1
Introduction

Process control, as it has been known for many years, was first developed in the process industries. Although starting with local measurement devices, the system has since progressed to centralized measurement and control (central control rooms) and computer hierarchical/plantwide control. Recent developments in process control have been influenced by improvements in the performance of digital computers suitable for on-line control. Moreover, while the performance of these units has improved significantly, their prices have fallen drastically. The price trends for small but more sophisticated minicomputers, despite the inclusion of more reliable electronics and increasing inflation, is shown graphically in Figure 1.1. By having high speeds of operation and storage capacities, the process computer can be used effectively in process control due to its insignificant capital cost. Once in place, the computer is usually operated in a timesharing mode with large numbers of input/output operations, so that the central processing unit (CPU) is typically in use only for about 5 % of the time. Thus, many industrial plants have 95 % of the computing power of a highly capable minicomputer programmable in a high-level language such as Fortran, C, Visual Basic, LabVIEW, etc., and available for implementing sophisticated computer-controlled schemes.

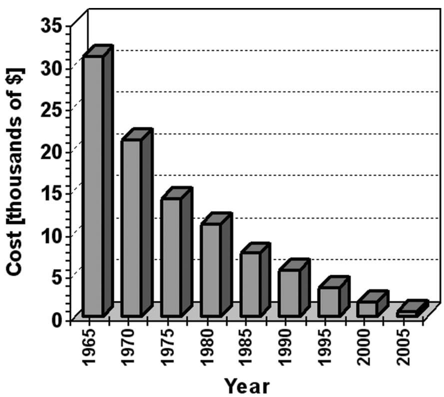

Figure 1.1 Price trends for real-time minicomputers.

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During the same time, *modern control theory* has undergone intense development, with many successful applications covering many areas of the industry. Most recently, several process control research groups have applied new sophisticated control algorithms and schemes to simulated, laboratory-scale – and even full-scale – processes. As a consequence, it is necessary for the process control engineer to design an economically optimal process control scheme based on a judicious comparison of the available control algorithms. The aim of this book is to offer assistance in this respect, and to provide a brief introduction to the theory and practice of the most important modern process control strategies. This is achieved by using industrially relevant chemical processes as the subjects of control performance studies.

1.1 Introductory Concepts of Process Control

A *control system* is a combination of elements which act together in order to bring a measured and controlled variable to a certain, specific, desired value or trajectory termed the "set/point of reference". The basis for an analysis of such a system is the foundation provided by linear system theory, which assumes a linear cause–effect relationship for the components of a system. Therefore, a component or *process* to be controlled can be represented by a block, as shown in Figure 1.2. The output variables are the "interesting" ones (technological parameters, yield, etc.), while the input variables are those which influence the outputs (e.g., mass or energy flows, environmental variables, etc.). Figure 1.2 illustrates the different types of *input* and *output* parameters used in the development and study of control algorithms. We refer to a variable as an *input* if its value is determined by the "environment" of the system to be controlled. We distinguish *disturbance* inputs and *manipulated* or *control* inputs. We are free to adjust the later but not the former. Variables, the values of which are determined by the state of the system, are referred to as *outputs* – some of these are measured, but others are not. *Controlled* variables must be maintained at specified setpoints. *Associated* variables are only required to stay within certain bounds, their exact value within bounds being of little interest.

An *open-loop* control system uses a controller or control actuator in order to obtain the desired response, as shown in Figure 1.3. In contrast to an open-loop control system, a closed-loop control system uses an additional measure of the

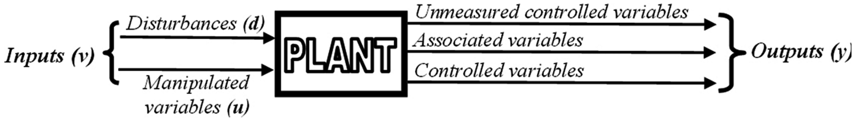

Figure 1.2 Definition of input and output variables considered for control system design.

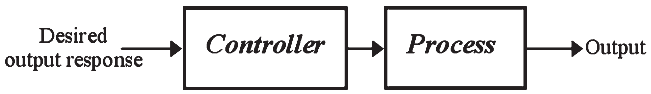

Figure 1.3 Open-loop control system.

actual output in order to compare the actual output with the desired output response. The measure of the output is called the *feedback signal*. A simple *closed-loop feedback control system* is shown in Figure 1.4. A standard definition of a feedback control system is as follows: *A feedback control system is a control system that works to maintain a prescribed relationship between one system variable and another by comparing functions of these variables and using the difference as a means of control.*

A feedback control system often uses a function of a prescribed relationship between the output and the reference input to control the process. Often, the difference between the output of the process under control and the reference input is amplified and used to control the process, so that the difference is continually reduced. The feedback concept has been the foundation for control system analysis and design.

Classical control theory is essentially limited to single-input single-output (SISO) systems described by linear differential equations with constant coefficients (or their corresponding Laplace transforms). However, the so-called *modern* control theory has developed to the point where results are available for a wide range of general multivariable systems, including those described by linear, variable-coefficient differential equations, nonlinear differential equations, partial differential, and integral equations.

The results of modern control theory include the so-called *optimal control theory*, which allows the design of control schemes, which are optimal in the sense that the controller performance minimizes some specified cost functional.

In addition to controller design, modern control theory includes methods for process identification and state estimation. *Process identification* algorithms have been developed for determining the model structure and estimating the model parameters, either off-line or adaptively on-line. These are useful both in the initial control system design and in the design of *adaptive control systems* which respond to such changes in the process characteristics. These might arise, for example, with the fouling of heating exchanger surfaces or the deactivation of catalyst in chemical reactors. *State estimation* techniques are on-line methods either for estimating

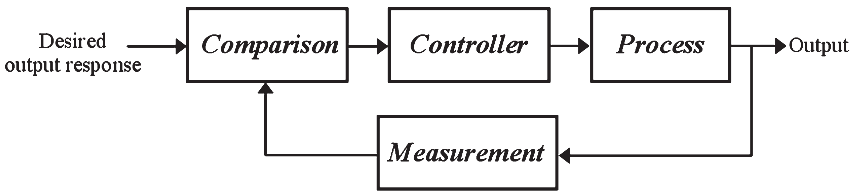

Figure 1.4 Closed-loop feedback control system.

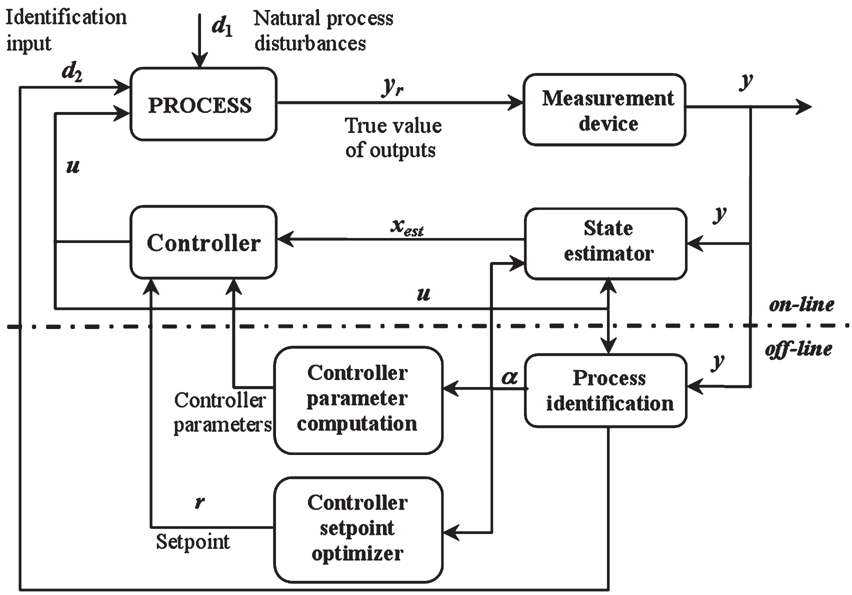

Figure 1.5 A comprehensive advanced computer control scheme.

system state variables which are not measured, or for improving the quality of all the state-variable estimates in the presence of measurement errors. In those processes where some sensors are not available, or are too expensive to be installed, on-line state estimation can be of significant practical importance.

The way in which all the components of a comprehensive computer process control scheme might fit together for a particular process is illustrated in Figure 1.5. Such a control scheme would consist of the following parts:

- The *Process*, which responds to control inputs u; to natural process disturbances d_1; and to special input disturbances d_2 used for identification. The true process state x is produced, but this is seldom measured either completely or precisely.
- *Measurement devices*, which usually are able to measure only a few of the states or some combination of states, and are always affected by measurement errors. The measurement device outputs y are fed to the –
- *State estimator*, which uses the noisy measurements y along with a process model to reconstruct the best possible process state estimates x_{est}. The process state estimates are passed to the –
- *Controller*, which calculates what control actions must be taken based on the state estimates x_{est}, the setpoints r (which themselves may be the subject of process optimization), and the controller tuning parameters. The controller parameters can be calculated either off-line or adaptively on-line, based on current estimates of the model parameters. The process model parameters must be determined from the –

- *Process identification block*, which takes user measurements from the process as raw data y (and may choose to introduce experimentally designed input disturbances d_1) in order to identify the process model parameters α. If the parameters are time-invariant, the identification is unique; however, if the process changes with time, then the identification scheme must be activated periodically to provide adaptation to changing conditions.

In most applications only a few of the components of this control structure are required.

1.2 Advanced Process Control Techniques

1.2.1 Key Problems in Advanced Control of Chemical Processes

The main features of chemical processes that cause many challenging control problems [1–3] are shown schematically in Figure 1.6.

1.2.1.1 Nonlinear Dynamic Behavior

Nonlinear dynamic behavior of chemical processes causes one of the most difficult problems in designing control systems. In the case of linear, lumped parameter systems, a very general model in the time domain form can be written as:

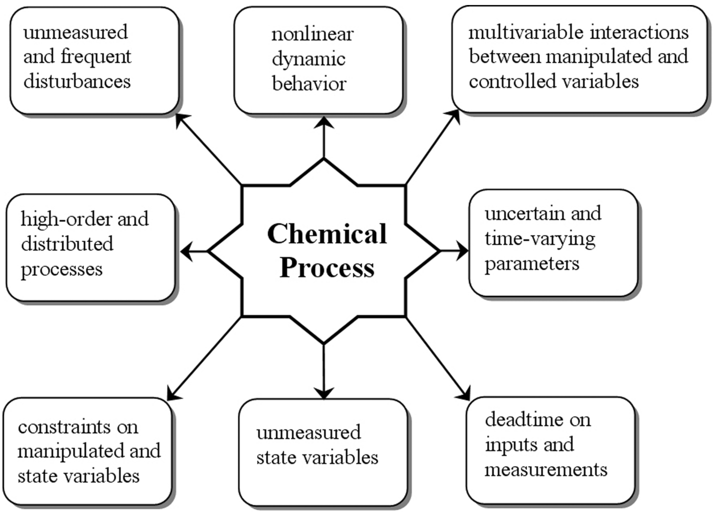

Figure 1.6 Common process characteristics, important in the choice of control strategy.

$$\frac{dx}{dt} = A \cdot x + B \cdot u + \Gamma \cdot d, \; x(t_0) = x_0 \tag{1.1}$$

$$y = C \cdot x \tag{1.2}$$

where x, u, y, and d are the vectors of states, controls (manipulated variables), outputs and disturbances, respectively. The state space matrices, A, B, C, and Γ, can be either constant or time-varying. For systems in Laplace transform domain, involving transfer functions the model can be represented in the form:

$$\bar{y}(s) = G(s) \cdot \bar{u}(s) + G_d(s) \cdot \bar{d}(s) \tag{1.3}$$

with:

$$G(s) = C(sI - A)^{-1}B \tag{1.4}$$

$$G_d(s) = C(sI - A)^{-1}\Gamma \tag{1.5}$$

These representations show the linear dependence between the manipulated inputs (u) and outputs (y); that is, a certain Δu variation will cause, in a certain time t, a linear proportional variation of y ($\Delta y = \alpha_t \Delta u$). Assuming that $d = 0$, (there is no unmeasured disturbance), once the linear model was identified (the coefficients of A, B, C, and Γ were determined), the trajectory of the outputs y can be predicted for any changes of the manipulated inputs, Δu, at any time using the linear model in one of the forms described above [Eqs. (1.1)–(1.2) or (1.3)–(1.5)].

In the case of nonlinear processes, there is no linear dependence between control variables and states (or manipulated variables), so that Eqs. (1.1)–(1.5) are no longer valid, and for predictions a much more general model must be used. Mathematically, a general nonlinear process model can be represented as follows:

- dynamic modeling equations:

$$\frac{dx}{dt} = f(x, u, q, d) \tag{1.6}$$

with the *initial conditions*:

$$x(t_0) = x_0 \tag{1.7}$$

- algebraic equations (equilibrium relationship, etc.)

$$0 = g_1(x, u, q) \tag{1.8}$$

- state-output relationship:

$$y = g_2(x) \tag{1.9}$$

where x are state variables, u are manipulated variables, q are parameters, d are measured and unmeasured disturbances, and y is the output (measured) variable.

In contrast to the case of a linear model, for nonlinear process model there is generally no analytical solution and the prediction must be made by numerically solving the model. Consequently, for nonlinear process models, computational demand is much higher than for the linear ones.

1.2.1.2 Multivariable Interactions between Manipulated and Controlled Variables

It is commonly believed that for SISO systems, well-tuned proportional, integral, derivative (PID) controllers work as well as model-based controllers, and that PID controllers are more robust to model errors. The offset-free constrained linear quadratic (LQ) controller for SISO systems, may be implemented in an efficient way so that the total controller execution time is similar to that of a PID [4].

Unfortunately, most multivariable systems have significant coupling between outputs and controls, and these pose great difficulties in control system design. In the case of multiple input-multiple output (MIMO) systems, any manipulated input can have effects on more outputs. Thus, the choice of appropriate control loops with the best control performances demands detailed study and can be very difficult. One of the main advantages of most advanced control strategies is that they can explicitly handle the multivariable interactions. Due to their multivariable nature, advanced control strategies – such as model predictive control techniques (MPC) – allow the control problem to be addressed globally. Thus, one must determine only the best set of manipulated inputs for a certain set of controlled outputs, and there is no need for detailed study of the individual interactions between the inputs and outputs. However, in the choice of the best control set, a study of the interaction problem for a certain MIMO system application is always useful.

1.2.1.3 Uncertain and Time-Varying Parameters

Most chemical processes are characterized by having uncertain and/or time-varying parameters. Time-varying parameters are common for batch and semibatch processes, when it is clear that most of the thermodynamic and physico-chemical properties of the system vary with time. Moreover, even for continuous processes when deviations from steady-state are frequent and the process variables vary in a wide operating range, the dependence of parameters on time should be taken into consideration.

For linear time-varying processes the state-space representation of the model [Eqs. (1.1)–(1.2)] is still valid, but in this case the elements of the state-space matrices A, B, C, and Γ are functions of time. The general model of nonlinear systems expressed by Eqs. (1.6)–(1.9), by its mathematical form takes explicitly into consideration the variation in time of the process parameters.

Among the multitude of parameters of a chemical process model, a significant number cannot normally be determined accurately, and this will lead to model/plant mismatch. The importance of uncertainties is increasingly being recognized by control theoreticians; consequently, they are being included explicitly in the formulation of control algorithms. MPC can handle model/plant mismatch in its closed loop, feedback form, by continuously adjusting the uncertain parameters so that the difference between the current measurements and the prediction from the previous step is a minimum.

1.2.1.4 Deadtime on Inputs and Measurements

One especially important class of systems in chemical process control is that of having time delays. This class of dynamic systems arises in a wide range of applications, including paper making, chemical reactors, or distillation. The principal difficulty with time delays in the control loop is the increased phase lag, which leads to unstable control system behavior at relatively low controller gains. This limits the amount of control action possible in the presence of time delays. In multivariable time-delay systems with multiple delays, these problems are even more complex. In these problems, the normal control difficulties due to loop interactions are complicated by the additional effect of time delays. Consequently, these aspects must be taken into consideration. The properly designed process model in its general nonlinear form expressed by Eqs. (1.6)–(1.9) explicitly involves time delays; however, to emphasize this feature in the literature one can often find the following general mathematical expression of the nonlinear model:

$$\frac{dx}{dt} = f(x(t-\Phi_x), u(t-\Theta), q, d) \tag{1.10}$$

$$x(t_0) = x_0 \tag{1.11}$$

$$0 = g_1(x, u, q) \tag{1.12}$$

$$y = g_2\left(x\left(t-\Phi_y\right)\right) \tag{1.13}$$

where Θ is the deadtime between manipulated and state variables, Φ_y is the deadtime between manipulated and output variables, and Φ_x is the deadtime on state variables.

From this model it can be seen that, in a very general form, deadtime can be included on process inputs and control variables as well as on unmeasured states.

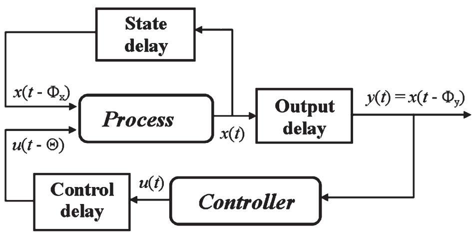

Figure 1.7 The structure of a controlled system having state, control and output delays.

For example, time-delay can be due to transport (flow through pipes) or measurement delays (analytical instrumentation, etc.). A good example of a multivariable time-delay nonlinear system with multiple delays is that of the distillation process.

A very general representation of systems having delays in the control variables $u(t)$, state variables $x(t)$ and output variables $y(t)$ is illustrated in Figure 1.7.

1.2.1.5 Constraints on Manipulated and State Variables

In chemical process control, constraints on state variables usually arise due to technological specifications, while those on manipulated variables are caused generally by the control hardware restrictions as well as the control system characteristics. For example, in systems with time delay in the control loop, the controller gain must be limited in order to avoid unstable behavior. In practice, the operating point of a plant that satisfies the overall economic goals of the process usually lies at the intersection of constraints. Therefore, in order to be successful, any control system must anticipate constraint violations and correct them in a systematic manner. Violations of the constraints must not be allowed while the operation is kept close to these constraints.

Constraints on manipulated and output/state variables can be expressed mathematically as follows:

$$y_{min} \leq y \leq y_{max} \tag{1.14}$$

$$u_{min} \leq u \leq u_{max} \tag{1.15}$$

$$|\Delta u| = \Delta u_{max} \tag{1.16}$$

where the limits of the state/output variables (y_{min}, y_{max}) and those of control inputs/manipulated variables (u_{min}, u_{max}, Δu_{max}) can be either constant or time-varying.

The usual practice in process control is to ignore the constraint issue at the design stage and then to “handle” it in an “ad hoc” way during the implementation. Therefore, these control structures are very system-specific, and their cost cannot be spread over a large number of applications, implying high design cost. Advanced control techniques usually provide intelligent methodologies to handle constraints in a systematic manner during the design and implementation of the control.

1.2.1.6 High-Order and Distributed Processes

On many occasions, the modeling of chemical processes leads to very high-order models. Although the general nonlinear model expressed by Eqs. (1.6)–(1.9) is a specific formulation for simple, low-order, lumped parameter systems which can be described by ordinary differential equations, this form can be also used for high-order and/or distributed parameter systems. Generally, in the case of high-order systems, an n^{th} order differential equation can be described by a system of n first-order differential equations by introducing $n-1$ fictitious state variables. For example, for a high-order system with one state variable, described by the n^{th} order differential equation below:

$$a_n \frac{d^n x}{dt^n} + a_{n-1} \frac{d^{n-1} x}{dt^{n-1}} + \ldots + a_1 \frac{dx}{dt} + a_0 x + b = 0 \tag{1.17}$$

is equivalent with the following system of n first-order differential equations:

$$\begin{aligned} \frac{dx}{dt} &= x_1 \\ \frac{dx_1}{dt} &= x_2 \\ &\vdots \\ \frac{dx_{n-1}}{dt} &= -\frac{a_{n-1}}{a_n} x_{n-1} - \ldots - \frac{a_1}{a_n} x_1 - \frac{a_0}{a_n} x - \frac{b}{a_n} \end{aligned} \tag{1.18}$$

where $x_1, \ldots, x_n - 1$ are fictitious states.

In this way, the general model described by Eqs. (1.6)–(1.9) can be extrapolated for high-order systems. However, for a MIMO system every high-order equation must be decomposed in a system of ordinary differential equations, and this – usually in the case of very high-order MIMO systems – can cause computational difficulties. For this reason, a model reduction is recommended in the case of high-order systems.

Distributed parameter systems are distinguished by the fact that the states, controls and outputs may depend on spatial position. Thus, the natural form of the system model is represented by partial differential equations or integral equations.

1.2.1.7 Unmeasured State Variables and Unmeasured and Frequent Disturbances

In most industrial processes, the total state vector can seldom be measured, and the number of outputs is much smaller than the number of states. In addition, the process measurements are often corrupted by significant experimental error, and the process itself is subject to random, unmodeled upsets. Both, unmeasured state variables and unmeasured disturbances can lead to a substantial model/plant mismatch, which appears as a reduction in quality control. However, each of these difficulties individually causes a very challenging control problem (according to most control specialists, the most important problem in MPC design): the consequences for both problems are differences between the predicted (y_p) and measured (y_m) outputs. Thus, the effects of the unmeasured disturbances can be included in the model error caused by the unmeasured state variables, and treated in the model/plant mismatch problem as a global, additive disturbance. Because unmeasured state variables and unmeasured disturbances manifest themselves in the quality of the predictions, which actually underlines the MPC strategies, the state estimation is an essential problem in practical NMPC applications.

1.2.2
Classification of the Advanced Process Control Techniques

The chemical process industry is characterized as having highly dynamic and unpredictable marketplace conditions. For example, during the course of the past 15 years we have witnessed an enormous variation in crude and product prices. The demands for chemical products also vary widely, imposing different production yields. It is generally accepted that the most effective means of generating the highest profit from plants, while responding to marketplace variations with minimal capital investment, is provided by integrating all aspects of automation of the decision-making process [6], which are:

- *Measurement*. The gathering and monitoring of process measurements via instrumentation.
- *Control*. The manipulation of process degrees of freedom for the satisfaction of operating criteria. This typically involves two layers of implementation: the single loop control which is performed via analogue controllers or rapid sampling digital controllers; and the overall control performed using real-time computers with relatively large CPU capabilities.
- *Optimization*. The manipulation of process degrees of freedom for the satisfaction of plant economic objectives. This is usually implemented at a rate such that the controlled plant is assumed to be at steady state. Therefore, the distinction between control and optimization is primarily a difference in implementation frequencies.
- *Logistics*. The allocation of raw materials and scheduling of operating plants for the maximization of profits and the achievement of the company's program.

Each of these automation layers plays a unique and complementary role in allowing a company to react rapidly to changes. Therefore, one layer cannot be effective without the others. In addition, the effectiveness of the whole approach is only possible when all manufacturing plants are integrated into the system.

Although, in the past, the maintenance of a stable operation for the process was the sole objective of control systems, this integration imposes more demanding requirements. In the process industries, control systems must satisfy one or more of the following practical performance criteria:

- *Economic*. These can be associated with either maintaining process variables at the targets dictated by the optimization phase, or dynamically minimizing an operating cost function.
- *Safety and environmental*. Some process variables must not violate specified bounds for reasons of personnel or equipment safety, or because of environmental regulations.
- *Equipment*. The control system must not drive the process outside the physical limitations of the equipment.
- *Product quality*. Consumer specifications on products must be satisfied.
- *Human preference*. There exist excessive levels of variable oscillations or jaggedness that the operator will not tolerate. There can also be preferred modes of operation.

In addition, the implementation of such integrated systems is forcing the processes to operate over an ever-wider range of conditions. As a result, we can state the control problem that any control system must solve as follows [5]:

> *"On-line update the manipulated variables to satisfy multiple, changing performance criteria in the face of changing plant characteristics."*

Today, the entire spectrum of process control methodologies in use is faced with the solution of this problem. The difference between these methodologies lies in the particular assumptions and compromises made in the mathematical formulation of performance criteria, and in the selection of a process representation. These are made primarily to simplify the mathematical problem so that its solution fits the existing hardware capabilities. The natural mathematical representation of many of these criteria is in the form of dynamic objective functions to be minimized and of dynamic inequality constraints. The usual mathematical representation for the process is a dynamic model with its associated uncertainties.

At present, there is an important number of advanced control techniques using either specific algorithms for particular systems, or very general methods with a wide application area and well-developed theory. A classification of these techniques is difficult because many of the algorithms are very similar, being obtained

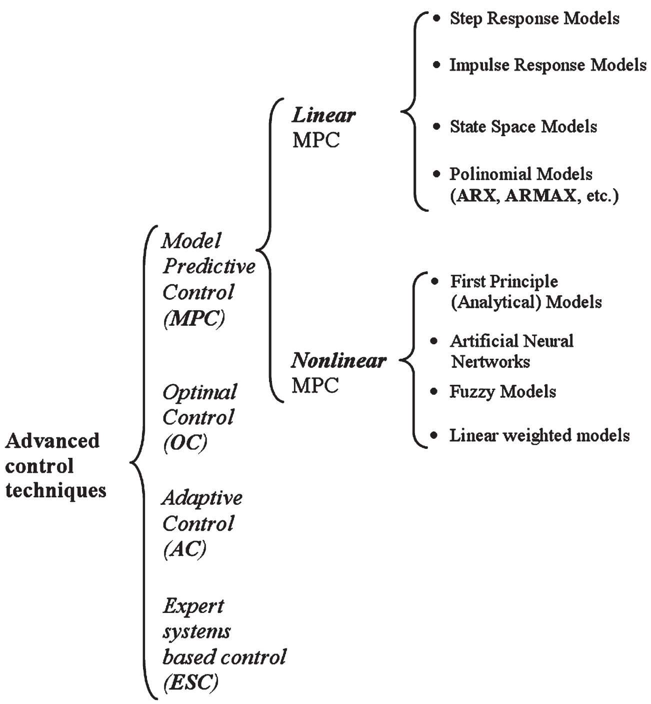

Figure 1.8 Classification of advanced control techniques.

from some more general methods with usually minor changes with regard to, for example, the performance criteria, optimization method, prediction horizon, and constraint handling. However, all of these algorithms have a common feature: all are based on a process model, described in different ways. The proposed classification, based on this feature, is presented in Figure 1.8. According to this, the advanced control techniques can be classified first in four conceptually different categories. The first and most important approach, the Model Predictive Control (MPC), can be classified further, for example, according to different model types used for prediction in the controller. This feature is usually the most significant difference among MPC algorithms.

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