

# A TRAINING SIMULATOR FOR COMPUTER-AIDED PROCESS CONTROL EDUCATION

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**H**ands-on challenges that demonstrate and reinforce important concepts benefit the learning process—this is especially true for the often abstract subject of process dynamics and control. Hands-on challenges can be motivating, can promote critical thinking, facilitate understanding in the use and limitations of the theory, and help prepare students for the challenges of the professional world.

Too often the application of textbook theory is limited to solving questions listed at the end of the chapter. One typical question is to have the student expand or extend a mathematical development presented in the book. Another is to provide bits of data and challenge the student to select and employ a combination of formulas to obtain a desired result.

Unfortunately, even when cleverly crafted, these textbook problems fall short of providing students with the depth or breadth of practice required for comprehension and mastery.<sup>[1,2]</sup> Thus, the Chemical Engineering Department at the University of Connecticut supplements the textbook with laboratory exercises. Hands-on laboratory exercises are extremely important to learning because they help students make the intellectual transition from theory to practice.<sup>[3]</sup> The abstractions presented in textbooks are literally brought to life through the tactile nature of a lab experience.

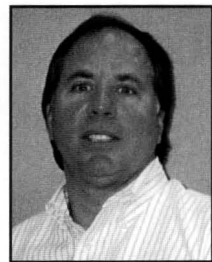
Unfortunately, the reality of the laboratory at the University of Connecticut is that each study can take many hours, and even days, to perform. Also, equipment failures and other problems teach the important lesson that the real world can be uncertain (this lesson is not usually intended to be the objective of a particular assignment, however). Thus, students rarely explore more than a very few central concepts in the lab.

A training simulator offers an alluring method for provid-

ing students with the significant hands-on practice critical to learning process control. The proper tool can provide virtual experience much the way airplane and power-plant simulators do in those fields. It can give students a broad range of focused engineering applications of theory in an efficient, safe, and economical fashion. And it can work as an instructional companion as it provides interactive challenges that track along with classroom lectures.

Process control is a subject area well suited to exploit the benefits of a training simulator.<sup>[4]</sup> Modern control installations are computer based, so a video display is the natural window through which the subject is practiced. With color graphic animation and interactive challenges, a training simulator can offer experiences that literally rival those of the real world.<sup>[1]</sup> These experiences can be obtained risk free and at minimal cost, enabling students to feel comfortable exploring nonstandard solutions at their desks. If properly designed as a pedagogical tool with case studies organized to

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present incremental challenges, we believe learning can be enormously enhanced for process control with such a training simulator.

## A CHEMICAL PERSPECTIVE

Each discipline views process control from a different perspective. To help orient the reader, consider these “typical” examples drawn from chemical process control:

**Process Variables:** temperature, pressure, pressure drop, level, flow, density, concentration

**Final Control Elements:** solenoid, valve, variable speed pump or compressor, heater or cooler

**Control Algorithms:** on/off, PID, cascade, ratio, feed forward, multivariable decoupler, model predictive

**Process Applications:** reactors, separators, distillation columns, heat exchangers, furnaces

Many chemical engineering processes are literally one-of-a-kind. Consequently, their associated control system will be unique in design and implementation.

Additionally, chemical processes can be nonlinear and nonstationary, and can have long time constants, significant dead time, and/or noisy measurement signals. Disturbances occur from numerous sources, including loop interaction

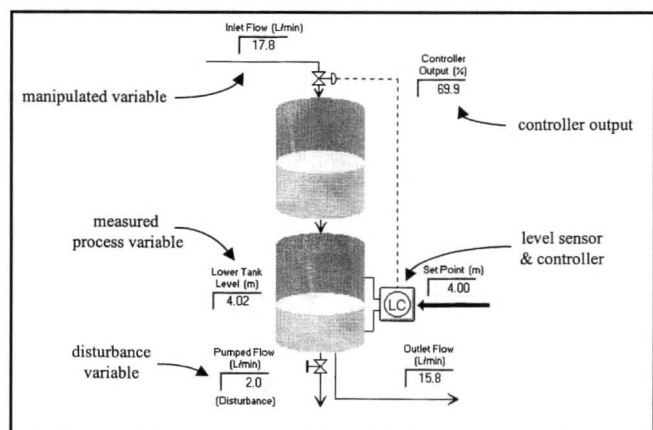


Figure 1. Gravity-drained tanks graphic.

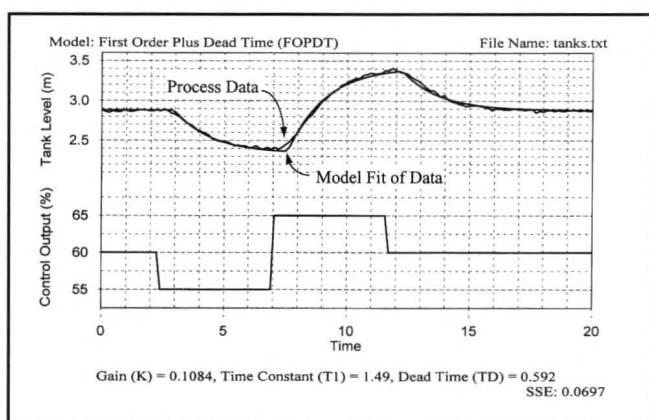


Figure 2. FOPDT model fit of text data.

from other controllers in the plant.

## EXAMPLE LESSONS

The following lessons have been drawn from the Control Station process control training simulator to illustrate the value such software provides the curriculum. We note that training simulators are distinguished here from tools such as Matlab,<sup>[5]</sup> which have a primary function of design, analysis, and simulation. The reader can download a free control-station demo at

<[www.engr.uconn.edu/control/](http://www.engr.uconn.edu/control/)>

### P-Only Controller Performance

The computer graphic display for the gravity-drained tanks process, shown in Figure 1, is two vessels stacked one above the other. Liquid drains freely through a hole in the bottom of each tank. The controller output signal manipulates the flow rate of liquid entering the top tank. The measured process variable is liquid level in the lower tank. The disturbance variable is a secondary flow out of the lower tank from a positive displacement pump, so it is independent of liquid level except when the tank is empty.

Students begin their studies with this process because its dynamic behavior is reasonably intuitive. If they increase the liquid flow rate into the top tank, the liquid levels rise in the tanks; if they decrease the flow rate, the levels fall.

The traditional place to begin a course is with the study of process dynamics. Students generate a step-test plot and compute by hand the first-order-plus-dead-time (FOPDT) model parameters: steady-state process gain,  $K_p$ , overall time constant,  $\tau_p$ , and apparent dead time,  $\theta_p$ . After they have gained mastery with hand calculations, they use tools that automate the model-fitting task so they can explore more practical tests. A Control Station fit of test data is shown in Figure 2 for the gravity-drained tanks.

Students use their FOPDT model parameters in tuning correlations to compute a P-Only controller gain,  $K_C$ . Figure 3 displays a Control Station strip chart showing set-point

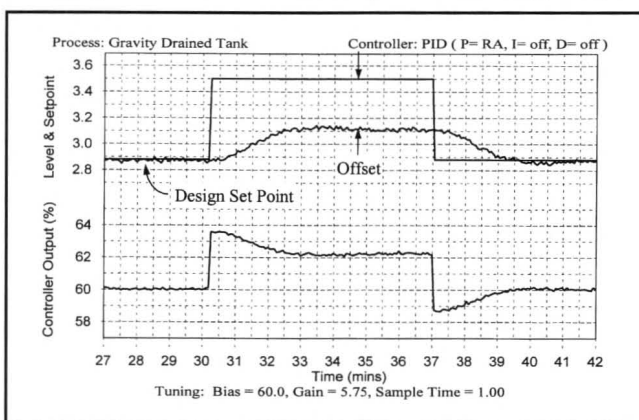


Figure 3. P-Only set-point tracking results in offset.

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tracking performance for the gravity-drained tanks under P-Only control. The  $K_C$  for the controller is computed from the integral time-weighted absolute error (ITAE) correlation,<sup>[6,7]</sup> using the FOPDT model parameters from Figure 2.

With this as a starting point, the students now turn to what-if studies. The investigation of Figure 4 explores how  $K_C$  impacts offset and oscillatory behavior for set-point tracking under P-Only control. Students also explore disturbance rejection under P-Only control. Is the best tuning for set-point tracking the same as for disturbance rejection? And, how is "best" tuning defined?

For this and all Control Station processes, the student can change the level of random noise in the measured process variable. They can also manipulate the controller output signal, set point, and disturbance variable using a step, oscillating, ramp, or pseudo-random binary-sequence (PRBS) signal sequence. The current version of Control Station of-

fers only one disturbance variable for each process, and this disturbance can be changed at will by the student. We note that this is not realistic in that a real plant can have many disturbances from a variety of sources that will affect the process, and as disturbances, they are generally not available for manipulation by the engineer. The students are made aware of this during class.

### PI Control and Nonlinear Behavior

The computer graphic for the countercurrent, shell and tube, lube oil cooler (a kind of heat exchanger) is shown in Figure 5. The controller-output signal manipulates the flow rate of cooling liquid on the shell side. The measured process variable is lube oil temperature exiting on the tube side.

Students learn an important lesson about process dynamics by studying the nonlinear character of this process as shown in Figure 6. The steady-state gain of the process

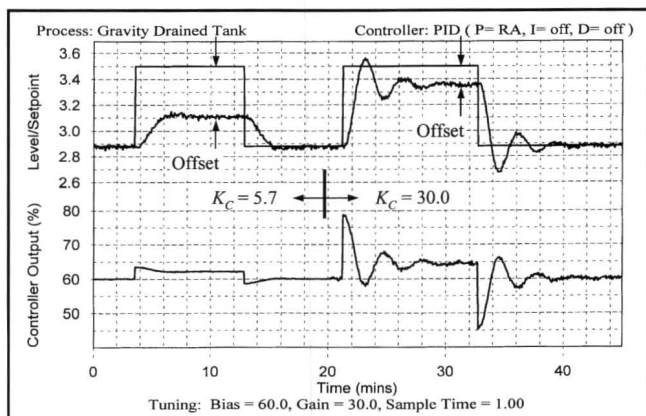


Figure 4. P-Only performance changes as  $K_C$  changes.

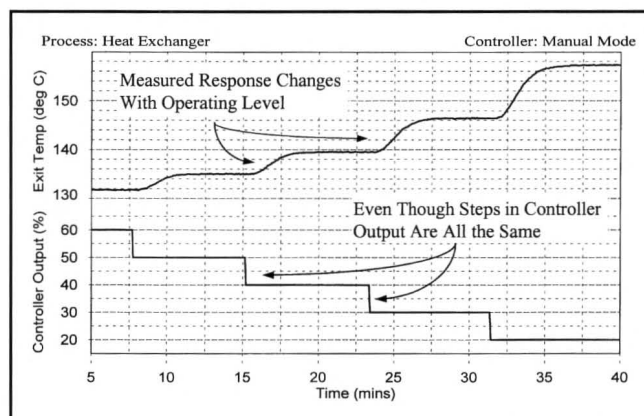


Figure 6. Heat exchanger displays nonlinear behavior.

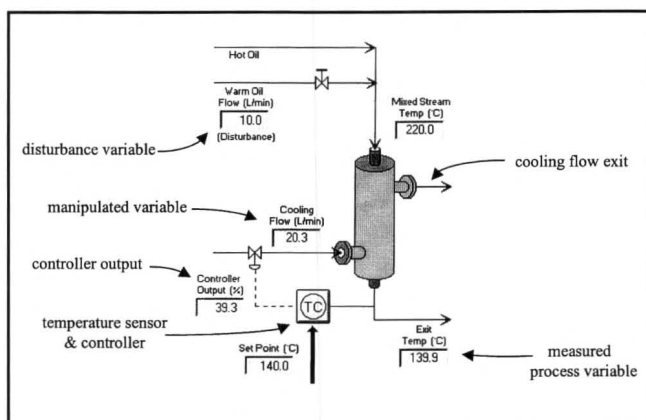


Figure 5. Heat exchanger graphic.

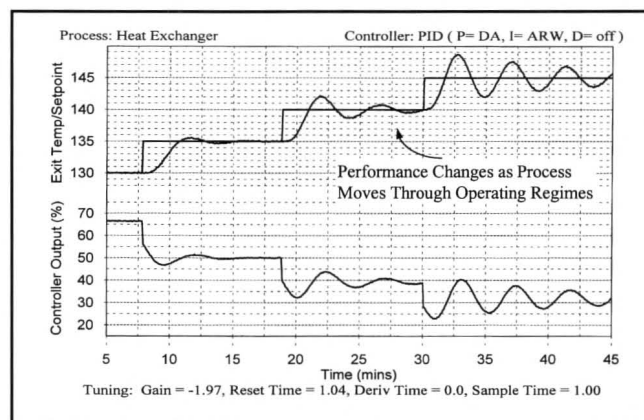


Figure 7. Nonlinear behavior impacts performance.

clearly changes as operating level changes. Less obvious is that the time constant of the process also changes.

For processes that have such a nonlinear character, the performance of a controller will change as the process moves across operating levels. Figure 7 illustrates this point. The exchanger is under PI control, and as the set point is stepped to different operating levels, the nonlinear behavior of the process clearly impacts set-point tracking performance. Thus, students learn that a controller is designed for a specific or design level of operation. Best practice is to collect dynamic test data as near

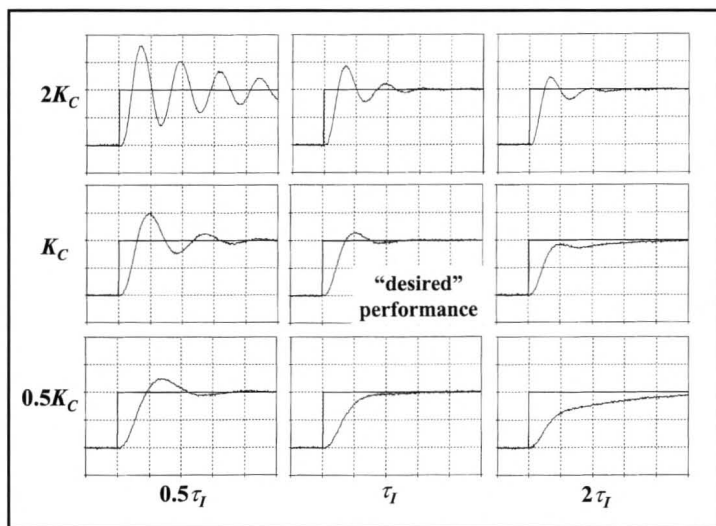


Figure 8. PI controller tuning impacts performance.

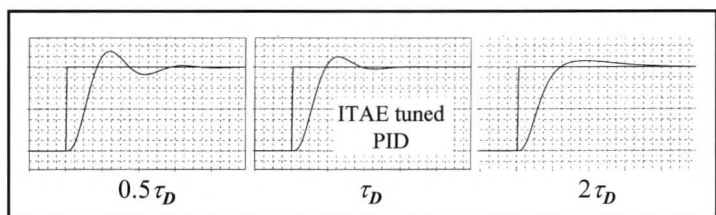


Figure 9. Derivative action impacts oscillatory behavior.

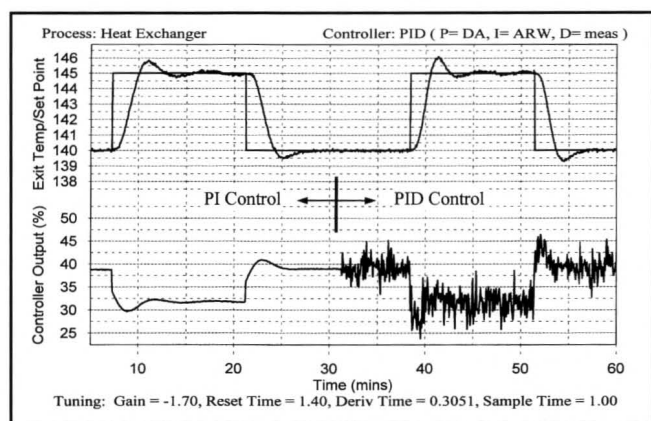


Figure 10. Measurement noise is amplified and reflected in controller output signal.

as practical to this design.

Figure 6 also shows that the heat exchanger has a negative steady-state gain. Students learn that a complete design includes specifying the action of the controller (reverse vs. direct acting).<sup>[6-8]</sup> They learn this concept because if they enter it wrong, the controller output will quickly drive the valve to either full open or full closed and it will remain there until the correct controller action is entered.

For what-if studies, students explore how PI controller tuning parameters interact and affect set-point tracking performance. Figure 8 shows a tuning map that they develop from an orderly tuning investigation using an ideal linear transfer function process available in Control Station.

### PID Control and Measurement Noise

Derivative action can decrease the process settling time because it resists rapid movement in the measured process variable.<sup>[6]</sup> In Control Station, the PID controller algorithm is currently implemented using the ideal (noninteracting) form<sup>[6-9]</sup> with a choice of derivative action either on controller error or process measurement. Students learn how derivative action impacts controller performance with studies similar to that shown in Figure 9, which focuses on the derivative time tuning parameter.

The center plot of Figure 9 shows the set-point tracking performance of a PID controller tuned using the ITAE<sup>[6,7]</sup> for set-point tracking correlation. For all plots in Figure 9,  $K_c$  and  $\tau_i$  remain constant and the measurement noise has been set to zero. The plot to the left in Figure 9 shows how the oscillating nature of the response increases as derivative action is cut in half. The plot to the right shows that when derivative action is too large, it inhibits rapid movement in the measure process variable, causing the rise time and settling time to lengthen.

When noise is added to the measured process variable, students learn that derivative action amplifies it and reflects it in the controller output signal. Figure 10 shows this quite clearly with a side-by-side comparison of a PI and PID controller. For this comparison, the same amount of measurement noise was used throughout the experiment. This study helps students visualize that a PI controller is not impacted by noise while the derivative action of the PID controller reflects and amplifies it in the controller output signal.

Students also compare derivative on controller error to derivative on process measurement. Watching the derivative on error “kick” after a set-point step is a more memorable experience than simply hearing about it.



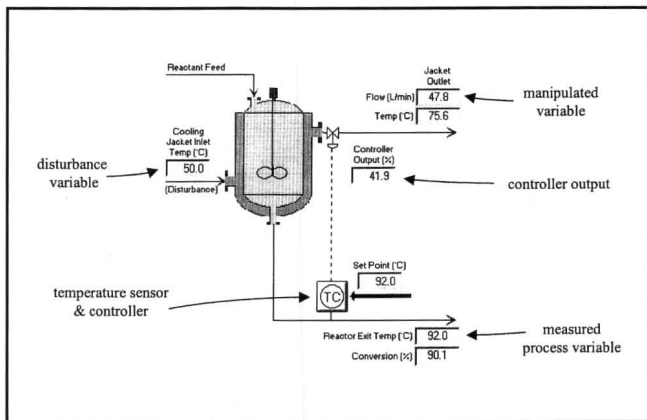


Figure 11. Jacketed reactor graphic.

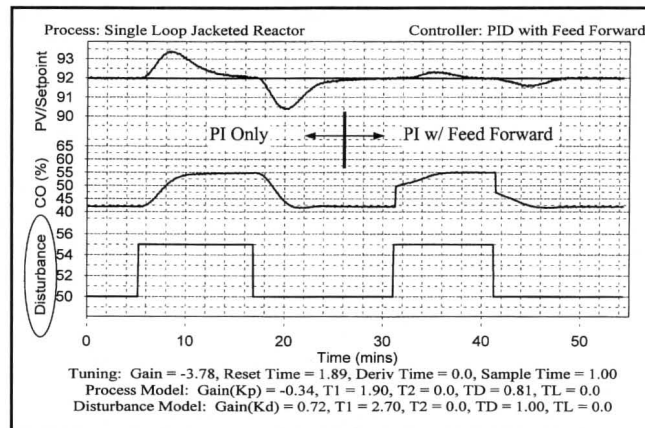


Figure 12. Benefits of feed-forward control.

### Cascade, Feed Forward, and Disturbance Rejection

The jacketed reactor graphic, shown in Figure 11, is a continuously stirred tank reactor in which an irreversible exothermic reaction occurs. Residence time is constant in this perfectly mixed reactor, so the steady-state conversion from the reactor can be directly inferred from the temperature of the reactor product stream. To control reactor temperature, the vessel is enclosed with a jacket through which a coolant passes.

The controller output manipulates the coolant flow rate through the jacket. The measured process variable is product exit-stream temperature. If the exit-stream temperature is too high, the controller increases the coolant jacket flow to cool down the reactor. The disturbance variable is the inlet temperature of coolant entering the cooling jacket.

The jacketed reactor can be run in three configurations: feedback control, as shown in Figure 11, feed forward with feedback trim, and cascade control. When the cooling jacket inlet temperature changes, the ability to remove heat changes and the control system must compensate for this disturbance. Cascade and feed forward are control strategies used for improved disturbance rejection.

Cascade design involves the tuning of two controllers. Feed forward requires identification of an appropriate process and disturbance model.

The rejection of a step change in the disturbance variable (jacket inlet temperature) for a single loop PI controller is compared in Figure 12 to a PI with feed forward controller. The benefit of feed forward is clear for this process because for the same disturbance, the measured process variable has a much smaller maximum deviation and a faster settling time.

Students compare single-loop, feed-forward, and cascade control in a series of exercises. They investigate tuning issues, which PID modes to use in a cascade, the order and accuracy of the models needed for feed-forward design, plant-model mismatch, dead-time issues, and a host of other interesting challenges.

### Control Loop Interaction and Decoupling

The graphic shown in Figure 13 is a binary distillation column based on the model of McCune and Gallier.<sup>[10]</sup> The column has two measured process variables and two manipulated variables. The reflux rate is used to control distil-

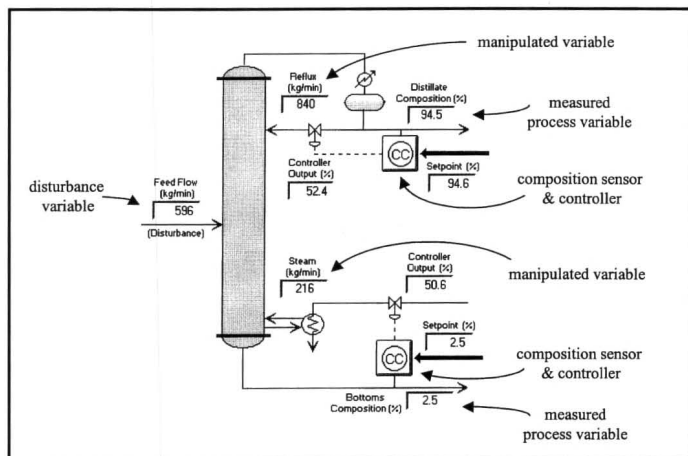


Figure 13.  
Distillation  
column  
graphic.

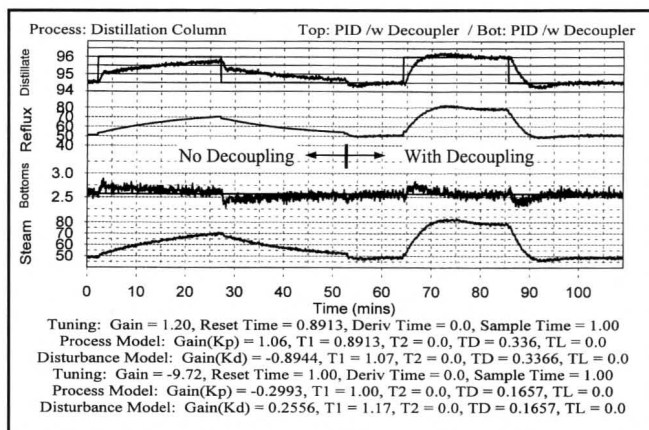


Figure 14. Distillation column shows loop interaction.

late purity and the steam rate is used to control purity of the bottoms stream.

Students use this process to explore the interactions that can occur in such multicontroller applications. Control-loop interaction occurs because when the distillate purity out of the top of the column is too low, the top controller compensates by increasing the flow of cold reflux into the column. This increased reflux flow will indeed cause an increase in the distillate purity. The additional cold reflux will work its way down the column trays, however, and eventually begin to cool the bottom of the column. This cooling causes the purity of the bottoms stream to move off set point and produce a controller error.

The bottom controller compensates by increasing the flow of steam into the reboiler. This produces an increase in hot vapors traveling up the column, which eventually causes the top of the column to begin to heat up. The result is that distillate purity again becomes too low. In response, the top controller compensates by again increasing the flow of cold reflux into the column.

This controller "fight" is shown on the left side of Figure 14. The upper trace shows the distillate composition responding to a step set-point change. Controller interaction causes the set point response to be quite slow since both controllers are working at cross purposes.

Decouplers are feed-forward elements where the measured disturbance is the controller output signal of another loop on the process. Two decouplers are required to compensate for loop interaction, one for each controller.<sup>[7]</sup> Like a feed-forward element, each decoupler requires identification of a process and disturbance model. The right side of Figure 14 shows that with decouplers in place, this loop interaction is dramatically reduced.

Students explore different controller modes, loop tunings, model structures, and many other design issues. With two controllers and four models for complete decoupling, students also learn how important bookkeeping is to the

control designer.

## CONCLUSION

Presented here are some examples of the lessons and challenges that a training simulator can provide. Space prohibits presentation of other studies available in Control Station, including the control of integrating processes, the use of the Smith predictor controller that is a simplest form of a model predictive controller, and a host of process identification methods and procedures.

We stress that we do not believe a training simulator is better than or a replacement for real lab experiences. In fact, we believe that hands-on studies with actual equipment are fundamental to the learning process.

We are of the opinion, however, that a training simulator like Control Station can provide students with a broad range of meaningful experiences in a safe and efficient fashion. These experiences can be obtained risk free and at minimal cost, enabling students to feel comfortable exploring non-standard solutions at their desk. We believe if a training simulator is properly designed, it can bridge the gap between textbook and laboratory, enabling significantly enhanced learning for process control theory and practice. If the readers would like to learn more, they are encouraged to contact Doug Cooper at

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or visit

<www.engr.uconn.edu/control>

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