ChE classroom

PROCESS CONTROL EDUCATION

A Quality Control Perspective

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There are a number of issues that warrant an examination of the current undergraduate course in process control. One is the notion of statistical quality control being used in industry. Statistical process/quality control (SPC/SQC) concepts[1] grew out of the discrete manufacturing environment as a response to competitive pressures, and current efforts aim at the notion of *zero defect.* In recent years, SPC concepts have also made their presence felt in the continuous-process industries,[2-4] and concepts such as control charts, control limits, common causes, and special causes are now commonly used as measures of product quality variability as well as to detect problems and take corrective actions. Automatic correction when a defect is detected is beyond the scope of SPC, however, so the word "control" in the acronym is somewhat misleading. For the buyers of products from processing industries, SPC measures represent proper evidence of the variability of product quality, and these measures often form the basis of purchasing contracts. One consequence of the success of SPC is that excellent communication appears to exist between statisticians and company management.

Similar communication among process control professionals and management, however, appears to be lacking, and one of the contributing factors is control "jargon." The control engineer speaks in terms of servo and regulatory responses, input suppression and penalty parameters, model uncertainties, exponential filters, and robustness. While there is no implication that these are unimportant, to tie them to product quality (the primary concern of management) is often difficult. A proper understanding of the role of both statistical process control *and* engineering process control in achieving product quality would improve communication between statisticians, management, and control specialists, and would considerably enhance the ability of control specialists to have a stronger impact on process and plant operations. Students should be aware of the importance of this kind of interaction.

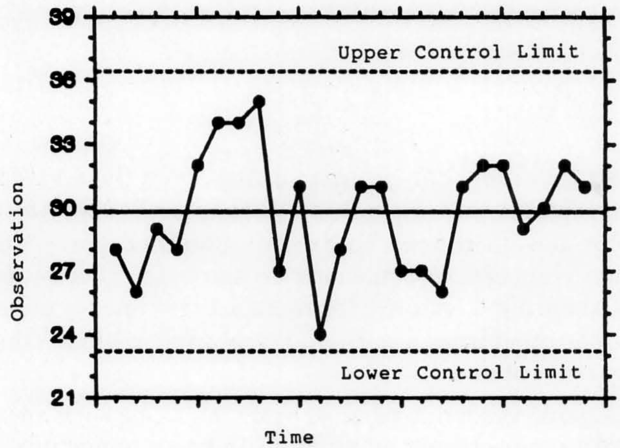
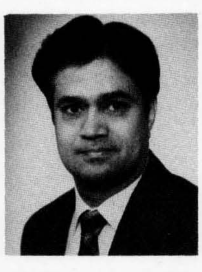


Figure 1. *Typical control chart*

Consider the Shewhart control chart[5] of a hypothetical discrete parts manufacturing process, shown in Figure 1. In discrete-parts manufacturing, the adjacent data points are assumed to be statistically independent of each other. In fact, the data from a process under statistical control are deemed to follow a Gaussian (normal) distribution.

The mean of the data is the center line on the Shewhart control chart. In light of the assumption of normality, then, 99.73% of the data will lie within $\pm 3\sigma$ limits from the mean; the $\pm 3\sigma$ limits are the so-called statistical control limits. If the data points lie within the control limits and are more or less ran-



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domly distributed, the variability is deemed to have been caused by *common causes.* Within the context of process control, common causes are those random disturbances whose detrimental effect upon product quality cannot be eliminated by any kind of control action. If a non-random pattern is detected, although the data points are within the control limits (*e.g.*, seven points in a row are above/below the central line, fourteen points in a row alternate up and down, etc.), there may be an *assignable (or special) cause* that should be investigated. Points outside the control limits are also said to have been caused by *assignable causes.* Assignable causes need to be investigated and corrective action must be taken.

In contrast, the data points on a chart similar to Figure 1, representing the quality variable from a continuous process and plotted as a function of the sampling interval, are invariably autocorrelated. Furthermore, the center line is the set point and not the mean of data points. The integral action in the controller will insure that the quality variable will return to the set point for certain types of disturbances. Thus, the closed-loop responses in the CPI do not obey statistical control concepts well. Recent research, however, has led to methods that can be used to analyze the autocorrelated data and make them amenable to statistical monitoring.

Process control practitioners have often obeserved that a *good* control algorithm is one which shifts much of the variability of an output onto the input, *i.e.* the manipulated variable.[6] In fact, an algorithm's performance is frequently measured in terms of its ability to shift the entire variability from the output to the input under ideal conditions.

An illustrative example of a heat-exchanger system taken from Downs and Doss[6] is shown in Figure 2. In this instance the control algorithm attempts to hold the exit temperature as closely as possible to the set point by suitably manipulating the flow of the heating medium. The ability to deliver offset-free performance is a key requirement in controller design. It has been pointed out that in industrial situations, manipulated variables often have their own processing units, and transferring an excessive amount of variability to them may not always be the the best approach. Thus, a control law

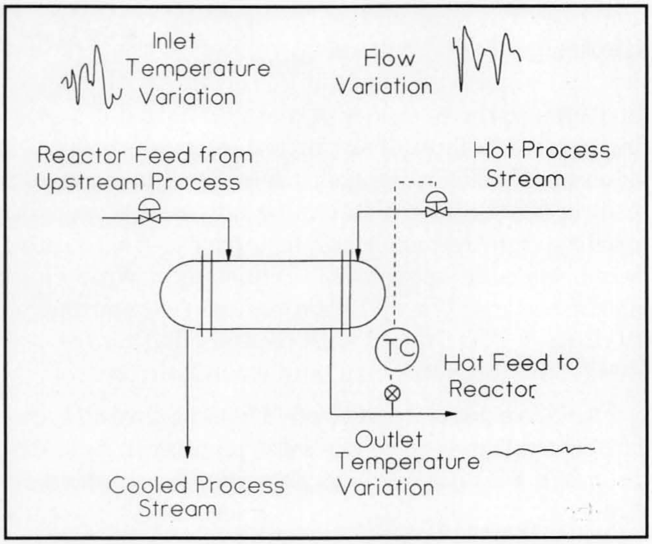

Figure 2. *A control algorithm shifts the variability of the output onto the input.*

should be designed so that only as much variability is transferred to the input as is necessary to produce a product of acceptable quality.

The foregoing discussion points out the need for suitable control laws and appropriate statistical tools which can handle autocorrelated output data for statistical monitoring purposes. We recently presented a unifying perspective that combines the best features of engineering process control (EPC) and statistical process control (SPC) for achieving total quality control of continuous process systems. In the following paragraphs we will briefly review the unifying methodology for EPC and SPC and will reveal what new material should be added to the traditional process control course to make it more effective in meeting the needs of industry.

UNIFYING METHODOLOGY FOR ENGINEERING AND STATISTICAL PROCESS CONTROL[7]

We propose a two-part procedure for achieving total quality control of continuous processes. In Part 1, we design a suitable control law to hold the output (reflecting the quality variable) within specifications in the presence of load disturbances and modeling errors. In Part 2, we analyze and massage the autocorrelated output data so as to render them amenable to statistical monitoring. The usual SPC rules may then be applied to keep the continuous process under statistical control.

Part 1
Engineering Control Systems Design

Many approaches to control are described in the literature. Just which approach to use depends on the type of process and on the personal preference of the designer. The basic requirement is that the control law must hold the quality variable within specifications in the presence of disturbances and modeling errors. In light of our introductory discussion, it is obviously desirable that the control law contains tuning constants which can be adjusted to improve quality or to reduce costs, in terms of the manipulated variable movements, consistent with client specifications. We will here review two approaches to control: PID control with feedforward control and dead-time compensation, and stochastic control.

The Standard Approach The standard PID controller continues to be the most popular in industry. the *ideal* PID controller is described by the transfer function

$$G_c(s) = K_c\left(1 + \frac{1}{\tau_I s} + \tau_D s\right) \tag{1}$$

There are several approaches to tuning this type of controller. Some of them involve open-loop testing, while others are based on closed-loop experimentation. The settings that result are meant to satisfy certain specified optimization criteria, such as minimum ISE (integral of the squared error), quarter decay amplitude ratio, etc.

The system performance deteriorates as dead-time in the loop increases. The notion of dead-time compensation is to remove the dead-time from the system's characteristic equation so that the system performance improves. There are two ways to achieve dead-time compensation: one (attributable to O.J.M. Smith[8]) is called the Smith predictor, while the other (attributable to C.F. Moore[9]) is called the analytical predictor.

In real-life applications, disturbances are invariably present. The controller must compensate for the negative effect of the disturbances on the process output. In those applications where disturbances can be measured, the notion of feedforward control may be employed. Figure 3 depicts the block diagram of the closed-loop system, showing PID control with dead-time compensation and feedforward control. The Smith predictor approach for dead-time compensation is shown in Figure 3 for illustrative purposes; Moore's analytical predictor may be employed instead if so desired. The arrangement shown in Figure 3 is industry standard. Blocks to implement PID control, lead lag, and dead-time compensation come standard with modern distributed control systems.

***Stochastic Controller Design*[10,11]** We know that for identical model structures (G_P and G_L) and identical closed-loop performance specifications (*e.g.,* minimum variance), there is really no difference between the design of feedback controllers for deterministic or for stochastic disturbances.[12] It is nevertheless important to be familiar with how controllers are designed for stochastic disturbances, because with this approach the closed-loop data can lend itself directly to statistical monitoring.

Consider a single-loop linear system that is perturbed by stochastic disturbances. A stochastic disturbance, called *noise,* is obtained by passing white noise, a_t (having zero mean and a constant variance σ^2_a), through a suitable model structure such as a first-order lag, an integrating type load such as a ramp, etc. The disturbance model structure is selected so that it is representative of the real-life situation. In fact, plant testing with PRBS (pseudo random binary sequence) signals followed by time series analysis can help identify the models that would be needed for designing the type of controller being discussed in this section. The purpose of the exercise is to design a control law which will minimize the variance. The output of the system, C_t, is related to the manipulated variable, M_t, and the noise, N_t, according to

$$C_t = \frac{\omega(z^{-1})}{\delta(z^{-1})} M_{t-F-1} + N_t \tag{2}$$

where F is the time delay in terms of number of sampling periods.

Equation (2) can be equivalently written as

$$C_{t+F+1} = \frac{\omega(z^{-1})}{\delta(z^{-1})} M_t + N_{t+F+1} \tag{3}$$

For minimum variance control, C_{t+F+1} must be set to

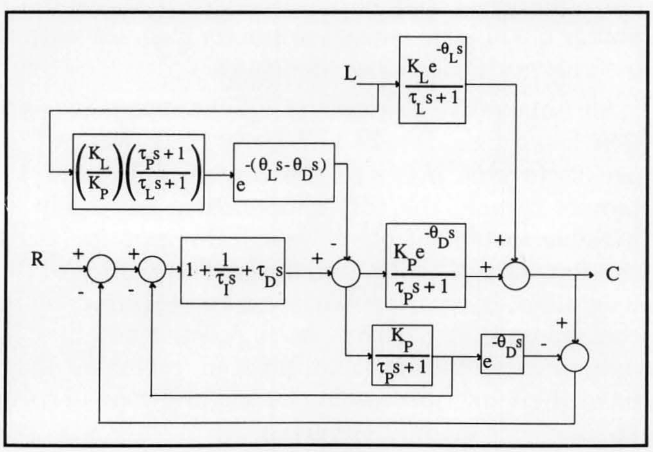

Figure 3. *The standard approach.*

zero. Equation (3) then gives

$$M_t = -\frac{\delta(z^{-1})}{\omega(z^{-1})} N_{t+F+1} \tag{4}$$

The control law given in Eq. (4) cannot be implemented since it requires knowledge of N_t, F+1 sampling instants into the future. Since future information can only be forecasted, Eq. (4) must therefore be written as

$$M_t = -\frac{\delta(z^{-1})}{\omega(z^{-1})} \hat{N}_{t+F+1} \tag{5}$$

where the caret ^ denotes an estimated value. For illustrative purposes, we will assume that the noise model is adequately described by

$$N_t = \frac{\theta(z^{-1})}{\phi(z^{-1})\nabla^d} a_t \tag{6}$$

Usually, the parameter d = 0, 1, or 2. It permits the designer to describe non-stationary types of disturbances. Following the procedure for forecasting the disturbance (see Reference 7 for details) leads to the control law

$$\nabla^d M_t = -\frac{\delta(z^{-1})}{\omega(z^{-1})} \frac{L(z^{-1})}{\phi(z^{-1})} \frac{1}{\psi_1(z^{-1})} e_t \tag{7}$$

where

$$e_t = C_t - C_t^{set}$$

Equation (7) is the minimum variance stochastic control law for single-loop systems. The choice of minimum variance (deadbeat control) invariably leads to excessive manipulated variable movements, but this difficulty can be overcome by incorporating a filter ahead of the controller. Here, the filter constant can be adjusted to improve quality or to reduce costs. The procedure has been shown equivalently leading to the IMC scheme[13] with a filter.[12]

It can be shown[12] that substitution of Eq. (7) back into Eq. (2) for a case where F = 0 gives

$$C_t = a_t \tag{8}$$

That is, the closed-loop output data are distributed according to a normal distribution, having zero mean and a constant variance. Thus, the output data can be used directly in preparing control charts (Shewhart, CUSUM, etc.). It should be pointed out, however, that for processes with dead-time under minimum variance control, the data points every F sampling intervals need to be used for control charting since the autocorrelation reduces to zero at lag F in this instance. As previously pointed out, minimum variance cannot often be specified because it leads to excessive movements of the manipulated variable. Furthermore, the quality requirements in specific situations may not call for such tight control—in which case it would be wiser to select tuning constants that will dampen the oscillations. Under these situations, industrial experience suggests that the output data will be autocorrelated.[14,15] The question remains: how can the autocorrelated data be massaged so that SPC rules can be applied? We take up this topic in the following section.

Part 2
Statistical Monitoring

We assume here that the feedback controller has been designed and the tuning constants have been selected properly. Thus, we can surmise that the process operates under the command of the selected controller, producing a product of acceptable quality in the presence of load disturbances and modeling errors. We want to apply SPC techniques to maintain the continuous process under statistical control. We can assume that the variance is greater than the minimum and that the output data are autocorrelated. Attempts to apply the traditional SPC rules will result in false signals due to the highly autocorrelated nature of the data; that is, no assignable causes would be found.

Problems arising due to autocorrelation can be overcome in one of two ways. In the first approach an autocorrelogram is prepared, showing how the autocorrelation coefficient reduces with increasing sampling intervals.[16] From such a plot, a sampling interval may be selected for which the autocorrelation coefficient is sufficiently small. A control chart can then be prepared using the selected sampling interval to which SPC rules may be applied as usual to detect the presence of assignable causes and to maintain the process under statistical control. A potential drawback of this approach is that the selected sampling interval may be too large, meaning that the process could go out of control before the next data point becomes available.

In the second approach, the thrust is to fit an appropriate time series model to the observations and then apply the control charts to the stream of residuals from the model.[15] Thus, if C_t represents the observation, and $\hat{C}_t$ represents the predicted value obtained from an appropriate model fitted to past data, then the residuals $e_t = C_t - \hat{C}_t$, representing the prediction error, will behave as independent and identically distributed random variables. Several time-series models have been suggested for this purpose. One is an autoregressive integrated moving average (ARIMA) model that is of the form

$$\phi_p\left(z^{-1}\right)\nabla^d \hat{C}_t = \theta_q\left(z^{-1}\right)a_t \qquad (9)$$

Another basis is the exponentially weighted moving average (EWMA) statistic. In this instance, the sequence of one-step ahead forecast errors

$$E_t = C_t - \hat{C}_t(t-1) \qquad (10)$$

are deemed to be independently and identically distributed and may be used to prepare control charts to which SQC can be applied as usual. Here, $\hat{C}_t(t-1)$ is the forecasted value of C_t made at time instant t-1. The EWMA approach is said to have computational advantages over the exact ARIMA approach, but the former is adequate when the observations are positively autocorrelated and the process mean does not drift too quickly.

Having reviewed the unifying procedure for total quality control in continuous process industries, we will now discuss the issue of fault diagnosis and the corrective measures that can be invoked to remedy the situation. We assume that the designer has access to the run-time charts and the appropriate control chart pertaining to the quality variable under assessment.

A variety of assignable causes can lead to out-of-control points on the control chart. For some, the remedy is in the domain of instrumentation and control, while for others the remedy may lie elsewhere. Some commonly encountered assignable causes in the domain of instrumentation and control are

- Malfunctioning control valve and/or sensor
- Changes in dynamic process parameters such as gain, time constants, and dead-time due to equipment fouling, catalyst decay, etc.
- Increasing system nonlinearities.

PROPOSED ADDITIONS TO COURSE CONTENTS

A number of excellent textbooks for undergraduate process control are available (a sampling is included in references 17 through 20 at the end of this article), and instructors typically cover a number of standard topics in the course (*i.e.,* the material in Chapters 1-16 of *Process Dynamics and Control*[18]). In light of the foregoing discussion, we feel the following material can also be added to the course contents.

➢ *Introduction to Process Control* It must be emphasized in the introductory chapters that the fundamental objective in process control is to produce products of a specified quality. Other aspects (such as maximizing throughput, environmental considerations, and safety) are extremely important, but the student should not lose sight of the fundamental objectives.

➢ *Statistical Process Control* A new chapter on statistical process monitoring should be introduced. Students need to understand the assumptions inherent in SPC—namely, normality of quality data. SPC measures (such as Shewhart and CUSUM charts) and concepts (such as common causes and assignable causes) need to be discussed, and the commonly used rules to detect out-of-control signals should be outlined.

➢ *Feedback Controller Design* During the discussion of the trade-offs between responsiveness and robustness in the controller design section, the instructor should introduce the new perspectives on trade-off between quality and costs, and the discussion should include a number of control laws that have the desirable properties. Since the design of control algorithms will require an appreciation of feedforward control and dead-time compensation, these concepts will also have to be introduced if they have not yet been covered.

➢ *Process Identification* The specified closed-loop performance can best be achieved when the process model accurately reflects the industrial plant. Pseudo random binary sequence (PRBS) testing is widely used by industry to identify plant dynamics. Time series analysis of the input-output data leads to transfer function models; step response models can also be evaluated. Because of predictable time limitations for instruction, we suggest that canned software packages be used to demonstrate the concepts.

➢ *Introduction to Stochastic Control* As previously mentioned, deterministic and stochastic design procedures will lead to the same control law for identical performance specifications and model structures. It is nevertheless desirable to expose the student to the basics of stochastic control. The important lesson here is that under ideal conditions, the closed-loop output obtained under minimum variance control has a normal distribution, and therefore it is directly usable in preparing control charts for statistical monitoring purposes. Here too, the instructor can highlight the trade-offs between quality and costs.

➢ *Unifying Methodology for EPC/SPC* The instructor should warn of the problems associated with the use of autocorrelated data in the CPI in preparing control charts—namely, that numerous false signals are likely to result. The procedure for massaging the autocorrelated data to make them amenable to statistical monitoring should be discussed.

➢ *Fault Diagnosis* The last item concerns what to do when the presence of assignable causes is detected. Expert systems are being used in some applications to deduce what actions to take when an assignable cause is detected. Again, due to time limitations, only an introduction to expert systems can be given here.

A study of the foregoing topics, together with the standard material currently covered, would lead to a more effective process control course.

While we have essentially focused on single-loop systems in this paper, the ideas can be extended to multivariable systems as well. A suitable (multivariable) controller would be needed, however, in order to maintain each quality variable of the multivariable system within specified limits. The discussion on statistical monitoring would remain unchanged.

CONCLUSIONS

We have offered some comments on the undergraduate process control course and have shown how the unifying methodology for engineering and statistical process control brings attention to the topics that should be studied to gain a fundamental understanding of engineering process control from a quality control perspective. We hope that the material presented here will be helpful to other process control instructors.

NOMENCLATURE

- a normally distributed random variable
- C controlled variable
- E error (set point - measured value)
- E_t forecast error, $C_t - \hat{C}_t(t-1)$
- F delay expressed as number of integer sampling periods
- G transfer function
- K gain
- k k^{th} sampling instant
- L load
- M manipulated variable
- N noise
- R set point
- s Laplace transform operator
- z z-transform operator

Subscripts

- c pertaining to controller
- D pertaining to derivative mode in Eq. (1)
- I pertaining to integral mode
- L pertaining to load
- P pertaining to process
- t pertaining to time
- ^ estimated value

Greek

- $\theta(z^{-1})$ polynomial in z^{-1}
- $\phi(z^{-1})$ polynomial in z^{-1}
- $\delta(z^{-1})$ polynomial in z^{-1}
- $\omega(z^{-1})$ polynomial in z^{-1}
- ϕ_p autoregressive polynomial of order P, $\left(1+\phi_1 z^{-1}+\phi_2 z^{-2}+\ldots+\phi_p z^{-p}\right)$
- θ_q moving average polynomial of order q, $\left(1+\theta_1 z^{-1}+\theta_2 z^{-2}+\ldots+\theta_q z^{-q}\right)$
- ε_t prediction error, $C_t - \hat{C}_t$
- ∇ backward difference operator $(1 - z^{-1})$
- σ standard deviation
- θ dead-time
- τ characteristic time constant
- ζ damping coefficient

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