Process Control Class for the Future Process Engineer

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Abstract

For most chemical engineering students their first jobs in industry will be as Process Engineers. A Process Engineer is assigned a process where operating conditions are established, and responsibility is to run the process day and night at those values. In short, their job is Process Control. So what tools are they given to do this job from their undergraduate curriculum? For many, it will be learning Linear Classic Control Theory with a focus on Single Input Single Output (SISO) processes which leaves them woefully unprepared to deal with nonlinear industrial plants that have Multiple Inputs and Multiple Outputs (MIMO). Instead, the authors detail a curriculum that quickly goes from Classic Control Theory to Internal Model Control (IMC) Based- PID Tuning of nonlinear processes. All exams are regulating nonlinear systems with load disturbances and noise culminating in 2 x 2 processes with pairings determined by Relative Gain Arrays and inclusion of static feedforward decoupling of loop interactions. Problem sets and Matlab code available on authors' website[1].

Keywords

Chemical Engineering Process Control, Undergraduate Control Course, Nonlinear processes, Proportional Integral Derivative (PID) Control, Internal Model Control-based PID Tuning

Introduction

Edgar *et al*, 2006[2] cites various chemical engineering education symposiums where faculty have strongly considered removal of process control from the curriculum, that it is a mature field, that it is unlikely to have much future impact on discovery of new technology. And yet every Process Engineer's main job is to regulate a process at a desired set of operating conditions 24 hours a day for seven days a week. So how do these views come about in academia? Control is an entity th

at is involved in almost all engineering fields yet stands apart from them. Faculty do not feel comfortable teaching control. They have all taken the course as undergraduates, but few would teach it themselves. This comes about in large part on how control is taught. It has become too esoteric with its own vernacular, and its over dependence on Laplace Domain mathematics, and it is too often removed from real world nonlinear systems due to over dependence on Transfer Functions that are not used in any other engineering classes. Several papers are out there over the past 15 years talking about need to revolutionize control education and yet it has not happened to any large extent[2][3][4][5][6]. Most textbooks are still based almost solely on Linear Control Theory, transfer functions, and traditional tuning techniques for Proportional Integral Derivative (PID) controller. Internal Model Control based PID tuning is still absent in majority of textbooks even though it is easiest and safest method to tune a PID controller, and brings the student closer to handling advanced controllers such as Model Predictive Control which are becoming more prevalent in all chemical process industries. Haugen and Wolden, 2013[3] provided a course outline for process control that include in part the following: leaving out Laplace Transforms and Transfer Functions, real time simulations, measurement noise included, experimental control, and feedforward control with nonlinear models[3]. Focus should be on practice before theory[3]. Yet even here Haugen and Wolden, 2013[3] put too much emphasis on SISO systems nor on the importance of teaching IMC based PID tuning, and too much reliance on frequency response analysis that is hardly used in industry, and has little basis for slower dynamics and hard to perturb sinusoidally chemical processes. Our proposition: less emphasis on Transfer Functions and linear SISO systems. Authors proposed preparation for students: nonlinear system behavior importance of operating regions, what is PID tuning how best do it using model based technique, concept of direct synthesis/model based control, methodology to get simple model fit and how to handle MIMO system, and inclusion of load disturbances and noise. Overall trying to mimic what they will see in the chemical process industry.

Background Theory

NL SISO Example: Van de Vusse Reaction Input Multiplicity and Inverse Response

The Van de Vusse reaction system consists of two reactions of A taking place in parallel (see eqn 1). The reactions are run in a continuous stirred tank reactor with constant volume, density, and temperature. The product that is desired is the concentration of B, C_b (moles B/L). This system exhibits as challenging of a control problem as one can expect for a single input and single output process. The reactions that occur are:

$$A \overset{k_1}{\rightarrow} B \overset{k_2}{\rightarrow} C \qquad A + A \overset{k_3}{\rightarrow} D \tag{1}$$

Complete modeling equations and control examples are in Aufderheide and Bequette, 2003[7]. The steady state plots for different feed concentrations are shown in fig. 1. The control objective is to operate as closely as possible to the optimum point to maximize the concentration of B. Operating points on the left side of the optimum are non-minimum phase. As the dilution rate is increased the right-half-plane zero moves to the left-half plane and the gain becomes negative. The gain at the optimum is zero. Control is very difficult since the desired operating point has a gain of zero and the dynamics on either side are very different. While the right hand side of the optimum can be controlled in almost a deadbeat fashion in a single sample time, the left hand side has a significant inverse response that requires the controller to not only change gain signs but be detuned significantly as

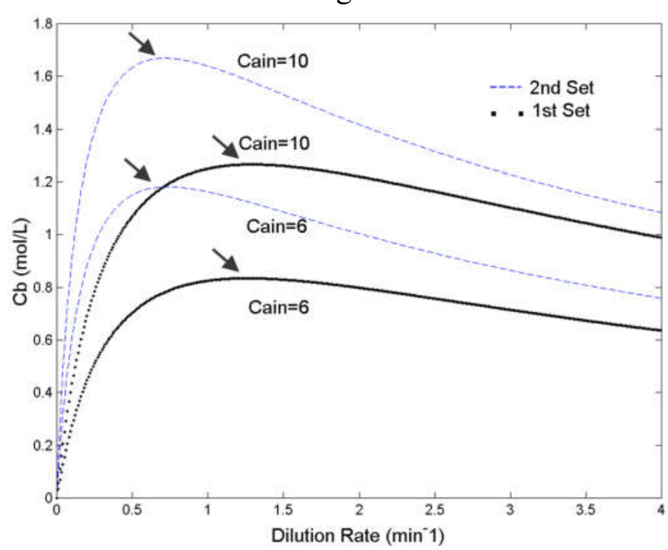

Fig.1. Steady state curves for different feed concentrations of Ca_{in} and for both sets of kinetic parameters[7]. Arrow (↘) indicating optimum.

well. Sample step responses for the nominal case (1^{st} set of kinetic parameters in Fig. 1) are shown in Fig. 2 after subtracting the initial C_b concentration to more readily compare them.

Note that the top two step responses are at steady states to the left of the optimal value so have inverse responses and positive gains. As the steady state dilution rate approaches the optimal value the gains approach zero and the inverse responses get longer. *Uss*=0.67 min^{-1} has approximately four times the process gain and two-thirds the inverse response time. However to the right of the optimal steady state dilution the process no longer has an inverse response and has negative gain.

For control, it is going to be difficult to regulate the process when on the left side of the optimal steady state value due to the significant inverse response times. If a standard fixed controller such as Proportional Integral Derivative (PID) Controller is used then it would be necessary to detune it considerably so that the controller does not attempt to operate aggressively while the system is in an inverse response. The reason for this is simple, the controller will assume that the process is going in the wrong direction and will apply a manipulation in the dilution rate opposite of what it should be. If tuning is aggressive can have the input increase such that now on the right side of the optimum where the process gain is now negative causing the fixed linear PID controller to fail. Therefor any attempt to use a single PID controller to regulate this system near the optimum value has a chance to fail miserably since any disturbance or a slight overshoot by the controller will bring the process to the other side of the optimum where the process gain has a change in sign.

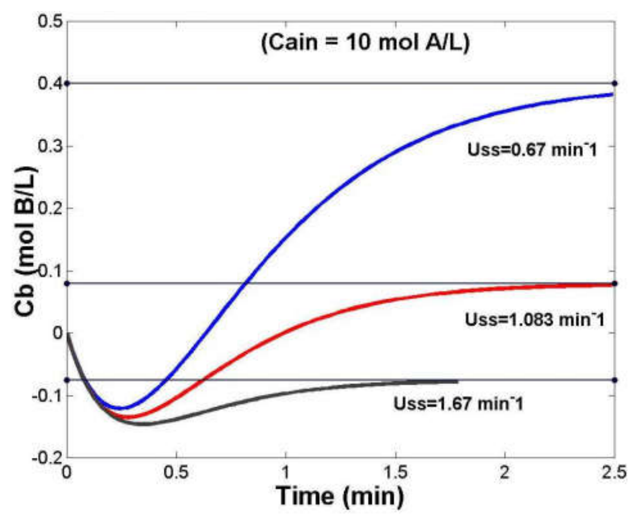

Fig.2. Sample step responses for the nominal case starting at steady state dilution rates, Uss[7]

Control at the optimal point is impossible. Recall that an effective controller gain is always proportional to the inverse of the process gain. The process gain at the optimal point in this system is zero. Therefor for the controller gain to keep the system exactly at the optimal point (without falling off slightly to either side) would have to be infinite. Other interesting point, yes it will take a lot of control effort to get near the optimum value since the process gain is approaching zero. However, once you are in the vicinity of the optimum point one can practically turn the controller off and as long as no disturbances occur the output will stay near the optimum value since the process gains near the optimum are very small so the system will not move that far away from the optimum on its own accord. Students run a series of exercises on the Van de Vusse reactor handling disturbances in feed concentration, input and output noise, and with changes in kinetic parameters to mimic catalyst poisoning.

MIMO Control with RGA and Static Feedforward Decoupling

It is critical for students' preparation to enter industry to have knowledge and strategy for handling systems with multiple inputs and outputs. Here we have done a variation of the case studies done by Bequette *etal*, 1998[4] which are projects done by students to design Multivariable-SISO controllers regulating etcher, lime kiln, cardiac patient, etc[4]. Bequette's projects involve 2 by 2 systems with an added disturbance input[4]. Processes are linear transfer functions with transport delays and input constraints as only nonlinearities. We have developed nonlinear processes that the students complete in a 2-3 hour exam period where like in Bequette's students use Relative Gain Array to determine input-output pairings and specific tuning rules depending if the process is decoupled, "amping", where relative gain is fractional due to control loops assisting in increasing the output, and "crunching" where relative gain is greater than one due to control loops restraining the output[8]. From step responses, students again fit FOPDT models and design individual controllers one at a time using tuning rules for their RGA results. Then both loops are closed and any tweaks in tuning are made. Lastly, students do static decoupling to help eliminate interactions between the two control loops[9]. Disturbance rejection simulations are tested including both input/output noise and various load disturbances.

Results

A SISO Example: pH Waste Tank

Waste water being discharged into any medium of water must first be neutralized to ensure that aquatic life is not destroyed. An acceptable range for waste water disposal is pH 6 to 8. pH control of waste water is difficult, this is due to the non-linearity of the process around the neutralization point and the frequent changes in the flowrate and composition of the streams. The system has

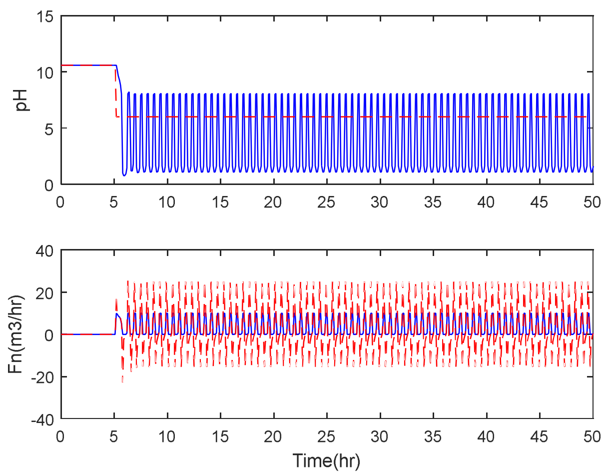

Fig.3. Large set point change where final pH is 6

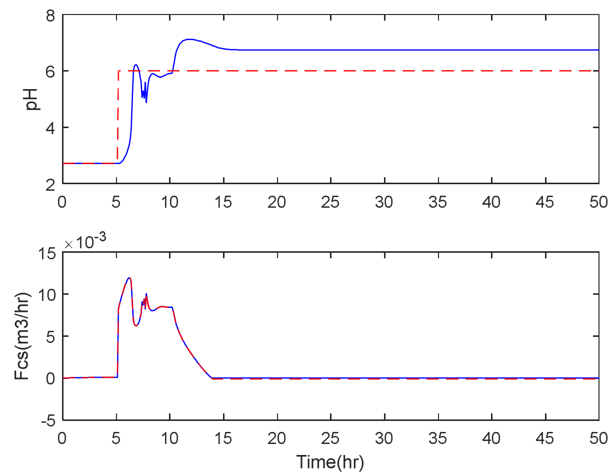

Fig.4. Disturbance in the feed flow rate

Top (output): Actual, Set point   Bottom(input): Actual, Calculated by PID

waste water from four processes being distributed to a tank where neutralization of these streams will be achieved. Nitric Acid and Caustic Soda are the neutralizing agents that will be used to attain an acceptable pH. The complete modeling equations are in Wilkes, *etal* 2012[10]. The FOPDT approximations and tuning parameters were calculated based on a step response of the pH. Figure 3 shows with a large set point change to a pH of 6, the system is unstable and the valve is slamming full open to fully closed. The problem here is that the step response and its resulting FOPDT is only accurate near the operating condition of pH= 10.5. Clearly the resulting controller is too aggressive in this new set of operating conditions that the system is being driven towards. The disturbance in the feed flow rate as seen in Figure 4, causes the system to be physically unrealizable. There is no way that the controller can achieve the desired setpoint. Figure 5 shows the pH staying within the acceptable pH band. Initially the process is outside of the band, fluid builds up in the tank and the controller tuning which was set for continuous flowing system is not aggressive enough to change the pH quickly. This all changes when at roughly 12 hours after the set point change the pH is within the acceptable band and the flow out is no longer zero. A great deal of caustic has been added to the system to manipulate the pH and the non-ideal mixing drives the pH too high above the set point, at which point the caustic flow goes to zero. The controller has done fine since the pH is within adequate environmental constraints for the vast majority of the run. This system illustrates the need for nonlinear dynamic models for regulation. A transfer function with a transport delay and input constraints would not provide instability in Figure 4, and the importance of what is an operating region. Nor could a band where process switched from fed batch to continuous be done with a linear transfer function.

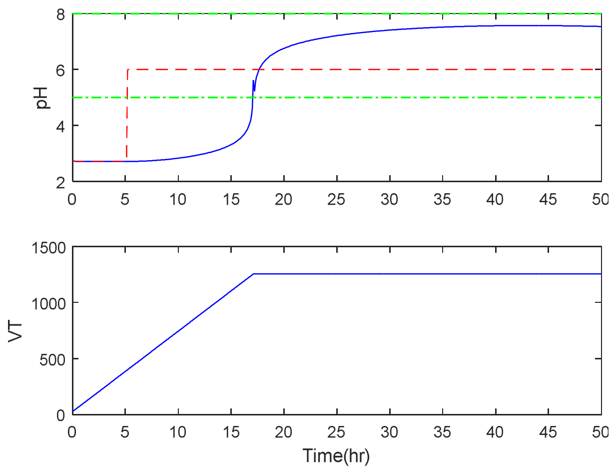

Fig.5. pH stays with 6 – 8 band prior to tank being emptied; Actual ▬▬, Set point – – , Band, – ·

MIMO Example: Regulating a Homopolymerization Reactor

The process being regulated is a methylmethacrylate free radical homopolymerization reaction in a continuous stirred tank reactor. The model and baseline conditions are modified from Choi (1986)[11]. The system can be very complex having very different steady state conditions, stability nodes, cycles, and bifurcations depending on the parameterization and operating conditions of the

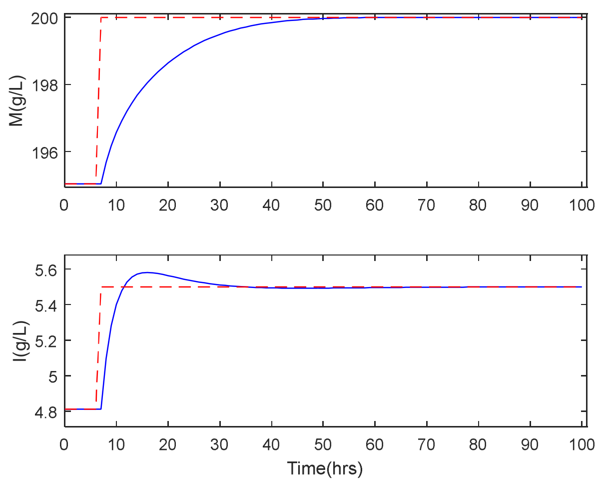

Fig.6. Best IMC based PI tuning with both loops closed

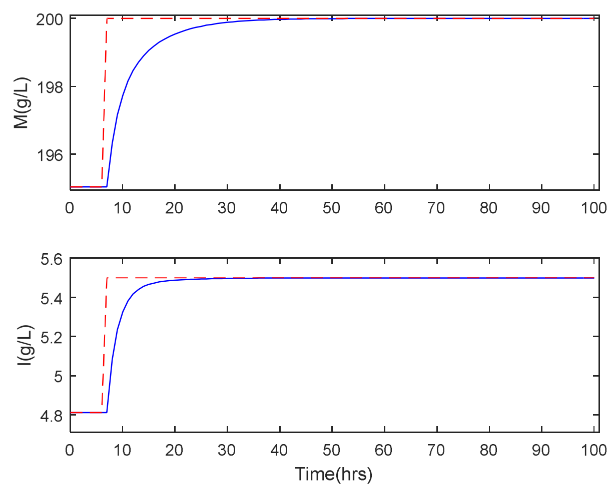

Fig.7. Feed forward static decoupling with both loops closed

Top (output): Actual ▬▬ , Set point – – Bottom(input): Actual ▬▬ , Calculated by PID – –

non-isothermal reactor. This example has been simplified here for a two controlled outputs, monomer concentration, *M*, and initiator concentration, *I*, by two inputs volumetric feed rate, *q*, and initiator feed concentration, I_f, the system was modified to be isothermal with the reactor temperature, T, to be treated as one of the disturbance inputs. The other disturbance input is the monomer feed concentration, M_f. Students were required to perturb the reactor, obtain process gains for each input/output combination, do a Relative Gain Analysis (RGA) to determine input/output pairs, calculate First Order Plus Dead Time models for the control loops, tune each loop separately, and then detune (if necessary) when both loops are closed. The results of the RGA were paired q vs M and I_f vs I. The system is "amping" and when both loops are closed will be destabilizing with faster performance and lower robustness. The magnitude of the interaction, is moderately high. Each individual control loop should be tuned somewhat overdamped with the foresight that when both are closed they will become less stable. After closing both loops may need to tweak further. Due to interaction level decoupling should help controller performance when all loops closed. Overall as seen in Fig. 6, this is very good control for an "amping" system. There is an increase in performance accompanied by a decrease in robustness in regulation of I which was expected. The resulting overshoot for I is roughly 15% which is fine and the controlled response has I's setpoint being reached in 7 hours with a total settling time of 60 hours which is not that good. So response is slightly to somewhat underdamped. However, the regulation of M is surprisingly not more underdamped but actually a little more overdamped now needing 55 hours to reach setpoint where before it was 40 hours. So the underdamped expectation from the RGA was seen really in I only. The purpose of static decoupling is to minimize interactions between control loops. Fig. 7 shows it works almost perfectly with both loops slightly overdamped. Control is excellent and settling time for M is slightly less to 38 hours instead of 40 hours without the decoupling. Similar results are seen for I with a settling time of about 30 hours which is ten hours less than before.

Discussion and Conclusions

Teaching process control is not an easy subject, and is absolutely critical for all Process Engineers to be successful in industry. Too often it is coupled with learning Matlab, or takes on additional burden of being only class that covers any process dynamics. These add to the difficulty in covering the large wealth of material in control that comes from Chemical, Electrical, and Mechanical engineering fields. In addition, control has its own lexicon, notation, and terminology which can be difficult for students to grasp. Without proper care by the Instructor it can quickly become very esoteric and seem devoid of the reality that many of the students will be in front of large machinery with several inputs and outputs that is highly nonlinear in nature and now have to regulate the process so it runs 24 hours a day, seven days a week. It is very daunting without a proper strategy and training to handle the situation adequately. No control class can handle all the topics in the field be it frequency responses, root-locus design, cascade control, anti-reset windup, gain scheduling, split ratio control, inferential control, model based control such as model predictive control, etc. Many worthwhile areas to teach the students must be put aside. We have presented here a curriculum that given those time constraints covers the skills absolutely needed to be successful in industry with the proper background and theory so students understand how they work. Many examples of tests for both SISO and MIMO processes in various engineering fields are available for download at authors' web site. All necessary Matlab files are provided with the scripts. Assessment examples for cascade control, gain scheduling, and MPC also are present for download.

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