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INTEGRATING AND TRENDING USM, FLOW COMPUTER, AND CHROMATOGRAPH DIAGNOSTICS TO IDENTIFY MEASUREMENT PROBLEMS

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INTRODUCTION

Today's smart measurement devices produce significant diagnostics information. When the diagnostics from the various devices are collected, trended, and integrated, operators can remotely and continuously identify measurement problems. The vocabulary associated with this topic is evolving. In the past, the industry used terms such as SCADA and Condition Based Monitoring to describe this process. These terms are being replaced by terms such as Industrial Internet of Things (IIoT) and Big Data Analytics, and even AI. In either case, this paper looks at the problems associated with collecting, trending, and integrating diagnostics information. It then gives examples of how diagnostics can be used to identify measurement problems. Finally, the paper provides an example of the reduction in exposure to Lost and Unaccounted For gas (LAUF) that operators may expect through implementing comprehensive diagnostic monitoring and analysis systems.

PART 1: PROBLEMS ASSOCIATED WITH COLLECTING, TRENDING, AND INTEGRATING DATA

Measurement Device Diagnostics

Most modern measurement devices produce considerable diagnostic information. For example, ultrasonic meters produce diagnostics about the configuration of the meter, about the health of each of the measurement paths, and information about conditions inside of the meter tube (i.e., contamination, debris, blockages, installation effects, or liquids). Likewise, Chromatographs produce useful diagnostic information such as response factors. API 21.1 allows for operators to install redundant pressure and temperature transmitters that can be used to verify the fiscal transmitter readings. API 21.1 calls this diagnostic redundancy verification (API 21.1 8.2.1.3 and 8.2.1.4).

Measurement System Diagnostics

Along with the diagnostics produced directly by the measurement devices, there is another set of diagnostics generated from combining information from the various measurement devices. For example, one of the standard testing procedures of an ultrasonic meter is to compare the ultrasonic meter's measured speed of sound to a speed of sound calculated using the AGA10 equation. The AGA10 equation's inputs are pressure, temperature, and the gas composition. So, this comparison, which is a diagnostic, provides information about the health of multiple pieces of the measurement system. Another example of this type of diagnostic is comparing the actual volume recorded by the ultrasonic meter to the actual volume recorded by the flow computer to identify pulse loop problems. Likewise, diagnostics can be used to identify other communications issues such as communication problems between the flow computer and the gas chromatograph. Other examples of these types of diagnostics are diagnostics associated with parallel flow and series flow. Many ultrasonic meters on the market today are designed with two meters incorporated into one meter body. Diagnostics that compare the two meters are an example of these types of diagnostics.

Measurement Calculation Diagnostics

A final level of diagnostics available to operators is recalculating the velocity, actual flow rate, standard flow rate, energy rate, and compressibility, and comparing these values to the values outputted by the ultrasonic meter and the flow computer. These diagnostics can be primarily used to identify device configuration issues.

The Challenge of Gathering and Using All the Diagnostics

Typically, Measurement Device Diagnostics reside in the end devices. Many operators collect snapshots of the diagnostics, for example, a maintenance log file from an ultrasonic meter (usually only a few minutes of information) during a scheduled, on-site meter test. It is not uncommon that the ultrasonic meter diagnostics are stored and reviewed by one part of an organization, the chromatograph diagnostics are stored and reviewed by another part of the organization, and the flow computer diagnostics are stored and reviewed by yet another part of the organization. In many cases, the information is incomplete, not organized such that information can be easily integrated (for example, frequency of the information and time stamping issues), and the information is siloed, making it difficult to produce the Measurement System and Measurement Calculation Diagnostics.

Because the diagnostics are siloed and because of the formatting issues between the diagnostic data sets and time stamp issues, operators must manually combine the information from the various sources, spending considerable time manipulating the data to produce useable Measurement System Diagnostics. Due to the difficulties of this process, it is often performed using basic analytical tools such as spreadsheets. Michael Risse, writing in an article in Control Engineering summed the problem up as follows,

> "In fact the most common method for extracting value from historian data is by using rudimentary analytic tools like spreadsheets. With this method, historian data is exported to spreadsheets. This data is then analyzed manually to create static reports, which are sent through the chain of command to decision-making personnel.
>
> In addition to relying heavily on human eyes to identify meaningful trends, using spreadsheets to glean actionable information from large volumes of data is a time- and labor-intensive process" (Risse, Control Engineering).

The following figure speaks to the "labor-intensive process." The figure illustrates the amount of time data scientists spend on the various tasks associated with their jobs. The role of a data scientist is similar to a measurement engineer or a measurement analyst. The figure shows that personnel involved in data analysis spend 79% of their time collecting and cleaning data sets. Only 9% of their time is spent analyzing the data (mining data for patterns).

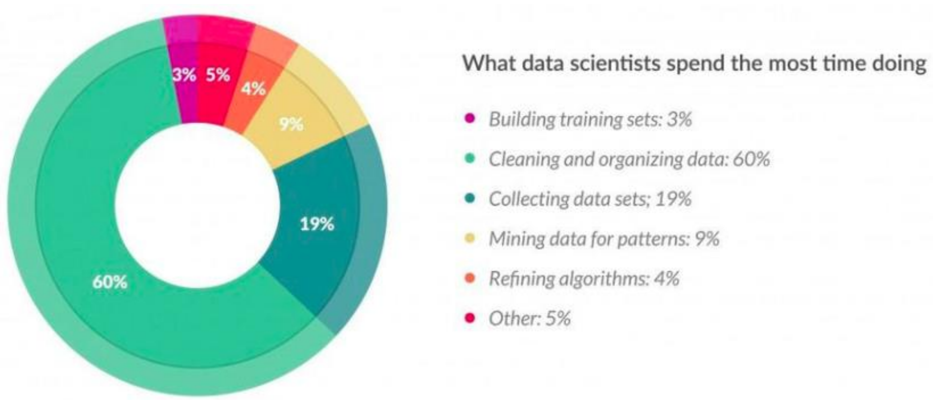


Figure 1: Time spent on various tasks associated with data analysis (Gil, Forbes)

Figure 2 below builds on this idea that it takes considerable effort to analyze diagnostics. The figure illustrates the 5 stages of IoT maturity. The figure was developed from a survey of Fortune 2,000 companies. The top left bar chart illustrates the percentage of the companies in each of the stages. The bottom right graph illustrates the percentage of the total ROI achieved at each stage. The top left graph shows that most companies have connectivity and dashboards, but have not mined the data to develop business logic algorithms. Yet, the bottom right graph shows that companies must achieve the automated business logic stage to realize significant return on investment. Working within the constraints of spreadsheets, and manually collecting and organizing the data provides very little return on the diagnostics available from the measurement systems. The figure shows that in order to realize significant ROI, the analytics must be converted into business logic and automated into their business process.

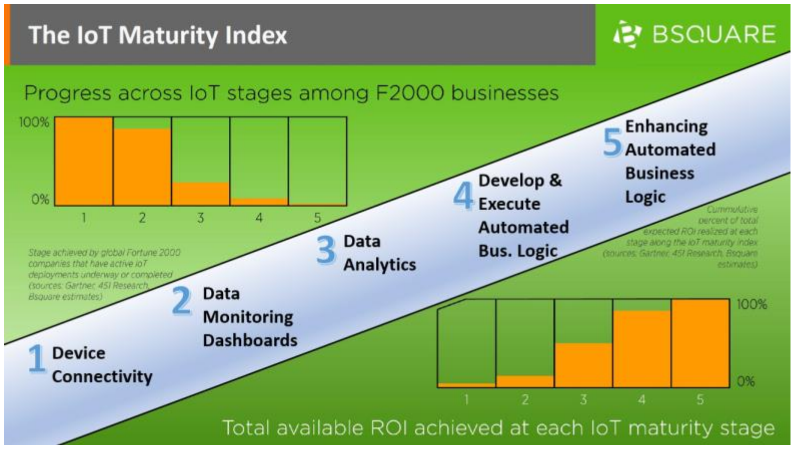


Figure 2: IoT Maturity Index and ROI (BSQUARE, Chicago)

PART 2: EXAMPLES OF HOW DIAGNOSTICS CAN BE USED TO IDENTIFY MEASUREMENT PROBLEMS

The following section of the paper looks at several examples of how collecting, trending, and integrating Measurement Device and Measurement System Diagnostics reduces operators' exposure to LAUF and gives operators better information to make operations decisions. Paul Stone, a principal consultant in information technology and services at British Petroleum recently wrote:

> "The biggest benefit of analytics, though, is that it provides the opportunity to predict what will happen, instead of recording what has happened or is happening. All these different data points allow people to spot patterns as they form, patterns that point to future conditions before they occur and, with all this extra data, we can take the right action ahead of time" (Stone, bp.com).

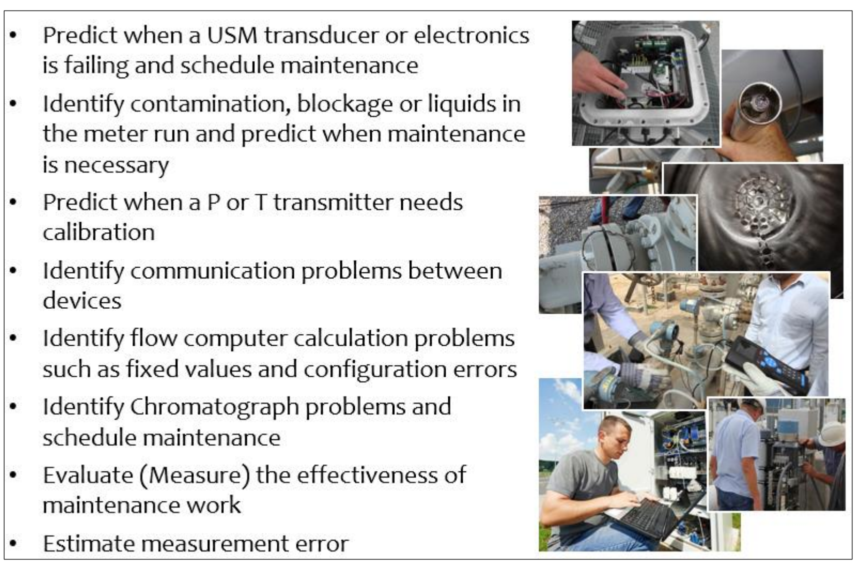
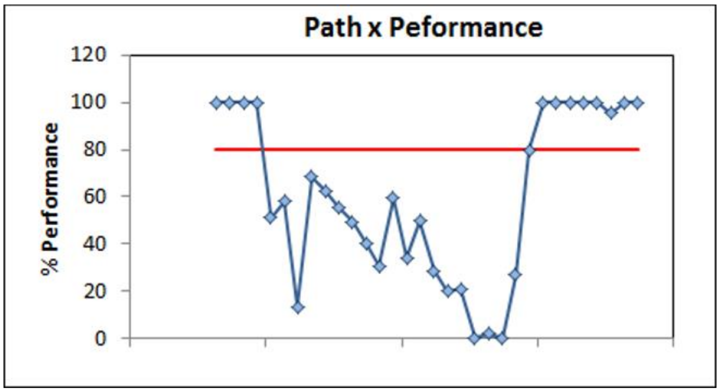


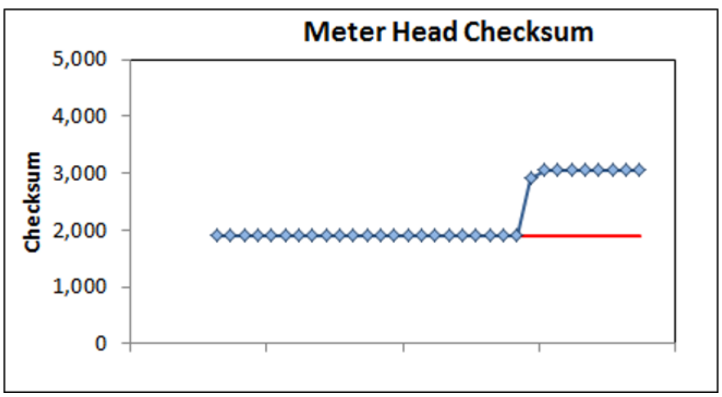
Figure 3: Examples of taking the right action

Example 1: Identification and Replacement of a Failed USM transducer

Graph 1 below illustrates the daily average path performance diagnostic trend with alert limits for an ultrasonic path. The trend begins at 100%, drops out of the normal range, becomes variable, and eventually goes to zero. With control charts and automated alerts, measurement teams become aware of issues as they happen. In this example, the measurement group was alerted soon after the trend dropped below the alert limit. The manager generated a work order to have the transducers replaced. Obtaining replacement transducers and scheduling a specialist to perform the repair work took about 3 weeks. The manager was able to easily verify that the work was successful with the trend returning to 100%. The ultrasonic meters also produce a configuration checksum diagnostic. The diagnostic tracks changes to the configuration. The work should have caused a change in the checksum. Graph 2 below illustrates the shift, further confirming that the maintenance was performed as expected. Instead of relying on spot reports such as maintenance files from before and after the maintenance, the manager can see the complete story, thus increasing the manager's certainty of the measurement.



Graph 1: Daily Path Performance Diagnostic Trend

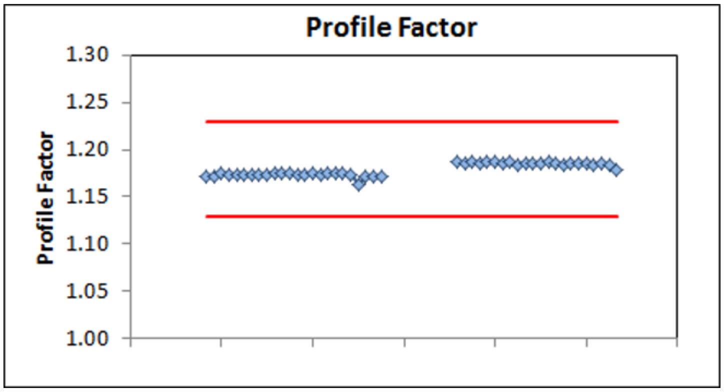


Graph 2: Daily USM Configuration Checksum Trend

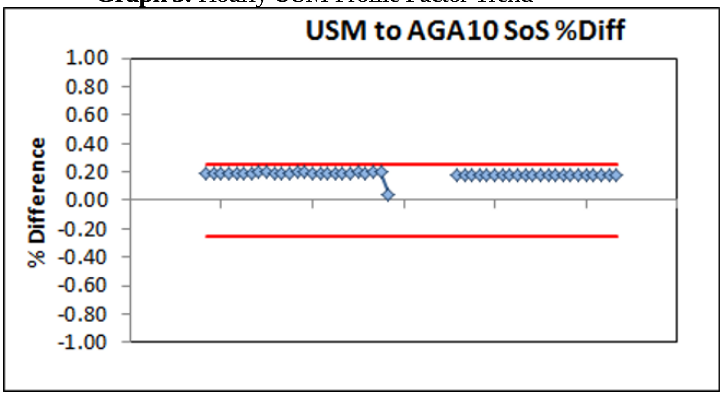
Example 2: Internal Meter Tube Inspection

The previous example illustrated actively using diagnostics to quickly respond to and correct a measurement problem. The following example illustrates the opposite. In this case, a meter run was broke down and internally inspected as part of a scheduled maintenance program, not based on meter diagnostics. The primary diagnostic for detecting contamination in an ultrasonic meter run is the Profile Factor. Graph 3 below illustrates the hourly Profile Factor trend for the 24 hours prior to and after the maintenance. The gap in the trend was during the maintenance. The graph shows that the Profile Factor was within the expected tolerances prior to the work indicating that the meter run was probably not contaminated. Graph 4 also illustrates the AGA10 SoS % Difference diagnostic trend during the same period, which is another high-level diagnostic to monitor during this type of maintenance. The work was performed and the meter tube was found to be clean. The meter run was reassembled and placed back in service. As expected, the graph shows that the Profile Factor returned to its previous trend following the maintenance.

In this example, money and resources were allocated to unnecessary work. The measurement supervisor had to arrange for a crew to break down the meter tube and perform the cleaning, and for a measurement specialist to be on location to manage the work. At least the diagnostics were able to confirm that the work was performed successfully, with the diagnostics returning to their previous trends.



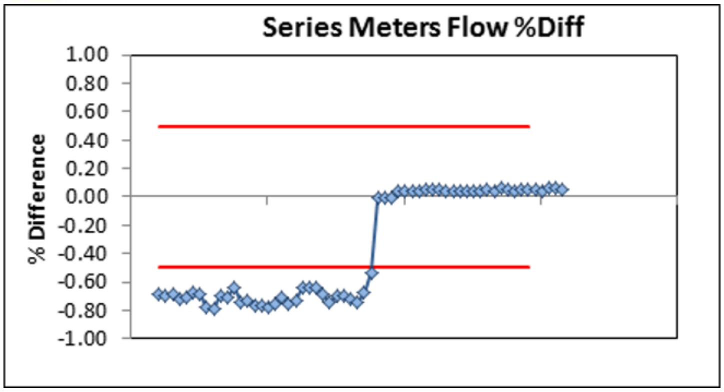
Graph 3: Hourly USM Profile Factor Trend



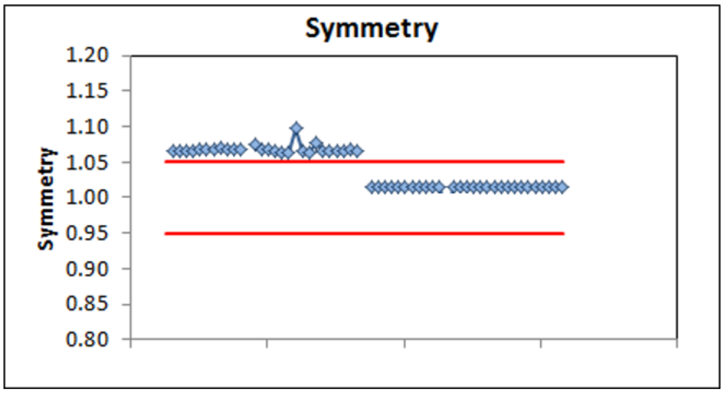
Graph 4: Hourly USM to AGA10 SoS % Difference Trend

Example 3: Detecting a Protruding Gasket

This example illustrates using Measurement Device and Measurement System Diagnostics to confirm maintenance work. In this case the diagnostics indicated an issue inside the meter tube which turned out to be a protruding gasket. Graph 5 below illustrates a Measurement System Diagnostic, the Series Actual Flow Rate % Difference between two ultrasonic meters built into one meter body. The graph illustrates hourly data prior to and after the maintenance. As a result of the maintenance, the diagnostic shifts from below the lower alert limit to within the alert limits. The Ultrasonic Meter Symmetry trend (Graph 6 below), the ratio of the two upper measurement chord velocities to the two lower chord velocities also shifted from above the upper alert limit to within the alert limits, further confirming the success of the maintenance work. Unlike the unnecessary work in Example 2, this maintenance returned the meter diagnostics to the expected trends. And, like in Example 1, instead of relying on spot reports such as maintenance files from before and after the maintenance, the manager can see the complete story, thus increasing the manager's certainty of the measurement.



Graph 5: Hourly Series Acf % Difference Trend

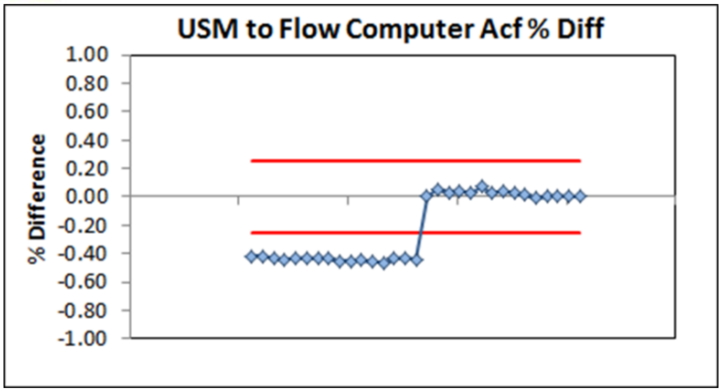


Graph 6: Hourly USM Symmetry Trend

Example 4: Detecting Communication Problems between Devices
Measurement systems depend on the reliable and accurate transfer of data between the various devices comprising the systems. In this example, there was a flow computer configuration problem that was causing the flow computer to under-register the actual volume from the ultrasonic meter by ~0.5%. The specific issue was that the k-factor in the flow computer was not set correctly.

One of the risks of siloed testing of measurement equipment is not checking the communication between devices. For example, it is common during on-site testing to collect and review maintenance files from the ultrasonic meter (siloed) and to verify the pressure and temperature measurements using certified standards and possibly the flow computer calculations (siloed). But, nowhere in the process are communications between the meter and the flow computer verified. Without developing easy-to-use diagnostics, the communication check is difficult, requiring collecting data from the ultrasonic meter and flow computer, combining and cleaning the data, and then comparing.

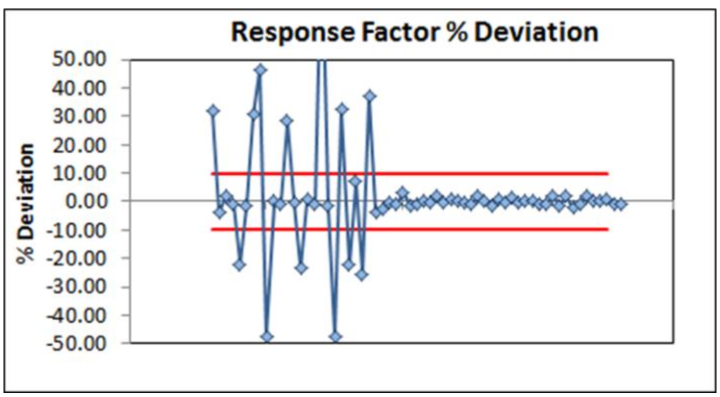
Graph 7 below illustrates a continuous diagnostic that accomplished the comparison task. The graph illustrates the trend of the actual volume recorded directly from the ultrasonic meter via Modbus and the actual volume recorded from the flow computer which in turn, received the volume from the ultrasonic meter via a frequency loop circuit. The diagnostic shows exactly when the k-factor was changed and allows for quick and easy calculation of the error.



Graph 7: Daily USM to Flow Computer Acf % Difference Trend

Example 6: Detecting Chromatograph Measurement Device Issues

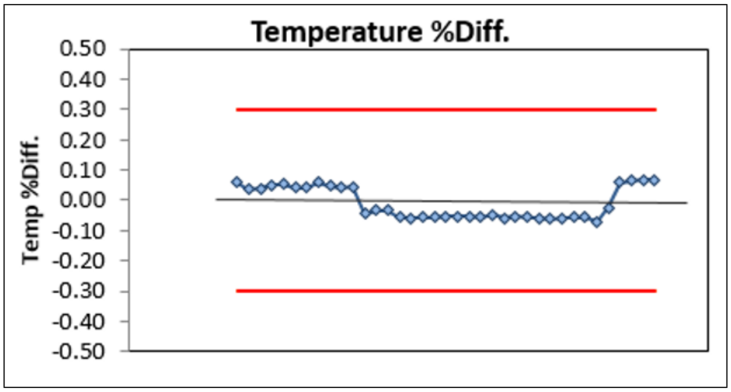
Example 1 illustrated using diagnostics to detect and trend the maintenance work associated with a failing ultrasonic transducer. Graph 8 below illustrates using trending to detect a chromatograph valve timing issue that was causing wide swings following each of the automatic, daily calibrations. The diagnostic remotely identified an issue, allowing the measurement manager to schedule maintenance. Following the maintenance, the diagnostic trend returned to its expected value, giving the manager confidence that the maintenance work was successful.



Graph 8: Daily Chromatograph Response Factor Deviation Trend

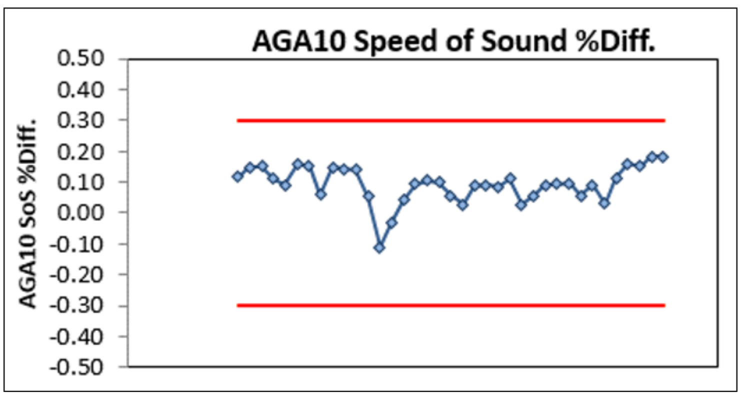
Example 7: Detecting Unnecessary Maintenance Work

It is common in the industry to perform on-site testing at large meter stations monthly. The following example illustrates an example of a potential problem associated with scheduled testing instead of using diagnostics to determine when to perform on-site verification and/or maintenance work. Graph 9 illustrates the daily percent difference between the fiscal temperature measurement and the redundant temperature measurement. The diagnostic trends slightly above zero, then shifts below zero for 30 days, before it shifts back up to its previous trend. The shifts correspond to on-site calibrations. The graph shows that the initial calibration work was undone, a month later. Both of the calibrations were unnecessary. In this example, the shift is small, on the order of a tenth of a percent of the volume. But, the meter was flowing significant volume. Thus, over the month, the shift accumulated to an appreciable amount.



Graph 9: Daily Temperature % Difference Trend

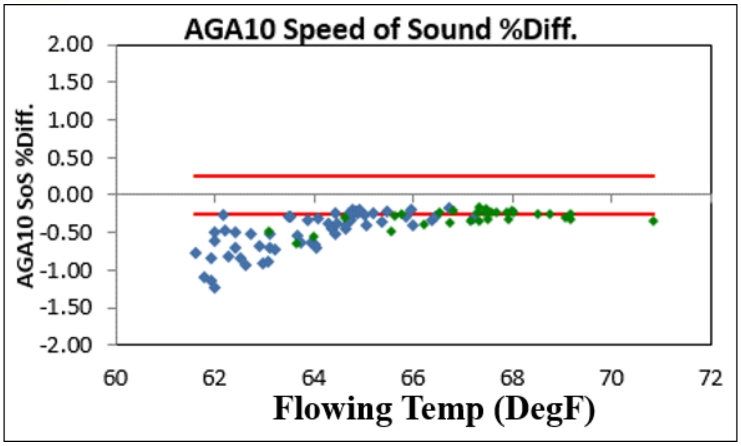
Graph 10 below develops the example a little further. The Temperature % Difference trend in Graph 9 clearly illustrates the shift. But, it does not provide any information on which of the temperature measurements shifted. Graph 10 illustrates the AGA10 SoS % Difference trend. Even though there is considerable noise on the trend, careful examination of the graph shows that the diagnostic shifted similarly to the Temperature % Difference trend. Since the AGA10 calculation uses the fiscal temperature measurement as an input to the calculation, the trend showed that the fiscal temperature transmitter was calibrated. This type of detailed analysis allows operators to pinpoint problems, remotely providing measurement certainty.



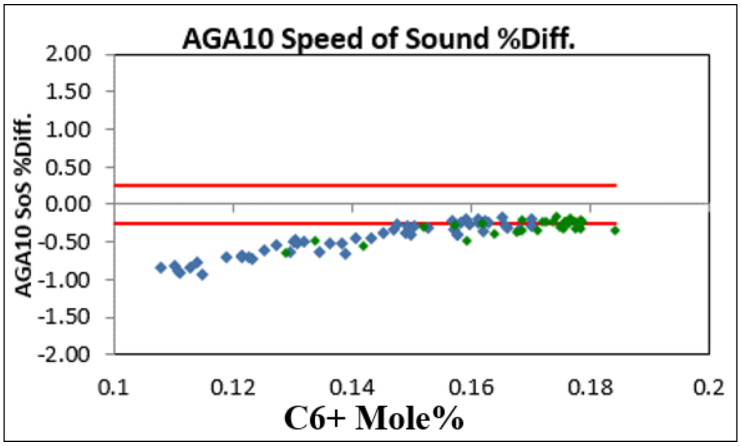
Graph 10: Daily AGA10 SoS % Difference Trend

Example 8: Using Integrated Data and Trending to Diagnose Hard to Detect Problems

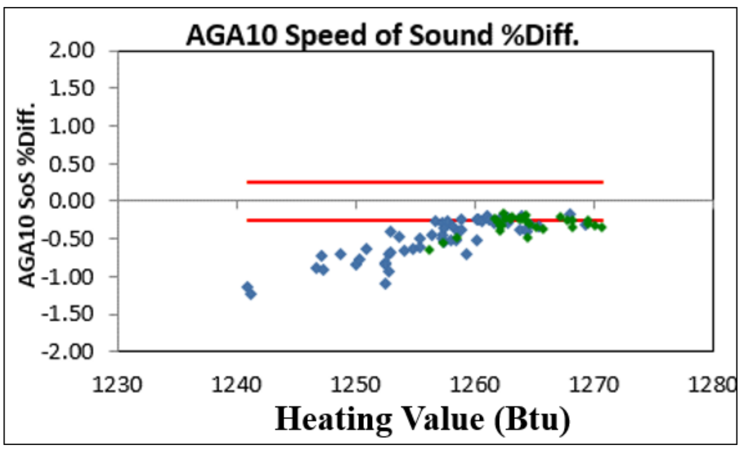
The final example integrates ultrasonic, chromatograph, and temperature data to use diagnostics to identify a problem with the gas sampling system. In all the previous examples the horizontal axis represented time, either daily of hourly. In this example, the gas temperature is on the horizontal axis. Each point represents a daily average. Graph 11 shows that the AGA10 SoS % Difference diagnostic trended at the lower alert limit at higher gas temperatures. The behavior changes when the gas temperature drops below 65 °F. The difference shifts lower and becomes variable. A possible cause of this behavior could be hydrocarbon dropout. Graph 12 illustrates the AGA10 SoS % Difference as a function of the C6+ mole percentage. The graph shows that as the C6+ mole percentage decreased (heavies decreased), the AGA10 SoS % Difference shifted lower. The analysis led to the conclusion that there was hydrocarbon dropout at the sample probe when the temperature dropped below 65 °F. Graph 13 shows that the issue was causing the heating value to be under reported by as much as 20 Btu at times.



Graph 11: AGA10 SoS % Difference vs. Gas Temperature



Graph 12: AGA10 SoS % Difference vs. Gas Temperature



Graph 13: AGA10 SoS % Difference vs. Heating Value

PART 3: EXAMPLE OF HOW DIAGNOSTIC MONITORING REDUCES LAUF EXPOSURE

The eight examples above illustrate how integrating and trending diagnostics can be used to remotely, and continuously detect measurement issues, verify the effectiveness of the maintenance work to resolve the issues, and to estimate the error associated with the issues. All of this leads to increased measurement certainty and reduced exposure to Lost and Unaccounted For risk. The question remains, how can an operator demonstrate the value of a diagnostic monitoring system?

A method for measuring the value of a diagnostic monitoring system is to develop a key performance indicator (KPI). One example of a KPI would be to measure the events (measurement issues) identified by the system, the average time it takes to resolve an event and the average impact of the event (estimated error caused by the event). The equation is illustrated below.

Lost and Unaccounted for Gas = **Number of Events identified per month** x **Average Resolution time of an event** x **Impact of the event (average estimated error in Mscf/d)**

Figure 4: Example KPI Equation

The following table (Figure 5) illustrates real results from a diagnostic monitoring system monitoring more than 100 metering stations for multiple years. The table has been normalized to show the results per 100 meter stations per year. The table categorizes events into 5 categories and gives the frequency of the issues, the resolution time, and the average impact.

The table shows that, on average, the diagnostic monitoring system identified events at 5 to 13% of the stations. The average event resolution time averaging 64 days. The highest impact events were ultrasonic meter electronics and transducer failures, followed by events associated with the flow computers. The next largest impact were ultrasonic meter operational issues, such as contamination and blockages, followed by events associated with the pressure and temperature measurements and chromatographs.

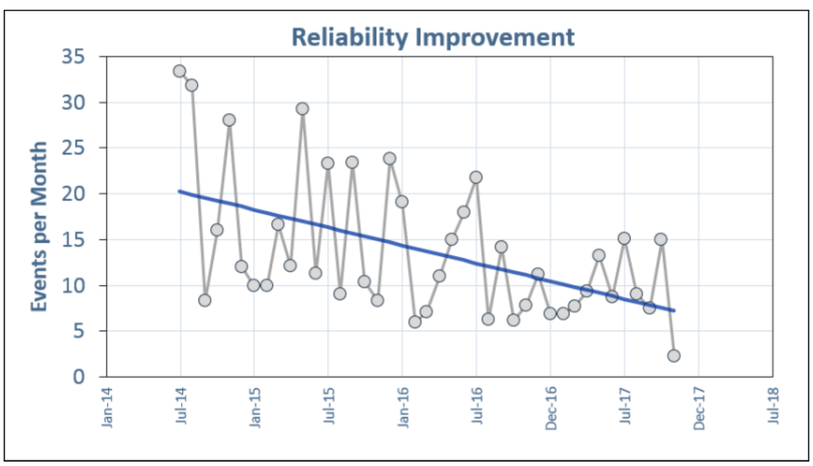
The results are specific to the set of meter stations monitored by the system; therefore, the results cannot be directly extrapolated to other sets of meter stations. But, the results give insight into what to expect. The table shows approximately $35,000 LAUF exposure reduction per meter station per year (calculated at a gas price of $3 per Mscf).

Issue	% of sites	Events per Year	Resolution days (avg)	Impact ($k)
USM Trx & electronics	8%	11	72	$1,900k
Flow computers	5%	7	49	$800k
USM operations	7%	9	87	$400k
P&T transmitters	7%	9	38	$250k
Chromatographs	13%	17	63	$100k
	21%	27	64	$3,450k

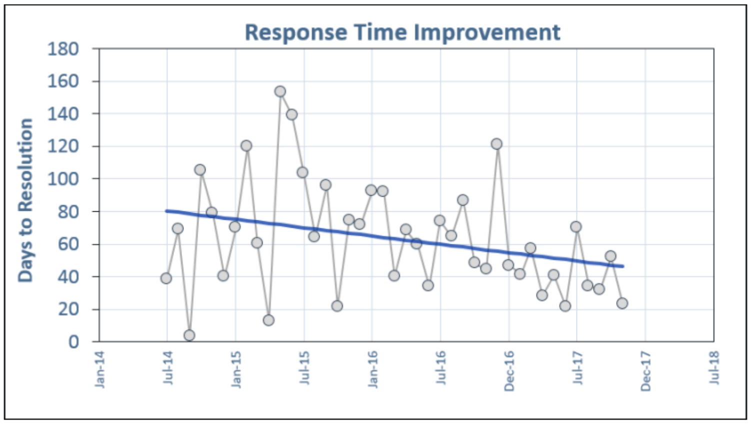
*Results based on data collected over three-and-a-half years from more than 100 metering stations normalized to 100 stations per year.

Figure 5: Diagnostic Monitoring System Results

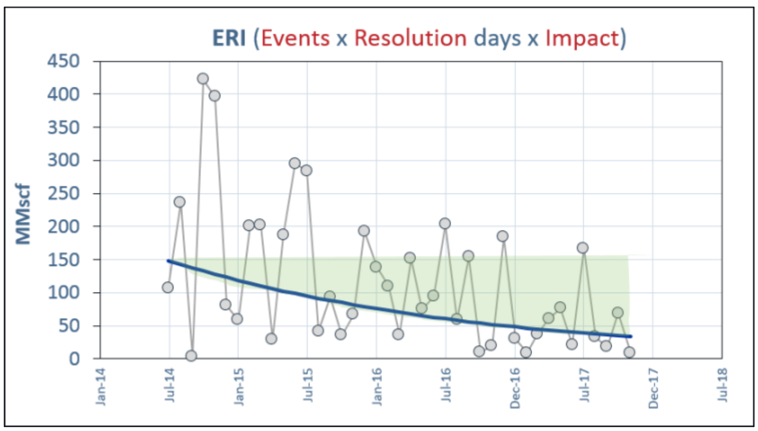
Examining the KPI equation shows that the first two terms, the number of events and the resolution time, can be controlled through operations. The impact term is hard to control. It is random and depends on the specific error. Graph 14 illustrates the number of events detected per month by the monitoring system. The graph shows that over the period the diagnostic monitoring system was operational, the number of events per month decreased, meaning the reliability of the measurement systems improved. Graph 15 illustrates the average response time. Like the number of events, the response time also decreased. The two graphs together suggest that measurement operations improved significantly while using the diagnostic monitoring system. Graph 16 illustrates the KPI and shows that per 100 meter stations, the LAUF exposure was reduced from 150 MMscf per month to less than 50 MMscf per month (shaded green area on the graph), yielding an ongoing exposure reduction of 1,200 MMscf per year, which equates to $3.5M or $35,000 per year per meter station (calculated at $3/Mscf gas price).



Graph 14: Events detected per Month



Graph 15: Resolution Time per Month



Graph 16: KPI reduced from 150 MMscf to less than 50 MMscf per Month

CONCLUSION

Today's smart measurement devices produce significant amounts of diagnostic information. Whether using the old vocabulary of SCADA and Condition Based Monitoring, or new terms such as the Industrial Internet of Things (IIoT), Big Data and Artificial Intelligence to describe collecting, trending, and integrating data, operators face big challenges in converting the data into actionable information that provides a return on investment.

Research shows that 80% of a measurement analyst's and engineer's time is spent on the task of collecting and cleaning data sets and less than 10% of their time mining the data for actionable results. Yet, research also shows that significant return on diagnostic information is not realized until the analytical techniques can be turned into business logic and automated into a company's business processes.

The examples given in the paper illustrate how to trend and integrate diagnostics to remotely and continuously detect measurement issues, verify the effectiveness of the maintenance work to resolve the issues, and to estimate the error associated with the issues. The technical examples begin to make a case for the value of proactively monitoring diagnostics. But, making a business case for it can be difficult. The paper develops a KPI to measure the value and shows real results from an operational, measurement, diagnostic system. The results show that the system improved measurement reliability, response time, and resulted in an overall reduction in exposure to LAUF.

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