How to lose money with inferential properties

Fourteen more rules that, if followed, will ensure that advanced control will drive the unit further away from optimum operation

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The hydrocarbon industry is remarkably inventive in providing a never-ending catalog of ways to jeopardize the benefits that advanced control should capture. Inferential properties, now commonplace in advanced control projects, offer another rich vein of examples. This article, like its predecessors,[1,2] presents a further list of rules.

Also known as "soft sensors" or "virtual measurements," inferentials are often applied to predicting product qualities from more easily measurable operating conditions. But they can be applied to almost any variable that is difficult or costly to measure directly. Examples include column flooding, coker drum outage, furnace coking, etc. Technologies range from simple linear formulae, through neural networks to semirigorous engineering calculations.

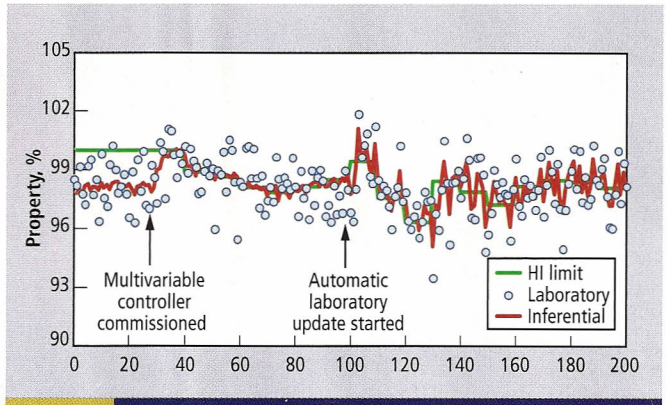

FIG. 1 Applying automatic laboratory updating usually reduces accuracy.

1. Don't bother with an inferential if there is an onstream analyzer. Of course, it is tempting to use the analyzer measurement directly in the control strategy, especially if the analyzer is believed to be accurate. However, most analyzers respond much more slowly to process changes than other instrumentation. The analyzer may be located well downstream, the sample system may introduce a significant delay and the analyzer itself may be discontinuous. By the time the analyzer first indicates a change in quality, the disturbance could have already persisted for a lengthy period and built up an inventory of off-spec material in the process.

Further, the slow dynamics will severely limit how quickly the process can be moved to the required operating conditions. Provided the inferential responds by changing in the correct direction, even if relatively inaccurate, its dynamic advantage can substantially reduce duration of off-spec operation. The analyzer measurement, through suitable dynamic compensation, can then be used to trim the inferential to maintain its accuracy.

An added advantage of this approach is that at least some form of control will be maintained during times when the analyzer is out of service. Further, a large difference between inferential and analyzer could help provide early detection of analyzer failure.

In situations where installing a new analyzer is being considered, early development of an inferential may provide an effective alternative. In capturing some of the benefits of improved quality control, it may reduce what remains to the point where the analyzer cost is no longer justified. Or, if an analyzer already exists, it may permit it to be moved to another stream where successful implementation of inferential technology proves elusive.

2. Implement automatic laboratory updating. By "remembering" what the inferential recorded at sample time, when the laboratory result later becomes available, it is possible to adjust the bias term of the inferential to force agreement with the laboratory. This is common practice for many vendors of inferential technology, with most providing the option of filtering this correction so that some tuneable fraction of it is applied.

However, even with such a filter in place, use of *automatic* updating almost always *reduces* accuracy of the inferential. The laboratory result is itself subject to random error; updating simply adds this to that of the inferential, increasing overall random error. This is illustrated in the case study shown as Fig. 1. Soon after commissioning a multivariable controller, the inferred property was found to more closely approach the upper limit and profitably reduce giveaway. However, the operator then noticed that laboratory results were often violating the specification and reduced the high limit.

The net effect was that there was little change in product giveaway. To improve what appeared to be an inaccurate inferential, the engineer implemented automatic laboratory updating. Even with filtering, the effect was to further *worsen* the situation.

Updating should only be applied if there is a *bias* or sustained error. Bias errors can arise because of changes in operating mode or underlying changes to the process caused by gradual effects such as catalyst deactivation. Often, such changes can be detected and included as part of the inferential tech-

Sample	Inferential	Laboratory	Error	Cusum
1	5.08	4.81	0.27	0.27
2	4.97	4.79	0.18	0.45
3	4.93	5.25	0.32	0.13
4	5.05	5.02	0.03	0.16
5	5.20	4.86	0.34	0.50
6	5.55	4.96	0.59	1.09
7	5.22	5.08	0.14	1.23
8	5.52	5.17	0.35	1.58
9	5.56	4.98	0.58	2.16
10	5.56	4.90	0.67	2.82
11	5.64	4.86	0.78	3.61
12	4.80	4.98	0.18	3.43
13	5.16	4.94	0.23	3.65
14	4.95	5.17	0.22	3.43
15	4.93	5.01	0.09	3.35
16	4.95	5.17	0.22	3.13
17	5.17	5.09	0.08	3.21
18	5.17	5.16	0.01	3.22
19	5.16	4.75	0.41	3.63
20	4.84	4.81	0.03	3.66

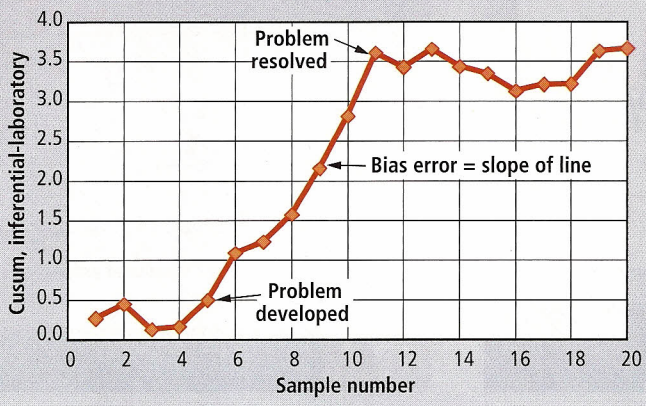

FIG. 2 The CUSUM can be used to distinguish a bias error from a random error.

nology itself. If this is not feasible, updating may be the only solution, but it should not be automatic following every laboratory result. Certainly, the inferential should be *checked* against every laboratory result but only updated if there is clear evidence of a bias error. The cumulative sum of errors (CUSUM) technique illustrated in Fig. 2 can be used to distinguish a bias error from random error.

3. Check inferential accuracy using line graphs. Probably the most common way used by vendors to convince the customer that an inferential is accurate is the line graph. The inferred property is compared with that measured. Fig. 3 gives a typical example.

Line graphs seem to trick the eye into believing that the relationship between the two parameters is stronger than it actually is. Fig. 4 displays the same data as a scatter diagram and reveals much larger potential errors. For example, if the measured property is 50, the inferred varies between 30 and 70—an error potentially as large as 40%!

4. Use scatter diagrams and Pearson R^2 to validate the inferential. Fig. 5 shows the trend of the stock market share price for an APC vendor. Fig. 6 shows performance of an inferential developed by the author. With an R^2 of 0.989, the author should by now have retired a wealthy man. However, closer inspection of the scatter diagram shows why not.

There are a few points where the predicted share price was significantly greater than the actual price. These points coincide with the sharp falls in July and October 1998. Predicting share price is trivial when there are no changes. Money is made by properly predicting the *variations*. The same is true in the process industry.

To measure effectiveness of an inferential, it is essential to compare its accuracy to variability of the measured property. Standalone measures such as correlation coefficients and standard error do not do this. Fig. 7 shows the parameter, $(1 - \sigma^2_{error}/\sigma^2_{property})$, where σ^2_{error} is the variance of the error (inferential versus laboratory) and $\sigma^2_{property}$ is the variance of the measured property (with APC off). Should this parameter fall below zero, the inferential will introduce disturbances into the process greater than those in place prior to the APC commissioning.

Under these circumstances, greater benefits would be achieved by "dropping" the inferential as a controlled variable. Since APC projects are often justified by halving the standard deviation, this parameter would seem to need to have a value of *at least* 0.75. In practice, since no APC perfectly controls the process, the value probably needs to be much greater.

5. Apply regression analysis without understanding the process. The easiest way of achieving this is to blindly

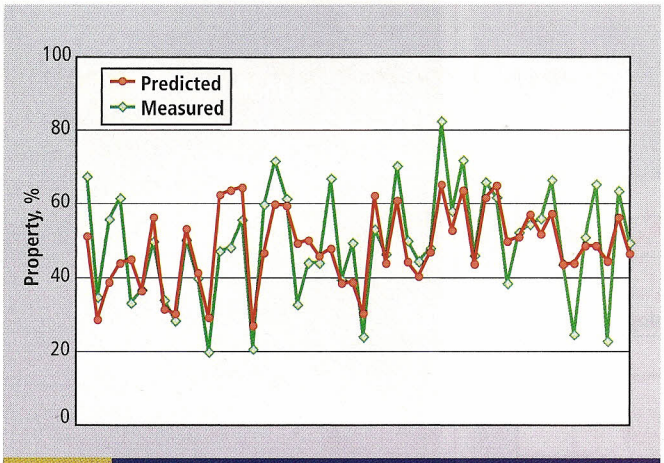

FIG. 3 Line graphs seem to trick the eye into believing the relationship between the two parameters is stronger than it actually is.

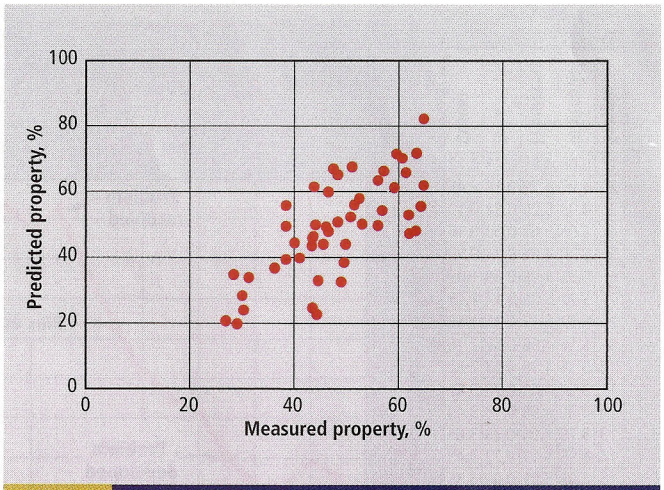

FIG. 4 A scatter plot highlights inferential inaccuracy.

FIG. 5 Stock market share price of an APC vendor.

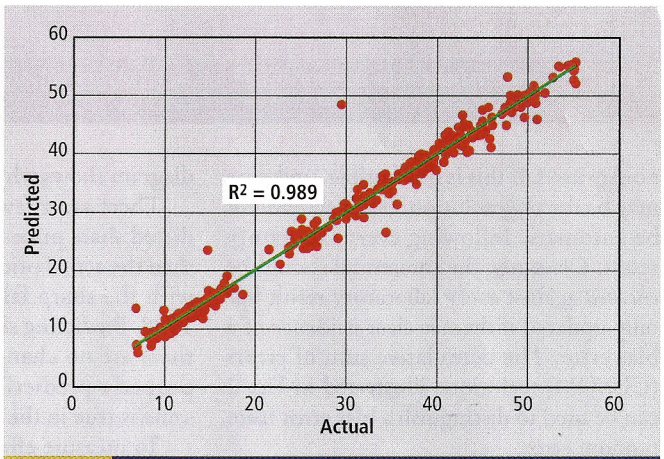

FIG. 6 Why the author has not made millions of dollars from predicting share prices.

apply a neural network. Doing so discards any knowledge of process behavior. While the resulting inferential may work well, its performance outside the range over which it was trained can be extremely unpredictable. In some cases, this has caused a reversal of the sign of the process gain with respect to the key manipulated variable—severely impacting process profitability.

Naively applying linear regression techniques can have a similar impact. With modern spreadsheets and statistical packages, it is relatively easy to extract large quantities of data from the process information database and search for all possible correlations. By including large numbers of process variables it will certainly be possible to apparently improve accuracy of the inferential. However, this is likely to be only a mathematical coincidence. If the inferential includes terms that make no engineering sense (or coefficients that have the wrong sign), it will fail during a process excursion.

6. Exclude terms that appear not to make engineering sense from regression-based inferentials. A common form of inferential for distillation product composition is a linear function of the variables column pressure, P, and tray temperature, T.

However, if pressure and temperature vary widely, regression will find a better fit if the term PT is also included. This might first appear to have no engineering meaning. Fig. 8 shows the true relationship between product composition and pressure and temperature. Including only P and T would imply that the relationship is a series of parallel straight lines. In the example shown, this gives a standard deviation of prediction error of 0.6 mol%. Including PT results in a closer match to the nonparallel lines, reducing the error to 0.3%. Use of a nonlinear function (e.g., T^2) instead of T reduces the error to 0.2%.

Similarly, if Q is the percent of heavy key in the overhead product then one would expect it to increase as tray temperature increases. This would lead one to reject the second term in the correlation:

$$Q = aT_1 - bT_2 + c$$

where T_1 and T_2 are temperatures on two different trays and a, b and c are positive numbers. However, this equation can be rewritten as:

$$Q = (a - b)T_1 - b(T_2 - T_1) + c$$

If T_1 is higher up the column than T_2, the term, $T_2 - T_1$, is a measure of fractionation. Provided $a - b$ is positive, the correlation indeed makes sense.

7. Ignore the dynamics of inputs to the inferential. Dynamic relationships between the measured property and each of the inputs will be different. For

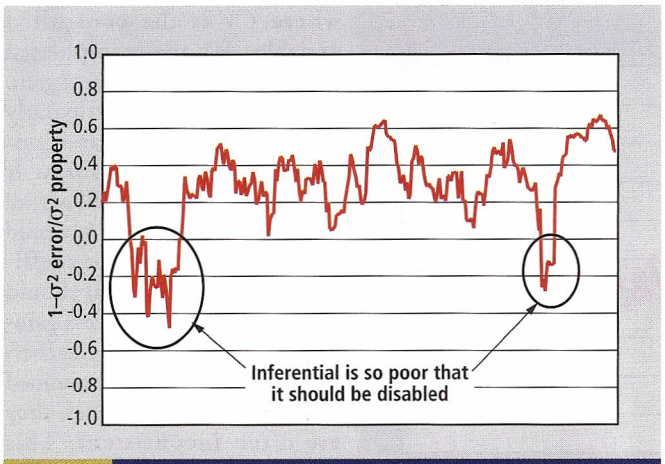

FIG. 7 Trending inferential accuracy can show when to abandon its use.

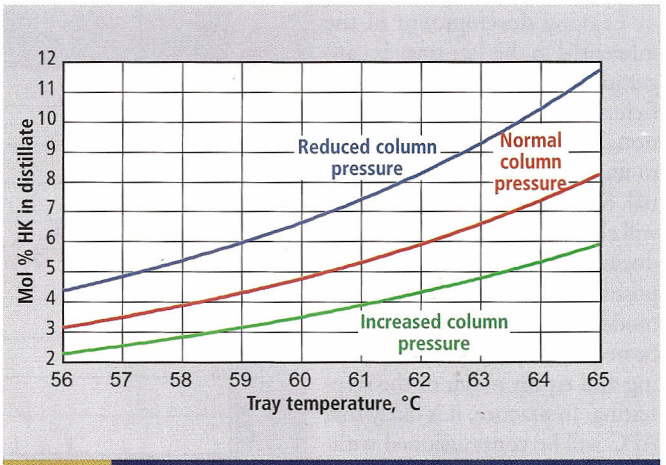

FIG. 8 Temperature and pressure have a nonlinear effect on product composition.

example, if the two tray temperatures in Rule 6 are far apart, their dynamics will be significantly different. The inferential is based on a steady-state analysis and will, therefore, display an unusual dynamic response. Indeed, under some circumstances it is likely to exhibit inverse response. While it is of course possible to dynamically compensate the inputs, dynamic compensation required can depend on the source of the disturbance. For example, the dynamic relationship between the measured property and T_1 could be quite different for reflux changes when compared to reboiler changes. If dynamics are a problem, it is often better to simplify the inferential to only include inputs that have dynamically similar effects on the measured property.

8. Always apply semirigorous engineering models in preference to regression analysis. As one might expect, suppliers of these semirigorous technologies claim that this approach is better. They certainly have some advantages.[3] Inferentials based on regression should strictly only be accurate over the range of operating conditions used in their development. Models based on process engineering techniques should in theory operate over the full range of possible operations and be readily adapted to take into account process modifications.

This would suggest that only two or three sets of test run data would be required to calibrate the model as opposed to the larger number of records needed for regression. One could argue, however, that one needs to check the model over a wide range of conditions to develop confidence that it is reliable. This is especially true since often the underlying technology is based on empirical (and sometimes suspect) general-purpose correlations published by others.

Some disadvantages to the more rigorous approach are that the models are usually more complex and, therefore, more costly to implement and maintain. Also, users often experience difficulty in retaining the expertise necessary for their support, and an inferential can effectively degrade to a "black box." Because they tend to use many more process measurements, more complex approaches are, therefore, more prone to instrument failure.

As with many process control technologies, there is no overwhelming argument for one approach over another. Both techniques have been applied successfully. Indeed, many sites will have a mixture of the two.

9. Stop monitoring inferential performance after project completion. Inferentials can degrade over time. Time-dependent parameters, such as catalyst activity and equipment fouling, can influence their accuracy. Changes in feed composition can often have a major impact, as will even minor process modifications. Inaccuracy can become greater than the normal variation in the measured property. Failure to monitor will then result in the controller degrading to the point where process performance will be improved by switching *off* the controller! See Rule 4.

10. Use Antoine or Clausius-Clapeyron equations to develop pressure-compensated temperatures. Pressure-compensated temperatures (PCTs) are frequently used in inferentials applied to distillation products. Compensating a tray temperature measurement for variations in column pressure, in theory, permits a closer relationship to be developed between product composition and the measured temperature.

While this is of course beneficial, there are many pitfalls in implementing such compensation—so many that a complete article could be written on the subject. But a common approach is to apply published equations that relate vapor pressure to temperature. Many of these equations, however, assume pure components and contain component-specific coefficients. Attempting to determine such coefficients for multicomponent systems is a significant cause of error. A simple test is to use the same equation to predict tray temperature from operating pressure. Usually the prediction is wildly wrong.

11. Design inferentials using only data collected during step-testing. Provided the process is permitted to reach steady state, step-test data can be extremely useful in developing inferentials. Indeed, the step-testing will often provide much greater variation in operating conditions than that which normal historical data will show.

Further, time-stamping of laboratory samples is likely to be more closely managed. However, relying solely on such an approach may not cover the whole operating region. For example, it may not take into account different feed compositions. It is unlikely to consider parameters that change over time, such as catalyst activity or equipment fouling. It probably will not allow for other parameters that cannot be changed on demand, such as ambient conditions.

Continued

Leaving development of the inferential to this late stage is dangerous. There is likely to be insufficient time to install any additional instrumentation necessary to improve or replace the inferential. Since any new measurements will clearly not have been collected during step-testing, it will not be possible to complete the dynamic modeling necessary. At best, it will be necessary to delay commissioning and repeat much of the step-testing. In practice, it is likely that APC will be commissioned without a key control variable.

12. Use historical data to develop an inferential. Most sites have had integrated laboratory and process information systems in place for several years. They are, therefore, likely to contain thousands of records that could potentially be used to develop inferentials by regression. In practice, however, there is usually little variation in the data. Operators will have adjusted the operating conditions to keep key properties close to operating targets.

Variation in the data is likely to be more due to random errors than to any change in operating conditions. Regression is, therefore, unlikely to produce a viable inferential. This is one of the arguments that suppliers of more rigorous techniques put forward. They require only a few points to calibrate their models. However, if the calibration data do not show a wide variation, what confidence is there that their model will work during excursions from normal operation?

The key is "quality not quantity." Using relatively few data sets where collection was properly managed over a wide range of process conditions instead of hundreds of historical data sets is far more likely to generate an effective inferential.

13. Don't bother with accurate time-stamping of laboratory samples. It might seem obvious that time-stamping becomes more important if a laboratory sample is taken when the process is not steady. One might, therefore, infer that the converse is true: if the process is steady, small errors in recording the sampling time have little effect. Fig. 9 illustrates the impact on an otherwise perfect inferential of a randomly determined sampling time error in the range of –10 to +10 minutes. With the process close to steady state, one might falsely conclude from the R^2 value that the inferential is of little value. This also illustrates the importance of Rule 4.

Even accurately time-stamped samples taken when the process is unsteady are likely to be of little value. Process dynamics dictate that the sampled property is the result of process conditions that were in place some unknown time before the sampling time.

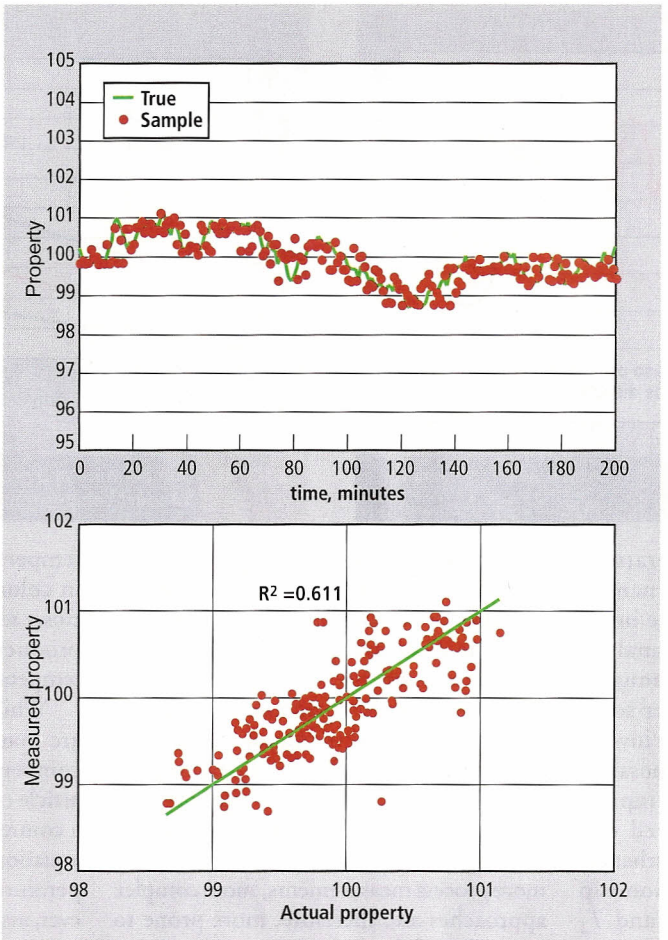

FIG. 9 Time-sampling of laboratory samples is important, even if the process is steady.

14. Don't check for consistency between the inferential and the multivariable controller. Multivariable controllers comprise a series of linear models of the form:

$$CV = K_1MV_1 + K_2MV_2 \ldots + K_nMV_n + bias$$

where CV is the controlled variable, MV the manipulated variable and K the process gain. Many inferentials, particularly those derived from linear regression, have the same form. If inputs to the inferential are all manipulated variables, it would seem obvious that the coefficients in the inferential should be the same as the process gains in the controller. Since the coefficients and gains are determined from different approaches, they are often inconsistent. This might result in the controller implementing a nonoptimum strategy or even becoming unstable.

Incidentally, it is common for an inferential to use a single manipulated variable as its input, i.e.:

$$CV = a_1MV_1 + a_0$$

One must question the value of this—even if a_1 is consistent with K_1. Its advantage appears limited to displaying the inferred property in the way the operator is used to seeing the measured property. Placing suitable limits on the manipulated variable would allow the controlled variable to be removed from the controller. **HP**

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Myke King founded Whitehouse Consulting in 1992. Previously, he was a founder member of KBC Process Automation, and prior to that he was employed by Exxon. Mr. King is responsible for consultancy services assisting clients with developing and executing advanced control and information system projects. He has 30 years of experience in such projects, working with many of the world's leading oil and petrochemical companies. Over 1,000 engineers have attended his training courses. Mr. King has an MA degree in chemical engineering from Cambridge University and is a fellow of the I.Chem.E. He can be contacted at mykeking@compuserve.com.