Chapter 13

PID Enhancements

Chapter Objectives

• Show how inferential control can dramatically reduce analyzer deadtime using several different examples.
• Demonstrate that scheduling of the controller tuning can improve the reliability of a PID controller applied to a nonlinear process.
• Illustrate how override and select controls are used to satisfy process constraints.
• Demonstrate the advantages of computed MV control for specific types of disturbances.

13.1 Introduction

This chapter is concerned with enhancements for PID controllers that are designed to overcome the effects of measurement deadtime, process nonlinearity, process constraints and specific disturbances. Inferential control can greatly reduce the effect of measurement deadtime, scheduling of controller tuning can compensate for process nonlinearity, override/select control provides a direct means to use PID controls on systems that encounter process constraints and computed MV control can be used to effectively reduce the effect of certain types of disturbances.

13.2 Inferential Control

To this point, it has been assumed that the sensor in a control loop provides a direct measurement of the CV. In fact, the output of the sensor only correlates with the value of the measured variable. For example, from Chapter 2, a thermocouple exposed to a process stream at a specific temperature generates a millivolt signal that correlates strongly with the temperature of the process stream. Likewise, the level in a tank can be inferred from the pressure difference between the top and the bottom of the tank and a flow rate can be estimated from the pressure drop across an orifice plate. In this section, it is shown that easily measured quantities, such as pressures, temperatures and flow rates, can be effectively used to infer quantities which are more difficult to measure, such as composition, extent of reaction and total cell mass in a bio-reactor. The inferred value of the CV can
be used as the value of the CV in a feedback control loop, greatly reducing the associated measurement delay, or to monitor the performance of a process.

There are three main reasons for using inferential measurement of a CV:

1. Excessive analyzer deadtime undermines the performance of a feedback loop. In Chapter 9, it was shown that a deadtime-to-time constant ratio in excess of 0.5 requires reduction to the aggressiveness of the controller and, therefore, the performance of the control loop suffers. Figure 13.2.1 shows the setpoint tracking performance for two FOPDT processes \((K_p=1, \tau_p=1, \theta_p=0.5; K_p=1, \tau_p=1, \theta_p=1.5)\). Both systems are tuned for a 1/6 decay ratio, but the process with the larger deadtime results in a much longer response time than the smaller deadtime process. Certain techniques, such as Smith Predictors, have been developed to directly compensate for the deadtime of a process using process models. Smith Predictors have been studied extensively in academia, but have rarely been applied industrially because the incremental improvement provided by the Smith Predictor is generally much less than the improvement associated with an inferential measurement. Smith Predictors are typically difficult to implement and their effectiveness is sensitive to modeling errors. Therefore, inferential measurements are the industrial method of choice for counteracting large measurement delays for CVs. Inferential measurements can greatly reduce the measurement deadtime because they are based on measurements (e.g., temperatures, pressures and flows) that have relatively low levels of measurement deadtime.

2. The total cost (i.e., the purchase price and maintenance cost) of an on-line analyzer can be excessive. Because inferential measurements are typically based on temperature, pressure and flow measurements, they are much less expensive to install and maintain.

3. An on-line analyzer may not be available, making inferential measurement the only option for feedback control or process monitoring.

For inferential control to be effective, the inferential measurement must correlate strongly with the CV of interest and this correlation should be relatively insensitive to unmeasured disturbances. Following are several examples that illustrate how inferential measurements can be effectively applied in the CPI and bio-tech industries.

**Example 13.1 Inferential Temperature Control for Distillation**

**Problem Statement.** Evaluate the use of tray temperature measurements to infer product compositions for distillation columns.

**Solution.** Tray temperatures correlate very well with product compositions for many distillation columns; therefore, inferential control of distillation product composition is a widely used form of inferential control. Figure 13.2.2 shows the correlation between propane content in the bottoms product and the tray temperature for two trays in the stripping section of a propane/butane binary column. Because this is a binary separation, the temperature and pressure of a tray define the composition on that tray. The largest temperature change for a fixed
change in the bottom product composition occurs for tray number 10; therefore, the temperature of tray 10 can be used to infer the bottom product purity of this column. Figure 13.2.3 shows the control diagram for inferential temperature control of the bottom product composition for this column. The tray temperature controller is cascaded to a flow controller on the steam. This case is equivalent to the cascade control example shown in Figure 12.2.2b. Nevertheless, this is an application of inferential control because the setpoint for the temperature controller in Figure 13.2.3 is chosen so that the desired bottom product composition is attained.

For a multi-component distillation column, the tray temperature does not define the product composition. The liquid on a tray can have the same concentration of light and heavy keys with different relative amounts of heavy non-key and light non-key, and the resulting tray temperature changes significantly. As the amount of heavy non-key is increased and the amount of light non-key is decreased, the tray temperature increases even though the proportions of light and heavy keys remain unchanged. Figure 13.2.4 shows a tray temperature in the stripping section of a multi-component distillation column as a function of the light key in the bottoms product for different ratios of heavy non-key to light non-key for the column feed (i.e., a light and a heavy feed). Note that the two curves are parallel with a difference of about 2°C. As a result, controlling a tray temperature to a fixed
temperature results in offset as the feed composition changes. To remove this offset, a composition controller that uses an on-line composition analyzer can be cascaded to the tray temperature control loop (Figure 13.2.5). In certain cases, laboratory analysis results taken once per shift or once per day are used by the operator to select the setpoint for the temperature controller in an effort to remove this offset.

Example 13.2 Inferential Reaction Conversion Control

Problem Statement. Consider an adiabatic fixed-bed reactor (Figure 13.2.6). Using macroscopic mole and energy balances for this system, develop an inferential estimate of the conversion in this reactor. Assume an irreversible first-order reaction.

Solution. The total rate of consumption of component A \( R_A \) can be expressed in terms of the fractional conversion of A \( X_A \), where \( X_A = \frac{(C_{A_o} - C_A)}{C_{A_o}} \).

\[
R_A = F_v C_{A_o} X_A
\]

Assuming no phase changes occur in this system, the macroscopic energy balance (Equation 3.4.3) for this process is given as

\[
0 = \rho F_v C_p (T_{in} - T_{out}) - \Delta H_{reac} R_A
\]

where \( C_{A_o} \) is the inlet concentration of A to the reactor, \( \Delta H_{reac} \) is the heat of reaction, \( F_v \) is the volumetric feed rate to the reactor, \( \rho \) is the average density of the process stream, \( C_p \) is the average heat capacity of the process stream, \( T_{out} \) is the temperature of the outlet stream from the reactor and \( T_{in} \) is the temperature of the inlet stream to the reactor. Substituting Equation 13.2.1 into this equation and rearranging yields

\[
X_A = \frac{\rho C_p}{\Delta H_{reac} C_{A_o}} (T_{out} - T_{in})
\]

Note that this relationship is not affected by changes in the feed rate although the feed rate will affect \( T_{out} \), and thus, affects \( X_A \). In an industrial reactor, there are heat losses, side reactions and variations in the physical parameters; therefore based on the form of Equation 13.2.2, the assumed inferential relationship is

\[
X_A = a (T_{out} - T_{in}) + b
\]

A plot of the experimental data for a reactor \( X_A, T_{out} \) and \( T_{in} \) can be used to determine \( a \) and \( b \) as well as check the validity of this functional form (i.e., a plot of \( X_A \) versus \( (T_{out} - T_{in}) \) should be linear). Note that the temperature difference across the reactor needs to be large enough that noise on the temperature measurement does not significantly affect the measured temperature drop across the reactor. Once \( a \) and \( b \) are identified, the inlet temperature \( T_{in} \) can be adjusted to maintain a fixed reaction conversion, \( X_A \). Periodically, composition measurements for the product leaving the reactor can be made and the results used to update the value of \( b \) in the previous equation. The value of \( b \), instead of the value of \( a \), should be updated with plant data because \( a \) is less likely to change significantly with changes in the operating conditions compared with \( b \).
Example 13.3 Inferential Estimate of Total Cell Mass for a Bio-Reactor

Problem Statement. Bio-reactors start with the contents of the seed reactor (Figure 1.1.2) and must grow the microorganisms to a level where the final products are produced. As a result, when operating a bio-reactor, it is important to monitor the total cell mass. The total cell mass can be measured on-line by drawing a sample of the reaction broth, removing the water from the sample and weighing the remaining cell mass. Thus, the mass of cells measured from the sample, the sample volume and the total volume of the bio-reactor are used to determine the total cell mass. This analysis is slow, and it is desirable to have more frequent cell mass estimates than are feasible to test by sampling the broth. Therefore, an inferential measurement of the total cell mass in a bio-reactor is useful. During the cell growth stages of a bio-reactor, CO$_2$ is evolved from the consumption of the substrate (e.g., glucose) for cell maintenance and cell growth. Develop an inferential measurement of the total cell mass in a bio-reactor (Figure 13.2.7). Assume that periodically broth samples are measured off-line for the mass of cells in the broth sample and at the same time the off-gas from the bio-reactor is measured for the CO$_2$ concentration and flow rate.

Solution. The CO$_2$ evolution rate resulting from maintaining the existing cells ($F_{CO_2}^{Main}$) is directly proportional to the current cell concentration, $x$, i.e.,

$$F_{CO_2}^{Main} = k_1 V x$$

where $k_1$ is a proportionality constant, $V$ is the volume of broth in the bio-reactor and $x$ is the cell concentration. The CO$_2$ evolution rate resulting from cell growth ($F_{CO_2}^{Growth}$) is directly proportional to the rate of cell growth, i.e.,

$$F_{CO_2}^{Growth} = k_2 V \frac{dx}{dt}$$

where $k_2$ is a proportionality constant. During the cell growth stage, the total CO$_2$ production rate is given as

$$F_{CO_2}^{Tot} = F_{CO_2}^{Main} + F_{CO_2}^{Growth} = k_1 V x + k_2 V \frac{dx}{dt}$$

13.2.4

During this stage, it is important that the cell growth is not inhibited by a large substrate concentration or limited by a substrate concentration that is too low. Therefore, during this phase it is reasonable to model cell growth as an exponential function of time, i.e.,

$$x = x_0 e^{at}$$
where \( \mu \) is an assumed constant and \( x_0 \) is the initial concentration of cells. Substituting this equation into Equation 13.2.4 and rearranging results in

\[
F_{CO_2}^{Tot} = Vx_0 e^{\mu t} (k_1 + k_2 \mu)
\]

13.2.5

Now consider how to match this model to process data. Assume that cell mass measurements are made periodically during the growth stage. Considering Figure 13.2.7, the total production rate of \( CO_2 \) can be determined using the measured concentration of \( CO_2 \) and the flow rate of the off gas. By applying Equation 13.2.5 to the cell mass measurement and its corresponding \( CO_2 \) generation rate at time \( t_1 \), the term \( (k_1 + \mu k_2) \) can be determined

\[
(k_1 + k_2 \mu) = \frac{F_{CO_2}^{Tot}(t_1)}{Vx(t_1)}
\]

Once \( (k_1 + \mu k_2) \) is determined, Equation 13.2.5 can be used to estimate the current value of the total cell mass \( (Vx_0 e^{\mu t}) \) based on the \( CO_2 \) generation rate using the following equation

\[
\text{Total Cell Mass}(t) = Vx_0 e^{\mu t} = \frac{F_{CO_2}^{Tot}(t)}{(k_1 + \mu k_2)}
\]

13.2.6

Because changes in the \( CO_2 \) generation rate are the most immediate indication of a change in the growth rate of the cells during the growth stage in a bio-reactor, Equation 13.2.6 provides a direct measurement of the total cell mass in the bio-reactor.

**Soft Sensors Based on Neural Networks.** In electric power generating stations, restricting the \( NO_x \) (nitrogen oxide compounds) emissions in the flue gas to acceptable levels is important because \( NO_x \) compounds contribute to air pollution. Typically, on-line analyzers are used to measure the \( NO_x \) in the flue gas from the boilers. Occasionally, the \( NO_x \) analyzers on a boiler fail. If the \( NO_x \) level is not measured, the power companies must pay a fine for emissions. Instead of installing additional on-line \( NO_x \) analyzers, which are quite expensive, a number of power companies have applied a type of inferential estimator to predict the \( NO_x \) level in their flue gas.

Instead of using one or two process measurements, all the measured process conditions (e.g., fuel feed rate, oxygen in the flue gas, heating value of the fuel, ambient air temperature, etc.) can be empirically correlated to predict the \( NO_x \) concentration in the flue gas. The empirical correlation is based on training an artificial neural network (ANN) to predict the flue gas \( NO_x \) concentration from all the available data. A network with three input nodes, four nodes in the hidden layer and one output node is shown schematically in Figure 13.2.8. Inputs to each node are summed and the resultant is transformed by a nonlinear...
function to calculate the node output. Weights (Figure 13.2.8) are multiplied by the values that pass through them and are selected to emphasize or de-emphasize individual inputs to a node. For Figure 13.2.8, there are a total of 16 adjustable weights for the neural network that can be selected such that the neural network matches the available process data. As a result, neural networks can be used as empirical nonlinear input/output models. A neural network for a NOx analyzer could have over 500 weights (adjustable parameters). This inferential NOx analyzer is also referred to as a soft sensor because the neural network software, along with the process measurements, is used to provide the on-line measurement.

ANN-based soft sensors are used for a variety of applications in the bio-tech industries. For example, during the product production phase of a bio-reactor (i.e., after the growth phase when the operating conditions are such that the microorganisms produce the desired product), the carbon from the substrate is converted by the cells into CO₂, aldehydes, the product and compounds to build cells. Due to the complex nature of this process, ANNs are used to correlate the total cell mass to several operating parameters of the process. Operating data and cell mass measurements are used to train these ANNs. Once trained the ANN is used to predict the total cell mass in the bio-reactor during the product phase of the operation. As another example, ANNs are used to estimate the concentration of product proteins inside microorganisms (e.g., E. Coli) based on the process operating conditions and certain measurements.

Self-Assessment Questions
13.2.1 Why are inferential measurements used industrially?
13.2.2 Indicate how an energy balance on a CSTR can be used to estimate the amount of conversion occurring in the reactor. What assumptions and limitations does this inferential estimator have?
13.2.3 What is a soft sensor?

13.3 Scheduling Controller Tuning

In Chapter 9, it was demonstrated that a controller on a nonlinear process becomes highly oscillatory in certain situations and can become extremely sluggish (e.g., Figure 13.3.1) at other times. If the process gain increases by over 50%, the controller is likely to ring or become unstable and if the process gain decreases by 50% or more, the process can be expected to behave sluggishly. Tuning PID controllers for the case with the largest process gain can eliminate unstable operation, but at the expense of largely sluggish performance. The combination of the magnitude of the disturbances and the inherent process nonlinearity determine the degree of variation in the FOPDT model parameters of the process. For a number of processes, certain measurements (e.g., the CV or a measured disturbance) directly indicate whether the process parameters have increased or decreased and by how much; therefore, scheduling of the controller tuning based on process measurements can be an effective means of compensating for process nonlinearity in certain cases. The CV and the feed rate are examples of such key process measurements that can typically be used to schedule the controller tuning.

Example 13.4 The Application of Scheduling of the Tuning Parameters for a CSTR

Problem Statement. Develop a scheduling procedure for a PI controller for the CSTR process presented in Example 3.4.
Solution. For the CSTR in Example 3.4, the reaction rate constant is represented by an Arrhenius rate expression, i.e.,

\[ k = k_o e^{-\frac{E}{RT}} \]

which indicates strong nonlinearity for this process with regard to changes in the reactor temperature. Figure 13.3.1 shows the response of temperature to feed composition disturbances under PI control. The controller is tuned for a region near the setpoint. The feed composition decrease causes the reactor temperature to increase and a feed composition increase causes the reactor temperature to decrease. Note that when the reaction temperature increases, the closed-loop response begins to ring and when the temperature decreases, the closed-loop response becomes sluggish.

Now consider an approach for which the controller aggressiveness is adjusted based on the reactor temperature. The PI tuning factor, \( F_T \) (Equation 9.11.2), is scheduled as a function of the reactor temperature (Table 13.1). Figure 13.3.2 shows a comparison between a conventional PI controller and a PI controller with scheduling for a severe feed composition upset for the endothermic CSTR. For the scheduled controller, \( F_T \) is adjusted based on the error from setpoint according to Table 13.1. For this case, scheduling of the controller tuning was able to maintain stability while a conventional PI controller was not. The slow movement towards setpoint indicates that not enough integral action is used when the reactor temperature is below setpoint. Scheduling the entire set of controller parameters can provide the correct integral action for each temperature region. This can be accomplished by tuning the controller at several different reactor temperatures and using the results to schedule each of the tuning parameters.
Example 13.5 The Application of Scheduling of the Tuning Parameters for a Heat Exchanger

Problem Statement. Develop a scheduling procedure for a PI controller for the heat exchanger process presented in Example 3.6.

Solution. Consider the heat exchanger shown in Figure 13.3.3. As the feed to the heat exchanger flows through the tube bundle, it is heated by steam condensing on the shell side. As the feed rate changes, the residence time of the feed in the tubes changes. Figure 13.3.4 shows the open-loop responses for three different feed rates. The feed rate is represented by the average fluid velocity (v) in the tubes. Both the gain and the dynamic response change as the feed rate is changed. Table 13.2 lists the FOPDT model parameters for each flow rate. Note that the gain and the deadtime of each change by about 250% from the largest to the smallest flow rates. The PI Cohen and Coon settings (Table 9.2) at each flow rate are also listed in Table 13.2. The controller gain changes by a factor of 5 while the reset time changes are more gradual. It is clear from these results that it is not reasonable to expect one set of PI controller settings to work effectively for significant changes in the feed rate to this heat exchanger. The temperature controller for the outlet of the heat exchanger tuned for v=7 ft/s becomes unstable when the feed rate is reduced to v=4 ft/s. Conversely, if the controller is tuned for the low flow rate condition, it performs sluggishly for the high flow rate conditions. Figure 13.3.5 shows results with and without scheduling of the controller tuning based on feed rate for a change in the velocity through the tubes from 7 to 4 ft/s. The controller without scheduling was tuned for a feed rate corresponding to v= 7 ft/s.
Figure 13.3.4 Open-loop response for a heat exchanger for different feed rates.

Figure 13.3.5 Closed-loop results for a step change in feed rate with and without scheduling of the controller tuning for the heat exchanger case.

Table 13.2
| FOPDT and PI Tuning Parameters for the Heat Exchanger Case as a Function of Feed Rate |
|-----------------------------------|--------------------|--------------------|
| Feed Rate (ft/s)                  | v=4 ft/s           | v=7 ft/s           | v=10 ft/s          |
|-----------------------------------|--------------------|--------------------|
| $K_p$                             | 0.25               | 0.15               | 0.11               |
| $\tau_p$                          | 10.7               | 9.9                | 10.0               |
| $\theta_p$                        | 10.2               | 5.8                | 4.0                |
| $K_c$                             | 4.2                | 10.8               | 21.3               |
| $\tau_I$                          | 12.0               | 8.8                | 7.3                |

Non-stationary Behavior. Consider a wastewater neutralization process (Figure 12.3.3). If the titration curve of the wastewater and the other process parameters remain fixed, the process is referred to as stationary or time-invariant. If the titration curve changes with respect to time, the process is non-stationary or time-varying. In the case of this pH control example, changes in the titration curve can have an overwhelming effect on the process gains. There are many more examples of non-stationary behavior that result in much more gradual process gain changes. The following are several examples of non-stationary behavior in the CPI and bio-tech industries:

1. Catalyst deactivation
2. Heat exchanger fouling
3. Fouling of trays in a distillation column
4. Feed composition changes that affect the process parameters ($K_p$, $\tau_p$, and $\theta_p$)
5. Changes in the production rate of bio-reactors due to an increase in the product concentration
6. A dramatic change in the type and rate of a product due to a change in the temperature in a bio-reactor
These effects can be large enough that controller retuning is required. If an overall tuning factor, $F_T$ (Equation 9.11.2) has been used, you can adjust $F_T$ in a straightforward manner to compensate for the non-stationary behavior. Control methods that adjust controller tuning to adapt to non-stationary behavior are referred to as **adaptive control** techniques. Adaptive control techniques can be effectively applied for processes that vary slowly. An adaptive controller is expected to handle gradual catalyst deactivation that occurs over several days, but is not expected to handle sharp changes in catalyst activity that occur within one hour. A number of commercially available adaptive controllers are referred to as **self-tuning controllers** and can usually be installed on a DCS or control computer. While there is a range of approaches used for self-tuning controllers, they are generally limited to processes that vary in a gradual, consistent manner.

**Self-Assessment Questions**

13.3.1 How does scheduling controller tuning prevent a nonlinear process from going unstable or behaving sluggishly?

13.3.2 How do you determine whether scheduling of the tuning parameters of a controller will be effective?

13.3.3 Why is the controller scheduling based on the CV for Example 13.4 and based on a measured DV for Example 13.5?

### 13.4 Override/Select Control

Constraints are a natural part of industrial process control. As processes are pushed to produce as much product as possible, process limits are inevitably encountered. When an upper or lower limit on a MV is encountered or when an upper or lower value of a controlled or output variable from the process is reached, it is necessary to alter the control configuration to prevent the violation of a constraint. **Effective industrial controller implementation requires that safeguards be installed to prevent the process from violating safety, environmental or economic constraints.** These constraints can be met using override/select controls.

**Example 13.6 Override/Select Control of a Gas-Fired Heater**

**Problem Statement.** Analyze the operation of the override/select controls for the gas-fired heater shown in Figure 13.4.1.

![Figure 13.4.1 A control diagram of a furnace fired heater with low select firing controls.](image)

**Solution.** Under normal operating conditions, the fuel flow rate is adjusted to control the exit temperature of the process fluid. As the feed rate of the process fluid increases, the furnace tube temperature increases. At some point, the upper limit on furnace tube temperature (an operational constraint) is encountered. The fuel flow rate to the furnace must be adjusted to keep the furnace tube temperature from exceeding its upper limit. If the tube temperature constraint is exceeded, damage to the furnace tubes results, significantly reducing their useful life. Figure 13.4.1 shows that the output of both control loops (the temperature controller on the process fluid and the temperature controller on the furnace tubes) are combined and the lower fuel feed rate is actually applied. The “LS” symbol in Figure 13.4.1 is called a **low select (LS)** and indicates that the lower fuel feed rate is chosen. There are two separate loops that use fuel flow rate as a MV and the LS controller switches between them as the flow rate...
of the process fluid changes. When the feed rate is sufficiently low that the temperature of the process fluid can be controlled to setpoint, the output of the process fluid temperature controller is selected because it is lower than the output of the tube temperature controller. That is, when the tube temperature is below the maximum tube temperature constraint, the tube temperature controller will call for an increase in the fuel firing rate, which is rejected by the LS. Likewise, when the tube temperature exceeds its upper limit, the output of the tube temperature controller is reduced by the tube temperature controller and it is selected by the LS. When the tube temperature controller is controlling the furnace firing rate, the outlet temperature is not controlled to setpoint because the output of the product temperature controller is rejected by the LS.

Example 13.7 Override/Select Control of a Distillation Column

**Problem Statement.** Analyze the operation of the override/select controls for the stripping section of the distillation column shown in Figure 13.4.2.

**Solution.** Flooding in a distillation column can result as the feed to a column is increased. The onset of flooding is usually identified when the pressure drop across the column or a portion of the column increases sharply. When the pressure drop across the column reaches an upper operational limit (usually identified by experience), the reboiler duty is switched from controlling the bottom product composition to maintaining operation at the maximum pressure drop across the column (Figure 13.4.2). A LS controller is used for this application. Two separate control loops use reboiler duty as a MV, and the LS controller switches between them as the feed rate to the process changes. When the column feed rate is reduced while operating at the maximum differential pressure across the column, the composition of the impurity in the bottoms product becomes less than its setpoint and the reboiler duty called for by the composition control loop will be less than that called for by the differential pressure controller. At this point, the LS controller uses the output from the composition controller. The control loop is switched when the column differential pressure reaches its upper limit and switches back when the bottom product is over purified.

Example 13.8 High Select Control of a Fixed-Bed Reactor

**Problem Statement.** Analyze the operation of the high select controls for the fixed-bed reactor shown in Figure 13.4.3.

**Solution.** A high select (HS) controller (Figure 13.4.3) can be used to control the maximum temperature in a fixed-bed reactor even when the maximum reactor temperature occurs at different locations in the reactor. For certain reactors, if the catalyst in the reactor exceeds an upper temperature limit, damage to the catalyst occurs. The HS controller chooses the largest temperature measurement from a number of temperature measurements and the largest reading is sent to the temperature controller. In this manner, the highest reactor temperature can be maintained below a preset upper limit. Low select (LS) controllers can also be used where the lowest reading is
selected from several readings.

Example 13.9 Override/Select Control of a Reboiler

Problem Statement. Analyze the operation of the override/select controls for the stripping section of the distillation column shown in Figure 13.4.4, which has an upper limit on its reboiler duty.

Solution. When the remote setpoint for the steam flow rate to the reboiler is consistently greater than the measured steam flow, a select controller switches to using the column feed rate as a MV to keep the bottom product purity on specification. When the column feed rate is adjusted back to its normal level and the control valve on the steam to the reboiler is no longer saturated (i.e., fully open), the control configuration is changed so that the reboiler duty is manipulated to control the bottom product purity. This is an example of the selection of a secondary MV when the primary MV reaches a limit (becomes saturated).

Example 13.10 Cross-Limiting Firing Controls for a Boiler

Problem Statement. Analyze the operation of the cross-limiting firing controls for a boiler shown in Figure 13.4.5.

Solution. For furnaces, it is important to ensure that excess air is always supplied with the fuel to prevent the formation of carbon monoxide (CO), a serious safety hazard. That is, when there is insufficient oxygen for complete combustion of the fuel to CO₂ and H₂O, CO will form. Furnaces are normally equipped with CO sensors that shut down the furnace if CO levels exceed specified limits. Cross-limiting firing controls (Figure 13.4.5) are designed to reduce the likelihood that CO is formed during changes in the firing rate to the furnace. To understand the schematic of cross-limiting firing controls, you must understand the flow control loop for the air addition to the furnace as well as the function of high and low selects in Figure 13.4.5. The setpoint to the flow controller for the air is the fuel equivalent to the desired air flow rate. The measured air flow rate is multiplied by the fuel-to-air ratio and the resultant is compared with the setpoint by the flow controller. Therefore, both FCs, the LS and the HS are based on the fuel firing rate.
Consider the firing rate increase shown in Figure 13.4.6a. The increased firing rate signal is rejected by the LS because the fuel flow rate corresponding to the measured air flow rate is smaller. On the other hand, the HS selects the increased firing rate signal because it is larger than the current measured fuel flow rate. As a result, the setpoint for the FC on the air flow rate receives the firing rate increase, which in turn increases the air flow rate. As the air flow increases, the fuel flow rate corresponding to the air flow rate increases, thus increasing the setpoint for the FC on the fuel. Therefore, for a firing rate increase, the air flow rate increases first followed by the fuel flow rate, thus maintaining an excess of $O_2$ preventing CO formation during firing rate increases. Similarly, for firing rate decreases (Figure 13.5.6b), cross-limiting firing controls cuts the fuel flow rate first and the air flow rate follows, thus maintaining an excess of $O_2$.

Self-Assessment Questions

13.4.1 How is a low select element (LS) used to satisfy certain process constraints?
13.4.2 When is a select element (S) required instead of a low select?
13.4.3 Why is the fuel/air ratio used for cross-limiting firing controls?
13.5 Computed Manipulated Variable Control

In certain cases, it is not possible to directly adjust the desired MV for a particular process. In these cases, by indirectly adjusting the desired MV, specific disturbances are effectively rejected. For example, consider the reboiler on a distillation column that uses waste heat in the form of quench water (water used to cool hot gases) to provide reboiler duty (Figure 13.5.1). The inlet temperature of the quench water can vary over a wide range, which is a significant disturbance for the distillation column. When the inlet temperature increases, extra boilup results for the column and the bottoms product becomes over purified. The composition controller on the bottoms product can eventually compensate for this disturbance, but this affects the variability in the products produced by the distillation column. The desired operation of the reboiler has the composition controller setting the reboiler duty directly. For steam-heated reboilers with constant enthalpy steam, the reboiler duty is directly related to the steam flow rate, but, for the case under consideration, the reboiler duty changes with inlet temperature as well as the flow rate of the quench water. The solution is to use a steady-state energy balance on the quench water to calculate the flow rate of the quench water that provides the desired reboiler duty. The macroscopic energy balance on the quench water is given by

\[ 0 = F C_p (T_{in} - T_{out}) - Q \]

where \( F \) is the quench water flow rate, \( C_p \) is the heat capacity of the quench water, \( Q \) is the rate at which heat is removed from the quench water and \( T_{in} \) and \( T_{out} \) are the inlet and outlet quench water temperatures. Rearranging to solve for the quench water flow rate yields

\[ F_{sp} = \frac{Q_{spec}}{C_p (T_{in} - T_{out})} \]

where \( F_{sp} \) is the setpoint for the flow controller on the quench water to the reboiler, \( Q_{spec} \) is the reboiler heat duty specified by the bottom product composition controller, \( C_p \) is the heat capacity of the quench water, \( T_{in} \) and \( T_{out} \) are the measured inlet and outlet temperatures of the quench water, respectively. In this manner, as the inlet and outlet temperatures for the quench water change, the quench water flow rate can be adjusted accordingly before upsetting the product compositions of the distillation column. Figure 13.5.1 shows how computed MV control can be applied to this case. The inlet and outlet temperatures, along with the specified reboiler duty, are input to the computation block where Equation 13.5.1 calculates the required quench water flow rate which, in turn, is passed on as the setpoint for the flow controller on the quench water.
Example 13.11 Computed MV Control for a Furnace

Problem Statement. Analyze the operation of the computed MV control for a furnace that is fired using two different types of gas with different heats of combustion.

Solution. Computed MV control can also be used to control a furnace that uses two different grades of fuel. Consider a process that produces a low-heating-value gas as a byproduct. It is desirable to burn all the low-heating-value gas in a furnace that is used to heat a process stream. Unfortunately, the production rate of the low-heating-value gas is not sufficient to provide all the heat duty for the furnace; therefore, natural gas is also fed to the furnace and the flow rate of natural gas is adjusted to control the temperature of the process stream leaving the furnace. Because the flow rate of the low-heating-value gas varies over a wide range, it represents a major disturbance for the temperature controller on the process stream leaving the furnace. A computed MV controller (Figure 13.5.2) can be used to calculate the flow rate of natural gas necessary to meet the heat duty requirements specified by the temperature controller using an energy balance for the heat duty of the furnace along with the heats of combustion for the low-heating-value gas and the natural gas. The macroscopic energy balance for the furnace is given by

\[ 0 = -F_{LHV} \Delta H_{c,LHV} - F_{NG} \Delta H_{c,NG} - Q \]

where \( F_{LHV} \) is the flow rate of the low-heating value gas, \( \Delta H_{c,LHV} \) is the heat of combustion of the low-heating-value gas, \( F_{NG} \) is the flow rate of natural gas to the furnace, \( \Delta H_{c,NG} \) is the heat of combustion of the natural gas and \( Q \) is the heat released in the furnace by the combustion of the low-Btu gas and the natural gas. Solving for the flow rate of natural gas yields

\[ F_{sp,NG} = \frac{Q_{spec} + F_{LHV} \Delta H_{c,LHV}}{-\Delta H_{c,NG}} \]

where \( F_{sp,NG} \) is the computed setpoint for the natural gas firing rate, \( Q_{spec} \) is the heat duty specified by the temperature controller, \( F_{LHV} \) is the measured flow rate of the low-heating value gas, \( \Delta H_{c,LHV} \) is the heat of combustion of the low-heating-value gas and \( \Delta H_{c,NG} \) is the heat of combustion of the natural gas. Note that \( \Delta H_{c,LHV} \) and \( \Delta H_{c,NG} \) have negative values because combustion is an exothermic process. In this manner, flow rate changes in the low-heating-value gas can be readily compensated for by the computed MV controller. Computed MV control is an effective means of providing heat duty control in certain cases.

Example 13.12 Internal Reflux Control

Problem Statement. Analyze the operation of internal reflux control applied to the column shown in Figure 13.5.3.
Solution. Distillation columns are particularly sensitive to sudden changes in ambient conditions, which usually accompany weather fronts and thundershowers. When the ambient air temperature drops sharply, the temperature of the reflux can also decrease sharply because of the increased cooling provided by the condenser. This subcooled reflux causes added condensation from the vapor in the top of the column, increasing the internal reflux ratio and improving the separation in the top portion of the column. On the other hand, the increase reflux can cause the bottom product to become less pure. In this case, it is much more desirable to control the internal reflux flow rate than the external reflux flow rate because ambient changes can effect the internal reflux of a column and upset the composition control for the column.

An energy balance based on equating the heat lost by the condensing vapor to the heat required to heat the subcooled reflux to the temperature of the top tray results in the following equation

\[ C_p F_e (T_{oh} - T_r) = \Delta F_{int} \Delta H_{vap} \]

where \( C_p \) is the heat capacity of the reflux, \( T_{oh} \) is the overhead temperature, \( T_r \) is the subcooled reflux temperature, \( F_e \) is the external reflux (the setpoint for the flow controller on the reflux), \( \Delta F_{int} \) is the change in the reflux caused by the condensing vapor and \( \Delta H_{vap} \) is the heat of vaporization of the vapor. \( \Delta F_{int} \) combines with the external reflux to form the internal reflux. Noting that the internal reflux is the external reflux plus the amount condensed \( (\Delta F_{int}) \), the equation for the internal reflux flow \( (F_{int}) \) is given by

\[ F_{int} = F_e (1 + C_p [T_{oh} - T_r] / \Delta H_{vap}) \]

This equation can be rearranged to calculate the external reflux that maintains a specified internal reflux \( (F_{int}^{spec}) \), i.e.,

\[ F_e = \frac{F_{int}^{spec}}{1 + C_p (T_{oh} - T_r) / \Delta H_{vap}} \]

This approach is called internal reflux control and is shown schematically in Figure 13.5.3. The composition controller sets the specified value of the internal reflux flow rate and the internal reflux controller calculates the corresponding external reflux flow rate, which is used as the setpoint for the flow controller on the reflux. In this manner, when changes in the reflux temperature occur, the internal reflux controller will make adjustments to the external reflux flow to maintain the specified internal reflux flow rate.
Self-Assessment Questions

13.5.1 What kind of disturbance is the computed reboiler duty controller designed to compensate for?

13.5.2 How does an internal reflux controller reduce the effect of changes in the cooling water temperature?

13.6 Summary

- Inferential control uses fast-responding process measurements, such as pressures, temperatures and flow rates, to estimate the value of the CV. Less deadtime associated with the measurement of the CV results and better feedback control performance is obtained.
- When the characteristics of a process \((K_p, \tau_p, \theta_p)\) change significantly with the value of a measured process variable (e.g., a CV or a DV), scheduling of the controller tuning parameters can result in improved control performance and reliability. For these cases, scheduling of the tuning parameters allows for the variation in the controller tuning as the process conditions change. Scheduling of the tuning parameters can provide stable controller performance without sluggish behavior.
- Override/select control switches between control loops when process constraints are encountered. High and low select controllers are applied to cases where the same MV is used by two different control loops to maintain process constraints. Override/select controls switch between MVs and possible control loops to meet the operational objectives of the process as process conditions change.
- Computed MV control is used when direct manipulation of the desired MV is not possible. For these cases, process measurements are used to calculate the flow rate that is adjusted to maintain the desired MV at its prescribed level.

13.7 Additional Terminology

Adaptive controller - a controller that adjusts its tuning parameters on-line in response to changes in the process.

Artificial neural networks - (ANN) a special class of nonlinear empirical models.

Cross-limiting firing controls - firing controls based on low and high selects that maintain excess air during changes in the firing rate to a furnace.

HS - high select controller.

Inferential control - the use of readily measured quantities, such as pressures, flows and temperatures, to estimate values of the CVs for control purposes.

LS - low select controller.

Non-stationary process - a process whose characteristics \((K_p, \tau_p, \theta_p)\) change in response to disturbances entering the process.

Self-tuning control - a controller that adjusts its tuning parameters on-line in response to changes in the process.

Smith Predictor - an approach that uses a process model to reduce the effects of deadtime.

Soft sensor - an algorithm that estimates the value of difficult-to-measure process variables using correlation functions based on available process measurements.

Stationary process - a process whose process characteristics \((K_p, \tau_p, \theta_p)\) remain constant with time.

Time-invariant process - a process whose process characteristics \((K_p, \tau_p, \theta_p)\) remain constant with time.

Time-varying process - a process whose characteristics \((K_p, \tau_p, \theta_p)\) change in response to disturbances entering the process.
13.8 Preliminary Questions

13.1 How do you determine which tray temperature should be used to infer the product composition of a distillation column?

13.2 Explain why inferential temperature control is extensively used industrially.

13.3 How do changes in the feed composition affect the use of inferential temperature control? How does you compensate for feed composition changes?

13.4 What assumptions were used in the derivations of Equation 13.2.2?

13.5 How would you evaluate parameters $a$ and $b$ in Equation 13.2.3 using plant data?

13.6 Explain how a neural network can be trained and then used as a soft sensor.

13.7 Identify a process for which scheduling of the controller tuning parameters is likely to be beneficial. Outline how the scheduling of the controller tuning parameters could be accomplished. Choose a system not described in the text.

13.8 Explain how the control configuration shown in Figure 13.4.1 can prevent the furnace tubes from overheating.

13.9 Explain how the control configuration shown in Figure 13.4.2 can prevent the distillation column from flooding.

13.10 Explain how the control configuration shown in Figure 13.4.4 can maintain the bottom product composition at setpoint for a full range of operation.

13.11 Explain how the control configuration shown in Figure 13.4.5 can prevent CO formation for a decrease in the firing rate.

13.12 Explain how the control configuration shown in Figure 13.5.1 can reduce the effect of changes in the quench water temperature on the bottoms product composition.

13.13 Explain how the control configuration shown in Figure 13.5.2 can reduce the effect of changes in the production rate of the low-BTU gas on the temperature of the stream heated by the furnace.

13.14 Explain how the control configuration shown in Figure 13.5.3 can reduce the effect of changes in the subcooling of the reflux on the overhead product composition.

13.9 Analytical Questions and Exercises

13.15** The operating pressure of a distillation column has a significant effect on the temperatures of the trays of the column. Indicate how a tray temperature used to infer the product composition can be compensated for pressure changes. Assume that the tray temperature varies linearly with column pressure. Indicate how you would determine all unknown parameters.

13.16** Construct an inferential estimate of the fouling of the heat exchanger shown in Figure P13.16. Indicate how this estimator could be used to schedule cleaning of the tube bundle.

13.17*** Consider the accumulator for a distillation column for which the distillate product flow rate is used to control the accumulator level and the reflux flow rate is used to control the composition of the overhead product (Figure P13.17). Draw a schematic showing select controls that will prevent the level
13.18** Consider the stripping section of the distillation column shown in Figure P13.18. Modify this schematic by adding override controls that prevent the column pressure from exceeding its upper limit by overriding the composition controller when the pressure reaches its upper limit.

13.19*** Consider the stripping section of the distillation column shown in Figure P13.19. Under certain conditions, the column floods if the steam addition rate is not restricted and, under other conditions, excess steam flow to the reboiler causes the maximum temperature limit on the reboiler to be exceeded, resulting in severe fouling of the reboiler. Draw a schematic showing the override/select controls that simultaneously prevents the column from flooding and from exceeding the upper limit on the reboiler temperature.

13.20*** From your fluids course, you know that the mass flow rate of a gas through an orifice meter is dependent on the pressure drop across the orifice plate and the temperature and pressure of the gas. Therefore, if the temperature and pressure of a gas change significantly, using the pressure drop across an orifice meter as a measurement of flow rate can result in significant error. Devise a computed flow sensor for the mass flow rate of a gas for which the temperature and pressure of the gas change significantly. List all the necessary equations and draw a schematic showing the computed mass flow rate controller.

13.21*** Consider the schematic for an exothermic CSTR shown in the Figure P13.21 in which the heat produced by the reactor is used to generate steam [after W.L. Luyben, *Process Modeling, Simulation and Control for Chemical Engineers*, Second Edition, McGraw-Hill, p. 292 (1990)]. Draw a schematic for this process including each of the following control features:

a. The level in the steam drum is controlled by the make-up water.

b. The pressure of the steam drum is controlled by the valve on the steam line to the steam header.

c. The temperature controller for the reactor is cascaded to the steam pressure control loop.
d. The level in the reactor is controlled by the product flow rate.

e. A low level in the steam drum overrides the setpoint for the flow controller on the feed to the reactor and cuts back on the feed to the reactor.

f. A high reactor temperature overrides the setpoint for the flow controller on the feed to the reactor and cuts back on the feed to the reactor.

**13.22** Develop a computed MV controller for the reboiler shown in Figure 13.5.1, assuming that steam is used for reboiler duty instead of quench water. The computed MV controller should be able to make adjustments in the steam flow rate to account for changes in the steam enthalpy; therefore, the steam temperature and pressure upstream of the control valve should be measured and used by the computed MV. Assume that there is no condensed water in the steam.