

BUILDING MULTIVARIABLE PROCESS CONTROL INTUITION USING CONTROL STATION®

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Multivariable loop interaction is a well-known control problem that is discussed in a host of popular texts.^[1-4] Computer tools such as Matlab/Simulink enable instructors and students alike to explore the phenomena by providing a high-level programming environment useful for simulating process control systems. The topics to be covered in a process control course, however, are numerous relative to the time allotted to them in the typical curriculum. Instructors must decide for themselves whether or not time spent with programming issues is time well spent in a process dynamics and control class. Many feel it is an appropriate use of time, and valid arguments can be made to support that viewpoint.

An alternative chosen by more than 150 college and university instructors around the world is the Control Station® training simulator. Control Station lets students design, implement, and test control solutions using a computer interface much like one they will find in industrial practice. It provides hands-on and real-world experience that the students will be able to use on the job. One of the primary benefits according to instructors who use the program is that the software is easy to use, permitting them to focus on teaching process dynamics and control issues rather than on program usage. Many students have related that because Control Station is so visual in its presentation, they believe it enhances their learning and knowledge retention.

Control Station provides a platform where broad and rapid experimentation can help students build fundamental intuition about a broad spectrum of process dynamic and control phenomena. Some of the topics that can be explored using the software include

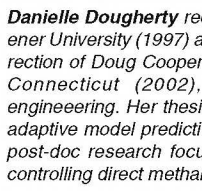
- Dynamic modeling of plant data
- Using process models parameters for controller tuning
- Tuning P-Only, PI, PID, and PID with Filter controllers

- Cascade controller design and implementation
- Feed forward control with feedback trim
- Smith predictor design for dead time compensation
- Parameter scheduling and adaptive control
- Dynamics and control of integrating processes
- Single and multiloop dynamic matrix control (DMC)

This paper will show how students can use Control Station to investigate the nature of multivariable loop interaction and how decouplers can minimize this undesirable behavior. The examples will demonstrate how students can use the software to quickly develop a host of multivariable process be-



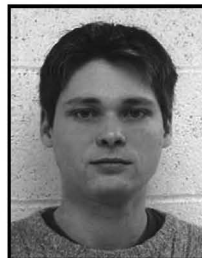
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haviors for exploration and study, and how they can then test the performance of control strategies using methods found in their text. Students performing this or similar study will certainly strengthen their understanding and intuition about this challenging subject.

MULTIVARIABLE CASE STUDIES

Multivariable process control is increasingly important for students to understand at an intuitive level because in many industrial applications, when one controller output signal is changed, more than one measured process variable will be affected. Control loops sometimes interact and even fight each other, causing significant multivariable challenges for process control. Control Station provides a means for students to gain a hands-on understanding of multivariable process behavior and to practice how to design and tune controllers that address these behaviors.

One multivariable case study available to students is the multitank process. As shown in Figure 1, the process comprises two sets of freely draining tanks positioned side by side. The two measured process variables are the liquid levels in the lower tanks. To maintain liquid level, two level controllers manipulate the flow rate of liquid entering their respective top tanks. In this process, each of the upper tanks drain into *both* lower tanks. This creates a multivariable interaction because manipulations by one controller affect both measured process variables.

The distillation column case study is shown in Figure 2. This is a binary distillation column that separates benzene and toluene. The objective is to send a high percentage of the benzene out the top distillate stream and a high percentage of

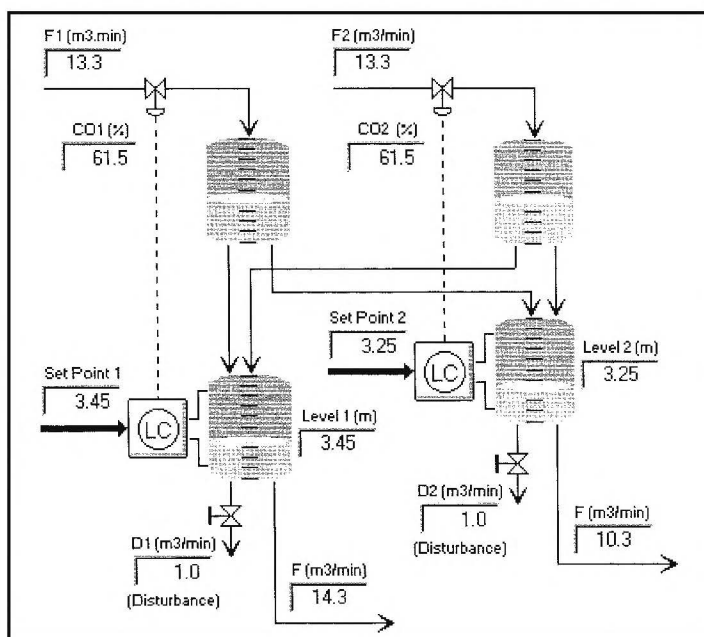


Figure 1. Control Station's multitank case study.

We do not believe that the training simulator should replace real lab experiences since hands-on studies are fundamental to the learning process, but a training simulator can provide a broad range of meaningful experiences in a safe and efficient fashion.

the toluene out the bottom stream. To separate benzene from toluene, the top controller manipulates the reflux rate to control the distillate composition. The bottom controller adjusts the rate of steam to the reboiler to control the bottoms composition. Any change in feed rate to the column acts as a disturbance to the process.

Multivariable loop interaction occurs in this process because when the benzene composition in the top distillate stream is below the set point, the top controller responds by increasing the cold reflux into the column. This cold liquid eventually spills to the bottom, cooling it and causing the bottom composition to move off the set point. The bottom controller "fights back" by increasing the flow of steam into the reboiler. The result is an increase of hot vapors traveling up the column that counteract the increased reflux by heating the top of the column.

MULTIVARIABLE CUSTOM PROCESSES

Control Station's multiloop *Custom Process* graphic, used to simulate general multivariable systems created from dynamic models, is shown in Figure 3. Following the nomenclature established in popular texts,^[1-4] G_{ij} represents the dy-

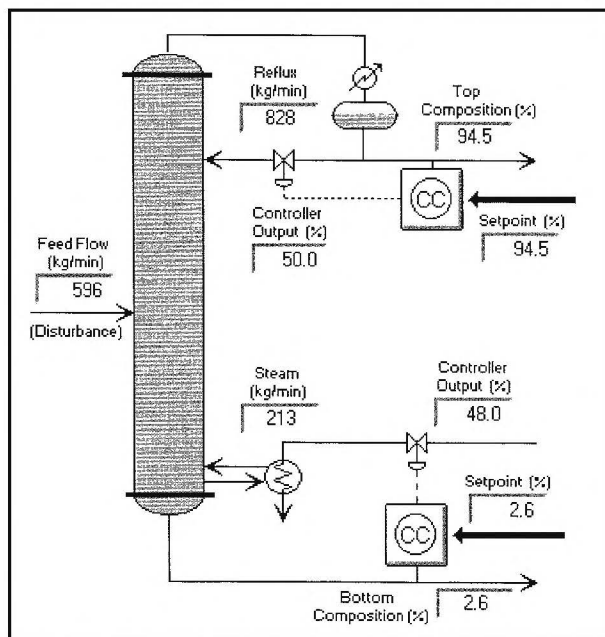


Figure 2. Control Station's distillation column case study.

dynamic behavior of the i^{th} measured process variable response to the j^{th} controller output signal. Hence, as can be seen in Figure 3, process G_{11} describes the direct dynamic response of measured process variable PV_1 to changes in controller output CO_1 , and interaction G_{21} describes the cross-loop dynamic response of PV_2 to changes in CO_1 .

RELATIVE GAIN AS A MEASURE OF LOOP INTERACTION

Before exploring different multivariable process behaviors, we introduce the concept of *relative gain*.^[5] Relative gain, λ , is popular because it

- Provides a convenient measure of loop interaction
- Is easy to compute
- Is dimensionless, so it is not affected by the units of the process data

Relative gain is computed from the steady-state process gains of the process models (K_{11} and K_{22}) and the cross-loop interaction models (K_{12} and K_{21}) that best describe observed process behavior (that results from model fits of process data). Following the nomenclature above, relative gain is computed as

$$\lambda = \frac{K_{11}K_{22}}{K_{11}K_{22} - K_{12}K_{21}} \quad (1)$$

In the remainder of this paper, we will show how Control Station helps students explore what the size and sign of λ implies for multivariable loop interaction and the ease with which a process can be controlled. Before starting that study, consider that our process has two controllers (CO_1 and CO_2) that regulate two process variables (PV_1 and PV_2). The controllers are connected to the process variables by wires and the connections can be wired one of two ways:

- 1) CO_1 controls PV_1 and CO_2 controls PV_2
- 2) CO_1 controls PV_2 and CO_2 controls PV_1

Each combination yields a different value of λ . An important lesson students learn is that *control loops should always be paired (wired) so the relative gain is positive and as close as possible to one*.

EFFECT OF K_p ON CONTROL LOOP INTERACTION

The students are taught the usefulness of relative gain as a measure of multivariable loop interaction by considering a variety of cases such as those listed in Table 1. These particular cases are simulated and studied here using Control Station's *Custom Process module*, as shown in Figure 3.

All of the direct process and interaction models used in the simulation studies are first order plus dead time (FOPDT). For each simulation case study, the direct process and cross-loop gains are listed in the table. All of the time constant and dead time parameters for the simulation case studies given in Table 1 are

Process time constant: $\tau_p = 10$

Dead time: $\theta_p = 1$

Also, all of the investigations use two PI (proportional-integral) controllers with no decoupling and with

Controller gain: $K_c = 5$

Reset time: $\tau_i = 10$

For all examples, when one PI controller is put in automatic while the other is in manual mode, that controller tracks set point changes with an appropriately small rise time and rapid damping. The issue the students study is process behavior when *both* PI controllers are put in automatic at

Case	direct $CO_1 \rightarrow PV_1$ K_{11}	cross-loop $CO_1 \rightarrow PV_2$ K_{21}	cross-loop $CO_2 \rightarrow PV_1$ K_{12}	direct $CO_2 \rightarrow PV_2$ K_{22}	λ
1	1	1.1	1.1	1	-4.8
2a	0	1.1	0.5	1	0.0
2b	-1	3.0	1.1	1	0.2
2c	1	-3.0	0.5	1	0.4
3	1	-1.1	0.5	1	0.6
4	1	0	0.5	1	1.0
5	1	1.1	0.5	1	2.2
6	1	1.1	.85	1	15.4

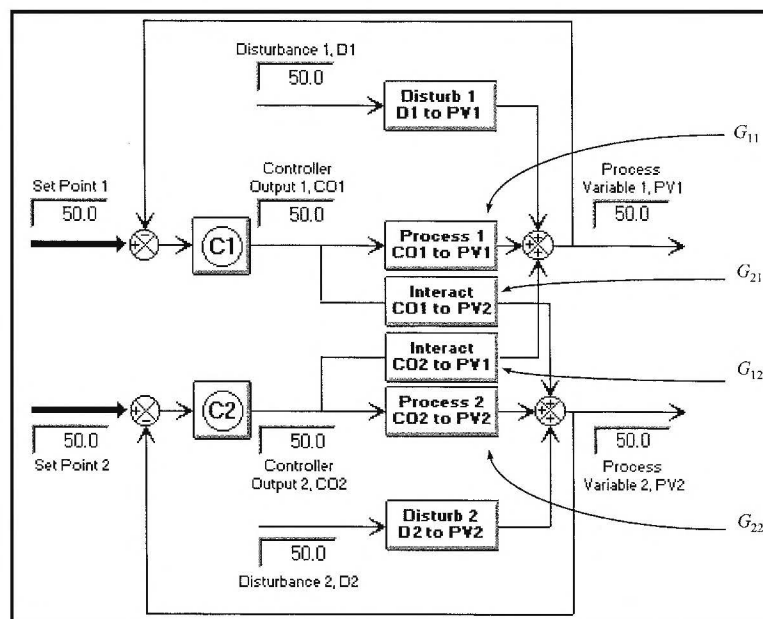


Figure 3. Control Station's multiloop custom process.

the same time.

► **Case 1: $\lambda < 0$** When the cross-loop interaction gains are larger than the direct process gain, as is true for Case 1 in Table 1, then each controller has more influence on its cross-loop measured process variable than it does on its own direct measured process variable. As listed in the table, the relative gain, λ , computed by Eq. (1) for this case is negative.

Figure 4 shows the set point tracking performance of the Case 1 process when both loops are under PI control with no decoupling (remember that for all simulations, $\tau_p = 10$ and $\theta_p = 1$; also, $K_c = 5$ and $\tau_I = 10$). As each controller works to keep its direct measured process variable on its set point, every control action causes an even larger disruption in the cross-loop process variable—and the harder each controller works, the worse the situation becomes. As can be seen in Figure 4, the result is an unstable, diverging system.

A negative relative gain implies that the loop pairing is incorrect. That is, each controller is wired to the wrong measured process variable. The best course of action is to switch the controller wiring. This switches the cross-loop gains in Table 1 to the direct process gains and vice versa.

Switching the loop pairing recasts Case 1 into a process

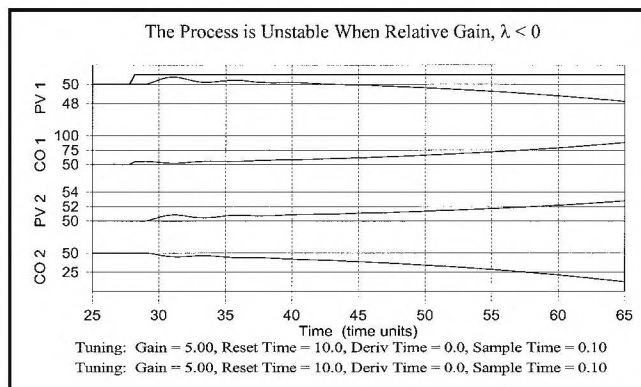


Figure 4. Incorrect loop pairing and an unstable process under PI control indicated by $\lambda = 0$.

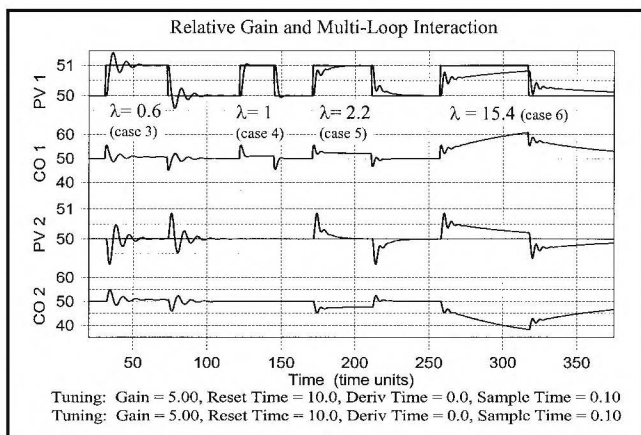


Figure 5. Impact of λ on PI control loop interaction with no decoupling.

with a relative gain of $\lambda = 5.8$, which is a loop interaction behavior between Case 5 and Case 6. As we will learn, a process with this relative gain is challenging to control, but it is closed-loop stable and the loops can be decoupled using standard methods.

► **Case 2: $0 < \lambda \leq 0.5$** For the relative gain to be exactly zero ($\lambda = 0$), one of the direct process gains must be zero. A direct process gain of zero means that a controller has no impact on the measured process variable it is wired to. Clearly, there can be no regulation if a controller has no influence.

Case 2a in Table 1 has $K_{11} = 0$, implying that CO_1 has no influence on PV_1 . Yet because the cross-loop gain K_{12} is not zero, changes in CO_2 will disrupt PV_1 . If a measured process variable can be disrupted but there is no means to control it, the result is an unstable process under PI control (no figure shown). Because both cross-loop gains are not zero in Case 2a, the loop pairing should be switched in this case to give each controller direct influence over a measured process variable. This would recast Case 2a into a process with a $\lambda = 1.0$, which is the interaction measure most desired. We study such a process in Case 4 below.

When the relative gain is near zero ($0 < \lambda \leq 0.5$), then at least one of the cross-loop gains is large on an absolute basis (e.g., Case 2b and 2c). Under PI control with no decoupling and using the base tuning values of $K_c = 5$ and $\tau_I = 10$, both of these processes are unstable and show considerable loop interaction (no figure shown). Detuning both controllers to $K_c = 2$ and $\tau_I = 10$ restores stability, but control-loop interaction is still significant.

Again, the best course of action is to switch the loop pairing. With the wiring switched, Case 2b yields $\lambda = 0.8$ and Case 2c yields $\lambda = 0.6$, putting both relative gains closer to the desired value of one. While both processes still display loop interaction, the processes become stable under PI control with no decoupling, even with the base case PI controller tuning values.

► **Case 3: $0.5 \leq \lambda < 1$** When the relative gain is between 0.5 and one, the cross-loop interactions cause each control action to be reflected and amplified in both process variables. As shown in the left-most set point steps in Figure 5 for a case where $\lambda = 0.6$, this interaction leads to a measured process variable response that includes significant overshoot and slowly damping oscillations.

This amplifying interaction exists when stepping the set point of either loop. It grows more extreme and ultimately leads to an unstable process as λ approaches zero (see Case 2). Moreover, the interaction becomes less pronounced as λ approaches one (see Case 4).

► **Case 4: $\lambda = 1$** A relative gain of one occurs when either or both of the cross-loop gains are zero. In Case 4, K_{21} is zero, so controller output CO_1 has no impact on the cross-loop measured process variable PV_2 . Since K_{12} is not zero as

listed in Table 1, however, changes in CO_2 will impact PV_1 .

The second set point steps in Figure 5 show the control performance of the Case 4 process when the set point of PV_1 is changed. As expected, the set point tracking actions of CO_1 have no impact on PV_2 . While not shown, a set point step in PV_2 would cause some cross-loop disruption in PV_1 because of loop interaction.

When both cross-loop gains are zero, the loops do not interact. Such a system is naturally and completely decoupled and the controllers should be designed and tuned as single-loop processes.

► **Case 5:** $\lambda > 1$ Opposite to the observations of Case 3, when the relative gain is greater than one, the control loops fight each other. Specifically, the cross-loop interactions act to restrain movement in the measured process variables, prolonging the set-point response. The third set point steps in Figure 5 illustrate this behavior for a case where $\lambda = 2.2$.

As stated earlier, a process with a relative gain that is positive and close to one displays the smallest loop interactions (is better behaved). For Case 5, switching the loop pairing would yield a very undesirable negative λ . This means that the loops are correctly paired and the significant loop interaction is unavoidable.

► **Case 6:** $\lambda \gg 1$ As the cross-loop gain product, $K_{12}K_{21}$, approaches the direct process gain product, $K_{11}K_{22}$, the relative gain grows and the restraining effect on movement in the measured process variables discussed in Case 5 become greater. This is illustrated in the right-most set point steps in Figure 5 for a case where $\lambda = 15.4$. Again, switching the loop pairing would yield a negative λ , so the loops are correctly paired and the significant loop interaction is unavoidable. Interestingly, as the cross-loop gains grow to the point that their product is larger than the direct process gain product (when $K_{12}K_{21} > K_{11}K_{22}$), then λ becomes negative and we circle back to Case 1.

DECOUPLING CROSS-LOOP K_p INTERACTION

After gaining an appreciation for the range of open-loop dynamic behaviors, students then explore decoupling control strategies. A decoupler is a feed-forward element where the measured disturbance is the action of a cross-loop controller. Analogous to a feed-forward controller, a decoupler is comprised of a process model and a cross-loop disturbance model. The cross-loop disturbance model receives the cross-loop controller signal and predicts an “impact profile,” or when and by how much the process variable will be impacted. Given this predicted sequence of disruption, the process model then back calculates a series of control actions that will counteract the cross-loop disturbance as it arrives so the measured process variable, in theory, remains constant at set point.

Here we explore how *perfect decouplers* can reduce cross-loop interaction. A perfect decoupler employs the identical

models in the decoupler as is used for the process simulation. Using the terminology from Figure 3, these decouplers are defined in the Laplace domain as

$$D_{12}(s) = -\frac{G_{12}(s)}{G_{11}(s)} \quad \text{and} \quad D_{21}(s) = -\frac{G_{21}(s)}{G_{22}(s)} \quad (2)$$

Students are reminded to be aware that in real-world applications, no decoupler model exactly represents the true process behavior. Hence, the decoupling capabilities shown here must be considered as the best possible performance.

► **Case 1:** $\lambda < 0$ A negative relative gain implies that the loop pairing is incorrect. Decoupling is not explored because the best course of action is to switch the controller wiring to produce a process with a relative gain of $\lambda = 5.8$. This loop interaction behavior is somewhere between Case 5 and Case 6 discussed below.

► **Case 2:** $0 < \lambda \leq 0.5$ A relative gain of *exactly zero* ($\lambda = 0$) implies that at least one controller has no impact on the measured process variable that it is wired to. There can be no regulation if a controller has no influence. Hence, decoupling becomes meaningless for this case and is not explored here.

When the relative gain is *near zero* ($0 < \lambda \leq 0.5$), PI controllers with no decoupling must be detuned to stabilize the multivariable system. When the PI controllers are detuned and perfect decouplers (the identical models are used in the decouplers as are used for the process simulation) are included, the result is an unstable system (no figure shown). Detuning the decouplers (lowering the disturbance model gain) will restore stability, but interaction remains significant and general performance is poor. Again, the best course of action is to switch loop pairing.

► **Case 3:** $0.5 \leq \lambda < 1$ When the relative gain is between

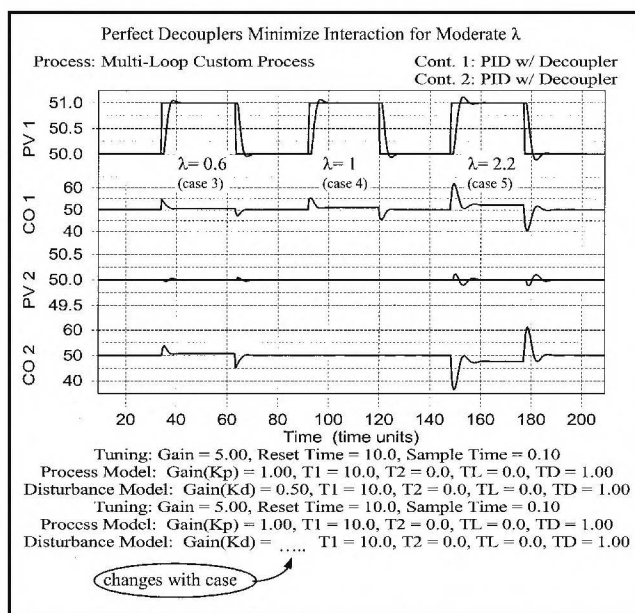


Figure 6. Decouplers work well when λ is near 1.

0.5 and one, the cross-loop interactions cause each control action to be reflected and amplified in both process variables. As shown in the left-most set-point steps in Figure 6 for the case of $\lambda = 0.6$, PI controllers with perfect decouplers virtually eliminate cross-loop interactions. This is not surprising since the relative gain is positive and close to one.

► **Case 4:** $\lambda = 1$ A relative gain of one occurs when either or both of the cross-loop gains are zero. In Case 4 of Table 1, K_{21} is zero, so controller output CO_1 has no impact on the cross-loop measured process variable PV_2 . Consequently, a perfect decoupler will provide no benefit for this loop, and as shown in Figure 6 for the middle set-point steps, while a perfect decoupler causes no harm, a decoupler implemented on a real process will likely have imperfect models and would then create loop interaction.

Table 1 shows that K_{12} is not zero, so changes in CO_2 will impact PV_1 . A perfect decoupler will virtually eliminate cross-loop interaction for information flow in this direction (no figure shown). Thus, the Case 4 system can address the multi-variable loop interaction with a single decoupler on the CO_2 to PV_1 loop.

► **Case 5:** $\lambda > 1$ When the relative gain is greater than one, the cross-loop interactions act to restrain movement in the measured process variables. The third set point steps in Figure 6 for the case where $\lambda = 2.2$ illustrate that perfect decouplers substantially eliminate both this restraining effect and the level of loop interaction. Again, this is not surprising since the relative gain is positive and reasonably close to one.

► **Case 6:** $\lambda \gg 1$ As the relative gain grows larger, the restraining effect on movement in the measured process vari-

ables due to loop interaction becomes greater. Case 6 in Table 1 is interesting because K_{21} is greater than K_{22} . This means that PV_2 is influenced more by a change in controller output CO_1 (its cross-loop disturbance) than it is by an equal change in its own controller output CO_2 . Switching loop pairing offers no benefit as this makes the relative gain negative.

With perfect decouplers as shown in the *right* set-point steps in Figure 7 (the decoupler employs the identical models as are used for the process simulation), the system is unstable. This cannot be addressed by detuning the PI controller because even with lower values for controller gain, K_c , the system is unstable.

For a decoupler to be stable, the gain of the cross-loop disturbance model must be less than or equal to the gain of the process model, or in this case, $K_{21} \leq K_{22}$. That is, a decoupler must pass through at least as much influence of a controller output to its direct process variable as it does for any disturbance variable.

To address this, we detune the decoupler by lowering the cross-loop disturbance gain of the bottom loop so that in absolute value, $K_{21} \leq K_{22}$ and $K_{21} \leq K_{11}$. Repeating the test in the *left* set-point steps of Figure 7 reveals a stable and reasonably decoupled system.

CONCLUSION

We have presented examples of the lessons and challenges associated with multivariable process control and shown how Control Station can provide a better understanding of these complicated systems. Space prohibits the presentation of other multivariable studies available in Control Station, including the use of dynamic matrix control for multivariable model predictive control.

We do not believe that the training simulator should replace real lab experiences since hands-on studies are fundamental to the learning process, but a training simulator can provide a broad range of meaningful experiences in a safe and efficient fashion. The training simulator can be used to bridge the gap between process control theory and practice. If readers would like to learn more, they are encouraged to contact Doug Cooper at cooper@engr.uconn.edu, or visit <www.engr.uconn.edu/control>.

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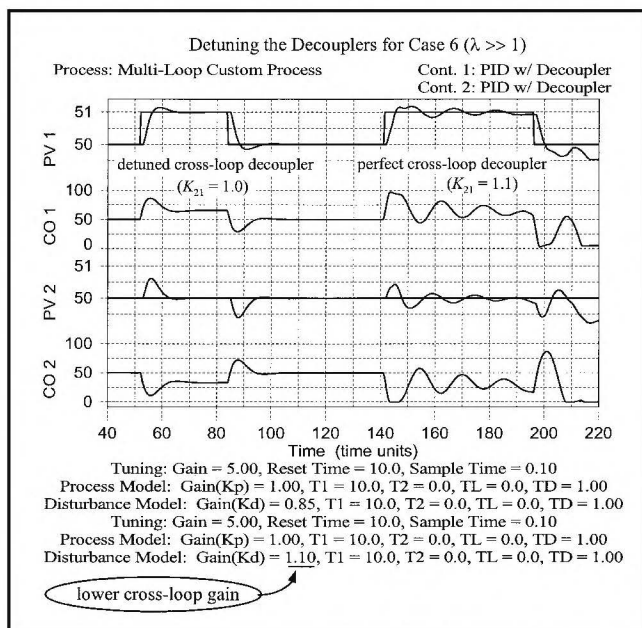


Figure 7. Decouplers can cause stability problems for large λ .