NONLINEAR PROCESS CONTROL

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Preface

In the past decade, the control of nonlinear systems has received considerable attention in both academia and industry. The recent interest in the design and analysis of nonlinear control systems is due to several factors. First and foremost, linear controllers usually perform poorly when applied to highly nonlinear systems or moderately nonlinear systems that operate over a wide range of conditions. On the other hand, significant progress has been made in the development of model-based controller design strategies for nonlinear systems. These techniques employ the nonlinear model directly in the controller calculation without the need for local linearization about an operating point. Finally, the development of inexpensive and powerful computers have made on-line implementation of these nonlinear model-based controllers feasible.

This research monograph is intended as an introduction to the design, analysis, and application of nonlinear control strategies for process systems. Individual chapters have been prepared by leading academic and industrial researchers. To make the monograph accessible to a larger audience, we have attempted to present a balanced view of the theoretical and practical issues. However, the very nature of nonlinear systems dictates the use of some advanced mathematical tools. Although the control techniques presented are applicable to a broad range of nonlinear systems, the application of these methods to nonlinear process control problems is emphasized. Case studies are presented to illustrate the controller design procedures. Comparisons with linear control techniques also are included to demonstrate the performance improvements that can be achieved by employing a nonlinear control strategy.

The monograph has seven chapters which cover three major topics related to nonlinear process control: nonlinear identification, nonlinear controller design, and nonlinear state estimation. Chapter 1 motivates the need for nonlinear process control systems and contains a discussion of several classic nonlinear control techniques. Because all of the control strategies discussed in the subsequent chapters presume the availability of a nonlinear process model, identification techniques for nonlinear systems are presented in Chapter 2. Several important topics from nonlinear systems theory are presented in Chapter 3. Although both Chapters 2 and 3 could easily warrant an entire book, they are presented primarily as a prelude to the nonlinear control and estimation techniques presented in the subsequent chapters.

The two most important controller design approaches for nonlinear process applications are discussed in Chapters 4 and 5. Feedback linearization techniques which yield exact linearization of the closed-loop system are presented in Chapter 4. Nonlinear model predictive control strategies, which are nonlinear generalizations of linear model predictive control schemes successfully applied in the process industries, are discussed in Chapter 5. Because it may be difficult or even impossible to obtain on-line measurements of all the state variables required for control, the design of nonlinear state observers is presented in Chapter 6. The use of artificial neural networks for nonlinear process identification and control is discussed in Chapter 7.

We have assumed that the reader has completed an introductory course in process control and has a working knowledge of elementary calculus. Some familiarity with linear state-space systems and linear controller design techniques is helpful but not essential. The book may serve as a concise reference for control engineers interested in nonlinear process control theory and applications. The book also can be used as a textbook in a graduate course on process control. Chapters 3–5 could be covered in a course in which nonlinear control is one of several topics.

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Chapter 1

Introduction

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Many common process control problems exhibit nonlinear behavior, in that the relationship between the controlled and manipulated variables depends on the operating conditions. For example, if the dynamic behavior of a nonlinear process is approximated by a linear model such as a first-order transfer function, the model parameters (*e.g.* steady-state gain, time constant, time delay) depend on the nominal operating condition. If the process is only mildly nonlinear or remains in the vicinity of a nominal steady state, then the effects of the nonlinearities may not be severe. In these situations, conventional feedback control strategies can provide adequate performance.

But many important industrial processes including high purity distillation columns, highly exothermic chemical reactions, pH neutralizations, and batch systems can exhibit highly nonlinear behavior. These processes may be required to operate over a wide range of conditions due to large process upsets or setpoint changes. When conventional PID controllers are used to control highly nonlinear processes, the controllers must be tuned very conservatively in order to provide stable behavior over the entire range of operating conditions. But conservative controller tuning can result in serious degradation of control system performance. There are other situations where conventional PID control is inadequate, for example, when the process gain changes sign (*e.g.* some reactor control problems).

Process control research has largely emphasized the analysis of linear systems (via transfer function and state-space models) and the design of linear controllers. In a similar vein, industrial practice has traditionally relied on linear control laws, the ubiquitous PI and PID control algorithms. But within the last 15 years, model-based control strategies such as model predictive control (MPC) have become the preferred control technique for difficult mutivariable control problems in oil refineries and pretrochemical plants [11]. Because the current generation of MPC systems are largely based on linear dynamic models such as step response and impulse response models, the resulting linear controllers must be conservatively tuned for highly nonlinear process.

In view of the shortcomings of linear controllers for highly nonlinear processes, there are considerable incentives for developing more effective control strategies that incorporate knowledge of the nonlinear characteristics. During the past decade, there have been a resurgence of interest in developing nonlinear control strategies that are appropriate for process control. The major objective of this book is to provide an overview of key issues and new research results in this important area.

1.1 Conventional Nonlinear Control Strategies

In the traditional strategy for nonlinear control problems, the objective is to make the closed-loop system behave more linearly by keeping the loop gain constant. For example, the nonlinearities associated with control valves can be reduced by using valve positioners or cascaded flow control loops. Nonlinear transformations of input or output variables also can make the loop gain more constant. For example, the nonlinear characteristics of orifice plate flow measurement can be compensated by taking the square root of the measurement prior to the control calculation. For composition control of high purity distillation columns, using the logarithm of a composition as the controlled variable can make the control loop more linear.

The gain scheduling technique has been widely used to compensate for nonlinear process characteristics [12]. In this approach the controller settings are adjusted to compensate for known nonlinearities so that the loop gain is kept as constant as possible. For example, if the process gain K_p varies with the throughput of the process, the controller gain K_c should be varied so the product, K_cK_p, is kept constant. In the general case, the controller could include the inverse of a known static nonlinearity such as a pH titration curve. But if there are significant time delays, this simple gain scheduling approach may be inferior to standard PID control [15].

Model-based control strategies for nonlinear processes have traditionally been based on local linearization and linear controller design based on the linearized model. If the model is updated on-line, the controller should be effective over a wider range of operating conditions. This philosophy provides the basis for the self-tuning approach to adaptive control [1].

1.2 Recent Developments

In recent years, there has been a resurgence of interest in developing improved control and identification strategies for nonlinear systems. The renewed interest has been motivated by several developments:

1. Advances in nonlinear systems theory which have led to controller design methods that are applicable to broad classes of nonlinear control problems.

2. The development of efficient identification methods for empirical nonlinear models, and their widespread availability in commercial software packages.

3. Continued improvement in the capabilities of computer-control hardware and software, thus making it feasible to incorporate complex nonlinear models in plant control systems.

Next we introduce two nonlinear controller design methods that have received considerable attention: input/output linearization and nonlinear predictive control. Other techniques such as sliding mode control [13] and fuzzy control [14] are beyond the scope of this book.

Recently, a new controller design method that provides exact linearization of nonlinear models has been developed [7]. Unlike conventional linearization via Taylor series expansion, this technique produces a linearized model that is independent of the operating point. An analytical expression for the nonlinear control law can then be derived for broad classes of nonlinear systems. This approach is usually referred to as *input/output linearization* or *feedback linearization* and is based on concepts from nonlinear systems theory. The resulting controller includes the inverse of the dynamic model of the process, providing that such an inverse exists. This general approach has been utilized in several process control design methods such as: generic model control [9], globally linearizing control [8], internal decoupling control [2], reference system synthesis [3], and a nonlinear version of internal model control [6]. Nonlinear systems theory and the input/output linearization approach are discussed in Chapters 3 and 4, respectively.

The success of linear model predictive control systems has motivated the extension of this methodology to nonlinear control problems. This general approach is referred to as *nonlinear predictive control*. The control problem formulation is analogous to linear model predictive control except that a nonlinear dynamic model is used to predict future process behavior. The required control actions are calculated by solving a nonlinear programming problem at each sampling instant [4, 5]. Thus, the potential benefits of the nonlinear approach must justify the greater computational complexity in comparison with standard linear techniques. Nonlinear predictive control is the subject of Chapter 5.

A key issue in model-based nonlinear control is what type of process model should be used. Physically-based models derived from first principles (*e.g.* mass and energy balances) are appealing because of the physical insight they provide and their applicability over relatively wide ranges of operating conditions. However, such models often are not available due the engineering effort and cost it takes to develop and maintain them. Another disadvantage is that they often contain a number of process variables that cannot be measured. One possible solution to this problem is state estimation, the subject of Chapter 6.

An alternative approach is to design the nonlinear controller using an empirical model or semi-empirical model which is developed from experimental data. In recent years, there has been considerable interest in developing nonlinear dynamic models from input/output data. While a variety of modeling techniques are available, the predominant tool for obtaining nonlinear empirical models is *artificial neural networks*. Neural network software packages are now commercially available which should hasten their widespread use in industry, including process control applications. An overview of nonlinear empirical models is presented in Chapter 2 while neural network models are considered in Chapter 7.

Table 1.1: Nominal Operating Conditions for the CSTR.

Variable	Value	Variable	Value
q	100 L/min	$\frac{E}{R}$	8750 K
C_{Af}	1 mol/L	k_0	7.2 x 10^{10} min^{-1}
T_f	350 K	UA	5 x 10^4 J/min·K
V	100 L	T_c	300 K
ρ	1000 g/L	C_A	0.5 mol/L
C_p	0.239 J/g·K	T	350 K
$(-\Delta H)$	5 x 10^4 J/mol		

1.3 Illustrative Example

In order to demonstrate the potential benefits that can result from using nonlinear control techniques, we consider a simulated chemical reactor. A nonlinear controller designed using the input/output linearization approach is compared to a linear MPC controller.

Consider the classical continuous stirred tank reactor (CSTR) for an exothermic, irreversible reaction, $A \rightarrow B$. Assuming constant liquid volume, the following dynamic model can be derived based on a component balance for reactant A and an energy balance [12]:

$$\begin{aligned} \dot{C}_A &= \frac{q}{V}(C_{Af} - C_A) - k_0 \text{exp}\left(-\frac{E}{RT}\right) C_A \qquad (1.1) \\ \dot{T} &= \frac{q}{V}(T_f - T) + \frac{(-\Delta H)}{\rho C_p} k_0 \text{exp}\left(-\frac{E}{RT}\right) C_A + \frac{UA}{V\rho C_p}(T_c - T) \end{aligned}$$

We have used standard notation where C_A is the concentration of A in the reactor, T is the reactor temperature, and T_c is the temperature of the coolant stream. The objective is to control T by manipulating T_c. Table 1.1 contains nominal operating conditions, which correspond to an unstable steady state. The open loop response in Figure 1.1 demonstrates that the reactor exhibits highly nonlinear behavior in this operating regime.

The nonlinear state-space model,

$$\begin{aligned} \dot{x} &= f(x) + g(x)u \qquad (1.2) \\ y &= h(x) \end{aligned}$$

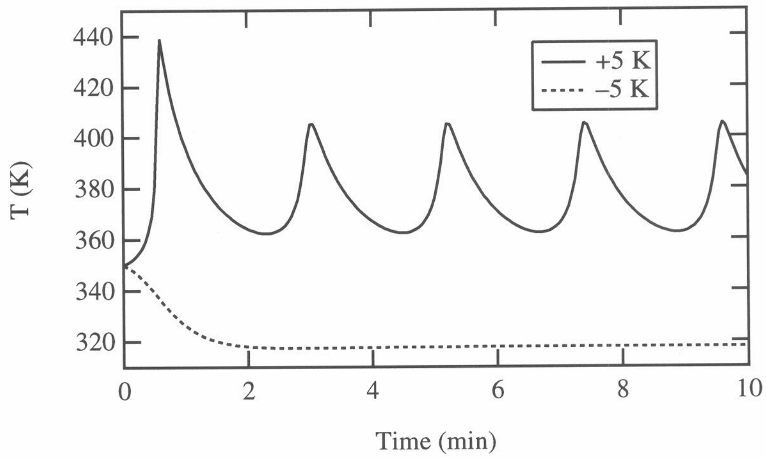

Figure 1.1: Open-loop response for ±5 K changes in T_c.

can be obtained by defining the state vector as $x = [C_A \;\; T]^T$, the manipulated input as $u = T_c$, and the controlled output as $y = T$. This model can be used directly in the input-output linearizing controller design, as discussed in Chapter 4. The linearizing controller is tuned such that the closed-loop system has a time constant of approximately 0.25 min. The linear MPC design is based on a linear deviation model which is obtained from the nonlinear model via first-order Taylor series expansion about the nominal operating point in Table 1.1. The control actions are calculated by solving an open-loop optimal control problem at each sampling instant, as discussed in [10]. The MPC cost function includes weighting coefficients $Q = 4$ and $R = 2$ which penalize deviations of the output from the setpoint and deviations of the input from its target value, respectively. The controller is tuned with a sampling period $\Delta t = 0.05$ min and a control horizon $N = 16$.

In Figure 1.2 the linear and nonlinear controllers are compared for ±25 K changes in the temperature setpoint. The MPC controller produces a sluggish response for the negative setpoint change, while overshoot and small oscillations are obtained for the positive change. This type of response is commonly observed when a well tuned linear controller is applied to a highly nonlinear process. By contrast, the nonlinear controller provides rapid and smooth responses for both setpoint changes. Note that the responses are perfectly symmetrical, indicating that that the closed-loop behavior has been completely linearized. This is a fundamental property of linearizing con-

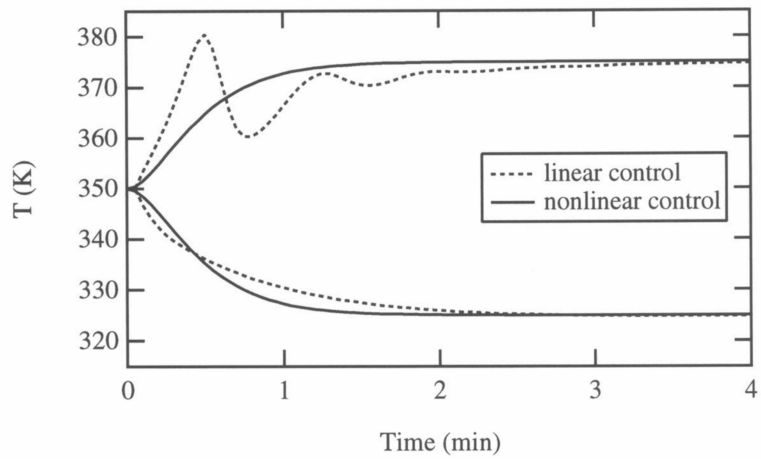

Figure 1.2: Closed-loop response for ±25 K setpoint changes.

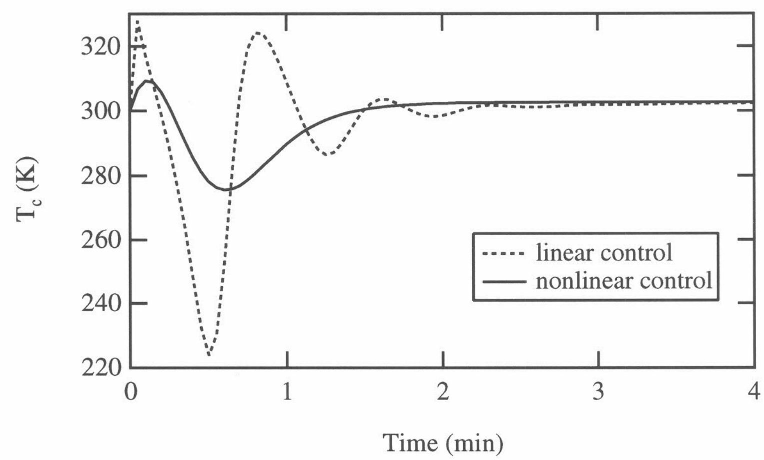

Figure 1.3: Control moves for +25 K setpoint change.

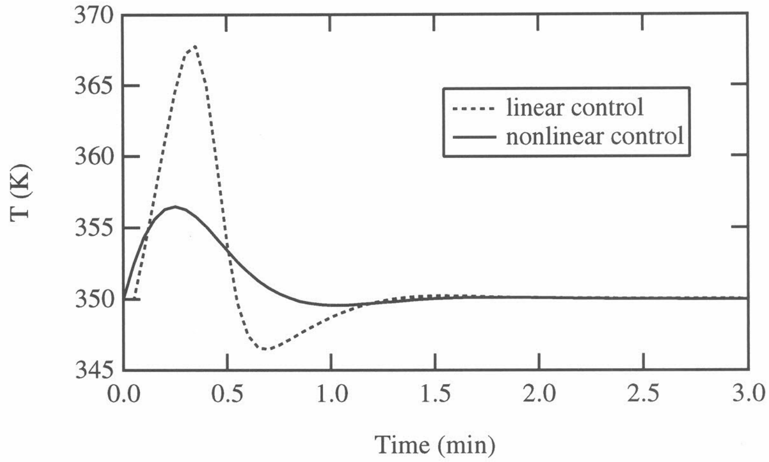

Figure 1.4: Closed-loop response for –150 K change in $\frac{E}{R}$.

trollers (see Chapter 4). Figure 1.3 shows the input moves produced by the controllers for the +25 K change. This result indicates that the superior performance of the nonlinear controller is not attributable to more aggressive control action, but rather to a more judicious use of the input.

Figure 1.4 compares the controllers for a –150 K step change in $\frac{E}{R}$. This type of unmeasured disturbance could be caused, for instance, by a sudden change in the reaction catalyst that results in a reduction of the activation energy. The linear controller yields large deviations from the setpoint, while the nonlinear controller provides very effective attentuation of the disturbance. This result demonstrates that nonlinear controllers can exhibit good robustness to modeling errors.

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