Increasing operating reliability and stability

JAMES GREMILLION
Emerson Process Management
The Woodlands, TX, United States
E: james.gremillion@emerson.com

Abstract

This paper discusses the emerging technology of "Process Analytics" which integrates with your DCS system to identify and evaluate abnormal conditions and identify the cause of the abnormality for the operator. The paper, as a prelude to the above, will cover existing and emerging techniques for stabilizing the process.

This Paper was presented at the Nitrogen & Syngas Symposium 2013 in Berlin.

Increasing operating reliability and stability

JAMES GREMILLION

Emerson Process Management

The Woodlands, TX, United States

This paper discusses the emerging technology of "Process Analytics" which integrates with your DCS system to identify and evaluate abnormal conditions and identify the cause of the abnormality for the operator. The paper, as a prelude to the above, will cover existing and emerging techniques for stabilizing the process.

INTERACTIONS

Even seemingly simple control loops can cause problems. For example, the two loops shown below look simple. One loop controls gas pressure while the second controls the flow. To implement these loops, you would purchase the flow transmitter and a suitable valve, install the equipment, connect it to your DCS then tune the controller based on rules or by using tuning tools built into the DCS. You would do the same for the pressure controller (**Figure** 1).

Fig. 1: A control application for gas pressure and flow

When you put the loops in automatic, a problem quickly becomes evident – the loops interact. When the flow controller moves the valve, the pressure changes. As the pressure controller adjusts its valve to compensate, the flow changes. The result is neither loop is able to control its “variable”. Both variables (the flow and the pressure) cycle rather than staying constant as intended.

Over the last few years sophisticated toolkits (such as Emerson’s Entech Toolkit) have come to market that can address the problem of interacting loops through analysis and specialized tuning techniques to minimize interactions such as this.

An alternative to advanced tuning techniques to minimize the interaction is to use a “matrix controller”. In this controller, the individual controllers are replaced by a matrix of the interactions of the key elements (Figure 2). The matrix must be composed of dynamic models since the response of real-world elements such as valves is not instantaneous but follows a response curve that must be included in the calculation.

Every second the matrix is inverted to solve for the valve positions to move the variables to the desired point (or hold them constant) without interaction.

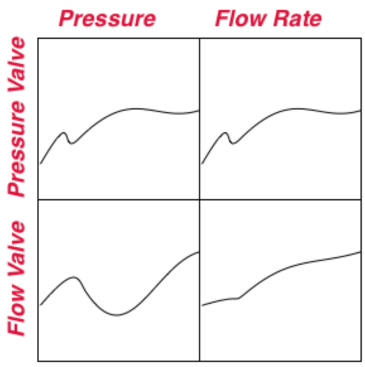

Fig. 2: A matrix to control the loops in figure

Not long ago controllers such as this matrix controller were mostly theoretical. A few years ago they were implemented, at great expense and effort, in dedicated computers. Now they are available as easy-to-use control blocks in the DCS controller itself.

These techniques to reduce interactions can be applied to any size control problem. In fact, since in reality the entire chemical plant is interactive since it is all connected, we could develop a matrix control solution for the entire plant to remove all the interactions. For a simple plant there maybe 2,000 control and measurement points that must be considered… that would be a 2000 x 2000 matrix with four million models. Such a matrix could not be solved every second by the matrix controller nor could we expend the time needed to develop models for the four million cells. So, for the present, we use matrix controllers for highly-interactive, complex control problems (e.g. a distillation column) and use our “toolkit” to minimize other interactions in the process.

VARIABILITY

Interactions are not the real concern. We addressed interactions because they are one of the major causes of variability.

Variability is caused by the inability of the control loop to hold the set point. “Interactions” is one cause. Other causes include sticking control valves, noisy flow signals, and many others. Since the purpose of a control loop is to hold the measurement (variable) to the setpoint by making continuous adjustments, we would have to say the loop is not performing well if the measurement is cycling.

The problem is worse than you probably can imagine.

“At least 2/3 of control loops underperform.”

The quotation above is from a paper given at the IFACS 2006 ADCHEM Conference. The conclusion is supported by several other studies done by customers and control companies. What this means is that variability, which the control schemes are designed to remove, is still “not removed”.

We have already discussed ways to reduce the interaction-variability problem – matrix controllers and toolkits such as the Emerson Entech Toolkit. The toolkits can find and help eliminate interactions that generate variability but they also serve to find easier-to-fix problems such as sticking valves. There is a cost involved in this added analysis needed to reduce variability, of course, so there must be an economic value.

The first economic impact of reduced variability is constraints. Every process has constraints – things you cannot exceed, such as metallurgical temperature limits, vessel pressure limits, etc. These constraints can be, and often are, the process bottlenecks. In figure 3 the graph on the left shows how we operate against a constraint with variability present. To keep the measurement from exceeding the constraint, we operate so that the peak of the variability does not cross the constraint. By reducing variability (the right graph), we can operate closer to the constraint, increasing production or reducing costs.

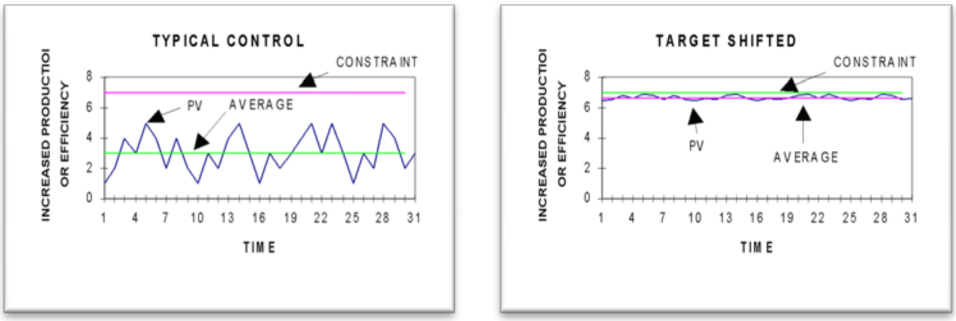

Fig. 3: Reducing variability allows you to operate closer to a constraint

The second effect of reduced variability is optimums. As shown in figure 4, the effect of variability on production is accentuated by the nonlinearity of the response of production to the hydrogen-to-nitrogen ratio optimum. Reducing variability has a large effect when applied to an optimum-control problem. Staying on optimum all the time has an obvious economic benefit and reducing variability keeps you on optimum longer.

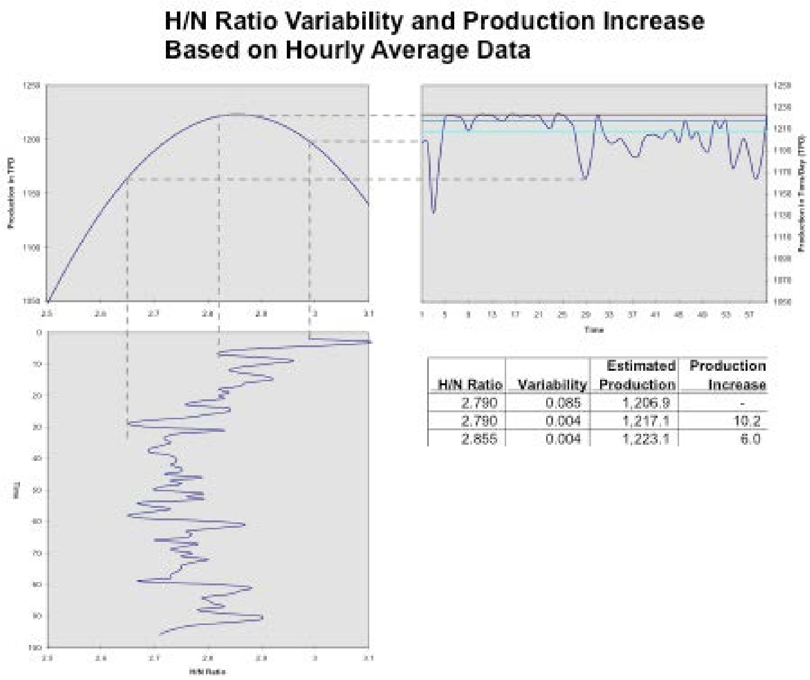

Fig. 4: Non-linearity found in optimum control makes variability costly

The third effect has nothing to do with control. Variability diminishes information value… variability destroys process information.

The first aspect of this effect is more obvious than the second. As you try to capture process data to calculate key data (KPIs, for example) to use in tuning the process, you must "filter" the data to remove the variability otherwise the variability will just be transferred to your calculated values. That "filtering" you must do diminishes the value of the information you are getting from the process because the calculated values are no longer timely (filtering = averaging).

The second aspect is the inability to use process data to quickly analyse problems. The variability of information makes any correlations you might try to make between an alarm condition and process conditions very difficult. Those “correlations you might make” may be hard to imagine if you have always lived with process variability. Their most important use would be in analysing an alarm condition to prevent “things” from getting worse.

“ALARMING CHANGES”

That statement, “prevent ‘things’ from getting worse”, is the essence of alarms – the reason we use and need alarms. In the earlier days of process control, alarms were difficult to implement, involving the installation of hardware and finding suitable panel space, so there were fewer alarms than today and the alarms were better understood by the process operators. Even in these “earlier days”, some alarms caused other alarms through interactions within the process and the configuration of the alarms themselves. For the latter, consider a “feed pump shutdown” alarm that also generates a “low flow alarm” for the flow out of the same pump. For the former, consider a rate-of-change alarm on the temperature in an exothermic reactor that is associated with a high cooling water temperature alarm. In both cases the alarm and the underlying cause would have been obvious to the operator.

With the introduction of DCS for process control, it became very easy to add alarms. By just checking a checkbox on a screen configuration, you can easily add every alarm to every variable. Where with mechanical alarms you might only have a high level alarm for a vessel, now you can add a high-high alarm, a low alarm, a low-low alarm, a rate-of-change alarm and a deviation alarm with no effort.

With the natural coupling of alarms (a rate-of-change alarm will probably result in a deviation alarm) and process interactions we have spoken about earlier, one alarm can generate many others. The end result is a condition known as alarm flooding. For a single cause, the operator may see 10 or 20 simultaneous alarms.

Alarm flooding has become a large enough problem that it has generated a sub-industry, alarm management. In applying alarm management to my earlier example of a “feed pump shutdown” alarm that also caused a “low flow alarm”, we would configure our alarm management so that the “low flow alarm” is inhibited whenever there is a “feed pump shutdown” alarm. This opens up questions on safety and other issues which also can be addressed using the alarm management systems. Things are getting more complex.

The real issue is not reducing the alarms but finding the root cause of the alarms... “what’s the problem?”

CONTINUOUS DATA ANALYTICS

If you recall our earlier discussion of the matrix controller, we developed models for each of the cells in the 4 x 4 matrix for the gas flow and pressure loops in order to remove interactions and make the control stable. Those same models could be used to evaluate the root cause of an abnormal process condition (alarm). For such a simple system the effort is not really worth it. However, if we were able to analyse a matrix covering the entire process (the 2000 x 2000, 4-million element matrix) to get to the root cause of an abnormal condition, it would be a valuable tool.

About 2009 Emerson began a research program with a major university to apply two technologies that have been around since the early 1900’s – Principal Component Analysis and Projection to Latent Structures. The English mathematician, Karl Pearson, developed Principal Component Analysis, the key technology, in 1901. Pearson is considered to be the father of mathematical statistics.

Using Pearson’s methods, we can reduce that four million-element matrix to a manageable size allowing us to actually analyse for the most likely root cause of an alarm.

The research program was completed and a beta product was produced. In 2010 several major chemical companies engaged in a test of what is now called Continuous Data Analytics. The tests were successful and the Continuous Data Analytics product is nearing release.

Continuous Data Analytics performs several important data analyses. First, Continuous Data Analytics determines the most likely variable causing an alarm condition. Figure 5 shows an alarm condition (the trend on the right) and the most probable causes of the abnormal condition on the left (the actual variable names have been concealed as this was part of the beta test at a customer).

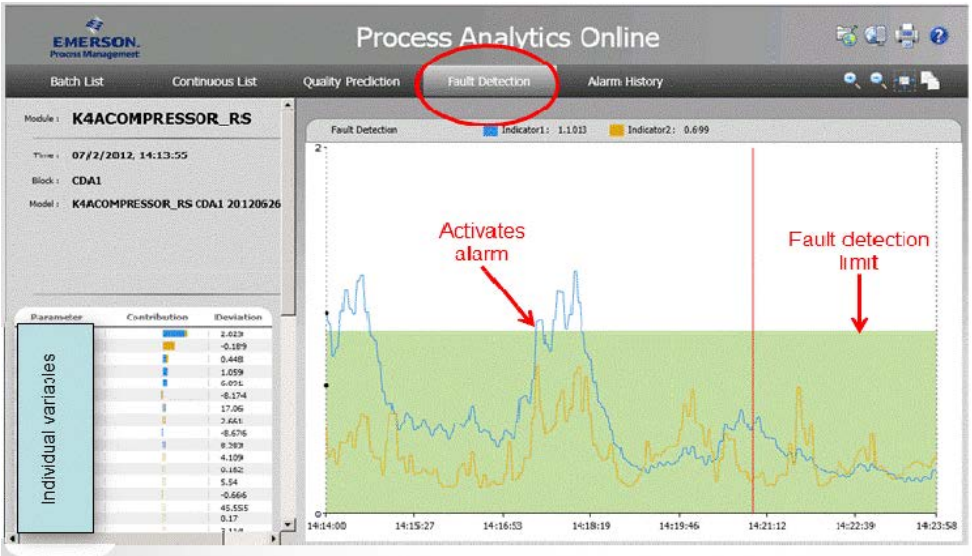

Fig. 5: Fault Detection in Continuous Data Analytics

A second analysis method allows the operator to see the future projections for key control measurements (Figure 6). In addition, the software can be used with laboratory measurements to develop an online, continuous analysis of analytical measurements. For instance, in one of the beta tests, Continuous Data Analytics predicted residual H_2S in a gas stream, a measurement restricted to complex laboratory analysis in the past.

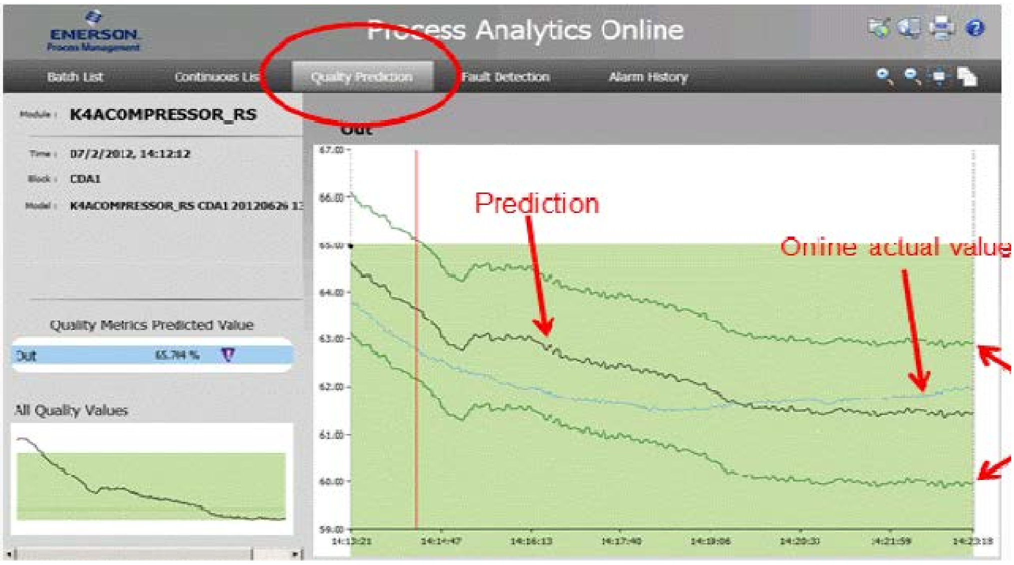

Fig. 6: Quality Prediction in Continuous Data Analytics

Continuous Data Analytics is a rapidly emerging technology that can become an effective tool for increasing reliability in chemical plants by identifying underlying faults rapidly and providing a prediction of coming quality and operational problems.

Continuous Data Analytics is in the final stages of development and there may be changes to what has been presented here but the underlying concepts and functionality are fixed.

WHAT CAN YOU DO?

The key to being able to apply any process-data-centric application like Continuous Data Analytics is to minimize process variability. A variability and interaction study (available from most control vendors) is the first step. The good news is that this first step can be very profitable. One chemical company, for example, saw a 45% production increase through reducing variability which allowed them to run closer to constraints and optimums. An aluminium company found an additional 12% production after implementing the recommendations from a variability and interaction study done by Emerson.

There are added maintenance benefits from reducing variability that haven't even been discussed here – reducing wear-and-tear on valves, for example – that can have large effects on your bottom line.

Begin with a study.

References

Angelle, Randy. A Presentation: "Ammonia Control – Process Consistency Benefits" (John H. Carter Co., 1996)

Rayner, R. Pump User's Handbook (Elsevier Science Publishers Ltd., 1995)

Belvins, T. A Presentation: "DeltaV Continuous Data Analytics" (Emerson Process Management, 2011)