Enhancing Process Control Education with the Control Station Training Simulator

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ABSTRACT: A process control training simulator can enhance learning by integrating the theoretical abstraction of textbooks with the tactile nature of the lab and plant. The primary objective of a training simulator is education. It can motivate, help with visualization, and provide hands-on practice and experience. This article explores the use and benefits of the Control Station training simulator for process control education. Examples presented illustrate how the standard curriculum can be enhanced with a series of hands-on exercises and study projects. © 2000 John Wiley & Sons, Inc. Comput Appl Eng Educ 7: 203–212, 1999

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INTRODUCTION

Practice in applying textbook control theory can greatly benefit the learning process. Such practice is motivating, promotes critical thinking, facilitates understanding in the use and limitations of the theory, and helps 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. A 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 then challenge the student to select and employ a combination of formulas to obtain a desired result.

Unfortunately, even when cleverly crafted, these one-dimensional challenges fall short of providing students the depth or breadth of practice required for learning and comprehension. Thus, the Department of Chemical Engineering at the University of Connecticut, like most around the world, 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. The abstractions presented in textbooks are literally brought to life through the tactile nature of lab experience.

The reality of the laboratory, unfortunately, is that each study can take many hours and even days to perform. Also, equipment failures and other problems teach the important but not always appropriate lesson that the real world can be uncertain. Thus, it can be difficult to have the students explore more than a very few central concepts in the lab.

An alluring method for providing students with the significant hands-on practice critical to learning process control is with a training simulator that provides virtual experience much the way airplane and power plant simulators do in those fields. The proper tool can provide students with a broad range of focused engineering applications of theory in an efficient, safe, and

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economical fashion. Such a simulator can work as an instructional companion as it provides interactive case study challenges which track along with classroom lectures.

Process control is a subject area well suited to exploit the benefits of a training simulator. 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 which literally rival those of the real world. These experiences can be obtained risk free and at minimal cost, enabling students to feel comfortable exploring nonstandard solutions at their desk. If properly designed as a pedagogical tool with case studies organized to present incremental challenges, learning can be enormously enhanced for process control.

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:

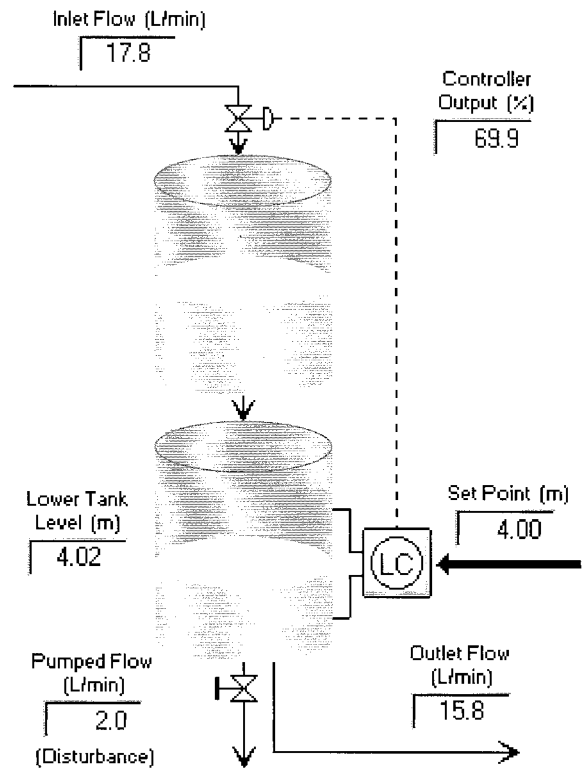

Figure 1 Gravity-drained tanks graphic display.

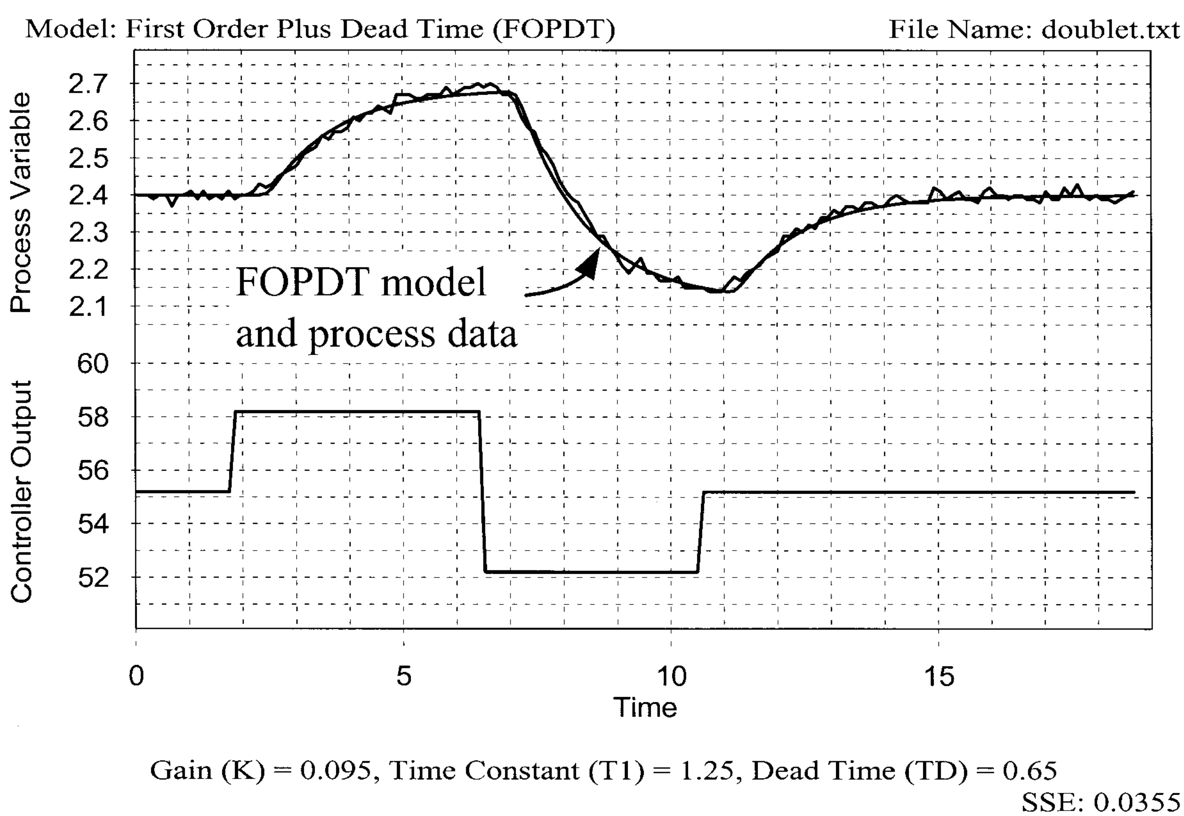

Figure 2 First-order plus dead time model fit of doublet test data.

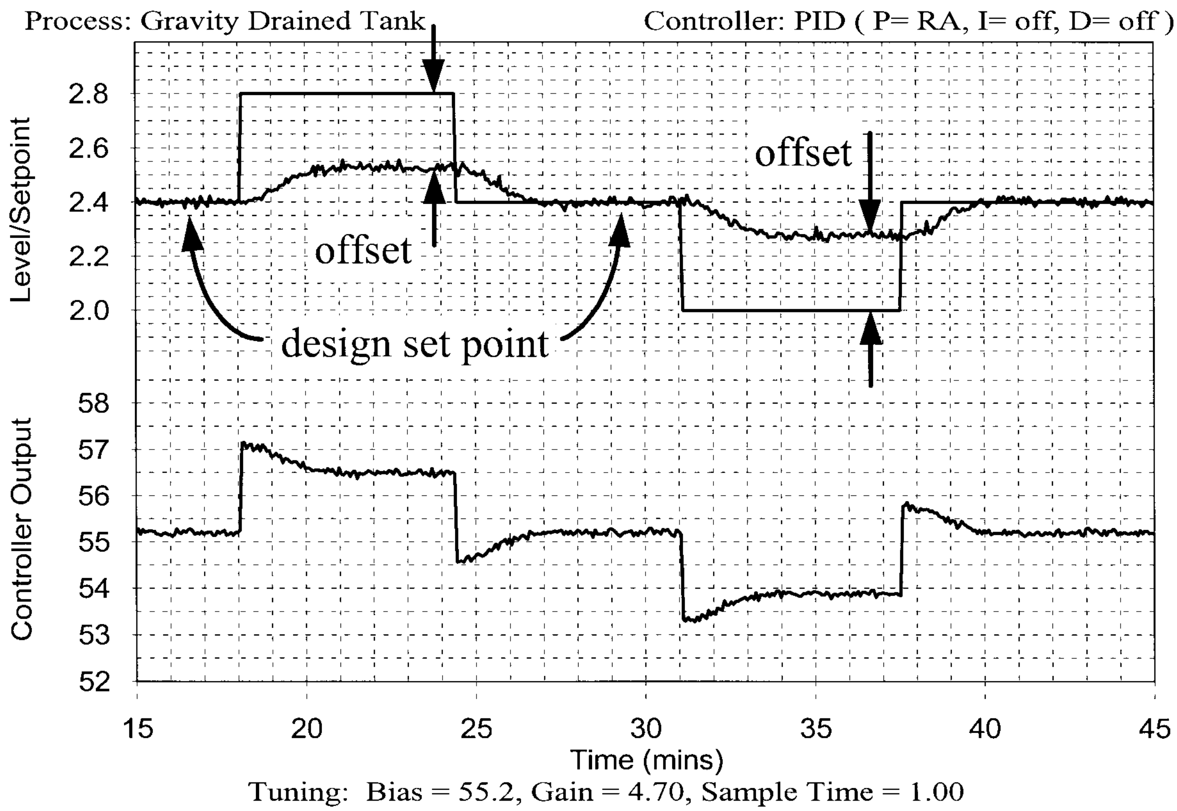

Figure 3 P-Only set point tracking results in offset.

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 decouplers, model predictive

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

The chemical engineering perspective considers each process to be one of a kind. Consequently, every control system can appear unique in design, implementation, and man–machine interface.

In addition, chemical processes are nonlinear and nonstationary, and have long time constants, significant dead time, and noisy measurement signals. Disturbances occur from numerous sources including loop interaction from other controllers in the plant.

EXAMPLE LESSONS

The following lessons were drawn from the Control Station [1] process control training simulator to illustrate the value such software provides the curriculum. We note that training simulators are distinguished in this work from tools such as Matlab [2], 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.

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 level rise in the tanks. If they decrease the flow rate, the level falls.

The traditional place to begin a course is with the

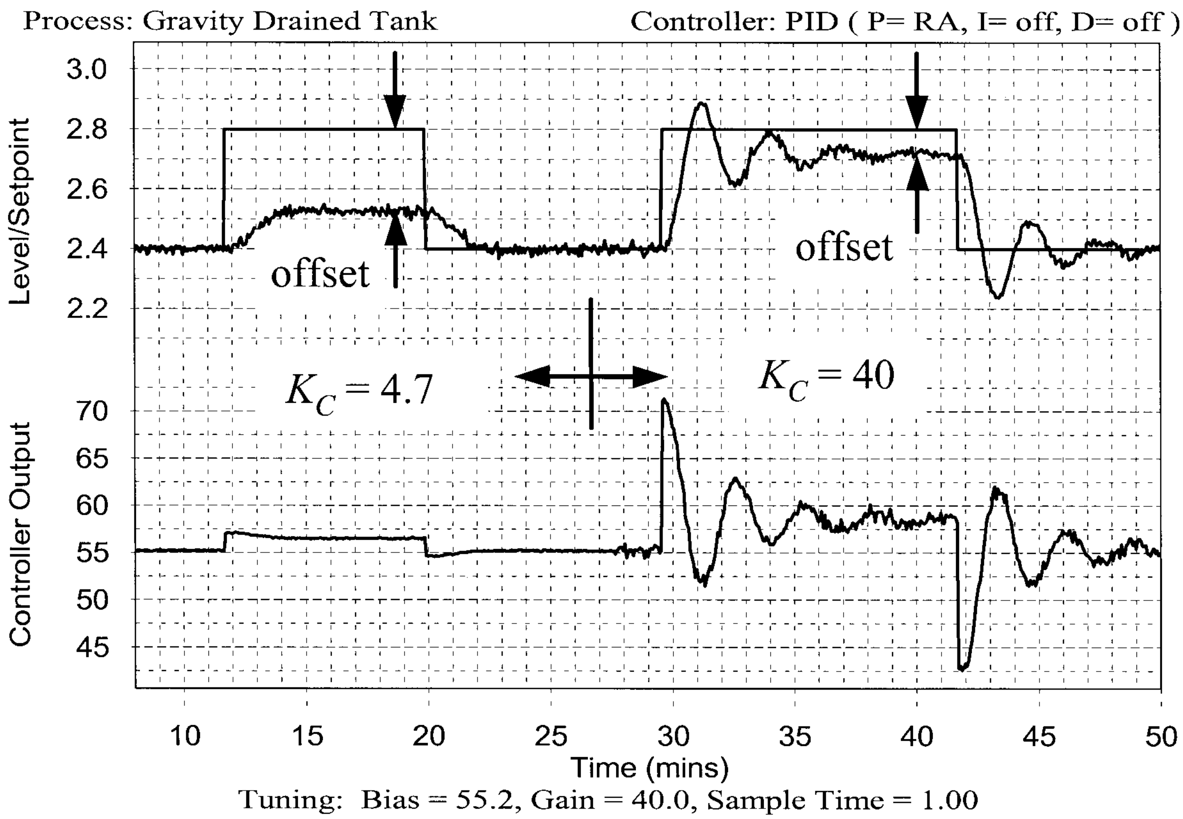

Figure 4 P-Only performance changes as K_C changes.

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, τ_P, and apparent dead time, θ_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 doublet 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 simulator strip chart of set point 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 using the FOPDT model parameters from Figure 2.

Then comes the what-if studies. The investigation of Figure 4 explores how K_C affects offset and damping 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?

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 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 affects set point tracking performance. Thus, students learn that a controller is designed for a specific or design level of operation. The best practice is to collect dynamic test data as near as practical to this design operating level.

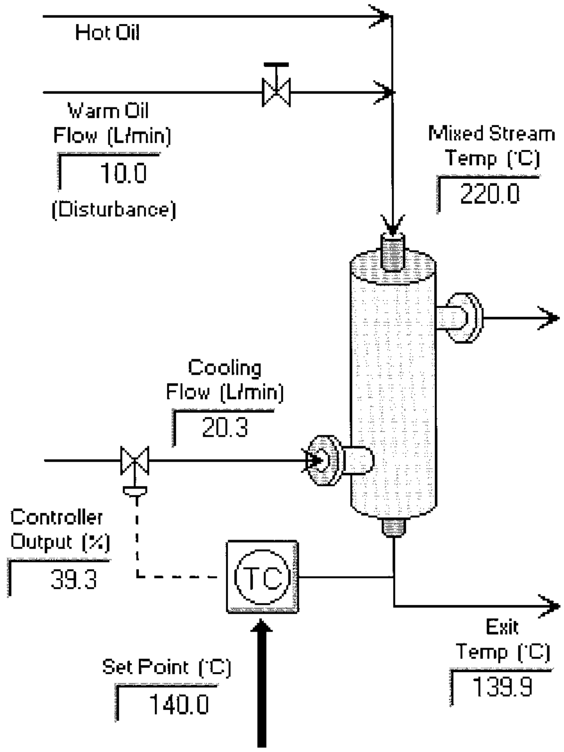

Figure 5 Heat exchanger graphic display.

Figure 7 also shows that the heat exchanger has a negative steady-state gain. Students learn that a complete design includes specifying the sense of the controller (reverse versus direct acting). 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.

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.

PID Control and Measurement Noise

Derivative action dampens oscillations because it resists rapid movement in the measured process variable. Students learn this by constructing Figure 9, which is a portion of a tuning map for derivative action. The center plot shows the set point tracking performance of a PID controller tuned using the ITAE for set point tracking correlation.

For all plots in Figure 9, K_C and τ_I remain constant and there is no measurement noise. The plot to the left 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

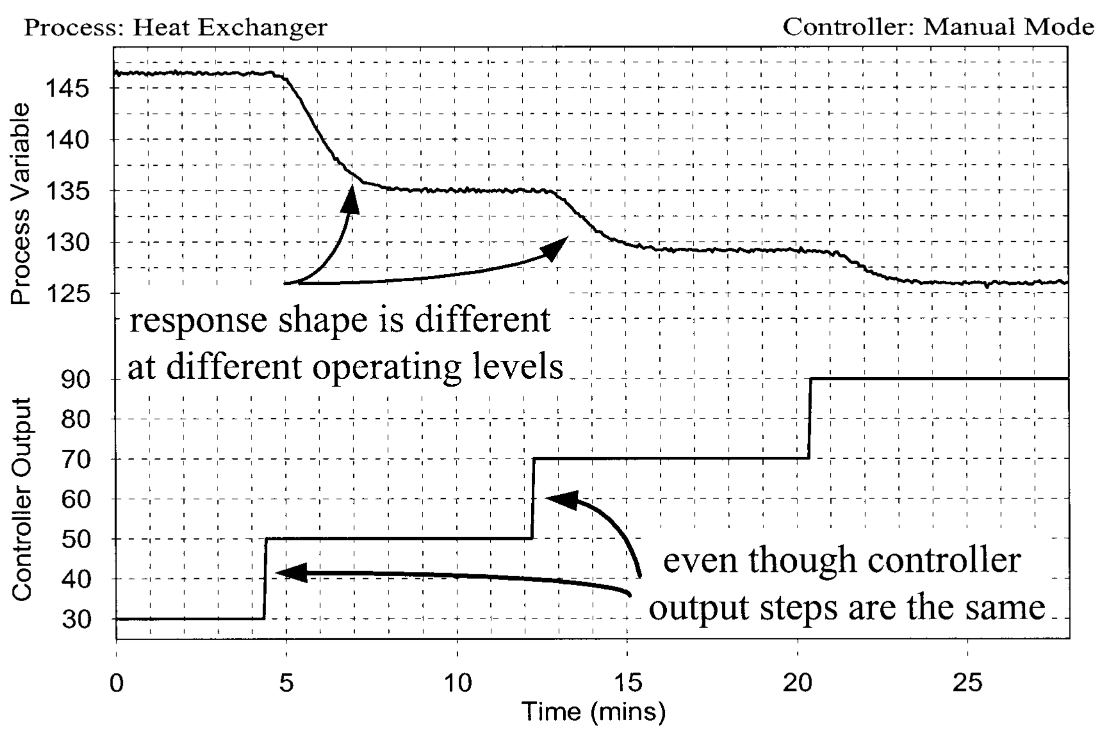

Figure 6 Heat exchanger displays nonlinear behavior.

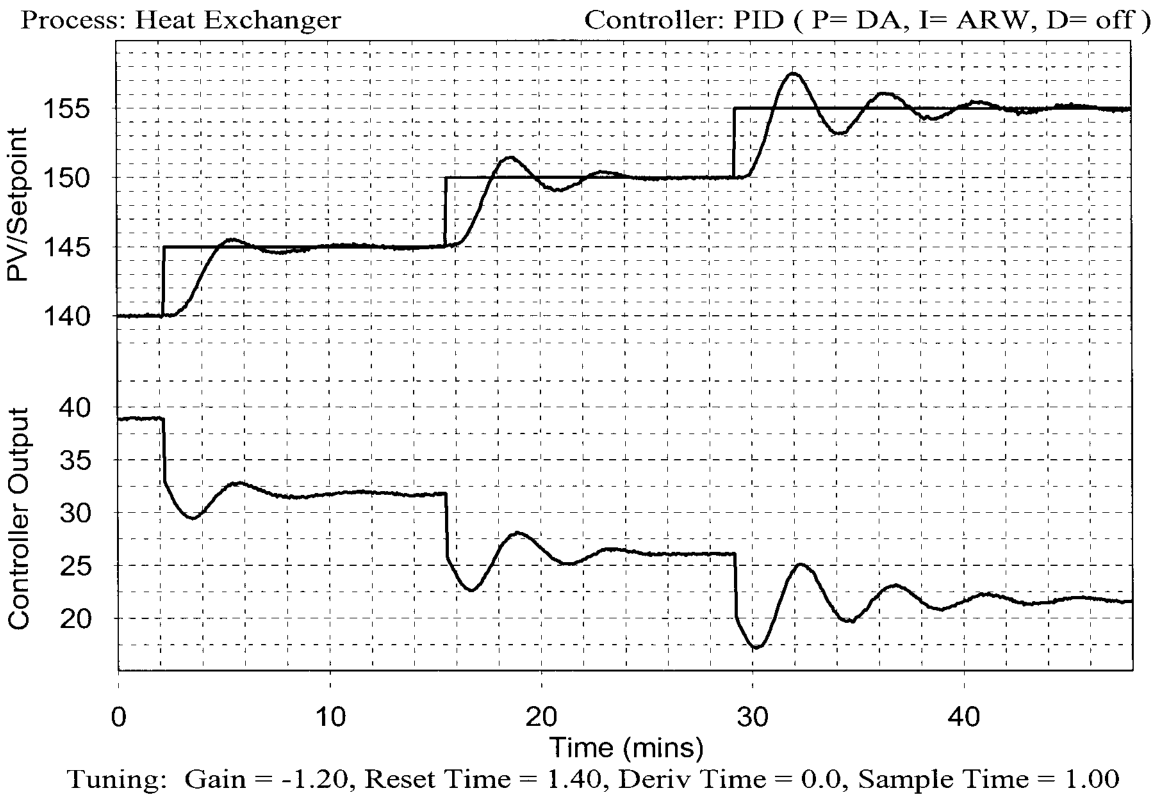

Figure 7 Nonlinear behavior impacts performance.

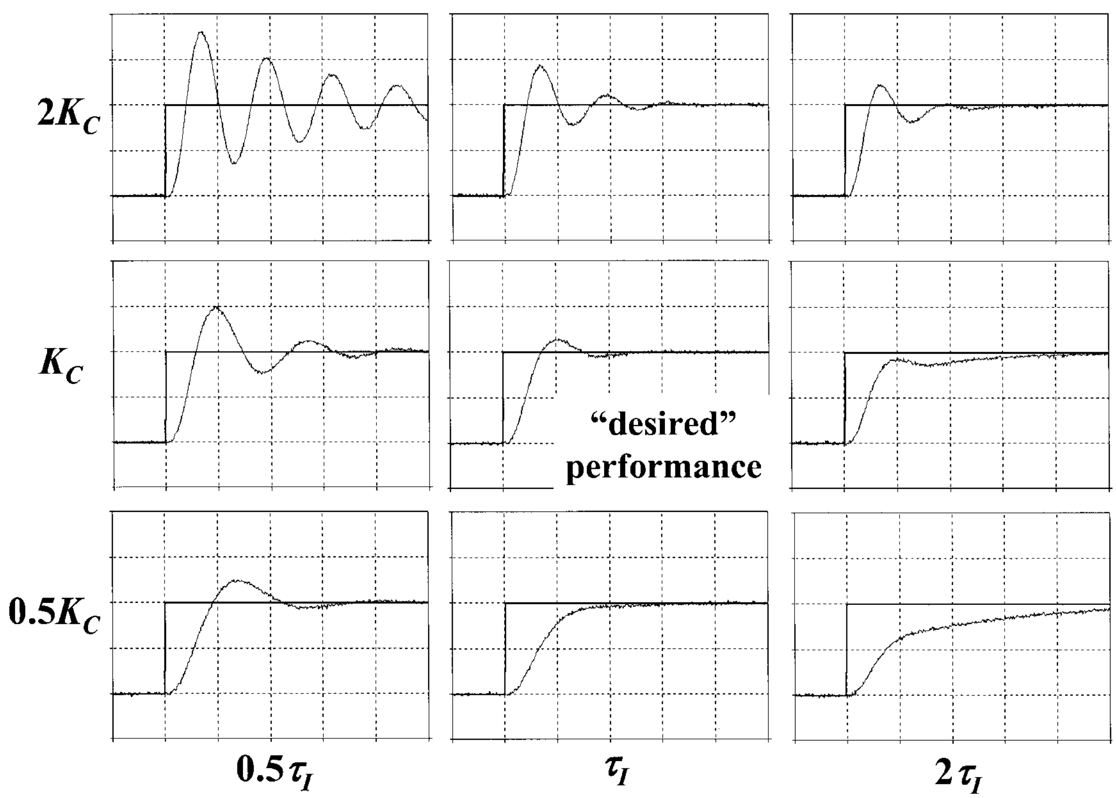

Figure 8 PI controller tuning impacts performance.

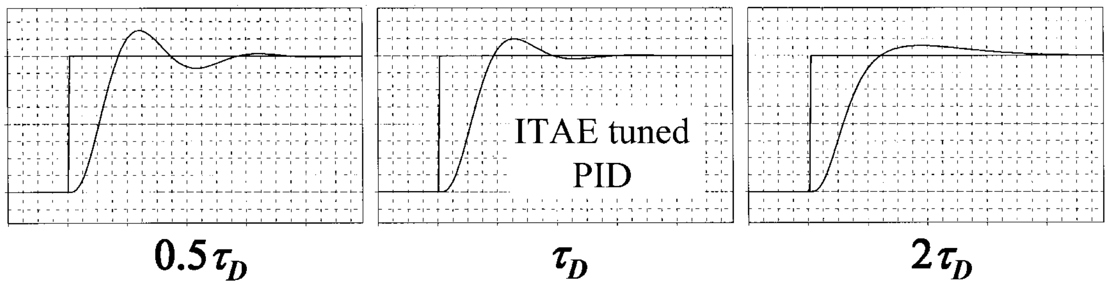

Figure 9 Derivative action affects oscillatory behavior.

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 illustrates this with a side-by-side comparison of a PI and PID controller.

Students also compare derivative on error to derivative on measurement. Watching the derivative on error "kick" after a set point step is a more memorable experience than simply hearing about it. Derivative filtering and four mode PID control are used in industry to address the problems resulting from measurement noise. Four-mode PID and filtering is scheduled to be added to Control Station in the near future.

Cascade, Feed Forward, and Disturbance Rejection

The jacketed reactor graphic, shown in Figure 11 for the cascade case, 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

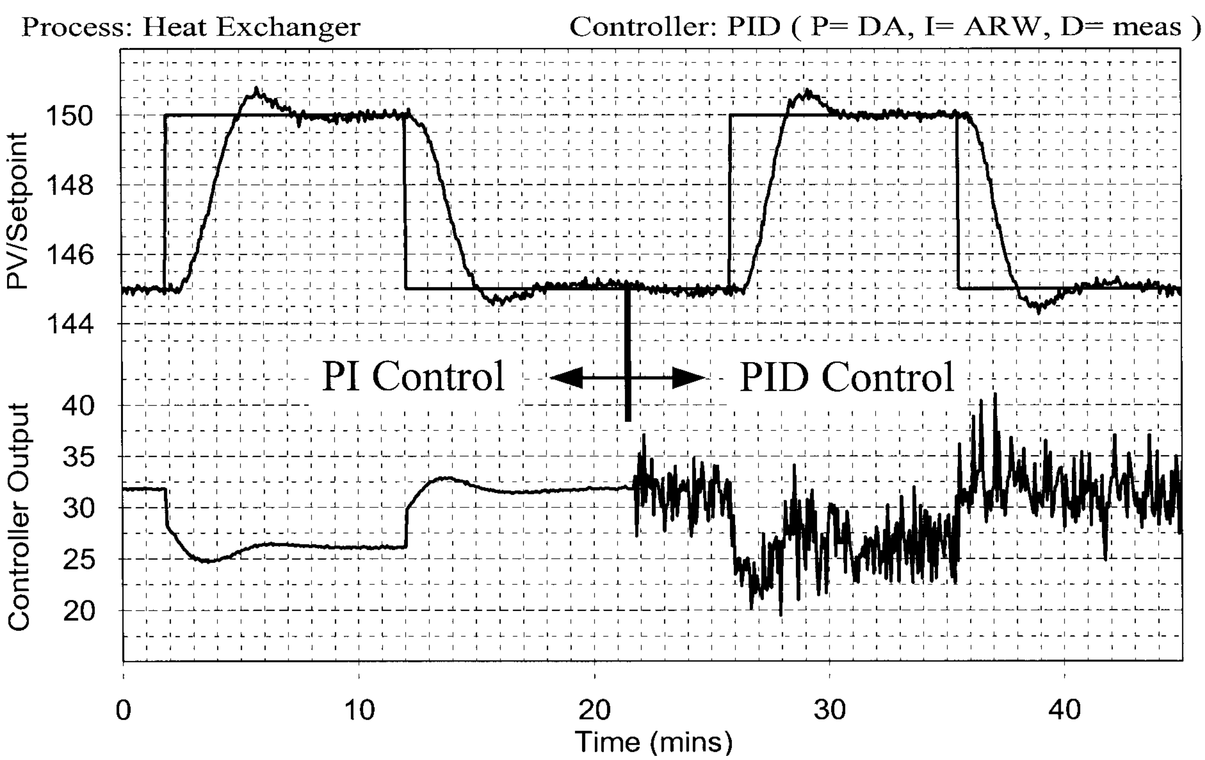

Figure 10 Measurement noise is amplified and reflected in controller output signal.

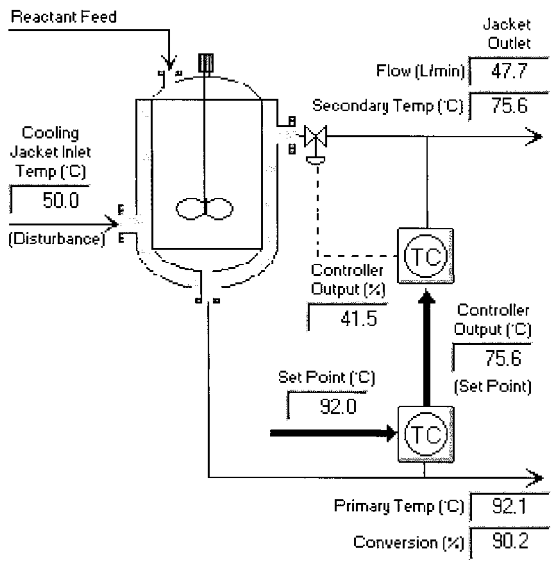

Figure 11 Jacketed reactor under cascade control.

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, feed forward with feedback trim, and cascade control as shown in Figure 11. 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, as shown in Figure 11. Feed forward requires identification of an appropriate process and disturbance model.

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

Students compare single loop, feed forward, and cascade control. They investigate tuning issues, which PID modes to use in a cascade, the order 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 distillation column graphic, shown in Figure 13, is a binary distillation column. The column has two measured process variables and two manipulated variables. The reflux rate is used to control distillate

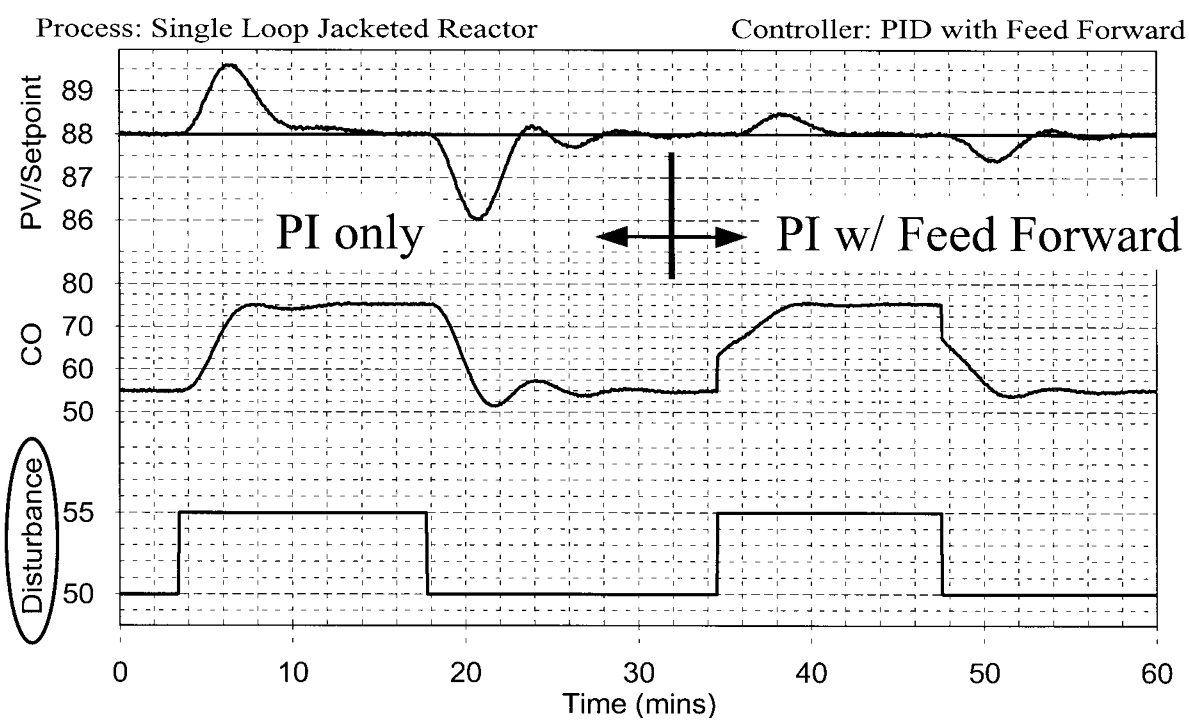

Figure 12 Benefits of feed-forward control.

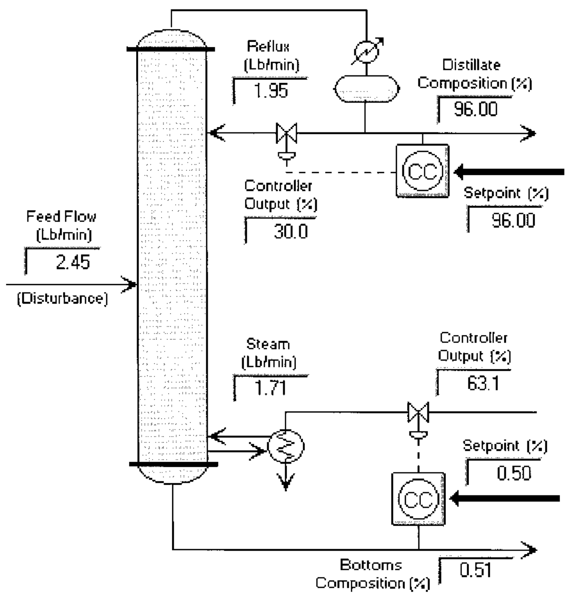

Figure 13 Distillation column graphic display.

purity and the steam rate is used to control the 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. However, the additional cold reflux will work its way down the column trays 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 bottoms composition, shown in the lower trace, to react unfavorably.

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. 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.

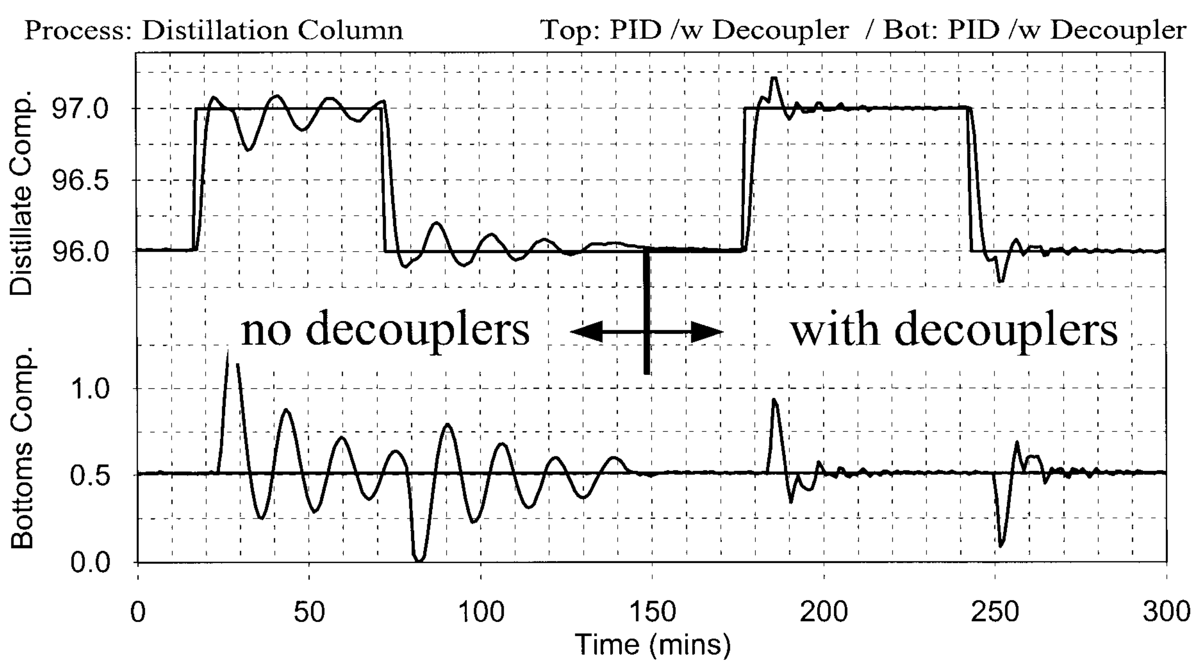

Figure 14 Distillation column shows loop interaction..

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

We have presented some examples of the lessons and challenges 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 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 proper training simulator 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 nonstandard solutions at their desk. If properly designed, a training simulator can bridge the gap between textbook and laboratory, enabling significantly enhanced learning for process control theory and practice.

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BIOGRAPHIES

Doug Cooper is a professor of chemical engineering at the University of Connecticut. He has been teaching and directing research in process control for more than 15 years. His research focuses on developing control methods that are both reliable and easy for practitioners to use. He has studied the control of fluidized bed incineration, heat exchange, distillation, injection molding, surge tanks, and catalytic reactors. Dr. Cooper's work experience in industry sparked his interest in teaching process control from a real-world perspective. This interest ultimately led him to develop the popular Control Station process control training simulator described here.

Danielle Dougherty was in born in Philadelphia, Pennsylvania, on September 15, 1975. She received a BS in chemical engineering from Widener University in 1997. She is currently working toward a PhD degree in chemical engineering under the direction of Doug Cooper at the University of Connecticut. Her current research interests included model predictive control and nonlinear adaptive control. Her thesis is on multivariable adaptive model predictive control.