SIMULATION AND IMPLEMENTATION OF SELF-TUNING CONTROLLERS

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Preface

Industrial self-tuning controllers have been commercially available for a number of years. Most of these controllers use a pattern-recognition method for process identification and controller tuning. Theoretical developments, however, focus primarily on adaptive controllers based on the minimization of a quadratic cost function, on design methods based on stability theory, and on pole placement techniques. In spite of the voluminous writings on these topics, industrial applications are very limited. This is due to the unavailability of a clear, concise description of the concepts, practical implementation, and software to investigate applications of self-tuning control. This book addresses these shortcomings and has selected three popular approaches to self-tuning control, describing them in a comprehensive manner.

Clarke and Gawthrop's self-tuning controller
Ydstie's extended horizon controller
The pole placement method

A simulator was developed to test, compare, and evaluate the approaches. Three different types of processes can be defined: a first-order process, a first-order process with delay, and a user-defined process in the form of a linear difference equation. For a selected self-tuning controller, parameter convergence, process input and output response, and trace variations are among the variables that can be graphically displayed.

The pole placement method was selected for practical implementation of a self-tuning PID controller for distillation tower overhead composition control. This process includes a considerable dead time, typical for many industrial processes. Therefore, the controller was extended with adaptive time delay compensation as an option. The practical implementation and implementation issues are described in detail.

Simulation and Implementation of Self-Tuning Controllers is practical in nature; it presents only the theory that is necessary for the successful implementation of a self-tuning controller. References to a more theoretical analysis are given in the text. The book provides a bridge between traditional continuous control and simple, practical self-tuning control. An extensive mathematical background is not required, as the mathematics are developed from a basic understanding of continuous time control. The book is, therefore, not only very useful to industrial practitioners of process control, but also very suitable as an introductory text for a graduate or undergraduate course in adaptive control.

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Contents

1

General Overview and Linear Difference Equation Models

The application of self-tuning control strategies started in the 1950s with the development of self-adaptive systems in aircraft for changing flight conditions. These efforts, however, were largely unsuccessful because of lack of theory and bad computer hardware. Renewed interest in adaptive control occurred in the 1970s due to significant theoretical developments (Åström and Wittenmark 1973; Clarke and Gawthrop 1975) and the availability of inexpensive microprocessor-based hardware. Presently, adaptive control systems are available commercially.

Although most processes can be controlled by using the simple three-term proportional-integral-derivative (PID) controller, there are situations that require the application of more advanced control techniques. Adaptive control becomes especially important when standard controllers have to be retuned repeatedly because of process changes. An adaptive control system is a system that automatically adjusts its controller settings to these changes.

The majority of the literature deals with processes in which changes cannot be measured directly. If, however, the process changes can be anticipated and measured or inferred from measurements, controller settings could be adjusted to process changes in a predefined manner. For example, different sets of controller settings could be used for different operating conditions. A simple control strategy would be to maintain a constant product of controller gain and process gain. If the process gain is known as a function of process conditions, controller gain could be

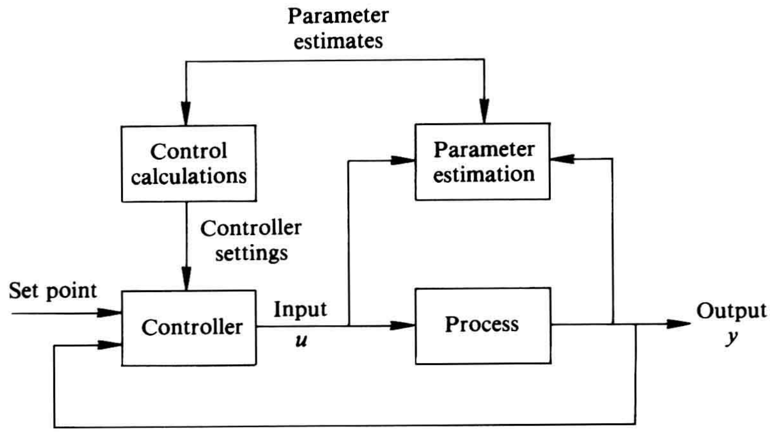


Figure 1-1 Self-tuning control system.

adjusted as a function of process conditions. This approach, called *gain scheduling,* has been successfully applied, for example, in pH control. However, gain scheduling is successful only if the process does not have an appreciable time delay. Because most of the literature deals with adaptive control strategies for processes in which changes cannot be directly measured or inferred, this book will focus on those applications.

A general approach to the design of an adaptive control strategy is to estimate the parameters in an assumed process model on-line and then adjust the controller settings based on the current model parameter estimates. A block diagram illustrating this approach is shown in Fig. 1-1. At each sampling interval the parameters in the process model are estimated recursively from input-output data of the process and the controller parameters are then updated. This approach is the basis of the self-tuning controller (Åström and Wittenmark 1973; Clarke and Gawthrop 1975) and the controller based on the pole placement design technique.

The dynamic model is assumed to be a linear difference equation model with constant parameters. Recursive least squares is generally applied as a parameter estimation technique, although other methods can be used, such as the maximum likelihood or instrumental variable method. In a self-tuning control system, the controller is usually designed in such a way that it minimizes a quadratic cost function or places the poles (and perhaps zeros) at desired locations. Self-tuning control systems usually do not have a PID structure, although this can be achieved by proper model selection, as will be shown later.

Self-tuning control techniques can be classified into two different methods: explicit and implicit. In the *explicit method,* a process model is used and the control calculations are based on the estimated model parameters. The model parameters do not directly appear in the control law. In the *implicit method,* the process model is converted to a prediction form that allows the future process output to be predicted from current and past values of the input and output variables by using a predictive model. The control calculations are eliminated because the model parameters are also used as control law parameters. In this case, the control law parameters are directly updated from input-output data.

Excellent review articles deal with the theoretical as well as practical aspects of self-tuning control (Parks et al. 1980; Åström 1980a,b, 1983; Harris and Billings 1981; Anderson and Ljung 1984; Seborg et al. 1986). Those of Åström (1983) and Seborg et al. (1986) list close to 120 pilot-scale or industrial applications of adaptive control. For a comprehensive theoretical analysis of self-tuning controllers, see Åström and Wittenmark (1984) and Goodwin and Sin (1984). Some of the latest developments in self-tuning control focus on the development of PID auto tuners for implementation in distributed control systems (Dumont et al. 1985), multivariable adaptive control using Laguerre polynomials (Dumont and Zervos 1987), the use of long-range predictive control ideas in combination with an ARIMA model for adaptive control purposes (Clarke 1987) and improved least-squares identification (Sripada and Fisher 1987).

PROCESS MODELS

Many processes are well represented by transfer function models of up to second order. These transfer functions may be expressed in continuous or sampled-data variables and are given here as a review.

Continuous Time Models

A common process model in the chemicals industry is the first-order lag transfer function:

$$G_1(s) = \frac{Y(s)}{X(s)} = \frac{K_p}{\tau s + 1} \tag{1-1}$$

where

s = Laplace operator ($s = d/dt$)
K_p = dynamic gain
τ = time constant: time to reach 63.2% of final value in response to a fixed change in input
X = process input as a deviation from steady state
Y = process output as a deviation from steady state

The step response of a first-order lag is shown in Fig. 1-2.

Some processes are inherently second order and can be expressed by the following function:

$$G_2(s) = \frac{K_p}{\tau^2 s^2 + 2\zeta\tau s + 1} \tag{1-2}$$

where

τ = time constant of the second-order process
$\omega_n = 1/\tau$ = natural frequency of the process
ζ = damping ratio
K_p = dynamic gain

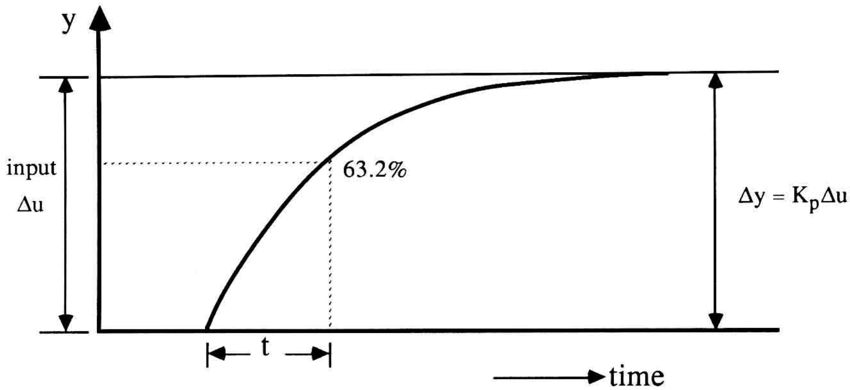


Figure 1-2 Step response of a first-order process.

The step response of second-order processes is shown in Fig. 1-3. The dynamic response of this process may be overdamped or underdamped. The type of response is determined by ζ and is as shown.

For $\zeta > 1$, response is overdamped or nonoscillatory
For $\zeta = 1$, response is critically damped
For $\zeta < 1$, response is underdamped or oscillatory

The natural frequency (ω_n) determines the period of oscillation.

Discrete Time Models

Although most chemical processes are inherently continuous in nature, the systems used to control these processes are increasingly based on digital computers and apply a sampled-data control algorithm. That is, control is implemented at discrete intervals of time with the interval denoted by T_s, the sampling period. If the

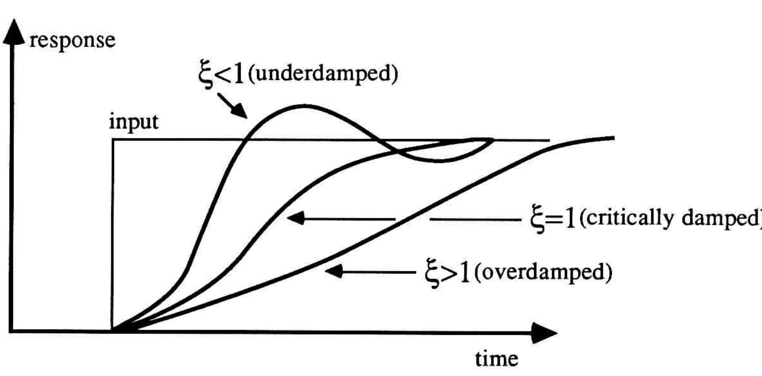
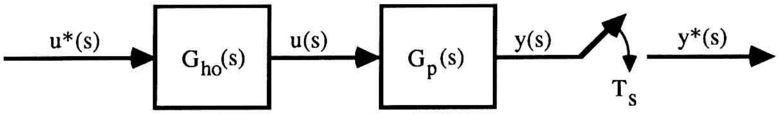


Figure 1-3 Step response of a second-order process.



$G_p(s)$	- continuous-time process transfer function
$G_{ho}(s)$	- zero order hold transfer function
y(s), y*(s)	- continuous and sampled-data output signal
u(s), u*(s)	- continuous and sampled-data input signal
T_s	- sampling period

Figure 1-4 Sampling of continuous time process cascaded with a zero-order hold.

computer control technique is model-based, a discrete time model of the process is required for control output calculation. An equivalent discrete transfer function representation of the first- and second-order continuous time transfer function model can be calculated using sampled-data techniques. This method cascades a zero-order hold (ZOH) with the continuous time transfer function and samples the process at a set sampling period, T_s. This process is depicted in Fig. 1-4. Sampled-data mathematical techniques are given in many standard textbooks (see, e.g., Jury 1958; Stephanopoulos 1984; Phillips and Nagle 1984; Åström and Wittenmark 1984).

The equivalent sample-data transfer function for Eq. (1-1) is of the form

$$H_1(z) = \frac{b_0}{z + a_1} \tag{1-3}$$

where a_1 and b_0 are coefficients of the sampled-data model and z is the forward shift operator, $Y(t) = z\,Y(t-1)$. The a_1 parameter is a function of the time constant and sampling time T_s. The b_0 parameter is a function of τ, T_s, and K_p.

The second-order transfer function of Eq. (1-2) takes the discrete form:

$$H_2(z) = \frac{b_0 z + b_1}{z^2 + a_1 z + a_2} \tag{1-4}$$

ZOH equivalents of various first- and second-order continuous time systems are given in Åström and Wittenmark (1984). See Table 1-1 for a partial listing.

The discrete transfer functions are often expressed as a ratio of polynomials in the forward shift operator:

$$H(z) = \frac{B(z)}{A(z)} \tag{1-5}$$

where

$$A(z) = z^{n_a} + a_1 z^{n_a - 1} + a_2 z^{n_a - 2} + \ldots + a_{n_a}$$

$$B(z) = b_0 z^{n_b} + b_1 z^{n_b - 1} + b_2 z^{n_b - 2} \ldots + b_{n_b}$$

TABLE 1-1 SAMPLING OF A CONTINUOUS TIME SYSTEM $G(s)$

This table gives the zero-order-hold equivalent of a continuous time system $G(s)$ in series with a zero-order hold. The sampled system is described by its pulse transfer function. For second-order systems the pulse-transfer function is given in terms of the coefficients of

$$H(z^{-1}) = \frac{b_1 z + b_2}{z^2 + a_1 z + a_2}$$

$G(s)$	$H(z)$ or the coefficients $H(z)$	
$\frac{1}{s}$	$\frac{h}{z-1}$	
e^{-sh}	z^{-1}	
$\frac{a}{s+a}$	$\frac{1-\exp(-ah)}{z-\exp(-ah)}$	
$\frac{a}{s(s+a)}$	$b_1 = \frac{1}{a}(ah - 1 + e^{-ah})$ $a_1 = -(1 + e^{-ah})$	$b_2 = \frac{1}{a}(1 - e^{-ah} - ahe^{-ah})$ $a_2 = e^{-ah}$
$\frac{ab}{(s+a)(s+b)}$	$b_1 = \frac{b(1-e^{-ah}) - a(1-e^{-bh})}{b-a}$ $b_2 = \frac{a(1-e^{-bh})e^{-ah} - b(1-e^{-ah})e^{-bh}}{b-a}$ $a_1 = -(e^{-ah} + e^{-bh})$ $a_2 = e^{-(a+b)h}$	
$\frac{\omega_0^2}{s^2 + 2\zeta\omega_0 s + \omega_0^2}$	$b_1 = 1 - \alpha\left(\beta + \frac{\zeta\omega_0}{\omega}\gamma\right)$ $b_2 = \alpha^2 + \alpha\left(\frac{\zeta\omega_0}{\omega}\gamma - \beta\right)$ $a_1 = -2\alpha\beta$ $a_2 = \alpha^2$	$\omega = \omega_0\sqrt{1-\zeta^2} \quad \zeta < 1$ $\alpha = e^{-\zeta\omega_0 h}$ $\beta = \cos(\omega h)$ $\gamma = \sin(\omega h)$

DISTURBANCE MODELS

The design of an optimal control law strongly depends on the type of disturbance. Control, in fact, is necessary because of disturbances. In stochastic control theory controllers are derived under the assumption that the disturbances are stochastic in nature. In a process environment, however, the majority of the process upsets are caused by such deterministic disturbances as operator setpoint changes, failure of a pump, loss of a coolant, rapid change in environmental conditions, and the like. MacGregor, Harris, and Wright (1984) developed discrete time models capable of representing deterministic disturbances occurring at random times. These are briefly discussed in the following sections.

Step Disturbances

Consider a disturbance process $N(t)$ that can be characterized by the following difference equation:

$$\Delta N(t) = \xi(t) \tag{1-6}$$

in which $\xi(t)$ is a random variable and Δ is the differencing operator $1 - z^{-1}$. The solution of Eq. (1-6) can be written as

$$\left.\begin{aligned} N(t) &= c_0(t) \\ c_0(t) &= c_0(t-1) + \xi(t) \end{aligned}\right\} \tag{1-7}$$

and represents a disturbance process $N(t)$ whose level $c_0(t)$ changes randomly with time; $\xi(t)$ represents magnitude of the level change at time t.

Most textbooks write the disturbance model in terms of the backward shift operator z^{-1}, $c_0(t-1) = z^{-1}c_0(t)$, as

$$N(t) = \frac{1}{1 - z^{-1}}\,\xi(t) \tag{1-8}$$

If the random variable $\xi(t)$ is zero most of the time but takes nonzero values at discrete instances, then random steps occur at these instances. The optimal controller designed for a step disturbance is identical to the optimal controller designed for a random walk type of stochastic disturbance that has the same generating function, $1/(1 - z^{-1})$.

A plot of the disturbance process is shown in Fig. 1-5, and one for a noise pattern is shown in Fig. 1-6.

Exponential Disturbances

Consider a disturbance process $N(t)$ described by

$$\Delta N(t) = \phi\Delta N(t-1) + \xi(t) \tag{1-9}$$

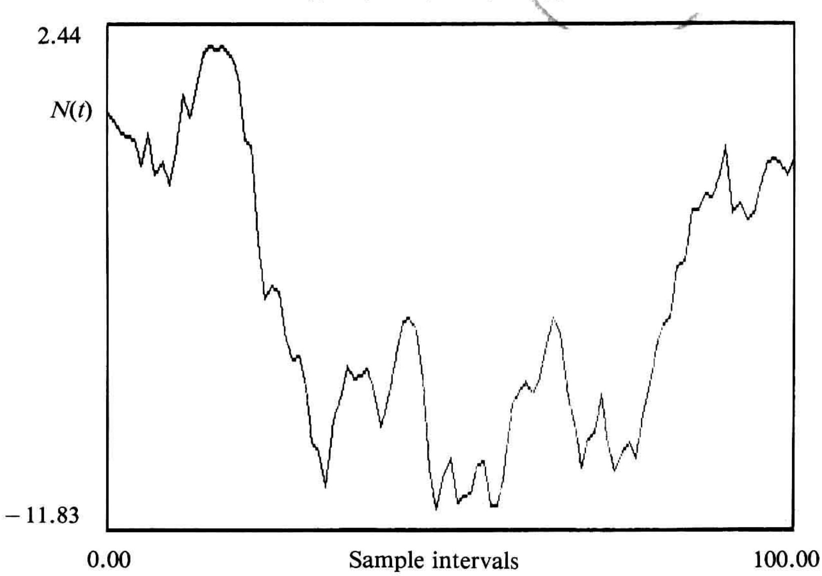


Figure 1-5 Disturbance $N(t) = \xi(t)/(1 - z^{-1})$ in which $\xi(t)$ is white noise (see Fig. 1-6).