Castillo2@dow.com).

## REFERENCES

1. Fortuna, L., Graziani, S., Rizzo, A., and Xibilia, M., “Soft Sensors for Monitoring and Control of Industrial Processes,” Springer, New York City (2007).
2. Lu, B., Castillo, I., Chiang, L., and Edgar, T.F., “Industrial PLS Model Variable Selection Using Moving Window Variable Importance in Projection,” *Chemometrics and Intelligent Laboratory Systems*, Vol. 135, pp. 90–109 (July 15, 2014).
3. Kordon, A., “Applying Computational Intelligence: How to Create Value,” Springer, New York City (2009).
4. Angelov, P., and Kordon, A., “Evolving Inferential Sensors in the Chemical Industry,” Chapter 14, pp. 313–336, in “Evolving Intelligent Systems: Methodology and Applications,” P. Angelov, D. Filev and N. Kasabov, eds., John Wiley & Sons, Hoboken, N.J. (2010).