

Inferential Control

CHAPTER

17

17.1 ■ INTRODUCTION

In all of the control methods considered to this point, the important variables have been measured, a situation which is desirable and most often possible. However, not all important variables can be measured in real time, that is, fast enough that timely control actions can be based on their measurements. There are various reasons for the lack of key measurements. First, some sensitive analyses have not been sufficiently automated to provide accurate, reliable measurements without human management of the procedure; thus, these measurements can be obtained only infrequently from a laboratory. There are even some properties that cannot be determined from intermediate material properties in a plant. Usually, these properties relate to the final use of the material; for example, some qualities of products such as soap, food products, or polymers depend on their application as final products and cannot be measured until the products are formulated and used. Second, even if the real-time measurement is possible, the cost of installing a sensor in the plant may not be justified by the potential benefits derived from the additional sensor, especially considering the alternative methods in this chapter. The cost is not typically high for conventional sensors for measuring temperature, pressure, flow, and level, but it may be prohibitive for an expensive analyzer with sample system and ongoing maintenance. Third, the sensor may not provide information in a timely manner. There are several reasons for slow feedback; for example, the analyzer may have a very long dead time because it must be located far downstream. Also, an analyzer may have a long processing time—one hour or longer—which would delay the feedback information. Finally, there may be no directly measurable

quantity; for example, the controlled variable may be the heat transferred in an exchanger.

The lack of measurements of key variables in a timely manner certainly offers challenges to achieving good control performance. However, unmeasured variables can sometimes be inferred from available measurements.

To infer: to achieve a conclusion based on information.

Here, the conclusion would be an estimate of the unmeasured variable. Thus, inferential control uses extra sensors to improve control performance. In this case, the extra information is additional measured variables that, while not giving a perfect indication of the key unmeasured variable, provide a valuable inference. The selection and use of these additional inferential variables requires process insight and adherence to the methods described in this chapter. Since inferential control is widely applied with great success, the analysis and design of inferential variables is important for engineers who design and operate plants, as well as for control specialists.

Since the characterization of variables as inferential may initially seem somewhat arbitrary, the general concept is explained here. All sensors depend on physical principles that relate the process variable to the sensor output, and thus no sensor “directly” measures the process variable. For example, a thermocouple temperature sensor provides a millivolt signal that is related to temperature (and the reference junction temperature), and an orifice flow sensor provides a pressure difference signal that is related to the flow (and fluid density). We normally consider the standard sensors for temperature, pressure, flow, and level as direct measurements, not inferential variables, because (1) they provide reasonably good accuracy and reproducibility, (2) they do not usually require corrections (e.g., for reference junction temperature), and, most importantly, (3) the relationship between the sensor signal and the process variable is not specific to a particular process. For example, essentially the same relationship between the pressure difference across an orifice and the flow through the orifice is used in thousands of plants. In contrast, a relationship between a reactor temperature and conversion is clearly specific to a particular process and is considered an inferential variable.

Since there is no generally accepted naming convention, we will refer to the variable we would like to control as the “true” controlled variable, $CV_t(t)$. The inferential variable, $CV_i(t)$, can be used because of a *process-dependent* relationship, which must be determined by the engineer. For example, a good inferential variable in Figure 17.1 is closely related to the true variable so that controlling $CV_i(t)$ will maintain $CV_t(t)$ close to its desired value. In most cases, the inferential variable is not as accurate as an on-stream sensor of the true variable. Also, the approximate relationship used for the inferential variable has a limited range, beyond which the inferential variable might not be satisfactory. It is important to remember that zero steady-state offset for the true variable is possible only when it is measured, perhaps infrequently, and used in the control system to adjust the set point of the inferential controller, $SP_i(s)$.

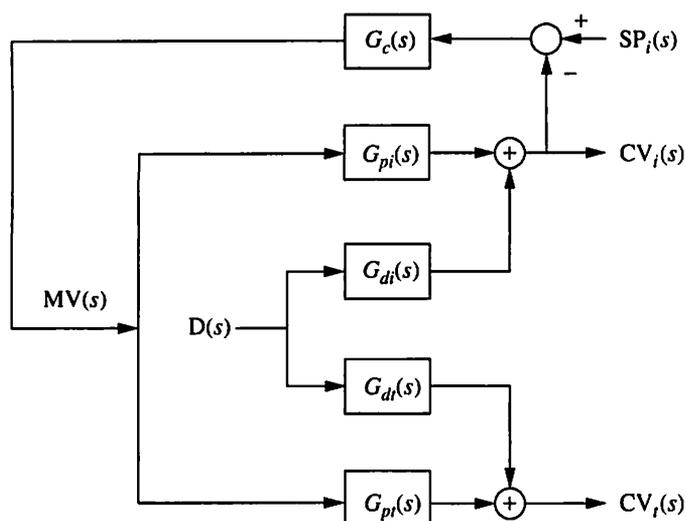


FIGURE 17.1

Block diagram of a feedback control system with a true controlled variable, $CV_t(s)$, and an inferential controlled variable, $CV_i(s)$.

Figure 17.1 can be used to determine the relationship necessary for good inferential control. First, the response of the true controlled variable to a disturbance can be evaluated.

$$\begin{aligned} CV_t(s) &= G_{dt}(s)D(s) + G_{pt}(s)MV(s) \\ &= G_{dt}(s)D(s) - \frac{G_{pt}(s)G_c(s)G_{di}(s)}{1 + G_{pi}(s)G_c(s)}D(s) \end{aligned} \quad (17.1)$$

A key goal of the control system is to maintain zero steady-state deviation in the controlled variable. This can be evaluated by applying the final value theorem to equation (17.1) with a step disturbance and PI feedback controller to give

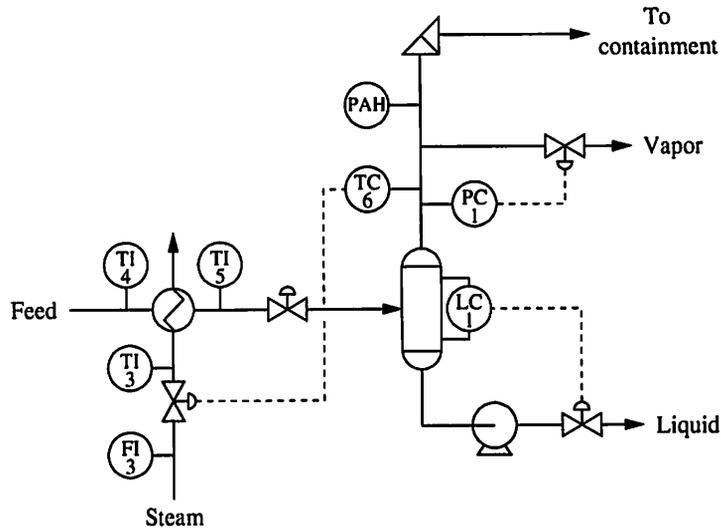
$$\lim_{t \rightarrow \infty} CV(t) = \lim_{s \rightarrow 0} CV(s) = K_{dt} \Delta D - \frac{(K_{pt} K_{di} K_c)/T_I}{(K_{pi} K_c)/T_I} \Delta D = 0 \quad (17.2)$$

Thus, the criterion for perfect steady-state inferential control in response to a disturbance is that $K_{dt}/K_{pt} = K_{di}/K_{pi}$.

As the process relationships deviate from this criterion, the performance of the inferential controller degrades. Thus, an important engineering decision is the selection of a proper inferential measured or calculated variable.

17.2 ■ AN EXAMPLE OF INFERENCE CONTROL

Application to a flash separator demonstrates the typical analysis steps for inferential control, along with a very common inferential variable. The process is shown in Figure 17.2 where a stream of light hydrocarbons is heated, the pressure of

**FIGURE 17.2**

Flash separator considered for inferential control of ethane composition in the liquid from the drum.

TABLE 17.1

Base-case data for flash process in mole percent

Component	Feed	Liquid	Vapor
Methane	10	1.3	19.8
Ethane	20	10.0	31.2
Propane	30	30.2	29.8
<i>i</i> -Butane	15	20.1	8.8
<i>n</i> -Butane	20	30.0	9.3
<i>n</i> -Pentane	5	8.4	1.1

the stream is lowered, and the liquid and vapor phases are separated in a drum. The base-case compositions of all three streams are given in Table 17.1. The true controlled variable is the ethane concentration in the drum liquid; however, an analyzer is not available, perhaps because of cost. (Accurate on-stream analyzers are commercially available for such a measurement.) The goal is to infer the concentration of ethane in the liquid stream leaving the drum, using the sensors shown in the figure. This goal may or may not be possible within the accuracy required; therefore, an analysis of the system is performed.

From a knowledge of vapor-liquid equilibrium, we expect that the temperature of the drum and the compositions will be related. In fact, the following model of the flash shows the relationship.

$$\begin{aligned}
 FM_{\text{feed}} &= FM_L + FM_V \\
 FM_{\text{feed}} Z_i &= FM_L X_i + FM_V Y_i \\
 Y_i &= K_i X_i
 \end{aligned}
 \tag{17.3}$$

where FM = molar flow
 X, Y, Z = mole fractions for liquid, vapor, and feed
 K_i = vaporization equilibrium constant depending on T, P
 P = pressure
 T = temperature

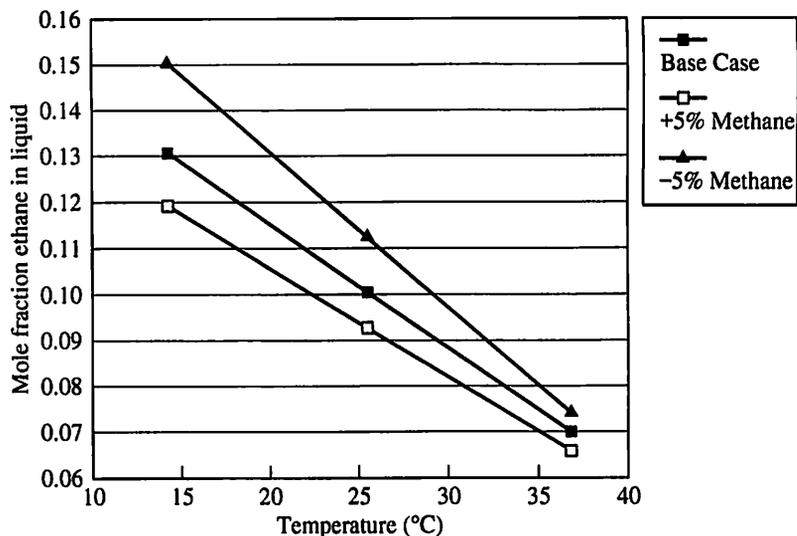
From equations (17.3) it can be seen that the liquid ethane composition is a function of the feed composition and the temperature and pressure in the flash vessel. (Further details on the flash calculation and the data used in this example can be found in Smith and Van Ness, 1987.) Let us assume that the drum pressure is controlled at essentially a constant value by adjusting a valve in the vapor line and that the temperature can be maintained at its desired value by manipulating the steam flow. If the feed had only two components, the temperature and pressure would uniquely determine the liquid and vapor composition; however, the feed has six components. Therefore, the pressure and temperature *do not* exactly define the compositions in the two phases. The essential question to answer is how closely the temperature is related to the liquid ethane composition, that is, how accurate an inference of liquid ethane concentration is supplied by the temperature when changes in the process operation occur.

The proposed inferential system is summarized by the following variables:

True variable	= x_e = liquid composition of ethane to be controlled at 0.10 ± 0.02 mole fraction	
Inferential variable	= T = temperature	
Manipulated variable	= heating medium flow	
Disturbance	= feed composition (as subsequently defined)	
Inferential relationship:	$x_e = \alpha T + \beta$	(17.4)

An analysis is performed to establish whether the relationship between the temperature and the liquid ethane concentration is satisfactory for inferential control. It is not possible to develop a closed-form analytical model of this process; therefore, the inferential model will be developed based on data representing the process. This data could be developed from mathematical simulation or plant experimentation. In this case, where excellent data exists for the vapor-liquid equilibrium, a simulation was performed to generate the relationship shown as the “base-case” line in Figure 17.3. The first step in evaluating the potential inferential relationship involves determining whether the sensitivities are appropriate. Figure 17.3 shows that the slope is about -0.0027 mole fraction per $^{\circ}\text{C}$, which means that the expected errors in the temperature measurement and control, here estimated to be $\pm 0.5^{\circ}\text{C}$, will not introduce a significant error in the calculated estimate of the ethane concentration.

Since the temperature has passed the first step, the analysis is extended to the second step by including *disturbances*: unmeasured input operating variables that are expected to change significantly. In this example, the feed composition is the major disturbance. The question is whether the temperature remains a satisfactory inferential variable when the feed composition changes; to answer this question, additional cases that characterize typical plant variability

**FIGURE 17.3**

The relationship between the flash temperature and the concentration of ethane in the liquid at the base-case pressure (1000 kPa). Changes in methane are compensated by changes in butane of equal magnitude and opposite sign.

have to be included in the analysis. In this example, the expected feed composition change from the upstream units involves offsetting differences in the methane and butane, which can be up to 5 mole %. The relationships between temperature and composition for the extremes of feed composition variation are shown in Figure 17.3. Clearly, holding the temperature constant is not equivalent to maintaining the ethane concentration constant. For the expected changes in feed composition and the expected accuracy in controlling the temperature, $\pm 0.5^\circ\text{C}$, the range of ethane liquid composition is from 0.091 to 0.117 mole fraction when the measured temperature is maintained at the proper value for no model error and nominal feed composition (25.5°C). Whether this accuracy is acceptable depends on the plant requirements; for this example it satisfies the stated objectives of inferential control (± 0.02 maximum error). Since the accuracy with the inferential variable is acceptable, the temperature provides an acceptable steady-state inferential measure of ethane concentration in the liquid stream, and the control strategy in Figure 17.2 could be appropriate. If it were not, perhaps due to a narrowing of the acceptable ethane concentration variation, an on-stream analyzer would be required.

If the steady-state accuracy is satisfactory, the dynamics of the potential inferential control system must be evaluated. Good dynamic responses, as discussed in Chapter 13, would have such characteristics as a fast response with a short dead time. For this example, the temperature could be controlled by adjusting the heating medium flow. Therefore, the dynamics seem favorable because the response would be fast. This judgment is supported by the dynamic response of this system presented in Chapter 24.

Recall that the temperature controller set point must be corrected based on a measure of ethane concentration to achieve zero offset. The composition feedback could involve the temperature set point being occasionally corrected by the operator based on infrequent measurements in the laboratory performed on samples

TABLE 17.2

Design criteria for inferential control**Inferential control is appropriate when**

1. Measurement of the true controlled variable is not available in a timely manner because
 - An on-stream sensor is not possible.
 - An on-stream sensor is too costly.
 - Sensor has unfavorable dynamics (e.g., long dead time or analysis time) or is located far downstream.
2. A measured inferential variable is available.

An inferential variable must satisfy the following criteria:

1. The inferential variable must have a good relationship to the true controlled variable for changes in the potential manipulated variable.
2. The relationship in criterion 1 must be insensitive to changes in operating conditions (i.e., unmeasured disturbances) over their expected ranges.
3. Dynamics must be favorable for use in feedback control.

Correction of inferential variable

1. By primary controller in automated cascade design
2. By plant operator manually, based on periodic information
3. When inferential variable is corrected frequently, the sensor for the inferential variable must provide good reproducibility, not necessarily accuracy

especially important to ensure that the inferential variable is adequate for the expected range of plant operating conditions. Usually, the initial selection is based on a steady-state analysis, and the dynamic response is subsequently evaluated.

Two similar approaches are used for designing inferential controllers. Both approaches are described in this chapter, along with industrial examples. One approach determines the best inferential variables based on data (experimental or simulation) from the process; this type will be referred to as the *empirical* approach. The inferential temperature in the previous flash control is an example. The other approach uses closed-form analytical models as a basis for inferential relationships. An example of this approach, which will be referred to as the *analytical* approach, is applied to a chemical reactor in Section 17.6. The application of either approach involves nearly the same steps to yield an inferential model for control. The analysis steps for each method are summarized in Table 17.3.

Application of the design criteria in Table 17.2 and the steps in Table 17.3 ensures that a proper inferential variable is selected, if one exists. These approaches are usually adequate, because inferential variables are employed to reduce, although not eliminate, large offsets due to disturbances. To reiterate, an inferential strategy can achieve zero offset only when the true controlled variable is ultimately measured and used to adjust the set point of the inferential controller.

TABLE 17.3

Steps required to design an inferential controller

Step	Empirical approach	Analytical approach
1	Select one or a few measured variables for evaluation based on process insight.	Select one or a few measured variables for evaluation.
2	Develop a <i>representative</i> set of data that contains typical changes in the manipulated and disturbance variables.	Derive the analytical model from fundamentals.
3	Develop a correlation between the measured inferential and true controlled variables by fitting the model to the data to determine the unknown parameters.	The analytical model provides the necessary correlations.
4	Evaluate the accuracy and reproducibility of the correlation against process needs. This evaluation should consider realistic levels of noise on the inferential variable.	Same, although sensitivity information can be obtained directly from the model.
5	Select the best of the inferential variables and evaluate the dynamic response for use in feedback control.	
6	If the best inferential variable is acceptable, design the control system including ultimate feedback from the true variable.	
7	If no measured variable has both acceptable accuracy and acceptable dynamics, then inferential control is not possible. An on-stream sensor should be purchased and installed, if available. If no sensor is available, then the control objectives cannot be achieved unless other steps, such as reducing disturbances, can be taken to reduce the variation in the true controlled variable.	

17.4 □ IMPLEMENTATION ISSUES

An inferential controller using a single measured variable is basically the same as any other single-loop or cascade controller, and no special implementation considerations are necessary. If the correction from the true controlled variable is made manually by the operator, a simple correlation is helpful in deciding the necessary change in inferential controller set point. In the flash separator example, the slope of the correlation in Figure 17.3 indicates that the temperature should be changed $+1^{\circ}\text{C}$ for a change of -0.0027 mole fraction ethane. As an example of how the person would use the correlation, if the laboratory analysis were 0.0040 mole fraction below the desired ethane concentration, the operator would implement a -1.5°C change in the temperature set point based on the correlation.

The situation changes when additional variables are used in the inferential relationship. In the flash separator, the strategy in Figure 17.2 might not be adequate if the drum pressure varied significantly, which can occur when the pressure is not controlled at the drum but varies with downstream units. A simple manner for considering this change would be to add an additional term, which would account for changing pressure, to the inferential correlation used to calculate the ethane

concentration. The enhanced inferential relationship would be

$$x_e = \alpha T + \gamma P + \beta' \quad (17.5)$$

Again, this expanded relationship would be developed based on representative data for the system over the expected range of pressures. The effect of pressure for the base case feed concentration is shown in Figure 17.5, which would provide information for an additional linear term that would be valid over a limited range. A correlation using two measured variables in the inferential control strategy is shown in Figure 17.6. This is often referred to as a *pressure-corrected temperature*, which refers to the correction of the relationship between temperature and composition to account for pressure changes.

The reliability of inferential controllers is the same as that of other similar systems. Controllers using additional variables would be expected to have lower reli-

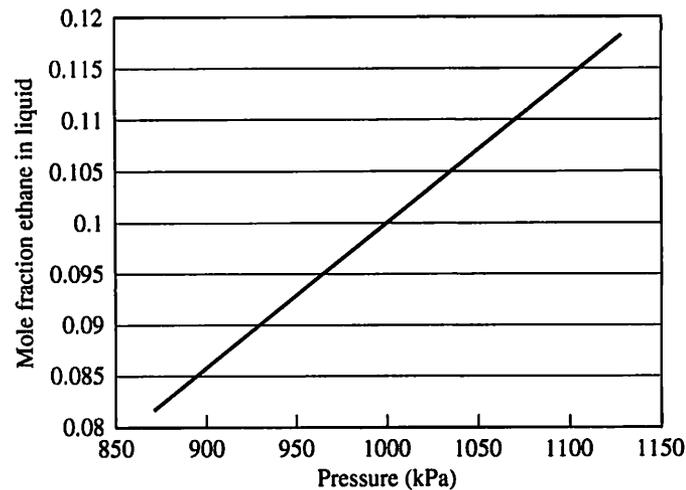


FIGURE 17.5

The effect of pressure on ethane concentration in the liquid from the flash process at the base case temperature and feed composition.

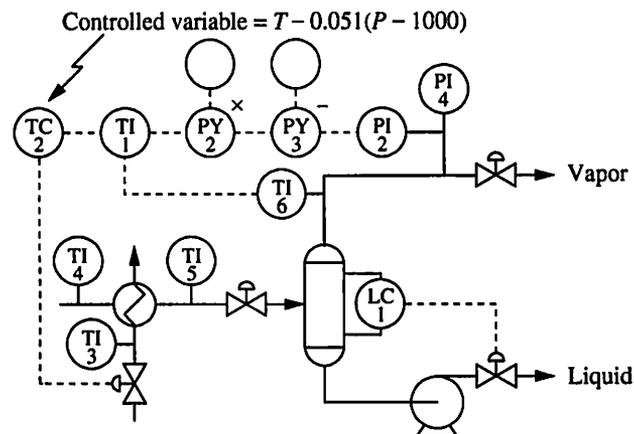


FIGURE 17.6

Enhanced inferential controller with compensation for changes in pressure.

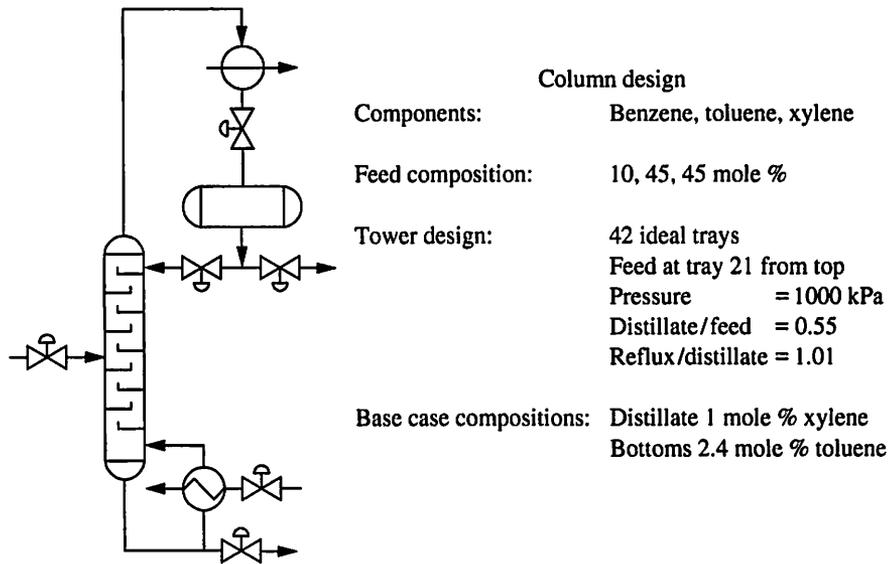
ability. For example, the pressure-corrected temperature controller in Figure 17.6 uses two measurements, and its reliability would be lower than the temperature-only design in Figure 17.2. Since sensors used in inferential control tend to have high reliability (their purpose is to replace the expensive and less reliable sensors), the slight loss in reliability is not usually a significant concern.

17.5 □ INFERENCE CONTROL EXAMPLE: DISTILLATION

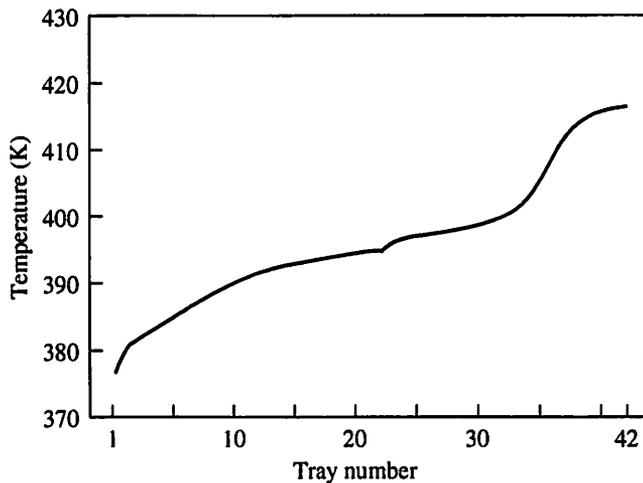
This example extends the concept of the flash separator to a distillation tower. In operating a distillation tower, the product purities are achieved by adjusting manipulated variables such as the reboiler heating medium and distillate product flows. On-stream analyzers can be used successfully to control distillation; however, each analyzer is expensive, and not all towers require such accurate control of both product qualities. Therefore, an important question arises concerning which tray temperature, if any, can be used to infer the product composition. An analysis will be described here that, by following the general inferential design criteria, provides an answer to this question. This example considers the distillation tower in Figure 17.7, where the top product composition is to be controlled, but no analyzer is available. The tower separates a feed that contains benzene, toluene, and xylene. The top product contains benzene and toluene and 1 mole % xylene, and the bottom product contains xylene and 2.4 mole % toluene. The temperature profile is given in Figure 17.8 for the base-case operation. The goal is to control the inferred top composition by adjusting the distillate flow. The potential inferential control strategy is summarized as follows:

True variable	= x_D = heavy key in distillate = 1 mole %	
Inferential variable	= T = tray temperature	
Manipulated variable	= distillate flow rate	
Disturbances	= reboiler duty, feed composition	
Parameters	= tray efficiency, thermodynamics	
Inferential relationship:	$x_D = \alpha T + \beta$	(17.6)

A procedure similar to the flash example is followed, except that several tray temperatures are initially considered, with the goal of selecting the best single temperature. The trays considered are numbered 1, 5, 10, and 30 from the top; all trays could be included in this analysis, but that would expand the number of graphs. As we learned in Chapter 16, transformations of highly nonlinear relationships can often improve the performance of linear control systems. In this example, the log of the composition is controlled to linearize the feedback loop; this feature is not required for inferential control but is a good practice in distillation control (e.g., Koung and Harris, 1987) and is included in the control design. Potential relationships between tray temperatures and overhead composition for changes in operating conditions are evaluated in Figure 17.9a through c for changes in the manipulated variable (distillate flow) and in the disturbances (reboiler duty and feed composition). The distillation tower is too complex to use an analytical model to determine the relationships. Therefore, the values in these figures

**FIGURE 17.7**

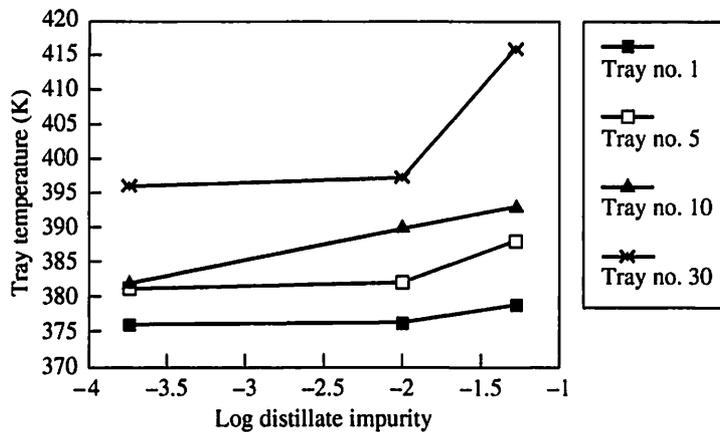
Parameters for the distillation tower investigated for inferential tray temperature control.

**FIGURE 17.8**

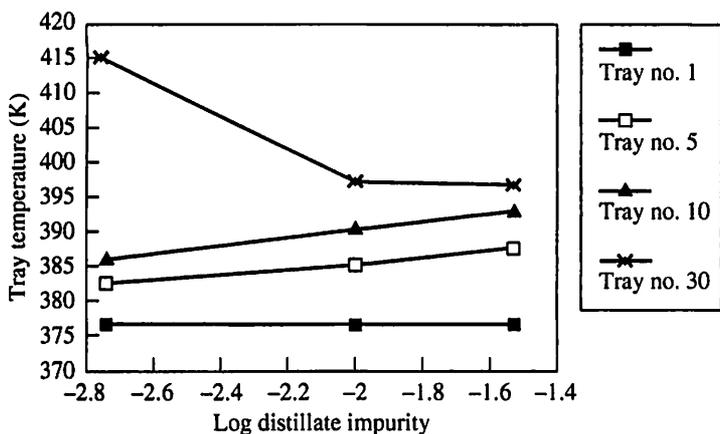
Tray temperature profile for the base case distillation tower.

were obtained by detailed steady-state simulations of the tray-by-tray model with accurate thermodynamic data (Kresta, 1992).

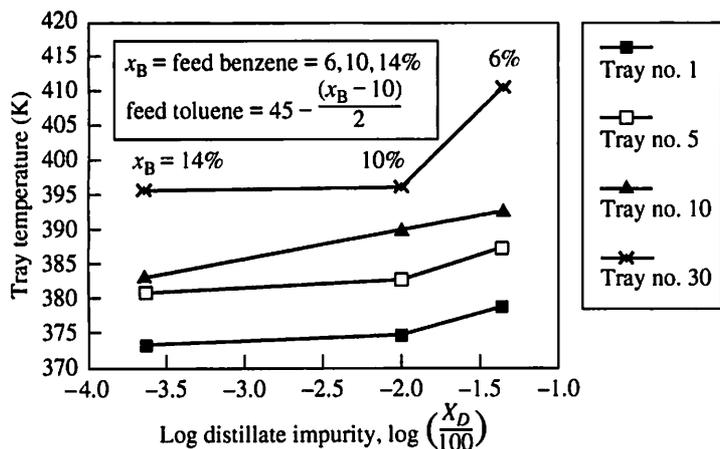
For good inferential control, the selected tray temperature would have nearly the same constant slope for all figures. Each of the candidate tray temperatures is evaluated individually to determine whether it satisfies the design criteria. The results in Figure 17.9a show the relationship as the manipulated variable changes, and the results in Figure 17.9b and c show the relationship as disturbances occur. All figures show clearly that the tray 1 temperature does not change significantly even though the tower operation and top product purity change. Thus, the top tray temperature would be a very poor inferential variable, because the sensor errors and low-magnitude noise would invalidate any correlation drawn from these



(a)



(b)



(c)

FIGURE 17.9

Relationship between tray temperature and distillate composition; (a) for $\pm 5\%$ changes in the distillate flow with the feed composition and reboiler duty constant; (b) for $\pm 5\%$ changes in the reboiler duty with distillate flow and feed composition constant; (c) for changes in feed composition with distillate flow and reboiler flow constant.

simulations; therefore, tray 1 will not be considered further. Additional analysis of the figures reveals that tray 30 is not acceptable, because the slope changes sign between Figure 17.9a and b. For this tray temperature, a temperature increase would indicate an increase in top purity for some situations and a decrease in top purity for other situations. This would not be a good inferential variable—a result that might be expected, because the feed tray is between tray 30 and the top product, which is usually not advisable in distillation tray temperature control. Of the remaining trays, both trays 5 and 10 have reasonably linear responses, with sensitivities much greater than the noise in the temperature sensors and not changing greatly for the three figures. Thus, the temperatures for trays 5 and 10 satisfy the steady-state criteria based on this open-loop data. The preliminary conclusion is that either tray 5 or 10 would be an acceptable inferential temperature.

To evaluate this preliminary conclusion, tray 7 was chosen as representative of either tray 5 or 10 and was controlled by adjusting the distillate flow as shown in Figure 17.10 for feed composition disturbances. The steady-state errors in top product composition are plotted in Figure 17.11 for the case without an analyzer resetting the inferential controller. This measure of performance is used to evaluate the reduction in steady-state offset from perfect control that could be achieved with inferential tray temperature control. As can be seen, the top composition remains much closer to its desired value compared with the results without inferential control (open-loop), indicating that, in this case, the tray 7 temperature is a good single-tray inferential variable. Thus, inferential control offers the potential for much improved control performance.

The dynamic response of the inferential controller should also be evaluated. In this case, the tray temperature, being in the top section of the tower, introduces only a few trays between the controlled and manipulated variables. The dynamic response between the manipulated distillate flow and the controlled temperature is expected to be fast. Thus, the selection would appear to be appropriate from a dynamic viewpoint.

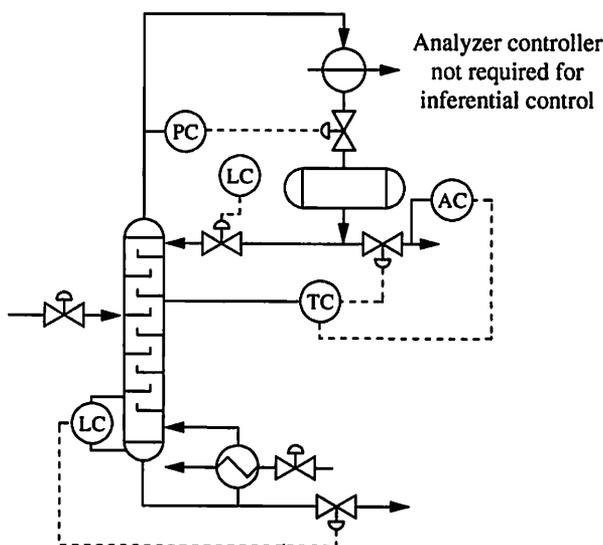


FIGURE 17.10

Control strategy for tray temperature inferential control.

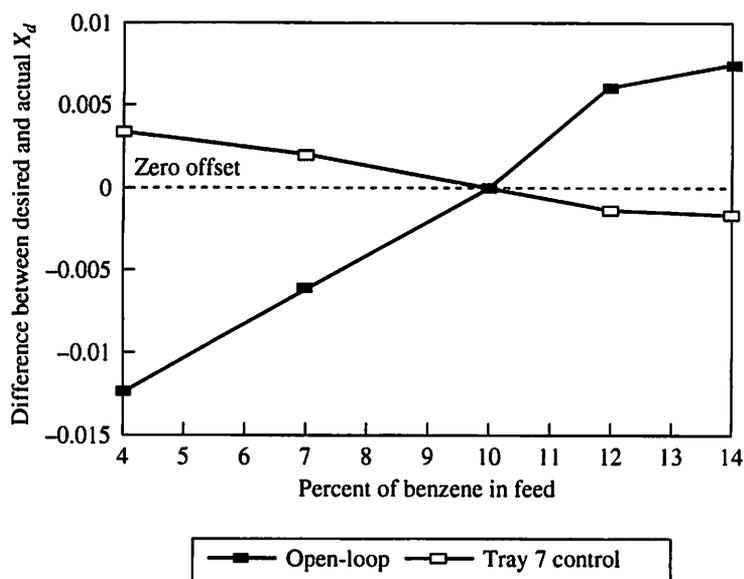


FIGURE 17.11

Steady-state offset for the distillation tower without control (open-loop) and with tray 7 inferential control (without analyzer feedback).

To achieve the zero offset performance at steady state shown in Figure 17.11, the tray temperature must be adjusted to correct small errors in the inferential relationship. This can be done by an operator, who would make manual changes to the set point based on periodic laboratory analyses. Alternatively, the tray temperature controller can be a secondary that is reset by an analyzer feedback controller. Such an approach is shown in Figure 17.10.

The procedure just described does not always identify a good tray temperature, because in some distillation towers no single tray temperature is a good inference of product composition. An example of this situation occurs when the key components have nearly the same volatility. The tray temperatures are not very different, so that the temperature variation due to composition changes is within the measurement accuracy of the sensor; in this situation the tray temperatures would not be expected to correlate with product composition. This situation occurs in the separation of propylene and propane by distillation, which demands a high-purity top product with a relative volatility of about 1.1 (Finco et al., 1989). To provide good product composition in these distillation towers, on-stream analyzers are usually provided.

The development of an empirical inferential model in this section followed the same steps used for the flash separator. Inferential tray temperature controllers designed using methods similar to the analysis in this section are widely applied in the process industries; in fact, far more distillation tower product composition controllers use tray temperature inference than use on-stream analyzers.

17.6 ■ INFERENCE CONTROL EXAMPLE: CHEMICAL REACTOR

The inferential control examples for the flash and distillation processes demonstrated the empirical inferential method, in which the model is based on fitting representative data. In this section the analytical method is demonstrated for a

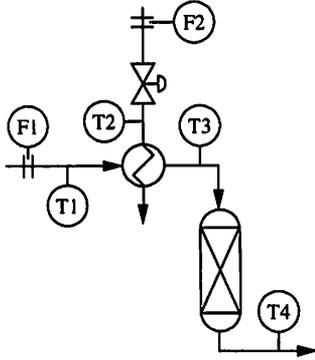


FIGURE 17.12

Packed-bed chemical reactor considered for inferential control.

process that can be represented by a simple closed-form model. The example in this section is the packed-bed reactor with an exothermic reaction shown in Figure 17.12. The goal is to control the moles reacted without an on-stream analyzer. Simplified steady-state material and energy balances, assuming no heat loss, for the packed-bed reactor with a single reaction occurring are

$$A \rightarrow B$$

$$\Delta T = -\Delta H_{\text{rxn}} \frac{C_{\text{Ain}}}{\rho C_p} X_A = \frac{-\Delta H_{\text{rxn}}}{\rho C_p} \Delta C_A \quad (17.7)$$

$$\Delta T = T4 - T3$$

where

- C_A = concentration of A, moles/volume
- ρ = density, mass/volume
- C_p = heat capacity, energy/(°C · mass)
- ΔH_{rxn} = heat of reaction, energy/mole
- X_A = fraction of feed reacted = $(C_{\text{Ain}} - C_{\text{Aout}})/C_{\text{Ain}} = \Delta C_A/C_{\text{Ain}}$

A brief summary of the inferential system being evaluated is

True variable	= ΔC_A = moles of A reacted	
Inferential variable	= ΔT = temperature difference	
Manipulated variable	= heating medium flow	
Disturbances	= inlet concentration, feed flow rate	
Parameters	= $\rho, C_p, \Delta H_{\text{rxn}}$	
Inferential relationship:	$\Delta C_A = \alpha \Delta T + \beta$	(17.8)

To evaluate the inferential measurement, the design criteria are applied; they require a good relationship between the true variable and the inferential variable when the manipulated variable is changed and little modification to the relationship when disturbances occur. On the first issue, there is clearly a strong relationship between temperature difference and amount reacted, which could provide a reliable inference as the inlet temperature changes. The success of this approach depends on the temperature difference being much larger than the sensor error and noise in the temperature sensors, as is often, but not always, the case. On the second issue, the relationship is insensitive to changes in operating variables such as feed rate and inlet composition as seen in equation (17.7). However, the relationship is dependent on parameters such as heat capacities and heat of reaction; if these parameters are relatively constant, they will not influence the accuracy of the inferential measurement. Therefore, controlling temperature difference across the reactor could provide good inferential control of amount reacted.

Notice that the analysis to this point is for steady-state conditions. As previously mentioned, the control system dynamics must also be investigated. A typical dynamic response of the inlet and outlet temperatures and the instantaneous temperature difference to a step increase in the heating medium valve position are given in Figure 17.13. The inlet temperature responds quickly, while the outlet temperature responds slowly, because of the time required to heat the catalyst. Therefore, the *instantaneous* temperature difference is not a good inference of reactor performance, even though the steady-state temperature difference is an

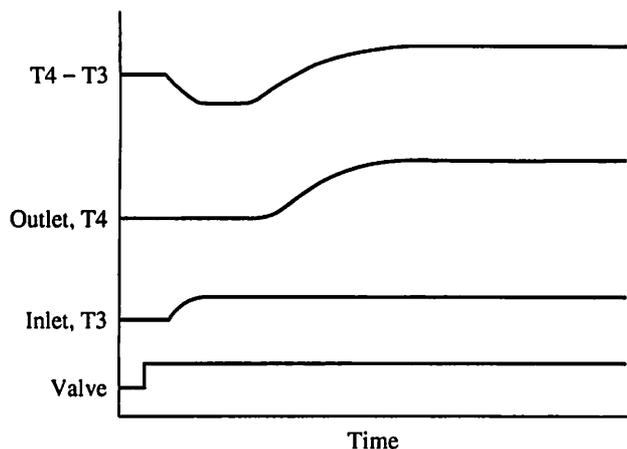


FIGURE 17.13

Plot of key variables for packed-bed reactor inferential control. Note the significant inverse response of the instantaneous temperature difference.

acceptable inferential variable. The figure demonstrates the complex inverse response between the manipulated (valve position) and potential controlled (ΔT) variables that results from this seemingly simple inferential control design. The initial inverse response can be a large multiple of the final change, and a PID controller might not perform well for this response, depending on the extent of the inverse response, as demonstrated in Example 13.8.

One method for using the available measurements is to wait for the process to achieve steady state before calculating a correction in the heating medium flow. This approach would result in very slow feedback and poor performance if frequent disturbances occur. A better control design for this example would compensate the temperatures used in the difference to account for the dynamics. One approach for this is shown in Figure 17.14, in which the inlet temperature is passed through a dynamic element that matches the outlet temperature response. The element TY-2 in the control strategy has the dynamics of the transfer function $T4(s)/T3(s)$. Then, the two temperatures can be compared and used for control with a PID control algorithm, which would not “see” the inverse response. Another approach would be to use a predictive control algorithm in place of the PID; predictive control, which employs a simple dynamic model in the control calculation and is able to control processes with complex responses like the one in Figure 17.13, is presented in Chapter 19.

If the goal in this example were to control the outlet concentration C_{Aout} rather than the conversion, the analysis would have to be repeated for this different true controlled variable. The relationship between outlet concentration and temperature difference is unchanged as equations (17.7); however, a key operating variable that might change significantly—inlet concentration—appears in the relationship, as follows.

$$\Delta T = \frac{-\Delta H_{rxn}}{\rho C_p} (C_{Ain} - C_{Aout}) \quad (17.9)$$

Therefore, maintaining the temperature difference constant does not ensure constant outlet concentration when the inlet concentration changes. Further study

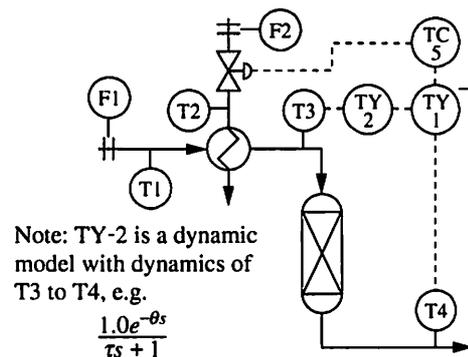


FIGURE 17.14

Design for packed-bed reactor inferential temperature difference control that does not have an inverse response.

would have to be performed to determine the typical variation in inlet concentration and whether this variation would introduce unacceptable errors in the inferential calculation of C_{Aout} .

One more possibility can be explored in the reactor example. In chemical reacting systems with multiple reactions, it is often important to control the selectivity of feed to the more valuable product as well as controlling the total conversion. Thus, we investigate here whether the temperature difference can be used to infer selectivity. The steady-state energy balance follows for a reactor with two parallel reactions in which the feed can react to either product B or product C.

$$\begin{aligned} A &\rightarrow B \text{ with moles reacted} = \xi_B \\ A &\rightarrow C \text{ with moles reacted} = \xi_C \\ \Delta T &= \frac{(-\Delta H_B)_{rxn}\xi_B + (-\Delta H_C)_{rxn}\xi_C}{\rho C_p} \end{aligned} \quad (17.10)$$

It can be seen from the equations that the selectivity is *not* uniquely determined when the temperature difference is specified. A measured temperature difference could be the result of many ratios of the products B and C. Therefore, the temperature difference is not a satisfactory inferential variable for selectivity in this case. In fact, if the ratio of ξ_B/ξ_C changes significantly during plant operation and the heats of reaction are different, the temperature difference is not even a good inference of the total conversion of reactant A.

The development of an inferential model based on fundamental modelling principles was demonstrated in this section.

When possible, the inferential control model should be based on fundamental modelling principles.

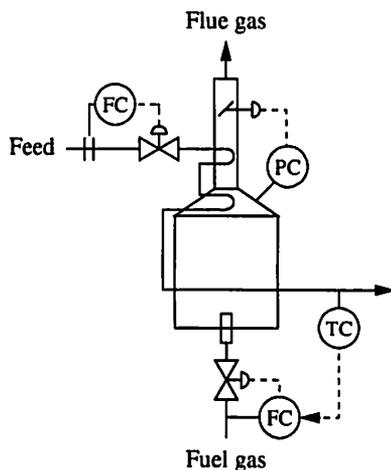


FIGURE 17.15

Fired heater process with basic controls considered for enhancement by inferential control.

This method provides excellent insight into the variables included in the model as well as the model structure. The model also provides insight into the accuracy of the inferential estimate for changes in the operating variables and physical properties.

17.7 ■ INFERENCE CONTROL EXAMPLE: FIRED HEATER

As another example, inferential control can be combined with cascade control to improve the performance of the fired heater shown in Figure 17.15. The outlet temperature of the fluid in the coil is to be controlled tightly, and a primary sensor is available for this purpose. As discussed in Chapter 14, this strategy benefits from a cascade design with a secondary fuel flow controller that corrects for some disturbances. However, the cascade does not correct completely for the effect of changing fuel gas density. The upset occurs because the heat of combustion changes as a result of changing fuel gas composition (density); thus, the heat transferred to the coil is disturbed. An improvement to the cascade control design in Figure 17.15 involves an inferential variable as the secondary of the cascade that indicates the heat released through combustion of the fuel gas. The best inferential variable of the heating value depends on the gas composition; a good inferential measure for a mixture of light hydrocarbons without hydrogen, which is a common industrial

fuel gas, is the mass flow rate of fuel (see question 17.7). To improve the response to a composition disturbance, the secondary controller in the cascade design could be altered to ensure that the mass flow, rather than the pressure difference across the orifice, is maintained constant. The potential inferential system is summarized as follows:

True variable	= Q	= actual rate of heat released via combustion	
Inferential variable	= F_m	= mass flow rate of fuel	
Manipulated variable	=	fuel valve position	
Disturbance	=	fuel composition	
Inferential relationship:	$Q = \alpha F_m + \beta$		(17.11)

The mass flow can be calculated as the product of the volumetric flow rate and the density according to the following equation:

$$F_m = K \sqrt{\frac{\Delta P}{\rho}} \rho = K \sqrt{\rho} \sqrt{\Delta P} \quad (17.12)$$

where ΔP = pressure difference across the orifice
 ρ = density of the fuel gas

The inferential calculation requires an additional measurement: the density of the fuel gas at the stream conditions. This measure can be used so that the secondary controller maintains the heat fired, rather than the ΔP , at the desired value. The improved control strategy shown in Figure 17.16 provides superior

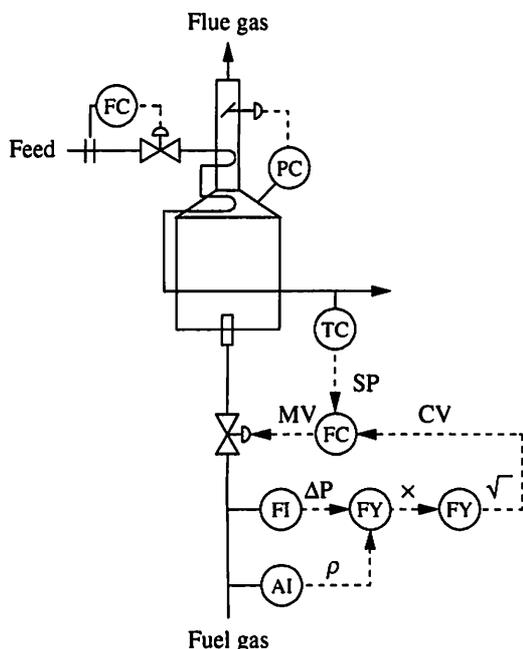


FIGURE 17.16

Fired heater with inferential control for better performance as fuel gas composition changes.

performance for disturbances in fuel composition, because it rapidly adjusts the fuel flow so that the total heat fired is maintained at its desired value. Control designs based on this principle have proved to be extremely successful in industrial applications (API, 1977). The reader should be aware that the other combustion inferential measurements and control calculations should be used for different fuel compositions, such as when hydrogen or inert gases are present (Duckelow, 1981); thus, the control design that is satisfactory for this example is not generally applicable for all combustion systems.

17.8 ■ ADDITIONAL TOPICS IN INFERENCE CONTROL

Application of the method described in the previous sections often leads to an adequate inferential model if one can be found. Several alternative approaches to inferential control require advanced mathematics to cover completely; thus, only the basic concepts are introduced here, along with references for further study.

Multiple Measurements

Often there are many measurements available for use in an empirical inferential model. If the measurements have independent effects on the true controlled variable, the method explained in this chapter can be used. However, the measurements may have correlated effects on the true controlled variable. In the correlated case, caution must be used when fitting the model to the empirical model. For example, an inferential model for the distillation example could be formulated using many (even all) tray temperatures and flows as follows:

$$(x_D)_i = \alpha_1 T_1 + \alpha_2 T_2 + \cdots + \alpha_{n+1} F_R + \alpha_{n+2} F_D + \cdots + \alpha_m P \quad (17.13)$$

where

- $(x_D)_i$ = calculated estimate of the true controlled variable
- T_i = temperature of i th tray
- F_R = reboiler heating medium flow rate
- F_D = distillate product flow rate
- P = pressure

The coefficients α_i could be determined from plant data using linear regression (e.g., Draper and Smith, 1981); however, the strong correlation among the input variables can lead to a model with poor predictive ability. Note that the tray temperatures will be strongly correlated among themselves, since adjacent tray temperatures tend to increase or decrease as the product purity changes. The difficulty arises because the large number of parameters enables the model to fit much of the “noise” in the data. More advanced statistical model building and diagnostic methods based on multivariate statistics are recommended when correlated inputs are used (Kresta et al., 1994; Mejdell and Skogestad, 1991).

Plant Conditions

It is important to recognize that the empirical model represents correlation between the inputs (inferential variables) and output (true variable) in a base-case set of data used in model building. This empirical model should be used only within the range of plant operating conditions used for building the model. Operating conditions

could be feed rates, feed compositions, product quality specifications, or control strategies. The empirical inferential model could give poor predictions when used outside the base-case conditions and should be reestimated when plant operations, including control structure, change (Kresta et al., 1994).

Kalman Filter

A powerful method exists when a fundamental dynamic model is available. The *Kalman filter* provides a method for using measured variables to update the fundamental model and provide a dynamic estimate of the unmeasured true controlled variable (Grewal and Andrews, 1993). This method requires mathematics beyond the general level in this book; considerable engineering effort; and, when applied, more intensive real-time computing. It should be considered when a dynamic inferential variable is required.

17.9 ■ CONCLUSIONS

The importance of inferential control cannot be exaggerated. Many variables are difficult or impossible to measure on-stream for use in automatic, real-time control. To counter this shortcoming, inferential control is widely applied in the process industries. It may seem surprising that most of the analysis in this chapter involved steady-state relationships. This situation results from two causes. First, the major benefits for inferential control often result from a substantial reduction of the steady-state offset of the true controlled variable from its desired value. To achieve this goal, the inferential variable with the most accurate steady-state relationship is desired, even if the dynamics of the inferential controller are not the best. This situation is demonstrated in the chemical reactor example, where the inverse response dynamics are not desirable.

Another reason for the emphasis on steady-state analysis is the lack of a generally accepted design method for dynamic inferential control based on empirical models. Some initial developments in this area are noted by Kresta (1992). Note that the Kalman filter also addresses dynamic control of unmeasured variables when fundamental models exist.

When engineers first encounter inferential strategies, they often believe that the designs were based on trial-and-error methods or perhaps developed through years of observing process behavior. To the contrary; the evaluation of inferential variables follows the procedure presented in this chapter. However, the insight required for selecting the proper measurements and process relationships cannot be condensed into a simple procedure. This is a critical step, because inferential relationships can be developed over time using plant data only if the design engineer has provided the appropriate sensors. An additional challenge is to determine the proper candidates from among the numerous existing sensors—a decision requiring process knowledge, tied to the understanding of the final application with noisy sensors and process disturbances. Engineers should view this situation as an opportunity to apply their technical and problem-solving skills to this important aspect of process monitoring and control, recalling that “engineering insight” usually comes from application of fundamental principles, quantitative analysis, and hard work.

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- Smith, J., and H. Van Ness, *Introduction to Chemical Engineering Thermodynamics* (4th ed.), McGraw-Hill, New York, 1987.

ADDITIONAL RESOURCES

For additional examples of selecting a single tray temperature for distillation control, see the following:

- Luyben, W., "Profile Position Control of Distillation Columns with Sharp Temperature Profiles," *AIChE J.*, 18, 1, 238–240 (1972).
- Tolliver, T., and L. McCune, "Finding the Optimum Temperature Control Trays for Distillation Columns," *In. Tech.*, 75–80 (September 1980).

Experimental design is a crucial step in collecting data for model structure selection and parameter estimation. Only the most rudimentary data was used in the examples in this chapter; experimental design is covered in

- Box, G., S. Hunter, and J. Hunter, *Statistics for Experimenters*, Wiley, New York, 1987.

QUESTIONS

- 17.1. (a) Discuss the inferential design criteria in your own words.
 (b) Why are cases with changes in disturbance and manipulated variables included when selecting an inferential variable?

- (c) Suppose that a recommendation were made to select an inferential distillation tray temperature that had a large slope ($\Delta T / \Delta$ (tray number)); would you use this method?
- (d) Discuss how specifications on product quality and economic values for energy and product quality would be used when evaluating an inferential variable.
- (e) Complete the block diagram in Figure 17.1 for closed-loop, feedback control of the true controlled variable, $CV_t(s)$, using cascade control. Give the required modes for both controllers in the cascade to ensure that there would be zero steady-state offset in the true variable for a steplike disturbance.

17.2. When the inferential controller is a secondary in an automated cascade design, the primary controller can be thought of as correcting the inferential model.

- (a) Given the following model for the control strategy in Figure 17.5, explain how the primary controller corrects the inference; that is, which parameter(s) are essentially modified through the feedback.

$$x_e = \alpha T + \beta$$

- (b) How does this feedback affect the stability of the secondary loop?

17.3. The measured variables used directly or in calculations for inferential variables described in this chapter have been outputs (causes) from the process. It would be possible to measure inputs, both manipulated variables and disturbances, and build an inferential model using process input variables.

- (a) Describe the similarities between inferential control using input variables and other enhancements covered in Part IV.
- (b) Discuss the differences between using process output and input variables for inferential control and when each would be preferred.

17.4. An analyzer feedback control system that adjusts the reboiler heating medium flow, as in Figure Q14.6, is subject to disturbances in heating medium temperature. Design an *inferential* controller, implemented as a cascade secondary, that would improve control performance for the disturbances noted. State the assumptions you have made in the design.

17.5. Consider the following questions for the flash process in Section 17.2.

- (a) How well would the temperature inferential controller perform if the feed had only two components: ethane and propane?
- (b) For the original feed composition and operating conditions in Table 17.1, how well would the temperature perform as an inference of the ratio of *n*-butane to *n*-propane in the liquid phase?

17.6. The series of two chemical reactors in Example 3.3 are considered in this question. The reaction is $A \rightarrow B$, and because of the cost of sensors, the measurements available are the feed flow, tank temperature, and second-tank composition of component A. Evaluate the use of these measurements for inferential control of the composition of component B in the second tank, which should be maintained within ± 0.05 mole/m³.

- 17.7.** Collect data on the heats of combustion for light hydrocarbons (C_1 to C_4), hydrogen, and carbon monoxide.
- (a) In Section 17.7, the proposal was made that the mass flow is an acceptable inferential variable for the rate of heat release upon combustion for a stream of light hydrocarbons only. Evaluate this statement for significant changes in the stream composition.
 - (b) Reconsider (a) when significant hydrogen has been added to the stream. Is mass flow an acceptable inference? If not, what measured or calculated flow quantity is an acceptable inferential variable?
 - (c) Reconsider (b) with significant carbon monoxide.
- 17.8.** Implementing an inferential controller using several measured variables should involve special care.
- (a) Provide a detailed description of the calculations required to implement the digital inferential controller using temperature and pressure shown in Figure 17.7. You should consider initialization, calculation of the controlled variable, the feedback controller, and reset windup protection.
 - (b) Assume that it is possible to check the validity of all measured signals used in (a); this might be achieved by ensuring that the signal is within the allowable range. Add the logic used to respond to an invalid measurement for pressure and temperature. (Hint: The logic should be different for the two measurements.)
 - (c) Discuss the use of filtering the measured variables in inferential control.
- 17.9.** A criterion for perfect steady-state inferential control in response to a disturbance is given in Section 17.1. Extend this approach to determine the criterion for perfect steady-state inferential control in response to a step change in the inferential controller set point. How would you determine which of these criteria is important for a potential application?
- 17.10.** The concentration of component B (C_B) in the reactor system in question 5.12 is to be controlled. It cannot be measured, but the feed concentration of component A (C_{A0}), reactor volume, and inlet flow can be measured. Propose an inferential variable for this system and discuss its strengths and weaknesses.
- 17.11.** Derive the model used for the inferential control of the fixed-bed reactor, equation (17.7).
- (a) Discuss how you would evaluate (1) the required accuracy (or reproducibility) for the temperature sensors, (2) the effects of heat transfer to the surroundings, and (3) the sensitivity of the inferential variable to changes in the feed flow rate. How would the results differ if a new, more active catalyst were used in the reactor?
 - (b) Suggest a modification to the control system design in Figure 17.15, employing an enhancement presented in Part IV, that would provide better performance for disturbances in T_2 .
- 17.12.** For the inferential control system with closed-loop analyzer feedback in Figure 17.5:

- (a) Can the concentration of the ethane and lighter components in the propane product be controlled by adjusting variables in the final distillation column? If yes, which variables?
- (b) The same analyzer could measure the amount of butane in the propane product. Could this variable be controlled by adjusting a manipulated variable in the distillation column? If yes, which variables(s)?
- 17.13.** The concentration of component A (C_A) is to be controlled in the non-isothermal CSTR in Section 3.6. It is not measured, but the following measurements are available: F , C_{A0} , T_0 , T , V , F_c , T_{cin} , and T_{cout} . Propose an inferential variable for this system and discuss its strengths and weaknesses.