How Much Is Another Measurement Worth?

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New measurements are valuable only if they increase the economic value of the plant. Evaluate a measurement investment by quantifying the expected improved financial performance.

In industrial plants, installation of new equipment is subject to financial constraints and has to be economically justified — in spite of what seem to be obvious possible improvements in performance. For instance, it might be difficult for an existing facility to financially justify new process measurements and meters such as:

- a new flow measurement that has a higher accuracy than the existing one, or an additional one where none currently exists
- a new online analyzer that replaces manual sampling and laboratory analysis
- a more-accurate temperature measurement in cases where precise temperature control is important
- a new measurement that might identify equipment problems earlier.

Similar difficulties may occur during the design of a new plant.

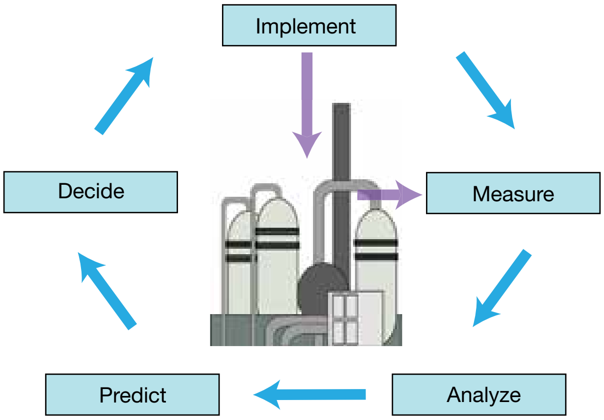
To justify any investment, consider the operating objectives of a typical large continuous processing plant. The goals can be summarized as "The Four Zeros":

- *safety* — zero serious safety incidents
- *sustainability* — zero significant environmental incidents, excess energy use, and excess waste
- *availability/reliability* — zero unscheduled downtime
- *financial optimization* — zero lost-profit opportunities.

These objectives are pursued by the plant management and the overall organization, with specific responsibilities delegated to individuals and groups that strive to meet the goals through a series of decision cycles.

A typical decision cycle for an existing plant (Figure 1) begins with measurements taken throughout the facility to determine current conditions or detect a change of state. The current and historical data are then analyzed to detect any anomalies or deviations from the target values. Based on specified criteria, which may be algorithmic or more qualitative in nature, a decision on what scenario to implement is reached. The actions are then implemented, and the cycle is repeated as necessary.

This framework is commonly used to make planning and scheduling decisions related to what products to make, when



▲ **Figure 1.** A typical decision cycle begins with measurements taken throughout the plant. These data are analyzed to detect any deviations from the goals. Engineers then predict the impacts of alternative actions on plant performance. After a decision is reached, the action is implemented, and the cycle can be repeated.

This article is based on a paper presented at the AIChE 2012 Spring Meeting, April 2012, Houston, TX.

to make them, and what feedstocks to purchase; decisions about the resources required for production; and decisions on when to perform maintenance on a particular piece of equipment. Reference 1 provides more information on plant decision cycles.

New measurements are of value if, and only if, they improve decisions in the plant, generally by reducing uncertainty in future predictions. This could involve:

• measuring something that was not routinely measured before (*e.g.,* sensor/transmitter diagnostics, acoustic signatures)

• increasing the accuracy (reducing uncertainty) of current measurements (*e.g.,* replacing volumetric flowmeters with more-accurate mass flowmeters)

• obtaining more-frequent measurements by replacing manual readings with automated instruments connected to an online database (*e.g.,* online compositional analyzers, rotating-equipment vibration meters, heat exchanger train temperature sensors, vessel wall thickness monitors).

The additional data provided by a new measurement may then be used to:

• compare what the plant is doing now, what it has done in the past, and what it is/was expected to do; model-based analysis may help with the comparison

• predict the impact of future decisions and hence reduce risk and uncertainty

• improve process control and guide future decision cycles.

The economic value of the new measurement is equal to the expected value of the (improved) decision after the installation of the measurement device less the value of a decision made without the measurement. This article explains how to quantitatively evaluate an improvement in measurement by calculating the potential return on investment.

Designing the control system to ensure safe and stable operation is an important issue. References 2 and 3 present a systematic procedure for the selection of controlled and manipulated variables and the design of the control structure to satisfy these requirements. References 4 and 5 explain how to choose a sufficient set of measurements to minimize instrumentation capital cost under different sets of constraints, such as precision, gross error detection, and availability.

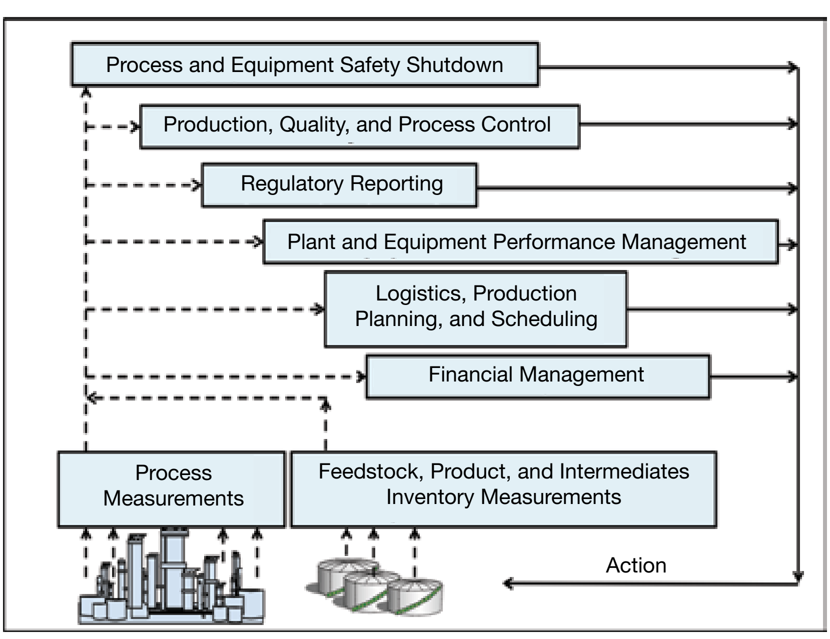
Accurately monitoring plant performance, including financial performance, depends on accurate mass and energy balances. References 6 and 7 provide an introduction to measurement theory in process plants with a particular emphasis on improving the accuracy of these balances.

Typical plant decision cycles

Figure 2 illustrates some of the major systems in the plant that might be impacted by better measurements. These can be ranked in approximate priority order as:

1. *Process and equipment safety shutdown*. The highest priority is always assuring the safe operation of equipment and the process itself. Safety shutdown systems represent an automated decision cycle. They generally acquire independent, sometimes redundant, measurements (*e.g.,* pressure and temperature) to detect when plant materials or equipment are in imminent danger of failure, and then take automatic action to bring the plant to a stable shutdown state. Decision cycles executed manually, such as technical reviews to determine safe operating and maintenance procedures and material selection, also depend on the measurements that are available.

2. *Production, quality, and process control*. Multiple measurements and control loops in the plant are designed to regulate the plant equipment to meet production rate targets and ensure that the products are within quality limits in the presence of external and internal disturbances and changing market demands. Level, flowrate, pressure, and temperature are common measured variables for these control loops. Additional controls may be in place to optimize energy usage or reactor conditions while meeting these goals. Setting



▲ **Figure 2.** These typical plant decision cycles, shown here in priority order (from top to bottom), may be improved by better measurements.

the desired operating modes and targets for these regulatory loops is the output of another decision cycle.

3. *Regulatory reporting*. Numerous regulations require sites to take specific measurements, often using online analyzers, and report calculated emissions. Failure to provide this information can result in fines or, in the extreme, loss of the plant's operating license.

4. *Plant and equipment performance management*. Production and quality targets cannot be met if the required equipment is not operating at an acceptable performance level. Many types of measurements, such as vibration and corrosion data, allow early detection of performance deterioration or possible failure, and facilitate decisions on when to take corrective maintenance action.

5. *Logistics, production planning, and scheduling*. Decisions about the types and quantities of raw materials to purchase and when to purchase them, as well as which products to manufacture, all depend on accurate measurement of current inventories and current production limits. It is also important to consider the projected future performance of the plant.

6. *Financial management*. For a plant to maintain profitable operation, it needs accurate measurements of how much product was made and sold (so customers can be properly invoiced) and the quantity of resources consumed (raw materials, energy, catalysts, etc.) so that appropriate financial performance indicators can be monitored.

These decision cycles are executed asynchronously, in parallel, at different frequencies and sometimes through overlapping actions.

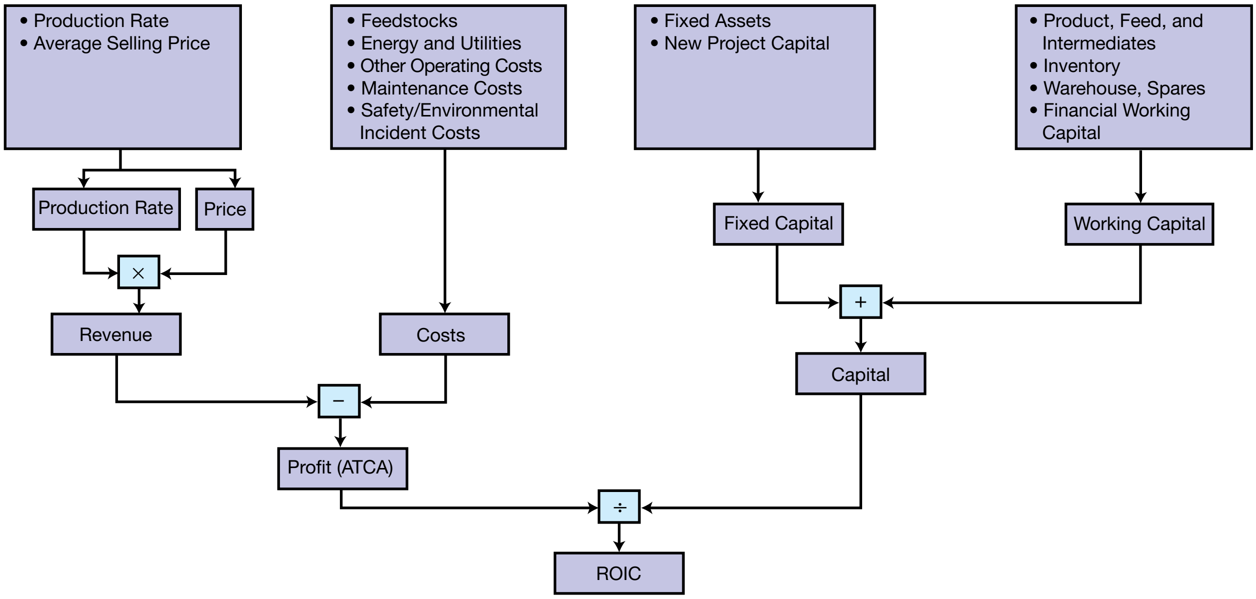
Plant and measurement economics

For the purposes of this article, assume that a sufficient set of measurements to ensure safe and stable operation and meet all regulatory and fiscal requirements already exists in the plant (or proposed plant). The focus here is on additional measurements that will improve the plant's performance against the operational objectives discussed previously — the Four Zeros.

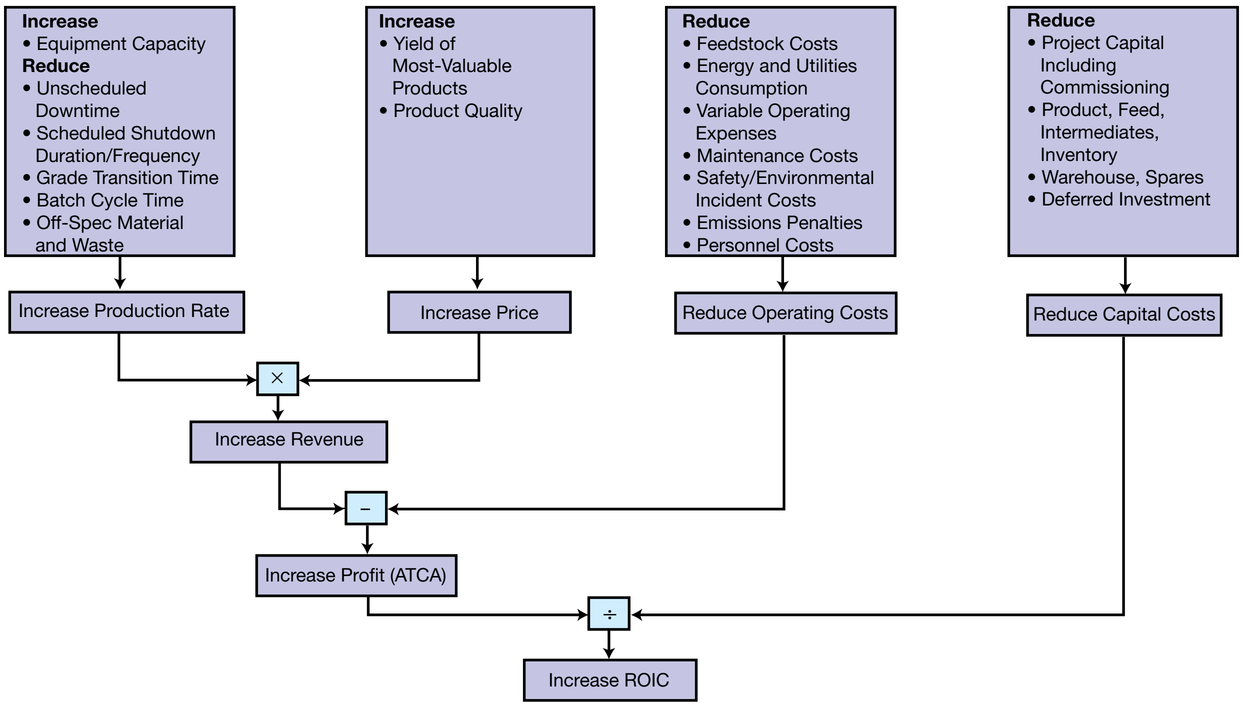
Improved monitoring is often a key to reducing adverse health, safety, and environmental (HSE) events. New measurements in these areas are generally evaluated on the basis of cost versus the amount of risk reduction rather than financial return (*i.e.,* the minimum investment that will yield the specified reduction in risk). Regulatory-related measurements are also normally chosen based on the minimum investment needed to meet applicable requirements.

However, other measurement improvements must be financially justified, because companies often have many more requests for capital than can be funded. Measurement projects compete for funds with other potential investments, such as research, new product development, manufacturing equipment upgrades, and so on. The economic impacts of new measurements must be considered within the context of the economic valuation of the plant. For a measurement to have positive financial impacts, it must increase the overall plant value.

There are many ways of gauging plant value. The generally accepted metric (the one used here) is return on invested capital (ROIC). Reference 8 provides more information on ROIC.



▲ **Figure 3.** As shown in Eq. 1, the return on invested capital (ROIC) is equal to the after-tax net income (ATCA) divided by the invested capital. The primary manufacturing variables that affect the ROIC are shown in the top boxes.



▲ **Figure 4.** To increase the ROIC, capital spending must be reduced, or ATCA increased. The top boxes list ways to do this.

Figure 3 depicts the calculation of ROIC, which in equation form is:

$$ROIC = \frac{ATCA_{\text{ (yearly value)}}}{IC_{\text{ (start of year)}}} \quad (1)$$

where *ATCA* is the after-tax net income (cash adjusted), and *IC* is invested capital, which is equal to the sum of the net fixed capital, working capital, and all other assets.

The primary manufacturing variables that affect the ROIC are shown in the top boxes in Figure 3. Other expense items that are not normally within the control of the plant staff — depreciation, corporate sales, general and administrative costs, research and development, interest, and taxes — are excluded from this analysis. Fixed capital includes the fixed assets in the plant (*e.g.,* the equipment) and new project capital. Working capital includes the operating cash, inventory (including spares), and financial working capital (*i.e.,* accounts receivable minus accounts payable). The primary variable costs include feedstocks, energy, other operating costs, and maintenance costs. Revenue is the product of the production rate and selling price.

To increase the ROIC, the capital must be reduced and/or the profit increased. Figure 4 depicts some of the many ways to increase profit and reduce capital spending in order to increase the ROIC. Many of these approaches can be carried out by adding a new measurement to the process.

Measurements can improve control performance beyond basic stability to increase yields of desirable products, thereby reducing raw material costs. Enhanced control performance may also allow stable operation closer to maximum production limits, shorten batch cycle times, reduce the time required to transition from one product grade's specifications to another grade's specifications, and reduce the amount of off-spec material produced. Actual measurements of plant disturbances can also improve control performance by allowing preemptive compensation action.

Expenses can be reduced by lowering energy and utilities usage through more-accurate energy balances, more-accurate calculation of the costs of operation, and better identification of opportunities for improvement. Keeping track of mass balances in the plant can also assist in problem identification by pinpointing where possible losses might be occurring.

Maintenance costs can be reduced via enhanced monitoring of process equipment. The information obtained can be used to detect performance deterioration, which allows more-efficient timing of equipment maintenance. The resulting improved reliability can also help reduce unscheduled downtime.

Potential capital savings include both fixed and working capital components. Working capital can be reduced through more-accurate measurement of current volumes and plant performance, which will support planning activities aimed at reducing required raw material, intermediates, and product inventories.

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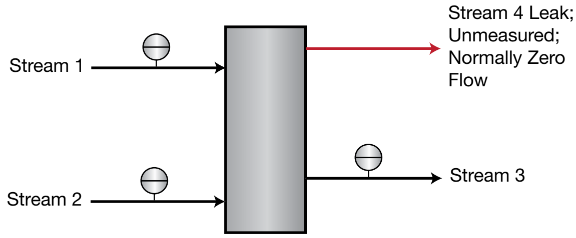


▲ **Figure 5.** In Example 1, there is flow in a line that should have no flow (Stream 4). This could be caused by leakage through a valve that is supposed to be closed, an open connection between two tanks that should be closed, or an unauthorized diversion of material flow.

It might be obvious to a chemical engineer that an improved measurement will enable improved decisions, but that is not sufficient to justify implementation of the measurement project. It is necessary to perform a financial evaluation that calculates the probability that the measurement data will be used to actually improve the decision cycle, and based on this probability, the expected value of the improvement.

Quantifying financial impact

To quantify the financial impact of an improved measurement:

1. identify the decision cycles that would be affected by the measurement
2. identify the financial variables that are functions of those decision cycles
3. estimate the potential increase in profit or reduction in capital that would be obtained through the improved measurement
4. calculate the return on investment.

Return can be calculated by many metrics, such as return on investment (ROI), net present value (NPV), or simple payback. Reference 9 provides more information on potential investment analysis as well as calculation procedures.

It is often difficult to justify investments that provide more-accurate flow measurement than an existing flowmeter. Exceptions to this are custody flow measurement, which is used for invoicing product shipments and confirming raw material purchases, and measurements for which a different technology can significantly reduce the effects of compositional disturbances, such as replacing volumetric measurement of fuel gas with direct mass-flow measurement. Example 1 illustrates a case where the improved accuracy can be justified.

Example 1: Valuing improved measurement accuracy

In this example (Figure 5), there is an unmeasured flow in a line that should have no flow. This could be caused by, for example, leakage through a valve that should be closed, a connection between two tanks that was inadvertently left open, or an unauthorized diversion of material.

To calculate the financial impact of improving the accuracy of the flow measurements on Streams 1–3, we use the concept of "value at risk" to estimate the effect of forecast uncertainty. For a specific scenario with certain assumptions about business conditions, the value at risk is the maximum loss that could occur at a specified probability level. This example determines the minimum value of the unmeasured flow in Stream 4 that is detectable, with a specified probability, under different levels of measurement uncertainty.

The decision cycles that would be impacted are process control and financial management.

Improved measurement accuracy reduces the minimum unmeasured flow that can be detected. Table 1 lists the original flow readings in column S_{io}. (For simplicity, no units are specified, as the procedure is the same regardless of the units of measurement.)

First, we find the best estimate of each stream's flowrate, S_{iE}, that satisfies the mass balance:

$$S_{3E} = S_{1E} + S_{2E} \tag{2}$$

while minimizing E, the weighted least-squares difference between the new and original readings:

$$E = w_1\left(S_{1E} - S_{1o}\right)^2 + w_2\left(S_{2E} - S_{2o}\right)^2 + w_3\left(S_{3E} - S_{3o}\right)^2 \tag{3}$$

where S_{3E} is the Stream 3 outlet flowrate and S_{1E} and S_{2E} are the Stream 1 and Stream 2 inlet flowrates, and w_1, w_2, and w_3 are weightings based on the relative measurement uncertainties.

Table 1. Investigating a possible leak with varying measurement uncertainties.

	Original Flow Reading, S_{io}	Flow, Mass-Balanced Converged, S_{iE}	Absolute Difference, $S_{io} - S_{iE}$	Flow Measurement Uncertainty, 3% Accuracy	Flow Measurement Uncertainty, 1% Accuracy
Stream 1	45	44.43	0.57	1.35	0.45
Stream 2	55	54.15	0.85	1.65	0.55
Stream 3	96	98.58	2.58	2.88	0.96
Conclusion	—	—	—	No Conclusion	Leak is Likely

Table 2. Estimating the leak magnitude in Example 1.				
	Original Flow Reading, S_{io}	Flow, Mass-Balanced Converged, S_{iE}	Absolute Difference, $S_{io} - S_{iE}$	Flow Measurement Uncertainty, 1% Accuracy
Stream 1	45	44.81	0.19	0.45
Stream 2	55	54.71	0.29	0.55
Stream 3	96	96.88	0.88	0.96
Stream 4 (Leak)	0	2.64	2.64	—

Weighted-least-squares minimization algorithms solve these equations iteratively: Initial estimates of S_{1E} and S_{2E} are selected, S_{3E} is calculated, and E is calculated, then new values for S_{1E} and S_{2E} are chosen and used to calculate new values for S_{3E} and E, and this process is repeated until the values of S_{1E} and S_{2E} that yield a minimum value of E are found.

Next, we calculate the uncertainty in the measurements and compare the differences. Assuming that the flow-measuring elements are well maintained and calibrated and that there is no reason to expect any of the measurements to have a larger error than any other, the weightings w_1, w_2, and w_3 are equal and are assumed to be unity in the calculation of E.

The iterative procedure using a standard nonlinear optimization algorithm (Microsoft Excel's Solver) gives the converged flow estimates shown in the third column of Table 1. The absolute difference between the original and converged readings is shown in the fourth column. Accuracy, by convention, is normally defined as twice the expected standard deviation of the measurement. Columns 5 and 6 display the uncertainty in the flows for each of the streams for two different levels of accuracy. If the flow accuracy is 3% (Column 5), no conclusion about the leak can be drawn, because the uncertainty values are higher than the calculated differences. If, however, the accuracy is 1% (last column), the uncertainty values are less than the calculated differences, and it is likely there is a leak.

We can also develop a plausible estimate of the leak rate (Table 2). The mass balance is calculated based on minimizing the weighted-least-squares relative error, using the assumed accuracy as the weight of each measured flow and a much lower accuracy as the weight for the unknown reading.

Here, we find the best estimate of each stream's flowrate, S_{iE}, that will satisfy the mass balance:

$$S_{3E} + S_{4E} = S_{1E} + S_{2E} \qquad (4)$$

and minimize, E, the weighted least-squares difference from original readings:

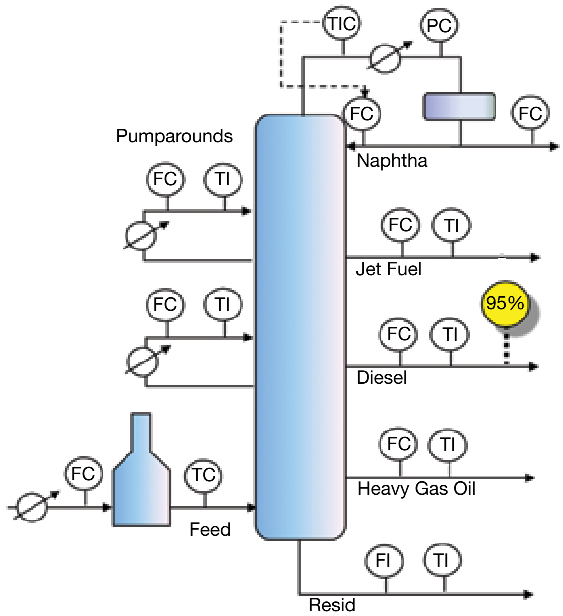
$$E = w_1\left(S_{1E} - S_{1o}\right)^2 + w_2\left(S_{2E} - S_{2o}\right)^2 + w_3\left(S_{3E} - S_{3o}\right)^2 + w_4\left(S_{4E} - S_{4o}\right)^2 \qquad (5)$$

However, because S_{4E} has a higher uncertainty, its weighting, w_4, is less than the other weightings. S_{4o} is assumed to be zero.

Once the magnitude of the leak has been estimated, its financial value can be calculated by multiplying that estimate by the stream's value. The value of the improved measurements is realized through the recovery of some or all of this potential loss. This must be weighed against the cost of installation of the more-accurate instruments.

Example 2: Economically justifying an online analyzer

A common question with regard to analyzers is whether or not there is an economic justification to replace periodic manual lab analyses with an online analyzer. For example, the refinery crude distillation unit in Figure 6 might add an online temperature analyzer to determine the quality of the



▲ **Figure 6.** In Example 2, an online analyzer could be added to determine the quality of the diesel stream in the refinery crude distillation unit.

diesel stream. This could be what is called a "95% distillation" analyzer. (The temperature at which 95% of the liquid in a standard laboratory batch distillation column has been vaporized is known, by convention, as the 95%-distilled temperature.)

Clearly, a more-frequent analysis will lead to better control. But how much better, and how much is that better control worth? The decision cycle involved in this example is the production, quality, and process control cycle.

To calculate the benefits of more-frequent analysis, we need to identify the disturbances to the control loops that make it difficult to maintain control, and compare how the control system responds to these disturbances when it relies on manual analysis versus more-frequent online analysis. This involves evaluating the expected standard deviation of the controlled variable and calculating how a reduction in standard deviation can be used to increase the economic performance of the process. To do this, we use the following procedure:

1. Develop a model of the process and the control loop, including the loop-tuning methodology.
2. Develop a model of the disturbances to the control loop.
3. Determine the expected standard deviation of the loop based on each type of measurement (lower accuracy and higher accuracy).
4. Calculate the financial impact of the reduction in standard deviation achieved by the more-accurate measurement.

Modeling the process and the control loop. For the diesel control loop, assume that the loop's controlled output is the 95%-distilled value described earlier. The open-loop dynamic response (G_P) of the control loop output to the manipulated variable (diesel flowrate) is defined as first-order plus time delay (one of the most common dynamic models in process plants).

This is expressed in transfer function notation as:

$$G_P(s) = \frac{K_P e^{-sT_P}}{\tau_P s + 1} \tag{6}$$

where K_P is the open-loop process gain, T_P is the intrinsic process delay time (measured at the point of product sampling), τ_P is the process time constant, and s is the transform variable.

The observed delay time (T_O, measured at the time the analysis is available for control action) is a function of the intrinsic delay time and the time between samples (T_F) plus any analysis and communication time. Since a disturbance could begin at any time between the taking of samples, the average sample delay can be approximated as half the sampling interval. Assuming the analysis time and communication time are negligible compared to the sampling time, the average observed delay time is:

$$T_O = T_P + 0.5T_F \tag{7}$$

Control loop performance can be evaluated based on setpoint response or disturbance rejection or some combination of the two criteria. Since setpoints for most continuous processes are changed infrequently, disturbance rejection is used here. The closed-loop response to disturbances depends on the type of controller and the method of tuning. However, the potential performance is always limited by the amount of delay time.

The specific response also depends on the control loop algorithm. This example uses the popular proportional-integral (PI) controller algorithm and lambda tuning. The adjustable parameters for PI control are the controller gain (K_C) and the reset time (T_R). Lambda is selected for relatively aggressive tuning:

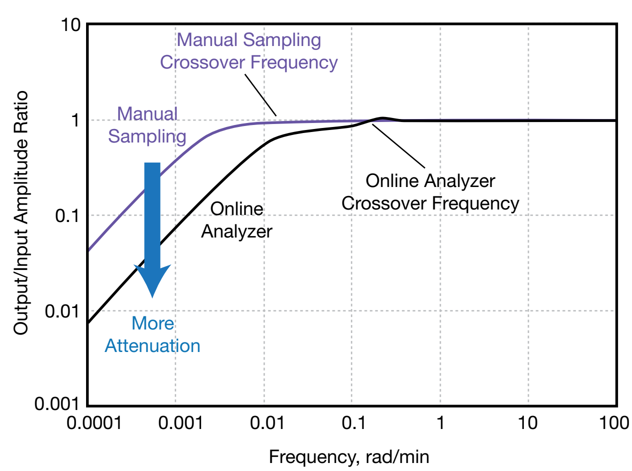
$$\lambda = 2 \times \max\left(T_O, \tau_P\right) \tag{8}$$

and the process time constant is used as the reset time:

$$T_R = \tau_P \tag{9}$$

Table 3. Controller tuning constants for Example 2, with $K_P = 1$, $T_P = 20$ min, and $\tau_P = 15$ min.

Analysis	T_F, min	T_O, min	λ, min	T_R, min	K_C
Manual	240	140	280	15	0.0357
Online	20	30	60	15	0.1667



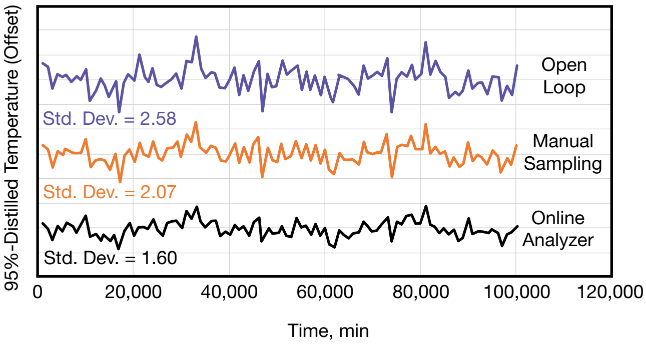
▲ **Figure 7.** The closed-loop response to disturbances can be illustrated by plotting the sensitivity function on a Bode plot. An online analyzer allows attenuation of disturbances with a significantly higher range than the manual sampling method.

The gain is then calculated by:

$$K_C = \frac{T_R}{K_P(\lambda + T_O)} \tag{10}$$

As these equations indicate, reducing the observed delay time allows a higher gain to be used, which will improve the controller's performance. See Ref. 10 for more information on lambda tuning.

Let's assume $K_P = 1$, $T_P = 20$ min, and $\tau_P = 15$ min, that manual sampling is performed every 4 hr, and that the online analyzer under consideration has a sampling time of 20 min. Using the lambda tuning equations (Eqs. 6–8) gives the tuning constants listed in Table 3.



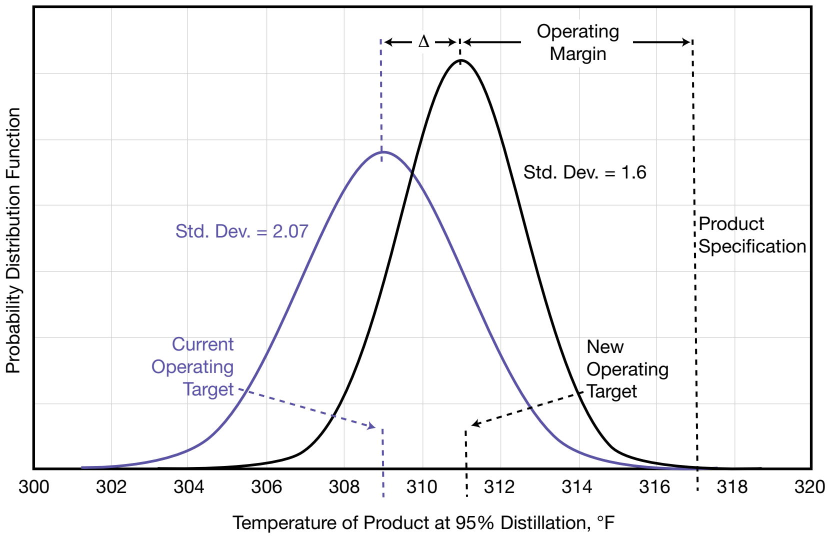
▲ **Figure 8.** The standard deviation of the process variable in two modes (open loop, and under control using manual sampling) is plotted in the top and middle graphs. The bottom plot of simulated disturbance data reveals a lower standard deviation when the online analyzer is used.

Modeling the loop disturbances. The closed-loop response to disturbances can be illustrated in several different ways. Plotting the sensitivity function, $S(s) = 1/[1+G_C(s)G_P(s)]$, on a Bode plot provides a graphical interpretation.

Figure 7 is a Bode plot for this example. Following Bode plot convention, the disturbances to the system are plotted on the x-axis in units of radians per minute (2π times the frequency in cycles per minute), and the amplitude ratio — the ratio of the magnitude of the loop output to the magnitude of the input disturbance at a selected frequency — is plotted on the y-axis. Both are plotted on a log scale to reflect the wide range of values typically encountered in plant operation.

The attenuation for a disturbance of a specific frequency is equal to the amplitude ratio corresponding to that frequency on the Bode plot. The lowest frequency at which the amplitude ratio equals one is called the crossover frequency. Disturbances with a frequency lower than the crossover frequency will be attenuated by the control loop, while the control loop will be ineffective for disturbances with a frequency higher than the crossover.

The Bode plot also illustrates the impact of the delay time and hence the tuning constants on performance. Figure 7 shows that switching to an online analyzer allows attenuation of disturbances with a significantly higher range, *i.e.,* the highest frequency with an attenuation less than one is significantly higher with the online analyzer.



▲ **Figure 9.** In Example 2, the product specification is 319°F. The curve with a standard deviation of 2.07 represents the operation with manual sampling; it has an actual operating target of 309°F. The curve with a standard deviation of 1.6 represents operation with automatic analysis, which would allow the operating target to be increased to 311°F. The operational buffer can be reduced without increasing the probability of violating the product specification because of the online analyzer's lower standard deviation.

Determining the expected standard deviation of the loop. The next step is to characterize typical process disturbances in order to determine the impact of the increased attenuation. Ideally, this is done by recording two sets of time-series data on the process variable of interest — one in open-loop operation and the other under control using manual sampling — as depicted by the top two graphs in Figure 8. Next, the standard deviation of the process variable in these two modes is calculated. The impact of the increased attenuation can be determined by control loop simulation that compares the open-loop and manual sampling performance to the performance of the system with the online analyzer, as shown in Figure 8. (Alternatively, a power spectrum analysis can be performed on the open-loop data to determine the dominant disturbance frequencies, and then the expected attenuation calculated directly from the Bode plot attenuation ratios.)

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Calculating the financial impact. Finally, we calculate the financial value of the expected reduced standard deviation. This involves first determining the current operational buffer between the operating targets and the actual product specifications (or other operating limits), and then calculating how much this operational buffer can be reduced as a result of the lower standard deviation without increasing the probability of violating the product specification *(11, 12)*. This is illustrated in Figure 9.

The product specification is based on the distillation curve for the product, specifically the temperature at which 95% of the product has been distilled. The specification value here is 319°F. The two bell-shaped curves represent the observed frequency distribution of product analyses. The curve with a standard deviation of 2.07 represents the operation with manual sampling. To avoid making off-spec product, the actual operating target is set below the specification, at a value of 309°F. The curve with a standard deviation of 1.6 represents operation with automatic analysis, which would allow the operating target to be increased to 311°F at the same (or lower) probability of violating the product specification limit. This will enable more of the material that was previously removed as lower-value heavy gas oil (HGO) to be converted into the more-valuable diesel product (Figure 6).

Assume that the crude unit has a capacity of 200,000 bbl/day, that the diesel's value is $10/bbl higher than that of the HGO, and that increased diesel yield can be achieved 50% of the time. Assume also that the operating target increase due to the lower standard deviation allows a 0.1% increase in the expected yield of diesel (at the same probability of violating the product specification).

The financial value of the improved measurement is determined by multiplying the following quantities:

- the daily production rate
- the number of operating days per year
- the differential product value
- the fraction of time that the benefit can be claimed
- the expected yield increase.

Numerically, this is:

$$\text{Value} = 200{,}000\ \text{bbl/d} \times 350\ \text{d/yr} \times \$10/\text{bbl} \times 0.5 \times 0.001 = \$350{,}000/\text{yr}$$

If the expected installed cost of the analyzer is $250,000, then the simple payback is 8.5 months.

As stated previously, these specific quantitative results are for the selected control algorithm and tuning constants. The conclusion, though, is independent of these factors: Reducing excessive delay time in a loop always increases the potential attainable performance.

Closing thoughts

Determining the financial justification for additional measurements in existing or proposed new process plants is a common issue. New measurements are of financial value only if they increase the economic value of the plant. This increase is created through improving predictive outputs of the plant decision cycles. Measurement investments can be evaluated by identifying the decision cycles impacted and quantifying the improved financial performance expected. CEP

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